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MOVIE RECOMMENDATION BASED ON BRIDGING MOVIE FEATURE AND USER INTEREST

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Abstract: The traditional collaborative filtering algorithms have bad performance in the case of data sparsity, and are difficult to track the change of user interest. Even though many improved algorithms are proposed to solve these problems, it is still necessary for further improvement. In this paper, a novel hybrid recommendation algorithm is proposed to resolve the two issues by bridging the movie feature and user interest. In the proposed algorithm, the movie feature vector is formed based on the attributes of the movie, and is combined with the user rating matrix to generate the user interest vector. The movie feature vector and user interest vector are mutually updated in an iterative way, and then the user similarity matrix is constructed based on the user interest vector, which is usually difficult to be obtained in the case of data sparsity. Furthermore, the long-term and short-term interests are considered in the generation of the user interest vector, which aims to make the recommendation results adapt to the change of user interest. The experiments on the Movie lens dataset show that the proposed algorithm outperforms some existing recommendation algorithms on recommendation accuracy.

Keywords: Recommendation system, Data sparsity, Change of user interest, User interest, Movie feature

Introduction

As the development of multimedia network, the number of online movies has been increasing rapidly in recent years, and the great number of movie websites made users face to a wealth of movie resources. How to serve users with the movies consistent with their interest is a challenge in improving both the quality of service (QoS) of websites and the quality of experience (QoE) of users. Recommendation system is an effective technique to deal with this challenge. Most of the recommendation algorithms can be roughly classified into three types, which are content-based recommendation algorithms [1,2], collaborative filtering recommendation algorithms [3,4], and hybrid recommendation algorithms [5,6]. Content-based recommendation systems analyze movie descriptions to identify movies that are of particular interest to the user. Though such algorithms are simple, they are not sensitive to the changes of user interest so thatthey can't give the results which the user feel novel. The collaborative filtering recommendation

Table 1
User-Movie Rating Example.

	Wolverine	Hulk	Iron Man	Spider-Man	Young Style	So Young
A	4	5		5	5	
B	5		5	4		
C			1		5	5

