Decorative Art Pattern Mining and Discovery Based on Group User Intelligence

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ABSTRACT

With the continuous development of real estate and the increasing personalization of people, more and more homeowners are willing to search for and discover their preferred decorative art patterns via various house decoration websites or platforms. Through browsing and analyzing existing house decoration cases on the web, a new homeowner can find his or her decorative art patterns; however, the above decorative art pattern mining and discovery process is often time-consuming and boring due to the big volume of existing house decoration cases on the web. Therefore, it is becoming a challenging task to develop a time-efficient decorative art pattern mining and discovery method based on the available house decoration cases provided by historical users. Considering this challenge, a novel LSH-based similar homeowners clustering approach is proposed. A set of experiments are designed to validate the effectiveness and efficiency of the proposal.

KEYWORDS

Decorative Art, Group Decision-Making, Locality-Sensitive Hashing, Pattern Mining, Similar Users

1. INTRODUCTION

With the ever-increasing growth of real estate industry and the diversity of house owners' personalized preferences, people are apt to decorate their houses sufficiently to meet their respective aesthetic standards (Yuan, 2013; Barua, 2019; Yu, 2018; Chen, 2017; Beneðeld, 2019). For example, young house owners often prefer to decorate their houses according to modern decoration styles such as landscape painting style and cartoon style, while elder people may prefer great man style instead of other complicated ones. Today, house decoration has become a crucial and important industry all over the world and has provisioned people with various and diverse house decoration styles to meet the personalized requirements from different individuals.

With the gradual popularity of Web (Xue, 2020; Srinivasan, 2021; Kou, 2020; Sridharan, 2021; Wu, 2021), people are apt to publish their house decoration cases on the Web for the purpose of case sharing and attraction of readers. On one hand, such shared house decoration cases offer new house owners more case references or decoration experiences, and on the other hand, place a heavy burden

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on the decoration style or art selection, because there are so many available house decoration cases generated from past decoration behaviors of historical users. For example, Fig.1 presents three kinds of decoration art works with distinct decoration styles (e.g., Space Formation with different elements, A Single Boat floating on a river, Night with static moon and stars).

Figure 1. Different decoration styles or arts

In this situation, a challenge is raised to help new house owners to find out their interested or preferred decoration arts or styles accurately and quickly. Recommender systems have been proven a promising way to realize the above goal. While existing recommendation solutions seldom optimize recommendation accuracy and privacy-preservation simultaneously. Inspired by this challenge, a novel decorative art pattern mining and discovery approach (abbreviated as DPMD) is put forward in this paper, which is mainly based on the Locality-Sensitive Hashing technique (LSH) (Qi, 2020; Qi et al, 2020) that is widely adopted and welcome in the domain of information retrieval. Generally, the major contributions in this research are two-fold:

- (1) We introduce a novel LSH-based similar house owners clustering approach DPMD, to achieve time-efficient and privacy-aware decorative art work recommendations. This way, we can balance user privacy and recommendation accuracy well.
- (2) We design a set of experiments to validate the effectiveness and efficiency of our proposal in terms of making decorative art pattern mining and discovery. Through comparisons with related approaches, we prove the feasibility of our proposed decorative art pattern mining and discovery solution for house owners.

The reminder of this paper is organized as follows. Section 2 presents a motivating example to illustrate the research value and significance of this paper. In Section 3, we elaborate the concrete steps of our proposed decorative art pattern mining and discovery solution based on the historical house decoration cases and ratings on various decoration elements. A group of experiments are designed and executed in Section 4, through which we demonstrate the effectiveness and efficiency of our proposed resolution. At last, in Section 5, we conclude this research work and point out the possible research topics in the future work.

