Computer Network Security Defense Model

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Abstract. With the rapid development of the Internet industry, hundreds of millions of online resources are also booming. In the information space with huge and complex resources, it is necessary to quickly help users find the resources they are interested in and save users time. At this stage, the content industry's application of the recommendation model in the content distribution process has become the mainstream. The content recommendation model provides users with a highly efficient and highly satisfying reading experience, and solves the problem of information redundancy to a certain extent. Knowledge tag personalized dynamic recommendation technology is currently widely used in the field of e-commerce. The purpose of this article is to study the optimization of the knowledge tag personalized dynamic recommendation system based on artificial intelligence algorithms. This article first proposes a hybrid recommendation algorithm based on the comparison between content-based filtering and collaborative filtering algorithms. It mainly introduces user browsing behavior analysis and design, KNN-based item similarity algorithm design, and hybrid recommendation algorithm implementation. Finally, through algorithm simulation experiments, the effectiveness of the algorithm in this paper is verified, and the accuracy of the recommendation has been improved.

Key words: Artificial Intelligence, Knowledge Label, Label Personalization, Dynamic Recommendation

1. Introduction

In the past few decades, personalized recommendation technology has developed rapidly and has been widely used in the business field. It is convenient for users to find interesting resources and save time [1-2]. At the same time, to improve the utilization of system resources, and to improve the user's credibility and loyalty of the personalized recommendation system, this graduation project studied the knowledge tag personalized dynamic recommendation system based on artificial intelligence algorithms [3-4].

In recent years, our country has also begun to conduct research on personalized services. After in-depth research by scholars and engineers and technicians, some achievements have been made in theoretical research and practical applications. Guo Q introduced content-based recommendation technology, and added a joint K-means and naive Bayes algorithm to improve the accuracy of the algorithm on the basis of traditional content-based recommendation[5]. Aliannejadi M adopts an item-based collaborative filtering recommendation algorithm on the Weibo-based online learning resource platform to solve the cold start problem of the recommendation system [6]. Wang X designed...
a library recommendation system based on user collaborative filtering algorithm. By analyzing the information in the library borrowing system, it recommends potentially interesting book resources for users with the same interest preferences [7]. The current personalized recommendation technologies commonly used in personalized recommendation systems mainly include content-based recommendation, collaborative filtering recommendation, tag recommendation, etc., to obtain a list of resources to be recommended by users. Finally, resource filtering technology is used to make the final recommendation more accurate and efficient [8].

This paper mainly uses analysis and comparison, and proposes a hybrid recommendation algorithm by comparing content-based filtering and collaborative filtering algorithms.

2. Optimization of Personalized Dynamic Recommendation System of Knowledge Label Based on AI Algorithm

2.1 Comparison between Content-Based Filtering and Collaborative Filtering Algorithms
Content-based filtering has the following advantages:
(1) In the case of new users and new products, the content-based filtering method can calculate the similarity between users and products and match them according to their basic characteristics. The relevance only depends on the project itself.

(2) The content-based filtering algorithm does not depend on the scoring matrix, so it eliminates the problem of sparse matrix.

Because the information content of the project is often very complex, the analysis of project information through content-based filtering technology is often not accurate enough, and the extraction of simple project information can basically meet, but in some specific fields such as graphics, there is currently no effective in the industry. Even for some complex text resources, due to the complexity of text analysis, the meaning of the text expression through computer analysis often shows large deviations, and the recommended information is limited to certain specific ranges, and the scalability is poor[9-10].

Collaborative filtering can make up for the shortcomings of content-based filtering. In collaborative filtering, the user’s preference is predicted by finding the nearest neighbors of the target user, and then recommendations are made. The nearest neighbor users can be understood as their own friends or colleagues, who have relatively similar personal characteristics, and recommend information to users based on the judgment of neighbor users. Collaborative filtering does not care about the content of information, so it avoids the difficulty of content analysis of information. There are two main ways to obtain user ratings for items through automated means. One is through the display rating mechanism, which is accurate, but requires users to rate items one by one. The user experience is poor, and the other is the implicit method is mainly to predict the user’s preference for the item through the implicit analysis of the user's behavior record. The implicit method can recommend high-quality products for the user without affecting the normal use of the user [11-12].

