TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 14/22 pp174–184
DOI: 10.26599/TST.2023.9010012
Volume 29, Number 1, February 2024

Composite Recommendation of Artworks in E-Commerce Based on User Keyword-Driven Correlation Graph Search

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Abstract: With the ever-increasing diversification of people's interests and preferences, artwork has become one of the most popular commodities or investment goods in E-commerce, and it increasingly attracts the attention of the public. Currently, many real-world or virtual artworks can be found in E-commerce, and finding a means to recommend them to appropriate users has become a significant task to alleviate the heavy burden on artwork selection decisions by users. Existing research mainly studies the problem of single-artwork recommendation while neglecting the more practical but more complex composite recommendation of artworks in E-commerce, which considerably influences the quality of experience of potential users, especially when they need to select a set of artworks instead of a single artwork. Inspired by this limitation, we put forward a novel composite recommendation approach to artworks by a user keyword-driven correlation graph search named $\text{ART}_{\text{com-rec}}$. Through $\text{ART}_{\text{com-rec}}$, the recommender system can output a set of artworks (e.g., an artwork composite solution) in E-commerce by considering the keywords typed by a user to indicate his or her personalized preferences. Finally, we validate the feasibility of the $\text{ART}_{\text{com-rec}}$ approach by a set of simulated experiments on a real-world PW dataset.

Key words: composite recommendation; artwork; user keywords; E-commerce; correlation graph search

1 Introduction

With the continuous progress of the economy and society worldwide, people's daily life has changed significantly. For example, in the age of poverty, people were more focused on foods and vegetables to avoid the risks due to the lack of goods provision. However, with the advent of a booming economy, people's living conditions have improved considerably[1, 2]. In this situation, people have shifted their focus from material life to mental life, which gave birth to a series of novel commodities or investment goods that reflect the quality or level of people's mental life, e.g., artworks[3]. To date, artworks (both real-world artworks, e.g., a paper painting, and virtual artworks, e.g., an Internet painting) have become an essential part of people's daily life and have received increasing attention from the public[4].

However, with the ever-increasing prosperity of Internet technology, the volume of artworks in the physical and virtual world is increasing rapidly in E-commerce. Moreover, the formats, types, styles, and sources of artworks are increasingly becoming more

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∗ To whom correspondence should be addressed.
Manuscript received: 2023-01-20; revised: 2023-02-15; accepted: 2023-02-24

complex and diverse[5]. Thus, how to recommend appropriate artworks to potential users in E-commerce is becoming a practical and emergent task to alleviate the users' burden in artwork selection. Existing artwork recommendation research mainly focuses on the recommendation of a single artwork to a potential user but neglects the more practical but complex recommendation scenarios in which the recommender system needs to return a set of artworks instead of a single artwork. In this situation, the quality of experience (QoE) of potential users is reduced considerably, especially when they need a group of related artworks (i.e., an artwork composition) instead of a single artwork[6–9]. For example, Fig. 1 shows four paintings that contain the elements bird, flower, sun, people, fish, etc. In this situation, if user Tim needs a painting composition that contains two keywords collectively, e.g., bird and people, then several painting compositions can satisfy Tim's requirements collectively, such as (a) + (b), (b) + (c), (a) + (d), and (c) + (d). Notably, other painting compositions, such as (a) + (c) (without the element "people") and (b) + (d) (without the element "bird"), do not satisfy Tim's requirement. Thus, Tim will face the huge challenge of picking the best painting composition from all the candidates because the recommender system should consider not only the keywords (i.e., bird and people) typed by Tim but also the correlations among all four paintings because unrelated paintings often indicate poor compatibility or composability and poor QoE of users in E-commerce[10]. Here, if a single artwork satisfies all the required elements depicted by a set of keywords from a target consumer, then such an artwork will be the optimal solution for the consumer. However, in most cases, a single artwork cannot satisfy all elements of the target consumer. In this situation, we need to search for a set of artworks that can collectively satisfy the required multiple elements. This goal is the focus of this paper.

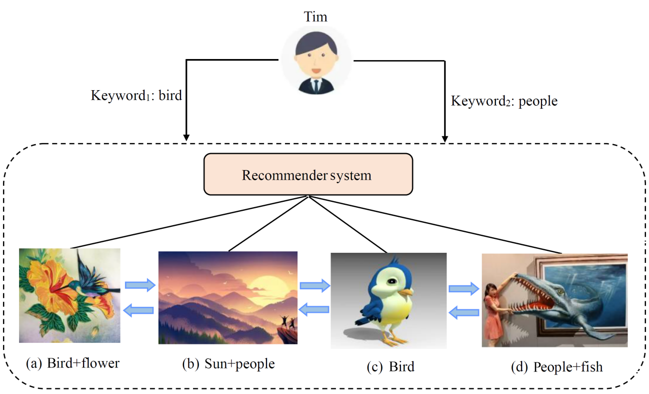

Fig. 1 Keyword-driven composite artwork recommendation: An example and challenges.

