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Using deep learning and visual analytics to explore hotel reviews and responses

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ABSTRACT

This study aims to use computational linguistics, visual analytics, and deep learning techniques to analyze hotel reviews and responses collected on TripAdvisor and to identify response strategies. To this end, we collected and analyzed 113,685 hotel reviews and responses and their semantic and syntactic relations. We are among the first to use visual analytics and deep learning-based natural language processing to empirically identify managerial responses. The empirical results indicate that our proposed multi-feature fusion, convolutional neural network model can make different types of data complement each other, thereby outperforming the comparisons. The visualization results can also be used to improve the performance of the proposed model and provide insights into response strategies, which further shows the theoretical and technical contributions of this study.

1. Introduction

Today, an increasing number of travelers read online consumer reviews (OCRs) to plan their trips and to make purchasing decisions (De Pelsmacker, van Tilburg, & Holthof, 2018; Hernández-Ortega, 2018). This dynamic growth of online reviews has intensified the need for analyzing OCRs because these reviews contain consumer perspectives that may relate to perceived credibility (Casaló, Flavián, Guinalíu, & Ekinci, 2015a), corporate reputation (Baka, 2016), and consumer intentions to book hotels (Ladhari & Michaud, 2015).

From the business perspective, OCRs and persuasive communications are vehicles to build credibility and influence user decisions (Fan & Gordon, 2014; Zhang et al., 2016). Therefore, the hospitality and tourism industry is ideally suited for the application of social media analytics (Fan & Gordon, 2014). Lu and Stepchenkova (2015) investigated 122 journal articles and conference proceedings in the last decade and gained insights into how user-generated content has been applied in the tourism and hospitality industry. Most related studies collect a few hundred to a few hundred thousand guest reviews using analytical methods such as content analysis, text mining, machine learning, regression analysis, econometric modelling, or combinations of these techniques (Xiang et al., 2017). As for data sources, TripAdvisor is the most frequently used because it is considered a 'premier' sampling field and also the largest travel-related review site in the world (Banerjee & Chua, 2016; Pearce & Wu, 2018; Xiang et al., 2017).

In hospitability and tourism, social media analytics is a growing area (Fan & Gordon, 2014) because consumer reviews reflect experiences on services and have been studied to gain a better understanding of research problems (Schuckert et al., 2015). Most investigations have relied mostly on statistical- and survey-based studies or experiments (Lee & Cranage, 2012; Li et al., 2017; Wei et al., 2013a) due to data unavailability (Xie et al., 2016). To date, the intricate relation between online reviews and responses has not been well studied, despite the considerable effort made on studying the effect of volume and valence (De Pelsmacker et al., 2018), travel motivation (Pearce & Wu, 2018), customer satisfaction, opinions and sentiments (Xiang et al., 2015), online reviews and hotel business performance (Xie et al., 2014), and perceived helpfulness of online reviews (Schuckert et al., 2015). This is unfortunate given that online reviews represent customers' opinions, satisfaction, and attitudes toward a hotel, and effective responses are likely to enhance the perceived hotel quality (De Pelsmacker et al., 2018; Torres et al., 2015) and boost business.

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Online review platforms enable managers to resolve customers' complaints and engage potential customers by responding publicly to online reviews (Lui et al., 2018; Park & Allen, 2013). Despite the potential value of responding to online reviews, little research has investigated response management strategies in the hotel industry (Lui et al., 2018; Schuckert et al., 2015). We investigated the question by collecting online reviews and hotel responses from 43 London hotels. Next, we analyzed current practices such as proactive and non-proactive hotel responses (Li et al., 2017) to positive and negative reviews. We extended our previous study and analyses (Ku et al., 2019) to transform online reviews and hotel responses on the travel website into actionable insights and knowledge. The aim of this study is to use the advanced techniques of deep learning, visual analytics, and natural language processing (NLP) in order to analyze hotel reviews and responses, identify response strategies, and offer strategic recommendations to hotel practitioners. Hospitality practitioners can discover hidden online review patterns and consumer booking behavior, which may in turn offer insights into exploring and implementing drivers to take necessary actions to improve service quality and customer satisfaction.

This paper is structured as follows. Section 2 starts with a brief literature review on online consumer reviews and ratings, hotel responses, NLP and deep learning, and previous research on online reviews, typically on TripAdvisor. Section 3 draws on our initial visual analytics with 43 representative hotels to develop deep learning models. To achieve this, our analytical framework includes web scraping, data preprocessing, visual analytics, and deep learning-based NLP. We then describe our experiments with our proposed model and compare it with existing algorithms. Finally, we discuss the main findings, decision-making implications, limitations, and future research directions.

2. Related work

2.1. OCRs and ratings

Smart tourism technologies such as online tourism applications, online travel agents, social media, and mobile applications play an increasingly important role in travel planning (Huang, Goo, Nam, & Yoo, 2017; Xiang et al., 2015). Travelers often reply on OCRs, which is a form of electronic word-of-mouth (eWOM), to make purchase decisions (Filieri, 2016). Huang et al. (2017) further point out that the travel decision-making process is not sequential but involves four iterative phases: idea formation, information searching, evaluating alternatives, and booking. The overall process aims to reduce uncertainty (Fang, Ye, Kucukusta, & Law, 2016) and potential risks associated with the purchasing (Sparks et al., 2016); or, in other words, tourists usually read online ratings and reviews to plan their trip (Mauri & Minazzi, 2013).

The proliferation of OCRs and ratings are likely to influence consumers' purchase decision (Hudson & Thal, 2013; Mauri & Minazzi, 2013), re-visit intentions (Mauri & Minazzi, 2013; Zhang & Mao, 2012), search behaviors (King et al., 2014; Serra Cantallops & Salvi, 2014), online and product sales (Öğüt & Taş, 2012; Ye et al., 2009, 2011), and even intention to book a hotel (Zhao et al., 2015) as well as their attitudes toward the hotel (Vermeulen & Seegers, 2009). A higher review rating can increase online hotel sales (Öğüt & Taş, 2012) and boost online bookings (Ye et al., 2011). A similar result was found by Noone and McGuire (2013) by examining the relation between online reviews and online hotel booking. The ratings represent customers' satisfaction towards the hotel they stay in (Liu et al., 2015), and with TripAdvisor, customer reviews can include ratings on six aspects: value, location, sleep quality, rooms, cleanliness, and service. Such rating information is valuable because it contains the valence of OCRs. One study shows that a 10% increase in customer ratings can boost hotel room sales up to 5% (Ye et al., 2011). A similar result was found by Öğüt and Taş (2012) who reported that a 1% increase in customer ratings can raise sales per room up to 2.68% and 2.62% in Paris and London, respectively.

The valence of OCRs can be classified into positive and negative forms. Based on social cognition theory (Pan & Chiou, 2011), negative information is perceived to be more influential than positive information (Dickinger, 2011; Xiang et al., 2015). Casaló, Flavián, Guinalíu, and Ekinci (2015b) conducted survey studies with 46 participants to better understand the perceived usefulness of OCRs and suggested that negative online reviews were more useful than positive reviews, typically for high risk-averse travelers. However, positive reviews were likely to influence a consumer's decision making (Xiang et al., 2015) and increased customer revisit intention (Zhang & Mao, 2012). A higher volume of positive reviews may also lead to better hotel ratings and hotel performance (Gu & Ye, 2014; Sparks et al., 2016).

Ratings and rankings have created challenges and opportunities for service providers because improving online ratings may lead to more online bookings (Liu et al., 2015; Ye et al., 2011). Therefore, it would be useful to know how hotel managers respond to positive and negative reviews today.

In addition to OCR ratings and valences, it is equally important to understand different traveler types. Based on the reviews on TripAdvisor.com, the traveler types can be classified into business, couple, family, friend, and solo. Banerjee and Chua (2016) collected 39,747 ratings and found that travelers' rating patterns differed between independent and chain hotels based on travelers' profiles and geographical regions (i.e., the Americas, Asia, Europe, and Africa).

2.2. Hotel responses

The number of responses to online reviews has increased on travel review websites (Schuckert et al., 2018). Contemporary studies (Levy et al., 2013; Melo et al., 2017) point out that hotel managers should establish a digital marketing plan to actively manage online presence. It is therefore extremely important to proactively analyze online reviews and have a clear response strategy.

Gu and Ye (2014), for example, found that unsatisfied customers' future satisfaction increases when they receive responses from hotel managers. Some empirical research reports that manager responses can have a negative impact on customers' purchasing intention (Mauri & Minazzi, 2013), so it is imperative that hotel managers take appropriate corrective actions to mitigate negative outcomes. Timely responses to negative reviews can build a hotel's reputation and customer loyalty, which can elevate the hotel's ratings (Liu et al., 2015).

Park and Allen's (2013) case studies on 34 4- and 5-star hotels revealed neither pattern nor standard in how the selected hotels responded to online reviews. They found the overall response rate ranged from 0 to 64.9% and the response rate of negative reviews ranged from 0 to 45.8%. Liu et al. (2015) used correlation analysis to analyze the response rate of 187 Hong Kong hotels from all classes (from 1- to 5-star). They found that high-class hotels tended to adopt response management, but the response rate showed no significant difference between different classes of hotels. To test the factors that may influence the helpfulness of online reviews, Kwok and Xie (2016) collected 56,284 reviews and 10,797 hotel responses from 1405 hotels on TripAdvisor and tested the data using a linear regression model. They discovered that ratings, the number of words, reviewer's gender, reviewers' experience, visited cities and hotel responses may influence customers' perceived usefulness of online reviews.

Managing online reputation is an effective approach to improve consumer satisfaction (De Pelsmacker et al., 2018; Kim et al., 2015) and it is less expensive than enhancing facilities directly (Schuckert et al., 2018). However, seeking effective approaches to manage eWOM, especially if its negative, is a widely recognized challenge for hospitality management (Sparks et al., 2016). Hotel managers should go beyond the reading of consumer postings, and focus on responding to consumer reviews in a timely, proactive, and consistent manner (Kwok & Xie, 2016). Doing so opens new opportunities to engage consumers and communicate with potential customers. The perceived and proactive responses by the manager can be part of a hotel's customer relationship management strategy (Liu et al., 2015). For example, hotel managers may invite guests back in the future and try to win back customers who post negative reviews. With the increase in online reviews, hospitality businesses can shift from the role of passive listening to one of proactive engagement by managing responses (Gu & Ye, 2014). However, little is known about the current practice by hotel managers and their strategies to respond to positive and negative reviews. In this study, we not only identify proactive and non-proactive responses, but also provide recommended strategies to hospitality practitioners.

2.3. NLP and deep learning

With a plethora of digital data increasingly becoming available for analysis, machine learning and NLP techniques have received much interest in many research fields (Xiang et al., 2017). NLP is a subfield of artificial intelligence and employs computational models to process natural language by learning cognitive activities of human brains (Cambria & White, 2014). Popular NLP tasks include information extraction, information retrieval, text summarization, question answering, topic modelling, and more recently, sentiment analysis and opinion mining. Today most NLP techniques rely on keywords, word co-occurrence, and frequencies of words, and syntactic information of text (Cambria & White, 2014). This poses a major challenge to analyze user-generated content because semantic relationships between words are often ignored (Zhang et al., 2015).

To extract sentiments or opinions of online reviews, machine learning techniques can be used. Opinion extraction identifies opinion holders from the given text, whereas sentiment analysis assigns a polarity such as positive, neutral, and negative to the extracted subjectivity. Extracting user opinions requires several NLP steps such as tokenization, word segmentation, part-of-speech (POS) tagging, stemming, and stop word removal. NLP toolkits, such as NLTK (https://www.nltk.org), OpenNLP (https://opennlp.apache.org) and Stanford's CoreNLP (https://stanfordnlp.github.io/CoreNLP/) are widely used in research projects (Sun et al., 2017) for text preprocessing. 'Furthermore, machine learning models, such as Naïve Bayes, maximum entropy, and support vector machine (SVM), are often trained to determine the polarities of online reviews (Dragoni, Federici, & Rexha, 2018). For instance, Parkhe and Biswas (2016) and Manek et al. (2017) utilized Naïve Bayes and SVM to learn a classifier for sentiment analysis of movie reviews. However, the requirement of annotated training data and domain-specific lexicons creates a major challenge for cross-domain and cross-lingual situations (Sun et al., 2017).

More recently, deep learning algorithms have shown promise with high accuracy, such as convolutional neural networks (CNN) and recurrent neural networks (RNN) that are both machine learning methods based on learning data from multiple deep layers of modules. In tourism, for instance, Kim et al. (2017) applied a deep learning approach based on the Stanford sentiment analysis to analyze the sentiments of 19,835 online reviews of Paris from www.virtualtourist.com. They noticed that different tasks perform better with higher scores when suitable algorithms were applied: CNN, for example, is good at extracting significant n-gram features to generate "informative latent semantic representation" in NLP classification tasks (Poria et al., 2016; Young et al., 2017), while RNN is effective at processing data in a sequential format. The most important strength of RNN is that it can integrate previous information into the current neural state. Therefore, in order to prevent loading too much previous information, RNN is usually chosen to deal with tasks with short texts (Lee & Dernoncourt, 2016). For example, CNN has been used for sarcasm detection based on sentiment analysis in Spanish (Chaturvedi, Cambria, & Vilares, 2016), while Al-Smadi, Qawasmeh, Al-Ayyoub, Jararweh, and Gupta (2018) used RNN, SVM, and NLP resources to conduct aspect-based opinion mining on Arabic hotel reviews, and their approach outperformed other machine learning methods.