Collaborative filtering relies on the rating matrix of users and items, so it can be completely independent of the item itself, but it will inevitably lead to some shortcomings:

(1) Cold start problem
When a new user logs on to the website, the data set does not contain any information about the user, and the closest user of the new user cannot be found through collaborative filtering technology, so recommendation results cannot be obtained, which is called a cold start problem; for the case of newly added items It is also called a cold start problem. The newly added items have not been rated by any users, so it is difficult to be recommended to users as recommended items.

(2) Sparsity problem
The relatively big problem encountered in the implementation of collaborative filtering algorithm is the problem of sparsity, which has become one of the main defects of collaborative filtering algorithm.
The so-called sparsity problem means that in a relatively large system, due to the large number of projects and users, a huge matrix is formed, and in the matrix, the projects evaluated by users account for only a small part.

2.2 The idea of hybrid recommendation algorithm

Through the above analysis based on content filtering and collaborative filtering algorithms, a solution to the sparse matrix is found. The basic idea of the hybrid recommendation algorithm is given below.

The basic idea of the hybrid recommendation algorithm is to combine content filtering technology and collaborative filtering technology, first use user basic characteristic data and user historical access information records for data mining, extract the basic characteristics of items through the KNN algorithm, and calculate the correlation between items, and then predict and fill the sparse matrix generated in collaborative filtering according to the recommendation technology based on content filtering. Before the collaborative filtering algorithm, fill the sparse matrix into a dense matrix. The filled data has a certain degree of credibility, and then the dense matrix is filled. The matrix performs collaborative filtering to solve the sparsity problem of the matrix.

2.3 Hybrid recommendation algorithm

(1) Analysis and design of user browsing behavior

There are two main ways to obtain user ratings for items. The first is to provide a direct and accurate rating by asking users to rate the browsing items through a displayed scoring mechanism. Another way is to implicitly obtain the user's preference for the item based on the user's browsing behavior. For example, operations such as browsing items multiple times, staying on the item for a long time, copying the content of the item, etc., all indirectly reflect the user's preference for the item.

There are the following implicit scoring calculation formulas through related record data:

\[ m_{ij} \] is the number of times that user i has opened project j, and \( n_{ij} \) is the total time that user i stays on the page of project j, which is obtained by calculating the time difference between opening and closing. \( k_{ij} \) is the number of copy operations performed by user i on the project page of j. Finally, the implicit score of user i for item j can be calculated as (a, b, and c are the weights of numerical value to item score):

\[ mark = m_{ij} \times a + n_{ij} \times b + k_{ij} \times c \] (1)

(2) Project similarity algorithm design based on KNN

By comparing the feature similarity between content, targeted prediction information is recommended for users. The classic KNN (K-Nearest Neighbor algorithm) algorithm is used here to find the K most similar samples in the feature vector space, and then calculate the similar items with the largest correlation according to the items, and recommend them to users.

3. System Test

3.1 Introduction to the experiment

The evaluation of the knowledge tag personalized dynamic recommendation system is an important measurement index of the recommendation system. At present, the recommendation system has two methods to measure the efficiency of recommendation algorithms; online and offline evaluation methods.

Online evaluation is a form of online survey or voting to obtain users' evaluation of the recommendation system service. Offline evaluation mainly uses the data in the system and the data performance indicators of the statistical system to evaluate and measure the performance of the recommender system. The experiment in this article adopts offline evaluation method, which mainly includes evaluation indicators such as average absolute error, accuracy rate, recall rate, and F value.
3.2 Experimental Data
User data mainly comes from registered users in the personalized dynamic recommendation system of knowledge tags based on artificial intelligence algorithms. At present, the number of successfully registered users in the recommendation system is 453; the number of highly active users is more than 380, so the number of effective users is 386.

3.3 Evaluation Criteria

(1) Mean absolute error (MAE)
The smaller the MAE value, the more accurate the scoring prediction function of the recommendation system, and the better the algorithm quality of the recommendation system.

(2) Accuracy rate, recall rate and comprehensive evaluation index
In the field of information retrieval and statistics, precision and recall are mainly used to evaluate the quality of the system. The application in the recommendation system is mainly to evaluate the quality of recommendation results.

