STAT628 Module 3 - Group 2

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1 Introduction

Our analysis focuses on restaurants that provide fast food to customers and had been on Yelp during the period from October 2004 to December 2019. We are motivated to analyze this category of restaurants because we find that their Yelp reviews were not as good as other categories of restaurants, the average stars only 2.69 during the period. This category of restaurants has not been serving customers well and need to be advised to improve.

In this project, we will explore what factors significantly affect customers' reviews. We will focus on the four major areas: food, waiting time, service, and sanitary conditions of restaurants, and answer the questions like: (1) will using fresh food materials be helpful to improve Yelp review and by how much? (2) is reducing waiting time considered important by consumers? (3) how important is staff service in Yelp review? and (4) will cleaning restaurants better be useful to improve review stars? We will provide suggestions to the restaurants accordingly.

2 Data Pre-Processing

Our data set is obtained from Yelp, a company that recently released some of its reviews to the public. The data are stored in json format, including information of reviews, businesses, users, and tips. Given our study subject, we first select businesses in business json file with "fast food" listed in its category. Then we select reviews for the chosen businesses from review json file through the common variable "business_id" in both business and review files. We further select users from user json file through the variable "user_id" in the selected reviews and tips from tip json file through "business_id" in selected businesses. We end up with 33,262 reviews by 21,741 users for 1,638 restaurants serving fast food with 5,823 tips. The four selected files are transferred in csv format and analyzed in R.

To process text data in reviews, we utilize the R package "tidy2vec" to break the text into individual tokens with ngram=1L or 2L (i.e., one word or a set of two consecutive words) and transform the list of tokens into a vector space. We prune words occurring less than 10 times and those appearing in less than 0.1% of reviews. We then create a document-term matrix (DTM) for our further analysis. In total, we have 15,163 words in the DTM.

3 Exploratory Data Analysis

In total, there are 1,638 restaurants reviewed on Yelp serving fast foods. These restaurants are located in the states of Illinois, Ohio, Wisconsin, and Pennsylvania, with average stars ranging from 2.64 to 2.82. As shown in the Figure 1, the distribution of stars for those restaurants is skewed to the right with a mean value of 2.69 and standard deviation of 0.94. It is therefore critical for those restaurants to find out the causes of the low ratings in order to make improvements.

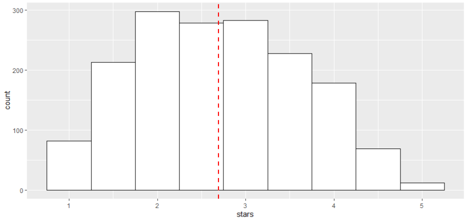
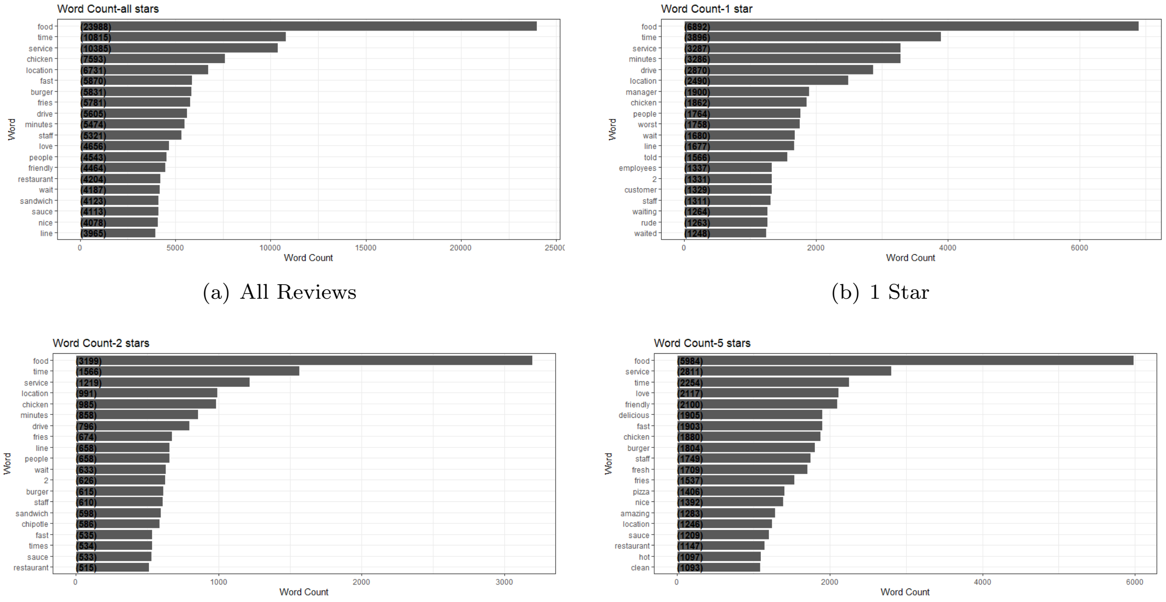


Figure 1: Histogram of review stars



(a) All Reviews

(b) 1 Star

(c) 2 Stars

(d) 5 Stars

Figure 2: Words Frequency

To explore which aspects are considered important by consumers, we examine the frequency of words appearing in reviews. We exclude words that are not useful for an analysis, typically extremely common words such as “a/an”, “the”, “of”, “to”, and so on. We plot not only the frequency of top 20 words appearing in all reviews, but also for each star level. But due to space limitation, we only show the plots of words for all reviews and reviews with 1, 2 and 5 stars. See Figure 2.

