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A Case Study of Applying SOM in Market Segmentation of Automobile Insurance Customers

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Abstract

Over the last decade, it has been observed that automobile insurer organizations are being tasked with a new challenge characterized by increased competition, increased requirements of automobile insurance quality and an increasing emphasis on time-to-market. Furthermore, knowledge regarding what customers think, what they want, and how to serve them is quite useful for insurance organization wishing to generate suitable strategies in competitive markets.

Keywords: *Data mining, Self Organization Maps(SOM),Customer Relationship Management(CRM), Customer segmentation, Automobile insurance*

1. Introduction

Nowadays, how to make marketing strategies has been an essential issue for automobile insurance industry [1]. Automobile insurance aims at covering different types of claim incurred as a result of traffic accidents which after joining World Trade Organization, insurance industry has rapid growth. Over the last decade, it has been observed that automobile insurer organizations are being tasked with a new challenge characterized by increased competition, increased requirements of automobile insurance quality and an increasing emphasis on time-to-market. Furthermore, knowledge regarding what customers think, what they want, and how to serve them is quite useful for insurance organization wishing to generate suitable strategies in competitive markets. Owing to disparate desires, interests, and needs, gaining a comprehensive understanding of customers is difficult. Since an organization cannot normally serve all customers in a market [2].

The diversity of customers' preferences and needs is a challenge for insurer organization to manage their customers through providing a variety of attractive, personalized, and satisfactory service [3]. Therefore customer segmentation can improve archiving to marketing purposes. Customer segmentation divides customers into groups, with the members of each group having similar needs, characteristics, or behaviors. Segmentation also represents the key element of customer identification in customer relationship management .After segmenting customers, organizations can then use further strategies such as customer attraction to maintain relationships with customers and gain more profit from them, one-to-one marketing, and detecting and predicting changes in customer behaviors'.

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Accordingly, this paper investigates the following research issues in Iran's automobile insurance business: What exactly are the customers' "needs" and "wants" for automobile insurance? How can help insurer to personalize its marketing campaigns? What would be characteristics of new developed insurance service to increase profit according to the knowledge of customers? Can the knowledge of customers be transformed into recommender systems or replenishment systems?

Data mining tools are a popular means of analyzing to obtain a deeper understanding of each customer's behaviours. The knowledge extracted from data mining results is illustrated as knowledge patterns and rules in order to propose suggestions and solutions to automobile insurer. In the last decade Self Organizing Maps (SOMs) have become a valuable data mining tool for extracting the knowledge patterns and rules with process/reaction monitoring and unsupervised classification purposes [4-8]. In this paper, an attempt was made to apply unsupervised Self Organizing Map for classification of customers of insurance services based on their behaviours and needs.

The rest of this paper is organized as follows. The background of the data mining approach including clustering analysis, customer segmentation and Self Organization Map (SOM) process is reviewed in Section 2. Section 3 introduces our system framework and implementation of customer segmentation to analysis of customers and Section 6 presents a brief conclusion.

2. Research Methodology

A competitive learning approach is proposed for one-to-one marketing, and detecting and predicting changes in customer behaviors'. The idea behind this approach is to provide mechanisms for improving customer relationship management for automobile insurance organization through providing a one-to-one marketing and variety of attractive, personalized, and satisfactory service based on their needs and behaviours. To analysis of developed one-to-one marketing, it is necessary to give a brief review of data mining, SOM, customer segmentation and their framework.

2.1. Data mining

Due to the information technology improvement and the growth of internet, enterprises are able to collect and to store huge amount of data. These massive databases often contain a wealth of important data that traditional methods of analysis fail to transform into relevant knowledge. Specifically, meaningful knowledge is often hidden and unexpected, and hypothesis driven methods, such as on-line analytical processing (OLAP) and most statistical methods, will generally fail to uncover such knowledge. Inductive methods, which learn directly from the data without an a priori hypothesis, must therefore be used to uncover hidden patterns and knowledge [9].

