Discovering Multiple Clusters of Sightseeing Spots to Improve Tourist Satisfaction Using Network Motifs

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SUMMARY Tourist satisfaction plays a very important role in the development of local community tourism. For the development of tourist destinations in local communities, it is important to measure, maintain, and improve tourist destination royalties over the medium to long term. It has been proven that improving tourist satisfaction is a major factor in improving tourist destination royalties. Therefore, to improve tourist satisfaction in local communities, we identified multiple clusters of sightseeing spots and determined that the satisfaction of tourists can be increased based on these clusters of sightseeing spots. Our discovery flow can be summarized as follows. First, we extracted tourism keywords from guidebooks on sightseeing spots. We then constructed a complex network of tourists and sightseeing spots based on the data collected from experiments conducted in Kyoto. Next, we added the corresponding tourism keywords to each sightseeing spot. Finally, by analyzing network motifs, we successfully discovered multiple clusters of sightseeing spots that could be used to improve tourist satisfaction.

key words: multiple clusters of sightseeing spots, improvement of tourist satisfaction, network, information processing

1. Introduction

The tourism industry is the third-largest industry globally and researchers worldwide are devoting significant attention to this industry [1]. It is necessary to improve the satisfaction of tourists for the continued development of the tourism industry [2]. Many methods have been proposed for improving tourist satisfaction, such as decorating sightseeing spots and improving transportation to and between sightseeing spots. However, these methods have several limitations and require significant money and labor investments. Therefore, this study focused on improving the satisfaction of tourists and developing a method with a broad scope of application. There are various ways of thinking about tourist satisfaction. For example, it could refer to the satisfaction level of the tourism industry as a whole or it could refer to the satisfaction levels of individual sightseeing spots. In this study, we mainly focused on the satisfaction levels of individual sightseeing spots. We derived the tourist satisfaction of each sightseeing spot in five levels of evaluation by tourists.

Tourism theme is a significant factor that affects travel experiences and it can be provided and supported through the design and management of tourist experiences [3]. However, in tourism research, most research has focused on generalized narratives, with only a few researchers explicitly analyzing tourist stories and themes [4]. Therefore, in this study, we attempted to improve tourist satisfaction by considering the themes of sightseeing spots. Tourism keywords and tourism themes are considered as the same concepts in this research.

Tourism has always been a networked industry that provides an ideal context for studying networks [5]. Therefore, we propose an analysis model for tourist destinations by combining network analysis and tourism themes to improve tourist satisfaction. The proposed model can discover multiple clusters of sightseeing spots with the same theme that can be used to improve tourist satisfaction. The term “multiple clusters” refers to many meaningful clusters organized from different perspectives. In this study, we focused on multiple clusters of sightseeing spots, which are expected to improve tourist satisfaction when the sightseeing spots in clusters are visited as a group. The main contributions of this study can be summarized as follows:

• An analysis model is proposed to discover clusters of sightseeing spots. Tourists who completely experience clusters of sightseeing spots will be more satisfied than those who do not have a full experience.
• Keywords are added to each sightseeing spot based on data collected from guidebooks and combined with data collected from an experiment in Kyoto to discover multiple clusters of sightseeing spots.
• Statistical methods are used to verify the effectiveness of multiple clusters of sightseeing spots discovered by the proposed analysis model. Additionally, we evaluated multiple sightseeing spots discovered through a tourist experience experiment.

2. Related Work

2.1 Tourist Satisfaction Improvement

Many methods have been proposed to improve tourist satisfaction. Blazeska et al. [6] evaluated the impact of infrastructure improvements on tourist satisfaction and determined that improving public infrastructure has a positive impact on tourist satisfaction. However, this method is costly and some improvements are tasks that can only be conducted by the government. Lin et al. [7] considered the professional ability of tour guides as a tourism product. Therefore, their idea for improving tourist satisfaction was to im-
prove the professional ability of tour guides. Nield et al. [8]
investigated the impact of food service on tourist satisfaction
and stated that high-quality food services can be used to
improve tourist satisfaction. However, these methods have
several limitations. For example, Lin et al.’s method cannot
improve the satisfaction of self-guided tourists and Nield et
al.’s method does not work for tourists who do not eat at
tourist destinations.

The analysis model we propose for improving sight-
seeing spots only requires the collection of information re-

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Fig. 1 Tourism keyword generation subsystem.

about tourists and sightseeing spots. Based on our anal-

ysis model, we can generate multiple clusters of sightsee-

ing spots and improve the satisfaction of tourists by guid-

ing them to experience these clusters of sightseeing spots.
Additionally, the proposed analysis model focuses directly
on sightseeing spots so that we can present tourists with in-
formation regarding attractive clusters of sightseeing spots.
Therefore, our model represents a novel method for improv-

ing the satisfaction of tourists.

2.2 Network Analysis

In recent years, networks have gradually been applied to the
study of tourism. Zhuang et al. [9] used social networks and
calculated the weight of each node in a network to identify
obscure sightseeing spots. Narangajavana Kaosiri et al. [10]
evaluated the influence of various factors on tourist satisfac-
tion by calculating the weights of links in social networks.
However, in our research, we attempted to use a complex
network to discover multiple clusters of sightseeing spots
to improve tourist satisfaction based on network motifs. To
the best of our knowledge, ours is the first attempt to apply
network motifs to the tourism industry.

