



A naive Bayes strategy for classifying customer satisfaction: A study based on online reviews of hospitality services

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ABSTRACT

This research assesses whether terms related to guest experience can be used to identify ways to enhance hospitality services. A study was conducted to empirically identify relevant features to classify customer satisfaction based on 47,172 reviews of 33 Las Vegas hotels registered with Yelp, a social networking site. The resulting model can help hotel managers understand guests' satisfaction. In particular, it can help managers process vast amounts of review data by using a supervised machine learning approach. The naive algorithm classifies reviews of hotels with high precision and recall and with a low computational cost. These results are more reliable and accurate than prior statistical results based on limited sample data and provide insights into how hotels can improve their services based on, for example, staff experience, professionalism, tangible and experiential factors, and gambling-based attractions.

1. Introduction

With the increased popularity of online bookings, 53% of travelers state that they would be unwilling to book a hotel that had no reviews (Prabu, 2014). Ye, Law, Gu, and Chen (2011) report that a 10% increase in travel review ratings would increase bookings by > 5%. In restaurants, an extra half-star has a significant effect on the popularity of a service, creates satisfaction and trust in a product, and, consequently, helps restaurants sell out 19% more often (cf. Clemons, Gao, & Hitt, 2006; Duan, Gu, & Whinston, 2005; Ghose & Ipeirotis, 2011; Park, Lee, & Han, 2007; Zhang, Ye, & Law, 2011; Zhu & Zhang, 2010). Therefore, 75% of travelers worldwide consider electronic word of mouth (eWOM) an essential information source when planning their trips (cf. Chong, Khong, Ma, McCabe, & Wang, 2018; Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). It is quickly and easily available to anyone and remains accessible over time (Gretzel & Yoo, 2008; Litvin, Goldsmith, & Pan, 2008; Manes & Tchetchik, 2018; Reza Jalilvand & Samiei, 2012). Although online reviews are poorly structured, they are helpful in discerning guests' preferences and demands and in understanding what makes guests return or avoid a hotel. Users become fans or friends of other users and can rate or compliment other users' reviews.

The concept of eWOM is defined as “all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers” (Litvin et al., 2008, p. 4). It is an opportunity to have indirect

experiences, enhance market transparency by freely sharing guests' experiences, ratings, or knowledge, reduce search costs for customers, develop hotels' online reputations, and efficiently attract guests, thereby enhancing (or, conversely, undermining) long-term online relationships and genuine customer loyalty (Gretzel & Yoo, 2008; Park et al., 2007; Tsao, Hsieh, Shih, & Lin, 2015; Ye et al., 2011). Likewise, eWOM exerts a greater influence than traditional word of mouth (WOM) (Pan & Zhang, 2011) because of its speed, convenience, one-to-many reach, and absence of face-to-face human pressure (Sun, Youn, Wu, & Kuntaraporn, 2006). Exposure to online reviews therefore enhances users' consideration of hotels based on awareness of the hotel and attitudes toward the hotel when forming opinions (Vermeulen & Seegers, 2009).

Academic research offers several non-traditional approaches to reducing the huge variety of terms employed by guests and discovering themes about hospitality services as abstract notions or distributions over a fixed vocabulary (cf. Guo, Barnes, & Jia, 2017; He et al., 2017; Ren & Hong, 2017; Sánchez-Franco, Navarro-García, & Rondán-Cataluña, 2016; Sánchez-Franco, Roldán, & Cepeda, 2018). Individuals analyze reviews by focusing not only on the summary (i.e., star ratings) but also on the content of customers' *natural* texts based on subjectively experienced intangibles (Chaves, Gomes, & Pedron, 2012; Serra-Cantalops & Salvi, 2014). In this study, we analyze an initial dataset of 47,172 reviews of hotels in Las Vegas (USA) that are registered on Yelp. Yelp is a review aggregator of travel-related contents, much like

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TripAdvisor or Trivago. We identify the most relevant features of the hospitality encounter to classify ratings based on guests' post-trial experiences. We apply a machine learning approach based on extracting the best features of the reviews to classify online hotel reviews as positive or negative. We do so using the naive Bayes method (cf. Duda & Hart, 1974; Langley, Iba, & Thompson, 1992).

