Biased Review NLP

Darren Huang
darrenhu@usc.edu

Frank Zhuang
frankzhu@usc.edu

Varun Punater
punater@usc.edu

Abstract

There is often an issue, more specific to non-American foods in the US, of seeing if a restaurant's negative reviews are justifiable or due to the customer not being used to the taste of the food. A specific example would be if a negative review was left on a Korean restaurant for having food that was too spicy where culturally that level of spice is considered the norm. We try to see if we can detect whether or not this form of bias exists in restaurant reviews.

1 Introduction

When someone craves a certain cuisine and searches for restaurants that serve it, the natural instinct is to click on the first restaurant that pops up. However, what if certain cultural differences between the restaurant or its food are more prone to biased reviews by the average American thus leading to lower review scores unrelated to the quality or taste of the food? Applications of this would allow for inferences in how there may be inherent biases in the sentiment and emotions conveyed through the language of reviews.

2 Working Hypothesis

Are certain cuisine types prone to biased reviews, judged through aggregated review sentiment and emotion analysis, given the same food quality?

3 Approach

Conduct sentiment and emotional analysis on an existing database. We will then use the Yelp data set, which contains 6,900,280 reviews, to identify reviews that are biased.

We aim to perform sentiment and emotional analysis on reviews pertaining to a specific set of cuisine types. We then desire to adjust the ratings of the cuisines and see whether the overarching trends change according to rating, or if there are certain characteristics that are retained at all rating levels. These inferences are used to ascertain whether there are subliminal biases in the reviews of certain cuisines.

Subsequent analysis would also look at the type of cuisines that are subject to certain biases, for example if they are predominantly immigrant cuisines, or the race commonly associated with the cuisine and so on. Additionally, we can also see if there are any bigger trends generally within the state that a restaurant's located which might affect the biases that their reviews contain.

4 Related Work

Research on sentiment analysis and racism detection based on restaurant reviews already exists and has been researched in great detail. Our goal is to combine the two to see if these factors prevalent based on the location and cuisine type of the restaurant.

- Sentiment analysis of customers who use delivery services (Adak et al., 2022). This paper gives us a guide to use to analyze different contexts within reviews of a restaurant and its food. This is useful when we seek to use cuisine as a guiding feature for our analysis.

- What factors affect consumers' dining sentiments and their ratings: Evidence from restaurant online review data. (Tian et al., 2021). This paper observes the links between consumer ratings and their sentiments, and analyzes whether the data skews in any particular way. This source is a good guide to form a framework of judging and analyzing the trends we might also find.

5 Preprocessing Data

Our data is obtained from the Yelp's Open Dataset, which contains over 6.9 million reviews from

150,000 businesses. For the purpose of this paper, we only considered businesses that contained the "Restaurant" tag and omitted any businesses that contained either the "Cafes" or "Fast Food" tag. Furthermore, to avoid reviews discussing about the brand of a restaurant rather than the food, we choose to remove chain restaurants from our data set as well. This is determined by whether a four or more restaurants share the same name. For simplicity, we also omitted restaurants that contained multiple cuisine tags. This resulted in the data set containing 18,803 restaurants.

After obtaining our valid restaurants, we then kept restaurant reviews that had a business id associated with our data set, resulting in 2,020,862 reviews.

Cuisine	#Restaurant	#Review
American (Trad.)	3418	367743
American (New)	2606	370935
Cajun/Creole	422	107109
Southern	269	43154
Soul Food	229	10043
Mexican	2656	257873
Latin American	313	22061
Cuban	121	9948
Italian	2844	271858
Mediterranean	468	40447
Greek	184	12944
French	208	24690
Irish	126	12280
Spanish	85	10755
Chinese	1703	109808
Japanese	1102	139404
Thai	583	70686
Vietnamese	512	51291
Indian	678	62779
Korean	276	25054

Figure 1: Frequencies of restaurant and review grouped by cuisine type

We cut out any cuisine types that had a minimal amount of restaurants associated with them, and were left with 20 cuisine types, that can be split into 3 sub-categories: the Americas, which consisted of new and traditional American, Cajun/Creole, Southern, Soul Food, Mexican, Latin American, and Cuban; European, which consisted of Italian, Mediterranean, Greek, French, Irish, and Spanish; and Asian, which consisted of Chinese, Japanese, Thai, Vietnamese, Indian, and Korean.

6 Findings

6.1 Sentiment Analysis

After parsing the reviews down to ones that we could use, we then ran multiple sentiment analysis / text-classification models from Hugging Face on our data. We used two types of models: one that analyzed the reviews sentiment and one that sorted the reviews into different emotions.

For the sentiment analysis, we used two BERT models: Adityano Ratu's Yelp Restaurant Review Sentiment Analysis Model (Ratu) and Cardiff NLP's Twitter RoBERTa Sentiment Analysis Model (CardiffNLP). Both models used the review text as an input and returned a sentiment classification as the output. The review's sentiment would then be measured by the model-assigned values of each of the three labels: negative, neutral and positive.

