Identifying Prospective Visitors and Recommending Personalized Booths in the Exhibition Industry

Hyun Sil Moon* · Jae Kyeong Kim** · Il Young Choi***

Abstract

Exhibition industry is important business domains to many countries. Not only lots of countries designated the exhibition industry as tools to stimulate national economics, but also many companies offer millions of service or products to customers. Recommender systems can help visitors navigate through large information spaces of various booths. However, no study before has proposed a methodology for identifying and acquiring prospective visitors although it is important to acquire them. Accordingly, we propose a methodology for identifying, acquiring prospective visitors, and recommending the adequate booth information to their preferences in the exhibition industry. We assume that a visitor will be interested in an exhibition within same class of exhibition taxonomy as exhibition which the visitor already saw. Moreover, we use user-based collaborative filtering in order to recommend personalized booths before exhibition. A prototype recommender system is implemented to evaluate the proposed methodology. Our experiments show that the proposed methodology is better than the item-based CF and have an effect on the choice of exhibition or exhibit booth through automation of word-of-mouth communication.

Keywords : Recommender Systems, Recommendation, Exhibition Industry, Prospective Visitor

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1. Introduction

An exhibition (as referred to as trade show or trade fairs), which is defined as displaying exhibitors' products to visitors and the press [Browning and Adams, 1988; Kozak and Kayar, 2009], has been held to stimulate the national economy in many countries like USA, German, Hong Kong, and Korea etc (see, for example, www.cesweb.org, www.ifa-berlin.de, www.electronicasia.com, and www.ledexpo.com, etc.). According to UFI, the global association of the exhibition industry, 1,793 exhibitions were held and revenues from exhibition was approximately US$3.45 billion in Asia in 2008 [UFI, 2009].

In such a competitive environment, the success of an exhibition depends on number of customers (visitors and exhibitors) [Munuera and Ruiz, 1999]. Accordingly, exhibition organizers should satisfy customer needs and provide an attractive opportunity to the customers. To accomplish these objects, a lot of exhibition organizers provide a variety of information in the form of electronic catalogs. However, visitors typically devote a lot of time and effort to find the needed booth information owing to choices dramatically increased by the internet.

To solve these problems, a number of studies have focused on building the suitable guidance to the pre-inputted exhibit booth [Abowd et al., 1997; Sumi et al., 1998; Mathes et al., 2002; Pateli et al., 2004]. Abowd et al. [1997] developed CyberGuide, which operates in a mobile device, to provide visitors with route and direction based on their location and orientation. Sumi et al. [1998] proposed C-Map in order to guide visitors based on their location and interests. Mathes et al. [2002] couducted mEXPRESS, which is a part of a European-funded project for supporting and facilitating the professional exhibition industry in a context-aware manner, to offer the navigation plan based on visitors' location. And Pateli et al. [2004] developed Wireless Exhibition Guide to provide navigation service for reaching a visitor-defined point at exhibition.

Some studies have focused on providing the personalized exhibition [Cornelis et al., 2007; Guo and Lu, 2007]. Cornelis et al. [2007] proposed a methodology using fuzzy logic for recommending trade exhibition. Guo and Lu [2007] developed Smart Trade Exhibition Finder using semantic similarity and the traditional collaborative filtering for suggesting the suitable international trade exhibition to particular businesses.

However, no study before has proposed a methodology for identifying and acquiring prospective visitors although it is important to acquire them. Accordingly, we propose a methodology for identifying, acquiring prospective visitors, and recommending the adequate booth information to their preferences in the exhibition industry.

The rest of this study is organized as follows. Chapter 2 reviews related researches. Chapter 3 illustrates research framework and explains suggested algorithms. Chapter 4 is dedicated to a small example to help readers understand the method. Architecture of an exhibition recommender and prototyping system are presented in chapter 5. Several experimental results are given in chapter 6. Finally, summaries and future works are shown in chapter 7.

2. Related Work

2.1 Acquisition of the Prospective Customer

Customers are important intangible assets of a firm [Gupta and Lehmann, 2003; Ryu et al., 2009]. Accordingly, a number of firms make efforts to acquire prospective customers, who are not yet customers but exist in the target market, through mass media such as television advertising and personalized contacts such as e-mails and promotion calls [Villanueva et al., 2008].

Acquisition of prospective customers is defined as the first-time purchase by new or lapsed customers [Gupta and Zeithaml, 2006]. A number of studies have been conducted to acquire prospective customers [Chou et al., 2000; Kim and Street, 2004; Schweidel et al., 2008; Libai et al., 2009]. Chou et al. [2000] proposed a method using SLIQ (decision tree component in IBM's data mining toolkit) for acquiring prospective customers without conducting marketing campaign. Kim and Street [2004] developed a prediction model for identifying prospective households, in which they used artificial neural networks and genetic algorithms. Schweidel et al. [2008] developed a bivariate timing model for customer acquisition and retention. Libai et al. [2009] proposed a multifirm model that could capture the complex dynamics of customer acquisition and retention.

However, no study before has proposed a methodology for acquiring prospective visitors in the exhibition industry. Moreover, such studies for acquiring prospective visitors in other industry primarily overlooked effectiveness of word-of-mouth communication. Because word-of-mouth communication is effective enough to persuade customers, prospective customers can be acquired from WOM communications [Villanueva et al., 2008].

In this study, a prospective customer is defined as a customer who didn't see a target exhibition but saw the similar exhibition to the target exhibition.

2.2 Collaborative Filtering

Collaborative filtering system is a recommendation techniques that present an alternative information evaluation approach based on the judgments of human being. It attempts to automate the word-of-mouth recommendations received from family, friends, and colleagues. In general, the collaborative filtering system is broadly classified into item-based collaborative filtering system and user-based collaborative filtering system.

Item-based collaborative filtering is a recommendation technique based on similarities between the various items [Ahn, 2009]. The idea behind item-based collaborative filtering is that there is high probability that a customer will purchase items that are highly similar to items which the customer already purchased in the past. On the contrary, user-based collaborative filtering is a recommendation technique based on the similarities between users. The idea behind user-based collaborative filtering is that there is high probability that a customer will purchase items which were frequently purchased by a set of customers with the high degree of similarity between the customers, known as neighbors.

