Similarity and consistency in online ratings: a self-organizing map analysis

ABSTRACT:

This paper adopts Self-Organizing Maps (SOMs) to analyse similarity and consistency in online ratings. The data set comprises online ratings gathered from eleven online platforms from 1,165 hotels. Our results suggest that there is a similar pattern of online ratings across most of the analysed platforms, except for Yelp and HolidayCheck; in addition, the evaluation patterns of the analysed hotels are stable over time; furthermore, the analysed attributes do not contribute decisively to explain the overall evaluation of an hotel, which implies that consumers use a non-compensatory evaluation model regardless of platform. Our results show that there is no difference between the evaluation patterns between the platforms that insist on prior reservations being made and those that do not. Two main implications are derived from this research: SOMs are shown to be useful tools for simplifying visual representations, and tourism online platforms are trustworthy sources of information. The results have been confirmed by means of two qualitative studies, a focus group with hotel managers and an in-depth interview with the manager of the dataset provider.

KEYWORDS

Self-Organizing Map; Online Ratings; Social Media; Visual Data Mining.

1. INTRODUCTION

Online reviews are a major driver of brand choice and sales (Park & Nicolau, 2015). Academic studies are increasing their focus on online reviews and hotel bookings (Sparks & Browning, 2011; Guo, Barnes & Jia, 2017) and meta-analyses (Floyd, Freling, Alhoqail, Cho & Freling, 2014; You, Vadakkepatt, & Joshi, 2015) show the influence of online reviews on sales. YouGov (2014) reports that the Americans who participated in the Omnibus survey tended to read online consumer reviews before booking a hotel or rooms to rent. Another study, reported by UNWTO (2014), shows that guest reviews are "important" or "very important" for more than 70% of international travellers and, more interestingly, consumers tend to visit, on average, almost 14 different travel-related sites when researching a trip. Indeed, the number of platforms has increased and the number of online reviews is massive. However, little is known about the similarities or differences between the online reviews across multiple platforms.

Despite the growing research on online reviews, there is an emerging need for research on the variability-similarity of online ratings across platforms and over time. As Babić, Sotgiu, De Valck, & Bijmolt (2016) posit, there is insufficient evidence of the effectiveness of eWOM across platforms. Previous literature on eWOM has addressed comparisons of a variety of technologies (e.g. chat, text messaging, social networks) (see Gvili & Levy, 2016). However, cross-channel comparisons within a single type of platform have been almost completely neglected (Xiang, Du, Ma & Fan, 2017). The literature on social media data discusses potential platform biases and data authenticity (Ruths & Pfeffer, 2014) and bias arising from using a single platform (Tufecki, 2014). Only recently, Xiang et al. (2017) compared three online review platforms, TripAdvisor, Expedia and Yelp, in terms of information quality regarding one tourism destination (i.e. Manhattan, NYC). Here, and with a different research angle, we expand the number of platforms and the number of tourism destinations analysed.

The analysis of the similarity-dissimilarity and the consistency-inconsistency of online content posted on platforms is relevant for both tourists and tourism managers. Given the growing number of platforms, tourists and managers have to check online reviews on several platforms to get an accurate overall picture of a hotel, which is time consuming. Alternatively, if one of the platforms could provide representative content then tourists and managers would check just that one, at their convenience. Whatever the case, managers and tourists may need a summary of data for managing the valuable information that comes from multiple online reviews. Scholarly research also calls for the simplification of the current models and speed improvements in algorithms in data-rich environments (Wedel & Kannan, 2016), such as online rating platforms.

Visual representation of data is an area of growing attention in different fields, from medicine to architecture and in business activities in general (see Keim, Mansmann, Schneidewind, Thomas &

Ziegler 2008). Self-Organizing Maps, SOMs, introduced by Kohonen in the 1980s, are part of a bundle of artificial neural networks techniques. This artificial neural model is able to convert complex, nonlinear statistical relationships between high-dimensional data items into geometric relationships in a low-dimensional space (Kohonen, 2001). The key point is to maintain neighbourly relations between patterns in an original space (which considers all the variables) and a transformed space (which has two to three dimensions, the most widely used being a two-dimensional space). Thus, patterns that are close in the original space remain close in the transformed space. In this way, different data evaluation patterns can be directly visualized, analysing the spatial distribution of values in the transformed space. It should be noted that this tool allows a simultaneous visualization of all the variables and all patterns. As Li, Law & Wang (2010) posit, "SOM as an unsupervised process provides a more efficient way to group high-dimensional data items into a set of clusters when comparing with existing tools" (p. 117).

SOMs are some of the most widely used multi-dimensional data visualization techniques (Kohonen, 2001) as they allow the quantitative relation of variables that form sets of N-dimensional data. Despite the huge number of scientific papers in fields such as engineering, medicine or biology, surprisingly their application to economic research lags behind (see Oja, Kaski & Kohonen, 2002). In tourism, only a few papers published in the 1990s, notably by Mazanec (1995) and early in 2000 by Moutinho and others (Curry, Davies, Phillips, Evans & Moutinho, 2001) were based on this technique. However, most of these studies were cluster analyses (Curry, Davies, Evans, Moutinho, & Phillips, 2003). Indeed, additional applications of SOMs in tourism are still scarce (see Li, Law, & Wang, 2010), have been published in non-tourism journals (e.g. Brida, Disegna & Osti, 2012) and not aimed at e-WOM analysis. The only similar research has been undertaken by Babić et al. (2016), who compared different e-WOM studies through a meta-analysis and Phillips, Zigan, Silva and Schegg (2015) who used data from TrustYou. The present research differs from Babić et al. (2016) in three ways: (i) they compare different types of platforms; (ii) they analyse different products and services; and (iii) their study is a meta-analysis; our focus is on analysing multiple platforms within the same type of platform, for a specific service (i.e. hotel bookings) and, by using SOMs, we apply a novel methodological approach towards analysing online reviews. Phillips et al. (2015) used the same data source as this research but they focused on just one platform, used a smaller dataset and applied partial least squares path modelling, not SOMs.

As Bloom (2004) claimed, research in clustering tourists needs to overcome the limitations deriving from linear techniques. Our aim here is to overcome the aforementioned research gaps by achieving three research goals. First, to identify whether common patterns of online ratings emerge in the same type of platforms, both across platforms (online similarity) and over time (online consistency); second, to analyse consistency between individual scores and overall scores in online reviews; third, to propose a SOM analysis for simplifying data analysis and to embrace non-linear relationships. To do so, 27 monthly online reviews from eleven platforms rating 1,165 Spanish hotels are used as a data set, covering the period January 2012 to March 2014. To the best of our knowledge, this is the first attempt to analyse similarities between platforms with online ratings using SOMs.

This paper contributes to the literature, both conceptual and methodological. From a conceptual viewpoint, the analysis of the (dis)similarity of online ratings between platforms and over time provides knowledge of how users rate the same type of service on different platforms and over time, respectively. Similarly, the analysis of (in)consistency might be considered as a valuable composite measurement. From a methodological point of view, this study introduces SOMs as effective means of parsing large data sets from different sources. This technique provides a practical visual representation and easy to use analytical tool but also offers objective measures (e.g. neighbourhood function) that may support initial conclusions derived from a visual analysis. In other words, this research suggests a new approach, which provides an efficient method for analysing a very great number of online reviews.

2. CONCEPTUAL FRAMEWORK.

2.1. Similarity in online ratings across different platforms

Much academic attention has been devoted to eWOM, the studies having different goals and levels of analysis (for a review, see Confente, 2015). Online reviews as a specific eWOM domain are growing dramatically, especially for accommodation services (Filieri & McLeay, 2014). An online rating represents the score associated with online reviews. Hotel managers and academic researchers aim to parse huge amount of available data coming from different types of platforms. Indeed, an online rating might derive from reviews posted on these three main source types: hotel websites, travel agency websites (i.e. Booking.com) and social media sites (i.e. Facebook). In this new scenario, characterised by multiple information channels, the research looks for integrative approaches in order to provide effective and quick analyses. In order to get a clear picture of the information provided by multiple platforms, it is effective to analyse the similarity between customer reviews derived from different sources. This approach is interesting not only because of its managerial usefulness but also because of its more general impact on consumer research. First, a similarity in ratings across different platforms assumes a non-segmented distribution of reviews across platforms. On the other hand, if online ratings follow a different pattern by platform, it might be attributed to three reasons: (i) differences in the consumer's criteria in each platform; (ii) differences in the service experienced or (iii) different users' profile by platform. A basic attempt to verify patterns in online reviews is to segment users by demographic variables, including nationality (see Alarcón-del-Alamo, Gómez-Borja & Lorenzo-Romero, 2015). Our approach is different. We argue that analysing the similarity of online ratings across different sources should help managers and researchers in segmentation research to provide timely and meaningful results. If some similarities in online ratings emerge across platforms, two main benefits would be derived. First, this would simplify data analysis, eliminating the need for data integration from similar platforms, which would be less time consuming and entail lower research costs. Second, it would facilitate efficient and prompt responses from managers, a critical factor (Wedel & Kannan, 2016). Then it might be argued that, if similarity exists, the service is equally rated and perceived whatever platform is used. Therefore, our first research question is devoted to analysing the similarity of online ratings across platforms.

Research Question 1: Do online ratings follow a similar pattern across different platforms?

2.2 Consistency in online ratings

The second area of interest in parsing online ratings regards the scores given to specific hotel services as opposed to the hotel´s overall evaluation. However, little is known about the internal consistency between these overall values and the scores given to the specific hotel services.