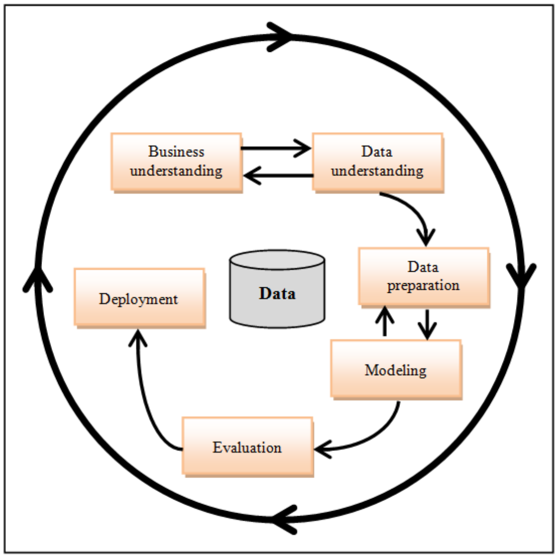

Figure 1. The phases of a data mining process

The explosive growth in databases has enforced academia and industry to use of data mining techniques for extracting frequent structural patterns that may convey important information. Therefore, data mining techniques has become an increasingly popular area for extracting information from the database in different areas due to its flexibility of working on any kind of databases and also due to the surprising results [7, 10]. Data mining is an interdisciplinary field that combines artificial intelligence, database management, data visualization, machine learning, mathematic algorithms, and statistics [11].

The life cycle of a data mining project consists of six phases. Figure 1 shows the phases of a data mining process. The sequence of the phases is not rigid. Moving back and forth between different phases is always required. It depends on the outcome of each phase which phase or which particular task of a phase, has to be performed next. The arrows indicate the most important and frequent dependencies between phases. We provide a brief description of these six phases in the following sections.

2.1.1. Business understanding

This initial phase focuses on understanding the project objectives and requirements from a business perspective, then converting this knowledge into a data mining problem definition and a preliminary plan designed to achieve the objectives.

2.1.2. Data understanding

The data understanding phase starts with an initial data collection and proceeds with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data or to detect interesting subsets to form hypotheses for hidden information.

2.1.3. Data preparation

The data preparation phase covers all activities to construct the final dataset (data that will be fed into the modeling tool(s)) from the initial raw data. Data preparation tasks are likely to be performed multiple times and not in any prescribed order. Basic tasks in data preparation phase are as follows [5]:

Data table and record: The data sources are first located, accessed, and integrated. Next, selected data is put into a tabular format in which instances and variables take place in rows and columns, respectively.

Data cleaning involves techniques for filling in missing values, smoothing out noise, handling outliers, detecting and removing redundant data.

Data integration and transformation: Sometimes it is useful to transform the data into a new format in order to extract additional information. It is useful to be able to summarize a large data set of data and present it at a high conceptual level. Dates are a good example of data that you may want to handle in special ways. Any date or time can be represented as the number of days or seconds since a fixed point in time, allowing them to be mapped. In the data matrix, the month of the year is used instead of date for detecting seasonal knowledge [12].

Data reduction and projection: This includes finding useful features to represent the data (depending on the goal of the task) and using dimensionality reduction, feature discretization, and feature extraction (or transformation) methods. Application of the principles of data compression can play an important role in data reduction and is a possible area of future development, particularly in the area of knowledge discovery from multimedia data set [13].

Discretisation: This is a form of data reduction, reduces the number of levels of an attribute by collecting and replacing low-level concepts with high-level concepts.

real world data tend to be dirty, incomplete, and inconsistent. Data preprocessing techniques can improve the quality of the data, thereby helping to improve the accuracy and efficiency of the subsequent mining process. Data preprocessing is therefore an important step in the knowledge discovery process, since quality decisions must be based on quality data. Detecting data anomalies, rectifying them early, and reducing the data to be analyzed can lead to huge pay-offs for decision making [13].

