How to Meet the Diverse Needs of Consumers: Big Data Mining based on Online Review

Gu Wei
University of Science and Technology Beijing
guwei@ustb.edu.cn

Hu Rui
Beijing City University
Hurui870929@hotmail.com

Song Yanan
University of Science and Technology Beijing
ynsong@ustb.edu.cn

Abstract

This article applied Word2vec and image mining on OCRs analysis. Data from Dianping.com showed that in Beijing, good taste is the primary factor for customers to choose a restaurant. Unlike the general opinion, careers and locations have little influence on cuisine choice in Beijing. Hot pot is the most popular one all over the city. Warm color, medium dark light and saturation with certain amount of grey are three key aspects for an enjoyable dining environment. Offline mouth to mouth recommendation is the most useful way to spread a restaurants reputation. So making the antecedent consumer satisfy is the most applied way to appeal new ones. This findings can help restaurant owners to run a better business and promote the satisfactory.

1. Introduction

Dining culture is an important part of the cultural system, especially in China. It’s composed by mainly four parts: dish culture, restaurant culture, service culture and marketing culture. On one side, owners try their best to attract consumer; on the other hand, consumers offer their feedbacks to help the restaurants to improve their products and service. Therefore, capturing the first-hand information of consumers’ reviews is critical for restaurant owners to enhance their core competitiveness.

According to consumer behavior theory, the consumer purchase process is a process of collecting information and comparing and selecting information [1],[2]. Now, because of the internet, instantly available online commentary information has become an important decision-making reference for consumers. Back in 2009, Nielsen Global Survey of Trust in Advertising had shown that 91% of Chinese online consumers trust the products recommended by others (acquaintances), and 78% of respondents trust the opinions expressed on the Internet [3]. The influence of on consumer shopping decisions is gradually increasing, whether they come from acquaintances in life or strangers on the Internet [4]. Vendors have also recognized this and built platforms to encourage consumers to comment and share. Dianping.com in China is a successful example [5].

The Dianping.com was established in Shanghai in April 2003, about 12 months earlier than Yelp. Dianping.com is China's leading local life information and trading platform, and also one of the earliest independent third-party consumer review website in the world. Dianping.com not only provides information services such as restaurants’ information, consumer reviews and coupons, but also provides O2O (Online To Offline) trading services such as group purchases, restaurant reservations, takeaways and electronic membership cards.

As of the fourth quarter of 2017, the number of registered independent users in Dianping.com has exceeded 590 million, and the active users in the APP have reached more than 250 million. With over 250 million of valid comments, more and more merchants were attracted. At the end of 2017, 30 million vendors have become the member of Dianping.com.

Among all the information on Dianping.com, online consumer reviews (OCRs), which is based on words- of- mouth (WOMs), have helped customers to learn about the strengths and weaknesses of different products and to find the ones that best suit their needs. OCRs are online WOMs. Some studies suggest that customers show more interest toward user-generated product information on the Internet than the information vendors provided [6].

As the first scholar to define WOMs, Amdt proved that product-related comments can help increasing the acceptance of new products by using experimental methods, that is, WOMs can play an important role in the acceptance and diffusion of new products effect [7]. The author defines WOMs as information about relevant opinions and evaluations disseminated in

URI: https://hdl.handle.net/10125/64091
978-0-9981331-3-3

social interactions between people, emphasizing that WOMs is a non-commercial purpose, face-to-face communication behavior. As time has evolved, the definition of WOMs has been gradually improved.

Westbrook broadens the definition, which is: All informal exchanges about the possession, use, and characteristics of products and services [8]. This definition mainly emphasized that WOMs is a daily communication between people, not information about product knowledge released by merchants through media channels, that is, word of mouth is not for business purposes, and exists in people's daily communication.

Swan and Oliver, through a questionnaire survey and a review of previous research, found that WOMs can be simply defined as: a positive description of the product or service between consumers [9]. This definition is more straightforward than the definition of Amdt (1967). Tax defined WOMs through research and development: informal communication between consumers, positive or negative, about the characteristics of suppliers, their products, or services [10]. This definition not only expanded the definition of WOMs on the basis of previous research, but also clearly suggested that it can include both positive and negative aspects. This definition laid a certain foundation for future research.

With the emergence and gradual development of the Internet, WOMs has gradually changed from offline communication to online product evaluation and virtual community commodity discussion. Then OCRs appeared. Compared with the traditional ways, the essence of OCRs has not changed greatly, and the biggest change is the way of information dissemination.

