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Collaborative Filtering Recommendation Algorithm with Item Label Features

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Abstract

The traditional item-based recommendation algorithm only considers the user's score when calculating, but the actual user's score has a malicious evaluation, which seriously affects the accuracy of using the score for prediction. At the same time, the user's evaluation is small, and the amount of usage will also affect the accuracy of the recommendation. Aiming at the above two problems, this paper proposes a collaborative filtering recommendation algorithm with the characteristics of the item label. Firstly, the item label feature and the user's behavior data are comprehensively considered. Secondly, the user's feature data on the label selection is calculated, and finally the item is calculated in combination with the feature data. Similarity, thus making recommendations for users. Experiments show that the algorithm can solve the cold start problem of data well, and the interpretation of the recommended results is also convincing.

Keywords

Collaborative filtering, Item label, User characteristics.

1. Introduction

With the development of computer frontier technologies such as mobile Internet and Internet of Things, information has exploded and increased the burden of people searching for data. Personalized recommendation algorithms have emerged. The traditional recommendation methods can be divided into three categories, namely social recommendation, content-based recommendation and collaborative filtering recommendation. The collaborative filtering recommendation algorithm has been favored by major Internet companies in recent years because of its advantages of easy implementation and good recommendation. The development is relatively rapid. The classic collaborative filtering recommendation algorithm can comprehensively consider users and items for recommendation, and calculate the similarity by the user's scoring matrix of items, but such recommendation method can not make reasonable recommendation when the scoring matrix is sparse, the user historical data volume Seriously affect the accuracy of the recommendation, so that the algorithm needs to solve a certain data cold start problem in practical application. In [3], a collaborative filtering recommendation algorithm based on matrix decomposition and clustering is proposed to solve the problem of matrix high dimension and high sparsity by matrix dimensionality reduction. Literature [4] proposes to recommend the user through the label characteristics of the item to improve the accuracy of the recommendation. Literature [5] proposes a collaborative filtering algorithm that combines item type and density peak clustering. It first analyzes user preferences based on user historical data and item types, and then uses tag information to further mine users by introducing density peak clustering method. Personality preferences.

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Most of the existing algorithms are based on the user's collaborative filtering recommendation for the item's scoring matrix, but the user's rating is instructive. With the commercialization of the application, many malicious evaluations seriously affect the objectivity of the scoring and interfere with the accuracy of the recommendation[6]. This paper proposes a collaborative filtering recommendation algorithm with tag features, introduces the tag features of the article, and analyzes the user's tag characteristics in combination with the user's historical data, which reduces the impact of malicious scoring on the accuracy of the recommendation results. At the same time, the collaborative filtering based on the item can reduce the difficulty of solving the problem and reduce the amount of data to be calculated when the number of items does not change greatly and the number of users is large.

2. ItemCF algorithm

The collaborative filtering recommendation algorithm is divided into the dimensions of the scoring matrix and can be divided into item-based collaborative filtering (ICF) and user-based collaborative filtering (UCF). The difference between the two algorithms lies in the angle of use of the scoring matrix. The user-based collaborative filtering first finds users with similar records through the user's scoring matrix, and then recommends items that the similar users like and the target users do not score. Item-based collaborative filtering recommends similar items to users by analyzing whether the two items are similar.The advantages and disadvantages of the two algorithms on different issues are shown in Table 1.

Table 1 Comparison of ICF and UCF

Index	ICF	UCF
Applicable situation	The area where the long tail items are abundant and the user's individual needs are strong.	Time-sensitive, areas where users' personal interests are less obvious.
real-time	The user's new behavior will definitely lead to real-time changes in the recommendation results.	The user has a new behavior that does not necessarily result in an immediate change in the recommendation result.
performance	Applicable to occasions where the item is significantly smaller than the user.	Suitable for occasions with few users.
Recommended result	Using the user's historical behavior to make recommendations for the user can make the user more convinced.	It is difficult to provide a recommended explanation that convinced the user.
Recommended object	Items are recommended subjects, such as shopping sites.	Artificially recommended subjects, such as social networking sites.

From the comparison between ICF and UCF in Table 1, it can be seen that based on the user and the article-based application for different occasions and different situations, the background of this study is the museum's cultural relic recommendation. After the analysis of the research topic, the recommendation of this topic is based on the article. The main body, and the actual situation is that the number of users is much larger than the number of cultural relics, and the relics are not updated frequently. Therefore, the research of the article can reduce the difficulty of recommendation, and can also avoid the influence of user malicious scoring on the recommendation result, thereby improving the accuracy of the recommendation.

