A Weighted Multi-attribute Method for Personalized Recommendation in MOOCs

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ABSTRACT

In recent years, with the rapid development of MOOC (massive open online course), more and more people get knowledge from the Internet. The big data analysis for MOOC has become a new research direction and it has been a focus that how to recommend individually personalized videos for MOOC users. To date, the most widely used personalized recommendation technology is collaborative filtering (CF) technology. In this paper, we propose a personalized recommendation algorithm—multi-attribute weight algorithm (MAWA) based on CF. Firstly, MAWA calculates separately the weights of the attributes and attribute values of the resources for the target user. Secondly, the two weights of a video are used to get a recommendation value. Finally, the resources with N highest recommendation values are recommended for the target users. The MAWA in this paper makes up for the shortcomings of traditional CF algorithm and it can be shown from the experiment in this paper that the recall rate of MAWA is 28.3% higher than CF, which means that the recommendation results of MAWA is more accurate than those of CF. The contribution of this paper is to weight the attributes and attribute values respectively, which can reflect the users' preferences in both coarse granularity and fine granularity.

CCS CONCEPTS

•**Social and professional topics→User characteristics;**

Social and ***professional topics****→Computing education ;*

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ICCSE'17, July 6–9, 2017, Beijing, China

ACM ISBN 978-1-4503-5375-5/17/07$15.00
https://doi.org/10.1145/3126973.3126981

KEYWORDS

multi-attribute weight algorithm, collaborative filtering algorithm, MOOC, video recommendation technology

1 INTRODUCTION

1.1 Background and Related Work

With the progress of computer science and technology, people are closely linked with the Internet in many aspects of life. For example, in the field of education, more and more people can receive quality education by Internet. Oneofthe most outstanding distance education method is the Massive Open Online Course (MOOC). The MOOCs combine the picture, voice and flash with the online courses[1], which greatly encourages the students' interests. Hundreds of thousands of students are using the MOOC to learn the lessons which they are interested in. The MOOC videos on the Internet have increased exponentially. The data from the ministry of theonline education research center shows that in 2016, the Coursera platform cooperates with manyuniversities and enterprises from 28 countries in the world. And the MOOC platform needs to satisfy different users' demands. So therecommendation technology abouteveryone's characteristic has become a research point both in academic field and in industrial field.

The recommendation technology ofinformation was put forward in the early days of e-commerce. At that time, the users would get the same recommendation set because the recommendation technology treat all users in the same way. As time went by, the personal technology of recommendation isemerging to recommend resources for users individually. Nowadays, there are three major recommendation approaches: collaborative filtering [2-11], content-based filtering[12-14] and knowledge-based recommendation[15]. In this paper, we focus on the collaborative filtering because it obtains better results than the other recommendation methods [16,17]. However, there are two main interrelated problems about the collaborative filtering (CF): one is the cold start problem [18] and another is the sparse matrix problem [19].

In the academic field, many scholars have studied the collaborative filtering technology and made a great progress. In [20], Karypis and Sarwar B propose SVD (singular value decomposition) method to release the influence of sparse matrix problem of the CF. In [21], F Ortega and J Bobadilla et.al. use Pareto dominance to eliminate less representative users by pre-filtering process while retaining the most promising neighbors. In [22], YH Guo and G Deng propose a new personal technology of recommendationwhichbased on traditional CF algorithm inorderto improve the e-commerce recommender system. In [23], J Zhang and Z Lin et.al. present an approach to computer similarity between genres as similarity in order to lower sparsity of the user-item score matrix. In [24], JF Zhou, X Tang and JF Guo also try to lower sparsity of the user-item score matrix by using a new revised conditional probability expression.

In the industry field, the collaborative filtering technology was first used in Grouplens system which helped users find news that might be satisfiedwiththe users' preference[4]. In the early 21th century, CF was applied on e-commerce system, such as Amazon, Ebay, Taobao and so on, which obtained great results. Apart frombeing used in e-commerce, the collaborative filtering technology was alsoapplied on Video Recommender that was a movie recommendation system developed by Bell Core. CF was also applied on themusic community suchasLast.fm.