The purpose of using Adityano Ratu's Yelp Restaurant Review Sentiment Analysis Model was to use a specialized model for sentiment analysis of the reviews. This model specialized in analyzing review sentiment, and hence was used for inferences. The purpose of using Cardiff NLP's Twitter RoBERTa Sentiment Analysis Model was to obtain a baseline of the sentiment in the review text. This model was not trained with reviews in mind, however it would provide useful information of the generalized sentiment of a particular review. Combining the inferences gained through using both models, we could then observe the sentiment trends across cuisines with a review specific estimation, and a general estimation for additional context.

During the testing phase we analyzed 1000 randomly selected reviews per cuisine type. For each review we passed it into the two models and obtained raw values for each of the three labels. It must be noted that the Yelp Model had a limitation of only accepting a maximum of 512 tokens from an input. For the sake of consistency, this token limit was also applied to the RoBERTa Model. Once we obtained the results from the models, the next step was to apply the softmax function across the raw values to generate a probability distribution across the labels. Hence, the results were categorized as the likelihoods of the negative, neutral, and positive labels. We aggregated the sentiment likelihoods across the labels for both models for the 1000 randomly sampled reviews and found the average likelihoods per label per cuisine type. The results can be viewed in the table below.

Table 1: Sentiment Analysis Scores (3 d.p.)

Cuisine	Yelp Avgs			RoBERTa Avgs		
	Neg	Neu	Pos	Neg	Neu	Pos
American (Traditional)	0.176	0.141	0.683	0.163	0.110	0.727
American (New)	0.178	0.110	0.712	0.161	0.105	0.733
Cajun Creole	0.179	0.108	0.713	0.160	0.098	0.742
Southern	0.166	0.109	0.724	0.155	0.109	0.736
Soul Food	0.230	0.113	0.658	0.206	0.120	0.674
Mexican	0.168	0.102	0.731	0.152	0.100	0.748
Latin American	0.128	0.085	0.787	0.129	0.093	0.778
Cuban	0.139	0.093	0.767	0.136	0.097	0.768
Italian	0.210	0.104	0.686	0.175	0.112	0.713
Mediterranean	0.125	0.089	0.786	0.121	0.083	0.796
Greek	0.181	0.094	0.725	0.163	0.096	0.740
French	0.127	0.111	0.762	0.125	0.105	0.770
Irish	0.205	0.141	0.653	0.183	0.124	0.692
Spanish	0.124	0.121	0.755	0.119	0.096	0.785
Chinese	0.213	0.127	0.661	0.210	0.120	0.670
Japanese	0.188	0.117	0.695	0.181	0.105	0.714
Thai	0.152	0.111	0.737	0.147	0.091	0.762
Vietnamese	0.148	0.112	0.740	0.149	0.096	0.755
Indian	0.153	0.106	0.741	0.158	0.098	0.744
Korean	0.120	0.129	0.752	0.121	0.115	0.764

Through the results seen in the table below (*Table 1*) we can observe the sentiment analysis average probabilities for the reviews for both models across the cuisines. A larger trend that we can observe across all cuisines is that the likelihood of a positive review is the highest by a large margin, whereas negative and neutral reviews are typically less likely, in that order specifically. This leads us to think about whether it is more common for people leave a review given that they had experienced a positive experience, as opposed to a negative or neutral one. This is an inference of the distribution of the reviews themselves, which we might need to possibly account for in the future.

We can also observe the similarity amongst the sentiment classifications across both models, with no notable divergence in the likelihood of the sentiment for any specific cuisine. It must be noted that the RoBERTa model seems to judge a slightly higher likelihood of positive sentiment as opposed to the Yelp model, with slight compensatory decreases in the neutral and negative likelihoods.

We can also look at the specific likelihoods for the different label types. The Yelp model finds that Soul Food has the highest likelihood of negative review sentiment, followed closely by Chinese, Italian, and Irish cuisines. On the other end, Latin American and Mediterranean cuisine fare the best in terms of the likelihood of positive review sentiment.

6.2 Emotional Analysis

For the emotion model, we used SamLowe's RoBERTa model, which categorized text into 28 different emotions, which are: amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise, neutral. Due to the rate of the Hugging Face transformer pipeline, only 1000 reviews were randomly selected from each cuisine type for the emotion classification. All 28 emotions were counted, but for the sake of formatting only the results for disgust, surprise, confusion, and nervousness are shown (*Table 2*). This preliminary run through already generates some interesting results, such as Soul Food having the highest disgust and nervousness counts, as well as one of the highest surprise counts. Irish cuisine is also high up on these negatively-connotated emotions, band while Chinese cuisine does not have high surprise count, it does have high disgust and confusion counts.

