Analysis Report on Online Word-of-Mouth for User Reviews on Third-Party Review Websites: A Case Study of Jinan's Dianping Merchants

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Abstract

With the increasing digitization of lifestyles, a vast number of consumers rely on online reviews, particularly positive ratings and feedback on websites, to guide their purchasing decisions. This study delves into the realm of user reviews, focusing on the aspects of the source of communication, content dissemination, and the impact of feedback on businesses. By utilizing web scraping techniques to gather data from Dianping, one of the leading review platforms in China, this research examines the distinctions and commonalities between spam and non-spam users in terms of identity, geographic distribution, frequency of reviews, ratings given to establishments, and timing of posts. Additionally, the study explores the differences in content dissemination between these two categories of users. Through textual analysis of review content and an examination of the implications for business performance, this research offers practical suggestions based on the quality of merchant reviews.The objective of this study is to construct a model for detecting spam comments using machine learning classification algorithms, with the aim of reducing the cost of identifying spam comments on the Dianping website.

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1 Introduction

As one of China's pioneering third-party review websites, Dianping has been committed to providing netizens with information on dining, leisure, and entertainment services, including merchant details, group buying options, and user reviews. Consumers often consult these reviews when making purchasing decisions, and the digital footprints of others undeniably influence potential buyers. This report classifies reviews from the perspective of information utility into two categories: spam and non-spam. Spam reviews are identified as those that fail to provide authentic and useful information to consumers and may even mislead them. These primarily include fake, malicious, meaningless, and irrelevant reviews. Restaurant businesses have recognized the potential of reviews for online empowerment, leading some unscrupulous merchants to employ paid reviewers to artificially boost ratings and attract customers. This demand-driven black market industry inflicts significant harm on consumers, legitimate businesses, and the broader internet platform ecosystem. The proliferation of spam reviews on Dianping not only diminishes the platform's credibility but also undermines the consumer's right to be informed.

2 Problem Statement

In April 2019, the Dianping platform launched the "Qing Feng Action," a rigorous campaign against rule violations. Throughout 2020, a total of 33.69 million inappropriate reviews were processed, and 45,000 merchants were penalized. Concurrently, the platform updated its algorithms for filtering fake reviews and established more comprehensive review guidelines to combat illegitimate promotions and dishonest practices. Despite these stringent regulations, a significant number of spam reviews cunningly evaded detection, appearing on the Dianping platform in increasingly indistinguishable forms. From a communication studies perspective, the phenomenon of spam reviews can be considered a purposeful act of dissemination. Harold Lasswell once proposed the 5W model of communication, suggesting that all communication activities encompass five basic elements: the communicator, the message, the medium, the receiver, and the effect. Based on this framework, our analysis primarily focuses on the communicator, the content of dissemination, and the feedback from reviews to the merchants. Given this background, the following research questions are proposed:

What are the differences between the communicators of spam and non-spam reviews in terms of identity, geographic location, frequency of posting reviews, ratings given to the stores, and timing preferences?

Are there distinct high-frequency words in spam versus non-spam reviews? What are the themes and the proportional representation of these themes in the content? What is the nature of the lexical items constituting the text in both types of reviews?

How do the emotional experiences conveyed by users in spam and non-spam reviews towards the stores differ?

How can merchants derive valuable feedback from review content to improve their business practices?

How can we efficiently select feature indicators to build a spam comment classification model?

3 Research Methodology

3.1 Data Source and Description

Our research utilized Python web scraping tools to collect all reviews (totaling 10,293) from five Dianping restaurants in Jinan, including Lu's Noodle Soup (Wangxiangcheng branch), Kuishengju Century-old Braised Food (Xianxixiang branch), Andong Korean Cuisine (Wangxiangcheng branch), Mama's Pepper Pride (Kuanhouli branch), and Dajili ChaoShan Beef Hot Pot (Shandalu branch) from March 22, 2018, to February 13, 2022. The collected data fields include reviewer ID, taste ratings, service ratings, and review content. Detailed variable descriptions are provided in Table 1 (see Appendix). These selected restaurants are located in three distinct business circles in Jinan, namely

Wangxiangcheng, Shandalu Honglou, and Quancheng Road, covering a broad range of customer profiles and offering diverse cuisines such as Shandong, Sichuan, Cantonese, and Korean, which adds representativeness to our data analysis.

