IJAPIE-2016-10-407, Vol 1(4), 45-54

INTERNATIONAL JOURNAL OF ADVANCED PRODUCTION AND INDUSTRIAL ENGINEERING

(A Blind Peer Reviewed Journal)

Customer Base Analytics to improve CLV for Telecom industry using clustering techniques and Decision Tree

Shivali Vij[1] , Smridhi Gupta[2], R. Srivastava[3]

(Mathematics Department, Delhi Technological University, Delhi, India,)

Email: vijshivali@gmail.com , gupta.smridhi@gmail.com

Abstract : *We view marketing as an investment, and not as an expense. This paper outlines a general methodology to segment customers according to purchase pattern , data from customer services records and behavioral features . We have addressed the problem using clustering algorithms and decision trees, and suggested not only customer segments, but how much marketing investment must be made per segment and expected return. Applying our method to telecom industry, We have applied concept of CLV to maximize customer equity, and gave suggestions of kind of offerings to be made per segment, tailored to turn the customer into a more profitable one. We also suggested limits on the amount that can be spent on different customers to reap long term returns. Instead of averaging CLV for a segment, we employed summation of individual CLVs incorporating their segment, which hasn't been done before. Our findings can be molded according to other non contractual settings, and provide marketing managers insights on their customer base.*

Keywords: *Marketing, Customer base segmentation, CLV, K-means Clustering, Decision Tree, churn analysis, retention*

I. INTRODUCTION

INTRODUCTION

Many companies have now come to the conclusion that understanding of their customers and purchase behavior is valuable and important. A non-contractual setting suffers from the problem that customers have the opportunity to continuously change their purchase behavior without informing the company about it. More specifically,In the telecommunication industry, customers are allowed to choose amongst various service providers and actively exercise their rights of switching from one service provider to another. In this competitive market, customers demand customized products and better services at low prices, while service providers constantly focus on new customer acquisitions as their business goals. Given the fact that the telecommunications industry experiences an average of 30-35 percent annual churn rate and it costs 5-10 times more to recruit 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 pain. Many telecommunications companies deploy retention strategies in synchronizing programs and processes to keep customers longer by providing them with tailored products and services. With retention strategies in place, many companies start to include churn reduction as one of their business goals. Churn analysis typically tries to define predictors of customer defection. Efforts do not need to be made for the entire customer base. Some customers are not worth the effort to develop a long-term relationship, since their net contribution to profits is negative. These customers do not bring in the minimum required business but demand high quality customer services which leads to core costs to the company. Strategies should be in line with the relationship potential of each customer individually. It is a well-known phenomenon that a small percentage of customers accounts for a large percentage of profits .Moreover, a significant part of the customer base is even not profitable. This project uses K-means clustering to identify loyal customers(no investment on CRM), potential customers (further analyzed using decision trees) and customers that give very low or negligible returns. The project has then used the concept of decision tress to figure out the strategies that need to be employed to increase the CLV of all customer segments in terms of Churn , Retain , promote and up sell.

LITERATURE REVIEW

According to the literature, investing in customer retention is often more efficient than acquiring new customers. Hence, a considerable amount of research has addressed factors and strategies to retain customers. Several papers emphasize that it may not be profitable to retain every customer. Customers are not profitable if the costs generated to serve them exceed revenues in the long term, Rather, the relationship between costs and value must be taken into consideration. Thus, firms should consider reducing services for the less or no profitable customers or even terminate the relationship entirely.Another strategy consists of increasing a customer ' s value for the firm by converting him / her into a member of a higher profitability segment. This tactic, again, can be achieved if the main value drivers are known to the company. Thus, valuation of customers and knowledge of customer features and behavior that allow prediction of a customer ' s value segment are indispensable for optimizing marketing investments. K means clustering is the clustering technique which has been used to segment customers, which is a very suitable technique for a large number of variables, K-Means is computationally fast; also produces tighter clusters. Preliminary analysis has been done to find factor strength and redundancy before applying K means.

