Tourism Travel and Research Association: Advancing Tourism Research Globally

2017 ttra International Conference

Categorization of Destinations and Formation of Mental Destination Representations: A Parallel Biclustering Analysis

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Introduction

Tourist segmentation is an important tool for both academicians and managers in the quest to better understand tourist behavior and plan marketing activities accordingly. Likewise, consumer segmentation is an important research topic within marketing research where value possessions, needs and wants of consumers are becoming increasingly heterogeneous within countries and increasingly homogeneous across countries (Steenkamp and Ter Hofstede 2002; Ter Hofstede, Steenkamp and Wedel 1999).

According to Dolnicar, Kaiser, Lazarevski and Leish (2012), market segmentation has been studied by tourism researchers since its introduction in the 50's (Clayclamp and Massy 1968; Smith 1956). One important challenge that Dolnicar et al. (2012) emphasizes is the high dimensionality of tourism data. Dolnicar (2002) empirically investigates this dimensionality issue by reviewing 47 studies that employ a posteriori segmentation method and points out that the number of variables included in the extant tourism literature is far higher than the number which is recommended by the segmentation literature (e.g. Formann 1984). To address the challenge for segmenting high dimensional data typically used in the tourism research, Dolnicar et al. (2012) introduces the biclustering approach (Kaiser and Leisch, 2008) which allows for simultaneous clustering of both variables and cases.

Dolnicar et al. (2012) states that the algorithm chosen in their study has first been introduced in the bioinformatics literature by Prelic, Bleuler, Zimmerman, Wille, Bühlmann, Gruissem, Henning, Thiele and Zitzler (2006). However, a theoretical principle of the biclustering approach, a so-called "blockmodels", has already been developed and applied in 1976 to the social science research by White, Boorman, and Breiger (1976). In White et al. (1976), the blockmodel extracts social structures by interpreting the relational patterns among types of ties (variables) found in a set of people (cases). The principle of the relational modeling approach used in the blockmodels has been extended as stochastic blockmodels (Wasserman and Anderson 1987; Anderson and Wasserman, 1992) and further advanced by a recent development of the nonparametric Bayesian relational modeling approach, a so-called Infinite Relational Model (IRM) (Kemp, Tenenbaum, Griffiths, Yamada and Ueda 2006; Xu, Tresp and Kriegel 2006) (see also Schmidt and Mørup 2013; Mørup, Madsen, Dogonowski, Siebner and Hansen 2010), of which principle is highly relevant to the statistical segmentation approach employing the mixture model (Assaf, Oh and Tsionas 2015; Ter Hofstede, Steenkamp and Wedel 1999; Wedel and Kamakura 2005). As the IRM approach in Kemp et al. (2006) employs the Bayesian framework, the approach enables to design a more flexible clustering analysis with robust clustering performance (Albers, Mørup, Schmidt and Glückstad under review) compared to the conventional biclustering approaches such as Dolnicar et al. (2012) and the mixture models based on the maximum likelihood (Assaf, et al. 2015; Ter Hofstede, et al. 1999; Wedel and Kamakura 2000). This paper introduces an analytical segmentation method that employs the IRM tool developed by Mørup et al. (2010). For the first time in tourism research, the IRM, based on a Bayesian relational modeling framework, allows to design and conduct a segmentation analysis by simultaneously biclustering multiple datasets consisting of cases and variables in a parallel format.

The next section elaborates the theoretical foundation of our segmentation analysis, i.e., mental representation and destination image. For demonstrating how the parallel biclustering method works for analyzing tourism data as it has been shown in the previous research in the neuro science (Mørup et al. 2010) as well as in the cognitive psychology and artificial intelligence (Glückstad, Herlau, Schmidt, Rzepka, Araki and Mørup 2013) disciplines, we conduct a pilot study that compares patterns of associations which five individuals hold about 23 European destinations. Subsequently, this paper elaborates potential contributions the Bayesian relational modeling framework makes to the tourism research discipline by outlining a conceptual idea of the segmentation analysis that enables the simultaneous biclustering of individuals (cases) and their associations (variables) for multiple destinations in a parallel format.

