A Stochastic Approach for Valuing Customers: A Case Study

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Abstract

The more competition among industry participants severe, the more companies try to retain their customers and acquire new customers from their competitors. To gain competitive advantage, many companies are adopting and deploying more refined and sophisticated Customer Relationship Management systems. In the marketing area, a personalized marketing paradigm has already been infiltrated into our lives. To support personalized marketing, it is necessary to identify an individual customer’s true value. Various researches on customer value have conducted under the name of Customer Lifetime Value (CLV), Customer Equity, Customer Profitability, and LifeTime Value.

In this paper we present issues of calculating individual customer’s lifetime value to deploy more personalized CRM activities. We propose a new method to calculate individual customer’s lifetime value dynamically. The feasibility of the suggested model is illustrated through a case study of the wireless telecommunication industry in Korea. Data mining techniques are used to predict lifetime value of a customer. Marketing implications will be discussed based on the result of individual CLV.

Keywords: Customer lifetime value, Customer relationship management, Stochastic model, Data mining

1. Introduction

The more a marketing paradigm evolves, the more a long-term relationship with customers gains its importance. CRM, a recent marketing paradigm, pursues a long-term relationship with profitable customers. It can be a starting point of relationship management to understand and measure the true value of customers since marketing management as a whole is to be deployed toward the targeted customer, profitable customers, to foster customers’ full profit potential. The firm must first determine that the relationship has the potential to be profitable before investing the resources required to develop the relationship.

When evaluating customer lifetime value, marketers are often reminded of the 80/20 rule (80% of the profits are produced by top 20% of profitable customers and 80% of the costs, by top 20% of unprofitable customers, vice versa) [7].

It is required to know individual customer’s value to a firm since a firm has to foster profitable customers to optimize marketing efforts. Therefore we need a research foundation for the recent but growing interests in Customer Lifetime Value and its marketing applications.

This paper aims at proposing a new model for measuring customer lifetime value considering both customer relationship dynamics with a firm and marketing potential. Customer relationship dynamics denotes the change of customer relationships with a firm such as customer retention, customer churn, customer winback, and customer loss. Since customers form a variety of relationships with a firm, a CLV model should regard these relationship changes in calculating the value. Another considerable aspect of CLV is marketing potential.
Customer value may be increased by up-selling/cross-selling promotions. It is necessary to add marketing potential as a components of a CLV model to consider full profit potential of a customer.

This paper is organized as follows. Section 2 reviews some related works on customer valuation and categorizes research directions of the past customer valuation studies. Section 3 proposes a new model for measuring CLV. The suggested model is implemented and verified through an industrial case study in Section 4. Section 5 deals with some marketing implications. Finally, in Section 6, concluding remarks of the paper are discussed, along with further research directions.

2. Related Works

Customer value has been studied under the name of LTV (Life Time Value), CLV (Customer Lifetime Value), CE (Customer Equity) and Customer Profitability. The previous researches contain several definitions of CLV. The differences between the definitions are relatively small.

CLV can be defined as the sum of the revenues gained from a company’s customers over the lifetime of transaction after the deduction of the total cost of attracting, selling, and servicing customers, taking into account of the time value of money [13].

The literatures in customer lifetime value research have taken multiple directions. However, the main directions of previous studies in CLV research are classified into four categories. The first one is developing structural models to calculate CLV for a customer or customer group. These articles analyze the profit/cost components of transactions and estimate lifetime-long customer value contribution to a firm [1, 3, 11, 24, 4]. Researchers have used empirical methods to examine a range of issues concerning which a customer or segment of customers a firm should focus on attracting and retaining, since not all customers are profitable [9]. Based on RFM (Recency, Frequency, Monetary) model, Pfeifer suggested a Markov chain model to calculate CLV [22]. Each RFM variable is used as a state in Markov chain.

