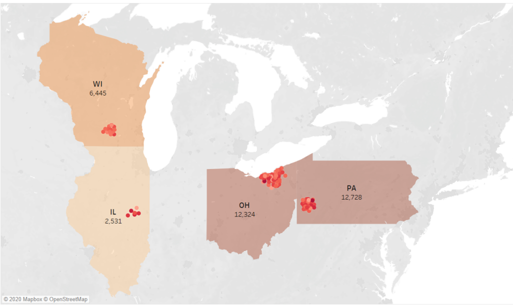
Introduction

The first Chinese restaurant at U.S. opened in 1849, since then Chinese Cuisine had established its significant role at American's catering industry. The business has been providing tons of opportunities for Chinese Immigrants to make living in U.S. In order to generate insightful advice for people in this industry and help them improve ratings on Yelp, we looked into the reviews' dataset provided by Yelp and analyzed the relation of food and service with restaurants' rating. Specifically, for food, we analyzed different flavors and meats served at Chinese Restaurants, while for service, we analyzed restaurants' attributes like whether they accepting credit card, or whether they having TV or WIFI etc. We mainly focused on the Chinese Restaurants, including subcategories of Szechuan, Taiwanese, Dim Sum, and Cantonese in Madison, Cleveland, Pittsburgh, and Urbana-Champaign.

Data Pre-Processing

We apply R's *jsonlite* to read business.json and review.json. After filtering businesses (and associated reviews) with keywords "Chinese" (from Yelp Fusion API), convert them into CSV files. We also use functions in *tidytext* package such as *unnest_tokens* to split review into tokens, *anti_join* to filter the stop words, words with low frequency across reviews and words start with 0-9. In this way, our final data are a $n \times p$ review-to-word matrix with $n = 34068$ reviews and $p = 6528$ words and an n-vector of star ratings.



(a) Restaurants and Review Distribution

(b) Word Cloud

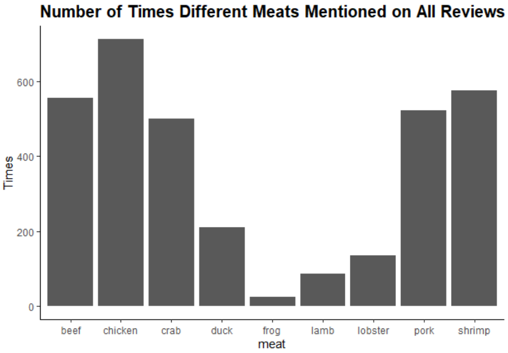
Figure 1

Exploratory Data Analysis (EDA)

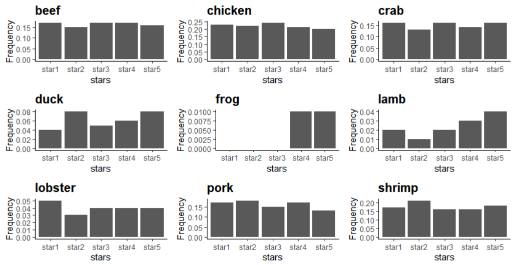
Food

a.Meats Served at Chinese Restaurants: Based on online research, we selected a list of meats which are commonly served in Chinese restaurants. This list includes "Beef", "Shrimp", "Pork", "Chicken", "Frog", "Crab", "Duck", "Lamb", and "Lobster". In order to investigate the popularity of these meats appeared in Chinese cuisine, we firstly visualized the number of times each meat mentioned on reviews in our Yelp dataset (Figure 1) by bar chart. To further investigate the relation of meats mentioned on reviews with restaurants' ratings, we also visualized the word frequency for each type of meats under different star levels.

b. Taste of Foods: Besides the meats, we also examined the key words for taste. We selected six words including "Bitter", "Salty", "Sour", "Spicy", "Sweet" and "Umami", and visualized their word probability to observe how these words related to the ratings of reviews.

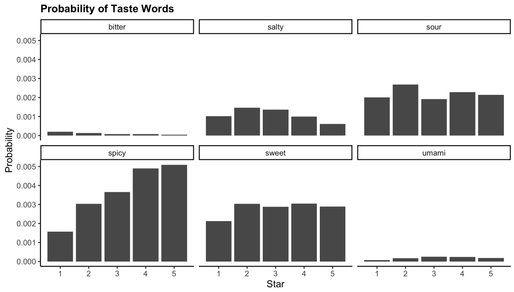


(a) Meats mentioned in reviews

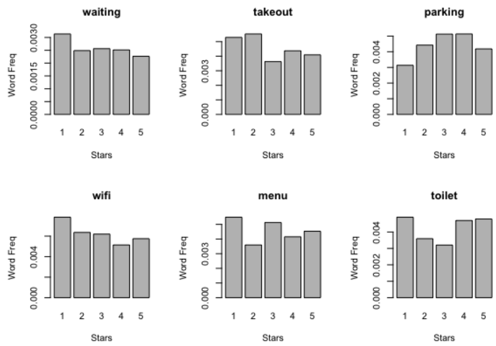


(b) Word Frequency Bar Plot(Meat)

