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Emotional Analysis of User Online Reviews based on Text Mining

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Abstract

With the rapid development of the Internet and the rise of web2.0, user-generated content has gradually become the dominant content of websites. In order to eliminate the uncertainty of goods, consumers often rely on product reviews to help them make decisions. Hotels can also adjust the operation strategy of e-commerce platform by mining consumers' online reviews Based on the Chinese text analysis technology, this paper studies online user reviews of hotels through the construction of emotional dictionary, the collocation of evaluation objects and evaluation words. Through the emotional analysis of the reviews, the following conclusions are drawn: consumers are more concerned about the room area, but less about the environmental of the hotel; in the positive reviews, consumers generally have higher satisfaction with the environmental factors, while in the negative reviews, they are less satisfied with the food factors.

Keywords

Text Mining; Text Semantic Analysis; Sentiment Analysis; Online User Reviews.

1. Introduction

In today's era, big data mining can be used for stock price forecasting[1], exploring user experience[2], making personalized recommendations[3], and so on. With the rapid development of the Internet, big data is being generated through Internet traffic (such as clickstream), mobile transactions, user-generated content, and social media. Among them, User generated content (UGC) gradually dominates the way website content is generated. UGC means that users share or display their original content through the Internet platform. Table 1 shows some UGC application forms:

Table 1. Part of the UCG application forms

UGC From	Representative website
Online writing	Wiki, Baidu
Video sharing	YouTube, MetaCafe, Vimeo
Social Media	Facebook, Instagram
Music sharing	Spotity, iTunes
Review	Tripadvisor, yelp
Micro blog	Twitter, Sina weibo

Online user reviews are an important form of UGC. Online user reviews can promote the development of e-commerce from the following two aspects [4]: (1) By browsing the online reviews of other consumers can reduce the impact of product information uncertainty, thereby helping consumers make more informed decisions. (2) Enterprises can improve the quality of products and adjust the operating strategies of e-commerce platforms by mining online reviews of consumers. Online user reviews can increase the channels for companies to communicate with consumers, and they can also make companies more profitable.

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More and more scholars have begun to study online user reviews of hotels. Since consumers cannot know the information before they check into the hotel, most consumers choose to browse the reviews of others to obtain information to eliminate the uncertainty of hotel information. The hotel interacts with consumers through reviews and improves their serivices based on reviews. The importance of reviews can be imagined. Although large number of scholars have studied hotel reviews, most of these papers studied the quantitative relationship between reviews and satisfaction (some reviews have a scoring function, and consumers can make an evaluation of 1-5 points), the number of reservations, and the channels of reservations [5], they did not involve the emotional mining of reviews.

For example, Siqing Zhuo and Yongzhou Feng used negative binomial regression to conduct an empirical analysis of factors affecting the usefulness of online reviews on TripAdvisor.com's 4258 hotel review data [6]. The study found that the length of review content, review extremeness, number of votes for review usefulness, user approval and personal information disclosure have a significant positive impact on the usefulness of online reviews.

Lee evaluated the relevant reviews of online travel reviews from TripAdvisor.com to understand whether the author who giving useful reviews(reviews on TripAdvisor.com can be rated "useful" by other consumers) Or "useless") has similar characteristics based on the social demographic characteristics and behavioral factors [7]. Experimental results show that consumers tend to think that low-rated reviews are more useful than high-rated reviews, and that those do not provide personal information are more useful. These two studies point out that online hotel reviews will increase the visibility of hotels, whether they are positive or negative.

On the other hand, due to the massive growth of social media and UGC, opinion mining and sentiment analysis play an important role in big data analysis. In fact, opinion mining and sentiment analysis are considered very suitable for various types of market intelligence applications (Pang and Lee) [8]. The sentiment analysis technology used to extract opinions from unstructured UGC can be used as an excellent tool for intelligent tasks including reputation management, public relations, tracking public opinions, and market trend forecasting. Sentiment analysis and opinion mining are based on technologies such as natural language processing (NLP), information retrieval (IR), information extraction (IE) and artificial intelligence (AI). Typical tasks of sentiment analysis including (1) Finding documents related to a specific topic or purpose; (2) Preprocessing the collected files, such as marking the file as a single word and extracting relevant information from it; (3) Determining consumer sentiment towards the product or company (Schmunk et al.,)[9]. Compared with more extensive text mining methods, sentiment analysis may be considered as a special type of text mining, which focuses on identifying subjective statements and containing opinions and emotions, especially in UGC on the Internet.