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3. ICF algorithm with label features

The classic collaborative filtering recommendation algorithm is based on the user's calculation of the similarity of the item's scoring matrix. The advantage of this is that the calculation of the first-hand data of the user and the item can reduce the difficulty of data collection and maintain the authenticity of the data. In recent years, in the application of the Internet, the labeling characteristics of articles and users have become more and more widely used, such as Sina Weibo, QQ, Taobao, etc., by introducing labels, the characteristics of things can be more specifically described, not just attention[10-13]. The user of the item uses historical features. Aiming at the shortcomings of traditional collaborative filtering recommendation algorithm only relying on user historical data, this paper proposes an ICF algorithm with tag features, which combines user's historical data and item tag features to collaboratively filter users.

3.1 Algorithm principle

This paper takes the museum's cultural relics recommendation as the research object. The dataset used by the algorithm is the collected cultural relics tag dataset and user behavior dataset, and the algorithm is improved according to the user behavior dataset and the cultural relic tag dataset. First, define the tag set of the artifact as $LB = \{L_p, p = 1,2,\cdots,S\}$, and the set of artifacts is $IT = \{I_q, q = 1,2,\cdots,M\}$, and the user's set is $US = \{u_r, r = 1,2,\cdots,N\}$, these three sets are the basic elements that make up the two data sets, namely the artifact-tag dataset and the user-creature dataset.Let the cultural relics $I_i \in IT$ have $S(I_i)$ mutually non-repeating labels, and the label set of the cultural relics I_i can be represented as
$L(I_i) = \{l_x | l_x \in LB, \text{when } x \neq p, l_x \neq l_p, \text{and } x, p = 1,2,\cdots S(I_i)\}$,where $S(I_i) \leq S$.

If there are $K(u_r)$ artifacts in the behavior data of the user $u_r \in US$, the collection of artifacts of the user u_r can be expressed as $I(u_r) = \{I_i | I_i \in IT, i = 1,2,\cdots,K(u_r)\}$, where $K(u_r) \leq M$.

According to the above two definitions, the selection probability values of all the cultural relics in the collection of cultural objects $I(u_r)$ of the user $u_r \in US$ to the label $L_p \in LB$ can be expressed as follows.

$$P(u_r, L_p) = \frac{\sum_{I_i \in I(u_r)} \sum_{l_x \in L(I_i)} \delta(l_x, L_p)}{\sum_{I_i \in I(u_r)} S(I_i)} \tag{1}$$

The function δ is expressed in detail as $\delta(l_x, L_p) = \begin{cases} 1 & l_x = L_p \\ 0 & l_x \neq L_p \end{cases}$. The function $S(I_i)$ represents the number of tags of the artifact I_i, and the function $P(u_r, L_p)$ represents the selection probability value of the user u_r to the tag L_p. If the artifact containing the label L_p never appears in the user's behavior data, the user has a selection probability value of 0 for the label L_p, so the value of the function $P(u_r, L_p)$ is as follows.

$$P(u_r, L_p) = \begin{cases} \frac{\sum_{I_i \in I(u_r)} \sum_{l_x \in L(I_i)} \delta(l_x, L_p)}{\sum_{I_i \in I(u_r)} S(I_i)} & L_p \in L(I_i) \\ 0 & L_p \notin \end{cases} \tag{2}$$

In the above, $P(u_r, L_p)$ represents the selection probability value of the user u_r for the tag L_p. For all $L_p \in$ LB, the selection score value of the user u_r for the artifact I_i can be expressed as follows.

$$R(u_r, I_i) = \sum_{L_p \in LB} \sum_{l_x \in L(I_i)} \delta(l_x, L_p) \quad P(u_r, L_p) \tag{3}$$

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The function $\delta(l_x, L_p)$ is the label judgment function in the formula (1), and $P(u_r, L_p)$ is the label selection probability function in the formula (2). For each user $u_r \in US$ and label $L_p \in LB$, there is a computable selection score value $\mathrm{R}(u_r, I_i)$ corresponding to the artifact $I_i \in IT$. It is worth noting that the artifacts contain all the artifacts in the collection IT, and the labels contain all the labels in the collection LB, so that the result is the rating value of the specified user u_r for all artifacts, and all the labels in the label set LB are comprehensively considered.

