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An LTV model and customer segmentation based on customer value: a case study on the wireless telecommunication industry

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Abstract

Since the early 1980s, the concept of relationship management in marketing area has gained its importance. Acquiring and retaining the most profitable customers are serious concerns of a company to perform more targeted marketing campaigns. For effective customer relationship management, it is important to gather information on customer value. Many researches have been performed to calculate customer value based on Customer lifetime value (LTV). It, however, has some limitations. It is difficult to consider the defection of customers. Prediction models have focused mainly on expected future cash flow derived from customers' past profit contribution.

In this paper we suggest an LTV model considering past profit contribution, potential benefit, and defection probability of a customer. We also cover a framework for analyzing customer value and segmenting customers based on their value. Customer value is classified into three categories: current value, potential value, and customer loyalty. Customers are segmented according to three types of customer value. A case study on calculating customer value and segmenting customers of a wireless communication company will be illustrated.

Keywords: Lifetime value; Customer segmentation; Customer value; Data mining; Customer churn

1. Introduction

Customer relationship management (CRM) has become one of the leading business strategies in the new millennium. It is difficult to find out a totally approved definition of CRM. We, however, can describe it as 'Managerial efforts to manage business interactions with customers by combining business processes and technologies that seek to understand a company's customers' (Kim, Suh, & Hwang, 2003), i.e. structuring and managing the relationships with customers. CRM covers all the processes related to customer acquisition, customer cultivation, and customer retention. Even though we put aside the existing studies, which assert that it costs more to acquire new customers than to retain the existing customers, we can imagine that customer cultivation and retention are more important than customer acquisition because lack of information on new customers makes it difficult to select target customers and this will cause inefficient marketing efforts.

Therefore, in customer cultivation and retention, 'How big profits a certain customer can contribute to a company' is an important issue. Moreover, precise evaluation of customer value and targeted customer segmentation must be critical parts for the success of CRM especially for the industries like wireless communication industry, which are in the middle of stiff competitions and rapid customer churn.

Generally, three core works are necessary for the increase of customer value: up-selling, cross-selling, and customer retention (Kim, 2000). Up-selling is selling the same kinds of products that a customer has already bought and cross-selling is selling what a customer have never bought, i.e. new kinds of products for the customer. Customer retention means the effort to keep our customers being stayed as ours, prohibiting them from changing their minds. It is reasonable to consider these three sides when we consider customer value, accordingly. The scope of CRM activities is shown in Fig. 1.

Understanding the value of customers and the most profitable customers are essential to retain customers (Hawkes, 2000).

This paper aims at suggesting a new lifetime value (LTV) model and customer segmentation considering customer defection and cross-selling opportunity. We will also

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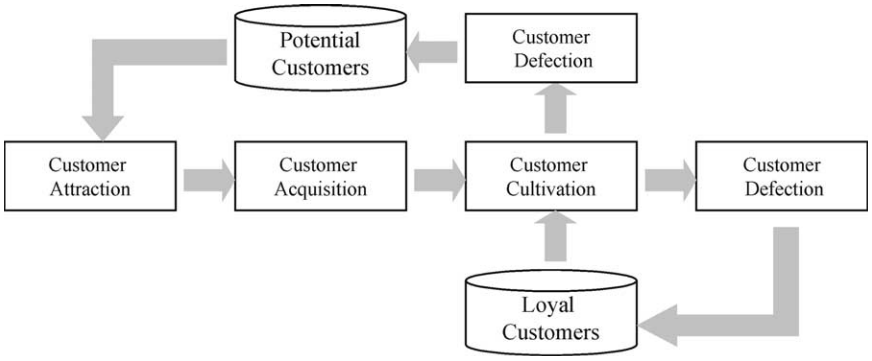

Fig. 1. The scope of CRM.

propose brief marketing strategies after segmenting customer base. This paper is organized as follows. Section 2 reviews the previous studies related to customer value. This part illustrates the limitations of existing studies and prepares the background reasons of this paper. Section 3 proposes a calculation model for measuring customer value applicable to a wireless telecommunication company. We apply real data of a wireless company to the model in Section 4. In Section 5, we perform customer segmentation with the result of customer value derived in Section 4 and proposes brief marketing strategies based upon the result of customer segmentation. Finally, Section 6 concludes this paper with the remark on the weaknesses of this study and future research directions.

