

Retraction

Retracted: Research of the Context Recommendation Algorithm Based on the Tripartite Graph Model in Complex Systems

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] F. Long, "Research of the Context Recommendation Algorithm Based on the Tripartite Graph Model in Complex Systems," *Complexity*, vol. 2020, Article ID 7945417, 11 pages, 2020.

Research Article

Research of the Context Recommendation Algorithm Based on the Tripartite Graph Model in Complex Systems

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With the rapid development of information technology, the information overload has become a very serious problem in web information environment. The personalized recommendation came into being. Current recommending algorithms, however, are facing a series of challenges. To solve the problem of the complex context, a new context recommendation algorithm based on the tripartite graph model is proposed for the three-dimensional model in complex systems. Improving the accuracy of the recommendation by the material diffusion, through the heat conduction to improve the diversity of the recommended objects, and balancing the accuracy and diversity through the integration of resources thus realize the personalized recommendation. The experimental results show that the proposed context recommendation algorithm based on the tripartite graph model is superior to other traditional recommendation algorithms in recommendation performance.

1. Introduction

With the rapid development of the Internet and the increasing popularity of smart phones, the information that people can access was increasing in complex systems. It became difficult to obtain information and easy to get lost in a huge amount of information. The data included information of major websites and mobile APPs. If the data had given a certain treatment, the information could have been more user-friendly and more efficient. Meanwhile, users would have been provided with a friendly experience, and the information provider could have had a higher revenue. So, the recommendation system came into being [1–4]. The introduction of complex context information brings more ideas to improve the efficiency of the recommendation algorithm. The main complex context information includes user context information, such as users' ages, occupation, and region; physical context information, such as location, weather, and time. There is much complex context information that could be considered by the recommendation algorithm. The context information can bring more accurate recommendations to the users of the recommendation system for complex real-world applications [5–9].

By applying recommendation technology, users are no longer passive recipients of services, but become active participants, directly affecting the way and content of services. With the rapid development and popularization of mobile information services and the continuous advancement of data collection technology, the dimension of the information we can collect has been continuously improved [10]. Traditionally, only the “user-item” two-dimensional recommendation model considers the amount of information collected. Relatively few data can be obtained with relatively low data dimensions, but in the context of mobile information services, relying only on the “user-item” two-dimensional recommendation model cannot generate a user for a given situational context effective personalized recommendations [11–14]. Therefore, it is very important and urgent to provide personalized recommendations for mobile users in specific situations.

There are three commonly used context-aware recommendation algorithms, and they are contextual prefiltering, contextual postfiltering, and contextual modeling. In this paper, a context recommendation algorithm based on the tripartite graph is proposed for the three-dimensional model. Improving the accuracy of the recommendation by

the material diffusion, through the heat conduction to improve the diversity of the recommended objects, and balancing the accuracy and diversity through the integration of resources thus realize the personalized recommendation of users. This algorithm focuses on projects with high popularity and improves the accuracy of recommendation. The experimental results show that the proposed recommendation algorithm on the accuracy and recall evaluation index has obvious improvement in performance than the traditional recommendation algorithm.

The remainder of this paper is organized as follows: Section 2 introduces the related work. Section 3 is the description and theory of the context recommendation algorithm based on the tripartite graph model. Section 4 presents the experimental process and results. The summary of the related work of our proposed model and algorithm and the conclusion of the paper are given in Section 5.

2. Related Work

The most important recommendation algorithms are the collaborative filtering algorithm and the content-based recommendation algorithm. However, there are certain problems that are hard to be solved in the two basic algorithms. Therefore, accuracy of the single recommendation algorithm is difficult to improve. Many scholars have shifted their goals from traditional recommendation algorithms, focusing on the research of context-based recommendation systems.

The research direction and application fields include shopping, tourism, catering, and other aspects, but they focused on proposing improved algorithms which are based on traditional algorithms. The contrast of advantages and disadvantages of various algorithms based on context perception is relatively rare. The fields and data types applicable to different context-aware algorithms are not studied. Kang et al. proposed not only paying attention to the explicit context information, but also implicit context information. And, they used the packet sniffing technique [15]. Ohbyung Kwona and Jihoon Kim proposed a way to discover the user's portrait by depicting the user's outline tree [16]. Since 2012, related research has exploded. Dao et al. combined user preferences and contextual interaction information and proposed a location-based advertising recommendation algorithm [17]. Sánchez-Pi et al. proposed the construction of a knowledge-based context-aware system [18]. Kasaki et al. proposed a localized adaptive modification model using a vector space model and saved time to obtain user-related information [19]. Unger et al. made a breakthrough in the acquisition of contexts, improving the accuracy of recommendations by extracting implicit context information from users' data [20].

The contrast of advantages and disadvantages of various algorithms based on context perception is relatively rare. Before 2016, there were not many research studies on context-aware recommendation algorithms. Most of them focused on the research of collaborative filtering algorithms. Such research is rare. There are three commonly used context-aware recommendation approaches, and they are

contextual prefiltering, contextual postfiltering, and contextual modeling [21]. Among them, Lee et al. proposed a novel TV system that combines gesture control, tag ranking, and context awareness, providing personalized recommendations [22]. Cai et al. used collaborative filtering to generate contextual concept ontology [23]. Ji et al. proposed an improved matrix approximate based on the clustering model [24]. Wang et al. proposed a hierarchical recommendation model based on the context tree structure, calculated situation transfer in the first layer, and recommended items in the second layer [25].

