A Model for Customer Lifetime Value Focusing on the Manufacturing Supplier Industry

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ABSTRACT

Customer Relationship Management (CRM) assumes that firms can become more profitable if they can invest in superior customer. Many studies have been performed to calculate customer value based on the Customer Lifetime Value (CLV). In this paper, we propose a customer value calculation model that focuses on the industry of build-to-order manufacturing using data mining techniques and time series analyses. The proposed model combines data mining and time series analysis. First, it classifies the customers into three groups (superior, middle, inferior) by using data mining methods. Second, it predicts customer value using a time series analysis for each group of customers. We evaluate the proposed model to estimate the future value of customers using sales data for a firm in the manufacturing industry. The result shows that the model can identify superior customers in the long term.

Keywords: CLV, RFM, CRM, Data Mining, Manufacturing Industry

1. INTRODUCTION

For allocating resources, it is important to estimate the Customer Lifetime Value (CLV) correctly, especially for business to business firms. When businesses estimate the CLV, it becomes possible to create a marketing strategy for supporting efficient activity, and increasing the budget for new business development. The CLV represents the present value of the expected benefits (gross margin) minus the burdens (direct costs of servicing and communicating) imposed by customers [1]. CLV has become a general indicator in customer relationship management [2] and in customer equity approaches to marketing [3,4].

In some Asian countries, most manufacturing industries supply a product to one specific major company. As cost cutting become important for the major company, it is common for them to request lower-priced products from the manufacture supplier. A problem arises because the major companies have more power, so the supplier will tend to lower their prices. This leads to increased competitiveness among supplier to manufacturing industries. Supplier often lack of the ability to acquire a new customers. Only a few suppliers are able to acquire new customers by minimizing the number of non-profitable customers. Therefore, most suppliers need to calculate the customer value in order to gain more profit.

This paper proposes a customer value calculation model that focuses on the industry of build-to-order manufacturing using data mining techniques and time series analyses. The distinguishing feature of the proposed model is the point of taking into consideration each customer's characteristics in the manufacturing industry, and applying a different calculation technique for every characteristic of the customer group. In the experiment, we estimate customer value of five years into the future. The proposed model indicates that it is better to identify the superior customers. We consider that identifying superior customers leads to optimize operating costs, and brings in new customer.

2. RELATED WORK

Many studies have discussed the evaluation of CLV. Hughes [5] proposed a method for RFM scoring by using RFM data that involved sorting individuals into five customer groups. Different marketing strategies could then be adopted for different customers. Goodman [6] suggested that the RFM method should avoid focusing on less profitable customers, allowing resources to be diverted to more profitable customers. Stone [7] suggested that different weights should be assigned to RFM variables depending on the characteristics of the industry. In analyzing the value of customers who used credit cards, he suggested placing the highest weighting on the Frequency measure, followed by Recency, with the lowest weighting on the Monetary measure.

Edward and Malthouse [8] predicted CLV for a B2B company. In the research, authors used a linear regression estimated with iteratively re-weighted least squares (IRLS), as described in Neter et al. [9] and estimated IRLS for the business-to-business company. They evaluated its predictive accuracy by a classification test. A partial goal of CLV is to separate the “best” customers from others. For simplicity, they assumed that the top 20% based on actual CLV values in the target period were the “best” customers.

3. CHARACTERISTICS OF THE MANUFACTURING INDUSTRY

Compared to a B2C business model, a B2B business model such as for a manufacturing industry has fewer customers, and the product’s unit price and the customers’ repeat rate are high. However, since the purchase is judged rationally and objectively, it also features a long time before the merchandise purchase. Therefore, when a company gets into a confidential relation with a customer, the possibility of the customer continuously purchasing a product which he had previously purchased is high. A customers who left in spite performed buy, potentially without going satisfied customer care or products and moved to other companies is high??. In this study, we assume that customers with a strong, confident relationship with the supplier will perform long-term and periodic purchases, whereas customers with a low-confidence relationship will move to other companies.

4. LITERATURE REVIEW

4.1. RFM

RFM analysis is a marketing technique used for analyzing customer behavior such as how recently a customer has purchased, how often the customer purchases, and how much the customer spends. It is a useful method for improving customer segmentation by dividing customers into various groups for future personalization services and to identify customers who are more likely to respond to promotions.

Bult and Wansbeek [10] defined RFM as follows.
(1) R (Recency): The period since the last purchase; a lower value corresponds to a higher probability of the customer making a repeat purchase.
(2) F (Frequency): Number of purchases made within a certain period; higher frequency indicates greater loyalty.
(3) M (Monetary): The money spent during a certain period; a higher value indicates that the company should focus more on that customer.
We provide below an example of how to interpret the RFM analysis result. A customer with a high R score is more likely to use that product in the future. However, there is a high probability that a customer with a low R score was taken by another company. A high F score implies a frequent customer. Although a customer with a high F score and a low R score was frequent customer once, he is considered to now have been taken by another company. A customer with a high M score indicates purchasing power. RFM is generally estimated using five ranks, and each customer's characteristics are represented with their own combination.