2. Related works

2.1. The definition of LTV

Customer value has been studied under the name of LTV, Customer Lifetime Value, Customer Equity, and Customer Profitability. The previous researches contain several definitions of LTV. The differences between the definitions are small. Table 1 shows the definitions of LTV.

Considering the definitions above, we define LTV as the sum of the revenues gained from company's customers over the lifetime of transactions after the deduction of the total cost of attracting, selling, and servicing customers, taking into account the time value of money. The building block of LTV over time frame is shown in Fig. 2.

The horizontal axis denotes the type of relationship over time frame while vertical, type of customer value toward a company. A company forms various relationships according to the relationship stages—rudiment, beginning, fosterage, and expiry stage. A customer also gives a company various revenues, costs, and opportunities and potential benefits.

2.2. Models of LTV calculation

There are a lot of researches on calculating customer value. The basic concept of these researches, however, focused on Net Present Value (NPV) obtained from customers over the lifetime of transactions (Bayón, Gutsche, & Bauer, 2002; Berger & Nasr, 1998; Gupta & Lehmann, 2003; Roberts & Berger, 1989). Dwyer (1997) tried to calculate LTV through modeling the retention and migration behavior of customers. Focused on making decision of marketing invest, Hansotia and Rukstales (2002) suggested incremental value modeling using tree and regression based approach. Hoekstra and Huizingh (1999) also suggested a conceptual LTV model and categorized input data of the model into two types, source of interaction data and time frame. Most LTV models stem from the basic equation, although we have many other LTV calculation models having various realistic problems. The basic model form based upon the proposed definition is as

Table 1
Definitions of LTV

Definition	Article
The present value of all future profits generated from a customer	Gupta and Lehmann (2003)
The net profit or loss to the firm from a customer over the entire life of transactions of that customer with the firm	Berger and Nasr (1998)
Expected profits from customers, exclusive of costs related to customer management	Blattberg and Deighton (1996)
The total discounted net profit that a customer generates during her life on the house list	Bitran and Mondschein (1996)
The net present value of the stream of contributions to profit that result from customer transactions and contacts with the company	Pearson (1996)
The net present value of a future stream of contributions to overheads and profit expected from the customer	Jackson (1994)
The net present value of all future contributions to overhead and profit	Roberts and Berger (1989)
The net present value of all future contributions to profit and overhead expected from the customer	Courtheoux (1995)