Newman et al. [11] proposed the definition of modu-

ularity, which is used as a quality measure for graph cluster-
ing. Subsequently, many studies have been conducted on
clustering methods for networks. For example, a cohesion-
based modularity clustering method proposed by Newman
et al. [12] continuously selects the two communities with
the most significant increases in modularity to merge for
clustering. Brandes et al. [13] proposed a greedy cluster-
ing method and provided a theoretical basis for modular-
ity clustering methods. However, these clustering methods
mainly focus on modularity structures in undirected graphs.
In some complex networks, link relationships often exhibit
asymmetry and directionality.

In this study, our analysis model for discovering mul-
tiple clusters of sightseeing spots was constructed as fol-
lows. First, network motifs were calculated and used to
design the structures of cluster. Next, nodes conforming to the
designed structure were filtered based on their attributes to
obtain multiple clusters of sightseeing spots. Therefore, the
proposed analysis model for discovering multiple clusters of
sightseeing spots can be applied to asymmetric, directional,
and weighted complex networks. Additionally, it is possible
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mand. Therefore, in contrast to the clustering methods dis-
cussed above, which focus on asymmetric, directional, and
weighted complex networks, this study attempted to design
a clustering method focused on improving tourist satisfac-
tion.

3. Methods

The methods proposed in this paper utilize two main compo-
nents: a tourism keyword generation subsystem and tourist
destination analysis model.

3.1 Tourism Keyword Generation Subsystem

The tourism keyword generation subsystem (generation
subsystem) is designed to generate tourism keywords for
each sightseeing spot. In this study, tourism themes and key-
words have the same meaning. The structure of the genera-
tion subsystem is presented in Fig. 1. There are two types of
inputs for the generation subsystem. The first type consists
of data from guidebooks. The second type consists of sight-
seeing spot data from tourist destinations. This subsystem
is divided into three stages for “guidebook information pro-
cessing,” “tourist destination information processing,” and
“matching sheets and associations.”

3.1.1 Guidebook Information Processing

Guidebook information processing covers the components
from “Catalog Data from Guidebooks” to “Tourism Key-
words” in Fig. 1 and its goal is to generate tourism keywords
for tourist destinations. The specific process is defined as
follows.

First, we extract all information from the catalog in
a guidebook, which introduces sightseeing spots as tourist destinations [14]. We then perform morphological analysis on the extracted catalog information [15]. In this manner, we can extract many “words,” which are actually morphemes [16]. In this study, we generally used the morphemes of “general of nouns” as candidates for tourism keywords. This is because this morpheme contains fewer words related to regions, organizations, and human names compared to other morphemes [17].

Because most words in the morpheme “proper nouns of nouns” are proper nouns, we removed “proper nouns of nouns” from “general of nouns” and the remaining words were considered as candidates for tourism keywords [18]. We then counted the frequency of each word. For the tourism keyword candidate data, we determined that the more famous a sightseeing spot, the higher the probability that a sightseeing spot will be introduced and recommended in a guidebook. Therefore, tourism keyword candidates with high frequencies can be widely recognized by the public and serve as valuable tourism keywords. We utilized a box plot [19] to extract tourism keywords with high frequencies. The extracted words are tourism keywords that are directly generated from tourist destinations.

3.1.2 Tourist Destination Information Processing

This process covers the area from “Sightseeing Spots” to “Matching Sheets” in Fig. 1. The goal of this process is to identify tourist spots around the target destination. Field surveys were conducted to identify the sightseeing spots around tourist destinations [20]. The data on these sightseeing spots were then inputted into the matching sheets to be matched with tourism keywords.

3.1.3 Matching Sheets and Associations

“Matching Sheets and Associations” covers the area from “Matching Sheets” to “Tourism Keywords for Each Sightseeing Spot” in Fig. 1. A matching sheet is a matrix designed for associating tourism keywords with sightseeing spots. The horizontal rows in the matrix represent sightseeing spots and the columns represent tourism keywords. The horizontal and vertical staggered entries contain values of zero or one representing whether the tourism keywords match the corresponding sightseeing spots. A value of zero indicates no match and a value of one indicates a match. Therefore, a sightseeing spot may match several tourism keywords. Some locals who are very familiar with the various sightseeing spots around the tourist destination were invited to fill in matching sheets with values of zero and one. Next, we applied an AND operation to the matching sheets to obtain a final matching sheet. Based on the final matching sheet, we extracted all correspondences between sightseeing spots and tourism keywords.

3.2 Tourist Destination Analysis Model

The tourist destination analysis model (analysis model) is the backbone of the proposed method. It consists of the following three main components: “evaluation collection,” “evaluation complex network and subnetwork,” and “multiple clusters of sightseeing spots discovery” as shown in Fig. 2.

3.2.1 Evaluation Collection

For our analysis model, we utilized a questionnaire survey to quantify tourist satisfaction with sightseeing spots. The collected data are presented in Fig. 2 and consist of tourist data, sightseeing spot data, and evaluation data. Tourist data include a serial number for each tourist, which is used to distinguish tourists. Sightseeing spot data include a serial number for each sightseeing spot. These serial numbers are different from those of the tourists. Evaluation data contain the evaluations provided by different tourists for different sightseeing spots. Therefore, by combining these data with...
the sightseeing spots identified previously, we can obtain the following dataset:

- Set of tourists and set of sightseeing spots around the tourist destination.
- Relationships between sightseeing spots and tourists representing which sightseeing spots have been visited by tourists.
- Evaluations assigned by tourists to sightseeing spots collected through a questionnaire survey.

3.2.2 Evaluation Complex Network and Subnetwork

The evaluation complex network is a network containing three types of data: tourists, sightseeing spots, and evaluations assigned by tourists to sightseeing spots, as shown in the analysis system section of Fig. 2. In this complex network, nodes are composed of tourists and sightseeing spots. The links between nodes represent which tourists have visited which sightseeing spots and the weights of the links represent the evaluations of sightseeing spots assigned by tourists.

