Monitoring travel-related information on Social Media through sentiment analysis

M.R. Gonzalez-Rodriguez, M. R. Martinez-Torres,
Business and Management department
University of Seville
Seville, Spain
rosaglez@us.es, rmtorres@us.es

S. L. Toral
E. S. Ingenieros
University of Seville
Seville, Spain
storal@us.es

***Abstract*—Tourist destinations are increasingly affected by the travel-related information shared through the Web. More and more people first check the previous experiences of other customers before doing their own decision-making. This paper explores the image of travel destinations by analysing the content of opinions shared using sentiment analysis techniques. A sentiment score is obtained and analysed considering several tourist features of the travel destination as well as the usefulness of shared opinions. A well known e-word of mouth community and the city of Barcelona have been used as a case study. The results obtained reveal the sentiment orientation towards the city of Barcelona and its tourist offer. Finally, a sensitivity analysis related to the calculation of the sentiment score is included.**

Keywords—Social Media; sentiment analysis; travel-related information; tourism 2.0

I. Introduction

Destination image is one of the topics that are widely studied in the literature. This is because it is considered a powerful tool for destination marketers in order to obtain a high competitive advantage in the tourist markets [1], [2]. It is commonly accepted that destination image highly influences the destination choice as well as the future behavioural purchase intentions [3].

Recently, studies on tourism have examined the image formation process of the pre-visit experience using different sources of information, generally beyond the destination marketer organisations (DMOs) [4]. The image formation prior to the visit has been highly influenced by the information provided by travellers' worth of mouth (WOM). This is related not only to the service quality but also to the quality of the experience in the tourism destination [5]. Thus, WOM has been sought as a credible source of information for the destination choice. On the other hand, service quality [6], [7] and, more recently, the quality of experience [8] and perceived value [9], [10] appear to be the key drivers for the intention to revisit and the willingness to recommend a destination. This leads to new destination image perceptions after the visit.

The development and acceptance of information technologies have changed the sources of information for the image formation process. This has been traditionally focused on WOM, media, travel guidebooks, brochures and magazines [11]. The growing trend of online communities [12] has encouraged customers to interact and share experiences through an increasing number of reviews, based not only on product quality but also on service experiences [13]. As a consequence, highly-involved virtual customers seek and learn from online consumer reviews displayed in online travel communities. This way, they can acquire information and create their own travel experience for a tourist destination [14]. Decision-making based on others' previous experience can also lead to wrong decisions, as decision criteria can be different for different customers. However, the information quality in virtual communities is assured through peer evaluation in terms of the utility score given by other community members. Trust and previous experience are also key mechanisms to reduce the uncertainty from users' reviews [15], [16]. Although the user posting the reviews can also score the product or service under review, this study proposes going further in the analysis of the content of shared reviews. More specifically, this study proposes to measure a sentiment score associated with each review and decide about its sentiment (positive or negative) orientation. The sentiment orientation can then be used to measure the image destination in the case of travel experiences. It can also be correlated with some other available information, such as scores received or previous experience. The rest of the paper is organised as follows: section II includes the most relevant work in this field. Section III introduces the case study as well as the methodology for calculating the sentiment score. Section IV shows the results obtained and, finally, conclusions are detailed in section V.

II. Related Work

It is widely accepted that image is the ability to influence customers' perception of the products and services offered [17] and therefore their purchase decision-making. However, there seems to be a general agreement that the destination image formation process is a complex task with no consensus concerning the measurement process. In the service literature, researchers admit that image can be seen as a multidimensional construct formed by the cognitive and the affective dimensions [18]. The cognitive component is determined by the evaluation of the destination's objective attributes according to external stimulus, including sources of information, past experience and WOM. These stimuli allow travellers to gather knowledge or beliefs about a certain destination [19]. The affective counterpart is focused on feelings. These in turn depend on the socio-psychological travel motivation and psychological and personal circumstances [20]. The study of the cognitive and the affective dimensions enable a better comprehension about the mental representation of the idea of a certain destination.

The projected representation considered in the literature as a "push factor" in the election of a tourist destination appears to be of great interest for its adequate promotion and commercialisation [21]. A positive mental representation becomes a high-perceived costumer value influencing future buying behaviour [22].