And now, we found out that OCRs is not only helpful to consumers while making their decisions, but also valuable to merchants to make their business strategy and get higher profits in market.

In this research, we pick food industry as our area, and Dianping.com as our OCRs data source. Millions of consumers' comments make the dianping.com a big data warehouse. The story we are trying to tell is about how to find the itchy point of consumers. This research applied text mining and image mining techniques to extract information from OCRs in dianping.com and provide reference for the optimization and development of catering industry.

The structure of this research is arranged into seven parts: section one will give a brief introduction about the background and topics of our study. Section two is a review of past literatures in OCR mining and consumer demands field. Section three gives a logical roadmap of this research and the process of data and variables,. Section five describes the methodology we use and section six summarizes the findings.

2. Literature Review

2.1. Early Definition of OCRs

In the academic world, there are mainly the following definitions or conceptual explanations of OCRs:

Tab 2-1 Early definition of OCRs

Author	Year	Definition	Explanation
Gelb and Johnson[11]	1995	Online Word of Mouth	It defines the term "word-of-mouth" and discusses its antecedents, or factors which influence its origin, and consequences, or the resulting opinions of the hearers. It also works when the communication is online.
Stauss[12],[13]	1997,2000	Online Word of Mouth	In the field of marketing and management, opportunities and threats to business are brought about by the increase in online discussion and communication among consumers. At the same time, in its research, the exchange or report on consumer information on the Internet between consumers is defined as "internet consumption exchange", and it is considered that this kind of communication is a kind of word of mouth.
Hanson[14]	2000	Electronic Word of Mouth	The computer-based network word-of-mouth communication is defined as online word-of-mouth or electronic word-of-mouth. Among them, the network includes: emails, online forums, user groups, and portal discussion forums.
Christiansen and Tax [15]	2000	Communication between online sender and receiver	The behavior of a web user (word-of-mouth sender) posting an article on the web is equivalent to a word-of-mouth communication behavior between people, except that the form of information presentation is converted from an "auditory" to a "written".

Gelb and Sundaram[16]	2002	Word of Mouse	In contrast to word of mouth, the British Economist magazine proposed the "rat monument" in 1998. The term means the power of the computer accessories mouse to drive the spread of word of mouth. Consumers can use the Internet to To be more familiar with friends who are more familiar with their usual communication circles, but they have similar consumption habits. Interested or consumer experience consumers exchange product information. This greatly expanded The source of consumer product information, in addition, most consumers are non-businesses, and do not have commercial purposes to promote products, Most of them reflect their consumption experience truthfully, so the information is more reliable.
Chatterjee [17]	2001	Internet Word of Mouth	The way in which product information is exchanged through the Internet is defined as Internet word of mouth or online word of mouth. The content is the exchange of information about products between consumers, through communication platforms (such as bulletin boards) or personal chat channels. Emphasis is placed on the communication of word-of-mouth information based on the network. The main task is to complete the exchange of product information.
Dellarocas [18]	2003	Reputation system	Internet word of mouth is defined as an online customer feedback system, also known as a reputation system, that is, using the two-way communication ability of the network, individuals share experiences and opinions on the network for companies, products, services and even events.
Datta et. al[19]	2005	Online communication system	A large number of potential, current or former consumers use online platform to communicate on experience.

2.2 Antecedent and Consequence Research on OCRs

The antecedent of OCRs refers to the cause of OCRS, or the variable that can affect it. The consequences of OCRs refer to the impact of it on consumer behavior and market outcomes. The following sections will focus on the antecedent and consequences in recent years.

Researches about consequences of OCRs are rich. The table below showed the major views:

Tab. 2-2 Recent research on consequences of OCRs

Author	Area	Point of view	Method
Yang & Mai, 2010[20]; Chevalier & Mayzlin, 2006[21];	Number of comments	The number of online reviews is an important clue for consumers to measure product quality, The conclusion that the number of online reviews is positively related to product sales	Correlation analysis
Kim & Yoon, 2016 [22]		The more online discussions about a certain good or service, the more opportunities consumers have for the goods or services.	Statistics
Bickart & Schindler, 2001[23]		The number of online reviews can indicate the purchase rate or popularity of the product or brand; and when consumers find that the number of reviews they have purchased is high, they will think that their choice is correct.	Statistics
Zhang & Zhu, 2011[24] Balan & Mathew, 2016[25]	Positive vs negative comments	The direction of online reviews can reflect consumer satisfaction with a product or service.	Induction; Text mining
Helm, 2000[26]; Godes & Mayzlin, 2004[27]		Positive online commentary is considered to enable consumers to better recognize the advantages of the product, thereby significantly affecting their attitude towards products and brands, and increasing consumers' willingness to purchase. Some researchers believe that negative comments are more likely to attract people's	Statistics; Text mining