A network motif is an essential indicator for describing the characteristics of a network [21]. Therefore, it can be considered that a network motif with high frequency can represent the preferred travel modes of most tourists to a certain extent. We adopted the structural characteristics of network motifs as cluster structures. To discover network motifs, we used the ESU algorithm [22], which can detect network motifs with sizes ranging from two to eight nodes in complex networks. In summary, we first calculated all subgraphs of the target size within the complex graph and then identified network motifs after merging isomorphic graphs. We did not consider the weights of links in the discovery of network motifs. The discovery flow is defined as follows:

As shown in Algorithm 1, \( G \) represents the evaluation complex network. \( V \) represents the set of all nodes in the graph, which represent tourists and sightseeing spots. \( E \) represents the set of all edges in \( G \) (with directions), which represent the visiting relationships between tourists and sightseeing spots. Two sets \( V_{\text{subgraph}} \) and \( V_{\text{extension}} \) represent the currently generated subgraph node and candidate node for subsequent traversal, respectively. \( k \) represents the node size of the network motifs and is tunable. The primary process for discovering network motifs consists of traversal and recursion starting from a starting node and adding nodes that satisfy the following conditions for \( V_{\text{extension}} \) in each iteration.

After obtaining the network motifs, we proceed to the next step of generating an evaluation subnetwork. First, all subnetworks that conform to the connection structure are extracted as evaluation subnetworks according to the node connection structure in the network motif with the highest frequency. We then remove tourist nodes and links from the evaluation subnetwork and let the number of removed nodes be \( z \). To avoid confusion, we refer to the evaluation subnetworks retaining only sightseeing spots as cluster candidates. Next, we add various attributes to the nodes of these cluster candidates to discover multiple clusters of sightseeing spots.

3.2.3 Multiple Clusters of Sightseeing Spots Discovery

Multiple clusters of sightseeing spots discovery is divided into two parts. The first part is discovery preparation, which adds various attributes to the nodes in cluster candidates. The second part filters out multiple clusters of sightseeing spots based on the discovery conditions and attributes of nodes in the cluster candidates.

The attributes added to the nodes in each cluster candidate include the number of visits to clusters, tourism keywords, overall average, and partial average evaluations. The number of visits to clusters is not the number of times that any node in the cluster has been visited, but the number of tourists visiting all nodes in the cluster during a trip.

We then calculate the overall average evaluation (OAE) and partial average evaluation (PAE) values. The OAE represents the average of the evaluations assigned by all tourists who have visited a sightseeing spot in the evaluation complex network. For example, \( OAE_s \) in the formula below represents the average evaluation assigned by all tourists who have visited sightseeing spot \( s \). The PAE represents the average evaluation of a sightseeing spot in a specific cluster. It is defined as the average of the evaluations assigned to the corresponding sightseeing spots by all tourists who visited the cluster. For example, \( PAE_{ms} \) in the formula below represents the average evaluation assigned to sightseeing spot \( s \) by all tourists who have visited cluster \( p \).

\[
OAE_s = \frac{1}{l} \sum_{m=1}^{l} (t_m, s), \quad i \in \mathbb{N}^+ \text{ and } (t_m, s) \neq \emptyset.
\]

The calculation method for the OAE is defined in the formula above, where \( t \) and \( s \) represent tourists and sightseeing spots, respectively, in the evaluation complex network. \( m \) represents the number of times that \( s \) has been visited. In summary, the average value of the evaluations assigned by all \( t \) who have visited \( s \) is defined as the OAE.
We began by generating appropriate tourism keywords for our application [24], which allows tourists to record information on their mobile phones.

Our experiment in Kyoto considered 17 tourists and 80 sightseeing spots [23]. The experiment allowed tourists to travel freely among the 80 sightseeing spots by referring to our application [24], which allows tourists to record information on their mobile phones.

4.1 Tourism Keyword Generation Subsystem

We began by generating appropriate tourism keywords for the tourist destinations. The generation method was described in Sect. 3.1.1. First, we selected 23 guidebooks with publication dates ranging from 2011 to 2017 focusing on introducing sightseeing spots in Kyoto. We then extracted all of the catalog contents of the 23 guidebooks as text data. Next, we performed morphological analysis on the extracted text. We then selected the “[Noun : Proper]” tags from the results of morphological analysis and removed words from the noun sets that did not match the tourism keywords, such as region names, human names, and organization names. The words remaining in the set were considered as tourism keyword candidates. The number of words at this point was 821. We used a box plot to extract the tourist keywords with the highest frequencies among the tourism keyword candidates. These candidates are the tourism keywords that will be used in the matching sheets and the number of candidates is 112. To identify the tourism keywords related to each sightseeing spot, we entered 80 sightseeing spots and 112 tourism keywords into the matching sheets. We then let Kyoto natives, who are very familiar with the target sightseeing spots, fill out matching sheets. Next, we applied an AND operation to the resulting tables and added the corresponding tourism keywords to the sightseeing spots. As a result, we obtained 80 sightseeing spots and their corresponding tourism keywords.

