A Model for Customer Segmentation Based On Loyalty Using Data Mining Approach and Fuzzy Concept in Iranian Bank

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Abstract

Data mining is a new technique which can help researchers to discover data’s patterns and predict the future behaviors. Predicting customers’ loyalty, specifically bank customers, is a concept which has attracted more attentions recently. This study has proposed a new procedure using the indexes of RFM model with two new additional indexes joining k-means algorithm with k-optimum according to davies-bouldin index in order to estimate customers’ loyalty numbers and then classifying customers in for groups based on expanding the Dick- Basu model with using fuzzy concept. The proposed model is implemented in the card payment service of bank A. 287 number of card reader systems are surveyed and clustered in 22 clusters. Finally, for the identification and classification of customers loyalty, after determination of membership degree of each cluster the label of the clusters are determined, and customers are classified in four sets of loyal, disloyal, spurious loyalty and latent loyalty. The results indicate that when we combine behavioral loyalty and attitudinal loyalty, we can obtain a better degree of loyalty. These features helped the bank A to retain the customers whom are going to churn by using creative and attractive strategies for each class of the customers.

Keywords: Customer Segmentation, Loyalty, RFM Model, Switching Cost, Banking

1. Introduction

Detection of customers’ loyalty, specifically bank customers, is a concept which has attracted more attentions recently. In a complex and dynamic bank system environment, the smallest difference in the services is leading to the massive transfers in this industry so there is a need for customers’ detection regarding to loyalty.

CRM is to achieve the needs of customers and to enhance the strength with customers for company (Thompson and Sims, 2002). Some potential benefits of CRM are as follows: (1) Increased customer retention and loyalty, (2) Higher customer profitability, (3) Value creation for the customer, (4) Customization of products and services, (5) Lower process, higher quality products and services (Jutla, 2001; Stone, 2006).

A lot of researches are published on the customers’ clustering. Many of them have utilized RFM model indices for clustering. RFM analysis has been used widely for customer loyalty. This technique utilizes customer past behavior and emphasis that customer past purchase experiences indicate future behaviors (Kumar and Reinartz, 2006). But the weakness of this model in loyalty measurement is that it doesn’t show the customers attitude about the bank. In other words, it doesn’t survey the attitudinal loyalty directly. A conceptual model proposed by Dick and Basu which classifies customers regarding their loyalty in 1994. In their survey research, by designing a questionnaire they perform the evaluation of attitude and purchase behavior of customers by themselves. The weakness of this model was
considering customers in various classes in an absolute manner. Another weakness of the model was asking customers themselves for identification of their behavior.

In this article, Dick-Basu model is used for classification of customers regarding their loyalty or disloyalty; and for elimination of its weakness in customers’ classification the fuzzy logic is utilized. The main objective of this study is providing a model for calculating the degree of loyalty and finding a way for segmenting customers based on it.

The rest of this paper is organized in the following: In Section 2 we describe an overview of the related works, while Section 3 presents the proposed procedure and briefly discusses its architecture. Section 4 describes analytically the experimental results. Section 5 is discussion and Finally, Section 6 concludes the paper.

2. Related works

This research tries proposing a model based on developing the RFM model and developing Dick-Basu model for classification of customers regarding loyalty. This section mainly represents some techniques for clustering customer. Thus, this study reviews related studies of the customer relationship management, customer loyalty, K-means algorithm, RFM analysis and switching cost.

2.1 CRM and customer segmentation

CRM is a philosophy of business operation for acquiring and retaining customers, increasing customer value, loyalty and retention, and implementing customer-centric strategies. CRM, devoted to improve relationships with customer, focuses on a comprehensive picture on how to integrate customer value, requirements, expectations and behaviors via analyzing data from transaction of customer (Peppard, 2000). CRM usually utilizes IT to help an enterprise managing relationships with customer in a systematic way, improving customer loyalty and increasing overall business profits (Kalakota and Robinson, 1999). It has been estimated that it costs five times as much to attract a new customer as it does to retain an existing one, according to research by the American management Association (Kotler, 1994; Peppers & Rogers, 1996) and this relationship is particularly obvious in the services sector (Ennew and Binks, 1996). Therefore, enterprises understand the importance of developing a good close relationship with existing and new customers. Instead of attracting new customers, they would like to perform as well as possible more business operations for customers in order to keep existing customers and build up long-term customer relationship (Cheng and Chen, 2009).

