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RESEARCH PAPER

Presenting a Model for Calculating ISACO Customers Lifetime Value by Markov Chain Using Data Mining Techniques

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ABSTRACT
One of the key issues in studies on customer relationship management (CRM) and marketing budget allocation is to calculate the customer's lifetime value and apply it to macro-management decisions. A major challenge in this issue is considering the possibility of changes in the behavior of customers with the turn of time in the model. In this study, a new approach has been used to estimate the parameters of the model proposed for calculating the future lifetime value of Iran Khodro Spare Parts and After-Sale Services Co. (ISACO) customers. This method takes into consideration the possibility of changes in customer behavior throughout their interaction with the company. In this article, the customers of ISACO are first classified using clustering techniques and use multilayer neural network to calculate the monetary value of each group of customers during a specific period of time. Then, the Markov chain approach is used to develop a model for calculating the lifetime value of ISACO's customers considering the possibility of changes in their behavior in different periods. The results obtained here can be used in the allocation of marketing budget and adoption of macro-management decisions to envisage various projects for customers with different lifetime values.

KEYWORDS: *customer lifetime value, Future value, ISACO, Markov chain, clustering, neural network.*

1. Introduction

The customer lifetime value (CLV) is a key and useful concept in interactive marketing. This concept helps companies acquire strategic competitive advantages [1]. It is necessary for firms to understand customers and predict their needs for more success in business [2]. CVL is defined as the value of customer earnings based on the customer's long-term relationship with the company during his lifecycle [3]. For a company, CVL is the net contribution margin acquired from a customer during the period of time when the customer interacts with the company minus marketing, sale and customer servicing costs while taking into consideration the time value of money [4].

An exact assessment of the profitability of customers is a key element in the success of customer relationship management (CRM) plans. CRM refers to the technology and systems that help the company serve, satisfy, and retain customers [5]. Nonetheless, it would not be so easy to assess the profitability of customers as such assessment would have to include customer future profit projections [6]. Today, a growing number of companies are focused upon long-term relations with customers and, subsequently, on growth and higher profitability. Therefore, identifying the potential of profitable customers and winning their long-term loyalty in a competitive business environment would be a key factor [7]. As a result of this approach, marketing activities and approach assessments are organized mainly in the content of customer relationships rather than products [8]. However, with an increased understanding of the importance of customer loyalty, companies have shifted further to customer-oriented approaches in their strategies and, therefore, the customer's lifecycle has become a fundamental concept in the marketing strategy. From the standpoint of a

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customer-oriented approach, a customer is not treated as a company asset. This approach further concentrates on attracting customers and retaining them [9]. The retained customers may form the foundation of sustainable competitive advantage. In modern economy, where a growing number of companies are providing the same services and customer relationships has become a vital issue, such an approach is more suitable. A precise estimate of customer profitability empowers the company to make better decisions with regard to the allocation of marketing resources to customers [10]. As a consequence of this attitude, customers of a company will be considered as assets [9]. A precise estimate of future customer profitability empowers a company to make better decisions with regard to the allocation of marketing resources to customers [10]. For instance, a retailer may choose to increase services for customers with a higher lifetime value and send direct notices to customers with a low lifetime value [11].

Through this article, first, the literature of CLV is reviewed. Second, the methodology of this research, key variables, and estimation methods of parameters are completely explained. Then, the results of the proposed method are demonstrated briefly. In the final section, the conclusions are described.

2. literature Review

As mentioned before, estimating the revenue of a customer is not simple, because, for this purpose, one should estimate the future value of a customer. The longer a customer is retained, the higher the value he/she brings to the company, which explicitly explains the importance of CRM [12]. In literature, the customer's lifetime value is also entitled Customer equity and Customer profitability. Lifetime value (LTV) of a customer includes the benefit gained from a customer during his/her lifetime (LT), which is the period customer remains with the company [6].

The studies conducted on CLV are divided into three groups:

The first group comprises research conducted to develop models for calculating CLV. This kind of research focuses on topics such as cost of acquiring customers, cost of maintaining customers, flow revenue from customers, and other costs of marketing. Ref. [13], [14], [15], [16], and [17] can be grouped in this category. Ref. [18] reviewed all CLV formulations of the past 3 decades briefly.