4.2 Tourist Destination Analysis Model

Based on the data from our experiment, we constructed a complex network, as discussed in Sect.3.2. We then calculated the highest-frequency motifs in the network by setting $k$ to three, four, and five, meaning the selected numbers of motif nodes were three, four, and five. Therefore, we obtained three different sets of multiple clusters of sightseeing spot results with numbers of nodes equal to three, four, and five [25]. We then removed the non-sightseeing spot nodes, so the numbers of motif nodes were two, three, and four, respectively. Next, we extracted all evaluation subnetworks, which are the same as the highest-frequency motif structures from the complex network. Subsequently, we integrated the subnetworks with the same sightseeing spots into sets, which are called subnetwork sets. We then expressed the subnetworks in each subnetwork set in the form of subsets of sightseeing spots and subsets of evaluations for each sightseeing spot. We merged similar sightseeing spot subnetworks into a single sightseeing spot subnetwork for each subnetwork set. Based on the evaluation subset of each sightseeing spot subset, we calculated the average (partial average) evaluation value of each sightseeing spot in the subnetwork set and replaced all evaluation subsets in each sightseeing spot subset with the partial evaluation results of each sightseeing spot subset, which represent the partial averages of each sightseeing spot in this type of subnetwork. Next, we added the numbers of previous sightseeing spot subsets to the frequency subset, which represents the number of times a given type of subnetwork has been visited. Therefore, there were only three subsets remaining in each of our subnetwork sets: a sightseeing spot subset, partial average evaluation of each sightseeing spot, and frequency.

\[ \text{PAE}_{st} = \frac{1}{i} \sum_{i=1}^{T} (t_i, s) \in \mathbb{N}^+, \]

\[ \forall x \in \{s_0, s_1, \ldots, s_{k-1}\} \rightarrow (t_i, x) \notin 0 \}

The calculation method for the PAE is defined in the formula above, where $p$ denotes the cluster number. The subscript $l$ represents all tourists $t$ who have visited all sightseeing spots $s$ in cluster $p$. $k$ is the previously determined sightseeing spots $s$ and $z$ is the number of nodes removed. Therefore, the subscript $k - z$ represents the sequence numbers of all $s$ in cluster $p$. PAE is the average value of the evaluations assigned by all visitors who have visited all the nodes in a cluster. After adding the attributes defined above to the nodes in the cluster candidate, we can discover clusters based on the following conditions.

Tourism keywords (TKs) represent the tourism keywords owned by each sightseeing spot in a cluster. The visit number of a cluster (VNC) represents the number of people who visited all sightseeing spots in that cluster. The link number (LN) represents the number of edges in the evaluation complex network and the number of sightseeing spots (SN) represents the total number of nodes in the evaluation complex network. Based on these symbols, Formula 1 for the discovery conditions is deined as follows:

\[ \text{Formula 1} = \begin{cases} 
\{TK_1\} \cap \{TK_2\} \cap \cdots \cap \{TK_{k-1}\} \neq \emptyset, \\
\sum_{s=1}^{z} (PAE(s) - OAE(s)) > 0, \\
VNC > (LN + SN) 
\end{cases} \]

The conditions corresponding to the three cases above can be summarized as follows.

- Each sightseeing spot in the cluster must have at least one tourism keyword.
- The sum of the PAEs of each sightseeing spot in the cluster must be greater than its OAEs.
- The number of times each sightseeing spot in the cluster is visited must be greater than the average number of times each sightseeing spot in the destination area is visited.

Clusters of sightseeing spots that meet these three conditions are the targets discovered by the proposed method.

4. Experiments

Our experiment in Kyoto considered 17 tourists and 80 sightseeing spots [23]. The experiment allowed tourists to travel freely among the 80 sightseeing spots by referring to our application [24], which allows tourists to record information on their mobile phones.
subset. For each sightseeing spot in each subnetwork set, we added the corresponding tourism keyword set and overall average value to the subnetwork set as a subset. Finally, we analyzed all subnetwork sets and selected the subnetworks that met the target conditions. These sightseeing spot subsets of subnetworks represent multiple clusters of sightseeing spots.

5. Results and Discussion

5.1 Tourism Keyword Generation Subsystem

We obtained 821 tourism keyword candidates by processing guidebooks and selected 112 tourism keywords from the candidate box plots. Some examples are “Traditional Store,” “Water,” “Temple,” “Shrine,” “Alley,” “History,” “Gourmet,” “Buddha Statue,” “Cafe,” and “Machiya.” A machiya is a traditional wooden townhouse typified in the historical capital of Kyoto. Because the ancient capital of Kyoto has a thousand years of history, many traditional cultures have been preserved and are displayed to tourists as sightseeing spots. It is apparent that these tourism keywords represent many features of Kyoto. Tourism keywords can be used to describe historical cultures or buildings. Therefore, it is clear that the tourism keywords we selected reflect the characteristics of Kyoto sightseeing spots.

Next, we matched 112 tourism keywords with 80 sightseeing spots. Table 1 shows examples of the matching results for three sightseeing spots. Because the tourism keywords for each sightseeing spot are determined by Kyoto locals, there are only a few tourism keywords matched with each sightseeing spot. Therefore, the tourism keywords matched with sightseeing spots can be said to represent their characteristics accurately. As an example, the Heian-jingu Shrine is a famous sightseeing spot in Kyoto. It was built to commemorate the 1100th anniversary of the Heian period in 1895. The tourism keywords matching the Heian-jingu Shrine in this study were “shrine” and “history.” The “shrine” itself is undoubtedly the most prominent feature of the sightseeing spot and the word “history” represents the century-old history of the Heian-jingu Shrine. Therefore, it can be said that the tourism keywords matched with each sightseeing spot can adequately represent the characteristics of the sightseeing spots.

