Modelling the Consistency between Customer Opinion and Online Rating with VADER Sentiment and Bayesian Networks

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***Abstract*— Customers have access to different sources of information, and generate their own content and share their views and experiences which are expressed through online review comments and ratings about products and services. However, the increasing amount of data has reached a level that makes manual processing impossible, requiring data-driven approaches. Sentiment analysis is rapidly emerging as an automated process of examining semantic relationships and meaning in reviews. Despite the large amount of research works dealing with sentiment analysis, the consistency between the customer opinions expressed in review comments and the rating that they provide has not been explored. In this paper, we propose an approach incorporating the Valence Aware Dictionary for Sentiment Reasoning (VADER) algorithm for extracting the polarity of the review comments and Bayesian Networks for revealing the relationships between the aforementioned sentiment scores and the online rating. The proposed approach was validated in the tourism domain using a dataset with hotel reviews, extracted from the TripAdvisor.**

Keywords—sentiment analysis; probabilistic model; machine learning; data analytics; hotel review; tourism management; opinion mining.

I. INTRODUCTION

Customers have access to different sources of information, and generate their own content and share their views and experiences which are expressed through online review comments and ratings about products and services. However, the increasing amount of data has reached a level that makes manual processing impossible, requiring data-driven approaches. Sentiment analysis is rapidly emerging as an automated process of examining semantic relationships and meaning in reviews. Analyzing the sentiment tendency of consumer evaluation can not only provide a reference for other consumers but also help businesses on e-commerce platforms to improve service quality and consumer satisfaction [1].

E-commerce platforms use ratings in order to quantify customer's preferences and satisfaction on products and services. Several techniques like clustering, nearest-neighbour methods, matrix manipulations, point-of interest modelling have been used to model user interest patterns so as to maximize purchase satisfaction [2]. However, these ratings are biased by certain hidden factors like brand adherence and product-prejudice [2]. On the other hand, review comments is a valuable source of data related to customers' opinions. However, different people use different ways of expressing themselves, leading to variations in the sentiment scores. In addition, the customers select some main points to be mentioned in the review comments. However, there are various aspects that affect their level of satisfaction and their preferences that are not mentioned at all and remain at their own mind. In this sense, there may be review comments with similar content and sentiment but different ratings. These facts lead to inconsistencies between the customer opinions expressed in review comments and the rating that they provide.

Despite the large amount of research works dealing with sentiment analysis, the consistency between the customer opinions expressed in review comments and the rating that they provide has not been explored. In this paper, we propose an approach incorporating the Valence Aware Dictionary for Sentiment Reasoning (VADER) algorithm for extracting the polarity of the review comments and Bayesian Networks for revealing the relationships between the aforementioned sentiment scores and the online rating. The proposed approach was validated in the tourism domain using a dataset with hotel reviews, extracted from the TripAdvisor.

The rest of the paper is organized as follows: Section II describes the related work with a focus on sentiment classification of review comments and analysis of review rating. Section III presents the proposed approach for modelling the consistency between customer opinion and online rating. Section III presents and discusses the results of the application of the proposed approach to the e-tourism domain. Section IV concludes the paper and outlines our plans for future work.

II. RELATED WORK

Sentiment analysis uses algorithms to extract and analyse opinions from text (e.g., customers online reviews), as well as to identify positive, neutral and negative opinions to measure a customer's attitude toward an issue [3]. In other words, sentiment analysis aims at identifying the polarity of text by extracting sentiments, opinions and emotions [4][5]. There is a wide range of applications, from customer satisfaction to political opinions [5], or even diagnosis of health care related problems identified by the patients themselves [6]. Sentiment analysis does not correspond to one single problem but it may incorporate several different objectives, such as: sentiment classification (e.g., polarity determination, vagueness resolution), subjectivity classification, and opinion spam detection [2][3][7].

A. Sentiment Classification of Review Comments

Sentiment classification is a widely explored research area with a variety of methods and techniques that have been proposed in the literature. There are three main categories of approaches [7][8]: (i) lexicon dictionary-based methods; (ii) machine learning-based methods; and, (iii) hybrid methods.