6.3 Data Analysis

After analyzing the data from the resulting tables, we find that when we ranked from cuisines from high to low with respect to negativity scores, the distribution of the different subgroups were evenly split. In fact, for the sentiment analysis scores outputted from the twitter model, we found a symmetrical distribution wherein half of the subgroup counts, in this case four American cuisines, three European cuisines, and three Asian cuisines, surpassed the average negativity scores, while the remaining halves registered scores below the average. While there was some discrepancy between the sentiment analysis scores from the two models, they roughly had the same ordering for the cuisines.

However, looking at the sentiment tables as well as the emotion table, a few cuisine types do stand out. Specifically, Soul Food, Chinese, and Irish cuisines exhibit the highest levels of negative sentiments and are notable for their elevated counts in negatively connotated emotions. Italian and Japanese cuisine follow the same trends, just slightly below. Given these results, we try more analytical methods to better understand the meaning correlation between the patterns in the sentiment tables and the emotion table.

6.4 K-Means and Principal Component Analysis (PCA)

Our goal to find hidden biases led us to use K-Means and Principal Component Analysis to observe hidden trends in the data.

Our first step was to featurize our a random sample of the reviews. We randomly sampled 1000 reviews from each cuisine type. Next, we chose to use the previous two models to featurize the reviews. We passed in the review text of each review into the RoBERTa Sentiment Model and the Emotional Model and obtained the output tensors from both. We then concatenated these tensors along with its associated rating

Our output from using this featurized input was inconclusive. There seemed to be no suitable k value that fit an acceptable choice of the elbow criterion. For this reason, we chose to proceed with using the power of dimensionality reduction to understand the hidden trends that could guide us to whether or not biases existed in these featurized inputs.

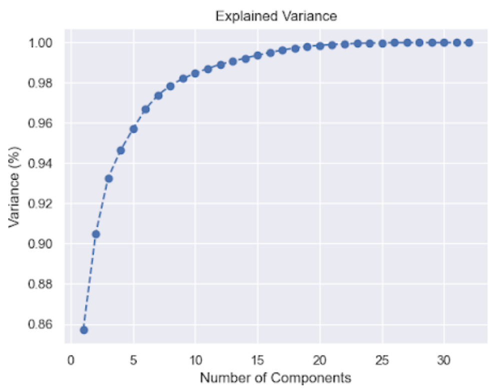
Our premise when applying PCA was to use the Cumulative Explained Variance as a threshold for chosing some number of components. A suitable threshold could be a ratio of or above 0.95.

Our next step would be then to choose some number of these principle components and then apply k-means once again to observe whether clustering would occur and the cuisine-based trends that may exist within and across the clusters.

We used two approaches using the previous framework. The approaches only differed by what part of the featurized input they used. Our first approach included the review in the final tensor used for PCA and K-means, whereas our second approach chose to not include that and observe how our inferences would change.

6.4.1 Approach 1:

Figure 2: Cumulative Explained Variance (Approach 1)



Using Approach 1, we could see that a good choice of principle components would be around 7 which had an Cumulative Explained Ratio of about 0.97. Looking at the two components with the highest individual Explained Ratio values, we could then see the input features that mattered the most for each principle component.

We found these values by taking the absolute value of each imput feature. Using this approach, we could see that the Rating mattered the most for component 1 and the Admiration mattered the most for component 2. Another interesting component found was component 5 for which Disapppointment was the most important.

We then passed in the modified dataset and ran k-means on it. We notice that $k = 5$ seemed like an appropriate choice using the Elbow Criterion. We measured the loss using Within-Cluster Sum of Square (WCSS) loss.

Table 2: Counts of strongest emotion of a given review, sorted and summed by cuisine type

Cuisine	disgust	surprise	confusion	nervousness
American(New)	11	14	11	0
American(Trad)	15	15	5	0
Cajun/Creole	9	4	9	0
Chinese	15	11	13	0
Cuban	8	7	5	0
French	5	14	5	0
Greek	10	7	4	0
Indian	9	8	8	0
Irish	15	15	14	1
Italian	13	3	10	0
Japanese	9	7	8	0
Korean	5	13	5	0
LatinAmerican	9	10	4	0
Mediterranean	7	7	12	0
Mexican	16	8	7	0
SoulFood	20	14	4	2
Southern	8	10	7	0
Spanish	9	10	9	0
Thai	9	12	9	0
Vietnamese	12	11	11	0

Figure 3: WCSS Loss (Approach 1)