However, collaborative filtering system poses some issues such as sparsity problem, scalability problem and new item ramp-up problem [Balabanovic and Shoham, 1997, Avery and Zeckhauser, 1997; Sarwar et al., 2000; Jian et al., 2004; Kim and Ahn, 2009], although the system is the one of the most successful recommender systems [Goldberg et al., 1992; Resnick et al., 1994; Hill et al., 1995; Shardanand and Maes, 1995; Balabanovic and Shoham, 1997; Konstan et al., 1997; Canny, 2002; Cho et al., 2002; Cho and Kim, 2004; Ahn et al., 2004; Kim et al., 2009]. Therefore, various researches which combine collaborative filtering with content-based filtering to recommend items of which feature value are similar to those of items the target customer liked in the past, have been proposed to address these problems [Balabanovic and Shoham, 1997; Cho et al., 2002; Kim et al., 2004; Melville et al., 2002].

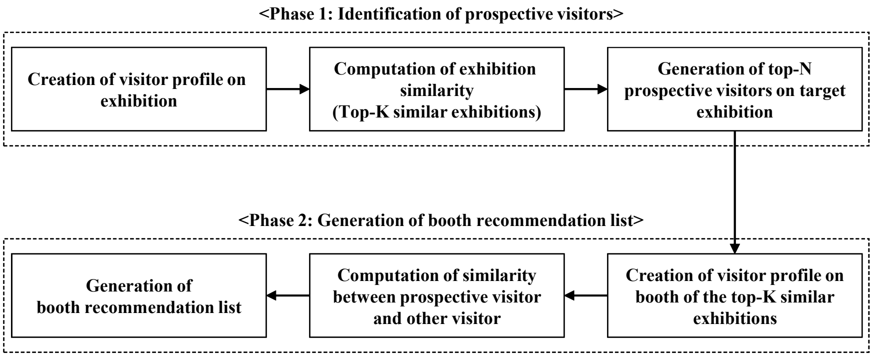
We combine collaborative filtering (item-based collaborative filtering and user-based filtering) as a tool for acquiring prospective visitors and automating word-of-mouth communication, with exhibition taxonomy as a tool for resolving the problem of collaborative filtering.

3. Methodology

3.1 Overall view

The key underlying concept of our proposed methodology is adopting from the work on identifying prospective visitors of a target exhibition and resolving the complexity in finding the adequate booths to their preference. Especially, we assume that a visitor will be interested in an exhibition within same class of exhibition taxonomy such as exhibition which the visitor already saw.

The proposed methodology consists of the following two phases shown in <Figure 1>. In the first phase, we analyze visitors' preference on exhibitions which they saw in the past. And we identify the similar exhibitions to a target exhibition. After identifying the similar exhibitions, we select top-N list of prospective visitors on the target exhibition.



〈Figure 1〉 Overall Procedure

In the second phase, we analyze a preference of prospective visitors or visitors who saw the target exhibition and the similar exhibition, on booth of top-k similar exhibitions. And we identify visitors as known neighbors who have exhibited the similar behaviors to the prospective visitor. After forming the prospective visitor's neighborhood, we compare booths of the target exhibition with the booths which neighbors saw at the target exhibition in the past and generate booth recommendation list for the prospective visitors.

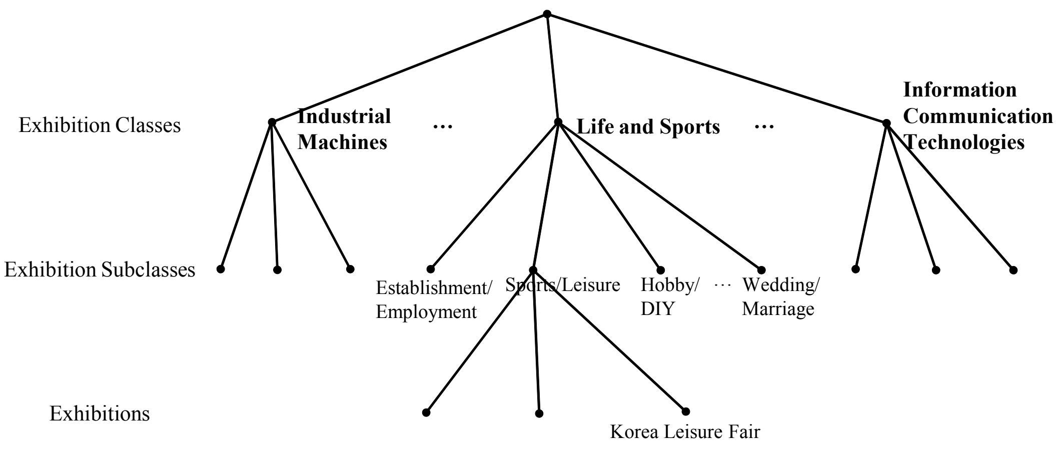
3.2. Phase 1 : Identification of Prospective Visitors

The original data representation for exhibition recommender systems has some problems for nearest-neighbor recommendation procedure, such as sparsity and scalability problem. To solve these problems, exhibition taxonomy plays an important role in the knowledge discovery process.

<Figure 2> shows an example of taxonomy for exhibitions of Korea. The exhibition taxonomy is used for identifying similar exhibitions and grouping them together, by specifying the level of aggregation in the exhibition taxonomy.

The exhibition recommender system helps to find the exhibition which is matched to the visitor profile. As visitor profile on exhibition is a collection of m customers' preference on n exhibition in the exhibition industry, our visitor profile on exhibition is represented by the matrix of preference ratings $R=(r_{ij})$ as follows;

$$r_{ij}=\begin{cases} 1, & \begin{array}{l} if \ \ the \ \ i^{th} visitor \ \ saw \\ the \ \ j^{th} exhibtion \end{array} \\[1ex] 0.5, & \begin{array}{l} if \ \ the \ \ i^{th} visitor \ \ didn't \\ see \ \ the \ \ j^{th} exhibition \\[1ex] but \ \ he/she \ \ saw \ \ exhibition \\ within \ \ same \ \ subclass, \end{array} \\[1ex] 0.25, & \begin{array}{l} if \ \ i^{th} visitor \ \ didn't \\ see \ \ the \ \ j^{th} exhibition \\[1ex] but \ \ he/she \ \ saw \ \ exhibition \\ within \ \ same \ \ class, \end{array} \\[1ex] 0, & otherwise \end{cases} \qquad (1)$$



〈Figure 2〉 Exhibition Taxonomy

where i = 1 to m, j = 1 to n, m is the total number of visitors, and n is the total number of exhibitions.

