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An Intelligent Recommendation System based on Customer Segmentation

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ABSTRACT

Collaborative filtering has been known to be one of the most successful recommendation methods, but its application to e-commerce has exposed well-known limitations such as sparsity and scalability, which would lead to poor recommendations. Developing an intelligent recommendation system based on customer segmentation is a good way to overcome the problem of collaborative filtering algorithm. This paper presents an intelligent recommendation methodology by which we are able to get further effectiveness and quality of recommendations when applied to an Internet shopping mall. A simple case study on the feasibility has been verified. The loyalty of customers (or customer lifetime value) is also ranked by FCM clustering approach.

Keywords: Customer Segmentation; Fuzzy Data Mining; Fuzzy Cluster; collaborative filtering; role fuzziness ; demand fuzziness ; RFM

INTRODUCTION

In recent years, progress has been made in the intelligent recommendation system. To date, one of the most promising technologies which the system employed is collaborative filtering [1-4].However, collaborate filtering has several drawbacks, such as weak scalability and low recommendation quality etc., In some ways the less time an algorithm spends searching for neighbours, the more scalable it will be, and the worse its quality. Thus, only discussing the solution from the algorithm perspective is maybe not a good way. If we take the recommendation process as a whole, we can find the customer segmentation is closely linked with the recommendation result.

Customers' segmentation can help companies target customers and make proper campaign, and then drive improved customer relationships. Recommendation based on customer segmentation is more reliable than that based on pure mathematical application. Because marketer concerns himself with the recommendation result rather than an accurate calculation result.

Since the potential customers' behaviors cannot be acquired, the association between the potential customers and the current customers can hardly be explored. Fortunately, association rules have been employed in customer analysis for many years; there are also some basic models such as RFM model etc. available; data clustering technique plays an important role in supporting the theory application in customer segmentations.

Based on previous analyses, this study proposes a framework of intelligent recommendation system based on customer segmentation. Link between the potential customers and the current customers is

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explored. RFM model is revised for the easy usage for mapping of the potential customers and FCM clustering (fuzzy C_means Clustering). For good combination of revised RFM models and clustering methods, fuzzy calibration method and fuzzy c_means clustering approach are explored in this study. In our approach, we utilizes fuzzy calibration method to give the fuzzy value of the number of purchases (F) and the average purchase amount (A),then we use fuzzy c_means clustering method to segment customers.

The rest of the paper is organized as follows: Section 2 presents an overview of the related works. Research model and proposed procedure is presented in section 3. The empirical case study is made in section 4. Conclusions and future research direction followed in Section 5.

RELATED WORKS

This section mainly explores recommendation system, clustering methods, and customer segmentation based on RFM model.

Recommendation System

Recommendation system is defined as the system which recommends an appropriate product or service after learning the customers' tendency and desire[5].Recommendation system is also the one that can recommend an item to a user based upon a description of the item and a profile of the user's interests[6]. It can be classified into three categories, i.e. recommendation system mainly based on product[5][7], mainly based on web, especially on customer profile[8-11]; mainly based on agent[12].

In terms of helping end users effectively search, the recommendation system discussed in the prevailing literatures includes eSseNSe, Hypersuit,Grouper, Cha-cha, InCommonSense, Neto, Exactor. In terms of customers' service and market analysis tools, the recommendation system called PCFinder was explored in literatures[13].

To date, there are lots of recommendation system appeared, such as personalized recommendation system[14], fuzzy_based recommendation system[15], FAB Hybrid recommendation system[16] agent_based recommendation system[12] mobile product recommendation system[7] .

Montaner, Lopez, and Rosa (2003) suggest advanced classification of Internet-based intelligent recommendation system[17]. They distinguish the recommendation methods into content-based filtering, collaborative filtering, and hybrid of which previous two methods are combined. And, cosine similarity, naive bayesian (NB) classifier, Pearson r correlation, etc. are being used as key similarity measure for recommendation.

Another classification of the recommendation methods is proposed[9], i.e. collaborating filtering based on item, method based on clustering, method based on association and sequence rule, diagram method and hybrid techniques.