We obtain satisfying results in predicting customer's offer reactance using decision trees , which have some important advantages over other methods, including high flexibility and ability to handle categorical variables. Its very important to classify customers according to their attributes and thus implement profit maximizing marketing strategies. In order to ascertain that sufficient marketing efforts are focused on the most profitable customers, it is crucial for marketing divisions to evaluate the customer lifetime value. One measure used by several researchers in recent years to express long run customer profitability is Customer lifetime value is mostly defined as the sum of the discounted net cash flows generated by a customer during his / her relationship with the company. Lifetime value is a key method of determining the value of a telecom subscriber, and of evaluating the strategies used to market to these subscribers. Customer Lifetime Value is the net present value of customers calculated profit over a certain number of months. Lifetime value can be used in the development of marketing strategy and tactics. Customer lifetime value is a powerful and straightforward measure that synthesizes customer profitability and churn (attrition) risk at individual customer level. For existing customers, customer lifetime value can help companies develop customer loyalty and treatment strategies to maximize customer value. For newly acquired customers, customer lifetime value can help companies develop strategies to grow the right customers. The calculation of customer lifetime value varies across industries. In the telecommunications industry customer average usage and up gradation of plans (data, SMS) are the two major components to calculate the customer lifetime value.

Too often, however, because of data availability and complexity constraints, models only predict the average customer lifetime value at an aggregate level for the whole customer base value without taking into consideration characteristics of the single customer. This limitation is a serious drawback, since profitability is usually not distributed uniformly among customers 10 and a primary objective of the lifetime value approach is to identify highly profitable customers in order to keep existing ones and attract others. 11 Equally, some customers may be nonprofit able for the company because the costs to serve them are too high or because they cannot be reached by marketing actions, leading to a negative return on investment. Obviously, investments in these customers should be avoided.

III. METHODOLOGY

1. Data collection for 10407 customers
2. We employed decision tree on testing data which comprised of 440 entries. Results from decision trees were matched against testing data and found that one feature was particularly misleading.
3. Feature engineering was done to identify the important features for further analysis . Previously found misleading feature was modified and new features were created. Features were created on ideas like RFM (Regency, Frequency and monetary), customer ratings on basis of service centers and from data mined about switching behavior, as well as liability on company if customer exploits the services by blocking the servers.
4. Cluster analysis was done using K-means Clustering and three clusters were formed of loyal customers(no investment on CRM), potential customers (further analyzed using decision trees) and customers that give very low or negligible returns ("Let go" group). This segmentation was based on CLV values.
5. The potential customer data was further fed into decision tree and further classified into four categories – Churn , Retain, promote and up sell . Different marketing strategies are applied to different category of customer.
6. Customer lifetime value is compared for all individual categories of customers as well as that of the raw data

IV. TELECOM DATA VARIABLE EXPLANATION

We had the telecom data of 10407 customers with the following attributes.

Customer Information

- Customer Id : unique identifier for customers
- Age
- Customer_class: Customers were assigned four classes namely 1-VIP,2-Corporate,3-Household,4-Low profit.

Usage data

- Average recharge amount per month in last 3 months
- Average recharge amount per month in last 6 months
- Average recharge amount per month in last 9 months
- Average recharge amount per month in last year
- Overdue account: The amount unpaid by the user.
- Number of Incoming calls in last 3 months
- Number of Incoming calls in last 6 months
- Number of Incoming calls in last 9 months
- Number of Incoming calls in last 12 months
- Number of outgoing calls in last 3 months
- Number of outgoing calls in last 6 months
- Number of outgoing calls in last 9 months
- Number of outgoing calls in last 12 months

- Number of days since last transaction : The number of days that have passed after the user last recharged their phone.

Upgraded Services Usage data

- Months of net plan activation : The number of months for which the net plan of user has been active .
- Months of SMS plan activation : The number of months for which the SMS plan of user has been active .

Offer Reactance
- Previous offers given: The number of discount offers previously given to the user.
- Adopted offers? : The number of discount offers accepted by the user.

Data from Customer Service
- Sub_Plan-Change_Flag: TRUE if the users has changed its original plan.
- ID_Change_Flag: Customers who often change their account information may churn. If this flag is set to 1 they will churn.
- Black_List_Count - Customers who have been black listed for more than 2 times in the past six months are about to churn.
- Tele_Change_Flag – Customers who often change their phone numbers shows their dissatisfaction with the operator's service. If this count is > 2 those are probable to churn.
- Pay_Metd_Change – Customers shows their dissatisfaction by changing their payment method often. If this count > 3 they may quit the service.

