INTERNATIONAL JOURNAL OF CIRCUITS, SYSTEMS AND SIGNAL PROCESSING
DOI: 10.46300/9106.2021.15.123 Volume 15, 2021

A Novel Filtering Recommendation Algorithm for User Emergency Information Adoption

Xiaoying Yao[1,2], Chunnian Liu[1], Yingfei Zhu[3]
[1]School of Management, Nanchang University, Nanchang, Jiangxi, China
[2]School of Vocational Education (Technology), Jiangxi Agricultural University, Nanchang, Jiangxi, China
[3] Food Inspection and Testing Institute of Jiangxi Province, Nanchang, Jiangxi, 330001, China

Received: February 22, 2021. Revised: July 18, 2021. Accepted: August 25, 2021. Published: August 26, 2021.

***Abstract*—Emergency case data resources are widely distributed and heterogeneous. At the same time, the command of emergency field needs the cooperation of multiple departments. Therefore, it is urgent to establish an emergency analysis and mining platform, realize the sharing and collaboration of emergency data resources among multiple departments, and assist emergency command and scheduling. According to the actual situation of the current emergency, a similarity measure method (TCRD) is proposed to solve this problem by adding temporal information to reflect information adoption, which integrates user context information and temporal information. Firstly, the temporal information of historical adoption behavior is expressed as a binary coded characteristic matrix, and then the characteristic matrix is mapped into a feature vector by using restricted Boltzmann machine, and finally added to the similarity measurement formula. The improved TCRD method can measure the similarity more accurately, and further improve the quality of emergency information adoption recommendation results.**

***Keywords*—Emergency Information Adoption, Filtering Recommendation Algorithm, NSGA-II Algorithm, RBM method**

I. INTRODUCTION

THE deepening of the exploration in the field of emergency, the deep data mining and knowledge discovery of emergency cases have increasingly become the focus of attention [1-2]. Information adoption is improved in the field of emergency[3], a lot of emergency application systems is built[4], and a huge auxiliary role in the process of emergency response is played. Some important functions of these application systems are the sharing, analysis and mining of emergency case information resources.

The emergency case resources of public emergencies are rich[5-6]. The information is collected by the emergency command departments all over the country, analyzed and processed by each emergency command center, and the results are used to assist the future emergency command. However, the information processing of many emergency departments is still basically based on the traditional functions such as adding, deleting, modifying and checking, and statistics[7]. The intelligent analysis ability of data is very limited, which makes the regularity hidden behind the data can not be effectively identified, and affects the efficiency and effect of emergency resource allocation and emergency business implementation. How to effectively realize the in-depth analysis of a large number of emergency information data is a great challenge for emergency departments.

The development of the network has promoted the rapid dissemination and popularization of information. The massive amount of information makes people have more choices when they encounter problems, but it also brings great trouble to people. In particular, finding the content of concern from a wide variety of emergency information is bound to waste a lot of time and energy[8]. Facing such a severe problem of information overload, how to help users obtain the content they pay attention to from a large amount of information has become a major challenge. In this context, recommendation system came into being as an effective means [9-10]. Among them, collaborative filtering algorithm has been widely used because it does not need specific domain knowledge, can process complex unstructured data, has strong interpretability, is easy to implement and has good recommendation effect [11-12]. However, the collaborative filtering algorithm also has some disadvantages, such as scalability [13]. Generally speaking, the response time of users for accessing the recommendation system will be relatively long, which will affect the data sparsity of real-time recommendation of users[14]. When the historical score data is very sparse, the effect of recommendation is often unsatisfactory. Cold start [15] is impossible to recommend a project to a user because there is no historical behavior data of the user or attribute information of the project in the system for the first time.

To solve the above problems, the recommendation system inevitably needs to study and overcome some difficulties. By improving the similarity measurement formula, this paper alleviates the troubles of low precision of similarity calculation in the case of sparse data. On the premise of improving the accuracy of the recommendation system, the coverage and overall recommendation quality can be improved.

II. RECOMMENDATION ALGORITHM AND RELATED TECHNOLOGY

Personalized recommendation system has made rapid development since it came into being. Various technologies have been put forward one after another, and achieved good results in practical application. This section introduces several algorithms commonly used in recommendation system in detail, and introduces the similarity measurement methods commonly used in collaborative filtering algorithm.

A. Common Recommendation Algorithms

According to the features of users' previous interactive projects, content-based recommendation analyzes users' concerns, builds preference tags for them, searches for information similar to the selected projects of target users in candidate project set, and generates recommendation list.

The specific process of content-based recommendation algorithm is as follows.

Step 1. Item feature representation: extract the attribute features of each item.

Step 2. Learn the characteristics of users' attention: learn the characteristics of users' attention according to the items that users have paid attention to in their history.

Step 3. Generate recommendation list: calculate the correlation between user concerns and project features, and recommend the most relevant group of projects to users.

Because the content-based recommendation takes the items selected by users' history as reference, the system tends to recommend similar items for users, resulting in a single recommendation result.

The specific flow of user based collaborative filtering algorithm is as follows.

Step 1. According to the scoring data, measure the similarity between users and find the nearest neighbor set of users.

Step 2. Forecast the score on the non scored items according to the score of the nearest neighbor.