For example, in Fig. 1, (a) and (b) are both plane paintings, and (c) and (d) are three-dimensional paintings. Therefore, (a) and (b) and (c) and (d) are more compatible or composable. In this situation, if we recommend the painting composition (b) + (c) to Tim merely based on his typed keywords bird and people, he will probably not be satisfied with the recommended results as (b) and (c) are often less compatible or composable.

To tackle the abovementioned challenge, we put forward a composite recommendation approach to artworks by the user keyword-driven correlation graph search named $\text{ART}_{\text{com-rec}}$. Through $\text{ART}_{\text{com-rec}}$, the recommender system can output a set of artworks (e.g., an optimal artwork composite solution) by considering both the keywords typed by a user (e.g., Tim) to indicate his or her personalized preferences and the correlations between different artworks (e.g., (a) and (b) in Fig. 1 are more compatible or composable, and (b) and (c) are less compatible or composable). Finally, we validate the feasibility of $\text{ART}_{\text{com-rec}}$ through massive simulation experiments deployed on a real-world dataset, i.e., the PW dataset.

In summary, the academic contributions of this article are described briefly as follows:

(1) We propose an artwork correlation graph by analyzing and quantifying the correlations between different artworks in E-commerce. This correlation graph measures the correlation degree of artworks and ensures that the recommender system returns a set of correlated artworks to enhance the user satisfaction degree.

(2) Based on the generated artwork correlation graph, we put forward a keyword-based and correlation-aware composite artwork recommendation algorithm $\text{ART}_{\text{com-rec}}$ through a Steiner tree search process over the artwork correlation graph.

(3) Lastly, we deploy a set of simulated experiments on a classic Programmable Web (PW) dataset retrieved from ProgrammeableWeb.com. The reported comparison results with related literature prove the innovation and advantages of $\text{ART}_{\text{com-rec}}$.

We structure the remainder of this article as below. Section 2 discusses the investigation of related works. Section 3 presents an artwork correlation graph and its model. Section 4 introduces the concrete details of the proposed $\text{ART}_{\text{com-rec}}$ approach based on the artwork correlation graph. Section 5 shows comparisons with related approaches. Section 6 provides the conclusions and future work directions.

2 Related Work

In Ref. [11], the authors studied artwork metadata and neural visual features, used a deep neural network (DNN) to extract visual features, and put forward a new method in the field of content-based artwork recommendation for physical paintings. In Ref. [12], the authors compared the recommendation performance of the DNN method for visual feature extraction (VFE) with the corresponding attractiveness-based explicit method. An in-depth analysis was also conducted to explore whether the embedded characteristics of DNN are related to some VFEs. The experimental results showed that DNN features are better than VFE features, but some VFE features are more suitable for physical artwork recommendation. In addition, to reduce resource usage, most articles[13, 14] have proposed the improvement of the training efficiency of deep learning models. In Ref. [15], the authors attempted to explore the effective use of collaborative filtering in artworks and the main factors affecting its application. The results showed that collaborative filtering can be used to estimate the preferences of participants effectively, and the popularity of artworks and artwork knowledge level have a significant impact on the accuracy of evaluation results. In Ref. [16], the authors proposed a hybrid recommendation approach that combines the semantic approach to ontology's museum domain representation with the semantically enhanced collaborative filtering approach. The model constructed by the hybrid recommendation method can be integrated based on the physical environment, location of visitors, and the length of visitors' visits to the museum to generate a personalized artwork recommendation. However, the above studies only considered the historical user-artwork interaction information and neglected the key content information of artworks, which decreased the recommendation accuracy.

In Ref. [17], the authors defined a recommendation system based on rich semantics and content. Given this definition, the authors introduced the concept of artwork recommendation based on the user profile composed of museums and user ratings of artworks. In Ref. [18], the authors used a content-based approach to model users and implemented artwork recommendations. In addition, the hash index technique was introduced to improve the recommendation performance. In Ref. [19], the authors mainly used the cultural heritage information display tool to build a user model to transform the museum guide based on user interests and the mobile devices used in museum spaces. When users evaluate artworks in a museum, the user model is updated in time to achieve personalized recommendations integrated online and on-site. In Ref. [20], the authors attempted to perform recommendations in data queries by replaying historical data. However, the above literature only considered the artwork content information and overlooked the historical user-artwork interaction information, which plays a key role in user preference prediction. As a result, the recommendation accuracy was reduced.