In recent years, the hybrid recommendation algorithms havebeen proposed to handle the issue of data sparsity and make therecommended results satisfy the user's current interest. In orderto relieve the influence caused by data sparsity, Fang et al. [8] pro-posed to combine the tag-based transfer learning and SVD-basedmatrix decomposition to relieve the influences caused by data spar-sity with the auxiliary of movie tags. Deng et al. [9] and Shindeet al. [10] proposed to handle the issue of data sparsity by reducingthe dimension of similarity calculation between users via cluster-ing the rating matrix. Stanescu et al. [11] proposed to improve therecommendation accuracy by exploiting either user tags or moviekeywords, which can provide more information in addition to therating matrix for calculating the similarity between users. Leng et al.[12] defined neighbor tendency, based on which the preliminaryneighborhood was formed, and then the issue of data sparsity isrelieved by modifying the preliminary neighborhood via the equiv-alence relation similarity. Geng et al. [13] proposed a deep model tomap the feature of users and images to a unified space to address theissue of data sparsity. In order to make the recommendation resultsadapt to the change of user interest, Xing et al. [14] proposed to thetime-based and item similarity-based data weighting methods totrack the change of user interests and improve the recommenda-tion accuracy. Ullah et al. [15] proposed a hybrid recommendationalgorithm with the consideration of temporal information, whichcan give the recommendation for user at a specific time. Wang et al.[16] assigned the greater weight to the interest closer to the gath-ering time and improved the recommendation accuracy. Li et al.[17] used the long-term interest and short-term interest to filterand introduce the "somewhat novel" recommendation results con-secutively. Cheng et al. [18] proposed to consider the user's socialinformation, for example user's response information and socialrelationship, to improve the recommendation accuracy and trackthe change of user interest. Some algorithms [19,20] made somecontributions on the construction of vector space models.In this paper, a hybrid recommendation algorithm is proposed toresolve both the issues of data sparsity and change of user interestswith integrating the information of both movies and users. The userinterest vector is formed by combing the user rating matrix and thefeature vector of movies, and iteratively updated along time to gen-erate the hybrid interest vector of the user. The similarity matrixbetween users can be constructed according to the hybrid interestvector and rating matrix of the user with less influences caused bydata sparsity. Meanwhile, during the generation of the user interestvector, both long-term interest and short-term interest are con-sidered via giving adaptive weights to the rating according to therating time, which is helpful to make the recommendation resultsadapt to the change of user interest. The proposed recommendationalgorithm is evaluated on the Movielens dataset, and its perfor-mance demonstrates that the combination of user rating matrix andfeature vectors of movies, and the interest-related weighting arehelpful to improve the recommendation accuracy. The frameworkof the proposed algorithm is shown in Fig. 1.2. Feature vectors of moviesAs we all know that, the collaborative filtering algorithm isvulnerable to the data sparsity of the rating matrix, because itmeasures the similarity between users according to the similar-ity between users' ratings, and ignores the impact of movies on thesimilarity calculation. In this paper, we introduce the attributes ofmovies into the calculation of the similarity between users, whichaims to provide more information for the similarity measurementand relieve the influences caused by data sparsity. Here, we obtainmovies' attributes by analyzing the text descriptions of movies,because they are easy to be accessed and understood. The movies'attributes include director, screenwriter, starring, genre, and so on.In experiments, these attributes can be obtained from the datasetor crawled from the source website of the movies. These attributesare used as movie features for recommendation.The movie set is denoted as T = {t1, t2, . . ., tn}, the feature vec-tor of each movie is denoted as ftj= {wtj1, wtj2, . . ., wtjl}, wherewtjkdenotes the weight of the attribute pkin the movie tj. Theattribute pkis the attribute of the movie. l is the length of vector,and j, k denote the order of movies and movie attributes, respec-tively. The feature vector ftjof the movie tjcan be initialized viaEq. (1), where the weight wtjkwill be 1, if the corresponding moviehas the attribute pk. Otherwise it will be 0. And then ftjwill beupdated with the user interest vector iteratively according to theimportance of the attribute pkto the user's rating, which will bedescribed in Section 4. (1)3. User interest vector3.1. Data sparsityThe number of movies that a user rated is very small due to thehuge watching time, so that the number of the common moviesrated by different users is much smaller. It is the reason thatuser-movie rating matrix is usually sparse. However, the tradi-tional collaborative filtering algorithm measured the user interestsmainly based on the rating matrix and calculated the similaritybetween users according to user interests, so it has low recom-mendation accuracy in the case of data sparsity. Therefore, in thispaper, we propose to exploit the attributes of movies, e.g. director,actors and style, to represent the user interest. It can feed the sim-ilarity measurement between users with more information fromthe movies rated by users in addition to the information from theusers' own. It is helpful to alleviate the influence of data sparsity onrecommendation accuracy.3.2. Change of user interestThe preference of users to movies usually changes over time,which is not considered in the traditional recommendation algo-rithms, and it is the reason that the recommendation results ofthe traditional recommendation algorithms often can't satisfy theusers. Given the theory of psychology, the user interest is composedof long-term interest and short-term interest. The long-term inter-est is formed gradually relying on user habits during a long period,while the short-term interest emerges due to the influence of theenvironment in a short period. Therefore, we propose to definea time-based weight, i.e., WDui,tj, to represent the impact of themovie tjon the user uiaccording to these two kinds of interests. (2)where dnowdenotes the current time, and dui,tjdenotes the timewhen the user uirated on the movie tj. ˇ ∈ (0, 1) is the weightfactor, which controls the impact of the long-term interest. (1 −ˇ) · e−_dnow−dui,tj_reflects the impact of recently rated movies onthe user interest, i.e., the impact of the short-term interest. As thewtjk = _1pk ∈ tj 0pk /∈ tj WDui,tj = ˇ + (1 − ˇ) · e−_dnow−dui ,tj_

