

# Chapter 124

## Customer Lifetime Value Measurement using Machine Learning Techniques

**Tarun Rathi**

*Indian Institute of Technology Kharagpur, India*

**Vadlamani Ravi**

*Institute for Development and Research in Banking Technology (IDRBT), India*

### ABSTRACT

*Customer Lifetime Value (CLV) is an important metric in relationship marketing approaches. There have always been traditional techniques like Recency, Frequency and Monetary Value (RFM), Past Customer Value (PCV) and Share-of-Wallet (SOW) for segregation of customers into good or bad, but these are not adequate, as they only segment customers based on their past contribution. CLV on the other hand calculates the future value of a customer over his or her entire lifetime, which means it takes into account the prospect of a bad customer being good in future and hence profitable for a company or organization. In this paper, we review the various models and different techniques used in the measurement of CLV. Towards the end we make a comparison of various machine learning techniques like Classification and Regression Trees (CART), Support Vector Machines (SVM), SVM using SMO, Additive Regression, K-Star Method and Multilayer Perception (MLP) for the calculation of CLV.*

### INTRODUCTION

Customer Lifetime Value has become a very important metric in Customer Relationship Management. Various firms are increasingly 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 to allocate resources accordingly (Kumar and Reinartz, 2006). Besides, CLV of current and future customers is also a good measure of overall value of a firm (Gupta, Lehmann and Stuart 2004).

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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, and  $\delta$  is the discount rate.

## **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

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