

Research Article

An Empirical Study on Customer Segmentation by Purchase Behaviors Using a RFM Model and *K*-Means Algorithm

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In this paper, we base our research by dealing with a real-world problem in an enterprise. A RFM (recency, frequency, and monetary) model and *K*-means clustering algorithm are utilized to conduct customer segmentation and value analysis by using online sales data. Customers are classified into four groups based on their purchase behaviors. On this basis, different CRM (customer relationship management) strategies are brought forward to gain a high level of customer satisfaction. The effectiveness of our method proposed in this paper is supported by improvement results of some key performance indices such as the growth of active customers, total purchase volume, and the total consumption amount.

1. Introduction

In the e-business world, online shopping has become the most popular trading pattern in China. Statistics show that the national online retail sales reached RMB 10,632.4 billion in 2019. In such an online environment, customer purchase behaviors change dynamically. An excellent customer-oriented marketing strategy for predicting customer online behaviors based on data mining is therefore much needed by selling enterprises.

Data mining, which can discover hidden knowledge of great pertinence from enormous amounts of online transaction data, is the most suitable method for customer purchase behavior analysis. In particular, in the present era of big data, data mining is deemed to have broad applications prospects across the industry. There have been many excellent theories about data mining with wide industrial applications in the past two decades. Interested readers may refer to references [1–4]. They provide comprehensive reviews of data mining techniques and their industrial

applications. As to the applications, it includes banking and finance [5, 6], retail [7], telecommunication, and insurance [8–12].

In the research of Ngai et al. [4], data mining tools were used to analyze customer data within a CRM framework. Data mining can dig up useful information to analyze customer behaviors and characteristics. It is therefore of great significance to enterprises hoping to acquire and retain potential customers, helping them maximize customer value and supporting their customer management and market strategy decisions. Undoubtedly, application of data mining in the CRM domain is an emerging trend in the era of big data economy. One of the most widely used data mining models is clustering or segmentation, which divides customers into major groups based on similarity [4].

In this paper, we base our research on a real-world data of an enterprise in Beijing, China. We realize customer segmentation and propose managing strategies by combining RFM and *K*-means methods. With online transaction data collected from November 2017 to April 2019, we create

a standardized dataset for further analysis. On this basis, we utilize a RFM model and K -means algorithm to conduct customer segmentation and value analysis. A PCA method is then used to determine the weight of RFM indicators. Customers are classified into four groups based on their purchase behaviors. On this basis, different CRM strategies are brought forward to gain a high level of customer satisfaction. Changes of some key performance indices as a result of adoption of the method proposed in this paper are given, including increase in total purchase volume and total consumption amount, thereby showing the obvious effectiveness of this method.

The rest of the paper is organized as follows. Relevant research studies are reviewed in Section 2. In Section 3, the methodology and the model employed for the present research are described. Results of empirical experiments are given in Section 4. Section 5 concludes our research with some marketing strategies recommended.

2. Relevant Works

2.1. RFM Model. The RFM model was first proposed by Hughes of the American Database Institute in 1994 [13]. As a popular tool of customer value analysis, it has been widely used for measuring customer lifetime value [14] and in customer segmentation and behavior analysis [15]. In the following paragraphs, we provide a brief description of the RFM model in the above literature.

RFM is short for recency, frequency, and monetary, which refer to recency of the last purchase, purchase frequency, and monetary value of purchase, respectively. R (recency) represents the time interval between a customer's last purchase date and end date of a statistical period. The shorter the interval, the bigger the value of R . F (frequency) indicates the number of purchases made by the customer during the statistical period. The larger the value of F , the higher the customer loyalty and the stronger intention to purchase again. M (monetary) represents the total amount the customer spends in purchase during the statistical period. Generally speaking, the higher the total purchase amount, the more loyal the customer. It can serve as a direct measure of production capacity of a selling enterprise.

Research studies show that the greater the value of R or F , the greater the likelihood that the corresponding customer will conduct a new transaction with the seller. In addition, the larger M is, the more likely the corresponding customer will purchase products or services from the seller again. While Hughes attached equal importance to these three variables [13], Stone believed that the importance of the three variables varies among industries due to their different characteristics, suggesting unequal weights of these variables [14].