4.2. THE HOLT-WINTERS FORECASTING PROCEDURE

Exponential smoothing methods [11,12] are popular, easy to use, and generally work well. The Holt-Winters method generalizes this approach to deal with trends and seasonality. The multiplicative seasonality version of the method is presented in expressions (1) to (4). It assumes an additive trend and estimates the local slope, T_t , by smoothing successive differences, (S_t - S_{t-1}), of the local level, S_t. The local s-period seasonal index, I_t, is estimated by smoothing the ratio of the observed value, X_t, to the local level, S_t.

$$S_t = \alpha \left({X_t}/{I_{t-s}} \right) + (1-\alpha)(S_{t-1} + T_{t-1}) \quad (1)$$

$$T_t = \gamma \left({S_t}/{S_{t-1}} \right) + (1-\gamma)T_{t-1} \quad (2)$$

$$I_t = \delta \left({X_t}/{S_t} \right) + (1-\delta)I_{t-s} \quad (3)$$

$$\widehat{X_t}(k) = (S_t - kT_t)I_{t-s+k} \quad (4)$$

Here, $\propto$, γ and δ are smoothing parameters, and $\widehat{X_t}(k)$ is the k-step-ahead forecast. The seasonality is multiplicative in the sense that the underlying level of the series is multiplied by the seasonal index.

4.3. K-MEANS CLUSTERING

K-means is one of the simplest unsupervised learning algorithms that solves the well known clustering problem. The procedure follows a simple and easy way to classify a given data set in to a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed with care, because different locations will lead to different results. The best choice is to place them as far away from each other as possible. The next step is to take each point belonging to a given data set and associate it with the nearest centroid. When no point is pending, the first step is completed and early grouping is considered to be complete. At this point, we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop, we may notice that the k centroids change their locations step by step until no more changes are made, in other
words until the centroids do not move any more. Finally, this algorithm aims at minimizing an objective function, in this case a squared-error function.

5. PROPOSED MODEL

This section first defines the customer value in this research. Next, the flow of the whole proposal model is presented. We define CLV as the sum of the revenues gained from a given customer over the lifetime of transactions. Therefore, in this study, we attempt to predict the value correctly by focusing on the profits obtained from a future customer.
In the proposed model, each customer's future value is predicted using sales data. First, we classify the customer using RFM analysis because the sales data has characteristics that change with a customer's group. A customer who is purchasing frequently and continuously indicates a certain amount of regularity. Moreover, a customer who is not purchasing frequently and continuously has a high possibility of being taken by other companies. The flow of the proposed model is diagrammed in Fig. 1.

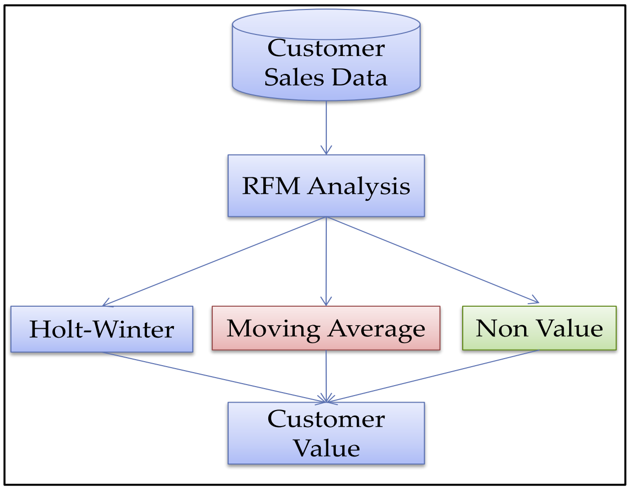

Fig. 1. The flow of a proposal model

5.1. CUSTOMER CLASSIFICATION BY RFM ANALYSIS

First, we analyze each customer's purchase tendencies using an RFM analysis. The numerical value of the computed RFM is classified into five ranks according to the k-means method. (The best value is rank 5, the worst value is rank 1.) An example of RFM analysis is given in Table 1.

Second, the customers were classified into three groups based on the RFM clusters.

1. Superior customer group
This group consists of the customers for whom both RF scores exceed 4. A customer in this group is a customer who has traded continuously right up to the present. The company needs to demonstrate continuous interest in dealing with such a customer.

2. Inferior customer group
This group consists of customers for whom both RF scores are less than 2. A customer in this group will seldom generate future income. It may become a waste of operating cost to pursue business with such a customer.

3. Medium customer group:
This group consists of customers who are not included in the above classifications. Customers in this group do not have significant distinguishing features. However, the customers in this group include customers whose R score alone is high. The company needs to build a stronger relationship while continuing to trade with such a customer.

5.2. CALCULATING THE CUSTOMER VALUE

As stated above, we assumed that there is a tendency in the sales data for every characteristic of the customer. We present two hypotheses. The first is that the sales data of the superior customer group has a periodic law (i.e., seasonality). The second is that the inferior customer group has moved to another company. Therefore, we apply a predictive method to each group.