3.2 Manual Annotation of Spam Reviews

To accurately identify spam reviews, we manually annotated the dataset based on detailed coding rules. Our coding criteria were influenced by Ben Popken's "30 Ways You Can Spot Fake Online Reviews" and our extensive user experience in reviewing comments. Examples of spam review identification include "overuse of flamboyant, hollow adjectives and extensive descriptions of food preparation and origin." The specific coding rules are listed in Table 2 (see Appendix). Three annotators independently completed the manual annotation process, achieving a consistency reliability of 0.71 according to Fleiss' multi-rater kappa method.

3.3 Social Network Analysis

Based on the collected dataset, we constructed two bipartite networks: user-city and user-identity. Using Gephi software with OpenOrd and Force Atlas algorithms, we generated network structure models depicting users in relation to their locations and identities. The analysis aimed to uncover the differences between spam and non-spam reviewers in terms of user geography and identity.

3.4 Content Analysis

- Word Frequency Analysis:We utilized the jiebaR package in R for Chinese text segmentation. To enhance accuracy, we incorporated a stop word dictionary, user dictionary, and a food-related vocabulary from the Sogou cell dictionary. Post-segmentation, we calculated the high-frequency words in both spam and non-spam reviews and created word clouds using the wordcloud package.

- LDA Topic Modeling:The Latent Dirichlet Allocation (LDA) model, a classical text statistical modeling method, was employed to distill and summarize themes within the text. We input the processed data into the model, set an appropriate number of topics, and after 200 iterations, obtained the document-topic and topic-word probability distribution matrices. Using R, we modeled the LDA topics for both spam and non-spam reviews and identified the main themes based on high-frequency words.

- Part-of-Speech Tagging:Building upon the word segmentation, we further analyzed the parts of speech for each word, using the jiebaR and tidyverse packages in R. This step helped us delve deeper into textual analysis, such as tagging "Daming Lake" as a proper noun (ns), "Andong Stewed Chicken" as a noun (n), "Lobby Manager" as a proper noun (nr), and so on.

3.5 Sentiment Analysis

For sentiment analysis, we used the snownlp package in Python, which scores text on a scale of 0 to 1, with higher scores indicating more positive sentiments and scores closer to 0 indicating more negative sentiments.

3.6 Multiple Regression Analysis

We conducted a multiple regression analysis on all reviews for each merchant. Based on the four themes identified by the LDA model, we extracted the high-frequency words for each theme, calculated their frequency in each review, and used these as independent variables with the rating as the dependent variable. The regression coefficients provided insights into how different thematic content influences store ratings, offering valuable feedback for merchants to refine their business strategies.

3.7 Naive Bayes algorithm

The Naive Bayes algorithm is a classification methodology predicated upon Bayes' Theorem and the presumption of feature conditional independence, constituting its critical theoretical underpinnings. It adjudicates the categorization of an item by computing the likelihood of occurrence within various classes. Absent extraneous conditions, the Naive Bayes classifier elects the class that maximizes the conditional probability under the given premises.

4 Research Findings

4.1 Communicators

In today's platform-driven era of communication, platforms empower individuals, granting them equal opportunities and rights to disseminate information just like enterprises, governments, and media institutions. When users register on Dianping, they automatically become members and gain the right to review businesses. As their contribution increases, their user level (ranging from Lv1 to Lv8) upgrades accordingly, earning them membership privileges as shown in Table 3 (see Appendix). Users can also ascend to VIP status through sustained effort (regular users can apply for VIP status after fulfilling certain criteria, including a membership duration of 3 months, a credibility score of 12, and a minimum of 3 approved reviews of 100 words in the past 3 months), enjoying more attractive VIP benefits such as complimentary meals. However, maintaining VIP status requires persistent digital labor, such as submitting at least 4 approved 100-word star-rated business reviews each month. Failing to meet this quota leads to a downgrade in status.

