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Sentiment Analysis in Tourism: Capitalizing on Big Data

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Abstract

Advances in technology have fundamentally changed how information is produced and consumed by all actors involved in tourism. Tourists can now access different sources of information, and they can generate their own content and share their views and experiences. Tourism content shared through social media has become a very influential information source that impacts tourism in terms of both reputation and performance. However, the volume of data on the Internet has reached a level that makes manual processing almost impossible, demanding new analytical approaches. Sentiment analysis is rapidly emerging as an automated process of examining semantic relationships and meaning in reviews. In this article, different sentiment analysis approaches applied in tourism are reviewed and assessed in terms of the datasets used and performances on key evaluation metrics. The article concludes by outlining future research avenues to further advance sentiment analysis in tourism as part of a broader Big Data approach.

Keywords

Big Data, sentiment analysis, social media, lexicon, machine learning

The use of Big Data is rapidly entering the domain of tourism research (Fuchs, Höpken, and Lexhagen 2014). The four Vs of Big Data, namely volume (scale), variety (different types of data), velocity (high speed, and real time), and veracity (uncertainty, and validity), are particularly relevant in consumer research (IBM n.d.), with its increasing need for real-time and customized information. The tourism industry, as an industry where customer experience is crucial for its growth and reputation, has mainly adapted to the evolving technology and the availability of new data sources. Most tourist services are now available on the Internet through online booking websites. In addition, travel is one of the dominant topics on social media, for example, on Facebook and Twitter (Neidhardt, Rümmele, and Werthner 2017; Travelmail Reporter 2013). It is, thus, not surprising that tourism has been recognized as the number one sector in terms of online engagement (Mack, Blose, and Pan 2008).

All Internet-based activities leave a digital footprint. It is timely to examine how tourism researchers are making use of these data, and whether these new types of data form a part of a new research paradigm that entails novel methodologies and has the potential to further advance our theoretical understanding of tourism. To date, online data sources have mainly been used in applied research, whereby advantage was taken of the large and often free-of-charge volumes of data that provide insights into activities of the tourism/travel industry and its customers. Not surprisingly, the focus of previous research was on business strategy development, innovation and product development, and marketing campaigns (Ellion 2007; Kuttainen et al. 2012; Pan, MacLaurin, and Crotts 2007).

In the context of tourism, a service-based industry that relies on positive customer emotions and feedback, the concept of visitor satisfaction is of critical importance. Satisfaction as a theoretical construct has been explored and discussed for a long time, and multiple instruments exist to operationalize and measure it (Wang 2017). It, however, mostly relies on collecting data through surveys. It is well established that survey-based approaches suffer from several shortcomings, including costs and logistics, and potential for multiple bias. Since visitors made a high investment in their travel, their responses to the survey questions may reflect an inherently positive assessment as a result of confirmation bias (Dodds et al. 2015). Interviewer bias and cultural influence in answering particular questions are other known problems of survey-based approaches (Veal 2006). In addition, questionnaires cover only predetermined aspects of the destination and, thus, they lack comprehensiveness. On the contrary, the availability of online user-generated content (UGC)

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and new technologies provided researchers with a new approach that travelers' perceptions and possibly their level of satisfaction can be approached through "sentiment analysis." Sentiment analysis, in general, aims to determine the overall contextual polarity of a text document, a review, an opinion, or an emotion expressed in online UGC, whereby polarity can be positive, neutral, or negative. While highly relevant for tourism, sentiment analysis in tourism is only beginning to gain in popularity (Feldman 2013; Gao, Hao, and Fu 2015; Ribeiro et al. 2016).

The purpose of this article is to review and critically examine the state-of-the-art sentiment analysis methods in tourism research. To advance this type of analysis for the particular domain of tourism and to understand whether such Big Data–based approaches offer new research pathways, this review asks the following questions:

1. What are the key elements and methods used in sentiment analysis?
2. To what extent has sentiment analysis been applied in tourism, and how do different methods perform?
3. Can sentiment analysis, as part of a wider Big Data approach, be a novel way of improving tourism research methods and increase theoretical understanding in tourism?

Background: The Digitally Supported Tourism Industry

Technological changes related to the Internet, including smartphones and tablets, have revolutionized the tourism industry from a brick-and-mortar and person-to-person service industry to a heavily digitally supported and omnipresent travel service network. Individual travelers or groups now have much greater control over planning, building and personalizing their trips. They not only interact with a range of platforms and online intermediaries to extend their knowledge in relation to traveling and decision making in tourism, but also associate with other travelers who share their experiences. Travelers have access to online platforms to provide feedback and make recommendations for other travelers (Neidhardt, Rümmele, and Werthner 2017; Yang, Mao, and Tang 2017; Ye, Zhang, and Law 2009). As a result, new Internet technologies have empowered people who previously did not have a voice (Hepburn 2007). The most successful professional platforms in relation to travel and tourism are TripAdvisor, Expedia, VirtualTourist, and LonelyPlanet (Bjorkelund, Burnett, and Norvag 2012; Gretzel, Yoo, and Purifoy 2007; Rabanser and Ricci 2005). TripAdvisor alone counts 350 million unique visitors per month on their website and generates over 320 million reviews that cover accommodations, restaurants, and attractions (TripAdvisor, 2016). Information provided through these independent platforms has been found to be superior and more trustworthy compared with companies' websites and professional reviews (Akehurst 2009; Gretzel, Yoo, and Purifoy 2007; Rabanser and Ricci 2005; Xiang, Gretzel, and Fesenmaier 2009).

In addition to professional systems, online social media, such as Twitter, Instagram, Facebook, Foursquare, Sina Weibo, and Google Plus, play a significant role in creating electronic word-of-mouth (e-WOM) (Confente 2015; Garcia-Pablos et al. 2016; Leung et al. 2013; Phillips et al. 2017). Importantly, online social media, travel professional websites and platforms, and blogs present inexpensive means to gather rich, authentic, and unsolicited data on travelers' opinions. While personal advice often ranks as the most influential source of pretrip decision making, the overall credibility of blogs and online social media compared to that of traditional WOM is relatively high (Akehurst 2009). Therefore, social media and blogs nowadays complement opinions attained from relatives, friends, colleagues, and official sources (Cantallops and Salvi 2014; Chua and Banerjee 2013; Filieri, Alguezaui, and McLeay 2015; Hepburn 2007; Mack, Blose, and Pan 2008).

However, as the volume of online information is increasing at an extremely fast pace, searching, manipulating, and aggregating the data to extract relevant and useful insights about tourists' attitude, behavior, and experience quality becomes a tedious and time-consuming task for both travelers and industry users as well as professional and academic researchers (Cantallops and Salvi 2014; Ellion 2007; Dodd 2014; Xiang, Schwartz, Gerdes, et al. 2015; Ye, Zhang, and Law 2009). To analyze large data volumes more effectively, the demand for automatic multiaspect algorithmic and machine-operated systems is increasing.

The importance of using social media data and data mining tools and procedures in tourism was studied in the literature (Dhiratara et al. 2016). Data collection, data cleaning, mining process, and then evaluation and understanding of the results are the major steps used in most of the applications in relation to social media data analysis in tourism (Hippner and Rentzmann 2006; Schmunk et al. 2014). Text summarization and text classification along with natural language processing (NLP) are earlier technologies used to facilitate information processing and data analysis (Cantallops and Salvi 2014; Ghose, Ipeirotis, and Li 2012; Pan, MacLaurin, and Crotts 2007; Stringam and Gerdes 2010; Xiang, Schwartz, Gerdes, et al. 2015).

Besides, sentiment can also be modeled by machines for automation, and integration across various applications (Choi, Lehto, and Morrison 2007; Rabanser and Ricci 2005). Sentiment analysis basically refers to the use of computational linguistics and NLP to analyze text and identify its subjective information. While research on sentiment analysis goes back to the 1970, only recently it has received increasing attention from both researchers and practitioners (Brob 2013; Pang, Lee, and Vaithyanathan 2002). The interest is driven by (1) escalation of web- and social-media-based information, (2) evolution of new technologies, especially machine learning approaches for text analysis, and (3) development of new business models and applications that make use of this information. Despite its popularity, sentiment analysis is still in its infancy compared to earlier technologies, such as data mining and text summarization (Pan, MacLaurin, and Crotts 2007).

This review argues that sentiment analysis can become an important tool in tourism research. Moreover, it may be an indication of how data-driven research models might be of relevance to tourism research. While this review will not provide a final answer to such challenging questions, it will examine tourism-specific material to further explore whether Big Data is merely a continuation of inductive science (Fricke 2015) or whether it is the "end of theory" and constitutes a radically new paradigm (Anderson 2008; Kitchin 2014). In the meantime, the following postulates are useful:

- The volume of online data relevant to the tourism context is increasing exponentially. Data can be structured, semistructured, unstructured, textual (in different languages), pictorial, or audiovisual. For example, in the case of online surveys as a source of structured data, the first company in Australia registered in 2001. In 2013, more than 40 companies and 150 market and social research consultancies provide services using online surveys (Dolnicar, Grün, and Yanamandram 2013; Stantic and Pokorný 2014).
- Online data related to tourism activities are generated at such velocity that they outstrip the potential of traditional (paper and pen) surveys to capture events in real-time in order, for example, to monitor service quality and recovery.
- Tourism is part of the "experience economy" and those involved in the travel industry are increasingly seeking to understand the emotional and experiential elements of tourist activities (Ma et al. 2017).
- Online platforms represent a two-way avenue of producing and consuming information, and "co-creating experiences" (Sigala 2016).
- Integration of multiple Big Data sources, e.g., heterogeneous data sources, in the form of structured and unstructured data, such as customer feedback, reservation and booking data, and web search/navigation data, in customer and supplier sides (Höpken et al. 2013; Höpken et al. 2015), may reveal new insights that were not able to be detected with traditional approaches.