Clustering and Data Mining Techniques

Clustering algorithms are a class of data reduction techniques. Hierarchical clustering algorithms start with n clusters, where n is the number of observations, such as people, each with information on k dimensions, such as demographic data. The distance between observations is calculated in k-dimensional space. The two closest points are merged into a cluster. This process continues until all observations are in one cluster. One then has to determine the number of clusters using a decision rule [18].

In non-hierarchical clustering, the researcher specifies the number of clusters in the data set a priori. Since this approach matches the vector quantization problem, a non-hierarchical method is used here for comparison. The K-means procedure, as used by FASTCLUS in SAS [19], selects M random points from the data set. These are used as cluster seeds and all other points are assigned to the nearest cluster seed. Successive iterations involve replacing the current cluster seed by the cluster mean and then reassigning all points to the nearest new cluster seed. The process continues until there is no change in cluster means from the previous iteration or the difference is very small.

Fuzzy clustering analysis method can be roughly divided into three categories [20],

1) Number of categories is not given, according to different requirements of things up clustering. Such methods are based on clustering fuzzy equivalent matrix, called Dynamic fuzzy equivalent matrix for the cluster analysis.
2) Number of categories is given, to find out the best of things classifications Case. Such method is based on the objective function clustering called fuzzy c-Means (FCM) clustering algorithm or fuzzy ISODATA clustering analysis.
3) In the case of perturbation meaningful, according to the fuzzy similarity matrix Array clustering. Such method is called perturbation-based fuzzy clustering analysis.

The data mining techniques include classification, clustering, association rules, regression analysis, sequence analysis, rule-based reasoning approach, genetic algorithms, decision trees, fuzzy logic, inductive learning systems, statistical methods, and so forth [21].Generally, no tool for data mining in customer segmentation is flawless. There are some uncertain drawbacks in it. For example, in terms of decision trees, too many instances lead to large decision trees which may decrease classification accuracy rate and do not clearly create the relationships which come from the training examples. In terms of artificial neural networks, number of hidden neurons, number of hidden layers and training parameters need to be determined, and ANN has long training times in a large dataset especially. Moreover, ANN served as "black box" which leads to inconsistency of the outputs, is a trial-and-error process. In genetic algorithm, GA also has some drawbacks such as slow convergence, a brute computing method, a large computation time and less stability. In association rules, major drawback is the number of generated rules is huge and may be a redundancy.

Clustering seeks to maximize variance among groups while minimizing variance within groups [22]. Many clustering algorithms have been developed, including K-means, hierarchical, fuzzy c-means, etc. Some of them have been employed in customer segmentation[21-28].

Customer Segmentation Based on RFM Model

In recent years, RFM model has not only a great popularity in research area of customer segmentation but also in practice. RFM method is very effective attributes for customer segmentation[29].

Hughes (1994) proposed three behavioral variables in RFM analysis[30]. The calculated RFM values are summarized to clarify customer behavior patterns. Recency (R) denotes the latest purchase amount. Frequency (F) denotes the total number of purchases during a specific period. Monetary (M) denotes monetary value spent during one specific period. Then the result is sorted. On the basis of the sorted results, all customers will be classified into three categories in accordance with 20 percent, 60 percent, and 20 percent. At last, different strategies will be implemented for the different types of customers. The factors in RFM analysis are behavioral.

However, RFM method has some drawbacks. The drawbacks of RFM analysis lie in four aspects. First, the analysis process is complex. Second, it takes more time. Third, too many segments can be obtained. Fourth, multi-collinearity between the variables F and M will exist. Thus, a revised method is proposed by Marcus. He used the number of purchases (F) and the average purchase amount (A) construct two-dimensional matrix model based on CLV (customer lifetime value) to correct the RFM method [31].

In order to overcome the shortcomings of RFM analysis, Marcus (1998) proposed amendments to the RFM model. He used the number of purchases (F) and the average purchase amount (A) construct two-dimensional matrix model based on CLV (customer lifetime value) to correct the RFM method [31]. The matrix required information including customer code, purchase date, purchases per day. Number of purchases is determined by a number of different dates of purchases. The average purchase amount is equal to the ratio of the total purchase amount (sum of day purchases) and the number of purchases in the specified time interval. Eventually all customers dispersed in a predetermined two-dimensional matrix of four quadrants. For each customer group or across customer groups, different marketing strategies or tactics should be adopted.