In research on the context recommendation algorithm, a lot of scholars have contributed to it. Among the above existing literature studies, some only use the two-dimensional model to calculate the recommendation list. Most of the papers on the research of 3D models focus on the label-based 3D model. The research aspect is relatively narrow and limited [26–30]. In this paper, the context recommendation algorithm based on the tripartite graph model is introduced. Research is more innovative and has improved accuracy in recommendations.

3. User-Item-Context Tripartite Graph Model

3.1. Tripartite Graph Model. The context incorporation task is the process of managing and interpreting the modeled context to be directly integrated in the recommendation system. This step consists of identifying the user and his/her preferences extracted from his/her implicit and explicit interactions with the system. These preferences are sensitive to the user's context and the change from a context to another. Then, the so-called contextual profile, the user's preferences in a given context, can be defined by the tuple (user, preferences, and context). These tuples can be saved in a database and have to be regularly updated to keep track of the evolution of the user's interests.

The application of context-aware algorithms is based on context acquisition. Current technology of shallow context acquisition can already be achieved. The user's latitude and longitude position, weather conditions, time information, etc., can be obtained through mobile devices. Age, gender, and other information, but deep-level information processing is currently relatively small, such as obtaining the user's location type, time type, and deep-level context information, have a greater effect on algorithm recommendation. The current research on this type of information is mainly obtained through user surveys and is provided voluntarily by users.

The context plays an important role in the user's selection of the item. The interest of the user will also migrate due to the context. If the context is not introduced, the interest changes in different contexts are not observed. In different contexts, users may feel different for the same item. For example, people will watch action movies with friends, but they may choose other types of movies when they are with family. The traditional algorithm ignores these interest migrations, and the recommendation is not personalized enough. The three-dimensional model formed in the context

introduced in this paper is more effective in improving the limitations of the recommendation algorithm.

Among the basic graph theory algorithm, the bipartite graph is commonly used in the related network model. In the bipartite graph, there are two sets of sets U and I :

$$U = \{u_1, u_2, u_3, \dots, u_i\}, \quad (1)$$

$$I = \{i_1, i_2, i_3, \dots, i_j\}. \quad (2)$$

The recommendation of the item is realized by the bipartite graph model. We should ensure that the intersection between the two sets is an empty set and is not affected by each other. Each element in the two sets is treated as a different point in the graph, representing a two-dimensional model of the user item. The elements between the same set are not connected by edges, and the edges between different sets are connected indicating that the user likes the project, forming a binary group $\langle u_i, i_j \rangle$. That constitutes an undirected bipartite graph model. The bipartite graph model is shown in Figure 1.

The tripartite graph model is an upgraded version of the bipartite graph model and can be viewed as a merged version of two bipartite graphs. It includes three sets U , I , and C , where the set $C = \{c_1, c_2, c_3, \dots, c_k\}$. Each set ensures that the two-two intersections are empty sets, so that the points of the three sets in the figure can be obtained. Similar to the bipartite graph model, the collections are guaranteed to be bottomless. There are two sets of two-tuple relations in the figure. There are two sets of edges connected, which are $\langle u_i, i_j \rangle$ and $\langle i_j, c_k \rangle$. The former indicates that the user likes the project, and the latter indicates that the project is in a certain context. We can realize the recommendation through the three-tuple relationship. The tripartite graph model is shown in Figure 2.

Through Figures 1 and 2, the concept of the model is intuitively felt. The item acts as a transfer station, communicates with the user's information, communicates with the context information, and finally the recommended list of items is a recommendation algorithm. It is more comprehensive compared with the traditional algorithm.

3.2. Tripartite Graph Model Based on Mass Diffusion.

When the bipartite graph is used to obtain the recommended result, the item is associated with the user to obtain the order of the item's preferences. The commonly used algorithms are the mass diffusion algorithm and the heat conduction algorithm. It can be understood from the existing literature that the mass diffusion algorithm is energy conservation while the heat conduction algorithm is not. The two algorithms play different roles in the field of recommendation algorithms. The mass diffusion algorithm is usually likened to a convex lens, which can focus on items with high heat. The heat conduction algorithm is like a concave lens, which can focus on the item which is more unpopular, thus increasing the diversity of recommendations.

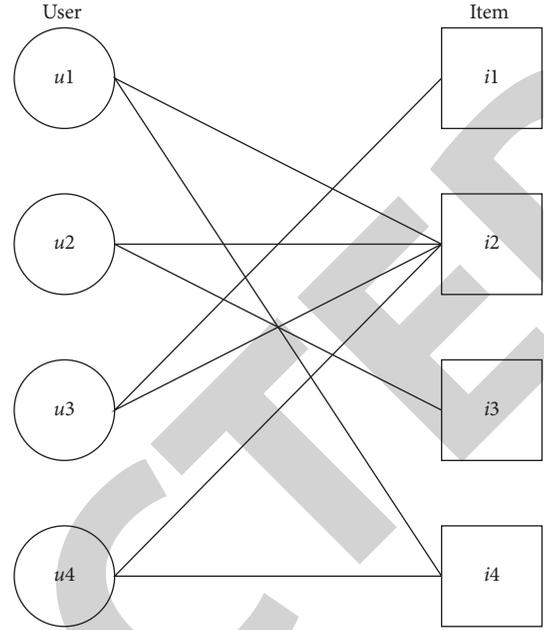


FIGURE 1: Bipartite graph model.

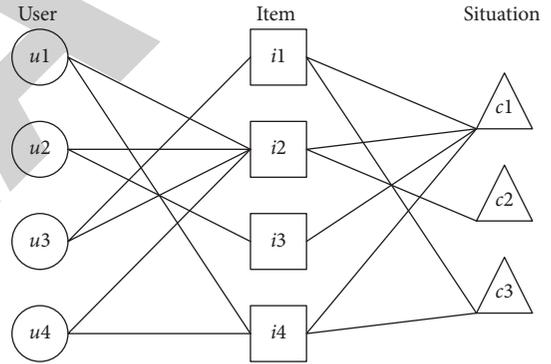


FIGURE 2: Tripartite graph model.