In the following, sentiment analysis is reviewed to provide a starting point for future discussions on how Big Data can be used in the tourism context. As an interdisciplinary research domain, sentiment analysis approaches draw on progress in several areas, including computer science, information technology, and linguistics. Therefore, a brief overview of the technical aspects of sentiment analysis is provided, followed by an assessment of sentiment analysis methods in the tourism domain, including an evaluation of datasets and performances. The article concludes with recommendations for future research in this area, including an assessment of the potential of using Big Data in the tourism domain.

What Is Sentiment Analysis?

Opinion mining based on sentiment orientation was studied in recent years to understand perceptions and characteristics of population or market groups, and to determine the credibility of content and motivations for posting reviews (Ribeiro et al. 2016). Different sentiment analysis methods were developed in various domains, triggering a small number of review articles on this topic (Gonçalves et al. 2013; O'Leary 2011; Ribeiro et al. 2016). None of the reviews to date focus on tourism.

Overview

Sentiment analysis, in particular in relation to customer reviews, is built on the premise that information provided through text (e.g., a review) is either subjective (i.e., opinionated) or objective (i.e., factual). Subjective reviews are based on opinions, personal feelings, beliefs, and judgment about entities or events. Objective reviews are based on facts, evidences, and measurable observations (Feldman 2013). Consumer reviews and social media posts often reflect happiness, frustration, disappointment, delight and other feelings (O'Leary 2011). Tapping into these large volumes of subjective e-WOM is of great value to tourism organizations and businesses who seek to improve customer management and business profitability (Choi, Lehto, and Morrison 2007; Kuttainen et al. 2012; Ye, Zhang, and Law 2009).

Methodologically, sentiment analysis represents a polarity classification problem. Considering different numbers of classes, sentiment polarity classification can be conceptualized as binary, ternary, or ordinal classification. In a binary classification, we initially assume that a given customer review is subjective. In other words, a binary classification assumes that the given text is predominantly either positive or negative, and then it determines the polarity of the given review as "positive" or "negative." The definition of the two poles of sentiment as positive and negative depends on the particular application and domain. For example, in the context of tourism, "positive" and "negative" may, respectively, refer to "satisfied" and "unsatisfied," but further research to link sentiment polarity to the theoretical constructs of satisfaction would be required.

Reviews may not always be subjective, therefore, the binary classification needs to be extended to a ternary classification that contains a third, "objective" category. In the ternary classification problem, the classifier implicitly performs a classification to differentiate between objective and subjective sentences, providing a class-label as "positive," "negative," or "neutral." Neutral polarity is sometimes interpreted as a polarity between positive and negative. The sentiment analysis can also be treated by the means of a cascaded approach, composed of a binary classifier to differentiate between subjective and objective reviews and a binary polarity classifier to further classify subjective reviews into two groups, namely positive or negative. Objective reviews generally do not contain those words that are clearly defined as positive or negative in a dictionary. They may also contain mixed polarities without a clear perspective of direction. In addition to the simple binary and ternary classification, ordinal classification can be performed by the means of a rating scale (e.g., one to five stars) of the sentiment strength (Brob 2013).

In sentiment analysis, it is also important to understand what a sentiment relates to. The detection of a target and aspect (i.e., topic detection; Menner et al. 2016), relates to determining the subject of a sentiment expression. Sentence-level sentiment analysis supports aspect-based review mining. Based on the level of granularity of analysis, a sentiment aspect may refer to a concrete or tangible entity or to a more abstract topic. A target or an aspect might be referred to either implicitly or explicitly. Reviews with explicit targets or aspects are easier to analyze than those with implicit ones. A hotel review may be composed of different aspects of a hotel, for example, "the size of the bed was small and there was a noisy refrigerator" is a review, which explicitly describes two aspects of a "hotel room" as "small bed" and "noisy." Whereas in the review "hotel was expensive!," the word "expensive" is an implicit aspect that refers to the "price" of the hotel. Aurchana, Iyyappan, and Periyasamy (2014) found that extracting both implicit and explicit aspects accurately in reviews results in an increase in the accuracy of sentiment analysis results.

A comprehensive sentiment analysis also includes data on who provided the information and at what point in time. Thus, sentiment analysis of an opinion or review can be technically formulized by a quintuple (o, h, t, a, p), where o is an opinion, h is the opinion holder, t is the time when the opinion o is expressed by h, a is a topical aspect of the opinion o, and p is the polarity orientation of the opinion o in relation to aspect a (Liu 2010).

Sentiment analysis can be employed at the word, sentence, paragraph, and document levels. Relatively less research has focused on sentence-level analysis, since it is more challenging to accurately extract polarity from a small number of words compared with paragraphs and documents (Brob 2013; Choudhury 2016; Höpken et al. 2016; Schmunk et al. 2014; Ribeiro et al. 2016). For a clear explanation and understanding of the different sentiment analysis methods, the relevant key terms are defined in Table 1.

Sentiment Analysis Methods

Sentiment analysis comprises a multistep process: (1) data retrieval, (2) data extraction and selection, (3) data preprocessing, (4) feature extraction, (5) topic detection, and (6) data mining process (e.g., Hippner and Rentzmann 2006; Schmunk et al. 2014).

Data retrieval requires the identification and definition of the data source, for example, a commercial service provider portal or a social media network. To collect the review data from these sources, a specific web crawling mechanism is necessary to fetch data and then save them in a database considering the format of data (Menner et al. 2016; Schmunk et al. 2014). After collecting data in a database, review data need to be extracted from within a set of heterogeneous data fields. For example, in the case of TripAdvisor data, a review is embedded within a retrieved HTML document, which is composed of different elements, such as footers or headers, tags, and the review text itself (Menner et al. 2016; Schmunk et al. 2014). The review text needs to be extracted using appropriate expressions. Each extracted review contains one or several sentences reflecting the reviewer's opinion.

Different tasks including splitting a review into sentences, splitting a sentence into words, tokenisation, filtering of stop-words, part-of-speech (POS) tagging, stemming, and the transformation to lower/upper cases are performed on reviews in the preprocessing step to prepare them for the next step (i.e., feature extraction) (Schmunk et al. 2014). POS tagging is an important preprocessing task that generally forms a part of sentiment analysis by assigning each word a particular label (e.g., noun, verb, and adjective).

Feature extraction is known as the process of deriving a set of discriminative, informative and nonredundant values to numerically represent a review or text. One of the commonly used feature extraction techniques is based on term occurrences, called term frequency (TF) or term frequency–invers document frequency (TF-IDF). Using the TF feature extraction technique, reviews or sentences are converted into a "term document matrix" (Pang, Lee, and Vaithyanathan 2002; Hippner and Rentzmann 2006; Menner et al. 2016).

Topic detection is a multiclass classification problem where a text is classified to an appropriate topic class based on its content and application. Topic detection research is going back to 1998 where topic identification in the context of broadcast news was studied (Allan et al. 1998). Hu and Liu (2004) later proposed a method to summarize customer reviews based on different product features. Suggested approaches mainly involved word dictionaries, clustering, and similarity measures. Since, the overview of topic detection methods in the literature is out of the scope of this article, readers are referred to Menner et al. (2016) for an overview.

In the data mining process, different types of sentiment analysis methods can be distinguished in the literature,

Table 1. Key Terms and Definitions.

Key term	Description
Aspect	Every topic or target (see below) in sentiment analysis has different features and characteristics. For example in tourism-related text, "restaurant" as a potential target has various aspects, such as the food and atmosphere, ambiance, cleanness, price, and location.
Bag of words (BoW)	The BoW is a feature extraction method where the frequency of occurrence of each word in a given text/review, disregarding word order and grammar rules in the text, is used as a feature.
Classification and classifier	In machine learning, classification is the procedure that helps identify to which set of predefined groups a new sample belongs to. The model, which is called classifier, needs to initially "learn" based on a training set of data that contains instances of text (or individual words) that are representative of a particular group. Once trained, the classifier can then perform the classification task on a new sample.
Confusion matrix	It is a table used to describe the performance of a classifier on a set of test data for which the true labeled are known.
Experimental analysis	To evaluate the performance of an algorithmic model, a set of tests/experiment is performed using training and testing data. Considering the results obtained from the test data, evaluation metrics are also computed. This process is called experimental analysis.
Feature extraction	Feature extraction is the process of building or deriving a set of discriminative, informative, and nonredundant values from a set of data, which eventually facilitates the learning process.
Information gain (IG)	IG is a feature selection strategy, which uses more important features or more discriminative features for the classification purposes.
Maximum entropy	Maximum entropy is a classifier, which mainly relies on the concepts of data uniformity and entropy. In the maximum entropy classifier, it is assumed that the probability distribution of the prior data that best represents the current state of data/knowledge should have the largest entropy.
N-gram	An N-gram is an adjacent order of N items in a given text (review) or speech. In a text (review) the items can be letters or words.
Naïve Bayes	Naïve Bayes is a probabilistic classifier that works based on a strong assumption that features are all independence.
K-nearest neighbor (K-NN)	K-NN is an instance-based and nonparametric classifier used for classification, where K denotes the K closest training samples. The K-NN algorithm is one of the simplest machine learning algorithms.
Part of speech (POS)	POS is a category of words (lexical items) which have similar grammatical properties (syntax, morphology) in English. Noun, verb, adjective, adverb, pronoun, preposition, conjunction, interjection, and sometimes numeral, article, or determiner are commonly listed English parts of speech.
Polarity	In sentiment analysis, the main problem is to determine to which extent a review is positive or negative. The positivity and negativity of reviews are two main poles of human feeling. Therefore, a review generally belongs to either positive or negative polarity.
Support vector machine (SVM)	SVM is a supervised machine learning algorithm, which uses a separating hyperplane/line to categorize the given data. The hyperplane/line needs to be trained using labeled data in such a way that optimally segregates the data.
Conditional random fields (CRF)	CRF is a discriminative undirected probabilistic model that is especially used in NLP to pars a sequential data or predict sequences of class labels for sequences of input samples.
Target	In sentiment analysis, the topic (or particular subject of text) against which the analysis is performed is known as target. In tourism context, for example, restaurants or hotels are targets.
Term frequency (TF)	TF is the number of times an item (letters or words) occurs in a review.
Term frequency–inverse document frequency (TF-IDF)	TF–IDF is the product of TF and IDF. The IDF is a measure to show whether a term is common or rare across all reviews.
Unigram	Unigram is a special case of N-gram (defined above) where N = 1.
Weakly labeled data	Data with the class labels determined heuristically by machine and not manually by human beings (such as star rating)

namely (1) machine learning, (2) rule-/dictionary-based, and (3) hybrid approaches (Feldman 2013; Ribeiro et al. 2016). Machine learning methods are further categorized into supervised and unsupervised approaches. The dictionary-based approach also includes a subcategory called semantic-based approach (Tsytsarau and Palpanas 2012). A detailed description of these five categories is provided in the following.

