International Journal of Computing and Artificial Intelligence

E-ISSN: 2707-658X
P-ISSN: 2707-6571
IJCAI 2020; 1(1): 21-27
Received: 13-11-2019
Accepted: 15-12-2019

Amir Ehsani
Department of Computer Engineering, Khoy Branch, Islamic Azad University, Khoy, Iran

Abdolreza Hatamlou
Department of Computer Engineering, Khoy Branch, Islamic Azad University, Khoy, Iran

Corresponding Author:
Abdolreza Hatamlou
Department of Computer Engineering, Khoy Branch, Islamic Azad University, Khoy, Iran

Identifying loyal customers and predicting customers purchase behavior using k-means and SOM algorithms

Amir Ehsani and Abdolreza Hatamlou

DOI: https://doi.org/10.33545/27076571.2020.v1.i1a.5

Abstract
Despite the importance of data mining techniques to customer relationship management (CRM) and measuring customers loyalty and profitability, there is a lack of resources and articles related to this topic. Data mining is a useful tool to help companies for mining patterns and discovering hidden information in customers' data. In this study we cluster customers using k-means and SOM clustering algorithms with respect to apply RFM analysis based on behavioral characteristics such as recency, frequency and monetary variables and identify loyal customers and determine degree of loyalty. Then we apply C5.0 model on the resulting clusters to predict future customer behavior. In the end, evaluate accuracy of classification and compare the results. Proposed model implemented on M&S clothing store's dataset. Results of this study provide a background for identifying valuable and key customers and analysis their characteristics and loyalty.

Keywords: Data mining, customer relationship management, classification, clustering

Introduction
Nowadays development of business competition and firms effort for outpacing from each other, led to decrease of profits in business activities. To survive competition and sustain profits, firms must identify and retain customers of high value and profit potentials [6]. The most important principles for achieving these goals is customize marketing strategies and fulfill the needs of different customers and establishment of effective communication with customers [6, 7]. A successful customer-oriented marketing strategy is very important in the sense that it can help to strengthen the relationships between the customers and the business [1]. Understanding customer characteristics and satisfying customer requirements not only can improve the customer loyalty but can make great profit by decreasing the risk of business operation [2]. Creating a loyal 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 with customers [3]. Data mining technique help companies to move forward to customer-oriented marketing by understanding the purchasing behavior of different groups of customers [1, 7] and identifying loyal customers. Data mining is a process that discovers patterns and relationships between data using data analysis and various modeling technique [8]. Integration of RFM analysis and data mining techniques provides useful information for current and new customers. This study presents a way that analysis real customers value and investigates behavioral characteristics using clustering based on RFM attributes and apply C5.0 classification model on the outputs of clustering algorithms and demographic variables to predict future customers behaviors such as how recently the customer will probably purchase, how often the customer will purchase, and what will the value of his/her purchases. In proposed model (1) first k-means and SOM clustering algorithms are used to find customer segments with similar RFM values. (2) Then, using the results of clustering and customer demographic variables, C5.0 classification model predicts future customers' behaviors. (3) Finally, using n fold cross method measure accuracy of classification rules. The rest of paper is organized as follows: section 2 describes the needed concepts RFM analysis, k-means and SOM algorithms and C5.0 classification model briefly. Section 3 reviews related works on customer value. Section 4 applies mentioned algorithms on case study, and last section concludes the paper.

2. Basic Concepts

2.1. RFM model

The RFM model is proposed by Hughes (1994) [9], and it is a model that is using on direct marketing [10]. This technique identifies customers' behavior and describes Customer behavior characteristics based on these three variables:

(1) Recency of the last purchase (R).

R represents recency, which refers to the interval between the time that the latest consuming behavior happens and present. The shorter the interval is, the bigger R is.

(2) Frequency of the purchases (F).

F represents frequency, which refers to the number of transactions in a particular period, for example, two times of one year, or two times of one month. The many the frequency is, the bigger F is.

(3) Monetary value of the purchases (M).