VI. FEATURE ENGINEERING

Due to the nature of the data, such as one customer having distinct relstionship in terms of transaction and usage , it is necessary to merge the transactions of each customer into a row and engineer new features in order to segment customers in different categories.Upon considering the importance of the time proximity from the offer date, the ratio of amount spent between 3,6,9,12 are also included as features. A feature called Profit score was also added for convenience in order to segment customer into four categories:If the ratio of profits kept on increasing then they were put in the category-increasing; if the ratio of profits first increased and then decreased the customers were put in the category-unsatisfied; if the ratio of profits first decreased and then increased the customers were put in the category- might have received offer; if the ratio of profits kept on decreasing the customers were put in the category- churn.

The collated list of features engineered is as follows:

1. Are profits increasing 3 vs 6 ? :Ratio of profits for 3 to 6 months were calculated.
2. Are profits increasing 6 vs 9 ? :Ratio of profits for 6 to 9 months were calculated.
3. Are profits incresing 9 vs 12 ? :Ratio of profits for 9 to 12 months were calculated.
4. Liability(outcoming-incoming) : Liability was calculated for all monthly intervals i.e. 3,6,9 & 12.
5. Mean Liability: Mean of all monthly liabilities was taken.
6. Profit score: Customer were segmented into might have received offer, increasing, unsatisfied or churn on the basis of ratio of profits for different months.
7. Maximum inactive time: The maximum time for which the user didn't use the internet or the SMS plan was calculated by subtracting the active months from line tenure.
8. Upgraded plan : If the customer has been inactive for more than half of its line tenure then it was given a negative weight, if it has been active since a quarter of its line tenure, then it has been given a positive weight.
9. Potential future loss : It has been calculated as the sum of overdue cost and all negative factors into a weight of -50.
10. Offer adaptability : It is a product of previous offers given into offer accepted.

VII. TECHNIQUES USED AND ANALYSIS

A) Decision Trees

Decision trees have become very popular for solving classification tasks because they can deal with predictors measured at different measurement levels (including nominal variables) and because of their ease of use and interpretability.

A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.

A 1.1) Initial Analysis on Training data

On the training data of 440 customers, we did basic central tendency analysis(Table 1) for the average amount earned per customer in one year .

Table 1

Count	441
Mean	166.95
Median	156

We studied the data , and started the preliminary analysis. We used growing method CHAID for our decision tree using given Profit score as dependant variable, we used independent variables as Mean Liability value, Upgraded plans, Potential future loss, offer adaptability, Age, Line_Tenure (months), Customer_Class.

A 1.2)Result of initial analysis

Our initial classifier is heavily skewed towards the values that are higher in number. We see that it simply classified all values in "unsatisfied" range in our decision tree (Figure 1), without checking other factors into account. Accuracy of 89.2 % is misleading, since that's exactly how much the data was initially spread (Table 2).

.

Table 1

Classification

Observed	Predicted				
	churn	increasing	might have received offers	unsatisfied	Percent Correct
churn	0	0	0	8	0.0%
increasing	0	0	0	17	0.0%
might have received offers	0	0	0	11	0.0%
unsatisfied	0	0	0	297	100.0%
Overall Percentage	0.0%	0.0%	0.0%	100.0%	89.2%

Growing Method: CHAID
Dependent Variable: Profit score

A1.3) Reapplying Feature engineering

Profit score : Previously profit score gave us skewed results so w suggest a modified version called updated Profit score which was calculated by multiplying the ratio for all monthly profits.

We created another feature called group which segmented customers into loyal, potential and let go in order on the basis of their line_tenure and overall performance as a customer.

A1.4)Re-segmenting using decision tree and newly made factor to check its correctness

We used the CHAID growing method again for our decision tree (figure 2) , this time we took newly created feature 'Group' as dependent variable.

We identify the importance of factors like Mean liability value and its cutoff value of 24.5 based on chi square estimates. Line tenure , with a cutoff of 15 months also serves as a good estimates, i.e if a customer has been with us for 1 year and 3 months, we expect them to yield a good CLV.

