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Retraction

Retracted: Precision Marketing Optimization Model of e-Commerce Platform Based on Collaborative Filtering Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Yu, "Precision Marketing Optimization Model of e-Commerce Platform Based on Collaborative Filtering Algorithm," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2906955, 10 pages, 2022.

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Research Article

Precision Marketing Optimization Model of e-Commerce Platform Based on Collaborative Filtering Algorithm

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e-commerce mode shows great modern commercial value. In particular, online shopping has become a fashion and trend for people because of its convenience and rapidness. How to find the information users that need accurately and quickly in the increasing network information and recommend products is a big problem. Although precision marketing was mainly used in e-commerce activities in the past, due to factors such as the technical basis and data analysis ability at that time, there was not enough technical ability and theoretical basis to deeply mine and make use of the existing data. The collaborative filtering algorithm is one of the most widely used and successful recommendation techniques, but it has obvious defects. In this paper, the nearest neighbor collaborative filtering recommendation algorithm based on statistical eigenvalue classification is proposed in the collaborative filtering algorithm. By calculating the similarity between items, the user's rating of unrated items is preliminarily predicted, the nearest neighbor of items is formed, and the classified cluster of items is formed. The matrix is filled by the similarity between related items. The cold treatment problem is solved under the optimization of the ant colony algorithm. In the experiment of the model, the optimization rate for the cold start problem is 87.3%.

1. Introduction

With the development of e-commerce in my country, the popularization of computer information technology, and the Internet, the marketing system in the new era has also developed significantly [1]. The total online retail sales have accounted for one sixth of the total retail sales of social consumer goods [2]. e-commerce has become a powerful boost to China's consumption and economic growth [3]. After nearly two decades of development, China's e-commerce market is basically mature. A retail system represented by online retail giants such as Taobao, http://jd.com, and Amazon has been formed in China, and the industrial competition pattern has been basically formed [4]. For a large number of network and information resources, the precision marketing system is a good carrier. It can provide users with more convenient and personalized services. According to the different needs of users, it can flexibly adjust various information services. It is said that the precision marketing system is an effective method and means to solve the problem of information overload [5]. However, the sharp increase is not only the number of users but also a variety of products and accumulated user transaction data. As a result, users have to spend a lot of time to choose the product that suits them in such a variety of products and massive data [6]. The business recommendation system can not only quickly help customers find the required commodity information in a variety of complex information but also compare the commodity information and help customers judge [7]. For merchants, the recommendation system can also record customer information and can also carry out corresponding business promotion activities to customers through the platform and lay the foundation for recooperation with customers [8]. In order to better attract customers, help customers find the products they need and improve the quality of sales, and product recommendation systems are gradually being applied to e-commerce websites [9]. The recommendation system plays a role similar to that of a shopping guide in the e-commerce system. It actively recommends different products for different users according to their preferences.

The traditional marketing method has large capital investment, single form, high cost, and unsatisfactory effect. For enterprises, the return on investment is not high. With the development of the Internet, big data technology is becoming more and more mature, and the combination of e-commerce and big data has an impact on the traditional medical device industry, gradually transforming the marketing mode of wide distribution and high investment to an accurate and refined marketing mode that can improve the return on investment, actively tap the needs of consumers, and meet the personalized needs of consumers. At present, the key problems in the economic environment are that the competition in the industry is more complex, the previous marketing model is relatively weak, and the phenomenon of homogeneity is more serious [10]. The biggest problem with the marketing methods of electronic part market is the thinness of marketing forms, and most of them still adopt the traditional marketing system as the center [11]. The collaborative filtering recommendation system is one of the most widely used and successful recommendation systems at present. It is applied to all fields of life [12]. Memory-based collaborative filtering algorithms are recommended based on user item ratings and are divided into user-based collaborative filtering algorithms and item-based collaborative filtering algorithms.

Collaborative filtering, also called social filtering, provides users with personalized service and filtering through similarity principle. The similarity principle of collaborative filtering holds that if users' ideological level, values, and knowledge level are similar, then they will have the same or similar information needs [13]. In a very large optional space, any system that can output personalized recommendations or provide a method to accurately guide users to find information they are interested in or useful [14]. These systems have a remarkable characteristic in the use environment; that is, the information currently possessed by the network far exceeds the ability of users to retrieve the exact required information. With the improvement of customer demand, customers need high-quality recommendations. With the development of data mining technology, its application can make the system know more about customers' demand indicators, understand customers' needs more reasonably and comprehensively, recommend their favorite products to customers, improve the recommendation quality, and enhance the pertinence of e-commerce. Because collaborative filtering algorithm also has some problems, such as lack of cold start, real-time recommendation, and user emotional factor analysis, this paper puts forward some innovations in the following points:

① This paper proposes an item nearest neighbor collaborative filtering recommendation algorithm based on statistical eigenvalue classification. By calculating the similarity between items, the user's rating for unrated items is preliminarily predicted, the nearest neighbors of the items are formed, and the classified item clusters are formed. The similarity relationship between related items is filled in a matrix.

② Based on the traditional collaborative filtering recommendation algorithm, a hybrid collaborative filtering recommendation algorithm combining time and knowledge reasoning is proposed. The algorithm combines time filtering function to solve the problem of users' interest changing with time and combines knowledge-based recommendation algorithm to solve the problems of cold start and data sparsity.

