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How TripAdvisor's reviewers level of expertise influence their online rating behaviour and the usefulness of reviews

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Dissertation submitted as a partial requirement for the conferral of Master of Hospitality and Tourism Management

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September 2017

Abstract

The internet has improved the buying behaviour of customers. The development of technologies has led to the dissemination of opinions on social networks where customers buy goods and services. These comments on social networks started to be a part of the purchasing process. Until a few years ago, customers used to choose their itineraries based on tourist guides or brochures. Nowadays, customers' reviews have changed the way a destination is portrayed, enhancing the description of a product or a service to a level that not even the supplier was able to reach before. There are different types of reviewers. The aim of this study is to identify both reviews, experts and non-expert reviewers and analyse the way they write their reviews. Reviews of five hotels taken from the *TripAdvisor* website were used in order to conduct this study. After analyzing a great set of variables, the results show that there is not much different on the amount of positive/negative reviews written by a reviewer, however, there is a difference in the deeper meaning of a review when it is positive than when it is negative. The expert reviewer tends to be more emotional when writing positive reviews than negative reviews. Regarding the usefulness of the reviews, there is no significant difference in usefulness of a review whether is an written by an expert reviewer or by a non-expert reviewer. The results also indicate that being an expert does not influence the rating a reviewer gives to a hotel stay either. The study was conducted by using Lexalytics program to analyze a *Natural Language Processing (NLP)* used to classify reviews according to their polarity. With this study, a new research in study was filled. This study gives insights on the polarity of a review depending on the type of reviewer. The results of this study are also important for hotel managers in order for them to understand the type of guest in house.

Key Words: Expert reviewer, non-expert reviewer, TripAdvisor, rating behavior

Sumário

O desenvolvimento da tecnologia, com ênfase na internet e nos seus desenvolvimentos ao longo dos anos, melhorou o comportamento dos clientes e levou à disseminação de opiniões em redes sociais onde os clientes compram productos e serviços. Os comentários feitos a um produto ou serviço nas redes sociais começaram a fazer parte do processo da compra. Até há uns anos atrás, os clientes escolhiam os itinerários para as suas viagens com base em guias turísticos e brochuras. Recentemente, os comentários de clientes mudaram a maneira que um destino é explicado e ilustrado, melhorando, desta forma, a descrição de um produto/serviço a um nível que nem mesmo os fornecedores destes tinham alcançado ainda.

Há diferentes tipos de *reviewers.* O objectivo deste estudo é identificar ambos tipos, *expert* e *non-expert* e analisar o estilo de *reviews* escrita por estes. Experts são assim denominados se tiverem escrito mais de dez reviews; por outro lado os non-expert reviewers são assim denominados se tiverem escrito menos de 10 reviews. Para este estudo, foi utilizada informação de cinco hotéis de Orlando, Florida, retirada do TripAdvisor. Depois de uma análise das variáveis, os resultados mostram que não há grande diferença no que toca ao volume de comentários positivos/negativos escritos por um utilizador. Por outro lado, existe uma diferença na emoção dada a cada comentário, entre os utilizadores. O *expert reviewer* tende a ser mais emocional quando escreve comentários positivos do que quando escreve comentários negativos. Relativamente a utilidade de cada comentário, não há grande diferença no que toca a ser um expert reviewer ou um non-expert a escrever um comentário. Os resultados indicam, também, que ser um expert não tem qualquer influência na avaliação que um utilizador dá a sua estadia num hotel. Este estudo foi feito com base no programa Lexalytics, com objectivo de analisar a *Natural Language Processing (NLP)* usada para classificar os comentários de acordo com a sua polaridade.

Palavras-chave: Expert reviewer, non-expert reviewer, TripAdvisor, rating behavior

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1. Introduction

The internet has changed radically the customer purchasing behaviour (Buhalis & Law, 2008). Technological developments in the last decades led to the spread of opinions in social websites where consumers purchase goods and services. Consumers expose their opinions in such a way that these opinions have become part of the purchasing process (Chevalier & Mayzlin, 2004). In fact, until a few decades ago, travellers used to choose their itineraries and choose in which hotels to stay in based on tourist guides, pamphlets, web sites and booklets (Simeon & Martone, 2016). Currently, though, customers share their opinions and experience on web sites, which takes the "picture" of a destination to a higher level, bigger than the description from the supplier itself (Stepchenkova & Zhan, 2013). Consumers tend to give more credit to online reviewers, rather than to the information given by the local tourist information points or websites. Previous visitors are perceived to be more truthful than local companies, since they do not have a commercial motivation (Park & Gretzel, 2007).

Online consumer reviews have become a vital source of information for buyers, replacing for other forms of business-to-consumer (Zhang, Craciun, and Shin 2010) (Jiang & Chen, 2007, Nielsen, 2010) and offline word-of-mouth (WOM) communication about the service providers' quality. Thus, eWOM (electronic word-of-mouth, i.e. online reviews, evaluations, recommendations, etc.) has emerged and is being used more and more by consumers in order to share their experiences about a product or a service (Mendes et al. 2012; Rezabakhsh et al., 2006). These reviews are perceived as risk reducers to buyers (Yoo & Gretzel, 2008). Shoppers want to read about previous buyers' experiences with a product or a service without having to experiment it themselves and by perceiving them as references, the consumer's actions are influenced . Consequently, nowadays, roughly three quarters of consumers use online reviews before choosing their travel itineraries (Zhang et al., 2014) and about 50% of consumers use online reviews before making their travel purchase (Compete, Inc., 2006).

Recently, Web 2.0 technologies, also denoted as Internet-based applications, have given power to users because they easily share their opinions on user-generated content on online communities (O'Reilly, 2007). Since online reviews are considered to be one of the greatest ways of getting pre-travel information (Simeon & Martone, 2016), it is safe to say that Web 2.0 has enlarged the tourism market and has contributed highly to the development of user-generated content.

Having online reviews become so popular, a new label of expert reviews on travel websites has been created, mainly because consumers perceived expert reviewers as being more experienced and accurate. For example, TripAdvisor.com, an American travel online company that is responsible for providing reviews of travel related content, distinguishes between “expert travellers” and other travellers. The identification of the factors that affect the perceived usefulness of online reviews have become a topic of interest in previous studies, due t the vital role they play in the decision-making process (Cheung et al. 2008). According to Liu and Park (2015) the messenger’s identification is key to ensure a trustworthy information, i.e., users believe that identity disclosure develops confidence in the information provided. In this line of thought, the levels of a reviewer reputation and expertise considerably affects the usefulness of a review (Racherla & Friske, 2012).

Previous literature lacks research on expert online reviews. The lack of study on this area is surprising since the majority of websites nowadays grants a status to reviews (e.g. Amazon.com) or comprises reviews by experts or critics on their websites (e.g. movies websites like IMDb.com) (Plotkina & Munzel, 2016). Lately, researchers started putting reviews written by peer customers into perspective, especially their use and impact, as these expert reviews are easily available (Bertrandias & Vernette, 2012). Nevertheless, the consequences of subsequent behaviour still lacks research.

Consequently, this research focuses on comparing online reviews written by experts with those written by peer customers. It uses 1,500 reviews from TripAdvisor written about five different hotels in Orlando, Florida. Using quantitative results, text mining analysis and sentiment analysis the current thesis studies how the effect of expert reviews on the hotel industry may be of importance to the design of travel websites and to hotel managers all over the globe. Although the information on TripAdvisor is available for everyone to read, it becomes impossible for a single person to read all of them. In this line of thought, advanced sentiment classification methods are used to automatically categorise expert reviews and non-expert reviews into positive or negative. Sentiment classification is a class of freshly advanced web mining techniques that conduct analysis on sentiment or opinions (Liu et al., 2005; Pang et al. 2002; Turney, 2002). In general, sentiment classification, also known as sentiment analysis, aims at mining text of written reviews from shoppers for products and services, and classifying the reviews into positive or negative opinions, having in mind expert and non-expert reviewers. The classification method was applied to the computing areas of information retrieval and natural language processing (Beineke et al. 2004; Godbole and Srinivasaiah 2007; Pang et al. 2002; Turney and Littman 2003).

Even though researchers, such as Choi et al (2007) and Pan et al (2007), have begun to explore content analysis of travel blogs, sophisticated web mining methodologies still are in need of an integration into travel blog analysis.

The main theoretical contribution this study has to offer is to investigate the effects of website-recognised expert reviews on travellers' rating behaviour. Our study also aims to fill in the gap of the literature research above mentioned by analysing the power of expert identity in a social media context. This quantification aims to have practical contributions as well, as it might be useful in designing travel websites and improving electronic word of mouth regarding hotels on travel websites. Furthermore, it is believed that the results of the study will help hotel managers to better understand frequent travellers.

2. Literature review

2.1 Tourism industry in the Web 2.0 Era

Web 2.0 technologies have been developed to enhance the interaction and collaboration within the online community. Internet-based applications on the era of Web 2.0 empowers users to communicate with each other sharing views and opinions (O'Reilly, 2007). With the development of Web 2.0, tourists and travellers were granted with a range of opportunities to make their travel opinions public to the web world by sharing them on websites and public networks (Stepchenkova & Zhan, 2013). Communication that isn't self-promoted affect destination images more than messages by Destination Marketing Organisations (DMOs) and travel intermediaries (Connell, 2005), which change the control over the information transmitted to consumers. Thus, the encouragement in participating and the sharing of opinions between consumers has revolutionised the travel information (Eichhorn, Miller, Michopoulou, & Buhalis, 2008).

In fact, the growth of new Information and Communication Technologies (ICTs) has changed the relationship between companies and consumers, especially in the case of service companies. The previous methods of communication and distributing information have gone through major changes and are now perceived as out-dated. The tourism sector was affected as well. The tourist information points, which used to own all the information travellers needed have now been replaced due to the progressively increase in knowledgeable consumers (Alvarez, et al. 2007). These consumers have become self-sufficient in a way that they can find information on their own, on the previously mentioned: blogs, websites, social networks and travel communities. On the other hand, travel companies can gain from the development of the Travel 2.0 in a way that they can shape their products and services according to what consumers want. Some travel communities like TripAdvisor.com, enable users to plan their itinerary (flights, hotels, transportation or activities, etc) and access information from previous users. In fact, TripAdvisor.com allows hotels around the world to be reviewed and put under discussion (Buhalis & Law, 2008).

