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A Bayesian Approach for Personalized Booth Recommendation

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***Abstract*— The applications of new information and communication technologies in the exhibition industry provide lots of opportunities for improving value of exhibition service. Especially exhibit organizers can help the visitors to find the information they are looking for through a recommender system using the ubiquitous technologies. However, existing recommender systems in the ubiquitous exhibition environment can't reflect a visitor's dynamic preference since those systems utilize information of the pre-inputted exhibit booths. Therefore, we suggest a recommendation methodology for tour guidance modeled by a Bayesian network in the ubiquitous exhibition environment. A Bayesian network can reflect a visitor's dynamic preference on the exhibit booths over time. We expect that the proposed methodology will be stable and accurate to identify the visitor's dynamic preference and to recommend the exhibit booth.**

Keywords-component; Recommender system; Bayesian network; Exhibit booth recommendation

I. INTRODUCTION

An exhibition (i.e., trade fairs), which is defined as displaying exhibitors' products to visitors and the press [2][8], contributes to the economy in many countries. In addition, the exhibition industry plays an important role as the effective sales and marketing tools [13]. However, the exhibition industry recently stands at the crossroads of change by the advent of new information and communication technologies. Thus exhibition organizers have to continuously seek and adopt new technologies to generate value for their shows.

The introduction of ubiquitous technologies in the exhibition industry enables exhibition organizers to have a lot of opportunities for improving value of exhibition service. The exhibition organizers can help the visitors to find the information they are looking for and guide them to the exhibit booths they want to see by adoption of the ubiquitous technology. However, the existing recommender systems in the ubiquitous exhibition environment can't reflect a visitor's dynamic preference since those systems utilize information of the pre-inputted exhibit booth.

As a solution to such a problem, we suggest a recommendation methodology based on a Bayesian network for tour guidance in the ubiquitous exhibition environment. First, a Bayesian network is used to reflect a visitor's dynamic preference on the exhibit booth over time because a Bayesian network provides causal influence. Second, context information is used to recommend a suitable exhibit booth to a visitor's preference at the proper time. In this study, location is used as context information.

II. RELATED WORK

A. Recommender system in the exhibition environment

As recommendation service in the exhibition environment, one may refer to service provided for the personalized tour guidance or exhibition. Most of the recommender systems focus on building tour guidance at exhibition hall [1] [14] [10][12]. Those systems use context information for recommending proper tour guidance to a visitor's preference at the proper time. For example, CyberGuide [1], which is a mobile context-aware tour guide, provides visitors with route and direction based on their location and orientation. C-Map [14], which is the context-aware mobile assistant project, provides visitors with tour guidance based on location and individual interests at exhibitions. mEXPRESS [10], which is a part of a European-funded project for supporting and facilitating the professional exhibition industry in a context-aware manner, offers a navigation plan based on visitors' location. And Wireless Exhibition Guide [12] provides navigation service for reaching a visitor-defined point at exhibition.

Some recommender systems focus on providing the personalized exhibition. Cornelis et al [5] proposed a methodology for recommending trade exhibition. It adopts fuzzy logic for capturing the relationships between users and items. Guo and Lu [6] developed Smart Trade Exhibition Finder for suggesting the suitable international trade exhibition to particular businesses by integrating the techniques of semantic similarity and the traditional collaborative filtering.

However, the existing recommender systems in the exhibition environment are static since they utilize the pre-inputted exhibit booth. Therefore they need to reflect a visitor's dynamic preference on the exhibit booth over time.

B. Recommender system using Bayesian network

A Bayesian network is a probabilistic graph model for relationships among a set of objects [7]. That is, a Bayesian network provides causal relationship by the Bayes' rule.