The destination image literature review reveals that most of the studies have been traditionally focused on the image's cognitive component to formulate the idea in the tourists' minds [23]. These studies emphasise the use of tangible attributes related to the tourist resources of the specific destination [24]. However, a growing number of studies also highlight the importance of jointly evaluating the cognitive and affective perception of a tourist destination [25], [26]. Moreover, Kim and Richardson [20] admit that in a tourist context the affective attributes of a destination are even more important than the evaluation of the tangible attributes.

Traditionally, two methodologies have been applied to measure the destination image: structured and unstructured techniques. Structured methodology is focused on the assessment of a battery of relevant attributes for a destination previously identified in the study by the researcher. Structured methodology using Likert or semantic scales has been frequently applied in the literature, including tangible attributes [27] and affective attributes [28], [20] to measure the destination image. However, it is widely recognised that this technique cannot capture those attributes that could be considered of special relevance by the respondents [29] and the unique component of the destination [30]. On the other hand, the unstructured technique based on open-ended questionnaires apprehends the holistic components and unique features of a destination image [31], [32]. But in this case, the great variability in the individual description and impressions of a destination makes any comparative analysis difficult. Thus, as identified by Echtner and Ritichie [33], due to its inherent mental representation complexity the measurement of the destination image justifies using a combination of structured and unstructured methodologies.

While past qualitative and quantitative research was focused on defining the multi-attribute destination image, recent studies have explored the role of information sources in the creation of the destination brand image. Stokes and Lomax [5] recognise the strong influence of WOM information in the brand image creation. They suggest that DMOs and entrepreneurs should have a high understanding of that information source as part of their marketing strategy to create an engaging, memorable and newsworthy travel experience. Further evidence of the power of WOM as a brand image builder can be also found in Hanlan and Kelly [34]. They identified the dominant attributes image in the individual mental representation. The rapid and growing development of the Web2.0 providing efficient tools to create and share ideas (eWOM) through the World Wide Web has led to a new image measurement paradigm. Online travel communities, blogs and forums encourage people to share information about a wide variety of destinations. This helps other information seekers to create their own destination image. Since the information on the web is unstructured, a new field within content analysis based on sentiment orientation is starting to appear in the tourist literature [35], [36]. Marketer planners are increasingly using sentiment analysis to develop their marketing strategies according to the consumer attitudes manifested through e-WOM communities. Until recently, most research based on sentiment analysis was focused on product reviews rather than on service reviews. This research means to fill this gap in the literature by examining electronic reviews in the online community Ciao as an information source for the creation of a destination brand image.

III. CASE STUDY AND METHODOLOGY

The case study is based on a well-known e-WOM community, covering a wide variety of products and services. The next subsections introduces e-WOM communities as well as the data collection and the methodology applied.

A. *e-WOM communities*

The emergence of Internet and the Web 2.0 has changed the way in which users look for information and their purchase decisions. Previously, much of this information was received directly from companies or from friends or relatives in informal conversations. However, traditional WOM has now its digital counterpart with e-WOM. e-WOMs allow consumers to share their experiences, exchange product- and service-related information and socially interact with other consumers [37]. e-WOM takes place in a computer-mediated context and, in contrast with traditional WOM, conversations are visible to the rest of the consumers. This fact makes these communities ideal for researchers because plenty of information can be obtained via the web. Typically, reviews or posted experiences are rated by the rest of the community in terms of their usefulness [38]. This information is useful for consumers to distinguish malicious opinions. As Internet is a relatively anonymous medium, vendors can be tempted to manipulate opinions by over scoring their products or services and persuading against competitors. Additionally, some data about users who share reviews are also displayed, such as previous experience posting information, activities, reputation or the date they joined the community [39].

B. *Data collection*

Data were collected from the website ciao.co.uk. This is a well-known e-WOM community that covers a wide variety of products and services. The website is organised in 28 main categories. One of them is the category 'Travel', which in turn is divided into continents, countries and cities within each continent. This study is specifically focused on the city of Barcelona, which is one of the top touristic destinations in Spain. Basically, Ciao distinguishes four areas related to the experience of travelling to Barcelona: *Hotels*, *Attractions*, *Restaurants* and *Pubs, Bars & Nightlife*. Registered Ciao users can freely post reviews about any of these subcategories related to travelling to Barcelona. These reviews can receive a score from the rest of the community and this is also publicly displayed. Finally, some statistics about users are also available, such as the date they joined the community, the number of previous submitted reviews or a trust score given by the number of community members who specifically trust a given user. All this information as well as the content of the reviews was collected using a web scraper developed in R. The function *readLines()* from the base package, that reads data from a URL, was used to access the shared reviews. However, webpages are formatted in HTML code, and accessed data contains both the webpage content and the HTML tags. Therefore, it is necessary to parse the HTML file using the *htmlParse()* function . This generates an R structure representing the HTML tree. Once online webpages are available as an R structure, meaningful data can be easily identified using regular expressions that are also supported in R, for instance, in packages such as XML. Table 1 summarises the information collected.

