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Improved Recommendation Sorting of Collaborative Filtering Algorithm

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Abstract. The traditional collaborative filtering algorithm has no overall quantitative understanding on users' preference. This paper proposes a collaborative filtering algorithm based on improved recommendation sorting. Based on the traditional collaborative filtering rating prediction, three kinds of weighted sorting strategies are proposed to recommendation list, which are based on the combination of users' preference vector and item quality. Experiments on the MovieLens data set show that, in the same rating prediction process, the recommended results of the improved sorting have a significant increase of nearly one time in the precision, recall and F1 indicators.

Introduction

With the rapid development of information technology and the Internet, the resources on the Internet show an explosive growth. However, while people can obtain the required information in a fast, convenient, low-cost way, we have to spend more time on looking for these information, which is called “information overload” [1].To address these issues, we have explored personalized recommendation system, which can help users in the search of interesting items among a large set based on users’ preference.

Among the different types of recommendation systems, collaborative filtering is the most wildly used and effective recommendation technique. The idea of collaborative filtering can be understood as two parts, collaboration and filtering. Collaboration is reflected in process of prediction score, the effect of filtering is reflected on the sort of recommendation results. In recent years, scholars’ work on improving collaborative filtering point of view, mainly concentrated on mitigating problems of prediction score during the collaborative process, such as data sparse, scalability and cold start and other issues. The traditional collaborative filtering treats the users’ rating as the user’s preference or degree of interest, which is the reason that scholars’ work on improving the collaborative filtering is limited to improve the accuracy of the score prediction. In fact, the score prediction is a means of users’ feedback evaluation. If the rating is not a preference but only the evaluation, the traditional collaborative filtering recommendation just recommends those objects which are predicted to get high evaluation to users. Such a recommendation is meaningful, but the personalization of the recommendation results is in a loss of real preference for a significant portion of the user.

In this paper, we address these issues by proposing an improved recommendation sorting of collaborative filtering algorithm. First, we see the probability distribution of the user's rating behavior data on the item classification as the user's preference vector, so that the users’ preferences will have range as well as size. Secondly, the information filtering is achieved through the sorting result of the recommendation list. Based on the traditional collaborative filtering score prediction, we propose three recommended list weighted sorting strategies combining the user preference vector and the project quality weight ,so that the recommendation results meet the user s’ preference better. Finally, we should pay more attention to the comparative evaluation of multiple metrics in the experimental evaluation of improving the traditional collaborative filtering recommendation algorithm.

Related work

At present, recommendation system is an important means of information filtering, and the recommended techniques include Association Rules, Content-Based Recommendation, Collaborative Filtering and Hybrid Approach [2] .Among the different types of recommendation systems, collaborative filtering is the most wildly used and effective recommendation technique(Adomavicius &Tuzhilin, 2005; Herlocker, Konstan,Borchers,&Riedl,2000).

There are two basic methods of automatic collaborative filtering—user-based and item-based. User-based collaborative filtering algorithms focus on the similarity among users and thus have problems with scalability as the number of users increases. Item-based collaborative filtering algorithms improve scalability by focusing on the similarity among items using user ratings rather than on the similarity among users themselves (Sarwar,Karypis,Konstan,&Riedl,2001).

At the same time, collaborative filtering also has problems such as data sparsity, scalability and cold start, many scholars have carried out a lot of work from different aspects. Item-based collaborative filtering algorithms improve scalability by focusing on the similarity among items using user ratings rather than on the similarity among users themselves (Sarwar, Karypis, Konstan, & Riedl, 2001). Huang et al. [3] adaptively select the neighbors of the prediction target by the user and the similarity calculation of the product to improve the accuracy of the score prediction.Zhang et al [4] based on the cloud model, Zhang Feng et al [5] used BP neural network, Hou Cuiqin [6] proposed a compressed sparse user scoring matrix, through the above improvements to alleviate the affects of scoring data sparsity on collaborative filtering recommendation quality, and improve the accuracy of score prediction.However, the subsequent works on improvements of collaborative filtering mostly focused on the rating prediction of collaborative process, and lack the evaluation of information filtering effects on recommended items.So in this paper,we pay more attention on the sorting result of the recommendation list.

In the aspect of evaluation metrics of recommendation system, Zhu Yu-xia summed up the existing evaluation metrics system of recommender system in literature [7], divided the evaluation metrics into four main aspects :accuracy metrics, weighting metrics based on sorting, Coverage metrics and diversity and novelty metrics. MAE, Coverage, Precision and Recall were used to compare the three models in collaborative filtering model evaluation [8].In this paper,we use precision, recall and F1 indicators.