For the user $u_r \in US$ formula (3), the user's u_r selection score vector for all artifacts can be calculated. The method adopted in [4] is to use the user-selected score matrix to perform UCF, calculate the Top-N users similar to the target users, and finally calculate the predicted value of each item by the predicted score formula, and recommend according to the ranking of the scores. However, this method neglects that the label score vector for different artifacts $I_i \in IT$ can be equal or approximated by the formula (3), and the scores are similar in the user-selected score matrix, but this is based on different The distribution of the tag score values is calculated, which does not indicate that the artifacts with similar item selection scores are similar. The impact of this will be the diversity of recommendations, but the interpretation of the recommendations is not convincing, and it is difficult to recommend long tails.

The method adopted in this paper is to still use the artifact-tag selection probability value matrix of the target user u_r for ICF calculation, and make full use of the characteristics of the cultural relic tag for recommendation. The score of the item Top-N is obtained by the sorting method of the item selection score vector of the target user u_r. Suppose we select the first n items of the scores as the sample artifacts based on our collaborative filtering. The cosine similarity calculation is used in this paper. Methods as below.

$$sim(I_i, I_j) = \frac{\sum_{l_p \in LB}(P_{I_i l_p} \cdot P_{I_j l_p})}{\sqrt{\sum_{l_p \in LB} P_{I_i l_p}^2} \cdot \sqrt{\sum_{l_p \in LB} P_{I_j l_p}^2}} \tag{4}$$

Where $I_i \in IT$ represents all the artifacts in the collection of artifacts, $I_j \in IT(n)$ represents the selected Top-N sample artifacts, $P_{I_i l_p}$ is the selection probability value of the artifacts I_i for the labels l_p, and $P_{I_j l_p}$ is the artifacts I_j for the labels l_p The probability value of the selection.

Collaborative filtering according to formula (4) calculates the cultural relics similar to the sample relic I_j as the basic data of the recommendation. Here, each sample artifact selects m neighbors, so that n sample artifacts and $n \cdot m$ neighbors are generated. Cultural relics, in which the sample cultural relics I_j are reserved as recommended data, $n \cdot m$ neighboring cultural relics need to be calculated and sorted by selecting the prediction function, and the top ranked cultural relics are selected as the cultural relics recommended to the target user.

$$H(r, S_{ij}) = \bar{r} + \frac{\sum_{j=1}^{n}(r_i - \bar{r}) \cdot S_{ij}}{\sum_{j=1}^{n} S_{ij}} \tag{5}$$

Equation (5) is a selection prediction function of the user u_r for neighboring artifacts. Let $n \cdot m$ neighboring artifacts be T, where r is the user u_r selection score for all artifacts. S_{ij} is the similarity of the neighboring artifact $I_i \in T$ to the sample artifact I_j, and $i \leq n \cdot m$. r_i is the selection score value of the neighbor artifact I_i. $\bar{r}$ is the average of the user's selection scores for all artifacts. It should be noted that the artifact I_i here is different from the I_i in the above, and represents the artifacts in the collection of neighbors T, rather than the artifacts in the collection IT of all artifacts. According to formula (5), we can calculate the predicted value of the user u_r for $n \cdot m$ recommended artifacts. By sorting, we can select the top k artifacts as the predicted recommended artifacts, and the final recommendation result is n sample artifacts and k predictions. Recommended collection of artifacts.

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3.2 Algorithm flow

The input of the algorithm is a cultural object tag data set and a user behavior data set, which are converted into a artifact-tag matrix and a user-creature matrix which can be used for calculation through file import processing.

Step 1: Select the specified target user u_r, obtain the historical data of the user u_r, and extract the user-creature behavior feature vector.

Step 2: Calculate the selection probability value vector of the user u_r for the label set LB by using the formula (1) according to the user-creature behavior feature vector and the artifact-tag matrix, as the user's label selection feature.

Step 3: Calculate the probability value vector of the label selection according to the artifact-tag matrix and the second step, and calculate the artifact-tag selection probability value matrix of the user u_r for all the cultural objects IT by using the formula (2), which is the label selection feature of the user u_r. The mapping on the collection of artifact labels can only explain the behavioral characteristics of the user u_r.