The fastest way to build a successful customer- focused business is to divide the customer base into groups or segments in order to identify customers with the greatest profit potential. Customer understanding is the core of CRM: “Proper customer understanding and action ability lead to increased customer lifetime value. Incorrect customer understanding can lead to hazardous actions. Similarly, unfocused actions, such as unbounded attempts to access or retain all customers, can lead to decrease of customer lifetime value (law of diminishing return). Hence, emphasis should be put on correct customer understanding and concerted actions derived from it.” (Jiang, 2008). Kucukkancabas (2007) defined customer segmentation as “the process of dividing customers into distinct, meaningful, and homogeneous subgroups based on various attributes and characteristics. It is used as differentiating marketing tool. It enables organizations to understand their customers and build differentiated strategies, tailored to their characteristics.”
Xiaoyu (2009) further explained this concept as “a process that divides customers into smaller groups called segments. Segments are to be homogeneous within and desirably heterogeneous in between. In another words, customers of the same segments possess the same or similar set of attributes. But customers of different segments have differing sets of attributes.” Predictive CRM covers a variety of customer care activities, such as: customer acquisition and market research, customer conversions, customer attrition and churn management, debt collection management, risk management, fraud detection, transaction audit, cross-selling, up-selling, re-selling, customer loyalty programs, trend monitoring, call center analytics.

2.2 customer loyalty

Creating a loyal B2B customer base is not only about maintaining numbers of customer overtime, but it is creating the relationship with business customers to encourage their future purchase and level of advocacy. Equipped with the knowledge of their business customers’ loyalty levels, a supplier will be able to Figure how their endeavors to maintain good relationships can contribute to its profit levels. Some authors believe that loyal customers offer a steady stream of revenue for a company by remaining with the brand/supplier and rejecting the overtures of competitors (Lam, 2004; Reichheld and Teal, 1996).

Ruyter (1998) has suggested that nature and power of relationship between the quality of received services and customer loyalty should be specified for any company with different levels of industry. Also, people like Bloemer and Kasper (1995), Fullerton (2005) are scholars that have brought the service quality in their models for the definition of loyalty and have a strong belief that the service quality has positive and significant effect on loyalty. Several authors have proved the effects of satisfaction on customer loyalty. These researchers have suggested that customer satisfaction is an important variable in explaining customer loyalty. Loyalty to the services has more dependence on development of interpersonal relationships, to the extent with loyalty to the products, for the interactions of one person to another are opposed as an essential element in the marketing services. Recent literature has shown that several researchers have examined the behavioral and attitudinal loyalty. In an early school of thought Tucker (1964) argued that behavior (past purchases of the brand/product) completely accounts for loyalty. Consistent with this viewpoint, Jacoby and Chestnut (1978) observed that in behavioral loyalty studies the focus was on interpreting patterns of repeat purchasing in primarily panel data as a manifestation of loyalty. Dick and Basu (1994) have developed a framework for customer loyalty, including loyalty behavior and loyalty attitudinal measurement. The authors showed that loyalty can be the combination of attitudinal loyalty and behavioral loyalty. Fig. 1 shows the loyalty framework that was developed by them.
2.3 K-means clustering algorithm based on the Euclidean distance function

Clustering is the process of grouping a set of physical or abstract objects into groups of similar objects. A cluster is a collection of data objects that are similar to one another within the same cluster and are dissimilar to the objects in other clusters (Han & Kamber, 2001).

K-means is one of the well-known algorithms for clustering, originally known as Forgy’s method (Forgy, 1965), and it has been used extensively in various fields including data mining, statistical data analysis and other business applications. Thus, this study proposes the K-means algorithm to build clusters by attributes (i.e. R–F–M attributes). The K-means algorithm for partitioning is base on the mean value of the objects in the cluster. Mac Queen (1967) suggested the term K-means for describing an algorithm that assigns each item to the cluster with the nearest centroid (mean).