After representing a visitor profile on exhibition, we calculate the similarity between a target exhibition and other exhibition within each exhibition class, and form the similar exhibition to a target exhibition. The similarity between the target exhibition T and other exhibition b is computed based on the Pearson-r correlation coefficient [Shardanand and Maes, 1995; Kim et al., 2004].

$$sim(T,\ b) = corr_{Tb} \equiv \frac{\sum_{i=1}^{n}(r_{iT} - \bar{r}_T)(r_{ib} - \bar{r}_b)}{\sqrt{\sum_{i=1}^{n}(r_{iT} - \bar{r}_T)^2 \sum_{i=1}^{n}(r_{ib} - \bar{r}_b)^2}} \quad (2)$$

here, n is a total number of exhibitions, r_{iT} and r_{ib} are the visitor i's ratings on the target exhibition T and the other exhibition b, and $\bar{r}_T$ and $\bar{r}_b$ are the average ratings of the target exhibition T and the other exhibition b, respectively.

Finally, we generate the top-N prospective visitors based on $EVLS(i,\ T)$, which denotes the *exhibition visit likelihood score* of the visitor i for the target destination T [Kim et al., 2004]. We compute the EVLS as follows;

$$EVLS(i\ t) = \frac{\sum_{K \in similar\ exhibitions} r_{ik} \times sim(T, k)}{\sum_{k \in similar\ exhibitions} sim(T, k)} \quad (3)$$

where i denotes the visitor who saw the similar exhibitions but didn't see the target exhibition T. $r_{ik}$is the visitor i' rating of on k^{th} similar exhibition and $sim(T,\ k)$ means the similarity between the target exhibition T and k^{th} similar exhibition.

The higher the $EVLS$, the greater the likelihood that a visitor will select the exhibition. Therefore, we sort the visitors according to their $EVLS$ and return N visitors with the high $EVLS$ values as the prospective visitors.

3.3. Phase 2 : Generation of Booth Recommendation List

To provide the adequate booth list of the target exhibition to the prospective visitors' preference, this phase is composed of three steps. First step is to create visitor profile on booth of k^{th} similar exhibition. A visitor profile is the matrix of preference ratings, $P = (p_{im}^k)$, on booths of the top-k similar exhibitions as follows;

$$p_{im}^k = \begin{cases} 1, & if\ the\ visitor\ i\ saw\ the\ booth\ m \\ & of\ k^{th}\ similar\ exhibition \\ 0, & otherwise \end{cases} \quad (4)$$

where i means a prospector or a visitor who saw the target exhibition and k^{th} similar exhibition, and m means the booth of k^{th} similar exhibition.

Second step is to compute similarity between a prospective visitor and the other visitor and to form the neighborhood of the prospective visitors, who has high degree of similarity. Given a visitor profile, the similarity between a prospective visitor p and other visitor c on k^{th} similar exhibition is computed based on the Pearson-r correlation coefficient as follows

[Shardanand and Maes, 1995; Kim et al., 2004];

$$sim(p^k,\ c^k) = corr_{pc} = \frac{\Sigma_{m=1}^{n}(p_{pm}^k - \bar{p}_p^k)(p_{cm}^k - \bar{p}_c^k)}{\sqrt{\Sigma_{m=1}^{n}(p_{pm}^k - \bar{p}_p^k)^2 \Sigma_{m=1}^{n}(p_{cm}^k - \bar{p}_c^k)^2}} \quad (5)$$

here, p^k and c^k are a prospective visitor and the other visitor at k^{th} similar exhibition. p_{pm}^k and p_{cm}^k are the prospective visitor's rating and the other visitor's rating on booth m of k^{th} similar exhibition, and $\bar{p}_p^k$ and $\bar{p}_c^k$ are the prospective visitor's average rating and the other visitor's average rating on all booths of k^{th} similar exhibition, respectively.

Accordingly, similarity between a prospective visitor p and other visitor c considering exhibition similarity is defined as follows;

$$sim(p,\ c) = \frac{\sum sim(T,\ k) \cdot sim(p^k,\ c^k)}{\sum sim\ (T,\ k)} \quad (6)$$

where $sim(T,\ k)$ means the similarity between the target exhibition T and k^{th} similar exhibition defined by equation (2).

Final step is to generate booth recommendation list. First, we calculate *booth visit likelihood score* ($BVLS$) for the prospective visitors in the target exhibition [Kim et al., 2004]. $BVLS(p,\ b)$ is calculated as follows;

$$BVLS\ (p,\ b) = \frac{\sum_{i \in N} r_{ib} \times sim(p,\ i)}{\sum_{i \in N} sim(p,\ i)} \quad (7)$$

here p is a prospective visitor and b is a booth of a target exhibition. r_{ib} is rating of neighbor i on the booth b and $sim(p,\ i)$ means the similarity between a prospect visitor p and his/her neighbor i.

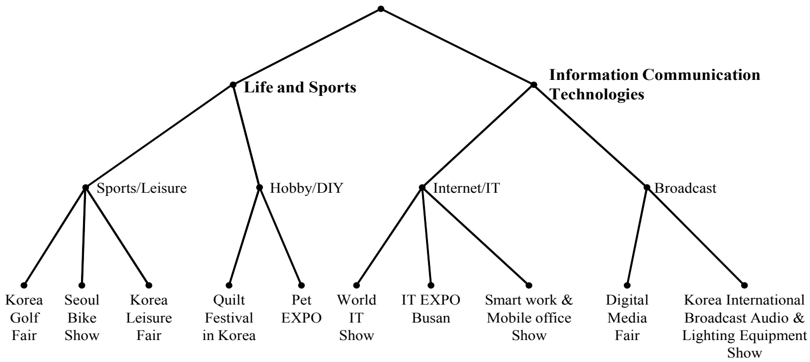
The higher the $BVLS$, the greater the likelihood that a prospective visitor will see the booths. Therefore, we sort the booths according to their $BVLS$ and return N booths with the high $BVLS$ values as the candidate booths.

