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# Customer Value Assessment Methodology Using DM Approach

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**ABSTRACT**

The purpose of this study is to segment customers by value and observe different various characteristics in different clusters. We propose a new segmentation method based on DM and most commonly used CRM models; RFM, and demographic variables. The method is based on two-phases clustering model by k-means and SOM techniques and has been implemented in chain stores B in Iran. The descriptive findings of the study were rated clusters and pattern types of these customers to identify the target customers' positions. The existing customers were divided into 35 groups.
In this chain store, each customer has a transaction record that stored in the store's database but for Demographic data they were asked telephonic. Beyond simply understanding customer value in each cluster, the chain store would gain the opportunities to establish better customer relationship management strategies, improve customer loyalty and revenue and find opportunities for up and cross selling.

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*K-Means algorithm*

## 1.Introduction

Changes in consumer shopping habits and emerging technologies are bringing heavy transformation across the retail industry. Consumers are challenging the industry to adapt to the ways they live and shop today. Supported by emerging technologies, consumers have become more focused than ever on price and convenience. Hence, retailers have to be able to very clearly differentiate themselves through excellent customer service that is further enabled through technology. This is all the more important to avoid or reduce customer churn, since the cost of acquiring new customers is much higher as compared to that of retaining them [1]. The key to survive in this competitive industry lies in better understanding of customers. One of the approaches used to understand customers and identify their homogenous groups is customer clustering and segmentation [2]. Customer Segmentation is an increasingly significant issue in today's competitive commercial area. Many literatures have reviewed the application of DM technology in customer segmentation, and achieved sound effectives [3]. Data minig (DM) methodology has a tremendous contribution for researchers to extract the hidden knowledge and information [4]. Customer analysis is required for segmentation, which enables department stores to be coordinated with customer's behavior. In addition requirement of specific customer groups and marketing programs can be distinguished by segmentation and give more clarity to the planning process.

Input variables used in the segmentation process determine the step of CRM we are dealing with. Demographic variables and RFM are the most common input variable used in the literature for clustering customers. However demographic variables deal with all the stages of CRM, their role in customer attraction is more significant. On the other hand, RFM are mostly used in the customer retention and development. In this study we aim at combining these two input variables in an innovative approach for customer segmentation using the well-known DM clustering technique, K-means and self-organization map.

### 1-2. Application of DM techniques in CRM

DM techniques are capable of extracting hidden customer characteristics and needs from large databases. Application of DM in CRM has attracted the attention of practitioners and academics. The rate of related research continues to increase. All of the DM models, such as association, classification, and clustering, could support CRM elements, which include customer identification, customer attraction, customer retention, and customer development [5].

## 2. Literature review

Customer value issue is an important part of CRM. There are several methods to find customer value. These methods divided to popular metrics and strategic metrics. Some of popular customer-based value metrics contains Size of Wallet (SOW) and Share of Wallet (SW). SOW refers to “total volume of a customer’s spending in a category”. SW refers to “proportion of category volume accounted for by a brand or focal firm within its base of buyers” [6]. Du et al. have combined SOW and SW and segmented customers to develop effective strategies in each group and have identified the valuable customers [7]. Strategic metrics contains RFM, Past Customer Value (PCV) and Life Time Value (LTV).

RFM analysis has been used in direct marketing for several decades [8]. This technique identifies customer behavior and represents customer behavior characteristics by three variables as follows:

Recency: refers the duration time between last customer purchasing and present time.

Frequency: refers the total number of customer purchasing during life time.

Monetary: refers the average money spending during past customer purchases.

In Classis RFM analysis, at first customers are arranged ascending according to R value and divided into 5 groups. All groups are assigned ranking numbers from 5 down to 1. After that customers are arranged descending according to F and M value and again the numbers (5 down to 1) are assigned to each group. So (5*5*5=125) groups are defined according to recency, frequency and monetary values [9, 10]. (Hughes, 1994; Stone, 1995).

According to [11], “Past customer value is a model which extrapolates the results of past transaction into the future.” PCV emphasis customer past monetary purchase can indicate future behaviors. PCV return the past monetary value into present time. LTV models, prospect the future monetary value of customer and time duration that customers will be active. These models convert the future net profit achievement from customers into present. There are various models for LTV calculation. Some of financial LTV models have applied direct cost and marketing cost. Some of have considered customer retention rate in customer lifetime [12, 13].