Variable	Description
text	Body of the posted review
size	Size of reviews in words
user	Alias and link to the user statistics
Date	Date on which the user became a member of Ciao
Reviews	Number of previously posted reviews
Trust	Members trusting this user
Subcategory	Hotels, Attractions, Restaurants, Pubs_Bars_Nightlife

Table 1. Information extracted from reviews posted in the category Travel -> Spain -> Barcelona

C. *Sentiment analysis*

Sentiment analysis refers to detect and classify the sentiments expressed by an opinion holder. There are two main approaches to the problem of automatically extracting sentiment. A lexical-based approach involves calculating the semantic orientation for a document from the semantic orientation of words or phrases in the document. This is based on a predefined list of words, where each word is associated with a specific sentiment. Machine learning techniques involve building classifiers from labelled instances of texts or sentences through a supervised classification process [40]. The advantage of machine learning techniques is that they can create trained models for specific contexts. Nevertheless, they also require the availability of labelled data. This compromises their applicability to new data. This study follows the first approach based on AFINN-111, which is a list of English words rated for valence with an integer between minus five (negative) and plus five (positive) for 2477 word forms [41]. Although the original ratings vary between -5 and +5, a reclassification in a lower number of categories was done to clearly highlight the semantic orientation. As a result, four categories were distinguished: very negative (Vneg, rating -5 and -4), negative (Neg, rating -3, -2, or -1), positive (Pos, rating 1, 2, or 3) and very positive (Vpos, rating 4 or 5). For each review, the number of words belonging to each category was calculated, and the final sentiment score was obtained as:

$$Sentiment = (-w_2) \cdot Vneg + (-w_1) \cdot Neg + w_1 \cdot Pos + w_2 \cdot Vpos$$

w_1 and w_2 being two weight factors that consider the relative importance of very positive or negative terms with respect to the positive or negative terms. Obviously, it is required that $w_2 > w_1$ to emphasise the weight of very positive or negative terms. In general, people avoid being too extreme in their opinions, so the presence of very positive or negative words should be considered as a clear semantic orientation.

IV. RESULTS

A total of 200 posted reviews about the city of Barcelona posted were collected at Ciao.co.uk using the web scraper developed.

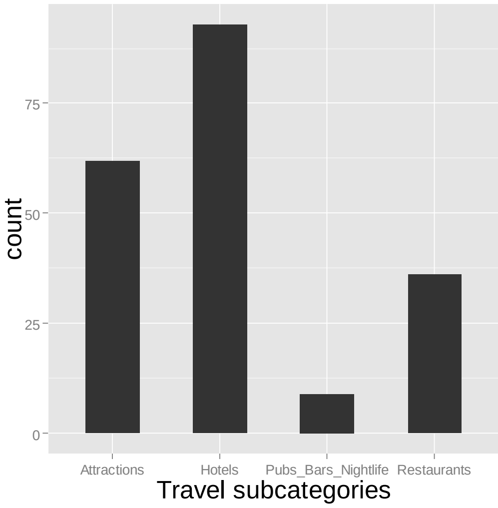

Figure 1. Opinion distribution by travel subcategories.

The distribution of the opinions by travel subcategory is also important to understand those attributes of the destination that should be improved. Figure 1 shows how many reviews each travel subcategory has received, revealing those tangible aspects of the city which are more assessed by travellers. Hotels, followed by Attractions and Restaurants are the categories receiving more attention from travellers. In contrast, Pubs, Bars and Nightlife received a lower number of reviews. This fact can be explained by the wide variety of pubs and bars in Barcelona which makes it more difficult for users to become engaged in discussions about them.

The sentiment analysis approach proposed has been applied to the reviews collected. As a result, and using the referenced dictionary, 6660 terms belonging to the four categories considered (VNeg, Neg, Pos, Vpos) were identified. Table 2 and Figure 2 describe the distribution of the sentiment reviews by travel subcategory.

