STAT 628: Module 3

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Introduction

Yelp is a powerful platform for business owners to collect information about their business and customer satisfaction. In this project, we analyzed the customer's reviews and various other attributes of restaurants and pubs in Wisconsin, trying to extract useful information and give suggestions to businesses. Among these establishments, our specific goals were to analyze the most important facilities and services that customers prefer and then provide suggestions to pubs to improve their star ratings. The rating of a restaurant is measured in stars from 0 to 5. Specifically, we asked how different facilities affected the star ratings, the affect the work hours might have on the rating and what additional services could improve the rating. We first preprocessed the data, then we did the exploratory data analysis. Next, we built a multiple regression model by stepwise selection to predict the rating of a business. In the following sections, we cover the details of our analysis.

Preprocessing

Data and Sample Size

All the data provided by Yelp are stored in four JSON datasets. The first dataset contains information about businesses, including different facilities offered and the stars rankings. The second dataset that was useful for our analysis contained the reviews and the number of stars each reviewer gave to a business. The third dataset contained the text of the shorter reviews called tips. We mainly focused on the following features: stars, working hours and facilities/attributes of the data in business JSON file, and the content of reviews in review json file. After filtering all the open restaurants with a full bar service in Wisconsin, we got 466 pubs with 69 attributes and its stars ratings, 50569 reviews, and the corresponding business id.

Clean Attribute Variables

To obtain attributes of each pub, we separated *BusinessParking*, *GoodForMeal*, and *Ambience* into several binary variables like valet, or romantic. These features are then cleaned for redundant characters(i.e. "u'free'" is the same as "free"). To deal with the missing values of both nominal and ordinal variables, we interpolated by the mode.

Create new predictors with sentiment Analysis

After a thorough preprocessing of the data, we focused on further investigation into the reviews and tips. Before the sentiment analysis and developing the polarity score, we tokenized the text of the reviews, by separating lengthy sentences into single words and their counts. Next, we removed the stop words, which are the words that don't contribute to the sentiment like "the" or "he/she". To obtain the sentiments of the reviews for each pub, we created a new predictor called positive review ratio by dividing the number of positive reviews by the number of reviews of each pub. Then we counted the number of positive words and negative words in each review. Finally, we calculated the sentiment of each review by subtracting the number of negative words from the number of positive words. The sentiments of each word are defined and stored in a lexicon which is provided by the *tidytext* library. After conducting sentiment analysis of each review, we grouped the reviews by business id to get the number of positive reviews. The two separate datasets, the review dataset and the business dataset, were merged by business id column.

Exploratory Data Analysis

Part of our EDA was to plot a histogram and visually explore the star distribution in the proportion to a specific attribute. Here we will focus on a few significant findings.
In the first example (Figure 1), we tested the importance of delivery option and its effect on the stars ratings.

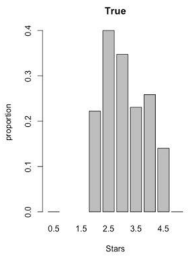
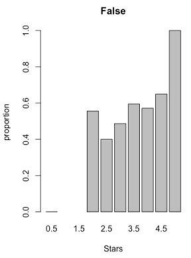
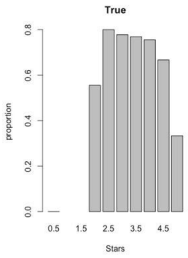


Figure 1: Delivery





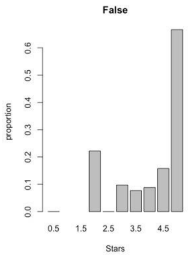


Figure 2: Takeout

From the plot it seems like the delivery does affect the star ratings(even it is slighter). In our second example (Figure 2), we tested the hypothesis if the high ratings are related to takeout being offered. From the plot, it seems that it has influence on the ratings. In order to confirm these relationships, we do the statistical analysis in the next part to justify them.

