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Strategic Visitor Flows (SVF) analysis using mobile data

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Abstract

'Visitor flows' (VF) is defined as the generalized spatial movement patterns of travellers and have always been relevant in tourism studies. Nowadays, VFs are important for understanding *travel networks* which go beyond the specific spatial dimension to include informational or virtual dimensions such as travellers' experiences. Travel network modelling is not only a valuable marketing tool helping to increase value in the supply chain but also it challenges the traditional organisation of destination management organizations (DMO's). DMO's have to reshape their governance model from a static-central model to a dynamic network; destination managers have to change from *flows of powers* to *power of flows* Castells, 1989) VF in this broader picture moves from merely descriptive to strategic VF (SVF). The aim of this research is to show empirical evidence of SVF in the Fribourg region in Switzerland by exploiting mobile phone data.

Keywords: spatial movement patterns of travellers, network models; mobile phone data.

"From *flows of power* to the *power of flows*" (M.Castells, 1989)

1 Introduction

The monitoring of visitor flows (VF), namely the general or aggregate patterns of movements in a given area, not only sheds some light on the most and least visited places but also gives relevant information about demand segmentation (Orellana et al., 2012: 367). Seminal research last century has shown the relevance of the spatial dimension in market segmentation (Dredge, 1999; Gunn, 1994; Lue et al., 1993) and confirmed the network nature of this approach (Leiper, 1990). Nevertheless, empirical research was difficult because of the lack of appropriate data describing these patterns (Leiper, 1989).

In the twenty-first century, the research agenda of network studies in tourism has sought to overcome the spatial dimension (i.e. geo-localisation aspects) and take into account virtual dimensions, referred to as *travel networks*. Evidence showing this virtual dimension consists of the following: Firstly, travellers are creators and co-creators of the information contained by networks which support travel planning; secondly, travellers share their experiences in community-based space and finally, technologically supported networks are ubiquitous meaning that the information can be found before, during and after the trip (Stienmetz & Fesenmaier, 2013,:Pan & Fesenmaier, 2006; Wang & Fesenmaier, 2004; Wang & Xiang, 2007; Zach & Gretzel, 2011; Zheng Xiang et al., 2008). The concept of destination is also affected by this traveller network conception. Physical and virtual elements both contribute to the creation of value and also make the analysis of the whole value system more difficult (Stienmetz & Fesenmaier, 2013).

Moreover, in the tourism sector, the process of disintermediation (Buhalis & Law, 2008) and re-intermediation in the distribution of tourism services (Kracht & Wang, 2010) has increased the complexity of the business structure (Stienmetz & Fesenmaier, 2013); one example of this is distribution channels (Scaglione & Schegg, 2015; Schegg & Scaglione, 2013).

As a result, a shift of information and decision centrality into placeless and timeless networks has been observed, and also happens in other sectors. *Organisations* are changed to *flows*, these latter become the units of work, decision and output (Castells, 1989: 142). “Thus, the dialectic between centralization and decentralization, the increasing tension between places and flows, could reflect, in the final analysis, the gradual transformation of the *flows of power* to the *power of flows*.”

The concept of Destination Management Organisations (DMO’s) articulated in the early 70’s as a comprehensive and static system has failed, at least in the last three decades. The failure cycle is described by the impossibility of traditional DMOs to reconcile three different logical systems: territorial, business and travel experiences (Beritelli et al., 2014). A destination value system is composed as a set of four different but overlaying networks: the marketing and promotion level, experience design level, partnership configuration and sales & distribution (Stienmetz & Fesenmaier, 2013).

This research focuses on the aspects of travel networks and the spatial dimension. The main aims are twofold. On the one hand, to show the utility of mobile data in grasping generalized patterns of tourist movements in the canton of Fribourg, Switzerland, and on the other hand, to show methodological approaches that seem to be appropriate in a Big Data environment to solve problems based on network metrics.

The paper is organized as follows. The following section is the literature review which will give an overview of the typical elements of space location patterns in relation with the mathematical theory of networks, then the families of space-location data used in empirical research. The third section describes the data; the fourth section presents the results of the network analysis and after this comes the conclusion, which presents limits and gives a future research agenda.

