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Методические рекомендации и демонстрационная версия заключительного этапа по направлению «190. МЕНЕДЖМЕНТ»

Трек «Экономика впечатлений: менеджмент в индустрии гостеприимства и туризме» **КОД – 190.3**

Прочитайте научную статью[1] и сделайте ее критический анализ на русском языке в соответствии с вопросами, приведенными в конце текста задания.

Abstract
This study aims to establish a relationship between customer sentiments in online reviews and customer ratings for hotels. Customer sentiment refers to the emotions expressed by customers through the text reviews. These sentiments can be positive, negative or neutral. The study explores customer sentiments and expresses them in terms of customer sentiment polarity. Our results find consistency between customer ratings and actual customer feelings across hotels belonging to the two categories of premium and budget. Customer sentiment polarity explains significant variation in customer ratings across both the hotel categories. With regard to managerial implications, the study finds that, when compared with premium hotels, managers of budget hotels should improve their staff performance and hotel services. The present study is not exhaustive and other factors like customer review length and review title sentiment can be analyzed for their effects on customer ratings.

1. Introduction
Travel is an integral part of our lives. According to Pavaan Nanda, co-founder of Zostel, “Travel is seen as a mode of self-realization, exploration and experiencing different forms of lifestyles. Leisure travel is not a product of luxury but rather considered a necessity to consolidate one's energy.” (Tripzuki, 2013). In 2015 international tourism market grew by 4%, with 1184 million tourists travelling worldwide. This was led by 5% growth in Europe, the America, Asia and the Pacific. In 2016, international tourist arrivals are expected to grow by 4% worldwide (UNWTO, 2015). The Travel and Tourism Competitiveness Index Ranking (2015) indicate Europe (represented by 6 countries) in the top 10, making it the best continent for travel. Spain tops the ranking list helped by surge in international tourists coming from emerging countries like China, Brazil and Mexico. Emerging countries are also seeing an uptrend in the inflow of international tourists. Countries like Morocco and Saudi Arabia are upcoming attractions in the Middle East e North Africa region. Similarly, in the Sub-Saharan Africa region, Mauritius and Botswana are preferred by travelers. As far as cities are concerned, Hong Kong tops the list for travelers, closely followed by London (Euromonitor, 2016).

The dynamic landscape of global tourism industry is reflected through the advent of new destinations like mountain tourism in Korea (UNWTO, 2015). The tourism industry is also growing through non-conventional sub-divisions like indigenous tourism and eco-tourism. Countries like Australia and Canada have well developed indigenous tourism industries, popularly known as

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[1] Использованы фрагменты статьи Geetha, M., Singha, P., & Sinha, S. (2017). Relationship between customer sentiment and online customer ratings for hotels-An empirical analysis. *Tourism Management*, 61, pp. 43-54.

Aboriginal tourism (Aboriginal, 2016). Similarly, eco-tourism has been popular in countries like Costa Rica, Jordan and South Africa (Ecotourism, 2016).

For both host and the tourists' home countries, tourism industry helps to generate substantial economic benefits. Developing countries often promote themselves as tourism destinations to gain from the expected economic improvement (UNEP, 2016). Local economic development and enhanced tourism can only be realized with the hotel industry (Jones, Hillier, & Comfort, 2014). One such instance can be found in China, where the hotel industry is seeing increased revenue growth spurred by quick economic development, rising purchasing power, and reduced transportation costs (Xu, 2010; Zhang, 2011). Because of the micro nature of the hotels, they can generate employment through their labor intensive structure and can boost local spending quickly (Udemy Blog, 2014). So, it is imperative for a growing economy like India, to keep the hotels running efficiently and contributing to the country's Gross Domestic Product (GDP).

