Optimization of Personalized Recommendation Strategy for E-commerce Platform Based on Artificial Intelligence

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This article addresses the problems of "resource overload" and "information confusion" in the current e-commerce platform. This paper proposes a personalized recommendation strategy for e-commerce platform based on artificial intelligence considering the collaborative filtering method as the basic algorithm. The article proposes an optimized strategy using artificial intelligence to obtain satisfactory results. Based on this proposed personalized recommendation model, users are clustered by using ontology context information, further considering the influence of user preference and user trust relationship on similarity calculation. This method can alleviate the problems of data sparsity and cold start to a certain extent, effectively improve the recommendation quality. It further increases the diversity of recommendation results, and meet the needs of users and enterprises. Through the change of parameter α under different data sets, when $\alpha \in (1.84,1.88)$, the accuracy and recall rate of recommendation results remain at a high level. The personalized recommendation method can be applied to various situations such as social network friend recommendation and e-commerce platform commodity recommendation. The proposed work has a wide range of applications, especially for enterprises that master the user's rich dimensional situation information. This method has a prominent recommendation effect with the help of detailed analysis of the user's complex situation.

Povzetek: Članek obravnava težave preobremenitve z viri na obstoječih e-trgovinskih platformah. Predlaga se strategija personaliziranega priporočanja, ki temelji na umetni inteligenci in algoritmu kolaborativnega filtriranja.

1 Introduction

Artificial intelligence (AI) is a frontier science and interdisciplinary subject. At present, there is no unified theoretical system or even a unified definition in the world. Generally, it can be considered that artificial intelligence is a new technical science to study and develop theories, methods, technologies and application systems for simulating, extending and expanding human intelligence. As a branch of computer science, its main research contents include robot, language recognition, image recognition, natural language processing and expert system. Artificial intelligence is a simulation of human consciousness and thinking process. Although it is not human intelligence, it can simulate human thinking process and even surpass human wisdom in the future [1]. Artificial intelligence has gone through a long development process since its birth. We can sort out the context of the development of artificial intelligence from the two dimensions of time and technology. From the technical dimension, some scholars divide the development of artificial intelligence into three stages: computational intelligence, perceptual intelligence and cognitive intelligence. Computational intelligence is the primary stage of artificial intelligence. It mainly refers to the intelligence presented by the computer through its super large memory and supercomputing function. In this stage, logic is emphasized, but knowledge is ignored. Perceptual intelligence means that computers can simulate human perception with the support of big data, deep learning algorithms and other technologies, and then complete some tasks that originally need to be completed by humans, such as language recognition, image recognition, AR / VR and other technologies. Cognitive intelligence is not only the ultimate goal of the development of artificial intelligence, but also a key research field that people are committed to breaking through at present. It aims to enable computers to think and reason like people [2]. Since the concept of personalized recommendation was first proposed in the 1990s, it has quickly become a hot topic in academia, industry and other fields, and has maintained a high research heat. The core of personalized recommendation system is machine learning user interest. It is an advanced business intelligence platform based on massive data mining to help e-commerce websites provide fully personalized decision support and information services for their customers [3]. In essence, personalized recommendation system is to replace users to evaluate products they have never seen, automatically complete the process of personalized selection, help users explore interest, stimulate purchase desire and meet their personalized needs. At present, personalized recommendation system is widely used, especially in the field of e-commerce. Businesses analyze their interests and hobbies according to the browsing, clicking, collection, purchase and other behaviors of e-commerce users, and recommend products that they may be interested in (such as daily necessities, books, audio-visual products, etc.). For businesses, the needs of users are usually unclear and vague. If the goods that meet the fuzzy needs of users can be recommended to users, the potential needs of users can be transformed into real needs, so as to improve product sales [4].