2. MOTIVATION

As Fig.1 shows, each decorative art work is often comprised of a series of decorative elements such as image, color, texture and material. Two users (i.e., house owners), i.e., *Tom* and *Judy* rated some elements of decorative arts, whose rating values are shown in Fig.2 (e.g., 5* and 4*; the larger, the better). In this situation, these rating values towards different decorative elements from historical users

provide a promising basis to evaluate the decorative preferences of *Tom* and *Judy*. In this situation, to judge or evaluate whether *Tom* and *Judy* have the same decorative preferences towards houses, we need to calculate the similarity degree of *Tom* and *Judy* according to their ratings towards different elements.

Figure 2. User rating-based decorative pattern mining and discovery: an example

Traditional user preference similarity calculation methods such as collaborative filtering (CF) are often time-consuming as there are often too many user-element rating records (Wang, 2021; Liu, 2021). In addition, CF-based user preference similarity calculation methods need to read all the sensitive user rating records, which raises users' concerns on privacy leakage (Xu, 2020; Khazbak, 2020; Chen, 2019; Liu, 2019; Xu, 2020; Liu, 2017). Therefore, we need to address users' concerns from the above two perspectives. Inspired by this bservation, we bring forth a novel decorative art pattern mining approach based on LSH technique, i.e., DPMD. The details of the proposed DPMD approach are introduced in the next section.

3. METHOD

In general, the proposed decorative art pattern mining and discovery algorithm, i.e., DPMD consists of the following four steps. First, we extract representative features of decorative art works. Second, we transform the user ratings over the extracted features into a user vector based on LSH (the basic idea of LSH is that we can use an LSH function to convert a sensitive user vector into a less-sensitive user index; furthermore, if two users have the same index value, then they can be considered as similar with high probability), which often contains less user privacy and can denote the personalized preferences of the user. Third, we cluster users with similar rating preferences when selecting decorative art works, through which we can further discover the users with close preferences. Fourth, we recommend appropriate decorative art works to a target user based on his or her similar users. Fig.3 summarizes the above four steps with a more intuitive flowchart.

Step 1: Feature extraction of decorative art works.

For a decorative art work (e.g., the three works with diverse styles in Fig.1), there are often some attributes that can depict the overall style of the decorative art work, such as colors, textures, images, materials, brands, producers, and so on (see Fig.2). From the above attributes, we can extract the common focuses of users when they rate a decorative art work, e.g., (color, texture, image, material); thus, we can use the extracted features to represent the major characteristics of decorative art works.

Step 2: Model user ratings on features into a preference vector.

For a decorative art work, a user often left a set of ratings over the decorative art work's features. For example, user *Tom* may rate a decorative art work he bought or selected with a score vector (5*, 3*, 3*, 4*) corresponding to the feature vector (color, texture, image, material). Thus, a user may leave multiple rating vectors towards his or her selected decorative art works. Here, we take their average rating vector. For example, if *Tom* selected 2 decorative art works and their rating vectors

Figure 3. A flowchart of our proposed DPMD solution

are $V_{Tom,1}$ (5*, 3*, 3*, 4*) and $V_{Tom,2}$ (3*, 5*, 1*, 4*), respectively; then the average rating vector for Tom would be V_{Tom} (4*, 4*, 2*, 4*). In this situation, V_{Tom} (4*, 4*, 2*, 4*) could be regarded as the rating preferences of Tom regarding the decorative art works.

Step 3: Cluster users into different groups based on their preference vectors.

After Step 1- Step 2, we can get an average rating preference vector for each user, e.g., V_{Tom} (4*, 4*, 2*, 4*), V_{Jack} (3*, 5*, 4*, 3*), V_{Judy} (5*, 3*, 2*, 5*). Next, we need to analyze these rating preference vectors and mine the potential decorative art patterns existing in historical user rating data. Such a preference analysis process is often time-consuming as there are so many user rating data shared in various house decoration websites or platforms. In addition, users' rating data are often sensitive enough as they contain partial privacy of users (Wang, 2020; Zhang, 2020; Xu et al, 2020; Sun, 2021; Qin Liu, 2019; Tianen Liu, 2020). Hence, from the security perspective (Alaoui, 2021; Xiaolong Xu, 2020; Guezzaz, 2021; Xiang Chen, 2020), it is becoming a challenge to develop a time-efficient and privacy-aware decorative art pattern mining and discovery method.