In Ref. [21], the authors mainly summarized the particularity of the artwork recommender system in museums, and analyzed as well as discussed the different methods to use the particularity of this field. The authors first summarized the different methods used to extract features related to the recommendation task from an artwork. Second, the authors put forward a new method to realize artwork modeling to complete a recommendation. In Ref. [22], the authors solved the problem of generating and recommending a sequence of artworks for a group of visitors, proposed a general framework for solving the said problem, and evaluated the implementation of prototypes through offline analysis and simulation of the environment. In Ref. [23], the authors studied and analyzed the color characteristics of film animation and quantified the application effects of machine learning in video artwork and film animation. Through three classic machine learning algorithms, the authors discussed the distribution rule of color features of film animation and their influence on artwork text from the perspective of machine learning. Experimental results showed that the extreme learning machine achieved an optimal prediction performance. However, the above literature did not consider the composite artwork recommendation problem, which is more popular.

With the above analyses, we can conclude that the existing research on artwork recommendation seldom considers the artwork content, user-artwork interaction matrix, and composite recommendation scenarios simultaneously. In view of this limitation, a keyword-based and correlation-aware composite artwork recommendation approach, $\text{ART}_{\text{com-rec}}$, is put forward in the following sections.

3 Artwork Correlation Graph

To depict the correlation between different artworks, we introduce an artwork correlation graph (Definition 1) based on historical user-artwork interaction information (e.g., whether two or more artworks have been preferred and chosen by an identical user in the past).

Definition 1 Artwork correlation graph. Artwork correlation graphs describe the correlations between different artworks based on historical user-artwork interactions, which can be formalized with $G(N, \check{K}, E)$, where N denotes the artwork set or node set $\{N_1, N_2, \ldots, N_n\}$, $\check{K}$ is the keyword set $\{k_1, k_2, \ldots, k_m\}$ that depicts the tags of artworks, and E represents the edge set $\{e_{ij} \mid N_i \in N, N_j \in N, \text{ and } \mathrm{corr}(N_i, N_j) = 1\}$. Here, $\mathrm{corr}(N_i, N_j)$ means whether N_i and N_j are compatible or composable. Concretely, $\mathrm{corr}(N_i, N_j)$ can be calculated using Eq. (1).

$$\mathrm{corr}(N_i, N_j) = \begin{cases} 1, & \text{if } N_j \text{ and } N_j \text{ have been} \\ & \text{selected together;} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Here, the edges in an artwork correlation graph are undirected because we argue that the artworks that form a composition have no evident sequential or other directed relationships. In other words, the artworks in a composition are all equal.

We use the example in Fig. 2 to illustrate the artwork correlation graph introduced in Definition 1. Here, 15 artworks are present, and their correlation relationships are depicted by the edges in Fig. 2. For each artwork, one or multiple keywords are used to describe the content of an artwork, e.g., N_{11} $\{k_3, k_6\}$ indicates that artwork N_{11} has two keywords: k_3 and k_6. Thus, the 15 artworks and their interconnected 22 edges in Fig. 2 form an artwork correlation graph, which is the basis for subsequent artwork composition recommendations.

4 Artwork Composition Recommendation: ART$_{\text{com-rec}}$

According to the artwork correlation graph introduced in Fig. 2, we can formulate the artwork composition

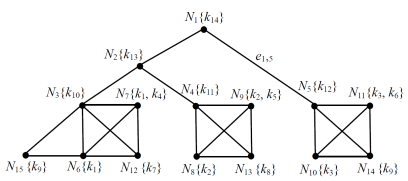

Fig. 2 Artwork correlation graph: An example.

recommendation scenario considering the artwork compatibility or composability as follows. A target user (e.g., Tim) enters three keywords $K\{k_1, k_3, k_9\}$ to seek for a group of artworks with the contents described by $\{k_1, k_3, k_9\}$. As shown in Fig. 2, artworks N_6 and N_7, N_{10} and N_{11}, and N_{14} and N_{15} contain k_1, k_3, and k_9, respectively. Thus, with the keywords $K\{k_1, k_3, k_9\}$ typed by Tim, we aim to find a qualified tree that connects a node from $K\{N_6, N_7\}$, a node from $K\{N_{10}, N_{11}\}$, and a node from $K\{N_{14}, N_{15}\}$. In addition to the above three nodes, we need to discover a set of bridging nodes that do not cover k_1, k_3, and k_9 to ensure that the three previously selected nodes are interconnected to be a tree (i.e., Steiner tree).

Definition 2 Steiner tree. Assume an undirected graph $G(N, \check{K}, E)$ and a node set $N' \subseteq N$. Then, we can find a Steiner tree T associated with N', if T is a subtree of G and T connects each node in set N'.