One way to improve the hotel industry is by better understanding of customers through ratings and reviews. Online customer ratings play a key role in the hospitality industry (Xie, Zhang, & Hang, 2014). Online hotel reviews also provide comparative and benchmarking insights about customer satisfaction (Mauri & Minazzi, 2013; Zhou, Ye, Pearce, & Wu, 2014). Online review websites that are dedicated to the rating of hotels have been gaining immense popularity (Buhalis & Law, 2008) because of increased impact of tourism, which contributes to 9.4% of global GDP (Baumgarten & Kent, 2010). Using consumer feedback, hotel ratings are assigned by few online websites. Ratings by these websites consider the number of reviews, age of the reviews, and quality (valence) of the reviews. 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. Also this study needs to be performed across different domains of hotels to get better insights. Objective of our study is to analyze whether the perceived sentiments in opinions of the customers are consistent with the hotel ratings provided by them led to the following research questions:

Research question 1: Can customer review sentiments explain the customer ratings provided for hotels?

Research question 2: Is the relationship between customer review sentiments and hotel ratings are consistent across hotel categories of budget and premium?

3. Methodology

3.1. Sentiment analysis

Data in the form of texts is one of the major forms of unstructured data. It forms a large repository of information provided we can extract the right content from it. One way to do this is through sentiment analysis. Sentiment Analysis has emerged as an important aspect in text analytics. Sentiment is an attitude, thought, or judgment prompted by feeling and sentiment analysis, which is also known as opinion mining, studies people's sentiments towards certain entities (Fang & Zhan, 2015). When compared with more traditional market research methods (e.g. surveys or opinion polls), sentiment analysis has the advantage of being more cost and time efficient. Also, it is a nonintrusive method to extract consumers' opinions and sentiments in realtime avoiding recall biases generally associated with post consumption self-report measurements (Rylander, Propst, & McMurtry, 1995).

Sentiment analysis has been performed on various domains like twitter and amazon reviews to gauge customer sentiments. But, a comprehensive study of customer sentiments in the hotels domain is still lacking. Most analyses have focused on analysis through ready-made online software. No inherently generated algorithm has been used so far. Our study aims to address these issues.

3.2. Location for data collection

Tourism industry in India has evolved into a thriving domain. In tourism, there was a rise of nine per cent during last year and 14 per cent in the previous year. India ranks 7th in numbers of World Heritage sites (World Economic Forum, 2007). Goa is one of the major tourist spots in India (Touropia, 2015; About Travel, 2016). Goa is poised to have 10 million tourists arriving by 2017.

The Investment Promotion Board (IPB) in India has approved the proposal for 11 projects including five-star hotels, with an investment of about Rs. 1000-crore in Goa (The Economic Times, 2015). Goa Tourism would soon launch an e-commerce site to enable domestic and foreign tourist book online their boarding and lodging, as well as, activities like adventure and water sports, music festival tickets, restaurants and river cruises (NDTV, 2015).

With all these initiatives in place, Goa is becoming one of the most important destinations in the Indian tourism landscape. To stay relevant in today's connected world, hotels in Goa need to maneuver their online presence and resources to attract tourists and provide better service. The distribution of hotels in GOA is as follows: There are a total of 496 hotels in Goa, out of which 110 belong to the budget category. Premium category hotels include both luxury and resort type hotels and are 138 in number. The remaining 248 hotels belong to other categories including mid-range (Tripadvisor, 2016). Some of the well-known hotel brands finding their presence in Goa are Clarion, Golden Tulip, Hyatt, Marriott, Vivanta and Taj Exotica. Apart from hotels, other popular staying options available for travelers are guest houses, specialty lodging and holiday rentals. These are well distributed throughout popular destinations in Goa like Panaji, Calangute, Candolim, Vasco Da Gama, Dona Paula and Baga. For the non-conventional tourists, Goa offers unique heritage and boutique stays, backpacker & adventure stays and beach huts, tents and cottages (Planet Goa, 2016).

3.3. Data analysis

Different classification techniques have been previously used for classifying words as per underlying sentiment. Pang, Lee, and Vaithyanathan (2002), Ye, Zhang, and Law (2008) and Kang, Yoo, and Han (2009) applied a traditional topic-based document classification method to classify a review document as positive or negative. Dave, Lawrence, and Pennock (2003) had used a score function formula to determine positive and negative sentiments stochastically. Myung, Lee, and Lee (2008) used a syntax analyzer for product review analysis and extracted a sentiment word candidate from a predicate.