Considering the above challenges, LSH technique is employed to achieve the time-efficient and privacy-aware decorative art pattern mining and discovery purpose, as LSH is essentially an effective similar neighbor search method with privacy-preservation capability and a low time complexity $O(1)$. The basic idea of LSH-based decorative art pattern mining and discovery solution is: we first convert the sensitive user rating vectors into less-sensitive index and then recognize those users with similar rating preferences based on index values with less sensitivity.

Next, we clarify the concrete index creation process for users. Here, we assume that there are n features for decorative art works, denoted by V ($fe_1, fe_2, \dots, fe_n$), and there are m users who left ratings, denoted by $U = \{u_1, u_2, \dots, u_m\}$. As $fe_1, fe_2, \dots$ and fe_n are all numeric values, we generate the corresponding LSH functions as in (1)-(2). Here, W denotes an n -dimensional vector and each dimensional value of W , i.e., w_j is a random value among range $(-1, 1)$.

$$W = (w_1, w_2, \dots, w_n) \quad (1)$$

$$w_j = \text{random}(-1, 1) \quad (j = 1, 2, \dots, n) \quad (2)$$

Next, we get the dot product of vectors V and W and then obtain a real value h as in (3). Here, we make the mapping or conversion in (4) for h value. We repeat the calculation process formalized in (1)-(4) p times, after which we get p values of h , i.e., $h_1, h_2, \dots, h_p$. Thus, we derive a Boolean value vector $H(h_1, h_2, \dots, h_p)$. This vector can be considered as the index value of a user. Then for

Table 1. Examples of q LSH tables

	$W_1 \otimes H_1$	$W_2 \otimes H_2$	...	$W_m \otimes H_m$
Z_1	$W_1 \otimes (0, 1, 1, 0)$	$W_2 \otimes (0, 0, 1, 1)$	...	$W_m \otimes (0, 0, 0, 1)$
Z_2	$W_1 \otimes (1, 1, 0, 0)$	$W_2 \otimes (1, 1, 0, 0)$	...	$W_m \otimes (1, 1, 0, 1)$
...	...	...	...	...
Z_q	$W_1 \otimes (1, 0, 1, 1)$	$W_2 \otimes (0, 1, 1, 1)$	...	$W_m \otimes (1, 0, 1, 0)$

each user in set U , we can create an index and afterwards, we get the index values for all the m users in set U , i.e., $H_1, H_2, \dots, H_m$.

This way, the rating vector W of each user is converted into a corresponding index H , whose advantages are two-fold: (1) the mapping or hashing process described in (1)-(4) is often done offline, whose time complexity is $O(1)$; such a low time complexity can enable a quick index creation without wasting much computational time. (2) with index values $H_1, H_2, \dots, H_m$, we can make the subsequent similar user clustering process without involving the sensitive user rating vectors $W_1, W_2, \dots, W_m$, which enables the decorative art pattern mining and discovery process a good capability of privacy-preservation.

$$h = V * W = (fe_1, fe_2, \dots, fe_n) * (w_1, w_2, \dots, w_n)^T = \sum_{j=1}^n fe_j * w_j \quad (3)$$

$$h = \begin{cases} 1 & \text{if } h > 0 \\ 0 & \text{if } h \leq 0 \end{cases} \quad (4)$$