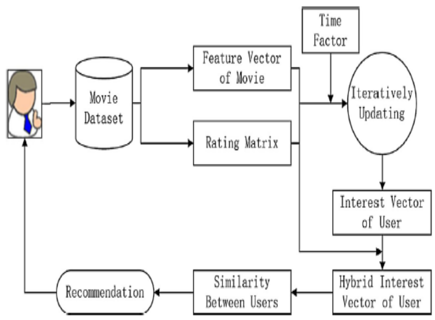

Fig. 1. The framework of the proposed hybrid recommendation algorithm.

time goes, i.e., dnowbecomes larger and larger than dui,tj, WDui,tjtends to be equal to ˇ and the long-term interest becomes the mainfactor.3.3. User interest vectorIn this paper, we construct the user interest vector based onthe feature vector of movies and the historical rating of the user.Although rank and interest are two different concepts and themovie with the highest rank is not necessarily the one the useris most interested in, it is the best choice so far to use the ratingto represent the users' interest. Let U ={u1, u2, . . ., un}denote theuser set and fui=_wui1, wui2, . . ., wuil_denote the interest vectorof the user ui. wuikdenotes the preference degree of the user uitothe attribute pk, pkis the attribute of the movie, and l is the length ofthe interest vector. The interest vector can be obtained as follows:1) Collect all the movies rated by the user uiaccording to the ratingmatrix and form the movie collection Tui= {ti1, ti2, . . ., tin};2) Obtain the feature vector of the movie tjin Tuifrom the moviefeature matrix, and denote it as fui;3) Define the interest vector of the user uias the weighted sum ofthe feature vector of each movie in Tui, and obtain the interestvector of the user uivia Eq. (3). (3)where rui,tjis the rate that the user uigives to the movie tj.Furthermore, we propose to adopt an inverse feature frequencyto measure the importance of the attributes in the spirit of TermFrequency-Inverse Document Frequency (TF-IDF) [20], because thepopular attributes, which show the common preferences of mostusers, can't reflect the personalized interest of a specific user andcan't be used to differentiate users. The inverse feature frequencyis defined as: (4)where AUN denotes the total number of users in the whole systemand PUNkis the number of users who likes the attribute Pk. There-fore, it can be seen from Eq. (4) that the inverse feature frequencyof one attribute will be 0, if it is a common preference of all theusers.fui = _tj ∈ Tui ftj · rui,tj · WDui,tj idfpk = log_ AUN PUNk

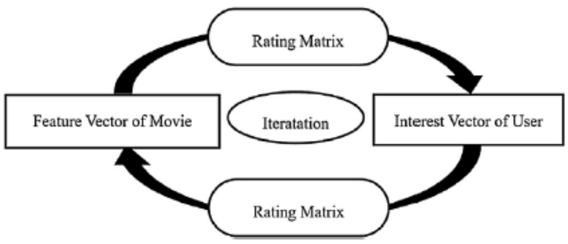

Fig 2. Iteratively updating of movie feature vector and user interest vector.

Meanwhile, the mean score¯ruiof the user uiis considered todrag the rating degree of different users to the same level. Finally,the interest vector of the user uican be given as follows: (5)And the weight wuikin fuiis: (6)where Max_|fui|_is used for normalization.4. Bridging movie feature and user interestAs we all know that the rating to a movie can reflect the favordegree of the user and the same movie will receive different ratesfrom people with different preferences. Because the user interest onmovies usually varies with the attributes of movies, such as direc-tor, actor, and so on, the influence of user rating can be describedby the attributes of the movie to some extent. That is to way, themovie feature and user interest have mutual influence betweeneach other. Therefore, we proposed to update the feature vectorof the movie and the interest vector of the user simultaneouslyand iteratively through bridge them with the rating matrix of theuser. The iteratively updating of the movie feature vector and userinterest vector is shown in Fig. 2.The movie feature vector can be updated as follows:1) Collect the users who rated the movie tjto form the user set,Utj= {uj1, uj2, . . ., ujn};2) Generate the interest vector of the user uji, which is denoted as