2 Literature review

2.1 Visitor flow elements

The concept of multi-destination trips has enlarged studies taking into account single destination trip models (Lue et al., 1993). The spatial structure theories show that the supply of recreation opportunities could affect the trip experience both in nature and other dimensions (Kim & Fesenmaier, 1990). Thus, the modelling of travellers' spatial patterns becomes relevant. Five prototypical spatial patterns were proposed: the single destination pattern (most activities within one destination), the en route pattern (several destinations visited en route to a main one), the base camp pattern (nowadays called *Hub*, other places visited while at a primary destination), the regional tour pattern and the trip chaining pattern (touring circuit), (cf. Gunn, 1994: 126-127; Lue et al., 1993: 294, Fig. 2). The concepts similar to spatial trip patterns are discussed below.

Firstly, there is the *travel itinerary* by Lew and McKercher (2002) who present a comprehensive comparison table of tourist itinerary models . The basic structure of the travel itinerary pattern is origin-destination-origin where lines are routes in between. The interest of each destination is relative to the whole destination in the itinerary with single destinations and hub and tour patterns; two new concepts are added: *gateway* (the first destination reached before beginning a multiple destination itinerary) and *egress* destination (the last destination visited before going back home).

Secondly, *the linear paths* models aims to "reflect the geometry of tourism movements away from their accommodation point" (Lew & McKercher, 2006: 417). The linear path simplifies the actual spatial movement shaped by geography and is independent of territorial distance and means of transportation. They add a new one to the patterns cited above: the random exploratory path. The travellers following such patterns, which could not be assimilated to any of the others, do not follow a systematic exploratory strategy and they show flexible and opportunistic behaviour.

Another concept close to spatial patterns is *generalized sequential patterns* (GSPs) described as the "the sequence in which the places are visited, regardless of the trajectory followed. The term 'generalized' implies a relative order and not an absolute order: GSPs are temporal structures used to find commonalities in the order that places are visited."(Orellana et al., 2012: 673).

Finally, trips representing the multiplicity of city pattern within the United States are modelled as a network, and the most important elements of network theory are employed in the analysis (Hwang et al., 2006).

The network analysis toolbox turns out to be an appropriate strategy for the analysis of spatial patterns of movements (VF). This approach provides several metrics useful for describing different aspects of the structural and dynamic characteristics of the object of study (Baggio & Del Chiappa, 2016; Baggio et al., 2010). Some of the main measurements that allow the characterisation of topology and behaviour of actors, such as VF, are used in our analysis: the distribution of each node connection (degree distribution), the length of the paths connecting any two nodes (in number of links), and the mesoscopic structure of the network (number and type of clusters of nodes). These are better described, along with the results, in section 4.

Tourism attraction system studies, both theoretical (i. e. Leiper, 1990; Lew, 1987) and empirical (Gunn, 1994, ch. 5; Richards, 2002), have also used network concepts. Leiper defined the *tourist attraction system* as "an empirical connection of tourist, nucleus and markers" (Leiper, 1990: 367). Nucleus is the central element of a tourism attraction system, and it could be any feature or characteristics of a place that travellers visit. A marker is the link, namely an item of information that links the human and the nuclear element of an attraction system and allows one to distinguish the nucleus from other similar phenomena . The centrality of the nucleus in the attraction system does not mean that such attractions are isolated elements; the expression *nuclear mix* was coined by Leiper (1990: 374) as a combination of nuclei which are *significant* in the experience during the trip. Nevertheless, there is hierarchical classification of nuclei: primary, secondary and tertiary. This classification mainly relies on the traveller's knowledge of their existence before they arrive at the site or destination. Tourists could suspect the existence of the secondary attraction but probably not of the tertiary ones.

The analysis of time-space consumption gives important knowledge and will help to cluster data in terms of tourist behavioural patterns (Botti et al., 2008; Grinberger et al., 2014). Leask (2010), in a very complete review of attraction concepts, points out that the term visitor attraction is now preferred to tourism attraction in order to include day-trippers as well.

