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Customer Lifetime Value Measurement using Machine Learning Techniques

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INTRODUCTION

Customer Lifetime Value has become a very important metric in Customer Relationship Management. Various firms are increasing relying on CLV to manage and measure their business. CLV is a disaggregate metric that can be used to find customers who can be profitable in future and hence be used allocate resources accordingly (Kumar and Reinartz, 2006). Besides, CLV of current and future customers is a also a good measure of overall value of a firm (Gupta, Lehmann and Stuart 2004).

There have been other measures as well which are fairly good indicators of customer loyalty like Recency, Frequency and Monetary Value (RFM), Past Customer Value (PCV) and Share-of-Wallet (SOW). The customers who are more recent and have a high frequency and total monetary contribution are said to be the best customers in this approach. However, it is possible that a star customer of today may not be the same tomorrow. Matlhouse and Blattberg (2005) have given examples of customers who can be good at certain point and may not be good later and a bad customer turning to good by change of job. Past Customer Value (PCV) on the other hand calculates the total previous contribution of a customer adjusted for time value of money. Again, PCV also does not take into account the possibility of a customer being active in future (V. Kumar, 2007). Share-of-Wallet is another metric to calculate customer loyalty which takes into account the brand preference of a customer. It measures the amount that a customer will spend on a particular brand against other brands. However it is not always possible to get the details of a customer spending on other brands which makes the calculation of SOW a difficult task. A common disadvantage which these models share is the inability to look forward and hence they do not consider the prospect of a customer being active in future. The calculation of the probability of a customer being active in future is a very important part in CLV calculation, which differentiates CLV from these traditional metrics of calculating customer loyalty. It is very important for a firm to know whether a customer will continue his relationship with it in the future or not. CLV helps firms to understand the behavior of a customer in future and thus enable them to allocate their resources accordingly.

Customer Lifetime Value is defined as the present value of all future profits obtained from a customer over his or her entire lifetime of relationship with the firm (Berger and Nassr, 1998). A very basic model to calculate CLV of a customer is (Kumar, V., 2007):

$$CLV_i = \sum_{t=1}^{T} \frac{(\text{Future Contribution Margin})_{it} - (\text{Future Cost})_{it}}{(1+\delta)^t}$$

where,

i is the customer index,
t is the time index,
T is the number of time periods considered for estimating CLV,
δ is the discount rate.

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LITERATURE REVIEW

There are various models to calculate the CLV of a customer or a cohort of customers, depending on the amount of data available and the type of company.

Blattberg, Getz and Thomas (2001) calculated average CLV or CE as the sum of return on acquisition, return on retention and return on add-on selling rate across the entire customer base. Rust, Lemon and Zeithaml (2004) used a CLV model in which they considered the case where a customer switches between different brands. However, in using this model, one needs to have a customer base which provides information about previous brands purchased, probability of purchasing different brands etc. Gupta, Lehman and Stuart (2004) have calculated CE by summing up the CLV of all the customers and taking its average. Berger and Nassr (1998) calculated CLV from the lifetime value of a customer segment. They also took into account the rate of retention and the average acquisition cost per customer. V. Kumar (2007) has shown individual level approach and aggregate level approach to calculate CLV. He has linked CLV to Customer Equity (CE) which the average CLV of a cohort of customers. Dwyer (1997) have used a customer migration model to take into account the repeat purchase behavior of customers. Various behavior based models like logit-models and multivariate Probit-models have also been used (Donkers, Verhoef and Jong, 2007) and models which takes into account the relationship between various components of CLV like customer acquisition and retention are also used (Thomas 2001). Hansotia and Wang (1997) used Logistic Regression, Malthouse and Blattberg (2005) used linear regression for predicting future cash flows, Dries and Poel (2009) used quantile regression, Haenlein et al. (2007) used CART and markov chain model to calculate CLV. An overview of various data mining techniques used to calculate the parameters for CLV have been compiled by Aeron, Kumar and Janakiraman (2010). Besides this, many researchers also use models like Pareto/NBD, BG/NBD, MBG-NBD, CBG-NBD, Probit, Tobit, ARIMA, Support vector machines, Kohonen Networks etc., to calculate CLV. Malthouse (2009) presents a list of these methods used by academicians and researchers who participated in the Lifetime Value and Customer equity Modelling Competition.

Most of the above mentioned models are used either to calculate the variables used to predict CLV or to find a relationship between them. In our research, we have used several non-linear techniques like Classification and Regression Trees (CART), Support Vector Machines (SVM), SVM using SMO, Additive Regression, K-Star Method and Multilayer Perceptron (MLP) to calculate CLV which takes care of the relationship between the variables which act as input variables in the prediction of CLV. Further we also make a comparison of these techniques to find the best fitted model for the dataset we used. Fader, Hardie and Lee (2005) have shown that RFM variables can be used to build a CLV model and that RFM are sufficient statistics for their CLV model. Khajvand and Tarokh, (2010) have presented his model for estimating customer future value based on the data given by an Iranian Bank. In this model they got the raw data from an Iranian Bank and calculated the Recency, Frequency and Monetary value of each customer. Using various clustering techniques like K-mean clustering, they segment the data into various groups and calculate the CLV for each cluster. Dries and Van den Poel (2009) have used quantile regression to calculate CLV. It extends the mean regression model to conditional quantiles of the response variables like the median. It provides insights into the effects of the covariates on the conditional CLV distribution that may be missed by the least squares method. In prediction of the top x-percent of the customers, quantile regression method is a better method than the linear regression method. The smaller the top segment of interest, the better estimate of predictive performance we get. Malthouse and Blattberg (2005) used ANN to predict future cash flows. Aeron and Kumar (2010) have mentioned

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