According to the choice decision framework drawn from consumer behaviour literature (Johnson & Meyer, 1984), two main sets of models can be identified. First, under a compensatory choice model, an overall score would reflect a summary effect of the different scores given to specific services. However, consumers may follow a non-compensatory choice process that leads to a higher relevance being given to some attributes. In this study, non-compensatory models are associated with inconsistency in scoring the overall rating. Accordingly, if consistency emerges, overall scores would be a valid measure for managers, tourists and even for researchers, in order to derive a clear and simple picture from the huge amount of data available.

We do not suggest that it is irrelevant to analyse inconsistencies. Rather, we suggest that if consistency emerges, tourists are not granting more importance to some specific services at the expense of others. A basic example may clarify this. Let us take the example where hotel H gets an overall evaluation of 9 out of 10, and its service A gets 9, service B gets 8 and service C only 4, using the same scale range. Two main explanations can be given for the overall score of 9: (i) the tourists are not consistent or (ii) they do not assign much relevance to service C in their overall hotel experience. Alternatively, tourists may composite or calculate mentally an average score and, consequently, each service would be given a similar weight by the customer as in a compensatory scheme, as previously discussed. Whatever is the case (i.e. not to give importance to one attribute or to give it a similar importance to the others), if there is consistency in the scores given to each attribute and the overall score, this suggests that overall scores are an appropriate and unique measure for parsing a large amount of online reviews. If this is not the case, two alternative explanations can be given. It can be argued that tourists are not consistent in their evaluations or, alternatively, they are weighting each item differently, reflecting the fact that they attach more importance to some services over others.

Other approaches with a deeper understanding of how consumers utilize user-generated content, such as Grounded Theory (Papathanassis & Knolle, 2011), might be adopted for individual case analysis. At aggregate level, Guo, Barnes, & Jia (2017) analyse 266,544 hotel online reviews and find that five out nineteen main dimensions are key determinants of consumer satisfaction. However, our perspective here differs from prior studies. We aim to analyse a large data set, reflecting major patterns, in two ways: (i) a consistency effect, previously not addressed in the literature; and (ii) a stability effect over time. The latter has been discussed in the social media field by Claster, Pardo, Cooper and Tajeddini (2013), who showed that stability in tweet content is a contextual issue which depended on the tourist destination. However, we look at both consistency and stability. Therefore, the next two research questions are focused on these effects. Hence, we aim to research the following:

Research Question 2: Is there a pattern of consistency between scores given to each attribute and the overall score (a) within each platform and (b) across platforms?

Consistency can be also analysed over time. Consistency over time is defined as the stability of the given scores, both overall and for specific services. If similar scores are maintained over time they can be attributed to either the achievement of the same level of service performance over time or to unchanged perceived value even with a different level of service performance. On the contrary, instability might be attributed to a change in service performance or to the user's perception. Therefore, the following research question aims to evaluate consistency over time:

Research Question 3: Is there a pattern of stability over time for scores given to each service and the overall score, both (a) within each platform and (b) across platforms?

A straightforward consequence might be derived from these research questions. If internal consistency exists, overall measures are good estimators for analysing data. If the pattern persists over time, overall scores might be used as a proxy variable in a prospective analysis, both at industry and hotel levels. Even if a hotel has changed its service levels, and the overall scores stay stable, this may reflect that tourists do not note the change or they do not see it as relevant.

2.3. Influence of booking versus trust in online ratings.

Online review platforms are gaining in popularity. They have different formats in terms of their user review requirements. Some platforms only accept reviews from customers who actually booked, and stayed at, a hotel through their website (e.g. Booking.com), while other platforms (e.g. TripAdvisor) allow the posting of online comments and review scores based on the trust placed in users' declarations regarding their visits. There has been limited research as to whether posting patterns differ depending on the platform's requirements. Babić et al. (2016) suggest that the effect of eWOM on sales may be greater for platforms imposing eWOM posting costs. As Bilgihan, Barreda, Okumus and Nusair (2016) posit, perceived ease of use and belief in integrity positively influence knowledge-sharing behaviour. Hence, integrity must play a key role in online reviews. Since integrity is a self-regulated activity, we aim to explore whether online reviews in platforms that involve hotel stays differ from those posted on platforms where online comments rely on a personal declaration. Therefore, we posit this research question:

Research Question 4: Is there any difference between online ratings posted on platforms where a reservation is a prerequisite, and those based on the user's integrity?

A remaining issue is whether SOMs are the appropriate methodological approach to address the research questions. SOMs meet the following practical criteria, all potentially attractive for analysing online reviews, for five reasons. First, SOMs are appropriate for large data sets, including user generated content (Lu, & Stepchenkova, 2015); second, SOMs are able to reduce a higher-dimensional input space to a lower-dimensional map space, facilitating visual interpretation. If that is indeed the case, SOMs would be aligned to the growing trend of adopting visual interpretation, a recent development in tourism research (Cheng & Edwards, 2015); third, the technique is based on competitive learning (i.e. each data vector recalculates the solution) that helps the dynamics; fourth, they allow outputs to be compared through the use of an objective indicator, named neighbourhood function; finally, they are suitable for non-linear data sets.

Despite the growing number of papers on data visualization and SOMs published in the artificial intelligence and expert systems fields, in tourism such research is scarce. Only a few papers have adopted SOMs in tourism, mainly for clustering purposes, such as Mazanec (1992, 1999, 2001) and Bloom (2005). SOMs adoption in related fields, such as business, is also scarce, but with notable exceptions. See, for example, Calderón-Monge, Pastor-Sanz & Ribeiro-Soriano (2016) on franchising, or Hadjinicola, Charalambous & Muller (2013) on product positioning. To the best of our knowledge, this is the first paper that uses SOMs to analyse online ratings in tourism. One related exception is Claster et al. (2013), but this study used only tweets as input data. Our study differs from Claster et al. (2013) in two ways: first, our analysis is based on more than one platform and, second, it also considers consistency over time. Given this scarcity of SOM research into online reviews, we propose the following research question:

Research Question 5: Is the SOM a suitable approach for analysing online reviews?

3. SELF-ORGANIZING MAP (SOMs)

Self-organizing maps, SOMs, are one of the most popular currently available visualization tools. The SOM is an Artificial Neural Network (ANN) proposed by Teuvo Kohonen in the 1980s (Kohonen, 2001); and, since then, it has been analysed and employed extensively. SOMs and their variants have been employed very often, in a wide variety of domains, such as finance (Deboeck & Kohonen, 2000), medicine (Alakhdar, Martínez-Martínez, Guimerá-Tomás, Escandell-Montero, Benítez, & Soria-

Olivas, 2012), engineering (Kohonen, 2001; Díaz, Cuadrado, Diez, Domínguez, Fuertes, & Prada, 2012) and even in the field of animal sciences (Soria, Martín, Fernández, Magdalena, Serrano, Moreno, 2006; Fernández, Soria, Martín-Guerrero, & Serrano, 2006; Magdalena, Fernández, Martín, Soria, Martínez, Navarro, & Mata, 2009).

In contrast to SOMs, classical techniques can only deal with accurate visualizations of whole data sets when the number of features required is three or lower; to represent a higher number of features, 3D projections need to be carried out, establishing restrictions (such as maintaining a fixed set of variables and representing the rest). Such a restriction allows only a partial representation of the information. Moreover, most real data sets are formed by more than three features, making graphical representations difficult, or impossible. For that type of representation, which makes it possible to find patterns in data sets with high dimensionality, SOMs are especially appropriate; in particular, SOMs produce a low-dimensional (typically 2D) representation of high-dimensional data by identifying data that are similar in the input space, and grouping them on a grid (Kohonen, 2001). The most appealing characteristic of SOMs is that the underlying mathematics ensures that the map is a faithful representation of the original data; that is, when two data points have similar features they are represented as close to each other in the resulting map.

This neural model seeks to find and visualize patterns in N-dimensional data sets where the key working principle is to keep a neighbourhood relation between the original space of the N-dimensional data (input space) and the regular low-dimensional grid (output space). Regarding its structure, a SOM consists of elements of a process, called neurons, organised on a regular low-dimension grid (normally in two dimensions), as mentioned above. The number of neurons may vary from a few dozen up to several thousand. Each neuron is presented by a N-dimensional weight vector m = [m1, . . . , mN], where N is equal to the dimension of the input vectors (the number of variables that describe the problem).

In SOM design, the first choices are the selection of the map type and the number of neurons selected (as this will determine the size of the low-dimensional grid). The first step for this algorithm is the weight initialization, which creates a great number of possibilities. When the initial values of synaptic weights have been selected, the next step is to get them closer to the optimum values by means of an iterative procedure. After the SOM training process, it is very easy to project the map onto the different features; these projections are called component planes (Kohonen, 2001), also known as component maps. The component planes can be plotted so that information regarding each single variable can be visualized, allowing the most complete representation of reality and showing the relationships between the different analysed variables. A component plane of a SOM is a map where, for each neuron, only one component of its weight vector (corresponding to a given input variable) is shown; thus, in experiments a total of N component planes (where N is the data dimension or the number of variables) can be displayed. Therefore, input patterns mapped onto certain areas of a component plane maintain their graphical positions in all other component planes. Since all the component planes actually belong to the same map, a certain area of the map can be simultaneously analysed for the different features, determining the qualitative relation between the variables.

In the component plane, each neuron in the SOM grid is coloured based on the value of the i-th component of its weight vector; higher values are usually depicted in red and lower ones in blue. Thus, component planes tend to show some parts of the map as having a similar colour; this means that similar input vectors are clustered in those particular areas of the map, that is, similarly coloured neurons within a plane represent a set of input vectors that are similar according to that specific variable. The same region within every plane (say, the upper left corner) identifies the same set of records, but different planes focus on a different variable.