In weighted RFM, each variable is weighted according to expert opinion with AHP analysis. So weighted average, makes RFM rank [11]. Some of Studies such as [14, 15], have used classic RFM to define customer value and some of them such as [16, 17, 18, 4, 19], have used weighted RFM.

Sant’Anna and Ribeiro have prospected future customer acquisition profits with BG/BB model and customer lifetime with Gama/Gama model and have calculated LTV with multiplying these two values [20]. Glady et al. have prospected number of future customer transaction and his/her profit with Pareto/NBD model in order to LTV calculation [21]. Fruchter and Sigué have extended a well-known mathematical model of “love dynamics. They have indicated that the growth of buyer and seller’s commitment to the relationship is a sum of negative and positive terms. Negative terms contain propensities for opportunism, while the positive terms describe each partner’s trust in the commitment of the other. They have developed LTV model according to this commitment [22]. Table 1 shows different methods used for customer value according to prior studies.

**Table 1**. Customer value models

| models | References |
|---|---|
| SOW و SW | [11], [7] |
| RFM | [4], [14], [15], [16], [17], [18], [19], [23], [24] |
| LTV | [12], [13], [20], [21], [22], [25], [26], [27], [28] |

A major input for customer segmentation is RFM. Also a self-organizing map neural network is used to identify groups of customers based on repayment behavior and recency, frequency, and monetary behavioral scoring predictors. It also classified bank customers into three major profitable groups of customers. The resulting groups of customers were then profiled by customer’s attributes determined by using an Apriori association rule inducer [29]. Finally, a new procedure, joining quantitative value of RFM attributes and K-means algorithm into rough set theory (RS theory), is proposed to extract meaning rules, The data of this case study is from the electronics industry in Chang Hua, contains 401 records of company transactions that have been carried out in 2006 [17]. Besides, a combination of above mentioned input variables, also, has been utilized by researchers. For example, a novel approach that combines customer targeting and customer segmentation for campaign strategies is presented. This investigation identified customer behavior using a RFM model and then uses a LTV model to evaluate proposed segmented customers [30]. Some authors have used a combination of other different variables and measures to cluster customers. For instance, Lee and Park aimed at providing an easy, efficient, and more practical alternative approach based on the customer satisfaction survey for the profitable customers segmentation [31]. An anticipation model for potential customers in purchasing behavior is proposed. Their model is inferred from past purchasing behavior of loyal customers and the web server log files of loyal and potential customers by means of clustering analysis and association rules analysis [32]. Also Stone et al. have focused on proposing a customer segmentation framework based on DM and constructs a new customer segmentation method based on survival character. Their new customer segmentation method consists of two steps. Firstly, with K-means clustering arithmetic, customers are clustered into different segments by similar survival characters (i.e. churn trend). Secondly, each cluster’s survival/hazard function is predicted by survival analyzing, then, the validity of clustering is tested and customer churn trend is identified [33]. An integrating DM and experiential marketing to segment online game customers is investigated. The results can help the firms to predict and understand the new consumer’s purchase behavior [34].

In addition, as mentioned before, some authors have focused on the segmentation procedure from technical point of view. For example, a new methodology for cross national market segmentation is developed. The authors have proposed a two-phase approach (TPA) integrating statistical and DM methods. The first phase is conducted by a statistical

method (MCFA: multi-group confirmatory factor analysis) to test the difference between national clustering factors. The second phase is conducted by a DM method (a two level SOM) to develop the actual clusters within each nation [35]. In [36] support vector clustering (SVC) for marketing segmentation is used. A novel clustering algorithm based on genetic algorithms (GAs) to effectively segment the online shopping market is proposed [37]. Simultaneously, a novel market segmentation approach, namely the hierarchical self-organizing segmentation model (HSOS), for market segmentation of real world multimedia on demand in Taiwan is proposed [38].
Table 2 categorizes segmentation models proposed by different authors according to their input variables.