The advantage of applying deep learning to NLP is that it is independent from expert knowledge and lexical resources (Rojas-Barahona, 2016). The Deep neural network architecture of NLP consists of (1) an input layer, (2) multiple hidden layers, and (3) an output layer (Huang, Li, Yu, Deng, & Gong, 2013). Since the input layer requires numerical data, text data firstly need to be transformed to vectors for representation. In practice, a pre-trained word embedding (*input*) such as Word2-Vec by Tomáš Mikolov at Google (Mikolov et al., 2013) and GloVe (Pennington et al., 2014) by Stanford University can be used to represent words encoded as dense numerical vectors in an n-dimensional space (Rojas-Barahona, 2016). This word embedding process also captures the syntactic and semantic information from a text (Chen, Xu, He, & Wang, 2017). For example, Zhang et al. (2015) conducted a sentiment classification based on Word2Vec and the SVM^{perf} package with more than 100,000 Chinese comments on clothing products; the experiment results reached 90% classification accuracy. The *hidden layers* were then constructed to exploit the complex compositional nonlinear functions through higher and lower layers which are composed of a great number of neurons. Each neuron receives inputs $x_1, x_2 \ldots,$ and is multiplied by the associated weights, and then, the activation function a (Eq. (1)) combines the weighted input data and bias to generate a single output. According to the data's property, there are different activation functions that researchers could use: the *Sigmoid* function (Eq. (2)), *ReLU* function (Eq. (3)), and Tanh function (Eq. (4)) range from 0 to 1, 0 to a, and -1 to 1, respectively. Acquired from the output of the last hidden layer z, the output layer can predict the probabilities of each class using the *softmax* function. As a result, the highest probability class would be the predicted class (Huang et al., 2013).

$$\mathrm{o} = \mathrm{s}(\mathrm{a}) = \mathrm{s}(\sum_i w_i x_i + b) \tag{1}$$

$$sigmoid \quad (\mathrm{a}) = \frac{1}{1 + e^{-a}} \tag{2}$$

$$ReLU \quad (\mathrm{a}) = \max(0, \mathrm{a}) \tag{3}$$

$$\tanh(a) = \frac{e^{2a} - 1}{e^{2a} + 1} \tag{4}$$

$$softmax\ (z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}} \tag{5}$$

CNN has been used in many successful NLP tasks (Do, Prasad, Maag, & Alsadoon, 2019). The typical architecture of CNN is assembled with four layers: (1) an input layer, which represents numerical word vectors with n vector dimensions and m length of a sentence; (2) a convolutional layer, which uses filters to generate new features with an activation function; (3) a max-pooling layer, which selects the maximum value in response to a filter size; and (4) an output layer, which yields the most probable class under a fully-connected layer using the *softmax* function. In addition, a drop-out layer could be added among the CNN processes to avoid over-fitting.

2.4. Previous tourism and hospitality research on TripAdvisor and deep learning

TripAdvisor has become the largest travel-related review platform in the world and is a major data source for researchers to conduct social media analytics in hospitality and tourism (Xiang et al., 2017). Since the goal of this study is to analyze hotel reviews and responses on TripAdvisor, we conducted a search for relevant research studying online reviews and responses. We used 'TripAdvisor' as a keyword to search three leading tourism and hospitality journals with an A^+ ranking:

Tourism Management, *Journal of Travel Research*, and *Annals of Tourism* based on the Australian Business Deans Council (ABDC) journal quality list.[1] We searched each publisher's database directly and included forthcoming papers. The final search was completed on October 21st, 2019. As shown in Fig. 1, *Tourism Management* had 133 articles using the keyword 'TripAdvisor, followed by the *Journal of Travel Research* (68 articles) and *Annals of Tourism Research* (46). Among the 133 papers in *Tourism Management*, 7 articles were either in-press or published in 2020, and so are not listed in the following figure since 2020 was not finished at the time of writing this paper. However, we still included these articles into our examination.

Next, we manually examined the data collection, data analysis, and research methods from the 247 collected articles. We excluded studies and research notes which mentioned 'TripAdvisor' only and did not use, collect, or analyze online review data. After filtering irrelevant articles, a total of 66 studies were kept for further analyses. The key results are presented in Appendices A and B, with the former listing studies related to hotel reviews on TripAdvisor and the latter listing studies related to online reviews such as attractions, restaurants, and flight reviews from single or multiple data sources. Factors such as reviewer profile, travel types, and aspect ratings are available on TripAdvisor, but not on all online platforms, so these factors are not included in Appendix B.

Among the 66 studies, only five articles (Zhang et al. (2020), Lui et al. (2018), Li et al. (2017), Sparks et al. (2016), and Baka (2016)) studied hotel reviews and responses together. Further, most studies collected and analyzed numerical data such as hotel ratings, prices, number of words, and hotel stars. Nuance factors such as reviewer profile (e.g., reviewer activities and contributions), traveler types (e.g., solo, business, family, couple, and friend), and aspect ratings (e.g., value, location, sleep quality, rooms, cleanliness, and service) have not been well-studied.

Visualizations can bridge the gap between human analysts and machines, typically for analyzing big data. From the collected articles, we observed that most studies used static bar and line charts (Wang et al., 2020) to present research results. An interactive visualization can be used to explore data and identify hidden patterns, with the output of interactive visualizations being used to fine-tune the performance of machine learning. Rose and Willis (2018), for instance, collected 9030 Twitter images and visualized the tweeted images related to smart cities. They explored the patterns and colors of images and tried to understand the features of smart cities. For tourism research, Kirilenko et al. (2019) used geographical analysis to discover the distributions of tourist reviews in Florida and to gain a better understanding of tourist clustering.

For data analyses and research methods, most studies have used statistical (Li et al., 2017), logistic (Gao, Li, Liu, & Fang, 2018), regression (Zhang & Cole, 2016), and econometric models (Yang & Mao, 2019). Other popular methods include a survey (Kim & Stepchenkova, 2015; Sparks et al., 2016), content (Su & Teng, 2018), and geographical analysis (Kirilenko et al., 2019). More recently, sentiment analysis (Kirilenko et al., 2018), text mining (Zhang et al., 2020), and NLP (Stamolampros et al., 2019) have become popular research methods. Kirilenko et al. (2018) have investigated sentiment analysis used in tourism research, which can be classified into lexicon-based and machine learning methods, e.g., Naïve Bayes, SVM, and k-nearest neighbors (k-NN). Most studies applied NLP and text mining techniques to conduct topic modelling, concept analysis, and sentiment analysis. This is understandable because software packages such as Leximancer[2] can be applied directly, and sentiment lexicons such as SocialSent[3] can be downloaded. More advanced text mining research, on the other hand, requires a deeper knowledge of programming, model construction, and performance experiments.

We also extended our reviews to the literature tables in the collected articles, e.g., 34 articles from Hu, Teichert, et al. (2019) and Hu, Zhang, et al. (2019), p. 20 articles from Yang et al. (2018), p. 12 articles by Li et al. (2017), and 22 articles by Xiang et al. (2017) and Guo, Barnes, and Jia (2017), and found similar results. For example, Hu, Teichert, et al. (2019) and Hu, Zhang, et al. (2019) reviewed 34 related to customer loyalty, satisfaction, and re-visit intentions and found only three studies using text mining analysis. The rest of the studies used surveys, interviews, and statistical analyses, which is consistent with the findings of Vu et al. (2019) as well as our own. Both Hu, Teichert, et al. (2019) and Hu, Zhang, et al. (2019) and Vu et al. (2019) further recommended that other sophisticated text mining techniques can be used to cover a broader range of hotel attributes.

Finally, we searched the articles related to 'deep learning' from *Tourism Management,* the *Journal of Travel Research,* and *Annals of Tourism Research* and 11 articles were returned. Among these 11 articles, 2 are review papers and 7 are irrelevant to 'deep learning' but just mentioned 'deep learning.' Both deep learning-associated articles were published in 2019: Law et al. (2019) used a deep learning approach to forecast tourism demand, while Zhang et al. (2019) analyzed photos to discover tourist behavior and perceptions using deep learning techniques. However, none of these studies used NLP techniques. Further search on Google Scholar was conducted using keywords such as online reviews, TripAdvisor, machine learning, and deep learning. We found that machine learning and deep learning techniques were mostly used in sentiment analysis and opinion mining (Sun et al., 2017; Valdivia et al., 2017, 2019), computer vision and image processing (Giglio, Pantano, Bilotta, & Melewar, 2020, 2019; Ma et al., 2018), and medical text analysis (Dreisbach, Koleck, Bourne, & Bakken, 2019; Wu et al., 2020). In other words, the use of deep learning-based NLP and visualization for business strategies and decision making is still in its infancy. Alaei, Becken, and Stantic (2019), Cheng, Fu, Sun, Bilgihan, and Okumus (2019) and Li et al. (2018) suggested that using more advanced techniques such as deep learning can help tourism research gain deeper insights from different aspects of tourism data.

Few studies, therefore, have shed light on deep learning and NLP techniques on tourism and hospitality research, especially on hotel response strategies. Consequently, this paper employs the three major techniques of deep learning, NLP, and visual analytics with nuance factors such as reviewer profile, aspect ratings, sentiment, and temporal factors to offer strategic insights to hotel practitioners.

3. Methodology

What is missing thus far in the existing literature on the application of social media analytics, particularly for hospitality management, is an integrated framework to gain insights into customer reviews and hotel responses. Thus, we developed an analytical framework (see Fig. 2) that includes the components of data selection, web scraping, data pre-processing, visual analytics, and deep learning-based NLP, which correspond to each section and subsection in this study.

3.1. Data selection

According to the Mastercard Global Destination Cities Index 2018 (Julia, 2018), London has been one of the most popular cities for international travelers among the top 162 destination cities. Based on the visitor volume and average spending in 2017, London was selected in this study because it is an English-speaking city and we aim to analyze English reviews. Table 1 shows that London had 19.83 million visitors in 2017 and the average length of stay was 5.8 nights with an average spending of $153 per day.

There were approximately 1088 hotels in London based on the TripAdvisor search results for 2018. According to Brand Finance, Hilton was the most valuable hotel brand ($6330 million) in 2018 (Richard,

[1] ABDC Journal Quality List, https://abdc.edu.au/research/abdc-journal-list/.

[2] Leximancer, https://info.leximancer.com/.

[3] SocialSent, https://nlp.stanford.edu/projects/socialsent/.

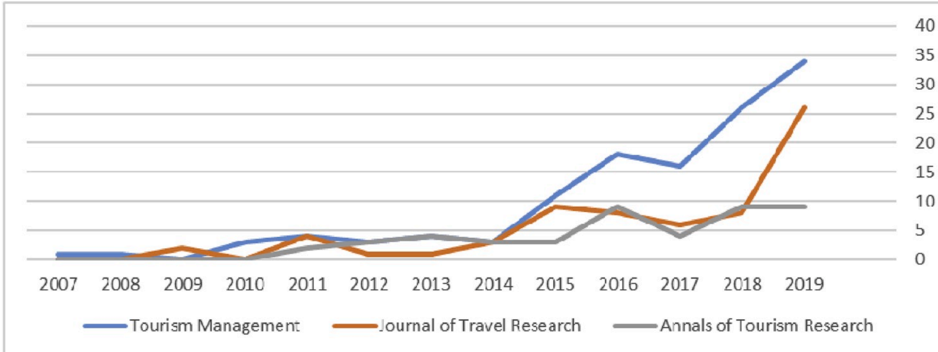

Fig. 1. The number of articles containing the keyword 'TripAdvisor' from three leading tourism and hospitality journals.

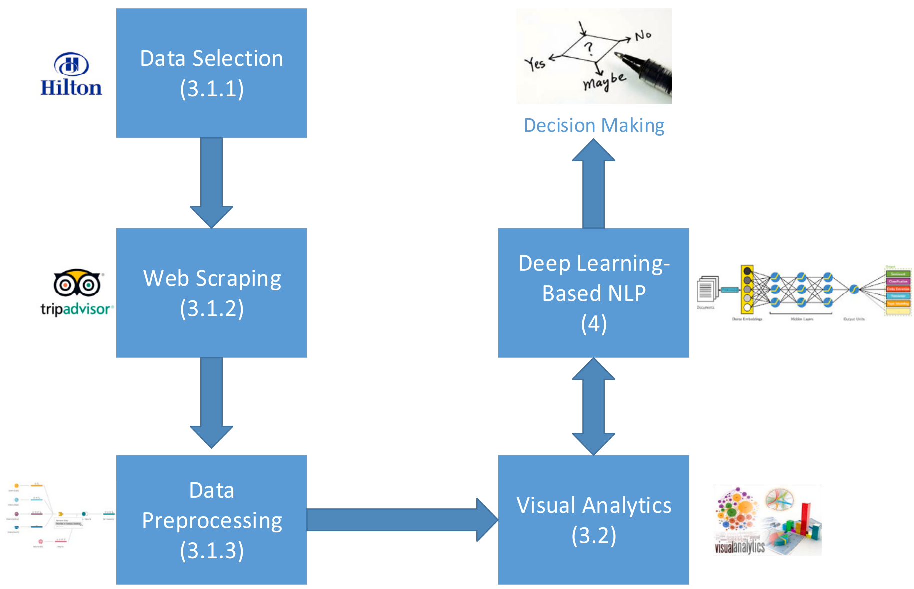

Fig. 2. The general analytical framework for hotel review & response analysis.