Use of a lexicon has been found perennial in any classification technique. Sista and Srinivasan (2004) in their study focused on classification experiment of movie reviews through the use of a lexicon constructed using the General Inquirer Lexicon and the WordNet database. The lexicon was used as part of the Naïve Bayes algorithm. Fahrni and Klenner (2008) constructed a self-made lexicon with a two-stage model, and the classification performance was good when the self-constructed lexicon and Senti-WordNet were used simultaneously. Cho and Lee (2006) manually constructed a lexicon in order to find eight kinds of basic emotions in a person from the lyrics of songs, and performed a classification experiment using a supervised learning algorithm. For our study, we have considered a lexicon of positive and negative words, as used by Hu and Liu (2004) and Liu, Hu, and Cheng (2005).

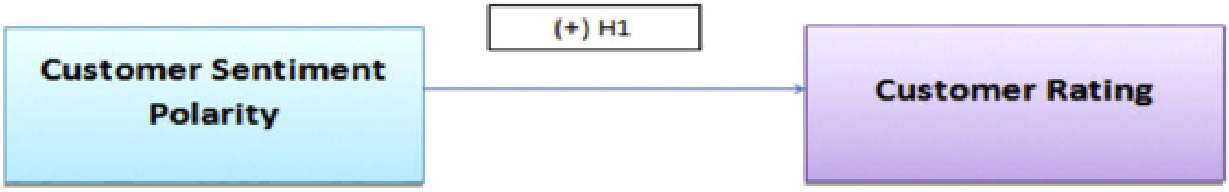

Fig. 1. Conceptual model.

For our classification algorithm, we have used the Naïve Bayes classification technique. We have chosen this algorithm among various other algorithms because of its demonstrated success. Miao, Li, and Dai (2009) measured the ranking of reviews by analyzing the quality of an opinion with a study on the sentiment mining and retrieval system using the Naïve Bayes algorithm. Tan and Zhang (2008) classified Chinese documents as positive and negative. Here, Naïve Bayes was used as one of the classification techniques. Naïve Bayes uses the lexicon of words to match words from documents against the lexicon. Then it assigns each word the probability of being positive or negative, independent of other words.

But, before the above mentioned techniques can be employed, the text data needs to be processed and made ready for analysis. All the reviews per hotel were collected column-wise in MS Excel and the files were saved in CSV (Comma Delimited) format for easy readability in the R environment. This was followed by the data cleaning step using "tm" package and "SnowballC" package in R.

After the data was cleaned, all the words were loaded in a term document matrix. Matrix sparsity was reduced to 10% to remove all irrelevant terms.

4. Findings and discussion

4.1. Exploratory data analysis

As part of the exploratory data analysis, we looked at most common words in reviews in both the categories. The top terms included words like "hotel", "good", "staff", "service", etc. The results are shown in Figs. 6-7

Wordclouds provide better visual representation and help to make comparisons between the two categories. Higher the usage frequency of a word, larger will its presence in the word cloud. From the above charts and wordclouds, it is evident that certain terms have been used more frequently in case of premium category hotels than for budget category hotels. But, just the mere difference in frequency in the usage of these terms does not allow us to draw sufficient conclusion regarding each category of hotels. We must look at the correlations among the terms and how frequently they have been used with other terms so that we can draw some meaningful results. We did this through the usage of cluster anal- ysis. Clustering techniques have been used previously to detect polarity in a supervised way (Cambria, Mazzocco, Hussain, & Eckl, 2011). Here we have used clustering as an unsupervised statistical learning method. In unsupervised learning, we do not have any associated response variable. So, the aim is not prediction, but to find interesting patterns and insights within the data. Some of the questions we wished to answer through this analysis were whether there were informative ways to visualize the data and discover subgroups among the words (James, Witten, Hastie, & Tibshirani, 2016). Using the Euclidean distance matrix, being represented in terms of correlation between terms, hierarchical clustering was performed across both the categories. This analysis allowed us to see the different clusters formed by terms based on how strongly they are correlated in terms of usage, and how the smaller clusters in turn combined to form bigger clusters see (Figs. 8 and 9).