On the other hand, the customer segmentation based on revised RFM model is still an underutilized approach, although there are numerous approaches for identifying customers' segmentation. The fundamental barrier which obstructs the implementation of revised FRM model seems to be the Effective combination of models and methods.

Customer segmentation methods can be classified into two categories, i.e. market research or data mining methodologies. The advantage of market research lies in three aspects, first, you can tap and target potential customers; second, you can conduct it timely; third, segmentation criteria is in accordance with the real situation. Its disadvantage lies in low efficiency, large capital and time consuming.

The prevailing RFM model mainly solve the problems that how much value the current customer is and what about the loyalty. For instance, Literature [32] presents a new model that links the well-known RFM (recency, frequency, and monetary value) paradigm with customer lifetime value (CLV).Literature [33] developed a novel product recommendation methodology that combined group decision-making and data mining techniques. Liu D R, Shih Y Y believe that recommender systems increase the probability of cross-selling; establish customer loyalty. Clustering techniques were then employed to group customers according to the weighted RFM value. Finally, an association rule mining approach was implemented to provide product recommendations to each customer group. In Miglautsch J R.'s point of view, direct marketing is fundamentally the scientific control of customer acquisition and contact. He addresses the fundamental questions of RFM (recency, frequency and monetary). Since direct marketing segmentation is a science, it is important to quantify customer behaviour so that the short- and long-term effect of the segmentation formulae can be tested. The purpose of RFM is to provide a simple framework for quantifying customer behaviour. Too often, direct marketers will use static customer selections. Why RFM is a superior method for selecting customers was explained clearly in literature [34].

The revised RFM model can be hardly incorporate into it with high efficiency. Inherent in the basics of RFM are built its fundamental limitations. RFM alone by definition cannot move beyond this point. Segmentation of 1-1-1 requires the creation of additional variables. As you attempt to move beyond the 1-1-1s, and as your variables proliferate, you will find it necessary to understand automated analysis. As you investigate this process, remember, the 1-1-1s are your biggest customer segment and probably your greatest untapped potential(see table 1)[35].

Table1. *Quantitative value of R–F–M attributes (Hughes, 1994)*

R	F	M	R	F	M	R	F	M	R	F	M	R	F	M
5	5	5	4	5	5	3	5	5	2	5	5	1	5	5
5	5	4	4	5	5	3	5	4	2	5	4	1	5	4
⋮	⋮	⋮	:	·	:	·	:	·	:	·	:	·	:	·
5	1	1	4	1	1	3	1	1	2	1	1	1	1	1