This paper studies the sentiment analysis of consumer experience by mining hotel user reviews, and achieves the following goals:

(1) To understand which aspects of the hotel the consumers have opinions and suggestions on, and which aspects they are satisfied with.

(2) To understand the reasons why consumers feeling dissatisfied or satisfied.

(3) For hotels, provide relevant countermeasures to help improve customer experience.

This paper focuses on the issue of "review sentiment analysis based on text analysis technology". The first chapter gives the theoretical basis of the research. The second chapter gives the process of the research experiment, expounding in detail how to operate the experimental data. The third chapter discusses and analyzes the experimental results. The fourth chapter gives relevant suggestions for the hotel based on the experimental results; The fifth chapter gives conclusion. This paper used python3 to complete the experimental part.

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2. Experimental Process

2.1. Experimental Design

In order to analyze the sentiment in online user reviews, large-scale text analysis is required. This paper selected a publicly available data set of Tripadvisor.com. Figure 1 shows a screenshot of the user reviews page from Tripadvisor.com. It can be seen that a hotel has consumer reviews from all over the world. In addition to these text reviews, there are other types of information, including traveler rating, time of year (by season), etc.

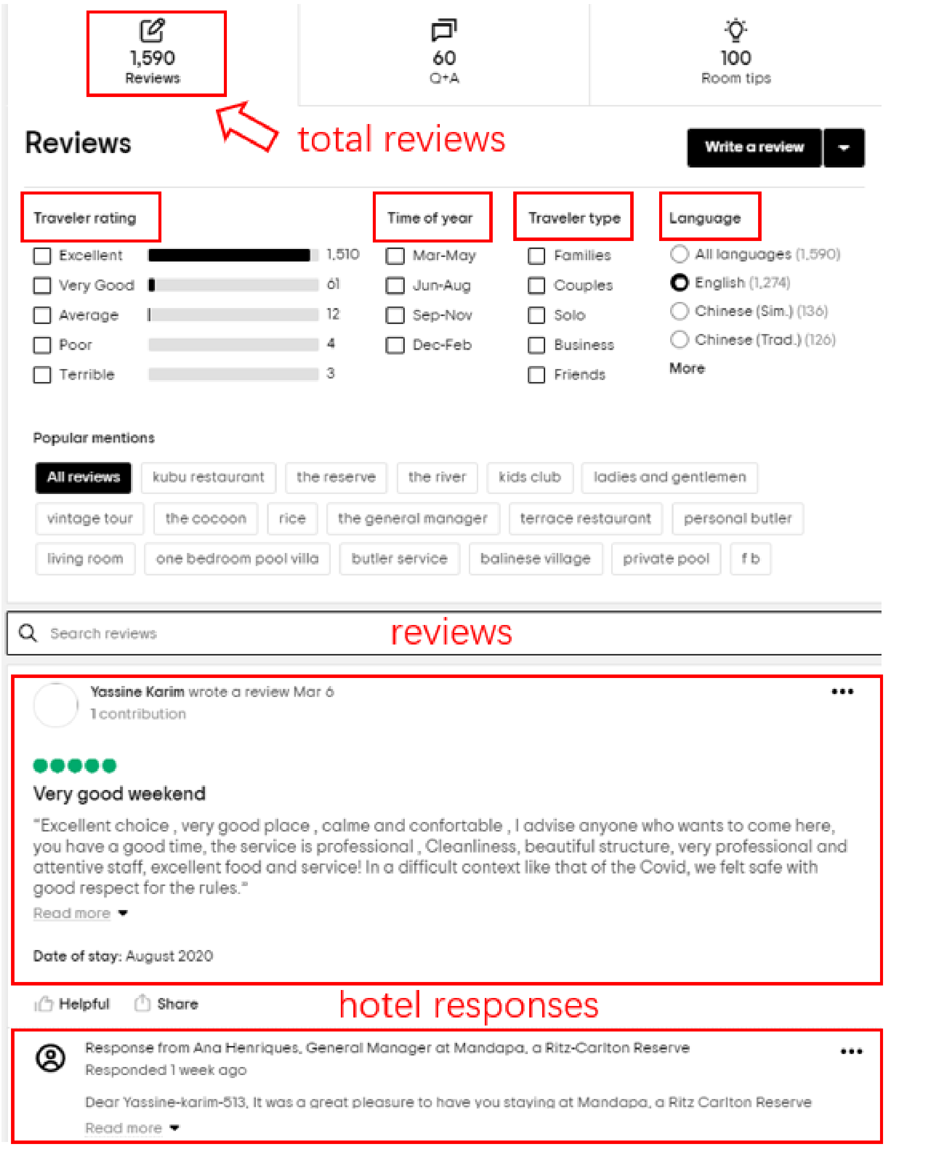

Figure 1. Screenshot of reviews page of Tripadvisor.com

The flow chart of the experiment is shown in Figure 2:

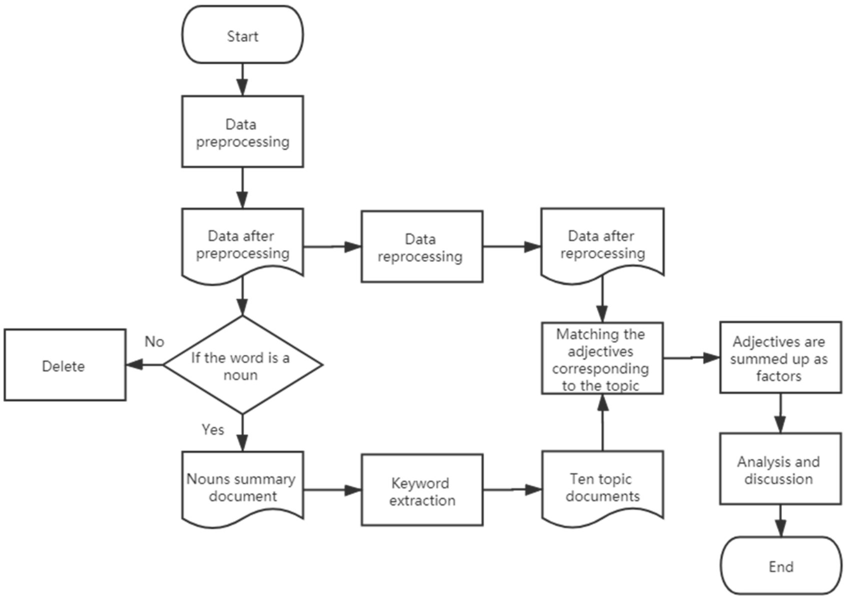

Figure 2. Flow chart of experiment

2.2. Data Collection

