An Empirical Assessment of Customer Lifetime Value Models within Data Mining

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Abstract. Customer lifetime value has been of significant importance to marketing researchers and practitioners in specifying the importance level of each customer. By means of segmentation which could be carried out using value-based characteristics it is indeed possible to develop tailored strategies for customers. In fact, approaches like data mining can facilitate extraction of critical customer knowledge for enhanced decision making. Although the literature has several analytical lifetime value models, comparative assessment of the existing models especially within the context of data mining seems a missing component. The aim of this paper is to compare two different customer lifetime value models within data mining. The evaluation was carried out within the context of customer segmentation using a database of a company operating in retail sector. The results indicated that two models yield the same segmentation structure and no statistical differences detected on the select control variables. However, the remaining model produced rather different segmentation results than their peers and it was possible to identify the most lucrative model according to the statistical analyses that were carried out on the select control variables.

Keywords: Customer lifetime value, Customer segmentation, Lifetime value modelling, Data mining, Customer analytics

1 Introduction

Customer lifetime value (CLV) modelling is an analytical component of customer relationship management and has been widely utilized by a variety of companies across different sectors including finance and insurance, retail and telecommunications in order to identify the differences between the customers. It is a measurement of a firm's net cash flows generated by its customers within specified lifetime dura-

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tion (Gupta & Lehmann, 2003). Calculating lifetime value of customers precisely can help companies to position them and to differentiate the most appropriate services. There have been several lifetime value models in the related literature and these models can be classified into two groups: past customer behavior models and future-past customer behavior models. There are mainly two differences between these models. The first difference is based on the assumption that whether the customers who are subject to assessments will be active or not in the future, while the second difference stems from the inclusion of costs of customers into the models. PCV Model (past customer value); RFM Model (recency, frequency, monetary); SOW Model (share of wallet) can be included in the first category which calculate the lifetime values by only using the past data of customers. As far as the second category of the models is concerned, although they all take the future behavior of customers into consideration (Kumar, 2005), some analytical models (Berger & Nasr, 1998; Gelbrich & Wünschmann, 2007; Gupta & Lehmann, 2003; Rust, Venkatesan & Kumar, 2004) include acquisition cost when calculating lifetime values while some others (Bauer, Hammerschmid & Braehler, 2003) do not so. The vast majority of the literature focuses on the latter category of the models either in modelling or empirical form, however, the current literature lacks of comparative research on evaluating those CLV models, especially within the context of segmentation (Lemon and Mark, 2006).

The aim of this paper is to make a comparison between two customer lifetime value models from segmentation perspective within data mining. The rest of the paper is organized as the followings. The empirical studies of the related literature are provided in Section 2. Section 3 presents the research method followed. Empirical research results, including calculation of lifetime values for each model and the segmentation structures obtained by the comparative models, and their assessments were presented in section 4. In the last section of the article, conclusions and recommendations from both academic and practical points were provided.

2 Literature Review

When the current literature on customer lifetime value modelling is examined the models can simply be classified into two groups: the models that take into account past customer behavior and the models consider both past and future behaviors. Every past costumer behavior group models have unique parameters which is directly related to model's characteristics. Among the models RFM is most widely used one and it has been utilized in marketing areas for almost decades (Gupta et al., 2006). The future-past customer behavior models share the same principle that for every customer how long it will be active is determined then net present values of these customers are calculated throughout the activation period. Based on this principle most of the models use common variable/constant parameters such as retention rate, marketing cost, cash flow ratio and reduction rate.