ARCHITECHTURE

Framework of Intelligent Recommendation System

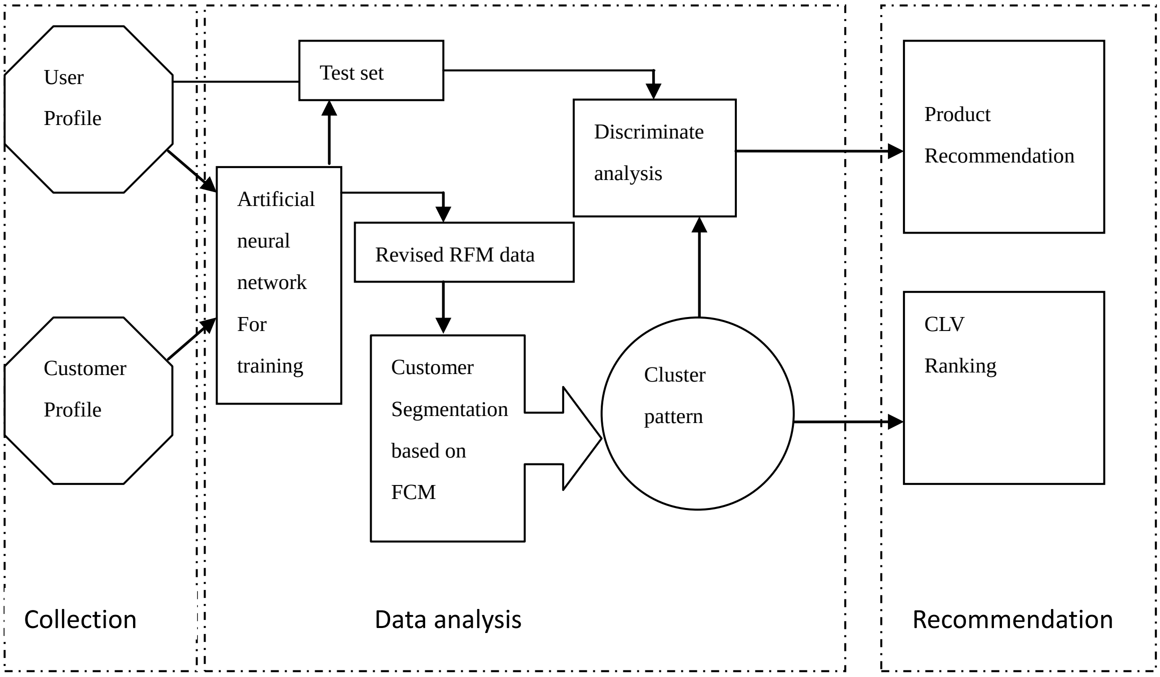

Fig1. *Framework of Intelligent Recommendation System*

The Proposed Procedure

In this subsection, we further explain the proposed procedure for product recommendation. The proposed procedure can be divided into three processes: (1) data collection; (2) data analysis; (3) product recommendation.

The computing process is introduced step by step as follows:

Step 1, tracking the various situations which potential customers become real customers. The users' history, attribute was recorded in database. They can be numbered by the first visit of company's webpage and observed in a whole period including before purchase; purchases; next purchases etc..

Step 2, splitting dataset into training data and testing data, using fuzzy neural network to map the user attribute data to revised RFM data.

Users who access an enterprise B / S website tend to have a certain degree of ambiguity. Role fuzziness, demand fuzziness are the attributes of the users.

Step 2_1, the numbered user roles fuzzy similar matrix $R = \begin{Bmatrix} r_{11}, r_{12}, \ldots\ldots, r_{1n} \\ r_{21}, r_{22}, \ldots\ldots, r_{2n} \\ r_{31}, r_{32}, \ldots\ldots, r_{3n} \\ \ldots\ldots\ldots\ \ldots\ldots\ldots\ .. \\ r_{n1}, r_{n2}, \ldots\ldots, r_{nn} \end{Bmatrix}$ can be obtained.

Step 2_2, the users demand fuzzy similar matrix can be obtained by the revised RFM model.

This sub-step process is divided into four parts introduced as follows,

(1) The numbered users' purchase record can be depicted by number of purchases (F) and the average purchase amount (A).

(2) Scale the F and A by five levels (i.e. very high, high, medium, low, and very low) based on Guass fuzzy membership function.

(3) Several fuzzy rules are designed, e.g. if F is very high and A is very high, then CLV is very high etc...

(4) Yield quantitative value of fuzzy demand (in other words, customer life value).

Step 3, Cluster customer value by fuzzy C-means algorithm.

According to quantitative value of revised RFM attributes for each customer, partition data (m objects) into c clusters using the fuzzy c-means algorithm for clustering customer value.

Firstly, let c = 5 clusters by clustering methods.

Repeat for l=1,2..........

Step 3_1, compute the cluster prototypes (means),

$$p_i^{(l)} = \frac{\sum_{k=1}^{N} (u_{ik}^{(l-1)})^m x_k}{\sum_{k=1}^{n} (u_{ik}^{(l-1)})^m}, 1 \le i \le c$$

Step 3_2, compute the distance,

$$(d_{ik})^2 = (x_k - p_i^{(l)})^T A (x_k - p_i^{(l)}), 1 \le i \le c, 1 \le k \le n,$$

Step 3_3, Update the partitions matrix,

For $1 \le k \le N$

If $(d_{ik})^2 > 0$ for all $i = 1, 2, \ldots\ldots, c$

$$u_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{c} (d_{ikA} / d_{jkA})^{2/(m-1)}}$$

Otherwise

$u_{ik}^{(l)} = 0$ if $d_{ik} > 0$, and $u_{ik}^{(l)} \in [0,1]$ with

$$\sum_{i=1}^{c} u_{ik}^{(l)} = 1$$

Until $\| u^{(l)} - u^{(l-1)} \| < \varepsilon$

Step 4 CLV Ranking

The traditional CLV ranking was derived to help develop more effective strategies for retaining customers and thus identify and compare market segments. The CLV ranking in this step has the same aim as the above mentioned, as well as the aim for exploring the potential customers by the mapping between the record of new visitors on the company's website and the revised CLV value of current customers. The ranking of clusters proceeds as follows. The revised RFM values of each customer were normalized.