Lexicon dictionary-based methods deal with creating a sentiment lexicon, i.e., words carrying a sentiment

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orientation [9][10]. These methods can create the dictionary from initial seed words, corpus words (related to a specific domain) or combining the two. Frequently, the dictionary is fed with synonyms and antonyms [8]. One of the most well-known dictionary-based algorithms is VADER [11]. The increasing amounts of data generated by commercial platforms in which the customers are able to rate and comment on products and services has fostered the emergence of various data-driven approaches for sentiment analysis [12]. However, the machine learning approach requires an already labelled dataset to learn from, and it is not certain that knowledge learned in one domain is transferable to another domain [5]. Such approaches usually require human intervention to obtain the sentiment category of the input text. Traditional machine learning methods commonly used include Naive Bayes [13][14], Support Vector Machine [13][15], K-Nearest Neighbor [16], maximum entropy [17], logistic regression [18], Random Forest [19] and conditional random fields model [1].

B. Analysis of Review Ratings

Several research works propose approaches, methods and algorithms that also incorporate the review ratings provided directly by the customer. Chua and Banerjee [20] examined review helpfulness as a function of reviewer reputation, review rating, and review depth. Chen et al. [21] introduced an attention mechanism to explore the usefulness of reviews, and proposed a Neural Attentional Regression model with Review-level Explanations (NARRE) for recommendation. Hassan and Shoaib [22] presented a Gated-Recurrent-Unit (GRU) based Recurrent Neural Network (RNN) architecture for multi-class review rating classification problem. Their model incorporates domain-specific word embeddings and does not depend on the reviewer's information. Ahmed and Ghabayen [23] proposed a review rating prediction framework using deep learning. Seo et al. [24] proposed to model user preferences and item properties using Convolutional Neural Networks (CNNs) with dual local and global attention, motivated by the superiority of CNNs to extract complex features. By using aggregated review texts from a user and aggregated review text for an item, their model can learn the unique features (embedding) of each user and each item. Songpan [25] proposed the analysis and prediction rating from customer reviews who commented as open opinion using probability's classifier model. Overall, the embodiment of review ratings along with the review comments shows a potential to further enhance the algorithms in providing predictions but also extracting useful insights on the performance of products and services. However, they pose additional challenges to their modelling capabilities due to the inconsistencies existing between the review text and the review rating.

III. The Proposed Approach for Modelling the Relationship between Customer Sentiment and Online Rating

In this section, we present our proposed approach for modelling the consistency between customer opinion and online rating. Customer opinions may be explicitly mentioned with the use of ratings and binary feedback, implicitly mentioned through online review comments, and not mentioned at all by not expressing their preferences, satisfaction or dissatisfaction for specific aspects. This classification is depicted in Figure 1. Most of the time, there are combinations of opinion's expression.

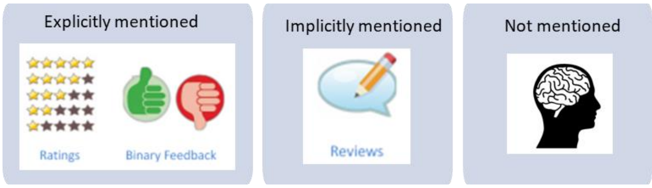

Figure 1. The steps of the proposed approach.

The proposed approach consists of five steps that are described in the following sections: (A) Data Acquisition; (B) Extraction of Sentiment Scores with the VADER Algorithm; (C) Assignment of Sentiment Scores to a Discrete Scale; (D) Modelling the Relationships between Sentiment and Review Rating with Bayesian Networks; and, (E) Evaluating the Consistency between Customer Opinion and Online Rating.

A. Data Acquistion

In this step, the data are acquired from the database storing the review comments and the online rating about the product or service, provided by the customer. Then, they are pre-processed by being subject to cleaning in order to remove records that do not include either the review comment or the review rating. Finally, the acquired data are structured so that they feed into the next steps for further processing.