Step 3. Form a recommendation list.

Common similarity measurement methods will be introduced below. There are two ways to select the neighbor set of target users: one is to set a threshold, and those whose similarity is greater than the threshold are merged into the neighbor set. Another way is to specify the value of *K* directly, and merge the first k users most similar to the target users into the set.

Both item based and content-based recommendation algorithms calculate the similarity between items. The difference is that the former uses the user's historical behavior information [16], while the latter uses the attribute characteristics or content of the project itself to calculate the similarity.

According to the scoring matrix of users and information, some methods is used to train the prediction model for the target users offline and predict user rating online. The prediction score of user *u* for information *C* is expressed.

$$r_u^{(c)} = E(r_u^{(c)}) = \sum_{i=1}^{R} i \times pr(r_u^{(c)} = ir_u^{(c')}) \tag{1}$$

Among them, C_u represents the set of items scored by user u, c' represents the items in set C_u, *i* represents the score of user *u* on item c', *i* is between 1 and R, they represent the lowest and highest score of user on item respectively. The meaning of formula (1) is to predict and score the item *c* not scored by user *u*.

The key step is the establishment of model. The common methods include decision tree, Bayesian classifier, matrix decomposition, graph model and neural network. Matrix factorization model [17] is a common technology in model-based collaborative filtering algorithm, which has been widely used because of its excellent performance and versatility. Matrix decomposition decomposes the original scoring matrix into user and project potential vectors to recommend users more accurately. Common matrix factorization algorithms include standard [18], biased [19] and matrix factorization based on decomposing machine [20]. Collaborative filtering algorithm is one of the development trends of recommendation algorithm. There are two common methods. One is to directly use the nonlinear modeling ability of neural network to simulate the interaction between users and projects. The other is to use neural network to extract unstructured features such as text and image, and then combine with traditional recommendation algorithm to generate recommendation information for users.

B. Common Similarity Measurement Formula

Similarity measurement is an important part of memory, which is related to the accuracy of the nearest neighbor set. Taking the calculation of similarity between users as an example, the following introduces several common similarity measurement methods in recommendation system.

a.Euclidean distance.

Suppose that the user's score of items in the recommendation system is expressed as an n-dimensional vector, and the score of the non scored items is filled with 0. The scoring vectors of existing users a and b are $r_a = [r_a^{(1)}, r_a^{(2)}, ... r_a^{(n)}]$ and $r_b = [r_b^{(1)}, r_b^{(2)}, ... r_b^{(n)}]$, and the similarity of users a and b is calculated by Euclidean distance, which is expressed as follows.

$$d(a,b) = \sqrt{\sum_{i=1}^{n} (r_a^{(i)} - r_b^{(i)})^2} \tag{2}$$

Among them, $r_a^{(i)}$ and $r_b^{(i)}$ represent the score of item *i* given. The value calculated by formula (2) is usually large. In practical application, the similarity between users is usually taken in [0,1], so formula (2) is normalized as follows.

$$sim(a,b) = \frac{1}{1 + d(a,b)} \tag{3}$$

Suppose that in the recommendation system, the feature vector of the basic attribute of user *u* is expressed as $C_u = [C_u^{(1)}, C_u^{(2)}, ... C_u^{(c)}]$, where *c* represents the number of attribute features. If the attribute eigenvectors of known users *a* and *b* are C_a and C_b respectively, then

$$d(a,b)=\sqrt{\sum_{i=1}^{c}(C_a^{(i)}-C_b^{(i)})^2} \tag{4}$$

Among them, $C_a^{(i)}$ and $C_b^{(i)}$ are the i-th dimension attribute features of users a and B respectively.

b.Cosine similarity

The cosine similarity can calculate the similitude between users *a* and *b*. Its specific expression is

$$sim(a,b)=\frac{\sum_{i=1}^{n}r_a^{(i)}r_b^{(i)}}{\sqrt{\sum_{i=1}^{n}\left(r_a^{(i)}\right)^2}\sqrt{\sum_{i=1}^{n}\left(r_b^{(i)}\right)^2}} \tag{5}$$

where *n* is the total number of items.

This method does not consider the influence of the difference of user rating scale on the similarity between users. Take the emergency information adoption recommendation system as an example: the score of user *a* is relatively strict, and a score of 3 indicates that he is very concerned about the information, and the user's score on all information is low. While user *b* is used to scoring high, scoring all the information he has paid attention to above 3 points. Considering the factor of scoring scale, the preferences of the two users are actually relatively similar.

c.Modified cosine similarity

Measure the similarity between users *a* and *b*, and the modified cosine similarity can be expressed as

$$sim(a,b)=\frac{\sum_{i\in I_{a,b}}^{n}(r_a^{(i)}-\overline{r}_a)(r_b^{(i)}-\overline{r}_b)}{\sqrt{\sum_{i\in I_a}^{n}\left(r_a^{(i)}-\overline{r}_a\right)^2}\sqrt{\sum_{i\in I_b}^{n}\left(r_b^{(i)}-\overline{r}_b\right)^2}} \tag{6}$$