2. Theoretical framework and research questions

Infomediation systems generate a significant amount of free online content about subjectively experienced intangible goods or experiences. They also transform how individuals search for interesting or unique experiential services and modify how travelers select hotel accommodation. Therefore, infomediation systems are a critical success factor to compete in the hospitality industry (Raguseo, Neirotti, & Paolucci, 2017; Sparks, So, & Bradley, 2016). Because of the high costs typically associated with investment in the hospitality industry, it is sensible to study the service features that travelers describe, relive, reconstruct, and share in their online reviews (cf. Sánchez-Franco et al., 2018).

Online reviews are considered a key source of relevant user-generated content (UGC) (cf. Pan, MacLaurin, & Crotts, 2007; Racherla, Connolly, & Christodoulidou, 2013). This UGC plays an increasingly important role in consumer attitudes and purchase intentions, particularly in relation to travel services (Litvin et al., 2008; Liu & Park, 2015; Marchiori & Cantoni, 2015; Wu, Shen, Fan, & Mattila, 2017). On Yelp, reviewer satisfaction is represented by the number of stars awarded by the reviewer. These star ratings can be interpreted as an overall assessment of the customers' post-consumption experience. Such ratings are so critical that an extra half-star allows restaurants to sell out more frequently. However, individuals also analyze reviews by focusing on the UGC (Sánchez-Franco et al., 2016, 2018). The UGC provided by *actual travelers* tends to be more independent, empathetic, and trustworthy (Wilson & Sherrell, 1993; cf. Bickart & Schindler, 2001; Gretzel & Yoo, 2008; Huang & Chen, 2006; Sparks et al., 2016). Searching for information that is relevant to travelers' plans, including destinations, attractions, amenities, and accommodation such as hotels, guesthouses, and retreats, has thus become an indispensable step in the decision-making process.

Online reviews describe travelers' experiences of staying in hotels and reflect travelers' assessments of these hotels. These reviews are based on the way travelers live, think, and enjoy life in attractive destinations, and they reflect customers' satisfaction with the corresponding staying experience. Satisfaction is defined here as a guest's perception of how well needs, goals, and desires have been met (cf. Oliver, 1999; Yoon & Uysal, 2005, for a detailed review). Satisfaction, which is related to the service provider's performance, is indeed a key measure of a hotel's effectiveness at outperforming others. If travelers are satisfied with what they experience from hospitality services, their revisit intentions may be positively influenced (Park et al., 2007). More satisfied guests have higher-quality relationships with hospitality providers (cf. Dorsch, Swanson, & Kelley, 1998).

We adopt a product-feature-oriented approach to address two goals. The first is to explore the effectiveness of applying features of the guest experience to predict how well the whole relationship meets guests' expectations and predictions (Sánchez-Franco et al., 2018). The second is to understand how customer feedback and complaints can be used to improve customer satisfaction. Three assumptions are made. The first is that guests' satisfaction plays an important role in enhancing a hotel's demand based on the number of Internet users and their frequent interactions (Xu & Li, 2016). The second is that guests' satisfaction has a profound impact on both consumers and business organizations (Niu & Fan, 2018). The third is that guests' satisfaction consequently leads to improved financial performance (cf. Sparks & Browning, 2011) and higher efficiency (cf. Assaf & Magnini, 2012). Based on these assumptions, the purpose of this study is to identify differences in the perceived importance of features of the guest experience and in travelers'

satisfaction with the service. The following research questions are therefore addressed: What makes a good (or bad) hotel? What are the major concerns or features (e.g., in-room facilities, cleanliness, or staff skills) and supplementary services (e.g., dining and fitness facilities) that guests consider when assessing a hospitality service? Answering these questions is essential to understand travelers' perceptions of hospitality services and, more specifically, to design and implement systems to classify online reviews. Analyzing the text content of online reviews can provide fresh insight into what constitutes a satisfying experience.