Figure 2



(a) Word Probability Bar Plot (Taste)



(b) Word Frequency Bar Plot (Service)

Figure 3

Service

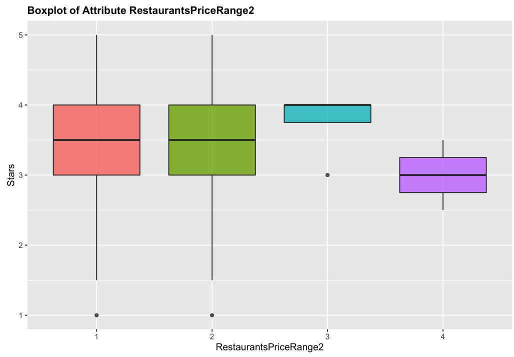
a.Basic Service: In this section, we want to explore the relationship between service and ratings. Based on our experience, We first do a sanity check with words we know are associated with service. In this way, we selected six words: "wifi","parking","menu","toilet","waiting" and "delivery" to visualize the word frequency for each word at different stars levels so that we can examine how they are related to ratings.

b.Business attributes: In this section, we investigated a series of business attributes' relation with ratings of reviews(1,2,3,4,5) including "Noise Level", "Price Range", "The Availability of TV", and "Whether They Accepting Credit Cards or Takeout". By using Boxplot, we can easily determine the variability, the quartiles, and the skewness of our data.

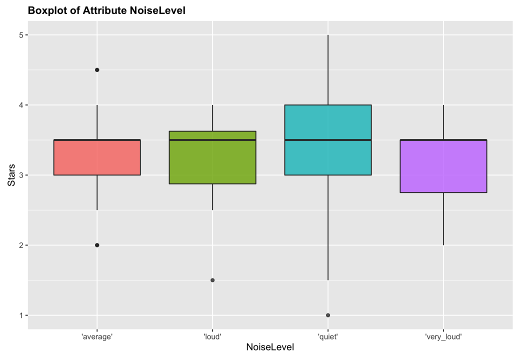
Part 1: Key Findings About Businesses

Findings-Foods:

Figure 2a: We can easily fount that "chicken" is the most mentioned meat among all, followed by "Shrimp", "Beef", "Pork", and "Crab" with small gaps between each other. However, compared to these meats mentioned before, "Duck", "Lobster", "Lamb", and "Frog" appeared much fewer times in the reviews. Among these four meats, "Duck" has been mentioned relatively more than other three and "Frog" is the least mentioned meat in reviews.
Figure 2b: We can tell that except "Duck", "Frog", and "Lamb", the word frequencies are evenly distributed among five levels of stars. However, for "Frog" and "Lamb", there is an obvious trend that when these two kinds of meats mentioned on reviews, corresponded restaurants' ratings are most

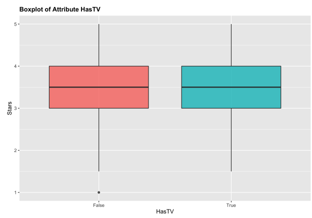


(a) Price Range

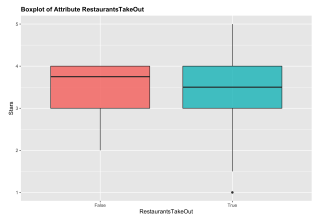


(b) Noise Level

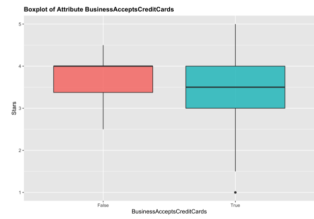
Figure 4: Boxplot 1



(a) TV



(b) Takeout



(c) Credit Cards

Figure 5: Boxplot 2

likely to be in level 4 and level 5.
Figure 3a: we can obviously see that "Spicy" is the most mentioned word among these six words, while "Bitter" and "Umami" are the least mentioned. As we can see, for "Sour" and "Sweet", the words are relatively distributed evenly across five levels. However, the restaurants with "Salty" mentioned on reviews lean toward to negative feedback, while the restaurants with "Spicy" mentioned on feedback seems more likely to have higher rating scores.