K-Means is very sensitive to the choice of a starting point for partitioning the items into K initial clusters. We can compare the performance of different clustering methods using intraclass method when the number of fixed cluster of K value is defined as $F(k) = \frac{1}{k} \sum_{n=1}^{k} \sum_{c_i} \text{Dist}(c_i, c_n)$ (Seyed hosseini, 2010).

Based on the concept above, the computing process for K-means is presented as follows:

Step 1: Partition the items into K initial clusters. Firstly, partition the items (m objects) into K initial clusters.

Step 2: Proceed through the list of items. Assign an item to the cluster whose centroid is nearest (distance is computed by using Euclidean distance with either standardized or un-standardized observations) and re-calculate the centroid for the cluster receiving the new item or for the cluster losing the item.

Step 3: Repeat Step 2 until no more reassigning. Rather than starting with a partition of all items into K preliminary groups in Step 1, we could specify K initial centroids (seed points) and then proceed to Step 2. The final assignment of items to clusters will be, to some extent, dependent upon the initial partition or the initial selection of seed points. Experience suggests that most major changes in assignment occur with the first reallocation step.
2.4 RFM analysis

RFM analysis has been used in direct marketing for several decades (Baier, 2002). 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.

RFM analysis is utilized in many ways by practitioners; therefore, RFM analysis can mean different things to different people. Classic RFM implementation ranks each customer on valuable parameters against all the other customers, and creates an RFM score for each customer/product (Hughes, 1994; Stone, 1995).

2.5 Switching cost

Fornell (1992) argues that switching barriers (costs) may increase customer loyalty. Porter (1988) defines switching costs as the one-time costs for buyers of switching from one supplier’s product to another’s. In addition to objectively measurable monetary costs, there may also be time and psychological effort involved in facing the uncertainty of dealing with a new service provider (Bloemer, 1998; Klemperer, 1995). Hence, switching costs are partly consumer specific (Shy, 2002). Markets with switching costs are generally characterized by consumer lock in where it is observed as consumers repeatedly purchase the same brand even after competing brands become cheaper. One important consequence of having consumer lock-in is the ability of firms to charge prices above managerial costs (Shy, 2002). Therefore, consumer switching costs negatively affect consumers’ sensitivity to price (Klemperer, 1987) and so positively affect consumer loyalty (Jones, 2000). According post-purchase cognitive dissonance theory (Ettl, 1997), the consumer who has collected information in order to decrease anxiety about a wrong purchase decision (psychological switching costs”) will marshal all past purchase decision. In this process, if the customer switched, the comparison would be between the switched brand and last brand. Hence, in order to decrease cognitive dissonance, customers prefer the brand they have used and been satisfied with before (Klemperer, 1995).

In our paper we focus on credit users’ segmentation task in banking industry. Banks should classify their customers and adopt different marketing strategies for each observed class. The classification usually encompasses the evaluation of customers, their segmentation according to the values and finding the characteristics of different customers.

3. Methodology

This section briefly introduces the research model of this study and the proposed procedure for classifying customer based on loyalty. In recent years, data mining has not only a great popularity in research area but also in commercialization. Nowadays, by utilizing data mining tools for assisting CRM, some techniques, which include DT, ANN, GA, AR, etc., are usually used in some fields such as engineering, science, finance, business, to solve related problems with customers (Witten & Frank, 2005). Generally, no tool for data mining in CRM is perfect because there are some uncertain drawbacks in it. For example, in DT, too many instances lead to large decision trees and decrease classification accuracy rate. In ANN, it has long training times in a large dataset especially, and it is a trial-and-error
process. In GA, it has slow convergence, a large computation time and less stability. In AR, it may generate huge
rules that may be a redundancy (cheng & chen, 2009).
The main objective of this model is to calculating the degree of customers’ loyalty and segmenting customers based on it. In previous researches usually RFM model parameters used to segmentation. But the weakness of this model is that it does not show the customer’s attitude regarding the bank. In other words, the attitudinal loyalty has not been evaluated directly. Although many customers have a great deal of transactions that indicates the loyalty of them, when we asked customer’s opinion regarding bank, they constantly complained and announced the habit, availability, and such factors were the only reasons of their connection to the bank. So these studies will intensify the required usage of attitudinal loyalty beside behavioral loyalty measures.
Also the researches that were measured customer loyalty were just contented customer rating based on their loyalty degree and ranking customers’ clusters based on this degree. This method can represents the numerical value of customer loyalty, but it does not still help in identifying loyal and disloyal customers and cannot differentiate customer’s loyalty. Therefore, in this study we have used the model of Dick and Basu. We have put customers in four groups of loyal customers, disloyal customers, spurious loyalty customers, and latent loyalty customers. We have used fuzzy logic for determining how much each customer belongs to the considered groups.

