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Tourist movement patterns understanding from the perspective of travel party size using mobile tracking data: A case study of Xi'an, China

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ABSTRACT

Travel party size has been shown to affect tourists' behavior. However, due to a previous lack of big-data analytical techniques, there remains limited research on the effect of party size on tourist movements from a large-scale perspective. This paper presents an empirical case study on the understanding of tourist movement patterns from the perspective of party size using mobile tracking data in Xi'an, China. A Fine-grained Travel Party Partition (FTPP) method is proposed to automatically distinguish accompanied tourists from a dataset of all tourists in Xi'an. After aggregating travel parties according to the size, tourist movement patterns are compared across different party sizes from demographic, spatial and temporal aspects. We further discuss how the obtained insights can help the stakeholders in travel package improvement, connectivity enhancement among attractions, attraction planning and management, and personalized next-attraction recommendation.

1. Introduction

1.1. Tourist movement

Understanding tourist movement is vital to provide tourism managers for better decision making in managing destinations (Vu, Li, Law, & Ye, 2015). Tourist movements include the behavior of a tourist leaving his origin to reach certain destinations and moving around within each destination. Movement patterns are often mined to characterize tourist movements, including the compositional information, the spatial and temporal regularity of tourists (Chua, Servillo, Marcheggiani, & Moere, 2016). It can depict how tourists arrange travel agendas, and further contribute to easing overcrowding (Hallo, Manning, Valliere, & Budruk, 2005; Lew & McKercher, 2006), targeted marketing (Chancellor & Cole, 2008; Lew & McKercher, 2002; Lue, Crompton, & Fesenmaier, 1993; Xia et al., 2010), improving tourism management (Charles Chancellor, 2012; Cole & Daniel, 2003; Lew & McKercher, 2006; Mckercher & Lau, 2008), adjusting transport systems (Edwards & Griffin, 2013; Prideaux, 2000), and having a deeper insight into tourist preferences (Orellana, Bregt, Ligtenberg, & Wachowicz, 2012).

Movement patterns can be divided into two categories, inter- and intra-destination (Raun, Ahas, & Tiru, 2016; Smallwood, Beckley, & Moore, 2012; Xia, Zeephongsekul, & Arrowsmith, 2009; Zheng, Huang, & Li, 2017). Inter-destination movements refer to tourists moving from their origin to one or more destinations (Lau & McKercher, 2006; Leung et al., 2012). For example, Li, Meng, and Uysal (2008) examined the spatial pattern of tourist flow (e.g. tourist visits and travel propensity) from 1995 to 2004 in the Asia-Pacific region to benefit tourism management and destination marketing. For their part, Ahas, Aasa, Roose, Mark, and Silm (2008) explored tourist spatial pattern (e.g. the geographical distribution and linear movement) and temporal pattern (e.g. the temporal variation and the spent time) in Estonia to benefit regional planning. Similarly, Chua et al. (2016) characterized tourist flow in terms of spatial (e.g. the direction, circulation and centrality), temporal (e.g. the variation of tourists over time) and demographic (e.g. the origin distribution) pattern in southern Italy to benefit transport infrastructure improvement. In recent years, with the rapid development of tracking technology, intra-destination movements have attracted more attention (Raun et al., 2016). According to the different geographic scales of destinations, intra-destination movements refer to tourists transferring among attractions within a city or moving around within an attraction (Lau & McKercher, 2006; Raun et al., 2016). Hence, Xia et al. (2010) identified the dominant movement patterns of tourists travelling to Phillip Island over the period of a week to benefit travel package development and effective marketing strategy planning.

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Orellana et al. (2012) explored two movement patterns (the suspension pattern and sequential pattern) of tourists in natural recreational areas to discover tourists' preference. Developing models yet further, Zheng et al. (2017) built a movement prediction model, predicting the next location for tourists to provide support for personalized location-based recommendation, attraction management and real-time crowd control.

To better understand movement patterns during travel, many studies have divided tourists into segments and compared the differences among those segments (Birney, 1988). Generally, tourists can be segmented by criteria of socio-demographics, psychological and behavioral characteristics (Dibb, 2000). In terms of socio-demographic, studies have explored the effect of characteristics like age, gender and income on tourist movements. Cooper (1981) found that tourists with a lower income level were inclined to visit fewer attractions and stay longer, and tourists in different age groups preferred different attractions. Gitelson and Kerstetter (1990) found that younger tourists preferred leisure travels while women and middle-income tourists preferred exploratory travels.

Tourist movements can also be affected by psychological factors (e.g. tourists' purpose of visit, their opinions, etc). Poria, Butler, and Airey (2003) found that tourists who perceived places as part of their own heritage were more likely to visit frequently and stay longer than others. Rid, Ezeuduji, and Pröbstl-Haider (2014) found that tourists with different motivations (e.g. heritage & nature, authentic rural experience, learning, and Sun & beach) might seek out different travel experiences.

The actual behavior of tourists (e.g. spatial visits, length of stay, etc.) is also considered as segment criteria to understand their movements. Leveraging hierarchical clustering, Espelt and Benito (2006) segmented tourists according to the visited nodes, the duration of stay, etc., and four segments were identified: *Non-tourist* with the least visits and the shortest stay time, *Interested tourists* with more visits and longer stay time, *Erudite tourists* with the most visits and the longest stay time, and *Ritual tourists* with behavior almost identical to the average correlated values. Based on Monothetic Analysis, De Cantis, Ferrante, Kahani, and Shoval (2016) divided tourists according to their travel behavior (e.g. tour length, average speed, number of visited attractions and duration of stay) with GPS data, and identified seven segments, including segment A with the longest tour length, highest speed and more visits, and segment B with relatively shorter tour length and the lowest speed.

