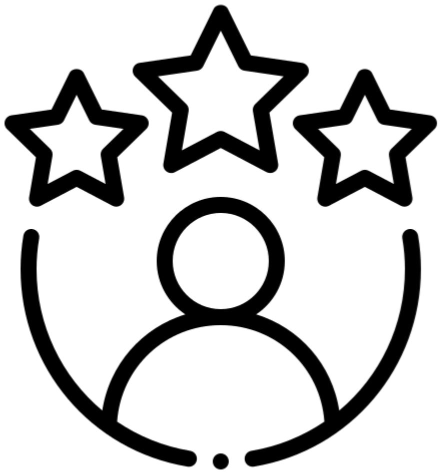

Rating 1.8

Analysis of Google Maps Reviews: A Case Study of 邱記10元碳烤

Group 11

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Introduction

In this age of digital interconnectivity, online reviews serve as a crucial lens through which consumers view and assess local businesses. Among these, Google Maps reviews stand out as a key influencer in shaping public opinion. This report presents a focused data analysis on the reviews of a specific charcoal grill snack shop, aiming to dissect the intricate relationship between the content of these reviews and the ratings they accompany. This particular shop, with its unique offering and local presence, provides an ideal case study to explore the broader implications of user-generated reviews in the context of small businesses.

Our analysis is structured around three critical considerations:

Temporal Dynamics: Reviews on Google Maps often capture a moment in time, potentially failing to reflect the evolving nature of a business. This analysis aims to explore how this static nature impacts the perceived quality and reputation of the charcoal grill shop, especially considering changes in management, menu, or customer service over time.

Selective Reviewer Participation: It is commonly observed that certain demographic segments are more inclined to leave reviews. This study seeks to identify the characteristics of these segments in the context of this charcoal grill shop. By understanding the profile of the reviewers, we aim to assess whether the reviews present a balanced view or a skewed perspective due to selective participation.

Polarization of Reviews: The tendency for reviewers in extreme situations—either highly satisfied or dissatisfied—to post reviews is a well-known phenomenon. This report investigates how this trend affects the overall rating and perception of the charcoal grill shop. Are the voices of the moderately satisfied or dissatisfied customers being drowned out by the extremes?

Through a meticulous analysis of the reviews of this charcoal grill snack shop, this report endeavors to offer insightful revelations not just about this specific establishment, but also about the broader dynamics of online reviews and their impact on small businesses. The findings aim to provide valuable insights for business owners, consumers, and review platforms alike, emphasizing the need for a more comprehensive understanding of the online review ecosystem.

Research Purposes

Based on my observations and subsequent inferences, it appears that there are inherent issues in Google reviews that prevent an accurate understanding of the true nature of businesses. I have identified three primary concerns regarding Google Maps reviews:

1. **Inability of Reviews to Reflect Temporal Changes**
2. **Biased Participation in Commenting**
3. **Irrationality in Comments**

This study will focus on analyzing the review data of 'Chiu's $10 Charcoal Grill', a local eatery, to explore and validate these issues. By examining this specific case, the research aims to shed light on the broader implications of these identified problems within Google Maps reviews.

The first issue addresses the inability of these reviews to reflect changes over time. User feedback is often a snapshot of a singular experience, lacking the temporal depth to track evolving service quality or environmental changes. This aspect of reviews potentially leads to a static and outdated perception of a place or service.

The second issue examines the representation bias in reviews, highlighting that only specific groups of people are inclined to leave feedback. This selective participation might skew the overall perception of a place, as it does not encompass the diverse experiences of all its visitors.

Lastly, the third issue explores the rationality of reviewers. It is observed that people often express extreme emotions in their reviews, either overly positive or negative, which may not accurately reflect the actual experience. This tendency towards irrationality in online reviews can distort a potential customer's expectation and perception.

This paper seeks to analyze these issues in-depth, using a combination of data analysis and sentiment examination to provide a more nuanced understanding of the nature of Google Maps reviews.

Methods

Data collection

Figure 1. Crawler flow chart

In the data collection phase of this research, the Python Selenium package was employed to systematically extract review data from Google Maps. This method enabled the efficient gathering of comprehensive review details, which includes the reviewer's name, associated personal information, the timestamp of each review, the content of the review, and the assigned rating. The dataset compiled for this study consists of a total of 112 unique entries, offering a robust foundation for subsequent analysis.