3.1 Research model
This study constructs a model for clustering customer based on loyalty degree. RFM attributes were used as the indexes of behavioral loyalty and switching cost and satisfaction were used as the indexes of attitudinal loyalty. Fig. 2 illustrates research model in this study.

![Fig. 2. The proposed model](image-url)
3.2 The proposed procedure

In this subsection, we further explain the proposed procedure for classifying customer based on their loyalty.

The proposed procedure is divided into 7 steps includes: 1. Data gathering, 2. Determining weights of each index by AHP method, 3. Determining k-optimum by Davies Bouldin index, 4. Clustering by k-means algorithm, 5. Determining the degree of behavioral loyalty and attitudinal loyalty for each cluster, 6. Determining the membership function of each cluster, 7. Labeling each cluster.

The computing process is introduced step by step as follows:

**Step 1: Data gathering**

This study includes customers’ feedback regarding Bank A and transactions’ record of customers who have installed card reader devices in their stores and funds have been transferred to their account by these devices. Data of feedbacks have been collected through surveys of target customers (customers who have installed devices in their stores) includes satisfaction (S) and switching cost (SC).

**Step 2: Determining weights of each index by AHP method**

In this step the relative weights of parameters, have been determined by experts in the field of e-commerce and CRM. Experts of Bank A compared each two variables and AHP processes were done.

**Step 3: Determining k-optimum by Davies Bouldin index**

Davies Bouldin index have been used to determining K optimum for the number of clusters in Matlab software. This index is a measure of the clustering quality that first had been proposed by Davies Boudin in 1979.

**Step 4: Clustering by k-means algorithm**

In this step k-means algorithm has been used to cluster the customers.

**Step 5: Determining the degree of behavioral loyalty and attitudinal loyalty for each cluster**

In this step, the degree of behavioral loyalty (BL) and the degree of attitudinal loyalty (AL) will be gained for each of the clusters by considering their weights in these formulas.

\[
AL_i = W_{sc} \times C_{sc}^i + W_{S} \times C_{s}^i
\]

(1)

\[
BL_i = W_{R} \times C_{R}^i + W_{F} \times C_{F}^i + W_{M} \times C_{M}^i
\]

(2)

\[
C_{sc}^i = \frac{\sum_{j=1}^{n_i} C_{sc}^j}{n_i}
\]

(3)

Where \( W_R, W_F, W_M, W_SC, W_S \) are the relative importance of the recency, frequency, monetary, switching cost, and satisfaction variables; \( C_R^i, C_F^i, C_M^i, C_{sc}^i \), and \( C_s^i \) are average index value of recency, frequency, monetary, switching cost, and satisfaction for cluster (i); \( BL_i \) is Behavioral loyal degree of cluster (i); \( AL_i \) is attitudinal loyal degree of cluster (i) and \( n_i \) is the number of customers in cluster (i).

**Step 6: Determining the membership number of each cluster**
In this study, four fuzzy sets were defined for segmenting customers based on their loyalty. Set of loyal customers, disloyal customers, spurious loyalty customers, and latent loyalty customers. It is necessary that fuzzy sets will be defined because if a cluster is in an ambiguous area which has appeared by lighter color, we cannot say certainty it belongs to which segment and should follows the strategies of which category. Therefore we should calculate the amount of membership degree in each segment to determine which group of strategies should be followed. Fig. 3 illustrated this segmentation.