2.1.4. Modeling

Modeling, in software engineering, is the process of creating a data model by making descriptions of formal data models, using data modeling techniques [9]. In this phase, various modeling techniques are selected and applied and their parameters are calibrated to optimal values. Typically, there are several techniques for the same data mining problem type. Data mining techniques according to the 'types of knowledge mined' (DM functionalities) can classify to clustering, association, classification, and so on for achieving descriptive/predictive data mining tasks [5]. Some techniques have specific requirements on the form of data. Therefore, stepping back to the data preparation phase is often necessary.

Data mining modeling is the critical part in developing business applications. The goal of modeling is to formulate business problems as data mining tasks. Modeling technology can provide quantitative methods for the analysis of data, to represent, or acquire expert knowledge, using inductive logic programming, or algorithms, so that AI, cognitive science and other research fields are afforded broader platforms for the development of DMT [7].

2.1.5. Evaluation

At this stage in the project you have built a model (or models) that appear to have high quality from a data analysis perspective. Before proceeding to final deployment of the model, it is important to more thoroughly evaluate the model and review the steps executed to construct the model to be certain it properly achieves the business objectives. A key objective is to determine if there is some important business issue that has not been sufficiently considered. At the end of this phase, a decision on the use of the data mining results should be reached.

2.2 Customer segmentation using of Self organization map

Clustering and Segmentation is essentially aggregating customers into groups with similar characteristics such as demographic, geographic, or behavioral traits, and marketing to them as a group. Data mining techniques have been widely applied to different domains. As the transactions of an organization becomes much larger in size, data mining techniques, particularly the clustering technique, can be used to divide all customers into appropriate number of clusters based on some similarities in these customers. Facing the market with diverse demands, applying market segmentation strategy can increase the expected returns. Much of marketing research focuses on examining how variables such as demographics and socioeconomic status can be used to predict differences in consumption and brand loyalty. Segmentation problem should be considered as two different situations known character parameters and unknown character parameters. Character parameters are known means segmentation analysis deals with customers who have transactional or behavioral records stored in the enterprise database and the analytic parameters are predefined and are derived from analyzer interests [9].

One of the possible clustering methods is competitive learning. Given the training set of objects, competitive learning finds an artificial object (representative) most similar to the objects of a certain cluster. A commonly used application of competitive learning is the Kohonen Self Organising Map, or SOM, described by Kohonen in 1982 [14]. SOM is a popular unsupervised neural network methodology to clustering for problem solving involving tasks such as clustering, visualization and abstraction and market screening. Compared to traditional clustering techniques such as the K-means algorithm, SOM has the following advantages. SOM is inspired by the cortex of the human brain, where information is represented in structures of 2D or 3D grids, the theory of which is motivated via observing the operation of the brain [6]. SOM is trained by an unsupervised competitive learning algorithm and can automatically detect strong features in large data sets. While SOM maximizes the degree of similarity of patterns within a cluster and minimize the similarity of patterns belonging to different clusters, it can produce two-dimensional arrangement of neurons from the multi-dimensional space [6, 15].

Formally, SOM is a type of artificial neural network [11] with two fully interconnected layers of neurons, the input layer and the output or Kohonen layer (it's shown in Figure 2). The first step of Kohonen learning is competition. Given the training vector on the network's input and weight vector for each neuron of the Kohonen layer, the neuron with the minimal (usually Euclidean) distance between the weight and input vectors is excited or selected as the winner of the competition. The second step is adaptation. The neurons of the Kohonen layer are organized in a one-, two-, or three-dimensional lattice, reflecting its biological inspiration. A topological neighbor affecting function is defined on the Kohonen layer, assigning a degree of participation in the learning process to the neurons neighboring the winning neuron. In every learning step the weight vectors of the winning neuron and its neighbors are adjusted to move closer to the input training vector. The training algorithm proposed by Kohonen for forming a feature map is stated as follows [4, 6, 8]:

Step (1) Initialization: Choose random values for the initial weights w_i.

Step (2) Winner Finding: Find the winning neuron c at time t, using the minimum Euclidean distance criterion

$$C = \arg\min_i \|x - w_i\|, \quad i = 1, 2, \dots, M \tag{1}$$

where $x = [x_1, \dots, x_n] \in R^n$ represents an input vector at time t, M is the total number of neurons, and $\|.\|$ indicates the Euclidean norm.