RFM is widely used in customer value analysis, and researchers have extended it according to different aspects. Liu and Shih used an analytic hierarchy process (AHP) to determine the weight of RFM variables, a clustering method to group customers, and an association rule method to recommend products to customers in different groups [16]. Cheng and Chen combined RFM analysis with a rough set

theory to establish rules for customer classification [14]. Chiang proposed a RFMDR model (based on a RFM/RFMD model), an extended version of RFM analysis, to identify valuable online shopping customers for the industry and to generate fuzzy association rules [17]. Kolarovszki et al. have proposed a novel modeling method for postal services using multidimensional segmentation. This CRM design proves useful in postal service companies [18]. Song et al. proposed a statistic-based approach to evaluate potential users via time series. With this approach, it is possible to segment time intervals of RFM in a large-scale dataset [19]. In view of the fact that most RFM models are developed from a customer perspective rather than a product one, Heldt et al. proposed a RFM per product (RFM/P) model. In this model, customer values of all products are estimated separately first and then added together to obtain an overall customer value. Empirical analysis of financial companies and supermarkets can be performed on this basis [6]. Adnan Amin et al. studied the prediction of customer churn in the telecom industry under different conditions by using rough set, classification, and data transformation techniques [9–12].

2.2. K -Means Algorithm. Clustering is the process of dividing a set of physical or abstract objects into groups of similar objects. The K -means algorithm, as one of the most popular clustering algorithms, was first used by Macqueen in 1967 [20], and it has been used extensively in various fields including data mining, statistical data analysis, and other business applications.

The literature shows that one of the major applications of K -means is customer segmentation [21]. The K -means algorithm is widely used to effectively identify valuable customers and develop pertinent marketing strategies [22]. In particular, Cheng & Chen used a RFM model and K -means to perform customer relationship management, and experimental results demonstrate that the model they proposed is an effective method in customer value analysis [14]. Khalili-Damghani et al. proposed a hybrid soft computing approach on the basis of clustering, rule extraction, and decision tree methodology to predict segmentation of new customers of customer-centric companies. This approach was applied in two case studies in the fields of insurance and telecommunication, respectively, aiming to predict potentially profitable leads and to outline the most influential features available to customers during such prediction [8]. With the RFM model and K -means algorithm, a variety of dataset clusters are validated through calculation of silhouette coefficient [23]. Yizhang Jiang et al. successfully applied data mining methods such as c -means, transfer learning, and multiview learning in brain CT, EEG image segmentation, and multiview clustering research [24–26].

Compared with other clustering algorithms, the K -means algorithm is not only faster in calculation but it can also reduce the misclassification rate of data [27–29]. Thus, we use the K -means algorithm to cluster according to R-F-M attributes. The accuracy of this algorithm depends on initialization conditions and the number of clusters [30–32]. The famous elbow method is widely used to determine the

value of K . In the next section, we will introduce our method step by step.

3. Methodology

This section explains the proposed process of customer value analysis. The process consists of the following four steps shown in Figure 1: (1) data preprocessing or data preparation and preprocessing; (2) normalization of RFM model indices; (3) index weight analysis; and (4) customer clustering by the K -means algorithm, where every dimension of customer information is analyzed using the RFM model and K -means algorithm to classify target customers.

The research analysis process is introduced step by step as follows:

Step 1: data preprocessing

At first, an original dataset for the empirical case study based on RFM model parameters is selected. The original dataset is then cleaned to remove outliers and inaccurate values and give birth to an initial dataset. Next, by eliminating redundant attributes, the data are transformed into a format that is easier and more efficient to process for customer value analysis.

Step 2: normalization of RFM model indices

Given the large differences in the value ranges of the three indicators of the RFM model, i.e., time since last purchase, purchase frequency, and total purchase amount, in order to eliminate the impact of numerical values on the classification results, the min-max normalization method is used to standardize the data and obtain the initial standardized dataset (see formula (1)):

$$x'_{ij} = \frac{x_{ij} - \min\{x_j\}}{\max\{x_j\} - \min\{x_j\}}, \quad (1)$$

where x_{ij} represents the j -th index of the i -th sample.