This subsection attempts to show that the *tourism attraction system*, as was proposed in the '90s has been enriched and updated by the *travel networks* concept. Both are based on a network nature structure, but in the former model, touch points or nodes were mostly identified by their special locations; whereas in *travel networks* touch points could be either physical or virtual - roughly speaking, experiences and informational elements are included. Therefore, describing general spatial patterns of travellers' movements or VF is only part of the story but not the least interesting one, and so is the aim of this research.

2.2 From traditional data to Big data in VF

The study of spatial patterns of movements has used, as primary data, surveys or opinion polls (Hwang et al., 2006; Lew & McKercher, 2002) which were time-consuming and not very accurate (Vu et al., 2015). Most of the time they are based on information recalled by the interviewees. Another strategy was based on surveys based on diary reports of the trip (Stewart & Vogt, 1997). Exploratory methods were also used, such as expert opinions collected from multiple participant interviews (workshop) in order to individualize attractions and categorize them (i.e. getaway, egress) (Beritelli et al., 2014; Beritelli et al., 2015). All of those methods are rooted in a long academic research tradition and we can call them *small data approaches* (Baggio, 2016).

Different technologies allow the analysis of spatial-temporal visitors. Digital traces obtained via geo-tagged photos on social media (Instagram, Flick, etc) or mobile apps belong to the family called Volunteered Geographical Information (VGI) which an increasing number of scholars take advantage of for analysing either urban ~~or~~ visitor flows (i. e. Kádár & Gede, 2013; Vu et al., 2015). The family of VGI is useful for quantifying elements of the structure of the travel network (Zach & Gretzel, 2011). A recent research shows through empirical elements that VGI approaches seem not to contain biased information (Stienmetz & Fesenmaier, 2016).

‘Destination guest cards’ having a chip embedded give also insights into intra-destination VF. These cards which tourists obtain from destination management offices allow free or highly discounted access to partner attraction and transportation (Zoltan & McKercher, 2015). Another destination card has been offered to tourists in the canton of Fribourg since 2016, without having a chip but having a mobile app which can constantly be updated by service suppliers (i.e. ‘flash offers’) (Union fribourgeoise du tourisme, 2015). Analysis made on the first season of data collection gives coherent results when crossed to the results of the present research (Scaglione et al., 2016a).

Global Positioning Systems (GPS) are very popular in VF studies but with a small sample of volunteer participants (Birenboim et al., 2013). Two others techniques are land-based tracking systems and hybrid solutions that combine the two. Empirical research carried out on volunteers based proved that the three techniques could be effective tools for tracking tourism behaviour even though they show different levels of accuracy (Shoval & Isaacson, 2007).

The use of smartphones has increased in the everyday life of consumers such as when using social networks on mobiles phones (Scaglione et al., 2015). The increasing importance of mobile devices is also evident during vacation periods (Wang et al., 2016). The capabilities of mobile phone positioning databases has become, therefore, an interesting and pertinent tool for monitoring VF which can enlarge traditional data sources and VGI ones (Ahas et al., 2008). Two projects were run contemporaneously in the last years in Europe focusing on passive mobile data use. The first one was a Eurostat project named *Feasibility Study on the Use of Mobile Positioning Data for Tourism Statistics* (Eurostat, 2013). The second was a feasibility project named *Monitour* (Scaglione et al., 2016b) which was financed by Swiss research funds. Both projects had as a main objectve to study the feasibilty of using moblie phones to increase information about tourism frequentation.

The term *passive mobile positioning data* refers to automatically stored information stored in log files by mobile operators. The mobile geo-localisation information relies on the position of the *cell network*. A cellular network is physically placed at base stations which are usually towers supporting one or more directed antennae. The localisation of the *cell network* is determined by the base station (in the case of only one antenna) or several directed antennae. The size of the cell network is not fixed, depending on the load or number of phones connected, if the network is crowded, phones can switch not to the nearest base station but another one in the neighbourhood, the optimal distance from handset to antenna is less than 60 km (Ahas et al., 2008). Both the Eurostat and *Monitour* projects used the coordinates of the base station as proxy of the location of the mobile, which is to say the geo-localisation of the anonymized visitor. (cf. Eurostat, 2013: 18).

