A Novel Recommender System Based on Fuzzy Set and Rough Set Theory

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Abstract

Recommender System is an effective means of handling information overload and can provide personalized service as a useful information tool in e-commerce. In this paper, a novel automatic recommender system is proposed based on fuzzy c-means algorithm and rough set theory, including three main steps: data discretization, rules establishing and fuzzy reasoning. A method for fitting the results of FCM clustering is put forward by membership function and using it with attributes to achieve data discretization, in order to avoid the processing that each input data have to carry clustering operation for discretization. Using rough set theory, it can accelerate the speed of fuzzy reasoning through rules reduction with choosing closely relating attributes for commodity. Fuzzy reasoning method is also applied into commodity recommender system. Lastly, a case study conducted by the presented method is given, and the results show that this model can provide valuable advice for potential users and it is also an effective way for recommendation.

Keywords*: Fuzzy Set, Rough Set, Recommender System*

1. Introduction

The rapid growth of electronic business scale is bringing more goods to choose for customers, but it is also causing that the cost of searching for a product is getting higher and higher. Recommender system in E-commerce can provide recommendation, help customers find goods, meet users' needs, and turn the users from visitors to buyers. The user's loyalty can be improved by the interaction with websites while such system can make user escape from the searching task, and ultimately, to increase enterprise benefit [1]. Research on recommender system and personalized recommendation technology is a hot topic at home and abroad, and gradually becomes widely an application. Recommender system has been integrated into the operating system in many famous e-commerce, such as Amazon, CDNOW, eBay, Levis, Moviefinder and Reel [2]. In china, although there is a big gap in automatic and personalized recommendation, the relating theories are deepening step by step with the vigorous development of e-commerce [3]. The recommender strategy is becoming more intelligent with respect to the original classification based on content browsing and searching, which will be applied into e-commerce.

Recommender system is composed of the personalized recommendation and the non-personalized recommendation system. In order to produce precise recommendation and guarantee system in real-time, researchers put forward different recommendation algorithms. Typestry presented a recommender system based on collaborative filtering, and the user needs to point out the other similar, with his behavior [4]. Bayesian network technology used the training set to create corresponding model [5], where the model is expressed with the decision tree, and nodes and edges describe the user's information. Training model is very small, so the application of model is very fast. This method is suitable for user's interests with changing slowly. L.Q. Ou et al. made use of spanning tree algorithm to divide project matrix and calculate the similarity between projects [6]. The score of new project was carried by the similarity prediction according to the scores of existing projects by the users'. Aggarwal et al. proposed a model that total clustering was carried out by using neural network model [7]. The effect of high dimensional data clustering can be reduced by looking for tacit link among object attribute information. H.Y. Zhang proposed a recommender algorithm based on fuzzy clustering, in combination with attributes similarity and collaborative filtering technique [8]. However, there are still some deficiencies existing in various recommendation methods, such as describing in literature [9].

In this paper, we propose a method of intelligent commodity recommendation based on FCM, fuzzy set and rough set theory on the basis of existing research. Because there are many factors to the score evaluation for goods, it will the direct through all the score evaluation and analysis of goods, if factors directly using fuzzy inference will cause certain bad effect if using clustering algorithm for input space division with the increase of multiple fuzzy reasoning rules. Firstly, using clustering algorithm for input space division, it avoids the blindness of subordinate function determination. The results after clustering are fitted through the use of membership function. Secondly, the parameters of membership function are obtained in order to conduct data discretization, to overcome the drawback of input data discretization through clustering each time. Lastly, the fuzzy reasoning rules with combination explosion are solved by using rough set for attribute reduction.[13][14]

2. The architecture of recommender system

This paper proposes the e-commerce recommendation system architecture shown in Figure 1 which includes the following four subsystems:

1. The data pre-processing subsystem. Information that users access the site is stored in the back-end database in various forms, and can’t meet the requirements of data analysis. We need to make the data pre-processing on the users' information. Through the network crawler software, we construct an information data warehouse. Through the ETL (extract, transform, and load), the data integration and cleansing, we provide a clean, consistent, and integrated and reduction data sets for commodity recommendation information mining.