Table 1
Top 6 destination cities around the world.

	2017 Overnight visitors	2018 Growth forecast	Average length of stay	2017 Overnight visitor spending (USD)	Average spending per day (USD)
Bangkok	20.05 million	9.6%	4.7 nights	$16.36 billion	$173
London	**19.83 million**	**3.0%**	**5.8 nights**	**$17.45 billion**	**$153**
Paris	17.44 million	2.9%	2.5 nights	$13.05 billion	$301
Dubai	15.79 million	5.5%	3.5 nights	$29.70 billion	$537
Singapore	13.91 million	4.0%	4.3 nights	$17.02 billion	$286
New York	13.13 million	4.1%	8.3 nights	$16.10 billion	$147

2018), and for this reason, Hilton-associated hotels were selected. We first explored hotel information on Hilton Destination Travel Guides (Hilton Travel, 2018) (see Fig. 3). Next, we selected 43 Hiltons hotels operating in 2017 within 25 miles of London, based on the Hilton official website (Hilton London, 2017).

3.2. Data collection & web scraping

TripAdvisor is one of the fastest-growing travel sites, offering appropriately 702 million reviews with an average of 490 million monthly unique visitors (TripAdvisor, Inc. Earnings Press Release, 2018). Although we conducted initial data analyses with 40 hotels in our previous study (Ku et al., 2019), this study is different because we include the complete dataset with 43 hotels with new data collections, enhanced algorithms, and we conduct comprehensive visual analytics. For this purpose, we adopted C# with the Selenium package[4] to develop a crawler to retrieve or scrape hotel reviews and responses from the TripAdvisor web pages. Selenium is a browser automation tool, which supports multiple languages such as Python, Java, and C#. The collected data includes three important aspects: reviewer profile, hotel information, and hotel reviews and responses.

Regarding the reviewer profile, we gathered username, hometown and TripCollective[5] information related to the reviewer's activities. A reviewer receives points from TripCollective (a contributor program on TripAdvisor) based on types of activities such as writing a review (100 points) and posting photos (30 points), with the level of contribution

[4] Selenium.WebDriver, https://www.nuget.org/packages/Selenium.WebDriver.

[5] TripCollective, https://www.tripadvisor.com/TripCollective.

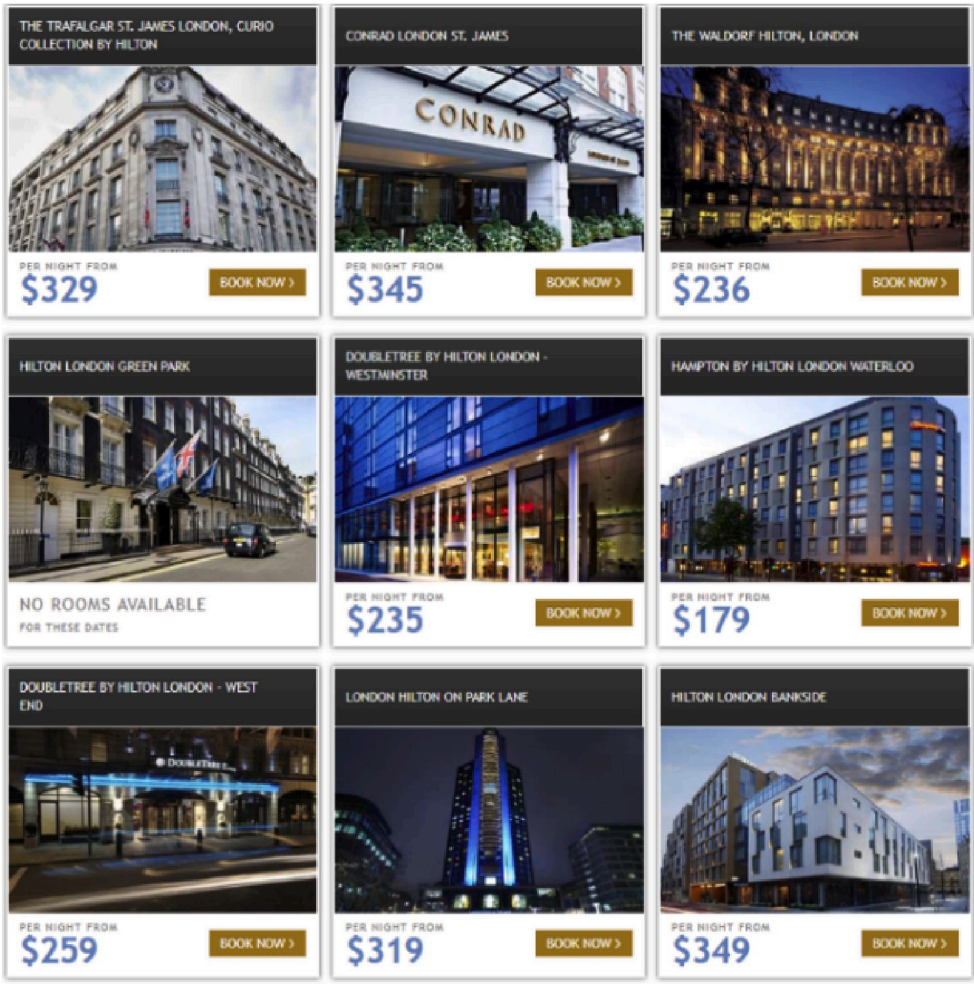

Fig. 3. A sample of hotel page from Hilton destination travel guides.

ranging from 1 (300 points) to 6 (10,000 points). Moreover, the hotel information was collected from three sections, as shown in Fig. 4, on each hotel page. For each hotel, we collected the hotel name, hotel class (star), the number of excellent, good, average, poor, and terrible reviews, an average of a price range, hotel address, location, amenities, type of rooms, hyperlink to the hotel website, and hotel descriptions. For each hotel review, shown in Fig. 5 with the highlighted sections, we collected the review title, review content, manager response, overall rating, aspect rating, traveler type, review date, response date, stay date, and reviewer information. The data were collected from the earliest available date (January 2010) for the selected hotels to the date that data analyses were conducted (October 2018). Table 2 lists an overall review of our data collection. In this research, we have collected data two times in two different years. We finished the initial data collection for the first part of the dataset in early July 2017. In August 2018, we have spent two months extending the dataset and completed the collection by the middle of October 2018. A final total of 113,685 reviews were collected. Among these, 86,907 reviews contained hotel responses, resulting in an overall 76.45% response rate. An average of the overall rating was 3.99 for all collected reviews.

3.3. Data preprocessing

Massive datasets pose immense challenges to data cleaning because manually editing datasets is impractical and ineffective (Franke et al., 2016). The collected raw data are semi-structured and contains noise information. Data preprocessing or wrangling is therefore a fundamental step to transform data into the right form for subsequent learning steps through data cleaning, extraction, transformation, and fusion (Zhou et al., 2017). We used Tableau Prep (King, 2018) to combine, shape and clean the data for data analysis. We first joined the two datasets of hotel data and review data, and then extracted keywords and values (e.g., traveler types and rating scores) out of the raw data. One major challenge we encountered was approximate date information (see Fig. 6). The date shown in the figure is an approximate date, such as 2 days and 2 weeks ago, rather than a precise date. To examine this issue, we first retrieved the date information of the same post several weeks later and found "2 days ago" can be longer than 2 days. As a result, we excluded the data records with approximate dates when we conducted the data analysis and updated the previous dataset.

Our initial data analysis shows that the Trafalgar Hotel had deleted hotel reviews with more than 1 year. To obtain more data from this hotel, we therefore collected the data twice, once in July 2017 and again September 2018. Next, we used the overall rating values to classify data into positive (a 4–5 rating value) and negative (a 1–3 rating value) reviews. The same classification approach was used by Park and Allen (2013) and Proserpio and Zervas (2017). A binary dimension 'Response or Not' was used to indicate whether a review contained a hotel response. Finally, we used the Google Map Geocoding API Get Started | Geocoding API, 2018 to automatically transform each hotel address into a pair of longitude and latitude values to show each hotel precisely on a map.

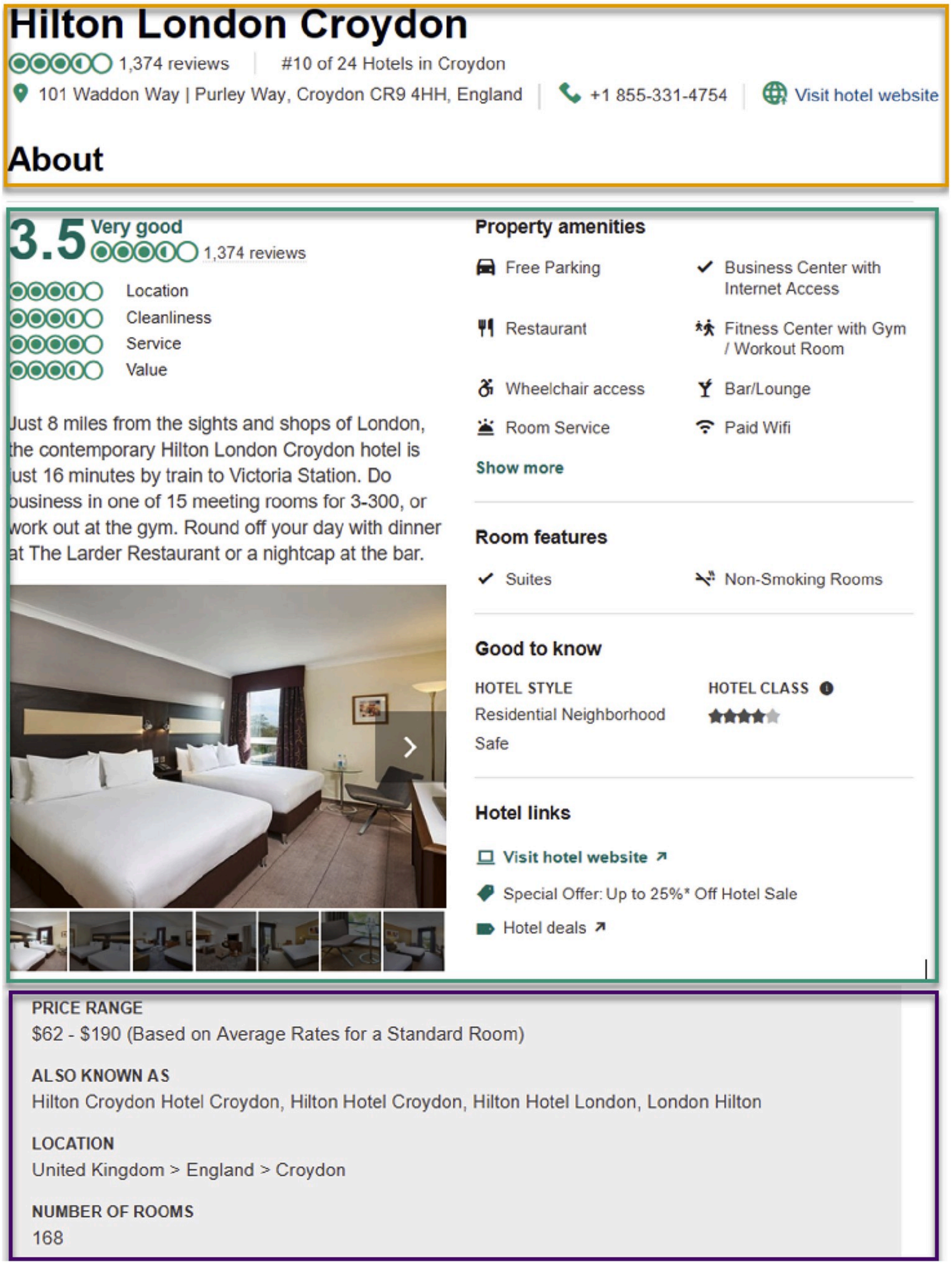

Fig. 4. A sample of hotel page from TripAdvisor – the Hilton London Croydon.

3.2. Visual analytics

An interactive visualization can bridge the gap between human and computational analysis (Hu, 2018), and can be used for data cleaning and data preprocessing (Puts et al., 2015). For example, Zhao et al. (2014) presented an interactive visual analysis system combined with machine learning techniques to detect anomalous tweets. In our study, we used interactive visualizations for an exploratory data analysis and for finding the patterns in the data. We used the visualization tool Tableau (Tableau, 2018) for visual analytics because of its popularity and flexibility.