This paper selected hotel reviews on Tripadvisor.com as the research object. Tripadvisor.com is the world's leading travel website. It mainly provides reviews and suggestions from travelers from all over the world. It comprehensively covers hotels, attractions, restaurants, airlines, and travel planning and hotel, attractions, and restaurant booking functions around the world. It has more than 570 million travel reviews and suggestions from real travelers.

The reviews were divided into 3,000 positive reviews and 7,000 negative reviews, a total of 10,000 reviews. The review period was from 2007 to 2008, and the review hotels were hotels in major cities in China.

2.3. Data Preprocessing

2.3.1. Data Description

The public data set was in the form of a single review stored in a single text document. First, we put a single review into two folders according to the positive and negative directions, and merged all the text documents in the same folder into one text document. After merging, the positive review document had a total of 7000 reviews and the size was 2261KB; the negative review document had a total of 3000 reviews and the size was 1445KB.

2.3.2. Data Cleaning

Data cleaning refers to the process of checking and proofreading experimental data, which can delete duplicate and interference information and correct errors. Through data cleaning, the experimental results can be made more accurate, so it is an indispensable step.

During the experiment, it was found that some of the reviews were repeated, which might lead to experimental errors. The repeated reviews in the text file were deleted. A total of 1611 positive repeated reviews and 520 negative repeated reviews were deleted. After deduplication, the size of the positive document was 1644KB, and the size of the negative document was 1090kb.