		attention. It is more helpful for consumers to distinguish between high-quality products and low-quality products than positive word-of-mouth.	
Filieri, Alguezaui & McLeay, 2015[28]	Length of comments	Characteristics such as the depth of online reviews have also been identified as important factors influencing the effectiveness of online reviews. The length of the information, that is, the level of detail of the information, is the key to the amount of information in the online review, and it is also the focus of whether the comment is adopted.	Interview
Siering & Muntermann, 2013[29]; Ghose & Ipeirotis, 2007[30]		When comments are long, it contains more information about the product or service, and it helps the consumer to reduce the perceived risk of the transaction process, which has a greater impact on consumers' attitudes towards products and brands. However, some studies have found that the shorter the sentence, the better it is for consumers to read and understand. Some studies have shown that the length of online commentary sentences does not significantly affect the role of online reviews for consumers. Therefore, there is no consistent conclusion about the impact of the depth of online commentary on consumer attitudes.	Questionnaire
Klein & Ford, 2003[31]; Jebb et al., 2016[32] T Ishibashi,2012[33]	Subjective vs Objective	Consumers prefer objective information when searching for online information, while subjective information is more concerned by consumers in the online environment. It is generally believed that strong information is rational and objective, weak information is emotional and subjective; strong information is more effective than weak information.	Metrology; Text mining

2.3 Application of online reviews on restaurant improvement

As the development of online review websites such as Yelp and Dianping, restaurant owners started to pay attention to these comments. They tried to leverage online reviews to improve services, build new sites, and develop new products and services.

The most popular research in this area is attracting customers. This is also our focus point. This field of research contains study on brand, food, service and user-stickiness [34 , 35]. The online reviews help merchants to find consumers' real opinion. Text classification is the most commonly used tools [36,37].

Another topic in this area is competitors' identification. It is of importance for restaurants to identify their competitors to gain competitiveness. Meanwhile, opinion-rich resources like online reviews sites can be used to understand others opinion toward restaurant services [38]. Experimental results reveal the effectiveness of the proposed competitiveness analysis using text analytics, which can identify top competitors and evaluate the market environment, as well as help the focal restaurant effectively develop a service improvement strategy[39,40].

Also, online rivews from social media can be used to predict the risk of food safty. A group developed a system for the discovery of foodborne illness mentioned in online Yelp restaurant reviews using text classification. The system is used by the New York City Department of Health and Mental Hygiene (DOHMH) to monitor Yelp for foodborne illness complaints[41,42,43]. It helped food safety regulators improve regulatory efficiency[44].

These researches cover a very broad range, but the tools they use are usually the same: text mining. However, on the online review websites, comment with pictures are encouraged. So, the value of images were neglected before. And images are the important source of dinning environment. So, in our research, both texts and images will be mined.

3. Theoretical Framework and data

3.1. Theoretical Framework

When consumers facing dining choices, there usually are three steps:

1. Browsing the OCRs on dianping.com to make a brief knowledge of the restaurant and form a first impression based on prior experience.
2. Based on the first impression, making decisions: dine here or leave. If they dined in the restaurant, a new judgement would be formed according to the taste, environment and service.
3. Based on practical experience, consumers will give ratings to the restaurant and write down comments. These comments compose new OCRs and become reference to later consumers.

These three steps become a behavioral loop.

3.2 Data and Variables

We collected over one million comments from dianping.com, covering 400 most popular restaurants in Beijing. "Popular" is defined by the number of comments. The data set include two parts: text and image. In the data cleanup process, images about dishes were weeded out. We dig out food and service information from word description, and environment information from both words and images. Because environment rating is based on objective standards such as decoration style, lights, temperature and so on, while the other two are based on subjective feelings. We believe that words describe emotional experience better than images, and images reflect facts more intuitively.

4. Methodology

4.1 Text Mining

We collected over one million pieces of data from Dianping.com we introduced before. These online comments dated back to 2008 and they were all collected from the 400 most popular restaurant in the urban district of Beijing. These data exist in a format that is mixed in graphics and text. In order to process these data with data mining tools, the following steps were taken. First, the comments were structured, and the images were matrixed. On the basis of the structured text, according to the contents of Table 4 to Table 6, the store rating results in the quantified form were analyzed by correlation and regression; the comment contents were processed by Word2vec, a semantic methods. The image analysis was mainly based on HSL extraction.