Step 4: According to the artifact-tag selection probability value matrix calculated in step three, the selection score value of the user u_r for all cultural relics IT is calculated by formula (3).

Step 5: Sort the selected scoring value vector in step four, select the first n cultural relics of the scoring value as the sample artifacts of the collaborative filtering, and at the same time, as part of the recommendation result.

Step 6: The sample cultural relics obtained in step 5 are used as the target cultural relics for collaborative filtering. The similarity degree of each sample cultural relic is calculated by the similarity formula (4), and the m nearest neighbor relics of each sample cultural relic are selected. Finally, There are $n \cdot m$ neighbors.

Step 7: We need to make a choice for the $n \cdot m$ neighbors that are calculated in step 6. According to formula (5), we can calculate the predicted value of the user u_r for the neighbors of the $n \cdot m$ neighbors, and eliminate the duplicate neighbors. Sorting can select the top k artifacts as the predicted recommended artifacts.

Step 8: The n sample artifacts obtained in step 5 and the k prediction recommended artifacts obtained in step 7 are used as the final recommendation results, and finally the ($n + k$) recommendation results are provided to the user and the recommended label reason is given.

Figure 1 shows the calculation flow of this algorithm.

4. Experimental evaluation

4.1 Experimental data

To verify the reliability and validity of the algorithm, the experimental part uses the public MovieLens data set as the experimental data set. Mainly use u.user (user information), u.item (movie information) and u.data (user movie rating) [7-9] of the MovieLens data set. In order to reduce the error, the test randomly confuses the data set at the beginning, and tests 80% of the data set as the training set, 20% of the data as the test set, and calculates the user's tag characteristics by using the data of the training set. The set of data is used for recommendation prediction. The length of the recommended list is increased from 5 to 50 in increments of 5. The analysis increases the recommended list length with the recommended list length and the traditional ICF algorithm recommends the list changes, and predicts the recommended results and the actual user in the test set. The score data is compared.

4.2 Evaluation index

Literature [6] systematically summarizes the evaluation methods commonly used in recommendation algorithms. The core idea of the evaluation index is to compare the difference between the predicted result data and the actual data. In this paper, the mean squared error (MSE) and the root mean square error (RMSE) are used to evaluate the prediction accuracy of the experimental results.

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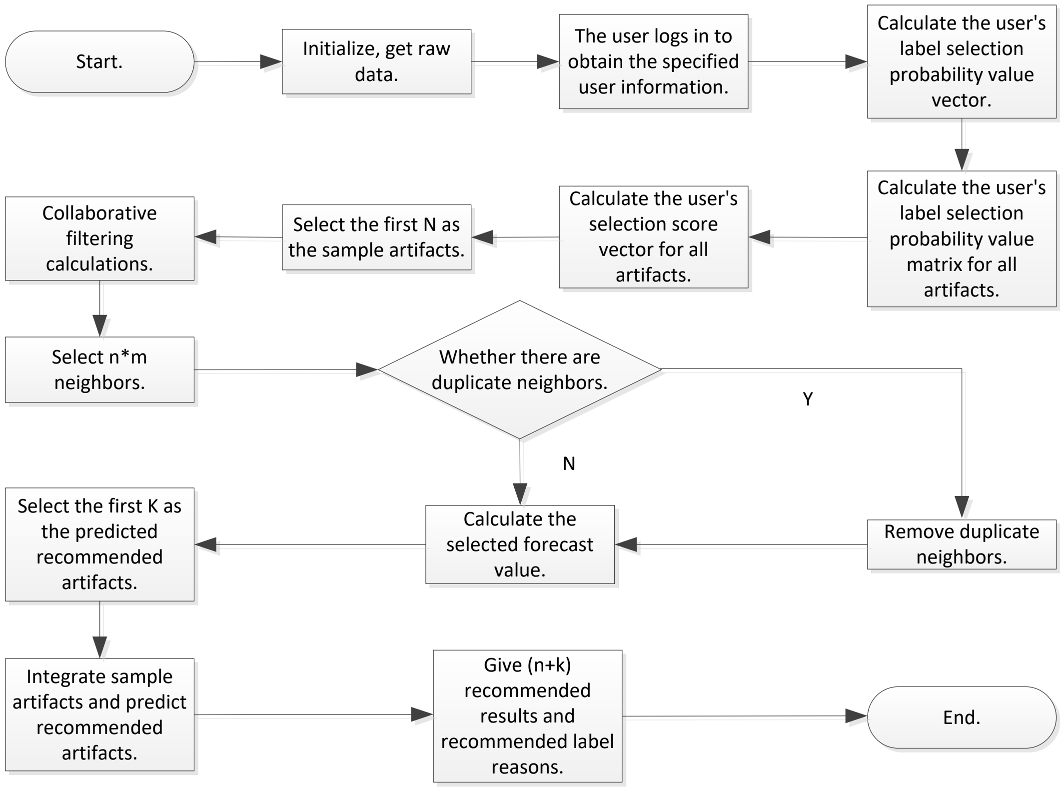