From the tree table, we come up with an initial decision algorithm as:

- 10% of the customers can be let go only on the basis of mean liability of -34.5 or less, i.e these customers are using a lot of free services and putting a stress on our servers but not recharging their plans or upgrading
- Another segment of customers with high overdue account (owns more than 200 on average) can be let go, these account for 3.6% of our users
- On basis of validation table, we observe 9.1 % of customers being directly classified into loyal on the sole basis of their accounts always being paid on time, or just up to 100 unpaid
- Rest customers have been classified as potential

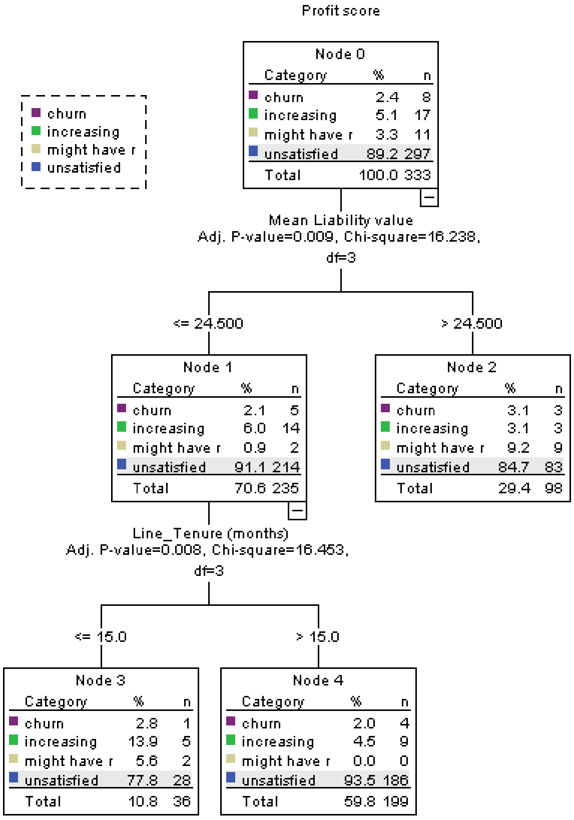


Figure 1

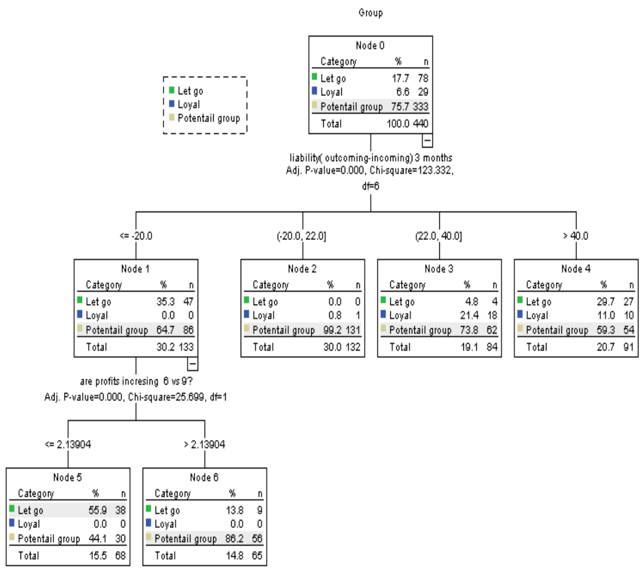


Figure 2

The classification gives an accuracy of 66.9% just by brute force, but we do not expect an improvement in CLV. This analysis pinpointed the important features and some cutoff ranges

A) K- Means Clustering

Clustering is the classification of objects into different groups, or more precisely, the partitioning of a data set into subsets (clusters), so that the data in each subset (ideally) share some common trait - often according to some defined distance measure

If k is given, the K-means algorithm can be executed in the following steps(Figure 3):

- Partition of objects into k non-empty subsets
- Identifying the cluster centroids (mean point) of the current partition.
- Assigning each point to a specific cluster
- Compute the distances from each point and allot points to the cluster where the distance from the centroid is minimum.
- After re-allotting the points, find the centroid of the new cluster formed.

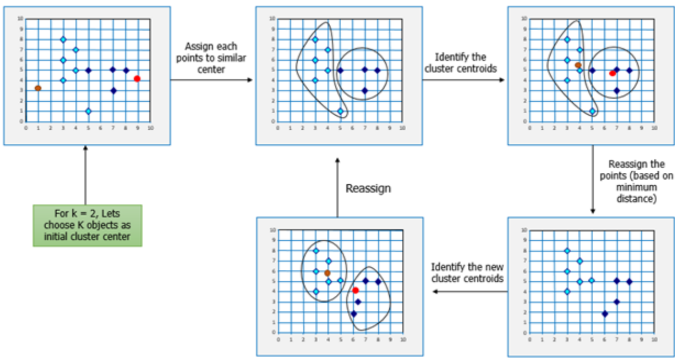


Figure 3

In the existing business literature, right customers and wrong customers have been defined and characterized differently by a number of researchers and practitioners. For example, Reichheld and Teal (1996) define right customers as "customers who will provide steady cash flows and a profitable return on the firm's investment for years to come, customers whose loyalty can be won and kept" .First, right customers are inherently predictable and loyal, preferring a stable and long-term relationship. Second, right customers are more profitable than others. In other words, they spend more money, pay their bills more promptly, and require less service. Lastly,right customers will find a company's products and services more valuable than those of its competitors.

