

Decision Rule Induction: Relieving Complexity in Detecting Defection



Suhel Ahmad, Alpana Srivastava, Seema Sharma

Abstract Customer attrition has become a serious problem globally, particularly in telecom service, resulting into substantial revenue decline. Attrition may result in accumulation of dues as a result of payment defaults. Proactive identification of potential attrite will help in retention as well as minimizing loss of revenue. For attrition detection many robust but complex algorithms are used. Depending on the severity of error, the complexity can be lessened and thus cost. Two methods of decision rules (IR & C5.0) are used to predict the attrition and predictive accuracy is judged with confusion matrix. Comparison between models is made by sensitivity and specificity. It was found that IR has a sensitivity of .60 against .69 for C5.0 and hence, the performance is not significantly different. It is suggested that IR could be used instead of more complex algorithms and also it can be adopted for benchmarking.

Key words: Customer attrition; IR; C5.0; Churn; Decision rules; Defection

I. INTRODUCTION

India, the second most populous nation, harvests second largest mobile market in the world. Having reached to a wireless tele-density of 90.11% (TRAI, 2018), the market is reaching to its natural saturation. Acquiring new subscriber's base is relatively difficult now. Competition and price war is increasing day by day (Daskalaki, Kopanas, Goudara and Avouris, 2003). Entry of new service provider JIO, its market capturing techniques with heavily discounted tariffs and exit of small players all happened within one and half year in India. In subscription based services particularly in telecom, it is threatened that service providers can lose significant subscriber's base within a year if unchecked. Customer Attrition, occurs when subscribers move from one service provider to another in the hope of better services, attractive pricing or aggrieved from the services of the previous operator (Linoff and Berry, 2011). In telecom service attrition is quite common and it ranges from 10 to 67% (Hughes, 2008). Attrition costs millions of dollar to the service providers. In saturated market retention activity is an important aspect to remain in business. Retention requires understanding the requirements of every subscriber at individual level along with their usage behaviour. Personalized Customer Relationship Management can help in customized offering.

However, telecom companies with millions of subscribers lack in intelligent mechanisms to understand user behaviour at individual level. Analytics and data mining can help to overcome the problem. Loss due to insolvent customer's not paying dues results into uncollectable debts (Daskalaki, et al., 2003). Insolvency can be detected well in advance and can save a lot of money due to non-payments.

Business practices are evolving parallel to technology and innovation. Maintaining traditional one to one relationship has again found its place even for large business houses. Customer relationship management has reached new heights in the time of advanced data capturing, warehousing and data mining technologies (Rygielski, Wang and Yen, 2002; Linoff & Berry, 2011). In today's business world business strategies has shifted from dollar to datum. Thanks to data capturing and warehousing technologies. Now we have many different means of recording and storing information about our customers. Now days we have large amount of data but we lack in information. Well quoted by John Naisbitt (1984): "We are drowning in information but starved for knowledge."

The telecom service provider has a distinct advantage of having so much data about customer demography, call details, roaming behaviour, billing and usage pattern data; which if they were able to leverage using advanced analytics to develop insight into customer behavior, can overcome challenges (Daskalaki, et al., 2003).

Telecom industry across globe is under intense pressure. Factors, which drive attrition are- competition, VoIP services and porting norms. Voice over IP (VoIP) applications e.g. Skype, Netflix, Whatsapp and Viber are also causing great revenue loss to mobile operators. It is expected that mobile operators will suffer a loss of \$170 Billion globally with CAGR drop of 2.7% between 2012-2020 (Allen, 2013). Estimates give an indication that VoIP alone will cause a loss of 479 Billion during this period.

Churn management (or looking into its bright side – retention) in telecom industry is an important application of data mining and advanced analytics. Though Indian market is not yet completely saturated, where churn occurs more, due to other driving factors like price bearing ability, network quality, service quality, competitive offers and different demographic factors it occurs very frequently. New customers must replace lost customers. Acquiring new customers is costlier than retaining existing one, and in near future new customers do not generate as much revenue as the existing one. People switching for telecom services, probably must be having it from some other provider. Therefore, the main source of subscriber base is people leaving from a competitor. It costs more to acquire a new customer, and cost of acquisition per customer goes up as response rate declines.

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At some point, it makes sense to hold the existing customer at lower cost rather than letting them go and acquire new one to replace. Identifying customers who are at risk and target incentives will help to retention as well as save money would have been wasted in providing incentives to those who do not need it (Neslin, Gupta, Kamakura, LU, & Mason, 2006).