There were also some hotel responses in the reviews, most of which were the hotel's positive reviews on themselves, which would affect the results of the experiment and make the results of the experiment unfair, so they were deleted. The document adjustment process is shown in Table 2:

Table 2. Document adjustment process

Size (KB)	Original document	Duplicate reviews and hotel responses	After deleting duplicates
Positive	2261	534	1727
Negative	1445	287	1158

2.3.3. Segmentation

Because the experiment was carried out on the Chinese review data, we needed to do word segmentation before experiment. We choosed the Jieba word segmentation model to complete this task .There are three segmentation modes in Jieba word segmentation: precise mode, full mode and search engine mode. Their functions and characteristics are shown in Table 3:

Table 3. Functions and characteristics of Jieba word segmentation model

Word segmentation model	Function	Characteristics
Precise mode	Try to cut the sentence as accurately as possible	Accurate, suitable for text analysis
Full mode	Scan all the words in the sentence	Fast, but can't solve ambiguity
Search engine mode	On the basis of precise mode, the long words are segmented again	Improve the recall rate and suitable for search engine

This paper adopted the precise mode, because the experiment only studied the nouns and corresponding adjectives in the reviews, so operations such as deleting stop words were not considered before segmentation.

2.4. Keyword Extraction

Keyword extraction was to find the subject in the review, and then analyzed the adjectives for the subject. The subject should be related to the hotel. In the keyword extraction, the following steps were carried out:

2.4.1. Part-of-speech Tagging

We used the Part-of-speech tagging function (jieba. posseg) in the Jieba function package to segment the document again and performed Part-of-speech tagging to extract the nouns in the document. During the Part-of-speech tagging, we noticed that because the word "服务" in Chinese could be used as both a noun(service) and a verb(serve), but in the Jieba Part-of-speech tagging function, service which should be tagged as a noun is listed as a verb, so all nouns were retained during actual code operations. In addition, the word "服务" was retained. The results of part of speech tagging are shown in Table 4:

Table 4. Part of speech tagging results

Positive noun retention results	距离(distance) 公路(highway) 公交(transit) 房间(room) 大床房 (king-size bed room) 早餐(breakfast) 酒店(hotel)街道(street)
Negative noun retention results	标准间 (standard room) 设施(facilities) 建议(proposal) 服务态度 (service attitude) 前台(reception) 客人(guest) 大堂(foyer)

2.4.2. Delete Single Word

Before extracting keywords, the operation of deleting single words was performed on the noun retention result. All single words were deleted uniformly to prevent the subsequent experimental steps from being affected.

2.4.3. Clustering

The clustering functions in SnowNLP, Jieba and the LDA topic probability model were used to cluster the summarized noun retention results, and 10 subjects were extracted. Because the LDA model is based on Bayesian probability, the results were different every time. The

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clustering results of SnowNLP and Jieba are the same every time. Table 5 shows the results of SnowNLP and Jieba and the three topic probabilities of LDA respectively.

Table 5. Display of keyword extraction results

Model	Result
SnowNLP	hotel, room, service, feeling, breakfast, front desk, waiter, facilities, price, environment
Jieba	hotel, room, breakfast, service, front desk, waiter, feeling, facilities, guesthouse, king- size bed
LDA	hotel, room, service, breakfast, front desk, feeling, waiter, price, facilities, environment
	hotel, room, service, front desk, breakfast, feeling, facilities, price, environment, waiter
	hotel, room, service, feeling, breakfast, waiter, front desk, facilities, environment, price

Considering comprehensively, since the waiter actually represents the service of the hotel, the following ten subjects are selected as the research objects: [' hotel', ' room', ' service', ' feeling', ' breakfast', ' front desk', ' facilities', ' environment',' guesthouse',' price'].

2.5. Data Reprocessing

Before matching the subject and its corresponding adjective, the original review data must be reprocessed to find the subject's corresponding adjective conveniently and accurately. This paper assumed that the adjective corresponding to each subject appears in a sentence with a dot (period, question mark, exclamation mark, comma, pause, semicolon, etc.) near the subject. If in the same review, there was a dot splitting the subject and the adjective, it was regarded as a match failure.