Among the results obtained, the nearest neighbor of each user is found, assuming that the choice of these nearest neighbors is related to the user's own choice. After finding the score of the target user u for the item i , the score of the most neighboring user for the item i is also found. Then, the mean of the nearest neighbors' score is calculated. If the mean value is bigger than the predicted score and the absolute value differs by more than a threshold value, the result is the predicted score adding the quotient of mean and predicted values. If the mean is equal to the prediction result or the absolute value difference is less than a threshold, no operation is performed. If the mean is smaller than the predicted score, the result is the predicted score subtracting the quotient of mean and predicted values.

The energy of each item is shown in the following equation:

$$c_{i,j} = \begin{cases} 1, & \text{user likes it,} \\ 0, & \text{user does not like it.} \end{cases} \quad (3)$$

According to the historical behavior of the user, the user's preference for the item is obtained. One means that the user likes the item, and zero means dislike. The total number of items preferred by the user is the total energy in the algorithm.

The first step of diffusion is from the item to the user. The user obtains energy from the item, and the item spreads the energy to the user by equally distributing the energy of each item to each purchased user. The energy obtained by the user is shown in the following equation:

$$b_\alpha = \sum_{l=1}^n a_{\alpha l} \left(\frac{c_l}{k(O_l)} \right), \quad (4)$$

in which $k(O_l) = \sum_{i=1}^m a_{il}$ represents the degree of the item and c_l represents the initial energy possessed by the item. The energy value owned by each user is obtained by one-step diffusion, and then the second step is performed.

The second step of diffusion is from the user to the item, which distributes the user's energy equally to the related items, and each item sums the collected energy to obtain the total energy, as shown in the following equation:

$$c'_j = \sum_{\alpha=1}^m a_{\alpha j} \left(\frac{b_\alpha}{k(U_\alpha)} \right), \quad (5)$$

in which $k(U_\alpha) = \sum_{j=1}^n a_{\alpha j}$ represents the degree of the user and b_α is the energy obtained by the user as described above. One of the recommended coefficients of the model is obtained by averaging the energy obtained in the first step by the second material diffusion.

In the bipartite graph, the elements in the figure have been replaced, but the idea of the bipartite method has not changed. Two-step diffusion is used to generate the recommended probability. The first step is to spread from the item to the context. The initial energy is related to whether the user likes the item. One means that the user likes the item, and zero means dislike. According to the relationship between the context and the item, the energy of the item is evenly distributed. For each occurrence of the context, the energy obtained by each context is the sum of the energy allocated to all related items.

$$d_\beta = \sum_{h=1}^p a_{\beta h} \left(\frac{c_h}{k(S_\beta)} \right), \quad (6)$$

in which $k(S_\beta) = \sum_{k=1}^q a_{\beta k}$ represents the degree of the context, c_h represents the initial energy possessed by the item, and c_h and c_j correspond to each other. The equation represents the energy of each context. The energy value of the context is obtained by the diffusion of the first step, and then the second step is still required to spread.

The second step is from the context of the item. Like the first step, the energy obtained by the context is divided into all the items, and the energy of each item is accumulated and obtained:

$$c'_t = \sum_{\beta=1}^q a_{\beta t} \left(\frac{d_\beta}{k(F_t)} \right), \quad (7)$$

in which $k(F_t) = \sum_{t=1}^p a_{\beta t}$ represents the degree of the item and d_β represents the energy value obtained by the context. In the second diffusion, the average value of the energy obtained from the previous diffusion is obtained.

It can be seen from Figure 3 that by processing of the tripartite graph model based on mass diffusion, the recommendation value of the items can be calculated and the recommendation sequence can be obtained. The recommendation sequence is $\{i_3, i_2, i_5, i_1, i_4\}$.

3.3. Tripartite Graph Model Based on Heat Reduction.

This section discusses the heat conduction method. As mentioned earlier, the heat conduction method is a divergent method that recommends unpopular items for users to increase the diversity of recommendations. Like the tripartite graph model based on mass diffusion, this model is divided into two bipartite graphs, and two heat conduction methods are used, respectively. Finally, the values of the two graphs are fused to obtain the coefficients recommended by the model.

The energy of each item is in the same way as mentioned above:

$$c_{i,j} = \begin{cases} 1, & \text{user likes it,} \\ 0, & \text{user does not like it.} \end{cases} \quad (8)$$

According to the user's historical behavior, the user's preference for the item is obtained. One means that the user likes the item, and zero means dislike. The total energy in the heat conduction method is not conserved.

Similarly, the first step of conduction is from the item to the user. The user obtains the temperature of the item, and the item transmits the temperature of the user. The method of transferring the temperature is to divide the sum of the temperature of the user's favorite item by the degree of the user, and the temperature obtained by the user is as the following equation:

$$b_\alpha = \sum_{l=1}^n \frac{a_{\alpha l} c_l}{k(U_\alpha)}, \quad (9)$$

in which $k(U_\alpha) = \sum_{j=1}^n a_{\alpha j}$ represents the degree of the user and c_l represents the initial temperature possessed by the item. The temperature possessed by each user is obtained by the first step of conduction, followed by the second step of conduction.