1.2 Summary of Content and Contributions

Although some aspects ofthe collaborative filtering haveimprovedby many scholars, the CF still can be improved in other aspects. In this paper, we combine the CF's basic idea with the attributesof MOOC videos' structure'sfeature to propose a new personal algorithm ofrecommendation. The results of this paper can be used in other fields as well.

The rest of this paper is organized as follows. First, we introduce the basic idea of the collaborative filtering technology and the process of the collaborative filtering technology. We analyze the process of the CF and find its advantages and shortcomings which haven't been resolved completely.Second, we propose a multi-attribute weight algorithm using the attribute weight and attribute value weight to get accurate users' preferences. At last, we conduct an experiment to verify the MAWA's recommendation result is more accurate than the CF's.

Our main contributions include two aspects: (1) using attribute weight and attribute value weight to reflect the users' preferences in both coarse granularity and fine granularity; (2) making up for the two main shortcomings of CF, while many other improved approaches solve only one of them.

2 Collabratve Filtering Technology

In this part, we will introduce CF algorithm, describe the procedure of CF algorithm and analyze the advantages and shortcomings of CF algorithm.

2.1 Sample Fabrication Introduce to collaborative Filtering Technology

CF technology was proposed by scholars in 1990s to make up for the shortcomings of the content filtering technology. Since CF algorithm appeared, CF technology has been a research hotspot because of its solid theoretical basis. The CF technologysupposes that the preferences of users will not change over time. Typically, collaborativefiltering can be divided into user-based and item-based. The difference between them lies in that the former tries to find the collections of similar users and recommend the historical resources of the target user's similar users, while the latter tries to find the collections of similar resources and recommend the resources which are similar to the target user's resource history.The CF technology can find out the new resources which are similar to the target user's resource history. It means that CF technology can detect the potential resource that the target user may be interested in.

2.2 Similarity Measurement

Since both user-based collaborating filtering and item-based collaborating filtering need to measure the similarity, we will introduce the three most popular similarity measure methods below. Take the user-based collaborating filtering for example. The user-item score matrix R is an m*n matrix, which means there are m users and n items. $R_{u,c}$ means that the user u give the item c a score $R_{u,c}$.

2.2.1 Cosine similarity

Theuser's scores of the items are considered as an n-dimensional vector, and the cosine angle between the users' score vectors represents the similarity between the users.The cosine similarity formula is as follows:

$$sim(u_i,u_j) = \frac{\sum_{c=1}^{n} R_{i,c} \cdot R_{j,c}}{\sqrt{\sum_{c=1}^{n} {R_{i,c}}^2}\sqrt{\sum_{c=1}^{n} {R_{j,c}}^2}} \qquad (1)$$

In (1), $sim(u_i,u_j)$ represents the similarity between user u_i and user u_j.

2.2.2 Modified cosine similarity

The cosine similarity's has a shortcoming that the user may not score the item, which will result in errors in the results. To make up for this, modified cosine similarity is proposed.

The user u_i and u_j have scored twoitem sets I_i and I_j respectively. The items in both I_i and I_j form a set I_{ij}. The modified cosine similarity formula is as follows:

$$sim(u_i,u_j) = \frac{\sum_{c\in I_{ij}}(R_{i,c}-\overline{R_i})(R_{j,c}-\overline{R_j})}{\sqrt{\sum_{c\in I_i}(R_{i,c}-\overline{R_i})^2}\sqrt{\sum_{c\in I_j}(R_{j,c}-\overline{R_j})^2}} \qquad (2)$$

In (2), $\overline{R_i}$means u_i's average score of items which have been scored by user u_i.

2.2.3 Pearson correlation coefficient

The setI_{ij}contains items that both $u_i$and $u_j$have scored. The Pearson correlation coefficient formula is as follows:

$$sim(u_i, u_j) = \frac{\sum_{c \in I_{ij}} (R_{i,c} - \overline{R_i})(R_{j,c} - \overline{R_j})}{\sqrt{\sum_{c \in I_{ij}} (R_{i,c} - \overline{R_i})^2} \sqrt{\sum_{c \in I_{ij}} (R_{j,c} - \overline{R_j})^2}} \quad (3)$$

2.3 Process of User-based Collabrative Filtering Algorithm

The main process of user-based collaborative filtering algorithm can be divided into three stages:

2.3.1 Establish the user model.

Use m*n matrix R to represent the user-item score matrix, containing m users and n items. The element of matrix is the score that the user has given to the item, ranging from 0 to 10. When the element is 0, it means that the user hasn't use the item or hasn't given a score to the item.