2. User commodities prefer detection model subsystem, mainly including the following steps:

(1) Construct the decision table. Remove the related factors of the important descriptions about the commodities from the data warehouse as the condition attribute. The evaluation about whether it is worth buying is as the decision attribute. Forming a two-dimensional decision-making table, each line in the table describes an object and of each list describes an attribute of the object.

(2) Attribute discretization. In order to quantify the decision table with the greatest consistency, I use the fuzzy clustering method to realize the clustering on the sample set and make the curve fitting on the results of the clustering to achieve the discretization of the sample.

(3) Rough reduction. After the discretization of the decision-making table, we should apply the rough set to simplify the decision-making table, mainly including the condition attributes and the simplification of attribute values.

3. Commodity association rule subsystem. Make the association rule mining on the commodity subclass hierarchy and find the sub-classes that users are interested in; The fuzzy theory is an important tool to deal with the system uncertainty. Later in this paper, we apply the fuzzy discretization method and the reduction results of the inference rules to establish inference rule sets.

4. Personalized recommendation sub-system, we apply the Max-Min fuzzy inference method to get the related information of the recommended products and the purchase guidance.

The user commodity preferring detection model sub-system, clustering and association rule subsystem are working offline. This design minimizes the pressure of the server and improves execution efficiency of the system.

When a user visits the site, the user information will be passed from the WWW server to the database server. The data pre-processing sub-system extracts periodically the user data from the database server, and then submits the pre-processing data to the user commodity preferring detection model subsystem. Commodity association rule sub-system regularly re-runs based on the latest data and saves the results. Association rule sub-system makes the associated data mining on the commodity sub-classes, produces the commodity classification. Personalized recommendation sub-system based on the current users' accessing information makes the personalized recommendations for the users and feedbacks to the WWW server. Then, WWW server based on the actual link that the users click add a collection of Web links on the target web page and feedbacks to the user for browsing.

3. The key methods of the system

3.1. Data discretization

In the commodity recommendation rule extraction based on the rough set theory, it requires the discrete data (such as Integer, String, etc.) to express the value of the decision table. We need to make the

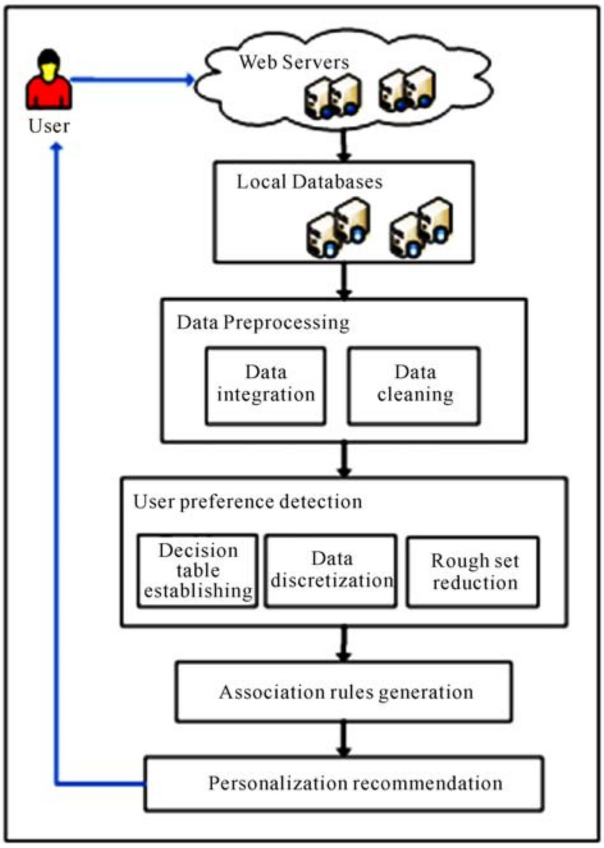

Figure 1. The architecture of recommend system

discrete processing on the commodity evaluation data. At present, the main methods discrediting the continuous data are as follows, such as principal methods of discrete-width interval method, such as the equal-width interval method, the equal-frequency interval method, the statistical method, the filtering method, the genetic algorithm and so on. The discrete of the continuous attribute is to divide the continuous attribute range into several intervals, each interval with different codes, so the continuous attribute value will be converted into the discrete attribute value. Here, we use the fuzzy clustering algorithm to realize the fuzzy clustering on the sample space. Because of its adaptability, easy operation, it is widely used in many fields, such as the image segmentation, speech recognition and so on.

