Journal of AI and Data Mining
Vol 7, No 2, 2019, 331-340
DOI: 10.22044/JADM.2018.6035.1715

Analyzing Customers of South Khorasan Telecommunication Company with Expansion of RFM to LRFM Model

V. Babaiyan* and S. A. Sarfarazi

Department Of Computer Engineering, Birjand University of Technology, Birjand, Iran.

Received 23 July 2017; Revised 27 December 2017; Accepted 07 March 2018
**Corresponding author: babaiyan@birjandut.ac.ir (V. Babaiyan).*

Abstract

Telecommunication companies use data mining techniques to maintain good relationships with their existing customers, attract new customers, and identify profitable/unprofitable customers. Clustering leads to a better understanding of customers and its results can be used for definition and decision-making for promotional schemes. In this research work, we use the 999-customer purchase records in the South Khorasan Telecommunication Company collected during a year. The purpose of this work is to classify customers into several clusters. Since the clusters and the number of their members are determined, the high-consumption users will be logged out of the system and the high-value customers who have been missed will be identified. We divide the customers into five categories: loyal, potential, new, missed, and high-consumption using the Clementine software, developing the RFM model to the LRFM model and the Two_Step and K_Means algorithms. Thus this category will be a good benchmark for a company's future decisions, and we can make better decisions for each group of customers in the future.

Keywords: *LRFM Model, Two_Step Algorithm, K_Means Algorithm.*

1. Introduction

Data mining is the concept of extracting hidden information from large amounts of database and detecting the interesting patterns from a massive dataset. Many people treat data mining as a synonym for common knowledge discovery in databases (KDDs). Data mining is the process of exploration and analysis by automatic or semi-automatic means in a large quantities of data to discover knowledge. In fact, such studies and explorations can be considered as the same ancient and comprehensive knowledge of statistics. Nowadays, the main differences of the information in view of the scale, extent, and a variety of fields and applications as well as the dimensions and size of data are that they demand machine techniques related to learning, modeling, and training.

Data mining is the process of analyzing data from different perspectives and summarizing it into useful information. The purpose of extracting this useful information is to reduce costs and increase revenue or both of them. Data mining softwares are tools that can be used for data analysis and allow user to analyze data from different dimensions or angles and discover unknown relationships between them.

The identification of customers and their needs are important factors that manufacturers take help of them to gain competitive advantage in either the delivering product or service to the customers. Companies should prioritize their customers and increase their focus on key customers. The importance of this issue is that by disconnecting customers from the company and their willingness to join rival companies not only does it cause financial losses but it also causes reputational and credibility damage, and the existing customers may also share their negative experiences with potential customers. Thus the trust of potential customers will be eliminated. Organizations can meet their basic goals including gaining competitive advantage by identifying different groups of customers and their needs to achieve customer satisfaction (that leads to customer's loyalty in the long run) and make more profit. Also identifying the key customers and retaining them not only attract new customers but also are useful to fill the vacancies of those who have decided to cut ties with the company. Because that is mostly, it costs 5 times more to acquire a new customer than to retain an existing one.

Also companies are more probable to succeed in selling their products or services to the existing customers compared to the potential customers [1].

Classification is one of the key issues in customer relationship management. In classifying customers, we split the total customer population into smaller groups so that the members of a group have similar features. Ideally, an organization should have a good understanding of all its customers, which it is not possible in the real world. Customer classification and clustering helps managers to have a better understanding of their needs. Data mining tools are used to implement various customer's classification and clustering using a variety of techniques. The most popular data mining tools in terms of popularity are, respectively, the R programming language [2] Python programming language [3], Clementine, version 13 called SPSS Modeler, VKa software, and MATLAB software.

1.1. Key concepts in data mining

Bagging: The ability to discover unknown relationships within the information. These relationships point to whether a set of items increases the likelihood of other items. This feature is basically a way to search and discover that tells which items are related together. It is also referred to as market basket analysis or association rules.

Boosting: Actually, it evaluates the characteristics of a dataset and then assigning them to a set of pre-defined groups. Boosting is the most commonly used feature of data mining. Data mining can be applied by using the historical data to build a model or a view of a group according to the data features. Then a so-defined model can be used to classify the new datasets. It can also be used for future forecasts by specifying the form that is compatible.

Sequential patterns: Like bagging, sequential features have the property that they can connect the events together. In association rules or market basket analysis, a series of items are evaluated as sequential items, and they use tools such as time series to determine order. Moreover, sequential features have a new feature that can estimate the time interval between two events. For example, they provide the ability to make conclusions such as "80% of people who buy computers will also buy printer in a year". In this way, it is possible to identify a kind of introductory purchases that determine the potential for upcoming purchases in the future. As a result, these analyzes are severely used in sales promotion.

Clustering: Clustering is the task of grouping a set of objects in such a way that it divides a heterogeneous group into several sub-groups. This process has a fundamental difference with the classification because there are no training patterns in this model. Clustering automatically defines distinctive features of sub-groups and organizes them. It is a type of indirect data mining capability. These tools divide the database into several parts based on the data properties and create groups of records that represent or have a certain attribute. The patterns obtained are institutionalized in the essence of the database and indicate some unexpected and worthy information of the company.