The above word frequency justifies the areas on which we target in this module, including food quality, waiting time, service, and sanitary conditions. For example, the most frequently occurring words “food”, “chicken”, “burger/burgers”, “fries”, “sandwich”, “sauce”, “cheese”, “fresh”, “pizza”, “hot”, “delicious”, “menu”, and “meat” are all related to food; “time”, “fast”, “minutes”, “wait/waiting”, “line”, and “quick” are related to waiting time; “service”, “staff”, “friendly”, “experience”, “manager”, “employees”, “home” may be related to services; and “clean” is related to restaurant sanitary conditions.

4 Key Findings About Restaurants Serving Fast Foods

Given the large number of words occurring in reviews, we utilize Lasso regression to do the word selection and find aspects significantly affecting customers’ rating. A dummy variable is created which is equal to 0 if the star is 1 or 2 and equal to 1 otherwise. Subsequently, a binomial logistic regression model with the dummy variable as the response variable and the created DTM as the covariates is run for the Lasso regression. The optimal λ that minimizes MSE is selected through cross validation which is equal to 0.0015. The Lasso regression selects 3,204 from 15,163 words and R2 is as high as 0.81, indicating a satisfactory prediction. To test the statistical significance of those non-zero parameters, we use R package “selectiveInference” to calculate their p-values. Among these 3,204 non-zero parameters, 244 are statistically significant at 95% level.

As our main purpose is to provide useful suggestions to the restaurants, we exclude those general words which cannot provide insights into any related areas, such as “finally”, “well done”, “dissatisfied”, “terrible”, “fun”, “order them”, “items in”, “were like”, “supposedly”, “began to”, and “ordered some”, etc. And the speed of our statistical analysis could be much improved if we added those words into stop-words list. We thus focus on the significant words that can be directly linked to one of the four targeted areas. The selected significant words grouped in targeted areas with parameter estimates and p-values are listed in Table 1 below. The limitation of using binomial model is that specific effects cannot be captured for each star level.

Table 1: Significant Words Grouped in Targeted Areas

	Word	Parameters	p-value		Word	Parameters	p-value
Service	Poor_service	-1.07	0.01	Waiting Time	40_minutes	-0.64	0.04
	decent_price	0.62	0.02		Quick	2.10	0.04
	apologies	-1.79	0.05		for_15	-0.38	0.00
	horrible_service	-0.73	0.04		for_20	-0.79	0.01
	friendliness	2.10	0.05		slow_and	-0.73	0.00
	attitude	-0.23	0.02		Fast	0.68	0.04
	rude	-1.35	0.02		minutes_to	-0.23	0.02
	the_service	0.09	0.02		in_line	-0.31	0.00
	incompetent	-1.05	0.02		over_15	-0.91	0.01
	Delivery	0.63	0.05		waited	-0.19	0.00
	greet	0.34	0.03				
	their_job	-0.33	0.04				
Food	is_cold	-1.64	0.02	Sanitary Condition	clean_and	0.21	0.05
	not_fresh	-1.81	0.02		dirty_tables	1.29	0.05
	Huge	0.61	0.02				
	kids_meal	1.02	0.03				
	ingredients_and	0.74	0.03				
	were_delicious	0.37	0.05				
	Great_food	0.80	0.05				

5 Recommendations for Businesses

In our results, a positive parameter suggests that the restaurant becomes more likely to get more stars with this word, while a negative one suggests the opposite. From the category of "service", we can reasonably deduce from words "apologies" and "incompetent" that mistakes made by staff members can negatively affect consumers' review, indicating the importance of employee training. Consumers are also concerned with ingredients in foods, exampled by words "not fresh" and "ingredients". Food portion may be appealing to consumers as indicated by word "huge". While long waiting time in line can result in negative reviews, "quick" and "fast" service can improve ratings.

By calculating the odds ratio, we can find how much the related aspects can affect the likelihood of consumers' review stars falling into $\{3, 4, 5\}$. For example, the likelihood of the restaurant with "friendly" staff getting 3, 4, or 5 stars is 8 times of that without "friendly" staff; the likelihood of the restaurant with "rude" staff getting more stars is only $\frac{1}{4}$ of that without rude staff. In addition, the likelihood of restaurants with "quick" service getting more stars is 8 times of that without "quick" service; and the likelihood of restaurants with "delicious" food or "great food" is 1.4 or 2.2 times of that without these two words, respectively. We note that restaurants with "dirty tables" still have higher likelihood to get more stars. One reason may be that people tend to use it in negative sentences. If we use "ngram"=3 or more, maybe we will find that it should be "no dirty tables". Correcting this kind of mistake is also the direction of our next improvement.