The second group comprises the research set to offer customer-based analyses. In this kind of research studies, different methods are proposed to analyze information gained from available customers and to predict a probable value of future customers' transactions. In this category, researchers are focused on single customers as sufficient as groups of customers and using empirical methods to suggest which kind of customer or group of customers should be absorbed and protected, because all customers are not profitable for a company. This category of research, which is focused on customer segmentation according to CLV, can be found at Ref. [19], [20], [21], [22], [23], [24].

Finally, the third category comprises research that studies the impact of CLV on managerial decisions through analytical models such as [25], [26], [27], [28]. Special focus on this area is about the effect of customer's loyalty on CLV and company's profit.

The analysis of customer lifetime value is seeing a strongly increasing interest in the marketing community. This interest has been sparked for three reasons. First, firms are interested in the customer management process, for which an understanding of the lifetime value concept is a prerequisite. Second, the Marketing Science Institute has elevated the topic to a capital research priority- which reflects the interest of both academics and managers. Third, given this high interest of multiple constituencies, empirical evidence is particularly scarce in this domain [29]. Few Practical research studies in this area have been conducted such as [30], [31], [32], and [33]. Such empirical researches need to use a large amount of transactional or historical data to derive CLV-based analyses. In order to obtain such outcomes from this large amount of data, it is common to utilize data mining techniques such as clustering [34], decision tree [35], neural network [36], support vector machine [34], regression [37], and synthetic data mining methods [38].

Today, companies are relying on such concepts as CLV to create and retain long-term relationships with high-value customers [8]. The companies attaching importance to the retention of customers and interactive marketing may choose to consider special privileges for their faithful customers or customers with a high lifetime value. Moreover, they may decide to increase the lifetime value of customers with a lower profitability [39]. Recently, some Iranian companies have paid more attention to CRM concept and CLV as a key measurement. Senior managers of these companies are interested in utilizing such concepts and analyses in order to make better managerial decisions.

Iran Khodro Company was founded in August 1962 to produce various types of autos. Nowadays, it produces one million auto per year including 60 different kinds. With its 20,000 manpower, it is the largest automotive manufacturer in the Middle East. ISACO, founded in 1977, is a commercial and service company including the administrative buildings and central warehouses. The company's domain of activity includes supplying automotive parts and services, customer services, dealer and service network, parts sourcing, warranty sales, etc. for all automobiles manufactured by Iran Khodro Company.

One of the main concerns of ISACO's senior managers is to recognize profitable customers in order to allocate marketing budgets for increasing their loyalty and, subsequently, increasing the company income. Thus, calculating the customer lifetime value as a key indicator is necessary.

The objective of this practical research is to develop a model to calculate the lifetime value of ISACO's customers while taking into consideration possible changes in their behavior throughout time. At the end, a roadmap is derived to calculate ISACO's CLV. Senior managers of ISACO can use the proposed roadmap to calculate CLVs and make better managerial decisions. Moreover, other companies can recall this roadmap and utilize their own historical data to calculate their CLVs. In this study, one-year transactional data of ISACO customers (from 1395 AH to 1396 AH) are analyzed. To model the probability of changing customer behavior, the Markov chain approach is utilized. Due to the existene of a large amount of data, some data mining techniques such as classification, clustering, and neural network are used in this paper to estimate the future value of ISACO customers. The research approach is completely explained in the following section.

3. Methodology

The approach used in this research is both quantitative and qualitative. It is exploratory research and the research method is the case study. Since the behaviors of customers are considered during a time period, this study is a longitudinal research type. Through this paper, we are trying to answer two questions: 1-what is the current value of recent customers? 2- what is the future value of these customers? To answer question No. 2, we need to answer 3 sub questions: first, how long will the customer remain with the company; second, how would be the possible behavior of customers during their lifetime; third, how much is the revenue of customers during their lifetime.

To answer 2 main questions, available one-year transactional data of ISACO are analyzed. To answer sub question 1, decision tree, which is a data mining technique, is utilized. To answer sub question 2, principal component analysis (PCA), clustering, and Markov chain approach are utilized which are powerful mathematical methods to model this kind of uncertainty. To answer sub question 3, a neural network is used. The different phases of research are shown in Figure 1.

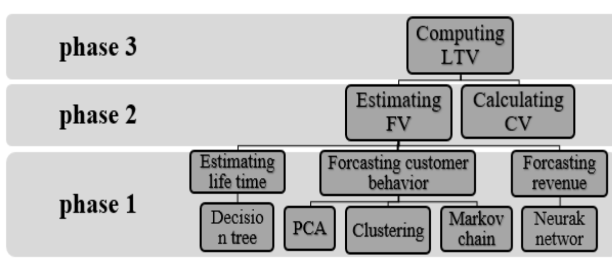

Fig. 1. Clusters created by K-means

It is necessary to mention that all results are derived using SPSS modeler 18, R 3.6.0, and SPSS 24 software.