1.2. Classification of data mining applications in telecommunication industry

In order to classify data mining applications in telecommunication companies, there are a number of approaches including:

- Classification based on data mining methods:

This classification includes clustering, regression, categorization, pattern discovery, etc. In this type of classification, the goal is to evaluate and improve the data mining techniques and apply new methods to solve problems.

- Classification by scope:

In this type of classification, the aim is to improve and provide new data mining solutions in the scoops of telecommunication organizations, for example, Landline phone, Mobile phone, data, and ADSL.

- Classification by purpose:

In this type of classification, the goal is to detect new domains of data mining in telecommunications with the focus of attracting and retaining customers. This group includes the following: targeted marketing, increased profits, increased customer satisfaction, more. According to the studies carried out, it can be said that a comprehensive classification of the previous activities in the telecommunication industry has not taken place. Since the main purpose of these companies is to increase benefits and customer satisfaction through providing appropriate services to subscribers, the approach of this research work to classify data mining applications is based upon the behavior of subscribers. For this

purpose, we performed clustering using the LRFM model, described in Section 3.
In the following section, we look at the previous research works on customer clustering.
In the third section, we explain the proposed model, which describes the customer categories based on the development of the RFM model to LRFM. In the fourth section, we evaluate and implement this algorithm in the Clementine environment. In the last section, we will present the final conclusions about this work.

2. Previous research works on data mining methods

In a study in [4], the authors have simulated a model for analyzing the customer buying behavior in supermarkets. This simulation model shows information about what the customer is doing inside the store such as how to navigate the store, product layout, product purchase or not buying product.
In [5], the author has used the RFM model to classify his own specialized customers. This study is very useful in designing marketing strategies for different customers.
In article [6], the authors have used the RFM model analysis to gain value for future customers. The RFM analysis helps to improve the relationship with customers.
In [7], the authors have looked over the trustworthy customers in the supermarket industry. This research work has analyzed the products that can be purchased by the customers together.
In [8], a data mining process has been performed on 1000 customer data using the RFM model. With the help of MATLAB software and customer transactional data analysis, 51 clusters were created, and then the customers were divided into 8 groups.
In [9], a new model based on the RFM model has been introduced. In this model, customer's trustworthiness was also presented as a new factor in the model. This model includes three factors: shopping novelty, repetition or frequency, and customer trustworthiness. The main purpose of this work was customer classification and evaluating them based on their past history. A major failure of the model is putting customers with a high RFM score continuously (frequently targeting customers would be harassing them), and another drawback is the deterioration of customers who have less score. A company can increase its credibility by considering its past customers. In this model, the old customers will be considered properly and regularly.
In [10], the new TRFM model has been introduced to investigate the customer data. In this work, the model has been implemented with the help of Eclipse Java EE IDE, and the data for 8400 supermarket customers has been explored. Recently, the repeat and the amount of customer purchases have been of concern in the traditional RFM model, while in the TRFM model, in addition to the above factors, the time spent by the customer in the supermarket is also considered. Customers with the highest TRFM score are the best ones. They are customers who spend less time shopping in the supermarkets, and they are more pleasant compared to the customers who spend more time.
In a study conducted in [11], the objective was to provide a framework for division of insurance customers of the PASARGAD Insurance Company according to the effective factors on lifetime customer value. For this purpose, a series of transactions related to 384 customers of the PASARGAD Insurance Company in the spring of 2015 were considered fortuitously. Transaction information includes customer purchasing novelty, repetition or frequency of extended insurance policy within six years, and the amount of money that customers paid in their last insurance contract. According to the RFM model and analysis of these data, the customers were divided into 4 golden categories: highly-valued, loyal, fix, and extremely valuable.
In [12], 180 customer information who had been referred to a restaurant for lunch were analyzed using the RFM model. Out of the 180 customers reviewed, 100 of them had a high score in the rating system. This result will help restaurant management to have effective plans for their ads in the future.
In [13], the RFM model has been used for customer analysis and classification. During this analysis, the customers were divided into eight logical categories. The results will help to make better decisions to improve sales, marketing, and making decisions in retail environments competitively.

2.1. Applying data mining to categorize subscribers and identify type of subscribers of telecom companies

Good pay and non-creditworthy customers are important issues that have mostly great impacts on earnings and claims, especially for some telecom companies that initially provide the service and then issue invoices. In this regard, in [14], the author has used some data mining techniques for

customer identification, and its analytical results have been presented.
In [15], the researchers have reviewed 61 journal articles to survey the pros and cons of the renowned data mining techniques used to build predictive customer churn models in the field of telecommunication and thus provide a roadmap to researchers for knowledge accumulation about data mining techniques in telecom.
In [16], the researchers have aimed to develop a model to predict the churn to rival companies. The model can help companies to know the reasons that may lead to the churn. The three classifiers CN2 (Rules Leaner), Decision Tree, and Naive Bayes were used to build the model.
In another study [17], a new K_Means clustering method has been proposed to evaluate the cluster customers' profitability in the telecommunication industry in Sri Lanka. Furthermore, the RFM model has been mainly used as an input variable for K_Means clustering and distortion curve used to identify the optimal number of initial clusters. Based upon the results obtained, the telecommunication customers' profitability in Sri Lanka were mainly categorized into three levels.
In [18], an improved fast hierarchical clustering algorithm (IFHCA) was firstly proposed. Then a method for identifying dial-up user preferences based on IFHCA was presented in order to discover the pattern of users' preferences and recommend the most appropriate services. Finally, the authors analyzed the relationship between users' preferences with on-line duration and traffic.