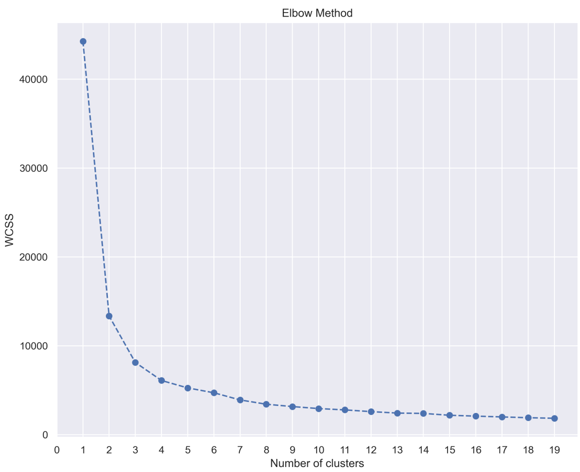
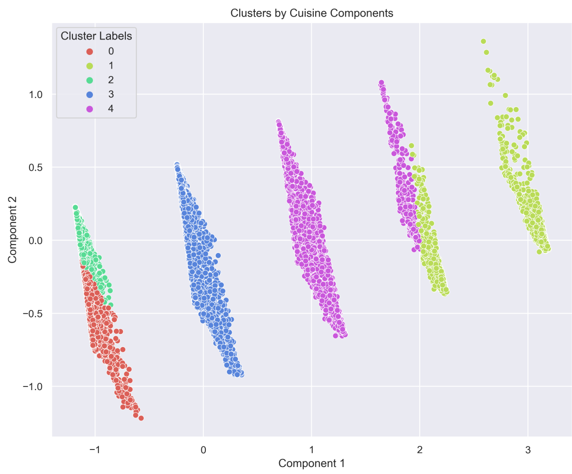


Figure 4: PC1 v. PC2 (Approach 1)



Upon viewing the clusters, we can see that for the principle components 1 and 2 the colored-in clusters don't really line up with what seems to be visually observed, however that could be explained with a more higher-dimensional view of the results.

6.4.2 Approach 2:

Approach 2 differed from Approach 1 in the input features to PCA and K-Means. We chose to not include the rating this time around since it appeared to be one of the features that was given the highest values in the PCs of Approach 1. The outcome of this choice can be seen in the Cumulative Explained Variance Plot.

Here we see that for the first principle component the Explained Variance Ratio is far lower than that of the first PC using Approach 1. This shows us the difference in what can be captured using PCA with and without the rating as a feature.

We still keep the number of PCs chosen as 7. When we look at the input features that are

Figure 5: PC1 v. PC3 (Approach 1)

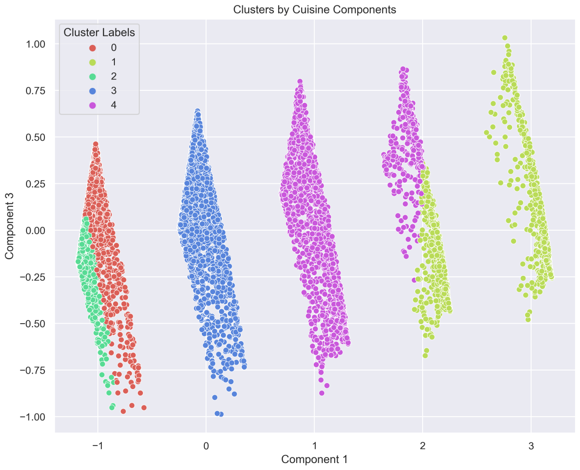


Figure 6: Cumulative Explained Variance (Approach 2)

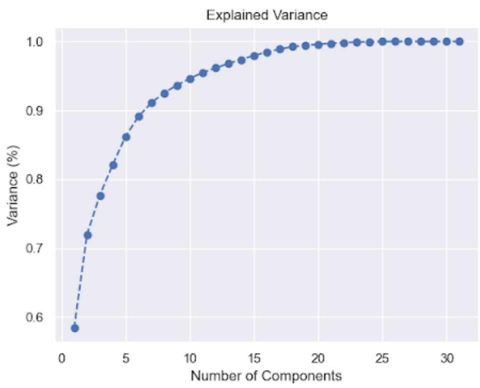


Figure 7: WCSS Loss (Approach 2)

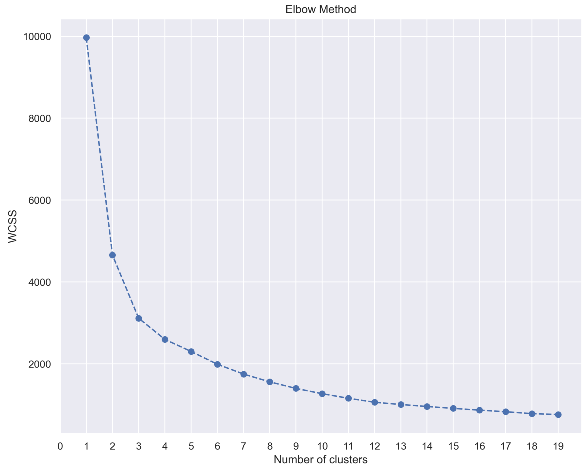
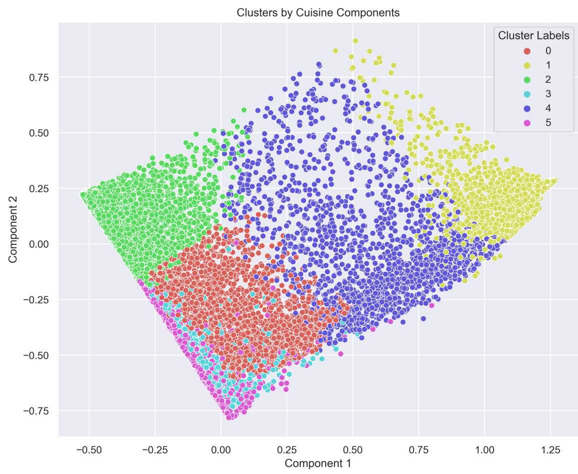


Figure 8: PC1 v. PC2 (Approach 2)



weighted the most, we can see a difference. We see that positive sentiment and admiration are weighted really highly for the first principle component, along with negative sentiment for PC 2. We also see other PCs which weigh Joy, Admiration, and Disappointment really highly, keying us into the emotions that matter across the reviews we've seen.