The predisposition of consumers to participate in communities that share their interests and to browsing online with the possibility to do so on a tablet or smartphone has enriched the travel experience, from the search, experiment to the involvement and the post visit experience (Qi et al. 2008). Online reviews are considered to be the greatest resource of pre-travel information by about a third of prospect visitors who research most of this information on websites, social networks or travel communities (Simeon & Martone, 2016). More than 70% of visitors claim that online reviews are the best source information before travelling (Yoo & Gretzel, 2008). Hence, tools as travel communities or social networks play a vital role for operators and policy-makers of an area, as these allow them to have a large amount of data on behaviours, and insights of visitors (Schmallegger & Carson, 2008).

2.2 Online consumer behaviour in Tourism

There is an infinity of studies on consumer behaviour; in fact, many researches have used methods to describe the tourism decision-making process. The process models describe the decision process in which the decider proceeds consequently through a decision (van Raaij & Francken, 1984). Conceptual models demonstrate ways in which consumers refrain or channel their decision sets in a final decision (Um & Crompton, 1990). While some researchers have considered who makes the decision among families and couples (Litvin, 2004), the vast majority of the literature on tourists' decision-making assumed that the individuals make their own decisions. Nevertheless, because travel is social, and a big amount of tourist travel happens with other people, it has been recommended to investigate the decision-making in situations other than individual decisions (Decrop, 2006). Also, McCabe at al (2016), challenged rational choice models, proposing a series of heuristics that tourists may use on their decision-making.

Tourism researchers consider primarily individuals on their decision-making models. Engel et al (1985) followed Van Raaij & Francken (1984) in projecting their five-step sequence on going on vacation: 1) generic decision; 2) information acquisition; 3) shared decision-making; 4) holiday activities; and 5) satisfaction/complaints. Um & Crompton (1990), expanded by Crompton in 1992, used choice sets to describe how individuals restrain the decision from a set of choices to a final destination choice. In their study, the majority of the interviewed processed their destiny decision choices in that way (by going through a set of choices), however, there was a big exception: 24% proceeded directly from a set of awareness to the selection of destiny without identifying the suggested set. Later, Crompton (1992), acknowledged that their set of choice models were assumed as useful, only for non-routine decisions. In another exception, Petrick et al (2007) found that the majority of passengers on cruises did not use a choice set model, because they knew that they were going on a cruise as soon as they were on vacation. Even though the choice set might be logic, they should not be considered universal on all tourist decision scenarios. A limitation of the individual decision-making theory is that travel decisions are hugely influenced by outside forces (Moutinho, 1987). Gitelson and Kerstetter (1995) argue that, as tourism is a highly social event, the role of "others" in a travel party (including friends and family) must be considered.

Decrop (2005), compared directly groups of friends with couples and families that travel together, finding that the motive of group travel might be to share experiences and interest rather than choosing the destination itself. He confirmed explicitly the existence of decision delegation in travel situations with multi-individual, in which a person, formally or informally, makes the decision for the whole group. He also stated that the delegation of decision did not result in angry moods, leading him to conclude that the members were more concerned about the consensus than their own decision. This follows Mayo et al (1981), who argue that leisure activities is frequently secondary to the social interaction that occurs; and that a primarily aim of the group is regularly to spend time together. Decrop (2005), therefore suggested that the majority of group decision literature in which a group makes a decision (similar to juries), and probably is not applicable to tourism decision-making in a group.

Tourism decision making was suggested as too complex to be easily described in processes (Smallman & Moore, 2010). The interpretative structures try to describe how decisions are really made, instead of how individuals should make them (Decrop. 2014). Decrop & Snelders (2004) studied 25 Belgium households and determined that holiday planning it is not as linear or organised as previously conceived. Instead of using a decision process that is rational and limited, decisions turned out to be social and situational variable, and were affected by adaptability and opportunity. They found out that the information search was being used (not just pre-travel), and that the decision-making steps happened in diverse orders. Some respondents simply took advantage of opportunities such as special offers or suggestion by a friend to take a holiday. In this situation, alternatives were not compared, as suggested by older models. In a Dutch quantitative model, Bargeman and van der Poel (2006) also found out that the decision for vacation processes are "much less extensive and far more routinized than described in the rational choice models" (p. 707). Behaviours include problem resolution extended, limited and routinized. "Inertia" may also play a role in decision-making (McCabe et al 2016). Based on a double system theory, McCabe et al. (2016), theorised that tourists probably combine their rational and intuitive approaches in their decisions. They criticised the focus of researches on results, rather than investigated the process itself. Decrop (2010), argued that traditional models of decision-making are probably not adequate to all situations, as making choices in tourism might be a "constraint and opportunity-driven process" (p. 110). Hence, there might not exist a choosing of decision in the universal tourism process, since researchers found out that many steps in previous models could be omitted. Furthermore, a traveller might not even make the choices, since others can make them on the trip, by delegation.

Researchers on tourism decision making have branched away from decision-making processes into developing areas such as: social media influence in decision-making (Schroeder & Pennington-Gray, 2014) online buying behaviour (Berbegal-Mirabent, Mas-Machuca, & Marimon, 2016), electronic word of mouth (eWOM) (Litvin et al. 2008). For instance, (Chen et al. 2015), found out that eWOM has influence on stages of the decision-making process. However, there has been little development on general tourist decision-making models. Dellaert et al. (2014) proposed approaching tourism decision-making, using “mental representations”, which they believe better describes an oriented approach on their decisions. Decrop (2014) summarised their research and supplied new orientations for the study; however, they did not use empirical data.

2.3 The impact of User-Generated Content (UGC) and electronic word of mouth (eWOM) on the travel industry

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Since communication technology advanced and social media started to ease the exchange of information between consumers, the electronic word of mouth (eWOM) became a key product information sources (Kim and Gupta 2012). Another reason for this exchange is that consumers perceive that opinions given by other consumers are of higher value (Bickart & Schindler, 2001). Nevertheless, while face-to-face WOM occurs between people who are familiar or are perceived to be knowledgeable, eWOM is typically from unknown people whose reliability is unknown (Kim and Gupta 2012). A consumer’s pronunciation about the use of a product or service can contribute to the effort of power over companies. This is due to the large number of possible eWOM communication receivers, as reviews are available in the long-term and also available for companies to see whenever they want to (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). As negative consumer comments may affect the way a company and its image are viewed, public pronunciations (reviews, for example) may be used as a sign of power (Hennig-Thurau et al., 2004).

There is some research done on online consumer behaviour and UGC in the travel, marketing and information systems. According to Dellarocas & Awad (2007), user-generated content is considered to be a key tool for companies as they can use it to control consumer attitude toward their products. UGC may similarly increase the consumer’s intent to buy a product and likelihood that consumers will purchase a recommended product (Senecal & Nantel, 2004). In 2011, Gu and Chen assessed the effect of UGC on business performance using information taken from a major Chinese travel agency. The outcomes indicated that the tourist’s buying decision is strongly influenced by online travel reviews. In recent years, consumers are using more and more electronic word of mouth (eWOM) to share their experiences and opinions on products and services (Rezabakhsh et al., 2006). For instance, consumers are generating a great deal of content on online communities by providing their views on books, restaurants or hotels (George, & Scerri 2007).

Although the concept of travellers' use of UGC is relatively new, such content is quickly becoming more popular and more influential as travellers share their experiences and travel recommendations online (Connor, 2006). Travel review websites, such as TripAdvisor.com, IgoUgo.com, Virtualtourist.com, and Lonelyplanet.com help people interact with each other and offer exchange of advice on the internet (Chung and Buhalis, 2008). For example, TripAdvisor gives support to people in the pre-travel phase (e.g. research and travel books) as well as in the post- travel phase, to exchange previous experiences, write review on hotels and destinations, and upload photos and videos from their trips (Chung and Buhalis 2008). UGC is therefore empowering travellers to evaluate travel alternatives when making their travel plans (Connor, 2006).

The increase of the amount of information and communication technologies, since the 1980s, influenced the major industries, among them, the tourism industry (Buhalis & Law, 2008). Online reviews on TripAdvisor, Expedia and other travel-communities websites are a vital source of information for hotel guests (Kim et al. 2011). Consequently, negative reviews can hinder the attraction of new guests. As the removal of negative comments can only be done, on some websites, after a big change in management or major renovation, replying to bad reviews becomes the best solution (Paris, 2013).

Cheung and Lee (2012) based on social psychology literature, identified four perspectives that further clarify the reason behind why consumers spread eWOM in online platforms: egoism, collectivism, altruism, and *principalism*. *Egoism* is about serving people to benefit oneself. Investigators in psychology, sociology, economics and political sciences believe that all human actions are ultimately focused toward self-interest. *Collectivism* refers to attending the public good to benefit a group. *Altruism* suggests serving the masses to benefit one or more others. *Principalism* refers to serving the public good to support a principle, of either justice or utilitarian principle in which a person does a common good in other to benefit the greatest amount of people. Gorsuch and Ortberg (1983) discovered that in ethical circumstances, people stated their intentions to be in line with their sense of moral responsibility. Other researchers (Chelminski & Coulter, 2011 for eg) also found that social behaviour is often motivated by the "need to help others" or by a wish to improve social welfare. Consumers, especially on the internet, are more likely to do something to benefit other people, without expecting a reward. Thus, consumers may want to contribute to eWOM in order to alert other consumers about the negative experience they have undergone in order for them not to endure the same.

Previous studies confirmed that consumers will be more likely to write a negative comment if they are less satisfied with the service (Zeelenberg & Pieters, 2004). However, Chu and Kim (2011) identified normative social influence as a prompt of eWOM behaviour, particularly subjective norm. Since comments with a negative connotation are prone to be traced back to the name of the person who posted them; therefore, they prefer to avoid post negative comments since these are public – instead they would rather share their comments via offline WOM. Consumers may hesitate if they see others negative feedback towards such behaviour. The possibility of losing face is possibly emotionally unwanted. Richins (1982) noted that some feel they do not like to be perceived as *troublemakers* or opinion leaders. This would inhibit them from writing positive/negative reviews of satisfactory/unsatisfactory experiences.

Despite the previous findings, research is still trying to find what motivates people to write positive reviews. Hennig-Thurau et al. (2004) studied this issue more deeply, using previous investigations by Sridhar Balasubramanian (2001). The five motivations they found are focus-related utility (concern for other consumers and the company, for example), consumption utility (people looking for advice), approval utility (economic recompenses and self-elevation), moderator-related utility (convenience and problem-solving provision), and equilibrium utility (conveying positive emotions and expelling negative ones). Sun et al. (2006) also made a research on eWOM, regarding the music-related communication. They proposed that innovativeness, the use of internet and online social connection are of big importance when it comes to eWOM behaviour. Therefore, a reward system was created in order to classify the different types of reviewers.

