Four-Dimensional Shopping Mall: Sequential Group Willingness Optimization under VR Environments

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ABSTRACT

Nowadays, people get used to buying a variety of commodities from e-commerce platforms because of the convenience and easy access to Internet. As a result, the sales on e-commerce platforms have grown exponentially. It is promising to customize the online shops for different users under VR environments since users do not need to waste time of going upstairs or downstairs for finding interesting commodities. Therefore, in this demo paper, we propose a novel four-dimensional shopping mall that offers online group shopping services with the customized shop recommendation, where a group of friends in the proposed four-dimensional shopping mall can teleport to the next shop by one click. We formulate a Sequential group willingness Optimization (SION) problem, prove SION is NP-hard, and provide an efficient algorithm called ζ -GSS. The experimental results show that the solution quality of the proposed ζ -GSS is close to the optimal solution, while the execution time only requires 3.3%. Finally, we build the prototype of the four-dimensional shopping mall, which can be demonstrated for users to experience the next-generation online shopping.

KEYWORDS

New Human-Computer Interfaces, Social Networks, E-Commerce

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1 INTRODUCTION

Due to the convenience and easy access to Internet, people get used to buying a variety of commodities from e-commerce platforms. As a result, the sales on e-commerce platforms have grown exponentially. For example, the leading e-commerce platform, Amazon, has created 34.2, 74.5, and 136 billion U.S. dollars net sales

in 2010, 2013, and 2016, respectively.¹ Moreover, the retailers on Alibaba's platforms have also recorded 25.4 billion worth of gross merchandise volume on Singles' Day in 2017.² The exponential growth of online shopping has drawn considerable attentions and forced e-commerce enterprises to think what the next-generation e-commerce website is. Meanwhile, Virtual Reality (VR) significantly improves the user experience and has made a great success in many applications, e.g., games³, social platforms⁴. Therefore, it is promising to integrate VR into online shopping for providing convenient and almost real online shopping experiences.

In fact, Alibaba attempts to bring VR into their online shopping platform by recording the real-world shopping mall with VR. However, it is still a single-person shopping experience without considering the real-world group shopping scenarios.⁵ In real world, people usually hang out for shopping together since 1) shopping together improves their relationship and 2) the third party opinions help them make better decisions. Moreover, users still have to waste time of going upstairs or downstairs for finding interesting commodities, which does not fully take the advantage of VR since the layout of all the shops can be arbitrarily customized according to users' preferences. Therefore, in this paper, we propose a novel four-dimensional VR shopping mall where a group of friends can go shopping together and the layout of all the shops is determined according to the total willingness of users in the group.⁶

Four-dimensional shopping mall can not only provide the next-generation shopping experience but also enable the users with disability to shop with friends as in the real world without the spatial or physical constraints.⁷ To develop this system, one of the possible solutions is to exploit frequent pattern mining [2] or sequential pattern mining [8, 11]. For example, Amazon provides "The Customers Who Bought This also Bought..." for commodity recommendation. However, the social influence within the group is not considered in sequential pattern mining. On the other hand, willingness optimization can be applied to recommend the next

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¹<https://www.statista.com/statistics/266282/annual-net-revenue-of-amazoncom/>

²<https://reut.rs/2ACTzPU>

³<http://www.ibtimes.com/sony-ceo-wants-more-virtual-reality-competition-amid-playstation-vr-success-2593447>

⁴<http://www.businessinsider.com/facebook-social-vr-spaces-2017-4>

⁵<http://edition.cnn.com/videos/world/2016/11/28/alibaba-vr-shopping-stevens-pkg.cnn>

⁶The term "four-dimensional" originates from Einstein's theories of special and general relativity. That is, in fourth dimensional space, users can teleport into and out of subspace (3D).

⁷Please find our demo video in <https://vimeo.com/250472137>.

shop for a group of users [9]. Nonetheless, the effects of sequential willingness are not considered.

Therefore, we formulate a new optimization problem, named *Sequential group willingness Optimization* (SION), to resolve the unaddressed issues. Specifically, the objective of SION is to find a sequence of k shops that maximizes the willingness of a group who using the four-dimensional shopping mall together, i.e., users take a tour of k shops without going upstairs and downstairs to find the next shop. Based on previous work, the willingness can be modeled as the combination of preference and social influence [9]. We exploit Bayesian networks [4] to calculate the preference of each user for shop sequences and Linear Threshold model [6] to capture the social influence. One of the basic solutions is to greedily select a shop that leads to a maximum increment to the total willingness until k shops are selected. However, this greedy approach, though simple, is inclined to be trapped in a local maximum. Another solution is to enumerate all the possible shop sequences and select the sequence with a maximum willingness. Nonetheless, the number of combinations is $C_k^{|H|} \cdot k!$, which is intractable when the number of shops $|H|$ is large. To solve this problem, we propose the ζ -greedy sequence selection (ζ -GSS) algorithm, which iteratively finds solutions by maintaining top- ζ intermediate solutions (will be detailed in Section 3). Experimental results show that the solution quality of ζ -GSS is close to that of the enumerative approach, while the execution time is only 3.3%. We implement the prototype of four-dimensional shopping mall under the VR environment with Unity engine, which enables users to experience the next-generation online shopping. The contributions of this paper can be summarized as follows.

