Enhancing Dining Experiences through Advanced Analytical Insights: A Case Study of Biscuit Love: Gulch

Executive Summary

Our project leverages advanced data screening and text mining methods to analyze the business performance of Biscuit Love: Gulch, a prominent breakfast and brunch restaurant located in Nashville. By utilizing a comprehensive dataset from Yelp, which includes 4,247 reviews spanning from 2012 to 2022, this analysis aims to delve deep into the dynamics of customer feedback to unearth actionable insights that can significantly benefit merchants and consumers alike.

Project Objectives

In the digital age, user-generated content has become an important bridge between brands and consumers. Reviews and ratings not only influence potential customers' purchasing decisions, but also provide companies with valuable feedback to help them improve their products and services. However, traditional star rating systems often fail to fully capture the complex emotions and specific opinions of consumers. Therefore, we adopt a new analytical approach that segments the main topics in positive and negative reviews through sentiment analysis, aiming to reveal consumers' true feelings and deeper needs.

From the platform's perspective, the objective is to empower merchants by providing deeper insights into their operational strengths and areas for improvement. From the consumer's standpoint, the aim is to assist customers in selecting a dining establishment that more closely aligns with their preferences and expectations. So, we use the restaurant Biscuit Love: Gulch as an example for our analysis.

They could use our analysis outcomes to improve their appeal and reputation using the following ways：

1. Analyze customer reviews to identify what the restaurant does well and where it needs improvement.
2. Implement a new scoring system based on sentiment analysis to provide more objective ratings and help restaurants enhance their services.

Data Description

The Yelp dataset contains historical reviews of different restaurants in the US from 2012 to 2022. The dataset includes business information documents, reviews documents and customer ID documents, but we only focus on business information and review information. The whole review dataset is nearly 7 million rows and 9 columns, including review ID, user ID, business ID, rating stars (on a scale of 1 to 5), comments and comment date. We focus on the top 20 stores which have a total of 96 thousand rows and 10 columns. Because the review dataset only contains store IDs and does not include store names, we extract store names from business information dataset. The one of targets of our analysis, Biscuit love: gulch, has more than 4000 historical reviews in the dataset, which is one of the top 20 restaurants from Nashville.

However, there some shortcomings：

1. The comments include multiple languages.

2. There are plentiful misspelled words, buzzwords, and emoticons.
3. Exaggeration in the reviews.

Methodology

Keywords Extraction

This part is mainly to identify the top 10 most positive and negative key phrase base on the reviews we have. We implement two methods.

N-grams with TF-IDF

Step 1. We split the whole reviews of a business into two groups base on the star column, which are the good reviews (4, 5 stars) and bad reviews (1-3 stars).

Step 2. We use TF-IDF to vectorize the text format reviews into numbers matrix, and we set the n-gram range to be 1-3, which means we will consider the words of phrase between one word unigram to three words trigram, and business owners and easier to understand the context.

Step 3. Calculate the average TF-IDF score of each phrase, then we will base on the average score of each phrase to sort out the most positive 10 phrase and most negative 10 phrase by sort two sets of data in descending order.

Lasso Regression

Step 1. Similar with previous step, we use n-gram to split our whole reviews into one to three words phrase and using TD-IDF vectorizer to convert the string format variables into float matrix.

Step 2. Put the matrix into Lasso model. Due to we want to explore the relation between the stars and each phrase, using phrase to predict stars, therefore we put that two variables into the model.

a) Why choosing Lasso:
   i. Lasso regression can do feature selection, it can shrink the coefficient to zero to remove less important phrases from the model. We have too many columns of phrase, this feature is benefit to us.
   ii. Lasso regression adds L1 penalty to loss function, it can avoid the over fitting problem.

Step 3. Result review, two variable we will mainly focus on from the output of Lasso regression, which are phrases and their corresponding correlation coefficients. From the correlation coefficients, we can learn about the strength and direction between phrase and star. If the correlation coefficient tends to large positive number, which indicate phrase has a strong relation to positive reviews and high stars, and as the number tend to small negative, the phrase means has a strong relation to negative reviews and low stars.

Step 4. Result output: ranking phrases by the correlation coefficient value to. Top 10 positive phrase: phrases with the largest coefficient. Top 10 negative phrase: phrases with the lowest coefficient.