The second step of conduction is from the user to the item. The temperature of each item is the sum of the temperatures of all users who like it divided by the degree of the item:

$$t'_j = \sum_{\alpha=1}^m \frac{a_{\alpha j} b_\alpha}{k(O_j)}, \quad (10)$$

in which $k(O_j) = \sum_{i=1}^m a_{ij}$ represents the degree of the user and b_α is the temperature obtained by the user as described above. Through the second step of heat conduction, the average temperature value is obtained; that is, the obtained

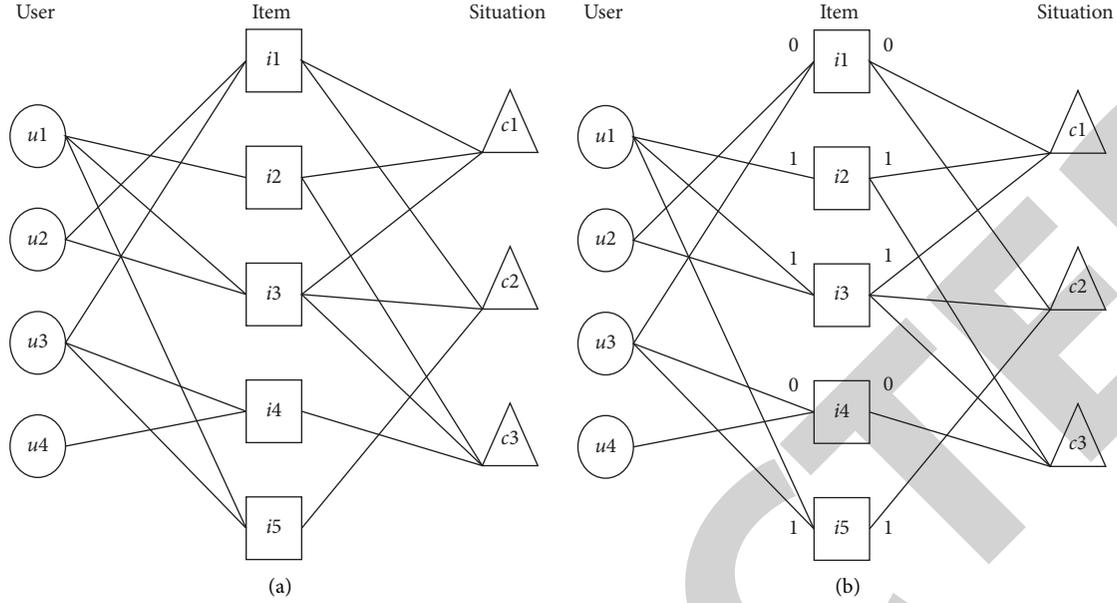


FIGURE 3: Processing of the tripartite graph model based on mass diffusion.

particle temperature value is one of the recommended coefficients of the heat conduction method.

The tripartite graph division method based on the heat conduction method is consistent with the material diffusion. For the item-context bipartite graph, the temperature of the calculated context is the sum of the associated item temperatures divided by the context:

$$d_{\beta} = \frac{\sum_{h=1}^p a_{\beta h} c_h}{k(F_t)}, \quad (11)$$

in which $k(F_t) = \sum_{t=1}^p a_{\beta t}$ represents the degree of the context, c_h represents the initial temperature possessed by the item, and c_h and c_j correspond to each other. The equation represents the temperature of each context. The temperature of the context is obtained by the first step of conduction, and the second step is to conduct the temperature on the article.

The second step is to get the temperature of the item from the context of the item and divide the temperature of the context associated with the item with the degree of the item:

$$t'_k = \frac{\sum_{\beta=1}^q a_{\beta k} d_{\beta}}{k(S_{\beta})}, \quad (12)$$

in which $k(S_{\beta}) = \sum_{k=1}^q a_{\beta k}$ represents the degree of the item and d_{β} represents the temperature obtained by the context. In the second conduction, the energy value obtained from the previous diffusion is averaged to obtain another recommendation coefficient.

Processing of the tripartite graph based on heat conduction is shown in Figure 4. Processing of the tripartite graph based on heat conduction is that nodes absorb resources from their adjacent nodes according to the number of adjacent nodes and the ratio of edge weight. After the

tripartite graph is divided into two bipartite graphs, the two recommended coefficients are obtained. In order to obtain the final recommendation coefficient, the average of the recommended coefficients obtained by the two is taken as the final recommendation coefficient:

$$\frac{E'}{2} = \frac{t'_j t'_k}{2}. \quad (13)$$

3.4. Mixed Model. The mass diffusion method and the heat conduction method are different in the recommendation system to improve the recommendation effect. The mass diffusion method focuses on improving the accuracy of the recommendation and the items with high popularity. The heat conduction method focuses on improving the diversity of recommendations. Therefore, the combination of the two methods is also a factor that is often considered, with the goal of ensuring accuracy and increasing the diversity of recommendations.

When mixing the two methods, it is usually a linear blending. We set the parameter λ , introducing parameters on the original three-part graph model, and construct a hybrid model:

$$e = \lambda E + (1 - \lambda) E'. \quad (14)$$

It is a common method in the hybrid model to change the value of the parameter λ to achieve the optimal effect of the model. In this paper, the influence of different parameter values on the model will also be explored.