Supervised Machine Learning Approach. A sentiment analysis method based on supervised machine learning involves

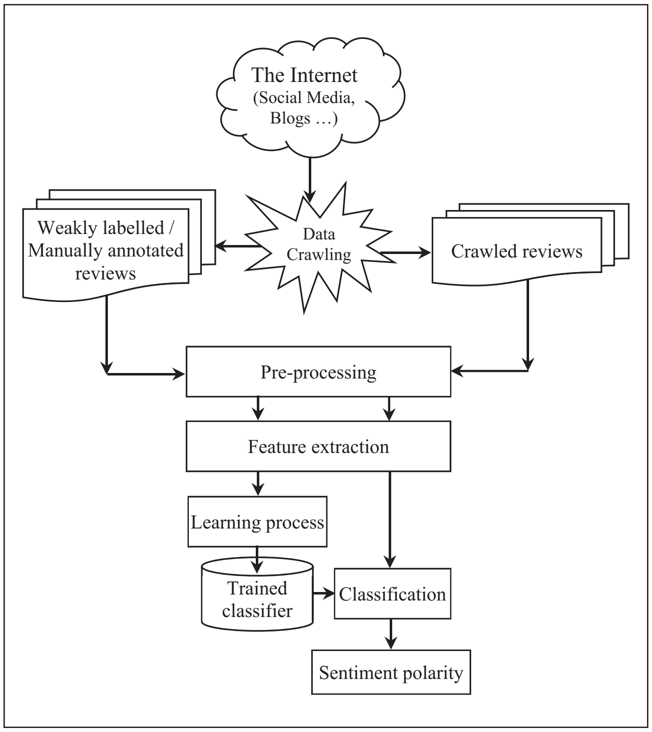

Figure 1. An overview of a machine-learning-based sentiment analysis system.

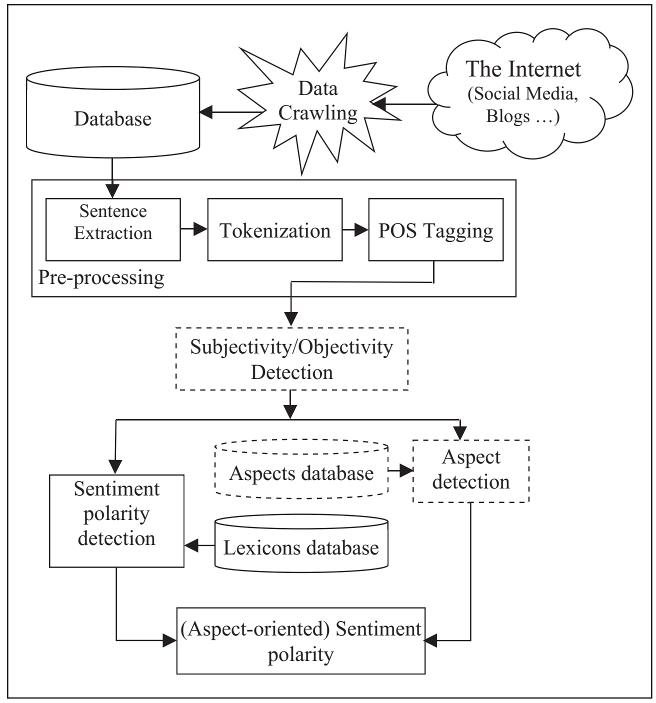

Figure 2. A general framework of the dictionary/rule-based sentiment analysis system. Dotted boxes indicate that these steps are optional or dependent on the particular model and application.

creating a model by using annotated data or weakly labeled corpora. In the manually annotation process, for example, "what a wonderful holiday!!!" is annotated as a sentence with "positive" sentiment polarity. Weakly labeled data are those data where the class labels were determined heuristically by a machine. For example, UGC on review platforms often contains weakly labeled data when reviewers assign categories (e.g., restaurant) and ratings (e.g., stars) to their reviews (Brob 2013).

Supervised machine learning approaches follow several steps (Figure 1). After applying preprocessing techniques to clean, segment and tokenize the text data, a feature extraction method is applied to characterize the review. Features extracted from the reviews are then fed to a classifier to train the classifier. The trained classifier is finally used to determine the polarity of new text. Support vector machine (SVM) and Naïve Bayes are the key machine learning methods used for sentiment analysis in the literature (Brob 2013; Kang, Yoo, and Han 2012; Markopoulos et al. 2015; Shi and Li 2011; Shimada et al. 2011; Ye, Zhang, and Law 2009), as they were conventionally designed for two-class classification problems. A SVM is a classifier which uses annotated data for training to obtain an optimal separating hyperplane/line to accurately categorize new samples data into different groups. A Naïve Bayes classifier is a probabilistic classifier, which uses Bayes's theorem in the classifier's decision rule, with an assumption that features are independent. SVM and Naïve Bayes methods need comparably less annotated data for training the models compared to the neural-network-based approach. Neural network and deep learning models (Irsoy and Cardie 2014; Socher et al. 2013) and the K-nearest neighbor method (Schmunk et al. 2014) were also employed for semantic analysis in the literature.

Unsupervised Machine Learning Approach. Cluster analysis, as an unsupervised machine learning approach, has been used for data mining, pattern recognition, and image analysis. Clustering is the task of grouping a set of data in such a way that items in a cluster are more similar to each other compared to those in other clusters. Clustering techniques, such as K-means (Xiang, Schwartz, and Uysal 2015), and statistical models based on the probability distribution of reviews in sentiment space (Rossetti et al. 2015) were employed in the literature for sentiment analysis of short text data. In addition, Naïve Bayes models were also adapted in an unsupervised fashion for sentiment analysis (e.g., Shimada et al. 2011).

Dictionary-Based Approach. As dictionary-, lexicon-, and rule-based approaches were used in the literature interchangeably, this review also uses the terms as synonyms. To provide an overview of dictionary-based methods, a complete framework of a common dictionary/rule-based sentiment analysis method is represented in Figure 2. In this approach, the detection of subjectivity versus objectivity can be integrated into the framework or it can be handled by the sentiment polarity detection process itself. Aspect or topic detection can also be included within the framework based on the specific needs of the application. Dictionary-based systems rely on the use of comprehensive sentiment lexicons and sets of fine-tuned rules. A sentiment dictionary can be created either by humans, by machine or by both humans and machine (semiautomatically). For instance, a dictionary may contain words, such as "good," "nice," "fantastic," "bad," "worse," and "ugly," with their associated values of polarity. While creating dictionaries, the polarities are assigned to the words without considering any contextual information.

Different methods were developed for dictionary-based approaches (Bjorkelund, Burnett, and Norvag 2012; Bucur 2015; Garcia, Gaines, and Linaza 2012; Hutto and Gilbert 2014; Levallois 2013). SentiWordNet by itself (Bucur 2015; Garcia, Gaines, and Linaza 2012), and in combination with a simplified Lesk algorithm, was also used in sentiment analysis (Bjorkelund, Burnett, and Norvag 2012). The Lesk algorithm is an algorithm for disambiguating word sense that works based on the hypothesis that words in a given "neighborhood" have the same topic (Bjorkelund, Burnett, and Norvag 2012). Valence aware dictionary for sentiment reasoning (VADER) is a method that has provided promising results on Twitter data (Hutto and Gilbert 2014). VADER combines a lexicon and a series of intensifiers, punctuation transformation, and emoticons, along with some heuristics to compute sentiment polarity of text. Five general rules that embody grammatical and syntactical conventions for emphasizing sentiment intensity are used for computing the sentiment polarity. The VADER sentiment lexicon is composed of more than 7,000 items, along with their associated sentiment intensity measures, validated by humans and specifically adapted to sentiment in microblog-like contexts, such as Twitter (Hutto and Gilbert 2014). Umigon is another dictionary-based method, which uses a lexicon with heuristics for sentiment detection in Twitter reviews (Levallois 2013). It is a fast and scalable method, which can handle negations, elongated words, and hashtags. Umigon provides additional semantic features, such as time or subjectivity (Levallois 2013).

Semantic Approach. The dictionary-based approach was improved by introducing semantic-based analysis methods (Tsytsarau and Palpanas 2012). The semantic approach is mainly a rule-based linguistic model to obtain a polarity for each text segment. In this approach a dictionary of domain-specific terms and their associated polarity values is required.

Hybrid Approach. In hybrid approaches, dictionary and machine learning-based approaches can work in parallel to compute two sentiment polarities. The results obtained from the dictionary and machine-learning-based methods are then combined to provide a final sentiment polarity. It is also possible to design a sentiment analysis model by incorporating both dictionary- and machine-learning-based methods at different stages of the model (Waldhör et al. 2008; Claster, Dinh, and Cooper 2010; Claster, Cooper, and Sallis 2010; Kasper and Vela 2011; Claster et al. 2013; Pappas and Popescu-Belis 2013; Schmunk et al. 2014; Chiu et al. 2015). The sentiment-aware nearest neighbor (SANN) model is a combination of dictionary-based and learning-based approaches that initially classifies a text as either a subjective or objective review (Pappas and Popescu-Belis 2013). If the text is objective, then the task of sentiment analysis is over. However, if the text is subjective, it is then further classified as either positive or negative. For a text with zero polarity, the neutral label is assigned (Pappas and Popescu-Belis 2013).

Review of Tourism-Focused Sentiment Analysis

Building on the technical overview of sentiment analysis, this section explores how sentiment analysis has been applied in tourism. Of particular interest is whether tourism-related studies are using state-of-the-art methods or whether there are further opportunities to advance the application of sentiment analysis.