The second direction focuses on the strategic use of CLV in customer management. In the early stage of CLV research, many studies were conducted to present a competitive advantage gaining from CLV [23, 25, 27, 28, 17], the role of CLV in marketing [McDonald, 1997], CLV-based segmentation [29, 13, 16], and managerial implications [28, 20, 21, 26].

The third direction is normative models used mainly to understand the issues concerning CLV [15]. Normative models provide us with an opportunity to explore common beliefs in making decisions regarding CLV without the ‘noise’ encountered in empirical studies. Such models provide valuable insight for policy-making. A typical example of normative models covers the traditional belief that long lifetime customers are more profitable than newly acquired customers. Numerous researchers and practitioners have provided many reasons in support of this belief. Recent research, however, to explore this issue has found contradictory evidence - it depends on industry characteristics whether the past duration affects profitability of customers positively or not [7].

Finally, the last area has been devoted to developing analytical models which help decision making relevant to marketing management, such as promotion, campaign, pricing, and budget allocation.

The era of mass marketing is being replaced by an era of targeted marketing. Knowledge of CLV enables firms to develop customer-specific marketing programs leading to an increase in efficiency and effectiveness of such programs. The Internet is undoubtedly a major instrument of such targeted marketing; the direct marketing concepts of CLV can be extended to be useful in interactive scenarios. CLV, if carefully calculated with a widespread organizational buy-in, becomes the first metric to apply for customer planning [20].
If classified in detail, the structural model can be divided into eight sub-models according to the classification criteria shown in Table 1. In the individual model, an individual customer’s CLV is calculated while value is calculated per segment in the segment model. The literatures show that the traditional marketing’s focus is on targeted markets, hence CLV is computed for a group of customers. In customer-based marketing, however, the focus is shifted onto individual customers, and data should be collected and analyzed at an individual level correspondingly. CLV should be computed for each individual customer.

With the prediction data perspective, the retrospective model primarily deals with the past transaction data to forecast only future cash flows. The prospective model, however, considers not only future cash flows from the past transaction history but also marketing potential such as up-selling, cross-selling, and additional sales caused by customer satisfaction [14].

The contractual models assume that transaction is executed based on a contract between a customer and a firm, while non-contractual models, not [5], [2]. In the contractual model, compared with the non-contractual model, customer churn is less observed since early termination of a contract results in penalties generally. Typically it is expected that customer churn occurs at the end of a contract in the contractual models. To analyze CLV in contractual settings, Bolton (1998) models the duration of the customer’s relationship with an organization that delivers a continuously provided service, such as utilities, financial services, and telecommunications [5]. Beonit (2009) used quantile regression to consider skewness of customer attributes [8].

According to the distinct characteristics of products, the purchase of goods is done periodically or almost continuously. In the case of a continuous model, a revenue stream happens continuously and an integral form of CLV formula is needed to add up the revenue. Table 1 presents classification of the previous researches on CLV.

### Table 1. Classification of the CLV Researches

<table>
<thead>
<tr>
<th>Focus</th>
<th>Category</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structural Model</td>
<td>Customer Unit</td>
<td>Individual model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Segment (Customer base) model</td>
</tr>
<tr>
<td></td>
<td>Prediction data</td>
<td>Retrospective model</td>
</tr>
<tr>
<td></td>
<td>Transaction</td>
<td>Prospective model</td>
</tr>
<tr>
<td></td>
<td>Purchase cycle</td>
<td>Contractual model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Non-Contractual model</td>
</tr>
<tr>
<td>Strategic Model</td>
<td></td>
<td>Discrete model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Continuous model</td>
</tr>
<tr>
<td>Normative Model</td>
<td></td>
<td>Relationship between Duration and cost</td>
</tr>
<tr>
<td>Analytic Model</td>
<td></td>
<td>Resource allocation (Budget allocation) / Pricing</td>
</tr>
</tbody>
</table>

### 3. A Dynamic Model for Measuring Customer Lifetime Value

Since customers form a variety of relationships with a firm such as customer retention, customer churn, customer winback, and customer loss, a CLV model should regard these relationship changes in calculating the value. Customer defection is regarded as a major issue in CRM. Customer winback, compared to customer defection, attracts little attention in CLV model. However customer winback should be included in customer valuation to evaluate customer true value. Since profiles of defecting customers are already stored in a
firm’s database, it is important to consider a winback rate. Therefore, the service cost of a wonback customer is less than that of a new customer.