4.1.1 Descriptive Analysis of User Identity

We created bipartite user-identity networks based on the spam and non-spam review datasets.Analysis revealed that non-VIP members constitute the largest node center in both spam and non-spam user groups. Comparative analysis indicates that among spam reviewers, 707 were VIP members, accounting for 26.35%; whereas in non-spam reviews, VIP members numbered 1,515, accounting for 36.70%. This suggests a lower proportion of VIP members in spam reviews, likely due to the sustained digital effort required to maintain VIP status, a commitment not typical of the majority. Often, paid reviewers employed by merchants use temporary accounts and are less likely to invest time in maintaining a VIP status.

4.1.2 Descriptive Analysis of User level

We compared the member levels in both spam and non-spam reviews as shown in Figure 3 . Analysis showed that in the same member level, spam reviews tend to have higher ratings than non-spam reviews. Correlation tests conducted on member levels, like counts, and related fields revealed a strong positive correlation in both spam and non-spam reviews. For example, in spam reviews, there was a positive correlation of 0.14 between member level and like counts, and 0.23 with follower counts. There was also a positive correlation of 0.43 between follower and like counts. As seen in Figure 1, lighter blue dots indicate higher member levels, corresponding to higher follower and like counts.

4.1.3 Descriptive Analysis of User Level

This suggests that higher-level members play the role of opinion leaders on the review platform, influencing others through information sharing and viewpoint expression. Other consumers tend to trust these high-level users, believing them to provide more authentic

Figure 1: Correlation Graph between User Membership Level and Number of Followers and Likes

and effective information.

4.1.4 Geographic Distribution of Users

By analyzing the spam and non-spam review datasets, we constructed bipartite networks of users and cities based on spam and non-spam reviews, as shown in Figures 2 and 3 (see Appendix). The analysis revealed that in the city distribution of spam reviews, Jinan had a centrality of 1369, accounting for 65.25% of the data; in non-spam reviews, Jinan's centrality was 2356, accounting for 70.58%. It was observed that Jinan, Shanghai, and Beijing were the most prominent nodes in both spam and non-spam reviews.

Figure 2: Spam Reviewers Distribution

Figure 3: Non-Spam Reviewers Distribution

4.1.5 Volume of User Reviews

We created density graphs of the time series of marked spam and non-spam reviews, as illustrated in Figures 4 and 5. The overall density of reviews on Dianping gradually increased over time, but there was a significant decrease from January to mid-April 2020 due to the severe and complex situation of the pandemic, which greatly impacted the traditional catering industry. The usage of Dianping gradually rebounded with the improvement of the pandemic situation.

4.1.6 User Rating Patterns

Statistical analysis of the rating patterns of spam and non-spam reviews revealed that the positive rating percentage in spam reviews (91.07%) was higher than in non-spam reviews

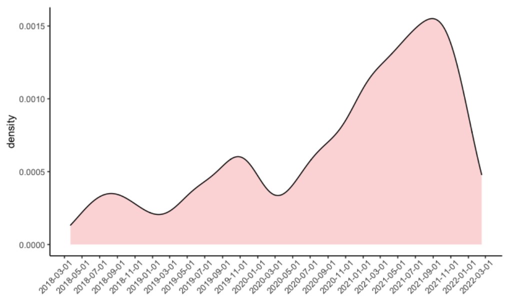

Figure 4: Spam Reviewers Distribution

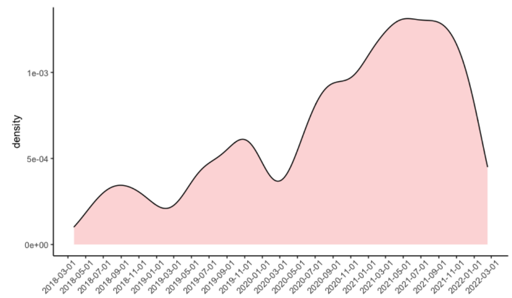

Figure 5: Non-Spam Reviewers Distribution

(85.05%), while the negative rating percentage in spam reviews (1.94%) was lower than in non-spam reviews (3.29%).