The basic concept of customer lifetime value calculations is based on net present value obtained from a customer's transactions during his lifetime. Lifetime value of customers (LTV) or Net present value of a customer comprises two components: current value (CV) which is the past profit contribution obtained from historical transactions of customer and future value (FV), which is the estimated value of a customer in the future [6]. Therefore, the lifetime value of the k^{th} customer is computed through Equation (1).

$$LTV_k = CV_k + FV_k \tag{1}$$

If the customer's interaction with the company has started m periods ago, the current value of the k^{th} customer is calculated using Eq. (2).

$$CV_k = \sum_{t=-m}^{0} \pi_k(t) \prod_{d=t}^{0} (1 + r(d)) \tag{2}$$

where $\pi_k(t)$ is the margin created by the k^{th} customer in the t^{th} period, and r(d) is the banking interest rate in the t^{th} period. Let the number 0 denote the current time period and -1 denote one period before current time, and so on. When historical data of a company are available, the current value of the k^{th} customer for a specific time duration can be calculated through the customer acquisition costs in that specific period. The banking interest rate should be also fitted into the formula for that period.

Therefore, the current value for a specific time period of an ISACO customer is calculable based on the transactional data registered for each customer in ISACO's database. The banking interest rate can also be obtained from Iran central bank website in that period.

Estimating the future value of a customer is more difficult and complicated than computing the CV of that customer. In order to calculate FV, it is necessary to predict two items: first, the length of time which customer remains with the company and, second, profit contributed from that customer during the concerned period. In addition, to have a better estimation of FV, it is necessary to consider the probability of changing the behavior of a customer during the lifetime. Eq. (3) presents the formula of estimating FV of the k^{th} customer [6].

$$FV_k = \sum_{t=1}^{n_k} I_k P^t \pi_k(t) \tag{3}$$

where n_k represents the k^{th} customer's lifetime period, i.e., the period of time during which we expect the customer to interact with the company and I_k represents the initialization vector for the k^{th} customer; the modes of this vector are zero and one and indicate the statuses of customer's behavior. For instance, if we consider five behavior statuses for a customer, this vector will have only one member and the remaining four will be zero. It is proven that, for a customer, only one state may occur during a period of time. P^t is the matrix of probability of transition in customers' statuses in the t^{th} period. This matrix is obtained from the behavioral statuses of customers using a Markov chain. The elements of this matrix are the portability of a customer's transition from one behavioral status to another. $\pi_k(t)$ represents the vector of margins achieved from the k^{th} customer under different behavioral statuses, indicating the customer's level of contribution.

To calculate the FV of ISACO' customers, it is required to estimate the parameters of Equation (3), which is the main contribution of this research. The method for estimating the foregoing parameters is explained in the following sections.

4. Laying Out Variables and Data Standardization

The research data comprises the number of transactions by each customer for the 1395-96 AH period. In the ISACO database, 13 primary variables are recorded. Using all recorded variables such as the code of service center is not useful in this research. The variables used in this research are divided into two groups: The first group includes the primary variables of dataset that we have directly obtained from the registered transactions; the second group comprises secondary variables that are artificially created from the primary variables for modeling, facility, and higher precision of modeling. Table 1 outlines and describes these variables.

Tab. 1. Modeling variables

No.	Variable Name	Type	Scale	Use in Research
1	Customer Code	Primary	Quantity	Key indicator, exclusively used to identify customers without being integrated into modeling
2	Number of Referrals	Primary	Quantity	Used for updating dataset and creating secondary variables
3	Total Costs	Primary	Quantity	Used to create secondary variables
4	Customer Average Costs	Secondary	Quantity	Calculated from dividing total costs by the number of customer referrals and serves an independent modeling variable
5	Distance Traveled on Vehicle	Primary	Quantity	Used to create secondary variables and serves as an independent input variable in the model
6	Vehicle Age	Primary	Quantity	Used to create secondary variables and serves as an independent input variable in the model
7	Average Vehicle Displacement	Secondary	Quantity	Calculated by dividing the distance traveled on vehicle by the age of vehicle and serves as an independent modeling variable
8	Customer Turn	Secondary	Quality	Equals either 0 or 1, indicates customer's willingness to stay or leave, serves as logistic regression classification model variable to calculate the customer lifetime