M represents monetary, which refers to consumption money amount in a particular period. The much the monetary is, the bigger M is [2].

According to the literature researches showed that the bigger the value of R and F is, the more likely the corresponding customers are to produce a new trade with enterprises [11]. Valuables customers who are their recency, frequency and monetary rankings are high. RFM method is very effective attributes for customer segmentation [12]. This research assumes that three attributes have same importance or weights.

2.2. K-means

K-means algorithm is a Non-hierarchical method that is very popular among clustering algorithms because of its simply use and fast execution and it is very useful in customer segmentation, pattern recognition, information retrieval and so on [13, 14, 15]. The formula of K-means method is as follows, where the distance between two points X_r and X_s is given by the square root of the sum of the squared distance over each coordinate, and $X_r = X_{r_1}, X_{r_2}, X_{r_3}, ..., X_{r_i}, ..., X_{r_n}$ and $X_s = X_{s_1}, X_{s_2}, X_{s_3}, ..., X_{s_i}, ..., X_{s_n}$, and each C_i in Eq. (1) represents the weight. If the weights are normalized, then $\sum_{i=1}^{n} C_i = 1$ [16].

$$d(X_r, X_s) = \left[\sum_{i=1}^{n} C_i (X_{r_i} - X_{s_i})^2\right]^{1/2} \quad (1)$$

K-means algorithm consists of two main steps [14]: First, the assignment step where the instances are placed in the closest class. Second, the re-estimation step where the class centroids are recalculated from the instances assigned to the class. One of the main problems of K-means algorithm is to select the best value of K [16]. Kuo *et al.* (2002) have pointed out that non-hierarchical methods, such as K-means method, can have higher accuracy if the starting point and the number of clusters are provided [15]. Punj and Steward (1983) [17] suggested a two-stage method by deploying Ward's minimum variance method to determine the number of clusters for K-means method. On the other hand, Kuo *et al.* (2002) [15] have proposed a modified two-stage method by applying self-organizing feature maps to determine the number of clusters for K-means method. The reason is that self-organizing feature maps can converge very fast since it is a kind of learning algorithm that can continually update or reassign the observations to the closest cluster. Therefore, this study uses self-organizing feature maps to determine the number of clusters for K-means method.

2.3. Self-organizing maps (SOM)

SOM is the clustering algorithm based on the unsupervised neural network model. Since it was suggested by Kohonen (1982), it has been applied to many studies because of its good performance [18].

SOM maps high dimension data into lower dimension space and maintains original topological structure. Working principle of SOM network is that when the network receives inputs from outside, will divide the inputs into several regions, shown as Fig (1). Each region responses differently to the input patterns, the inputs owning similar features are closer to each other, otherwise distant. The function of SOM is to lower the dimension of multiple dimension data and keep original relations among data [19].

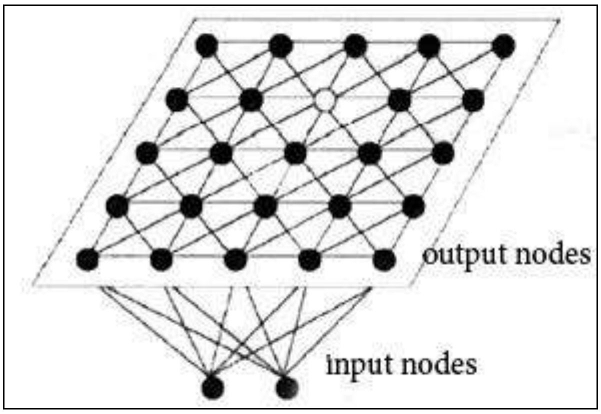

Fig 1: SOM Network

The process of SOM is as follows:

(1) Initialize the weights as random small numbers.