As we analyzed in the first paragraph of this section, each node probably contains multiple keywords, and each keyword is probably covered by multiple nodes. Therefore, each keyword k_i corresponds to a node set N_Set_i ($1 \leqslant i \leqslant m$; m denotes the number of keywords typed by a user), in which each node covers k_i. Thus, we need to select one node $N_{x(i)}$ from each node set N_Set_i to finally form a tree connecting $N_{x(1)}, N_{x(2)}, \ldots, N_{x(m)}$. Such a tree is called a group Steiner tree.

Definition 3 Group Steiner tree. Assume an undirected graph $G(N, \check{K}, E)$ and m node sets $N\_\mathrm{Set}_1, N\_\mathrm{Set}_2, \ldots, N\_\mathrm{Set}_m \subseteq N$. Then, we can conclude that tree T is a group Steiner tree containing m nodes if T is a Steiner tree, and T is with one node in each N_Set_i ($1 \leqslant i \leqslant m$).

In general, for an artwork composition recommendation scenario with m keywords in $K = \{k_1, k_2, \ldots, k_m\}$, multiple qualified artwork composition solutions (i.e., multiple group Steiner trees) can be found. In this situation, we need to guarantee that only one optimal group Steiner tree is returned to the user. As we analyzed in the example of Fig. 1, we expect that the returned artworks coincide with the "fewer is better" rule. Therefore, the "optimal group Steiner tree" here should be a minimum group Steiner tree that contains the fewest nodes. The nodes here include two parts: keyword nodes (denoted by set KN), which cover all requested keywords $\{k_1, k_2, \ldots, k_m\}$, and bridging nodes (denoted by set BN), which do not cover any keyword in K but connect the nodes in KN into a tree.

According to the above analyses, our previous artwork composition recommendation problem, which is introduced in Fig. 1, can be converted to a minimum group Steiner tree search problem that can be solved with the following steps of our proposed $\text{ART}_{\text{com-rec}}$ approach. Here, the foundation of $\text{ART}_{\text{com-rec}}$ is the artwork correlation graph $G(N, \check{K}, E)$ exampled in Fig. 2.

Step 1: Generation of keyword node sets

As we introduced previously, each node covering at least one requested keyword in set $K=\{k_1, k_2, \ldots, k_m\}$ is called a keyword node. In this step, we generate all keynote node sets, $N\_\text{Set}_1, N\_\text{Set}_2, \ldots, N\_\text{Set}_m$, based on the requested keywords $\{k_1, k_2, \ldots, k_m\}$ and the artwork correlation graph $G(N, \check{K}, E)$ based on Eq. (1). Here, each keyword k_i corresponds to a keyword node set N_Set_i. Moreover, if $N\_\text{Set}_i = \phi$, then no qualified nodes cover the requested keyword k_i. In this situation, the artwork composition recommendation process fails. Otherwise, our approach proceeds to Step 2.

$$N\_\text{Set}_i = \phi N\_\text{Set}_i = \{N_i \mid N_i \subseteq N \text{ and } N_i \text{ covers } k_i\} \quad (1 \leqslant i \leqslant m) \tag{2}$$

Step 2: Tree growth and tree merging

For the requested keywords $K = \{k_1, k_2, \ldots, k_m\}$ by a target user, we obtain their respective keyword node sets $N\_\text{Set}_1, N\_\text{Set}_2, \ldots, N\_\text{Set}_m$ in Step 1. Then, in accordance with Definition 3, we can select one node from each of $N\_\text{Set}_1, N\_\text{Set}_2, \ldots, N\_\text{Set}_m$ to form a set of keyword nodes $N_{x(1)}, N_{x(2)}, \ldots, N_{x(m)}$. However, we do not need $\{N_{x(1)}, N_{x(2)}, \ldots, N_{x(m)}\}$ because it is only a node set instead of a connected tree. In other words, we need to discover a set of bridging nodes to connect $N_{x(1)}, N_{x(2)}, \ldots, N_{x(m)}$ to a tree. Next, we introduce how to achieve the above goal. In general, the bridging nodes can be discovered through two operations about tree search: tree growth and tree merging. Next, we introduce their concrete operation processes.