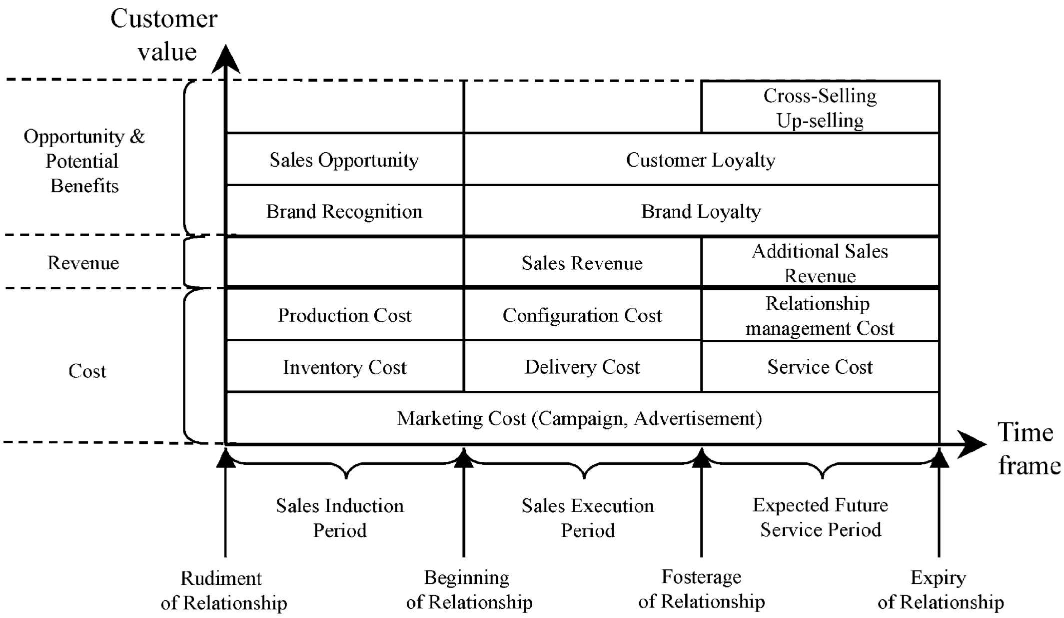

Fig. 2. Building block of lifetime value over time frame.

follows

$$\mathrm{LTV} = \sum_{i=1}^{n} \frac{(R_i - C_i)}{(1+d)^{i-0.5}} \tag{1}$$

where i is the period of cash flow from customer transactions, R_i the revenue from the customer in period i, C_i the total cost of generating the revenue R_i in period i, and n is total number of periods of projected life of the customer under consideration. Therefore, the numerator is the net profit that has been obtained at each period while the denominator transforms the net profit value into the current value. The calculation model above is the most basic model that ignores the fluctuation of sales and costs. Expanding this basic model, many researchers including Berger and Nasr (1998) have proposed LTV calculation models, which reflect the fluctuation of sales and costs (Blattberg & Deighton, 1996; Jain & Singh, 2002).

$$\mathrm{LTV} = \sum_{i=0}^{n} \pi(t) \times \frac{1}{(1+d)^i} \tag{2}$$

where $\pi(t)$ is the function of customer profits according to time t. Formulating precise $\pi(t)$ is the most important factor in calculating LTV precisely.

Colombo and Jiang (1999) developed a stochastic Recency Frequency Monetary model to rank customers in terms of their expected contribution. Pfeifer and Carraway (2000) proposed Markov Chain Models for modeling customer relationships.

LTV models evaluate the long-term value of customers focused on the entire lifetime of customers. The lifetime of customers describes the period that the customers are staying as customers. However, the long-term value does not fit for the industry having stiff competitions and rapid changes of market environments. Especially, it is not easy to evaluate the LTV of customers in the wireless communication industry, which are very sensitive to the external environments and the customer defections. Hence, this study focuses on the short-term value of customers of a wireless communication industry. Since customer value cannot be evaluated at a time, it has to be regularly and continuously renewed for covering the disadvantages of the short-term based evaluation.

Furthermore, the evaluations of customer value in previous studies have treated prediction method with regression models simply based on profits from customers to calculate the future value of customers. That is to say, considering the changing profit contribution obtained from customers in the past, the existing models calculate the future worth and then define the LTV of customers with the projected value of the future worth. Therefore, the LTV model above is not capable of considering potential values of customers, not available from the past profit contribution, which would be able to be the profits of companies.

Last, the models mentioned above do not considered the defection of customers. Although we have a customer who has very high value to our company, this information can conclude improper marketing strategies if we don't pay careful attention to the possibility of the customer defection. Hence, it is reasonable to consider the probability of individual customer's churn rather than to consider only the total decreasing rate of whole customers. Verhoef and Donkers (2001) used two dimensions, current value and potential value, to segment the customers of an insurance company. We use three dimension, current value, potential value, and customer loyalty, to consider the customer defection in this study.

3. A new LTV model

Customer defection is a hottest issue of highly competitive industries. Defection problem is also a critical issue of LTV model because it affects the length of service period and the future profit generation. Though a customer contributes much money, he may have low LTV due to his high churn probability.

