Assessing the Impact of Hotel Services on Customer Rating Using Fuzzy String Matching and Belief Networks

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*Abstract***— Online review comments have become a popular and efficient way for sellers to acquire feedback from customers and improve their service quality. These online reviews in the e-tourism era, in the format of both textual reviews (comments) and ratings, generate an electronic Word Of Mouth (eWOM) effect, which influences future customer demand and hotels' financial performance, and thus, have significant business value. This paper proposes an approach for hotel quality evaluation according to online review comments and ratings using Fuzzy String Matching (FSM) for mining customers' opinions and Bayesian Belief Networks (BBN) for evaluating the attributes that contribute to the review rating. The proposed approach was applied to a dataset from TripAdvisor. The results show that the proposed approach is able to model the complex dynamics of online hotel review data, which are derived from both the textual nature of the review comments and the uncertain relationships between these comments and the review rating.**

Keywords-e-tourism; data analytics; machine learning; tourism management; service quality.

I. INTRODUCTION

Online comments have become a popular and efficient way for sellers to acquire feedback from customers and improve their service quality [1]. According to a survey, with the increased popularity of online bookings, 53% of travellers state that they would be unwilling to book a hotel that had no reviews, while a 10% increase in travel review ratings would increase bookings by more than 5% [2]. Customer online reviews of hotels have significant business value in the e-commerce and big data era, while they affect room occupancy [3], revenue, prices [4] and market share [5]. These online reviews in the e-tourism era, in the format of both textual reviews (comments) and ratings, generate an electronic Word Of Mouth (eWOM) effect, which influences future customer demand and hotels' financial performance [6].

Hotel owners want to know the details about hotel guests' experiences, to improve the corresponding product and service attributes, and customers' overall evaluation of the hotel stay experience, to obtain a snapshot of the hotel's operational performance and overall customer satisfaction [7][8]. Although the direct measurement of customer ratings in terms of closed-ended survey questions can show overall customer satisfaction in a direct way [7][8], they suffer from confounding the data of customers' true evaluation because of variations in survey design from different approaches [9].

Recently, many studies have focused on textual reviews [8][10]. In contrast to a pre-designed questionnaire survey, online textual reviews have an open-structured form and can show customer consumption experiences, highlight the product and service attributes customers care about, and provide customers' perceptions in a detailed way through the open-structure form [8]. The provided information is free from obvious bias and is helpful in understanding and assessing hotel performance [11]. In addition, such information is inexpensive and efficient to collect [12]. However, the exploitation of online textual reviews is still largely underexplored [8], while there is a lack of advanced data analytics approaches and algorithms for modeling complex dynamics of online hotel review data.

Hotel quality evaluation from online reviews is an emerging research field; however, the vast majority of existing research works have been performed from a tourism management perspective. Therefore, the applied methods and algorithms are limited to descriptive statistics, e.g., using well-established regression models. However, the increasing amount of online reviews as the core means for customers to express their level of satisfaction about a hotel pose significant challenges to the data analytics and computer science community for the development of advanced data analytics models aiming at providing a higher level of intelligence and thus, increased business value.

In this paper, we propose an approach for hotel quality evaluation from online reviews using Fuzzy String Matching (FPM) and Bayesian Belief Networks (BBN). The objective is to provide a unified algorithm, which both: (i) mines customers' opinions from online hotel reviews (review comments and rating); and, (ii) evaluates the hotel performance by identifying how the various attributes (e.g., location, cleanliness, breakfast, etc.) affect the overall review rating. The rest of the paper is organized as follows: Section II presents the related work on methods and approaches for hotel evaluation based on online review comments. Section III describes the research methodology and the proposed approach for hotel quality evaluation from online reviews using FSM and BBN. Section IV presents the results from the adoption of the proposed methodology on a dataset from TripAdvisor. Section V concludes the paper and outlines our plans for future work.

II. Related Work

The business value of online consumer reviews has emerged in recent year in the hotel industry aiming at solving the problems confronted by the traditional hotel service quality assessment methods [13]. For example, Kim and Park [14] performed hierarchical multiple regressions in order to examine the effects of traditional customer satisfaction relative magnitude and social media review ratings on hotel performance and found that social media review rating is a more significant predictor. In the traditional hotel quality assessment, domain experts or customers are asked to fill in a questionnaire and score each evaluation index to be used in a service quality assessment model [15]-[17]. On the contrary, online comments are made by a large amount of customers with actual user experience shortly after the consumption is completed. In addition, the increasing amount of reviews-related data pave the way for the use of advanced data analytics and machine learning algorithms that outperform traditional statistical methods based on sampling [2].