To regard the time variant characteristics of customer relationship with a firm, we adopt the Markov chain model to express the customer relationship dynamics. Before expressing the customer relationship in terms of the Markov chain model, we should define the states of the Markov chain. The relationship with a customer can be classified into three states, P (potential customer state), D (defected customer state), and A (active customer state). Figure 1 shows the Customer Relationship Dynamics (CRD) using the Markov chain.

Figure 1. Customer Relationship Dynamics

CRD represents the changing relationship of a customer with a firm during a customer’s lifetime. Customers are acquired from the potential customer (P) state and defect from the active customer (A) state and become the defecting customer (D) state. Some of defected customers are wonback to an original firm and move to the active customer state but the others are lost and move to the potential customer state. Each state change is represented by the probability of movement from one state to the other. Within the active customer state, there are many substates representing possible states while a customer served by a firm.

In this paper we consider the cross-selling and up-selling potentials of a customer as customer profit potential. Staying as an active customer, he or she receives various marketing promotions from a firm. Figure 2 shows a graphical representation of the Markov chain model considering customer relationship dynamics such as the customer acquisition rate, the customer churn rate, the customer winback rate, and up-selling and cross-selling probability. The subscript m and n denote the number of cross-selling options and the number of up-selling options respectively. The rectangular area of Figure 2 denotes customer retention. Though customers stay at customer retention area, their state varies with cross-selling and up-selling acceptances. Hence we can classify customer retention into three types: positive retention, status quo retention, and negative retention. Positive retention represent customers are retained by cross-selling and/or up-selling and positive profit stream while negative retention fails in cross-selling and up-selling promotion and, furthermore, customer quit cross-sold and up-sold products. Positive retentions are depicted by forward horizontal arrows and downward vertical arrows. Therefore the profit stream of negative retention is decreasing compared with the previous states while the absolute profit is positive. The negative retentions are depicted by backward horizontal arrows and upward vertical arrows. The status quo retention is maintaining the current status and represented by recursive arrows.
A horizontal move denotes a state change by up-selling while vertical by cross-selling. Therefore, state $A_{i,j}$ represents the up-selling and cross-selling results of a customer. We can divide the movements within the active customer state into six directions.

- Downward vertical movement ($A_{i,j} \rightarrow A_{i+1,j}$): A customer accepted the cross-selling promotion $(i+1)$
- Upward vertical movement ($A_{i,j} \rightarrow A_{i-1,j}$): No response to the cross-selling promotion $(i+1)$ and quit cross-sold product $i$
- Forward horizontal movement ($A_{i,j} \rightarrow A_{i,j+1}$): A customer accepted the up-selling promotion $(j+1)$
- Backward horizontal movement ($A_{i,j} \rightarrow A_{i,j-1}$): No response to the up-selling promotion $(j+1)$ and quit up-sold product $j$
- Recursive movement ($A_{i,j} \rightarrow A_{i,j}$): No response to the cross-selling promotion $(i+1)$ and to the up-selling promotion $(j+1)$
- Defective movement ($A_{i,j} \rightarrow D$): A customer has no response to the promotions and defects

### 3.1. Individual CLV Equation

With a CRD perspective, customers do not stay at one state. They are moving constantly and the movement causes changes in customer profitability. For instance, a firm loses sales opportunities for a customer if he or she defects. Defected customers receive marketing promotions for customer winback. When defected customers win back after receiving marketing promotion, the promotion turned out to be successful one. In short, customers generate a variety of profits and costs as their relationship with a firm change. Therefore it is necessary to consider CRD in representing individual CLV. The dynamic nature of customer relationship results in dynamic change of individual CLV while the structural model provides static monetary value of a customer. Hence, it is necessary to build an extended model to represent CRD.