We propose three recommended list weighted sorting strategies combining the user preference vector and the project quality weight ,so that the recommendation results meet the user s' preference better, which can proved with precision, recall and F1 indicators.

Improved Sort of Recommended Lists

Users' Preference Weights The items in the recommendation system are generally classified. The classification can be expressed as: Classification = {C1, C2, ..., Ci, ..., Ck}, Ci is the i-th class of k classes. The users' preferences are distributed in some categories in the overall category ,so that the user's category preference vector in the category can be expressed as User_Pref = {P1, P2, ..., Pi, ..., Pk}, where Pi is the probability of items belonging to the i-th class in k classes evaluated by the user , and $\sum_i^k pi = 1(0 \le pi \le 1, 1 < k < n)$. The classification vector for any item, expressed as Item_classif={I_1,I_2,…,I_i,…,I_k},where the value of Ii is 0 or 1. When the item I belongs to i-th class, the value is 1, otherwise, the value is 0. It should be noted that an item can not only belong strictly to a classification, but also belong to different categories. The combination of the user preference vector and the item classification vector can determine the probability of the recommended target item in the user's preference range.

Recommendation system is wildly used in e-commerce, film sites, music sites and other practical applications. The items are general classified in these sites. Classification can bring a lot of benefits, such as to describe the classified characterization, to facilitate the management of the item set in system. At the same time, it can also better represent the user's preference range. Here we make

hypothesisn1: a user's rating of a item can only reflect the individual's evaluation of the item, the probability distribution in category of all the items which users have evaluated can reflect the user's preferences. Therefore, the users' preference vectors present the range and size of users' previous preferences when recommend to users next time. Based on this assumption to explain the traditional collaborative filtering recommendation, it can be considered that predicting the user's evaluation is not enough, predicting the users' selected range is also critical.

Item Weight of Pros and Cons Collaborative filtering recommendation is based on user evaluation matrix, here we make hypothesis 2: A large number of users evaluate items with score, which can reflect the quality of the item. Therefore, the pros of an item can be expressed by the average score, Item_avg_rating. Of course, only when an item is rated a certain number of times by the user, the average score can reflect the pros and cons of the project. The higher average score of the item gets, the item's quality is better, vice versa. It can be considered that a high predictive score item to user may not in good quality. When a item is evaluated in poor quality by a certain number of users, we should avoid to recommend the item to the users, in order to protect the users' experience, while achieving the purpose of survival of the fittest.

Recommended List Sorting Strategies Strategy 1: These items are ranked in descending order according to the prediction score of the target items, and the first N items of the ranking will be recommended to the user.

$$\text{Ordering\_strategy1} \leftarrow \text{order(PRui)[1:N]}$$

This strategy is the traditional collaborative filtering sorting of recommended list. It recommends the appropriate number of N items which get the highest prediction scores from the users. Here, according to hypothesis one, the prediction score is high, that is, the user tends to give the item a high score, but the item is not necessarily within the range of user's existing preferences. Therefore, the user's preference vector indicates a preference extent and the size of an aspect preference of the user in the next recommendation to the user. Based on this hypothesis to explain the traditional collaborative filtering recommendation, it can be considered that the prediction user's evaluation is not enough, and it is also the key to predict the range of the user's more likely choice.

Strategy 2 We introduce the preference vector weight on classification of the target user ,and rank the items according to the product of the preference vector and the target items' prediction score in decreasing order, and recommend the first N items of the ranking to the users.

$$\text{Ordering\_strategy2} \leftarrow \text{order}(\sum \text{User\_Pref*Item\_classif*PRui})\text{[1:N]}$$

The improvement in the ranking of the strategy is to recommend the user's target items that not only are tended to evaluate high score by the users, but also belong to the classification in the user's preferences, so that they tend to be the user's core preferences. Therefore, the advantage of this strategy is that the recommendations are more in line with the user's existing preferences, in order to improve the user experience.

Strategy 3: We introduce the item weight of pros and cons, and rank the items according to the product of the item weight of pros and cons and the target items' prediction score in decreasing order, and recommend the first N items of the ranking to the users.

$$\text{Ordering\_strategy3} \leftarrow \text{order(Item\_avg\_rating *PRui)[1:N]}$$

The improvement of the strategy is to recommend the user's target items that not only are tended to evaluate high score by the users, but also are thought of in good quality. Therefore, the advantage of this strategy is that the recommendations introduce a mechanism of survival of the fittest, in order to make sure the good quality of recommended items and improve the user experience.