Fig. 1 Algorithm flow

$$MSE = \frac{1}{|E^P|}\sum_{(u,\alpha)\in E^P}(r_{u\alpha}-r'_{u\alpha})^2 \tag{6}$$

$$RMSE = \sqrt{\frac{1}{|E^P|}\sum_{(u,\alpha)\in E^P}(r_{u\alpha}-r'_{u\alpha})^2} \tag{7}$$

This paper studies the nature of the ICF algorithm in the recommendation algorithm. Considering the impact of the malicious score and the cold start of the user data on the experimental results, the algorithm uses the item-based recommendation as the entry point, only whether the user has used it. The item is not the rating value to recommend the item to the user, and the reasonable recommendation reason is given by calculating the user's tag preference characteristics. This paper takes the ranking of recommended items as the evaluation index, calculates the error between the predicted ranking and the actual ranking, and uses formula (6) and formula (7) to calculate the index value.

The classification accuracy of the recommendation algorithm is also an important indicator to measure the pros and cons of the algorithm. The classification accuracy can evaluate whether the recommendation result correctly predicts the user's preference, and is applicable to the system where the user has obvious dichotomous preference for the item. The evaluation mechanism used in this experimental data is a 5-point system. Therefore, this paper adopts a general processing method, and the score of more than 3 stars is taken as the user's favorite rating, and the score of 3 stars or less is taken as the user's disliked rating. At present, the classification accuracy indicators commonly used in the recommended algorithms have accuracy, recall rate, F_1 index and AUC. The accuracy and recall rate are used as the evaluation indicators for the classification accuracy of the recommendation algorithm.

Accuracy describes the probability that a user likes to recommend items in a list. Let the recommended list length be L. According to the above assumption, if the item with the user score

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greater than 3 in the recommendation list is the item that the user likes, and the number is N, the recommended accuracy rate is as follows[14].

$$P_u = \frac{N}{L} \tag{8}$$

The meaning of the accuracy rate P_u in the formula (8) is the ratio of the articles in the recommendation list that the user likes to the total number of recommendations, and the items in the recommendation list are compared with the list actually evaluated by the user, and the items that the user has not evaluated are defaulted as Items that you don't like. It can be seen that as the length of the recommendation list increases, the change in accuracy is uncertain, which is influenced by the number of items evaluated by the user and the user's rating habit.

The recall rate describes the probability that a user's favorite item is recommended. Assuming that the number of items that the user likes in the test set is L_l, and the number of items that the user likes in the recommended list is N, the recall rate recommended for the user u is as follows.

$$R_u = \frac{N}{L_l} \tag{9}$$

The meaning of the recall rate R_u in the formula (9) is that the proportion of the user's favorite items included in the predicted list of predictions of the algorithm accounts for all the favorite items of the user. The larger the length of the recommended list, the greater the possibility that the user likes the item. , so the recall rate is an indicator that increases as the list of recommendations increases.

Under normal circumstances, with the increase of the recommendation list, it is difficult to ensure that the accuracy rate and the recall rate increase together. The evaluation method of combining accuracy and recall rate is given in [7].

$$F_u = \frac{2P_uR_u}{P_u + R_u} \tag{10}$$

In formula (10), F_u combines the accuracy and recall rate with the length of the recommended list, and calculates the harmonic mean of the accuracy and recall rate as the evaluation value of the classification accuracy. If the accuracy and recall rate are larger overall Then, F_u is also increased, that is, F_u is positively correlated with the expression P_uR_u.

4.3 Result analysis

At the beginning of the experiment, the data set was randomly scrambled, and the traditional ICF algorithm and the collaborative filtering recommendation algorithm with tag features in this paper were calculated using the same data set[15,16]. The average squared error index and the root mean square error were used to predict the experimental results. The accuracy was evaluated and the results were as follows.

