Museum Layout Evaluation Based on Visitor Behavior and Visiting Suggestion under Time Constrain

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Abstract

This paper proposed methods to evaluate the visitor path and suggested visiting routes by using collected statistical information from visitor. As every museum employs a unique method for arranging exhibits; it is unhelpful to devise specific best practices that are applicable across the industry. However, by tracking visitor behavior, we can generate statistical data that will yield insights about each visit, most popular attractions, and time spent by each visitor at a given Point of Interest (POI). This information can be used to evaluate the efficacy of exhibition arrangements. Therefore, we proposed methods to analyze visitor behavior in terms of visitor path and the number of visits at each POI versus the time spent at that Point. We create popular path in the museum from the probability of visitor travel from one POI to another. From the collected information, we can assign each POI into one of the following categories: good location and interesting object, good location and uninteresting object, bad location and interesting object, bad location and uninteresting object. These categories can be used to determine recommendations for improving the placement of exhibit layouts. Additionally, this recommendation system can be applied to the generation of exhibit recommendations for visitors. The proposed method was used to evaluate and generate recommendations for the ChaoSamphraya National Museum. Evaluation results reveal a path taken by most visitors, and identifies exhibit items according to our 4-box rubric. We then utilize the visitor path to create a suggestion system featuring the most highlighted object in the museum.

Keywords: visitor behavior analyses, suggestion system, museum mobile application.

1.Introduction

Most national museum in Thailand were erected more than 60 years. Due to a limited budget at the time, most museum had its architecture determined first, and the artifacts were arranged according to available space. The interior of this building is featured with a priceless hall, in which visitors are encouraged to wander. It is an extremely challenging task for the museum curator to arrange exhibits to attract visitors to every object. It is also very subjective to conclude whether any given arrangement is suitable or not, as this can vary by the visitors' interests. Nevertheless, we can analyze current arrangements by observing visitor behavior throughout their visit.Visitor behavior analysis is an established topic of interest for museum operators.

However, tracking the path that visitors take in museum is not an easy task. La-or et al. applied Radio Frequency Identification (RFID) wristbands in an attempt to track visitor movement, but due to the simplicity of the pilot project setup, which utilized only 5 Point of Interest (POI), the study yielded insufficient data for effective behavioral analyses. With the advent of smart phones, the tracking of museum visitors through mobile application has also become possibleas shown in work of Thitipong et al. Target audience behavior can be tracked by the number of hits at each POI, represented by a QR codeor Near Field Communication (NFC), which the mobile application can then use to acquire information about artifacts from museum servers. The curator can analyze the collected information and adjust their exhibits accordingly. Other works such as, Sookhanaphibarn et al .proposed a model called Path And Residing Time display (PARTY) to generate visitor circulation patterns from collected data, represented as 2-Dimensional layout independency visualizations. Although this model presents the density of the visitors at each POI, the sequential relationships between 2 points were left out from the analysis. As an alternative, Krueger et al proposed three different interactive visualization methods to reveal participant movement patterns, deduce behavior from participants' movements, and show transitions between sessions and topics. These diagrams present the movement of each individual participant and the total movements between points were left out. Meanwhile, Takayuki et al. analyses museum visitor trajectories via ubiquitous sensors in a Science Museum in terms of space, visitor patterns and relationships between patterns. Their analysis identifies crowded and uncrowned areas, with typical visitor patterns showing particular focus on highlighted displays such as robots. Xu et al. proposed the creation of a museum visitor guide by using A* path finding Algorithm that assists museum visitors in visiting as many items as possible. Visitors can select items of interest and the system will find the optimum path through the identified target pieces. However, this system does not account for time spent at each POI.

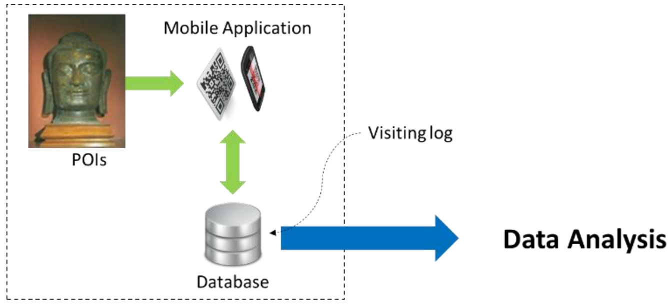
In this paper, we propose a model to analyze visitor behavior with regards to most visited routes, number of visits and time spent at each POI, in an extended model from work of La-or et al. and Pobsit et al. By comparing the two parameters, we divide POI into 4 categories according to two dimensions: location and exhibit quality. These categories can be used to determine optimal layout design. These categories also can be used as the preliminary foundation for suggesting popular POIs to visitor under time constraints. This method has been implemented at Chao Sam Phraya National Museum. Some recommendations on the layout as well as popular POI was issued to curator for further adjustment.The methodology of the proposed system is stated in section 2. The evaluation and discussion of museum paths and suggestion system are explained in section 3. The conclusion is stated in section 4.

2. Methodology

2.1 System Architecture

Thitipong et al. implements a system that generates a web-based function which enables museum curators to participate in mobile application development in terms of content management, as well as museum item management. When the visitor is within the museum facilities and connects to the internal Wi-Fi network, the mobile application connects to the museum database to acquire further details such as floor plans and media items that elaborate on specific displays as shown in Fig. 1. QR codes are used as the primary tool for visitors to access information from databases and displays. Although this system is based on a BYOD (Bring Your Own Device) concept by Proctor, the participating museums are required to provide basic infrastructural elements such as Wi-Fi.