The chapters of this paper are arranged as follows: The first chapter of this paper is the introduction, which discusses the background and significance of the topic selection of the paper and expounds the innovation points of the paper. The second chapter is the main body of this paper. It mainly combines the research results of collaborative filtering algorithm at home and abroad in the field of precision marketing of e-commerce and proposes innovative results and research ideas of this paper. The third chapter is the method part, which deeply discusses the application and principle of relevant algorithms and puts forward a new e-commerce precision marketing model based on the previous research results and the innovation of this paper. The fourth chapter of this paper mainly discusses the experimental part of the application of the algorithm. Through the experimental results and on the basis of sorting out the data, this paper establishes the e-commerce precision marketing model. The fifth chapter is the conclusion, which summarizes the research achievements and shortcomings of this paper and the prospect of the follow-up research.

2. Related Work

In the analysis, Zhan et al. discussed the definition of cross selling of "precision marketing business," which belongs to a scheme with certain practical value "Banks in the sale of various products, the seller of credit products sales transactions, easy to accept the relevant product introduction." After searching for products and services, we recognize the various needs of consumers and the most common in this process is cross selling [15]. Guan has established a corpus of user comment sentiment tendency, extracted the corpus words in previous user comments and formed a score according to the fuzzy algorithm, used the cloud model to form a user comment sentiment tendency vector, and formed the nearest neighbor by calculating the similarity between the cloud model vectors. Form a recommendation [16]. Geng et al. think that based on the similarity between products in product recommendation, according to the products you buy, find those similar products and recommend them. In model-based recommendation, prior knowledge is used to construct a model for recommendation and at the same time, the model needs to change with the change of users' preferences [17]. Jiang et al. believe that there are mainly two types of recommendation systems at present. One is the recommendation system with commodities as the recommendation object in the online shopping environment, which recommends products in line with users' hobbies, such as various books and audio-visual products. The other is the personalized recommendation system with web pages as the object, which mainly adopts the tail data mining method to recommend web pages in line with users' interests [18]. By analyzing the differences in mobile marketing strategies under different types of e-commerce platforms, it is helpful to inspire some e-commerce platforms according to the type of their own platforms, combined with the characteristics and advantages of mobile marketing, in differentiated marketing strategies for the development of mobile terminals of e-commerce platforms [19]. Khursan et al. think that with the increasingly fierce competition of e-commerce, enterprises are more and more eager for new marketing methods, and precision marketing is of great significance for e-commerce activities that can directly face customers. The guiding significance of direct contact with its customers has increased the stickiness of enterprises to customers [20]. Ren et al. put forward the marketing strategy, which mainly studies the various situations faced by the enterprise's marketing under the current market conditions. In other words, the marketing strategy mainly studies how to accurately understand, analyze, select, and seize market opportunities to meet the shopping needs of consumers in the market environment and marketing environment, so as to maximize the wealth of enterprises and make their long-term survival and development [21]. The development of the theory and system of precision marketing by Mitenkova et al. is exactly the marketing theory developed on the basis of catering to the current trend of consumer demand diversification. The development of the precision marketing theory system requires powerful tools for collecting and analyzing consumer behavior. The collaborative filtering algorithm is just such a tool; so, the two can be deeply combined [22]. Li thinks that there are three common problems in recommendation system: data sparsity, cold start, and scalability, which will directly affect the accuracy of recommendation. Therefore, how to overcome these problems, consider a variety of recommendation-related factors at the same time and improve the recommendation quality while ensuring the privacy of users is very important [23]. Sánchez-Ramírez et al. proposed that with the development of information technology, information sharing not only brings convenience to people but also brings certain harm. For example, online fraud and phishing damage the interests of consumers everywhere, so that people have to pay attention to the security of their own information while engaging in e-commerce. How to protect the privacy of customers and the security of important information such as accounts is also an important topic to be faced by e-commerce [24]. Hancová et al. analyzed the characteristics of data sets representing user preference information and compared two algorithms, user-based collaborative filtering and item-based collaborative filtering, as well as their commonalities and differences in recommender system applications. Based on the existing points, advantages, and disadvantages, an improved combination algorithm is proposed [25]. Raj and Mohanasundaram think of mobile Internet and big data. His book "Mobile Internet Thinking: Business Innovation and Reconstruction" points out the differences between mobile Internet thinking and Internet thinking and puts forward the "9H" model of mobile Internet thinking with emphasis has guiding significance for traditional enterprises to realize the transformation of mobile Internet [26]. Gaber et al. analyze not only the purchase behavior but also the corresponding purchase psychological expectation, so that businesses can provide accurate marketing strategies. So as to finally achieve the goal of win-win for consumers and businesses. Further elaborated on precision marketing, he believed that precision marketing is to achieve precise positioning through technical means [27].

Based on the research of the abovementioned related work, this paper determines the positive role of the collaborative filtering algorithm in the field of e-commerce precision marketing and builds a collaborative algorithm model that combines multiple algorithms: in-depth analysis and research, more effective use of data, mining of valuable knowledge hidden behind data, and discovery and identification of potential problems that affect precision e-commerce marketing.

3. Methodology

3.1. Research and Analysis of Related Theories

3.1.1. Collaborative Filtering Algorithm in Electronic Commerce. With the rapid development of the Internet, e-commerce has also developed in a coordinated way. In recent years, with the popularization and development of the network and the improvement of computer data storage capacity, especially the development of big data and cloud computing, a large amount of data information has been generated in the network. The definition given by Precision Association is as follows: precision includes two aspects: user information and technology, through which the online connection between business and customers can be built. From the above definitions, we can see that precision is mainly composed of two aspects: targeted, which can provide different services according to the needs of different users, and automatic, which can be automatically provided to users through the analysis of past historical data. Precise service is as follows: usually, collaborative filtering methods first analyze the correlation between users and products in the collected scoring data and then generate personalized product recommendations for users according to this correlation.