One of the key requirements for understanding our research questions is the understanding the customer sentiments hidden in the reviews. The cluster analysis helps us in understanding these sentiments better by looking at the terms used by the customers in their reviews. The Height of the cluster dendrograms is inversely proportional to the correlation between terms. Highly correlated terms form cluster at lower points of the dendrogram. Also, two words at the same height, but belonging to different clusters, will have very far correlations.

Fig. 6. Wordcloud for budget category.

4.2. Predictive data analysis

To test our hypothesis, we used simple linear regression. The regression model tries to determine whether a linear relationship exists between customer rating and customer sentiment polarity. Here, customer sentiment polarity is the independent variable and customer rating is the dependent variable. We wish to find out whether a linear change in customer sentiment polarity leads to a linear change in customer rating. Customer Rating is obtained directly from the website. Polarity is “positive” when the above ratio is greater than 1.5, “neutral” when it is between 1 and 1.5 and “negative” when it is 0 to less than 1. To determine the polarity and sentiment of each review, Naïve Bayes Classification algorithm was used against a lexicon of words. The algorithm was already trained against an extensive repository of sentiment based words. It comes as default in the “sentiment” package in R. As we can see from the above plots, for budget category hotels, negative emotions and negative sentiments are more than those for premium category hotels.

Fig. 7. Wordcloud for premium category.

Customer Sentiment Polarity = Positive Words/Negative Words of the reviews

From the above regression analysis for budget category hotels, we find that the value of the t statistic for the slope is 3.77. This is greater than the critical t value of 2.1 for a 1⁄4 5% and degrees of freedom 18. Thus we find support for the linear relationship be- tween customer sentiment polarity and customer rating. The standard errors for intercept and slope are multiplied with FPC factor of 0.91 to compensate for sample size being greater than 10% of the population. So, the actual standard errors are 0.19 and 0.009 respectively. The coefficient of determination or R square has a value of 0.44. So, 44% of the variation in the customer ratings is explained by customer

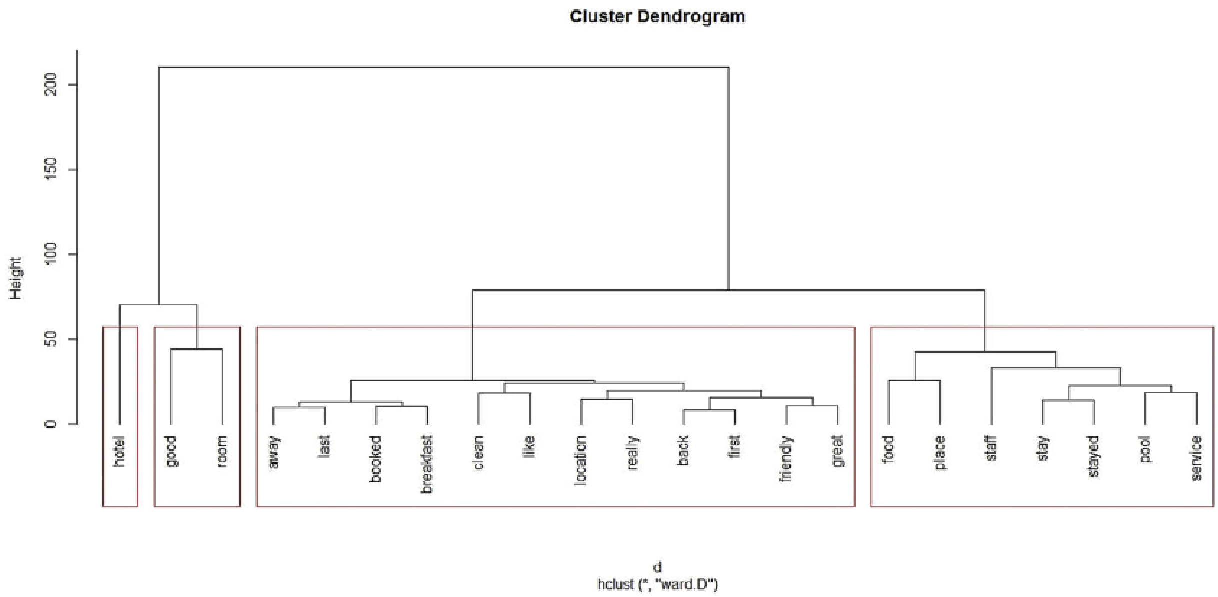

Fig. 8. Cluster dendrogram for budget category.

sentiment polarity.