Technical attributes of online textual reviews can explain significant variations in customer ratings and can have a significant effect on customer ratings [18][19]. In this direction, Zhao et al. [8] developed an approach for predicting overall customer satisfaction using the technical attributes of online textual reviews and customers' involvement in the review community. They calculated subjectivity and polarity measurements by using naïve Bayes classifier and sentiment analysis. Berezina et al. [10] investigated the underpinnings of satisfied and unsatisfied customers by applying text mining on online reviews.

The literature is rich of methodologies based on descriptive statistics aiming at providing insights on hotel quality performance for various datasets. Xie et al. [20] applied statistical methods in order to assess how several characteristics, such as timeliness of the response, length of the response, number of responses, etc., contributes to the hotel's financial performance. Figini et al. [21] compared the rating dynamics of the same hotels in two online review platforms, which mainly differ in requiring or not requiring proof of prior reservation before posting a review (respectively, a verified vs a non-verified platform). Xie et al. [22] examined the effect of factors of online consumer review, including quality, quantity, consistency, on the offline hotel occupancy (i.e., how popular the hotel is among consumers).

De Pelsmacker et al. [3], the extent to which digital marketing strategies influence hotel room occupancy and revenue per available room and how this mechanism is different for different types of hotels in terms of star rating and independent versus chain hotels was investigated. Li et al. [23] examined the determinants of customer satisfaction in hospitality venues through an analysis of online reviews using text mining and content analysis. Zhao et al. [24] investigated the impacts of online review and source features (usefulness, reviewer expertise, timeliness, volume, valence and comprehensiveness) upon travelers' online hotel booking intentions by applying factor analysis and regression analysis. Zhou et al. [11] compared customer satisfaction by classifying several attributes influencing customer satisfaction in: satisfiers, dissatisfiers, bidirectional forces, and neutrals. Ye and Yu [25] applied qualitative research methods and extracted six main factors influencing the positive or negative emotions of the comments of travelers staying in the hotel.

Radojevic et al. [26] conducted a multilevel analysis of factors affecting customer satisfaction, such as service encounter, visitor, visitor's nationality, hotel, and destination. Nunkoo et al. [27] applied a multi-group analysis and an importance-performance map analysis by means of Partial least squares structural equation modeling (PLS-SEM) in order to differentiate between service quality performance scores and their influences on customer satisfaction across accommodation with a different star grading. Schuckert et al. [28] assessed social media content produced by customers and related review-management strategies of domestic and international hotel chains with the use of multilevel regression.

As mentioned earlier, the increasing amounts of reviews-related data require advanced data analytics and machine learning methods for exploiting the full potential. To this end, Sánchez-Franco et al. [2] assessed whether terms related to guest experience can be used to identify ways to enhance hospitality services. They developed a model based on naïve Bayes classifier in order process vast amount of data and to classify reviews of hotels. Ku et al. [29] developed a framework in order to integrate visual analytics and (deep) machine learning techniques, such as clustering for text classification and Convolutional Neural Networks (CNN), to investigate whether hotel managers respond to positive and negative reviews differently and how to use a deep learning approach to prioritize responses. Reference [1] combined fuzzy comprehensive evaluation and fuzzy cognitive maps aiming at identifying the causal relations among evaluation indexes from online comments. Based on this, their proposed approach recommends more economical solutions for improving the service quality by automatically getting more trustworthy evaluation from a large amount of less trustworthy online comments.

III. Research Methodology

Our research methodology consists of four main steps: (i) Extracting the evaluation criteria from online comments; (ii) Mining customers' opinions using FSM; (iii) Assignment of sentiment scores to a discrete scale; and, (iv) Applying BBN for assessing the impact of hotel services to the customer rating. These steps are described in detail in the following sub-sections.

A. *Extracting the Evaluation Criteria from Online Comments*

The proposed approach utilizes three fields from the online hotel reviews: (i) *review title*; (ii) *review comments*;

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and, (iii) *review rating*. This step of the methodology processes the *review title* and the *review comments* in order to extract the evaluation criteria from the online comments. More specifically, based upon an evaluation index for hotel service quality [1], this step identifies the criteria mentioned in the hotel reviews under examination, e.g., location, price, breakfast, room space, etc. In this way, the criteria are defined dynamically out of the pre-defined list, according to the dataset of the available online comments. The extracted evaluation criteria are further processed with the use of Fuzzy Pattern Match Template (FPMT), as we describe in Section III.B. Moreover, along with the review rating, they derive the parent nodes of the BBN, as we describe in Section III.C and Section III.D.