User-based collaborative filtering methods, product-based collaborative filtering methods, and model-based collaborative filtering algorithms have their own advantages. But generally, there are the following problems: First, the cold start problem is as follows: for a new user, the collaborative filtering algorithm cannot make similar recommendations based on its past behavior. Similarly, for new products, the algorithm cannot accurately recommend them to those users who need them. Then, data sparseness is as follows: although there are countless users, products, and corresponding interactive data in the field of e-commerce, there are very few users who are really willing to give display ratings, which will make the user product matrix extremely sparse and make the efficiency lower. Finally, scalability is as follows: With the rapid expansion of the interactive data between users and products in e-commerce, the user product matrix obtained by the traditional collaborative filtering algorithm will also become a very large matrix, which will lead to the difficulty of storage and the efficiency of operation. Table 1 below shows the scoring matrix of users and products.

The above R represents the rating of a certain user U on the product I, and this rating can be regarded as the user U's selection and preference for the product I. Thereby, a set of "nearest neighbors" can be formed; that is, a set of so-called shortest distances set to find the most similar set. Generally, cosine similarity can be used to judge the similarity of users, which is expressed as follows:

$$sim\left(\bar{u}_i, \bar{u}_j\right) = \frac{\bar{u}_i \bullet \bar{u}_j}{\|\bar{u}_i\| * \left\|\bar{u}_j\right\|}. \quad (1)$$

The numerator is the inner product of two user rating vectors, and the denominator is the product of two user vector modules. In addition, the correlation similarity can measure the parameters of user evaluation. When collecting the intersection of scores, the similarity between users can be expressed as follows:

$$w(a, i) = \frac{\sum_{j\in I_a \cap I_i}\left(r_{aj} - \bar{r}_a\right)\left(r_{ij} - \bar{r}_i\right)}{\sqrt{\sum_{j\in I_a\cap I_i}\left(r_{aj} - \bar{r}_a\right)^2 \sum_{j\in I_a \cap I_i}\left(r_{ij} - \bar{r}_i\right)^2}}, \quad (2)$$

where $\bar{r}_a, \bar{r}_i$ is the average score of user a, i. According to the size of $w(a, i)$, N similar users are selected as the nearest adjacent set of target users. The resulting recommendation effect can also be expressed as follows:

$$P_{u,j} = \bar{r}_a + k \sum_{i=1}^{N} w(u, i)\left(r_{ij} - \bar{r}_i\right). \quad (3)$$

Through the above calculation, the information required by the user can be obtained; that is, the top-N items with the highest scores are used as the recommended result to the target user.

3.1.2. Precise Marketing Optimization Recommendation. Generally, precision marketing is defined as follows: by improving the marketing performance goal and planning to provide information or services to potential target consumers, so that consumers' purchasing intention will be influenced imperceptibly. Its purpose is to realize low-cost expansion, realize customized product requirements of customers, and establish a personalized communication service system for customers. Therefore, we can also see that customers are the core element of precision marketing. Figure 1 below shows the basic process of collaborative filtering recommendation.

As can be seen from the concept, the key point of precision marketing is the word "correct," which emphasizes the degree of precision and accurate judgment. Precision marketing generally has the following characteristics: The first is the measurability of the effect. Because the marketing links are controllable and the results can be measured, the marketing workers can carry out supporting experiments and testing activities on the relevant influencing factors, and the obtained results will moderately control the previous marketing strategies to ensure that the marketing strategies can achieve a more ideal state. Secondly, it is targeted at the target group. This is also the core point of precision marketing, which effectively divides relevant target and nontarget consumers and only carries out supporting communication work for target groups. Then, it is the reasonable control of the cost. After exploring the relevant target audience, it needs to try to control the waste problems and achieve a more ideal return on investment. Finally, there is the dynamics of precision. This is very important, because the precision marketing system cannot be achieved overnight; so, it needs to be developed gradually and can only be developed on the basis of huge data. Moreover, the accuracy is not absolute. Generally, it belongs to the scope or reasonable range, and the applicability scheme is obtained after proper matching and adjustment. Only in this way can the supporting marketing activities be carried out more accurately than in the past; so, the whole process is dynamic rather than static.

Table 1: is a schematic diagram of the rating matrix of users and products.

	I_1	I_2	...	I_t
U_1	$R_{1,1}$	$R_{1,2}$	...	$R_{1,t}$
U_2	$R_{2,1}$	$R_{2,2}$	...	$R_{2,t}$
...	...	...	...	...
U_s	$R_{s,1}$	$R_{s,2}$	...	$R_{s,t}$

Data cleaning completes the removal of traces of temporary data and realizes the recording of error logs and the backup of request interface. After the user visits some webpages, such as some pictures and videos, the data occupies a large amount of storage, and the information will be automatically downloaded when browsing the webpage next time. These data have no reference value and also affect the recommendation efficiency and quality. The reference value of precision marketing is too small. The flow chart of the data cleaning and purification algorithm in this part is shown in Figure 2.

3.2. Algorithm Design of Optimization Model. After understanding the relationship between precision marketing and collaborative filtering algorithm, it is necessary to design the algorithm part of the optimized model to effectively solve or improve the problems of cold start and data sparseness in previous collaborative filtering algorithms. The attribute set of the item itself is $T = \{T_1, T_2, \cdots, T_n\}$, and the item set is $I = \{I_1, I_2, \cdots, I_m\}$. The rows of the matrix represent different items, and the columns of the matrix represent different attributes of each item. A_{ji} represents whether the j item has