Among them, $I_{a,b}$ represent the item set scored by users a and B at the same time, I_a and I_b represent the item set scored by them respectively, and $\overline{r}_a$ and $\overline{r}_b$ represent the average score of items in I_a and I_b respectively. This method makes up for the influence of scoring scale by subtracting the average value of users' scores.

d.Pearson Correlation Coefficient

When calculating the Pearson similarity between items *i* and *j*, the formula is expressed as

$$sim(a,b)=\frac{\sum_{u\in U_{i,j}}^{n}(r_u^{(i)}-\overline{r}_i)(r_u^{(i)}-\overline{r}_j)}{\sqrt{\sum_{u\in U_{i,j}}^{n}\left(r_u^{(i)}-\overline{r}_i\right)^2}\sqrt{\sum_{u\in U_{i,j}}^{n}\left(r_u^{(i)}-\overline{r}_j\right)^2}} \tag{7}$$

Where $\overline{r}$ and $\overline{r}_j$ respectively represent the average scores, and $U_{i,j}$ represent the set.

e.Jaccard coefficient

Jaccard coefficient can approximately measure the overlap of their preferences, as show in formula (8).

$$sim(a,b)=\frac{|I_a\cap I_b|}{|I_a\cup I_b|} \tag{8}$$

The numerator is the number of items scored by both users *a* and *b*, and the denominator represents the total number. It can be seen that the similarity between users only depends on the number of common scoring items. The more common items, the closer their preferences are.

The similarity between users is usually affected by many factors. In terms of scoring factors, on the one hand, it is the user's choice, which is reflected in the scored items. The more common scoring items among users, the closer their attention. On the other hand, the user's evaluation after selecting an item is reflected in the score value of a given item. When measuring the similarity between users, we should comprehensively consider the impact of these two aspects. The traditional similarity measurement either focuses on the scoring value or the number of common scoring items of users, and does not comprehensively consider the joint effect of the two.

III. Collaborative Filtering Recommendation Algorithm

A. Similarity Calculation

In this section, the CRD method is optimized, and the time sequence information reflecting the adoption of emergency information is considered. A similarity measure method (TCRD) is proposed, which integrates user context information and time sequence information. The TCRD method is represented as follows.

$$\begin{aligned} sim(a,b)=&\sum_{i=0}^{R-1}w_r^{(i)}v_{a,b}^{(i)}+\frac{1}{c}\sum_{j=1}^{c}w_c^{(j)}c_{a,b}^{(j)}\\ &+\frac{1}{T}\sum_{l=1}^{T}w_t^{(l)}t_{a,b}^{(l)} \end{aligned} \tag{9}$$

Where T is the number of temporal features, $t_{a,b}^{(l)}$ is the difference between user a and user b in the L-dimensional time series feature, $w_t^{(l)}$ is weight coefficient of $t_{a,b}^{(l)}$ and it indicates the influence of $t_{a,b}^{(l)}$ on user similarity, The value range of each component in vector w_t is defined as $0\le w_t^{(l)}\le 1$.

B. Temporal Information Representation

The historical interaction between users and emergency information is regarded as time series, and the characteristic information of emergency information is expressed in the form of binary code. The feature vectors of emergency information at each sampling time point are connected in a parallel way, so that the user's historical behavior information is expressed in the form of a feature matrix composed of 0 and 1. The time sequence information includes the user's historical receiving information, that is, the adoption type. The change of user adoption type implies the change of information emergency level in different time periods.

The dimension of feature vector corresponding to each emergency information category is set to 18, which is the total number of emergency information categories. In fact, each dimension represents an emergency category. If an information belongs to this category, the location is 1. Otherwise, the location is 0. In Movielens 1M data set, users score the emergency information. Due to the scattered time for users to score the information emergency level, it is impossible to select n pieces of information that they have adopted by fixing the same time interval for all users. In a certain period of time selected by people, some users may have adopted n emergency information, while most users have adopted more or less than n information. The temporal feature matrix constructed by this method will be very sparse, which will affect the accurate grasp. Therefore, according to the time stamp, we select n information recently adopted by each user to construct the temporal characteristic matrix of user's historical adoption behavior. For the case that the total number of information scored by some users is less than *N*, this paper uses the method of filling the information feature vector with 0 in the time interval to make it still constitute the feature matrix of *N*×18.

C. Time Sequence Features with Restricted Boltzmann Machine

After the selected user's historical emergency information is expressed as a temporal feature matrix, the matrix is very sparse. If the matrix is directly added to formula (10), the feasibility is not high. On the one hand, it will cause too many features in the similarity formula and increase the complexity. On the other hand, if the historical information is simply quantified and added into the formula, it can not reflect time sequence information on user similarity. Therefore, it is important to find a feature learning method which can not only reduce the dimension, but also learn the temporal relationship of features. Therefore, the constrained Boltzmann machine (BM) is used to construct the time series feature vector.

It has been widely used in some deep learning methods to represent user's feature information in the form of binary coding. These methods usually use an embedding layer to transform sparse binary coding into dense vector. Similarly, this paper also carries on the corresponding processing. After the temporal information of user's historical information adoption behavior is expressed as a binary coded feature matrix, the feature matrix is mapped into a feature vector by the restricted BM. We use the restricted BM to map the eigenmatrix to eigenvector, which is interpretable. If the binary code is directly expressed as a vector, the vector will be very sparse. When it is added to the similarity formula, the number of parameters in the third term will be too many, which will affect the accuracy of similarity calculation. At the same time, when using heuristic algorithm to learn weight parameters, it is not conducive to the convergence of the results. By unsupervised training, the constrained Boltzmann machine represents the underlying features as high-order abstract features, which can not only achieve the effect of dimension reduction, but also indirectly learn the temporal relationship between users and information adoption interaction.

