Research Article

E-Commerce Recommendation Technology Based on Collaborative Filtering Algorithm and Mobile Cloud Computing

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Personalized recommendation technology, as one of the core technologies of an E-commerce platform, has attracted a lot of attention with the rise of E-commerce in the Internet industry. Mobile cloud computing-based E-commerce has also exploded in popularity. You can buy whatever you want without leaving the house. Consumers are becoming increasingly receptive to online shopping as a result of this convenience; the E-commerce model demonstrates great modern business value. With its convenient and quick characteristics, online shopping has become fashionable and trendy; however, the popularity of the Internet and the rapid development of E-commerce has resulted in information overload, making it difficult for users to find the goods they require among a vast amount of product information. As a result, the E-commerce recommendation system was born. However, there is currently very little in-depth research on personalized recommendation technology in the field of o2o E-commerce, and most existing recommendation algorithms need to be improved in terms of accuracy and recommendation efficiency.

1. Introduction

The Internet first appeared in China at the end of the twentieth century, ushering mankind into a highly information age [1]. It has now become one of the most important technologies influencing China’s economic and social development, as well as changing people’s lifestyles [2]. Simultaneously, network information is growing at an alarming rate, and the speed with which news, advertising, education, the economy, sports, art, and other information are updated is increasing. It is critical for E-commerce to develop its own long-term development strategy and reap the maximum benefits from it [3]. Many large websites, both domestically and internationally, offer users’ recommendation functions. Many prototypes of personalized recommendation systems have appeared, with positive application results. Traditional trade behavior has changed as E-commerce has grown in popularity [4]. Its gradual establishment and perfection have liberated traditional business operations from existing rules, as well as having a significant impact on related business forms, trading forms, circulation modes, and marketing modes. On the one hand, users feel as if they are in a vast sea of information, and it is difficult to find the goods they require in a timely manner [5]; on the other hand, businesses cannot have the same level of interaction with customers as they can in physical stores [6]. The explosive growth of the amount of information and users also makes people encounter another problem: the simultaneous presentation of excessive information makes it impossible for people to quickly obtain the information they need from massive data, and a variety of information that is difficult to distinguish between true and false disturbs people’s judgment [7]. How to provide useful information to users in an appropriate way is a problem to be solved. Especially for E-commerce websites, it has become a new marketing idea to actively recommend products that users may need to users. It is also a major problem in Internet technology [8]. Research scholars and E-commerce enterprises pay more and more attention to the recommendation system [9].

With the rapid development of personalized recommendation technology abroad, domestic personalized recommendation is also gradually applied to various fields, among which E-commerce websites are the most widely used, such as Jingdong Mall, Meituan, and Taobao, and all
use various types of personalized recommendation technologies to varying degrees, among which the recommendation technology based on collaborative filtering (CF) is more popular [10]. For enterprises, E-commerce not only provides a new avenue for growth, but it also provides a wealth of product information and expands business opportunities [11]. The ability of the o2o E-commerce model to efficiently obtain useful knowledge from massive data, dynamically analyze customers’ personalized needs, provide customers with goods in line with their preferences in real time, and actively and effectively improve the recommendation level is of great practical and theoretical significance [12]. To begin with, E-commerce websites store a variety of data types, such as transaction details, browsing times, registration times, and search times for the same topic. High-quality results recommend excellent recommendation models, and rich data from mobile phones in E-commerce websites can establish a variety of models [13]. Second, the E-commerce system can reduce the manual collection of mobile phone data, lowering the risk of error due to human error and external noise [14]. Time and cost can be reduced through network collection, and the feasibility is very high [15]. Thirdly, to measure the personalized recommendation indicators, now E-commerce can flexibly change according to these indicators and provide personalized services for different users. Fourthly, for merchants, the convenience of E-commerce can stimulate customers’ desire to buy, tap the purchasing potential, and increase the sales volume of websites [16]. Fifth, in the fierce competition of E-commerce, the products built by each family are more and more similar, and everyone is changing and improving to build an excellent recommendation system, which will increase the advantages in the competition in the same industry and become a huge driving force for the rapid development of websites. However, there are still many deficiencies in this technology in China, and there is a big gap between this technology and foreign countries [13]. There are also a series of bottlenecks such as sparsity, cold start, and scalability. Most of the data found by traditional technologies are difficult to be similar to the target data, and their accuracy is not enough [17].