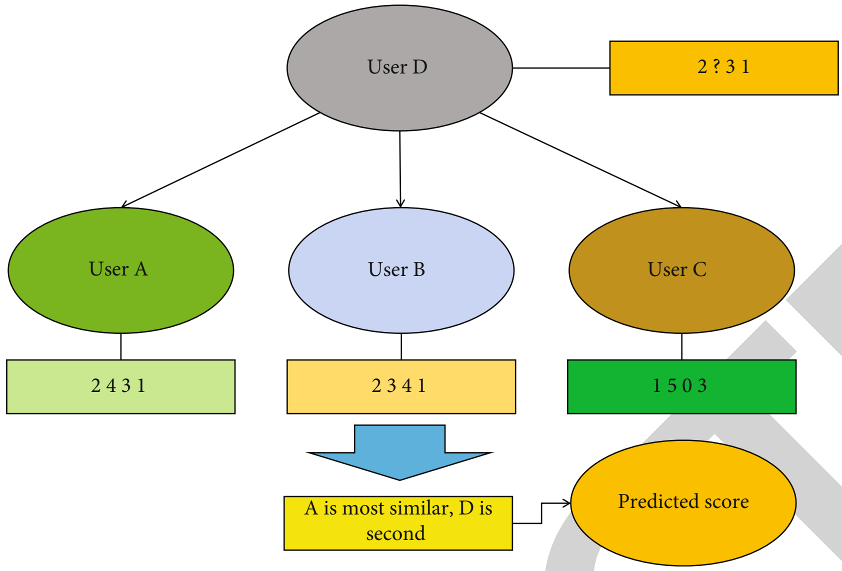

FIGURE 1: The basic process of collaborative filtering recommendation.

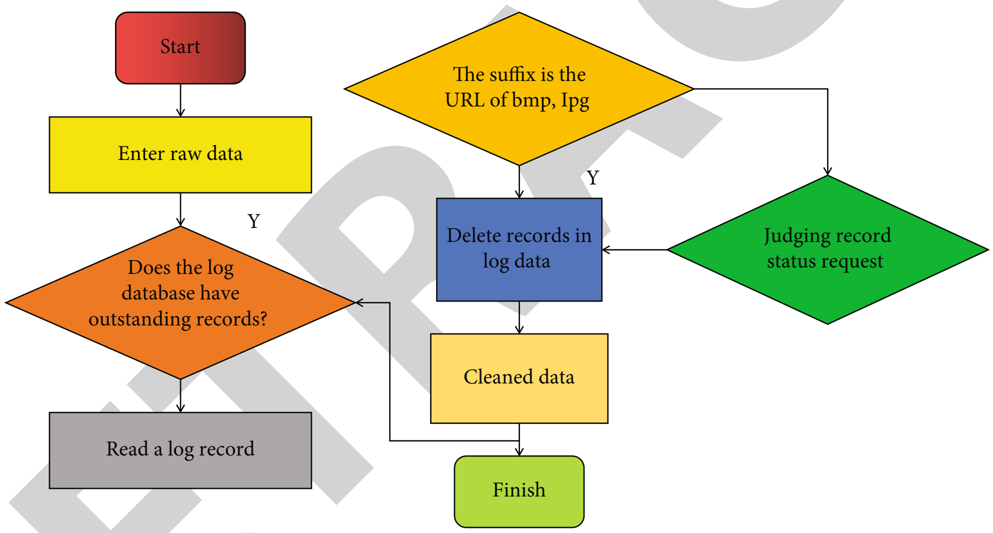

FIGURE 2: Flowchart of data cleaning and purification algorithm.

the attribute of i and can only take 0 or 1. When the j item has the attribute of i, take 1; otherwise, take 0. Since the value of A_{ji} can only be 0 or 1, we can use logical symbols for operation. At this point, the attribute similarity can be as follows:

$$sim_u(I_t, I_p) = \frac{\sum_{i=1,j=1}^{n}(A_{ti}\&A_{pj})}{\sum_{i=1,j=1}^{m}(A_{ti}\&A_{pj}) + \sum_{i=1,j=1}^{n}(!A_{ti}|A_{pj}) + \sum_{i=1,j=1}^{n}(A_{ti}|(!A_{pj}))}, \quad (4)$$

wherein A_{ti} indicates whether the item t has the i-th attribute among the n attributes. A_{pj} indicates whether the item p has the j-th attribute among the n attributes. If A_{ti} = 1, otherwise $A_{ti} = 0$. Similarly, $A_{ti}\&A_{pj}$ means that when A_{ti} and A_{pj} are both 1, the result will be 1; otherwise, the result will be 0. $!A_{ti}$ means that when A_{ti} is 0 or 1, the result is 1 or 0. It means that the result is $A_{ti}|A_{pj}$ only when A_{ti} and A_{pj} are both 1; otherwise, the result is 1. Through the above formula, similar neighbors and mobile phone similar neighbor sets can be obtained. Therefore, at this time, it is necessary to predict the user's score value for the nonrated items.

$$c_{u,I_t} = \frac{\sum I_p \in M_N^{\mathrm{sim}_T(I_t,I_p)*R_{u,I_p}}}{\sum I_p \in M_N^{|\mathrm{sim}_T(I_t,I_p)|}}. \quad (5)$$

Among them, A_{ti} represents the predicted rating value of c_{u,I_t} user u for the missing item I_t. M_N represents the first I_t similar neighbors that item n looks for. R_{u,I_p} represents user u's rating for item I_p.