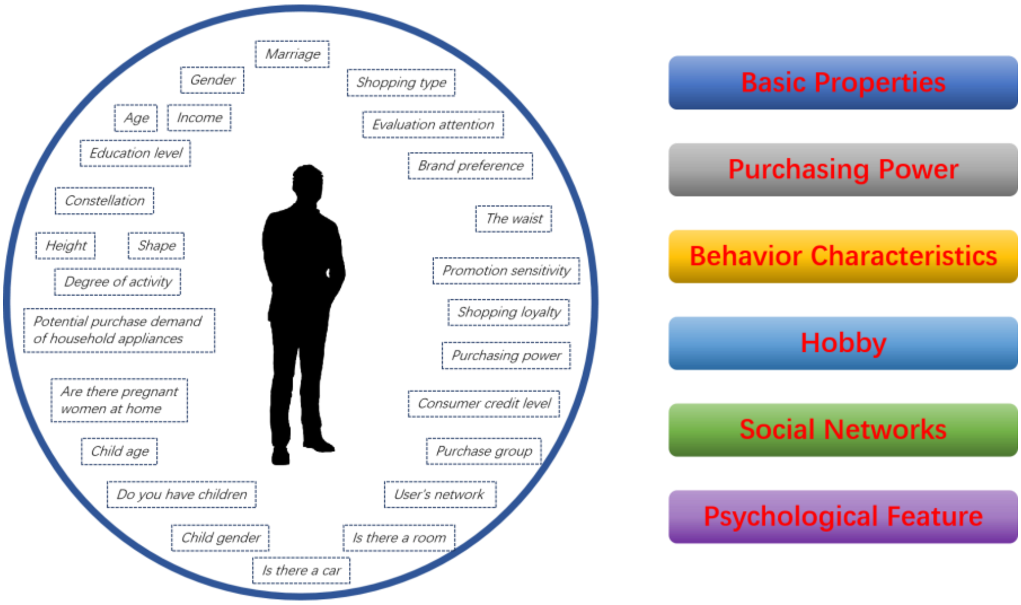

Figure 1: Concept diagram of personalized recommendation of e-commerce platform.

The core of personalized recommendation system is personalized recommendation method, which determines the quality of recommendation service. Figure 1 shows the concept of personalized recommendation of e-commerce platform.

This article contributes in addressing the problems of “resource overload” and “information confusion” in the current e-commerce platform. A personalized recommendation strategy for e-commerce platform based on artificial intelligence is proposed, considering the collaborative filtering method as the basic algorithm. The article proposes an optimized strategy utilizing the personalized recommendation model in which users are clustered by using ontology context information. This method can alleviate the problems of data sparsity and cold start to a certain extent, effectively improve the recommendation quality. It further increases the diversity of recommendation results, and meet the needs of users and enterprises. The proposed work has a wide range of applications, especially for enterprises that master the user's rich dimensional situation information.

The rest of this article is structured as: section 2 presents the literature review followed by the explanation of collaborative filtering method in section 3. Section 4 presents the results of the experimentations performed and the conclusion is provided in section 5.

2 Related work

In this section various state-of-the-art work in the field of personalized recommendation based on Artificial Intelligence are discussed.

Meng said that personalized recommendation methods originated from data mining technology. Scholars' research on personalized recommendation methods is more to improve and innovate them from the technical level [5]. In the era of e-commerce, enterprises provide a large number of goods to consumers through self-built e-commerce platforms or third-party e-commerce platforms. Dong and Zhou said that from the perspective of consumers, although rich goods increase consumers' selectivity. However, usually consumers cannot understand all the goods at a glance through the screen, nor can they directly check the quality of the goods. It takes a lot of time to fully understand these goods [6]. Therefore, Sanda *et al.* proposed that consumers need an e-shopping assistant, which can recommend products that consumers may be interested in according to their own interests [7]. Wei believe that personalized recommendation methods can help both e-commerce enterprises and traditional enterprises to quickly and accurately find the potential needs of users in an increasingly fierce competitive environment and meet the differentiated characteristics of users [8].

Aftalion and Bonnans said that the emergence of personalized recommendation can also solve the problems of “resource overload” and “information confusion” faced by users, and help individual users quickly and accurately obtain useful content from a large amount of information. In conclusion, the research on personalized recommendation is of great necessity [9]. Wei and Meng believe that with the popularization and deepening of e-commerce application in people's daily life, consumers put forward higher requirements on how to more conveniently and quickly obtain the information resources they need, and the recommendation effect of traditional personalized recommendation methods in some scenarios is not satisfactory [10]. Lv said that at the same time, the concept of ubiquitous computing and the rise of ubiquitous commerce, a new business model, have made scholars fully realize that users' environmental information will have an important impact on their consumption decisions [11]. Therefore, Alhamid et al. said that personalized recommendation research based on social network context will be paid more and more attention [12]. Rana et al. said that in the e-commerce environment, especially in the mobile commerce environment, users' mobility, diversity of needs and dependence on context are particularly prominent [13]. Zhao said that the emergence of personalized recommendation service is to analyze and model consumers' historical behavior data with the help of certain methods or tools, evaluate consumers' preferences, and recommend products that target users may like [14]. Therefore, the explicit preference theory shows that the personalized recommendation method is reasonable and scientific. An approach through wavelet frames on the micropolar fluid flow is presented which is considered for high mass transfer [15]. The vibration on laminated skew sandwich plates is studied through finite element [16]. In another study numerical simulation based on space time fractional equation are evaluated [17]. The work can further be experimented with the integration of other Artificial Intelligence approaches and Machine learning as studied from several studies [18-20].