3. Method

3.1. Data collection

We analyzed data from the 9th Yelp Dataset Challenge to understand guests' preferences, filtering records whose category contained the term "Hotels." The Yelp dataset was imbalanced in terms of location. The city of Las Vegas (Nevada, USA) was selected to remove noisy data (e.g., data containing inconsistent features based on different destinations). It was also selected because of its prestigious reputation for hosting festivals and events and its competitive advantage in entertainment driven by tourism and gambling pleasure (Douglass & Raiento, 2004; Rowley, 2015). The number of tourists visiting Las Vegas grew from 35.1 million in 2002 to about 40 million in 2016. Las Vegas generates controversial feelings capable of affecting tourists' perceptions, as reflected in guests' opinions.

Our dataset contained 47,172 reviews of hotels for the period March 2005 to January 2017. We used the textcat package based on the R 3.4.1 statistical tool to recognize English in the reviews (cf. Hornik et al., 2013). We thereby avoided bias and kept the language variable consistent across texts. We also restricted the number of classes and considered 1-star (7879 reviews) and 5-star (8960 reviews) reviews (cf. Mudambi & Schuff, 2010) to sharpen the focus of our analysis. The slight imbalance in scores may owe to the guests' tendency to make positive rather than negative evaluations.

3.2. Data analysis

The Yelp dataset contained a considerable amount of plain data on businesses, users, and reviews. It was pre-processed to cleanse the data and identify trends (cf. Krippendorff, 2012; Raychaudhuri, Schütze, & Altman, 2002) by applying R 3.4.1 on macOS High Sierra with an Intel Core i5 (1.8 GHz) and 8 GB of memory. First, we discarded punctuation, capitalization, digits, and extra whitespace, tokenized and depluralized the terms, removed a list of common stop words to filter out overly common terms, and eliminated non-English characters. We also omitted terms shorter than a minimum of three characters and stemmed terms using the Porter stemming algorithm. Second, we selected a dictionary based on tf-idf values (cf. Blei & Lafferty, 2009; Grün & Hornik, 2011; Salton & McGill, 1986) above the median (plus the terms "bed" and "staff"). The tf-idf approach increased proportionally to the number of times that a term appeared in a review, but it was offset by the frequency of the term in the corpus. This process yielded a vocabulary of 424 terms. Third, we built a document term matrix (DTM). A DTM is defined as a bag of words to represent text where every term is conceptualized as a feature that occurs in a document (Wallach, 2006; Zhang, Rong, & Zhou, 2010). For training and testing, the DTM was divided as follows: 80% (13,472 reviews) for training and 20% (3367 reviews). Testing was conducted by applying the caret package (version 6.0-78; cf. Kuhn, 2008). We trained and tested the naive Bayes classifier using the e1071 R package (created by Meyer et al., version 1.6-8).

Next, an automatic text classifier was built using a learning process from the set of pre-labeled reviews to select features capable of discriminating samples that belonged to different classes (e.g., very positive 5-star ratings or very negative 1-star ratings) and identify the class

to which a new review belonged. Naive Bayes is based on Bayes' theorem. It offers “a competitive classification performance for text categorization compared with other data-driven classification methods” (Forman, 2003; Genkin, Lewis, & Madigan, 2007; Tang & He, 2015; Yang & Pedersen, 1997; cf. Tang, 2016, p. 2509). Classifying non-structured text is a complex task because of the high dimensionality of the feature space and the high level of redundancy that may exist in the bulk of available data. Although the high dimensionality and redundancy cause poor predictive performance, feature (i.e., term) selection in text categorization in this study aimed at identifying the most relevant, explanatory input terms in the dataset to improve performance and increase the comprehensibility of the mining results.

We applied a filter-based approach to identify significant features and discard redundant features. A filter-based approach reduces the dimension of the feature space, accelerating the learning process and improving the precision of 1-star versus 5-star rating classification. A two-step filter approach was applied. We selected the top-ranked features based on tf-idf values and subsequently applied a maximum relevance minimum redundancy (MRMR) approach based on a mutual information statistical measure (Peng, Long, & Ding, 2005). First, terms that could be strongly associated with other terms but weakly associated with star-ratings (i.e., lowly predictive) were discarded. Second, we applied a heuristic approach to determine an appropriate number of features by iteratively testing the naive Bayes algorithm. Naive Bayes, a simple but efficient classifier, has been shown to work well in many domains. It offers a suitable classifier for large datasets (Abellán & Castellano, 2017). Given that our research aim was to enhance classification rates, the features were selected according to the rates of change of their Matthews correlation coefficient (MCC) (cf. Matthews, 1975; see Eq. (1)). The MCC provided a coefficient of the correlation between the observed and predicted binary classifications by simultaneously considering true and false positives and negatives.