Sentiment Analysis

The sentiment analysis implements the VADER lexicon, the lexicon is advanced on processing social media content, it would consider emoticons, punctuations, slang, acronyms, and so on internet often used expression methods.

Step 1. Conduct preliminary sentiment analysis on reviews. We set the compounding polarity to 1-5 five groups of sentiments (1: Very Negative, 2: Negative, 3: Neutral, 4: Positive, 5: Very Positive).

Step 2. We base on the preliminary sentiment analysis result and get the max score and min score which mainly between 0.9 to -0.9, so we set 0.36 (1.8 / 5) be the distance between each group. Therefore, the threshold we set is [-0.54, -0.18, 0.18, 0.54].

Step 3. Create a new column in the original dataframe and store the new sentiment score into the column. Besides that, an average score is calculated by combining the star rating we have and sentiment class we generated, providing a more objective view of the overall sentiment.

User interface (Figure 1)

We use ipywidgets package to allow users can switch the business they want to analysis, and then to choose which analysis they want to perform.

Step 1. Select a business: Obtain the unique business name from the dataframe to a list, users then can select the business from the list.

Step 2. Select a task: Choose between "Sentiment Analysis" and "Keyword Extraction" to perform the analysis on the business they already selected.

Result

In the case we set the Biscuit Love: Gulch as the example to adjust and display our analysis and methods. Hence, the result we will also focus on talking about this business result.

Keywords Extraction:

From the keywords extraction result, we get these possible meaningful and interesting phrases, which may can get some business insight. In the positive part, we learn customers love the nasty princess, Bonuts, chronic bacon (three meals' name in the store), hot chicken, and the orange juice. And its breakfast period is the most popular in the whole day. From the negative part, business owners can learn the part they still need to be improved, like some customers said that "biscuit dry", and "biscuit hard", owners and chief can think about whether they can ask customers' taste before purchase and make it (similar with steakhouse). Additionally, some people said, "heavy sweet", so owners need to think about reduce the sugar add. (Figure 2, 3)

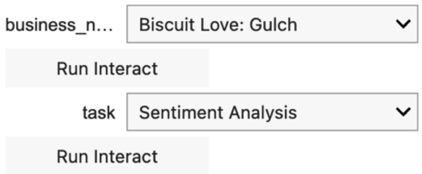
Sentiment Analysis:

From the result table, we find customer tend to give a lower star even if the review is pretty positive, but this is in line with customer habits, consumers will be relatively strict, and they may not think it's perfect. However, there isn't a store perfect. (Figure 4, 5, 6)

Conclusion

Our analysis of Biscuit Love: Gulch's Yelp reviews using text mining and sentiment analysis has provided valuable insights into customer experiences and preferences. Techniques like TF-IDF and Lasso regression identified strengths and areas for improvement, such as the popularity of unique dishes and issues with food texture and sweetness. These findings suggest actionable steps for enhancing service quality and customer satisfaction. Additionally, the user-friendly interface we developed allows for easy exploration of data, helping both business owners and customers make informed decisions. This project highlights the importance of data-driven approaches in understanding and improving the dining experience in the competitive restaurant industry.

Figures



(Figure 1: Interaction interface)

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ngram result:
Top Bigrams for Good Reviews (4 and 5 stars):
                         ngram  tfidf_score
13966   comparably star granted     0.023016
65994                  din time     0.016137
118448         hot mess chicken     0.014659
110656  place satisfy instagram     0.014587
19228          orange juice bit     0.014422
91353     friday afternoon take     0.014062
27614      comfortable eat want     0.013162
102847    place definitely hype     0.012825
39803                      hint     0.011610
104249             provide east     0.011072

Top Bigrams for Bad Reviews (1 and 2 stars):
                       ngram  tfidf_score
5301    brunch pancake pantry     0.032386
26958                  bar co     0.022062
49075  biscuit typical trendy     0.018731
45660    average review thing     0.016503
11353        huge portion tho     0.015007
28275       heavy sweet heavy     0.013356
37745          land nashville     0.012152
8047               good quite     0.011788
53116       everyone nice east     0.010439
36964            real frankly     0.010223

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(Figure 2: The output result of TF-IDF with N-grams)