4. Experiment Analysis

The hardware environment of this experiment is Intel Core i5 processor, 8G memory. The software environment is 64-bit Windows operating system, VMware Workstation Pro

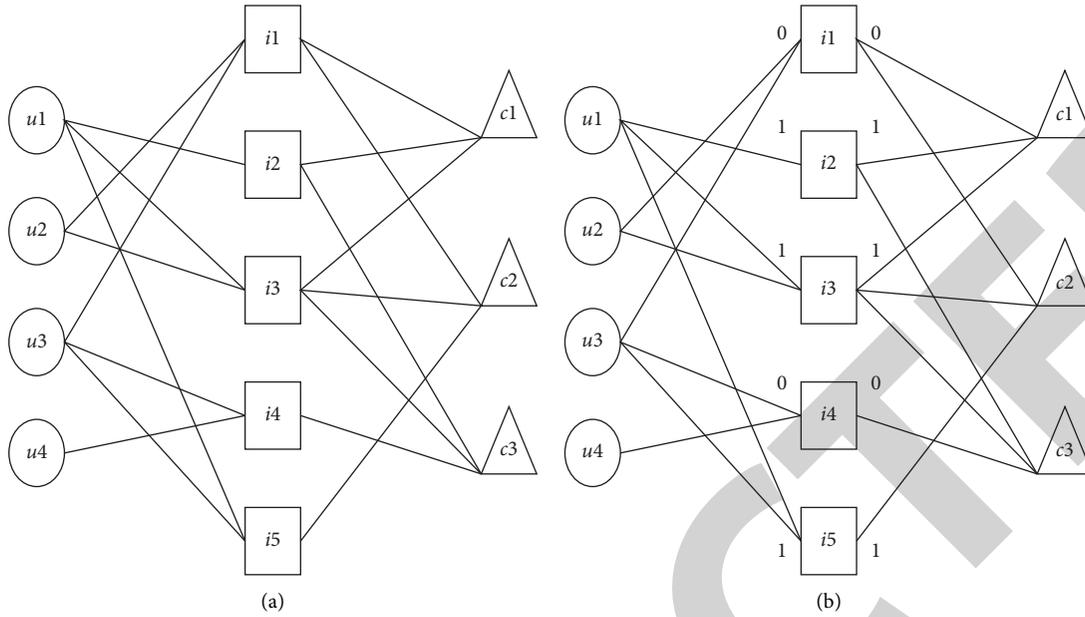


FIGURE 4: Processing of the tripartite graph based on heat conduction.

Virtual Machine, CentOS7 operating system, Open JDK1.8, Python3.7, and Anaconda for Python3.7.

The data of this experiment are mainly from the questionnaire survey of college students' movie-watching context. A total of 107 users' data are collected. In order to ensure the accuracy of the data, they are not excessively sparse. Some invalid questionnaires are eliminated. The data of 96 users were retained, including 2145 data.

In this experiment, the original data set is about the user's rating of the item, and the score range is 1–10 points. User's rating reflects the user's satisfaction with the item. The recommendation algorithm should refer to this satisfaction.

As shown in Figure 5, user A and user B scored item 1, but the score is completely different. So, the similarity between users is very low. Therefore, when the tripartite graph model is established, only the items that the user likes are selected. The connection line between the user and the item indicates that the user prefers an item above a certain rating range.

The evaluation parameters used in this experiment are a standard for evaluating the quality of the recommended results. The precision of the recommended results and the recall rate are used. Precision measures the proportion of recommended items that result relevant to the users, that is, those recommended items that the user actually consumes. Recall measures the proportion of consumed items that were correctly recommended; that is, the fraction of items relevant to the user that was suggested by the system. Recall and precision are usually considered together as two facets of the quality of the recommendation. The recall and precision are given as follows:

$$\text{precision} = \frac{\text{hits}}{\text{items_relevant}}, \quad (15)$$

$$\text{recall} = \frac{\text{hits}}{\text{items_recommended}}, \quad (16)$$

where *hits* are the number of correct recommendations, *items_relevant* is the number of all possible items that can be recommended for a given user, and *items_recommended* is the number of items recommended to a user. The precision and the recall rate are between 0 and 1. The closer it is to 1, the better the effect of the recommendation algorithm is. Closer to 0 indicates that the recommended effect of the recommendation algorithm is very poor.

This article also uses novelty to judge the novelty of an item:

$$\text{novelty} = \frac{\sum_{i=1}^m p(i)}{l}, \quad (17)$$

in which $p(i)$ represents the degree of the item in the recommendation list and l represents the length of the recommendation list. In this paper, the average popularity is used to represent the novelty, and the smaller the value, the more novel the item.

The original data of this experiment are about the user's score on the movie in some contexts. It is converted into the connection between the user and the item, the item and the context, and the connection between the user and the item. We establish the connection between the item and the context, and the form is shown in Table 1.

If the users give the item with rate greater than or equal to 8, we consider the users to be very fond of the items. Based on this rule to establish the connection between the users and the items, as well as the connection between items and context, the total number of filtered data is 1451. Some relevant predictions are made for these data. For this experiment, two control experiments were set up to determine the precision and recall rate under the collaborative filtering algorithm and the user-item bipartite graph algorithm and compare the results of the algorithm.

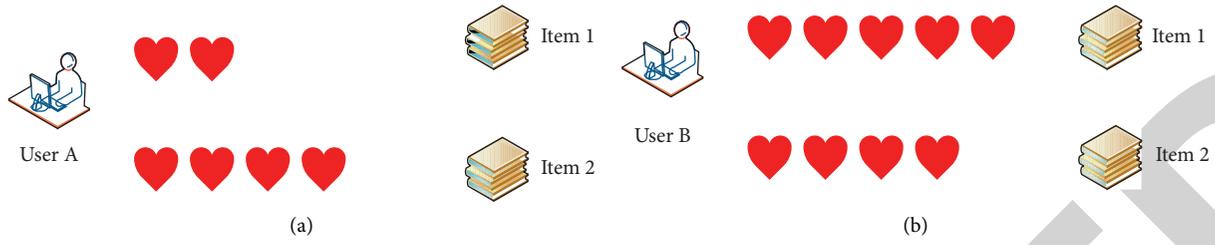


FIGURE 5: The score of items.