3.2.1. Spatial analysis

Fig. 7 lists the selected hotels in this study. An interactive, street-level map was first developed, which enabled us to interactively explore the 43 Hilton-affiliated hotels interactively. The red-blue diverging colors (4 stepped colors) are used to indicate higher (blue) and lower (red) hotel ratings. A circle represents each hotel, where the bigger the size of the circle the greater the number of online reviews. Each hotel is labeled a star rating number from 3.5 to 5, and can be selected to reveal detailed information such as the aspect ratings, average minimum and maximum price, and the number of reviews of each hotel. The drop-down box (a filter) enables investigators to select a year from 2012 to 2018 to explore the rating changes for each hotel. The purpose of this spatial analysis is to observe the relation between hotel locations and other factors such as hotel price, aspect ratings, and overall ratings. The initial analysis indicates there is no evident relation found on this interactive map.

3.1.2. Response rate analysis

Responding to guest reviews and encouraging guests to post reviews are common management strategies for to stimulate online

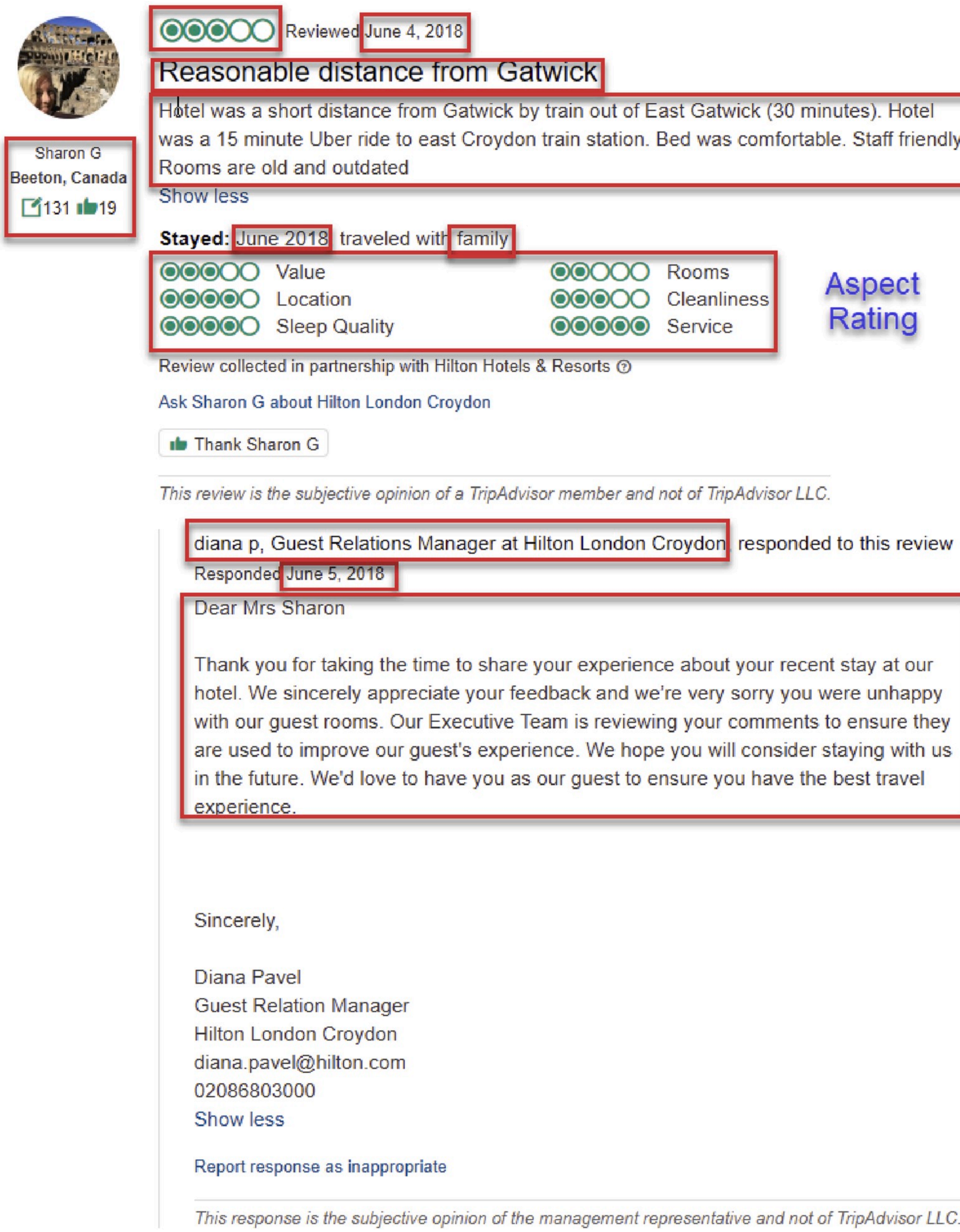

Fig. 5. A sample of hotel review from TripAdvisor – the Hilton London Croydon.

Table 2
Distribution of the sample.

Hotel star	Number of hotels	Number of reviews	Average overall rating
3	1	2423	4.39
3.5	2	4239	4.12
4	37	96,028	3.93
5	4	10,995	4.39
Total	43	113,685	3.99

conversations (De Pelsmacker et al., 2018). Torres et al. (2015) further point out that placing greater value on guest reviews is more likely to improve the perceived hotel quality. An online review can be positive or negative based on the overall rating and the associated aspect ratings, and a hotel manager may or may not respond to the review. Therefore, it would be enlightening to investigate the proportion of responses and non-responses for positive and negative reviews based on the review sentiments. To gain a holistic view of the response rate of each hotel, Fig. 8 displays a partial visualization for the percentage of reviews with hotel responses (in blue) and without (in red) for both positive and negative sentiments.

Overall, three hotels, Double Tree by Hilton Woking with 710 reviews, Hilton London Green Park with 2246 reviews, and Hampton by Hilton London Waterloo with 2423 reviews have the highest non-response rates, which are greater than 78% for positive and 60% for negative reviews. This visualization also reveals that the three 5-star hotels have the relatively higher response rates of 75%–98% than the three 3- and 3.5-star hotels with the response rates of 11%–60% for positive and negative reviews. The 37 4-star hotels show a diversity in the results with high, average, and low response rates.

Based on this visual exploration, we can classify hotels into three categories: negative-response preference, positive-response preference, and neutral preference. If the difference of response rate between positive and negative reviews is less than 10%, the hotel is classified into

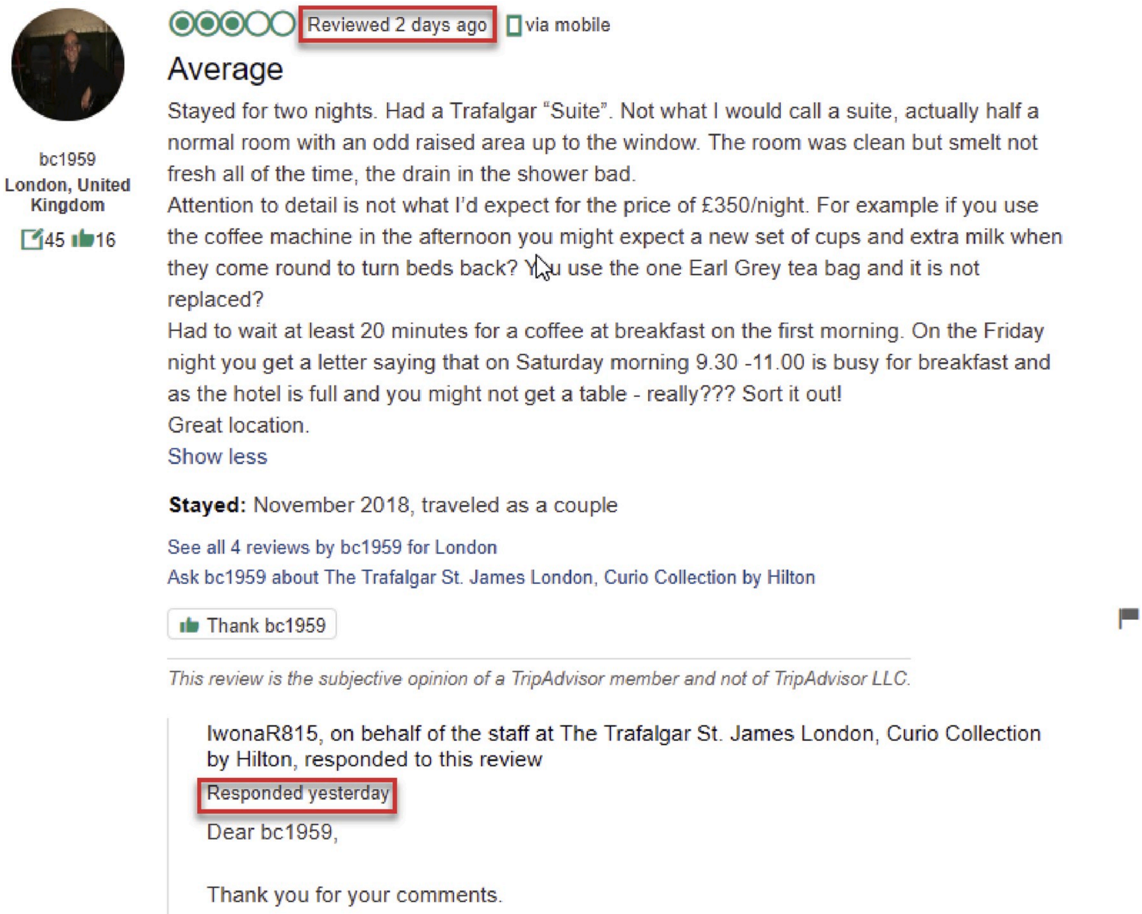

Fig. 6. A sample hotel review with ambiguous dates.

neutral preference; otherwise, it is classified into negative- or positive-response preference. As shown in Fig. 9, 29 hotels have a neutral preference to respond to positive and negative reviews, while 11 and three hotels prefer to respond to negative and positive reviews, respectively.

Our analysis findings are similar to those of Park and Allen (2013) who discovered no pattern in how the hotel managers responded to online reviews for 34 hotels. Additionally, they argued that the hotels did not have a clear strategy to respond to online reviews even among hotels with the same brand, which is consistent with our observation. Although previous studies have shown that consumers are influenced by negative reviews when making purchase decisions (Berger, Sorensen, & Rasmussen, 2010; Sen & Lerman, 2007), our analysis reveals that 67% of hotels have a neutral preference to responding online reviews. That is, most hotel managers appear to put an equal amount of effort responding to both positive and negative reviews.

3.1.3. Treemap analysis

We collected hotel rating and review data from 2012 to 2018. A treemap visualization was then used to display the intricate relations between rating, review, and time among all 43 hotels. Each nested rectangle represents a hotel, which is then tiled with smaller rectangles representing each hotel in a specific year. The red-blue diverging color and size dimensions are correlated with the higher (deeper-blue) and lower (deeper-red) ratings and the number of reviews, respectively. In this example (see Fig. 10), we can see that the Hilton London Euston has a relatively lower rating value 1.96 in 2015 with fifty-three reviews. However, applying the same overall rating to compare all 43 hotels will be difficult for a hotel manager to make self-improvement. To address this issue, a single hotel can be selected, and the year dimension is then divided into months. In this example (see Fig. 11) the Hilton London Green Park is selected, and a deeper-red color indicates a relatively lower rating 2.9 with 30 reviews and 21 reviews in July and August 2017, respectively. By repeating this analysis with days instead of months, the hotel manager can efficiently identify the most positive and negative reviews and respond to the critical reviews first.

3.1.4. Box-and-whisker analysis

The temporal dimension of sentiments and ratings is often overlooked. In this analysis, we used box-and-whisker plots to reveal the relations between multiple dimensions, including the temporal, overall rating, traveler type, and the number of reviews for all hotels. In Fig. 12, each box represents the values between the first and third quartiles, with the second quartile indicating the median values. The whiskers, two lines outside of the box, represent the lowest and highest observations. Each circle denotes an average overall rating in a month and quarter (Q1 – Q4), and a larger circle size means more reviews; for colors, blue, orange, red, and green are used for the four quarters in a year. In this figure, a lower rating usually occurs in the third and fourth quarters of the year, and in general, business travelers tend to rate lower, while couple travelers tend to rate higher. Banerjee and Chua (2016) also reported a similar finding. Lower ratings occur mostly in Q3 (red circles) and Q4 (green circles) for all known traveler types. Outliers are the circles outside of the plot and are excluded in this visualization. By repeating this analysis, we can identify each type of traveler's behavior and preference in a specific month and quarter of the year.