B. Extraction of Sentiment Scores with the VADER Algorithm

In this step, the online review comments are processed in order to extract their sentiment scores with the use of the VADER algorithm for sentiment analysis, an algorithm that has been proved to outperform several other sentiment analysis lexicons [11]. VADER sentiment is a lexical sentiment classifier and it is used to do initial sentiment labelling of each review comment [11]. A sentiment lexicon is a lexicon where the words have been annotated with semantic scores, often between -1 and 1. VADER sentiment can also aggregate sentiment scores from individual words into sentence scores. The support for sentence sentiment also takes into account booster words (e.g., "very" in "very happy") and negation words (e.g., "not" in "not happy") [5].

VADER uses a combination of qualitative and quantitative methods in order to produce a sentiment lexicon that is especially attuned to microblog-like contexts. These lexical features take into account generalizable rules that embody grammatical and syntactical conventions that humans use when expressing or emphasizing sentiment intensity [11]. VADER is applicable to various domains, such as social media text as well as product and service reviews.

C. Assignment of Sentiment Scores to a Discrete Scale

In this step, the sentiment scores extracted from the previous step 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. Modelling the Relationships between Sentiment and Review Rating with Bayesian Networks

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 Bayesian Networks. A Bayesian Network (BN) is a powerful tool for knowledge representation and reasoning under conditions of uncertainty and visually presents the probabilistic relationships among a set of variables [26]. A BN 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, BNs 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 $v \in V$ 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 $(v_i, v_j) \in E$ represents the conditional dependence between two nodes v_i, $v_j \in V$ 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 the set of parents for a node $v \in V$.

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 $\theta_{xi|\pi i} := P(x_i|\pi_i) \in \Theta$ 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

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

E. Evaluating the Consistency between Customer Opinion and Online Rating

In the last step of the proposed approach, the consistency between the customer opinion and the provided rating is evaluated in order to identify the customer behaviour. Moreover, these results may reveal the level of satisfaction of the customer when this is not explicitly evident from the review comments. For example, a customer may not mention some aspects, although they affect their opinion and thus, the online rating.

IV. APPLICATION IN HOTEL ONLINE REVIEWS FROM THE TRIPADVISOR

In this section, we present the application of the proposed approach in the tourism and hospitality industry. More specifically, we used a dataset of hotel online reviews and ratings from the TripAdvisor in order to evaluate the proposed approach for modelling the inconsistency between the review comments and the review rating. Finally, the implemented model is validated as a predictor and a learning mechanism for the adoption of future records.

A. The Tourism and Hospitality Industry

Recently, data available online related to tourism is increasing exponentially [27]. Sentiment analysis can effectively aid decision making in tourism, by improving the understanding of tourist experience [8]. Sentiment analysis of hotel guests' online reviews has undergone major developments in recent years [28]. 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 [29].

Online customer ratings play a key role in the hospitality industry [29]. Online hotel reviews also provide comparative and benchmarking insights about customer satisfaction [29][30]. Although, overall customer ratings are provided in these websites, there is a need to understand how far these ratings are consistent with the actual customer sentiments expressed through the reviews [31]. To this end, modelling the complex dynamics of online hotel review data in order to derive meaningful insights is of outmost importance [32].

B. The TripAdvisor Dataset

TripAdvisor is an American travel website company providing reviews from travellers about their experiences in hotels, restaurants, and monuments [8].