It can be seen from Fig. 2 and Fig. 3 that the proposed algorithm and the traditional ICF algorithm have significant improvement on the MSE and RMSE indicators. The MSE indicator is sensitive to the accuracy of the low score, in order to verify the recommended items in the label distribution. The characteristics of the recommended item label selection probability statistical value curve are used to visually analyze the recommended item label characteristics.

It can be seen from FIG. 4 that the traditional recommendation algorithm has randomness for the label consideration, ignoring the user's preference for the nature of the item label when the item is selected, and the algorithm of the present invention strictly recommends the user's preference for the label.

The evaluation of classification accuracy in this experiment uses the blending average of accuracy and recall rate[17]. The experiment gives a comparison between the algorithm and the traditional ICF algorithm on two indicators. The results are as follows.

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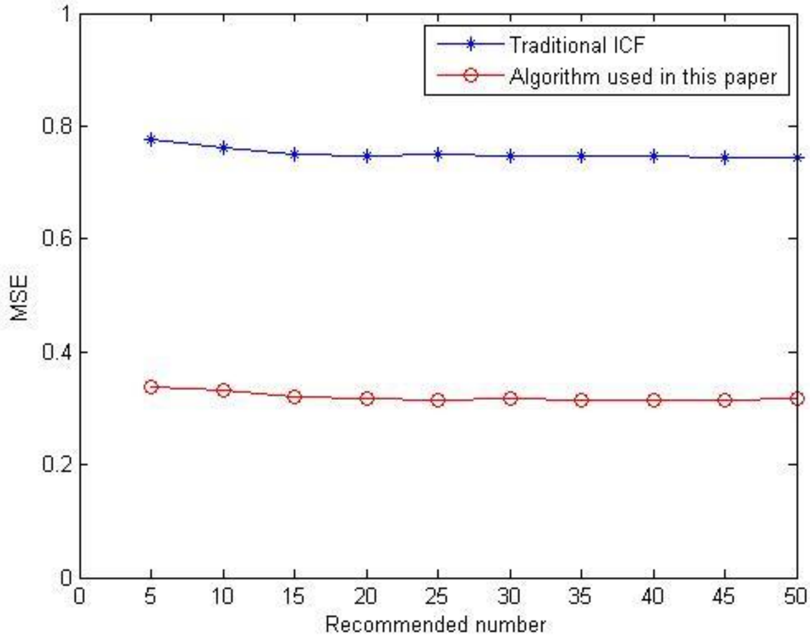