![Fig. 3. Four areas of customer segmentation based on loyalty](image)

The areas that are brighter are ambiguous regions. This means that for example, if the cluster is in this region with black dots, we cannot say certainty that it is spurious loyalty cluster or not. Therefore, in this model, for showing the extent belongs of each cluster to each set we have calculated the membership degree. In fact this degree has been defined for each cluster and represented the membership amount of the cluster to the defined fuzzy set. As regards whatever it closes to center from corner points of (A1, A2, A3, and A4) the ambiguity will be more. This means that the clusters are located in the central region cannot be conclusively commented. Table 1 shows some parameters for calculating the membership functions.

### Table 1. Defined parameters for obtaining the membership function

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_1(x)$</td>
<td>Membership function of disloyal fuzzy set</td>
</tr>
<tr>
<td>$\mu_2(x)$</td>
<td>Membership function of latent loyalty fuzzy set</td>
</tr>
<tr>
<td>$\mu_3(x)$</td>
<td>Membership function of loyal fuzzy set</td>
</tr>
<tr>
<td>$\mu_4(x)$</td>
<td>Membership function of spurious loyalty fuzzy set</td>
</tr>
</tbody>
</table>

Also the uncertainty amount of membership in corner points are lower and as we move toward the center the radius membership of fuzzy set will be less, so the Gaussian function is an appropriate function for calculating this degree in fuzzy sets. Fig. 4, 5, 6, 7 and 8 show the membership function of the fuzzy sets in MATLAB software and related functions are the following equations:
\[ \mu_1 = e^{-\frac{x^2+y^2}{0.18}} \]  
\[ \mu_2 = e^{-\frac{x^2+(1-y)^2}{0.18}} \]  
\[ \mu_3 = e^{-\frac{(1-x)^2+(1-y)^2}{0.18}} \]  
\[ \mu_4 = e^{-\frac{(1-x)^2+y^2}{0.18}} \]  

Fig. 4. Membership function of disloyal customers in fuzzy set

Fig. 5. Membership function of spurious loyalty customers in fuzzy set
Fig. 6. Membership function of loyal customers in fuzzy set

Fig. 7. Membership function of latent loyalty customers in fuzzy set

Fig. 8. Membership function of the fuzzy sets for Customer Segmentation
**Step 7. Labeling each cluster**
In this step, the member of each fuzzy set is defined by AL, BL and μ values. The number of clusters' membership can be used for ranking clusters in each set. In this case, the clusters are arranged decreasing order based on their membership number. Clusters that have less membership degree should be checked by bank’s experts to determine which set of strategies will be followed. For example, if the cluster A is located in spurious loyalty set with 0.2 membership it can be stated that cluster A is a member of the spurious loyalty region only the extent of 0.2 and the way of dealing with this cluster are analyzed according to bank’s experts.

**4. Empirical study**
In this section, we introduce the empirical case (Bank A) and the computing process using bank A dataset.

**4.1 The introduce of bank A case**
Bank A, founded in 1969 in Tehran, is a governmental retail bank. The developed methodology was implemented for the card devices of this bank which is imported from abroad, but there are several limitations to import these devices. That’s why banks are looking to optimize the number of reader devices are used by customers. This means that the knowledge of various customers is very important for the Bank’s experts so that they give reader devices to the clients who are more profitable for them. Regarding the needing of Bank A to classify acceptors of reader devices, the proposed model has been implemented in this bank.

**4.2 The computing process using bank A dataset**
A practical collected dataset, the bank in Iran, is used in this empirical case study to demonstrate the proposed procedure from 2011/6/20 to 2012/6/20. The computing process using bank A dataset can be expressed in detail as follows:

**Step 1:** At first, select the dataset of bank A, which is extracted only from the raw data in 2011, then delete the records which include missing values and inaccurate values, and eliminate the redundant attributes. Next, change the data into appropriate formats. Finally, the dataset remains 287 instances which are characterized by the following seven fields: (i) ID, (ii) Recency (Rcen), (iii) Frequency (Freq), (V) Monetary (Money). For the 2 other index, switching cost (sc) and satisfaction(s) use the questionnaire from these 287 instances. For these 287 instances the partial data of bank A dataset is shown in Table 2.
Table 2. The partial data of bank A dataset

