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A Real-Time Booth Recommendation based on Partial Path Information

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***Abstract*— The exhibition industry has showed steady growth in both terms of the size of an exhibition and the amount of money it generates. As the ubiquitous environment, there is much useful information for inferring visitors' preference. However, the development and provision of such services have some issues. They are not designed as user-friendly systems and taken account of the preferences and interests of visitors. For satisfaction of visitors, exhibitions need to meet the needs for personalization. Therefore, we suggest a personalized booth recommendation methodology for real-time exhibition guidance in ubiquitous exhibition environment. In a computer supported ubiquitous learning environment, visitors' booth visiting path can play a key role for reasoning visitors' preference. In this study, by considering the booth visiting path of target visitors, we expect to reflect visitors' dynamic preference so that have improved accuracy compared to traditional Collaborative Filtering. Moreover, as we suggest a simple algorithm for fast predictions in recommender systems, we can also solve scalability problems.**

Keywords- Recommender System; Booth Recommendation; Collaborative Filtering; Ubiquitous Exhibition

I. INTRODUCTION

An exhibition is defined as market events of a specific duration, which are held at intervals and bring together a large number of companies to present their main product range to either business or private visitors [7, 15]. The exhibition industry a multi-billion dollar industry, also it has continuously demonstrated its growth in event size as well as the number of the event attendants by both public and private sectors. While the challenges in assessing economic returns from the exhibition industry have been studied, the eventual success of an exhibition resides largely in its ability to meet the objectives of three primary constituents which consist of the visitors, exhibitors, and show organizers [3, 10].

Visitors use the exhibition as an information source for many purposes such as information gathering for possible purchases in the future, learning market trends, job improvements, and general industry awareness [21, 23]. Moreover, visitors assume that an exhibition should be an industry showcase in which they can experience new products and services as well as gather information in short time [5]. However, an exhibition has originally information-rich environment. The growing size of exhibitions (e.g., 4,157 companies from 68 countries exhibited at CeBIT 2010) naturally creates an information overload [2]. Poor overall ratings on an exhibition by visitors are often caused by booth personnel problems [8]. And visitors' dissatisfaction stems from failing to connect with the right types of booth personnel. Booth personnel should be knowledgeable and proficient enough to establish contacts with people who entered the booth for lead efficiency of the exhibitors [11]. Therefore, an exhibition needs to develop new applications that will benefit visitors.

Recommender systems can be the right types of booth personnel. Especially, in ubiquitous environment, there is much useful information to infer visitors' preference in recommender systems (e.g., visitors' current location, booth visit path, and so on). Recommender systems use the opinions of a group of users to help individuals of the group more effectively identify interest from a potentially overwhelming set of choices [18]. One of the most successful and widely used technologies for building recommender systems called Collaborative Filtering (CF). CF has been developed and improved over the past decade to the point where a wide variety of algorithms exist for generating recommendations [14]. However, traditional recommender systems use only neighbors' evaluations or behaviors for a personalized prediction. Therefore, they can not reflect visitors' dynamic preference, as well as have a lack of accuracy in exhibition environment within some defined paths. Due to complexity of algorithms, moreover, they are not able to give a recommendation at the right time in ubiquitous environment.

This study proposes methodology to recommend booths to target visitors. As ubiquitous computing technologies have been adopted in exhibition environment, we can get more information like a location which can be used for reasoning visitors' preferences. By using a simple algorithm to consider the booth visiting path of target visitors, we attempt to solve several problems of traditional collaborative systems.

The rest of this study is organized as follows. Chapter 2 reviews related researches. Chapter 3 explains suggested algorithms and Chapter 4 is dedicated to a small example to help readers understand the method. Finally, Chapter 5 shows the result of experiment and conclusion is in chapter 6.

II. RELATED WORK

A. *Application of ubiquitous environment in exhibition*

The development of applications for exhibitions is based on indoor mobile communication technologies. For example, Bluetooth is the short-range radio standard for connecting devices and data transfer, and provides higher accuracy than WLANs [24]. And RFID technology has high accuracy due to the extremely short operating range [6]. They will probably transform the exhibition industry in fundamental ways.

Nowadays, several applications already exist that partially support exhibitions. For example, conference Assistant [1] employs context information to assist conference attendees. The assistant automatically processes the conference schedule, topics of presentations, visitors' location, and so on. However, the development and provision of such services generates some drawbacks. They need to be carefully assessed in order to identify the most promising ones and design a user-friendly system considering the preferences and interests of visitors.

B. *Recommender systems considering the sequence*

Collaborative filtering systems collect visitors' opinions on a set of objects. They use ratings provided by the users or those implicitly computed, to form neighbor groups to predict a user's interest in an item [13]. Depending on data type in use for CF, it can be classified into either user-based CF or item-based CF [12].