(1) Tree growth. Tree growth operation can be described more intuitively in Fig. 3. In Fig. 3, the left tree is denoted by $T(N_1, K')$, where N_1 is the root node of the tree, and K' represents the set of requested keywords covered by the tree ($K' \subseteq K$). Our goal is to search for a tree covering the m keywords typed by the user, i.e., $K = \{k_1, k_2, \ldots, k_m\}$. Therefore, we need to grow the tree $T(N_1, K')$ to let it cover more keywords in K. During the tree growth process, any non-root node can be grown into a new tree. For example, in Fig. 3, $T(N_1, K')$ owns two non-root nodes, i.e., N_2 and N_3. Therefore, N_2 can grow as a new tree rooted with N_2 (i.e., $T(N_2, K')$ in Fig. 3) and N_3 as another new tree rooted with N_3 (i.e., $T(N_3, K')$ in Fig. 3). Thus, the left small tree $T(N_1, K')$ with three nodes and a keyword set K' is extended to become the right large tree $T(N_1, K'')$ with more nodes and a new keyword set K'', where K'' is available from Eq. (2). Given that we merely add the bridging nodes instead of keyword nodes in each tree growth operation, $K'' = K'$ holds.

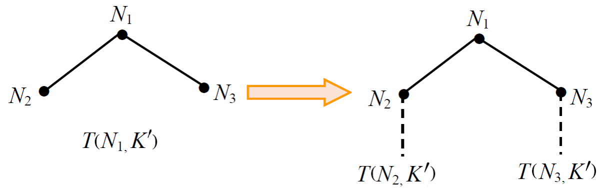

Fig. 3 Tree growth operation: An example.

Here, we need to evaluate whether we should grow the tree to $T(N_2, K')$ or $T(N_3, K')$, as we can only add one new node in each tree growth operation. As we analyzed previously, the returned tree must contain the fewest nodes. Therefore, we need to count the nodes of $T(N_2, K')$ or $T(N_3, K')$, which are denoted by $w(T(N_2, K'))$ and $w(T(N_3, K'))$, respectively. Finally, we grow the tree toward the direction leading to fewer nodes. More formally, the above selection procedure can be expressed by Eq. (3),

$$K'' = K' \cup (\text{Key}(T(N_2, K')) \text{ or } \text{Key}(T(N_3, K'))) \tag{3}$$

$$w\left(T_{\text{grow}}\left(N_1, K'\right)\right) = \min_{x \in \text{Neighbor}(N_1)} \{w(T_{\min}(x, K') + N_1)\} \tag{4}$$

where $\text{Neighbor}(N_1)$ denotes the neighbors of node N_1 (for example, in Fig. 3, $\text{Neighbor}(N_1) = N_2$, N_3), $T_{\min}(x, K')$ means the tree covering the fewest nodes among all candidates with root node x, and $T_{\text{grow}}(N_1, K')$ represents the final tree after one tree growth operation.

(2) Tree merging. Tree merging operation can be described more intuitively in Fig. 4, where the left two small trees, $T(N_1, K_1')$ and $T(N_1, K_2')$, are both rooted at node N_1, and their covered keyword sets are K_1' and K_2', respectively. As these trees share the same root node N_1, they can be fused to become a larger tree also rooted at N_1, namely, $T(N_1, K')$, as shown in Fig. 4. In Eq. (5), "$\oplus$" denotes the merging operation. In the larger tree $T(N_1, K')$, more keywords are covered than those in the two smaller trees $T(N_1, K_1')$ and $T(N_1, K_2')$.

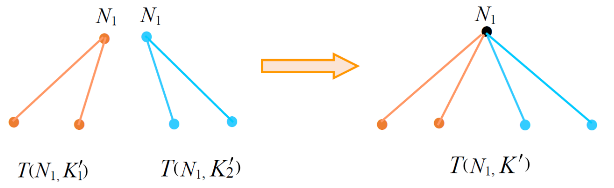

Fig. 4 Tree merging operation: An example.

More concretely, K' is the union of the two keyword sets K_1' and K_2'. The above tree merging process can be described using Eqs. (4)–(6).

$$w\left(T\left(N_1, K'\right)\right) = w\left(T\left(N_1, K_1'\right) \oplus T\left(N_1, K_2'\right)\right) \tag{5}$$

$$K' = K_1' \cup K_2' \tag{6}$$

However, multiple trees may be rooted at node N_1. Therefore, each tree can be merged with any other tree, which often leads to many possible tree merging solutions. In this situation, we need to discover the optimal tree merging solution with the fewest nodes. We use Eq. (7) to achieve the above goal, where $T_{\min}(N_1, K_1')$ means the tree (rooted at N_1, covering keywords from K_1') with the fewest nodes among all the candidate tree merging solutions. Finally, we only return a qualified tree rooted at node N_1 and with a minimal number of nodes.