- We formulate a new optimization problem, namely SION, to consider the preference of sequential shops of users and social influence within the group for automatic planning of sequential shop recommendation. To the best of our knowledge, there is no real system or existing work in the literature that addresses the sequential shop recommendation based on both shop preference and social influence.
- We prove that SION is NP-hard and design Algorithm ζ -GSS to find the solution to SION. Experimental results demonstrate that the solution quality of ζ -GSS is very close to the optimal solution obtained by the enumerative approach, while the execution time is at most 3.3% of the enumerative approach.
- We build the prototype of the four-dimensional shopping mall to demonstrate the novel idea with hTC VIVE and Unity engine. This demonstration enables users to experience the next-generation online shopping. The research result has the potential to be adopted as the key technology of a new startup or as a value-added service in existing e-commerce websites.

The rest of this paper is organized as follows. Section 2 presents the related work. The problem formulation, hardness result, and proposed algorithm are detailed in Section 3. Section 4 presents the demonstration plan and experimental results. Finally, Section 5 concludes this paper.

2 RELATED WORK

One of the commonly-used technologies to discover the associations among shops is frequent pattern mining algorithms, which find shops frequently appearing together in purchasing transactions [2]. Wang et al. further propose top- k frequent pattern mining to improve the mining efficiency [10]. However, those existing works, focusing on capturing the common shopping behaviors of individuals without taking sequential information and social influence between customers. On the other hand, a variety of sequential pattern mining algorithms, such as apriori-based methods and pattern-growth methods, have been developed for mining frequent patterns more efficiently. Yun et al. [11] further focus on mining the weighted maximal frequent patterns in streaming data. Bai-En et al. proposed a framework for mobile commerce planning applications [8]. However, previous work focus on individual users and does not take social influence into account.

With a great success on business applications, such as product promotion, spread maximization, social influence diffusion in social networks has attracted a lot of interests. Kempe et al. propose two influence diffusion models, Independent Cascade (IC) and Linear Threshold (LT), which are widely adopted with many variants, and propose a $1 - 1/e$ approximation greedy algorithm [6]. Hung et al. further propose an influence learning model and influence maximization algorithm for considering social influence and item inference together [5]. Instead of finding individual influentials, Li et al. further propose to find the influential community for encouraging the social engagement on social networks [7]. However, previous studies do not consider the sequential willingness. In contrast, we incorporate sequential preference and social influence together to better estimate the total willingness of the group.

3 SEQUENTIAL GROUP WILLINGNESS OPTIMIZATION

3.1 Problem Definition

Let H and $h_x \in H$ denote the shop set and x -th shop. First, a Bayesian network B_i is constructed according to the historical browsing records to calculate the sequential willingness of user i efficiently. Specifically, for finding user i 's preference of the shop sequence with size t , given previous shop sequences with size $t - 1$, $S_{t-1}^i = (s_1^i, s_2^i, \dots, s_{t-1}^i)$, we can calculate the conditional probability that user i likes shop h , i.e., $P^i(h|(s_1^i, s_2^i, \dots, s_{t-1}^i))$, and then multiply the $P^i((s_1^i, s_2^i, \dots, s_{t-1}^i))$. Notice that the order of the given variables may make difference in the conditional probability, i.e., $P^i(h|(A, B))$ may not be equal to $P^i(h|(B, A))$, since users have preference on the order of shops. For example, users usually choose a bike first before buying the bike accessories. Second, for the social influence, Linear Threshold Model is adopted. Consider a user group graph $G = (V, E)$, where $v_i \in V$ represents user i associated with the preference of a shop sequence S , i.e., $P^i(S)$, and $e_{i,j} \in E$ represents the social influence relation from v_i to v_j . Let N_{v_i} be the set of neighbors connected to v_i . Let $\tau_{i,j}$ and $\tau_{j,i}$ denote the social influence scores from v_i to v_j and from v_j to v_i , respectively. A user i is activated with a shop sequence S when the summation of the preference of a shop sequence and the social influence score from neighboring active users, denoted as $\tilde{N}_{v_i}$, is greater than the

i	$P^i(A)$	$P^i(B)$	$P^i(C)$	i	$P^i(B (A))$	$P^i(C (A))$	$P^i(A (B))$	$P^i(C (B))$	$P^i(A (C))$	$P^i(B (C))$
1	0.6	0.5	0.8	1	0.1	0.1	0.8	0.2	0.9	0.4
2	0.4	0.3	0.5	2	0.1	0.2	0.5	0.3	0.5	0.6
3	0.7	0.4	0.3	3	0.1	0.2	0.3	0.7	0.5	0.1