3. Development of RFM model to LRFM

The LRFM model is a method for customer clustering that we use in customer relationship management. In this model, the customers are categorized based on four features:

- customer relationship **L**ength
- purchase **R**ecency
- purchase **F**requency
- purchase **M**onetary

(Length, recency, frequency, and monetary)
The word LRFM has been innovated by the first letter of each of these four attributes. In this study, we started clustering tutorials with Clementine software using the above model. According to [19 and 20], the RFM model cannot detect the customers with long-term and short-term relationships with the organization. In their research work, they suggested the idea of customer relationship length and examined its impact on customer loyalty and profitability. They said that increasing the customer relationship length would improve the customer loyalty. They defined this variable, which represented the time interval between the first and last customer's purchases in the period examined. The RFM model chooses the customers who have recently created a high financial value for the company and have purchase frequency in a short-term more than the average purchase frequency among customers as valuable customers, while the length of relationship with the company has been ignored. Thus the aspect of customer relationship length {Length (L)} is added to the RFM model. The customer relationship length with the organization indicates the length of the time that a customer has started a relationship with the organization. According to the studies conducted in [20], the field is provided for more accurate analysis of customers by adding index L (Customer relationship length). As shown in figure 1, they proposed a matrix called value matrix for the purchase (F) and monetary value (M).

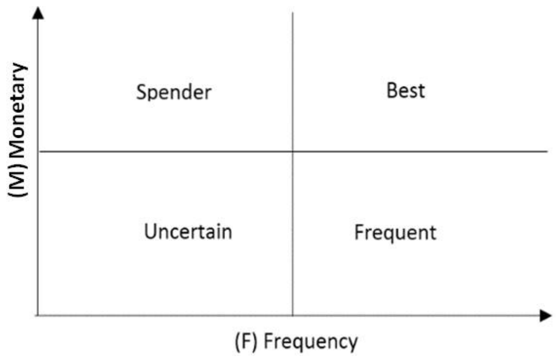


Figure 1. Customer value matrix [20].

It also claims that a longer customer relationship shows a greater customer loyalty and a shorter recent transaction time. Two other indicators, customer relationship length (L) and recent transaction time (R), are defined as the customer loyalty matrix. This matrix is depicted in figure 2.

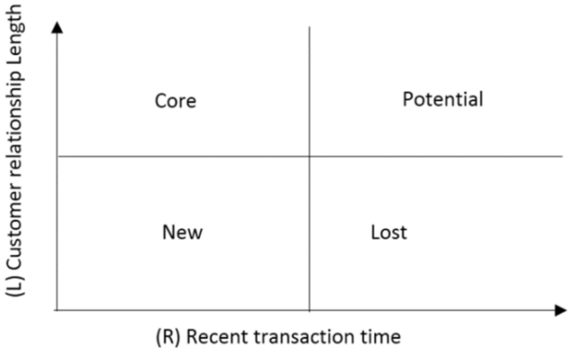
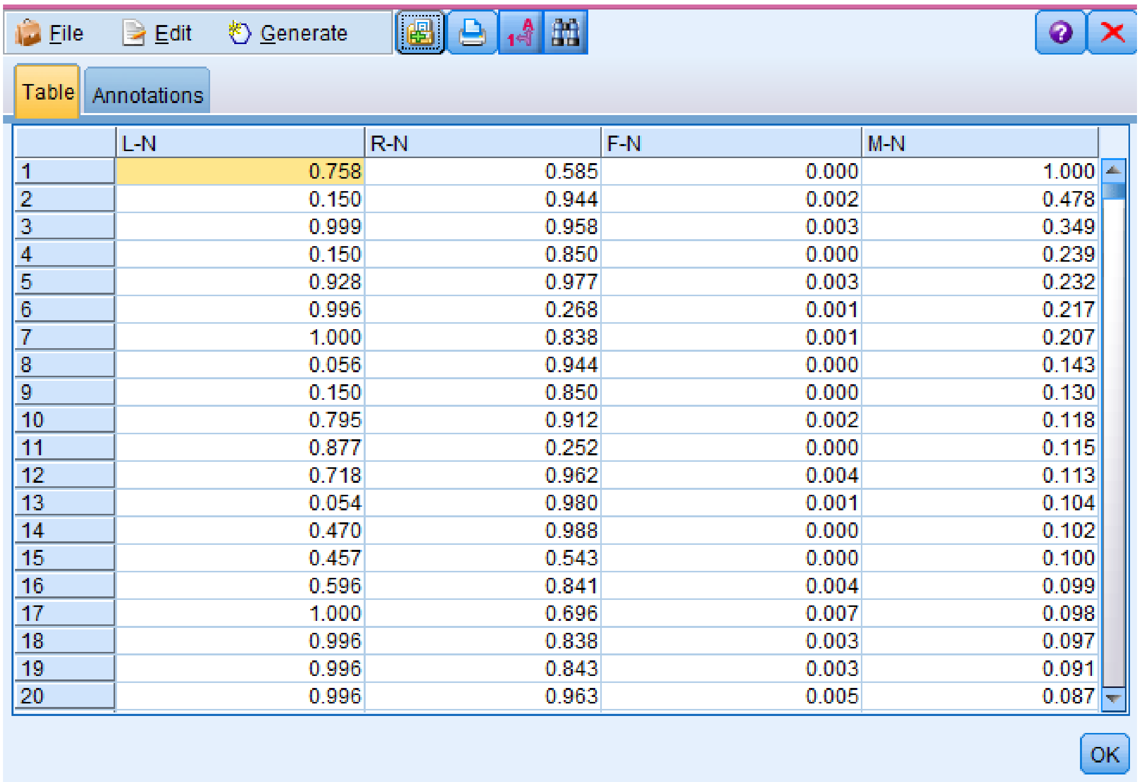