In short, our approach had three notable features. First, we initially sorted the features (terms) according to their relevance in determining class labels based on tf-idf values and MRMR metrics. Second, each naive Bayes model was based on increasing the number of sorted features each time from 1 to 424 features. For each cumulative number i of terms, a naive Bayes classifier was executed. We employed 10-fold cross validation (i.e., the training data were randomly split into 10 mutually exclusive folds). This trained the classifier on nine sets and tested it using the one remaining set. We estimated the MCC values applied to increasing the number of candidate features and selected the model that gave the maximum MCC value. The comparison of feature selection obtained by estimating MCC values is summarized in Fig. 1. Fig. 2 also shows the results for average accuracy, precision, recall, F1 score,

Kappa, and area under the curve (AUC) as we varied the number of features. Third, rates i of MCC change (between term i and term $i - 1$) were calculated as $MCC_i - MCC_{i-1}$. Our approach omitted features whose rates of MCC change were negative.

Matthews correlation coefficient

$$MCC = \frac{TP \times TN - FP \times FN}{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}$$

TN: true negative; TP: true positive; FN: false negative; FP: false positive.

(1)

4. Results

Although satisfaction classification was likely to have clear feature dependencies, our best model (based on the MRMR metric) had an MCC measure of 0.734. The optimal number of features in the naive Bayes model was 209. Fig. 3 shows the top-ranked features for the best model.

The resulting classifier was also evaluated using additional standard metrics (see Fig. 4). For our prediction based on hotel ratings, the recall (based on false negatives) and precision (based on false positives) of the classifier were equally important. We assessed both precision and recall in their combined form using the F1 score. This score is used extensively in text classification. The F1 score, precision, and recall are highly informative evaluation metrics for binary classifiers (cf. Saito & Rehmsmeier, 2015). Having established the reference class as a 1-star rating, we observed an F1 score equal to 0.85. The precision score was equal to 0.89. It was conceptualized as 89% correct predictions (TP) of all classified ratings (TP: 1280 plus FP: 163). Recall was equal to 0.81 and was conceptualized as 81% correct predictions (TP) of relevant ratings (TP: 1280 plus FN: 295). Having established the reference class as a 5-star rating, we observed an F1 score equal to 0.88. The precision value was equal to 0.85 (TP: 1629 plus FP: 295). Recall was equal to 0.91 (TP: 1629 plus FN: 163). In short, more negative reviews (1-star scores) were wrongly recognized as positive reviews (5-star scores). Fig. 4 shows a higher recall of positive reviews and a higher precision of negative reviews.

The Kappa metric was used to compare observed accuracy with expected accuracy (cf. Cohen, 1960). Kappa values of 0, 1, > 0, and < 0 indicate chance, perfect, above chance, and below chance agreement, respectively (Cohen, 1960). The Kappa value was 0.73. The AUC of the receiver operating characteristics (ROC) (cf. Fawcett, 2006) is associated with the classifier's ability to avoid false classification. It is calculated using the table of confusion. The ROC is associated with the trade-off between a classifier's true positive rate (sensitivity, or TPR, on the y-axis) and false positive rate (specificity, or FPR, on the x-axis). An