2.4 Expert reviewers and rewarding systems

Expert reviews serve four different purposes: providing advertising and information, building brand status, creating consumption experiences (since consumers have read about a certain product, its consumption experience might shift depending on the review itself), and influencing consumers' preferences (Cameron, 1995). A few studies suggest that consumers tend to follow the opinion of expert sources while making shopping decisions (Ashenfelter & Jones, 2013; Austin, 1983; Hilger, Rafert, & Villas-Boas, 2011). As these sources are expected to offer useful and dependable information (i.e. trustworthy) about product features and worth (Chen & Xie, 2008; Eliashberg & Shugan, 1997; Bristor, 1990), consumers see the information from an expert as truthful and valuable, and this information is inclined to exercise major effect on consumer attitudes toward brands, shopping intentions and behaviour (Austin, 1983; Holbrook, 1999). Zhang, Craciun, & Shin, (2010) found that in reviewing a product or a service, consumers are inclined to reach for information from experts, which offer more impersonal information. Preceding literature on the effect of expert reviews tends to give emphasis to experts comments, from financial reports by financial analysts (Barber, Lehavy, McNichols, & Trueman, 2001) to expert reviews in restaurant booklets such as Gault Millau (Chossat & Gergaud, 2003).

Results found by Plotkina & Munzel (2016), give support to the theory that online reviews influence the readers intentions. These authors found that expert's reviews seem to influencing on the promotion of new products with features that are more difficult to assess before purchase. On the other hand, a negative review from a regular consumer diminishes the receiver's intention to acquire the new product to a great extent than from an expert review.

On this line of thought, Zhang, Zhang, & Yang, (2016), revealed that as the number of all reviews increases, the hotel ratings tend to decrease, whereas when the number of expert reviews tend to increase, the hotel ratings tend to increase as well. Furthermore, the above-mentioned authors discovered that expert reviews are able to decrease the difficulty that travellers have in assessing which reviews are relevant to their choices.

In the case of TripAdvisor, for example, the website itself has come up with a tool that grants reviewers with the level of expertise in which they are. The website offers a program, which recognizes the reviewer each time they add information to it, called TripCollective. Every time a consumer writes a review, he or she gains TripCollective points, and from the moment a reviewer gains points, they belong automatically to the program. For example, the review itself gives 100 points, if the reviewer includes a picture or a video, the website grants 30 points for each one of them. The TripCollective levels depend on the points a consumer may amount. In order to reach TripCollective level one, one must reach 300 points. To become level two, a reviewer needs 500 points. Finally, the last level that a reviewer may achieve is level 6, with the amount of 10,000 points.

There are six types of expertise levels on TripAdvisor. A consumer can only reach a particular level depending on the points they have as a reviewer. Reviewers earn points depending on their review: reviews with pictures or videos are more thorough, granting users more points (see Fig. 1). The minimum points a reviewer may have to reach level one is 300 points, and to reach level six is 10,000 points. In addition, the reviewer accumulates points with all the reviews they write on TripAdvisor. The level of each reviewer is shown next to the review so the consumer can see it. Some other travel websites also evaluate consumers' reviews. For example, reviews on Yelp are rated based on how useful, funny or cool they are. This way it becomes easier for consumers to evaluate the online reviews, being each one extremely different from the other, being rated from useful to useless (Zheng, Zhu, & Lin, 2013).

Contributions	Trip Collective points
Review	100 points
Photo	30 points
Video	30 points
Forum Post	20 points
Rating	5 points
Traveler Article Creation	100 points
Traveler Article Edits	5 points
Helpful Vote	1 points

Figure 1 List of Trip Collective Points for reviewers to collect (Source: adapted from TripAdvisor.com)

TripAdvisor "rewards" consumers for their reviews by giving badges. Badges are a way of displaying a consumer's knowledge and expertise. A reviewer collects badges as he or she contributes to TripAdvisor, by writing reviews and adding pictures and videos. The review badges are based solely on the amount of reviews a consumer writes and not on the quality of reviews. The badges go from "New Reviewer", with one review, to "Top Contributor" with more than 50 reviews (Fig. 2), and are placed next to the reviewers name, alongside the Trip Collective level. Users can check their level and points at any given time by accessing their account, as the points and badges are automatically awarded to reviewers when they reach each step. To make it simpler and more comprehensible, the contributors were divided into two groups: high-level contributors and low-level contributors. Users are considered "experts" only if they have written ten reviews or more. Furthermore, even if a reviewer has gone months without writing a review, this does not affect their level.

	Reviewer Badge	Number of reviews
	New Reviewer	1 reviews
	Reviewer	3 reviews
	Senior Reviewer	5 reviews
	Contributor	10 reviews
	Senior Contributor	20 reviews
	Top Contributor	More than 50 reviews

Figure 2 List of the reviewer badges regarding the amount of reviews written (Source: adapted from TripAdvisor.com)

TripAdvisor has expanded to other expertise levels, where a reviewer can be awarded with an "Expertise badge", which is given when a user shows off their unique knowledge on a single category, such as hotels, restaurants or atractions. Thus, everytime a reviewer adds three reviews within one single category they will receive an upgraded Expertise badge in that category, like the ones exhitited in Figure 3.

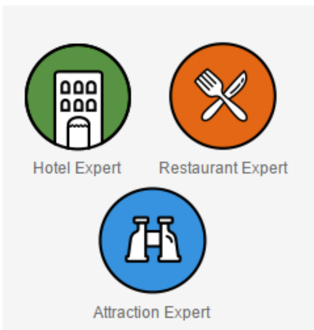

Figure 3 Expertise badges (Source: adapted from tripAdvisor.com)

This paper contrasts from the previous literature in a way that the expert reviews we consider are reviews written by normal consumers and are considered experts by the website itself, based on a point system. Whether being an expert influences the rating these "experts" give, is an empirical question. In this line of thought, this study focuses on how being a top contributor (expert) influences the rating behaviour and thoroughness of the reviews.

In a subsequent stage, and having in mind previous literature, a sentiment analysis regarding each online review is going to be conducted, and a correlation of each sentiment associated to the rating given by each user to the experience in the hotel that they previously stayed. Nevertheless, and given the amount of existing data, understanding the general opinion of online reviewers, with emphasis to expert reviewers, is a consuming-time process, and analysing only a few opinions is limiting and might lead to biased conclusions (Zhang et al. 2011). Therefore, this reserach uses text analysis techniques that enables big quantities of data and its sentiments to be analysed. The use of these techniques enables the analysis of a big quantity of information rather than the common manual analysis and in a more efficient way (Fan, Wallace, Rich, & Zhang, 2006).

Online reviewers may not have truthful information about a product or service when viewing a shopping listing or website, and therefore they might not be able to access its precise value prior to the purchase. In 2012, Baek, Ahn, & Choi explored review credibility through sentiment analysis for mining review text. It is a dual process theory and it was discovered that purchasers have a habit of concentrating on different information sources of reviews. Peripheral cues, such as star ratings and ranking of the reviews are perceived as useful data upon search stage, whereas central information processing, such as number of total words that constitute a review and number of negative words, is significant on the stage of assessing the options (Liu and Park 2015). Nevertheless, does it influence a consumer's choice if an expert reviewer writes the review? Do consumers find it more credible?

2.5 Text mining and sentiment classification

Text mining is a specific technique of data mining that is centred on analysing the value of unstructured information such as raw text, contained in a collection of occurrences of the problem being studied (Fan et al., 2006). In other words, text mining is the process of obtaining important information from text. This important information is generally obtained by the elaboration of tendencies and patterns through statistical patterns of learning. Although some data is still structured, it is estimated that a majority of existing data is unstructured, i.e. textual (Sánchez, Martín-Bautista, Blanco, & De La Torre, 2008). In fact, in the last few years, the quantity of textual data has grown exponentially, being the internet one of the best examples of it. The use of web tools such as blogs, social networks, wikis and discussion forums, has made it possible to access to a much bigger amount of information than any other moment in history (Blake, 2011). Nevertheless, and even though structured data might be analysed thought traditional structured data analysis techniques (data mining), textual information requires specific analysis to deal with challenges in the text itself (Lee et al., 2010). Text is full of barriers (such as orthographic error, slang or implicit meanings) and, in spite of humans having the capacity of understand text through all these barriers, the quantity of information is so huge, that it becomes impossible for humans to do it efficiently (Lee et al., 2010; Mostafa, 2013). Text mining is able to analyse big amounts of non-structured or semi-structured data, efficiently.

Sentiment classification, also referred as sentiment analysis or opinion mining, is able to achieve the tasks of automatically understanding the online reviews and classify them in positive, neutral or negative valence (Liu et al., 2005; Pang et al., 2002; Turney, 2002). Mining opinions from web reviews is a difficult process and requires more than just text mining techniques. There are different issues related to this: expert reviewers' information has to be taken out of websites in which search engines play a key role; and, it is important to distinct the data of reviewers from non-expert reviewers (Ye, Zhang, & Law, 2009). Pang et al., 2002 discovered that text-mining algorithms on sentiment analysis do not work as well as on traditional topic-based categorisation. Keywords identify these topics; however, sentiment is expressed in a more indirect way. Hence, sentiment classification entails more understanding than the regular topic-based classification (Pang et al., 2002).

Sentiment analysis, or opinion mining have major applications such as the automatic preservation of reviews and web communities, suggesting recommendations systems and the improvement of human-computer interactions. This tool is an excellent method for extracting data from unstructured documents and managing major Business Intelligence tasks, as it performs prediction in sales or in other relevant data. Furthermore, by tracking public opinions it contributes for reputation and brand management (Pang et al. 2002).

By analysing travel blogs, it can be concluded that electronic word-of-mouth has a strong influence on the final decision of shoppers as well as of tourism managers. Users read the published reviews and then make their decisions. Even though information is available in many sources, it is impossible for a single person to read all reviews (Ye et al., 2009). Hence, there is a huge need for a sophisticated technique that can automatically evaluate the attitudes of users in their reviews. Sentiment classification techniques can categorise millions of reviews and separate them into negative, neutral and positive in a way that is useful for managers to use. However, there are special challenges when dealing with tourist reviews. Word semantics, for example, on particular areas have different meanings. For example, “unpredictable” camera suggests a negative connotation to that camera, whereas a tour with an “unpredictable” experience has positive meaning attached to it (Ye et al., 2009). One solution to this problem could be the word sense disambiguation and inferring semantic orientation from association (Turney, 2002). Dave et al., in 2003, offered semantic classification for positive and negative reviews using natural language processing and various learning algorithms. In 2004, Hu, Liu, & Street suggested the review-summarizing method based on opinion mining, which offers a process for summarizing characteristics of subjective opinions.