For a long time, the recommendation results are not ideal, so how to provide accurate recommendation results for different users has become a research hotspot of scholars in relevant fields at home and abroad, which also highlights the important position of recommendation technology in the field of E-commerce research [18]. A good personalized recommendation system can bring a win-win situation for users and websites. Due to the continuous penetration of E-commerce into our real life, under the conditions of the rapid development of E-commerce technology and the continuous growth of user demand, the personalized recommendation of E-commerce is facing new challenges. Customers urgently hope that E-commerce can provide a type of shopping function, so enterprises are more and more difficult to survive in the competition. Only enterprises that fully meet and meet the needs of users can occupy a dominant position in the broad market. This paper systematically optimizes the E-commerce model based on CF algorithm to improve people’s sense of trust.

2. Literature Review

Reference [19] suggests using time window information to distinguish users’ behaviors over time periods and improve rating prediction accuracy. To improve the accuracy of the recommendation, the corresponding attenuation factor is introduced based on the time when the item is added to the system. Reference [20] provides a detailed classification and examples of recommender systems in E-commerce applications, as well as how they provide one-on-one personalized service and capture user loyalty; while these systems have proven to be successful in the past, their widespread adoption is still a work in progress. The application also revealed its flaws, such as the data set’s sparseness and the issues associated with high dimensionality. Reference [21] proposes a fuzzy mean clustering-based environment-aware recommendation algorithm. Because of the difficulties people have with environmental perception, fuzzy clustering is used to group the data, and qualified non-membership data is mapped into membership data to improve the recommendation. The algorithm’s accuracy overcomes the problems associated with traditional hard clustering. The core idea in Reference [22] is to use the user trust network to select trustworthy neighbors; however, the current development, which is based on emotional recommendation technology, has made significant advances and improvements. Tsinghua University, for example, has identified the emotional corpus of some tourist attraction descriptions. Researchers value literature [23] more than other recommendation technologies because it supports novel recommendations, deals with unstructured complex objects (such as videos and images), and improves recommendation quality. It has a wide range of applications and is very successful, but traditional collaborative filtering’s problems of sparsity, scalability, and accuracy are impeding its further development. Reference [24] improves the traditional collaborative filtering algorithm and proposes an improved collaborative filtering algorithm based on concept hierarchy, through which the recommendation strategy of the recommendation system is implemented; the recommendation algorithm comprehensively analyzes the Web logs, user registration information, orders on the server side information, cookies and other data, and data cleaning of related raw data to realize Web data mining, but the initial cluster center will affect the stability of the clustering result. When processing a large amount of data, the iterative fuzzy clustering is easy to fall into local extreme points and cannot achieve the optimal solution. Although some researchers have proposed to integrate artificial intelligence algorithms such as neural networks and evolutionary computing into fuzzy clustering, however, this problem cannot be comprehensively solved. In Reference [26], after the introduction of the recommendation system, the search method for users to find targets will change from the previous active to the so-called “passive” today, that is, recommending potential targets that users want to purchase or forming a list based on the history of browsing information and recommending to the users. Literature [27] mentions that the research recommendation network can promote the development of my country’s network information personalized service and can make my country’s personalized information service achieve leap-forward development and catch up with the development level of
western developed countries, which has a very far-reaching display significance. Almost all the large-scale E-commerce systems in Reference [28] use various recommendation systems to varying degrees, among which the Item-to-Item algorithm is the most successful, and its click-through rate and conversion rate far exceed those of the same type of merchants with traditional servers.

The above literature shows that the current E-commerce system is widely used around the world. China's current development stage lags behind that of other countries. The model recommendation personality is not prominent at this point, the relevance of the recommendation is insufficient, and the system is a single recommendation. Chinese researchers, on the other hand, are actively studying and testing ways to improve the traditional algorithm. The potential commercial value of recommendation systems is increasing day by day as their accuracy improves.