The temporal information of user's historical behavior is expressed as a M×N feature Matrix V, which is constructed by temporal information representation method. v_i^l is the element of the i-th column in the l-th row of the matrix V, and its value is 0 or 1. The hidden layer *h* is the eigenvector of the *T* dimension, and h_j is the *j*th element of the hidden layer vector. The function of the model is

$$E(V,h) = -\sum_{i=1}^{N}\sum_{j=1}^{T}\sum_{l=1}^{M} w_{ij}^l h_j V_i^l - \sum_{i=1}^{N}\sum_{l=1}^{M} V_i^l b_i^l - \sum_{j=1}^{T} h_j b_j \tag{10}$$

where w_{ij}^l represents the connection weight between node V_i^l and node h_j, and b_i^l and b_j represent the offset term.

The joint probability distribution of joint configuration is expressed by Boltzmann distribution as

$$P(V,h) = \frac{\exp(-E(V,h))}{\sum_{V,h}\exp(-E(V,h))} \tag{11}$$

Where the denominator represents the normalization factor.

According to formulas (10) and (11), given the hidden cell state, the activation probability of the visible cell is calculated as follows.

$$P(V_i^l) = \frac{\exp(b_i^l + \sum_{j=1}^{T} h_j w_{ij}^l)}{\sum_{z=1}\exp(b_i^z + \sum_{j=1}^{T} h_j w_{ij}^z)} \tag{12}$$

Given the visible element, the activation probability of the hidden element is calculated as follows

$$P(h_j) = \frac{1}{1+\exp(-b_j - \sum_{i=1}^{N}\sum_{l=1}^{M} V_i^l w_{ij}^l)} \tag{14}$$

According to formula (13) and formula (14), the restricted Boltzmann machine uses the contrast divergence algorithm for training. Generally, the estimation of the model can be obtained by running once. Updating the hidden layer with the visible layer and updating the visible layer with the hidden layer is called one run). Through the continuous iterative solution of the above two equations, the temporal feature matrix of the visible layer can be transformed into the temporal feature vector of the hidden layer, so as to achieve the purpose of dimension reduction. In addition, because the construction of timing feature matrix is based on the interaction sequence between users and projects, the timing vector obtained by training RBM can retain the timing characteristics of users' historical behavior data to a great extent.

D. Algorithm Steps

The difference is that RBM is used to preprocess the temporal features before adding the reduced dimension feature vector to the similarity measurement formula.

The specific implementation steps of TCRD based collaborative filtering algorithm are as follows.

The input variables are scoring matrix *r*, user context information matrix U_{type}, item attribute matrix I_{type}

The output variable is the recommendation list *H*(*u*) of user *u*.

DOI: 10.46300/9106.2021.15.123 Volume 15, 2021

Step 1. Processes the matrix r and I_{type}, and represents the historical behavior information of each user as a timing feature matrix V in binary coding form according to the timing feature construction method.

Step 2. Uses the restricted Boltzmann machine to reduce the dimension of the timing feature matrix V into a T-dimensional timing feature vector, and then combines the timing feature vectors of each user into a timing feature matrix t.

Step 3. The user context information matrix U_{type}. After preprocessing, the attributes are expressed into corresponding numerical forms to obtain the processed matrix $U'_{type.}$

Step 4 the matrix r, U'_{type} and V as the input of formula (10), the weight parameters in the formula are solved by NSGA-II algorithm.

Step 5. Substitutes the weight parameters in Step 4 into formula (10) to obtain the similarity measurement formula TCRD integrating user context information and timing information and uses the formula to calculate the similarity.

Step 6. Calculates the score of user u on the item by using formula (8) for the set U_k.

Step 7. Selects the top h items with the highest prediction score.

In this section, the temporal information of user's historical behavior is added based on the CRD method, and a similarity measurement method TCRD is proposed, which integrates user context information and temporal information. Then, the construction method of temporal feature matrix is introduced. Then, the temporal feature matrix is mapped to feature vector by using restricted Boltzmann machine. Finally, the temporal feature matrix is mapped to feature vector by using restricted Boltzmann machine, and user context information and temporal information are described.

IV. EXPERIMENTAL DESIGN

In this section, four groups of comparative experiments are designed . (1) In order to verify the advantages of RBM method, PCA, LLE and RBM dimension reduction methods are tested respectively, and the performance of TCRD based collaborative filtering (CF) algorithm corresponding to the three methods is compared. (2) When RBM is used for characters dimension reduction, the quantity of iterations needed for convergence of the method is explored, and the corresponding number of iterations when the loss function is basically stable is determined by observing the corresponding loss function values under different iterations. (3) The CF algorithm with RD, CRD and TCRD contrasts the CF algorithms with cosine similarity, Pearson similarity and weighted similarity measure, respectively. (4) By comparing the performance of CF algorithms based on RD, CRD and TCRD in different iterations, on the one hand, it verifies that the basic Rd method has better performance by adding context features and temporal features. On the other hand, it verifies the feasibility of the algorithm.