Identified Studies and Datasets Used

To identify sentiment analysis studies in tourism, combinations of key words, such as "sentiment analysis of tourism," "tourism sentiment data," "sentiment analysis of hotel reviews," and "sentiment analysis of restaurant reviews" on Google search engine, instead of a specific search within Scopus and Web of Science websites, has been used to broadly search and retrieve relevant articles published on the Internet. We have further studied recent review articles on sentiment analysis to extract those references that dealt with tourism. As a result, we believe that a critical mass of tourism-related sentiment studies have been identified for this review.

An overview of seminal tourism-related studies and their specific datasets is provided in Table 2. Tourism researchers have typically used two types of online content for their sentiment analysis: reviews of tourism obtained from professional websites (e.g., TripAdvisor, Booking, and Ctrip) and social media posts (e.g., Twitter). Both types of sources usually contain short text. Twitter, for instance, allows tweets of only 140 characters in length, lending itself to a mostly sentence-level sentiment analysis. Manual and automatic annotation processes were used to label the reviews to train and evaluate the sentiment analysis methods. It is also noted that most of the datasets used in the literature relate to hotel accommodation (e.g., Kasper and Vela 2011 and 2012; Tan and Wu 2011; Bjorkelund, Burnett, and Norvag 2012; Gräbner et al. 2012; Bucur 2015; Marrese-Taylora et al. 2013; Markopoulos et al. 2015; Rossetti et al. 2015). A small number of studies focus on restaurants (Ganu, Elhadad, and Marian 2009; Zhang et al. 2011) and airlines (Misopoulos et al. 2014).

Table 2. A Brief Overview of the Methods and Datasets Previously Used for Sentiment Analysis in the Domain of Tourism.

Study	Type of approach	Source of data	Language	Type of reviews	Annotation type	No. of reviews	No. of annotated data	No. of positive reviews	No. of negative reviews	No. of neutral reviews
Zheng and Ye (2009)	Machine learning	Ctrip.com	Chinese	Hotel	Manual	479	479	292	187	0
Brob (2013)	Machine learning	Tripadvisor.com	English	Hotel	Manual	417,170	310	195	68	47
Bjorkelund, Burnett, and Norvag (2012)	Machine learning	Tripadvisor.com, Booking.com	English	Hotel	Automatic	794,962	794,962	Not reported	Not reported	Not reported
Markopoulos et al. (2015)	Machine learning	Tripadvisor.com	Greek	Hotel	Semiautomatic	1,800	1,800	900	900	0
Pablos, Cuadros, and Linaza (2015)	Machine learning	zoover.com	6 languages	Hotel	Manual	1,200	1,200	Not reported	Not reported	Not reported
Xiang, Schwartz, and Uysal (2015)	Machine learning	Expedia.com	English	Hotel	Automatic	60,648	60,648	Not reported	Not reported	Not reported
Gindl, Weichselbraun, and Scharl (2010)	Machine learning	Tripadvisor.com	English	Travel	Manual	1,800	1,800	900	900	0
Ye, Zhang, and Law (2009)	Machine learning	Travel.yahoo.com	English	Travel	Automatic/manual	1,191	1,191	600	591	0
Ganu, Elhadad, and Marian (2009)	Machine learning	Citysearch	English	Restaurant	Manual	52,264	3,400	1,904	612	1,884
Kang, Yoo, and Han (2012)	Machine learning	Restaurant websites	English	Restaurant	Automatic/manual	70,000	11,400	5,700	5,700	0
Zhang et al. (2011)	Machine learning	OpenRice.com	Cantonese (Chinese)	Restaurant	Automatic/manual	1,800	1,800	900	900	0
Rossetti et al. (2015)	Machine learning	Yelp, Tripadvisor.com	English	Hotel and Restaurant	Automatic	3,733, 12,342	3,733, 12,342	Not reported	Not reported	Not reported
Shimada et al. (2011)	Machine learning	Twitter	English	Tourism	Automatic/manual	10,000,000	200,000/116	100,000/64	100,000/52	0
Misopoulos et al. (2014)	Lexicon-based	Twitter	English	Airlines	Automatic/manual	67,953	67,953/(1,587)	Not reporter (271)	Not reporter (335)	61,158 (981)
Gräbner et al. (2012)	Lexicon-based	Tripadvisor.com	English	Hotel	Automatic	80,000	80,000	Not reported	Not reported	Not reported
Garcia, Gaines, and Linaza (2012)	Lexicon-based	Tripadvisor.com	Spanish	Hotel and restaurant	Automatic/manual	1,994	1,994/40	Not reported	Not reported	Not reported
Bucur (2015)	Lexicon-based	Tripadvisor.com	English	Hotel	Manual	3,000	3,000	1,500	1,500	0
Marrese-Taylora et al. (2013)	Lexicon-based	Tripadvisor.com	English	Hotel and restaurant	Manual	200	200	Not reported	Not reported	Not reported
Tan and Wu (2011)	Lexicon-based	Ctrip.com	Chinese	Hotel	Manual	4,000	4,000	2,000	2,000	0
Xiang, Schwartz, Gerdes, et al. (2015)	Semantic approach	Expedia.com	English	Hotel	Automatic	60,648	60,648	Not reported	Not reported	Not reported
Kasper and Vela (2011 and 2012)	Hybrid	Web, blogs	German	Hotel	Manual	4,792	4,792	2,240	1,183	938
Chiu et al. (2015)	Hybrid	Wretch and Yahoo Blogs	Chinese	Hotel	Manual	2,147	2,147	1,899	248	0
Schmunk et al. (2014)	Hybrid	Tripadvisor.com, Booking.com	English	Hotel	Manual	1,516	1,516	Not reported	Not reported	Not reported
Claster, Dinh, and Cooper (2010), Claster, Cooper, and Sallis (2010), Claster et al. (2013)	Hybrid	Twitter	English	Tourism	Automatic/manual	70,570,800	200	Not reported	Not reported	Not reported

Both supervised and unsupervised machine learning, dictionary-based, semantic, and hybrid sentiment analysis approaches were used in the tourism literature. In terms of supervised machine learning approach for sentiment analysis in tourism, SVM (Ganu, Elhadad, and Marian 2009; Ye, Zhang, and Law 2009; Zheng and Ye 2009; Shi and Li 2011; Zhang et al. 2011; Brob 2013; Markopoulos et al. 2015; Pablos, Cuadros, and Linaza 2015; Schmunk et al. 2014), Naïve Bayes (Schmunk et al. 2014), conditional random fields (CRF) (Pablos, Cuadros, and Linaza 2015), nearest neighbor (Schmunk et al. 2014), and entropy-based classifiers (Brob 2013) were employed. Different types of features, such as TF (Ye, Zhang, and Law 2009), TF-IDF (Shi and Li 2011), stemmed word (Ganu, Elhadad, and Marian 2009), bag-of-words (Markopoulos et al. 2015), information gain (IG) (Zheng and Ye 2009), N-gram (Brob 2013; Kang, Yoo, and Han 2012; Markopoulos et al. 2015; Zhang et al. 2011; Pablos, Cuadros, and Linaza 2015) were proposed to characterize tourism reviews.

An unsupervised machine learning approach based on Naïve Bayes classifier was implemented by Shimada et al. (2011) to produce a sentiment analysis of tourism data at the sentence level. The Naïve Bayes sentiment classification approach was trained using automatically labeled data. Emoticons, such as ☺ and ☹, were used to represent positive and negative seeds to label data for training instead of words, such as "excellent" and "poor." Therefore, reviews that contained a smiley face, for example, were considered as positive and those with an angry face were classed as negative (Shimada et al. 2011). K-mean clustering techniques and statistical models based on probability distribution of reviews in sentiment space (Rossetti et al. 2015; Xiang, Schwartz, and Uysal 2015) were also employed on tourism data.

Several tourism studies have drawn on dictionary-based approaches. Misopoulos et al. (2014) used a lexicon type method to assess the polarity of Twitter posts relevant to an airline service delivery. The results revealed those areas/aspects of the airline customer service where customers were dissatisfied, satisfied, or even delighted. The analysis was, however, based on a limited number of 20 keywords (10 positive and 10 negative), which posed a significant restriction to the findings from this research. Moreover, negation was not incorporated in the system to accurately capture the meaning of opinions, such as "not bad." Another example can be found in Sharma, Kulshreshtha, and Paygude (2015) who analyzed travel reviews at the sentence level using a lexicon-based system. Other dictionary-based analysis focused on hotel and restaurant customer reviews (Bucur 2015; Gräbner et al. 2012; Marrese-Taylora et al. 2013; Schmunk et al. 2014). The dictionary used in Gräbner et al.'s (2012) study was a hotel domain-specific lexicon of semantically relevant words. Previous research established that features with high intensity over different time periods can be useful to detect abnormal changes in hotel reviews, and to analyze the reasons for these changes. Such trends can be particularly useful when visualized (e.g., on a map) to potential customers (Bjorkelund, Burnett, and Norvag 2012).

A semantic approach for text analysis was proposed by Xiang, Schwartz, Gerdes, et al. (2015) to understand hotel guest experience and their satisfaction. As a part of the system proposed by Kasper and Vela (2011 and 2012), a rule-based linguistic model using semantic information helped to obtain a polarity for each text segment in addition to topic identification. In this approach, a domain-specific dictionary was, however, used that makes this system domain dependent.