4.1.7 Temporal Distribution of User Reviews

By breaking down the publishing time field into date and hour information, we observed that spam reviews peaked on Saturdays, while non-spam reviews peaked on Sundays. In general, most users prefer to post reviews on weekends, which aligns with the standard workweek and weekend arrangements. The 24-hour distribution of both spam and non-spam reviews, illustrated in figure 6, showed a concentration of activity from 9 am to 11 pm, aligning with typical consumer habits.

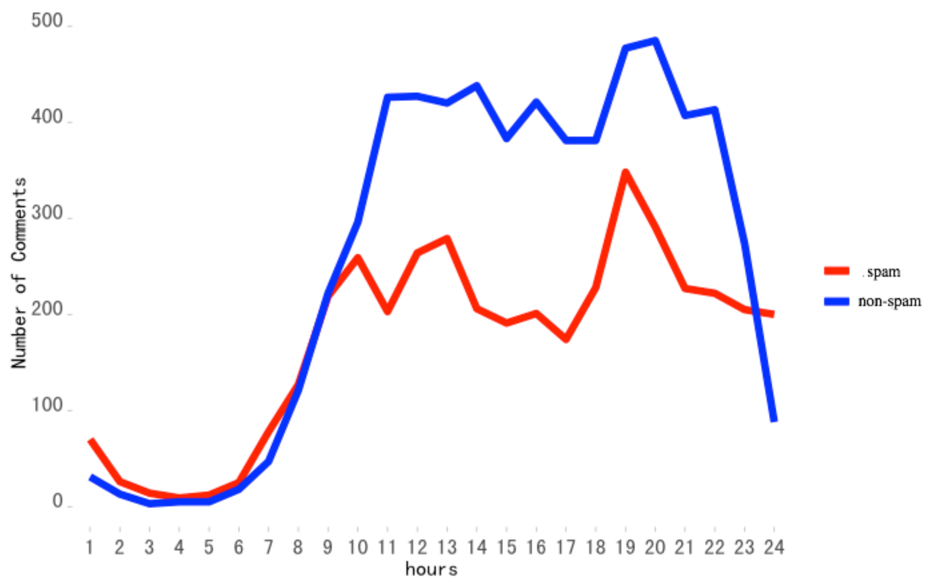

Figure 6: Hourly Review Distribution

4.2 Content Dissemination

4.2.1 Text Frequency Analysis

As shown in Figures 7and 8, there is a considerable overlap in the high-frequency words between the junk review set and the non-junk review set. The top ten high-frequency words in both include "tasty," "eat," "flavor," "service,""environment" and "good" .This also indicates that there is not much difference in textual expression between junk and non-junk reviews. Some junk reviews are highly realistic in imitation, disguising themselves convincingly.

Figure 7: Spam reviews high-frequecy words

Figure 8: Non-Spam reviews high-frequecy words

4.2.2 Text Topic Content

This study utilized the LDA (Latent Dirichlet Allocation) topic model to summarize the four main themes of junk review text content, which are "recommended dishes," "dining methods," "service experience" and "store features." The four main themes of non-junk reviews are "taste and flavor," "store features," "dining methods," and "service experience." Through the average probability rose diagrams of these four themes (as shown in Figures 9 and 10). Textual content in spam comments tends to recommend dishes and introduce dining methods, such as "spicy fried kidney, milk soup purslane, traditional Ji'nan fried meat are all distinctive of Ji'nan. The sweet and sour carp is also well made, without any muddy taste." In contrast, non-spam comments often discuss the taste and flavor of dishes and the characteristics of the restaurant, providing detailed and genuine

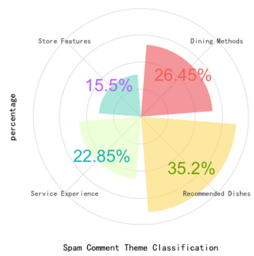

Figure 9: Spam reviews Thematic Distribution

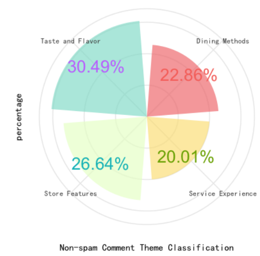

Figure 10: Non-Spam reviews Thematic Distribution

feedback based on the actual dining experience. Spam comments frequently mention dish names or critique the dining method, often appearing somewhat hollow, while non-spam comments are rich, specific, and realistic due to authentic experiences.