Table1. Data information table

```
RangeIndex: 112 entries, 0 to 111
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   names          112 non-null    object
 1   ratings        112 non-null    int64
 2   comments       96 non-null     object
 3   dates          112 non-null    object
 4   local_guide    39 non-null     object
 5   num_comments   112 non-null    int64
 6   num_photos     112 non-null    int64
dtypes: int64(3), object(4)
memory usage: 6.2+ KB
```

Data Processing

In the data processing stage, this research conducted a phased analysis based on the three main topics previously outlined. Firstly, in the first topic, I charted the variation of reviewers' ratings over time, subsequently calculating the trends in these ratings as well as the annual quantity of reviews. This was instrumental in observing the impact of time on review behaviors. Then, for the second topic, I created a scatter plot to analyze the relationship between review ratings and the length of the review text, examining the behavioral differences among various rating groups. Additionally, employing the Mann-Whitney U test, I further explored the median differences in ratings between these groups, which aided in more accurately distinguishing them.

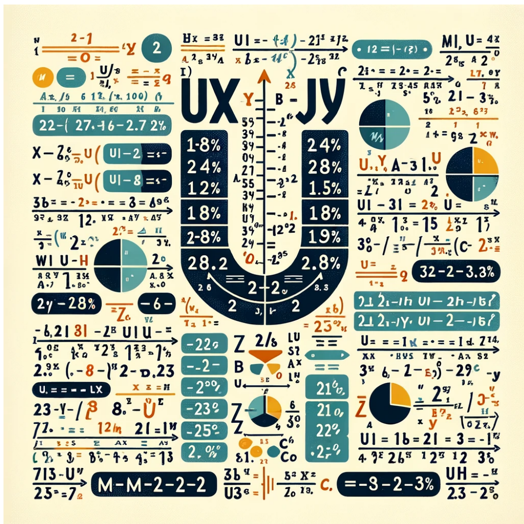


Figure 2. Educational illustration of the Mann-Whitney U test

In the third topic, the analysis focused on examining the level of rationality across different groups. Ultimately, this led to the generation of word clouds based on group segmentation, providing insights into the aspects of a local eatery that are most concerning to the public.

This translation maintains a professional and academic tone, suitable for a research report, and clearly outlines the methodology and analysis conducted in each phase of the study.

Sentiment Analysis

In the sentiment analysis segment of the study, I employed the SnowNLP package, a tool whose model is trained on datasets in Chinese. This specific focus on Chinese data allows for a more effective sentiment analysis of my dataset. Additionally, I examined the differences in sentiment analysis performance between traditional and simplified Chinese, contributing crucial insights to the third phase of the topic. This exploration also involved detailing the data processing workflow tailored for this phase.

Test One demonstrated that the sentiment analysis scores generally align with expectations. Test Two revealed an unexpected decrease in sentiment scores when traditional characters predominate in a sentence. Test Three informed us that the model struggles to accurately analyze overly subtle expressions.

評論：這是一個很棒的產品！
情感分數：0.8504302211064388

評論：这是一个很棒的产品！
情感分數：0.858701323608539

評論：真的很糟糕，我不喜歡。
情感分數：0.5095142011919661

評論：真的很糟糕，我不喜欢。
情感分數：0.5918518834399712

Figure 3. Sentiment Analysis Test 1

評論：還行，可改進。
情感分數：0.14825344966157183

評論：还行，可改进。
情感分數：0.7656440352158514

評論：垃圾爛透了
情感分數：0.1650209291839938

評論：垃圾烂透了
情感分數：0.025103848136498907

Figure 4. Sentiment Analysis Test 2

評論：去給你媽摺蓮花。
情感分數：0.17633664112818026

評論：去给你妈折莲花。
情感分數：0.6939150675662011

Figure 5. Sentiment Analysis Test 3

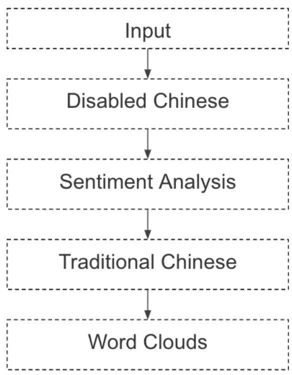


Figure 6. Sentiment analysis flow chart

Results

In this section, we will meticulously present the results pertaining to the three critical issues identified in our analysis of Google Maps reviews. These findings are crucial in understanding the complex dynamics of user-generated content and its impact on public perception.