<table>
<thead>
<tr>
<th>ID</th>
<th>Rcen</th>
<th>Freq</th>
<th>Money</th>
<th>SC</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0154</td>
<td>53.53806</td>
<td>1673.45</td>
<td>7.69E+10</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>0163</td>
<td>2.659894</td>
<td>1595.497</td>
<td>4.41E+09</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>0171</td>
<td>32.98047</td>
<td>719.8387</td>
<td>1.05E+11</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Step2: The relative weights of parameters have been determined by experts in the field of e-commerce and CRM. 5 Experts of Bank A compared each two variables and AHP processes were done. The matrix of group decision making for determining the relative importance weights of the R, F, M variables and SC, S variables are shown in Table 3 and table 4.

Table 3. The initial matrix of paired comparisons in behavioral loyalty

<table>
<thead>
<tr>
<th></th>
<th>R</th>
<th>F</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>1</td>
<td>0.5</td>
<td>0.25</td>
</tr>
<tr>
<td>F</td>
<td>2</td>
<td>1</td>
<td>0.8</td>
</tr>
<tr>
<td>M</td>
<td>2</td>
<td>1.25</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4. The initial matrix of paired comparisons in attitudinal loyalty

<table>
<thead>
<tr>
<th></th>
<th>SC</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC</td>
<td>1</td>
<td>0.14</td>
</tr>
<tr>
<td>S</td>
<td>7</td>
<td>1</td>
</tr>
</tbody>
</table>

Step3: Davies Bouldin index have been used to determining K optimum for the number of clusters in Matlab software. According to this index we set the number of clusters at 22 for K-means algorithm which is showed in Fig. 9.
Fig. 9. The number of optimized clusters based on DB index

**Step 4**: The 287 instances were clustered into 22 clusters in this step, which is showed in Fig. 10 and 11. The number of customers in each cluster is showed in Table 5.

![Clustering with k-means algorithm](image1)

Fig. 10. Clustering with k-means algorithm

![Clustering with k-means algorithm](image2)

Fig. 11. Clustering with k-means algorithm
Table 5. Number of customer in each cluster

<table>
<thead>
<tr>
<th>cluster</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>No.of customers</td>
<td>13</td>
<td>15</td>
<td>26</td>
<td>2</td>
<td>7</td>
<td>18</td>
<td>12</td>
<td>33</td>
<td>7</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>cluster</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
<td>19</td>
<td>20</td>
<td>21</td>
<td>22</td>
</tr>
<tr>
<td>No.of customers</td>
<td>14</td>
<td>13</td>
<td>9</td>
<td>7</td>
<td>13</td>
<td>5</td>
<td>33</td>
<td>3</td>
<td>5</td>
<td>21</td>
<td>12</td>
</tr>
</tbody>
</table>

Step5: The number of behavioral loyalty and attitudinal loyalty for each cluster where calculated which is showed in table 6.

Table 6. The degree of behavioral loyalty and attitudinal loyalty in clusters

<table>
<thead>
<tr>
<th>Cluster</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree of behavioral loyalty</td>
<td>0.29</td>
<td>0.84</td>
<td>0.45</td>
<td>0.36</td>
<td>0.59</td>
<td>0.47</td>
<td>0.29</td>
<td>0.7</td>
<td>0.42</td>
<td>0.48</td>
<td>0.58</td>
</tr>
<tr>
<td>Degree of attitudinal loyalty</td>
<td>0.39</td>
<td>0.83</td>
<td>0.32</td>
<td>0.98</td>
<td>0.49</td>
<td>0.3</td>
<td>0.92</td>
<td>0.91</td>
<td>1</td>
<td>1</td>
<td>0.74</td>
</tr>
<tr>
<td>Cluster</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
<td>19</td>
<td>20</td>
<td>21</td>
<td>22</td>
</tr>
<tr>
<td>Degree of behavioral loyalty</td>
<td>0.71</td>
<td>0.61</td>
<td>0.17</td>
<td>0.44</td>
<td>0.49</td>
<td>0.51</td>
<td>0.57</td>
<td>0.44</td>
<td>0.43</td>
<td>0.19</td>
<td>0.45</td>
</tr>
<tr>
<td>Degree of attitudinal loyalty</td>
<td>0.32</td>
<td>0.88</td>
<td>0.74</td>
<td>0.64</td>
<td>0.7</td>
<td>1</td>
<td>0.31</td>
<td>1</td>
<td>0.98</td>
<td>0.47</td>
<td>0.304</td>
</tr>
</tbody>
</table>

Step6: The membership number of each cluster is evaluated which is showed in table 7.