4. DATASET DESCRIPTION.

Data came from user-generated ratings derived from eleven online reviews from the following booking sites: Agoda, Booking, Expedia, Holidaycheck, Hostelworld, Hotels, Travelocity, TripAdvisor, Trivago (UK), Trivago Germany and Yelp. These online review platforms capture a rich diversity of sources of tourists ratings, as follows: (i) they are all international and popular (ii) they differ in being tourism biased, tourism specific (e.g. Expedia) and non-specialized on tourism (e.g. Yelp); (iii) there are pure online review platforms (e.g. TripAdvisor) and pure online travel agencies (e.g. Booking); (iv) some have booking requirements for posting comments (e.g. Agoda) and some need just the user's declaration (e.g. Trivago), as seen in Table 1.

Table 1. Requirements for online reviews by platform

Platform	Posts	Specialization	Requirement for online reviews
1. Agoda	The Priceline Group	Tourism	Reservation and stay are required
2. Booking	The Priceline Group	Tourism	Reservation and stay are requested
3. Expedia	Expedia Inc.	Tourism	Reservation and stay are requested
4. Hotels	Expedia Inc.	Tourism	Reservation and stay are requested
5. Travelocity	Expedia Inc.	Tourism	Reservation and stay are requested
6. Holidaycheck	HolidayCheck AG	Tourism	None
7. Hostelworld	Hostelworld Group	Tourism	None
8. TripAdvisor	TripAdvisor, Inc	Tourism	None
9. Trivago (Germany)	Expedia Inc.	Tourism	None
10. Trivago (UK)	Expedia Inc.	Tourism	None
11. Yelp	Yelp Inc.	Not	None

This dataset encompasses online ratings from 1,165 hotels operating in Spain. Data were gathered by TrustYou (www.trustyou.com), which operates a reputable online monitoring system featuring over 35,000 hotels worldwide. Phillips et al. (2015) also used a data source similar to TrustYou but focused only on 235 hotels operating in Switzerland. Our research is based on monthly data from January 2012 to March 2014 for each hotel and for each online review posted on the aforementioned platforms. Table 2 provides the details of the six variables included in our analysis as provided by TrustYou.

Table 2. Variables used in the analysis

Variable	Description	Range
Overall Score (1) (2)	Overall Score refers to the rating that review sites give to each hotel. The previous 24 months of data are used when calculating the score.	0-100
Performance (1) (2)	Average of the hotel's ratings over the time period. TrustYou normalizes the ratings to the user scaling.	0-100
Hotel	Sentiment analysis of phrases related to the category "Hotel"	0-100
Location	Sentiment analysis of phrases related to the category "Location"	0-100
Service	Sentiment analysis of phrases related to the category "Service"	0-100
Internet	Sentiment analysis of phrases related to the category "Internet"	0-100

(1) Measured at an aggregate level and on each platform **regarding** reservation confirmation or stay or both. See table 2 for details.

(2) The past 24 months are used with the following weights: 100% for the last 6 months, 50% for the remainder.

Overall, available data consisted of online comments for 1,165 hotels by 6 variables and by 11 platforms for 27 consecutive months. The average monthly data were grouped by quarter years that reflect a common season. The software used was Matlab SOM Toolbox, accessible at http://www.cis.hut.fi/somtoolbox/

5. DATA ANALYSIS AND RESULTS

5.1. Data Analysis

In order to present meaningful results, data for the 27 months were arranged by quarters, following a three-stage strategy. Stage 1 generates the SOM using data from the first quarter; this SOM will be use as the baseline for the rest of quarters; therefore the representation of the quarters will highlight the differences respect to the first one.

The learning parameters, discussed below, are**:** (i) Initialization. Two different types of parameter initialization of the model (synaptic weights) were conducted. On the one hand, random initialization and, on the other, principal component analysis of the inputs. (ii) Neighbourhood function. The Gaussian, bubble and cut gauss functions were used as neighbourhood functions to update the neuron coefficients close to the winner neuron. (iii) Learning algorithm. Two types of algorithms were used for SOM training: (a) Sequential. Synaptic weights are updated for each database pattern, and (b) Batch. Here the weights are updated when all database patterns are analysed. This algorithm is faster than the previous one because it requires fewer updates. However, this algorithm usually provides poorer results.

In Stage 2, the coefficients (synaptic weights) of the first SOM are used as initial values for the second (SOM that takes into account data from the second quarter); in this way, possible changes between quarters can be visualized in the same spatial area of the SOM. This way, the SOMs highlight the differences in behaviour among quarters, and each quarter is easier to visualize and interpret. The other learning parameters discussed above are maintained.

In Stage 3, the similarity between the variables for different quarters can be obtained by visually comparing both maps. A numerical approach establishes correlations between the synaptic weights of the neurons that form the maps for each quarter. That is, the correlations between the vectors of the neurons are carried out for each pair of data sets. Finally, these relationships are averaged by dimension. That is, the SOMs represent images that can be used to visualize the similarity among them expressed mathematically.

For that purpose we used the classic correlation expression as depicted in Equation (1):

$$r = \frac{\vec{m}_1 \cdot \vec{m}_2}{\|\vec{m}_1\| \cdot \|\vec{m}_1\|} = \frac{\vec{m}_1 \cdot \vec{m}_2}{\sqrt{\sum_{d=1}^{N} (m_{1d})^2} \cdot \sqrt{\sum_{i=1}^{N} (m_{2d})^2}}, \quad (1)$$

where m_k are the neuron coefficients and N is the number of dimensions. Qualitatively this determines the similarity between different SOM analyses.

5.2. Results

The results show that SOMs allow both the visualization of the qualitative relationships between variables as well as the correlations between the variables under study**.** Both analyses will allow us to address the research questions in this paper. For the analyses the following platforms were discarded - Travelocity, Hostelworld and Trivago Germany - for having insufficient online ratings during the study period. We thus focussed on the following eight platforms: Agoda, Booking, Expedia, Holidaycheck, Hotels, TripAdvisor, Trivago (UK) and Yelp.

In order to analyse the similarity of online ratings across the different platforms, Figure 1a represents the component map, obtained from the global score of the platforms for the first quarter. Figure 1b represents the correlations between the quarterly global score for each platform, obtained from Equation 1. From this value, it is observed that the correlations of the different quarters are all very high, with correlations between 0.9 and 1. This high correlation allows us to analyse the SOM derived only from the first period analysed (first quarter), since the other quarters are very similar, as indicated by the high correlation values.

Figure 1a shows the great similarity between all online ratings by platform. In particular, the greatest similarities can be found in the Booking, Expedia (online travel agencies), Trivago and Tripadvisor (online review) platforms. The visual patterns of the Yelp ratings are the most differentiated from the other platforms. The lower left corner is where that difference appears most clearly. This finding shows a similar behaviour to the online ratings on tourist platforms and a difference between these platforms and the non-tourist platforms, as represented by Yelp. Figure 1b shows the correlations between online ratings by quarter, showing values higher than .94, except on; platform 3, Trivago, which ranges from .90 to .92; platform 6, Yelp, with a correlation value of around .93; and platform 7, Agoda, which has correlation values between .92 to .94. Overall, the high values of the correlations between the online ratings for each quarter for each platform show the existence of a common pattern over time in the four quarters analysed.

Figure 1a. Component planes of the overall scores across platforms for the first 3-month period.