Most of the studies on future-past customer behavior models use retention rate to determine the activation period (Blattberg & Deighton, 1996; Berger & Nasr, 1998; Bauer et al., 2003; Gupta & Lehmann, 2003). However, some of the models use dif-

ferent set of criteria such as loyalty (Kim & Cha, 2002), number of purchase period (Dwyer, 1997), length of service (Gelbrich & Wünschman, 2007), recent transaction time / recency (Chang & Tsay, 2004; Fader , Hardie & Berger, 2004), frequency of buying (Chang & Tsay, 2004; Fader et al., 2004; Rust et al., 2004; Ramakishnan, 2006). Within the activation period, determination of the monetary values of all customers is crucial. Therefore, almost every future-past customer behavior models include a monetary-oriented variable. The most common variables in these models are; marketing cost (Berger & Nasr, 1998; Venkatesan & Kumar; 2004; Gelbrich & Wünschman, 2007; Kumar et al., 2008), cash flow ratio (Dwyer, 1997; Berger & Nasr, 1998) and reduction rate (Gelbrich & Wünschman, 2007). Also, different parameters and variables complement these monetary values like acquisition rate and cost (Blattberg & Deighton, 1996; Gupta, Lehmann & Stuart, 2004), discount rate (Blattberg & Deighton, 1996), purchase intention (Kim & Cha, 2002), monetary value (Chang & Tsay, 2004), expected revenue (Malthouse & Blattberg, 2005), contributed value (Aeron, Bhaskar, Sundararajan, Kumar & Moorthy, 2008).

It is possible to find empirical studies in the related literature that utilized one of the past customer behavior models. Most of the empirical studies use RFM models or its extensions. These studies use different datasets from different sectors such as retail (Lin & Shih, 2011), Banking (Khajvand & Tarokh, 2011), textile (Golmah & Mirhashemi, 2012), wholesale (Chuang & Shen, 2008), healthcare (Khajvand, Zolfaghar, Ashoori & Alizadeh, 2011) and charity organizations (Jonker, Piersma & Van den Poel, 2004). Some authors use well-known RFM extension called LRFM (or RFML) which include one or more parameters related to relationship length (or period of activity) (Lin, Wei, Weng & Wu, 2011; Wu, Lin & Liu, 2014). Considerable amount of studies use different methods including generalized regression, logistic regression, quantile regression, latent class regression, CART, Markov chain modelling, neural network to create past customer behavior model (Haenlein, Kaplan & Beeser, 2007).

Aforementioned future-past customer behavior models were used in different empirical studies in the related literature too. Reinartz & Kumar (2000) utilized Berger & Nasr (1998)'s model in retail sector. The same model or an own conceptual model was also used in petroleum (Gloy, Akridge & Preckel, 1997), retail (Chen, Yang & Lin, 2009), telecommunication (Hwang et al., 2004), banking (Glady, Baesens & Croux, 2009) sectors and with internet company datasets (Gupta et al., 2004). Additionally Kim Jun, Sung & Hwang (2006), and Glady, Lemmens & Croux (2015) used Kim & Kim (1999)'s basic structural model as well as Fader et al. (2004)'s and Fader, Hardie & Lee (2005)'s models. Wu & Li (2011) performed a CLV calculation using the models of Kim & Cha (2002). Kumar et al. (2008) adapted three different CLV models that belong to Reinartz & Kumar (2000), Rust et al. (2004) and Venkatesan & Kumar (2004) to perform an empirical study in information technology sector.

In recent years, customer analytics has attracted a great deal of attention from both researchers and practitioners. Data mining can help companies to select the right prospects on whom to focus, offer the right additional products to company's existing customers and identify good customers who may be about to leave. Data mining can predict the profitability of prospects as they become active customers, how long they

will be active customers, and how likely they are to leave. In addition, data mining can be used over a period of time to predict changes in details.

The significance usage of data mining techniques provides advantages in the areas of modeling CLV, including performing analysis based on CLV and evaluating the optimal method for identifying customer lifetime value in many industries such as retail, insurance, banking, telecommunication, financial services (Kim et al., 2006; Chen et al., 2009; Khajvand & Tarokh, 2011; Lin et al., 2011; Golmah & Mirhashemi; 2012; Hu et al., 2013). These techniques include decision tree, clustering, logistic regression, artificial neural network, support vector machine, random forests, survival analysis, association rule a priori and self-organizing maps. On one hand, while modeling techniques provide capability of CLV estimation, companies have competitive advantages in terms of making decisions due to the analysis activities based on CLV via data mining.