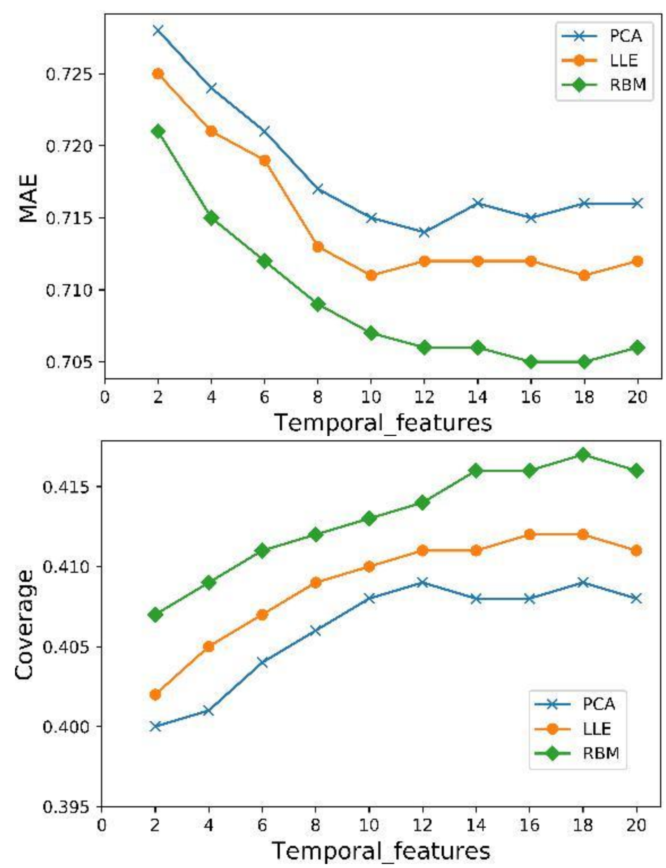
A. Experiments of Dimension Reduction Algorithms

In this section, RBM, PCA and LLE are used to reduce the dimension of the constructed time series feature matrix, and the performance of the corresponding TCRD with CF algorithm is compared.

The user rating time stamp is used as the sampling time, and 50 emergency information recently scored by users are selected. Using the feature representation method, the emergency information of each user is represented as a 50×18 time series feature matrix. The quantity of nodes in the visible layer of the restricted BM is determined by the number of columns of the temporal characteristic matrix, that is, the total quantity of categories of information is 18. The quantity of nodes in the hidden layer is determined by the dimension of the reduced time sequence vector, and the number of real-time sequence features. The training method is contrast divergence, and the Learning-Rate is gave to 0.01.

When NSGA-II algorithm is used to solve the weight parameters in formulas (3-1), (3-2) and (4-1), 10 groups of weight vectors are randomly initialized, the crossover probability is set to 0.8, the mutation probability is set to 0.05, and the number of iterations is set to 30. In theory, we don't need to specify the value range of the parameters of the similarity measurement formula. NSGA-II algorithm can solve the optimal value independently. Considering the increase of the convergence speed of NSGA-II algorithm, the parameter value of the score difference item is set as $0.8 \le w_r^{(0)} \le 1$, $0.6 \le w_r^{(1)} < 0.8$, $0.4 \le w_r^{(2)} < 0.6$, $0.2 \le w_r^{(3)} < 0.4$, $0 \le w_r^{(4)} < 0.2$ for. The reference value of context information item is $0 \le w_c^{(j)} \le 0.3$. The reference range of temporal information items is $0 \le w_t^{(l)} \le 1$. The nearest neighbor is set to 60.

RBM, PCA and LLE methods can decrease the dimension of temporal characters matrix. The performance of TCRD-CF on movielens dataset is shown in Figure 1.



