

Big Data Analytics for Tourism Destinations

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INTRODUCTION

Although information and communication technologies (ICT) were an important issue for Travel & Tourism (T&T) since the 1960ies (i.e. computer reservations systems, global distribution systems; Werthner & Klein, 1999), the difference today is that ICT has become a strategic issue for every tourism business (Buhalis, 2006). The special benefit tourism gains from ICT can be put down to the characteristics of the tourism product, being a service bundle ideally portrayed by electronic media and being jointly delivered by (usually) small-sized enterprises. Indeed, T&T is a highly information intensive sector, and not surprisingly, T&T represents the largest branch within the e-Commerce sector. In 2012, 45% of the EU online sales volume has been generated by the T&T sector, whereat in 2008 this figure stood only at 25%. Moreover, in the US already 51.5% of the total travel revenue is generated online (E-Marketer, 2012). However, although tourism shows high penetration rates with respect to web-based marketing & distribution, shortcomings become evident with respect to e-business networks (supply-chains) and integrated process automation (e-procurement, enterprise resource planning, etc.). Finally, significant adoption gaps are ascertained for ICTs in tourism SMEs to support market research, product development and strategic decision making (e-Business Watch, 2006).

The attractiveness of tourism destinations particularly depends on how communication and information needs of tourism stakeholders can be satisfied through ICT-based infrastructures so that sustainable knowledge sources can emerge (Buhalis, 2006). Although huge amounts of customer-based data are widespread in tourism destinations (e.g. web-servers store tourists' website navigation, databases save transaction and survey data, respectively), these valuable knowledge sources typically remain unused (Pyo, 2005). However, managerial effectiveness and organisational learning could be significantly enhanced by applying methods of *business intelligence* (BI) and *big data analytics* (Wong et al., 2006; Shaw & Williams 2009), offering reliable, up-to-date and strategically relevant information, such as tourists' travel motives and service expectations, information needs, channel use and related conversion rates, occupancy trends, quality of service experience and added value per guest segment (Min et al., 2002; Pyo et al., 2002). This makes clear why ICT and methods of BI are playing a crucial role in effectuating a *knowledge destination* by enhancing large-scale intra and inter-firm knowledge exchange. Indeed, the major challenge of knowledge management for tourism destinations is to make individual knowledge about customers, products, processes, competitors or business partners available and meaningful to others.

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The objective of this chapter is to address the above deficiencies in tourism by presenting the concept of the tourism knowledge destination – a specific knowledge management architecture that supports value creation through enhanced supplier interaction and decision making. Information from heterogeneous data sources categorized into explicit feedback (e.g. tourist surveys, user ratings) and implicit information traces (navigation, transaction and tracking data) is extracted by applying semantic mapping, wrappers or text mining (Lau et al., 2005). Extracted data are stored in a central data warehouse enabling a destination-wide and all-stakeholder-encompassing data analysis approach. By using machine learning techniques interesting patterns are detected and knowledge is generated in the form of validated models (e.g. decision trees, neural networks, association rules, clustering models). These models, together with the underlying data (in the case of exploratory data analysis) are interactively visualized and made accessible to destination stakeholders. The technical architecture and implementation issues are discussed based on a prototypical implementation for the leading Swedish tourism destination, Åre (Höpken et al., 2015).

BACKGROUND

Since the widespread adoption of computerized reservation and booking systems in the 1980ies, comprehensive databases are available for all types of tourism transactions, i.e. the complete booking and consumption behavior (e.g. Passenger Name Record (PNR) databases of global distribution systems (GDS) or the airline on-time performance database of the Bureau of Transportation Statistics; BTS, 2012). Immediately, especially airline companies started to analyze such data as input to process and product optimization. A first prominent example in the area of revenue and yield management is the DINAMO system, introduced by American Airlines in 1988 (Smith et al., 1992). Further early examples can be found

for demand forecasting (Hueglin & Vannotti, 2001), prediction of cancellation or no-show behavior (Subramanian et al., 1999), or customer segmentation (Min et al., 2002).

Only very recently, data mining (DM) became increasingly important for tourism branches, due to its ability to discover previously unknown patterns in huge databases through explorative techniques and - compared to most statistical methods - to also identify non-linear relationships (Fuchs & Höpken, 2009; Fuchs et al., 2010; Höpken et al., 2011). Although, the potential of DM is not fully used in tourism yet, all major DM techniques are principally applied. More precisely, descriptive data analysis is widely used in form of reports or online analytical processing (OLAP) to visualize tourism arrivals depending on dimensions, like time/season, travel type or customer origin (TourMIS; Wöber, 1998; Destinometer; Fuchs & Weiermair, 2004). Methods of supervised learning, like classification, estimation and prediction are used to explain tourists' booking/cancellation or consumption behavior (Morales & Wang, 2008) and to predict tourism demand (Vlahogianni & Karlaftis, 2010). As a method of unsupervised learning, clustering is one of the most heavily used DM techniques in tourism, mostly applied to the task of customer segmentation as input to product differentiation, dynamic pricing or customer relationship management (Xia et al., 2010; Kuo et al., 2012).

With the uptake of the World Wide Web and its tremendous adoption in tourism, the topic of web DM gained more and more attention. *Web content mining*, i.e. the analysis of content from online platforms and websites, first of all deals with the analysis of user generated content (UGC), i.e. tourists' feedback and comments in blogs or review platforms, which currently constitute one of the most intensively researched topics in tourism (Bronner & Hoog, 2011). Methods of text mining are applied to the tasks of feedback aggregation and opinion mining or sentiment detection, typically based on statistical or linguistic approaches (Gräbner et al., 2012; Schmunk et al., 2014).

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