Data pre-processing

With over one million pieces of data, the text part and image part were seprated. All data were divided into three parts: score, in format of int. in python; text, in format of str. in python and image, in format of jpeg in python.

For the text, two procedures will be taken: purification, tokenization and stop words removal. Data from crawler contain lots of tags in html, so wo have to purify them before any processing. Considering the large amount of data, Beautiful Soup (https://www.crummy.com/software/BeautifulSoup/) was used in our research. And then, an improved algorithm of Jieba in python was brought in to finish the takonization process. Tokenization is a form of lexical analysis whereby a stream of text is broken up into words, phrases, or other meaningful elements called tokens. And among these tokens, Chinese words such as “and” and preposition words exist.. These are called stop words. Stop words are words that do not contribute to the meanings of the text and are usually filtered out before the processing of natural language data. The stop words list which includes 1408 most commonly used stop words was used.

After the pre-processing, there are 934,657 reviews been analyzed, which means each of the 400 restaurants provide 2337 online Chinese reviews on average. The thesaurus formed by this step contains over 40 million Chinese words.

Words frequency statistics

The sample we choose were the 400 most popular restaurant in Beijing. So, we assume that all the attitude towards these restaurants are positive. The main purpose of our research is finding out the reason why these restaurants are recommented by customers. So, we want to find out their favorite cuisine and how they find these places. These information can be collected by words frequency statistics.

The frequency statistics is realized by “sorts” fuction in python. The words with high frequency are classified into three types according to their virtues: “noun”” verb”” adjective”. The nouns are usually used to point out certain dishes. Verbs, except for “eat” “taste” “drink”, always appear in the sentence where customers describe how they find a certain restaurant. Adjectives are for the description of their emotional feelings.

Text feature selection

There are four ways to select features: (I) transforming the original features into fewer new features by means of mapping or transformation; (2) selecting some of the most representative features from the original features; (3) according to experts The knowledge selects the most influential features; (4) using mathematical methods to select and find the most characteristic of the classified information. This method is a more accurate method, and the interference of human factors is less, especially suitable for text. Application of automatic classification mining system. In this study, we chose the mathematical method to solve our problem.

TF-IDF is used in this step. TF means the number of times the word frequency (TF, Term Frequency) appears in the document and Inverse Document Frequency (IDF, Inverse Document Frequency) refers to the weight of a word. Its value is inversely proportional to the common degree of the word.

TF-IDF (Term Frequency - Inverse Document Frequency) is a measure of whether a word segmentation is a keyword or not.

TF calculation formula: TF = number of times the word appears in the document
IDF calculation formula: IDF = log (total number of documents / (number of documents containing the word + 1))
TF - IDF calculation formula: TF-IDF = TF * IDF

Sklearn package is the tool for TF-IDF calculation.

In this step, a score will be given. The corpus with higher score represent the main idea of comments. The dish preference and reputation spreading can be extracted here.

Image Mining

With over 60 thousands of images, the following procedures were taken to analyze them.

First of all, the image materials have to be pre-processed. There are many dirty data and destroyed data in large image database. These data can make the mining process confused and lead to unreliable output. It is necessary to clean the data in order to improve the quality of data. Image data not only has a large amount of data and abundant information, but also the original image can not be directly applied to data mining. Before using mining tools, besides necessary data cleaning, image data should be pre-processed according to the characteristics of mining tools and mining purposes. So, in our research, any images with pixel lower than 300*400 were deleted. And those images with unrecognizable subject were also excluded.

After pre-processing, about 45 thousands of images were left.

Then, in order to fulfill one of our purpose, which is to find out the most popular light atmosphere, HSL analysis was taken. The H (hue) component of HSL represents the range of colors that the human eye can perceive. These colors are distributed on a flat hue circle, ranging from 0° to 360°, and each angle can represent a kind of color. The S (saturation) component of HSL refers to the saturation of color. It uses 0% to 100% of the value to describe the change in color purity under the same hue and brightness. The larger the value, the less gray in the color, and the more vivid the color, the change from gray to solid. The L (lightness) component of HSL refers to the brightness of the color. It also uses a range of values from 0% to 100%. The smaller the value, the darker the color, the closer it is to black; the larger the value, the brighter the color, the closer it is to white.