Step 5 Using FNN Model to verify users' testing set

According to the weightiness from the FNN model, the F and A in a revised RFM model of the test data can be obtained. That means the new visitor who has no purchasing record has a simulated purchasing record. The CLV ranking of the clusters was derived according to their total value. Customers in a cluster with a higher rank are more loyal.

Step 6 Discriminate analysis

Through fuzzy C-means algorithm, the training samples i.e. the definite cluster of the real customer has been obtained. A criterion can be derived from the data in the training samples. The observed values of test data which the cluster is unknown can be discriminated through the predictor variables.

As all points in FCM clusters has been known, the center of each cluster can be obtained. As long as the definition of how to calculate the distance, any given point (enterprise) to the three centers of the three distances can be gotten.

Obviously, the easiest way is to find the shortest distance from the center. That cluster is the test data should belong to. The distance is usually the so-called Mahalanobis distance. The various mathematical functions to compare the distance from the center are called discriminant functions.

Step 7 Item recommendation

Two popular versions of recommendation algorithms are collaborative filtering and cluster models.

Collaborative filtering works by building a database of preferences for items by users. A new user, Neo, is matched against the database to discover neighbors, which are other users who have historically had similar taste to Neo. Items that the neighbors like are then recommended to Neo, as he will probably also like them[36].

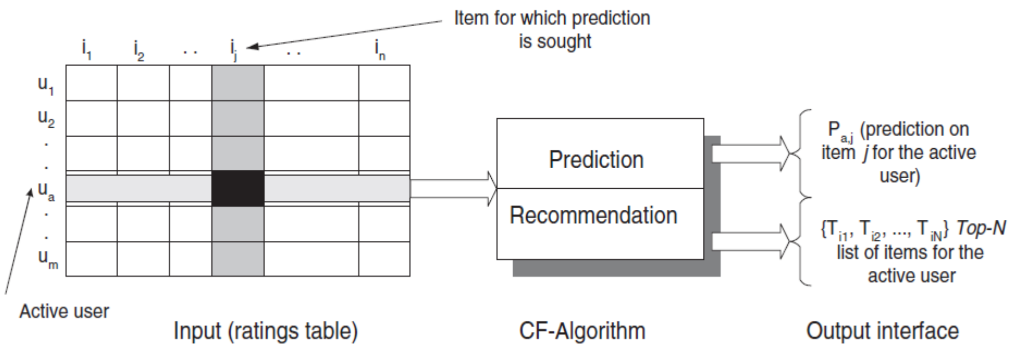

Fig2. *The Collaborative Filtering Process (sourced from literature [8])*

Cluster algorithm's goal is to assign the user to the segment containing the most similar customers. It then uses the purchases and ratings of the customers in the segment to generate recommendations.

Recommendation algorithms are best known for their use on e-commerce Websites, where they use input about a customer's interests to generate a list of recommended items. At present, many applications use only the items that customers purchase and explicitly rate to represent their interests, but they can also use other attributes. Amazon revises it by using Item-to-item collaborative filtering algorithm. To overcome the shortage of the available data in their algorithm, we use the searching keywords to generate a list of recommendation item. The detail is illustrated in another paper of the authors.

EMPIRICAL CASE STUDY

In this section, we introduce the empirical case (some data collected from B store's website and cashier software) and the computing process using the dataset.

4.1 The key computing process using the dataset

The computing process using a practical collected dataset can be expressed in detail as follows:

Step 1, the dataset has been preprocessed and putted into a file named clustertest.dat.

Step 2, a similarity fuzzy matrix are established; data from the fuzzy matrix and the company' web site are also been trained by ANN model.

A mapping between the requirements of new visitors and real customers' behaviors are obtained.

Step 3, load clustertest.dat into the workspace in MATLAB software package.