(2) Put an input sample, X_i, into the SOM network, and the distances between weight vectors $W_j = (W_{j_1}, W_{j_2}, ..., W_{j_m})$, and the input sample, X_i, are calculated. Then, select the neuron whose distance with X_i is the shortest, as in Eq (2). The selected neuron would be called the 'winner'.

$$\min D(j) = \sum (W_{ji} - X_i)^2 \quad (2)$$

(3) Update the weights of the winner as well as its neighbors by the following equation when α is assumed to be the learning rate.

$$W_j^{NEW} = -W_j + \alpha \| X_i - W_j \| \quad (3)$$

(4) Iterate Steps (2) and (3) until the stop criterion is satisfied [18].

2.4. C5.0

As one of the most widely used data mining algorithms, decision tree has benefits such as high accuracy, simpliness and efficiency. Concept of decision tree come from Concept Learning System (CLS) was proposed by Hunt. E.B *et al* in 1966. Based on it, a lot of algorithms have emerged. Among these, the most famous algorithm is ID3, which was proposed by Quinlan in 1986. Based on improvement of this method Quinlan invented C4.5 algorithm in 1993. Because of better data management, another algorithm called C5.0 developed based on C4.5 algorithm. It includes all functionalities of C4.5 and applies a bunch of new technologies, among them the most important application is “boosting” technology for improving the accuracy rate of identification on samples [21]. We describe the way of C4.5 decision tree construction. C5.0 decision tree construction idea is the same as C4.5. Given a set S of cases, C4.5 first grows an initial tree using the divide-and-conquer algorithm as follows:

1. If all the cases in S belong to the same class or S is small, the tree is a leaf labeled with the most frequent class in S.
2. Otherwise, choose a test based on a single attribute with two or more outcomes. Make this test the root of the tree with one branch for each outcome of the test, partition S into corresponding subsets S1, S2,... according to the outcome for each case, and apply the same procedure recursively to each subset.

C5.0 improve accuracy rate of decision tree but in practice modeling depends on learning samples.

3. Related works

Ching Hsue Cheng (2009) and You Shiang Chen (2009) first used RFM model as input variables for obtaining quantitative values then apply K-means algorithm for clustering customers' values and finally used rough set theory for discovering association rules [22]. Huang, Chang, and Wu (2009) applied K-means method, Fuzzy C-means clustering method and bagged clustering algorithm to analyze customer value for a hunting store in Taiwan and finally concluded that bagged clustering algorithm outperforms the other two methods [23]. Kyoung jaekim, Hyunchul (2007) used new clustering algorithm based on GA for clustering customers of a store [18]. Rein artz and Kumar (2000) proposed customer lifetime value. They study on profitability and loyalty and introduced a new method for increasing CLV to improve loyalty [24].

4. Methodology

This section briefly describes proposed procedure and model. The purpose of this paper is identifying loyal customers and analysis their lifetime values using clustering methods and predicting future purchase behavior of customers with proposed classification method. Finally compare accuracy of classification results of each clustering methods and select best algorithm among them. To achieve this goal, using k-means and SOM clustering algorithms to cluster RFM analysis outputs and by having the results of clustering and demographic characteristics of customers and by applying C5.0 decision tree on them, we predict future purchase behavior of customers. In the end investigate accuracy rate of clustering algorithms with n-fold cross method.

Research Model

Figure 2 shows steps of proposed model. Data preprocessing, RFM analysis, clustering the customers, predict purchase behavior and evaluation and comparison of prediction outcomes. Proposed model can be used to improve marketing strategies and taking full advantage of customers' information and identifying loyal customers and achieve more profit.

The proposed procedure

In this subsection, we further explain the proposed procedure. It can be divided into five processes:
(1) Select the dataset and preprocess data; (2) in the next step, use recency, frequency and monetary as transaction data for RFM analysis until customers be sorted based on RFM attributes. (3) By using SOM and K-means algorithms cluster customers with same RFM value and determine customer lifetime value. (4) Extract rules by C5.0 decision tree based on customers' demographic data and outcomes of the clustering step. (5) n-fold cross technique used to evaluate accuracy of classification step on k-means and SOM algorithms outcomes and we introduce best clustering method. The computing process introduces completely as follows:

Step one: Preparation and data preprocessing

This step is the most expensive and time consuming step of the process and implemented by data mining application called spss statics. Data preprocessing step is needed to make knowledge discovery easier and correctly. Data preparation operations consist of reduction in number of attributes, outlier detection, normalization and discretization. In fact this process makes the C5.0 prediction more accurate. For this, first convert last customers purchase values date from hijri to AD in order to usable for data mining. Monetary values are Iran's rial currency. Dataset selected from 1000 customers of M&S clothing store. For this, select customers that buy from store from 6 August 2013 to 11 February 2014 and investigate their transaction in this period. Table 1 shows example of customers' transaction. First column present customers ID, second column present last customer transaction date, third column is frequency of purchase and last column shows that customer how spent money for purchase on this period. Table 2 shows customers demographic values. Demographic characteristics using for predict future purchase behavior of customers by C5.0 model. Demographic variables applied in this study are age, marital status, address and job status. In data preprocessing step, age variable divided to 4 groups such as under 20 years old, 20 to 30 years old, 31 to 50 years old and above 50. Marital status divided to single and married, address divided to 6 region and job status divided to employed, unemployed and retired. After data preparation and processing and define transaction and demographic variables going to data analysis step. Data analysis step implement in IBM spss modeler software.

Step 2: RFM analysis

In this step, inputs are recency, frequency and monetary. 5, 4,3,2,1 are assigning to each attributes in order to highest value. Then Sort the data of each attributes by descending or ascending order. Partition the three R-F-M attributes respectively into 5 equal parts and each part is equal to 20% of all. The five parts are assigned 5, 4, 3, 2 and 1 score and repeat this procedure for each attributes. There are total 125 ($5 \times 5 \times 5$) combinations. Then merge R, F and M scores of each customer so that gain customer RFM scores. Table 3 shows RFM analysis result of some customers. As you can see, in the sixth row customer's score is 555. This customer has most of purchase and highest amount of spending and purchase recently. But the customer with rank 111 is a cheap customer that he/she doesn't spend a lot for purchase and has the least number of purchases and purchased long time ago.

Step 3: Clustering

This step divides customers into numerous groups with similar RFM values, and assigns each customer to an appropriate segment. Inputs of clustering step are outcomes of RFM analysis that is R, F and M. we use SOM and K-means clustering algorithms in this study. SOM determine optimal number of clusters. In this study, SOM grouped customers into 12 clusters. So we use this number of clusters for k-means. K-means algorithm is one of those algorithms that must have number of clusters in the beginning. For this set k = 12. k-means segment customers to 12 clusters with similar RFM values such as the smallest cluster has 3 members and the largest cluster has 255 members and the ratio of largest to smallest is 85. In other method, SOM algorithm customers grouped into 12 clusters optimally. So that the smallest cluster has 3 members and the largest cluster has 176 members. The number of input and output layer after execution is 3 and 12 respectively. Table 4 and 5 shows results of three clusters with size of each cluster and average values of R, F and M. Last row presents total average for all customers.

Last column called RFM patterns presents degree of loyalty and value ability of each cluster. Upward 🡡 and downward arrow 🡣 shows if the average R (F, M) value of a cluster exceeded the overall average R (F, M) or not. 8 possible combinations of input (RFM) can be obtained. For example, R🡣F🡡M🡡 represents that the average recency value of a customer segment is smaller than overall average, while frequency and monetary average values are greater than overall averages. Now we discuss about loyalty of each cluster and customers value and then suggest appropriate strategy for dealing shops with customers.

R🡣F🡡M🡣: These customers have high loyalty but for low monetary and delay in shopping, store should propose specific options for increase their monetary.

R🡣F🡣M🡡: These are valuable customers but their loyalty is low, so may in the future turn to other stores.

R🡡F🡡M🡡: These customers are in the highest rating category of value and loyalty, and they are potential customers, so bank must provide specific services and discounts for these valuable customers.

R🡣F🡣M🡣: These groups of customers have lowest value for store, so store should have a plan to confute them to further purchase.

R🡡F🡣M🡣: these customers are first time buyers and have low monetary. They are not valuable too much but if they purchase again can be valuable customers.