With the results of sentiment classification, customers would have enough information to know which products they should buy, and sellers would know the response from customers and would compare it to the competitors. With the development of computer technology, sentiment classification has been in the centre of recent research endeavours (Ye at al, 2009). The method has been executed in diverse domains such as movie reviews, product reviews, customer feedback and legal blogs (Beineke et al., 2004; Conrad & Schilder, 2007; Liu et al., 2005; Pang et al., 2002). One other potential application consists of extracting ideas or reviews from discussion forums, for example, blogs, and assimilating automatic review mining together with search engines to automatically deliver valuable statistical information of search results or to construct sentiment analysis systems for specific products or services (Ye et al., 2009).

Regarding hospitality and tourism , Ye et al., 2009 studied sentiment classification techniques, which were included in the field of mining reviews from travel blogs. They have specifically compared three supervised machine-working algorithms of Naïve Bays, SVM and the character based N-gram model for sentiment analysis on the reviews from travel blogs of seven popular travel destinations among US and Europe, achieving an accuracy of at least 80%. Another interesting study on hospitality and tourism was conducted by Blair-Goldensohn et al. in 2008. The authors developed a system that summarizes the sentiment of reviews for a local service such as a hotel or a restaurant. In particular, these authors use aspect-based summarization models, in which a summary is constructed by extracting important characteristics of a service, concentrating the sentiment per aspect and selecting aspect-relevant text. This study provided an instrument for further reducing the amount of information needed to produce extremely accurate sentiment classifications. The utmost advanced decision support and business intelligence systems regularly integrate machine-learning methods, primarily data mining for analysing patterns hidden in data that is able to be translated into useful knowledge (Witten & Frank, 2005).

Liu & Zhang (2012) explore a set of concepts, which are important for sentiment analysis. The authors present some definitions of sentiment analysis, such as opinion, polarity, opinion holder, entity, aspects, subjectivity and emotion. *Opinion* is just a sentiment, an attitude, emotion or evaluation that could be either positive or negative towards an entity or an aspect of an entity conveyed by the opinion holder (Liu & Zhang 2012). *Polarity* also known as sentimental orientation, referrers to the linked sentiment to an opinion, which could be either positive, negative or neutral. The so-called *opinion holder* is the one who expresses the opinion. For example, comments regarding products, services or even blogs, the opinion holder is the publication author. Nevertheless, when the aim it to gather the general opinion of the authors, the opinion holder it not necessarily relevant. The *entity* is the object, which is under evaluation by the opinion holder. The *aspects* are the entity's attributes. A person is *subjective w*hen uses their feelings when expressing themselves, rather than real facts about a reality. *Emotions* go beyond positive or negative feelings, being associated to more profound levels, such as love, joy, anger, sadness and fear.

There are two major approaches to detect the polarity of sentiments; machine learning and sentiment lexicon (Caro & Grella, 2013; Medhat et al., 2014). The former is divided into supervised and non-supervised methods, and the later in corpus-based and dictionary-based.

On machine learning analysis, learning algorithms are applied. After being trained under a representative set of data, they are able to classify new documents (Pang et al. 2002; Zhang et al. 2011). On supervised methods, a finite quantity of classes can be defined in each document (Feldman, 2013). On investigation analysis, the *classes* frequently match the sentiment polarity that is to be determined (positive, negative or neutral for example). After the classes are defined, a set of data is built for practice. In various investigations, in order to denoted the polarity, the documents are associated with an evaluation already linked to the comment, i.e., the documents about a products might be, for example associated to the rating given by consumers. After the practice set is created, a machine-learning algorithm is applied, which learns the documents' classification patterns for each individual class. In the end, the model, after learning to classify each document regarding each class, is able to categorise new documents of each class.

On non-supervised methods, the aim is to gather similar documents on the same group, separating different documents into different groups (Blake, 2011). Unlike supervised methods, this method doesn't require prior knowledge of which class each document belongs to, since the documetns are gathered in accordance to each similarity (clusters). Each cluster is then labeled regarding their characteristics. The model is, then, ready to classify new documents in the classes they are most similar to.

When a set of words or expressions are classified according to its polarity, based on a set of dictionaries, sentiment lexicon is used. In this regard, a sentiment lexicon is a list of words in that each one is associted to its polarity. The creation of lexicons can be done manually, though. There are two main methods to do it: dictionary based and corpus based. Due to the long duration of manual procedures, manual classification is typically combined with automatic tecniques (Liu & Zhang, 2012).

The dictionary-based technique starts by manually building a small list of words linked to its sentiment (seed list), from the set of data ready to be analysed (Feldman, 2013). Afterwards, a dictionary is used with the purpose of expanding the seed list through synonyms and antonyms detected by it. A setback from using the dictionary-based technique is that this method does not have the domain of the study (Liu & Zhang, 2012).

When a word lexicon linked to a specific domain is wanted, corpus-based method is applied (Feldman, 2013). In this method, lexicons are usually created from syntactic rules, occurence patters and small seed lists (Caro & Grella, 2013; Liu & Zhang, 2012). In order to build lexicons dependent to the domain, natural language processing tecniques are put into consideration, which allows doing text analysis to a deeper level contemplating the text on the documents and the associated polarity (Caro & Grella, 2013). There are many available lexicons available for use, however it is quite difficult to build and keep an universal lexicon that gathers the various domains that exist, because, and as explained before, a word might have a positive connotation in one domain and a negative connotion on another (Qiu, Liu, Bu, & Chen, 2011). Additionally, the use of available lexicons for sentiment analysis is by itself limitating, as it is hard for the lexicon to contemplate all of the existing expressions (Qiu et al., 2011).

Sentiment analysis can be also used on variou levels, i. e., might be applied to complete documents (document level), each sentence of the document (sentence level), or to various aspects mentioned (aspect level) (Feldman, 2013). The document level analysis evaluates the polarity of each document as a whole, for example, the polarity of a review about a product or service (Bing & Zhang, 2012). Upon completion, it is assumed that the opinion is expressed by only an opinion holder and about an unique entity (Feldman, 2013; Liu & Zhang, 2012). Normally, when reviews on products or services are under evaluation, the author gives their personal opinion about a specific product. Nevertheless, when these reviews are being analysed, they might be involved in a variety of opinion holders, or in the case of a blog, the author might write a comparative review on two different products.

When a single document has many opinions about various entities it is important to do a more thorough analysis (Feldman, 2013). A few studies on sentence level evaluate two issues: subjectivity classification and sentiment classification of subjective sentences (Feldman, 2013; Liu & Zhang, 2012). Investigation on this approach, after detecting sentences subjectivity, focuses on objective sentences finding the polarity of subjective sentences. There are still some works that only focus on one of the two tasks. Pang and (2004) and Turney (2002) initially found out, on their investigations, subjectivity of sentences, and only investigated their polarity of subjective sentences. On the other hand, Caro & Grella (2013) merely did research on the polarity of subjective sentences regarding restaurants, suggesting an algorithm with propagation rules in which each phrase was associated to a polarity score, that was propagated regarding the sentence structure.

Sentence analysis, even though are more detailed than document analysis, they could be, sometimes, incomplete (Liu & Zhang, 2012). Sentence structure analysis are normally effective when the sentence only expresses the opinion about an aspect. Neverthless, and a lot of times, sentences have bigger complexitty levels, as authors give their own opinions on more than an aspect of the same sentence. The detection of a feeling on the structure level it useful, however, when ignoring the polarity od the aspects leads to an enormous loss of information (Feldman, 2013). Hence, in order to detect a more detailed information on various attributes, it becomes necessary to analyse the sentiment on the aspect level. For that, it is important to notice a priori the variety of aspects that are under evaluation by the opinion holder, and then evaluate the polarity of each individual evaluation (Liu & Zhang, 2012). In order to evaluate this polatiry a conceptual model was put into prespective and hypothesis were formulated in order to study it,

3. Conceptual Model and Hypothesis Formulation

Prior experience with a service changes opinions and foretells a behaviour tending to favour the provider (Kim et al. 2009). Consumer involvement theory suggests that repetition or revisit may result from a pre-existing awareness, the effect of prior experiences, engaging the consumers and making them identify less risk for future consumptions (Bargeman & van der Poel, 2006; Laurent & Kapferer, 1985). By the same token, cognitive references theory by Folger (1987) and supported later by Van Zomeren et al (2004) and Cropanzano et al (2001), reasons that a person appraises behavior levels based on past events. The relationship between the consumer and the provider increases people's cognizance of their past experiences when evaluating a service and their satisfaction with a present experience causes a strong commitment to the service provider (Bloemer & Ruyter, 1998; Cretu & Brodie, 2007). Consumers who have gathered positive experiences lean towards a positive attitude and preference towards the provider; higher expectations of the continuity of a relationship have a more positive attitude than customers with low expectations of continuity (Oliver, 1999; Yoon & Uysal, 2005).

This investigation also focuses on giving a more thorough analysis of review source (weather a reviewer is written by an expert or if it is not), and whether this has any influence on the negativity of reviews written. In this study, the designated expert reviewer is considered to be of high quality, having the above mentioned to have at least written ten reviews. Experts are considered experts by the website itself when they must gather determined characteristics in order to be called experts. In other words, the designation of "expert" is based on the times a reviewer has posted a comment (contribution) rather than on the person who has written it. It is easy for consumers to spot top contributors as the contribution badge is placed next to the review itself.

TripAdvisor expert labelling is based on prior knowledge and therefore consumers may be more prone to favour the provider, particularly due to their positive attitude and informed perception of the alternatives and risks. This way we hypothesise the following:

H1a: Expert reviewers tend to write more positive reviews than non-experts
H1b: Expert reviews write reviews with a deeper tone than non-expert reviewers

Information on consumer behaviour has found strong evidence that negative information has more value to the receiver of WOM communication than positive information, hence consumers weight negative information more heavily than positive information on judging tasks and decision-making (Kanouse & Hanson, 1987; Xie et al 2014). A frequently cited reason is that negative information is rare and unexpected (Yin et al., 2014) and it is assumed to be more useful or helpful for decisions (Cao et al., 2011; Willemsen et al. 2011). Expressing less favourable attitudes tends to attract attention (Kanouse & Hanson, 1987) and grow one's chance of being respected and valued (Schlosser, 2005). Weather TripAdvisor negative reviews are considered more useful or not remains a question to the literature. However, given the literature above we hypothesize that:

H2: Negative reviews are more useful than positive reviews

In theory, a person rates a service/product, in accordance to their post-buying opinion. Nevertheless, a sum of recent researches have come to the conclusion that there are some dynamics involved in this online shopping rating behaviour (Godes and Silva 2012; Li and Hitt 2008; Moe and Trusov 2011). These investigations, found that some ratings are influenced by opinions of others and not only to their unbiased personal opinion.

