J Inf Process Syst, Vol.19, No.5, pp.576~589, October 2023
https://doi.org/10.3745/JIPS.01.0096

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

Personalized Recommendation Algorithm of Interior Design Style Based on Local Social Network

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Abstract
To upgrade home style recommendations and user satisfaction, this paper proposes a personalized and optimized recommendation algorithm for interior design style based on local social network, which includes data acquisition by three-dimensional (3D) model, home-style feature definition, and style association mining. Through the analysis of user behaviors, the user interest model is established accordingly. Combined with the location-based social network of association rule mining algorithm, the association analysis of the 3D model dataset of interior design style is carried out, so as to get relevant home-style recommendations. The experimental results show that the proposed algorithm can complete effective analysis of 3D interior home style with the recommendation accuracy of 82% and the recommendation time of 1.1 minutes, which indicates excellent application effect.

Keywords
Interior Design, Location-based Social Network, Personalized Recommendation

1. Introduction

Rapid advance and popularity of computer network technology grows people's dependence on the network. Currently, the Internet is an indispensable part of social life and work. Moreover, as computer graphics processing technology develops, various advanced 3D design and visual display means emerge, so that three-dimensional (3D) modeling and virtual reality technology has become a popular direction in the current space design application industry [1]. Compared with the traditional offline two-dimensional or physical display, product display or online shopping based on 3D modeling and virtual reality technology is conducive to not only appearance display and human-computer interactive browsing, but also the immersive shopping experience, literally better visual effects.

Relevantly, the interior design platform based on 3D modeling and virtual reality technology is gradually gaining research attention in this respect [2]. But in reality, although 3D interior design platform can provide an intuitive home and scene experience, the style diversity and users' own interests are reasons for wrong decisions in interior design, or even overall style mismatch, which affects shopping experience.

To solve this, professional interior designers also need assistance [3]. Actually, online home design or shopping websites cannot provide one-to-one real-time professional human services for each online user.

Manuscript received April 5, 2022; first revision June 16, 2022; second revision July 26, 2022; accepted August 20, 2022.
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One proposal from the study [4] was an automatic indoor scene generation algorithm by case-based reasoning and collaborative filtering technology. According to the indoor circulation path, the two-dimensional house map was divided into functional areas. Case-based reasoning and collaborative filtering technologies were then used to generate 3D scenes and diverse indoor scene. This method generates scenes faster, but the accuracy of interior design style recommendations is poor. Other study [5] proposed an interior design project recommendation method based on collaborative filtering technology. Firstly, current recommendation researches on interior design projects at home and abroad are analyzed, so as to define the shortcomings of various recommendation methods. Then interior design users and project characteristics can be selected out, and the similarity measurement calculation formula is designed. Next, the indoor design project recommendation results are obtained according to the predicted scores of the k-nearest neighbor users. This recommendation algorithm has higher accuracy, but takes a long time.

Therefore, this paper proposes a personalized recommendation algorithm for interior design style based on local social network, including the data collection of indoor space design interest, home-style feature definition, and style association mining. Also, user behavior data is analyzed through the location-based social network. To establish an accurate user interest model, the apriori algorithm and the association rule mining algorithm are combined based on the local social network. Finally, online users complete the unified selection of home styles.

2. Personalized Recommendation Algorithm of Interior Design Style

To study the personalized recommendation algorithm of interior design style, favorable features by users of the interior design styles should be firstly defined and analyzed. Through the location-based social network algorithm, users can get recommendations accordingly together with preliminary recommendation results. Finally, a personalized user-oriented recommendation engine for interior design websites based on positioning social network technology is designed, and an independent design beyond the website system is also adopted. Both online and offline methods are used to provide recommendation services and user recommendation data. Finally, the recommendation list generated by the engine is presented to website users.

2.1 Interior Design Style Interest Feature Evaluation Algorithm

As this paper studies and applies the recommendation algorithm for interior design scheme of the interior design websites, corresponding websites are taken into consideration to improve the relevant algorithm. Currently, there are few user interests in interior design, with even less users and projects, along with lesser explicit and implicit scoring behavior of users. Considering the scalability and recommendation accuracy, the advantages and disadvantages of the location-based social network algorithm, together with current interior design websites, an optimized version is designed for interior design scheme. To be noted, this algorithm is mainly divided into two stages [6]. In terms of interior design recommendation, this paper studies the influence of user cognition on recommendation technology acceptance behavior on e-commerce websites. Here, association recommendation algorithm is a common data mining method in e-commerce system in recent years, typically apriori algorithm. In order to support online users in unified home style selection and get the recommendation results, all the existing 3D model data sets in the platform are collected as the training set [7]. The 3D model of interior design is defined by home style features, and the transaction set is established. Finally, the typical association rule mining algorithm is used to analyze the scene style features. Firstly, this paper optimizes the collection process of style interest features, as shown in Fig. 1.