3 Collaborative filtering method

The memory-based method is also known as the user based collaborative filtering method. Its recommendation calculation depends on the user's evaluation of the commodity rather than the content information of the commodity itself. Its logical order is to first find other users with similar interests with the target user, and then use the scoring information of the commodity to make relevant prediction [21]. The main idea is to determine the nearest neighbor set by calculating the similarity between users, then predict the preference of the target user according to the score of the nearest neighbor on the commodity, and recommend the first several items with the highest prediction score to the user. For example, in an e-commerce website, the system predicts the possible interests and hobbies of the target user according to the scoring information of all over hit products and the similarity between users, and displays these products in the user's personal account [22]. It is assumed that there is a set of users $U = \{u_1, u_2, \dots, u_m\}$, a collection of goods (objects) $O = \{o_1, o_2, \dots, o_n\}$, $R_{i,j}$ indicates that the selected target user i scores the unselected product j, which needs to be obtained through the scoring prediction of the product by his similar users [23]. If U' represents the user set with the highest similarity with the target user i, the functional expression of the prediction score $R_{i,j}$ is as follows:

$$R_{i,j} = \frac{1}{m} \sum_{u \in U'} R_{u,j} \tag{1}$$

Where m is the number of users in U', and the prediction calculation is based on the simplest weighted average. In addition, there are other improvements based on weighted calculation, such as considering the influence of time factors to form a new expression:

$$R_{i,j} = \frac{1}{m} \sum_{u \in U'} \left(R_{u,j} \times Q_{u,j} \right) \tag{2}$$

Where Q represents a time series, and $Q_{u,j}$ represents the time point at which user U' selects or evaluates commodity j. Compared with formula 1, formula 2 incorporates the influence of time factors to improve the accuracy of recommendation [24].

In addition to the weighted prediction score, the most important thing is the similarity measurement between users. Similarity measure is to calculate the degree of similarity between individuals. The smaller the value of similarity measure, the smaller the similarity between individuals. The larger the value of similarity, the greater the individual difference. At present, there are many methods, among which the thre most commonly used methods are cosine similarity, Pearson correlation and jacquard correlation coefficient [25]. In fact, the value range of correlation is - 1 to 1. A positive value indicates that there is a positive correlation between the two vectors (variables), i.e., changes in the same direction, and a negative value indicates that there is a negative correlation between the two vectors (variables), i.e., changes in the opposite direction. In personalized recommendation, similarity generally only considers the positive relationship, and the corresponding similarity value range is 0 to 1. 0 means no similarity and 1 means complete similarity. Cosine similarity uses the cosine of the angle between two vectors in vector space as a measure of the difference between two individuals. The closer the cosine value is to 1, the closer the included angle is to 0 degrees, which means that the two vectors are more similar. Cosine similarity can be used in vector comparison in any dimension, especially in high-dimensional positive space. For example, in information retrieval, each term has different degrees. A document is represented by a weighted feature vector, and the calculation of the weight depends on the frequency of the term in the document [26]. Cosine similarity can give the similarity of two documents in terms of their topics. The expression formula of cosine similarity is:

$$Sim(i, f) = \frac{\sum_{j \in O(i) \cap O(f)} R_{ij} \cdot R_{fj}}{\sqrt{\sum_{j \in O(i) \cap O(f)} R_{ij}^2} \cdot \sqrt{\sum_{j \in O(i) \cap O(f)} R_{fj}^2}} \tag{3}$$

Where $Sim(i, f)$ represents the similarity between user i and user f (the value range of similarity is 0 to 1 and is a continuous value, 1 represents that the two users are completely similar, 0 represents that they are completely dissimilar). $O(i)$ and $O(f)$ represent the set of goods selected by user i and user f respectively. R_{ij} and R_{fj} represent the scoring (evaluation) of product j by user i and user f respectively [27]. The advantage of cosine similarity is that it distinguishes differences in direction and is not sensitive to absolute values. Users' ratings of content are more used to distinguish similarities and differences of interest. It is precisely because cosine similarity is not sensitive to numerical values, that is, the difference of user rating scale is not considered, which also reduces the accuracy of user similarity calculation results. The emergence of Pearson correlation is to solve the problem of the difference of user scoring scale. The calculation results are corrected by subtracting the average score of the user for all items from each element in the user scoring vector [28].