In Table 1, the number of Referrals shows how many customers go to a service center of ISACO in the corresponding period of time. Total cost refers to the amount of money that a customer pays to ISACO during the studied time period. Variable No. 4 is a secondary variable obtained from dividing two explained primary variables. Variable No. 5 shows the distance that an auto traverses until visiting a service center. It is obtained from the odometer of the vehicle. Vehicle age represents the period of time between handing over the auto to the customer from company for the first time and referring to the service center. Variable No. 7 is a secondary variable and is obtained from dividing variable No. 5 by variable No. 6.

Due to the high correlation between the number of referrals and total costs on the one side and between the distance traveled on vehicle and the vehicle age on the other, instead of using them directly in the classification modeling, the average customer costs and average displacement are used as secondary variables because that would contain the data of the two dependent variables. That would also help resolve the problem of collinearity, further update the dataset, and create more logical outputs. Table 2 shows the results of the correlation test between the research variables. Finally, variable No. 8 is a binary variable and will be used to predict the time period that a customer remains with the company.

The table data shows a high correlation with a coefficient of 0.875 between costs and the number of referrals and a significant correlation with a coefficient of 0.635 between the distance traveled on vehicle and the age of vehicle. There is also a correlation between other variables; however, it is not high enough to affect the final results.

Tab. 2. Test of correlation between variables

		Number of Referrals	Costs	Distance Traveled	Age
Number of Referrals	Pearson Correlation	1	.875**	.031**	.018**
	Sig. (2-tailed)		.000	.000	.000
	N	37974	37974	37974	37974
Costs	Pearson Correlation	.875**	1	.042**	.035**
	Sig. (2-tailed)	.000		.000	.000
	N	37974	37974	37974	37974
Distance Traveled	Pearson Correlation	.031**	.042**	1	.635**
	Sig. (2-tailed)	.000	.000		.000
	N	37974	37974	37974	37974
Age of Vehicle	Pearson Correlation	.018**	.035**	.635**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	37974	37974	37974	37974

**. Correlation is significant at the 0.01 level (2-tailed).

4-1. Dataset cleansing and updating

Before any analysis in data mining, an important step to take is to verify the quality of data and prepare them for modeling. Updating data involves all measures including identifying and dropping lost data, identifying outliers, and other data that could be necessary for the optimization of dataset.

A major step in data identification is data cleansing. This stage of data analysis and data mining is so important that any disregard for it would overshadow the entire process of data mining and subsequently the final results. In brief, outliers refer to data that are either bigger or smaller than other data within a dataset. Outliers are significantly different from our expectations. They may result from:

- Incorrect observed measurements (human error in data recording)
- Gathering data from various populations
- Measurement for a rare incident or event
- Skewness of dataset in relative frequency distribution curve

Identifying outliers is a time-consuming process, particularly when it comes to big datasets. Numerous methods have been developed for distinguishing the outliers. In this research, the Box Plot and Median Absolute Deviation (MAD) methods are used.

Once the data are prepared, an attempt will be made to estimate the parameters. In the next section, estimating the lifetime of a customer is explained.

4-2. n_k estimate

As explained earlier, n_k represents the customer lifetime, i.e., the period during which we expect the customer to remain loyal to the company. To estimate n_k, customer average costs and average displacement of vehicle are used as independent and predictor variables. The target variable is considered as the customer's decision to either remain or leave. In other words, if the kth customer visits the company only once, he/she will receive label 0 (leaving company after the first reception), and if he refers more than once, he will receive label 1 (remaining in the company after the first reception). Table 3 provides some records where a target variable is predicted.

Tab. 3. Some records with predicted target variables

Target Variable (Remain or Leave)	Vehicle Average Displacement	Customer Average Costs	Customer Code
1	2254	176603	9108328
1	2042	304838	9108575
.			.
.			.
.			.
0	3399	205532	9189545
.			.
.			.
.			.
0	1944	49500	9789568

Now, by using data mining classification techniques, the customers are classified and the probability of 0 or 1 is calculated, i.e., remain or stay. This study has used the three common classification algorithms of logistic regression, decision tree, and support vector machine. Table 4 summarizes the results. It is noted that 80% of data are considered as training sets and the remaining 20% as test sets.