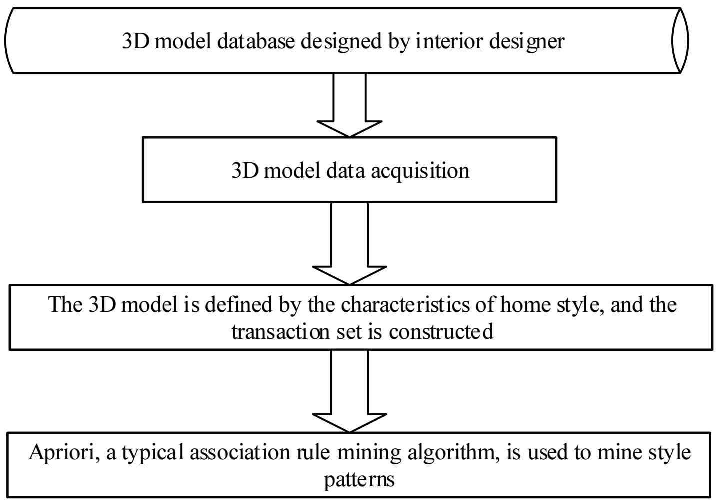

Fig. 1. Collection process of interior design style interest features.

Furthermore, the contour of the home model is described by hog features.

$$R = min\sum_{p=1}^{p} \pi^p \, \|X^p - U^p V^p\|_F^2 + \mu||n\pi||_2^2, \tag{1}$$

where X^p represents the interior design style characteristic matrix of the p-th perspective; U^p and V^p represent the base matrix and coefficient matrix of the p-th perspective, respectively; μ represents a smoothing factor, π^p represents the weight of the p-th perspective, and n represents the total number of perspectives [8]. The standard K-means that clustering algorithm is used for clustering observation, and the IDF value of each interior design style interest feature cluster is obtained by the following equation:

$$IDF(c) = \frac{|\{m \in M : c \in m\}|}{NR}, \tag{2}$$

where c is the interior design style cluster, N is the total number of models included in this class, and M is the effective recommendation amount of the model. Right IDF is crucial to the right style features [9]. Assuming $I_i = \{e_{\mathrm{i1}}, e_{\mathrm{i2}}, \ldots, e_{\mathrm{id}}\}$ is the style element item set of the class I 3D model, where e is the label of the style element, so that $S(i,j)$ represents the number of times the class j behavior occurs for the class i user. For the convenience of statistics and analysis, $S(i,j)$ is normalized as follows:

$$Q_{i,j} = IDF(c) * \frac{S(i,j) - Min(S(i,j))}{Max(S(i,j)) - Min(S(i,j))}, \tag{3}$$

Where $Max(S(i,j))$ and $Min(S(i,j))$ represent the maximum and minimum number of j-type behaviors of the i-th user in a certain period of time respectively. If the weight is W_j and the proportion of behavior

j in all behaviors of the user is $P(Q_{i,j})$, the entropy calculation method of behavior j is as follows:

$$I_j = -\sum_{i=1}^{n\Sigma\left(P(Q_{i,j})\right)(Q_{i,j})} log, \tag{4}$$

where $Q_{i,j}$ is the number of times that the i-th user conducts behavior j; n is the total number of all behavior categories of the i-th user [10]. According to the above formula, the weight of behavior j can be obtained, and the calculation method of interest feature category is as follows:

$$\mathrm{WB}_j = \frac{1-I_j}{m-\sum_{j=1}^{m} I_j}, \tag{5}$$

where m is the total number of all behavior categories [11]. Based on the above algorithm, the characteristics of interest categories can be defined, so as to better improve the reference basis for personalized recommendation methods.