**Table 2.** Summarization of input variables used in segmentation models

| Input Variables Used | Refrences |
|---|---|
| Demographic | [38], [39], [31] |
| RFM | [19], [17] |
| LTV | [40] |
| Demographic +RFM | [29], [23] |
| Demographic +LTV | [25] |
| LTV+RFM | [30] |
| Demographic +RFM+LT | [3] |
| Others | [32], [35], [34], [33], [36], [37], [41] |

### 2.1. Self-Organizing Map

The Self-Organizing Map (SOM) is a competitive learning or self-organization, has been shown as one of the most popular unsupervised competitive neural network learning models, for clustering and visualization in a number of real world problems proposed by[42;43]. By nature, it can cluster all input data points into mutually exclusive groups and thus, can present the relationship between clusters in a high dimensional space. SOM usually consists of two layers: an input layer and an output layer. Each of the variables of the input neuron is linked with every output neuron by a weighted connection.
Every output neuron competes with others to become the winning neuron. When SOM is employed in judging which cluster a new input point belongs to, the point is assigned to the cluster of the winning neuron [44].

### 2.2. K-Means clustering algorithm based on the Euclidean distance function

In k-means algorithm first, K members are randomly selected out of N members as Cluster Centers and then, the remaining N–K members are allocated to the nearest clusters. Then, the cluster centers are recalculated and members are allocated to the clusters based on the new centers and this operation is repeated until cluster centers are fixed and do not change [45].

### 2.3. DM tool, SPSS Clementine

In this study, SPSS Clementine is employed as a data-mining tool for analysis. The difference between SPSS Clementine and other software is that its data processing is carried out through the use of nodes, which are then connected together to form a stream frame. In addition, data visualization can be presented to users after the mining process is completed. SPSS Clementine's visual interface invites users to apply their specific business expertise, which leads to more powerful predictive models and shortens time-to-solution [46].

## 3. Customer value descriptive model

We briefly introduce the proposed procedure for classifying customer value. The proposed model is based on the use of some DM techniques and customer value analysis to improve CRM. It has been implemented B chain stores in Iran. In order to segment these customers, our research approach is categorized into two phases using weighted RFM and demographic variables. Weighted RFM is used in the first stage as the input values of K-means clustering; we evaluate the optimum K based on Davies–Bouldin Index in order to use in this algorithm. Also pattern type has been assigned to each segment. Then the demographic data, based on age, education and gender, is used to cluster each segment resulted from stage one by SOM. After that ranking scores have been assigned to each group of customers (see Figure 2).