Finally, a few tourism researchers have used hybrid methods. The work proposed by Waldhör and Rind (2008) is an early attempt in the field of tourism. The authors propose to combine a linguistic parsing methodology with information and terminology extraction methods to determine sentiment polarity of online blog reviews. Using binary choice keywords and a Naïve Bayes algorithm helped measure sentiment polarities of tweets related to different tourist destinations (Claster, Dinh, and Cooper 2010; Claster, Cooper, and Sallis 2010; Claster et al. 2013). Binary choice keywords are two sets of subjective keywords that constitute antonyms, for example, bad versus good. Another sentence-level hybrid sentiment analysis system was presented by Kasper and Vela (2011 and 2012) in the context of German-language hotel reviews. The study first applied a language filter to select reviews written in German. The filtered texts were then disaggregated into individual sentences, and these sentences were subjected to a polarity classifier and a linguistic information extraction process for detecting respective topics and their polarities. For the information extraction, a dictionary of hotel-specific terms and a sentiment dictionary that associates basic polarity values with these terms were created. The polarity values from the statistical and the linguistic classification were then combined into a joint global polarity value to present the sentiments on the user interface. Sentiment analysis on Chinese e-WOM was proposed by Chiu et al. (2015). Combining a supervised probabilistic model and a heuristic n-phrase rule was used to effectively obtain customer opinions about hotel attributes. Schmunk et al. (2014) further discussed a system to initially detect the subjectivity of a sentence by a dictionary-based method. Then, the classification of the sentence into positive or negative was performed using bigrams features along with a SVM classifier (Schmunk et al. 2014). However, this type of approach suffers from the promoting of the errors occurred in the first step to the subsequent steps of the system. This drawback may be mitigated by using a backward feedback from the current to the earlier steps.

It is also noted that for subjectivity detection, SVM, Naïve Bayes, and K-nearest neighbor methods with regard to machine learning approach, and dictionary-based approach were applied to tourism (Schmunk et al. 2014). In addition, for topic detection, SVM, Naïve Bayes, and K-nearest neighbor methods (as supervised machine learning approach) terminology and dictionary-based approach as well as frequent words, latent-semantic indexing, sequential pattern mining, and cluster analysis (as unsupervised techniques) were applied in the tourism context (Brob 2013; Markopoulos et al. 2015; Höpken et al. 2016; Schmunk et al. 2014). These methods can detect explicitly mentioned topics in reviews.

In summary, a relatively broad range of studies exist in the domain of tourism, mainly in relation to hotels and accommodation. Most studies have used data written in English for sentiment analysis, but few used reviews written in Chinese, Spanish, and German (Zheng and Ye 2009; Tan and Wu 2011; Garcia, Gaines, and Linaza 2012; Kasper and Vela 2011; Zhang et al. 2011). Furthermore, our review revealed that most tourism sentiment analyses are based on a machine learning approach, although a considerable number of studies have also used a dictionary-based approach. The main advantage of the latter is that there is no need for annotated text corpora for training sentiment extraction models. Moreover, creating a lexicon is a one-time effort and can be used forever and often across different domains. The more sophisticated hybrid approaches have only been used in a few instances, indicating future research opportunities. In most cases, publicly available dictionaries were used or adapted to the tourism context. Domain-specific lexica are rarely used, thus, compromising the quality of the sentiment analysis. A possible way forward is to use an aspect-dictionary-based method first to initially determine a review aspect (e.g., food quality in a restaurant), followed by a machine learning method to obtain the sentiment polarity of a review. This could begin by using weakly labeled data for an initial training of a model and complete the task by using manually annotated data to obtain a refined model.

Evaluation Metrics

As mentioned earlier, most sentiment analysis methods provide either a two-class (positive and negative) or a three-class (positive, neutral, and negative) classification. It is important to evaluate and quantify the performances of different methods. A clean and unambiguous way to present the prediction results of a classifier is to use a confusion matrix, which is also called contingency table (see Table 3 for a three-class problem). Each letter in Table 3 denotes the number of review instances, which belong to the original class provided by an annotation process and are anticipated as predicted class obtained from a classifier, where class labels are positive (*Pos*), neutral (*Neu*), and negative (*Neg*).

The Accuracy (A) is one of the evaluation metrics commonly used in the literature (Ribeiro et al. 2016). It is simply the number of correct predictions of sentiment made, divided by the total number of predictions made. The accuracy measures how accurate the method is in its prediction of the correct output. The metric A, as shown in Formula (1), assumes that every correct classification of the input reviews independent of the class label has an equal weight.

Table 3. Confusion Matrix of the Results Obtained for a General Three-Class Classification Problem.

		(Predicted)		
		Pos	*Neu*	*Neg*
(Original)	*Pos*	a	b	c
	Neu	d	e	f
	Neg	g	h	i

$$A = \frac{a+e+i}{\mathrm{a+b+c+d+e+f+g+h+i}} \qquad \text{Formula (1)}$$

Precision, Recall, and $F1$-measure are the other three evaluation metrics frequently used for evaluating the results of sentiment analyses (Brob 2013; Markopoulos et al. 2015; Ribeiro et al. 2016). Considering a sample sentiment analysis system of three classes, and using the definitions provided in Table 3, the Precision (P) of a class, for example positive (*Pos*), is defined as the ratio of the number of instances correctly classified as the class *Pos* relative to the total number of instances predicted as the class *Pos*. The Recall (R) of a class, for example *Pos*, is then defined as the ratio of the number of instances correctly classified as the class *Pos* with respect to the total number of instances, which actually should be classified as the class *Pos*. The $F1$ measure is a weighted harmonic mean of both, the Precision and Recall. The described metrics for the three-class problem can easily be adapted for the two-class problem by removing the Neutral column and row from Table 3. Based on the above-mentioned definitions, the P, R, and $F1$ measures of the *Pos* class are computed as follows:

$$P(Pos) = \frac{a}{(a+d+g)} \qquad \text{Formula (2)}$$

$$R(Pos) = \frac{a}{(a+b+c)} \qquad \text{Formula (3)}$$

$$F1(Pos) = \frac{2 \times P(Pos) \times R(Pos)}{P(Pos) + R(Pos)} \qquad \text{Formula (4)}$$

Performance of Sentiment Analyses in Tourism Studies

The evaluation analyses, as introduced earlier, were performed on available tourism datasets (Table 4). The results indicate that the majority of tourism-related sentiment analysis studies used a binary polarity classification (e.g., Zheng and Ye 2009; Ye, Zhang, and Law 2009; Gindl, Weichselbraun, and Scharl 2010; Shimada et al. 2011; Zhang et al. 2011; Bjorkelund, Burnett, and Norvag 2012; Kang, Yoo, and Han 2012). Some studies followed a slightly different approach, whereby the sentiment analysis was divided into

Table 4. Sentiment Analysis Results Obtained from Different Methods in the Domain of Tourism.

Study	Feature	Classifier	Dataset	No. of annotated reviews	No of classes	*A*	*P*	*R*	*F*1-measure
Binary classification									
Kasper and Vela (2011)	N-gram	Statistical classifier	Hotel reviews	4,792	2	0.82	—	—	0.80
Bjorkelund, Burnett, and Norvag (2012)	N-gram	Dynamic language model classifier	Hotel reviews from tripadvisor.com	501,083	2	0.90	—	—	—
Gindl, Weichselbraun, and Scharl (2010)	Stemmed words	Naïve Bayes	Travel reviews	1,800	2	—	0.81	0.78	0.78
Ye, Zhang, and Law (2009)	TF	Naïve Bayes	Travel reviews	1,191	2	0.807	0.82	0.82	—
Ye, Zhang, and Law (2009)	TF	SVM	Travel reviews	1,191	2	0.851	0.851	0.851	—
Zheng and Ye (2009)		SVM	Hotel reviews	479	2	0.912	0.912	0.901	—
Markopoulos et al. (2015)	Unigram	SVM	Hotel reviews	1,800	2	0.718	0.65	1	0.79
Bjorkelund, Burnett, and Norvag (2012)	N-gram	Dynamic language model classifier	Hotel reviews from booking.com	293,879	2	0.66	—	—	—
Shimada et al. (2011)	Unigram	Naïve Bayes	Tourism information	116	2	0.92	—	—	—
Kang, Yoo, and Han (2012)	N-gram	Naïve Bayes	Restaurant reviews	11,400	2	—	0.737	0.728	—
Zhang et al. (2011)	N-gram	SVM	Restaurant reviews	1,800	2	0.948	0.948	0.948	—
Zhang et al. (2011)	N-gram	Naïve Bayes	Restaurant reviews	1,800	2	0.957	0.957	0.957	—
Chiu et al. (2015)	N-gram	SVM, statistical classifier	Hotel reviews	442	2		0.89	0.91	0.89
Two-step classification									
Marrese-Taylora et al. (2013)	Lexicon	Lexicon-based method	Hotel and restaurant	200	2/3	—	0.90	0.93	0.92
Multiclass classification									
Kasper and Vela (2012)	N-gram	Statistical classifier	Hotel reviews	4,792	3	0.81	—	—	—
Schmunk et al. (2014)	Bigrams	SVM + Lexicon	Hotel reviews	1,516	3	0.768	—	—	—
Pablos, Cuadros, and Linaza (2015)	Unigram	SVM + CRF	Hotel reviews	1,200	3		0.76	0.49	0.59
Brob (2013)	Unigram	SVM	Hotel reviews	310	3	—	0.67	0.66	0.68
Gräbner et al. (2012)	Lexicon	Lexicon-based method	Hotel reviews	80,000	3	—	0.68	0.57	0.62
Ganu, Elhadad, and Marian (2009)	Stemmed words	SVM	Restaurant reviews	3,400	4	0.81	0.51	0.45	0.48
Bucur (2015)	Lexicon	Lexicon-based method	Hotel reviews	3,000	3	0.72	0.737	0.856	0.792
Garcia, Gaines, and Linaza (2012)	Lexicon	Lexicon-based method	Hotel and restaurant	1,994/40	3	0.80	—	—	—

Table 5. Comparison of the Sentiment Analysis Results Obtained from Different Methods on Sanders's Twitter Dataset (Sanders 2011).