II. REVIEW OF LITERATURE

For telecom, churn simply means loss of whole or part of services to another MSP. Churners can be categorized into three types (Linoff and Berry, 2011). *Voluntary Churn* (customer will decide their own to choose another operator), *Involuntary Churn* (*Forced Attrition* arises when operator rather than subscriber decide to move) and *Expected Churn* (customer no longer in target market). Churners can also be classified as *Account Churn* (lost customer completely), *Product Churn* (lowered product profile) and *Decrease Spend*.

It costs five to ten times more to acquire a new customer than to retain an existing one (Athanasopoulos, 2000; Colgate and Danaher, 2000). With high cost of acquiring new prospects, it makes more sense to do business and earn profit with the existing customers by serving them better (Rygielski, et al., 2002). Customer retention through improved CRM is also helpful as long tenure customers are less sensitive to offers from competitor (Ganesh, Arnold, and Reynolds, 2000) and spread positive word of mouth. Dissatisfied customers however, do the other way and spread negative word of mouth (Colgate and Danaher, 2000; Ganesh, et al., 2000). Market shrinkage is resulting into customer focused business rather than product focused and performance matrix is changing from market share to wallet share (Rygielski, et al., 2002).

For churn management or customer retention, service provider need to identify the potential attrite and time to defect. Predictive accuracy, comprehensibility and justifiability are the three important aspects to any predictive model (Verbeke, Martens, Mues, and Baesens, 2011). In subscription based services early targeting using analytics can manage to double the profit (Burez and Poel, 2007). In competitive market with significant degree of saturation, customers are the most valuable asset for companies (Hadden, Tiwari, Roy, and Ruta, 2008). Organizations are now looking ways to more satisfy their customers in order to increase loyalty and thus prevent churn. Customer satisfaction and loyalty levels are suggested to be moderated by switching barriers (Aydin and Ozer, 2006). It has been argued that wireless carriers should build trust with their customers. Customers' dissatisfaction on pricing is found to be a major churn determinant in the service industry. Oyeniyi and Joachim (2008) have established a relationship that if appropriate retention measures are not taken, loyalty might be lost. In addition, they investigated many potential factors affecting retention like customer service, customer satisfaction and churn behavior and intention.

Method used matters in predictive accuracy and has staying power of at least three months (Neslin, et al., 2006). Further, they explained that logistic regression (Antipov and Pokryshevskaya, 2010) and decision trees (Hadden, et al., 2008) perform relatively better than other methods. Wang et al., (2009) proposed a recommender system for wireless companies and established that a decision tree model fits

well to understand and reduce attrition. Rule induction model such as C4.5 works well in instance based learning and classification modeling (Verbeke, et al., 2011). Boosting of model overshoot plain model and the accuracy goes up to 97% for decision trees and logistic regression (Vafeiadis, Diamantaras, Sarigiannidis, & Chatzisavvas, 2015). However, with decision tree predictive accuracy goes up (Hassouna, Ali, Elyas, and Trab, 2015). Chi-squared automated interaction detection CHAID and neural network has a particular dichotomy (Rygielski, Wang, and Yen, 2002). If predictor variables are mostly numerical, logistics regression qualify over decision trees. However, if categorical predictors dominate the data, decision trees outperform over logistics regression (Rygielski, Wang, and Yen, 2002). Fitting a general model for all records underperforms and leads to heterogeneous results. The heterogeneity can be lessened by grouping the records and fitting separate model for each group (Antipov and Pokryshevskaya, 2010). It can improve the predictive accuracy by up to 7%. Usage and billing comes first in priority order of variable importance followed by demographic variables in churn prediction models (Khan, Jamwal, and Sepehri, 2010). In their effort to predict churn in cellular phone discovered that Artificial Neural Network could identify churn with an accuracy of 92%.

In almost all efforts in detecting or predicting defection, researchers and industries tries to encompass every bit of information within the model which obviously results into a superior model (Keller, 2014) but in parallel it violates the principle of parsimony (Sober, 1981) which states that explanation should be kept simple.

Many sophisticated methods and algorithms have been proposed to model churn behaviour and classify the risk associated with attrition. However, in order to achieve marginal predictive accuracy sometimes we do a greater investment of time and economy. If the cost of error is not much higher, simpler methods can be tested as their fairly simple, economical without compromising much for accuracy. In this study, it has been tried to find usability of 1R method to classifying attrition compared against complex algorithm C5.0 (though relatively simpler as compared to other black box approaches like neural network and support vector machine).