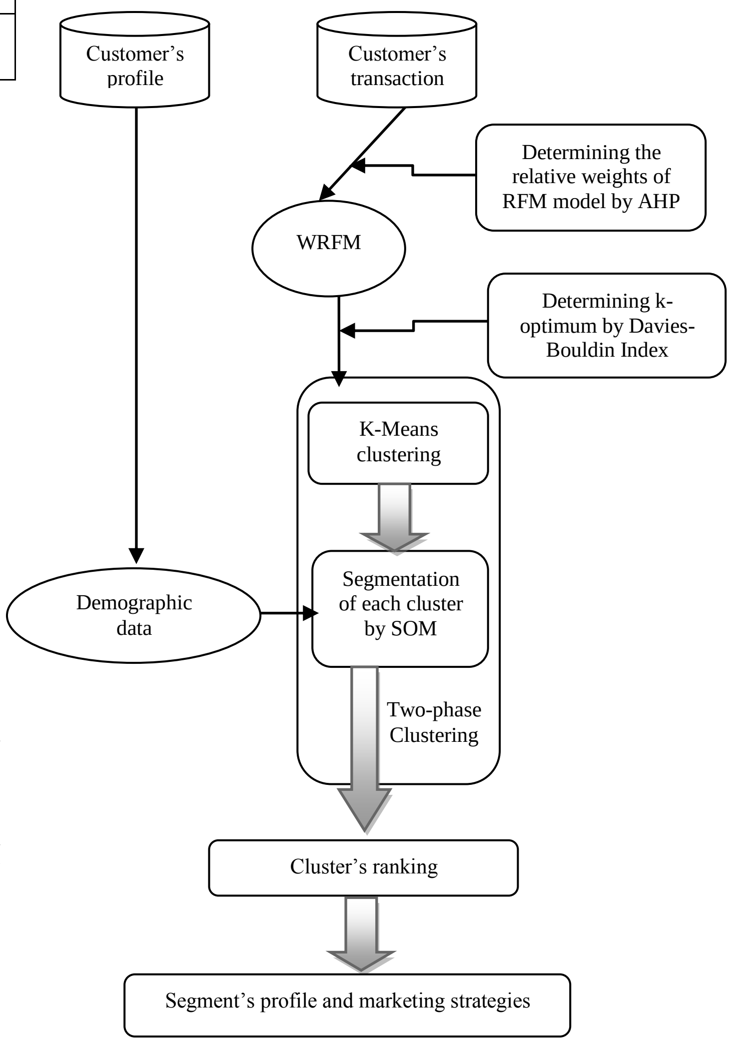


**Figure 2.** Research framework

The age of our sample customer is between 11 and 70 years old, we transferred these ages to the distance of [0,1]. Also we divided the education parameter to 4 degree: Diploma and under of it, Bachelor and Associate degree, Masters, PhD. But we use first three divisions in the data table, because if all of these sections will be zero it means that the customer's education is PhD. Regarding gender we indicated zero for women and one for men.

As in every other DM processes, here the first step is to prepare the data at hand. Data preparation involves tasks such as filling missing data, removing outliers, feature extraction, and feature selection. In the proposed approach, it is assumed that all the required tasks are conducted for the data in "Customers' Transactions" and "Customers' Profiles" databases (Table 3).

**Table 3.** The partial data of chain stores B after preparing data

| Customer Number | Gender | Age [0,1] | Diploma and under of it | Bachelor and Associate | Masters | WR | WF | WM | WRFM |
|---|---|---|---|---|---|---|---|---|---|
| . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . |
| 1-0003439 | 0 | 0.322033898 | 0 | 0 | 1 | 0.08214956 | 0.0073125 | 0.09 | 0.177791 |
| 1-0002445 | 1 | 0.728813559 | 0 | 0 | 1 | 0.054979472 | 0 | 0.10 | 0.154753 |
| 1-0000367 | 1 | 0.661016949 | 0 | 1 | 0 | 0.088222874 | 0.0073125 | 0.07 | 0.162217 |
| 1-0003573 | 1 | 0.440677966 | 0 | 1 | 0 | 0.088222874 | 0 | 0.00 | 0.090213 |
| 1-0000633 | 1 | 0.254237288 | 0 | 1 | 0 | 0.019818182 | 0 | 0.00 | 0.022008 |
| . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . |

## 4. Results

The relative weights of R, F and M variable, have been determined by experts in the field of e-commerce and CRM. Experts of chain stores B compared each two variables and AHP processes were done (Table 4). As result the R, F and M weight were 0.109, 0.351 and 0.524 respectively. In our case study monetary is the most important variable.

Measuring the value of each segment is possible by computing the integrated rate of each cluster namely $BV$ as follows:

$$BV_i = W_R \times C_R^i + W_F \times C_F^i + W_M \times C_M^i \tag{1}$$

where $W_R$ , $W_F$ and $W_M$ are the relative importance of the RFM variables; $C_R^i$ , $C_F^i$ and $C_M^i$ are average index value of RFM for cluster (i); $BV_i$ is Behavioral value of cluster (i). This enables us to choose the best segment for finding the valuable customers, who will probably make more net value for business. After the segments are identified, they should be analyzed and compared regarding the values of different features.

**Table 4.** The matrix of group decision making by AHP

| | R | F | M |
|---|---|---|---|
| R | 1 | 0.294 | 0.204 |
| F | 3.4 | 1 | 0.625 |
| M | 4.9 | 1.6 | 1 |

After evaluating the weight of each variable with AHP analysis, we determined optimum k for 347 customers by Davies Bouldin Index in Matlab software. We set the number of clusters at 6 for K-means algorithm and it has been used in order to customer segmentation. Table 5 shows the result of customer segmentation according to normalized weighted R, F and M value. Each variable R, F and M is higher ($\uparrow$) or lower ($\downarrow$) than its overall average so we can have (2*2*2=8) different Pattern types that shows in the table.

**Table 5.** 6 Cluster ranking of 347 customers by weighted sum of normalized RFM value

| Cluster | No. of customer | Weighted recency | Weighted Frequency | Weighted Monetary | WRFM | Rank | Pattern Type |
|---|---|---|---|---|---|---|---|
| 1 | 100 | 0.093 | 0.005 | 0.052 | 0.015 | 6 | $R\uparrow F\downarrow M\downarrow$ |
| 2 | 1 | 0.093 | 0.351 | 0.136 | 0.58 | 1 | $R\uparrow F\uparrow M\uparrow$ |
| 3 | 85 | 0.021 | 0.002 | 0.043 | 0.066 | 5 | $R\downarrow F\downarrow M\downarrow$ |
| 4 | 9 | 0.087 | 0.026 | 0.349 | 0.462 | 2 | $R\uparrow F\uparrow M\uparrow$ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 5 | 57 | 0.052 | 0.004 | 0.102 | 0.158 | 3 | $R\downarrow F\downarrow M\uparrow$ |
| 6 | 95 | 0.06 | 0.002 | 0.017 | 0.079 | 4 | $R\uparrow F\downarrow M\downarrow$ |
| Overall Average | 0.059414 | 0.00512 | 0.06 | 0.125 | | | |