Strategy 4 We introduce the the preference vector weight and t the item weight of pros and cons of the target user at the same time, rank the items according to the product of the two weights and the target items' prediction score in decreasing order, and recommend the first N items of the ranking to the users.

$$\text{Ordering\_strategy4} \leftarrow \text{order}(\sum(\text{User\_Pref*Item\_classif})\text{*Item\_avg\_rating *PRui})\text{[1:N]}$$

The strategy is a combination of strategy 2 and strategy 3, integrating the advantages of these two strategies. To maximize the protection of the recommended quality in order to enhance the user experience, in other words, the recommended items not only have high prediction score but also are

within the range of user's existing preferences, in addition the quality of the project itself is also guaranteed.

Experimental environment, data sets and evaluation metrics

Experimental environment is a PC, configured with Intel i3 350M processor 2.26GHz, RAM 4GB and Windows 7 operating system. Development tool is RSudio, achieving programming the algorithm with R language .

The dataset is a set of MovieLens real score data provided by the University of Minnesota, USA. The dataset is widely used in the improvement of collaborative filtering technology. The MovieLens-100K contains 1,0000 ratings (5 points) from 943 users for 1,682 movies, and each user rates at least 20 movies, all of which belong to 19 movie classifications.

The choice of experimental evaluation metrics is an important part of the experiment. Reasonable evaluation metrics can evaluate the performance of the algorithm well and help to find how to improve the algorithm. We use the most commonly used MAE (Mean Absolute Error) [20] as the evaluation metric to evaluate accuracy of prediction score. The accuracy of the recommended results was measured by calculating the difference between the prediction score and the real evaluation data. The smaller MAE value is, the higher accuracy of the prediction scores is. Assuming that the predicted set of user ratings is $\{p_1, p_2, ..., p_N\}$, the corresponding actual user rating set is $\{q_1, q_2, ..., q_N\}$, the specific MAE calculation formula is

$$MAE = \frac{\sum_{i=1}^{N} | p_i - q_i |}{N} \quad (5)$$

The classical precision, recall and F1 values were used as the evaluation metrics for the different sorting strategies of the recommended lists. Specific formula is as follows:

$$\text{Precision} = \frac{|\cap(PredictionSet, ReferenceSet)|}{|PredictionSet|} \quad (6)$$

$$\text{Recall} = \frac{|\cap(PredictionSet, ReferenceSet)|}{|ReferenceSet|} \quad (7)$$

$$\text{F1} = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (8)$$

Here PredictionSet is the set of items ’scoring data predicted by the algorithm, and ReferenceSet is the real item scoring data set. F1 value can be used as the final evaluation metric of the filtering affects with recommended sorting results.

Experimental Results and Analysis

The impact of neighborhood size on MAE

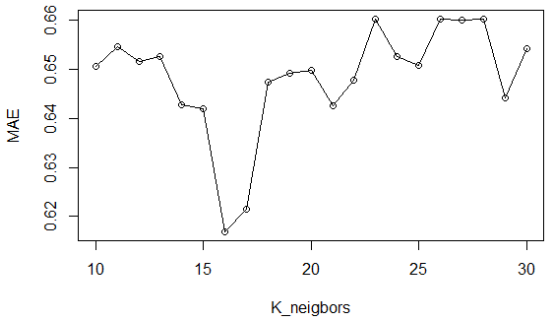

Figure 1 The impact of neighborhood size on MAE

From the distribution of the number of nearest neighbors on the cosine similarity between 10 and 30 in Fig. 1, the MAE evaluation of the prediction score shows that the best prediction accuracy is achieved when neighborhood size is 16. Therefore, in the process of improving the collaborative

filtering recommendation, the prediction scores are predicted on the number of 16 neighbors on the cosine similarity.

Comparison of the results of different sorting strategies

The aim of the experiment is to compare the traditional collaborative filtering recommendation process with the three improved sorting strategies which introduce the users' preference classification weight and the items' quality weight. Strategy 1 is the traditional collaborative filtering recommended sorting, that is simply sort according to the prediction score to recommend. The three improved sorting strategies are strategy 2, 3 and 4. Strategy 2 introduces the preference vector weight on classification to weighted sorting strategies, strategy 3 introduces weight of item quality of pros and cons to weighted sorting strategies, and strategy 4 integrates prediction score, users' preference vector and weight of item of pros and cons. Theoretically, the improved sorting strategy should be improved in the evaluation metrics, it has been verified in the experiment.