2.3.2 K nearest neighbor query

Firstly, use the similarity measure methods to measure the similarities between target user and other users. Secondly, select k users with the highest k similarity degrees to be the neighbors of the target user. Finally, form a neighbor set with the k selected users in non-incremental order of the similarity degrees.

2.3.3 Generate recommendations

Use the neighbor set in step 2 and the formula below to predict the user's score for each item. Recommend N items with top N predicted scores. The predicted scores are calculated as follows:

$$p_{u,i} = \overline{r_u} + \frac{\sum_{n \in N} sim(u,n)(R_{n,i} - \overline{r_n})}{\sum_{n \in N} sim(u,n)} \quad (4)$$

In (4), $\overline{r_u}$ means u's average score for all items and N_u is u's neighbor set.

2.4 The Advantages and Shortcomings of CF

Both the user-based collaborative filtering and the item-based collaborative filtering have achieved great success in many fields in practice. Based on the theory and process of CF introduced above, the advantages and shortcomings of CF are summarized as follows:

2.4.1 The advantages of CF:

a) CF is easy.As we can see from this paper,CF only needs a user-item score matrix and conducts simple calculation based on this matrix, so the CF is very easy to be applied in practice.

b) CF can be applied on many different fields. The CF can be applied to both structured and unstructured resources, so the CF can be applied widely.

c) CF can detect users' new interest points.As mentioned above, CF can recommend the new resources to target users to help users detect their new interest points.

2.4.2 The shortcomings of CF:

a) Cold start problem. The CF generates recommendation set according to the resources that the users have used and scored. So only if one resource has been used and scored by at least oneuser, it can be recommended to other users. However, when there is a new resource, it hasn't been scored by any users, so it has no chance to be enrolled in the recommendation set.

b) Sparse matrix problem. As mentioned above,the CF calculates on user-item score matrix. The matrix is sparse because the average amount of items that one user has used is less than 1% of the total and many users don't score the items initiatively. So the similarity measurements between users are not accurate and the neighbor set is not reliable, resulting in low recommendation efficiency.

3 Multi-attribute Weight Algorithm

In part II, we introduced CF technology and analyzed its shortcomings. In order to overcome these shortcomings, we propose multi-attribute weight algorithm.

3.1 Introduce to Multi-attribute Weight Algorithm

Suppose that an item can be described by some constant attributes and the target user likes one item because it has some attributes that the user likes.Based on these twoassumptions, we can recommend some resources to the target user according to the attributes. Based on CFtechnology and the assumption, we propose the multi-attribute weight algorithm which uses attribute weight to represent the user's preference on attribute and attribute value weight to represent the user's preference on attribute value under an attribute.

The MAWA calculates on the user-attribute valuematrix R. The M*N matrix R means that there are M users and Nattribute values for an attribute. The element of R is the number that the user has visited the attribute value. If the item can be described by T constant attributes, there will be T matrices in total.

The MAWA can make up for the shortcomings of CF. With regard to cold start problem, the MAWA uses the attribute value instead of item in matrices. When new resource comes up, the new resource mostly has the common attribute values with the old resources. The probability that the new resource doesn't have any common attribute values under T attributeswith the old resources is almost 0. Thus, the new resource has the chance to be included in the recommendation set according to its common attribute values with the old resources. As to sparse matrixproblem, since the amount of attributes and the amount of attribute values are bothconstant and they are far less than the amount of the items, so the user-attribute value matrices couldn't be as sparse as the user-item score matrix.

The MAWA calculates onthe user-attribute value matrices to find every attribute value'sneighbor attribute values by the means of CF and recommend the resources which has the target user's favorite attribute and attribute value or their neighbors.