Pearson correlation is a kind of linear correlation, which is a statistic used to reflect the linear correlation degree of two variables. In the standard formula, R is used to represent the correlation coefficient between vectors, n is used to represent the total number of samples, and X, Y, X' *and* Y' are used to represent the observed values and mean values of the elements in the two vectors respectively. R describes the degree of linear correlation between two vectors. The greater the absolute value of R, the stronger the correlation. The smaller the absolute value, the weaker the correlation. The expression formula of Pearson correlation is [29]:

$$Sim(i, f) = \frac{\sum_{j \in O(i) \cap O(f)} \left(R_{ij} - \overline{R}_i\right) \cdot \left(R_{fj} - \overline{R}_f\right)}{\sqrt{\sum_{j \in O(i) \cap O(f)} \left(R_{ij} - \overline{R}_i\right)^2} \cdot \sqrt{\sum_{j \in O(i) \cap O(f)} \left(R_{fj} - \overline{R}_f\right)^2}} \quad (4)$$

Where $Sim(i, f)$ represents the similarity between user I and user f, $O(i)$ and $O(f)$ represent the set of products selected by user i and user f respectively, R_{ij} and R_{fj} represent the scoring (evaluation) of product j by user i and user f respectively, and $\overline{R_i}$ and $\overline{R_f}$ represent the average score of all products by user i and user f respectively [30]. Jackard correlation coefficient was originally used to measure the similarity between two sets, which was defined as the ratio of the intersection of sets to the union of sets. The expression formula of jacquard correlation coefficient is:

$$Jaccard(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (5)$$

Where $Jaccard(A, B)$ represents the similarity between sets A and B. If sets A and B are empty, $Jaccard(A, B) = 1$ is defined. Obviously, $0 \le Jaccard(A, B) \le 1$, the larger the value, the more similar the two data sets [31]. Jackard correlation coefficient is actually more suitable to describe the similarity measure between vectors with discrete dimension characteristics. For the user similarity calculation in the collaborative filtering method, discrete data such as user score information are used, which is very suitable to use the $Jaccard$ correlation coefficient [32].

4 Results and analysis

This section presents the result analysis obtained for from the proposed model of personalized recommendation based on Artificial Intelligence.

Parameter α is involved in collaborative filtering recommendation model, and its optimal value needs to be determined through experiments. The optimal value range of α should be between 1.6 and 2. A positive value of parameter α indicates that unpopular goods contribute more to the similarity between the two users and popular goods contribute less. In order to quickly find the optimal value of parameter α, we still use the idea of binary search in the iterative process. Considering that the parameter value will take two decimal places, the spacing between each value in the iteration is set to 0.01, that is, the step size is 0.01 [33, 34]. The above strategy can effectively reduce the computational complexity and memory consumption. Figure 2 and 3 show the change of test index ranking score of the improved collaborative filtering recommendation method with the change of parameter α value under different data sets (recommendation list length L = 50). It can be seen from the figure that when α = 1.86, the ranking score under the two data sets reaches the minimum, that is, the products potentially liked by users are ranked in the high position. The results show that the unpopular goods contribute more to the similarity calculation between two users. This method can find the unique interests of users, improve the accuracy of recommendation results and increase the diversity of recommendation results. Of course, in practical application, users can also adjust the value of parameter α according to their own needs [35, 36].