Then we explored the plots that showed us the frequency of some words in the reviews and how it was

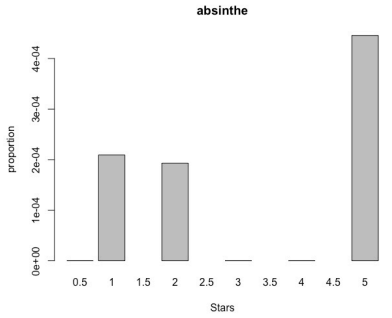


Figure 3: Absinthe

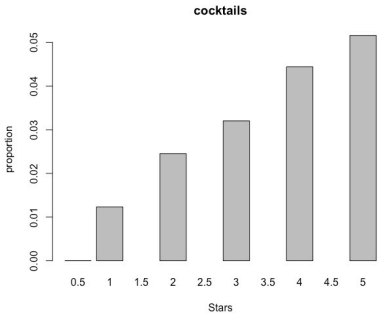


Figure 4: Cocktails

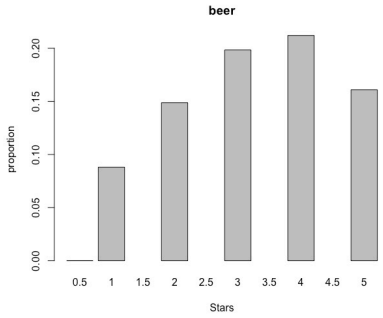


Figure 5: Beer

related to the distribution of the stars. As an example, the rating distributed differently based on the various alcohol beverages mentioned in the reviews. Words like ”ordinary” are not related with high ratings. We used Wilcox test to draw the conclusions.

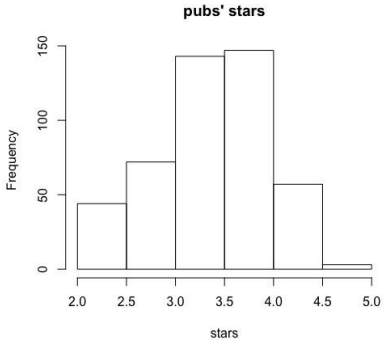


Figure 6: pubs’ stars

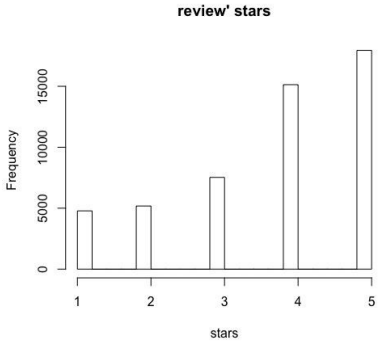


Figure 7: reviews’ stars

Finally, we looked into overall distribution of the star ratings among all the restaurants and bars in Wisconsin, and the distribution of the stars among each review. There are no bad ratings that are less than 2 stars, and the number of ratings that are 5 stars is very small. When we look at the number of stars each reviewer gave, it seems like in general the users tend to give more positive than the negative reviews.

Statistical Analysis and Model Diagnostics

In the table, we provide the summary of our statistical analysis. The data driven business plan is elaborated upon in the next section.

Hypothesis	Method	p-value
High Ratings are not related with takeout offered	chisq-test	0.466
High Ratings are not related with the presence of TVs	chisq-test	0.002
High Ratings are not related with the word 'ordinary' in reviews	wilcox-test	0.071
High Ratings are not related with offered delivery	chisq-test	0.007
High Ratings are not related with a pub being good for dancing	chisq-test	0.763
High Ratings are not related with the work hours on Friday	wilcox-test	0.125