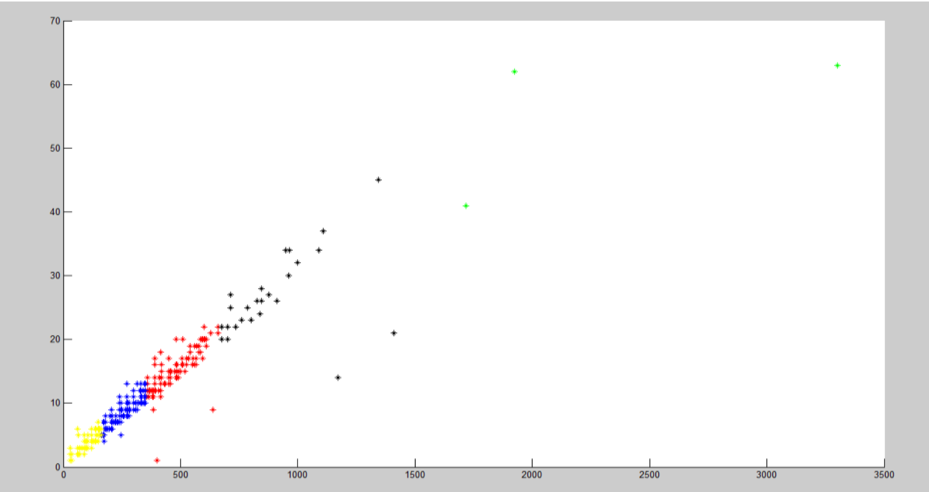

Fig3. *Cluster plot about the customer dataset based on FCM*

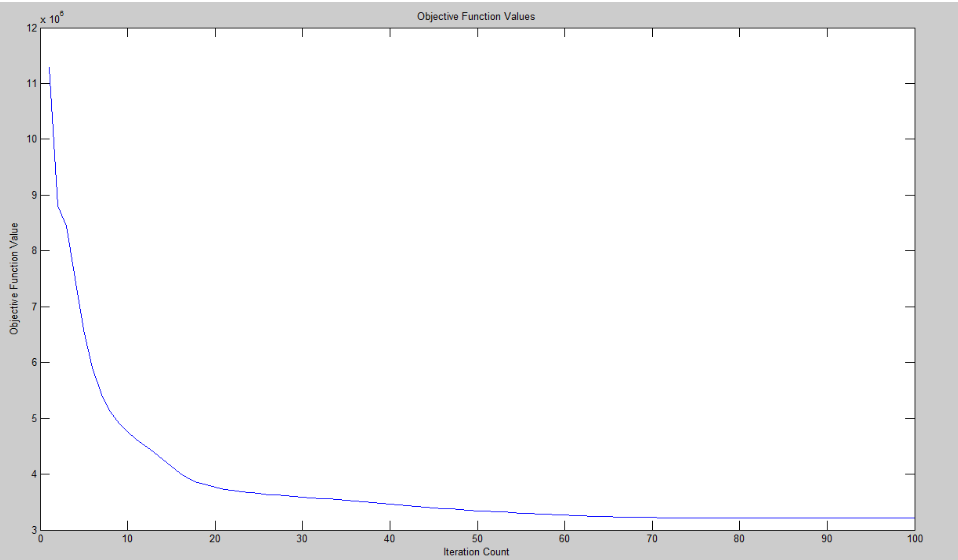

Fig4. *The objective function plot (the progress of the clustering)*

Fig. 3 and Fig.4 shows 5 clusters obtained by FCM and the clustering progress.

An alternative step is to preprocess the data and normalized the dataset as follows, Step 2-1: Define the scaling of F–M attributes. This sub-step process is mainly divided into five parts introduced in the following:

(1) Define the scaling of two F-M attributes, which are very high, high, medium, low, and very low.

(2) Sort the data of two F-M attributes by descendant order.

(3) Partition the real data of F–M attributes respectively into 5 scaling in B-store dataset with 871 instances (see Table 2).

(4) Yield quantitative value of F–M attributes based on Table 3 as input attributes for each customer (see Table 4).The calibration equation is, $x_i = \frac{x_i - x_{min}}{x_{max} - x_{min}}$ among them, x_i depicts the calibration value; x_{max} and x_{min} depict the maxim and minim value among the observable values of 871 instances respectively.