Thus, the mappings from W to H forms an LSH table (denoted by Z), which is exemplified in Table 1. Table 1 presents the examples of q LSH tables: $Z_1, Z_2, \dots, Z_q$. Then according to the rules of LSH, two users u_i and u_j (their corresponding rating preference vectors are W_i and W_j , respectively) are similar if and only if equation in (5) is satisfied. For example, users u_1 and u_2 can be regarded as similar because $H_1 = H_2$ holds in table Z_2 (in Z_2 , the index values for u_1 and u_2 are both $(1, 1, 0, 0)$). This way, for a target user $u^\#$, we can get his or her similar users (denoted by $Sim(u^\#)$) according to the created p tables. In other words, $Sim(u^\#)$ can be calculated by (6).

$$u_i \text{ and } u_j \text{ are similar iff } H_i = H_j \text{ in any of } Z_1, Z_2, \dots, Z_q \quad (5)$$

$$Sim(u^\#) = \{ u_i \mid u_i \hat{=} U, u_i \text{ and } u^\# \text{ are similar} \} \quad (6)$$

Step 4: Decorative art work recommendations for a target user.

In Step 3, we have obtained a set of similar users of the target user $u^\#$, i.e., $Sim(u^\#)$. Next, with the known ratings of users in set $Sim(u^\#)$, we can predict the missing rating data of $u^\#$ over certain decorative elements in set $V (fe_1, fe_2, \dots, fe_n)$. The basis rationale of rating prediction is that similar users are probably owning the same ratings over the identical decorative elements. In concrete, the rating prediction process can be formalized by (7). Here, $u_i fe_j$ denotes user u_i 's rating value over feature fe_j ($i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$); $|Sim(u^\#)|$ represents the size of vector $Sim(u^\#)$. In other

words, $u^\# \cdot fe_j$ is equal to the average rating of the similar users of $u^\#$ over feature fe_j . Finally, with the predicted $u^\# \cdot fe_j$ value, we can make appropriate decorative art work recommendations.

$$u^\# \cdot fe_j = \frac{1}{|Sim(u^\#)|} * \sum_{u_i \in Sim(u^\#)} u_i \cdot fe_j \quad (7)$$

4. EXPERIMENTS

A set of experiments are deployed to validate the feasibility of our proposed DPMD method. Experimental dataset is WS-DREAM (Qi, 2020). The dataset records the feedback data of 339 users towards 5825 items. The two methods for comparisons include user-based CF (User-CF) (Qi et al, 2020) and item-based CF (Item-CF) (Qi et al, 2020). Evaluation metrics are MAE (Qi et al, 2020) (for measuring system accuracy, smaller is better) and Time cost (Qi et al, 2020) (for measuring system efficiency, smaller is better). The experimental environments include Python 3.6 programming language and Lenovo computer (2.6GHz processor, 8.0GB RAM, Windows 10 operating system). Each experiment is run 100 times and finally their average results are used for comparison illustrations. Here, m and n denote the sizes of user set and feature set, respectively.

In concrete, four sets of experimental comparisons are enacted and displayed, respectively.

Profile 1: Accuracy of DPMD, User-CF and Item-CF.

In this profile, we measure the accuracy of DPMD and compare it with two ones: User-CF and Item-CF. Concrete running results are reported in Fig.4. Parameters p (size of hash function set) and q (size of hash table set) are both equal to 10. In Fig.4(a), m is varied from 50 to 300 and n is equal to 5000; while in Fig.4(b), n is varied from 1000 to 5000 and m is equal to 300. It can be seen from Fig.4 that the MAE value of DPMD algorithm is always smaller than those of User-CF and Item-CF, which indicates a higher accuracy performance of DPMD. It can be explained by the following fact: DPMD algorithm utilizes LSH technique to search for similar users of a target user, which can guarantee that only those similar users are returned for subsequent missing rating data prediction. As a result, the prediction accuracy is increased accordingly.

Profile 2: Efficiency of DPMD, User-CF and Item-CF.