Schlosser (2005) found that an individual reviewer is more likely to bend their review according to what others have previously posted. She proves that there is a differentiation effect where reviewers who consider themselves as experts try to differentiate themselves by writing more negative reviews. This is a contrast to investigations who have shown that people can be exposed to bandwagon effects and assume the opinion of the majority (Marsh, 1985; McAllister & Studlar, 1991). Based on these studies, Moe and Schweidel (2013) concluded that individuals are heterogeneous and may be subject to either differentiation or bandwagon effects. Overall, these researches emphasise the fact that opinions posted before influences opinions on what to post. Consequently, we consider that there are a number of significant covariates that influence the ratings given by reviewers to a product or a service.

Weather expert reviews are prone to give lower rates to hotels, in specific, than regular reviews it still to be investigated. Travelers are often overwhelmed by the quantity of information existing on the web, and it is challenging to trace what they are searching for (Pan and Fesenmaier 2006). Hence, information overload has forced website operators to improve site design and the organization of information.

In more recent years, Zhang et al (2016) conducted a study on a Chinese website in order to study the effects of online user-generated "expert reviews" on travellers' behaviour. They found that the lodging experiences (measured by the complete amount of previous reviews) of a reviewer have a positive impact on their rating, which shows a different effect from expert reviews. The investigators concluded that a traveller's lodging experience enhances their ability to better analyse a situation and smooth the creation of correct quality expectations. Travellers with a higher level of expertise will better understand other individuals' hotel comments because of their similar professional knowledge. Therefore, the number of expert reviews a user has written can moderate the influence of hotel expert reviews on his/her online rating for the hotel.

Given that experts in TripAdvisor are the ones who have higher experience but they may not be experts in the field, we hypothesise the effect that expert reviewers in this case have on hotel ratings:

H3: Expert reviewers rate hotels higher than non-experts

4. Methodology

4.1 Description of data

The universe of study for this investigation are TripAdvisor users that write reviews regarding past experiences. TripAdvisor is the world's largest travel site (comScore, Inc, 2016), empowering travellers to discover the full potential of every trip.

TripAdvisor offers advice to millions travellers worldwide, with its planning features and travel choices with endless links to hotels, restaurants and attractions. Websites which use the TripAdvisor brand sites make up the major travel community in the world, attaining 350 million average monthly unique visitors (TripAdvisor Q1 2016 Results), and reached 385 million reviews and opinions on 6.6 accommodations, restaurants and attractions. The sites operate in 48 markets worldwide (tripadvisor.com).

TripAdvisor is the world´s largest travel website that empowers travellers to release the full potential of every trip. Millions of travellers offer a wide range of itinerary choices, and the website uses a planning tool that checks hundreds of websites in pursuit of the best hotel prices (TripAdvisor.com). Checking an online review website has almost become a routine before going on a trip. Advanced studies, therefore, bring to light that the eWOM influences the decision-making behaviour of potential hotel customers (Liu & Zhang, 2014; Mauri & Minazzi, 2013) and 77.9% of TripAdvisor users referred to eWOM for selecting their hotel (Park & Gretzel, 2007). The main feature the website offers it to write and browse beyond 800,000 hotels, 2 million of restaurants and 400,000 attractions worldwide. The website offers opportunities for customers to include pictures and videos of their experiences in restaurants, hotels and attractions by comparing all of them and offering the search of personalised results depending on each customer’s wants and needs (Simeon & Martone, 2016). With the aim of providing decision support tools, the attractiveness of a hotel in the Orlando area chosen has been evaluated through an analysis carried our using the TripAdvisor’s database. The analysis has examined the universe of the extracted online reviews to five chosen hotels in Orlando: Rosen Shingle Creek Orlando, Hyatt Regency Orlando, Rosen Center Hotel, Hilton Orlando and Hilton Grand Vacations Las Palmeras.

This paper’s main goal is to investigate the effects that an expert has on web reviews. Thus, the aim was to distinguish as many expert reviewers as possible. The area studied was Orlando, Florida in the United States of America. Five hotels were put into perspective for this study; all on the same area, hence with the same target. The area where the hotels are located are close to the Orange County Convention Centre and to the Orlando Theme Parks. Therefore, the five hotels target business guests and well as leisure guests who travel in families, with friends, couples or alone. All types of reviews were extracted. On the recollection of data were separated into “expert reviews” and “non-expert reviews”. Being branded “experts”, the costumers who wrote more than 10 reviews on the travel website, and “non-experts” the ones who wrote less than 10 reviews. A total of 1,445 reviews were taken from TripAdvisor.com. All the comments were extracted from 2012 to 2016.

The sample is below illustrated:

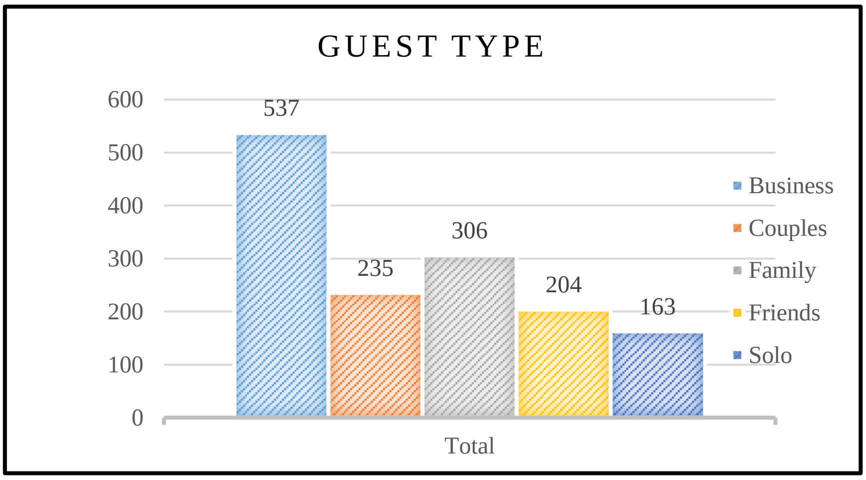

Figure 4 - Number of reviews by guest type

This study evaluates three types of travellers:

- ❖ Business traveller – the type of guest who travels for business and whose expenses are paid by the business he/she works for
- ❖ Couples, family or friends – type of travellers who travel with their significant other, family or friends
- ❖ Solo – solo travellers are the ones who travel alone

The sample is composed of 537 business guests, 235 guests who travelled in couples, 306 who travelled with their families, 204 who with their friends, and that 163 travelled alone.

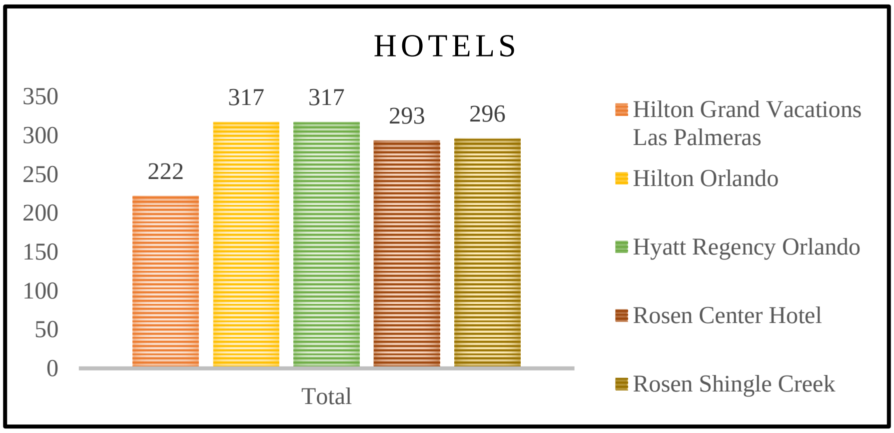

Figure 5 - Number of reviews by hotel

On the five hotels chosen to do the search on, 222 reviews belong to guests who stayed at Hilton Grand Vacations Las Palmeras, 317 to guests to stayed at Hilton Orlando, 293 to guests to stayed at Hyatt Regency Orlando, 293 to guests who stayed at Rosen Center Hotel, and finally, 296 to guests who stayed at Rosen Shingle Creek. Figure 5 shows the distribution of reviews by hotel.

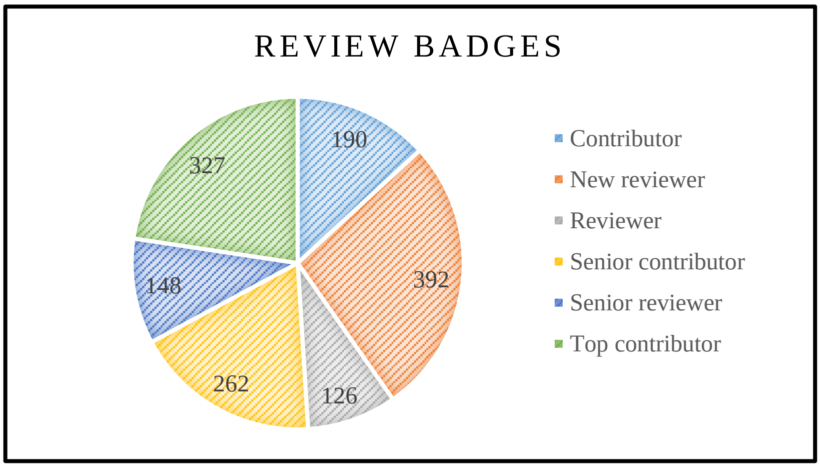

Figure 6- Number of reviews based on review badges

In regards to reviewers' review badges, New Reviewers wrote 392 of the reviews on the sample, Reviewers wrote 327 reviews and Senior Reviewers wrote 148 reviews. Expert reviewers Contributors wrote 190 reviews, Senior Contributors wrote 262 reviews and finally, Top Contributors wrote 327 reviews.