The next section describes more precisely the mobile data used in this research.

3 Data

Swisscom, which is the major Swiss mobile provider having 60% of the market is a partner of this research and provided a set of test data.

The data consists of 18,138 anonymized mobile users belonging to one of the top European incoming countries in Fribourg canton tourism. The period under study is 11 days, from 17 and 28 August 2014. For confidentiality purposes, Swisscom has anonymized the users using Hashing-Algorithm techniques and shifting of the date; no characteristics of the users are given. From hereafter we will refer to the anonymized mobile users as AMU. It is worth noting that this anonymization process does not affect the results of this research, whose aim is to show the inference of SVF using mobile data.
The data is comprised of 2G A Interface data, 2G IuPS Interface data, 3G IuCS data and 3G IuPS data, technology which does not allow accurate geo-localization of the mobile position, i.e. it was not possible to associate the data to specific tourist attractions. Thus, the authors used the position of the cells (namely antennas) as proxy for the geo-localization of AMU, and they acknowledged that this is a limitation of this research. There are approximately 1,500 cells.
In order to identify SVF, the authors programmed a customized routine in Java which was run by the computer center of Swisscom in order to yield a file consisting of trajectories. The structure of that file has the following fields: AMU, trajectory identification, time stamp, duration and cell identification. The time stamp field indicates the moment when AMU was captured by the cell identified in the observation. The duration indicates the period of time that the AMU remained captured by the latter cell, but this data was not used in this first analysis.
The data includes 18,138 trajectories having a mean duration of 3 days and 15 hours and a standard deviation of 2 days 14 hours. The median number of trajectories per AMU is 13.

4 Network analysis

The network has been built in the following way. Records were given a unique identifier, *anonymized_userid-day*, then the different tracks were extracted. The length of a track is the number of different points (antennas) on the track. We notice here that a time window of one day has been used since we are interested in the daily mobility patterns (n.b.: all positions recorded in one day belong to the same track). The tracks were then combined into a network whose nodes are the antennas and links are all the trajectories (cumulated) followed by people going from one antenna location to another.

The network is directed and weighted (the weight is the number of trajectory segments that connect two locations). Self-loops, that correspond to individuals that spend the whole day in a single location were removed. All scripts were written in Python and analyses used the Python *Networkx* library (Hagberg et al., 2008), Pajek was used for visualisation (Batagelj & Mrvar, 1998).

The network has 1430 nodes and 21,122 links (13 933 have weight=1). The average (unweighted) degree is 29.54. The average weighted degree is: 44.92. The network is practically connected (only 14 nodes are isolated). Its density (number of links/max possible no. of links) is 0.01, reciprocity (% of nodes connected bidirectionally) is 0.47. Considering the network unweighted (so considering only how antennas are connected by user trajectories) the average path length (no. of antennas traversed) is 3.2 and the diameter (longest distance between 2 antennas) is 10. The weighted degree distributions (in-degree and out-degree, see Fig. 1) are consistent with a power-law (for the main tail) distribution with parameters (quite similar): InDegree exponent = 2.91±0.17; OutDegree exponent = 2.97±0.19 (calculations were made according to Clauset et al., 2009).