Fuzzy C-Means clustering algorithm is described as follows.

Set the sample space $X = \{x_1, x_2, \ldots, x_n\}$. The X is divided into m classes and m is a positive integer greater than one which you can use the fuzzy matrix $u = (u_{ij})$ to represent, u_{ij} represents that the first i sample belongs to the first j category of the exclusion measure. This definition is as follows:

$$u_{ij} = \frac{\|x_i - c_j\|}{\sum_{k=1}^{m}\|x_i - c_k\|} \tag{1}$$

C_j is the first j cluster center, $\|x_i-c_j\|$ represent the Euclidean distance from the xi to the c_j. Clearly, if it is the nearest from the sample point xi to the first j cluster center c_j, the exclusion is smaller, that is to say, the u_{ij} is smaller. In the formula:

$$u_{ij} < 1,\ \sum_{i=1}^{n} u_{ij} = 1, i = 1,2,...,n,\ j = 1,2,...,m$$

The objective function F(u,C)of the FCM is defined as follows:

$$F(u,C) = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(u_{ij}^{b} \times \left\|x_i - c_j\right\|\right) \tag{2}$$

In the formula, b is the fuzzy index. Obviously, $\|x_i-c_j\|$ is smaller and u_{ij} is smaller, so the F is smaller. Continually modify the value of cluster centers, and then calculate the F (u, C) followed in turn until you get the desired results. Therefore, FCM algorithm is the iterative convergence process to minimize the objective function F (u, C). Due to constantly modifying the cluster center, so the clustering center is set to the formula (3):

$$C = \frac{\sum_{i=1}^{n} u_{ij}^{b} \times x_i}{\sum_{i=1}^{n} u_{ij}^{b}} \tag{3}$$

So we can determine the iterative process of the FCM clustering algorithm:

Step 1: Set the number of clusters and the fuzzy index m.

Step 2: Randomly get the m cluster centers c_m^0 and 0 indicates the current number of the iterations.

Step 3: Calculate the objective function making use of the current cluster center obtained equation (1), and then update the cluster centers c_j by using the current rejection degree u_{ij}. Repeat the third step until the objective function achieves the minimum or is lower than the given threshold ε.

In the clustering operation, if we make the fuzzy processing for each input data through the clustering, it will produce bad results. On the one hand, due to the slower clustering, it will seriously affect the overall system performance; On the other hand, because each cluster use the different data set and the cluster center will be different too, it will cause the unstable system structure. Therefore, this paper fits the results obtained by clustering through the usual membership function and gets the parameters of the membership function to realize the system discretization.

3.2. The introduction of the rough set theory

Since Z. Pawlak proposed the rough set theory in the 80 years of 20th century, it has been successfully applied in many fields. It not only has the ability to simulate the human logical thinking, but also can effectively analyze and deal with the imprecise, inconsistent and incomplete information. It can also find and reveal the inherent law among the data to extract the useful information. The main advantage of this method is that it does not require a pre-given the description of the number and the model hypothesis about certain characteristics and attributes. But merely making use of the rough set theory may not always be able to effectively describe the imprecise or uncertain practical problems of the data. Combined with the other theories to form a more effective way to solve the technical problems is the current focus of the study. For example: the combination of rough sets and the fuzzy clustering [7-8], They are both the promotion of the classical set theory in dealing with the uncertainty or inaccuracy of issues and both can be used to describe the imprecision and the incomplete of the knowledge, but on different focuses. They can also be combined in order to play their respective advantages too.

The main idea of the rough set theory, on the premise of maintaining the same classification ability and through the knowledge reduction, exports the decision-making and the classification rules. At present, the rough set theory has been successfully applied in the fields, such as the machine learning, the decision analysis, the process control, the pattern recognition and data mining.

