615 final

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Review Analysis

This study use review file in Yelp dataset. There is a stars variable record the stars of each business. This study wants to mark the stars of those business as High, Mid, and Low. When stars greater to 4, rate is High. When stars is greater and equals to 3, and lower and equals to 4, rate is Mid. When stars is lower than 3, rate is Low.

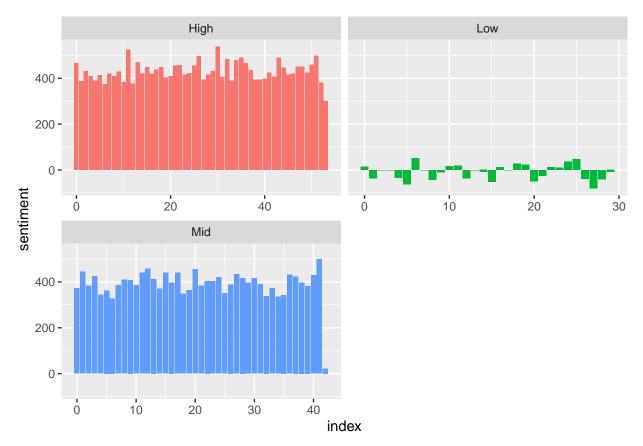
The study apply text analysis by using text variable and rate variable. Text is review from users about business in Yelp. At first, the study separate the text variable in to words. In the other words, the study splits sentences into words, and group by the Rate variable. Since this study wants to analysis review for different Rate.

Sentiment

The current study want to analysis the positive/negative sentiment about the review from userd. The the study use lexicon from tidytext package, and we use bing lexicon categorizes words to apply this analysis. The bing lexicon categorizes words has positive and negative categories.

The study want to estimates how sentiment changes within different Rate categories. After that the study find the sentiment score for each word usinf Bing lexicon and inner_join() methods. Because the review section is too large, it is not good for doing text analysis. Then, the study decide using 80% lines to apply this analysis.

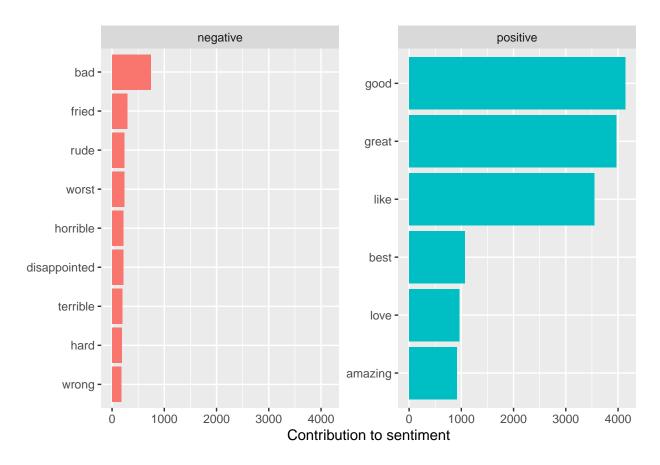
According to the following plot, users post positive review to business in High and Mid Rate. Users post a higher positive sentiment score to business in High Rate. There are some negative score to business in low Rate. It means that people will post neighbor review to business in low Rate.



Then the study wants to know what is the most common positive score and neightive score for the review from users. The current study uses count() with arguments of both word and sentiment, we find out how much each word contributed to positive and negative sentiment.

The following plot shows that the words contirbutes the most to negative is bad. The words contirbutes the most to positive is good.

Selecting by n



Words Clouds

The following plot is words clouds. It shows the most frequency words are food, service.

- ## Joining, by = "word"
- ## Warning in wordcloud(word, n, max.words = 100): service could not be fit on
- ## page. It will not be plotted.
- ## Warning in wordcloud(word, n, max.words = 100): food could not be fit on
- ## page. It will not be plotted.

price sauce people
restaurant
customer drinks
awesome
night experience people
minutes
fresh lunch
wait lot staff bar feel 3day people times
restaurant bad left3 wait 5 home dinnertaste
times love 5 recommend nice happy
burger eat perfect hotbeer table excellent fresh
price vegas
manager meal
manager meal
manager meal

Service of friendly2

Told anight food
experience menu
super experience
pretty chicken chicken
called

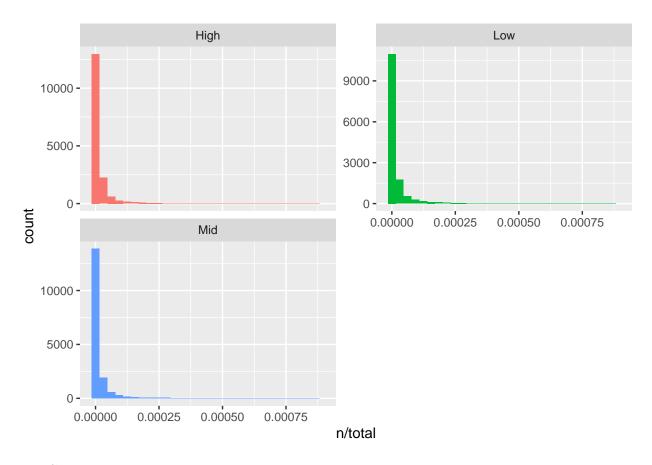
amazing

The study use group_by and join to get the most frequence words in Reviews text from users in Yelp.