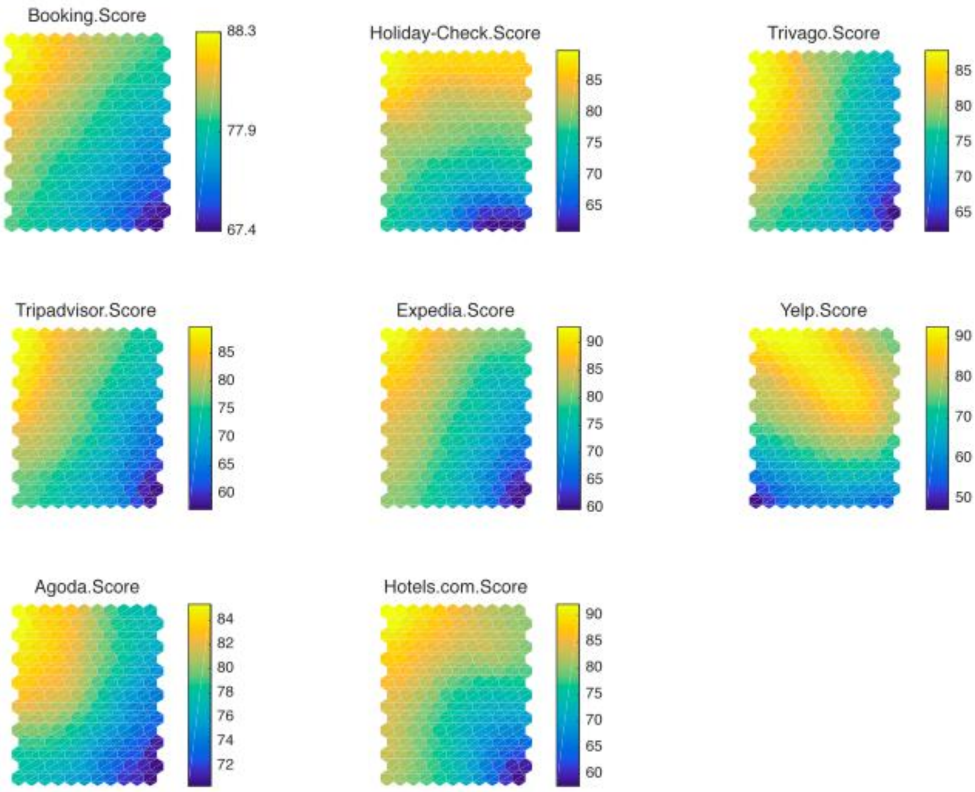
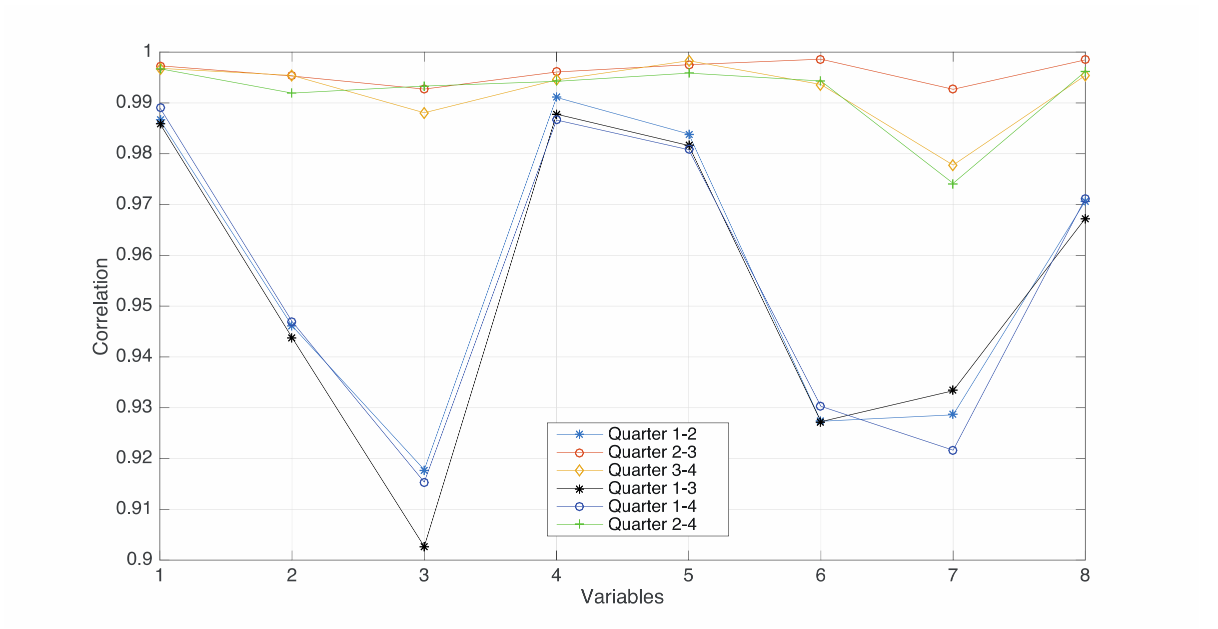


Figure 1b. Correlations between the different SOMs by quarter.



1) Booking Score; 2) Holiday Check Score; 3) Trivago Score; 4) Tripadvisor Score; 5) Expedia Score; 6) Yelp Score; 7) Agoda Score; 8) Hotels.com Score.

In order to analyse the relationship between the attributes and the global score, Figure 2a shows the SOM of the overall score for the first quarter for each platform and the score by attribute based on the sentiment analysis of the following attributes: hotel, location, service and internet (as depicted in table 2). Figure 2b shows the correlations between quarters based on Equation 1. Again, it is observed that there is a very high correlation between different quarters except in Yelp, 6 and in location, 10. In this latter, the difference between the first and the third quarters was particularly significant, with a value close to .6. If quarters are compared it is observed that the third and the fourth are very similar in all variables (the correlations never fall below .9 for all platforms).

Regarding the SOM analysis of the overall scores, Figure 2a shows the similarity in the overall scores for the different online review platforms, except for Yelp.com which, as in the previous analysis, behaves differently from the rest. It is also noted that the lowest score values for the different online review platforms (bottom left corner of the maps) corresponds to the lowest scores for location and service and low Internet scores. Consequently, none of the analysed attributes alone is strong enough to determine the overall score pattern on any of the platforms. This result is in line with Park and Nicolau (2015), who found a similar asymmetric relationship between overall sentiment and overall rating, using only Yelp. However, we can identify the following four additional findings. In the first place, a very bad score for service is associated with a bad overall score, except in the case of Yelp, which, as we saw in the previous section, does not follow the same pattern. Secondly, no hotel with a very good location rating is among the most generally highly rated on any of the platforms. In terms of hotel location our results are partially aligned with those of Xiang and Krawczyk (2016), who used semantic analysis on online reviews in Manhattan, and found that hotel location is a significant factor in the guest experience, but that location was ranked only fifth in the list of terms reflecting the guest experience. Third, the hotels with the highest overall scores do not have the highest location scores. Finally, the hotel and service sentiment assessments follow a similar pattern and give higher values than location and the Internet in almost all the maps.

Figure 2a. Component map for the first quarter comparing the overall platform scores and scores by attribute (hotel, location, service and internet)

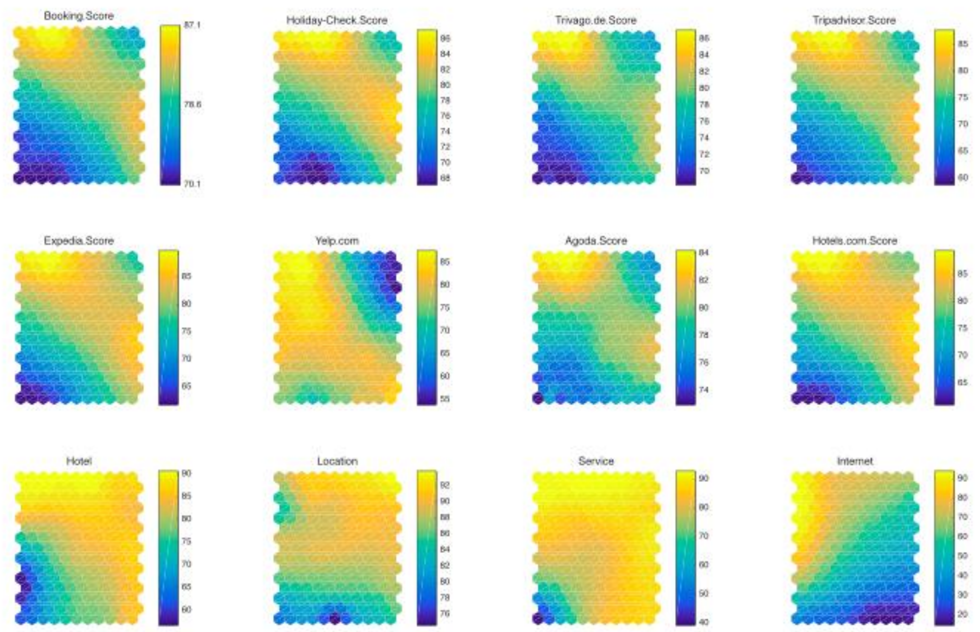
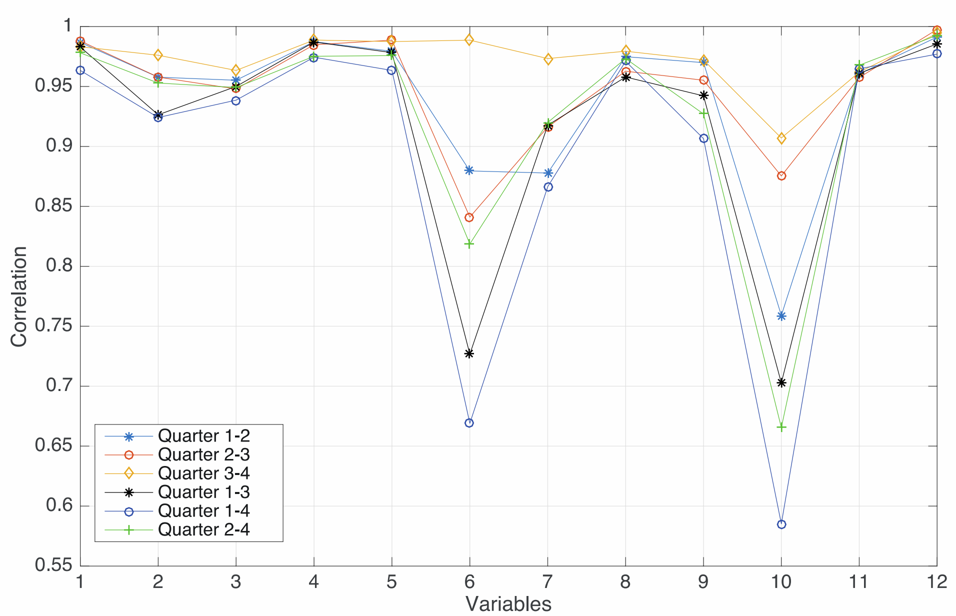


Figure 2b. Temporal correlations across the different SOMs for each quarter



1) Booking Score; 2) Holiday Check Score; 3) Trivago Score; 4) Tripadvisor Score; 5) Expedia Score; 6) Yelp Score; 7) Agoda Score; 8) Hotels.com Score; 9) Hotel; 10) Location; 11) Service; 12) Internet.

In summary, if the variables of Figure 2a are analysed, it is observed that there is not one single attribute that determines the overall score pattern for the different platforms. Consequently, tourists in their overall hotel evaluations are valuing more attributes than the four previously described.