However, there is evidence to suggest that right customers may not remain loyal, not because of their dissatisfaction, but because of a higher performing, more innovative and competitive offer in the marketplace (Fredericks and Salter, 1998; Keaveney, 1995). Therefore, companies should carefully categorize their right customers into those more likely to switch and those less likely, and formulate appropriate strategies to retain them. Right customers should be more satisfied than wrong customers, though there may be satisfied customers who are problematic and Retaining and divesting customers unprofitable (e.g. satisfied switchers), or dissatisfied customers who are loyal and profitable (e.g. dissatisfied stayers).Having synthesized the different definitions and characteristics of right and wrong customers, customers should be segmented and dealt with according to different levels and configurations of customer behavior. Therefore, this paper uses K-means clustering to cluster the customers into loyal, potential and let go group (table 3).

Table 2

Number of Cases in each Cluster

	1	3760.000
Cluster	2	1127.000
	3	5520.000
Valid		10407.000
Missing		.000

Cluster 1 represents **loyal customers (36% ;** figure 4) ,cluster 3 represents **potential customers (53%)**, cluster 2 has been labeled as the **let go (11%)** group and has been discarded as these have net negative CLV**.**

Cluster 3 gets reduced expenditure in customer service calls and no efforts are made to retain them unless they elevate their usage enough to make it to potential customers list

For cluster 2: We do further analysis and suggest profitable marketing strategies according to the customer behavior.

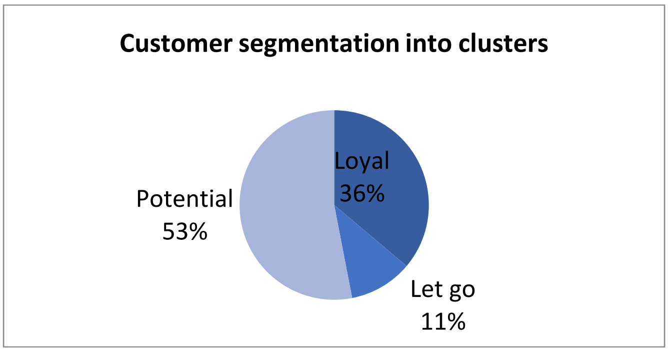


Figure 4

B) Analysis of loyal customer base

Table 3

Loyal Customers	3760
Previous offers given	2349
Adopted offers	1651

Table 4 clearly shows that out of the 3760 loyal customers only 43% customers adopted the discount offers that were given to them, this implies that the company doesn't need to spend on marketing by giving discounts to this particular group but the company should provide them hassle free services and retain their loyalty. Future offers can be provided to that section of loyal group that hasn't received any offer yet.

C) Application of Decision Trees for further segmentation of potential customers

The customers in the potential group were now segmented into 4 categories :

1. CHURN

The profitable customers that may churn , which means retaining them is profitable and urgent

2. RETENTION

These customers do not immediately respond to the discounts and offer but expected future value is very high.

3. PROMOTION

These customers are the highest revenue makers so they get offers only on high end products . Any marketing effort of them is though up selling and cross selling.

