# How customer reviews interact with internal and external factors

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## Introduction

In the Web 2.0 generation, people interact and collaborate with each other in a virtual community through social media. With Web 2.0 now widespread, platforms such as Yelp, TripAdvisor, and Expedia, which allow~~s~~ users to upload reviews, photos, and other user-generated content (UGC), are commonly used. Understanding the significance of online customer reviews, both the ratings and the comments, as a form of electronic word-of-mouth communication (eWOM), is an important managerial topic.

On the one hand, user-generated content in the digital world contains a valuable source of information for customers unfamiliar with the product or service. More than 85% of the customers cite reviews, as a considerable influence on purchase decisions (Pfeffer, 2015) and over 76% of consumers trust online reviews (Nielsen 2015); thus, buying decisions will ultimately be shaped by reviews. Thus, providing customer reviews online represents an essential business strategy to improve product sales (Zhao, Wu, Hua & Fang, 2019). Additionally, for business managers, customer reviews provide a powerful and cost-efficient marketing channel which does not involve a significant advertising budget (Lei, 2016).

There have been a number of longitudinal surveys about customer reviews. By the broad application of text mining approaches, some research has unlocked customer sentiment analysis to explore their overall satisfaction as related to online rating schemes (Gallagher, Furey & Curran, 2019). Other research has focused on the data, including the number of ratings, the average rating reviews, and the number and length of written comment (Mudambi

& Schuff, 2010; Schindler & Bickart, 2012), in order to determine helpfulness of the customer review. What much of this research has ignored is the effect of external factors such as the climate index on customer reviews. Since weather can change customer buying behaviours (Molla, 2016), it is possible that the number of customer reviews posted will also be influenced by seasonal changes in climate.

The objective of this study is to determine whether customer review behaviours respond to both internal and external factors. In this paper, we define internal factors as customer behaviours and business responses (e.g., business's display rating, location chosen, business status), and external factors as everything that neither customer nor business manager can determine, including seasonal weather changes. The preliminary results of this study aim to extend the previous studies and throw a more comprehensive light on the Voice of Customer (VOC). The first part of this paper is going to discuss the interaction between review features and internal factors, using a data set provided by Yelp.com. The effect of business internal factors to the online review components will be delved. In the second part, the hypothesis that climate factors could explain the fluctuation in review numbers is examined by applying a multiple linear regression model. We will test the accuracy of our model if the hypothesis holds true and discuss the implication of our findings for giving business responses.

## Data

There are three major datasets involved in this study. To investigate customer reviews, we obtain customer review data from Yelp.com. Yelp is an American public company that owns Yelp.com website and Yelp mobile app, publishing crowd-sourced reviews about businesses. The dataset is a subset of Yelp's business, reviews and user data which contains information about businesses across 11 metropolitan areas in four countries. We download the first two subsets. The subset of business contains 209,393 businesses with 14 variables, which we only keep 9 variables for further usage (business_id, name, city, state, latitude, longitude, stars, review_count, is_open). The subset of reviews contains 1,320,761 observations with 5 variables, which we only keep four variables (user_id, business_id, text, date) and calculate the text length and apply sentiment analysis using the Python package "TextBlob" which assigns positive, neutral or negative to each comment. Since there is no information about the display rating of certain businesses in the subset of reviews, we merge these two datasets.