5.2 Tourist Destination Analysis Model

For our analysis model, we first constructed an evaluation complex network using data collected from an experiment conducted in Kyoto. Then, according to this complex network, we calculated network motifs based on three different sizes, as shown in Table A-1 in the appendix. The sizes in this table represent the numbers of nodes in the network motifs. The structure in each table represents the connection mode of the adjacent subnetwork and the frequency represents the proportion of adjacent subnetworks among all adjacent subnetworks with the same number of nodes. Therefore, we can easily identify the structures with the highest frequencies among the network motifs of each size and use these structures for the evaluation subnetworks in the next step. By using the network motifs, we discovered three types of clusters of sightseeing spots with the potential to increase tourist satisfaction. The numbers of clusters were 125 (two size), 166 (three size), and 144 (four size). Six examples are presented in Table 2. Next, we performed statistical analysis on the obtained results. Based on these analysis results, we will discuss the three-size cluster in Table 2.

As shown in Table 1, we calculated the proportions of clusters of sightseeing spots for changes of evaluation (> 0 and < 0) in all subnetworks (all combinations) of the same size. Regarding the case of a result equal to zero, because the number of samples was too small, we did not analyze this case in this study. As described above, a partial average evaluation represents the evaluations assigned to sightseeing spots by tourists who have visited all the sightseeing spots in a cluster of sightseeing spots. The overall average evaluation represents the average of the evaluations assigned by all tourists who have visited the sightseeing spots in considered in experiment. “Changes of evaluation” in Table 3 represents the partial evaluation average of a sightseeing spot in a cluster minus its overall evaluation average. “All combinations” refers to the number of subnetworks that have the same structure as the motif, regardless of the number of people visiting the sightseeing spots and changes in partial averages. For example, 3156 represents a total of 3156 two-size combinations in the table. There are 2102 combinations in which each sightseeing spot has been visited more than four times. One can see that as the size of the cluster increases, the “proportion of combinations of common keywords for all sightseeing spots” decreases. This is because the number of sightseeing spots with the same tourism keywords

| Examples | Sightseeing Spots | Common Tourism Keywords |
|----------|------------------|-------------------------|
| 2-Size   | Heian-jingu Shrine, Stone 1 | History |
| 2-Size   | Traditional Store 5, Traditional Store 6 | Traditional Store |
| 3-Size   | Traditional Store 1, Traditional Store 2, Traditional Soter 3 | Traditional Store |
| 3-Size   | Well 1, Fulukawamachi Bridge, Traditional Store 4 | Water |
| 4-Size   | Shopping Street 1, Alley 2, Alley 3, Alley 4 | Alley |
| 4-Size   | Cafe 1, Cafe 2, Cafe 3, Cafe 4 | Cafe |
is fixed. However, as the size of the cluster increases, the numbers of permutations and combinations increase rapidly. Furthermore, the number of tourism keywords is very small (only two or three for each spot). Therefore, when the size of a cluster is greater than two or three, there are no clusters with that many tourism keywords.

It is apparent that for each cluster size, the proportion of combinations of common keywords for all sightseeing spots when the evaluation change is greater than zero is greater than that when the evaluation change is less than zero. In other words, after tourists have completely visited all spots in a cluster, the evaluations of each sightseeing spot by tourists are more favorable than those from tourists who have not completely visited all sightseeing spots in a cluster. Therefore, the significance of multiple clusters of sightseeing spots is that tourists who travel based on these clusters have fully experienced several sightseeing spots with the same tourism keyword, so they assign more favorable evaluations to the sightseeing spots in multiple clusters of sightseeing spots than tourists who have not fully experienced all the sightseeing spots in a cluster. In other words, if tourists have completely experienced various sightseeing spots with common keywords, these common keywords may have a positive impact on the satisfaction of tourists. To verify the effectiveness of our data, we performed analysis of variance based on sampling experiments.

The first analysis of variance was performed to determine if changes of evaluation affected changes in the proportion of combinations of common keywords for all sightseeing spots. We designed three experiments for three clusters sizes.

- All other conditions were fixed. We evaluated whether the change in the proportion of combinations of common keywords for all sightseeing spots was significant for changes of evaluation $> 0$ and changes of evaluation $< 0$.
- All other conditions were fixed. We evaluated whether the change in the proportion of combinations of common keywords for all sightseeing spots was significant for changes of evaluation $> 0$ and under no conditions.
- All other conditions were fixed. We evaluated whether the change in the proportion of combinations of common keywords for all sightseeing spots was significant for changes of evaluation $< 0$ and under no conditions.

The results of our experiments are summarized in order below.

- We calculated $p < 0.01$. Therefore, under changes of evaluation $> 0$ and changes of evaluation $< 0$, the change in the proportion of combinations of common keywords for all sightseeing spots is significant. The trend of this change is that the proportion of combinations of common keywords for all sightseeing spots for changes of evaluation $> 0$ is greater than that for changes of evaluation $< 0$.
- We obtained a result of $p < 0.01$. Therefore, under changes of evaluation $> 0$ and under no conditions, the change in the proportion of combinations of common keywords for all sightseeing spots is significant. The trend of this change is that the proportion of combinations of common keywords for all sightseeing spots for changes of evaluation $> 0$ is greater than under no conditions.
- We obtained a result of $p < 0.01$. Therefore, under changes of evaluation $< 0$ and under no conditions, the change in the proportion of combinations of common keywords for all sightseeing spots is significant. The trend of this change is that the proportion of combinations of common keywords for all sightseeing spots under no conditions is greater than that for changes of evaluation $< 0$.