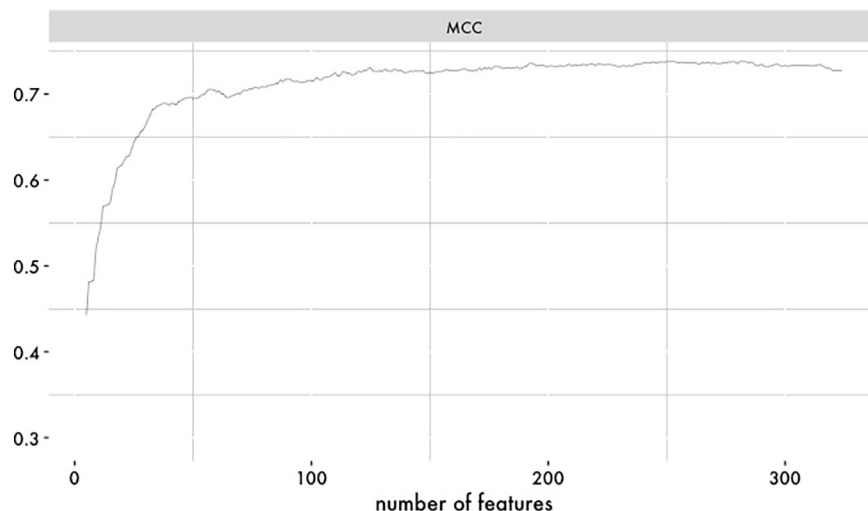


Fig. 1. Evolution (by number of features) of the Matthews correlation coefficient (MCC).

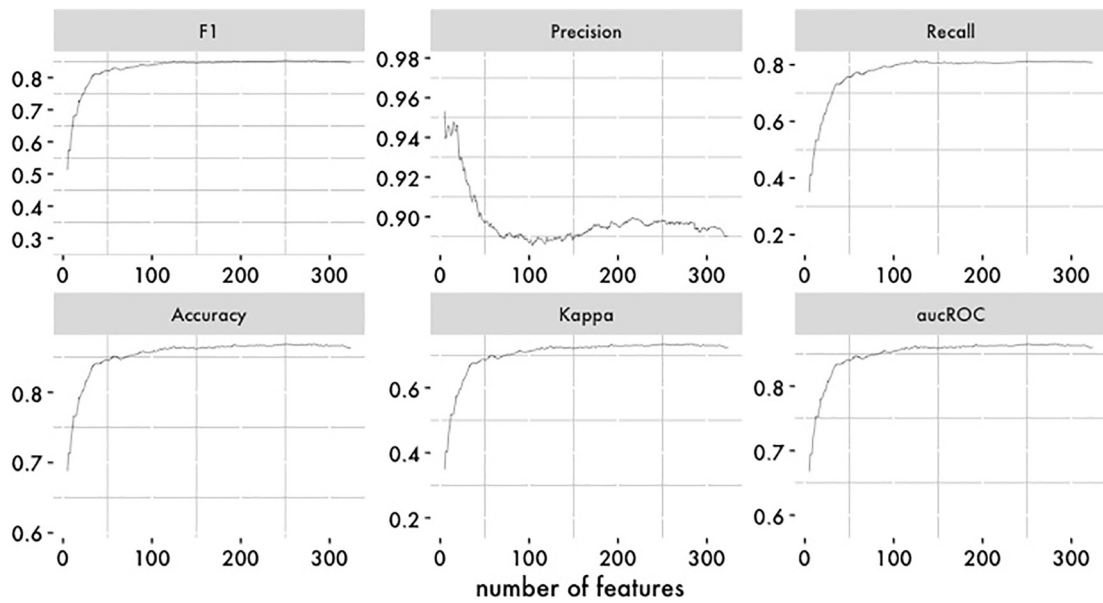


Fig. 2. Evolution (by number of features) of the classification-based metrics.