As table 5 shows cluster 2 has one customer, it may be outliers. So with putting aside it we determined optimum k for 346 customers by Davies Bouldin Index. We set number of clusters at 5 and again perform K-means algorithm. The results with 5 clusters have been shown in table 6 and there are no outlier customers, so they are valid.

**Table 6.** 5 Cluster ranking of 346 customers by weighted sum of normalized RFM value

| Cluster | No. of customer | Weighted Recency | Weighted Frequency | Weighted Monetary | WRFM | Rank | Pattern Type |
|---|---|---|---|---|---|---|---|
| 1 | 100 | 0.093 | 0.005 | 0.052 | 0. 15 | 3 | $R\uparrow F\downarrow M\downarrow$ |
| 2 | 85 | 0.021 | 0.002 | 0.043 | 0.066 | 5 | $R\downarrow F\downarrow M\downarrow$ |
| 3 | 9 | 0.087 | 0.026 | 0.349 | 0.462 | 1 | $R\uparrow F\uparrow M\uparrow$ |
| 4 | 57 | 0.052 | 0.004 | 0.102 | 0.158 | 2 | $R\downarrow F\downarrow M\downarrow$ |
| 5 | 95 | 0.06 | 0.002 | 0.017 | 0.079 | 4 | $R\downarrow F\downarrow M\uparrow$ |
| Overall Average | 0.0626 | 0.0078 | 0.1126 | 0.183 | | | |

As have been shown at table 6, 4 pattern types have identified. Cluster 3 with $R\uparrow F\uparrow M\uparrow$ pattern is the highest ranking. This segment contains loyal customers, because they have purchase recently, the total number of their purchasing is high and they have spent much money and also this segment has least customers. These customers are valuable for firm. The least customers have been belonged to this segment. Second valuable segment is cluster 4 with $R\downarrow F\downarrow M\downarrow$ pattern contains old customers, because they have not purchased recently and their frequency and monetary values are low. This cluster's pattern is same as cluster 2 with fifth ranking and disloyal customers. Third valuable segment is cluster 1 with $R\uparrow F\downarrow M\downarrow$ pattern contains new customers, because they have purchased recently but their frequency and monetary values are low. The most customers have been belonged to this segment. Finally the forth valuable customers are belonged to cluster 5 with $R\downarrow F\downarrow M\uparrow$ pattern type. They have not purchased recently and their frequency value is low but their monetary value is high.

Now we segment each cluster base on their demographic variables by SOM in SPSS Clementine software, the result are shown in table