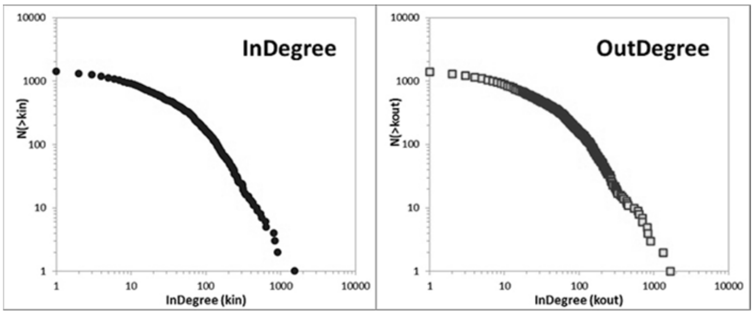

Fig. 1. Cumulative degree distributions (in- and out-degree)

Using the idea of a bow-tie structure, i.e. a large connected component, an IN and OUT components with a unidirectional connection, and a disconnected (DISC) component (Broder et al., 2000), we have the following split: connected component (SCC): 97.0%; IN: 1.1%; OUT: 0.9%; other (disconnected nodes): 1.0%.

A second possibility to explore the inner (mesoscopic) structure of a network is that of running a modularity analysis. A software algorithm finds the best set of subnetworks (clusters, modules) so that the nodes belonging to a group are more densely connected within the group than to other groups. A modularity index Q measures the level of separation. Q is normalized so that Q=0 means no separation (no modules found), and Q=1 complete separation into well-defined modules. Among the many possible algorithms proposed we used the *Louvain* method (Blondel et al., 2008), which gives a good resolution power, while providing a small number of well-balanced clusters.

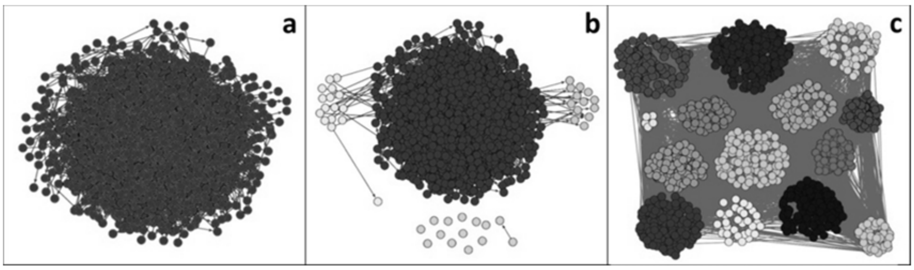

Fig. 2. The network (a), its bow-tie components (b), and the clusters from the modularity analysis (c)

The analysis found 14 communities (plus one with the disconnected nodes) and a modularity index Q=0.665, showing thus a set of relatively well-defined groups. Fig. 2 shows the network, its bow-tie components and the clusters uncovered.

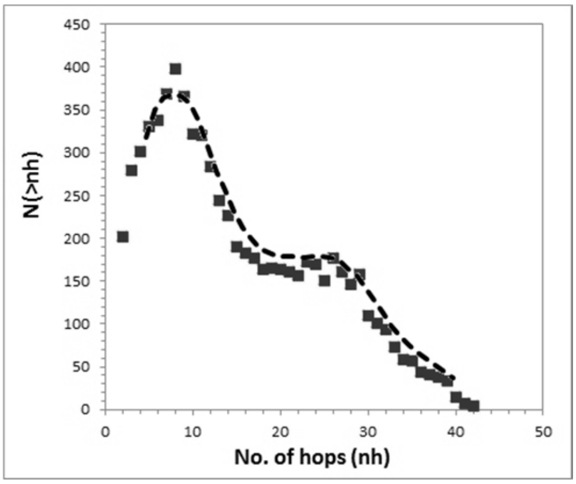

Fig. 3. The most popular paths in terms of number of visited locations (dotted line has the sole purpose of guiding the eye for a better visualization of the pattern)