If the u is the non-empty finite domain, R is the binary equivalence relation on the U, that is to say, R is reflexivity, symmetry and transitive. If there are two elements x and y, xRy, then we can call that the x and y are non-identifiable. The sequence pairs apr_R=(U, R) are called as the approximation space. U/R is the all of the equivalence class to generate the R on the U, constituting a division of U. Sign the equivalence class $[x]_R$={y|xRy}. In order to present the sub-set A of the U in the approximation space apr_R, we can define a pair of the approximation Operators, the lower approximation and upper approximation, as follows:

$$\underline{\mathrm{apr}_R}(A)=\{x\in U|[x]_R\subseteq A\} \tag{4}$$

$$\overline{apr_R}(A)=\{x\in U|[x]_R\cap A\neq\Phi\} \tag{5}$$

We call the sequence pairs ($\underline{\mathrm{apr}_R}(A)$, $\overline{apr_R}(A)$) as the fuzzy set of the set A. Separately record the membership function of A and R as the μ_A, μ_R, then the lower approximation and upper approximation of the set A can be presented through the two methods as follows:

$$\mu_{\underline{apr_R}}(A)(x)=\inf\{\mu_A(y)|y\in U,xRy\} \tag{6}$$

$$\mu_{\overline{apr_R}}(A)(x)=\inf\{\mu_A(y)|y\in U,xRy\} \tag{7}$$

$$\mu_{\underline{apr_R}}(A)(x)=\inf\{1-\mu_R(x,y)|y\in A\} \tag{8}$$

$$\mu_{\overline{apr_R}}(A)(x)=\inf\{\mu_R(x,y)|y\in A\} \tag{9}$$

According to the formula (6) to (9), Intuitive meaning of the lower approximation and upper approximation can be explained as follows: x is the element of the U, $x\in\underline{apr_R}(A)$. Only if All the elements y realize the establishment of xRy, y∈A, or all the elements y don't belong to A, then μ_R (x, y)=0; x is the element of the U. Set $x\in\overline{apr_R}(A)$, x∈$\underline{\mathrm{apr}_R}$(A), Only if at least one element y make the xRy established and y∈A, or all the elements y belong to A, then μ_R (x, y)=1. On the other hand, through these four formulas, we can calculate the lower approximation and upper approximation of the membership function, the rough set of the A.

3.3. The establishment of the inference rules

After constructing the decision table by the correlated algorithm of the rough set, if the decision table don't make the attribute reduction, then the fuzzy inference calculation will be very great. Here, we establish the fuzzy inference rule set by using the rough set theory, simplifying the decision table, the attribute reduction and attribute value reduction. Before and after the reduction, it does not change the decision-making attributes of the decision table. This paper applies the reduction algorithm based on the importance of the attributes [12].

The dependent degree of the attribute set D to the B is defined as: r(B, D) = $|POS_B(D)|/|U|$. In the formula, POSB (D) is the positive region divided by the attribute set B. If D is the decision attribute set, then the r(B, D) indicates the probability that any x∈U can be properly divided into the decision-making class after the B dividing the U; at the same time, it describes the ability that the condition attribute B portrays the decision attribute D.

Definition 1: The dependent degree based on the conditional attribute set B and the decision attribute set D, the importance of attributes are as follows:

$$Sig(a,B,D) = r(B+\{a\},D) - r(B,D) \tag{10}$$

$Sig(a,B,D)$ presents the importance of the attribute a when the currently attribute set is B. The greater importance, the impact is greater on the decision-making division. Compared to the decision-making attribute, it is more important.

The specific steps based on the attribute importance algorithm are as follows:

Input: The decision table S = (U, A, V, f). In the table, A=C∪D, C and D are respectively the condition attribute set and the decision attribute set.

Output: An attribute reduction R of the decision table S.

Step 1: Set the initial attribute reduction set R = Core (C, D), B = C-R;

Step 2: Calculate r (C, D) as the stop condition;

Step 3: If the R satisfy the r (R, D) = r (C, D), then the algorithm is terminated and the output R is a reduction.

Otherwise, turn to the Step 4;

Step 4: According to the formula (10), we calculate an important degree of each attribute in the B and choose the attribute a that make the attribute importance obtaining the maximum value; if there are multiple properties and the attribute importance are set the same maximum value, then we select the attribute a that get the smallest combinations with the R;

Step 5: R=R∪{a}，B=B-{a}, then turn to the step 3 to continue.