Second, we compare booths of the target exhibition with the booths which neighbors saw at the target exhibition in the past. In general, booth is composed of exhibitor and product. It is evaluated to be either true if a booth of the target exhibition and the booths which neighbors saw at the target exhibition in the past are same, otherwise false. Therefore we recommend the booths with the true value to the prospective visitors.

4. An illustrative Example

For a better understanding of the proposed methodology, we now present a simple example in a ubiquitous exhibition environment. We suppose that there are fifteen visitor and ten exhibitions. Given exhibition taxonomy as shown in <Figure 3>, consider a visitor profile on exhibition as shown in <Table 1>. Note that exhibition names from Korea Golf Fair to Korea International Broadcast, Audio and Lighting Equipment Show are called E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8, E_9 and E_{10}, respectively.

We will consider the process of identifying prospective visitors for the exhibition E1 and generating booth recommendation list for them.



<Figure 3> An Example of Exhibition Taxonomy

<Table 1> An Example of the Visitor Profile on Exhibition

	Life and sports					*Information Communication Technologies*				
	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}
V_1	1	0.5	0.5	0.25	0.25	0	0	0	0	0
V_2	0.5	0.5	1	0.25	0.25	0.25	0.25	0.25	0.5	1
V_3	0	0	0	0	0	1	0.5	0.5	0.25	0.25
V_4	0.5	0.5	1	1	0.5	1	0.5	1	0.25	0.25
V_5	1	0.5	0.5	1	0.5	1	0.5	0.5	0.25	0.25
V_6	0	0	0	0	0	0.25	0.25	0.25	1	0.5
V_7	1	0.5	0.5	0.25	0.25	0.5	0.5	1	0.25	0.25
V_8	0	0	0	0	0	1	0.5	0.5	0.25	0.25
V_9	0.5	1	1	1	0.5	0	0	0	0	0
V_{10}	0.25	0.25	0.25	1	1	0	0	0	0	0
V_{11}	1	0.5	0.5	1	0.5	0.25	0.25	0.25	1	0.5
V_{12}	0	0	0	0	0	1	0.5	1	0.25	0.25
V_{13}	1	0.5	0.5	1	0.5	0.5	1	1	0.25	0.25
V_{14}	0.25	0.25	0.25	0.5	1	0.25	0.25	0.25	1	0.5
V_{15}	0.5	1	0.5	0.5	1	0	0	0	0	0

4.1 Phase 1 : Identification of the Prospective Visitors

Given a visitor profile on exhibition, identification of prospective visitors is composed of two steps; computation of exhibition similarity in the same exhibition class and generation of prospective visitors for the target exhibition. In the first step, we use the Pearson-r correlation coefficient to identify the similar exhibitions to a target exhibition in the same exhibition class. Given a target exhibition, E_1, the similarities between E_1 and the other exhibitions within same exhibition class, life and sports are represented in <Table 2>. When we assume that the size of the similar exhibition to E_1 is 2, the similar exhibitions are E_2, and E_4 having high similarity values.

<Table 2> Similarity Value

	E_2	E_3	E_4	E_5
E_1	0.601	0.543	0.545	0.240

After the similar exhibitions are found, we compute the $EVLS$ on the target exhibition by visitors, V_4, V_9, V_{10} and V_{15} who didn't see E_1 but saw E_2 and E_4, to identify prospective visitors as follows.

$$EVLS(V_4,\ E_1) = \frac{(0.601 \times 0) + (0.545 \times 1)}{0.601 + 0.545} = \frac{0.545}{1.146}$$

$$EVLS(V_9,\ E_1) = \frac{(0.601 \times 1) + (0.545 \times 1)}{0.601 + 0.545} = \frac{1.146}{1.146}$$

$$EVLS(V_{10},\ E_1) = \frac{(0.601 \times 0) + (0.545 \times 1)}{0.601 + 0.545} = \frac{0.545}{1.167}$$

$$EVLS(V_{15},\ E_1) = \frac{(0.601 \times 1) + (0.545 \times 0)}{0.601 + 0.545} = \frac{0.601}{1.167}$$

Suppose that the size of prospective visitors is 2. As the result, two visitors are selected as the prospective visitors; V_9 and V_{15}.

4.2 Phase 2 : Generation of Booth Recommendation List

Suppose that the profile of the prospective visitors or visitors who saw the target exhibition and the similar exhibition, on booth of top-k similar exhibitions is as shown in <Table 3>. For instance, V_4 saw booths, B_5 and B_{10} in the exhibition, E_4, B_2 and B_7 in the exhibition, E_6, and B_3, B_6, B_8 and B_9 in the exhibition, E_8.

Given a visitor profile on booth, generation of booth recommendation list is composed of two steps; Computation of similarity between a prospective visitor and other visitor, and generation of booth recommendation list. In the first step, we use the Pearson-r correlation coefficient to identify the neighbors of prospective visitors. Given prospective visitors, V_9 and V_{15}, the similarities between prospective visitors and the others, who already saw the target exhibition, for k^{th} similar exhibition are represented in <Table 4>.