TABLE 1: The items that users prefer (part).

	User_id	Movie_id	S_id	Score
0	1101	2102	20.0	8.0
3	1101	2110	13.0	8.0
4	1101	2113	10.0	10.0
5	1101	2115	10.0	10.0
6	1101	2116	5.0	8.0
8	1101	2120	13.0	9.0
9	1101	2121	13.0	8.0
11	1101	2125	7.0	9.0
17	1101	2132	13.0	9.0
19	1101	2135	21.0	9.0
20	1101	2136	13.0	8.0
21	1101	2137	19.0	8.0

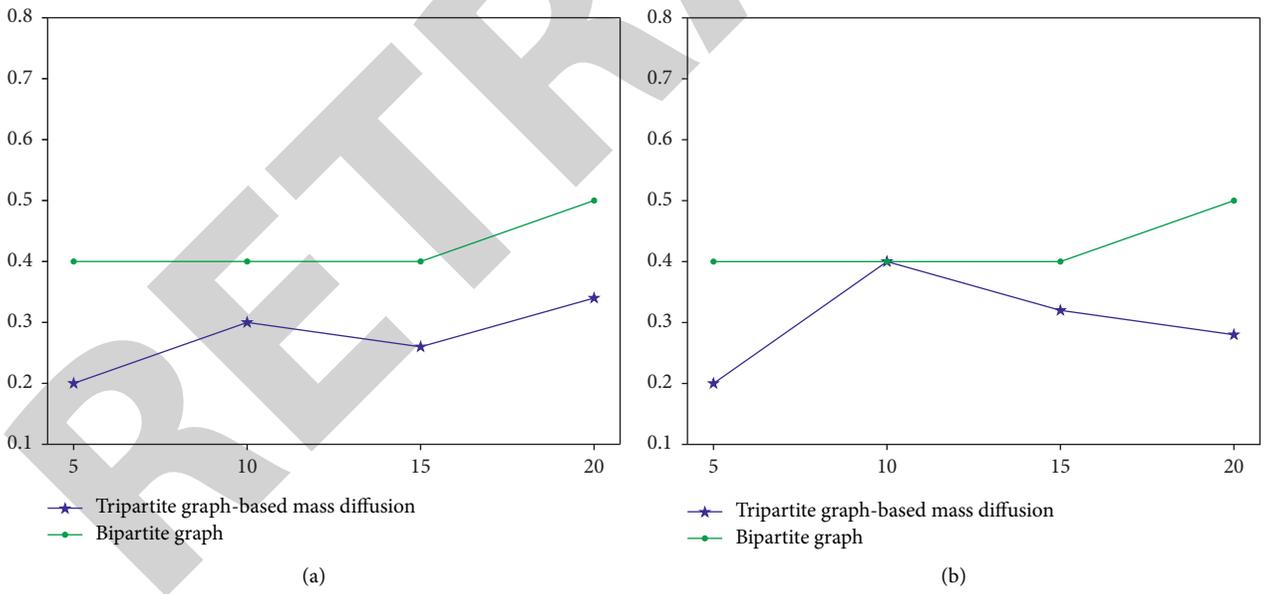


FIGURE 6: Continued.