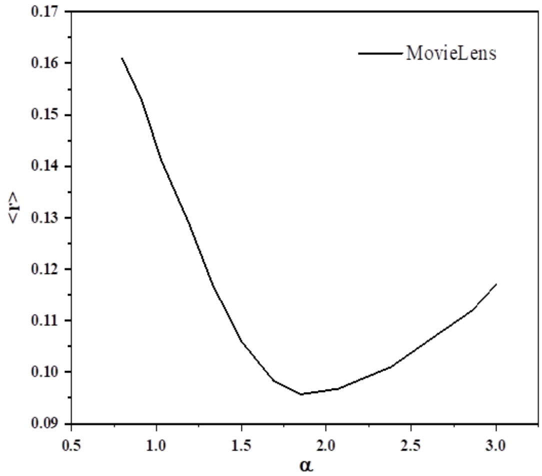

Figure 2: Performance influence curve of different values of parameter α in movie lens dataset on the recommended method.

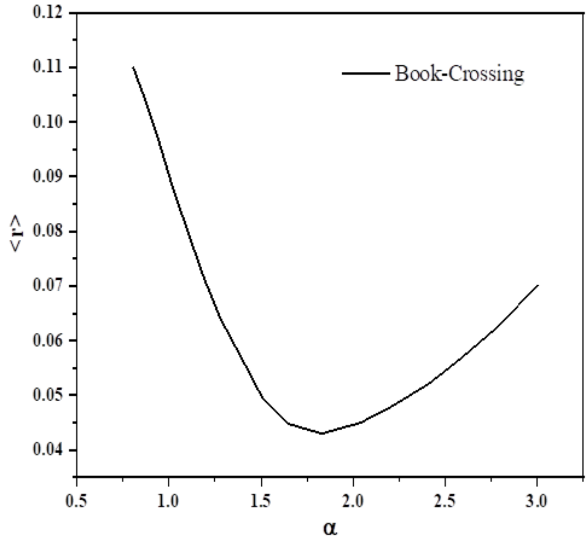

Figure 3: Performance influence curve of different values of parameter α in Book Crossing dataset on the recommended method.

When the data sets movie lens and Book Crossing and the length L of recommendation list are 50, when the parameter value is 1.86, the ranking score $(< R >)$ reaches the minimum. The current experimental results come from the average of 5 random segmentation of data according to 80% test set and 20% training set. Accuracy and recall are often used to measure the effectiveness and efficiency of recommended methods.

When the length of the recommendation list is increased, the number of hits of potentially favorite products by users can be increased, thus improving the recall rate, but it may reduce the accuracy of recommendation (facts have proved that increasing the recall rate will basically reduce the accuracy rate). Therefore, it is necessary to find a balance between accuracy and recall, so as to have high accuracy and high recall at the same time. Under an appropriate recommendation list length, the accuracy reflects the precision of the recommended method, and the recall reflects the recall of the recommended method. Generally speaking, the length of the recommendation list shall not exceed 100, that is, the number of recommended products shall not exceed 100. Figures 4 and 5 show that under the movie lens data set, corresponding to the length of the recommendation list L = 50, the standard accuracy and recall rate of the test index change with the change of the parameter α value. It can be seen from the figure that when the parameter α = 1.86, the accuracy and recall of the recommended results reach the highest. In addition, when α ∈ (1.84,1.88), the accuracy and recall of the recommended results remain at a high level.

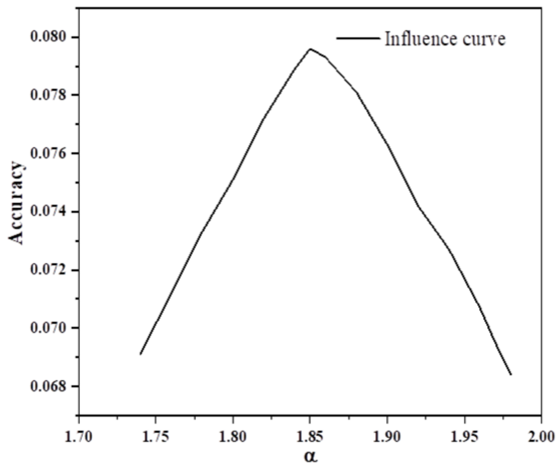

Figure 4: Influence of different values of parameter α on the accuracy of the recommended method.

Under the condition that the data set movie lens and the length of recommendation list L = 50, when the parameter value is 1.86, both indicators reach the highest value. The current experimental results come from the average of 5 random segmentation of data according to 80% test set and 20% training set.

Figures 6 and 7 show that under the book crossing data set, corresponding to the length of the recommendation list L = 50, the standard accuracy and recall of the test index change with the change of the parameter E value. It can also be seen from the figure that when the parameter α = 1.86, the accuracy and recall of the recommended results reach the highest at the same time. In addition, when α ∈ (1.84,1.88), the accuracy and recall of the recommended results remain at a high level.