(a)

i	$P^i(A (B,C))$	$P^i(A (C,B))$	$P^i(B (A,C))$	$P^i(B (C,A))$	$P^i(C (A,B))$	$P^i(C (B,A))$
1	0.8	0.6	0.1	0.7	0.2	0.2
2	0.7	0.2	0.2	0.2	0.4	0.2
3	0.4	0.1	0.3	0.8	0.2	0.3

(c)

Figure 1: An illustrative example of Bayesian probability table.

Figure 2: An illustrative example of social influence model.

user activation threshold θ_{v_i} .

$$P^i(S) + \sum_{v_j \in \tilde{N}_{v_i}} \tau_{j,i} \geq \theta_{v_i}. \quad (1)$$

The willingness of a user is added to the total willingness of the group only if he is activated to encourage that every user feel satisfied with the shop sequence. Let σ denote the activation set. The goal of *SION* is to find a sequence of shops S with size k such that the total sequential willingness of all the users in the group is maximized, i.e.,

$$\operatorname{argmax}_{S=(s_1, s_2, \dots, s_k)} \sum_{v_i \in V \wedge v_i \in \sigma} (P^i(S) + \sum_{v_j \in \tilde{N}_{v_i}} \tau_{j,i}). \quad (2)$$

Take Figures 1 and 2(a) as an illustrative example. The preference of user 1 for shop sequence (C,A,B) can be calculated by $P^1(C) \cdot P^1(A|(C)) \cdot P^1(B|(C,A)) = 0.8 \cdot 0.9 \cdot 0.7 = 0.504$. In the same manner, the preference of users 2 and 3 for shop sequence (C,A,B) is $0.5 \cdot 0.5 \cdot 0.2 = 0.05$ and $0.3 \cdot 0.5 \cdot 0.8 = 0.12$, respectively. Since $0.504 \geq \theta_{v_1} = 0.2$, user 1 is activated, and the social influence scores $\tau_{1,2}$ and $\tau_{1,3}$ are respectively added to the willingness of user 2 and 3. As such, users 2 and 3 are activated, and the total willingness can be calculated with Equation 2 as $0.504 + 0.05 + 0.5 + 0.3 + 0.12 + 0.4 + 0.3 = 2.174$. Take another example by replacing the social influence graph as Figure 2(b). After calculating the same shop preference, user 3 is not activated since the willingness of user 3 is $0.1 + 0.12 = 0.22 < 0.3$. Therefore, the total willingness is $0.504 + 0.05 + 0.5 = 1.054$. *SION* is challenging due to the computation of different sequence combinations, while the tradeoff in sequential willingness and social influence also complicates this problem because it is no longer able to only use Bayesian network to simplify the computation. Indeed, the following theorem shows that *SION* is NP-hard.

THEOREM 1. *SION is NP-hard.*

PROOF. Due to the space constraint, the proof is omitted. Intuitively, *SION* without considering social influence is the same as the maximum probability assignment (MPA) problem, which is proved to be NP-hard in [1]. $\square$

3.2 Algorithm Design for *SION*

Naturally, a greedy approach is to incrementally construct the shop sequence by sequentially choosing a shop that leads to the largest willingness at each iteration. For example, Figures 1 and 2(a) present an illustrative example with 3 users (v_1 , v_2 and v_3) and 3 candidate shops (A , B and C). Figures 1 (a)-(c) show the conditional probability of each user to the shop sequences, while Figure 2(a) shows the social influence scores and the thresholds. According to the total preferences of shops A , B and C , i.e., $0.6 + 0.4 + 0.7 = 1.7$, $0.5 + 0.3 + 0.4 = 1.2$, $0.8 + 0.5 + 0.3 = 1.6$, shop A will be first selected. However, the social influence is not considered. Therefore, when considering shop A , user 1 is activated, and thus the social influence scores $\tau_{1,2}$ and $\tau_{1,3}$ are added to users 2 and 3, respectively. The total willingness is $0.6 + 0.4 + 0.5 + 0.3 + 0.7 + 0.4 + 0.3 = 3.2$. Afterward, we calculate $P^i(A) \cdot P^i(C|(A))$ and $P^i(B) \cdot P^i(B|(A))$ for each user, add the corresponding social influence scores, and select the shop that leads to the largest willingness. The iteration continues until k shops are selected. However, this approach, though simple, is inclined to trap in a local maximum. When $k = 2$, the preference of sequences starting with shop A is small since $P^i(B|(A))$ and $P^i(C|(A))$ are small for all i .