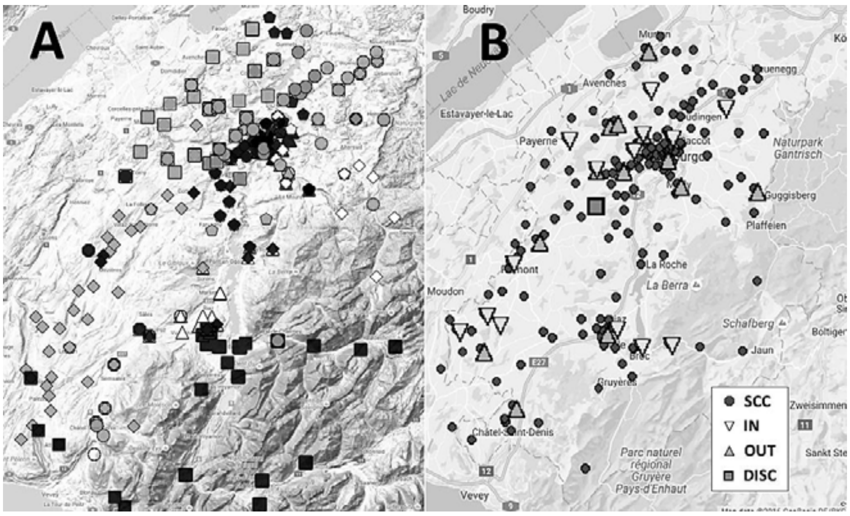

Fig. 4. The geographic rendering of the different modules found (panel A: different shapes represent the different modules) and of the bow-tie components (panel B: SCC=connected component, IN, OUT components and DISC=disconnected elements)

A geographic rendering of the modules uncovered shows well this fact highlighting the mostly *local* nature of the movements recorded (Fig. 4).

5 Conclusions

The results using network analysis techniques on passive mobile positioning data yield the following results. Firstly, the modularity clustering seems to be useful to identify Leiper nuclear-mix patterns. Secondly, the bow-tie structure obtained is in line with the node itinerary classification by Lew and McKercher (2002) allowing to identify getaway and egress ones. Thirdly, network analysis clusters VF in paths weighted by popularity. Last but not least, network analysis seems to be suitable for dealing with large amounts of data such as those on passive mobile positioning.

The analysis of guest – cards of Fribourg described in section 2.2 yields similar results showing that the bow-tie structure is well present also in that network. An extended analysis of these data, using attractions as nodes, will shed some light on the following question: are gateway really entry nodes or are just an artefact of the method? This is part of the future research plan.

This research does not aim to fully explain every aspect of VF, but it shows how the application of network analysis can help in grasping an important aspect, the spatial one. Then, with a good knowledge of the destination and its peculiarities, the results can be interpreted in order to provide useful insights into the understanding of the real movements of people. This will enable improvement of marketing promotions and the design of new products or services that have a better connection with the travellers' preferences and needs.

Data used in this research belongs to one specific European country, replication of this methodology on other countries and cross comparisons will be useful in finer tuning the methods and gaining wider knowledge of the phenomenon. Finally, the results reported here will be compared with those obtained in expert workshops at destination in order to increase the level of collaboration between the different providers and stakeholders.

References

Ahas, R., Aasa, A., Roose, A., Mark, Ü., & Silm, S. (2008). Evaluating passive mobile positioning data for tourism surveys: An Estonian case study. *Tourism Management, 29*(3), 469-486.

Baggio, R. (2016). Improving Tourism Satistics : Merging official records with Big Data. *Proceedings of the Big Data in Tourism & Business Intelligence in the Travel & Tourism Domain, Mid Sweden Universuity*, 89-92.

Baggio, R., & Del Chiappa, G. (2016). COMPLEX TOURISM SYSTEMS: A QUANTITATIVE APPROACH. *Management Science in Hospitality and Tourism: Theory, Practice, and Applications*, 21.

Baggio, R., Scott, N., & Cooper, C. (2010). Network science - a review focused on tourism. *Annals of Tourism Research, 37*(3), 802–827.

Batagelj, V., & Mrvar, A. (1998). Pajek-program for large network analysis. *Connections, 21*(2), 47-57.

Beritelli, P., Bieger, T., & Laesser, C. (2014). The New Frontiers of Destination Management: Applying Variable Geometry as a Function-Based Approach. *Journal of Travel Research, 53*(4), 403-417.

Beritelli, P., Reinhold, S., Laesser, C., & Bieger, T. (2015). *The St.Gallen Model for Destination Management*. St.Gallen: IMP-HSG. from https://www.alexandria.unisg.ch/Publikationen/238469.