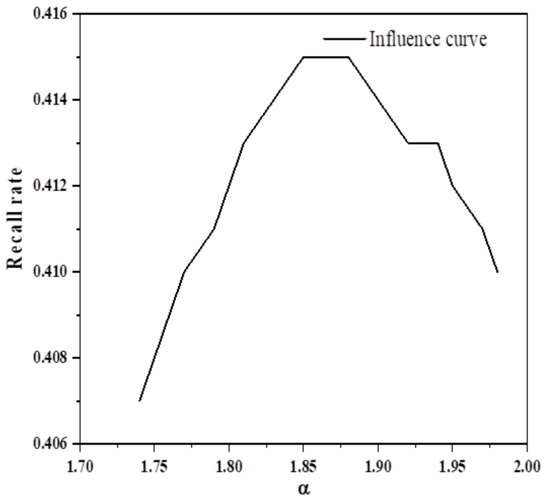

Figure 5: Effect of different values of parameter α on the recall rate of the recommended method.

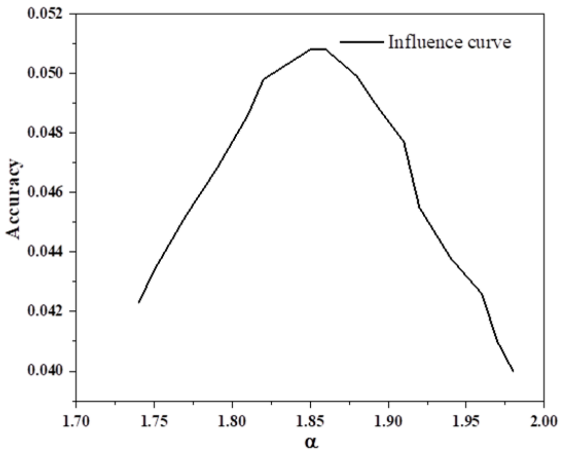

Figure 6: Influence of different values of parameter α on the accuracy of the recommended method.

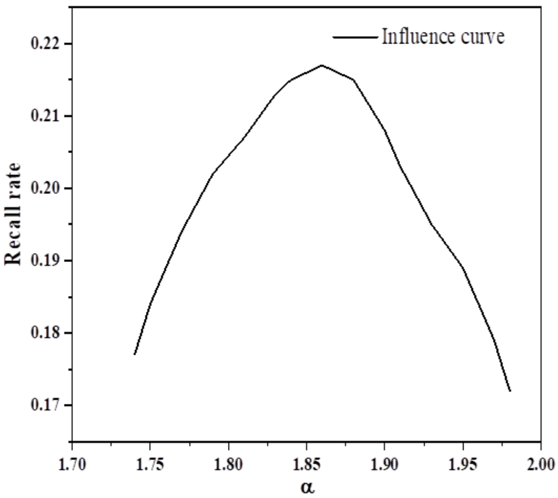

Figure 7: Effect of different values of parameter α on the recall rate of the recommended method.

When the data sets movie lens and Book Crossing and the length of recommendation list L are 50, when the parameter value is 1.86, both indicators reach the highest value. The current experimental results come from the average of 5 random segmentation of data according to 80% test set and 20% training set.

Through the test of the above three indicators (mainly measured by accuracy indicators), we iteratively obtain that the optimal value of the parameters in the model is 1.86. At this value, our recommended method achieves the optimal accuracy and the highest recall rate.

5 Conclusions

The development of e-commerce, especially the rapid development of mobile commerce, has brought greater challenges and opportunities to personalized recommendation services. The research on Personalized Recommendation theory and technology has attracted great attention of global academic circles. The research on Personalized Recommendation Based on context perception and personalized recommendation based on social relations in e-commerce environment has become a research hotspot. By comparing the parameters under different data sets α, the optimal value of the parameters in the model of 1.86 is achieved. Although some research results have been obtained, there are still some challenges in both theoretical research and practical application, especially for personalized recommendation in the field of e-commerce. There are few methods to integrate ontology situation, context situation and social relationship situation, lack of effective treatment of user interest drift, and lack of targeted recommendation strategy design for enterprises on demand. Therefore, it has become an important task to study a variety of personalized recommendation methods to meet the needs of different enterprises.

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