Step (3) Weights Updating: Adjust the weights of the winner and its neighbors, using the following rule:

$$w_i(t+1) = w_i(t) + \eta(t) h_{ci}(t)[x_j(t) - w_i(t)], \tag{2}$$

$$h_{ci}(t) = exp\left(-\frac{\|r_c - r_i\|^2}{2\sigma^2(t)}\right) \tag{3}$$

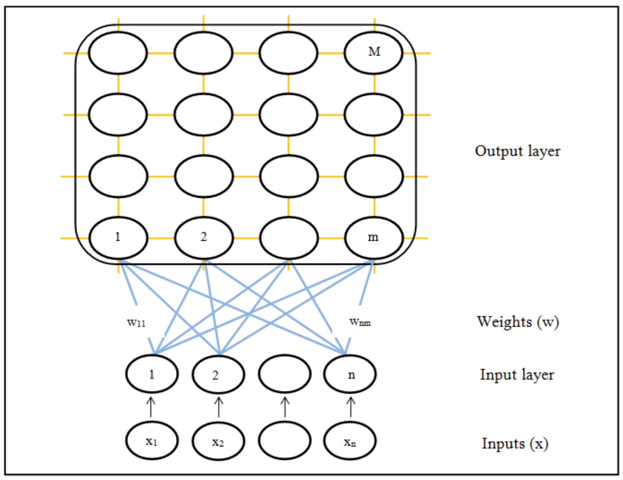

Figure 2. The structure of self organization map (SOM)

Where $x_j(t)$ represents an input data at time t, $h_{ci}(t)$ is the topological neighborhood function of the winner neuron c at time t, $\eta(t)$ is a positive constant called "learning-rate factor", $r_c \in R^2$ and $r_i \in R^2$ are the location vectors of nodes c and i, respectively. $\sigma(t)$ defines the width of the kernel. Both $\eta(t)$ and $\sigma(t)$ will decrease with time. It should be emphasized that the success of the map formation is critically dependent on the values of the main parameters (*i.e.*, $h_{ci}(t)$ and $\eta(t)$), the initial values of weight vectors, and the prespecified number of iterations.

In the case of a discrete data set and fixed neighborhood kernel, the sum of the squared-error of SOM can be defined as follows:

$$SSE = \sum_{j=1}^{n} \sum_{i=1}^{M} h_{ci} \left\|x_j - w_i\right\|^2, \tag{4}$$

where n is the number of training samples, and M is the number of map units. Neighborhood kernel h_{ci} is centered at unit c, which is the best matching unit of input vector x_j, and evaluated for unit i.

3. Research Application

To develop operating strategies in competitive markets, the insurer organizations must first understand customer's characteristics and needs based on customer's expectations, and then ineffective strategies can be avoided, saving money and time. Thus, customer segmentation becomes important for insurance organization to recognize the customers', solving their problems, increasing their satisfaction, and enhancing their loyalty.

3.1. Iran automobile insurance at present

To date, there are a total of 23 insurance companies that all of them are local firms in active operation in Iran, since the first insurance organization was started 78 years ago. In 2011, Iran was ranked 46th worldwide with total premium revenue of US$7 million according to the Swiss reinsurance company Sigma. This indicates that Iranʹs insurance market has expanded to a significant position in the international insurance arena.

3.2. Data source

Insurers are bound by the Private Data Protection Statute and are not permitted to disclose any information on their clients to other parties, which has restricted thorough research on existing automobile insurance policy purchases data based on related databases. This study therefore collected such data by means of a questionnaire.

Those subjects were automobile insurance consumers. Furthermore, the questionnaires are designed to survey the subjects' previous experiences with their purchases, and services rendered to them by the insurers. Information collected through the questionnaires is used to establish a database. The items in the questionnaires can be generally divided into four parts:

Part 1. Basic data includes seven questions: gender, age, education, occupation, residence, marital status and annual income.

Part 2. Automobile characteristics include five questions: automobile type, automobile application, financial value of automobile, produced year and county of its manufacturer.