Authors	Feature	Classifier	No. of classes	*A*	*P*	*R*	*F*1-measure
Binary classification							
Pappas and Popescu-Belis (2013)	POS + lexicon	Lexicon + nearest neighbor model	2	0.70	0.72	0.71	0.715
Levallois (2013)	Lexicon	Lexicon-based method	2	0.82	0.83	0.82	0.82
Hutto and Gilbert (2014)	Lexicon	Lexicon-based method	2	0.77	0.79	0.77	0.78
Two-step classification							
Pappas and Popescu-Belis (2013)	POS + lexicon	Lexicon + nearest neighbor model	3	0.55	0.46	0.39	0.42
Multiclass classification							
Levallois (2013)	Lexicon	Lexicon-based method	3	0.66	0.58	0.56	0.57
Hutto and Gilbert (2014)	Lexicon	Lexicon-based method	3	0.60	0.50	0.69	0.58

two subtasks, namely (1) classifying sentences into objective and subjective sentences and (2) then determining the polarity of the subjective sentences (Marrese-Taylora et al. 2013; Riloff and Wiebe 2003). Furthermore, a few studies followed an approach that involved determining polarity of sentences by using multiclass classifiers in a single step; that is, they relied on a three-class classifier (e.g., Ganu, Elhadad, and Marian 2009; Gräbner et al. 2012; Brob 2013).

It is worth mentioning that the results are not directly comparable, as the sizes of the databases, the number of classes and the types of data are quite different for the evaluation of each method. There is some indication, however, that better results in terms of accuracy and F-measure were obtained when only two classes (positive, negative) were used in the experimentations. To have a fair comparison of the results obtained using Twitter reviews, three methods (Levallois 2013; Pappas and Popescu-Belis 2013; Hutto and Gilbert 2014) along with a publicly available Twitter-based dataset for products (Sanders 2011) were further considered for experimentation. The results are presented in Table 5. The method proposed by Levallois, (2013) has provided the best results in the binary classification problem. However, VADER (Hutto and Gilbert 2014) delivered the best results in the multiclass classification case. As these methods have provided reasonably good performances on Twitter data, and their lexicons also contain tourism-related words and emoticons, they are applicable to the tourism domain.

Synthesis of the Tourism-Specific Results

Based on the above insights, it can be noted that the majority of tourism sentiment analyses used a machine learning approach, often trained with small annotated datasets, as this process needs considerable human resources. In future more sophisticated sentiment analyses could draw based on machine learning approaches using larger annotated datasets in combination with weakly annotated data to learn more complex rules making the use of potential correlations within data. Furthermore, future studies using lexicon-based methods could improve their performance by further adapting sentiment lexicons to the tourism domain.

From the results reported in the literature, we noted that most sentiment analysis methods perform better in classifying positive sentences than negative or neutral sentences. One reason might be because of the existence of a larger number of positive texts in datasets that bias the databases and lexicons toward positivity, as human language is inherently biased toward positivity (Dodds et al. 2015). Moreover, analyzing the negation in reviews is semantically a complex task. Related to the issue of bias, the review shows that the overall prediction performance of the methods can still be improved in both two-class and three-class sentiment analysis, but particularly in three-class approaches. It appears that neutral reviews are difficult to detect in most of the sentiment analysis methods (Ribeiro et al. 2016). To address the above issues, tourism-specific analysis might benefit from transferring insights generated from other domains, for example, sentiment analysis of movies, products or advertisement. Should new areas of tourism be explored, beyond the current focus on hotels and restaurants, then new data sources and domain-specific lexicons need to be considered.

Assuming further refinements, it is important to investigate whether these types of large scale sentiment analyses might impact on the tourism and travel industry in that they define new forms of customer feedback and service standards that are possibly tailored to specific market segments. Broader approaches that take a broader destination-based methodology would be necessary. Such analyses would have to seek to understand the significant societal implications of social media, and Big Data beyond tourism (Ahlqvist et al. 2010). Recognizing the embeddedness of social media in people's lives and behaviors will also help the tourism industry to develop better systems for product development and delivery, market research, and risk management, to name a few.

Advancing sentiment analysis, both conceptually and practically, means to focus analyses on specific targets or aspects mentioned in text. Target-specific polarity detection is a key challenge in the field of sentiment analysis, as the sentiment polarity of words and phrases may depend on the aspect. For example, considering the adjective word "small," in the case of "small room" can be interpreted as negative, but in relation to a "handbag" it might be seen as positive. Further research on the relations between targets and expressions, and implications for sentiment, is necessary. Targets can be further defined through their aspects, and relations among aspects of a target can be modeled using ontology learning techniques (Maedche and Staab 2001). However, depending on the application and the rules of grouping, hierarchical relationships between aspects and target can be different. Creating an appropriate taxonomy for aspects related to a target helps to determine more precise aspect-oriented sentiment analysis. One important problem in aspect-oriented sentiment analysis is to discover implicit aspects. Consider the following two reviews, for example: "our luggage was delivered very quickly," and "it took an hour time to receive our luggage!!!" The first example includes a subjective assessment ("quickly"), the second example merely states a fact (an hour time = late delivery). To provide a negative evaluation of the luggage delivery process in the second example, common sense knowledge is required to interpret that an hour is not acceptable for luggage delivery. In the literature, this form of implicit sentiment is referred to as objective polar utterance (Fang et al. 2016) or evaluative fact (Gräbner et al. 2012), or it is denoted as a polar fact (Leung et al. 2013).

In relation to the features, different types of features, such as lexical features (e.g., N-grams and Bag of Opinions), knowledge-based features (e.g., sentiment lexicons), linguistic features (e.g., lemmatization, and syntax), and sentiment shifter features (e.g., negation, intensification, and neutralization) have frequently been considered for sentiment analysis in other domains. These features can also be employed on tourism-related data to study their performance and applicability. Regarding the role of features in sentiment analysis, it is noted that sentiment shifters and negations most probably modify the sentiment polarity of an individual expression, a sentence, or even a whole document. The word order and contextual and dependency structure of individual phrases may also affect the polarity of a sentence. Features derived based on a sentiment lexicon improve sentiment analysis results. It has further been shown that the use of a simple bag of words (BoW) representation for sentiment analysis provides less favorable results compared to a traditional topic classification, as in sentiment analysis, semantic information also needs to be modeled by BoW, which is a difficult task. Considering higher order N-grams and complex linguistic features are helpful for polarity classification and can improve the results significantly. However, the use of higher order N-grams and complex linguistic features is beneficial when large corpora are available for training the models. When using smaller corpora, a feature selection step is necessary to obtain satisfactory sentiment analysis results.

In relation to the kind of data used for sentiment analysis in tourism, we noted that most of the travel agencies and hotel booking service providers employ scalar ratings to rate users' reviews, for example, star scores between one and five. Such scores alone cannot help managers or service providers understand what the issues are and where improvements are necessary. However, from an analytical perspective, the user-provided scores function as weakly labeled data, and can improve the classification accuracy, as well as help to verify polarity.

Concluding Remarks and Future Directions

While compelling in theory, in practice, the task of extracting and processing increasingly high velocity and large volumes of data has become very complex and made it necessary to develop automated machine-based approaches. Various methods exist to extract sentiment from online text, and these have been reviewed in this article, both from a general and a tourism specific perspective. Due to the difficulty of detecting and finding implicit aspects in reviews, aspect-oriented sentiment analysis is still a challenging problem. In relation to aspect-oriented sentiment analysis, future research requires close collaborations between domain experts (i.e., tourism researchers), information technology and NLP scientists to initially create and make publicly available some specific dictionaries for topics/aspects as well as annotated review databases related to industries involved in tourism. This will first help to design a more sophisticated aspect-oriented sentiment analysis model to better deal with the problem of implicit aspect detection in reviews. Second, it will enhance the research in the tourism domain by making new hypothesis, for example, finding/understanding the relation between satisfaction and sentiment (Xiang, Schwartz, Gerdes, et al. 2015) and then estimating tourist satisfaction, as one of the key concepts in tourism, by analyzing aspect-oriented sentiment of text.

Moreover, using Big Data and deep learning approaches can help tourism research to discover dynamics based on large interconnected sets of data and getting more insight from different aspects of Big Data. Tourism research may further move into a new area, where theory driven approaches and data driven practices can support each other to understand or explain phenomena as well as to realize new dimensions in theories. This review article concludes by suggesting that tourist sentiment analysis is the tip of an iceberg toward a new research paradigm for tourism. Sentiment analysis is only the beginning of more complex approaches using Big Data. In particular, the integration of several types of data has a great potential for generating future insights at scales not seen before. Combining sentiment scores with other data, such as information on transport, weather, the environment, special events, crises, and other destination components may give rise to finding patterns that could not been seen and understood before. For example, the relative importance of weather conditions on visitor satisfaction, moderated by any other potential factors captured through various datasets, could be investigated. Adding other nontraditional data, such as imagery shared through Twitter or other social media, video footage (including security cameras), and electronic transaction footprints, enhanced by deep learning and object recognition technology can provide valuable information and reveal interesting insight that could not be hypothesized to those involved in tourism research and practice.

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References

Ahlqvist, T., A. Böck, S. Heinonen, and M. Halonen. 2010. "Road-Mapping the Societal Transformation Potential of Social Media." *Foresight* 12 (5): 3-26.

Akehurst, G. 2009. "User Generated Content: The Use of Blogs for Tourism Organisations and Tourism Consumers." *Service Business* 3:51-61.

Allan, J., J. G. Carbonell, G. Doddington, J. Yamron, and Y. Yang. 1998. "*Topic Detection and Tracking Pilot Study Final Report*." In *Proceedings of the Broadcast News Transcription and Understanding Workshop*, 194-218. Burlington, MA: Morgan Kaufman.

Anderson, C., 2008. "The End of Theory: The Data Deluge Makes the Scientific Method Obsolete Science." *Wired*, June 23. http://www.wired.com/science/discoveries/magazine/16-07/pb_theory.

Aurchana, P., R. Iyyappan, and P. Periyasamy. 2014. "Sentiment Analysis in Tourism." *International Journal of Innovative Science, Engineering and Technology* 1 (9): 443-50.

Bjorkelund, E., T. H. Burnett, and K. Norvag. 2012. "*A Study of Opinion Mining and Visualization of Hotel Reviews*." In *Proceedings of the 14th International Conference on Information Integration and Web-Based Applications and Services*, 229-38. New York: ACM.

Brob, J. 2013. "Aspect-Oriented Sentiment Analysis of Customer Reviews Using Distant Supervision Techniques." PhD diss., University of Berlin.