As an example, suppose there are five variables *A*, *B*, *C*, *D* and *E*. Let us assume that the conditional distribution is given as follows;

$P(C|A)=2/3$, $P(C|B)=1$, $P(D|A)=1/2$, $P(E|C)=1$

The structure of the Bayesian network is shown in Fig 1. The circles correspond to the variables and the arrows indicate transition probabilities from one variable to other variable. For example, the transition probability from variable *A* to variable *C* is 2/3 but the transition probability from variable *A* to variable *D* is 1/3

A Bayesian network has used in the studies of the recommender systems. These studies show that a Bayesian network provides a flexible method for a visitor's behavior prediction [3][4][9][15]. Therefore, we adopt a Bayesian network to discover the exhibit booth that visitor is more likely to see at the time T based on his/her previous behavior in the exhibition environment.

III. METHODOLOGY

A. Overview

Our study assumes the ubiquitous exhibition environment which can track the locations and routes of the visitors in real-time. Thus a visitor is able to receive information of the suitable exhibit booth to his/her preference through the ubiquitous device.

The underlying key concept of our proposed methodology is adopted from the work on analyzing a visitor's behavior over time. A Bayesian network model is adopted to analyze a visitor's behavior. In general, a Bayesian network provides the casual influence among a set of objects. Therefore, we are able to predict the visitor's behavior at the specific time. In other word, a finite number *m* of the preceding exhibit booths is used to identify the visitor's behavior and then recommendation of the exhibit booth for a target visitor is made at the time *T*.

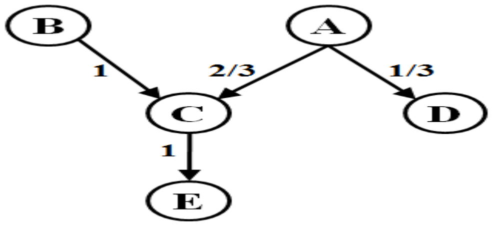

Figure 1. An Example of a Simple Bayesian Network Structure.

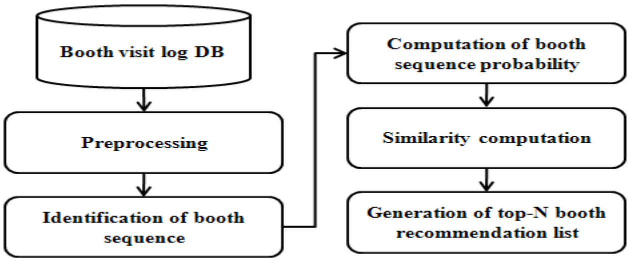

Figure 2. Overall Procedure

The proposed methodology consists of the following five steps shown in Fig 2. In the first step, we preprocess data to be collected from the ubiquitous exhibition environment for extracting a visitor's preference on the exhibit booth. We assume that the time spent in front of the particular exhibit booth is the crucial indicator [11]. In the second step, we identify the visitors' behavior sequences as time passes. These visitors' behaviors are profiled as a trajectory, which makes it possible to track the dynamics of visitors' behaviors. In the third step, Bayesian probabilities are calculated based on the trajectory of visitors' behaviors. And then we construct Bayesian networks using the trajectory. In the fourth step, we compute similarity between trajectory of the target visitor and that of the others during the previous *m* exhibit booths before *T*. And then, we generate the top-*N* exhibit booths that the target visitor is most likely to see in the Bayesian network.

B. Preprocessing

We identify a visitor's preference on the exhibit booth in the preprocessing step. In general, the time spent in front of the particular exhibit booth is important to identify a visitor's preference [11]. If the time spent in front of the particular exhibit booth is short, it may be assumed that the visitor doesn't prefer the exhibit booth. Therefore we assume that the visitor is interested in the booth if a visitor spent much time in front of the particular exhibit booth.

As an example, suppose that visitor *i* spent time in front of the exhibit booths as Table I. Let us assume that the visitor *i* is interested in the exhibit booth if the spent time is over 500 seconds. Then, the visitor *i* prefers the exhibit booths B_2, B_3, B_5 and B_6 because the spent times in front of the exhibit booth B_1, B_2, B_3, B_4, B_5 and B_6 are 119 seconds, 655 seconds, 839 seconds, 299 seconds, 659 seconds and 1721 seconds, respectively.