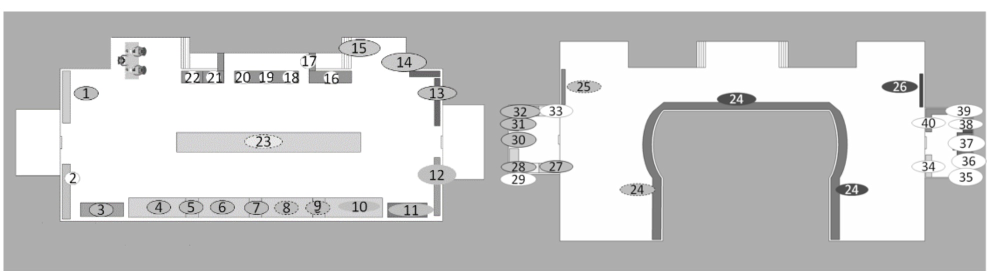
Fig. 1: Diagram of implement mobile application system that keep visiting log for further data when visitor acquire more information about POI via QR-code



Currently, there are three museums involved in this project: The Science Museum, Information Technology Museum, Chao Sam Phraya National Museum. In this paper, we evaluate the behavior of visitors at Chao Sam Phraya National Museum, using various statistics related to each display item to analyze the current layout design. Chao Sam Phraya National Museum is a two-storied building erected since 1957located in AyutthayaProvince as shown in Fig.2. Museum administrators selected 40 POIs to incorporate into the mobile application; the contents of these POIs include photos, diagrams, descriptions, audio files and video. We asked participants to install the mobile application in question during their visit; we then collected information generated by the application users from January 4, 2015 to December 31, 2015, to reach a total of 1,500 persons. With the "museums pool "mobile application we were able to track number of visit per POI as well as the order in which each POI was visited.

Fig. 2. Chao Sam Phraya National Museum at Ayutthaya province

Fig. 3 Floor plan of ChaoSamprаya National Museum



(a) First Floor (b) Second Floor

Fig. 4 The actual installation system at ChaoSamphraya National Museum.

(a) Example of QR code on the first floor (b) Example of QR code on the second Floor

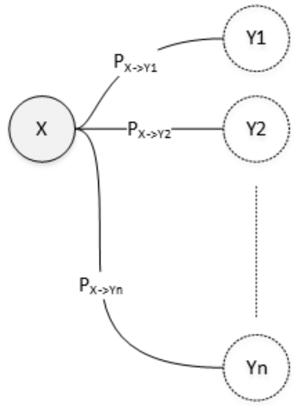
2.2 Model for Visitor Path

In this paper, we estimate the most visit route from the collected data by using the La-or et al. model. There are many possible ways to travel from one POI to another. To simplify the problem, we assume that visitors walk following the number show in the exhibition. Let X be the first POI, therefore there are n POI's [Y_1, Y_2, …, Y_n] around X as shown in Fig. 5. $P_{X\to Yi}$ is the probability of traveling from X to Y_i, calculating from the number of visitor who traveled from X to Y_i divided by the total number of visitor who stopped at X and traveled to all POI's as shown in Eq. 1.

$$P_{X\to Y_i} = \frac{M_i}{\sum_{j=1}^{n} M_j} \qquad (1)$$

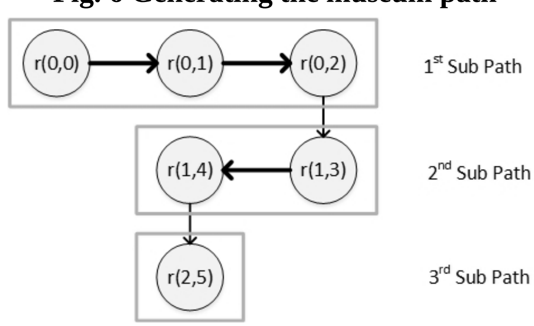
Where $P_{X\to Yi}$ is the probability of $X\to Y_i$and $M_i$is the number of hits from X to Y_i.

Fig. 5 The probability of traveling from *X* to all possible *Y's*



From Eq. 1, we can create a diagram connecting each POI with the probability as shown in Fig. 5. From the diagram, we can generate a popular museum path by choosing the path with most visit or highest probability of travel. Let $X_i \mid i \in \mathbb{N}_0$where X is the POI and i is the position number as shown in the diagram(for example X_3represents POI3 and X_4represents POI4).Let$P_{X_a\to X_b} \mid a, b \in i$ be the probability that a given visitor travels from X_a to X_b. The probability is calculated from the collected data as shown in Fig. 4. Let$R = \{r(m,n) | m, n \in \mathbb{N}_0\}$ be the visiting route, which consist of a set of reference POI, $r(m,n)$, where$m$is number of sub-paths and$n$ is order of visiting POI's.In other words, $R = \{r(0,0), r(0,1), r(0,2), r(1,3), r(1,4), r(2,5)\}$ represents the visiting route consisting of three sub-paths($m_{max} + 1 = 3$) and consist of 6 POI's($n_{max} + 1 = 6$) where sub-path 0 is $r(0,0) \to r(0,1) \to r(0,2)$, sub-path 1 is $r(1,3) \to r(1,4)$ and sub-path 3 is $r(2,5)$, as shown in Fig. 6.

Fig. 6 Generating the museum path

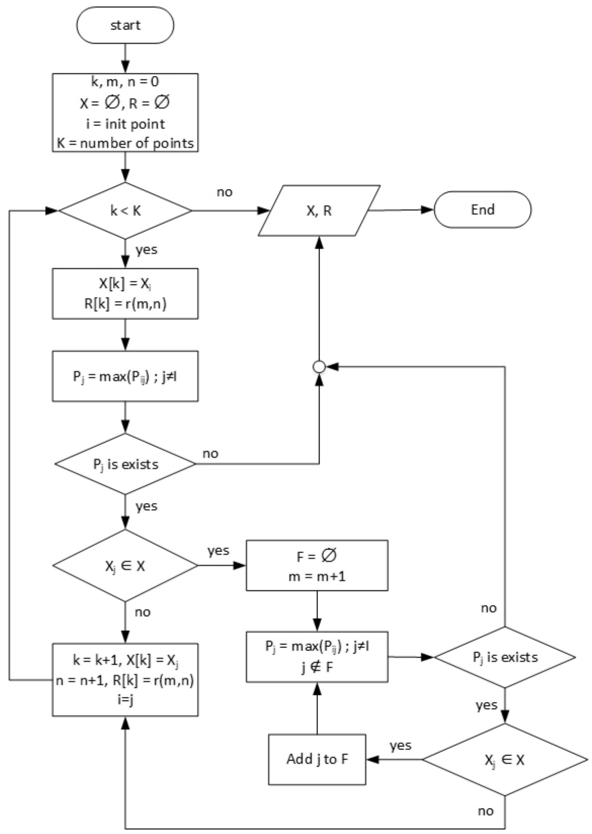


The visitor path can be created by the following flowchart. The proposed model generates the most popular path and represents it in terms of $XandR$. Let $k, m, n \in \mathbb{N}_0$be 0for the initial state.
In order to create any path R,we proposed a method that maps between a POI $X_i$and a reference point $r(m,n)$is needed where m in each$X_i$case is chosen by the following rule:

- Let R_{mode} be the most popular path calculated from the highest probability.
- The current reference visitor position is$r(m,n)$ at POIX_a .
- The next reference visitor position is $r(m, n+1)$ mapped to POI X_k which is $MAX(P_{X_a\to X_k})$ including X_k that was not passed in the path R_{mode} taken thus far.
- In case of no available$X_k$the next reference visitor position$r(m+1, n+1)$ is considered.

- The next reference visitor position $r(m+1, n+1)$maps to $X_{l_1}$where $l_1 \notin \{k\}$ and $MAX(P_{X_a \to X_{l1}})$ including X_{l_1} that was not passed in the pathR_{mode} taken thus far.
- In case of no available$X_{l_1}$the next reference visitor position$r(m+2, n+1)$ is considered and mapping with$X_{l_2}$where $l_2 \notin \{k, l_1\}$ and $MAX(P_{X_a \to X_{l_2}})$includingX_{l_2}that was not in previousR_{mode} .

Fig. 7 Flow chart of creating visitor path



2.3 Model for Layout Evaluation

Normally, museum arrange exhibition in term of time line or similarity of the object. In this paper, we called this arrange as exhibition zone. Each zone contains similarity object or object from the same period. We consider this as a physical constrain. The number of items in each zone are varies depend on the curator suggestion and the space.In order to evaluate the exhibition arrangement, we apply scoring method which is calculated from two parameters;the number of visits accrued at each POI, and the corresponding amount of time spent at that POI. The number of visits is used as representative of the attractiveness of the artifact location, while the time spend is used as representative of visitor interest in the given POI.In each parameter, we classified the POI into two groups according to our criteria.For the number of visits parameter, we apply the average number of visits at the museum (called the global mean, F_{avg}) as a threshold to classify POIs into high number of visits and low number of visits.Nevertheless, by using this threshold, some exhibition zone will consist only low number of visiting POI. In that case that zone might be eliminate from the suggestion item. In our model, each zone should have at least one or two items in the suggestion item. Therefore, we apply another threshold which is the median of number of visits in that zone only, we called the local median (F_{median}).

The second parameter, the time spend, POIs are divided into two group: high time spendand low timespend. We also used the average value of total timespend, the global mean (T_{avg}), as the threshold to divided POI. In order to avoiding some zone, consist only POI that has low timespend, we apply the local median (T_{median}) of each zone as a second threshold. With the two parameters we have identified so far, we can create a matrix as shown in Fig. 8, which classifies POI into 4 categories: A, B, C and D.Category A is defined as the group of POIs with a high number of visits and high time spend. Category B is defined as the group of POI with a high number of visits and low time spend. Category C is defined as the group of POIs with a low number of visits and high time spend. Finally, category D is defined as the group of POIs with a low number of visits and low time spend.

After assign each POI into the 4 categories, then we score POI according to its categories, A= 3, B and C = 1 and D = 0. Then we evaluate each POI by its score.The Flow chart of our method is shown in Fig. 9.

Fig. 8 Matrix of number of visit and time spent.

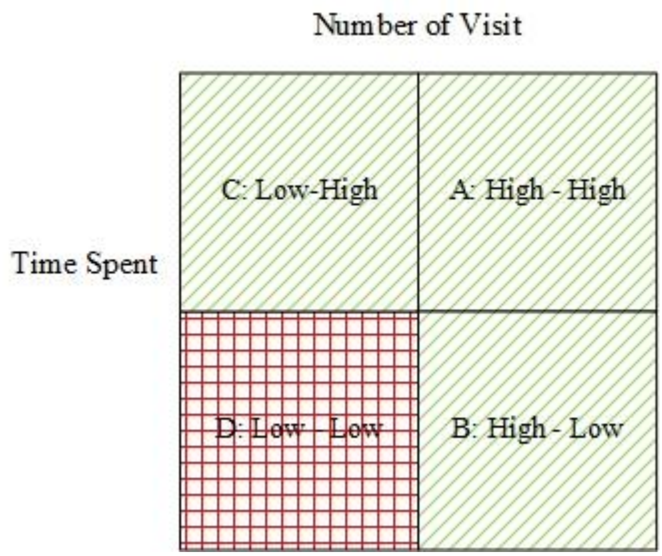
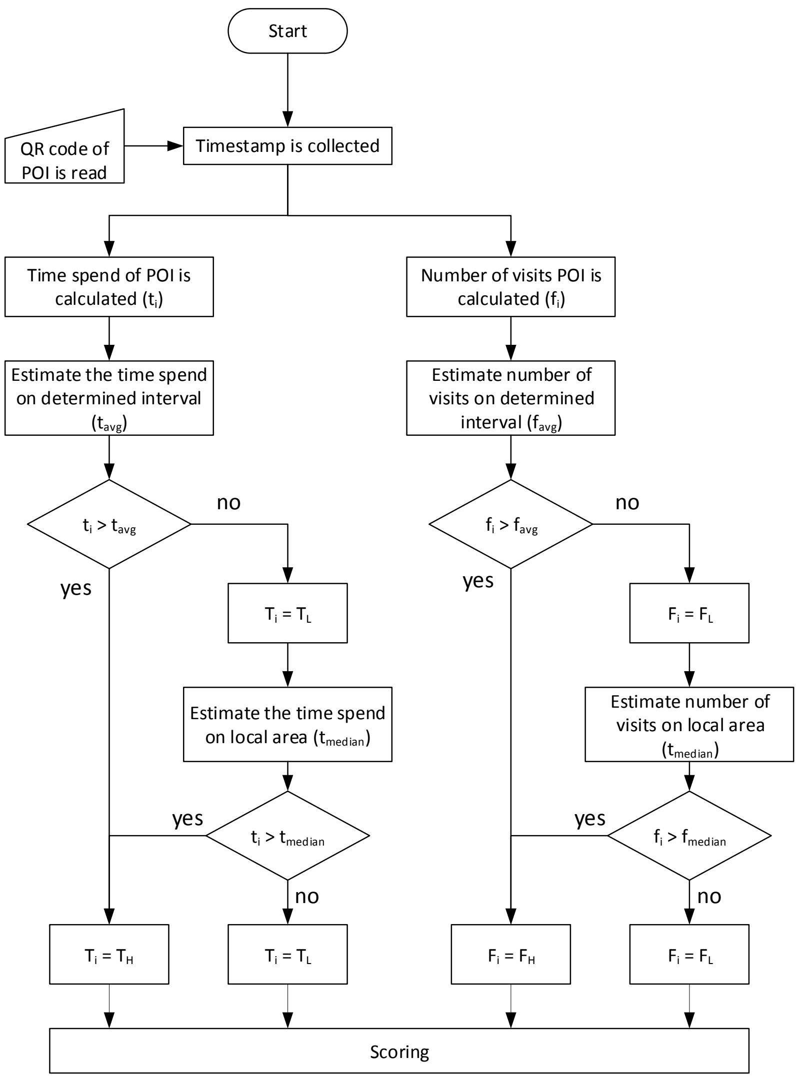