R🡣F🡡M🡡: These customers have high loyalty and monetary but they don't shopping long time, then maybe there is a problem to their connection with store. So it is better calling them. For example send email to them and promoting new products until they active again.

R🡡F🡣M🡡: these customers are valuable for store. Although frequency are low but they are valuable customers because recency and monetary are high. R🡡F🡡M🡣: Because of high amount of recency and frequency can be expected them to be potential and valuable customers in near future and spend too much for purchase.

Tables 6, 7 and 8 show minimum, maximum and average of recency, frequency and monetary of clusters by SOM and k-means algorithms.

Step 4: predict purchase behavior

A customer segment is not as enough to identify, and then to predict customer’s behavior. So we need to make connection between demographic variables and clustering outcomes and use C 5.0 model to extract specific rules. Inputs of C 5.0 model are age, marital status, address, job status and RFM patterns from clustering step. RFM pattern is target variable and others are inputs for C 5.0 model.

You can see part of C 5.0 model output that applied on k-means and SOM clustering algorithms.

if age category in [20-30 31-50 >50] and Address = "region 2" and Job = "employed" then R🡡F🡡M🡡 OR
if age category in [31-50 >50] and Address= "region 5" then R🡡F🡡M🡡

(C5.0 model applied on k-means algorithm)

if age category in [20-30 31-50 >50] and Address = "region 2" and Job = "unemployed" then R🡡F🡣M🡡 OR
if Address = "region 2" and Job = "employed" then R🡡F🡣M🡡

(C5.0 model applied on SOM algorithm)

Step 5: Evaluation and comparison

In this study, we use n-fold cross technique for evaluating C5.0 outcomes. Result of evaluation for applying C5.0 model on k-means algorithm conclude 0.6 as error and evaluation for applying C5.0 model on SOM algorithm conclude 1. With comparison of these errors we find out if C5.0 model apply on clusters of k-means algorithm can be stronger and more accurate compared to applying C5.0 model on SOM algorithm.

5. Conclusion

Because importance of customer satisfaction in business, there are many studies related to customers profitability and loyalty. Knowledge of customer lifetime value can provide basic information for determining appropriate strategies. Furthermore stores and companies need to know loyal customers and so they can motivate different groups of customers to increase profitability. Although customer attraction is necessary for companies but customer retention is more important for financial success. In this study we presented some clustering algorithms for challenging the optimal number of clusters and customer lifetime value analysis and predict customer behavior based on clustering algorithms and evaluated accuracy of clustering methods. For case study consider purchase behavior and demographic variables of 1000 customer of M&S clothing store and using k-means and SOM algorithms to group customers to clusters with similar RFM values and indentify loyal customers. Then apply C5.0 model to predict characteristics of consumer behavior. C5.0 outputs consist of set of decision rules that companies can find out which groups of customers have more importance. Then with n-fold cross evaluation propose k-means performance. For future works, first use other versions of RFM instead of it, for example WRFM, TRFM and FRAT. Second use websites visitors (RFD) and social networks (RFR) instead of store's dataset. Third use other classification method like CHAID or KNN or Bayesian networks instead of C5.0 model.