Therefore, we propose the ζ -greedy sequence selection (ζ -GSS) to further improve the solution quality. ζ -GSS first takes each individual shop separately as shop sequences with size 1, i.e., $S_1^1, S_1^2, \dots, S_1^{|H|}$. Their total willingness $W_1^1, W_1^2, \dots, W_1^{|H|}$ are then derived with Equation 2. Afterward, according to the total willingness, top- ζ sequences are kept and reordered as $S_1^{(1)}, S_1^{(2)}, \dots, S_1^{(\zeta)}$, while the remaining sequences are deleted. Next, each of the ζ sequences is expanded into sequences with size 2. For example, $S_1^{(1)}$ is expanded by separately adding one shop from $H - S_1^{(1)}$. Afterward, according to the total willingness, top- ζ sequences are kept and reordered as $S_2^{(1)}, S_2^{(2)}, \dots, S_2^{(\zeta)}$. In other words, ζ subsequence with size t of the largest willingness are kept and utilized to generate the candidate sequences with size $t + 1$ iteratively until k shops are selected.

In ζ -GSS, ζ serves as a parameter for controlling the solution quality and execution time. When ζ is large, most of the search space can be explored, which results in a solution with higher total willingness. However, when ζ is too large, the execution time of ζ -GSS is close to that of the enumerative approach.

4 EXPERIMENTAL RESULTS

4.1 Demonstration Walkabout

In this demonstration, we will demonstrate the interactive four-dimensional shopping mall using hTC VIVE. The prototype is built with Unity 2017.1.11f1 Personal(64bit), Photon Unity Network free 1.86, Steam VR Plugin 1.2.2, VRTK, 3ds Max 2016, and Microsoft Visual Studio 2017. The demonstration requirements are two power sockets and an at least 8 meters by 6 meters space. We will bring

Figure 3: A real demonstration example of a VR interaction.

two HTC VIVE devices with two VR-ready laptops for the demonstration. Figure 3 shows the real scene of the four-dimensional shopping mall. Users are first asked to login their Facebook account for deriving their shop preference and social influence scores. After running ζ -GSS with a specified k , system will return the best-matched shop sequence in the shop database. Afterward, users can explore the shops in the virtual environment and interact with each other. All the commodities in the shops are interactive. When users pick commodities, the related information, e.g., price, descriptions, features, are shown in front of them. Users can throw any commodities into a shopping cart and the TV wall will display the current selected items with a total price. After finishing exploring this shop, users can click on the “Next” button to teleport to another shop. The pointer to a screencast can be found in <https://vimeo.com/250472137>. It is worth noting that all the 3D models of the commodities in the demonstration are free or built by ourselves. For a real commercial use, it is convenient to build the 3D models of commodities by 3D scanners, which usually requires less than 3 seconds for a commodity.

4.2 Numerical Results

Here, we conduct comprehensive experiments using a real dataset (Dataset *Gowalla*) to evaluate the proposed ideas and algorithms. Dataset *Gowalla* contains 196,591 users, 950,327 links, and 6,442,890 check-ins [3]. Users whose number of check-ins are less than 10 are first filtered. Afterward, we randomly select a user and add her 4 close friends according to the number of common friends as a group. Note that the reported values are the average of 50 random group selection. We compare the proposed ζ -GSS with a greedy algorithm (Greedy) and an enumerative approach (OPT, i.e., the optimal solution).

Figure 4(a) show the objective values with different k . As k increases, all the total willingness decreases since it is not easy to find a long shop sequence that every one in the group feels satisfied. The performance of ζ -GSS are close to that of OPT, whereas Greedy is only 50% of OPT when $k = 8$. Figure 4(b) shows the execution time with different k . The result manifests that ζ -GSS is at most 3.3% of OPT with different k . As k increases, the execution time of OPT become intractable for a real use.

Figure 4: Comparisons of objective and running time in various k on Dataset *Gowalla*.

5 CONCLUSION

With the rapid growth of e-commerce and VR, it is promising to integrate VR into online shopping for providing convenient and almost real online shopping experiences. Therefore, we formulate a new optimization problem, namely SION, to consider the preference of sequential shops of users and social influence within the group for automatic planning of sequential shop recommendation, and propose the ζ -GSS algorithm to solve it. The prototype of the four-dimensional shopping mall with HTC VIVE and Unity engine demonstrates the practicability of the novel idea. In the future, we plan to 1) study the difference between the single-person shopping and group shopping and analyze users’ feedbacks for designing a better system, and 2) extend our work to WebVR⁸ for constructing a ubiquitous experiment platform.

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⁸<https://webvr.info/>