fuji;fui = ⎡⎢⎣ idfp1 idfp2 . . . ⎤⎥⎦_tj ∈ Tui ftj · (rui,tj − ¯rui) · WDui,tj wuik = log _ AUN PUNk __tj ∈ Tuiwtik · (rui,tj − ¯rui) · WDui,tj Max| _fui_ |

3) wtjkcan be updated to w_tjkaccording to the rating matrix asbelow; (7)where Wujikis the weight of attribute Pkin the interest vector ofthe user uji. Max_|fti|_is used for normalization.Consequently, the interest vector of the user ujiis updatedaccording to Eqs. (5) and (6) with the updated feature vector ofthe movie tj, w_tjk. The accuracy with the updated movie featureand user interest will tend to stable and reach the best after severaliterations, which will be demonstrated in the experiments.Compared with the previous methods, the contributions of thispaper are: 1) We obtained more real and accurate interest vectorthrough the iterations between feature vector of movie and inter-est vector of user; 2) We model the user's interest based on theattributes of movies, which makes the modeling granularity morereasonable and is helpful to resolve the problem of data sparsity;3) We take the time factor into account of optimizing the user'sinterest vector, which makes the recommendation result more con-sistent with the change of user's interest.5. Recommendation based on user interest vectorIn this paper, we propose to combine the similarities based oninterest vector of users and rating matrix to find the k nearest neigh-bors to the target user, and predict the preference degree of a targetuser toward the movie he/she has not seen, i.e., to predict the rat-ing of the user to the movie, and then recommend the movies withhigh predicted rating to the target user. Here, simF(ui, uj) denotesthe similarity between users based on their interest vectors, andsimM(ui, uj) denotes the similarity between users based on theirrating on movies.Accordingly, the similarity between users is defined as follows: (8)where 0 ≤ ωui,uj≤ 1 and it can be adjusted according to the interestvector of the user. For instance, if the user's preference to movie ismainly decided by some attributes, e.g., the movie style, and hisrating towards the movies with this style is stable, ωui,ujshouldbe large as the interest vector plays the dominant role. Otherwise,ωui,ujshould be small.In order to determine the value of ωui,uj, we measure the intereststability of the user on a specific attribute according to the varianceof his rating. That is, small