Running k-means also led to a slight difference in what made for a good choice of k using the elbow criterion.

Here we see that choosing $k = 6$ might be a better choice according to the elbow criterion. When we plot the clusters across the PCs we can notice a difference when comparing it to Approach 1.

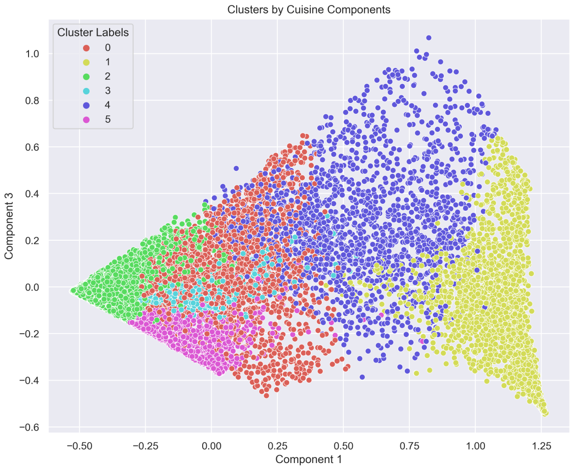
The clusters appear to be far less sparse in the chosen dimensions as compared to the previous approach. Of course, one similarity would be that the clusters need not make that much sense in a two dimensional view, however the difference across methods provides some additional understanding with respect to the importance of ratings when we apply PCA.

6.5 TF-IDF

To get a deeper understanding of the data, we decided to run Term Frequency - Inverse Document Frequency (TF-IDF) to see the most relevant words for each cuisine type. Figure 25 shows the most relevant words in Asian cuisine; Figure 26 shows the most relevant words in American cuisine; and Figure 27 shows the most relevant words in European cuisine. When computing, we decided to only include adjectives as other parts of speech are generally neutral in nature and would provide minimal insight into the connotation of the cuisine type. To summarize each cuisine type, we took the average of each word's score across all reviews of that cuisine type. From there, we then used 25 words from each cuisine type with the largest TF-IDF score for analysis.

Based on Figure 24, we can see that the only

Figure 9: PC1 v. PC3 (Approach 2)



two notable words with negative connotation are "bad" and "disappointed" which are placed in 16th and 21st place respectively. The majority of the words were either positive in nature, or neutral. While all cuisines had "bad" within the top 25 most relevant words, "disappointed" was 26 for Spanish and 33 for Irish cuisine with Irish cuisine being an outlier. However, aside from that, the cuisines shared similar words and rankings.

7 Conclusion

We started off the project with the goal to try to see if we could use language models to find any trends within the language used to describe certain cuisine types, extrapolating to find biases against any specific cuisine type. We ran the gathered reviews through BERT models to determine both sentiment and emotional analysis, and then used K-Means and PCA to try to find trends. When this did not work as well as we hoped, we also implemented TF-IDF on the review text.

From our findings so far, there does not seem to be a statistically significant difference between the vocabulary used to rate the different cuisine types. While there is a general trend of certain cuisine types being more prone to negative reviews than others, there is nothing that stands out from our results that points to any specific kind of discrimination against any cuisine type. We can see some trends against certain cuisines such as Soul Food, Chinese, and Irish from the raw data from the BERT models, but running PCA and TF-IDF did not reveal any further insight into any specifics that would have caused this. One finding however is that from our testing methods, there does not seem to be a noticeable difference in how European, Asian, and American cuisines are rated.

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A Appendix

A.1 PC Values

Figure 10: PC1 Feature Values (Approach 1)

Figure 11: PC2 Feature Values (Approach 1)

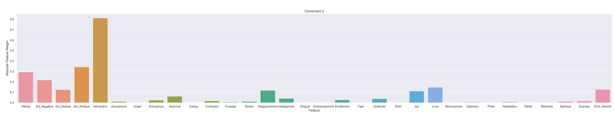

Figure 12: PC3 Feature Values (Approach 1)

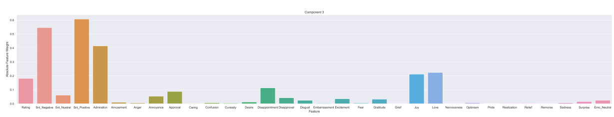

Figure 13: PC4 Feature Values (Approach 1)