Fig. 9 Flow chart of creating the score for each POI.



After assign each POI into 4 categories, curator can utilize this criterion as a tool to make decision on which POI should be keeping in the exhibition and which one should be opt out.

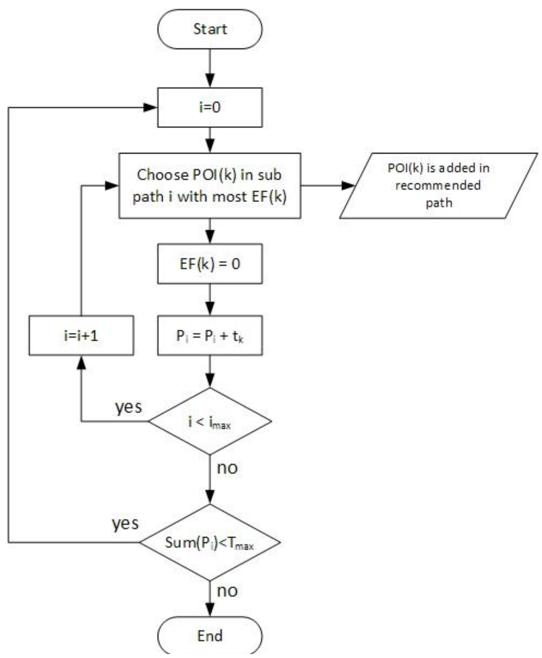
2.4 Model for Visiting Suggestion Based on Time Constrain

The previous sections, we have identified the most visited routes and the POIs with the highest scores. In this section, we will introduce a suggestion system based on the previous results. First, we calculate the effective factor (EF), which is the score of each POI, divided by the average time spent at that POI as shown in Eq. 2. We used this criterion to determine whether this POI will be included in the suggestion route.

$$EF = \frac{POI_{score}}{POI_{timespent}} \qquad (2)$$

To generate a suggested route, we apply the process shown in Fig. 10. We start from the first sub path $i=0$ that we received from section 2.2., then we choose the highest EF of POI in that sub path (i) and add the time spend at that particular POI to the total time spend for this sub path (Pi). Then the process moves to the next sub path and selects the highest EF in the second path. We then add the time spend at that particular POI to the second sub path. We repeat this process until we reach the maximum path possible. Then we sum the time spent in each path. If the total time spend, Sum (Pi), is less than the available set time T_{max}, we then repeat the process of each sub path. If the total time spend, Sum (Pi), is more than T_{max} then we stop the process and provide the recommended path with the available set time constraint.

Fig. 10. Flow chart outlining the process of generating suggested routes.