Figure 2. Customer clustering on a customer loyalty matrix basis [20].

In this work, like the model presented in [21], we did segmentation and calculated the customer lifetime value and identified the valuable customers.

4. Evaluation and implementation

The internet service system of South Khorasan Telecommunication Customer segmentation leads to the correct recognition of customers so that it can be used to define and decide on more specialized promotional projects. We used clustering to segment our customers, which is one of the data mining methods. Based on this, the customers were divided into loyal customers, potential customers, missing customers, new customers, and customers with high consumption of services. The database uses customer records, which include a 999 customer record purchase history table in a single year. The database uses the customer records, which include a 999 customer acquisition history table in a one year. This table contains 1,000 records and 4 fields that include the customer relationship length, recency of latest bought, number of purchase frequency, and purchase monetary, which are used for clustering. A part of the customer record table is shown in figure 3.



	L-N	R-N	F-N	M-N
1	0.758	0.585	0.000	1.000
2	0.150	0.944	0.002	0.478
3	0.999	0.958	0.003	0.349
4	0.150	0.850	0.000	0.239
5	0.928	0.977	0.003	0.232
6	0.996	0.268	0.001	0.217
7	1.000	0.838	0.001	0.207
8	0.056	0.944	0.000	0.143
9	0.150	0.850	0.000	0.130
10	0.795	0.912	0.002	0.118
11	0.877	0.252	0.000	0.115
12	0.718	0.962	0.004	0.113
13	0.054	0.980	0.001	0.104
14	0.470	0.988	0.000	0.102
15	0.457	0.543	0.000	0.100
16	0.596	0.841	0.004	0.099
17	1.000	0.696	0.007	0.098
18	0.996	0.838	0.003	0.097
19	0.996	0.843	0.003	0.091
20	0.996	0.963	0.005	0.087

Figure 3. Customer records in database.

The LRFM model is used to determine the value of customers. At this point, the customers are normalized based on the variables L, R, F, and M using two algorithms Two_Step and K_Means, and then they are clustered using the Clementine software.

K_Means clustering is a hierarchical method of classifying/grouping items into K groups (where k is the number of pre-chosen groups). The grouping is done by minimizing the sum of the squared distances (Euclidean distances) between the items and the corresponding centroid.

The Two_Step clustering method is a scalable cluster analysis algorithm designed to handle very large datasets. It can handle both the continuous and categorical variables/attributes. It has two steps:

1) Pre-cluster the cases into many small sub-clusters; 2) Cluster the sub-clusters resulting from the pre-cluster step into the desired number of clusters. It can also automatically select the number of clusters [22].

The clustering results are shown in figures 4-9 below.

As one may see in figure 4, the clusters 1 and 2 in the K_Means algorithm have very few populations but in the Two_Step algorithm, these two clusters have a greater share of the population.

Figure 5 shows a comparison between the clusters generated by the two mentioned algorithms. In this figure, despite the clustering of 5 clusters in the K_Means method, the populations of clusters 1 and 2 are negligible.