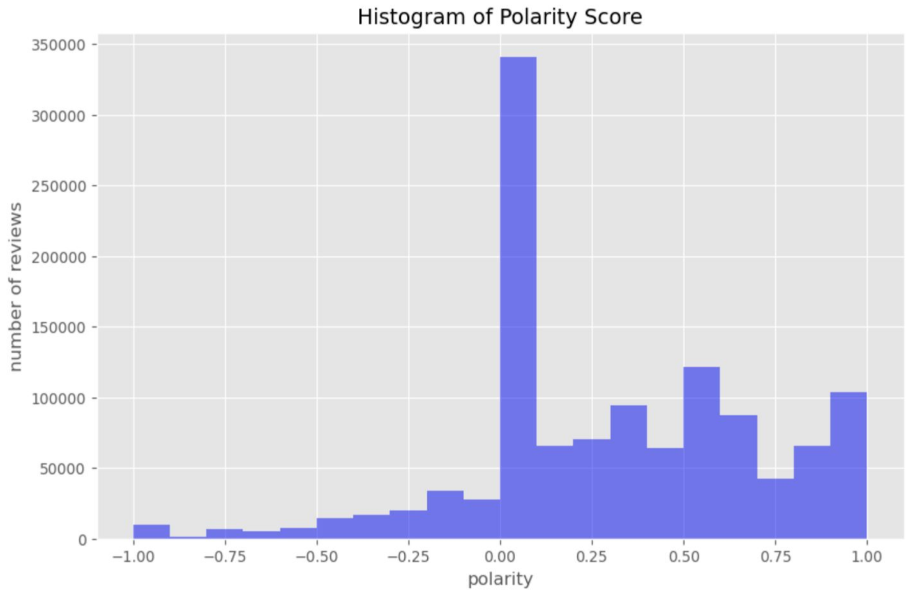
In order to find whether location plays a role in customer review number, we visualize Toronto's major roads and buildings on the map. The city's shapefile (2011 Census - Boundary file) is provided by Statistics Canada, and the other two are offered by Canadian Open Data and Free Geospatial Data Resources (place the source link into the footnote).

For the external factors involved in this study, the data of climate factors is generated through HTML-based web-scraping. We obtain the data through this method because there is no data set containing relative information available and the data will be updated by the provider periodically. The selected variables describe the weather condition in Toronto, Canada: average monthly sunshine hours[1], monthly rainfall days, monthly average daylight hour and average sea temperature[2].

Summary Statistics

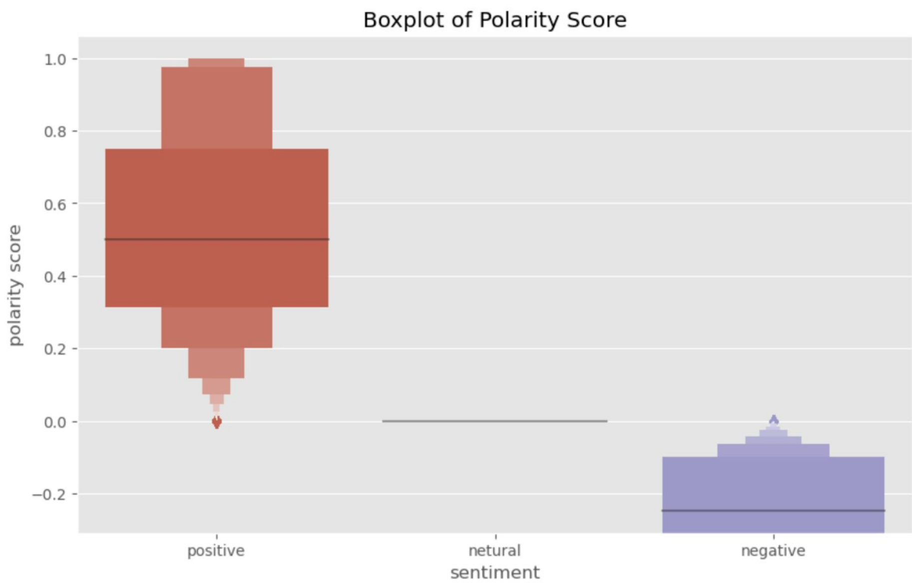
Histogram of Polarity Score (figure.1)

[1] Source: https://en.wikipedia.org/wiki/List_of_cities_by_sunshine_duration
[2] Source: https://www.weather-ca.com/en/canada/toronto-climate#rainfall