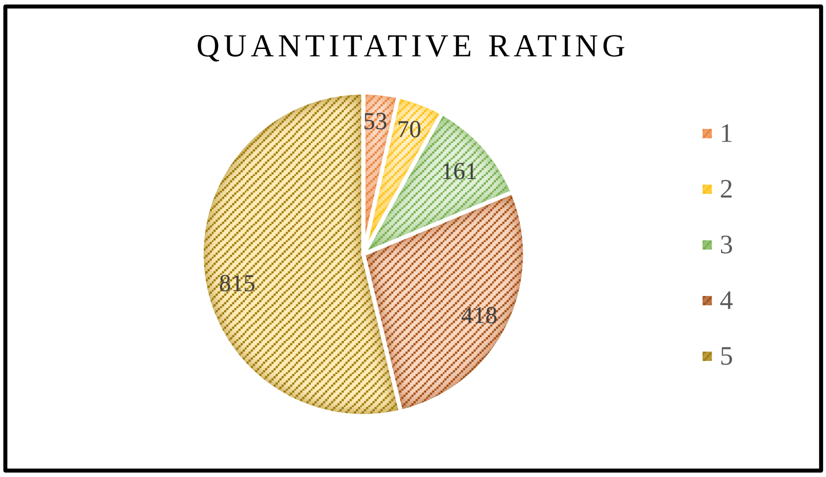

Figure 7- Guest reviews by quantitative ratings

The sample is composed by 815 reviews with a rating of 5, 418 with a rating of 4, 161 with a rating of 3, 70 with a rating of 2 and only 53 reviews with a rating of 1. Hence, the lower the rating the fewer amount reviews written.

4.2 Sentiment analysis tool

To conduct the study we decided to use the publically available system, Lexalytics as our sentiment analysis tool (Lexalytics, 2017). The data analysis consists of five steps. It began by extracting the data, in this case from *Tripadvisor.com*, and put it into an excel sheet. *Natural Language Processing (NLP)* was used to classify reviews according to their polarity. NLP "is the study of making computers understand how humans naturally speak, write, and communicate" (Lexalytics 2017, Lawrence, 2014; Williamson & Ruming, 2015).

Figure 8 - The five steps of data analysis

This way, computers can execute sentiment analysis and other text analyses on a vast scale and deliver meaningful data. On this stage, NLP processed our large database by understanding each review. NLP is part of the text mining stage and consists on the extraction of the semantic characteristics in text. On the classification phase, the polarity of the text is attributed. The last stage consists on exhibiting the results found by Lexalytics.

When analysing the sentiment strength, Lexalytics delivers one single specific score in 2 decimal places between -1 and +1. The software includes a very large dictionary of sentiment bearing phrases in many different languages along with their relative score.

These scores were pre-determined by how frequently a given phrase occurs near a set of known positive words (e.g. good, wonderful, and spectacular) and a set of negative words (e.g. bad, horrible, and awful) (Lexalytics, 2017). This software recognises the emotive phrases within a document, scores these phrases (roughly -1 to +1), and then combines them to distinguish the overall sentiment of a sentence. This automatic sentiment scoring is not affected by any human biases and will score each sentence the same every time it is exposed to the system. In addition, its incomparable classification engine, which entails no training and the ease of the use of the system, makes it uniquely suitable for this study.

The first studies in this field were published only in 2007; three articles approach the unexpected influence of the media on companies and on the tourism industry – unexpected because such companies and the industry itself were losing the control on what was being written about them on social media networks (Dwivedi et al 2007; Thevenot, 2007; Zeng & Gerritsen, 2014). These authors concluded that the growth and the social media impact should not be ignored. Furthermore, the social media needs to be constantly monitored by tourism with replies and real time interactions (Grant-Braham, 2007).

In order to use the sentiment analysis tool on the diverse area of business, it is essential to use tools where the use of techniques based on dictionaries and automatic learning is predominant. This means that these tools use data found on lexicographic resources to assign sentiment to a big number of words, distinguishing the polarity of each document between positive, neutral and negative (Lawrence, 2014). After the text mining and sentiment analysis, the set of structured information based on the non-structured data is obtained.

5. Results

SPSS Statistics 22 was used to test the three hypothesis. A set of tests were conducted to check for analysis of variance assumptions in order to understand the best statistical tests to use in this case. For the parametric tests, the variables have to respect three assumptions: (1) the dependent variable should be approximately normally distributed for each category of the independent variable, (2) there needs to be homogeneity of variances and, (3) the dependent variable should be measured at the interval or ratio level (i.e., they are continuous). On the other hand, non-parametric tests are less rigid and do not require that the sample is normally distributed and can be used with ordinary or categorical variables. The variables analysed were the following*: Expert* (nominal variable that simply describes a reviewer as an expert or non-expert), *DocumentSentiment* (scale variable that measures the degree of the sentiment of a review), *DocumentSentiment score* (nominal variable used to describe if a review has a positive/negative/neutral meaning), *Useful* (nominal variable that describes a review as being useful or not), and *QuantitativeRating* (nominal variable that rates a review from 1-5).

The *Expert* variable was converted into *Expert_Recoded*, and the *Useful* variable was converted into *Useful_Recoded* because it has to be presented by ranks. Expert reviewers were transformed into 1 and non-expert reviewers into 0, as it is explained below. Useful reviews were transformed into 1 and not useful reviews were transformed into 0.

As it can be seen on table 1, the variable *DocumentSentiment score* is not a continuous variable. The table 1 presents the results from two well-known tests of normality, Kolmogorov-Smirnov Test and Shapiro-Wilk Test. Shapiro-Wilk Test is more appropriate for small sample sizes (< 50 samples). Therefore, we will use Kolmogorov-Smirnov. Since $p=0.000$, i.e., $p<0.05$, it could be concluded that variable *DocumentSentiment score* does not follow a normal distribution.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Document Sentiment	,070	1449	,000	,967	1449	,000

a. Lilliefors Significance Correction

Table 1 - Normality test of the Document Sentiment variable

As it can be seen on table 1, the variable DocumentSentiment is not normally distributed by each level of the Expert variable either and p=0.000.

Tests of Normality

Expert_RECODED		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Document Sentiment	,00	,084	661	**,000**	,975	661	,000
	1,00	,068	786	**,000**	,959	786	,000

a. Lilliefors Significance Correction

Table 2 - Normality test of the Document Sentiment and Expert variables

As it can be seen on table 3, the variable D*ocumentSentiment* is not normally distributed by each level of the *useful_RECODED* variable, as p=0.000.

Tests of Normality

useful_RECODED		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Document Sentiment	,00	,089	294	**,000**	,973	294	,000
	1,00	,067	1153	**,000**	,964	1153	,000

a. Lilliefors Significance Correction

Table 3– Normality test of the Document Sentiment and useful variables

Regarding the *QuantitaveRating* variable, as it is a scale variable, Kolmogorov-Smirnov test was conducted. It was concluded that the variable does not follow a normal distribution, as p=0,000, as showed on table 4.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Quantitative rating	,312	1449	,000	,727	1449	,000

a. Lilliefors Significance Correction

Table 4– Normality test of the Quantitative rating variable

Since none of the tested variables presents a normal distribution. Therefore, non-parametric tests were conducted.

5.1 Sentiment Polarity of Expert and Non-Expert Reviews

Table 5 represents the descriptive statistics for the variable *DocumentSentiment* in the current study. Among 1,445 reviews, expert reviewers (contributor, senior contributor and top contributor) write more positive reviews than non-expert reviewers do. The average number of positive reviews written by experts is 79,57%; the average of number of positive reviews written by non-experts is 74,12%. On the other hand, non-experts have a 9,74% of negative reviews written in contrast to the 4,82% negative reviews written by expert reviews.

	Document sentiment			
Expert?	**Negative**	**Neutral**	**Positive**	
No	9,74%	16,13%	74,12%	100,00%
Yes	4,82%	15,61%	79,57%	100,00%
Total	**7,06%**	**15,85%**	**77,09%**	**100,00%**

Table 5 – Descriptive statistics for variables "expert" and "document sentiment" – number of reviews by polarity

To do a statistical analysis on the quantity of reviews written by experts and non-experts in order to validate H1, a Chi-Square test was conducted (*table 6 and 7*). This test is used to discover if there is a relationship between the two categorical variables – *Expert* and *DocumentSentiment.* Pearson Chi-Square's value is $\chi2(2)=13.353$, $p=.001$, as seen on the below tables (6&7).

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	13,353[a]	2	,001
Likelihood Ratio	13,355	2	,001
N of Valid Cases	1449		

a. 0 cells (,0%) have expected count less than 5. The minimum expected count is 46,60.

b.

Expert_RECODED * Document Sentiment +/- Crosstabulation

Count

		Document Sentiment +/-			
		negative	neutral	positive	Total
Expert_RECODED	,00	64	106	492	662
	1,00	38	122	627	787
Total		102	228	1119	1449

Table 6 & 7 – Chi-square test conducted on Expert_Recoded variable and DocumentSentiment

The results of table 8 show that somewhere across the contingency table there is a disproportionate number of reviewers – expert or non-experts - in one or more of the sentiment score groups, meaning that there is something deviant between the observed and the expected cell frequencies. It was essential then, to conduct a post hoc test. In order to conduct this test, the study of residuals was conducted. These residuals are basically Z scores; and the absolute z scores that are greater or lower than 1.96 ($z>1.96$), are *statistically significant*.

Document Sentiment +/- * Expert_RECODED Crosstabulation

			Expert_RECODED ,00	Expert_RECODED 1,00	Total
Document Sentiment +/-	negative	Count	64	38	102
		% within Document Sentiment +/-	62,7%	37,3%	100,0%
		% within Expert_RECODED	9,7%	4,8%	7,0%
		Adjusted Residual	3,6	-3,6	
	neutral	Count	106	122	228
		% within Document Sentiment +/-	46,5%	53,5%	100,0%
		% within Expert_RECODED	16,0%	15,5%	15,7%
		Adjusted Residual	,3	-,3	
	positive	Count	492	627	1119
		% within Document Sentiment +/-	44,0%	56,0%	100,0%
		% within Expert_RECODED	74,3%	79,7%	77,2%
		Adjusted Residual	-2,4	2,4	
Total		Count	662	787	1449
		% within Document Sentiment +/-	45,7%	54,3%	100,0%
		% within Expert_RECODED	100,0%	100,0%	100,0%

Table 8– Crosstabulation – contingency table analysis on Expert_Recoded variable and Document Sentiment

By looking at the adjusted residuals, it can be seen that there are **four** deviant values. The adjusted residual for Experts who write positive reviews is 2.4 corresponding to 79.7% - this value is what was expected (since it was hypothesised that expert reviewers write a higher amount of positive reviews than non-experts). Furthermore, there are 56% expert reviewers writing positive reviews, and 44% non-expert reviewers writing positive reviews. On the other hand, non-experts who write positive reviews showed an adjusted residual value of -2.4 corresponding to 74.3%, which is statistical significantly different from what was hypothesised. Expert reviewers and non-expert reviewers who write negative reviews showed an adjusted residual value of -3.6 and 3.6 respectively. These values are statistically significant. Meaning that expert reviewers write less reviews with a negative connotation less than expected and that non-expert reviewers write more reviews with a negative connotation than expected. The results confirm and support H1a.