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variance means the user interest is stableon the attribute, e.g., the movie style. Here, the rating variance ofthe user uion the attribute pkis defined as below: (9)where¯rpkis the mean rating of the user uitowards the attribute pk,N is the amount of movies with the attribute pk, which are rated bythe user ui.Consequently, the average rating variance on all the attributes,which is denoted as below, can reflect the interest stability of a user. (10)Therefore, ωui,ujcan be calculated as follows: (11) X=varmax−max(varui,varuj)varmax−varmin, varmaxand varminare the maxi-mum and minimum of the average rating variances on all attributesin the user set Utj, respectively. max(., .) is the function to select thebigger one of the two variables.Eq. (11) shows that when analyzing the similarity of two users,the weight parameter ωui,ujis determined by the one who hasthe lower interest stability. In other words, the similarity betweentwo users will be determined by their interest vectors, only if theirinterest vectors are both stable.The similarity between two users based on interest vector isdefined as the cosine similarity in [21]. (12)where l is the length of interest vector.The similarity between two users based on interest vector isdefined as the Pearson similarity in [21]. (13)Based on the similarity matrix given in Eq. (13), the predicted ratingof the user uito the movie trcan be obtained as below. Given thepredicted rating, the movies with top ratings will be selected as therecommendation results to the user ui. (14)where Nui= {n1, . . ., nk} is the neighbor set of the user ui, and niisone of the neighbors. sim(ui, ni) is the similarity between the user uiand its neighbor ni. rni,tris the rating of the neighbor nito the movietr.¯ruiand¯rniare the average rates of the user uiand neighbor ni,respectively. r_ui,tris the predicted rating of the user uito the movietr, and tris the movie that the user uihasn't seen.6. Experimental results and analysis6.1. Dataset and evaluationIn this paper, the MovieLens dataset (http://grouplens.org) pro-vided by GroupLens research project of the University of Minnesotais used, which is a standard dataset and is often used in recommen-dation system research. In this paper, ml-100k data set version ofthis dataset is used, in which there are 100,000 ratings (1–5) from943 users on 1682 movies, each user has rated at least 20 moviesand the data was collected during the seven-month period fromSeptember 19th, 1997 through April 22nd, 1998. The data formatin MovieLens dataset is show in Table 2. Obviously, the genres ofmovies are given.In addition to the information we can obtain from the Movie-Lens dataset directly, other information we need, such as director,writer, stars and so on, can be crawled from the movie sourceaddress provided by the dataset. The data format of the crawledfeatures are shown as in Table 3.The experimental dataset is divided into training and test sets. Inthe experimental data, the access records in the last 10 days of eachuser are used as the test set, and the other access records are usedas training set, which can be used to generate the interest vector ofusers. The training set is 89.355% of the whole data and the test setis 10.645%, respectively.In this paper, the Mean Absolute Error (MAE) is used to evaluatethe performance of the recommendation algorithms because MAEcan reflect the accuracy of the predicted rating by calculating themean error between the predicted and the true ratings.

The smaller

w_tjk = _uji ∈ Utj wujik · (ruji ,tj − ruji) Max| _ftj_ | sim(ui, uj) = ωui,ujsimF (ui, uj) + (1 − ωui,uj)simM(ui, uj) var(ui, pk) = 1N_tj ∈ Tui ,pk ∈ tj (rui,tj − ¯rpk)2 varui = 1l_lk=1var(ui, pk) ωui,uj = −X2 + 2X simF (ui, uj) = _lm=1wuim · w ujm _ _lm=1w2uim__lm=1w2ujm simM(ui, uj) = _tr ∈ T (rui,tr − ¯rui) · (ruj ,tr − ¯ruj) __tr ∈ T (rui,tr − ¯rui)2 ·__tr ∈ T (ruj ,tr − ¯ruj)2 r_ui,tr = ¯rui + _ni ∈ Nui sim (ui, ni) · (rni,tr − ¯rni) _ni ∈ Nui sim (ui, ni)

6.2. Impact of timeIn the proposed algorithm, the parameter ˇ in Eq. (2) is the timefactor, which can adjust the sensitivity of the proposed algorithmto the change of user interest. In order to demonstrate the impactof ˇ, we compare the performance with different ˇ, which is shownin Fig. 3. In Fig. 3, ˇ is set to be 0, 0.25, 0.5, 0.75 and 1.0, the numberof iterative updating is 5, and the amount of neighbor ranges from20 to 50. It can be seen that the best recommendation accuracyis obtained when ˇ is 0.25. It demonstrates that the short-terminterest contributes 75% to user interest and the long-term interestcontributes 25% according to Eq. (2).6.3. Improvement with iterationsThe convergence of the iterative updating between the userinterest vector and the feature vector of movies is analyzed asshown in Fig. 4. In the iterative updating process, the MAE betweenthe interests of the current iteration and last iteration is calculatedas below. (16)where N is the total number of users, fuiand˜fuiare the interestvectors of user uiin the current iteration and last iteration, respec-tively.It can be seen from Fig. 4(a) that the fMAEbegins convergent after5 iterations and reaches stable since the 10th iteration.Furthermore, the MAEs with different numbers of iterativeupdating are compared in Fig. 4(b), where ˇ is 0.25 and the num-ber of iteration is from 0 to 5. It can be concluded from Fig. 4(b)that the iterative updating can improve the prediction accuracy asthe accuracy with 4 iterations is at least 1.5% higher than that with1 iteration, and the recommendation accuracy keeps at the samelevel after 4 iterations.6.4. Comparison experimentsIn order to demonstrate the performance of the proposed algo-rithm in recommendation accuracy, several algorithms are used forthe comparison experiments, which are1) the collaborative filtering algorithm based on user in [12], whichis referred as User-based CF and adopted the rating method pro-posed in [22];2) the collaborative filtering algorithm based on two-phase nearestselection in [12], which is referred as TPNS, and the two-phasenearest selection method is designed to relieve the problem ofdata sparsity;3) the collaborative filtering algorithm based on time weighting in[16], which is referred as TWCF and introduced the time factorinto the rating prediction;4) the combination of the algorithms in [12] and [16], which isreferred as TPNS + TWCF, and aims to not only solve the problemof data sparsity but also track the latest interest of user by thecombination.5) our proposed algorithm, which is referred as IVU. Here we takeinto account of the tradeoff between the computation and per-formance and set the iteration number to 5 with ˇ is 0.25.It can be seen from Fig. 5 that the recommendation accuracy canbe improved by adding either the content information of movie,$fMAE = 1N\_ui \in U(fui - \tilde{}fui)$