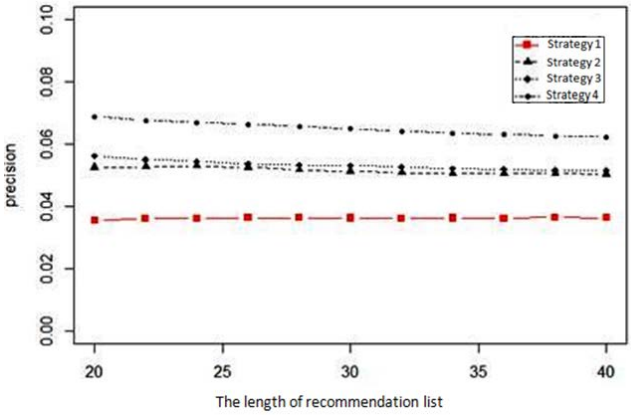

Fig.2 Comparison of the accuracy results of different sorting strategies recommended results

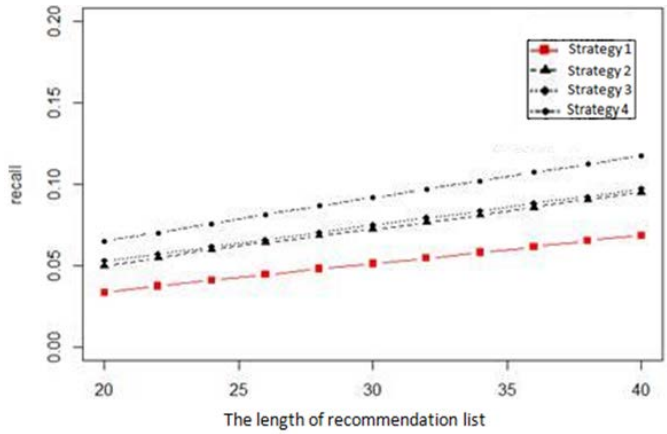

Fig.3 Comparison of the Recall rate of different sorting strategies recommended results

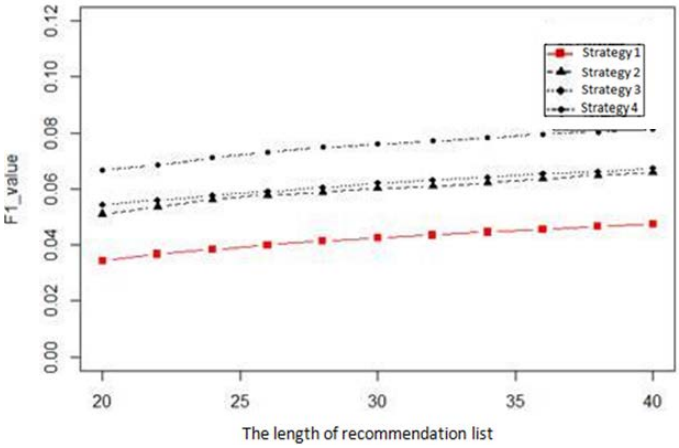

Fig.4 Comparison of F1 of different sorting strategies recommended results

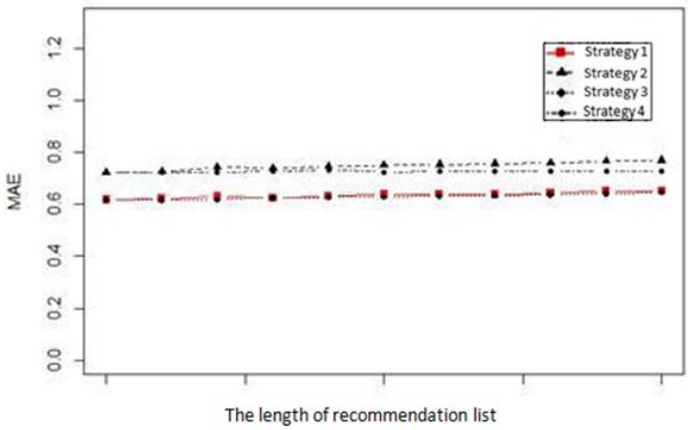

Fig.5 Comparison of MAE of different sorting strategies recommended results

It can be observed from Fig. 2 that the accuracy of recommendation results indicates that the length of the recommended list has a certain influence on the precision within a certain range, and the accuracy will decrease with the increase of the recommended list length. Compared with the traditional Collaborative Filtering Recommended Sorting Strategy 1, the improved sorting strategies 2,3,4 have a significant improvement in accuracy, among them the comprehensive sorting strategy 4 has a significant improvement. Accuracy indicates the proportion of items that are recommended and actually selected by the users in the set of items recommended to them. The greater the value of accuracy is, in other words, the greater the proportion of items recommended to the users to be accepted or selected by the user is, the better the recommended effect is, vice versa. The accuracy of

strategy 2 and strategy 3 is significantly higher than that of strategy 1, which validates two assumptions of users' preference classification weight and item weight of pros and cons. The recommended effect only recommend by prediction score can be improved a lot, the comprehensive weighted sorting strategy 4 improves more significant.