Tab. 4. Classification accuracy index

Model	Logistic regression	Decision tree	Support vector machine
Classification accuracy	65.8%	73%	71%

The results obtained here indicate that the decision tree model is more accurate than the other two models. Therefore, the decision tree is used to model the probability of customer U-turn. For example, the probability of the first customer (code 9108328) receiving a label 0 is 0.198, i.e., this customer is 19.5% likely to leave the company after his first reception. The question here is to know how the number of customer referrals may be calculated.

For this purpose, statistical distribution can be used. Discrete geometric distribution (Eq. (4)) shows the probability of reaching the first success after n-1 failures in the Bernoulli trial. If the remaining option is considered as success and the leave option as failure, then it becomes possible to calculate the average number of necessary tests for achieving the first success. That would be an approximation for the number of periods during which the customer is expected to remain loyal to the company.

$$Pr\{y = n\} = p_k^c(1 - p_k^c)^{n-1} \qquad (4)$$

This function is the density of the probability of discrete geometric distribution. By using the mathematical expectation (shown in Eq. (5)) of this distribution, n can be estimated as follows:

$$n_i = E[y] = {}^1/_{p_k^c} \qquad (5)$$

Against the above, consider the example of the same customer who is 19.8% likely to leave the company. Normally, it is expected that he will remain loyal for $\frac{1}{0.198} = 5.05{\sim}5$ more periods. In the same manner, the lifetime for all customers can be calculated.

In the following section, the estimation of initialization status vector of a customer is described.

4-3. I_k estimate

In order to form the I_k vector, we first need to classify the behavioral states of customers and see how the kth customer behaves in a specific period of time. For this purpose, the clustering technique and the k-means algorithm are used. The customers are classified based on the variables of vehicle age, average costs, and distance traveled on vehicle. Each cluster represents a behavioral state or a status that would help us form a Markov chain and calculate the probability of transition of states. Therefore, the length of vector I_k depends on the number of states obtained from clustering.

Tab. 5. Davies-bouldin index for various number of clusters

K	1	2	3	4	5
DB-Index	-	-	0.4789	0.5251	0.4925
K	6	7	8	9	10
DB-Index	0.4915	0.4952	0.4955	0.5331	0.5491
K	11	12	13	14	15
DB-Index	0.5203	0.5223	0.5247	0.5361	0.5372
K	16	17	18	19	20
DB-Index	0.4850	0.5536	0.5012	0.5169	0.5251

The method used for the labeling of customer behaviors is that we first cluster the customers by applying the k-means method to variables. Before clustering, we have to estimate the number of clusters (K). This study uses the Davies-Bouldin Index (DBI) to estimate an optimal K. This index shows the optimal clustering by maximizing the similarity of data within a cluster while minimizing the similarity of data between clusters. The clustering that minimizes this index will be the optimal clustering whose product will be an optimal K. The results obtained for various K's are shown in Table 5. Therefore, from Table 5, it is concluded that the optimal number of clusters is 3. The final clusters are shown in Fig. 2.

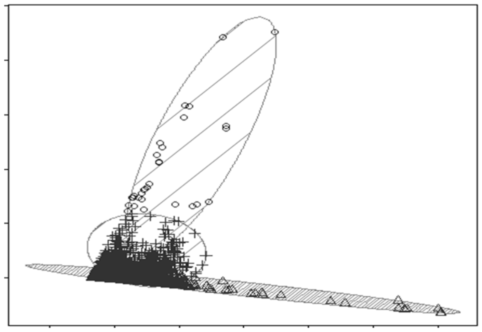

Fig. 2. Clusters created by K-means

Since there is a mean value for each variable in each cluster, we need to have a table like Table 6 in order to define the final clusters.

Tab. 6. Average parameters for each cluster

No.	Clusters	Average Costs	Distance Traveled	Vehicle Age	Number
1	Cluster-1	43306567.4	26073.77	13.4	30
2	Cluster-2	409799.5	19625.76	14.4	25,622
3	Cluster-3	6894026	48088.12	23.42	690
Total Average	*	628500.41	20378.64	14.63	26,342

Table 6 shows that the largest frequency (97%) belongs to Cluster-2. For each cluster, an average value has been calculated. The next step is to calculate the total weighted average for the clusters of each variable. Then, the customers are labeled as H if their value is higher than the total average and L if their value is lower than the total average. Each customer will receive his particular label. The results of the labeling are seen in Table 7.