3.4. The fuzzy reasoning in the commodity recommendation

In order to get the related information and the buying guidance of the commodity recommendation, the detail is as follows:

(1) The Fuzzy conditional reasoning of the Fuzzy conditional statement ""if A then B else C"

If A is the Fuzzy sub-set on the domain X, and B and C are the sub-sets on the domain Y, then the Fuzzy relationship R of the "if A then B else C" on the domain X×Y:

$$R = (A \times B) \cup (\overline{A} \times C) \tag{11}$$

Based on the inference synthesis rules and according to the Fuzzy relationship R, we can obtain the Fuzzy set B1 corresponding to the given Fuzzy sets A1 through the formula (11):

$$B_1 = A_1 * R \tag{12}$$

The Fuzzy set B1 is the Fuzzy conditional reasoning under the premise of the A = A1"if A then B else C". In the Fuzzy controller, we can get the output B1 of the Fuzzy controller if we input the A1 with the "if A then B else C" control rule and apply the formula (11) and (12).

(2) The Fuzzy conditional reasoning of the Fuzzy conditional statement "if A and B then C"

If A, B and C are separately the Fuzzy sets on the domain of X, Y and Z, A and B are the input Fuzzy sets of the Fuzzy controller, and C is the output Fuzzy sets. In this case, the ternary Fuzzy relation R determined by the Fuzzy conditional statement "if A and B then C" is as follows:

$$R = (A \times B)^{T1} \times C \tag{13}$$

In the formula, $(A\times B)^{T1}$ is the nm-dimensional list vector constituted by the Fuzzy relation matrix $(A_1\times B_1)_{\mathrm{nm}}$ in which n and m are the number of domain elements in the Fuzzy sets A and B. Based on the inference synthesis rules and according to the Fuzzy relation formula (13), we can obtain the output Fuzzy set C1 corresponding to the given input Fuzzy sets A1 and B1:

$$C_1 = (A_1 \times B_1)^{T2} * R \tag{14}$$

In the formula, $(A_1\times B_1)^{T2}$ is the nm-dimensional column vector constituted by the Fuzzy relation matrix $(A_1\times B_1)_{\mathrm{nm}}$ in which n and m are the number of domain elements in the Fuzzy sets A and B.

4. Experiment and analysis

In order to prove the correctness of the system proposed in this paper, we use the system to make the intelligent recommended test of the mobile products. The data is from the mobile phone information website, http://digi.tech.qq.com/mobile/ and the site provides the related rating information of the cell phones. These scores are from the network users.

4.1. Data Preprocessing

We use the web spiders to make the Web content mining. We download the qualitative or quantitative evaluation of the mobile phone review sites to the local databases. The reptile based on the target data model is the data on web pages and the crawled data generally conforms to certain patterns or can be transformed or mapped to the target data model.

Experimental data mainly is from the users' evaluation. Due to a huge number of users on the network, we can consider that the rating of a user on a mobile phone is more objective as a comprehensive description of the product information. Evaluation data is a quantitative continuous data and different sites define differently. Among these data, it often occur a number of continuous values, so we need to standardize these continuous data. We make the pre-processing on the collected data, including the noise removal, de-duplication and so on.

4.2. The construction of the membership function

The data includes the evaluation of mobile phones, including the appearance, function, operation, batteries, price and so on. We collected popular styles of the major cell phone brands nearly two years, such as NOKIA, LG, SAMSUNG, including some pre-sale models. Using the vague language to describe, we have collected the following data format of the cell phone ratings: Poor: 0-1 .5, general: 1.5-2.5, middle: 2.5-3.5, good: 3.5-4.5, great: 4.5-5.

In this step, we have to select the appropriate membership function to make the FCM clustering. Through the experiment on the collected data , we found that the middle curve of the membership function obtained by the cluster is very close to the Gaussian type, and the curve near the two ends are close to the Sigmoid type function. After some sets of the data clustering, we found that the clustering results of the standard FCM function in the one-dimensional are all with this feature. Gaussian type function and Sigmoid type all have a very good smoothness and also have a clearer physical meaning. They are membership functions commonly used in fuzzy systems. Therefore, after the analysis of the data, in this paper, we use the membership function Gaussmf and Psigmf to fit the membership function. After fitting, the membership functions and the corresponding coefficients are shown in Table 1. Through the above processing, the fuzzy rule set is transformed from the clear rules of each node, which using poor, general, middle, good and great to replace the digital quantity of clear rules.