Mental representation and destination image

Understanding and measuring individuals' mental destination representations is one of the most frequently studied topics in tourism research (Josiassen, Assaf, Woo and Kock 2016). Whereas understanding mental destination representations, often referred to as destination image, is crucial to explain tourists' destination choices and a destination's attractiveness in tourists' minds, this research stream may also contribute to develop effective communication strategies directly towards identified and targeted tourist segments. Communication scholars suggest that communication is an inferential process (Grice 1989; Sperber and Wilson 1986). According to the relevance theory of communication (Sperber and Wilson 1986), a communicator must send a stimulus (e.g., words, images) that is "precise enough, and predictable enough, to guide hearer towards the speaker's meaning. (Wilson and Sperber 2002, p250)" This implies that a tourism marketing manager (communicator) must develop a communication strategy providing a stimulus that is predictable enough for a target segment (hearers) to associate with and to evoke their motivations to visit a destination. The previous research on the destination image (e.g., Beerli and Martin 2004; Baloglu and McCleary 1999; Echtner and Ritchie 1991) focuses on hearer's standpoint and argues that the personal factors (psychological values, motivations, personality and socio-demographic characteristics) and the stimulus factors (i.e. prior knowledge about a destination acquired through secondary or primary information sources) influence the formation of the cognitive and affective image of a destination thereby the overall destination image. The ultimate aim of the present study is to provide an understanding of: i) who are the hearers (target segments) whom a marketing manager communicates to; and ii) what they associate with a destination by assuming that the associations are highly influenced by their prior knowledge and experience about a destination.

As mentioned above, the prior knowledge plays an important role in communication because hearer's inference about a destination is based on individual's prior knowledge and experience. The impact of the prior knowledge has long been studied among mental representation researchers in the discipline of cognitive psychology. Interestingly, among the researchers who investigated this issue are Charles Kemp and his colleagues who have developed the IRM algorithm that is applicable to the study of humans' categorization and concept learning (Kemp, Tenenbaum, Niyogi and Griffiths 2010). Kemp et al. (2010) states "concepts are organized into systems of relations, and that the meaning of a concept depends in part on its relationships to other concepts (Block 1986; Carey 1985; Field 1977; Goldstone and Rogosky 2002; Quillian 1968; Quine and Ullian 1978)". This implies that humans' categorization and concept learning process can be best described as the knowledge approach (Murphy and Medin, 1985; Keil 1989; Wisniewski and Medin 1994) that builds upon the well-known "prototype view (Rosch 1978)" and its opposing "exemplar view (Medin and Schaffer 1978)". The main argument in the knowledge approach is:

"When we learn concepts about animals, this information is integrated with our general knowledge about biology, about behavior, and other relevant domains. … This relation works both ways: Concepts are influenced by what we already know, but a new concept can also affect a change in our general knowledge. Thus, if you learn a surprising fact about a new kind of animal, this could change what you thought about biology in general. … and if something you learn about a new animal doesn't fit with your general knowledge, you may have cause to question it or to give it less weight (Murphy 2002, p.60)."

Contrasting this to the current study of tourist destination image, destination image is strongly connected to people's prior knowledge acquired through their experience or secondary information about a place, a city, a country, a region, a political or a religious district and so on. Destination image can be modified if people experience or learn a new thing about a destination. From this viewpoint, the investigation of the present associations which individuals hold about destinations is equally important for targeting consumer segments and developing communication strategies as the research on behavioral intension and attitudes does. With this in mind, the next section explains how the IRM method developed by a group of cognitive psychologists can be applied to analyze patterns of associations which individuals hold about multiple destinations.

Pilot study: methodology

The main purpose of this pilot study is to demonstrate how the IRM tool enables to visualize patterns which individuals associate with multiple destinations. Hence our analysis is inherently explorative and inductive. Before collecting empirical data, we have created a list of common attributes characterizing 23 European and 11 Asian countries extracted from microblog postings in "Destination of the Week" of reddit.com, which systematically covers a wide range of destinations in a structured way and is suitable for a below mentioned concordance analysis. By use of a publicly available concordance tool (Anthony 2014), frequencies of words appearing in all comments describing about the 34 countries are computed. In total 13459 word types out of 232853 word tokens appear in the text corpora consisting of these postings. Among the most frequent word types, we have selected nouns and adjectives relevant to describe these destinations, and created a common list of attributes (71 attributes generic for 34 destinations). In this pilot study, we have recruited three Japanese residing in Japan and two Danish/Japanese residing in Denmark. The demographics, prior travel experience and three major motivations expressed by these respondents are indicated in Table 1.