Part 3. Automobile insurance information includes five questions: previous insurer organization, number of years which don't have any accident, the days that past from period of insurance and automobile insurer organization that wishes to purchase it as the future automobile insurance.

Part 4. The importance of effective factors in selection of automobile insurance include five questions: insurance cost, discount, pardon for penalties caused to postponement of holding a new insurance, the satisfaction of previous insurer organization, the brand of insurer organization and native of insurer organization.

Questionnaires were distributed among potential customers automobile insurance through the Email in Iran. A total of 2000 questionnaires were distributed, and 1307 were collected. For this study, we get the data used in this study from the collected Questionnaires.

3.3. Data preparation

The data sources are first located, accessed, and integrated. Next, selected data is put into a tabular format in which instances and variables take place in rows and columns, respectively. A labeling is used for a better understanding of results. By means of this labeling, a number is assigned to each questionnaire.

Since the input to the data mining model affects the choice of a data mining algorithm and the results, we attempted to remove polluted data such as incorrectly coded input (*e.g.*, typos) or inconsistent input (*e.g.*, outliers or anomalous answers) from the database by filtering out the Excel file. Effective (1260) questionnaires were amassed other than 47 invalid pieces containing omissions and incomplete answers. Effective collection ratio was 63%. The experimental dataset is randomly divided into two groups with 66% of the data serving as a training set and the remaining 34% serving as a testing set.

3.4. SOM implementation

In this section we use SOM toolbar in MATLAB software[16] to cluster customers into subgroups or segments. The computer used was a Pentium IV CPU at 2.5 GHz and 512 Mb of RAM. Before the training process begins, data normalization is often performed. The linear transformation formula to [0, 1] is used:

$$y_t = \frac{x_t}{x_{max}} \tag{5}$$

Where y_t and x_t represent the normalized and original data; and x_{max} represent the maximum values among the original data.

The determination of the size of SOM is not an easy task, because a network with a greater number of cells would have hindered the visualization of the labels in each neuron. In the same way, a smaller map than the one used by the authors would cause many labels to be overlapped. It is recommended [17] that the number of neurons in the map training set and the length and width of the map should be proportional to the magnitude of the first eigenvalues obtained by the decomposition of the training set. The ratio calculated by the first two calculated eigenvalues in this case is 1.96. Having that in mind (and also the heuristic method in SOM toolbar of MATLAB[16]) we started the search for the optimal size of the map. After several trials, we chose a map with a size 16×13. The used map had plain boundary conditions, a hexagonal grid, Gaussian neighborhood function, and linearly decreasing learning rate.

The SOMs were trained using the batch training algorithm in two phases: (1) rough training phase which lasted 1000 iterations with an initial neighborhood radius equal to 5, a final neighborhood radius equal to 2, While a learning rate starts at 0.5 and end at 0.1, and (2) fine training phase which lasted 500 iteration cycles, While a learning rate starts at 0.1 and end at 0.02, we do set the neighborhood partitions started at 2 and end with 0.

After the training was finished, the prediction abilities of the SOMs were examined using the statistical metrics and data set consisting of 1260 customers. The evaluation based on the mean absolute error (MAE) and root mean square error (RMSE), which are widely used for evaluating results of time-series forecasting. The MAE and RMSE are defined as follows:

$$\text{MAE}=\frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t| \tag{6}$$

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \tag{7}$$

Where y_t and $\hat{y}_t$ are the observed and the forecasted rice yields at the time t. By using of Eqs. (6) and (7) and data of new cutomers, MAE and RMSE calculated as 0.04425 and 0.058988, respectively. These low amounts for MAE and RMSE can demonstrate the appropriateness and precise of our modeling and forecasting.

3.5. Customer segmentation

It has been stated in Section 2.2 that SOM map is a valuable tool to group (aggregate) and classify (disaggregate) customers based on their expectations and needs. This section explains how to use results of SOM to classify the customers and extracting the knowledge patterns and rules.