We performed the above experiments on clusters of sightseeing spots of each size. We obtained the same results and trends for all sizes. Therefore, based on these results, we can conclude that the changes in the proportion of combinations of common keywords for all sightseeing spots under different conditions are significant. The changing trends under different conditions also verified our hypothesis that if tourists can fully experience one or more tourism keywords at several sightseeing spots, they may be more easily satisfied. Therefore, we identified these types of sightseeing spots as clusters with the potential to increase tourist satisfaction.

The following two three-size clusters of sightseeing spots were part of our discovery.

| size           | 2-size cluster of sightseeing spots | 3-size cluster of sightseeing spots | 4-size cluster of sightseeing spots |
|---------------|-----------------------------------|-----------------------------------|-----------------------------------|
| number of combinations | 1516                             | 81767                             | 1558901                            |
| number of combinations when visits $> 4$ | 2102                             | 25960                             | 189781                            |
| proportion of combinations of common keywords for all sightseeing spots | 12.147% | 20.630% | 7.623% | 1.320% | 1.880% | 0.572% | 0.159% | 0.399% | 0.089% |

* changes of evaluation = partial evaluation average – overall evaluation average
The results are summarized below.

- The first cluster of sightseeing spots is composed of traditional stores 1, 2, and 3. Traditional store 1 has a history of more than 30 years and sells malted rice. Traditional store 2 has a history of 150 years and mainly sells female cosmetics and hair care products. Traditional store 3 mainly sells traditional pickles and its history is over 117 years. The common tourism keyword for these three sightseeing spots is “traditional store” and the average increase in the evaluations assigned to each sightseeing spot was 0.82. In other words, the evaluations assigned by tourists who visited these three sightseeing spots were nearly 16.4% higher than the evaluations assigned by tourists who only visited a portion of these spots. This result can be explained as follows. Although these three sightseeing spots are all traditional stores, their forms and the products they sell are different. In other words, tourists can experience three different types of content at these three traditional stores and these three types of content are all part of Kyoto’s century-old culture. Therefore, tourists will be more satisfied when they visit all three sightseeing spots.

- The second cluster of sightseeing spots is composed of well 1, Furukawamachi bridge, and traditional store 4. Well 1, which is located in a small alley, was used to draw water in daily life long ago. The Furukawamachi bridge, which was rebuilt in 1907, serves as a city road in Kyoto and the river under the bridge is very clear. Traditional store 4 opened in 1860 and sold tea. The common tourism keyword for these three sightseeing spots is “water.” When visitors visit well 1, they can learn about the way people fetched water in the past. When tourists visit the Furukawamachi bridge, they can enjoy a clear river under the bridge. Because the prerequisite for a perfect cup of tea is clean water, visitors can enjoy the combination of water and tea when they visit traditional store 4. Therefore, after tourists have visited all three sightseeing spots, they will be more satisfied based on the different types of enjoyment provided by water.

To analyze the influence of the number of visitors on the proportion of combinations of common keywords for all sightseeing spots, we designed an analysis of variance experiment. In this experiment, we did not consider the condition of changes of evaluation.

- All other conditions were fixed and we analyzed whether the change in the proportion of combinations of common keywords for all sightseeing spots was significant with visits > 4 and under no condition.

The results are summarized below.

- We calculated $p < 0.01$. Therefore, for visits > 4 and under no conditions, the change in the proportion of combinations of common keywords for all sightseeing spots is significant. The trend of this change is that the proportion of combinations of common keywords for all sightseeing spots under no conditions is greater than that when visits > 4.

We found that incorporating visits > 4 had an influence on the proportion of combinations of common keywords for all sightseeing spots. After incorporating visits > 4, this proportion dropped. This is because when there is no condition of visits > 4, many clusters have only been visited by one person, meaning those clusters only represent personal preferences and have no practical meaning. Therefore, we set visits > 4 to remove these clusters so that the discovered clusters would be more effective for most people.

Based on the conclusions above, we confirmed that the multiple clusters of sightseeing spots we discovered were effective. As a result, it is conceivable that one could improve the satisfaction of tourists by guiding them to experience all of the sightseeing spots in a cluster. Additionally, it is expected that continuous tours of a series of tourism resources with the same tourism theme will improve the satisfaction and excitement of tourists. For example, the importance of experience design in tourism has been demonstrated and a theoretical framework has already been considered[26]. Additionally, Zhong et al. [27] demonstrated the importance of storytelling in sightseeing experiences. Kyoto is one of the representative tourist destinations in Japan and model plans for tourism are often developed according to various tourism themes[28]. Therefore, it can be concluded that unifying tourism themes and specific results in Kyoto play a vital role in improving the satisfaction of tourists. Additionally, we discovered many different clusters of sightseeing spots, so we can select different clusters of sightseeing spots based on the development policies of local tourism industries to improve the satisfaction of tourists.

6. Evaluation

To verify the effectiveness of the discovered multiple clusters of sightseeing spots, we conducted an experiment on the clusters. This experiment is summarized below.

We invited eight participants between 20 and 30 years of age to experience two three-size clusters of sightseeing spots (cluster 1 and cluster 2) and two control groups. The two three-size clusters are defined as follows:

- Cluster 1 consists of traditional store 1 (Store A), traditional store 2 (Store B), and traditional store 3 (Store C).
- Cluster 2 consists of well 1 (Well E), Furukawamachi bridge (Bridge F), and traditional store 4 (Store G).