Table 7. Determining the membership number of each cluster

<table>
<thead>
<tr>
<th>Cluster</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Membership number</td>
<td>0.27</td>
<td>0.74</td>
<td>0.18</td>
<td>0.49</td>
<td>0.11</td>
<td>0.18</td>
<td>0.61</td>
<td>0.59</td>
<td>0.38</td>
<td>0.28</td>
<td>0.26</td>
</tr>
<tr>
<td>Cluster</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
<td>19</td>
<td>20</td>
<td>21</td>
<td>22</td>
</tr>
<tr>
<td>Membership number</td>
<td>0.36</td>
<td>0.4</td>
<td>0.58</td>
<td>0.17</td>
<td>0.16</td>
<td>0.26</td>
<td>0.21</td>
<td>0.34</td>
<td>0.35</td>
<td>0.23</td>
<td>0.2</td>
</tr>
</tbody>
</table>
Step 7: In this step, the member of each fuzzy set is defined by $AL$, $BL$ and $\mu$ values. The number of clusters' membership can be used for ranking clusters in each set. In this case, the clusters are arranged decreasing order based on their membership number. Clusters that have less membership degree should be checked by bank’s experts to determine which set of strategies will be followed. For example, if the cluster A is located in spurious loyalty set with 0.2 membership it can be stated that cluster A is a member of the spurious loyalty region only the extent of 0.2 and the way of dealing with this cluster are analyzed according to bank’s experts. The results is showed in table 8.

Sets of the loyal customers: $\{(2, 0.74), (8, 0.59), (13, 0.4), (11, 0.26), (17, 0.26)\}$

Sets of the disloyal customers: $\{(1, 0.27), (21, 0.23), (22, 0.2), (3, 0.18), (6, 0.18)\}$

Sets of the latent loyalty customer: $\{(14, 0.58), (4, 0.49), (9, 0.38), (20, 0.35), (19, 0.34), (10, 0.28), (15, 0.17), (16, 0.16)\}$

Sets of the spurious loyalty customers: $\{(7, 0.61), (12, 0.36), (18, 0.21), (5, 0.11)\}$

Table 8. Determining the label of clusters

<table>
<thead>
<tr>
<th>cluster</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lable</td>
<td>Disloya l</td>
<td>Loya l</td>
<td>disloya l</td>
<td>latent loyalty</td>
<td>spuriou s loyalty</td>
<td>disloy al</td>
<td>spuriou s loyalty</td>
<td>Loyal</td>
<td>latent loyalty</td>
<td>latent loyalty</td>
<td>Loya l</td>
</tr>
<tr>
<td>Cluster</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
<td>19</td>
<td>20</td>
<td>21</td>
<td>22</td>
</tr>
<tr>
<td>Lable</td>
<td>spuriou s loyalty</td>
<td>Loya l</td>
<td>Latent loyalty</td>
<td>latent loyalty</td>
<td>latent loyalty</td>
<td>Loyal</td>
<td>spuriou s loyalty</td>
<td>latent loyalty</td>
<td>latent loyalty</td>
<td>loyal</td>
<td>Loya l</td>
</tr>
</tbody>
</table>

5. Discussion and finding

We consult the experts and experienced managers of support services and card payment system unit in Bank A of Tehran regarding on the research results, they expressed that clusters of customers should be examined in terms of the growth rate of the monetary value in one month. So after segmenting customers, in terms of bank managers the amount of monetary value and customer satisfaction was introduced as the most important variable, Monetary value of segmented customers in another month period were reviewed again and this value was calculated in the new month period once more. These calculations are shown in Table 9. In this table, for each cluster, the total weighted monetary value (before and after segmentation) and also the growth rates of weighted monetary value for customers of each cluster is shown.
Table 9. Growth rates of customers weighted monetary value in each cluster before and after one month