We, therefore, suggest a new LTV model of individual customer considering churn rate of a customer. The modified LTV model is shown in Eq. 3.

$$\mathrm{LTV}_i = \underbrace{\sum_{t_i=0}^{N_i} \pi_{\mathrm{p}}(t_i)(1+d)^{N_i-t_i}}_{\text{Past Profit Contribution}} + \underbrace{\sum_{t_i=N_i+1}^{N_i+E(i)+1} \frac{\pi_{\mathrm{f}}(t_i)+B(t_i)}{(1+d)^{t_i-N_i}}}_{\text{Expected Future Cash Flow}} \quad (3)$$

t_i service period index of customer i
N_i total service period of customer i
d interest rate
$E(i)$ expected service period of customer i
$\pi_{\mathrm{p}}(t_i)$ past profit contribution of customer i at period t_i
$\pi_{\mathrm{f}}(t_i)$ future profit contribution of customer i at period t_i
$B(t_i)$ potential benefit from customer i at period t_i

The sum of $\pi_{\mathrm{p}}(t_i)(1+d)^{N_i-t_i}$ represent NPV of the past profit contribution, where $\pi(t_i)$ is the profit contribution of customer i at period t_i and $(1+d)^{N_i-t_i}$ is the interest rate factor, which transforms the past profit into the present value. The future cash flow can be derived from the sum of the expected future profit and potential benefits during the expected service period of customer i.

The existing LTV models have focused on financial contribution estimated from past history of profit generation, and converted the contribution to present value. The suggested model, however, focuses not only on past profit contribution, but also on future financial contribution, potential profit generation of a customer, and expected service periods.

4. Calculating Customer Value

In this paper we evaluate customer value with three viewpoints—current value, potential value, and customer loyalty. The potential value represents a measure of cross-selling possibility while the customer loyalty denotes a measure of customer retention.

After segmenting customer base with three viewpoints, this paper proposes marketing strategies according to the segmentation results. Fig. 3 shows the conceptual framework of this study. We will explain this research according the framework.

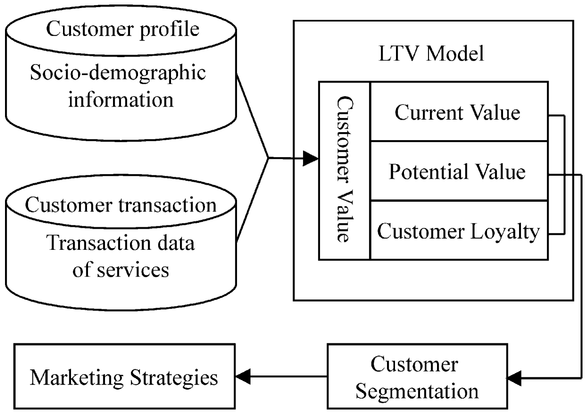

Fig. 3. Conceptual framework.

4.1. Data description

Raw data of this study are six-month service data of one wireless communication company in Korea. The data can be categorized roughly into two, socio-demographic information and usage information of wireless service. This dataset is composed of 200 data fields and 16,384 records of customers. About 2000 data were randomly extracted for this study and 101 data fields among 200 data fields were extracted according to the result of eliminations for unessential data fields. The mean value for continuous values and the mode value for class variables substituted for missing values. In addition, we divided the entire dataset at the ratio of seventy-to-thirty, training set and validation set, respectively.

4.2. Current value

We define current value as a profit contributed by a customer during a certain period (for six months), not as a cumulative value from the past to the current point. Current value can be obtained from a simple calculation with the data fields as stated before. In this paper, we settled current value as the average amount of service charge asked to pay for a customer minus the average charge in arrears for a customer, regarding six months for calculation. As there is no field related to the average amount in arrears in the data, the average amount in arrears were calculated from the cumulative amount in arrears divided by the total period of use.

$$\text{Customer Value} = \frac{(\text{Average amount asked to pay} - \text{Cumulative amount in arrears})}{\text{total service period}} \quad (4)$$

4.3. Potential Value

As mentioned before, it is important to consider cross-selling and up-selling as well to calculate customer value (Kim & Kim, 1999). In particular, cross-selling opportunity needs to be considered to evaluate customer value in the wireless communication industry since many profitable optional services are available for customers. We define here potential value of customers as expected profits that can be obtained from a certain customer when a customer uses the additional services of a wireless communication company. Eq. (5) evaluates potential values

$$\text{Potential value}_i = \sum_{j=1}^{n} \text{Prob}_{ij} \times \text{Profit}_{ij} \quad (5)$$

where Prob_{ij} is the probability that customer i would use the service j among n-optional services. Profit_{ij} means the profit that a company can get from the customer i who uses the optional service j. In other words, the equation above means expected profits from a particular customer who uses optional services provided by a wireless communication company. The expected profits will become potential value we need to evaluate.