Step 3: indicator weight analysis

Index weight refers to the value and relative importance of each inspection index of a measured object. Since the research object of this paper is characterized by a large number of customers and massive consumption data, a principal component analysis method is used to assign weights to the RFM model. Principal component analysis is a statistical analysis method that transforms multiple indicators into a few comprehensive ones through dimensionality reduction technique. The weight of each indicator is equal to the variance contribution rate of the principal component. The greater the variance contribution rate, the higher the importance of the principal component. The computing process is described as follows:

Step 3.1: a principal component analysis model is constructed in the following equation:

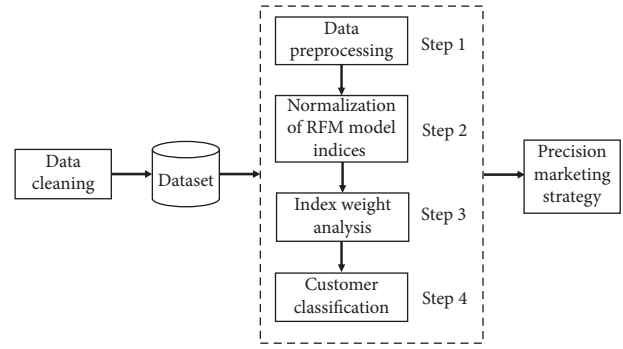


FIGURE 1: Steps of the proposed process.

$$\begin{cases} F1 = X_1U_{11} + X_2U_{12} + \cdots + X_mU_{1m}, \\ F2 = X_1U_{21} + X_2U_{22} + \cdots + X_mU_{2m}, \\ F3 = X_1U_{31} + X_2U_{32} + \cdots + X_mU_{3m}. \end{cases} \quad (2)$$

$$U_i = (A_i / \sqrt{h_i}), \quad (3)$$

where the coefficient matrix U_{ij} contains the proportional coefficients of a principal component as a linear combination of the original variables: $i(1, 2, 3, \dots, p)$, $j(1, 2, 3, \dots, m)$. In typically cases, m and p represent the composite principal component score and W represents the weight indicating the variance contribution rate of the component. Weight normalization is achieved with the following formula:

$$\begin{aligned} F &= F_1^* (W_1 / (W_1 + W_2 + W_3)) \\ &+ F_2^* (W_2 / (W_1 + W_2 + W_3)) \\ &+ F_3^* (W_3 / (W_1 + W_2 + W_3)), \end{aligned} \quad (4)$$

where F is the dataset for subsequent clustering.

Step 4: clustering the customers by K -means algorithm

Step 3.2: the formula for calculating the principal component load matrix U , the factor load matrix A , and the eigenvalue λ is as follows:

First, K initial cluster centers C_i ($1 \leq i \leq K$) are selected randomly from the dataset, and the Euclidean distance between the remaining data objects and the cluster center C_i is calculated. The cluster center C_i closest to the target data object is identified, and the data objects are allocated to the cluster corresponding to that cluster center C_i . Next, the average of all data objects in each cluster is derived as the new cluster center to initiate the next iteration. This process is repeated until the cluster center ceases to change or the maximum number of iterations is reached.

Formula (5) is the calculation of the Euclidean distance between the data objects in the space and the cluster center.

$$d(x, C_i) = \sqrt{\sum_{j=1}^m (x_j - C_{ij})^2}, \quad (5)$$

where x is the data object, C_i is the i -th cluster center, m is the dimension of the data object, and x_j and C_{ij} are the j -th attribute value of x and C_i , respectively.

The selection of the value of k as the number of clusters has great implications for the clustering results. In practice, the elbow method is generally used to determine the best k value. The relationship curve between SSE and k takes the shape of an elbow, and the value of k corresponding to this elbow is the true cluster number of the data. The core indicator of the elbow method is SSE (sum of the squared errors), as shown in the following formula:

$$SSE = \sum_{f=1}^k \sum_{x \in C_i} |d(x, C_i)|^2. \quad (6)$$

Among them, C_i is the i -th cluster and SSE is the clustering error of all samples, serving as a measure of the quality of clustering.

4. Empirical Case Study

In this section, we introduce an empirical case and a computing process using a real transaction dataset. Through customer grouping, we extract the purchase behavior characteristics of each type of users and then develop accurate marketing strategies on this basis.

4.1. Numerical Experiments. The dataset consists of 10,248 purchase data entries created at a community shopping platform from November 1, 2017 to April 15, 2019, involving 1,013 customers. This platform sells 134 types of commodities, mostly including cooked food and pasta. The following data processing steps are carried out in our research:

Step 1: data cleaning

The data entries are initially composed of 12 components such as user ID, product ID, quantity purchased, and consumption date. The three components user ID, consumption amount, and consumption date are selected, and outliers and abnormal information are removed to form the initial dataset (See Table 1).