2.2 Optimization of Personalized Recommendation Steps of Interior Design Style

Through the location-based social network algorithm, users can get preliminary recommendations. Top-N items are selected as the input of the next part, so as to realize less influence of remote users, smaller calculation range of user item score matrix of location-based social network algorithm, and higher calculation efficiency of the algorithm [12]. Considering the idea of such algorithm project and the influence of project similarity, the cosine similarity and project type similarity between projects are integrated to weigh the location-based social network algorithm, which is different from the method that only the average score difference between projects rather than project similarity is used to predict the score [13]. From the above aspects, the process of feature category recommendation of interior design scheme is optimized, as shown in the following Fig. 2.

Further, the location-based social network algorithm is also adopted to calculate the Pearson correlation coefficient method with higher accuracy by the users' neighboring group. The nearest neighbor algorithm is based on the similarity threshold algorithm, and the recommended design scheme list is submitted to the location-based social network algorithm as the input [14]. The whole algorithm is functioned by Apache Mahout's taste component, which is designed to meet the scalability and flexibility requirements of the interior design recommendation engine. Then it is further developed into a business logic module in the form of web service and HTTP, which is integrated into the interior design website system [15]. Here are two scoring methods for user behavior records. One is explicit scoring [16-18], literally the website server records the users' evaluation scores for the item or lets the users decide how much they like these items. The other is to record individual user's behavior pattern instead of scoring, such as website users' collection, purchase items, etc., which is called implicit scoring. In the recommendation process, user behaviors need to be converted to score values to calculate and individual user's score from explicit scoring is easier to gain. Therefore, the implicit score should conduct conversion accordingly [19]. The interior design scheme is scored by the 5-point rank, and the implicit scoring behavior can be converted according to the user's preference degree. For example, if the browsing item is set at 1 point, the careful browsing can be set to 2 points [20]. On most websites, users seldom give explicit ratings to items. One of the most important principles is that in order to cater to users' habits, the website design allows users to reduce the tedious operation to the maximum [21]. Explicit scoring requires a high degree of user cooperation and participation, which obviously violates the user habits and the principles of website design. Despite that, explicit ratings can largely reflect the user's preference. Through investigations, major behaviors among general users of the interior design websites are shown in Table 1, including the design of corresponding implicit scoring.

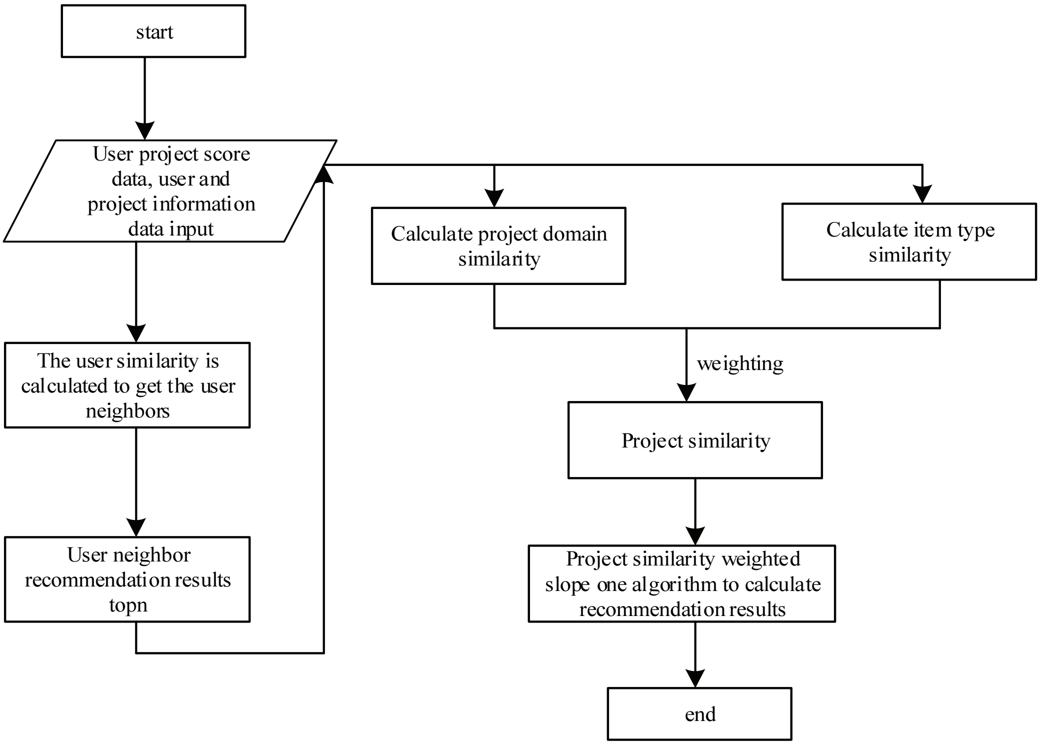

Fig. 2. Recommendation process of feature category of interior design scheme.