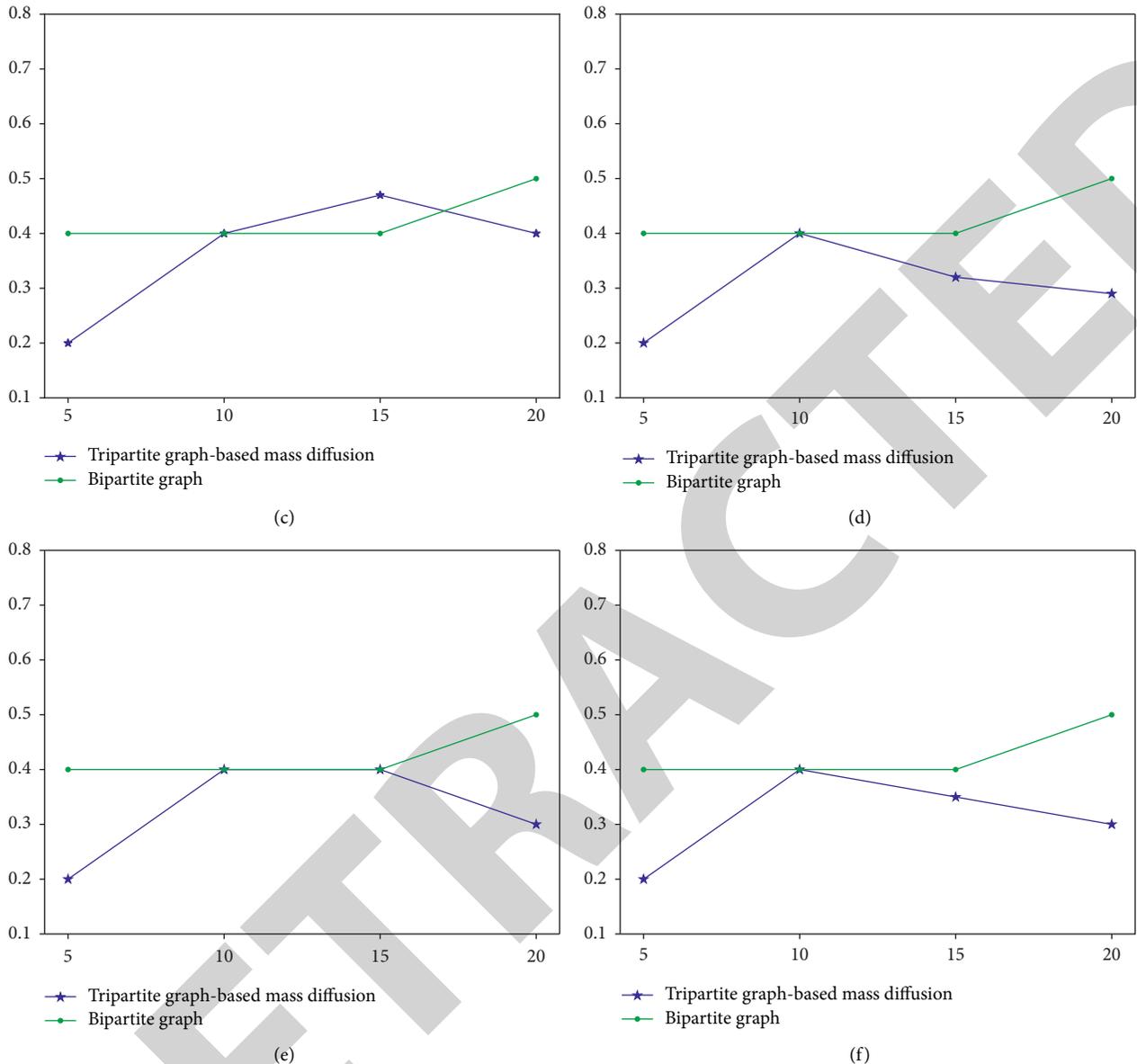


FIGURE 6: Precision of the hybrid model algorithm.

In the experiment, the user 1101 is taken as an example. The movie is recommended to be selected under the contexts 1, 5, 9, 13, 17, and 21, and 5, 10, 15, and 20 different movies are recommended, respectively. The comparison result of the accuracy rate and the recall rate is shown in Figures 6 and 7.

We calculate the novelty of the recommendation. The calculation base of the novelty is 20 when the recommended item is as shown in Table 2.

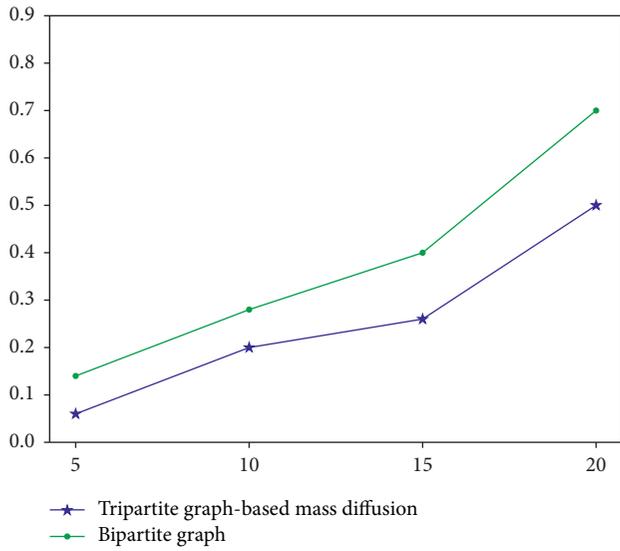
It can be seen from the comparison of the experimental results that in the experimental data set, the performance of the algorithm is not excellent enough. The precision rate is less reduced, and the recall rate is also somewhat reduced. When the recommended number of items is 10, the precision and recall rate of the algorithm are optimal.

Meanwhile, the novelty has also improved. Compared with the bipartite map recommendation algorithm, the items recommended by the three maps are more novel.

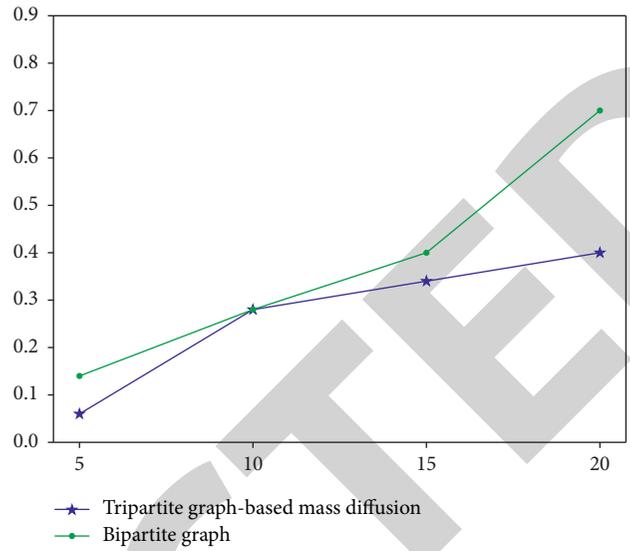
After the experiment, the precision and recall rate of the tripartite graph model based on heat conduction are almost zero, and the novelty is very high. Due to the divergence of the algorithm, the items focused on the unpopular, and the recommended results are not in line with actual needs, nor suitable for this data set.

In the hybrid algorithm, several of the mixed parameters are selected, which are 0.1, 0.3, 0.5, 0.7, and 0.9. We calculate the accuracy, recall, and novelty for each result as shown in Table 3.