III. THE STUDY DESIGN

C.50 and 1R algorithms are used to formulate decision rules over the data. Sampled data from mobile users has been modeled in strict accordance to CRISP-DM (Chapman, et al., 2000). Overall predictive accuracy of individual model (decision rule) is compared using confusion matrix. Specificity and sensitivity are used to visualize the predictive accuracy and usability of both models. All the analysis and data preparation is performed using R (R Core Team, 2018) statistical tool.

3.1 Data

Using structured questionnaire, data has been recorded from provinces of India. Altogether, the sample size includes 590 Records over 32 predictor variables and one outcome variable indicating whether the subscriber is will to stay or prone to leave the subscription (Appendix A). Using random sampling method,

districts and location within the district has been identified for the sampling purpose. The data comprises records from 73 locations of 14 districts. The sample is quite rich and varied in terms of its diversity. Records have been collected in such a way that it comprises respondents from almost every section of the society. Responses from different gender, occupation, educational and economic class have been well incorporated to make it rich and varied.

3.2 Data Preparation

Most of the variables in the data are categorical in nature. Regrouping of categories is performed to lessen the number of distinct categories within a variable. The data set containing 590 records has been partitioned into training and test data set. The training data set contains 492 records (83%) and test set contains 98 (17%). Test data set is used to adjust, validate the model and judge the predictive accuracy. Two numeric variables AGE and N_CALLS has been standardised using z-score standardisation. N_SMS, another numeric variable has been regrouped and converted into factor, as it has very low number of distinct values to be considered as interval actually.

IV. METHODOLOGY

C5.0: The algorithm is an improved version of C4.5 (Quinlan, 2014) which itself is an extension of Iterative Dichotomiser3 (ID3). Solutions to decision trees and rules are transparent in their interpretations. C5.0 algorithm produces somewhat bushy tree by splitting into as many branches as the distinct categories. It utilises the concept of entropy and information gain to measure the node homogeneity as:

$$Entropy(E) = \sum_{i=1}^c -P_i \log_2(P_i)$$

Where, P_i proportion of values falling into class level I and C = number of class levels. After each split, entropy is combined as $Entropy(E) = \sum_{i=1}^n w_i Entropy(P_i)$. Finally the information gain is obtained by:

$$Information\ Gain = Entropy(Before\ Split) - Entropy(After\ Split)$$

The algorithm chooses best split which maximises information gain and continues until pure node is obtained or no split is possible and full tree is grown.

1R: one step above ZeroR (a rule learner without a rule) considers only one most important variable for defining the classification rule (Holte, 1993). The algorithm classifies the data according to values of a single attribute and predicts the mode as classification result. It also utilizes the concept of entropy and information Gain. Although very simple, many times 1R outperform the other black-box complex algorithms.

Confusion Matrix: A matrix or tabular representation of classes predicted by model against actual class for the test data. It is used to evaluate the performance of classification model. The three measures used are:

Accuracy: Overall, how often is the classifier is correct?

$$= \frac{(TP+TN)}{Total\ Number\ of\ Obseavations\ in\ Training\ Data\ Set}$$

Sensitivity: when it actually yes, how often it predicts yes?

$$= \frac{TP}{TAP}$$

Specificity: When it's actually no, how often does it predict no?

$$= \frac{TN}{TAN}$$

Here,

TP = True Positive

TN = True Negative

TAP = Total actual Positive

TAN = Total Actual Negative

Data Analysis and Modelling

Five different models are generated using same test data and their performance is evaluated using the same test data set. The results are summarized in table 1 and the explanations are:

- Initially using C5.0 function under C50 package (Kuhn and Quinlan, 2017), a model is built which shows 86.78 per cent predictive accuracy on training data set. However, the accuracy is dropped to 62.25% with test records, which is common in data mining tasks.
- In the second model trials are increased from 1 to 3 to make more than one model and then voting of model determines the prediction class. Trials were checked from 3 to 20, but best performance was achieved in the case of three trials. The model surprisingly gives 99.59% accuracy on training data set but unfortunately its accuracy dropped to 66.32%. However, it is better than our first model.
- The third model was built using cost assigned to each type of error to check the model performance and incline it to less serious mistake and avoiding otherwise. Here in case of attrition, a false negative is more serious and hence has been assigned a cost of 2. The overall performance of model is found to be only 54.08% which is least in all instances, but it takes care of the mistakes and hence reports true negative to 97.36% which is highest in all model incidences.
- The fourth model, ZeroR, a decision rule without a rule considers the mode class to project as our predicted class. This model is actually not a model in itself, but it serves as a bench mark for judging the usability of other models. Here, in this case the ZeroR model predicts that no attrition (churn) will happen with a predictive accuracy of 57.14% on our test data set.
- Our fifth, the final model 1R is constructed using 1R function available under RWeka (Hornik, Buchta and Zeileis, 2009) package. N_CALLS_Z (normalized values of number of calls) was selected by the algorithm as the single predictor to form the decision rules and this predictor is able to classify the records with an overall precision of 62.24 which is not bad as compared to other models.