Joining, by = "review.Rate"

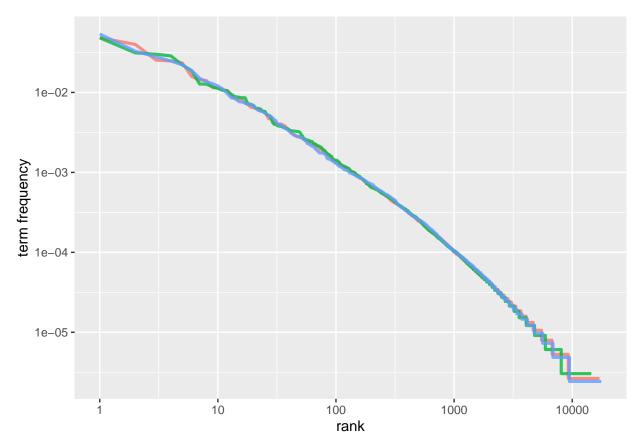
n is the number of times that word is used in Reviews text and total is the total words in Reviews text. In the followling figure, it shows that the distribution of n/total for each Rate category.

- ## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
- ## Warning: Removed 454 rows containing non-finite values (stat_bin).
- ## Warning: Removed 3 rows containing missing values (geom_bar).



Zipf's Law

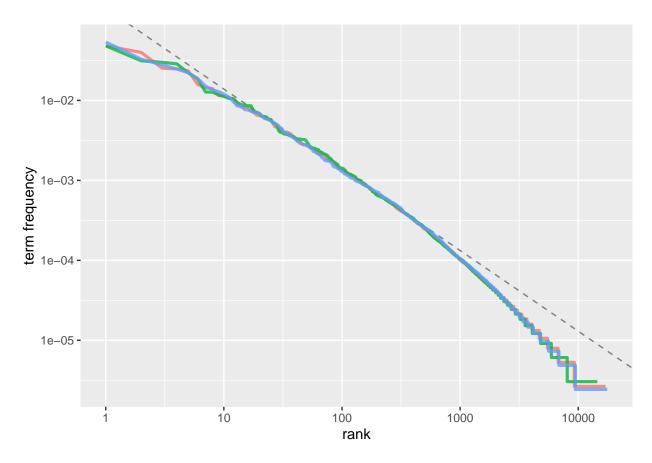
The study use Zipf's Law for Reviews text. The rank variable gives the rank of each word in the frequency table, and the table is order by n. Zipf's Law is visualized by the plot of freq_by_rank. Rank is on x-axis and term frequency is on y-axis. The plot is on log scales.



According to the plot, we can see that three categories are similar to each other, and the relationship between rank and frequency have a negative slop. The study fit a linear regression with log(termfrequency) and log(rank).

```
##
## Call:
## lm(formula = log10(`term frequency`) ~ log10(rank), data = rank_subset)
##
## Coefficients:
## (Intercept) log10(rank)
## -0.8401 -1.0138
```

After get the linear regression, we add the fitted line into ggplot.



Consecutive Words

Next, the stuy wants to analysis the most common phrase for three Rate category. The study use unnest_tokens() to estimate the pairs of two consecutive words. The study separate the phrase in word1, and word2. After delete the words does not have meaning, the study use unite() to recombine word1 and word2.

The study compute the tf_idf for bigrams across Rate category. tf_idf return how important a phrase in review text of users in Yelp. The following plot visualized the tf_idf within each Rate category.

```
## Warning in kableExtra::kable_styling(., bootstrap_options = c("striped", :
## Please specify format in kable. kableExtra can customize either HTML or
## LaTeX outputs. See https://haozhu233.github.io/kableExtra/ for details.
```

bigram	n	tf	idf	tf_idf
horrible service	23	0.0007358	1.098612	0.0008084
horrible customer	18	0.0005759	1.098612	0.0006327
amazing job	25	0.0005485	1.098612	0.0006025
slow slow	15	0.0004799	1.098612	0.0005272
terrible customer	15	0.0004799	1.098612	0.0005272
worst customer	15	0.0004799	1.098612	0.0005272
	horrible service horrible customer amazing job slow slow terrible customer	horrible service 23 horrible customer 18 amazing job 25 slow slow 15 terrible customer 15	horrible service 23 0.0007358 horrible customer 18 0.0005759 amazing job 25 0.0005485 slow slow 15 0.0004799 terrible customer 15 0.0004799	horrible service 23 0.0007358 1.098612 horrible customer 18 0.0005759 1.098612 amazing job 25 0.0005485 1.098612 slow slow 15 0.0004799 1.098612 terrible customer 15 0.0004799 1.098612

Selecting by tf_idf