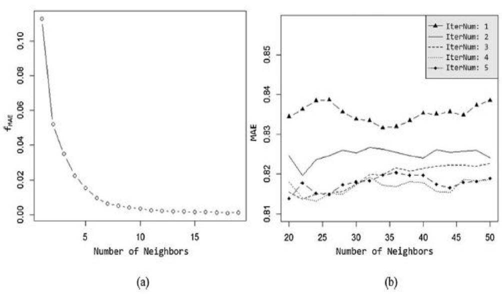

Fig. 4. (a) Convergence of MAE with iterations. (b) MAE comparisons with various iterations.

time factor, or both. The MAE of the proposed method is 1%–12%lower than that of any of the other methods. For instance, in theTPNS algorithm, though the influence of data sparsity to perfor-mance can be relieved by improving the user neighbors selectingmethod, the similarity between users is not dense enough as it isstill established in view of rating. In the proposed method, the userinterest vector is obtained and updated via the feature vector ofmovies, which brings about the robustness to rating data sparsityand adaptation to the change of user's interest taking into accountof the stability of user's interest, so the recommendation accu-racy is improved further. Furthermore, the comparison between theTPNS + TWCF and our proposed algorithm shows that the iterativelyupdating method is helpful to improve the performance.7. ConclusionIn this paper, a novel hybrid recommendation algorithm is pro-posed based on the spirit of integrating the movie feature anduser interest to calculate the similarity between users. In this algo-rithm, the feature vector of movies and rating matrix of users arecombined, the interest vector of users is generated and updatedthrough an iterative manner, and then the interest vector and ratingmatrix of users are combined to generate the hybrid interest vec-tor of users, which is used to calculate the similarity between users.Experimental results show that the proposed algorithm relieves theproblem caused by data sparsity and the change of user's interest,and provides more accurate recommendation results than someexisting algorithms.Our future work will focus on two aspects. The first one is toimprove the performance by exploiting better similarity comput-ing method [23] which adapt to recommender system. The secondone is to improve the performance by introduce the characteristicsof rerating time into the change of user's interest, for exam-ple, to distinguish the difference between holidays and workdays.Additionally, some feature analysis and representation algorithms[24–28] are promising and their spirits may be helpful to our user'sinterest vector representation, which will be considered in ourfuture work.AcknowledgmentsThis work is supported in part of Natural Science Foun-dation for Distinguished Young Scholars of Shandong Province(JQ201718), Key Research and Development Foundation of Shan-dong Province(2016GGX101009), Natural Science Foundation ofChina (U1736122), and Shandong Provincial Key Research andDevelopment Plan(2017CXGC1504).

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