Some of user-based CF used time-based discounting of ratings to account for drift in user interests [4, 22]. Traditional user-based CF does most of the computation for similarity between users as it needs to scan all the users at once to find similar users among them and scan all the items to find the items that they have selected [12]. So, it has a limitation in scalability and other applications except E-commerce. Moreover, because visitors in exhibitions seldom return to previous visited booths, recommender systems do not need to consider repetition of a visit which time-based discounting models in Websites does.

A kind of item-based CF, Clicksteram-based CF [16], has received much attention as a way of doing collaborative filtering. The common predicted models for CCF recommendation are the Markov Model. Markov Chains provide a simple way to capture sequential dependence [19], but do not take into consideration the long-term memory since they are based on the assumption that the next state to be visited is only a function of the current one. So Higher-order Markov models [17] appeared to predict navigational paths. However, there exists a trade-off between improved coverage and exponential increase as the order increases. Such complex models often require inordinate amounts of training data, and the increase in the number of states may even have worse prediction accuracy and can significantly limit their applicability for applications requiring fast predictions such as exhibitions [23]. And the adoption of the structure information may limit the extension of the models into other domains.

III. METHODOLOGY

A. *Overview*

This study assumes the ubiquitous environment which can track the booth visit paths of visitors in real-time. The key underlying concept of proposed methodology is an agreement of booth visit paths between visitors, i.e., the more same booths they visited at the same time, the higher their similarity gets.

The proposed methodology consists of two-phase flow. In the first phase, we preprocess data to be collected from the ubiquitous environment to summarize it in a matrix form. We assume that the target visitor only wants to receive a next booth recommendation from the booth they are located when they request a booth recommendation. As summarizing from whole data in the ubiquitous environment, we can reduce the complexity of calculating similarities. Next, we compute similarities between paths of the target visitor and those of the others during the previous *m* exhibit booth before time t(p) where *p* means requesting time of the target visitor. And then, based on similarities, we generate the top-n exhibit booths that the target visitor is most likely to see in the Booth Visit likelihood Score. More detailed steps of proposed methodology are shown in Fig. 1.

B. *Preprocessing*

When the target visitor *i* requests a booth recommendation at *t(p)*, and his/her past booth visiting path is represented as $B_{i,t(p)}$, his/her candidate neighbor set is defined as

$$N_i = \{u_j \mid B_{i,t(p)} \in B_j\} . \quad (1)$$

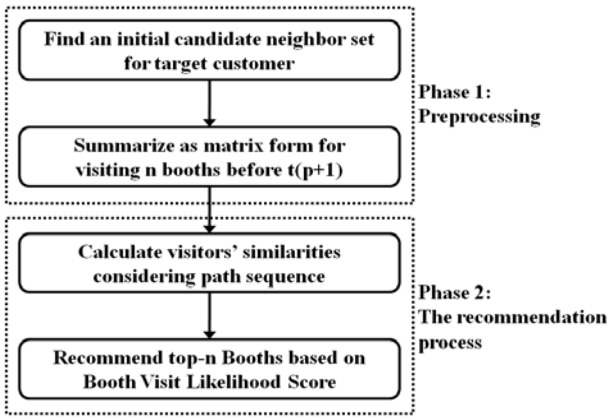

Figure 1. Overall Procedure

According to this procedure, we can limit the number of his/her neighbors, to reduce the computation time. Then, we summarize it in a matrix form for visiting *n* booths until *t(p+1)*. Therefore, booth visit log of the target user and candidate neighbors can express $t(p+1)\times m$ matrix where *m* means the number of the candidate neighbors.

Through preprocessing, we obtain two advantages for the recommendation process. First, traditional CF has scalability problems of scanning all the users and the items. However, we expect to solve the scalability problems as our proposed methodology limits the number of items and visitors. Second, as we treat only candidate neighbors before computing the similarity, we can easily find neighbors of target visitors and improve accuracy and convergence for a pre-choice of similar visitors.

C. The Recommendation Process

With $t(p+1)\times m$ matrix, we calculate the similarity between the target user and candidate neighbors following as

$$W_{ij} = \sum_{n=1}^{p} \alpha^{p-n-1} \quad . \tag{2}$$

If there was a same booth at *t(n)* between the target visitor *i* and candidate neighbor *j*, α means a sequence decay parameter ($0<\alpha\leq 1$), otherwise $\alpha=0$.

As we use a simple algorithm to compute similarities between visitors, we expect a positive effect in terms of computing time.