TABLE I. DATA SAMPLE FROM THE TRIPADVISOR

ID	*Review Title*	*Full Review*	*Rating*
1	Great location, comfortable. Neo-classical boutique hotel	Nice. Brilliant location opposite the cathedral. Bed and linen ideal for a good night's sleep. Good combination of design in neo-classical building. Quiet. The roof terrace is currently very trendy for an early evening drink. Great view. The "8 hours before sunrise" cocktail is, incidentally, fun and delicious. Breakfast has a good choice and is good quality. Staff professional and friendly. We will definitely want to revisit.	5 of 5 bubbles
2	Fairly nice hotel, not much amenities	If you want a hotel walking distance from town but don't want to be in the center of town, then this place is good. Not much on amenities and while they tell you not to drink/brush your teeth with the water, they will provide bottled water-at a fee! That just didn't feel right. The staff was friendly and the breakfast was fine-nothing out of the ordinary.	3 of 5 bubbles
3	Not worth it!!	We stayed 4 nights. We had arranged with the hotel shuttle to pick up us. It was confirmed twice. After 45 min of no show we finally took a taxi and paid 20 Euros!! The room was a little dirty. The worse part was the bathroom, towels, and the pillows they have as headboards!! We thought we will be able to walk to the town. It was impossible, there are no side walk, and the road is just dirt and not safe to walk on the street. The hotel free shuttle into the Town (which leaves every 2 hours) was good. This was the only way into town because of the hotel's location and a small number of taxis on the island. The breakfast buffet was very good and the staff here was very friendly.	2 of 5 bubbles

Tourists can read the accumulated opinions of millions of everyday tourists. Linked to this is the bubble rating (user rating), a 1–5 scale. Together with this rating, users include their opinions, which can cover the performance of a restaurant, hotel, or tourist spot. The dataset under consideration consists of 10,276 online reviews from the TripAdvisor. A sample of 3 records is shown in Table I. After pre-processing, each record includes the review title, the full review, and the rating.

C. Implementation

The implementation of the proposed approach was performed using the Python programming language. The VADER algorithm that extracts the sentiment scores out of the review comments was implemented with the use of the Natural Language ToolKit (NLTK) library (version 3.6.2) [33]. NLTK provides easy-to-use interfaces to over 50 corpora and lexical resources such as WordNet, along with a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning.

The Bayesian Network that models the relationships between the extracted sentiments and the review rating was implemented with the use of the PyBBN library and PyMC3 library. The former incorporates the junction tree algorithm or Probability Propagation in Trees of Clusters. PPTC is applied to BNs with all discrete variables. When dealing with a BBN with all Gaussian variables, exact inference is conducted through an incremental algorithm manipulating the means and covariance matrix. The latter performs Bayesian estimation, particularly using Markov Chain Monte Carlo (MCMC).

D. Results

The VADER algorithm extracts the sentiment score for each record. The sentiment scores are assigned to 5 discrete classes as it was described in Section III.C. The output of the algorithm provides a dataset with all the record IDs along with the Rating (R) ("bubbles"), each one assigned to a sentiment score (ranging from -1 to +1), and an associated class of the Discrete Scale (DS) ("DISASTER", "MANY THINGS NEED TO BE IMPROVED", "FAIR ENOUGH", "PERFECT", "ABSOLUTELY PERFECT"). Table II presents a sample output based on the records presented in the data sample of Table I.

It can be noticed that the rating does not always match to the discrete scale as derived from the sentiment scores. For instance, the comments with IDs 2,3, and 5 are assigned to "ABSOLUTELY PERFECT", since their sentiment scores are far above +0.6; however, all of these three comments are accompanied with a different rating provided by the customer. Such inconsistencies between the rating provided by the customer and the discrete scale as derived from the sentiment score exist in the whole dataset. In order to model those relationships and reveal the inconsistencies, the aforementioned output of all the records feeds into the Bayesian Network.

More specifically, the Bayesian Network consists of two layers. The upper layer includes the parent nodes with the values of the discrete scale that has been derived from the sentiment scores. The lower level includes the child nodes with the values of the online rating. Therefore, it is possible to estimate the probability of receiving a specific rating given the discrete scale. The structure of the Bayesian Network is depicted in Figure 2. Every parent node is linked to every child node. Based upon this structure, the Conditional Probabilities Table (CPT) is calculated for each node.

TABLE II. SAMPLE OUTPUT FROM THE VADER ALGORITHM

ID	*Rating*	*Sentiment Score*	*Discrete Scale*
1	5 of 5 bubbles	0.987	ABSOLUTELY PERFECT
2	3 of 5 bubbles	0.8504	ABSOLUTELY PERFECT
3	2 of 5 bubbles	-0.5471	MANY THINGS NEED TO BE IMPROVED

Based upon this structure, the parameters of the Bayesian Network are learned. Table III presents the resulting conditional probabilities of receiving a specific rating (R) given a specific discrete scale (DS) that has been derived from the sentiment score. In this way, the consistency between the customer opinion and the provided rating is evaluated in order to identify the customer behaviour. Moreover, these results may reveal the level of satisfaction of the customer when this is not explicitly evident from the review comments.