3.2 Process of Multi-attribute Weight Algorithm

The main process of multi-attribute weight algorithm is as follows:

3.2.1 Calculte the similarity between attribute values.

If the item can be described by T constant attributes, then there will be T user-attributes value matricesR_1,R_2...R_s toR_T.For each user-attribute value matrix R_s, use the cosine similarity measurement to calculate the attribute values' similarity with other attribute values of the attribute S.

$$sim(s_a, s_b) = \frac{\sum_{u=1}^{n} R_{u,s_a} \cdot R_{u,s_b}}{\sqrt{\sum_{u=1}^{n} R_{u,s_a}{}^2}\sqrt{\sum_{u=1}^{n} R_{u,s_b}{}^2}} \quad (5)$$

In (5), $sim(s_a, s_b)$represents the similarity between attribute value s_a and s_b. R_{u,s_a} means the times of resources with attribute value $s_a$that the user U has used.

3.2.2 Find the neghbor set of attribute value.

Select K attribute values withtop ksimilarity degrees to be the neighbors and form a neighbor set with the k selected items in non-incremental order of the similarity degrees.

3.2.3 Get the recommended attribute value set.

For every attribute value, predict the times that the target useruses it.SelectL recommended attribute values with top L prediction values to form a recommended attributed value set. The prediction formula is as follows:

$$P_{u,s_a} = \overline{P_{s_a}} + \frac{\sum_{s_b \in C} sim(s_a,s)\left(R_{u,s_b} - \overline{P_{s_b}}\right)}{\sum_{s_b \in C} sim(s,s_b)} \quad (6)$$

In (6), P_{u,s_a} representsthe predicted amount that user U uses attribute value s_a. $\overline{P_{s_a}}$ is the average amount that all users use attribute value s_a. The C means the neighbor set of attribute value s_a.

3.2.4 Calculate the weight of attribute values.

For each attribute value, calculate its weight for target user U. If the attribute value is not included in recommended attribute value set of target user U,its weight is 0. The weight formula of attribute values is defined as follows:

$$W_{u,s_a} = \begin{cases} \frac{P_{u,s_a}}{\sum_{s_i \in L_s}\left(P_{u,s_i}\right)} & , \quad s_a \in L_s \\ 0 & , \quad s_a \notin L_s \end{cases}$$
(7)

In (7), W_{u,s_a} represents the weight of attribute value $s_a$for user U.L_s is the recommended attribute value set of attribute S.

3.2.5 Calculate the weight of attributes.

For target user U, calculate the standard deviation for each attribute to represent the interest distributions. The bigger the standard deviation is, the more concentrated the target user's interests are. The weight formula of attributes is as follows:

$$Q_{u,s} = \sqrt{\frac{1}{n_s}\sum_{k=1}^{n_s}(R_{u,s_k} - \overline{R_{u,s}}\ \ )^2} \quad (8)$$

In (8), $Q_{u,s}$ represents the standard deviation of attribute S for target user U. The $\overline{R_{u,s}}$ is user U's average use times for attribute S. Andn_s is the number of attribute values of attribute S.

3.2.6 Generate the recommendationset.

For target user U, calculate the value of all attributes for each resource. Select the N recommended resources with highest N recommendation values to form a recommendation set. Recommend the resources in recommendation set to target user. The recommendation value formula is as follows:

$$V_{u,\mathrm{t}} = \sum_{S=1}^{S} W_{u,s_t} * \left(\frac{Q_{u,s}}{M_s}\right) \quad (9)$$

In (9), the$V_{u,\mathrm{t}}$represents the resource t's recommendation value for user U. The M_s is a controllingcoefficient that can help modify the attribute weight to achieve a better recommendation efficiency.

4 Experimental Results and Discussion

In the part II and part III, we respectively introduce the collaborative filtering technology and multi-attribute weight algorithm. In this part, we compare the efficiencies of the two algorithm using true data set from MOOC College.

4.1 Data set and evaluating indicator

In this paper, we use the web crawler to get the true data set from MOOC College. The data set we use contains 978 MOOC videos, 30 users and 2026 score records. The scarcity of user-item score matrix is 6.9%. We select 4 constant attributes to represent the MOOC videos, which are language, platform, school and video score. In more detail, the language contains Chinese and English. The videos are originally from 18 different platforms and 73 different schools. The scores vary from 0 to 10.