3. E-Commerce Recommendation and Collaborative Filtering Algorithms

3.1. An Overview of E-Commerce Recommendation Systems. Most people are gradually accepting of the Internet transaction format. More and more businesses are developing their own E-commerce platforms in the hopes of conducting business activities over the Internet, lowering operating costs, and expanding business opportunities [29]. In the context of E-commerce, an E-commerce personalized recommendation system is an application system that provides personalized products and services to various users. Users should be able to recommend products that they have not seen before, so that they can not only save time browsing but also improve the enterprise's sales quota. Users are actively provided with content information or browsing suggestions in the form of recommendations based on the discovered user preferences, and users are given one-on-one guidance and services. It is currently being researched and used in fields such as E-commerce, distance education, and information retrieval. For example, a salesperson who is familiar with a customer's preferences will be more aware of his preferences if he is a regular at a convenience store. He knows what he wants to buy and when he wants to buy it. With new products, the salesperson can delve deeper into the customer's preferences in order to introduce and recommend new products, increasing turnover. In fact, the personalized recommendation system is just like our salesperson. Its main role is to find out the user's goals, consumption methods, and personal hobbies. The recommendation system of E-commerce is to provide customers with products they may be interested in during visitors' visit to the website and then facilitate the transaction and complete the purchase of this product. Generally speaking, a successful and efficient personalized recommendation system can bring the following advantages to E-commerce websites and website users:

(1) It provides users with “specific choice,” shortens the time for users to choose commodities, improves the efficiency of users' purchasing from massive commodity information, and brings users a better experience

(2) It can actively provide customers with products of interest, broaden users' horizons, even help users develop new interests, and bring different experiences to customers

(3) For users who do not have strong desire to buy, suitable recommendation can just improve users' desire to buy and turn an ordinary website visitor into a buyer

(4) When users get a good shopping experience from the recommendation, they will actively change from a wait-and-see user of a website to a loyal user, thus increasing the number of visits to the website.

The structure of E-commerce personalized recommendation system is mainly divided into input module, recommendation method module, and output module. The structure of E-commerce system is shown in Figure 1.

The output module mainly inputs the current behavior of the user and the behavior in the process according to the time division, such as the input of personalized registration information, which includes the user's name, age, and occupation, and invisible data to recommend; in E-commerce modeling, users will definitely only choose their favorite products, and the system can provide them with personalized services based on customer behavior. The user scores the products purchased, and the values are used as input to the model when entering keywords/product attributes. Furthermore, in a mobile E-commerce environment, the user's contextual information, such as location and weather, is used to personalize recommendations.

The method of personalized recommendation is at the heart of the process. The performance of personalized recommendations is influenced by different recommendation methods, which have an impact on the recommendation effect. Furthermore, the requirements for recommendation methods vary by field of personalization. The output of personalized recommendation takes two forms in various output module applications, depending on the application requirements: output from related products and output from mail or short messages.

3.2. Recommendation Technology Based on Collaborative Filtering Algorithm. In our daily life, we often ask our good friends for advice when choosing products to help us make decisions. CF applies this idea to personalized recommendation, that is, recommending suitable items to target users based on the evaluation of certain items by users with similar interests. Taking books as an example, if two users have browsed or bought the same books, they are likely to have potentially similar hobbies and purchase similar books in the future. That is to say, user A and user B have many purchases that are the same or similar. User A bought a book, but user B does not know the purchase record of user A, so this book is likely to be recommended to user B. The structure based on CF technology is shown in Figure 2.

CF generally consists of two parts, as follows:

The user's CF recommendation algorithm is used in the first part. The user's nearest neighbor query algorithm is used in the traditional CF recommendation system. As a result, it suffers from poor scalability and insufficient
stability. The score prediction analysis is introduced into the project, and when combined with the effect of data sparsity, a modified conditional probability calculation of project similarity is used to propose an optimized CF recommendation algorithm. The findings are more practical and accurate, and the quality of the recommendations is improved. Compared to the traditional CF algorithm based on the nearest neighbor recommendation item, this algorithm effectively alleviates the sparse data set caused by the above problem and improves the recommendation system’s recommendation quality significantly. The process can be roughly divided into three stages, as shown in the diagram above.

(1) Modeling Data Representation according to Users’ Scores and Effective Measuring of the Similarity between Users. All users’ information forms a matrix, also called user item scoring matrix, which is denoted as $R$:

$$
R = \begin{bmatrix}
R_{11} & R_{12} & \cdots & R_{1n} \\
R_{21} & R_{22} & \cdots & R_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
R_{m1} & R_{m2} & \cdots & R_{mn}
\end{bmatrix}, \quad \tag{1}
$$

where $M$ represents the number of users in the system, $n$ represents the number of items, and the value of matrix element $R_{ui}$ represents the score of user $u$ on item $i$. The value of $R_{ui}$ is generally in a certain value range, usually an integer of 1-5, and the items that the user does not score are replaced by 0. The larger the $R_{ui}$, the higher the user U’s evaluation of project I and vice versa.