A questionnaire is designed in a way that 71 attributes selected from the aforementioned procedure are presented for each of the 23 European destinations. Each of the five respondents are asked to tick attributes which the respective respondents associate with each of the 23 respective European countries as a travel destination. The reason we only used the 23 European destinations without including 11 Asian destination is to reduce the workload of the five respondents who have in average spent 30-40 minutes to complete this questionnaire. The collected data has been organized in a two-dimensional matrix where 23 European destinations and 71 attributes are listed in X and Y axes, respectively. This implies that a respondent *s* has association with attribute *y* for *x* destination. Specifically, when a respondent (*s*) selects an attribute (*y*) associated to a destination (*x*), a link (binary {1, 0} - when association exits 1, otherwise 0) between the attribute and the destination is established. In this way the five matrices representing the respective five respondents are created.

The two axes X and Y are simultaneously clustered for these five matrices in parallel by the IRM tool. The key algorithm of the IRM tool (Mørup et al. 2010) which is the extension of Kemp et al. (2006) is defined in the following generative model:

$$Z^{(1)} \sim CRP(\gamma^{(1)}) \quad \text{first mode (destinations: 23 EU countries)}$$

$$Z^{(2)} \sim CRP(\gamma^{(2)}) \quad \text{second mode (attributes: 71 attributes)}$$

$$\eta_{ab}^{(s)} \sim Beta\ (\beta_0^+ , \beta_0^-) \quad \text{interactions}$$

$$R_{xy}^{(s)} \sim Bernoulli\ (\eta^{(s)}_{z_x^{(1)}, z_y^{(2)}}) \quad \text{links}$$

The first and second lines above respectively partition 23 destinations and 71 attributes into $Z^{(1)}$ and $Z^{(2)}$ clusters according to a distribution called Chinese Restaurant Process (CRP) (Pitman 2002). The third line defines how a country cluster "*a*" identified for the first mode and an attribute cluster "*b*" identified for the second mode are interacted for each respondent s^{th}, according to Beta distribution. Finally, the fourth line optimizes distributions of binary relation for each respondent s^{th} between a destination "*x*" and an attribute "*y*" according to the Bernoulli distribution. In this way, the IRM tool identifies an optimal distribution of binary links by splitting both members in the first mode (X) and in the second mode (Y) given by five respondents in parallel.

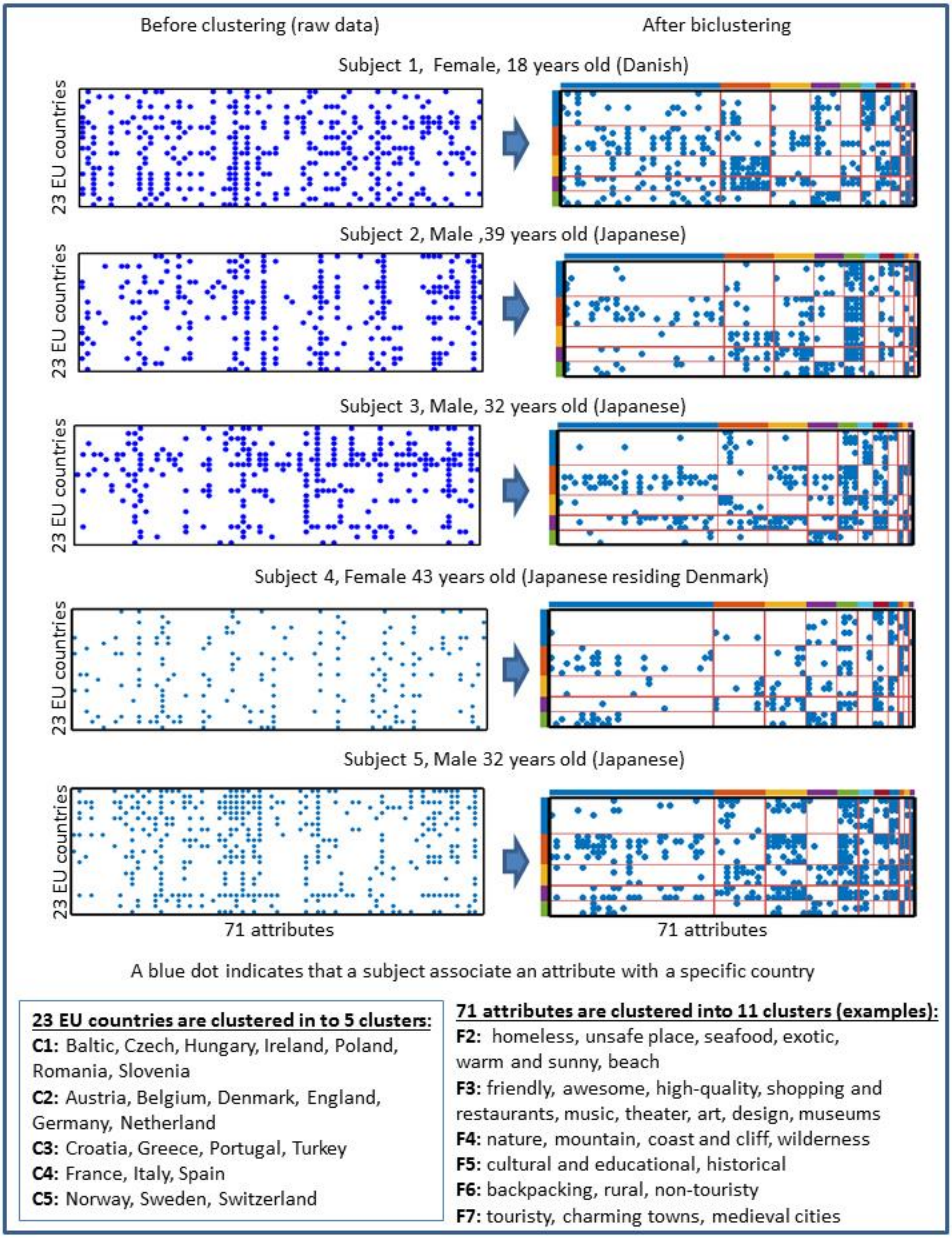
Table 1: Profiles of the five respondents