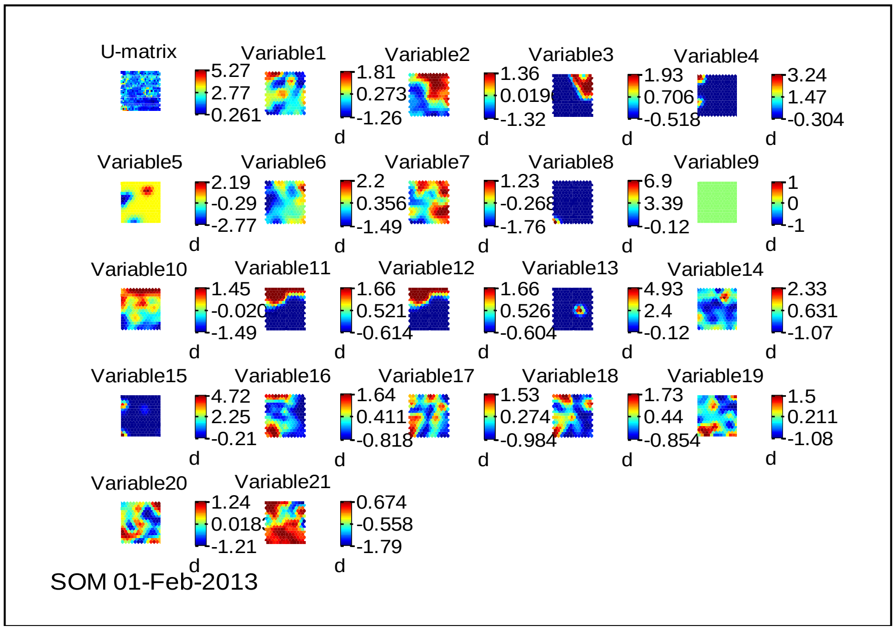

Figure 3. The insurance customer data set in 16×13 SOM

Figure 3 shows The insurance customer data set in 16×13 SOM based on each variable and its U-matrix. A U-matrix is a map of distances between each of neurons and all its neighbors and slices are the two-dimensional combinations of the SOM weights. With the U-matrix map, the easiest way to examine whether there are distinct clusters present in a given data set is to utilize the distance matrix. This matrix represents the distances between each neuron and all its neighboring ones, and is able to reveal the local cluster structure of the map. The further the distance is, the higher the difference between them will be, which is resulted in a higher similarity. The distance between two neurons is represented by a color-coding scheme. Different colors are used to represent different distances, such as red stands for the nearest neighborhood distance, and grey stands for the farthest (Figure 4).

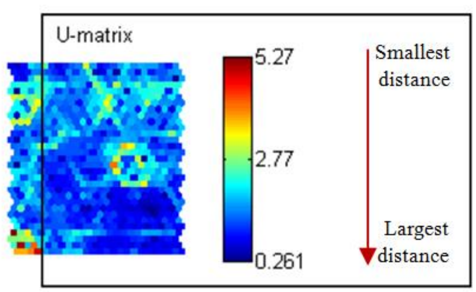

Figure 4. U-matrix of customer data set in 16×13 SOM

The 1307 customers of automobile insurance can be segmented to 4 follows clusters based on U-matrix that it is shown in Figure .

a) *Customers that cost is important for them:* These customers have low annual income and financial value of automobile. They seldom have any occupation and the insurance cost is an important factor to select insurance organization in this cluster (cluster 3). Cluster 3 has the least number of 312 (312/1260=0.248%) customers. They have the highest churn rating and it doesn't ensure organization/ customer relationship is maintained in the long-term. An implication for this extracted phenomenon is that insurance organizations can have greater contribution of company's revenue from these customers by sending themselves discount schedule to them.

b) *Customers that quality of services is important for them:* Based on the information from U-matrix, Clusters 4 has the lowest number of customers. It has 120 (120/1260=9.5%) customers, while the highest monetary rating, 0.440, is gained from its customers since their financial value of automobile is high. They choice an insurer organization as their automobile insurance which has a popular brand with high quality in developed services. Moreover, they are loyal both in attitude and behavior in the automobile insurance. Loyal customers are profitable as they would contribute positively to the success of their insurance experience. Therefore, the insurer organizations should focus on the customers of this cluster by increasing customer loyalty through providing customized services to encourage their future purchase.