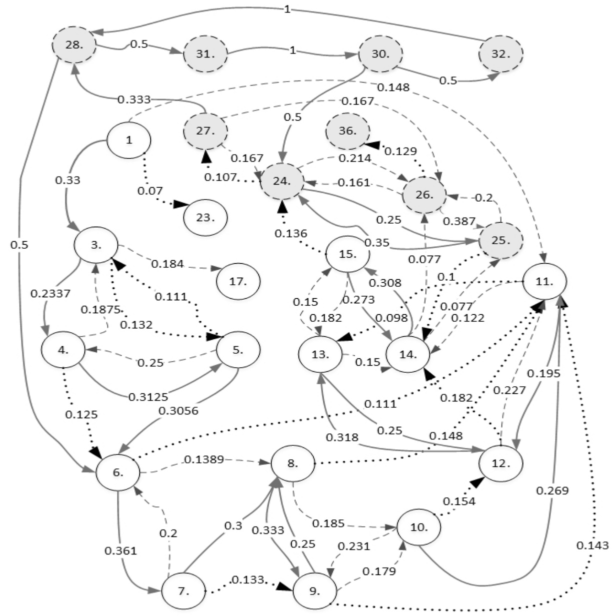


3. Results and Discussion

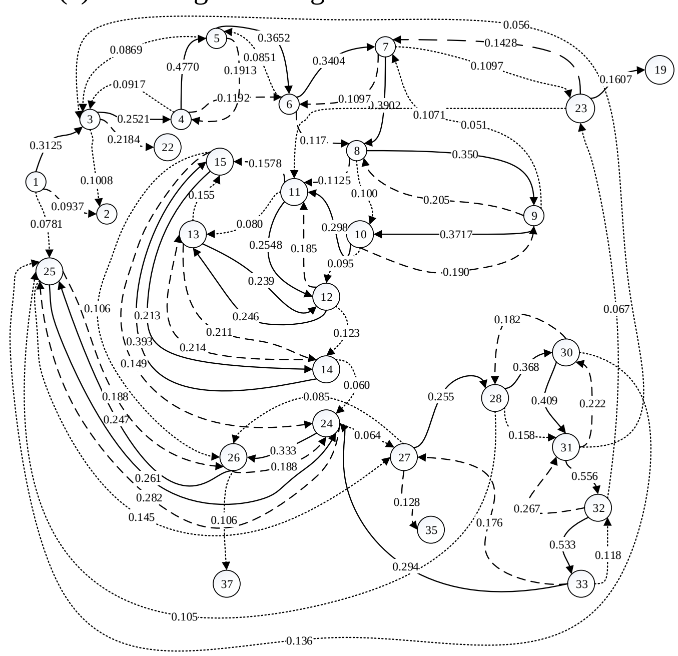
3.1 Model of Visitor Path

We collected visitor log from January 2015 to December 2015. Before we apply our model, some data cleaning is needed. The first step is drawing a diagram of POI which shown three highest probabilities to the next POI, as shown in Fig 11. Each POI is represented by a number; the connected line represents the probability of moving to the next POI. Only 3 highest probabilities are shown in this diagram. The solid line represents the highest probability path, dash line represents the second highest probability path, and dotted line represents the third highest probability path.

Fig. 11 Diagram of probability representing the likelihood of each path from a given POI, showing the 3 highest probability paths



(a) This diagram using 6 months collected data.

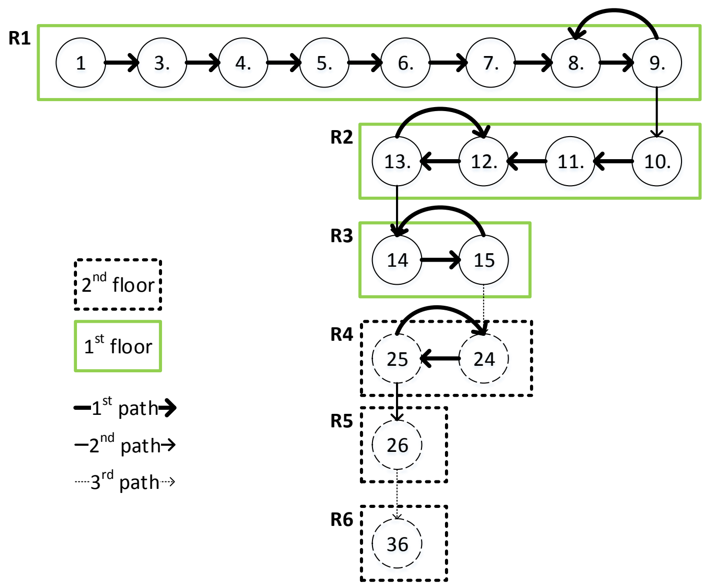


(b) This diagram using 12 months collected data.

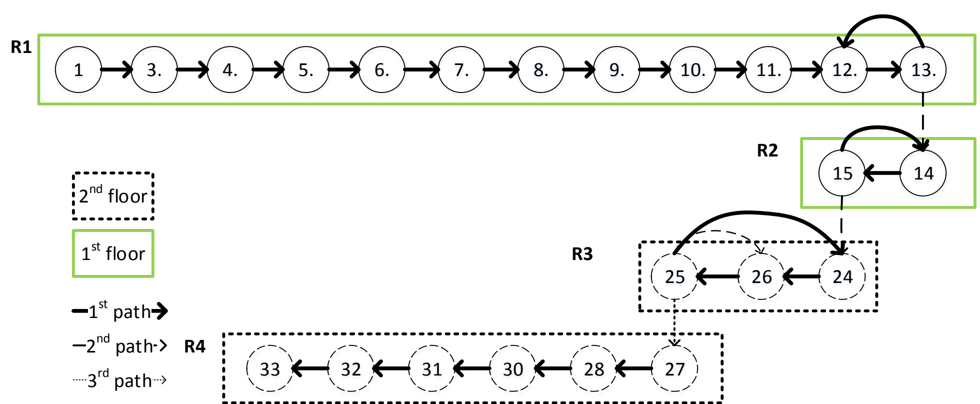
Fig. 11 (a) illustrates the visitor path after collecting data for 6 months [La-or et al 2016]; note that there are 6 sub paths. The visitor path was created from the route of highest probability. Whenever the highest probability is not possible, the second highest probability is chosen to create the second sub path. As seen in Fig. 12 (a), the most popular destination from POI 9 is POI 8, which is already encompassed in the path; therefore, the second highest probability is chosen which is POI 10. It can be seen that the first sub-path ends at POI 9 and the second sub-path starts at POI 10. At this point in our investigation, the number of visitors observed was approximately 164 persons. A possible challenge to be concluded from the results will be whether we have enough data to calculate the route. Another challenge involves the sub path on the second floor, which due to museum policy, cannot be incorporated into the path as visitors are prohibited to take photos in the two small rooms located on both ends of the second floor. Consequently, the visitors rarely view the POI's in the small rooms. Therefore, we have made some adjustments on the second floor to account for these policies, such as creating more visible signs at the entrance of both rooms, and including instructions on how to get information about artifact within those areas.

Fig. 12 (b) shows the visitor path after a year of collecting data. Now the path is longer and consists of 4 sub-paths, R1- R4. Fig. 13 illustrates the visitor path within the museum layout. The results show the consistency of the route along the floor plan of the first floor. On the second floor, the sub-path is longer than the one in the Fig 12 (a). This maybe the result for the adjustments in signage mentioned above.