$$K_1' \cap K_2' = \varnothing \tag{7}$$

Step 3: Optimal tree generation

After the iterative invocation of the two operations introduced in Step 2, we can finally generate an optimal group Steiner tree covering m keywords with the fewest nodes. The optimization process can be formalized with Eqs. (8) and (9). If only one root node N_1 exists in the original tree $T_{\min}(N_1, K')$, then the weight of $T_{\min}(N_1, K')$ is equal to 1 (which is the simplest case and corresponds to Eq. (8)). Otherwise, the original tree $T_{\min}(N_1, K')$ can be extended to a larger tree containing more nodes and covering more keywords by the tree growth and tree merging operations iteratively, which is formalized with Eq. (9), where $T_{\text{grow}}(N_1, K')$ and $T_{\text{merge}}(N_1, K')$ are available in Eqs. (3) and (7), respectively.

$$w\left(T_{\text{merge}}\left(N_1, K'\right)\right) = \min\left\{w\left(T_{\min}\left(N_1, K_1'\right) \oplus T_{\min}\left(N_1, K_2'\right)\right)\right\} \tag{8}$$

$$w\left(T_{\min}\left(N_1, K'\right)\right) = 1, \quad \text{if} \left|K'\right| = 1 \text{ and } N_1 \in N\_\text{Set}_i \tag{9}$$

$$w\left(T_{\min}\left(N_1, K'\right)\right) = \min\left\{w\left(T_{\text{grow}}\left(N_1, K'\right)\right), w\left(T_{\text{merge}}\left(N_1, K'\right)\right)\right\} \tag{10}$$

Thus, through Steps 1–3 of the $\text{ART}_{\text{com-rec}}$ approach, we can finally derive a minimal group Steiner tree T based on the keywords typed by a user. In the context of artwork composition recommendation, the nodes in T denote the returned artworks that not only can cover the content keywords requested by a target user but also are composable or compatible with each other. Meanwhile, only a small number of artworks are returned to the target user. The concrete procedure of $\text{ART}_{\text{com-rec}}$ can be formulated in detail as follows. The concrete procedure of $\text{ART}_{\text{com-rec}}$ can be formulated in detail as in Algorithm 1.

5 Experiment

A group of experiments is conducted to show the feasibility and performances of the $\text{ART}_{\text{com-rec}}$ approach. In concrete, a dataset crawled from programmableweb.com is used for the simulation of the artwork composition recommendation scenario (18 478 application programming interfaces (APIs) and 6146 mashups are present in the dataset[24]). In the dataset, the mashup-API invocation records are used to generate

Algorithm 1 $\text{ART}_{\text{com-rec}}$ $(G(N, \check{K}, E), K)$

Input: (1) $N = \{N_1, N_2, \ldots, N_n\}$: artwork set.
(2) $\check{K} = \{k_1, k_2, \ldots, k_M\}$: set of tags of artworks in N.
(3) $E = \{e_{ij} \mid N_i \in N, N_j \in N \text{ and corr}\left(N_i, N_j\right) = 1\}$: edge set.
(4) $K = \{k_1, k_2, \ldots, k_m\}$

Output: out result

```
    Construct G(N, Ǩ, E) by Definition 1
1:  for each k_i ∈ K do
2:      Generate N_Set_i by Eq. (1)
3:      for each N_x(j) ∈ N_Set_i do
4:          Construct tree T(N_x(j), K') where K = k_i;
5:      end for
6:  end for
7:  for each N_Set_i do
8:      pick a tree T(N_x(j), K')
9:  end for
10: Generate T(N_x(1), K'), T(N_x(2), K'), ..., T(N_x(m), K')
11: for each T(N_x(ij), K') do
12:     Grow it based on Eqs. (2) and (3)
13: end for
14: for each T(N_x(ij), K'_1) and T(N_x(ij), K'_2) do
15:     Merge them based on Eqs. (4)–(7)
16:     Repeat Lines 7–13
            Until obtain T_min(N, K) based on Eqs. (8) and (9)
        End Repeat
        Return T_min(N, K)
17: end for
```

the artwork correlation graph introduced in Definition 1. Each API and its functional tags are used to simulate an artwork with content tags. Four related approaches are compared with $\text{ART}_{\text{com-rec}}$, i.e., random[24], greedy[24], SSR[25], and SPR_CR approaches[26]. Evaluation metrics include the number of returned nodes, success rate, and time cost. The experiment hardware and software configurations are a 2.40 GHz processor, 16 GB RAM, Win-10, and Python 3.6. To minimize the negative influence brought by network traffic and random data, we repeat each set of experiments 100 times.