Tab. 7. Labeling of customers

Label	LLL	LLH	LHL	LHH	HLL	HLH	HHL	HHH
Frequency	15,208	2,033	1,894	7,156	33	2	1	15

This table shows that most customers (15,208) are labeled LLL, i.e., their average costs are below 628500.41 and the distance traveled in their cars is below 20378.64, while the age of their vehicle is below 14 years. The labels HHL, HLH, HHH, and HLL with meager frequencies are seen as outliers (rarely do they occur to a customer; only 2% of customers are labeled as such) and, therefore, can be dropped. After putting final touches to the status of customers, we will be able to form the I_k vector.

In the next section, the estimation of transition matrix of the Markov chain is completely explained

4-4. P^t estimate

A Markov chain is a memoryless random process for calculating the probability of transition from one state to another. The number of this state is countable. Memorylessness means that the next state depends only on the current state and what precedes has no impact. Generally speaking, it is impossible to predict the state of a Markov chain in a specific spot in the future. However, the future statistical features of a system are predictable. The changes in the states of a system are known as transition and the probabilities attributed to this change of states are referred to as probabilities of transition. A group of states and probabilities of transitions can constitute a Markov chain. Conventionally, it is assumed here that there is always a future state and, therefore, the process continues for eternity. The mathematical interpretation of what was said above is deducible in Eq. (6).

$$Pr(X_{n+1} = x | X_1 = x_1 . X_2 = x_2 . \dots . X_n = x_n) = Pr(X_{n+1} = x | X_n = x_n) \quad (6)$$

Therefore, it is realized that, in a Markov process, the probability of transition from one state to another in the future depends on the current state. This matrix shows the probabilities of the transition of customers from one state to another.

To predict future states, we would have to calculate the higher powers of this matrix.
P^t represents the matrix of transition or behaviors of ISACO customers, as explained earlier. The entries of this matrix are all probabilities calculated by a Markov chain. Naturally, P^t is a square matrix with an equal number of rows and columns. It depends on the number of states obtained from clustering. Given the number of states obtained from labeling explained in the previous section and using the labeled data, the 4*4 transition matrix is calculated as shown in Eq. (7).

$$P = \begin{array}{c} State \\ LHH \\ LHL \\ LLH \\ LLL \end{array} \begin{array}{c} \begin{array}{cccc} LHH & LHL & LLH & LLL \end{array} \\ \begin{bmatrix} 0.330 & 0.087 & 0.095 & 0.488 \\ 0.315 & 0.123 & 0.097 & 0.466 \\ 0.319 & 0.086 & 0.112 & 0.484 \\ 0.234 & 0.057 & 0.062 & 0.648 \end{bmatrix} \end{array} \quad (7)$$

After clustering and calculating various states of customers via a Markov chain, the probability of transition from one state to another was calculated.
In the following section, the method used for estimating vector of margins achieved from customers will be explained.

4-5. $\pi_k(t)$ estimate

$\pi_k(t)$ is the vector of the predicted margin for the k[th] customer in all behavioral states during period t. This vector is shown in Eq. (8).

$$\pi_k(t) = \begin{bmatrix} \pi_{k.1}(t) \\ \pi_{k.2}(t) \\ \vdots \\ \pi_{k.L}(t) \end{bmatrix} \quad (8)$$

Each row in the vector $\pi_k(t)$ indicates margins generated by the k[th] customer in various behavioral states. For instance, the first row indicates the predicted margins for the k[th] customer in State 1 (i.e., LHH) during period t. This vector is obtained from the Perceptron multi-layer neural networks. An important feature of the neural networks model is the resistance of this algorithm to lost data and outliers. Furthermore, due to the non-linear nature of this model, the algorithm is also resistant to such problems as collinearity between independent variables. The independent variables are the distance traveled on the vehicle and the vehicle age, while the target variable is customer costs for each period, indicating the customer activity.