As time goes by, some interest preferences may not change, but some interest preferences tend to change, and the traditional collaborative filtering recommendation marketing algorithm does not distinguish them. At this time, the time weighted collaborative filtering algorithm is introduced. The logistic equation is a differential equation with separable variables. It is a continuous, monotonically increasing S-shaped curve with the parameter k as the upper asymptote. Its change speed increases slowly at the beginning, increases faster in the middle section and then decreases, and tends to be stable. The weight function of time is expressed as follows:

$$f\left(t_{pi}\right) = \frac{1}{1 + 6.8 \exp\left(0.1\left(t_{pi} - t_n / t_m - t_n - 1\right)\right)}. \tag{6}$$

When the time is not negative, the time function value range is $(0, 1)$. $f(t_{pi})$ is a monotonically increasing exponential function. t_0 is the reference time for the user to visit the recommended marketing system, t_{pi} is the time interval between the user's visit time and the reference time, t_m is the difference between the user's latest visit time and the reference time, and t_n is the user's first visit time difference from reference time. When the time function $f(t_{pi})$ is larger, the data is newer, the time weight value is larger, and the reference value is higher. The numerical value is the best value for fitting the deformation of logistic curve to make it more in line with the user's time preference for the project. After filling in the matrix, the final formula is obtained by adding the time weight function on the basis of the original calculation formula of the target user for the nonrated items, as shown in the following formula:

$$\widehat{P}_{u,i} = \bar{R}_u + \frac{\sum_{p \in \mathrm{NBU}} \widehat{\mathrm{sim}}(u,p) * \left(R_{p,i} - \bar{R}_p\right) * f\left(t_{pi}\right)}{\sum_{p \in \mathrm{NBU}} \left(\left|\widehat{\mathrm{sim}}(u,p)\right|\right) * f\left(t_{pi}\right)}. \tag{7}$$

$\widehat{\mathrm{sim}}(u,p)$ represents the similarity between user u and user p in the filled virtual matrix. $\widehat{P}_{u,i}$ represents the matrix-filled and time-weighted predicted score for item u by target user i. It represents the highest similar neighbor set of NBU target user u. For the cold start problem, this paper uses ant colony foraging principle to cluster the existing users of the collaborative filtering algorithm. Through the special values of parameters α and β and the iterative process of probability conversion function, new users or new items are assigned to their clusters, and the connection between new users or new items and users or items in clusters is realized. The average interest preference in clusters is used to predict the interest preference of new users or new items and finally, recommendations are generated. Figure 3 shows the basic diagram of ant colony system.

The basic principle of the ant colony algorithm is as follows: ants will release pheromones on the path they forage through, and pheromones are also called pheromones. Ants can perceive this pheromone in the process of movement and can also perceive the intensity of the pheromone and tend to choose the path direction of the intensity of the pheromone to move. Other ants sense this pheromone and choose a foraging route. Aiming at the problem that the user neighbor set is often not accurate enough, a proportion coefficient is introduced into the correlation similarity method. Its definition is shown in the formula:

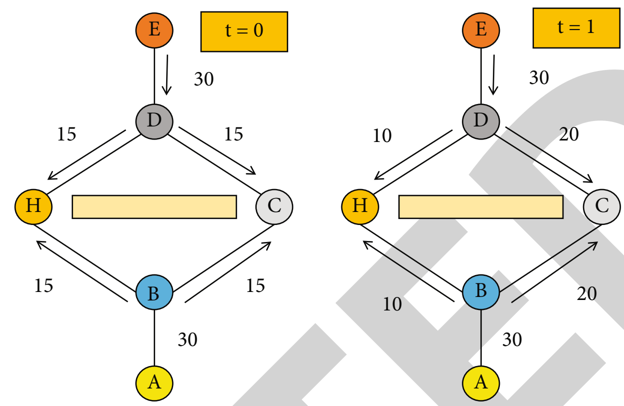

Figure 3: Basic schematic diagram of the ant colony system.

$$\lambda = \frac{M(u,v)}{N(u,v)}. \tag{8}$$

Among them, $\lambda \in (0, 1)$. The collaborative filtering algorithm itself has the problem of cold start of new users. Since the traditional similarity measurement methods are based on user scores, it is impossible to accurately find the similar neighbor users of the target user at this time, so as to generate recommendations. Based on the pheromone updating mode, the formula expression is proposed:

$$\tau_{i,j}(t+n) = (1-\rho) * \tau_{i,j}(t) + \tau_{i,j}(t), \tag{9}$$

where ρ represents pheromone volatilization factor and $\rho \subset [0, 1]$, and $(1\text{-}\rho)$ represents residual factor of information. $\tau_{i,j}(t)$ indicates the information increment of the similarity of two users' scores. In the initial state, $\tau_{i,j}(t) = 0$. The probability $P_{i,j}$ of ant transfer path in the ant colony algorithm can be used to calculate whether user u_i and user u_j become a class. Then, the probability function is expressed as the formula:

$$P_{i,j} = \frac{\left[\tau_{i,j}\right]^{\alpha} \bullet \left[\eta_{i,j}\right]^{\beta}}{\sum_{t=1, t \neq i}^{n} \left[\tau_{it}\right]^{\alpha} \bullet \left[\eta_{it}\right]^{\beta}}. \tag{10}$$

There are n users set as $S = \{u_t | t = 1, 2, \cdots, n\} t = 0$. For a specified user U_i, calculate the probability values of other $n - 1$ users, namely, $P_{i,1}, P_{i,2}, \cdots, P_{i,n-1}$ and select the user$P_{i,x} (i \neq x)$ corresponding to the largest U_x; then, the user U_i is merged into the cluster to which the user U_x belongs.