4.2.3 Textual Part-of-Speech Analysis

Based on the statistical frequency of parts of speech,, both junk and non-junk comments predominantly consist of nouns, followed by verbs, adjectives, and numerals. Junk comments notably contain a higher usage of verbs, numerals, and locative words than non-junk comments. Common verbs in junk comments include "give away," "send," "taste," "dip," and "stir-fry," and there is a frequent usage of locative words such as "southeast corner," "inside," "outside," and "nearby" to describe the precise location of the stores.

4.2.4 Sentiment Analysis of Comments

By observing the sentiment trend graphs over time for five businesses, we can discern differences in the density of sentiment trend lines between junk and non-junk comments. Junk comments tend to have sparser sentiment trend graphs, whereas non-junk comments are more compact. This reflects a greater stability in the density of non-junk comments, while junk comments exhibit larger fluctuations. Taking Kui Sheng Ju (Xianxi Alley branch) as an example, as shown in Figure 11 , we can observe a concentration of positive reviews from September to early December 2020, with sentiment probability values nearing 1. For instance, on October 6, a user commented, "Ming Lake's three treasures: potherb mustard, lotus root, and water bamboo, each uniquely flavored and refreshing. The fish fillets in wine sauce were tender and subtly flavored...," rating it 4.5 stars. On December 17, another user commented, "Start the meal with a bowl of chicken soup to care for your stomach..." and rated it 5 stars. In contrast, Figure 12 (see Appendix) shows that non-junk comments from the early days of Kui Sheng Ju exhibit more significant fluctuations in sentiment probability values, with some showing negative sentiment, such as a user commenting on November 11: "Except for the sweet and sour carp, the other dishes are not worth the price," rating it 2.5 stars, and on November 16: "Very disappointing, don't come! I wanted to have dumplings on the start of winter, attracted by the impressive decoration and the claim of being an established restaurant. I had high hopes for the dumplings but was greatly let down..." and rating it 0.5 stars. Taking Lv's Geda Soup (Wanxiang City

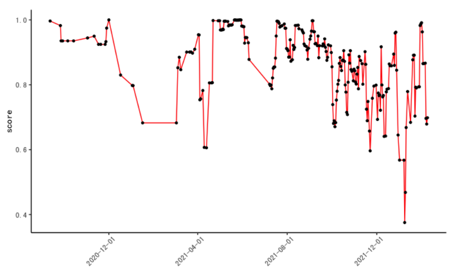

Figure 11: Spam reviews of Kui Sheng Ju

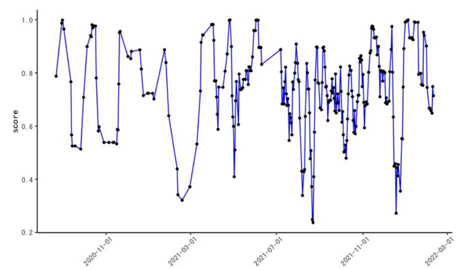

Figure 12: Non-Spam reviews of Kui Sheng Ju

branch) as another example, the sentiment probability values are not only related to the consumer experience of food, service, and environment, but also to the restaurant's own brand image. As shown in Figure 13, Lv's Geda Soup (Wanxiang City branch) experienced significant negative sentiment in February, June, and September 2021. This was due to food safety incidents such as the use of fresh eggs with veterinary drug residues in February 2021 in Qingdao, non-compliant cleaning and disinfection of utensils in Jinan in June 2021, and sewage disposal violations in Qingdao in September 2021, leading to fines. These public relations incidents damaged the brand image of Lv's Geda Soup, affecting consumer sentiment and resulting in greater fluctuations in sentiment probability values.