Bucur, C. 2015. "*Using Opinion Mining Techniques in Tourism*." In *Proceedings of the 2nd Global Conference on Business, Economics, Management and Tourism*, 1666-73. Amsterdam: Elsevier.

Cantallops, A. S., and F. Salvi. 2014. "New Consumer Behavior: A Review of Research on eWOM and Hotels." *International Journal of Hospitality Management* 36:41-51.

Chiu, C., N.-H. Chiu, R.-J. Sunga, and P.-Y. Hsieh. 2015. "Opinion Mining of Hotel Customer-Generated Contents in Chinese Weblogs." *Current Issues in Tourism* 18 (5): 477-95.

Choi, S., X. Y. Lehto, and A. M. Morrison. 2007. "Destination Image Representation on the Web: Content Analysis of Macao Travel Related Websites." *Tourism Management* 28 (1): 118-29.

Choudhury, N. N. 2016. "Sentiment Analysis of Twitter Data for a Tourism Recommender System in Bangladesh." Master's thesis, Aalto University.

Chua, A. Y. K., and S. Banerjee. 2013. "Reliability of Reviews on the Internet: The Case of TripAdvisor." In *Proceedings of the World Congress on Engineering and Computer Science*, 453-57. New York: Springer.

Claster, W. B., M. Cooper, and P. Sallis. 2010. "Thailand-Tourism and Conflict Modelling Sentiment from Twitter Tweets Using Naïve Bayes and Unsupervised Artificial Neural Nets." In *Proceedings of the Second International Conference on Computational Intelligence, Modelling and Simulation*, 89-94. New York: IEEE.

Claster, W. B., Q. H. Dinh, and M. Cooper. 2010. "Naïve Bayes and Unsupervised Artificial Neural Nets for Cancun Tourism Social Media Data Analysis." In *Proceedings of the Second World Congress on Nature and Biologically Inspired Computing*, 158-63. New York: IEEE.

Claster, W. B., P. Pardo, M. Cooper, and K. Tajeddini. 2013. "Tourism, Travel and Tweets: Algorithmic Text Analysis Methodologies in Tourism." *Middle East Journal of Management* 1 (1): 81-99.

Confente, I. 2015. "Twenty-Five Years of Word-of-Mouth Studies: A Critical Review of Tourism Research." *International Journal of Tourism Research* 17:613-24.

Dhiratara, A., J. Yang, A. Bozzon, and G.-J. Houben. 2016. "Social Media Data Analytics for Tourism: A Preliminary Study." In *Proceedings of the KDWeb 2016*. http://ceur-ws.org/Vol-1748/paper-12.pdf.

Dodd, J. 2014. "Twitter Sentiment Analysis." http://trap.ncirl.ie/1868/1/johndodd.pdf.

Dodds, P. S., E. M. Clark, S. Desu, M. R. Frank, A. J. Reagan, J. R. Williams, et al. 2015. "Human Language Reveals A Universal Positivity Bias." *Proceedings of the National Academy of Sciences USA* 112 (8): 2389-94.

Dolnicar, S., B. Grün, and V. Yanamandram. 2013. "Dynamic, Interactive Survey Questions Can Increase Survey Data Quality." *Journal of Travel and Tourism Marketing* 30:690-99.

Ellion. 2007. "Web 2.0 and the Travel Industry: Practical Strategies for Exploiting the Social Media Revolution." ICT-Technical Reports. http://www.elliontravel.com/pdfs/41.pdf.

Fang, B., Q. Ye, D. Kucukusta, and R. Law. 2016. "Analysis of the Perceived Value of Online Tourism Reviews: Influence of Readability and Reviewer Characteristics." *Tourism Management* 52:498-506.

Feldman, R. 2013. "Techniques and Applications for Sentiment Analysis." *Communications of the ACM* 56 (4): 82-89.

Filieri, R., S. Alguezaui, and F. McLeay. 2015. "Why Do Travelers Trust TripAdvisor? Antecedents of Trust towards Consumer-Generated Media and Its Influence on Recommendation Adoption and Word of Mouth." *Tourism Management* 51:174-85.

Fricke, M. 2015. "Big Data and its Epistemology." *Journal of the American Society for Information Science and Technology* 66 (4): 651-661.

Fuchs, M., W. Höpken, and M. Lexhagen. 2014. “Big Data Analytics for Knowledge Generation in Tourism Destinations—A Case from Sweden.” *Journal of Destination Marketing and Management* 3 (4):198-209.

Ganu, G., N. Elhadad, and A. Marian. 2009. “Beyond the Stars: Improving Rating Predictions Using Review Text Content.” In *Proceedings of the 12th International Workshop on the Web and Databases*, 1-6. New York: ACM.

Gao, S., J. Hao, and Y. Fu. 2015. “The Application and Comparison of Web Services for Sentiment Analysis in Tourism.” In *Proceedings of the 12th International Conference on Service Systems and Service Management*, 1-6. New York: IEEE.

Garcia, A., S. Gaines, and M. T. Linaza. 2012. “A Lexicon Based Sentiment Analysis Retrieval System for Tourism Domain.” *e-Review of Tourism Research* 10 (2): 35-38.

Garcia-Pablos, A., A. L. Duca, M. Cuadros, M. T. Linaza, and A. Marchetti. 2016. “Correlating Languages and Sentiment Analysis on the Basis of Text-Based Reviews.” In *Information and Communication Technologies in Tourism 2016*, edited by A. Inversini and R. Schegg, 565-77. New York: Springer.

Ghose, A., P. G. Ipeirotis, and B. Li. 2012. “Designing Ranking Systems for Hotels on Travel Search Engines by Mining User-Generated and Crowd Sourced Content.” *Marketing Science* 31 (3): 493-520.

Gindl, S., A. Weichselbraun, and A. Scharl. 2010. “Cross-Domain Contextualisation of Sentiment Lexicons.” In *Proceedings of the 19th European Conference on Artificial Intelligence*, 771-76. Amsterdam: IOS.

Gonçalves, P., M. Araújo, F. Benevenuto, and M. Cha. 2013. “Comparing and Combining Sentiment Analysis Methods.” In *Proceedings of the First ACM Conference on Online Social Networks*, 27-38. New York: ACM.

Gräbner, D., M. Zanker, G. Fliedl, and M. Fuchs. 2012. “Classification of Customer Reviews Based on Sentiment Analysis.” In *Information and Communication Technologies in Tourism 2012*, edited by M. Fuchs, F. Ricci, and L. Cantoni, 460-70. New York: Springer.

Gretzel, U., K. H. Yoo, and M. Purifoy. 2007. “Online Travel Review Study: Role and Impact of Online Travel Reviews.” ICT-Technical Reports, Laboratory for Intelligent Systems in Tourism. http://hdl.handle.net/123456789/877.

Hepburn, C. 2007. “Web 2.0 for the Tourism and Travel Industry: A White Paper.” ICT-Technical Reports, Laboratory for Intelligent Systems in Tourism. http://hdl.handle.net/123456789/390.

Hippner, H., and R. Rentzmann. 2006. *Text Mining*. Ingolstadt: Springer-Verlag.

Höpken, W., M. Fuchs, G. Höll, D. Keil, and M. Lexhagen. 2013. “Multi-dimensional Data Modelling for a Tourism Destination Data Warehouse.” In *Information and Communication Technologies in Tourism 2013*, edited by L. Cantoni and P. Xiang, 157-69. New York: Springer.

Höpken, W., M. Fuchs, D. Keil, and M. Lexhagen. 2015. “Business Intelligence for Cross-Process Knowledge Extraction at Tourism Destination.” *Journal of Information Technology and Tourism* 15 (2): 101-30.

Höpken, W., M. Fuchs, T. Menner, and M. Lexhagen, 2016. “Sensing the Online Social Sphere—The Sentiment Analytical Approach.” In *Analytics in Smart Tourism Design—Concepts and Methods*, edited by Z. Xiang, A. Alzua, and D. Fesenmaier, 129-46. New York: Springer.

Hu, M., and B. Liu. 2004. “Mining and Summarizing Customer Reviews.” In *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, edited by W. Kim, et al., 168-77. New York: ACM.

Hutto, C., and E. Gilbert. 2014. “Vader: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text.” In *Proceedings of the 8th International AAAI Conference on Weblogs and Social Media*, 216-25. Palo Alto, CA: AAAI.

IBM. n.d. “The Four V’s of Big Data.” http://www.ibmbigdatahub.com/infographic/four-vs-big-data.

Irsoy, O., and C. Cardie. 2014. “Opinion Mining with Deep Recurrent Neural Networks.” In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, 720-28. New York: ACM.

Kang, H., S. J. Yoo, and D. Han. 2012. “Senti-lexicon and Improved Naïve Bayes Algorithms for Sentiment Analysis of Restaurant Reviews.” *Expert Systems with Applications* 39 (5): 6000-6010.

Kasper, W., and M. Vela. 2011. “Sentiment Analysis for Hotel Reviews.” In *Proceedings of the Computational Linguistics-Applications Conference*, 45-52. New York: IEEE.

Kasper, W., and M. Vela. 2012. “Monitoring and Summarization of Hotel Reviews.” In *Information and Communication Technologies in Tourism 2012*, edited by M. Fuchs, F. Ricci, and L. Cantoni, 471-82. New York: Springer.

Kitchin, R. 2014. “Big Data, New Epistemologies and Paradigm Shifts.” *Big Data and Society* 1 (1). http://journals.sagepub.com/doi/abs/10.1177/2053951714528481.

Kuttainen, C., M. Lexhagen, M. Fuchs, and W. Höpken. 2012. “Social Media Monitoring and Analysis of a Swedish Tourism Destination.” In *Proceedings of the 2nd Conference on Advances in Hospitality and Tourism Marketing and Management*. http://miun.diva-portal.org/smash/record.jsf?pid=diva2%3A577845&dswid=-4159.

Leung, D., R. Law, H. van Hoof, and D. Buhalis. 2013. “Social Media in Tourism and Hospitality: A Literature Review.” *Journal of Travel and Tourism Marketing* 30 (1-2): 3-22.