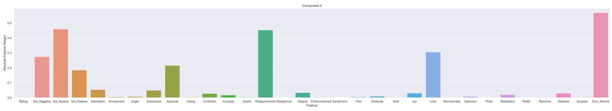

Figure 14: PC5 Feature Values (Approach 1)

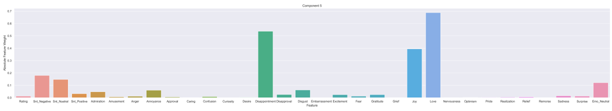

Figure 15: PC6 Feature Values (Approach 1)

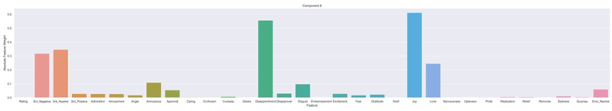

Figure 16: PC7 Feature Values (Approach 1)

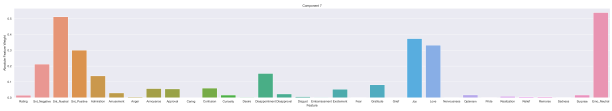

Figure 17: PC1 Feature Values (Approach 2)

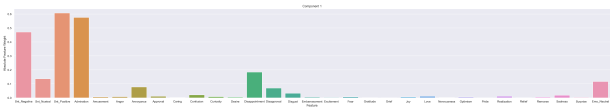

Figure 18: PC2 Feature Values (Approach 2)

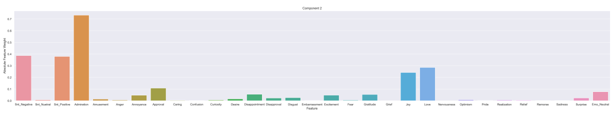

Figure 19: PC3 Feature Values (Approach 2)

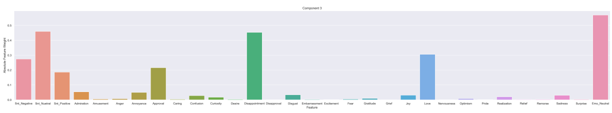

Figure 20: PC4 Feature Values (Approach 2)

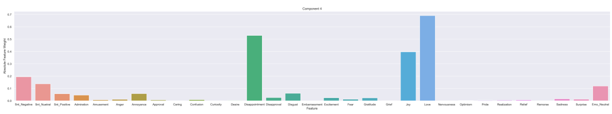

Figure 21: PC5 Feature Values (Approach 2)

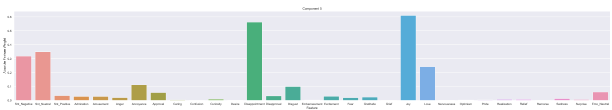

Figure 22: PC6 Feature Values (Approach 2)

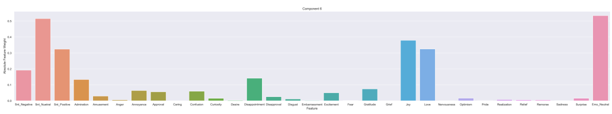

Figure 23: PC7 Feature Values (Approach 2)