Step 2: the range method is used to standardize the initial dataset and get an initial standardized dataset

Step 3: principal component analysis is performed to objectively weight RFM indicators to obtain a final standardized dataset

4.2. User Classification Results. The K -means clustering algorithm is used to cluster the data. Judging by the elbow method (see Figure 2), the decrease in SSE is not significant when K is higher than 4. Hence, choosing $K=4$ would yield favorable result.

A sk-learn open-source library in Python language is used to implement the K -means algorithm, and the results are shown in Figure 3.

TABLE 1: Some data entries in the initial dataset.

Employee_id	Price_total	Date_added_c
YH170929000003	37.5	2017/11/1 19:39
YH170914000002	12.5	2017/11/1 20:29
YH170623000003	12.5	2017/11/2 07:46
YH170623000003	24	2017/11/2 07:46
YH170307000001	12.5	2017/11/2 12:48
YH170923000001	25	2017/11/2 13:15
YH170317000002	75	2017/11/2 17:36
YH170317000002	12	2017/11/2 17:36

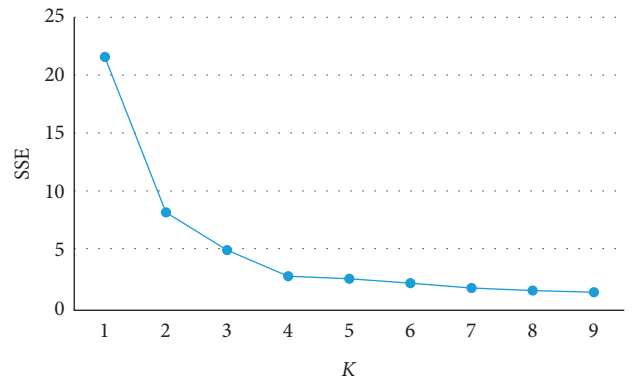


FIGURE 2: Result of optimal user cluster number with elbow method.

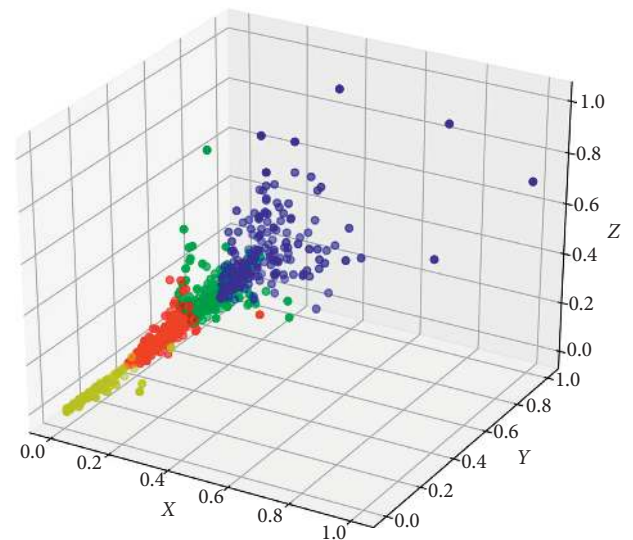


FIGURE 3: User clustering scatterplot based on K -means algorithm.

In the plot, X axis represents total purchase amount, Y axis represents the most recent purchase time, and Z axis represents purchase frequency.

It can be seen that the overall user data are close to 0 on X axis that represents the total purchase amount. In the range method, the customer with the highest total purchase amount is taken as the maximum value. The plot shows that a small number of customers far exceed the average purchase amount. Their user ID and corresponding purchase records are extracted as shown in Table 2.

TABLE 2: Extracted data of individual outliers.

Employee_id	Price_total	Last_time	Fre
YH170317000002	3167.5	2019/3/26 14:33	86
YH171201000030	2394.5	2019/1/21 14:01	108
YH180212000003	2251.5	2019/1/21 11:22	44
YH171116000009	1513	2019/1/26 22:54	37

It can be seen from the above customer purchase data that these customers have a larger total purchase amount, a higher purchase frequency, and a shorter time since last purchase, and the combined result of which is better performance on all three axes, thus making them appear as outliers of varying degrees.

At the same time, the indicators of different groups of customers and those of all customers as a whole are also extracted for analysis (see Table 3).

The four outlier user IDs extracted previously can be traced to Group 2, which is characterized by a large total purchase amount and a high purchase frequency. These users' purchase data are therefore in line with the overall characteristics of this group, thus proving rationality of the above clustering.