	VNeg	Neg	Pos	VPos
Hotels	4	749	1887	89
Attractions	2	500	1360	104
Restaurants	4	582	1086	37

Pubs&clubs	0	77	171	8

Table 2. Distribution of sentiment reviews by travel subcategories.

It can be noted that users don not tend to use very positive or very negative terms. A positive bias towards the city of Barcelona can also be observed, although the negative sentiment scores deserve special attention by destination marketing planners. In general, travellers appear to be reluctant to give very polar opinions to any subcategory.

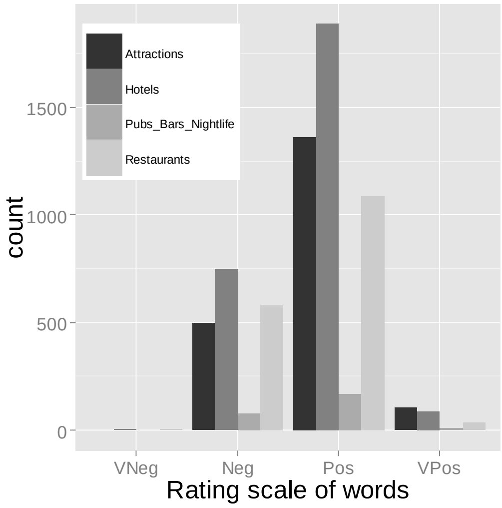

Figure 2. Distribution of sentiment reviews by travel subcategories

Sentiment scores were calculated for the 200 reviews about the city of Barcelona, considering the score described in section III with weight factors $w_1=2$ and $w_2=5$.

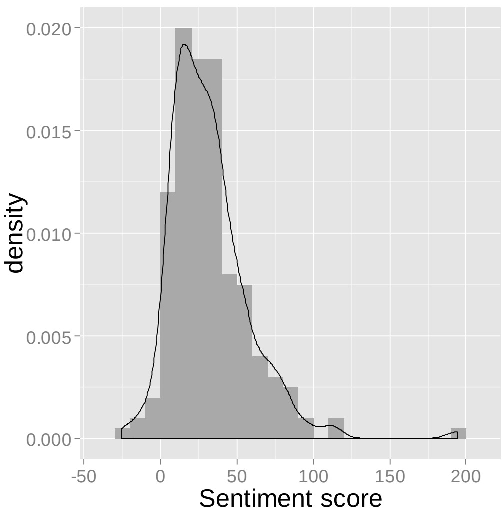

Figure 3. Sentiment Scores histogram with fitted density curve

Figure 3 shows the histogram of sentiment scores with its density curve superimposed. The result obtained exhibits a clear right skewed distribution. This means that most travellers have a positive orientation towards Barcelona as a tourist destination. Additionally, and due to the chosen weights, the sharp shape of the histogram means that most opinions are concentrated in a narrow range of sentiment scores.

Several subsequent analyses have been performed to detect if the sentiment score is affected by travel subcategories or the perceived utility of reviews. Table 3 provides the analysis of the variance (ANOVA) results to test for any significant differences among the mean scores for the four travel subcategories.

	N	Mean	F value	Sig
Hotels	93	29.04	1.084	0.357
Attractions	62	35.97		
Restaurants	36	35.28		
Pubs & clubs	9	25.33		

Levene Test=1.4754, Sig. = 0.2225

Table 3. ANOVA results for subcategories of the city of Barcelona.

Levene's test is not significant. This means that the homogeneity of variance assumption was not violated. The ANOVA results show that there are no differences in mean sentiment scores among the travel subcategories

The utility of reviews is another important aspect for customers when making decisions about travelling. The ANOVA test has been applied to detect possible differences in sentiment mean scores among different utility perceptions.

Table 4 shows a significant F value, which indicates differences in the sentiment scores' means but it does not provide a multiple pairwise comparison.

	N	Mean	F value	Sig
Helpful	42	16.76	22.67	0.000
Very Helpful	96	28.28		
Exceptional	62	46.98		

Levene Test=7.3868, Sig. = 0.0001

Table 4. ANOVA results for utility of reviews.

For this purpose, the Tukey post-hoc test has been used to determine the differences in sentiment scores between each pair of utility categories. The sentiment score mean is higher whenever the review's utility perceived by the online visitors is also higher.

	diff	Sig.
helpful-exceptional	-30.22	0.000
very helpful-exceptional	-18.70	0.000
very helpful-helpful	11.52	0.023

Table 5. Results of the Tukey post hoc test.