It can be observed from Figure 3, the comparison of the recall rate of the recommendation results shows that the length of the recommendation list has a significant influence on the recall rate within a certain range, and has a positive correlation. Compared with the traditional Collaborative Filtering Recommended Sorting Strategy 1, the improved sorting strategies 2, 3, 4 have a significant improvement in recall rate, among them the comprehensive sorting strategy 4 has a significant improvement. Recall rate indicates the proportion of items that are recommended and actually selected by the users in the set of the items actually selected by the user. The greater the value of recall rate is, the better the recommended effect is, vice versa. The recall rate of strategy 2 and strategy 3 is significantly improved than that of strategy 1, which validates two assumptions of users' preference classification weight and item weight of pros and cons. In addition, the comprehensive weighted sorting strategy 4 improves more significant.

Evaluation metric F1 value is a combination of precision and recall rate. In the different recommended list length of the sorting strategy recommended F1 evaluation results shown in Figure 4. The evaluation metric F1 value depends on the length of the recommended list, which increases with the recommended list length increases. Compared with the traditional Collaborative Filtering Recommended Sorting Strategy 1, the improved sorting strategies 2,3,4 have a significant improvement inF1, among them the comprehensive sorting strategy 4 has a significant improvement. The F1 validates two assumptions of users' preference classification weight and item weight of pros and cons as the only comprehensive metric, can indicates strategy 2 and strategy 3 is significantly improved than that of strategy 1. In addition, the comprehensive weighted sorting strategy 4 improves more significant.

It can be observed from Figure 5, the distribution of the MAE of the recommendation results indicates that the length of the recommendation list does not have a significant effect on the accuracy of the prediction score. In the same score prediction process, the prediction scores of the recommended items have high predictive accuracy in the recommendation process with different recommendation list sorting strategies. Among them, the MAE of the prediction score of recommendation results from traditional collaborative filtering sorting strategy 1recommendation process is almost the same as the MAE of the most significant comprehensive weighted sorting strategy 4. The weighted sorting strategy 2 and the strategy 3 have only a small amount of deviation on MAE.

According to the results and analysis of the experiment, we can draw three important conclusions:

First, the traditional collaborative filtering algorithms think that the score is the degree of interest, so that the recommendation results miss a considerable part of the user's real preferences, and weaken the recommended system information filtering capabilities.

Second, the collaborative filtering recommendation (CF) should consist of three important processes: (1) Finding the most similar neighbors by computing the similarity; (2) Generating the prediction score of user's target items by combining the neighbor's score and similarity weight method; (3) Weighted sorting the items by prediction score to generate a recommendation list, incorporating the users' preference and the weight of the factors important to the user experience perception.

Thirdly, the quality of collaborative filtering is only evaluated by the accuracy of scoring. The evaluation ability of collaborative filtering is not sufficient. We should pay more attention to multi-metrics evaluation.

Conclusions and Prospects

Internet will promote the transformation and upgrading of the production service industry, users need to meet the higher requirements of the personalized service experience background. This paper

proposes an improved sorting recommendation collaborative filtering algorithm based on a large number of improved researches about collaborative filtering, which is a hot collaborative filtering recommendation technology for academic and industrial applications. The improvement of this algorithm weakens some advantages of the collaborative filtering recommendation technology. For example, the recommendation results of the weighted sorting weaken the ability of new recommendation. However, the improved collaborative filtering recommendation algorithm should have better recommendation ability and user experience in recommendation system application of content-based websites such as movie video and music website. In summary, this paper proposes that excellent recommendation should have the following three aspects: (1) to obtain the users' preference vector accurately; (2) the collaborative filtering score prediction accuracy is within the acceptable range; (3) The results of recommend list are in accordance with the order of the users' preference vector and the items of pros and cons. It should be pointed out that the recommendation result s of the recommendation system should not only be personalized, but also be in accordance with the users' preference.

Future work on collaborative filtering recommendation can pay more attention to the weighted ordering of recommended lists, because information filtering is achieved by sorting. At the same time, the recommended system has the needs the corresponding Internet business models, its recommended ability should not only meet the personalized requirements of users, but also pay attention to the issues like profitability of the platform, management of recommended item resource, etc. Therefore, it is necessary to concern and research more management science, marketing disciplines areas.

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