TABLE I. AN EXAMPLE OF THE TIME WHICH VISITOR *I* SPENT IN FRONT OF THE EXHIBIT BOOTH

Exhit booth_ID	Entrance	Departure
B_1	10:08:10	10:10:09
B_3	10:21:41	10:35:40
B_5	10:42:01	10:53:00
B_2	10:10:41	10:21:36
B_4	10:36:41	10:41:40
B_6	10:54:30	11:23:11

C. Identification of visitors' behavior trajectory

All visitors have a behavior trajectory based on the previous exhibit booth. That is, exhibit booth which a visitor will see at the time *T*, depends on context consisting of a finite number *m* of the preceding exhibit booths.

We assume that an exhibition consists of *q* booths as follows;

$$B = \{B_1, B_2, ..., B_q\} \tag{1}$$

Let R_i be the behavior trajectory of the visitor *i*. Behavior trajectory of the visitor *i* is define as follow;

$$R_i =< B_{i,T-m}, ..., B_{i,T-1}, B_{i,T} > \tag{2}$$

$$where \quad B_{i,T-k} \in B, \quad k = 0,1,2,..., m, \quad , m \geq 0$$

For example, the behavior trajectory of the visitor *i*, R_i, is < B_2, B_3, B_5, B_6>. If *m*=2 then the previous two exhibit booths is used to calculate a Bayesian probability. That is, it means that if the visitor *i* first saw B_2 and second saw B_3, probability that he/she will see B_5 next is high or if the visitor *i* first saw B_3 and second saw B_5, probability that he/she will see B_6 next is high.

D. Computation of exhibit booth sequence probability

We use a Bayesian probability to calculate probability that a visitor will see the specific exhibit booth at the time *T* because probability to see the specific exhibit booth, depends upon the previous *m* exhibit booths,

Let *BP* be Probability to see the exhibit booth at the time *T*, given the previous m exhibit booths. Then *BP* is defined as follow;

$$BP = P(B_T \mid B_{T-m}, ..., B_{T-1}) \tag{3}$$

$$where \quad B_{T-k} \in B, \quad k = 0,1,2,..., m, \quad m \geq 0$$

However, there is a scalability problem if all the Bayesian probabilities are computed. Object of this study is to recommend exhibit booth to a target visitor at the time *T* when the target visitor saw an exhibit booth at the time *T*-1. Accordingly, we modify *BP* as follow;

$$BP = P(B_T \mid B_{T-m}, ..., B_{T-1}) \tag{4}$$

$$where \quad B_{T-k} \in B, \quad , \quad k = 0, 1, 2, ..., \quad m, \quad m \geq 0,$$

$$but \quad B_{T-1} = B_{t,T-1}$$

E. Similarity Computation

To predict a target visitor's behavior trajectory, it is necessary to know the degree to which the behavior trajectory of the target visitor during is similar to the conditional part of the *BP*.

Let R_t be the behavior trajectory of the target visitor *t* and *BC* be a conditional part of the *BP*. R_t and *BC* for the previous *m* exhibit booths is define as follows;

$$R_t =< B_{t,T-m}, ..., B_{t,T-1} > \tag{5}$$

$$BC =< B_{T-m}, ..., B_{T-1} > \tag{6}$$

We define the similarity between R_t and *BC* as follows;

Let *RS*(*BC*, R_t) be similarity between *BC* and R_t.

$$RS(BC, R_t) = \sum_{k=1}^{m} S_{T-k} \tag{7}$$

$$S_{T-k} = \begin{cases} (1/2)^k & if \quad BC_{T-k} = B_{t,T-k} \\ 0 & otherwise \end{cases}$$

The above definition indicates that, if the previous k^{th} exhibit booth in the behavior trajectory of a target visitor *t* is equal to the previous k^{th} exhibit booth of the conditional part of *BP*, then S_{T-k} is $(1/2)^k$ but is otherwise equal to zero.

F. Generation of top-N exhibit booth recommendation list

For each target visitor, this step involves a top-*N* recommendation list of exhibit booths that the target visitor is more likely to see in the exhibition environment.