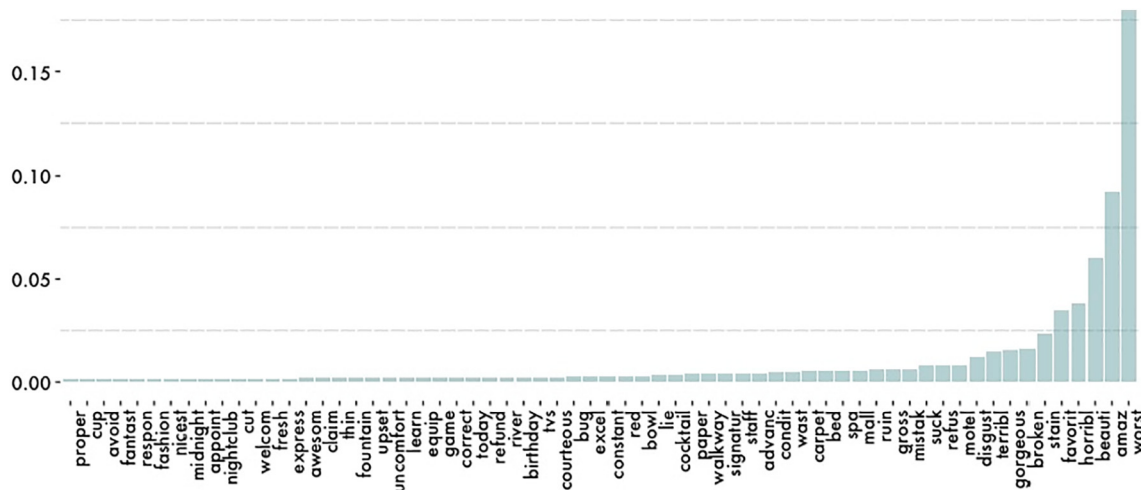


Fig. 3. Top-selected features based on positive rates of change of the Matthews correlation coefficient (MCC).

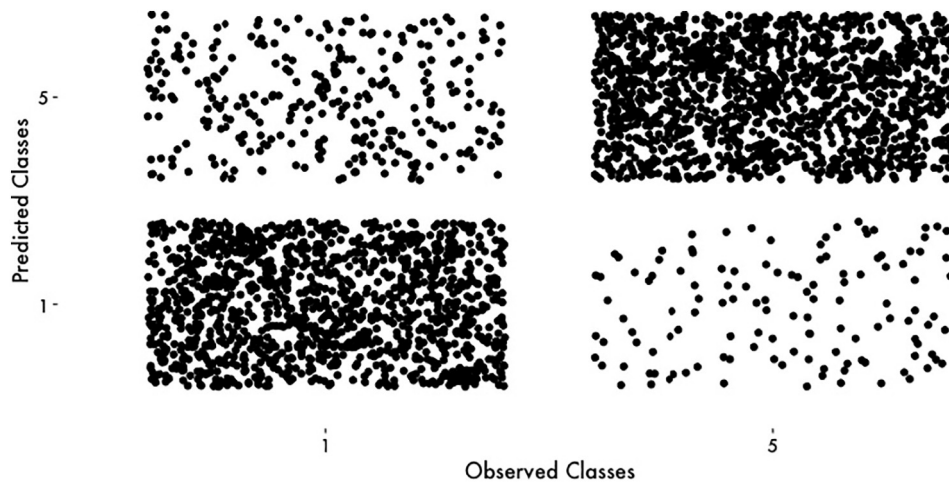


Fig. 4. Table of confusion for performance evaluation.

based on certain criteria (cf. Ngai, Xiu, & Chau, 2009, p. 2595). By using techniques for Natural Language Processing, we confirm that naive Bayes offers an effective and efficient classification algorithm in polarity analysis of reviews in marketing. The results should be more reliable and accurate than prior statistical results obtained from traditional satisfaction surveys based on small data samples. Despite its naive design and apparently over-simplified assumptions, these (negative) concerns have a small impact on performance.

5.2. Managerial implications

This study was based on a large, unstructured, complex dataset. The results of the study can help hotels allocate resources to the areas that matter to guests, identify guests' perceptions, explore and assess the influence of these perceptions on meeting guests' needs, and identify key communities of terms around which guests positively or negatively evaluate hospitality experiences.

If a hotel company seeks to satisfy guests, managers must consider classifying features of the hotel when allocating marketing resources. Attributes or benefits based on staff experience (i.e., intangible cues related to the immaterial nature of services, such as interacting with friendly employees) and professionalism were identified as an essential community of terms. Likewise, a core (tangible and experiential) community of terms based on poor design and upkeep of rooms and furnishings and experiential aspects such as cleanliness or dirtiness is an essential driver. For hotel guests, attributes or benefits based on staff experience and professionalism (i.e., interpersonal aspects of the service such as interacting with employees who are rude or who deliver a poor service) are important elements when evaluating hotel quality. Nevertheless, core or functional reviews (e.g., poor room design or upkeep) determined by tangibility should also be addressed. Moreover, events in Las Vegas such as gambling-based attractions are key marketing propositions in promoting hotels and hospitality experiences.