In order to analyse the (dis)similarities between the online ratings by platform, we used hotel performance based on consumer evaluations (see table 1). For this, only those platforms with the largest number of online ratings were selected. Figure 3a depicts the relationships between performance and platform in the first quarter. Also in Figure 3a of the component map we can see that performance across the platforms does not follow a similar pattern, although it is noteworthy that those hotels that are scored as having the best performance on one platform have it all platforms. When scores descend from the maximum score, the pattern diffuses across the platforms. It is observed that for average and low scores each platform presents a different pattern; so there is no agreement between them in that score range. On the other hand, Figure 3b shows stability over time across platforms (RQ3), demonstrated by the temporal correlation between quarters, showing again a high correlation (above 0.9), which evidences the same temporal behaviour by platform, so that only the first quarter need be analysed.

Figure 3a. Component planes of performance across platforms for the first quarter.

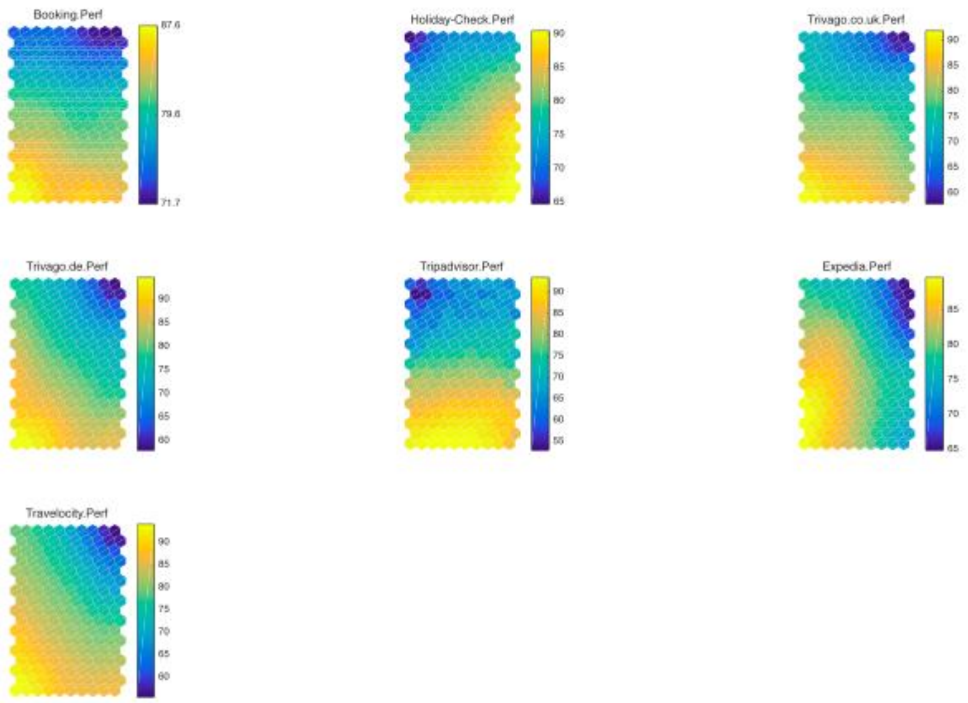
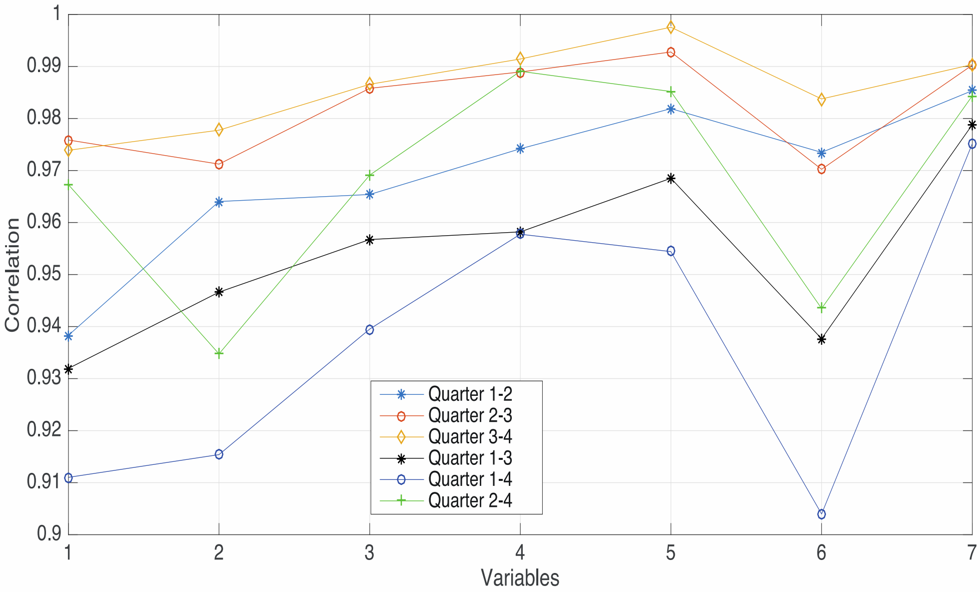


Figure 3b. Temporal performance correlations across the SOMs for each quarter



1) Booking Perf.; 2) Holiday Check Perf.; 3) Trivago.co.uk.Perf.; 4) Trivago.de. Perf.; 5) Tripadvisor Perf.; 6) Expedia Perf.; 7) Travelocity Perf.

In order to analyse if performance captures behaviour similar to the sentiment analysis of the four attributes (RQ3a), Figure 4a shows the component map depicting the average hotel performance on the platforms and the average sentiment by attribute. From this map the following findings are observed: (i) There is a similar pattern between performance and the service attribute, ensuring, at least, that a very good service evaluation implies very good overall performance; (ii) A very good evaluation of hotel and location also implies a very good performance score, although this relationship is not maintained for poorer evaluations; (iii) The internet score does not show any special relationship pattern with performance.

Figure 4b shows the temporal correlation between quarters for the different self-organized maps. The correlations are above .9, except for variable 3, hotel location, whose correlations by quarter are between .55 and .65. Perceptions about location have a temporal dependency**.** This dependence can be explained by the season during which the hotel is visited. As an example, in a coastal city, in summer the beach may be attractive but, in winter, the historical centre may be more interesting. Consequently, the location assessment will differ depending on the quarter.

Figure 4a. Component map of average performance on all platforms and score by attribute.

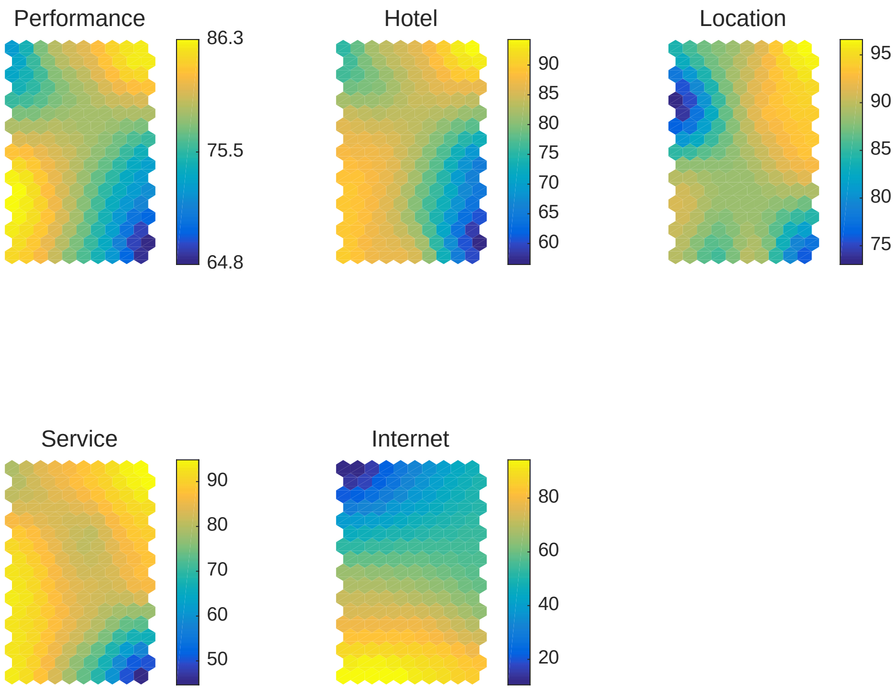
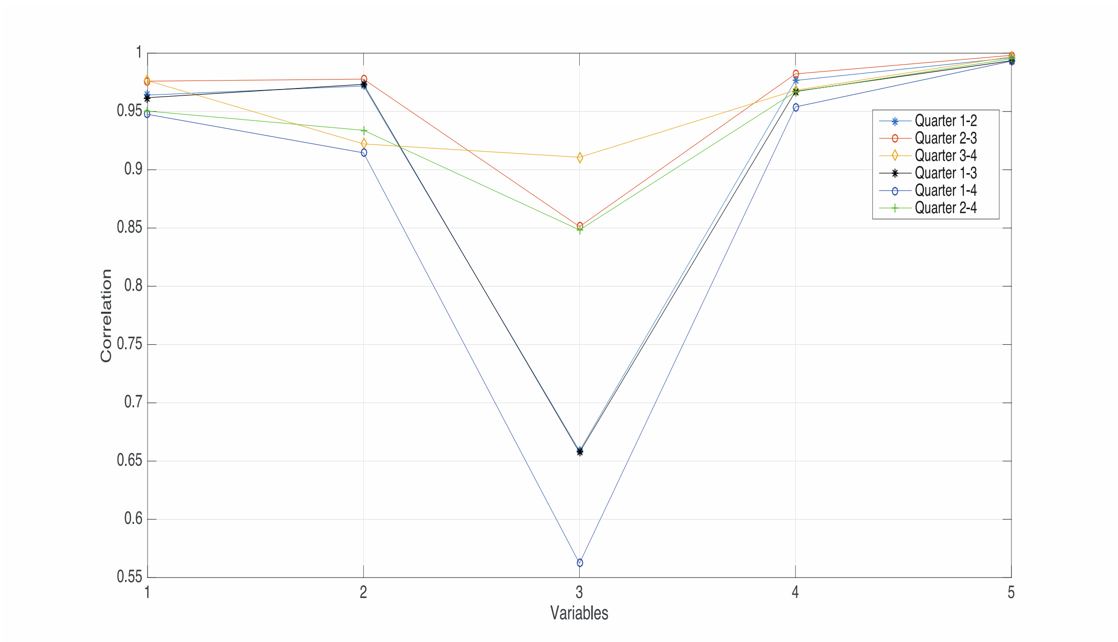


Figure 4b. Temporal correlations across the SOMs for each quarter



1) Overall Performance; 2) Hotel; 3) Location; 4) Service; 5) Internet.