Table 1. User behavior analysis of home decoration website

User behavior	Scoring mode	Corresponding score value	Explain
Simple browsing	Implicit	1 point	Users can browse the pictures by clicking the design scheme
Browse carefully	Implicit	2 points	Full screen browsing when users view decoration design scheme pictures
Give the thumbs-up	Explicit	3 points	Users click "like" button
Download	Implicit	4 points	Users download a set of decoration design
Collection	Implicit	4 points	Users click the collect button
Purchase	Implicit	5 points	Users click to buy products related to the design

For those home decoration websites, the interior design process usually involves: the first part is the preliminary work, including understanding the decoration process, price quotation, reference decoration design scheme and consulting relevant personnel. Then is the decoration process involving the entire project budget, including how to choose the right designer, materials and decoration company, purchase of household goods, and so on [22]. Finally, the acceptance of design results. To be noted, in order to provide personalized design scheme recommendation system, websites need to collect and process users' behavior data, together with corresponding data mining in the background, so as to provide better design schemes. In this aspect, a well-functioning recommendation engine needs three parts: user behavior log collection, offline preprocessing, and recommendation. Through the analysis of current interior design websites, and considering the usability and practical significance, the following interaction diagram of interior design scheme recommendation engine is used to describe the functions that need to be covered, as shown in Fig. 3.

The data mainly includes the explicit and implicit ratings of users, such as browsing, downloading, like, purchase and other user behavior records. As data source, these interior design websites mainly serve consumers with decoration needs. Usually, these users need to register on the interior design websites, browse the decoration design scheme, contact relevant decoration companies and purchase relevant products. That is, the information about website users, design scheme and user behavior data, are key to excellent recommendation service for target users. However, it is not wise to process a large amount of user behavior data directly in the website background. In order to minimize the impact on the normal operation of the front and back-end of the website together with the user experience, a large amount of data is separated from the website for offline processing. At the same time, it is necessary to extract, convert and load a large amount of user behavior data to figure out the characteristics of users and project data collection. Then through the processed user behavior data, user and decoration design information, combined with the improved location-based social network algorithm, the website users can receive possible design recommendation list offline, thus realizing relevant real-time website service.