First, adjusted the punctuation marks. We converted all periods, question marks, exclamation marks, commas, semicolons, tilde, ellipsis (including full-width and half-width, Chinese symbols and English symbols) in the reviews into half-width Chinese commas, and convert colons to a space. Use the Jieba package again to segment the review data. At this time, it was found that the word "服务(service)" appeared less frequently because the word segmentation system would not segment words such as "服务态度(service attitude)" and "服务水平(service level)". In order to solve this problem, in the document after word segmentation, we used the replacement function to replace all "服务" with "服务" (with spaces), to solve the problem that the word "服务" cannot be accurately segmented.

Finally, we used python to replace all "," (Chinese, half-width) with newline characters in the reviews that have been divided into words, so that it is convenient to find the adjectives corresponding to the subject. As long as the subject appeared in a line, just keep the adjectives appeared in the line .

2.6. Building a Sentiment Dictionary

In this step, the adjective matching of a single subject was performed, and the positive and negative review data were read line by line through python. When a specific subject, such as "hotel" appeared in the row of data, all adjectives in this line were retained. Considering the inaccuracy of word segmentation, it was easy to divide words such as "不差(not bad)" and "不美丽(not beautiful)" into "不(not)/差(bad)" and "不(not)/美丽(beautiful)". After retaining adjectives, only "差(bad)" and "美丽(beautiful)" could be retained, completely inverting the original intent of the author. so while retaining the adjectives, all the "不(not)" characters were kept together to ensure the original intent of the review.

Through the above operations, 20 documents with positive and negative adjectives about ten subjects were obtained. Because not every line of review has a subject, there would be a lot of blank lines in the document, and there are no adjectives after some "不(not)" words. Through the python, we deleted the blank lines in the document first, and then deleted the "不(not)"

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words without adjectives after the word "不(not)", and finally manually judged whether the remaining "不(not)" characters should relate to the adjectives behind it (judging by the meaning of words and comparing the original text). So far, a collection of adjectives about 10 subjects had been obtained. For example, after matching, the following results are obtained: hotel--prosperous;service--enthusiasm; facilities--poor.

Table 6 shows the adjective matching results of some subjects:

Table 6. Results of single subject matching adjectives

Subject	Positive adjective	Negative adjectives
Hotel	小(small) 不错(good)	差(poor) 一般(common)
Service	好(well) 不错(good)	差(poor) 一般(common)
Price	低(low) 不贵 (not expensive)	特贵 (Very expensive) 高(high)
Facilities	不错(good) 新(new)	简陋 (simple and crude) 老(old)
Environment	不错(good) 好(well)	很脏 (very dirty) 不舒服(uncomfortable)

After obtaining the set of adjectives, the adjectives were marked with emotions, which were divided into three types of emotions: positive, negative, and neutral, to obtain an sentiment dictionary.

2.7. Factor Summary and Quantitative Analysis

When constructing the sentiment dictionary, we found that some adjectives are not aimed at the subject. This is because of the Chinese way of writting. When the user says " This hotel is not expensive", the hidden meaning actually refers to " The price of this hotel is not expensive". Therefore, according to the matching results of adjectives, this paper summarized adjectives into the following 8 factors, and some of the corresponding adjectives are shown in Table 7:

Table 7. Summary factors and corresponding adjectives

Summary factors	Price	Service	Location	Facilities	Food	Hygiene	Area	Environment
Adjective	expensive high low cheap	kind impatient indifference odious	far near convenient inconvenient	old used new simple	Unpalatable delicious abundant various	clean dirty neat unclean	big small spacious narrow	noisy quiet elegant chaos

Then, according to the sentiment dictionary, we counted the number of positive/negative adjectives in each factor in the positive and negative reviews. The statistical results are shown in Table 8 and Table 9:

Table 8. Statistics of adjectives in positive reviews

	Price	Service	Location	Facilities	Food	Hygiene	Area	Environment	Total
Positive	135	297	161	235	201	446	643	108	2226
Negative	403	62	76	333	101	101	353	7	1436
Total	538	359	237	568	302	547	996	115	3662