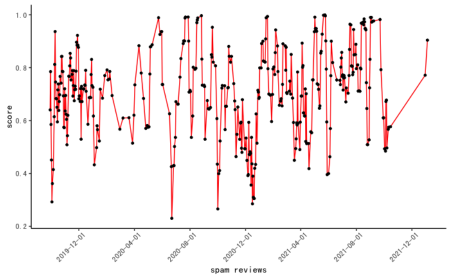

Figure 13: Spam reviews of Lv's Geda Soup

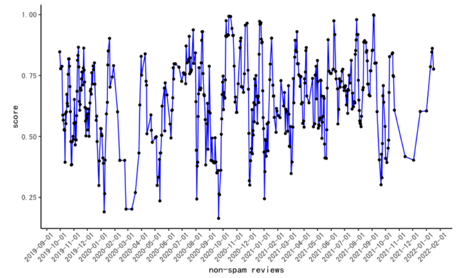

Figure 14: Non-Spam reviews of Lv's Geda Soup

4.2.5 The impact of review content on business feedback effectiveness

In the statistical modeling analysis exemplified by the reviews of Dajili Chaoshan Hotpot (Shandong University branch) and Anton Korean Cuisine (Wanxiang City branch), it is observed that both models exhibit highly significant F-tests with p-values less than 0.001. Specifically, the t-test results for Dajili and Anton establishments show that the four explanatory variables - store features, service experience, taste and flavor, and dining style - are significantly non-zero at the 1% level.

For both Dajili and Anton's models, the regression coefficients for the variable 'service experience' are negative, indicating that customers have a relatively poor service experience at both establishments. This factor is identified as a primary influencer on the shop's rating.

Tables 15 and 16, derived from randomly selected representative reviews from the Dazhong Dianping website for both Dajili and Anton, reveal that regardless of the review being positive or negative, issues related to poor service level are mentioned. This includes customer hospitality concerns, unavailability of staff when needed, and poor attitude of service personnel.

In terms of store features, customers recognize and appreciate the unique and delicious signature dishes such as Dajili's hand-beaten beef balls, Diao Long Ban, and Anton's Korean fried chicken and Xingpi tea. Additionally, users are satisfied with Dajili's Hong Kong style food stalls and Guangzhou street food style dining, and they are impressed with

Anton's simple and modern décor.

Regarding the dining style, it is evident that Dajili offers a superior dining experience compared to Anton, with the former being a positive aspect and the latter a negative one. Dajili received more positive reviews for its Chaoshan hotpot dining style, with users appreciating the meat dipping method, while preferences vary for Korean cuisine, with a tilt towards barbecue and mixed opinions on chicken cooking and consumption methods (stewed or fried chicken).

The above translation maintains academic formalness and conciseness, reflecting the statistical and qualitative insights derived from customer reviews on service quality, store features, and dining preferences.

4.3 Research Conclusions and Recommendations

Through the use of computational communication methods, we analyzed the dissemination subjects, content, and the feedback of the content on merchants in the food and beverage comment sections. We have arrived at the following conclusions:

Dajili Chaoshan Hotpot Regression Analysis Model

Variable Name	Regression Coefficient	Standard Error	p-value	Variance Inflat
Intercept Term	3.80252	0.08439	<0.001	
Shop Features or Store Specialties	0.78898	0.13454	<0.001	1.3228
Service Experience	-1.43412	0.19887	<0.001	1.3622
Taste and Flavor	0.8842	0.14317	<0.001	1.4079
Dining Style or Eating Method	0.40186	0.15637	<0.01	1.3404
Global Test of the Model	P-值<0.001		Ajusted-R^2	0.166

Figure 15: Dajili

Anton Korean Cuisine Regression Analysis Model

Variable Name	Regression Coefficient	Standard Error	p-value	Variance Infla
Intercept Term	3.7118	0.1501	<0.001	
Shop Features or Store Specialties	2.4482	0.2231	<0.001	1.1650
Service Experience	-2.8869	0.3125	<0.001	1.1651
Taste and Flavor	1.1936	0.2026	<0.001	1.1395
Dining Style or Eating Method	-2.3115	0.3011	<0.001	1.1589
Global Test of the Model	P-值<0.001		Ajusted-R^2	0.314