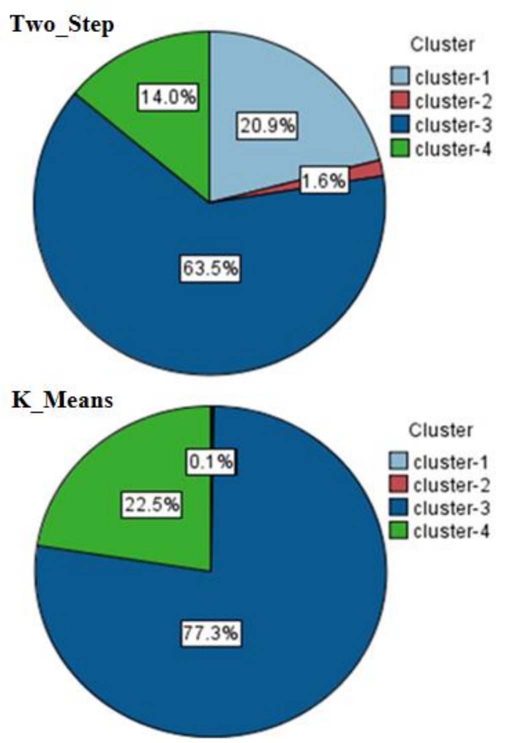


Figure 4: Two_Step and K_Means with 4 clusters.

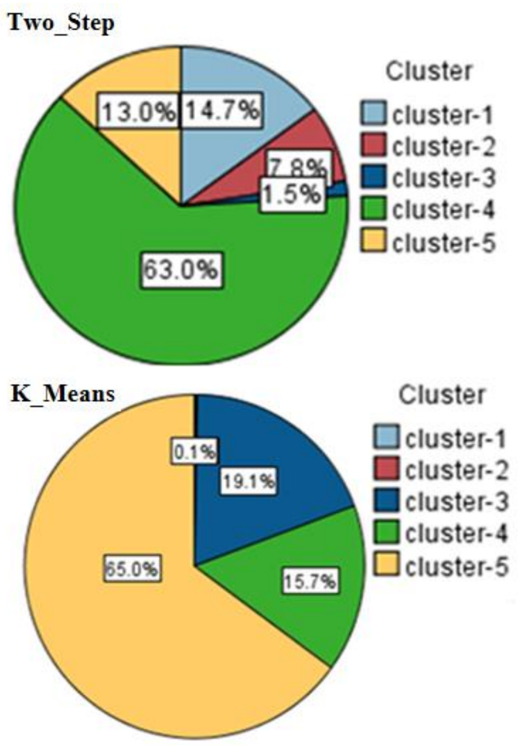


Figure 5: Two_Step and K_Means with 5 clusters.

Figure 6 shows a comparison of the results of clustering to six clusters by the two algorithms. In this figure, we can also see that the population is not distributed between clusters in the K_Means algorithm.

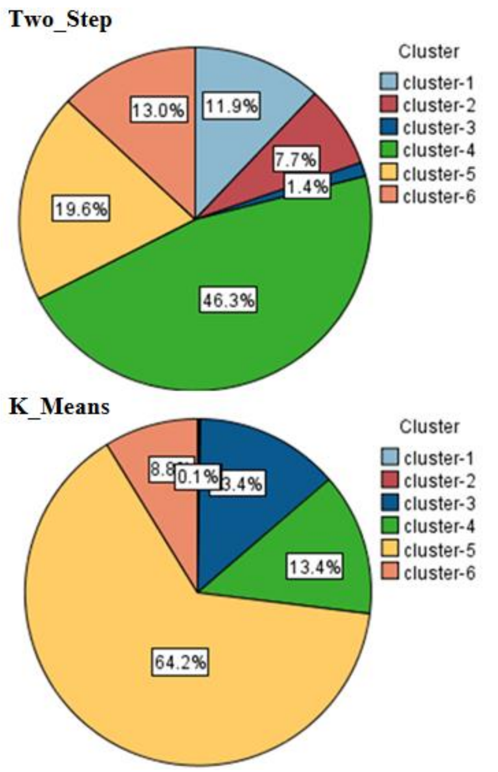


Figure 6: Two_Step and K_Means with 6 clusters.

Figure 7 shows clustering to seven clusters by the two algorithms; according to the results depicted, the difference between the two algorithms is observable.

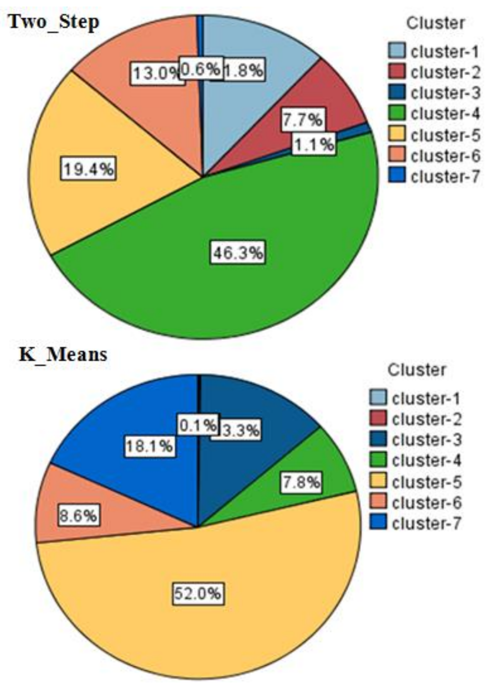


Figure 7: Two_Step and K_Means with 7 clusters.

In figure 8, the results of clustering with eight clusters are shown. As it can be seen, the distribution of population in clusters has increased using the Two_Step algorithm.