When the existing empirical studies are reviewed, there are many different models which either use past or past-future information to calculate CLV values. However, it is difficult to find a comparative study with regards to the evaluation of different lifetime value models from practical benefits and academic point of view, especially within the scope of data mining and segmentation. This paper contributes to the current literature by providing the results of an empirical work conducted on two different representative models, which are RFM and Gelbrich & Wünschmann Model (GWM), using a database in a comparison based on data mining methodology with a special focus on segmentation.

3 Methodology

Some of the previous empirical lifetime value studies that used large-scale customer data demonstrate the broad usage of data mining methodology for the lifetime value-modelling problem and the usefulness of such methodology. The aim of this study is to compare two different customer lifetime value models within the context of customer segmentation. Based on the classification provided in the previous section two representative models from the groups of models were compared and an assessment using some control variables were carried out within segmentation context. In order to accomplish that the variables in the acquired databases were operationalized based on some assumptions for each model and they were put them in place to perform the analyses and the comparison.

The dataset was procured from a supermarket retail chain in the UK that includes four consecutive months of around 300,000 customers. A simple random sampling methodology was employed and approximately 1% of the database was used as the study sample. A sample of 3,017 was obtained for conducting the analyses.

The dataset includes fields such as customer number, store ID, cashier ID, date of transaction, time of transaction, transaction value, number of unique products bought, total number of products bought and tender type. However, the data fields necessary to conduct the analyses were obtained. The operationalization of these variables for each model is provided in Table 1 and Table 2.

To understand methodology of the proposed comparison, it is important to be clear about the definitions of two models used in this study. By contrast to the other two models, RFM model is based on the past customer purchase behavior and R, F, M notations indicate Recency, Frequency and Monetary values, respectively.

Table 1. Operationalization of the variables for RFM model

Variable	Explanation	Operationalization
R	Duration between the last purchase date of a customer and current time	The present time was assumed to be 31.10.2003.
F	The number of transactions throughout a customer's lifecycle	The total number of orders given by a customer was taken as a single value.
M	The revenue that is gained from a customer during lifecycle	The revenues of customers were determined as their monetary values.

The formula of RFM equals to F+M-R for calculating lifetime value of each customer (Liu & Shih, 2005b). Gelbrich & Wünschmann's Model (GWM) is in the form of flow money in between customer and enterprise.

$$CLV=\sum_{i=1}^{n} \frac{Ri-Ki}{(1+r)^i} \qquad \textit{(Equation 1)}$$

The variables, operationalized in GWM formula is given below.

Table 2. Operationalization of the variables for GWM

Variable	Explanation	Operationalization
n	Expected life of a customer	n= $\frac{1}{1-r}$ (Reicheld, 1996) value depends on the retention rate of customer.
R_i	Total revenue of customer in period *i*	The revenues of customers were assigned as their monetary values.
K_i	Total cost of customer in period *i*	*Distribution Cost:* Cost for each customer was assumed to be variable and it changes for each purchase, which can be formulated as followings: For each purchase if the number of products is between 1-50 then the cost is £12; 50-150 then the cost is £10; 150-300 then the cost is £6; 300-600 then the cost is £2; 600 and more then no charge
r	Discount rate (annual)	Assumed to be 30%.

4 Empirical Results

4.1 Lifetime Value Assessment and Segmentation

For the purposes of this essay, the procedure applied in this section contains some specific steps. At the beginning, lifetime value assessments or calculations of all customers were carried out and then the corresponding segments based on these values were generated. Regarding RFM model, labelling process for all customers was carried out using the operationalization given in Table 3 according to their R, F, and M values that were calculated separately for each of them. To be more accurate, each individual value for a customer was compared with the corresponding average value of all customers. If R (F, M) value of a customer was higher than the average R (F, M) values of all customers this particular customer was labelled as RH (FH, MH),

while the R (F, M) value lower than the average R (F, M) was labelled as RL (FL, ML); where the second letters in the labels indicate the status of being high and low, respectively. In this way, with the aim of developing customer segments, eight different R-F-M combinations were generated. Subsequently, based on their R, F and M status, these combinations were classified into four groups. Table 4 gives information about four obtained segments and their descriptions together with number of customers in each dataset and the corresponding R-F-M combinations.