The suggested individual CLV model based on the Markov chain is as follows:

$$CLV_i = \lim_{N \to \infty} \sum_{N=0}^{N} \frac{T^i R}{(1+d)^i} \quad \cdots \quad (Eq. 1)$$
**T** is the one-step transition matrix of customer *i*. **R** is the reward vector of customer *i*. The reward vector is a \((mn+2)\times (mn+2)\) square matrix whose \(i^{th}\) column element represents the profitability of a customer while he or she remains at \(i^{th}\) rows state for one time period. To consider time value of money, discount rate \(d\), converts future profits into present one. All future profits changed into Net Present Value (NPV) and then added. The suggested model, therefore, converts the future profit potentials composed of the probability of customer staying at a state and profit contribution to net present value.

Figure 3 shows the one-step transition matrix which aggregates all customer states and inter-state transition probabilities. The individual CLV model is the infinite geometrical series as shown in Equation 2 and Equation 3. The matrix **I** is an \((mn+2)\times (mn+2)\) identity matrix.

\[
\begin{pmatrix}
C_{1,1} & C_{1,2} & \cdots & C_{1,2} & \cdots & C_{m,n} & D & P \\
C_{1,2} & C_{2,1} & \cdots & C_{2,1} & \cdots & \cdots & \cdots & \cdots \\
\vdots & \vdots & \ddots & \vdots & \ddots & \ddots & \ddots & \ddots \\
C_{n,n} & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
D & P & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
P & C_{1,1} & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\end{pmatrix}
\]

Figure 3. One-step Transition Matrix

**CLV**

\[
\begin{pmatrix}
\sum_{i=0}^{\infty} \frac{T^i}{(1+d)^i} R
\end{pmatrix}
\]

\[
CLV = \left\{ \frac{T^0}{(1+d)^0} + \frac{T^1}{(1+d)^1} + \cdots \right\} R \quad \text{(Eq. 2)}
\]

\[
CLV = \left\{ \frac{I - T}{(1+d)} \right\}^{-1} R \quad \text{(Eq. 3)}
\]

It is already proved that the inverse matrix of \(I - (1+d)T\) exists [30]. **CLV** is \((mn+2)\times 1\) column matrix whose \(j^{th}\) element denotes the cumulative profitability generated by customer *i* while he or she remains at the state.

### 3.2. Limiting Probability of CRD

Generally speaking, the one-step transition matrix has the limiting probability on condition that the Markov chain is irreducible and ergodic, i.e., positive recurrent and aperiodic. The CLV transition matrix, **T**, communicates among all states and the expected time, starting at state \(i\), until the process returns to state \(i\) is finite. Furthermore, all states have the period 1. Therefore the matrix **T** has the limiting probability.

The limiting probability of matrix **T** represents the long-run proportion of time a customer stays at a certain state. Letting \(\pi_i\) be the limiting probability of state *i* in matrix **T**, \(\pi_j\) is obtainable from the following equation:
\[ \pi_j = \sum_i \pi_i P_{ij} \cdot \sum_j \pi_j \quad \ldots \quad (Eq. 4) \]

where \( P_{ij} \) is the transition probability from state \( i \) to state \( j \)

The limiting probability enables marketing managers to identify CRD roughly, since it can provide marketing promotions for positive retention.

4. A Case Study on a Wireless Telecommunication Company in Korea

Churn is one of the most serious problems in the wireless telecommunication industry where customers join a cellular service for an introductory offer and then join a different company when the introductory offer of the original firm expires. In the initial stage of the wireless telecommunication business, churn may not be an important issue since acquisition of new customers can compensate for customer attrition from customer churn. As the market, however, becomes more saturated, customer churn becomes a critical concern for a telecommunication firm since the customer acquisition rate diminishes quickly and customer loss does not recover from customer acquisition. The wireless telecommunication industry in Korea already saturated since nearly 100% of adults use one or more mobile service(s). A customer has three possible optional services in this case. We assume that a customer accepts or cancels one cross-selling service in a given time period.