Accordingly, similarity between prospective visitors and other visitors considering exhibition similarity is shown in <Table 5>. When we assume that the size of the prospective visitors' neighborhood is 2, V_9's neighbor is V_1 and V_7,

〈Table 3〉 An Example of Visitor Profile on Booth of Top-k Similar Exhibition

	E_2										E_4									
	B_1^2	B_2^2	B_3^2	B_4^2	B_5^2	B_6^2	B_7^2	B_8^2	B_9^2	B_{10}^2	B_1^4	B_2^4	B_3^4	B_4^4	B_5^4	B_6^4	B_7^4	B_8^4	B_9^4	B_{10}^4
V_9	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	1	0	1	1	0
V_{15}	0	1	0	1	0	1	0	0	1	0	0	1	0	1	0	0	1	0	0	1
V_1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	1	0	0	1	0	0
V_5	0	1	0	1	1	0	0	0	0	0	1	0	1	0	0	0	1	0	0	1
V_7	0	0	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1
V_{11}	0	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0
V_{13}	0	0	1	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1

〈Table 4〉 Similarity Value for Top-k Similar Exhibition

	E_4					E_8				
	V_1	V_5	V_7	V_{11}	V_{13}	V_1	V_5	V_7	V_{11}	V_{13}
V_9	0.102	0.218	0.218	-0.327	0.218	-0.089	-0.250	-0.089	0.102	-0.408
V_{15}	-0.250	0.356	-0.535	0.356	-0.089	-0.089	0.167	-0.089	0.102	0.612

〈Table 5〉 Similarity Value

	V_1	V_5	V_7	V_{11}	V_{13}
V_9	0.011	-0.005	0.072	-0.123	-0.080
V_{15}	-0.173	0.266	-0.323	0.235	0.244

〈Table 6〉 Prospective Visitors' Neighbor Profile on Booths of the Target Exhibition in the Past

	B_1^1	B_2^1	B_3^1	B_4^1	B_5^1	B_6^1	B_7^1	B_8^1	B_9^1	B_{10}^1
V_1	1	1	0	1	0	1	1	0	1	1
V_7	0	0	1	1	0	0	0	1	1	0
V_5	1	1	0	1	0	0	0	1	1	1
V_{13}	0	1	1	1	1	1	0	1	1	0

〈Table 7〉 $BVLS$

	B_1^1	B_2^1	B_3^1	B_4^1	B_5^1	B_6^1	B_7^1	B_8^1	B_9^1	B_{10}^1
V_9	0.133	0.133	0.867	1.000	0.000	0.133	0.133	0.867	1.000	0.133
V_{15}	0.522	1.000	0.478	1.000	0.478	0.478	0.000	1.000	1.000	0.522

and V_{15}'s neighbor is V_5 and V_{13}.

In the second step, we create candidate booths based on $BVLS$ and compare the candidate booths with booths of the target exhibition. Consider that the booths, which V_1, V_5, V_7, V_{11} and V_{13} saw at the target exhibition E_1 in the past, are shown in <Table 6>.

First, we compute $BVLS$ on the booths rated by the prospective visitors' neighbors to generate the candidate booths on the target exhibition. $BVLS$ is shown in <Table 7>. When assuming that the size of the candidate booth is 4, candidate booths for V_9 are B_3^1, B_4^1, B_8^1 and B_9^1, and candidate booths for V_{15} are B_2^1, B_4^1, B_8^1 and B_9^1.

Suppose that B_2^1, B_3^1, B_4^1, B_8^1 and B_9^1 were set of {Samsung, TV}, {LG, TV}, {Daewoo, TV}, {Haier, TV} and {Sony, TV}, respectively. And, suppose that Samsung, LG and Sony display TVs, but Daewoo and Haier don't take part in the exhibition E_1. Thus, we will recommend the LG booth and the Sony booth to V_9. The Samsung booth and the Sony booth will be recommended to V_{15}.

5. An Architecture and Prototype System

5.1 Architecture for Exhibition Recommender System

The design, development, and database access for the recommender system in an exhibition environment can be represented by the three-tier architecture [Huang and Mak, 2000; Zhang and Jiao, 2007] as shown in <Figure 4>.

The first tire is related to the application for visitors. Visitors can connect to the http server to receive recommendations through their mobile devices or personal computers.

The middle tier is composed of the http server and the recommender server. The http server delivers recommendation information to visitors when they connect to the server. The recommender server plays an important role to acquire prospectors and provide recommendation information to them. The server consists of exhibition profiler, prospector generator, booth profiler and booth recommender, creates visitors' profile on exhibition or booth, calculates similarity among exhibitions or booths, and generates prospector list for a target exhibition or booth lists for the prospectors.

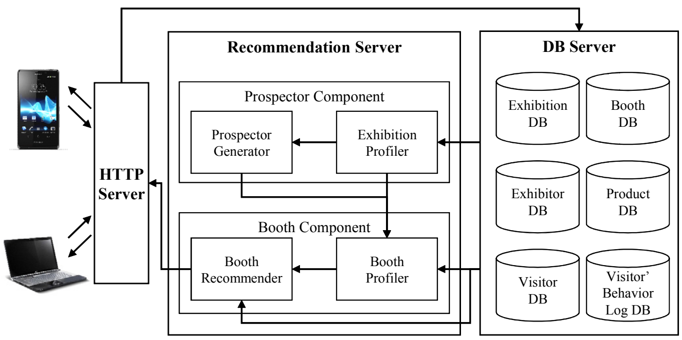
(1) *Exhibition profiler* : The exhibition profiler is responsible for creating a visitor profile on exhibition and computing the similarity between a target exhibition and the other exhibitions. This profiler returns the similar top-k exhibitions to the target exhibition. Then, the similar top-k exhibitions are passed directly to the next stage and to the booth profiler.

(2) *Prospector generator* : The prospector generator identifies visitors who didn't see the target exhibition but saw the similar exhibitions, and passes information of the visitors to the booth profiler. This generator computes the visitors' $EVLS$. And then, after the generator sorts the visitors according to their $EVLS$ and return N visitors with the high $EVLS$, information of the top-N visitors, what is called prospective visitors, is passed to the booth profiler.

(3) *Booth profiler* : The booth profiler is responsible for creating a visitor profile on booth of the top-k similar exhibitions and calculating the similarity between a prospective visitor and the other visitors. This profiler returns the similar top-M visitors, what is called neighbors, to the booth recommender.