After finalizing the EDA and after some statistical tests gave us the thorough insight in our data, we decided to use multiple regression model for predicting the future ratings if the owner makes changes and use tests above to give some advice. One of the main questions we wanted to answer was whether or not the work hours of a pub have any affect on the star rating. After standardizing work hours for each day of the week, we preceded to prepare other attributes for the regression model. These attributes were the predictors that we used in our model that we found that were significant to the star rating in our exploratory analysis. The predictors were work hours, restaurant attire, noise level, presence of WiFi, takeout and other attributes provided in the business dataset, along with the sentiment analysis of the reviews. Depicted in the model diagnostics plots, there is no significant deviation in QQplot and distribution trends in residual plots, therefore the model assumptions hold. According to ANOVA analysis' results,TV services, credit card acceptance, delivery services, and reservations requirement have significant influence to the rating of a pub with a p-value smaller than 0.001. Also, from the model we see that the percentage of positive sentiment review is really important to ratings. In the end, our model is good with adj R^2=0.6781.
Rough formula(Full version is in the appendix):

$$\begin{aligned} ratings = {} & \beta_0 + \beta_1 * CreditCard + \beta_2 * Reservation + \beta_3 * Goodforgroups + \beta_4 * TV \\ & + \beta_5 * Delivery + \beta_6 * Wifi + \beta_7 * lot + \beta_8 * valet + \beta_9 * latenight + \beta_{10} * divey \\ & + \beta_{11} * Mon + \beta_{12} * Sat + \beta_{13} * Pos\_Rev\_rate + \beta_{14} * trendy \end{aligned}$$

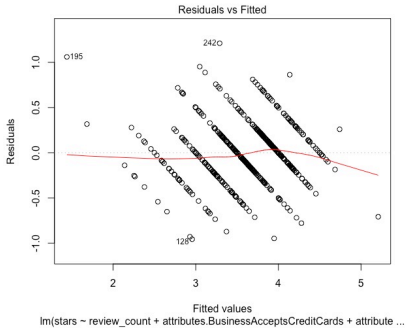


Figure 8: ResidualsVSFitted

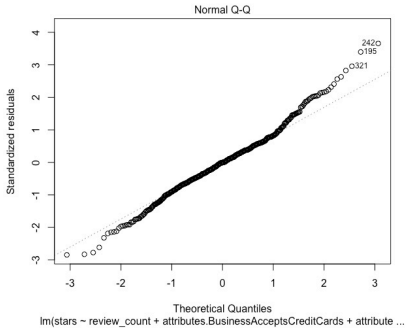


Figure 9: QQplot

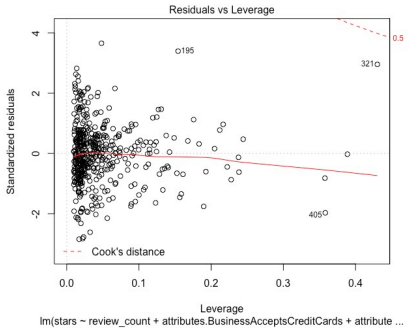


Figure 10: ResidualVSLeverage

Data-Driven Business Plan

Reflecting upon all of our findings, we will make recommendations for pubs in operations, service and food aspects. The picture of word frequency is in the appendix.

Operations

- Offering the **delivery service does not increase the ratings**. We suggest to cancel delivery services to save money.

- If a pub has TVs, they should play sports or mainstream music. If a pub does not have TVs, the **investment to install other things like a music stand should be made**. From our findings, the pubs without TV will have a tendency to get high ratings, even if the percentage is small, but it shows the trend. Then we do the chisq-test to see whether it can influence the stars, because it's p-value is 0.002, we refuse the null hypothesis, thinking TV are related with the stars. In addition, 3% of the tips with high ratings mentioned "atmosphere" as an important factor in their decision.
- To decrease spending, **do not providing space to dance**. This factor doesn't seem to have effects on a pub's ratings. This would be a good place to cut spending and invest in some other meaningful areas.
- Work hours during Friday do not affect ratings. This suggests that there might be an opportunity for the pubs to close earlier on Fridays to save some money. However, it seems like it would be good for a pub to be open longer on Mondays from the regression.
- Pubs that offer late-night food service could see an increase in ratings. A pub is good for meal at late night has a positive significant influence on pubs' rating with p-value equals to 0.02 in the regression.