Based on similarities, for each booth *b* at *t(p+1)* that the target visitor *i* didn't visit at until *t(p)*, its booth visit likelihood score $BVLS_{ib}$ is calculated as follows :

$$BVLS_{ib} = \frac{\sum_{j\in N_i} r_{j,t(p+1)} W_{ij}}{\sum_{j\in N_i} W_{ij}} \quad . \tag{3}$$

Where $r_{j,t(p+1)}$ is candidate neighbor *j*'s rating for the booth *b* at *t(p+1)*. $r_{j,t(p+1)}$ is 1 if candidate neighbor *j* visited the booth *b* at *t(p+1)*, otherwise it is 0. According to Booth Visit Likelihood Score, we recommend top-n booths.

TABLE I. A SEQUENCE DATA EXAMPLE

	t(1)	t(2)	t(3)	t(4)	t(5)	t(6)	t(7)	t(8)	t(9)
u_1	b3	b1	b11	b14	b4	b6			
u_2	b15	b13	b12	b14	b4	b6	b2	b5	b7
u_3	b8	b2	b3	b1	b11	b4	b13	b6	b15
u_4	b5	b4	b17	b14	b9	b15	b2	b10	b3
u_5	b20	b16	b9	b5	b13	b2	b15	b17	b14
u_6	b10	b3	b14	b1	b11	b4	b6	b18	b19
u_7	b13	b15	b1	b18	b5	b2	b20	b12	b7

TABLE II. SUMMARIZING AS MATRIX FORM

	t(1)	t(2)	t(3)	t(4)	t(5)	t(6)	t(7)
u_1	b3	b1	b11	b14	b4	b6	
u_2	b15	b13	b12	b14	b4	b6	b2
u_3	b3	b1	b11	b4	b13	b6	b15
u_6	b3	b14	b1	b11	b4	b6	b18

IV. AN ILLUSTRATIVE EXAMPLE

A. Preprocessing

Table 1 represents a sequence data example.

If the target visitor u_1 requests a booth recommendation at t(6), we first find an initial candidate neighbor set for u_1. In this example, candidate neighbor set is $\{u_2, u_3, u_6\}$. After selecting candidate neighbors, we summarize as matrix form for visiting 7 booths until t(7) like Table 2.

B. The Recommendation Process

Setting a sequence decay parameter α as 0.5, we calculate similarities between the target visitor and candidate neighbor. For example, in Table 2, u_1 and u_6 have visited the same booths at t(1), t(5), and t(6). So similarity between u_1 and u_6 calculate following as

$$W_{u_1u_6} = (0.5)^{6-5} + (0.5)^{6-4} + (0.5)^{6-0} = 0.765625$$

When we finish calculating similarities between target visitor and candidate neighbors, we recommend top-n booths at t(7) based on Booth Visit Likelihood Score. BVLS of booths at t(7) are represented in Table 3.

If we recommend only one booth to the target visitor u_1, b2 are recommended to the target visitor u_1.

V. EXPERIMENT

A. Data

For estimating the performance of our methodology, we use booth visit records which are collected at an IT industrial exhibition organized by 'L' company in 2008. Visitors of pre- registration or on-site registration have been received registration cards with RFID chip when they register on desk. Moreover, each booth has an RFID reader so that if it is interested for him/her, we lead a tagging on it.

Raw data of booth visit records contain 24 booths and 822 visitors. Each visitor has 1~22 booth visit records. In our experiment, not only compare the performance of recommendation between our methodology and traditional CF, but also we experiment the performance as the number of recommendation, booths, and neighbors change. So we use only visitors who have visited above 7 booths. And we assume that they who have visited almost of them have no preference in exhibition, so we remove the data of them who have visited 75% of all booths. Finally, to compare the

TABLE III. BOOTH VISIT LIKEHOOD SCORE

	b2	b15	b18
u_1	0.3889	0.2708	0.3403

TABLE IV. DATA IN USE

Visitors	Booths	Booth visit records in each of customers
316	24	7~17

performance, we use the data following as Table 4.

B. *The measure of the performance*

Generally, the measures to estimate the performance of the recommendation systems are precision and recall [9, 20]. In exhibition environment, visitors' preferences are continuously changed by different factors. So they need only one time recommendation when they request a recommendation. Therefore, we use only precision to estimate the performance.

To estimate the changes of the performance, we have changed three variances such as the number of recommendation, booths, and neighbors.

C. *Experimental Results*

Both methodologies which are used in experiment recommend top-n booths by Booth Visit Likelihood Score. Accordingly, we can compare the performance as the number of the recommendation changes. Fig. 2 is shown in results.

As a result, our methodology is shown higher performance at top-1 recommendation and top-2 recommendation. In ubiquitous environment, visitors' hand-held devices are limited in display size. Consequently, there are small spaces to show recommendation results so that our methodology is suitable to ubiquitous environment. Moreover, because it is shown high performance at top-1, 2, 3, there are no meanings of increasing the number of recommendation by the character of precision.