Table 3. Customer segments and descriptions

Segment	Description of the Segment	Number of Customers	Percent of Customers (%)
1	High Value Customers	220	7.30
2	Moderate-to-High Value Customers	1357	44.98
3	Low-to-Moderate Value Customers	1254	41.56
4	Low Value Customers	186	6.17

The other customer lifetime value model, GWM, lifetime value of each customer was calculated using Equation 1 provided in Table 2. Following this, in accordance with the corresponding calculated values, the consumers were sorted in a descending order for each model. To achieve an equivalent comparison base, in RFM and GWM models, the total numbers of segments were set equal to the segment structure generated by RFM model. Therefore, the first 220 customers in the ranking were described as "high value customers", the followed 1357 of them as "moderate-to-high value customers", the next 1254 of them as "low-to-moderate value customers" and the remaining 186 customers as "low value customers".

4.2 Results of the Comparison

Separate Assessment of the Segmentation Results for Each Model. Four different customer segments were obtained for two models. In order to ensure that the segments generated for each model can be identified according to the corresponding segmentation bases that were used during the segmentation process, ANOVA tests were performed at 0.05 level of significance for each segmentation structure, and results were obtained as given in Table 4. And it can be said that the average values of these variables were statistically different from each other.

Table 4. Average CLV values and result of ANOVA tests for each model

Model	Segment 1	Segment 2	Segment 3	Segment 4	F	Sig
RFM	0,56	0,15	-0,15	-0,49	4970,71	0.00
GWM	334,867	141,91	57,67	20,82	720,65	0.00

Verification of the Differences between Segmentation Structures of Each Model. Ensuring that the segmentation structure of each model is different from the other, the difference was set forth through calculating the similarity of the segmentation results. Cohen's Kappa index was used to measure the agreement between the segmentation structures obtained. An index value converges to "0" indicates that the agreement between segmentation results is low, while a value close to "1" designates high level

of agreement. However, any value between 0 and 1 can represent a certain level of agreement with a degree of randomness (Landis & Koch, 1977). The results of calculations demonstrated that the similarity percentage GWM and RFM were found to be 34%, respectively. It can be clearly seen that the segments generated by RFM and the segments obtained through GWM include different customers at a substantial amount. In another word, there is an observable defined pattern in the results of GWM compared to RFM model in terms of customers groupings. Therefore, it is possible to distinguish or discern the segment structures of each model. Such differences would provide a basis for further comparison of the models.

Comparison of the Models from Segmentation Perspective. The main objective of this research is to make a comparison of different lifetime value models at segment level for the purpose of discovering which one is superior to the others. The comparison was performed based on 'average revenues' of the segments using four control variables, namely, value per visit (average monetary value per visit/shopping), unique product variety per visit (number of unique products bought per visit/shopping), quantity per visit (total number of products bought per visit/shopping), and unique product variety per quantity (number of unique products bought over total number of products). Table 5 provides that information for each individual customer segment of the comparative models.

Table 5 illustrate the results of calculations of average revenues of customer segments for value per visit, for unique product variety per visit, for quantity per visit and for unique product per quantity. By considering all segments, there are statistically significant differences in the mean value, unique product variety and quantity per visit between different segmentation structures generated by two different models. However, for the case of unique product variety per quantity, the differences between models calculated for segment 1 is not significant due to its P value, therefore there is insufficient evidence to claim that some of the means may be different from each other. In the other cases, all the differences between segments are meaningful.