Findings-Service:

Figure 3b: We conclude that ’waiting’, ’wifi’ and ’takeout’ are more likely to associated with bad rating review, especially for ’wifi’, which contributes 0.78% for one star rating. However, ’parking’ tends to associated with high rating review.
Boxplot 1&2: From the boxplot of two-level attributes, we find that on average, having a takeout service decreases ratings by 0.3 stars, while whether having a TV makes no difference to ratings. From the boxplot of *Noiselevel* and *PriceRange2*, we find that on average, different levels of noise has no difference to ratings and the third category of price range(’3’) has the highest rating(4.0 stars), the fourth one(’4’) has the lowest rating(3.0 stars). When the restaurants are quiet, or their prices are at level 1 or level 2, the variability of ratings of reviews are high. In other words, these restaurants’ rating scores are spread apart. Besides, when restaurants do not accept Takeout or Credit Cards, the variability of the ratings are low. Considering the skewness, for “Noise Level”, except the condition of “quiet”, data in other conditions are all positively skewed. The positive skewness can be observed in data of the condition of “level 3” in Price Range and when restaurants do not accept credit card or takeout as well.
Test and model of attributes: We treat the stars as ordinal data considering how they are recorded, which means some popular methods such as t-test and linear regression are not suitable. So, we perform Wilcoxon-Mann-Whitney rank sum test and Kruskal-Wallis test for attributes with two levels and more levels, respectively. Several attributes show significance under 0.05 level. More details will be discussed in business plan part below.

Part 2: Recommendations for Businesses

According to analysis, our recommendations mainly focused on food and service. Food and service are two most critical factors which directly associated with the success of a catering business. In order to provide all-around recommendations and help owners of Chinese restaurants thrive, we will discuss the ideas of selection of meats provided, choices for tastes, and improvement on services based on our statistical analysis.

Selection of Meats: Chicken, shrimp, beef, pork, and crab are safe choices for Chinese restaurants. As we can see in Figure 2a, this list of meats is popularly mentioned on reviews with much more discussion than other options. Even though we cannot conclude that these meats are highly favored by the customers, we could know they are widely served at Chinese restaurants. Besides, with the word frequency analysis (Figure 2b), it is easy to see that the words of these meats are neutral since there is no obvious difference among frequencies across restaurants with different ratings. Thus, there is a small chance that serving these meats at Chinese restaurants will negatively affect reputations or ratings on Yelp.

Choices of Taste: Serving spicy foods would help with ratings on Yelp.

Compared with American food, Chinese dishes have a strong, consistent flavor, especially spicy. Therefore, some people are fascinated by the spiciness of Chinese food like hot pot, boiled fish, spicy crayfish…When we take a look at word frequency analysis for taste (Figure 3a), we can see in category of "Spicy", the frequencies of feedbacks associated with "Spicy" in level 4 and level 5 are saliently higher than that of lower ratings. Our observations from the plot are also well supported by testing. The result of Wilcoxon-Mann-Whitney U test shows the difference of ratings between review with and without spicy is significant under 0.05 level ($p = 2.2 \times 10^{-16}$). Also, when we fit a ordinal logistic regression, the coefficient of spicy shows that for a review including "spicy", the odds of being more likely to increase one star is 1.41 times that of without "spicy" in review.

Improvement on Services: Chinese restaurants should launch reservation service and lower noise level to improve ratings on Yelp.

According to our experience, restaurants with reservation service will not only save time for customers, but also give restaurants more time to provide better service based on customer needs. In our later analysis, we performed Wilcoxon-Mann-Whitney rank sum test, Kruskal-Wallis test, and fitting models for several business attributes to check whether there is significant difference among groups. After executed testing and model, we picked business attributes of "Reservation" and "Noise level" as our key attributes for ratings improvement since their p-values are significant and model coefficient indicates relations with ratings. For reservations attribute, the p-values of Wilcoxon-Mann-Whitney rank sum test is 1.482×10^{-5} which is significant under 0.05 level. In other words, there is a big chance that the ratings of Chinese restaurants which provides reservation service are different from that of restaurants which don't provide the service. "Noise Level" with 0.02 of p-value is also significant. In addition, based on our model coefficient, restaurants starting to provide reservation service are twice likely to increase half star for ratings than restaurants which continue not to provide this service while restaurants which lower one levels of its noise has 1.75 times more likely to improve ratings than restaurants keeping the same noise level.

Limitation: Our model and testing cannot reveal the causal relationship due to computational limitations. Most of our analysis are based on association, and the assumptions that extraneous variables' effects on ratings are not significant. Thus, there is a chance that counter intuitive results might show up in our analysis because there are other factors which were not captured by our model affecting outcome.

Contribution

Summary

- Introduction: Zeyu Li
- Data Pre-Processing: Yuxiao Li
- Exploratory Data Analysis: Zeyu Li, Yuxiao Li and Yuan Cao
- Part 1: Key Findings About Business: Yuxiao Li, Zeyu Li
- Part 2: Recommendations for Business: Zeyu Li, Yuxiao Li and Yuan Cao

Presentation

- Slides 1-9: Yuxiao Li
- Slides 10-12: Zeyu Li
- Slides 13-18: Yuan Cao

Github

- Yuxiao Li: Create *Code_yuxiao.R* about data pre-processing and service words in review
- Zeyu Li: Create *Code_zed.R* about meat words in review
- Yuan Cao: Create *clean.R, Code.R and business_attribute.R* about selecting restaurants, model of attributes and words about taste in review

Shiny

- Yuxiao Li: Revise and update UI part
- Zeyu Li: Revise and update server part
- Yuan Cao: Create UI and server of app