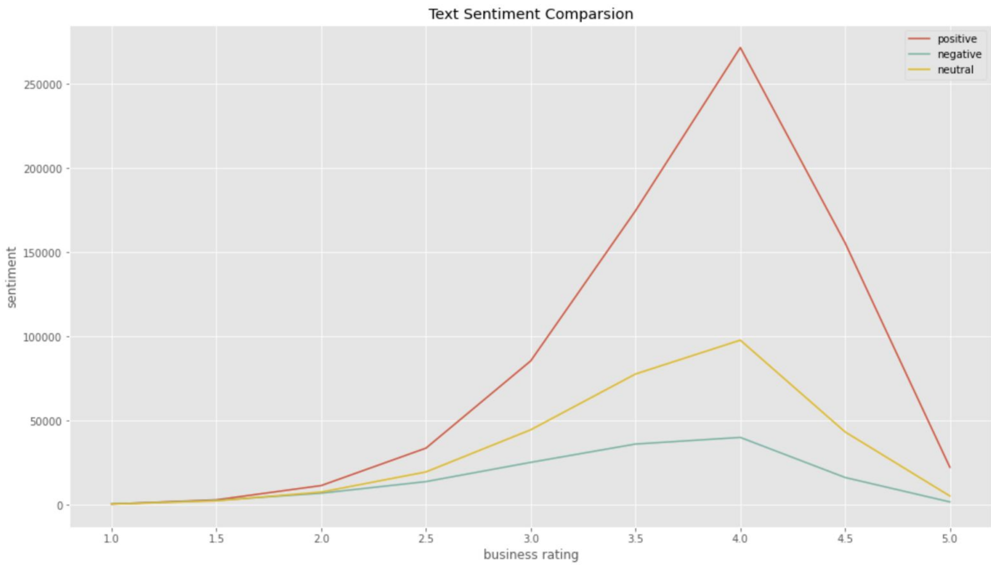

Note: We are able to perform sentiment analysis by using the TextBlob package in Python. TextBlob calculates sentiment using the WordNet Database and produces a polarity score for each sentence. Polarity is in the range of [-1,1] with continuous value, and the closer it is to 1, the more positive the content is defined. We define the positive polarity score as positive sentiment, zero as neutral, polarity score below zero as the negative sentiment. The figure shows the distribution of polarity score, in other words, the distribution of customer sentiment.

The Boxplot of distribution of polarity grading for three categories (figure.2)




Note: Boxplot is a standardized way of displaying the polarity score, it will tell us how tight the data are in three categories. We find that the mean polarity score is approximately +0.5, 0, -0.25 for positive, neutral, negative sentiment respectively. Additionally, the positive polarity has wider spread compared to negative sentiment.

Sentiment Distribution Across Business (figure.3)




Note: This multiple line plot interprets the distribution of reviews condition on display rating and sentiment analysis. It is obvious that positive sentiment contributes the largest proportion. The distribution is normally left-skewed, and positive, neutral, negative review numbers all reach the peak at stars 4.0.