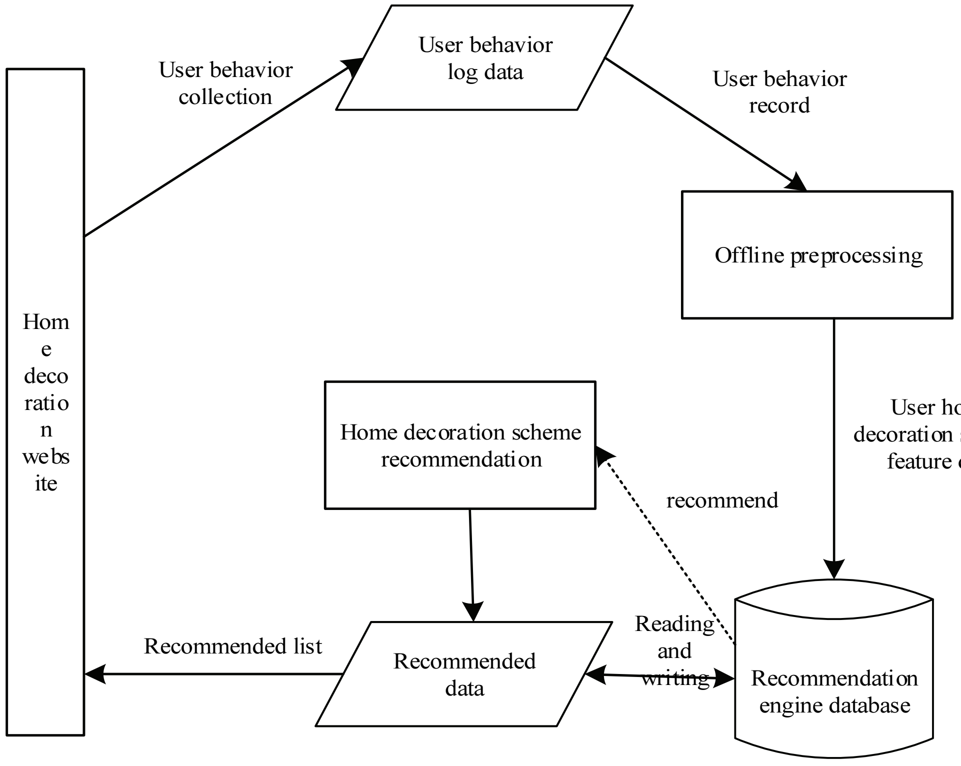

Fig. 3. Interactive diagram of the interior design style interest recommendation engine.

2.3 Implementation of Personalized Recommendation of the Interior Design Style

The personalized recommendation engine for the interior design website users based on location-based social network technology is designed. In order to minimize the impact on the website itself along with the mismatch between the recommendation engine and the interior design websites, the independent design beyond the interior design website system is adopted. The design of recommendation engine is mainly divided into module design, recommendation algorithm design, and database design. The recommendation engine of the interior design scheme relies on the interior design website system. Moreover, to have less impact on the normal operation of the interior design website, both online and offline methods are used to provide recommendation services to website users. The recommendation engine will be integrated into the architecture of the interior design website as a module offline. And the front page of the interior design website can easily obtain the recommendation list generated by the recommendation engine and present to website users. Here, Fig. 4 shows the overall architecture of the interior design proposal recommendation engine of the interior design website.

From the overall architecture of the recommendation engine, the user behavior logs recorded on the production server of the interior design website, as well as the user information and decoration design scheme information in the background database of the website will be transferred to the database of the recommendation system for storage, and then a large number of user behavior logs will be processed by ETL into the data necessary for recommendation, then through the location-based social network. After offline recommendations, the intermediate results will be submitted to the online recommendation module. Finally, the online module will display recommendation results for each corresponding website user. When target users log in to the website, they will get the personalized decoration recommendations. More specifically, the recommendation engine of the interior design website with location-based social network is divided into three modules: data collection, offline preprocessing, and the interior design algorithm recommendation. The functional structure of the recommendation engine is shown in Fig. 5.

According to Fig. 5, a large number of user behavior logs recorded by the website production server will be delivered to the backup server when the website has the least user visits. It can not only avoid the impact on the performance of the interior design website server, but also make full use of the limited storage resources of the backup server. At the same time, the user information and decoration design scheme of the website back-end database are synchronized to the backup server. After that, Rsync tool is used to synchronize the data in the backup server to Hadoop cluster for data mining of recommendation system. In addition to formulating data flow strategy, data collection also needs to fully collect website user behavior data and select appropriate data synchronization tools. Specifically, the server log recorded by normal interior design website contains incomplete user behavior records, typically Nginx log. Upgrading will not only cost extra money and storage space, but also put lots of space pressure to the website itself. Considering the current situation, a good choice is to modify the Nginx log format. As a result, the number of location-based and content-based interior design algorithms for traditional social networking sites will not be limited to current number of users. After general researches, when designers upload the design scheme to the website, the project description is very short. So that project type rather than only descriptions is far better to distinguish the similarity between the two design schemes. Considering the above situation, the algorithm part of the recommendation engine is shown in Fig. 6.