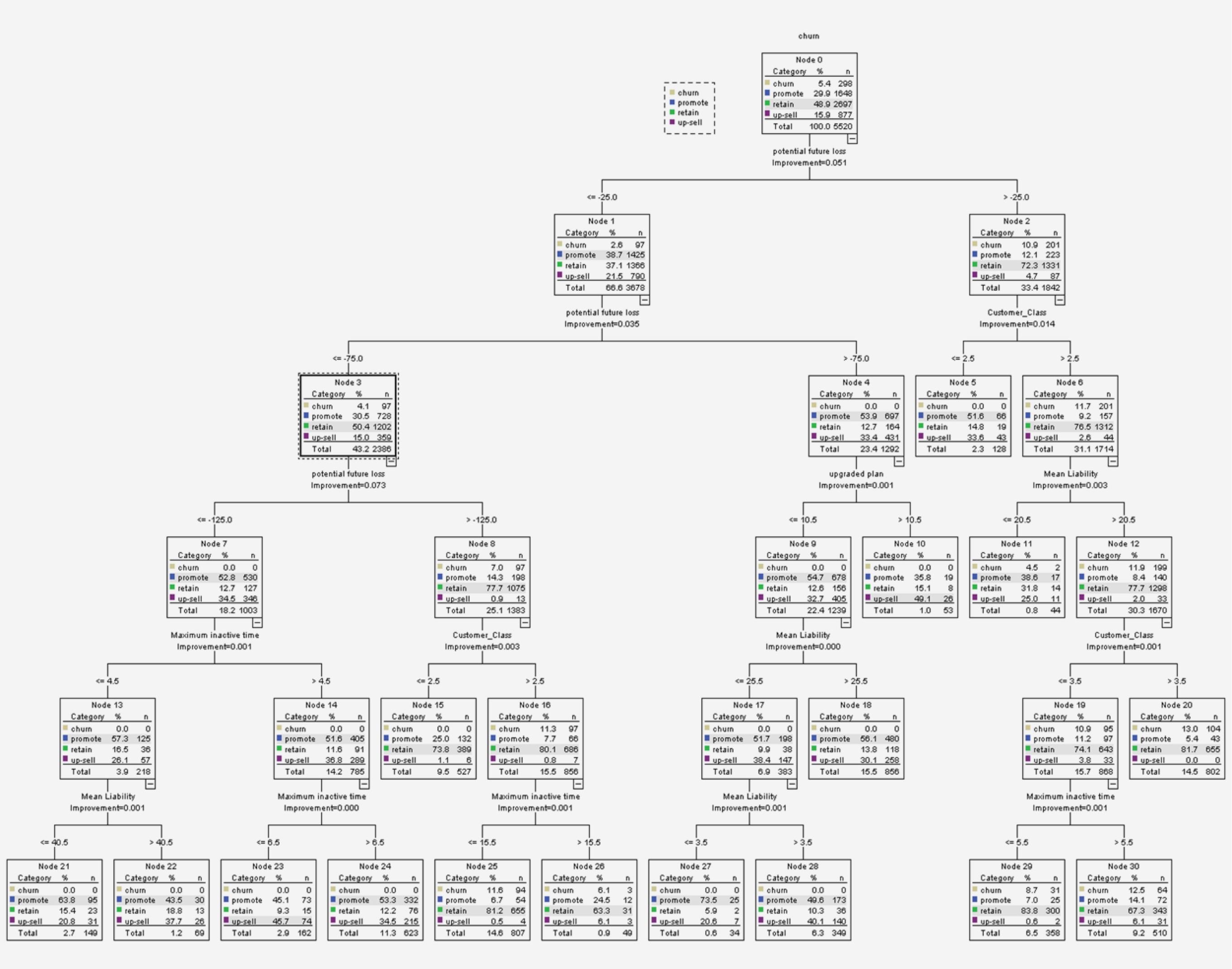
4. UP -SELLING

Best potential group to whom we will try and sell more expensive products through specialized marketing. This group can be upgraded and made to spend more without offering any major discounts.

Growing method CRT was used instead of CHAID on the variable churn to predict the category of customer amongst return , promote , upsell or churn.

Classification and regression trees are machine-learning methods for constructing prediction models from data. The models are obtained by recursively partitioning the data space and fitting a simple prediction model within each partition. As a result, the partitioning can be represented graphically as a decision tree. Classification trees are designed for dependent variables that take a finite number of unordered values, with prediction error measured in terms of misclassification cost. Regression trees are for dependent variables that take continuous or ordered discrete values, with prediction error typically measured by the squared difference between the observed and predicted values.CART tree suited our inputs and gave us better results as compared to CHAID because of the following:

1. In order to avoid over-fitting the data, both methods try to limit the size of the resulting tree. CHAID (and variants of CHAID) achieve this by using a statistical stopping rule that discontinuous tree growth. In contrast, CART first grow the full tree and then prune it back. The tree pruning is done by examining the performance of the tree on a holdout dataset, and comparing it to the performance on the training set. The tree is pruned until the performance is similar on both datasets (thereby indicating that there is no over-fitting of the training set). This highlights another difference between the methods: CHAID use a single dataset to arrive at the final tree, whereas CART uses a training set to build the tree and a holdout set to prune it. **Therefore we employed CART so that we could compare the results of the training data set and come to correct results.**
2. CART splitting rule allows only binary splits (e.g., "if Income<$50K then X, else Y"), whereas CHAID allow multiple splits. In the latter, trees sometimes look more like bushes.At each split, CHAID algorithm looks for the predictor variable that if split, most "explains" the category response variable. In order to decide whether to create a particular split based on this variable, the CHAID algorithm tests a hypothesis regarding dependence between the splitted variable and the categorical response(using the chi-squared test for independence). Using a pre-specified significance level, if the test shows that the splitted variable and the response are independent, the algorithm stops the tree growth. Otherwise the split is created, and the next best split is searched. In contrast, the CART algorithm decides on a split based on the amount of homogeneity within class that is achieved by the split. And later on, the split is reconsidered based on considerations of over-fitting. **It appeared to us CHAID is most useful for *analysis*, whereas CART is more suitable for *prediction***. In other words, CHAID should be used when the goal is to describe or understand the relationship between a response variable and a set of explanatory variables, whereas CART is better suited for creating a model that has high prediction accuracy of new cases. Therefore, we used a combination of both the trees to segment our customers and compare their lifetime values.



D1.1) Results of Decision Tree

- People with customer class 1 and 2 are put in promote section when their potential future loss is -25 or low (node 5).

- Customer class 3 and above members are also classified as promote if their mean liability on company is <20 i.e. they use more of paid service than free services. (node 11)
- People with customer class 1 and 2 with potential future loss between -75 to -125 are put in retain section and spending on them is cut.(node 15)
- Customers with loss of -25 to -75 are classified as up sell if they buy a lot of upgraded plans on SMS and net i.e the expected loss from them in case they falter can be made up by selling them services with more profit margin. (node 10). Cutoff of 10.5 in upgraded plans tenure decides this. If this criteria is not fulfilled but the customer has with condition of no liability (positive value) indicative of no stress on servers, then also this segment is given "upsell" offers (node 18)
- If customer class is 3 and above, with condition of no liability (positive value) with worse potential loss as 25, these are classified as retain (Node 20)
- Retaining efforts are also made for customers with inactive time <15.5 months. Others can be put in churn category. (Node 25)
- Node 29 and 30 are redundant because of decision trees shortcoming of changing fixed values to continuous, hence a division of 2.5 is made on customer class, expecting the split to have customers non existing customer class

Using these splits and critical conditions given by our division tree, we do CLV calculation on individuals per segment.

Table 4

Category	Marketing Strategy	Attributes included to calculate earnings	Attributes included to calculate expenses	Future earnings	Future expenses

Churn	We give them a small incentive (same as previous) to stay and assume that we retain only 30% of customers in the future	1.calls 2. net pack 3.SMS packs	1.overdue charges . 2. fix cost of 10 per head for offering promotion 3.loss of 25 per head if promotion offer is accepted by user . 4.liability on company for server charges if the user takes more incoming calls rather than spending on outgoing calls. 5.Potential future loss to company if the customer threats to switch, complains he is unsatisfied with service, is blacklisted often or requests to change information often.	assuming only 30 % of this group is retained, it is calculated as 0.3 into present earnings and discounted by risk free interest for this time period.	assuming only 30 % of this group is retained, it is calculated as 0.3 into present expenses and discounted by risk free interest for this time period.
Retain	We provide them good discounts in the present on the products they use, which increases probability of stay. Here, for CLV calculation, we assume an overhead charge of 50 per customer, which will lead to retention of 60% customers in future.	1.calls 2. net pack 3. SMS packs	1.overdue charges 2.fix cost of 10 per head for offering promotion . 3.loss of 25 per head if promotion offer is accepted by user . 4. liability on company for server charges if the user takes more incoming calls rather than spending on outgoing calls . 5.Potential future loss to company if the customer threats to switch, complains he is unsatisfied with service, is blacklisted often or requests to change information often.	assuming only 60 % of this group is retained, it is calculated as 0.6 into present earnings and discounted by risk free interest for this time period.	assuming only 60 % of this group is retained, it is calculated as 0.6 into present expenses and discounted by risk free interest for this time period.
Promotion	We take a small hit on net value of up selling products by offering such services on discount to make them regulars users of expensive products. We update the offer limit to 20 per user and discount limit to 50 per user in this case, hoping the future profits will increase by a mere 10% and add the assumption of retaining70% of this group due to our investment in them.	1.calls 2. net pack 3. SMS packs	1.overdue charges 2.fix cost of 25 per head for offering promotion 3.loss of 50 per head if promotion offer is accepted by user 4. liability on company for server charges if the user takes more incoming calls rather than spending on outgoing calls 5.Potential future loss to company if the customer threats to switch, complains he is unsatisfied with service, is blacklisted often or requests to change information often	assuming that our promotions increase the current sales by mere 10%, and that only 70 % of this group is retained, it is calculated as 0.7 * 1.1 * present earnings and discounted by risk free interest for this time period	assuming only 70 % of this group is retained, it is calculated as 0.7 into present expenses and discounted by risk free interest for this time period