DOI: 10.46300/9106.2021.15.123 Volume 15, 2021

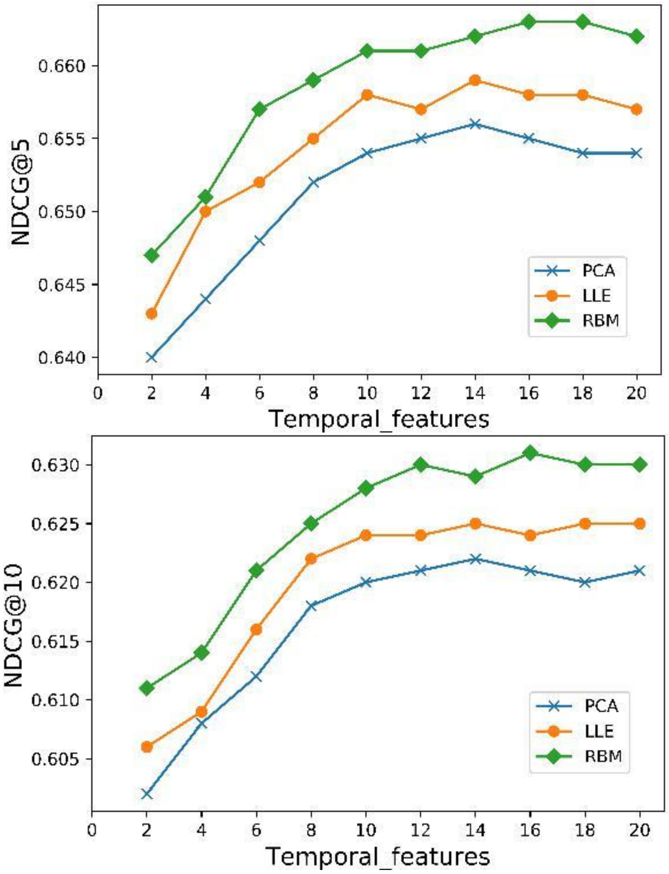


Fig. 1 The performance of TCRD-CF with different dimensionality reduction methods on Movielens

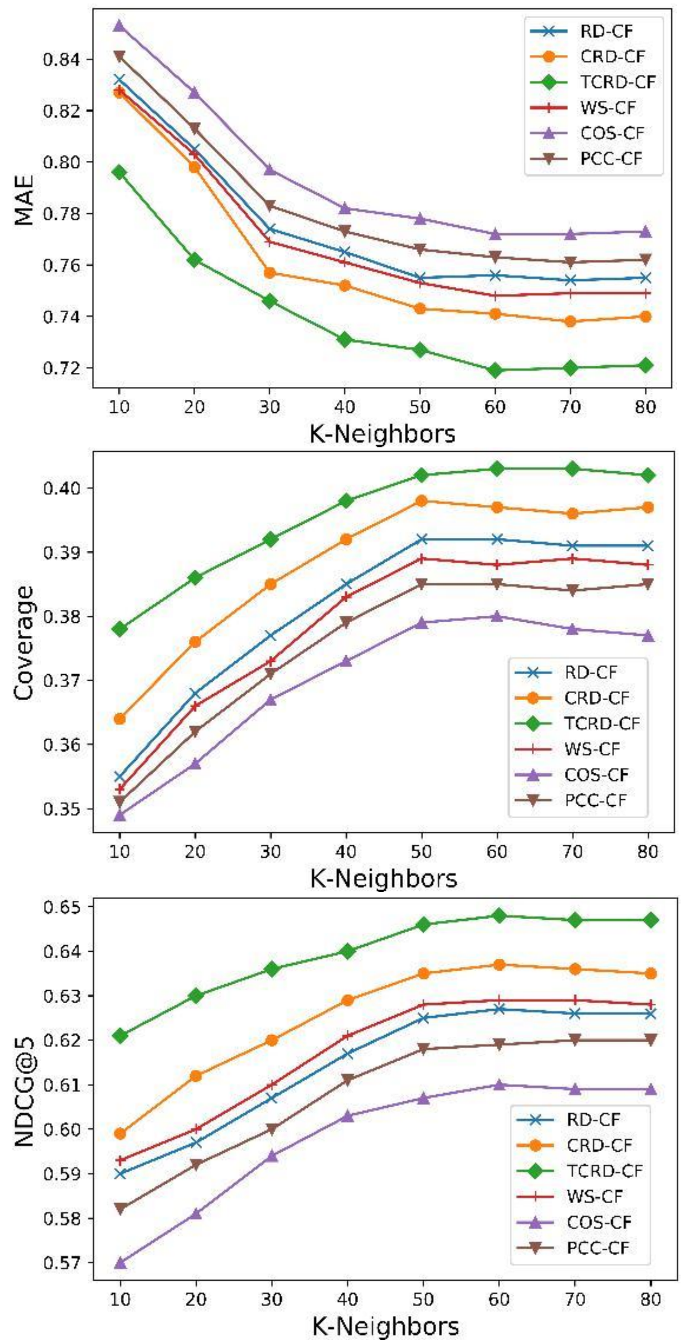
With the improvement of the quantity of temporal characters, the performance of TCRD-CF algorithm corresponding to the three dimensionality reduction methods is gradually improved from the experimental results, and more details are as follows. When the number of temporal features reaches 10, the algorithm has a disposition to be stable, which explains that the 10 dimensional feature after dimension reduction is enough to represent the original time series information. Too many features will promote the complexity of the model and the time required to achieve convergence. Compared with RBM, PCA and LLE, the performance of RBM is better than the other two, and LLE is better than PCA. This is because PCA can save as much original information as possible, which is a linear dimension reduction method. RBM and LLE both have the ability of nonlinear dimension reduction. LLE can make the reduced data better maintain the manifold structure of the original data. RBM can also use neural nodes to learn the relationship between temporal features and simulate the interaction between users and temporal information, At the same time, it can fit the given input data to the maximum extent.

B. Experiments of Recommendation Algorithms

This section of the experiment is to verify the effectiveness of RD-CF, CRD-CF and TCRD-CF algorithm and the three algorithms are compared with COS-CF, PCC-CF and WS-CF algorithm respectively.

The quantity of hidden layer nodes of the restricted Boltzmann machine is set to 10, and the quantity of iterations of NSGA-II algorithm is set to 30. The quantity of nearest neighbors is set to 10, 20, 30, 40, 50, 60, 70 and 80 respectively.