The reason for using three-size clusters is that the two-size clusters had insufficient travel content and travel time. Although the four-size clusters have sufficient travel content, visiting a four-size cluster takes a considerable amount of time. Therefore, we focused on three-size clusters. Then, to generate control groups of clusters, we selected the sightseeing spots closest to the average values of clusters of sightseeing spots. For sightseeing spots with the same average

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1The highest evaluation score is 5 and the lowest score is 1.
evaluation scores, we selected the spots with the highest numbers of visitors. Therefore, stone statue 1 (Statue D) was selected for cluster 1 and alley 1 (Alley H) was selected for cluster 2 to generate control groups. Therefore, the two prepared sets were defined as follows:

- Set 1: ABC (cluster 1), ABD (control group), ACD (control group), BCD (control group).
- Set 2: EFG (cluster 2), EFH (control group), EGH (control group), FGH (control group).

The average length of each sightseeing spot video was 40 s. To control the influence of variables, the length differences between the videos of each sightseeing spot were within 2 s. We adopted the experience mode of travel videos for the sake of convenience. To eliminate the influence of the order of viewing spots on satisfaction, we performed a randomized controlled experiment [29]. Therefore, each participant could only watch two videos (one of the four types in each set). Each video in each set was watched twice. The set from which each visitor began to watch, the type of video in the set the visitor watched, and the playing order of sightseeing spots in each video type were randomly determined. After experiencing the sightseeing spots, the participants evaluated each sightseeing spot in five levels. We then compared the data from this experiment to the data from the experiment conducted in Kyoto.

The results for sets 1 and 2 are presented in Tables 4 and 5, respectively. Experiment 1 was conducted in Kyoto. Experiment 2 represents the experience experiment for evaluating multiple discovered clusters of sightseeing spots. The rows for experiment 1 contain the sum of each sightseeing spot’s average evaluations assigned by all tourists who did not visit all of the sightseeing spots in the group in experiment 1. The rows for experiment 2 contain the sum of each sightseeing spot’s average evaluations assigned by all tourists who visited all of the sightseeing spots in the group in experiment 2. The difference (2-1) row contains the values of the experiment 2 row minus the values of the experiment 1 row.

For set 1, in Table 4, one can clearly see that the largest of the four groups in terms of difference (2-1) values is the ABC group, whereas the three control groups exhibit very small differences. This indicates that compared to the other three control groups, the evaluation values (experiment 2) assigned by the participants after they fully experienced group ABC are much greater than the evaluation values assigned by the participants who did not fully experience ABC (Experiment 1). In other words, when the participants completely visit ABC, their satisfaction increases. Additionally, according to the results in Table 5, completely visiting group EFG also improves satisfaction.

7. Conclusion

In this paper, we proposed an analysis model that can discover multiple clusters of sightseeing spots. Based on the proposed analysis model, we used data collected through experiments conducted in Kyoto to discover clusters of sightseeing spots. To the best of our knowledge, this is the first effort to discover multiple clusters of sightseeing spots using network motifs. The main contributions of this study can be summarized as follows.

- We proposed an analysis model for discovering multiple clusters of sightseeing spots. Tourists who fully visited these discovered clusters of sightseeing spots were more satisfied than those who did not. Additionally, the discovered multiple clusters of sightseeing spots revealed a new possibility for improving tourist satisfaction, which is closely related to the revitalization of tourism.
- Based on our analysis model, we used data collected from experiments conducted in Kyoto to discover clusters of sightseeing spots. We successfully combined tourism keywords with sightseeing spots and discovered multiple clusters of sightseeing spots.
- To determine the validity of the various multi-cluster sightseeing spots we identified, we conducted statistical data verification. The results proved the validity of the multiple clusters of sightseeing spots that we discovered. We then evaluated multiple clusters of sightseeing spots through an experience experiment.

In the future, we may plan for objects with multiple clusters of sightseeing spots to be more segmented. For example, multiple clusters of sightseeing spots could be generated for tourists of different ages, genders, and countries. These multiple clusters of sightseeing spots could then be customized for the relevant tourists. Tourist satisfaction will be significantly improved by visiting multiple clusters of sightseeing spots. Additionally, the proposed analysis model may not only be used for the tourism industry, but could also be applied to various other industries. For example, it could be used to improve the placement of goods in a store. By using our analysis model, one could understand how to place goods in a manner that makes customers more willing to buy those goods.

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References

[1] M. Lozano-Oyola, E.J. Blancas, M. González, and R. Caballero, “Sustainable tourism indicators as planning tools in cultural destinations,” Ecological Indicators, vol.18, pp.659–675, 2012.

[2] F. Meng, Y. Tepanon, and M. Uysal, “Measuring tourist satisfaction by attribute and motivation: The case of a nature-based resort,” Journal of Vacation Marketing, vol.14, no.1, pp.41–56, 2008.

[3] G. Moscardo, “The shaping of tourist experience: The importance of stories and themes,” The Tourism and Leisure Experience: Consumer and Managerial Perspectives, Aspects of Tourism, vol.44, pp.43–58, Channel View Publications, 2010.

[4] S. Huang and C.H.C Hsu, “Effects of travel motivation, past experience, perceived constraint, and attitude on revisit intention,” Journal of Travel Research, vol.48, no.1, pp.29–44, 2009.

[5] N. Scott, R. Baggio, and C. Cooper, Network analysis and tourism: From theory to practice, Aspects of Tourism, vol.35, Channel View Publications, 2008.

[6] D. Blazeska, Z. Strezovski, and A.M. Klimoska, “The influence of tourist infrastructure on the tourist satisfaction in ohrid,” UTMS Journal of Economics, vol.9, no.1, pp.85–93, 2018.