The graphical representation of the state transition is depicted in Figure 4.

**Figure 4. Graphical Representation of the Markov Chain for a Case Study**

4.1. Decision Variables of Individual CLV

To decide several probabilities for the one-step transition matrix of a customer, the probabilities of the customer denoted in Figure 3 should be calculated. We use data mining techniques to predict these probabilities. Data mining is to discover hidden useful information in large databases. Mining frequent patterns from transaction databases is an important problem in data mining [30]. Figure 4 shows the data mining procedure to predict various transition probabilities in the case study.
The mining result, then, is the individual customer’s predicted probabilities listed in Table 2. Therefore data mining plays a role of providing an individual transition matrix with input data as shown in Figure 6.

Since customer churn is a critical issue of the wireless telecommunication industry, we investigate the main cause of customer churn using Decision Tree as shown in Figure 7.

The most important factor indicating customer churn is variable DEL_STAT which is an arrear type of monthly charge. Misclassification rate is 7% which means churning customers are predicted 93% correctly by using Decision Tree model.
4.2. Building the one-step transition matrix

To build the one-step transition matrix of customer $i$, various probabilities are predicted by the data mining technique, Decision Tree. Table 2 shows the probabilities of customer $i$ forecasted by Decision Tree.

<table>
<thead>
<tr>
<th>Transition probability</th>
<th>Notation</th>
<th>Mined result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer churn</td>
<td>$P(churn)$</td>
<td>0.021</td>
</tr>
<tr>
<td>Positive retention</td>
<td>$P(p_{retention})$</td>
<td>0.072</td>
</tr>
<tr>
<td>Status quo retention</td>
<td>$P(s_{retention})$</td>
<td>0.928</td>
</tr>
<tr>
<td>Negative retention</td>
<td>$P(n_{retention})$</td>
<td>0.048</td>
</tr>
<tr>
<td>Customer winback</td>
<td>$P(winback)$</td>
<td>0.239</td>
</tr>
<tr>
<td>Customer acquisition</td>
<td>$P(acquisition)$</td>
<td>0.006</td>
</tr>
<tr>
<td>Customer loss</td>
<td>$P(loss)$</td>
<td>0.021</td>
</tr>
<tr>
<td>Stay at Defected customer</td>
<td>$P(d_{stay})$</td>
<td>0.761</td>
</tr>
<tr>
<td>Stay at Potential customer</td>
<td>$P(p_{stay})$</td>
<td>0.994</td>
</tr>
</tbody>
</table>
When the transition probabilities of a customer are estimated, the all probabilities should be normalized to obey the basic rule of the Markov chain, the sum of all outflow probabilities is 1. Since the outflow probabilities are estimated separately, the sum of those probabilities may exceed 1. The normalization of the outflows is performed by dividing the outflow probability by the sum of all outflow probabilities.

4.3. One-step transition matrix of customer i

The one-step transition matrix consists of the probabilities listed in Table 2. Figure 8 represents the one-step transition probabilities of customer i after normalizing the probabilities.

\[
T = \begin{pmatrix}
A_1 & 0.909 & 0.071 & 0 & 0 & 0.021 & 0 \\
A_2 & 0.045 & 0.868 & 0.067 & 0 & 0.020 & 0 \\
A_3 & 0 & 0.045 & 0.868 & 0.067 & 0.020 & 0 \\
A_4 & 0 & 0 & 0.048 & 0.931 & 0.021 & 0 \\
D & 0.234 & 0 & 0 & 0 & 0.745 & 0.021 \\
P & 0.006 & 0 & 0 & 0 & 0 & 0.994 \\
\end{pmatrix}
\]

Figure 8. One-step Transition Matrix of Customer i

4.4. Reward Vector of Customer i

The reward vector of customer i, the contributed profit while he or she stays at a certain state, is derived from an interview as shown in Table 3.