The performance of each recommendation algorithm on movielens dataset is shown in Figure 2. The abscissa is the quantity of nearest neighbors, and the ordinate is the evaluation index.



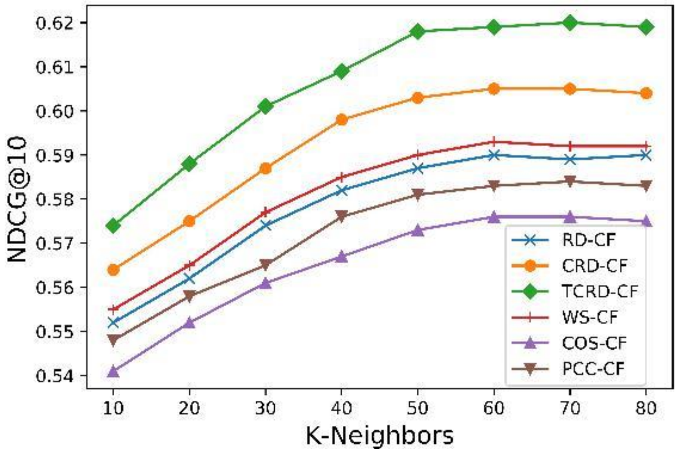


Fig. 2 The performance of different recommendation algorithms on Movielens

The results indicate that the performance of WS-CF, RD-CF, CRD-CF and TCRD-CF is better than that of COS-CF and PCC-CF under different number of nearest neighbors. Among them, TCRD-CF algorithm has the smallest MAE value and the highest coverage NDCG@5 and NDCG@10, which shows that TCRD-CF algorithm has the best recommendation performance among the five recommendation algorithms. The performance of different algorithms on the four evaluation indexes tends to be stable. When the quantity of nearest neighbors is 60, the four indexes are relatively optimal. The four indexes of TCRD-CF algorithm are improved by 7%, 4% , 6.5% and 7% by contrasting PCC-CF algorithm. This is because the proposed algorithm considers more factors affecting user similarity, which makes the similarity calculation between users more accurate. It shows that the proposed algorithm not only improves the accuracy of prediction score, but also improves the accuracy of ranking.

V. DISCUSSION

By observing the experimental results of WS-CF and RD-CF algorithm, we can see that the MAE and NDCG of WS-CF algorithm are slightly better, but the coverage is slightly worse. This is because WS-CF algorithm uses the single objective optimization algorithm and only takes MAE as the objective function to find the optimal MAE value. RD-CF algorithm uses multi-objective optimization algorithm to find a set of balanced solutions between MAE and coverage. In the actual recommendation system, more urgent information is recommended to users without sacrificing accuracy. This is also the reason why the multi-objective optimization algorithm is used in this paper.

By observing the experimental results of WS-CF, CRD-CF and TCRD-CF, we can see that CRD-CF and TCRD-CF are better than WS-CF in four kinds of performance, which shows that it is reasonable and effective to add the user's context information and timing information into the similarity measurement formula.

The recommendation system recommends specific personalized content for users according to their historical behavior. As a leader in recommendation system, collaborative filtering algorithm is widely used because it is easy to implement, can deal with unstructured data and has more accurate recommendation results. One of the key factors affecting the memory is the calculation of similarity.

VI. CONCLUSION

In this paper, the user similarity measurement method is studied.

(1) Firstly, the background and research significance of recommender system are introduced, and the research status at home and abroad is analyzed, which lays the foundation for the research. At the same time, it introduces the common recommendation algorithms and several common similarity measurement methods, focusing on the calculation of similarity between users.

(2) A similarity measure (TCRD) with user context information and temporal information is proposed. The performance of the recommender system is further improved by adding temporal information reflecting the change of emergency information. In order to learn the interaction between users and emergency information, the constrained Boltzmann machine is used to map the time series matrix into feature vector, which can reduce the dimension.

(3) Finally, the experimental results indicate that the proposed algorithm has lower average absolute error, higher coverage and recommendation quality than the CF algorithm with traditional similarity measurement method.

On the basis of the proposed collaborative filtering algorithm which integrates user context information and time sequence information, aiming at the shortcomings of the existing work, combined with the current research hotspots, the future research directions are as follows:

(1) When constructing features, we can try more auxiliary information in the future. For example, we can use neural network to transform the unstructured data (text and image, etc.) when users interact with projects into structured data, and then add it to the similarity measurement formula to further improve the performance of the algorithm.

(2) NSGA-II algorithm is not the best heuristic algorithm at present. When solving the weight parameters, we can try other more advanced algorithms to improve the speed and quality of algorithm training. Similarly, we can try a better dimension reduction method when processing temporal features.

(3) In the specific application, according to the different emphasis of the recommender system, different optimization objectives can be selected, such as RMSE and NDCG. At the same time, more than two objective functions can be selected, such as RMSE, COV and NDCG, but this will also increase the time overhead and complexity of the algorithm. In particular, if we only want to enhance a certain performance of the recommendation system, we can also use some single objective optimization algorithms to solve the parameters.

REFERENCES

[1] Rutkowski A F , Saunders C S . Growing Pains with Information Overload. Computer, 2010, 43(6),96-95.