[7] Y.-C. Lin, M.-L. Lin, and Y.-C. Chen, “How tour guides’ professional competencies influence on service quality of tour guiding and tourist satisfaction: An exploratory research,” International Journal of Human Resource Studies, vol.7, no.1, pp.1–19, 2017.

[8] K. Nield, M. Kozak, and G. LeGrays, “The role of food service in tourist satisfaction,” International Journal of Hospitality Management, vol.19, no.4, pp.375–384, 2000.

[9] C. Zhuang, Q. Ma, X. Liang, and M. Yoshikawa, “An: An obscure sightseeing spots discovering system,” 2014 IEEE International Conference on Multimedia and Expo (ICME), pp.1–6, IEEE, 2014.

[10] Y.N. Kaosiri, L.J.C. Fiol, M.Á.M. Tena, R.M.R. Artola, and J.S. García, “User-generated content sources in social media: A new approach to explore tourist satisfaction,” Journal of Travel Research, vol.58, no.2, pp.253–265, 2019.

[11] M.E.J. Newman and M. Girvan, “Finding and evaluating community structure in networks,” Physical Review E, vol.69, no.2, 026113, 2004.

[12] M.E.J. Newman, “Fast algorithm for detecting community structure in networks,” Physical Review E, vol.69, no.6, 066133, 2004.

[13] U. Brandes, D. Delling, M. Gaertler, R. Görke, M. Hoefer, Z. Nikoloski, and D. Wagner, “On modularity clustering,” IEEE Trans. Knowl. Data Eng., vol.20, no.2, pp.172–188, 2008.

[14] S. Mori, H. Nishida, and H. Yamada, Optical character recognition, John Wiley & Sons, Inc., 1999.

[15] T. Kudo, K. Yamamoto, and Y. Matsumoto, “Applying conditional random fields to Japanese morphological analysis,” Proc. 2004 Conference on Empirical Methods in Natural Language Processing, pp.230–237, 2004.

[16] T. Kudo, “Mecab: Yet another part-of-speech and morphological analyzer,” http://mecab.sourceforge.jp, 2006.

[17] T. Sato, T. Hashimoto, and M. Okumura, “Implementation of a word segmentation dictionary called mecab-ipadic-neologd and study on how to use it effectivley for information retrieval,” Proc. Twenty-Three Annual Meeting of the Association for Natural Language Processing, pp.NLP2017–B6, The Association for Natural Language Processing, 2017.

[18] M. Asahara and Y. Matsumoto, “Extended models and tools for high-performance part-of-speech tagger,” The 18th International Conference on Computational Linguistics, COLING 2000, vol.1, pp.21–27, 2000.

[19] D.F. Williamson, R.A. Parker, and J.S. Kendrick, “The box plot: A simple visual method to interpret data,” Annals of Internal Medicine, vol.110, no.11, pp.916–921, 1989.

[20] R.L. Oliver and J.E. Swan, “Consumer perceptions of interpersonal equity and satisfaction in transactions: A field survey approach,” Journal of Marketing, vol.53, no.2, pp.21–35, 1989.

[21] R. Milo, S. Shen-Orr, S. Itzkovitz, N. Kashtan, D. Chklovskii, and U. Alon, “Network motifs: Simple building blocks of complex networks,” Science, vol.298, no.5594, pp.824–827, 2002.

[22] S. Wernicke, “Efficient detection of network motifs,” IEEE/ACM Trans. Comput. Biol. Bioinf., vol.3, no.4, pp.347–359, 2006.

[23] Y. Ieiri, Y. Nakajima, and R. Hishiyama, “Construction of the method to discovery potential sightseeing spot based on information intergration process,” IEICE Trans. Inf. & Syst., vol.J101-D, no.9, pp.1325–1333, Sept. 2018 (in Japanese).

[24] Y. Ieiri, T. Mizukami, Y. Nakajima, R. Ayaki, and R. Hishiyama, “Effect of first impressions in tourism by using walk rally application,” 2017 International Conference on Culture and Computing (Culture and Computing), pp.1–6, IEEE, 2017.

[25] S. Wernicke and F. Rasche, “FANMOD: A tool for fast network motif detection,” Bioinformatics, vol.22, no.9, pp.1152–1153, 2006.

[26] I.P. Tussyadiah, “Toward a theoretical foundation for experience design in tourism,” Journal of Travel Research, vol.53, no.5, pp.543–564, 2014.

[27] Y.Y.S. Zhong, J. Busser, and S. Baloglu, “A model of memorable tourism experience: The effects on satisfaction, affective commitment, and storytelling,” Tourism Analysis, vol.22, no.2, pp.201–217, 2017.

[28] “Another kyoto.” https://www.kyototourism.org/en/, 2021.

[29] C.S. Peirce and J. Jastrow, “On small differences in sensation,” National Academy of Sciences, vol.3, pp.73–83, 1884.
Appendix A: Network Motifs

Table A.1: Discovered network motifs.

| Size-3 Network Motifs | Frequency  | Size-5 Network Motifs | Frequency  |
|-----------------------|------------|-----------------------|------------|
| [Diagram]             | 84.729%    | [Diagram]             | 2.6208%    |
| [Diagram]             | 15.271%    | [Diagram]             | 14.750%    |
| [Diagram]             | 6.2159%    | [Diagram]             |            |

| Size-4 Network Motifs | Frequency  |
|-----------------------|------------|
| [Diagram]             | 18.179%    |
| [Diagram]             | 65.280%    |
| [Diagram]             | 1.8729%    |
| [Diagram]             | 24.366%    |
| [Diagram]             | 8.4813     |
| [Diagram]             |            |

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