4.3.1. Prob_{ij} Calculation

First of all, we use the data mining method to calculate the Prob_{ij}. We first derive the variables that affect the fact whether customers use an optional service or not, with R^2 method based upon the socio-demographic information and purchasing behavior information of service. Finally, we get the Prob_{ij} from learning between these variables and the fact whether the additional service was really used or not. The proper data mining techniques used in this study are decision tree, artificial neural network, logistic regression, which are broadly used for classification problems. Furthermore, both misclassification rate and lift chart accomplished the comparative test of these data mining techniques above, selecting the most powerful one to finally calculate the Prob_{ij}. Fig. 4 shows the procedure of computing Prob_{ij}.

Since the company provides various optional services, we focus on the five optional services with the exception of fundamental ones that are provided for everyone. Table 2 describes the selected variables and data mining technique to calculate Prob_{ij} for each additional service. We chose the best method in predicting the use of optional services.

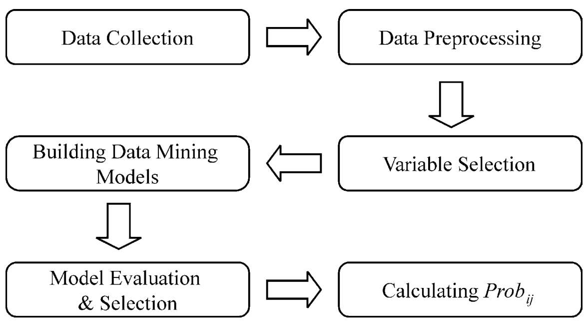

Fig. 4. Procedure for calculating Prob_{ij}.

Table 2
The number of selected variables and application methods

Optional service	Number of selected variables	Data mining method
Service 1 (SMS_IN0)	25	Decision tree
Service 2 (DEL_IN0)	7	Neural network
Service 3 (SOU_IN0)	19	Decision tree
Service 4 (INF_IN0)	22	Neural network
Service 5 (AUT_IN0)	19	Decision tree

4.3.2. Profit_{ij} calculation

Profit_{ij} means the expected profit when a company provides a customer with a certain optional service. It is available by substituting the cost of each optional service from the charge of each optional service. The charge and cost of each optional service is given by the telecommunication company.

Potential values can represent a measure of individual cross-selling opportunity. It can be used to recommend optional services to customers.

4.4. Customer loyalty

Customer loyalty can be defined as the index that customers would like to remain as customers of a company.

$$\text{Customer Loyalty} = 1 - \text{Churn rate} \quad (6)$$

Churn describes the number or percentage of regular customers who abandon relationship with a service provider. Customer loyalty can be a measure of customer retention. Level of customer retention can be derived from churn rate. It is significant for customer cultivation and retention to consider the churn rates. In particular, negative reputations have critical influences on the brand image of a company in the wireless communication industry that includes most of people as customers.

The existing studies on customer value have not treated the churn rate yet, limiting themselves to predict the future profit change of customers with the past profit history. The effective evaluation of customer value, however, should comprehend the leaving probability of each customer (Fig. 5).

Therefore, this paper measures the leaving probability for each customer to calculate the churn rate, using data mining techniques. Like the process to calculate the $Prob_{ij}$, we take several models (decision tree, neural network, and logistic regression) and then select an optimal model among them based on the result of comparative test with misclassification rate or lift chart method. Table 3 describes

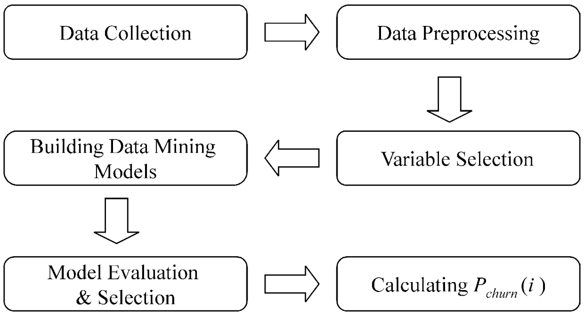

Fig. 5. Procedure for predicting churn rate.

the variables that have influences on the churn rate. These variables were derived from R^2 method.