We generate the top-*N* recommendation list based on *BVLS*(t,B_q), which denotes booth visit likelihood score of the target visitor *t* for the exhibit booth *q*. We compute the *BVLS* as follows;

$$BVLS(t, B_q) = \sum\{BP \times RS(BC, R)\} / \sum RS(BC, R_t) \tag{8}$$

where *BP* is a Bayesian probability that a target visitor *t* will see the exhibit Booth *q* at the time *T.*

The higher the *BVLS*, the higher probability that a visitor will see the exhibit booths. Therefore, we sort the exhibit booths according to their *BVLS* and return *N* booths with the high *BVLS* as the recommendation set

IV. ILLUSTRATIVE EXAMPLE

To help understanding of the proposed methodology, we present a simple example of exhibit booth recommendation in ubiquitous exhibition environment. We suppose that there are six visitors and ten exhibit booths. And we assume the each visitor saw exhibit booths as shown in Table II.

TABLE II. LOG DATA OF EACH VISITOR

Visitor ID	Exhit booth ID	Entrance	Departure
U_{001}	B_3	10:08:10	10:19:00
	B_4	10:19:10	10:28:20
	B_5	10:29:10	10:47:50
	B_6	10:48:00	11:18:00
	B_7	11:20:00	11:29:00
U_{002}	B_1	9:10:25	9:19:30
	B_2	9:21:30	9:37:10
	B_3	9:41:10	9:49:20
	B_9	9:50:10	10:08:13
	B_4	10:08:23	10:17:05
	B_5	10:17:17	10:27:43
	B_6	10:28:51	10:38:30
	B_{10}	10:39:45	10:50:13
	B_8	10:50:59	10:51:04
U_{003}	B_1	9:16:23	9:26:33
	B_5	9:28:51	9:37:13
	B_6	9:38:47	9:48:00
	B_4	9:48:11	9:51:58
	B_9	9:55:41	10:04:02
U_{004}	B_1	10:03:16	10:08:23
	B_2	10:08:57	10:17:25
	B_3	10:18:27	10:24:00
	B_4	10:25:19	10:35:28
	B_5	10:36:33	10:47:12
	B_6	10:47:11	10:59:12
	B_7	11:01:11	11:18:12
U_{005}	B_2	11:02:03	11:07:38
	B_1	11:07:47	11:23:21
	B_5	11:23:27	11:34:05
	B_6	11:35:19	11:47:04
	B_8	11:48:49	11:58:19
U_{006}	B_1	10:20:27	10:33:10
	B_2	10:34:10	10:39:20
	B_3	10:40:20	10:48:53
	B_4	10:49:03	10:58:01
	B_5	10:58:17	11:07:43
	B_6	11:13:01	11:33:31
	B3	11:36:45	11:45:13

TABLE III. EACH VISITOR'S PREFERENCE ON THE EXHIBIT BOOTH

Visitor ID	Exhit booth ID	Entrance	Departure
U_{001}	B_3	10:08:10	10:19:00
	B_4	10:19:10	10:28:20
	B_5	10:29:10	10:47:50
	B_6	10:48:00	11:18:00
	B_7	11:20:00	11:29:00
U_{002}	B_1	9:10:25	9:19:30
	B_2	9:21:30	9:37:10
	B_9	9:50:10	10:08:13
	B_4	10:08:23	10:17:05
	B_5	10:17:17	10:27:43
	B_6	10:28:51	10:38:30
	B_{10}	10:39:45	10:50:13
U_{003}	B_1	9:16:23	9:26:33
	B_5	9:28:51	9:37:13
	B_6	9:38:47	9:48:00
	B_9	9:55:41	10:04:02
U_{004}	B_2	10:08:57	10:17:25
	B_4	10:25:19	10:35:28
	B_5	10:36:33	10:47:12
	B_6	10:47:11	10:59:12
	B_7	11:01:11	11:18:12
U_{005}	B_1	11:07:47	11:23:21
	B_5	11:23:27	11:34:05
	B_6	11:35:19	11:47:04
	B_8	11:48:49	11:58:19
U_{006}	B_1	10:20:27	10:33:10
	B_3	10:40:20	10:48:53
	B_4	10:49:03	10:58:01
	B_5	10:58:17	11:07:43
	B_6	11:13:01	11:33:31
	B_3	11:36:45	11:45:13