Upsell	We update the offer limit to 20 per user and discount limit to 50 per user in this case, but only on upgrades . Such offers will lead to rise in future profits will increase by a around 30% and add the assumption of retaining 90% of this group due to our investment in them	1.calls 2. net pack 3. SMS packs	1.overdue charges 2. fix cost of 25 per head for offering promotion 3.loss of 50 per head if promotion offer is accepted by user 4. liability on company for server charges if the user takes more incoming calls rather than spending on outgoing calls 5.Potential future loss to company if the customer threats to switch, complains he is unsatisfied with service, is blacklisted often or requests to change information often	assuming that our promotions increase the current sales by 30%, and that 90% of this group is retained because of tailored offers, it is calculated as 0.9 * 1.3 * present earnings and discounted by risk free interest for this time period	assuming only 90 % of this group is retained, it is calculated as 0.9 into present expenses and discounted by risk free interest for this time period

For a total of 10480 customers, we tried to calculate earnings and expenses

Initial	Value
Earnings	2950822
Expense	-2252292
Future earnings	1327870
Future expenses	-1013531
CLV	1012869
CLV per head	97.3

We find that the with a initial allocation of resources, the CLV is 1012869 and CLV per head was a mere 97.3

Calculating the improved CLV using segmentation techniques and employing CRM:

The Customer life time value was calculated per group and was obtained as follows:

Group	CLV	CLV per head
Churn	161536.8	540.25
Retain	1112642	687.3255
Promote	420200.1	364.0302
Upsell	199928.8	253.0104

The total CLV of potential group is calculated as 1894307.7

Also, CLV per head shows that on an average, through our resource allocation, we are maximizing CLV of our potentail group, with special focus **to increase current earnings from churn and retain segment and future earnings from Promote and Up-sell segment.**

Total CLV after segmentation :

Loyal group	1043045
Potential group	1894307.7
Let go	175209

Total : 3112561.7

which is very high and a clear improvement over initial CLV by 207% .Our segmentation using clustering and applying decision tree leads to limits on expenditure per segment for optimal future profits.

We demonstrate how targeted marketing can lead to CLV improvement, and hence our marketing expenses led to net gain in customer equity.

CONCLUSION

Telecom companies should take advantage of what customer lifetime value brings to them. Companies have to integrate this into how they do business and use the CLV calculations to influence and get the maximum value from the customer by segmenting them properly applying the correct marketing strategies.

REFERENCES

1. Junxiang Lu, Ph.D., Predicting Customer Churn in the Telecommunications Industry — An Application of Survival Analysis Modeling Using SAS, Sprint Communications Company Overland Park, Kansas

2. Giuliano Tirenni Christian Kaise, Andreas Herrmann

Switzerland,15th January, 2007 , Applying decision trees for value-based customer relations management: Predicting airline customers 'future values Received (in revised form).

3.Ka-shing Woo Henry K.Y. Fock,Retaining and divesting customers: an exploratory study of right customers, "at-risk" right customers, andwrong customers, Journal of Services Marketing, Vol. 18.

4. studyErik M. van Raaija, Maarten J.A. Vernooijb, Sander van Triestc ,The implementation of customer profitability analysis: A case.

5.Finding Your Audience Through Market Segmentation,National Arts Marketing Project.

6. Francis J. Mulhern ,Customer profitability analysis: Measurement, concentration, and research directions.

7. Wouter Buckinx, Dirk Van den Poel ,Customer base analysis: partial defection of behaviourally loyal clients in a non-contractual FMCG retail setting.

8. Behram j. Hansotia [1], paul wang ,analytical challenges in customer acquisition.

9.Yaya Xi, Xiu Li, E.W.T. Ngai[b], Weiyun Ying[c] Customer churn prediction using improved balanced random forests.

10. Data source : BMGT431 Final Project, Published 21 March 2015, Kaggle.com