This result indicates that users tend to evaluate positive reviews better than negative reviews. This actually seems logical, as positive reviews are helping users to find accommodation or attractions, while negative reviews just make them continue looking for other alternatives.

Several other continuous variables collected were finally correlated with sentiment scores in Table 6, including (1) Sentiment scores, (2) Number of previous reviews, (3) Trust, (4) Size of reviews in words, (5) Time reviewers have been members of Ciao.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(1)	1				
(2)	0.18^{*}	1			
(3)	0.14	0.75^{***}	1		
(4)	0.57^{***}	0.59^{***}	0.69^{***}	1	
(5)	-0.03	-0.03	0.16	-0.06	1

Note: ***p<0.001; **p<0.01; *p<0.05

Table 6. Correlation Analysis

The sentiment score is positively correlated with the length of reviews and the previous experience of the reviewers. The first result seems to be logical, since the higher the length of the text, the clearer its semantic orientation. The positive, although weak, correlation with the number of previous reviews means that experienced users tend to review those services where they had a positive experience. Other results show that experienced users tend to be trusted and they also write more detailed reviews.

A sensitivity analysis was next performed to test the influence of weights in the sentiment score calculation. Several combinations of weights were chosen and applied, considering the restriction of $w_2 > w_1$. The histograms obtained are shown in Figure 4.

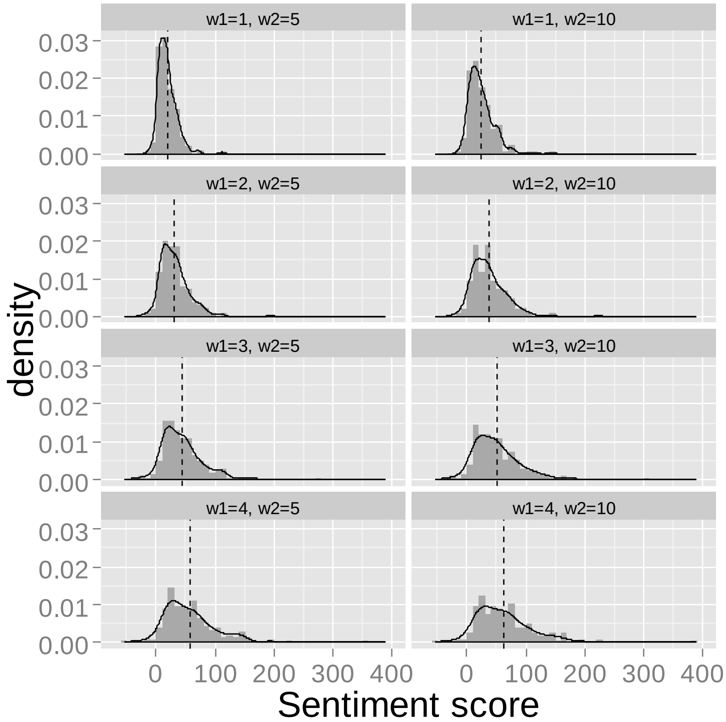

Figure 4. Sentiment Scores histogram with fitted density curve considering several weights combinations.

It can be noticed that, as weights become higher and the difference between w_2 and w_1 is also higher, the density curves exhibit a higher positive skew. Additionally, distributions become flatter, with a greater variety of scores. In general, a wider variety of scores is preferable to better identify those tourist features of the city that can be improved.

V. Conclusions

This paper proposed a sentiment score of travel destinations based on the content analysis of opinions shared through the web. The case study about the city of Barcelona shows that users are mainly focused on hotels and attractions, and their opinions tend to avoid the use of very positive or negative terms. According to the sensitivity analysis implemented, it is better to overweigh very positive or negative terms to achieve a higher variety of scores.

Acknowledgment

This work was supported by the Consejería de Economía, Innovación, Ciencia y Empleo (Ministry of Economy, Innovation, Science and Employment)viathe Research Project P12-SEJ-328, by the Fundación Hergar (Hengar Foundation) via the Research Project AIFH2014/005, and by the Programa Estatal de Investigación, Desarrollo e Innovación Orientada a los Retos de la Sociedad (State Programme of Research, Development and Innovation Orientated to the Challenges of Society) via the Research Project ECO2013-43856-R.

REFERENCES

[1] K. Chon, “The role of destination image in tourism: A review and discussion”, Tourist Review, Vol. 13, pp. 2-9, 1990.