4. Result Analysis and Discussion

On the basis of the above research and analysis, building a scientific, accurate, and practical marketing system is the

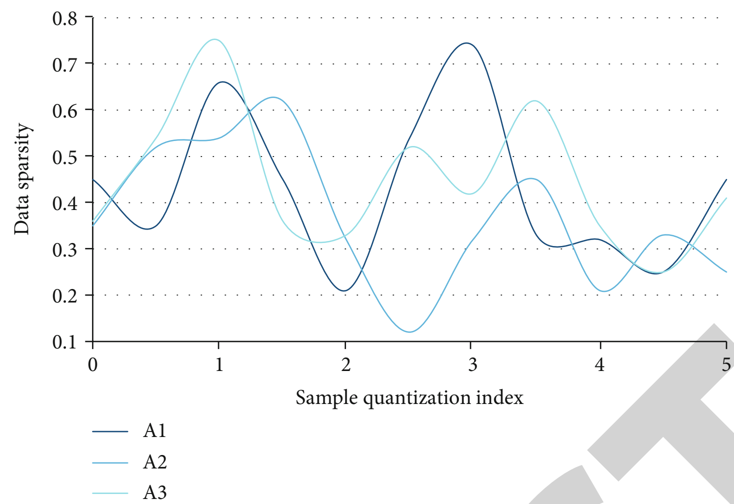

Figure 4: Analysis of the degree of sparsity.

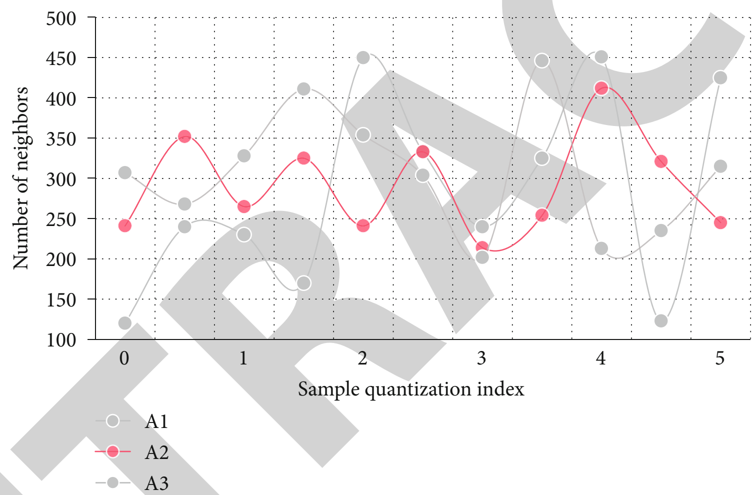

Figure 5: Analysis of the number of neighbors.

premise and foundation for the successful integration of correct recommendation marketing under the background of e-commerce. Therefore, the principles of integrity, comparability, scientificity, and practicality should be followed when establishing the evaluation index system. This paper designs a model to optimize e-commerce precision marketing based on the collaborative filtering algorithm and analyzes the sparsity, number of neighbors, cold start efficiency, average error reduction rate, and recommendation accuracy. It is expected to test the practicability and accuracy of the model on these important indicators. Assuming that A1, A2 ,and A3 are three sample sets of sparse degree and number of neighbors, the calculation and analysis of the model are obtained as shown in Figures 4 and 5 below.

Let M be the number of items evaluated by each user. When $M < 10$, the corresponding users are called new users, and the data sparsity is expressed by the proportion of new users to all users. The greater the proportion of new users, the greater the data sparsity. When the degree of data sparsity is changing from 0.1 to 1, it can be seen from the above figure that the algorithm designed in this paper can maintain stability on the whole when the data is very sparse, and the MAE value is relatively small. On the overall level, it is basically hovering around the water level of 0.52%. This will effectively reduce the impact of data sparsity on the recommendation effect and improve the recommendation quality. From the results, it can be concluded that with the increase of the number of neighbors, adding the time weight function to the final recommendation is much lower than the MAE value obtained by the original collaborative filtering algorithm, indicating that adding the time weight function can further improve the recommendation effect. Improve the physical examination effect to 75.9%. Let M1 and M2 be two sample sets of cold start efficiency, average error reduction rate, and recommended accuracy. The experimental analysis data are shown in the following Figures 6–8.

In the figure above, the cold start problem is an important problem designed and handled in this paper; so, it is necessary to study this data when analyzing the experiment. Through data analysis, it is found that the model designed in

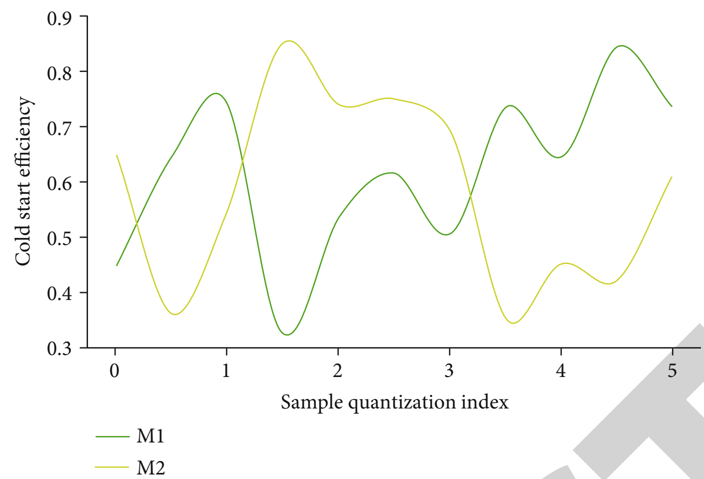

Figure 6: Cold start efficiency analysis diagram.

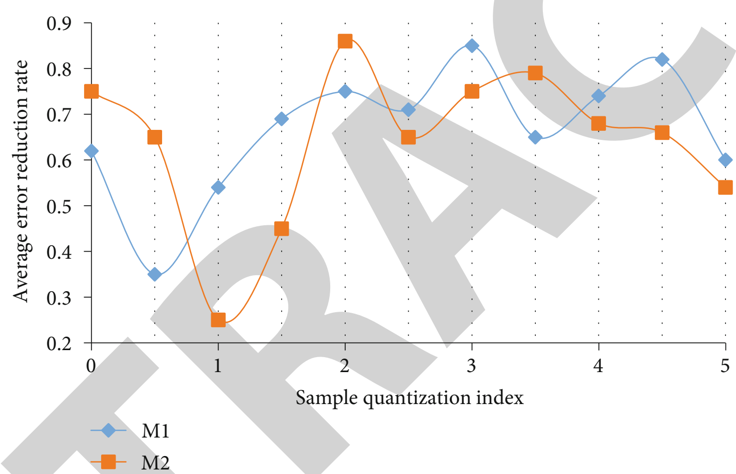

Figure 7: Analysis of the average error reduction rate.