<table>
<thead>
<tr>
<th>Cluster</th>
<th>No. of customers</th>
<th>The total weighted monetary value of each cluster after completing Segmentation</th>
<th>The total weighted monetary value of each cluster after one month of completing Segmentation</th>
<th>Growth rates of weighted monetary value before and after one month of completing segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13</td>
<td>0.3607</td>
<td>0.3707</td>
<td>1 %</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>0.7242</td>
<td>0.7342</td>
<td>1 %</td>
</tr>
<tr>
<td>3</td>
<td>26</td>
<td>0.1522</td>
<td>0.2102</td>
<td>5.8 %</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>0.4224</td>
<td>0.438</td>
<td>1.56 %</td>
</tr>
<tr>
<td>5</td>
<td>7</td>
<td>0.9102</td>
<td>0.9102</td>
<td>0 %</td>
</tr>
<tr>
<td>6</td>
<td>18</td>
<td>0.6754</td>
<td>0.6783</td>
<td>0.29 %</td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>0.3540</td>
<td>0.374</td>
<td>0.24 %</td>
</tr>
<tr>
<td>8</td>
<td>33</td>
<td>0.6001</td>
<td>0.6106</td>
<td>1 %</td>
</tr>
<tr>
<td>9</td>
<td>7</td>
<td>0.4611</td>
<td>0.4711</td>
<td>1 %</td>
</tr>
<tr>
<td>10</td>
<td>5</td>
<td>0.6148</td>
<td>0.6231</td>
<td>0.83 %</td>
</tr>
<tr>
<td>11</td>
<td>14</td>
<td>0.6446</td>
<td>0.6150</td>
<td>-2.96 %</td>
</tr>
<tr>
<td>12</td>
<td>14</td>
<td>0.7086</td>
<td>0.7286</td>
<td>2 %</td>
</tr>
<tr>
<td>13</td>
<td>13</td>
<td>0.7262</td>
<td>0.7285</td>
<td>0.23 %</td>
</tr>
<tr>
<td>14</td>
<td>9</td>
<td>0.2015</td>
<td>0.2215</td>
<td>2 %</td>
</tr>
<tr>
<td>15</td>
<td>7</td>
<td>0.4235</td>
<td>0.4380</td>
<td>1.45 %</td>
</tr>
<tr>
<td>16</td>
<td>13</td>
<td>0.5648</td>
<td>0.5742</td>
<td>0.94 %</td>
</tr>
<tr>
<td>17</td>
<td>5</td>
<td>0.5945</td>
<td>0.601</td>
<td>0.65 %</td>
</tr>
<tr>
<td>18</td>
<td>33</td>
<td>0.5686</td>
<td>0.5730</td>
<td>0.44 %</td>
</tr>
<tr>
<td>19</td>
<td>3</td>
<td>0.5150</td>
<td>0.5260</td>
<td>1.1 %</td>
</tr>
<tr>
<td>20</td>
<td>5</td>
<td>0.4961</td>
<td>0.5061</td>
<td>1 %</td>
</tr>
<tr>
<td>21</td>
<td>21</td>
<td>0.0917</td>
<td>0.0907</td>
<td>0.1 %</td>
</tr>
<tr>
<td>22</td>
<td>12</td>
<td>0.2462</td>
<td>0.2508</td>
<td>4.6 %</td>
</tr>
</tbody>
</table>

As is shown in Table 8 the amount of customer monetary value in cluster 3 has increased by about 5.8% within this time. However, the customer monetary value of clusters 11 has declined to 96/2%.

6. Conclusions

After assessing loyalty based segmentation, the results indicate that when we combine behavioral loyalty and attitudinal loyalty, we can obtain a better degree of loyalty. The application of proposed model is implemented in bank A, one of the retail banks in Iran. Fig. 12 shows Growth rates of weighted monetary value for 22 clusters of customers in the one-month period.
References