TABLE III. CONDITIONAL PROBABILITIES OF RATING GIVEN THE DISCRETE SCALE

		Discrete Scale (DS)				
	P(R|DS)	***DISASTER***	***MANY THINGS NEED TO BE IMPROVED***	***FAIR ENOUGH***	***PERFECT***	***ABSOLUTELY PERFECT***
Review Rating (R)	***1 of 5 bubbles***	45.27%	22.69%	17.99%	9.56%	1.14%
	2 of 5 bubbles	27.90%	21.85%	19.05%	14.67%	2.17%
	3 of 5 bubbles	19.97%	34.87%	33.33%	32.89%	9.04%
	4 of 5 bubbles	5.34%	11.76%	19.05%	25.56%	28.07%
	5 of 5 bubbles	1.52%	8.82%	10.58%	17.33%	59.57%

E. Discussion

The diagonal cells of Table III indicate the percentages of the exact consistency between the discrete scale as derived from the sentiment scores and the review rating as indicated by the customer. Based on the results, the highest consistencies exist in the extreme values, i.e. P(R = *1 of 5 bubbles | DS = "DISASTER"*) = 45.27% and P(*R = 5 of 5 bubbles | DS = "ABSOLUTELY PERFECT"*) = 59.57%.

Interestingly, for the rest of the review ratings, the highest percentages do not belong to the diagonal cells indicating a higher level of inconsistency between the customer opinion and the review rating. The greatest difference exists in the review rating of 2 bubbles, since P(*R = 2 of 5 bubbles | DS = "DISASTER"*) = 27.90%. The cases of 3 and 4 bubbles have a lower difference with the respective diagonal cells, i.e. P(*R = 3 of 5 bubbles | DS = "MANY THINGS NEED TO BE IMPROVED"*) = 34.87%, and P(*R = 4 of 5 bubbles | DS = "ABSOLUTELY PERFECT"*) = 28.07%.

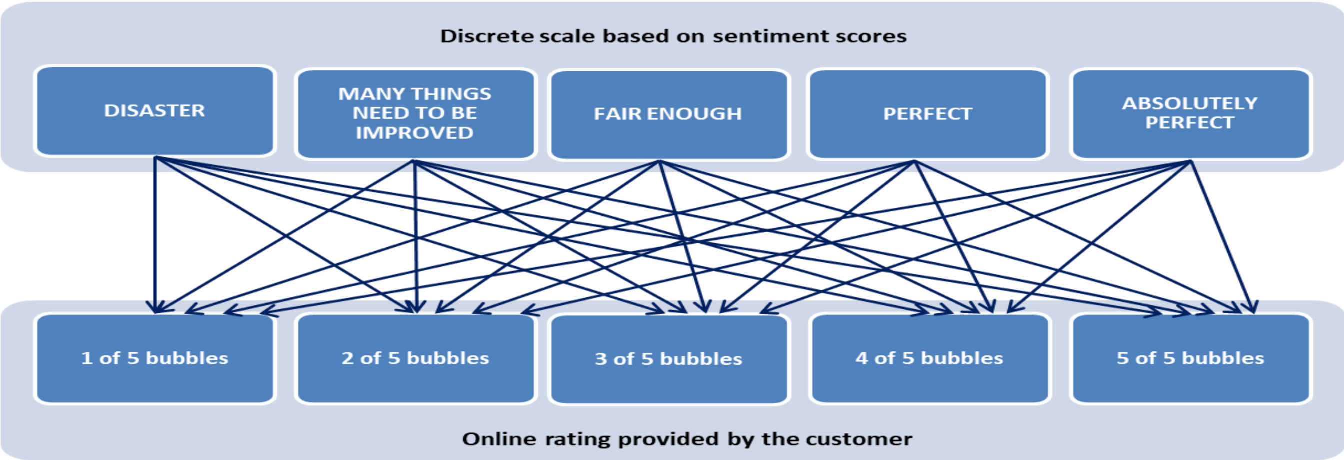

Figure 2. The structure of the Bayesian Network.