The recall rate in the field of information retrieval can be used to evaluate the effect of the CF and the MAWA. The higher the recall rate is, the more accurate the recommendation results are. First,division coefficient 'a' is utilized to divide the primitive data into two parts, one of which is the test set while the other one is the training set. For example, 'a' ranges from 0.1 to 0.9 by 0.1. The 2026*'a' resources are regarded as the training set and the rest are test set. Second, use the CF and the MAWA respectively to generate the recommendation set. Finally, use (10) to calculate the recall rate.

$$\text{recall} = (\text{recommendation set} \cap \text{testing})/|\text{testing}| \quad (10)$$

4.2 Experimental environment

First, we use python 2.7.12 to write the web crawler to get data set from the MOOC College and the data downloaded from the web is stored in mysql 5.7.17.Second, we set the controlling cofficients to be 5 5 2 and 10 for the four attributes. Then we use the matlab 8.3.0.532 to generate the recommendation sets using the CF and the MAWA and calculated the recalls for nine times with varying ‘a’. Finally we get a curve of recallsand an average recall.

4.3 Experimental results and discussion

The experimental results are shown in Table. 1and Fig. 1:

Table. 1. Table of two algorithms’ recalls

a	Personalized Recommendation Algorithm	
	Multi-attribute Weight Algorithm	Collaborative Filtering Algorithm
0.1	0.4026	0.3319
0.2	0.4185	0.3537
0.3	0.3865	0.3470
0.4	0.4173	0.3531
0.5	0.4205	0.3455
0.6	0.4494	0.3420
0.7	0.5519	0.3443
0.8	0.4691	0.3630
0.9	0.4921	0.3416

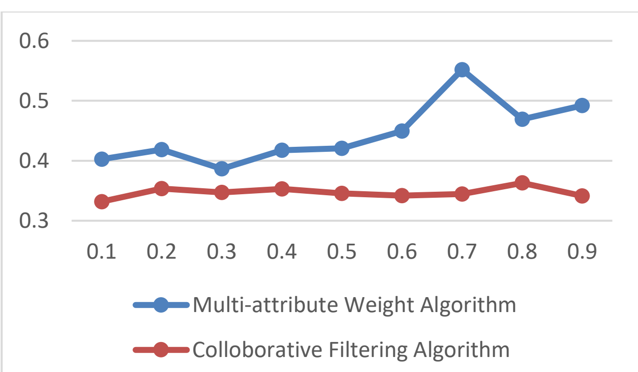

Fig. 1. Curve of two algorithms’ recalls

The average recalls of the CF and the MAWA are:

$$\overline{Recall_{CF}} = 0.3469$$

$$\overline{Recall_{MAWA}} = 0.4453$$

It is easy to see from the curve that the MAWA’s recall is higher than the CF and the average recalls show precisely that the MAWA can increase the recall of the CF by 28.3%. Since the MAWA and the CF are calculated on the same data set, the result proves that the MAWA can release the influence of the sparse matrix problem and improve the efficiency.

5 Conclusion and Future Work

In summary, we have performed both an experimental and theoretical study of the spin eigenmodes in dipolarly coupled bi-component cobalt and permalloy elliptical nanodots. Several eigenmodes have been identified and their frequency evolution as a function of the intensity of the applied magnetic field has been measured by Brillouin light scattering technique, encompassing the ground states where the cobalt and permalloy dots magnetizations are parallel or anti-parallel, respectively. In correspondence to the transition between the two different ground states, the mode frequency undergoes an abrupt variation and more than that, in the anti-parallelstate, the frequency is insensitive to the applied field strength. The experimental results have been successfully interpreted by the dynamic matrix method which permits to calculate both the mode frequencies and the spatial profiles.

ACKNOWLEDGMENTS

This work is supported by the National Natural Science Foundation of China (61572466) and by the Beijing Natural Science Foundation (4162059).

REFERENCES

[1] Al-Atabi, Mushtak, and J. Deboer. "Teaching entrepreneurship using Massive Open Online Course (MOOC)." Technovation 34.4, 2014, pp.261-264.

[2] Felfernig, Alexander, et al. "Basic Approaches in Recommendation Systems." Recommendation Systems in Software Engineering ,2014 , pp.15-37.

[3] Goldberg, By D, et al. “Using Collaborative Filtering to Weave an Information Tapestry.”Comm. ACM 1992.