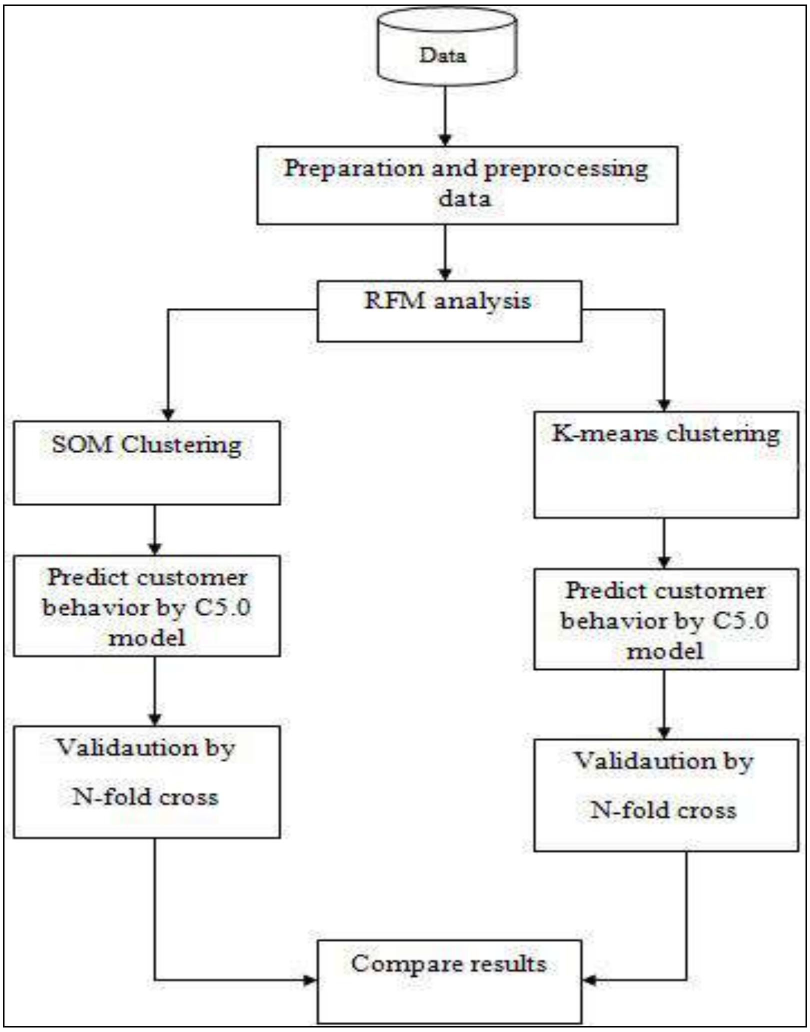

Fig 2: The proposed model

Table 1: Example of customers transaction

ID	(recency)	(frequency)	(monetary)
1	11/21/2013	4	310000
2	09/07/2013	2	3090000
3	10/28/2013	4	13925000
1000		1	1370000

Table 2: Demographic variables of some customers

ID	Age	Marital	Address	Job
85	>50	M	Region3	Emp
86	31-50	M	Region1	Unemp
87	31-50	M	Region4	Unemp
88	20-30	S	Region1	Unemp
89	<20	S	Region4	Unemp

Table 3: RFM analysis of customers

ID	R	F	M	RFM
1	3	4	2	342
2	1	2	4	124
3	3	4	5	345
4	5	4	5	545
5	4	4	5	445
6	5	5	5	551
7	1	1	1	111

Table 4: Clustering customers by k-means algorithm based on RFM

cluster	R	F	M	size	RFM pattern
1	3	3.33	2	3	R↓F↑M↓
2	1.53	1.1	4.14	58	R↓F↓M↑
3	4.72	2.33	4.67	131	R↑F↑M↑
4	1.45	1	1.54	255	R↓F↓M↓
5	4.36	1.01	1.32	88	R↑F↓M↓
6	4.65	4.39	4.96	23	R↑F↑M↑
7	3.34	1.09	3.19	123	R↑F↓M↓
8	2.55	2.14	4.41	44	R↓F↑M↑
9	3	1.05	1.58	62	R↓F↓M↓
10	5	1.21	3.58	52	R↑F↓M↑
11	1.48	1.1	3	71	R↓F↓M↓
12	3.76	1	4.70	90	R↑F↓M↑
Total	3.23	1.73	3.25	1000	

Table 5: Clustering customers by SOM algorithm based on RFM

cluster	R	F	M	size	RFM pattern
1	4.81	2.36	4.65	176	R↑F↑M↑
2	4.34	1.28	3	64	R↑F↓M↑
3	4.36	1.03	1.33	89	R↑F↓M↓
4	3.84	1.34	4.54	85	R↑F↓M↑
5	3	2.4	2.80	5	R↑F↑M↓
6	3	1.05	1.58	62	R↑F↓M↓
7	3	1.18	4.43	60	R↑F↓M↑
8	3	1	3	54	R↑F↓M↑
9	2	1.02	1.53	117	R↓F↓M↓
10	1.63	1.36	4.17	78	R↓F↑M↑
11	1.48	1.1	3	71	R↓F↓M↑
12	1	1.01	1.55	139	R↓F↓M↓
TOTAL	2.95	1.34	2.96	1000	