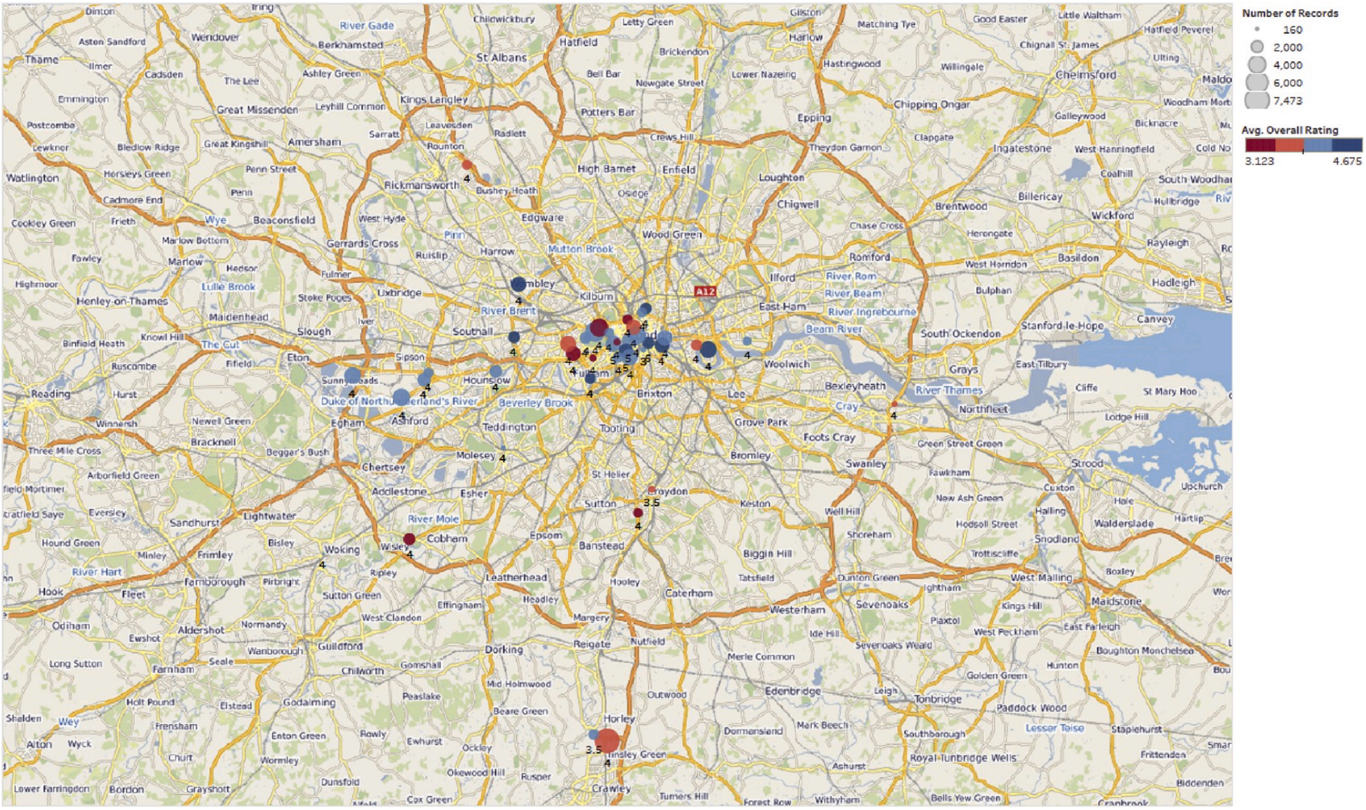

Fig. 7. Spatial analysis of the 43 hotels in London.

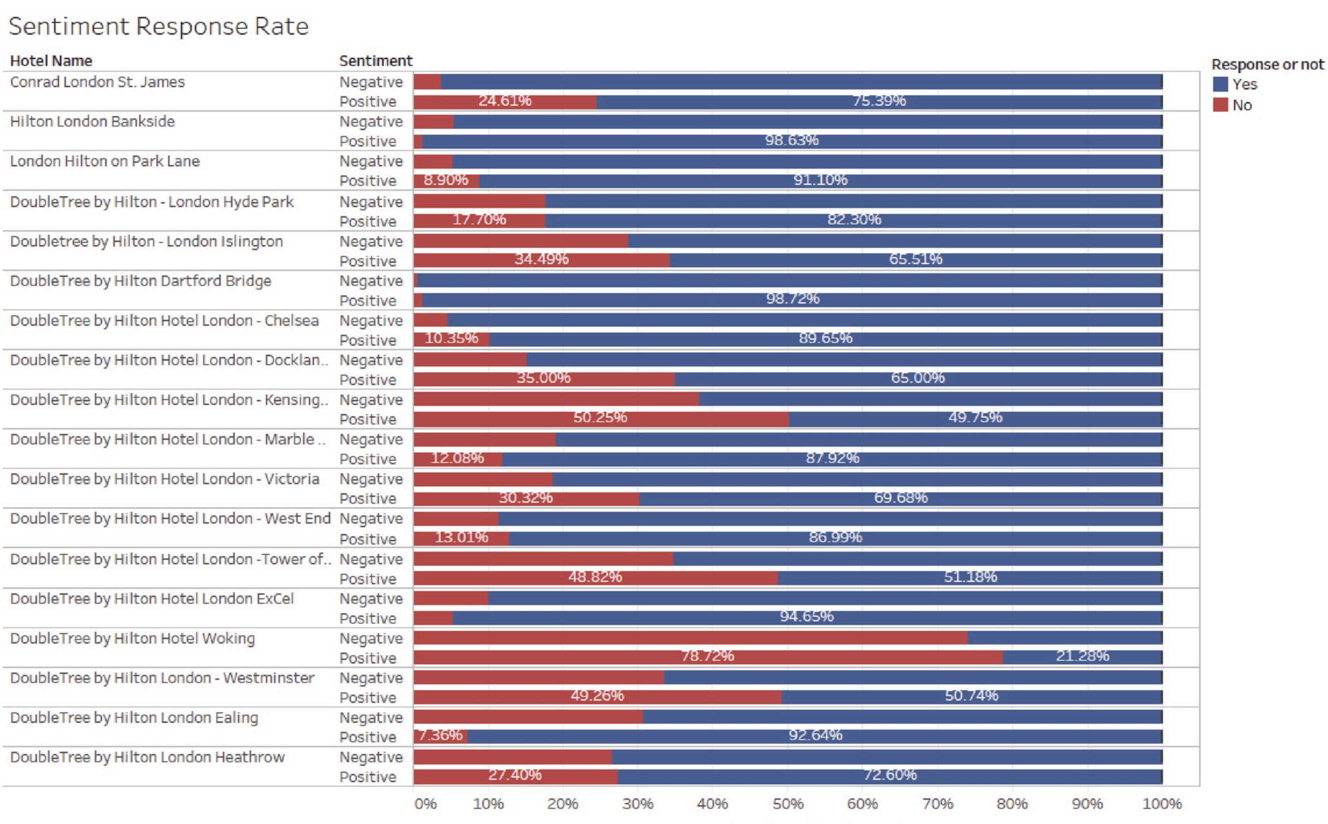

Fig. 8. Positive and negative response rates for the selected hotels in London.

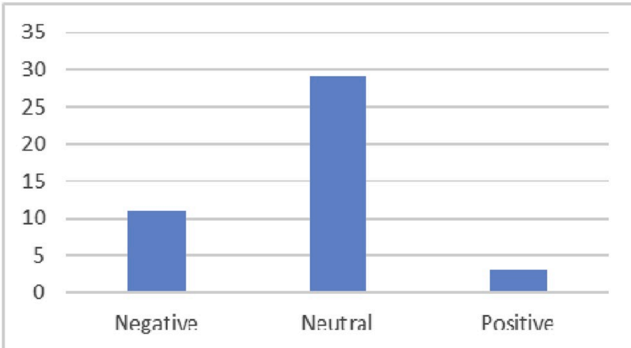

Fig. 9. A preference to respond to types of hotel reviews.

embedding, and a CNN model concatenating the hotel review features. To efficiently conduct machine learning, it is important to preprocess the raw text data, so we first transformed all words to lower case for consistency, then we filtered out the stop words such as "a" and "the," which contain very little information, and finally, we removed punctuation.

Word embeddings can be generated using the Word2Vec framework, of which there are two different models: the continuous bag-of-word based model (CBOW) and the skip-gram model. The CBOW model, which is different from the traditional bag-of-words model, predicts the current word based on a continuous distributed representation of the context. In contrast, the skip-gram model predicts words from a range before and after the current word. The quality of the skip-gram model improves as the range stretches, but this increases the computation effort (Mikolov et al., 2013).

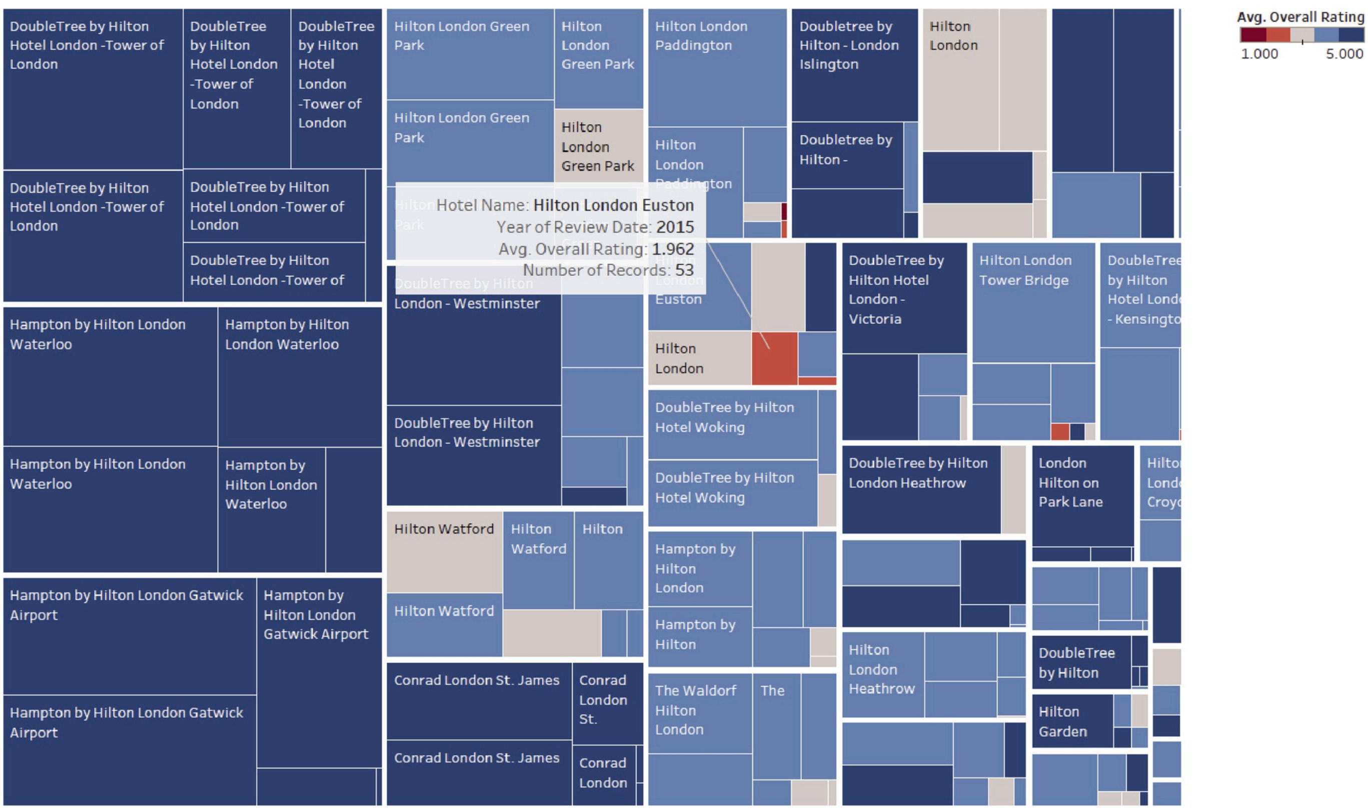

Fig. 10. Treemap analysis of 43 hotels in London with a time dimension.

4. Convolutional neural network-based multi-feature fusion for hotels responses

Learning hotel responses of high-quality hotels is crucial for hotel management. The decision to respond to a review may increase transaction and labor costs (Schuckert et al., 2015) and not to respond to a review may result in lost opportunities to retain customers (Yoo & Gretzel, 2008). As Liu et al. (2015) recommend that hotel managers adopt targeted response management to increase hotel ratings, it is important to prioritize the responses to online reviews. Leung et al. (2013) advise hotel managers to respond to online reviews and encourage scholars to further investigate hotel responses (Min et al., 2015).

To effectively detect proactive and non-proactive hotel responses, we propose a deep learning-based approach that integrates multiple CNNs (Kim, 2014, pp. 1746–1751) and multi-features for text classification. We classified proactive and non-proactive responding to a hotel review by developing a model with the three steps of preprocessing, word embedding, and a CNN model concatenating the hotel review features.