Comparing the customer indicators of each group with the averages of those of all customers leads to the following findings.

Customers in Group 1 have a longer time since last purchase. The purchase data they left on the platform are less noticeable due to earlier time of last purchase, smaller value of total purchase amount, and lower purchase frequency. Moreover, the number of such customers is relatively small. They can be regarded as customers with loss risks and requiring further observation. Certain resources should be invested on the platform to further analyze and understand such customers.

The purchase frequency and total purchase amount of customers in Group 2 are greater than overall averages, and their last purchase is also more recent, indicating that they are high-value T-APP customers. By bringing higher cash flow and profit to the platform, they constitute a group of high-value customers. The platform should put more effort into maintaining and improving the relationship with them.

The total purchase amount and purchase frequency of Group 3 customers are low, and they completed their last purchase at an earlier-than-average time. This implies that in spite of their recent purchase behavior on the platform, they have not formed a consumption habit there and are not in a position to generate great profits for the platform. They can be viewed as typical customers. The platform needs to cultivate their habits of using the platform and strive to convert them into active customers who can bring more profits.

Group 4 customers made their last purchase on a relatively recent date. Their indicators of total purchase amount and purchase frequency are close to the overall averages. These customers can be said to be more active and have

formed certain consumption habits on the platform. Notably, there is still much room for improving their total purchase amount and purchase frequency, meaning that they should be treated as high-potential customers. The marketing targets of the platform for them should focus on driving them from Group 4 to Group 2 with a higher purchase frequency and a higher purchase amount.

4.3. Precision Marketing Strategy. Through customer grouping, we can accurately extract the purchase behavior characteristics of each type of customer and make accurate marketing strategies.

Customer Group 1: These customers represent certain loss risks and need to be further observed. Active measures can be taken to make them feel more attached to the platform, including by informing them of attractive promotion activities like holiday discounts and clearance sales or sending SMS to remind them of gift packages offered for returning customers. More resources may be invested to increase loyalty of these users and consequently the value they bring to the platform. Users who have failed to respond to such information and engage in further purchase can be crossed off from the list of target customers in order to reduce marketing costs.

Customer Group 2: All indicators of these users are the highest and above the average. Apparently, they spend more time and money shopping on the platform, and for the platform operator, they represent an important value source. For these customers, especially VIP ones, marketing activities can focus on improving their purchase satisfaction and experiences and maintaining their loyalty to the platform.

Customer Group 3: These customers completed their last purchase at an earlier-than-average time, and their total purchase amount and purchase frequency are relatively low, implying that they have brought limited profits to the platform. Since they shop on the platform occasionally, their consumption behaviors can be stimulated by offering coupons for bringing in new visitors. The benefits of such offers are double. While inviting new comers to the platform, these existing customers themselves may become more willing to use the platform and even form a purchase habit there.

Customer Group 4: Although these customers have formed certain consumption habits, they have not left an impressive consumption record on the platform. Active efforts should be put by the platform into further cultivation of purchase will among such customers. Possible measures for this purpose include recommendation of favorite commodities at regular intervals, offer of subsidies, and preferential treatment for users recharging their purchase accounts, all designed to promote their further consumption on the platform.

TABLE 3: Customer indicators.

Customer group	Average time since last purchase	Average of total purchase amount	Average purchase frequency	Number of customers
Group 1	457.27	79.86	2.88	98
Group 2	46.93	452.15	25.47	184
Group 3	262.1	65.29	4.55	415
Group 4	157.54	156.25	10.71	316
Total	209.30	165.34	10.11	1013

These customers may also be gradually developed into higher-value ones, thus bringing more considerable profits to the company.

5. Conclusions

In this paper, customer purchase behaviors are analyzed systematically based on the online transaction data of a company by using RFM and *K*-means clustering algorithm. Customers are classified into four groups based on their purchasing behavior. Different CRM strategies are proposed accordingly to gain a high level of customer satisfaction. The obvious effectiveness of the analysis method proposed in this paper is proved by improvement of key performance indices of the company. The improvement results of some key performance indices are given in brief as follows. The number of active customers has grown by 529. The total purchase volume has increased by 279%, and the total consumption amount has increased by 101.97%.

In the future, there are two directions for further research. One is in theory, and the other is in practice. With the updating data each day, more suitable algorithms are much needed to match the new dataset for theoretical analysis. In practice, how to embed algorithm into the CRM system to support managers' decision making is a good way to help for performance improvement.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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