TABLE IV. BEHAVIOR TRAJECTORY OF EACH VISITOR WHEN M=3

Visitor_ ID	*T*-3	*T*-2	*T*-1	*T*
U_{001}	B_3	B_4	B_5	B_6
	B_4	B_5	B_6	B_7
U_{002}	B_1	B_2	B_9	B_4
	B_2	B_9	B_4	B_5
	B_9	B_4	B_5	B_6
	B_4	B_5	B_6	B_{10}
U_{003}	B_1	B_5	B_6	B_9
U_{004}	B_2	B_4	B_5	B_6
	B_4	B_5	B_6	B_7
U_{005}	B_1	B_5	B_6	B_8
U_{006}	B_1	B_3	B_4	B_5
	B_3	B_4	B_5	B_6
	B_4	B_5	B_6	B_3

TABLE V. BEHAVIOR TRAJECTORY OF EACH VISITOR WHEN $B_{i,T-1}=B_6$

Visitor_ID	*T*-3	*T*-2	*T*-1	*T*
U_{001}	B_4	B_5	B_6	B_7
U_{002}	B_4	B_5	B_6	B_{10}
U_{003}	B_1	B_5	B_6	B_9
U_{004}	B_4	B_5	B_6	B_7
U_{005}	B_1	B_5	B_6	B_8
U_{006}	B_4	B_5	B_6	B_3

A. *Preprocessing*

To infer visitors' preference on the exhibit booth, we assume that the each visitor is interested in the exhibit booth if the spent time is over 500 seconds. Then, each visitor's preference on the exhibit booth is as shown in Table III.

B. *Identification of visitors' behavior trajectory*

After discovering the each visitor's preference on the exhibit booth, we search all visitors' behavior trajectories based on the previous exhibit booths. Let R_i be the behavior trajectory of a visitor *i*.

$R_{001}=<B_3, B_4, B_5, B_6, B_7>$, $R_{002}=<B_1, B_2, B_9, B_4, B_5, B_6, B_{10}>$

$R_{003}=<B_1, B_5, B_6, B_9>$, $R_{004}=<B_2, B_4, B_5, B_6>$

$R_{005}=<B_1, B_5, B_6, B_8>$, $R_{006}=<B_1, B_3, B_4, B_5, B_6, B_3>$

Exhibit booth, which a visitor will see at the time *T*, depends on context consisting of a finite number m of the preceding exhibit booths. If we assume that a finite number m of the preceding exhibit booths is 3, behavior trajectory of each visitor is as shown in Table IV.

C. *Computation of exhibit booth sequence probability*

Object of this study is to recommend exhibit booth to a target visitor at the time *T* when the target visitor saw an exhibit booth at the time *T*-1. Let the behavior trajectory of a target visitor t be $R_t=<B_3, B_1, B_4, B_5, B_6>$. Because of $m=3$, we only consider $R_t=<B_4, B_5, B_6>$. That is, R_t is $<B_{t,T-3}=B_4, B_{t,T-2}=B_5, B_{t,T-1}=B_6>$. To calculate exhibit boot sequence probability, we use a Bayesian probability. However, we only compute a Bayesian probability when $B_{t,T-1}=B_6$, to solve the scalability problem. In other words, we calculate a Bayesian probability using Table V, which is behavior trajectory of each visitor when $B_{i,T-1}=B_6$

Thus *BP* is as follows;

$$P(B_T = B_3 \mid B_{T-3} = B_4, B_{T-2} = B_5, B_{T-1} = B_6) = 1/4$$
$$P(B_T = B_7 \mid B_{T-3} = B_4, B_{T-2} = B_5, B_{T-1} = B_6) = 2/4$$
$$P(B_T = B_{10} \mid B_{T-3} = B_4, B_{T-2} = B_5, B_{T-1} = B_6) = 1/4$$
$$P(B_T = B_8 \mid B_{T-3} = B_1, B_{T-2} = B_5, B_{T-1} = B_6) = 1/2$$
$$P(B_T = B_9 \mid B_{T-3} = B_1, B_{T-2} = B_5, B_{T-1} = B_6) = 1/2$$

The structure of a Bayesian network is shown in Fig 3.