In addition to the self-document embedding used by Word2Vec, recent empirical research has also regularly applied pre-trained instead of self-trained embeddings. Since researchers found that using pre-trained embeddings may accelerate performance (Liu, 2015), we utilized pre-trained word embeddings[6] of GloVe, an unsupervised learning algorithm. This algorithm transforms preprocessed hotel reviews into the document matrix, the rows of which are word vector representations of each token. Following Collobert and Weston (2008), we can effectively treat the document matrix as an image upon which we can perform convolutions. Fig. 13 shows the architecture of our proposed method, which consists of seven layers: the Input, Convolution, Max-pooling, Flattening, Concatenation, Fully-connected, and Softmax layers. The following summarizes each of the layers.

[6] https://nlp.stanford.edu/projects/glove/.

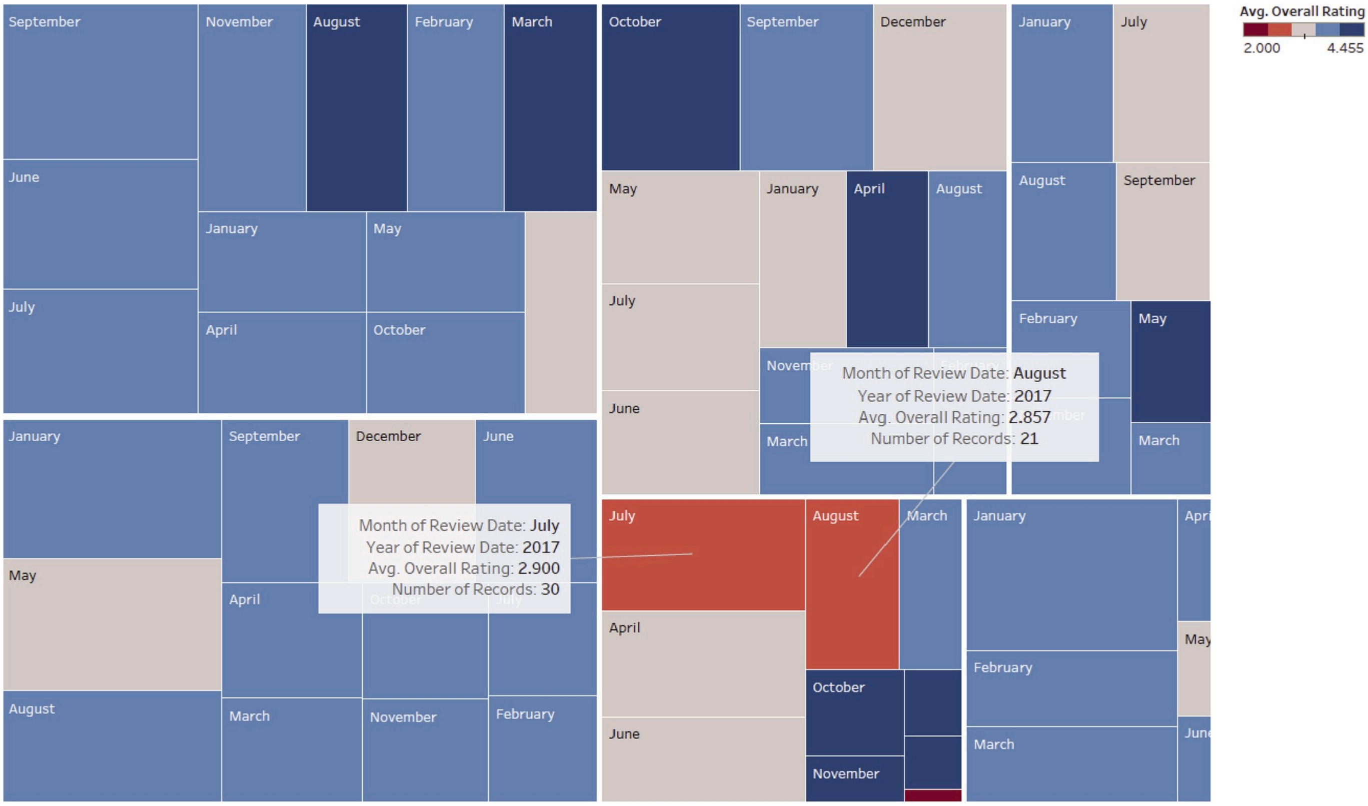

Fig. 11. Treemap analysis of hilton London Green Park with a time dimension. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4.1. *Input layer*

We used GloVe pre-trained word embeddings (i.e., glove.6B) to transform hotel reviews into a 300-dimension document matrix. We also set the maximum document length to 150, where longer documents were truncated, and shorter documents were padded with zeros.

4.2. *Convolution layer*

We acquired new feature c_i with the filter w, using the window of h words from i to $i+h$-1. Through activation function (s) and passing the bias (b), we obtained the c_i function as follows:

$$c_i = s(wx_{i:i+h-1} + b) \tag{6}$$

In this study, the activation function was set to *ReLU* and we depicted the three filter region sizes of 3, 4 and 5, with each having 256 filters. Filters perform convolutions on the document matrix and generate feature maps as follows:

$$\mathrm{c} = [c_1,\ c_2,\ \cdots c_{n-h+1}] \tag{7}$$

4.3. *Max-pooling layer*

The 1-max pooling was performed over each map to capture the largest value $\hat{c} = \max\{c\}$ from each feature map.

4.4. *Flattening layer*

After max-pooling, we concatenated the matrices processed by three different filter kernel sizes. Then we needed to flatten the joint matrix into 1 dimension with the aim of concatenating the 1-dimension additional features.

4.5. *Concatenation layer*

Deep learning can unearth the latent features by itself, usually relying on language input instead of feature engineering (Young et al., 2017). However, to enhance performance, a number of feature vectors can be put together with the neural networks (Do et al., 2019). In this research, we therefore integrated three aspects of the feature set into the CNN based on the following three visual analytics findings:

- *Sentiment Score*: We investigated the impact of sentiment score for recognizing the proactive hotel responses. The overall rating and aspect ratings are included in this feature set, which is equal to 1 if the overall rating is greater than 3; otherwise, it is 0; for the aspect ratings, we considered the aspects of service and cleanliness based on the observation of visualizations. Here, we used the rating score of both aspects for the feature values.
- *Temporal Interval*: From the temporal visualizations, we observed that the proactive hotel responses were impacted by different time periods. For instance, managers often cannot promptly respond to hotel reviews on Saturday since it is the busiest day. Based on this perspective, we considered the influence of the day of the week of hotel reviews when recognizing proactive hotel responses.
- *Reviewer Profile*: A reviewer's profile is related to the credibility and trustworthiness of a review (Filieri, 2016). Therefore, proactive hotel responses can be associated with the characteristics of travelers. For instance, a manager would be more likely reply to a hotel review from a senior traveler with a more credible profile than a junior one. This is because the hotel review posted by a senior traveler is more valuable as a reference. Taking this into account, we explored the characteristics of users, including traveler types {family, friends, couple, business, and solo} and contributor levels {1–6 levels} to develop our deep learning model. Each traveler can earn different

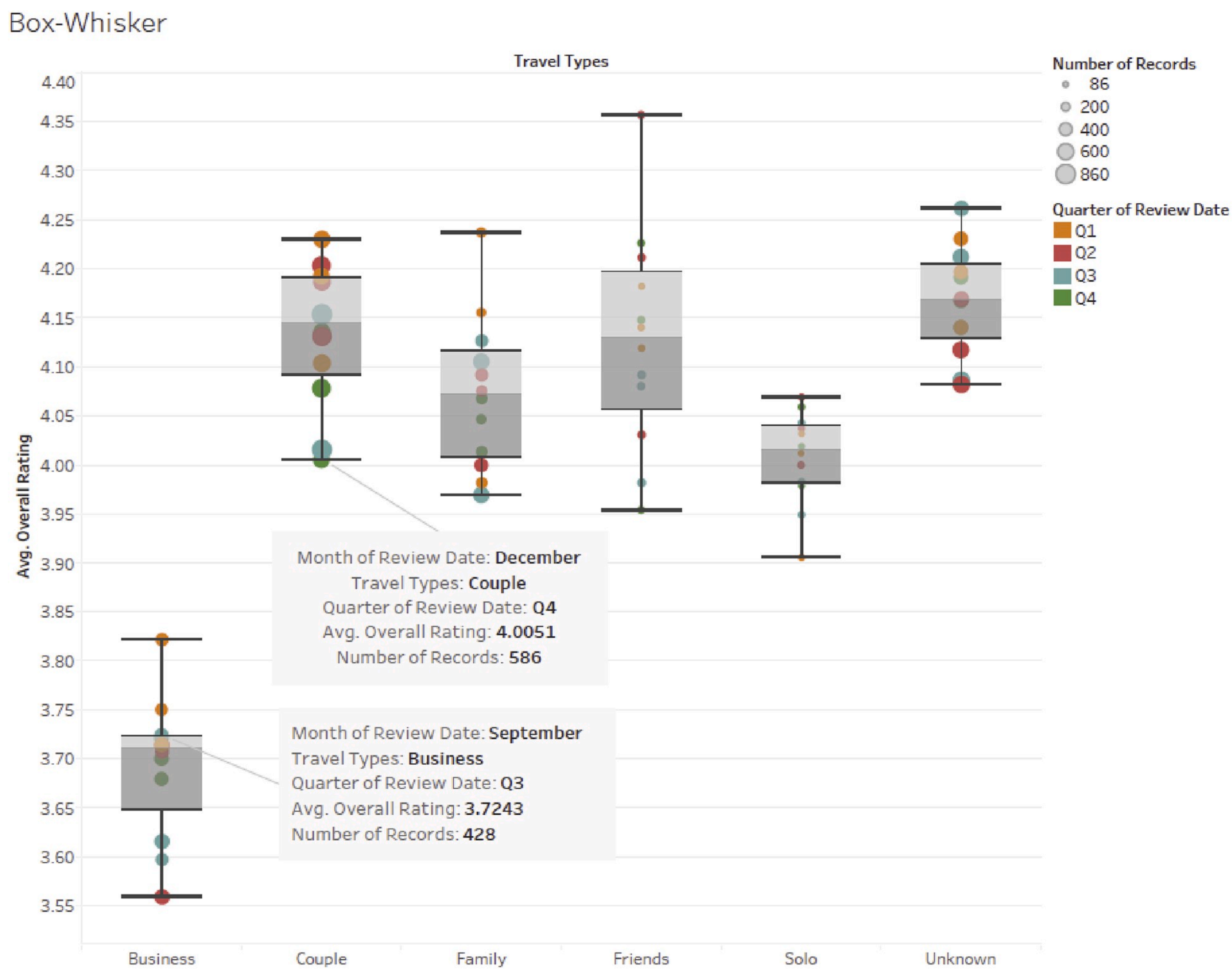

Fig. 12. Box-and-Whisker analysis of traveler types with a time dimension.

points according to the type of contributions to TripAdvisor review,[7] so to be a level 6 contributor, at least 10,000 points are required, compared to 300 points required by a level 1 contributor.

4.6. Fully-connected layer and softmax layer

Following the Concatenation layer, we designed two dense fully-connected layers to gradually reduce the dimension to 16. The final *softmax* layer then receives this 16-dim vector as an input and uses it to classify the hotel review; here we assumed a binary classification and hence depicted two possible output states.

The CNN model was implemented using Keras,[8] a Python deep learning library. For this, we used a binary cross-entropy as loss function and Adam as the optimizer. The batch size was set to be 256, and the training lasted for 10 epochs.

5. Experiment results and discussion

In this paper, we evaluated the algorithm performance by identifying proactive hotel responses in terms of the precision rate, recall rate, and the F_1-score, as well as the micro-average metrics to compare the average performance (Manning et al., 2008). First, we investigated the effect of additional feature sets of the hotel review that improves our multi-CNN model by adding features of sentiment score, temporal interval, and reviewer profile. Table 3 displays the system performances of our multi-CNN model (denoted as 3CNN) and the results of incrementally applying the extra three feature sets, denoted as + *SentimentScore*, +*TemporalInterval*, and +*ReviewerProfile*. Moreover, considering the response quality of different hotels is various.

In addition, we conducted an iterative k-means clustering analysis with visual analytics to generate three clusters using aspect ratings such as cleanliness and service ratings (see Table 4). The clusters were generated by selecting varying combinations of features and observing between-group and within-group sums of squares. We compared three clusters of hotels with higher, average, and lower aspect ratings to see if hotel response strategies were different. Among the three clusters, cluster 3 with eight hotels demonstrates the highest contribution level and rating values. We further investigated the relationship between each contributor level and rating by visualizing their relationships, but there were no corresponding results. Note that the average contributor level listed in Table 4 is part of the reviewer profile, which is included in the *concatenation layer* of our deep learning model.

As shown in Table 3, adding the features of sentiment score and temporal interval performs better than the 3CNN, which can improve about 2% F_1-score. This is because some hotel managers tend to only respond to the hotel reviews with an extreme sentiment, while other hotel responses are less consistent. That is, the sentiment factor can only increase the performance slightly. This echoes Park and Allen's (2013) findings as well our visualization results.

It is worth noting that the feature of temporal interval further

[7] TripCollective, https://www.tripadvisor.com/vpages/tripcollective_faqs.html.
[8] Keras, https://keras.io/.