Based on the above analysis, we have the following suggestions for restaurants serving fast food.

(1) Train staff to provide good services, be friendly, and reduce mistakes as much as possible. Additionally, keep price at a reasonable level. If possible, provide delivery service.

(2) Use fresh ingredients in food. Be kids friendly by providing kids meal. While providing delicious food is important, consider increasing the portion of some food (maybe one or two low-cost products) to appeal customers.

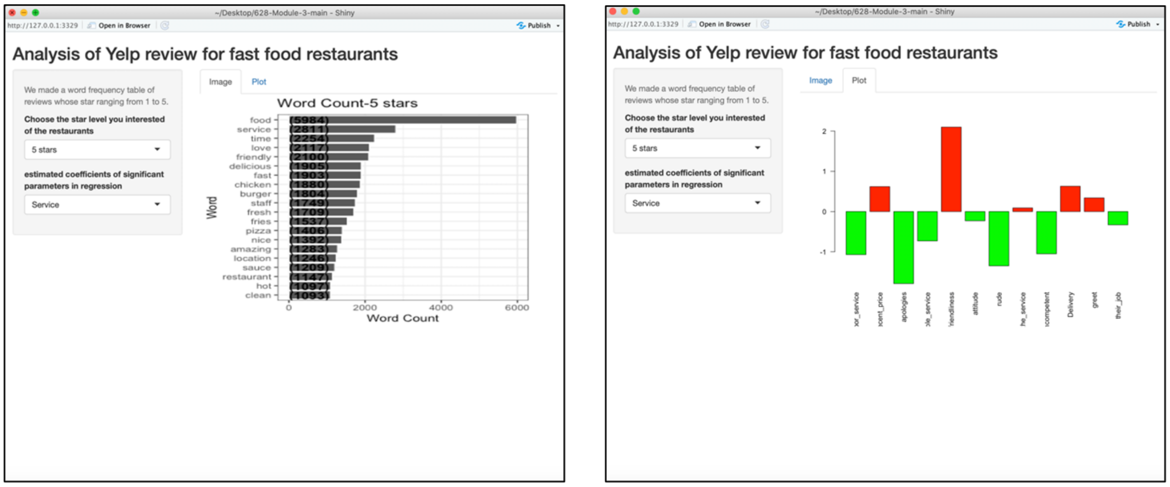
(3) Reduce waiting time. Customers going to restaurants serving fast food may highly likely prefer a quick meal. Prepare well ahead of rush hours and train employees to be more efficient.

(4) Clean the restaurants as thoroughly as possible. While consumers may be attracted by delicious food with a trade-off with sanitary condition, being clean can still help improve customers' reviews and avoid

health issues.
Our suggestions are based on a statistical analysis using a binomial logistic regression with LASSO. While it can provide odds ratio information, it cannot provide an estimate of an increase in stars if adopting any of the suggestions.

6 Visualize Our Analysis for Business Owners

To make it easier for business owners to understand our data analysis, we build an app based on R Shiny. Our analysis focus on two parts. The first part is to show the top 20 most frequent words for different star-level restaurants; and the second part is to show the key words in different aspects which significantly influence the star range, including food, service, waiting time, and sanitary conditions. Business owners can click the selection button of star levels, then on the right under ”image” will show the word frequency graph for the selected star. Business owners can also select an aspect they are interested in and on the right under ”plot”, it will give them a bar plot which shows the statistically significant coefficients of words obtained from the regression. It tells the owners which words and how they affect the final stars for their restaurants. Examples of the interaction are shown in the Figure 3.



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http://127.0.0.1:3329

Analysis of Yelp review for fast food restaurants

We made a word frequency table of reviews whose star ranging from 1 to 5.

Choose the star level you interested of the restaurants: 5 stars

estimated coefficients of significant parameters in regression: Service

(a) Example 1

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Analysis of Yelp review for fast food restaurants

We made a word frequency table of reviews whose star ranging from 1 to 5.

Choose the star level you interested of the restaurants: 5 stars

estimated coefficients of significant parameters in regression: Service

(b) Example 2

Figure 3: Interaction Examples

7 Conclusions

In this module, we utilized natural language processing along with binomial logistic regression with LASSO to analyze aspects that are critical to customers’ reviews on Yelp. Based on our analysis results, we provide useful suggestions for restaurants to improve their ratings.

8 Contributions

XW and FD cooperated on NLP and R coding, while ZJ worked on Shiny App. FD drafted the Executive Summary and XW and ZJ made edits. Every member contributes to the narrated presentation and Github page maintenance.