In order to analyse if there is a relationship between attribute sentiment and the average overall score across all the platforms, Figure 5a shows the component map of the average overall score of all the platforms and the sentiment score by attribute. From this map it is observed that there is a similar pattern between the average score across all the platforms and the specific hotel attribute. There is no relationship with the Internet score.

Figure 5b shows the temporal correlation between quarters for the different self-organized maps. The correlations are above .8. These results are similar to those obtained in the overall score analysis, reinforcing those obtained with respect to the overall score (Figure 3a and 3b), thus supporting the concept of stability within each platform and across platforms over time.

Figure 5a. Component map of average scores for all platforms and score by attribute.

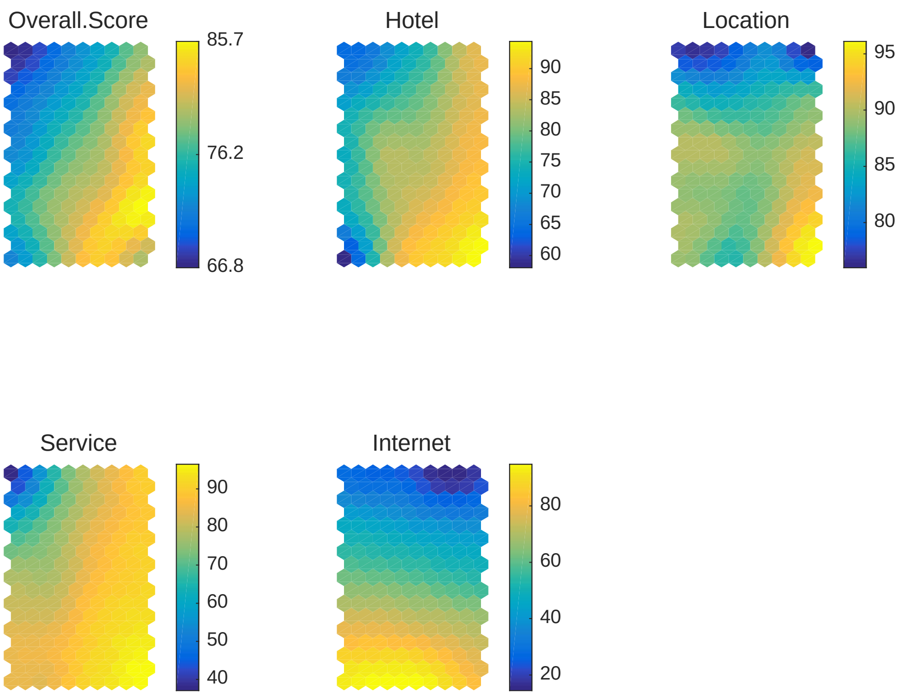
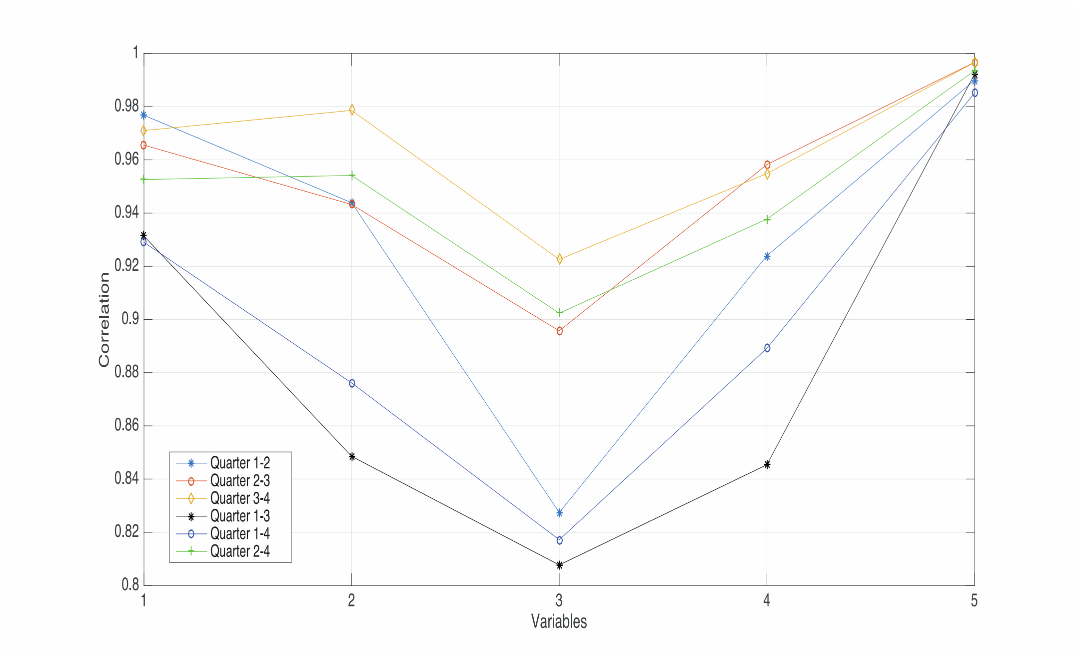


Figure 5b. Temporal correlations across the different SOMs by each quarter



1) Overall Score; 2) Hotel; 3) Location; 4) Service; 5) Internet.

5.3. Qualitative confirmation analysis

In line with recent calls for adopting mixed research methods (Molina-Azorin, 2016), an explanatory sequential design was adopted as suggested by Creswell and Creswell (2018). Therefore, after the quantitative study based on online reviews, we gathered information from a qualitative study. The qualitative study compromises two studies: a focus group with hotel marketing managers in charge of social media, and an in-depth interview with the Managing Director Spain of TrustYou. The aim of the qualitative study is twofold. First, to contrast our research findings derived form the SOM analysis. Second, to identify potential explanations and new insights for future research.

The focus group consisted of six hotel managers of hotel chains controlling 52 hotels with domestic and international tourism. Two researchers conducted the focus group as follows. First, each research question was introduced as an open question for triggering the comments of the six participants in terms of the value of such question and their views based on their own experience. After, one of the researchers showed the results of this research and opened a new discussion for confirming or discarding the research findings.

As far as the first RQ, participants confirmed the research findings. Everyone understood that the online review pattern behaves in a similar way between platforms. Although the scores of hotels were not identical in each platform, close similar and the order of online rating for each hotel in each platform was kept, except in specific cases or exceptional situations. None manager used Yelp, and they do not see it as a specific tourism platform.

RQ2 aimed to analyze the consistency of online ratings between the overall evaluation and the evaluation of each specific service. Participants showed diverse views. In some cases, an overall rating, either positive or negative, were transferred to each service. However, other participants showed the reverse, that is, posit that tourists are quite confident in assigning different ratings to each service independently. In any case, the "hotel variable" is seen as an umbrella that reflects the most the overall evaluation. Potential differences here were attributed to the type of tourist and their countries of origin.

The RQ3 aimed to analyze whether the online ratings of the hotel features vary over time and by platforms. The research findings suggest stability over time except for hotel location. Despite the physical location is stable, the participants view is that season is affecting online ratings. Thus, in non-stationary locations, online ratings of hotel location would not vary over time or platforms.

As far as the RQ4, participants confirmed the absence of differences in online ratings between platforms, as in research question one. They suggested that potential differences might occur between the type of guests rather than the type of platform.

One week after the focus group, an in-depth interview with the Managing Director Spain of TrustYou was implemented. TrustYou is the world's largest guest feedback online platform that monitors and analyzes hundreds of millions of online travel reviews of 600.000 hotels worldwide. In order to prevent potential bias from market development, the data set of this research was focused only in one and leading tourism market destination, Spain. The in-depth interview followed the same structure as the focus group. This, each research question was introduced as an open question for triggering comments and later on the research finding were introduced to open a new interview for confirming or discarding the research findings and stimulate further research ideas.

In terms of similarity between online ratings between platforms, RQ1, once again it was confirmed that the online review pattern behaves in a similar way between platforms. This result confirms the research findings and the focus group information. Furthermore, two interesting comments have arisen. First, platforms that do not require any proof of stay from their users to share publicly their opinion, such as TripAdvisor, tend to gather more reviews than other platforms with restricted access to publishing functionalities. This lack of verification makes platforms like TripAdvisor a primary option for publishing negative reviews triggered by disappointment, resentment or disagreement with the property's management. As a result, hotel scores tend to be slightly lower at TripAdvisor than the average score based on other travel platforms. Second, since the beginning of 2017 Yelp is not scrutinized because this platform does not bring a high volume of comments for hotels and also hotels managers do not pay attention to it. This confirms the anomaly of Yelp as a non-specialized platform in tourism, in comparison with the other 11 platforms.