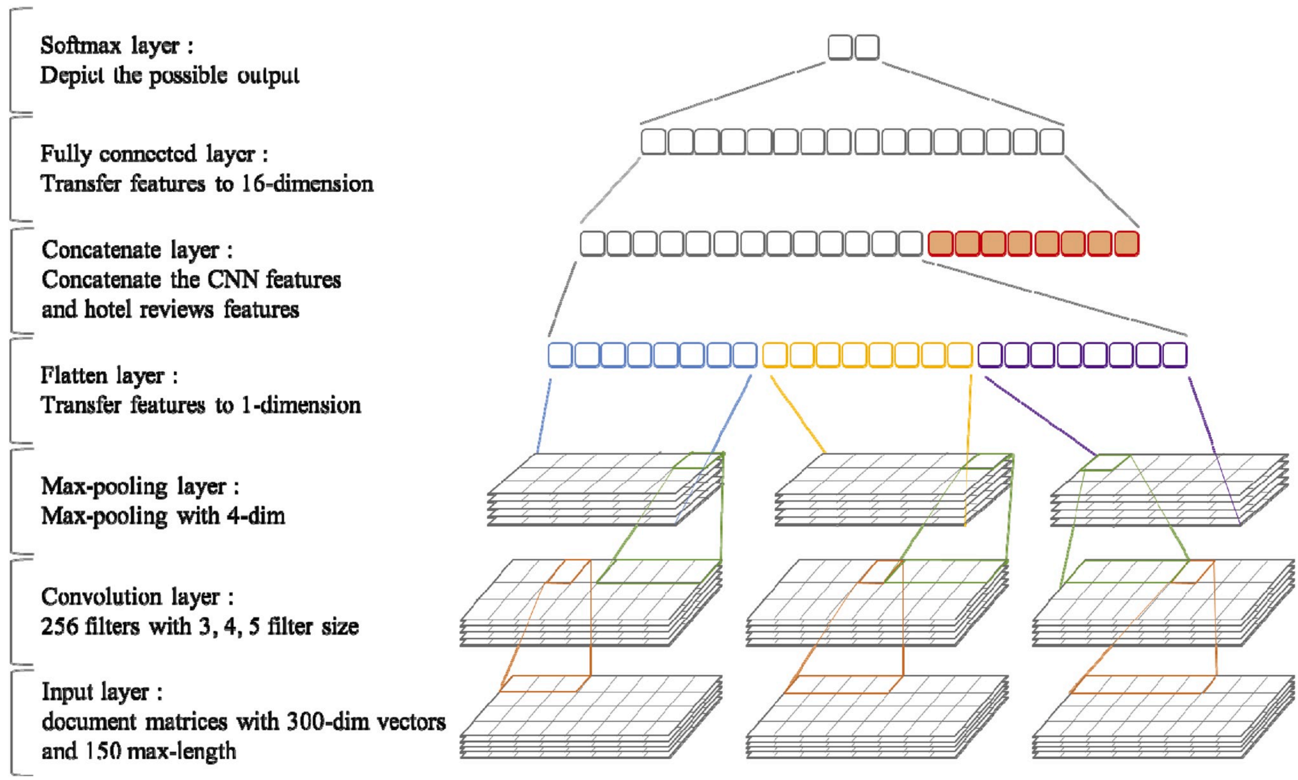

Fig. 13. Illustration of a CNN-based multi-feature fusion architecture for detecting proactive hotel responses.

Table 3
Incremental contribution of adding different features with and without clustering for detecting proactive responses.

System	Cluster	Proactive	Non-proactive	Micro-avg
		Precision, Recall, F_1-score (%)		
3CNN	without cluster	54.47/ 33.55/**41.52**	57.26/ 76.04/65.32	55.97/ 56.46/ 56.22
+SentimentScore	without cluster	56.08/ 29.11/38.33	57.08/ 80.52/66.80	56.62/ 56.84/ 56.73
+TemporalInterval	without cluster	57.98/ 31.60/40.91	57.92/ 80.43/67.35	57.95/ 57.94/ **57.94**
+ReviewerProfile	without cluster	57.47/ 28.75/38.33	57.34/ 81.83/**67.43**	57.40/ 57.37/ 57.39
3CNN	with cluster	52.61/ 32.47/40.15	57.36/ 75.55/65.21	55.25/ 56.40/ 55.82
+SentimentScore	with cluster	52.89/ 31.46/39.45	57.34/ 76.64/65.60	55.37/ 56.53/ 55.94
+TemporalInterval	with cluster	54.93/ 30.48/39.20	57.42/ 78.56/66.35	56.33/ 57.10/ 56.71
+ReviewerProfile	with cluster	55.95/ 28.93/38.14	57.52/ 80.74/67.18	56.87/ 57.47/ 57.17

improves the system performance, which indicates that proactive and non-proactive hotel responses are associated with a day of the week. Our further analysis indicates that Sunday and Monday account for the most proactive responses with 19.58% and 20.44%, respectively; this implies that nearly half of the proactive responses are made on these two days. In contrast, Thursday and Friday account the least proactive responses with 9.66% and 3.58%, respectively, which may relate to the degree of busyness preparing for the weekend peak stay time. However, the overall performance slightly decreases when the feature of the reviewer profile is added. This is because reviewer profile features for the number of proactive and non-proactive responses is not a significant difference in terms of *t*-test with a 95% confidence level. It is interesting to note that the overall results indicate there is no difference with and without clusters. The clusters cannot enhance the overall deep learning performance for at least three reasons: 1) the size of training sample, 2) the quality of clusters, and 3) the diversity of hotel types (1–5 star hotels). This is consistent with analysis results from the response rate visualizations. Therefore, we decided to conduct a further performance evaluation without clusters.

A comprehensive performance evaluation of the proposed CNN-based approach with other methods is provided in Table 5. In this experiment, the word embedding-based approaches represent each hotel review as an average of word embeddings (300-dimension embeddings) and are classified by the SVM (denoted as SVM). Next, we further compared our method to TextCNN, a well-known CNN-based text classification approach (Kim, 2014, pp. 1746–1751; denoted as *CNN*), and also to the bi-directional recurrent neural network method (Lai et al., 2015; denoted as *RNN*). To serve as baseline standards for comparison, we also included the results of Naïve Bayes (denoted as *NB*) and *k*-nearest neighbors (Guo, Wang, Bell, Bi, & Greer, 2006; denoted as *KNN*).

As a baseline, the Naïve Bayes classifier is a keyword statistics-based approach which only accomplishes a mediocre performance with a 43% F_1-score. The word embeddings-based methods (i.e., SVM) are more effective in extracting discriminative keywords and exhibit a more evenly distributed performance among both categories. Therefore, SVM further improves the performance to a 46% F_1-score. It is worth noting that the KNN simply calculates document similarity in the bag-of-words feature space which outperforms both NB and SVM. This is because the distribution of hotel review representations may be hard-divided and imperfectly independent so that NB and SVM are inferior to KNN. As

Table 4
Three Clusters of hotels.

Clusters	Number of hotels	Avg. contributor level	Avg. overall rating	Avg. max price	Avg. min price	Avg. service ratings	Avg. cleanliness ratings
1	11	3.09	3.47	216.81	93.70	3.83	3.85
2	24	3.17	4.12	215.15	94.5	4.22	4.50
3	8	**3.34**	**4.35**	**406.11**	**165.83**	**4.41**	**4.61**

Table 5
The performance result of compared methods.

System	Proactive	Non-proactive	Micro-avg
	Precision, Recall, F_1-score (%)		
NB	38.52/40.62/39.54	46.80/44.62/45.68	42.98/42.78/42.88
SVM	39.46/26.57/31.76	50.96/65.18/57.20	45.66/47.39/46.51
KNN	46.05/**44.14**/45.07	53.91/55.81/54.84	50.29/50.44/50.36
CNN	50.10/21.62/30.21	54.93/81.60/65.66	52.71/53.97/53.33
RNN	56.01/04.90/09.01	54.35/**96.71**/**69.59**	55.11/54.41/54.76
Our method	**57.98**/31.60/**40.91**	**57.92**/80.43/67.35	**57.95**/**57.94**/**57.94**

section 2.1 mentioned, RNN is expert in sequential processing and CNN is good at extracting features. As a result, the neural network model (i.e., RNN and CNN) can further improve performance to reach about 55% and 53% respectively. In this study, our method combined with multiple CNNs was able to extract latent linguistic features from hotel reviews through the convolution and pooling layers. Multiple dense layers were adopted to refine the discriminative features for identifying the proactive and non-proactive hotel responses. Moreover, we further fused the sentiment and temporal information into our multi-CNN model. Consequently, our model achieved the best precision, recall, and F_1-scores among the compared methods.

5.1. Response and review strategies

Based on our experiment results and visual analyses, we can offer the following strategic recommendations to hotel practitioners and travelers.

Response Strategy 1: We recommend that hotel managers identify types of travelers prior to their responses. Existing studies found that an increase in hotel review ratings can boost hotel reservations (Ye et al., 2011) and high-rated hotels can increase prices (Zimmermann et al., 2018). Further, Liu et al. (2013) mentioned that no prior study had examined the different types of travelers and their expectations. Therefore, we conducted additional visual analyses on types of travelers and aspect ratings. We found that couple travelers tend to rate higher, while business travelers tend to rate lower. Moreover, solo and business travelers care about available business facilities such as computers and printers that allow them to work while staying at the hotel. Family travelers prefer faster check-in and -out experiences and better sleep quality, while friends are more concerned about locations. Based on aspect rating analyses, each hotel can improve its service and facility based on the major source of customers. For example, hotels may provide faster check-in and -out services to all travelers, adjustable firmness of mattresses and pillows to family and business travelers and encourage more couple travelers to leave reviews of their staying experience.

Response Strategy 2: We recommend that hotel managers analyze online reviews actively and respond to negative and positive reviews strategically because online reviews may influence consumers' purchasing intention (Berger et al., 2010) and hotel reputation (Proserpio & Zervas, 2017). It has been found that strategic responses can also increase the perceived helpfulness of online reviews (Liu & Park, 2015). Our visual analytics indicates the hotel managers do not appear to respond to positive and negative reviews strategically. For example, DoubleTree by Hilton Woking has a high non-response rate, which is greater than 70%, regardless of whether responding to positive and negative reviews. We recommend that hotel managers respond to negative reviews timely and actively for the following reasons. First, a timely response to negative reviews can increase travelers' trust (Sparks et al., 2016) and is an important predictor of hotel performance (Kim et al., 2015). Second, after the hotel's response, the length of negative views tends to increase, and the number of negative reviews tends to decrease, which leads to higher hotel ratings (Proserpio & Zervas, 2017).

Response Strategy 3: We recommend that hotel managers strategically identify experienced reviewers and opinion leaders based on reviewer profiles. Kwok and Xie (2016) further point out that responses to opinion leaders' reviews will proactively influence the perceived helpfulness of the reviews. Opinion leaders are important promoters of products and services (Lin et al., 2018), and as such, hotel managers should further analyze the characteristics of reviewers such as years of review, number of positive and negative reviews, and traveler types. In this way, managers can even choose opinion leaders to work with in order to better understand how to promote their hotels to different types of travelers.

Response Strategy 4: Temporal factors and patterns remain underresearched in the current literature. Our analyses indicate that certain months, such as July and August, are more likely to receive more negative reviews. We recommend that hotel managers devote more resources for monitoring and providing timely responses to online reviews (Lui et al., 2018). In addition, response strategies should be adjusted based on the day of the work week, weekends, holidays and seasons to engage different types of travelers. For example, additional response representatives are required to deal with the sudden increase of reviews during holidays, weekends, and special events.

Review Strategy 1: When traveler types are added to the response rate analysis, unknown travelers receive a relatively lower response rate (62%) compared to other traveler types (>78%). Therefore, we recommend that travelers specify a travel type such as a couple, family, or friend if they would like to receive a response from the hotel manager. Moreover, since the time dimension was also added to our analysis, we found that hotel managers tend to respond to reviews during weekdays, typically Mondays, and July was the month with the highest response rate.

6. Conclusion, limitations, and future research

Sun et al. (2017) point out that even though computer vision and speech recognition have greatly improved with deep learning techniques in recent years, deep learning-based NLP is still in its infancy. Although existing studies are valuable in analyses of online reviews and their sentiments, they shed little light on response strategies. This paper addresses this shortcoming by investigating hotel review response strategies by using smart technologies such as deep learning and visual analytics as effective tools that can assist hotel representatives in their decision-making to prioritize responses to reviews.

This data-driven study has yielded theoretical, managerial, and technical contributions. First, this study adds to a growing body of tourism research on hotel response strategies by investigating the intricate relations between hotel reviews and managerial responses. Our study complements the existing research literature by examining traveler types, aspect ratings, review sentiments, temporal factors, and reviewer profiles. Secondly, this study goes beyond ratings and sentiment analysis by analyzing the linguistic features of reviews and responses to empirically identify response strategies. Thirdly, our study complements the existing research methods such as statistical and econometrics models and surveys by using visual analytics, deep learning, and NLP techniques.