Fig. 2 MSE

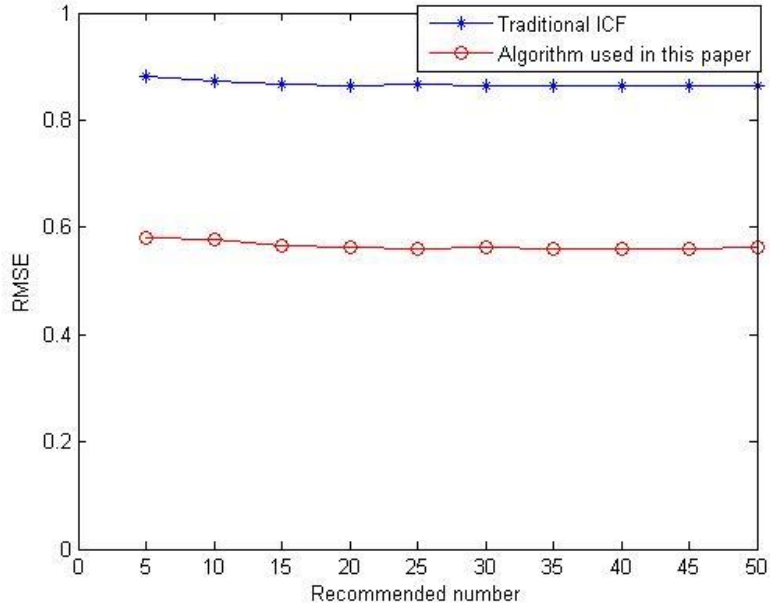

Fig. 3 RMSE

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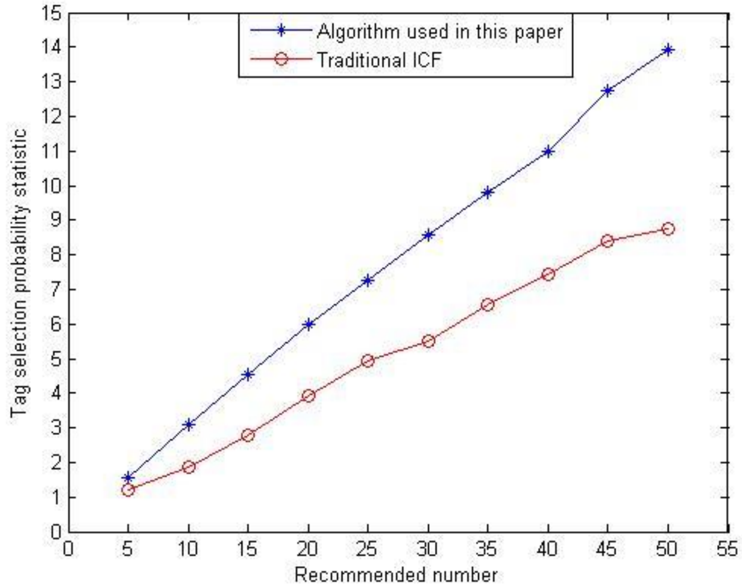

Fig. 4 Tag selection probability statistic

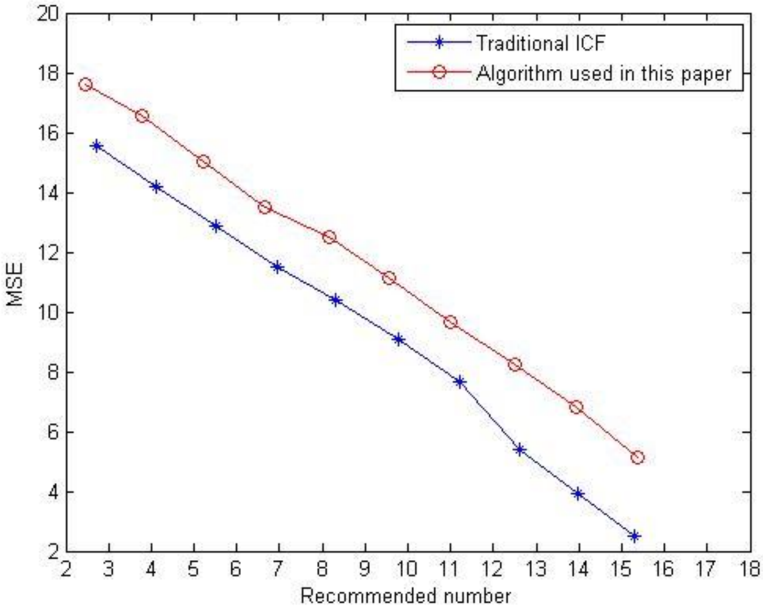

Fig. 5 P-R

It can be known from formula (10) that the larger the value of $P_u R_u$ is, the larger the value of F_u is, indicating that the recommended effect is better. Figure 5 is the P-R value of the traditional ICF and the proposed algorithm in the case of different lengths of recommended lists[18]. The classification accuracy of the algorithm is significantly better than the traditional ICF algorithm.

5. Conclusion

In view of the shortcomings of traditional ICF algorithm for false scoring and cold start of data, this paper proposes an ICF algorithm with tag features. Firstly, the tag is introduced into the data. By analyzing the user's personal historical data, the user is selected when selecting the item. According to this feature, the user is personalized and recommended. Finally, considering that the synthesized score value is not convincing for the interpretation of the result, this paper adopts the label selection value as the calculation target of collaborative filtering to optimize the algorithm. Finally, the experimental results show that the collaborative filtering recommendation algorithm with the tag

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feature of the article has a significant improvement on the prediction accuracy compared with the traditional ICF algorithm, because the recommendation process fully considers the tag feature and avoids the malicious score on the recommendation result. The impact not only improves the accuracy of the recommendation, but also the persuasive interpretation of the recommendation results. The experiment combines the accuracy and recall rate in the assessment of classification accuracy, and uses the harmonic mean of the two. The experimental results show that the proposed algorithm is better than the traditional ICF algorithm, and the recommendation is obtained when the user evaluation is less. The result is more accurate than traditional algorithms.

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