Birenboim, A., Anton-Clavé, S., Russo, A. P., & Shoval, N. (2013). Temporal Activity Patterns of Theme Park Visitors. *Tourism Geographies, 15*(4), 601-619.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment, 2008*(10), P10008.

Botti, L., Peypoch, N., & Solonandrasana, B. (2008). Time and tourism attraction. *Tourism Management, 29*(3), 594-596.

Broder, A., Kumar, R., Maghoul, F., Raghavan, P., Rajagopalan, S., Stata, R., Tomkins, A., & Wiener, J. (2000). Graph structure in the web. *Computer networks, 33*(1), 309-320.

Buhalis, D., & Law, R. (2008). Progress in information technology and tourism management: 20 years on and 10 years after the Internet—The state of eTourism research. *Tourism Management, 29*(4), 609-623.

Castells, M. (1989). *<<The>> informational city information technology, economic restructuring, and the urban-regional process*. Oxford etc.: Basil Blackwell.

Clauset, A., Shalizi, C. R., & Newman, M. E. (2009). Power-law distributions in empirical data. *SIAM review, 51*(4), 661-703.

Dredge, D. (1999). Destination place planning and design. *Annals of Tourism Research, 26*(4), 772-791.

Eurostat. (2013). Feasibility Study on the Use of Mobile Positioning Data for Tourism Statistics.

Grinberger, A. Y., Shoval, N., & McKercher, B. (2014). Typologies of tourists' time–space consumption: a new approach using GPS data and GIS tools. *Tourism Geographies, 16*(1), 105-123.

Gunn, C. A. (1994). *Tourism planning basics, concepts, cases* (3th ed.). Washington: Taylor & Francis.

Hagberg, A. A., Schult, D. A., & Swart, P. (2008). Exploring network structure, dynamics, and function using NetworkX. *Proceedings of the Proceedings of the 7th Python in Science Conferences (SciPy 2008), Pasadena, CA*, 11-16.

Hwang, Y.-H., Gretzel, U., & Fesenmaier, D. R. (2006). Multicity trip patterns: Tourists to the United States. *Annals of Tourism Research, 33*(4), 1057-1078.

Kádár, B., & Gede, M. (2013). Where do tourists go? Visualizing and analysing the spatial distribution of geotagged photography. *Cartographica: The International Journal for Geographic Information and Geovisualization, 48*(2), 78-88.

Kim, S. I., & Fesenmaier, D. R. (1990). Evaluating spatial structure effects in recreation travel. *Leisure Sciences, 12*(4), 367-381.

Kracht, J., & Wang, Y. (2010). Examining the Tourism Distribution Channel: Evolution and Transformation. *International Journal of Contemporary Hospitality Management, 22*(4-5), 736-757.

Leask, A. (2010). Progress in visitor attraction research: Towards more effective management. *Tourism Management, 31*(2), 155-166.

Leiper, N. (1989). Main destination ratios. *Annals of Tourism Research, 16*(4), 530-541.

Leiper, N. (1990). Tourist attraction systems. *Annals of Tourism Research, 17*(3), 367-384.

Lew, A. (1987). A framework of tourist attraction research. *Annals of Tourism Research, 14*(4), 553-575.

Lew, A., & McKercher, B. (2002). Trip destinations, gateways and itineraries: the example of Hong Kong. *Tourism Management, 23*(6), 609-621.

Lew, A., & McKercher, B. (2006). Modeling Tourist Movements: A Local Destination Analysis. *Annals of Tourism Research, 33*(2), 403-423.

Lue, C.-C., Crompton, J. L., & Fesenmaier, D. R. (1993). Conceptualization of multi-destination pleasure trips. *Annals of Tourism Research, 20*(2), 289-301.