c) *Customers that style of payment is important for them:* For Cluster 1, the average of education is above the total average. Besides, their occupation is as that they don't like pay all of costs in one time and prefer to pay in several installments. Pertaining to the marketing strategies for customers in Cluster 1, the insurer organizations should create payment convenience for this cluster which includes special groups such as teachers, nurses and etc.

d) *Customers that select insurer organization based on family and friendly relation:* Cluster 2 is a special group of patients for insurer organization. Cluster 2 has the most number of customers among clusters (438/1260=34.76%). They have different attributes. They have the highest loyalty rating and it ensures organization/ customer relationship is maintained in the long-term and the most revenues for the insurer organizations arise from them. In this regard, the customers of Cluster 2 can attract new customers. Since according to the so-called "20–80″ rule, a dramatic business improvement is often achieved by identifying the 20% of core customers and by maximizing the attention applied to them, they will attract the 80% of customers. Therefore, satisfying existing customers′ needs and build close relationships with them will be very imperative.

   Pertaining to the marketing strategies for customers in Cluster 2, the insurer organizations should enhance customer relationship management to keep in touch with the customers and find ways to meet their demand by attracting them to visit more often. For example, special attention and treatment is particularly vital to postgraduate customers when meet them and online services to simple relation to them.

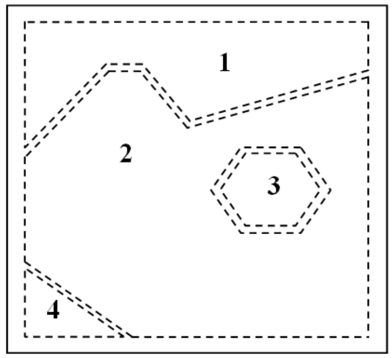

Figure 5. Graph of clusters obtained with U-matrix

To evaluate the prediction abilities of the SOMs we use the statistical metrics MAE and RMSE based on equations (6) and (7). The result for the training and testing data sets using of SOM is shown in Table 1.

Table 1. The statistical metrics MAE and RMSE for the training and forecast using SOM on data set

Training		Testing	
MAE	RMSE	MAE	RMSE
0.023457	0.032145	0.037856	0.040129

The low MAE and RMSE in Table 1 for training and testing data sets shows high performance SOM for clustering of insurance information data set used in this research.

4. Conclusion

The complex organizational structure of most of the companies that write a significant volume of automobile insurance makes it infeasible for a decision maker to cope with all underwriting decisions by using of traditional analysis methods. Hence, it is necessary to design some set of strategies and guidelines to ensure a maximum degree of consistency among customers.

Knowing customers one by one in some business is not commodious, so using customer segmentation method could be useful in this situation. Customer segmentation based on their needs, characteristics, or behaviors. Segmentation also represents the key element of customer identification in customer relationship management. After segmenting customers, organizations can then use further strategies such as customer attraction to maintain relationships with customers and gain more profit from them, one-to-one marketing, and detecting and predicting changes in customer behaviors'.

Accordingly, this paper investigates the CRM research issues in Iran's automobile insurance business by applying of unsupervised self-organizing maps for classification of customers of insurance services based on their behaviours and needs. To evaluate the prediction abilities of our model based on SOMs we use the statistical metrics MAE and RMSE. Moreover, the second criterion for model validity in this study was the views of management strategists. The management strategists of the insurance organizations on which the case study was conducted have said that they have found the results obtained from the suggested model to be meaningful and useful. Thus, as of August 2006, in view of the strategies followed in the last year the strategists claim that the strategies determined by the model in our study in May 2005 are indeed accepted as the “best solutions”.

Although we focus on automobile insurance, our approach may help managers in a variety of contexts to assess other insurances. Future research may research to life insurance. In addition, fuzzy numbers can be introduced in SOM methods to more effectively analyze cases having greater.

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