Fig. 12 Visitor paths from the proposed method

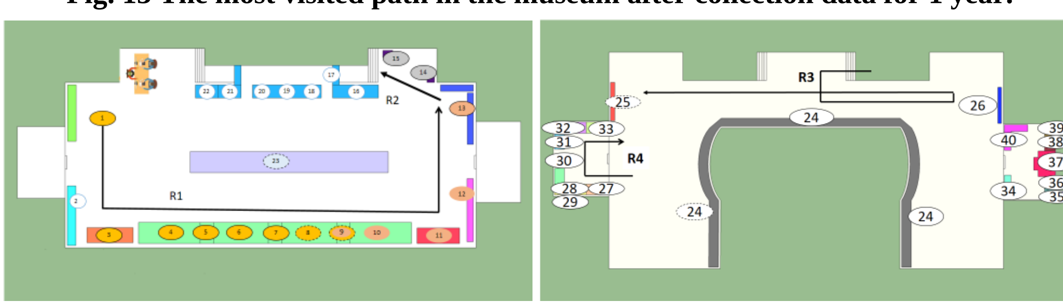


(a) Visitor path after collecting data for 6 months



(b) Visitor path after collecting data for 12 months

Fig. 13 The most visited path in the museum after collection data for 1 year.

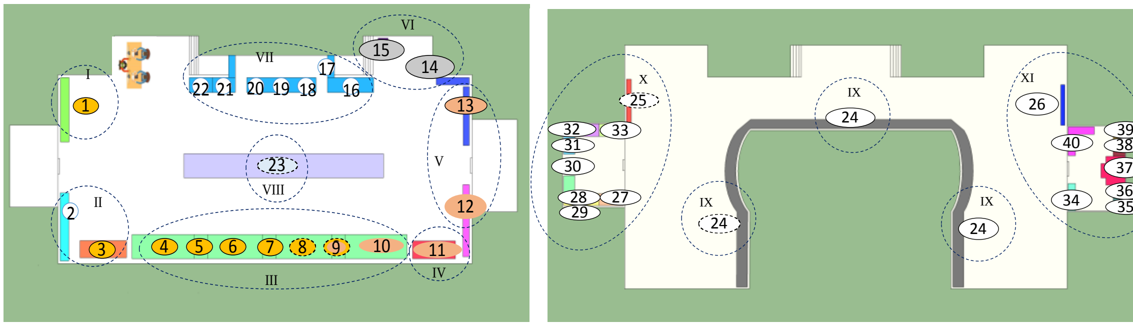


(a) First Floor. (b) Second Floor

3.2 Model for Exhibition Arrangement

Chao Samphraya National Museum has arranged 40 POIs according to the content relevancy of the exhibit as well as its location in Museum, which can be divided into 11 zones as shown in Fig. 14.

Fig. 14 The exhibition arrangement according to content relavancy of the exhibit and its location in museum.



(a) First Floor. (b) Second Floor

We apply the proposed arranging method to the 40 POIs in the Chao Samphraya National Museum. We first divided POI into two group via number of visits parameters by using threshold F_{avg}. The results shown in Fig.15 (a), it can be seen that only half of the POI is fall into the high category. It also can be seen that POI of both zone 10 and zone 11 are in the low number of visits which mean both zones might be eliminate later. Therefore, we apply the second threshold as shown in Fig. 15 (b). Now, at least half of the POI in zone 11 are in high number of visits.

Fig. 15(a) Number of visits at each POI where the red line represents the first threshold F_{avg}.

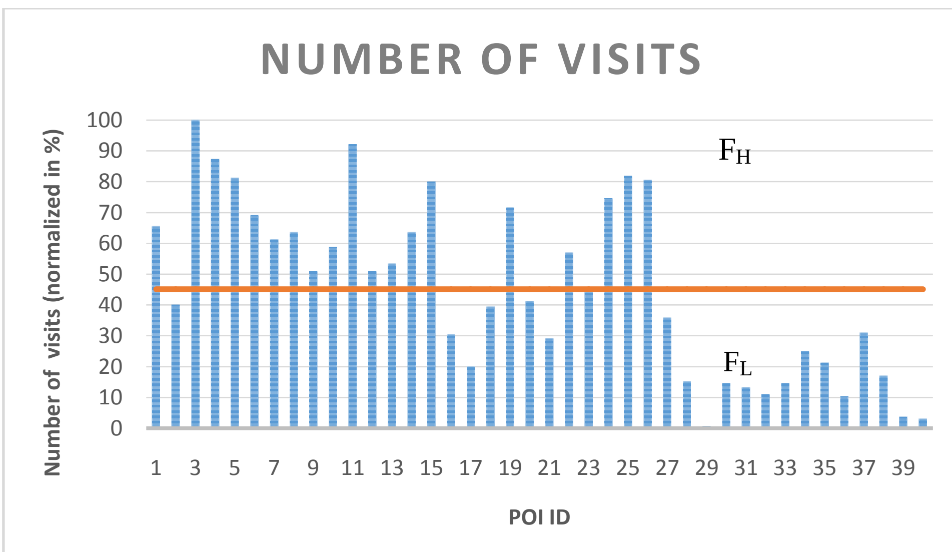
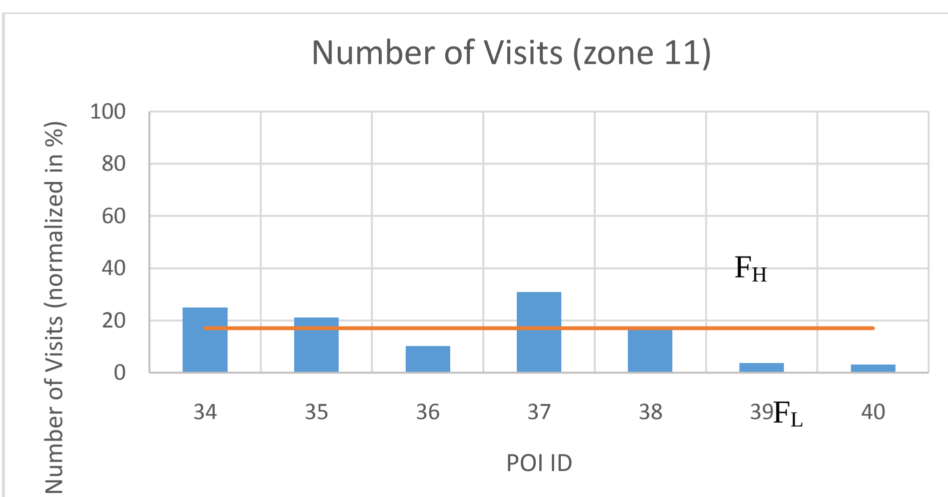


Fig. 15(b) Number of visits at each POI in zone 11 where the red line represents the second threshold F_{median}



For the time spent parameter, average time spent at a given exhibit is divided into 2 groups: higher time spend and lower spend Time as seen in Fig. 16(a).With the first threshold, some zones may display a relatively low time spend. Therefore, we used the median time spend in each zone to re-calculate the relative interest as shown by the example of zone 7 in Fig 16(b). From the previous graph, none POIs are considered high time spend POIs, whereas with the second criteria, we now we have 4 POIs considered as such.