Service

- To increase the ratings, **invest in staff training and bringing in more skilled staff**. From the reviews with low ratings, 36.8% people mentioned "service", 13.7% people mentioned "server", 14.5% people mentioned "staff", so pubs should pay attention to it. From the tips with high ratings, 7% people mentioned "service".
- To keep the high ratings, a pub should **keep encouraging staff, and potentially provide some extra benefits**. This will keep the motivation high and it will reflect on service.

Food

- To improve the ratings, a pub should **ensure the excellence in taste and quality**, with the emphasis on cheese, burgers, fish, fries and the beer selection. In addition, the pubs that are already satisfied with their ratings, in order to keep the customer satisfaction, they should safely explore and diversify their offers. To support our claim, we found that from the reviews with low ratings, 53% people mentioned "food", 21% people mentioned "drink", 17% people mentioned "price", to be the essential to a pub's rating. Among the tips with high ratings, 14% people mentioned "food" as an important factor.
- **Offer brunch**: in the tips for the pubs that have high ratings, 2% people mentioned brunch when reviewing the pub.

Limitations

- Our suggestions are relying on the data from Yelp, but there are still some NA in the dataset, so if NA are more than the other data in one column, the analysis maybe not precise.
- If every pub chooses to decrease its price, the situation will not change too much, besides, in the reality, there can't be this situation because the owner may come out new good with a high price to earn more money if he/she decreases the price of other goods, this will lead to new attributes in the analysis.

Conclusion

Overall, Yelp dataset provided in depth insights in the operations of businesses through the analysis of the reviews and business profiles, and it should find its place in improving strategies and business plans. We build a model to predict the future ratings after some changes done in the pub with adj R^2=0.6781

Contributions

Yinqiu Xu contributed to the preprocessing code, the sentiment analysis, the model and the model diagnostics. She wrote a part of the summary and set up the initial presentation deck. She also contributed to the design of the Shiny App. Xiaofeng Wang contributed to the preprocessing code, the statistical analysis and to drafting the data-driven business plan. He also wrote a part of the summary and created the Shiny app. Milica Cvetkovic contributes to the preprocessing code and the sentiment analysis. She wrote and edited the summary, created and edited the presentation deck.

1 Links

Link to our Shiny App
Link to our Github repository NLP-project-on-Yelp-data

2 Regression formula

$$\begin{aligned} Ratings = {} & 1.6558 + 0.0002 * review\_count + 0.0541 * CreditCard\_None - 0.2389 * Creditcard\_True \\ & - 0.3367 * Reservation\_None - 0.1097 * Reservation\_True - 0.1991 * Goodforgroups\_True \\ & - 0.1613 * HasTV\_True - 0.0676 * Delivery\_None - 0.0983 * Delivery\_True + 0.0051 * Mon \\ & - 0.0432 * Wifi\_False - 0.7870 * Wifi\_paid + 0.1130 * lot\_None - 0.1021 * lot\_False \\ & + 0.2698 * valet\_True + 0.0609 * latenight\_None + 0.1771 * latenight\_True - 0.0101 * Sat \\ & + 0.0332 * divey\_None + 0.1771 * divey\_True + 3.3189 * Pos\_Rev\_rate + 0.1548 * trendy\_None \\ & + 0.0791 * trendy\_True \end{aligned}$$

3 Frequency of words in reviews/tips

Word frequency in the low-rating reviews	
topic	frequency
food	0.534113
service	0.368345
cheese	0.142632
server	0.137636
salad	0.108847
staff	0.145129
sauce	0.11542
pizza	0.060339
drink	0.219272
beer	0.113448

Figure 11: Word frequency in low-rating reviews

Word frequency in the high-rating tip	
topic	frequency
food	0.14185
service	0.075472
beer	0.072744
menu	0.037054
cheese	0.036827
burger	0.050693
atmosphere	0.030689
fish	0.025915
fries	0.023187
brunch	0.020914

Figure 12: Word frequency in high-rating tips