[2] Al-Shamri M Y H. User profiling approaches for demographic recommender systems. Knowledge-Based Systems, 2016, 100, 175-187.

[3] Leng Y J, Qing L U, Liang C Y. Survey of Recommendation Based on Collaborative Filtering. Pattern Recognition & Artificial Intelligence, 2014, 27(8), 720-734.

[4] Burke R, Reasoning C. Hybrid Recommender Systems: Survey and Experiments. User Modeling and User-Adapted Interaction, 2002, 12(4), 331-370.

[5] Nikolakopoulos A N, Kouneli M A, Garofalakis J D. Hierarchical Itemspace Rank: Exploiting hierarchy to alleviate sparsity in ranking-based recommendation. Neurocomputing, 2015, 163, 126-136.

[6] Le H S. Dealing with the new user cold-start problem in recommender systems: A comparative review. Information Systems, 2016, 58(5), 87-104.

[7] Zhang D, Hsu C H, Chen M, et al. Cold-Start Recommendation Using Bi-Clustering and Fusion for Large-Scale Social Recommender Systems. IEEE Transactions on Emerging Topics in Computing, 2017, 2(2), 239-250.

[8] Umme Afifa Jinan, Ashikur Rahman Khan Given, Zayed-Us-Salehin, Fog Assisted and IoT Based Real-Time Health Monitoring System Implementation, International Journal of Applied Mathematics, Computational Science and Systems Engineering, Volume 2, 2020, pp. 99-106.

[9] Ghazarian S, Nematbakhsh M A. Enhancing memory-based collaborativefiltering for group recommender systems. Expert Systems with Applications, 2015, 42(7), 3801-3812.

[10] Rafeek Mamdouh, Hazem M. El-Bakry, Alaa Riad, Nashaat El-Khamisy, Converting 2D-Medical Image Files "DICOM" into 3D- Models, based on Image Processing, and Analysing their Results with Python Programming, WSEAS Transactions on Computers, Volume 19, 2020, Art. #2, pp. 10-20.

[11] Eirini Michalopoulou, Klimis Ntalianis, Analysis of Doctor-Patient Relationship in Social Media: the Case of Greece, WSEAS Transactions on Information Science and Applications, Volume 16, 2019, Art. #6, pp. 57-63.

[12] Patra B K, Launonen R, Ollikainen V, et al. A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data. Knowledge-Based Systems, 2015, 82(C), 163-177.

[13] Weidinger J , Sc Hlauderer S , Overhage S . "Information Technology to the Rescue? Explaining the Acceptance of Emergency Response Information Systems by Firefighters", IEEE Transactions on Engineering Management, 2021, (99),pp.1-15.

[14] C Schultz- Swarthfigure, Kelly A . "Is waiver of consent for the use of health information for research acceptable to emergency department patients?", Emergency Medicine Australasia, 2021, 33(2), pp.234-247.

[15] Huang Z, Chen C, Pan M. "Multiobjective UAV Path Planning for Emergency Information Collection and Transmission", IEEE Internet of Things Journal, 2020, 7(8), pp.6993-7009.

[16] Torpan S , Hansson S , Rhinard M , et al. "Handling false information in emergency management: A cross-national comparative study of European practices", International Journal of Disaster Risk Reduction, 2021, 57(2), 102151.

[17] Andreassen N, Borch O J, Sydnes A K. "Information sharing and emergency response coordination", Safety Science, 2020, 130, pp.104895.

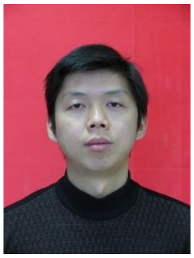
[18] Farzandipour M, Karami M, Arbabi M, et al. "Quality of patient information in emergency department", International Journal of Health Care Quality Assurance, 2019, 32(1),pp.56-70.

[19] Sato A, Nakajima M, Kohtake N. "Concept Design of Seamless Location Based Emergency Warning System with GNSS-Based Signals". Transactions of the Japan Society for Aeronautical and Space Sciences, 2019, 17(3), pp. 541-557.

[20] Alex S , Pattathil D P , Jagalchandran D K . "SPCOR: a secure and privacy-preserving protocol for mobile-healthcare emergency to reap computing opportunities at remote and nearby", IET Information Security, 2020, 14(6), pp.211-226.

Xiaoying Yao is a PhD candidate in management science an engineering of School of Management, Nanchang University, Nanchang, Jiangxi, China. And she works as lecturer in School of Vocational Education (Technology), Jiangxi Agricultural University, Nanchang, Jiangxi, China. She has 17 years'experience. Her current research intersts inclue Emergency management and Emergency information adoption.

Chunnian Liu,received PH.D degree in information science from School of Informtion Management Wuhan University,P.R.China April,2005. Now she works as Professor in School of Management, Nanchang University, Nanchang, Jiangxi, China. She has 16 years'experience. Her current research interests include Emergency management and Emergency information processing. Chunnian Liu is Corresponding Author.



Yingfei Zhu received bachelor's degree in prophylactic medicine of University of South China, Hengyang, Hunan, China. He works as Associate Senior Technician in Food Inspection and Testing Institute of Jiangxi Province, Nanchang, Jiangxi, China. He has 18 years' experience. His current research intersts include food safety inspection.