(4) *Booth recommender* : The booth recommender identifies booths of the target exhibition which neighbors saw in the past. The recommender computes the prospective visitor' $BVLS$ on the booth. This recommender sorts the booths according to their $BVLS$ and return booths with the high $BVLS$ values, what is called the candidate booths. This recommender compares the candidate booths with the displayed booth at the current target exhibition. And then, this recommender passes information of booths, which are composed of the same exhibitors and products as the candidate booths, to the http server.

The third tier is the database server for managing the data. We will discuss all of the details of this tire later.



<Figure 4> A Recommender System Architecture in an Exhibition Environment

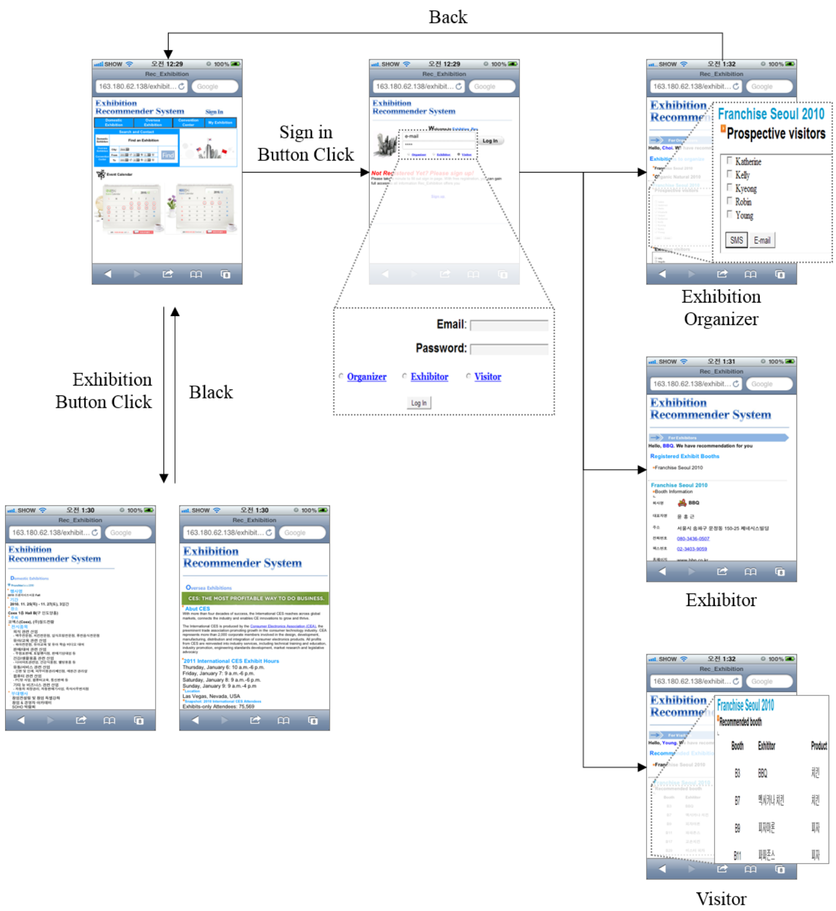
5.2 Prototype System

We have designed and implemented a prototype system for an exhibition environment, called *Exhibition Recommender System*. The objects of the *Exhibition Recommender System* are to acquire prospective visitors for a target exhibition and recommend booth information to them, based on visitors' profile of likes and dislikes. To implement the *Exhibition Recommender System* we have used Windows XP-based operating system and Microsoft Access 2007. And we have chosen Internet Information Server (IIS) as the http server.

The main function of the *Exhibition Recommender System* is to construct personalized exhibition and exhibit booth for each visitor. The key to the success of this system is its ability to select truly relevant exhibition and exhibit booth recommendations by using the proposed methodology.

The graphical user interface of the *Exhibition Recommender System* for accomplishing its object consists of a set of screens depicted in <Figure 5>. Summarizing contents of these major screens shortly follows like this.

When a customer (exhibition organizer, ex-



〈Figure 5〉 Navigational Structure of the Prototype System hibitor or visitor) connects to the *Exhibition Recommender System*, the system provides him/her with information of exhibition which is held currently or will be held later. And "Sign in" menu of main screen provides him/her with the possibility to login. Sign screen provides login functionality. If a customer is an exhibition organizer, the system displays list of prospective visitors and existing visitors for an exhibition which the organizer hosts. If a customer is an exhibitor, the system provides booth information that he/she registers in an exhibition or if a customer is a visitor, the system displays list of exhibitions and booths which the visitor is more likely to see.

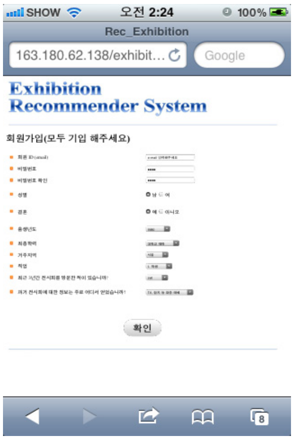
6. Experimental Evaluation

In this chapter, we evaluate the performance of the proposed methodology through developing the website to implement the experiments (see <Figure 6>). Using this website, we collected the real data and surveyed the users' reaction to recommendations.

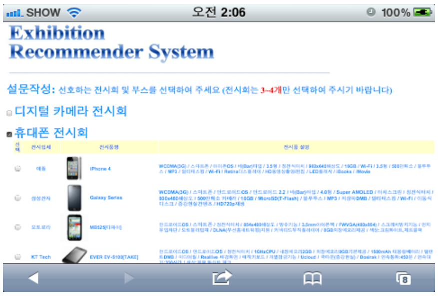
〈Figure 6〉 Main Screen of Exhibition Recommender System

6.1 Data Set

To carry out an experiment, we collected real transaction data from our website http://163.180.62.138. We conducted a survey for collecting transaction data on 220 exhibit booths of 11 exhibitions, and the users' reaction to the results of recommendations. The data is collected from 21st November 2010 to 6th January 2011. <Figure 7> shows the webpage to input user data and transaction data.