Positive reviews by guests can have a significant effect on other guests' decision-making processes. Conversely, negative reviews can easily undermine the loyalty of potential customers and cause them to focus on negative eWOM. The satisfaction (sentiment) classifier was associated with transforming UGC into quantitative data. These data were used to score comments as positive or negative and thereby shape important decisions for the future of hospitality organizations. In this study, we built a classification strategy that can be applied to businesses such as hotels, movie theaters, and so forth.

Our model helps hotel managers understand guests' satisfaction in terms of star ratings. Our model also helps process huge amounts of review data by using a supervised machine learning approach. Although guests' reviews are valuable to other guests and are essential in improving the service provided by hotels, the massive number of reviews makes it difficult for managers to obtain an intuitive hotel evaluation. The primary managerial contribution of this research is to provide an approach for summarizing hospitality service reviews by removing data considered non-informative for classification.

5.3. Limitations

This study has several limitations. First, it did not examine infrequent terms in the long tail of the distribution. A second limitation relates to self-selection bias when guests post their reviews. Third, the study focused on reviews of urban hotels in Las Vegas. These reviews might reflect some bias of visitors to Las Vegas. The location-based environment could influence the relative importance of features. Moreover, average star scores may be affected by a culture-conditioned response style (Dolnicar & Grün, 2007). Fourth, this research relies only on reviews from Yelp. Our dataset could thus have some invisible bias.

5.4. Suggestions for future research

Improving the interactive features and service-related information available on online services does not necessarily guarantee customer loyalty. Although customer reviews offer star-based ratings (an overall satisfaction measure ranging from negative 1-star reviews to positive 5-star reviews), these star ratings do not provide detailed information on customer loyalty. Accordingly, future studies should propose an evaluation of the additional effect of affective trust (Singh & Sirdeshmukh, 2000). Likewise, although a growing number of studies focus on the mechanisms through which UGC generates user satisfaction or trust (e.g., Sánchez-Franco et al., 2018; Sparks & Browning, 2011), future research should also assess the psychological sentiments through which attitudes based on the continuation of relationships are formed (Wetzels, de Ruyter, & van Birgelen, 1998). Finally, future studies should analyze gender-based differences because men and women cognitively structure hotel experiences using different criteria (Sánchez-Franco et al., 2016).

6. Conclusions

This study describes a supervised classification approach to identify the most relevant terms and their influence on hotel ratings. Yelp was used as a case study. The study focused on Las Vegas hotel reviews that were voluntarily posted by users. Given the increasing need for information organization and knowledge discovery from text data, we applied the MRMR approach based on the mutual information criterion to mine the complex features from guests' reviews and systematically perform feature selection. The aim of extraction and selection was to identify a subset of terms occurring in the training set and use this subset as features in text classification.

We applied the naive Bayes approach to solve the problem of dealing with huge numbers of service reviews, enable automatic detection of guests' satisfaction with a specific hospitality service (i.e., positive 5-star reviews or negative 1-star reviews), and consider brand building, product development, and quality assurance. The proposed opinion mining system enabled a binary classification of guests' reviews with a high MCC (> 0.73) by discarding terms that were strongly associated with other terms but weakly associated with star-ratings (i.e., lowly predictive). Most reviews were correctly classified as positive or negative (i.e., AUC > 0.86). Our proposed system was thus able to identify the polarity of guests' opinions. Despite being a naive classifier and despite its unrealistic independence assumption, the naive Bayes algorithm was able to classify reviews of Las Vegas hotels with high precision and recall (F1 score > 0.84 for both reference values) and with a low computational cost.

The results show that using term unigrams is an appropriate approach. The results indicate that the system is fast, scalable, and accurate at analyzing guests' reviews and determining guests' opinions.

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