Table 1 Example of RFM analysis

id	R (Actual value)	F (Actual value)	M (Actual value)	R	F	M
1	612	1	75600	3	1	1
2	299	37	4274760	4	1	1
3	2538	1	50400	1	1	1
4	5	144	13568520	5	2	2
5	54	62	2229675	5	1	1

1. Superior customer group
We apply the Holt-Winters method to this group because we think these customers have higher F and R and have been trading long-term in the past. Seasonality is included in the sales data.

2. Inferior customer group
We assume that the customers in this group do not have value. Therefore, we define the customer value of this group as 0.

3. Medium customer group
We apply the moving average method to this group. A moving average is one method of representing stationary process sequences and is often used to predict the future. When new data is obtained over time, the average method combines the new data with the data of a former certain fixed period and updates those central values one by one. The easiest technique involves taking the arithmetic average of a certain fixed period using the same weight; this is called a simple moving average (SMA). We predict the demand over the next year based on the purchase amount for a unit year in the past. The customer value is denoted by the following formulas.

$$Y_t = \frac{\sum_{k=-N}^{N} Y_{t-N}}{N} \quad (5)$$

where N is the period to predict, and Y_t is the predicted value for the next year.

6. EXPERIMENT

In the experiment, we used sales data for the manufacturing industry, which sells industrial products, such as molds. For each of these customers, we have the transaction history over a seven-year period. The transaction file gives the customer ID, date, commodity ID, and price for each transaction. We applied the proposed model using the customers of 104 companies represented in this data.

6.1. EVALUATION

For this evaluation, we use the first two years as the base period and the last five years as the target period. We evaluate its predictive accuracy in two ways.
The first way is the Spearman's rank correlation coefficient. This clarifies the similarity between two rankings. We compare the customer ranking based on the actual value and the customer ranking based on the predicted value. Spearman's rank correlation coefficient is given by the following formula.

$$r_s = 1 - 6 * \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n(n^2-1)} \quad (6)$$

Table 2 Allocation of TP, TN, FP, FN

		Actual	
		1	0
Predict	1	TP	FP
	0	FN	TN

Here, x_i,y_i are converted to ranks, and n is the size of the raw data. The value of r_s ranges from -1 to 1. It was determined that there is more correlation in the ranking of the two for values closer to 1.

The second approach is classification authorization, which Edward and Malthouse performed. We assumed that the top 20% based on actual CLV values in the target period are the "best" customers. Classification authorization was used to evaluate whether the proposed model predicted the actual top 20%. It is calculated using the following indices.

$$\text{accurary} = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

$$\text{recall} = \frac{TP}{TP + FN} \quad (8)$$

$$\text{precision} = \frac{TP}{TP + FP} \quad (9)$$

$$\text{F} - \text{score} = \frac{2 * recall * precision}{recall + precision} \quad (10)$$

TP, TN, FP, and FN in the formula represent True Positive, True Negative, False Positive, and False Negative. These are used to represent the distribution of the classification (Table 2).

6.2. RESULTS

After classifying 104 companies according to RFM, we found 23 customers in the superior customer group, 89 in the middle customer group, and 29 in the inferior customer group.
We present the results of the two evaluations below. Measures of Spearman's rank correlation coefficient are listed in Table 3. The r_s value is low as the period of prediction increases. Next, measures of classification authorization are summarized in Table 4. According to Table 4, accuracy is high through the whole period. However, recall, precision, and F-score for two and four years are somewhat low. Finally, the prediction error is given Table 5. The prediction error becomes high as the period of prediction increases.

6.3. DISCUSSION

Over five years, the r_s value remains high. In particular, the one-year value is very high. The proposed model is thus suitable for predicting customer ranking. Next, classification authorization again generally takes on a high value . However, the values for two and four years are somewhat low. The overall sales for these years are very low compared with the previous year, so an external factor may be involved. Finally, it is difficult to evaluate the prediction error. However, the amount of money for one typical customer's annual average purchases is about 4 million yen. Considering this, we think that the error for the first year is low. However, the errors for other years are quite high.

Table 3 Measures of Spearman's rank correlation coefficient

Future(t)	1year	2 years	3 years	4 years	5 years
rs	0.930	0.868	0.839	0.831	0.806

Table 4 Measures of classification authorization

	accuracy	recall	precision	F-score
1 year	0.90	0.75	0.75	0.75
2 years	0.87	0.65	0.65	0.65
3 years	0.88	0.70	0.70	0.70
4 years	0.84	0.60	0.60	0.60
5 years	0.90	0.75	0.75	0.75

Table 5 Prediction error

Future(t)	error (yen)
1 year	11,066,420
2 years	517,559,860
3 years	675,094,387
4 years	1,551,678,601
5 years	3,584,517,449

We believe the proposed model predicts well for one year into the future, and that it is suitable for classifying superior customers over a given period. The size of the prediction error seldom affected the classification accuracy.
A company can thus distinguish superior customers with high accuracy and can perform its operating activities efficiently by using this model in real situations.

7. CONCLUSIONS

In this paper, we proposed a customer-value calculation model that focuses on the industry of build-to-order manufacturing. In an experiment, we predicted customer value five years in the future. The proposed model indicates that it is best to distinguishing high-value customers. We believe the company can perform business activities efficiently by using the proposed model and can make a budget for new business development.

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