(a) Screen for Sign Up

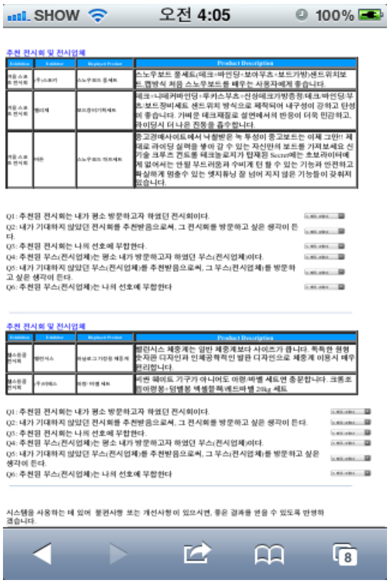


(b) Screen for Exhibitions and Exhibit Booths

〈Figure 7〉 Screens for Collections of Input Data

We collected member ID, age, gender, major and so on. Especially, e-mail as member ID is required to preserve privacy. In next step, users input the exhibitions and exhibit booths information that they experienced or preferred. This information was used to make user-based profile.

We received a total of 14 responses (35.9% of the experimental users) through survey to contain four questions such as checking the degree of satisfaction with the recommended exhibition and exhibit booths, and of novelty and serendipity. This survey was conducted in real time when the input data was collected. <Figure 8> shows the evaluation webpage.



<Figure 8> Screen for Evaluation

6.2 Evaluation Metrics

An exhibition recommender system supports exhibition decision making through the personalized recommendation. Therefore many researchers have measured the accuracy of the recommender system using metrics such as mean absolute error, recall and precision to evaluate success of the system [Good et al., 1999; Sarwar et al., 2000; Sarwar et al., 2001; Ahn et al., 2004; Herlocker et al., 2004; Kim et al., 2009].

However, good accuracy of the recommender system doesn't always mean the success of the system. For instance, the accuracy may increase if the popular items are recommended to a customer, but the customer will not be satisfied with the recommendation because it is obvious. That is, matching consumers with the most appropriate item is key to enhancing user satisfaction considering the novelty of the recommendation [Koren et al., 2009]. Thus we adopt the customer evaluation, which is the method to explicitly require the customer's feedback, to evaluate our proposed system.

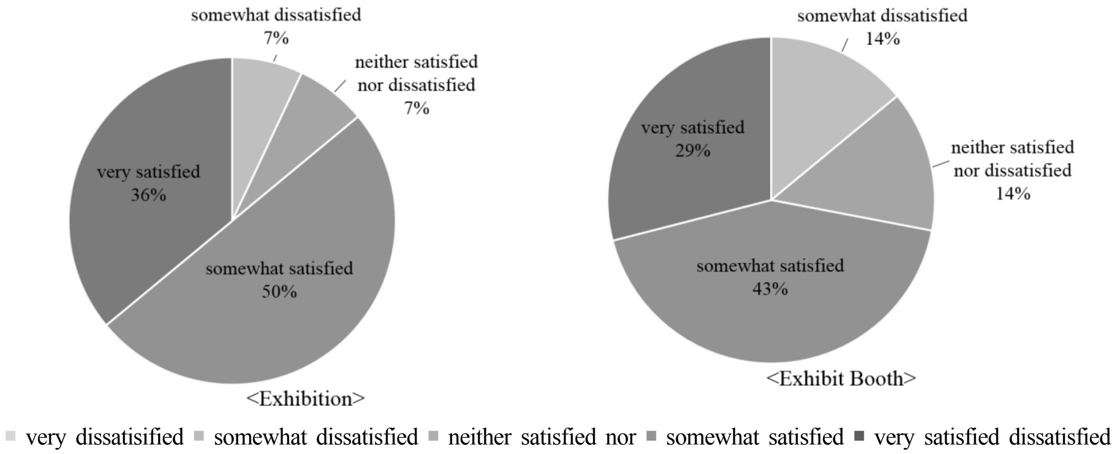
There are two research questions that we are interested in answering about the improvement of customer satisfaction through the novel and serendipitous recommendation. Satisfaction was measured on five-point scales (5 = 'very satisfied,' 4 = 'somewhat satisfied,' 3 = 'neither satisfied nor dissatisfied,' 2 = 'somewhat dissatisfied,' and 1 = 'very dissatisfied') to answer the question

- How well does the exhibition recommendation coincide with your preferences?
- How much does the exhibition recommender system provide the novel and serendipitous information?
- Obvious exhibition recommendation doesn't give user new information because he/she already has already been interested in the recommended information. But the more novel and serendipitous the exhibition recommendation, the higher the probability

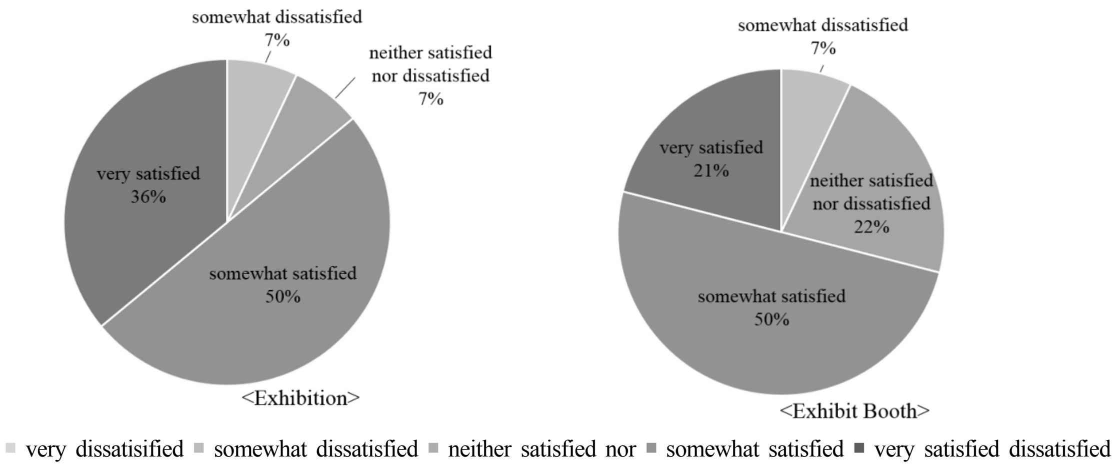
that the user will find the surprisingly interesting information he/she might not have discovered yet. Accordingly, we expect that our proposed methodology will provide the user with the novel and serendipitous recommendation information.