Similarly, from the regression analysis for premium category hotels, we find that the value of the t statistic for the slope is 2.21. This is greater than the critical t value of 2.1 for a 1⁄4 5% and degrees of freedom 18. Thus we find support for the linear relationship between customer sentiment polarity and customer rating. The standard errors for intercept and slope are multiplied with FPC

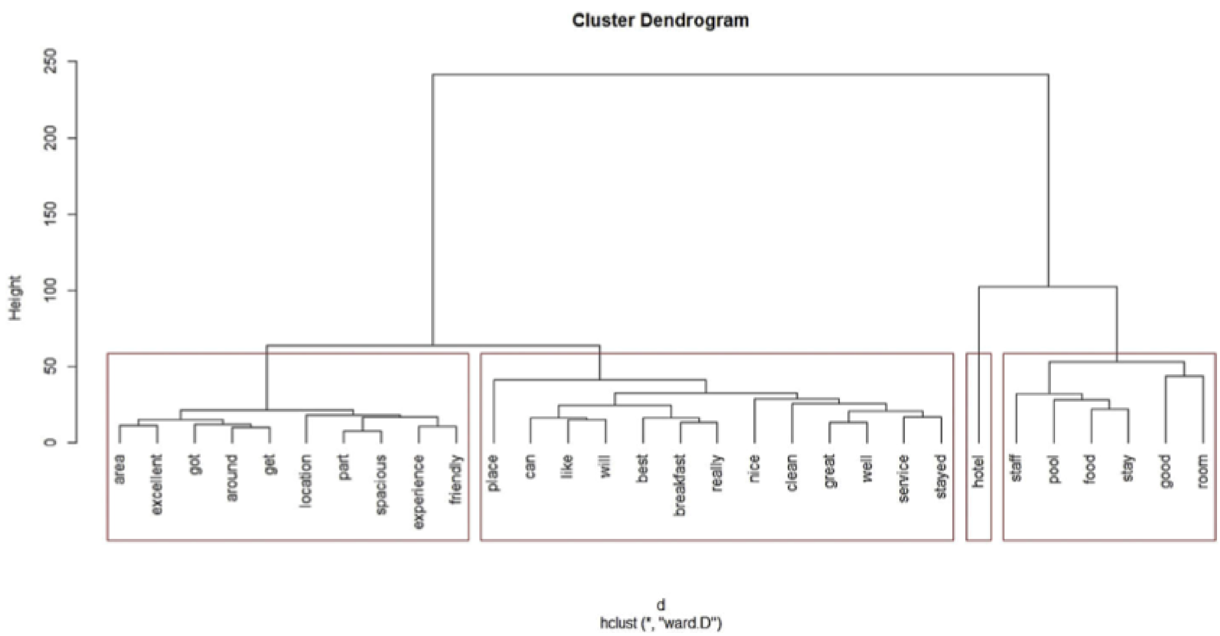

Fig. 9. Cluster dendrogram for premium category.

factor of 0.93 to compensate for sample size being greater than 10% of the population. So, the actual standard errors are 0.15 and 0.0055

5. Managerial implications

In a study by Xie et al. (2014), customer reviews and ratings are of great business value to hotels. Hotel sales and profitability were linked to customer reviews (Ye et al., 2009). A study by Torres et al. (2015) demonstrated that hotel ratings and reviews on online sites influence positively the size of online transactions done with regard to hotel bookings.