Table 9. Statistics of adjectives in negative reviews

	Price	Service	Location	Facilities	Food	Hygiene	Area	Environment	Total
Positive	89	36	21	53	8	53	162	8	430
Negative	137	96	58	324	53	53	265	14	1000
Total	226	132	79	377	61	106	427	22	1430

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This paper continued to count the proportion of positive and negative adjectives under various factors, as shown in Table 10 and Table 11：

Table 10. Proportion of adjectives in positive reviews

Proportion(%)	Price	Service	Location	Facilities	Food	Hygiene	Area	Environment	Total
Positive	25.09	82.73	67.93	41.37	66.56	81.54	64.56	93.91	60.79
Negative	74.91	17.27	32.07	58.63	33.44	18.46	35.44	6.0	39.21
Total	14.69	9.80	6.47	15.51	8.25	14.94	27.20	3.14	100

Table 11. Proportion of adjectives in negative reviews

Proportion(%)	Price	Service	Location	Facilities	Food	Hygiene	Area	Environment	Total
Positive	39.38	27.27	26.58	14.06	13.11	50.00	37.94	36.36	30.07
Negative	60.62	72.73	73.42	85.94	86.89	50.00	62.06	63.64	69.93
Total	15.80	9.23	5.52	26.36	4.27	7.41	29.86	1.54	100

See the next chapter for specific analysis results.

3. Result

This experiment used a public data set on the Internet, which contains 10,000 online user reviews of hotels, of which 7,000 are positive reviews, and 3,000 are negative reviews. When choosing adjectives, we chosed words that are highly related to the factors, and deleted some adjectives that cannot be clearly classified into which factors, such as "good", "bad", etc. In the 7000 positive reviews, a total of 3662 adjectives were reserved, including 2226 positive adjectives and 1436 negative adjectives. In the 3000 negative reviews, a total of 1430 adjectives were reserved, including 430 positive adjectives and 1430 negative adjectives.

First, we analyzed the distribution of adjectives in positive review. From the Table 10 , the following conclusions can be drawn:

1) Even if the praise is given, most consumers are still dissatisfied with the "price" factor, feeling that the price is too high and the cost/performance ratio is too low. Under the price factor, only 25.09% of adjectives are positive adjectives, and 74.91% of adjectives are negative adjectives. The ratio of the two is about 1:3 (positive: negative). Most consumers feel that hotel prices are too expensive.

2) Among the "environment" factors, positive adjectives accounted for 93.91%, which is the largest proportion of all factors. It can be inferred that consumers are most likely to be satisfied with the environment, and everyone has a relatively high acceptance of the environment. Following factors are "service" (82.73%), "hygiene" (81.51%), "position" (67.93%), "food" (66.56%), and "area" (64.56%).

3) Among all the adjectives, the adjectives (positive and negative) of the "area" factor accounted for 27.2% of the total number of adjectives. It can be inferred that consumers are most concerned about the size of the hotel room, and most of the reviews mentioned the size of the room. Followed by are "facilities" (15.51%), "hygiene" (14.94%), and “price“ (14.69%).

4) Among all the adjectives, the adjectives of "environment" factors (positive and negative) accounted for 3.14% of the total number of adjectives. It can be inferred that consumers do not care much about whether the surrounding environment of the hotel is noisy. Following factors are "position" (6.47%), "food" (8.25%), and "service" (9.80%).

5) For the factor of "facilities", the ratio of positive and negative adjectives is about 1:1, indicating that in the good reviews, customers still have mixed reviews on hotel facilities. Some customers think that the facilities are good, and of course they can give good reviews. Even if the facilities are not good, the reviews can finally be praised because of other factors.

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Then analyze the distribution of adjectives in negative reviews. From the Table 11, we can draw the following conclusions:

1) Among the factors of "food", negative adjectives accounted for 86.89%, which is the largest proportion of negative adjectives of all factors. It can be inferred that consumers are most likely to be disappointed by the factor of food, feeling that the food in high-star hotels is not worthy of the hotel's level, and the food in convenient hotels is more likely to make people dissatisfied. Following factors are "facilities" (85.94%), "position" (73.42%), and "service" (72.73%).