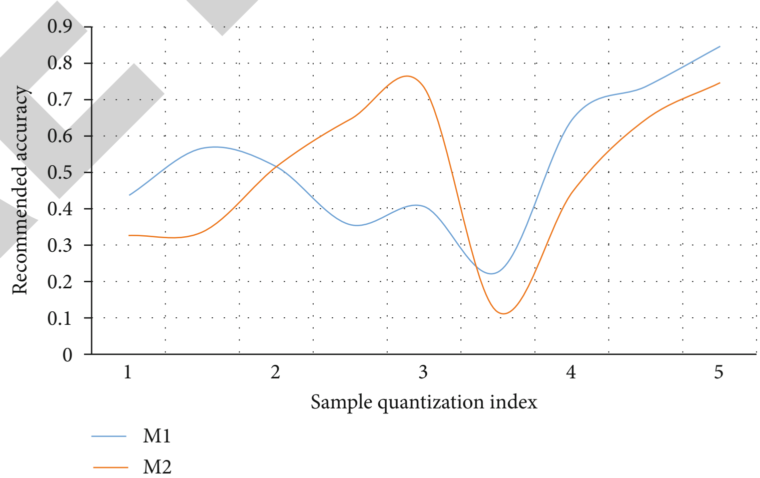

Figure 8: Recommended accuracy analysis diagram.

this paper has a great effect on the cold start efficiency when a large number of samples exist. In the data chart, it can be found that the volatility between 1 and 3 is much larger than that in other intervals. This is because in the clustering process, there are often repeated or lost situations, and it is also an important process of the travel data set at this time. Therefore, it is normal for the data to be unstable at this time. With the increase of the amount of data and sample set, the cold start efficiency will be highlighted, and the advantages of the model in this paper will become more obvious. Because of the embedding of ant colony algorithm, the optimization rate of the model designed in this paper for the cold start problem reaches 87.3%, which greatly improves the effect of precision marketing. The average error is in the range of 0-1, because the number of samples is small, and the analysis data is insufficient; so, the error will be very large at this time. After accumulating a large amount of data, the error reduction rate model is obviously improved through analysis, and the cumulative improvement rate is as high as 91.8%. This is a very practical data; so, it has great support for the applicability of the model. In terms of recommendation accuracy, this is a comprehensive data; so, it needs the previous experimental data, conclusions, and foreshadowing before it can be analyzed and studied. The most obvious thing in the above figure is the sudden drop in recommendation accuracy in the range of 3-4, which occurs under the influence of sparsity and the fluctuation of the number of neighbors. Since both are linearly related to accuracy, they inevitably have an impact on the final result.

5. Conclusions

With the rapid development of the economy and the continuous progress of Internet technology, the e-commerce industry has become a pillar industry in the current high-tech field. An important link affecting the industry is how to carry out precise marketing of e-commerce. This paper comprehensively analyzes the significance of recommendation algorithm in the field of e-commerce, introduces the current research status at home and abroad, and emphatically describes the collaborative filtering recommendation algorithm, including its model, algorithm implementation, and problems to be solved. The emergence of precision marketing has helped enterprises reduce marketing expenses, accurately locate target customers, improve the return on investment, and obtain more considerable benefits for enterprises. The main research work of this paper is to propose a recommendation algorithm based on collaborative filtering, which solves the scalability and sparsity of the algorithm in collaborative filtering recommendation to a certain extent. Fill the better predicted value into the original user-item set to generate a new user-item matrix with lower sparsity. The results show that with the increase of the number of neighbors, the MAE value obtained by adding time weight function in the final recommendation is much lower than that obtained by the original collaborative filtering algorithm, which indicates that adding time weight function can further improve the recommendation effect, and the comprehensive physical examination effect can reach 75.9%. Because of the embedding of the ant colony algorithm, the optimization rate of the model designed in this paper for the cold start problem reaches 87.3%, which greatly improves the effect of precision marketing. Through analysis, the error reduction rate model is improved, and the cumulative improvement rate is as high as 91.8%.

Data Availability

The figures and tables used to support the findings of this study are included in the article.

Conflicts of Interest

The author declares that he/she has no conflicts of interest.

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References

[1] F. Cui, H. Hu, and Y. Xie, "An intelligent optimization method of e-commerce product marketing," *Neural Computing and Applications*, vol. 33, no. 9, pp. 4097–4110, 2021.

[2] H. Zhang and J. Dong, "Prediction of repeat customers on e-commerce platform based on blockchain," *Wireless Communications and Mobile Computing*, vol. 2020, Article ID 8841437, 15 pages, 2020.

[3] M. K. Najafabadi, A. Mohame, and C. W. Onn, "An impact of time and item influencer in collaborative filtering recommendations using graph-based model," *Information Processing & Management*, vol. 56, no. 3, pp. 526–540, 2019.

[4] G. D. Park and J. Lee, "Performance improvement of a pressure sensor using fast median algorithm," *International Journal of Precision Engineering and Manufacturing*, vol. 23, no. 4, pp. 459–468, 2022.

[5] Q. Chen and Y. Chen, "Multi-view 3D model retrieval based on enhanced detail features with contrastive center loss," *Multimedia Tools and Applications*, vol. 81, no. 8, pp. 10407–10426, 2022.