[2] N. Tapachai and R. Waryszak, , “An examination of the role of beneficial image in tourist destination selection”, Journal of Travel Research, Vol. 39, Iss. 1, pp. 37-44, 2000.

[3] J. E. Bigné, M.I. Sánchez and J. Sánchez, “Tourism Image, Evaluation Variables and After Purchase Behaviour: Inter-Relationship”, Tourism Management, Vol. 22, pp. 607-616, 2001.

[4] N. Morgan, A. Pritchard, and R. Piggot, “New Zealand, 100 per cent pure. The creation of a powerful niche destination brand”, Journal of Brand Management, Vol. 9, Iss. 4-5, pp. 335-354, 2002.

[5] D. Stokes and W. Lomax, “Taking control of word-of-mouth marketing: the case of an entrepreneurial hotelier”, Journal of Small Business and Enterprise Develoment, Vol. 9, Iss. 4, pp. 349-57, 2002.

[6] J.S. Backman and S. Veldkamp, “Examination of the relationship between service quality and user loyalty”, Journal of Park and Recreation Administration, Vol. 13, Iss. 2, pp. 29-41, 1995.

[7] J.J. Cronin, M.K. Brady, and G.T.M Hult, “Assessing the effects of quality, value and customer satisfaction on consumer behavioral intnetions in service environments”, Journal of Retailing, Vol. 76, Iss. 2, pp. 193-218, 2000.

[8] C. Ching-Fu, C. Fushian, “Experience quality, perceived value, satisfaction and behavioral intentions for heritage tourists”, Vol. 31, Iss. 1, pp.29-35, 2010.

[9] R. Kashyap and D.C. Bojanic, “A structural analysis of value, quality, and price perceptions of business and leisure travelers”, Journal of Travel Research, Vol. 39, Iss. 1, pp. 45-53, 2000.

[10] J.F. Petrick, “Development of a multi-dimensional scale for measuring the perceived value of a service”, Journal of Leisure Research, Vol. 34, Iss. 2, pp.119-34, 2002.

[11] W. Kasper and M. Vela, “Sentiment Analysis for Hotel Reviews”, Proccedings of the Computational Linguistics-Applications Conference, pp 45-52, 2011.

[12] J. Hagel and G.A. Amstrong, Net Gain: Expanding Markets through Virtual Communities. Boston, MA : Harvard Business School Press, 1997.

[13] Y. Bart, V. Shankar, F. Sultan and G. Urban, “Are the drivers and role of online trust the same for all web sites and customers? A large-scale exploratory empirical study”, Journal of Marketing, Vol. 69, Iss. 4, pp.133-152, 2005.

[14] R.A. Shang, Y-C. Chen and H.J. Liao, “The value of participation in virtual consumr communities on brand loyalty”, Internet Research, Vol. 16, Iss. 4, pp.398-418, 2006.

[15] C.M. Riddings, D. Gefen, and B. Arinze, "Some antecedents and effects of trust in virtual communities", Journal of Strategic Information Systems, Vol. 11, Iss. 3-4, pp. 271-295, 2002.

[16] L.V. Casaló, C. Flavián and M. Guinalíu, “ Fundaments of trust management in the development of virtual communities”, Management Research News, Vol. 3, Iss. 5, pp. 324-338, 2008.

[17] V.A. Zeithml, and M.J. Bitner, Service Marketing. International Edition. Singapore: Mc-Graw Hill, 1996.

[18] S. Baloglu and M. Mangaloglu, “Tourism destination images of Turkey, Egypt, Greece, and Italy as perceived by US-based Tour Operators and Travel Agents”, Tourism Management, Vol. 22, pp. 1-9, 1999.

[19] A. Beerli and J.D. Martín, “Tourists’ Characteristics and the Perceived Image of Tourist Destinations: A Quantitative Analysis-A Case of Study of Lanzarote, Spain”, Tourism Management, Vol. 25, pp. 623-636, 2004.

[20] H. Kim and S.L. Richardson, “Motion Picture Impacts on Destination Images”, Annals of Tourism Research, Vol.30, Iss. 1, pp.36-39, 2003.

[21] L. Andreu, J.E. Bigné and C. Cooper, “Projected and Perceived Image of Spain as a Tourist Destination for British Travellers”, Journal of Travel & Tourism Marketing, Vol. 9, Iss. 4, pp.47-67, 2000.