All images coolected from the reviews are RGB color moded. So, we have to convert them to HSL mode to do the analysis.

The output of this step is the (h, s, l) value in the HSL space, where $h \in [0, 360)$ is the hue angle of the angle, and $s, l \in [0, 1]$ is the saturation and brightness.

After the HSL analysis, content-based intelligent image classification can be achieved by associating images with different information categories. Image classification is a supervised process. The process consists of three steps: 1) building an image representation model, extracting the features of the labeled sample images and establishing the description of each image attribute; 2) learning the sample sets of each category and establishing rules or formulas; 3) using the model to classify and annotate the unlabeled images. Commonly used classification methods include Bayes method of decision tree and neural network method. Other methods include K-nearest neighbor classification and rough set classification. Image clustering divides a given set of unlabeled images into meaningful clusters based on the content of the image without prior knowledge. It is often used in the early stage of the mining process. Its characteristic attributes are color, texture and shape.

The output of this step is the decoration style. In labeled samples, there are four attributes in images: elegant (such as Chinese traditional garden setting), simple (such as McDonald's), retro (such as high-end western restaurant) and unconventional (such as AI serving).

5. Results Analysis and Managerial Implications

Four questions will be answered in this section:

First, what is the crucial influential factor when consumers are rating a restaurant? After identifying the key factor, restaurant should spare more effort on it to attract diners.

Second, is there a certain relationship between the types of business district and cuisines? If there is, matching your own cooking styles and local consumers taste is the next thing decision makers will consider.

Third, what is the most popular decoration style? Words' might not be enough to describe the feelings in a restaurant, so images will be brought in to supplement this study.

Four, the reputation building, which means to find out what kind of communication channel is most easily accessible to customers? Internet enables everyone to access information from various ways, such as TV shows, comments from friends offline or strangers online, websites, billboards and so on. Proper promotion ways can save the advertising cost and achieve rapid increase in visibility among consumer groups.

5.1 Good taste outweigh other factors in rating a restaurant

Restaurants are not only places for people to enjoy a good meal, but also for families and friends to share a happy hour. So we believe that food taste, environment and service are three most important impact factors for restaurants. Mining data from 400 most popular restaurants in Beijing, the result turned out to be like this in table 6-1:

Table 5-1. Correlation among taste, environment, service and total score

	taste_score	envir_score	serv_score	total_score
taste_score	1	0.71790	0.68732	0.8317
envi_score	0.71790	1	0.74176	0.72626
serv_score	0.68732	0.74176	1	0.75174
total_score	0.8317	0.72626	0.751741	1

The taste of dishes has the most decisive influence in total rating. One vivid example is that a restaurant called “Mending meat pie”, which owns only three tables and one waiter, is rated 9.6 out of 10 by consumers. The reviews are all like “tastes amazing”, “The platoon can't stop the enthusiasm of the diners”, “worth the waiting”. That is to say, nice food is the foundation of a restaurant. Distinctive cuisine can offset the disadvantages of the environment and services to some extent. The positive impact of taste shows in all kinds of restaurants.

Environment and service plays almost equal role in deciding the total score. People who prefer upscale dining places pay more attention on environment and service. They are picky about overall quality of dining experience. The correlation between environment rating, service rating and total rating increased significantly in restaurants with over 200 yuan per capita consumption. The expectation on environment and service reach their peak when it comes to French restaurants, Japanese restaurants and Chinses restaurant who serve Huaiyang cuisines.

5.2 Consumers have evident preference on cuisine in Beijing

The text mining results shows that here are no evident differences on cuisine choice between different business areas. People’s working and living location has little impact on food taste.

In Beijing, hot pot, Japanese food, Beijing cuisine, and western food are the top four most popular food types, especially hot pot and Japanese. They each take 25% of the first place in 20 areas. These four also take the top four places in “taste rating list”. On the other hand, Yunnan & Guizhou dishes and Huaiyang dishes, which are also famous cuisine styles in China, are least popular in Beijing.

Fig. 5-1 hotpot and Japanese food

However, there are two exceptions based on online reviews. In these three business areas, consumers’ eating habits have local characteristics. The first group is Wangjing and Wu Daokou. Lots of young foreigners are living and studying there, especially Koreans. So Korean and Japanese food are your best choice if you want to have a successful business there. The second one is San Litun, where embassies gathered. Western food and Chinese hot pot are both popular there, but every restaurant that wants to survive there must have their own style. Consumers around this area have an elegant way of life. The price is not their primary consideration, but nice food and good atmosphere will meet their needs.