For each of the three identified issues, we have conducted a thorough investigation and will now detail the respective outcomes. Our analysis not only sheds light on the intricate aspects of these concerns but also provides a basis for further scholarly discussion and research in the realm of digital user feedback.

ISSUE 1. Inability of Reviews to Reflect Temporal Changes

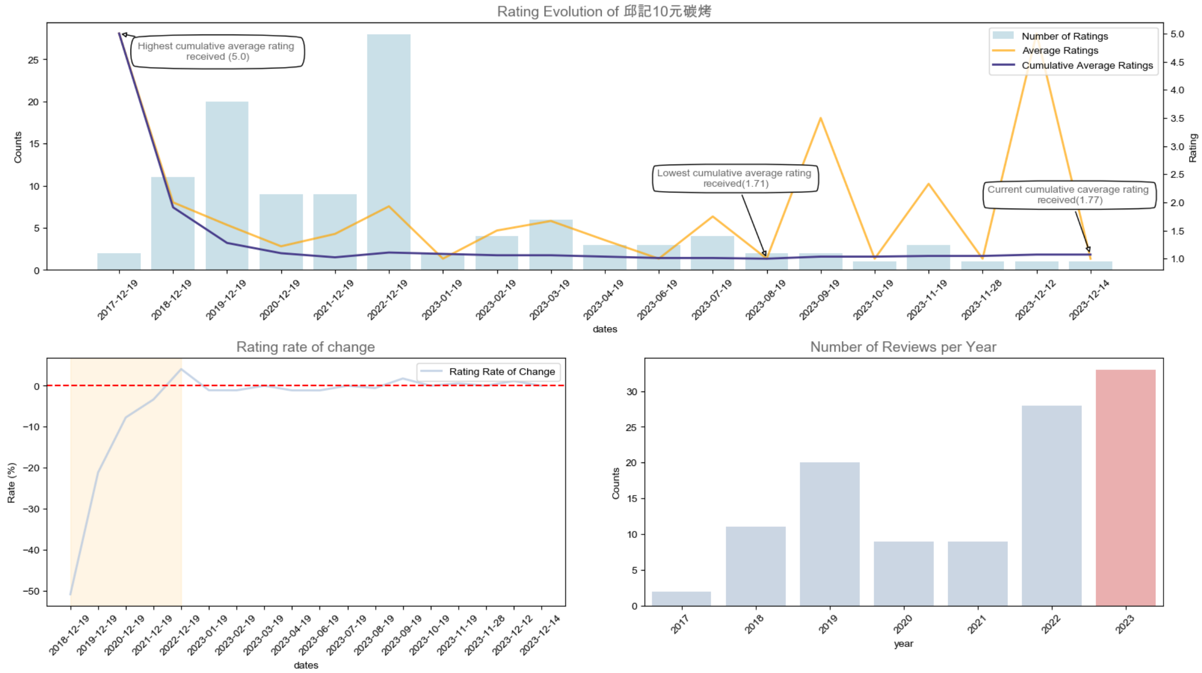


Figure 7. Rating Evolution of 邱記10元碳烤

Rating Evolution of 邱記10元碳烤

- The top left graph shows the evolution of ratings over time, indicated by dates on the x-axis. There are three lines tracking different metrics:
    - The blue bars indicate the number of ratings given at each time point.
    - The orange line represents the average rating at each time point.
    - The blue line traces the cumulative average rating over time.
- Notable annotations include:
    - The highest cumulative average rating received (5.0)
    - The lowest cumulative average rating received (1.71)
    - The current cumulative average rating received (1.77)

Rating Rate of Change

- The bottom left graph is a line graph showing the rate of change in ratings over a shorter timespan, also indicated by dates on the x-axis.
- The line dips below the x-axis, indicating a negative rate of change at certain points, meaning the ratings were getting worse. The shaded area might represent a period of significant decline.
- The dashed red line at 0% rate of change serves as a reference point to easily see positive or negative changes.

Number of Reviews per Year

- The graph on the right side is a bar chart showing the number of reviews per year from 2017 to 2023.
- It shows a general increasing trend in the number of reviews, with 2023 (indicated in red) having significantly more reviews than previous years.