The results also show the trend that the ratings of 2 and 3 bubbles tend to be higher than the discrete values derived from the sentiment score. On the other hand, the trend of the rating with 4 bubbles tends to be lower than the discrete values derived from the sentiment score. It should be noted that the nature of the discrete scale does not allow distinguishing the values that are close to the value that indicates a scale change. For example, the value -0.61 is assigned to the "DISASTER" scale, but there is a high uncertainty about whether it belongs to that scale or to the next one, i.e. "MANY THINGS NEED TO BE IMPROVED". This limitation will be addressed in our future work. However, even in this case, it can be noticed that a significant percentage of online review comments are not consistent with the provided rating. This is evident by the fact that the percentages belonging to cells that are not near the diagonal are relatively high.

These results validate the statement that there are usually inconsistencies between the review comments and the review ratings. As already mentioned, this fact occurs for two main reasons. First, different people use different ways of expressing themselves. For example, the phrase "very good" may reflect a different level of satisfaction among different customers. Therefore, there are variations in the sentiment scores extracted from the review comments. Second, the customers select some main points to be mentioned in the review comments. However, there are various aspects that affect their level of satisfaction and their preferences that are not mentioned at all and remain at their own mind. In this sense, there may be review comments with similar content and sentiment but different ratings.

The application of the proposed approach in the e-tourism domain reveals such kind of inconsistencies. From the business perspective, the proposed approach can support product and service managers to look beyond the ratings into the sentiments of the customers. Human language can express emotions which quantitative ratings cannot capture. On the other hand, customers can choose from services that brings them desired satisfaction. The proposed approach enables customers to look beyond online customer ratings while selecting products and services. It brings forth experiences of previous customers in a qualitative and interpretable manner, so that new customers can make informed decisions.

Going through several thousands of comments present online could be a tedious task. The proposed approach summarizes the underlying sentiments of the comments for customers to easily comprehend and decide. Sometimes, fake ratings can distort the actual image of the hotels for the customers. Our study presents a framework for relating ratings with reviews, which can be used for validation.

V. Conclusion

Customers have access to different sources of information, and generate their own content and share their views and experiences, which are expressed through online review comments and ratings about products and services. However, the increasing amount of data has reached a level that makes manual processing impossible, requiring data-driven approaches.

Despite the large amount of research works dealing with sentiment analysis, the consistency between the customer opinions expressed in review comments and the rating that they provide has not been explored. In this paper, we propose an approach incorporating the VADER algorithm for extracting the polarity of the review comments and Bayesian Networks for revealing the relationships between the aforementioned sentiment scores and the online rating.

The proposed approach was validated in the tourism domain using a dataset with hotel reviews, extracted from the TripAdvisor. The proposed approach is able to model effectively the aforementioned relationships in order to derive the consistency between the review comments and the online rating. The results showed there are usually inconsistencies between the review comments and the review ratings, because different people use different ways of expressing themselves, while the customers select some main points to be mentioned in the review comments.

However, there are various aspects that affect their level of satisfaction and their preferences that are not mentioned at all. From the business perspective, the proposed approach can support product and service managers to look beyond the ratings into the sentiments of the customers. On the other hand, customers can choose from services that brings them desired satisfaction.

Our future work will move towards the following directions: First, we will implement fuzzy logic approaches in order to address the issues related to the fact that different people use different ways of expressing themselves leading to variations in sentiment scores. Second, we will apply probabilistic and fuzzy approaches in order to relax the discrete scale derived from the sentiment scores in order to tackle with sentiments that are close to the borders between two discrete values. Third, we will examine how different aspects of the review comments (e.g., different services of the hotels) affect the overall sentiment and rating.

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