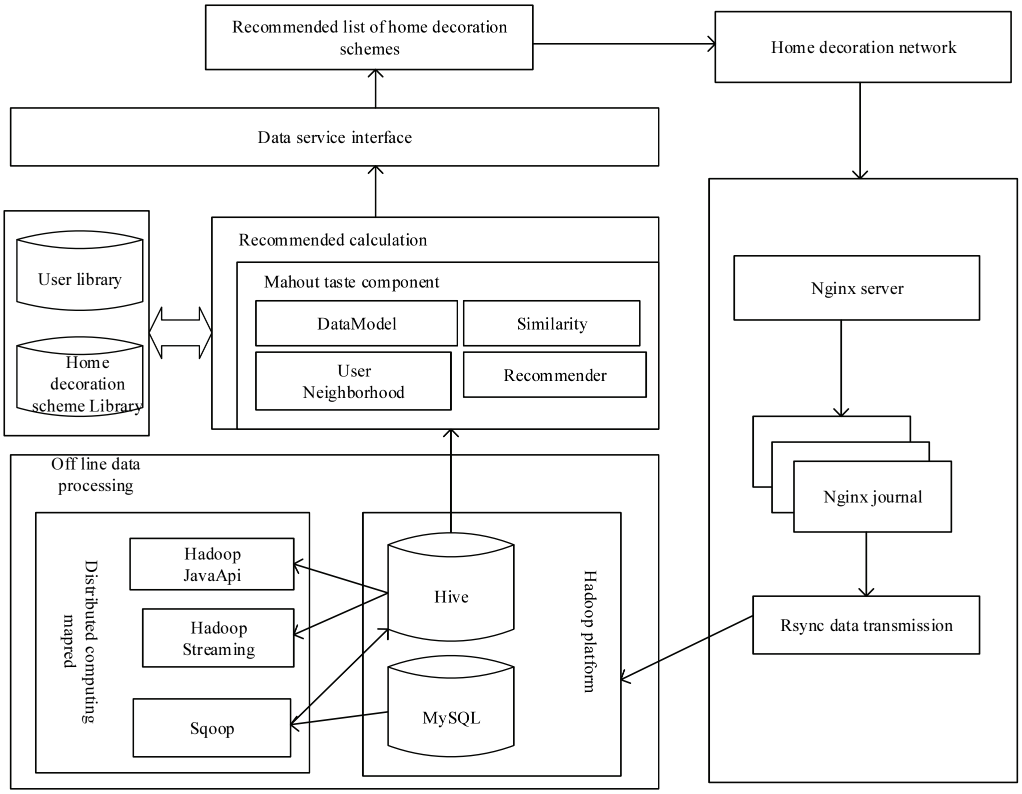

Fig. 4. Function structure optimization of recommendation engine.

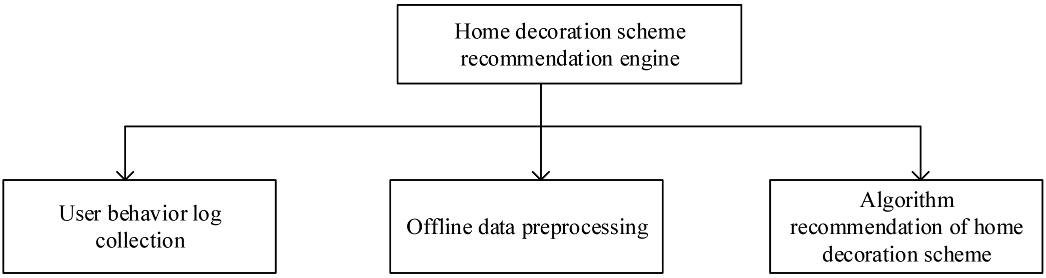

Fig. 5. Function division of the interior design recommendation engine.

The location-based social network algorithm is used to measure the similarity between users by cosine theorem, which is verified by experiments. The nearest neighboring algorithm adopts the neighboring algorithm based on the similarity threshold with higher accuracy with the threshold value of 0.5. The item similarity of the algorithm is weighed by cosine theorem similarity of user item matrix and item type similarity, in which the weight coefficient is 0.5, 0.3, and 0.7, respectively. After that, the recommended interior design scheme list is submitted to the location-based social network algorithm as input, which can better meet the requirements of enterprises for high scalability and flexibility of the interior design scheme recommendation engine.