**Table. 7.** demographic distributions of 346 customers in clusters

| No. of cluster in K-Means | Center of cluster in SOM | | Demographic data | | | |
|---|---|---|---|---|---|---|
| | x | y | No. of customer | Gender, male | Age | Education |
| 1 | 0 | 0 | 46 | 46 | [19-60] | Bachelor and Associate degree |
| | 0 | 2 | 12 | 0 | [21-50] | Bachelor and Associate degree |
| | 1 | 2 | 1 | 0 | 36 | PhD |
| | 2 | 1 | 3 | 3 | [26-52] | PhD |
| | 2 | 2 | 3 | 0 | [30-32] | Master |
| | 3 | 0 | 22 | 17 | [11-49] | Diploma and under of it |
| | 3 | 2 | 13 | 13 | [24-52] | Master |
| 2 | 0 | 0 | 19 | 13 | [11-41] | Diploma and under of it |
| | 0 | 2 | 13 | 13 | [26-50] | Master |
| | 1 | 0 | 6 | 6 | [40-70] | Diploma and under of it |
| | 1 | 1 | 1 | 1 | 28 | PhD |
| | 1 | 2 | 5 | 0 | [22-34] | Master |
| | 2 | 0 | 1 | 1 | 48 | PhD |
| | 2 | 2 | 3 | 0 | [37-49] | PhD |
| | 3 | 0 | 23 | 23 | [22-52] | Bachelor and Associate degree |
| | 3 | 2 | 14 | 0 | [18-41] | Bachelor and Associate degree |
| 3 | 0 | 0 | 2 | 2 | [24-60] | Bachelor and Associate degree |
| | 0 | 2 | 1 | 0 | 31 | Bachelor and Associate degree |
| | 2 | 1 | 2 | 2 | [30-42] | PhD |
| | 3 | 0 | 2 | 2 | [34-40] | Diploma and under of it |
| | 3 | 2 | 2 | 2 | [24-28] | Master |
| 4 | 0 | 0 | 21 | 21 | [19-55] | Bachelor and Associate degree |
| | 0 | 2 | 7 | 0 | [20-37] | Bachelor and Associate degree |
| | 1 | 2 | 1 | 0 | 46 | PhD |
| | 2 | 0 | 13 | 10 | [24-54] | Master |
| | 2 | 2 | 2 | 0 | [16-37] | Diploma and under of it |
| | 3 | 2 | 13 | 13 | [14-50] | Diploma and under of it |
| 5 | 0 | 0 | 10 | 0 | [23-46] | Bachelor and Associate degree |
| | 0 | 2 | 37 | 37 | [22-45] | Bachelor and Associate degree |
| | 1 | 0 | 2 | 0 | 45 | PhD |
| | 1 | 2 | 7 | 7 | [47-68] | Bachelor and Associate degree |
| | 2 | 0 | 3 | 0 | [22-41] | Diploma and under of it |
| | 2 | 1 | 2 | 2 | [43-50] | PhD |
| | 3 | 0 | 22 | 22 | [13-48] | Diploma and under of it |
| | 3 | 2 | 12 | 9 | [25-69] | Master |

Finally, by all kinds of the described demographic features, profile of each cluster could be constructed. This profile is shown in Table 7. The number of customers, their genders, their ages and educations of each cluster is illustrated in comparison with the others. For example, two men customers in cluster 3 with the center cluster (0,0) in SOM are 24 and 60 years old, their educations are bachelor and associate degree. So means that each cluster with different ranking can be described by their demographic features. This helps company to know their customers and choose suitable marketing strategies.

For the aim of illustrating the performance of the proposed approach another step has been taken. To compare the proposed model with the conventional methods, k-means model is chosen as the reference model. In other words, the proposed model is compared with k-means clustering algorithm with similar number of clusters. K-means is selected because "it has been used as the comparative standard in other, similar studies and is currently the most widely used and most popular segmentation technique" [47].

The result of the proposed model are compared with those of the traditional k-means algorithm when $k$ = 35 using Sum of the Squared Error (SSE). The remarkable distance between proposed model and k-means with $k$ = 35 could be seen in Table 8. Accordingly, the above implications are approved.

SSE is calculated as follows:

$$SSE = \sum_{i=1}^{k}\sum_{j=1}^{n_i}\left\|\left(c_i - o_{ij}\right)\right\|^2 \quad (2)$$

Where $n_i$ is the number of data objects in cluster $C_i$ and $o_{ij}$ is the $j^{th}$ data object in cluster $C_i$. The smaller the value of SSE, the better is the quality of the clustering [48].

**Tab. 8.** Comparison of the proposed clustering model with traditional K-means method

| Method | Model 2 | k-means (k=35) |
|---|---|---|
| SSE | 0.864 | 1.259 |

## 5. Conclusion

One of the key purposes of marketing is to identify the target customer position and analyze it by segmentation and then set marketing strategies to each segment in order to reduce the risk of significant customer's defection. To reach this request, this paper proposes a new segmentation method based on DM and most commonly used CRM models; RFM, and demographic variables.

The method is developed on two-phase clustering model based on k-means and SOM techniques. In application of the method on our case study (in chain store industry), the existing customers were divided into 35 groups of customers according to their shared transactional behavior and demographic characteristics. Profiles of customers in each group could be analyzed by marketers to make strategies for each group.

Beyond simply understanding customer value in each cluster, the chain store would gain the opportunities to establish better customer relationship management strategies, improve customer loyalty and revenue and find opportunities for up and cross selling. Further researches may aim at using larger data base with more fields to gain more accurate results from the model.

Finally, other descriptive methods can be used and their performance can be compared to reach the best selection.

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