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Lasso Result:
Top 10 Positive Phrases:
                   phrase  lasso_coeff
52035      nasty princess     1.758564
6690       best breakfast     1.686129
50961      must nashville     1.110952
37718         hot chicken     0.969071
22896          east nasty     0.895007
9418          bonuts must     0.784087
13828       chronic bacon     0.653324
25872 everything delicious     0.538861
55174        orange juice     0.427146
6684         best biscuit     0.304508

Top 10 Negative Phrases:
              phrase  lasso_coeff
32623   good biscuit    -0.905967
50537      much good    -0.969096
32283      give star    -1.237352
7560    biscuit good    -1.459053
7266 biscuit biscuit    -1.809805
7581    biscuit hard    -1.856910
81510   tourist trap    -2.074740
53587 nothing special   -3.352368
7435     biscuit dry    -4.423304
72198 somewhere else    -4.618242
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(Figure 3: The output result of N-grams with Lasso)

	VADER_polarity	VADER_score	text	stars	avg_stars
91793	5	0.5859	bonuts yogurt amazing seat arrive immediately ...	5.0	5.0
91794	5	0.9274	friendly service delicious cute atmosphere bon...	5.0	5.0
91795	5	0.9849	love definitely right word place sunday mornin...	4.0	4.5
91796	5	0.9842	nashville first time bff biscuit love definite...	5.0	5.0
91797	5	0.9805	biscuit love little spot tuck minute downtown ...	3.0	4.0
...	...	...	...	...	...
96035	5	0.9954	wow trip nashville highlight trip biscuit love...	5.0	5.0
96036	5	0.9595	yummmm biscuit arrived around 30am friday wrap...	4.0	4.5
96037	5	0.9313	good long eventually super nasty princess spic...	5.0	5.0
96038	5	0.9473	always little wary place hype long overall exp...	4.0	4.5
96039	4	0.4767	nice place eat pack may want early sunday	4.0	4.0

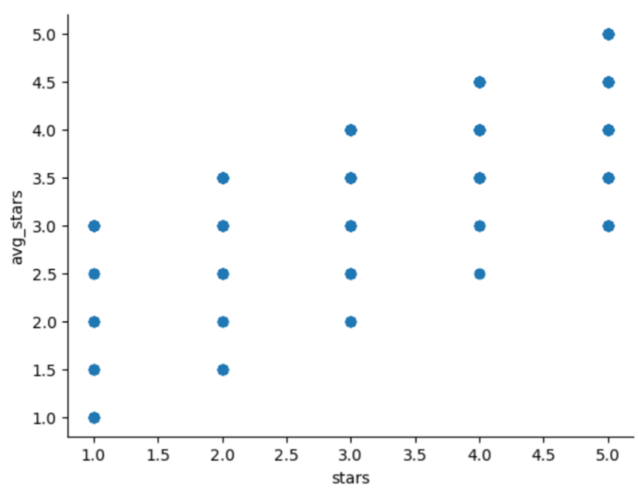
4247 rows × 5 columns

(Figure 4: Output result by VADER sentiment analysis)

	VADER_polarity	VADER_score	text	stars	avg_stars
0	5	0.8555	twice brunch enjoy immensely everything delici...	4.0	4.5
1	5	0.9371	first meal new orleans lunch special seafood s...	4.0	4.5
2	5	0.9931	service excellent atmosphere raw bar fantastic...	4.0	4.5
4	5	0.9589	oyster happy hour 7pm boyfriend share dozen oy...	4.0	4.5
5	2	-0.1949	place suck terrible service overprice mediocre...	1.0	1.5
...	...	...	...	...	...
4649	5	0.9413	staff super friendly attentive oyster good hap...	4.0	4.5
4652	3	-0.0133	wife across restaurant accident happy happen r...	5.0	4.0
4654	5	0.9871	guest hilton restaurant locate onsite first im...	3.0	4.0
4655	5	0.9459	little weird review john besh restaurant sexua...	4.0	4.5
4660	5	0.9524	definitely musteats best shrimp grit crab au g...	4.0	4.5

2264 rows × 5 columns

(Figure 5: The result only keeps the record with the predict star different with star value we already know)



(Figure 6: the relation between average stars we calculate and stars we knows)

Citation

Data Source: Yelp open dataset. Yelp Dataset. (n.d.). https://www.yelp.com/dataset