2) Like positive reviews, among all adjectives, the adjectives (positive and negative) of the "area" factor accounted for 29.86% of the total number of adjectives. It can be inferred that when consumers are dissatisfied with the hotel, the greater probability is not satisfied with the size of the hotel room, the area was mentioned in the reviews. Following factors are "facilities" (26.36%) and “price“ (15.80%).

3) Like positive reviews, among all adjectives, the adjectives of the "service"factor (positive and negative) accounted for 1.54% of the total number of adjectives. It can be inferred that consumers do not care much about whether the surrounding environment of the hotel is noisy. Following factors are "food" (4.27%), "position" (5.52%), "hygiene" (7.41%), and "service" (9.23%).

4) For the "hygiene"factor, the ratio of positive and negative adjectives is 1:1, which indicates that in the negative reviews, customers' evaluations of hotel hygiene are also mixed, and there is no uniform standard for identification. Some customers think that even if the sanitary conditions are acceptable, they will eventually give a bad review due to other factors.

4. Management Inspiration

Through the above data analysis results, we can get the following management inspiration to the hotel.

1) In the high score reviews, consumers are generally dissatisfied with the price factors.

The hotel pricing will lead to the high expectation of the hotel level. When the consumers arrive at the hotel, they find that they are different from their expectations, thus producing the idea of "too low price performance" and "too high price". Consumers are very sensitive to price fluctuations and will compare the prices of different hotels. Therefore, it is very important to have a competitive price.

2) Consumers are most likely to be satisfied with environmental factors and dissatisfied with food factors.

Environmental factors include the hotel's decoration style (simple / elegant), the surrounding environment of the hotel (noisy / quiet). Because the hotel decoration style is relatively unified, especially some chain hotels, consumers are used to such a style, and they are satisfied with the environmental factors. However, due to the fixed geographical location of the hotel, hotels in the urban area are inevitably noisy, the price of the hotel is more expensive, but the travel is more convenient, while the hotels in the suburbs are quiet and the price is cheap, but it is not convenient to travel. Therefore, the hotel does not have to pay much attention to environmental factors.

The general satisfaction of food factors is low, because the hotel is not good at the management of breakfast food, and there are many food deterioration, peculiar smell and other conditions, and the food types and quantity do not satisfy consumers. Consumers think that the star level and price of the hotel do not conform to the food situation, and the hotel needs to improve the quality, quantity and type of food.

3) The consumers most concerned for area factor.

The area is the most intuitive factor that consumers can feel when they enter the room. No consumer likes narrow rooms, no consumer will hate spacious rooms. But if the hotel wants to expand the room area, it will be necessary to transform the whole hotel, which costs too much. Therefore, how to decorate the room cleverly to achieve the visual expansion of the area is very important.

4) Consumers are least concerned about environmental factors

Although consumers are most satisfied with environmental factors, only a few comments have environmental factors. As mentioned above, the hotel environment factors are relatively stable, especially the decoration style of chain hotels are very similar, and the geographical location is relatively fixed, so consumers will not mention the hotel environment in the reviews, but pay attention to some factors with large differences among hotels, such as area and price.

5. Conclusion

The research in this paper is based on the sentiment analysis of hotel reviews based on text analysis technology. First of all, the introduction explains the background of the topic, pointing out that big data mining is indispensable and inseparable for business intelligence; web2.0 makes user-generated content become the dominant content of the website. With the continuous increase of Chinese Internet users, choosing to book hotels online has become a dominant trend. In order to eliminate product uncertainty, consumers rely on product reviews to help them make decisions.

After a brief introduction to the research methods and research framework of this paper, the second chapter elaborates the experiment process in detail, gives the experiment flowchart in the experiment design, and then introduces the experiment procedure according to the flowchart.

In the discussion of experimental results in Chapter 3, the experimental results made in Chapter 2 are analyzed. According to the proportion of the total number of adjectives of each factor in the total adjective review, and the proportion of adjectives of each factor under the high rating/low rating review, the corresponding conclusions can be drawn. In Chapter 4, we conduct an in-depth analysis of the conclusions given in Chapter 3, and discuss the fundamental phenomena and reasons behind these conclusions, hoping to give some inspiration to hotel management.

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