(2) Looking for the nearest neighbor user set, the similarity reflects the degree of difference between two objects or two features, and the greater the degree of difference, the lower the similarity. On the contrary, the smaller the degree of difference, the higher the similarity. There are usually several ways to measure

(I) Cosine Similarity Value in the Calculation Process. We introduce vector thinking, which has both magnitude and direction. Cosine of the included angle between directions can be regarded as a similarity measure and monotonically decreases within the included angle range according to cosine property, that is, the smaller the measure value, the greater the similarity. The formula is as follows:

$$
\text{Sim}(a, b) = \frac{\sum_{i \in I_{ab}} R_{ai} \cdot R_{bi}}{\sqrt{\sum_{i \in I_{ab}} R_{ai}^2 \cdot \sum_{i \in I_{ab}} R_{bi}^2}} \quad \tag{2}
$$

(II) As the name implies, modified cosine similarity measure is a modification based on the cosine calculation method, and cosine only has one fatal flaw: the recommendation is not accurate enough because the user’s rating scale is not taken into account. The modified cosine similarity measure method is based on the principle of subtracting the user’s rating by calculating the user’s rating on the project. The formula is as follows:

$$
\text{Sim}(a, b) = \frac{\sum_{i \in I_{ab}} (R_{ai} - \bar{R}_a) \cdot (R_{bi} - \bar{R}_b)}{\sqrt{\sum_{i \in I_{ab}} (R_{ai} - \bar{R}_a)^2 \cdot \sum_{i \in I_{ab}} (R_{bi} - \bar{R}_b)^2}} \quad \tag{3}
$$

(III) Correlation similarity measurement is the simplest but most practical way to calculate the similarity among the three kinds of similarity. Pearson correlation coefficient calculates the similarity formula
between target user A and a certain user B as follows:

\[ \text{Sim}(a,b) = \frac{\sum_{i \in I_{ab}} (R_{ai} - \bar{R}_a) \times (R_{bi} - \bar{R}_b)}{\sqrt{\sum_{i \in I_{ab}} (R_{ai} - \bar{R}_a)^2} \times \sqrt{\sum_{i \in I_{ab}} (R_{bi} - \bar{R}_b)^2}} \]  

(4)

(3) Generating recommendation is to finally predict the item score value after obtaining the similarity from the above and recommend some needed information, that is, to give the top items with the highest evaluation score (top-N) as the recommendation result to the target users

\[ K = \frac{1}{\sum_{u \in U} \text{sim}(a,u)} \]  

(5)

The CF of project-based projects in the second part is completely opposite to the above thought, but the algorithm is the same, implying that a user will prefer projects that are similar to those he has already purchased. The recommendation algorithm is much faster because this method does not require identifying neighbors. Because the number of users in most recommendation systems is far greater than the number of items, finding the relevance between items is much easier and more stable than finding the relevance between users, and thus, the item-based CF algorithm is better in terms of scalability than the user-based CF algorithm. The formula is as follows.

\[ P_{u,p} = \frac{\sum_{n \in N_p} \text{sim}_{p,n} \times R_{u,n}}{\sum_{n \in N_p} |\text{sim}_{p,n}|} \]  

(6)

The similarity between items can be calculated offline and saved in the database, so that it can be used directly when recommending, which saves the time of recommendation and improves the efficiency of recommendation. The disadvantage of project-based CF algorithm is that it does not have the novelty of recommendation, and it also lacks the ability of cross category recommendation and singular recommendation.

3.3. Basic Characteristics of Personalized E-Commerce Technology Recommendation

(1) E-commerce recommendation technology can better expand the pull demand, which is different from the passive information display of search engines in the past. We can organize information directly according to customers’ search to predict customers’ potential demand, accurately set products and services that are “congenial” for customers, actively push information to our customers, personalize it, and develop it to people in need

(2) Generate business stickiness, turn customers into repeat customers, and turn repeat customers into old customers, which is an important index to measure user loyalty. Accurate service can make customers feel dependent

(3) Support mass customization. This system not only recommends the configured products to customers but also assists customers to complete the module of product selection

(4) To create business opportunities, today’s consumers’ choices are not only based on the use value of commodities, but also on their social and spiritual values, which can increase customers’ sense of identity and promote consumption. This flexible way of consumption can also be quickly accepted by customers, bringing huge business opportunities to the market

4. Based on the Actual Measurement of E-Commerce Technology

Experiment 1. In order to ensure that the experimental data can ensure the optimal experimental effect of the experiment, the data set is sampled and analyzed, and the most intensive and effective part of the user rating data is extracted from the analysis results to carry out the experiment. Before conducting the experiment, the paper analyzes the number of users when a certain number of rating items is reached. The user rating system distribution is shown in Figure 3.