Levallois, C. 2013. “Umigon: Sentiment Analysis for Tweets Based on Terms Lists and Heuristics.” In *Second Joint Conference on Lexical and Computational Semantics. Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation*, 414-17. Stroudsburg, PA: ACL.

Liu, B. 2010. “Sentiment Analysis and Subjectivity.” In *Handbook of Natural Language Processing*, 2nd ed., edited by N. Indurkhya and F. J. Damerau, 627-66. Boca Raton, FL: CRC Press.

Ma, J., N. Scott, J. Gao, and P. Ding. 2017. “Delighted or Satisfied? Positive Emotional Responses Derived from Theme Park Experiences.” *Journal of Travel and Tourism Marketing* 34 (1): 1-19.

Mack, R. W., J. E. Blose, and B. Pan. 2008. “Believe It or Not: Credibility of Blogs in Tourism.” *Journal of Vacation Marketing* 14 (2): 133-44.

Maedche, A., and S. Staab. 2001. “Ontology Learning for the Semantic Web.” *IEEE Intelligent Systems* 16 (2): 72-79.

Markopoulos, G., G. Mikros, A. Iliadi, and M. Liontos. 2015. “Sentiment Analysis of Hotel Reviews in Greek: A Comparison of Unigram Features of Cultural Tourism in a Digital Era." In *Cultural Tourism in a Digital Era*, 373-83. New York: Springer.

Marrese-Taylora, E., J. D. Velasquez, F. Bravo-Marquezb, and M. Yutaka. 2013. "Identifying Customer Preferences about Tourism Products Using an Aspect-Based Opinion Mining Approach." In *Proceedings of the 17th International Conference in Knowledge Based and Intelligent Information and Engineering Systems, Procedia Computer Science*, 182-91. Amsterdam: Elsevier.

Menner, T., W. Höpken, M. Fuchs, and M. Lexhagen, 2016. "Topic Detection—Identifying Relevant Topics in Tourism Reviews." In *Information and Communication Technologies in Tourism 2016*, edited by A. Inversini and R. Schegg, 411-23. New York: Springer.

Misopoulos, F., M. Mitic, A. Kapoulas, and C. Karapiperis. 2014. "Uncovering Customer Service Experiences with Twitter: The Case of Airline Industry." *Management Decision* 52 (4): 705-23.

Neidhardt, J., N. Rümmele, and H. Werthner. 2017. "Predicting Happiness: User Interactions and Sentiment Analysis in an Online Travel Forum." *Information Technology Tourism* 17 (1): 101-19.

O'Leary, D. 2011. "The Use of Social Media in the Supply Chain: Survey and Extensions." *Intelligent Systems in Accounting, Finance and Management* 18 (2-3): 121-44.

Pablos, A., M. Cuadros, and M. Linaza. 2015. "OpeNER: Open Tools to Perform Natural Language Processing on Accommodation." In *Information and Communication Technologies in Tourism 2015*, edited by I. Tussyadiah and A. Inversini, 125-37. New York: Springer.

Pan, B., T. MacLaurin, and J. C. Crotts. 2007. "Travel Blogs and the Implications for Destination Marketing." *Journal of Travel Research* 46 (1): 35-45.

Pang, B., L. Lee, and S. Vaithyanathan. 2002. "Thumbs Up? Sentiment Classification Using Machine Learning Techniques." In *Proceedings of the ACL-02 Conference on Empirical Methods in Natural Language Processing*, 79-86. New York: ACM.

Pappas, N., and A. Popescu-Belis. 2013. "Sentiment Analysis of User Comments for One-Class Collaborative Filtering over TED Talks." In *Proceedings of the 36th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 773-76. New York: ACM.

Phillips, P., S. Barnes, K. Zigan, and R. Schegg. 2017. "Understanding the Impact of Online Reviews on Hotel Performance: An Empirical Analysis." *Journal of Travel Research* 56 (2): 235-49.

Rabanser, U., and F. Ricci. 2005. "Recommender Systems: Do They Have a Viable Business Model in E-tourism?" In *Proceedings of the ENTER Conference in Innsbruck, Austria*, 160-71. New York: Springer.

Ribeiro, F. N., M. Araujo, P. Goncalves, M. A. Goncalves, and F. Benevenuto. 2016. "SentiBench—A Benchmark Comparison of State-of-the-Practice Sentiment Analysis Methods." https://arxiv.org/abs/1512.018182015arXiv151201818N.

Riloff, E., and J. Wiebe. 2003. "Learning Extraction Patterns for Subjective Expressions." In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, 105-12. New York: ACM.

Rossetti, M., F. Stella, L. Cao, and M. Zanker. 2015. "Analysing User Reviews in Tourism with Topic Models." In *Information and Communication Technologies in Tourism 2015*, edited by I. Tussyadiah and A. Inversini, 47-58. New York: Springer.

Sanders, N. 2011. "Twitter Sentiment Corpus by Niek Sanders." http://www.sananalytics.com/lab/twitter-sentiment/.

Schmunk, S., W. Höpken, M. Fuchs, and M. Lexhagen. 2014. "Sentiment Analysis: Extracting Decision-Relevant Knowledge from UGC." In *Information and Communication Technologies in Tourism 2014*, edited by P. Xiang and I. Tussyadiah, 253-65. New York: Springer.

Sharma, D., A. Kulshreshtha, and P. Paygude. 2015. "Tourview: Sentiment Based Analysis on Tourist Domain." *International Journal of Computer Science and Information Technologies* 6 (3): 2318-20.

Shi, H.-X., and X.-J. Li. 2011. "A Sentiment Analysis Model for Hotel Reviews Based on Supervised Learning." In *Proceedings of the International Conference on Machine Learning and Cybernetics*, 950-54. New York: IEEE.

Shimada, K., S. Inoue, H. Maeda, and T. Endo. 2011. "Analyzing Tourism Information on Twitter for a Local City." In *Proceedings of the First ACIS International Symposium on Software and Network Engineering*, 61-66.

Sigala, M. 2016. "Social Media and the Co-creation of Tourism Experiences." In *The Handbook of Managing and Marketing Tourism Experiences*, edited by M. Sotiriadis and D. Gursoy, 85-111. Bingley: Emerald.

Socher, R., A. Perelygin, J. Y. Yu, J. Chuang, C. D. Manning, A. Y. Ng, and C. Potts. 2013. "Recursive Deep Models for Semantic Compositionality over a Sentiment Treebank." In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, 1631-42. Stroudsburg, PA: ACL.

Stantic, B., and J. Pokorný. 2014. "Opportunities in Big Data Management and Processing." *Databases and Information Systems* 270: 15-26.

Stringam, B. B., and J. Gerdes, Jr. 2010. "An Analysis of Word-of-Mouse Ratings and Guest Comments of Online Hotel Distribution Sites." *Journal of Hospitality Marketing and Management* 19 (7): 773-96.

Tan, S., and Q. Wu. 2011. "A Random Walk Algorithm for Automatic Construction of Domain-Oriented Sentiment Lexicon." *Expert Systems with Applications* 38 (10): 12094-100.

Tsytsarau, M., and T. Palpanas. 2012. "Survey on Mining Subjective Data on the Web." *Data Mining and Knowledge Discovery* 24 (3): 478-514.

Travelmail Reporter. 2013. "Travel Is the Main Theme among Facebook Posts—And We Can't Stay Offline while Away." *Daily Mail*, December 3. http://www.dailymail.co.uk/travel/article-2517369/Travel-dominant-theme-Facebook-postings–stay-offline-holiday.html.

TripAdvisor. 2016. "TripAdvisor webpage accessed on December 2016." https://www.tripadvisor.com/.

Veal, A. J. (2006). *Research Methods for Leisure and Tourism: A Practical Guide*. 3rd ed. Harlow: Prentice Hall.

Waldhör, K., and A. Rind. 2008. "E-Blog Analysis—Mining Virtual Communities Using Statistical and Linguistic Methods for Quality Control in Tourism." In *Information and Communication Technologies in Tourism 2008*, edited by

P. O'Connor, W. Höpken, and U. Gretzel, 453-62. New York: Springer.

Wang, Y. 2017. "More Important Than Ever: Measuring Tourist Satisfaction." Griffith Institute for Tourism Research Report No. 10. https://www.griffith.edu.au/__data/assets/pdf_file/0012/898176/Measuring-Tourist-Satisfaction.pdf.

Xiang, Z., U. Gretzel, and D. R. Fesenmaier. 2009. "Semantic Representation of Tourism on the Internet." *Journal of Travel Research* 47 (4): 440-53.

Xiang, Z., Z. Schwartz, J. H. Gerdes, Jr., and M. Uysal. 2015. "What Can Big Data and Text Analytics Tell Us about Hotel Guest Experience and Satisfaction?" *International Journal of Hospitality Management* 44:120-30.

Xiang, Z., Z. Schwartz, and M. Uysal. 2015. "What Types of Hotels Make Their Guests (Un-)happy? Text Analytics of Customer Experiences in Online Reviews." In *Information and Communication Technologies in Tourism 2015*, edited by I. Tussyadiah and A. Inversini, 33-45. New York: Springer.

Yang, Y., Z. Mao, and J. Tang. 2017. "Understanding Guest Satisfaction with Urban Hotel Location." *Journal of Travel Research*. Published online February 1. doi:10.1177/0047287517691153.

Ye, Q., Z. Zhang, and R. Law. 2009. "Sentiment Classification of Online Reviews to Travel Destinations by Supervised Machine Learning Approaches." *Expert Systems with Applications* 36:6527-35.

Zhang, Z., Q. Ye, Z. Zhang, and Y. Li. 2011. "Sentiment Classification of Internet Restaurant Reviews Written in Cantonese." *Expert Systems with Applications* 38:7674-82.

Zheng, W., and Q. Ye. 2009. "Sentiment Classification of Chinese Traveler Reviews by Support Vector Machine Algorithm." In *Intelligent Information Technology Application*, 335-38. New York: IEEE.

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