[4] Konstan, Joseph A, et al. "GroupLens: applying collaborative filtering to Usenet news." Communications of the Acm 40.3, 1997, pp.77-87.

[5] G. Adomavicus, A. Tuzhilin, “Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions.” IEEE Transactions on Knowledge and Data Engineering 17 (6) , 2005, pp.734–749

[6] J. Bobadilla, F. Ortega, A. Hernando, “A collaborative filtering similarity measure based on singularities”, Information Processing and Management 48 (2), 2011, pp.204–217.

[7] J. Bobadilla, F. Serradilla, J. Bernal. ”A new collaborative filtering metric that improves the behavior of recommender systems.” Knowledge-Based Systems 23, 2010, 520–528.

[8] J. Bobadilla, F. Serradilla, A. Hernando. ”Collaborative filtering adapted to recommender systems of e-learning.” Knowledge Based Systems 22, 2009, pp.261–265.

[9] J.L. Herlocker, J.A. Konstan, J.T. Riedl, L.G. Terveen. ”Evaluating collaborative filtering recommender system.” ACM Transactions of Information Systems 22 (1), 2004, pp.5–53.

[10] B. Jeong, J. Lee, H. Cho. “Improving memory-based collaborative filtering via similarity updating and prediction modulation.” Information Sciences 180 (5), 2010, pp.602–612.

[11] S.K. Lee, Y.H. Cho, S.H. Kim. “Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendation.” Information Sciences 180 (11), 2010, pp.2142–2155.

[12] Pazzani, Michael, and D. Billsus. “Learning and Revising User Profiles: The Identification ofInteresting Web Sites.” Kluwer Academic Publishers, 1997.

[13] N. Antonopoulus, J. Salter. “Cinema screen recommender agent: combining collaborative and content-based filtering.” IEEE IntelligentSystems , 2006, pp.35–41.

[14] J. Serrano, E.H. Viedma, J.A. Olivas, A. Cerezo, F.P. Romero. “A Google wave-based fuzzy recommender system to disseminate information in university digital libraries 2.0.” Information Sciences 181 (8) ,2011, pp.1503–1516.

[15] Alexander Felfernig, et al. "An Integrated Environment for the Development of Knowledge-Based Recommender Applications." International Journal of Electronic Commerce 11.2, 2006, pp.11-34.

[16] L.M. Campos, J.M. Fernández-Luna, J.F. Huete, M.A. Rueda-Morales. “Combining content-based and collaborative recommendations: a hybrid approach based on Bayesian networks.” International Journal of Approximate Reasoning 53, 2010, pp.785–799.

[17] J.L. Herlocker, J.A. Konstan, A. Borchers, J.T. Riedl. “An algorithmic framework for performing collaborative filtering.” SIGIR, 1999, pp.230–237.

[18] J.L. Herlocker, J.A. Konstan, J.T. Riedl, L.G. Terveen. “Evaluating collaborative filtering recommender system.” ACM Transactions of Information Systems 22 (1), 2004, pp.5–53.

[19] M. Papgelis, D. Plexousakis, T. Kutsuras. “Alleviating the sparsity problem of collaborative filtering using trust inferences.” Lectures Notes on Computer Science 3477, 2005, pp.224–239.

[20] Sarwar B M, Karypis G, Konstan J, et al. “Incremental SVD-Based Algorithms for Highly Scaleable Recommender Systems.” Conference on Computer and Information Technology. 2002.

[21] Ortega, Fernando, et al. "Improving collaborative filtering-based recommender systems results using Pareto dominance." Information Sciences 239.4, 2013, pp.50-61.

[22] Guo, Yan Hong, and G. Deng. "An Improved Personalized Collaborative Filterinng Algolrithm in E-Commerce Recommender System." International Conference on Service Systems and Service Management IEEE, 2006, pp.1582-1586.

[23] Zhang, Jinbo, et al. "An optimized item-based collaborative filtering recommendation algorithm." IEEE International Conference on Network Infrastructure and Digital Content, 2009. Ic-Nidc IEEE, 2009, pp.414-418.

[24] Feng, Zhou Jun, T. Xian, and G. J. Feng. "An Optimized Collaborative Filtering Recommendation Algorithm." Journal of Computer Research & Development 41.10,2004,pp.1842-1847.