The scale of the user set whose number of scoring items is within a certain range is represented by the point in the image. The number of users is growing in tandem with the number of user scoring items, but this growth is slow. When the number of scoring items reaches a certain level, the number of users almost stays the same. When the number of users is between 0 and 200, the number of users explodes, and the number of users skyrockets as the number of scoring items rises. As a result, this portion of the data is extracted for experiments, and using hierarchical data yields good experimental comparison results.

Experiment 2. Compare the improved algorithm’s average absolute error across different sparsity data sets and different numbers of nearest neighbors. The selected data set is divided into different data subsets according to certain standards under the same other test conditions. In general, k-
fold cross validation is used in machine learning to divide the data, remove the majority of the data for training, and use the remaining small portion of the data to calculate the error. The evaluation standard can be the mean value of $K$ calculations. The experimental results after 4 groups of tests are shown in Figure 4.

As can be seen from the above Figure 4, the number of nearest neighbors affects the trend of each curve, and different sparsity also greatly affects its value. Compare the traditional algorithm with the improved algorithm proposed in this paper, and compare the average value of its 4-cross validation experimental results. The results are shown in Figure 5.

As shown in the graph, when the number of nearest neighbors is less than 20, the improved algorithm’s value is lower than the traditional algorithm’s, implying that the recommendation accuracy is higher. After the nearest neighbor is greater than 20, the numerical value of the improved algorithm will be greater than that of the traditional algorithm, but the difference will be small. When the number of closest neighbors is small, the number of recommended nearest neighbors is no more than 20 in the E-commerce website’s recommendation system. The calculation of online recommendations takes less time and provides better real-time results.

Experiment 3. After calculating the scoring degree of each category of the project, analyze the best project scoring threshold through experiments. During the experiment, we set the value of the parameter as 0.1. When the number of user neighbors is 30, 60, and 90, we select seven different item scoring thresholds of 0.000–0.006 for the experiment. We can see that when the item scoring threshold is taken, the value is the lowest. Therefore, we selected the item scoring threshold for follow-up experiments. The scoring trend of the three groups of items is shown in Figure 6.

It can be seen from Figure 6 that when the parameter $\alpha$ is equal to 0.1, the value is the lowest, which makes the recommendation show the best effect. Here, the item rating threshold is selected, and then, different parameter values are selected for experiments when the number of neighbors is 0.
Figure 7: Comparison of MAE values based on interest bias filling and traditional algorithms.

Get three curves. It can be seen from Figure 7 that when the parameter is equal to the lowest value, the recommendation shows the best effect; The comparison of MAE values based on interest bias filling and traditional algorithms is shown in Figure 7.

5. Conclusion

To achieve more accurate and faster recommendation in the E-commerce mode, personalized recommendation must meet the special conditions of quick response to changes in user interests, high real-time online recommendation, high efficiency in processing big data, and so on. Every industry is paying increasing attention to recommended technology, and there is a high demand for it. Theoretical research on personalized E-commerce recommendation technology and implementation research are still in their early stages, and efficient, real-time, and accurate recommendation algorithms require more research and development. People have widely accepted personalized recommendation technology, particularly in the field of E-commerce, which has prompted its application in the industrial field as well as a thorough study of theoretical knowledge. Publicly adored, at the same time, it breathes new life into online marketing; the recommendation system has become an essential component of E-commerce and is widely used. The algorithm is just one component of the overall system. Perhaps a simple algorithm can have a big impact. In the follow-up, the system will compile statistics on the items that users have collected and have frequently browsed but not purchased and send them to users via mail over a set period of time. This paper analyzes the problems faced by the development of E-commerce and improves the traditional algorithm by combining it with the CF algorithm. The domestic algorithm is currently in widespread use, particularly in the case of sparse user evaluation data. Due to a time constraint, many aspects of the topic were left out of the article, and we will return to them later.

Data Availability

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

Conflicts of Interest

The author does not have any possible conflicts of interest.

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