6.3 Experimental Results and Discussions

This section presents experimental results, recommendation quality of the proposed methodology in terms of satisfaction of recommendation and, novelty and serendipity. In total, 14 users were included in the evaluation, and in terms of recommendation quality they were asked to rate the appropriateness of their personalized recommendations. The results are presented in <Figure 9>, and are mostly positive about the recommended exhibition and exhibit booths, despite a few who were less than impressed.



(a) Satisfaction for Recommendation



(b) Novelty and Serendipity

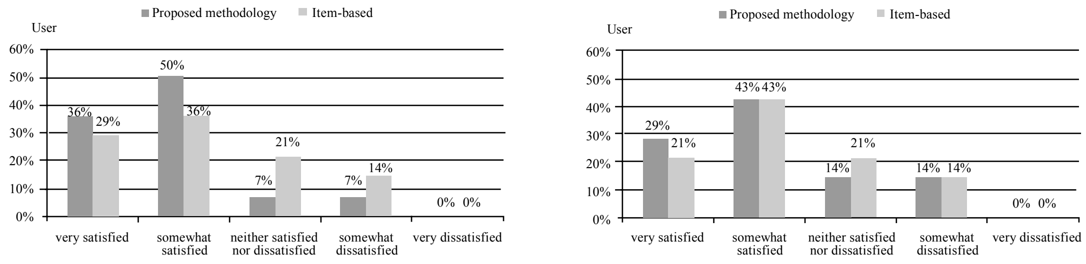
〈Figure 9〉 Personalization Quality

The personalized recommendation contained 1 exhibition, and between 1 and 3 exhibit booths and approximately 85% of users rated the quality of these recommendations as satisfactory or good. Further, over 86% of users rated that this system provides novelty and serendipity on exhibition and exhibit booth. Accordingly, we can see that the proposed system automates word-of-mouth communication.

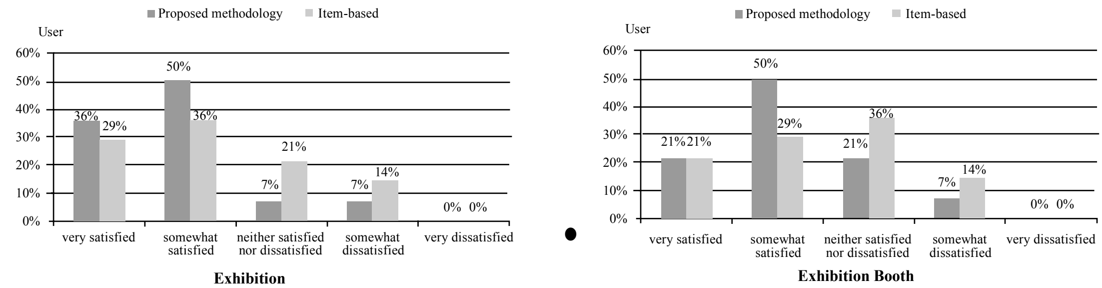
A second experiment was performed to evaluate the relative satisfaction, and novelty and serendipity of the proposed methodology and item-based CF as a benchmark used in *Exhibition Recommender System*. The results are presented in <Figure 10> and show the proposed methodology consistently outperforms the item- based CF. For example the proposed methodology produces approximately 86% of good recommendation per exhibition, compared to 65% for the item-based CF, whereas both of these techniques have not significantly different quality of booth recommendation.

Further, the recommender system using the proposed methodology helps the user find a surprisingly interesting item (exhibition or exhibit booth) he/she might not have otherwise discovered, compare to item-based CF. For example, approximately 86% and 71% of users rated that the proposed methodology provides novelty and serendipity on exhibition and exhibit booth whereas approximately 65% and 50% of users rated that the item-based CF provides novelty and serendipity on exhibition and exhibit booth.

In summary, our experiments showed that the proposed methodology is better than the item-based CF and have an effect on the choice of exhibition or exhibit booth through automation



(a) Satisfaction for Recommendation



(b) Novelty and Serendipity

<Figure 10> Comparison of Personalization Quality

of word-of-mouth communication.

7. Conclusion

The exhibition industry is characterized by the "Three Highs-high growth potential, high added-values, and highly beneficial innovations"; the "Three Larges-large output, large opportunities for employment, and large industry associations"; and the "Three Advantages-advantage over other industries in human resources, technological know-how, and the efficient utilization of assets." Today, countries all over the world hold exhibitions as a means to stimulate national economic development. In such a competitive environment, the success of an exhibition depends on number of customers (visitors and exhibitors).

So far, a lot of studies on exhibition recommender systems have focused on building the suitable guidance to the pre-inputted exhibit booth for visitor's satisfaction. There is no doubt that it is important to satisfy visitors. However, it is also important to acquire new visitors for successful opening of an exhibition. Accordingly, we proposed not only a methodology for acquiring the prospective visitors and satisfying the visitors, but also system architecture for the proposed methodology. This paper has three principle aspects.

First, it provides a methodology based on the principle of collaborative filtering for identifying and acquiring the prospective visitors of the exhibition, and for recommending the adequate booth information of the exhibition to the prospective visitors' preferences. Second, it proposes three-tier architecture for the suggested methodology. The first tire is related to the application for visitors. The middle tier is composed of the http server and the recommender server. The third tier is the database server for managing the data. Finally, a prototype system was developed the feasibility of the proposed architecture

To verify the personalization quality of *Exhibition Recommender System* by the proposed methodology, we carried out a user evaluation in terms of satisfaction of recommendation and, novelty and serendipity. Our experiments showed that the proposed methodology is better than the item-based CF and have an effect on the choice of a visitor's exhibition through automation of word-of-mouth communication.

However, there are some promising issues for future research. We hope to develop a more elaborate methodology to compare our suggested methodology with one of outstanding approaches. And we hope to conduct a real campaign to visitors using our methodology and to evaluate the performance. Finally, we should make experiments using a large number of samples in order to verify the value of the proposed methodology deeply.

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