Figure 16: Korean cuisine

The majority of users in our collected review data from five Jinan catering stores are non-VIP members, with a greater proportion of non-VIP users among the spam commenters. The reviewers are distributed across cities like Jinan, Shanghai, and Beijing, not exclusively local. The timing of the reviews tends to concentrate on Saturdays and Sundays, with a peak in the number of reviews between 19:00 and 20:00. There is a strong positive correlation between users' membership levels, their number of followers, and the number of likes received, indicating that higher member levels may lead to a more influential role on the platform, and their reviews can more significantly affect other users' evaluations of the stores.

Our word frequency analysis of spam and non-spam comments reveals many similarities in high-frequency words, indicating the concealment of spam comments. It is difficult for ordinary consumers to detect the flaws in the text, which also brings challenges for the platform to screen out spam comments. According to the LDA model statistical results, we found that spam commenters tend to recommend dishes and like to detail dining methods, such as "hot pot" or "dipping sauces". Non-spam comments focus more on discussing the taste and characteristics of dishes. In terms of word usage, spam comments more frequently use locative words to describe the location of the stores and prefer to use verbs like "offer" to emphasize the store's promotional benefits. After scoring the sentiment of the comments, we found that the sentiment trend line of spam comments is sparser, indicating the inconsistency in the intensity of users' ratings, with fluctuations over time. Particularly, during the early opening phase of a store named "Kuishengju," the sentiment probability of spam comments tended toward 1, indicating the presence of fake reviews generated by paid posters to attract popularity. Furthermore, the low sentiment probability values of "Lv's Geda Soup" store in 2021 correspond to the outbreak of its negative public relations events, suggesting that public sentiment events can also affect users' review emotions.

Our modeling of the four thematic probabilities corresponding to the review text and user ratings has found that store characteristics, service experience, taste, and dining methods all have a significant impact on the "Daji Li" Chaozhou hotpot (Shandong University store) and "Andong" Korean cuisine (Wanxiang City store). Based on the statistical results, we propose the following suggestions:

Daji Li Chaozhou Hotpot (Shandong University store) should continue to maintain high-quality ingredients, insist on making signature Chaozhou-style dishes, and use quality beef without using overnight meat, preserving the texture and taste of the beef balls. The store urgently needs to improve customer service experience, which seems to stem from two main reasons: the negligence of the waiters and the lack of standardized dining environment. The store operators can improve this through internal training and external supervision; for internal training: strengthen the training of waiters and cover the entire process from ordering to the end of dining, providing considerate service to customers; for external supervision: establish a complete comment feedback system, customer complaint feedback system, and store manager supervision system to seriously rectify problems reflected in customer comments and communicate the determination and importance of rectifications to customers.

Andong New Korean Cuisine (Wanxiang City store) faces two main issues: service experience and dining methods. The service issues are mainly due to the low level of service provided by the waiters and the insufficient number of waiters to handle the large customer volume. Improvements in the level of waiters can adopt a system similar to that of Daji Li Chaozhou Hotpot, through internal training and external supervision. The issue of waiter numbers can be resolved by limiting peak customer flow, expanding recruitment, and hiring part-time staff. The issue with dining methods is mainly due to the monotony of dining options; this can be addressed by expanding the store's dining methods to include a variety of Korean cuisine such as barbecued meats, fried chicken, stewed chicken, and hot pots, increasing customer choice. However, it is important to note that expanding dining options should not mean neglecting the taste and quality of dishes. The store should pay more attention to the research of dish flavors to retain customers and become a restaurant that boasts both popularity and quality.

This study has limitations: First, the volume of data crawled for this study is limited and more data is needed to verify the conclusions of the research; second, the study lacks cross-platform data analysis and only collected sample data from Dianping; third, the number of coders in this study is insufficient, and the accuracy of identifying spam and non-spam comments needs to be improved.