In this profile, we measure the execution efficiency of the proposed DPMD method and compare it with the other two ones: User-CF and Item-CF. Concrete running results are reported in Fig.5. Here, $p = q = 10$. In Fig.5(a), m is varied from 50 to 300 and $n = 5000$; while in Fig.5(b), n is varied from 1000 to 5000 and $m = 300$. It can be seen from Fig.5 that the computational time of DPMD is superior to the other two competitive approaches as the LSH-based similar user clustering solution is rather time-efficient (complexity is approaching $O(1)$). The low complexity also shows the applicability of our proposal in deal with big rating data.

Figure 4. Accuracy comparisons of three algorithms

(a) $n = 5000$

(b) $m = 300$

Figure 5. Execution efficiency comparisons of three algorithms

(a) $n = 5000$

(b) $m = 300$

PROFILE 3: ACCURACY OF DPMD WITH RESPECT TO p AND q .

According to Section 4, two key factors are involved in DPMD method, i.e., p (size of hash function set) and q (size of hash table set). Considering their influences, we design a test to measure the correlation between MAE of DPMD and factors p and q . Experimental results are presented in Fig.6. The reported data in Fig.6 shows a decline of MAE (i.e., an increment of prediction accuracy) with the growth of factor p . The results can be analyzed as follows: a larger p often means a stricter evaluation condition when we select a qualified similar user of a target user; as a result, only the “most similar” friends of the target user could be found for subsequent missing rating data prediction. Therefore, the prediction accuracy would be raised accordingly.

Figure 6. Accuracy of DPMD w.r.t. (p , q)

Profile 4: Efficiency of DPMD with respect to p and q .

As discussed in Profile 3, p and q are two key factors that can influence the prediction performances of the proposed DPMD algorithm. Inspired by this observation, we design an experiment to observe the relationship between the computational time of DPMD and the parameter pair (p , q), whose results are demonstrated in Fig.7. As the figure shows, the consumed time of DPMD algorithm decreases with the growth of p , which could be explained as follows: a larger p often means a stricter filtering condition when we evaluate a qualified similar user of a target user; as a result, only a smaller

Figure 7. Execution efficiency of DPMD w.r.t. (p , q)

number of “most similar” friends of the target user could be found for subsequent missing rating data prediction. Therefore, less time cost is needed to finish the final missing rating prediction process.

5. CONCLUSION AND FUTURE WORK

With the ever-increasing personality of user preferences towards decorative arts or styles, house owners are currently confronted with more and more decorative alternatives or candidates, which plays a heavy burden on the final decorative style selection decision-makings of house owners. In this situation, it is becoming a valuable and significant research task to mine and discover the same decorative patterns and then recommend appropriate decorative art works to a target user based on the users with the same decorative pattern. However, traditional solutions are often time-consuming and sensitive. Considering this challenge, a novel decorative art pattern mining and discovery method named DPMD is introduced in this paper, to achieve time-efficient and privacy-aware decorative art work recommendations. Finally, we validate the feasibility of DPMD via a set of experiments.

In the future research, we would like to further investigate more influencing factors in users' decoration selection decision-makings, such as time and location information of users (Malek, 2021; Xiang Chen, 2021). In addition, more performance metrics (e.g., network load (Xiaolong Xu et al, 2020; Li, 2021; Xiaolong Xu, Bowen Shen, 2020; Yun Li, 2021; Bi, 2021; Yun Li et al, 2020), diversity (Jianxin Li, 2020; Cai, 2020)) should be taken into considerations besides accuracy and time cost. Third, how to make full use of the cutting-edge learning techniques (e.g., deep learning, machine learning, transfer learning) (Huang, 2020; Xue, 2019; Yuvaraj, 2021) to further improve the algorithm performances is still requiring challenging efforts. Finally, our proposed DPMD method still needs to be improved by measuring and quantifying its capability of privacy-preservation; therefore, we will further investigate current privacy protection solutions such as (Zheng, 2020; Kaiyang Li, 2020; Lina Wang, 2020; Zhipeng Cai, 2020; Zheng, 2017) to pursue a feasible and scientific privacy measurement solution.

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