[6] Q. Wang, Y. Li, Y. Wang, and J. Ren, "An automatic algorithm for software vulnerability classification based on CNN and GRU," *Multimedia Tools and Applications*, vol. 81, no. 5, pp. 7103–7124, 2022.

[7] K. Chen, C. Z. Zeng, S. S. Pei, and W. C. Liang, "Normal gravity model for inertial navigation of a hypersonic boost-glide vehicle," *Journal of Zhejiang University-SCIENCE A*, vol. 23, no. 1, pp. 55–67, 2022.

[8] L. A. Brasileiro and V. P. D. Chiuffa, "Simulation of the optimal location for a distribution center of E-commerce operations in São Paulo State," *IEEE Latin America Transactions*, vol. 16, no. 6, pp. 1795–1800, 2018.

[9] C. Zhi, S. Deng, J. Han, and J. Yin, "Towards automatic detection and prioritization of pre-logging overhead: a case study of hadoop ecosystem," *Automated Software Engineering*, vol. 29, no. 1, pp. 1–32, 2022.

[10] J. Zhu, Q. Jiang, Y. Shen, C. Qian, F. Xu, and Q. Zhu, "Application of recurrent neural network to mechanical fault diagnosis: a review," *Journal of Mechanical Science and Technology*, vol. 36, no. 2, pp. 527–542, 2022.

[11] M. R. Hasan, Y. Daryanto, T. C. Roy, and Y. Feng, "Inventory management with online payment and preorder discounts,"

Industrial Management & Data Systems, vol. 120, no. 11, pp. 2001–2023, 2020.

[12] J. Chen, H. Wu, X. Zhou, M. Wu, C. Zhao, and S. Xu, "Optimization of internet of things e-commerce logistics cloud service platform based on Mobile Communication," *Complexity*, vol. 2021, Article ID 5542914, 11 pages, 2021.

[13] L. Mandow, J. L. Perez-De-La-Cruz, and N. Pozas, "Multi-objective dynamic programming with limited precision," *Journal of Global Optimization*, vol. 82, no. 3, pp. 595–614, 2022.

[14] X. Zhang, Y. Meng, Z. Liu, and J. Zhu, "Modified grey wolf optimizer-based support vector regression for ship maneuvering identification with full-scale trial," *Journal of Marine Science and Technology*, vol. 27, no. 1, pp. 576–588, 2022.

[15] W. Zhan, C. Sun, M. Wang et al., "An improved Yolov5 real-time detection method for small objects captured by UAV," *Soft Computing*, vol. 26, no. 1, pp. 361–373, 2022.

[16] S. Guan, "Smart e-commerce logistics construction model based on big data analytics," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 1–9, 2020.

[17] D. Q. Geng, H. W. He, X. C. Lan, and C. Liu, "Bearing fault diagnosis based on improved federated learning algorithm," *Computing*, vol. 104, no. 1, pp. 1–19, 2022.

[18] M. Jiang, L. Song, Y. Wang, Z. Li, and H. Song, "Fusion of the YOLOv4 network model and visual attention mechanism to detect low-quality young apples in a complex environment," *Precision Agriculture*, vol. 23, no. 2, pp. 559–577, 2022.

[19] A. N. Gupta, D. Kumar, and A. Singh, "Evaluation of water quality based on a machine learning algorithm and water quality index for mid Gangetic region (South Bihar plain), India," *Journal of the Geological Society of India*, vol. 97, no. 9, pp. 1063–1072, 2021.

[20] S. L. Khursan, A. S. Ismagilova, F. T. Ziganshina, and A. I. Akhmet'yanova, "Constructing a complete set of homodesmic reactions using the depth-first search procedure," *Russian Journal of Physical Chemistry A*, vol. 95, no. 7, pp. 1386–1393, 2021.

[21] P. Ren, S. Wang, M. He, and W. Cao, "Novel strategy based on improved Kalman filter algorithm for state of health evaluation of hybrid electric vehicles Li-ion batteries during short- and longer term operating conditions," *Journal of Power Electronics*, vol. 21, no. 8, pp. 1190–1199, 2021.

[22] E. F. Mitenkova, E. V. Solov'Eva, V. B. Manichev, and D. Y. Kozhevnikov, "MZK program for solving stiff Systems in Nuclide Kinetics Problems," *Atomic Energy*, vol. 130, no. 6, pp. 344–347, 2021.

[23] S. Li, "Structure optimization of e-commerce platform based on artificial intelligence and blockchain technology," *Wireless Communications and Mobile Computing*, vol. 2020, Article ID 8825825, 8 pages, 2020.

[24] E. E. Sánchez-Ramírez, A. J. Rosales-Silva, and R. A. Alfaro-Flores, "High-precision visual-tracking using the IMM algorithm and discrete GPI observers (IMM-DGPIO)," *Journal of Intelligent & Robotic Systems*, vol. 99, no. 3-4, pp. 815–835, 2020.

[25] M. Hančová, A. Gajdoš, J. Hanč, and G. Vozáriková, "Estimating variances in time series kriging using convex optimization and empirical BLUPs," *Statistical Papers*, vol. 62, no. 4, pp. 1899–1938, 2021.

[26] D. M. D. Raj and R. Mohanasundaram, "An efficient filter-based feature selection model to identify significant features from high-dimensional microarray data," *Arabian Journal for Science and Engineering*, vol. 45, no. 4, pp. 2619–2630, 2020.

[27] K. Gaber, M. B. E. Mashade, and G. A. A. Aziz, "A hardware implementation of flexible attitude determination and control system for two-axis-stabilized CubeSat," *Journal of Electrical Engineering & Technology*, vol. 15, no. 2, pp. 869–882, 2020.