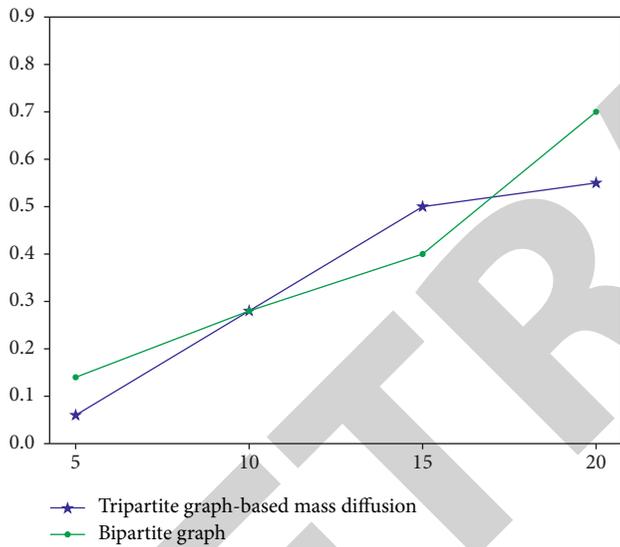
The performance of the hybrid model algorithm has basically stabilized when the value of λ is greater than 0.5.



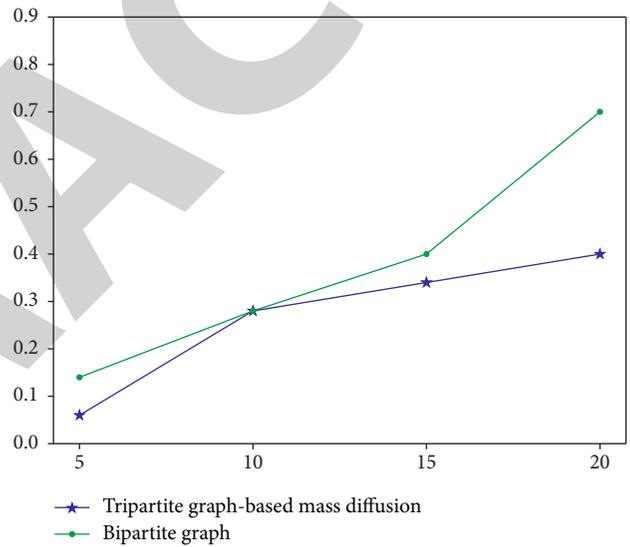
(a)



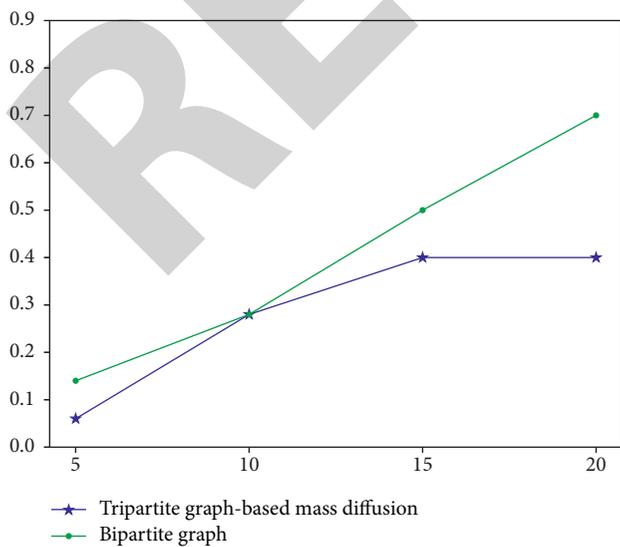
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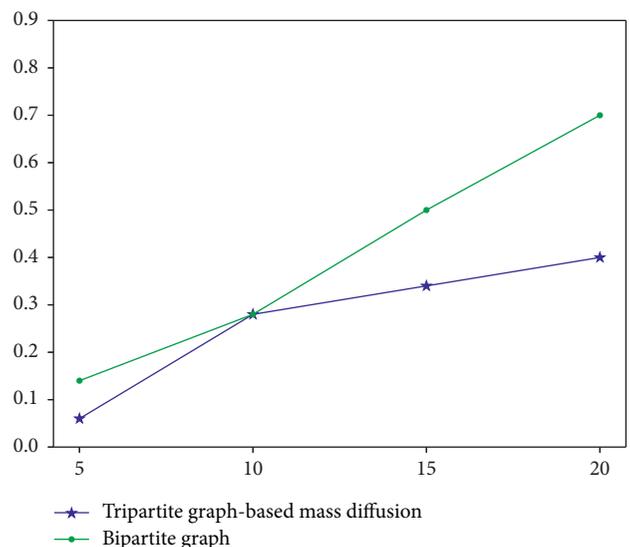
(c)



(d)



(e)



(f)

FIGURE 7: Recall of the hybrid model algorithm.

TABLE 2: Comparison of novelty.

	1	5	9	13	17	21
Bipartite graph				42.15		
Tripartite graph	41.65	39.05	40.5	39.05	41.35	39.85

TABLE 3: Mixed model.

	0.1	0.3	0.5	0.7	0.9
Precision	0.1	0.2	0.3	0.3	0.3
Recall	0.0714	0.1428	0.214	0.214	0.214
Novelty	15.4	28.05	34.45	39.05	39.05

The change of parameters has little change on the algorithm result. The novelty shrinks as the parameter increases, and the accuracy increases as the parameter increases.

5. Conclusion

In this paper, to solve the problem of complex contexts, a new context recommendation algorithm based on the tripartite graph model is proposed for the three-dimensional model in complex systems. This algorithm focuses on projects with high popularity and improves the accuracy of recommendation. The range of recommended results is very narrow. Part of the reason is that the number of items in the data set is not large, and the recommendation results are not obvious. There is an urgent need to improve. And, the most popular items should be given some punishment mechanisms to enable more user interest. However, the novelty of the algorithm is slightly improved, and the performance of the algorithm tends to be stable after the model parameters reach a certain value [5–14, 26–30].

Data Availability

The data used to support the findings of this study are available upon request from the corresponding author.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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