Function Gaussmf is a kind of Gaussian model, where parameter list is $[\sigma,\ \mathrm{c}]$. The mathematical model is $\mathrm{f}(x)=e^{-\frac{(x-c)^2}{2\sigma^2}}$, where x is variable, σ and c are parameters. In function Psigmf, parameter list is [a_1, c_1, a_2, c_2], which is the product of two Sigmoid function: $f_1(x)*f_2(x)$, the membership function of Sigmoid is given as: $f(x)=\frac{1}{1+e^{-a(x-c)}}$.

By clustering analysis, we get the data of discretization. Combined with rough set theory, we can get the decision table of discrete data shown in table 2. D is whether to recommend the mobile phone or not, 0 denotes yes while 1 says no.

4.3. The establishment of reasoning rule

Table 2 shows the fuzzy decision table after data discretization, but we didn't apply attribute reduction. Because the number of evaluation data attributes can be quite large, the fuzzy reasoning will be huge computation. Here, we use rough set to establish fuzzy reasoning rules, simplify decision-making table and don't change the decision attribute. Firstly, data preprocessing is conducted to combine the same elements which have the same conditions and the decision attributes. Then, according to the conflict elements, we take big probability principle, that is, quantity of rules are selected as the unity of decision attribute when having the same condition attributes and different decision values. Finally, remove any attribute if the table is still consistency, and it means that the condition attribute can be ignored. On the contrary, it should not be ignored. Through calculation of reduction, we know that the attribute of battery has few effects for mobile phone and so we get the decision table after attribute reduction based on rough set, as shown in table 3.

From 3, we can get the reasoning rules easily:

Table 1. Part of the function fitting and parameters

		Poor	**General**	**Middle**	**Good**	**Great**
Appearance	Function	Psigmf	Psigmf	Gaussmf	Psigmf	Gaussmf
	Parameter	[0.348 15.3 -1.33 21.3]	[0.428 8.3 -0.73 11.3]	[12.6 26.3]	[0.568 28.3 -1.73 33.5]	[14.7 46.1]
Operation	Function	Gaussmf	Psigmf	Psigmf	Psigmf	Psigmf
	Parameter	[9.7 31.5]	[1.228 14.3 -1.433 29.3]	[0.468 5.3 -1.713 15.3]	[0.368 5.3 -2.13 35.3]	[1.068 23.3 -2.43 34.4]
…	…	…	…	…	…	…

Table 2. The decision table for mobile phone

NO	**Appearance**	**Function**	**Operation**	**Battery**	**Price**	**D**
1	4	3.5	4	3	3	1
2	5	5	4	4	1	0
3	3	2.5	4	3	5	1
…	…	…	…	…	…	…

Table 3. The decision table for mobile phone after attribute reduction

NO	**Appearance**	**Function**	**Operation**	**Price**	**D**
1	4.1	3.4	4.1	3.4	1
2	4.6	4.7	4.2	1.2	0
3	3.2	2.4	4.4	4.5	1
…	…	…	…	…	…

Rule 1: If appearance is “good”, function is “middle”, operation is “good” and price is “middle”, and then recommend.

Rule 2: If appearance is “great”, function is “great”, operation is “good” and price is “poor”, then don't recommend.

Rule 3: If appearance is "middle", function is "general", operation is "good" and price is "great", and then recommend.

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So, we can get the information of phone recommendation.

4.4. Fuzzy reasoning

We got buying decision rules of mobile phone after attribute reduction through the methods described in section 4.3, however, in order to find the more hidden rules, we can also undertake fuzzy reasoning to find the deep recommender rules. In this experiment, we adopt the most common fuzzy reasoning, which generate the rules of the condition attributes for each rule with the least membership. And then the minimum value is allocated to each rule, which is the output value for the corresponding rules of fuzzy reasoning. After that, we find the maximum output value of fuzzy reasoning and it is the recommender mode. For example, we can get the rule by fuzzy reasoning as: If appearance is "general", function is "general", operation is "good" and price is "great", and then recommend.