D. *Similarity Computation*

When $R_t=<B_{t,T-3}=B_4, B_{t,T-2}=B_5, B_{t,T-1}=B_6>$, the similarity between R_t and *BC* as follows;

$$RS(<B_{T-3} = B_4, B_{T-2} = B_5, B_{T-1} = B_6>, R_t) = 7/8$$
$$RS(<B_{T-3} = B_1, B_{T-2} = B_5, B_{T-1} = B_6>, R_t) = 3/4$$

Accordingly, we find that $RS(<B_{T-3}=B_4, B_{T-2}=B_5, B_{T-1}=B_6>, R_t)$ is higher than $RS(<B_{T-3}=B_1, B_{T-2}=B_5, B_{T-1}=B_6>, R_t)$.

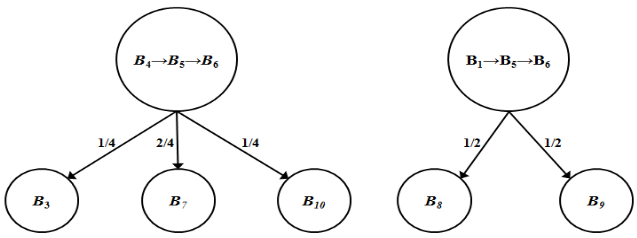

Figure 3. A Bayesian Network when $B_{i,T-1}=B_6$

TABLE VI. BVLS

B_3	B_7	B_8	B_9	B_{10}
0.219	0.438	0.375	0.375	0.219

E. Generation of top-N exhibit booth recommendation list

After computing the similarity between R_t and *BC*, we calculate *BVLS* to generate a top-*N* recommendation list of exhibit booths that the target visitor is more likely to see.

The *BVLS* is represented in Table VI. Suppose that the size of the recommendation is 3. As the result, exhibit booths B_7, B_8 and B_9 are selected as the recommendation set because the exhibit booths have high *BVLS*s.

V. Experimental Evaluation

We collected total 160 customers' real visit data at the Kid & Edu Expo 2010 from 4th November 2010 to 6th November 2010 in Korea. We employed 10-fold cross validation approach and F1 measure for our test. In 10-fold cross validation, the initial data are randomly partitioned into 10 mutually exclusive subsets which have approximately equal size. Training and testing is performed 10 times.

Our experimental results are shown in Figure 4. An interesting observation from Figure 4 is that performance of recommendation improves as we increase the number of *m* size, and is good regardless of the number of *m* size when top-*N* size is 2. We can see that recommendation based a Bayesian network reflects the visitor's dynamic preference and is applied to ubiquitous device with small screen size.

VI. Conclusion and Future Work

The existing recommender systems in the exhibition environment are static since they utilize the pre-inputted exhibition or exhibit booth. Therefore they need to reflect the visitors' dynamic preference on the exhibit booth over time. To address this problem, we suggest a recommendation methodology based on a Bayesian network because a Bayesian network provides causal relationship. The methodology is composed of five steps; preprocessing of booth visit log, identification of booth sequence, computation of booth sequence probability, Similarity computation and generation of a top-*N* booth recommendation list.

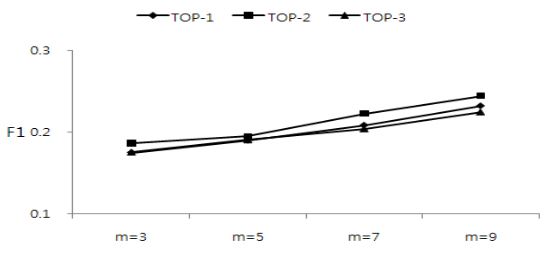

Figure 4. Impact of *m* Size at Each Top-*N*

The proposed methodology is expected to offer the adequate recommendation booth to visitor's preference in the ubiquitous exhibition environment. As future work, we plan to compare our suggested methodology with one of outstanding approaches.

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