The accuracy rate $P$, the ratio of the number of correct resources in the retrieval result to the total number of retrieval results, is mainly used to measure the accuracy of the recommendation system.

Recall rate $R$, the ratio of the number of related resources in the search result to the number of related resources in the total library, mainly detects the recall rate of the retrieval system.

In the recommendation system, the higher the accuracy rate and the recall rate, the better. But the fact is that there may be contradictions between the two. For example, there is only one correct search result. At this time, Precision is equal to 100%, but the Recall value is low. If you adjust the algorithm now and return all recommended results, when Recall is equal to 10%, the accuracy is low. Therefore, at this time, a comprehensive evaluation index is needed to measure the quality of the recommender system, and we introduce a comprehensive evaluation index (F-Measure). The mathematical expression of the comprehensive evaluation index is:

$$F = P*R*2/(P+R)$$

The F value in the formula is the harmonic average comprehensive evaluation index of the accuracy rate and the recall rate. When the F value is higher, the algorithm recommendation result of the recommendation system is better and more effective.

4. Analysis of Test Results

4.1 Analysis of the Experimental Results of the Overall Recommended Quality of the System
In the comparative experiment, the experimental data and conditions remain unchanged, based on the content recommendation model (control experiment system 1), based on the collaborative filtering recommendation model (control system 2), and mixed recommendation model three groups of systems for multiple rounds of repeated experimental tests, and the average absolute error experiment. The results are shown in Table 1.

|   | Hybrid recommendation model | Control system 1 | Control system 2 |
|---|----------------------------|-----------------|-----------------|
| 1 | 0.92                       | 1.12            | 1.13            |
| 2 | 0.87                       | 1.24            | 1.18            |
| 3 | 0.86                       | 1.11            | 1.14            |
| 4 | 0.91                       | 1.1             | 1.16            |
| 5 | 0.88                       | 1.09            | 1.13            |
| 6 | 0.87                       | 1.11            | 1.15            |

The experimental results of the system's comprehensive evaluation index F value are shown in
The experimental results of the overall MAE performance of the system in Table 1 and the comprehensive evaluation index F of the system in Figure 1 show that the MAE of the personalized education resource recommendation system using hybrid recommendation technology is significantly lower than that of the control experimental system 1 and 2, which shows that the recommendation of the hybrid recommendation algorithm is accurate. The result is small in error and the recommended algorithm is accurate. The F value of the hybrid recommendation system is significantly higher than that of the control test system 1, 2, which shows that the test method is effective. It can be seen that the hybrid recommendation algorithm improves the overall quality of the recommendation system.

4.2 System Stability

The experimental results are shown in Figure 2.

It can be seen from Figure 2: The MAE value of the hybrid recommendation system decreases, and the accuracy of the system algorithm improves: As the experiment time increases, the MAE value of the algorithm decreases, and the accuracy MAE does not continue to change after the 15th day. At this time, the algorithm efficiency convergence.

In order to avoid accidents, multiple rounds and multiple sets of experiments are carried out, and the experimental results are analyzed and discussed. The results prove that the hybrid recommendation algorithm proposed in this paper can effectively solve the new user cold that is common in traditional recommendation systems in the knowledge tag personalized dynamic recommendation system.
Post-movement, the overall recommendation quality is not high, and the recommendation service is not stable enough. It can be seen from the experiment that the hybrid recommendation system in this paper can provide reliable personalized resource recommendation services for the majority of users.

5. Conclusions
In the context of the vigorous development of artificial intelligence technology, information resources are also growing wildly. In the vast resource and information space, users are often confused and confused. The importance of establishing a personalized dynamic recommendation system of knowledge tags based on artificial intelligence algorithms is about to emerge. Personalized recommendation algorithm is the core of the resource recommendation system, and more and more researches on personalized recommendation algorithm continue to introduce new ones. This paper first compares content-based filtering and collaborative filtering algorithms, and then proposes the idea of hybrid recommendation algorithm, which improves the efficiency and stability of the recommendation system, and realizes the research on the optimization of the knowledge tag personalized dynamic recommendation system based on artificial intelligence algorithm.

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