	Gender	Age	Nationality	Residence	Visit Nordic	Visit West EU	Visit Mediterranean	Visit Post communist	Top three priorities when selecting a travel destination
Subject1	Female	18 y.o.	JP/DK	DK	Many times	Several times	Several times	Never	Comfort& security, Interests& adventure, Cultural distance
Subject2	Male	39 y.o.	JP	JP	Several times	Several times	Several times	Never	Interests & adventure Resort atmosphere & climate Cultural distance
Subject3	Male	32 y.o.	JP	JP	Once	Once	Once	Once	Interests & adventure Natural state Cultural distance
Subject4	Female	43 y.o.	JP/DK	DK	Many times	Many times	Several times	Several times	Interests & adventure Natural state Cultural distance
Subject5	Male	32 y.o.	jp	JP	Many times	Many times	Several times	Several times	Comfort& security, Interests& adventure, Cultural distance

Pilot study: results and discussion

As shown in Figure 1, the 23 European destinations and the 71 attributes are simultaneously clustered according to the associative relations (blue dots linking between them) expressed by the five individuals. Since response patterns of the five individuals are considered in parallel, the clusters identified for the destinations and attributes are identical for the all five individuals. For example, the 23 European countries are partitioned into five clusters: C1 (Baltic, Czech Republic, Hungary, Ireland, Poland, Romania, Slovenia); C2 (Austria, Belgium, Denmark, England, Germany, Netherland); C3 (Croatia, Greece, Portugal, Turkey); C4 (France, Italy, Spain); and C5 (Norway, Sweden, Switzerland). Some commonalities are found in the respective five identified clusters, e.g. C1 seems to be the former Eastern Europe, C3 seems to be the medieval destination with warm and sunny weather, C5 seems to have rich mountainous nature and so on. However, the result clearly displays differences in individuals' association patterns. For example, Subjects 1, 3 and 5 associate the C1 countries with F6 associations (backpacking, rural, non-touristy), while Subjects 2 and 4 do not. This may be supported by Table 1 showing that Subjects 1, 3 and 5 are younger than the other two subjects. While Subject 1 strongly associate the C3 and the C4 countries with F2 (homeless, unsafe place, seafood, exotic, warm & sunny, beach), Subjects 2 and 5 also indicate some degree of associations with F2 to the C3 and the C4. Table 1 displays that Subjects 1/5 and Subject 2 respectively selected "comfort & security" and "resort atmosphere & climate" as one of the most important travel motivations.