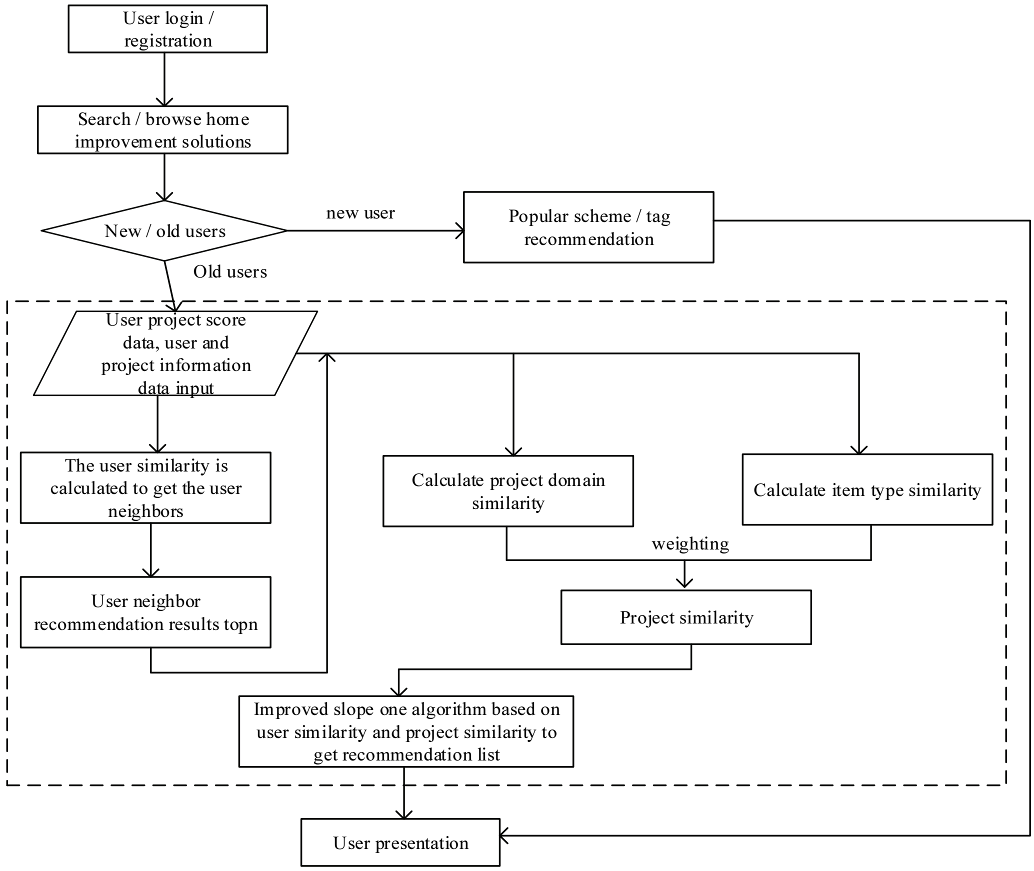

Fig. 6. Optimization steps of personalized recommendation for the interior design.

3. Experimental Results

The existing device discovery scheme takes a long time because the 48-bit UID search range (2^{48}) tends to induce very deep tree levels along the binary search tree. Thus, a new device discovery scheme is then proposed, which is called *partition-based* device discovery. In the proposed scheme, all devices in the network will be grouped into Np partitions, as shown in Fig. 2.

The personalized recommendation algorithm of the interior design style with location-based social network is simulated and tested. The configuration of simulation PC is Intel core i7-4785T CPU @2.20 GHz, 4 GB memory, Windows 7 operating system. The configuration of software and hardware environment is shown in the Table 2.

The experimental cluster uses two 3-node sl4540 servers, including one master node and one backup node, and the rest are slave nodes. The 3D model data acquisition process takes 4.2 hours for component sampling and feature calculation, with the support threshold of 0.2. In addition, the maximum number of style features in each mode is 10, and the minimum number is 2. In order to make a quantitative comparative analysis of style similarity, the following formula is used to mine the difference degree between different style pattern sets.

Table 2. Experimental environment

Configuration item	Configuration parameter
CPU	Intel Core i5-3210M 2.50 GHz
Available memory	11.9 G
Operating system	64-bit Window 8 Professional
Programming environment	Eclipset 4.2
Java version number	1.6.0_35
Hadoop cluster version number	IDH 2.5

$$Sim(P_i, P_j) = \frac{|P_i \cap P_j|}{|P_i \cup P_j|}, \tag{6}$$

where P_i and P_j represent the set of different style modes (which are suitable for different scenes). After randomly setting user scenarios, other scenarios of its nearest neighbors are mined according to the formula, and users are recommended and displayed in $Sim(P_i, P_j)$ order from large to small, so as to meet people's common expectations. Aiming at the home decoration design scheme of the interior design websites, a suitable location-based social network recommendation algorithm is studied and implemented. Taking 6,813 house types in the 3D-FRONT dataset (3D Furnished Rooms with layOuts and semaNTics) as the experimental dataset. Based on this, the data collection and transmission test results are shown in Tables 3–5.