Modeling is done separately for each group. For prediction, we have to enter the distance traveled by the vehicle and the vehicle age into the model as input in order to receive costs for each state as output. To calculate the vehicle age in the future, this study has to add the number of months in future periods to the current age of the vehicle. To calculate the expected traveled distance in each period, we can divide the traveled distance by the vehicle age to have the average distance traveled by the vehicle per month. Then, as we did for the vehicle age, the expected traveled distance is calculated based on the number of months in our predictions. For instance, the future participation vector for customer 9108328, for whom we had calculated the lifetime to be 5, is shown in Eq. (9).

$$\pi_1 = \begin{bmatrix} 3147277 \\ 4280332 \\ 2525648 \\ 7199921 \end{bmatrix}. \pi_2 = \begin{bmatrix} 2803929 \\ 4229195 \\ 2415604 \\ 7451910 \end{bmatrix}. \pi_3 = \begin{bmatrix} 2659485 \\ 4172660 \\ 2344267 \\ 7667170 \end{bmatrix}. \pi_4 = \begin{bmatrix} 2529253 \\ 4137380 \\ 2298235 \\ 7852159 \end{bmatrix}. \pi_5 = \begin{bmatrix} 2450415 \\ 4128035 \\ 2268620 \\ 8010505 \end{bmatrix} \quad (9)$$

Finally, estimating all parameters gives us a possibility to obtain CLV for each customer in the database based on the available data and using the methods explained earlier.
An instance (calculating the CLV of customer no. 9108328) is explained in the next section in order to show readers how the proposed method will be utilized to calculate all the CLV customers of ISACO.

5. An Illustrative Example

All the steps of the proposed roadmap were explained precisely in the previous sections. It is redundant to report all CLVs of ISACO customers; however, for instance, the steps of calculating CLV for customer no. 9108328 will be illustrated clearly in this section.
First, it is assumed that we are at the beginning of the year 1397 AH. The purpose is to calculate both current value and estimate the future value of the intended customer. Using the transactional data recording on ISACO database, customer no. 9108328 refed to the company only once in the

past year and spent 4944875 IRR in the company to receive a service. This cost may involve both the cost of a replaced part or the wage of a serviceman. Therefore, by assuming banking interest rates at 14% for 1395-96 AH., we have:

$CV = 4944875 * (1.14) = 5637157.$

Based on the process outlined in this study, the lifetime for this customer is estimated at 5 using the average of Poisson distribution, described in Section 4.2. The matrix of probability of transition for four states is estimated in Section 4.4. The matrix of predicted margins of this customer is obtained in Section 4.5. Hence,

$FV(1) = I.P^1.\pi(1) = 5164488$

$FV(2) = I.P^2.\pi(2) = 5503635$

$FV(3) = I.P^3.\pi(3) = 5640113$

$FV(4) = I.P^4.\pi(4) = 5714040$

$FV(5) = I.P^5.\pi(5) = 5789227$

$$FV = 5164488 + 5503635 + 5640113 + 5714040 + 5789227 = 27811503$$

Finally,

$$LTV = CV + FV = 5637157 + 27811503 = 33448660$$

The same methodology applies to the calculation of CLV for other customers of ISACO.

Conclusions are derived and explained in the next section.

6. Conclusion and Suggestions

Modern economy is mainly service-oriented. Companies create competitive advantages and make revenues via attracting and retaining their long-term customers. In today's world, any business managing to correctly identify customers of various categories uses this knowledge in marketing budget allocations and makes efforts to increase its customers' lifetime and, in doing so, will be able to adopt better strategies than its rivals and spend its limited budget more suitably. In light of such needs, a method was suggested for calculating the lifetime value of ISACO customers' including the current value and the future value of customers with the assumption of possible changes in their behavior throughout the period of their interaction with the company. In order to fulfill this calculation, lifetime of customers, their referral, and the related benefit belong to each manner should be estimated. The proposed method uses different combinations of data mining techniques and the Markov chain to prepare a suitable estimation of initial parameters. In this research, influential parameters were initially identified and the correlation between various variables was examined. The primary data were cleansed to obtain authenticated results. Then, the parameters of CVL, customer initialization vector, matrix of transition probability, and matrix of company revenue for each behavioral state were calculated using various data mining techniques, as explained in detail. Finally, LTV of an ISACO customer was calculated as an instance using the proposed method.

This method enabled us to calculate FV for all customers. As a consequence, after calculating LTVS of all customers, managers can use these results as primary information in allocation of marketing budget for different groups of customers with different LTVs. In addition, different options for servicing plans can be designed and executed for different groups of customers. Using the LTVs obtained from this research as an important measure in the CRM domain, managers could make better decisions for different categories of customers and adoption of appropriate managerial decisions with a view to increase CLV. In addition, all companies can implement the proposed roadmap described in this study and use their own transactional data to obtain their customer's LTV as a vital measure in managerial decisions.

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