Table 4 describes the result of comparative test for three alternative models using misclassification rate. We can see all of three models are generally well developed. Although the result from decision tree has little more accuracy than the others, the model cannot be judged as the best alternative.

Fig. 6 illustrates the result of performance test using the lift chart. The lift value means the ratio of the number of customers who actually left the company within a certain section to the total number of customers who left when we divide sections by sorting target customers in ascending order of high churn rate. The lift chart as proposed above generally shows the cumulative percentage of deviated customers. We conclude that the reliability of model is good when the graph is skewed to the left. From the lift chart below, we can conclude the data mining models to have reliabilities by seeing that populations within top 20% of churn rate can explain 90% of customer churn. There is little performance gap among three data mining models, logistic regression, neural network, and decision tree. The best model, logistic regression, is used to predict the churn rate of customers.

Table 3
Selected variables

Variable name	Description
SEX	Gender of a customer
SMS_IN0	Whether a customer uses SMS or not
CHG_NAME	The number of times the name in charge was transferred
CHG_PYMT	The number of times the way of payments was changed
CLASS_S	The level of a customer according to the cyber-point
DEL_STAT	Weather there is any delinquent charge
DEPOMETH	Payment method of deposits
D_DEGREE	The degree of amounts in arrears in the datum month
FEE_METH	Payment method of the registration fee
MDL_NBR1	Month passed after a phone launched
MUST_MON	The obligatory period of use
OCCU_GP	Occupation of a customer
PRICE_1	The type of monthly charge
VAS_CNT	The number of optional services used
INB_MDL	The number of inquiry on the phone

Table 4
Misclassification rate of selected techniques

	Misclassification rate: training set	Misclassification rate: validation set
Logistic regression	0.048	0.070
Neural network	0.049	0.070
Decision tree	0.052	0.0591

4.5. The simplified LTV model in the wireless industry

To calculate LTV of wireless phone users, we formulate Eq. (7) by simplifying Eq. (3). In the wireless industry, the expected service period can be derived from churn rate. The function $\tilde{\pi}_f(t_i)$ is obtained from regression of past profit data and $\tilde{B}(i)$ is a fixed value obtained from expected optional service profit of customer i as mentioned in Section 3.

$$\mathrm{LTV}_i = \underbrace{\sum_{t_i=0}^{N_i} \pi_p(t_i)(1+d)^{N_i-t_i}}_{\text{Past Profit Contribution}} + \underbrace{\sum_{t_i=N_i+1}^{N_i+\lceil 1/P_{\mathrm{churn}}(i)\rceil+1} \frac{\tilde{\pi}_f(t_i)+\tilde{B}(t_i)}{(1+d)^{t_i-N_i}}}_{\text{Expected Future Cash Flow}} \quad (7)$$

P_{churn} Expected churn rate of customer i
$\tilde{\pi}_f(t_i)$ Future profit function of customer i
$\tilde{B}(i)$ Potential benefit of customer i

In the simplified model, the way of calculating past profit contribution is the same as that of Eq. (3). The expected service time, $E[i]$, is replaced with $\lceil 1/P_{\mathrm{churn}}(i)\rfloor$ because service time y will follow *geometric* distribution. We, therefore, can calculate the expectation of service period using the following simple statistics.

Let y be the number of service time required until a customer stops his service and let P_{churn} be the churn probability of a customer. Then, the probability of mass function of service period is given by

$$p(n) = P\{y=n\} = P_{\mathrm{churn}}(1-P_{\mathrm{churn}})^{n-1}, \quad n = 1,2,3,\ldots$$

$$\therefore y \sim \mathrm{Geo}(P_{\mathrm{churn}}), \quad E[y] = 1/P_{\mathrm{churn}} \quad (8)$$

Then the service period of customer i can be estimated as $\lceil 1/P_{\mathrm{churn}}(i)\rfloor$, the nearest integer of $1/P_{\mathrm{churn}}(i)$.