Table 6: Comparison of minimum, maximum and average of recency in k-means and SOM

	Maximum		Maximum		Average	
	k-means	SOM	k-means	SOM	k-means	SOM
C1	28/9/2013	28/10/2013	31/12/2013	12/4/2014	16/11/2013	28/2/2014
C2	16/3/2013	25/11/2013	25/10/2013	20/3/2014	13/9/2013	1/1/2014
C3	25/11/2013	23/11/2013	20/3/2014	15/2/2014	7/2/2014	4/1/2014
C4	6/8/2013	30/10/2013	25/10/2013	9/1/2014	11/9/2013	9/12/2013
C5	23/11/2013	26/10/2013	15/2/2014	21/11/2013	4/1/2014	4/11/2013
C6	28/10/2013	26/10/2013	12/4/2014	20/11/2013	14/2/2014	13/4/2011
C7	26/10/2013	26/10/2013	12/1/2014	22/11/2013	19/11/2013	7/11/2013
C8	14/8/2013	26/10/2013	20/11/2013	20/11/2013	22/10/2013	4/11/2013
C9	26/10/2013	14/9/2013	20/11/2013	25/10/2013	4/11/2013	30/9/2013
C10	13/1/2014	25/10/2013	20/3/2014	18/9/2013	27/1/2014	19/3/2013
C11	10/8/2013	10/8/2013	19/10/2013	19/10/2013	17/9/2013	17/9/2013
C12	26/10/2013	06/8/2013	10/2/2014	12/9/2013	6/12/2014	26/8/2013

Table 7: comparison of minimum, maximum and average of frequency in k-means and SOM

	minimum		maximum		average	
	k-means	SOM	k-means	SOM	k-means	SOM
C1	3	1	4	6	3.33	2.38
C2	1	1	2	2	1.11	1.28
C3	2	1	3	3	2.33	1.03
C4	1	1	2	3	1.00	1.34
C5	1	2	2	4	1.01	2.40
C6	4	1	6	2	4.56	1.04
C7	1	1	2	2	1.08	1.18
C8	2	1	3	1	2.13	1.00
C9	1	**1**	2	3	1.04	1.01
C10	1	1	2	3	1.21	1.35
C11	1	1	2	2	1.09	1.09
C12	1	1	1`	2	1.00	1.00

Table 8: Comparison of minimum, maximum and average of monetary in k-means and SOM

	minimum		maximum		average	
	k-means	SOM	k-means	SOM	k-means	SOM
C1	1310000	2700000	1610000	67220000	145666	7214227
C2	2670000	160000	7880000	2640000	3730559	2148125
C3	2700000	260000	19400000	1650000	6356000	995842
C4	190000	2730000	1650000	13790000	1178274	5595411
C5	260000	1310000	1650000	2590000	990681	2092000
C6	3269000	230000	67220000	1650000	15375391	1204677
C7	1660000	2700000	4710000	13150000	2414959	5010500
C8	2680000	160000	12350000	2630000	5075454	2122222
C9	230000	190000	1650000	1650000	1204677	1199059
C10	1660000	2670000	4500000	7880000	2903076	3786025
C11	1660000	160000	2660000	2660000	2192816	2192816
C12	2730000	190000	1379000	1650000	5919333	1163884