[22] N. Tapachai and R. Waryszak, “An Examination of the Role of Beneficial Image in Tourist Destination Selection”, Journal of Travel Research, Vol. 39, Iss. 1, pp.37-44, 2000.

[23] S. Baloglu and D. Bringer, “Affective Images of Tourism Destinations”, Journal of Travel Research, Vol. 35, Iss. 4, pp. 11-15, 1997.

[24] J.E. Bigné and M.I. Sánchez, “Evaluación de la Imagen de Destinos Turísticos: Una aplicación Metodológica a la Comunidad Valenciana”, Revista Europea de Dirección y Economía de la Empresa, Vol. 10, Iss. 3, pp. 189-200, 2001.

[25] Y. Yoon and S. Kim, “An Assesment and Construct Validity of Destination Image: A Use of Second-Order Factor Analysis”, Working Paper, Virginia, USA, 2000.

[26] S. Pike and C. Ryan, “Destination Positioning Analysis Through a Comparison of Cognitive, Affective, and Conative Perceptions”, Journal of Travel Research, Vol. 42, Iss. 4, pp.333-342, 2004.

[27] D.J. Walmsley, and J.M. Jenkins, "Tourism Cognitive Mapping of Unfamiliar Environments". Annals of Tourism Research, Vol. 10, Iss. 2, pp. 268-286, 1992.

[28] S. Baloglu and M. Mangaloglu, "Tourism Destination Images of Turkey, Egypt, Greece, and Italy as Perceived by US-Based Tour Operators and Travel Agents", Tourism Management, Vol. 22, pp. 1-9, 2001.

[29] W.C. Gartner, “Image Formation Process”, Journal of Travel & Tourism Marketing, Vol.2, Iss. 2-3, pp.191-215, 1989.

[30] J.T. Coshall,”Measurement of Tourists’ Images: The Repertory Grid Approach”, Journal of Travel Research, Vol. 39, Iss. 1, pp. 85-89, 2000.

[31] H. Leemans, The multiform book: Using information in purchasing hedonic products. Delft: Eburon, 1994

[32] R. Govers and F.M. Go, “Deconstructing Destination Image in the Information Age”, Information Technology & Tourism, Vol. 6, pp. 13-29, 2003.

[33] C.M. Echtner and J.R.B. Ritchie, “The Measurement of Destination Image: An empirical Asseesment”, Journal of Travel Research, Vol. 31, Iss. 4, pp. 3-13, 1993.

[34] J. Hanlan and S. Kelly, “Image formation, information sources and an iconic Australian tourist destination”, Journal of Vacation Marketing, Vol. 11, no. 2, 163-177, 2004.

[35] S. Aciar, “Mining context information from consumers’ reviews”, I Proceedings of the Context-Aware Recommender Systems (CARS) Workshop, 2009.

[36] C. Haruechaiyasak, A. Kongthon, P. Palingoon and C. Sangkeetrakarn, “Constructing THai opinion mining resource: A case Study on hotel reviews”, in Proceedings of the Eighth Workshop on Asian Language Resources, 2010.

[37] V. Blazevic, W. Hammedi, I. Garnefeld, R. T. Rust, T. Keiningham, T. W. Andreassen, N. Donthu and W. Carl, "Beyond traditional word-of-mouth: An expanded model of customer-driven influence", Journal of Service Management, Vol. 24 Iss. 3, pp. 294-313, 2013.

[38] F. J. Arenas-Márquez, M.R. Martínez-Torres and S.L. Toral, "Electronic word-of-mouth communities from the perspective of social network analysis", Technology Analysis & Strategic Management, doi 10.1080/09537325.2014.923565, 2014.

[39] R. A. King, P. Racherla and V. D. Bush, "What We Know and Don't Know About Online Word-of-Mouth: A Review and Synthesis of the Literature", Journal of Interactive Marketing, doi 10.1016/j.intmar.2014.02.001, 2014.

[40] A. Ortigosa, J. M. Martín and R. M. Carro, "Sentiment analysis in Facebook and its application to e-learning", Computers in Human Behavior, Vol. 31, pp. 527-541, 2014.

[41] F. A. Nielsen, "A new ANEW: Evaluation of word list for sentiment analysis in microblogs", In Proc. of the ESW2011 Workshop on 'Making sense of Microposts: Big Things come in small packages, no. 78 in CEUR Workshop Proceedings, Heraklion, pp. 93-98, 2011.