(1) Comparison of the number of returned nodes

As we analyzed in the example in Fig. 1, we expect that the returned artworks coincide with the "fewer is better" rule. Therefore, the "optimal group Steiner tree" that we seek should be a minimum tree that contains the fewest nodes. To validate the feasibility of our $\text{ART}_{\text{com-rec}}$ approach in returning the fewest nodes, we test and compare the number of returned nodes by different approaches: $\text{ART}_{\text{com-rec}}$, random, greedy, SSR, and SPR_CR. Concrete comparison results are presented in Fig. 5, where the horizontal axis denotes the number of typed keywords by a target user (i.e., m varies from 2 to 6). As the comparison results show, the random, greedy, and SPR_CR approaches all contain high numbers of nodes as they do not adopt the "fewer is better" principle when searching for a set of compatible or composable qualified nodes. The remaining two approaches (i.e., $\text{ART}_{\text{com-rec}}$ and SSR) both adopt the "fewer is better" rule in compatible node discovery. Therefore, their returned nodes are less than those obtained with the random, greedy, and SPR_CR approaches. Moreover, our proposed $\text{ART}_{\text{com-rec}}$ outperforms SSR as a minimum Steiner group tree is guaranteed in $\text{ART}_{\text{com-rec}}$. The smallest number of returned nodes in $\text{ART}_{\text{com-rec}}$ indicates that the returned nodes are of the highest compatibility or composability.

(2) Success rate comparison of five approaches

We create an artwork correlation graph based on the 18 478 APIs and 6146 mashups in the programmeableweb.com dataset. Here, we measure the success rate of five approaches on the artwork correlation graph. Concretely, we use the tags of a real mashup in the dataset as the typed keywords and then observe whether the web APIs that constitute the mashup can be returned by the different approaches. If the answer is yes, then we conclude that it is a successful recommendation. The concrete comparison results are presented in Fig. 6, where the horizontal axis denotes the number of typed keywords by a target user (i.e., m varies from 2 to 6). As shown in Fig. 6, the random approach has the lowest success rate because it adopts a random search strategy in discovering a set of compatible or composable nodes. Meanwhile, our proposed $\text{ART}_{\text{com-rec}}$ approach performs better than the rest of the four approaches as $\text{ART}_{\text{com-rec}}$ can guarantee to return the most compatible or composable set of nodes through tree growth and tree merging operations. More concretely, the success rate of the $\text{ART}_{\text{com-rec}}$ approach is over 97.8% with respect to different m values.

(3) Time cost comparison of five approaches

Time complexity is often a key criterion in big data applications[27–32]. Here, we evaluate the time complexity of five approaches in finding a set of compatible or composable nodes based on the keywords typed by a target user. The number of keywords typed by the target user (i.e., m) varies from 2 to 6. Figure 7 shows the comparison results of concrete time costs of the five approaches. As Fig. 7 indicates, the consumed time of the SPR_CR approach remains unchanged when parameter m rises, given that SPR_CR is unrelated to the number of typed keywords. Meanwhile, the time costs of the remaining four approaches all increase with the growth of parameter m. Furthermore, our

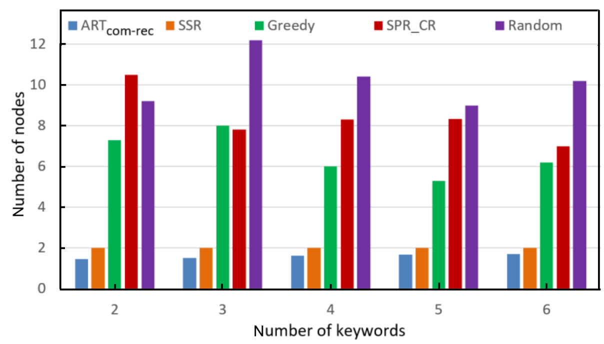

Fig. 5 Number of nodes returned by five approaches.

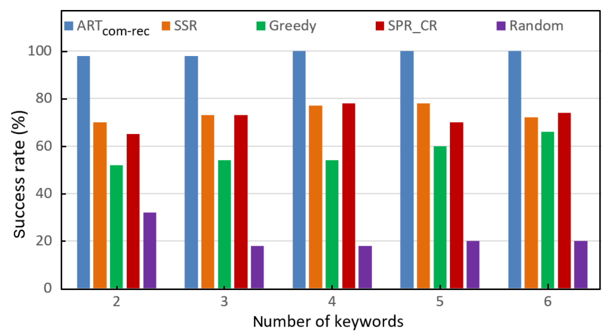

Fig. 6 Success rate comparison of five approaches.

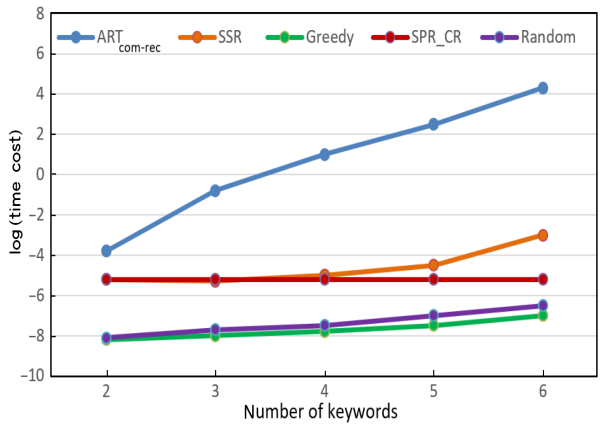

Fig. 7 Time cost comparison of five approaches.