Fig. 16 (a). The time spentat each POI where the red line represents the threshold T_{avg}.

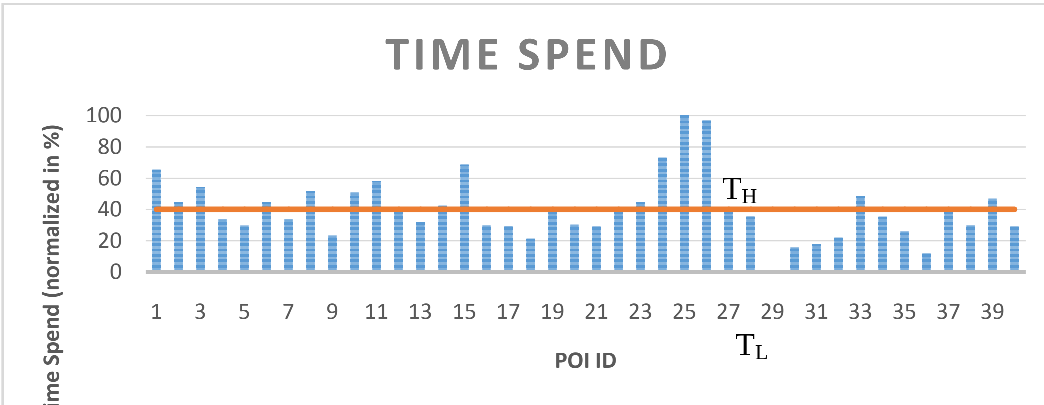
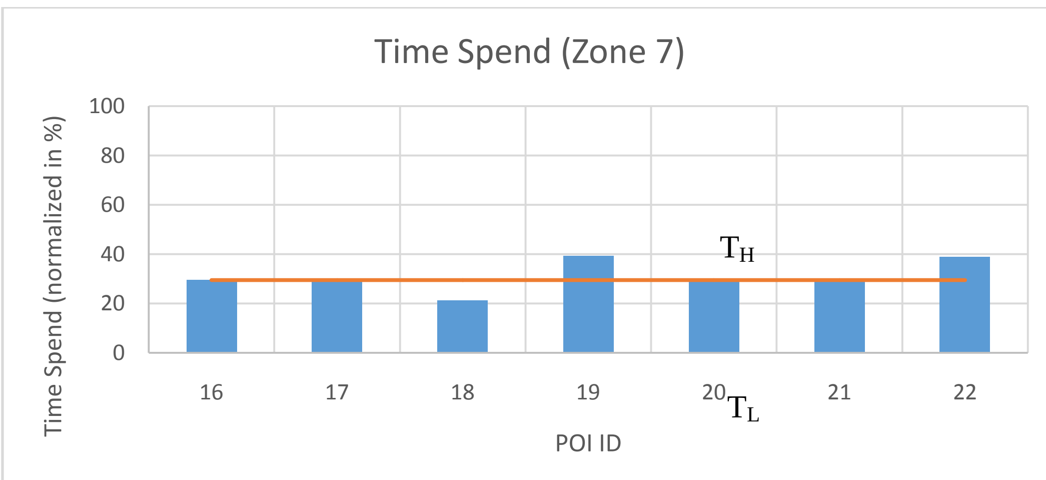


Fig. 16 (b). The time spentat each POI in zone 7 where the red line represents the threshold T_{median}.



At this stage, each POI is label as categories A, B, C and D according to its performance as shown in Fig. 17. Then we can score each POI according to its categories, A= 3, B and C = 1 and D = 0. POI that is in category A considers a best location and interesting object. POI that is in either category B and C consider has some draw back either its location or its attraction. It can be seen that with these 4 categories, category D characterizes the worst performing POIs. This can be interpreted as follows: the location of POI is not attractive and the content is not interesting. In order to give the fair chance for every POI and avoid any unusual event at any particular month effect the score of POI. We repeat this process and calculate only the data from each month not the accumulate data for 12 months and then sum the total results of these 12 months' score. The sum 12 months' score for each POI are shown in Fig. 18. The highest score is 36 and the lowest score is 0. It can be seen that only POI 29 that has 0 which mean its performance is in category D every month. The museum curator might need to take a closer look at this POI.From the result, we have recommended museum curator to consider some adjustment for POI that score less than 12. The number 12 come from the score of POI that at least in category B and C every month for 12 months.