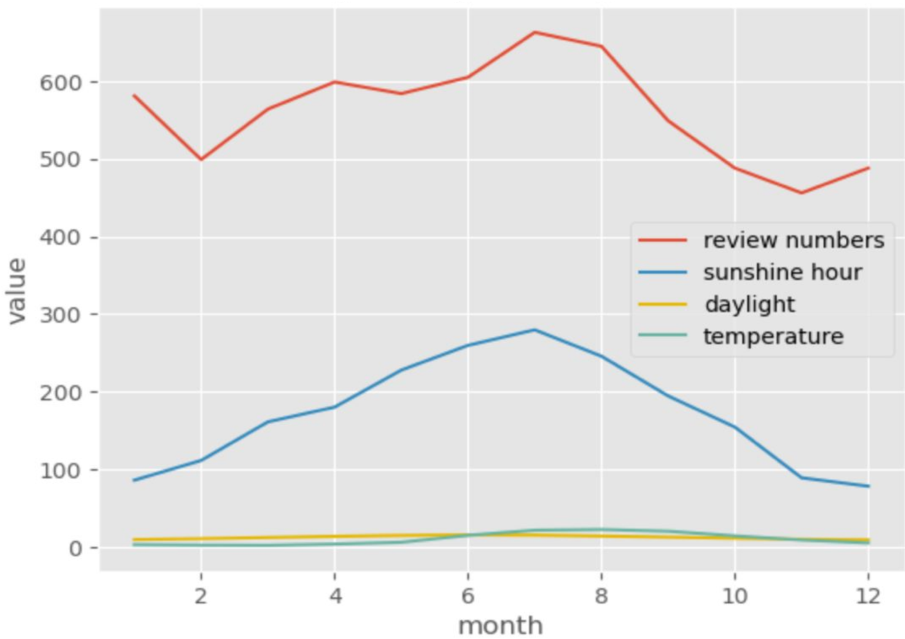
WordCloud (figure.4)


Note: The word cloud visualizes the words that appear most frequently in the comments. The bigger the word size is displayed, the more likely it will show up in the review. For example, “Love”, “Great”, “food”, “great service”, “amazing”, “awesome” are the top 6 words to be expressed. We find that most of the words are positive.

The Location Map (figure.5)


Note: The map shows the association between the location (major road, buildings) with customer reviews. The green dots represent the business located in Toronto while the orange dots stand for the business whose number of reviews is over 100.

Monthly Trend of Customer Reviews (figure.6)



Note: The figure shows the monthly trend of review numbers and external factors. The variable “sunshine hour” seems correlated with customer reviews, but whether those external variables play an important role in determining the review numbers will be investigated in the following paragraphs.

## Analysis

Customer reviews are the overall judgement of reviewers’ experience of the quality of products or service (Hu et al., 2008). In terms of the cognitive load theory in psychology that people have limited information-processing capacity, consumers are trying to reduce the amount of effort they expend on to carry out decisions (Hu et al., 2014). Businesses listed on Yelp.com have numerical reviewer rating stars, ranging from 1 to 5 on a discrete scale. Consumers review ratings could be helpful for those who seek to understand other consumers’ experiences, which can be divided into two categories: quality and quantitative. The quality features include the user's sentiment and the frequency of words. Review word length, review numbers are considered as quantitative features.

More than half of the total reviews posted on Yelp.com are positive. In the pursuit of understanding what the text really tells and whether comments will attract potential customers, we have to assign a sentiment score categorised as positive, neutral or negative to each feedback. The percentage of the three categories is 63.2%, 24.9% and 11.9% respectively. Also, the positive polarity has a wider spread (See figure.2) compared to negative sentiment meaning that unsatisfied people are more likely to have common expressions or patterns. Similarly, if the quality of service or products reach customer’s expectations or go beyond their expectation, reviewers will convey various kinds of expressions to describe their feelings. In all, customers are more likely to leave positive comments rather than negatives with more coloured words to describe their experience.

User's text sentiment distributes similarly within each category based on business rating stars. Although three sentiment review numbers tend to increase as business rating improves, the deviation between the positive and neutral/negative becomes larger and larger under stars 4.0. Each of the sentiments arrives its peak under 4.0 business rating and manifest a convergent tendency when heading stars 4.0. The left-skewed of the distribution (Figure.3) highly matches with the distribution of reviews by rating stars. Furthermore, it is interesting to find that even when business rating is quite low, the positive sentiment still has a higher proportion than that for a negative one, which indicates that customers are more willing to share a positive experience than negative ones. We can also conclude the number of reviews does not follow the increasing trend as business rating stars increase, if we trust the number of reviews of a restaurant, it might not lead us to the most favourable place recommended by previous customers. Therefore, as a customer seeking an unfamiliar place to visit, we shall consider both the number of reviews and the display rating stars.