Our study can help managers look beyond the hotel ratings into the sentiments customers are having regarding the hotels. Human language can express emotions which quantitative ratings cannot capture. With the help of the sentiment analysis done on the customer reviews in our present study, managers can look into these granular details and better respond to customer needs. From the exploratory analysis itself, it is clear that customers are having better sentiments with regard to premium hotels than budget hotels. In the most frequent terms used for both the categories, we see that the term "good" has been used 355 number of times for premium category hotels while for budget category hotels, it has been used 243 number of times. From the wordclouds, a comparative study of the words used for the categories reveal certain directions for managers to look at. The word "staff" has been referred to a more frequently in premium category hotels than in budget category hotels. The term "service" finds a mention in the premium category but not in the budget category.

Looking at the hierarchical cluster dendrogram plots, we find the term "staff" has been used more frequently with the term "good" for premium category hotels than for budget ones. This is evident from the closer clusters they form. This implies that though the premium hotels are doing a good enough job with regard to ensuring a good service from their staff, the budget category hotel managers need to look at ways to improve their staffing service. From further analysis of the hierarchical clusters, we observe that the term "service" appears in close clusters with the terms "great" and "well" for premium category hotels. But, for budget category hotels, the term shows no such correlation. So, managers in budget category hotels in Goa need to concentrate more on improving their service.

In the emotional classification of the reviews, we find that for the budget category hotels, the emotions are more negative and granular. Also, the ratio of number of positive to negative reviews is more for premium category hotels than in budget category hotels. Managers should be wary of such sentiments as word of mouth communications have lasting effects on hotel images. Westbrook (1987) defined word-of-mouth as: "informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers". Word of mouth communication has the potential to influence consumer purchase decisions, customer acquisition, and consequently results in increased revenue for organizations (Litvin, Goldsmith, & Pan, 2008; Trusov, Bucklin, & Pauwels, 2009). Responding to any such negative reviews is imperative for the hotel management (Sparks et al., 2015). Our study can help managers in dealing with negative reviews promptly by understanding them in a better way.

From the regression analysis, we find that the variation in hotel ratings is explained by the customer sentiment to a greater extent in case of budget category hotels than in case of premium hotels. So, it is possible that factors other than customer ratings are affecting the customer ratings for the premium hotels. Surveys can be conducted by the hotel management along with sentiment analysis to better understand customer grievances. Often, fake reviews on websites can tarnish the image of the hotels. Managers should find tools to manage these reviews.

Customer satisfaction is correlated with hotel services like housekeeping, reception, food and beverage, and price (Kandampully & Suhartanto, 2000). As hotel managers can review their services to improve customer loyalty, customers can also choose from services that brings them desired satisfaction. Our study enables customers to look beyond online customer ratings while selecting hotels in Goa. 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 for hotel reviewing purpose could be a tedious task. Our present study summarizes the underlying sentiments of the comments for customers to easily comprehend and decide. In addition, through our cluster analysis, customers can make deep dives into specific attributes of services provided by hotels in the two categories of budget and premium. 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. Differences exist between what hotel mangers perceive as customer value and what customer's actual experiences highlight. There is a need to align these differences in perception to optimize value delivered (Nasution & Mavondo, 2008). Our study provides a common ground for such alignment.

Вопросы для анализа статьи и выполнения задания

1. При подготовке олимпиадного задания из оригинальной статьи было изъято несколько важных логических блоков: как целых классических разделов научной статьи, так и совсем небольших по объёму текста, но весьма значимых сюжетов. Напишите, какие это логические блоки кроме (“Limitations”), и какое у них должно быть смысловое наполнение.
2. Достаточно ли авторы обосновали исследовательские вопросы для своего исследования?
3. Оцените качественный уровень концептуальной модели исследования. Какие у нее есть достоинства и недостатки?
4. Какие из приведенных в статье выводов по результатам исследования представляются Вам спорными, недостаточно обоснованными? Аргументируйте свой ответ.
5. В тексте задания отсутствует раздел “Avenues for future research”. Если бы Вы были автором статьи, какие бы направления будущих исследований в предметной области этого исследования Вы бы предложили для его развития?