Although the previous studies show that expert reviewers write a higher number of positive reviews than non-experts thus confirming H1a, an analysis was also performed to check the average strength of each review. A table with the mean strength of the negative, neutral and positive reviews was developed. Table 9 shows that strength in regards to the sentiment attached to the reviews, non-experts have an average of negative sentiment attached to reviews of -0.26 in contrast, expert reviews have a negative sentiment attached to reviews of -0.21. Oppositely, non-experts have a positive sentiment attached to reviews of 0.55; experts have a sentiment attached of 0.48.

	Document sentiment average by polarity			
Expert	**Negative**	**Neutral**	**Positive**	
No	-0,264	0,112	0,550	0,400
Yes	-0,207	0,110	0,477	0,387
Total	**-0,243**	**0,111**	**0,509**	**0,393**

Table 9 – Descriptive statistics for variables "expert" and "document sentiment" - average sentiment by polarity

This suggests that, although expert reviewers write more positive reviews (in number) than non-experts, they are usually more restrained in their feelings. While non-experts write a lower number of positive reviews than experts, when they write positive reviews they usually use stronger feelings to do so. In order to test if such effect was significant, a non-parametric Kruskal-Wallis test was used. Like most non-parametric tests, Kruskal-Wallis is performed on ranked data, therefore, before the analysis, the measurements observations are converted to their ranks in the overall data set. This test will be conducted in order to analyse the quality of the reviews written, i.e., whether the reviews written by experts have a more negative value or a more positive value than the reviews written by non-expert reviewers.

Ranks

Expert_RECODED		N	Mean Rank
Document Sentiment	,00	662	748,70
	1,00	787	705,06
	Total	1449	

Test Statistics[a,b]

	Document Sentiment
Chi-Square	3,911
df	1
Asymp. Sig.	,048

a. Kruskal Wallis Test

b. Grouping Variable: Expert_RECODED

Table 10 & 11 – Kruskal-Wallis test on Expert_Recoded variable

The Kruskal-Wallis H test on table 10 and 11 shows that there was a statistically significant difference between "expert reviewer" and "non-expert" when it comes to the level of intensity an expert/non-expert expresses a positive, neutral or negative option. With a $\chi 2 = 3.911$, $p = .048$, with a mean rank of 748.70 for "non-expert reviewer" and 705.06 for "expert reviewer", and with 1 degree of freedom. Therefore, the hypothesis *H1b* is not validated.

5.2 Usefulness of Expert and Non-Expert Reviews

As it is possible to see with on table 12, on 1445 reviews, 102 negative reviews were considered useful, nevertheless, a total 1,114 positive reviews were considered useful. 229 neutral reviews were considered useful. However, each reviewer is able to find useful (like) a review, i.e., many reviews have more than one "useful like". The reviews that had a positive connotation amount around 77% of all likes of the sample reviews. On the other hand, only about 6% of the reviews that were negative were considered useful. Neutral reviews had a total of around 16% of "useful likes".

Sentiment attached – number of reviews/percentage	Negative	Neutral	Positive	Total
Useful? (# of reviews)	102	229	1,114	1,445
Useful? (# of likes)	1,437	4,173	19,836	25,446
Useful? (percentage)	5.6%	16.4%	76,8%	100%

Table 12 – Descriptive statistics for variables "expert" and "review sentiment"- count of sentiment attached to reviews and its corresponding percentage

The Kruskal-Wallis H test on table 13 and 14 show there was no statistically significant difference between "useful" and "non-useful", $\chi2(1) = 1,470$, $p = .225$, with a mean of 750,37 likes for "non-useful reviews" and a mean of 717.28 likes for "useful reviews". Therefore, H2 (*Negative reviews are more useful than positive reviews)* is not supported.

Ranks

useful_RECODED		N	Mean Rank
Document Sentiment	,00	294	750,37
	1,00	1153	717,28
	Total	1447	

Test Statistics[a,b]

	Document Sentiment
Chi-Square	1,470
df	1
Asymp. Sig.	,225

a. Kruskal Wallis Test

b. Grouping Variable: useful_RECODED

Table 13 & 14– Kruskal-Wallis test on Expert_Recoded variable

5.3 Hotel Ratings of Expert and Non-Expert Reviews

All the review badges have a higher percentage of reviews written with when the rating is 5.The big majority of the badges increase the number of reviews when the rating increases as well. The badge that has the biggest percentage of 5 star rating is the New Reviewer, which is a non-expert reviewer. Overall, non-expert reviewers have a higher percentage of reviews written with 5 star rating. Nevertheless, non-expert reviewers have the higher percentage of reviews with 1 star rating.

	Expert		
Quantitative rating	**No**	**Yes**	**Total**
1	71,11%	28,89%	100,00%
2	67,69%	32,31%	100,00%
3	41,78%	58,22%	100,00%
4	36,41%	63,59%	100,00%
5	47,46%	52,54%	100,00%
Total	**45,47%**	**54,53%**	**100,00%**

	Expert		
Quantitative rating	**No**	**Yes**	**Total Geral**
1	32	13	45
2	44	21	65
3	61	85	146
4	146	255	401
5	374	414	788
Total	**657**	**788**	**1445**

Table 15 & 16 – Descriptive statistics for variables "expert" and "quantitative rating"

The Kruskal-Wallis H test showed that there was not a statistically significant difference between the different ratings. Meaning that there is no significant difference between experts and non-experts in the way they rate hotels on Tripadvisor. Table 17 and 18 shows that $\chi 2(1) = 0.039$, $p = .844$, with a mean of 727.13 for non-expert reviewers and a mean of 723.21 for expert reviewers. Therefore, H3 is not supported.

Test Statistics[a,b]

	Quantitative rating
Chi-Square	,039
df	1
Asymp. Sig.	,844

a. Kruskal Wallis Test

b. Grouping Variable: Expert_RECODED

Ranks

Expert_RECODED		N	Mean Rank
Quantitative rating	,00	662	727,13
	1,00	787	723,21
	Total	1449	

Table 17 and 18– Kruskal-Wallis test on Expert_Recoded variable

5.3.4 Decision Tree

To identify reviewers who are more likely to be expert , the classification and regression tree (C&RT) analysis was applied (Breiman et al. 1984). C&RT is a non-parametric technique used to examine the relations amongst a target outcome variable and a large number of potential predictors. Each predictor variable is studied by C&RT with the purpose of classifying the most significant predictor at each step to split the sample into two commonly exclusive and homogenous subgroups. Each C&RT splitting is an ideal equilibrium between sensitivity and specificity for predicting the outcome variable. This process was conducted repeatedly until the sample was split into completely homogeneous groups or until a pre-determined maximum level of splits was reached. The result was the classification tree. The starting group (entire sample) is called the root, each split is called as the branch, and the data subset resulting from the split is referred to as a node; the terminal or ending nodes are called leaves.

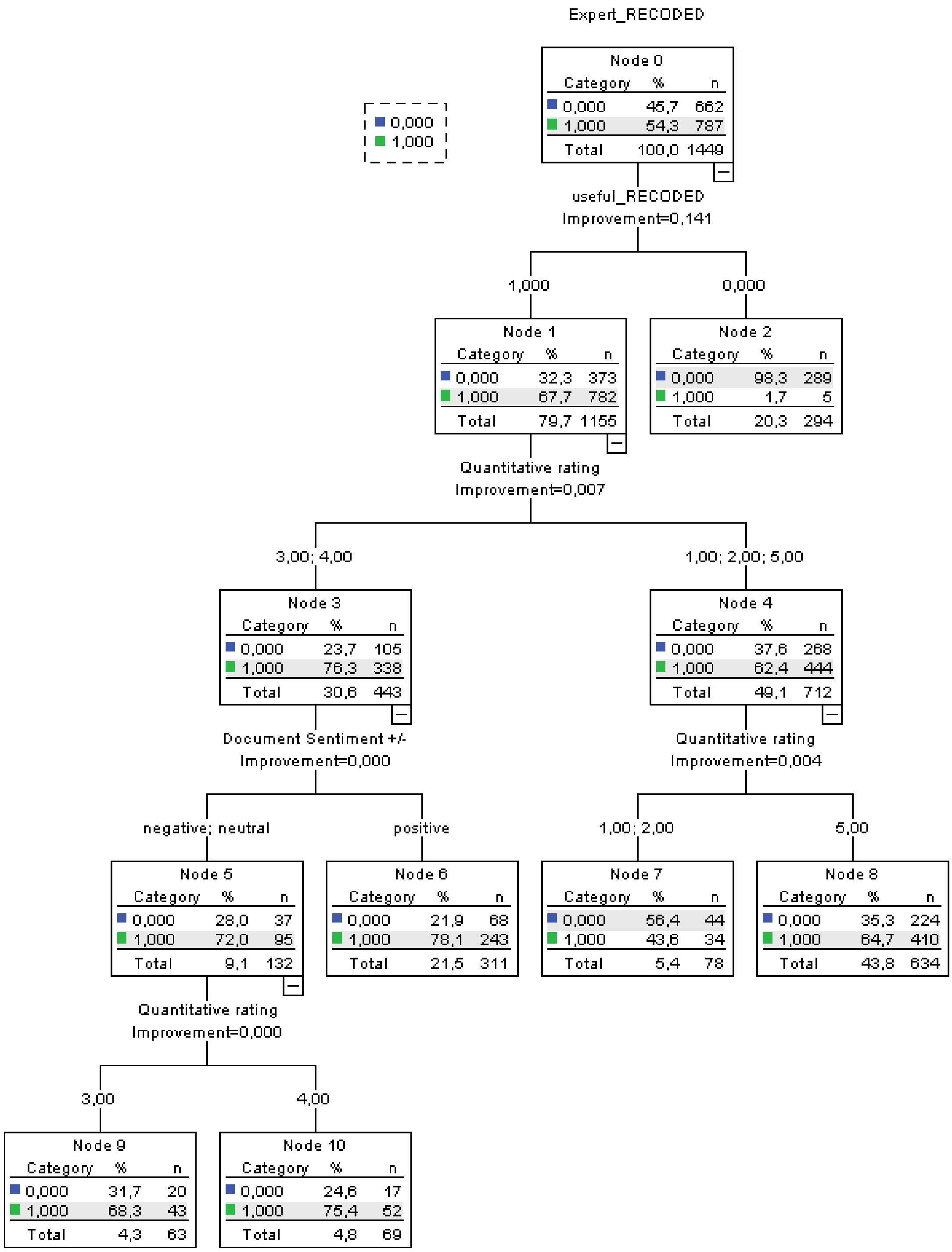

Table 19 – Decision tree on expert reviewer type

It is possible to see in the Decision Tree above (table 19), on the first splitting, out of 79.7% of useful reviews, 67,7% are written by experts reviewers. On the other hand, within the 20.3% of non useful reviews, only 1.7% of the reviewers are expert reviews.