5. Customer segmentation and marketing strategies

We have discussed the calculation method on customer value by dividing the value into current value, potential value, and customer loyalty. We can display the whole customers in three-dimensional space to see the distribution of customers. Each axis denotes current value, potential

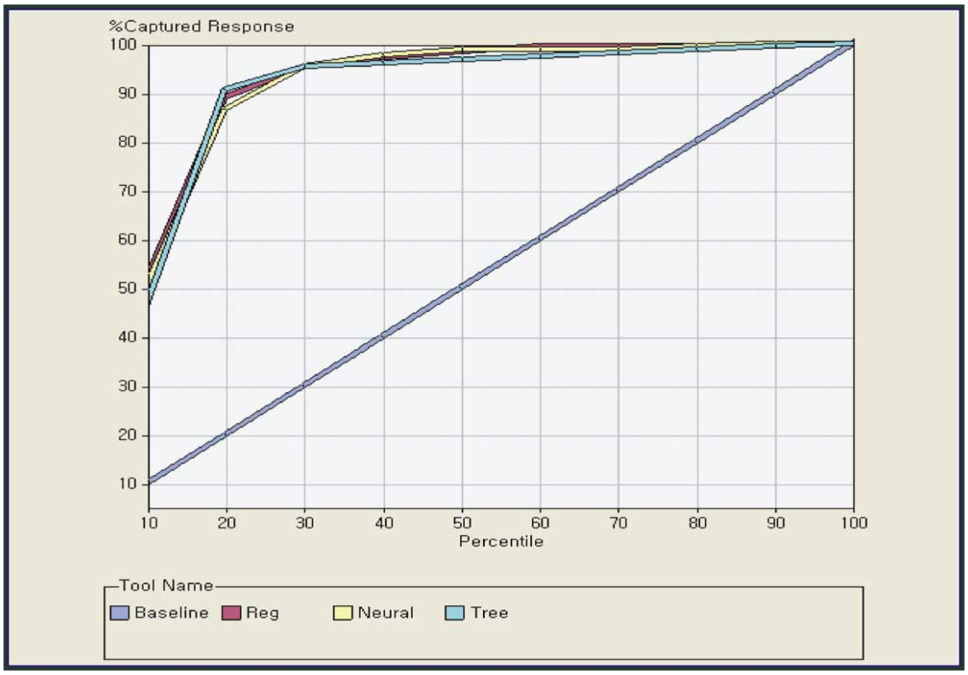

Fig. 6. Lift chart of the selected models.

value, and customer loyalty, respectively. Fig. 6 shows the result of customer segmentation.

Originally, the scales of three axes are different each other. We, therefore, convert the scale into real value between 0 and 1. As shown in Fig. 7, many customers are located in upper area of the cube, which means many customers have high customer loyalty. Nearly 30% of customers are scattered in the cube and have lower customer loyalty (<0.5). We can conclude that customer base can be segmented into two categories based on their customer loyalty. Customers whose loyalty is greater than 0.5 represent extreme high customer loyalty but the others are located sporadically in the cube. We can also conclude that more sophisticated data mining is required to analyze the high customer loyalty segment precisely.

Now it is possible for us to establish brief marketing strategies using the customer segmentation result. Marketing managers have to establish the strategies that can push customers toward the segment 1, high current value, high potential value, and high loyalty segment. In general, a wireless company can recommend high current-valued customers to use their mileage since high current-valued customers have enough mileage point and free coupons from their mileage can be used as rewards. If a customer has high potential value, the company may provide him with the opportunity of using free optional services for a few months. High potential value can lead to represent high cross-selling probability and profit generation.

Since it is important to retain good relationship with customer to strengthen the future customer profitability, a company can reduce the churn rate by issuing a membership card to low loyalty customers. Many wireless telecommunication companies have developed unique membership cards and they give customers many benefits such as free ticket for movies and discount coupon for entrance fee in the amusement parks. The card can be used to retain customers and weaken defection possibility.