<table>
<thead>
<tr>
<th>ID</th>
<th>Profit/Cost Drivers</th>
<th>Profit/cost (KRW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>Monthly Profit from Charge without optional service</td>
<td>(+)15,000</td>
</tr>
<tr>
<td>D2</td>
<td>Profit from a cross-selling service</td>
<td>(+)1,000</td>
</tr>
<tr>
<td>D3</td>
<td>Marketing cost for a cross-selling promotion</td>
<td>(-)3,000</td>
</tr>
<tr>
<td>D4</td>
<td>Marketing cost for a defected customer</td>
<td>(-)2,000</td>
</tr>
<tr>
<td>D5</td>
<td>Subsidy for a wonback customer</td>
<td>(-)20,000</td>
</tr>
<tr>
<td>D6</td>
<td>Marketing cost for acquiring a potential customer</td>
<td>(-)2,000</td>
</tr>
<tr>
<td>D7</td>
<td>Subsidy for an acquired customer</td>
<td>(-)20,000</td>
</tr>
</tbody>
</table>

The reward vector is calculated from Table 3. The reward vector of customer i, composed of profit or cost driver, is shown in Figure 9.
Figure 9. Reward Vector of Customer i

The \((m, n)\) element of the vector denotes the profit/cost of customer \(i\) who stays at state \(m\) and transferred from state \(n\). The profit includes the profit contribution at state \(m\) and marketing cost at state \(n\). For instance, element \((A_4, D)\) means that customer \(i\) moves from state \(A_4\) to state \(D\). Therefore the profit includes profit contribution from the monthly charge (\(D_1\)), three optional services (\(D_2^*3\)) and loss from subsidy for a wonback customer (\(D_5\)), marketing cost for acquiring a potential customer (\(D_6\)).

4.5. Lifetime Value of Customer i

Lifetime value of customer \(i\) can be derived through Equation 4 as shown above. Monthly interest rate are used for the discount rate, \(d\), and it is set as 0.3 (\%\/month). The result of Equation 3 is shown in Figure 10. As mentioned before, the diagonal elements are the lifetime value and, therefore, Figure 10 can be summarized as Figure 11.

\[
\text{CLV}_i = \begin{pmatrix}
2,244,096 & 2,244,096 & 2,244,096 & 3,247,096 & 1,161,731 \\
2,262,946 & 2,262,946 & 2,262,946 & 3,265,946 & 1,928,705 \\
2,282,095 & 2,282,095 & 2,282,095 & 3,285,095 & 2,262,946 \\
2,293,046 & 2,293,046 & 2,293,046 & 3,296,046 & 2,262,946 \\
1,928,705 & 1,928,705 & 1,928,705 & 2,931,705 & -1,361,950 \\
1,161,731 & 1,161,731 & 1,161,731 & 2,164,731 & -1,180,577
\end{pmatrix}
\]

Figure 10. CLV Matrix of Customer i

The sum of the diagonal elements in Figure 10 is the net CLV of customer \(i\). We, therefore, anticipate that customer \(i\) will contribute 7,542,656 (KRW) to the company during his lifetime.

While a customer stays at the Active Customer State, his CLV is positive. While staying at the Defected Customer State and the Potential Customer State, his CLV is negative, \(i.e.,\) generated more cost than profit. The negative profit contribution results from the poor winback rate (0.220) and acquisition rate (0.006).