$ART_{com\text{-}rec}$ approach consumes the most time compared with the other four approaches, as $ART_{com\text{-}rec}$ is an NP-hard problem that requires more time to discover an optimal node set. However, the time cost of $ART_{com\text{-}rec}$ is still acceptable when the number of typed keywords is limited to a small number (e.g., $m \leqslant 6$).

To reduce the time cost, we can search for a more near-to-optimal artwork composition solution instead of the optimal artwork composition solution pursued in this paper. In addition, minimizing the scale of the artwork correlation graph is a promising direction to improve the time complexity.

(4) Time convergence of $ART_{com\text{-}rec}$

Time convergence is also a key criterion in big data scenarios[2, 33–37]. In this profile, we observe the convergence of the time cost of our $ART_{com\text{-}rec}$ approach. The number of keywords typed by the target user (i.e., m) varies from 2 to 6. Each set of experiments is repeated 1–100 times. Figure 8 shows the concrete performance report. As Fig. 8 indicates, the consumed time of $ART_{com\text{-}rec}$ remains relatively stable when we execute the algorithm 100 times. This stability also explains the 100 repetitions of each set of experiments in this section, that is, to avoid the negative influence brought by network traffic and random data. The experimental results in Fig. 8 show the good convergence performance of $ART_{com\text{-}rec}$ in terms of time cost.

(5) Convergence of $ART_{com\text{-}rec}$ in terms of the number of returned nodes

Here, we measure the convergence of the number of returned nodes by $ART_{com\text{-}rec}$. Similar to the last profile, the number of keywords typed by the target user (i.e., m) is varied from 2 to 6; each set of experiments is repeated 1–100 times. Figure 8 displays the experimental results. As shown in Fig. 8, the number of nodes returned

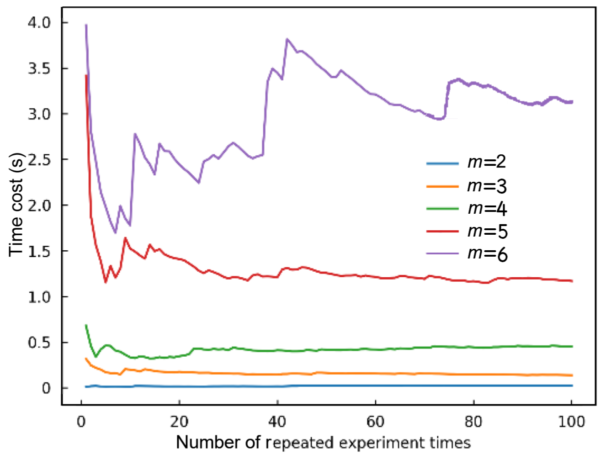

Fig. 8 Time convergence of $ART_{com\text{-}rec}$.

by $ART_{com\text{-}rec}$ remains approximately stable when we execute the algorithm 80 times. The high convergence demonstrated in Fig. 8 indicates the good performance of $ART_{com\text{-}rec}$ in searching for a set of compatible or composable nodes.

6 Conclusion and Future Work

With the ever-increasing popularity of artworks in E-commerce, a mechanism for recommending appropriate artworks to interested users is becoming a challenging task that calls for intensive studies. Existing research mainly investigated the problem of single-artwork recommendation but neglected the more practical and more complex composite recommendation of artworks in E-commerce. This condition considerably decreases the QoE of potential users, especially when they need to select a set of artworks instead of a single artwork. Inspired by this drawback, we propose a novel composite recommendation approach for artworks based on user keyword-driven correlation graph search, i.e., $ART_{com\text{-}rec}$. Finally, we prove the feasibility and efficiency of $ART_{com\text{-}rec}$ through several experiments on the real-world programmableweb.com dataset.

In the upcoming study, we will further optimize the artwork correlation graph by introducing edge weights, given that weight is often a significant factor in graph-based optimization algorithms[38–40]. Moreover, the time complexity of our $ART_{com\text{-}rec}$ is high. Therefore, a procedure on how to reduce its time complexity via lightweight techniques (e.g., computational offloading, approximation technique, etc.)[41–45] to accommodate the big data context is another challenge that requires intensive study in our future work. Third, time context is very important for most data flow-related optimization problems[46–48], such as recommender systems. Therefore, the time factor can be incorporated into our proposed recommendation algorithm to enhance the recommendation performances.

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