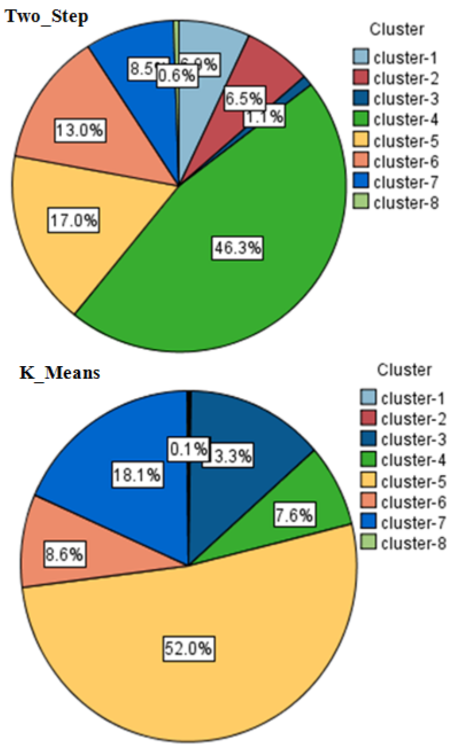


Figure 8: Two_Step and K_Means with 8 clusters.

In figure 9, customers are clustered into 9 clusters. As shown, a large number of customers are in one cluster, and the rest are distributed in the eight remaining clusters in the K_Means algorithm.

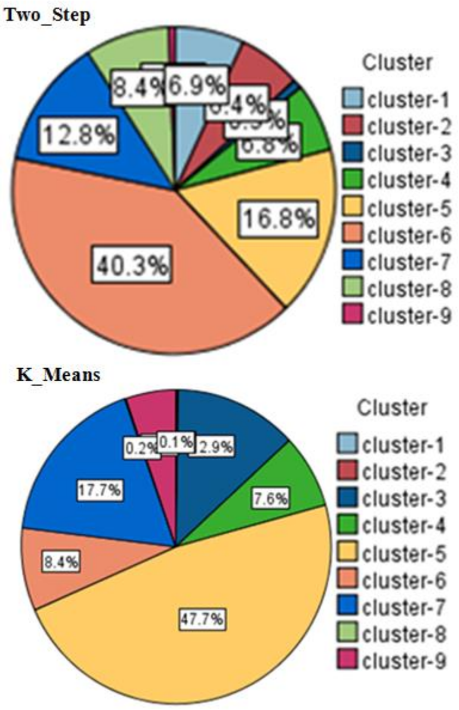


Figure 9: Two_Step and K_Means with 9 clusters.

After completing the clustering phase, the clusters must be evaluated. At this level, clustering is done. As in the assessment in [23], we used the Davies-Bouldin quality measurement index to evaluate clusters. In this Index, the least similarity between the cluster and the highest intra-cluster similarity are considered. The Davies-Bouldin criterion is based upon a ratio of within-cluster and between-cluster distances. It is one such measure, and hence, we have chosen that for cluster evaluation. DBI is defined as in (1):

$$DB = 1/K \sum_{j=1}^{k} \max_{j \neq i} D_{i,j} \tag{1}$$

Where $D_{i,j}$ is the within to between cluster distance ratio for the i^{th} and j^{th} clusters, as given in (2).

$$D_{i,j} = (\bar{d}_i + \bar{d}_j)/d_{i,j} \tag{2}$$

$\bar{d}_i$ is the average distance between each point in the i^{th} cluster and the centroid of the i^{th} cluster. $\bar{d}_j$ is the average distance between each point in the i^{th} cluster and the centroid of the j^{th} cluster. d_{ij} is the distance between the centroids of the i^{th} and j^{th} clusters. The maximum value for d_{ij} represents the worst case within to between cluster ratios for cluster i.
The optimal clustering solution has the smallest Davies-Bouldin index value. The Davies-Bouldin index results are summarized in table 1.

Table 1. Davies-Bouldin index results.

DB index	Number of clusters
0/178	4
0/0678	5
0/0435	6
0/0555	7
0/0486	8
0/0432	9

With respect to the Davies-Bouldin index calculation, which is due to two-benchmark proportion, density, and separation, it depends on the number of clusters. It can be deduced from table 1 that if the number of clusters is 9, the value of the Davis index is lowered, and as a result, we have a better clustering.
It can be concluded from their graph that which clustering method is more appropriate. Thus the K_Means algorithm is more inefficient than the

Two_Step algorithm because most of the data is located in one cluster. Thus the Two_Step algorithm is more suitable with 9 clusters. In the following, we analyze 9 clusters that are derived from the Two_Step algorithm.

In table 2, the number of data for each cluster and the coordinates of the central points of 9 clusters are determined, and according to this information, we analyze the clusters.

Customer features are analyzed by assuming that the central points of each cluster are representative of the whole points of the cluster. The features of each cluster are presented below.