The accuracy of the interior design style recommendation is tested before and after using the recommendation algorithm for 1,000 users, as shown in Table 5. From Table 5, the design style recommendation accuracy of the algorithm [4] is 73%, and the corresponding accuracy of the algorithm [5] algorithm is 71%. However, the proposed method achieves 82% accuracy. To explain it, the method in this paper analyzes the characteristics and style correlation of home style, establishes a user interest degree model, combines location social network, and uses association rule mining algorithm to perform association analysis on the interior design style 3D model data set. Therefore, the home style recommendation results are highly consistent with user expectations.

On this basis, the time consumption of three recommendation algorithms to recommend the interior design styles to 1,000 users is tested, and the comparison results are shown in Fig. 7.

From the analysis of Fig. 7, the recommendation time of the algorithm [4] is 5.5 minutes, and the recommendation time of the algorithm [5] is 5.6 minutes. However, the recommended time consumed by the proposed method is 1.1 minutes. That is, the proposed method is more accurate, with less recommendation time and validity.

Table 3. User project score table

Uid	Design_id	Operation_type	Preference	Timestamp
10035726	362814	download	4	1417738088

Table 4. Home decoration scheme similarity table

Design_id1	Design_id2	Type	Similarity	Timestamp
102476	23044	1	0.6	1417733621

Table 5. Comparison of recommendation accuracy results

User serial number	Algorithm		
	Song and Jia [4]	Ning [54]	Proposed
100	72	70	81
200	75	71	83
300	68	69	81
400	74	73	80
500	71	70	82
600	76	74	85
700	77	76	84
800	72	71	82
900	69	67	82
1,000	73	69	80
Average value	73	71	82

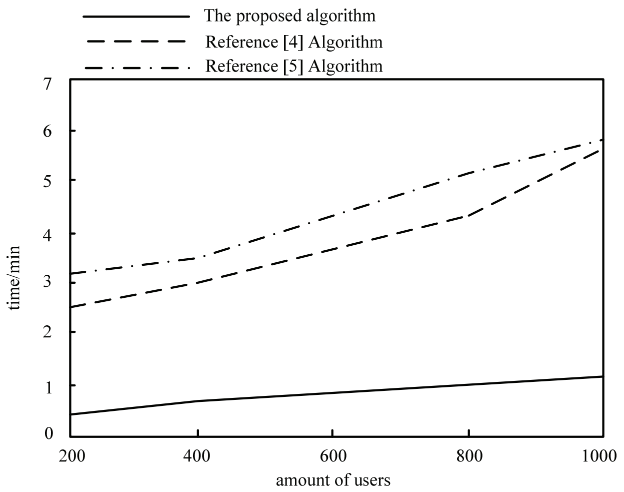

Fig. 7. Optimization steps of personalized recommendation for the interior design.

4. Discussion

This experiment is designed to compare the proposed personalized recommendation algorithm in this chapter and the traditional one. Compared with the indoor scene generation algorithm based on case-based reasoning and collaborative filter proposed in [4], and the indoor design project recommendation method based on collaborative filtering technology proposed in [5], the proposed one has significantly higher prediction accuracy. Moreover, current application also receives higher user satisfaction. This is because the algorithm in this paper analyzes user behavior data based on local social networks, establishes an accurate user interest model, and performs association analysis on the interior design 3D model data set through association rule mining algorithms, so as to obtain satisfactory home recommendations for users. Above all, the proposed personalized recommendation algorithm is significantly superior and fully meets the research requirements.

5. Conclusion

At present, the online shopping of the home improvement industry is gradually growing, but still remains in the initial stage of e-commerce, as consumers usually pay the most attention to the pictures, prices and brand reputations. Among them, poor user experience and inadequate satisfactory solutions within limited time are major weak points of relevant domestic market, which results in huge economic losses to this industry. To solve this, the recommendation system is a good choice. However, the processing efficiency of massive log and recommendation accuracy affected by the rapid growth of users are important factors that restrict the application of such system. In response to the above problems, this paper proposes a personalized recommendation algorithm for interior design style with location-based social networks, Hadoop, Hive, and other technologies. Through experiments, this method is fully verified with the user satisfaction rate of 82%.

Moreover, this algorithm can provide personalized recommendation of interior design styles, but does not consider the computational time, resulting in poor efficiency. Therefore, to realize higher efficiency, further researches will be conducted in this aspect in the future.

Acknowledgement

This study was supported by the Collaborative Innovation Mode of the Integration of Industry and Education under the National Strategy of Civil-Military Integration (No. 212400410445) and Henan Provincial Key Research and Promotion Project (Soft Science Research) in 2021.

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