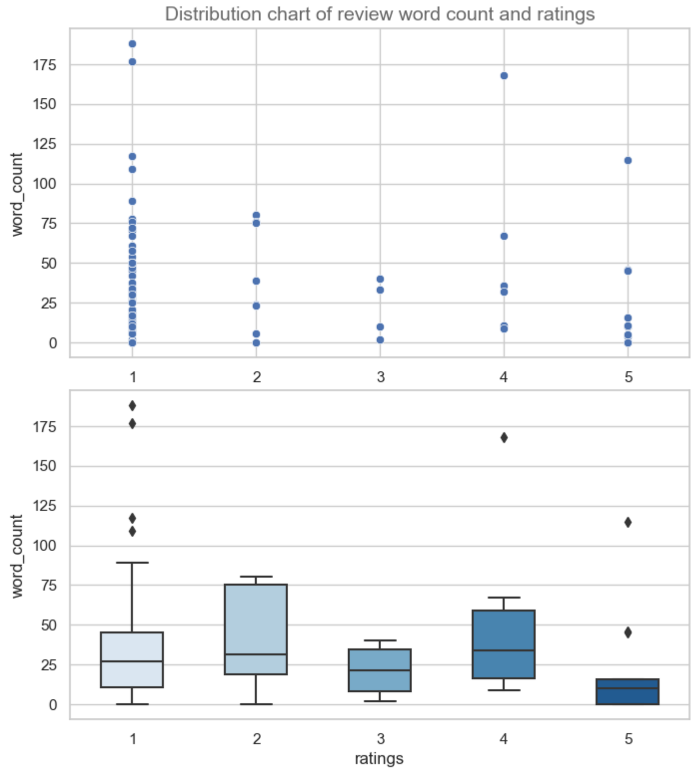
As observed, the ratings had already converged to around 1.7 prior to entering 2023, and even though there was an upward trend in new reviews, this did not alter the final outcome of the ratings.

Concurrently, it is noted that since 2023, the variability in ratings has neared zero, yet the number of reviews in 2023 has been the highest.

Such results reflect that the closer the reviews are to the current date of the restaurant, the less they are able to effectively influence the restaurant's overall rating, due to the base effect of the number of reviews, even though that year had the highest volume of reviews.

This outcome suggests that it is inherently challenging for people to comprehend the current status of the restaurant in real-time through Google Maps reviews, due to the influence of the cumulative review scores.

ISSUE 2. Biased Participation in Commenting



	ratings	word_count
count	112.00	112.00
mean	1.77	32.96
std	1.41	35.79
min	1.00	0.00
25%	1.00	8.75
50%	1.00	26.00
75%	2.00	45.00
max	5.00	188.00

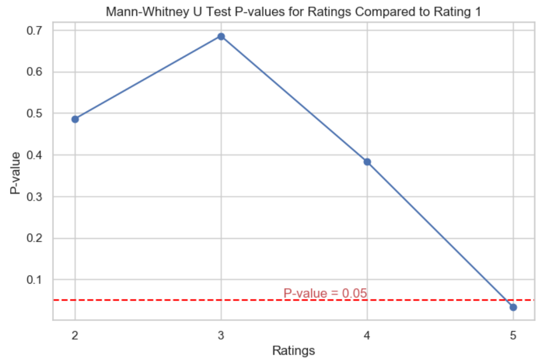


Figure 8. Data distribution chart of comment word count and score

From the scatter plot correlating the number of words in reviews with the scores, it is apparent that there is a higher frequency of individuals assigning a rating of 1, and within the group scoring between 1 and 4, there is minimal fluctuation in word count.
Furthermore, the results of the Mann-Whitney U test reveal a significant distinction between the group of reviewers who assigned a score of 5 and other groups.

Here we briefly summarize that there are indeed distinct cohorts of reviewers, with substantial differences in their respective sizes. It is evident that a larger number of people have articulated their poor consumer experiences at Qiu Ji (Chiu's Record) through negative ratings and expressions of dissatisfaction.

Regarding the number of words, there is a significant difference between the group giving a five-star rating and other groups. It is almost conceivable that ratings other than five stars often require more text to express discontent, whereas the vocabulary used for praise tends to be much more limited.