B. *Mining Customers' Opinions Using Fuzzy String Matching*

Since online comments are written in natural and informal language, there is the need to mine customers' opinions so that they subsequently feed into the BBN for further processing. FSM, alternatively mentioned as fuzzy string searching or approximate string matching, has been developed in the framework of fuzzy set and possibility theory in order to take into account the imprecision and the uncertainty pervading values, which have to be compared in a matching process [30]. This technique has proved effective for implementing patterns of approximate reasoning in expert system inference engines, and for designing retrieval systems capable of managing incomplete and fuzzy information data bases and vague queries.

In online review comments, different customers may use different words or phrases to express their opinions, while the comments may be vague. For example, poor cleanliness can be expressed as: "The room was too dirty", "Very dirty", etc. Regular expression is an efficient pattern match [31] technology to identify the specific pattern strings from a long text. A simple example of regular expression is "[\s\S]∗?[room|bathroom][\s\S]∗?dirty[\s\S]∗?" that can match "The room was too dirty." However, the regular expression method causes a binary value result: match or not match.

In the proposed approach, we apply FPMT [1] as an effective fuzzy string matching method to deal with the vagueness of the free text online comments. FPMT is a set of pattern strings with membership degrees, denoted as:

$$FPMT = \{(p_1, w_1), (p_2, w_2), \ldots, (p_i, w_i), \ldots, (p_n, w_n)\}$$

where p_i is a pattern string described by regular expression, and w_i is the membership degree that a string falls into the object FPMT when the string matches p_i. When a string matches multiple pattern strings at the same time, the max membership degree of these pattern strings will be selected as the final membership degree. Although this method results in some mismatched cases due to the limitation of pattern strings, this causes little impact on the final result, because there are many redundant comments with similar semantics.

The output of customers' opinions mining is a fuzzy evaluation of the extracted criteria. Specifically, first, the extracted evaluation criteria of hotel quality are assigned to a five-level Likert scale (1 – Very Low, 2 – Low, 3- Neutral, 4 – High, 5 – Very High), which serve as an equivalent to responses of a Likert scale questionnaire. Then, following the approach proposed by [32], this step considers the median of the resulting responses in order to represent the magnitude of causality among the evaluation criteria to be used as FCM concepts in Section III.C.

C. *Assignment of Sentiment Scores to a Discrete Scale*

In this step, the sentiment scores extracted from the previous step for each criterion are assigned to a discrete scale consisting of ranges of sentiment score values. The number of the scale items should be the same with the respective scale of the review rating so that they are directly comparable. For example, if the review rating takes values between 1 and 5 (which is the most common case), the sentiment scores are classified to a respective discrete scale:

- [-1, -0.6] is assigned to "DISASTER"
- (-0.6, -0.2] is assigned to "MANY THINGS NEED TO BE IMPROVED"
- (-0.2, +0.2] is assigned to "FAIR ENOUGH"
- (+0.2, +0.6] is assigned to "PERFECT"
- (+0.6, +1] is assigned to "ABSOLUTELY PERFECT"

D. *Applying Bayesian Belief Networks for Assessing the Impact of Hotel Services to the Customer Rating*

In this step, the relationships between the sentiment discrete scale created in the previous step and the review rating of the customer are modelled in a probabilistic model with the use of BBN. A BBN is a powerful tool for knowledge representation and reasoning under conditions of uncertainty and visually presents the probabilistic relationships among a set of variables [32]. A BBN has many advantages, such as combination of different sources of knowledge, explicit treatment of uncertainty and support for decision analysis, and fast responses.

More formally, BBNs are directed acyclic graphs whose nodes represent random variables from the domain of interest, in the Bayesian sense. Therefore, a BN is defined as a pair $B = (G, \Theta)$. $G = (V, E)$ is a Directed Acyclic Graph (DAG) where $V = \{v_1, \ldots, v_n\}$ is a collection of n nodes, $E \subset V \times V$ a collection of edges and a set of parameters Θ containing all the Conditional Probabilities (CP) of the network.