5. Conclusions

In the field of E-commerce, the recommender system can help users to quickly find the goods which they have strong interest in and can realize value-adding for enterprise at the same time. It has become the key module in e-commerce websites. At present, due to the fast development stage of e-commerce in such aspect, it is necessary to study on more intelligent and optimized intelligent recommender system and algorithm. This paper proposed a new model of intelligent recommender of network products for buyers based on FCM and rough set theory, where the partition of input space and the membership functions were set according to clustering algorithm. By means of the fuzziness of condition attributes and their indiscernibility, the attribute reduction was executed in order to extract the rules. The reasoning rules were formed which can simplify the number of attributes and provide advice as guidance. Experimental results showed that the automatic recommender system is correct and effective, and it can provide valuable information for the potential buying users.

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7. References

[1] Paul Resnick, Hal R Varian, "Recommender systems", "Communications of the ACM", ACM (The Association for Computing Machinery), vol.40, no.3, pp.56-58, 1997.
[2] J. Ben Schafer, Joseph Konstan, John Riedl, "Recommender Systems in E-commerce", In Proceedings of the 1st ACM conference on Electronic Commerce, pp.158-166, 1999.
[3] L. Liu, X.L. Ren, "Study on Recommender System and Its Research Progress", "Journal of information system", Tsinghua University, vol.2, no.1, pp.82-90, 2008.
[4] David Goldberg, David Nichols, Brian M. Oki, Douglas Terry, "Using Collaborative Filtering to Weave an Information Tapestry", "Communications of the ACM", ACM (The Association for Computing Machinery), vol.35, no.2, pp.61-70, 1992.
[5] W.D. Penny, S. J. Roberts, "Bayesian Multivariate Autoregressive Models with Structured Priors", In IEEE Proceedings on Vision, Image and Signal Processing, vol.149, no.1, pp.33-41, 2002.

[6] L.Q. Ou, L. Chen, Y. Ma, “Research on New Project Recommendation Methods in Collaborative Filtering Algorithm”, “Journal of Micro Computer Information”, Micro Computer Information press, vol.21, no.3, pp.186-188, 2005.
[7] C.C.Aggarwal, P.S.Yu, “Redefining Clustering for High-dimensional Applications”, “IEEE Transactions on Knowledge and Data Engineering”, IEEE, vol.14, no.2, pp.210-225, 2002.
[8] H.Y. Zhang, F. Ding, L.H. Jiang, “Collaborative Filtering Recommendation Based on Fuzzy Clustering”, “Journal of Computer Simulation”, vol.22, no.8, pp.144-148, 2005.
[9] Gediminas Adomavicius, Alexander Tuzhilin, “Towards the Next Generation of Recommender Systems: a Survey of the State-of-the-Art and Possible Extensions”, “IEEE Trans. on Knowledge and Data Engineering”, IEEE, vol.17, no.6, pp.739-749, 2005.
[10] Fan Tuan-Fang, Liu, Duen-Ren,Tzeng Gwo-Hshiung, “Rough Set-based Logics for Multicriteria Decision Analysis”, “European Journal of Operational Research”, Elsevier, vol.182, no.3, pp.340-355, 2007.
[11] Yaser E. Hawas, “A Fuzzy-based System for Incident Detection in Urban Street Networks”, “Transportation Research”, Elsevier, vol.15, no. 2, pp.69-95, 2007.
[12] X.H. Hu, N. Cercone, “Learning in Relational Database: A Rough Set Approach”, “Computational Intelligence”, Blackwell, vol.11, no.2, pp.323-337, 1995.
[13] Zheng-dong Zhao, Gang Wang, Wei Zhao, Hui-ling Chen, Wei Zhao, Lu-lu Li, “A Fuzzy Adaptive Multi-Population Parallel Genetic Algorithm for Spam Filtering”, “Journal of Convergence Information Technology”, AICIT, vol.6, no.2, pp.172-182, 2011.
[14] Shih-Jung Wu, “Fuzzy-Based Handover Decision Scheme for Next-Generation Heterogeneous Wireless Networks”, “Journal of Convergence Information Technology”, AICIT, vol.6, no.4, pp.285-297, 2011.