1.2. Party size

Many researchers (Cummings, Huber, & Arendt, 1974; East, Osborne, Kemp, & Woodfine, 2017; Money & Crotts, 2003; Sorkin, Hays, & West, 2001; Stasser & Davis, 1981) have verified that party size affects people's decision making. In the field of psychology, studies found that party size influenced the quality of decision-making (Cummings et al., 1974), members' confidence in the decision-making (Stasser & Davis, 1981) and the party performance (Sorkin et al., 2001).

Tourist movements are the embodiment of their decisions about where, how and when to visit during their travels (Xia, Zeephongsekul, & Packer, 2011). In tourism research, there are many studies focused on the effect of travel party size on tourist behavior. Kolyesnikova and Dodd (2008) measured the effect of travel party size on their consumption behavior. Tourists in smaller parties seemed to have a higher level of gratitude and obligation, resulting in higher spending on wine or souvenirs. East et al. (2017) examined the impact of party size on the stay time of tourists in a zoo, finding that larger the party size resulted in longer stay time. Many studies (Alegre & Pou, 2006; Barros, Correia, & Crouch, 2008; Fleischer & Rivlin, 2009; Thrane & Farstad, 2012) have explored the impact of travel party size on the length of stay at the destination. Some researchers (Alegre & Pou, 2006; Fleischer & Rivlin, 2009; Thrane & Farstad, 2012) believed that a larger party size lead to shorter travel duration, while other researchers (Barros et al., 2008) found that party size is positively related to the length of stay. Above all, in regarding tourism as a social practice (Larsen, Urry, & Axhausen, 2007), the party size as a measure of social ties among tourists definitely affects tourist behavior (Brown & Reingen, 1987). However, to our best knowledge, there remains limited research on the effect of party size on movement patterns, which can assist tourism managers in designing more appropriate and profitable strategies. Further, most of the aforementioned studies are conducted based on questionnaires. The limited and biased samples may result in non-universal results.

With the development of ICT (Information and Communication Technologies), researchers have paid more attention to GPS trajectories (O'Connor et al., 2005; Shoval & Isaacson, 2007; Tchetchik, Fleischer, & Shoval, 2009; Edwards & Griffin, 2013; De Cantis et al., 2016; Mckercher, Shoval, Ng, & Birenboim, 2012; Shoval, McKercher, Ng, & Birenboim, 2011), Bluetooth tracking data (Versichele et al., 2014) and user-generated data (Chua et al., 2016; Miah, Vu, Gammack, & McGrath, 2016; Zheng, Zha, & Chua, 2012, 2011) to better understand tourist behavior. However, tourists must intentionally open GPS or Bluetooth sensors in order to generate a record, and they may not choose to actively share travels, leading to sampled and sparse data (Versichele et al., 2014). Discovering travel party size requires a fine-grained analysis of tourist movement during travel, so these data sources like GPS and Bluetooth may not be suitable to support the identification of travel party size.

Mobile tracking data are passively collected without the direct participation of tourists, generating massive and continuous tracking data. In tourism, few studies using mobile tracking data have been conducted to bring insights into tourist behavior. Using positioning data generated from call activities, Ahas, Aasa, Ãœlar Mark, Pae, and Kull (2007a) examined the seasonality of tourist movement in Estonia and found differences in the spatial distribution of tourists during different seasons. Using mobile positioning data of foreign tourists, Raun et al. (2016) analyzed distribution of call activities, temporal variation of visits and the composition of tourists. However, because of the previous technical limitation, existing research only focuses on mining macro-level aggregated movement patterns, and cannot achieve the identification of fine-grained travel party size on a large scale.

This paper presents a large-scale empirical case study understanding tourist movement patterns from the perspective of party size in Xi'an, China. In order to obtain travel party sizes, a Fine-grained Travel Party Partition (FTPP) is proposed to automatically and efficiently distinguish accompanied tourists using city-level mobile tracking data from 12 million individuals on a distributed computing platform. Specifically, it first detects tourists in the period of interest from the whole population using a Map-Reduce based filtering strategy. Then it extracts attraction sequences of detected tourists using a Map-Reduce based extraction strategy. Finally, based on the extracted attraction sequences, community detection is used to partition tourists with similar spatio-temporal behavior into the same travel parties. After obtaining the travel parties, we aggregated these parties into five segments according to their sizes. Using these segments, we explored the effect of the party size on tourist movements.

According to Chua et al. (2016), tourist movements can be explored from three aspects: demographic, spatial and temporal information. Thus, in order to compare tourist movement patterns across different segments, we propose the following three research questions:

RQ1: What are the demographic patterns for different sizes of travel parties?
RQ2: What are the valuable spatial patterns for tourists in different sizes of travel parties?
RQ3: What are the valuable temporal patterns for tourists in different sizes of travel parties?

RQ1 aims to explore the origin distribution of tourists in different party sizes. RQ2 focuses on differences and similarities in visits and