Figure 2 depicts a simple biclustering analysis for two of the five individuals arbitrary selected. The results are obtained by running the IRM tool separately for each of the individuals. Figure 2 shows that the clusters extracted for them are not identical. I.e., the 23 European countries are partitioned differently, since the association patterns of the two individuals are obviously different. For instance, Subject 1 grouped C2 (Czech, Hungary, Poland, Romania, Slovenia) having strong association with F5 (backpacking, rural) and C3 (Croatia, Greece, Portugal, Spain Turkey) associated with F3 (family-oriented, exotic, warm and sunny, medieval cities) and F6 (unsafe, inexpensive). On the other hand, Subject 2 grouped C2 (Baltic, Croatia, Czech, Hungary, Romania) associated with F3 (inexpensive, local cuisine, medieval cities) and F5 (cultural, educational, historical), and C3 (Greece, Italy, Portugal, Spain, Turkey) associated with F4 (friendly, unreliable transport, exotic, warm and sunny) and F5 (cultural, educational, historical). The results clearly demonstrate that two individuals having different patterns of associations categorize destinations in dissimilar ways. The mental representation scholars who support the knowledge view (Murphy and Medin 1985) argue that such differences in categorization occur because prior knowledge possessed by individuals is not identical. During the data collection, we have asked the respondents their travel motivations and prior travel experiences (see Table 1). Subject 1 prioritizes "Comfort& security", "Interests& adventure" and "Cultural distance", while Subject 2 "Interests & adventure", "Resort atmosphere & climate" "Cultural distance. A short conversation with Subject 1 after the survey further reveals her generalization about C3 countries as "unsafe" countries closely connected with her travel motivations and her previous experiences in the C3. Although it is not obvious from the current results based on a small-size sample displayed above, the results of this pilot study imply that the individual differences in associations do most likely occur because of their personal factors (psychological values, motivations, personality and socio-demographic characteristics) and their prior knowledge acquired from secondary information source and from actual experience to visit or live in that country (Beerli and Martin 2004; Baloglu and McCleary 1999).



Before clustering (raw data)
After biclustering
Subject 1, Female, 18 years old (Danish)
23 EU countries
Subject 2, Male ,39 years old (Japanese)
23 EU countries
Subject 3, Male, 32 years old (Japanese)
23 EU countries
Subject 4, Female 43 years old (Japanese residing Denmark)
23 EU countries
Subject 5, Male 32 years old (Japanese)
23 EU countries
71 attributes
71 attributes
A blue dot indicates that a subject associate an attribute with a specific country
23 EU countries are clustered in to 5 clusters:
C1: Baltic, Czech, Hungary, Ireland, Poland, Romania, Slovenia
C2: Austria, Belgium, Denmark, England, Germany, Netherland
C3: Croatia, Greece, Portugal, Turkey
C4: France, Italy, Spain
C5: Norway, Sweden, Switzerland
71 attributes are clustered into 11 clusters (examples):
F2: homeless, unsafe place, seafood, exotic, warm and sunny, beach
F3: friendly, awesome, high-quality, shopping and restaurants, music, theater, art, design, museums
F4: nature, mountain, coast and cliff, wilderness
F5: cultural and educational, historical
F6: backpacking, rural, non-touristy
F7: touristy, charming towns, medieval cities

Figure 1

Figure 2

Conclusion and future research

The pilot study presented in this paper demonstrated how the IRM tool can be applied to analyze and compare patterns of associations which individuals have of multiple destinations. The results highlighted that individuals have different associations with respective destinations, thereby categorization of destinations also differs according to individuals' association patterns. The results are aligned with the argument that stimulus and personal factors influence the formation of destination image argued in the previous literatures (Beerli and Martin 2004; Baloglu and McCleary 1999). Our primary intention in this paper was to introduce a conceptual idea for identifying i) who are the hearers (target segments) whom a marketing manager communicates to; and ii) what they associate with a destination by assuming that the associations are highly influenced by their prior knowledge and experience about a destination. Our pilot study demonstrated that the Bayesian relational modeling framework is very flexible to design our future research by employing not only a simple biclutering design, but also a parallel biclustering (Mørup et al. 2010). Our future plan is to collect a larger size of data (e.g. 500 samples) that can be partitioned into segments according to patterns of destination image combined with the personal and stimulus factors for multiple destinations. Such function to segment and analyze people and associations for multiple destinations in parallel is unique but also highly useful to understand how people generalize about a destination by use of prior knowledge about other destinations when they do not know enough about a destination in question. Such analysis is valuable for marketing managers to develop a communication plan, e.g., to modify target segments' negative association (e.g. unsafe, non-touristy) to a destination generalized as part of a specific region; or to differentiating a destination with neighboring competitive destinations when a segment expresses positive associations for a group of destinations.

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