Orellana, D., Bregt, A. K., Ligtenberg, A., & Wachowicz, M. (2012). Exploring visitor movement patterns in natural recreational areas. *Tourism Management, 33*(3), 672-682.
Pan, B., & Fesenmaier, D. R. (2006). Online Information Search: Vacation Planning Process. *Annals of Tourism Research, 33*(3), 809-832.
Richards, G. (2002). Tourism attraction systems: Exploring Cultural Behavior. *Annals of Tourism Research, 29*(4), 1048-1064.
Scaglione, M., Baggio, R., Favre, P., & Trabichet, J.-P. (2016a). *Using Mobile data to monitor tourism flows-Advances and limits.* Paper presented at the 3rd Advances in Destination Management, Vail Marriott Mountain Resort (CO, USA) (June 17-19, 2016).
Scaglione, M., Favre, P., & Trabichet, J.-P. (2016b). Using Mobile data and strategic tourism flows. Pilot study Monitour in Switzerland*. Proceedings of the Big Data in Tourism & Business Intelligence in the Travel & Tourism Domain, Mid Sweden Universuity*, 69-72.
Scaglione, M., Giovannetti, E., & Hamoudia, M. (2015). The diffusion of mobile social networking: Exploring adoption externalities in four G7 countries. *International Journal of Forecasting, 31*(4,October–December 2015), 1159–1170.
Scaglione, M., & Schegg, R. (2015). The Impact of Attribute Preferences on Adoption Timing of Hotel Distribution Channels: Are OTAs Winning the Customer Race? In I. Tussyadiah & A. Inversini (Eds.), *Information and Communication Technologies in Tourism 2015* (pp. 681-693): Springer International Publishing.
Schegg, R., & Scaglione, M. (2013). Substitution Effects Across Hotel Distribution Channels. In Z. Xiang & I. Tussyadiah (Eds.), *Information and Communication Technologies in Tourism 2014* (pp. 801-812): Springer International Publishing. from http://dx.doi.org/10.1007/978-3-319-03973-2_58.
Shoval, N., & Isaacson, M. (2007). Tracking tourists in the digital age. *Annals of Tourism Research, 34*(1), 141-159.
Stewart, S. I., & Vogt, C. A. (1997). Multi-destination trip patterns. *Annals of Tourism Research, 24*(2), 458-461.
Stienmetz, J. L., & Fesenmaier, D. R. (2013). Traveling the Network: A Proposal for Destination Performance Metrics. *International Journal of Tourism Sciences, 13*(2), 57-75.
Stienmetz, J. L., & Fesenmaier, D. R. (2016). *Validating Volunteered Geographic Information: Can We Reliably Trace Visitors' Digital Footprints?* Paper presented at the 2016 ttra International Conference. from http://scholarworks.umass.edu/cgi/viewcontent.cgi?article=1257&context=ttra.
Union fribourgeoise du tourisme. (2015). *Be my guest*. Retrieved 18 August 2016, from http://www.fribourgregion.ch/fr/be-my-guest-fr.html.
Vu, H. Q., Li, G., Law, R., & Ye, B. H. (2015). Exploring the travel behaviors of inbound tourists to Hong Kong using geotagged photos. *Tourism Management, 46*, 222-232.
Wang, D., Xiang, Z., & Fesenmaier, D. R. (2016). Smartphone Use in Everyday Life and Travel. *Journal of Travel Research, 55*(1), 52-63.
Wang, Y., & Fesenmaier, D. R. (2004). Modeling Participation in an Online Travel Community. *Journal of Travel Research, 42*(3), 261-270.
Wang, Y., & Xiang, Z. (2007). Toward a Theoretical Framework of Collaborative Destination Marketing. *Journal of Travel Research, 46*(1), 75-85.
Zach, F., & Gretzel, U. (2011). Tourist-Activated Networks: Implications for Dynamic Bundling and EN Route Recommendations. *Information Technology & Tourism, 13*(3), 229-238.
Zheng Xiang, Wöber, K., & Fesenmaier, D. R. (2008). Representation of the Online Tourism Domain in Search Engines. *Journal of Travel Research, 47*(2), 137-150.

Zoltan, J., & McKercher, B. (2015). Analysing intra-destination movements and activity participation of tourists through destination card consumption. *Tourism Geographies, 17*(1), 19-35.

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