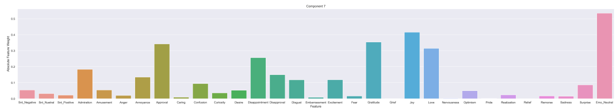

Figure 24: Word Cloud of all Cuisines

Figure 25: TF-IDF Values for Asian Cuisine

#	Chinese		Japanese		Thai		Vietnamese		Indian		Korean	
1	good	0.0320006	good	0.0308351	good	0.0322214	good	0.0324965	indian	0.0354180	good	0.0312322
2	chinese	0.0290581	great	0.0303088	great	0.0304415	great	0.0277484	good	0.0309507	great	0.0281071
3	great	0.0245100	fresh	0.0172015	delicious	0.0196367	vietnamese	0.0231366	great	0.0281894	delicious	0.0178423
4	delicious	0.0148159	delicious	0.0160284	nice	0.0141569	delicious	0.0187567	delicious	0.0195617	nice	0.0135897
5	hot	0.0132528	nice	0.0137522	fresh	0.0136469	fresh	0.0159530	nice	0.0133453	other	0.0120623
6	nice	0.0118242	other	0.0111441	little	0.0115153	nice	0.0134047	fresh	0.0111110	little	0.011684
7	fresh	0.0117668	little	0.0104628	hot	0.0105300	other	0.0127194	other	0.0106011	hot	0.011274
8	other	0.0112714	japanese	0.0093412	other	0.0104480	little	0.0107268	little	0.0096068	fresh	0.010388
9	little	0.0097794	much	0.0089772	green	0.0085988	much	0.0086769	authentic	0.0087829	much	0.009792
10	much	0.0092054	new	0.0080803	much	0.0082895	new	0.0082726	new	0.0086883	small	0.008515
11	authentic	0.0084147	special	0.0076812	authentic	0.0082894	authentic	0.0078710	vegetarian	0.0086125	authentic	0.008290
12	bad	0.0078992	small	0.0075737	red	0.0079357	small	0.0077934	much	0.0085373	new	0.008087
13	general	0.0076010	happy	0.0075386	new	0.0078865	hot	0.0069193	hot	0.0077879	many	0.006697
14	new	0.0075495	bad	0.0071119	small	0.0077064	many	0.0066616	many	0.0072136	different	0.006255
15	many	0.0066709	few	0.0063265	many	0.0064678	large	0.0066133	few	0.0065168	few	0.006180
16	few	0.0063215	many	0.0063261	special	0.0064229	bad	0.0064366	bad	0.0063837	next	0.006144
17	small	0.0062018	next	0.0055842	bad	0.0063217	few	0.0061060	different	0.0062921	bad	0.005875
18	special	0.0060630	disappointed	0.0055541	next	0.0062146	next	0.0058466	small	0.0061349	overall	0.005842
19	asian	0.0060342	last	0.0055093	few	0.0060520	special	0.0055887	fantastic	0.0059197	asian	0.005262
20	last	0.0055199	overall	0.0054965	disappointed	0.0060103	big	0.0054719	disappointed	0.0058932	happy	0.005061
21	next	0.0055157	different	0.0054651	fantastic	0.0054307	vegetarian	0.0054674	next	0.0057903	big	0.005015
22	disappointed	0.0054982	attentive	0.0052803	last	0.0052913	different	0.0052052	happy	0.0055559	disappointed	0.005004
23	large	0.0052960	fantastic	0.0050400	different	0.0052110	disappointed	0.0051068	attentive	0.0054446	attentive	0.004969
24	big	0.0050280	hot	0.0048872	happy	0.0050350	huge	0.0050131	last	0.0053309	full	0.004840
25	different	0.0049871	busy	0.0048537	large	0.0048922	overall	0.0049793	overall	0.0048531	last	0.004678

Figure 26: TF-IDF Values for American Cuisine

#	American (Trad)		American (New)		Cajun/Creole		Southern		Soul Food		Mexican		Latin America		Cuban	
1	great	0.0323828	great	0.0323448	good	0.0310868	good	0.0317695	good	0.0313823	good	0.0321304	great	0.0311399	great	0.0311542
2	good	0.0314127	good	0.0290498	great	0.0310538	great	0.0303356	great	0.0254229	great	0.0313363	good	0.0289318	good	0.0300678
3	nice	0.0134162	delicious	0.0150211	new	0.0166202	delicious	0.0162041	delicious	0.0173541	mexican	0.0244059	delicious	0.0205046	delicious	0.0191182
4	delicious	0.0129236	nice	0.0144052	delicious	0.0163432	hot	0.0119210	nice	0.0116658	delicious	0.0171955	nice	0.0127990	little	0.0122914
5	little	0.0096497	little	0.0102996	nice	0.0119844	nice	0.0116237	little	0.0102663	fresh	0.0128821	fresh	0.0112571	nice	0.0119222
6	other	0.0084317	other	0.0086796	little	0.0095795	little	0.0105810	other	0.0085341	nice	0.012171	little	0.010483	fresh	0.010508
7	much	0.0075654	fresh	0.0079881	other	0.0086951	new	0.0090047	hot	0.0084925	authentic	0.011363	peruvian	0.009462	authentic	0.009854
8	fresh	0.0071456	much	0.0077254	much	0.0082431	southern	0.0084621	much	0.0084675	little	0.010582	other	0.008733	other	0.008938
9	new	0.0068295	happy	0.0075270	red	0.0081483	other	0.0082929	fresh	0.0079206	other	0.008992	authentic	0.008518	black	0.008482
10	bad	0.0065765	small	0.0074712	fresh	0.0079878	much	0.0082106	new	0.0075690	much	0.008176	new	0.008375	small	0.007988
11	happy	0.0065267	new	0.0073459	french	0.0070501	fresh	0.0071567	small	0.0071427	happy	0.007797	much	0.007888	much	0.007836
12	few	0.0061358	few	0.0064067	next	0.0068621	green	0.0069875	disappointed	0.0068012	hot	0.006948	small	0.007801	hot	0.007579
13	hot	0.0059853	fantastic	0.0062307	fantastic	0.0062222	next	0.0060637	bad	0.0060616	new	0.006839	happy	0.007343	new	0.006474
14	next	0.0058340	next	0.0061405	small	0.0061020	small	0.0059167	next	0.0060491	small	0.006738	fantastic	0.006682	next	0.006113
15	big	0.0055071	special	0.0058948	bad	0.0060784	bad	0.0056244	few	0.0057848	bad	0.006513	different	0.006629	disappointed	0.005955
16	small	0.0055037	bad	0.0058252	hot	0.0055412	disappointed	0.0055496	black	0.0057701	few	0.005734	next	0.006014	many	0.005928
17	many	0.0054878	many	0.0057318	attentive	0.0051858	fantastic	0.0054981	big	0.0051308	fantastic	0.005499	hot	0.005860	few	0.005645
18	special	0.0053461	last	0.0056828	disappointed	0.0051569	big	0.0053446	last	0.0051176	next	0.005479	many	0.005637	fantastic	0.005633
19	last	0.0052744	hot	0.0054831	special	0.0051537	few	0.0051469	green	0.0051136	many	0.005476	few	0.005582	huge	0.005600
20	busy	0.0052499	attentive	0.0054631	many	0.0051311	many	0.0050874	different	0.0047901	disappointed	0.005287	colombian	0.005439	bad	0.005322
21	fantastic	0.0051627	overall	0.0051631	happy	0.0050968	different	0.0049996	open	0.0047059	last	0.005134	special	0.005417	large	0.005108
22	local	0.0049729	local	0.0049896	few	0.0050031	overall	0.0049798	many	0.0047016	different	0.005120	bad	0.004968	local	0.004897
23	huge	0.0048056	different	0.0048852	big	0.0049371	special	0.0047891	southern	0.0046160	big	0.005037	full	0.004955	real	0.004888
24	disappointed	0.0047761	disappointed	0.0047080	last	0.0048449	happy	0.0046495	overall	0.0045717	huge	0.004971	disappointed	0.004879	big	0.004706
25	live	0.0047327	big	0.0046649	overall	0.0047311	last	0.0045841	huge	0.0045698	special	0.004713	last	0.004775	special	0.004497