Table 2. Two_Step clustering results.

cluster	Cluster5	Cluster7	Cluster3	Cluster6	Cluster4	Cluster9	Cluster8	Cluster1	Cluster2
Size	47.7% 477	17.7% 177	12.9% 129	8.4% 84	7.6% 76	5.2% 52	0.2% 2	0.1% 1	0.1% 1
input	L-N 0.98	L-N 0.59	L-N 0.93	L-N 0.52	L-N 0.25	L-N 0.96	L-N 0.50	L-N 0.76	L-N 0.38
	R-N 0.95	R-N 0.97	R-N 0.13	R-N 0.49	R-N 0.89	R-N 0.72	R-N 0.90	R-N 0.58	R-N 1.00
	M-N 0.03	M-N 0.03	M-N 0.04	M-N 0.03	M-N 0.04	M-N 0.04	M-N 0.36	M-N 1.00	M-N 0.05
	F-N 0.01	F-N 0.01	F-N 0.00	F-N 0.00	F-N 0.02	F-N 0.00	F-N 0.00	F-N 0.00	F-N 1.00

Cluster 1: This cluster includes 69 customers, which is 6.9% of the total customers, and the central point's coordinates show that the length of the customer relationship and the recent purchase is lower than their average. Thus this cluster has included new customers.

Cluster 2: This cluster includes 64 customers, which is 4/6% of the total customers. The central point's coordinates show that the length of the customer relationship is greater than that of cluster 1. However, it is still lower than the average and their recent purchase is lower than cluster 1. Thus this cluster also includes new customers; less time passes from their last purchase than cluster 1.

Cluster 3: This cluster is different from the two clusters 1 and 2. The behavior of members in this cluster is different from the two clusters 1 and 2. This cluster has only 9 members, which is 0.9% of the total customers. Customer relationship length is low like the two clusters 1 and 2 but it has been a long time since their last purchase so that they can be placed in the category of missed customers.

Cluster 4: This cluster consists of 68 people, which is 6.8% of the total customers. According to the central point's coordinates, it can be concluded that the customer relationship length is high. This means that it has been a long time that the customer uses this system. Recency purchase has been low. This means that a customer has just made a purchase. By considering that its purchase frequency was lower than the average and its purchase price was high, it can be concluded that these categories of customers are loyal customers who have been using the system for a long time and the number of their purchases is low but the amount of their purchases is high.

Cluster 5: This cluster includes 168 customer, which is 8/16% of the total customers. This cluster is like cluster 3 with the difference that the customer relationship length is greater. Its frequency is much higher than average but these customers fall into the category of missed customers.

Cluster 6: This cluster that has the largest number of customers consists of 403 people, which is 6.8% of the total customers. Regarding the central point's coordinates, it can be concluded that the customer relationship length and the recency purchase are high, which means that it has been a long time since their last purchase. Their frequencies and purchase monetary are high. These customers are in the category of potential customers.

Cluster 7: This cluster consists of 128 people, which makes up 12.8% of the total customer. The cluster is like cluster 4 with the difference that its recency purchase is lower than the cluster 4. This means that it does not take long since the last purchase. The purchase monetary is also higher than cluster 4, and they are placed in the category of loyal customers.

Cluster 8: This cluster includes 84 customers, which is 8.8% of the total customers. The cluster is similar to clusters 3 and 5 with the difference that its customer relationship length is lower than the other clusters and these customers are in the category of missed customers.

Cluster 9: This cluster has the smallest number of people. It includes 6 people that represent 0.6% of customers. This cluster is like clusters 3, 5, and 7. The difference is that the customer relationship length is much lower than the rest of the clusters, and the frequency and monetary of purchases are high so that the purchase frequency is much higher than the rest of the clusters. It can be concluded that the customers of this cluster have had a lot of purchases in a very short time and it has been a long time since their last purchase and fall into the category of missed customers.

5. Conclusions and suggestions

Given what was said, customers can be divided into five categories:

Loyal customers: Cluster customers 4 are loyal customers. For all of them, the customer relationship length is more than average. Their recency index is lower than average. Frequency and monetary of purchases have different modes. These customers have used this system for a long time and so far they have continued to cooperate with telecommunications. For this group of customers, a policy can be considered to be appreciated for their collaboration with this system.

Potential customers: Customers in Cluster 6 are potential customers. For all of them, the customer relationship length and recency purchases are more than average. Frequency and monetary of purchases have different states. These customers have used this system for a long time; however, their recency purchase has declined recently. This indicates that the number of these customers may be placed in the missed customer group. To sustenance them, there needs to be a policy to increase their satisfaction and increase their purchases.

New customers: Customers of clusters 1 and 2 are new ones. The customer relationship length and recency purchases are less than average. Frequency and monetary of purchases have different states. There is no long-standing relationship with these customers. For these categories of customers, it is necessary to implement a strategy in order to maintain their co-operation because customer retention is more important than customer acquisition (it is more difficult).

Missed customers: 3, 5, 8, and 9 clusters are missed customers. This group of customers did not have a long relationship, and recently, they have not bought anything. Their frequency and monetary of purchases are different. There must be a strategy and a plan to diagnose why these customers are missing and do something to keep high-value customers in the system.