Fig. 8 shows eight customer segments. If we shifted the origin of coordinates in Fig. 6, we could divide the original cube into seven segments in Fig. 7. Customers of the segment 3, i.e. customers who have low current values and potential values but have high customer loyalty, should be moved to the segment 1 by long-term strategies. Segment 4,

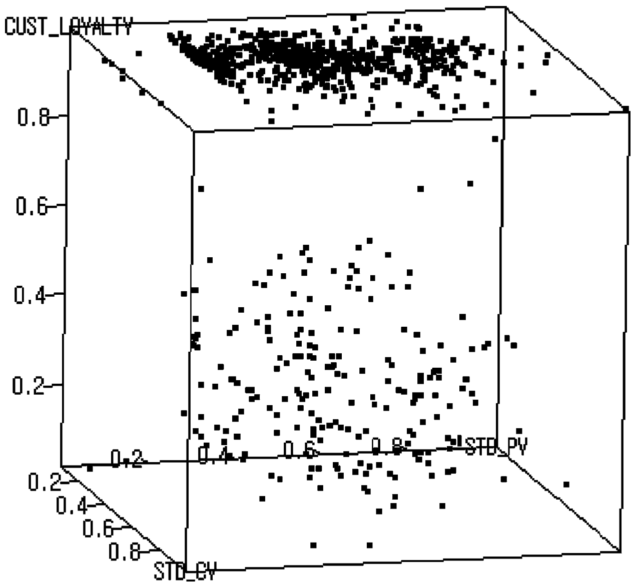

Fig. 7. Result of customer segmentation.

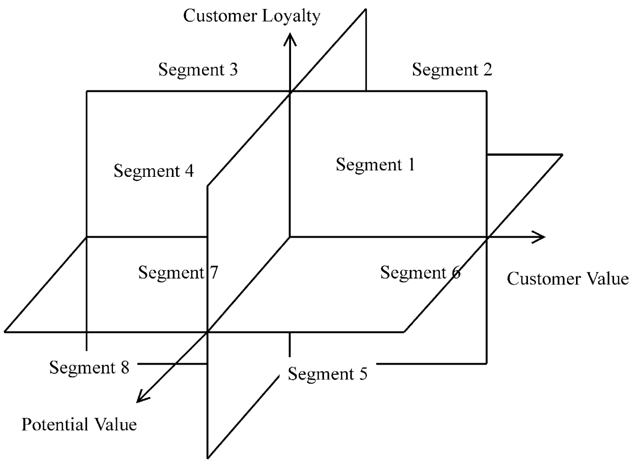

Fig. 8. Customer segmentation (after moving the origin).

customers who have high potential values and customer loyalty with low current value should be provided with cross-selling strategies such as new service marketing.

Customers of the segment 5, i.e. customers who have high current values and potential values but have low customer loyalty, should be pushed to the segment 1 by short-term strategies. Because customers in segment 5 have high profitability, retention strategy for segment 5 should be established by performing in-depth data mining to analyze the cause of high churn rate. Since customers in segment 7 have the lowest profitability, it is doubtful whether marketing activities on segment 8 will be effective or not.

Marketing managers can combine many basic strategies mentioned above to develop a customized strategy according to each customer segment.

6. Conclusion

Many CRM researches pertain to develop a comprehensive model of customer profitability since the question 'Who are profitable customers?' is a starting point of CRM. Many models have been researched to calculate LTV of a customer. Most of them focused on the future cash flow derived from the past profit contribution. In some industry, however, it is inadequate to consider only expected future cash flow to calculate LTV because stiff competition results in frequent customer defection and defection affects customer profitability much (Knox, 1998).

In this paper, we suggested an LTV model considering the past contribution, potential value, and churn probability at the same time. The model can also be used for customer segmentation. Three perspectives on customer value (current value, potential value, and customer loyalty) assist marketing managers in identifying customers segmentation with more balanced viewpoints. Current value provides financial viewpoint and potential value indicates cross-selling opportunity. Customer loyalty estimates durability of the previous two values.

In the future, we expect that this study will spur further extensions of developing the more general LTV models considering the characteristics of the industry and customers such as reactivation possibility, attracting/servicing cost and causes of customer defection.

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