6. References

1. Hui-Chu Chang, Hsiao-Ping Tsai. Group RFM analysis as a novel framework to discover better customer consumption behavior. Expert Systems with Applications. 2011; 38:14499-14513.
2. Cheng CH, Chen YS. Classifying the segmentation of customer value via rfm model and rs theory. Expert Systems with Applications, 2009, 4176-4184.
3. Seyed Hosseini SM, Maleki A, Gholamian MR. Cluster analysis using data mining approach to develop CRM methodology to assess the customer loyalty, Expert Systems with Applications, 2010; 37:259-5264.
4. Parvatiyar A, Sheth J. Conceptual framework of customer relationship management. In J. N. Sheth, A. Parvatiyar, & G. Shainesh (Eds.), Customer relationship management: Emerging concepts, tools and applications (5th ed) New Delhi: Tata McGraw-Hill Publishing. 2004.
5. Reichheld FF, Teal T. The loyalty effect: The hidden force behind growth, profits, and lasting value. Trans. Boston, MA: Harvard Business School Press, 1996.
6. Shian-Chang Huang a, En-Chi Chang b, Hsin-Hung Wu. A case study of applying data mining techniques in an outfitter's customer value analysis. Expert Systems with Applications. 2008; 36(2009):5909-5915.
7. Basiri M. Application of data mining technique in the customer relationship management. Proceedings of the 2007 4th National Conference on E-Commerce, Tehran, Iran. 2007
8. Gaurav Gupta and Himanshu Aggarwal. Improving Customer Relationship Management Using Data Mining. International Journal of Machine Learning and Computing, 2012, 2(6).

9. Hughes AM. Strategic database marketing. Chicago: Probus Publishing Company, 1994.
10. Baier M, Ruf KM, Chakraborty G. Contemporary database marketing: Concepts and applications. Evanston: Racom Communications, 2002.
11. Wu J, Lin Z. Research on customer segmentation model by clustering. ACM International Conference Proceeding Series, 2005, 113.
12. Newell F. The new rules of marketing: How to use one-to-one relationship marketing to be the leader in your industry. New York: McGraw-Hills Companies Inc, 1997.
13. Cheung YM. K-means: A new generalized K-means clustering algorithm. Pattern Recognition Letters, 2003; 24:2883-2893.
14. Davidson I. Understanding K-means non-hierarchical clustering. SUNY Albany Technical Report. 2002, 02-2.
15. Kuo RJ, Ho LM, Hu CM. Integration of self-organizing feature map and K-means algorithm for market segmentation. Computers & Operations Research, 2002; 29(11):1475-1493.
16. Buttrey SE, Karo C. Using K-nearest-neighbor classification in the leaves of a tree. Computational Statistics and Data Analysis, 2002, 40:27-37.
17. Punj G, Steward DW. Cluster analysis in marketing research: Review and suggestions for applications. Journal of Marketing Research, 1983; 20:134-148.
18. Kyoung-jae Kim A, Hyunchul Ahn. A recommender system using GA K-means clustering in an online shopping market. Expert Systems with Applications. 2007; 34(2008):1200-1209.
19. Ying Li, Feng Lin. Customer Segmentation Analysis Based on SOM Clustering. Business School of East China University of Science and Technology Shanghai, China. 2008.
20. Amuthan Prabakar Muniyandia, Rajeswarib R, Rajaramc R. Network Anomaly Detection by Cascading K-Means Clustering and C4.5 Decision Tree algorithm. International Conference on Communication Technology and System Design 2011. Procedia Engineering. 2011; 30(2012):174-182.
21. PANG Su-lin, GONG Ji-zhang. C5.0 Classification Algorithm and Application on Individual Credit Evaluation of Banks. Systems Engineering: Theory & Practice. 2009, 29(12).
22. Cheng CH, Chen YS. Classifying the segmentation of customer value via RFM model and RS theory, Expert Systems with Applications, 2009; 36(3):4176-4184.
23. Huang SC, Chang EC, Wu HH. A case study of applying data mining techniques in an outfitter's customer value analysis, Expert System with Applications, 2009; 36(6):5909-5915.
24. Reinartz Werner J, Kumar V. "The impact of customer relationship characteristics on profitable lifetime duration." (Allocation Time and Territory Management Optimization Models Customer/Account Analysis)Journal of Personal Selling & Sales Management June, 22, 2003.