Consumers pick up their places of eating mainly based on the taste, as we mentioned in section 6.1. These popular cuisines are not cheap. Based on 400 restaurant we select, the average cost of a meal is 95 yuan for each person. But if the meal cost far more than this level, like French dishes and Huaiyang dishes, there would be a significant decline in preference willing.

5.3 Customers are attracted by simple, elegant and orange hue

5.3.1 Decoration style’s impact on rating

The decoration style is the concentrated expression of the store style. Over 1500 images were selected in our research. Only those clear photos with pixels larger than 600*800 meet our needs. Image mining revealed the following facts.

It turns out that two decoration styles are consumers’ favorite: the simple way and elegant way. The simple way always appears in chain restaurant, fast food restaurant and café, where people would spend little time and dining efficiency is crucial for them.

The elegant way is the primary choice for upscale restaurants. Consumers choose these places not only for dining, but also for business discussions, important ceremonies and other issues that require for noble, luxurious feelings. Simple style is used in chain restaurant, fast food restaurant, café.

5.3.2 Environmental light’s impact on rating

In image mining, the hue, saturation and luminance are most important factors for the environment light. There are three basic conclusions:

- Warm hue is more attractive to consumers
- Medium saturation makes the dining process more comfortable
- Medium dark light allows people to enjoy their meal with relaxing mood

Tab. 5-2 HSL analysis of restaurants

	Hue	Saturation	Luminance
1	29.20139726	70.93818547	89.37573931
2	152.6111925	99.98284058	78.20063768
3	37.94717551	99.73022313	75.75087347
4	86.50044598	85.47354605	87.38254532
5	64.09893333	91.40910748	82.20274286
6	34.10680544	100.3197007	99.89576327
7	55.85474286	49.98198095	88.48458231
8	44.75384218	41.6942585	139.3691864
9	28.53369796	109.316634	96.67378776
10	53.63383611	61.34354605	113.3664322
11	34.28732028	77.7189691	109.3162404
12	43.87044898	47.36716735	94.86072109
13	27.16253878	70.74269388	98.92706667
14	35.85140408	62.31082993	100.2523646
15-400	…	…	…

As shown in table above, the light in a restaurant includes three aspects: hue, saturation and luminance.

In “Hue” column, red means warm, green means cold. In our 400 samples, about 56% were in “orange” range. This result indicates that people prefer relatively warm hum when they were dining. This seems a general rule in decoration around the world. Most popular chain restaurants like McDonald, KFC and red lobster are all in this range. Red, orange, yellow are their favorite color.

In “saturation” column, the darker color means higher saturation. Among 400 restaurants, medium saturation took majority (64%). This kind of decoration makes customers relax and wouldn’t draw too much attention, so they can focus on their food and conversation. But there are also exceptions. Some dessert shops like low saturation to create the mood of fresh and sweet, and some American restaurants use high saturation to make the diner feel welcoming and energetic. So, it’s important to match the style of restaurant with saturation.

In “luminance” column, lighter color means brighter light. Excessively bright lights can make you feel anxious and annoyed, and excessively dark lights influenced the dining experience. So, media dark luminance is most popular. This kind of light decoration allow people to enjoy their food in relax environment with clear view.

5.4 Both online comments and offline recommendations are importation in reputation building

There are four major ways of reputation spreading: friends’ recommendation; traditional media approaches like TV ads, billboard or pamphlet; online recommendation list on all kinds of apps and websites; walk by and be attracted to the restaurant.

Advices from acquaintances are adapted to be accepted than those ones from strangers or merchants. “My colleague used to recommend…”“I heard this restaurant from one of my friends…”“My friends and I came here often…” are most common expressions in our review samples. Recommendations from a trusted friend is quite appealing when facing a dining choice.

But information among friends is limited after all. If you want to try something new, recommendation list given by internet and all kinds of apps might be helpful. Those restaurants with high reputations online will be pushed to consumers with priority.

Offline communication and searching online lists are two active decision making ways. People can find what they need with initiative right. But traditional advertisements provide the information and consumers can only accept them passively. Only if the ads left any impression in their minds may lead consumers to the restaurant.

And coming across a restaurant occasionally is the least possible way for a person to decide where to eat. When consumers planned to enjoy a nice meal outside instead of at home, they are always with clear purpose. Specific demands, maybe not even conscious about it, are in their minds. So they are unlikely to pick a random restaurant.