Each node $v \epsilon V$ of the graph represents a random variable X_V with a state space $\boldsymbol{X_V}$ which can be either discrete or continuous. An edge $(v_i, v_j) \epsilon E$ represents the conditional dependence between two nodes $v_i, v_j \epsilon V$ where v_i is the parent of child v_j. If two nodes are not connected by an edge, they are conditional independent. Because a node can have more than one parent, let π_v be the set of parents for a node $v \epsilon V$. Therefore, each random variable is independent of all nodes $V \setminus \pi_v$. For each node, a Conditional Probability Table (CPT) contains the CP distribution with parameters $\theta_{xi|\pi i}$

$:=P(x_i|\pi_i) \epsilon \Theta$ for each realization x_i of X_i conditioned on π_i. The joint probability distribution over V is visualized by the BN and can be defined as

$$P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i|\pi_i) \quad (1)$$

The outcome indicates the probability of having a specific value of the overall rating given the values of different services (criteria). The user is able to perform queries in order to assess the impact of each criterion on the review rating, but also combinations of criteria.

IV. RESULTS

The proposed methodology was applied to a dataset from TripAdvisor. The nodes of the BBN are shown in Table I. These nodes represent the parent nodes derived from the extracted evaluation criteria from FPMT (C1-C9) along with the review rating (C10), which constitutes the unique child node of the BBN.

TABLE I. THE EXTRACTED EVALUATION CRITERIA

ID	Nodes		ID	Nodes
C1	Location		C6	Quiet
C2	Personnel		C7	Parking
C3	Cleanliness		C8	Interior Design
C4	Room Space		C9	Bed
C5	Breakfast		C10	Review Rating

After the fuzzy evaluation of the aforementioned criteria for each hotel, the BBN is created. The BBN consists of two conceptual layers: the upper layer includes all the evaluation criteria (C1-C9) and the bottom layer includes the review rating provided by the customer (C10). The structure of the BBN is depicted in Figure 1. All the parent nodes are linked to the child node. Based upon this structure, the CPT is calculated for each node. Based upon this structure, the parameters of the BBN are learned.

Upon queries, the Conditional Probability (CP) $P(C10|C_i)$ is calculated. Table II presents the results from some indicative queries. In addition, the queries may deal with specific evaluation criteria in order to assess their impact on the customers' overall review rating. According to the queries, the BBN derives more focused results, e.g., for a specific hotel, group of hotels, location, etc. Finally, the adopted modelling approach may serve as a classifier for predicting the review rating of a customer based upon their review comments. Table III presents the resulting confusion matrix that derives the precision and recall of the classifier as follows:

$$Precision = \frac{TP}{TP + FP} = \frac{41}{41 + 3} = 93.1\% \quad (2)$$

$$Recall = \frac{TP}{TP + FN} = \frac{41}{41 + 9} = 82\% \quad (3)$$

TABLE II. RESULTS FROM INDICATIVE QUERIES

Values of Parent Nodes	Values of Child Node	$P(C10\|C_i)$
C1={FAIR ENOUGH}, C2={PERFECT}, C3={MANY THINGS NEED TO BE IMPROVED}, C4={PERFECT}, C5={PERFECT}, C6={FAIR ENOUGH}, C7={MANY THINGS NEED TO BE IMPROVED}, C8={FAIR ENOUGH}, C9={DISASTER}	3 stars	0.332
C1={MANY THINGS NEED TO BE IMPROVED}, C2={PERFECT}, C3={DISASTER}, C4={DISASTER}, C5={PERFECT}, C6={FAIR ENOUGH}, C7={FAIR ENOUGH}, C8={PERFECT}, C9={DISASTER}	2 stars	0.241
C1={PERFECT}, C2={ABSOLUTELY PERFECT}, C3={MANY THINGS NEED TO BE IMPROVED}, C4={PERFECT}, C5={PERFECT}, C6={ABSOLUTELY PERFECT}, C7={FAIR ENOUGH}, C8={FAIR ENOUGH}, C9={PERFECT}	4 stars	0.214
C1={ABSOLUTELY PERFECT}, C2={ABSOLUTELY PERFECT}, C3={FAIR ENOUGH}, C4={ABSOLUTELY PERFECT}, C5={FAIR ENOUGH}, C6={FAIR ENOUGH}, C7={FAIR ENOUGH}, C8={FAIR ENOUGH}, C9={PERFECT}	4 stars	0.183
C1={FAIR ENOUGH}, C2={PERFECT}, C3={MANY THINGS NEED TO BE IMPROVED}, C4={FAIR ENOUGH}, C5={PERFECT}, C6={PERFECT}, C7={MANY THINGS NEED TO BE IMPROVED}, C8={PERFECT}, C9={FAIR ENOUGH}	3 stars	0.144
C1={FAIR ENOUGH}, C2={ABSOLUTELY PERFECT}, C3={FAIR ENOUGH}, C4={PERFECT}, C5={ABSOLUTELY PERFECT}, C6={FAIR ENOUGH}, C7={MANY THINGS NEED TO BE IMPROVED}, C8={FAIR ENOUGH}, C9={FAIR ENOUGH}	3 stars	0.139
C1={MANY THINGS NEED TO BE IMPROVED}, C2={PERFECT}, C3={FAIR ENOUGH}, C4={PERFECT}, C5={ABSOLUTELY PERFECT}, C6={PERFECT}, C7={FAIR ENOUGH}, C8={PERFECT}, C9={FAIR ENOUGH}	4 stars	0.091
C1={PERFECT}, C2={PERFECT}, C3={FAIR ENOUGH}, C4={PERFECT}, C5={ABSOLUTELY PERFECT}, C6={PERFECT}, C7={FAIR ENOUGH}, C8={MANY THINGS NEED TO BE IMPROVED}, C9={FAIR ENOUGH}	5 stars	0.073