Table2. *The partial data of B-store' dataset*

Card_id	the number of purchases (Frequency)	the average purchase amount(RMB hundred yuan)	Card_type
….	….	…	….
20120015	81	456.5(5.64)	Bonus
20120053	16	61(3.81)	Bonus
20120055	2	14.1(7.05)	Bonus
20120120	9	58.8(6.53)	VIP
20120128	8	46(5.75)	VIP
20120138	2	9.5(4.75)	Bonus
20120771	4	11(2.75)	Bonus
….	….	…	….

Table3. *The calibration rule of revised R-F-M attributes in dataset of B-store*

Scaling Name	F - Frequency	M - the average purchase amount(RMB Yuan)
Very High	Over 50 Records	Over 700
High	10-50 Record	600-700
Medium	3-9 Record	400-600
Low	2 Record	200-400
Very Low	One Record	Under 200

Table4. *fuzzy value of R–F–M attributes of B-store dataset*

Card_id	F	M
….	….	….
20120015	0.98	0.52
20120053	0.72	0.32
20120055	0.33	0.57
20120120	0.60	0.83
20120128	0.49	0.55
20120138	0.34	0.57
20120771	0.58	0.31
….	….	….

Step 4 CLV Ranking

Table 2 shows the average normalized revised RFM values of each cluster, denoted as C_F^j and C_M^j, respectively, for j = 1 to 5 (the number of clusters). C_F^j and C_M^j were computed by averaging the normalized revised RFM values of customers in cluster j. Let C_S^j be the total value of cluster j. C_S^j was computed as the weighted sum of C_F^j and C_M^j that is, $C_S^j = \omega_F C_F^j + \omega_M C_M^j$ .where ω_F and ω_M are the relative importance of the revised RFM variables. Fig.3 and table 5 shows the detail of the customer cluster.

Table5. *The cluster results by FCM with 5 classes on output*

Cluster_center	c_1	c_2	c_3	c_4	c_5
F	53.14	14.54	8.077	2.82	26.96
M	2020	456.49	245.38	84.56	880.95
Loyalty(output)	high	medium	low	Very low	Very high
Number of instances	25	121	296	426	3

For the conciseness step 5 to step 7 are omitted.

Findings and Discussions

In this study, an intelligent recommendation system is proposed. From fig 3 and fig.4, we can find the progress of clustering can be obtained easily. The main recommendation process and the auxiliary process are illustrated in section 3. For the real customer, the loyalty can be raked by the clusters. For the potential customers, the purchasing behavior can be predicted by the mapping between the real customers and potential customers. The recommendation item can be specific, since the customers' segmentation and mapping is scientific and concrete. However, it is an argument that the big data stored in the enterprises' database and from the enterprises' websites leads to the difficulties in the data analysis as well as the intelligent recommendation. A simple customer segmentation approach, low dimension of the purchase behavior of customers and low cluster number (e.g. 5 classes or 3 classes) can made the issue more valuable. The approach proposed in this work aims on it.

From the experimental and statistical results of empirical case study (B-Store), this study elucidates three findings as follows:

(1) Revised R-F-M models are more valid than the traditional one in customer segmentation as well as recommendation in terms of the efficiency.

(2) Effectively usage of customer segmentation can avoid the time-waste in collaborative filtering algorithms.

(3) Since the customer segmentation results match the principle of 80/20 (or Pareto principle) (Schmittlein& Schultz, 1998). The recommendation process based on customer segmentation can simple and concrete. This work is in accordance with Ethical Marketing. It also can enhance the efficiency and intelligence of the recommendation.

CONCLUSIONS

We have presented a methodology for intelligent recommendations in e-commerce and developed a recommender system implementing the methodology. The characteristics of the suggested methodology are as follows. First, the customer preference and the customer requirements association are automatically learned from searching keywords, unlike other recommendation methodologies which learn them from purchase records only. Then, in order to avoid the poor recommendations that will lead to disappoint customers, customers who are likely to buy recommended products are selected using ANN, fuzzy C_means cluster and discrimant analysis. Finally, the loyalty of customers (or customer lifetime value) is also ranked by FCM clustering approach.

As further researches, we will compare fuzzy c_means cluster with K_means cluster in customer segmentation and in our suggested recommendation system. It will also be interesting to compare our suggested methodology with a standard collaborative filtering based methodology in the aspect of recommendation performance. And it will also be an interesting research area to conduct a real marketing campaign to customers using this methodology and to evaluate the performance.

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