The number of total reviewers written that are useful is equal to 79.7%. In addition, on the second splitting – quantitative rating – 30.6% of these reviewers are the reviewers who gave a rating of 3 or 4, being the experts amounting to a total of 76.3%. The reviewers who gave a rating of 1, 2 or 5 are composed by 49.1% of the reviewers who wrote useful reviews. Of these reviewers, 62.4% are experts. Regarding the reviewers who attributed 3 or 4 to a review (30.6%), 9.1% wrote neutral reviews, and 21.5% wrote positive reviews. On the other hand, of the reviewers who gave a rating or 1,2 or 5, 5.4% gave a rating of 1 or 2, and 43.8% gave a rating of 5. Analyzing the last splitting, it visible that, out the 9.1% of negative and neutral comments, 4.3% gave a rating 3 and 4.8% gave a rating of 4.

Risk

Estimate	Std. Error
,254	,011

Growing Method: CRT

Dependent Variable: Expert

Classification

Observed	Predicted		
	No	Yes	Percent Correct
No	333	329	50,3%
Yes	39	748	95,0%
Overall Percentage	25,7%	74,3%	**74,6%**

Growing Method: CRT

Dependent Variable: Expert

Table 20 & 21 – Risk estimate and classification table of the model

Table 20 and 21 measure the performance of the model. As we can see on table 20, the estimate risk is .0254, which means that the model predicts the type of expert incorrectly 25.4% of the cases. This is verified by the classification table, which gives us a 74,6% chances of correct classification by the model. This model makes a better job when classifying the *Yes* category as it gives a 95% as correctly predicted, whereas only 50,3% are correctly predicted for the *No* category.

6. Discussion

This study empirically investigated whether TripAdvisor's reviewers level of expertise influence their online behaviour. Our results from *TripAdvisor.com* clearly suggest that the expert reviewers tend to write a bigger number of positive reviews than non-expert do. However, there is a significant difference between being an expert or non-expert reviewer when it comes to the level intensity of these positive/ negative reviews. The study's conclusions proposes that although expert reviewers write more positive reviews (in number) than non-experts, they are usually more restrained in their feelings. While non-experts write a lower number of positive reviews than experts, when they write positive reviews they usually use stronger feelings to do so. This effect could be because expert reviewers are more careful with words as they know that their status influences many people on their shopping behaviour. Therefore, they are more cautious when it comes to appraise or criticise a service or a product. On the other hand, expert reviewers and non-expert reviewers have the same influence on reviews' "usefulness" and rating behaviour; i.e., experts and non-expert reviews were regarded as having the same effect on the reviews usefulness and rating behaviour.

Previous studies by Kim et al. (2009) support the findings in a way that they claim that previous experience with a service predicts a behaviour that tends towards the provider. This might be because as hotel visitors have already some experience with what might go wrong with their visit to the hotel, they tend to be more compreensible than guest who do not have the same experience. The results are also in line with the consumer involvement theory (Bargeman & van der Poel, 2006; Laurent & Kapferer, 1985) that claims that revisit results from a pre-existing knowledge which makes guests identify risks in a more objective way. Some other aspects which may be related to the biggest number of positive reviews being written by expert reviewers is that consumers who have had positive experiences are more positive towards the provider; plus customers with a higher expectations of continuity of a relationship have a positive approach concerning the provider (Oliver, 1999; Yoon & Uysal, 2005). Customers with previous experiences and with high expectations of continuity are customers who are regarded to be experts, this way the finding go in line with previous literature.

Regarding the intensity of the sentiment attached to the reviews themselves, the results found that there is a noteworthy difference between the ones written by experts and non-experts.

Previous studies show strong evidence that negative information is more valuable than positive information. Supposedly, consumers give more importance to negative information rather than to positive information on decision-making (Kanouse & Hanson, 1987). The reasons for this is that negative information is more unexpected than positive information, which contributes to its usefulness (Cao et al., 2011; Willemsen et al., 2011; Yin et al., 2014). Some other authors just found that negative reviews are thought to be more intelligent and competent than positive ones (Amabile, 2012). However, on our sample of 1,445 reviewers, there is no significant difference between the usefulness of a negative review and a positive one. Both are regarded the same way. This could be because nowadays customers have a more variety of information available online to look when in doubt of purchasing a product/service and do not let some, for example, negative opinions be of more value than positive opinions. Customers might be able to understand better that one bad review does not describe the whole product, and look for other opinions about the same product. Alternatively, this could be simply because of the fact that reviewers do not click the button to like the comment even if they find it useful.

Theoretically, a buyer rates a service or a product after buying or consuming it. As stated before, and according to Godes and Silva (2012) there are now some factors that consumers have in consideration when rating a product/service; these findings led to the conclusion that opinions are influenced by others and not only by people's experiences. The opinions regarding this issue have always been controversial. For example, in 2005 Schlosser conducted a study which proved that consumers tend to influence their opinions based on what other people have previously posted; people who consider themselves as experts like to differentiate themselves from others by writing more negative reviews. However, some other investigations (Marsh, 1985; McAllister & Studlar, 1991) claim that people are exposed to bandwagon effects and accept the opinion on the majority as their own. In 2013, Moe and Schweidel came to realization that reviewers are all different from each other and are either subjected to differentiation or bandwagon effects. Our research of 1,445 people found that there is no connection between rating and expert/non-expert. Both groups of reviewers wrote reviews, which were classified from 1-5 stars, and its amount is not statistically different from each other.

It makes sense that reviewers with more expertise have more solidarity towards the provider, as they are used to different levels of service. People who travel a lot have a lot of experience when it comes to the service provided by hotels. It is easy for a guest who is constantly in hotels to forgive some bad service from a hotel than a person who stays in a hotel once a year, and who is obviously expecting the best. Expert travellers might accept that hotel service has flaws easier than non-expert travellers would.

7. Conclusion

This study focused on comparing online reviews written by experts with those written by non-expert reviewers, and analysing its content. There was a clear gap in the field of study regarding the study of the degree of the sentiment showed in review depending on the expertise of the reviewer. For example, Amabile, 2012 studied the polarity of reviews and their influence on customers, but did not research regarding the reviewer itself, and its level of expertise. Henning-Thurau et al, 2004 and Balasubramanian, 2001 contributed to this field by studying what motivates people to write positive reviews, and again do not complete the study by analysing the reviewer him/herself and their level of expertise. Until now, there was no investigation, which applied the sentiment analysis technique on analysing reviewers' level of expertise. This dissertation approaches this theme thoroughly, with the objective to fill this gap. Having the internet made available, the vast majority of information, website operators were forced to develop the web page design and organise information in a clear way. It was decided to focus on a leading travel website in the world, TripAdvisor, since the website has a design that clearly shows which reviewers are experts and which reviewers are not. This investigation delivers theoretical and managerial insights into the effect of the website design on travellers' reviews sentiment polarity, usefulness and rating behaviour, and the way these reviews can be managed.

This investigation complements a big emergent segment on tourist research on WOM by showing differences between expert reviews and non-expert reviews. Furthermore, it gives new insights on understanding the sentiment polarity that users use to describe their experiences – positive, negative or neutral. Our results reveal that expert reviewers tend to write more positive reviews than non-expert reviewers do. These findings are consistent with Kim, Choi, and Han (2009), who implied that previous experience positively affects their opinion regarding a particular service. I.e., a guest who is well travelled tends to be more understanding towards a service/product than a guest who is not used to travel.

Unlike what previous literature revealed, there was not found a statistically significant difference between expert and non-expert reviews when it came to hotel rating. Both reviewers have approximately the same probability of rating a hotel higher or lower. The same happened when usefulness was put into perspective. There was not found a statistically significant difference on the usefulness of reviews written by experts or non-experts. I.e., reviews written by experts were not regarded as more useful than non-experts reviews, unlike what it was expected; rather there was no difference found on the usefulness of both reviewers types.

From a managerial point of view, a primary inference across a comprehensive range of people is that the trade of product information via online reviews endows consumers by reducing the space between the provider and the buyer (Litvin et al. 2008). Nonetheless, the present propagation and extensive use of online reviews is not only an opportunity for business people, but also a hazard in a way that that people are not capable of processing big quantities of information. It is better to have available moderate quantities of information than a large quantity, or else buyers may blame online review platforms of information surplus, with poor website design management (Park and Lee, 2008). Hence, marketers have recently began using new strategies to find the expert reviews and major contributors among buyers and developing tactics to manage the impact of online reviews.

In the real world, having knowledge of the profile of the guests checking-in at a hotel is beneficial not only for the guests but also for managers. For example, Review Pro the world-leader in Guest Intelligence solutions for the hospitality industry provides managers with detailed information about the greatest weaknesses and strengths of the service provided. These type of guest intelligence solutions help hotels understand TripAdvisor's rankings and to increase positive reviews and avoid negative reviews. It also helps tracking the company's performance. Aligned with this tool, our finding have a lot of useful information for managers to understand guests' profile and do a personalised service to each individual guest. This would benefit not only the hotel but also guest satisfaction, leading to retention of clients.

There are a few limitations to this study. To our knowledge, our study is one of the first to analyse the differences between when a TripAdvisor expert writes a reviews and when a non-expert writes a review. However, using a single website in this paper can limit our results. It could be interesting to use our framework to other online reviews websites where reviewers can be linked to their level of expertise. Even if behaviour will change between contexts, it could be interesting to study it, within a bigger niche. On the other hand, the sample is limited to only 1,445 reviews. Therefore, using a wider range of reviews might increase the external validity of the current results.

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