The Precision results are quite satisfactory, while the Recall results can be further improved. The BN model sticks to the initially identified relationships, i.e., the ones that have

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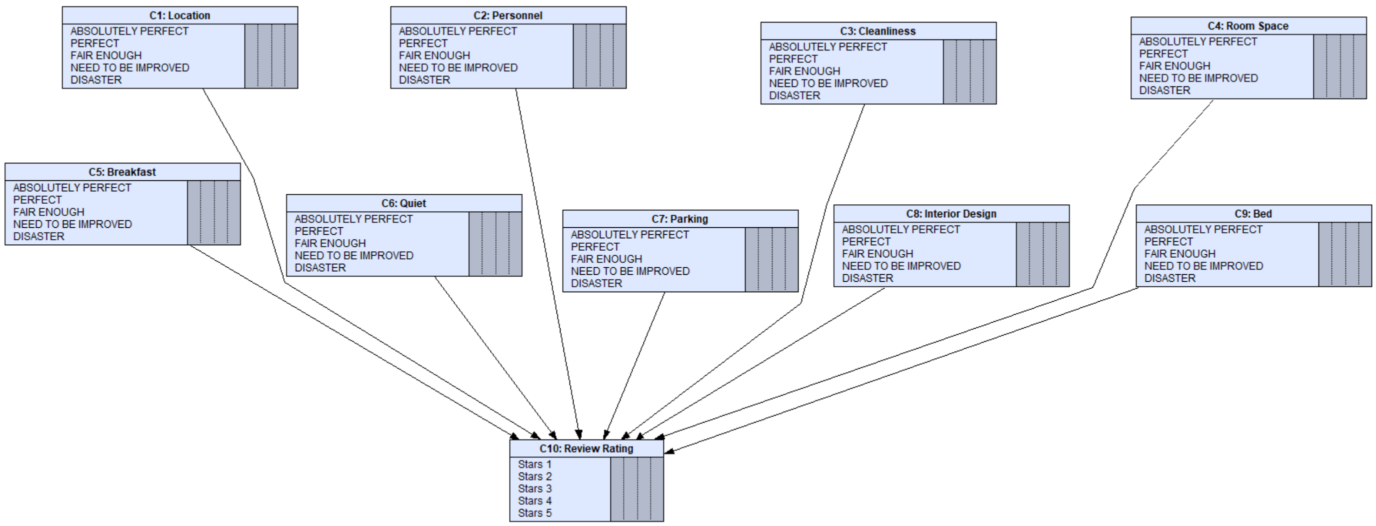

Figure 1. The Bayesian Network structure for assessing the impact of hotel services to the customer rating.

been mined during the model training. Therefore, when new relationships, not previously identified, are added, they may not be classified correctly.

TABLE III. CONFUSION MATRIX

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP) = 4125	False Negative (FN) = 905
Actual Negative	False Positive (FP) = 307	True Negative (TN) = 3231

V. CONCLUSIONS AND FUTURE WORK

Hotel quality evaluation from online reviews is an emerging research field, while the use of data analytics and machine learning methods are able to exploit its full potential in an e-tourism context. This paper proposed an approach for hotel quality evaluation according to online review comments and ratings using FSM for mining customers' opinions and BBN for evaluating the attributes that contribute to the review rating. The results show that the proposed approach is able to model the complex dynamics of online hotel review data, which are derived from both the textual nature of the review comments and the uncertain relationships between these comments and the review rating.

Regarding our future work, we plan to apply our methodology to further datasets, i.e. from different e-tourism platforms with different data structure and availability, and to investigate the role of user profiling in hotel selection. Moreover, we plan to investigate and develop approaches for detecting the fake reviews in order to increase the accuracy and the reliability of the sentiment analysis methods and algorithms.

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