From a managerial perspective, hotel managers can respond to reviews strategically and to maintain a good relationship with customers. Xie et al. (2016) advise hotels to adopt managerial response strategies, and it has been shown that the speed of response, for example, is important to service recovery (Gu & Ye, 2014; Zhao et al., 2019) and can enhance customer engagement (Li et al., 2017). The temporal factor and reviewer profile can be further used for market segmentation and improvement of hotel services and facilities.

The technical contributions of this study are evident. Our proposed analytical framework shows good explanatory power and outperforms existing machine learning methods such as NB, KNN, SVM, CNN, and RNN, and, thus can be expanded to conduct deeper analyses. What sets this study apart is that we presented a novel approach to integrating visual analytics and deep learning-based NLP models to gain insights into various aspects of hotel reviews and responses. Our visual analysis results demonstrate that the use of review sentiment, temporal interval, and reviewer profile together with rating information, can help hotel managers prioritize responses and develop response strategies.

There are, however, limitations to this study. First, the dataset represented only 43 Hilton-affiliated hotels in London. Further, the research findings derived from our visual analytics and the existing study (Park & Allen, 2013) indicate that most hotel managers do not adopt clear response strategies, which leads to a lower performance of deep-learning models. To further examine the performance of deep learning models, we need to include more cities, hotel brands, and hotels in our future studies. Second, the perception from the users' perspective was not studied. It would be instructive to investigate users' perceptions and satisfaction when they read hotel responses to both positive and negative reviews. Despite the limitations addressed above, our study provides new insights to demonstrate the power of integrating visual analytics and deep learning-based NLP to analyze hotel reviews and responses.

Declaration of competing interest

None.

Appendix A. Recent research related to hotel reviews on TripAdvisor from three leading journals

Author (year)	Publication Source	Reviews/ responses	Reviewer profile, temporal factor, travel type, aspect rating	Data analysis/research method	Visualization
Zhang et al. (2020)	*Tourism Management*	Hotel reviews and responses	Not available	Text mining (topic matching), SVM, econometric models, hypothesis testing	Result display: line chart
Wang et al. (2020)	*Tourism Management*	Hotel reviews	Travel type	Term frequency-inverse document frequency (TF-IDF), Word2Vec, ratio and rating analysis	Result display: bar and line chart
Hu, Teichert, et al. (2019) and Hu, Zhang, et al. (2019)	*Tourism Management*	Hotel reviews	Travel type	Structural topic model, text analysis, topic correlation analysis	Result display: network visualization
(Liu et al. (2019))	*Tourism Management*	Hotel reviews	Not available	Sentiment analysis based on a lexicon	Result display: sentiments image
Bi, Liu, Fan, and Zhang (2019)	*Tourism Management*	Hotel reviews	Temporal factor	LDA, SVM, regression model, statistical analysis	Result display: bar and line chart
Taecharungroj and Mathayomchan (2019)	*Tourism Management*	Hotel reviews	Aspect rating	LDA, Naïve Bayes, sentiment analysis	Result display: bar and distribution charts
Hu, Teichert, et al. (2019) and Hu, Zhang, et al. (2019)	*Tourism Management*	Hotel reviews	Travel type, aspect rating	Regression analysis, hypothesis testing, text mining	Result display: line chart
Gao et al. (2018)	*Tourism Management*	Hotel reviews	Reviewer profile, travel type, aspect rating	Logistic model, hypothesis testing	Not available
Lui et al. (2018)	*Tourism Management*	Hotel reviews and responses	Temporal factor	Statistical model, hypothesis testing	Not available
Radojevic et al. (2018)	*Tourism Management*	Hotel reviews	Travel type, aspect ratings, reviewer profile	Statistical model	Result display: line chart, histogram
Marine-Roig and Ferrer-Rosell (2018)	*Tourism Management*	Hotel review titles	Not available	Content analysis, keyword analysis, cognitive analysis	Not available
Liu et al. (2017)	*Tourism Management (Research Note)*	Hotel reviews	Aspect rating	Statistical analysis and data comparison	Result display: distribution chart, line chart
Xiang et al. (2017)	*Tourism Management*	Hotel reviews	Not available	LDA, Naïve Bayes, linear regression model, sentiment analysis	Result display: bar and line chart
Li et al. (2017)	*Tourism Management*	Hotel reviews and responses	Temporal factor	Statistical model, hypothesis testing	Not available
Guo et al. (2017)	*Tourism Management*	Hotel reviews	Aspect rating	LDA, text analysis, statistical analysis	Result display: bar line, and distribution chart
Geetha, Singha, and Sinha (2017)	*Tourism Management*	Hotel reviews		Sentiment analysis, Naïve Bayes, WordNet lexicon, clustering	Result display: bar chart and word cloud
Banerjee and Chua (2016)	*Tourism Management*	Hotel reviews	Travel type	Factorial analysis, ANOVA	Result display: line chart
Baka (2016)	*Tourism Management*	Hotel reviews and responses	Not available	Case study (no data analysis)	Not available
Yang et al. (2016)	*Tourism Management*	Hotel reviews	Temporal factor	Regression model	Result display: location map
de la Peña et al. (2016)	*Tourism Management*	Hotel reviews	Not available	Econometric model	Not available
Zhang and Cole (2016)	*Tourism Management*	Hotel reviews	Not available	Regression model	Not available
Li et al. (2015)	*Tourism Management*	Hotel reviews	Travel type, temporal factor	Statistical analysis	Result display: bar and line chart
Li et al. (2013)	*Tourism Management*	Hotel reviews	Travel type, aspect rating		Not available

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Author (year)	Publication Source	Reviews/ responses	Reviewer profile, temporal factor, travel type, aspect rating	Data analysis/research method	Visualization
				Fuzzy logic, aggregation function (Choquet Integral)	
Briggs, Sutherland, and Drummond (2007)	*Tourism Management*	Hotel reviews	Not available	Survey, ANOVA	Result display: bar chart
Radojevic et al. (2019)	*Annals of Tourism Research*	Hotel reviews	Travel type, aspect rating	Regression model	Result display: bar and line chart
Hernández, Kirilenko, and Stepchenkova (2018)	*Annals of Tourism Research*	Hotel reviews	Not available	Network analysis	Result display: Geo-visualization, bar chart
Filieri (2016)	*Annals of Tourism Research*	Hotel reviews	Not available	Interview	Not available
Phillips et al. (2019)	*Journal of Travel Research*	Hotel reviews	Not available	Data mining, sentiment analysis, decision tree	Result display: bar and distribution chart
Yang and Mao (2019)	*Journal of Travel Research*	Hotel reviews	Temporal factor	Econometric model	Not available

(*continued*)

Author (year)	Publication Source	Reviews/ responses	Reviewer profile, temporal factor, sentiment, travel type, aspect rating	Data analysis/research method	Visualization
Yang et al. (2018)	*Journal of Travel Research*	Hotel reviews	Travel type, temporal factor	Logit model, statistical analysis	Result display, spatial distribution
Mkono and Tribe (2017)	*Journal of Travel Research*	Hotel reviews	Not available	Netnographic approach	Not available
Radojevic et al. (2019)	*Annals of Tourism Research*	Hotel reviews	Travel type, aspect rating	Regression model	Result display: bar and line chart

Note: The selected articles are related to hotel reviews or responses on TripAdvisor. We are interested in the research methods, data attributes, and data analyses that have been used in analyzing textual hotel reviews. There are articles published out of Tourism Management, Journal of Travel Research, and Annals of Tourism Research. We also expanded our review to these articles to verify the consistency of our findings.

Appendix B. Recent research related to online reviews from three leading journals

Author (year)	Publication Source	Reviews/responses	Data analysis/research method	Visualization
Li and Ryan (2020)	*Tourism Management*	Online reviews	Concept analysis (Leximancer)	Result display: concept map, bar chart
Woodman et al. (2019)	*Tourism Management*	Lodge reviews	Manual review, bacteria measurement	Not available
Kirilenko et al. (2019)	*Tourism Management*	Attraction reviews	Geographical analysis	Data exploration and result display: map
Liu et al. (2019)	*Tourism Management*	Online reviews	Econometric models	Not available
Mellinas et al. (2019)	*Tourism Management*	Online reviews	Statistical model, hypothesis testing	Result display: line chart
Soler et al. (2019)	*Tourism Management*	Not available	Hedonic pricing model, descriptive analysis, regression model	Not available
Gerdt, Wagner, and Schewe (2019)	*Tourism Management*	Online reviews	Descriptive statistics, regression analysis, sentiment coding	Result display: line chart
Pantano et al. (2017)	*Tourism Management*	Online review of Empire State Building	Machine learning models using Mathematica	Result display: line chart
(Yang et al. (2018))	*Tourism Management*	Not available	Meta-analysis, hierarchical linear modelling, hypothesis testing	Result display: histogram
Liu et al. (2018)	*Tourism Management*	Attraction reviews	Statistical model, hypothesis testing	Result display: line chart
Batista e Silva et al. (2018)	*Tourism Management*	Not available	GIS and spatiotemporal mapping	Result display: density map
Su and Teng (2018)	*Tourism Management*	Negative museums reviews	Content analysis requires manual coding	Not available
Boo and Busser (2018)	*Tourism Management*	Online reviews	Automated and manual content analysis, concept extraction	Result display: concept map
Ganzaroli, De Noni, and van Baalen (2017)	*Tourism Management*	Restaurant reviews	Statistical model, hypothesis testing	Result display: bar chart
	Tourism Management	Hotel reviews		
Sparks et al. (2016)	*Tourism Management*	Negative online reviews, responses	Survey study, simulation, hypotheses testing	Result display: bar chart
Filieri, Alguezaui, and McLeay (2015)	*Tourism Management*	Not available	Hypothesis testing, structural equation modelling (SEM), Web Questionnaire (TripAdvisor)	Not available
Phillips et al. (2015)	*Tourism Management*	Positive online reviews	Artificial neural network, regression analysis	Not available
Lu and Stepchenkova (2012)	*Tourism Management*	Not available	Content analysis, chi-square analysis,	Result display: destination map
Zehrer et al. (2011)		Travel blogs	2x2 quasi experimental design, hypothesis testing	

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Author (year)	Publication Source	Reviews/responses	Data analysis/research method	Visualization
	Tourism Management			Result display: plot with Box & Whisker
Amaro, Duarte, and Henriques (2016)	*Annals of Tourism Research*	Not available	Questionnaire, k-means cluster analysis	Result display: box plot and line chart
Mkono (2016)	*Annals of Tourism Research*	Online reviews	Hermeneutic interpretation, netnography	Not available
Alaei et al. (2019)	*Journal of Travel Research*	Multiple tourism online reviews	Sentiment analysis (a review paper)	Not available
Gal-Tzur, Bar-Lev, and Shiftan (2019)	*Journal of Travel Research*	City forums	Questionnaire, statistical model	Not available
Bigné, William, and Soria-Olivas (2019)	*Journal of Travel Research*	Online reviews	Self-organizing Maps (SOM), in-depth interview, sentiment analysis	Result display: SOM and line chart
Fu, Hao, Robert, Li, and Hsu (2019)	*Journal of Travel Research*	Chinese travel news	Sentiment analysis	Result display: line chart
Vu et al. (2019)	*Journal of Travel Research*	Restaurant reviews	Text mining, sentiment analysis, statistical analysis	Result display: bar chart
Stamolampros et al. (2019)	*Journal of Travel Research*	Flight reviews	NLP, LDA, topic modelling, logistic regression	Not available
Gkritzali, Gritzalis, and Stavrou (2018)	*Journal of Travel Research*	City forum	Sentiment analysis	Result display: bar chart
Kirilenko et al. (2018)	*Journal of Travel Research*	Online reviews	Sentiment analysis	Not available
Phillips et al. (2017)	*Journal of Travel Research*	Online reviews	Hypotheses testing, statistical modelling	Result display: bar chart
Kim and Fesenmaier (2017)	*Journal of Travel Research*	Negative online reviews	Hypotheses testing, statistical analysis	Result display: bar chart
Murphy and Chen (2016)	*Journal of Travel Research*	Online reviews	Questionnaires, exploratory, observation method	Result display: bar chart
Tanford and Montgomery (2015)	*Journal of Travel Research*	Online reviews	Hypothesis testing, questionnaires, statistical analysis	Result display: line chart
Kazeminia, Del Chiappa, and Jafari (2015)	*Journal of Travel Research*	Online reviews	Content analysis, Leximancer, thematic analysis and semantic analysis	Result display: concept map

Note: The selected articles are related online textual reviews, e.g., restaurant reviews, travel reviews, and airline reviews. We are interested in the research methods and data analyses that have been used in analyzing textual reviews in tourism research. There are articles published out of Tourism Management, Journal of Travel Research, and Annals of Tourism Research. We also expanded our review to these articles to verify the consistency of our findings.

Author contributions

C.H. Chen conducted data collection; Y.C. Chang and C.H. Ku developed models, conducted data analyses, experiments, and wrote the manuscript.

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