Based on what we discussed above, advices for restaurants owners are:

- Getting your restaurant publicized is very important;
- Providing nice food and make every consumer satisfied is the most effective means of publicity. Because the actual customers can bring the spread of offline word of mouth to the store.
- Online reviews and lists are also important. Owners can use some incentives to encourage customers to write positive online commends.
- Less cost should be put in traditional ads. It’s not as useful as the other two.

6. Conclusion

Based on what we discussed above, advices for restaurants owners are:

- Nice food is always the most important thing for a restaurant. If you don't know what food style you want to begin with, hotpot and Japanese food could be your first choice in Beijing.
- Non-aggressive environment light and background color make the restaurant more welcome. The decoration style, simple or delicate, should be decided by positioning.
- Getting your restaurant publicized is very important. Providing nice food and make every consumer satisfied is the most effective means of publicity. Online reviews and lists are also important. Owners can Use some incentives to encourage customers to write positive online comments.

References

[1] Bettman J R, Park C W. Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis. Journal of Consumer Research. Oxford Academic[J]. Journal of Consumer Research, 1980, 7(3):234-248.

[2] Bettman J R, Zins M A. Constructive Processes in Consumer Choice. Journal of Consumer Research. Oxford Academic[J]. Journal of Consumer Research, 1977, 4(2):75-85.

[3] Nielsen Global Survey of Trust in Advertising Nielsen -2009.

[4] Salehan M, Dan J K. Predicting the performance of online consumer reviews[J]. Decision Support Systems, 2016, 81(C):30-40.

[5] Xie K L, Zhang Z, Zhang Z. The business value of online consumer reviews and management response to hotel performance[J]. International Journal of Hospitality Management, 2014, 43:1-12.

[6] B. Bickart, R.M. Schindler, Internet forums as influential sources of consumer information, Journal of Interactive Marketing 15 (3) (2001) 31–40.

[7] Amdt, Johan. Role of Product-Related Conversations in the Diffusion of a New Product [J]. Journal of Marketing Research, 1967, 4 (August) 291-295.

[8] Westbrook, R. A. Product/Consumption-Based Affective Responses and Post-purchase Processes [J]. Journal of Marketing Research, 1987, 24 (August): 258-270.

[9] Swan, John E. and Oliver, Richard L. Post-purchase Communications by Consumers [J]. Journal of Retailing, 1989, 65 (4): 516-533.

[10] Tax, S. S. The Role of Perceived Justice in Compliant Resolution Implications for Services and Relationship Marketing [D], Arizona State University. 1993.

[11] Gelb B, Johnson M. Word-of-mouth communication: causes and consequences.[J]. Journal of Health Care Marketing, 1995, 15(3):54-58.

[12] Stauss, B.. Global Word of Mouth Service Bashing on the Internet is a Thorny Issue [J]. Marketing Management, 1997, 6 (3) :23-30.

[13] Stauss B. Using New Media for Customer Interaction: A Challenge for Relationship Marketing[M]. Relationship Marketing. Springer Berlin Heidelberg, 2000:233-253.

[14] Hanson,W. A.. Principles of Internet Marketing, Ohio: South-Western College Publishing. 2000.

[15] Tim Christiansen, Stephen S. Tax. Measuring word of mouth: the questions of who and when?[J]. Journal of Marketing Communications, 2000, 6(3):185-199.

[16] Gelb,B. D and S. Sundaram. Adapting to Word of Mouse [J] .Business Horizen,2002, 45(4): 21-25.

[17] Chatteijee R.Online Review: Do Consumers Use Them?[J] Advances in Consumer Research, 2001, 28: 133-139.

[18] Dellarocas C. The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms[J]. Social Science Electronic Publishing, 2003, 49(10):1407-1424.

[19] PR Datta , DN Chowdhury , BR Chakraborty. Viral marketing: New form of word-of-mouth through internet [J]. Business review, 2005, 3(2): 69-75.

[20] Yang J, Mai E. Experiential goods with network externalities effects: An empirical study of online rating system[J]. Journal of Business Research, 2010, 63(9):1050-1057.

[21] Chevalier J A, Mayzlin D. The effect of word of mouth on sales: Online book reviews[J]. Journal of marketing research, 2006, 43(3): 345-354.