Table 1: Sensitivity and Specificity of five different models

S. No.	Model	Predictive Accuracy (%)		Sensitivity		Specificity	
		Training	Test	Training	Test	Training	Test
1	C5.0 (Single Iteration)	86.78	62.25	.89	.48	.85	.73
2	C5.0 (3 Iterations)	99.59	66.32	.90	.50	.95	.75
3	C5.0 (With error cost)	65.59	54.08	.97	.69	.63	.43
4	ZeroR	53.86	57.14	0	0	1	1
5	1R	64.21	62.24	.52	.60	.73	.64

V. CONCLUSION AND FURTHER RESEARCH

Among the five models using C5.0 and 1R algorithms, C5.0 with three iterations (trials) gives best overall predictive accuracy (66.32%) followed by 1R (62.24%). However, the seriousness of error lies towards true positive rate of prediction, and thus sensitivity index is to be considered with more concern and high value is preferred. C5.0 with cost assigned to errors results in highest sensitivity (.69) followed by 1R (.60). The gain using 32 variables and a complex algorithm seems marginal with C5.0. The predictive accuracy of 1R is not significantly different than C5.0. Thus, 1R can be our alternate method for classification purpose, particularly if sample size is small or cost of classification is high with complex algorithms. Also, apart from ZeroR as primary benchmark, 1R can also be used to set up a secondary benchmark for complex analysis and reporting. The only limitation with the study was its sample size and in future research a big sample particularly real-time data from service provider might give better results to strengthen the idea.

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Appendix A
(Variable Definition)

S.No.	Attribute	Description
1	NET_AREA	Division; UP EAST, UP WEST
2	LOC_TYPE	RURAL or URBAN
3	GENDER	MALE or FEMALE
4	EDUCATION	Level of education; Illiterate to Post Graduate
5	OCCUPATION	Unemployed, Student, Government, private, farmer, labour
6	MARITALS	Unmarried, Married, Married but Single living
7	INC_PM	Income Level
8	USER_TYPE	How long the user has been using Mobile Phone
9	MOB_TYPE	Normal, 2G, 3G, 4G
10	MSP1	Service provider for primary connection
11	CON_TYPE	Prepaid, Post-paid
12	PRV_CHURN	Previous history of attrition; Yes, No
13	AVMONEXP	Average monthly expenditure on Mobile Phone
14	CON_OLD	Service length of current subscription
15	CALL_CCS	Number of calls made to Customer Care Service
16	KNOW_CCS	Whether customer knows about CCS
17	INT_MOB	Whether use internet on mobile or not
18	INT_USE_PM	Amount (in GB) used per month
19	N_CALLS	Daily Average number of Calls
20	AV_CALL_DUR	Average Duration of Calls
21	MNP	Whether Subscriber Knows about MNP; YES, NO
22	NET_STR	NETWORK STRENGTH; POOR, AVERAGE, GOOD
23	NET_COV	NETWORK Coverage; POOR, AVERAGE, GOOD
24	TARIFF	Tariff Cost; POOR, AVERAGE, GOOD
25	ROAM	Roaming ; POOR, AVERAGE, GOOD
26	VQUALITY	Voice Quality; POOR, AVERAGE, GOOD
27	CDROP	Call Drop; POOR, AVERAGE, GOOD
28	INTBPACK	Internet Bundled Packs; POOR, AVERAGE, GOOD
29	PRO_CALL_SMS	Promotional Contacts; POOR, AVERAGE, GOOD
30	AGE	Age of the respondent
31	DUAL.CON	Whether customer uses dual SIM
32	FUT_CHURN	Whether willing to switch or will stay

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AUTHORS PROFILE



Suhel Ahmad is a research scholar at Amity University Uttar Pradesh, Lucknow Campus. He is a science graduate from University of Allahabad and Post Graduate in Management (MBA). His Ph.D. thesis involves study of customer attrition in wireless telecommunication in India and device a preventive mechanism through predictive modeling and analytics. His research interests include data analysis, modeling, data mining and machine learning. Recent interest includes text mining, sentiment analysis and social media mining. Currently he is working as visiting faculty at Babasaheb Bhimrao Ambedkar University, Lucknow and he is actively involved in teaching statistics, business analytics and operations research at graduation and post-graduation level. He has published 2 Scopus listed papers and presented 5 research articles in national and international conferences.



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