As far as RQ2, which aimed to analyze the consistency of online ratings between the overall evaluation and the evaluation of each specific service, the CEO showed this trend as feasible, since the hotel variable summarizes the overall rating. However, further research might analyze whether other potential services may vary, such as room cleanliness, food and beverages. These variables might be more subjective and score differently.

The RQ3 aimed to analyze whether the online ratings of the hotel features vary over time and by platforms. From TrustYou experience there must be stability between services and by platforms. However, our research findings suggested stability over time except for hotel location. From TrustYou lenses this results needs further elaboration. Some explanations were given depending on the type of hotel and destination. First, in peak seasons, the scores tend to be more critical because the higher price elicits higher expectations. Second, although hotel location is a tangible attribute it might be perceived differently depending on the season and the motives of travelling. Third, hotel location embraces related services such as transport services, recreational activities or other services that vary between seasons eliciting different scores depending on the type of destination and seasonality.

Lastly, from TrustYou perspective no differences arise between online ratings of platforms where the previous booking is necessary and those where no booking is required, RQ4. This view confirms our research findings and also the results form the focus group. Two comments arose that may enrich future research. Platforms, where no require previous booking confirmation, tends to gather a higher number of online comments that the counterpart's which require the previous booking. Also, platforms with a high volume of comments tend to dilute the extreme scores. The latter comment suggests an interesting research avenue based on the analysis of the tails in order to capture potential changes.

Overall, there was a consensus between the research findings and especially on the value and usefulness of the research. Furthermore, the focus group and the in-depth interview have opened a new research avenues focused on analyzing online reviews by type of tourists and countries of origin.

5.4. Discussion of results and implications

Using the results provided by the self-organized maps and the temporal correlations between scores by quarters, the main implications derived from the research questions are analysed below.

As to research question one (RQ1), our results suggest that there is a similar pattern of online review scores across most platforms, except for Yelp and HolidayCheck. This implies that, to a certain extent, users give homogenous evaluations on typical tourism platforms. This interesting finding suggests that from a practical point of view, hotel managers, and even customers, do not need to consult the scores given by each online review platform. Therefore, hotel managers do not require to make the additional analysis effort of looking at every platform, except for Yelp, a non-tourism specialist online review platform and, partly, as regards HolidayCheck. From an academic point of view this finding means that users tend to evaluate the same type of services as being equal, regardless of the platform, all of them being of the same nature. Accordingly, if tourists show similarity in their evaluations across online platforms, it can be derived from this that tourism online platforms are trustworthy information sources.

Research question two aims to analyse if there is a pattern of consistency between the scores given to each attribute and the overall score. Our results do not show a high level of consistency between the scores given to the four attributes measured through sentiment analysis and the overall score by each platform and between platforms, as figures 2a, 3a, and 4a show. Thus, location is less correlated than the other three variables. This may be attributed to the influence on the location score of the season during which the visit takes place**.** The consistency between specific attribute assessments and the global score awarded to an hotel (RQ2) is of importance in understanding which attributes contribute to the overall assessment and to analyse their relative importance in the evaluation of the hotel. It can be argued that tourists are not consistent in their evaluations or, alternatively, all attributes (e.g. location, Internet, hotel and service) do not equally contribute to the overall score. In effect, the average overall score has a pattern very similar to that of the hotel's sentiment assessment. However, the pattern differs extensively, as expected, when it comes to an attribute that is increasingly common in hotels, such as Internet availability. Another interesting implication is the different pattern observed between the overall score and the service attribute. This can be attributed to the different level of service usage according to type and category of hotel. This implies that SOMs are adequate when analysing large amounts of data and to answer questions of an exploratory nature. From a conceptual point of view, it can be stated that users follow a non-compensatory evaluation model, regardless of platform. Furthermore, our results, depicted in Figure 2b, show stability over time for each attribute, except for location, which is attributable to the fact that the assessment of a hotel´s location varies depending on the season of the year. So, comments about location can be positive for a coastal hotel during the summer but negative during the winter.

In relation to research question three, the results obtained in figure 2b indicate that there is stability over time in the overall scores and also in performance over time. (Figure 3b).

Possibly the most important current debate in relation to online comments is about the reliability of platforms that do not require prior reservations, as opposed to those that do (RQ4). The ability to define a pattern of correlation between platforms that require prior bookings (Booking.com type) with platforms that do not require them (e.g. TripAdvisor.com) is a topic of great interest as it indirectly affects the credibility of online commentators. In relation to research question four, the results indicate that there is no difference between the patterns of those platforms that require prior reservations and those that do not. This again implies that the behaviour of the consumer is homogeneous and not conditioned by the booking requirement of the platform, which is especially important with a requirement so fundamental in tourism, the prior reservation.

In relation to research question five, the results indicate that SOMs are useful tools to compare multiple online review platforms. Their main advantages for future research are as follows. First, SOM maps are easy to obtain and are in accordance with recent tourism research (Cheng & Edwards, 2015). Second, when the data comes from multiple databases (for example online platforms), SOMs allow a rapid comparison that can detect common patterns or differences. Third, SOMs allow the analysis of non-linear relationships. As Kohonen (2001) suggested, this artificial neural model is able to convert complex, nonlinear-related relations between high-dimensional data items into geometric relationships in a low-dimensional space. Fourth, SOM transform N-dimensional data sets into 2D representations. Finally, the correlations between SOM results help to analyse the relationships across platforms, or one platform over time.

6. CONCLUSIONS

Online ratings are typically used by tourists to help choose service providers and by managers to monitor hotel performance. From a conceptual viewpoint, online reviews can be seen as part of the service offered by online sites, that in turn affects the navigation experience (Küster, Vila and Canales, 2016), and supports purchase decisions (Babić et al., 2016).

Given the increasing number of platforms, tourists and managers have to consult several platforms to get an accurate, overall impression of reviews. Similarity between online reviews posted on each platform and consistency between overall scores and specific attributes, and over time, calls for specific research. Therefore, this study analyses four main areas of research: (i) consistency of online reviews over time on each platform; (ii) similarity across online platforms, that is, whether online ratings follow a similar pattern across multiple tourism and non-tourism platforms; (iii) online consistency between overall scores and attribute-based scores; (iv) whether online reviews differ depending on platform reservation requirements.

This paper adopts Self-Organising Maps to parse large amount of data about online ratings. As a result, we can test the accuracy of SOMs in analysing online ratings. Using data from 1,165 hotels and from 11 platforms over 27 months, this study addresses similarity and consistency in online ratings.

Our findings suggest that (i) tourist platforms follow the same patterns in online reviews, regardless of the platform. By contrast, the only non-tourism platform differs in its pattern of online evaluations; (ii) there is a lack of a clear, consistent pattern between the overall score and the scores given to each attribute, except for the generic hotel attribute, which in turns means that only this attribute captures the overall score given by tourists; the remaining three attributes analysed, location, internet and service, do not affect the overall evaluation; (iii) the stability of the assessments at the aggregate level remain stable over time, except for location; (iv) surprisingly, there are no differences in the evaluation patterns between those platforms that require prior hotel reservations as against those that do not require them as an evaluation condition. This finding can be interpreted as reflecting a high degree of sincerity in the evaluations; (v) all in all, SOM is shown to be a useful tool in parsing large data sets and simplifying visual representations.

This research has some limitations. Firstly, data have been analysed without any level of disaggregation by tourist type. Future research might look at country of origin of the online raters and at the expertise of the users. Secondly, although our research comprises more platforms and tourism destinations than previous, related studies, further research development should adopt a stimuli-response approach in order to look at the specific influence of any improvement in a hotel in comparison to its competitors. Thirdly, our study does not differentiate the type of hotel by stars. Future studies might analyse the (dis)similarity and (in)consistency by type of hotel and even by location.

7. REFERENCES

Alakhdar, Y., Martínez-Martínez, J.M., Guimerá-Tomás, J., Escandell-Montero, P., Benítez, J. & Soria-Olivas, E. (2012). Visual data mining in physiotherapy using self-organizing maps: A new approximation to the data analysis. In Magdalena-Benedito, R., Soria-Olivas, E., Guerrero, J., Gómez-Sanchis, J. & Serrano-López, A. (Eds.), *Medical applications of intelligent data analysis: research advancements*. Hershey PA, Information Science Reference IGI Global, (chapter 12). doi: 10.4018/978-1-4666-1803-9.

Alarcón-del-Alamo, M.C, Gómez-Borja, M.A., & Lorenzo-Romero, C. (2015). Are the users of social networking sites homogeneous? A cross-cultural study. *Frontiers in Psychology*, *6*, 1127. doi: 10.3389/fpsyg.2015.01127.

Babić R. A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. (2016). The effect of electronic word of mouth on sales: A meta analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297-318. doi: 10.1509/jmr.14.0380

Bilgihan, A., Barreda, A., Okumus, F., & Nusair, K. (2016). Consumer perception of knowledge-sharing in travel-related Online Social Networks. *Tourism Management*, *52*, 287-296.