4.6. Limiting Probability of Customer i

The limiting probability of the transition matrix of customer \(i\) represents the long-run proportion of time that customer \(i\) stays at a certain state. Table 4 shows the limiting probability of customer \(i\).
Table 4. Limiting Probability of the Transition Matrix

<table>
<thead>
<tr>
<th>Stage</th>
<th>state</th>
<th>Limiting probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active Customer State</td>
<td>A1</td>
<td>( \pi_1 = 0.178 )</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>( \pi_2 = 0.129 )</td>
</tr>
<tr>
<td></td>
<td>A3</td>
<td>( \pi_3 = 0.101 )</td>
</tr>
<tr>
<td></td>
<td>A4</td>
<td>( \pi_4 = 0.099 )</td>
</tr>
<tr>
<td>Defected Customer State</td>
<td>D</td>
<td>( \pi_D = 0.035 )</td>
</tr>
<tr>
<td>Potential Customer State</td>
<td>P</td>
<td>( \pi_P = 0.458 )</td>
</tr>
<tr>
<td>total</td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Customer \( i \) is expected to stay as an active customer having probability about \( 1/2 \). He or she also stays as a potential customer for almost half of the lifetime.

5. Marketing Implications

The lifetime value of customer \( i \) provides marketing managers with marketing implications. As we can see in Figure 12, customer \( i \) contributes negative profit during potential customer state, \( i.e., \) cost, to a firm. Therefore marketing managers should decide whether marketing for customer acquisition is effective when a customer is in state \( P \), the Potential Customer State. The decision is possible through a recalculated CLV after modifying the transition matrix \( T \) and the reward vector \( R \). Assume that a manager decides to improve profitability by stopping a marketing promotion for customer \( i \) when he stays at state \( P \). The cost drivers of a firm will change as in Table 5.

Table 5. New Cost Drivers for Customer \( i \)

<table>
<thead>
<tr>
<th>Cost drivers</th>
<th>Profit/cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Profit from Charge</td>
<td>(+15,000)</td>
</tr>
<tr>
<td>Profit from a cross-selling service</td>
<td>(+1,000)</td>
</tr>
<tr>
<td>Marketing cost for a cross-selling promotion</td>
<td>(-3,000)</td>
</tr>
<tr>
<td>Marketing cost for churn management</td>
<td>(-2,000)</td>
</tr>
<tr>
<td>Subsidy for a wonback customer</td>
<td>(-20,000)</td>
</tr>
<tr>
<td>Marketing cost for acquiring a potential customer</td>
<td>0</td>
</tr>
<tr>
<td>Subsidy for an acquired customer</td>
<td>0</td>
</tr>
</tbody>
</table>

Assume that the acquisition rate of customer \( i \) will be decreased by 0.0000001 which denotes the acquisition rate without acquisition promotion. The transition matrix and the reward vector are also changed like Figure 11 and Figure 12 respectively.
The result of CLV is shown in Figure 12. As seen in Figure 12, the total CLV decreases from 7,542,656 to 6,463,542. The result implies that acquisition promotion is effective and profitable for customer \( i \). We can discover that it is profitable for a firm to execute acquisition promotion for customer \( i \) since reducing acquisition expenditure for customer \( i \) result in the deduction of the overall profitability. Before performing marketing promotion, we can forecast its monetary result through the changes of a transition matrix and a reward vector.

### 6. Conclusion & Further Research Directions

This paper focused on the implementation of an individualized Customer Lifetime Value model. Customer relationship with a firm is embodied by a state of the Markov chain. The suggested CLV model provides not only the lifetime value of a customer but the fractionized lifetime value of a customer according to the state. The model also covers the long-run proportion of time for a state where he or she stays. The suggested model is illustrated by an industrial case study on the wireless telecommunication industry in Korea.

In future, we expect this work to spur further research on personalized stochastic CLV model, which includes the Markov chain model and other structural CLV models based on probabilistic revenue estimation. Another further research issue is to develop a personalized marketing strategy based on individual CLV. Individual CLV is expected to vary with changes of business environment. Therefore, marketing strategies should be built based on the result of sensitivity analysis. A sensitivity analysis can help the strategy development by deciding optimal budget allocation, forecasting profitability change, and measuring marketing effectiveness.
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References


Author

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