The evidence from these results suggest that there is a difference between the models based on Segment 1 and Segment 2, that the average revenues pertaining to valuable segment for GWM yields higher gain compared to the corresponding results of RFM model. On the contrary, when looking at the difference at Segment 3 GWM's average revenues seem to be lower in comparison with the associated results of their peers.

Table 5. Comparison of the Models from Segmentation Perspective

Segment	Value per Visit			Unique Product Variety per Visit			Quantity per Visit			Unique Product Variety per Quantity		
	RFM	GWM	Sig.	RFM	GWM	Sig.	RFM	GWM	Sig.	RFM	GWM	Sig.
1	62,08	137,44	0.00	10,67	24,54	0.00	13,42	28,68	0.00	26,44	30,08	**0.29**
2	65,46	75,77	0,00	12,11	13,54	0,00	14,68	16,45	0,00	26,89	30,05	0,00
3	55,60	36,04	0,00	10,20	7,31	0,00	12,37	8,70	0,00	31,85	28,87	0,00
4	47,85	15,34	0,00	8,75	3,71	0,00	10,70	4,42	0,00	30,57	23,30	0,00

General evaluations of differences lead us to the conclusion that the segmentation structures established by GWM were found to be more effective compared to RFM model, since the GWM seems to be more capable of enabling the assignment of the most valuable customers into the same segment. This means that GWM has the ability to facilitate performing attraction of lucrative customers in one group and classifying the new customers in a lower value segment in a better way.

5 Conclusion

Discovering differences between customers and specifying profitability of each customer have been one of the most important challenges in marketing. Firms can utilize CLV models in order to determine the characteristics of their customers. Moreover, through the means of customer segmentation, which could be carried out based on these value-based characteristics, organizations are able to develop appropriate strategies for supporting their decision making processes in customer relationship management context. This has become rather easy considering the availability of organized customer data and the approaches like data mining that can facilitate extraction of critical customer knowledge. Although the use of customer lifetime value for segmenting customers or formulating strategies tailored to them can be found in related literature, there has been a lack of comprehensive studies pertaining to analyzing different models and figuring out which model is superior to the others within data mining context. This study proposed a comparison to assess two different customer life time value models within data mining and from segmentation perspective by using value-related attributes as well as certain product-usage related control variables. In this context, at first, different CLV models were reviewed and two models that need the same set of variables were chosen for comparative assessment. One of these models is a past customer behavior model (RFM model), while the other model is future-past behavior model, Gelbrich & Wünschmann Model. Subsequently, the models were evaluated using the same data set based on the segmentation structure that they established. Comparisons were carried out based on 'average revenues' of the segments using four control variables via independent sample t-Test analyses. The results of the study demonstrated that GVM yielded better performance for all control variables and the segmentations obtained via this model could be seen more effective compared to RFM model.

In conclusion, the usage of CLV models and data mining techniques together gives a tremendous capability to the firms in recognizing high value customer groups. From this standpoint, this study provides two benefits to the current body of the literature as well as to the marketing practice. First, the article enhances academic understanding of existing CLV models from a taxonomic perspective. Second, the usage lifetime value and segmentation concepts within data mining context can provide a grasp of practical implementation in customer analytics area. In fact, comparison of the segmentation structures of two lifetime value models using four different control variables can facilitate a better comprehension from an empirical practice point of view. Nevertheless, a number of limitations of this study and areas for future research

could also be mentioned. One limitation is that only a specific database was used to assess these models. It is far better that more analyses could have been performed on different datasets for different types of sectors. In addition, another important point is that only two customer lifetime value models were utilized for comparisons since these models need the same set of variables. Other lifetime value models could have also been taken into account should it is possible to find common features for comparative assessment. Last but not least, some assumptions had to be kept in mind due to lack of specific consumer-related data/information. Making these assumptions more relaxed and building the research framework on obtaining data sets that could be more consistent with real conditions may ensure more robust results for future research.

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