[22] Kim K K, Yoon S. The Dynamics of e WOM and Business Outcomes: An Empirical Investigation of the Impact of Social Media on Box Office Revenue[M]// Celebrating America's Pastimes: Baseball, Hot Dogs, Apple Pie and Marketing?. Springer International

Publishing, 2016.
[23] Bickart B, Schindler R M. Internet forums as influential sources of consumer information[J]. Journal of Interactive Marketing, 2001, 15(3):31-40.
[24] Zhang K Z, Cheung C M, & Lee M K, et al. Examining the moderating effect of inconsistent reviews and its gender differences on consumers' online shopping decision[J]. International Journal of Information Management, 2014, 34(2): 89-98.
[25] Balan U M, Mathew S K. Online word of mouth using text mining: A review of literature and future directions[C]// Computational Intelligence: Theories, Applications and Future Directions. IEEE, 2016:1-6.
[26] Helm S. Viral Marketing - Establishing Customer Relationships by 'Word-of-mouse'[J]. Electronic Markets, 2000, 10(3):158-161.
[27] Godes D, Mayzlin D. Using online conversations to study word-of-mouth communication[J]. Marketing science, 2004, 23(4): 545-560.
[28] Filieri R, Alguezaui S, & Mc Leay F. Why do travelers trust Trip Advisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth[J]. Tourism Management, 2015, 51: 174-185.
[29] Siering M, Muntermann J. What Drives the Helpfulness of Online Product Reviews ? From Stars to Facts and Emotions[J]. 2013.
[30] Ghose A, Ipeirotis P G. Designing novel review ranking systems: predicting the usefulness and impact of reviews[C]// International Conference on Electronic Commerce. ACM, 2007:303-310.
[31] Klein L R, Ford G T. Consumer search for information in the digital age: An empirical study of prepurchase search for automobiles[J]. Journal of Interactive Marketing, 2003, 17(3):29-49.
[32] Jebb A T, Saef R, Parrigon S, et al. The Need for Cognition: Key Concepts, Assessment, and Role in Educational Outcomes[M]// Psychosocial Skills and School Systems in the 21st Century. Springer International Publishing, 2016.
[33] Ishibashi T. Preliminary Analysis of e-word-of-mouth by Text Data Mining : Case Study on hotels and Japanese inns in Izu Area[J]. Economic Review Shizuoka University, 2012, 17(2):1-11.
[34] Espinosa J A , Ortinau D J , Krey N , et al. I'll have the usual: how restaurant brand image, loyalty, and satisfaction keep customers coming back[J]. Journal of Product & Brand Management, 2018.
[35] Lu X , Ba S , Huang L , et al. Promotional Marketing or Word-of-Mouth? Evidence from Online Restaurant Reviews[J]. Information Systems Research, 2013, 24(3):596-612.
[36]Halawani Y M , Chin-Hooi Soh P , Chew K W , et al. A Proposed Research Framework for Online Consumer Reviews and Hotel Selection Decision[J]. Advanced Science Letters, 2015.
[37] Wang Q , Goh K Y . Investigating Consumers' Variety Seeking Behavior in the Light of Online Reviews: An Individual Level Panel Analysis[C]// 2012 45th Hawaii International Conference on System Sciences. IEEE, 2012.
[38] Wang H , Gao S , Yin P , et al. Competitiveness analysis through comparative relation mining: evidence from restaurants' online reviews[J]. Industrial Management & Data Systems, 2017, 117(4):IMDS-07-2016-0284.
[39] Song G , Hongwei W , Gang F , et al. Review of Comparative Opinions Mining Studies of Online Comments[J]. New Technology of Library & Information Service, 2016.
[40] Song G, Ou T, Wang H, et al. Identifying competitors through comparative relation mining of online reviews in the restaurant industry ☆ [J]. International Journal of Hospitality Management, 2018, 71:19-32.
[41] Effland T , Lawson A , Balter S , et al. Discovering foodborne illness in online restaurant reviews[J]. Journal of the American Medical Informatics Association, 2018.
[42] Harrison C , Jorder M , Stern H , et al. Using Online Reviews by Restaurant Patrons to Identify Unreported Cases of Foodborne Illness - New York City, 2012-2013[J]. MMWR. Morbidity and mortality weekly report, 2014, 63(20):441-445.
[43] Mccarthy M. Online restaurant reviews identify outbreaks of undetected foodborne illness.[J]. Bmj Clinical Research, 2014, 348(20):g3560.
[44] Harris K J , Ali F , Ryu K , et al. Foodborne illness outbreaks in restaurants and patrons' propensity to return[J]. International Journal of Contemporary Hospitality Management, 2018:00-00.