ISSUE 3. Irrationality in Comments

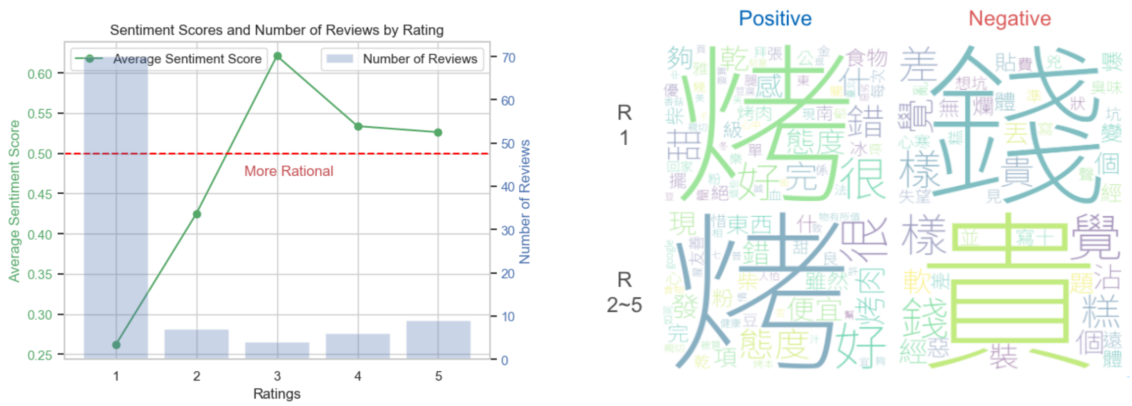


Figure 9. Sentiment Analysis Chart

When adopting a score threshold of 0.5 as indicative of a subdued emotional response within the context of review ratings, it becomes manifestly evident that individuals allocating a one-star rating are demonstrably exhibiting more pronounced emotional extremities. This observation is further compounded by the comparatively smaller volume of reviews, which results in a clustering of scores ranging from 2 to 5 that gravitate towards the 0.5 emotional response benchmark.

Expanding on this premise, we can deduce with a degree of conciseness that the segment of the population bestowing a one-star rating not only constitutes a numerically superior faction but also experiences and communicates a heightened level of emotional intensity. This phenomenon could suggest a correlation between the frequency of reviews and the expression of negative sentiments, wherein a larger number of strongly negative reviews could signify a pervasive sense of dissatisfaction that transcends minor grievances.

Delving into the analysis of the word cloud, which serves to visualize the variance in emotional expressions among different rating cohorts, a bifurcation emerges. This categorization stratifies the reviewers into two distinct groups: those who have imparted a one-star rating and those whose ratings oscillate between 2 and 5 stars. An examination of the prevailing sentiment within these word clouds reveals a salient trend: financial discontent features prominently as a central theme of consumer dissatisfaction. This trend is not only apparent but also pervasive, indicating that monetary considerations are a critical factor in the evaluative process of consumers. The predominance of financial dissatisfaction could imply that cost-related factors are a primary determinant in the negative experiences relayed by consumers, potentially overshadowing other aspects of their interaction with the product or service in question.

Conclusions

This study critically examined three salient issues regarding Google Maps reviews, leading to significant insights into the dynamics of user feedback and rating systems.

Issue 1: Inability of Reviews to Reflect Temporal Changes

It was observed that the scores in Google Maps reviews tend to converge in periods preceding the current rating year. Consequently, more recent comments seem to have a diminished impact on the overall ratings. This trend holds true even in cases where the volume of recent comments surpasses that of previous years, indicating a systemic lag in reflecting current customer experiences and sentiments.

Issue 2: Biased Participation in Commenting

`The analysis revealed a pronounced skewness in the distribution of ratings. A substantial majority of reviews comprised one-star ratings, suggesting a tendency towards extreme negative feedback. Moreover, a notable disparity was found in the median ratings between the group providing five-star ratings and other rating groups. This suggests that the voices heard in the reviews are predominantly from specific segments of the user base, potentially leading to a biased overall perception.

Issue 3: Irrationality in Comments

The study also highlighted the irrational nature of comments, especially among those giving one-star ratings. This group not only forms a majority but also tends to express more intense emotions. Conversely, individuals assigning higher ratings were fewer and exhibited a more restrained emotional expression. This imbalance suggests that the review system may be more reflective of negative experiences, thereby possibly distorting the overall picture of the businesses being reviewed.

In summary, the findings underscore the need for a more nuanced approach to interpreting Google Maps reviews, considering the inherent biases and limitations of the current system. This study provides a foundation for future research to develop more accurate and representative methods of gauging public opinion and customer satisfaction.

Division of work table

Works	Person in Charge
All	周語涵