Bloom, J. Z. (2004). Tourist market segmentation with linear and non-linear techniques. *Tourism Management*, *25*(6), 723-733. doi: 10.1016/j.tourman.2003.07.004

Bloom, J. Z. (2005). Market segmentation. A neural network application. *Annals of Tourism Research*, 32(1), 93-111. doi: 10.1016/j.annals.2004.05.001

Brida, J. G., Disegna, M., & Osti, L. (2012). Segmenting visitors of cultural events by motivation: A sequential non-linear clustering analysis of Italian Christmas Market visitors. *Expert Systems with Applications*, *39*(13), 11349-11356. doi: 10.1016/j.eswa.2012.03.041

Calderón-Monge, E.; Pastor-Sanz, I. & Ribeiro-Soriano, D. (2016). Franchising in Europe: Exploring the case of Spain with Self-organizing time maps. *Psychology & Marketing, 33*(7), 559–572. doi: 10.1002/mar.20897

Claster, W., Pardo, P., Cooper, M., & Tajeddini, K. (2013). Tourism, travel and tweets: algorithmic text analysis methodologies in tourism. *Middle East Journal of Management*, *1*(1), 81-99. doi: 10.1504/mejm.2013.054071

Confente, I. (2015). Twenty-Five years of word-of-mouth studies: A critical review of tourism research. *International Journal of Tourism Research*, 17(6), 613–624. doi: 10.1002/jtr.2029.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches*. 5th ed. Sage publications, USA.

Curry, B., Davies, F., Evans, M., Moutinho, L., & Phillips, P. (2003). The Kohonen self-organising map as an alternative to cluster analysis: an application to direct marketing. *International Journal of Market Research*, *45*(2), 191-214.

Curry, B., Davies, F., Phillips, P., Evans, M. & Moutinho, L. (2001), The Kohonen self-organizing map: an application to the study of strategic groups in the UK hotel industry. *Expert Systems*, 18, 19-31. doi:10.1111/1468-0394.00152

Cheng, M., & Edwards, D. (2015). Social media in tourism: a visual analytic approach. *Current Issues in Tourism*, *18*(11), 1080-1087. doi: 10.1080/13683500.2015.1036009

Deboeck, G.J. & Kohonen, T.K. (2000). *Visual explorations in finance with self-organizing maps*. (2nd ed.). New York: Springer-Verlag.

Díaz, A., Cuadrado, A., Diez, A.B., Domínguez, M., Fuertes, J.J. & Prada, M.A. (2012) Supervision of industrial processes using self-organizing maps. In Magdalena-Benedito, R., Martínez-Sober, M., J. M. Martínez-Martínez, J.M., Escandell-Montero, P. & Vila-Francés, J. (Eds.), *Intelligent Data Analysis for Real-Life Applications: Theory and Practice*. Hershey PA, Information Science Reference IGI Global, (chapter 11). doi: 10.4018/978-1-4666-1806-0.

Fernández, C., Soria, E., Martín-Guerrero, J.D. & Serrano, A.J. (2006). Neural networks for animal science applications: Two case studies, *Expert Systems with Applications*. 31 (2), 444–450. doi: 10.1016/j.eswa.2005.09.086

Filieri, R., & McLeay, F. (2014). E-WOM and accommodation: an analysis of the factors that influence travelers' adoption of information from online reviews. *Journal of Travel Research*, *53*(1), 44-57. doi: 10.1177/0047287513481274

Floyd, K, Freling, R, Alhoqail, S, Cho, H. Y. & Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis, *Journal of Retailing,* 90 (2) (2014) 217–232. doi:

10.1016/j.jretai.2014.04.004

Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism Management*, *59,* 467-483. doi: 10.1016/j.tourman.2016.09.009

Gvili, Y., & Levy, S. (2016). Antecedents of attitudes toward eWOM communication: differences across channels. *Internet Research*, *26*(5), 1030-1051. doi: 10.1108/IntR-08-2014-0201

Hadjinicola, G.C.; Charalambous, C. & Muller, E. (2013). Product positioning using a self-organizing map and the rings of influence. *Decision Sciences 44*(3), 431-461. doi: 10.1111/deci.12020

Johnson, E. J., & Meyer, R. J. (1984). Compensatory choice models of noncompensatory processes: The effect of varying context. *Journal of Consumer Research*, *11*(1), 528-541.

Keim, D. A., Mansmann, F., Schneidewind, J., Thomas, J., & Ziegler, H. (2008). Visual analytics: Scope and challenges. In Simoff, S., Böhlen, M. H., & Mazeika, A. (Eds.). *Visual data mining: theory, techniques and tools for visual analytics*. Berlin: Springer-Verlag, (pp 76-90). doi: 10.1007/978-3-540-71080-6_6

Kohonen, T, (2001). *Self-organization maps* (3rd ed.). New York: Springer-Verlag.

Kohonen, T., Oja, E., Simula, O., Visa, A. & Kangas, J. (1996) Engineering applications of the self-organizing map, *Proceedings of the IEEE*, 84 (10), 1358 –1384. doi: 10.1109/5.537105

Küster, I., Vila, N., & Canales, P. (2016). How does the online service level influence consumers' purchase intentions before a transaction? A formative approach. *European Journal of Management and Business Economics*, *25*(3), 111-120. doi: 10.1016/j.redeen.2016.04.001

Li, G., Law, R., & Wang, J. (2010). Analyzing international travelers' profile with self-organizing maps. *Journal of Travel & Tourism Marketing*, 27(2), 113-131. doi: 10.1080/10548400903579647

Lu, W., & Stepchenkova, S. (2015). User-Generated content as a research mode in tourism and hospitality applications: Topics, methods, and software. *Journal of Hospitality Marketing & Management*, 24(2), 119-154. doi: 10.1080/19368623.2014.907758

Magdalena, R., Fernández, C., Martín, J.D., Soria, E., Martínez, M., Navarro, M.J. & Mata, C. (2009). Qualitative analysis of goat and sheep production data using self-organizing maps. *Expert Systems*, 26 (2), 191–201. doi: 10.1111/j.1468-0394.2009.00477.x

Mazanec, J. A. (1992). Classifying tourists into market segments: A neural network approach. *Journal of Travel and Tourism Marketing*, 1(1), 39–60. doi: 10.1300/J073v01n01_04

Mazanec, J. A. (1995). Positioning analysis with self-organizing maps an exploratory study on luxury hotels. *Cornell Hotel and Restaurant Administration Quarterly*, *36*(6), 80-95. doi: 10.1016/0010-8804(96)81007-X

Mazanec, J. A. (1999). Simultaneous positioning and segmentation analysis with topologically ordered feature maps: A tour operator example. *Journal of Retailing and Consumer Services*, 6(4), 219–235. doi: 10.1016/S0969-6989(98)00037-X

Mazanec, J. A. (2001). Neural market structure analysis: Novel topology-sensitive methodology. *European Journal of Marketing*, 35(7/8), 894–916. doi: 10.1108/eum0000000005730

Molina-Azorín, J. F. (2016). Mixed methods research: An opportunity to improve our studies and our research skills. *European Journal of Management and Business Economics* 25 (2), 37-38

Oja, M., Kaski, S. & Kohonen, T. (2002). Bibliography of self-organizing map (SOM) papers: 1998-2001 addendum. *Neural Computing Surveys, 3*(1), 1-156.

Papathanassis, A., & Knolle, F. (2011). Exploring the adoption and processing of online holiday reviews: A grounded theory approach. *Tourism Management*, *32*(2), 215-224. doi: 10.1016/j.tourman.2009.12.005

Park, S., & Nicolau, J. L. (2015). Asymmetric effects of online consumer reviews. *Annals of Tourism Research*, *50*, 67-83. doi: 10.1016/j.annals.2014.10.007

Phillips, P., Zigan, K., Silva, M. M. S., & Schegg, R. (2015). The interactive effects of online reviews on the determinants of Swiss hotel performance: A neural network analysis. *Tourism Management*, *50,* 130-141. doi: 10.1016/j.tourman.2015.01.028

Ruths, D., & Pfeffer, J. (2014). Social media for large studies of behavior. *Science*, *346*(6213), 1063-1064.

Soria, E., Martín, J.D., Fernández, C., Magdalena, R., Serrano, A.J., Moreno, A. (2006). Qualitative modelling of time series using self-organizing maps: application to animal science. In *Proceedings of the 6th WSEAS international conference on applied computer science, ACS'06* (pp. 183–187). Wisconsin: World Scientific and Engineering Academy and Society (WSEAS).

Soria, E., Guerrero, J., Gómez, J. & Serrano, A.J. (Eds.). (2012). *Medical application of intelligent data analysis: research advancements*. Hershey PA: IGI Global, Ch. 12, pp. 186–193.

Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, *32*(6), 1310–1323. doi: 10.1016/j.tourman.2010.12.011

Tufekci, Z. (2014). Big questions for social media big data: Representativeness, validity and other methodological pitfalls. *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media, ICWSM*, *14,* 505-514.

UNWTO (2014). *Online guest reviews and hotel classification systems. An integrated approach.* UNWTO, Madrid. Available at http://dtxtq4w60xqpw.cloudfront.net/sites/all/files/pdf/online_guest_reviews_and_hotel_classification_sytems_an_integrated_approach.pdf. Accessed in December 5, 2015.

Wedel, W. & Kannan, P.K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing, 80*(6), 97-121. doi: 10.1509/jm.15.0413

Xiang, Z., & Krawczyk, M. (2016). What does hotel location mean for the online consumer? Text analytics using online reviews. In *Information and Communication Technologies in Tourism 2016* (pp. 383-395). Springer, Cham.

Xiang, Z., Du, Q., Ma, Y., & Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management*, *58*, 51-65. doi: 10.1016/j.tourman.2016.10.001

You, Y., Vadakkepatt, G. G., & Joshi, A. M. (2015). A meta-analysis of electronic word-of-mouth elasticity. *Journal of Marketing*, *79*(2), 19-39. doi: 10.1509/jm.14.0169

YouGov (2014). *Americans rely on online reviews despite not trusting them*. Survey data available at https://d25d2506sfb94s.cloudfront.net/r/14/YouGov_Omnibus_Online_Reviews_Gen_Pop.xlsx. Accessed in December 5, 2015.