High-consumption customers: Frequency and monetary of purchases of these customers are lower than average, and the length of the customer relationship and their recency purchases are different. Fortunately, out of a total of 1,000 customers, none of them are in this group. If there are some customers in this group, their contract should not be renewed after the termination of it.

In this research work, we were able to cluster the telecom customers, and we determined the number of members of each cluster but this work can be used at a wider level. For example, customers can be divided into further categories, for example, in terms of business and geographical area, and consider other criteria in segmentation. Given what was said, the LRFM model is suitable for performing customer telecommunication valuation. This model can be used in other domains like the bank.

References

[1] Armstrong, G., et al. (2014), Principles of marketing, 6th edition, ISBN: 9781486002696

[2] Pearson A.W, et al. (2016), An Introduction to R a Programming Environment for Data Analysis and Graphics, Version 3.3.2 (10-31)

[3] Miller, P. & Bryce, C. (2016), Learning Python for Forensics

[4] Schwenke, C., etal. (2010), Simulation and Analysis of Buying Behavior in Supermarkets, IEEE Conference on Emerging Technology and Factory Automation (ETFA), pp. 1-4

[5] Jainping, W. (2011), Research on VIP Customer Classification Rule Base on RFM Model. International Conference on Management Science and Industrial Engineering (MSIE), pp. 336-338

[6] Divya,D., et al. (2013), Data mining using RFM Analysis. International Journal of Scientific & Engineering Research, Vol. 4, Issue 12, pp.940-943

[7] Raorane, A. & Kulkarni, R. V. (2011), DATA MINING TECHNIQUES: A SOURCE FOR CONSUMER BEHAVIOR ANALYSIS, International Journal of Database Management Systems (IJDMS). Vol. 3, No. 3, pp. 45-56

[8] Margianti, E.S., et al. (2016). Affinity Propagation and RFM-Model for CRM'S Data Analysis.. Journal of Theoretical and Applied Information Technology, Vol. 84. No.2, pp. 272-282

[9] Kamath, A. & Dave, D. (2016). DA-RFR Model for Measuring Prospective Customer Value. International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 6, pp. 10754-10755

[10] Joshi, A., et al. (2016). Design & Analysis of Purchasing Behavior of Customers in Supermarkets using TRFM Model of Data Mining. International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 4, pp. 7799-7806

[11] Hamidi, K. & zamiri, A. (2016). identifying and segmenting customers of Pasargad insurance company through RFM model (RFM). International Business Management, Vol. 10, no. 18, pp. 4209-4214

[12] Elijah, O. (2016). Analysis of Purchasing Behaviour of Customers in Restaurants Using RFM Model of Data Mining. International Journal of Research,Volume. 03, Issue. 13

[13] Mohammadian, M. & Makhani, I. (2016). RFM-Based customer segmentation as an elaborative analytical tool for enriching the creation of sales and trade marketing strategies. International Academic Journal of Accounting and Financial Management, Vol. 3, No. 6, pp. 21-35. ISSN 2454-2210.

[14] Amal, M. Almana, et al. (2014). A Survey on Data Mining Techniques in Customer Churn Analysis for Telecom Industry, Int. Journal of Engineering Research and Applications, Vol. 4, Issue. 5, pp.165-171.

[15] Hashmi, N., et al. (2013). Customer Churn Prediction in Telecommunication A Decade Review and Classification, IJCSI International Journal of Computer Science Issues, Vol. 10, Issue. 5, No. 2, pp. 271-282.

[16] Rayan, M. & Tarig, M. (2016). Using Data Mining in Telecommunication Industry Customer's Churn Prediction Model, Journal of Theoretical and Applied Information Technology, Vol. 91, No.2, pp. 322-328

[17] Indika, H., et al. (2015). Mining Profitability of Telecommunication Customers Using K-Means Clustering, Journal of Data Analysis and Information Processing, 3, pp. 63-71

[18] GUO, M., et al, (2012). Analysis on preference patterns of ADSL users, The Journal of China Universities of Posts and Telecommunications, Vol. 19, Supplement. 2, pp. 73-79

[19] Reinart, z., et al. (2002). The mismanagement of customer loyalty, Harvard Business Review, vol. 80, no. 7

[20] Chang, H. H. & Tsay, S. F. (2004). Integrating of SOM and K-Mean in data mining clustering: an empirical study of CRM and profitability evaluation, vol. 11, no. 4, pp. 161-203.

[21] Alvandi, M., et al. (2012). K-Mean Clustering Method for Analysis Customer Lifetime Value with LRFM Relationship Model in Banking Services, International Research Journal of Applied and Basic Sciences, Vol. 3, no. 11, pp. 2294-2302

[22] Mooi, E. & Sarstedt, M. (2011). A Concise Guide to Market Research, # Springer-Verlag Berlin Heidelberg, DOI 10.1007/978-3-642-12541-6_9

[23] Harikumar, S. & PV, S. (2015). K-Medoid Clustering for Heterogeneous DataSets , Proceedings of the 4th International Conference on Eco-friendly Computing and Communication Systems, Vol. 70, pp. 226-237