In the quantitative features of customer reviews, review length is a potential indicator of customer satisfaction. Hu et al. (2008) argue that not all reviews have the same impact on customers. The word count for business on Yelp.com is in the range [1, 113] with an average around 10, the distributions only have slight differences across business rating stars; thus, the word length difference is not significant to conclude any influence on customer reviews in this study. Moreover, simply counting words will not lead to a precise conclusion. This is because not all the words are used to deliver influential and meaningful information to potential customers.

Another quantitative variable is the review numbers, which is positively associated with business location and performs a monthly trend. Since the importance of location selection is homogeneous across cities, we can clearly take Toronto as an example to illustrate the relationship between location selection and comment numbers. From the visualization (Figure.5), we find that the business receives comments above 100 are mainly located in downtown, in which the population density is more intense than other areas. We can conclude that businesses located in places with higher population mobility have a tendency to obtain more customer reviews. The business manager in those places can obtain more feedback to deliver a business response and improve its service or products, which gains competitive advantages. Furthermore, we find the area where the 5.0 stars businesses located highly coincides, which is the evidence that location will bring the market edge.

You can improve your business via customer review on the platforms even if you do not benefit from the location in the first place. According to the things mentioned above, the customer review numbers have a positive relationship with business stars (under 4.5). So how to improve your review numbers to attract more customers? BrightLocal survey found 74% of customers who were asked, 68% were willing to provide a review online (Bernazzani, 2020). This is great news for businesses! Do not hesitate to ask if your customers are enthusiastic to help you out, once you obtain more reviews on the platform, you will be exposed to more potential customers to prompt your sales. Also, for online platforms like Yelp.com, they can send notifications to viewers if they once visited the place and would like to leave a comment. Therefore, customers can not only help other viewers seeking advice but also give the business a chance to be known especially for business which does not gain advantage from location selection.

## Results

The data record the date of each comment posted on Yelp.com and we find that monthly total comment numbers follow the certain pattern. As shown in the figure.6 above, May, June, July have the highest review numbers. How can we explain these differences between each month? The apparent variation is climate change. As the previous study discussed in the introduction, weather can change customers' buying behaviour, it is possible that customer review numbers will be influenced as well since they are highly correlated.

If we can better understand the change in review numbers, business managers can indirectly predict their customer's behaviour and make some seasonal business responses. Weather change can disrupt the transportation system and put pressure on the supply chain; it will also have an impact on people's tendency to have outdoor activities. Seasonal climate changes include sunshine hours, daylight hours, snowfall, rainfall, temperature and other indexes. In order to test this hypothesis, we apply a multiple linear regression. If we prove that monthly change in weather would significantly determine the customer review numbers, for business managers it is not wise to compare review numbers by month as the external factor does not hold the same for each month. Instead, they should compare on a year-on-year basis.

There are four linear models in this study. We first have the regression on rainfall and temperature respectively to see how these two variables are good predictors to explain the review number. The third model uses daylight and sunshine hours since they represent the same climate index except for the fact that sun hour is cumulative for one month while the daylight is the average daylight hour in one month. The fourth model which consists of all variables is called the full model.

- Linear Regression Models

$$model\ 1:\ Y = \beta_0 + \beta_1 rain$$
$$model\ 2:\ Y = \beta_0 + \beta_1 temperature$$
$$model\ 3:\ Y = \beta_0 + \beta_1 daylight + \beta_2 sun\ hour$$
$$model\ 4:\ Y = \beta_0 + \beta_1 daylight + \beta_2 rain + \beta_3 temperature$$

- Variables

$Y$ : customer review numbers

*Rain*: Toronto average rainy days from Jan 2016 to Nov 2020

*Temperature*: average historical temperature in Toronto

*Daylight*: average daylight hours of a day by month

*Sun hour*: an average daily sunshine hour in Toronto by month

- Regression Model

$$model\ 1:\ Y = 506.4311 + 5.6328\ rain$$
$$model\ 2:\ Y = 523.5972 + 3.5683\ temperature$$
$$model\ 3:\ Y = 393.2752 + 5.7533\ daylight + 0.5602\ sun\ hour$$
$$model\ 4:\ Y = 311.6335 + 29.0484\ daylight - 12.6923\ rain + 1.3914\ temperature$$