Next, Fig. 3 shows the change of precision as the number of booths changes in recommendation process, i.e., time window means the number of visit booths when target visitors request a recommendation. Consequently, as our methodology recommend through booth visit sequence, it needs more information than traditional CF which has no considering about sequence. And it has a simple algorithm to compute similarities between visitors, there are many neighbors who have the same similarity when there is a little information about booth visit records. These results are also shown in Fig. 4. Fig. 4 shows the change of precision as the number of neighbors. The change of our

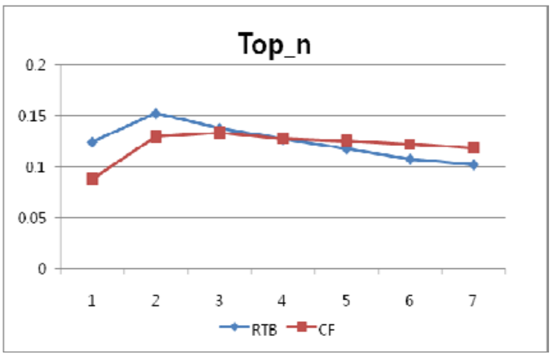

Figure 2. The changes of precision as the number of recommendations

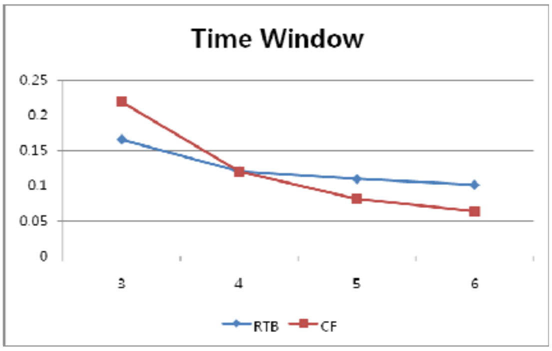

Figure 3. The changes of precision as the number of booths

methodology is hardly shown in Fig. 4 unlike traditional CF. Our methodology has many neighbors who have the same similarity at initial stage of recommendation, on the other hand, CF has neighbors who have various similarities. However, due to the complexity of computing similarities, CF is not suitable to real-time recommendation. Moreover, as it show steady growth as the number of neighbors increase, for more accurate recommendation, it needs more time than our methodology.

VI. CONCLUSION AND FUTURE WORK

A number of studies in exhibition industry reveal the needs for personalization. We can also get more information about visitors in ubiquitous environment. Especially the development of ubiquitous technology makes it possible to track down a location path which can play a key role in inferring visitors' preference.

However, a previous research in recommender systems has caused some drawbacks to be applied in the ubiquitous exhibition. For example, traditional CF has scalability of scanning all the users and items. And item-based CF systems based on Markov models are too complex to apply in the ubiquitous environment which requires real-time recommendation.

To diminish these problems, we proposed a methodology considering booth visit path in the ubiquitous exhibition environment. Our suggested methodology is composed of two phases; the first phase is preprocessing. Through preprocessing, we can achieve higher accuracy and convergence than the other recommender systems. The

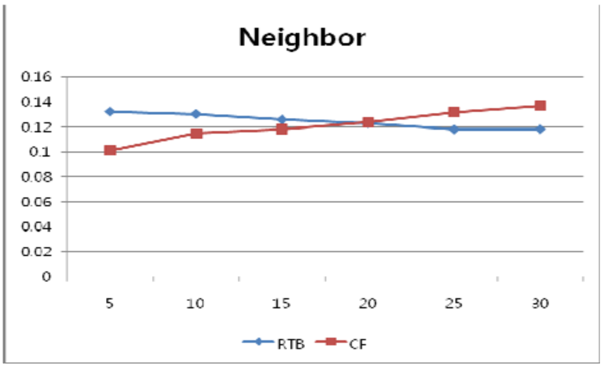

Figure 4. The changes of precision as the number of neighbors

second phase is the recommendation process. In the second phase, we suggested a simple algorithm to compute similarities among visitors so we can be expected to solve scalability problems caused in traditional recommender systems.

Through experimental results, we can see two advantages of our methodology. First, it shows the highest accuracy at top-2 recommendation. It means that our methodology is suitable to ubiquitous environment. Second, it shows easier slope than traditional CF as the number of neighbors change. Therefore, we can use only partial path information of the visitors.

In future work, we plan to implement the prototype system and experiment the performance of proposed methodology in real exhibition environment compared to traditional CF. Moreover, as our methodology has strict rules, there are many neighbors who have the same similarity. So we need to develop our proposed methodology to enhance more various neighbors who have more similar with the target visitor.

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