Figure 27: TF-IDF Values for European Cuisine

#	Italian		Mediterranean		Greek		French		Irish		Spanish	
1	great	0.0305124	great	0.0303423	great	0.0316049	great	0.0279705	great	0.0353327	great	0.0317785
2	good	0.0294224	good	0.0280522	good	0.0311672	good	0.0265601	good	0.0340514	good	0.0293441
3	italian	0.0178072	delicious	0.0216052	delicious	0.0193590	french	0.0192931	irish	0.0250540	delicious	0.0192222
4	delicious	0.0163895	fresh	0.0161759	fresh	0.0149204	delicious	0.0183312	nice	0.0154272	nice	0.0138325
5	nice	0.0135234	nice	0.0144874	nice	0.0134848	nice	0.0143452	delicious	0.0107481	spanish	0.0125371
6	fresh	0.0112302	little	0.0100732	little	0.0107187	little	0.0124616	other	0.0093777	little	0.011490
7	little	0.0104423	other	0.0088404	authentic	0.0093545	small	0.0092063	little	0.0093505	small	0.010786
8	other	0.0090621	much	0.0082320	other	0.0091201	other	0.0086693	live	0.0092289	other	0.009468
9	new	0.0080352	new	0.0080989	much	0.0079905	fresh	0.0086246	happy	0.0083878	much	0.008944
10	much	0.0078111	authentic	0.0074152	small	0.0068641	much	0.0082646	much	0.0081806	happy	0.007599
11	small	0.0074499	eastern	0.0070915	huge	0.0067428	special	0.0079520	few	0.0080251	few	0.007592
12	special	0.0069565	small	0.0069618	many	0.0063851	new	0.0075559	new	0.0071214	fantastic	0.007276
13	last	0.0066315	fantastic	0.0064514	next	0.0063290	fantastic	0.0069593	bad	0.0070743	next	0.007033
14	bad	0.0063259	next	0.0060020	large	0.0061583	next	0.0064558	last	0.0061424	many	0.007005
15	fantastic	0.0062743	few	0.0057448	new	0.0059108	many	0.0063881	next	0.0060943	last	0.006863
16	large	0.0061845	vegetarian	0.0057201	fantastic	0.0058936	few	0.0062331	many	0.0059886	new	0.006825
17	next	0.0061212	many	0.0056432	bad	0.0058897	last	0.0060852	fantastic	0.0056124	fresh	0.006614
18	few	0.0060015	different	0.0052622	few	0.0057936	happy	0.0056245	attentive	0.0055319	different	0.006452
19	many	0.0058970	hot	0.0052154	disappointed	0.0057167	attentive	0.0054381	special	0.0055246	special	0.006392
20	happy	0.0056510	last	0.0049964	big	0.0054231	bad	0.0053635	local	0.0054615	overall	0.006242
21	disappointed	0.0055129	disappointed	0.0049515	happy	0.0052673	overall	0.0052145	small	0.0051117	red	0.005844
22	hot	0.0052196	bad	0.0048932	special	0.0052364	disappointed	0.0049828	big	0.0050839	bad	0.005812
23	attentive	0.0050187	happy	0.0047292	last	0.0051560	such	0.0048923	busy	0.0049184	attentive	0.005620
24	huge	0.0049095	large	0.0045737	hot	0.0047412	full	0.0048685	large	0.0047980	authentic	0.005610
25	big	0.0047193	overall	0.0045521	full	0.0047095	different	0.0046835	hot	0.0047470	full	0.005564