Fig. 17. Graph shows the POI in each category

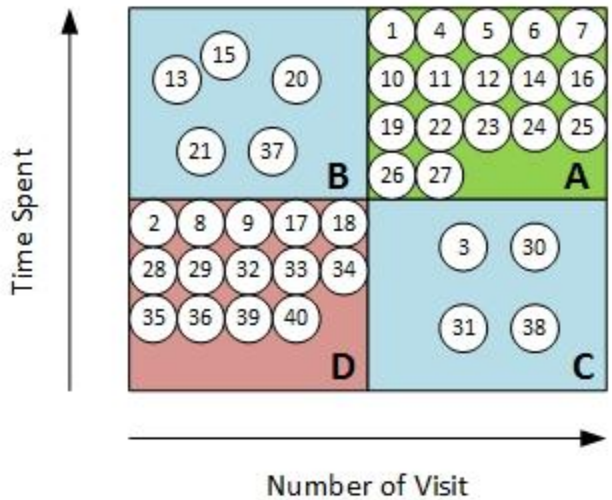
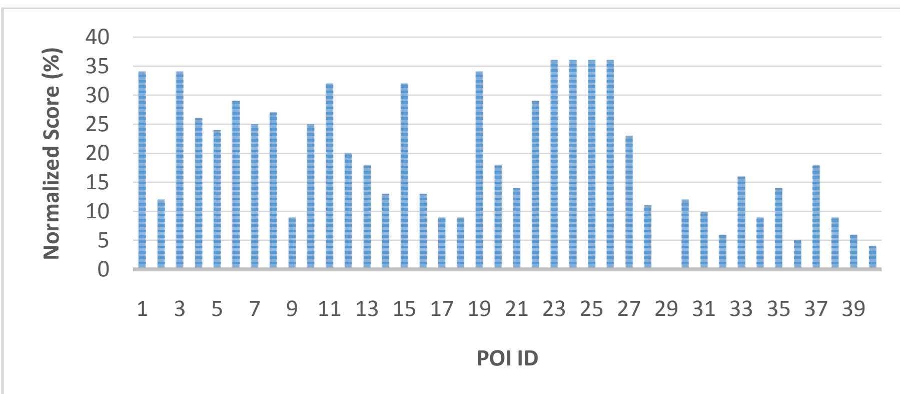


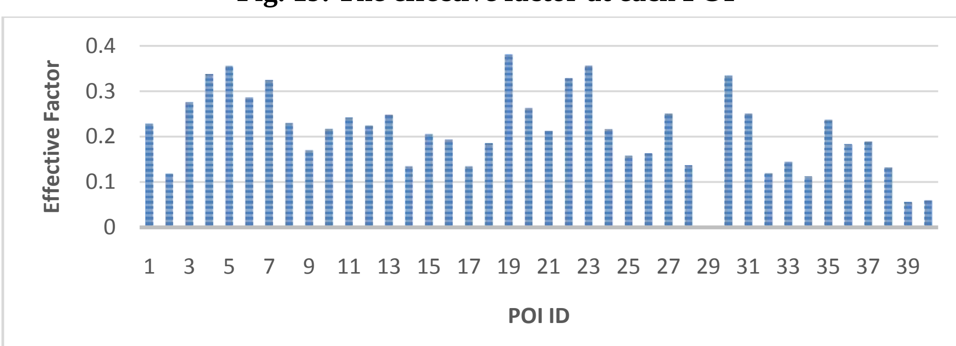
Fig. 18. The scoring of 40 POIs after 12 months.



3.3. Suggestion System with Time Constraint

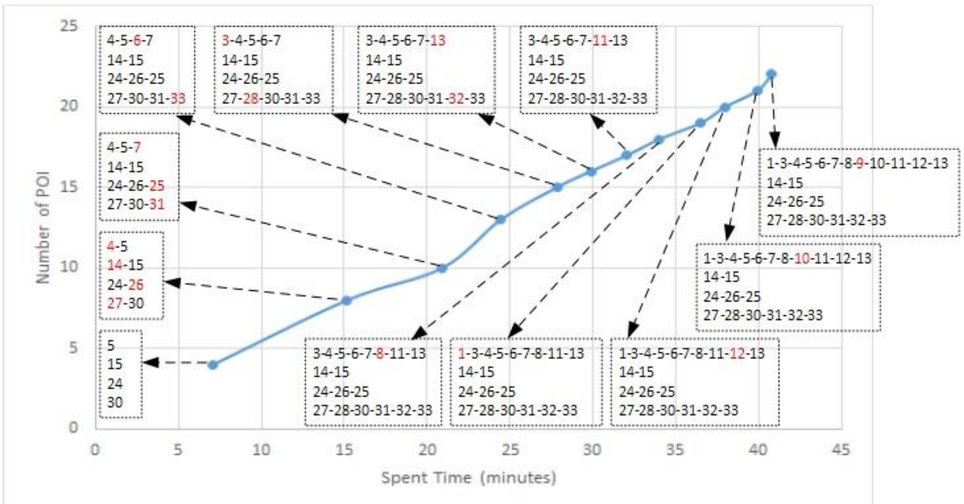
In this section, we use the effective factor from Eq. 2, which is the score of each POI, divided by the average time spent at that POI. We used this criterion to determine whether this POI will be included in the suggestion route. The effective factor of each POI of Chao SamPhraya National Museum is shown in Fig.19. We incorporate the highest values of EF into the suggested route.

Fig. 19. The effective factor at each POI



The results of the recommended items on the popular paths are shown in Fig. 20. If a visitor has less than 10 minutes to browse this museum, we recommend visitors to view exhibits 5, 15, 24 and 30 only which have the highest EF value. If the visitor has 30 minutes, they should also view items 3,4,5,6 and 13 in the first sub path, items 14 and 15 for the second sub path, items 24, 26 and 25 for the third sub path and item 27, 28, 30, 31,32 and 33 for the fourth sub path. We add the POI to the visitor list according to its EF value as well as the available time. From the Fig. 20, the red number is the new POI have been added to the suggesting list under the time constraint. The more time the visitor has, the more items they can visit. According to our calculations, it would take approximately 45 minutes to browse all popular items.

Fig. 20. The suggested pathof POIs according to time constraint.



3. Conclusion and Future Work

We proposed models to utilize collected data in the optimization of museum exhibit arrangement and suggestion of visitation routes. We created the popular path from the collected data. One observation from the result is that, the data should be big enough to reduce the effect of broken path in the popular path. Another observation is that not every POI is on the popular path. Therefore, it is depending on the museum policy to deal with the miss out POI.We also divided our POI into 4 categories according to the number of visits they received, and the time spent by visitors at that location. We give each POI a score according to its category.We recommend museum curators to improve their layout design according to POI scoring. After suggesting that curators remove POI that score less than 12, and receiving compliance (reducing POI since June 2016), we will collect data for further analysis. We also utilize the data collected to create a suggestion system for visitors with limited time by pointing out the most popular items in each exhibition and the corresponding time to be spent at each exhibit, improving the time management.

Acknowledgement

I would like to thank Chao Sam Phraya National Museum for providing the testing location.

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