From the regression output below, we find that in model 1 it seems like rainy days have a positive effect on customer review while model 4 shows the opposite result. In model 4, the estimated coefficient of variable rain is negative. Hence, we should compare AIC, BIC and R square adjusted to choose the model which explains the relationship best. We find that model 4 has the maximum R-squared adjusted and minimum AIC, BIC compared to others; thus, model 4 is an ideal model to explain our research questions. The p-values in model 4 are 0.002 (daylight), 0.060 (rain), 0.445 (temperature). Since in statistics inference p-value illustrates the significance of each variable, therefore, we can conclude that daylight hour is the most influential variable to the number of reviews which also has the largest coefficient.

| Table - OLS Regressions | | | | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| R-squared adjusted | 0.0493 | 0.1844 | 0.6462 | 0.7663 |
| AIC | 136.8351 | 134.9956 | 126.9726 | 123.9979 |
| BIC | 137.8049 | 135.9654 | 128.4273 | 125.9375 |

As discussed above, the climate index is proved to be valid and meaningful to explain the change in monthly review numbers. Secondly, among four climate factors, the daylight hour has the largest and positive impact on customer review behaviours. Therefore, external factors should be considered when analysing customer review numbers.

## Conclusion

This study is aimed to investigate if both internal and external factors will influence the online customer review numbers. This research question is answered throughout the analysis of the findings above. The preliminary findings of this paper will throw a more comprehensive light on the Voice of Customer (VOC). This section starts with summarizing the main findings and how the study will contribute to the industry.

Customers are more willing to share their positive experience online across all levels of business ratings. It is not astonishing that the total number of positive reviews exceed the number of negative reviews, but it is surprising to find that positive sentiments dominate even for businesses under 3.0 stars. Also, contrary to expectations derived from previous research, this study does not find a significant difference in word length among different business ratings that businesses are centralized among 10 words on average. Simply using word length to analyse customer reviews is not precise, we should classify meaningful words as not all words have the same influence.

For quantitative features, we find the customer review number is highly associated with the location. The places located in the area with intense population, road, and buildings are more likely to receive reviews. Those businesses gain a competitive advantage and can make business responses more frequently to improve their service or products. As for businesses that do not benefit from location selection, they should ask customers to leave a comment since more than half of the customer is willing to share their experience if asked to.

Furthermore, we capture the monthly trend in customer review numbers in our dataset, which could be explained by external factors such as climate index. The impact of climate change on customer reviews has been ignored by most of the researchers. After constructing the multiple linear regression model, we are able to examine that weather will influence the customer's behaviour. We find that rainy days, sunshine hours, daylight hours, temperature are good explanatory variables, and "daylight hour" is the most influential factor to customer review numbers. Some of the issues emerging from this finding relate specifically to business managers and online platforms like Yelp.com. Businesses should change their supply accordingly each month to meet the cost-efficient goal. In addition, business managers and online review platforms like Yelp.com should compare user's data on a year-on-year basis instead of the month-on-month ratio.

The biggest barrier of this study is the potential missing information in the dataset. For example, throughout the analysis, there are only 16 businesses in California, 15 businesses in New York,  5 businesses in Washington D.C. listed on Yelp.com, which makes us doubt the accuracy of the data itself. The incomplete dataset makes it hard to put our findings to a more generalized conclusion. Another limitation of this study is taking only one city as an example. It is because the results may appear to be coincident. Also, if the city does not have obvious climate change over the year, we cannot capture the influence of climate change in this study. A further study is therefore suggested if given a complete data set. We will then examine if the external factor (climate index) has a significant impact on monthly review numbers.

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