International
SOCIAL SCIENCES STUDIES JOURNAL
e-ISSN:2587-1587
Open Access Refereed E-Journal & Indexed & Publishing
Research Article

Article Arrival	:	15/10/2021
Published	:	20.12.2021
Doi Number		http://dx.doi.org/10.26449/sssj.3603
Reference		Palaniappan, N.,Shah, R. Zeitouny, M, Bizel, G. & Gilkey Jr., J. (2021). "Yelp Or Facebook?: A Comparative Analysis" International Social Sciences Studies Journal, (e-ISSN:2587-1587) Vol:7, Issue:91; pp:5275-5284

YELP OR FACEBOOK?: A COMPARATIVE ANALYSIS

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ABSTRACT

During the past decade, reviews have become a crucial part in the success of a business. User generated reviews have become important reference material in casual decision making, like dining, shopping, and entertainment (Wang & Zhao & North, 2013). Every restaurant owner is aware of the fact that good reviews can boost popularity and profitability, whereas terrible reviews have the potential of closing the businesses down. Customers tend to leave a review on various online websites in order to share their experience about different aspects of a restaurant they visited. It is crucial for restauranteurs to understand the impact of review websites such as Yelp, Facebook, Twitter or TripAdvisor's and their role in the success or downfall of a business. The objective of this research is to perform a comparative analysis of two platforms - Facebook and Yelp to understand and analyze customer sentiments on both platforms. It is focused on answering two simple questions: Are Facebook reviews more powerful than Yelp reviews? Which platform should a business prioritize while making decisions about his/her restaurant? It is achieved by implementing Natural Language Processing techniques such as topic modeling on the online customer reviews posted on both platforms. The insights thus obtained will be helpful for the business owner to strategize reputation management for their restaurant.

Keywords: Natural Language Processing (NLP), Topic Modeling, Text Analysis, Yelp, Facebook, restaurant reviews, online customer reviews, business, sentiment analysis, Word Clouds, LDA

1. Introduction

In the era of social media and digitalization, online customer feedback plays a trivial role in business sustainability. Word-of-mouth (WOM) communication is considered a valuable marketing resource for consumers and marketers. It is also a reliable and effective metric for measuring customer loyalty with critical implications for a product's success (Clement & Tse, 2003). WOM communication includes all forms of information exchange among consumers regarding the characteristics and usage of particular products, services, or vendors (Eliashberg & Shugan, 1997). It is widely considered to be a major driver for the diffusion of new products and services. Online product reviews have become a major informational source for consumers due to the fast spread of WOM (considering word of mouth as a person to person sharing of information) communication through the Internet (Hu & Liu & Zhang, 2008).

As the internet grows bigger, there is a high chance that someone might be reviewing a business somewhere online, and somewhere a review might be viewed to compare a business with another. A consumer may or may not possess any prior quality information about the product and may or may not have previously conducted business with the online vendors involved. In such a scenario, there are both financial and psychological uncertainties associated with the product and the online vendors (Hu & Liu & Zhang, 2008).

In this research it is focused on two review sharing platforms Yelp and Facebook to compare how people's reviews might differ from one platform to another and to see if people share similar thoughts and feelings on different platforms for the same business.

Among the two platforms, Yelp is specifically designed for reviews, making this platform more reliable to discover insights. Reviews remain at the core while Yelp transforms itself into its own social media community. A one-star increase in Yelp rating leads to a 5-9 percent increase in revenue (Luca, 2016). On an average Yelp receives 80 million unique visitors every month making it the internet's one of the largest social media platforms for reviews. Google is the only platform that receives more views than Yelp for reviews. 45% of the customers visit reviews on Yelp before making a purchase (Carù, 2013). The number of reviews for restaurants on Yelp are more than that on Facebook. There are more than 171 million reviews on Yelp and continues to be a strong source of restaurant reviews.

Most business owners are only going to ask for reviews from their happy customers, not the unhappy ones. Over time, these self-selected reviews create bias in the business listing – a bias that savvy consumers can smell from a mile away. is one of the largest social media platforms, where customers are connected with many other friends and a review from one user can impact the decision of hundreds of friends connected to that user. Facebook introduced a new feature on the platform, where it works as a recommendation system rather than the star system (Ortigosa et al., 2014). This means, rather than asking the customers to rate a business, it asks a simple question: "Do you recommend this business, yes or no?". This gives a very definitive answer about the business, but this method serves no justice to semi satisfied customers. They can leave a review if they choose to, but the main focus of Facebook as a platform will be on yes or no answers for recommendation rather than reviews (C. Cuizon et al., 2018). One of the limitations of the application is that it can only assess text reviews written in the English language. (Huang & Rogers & Joo, 2014). Figure 1 shows the importance of Facebook as a platform for recommendation.

Figure 1: Impact of different platforms used for business recommendation (*How Are Facebook Reviews Different Than Google and Yelp?*, 2018)

While it is true that recommendation is one of the factors that drives purchasing decisions of a customer, as a business owner, the more helpful insight would be to look for specific topics that the recommendations are based on (Pang & Lee, 2008). It is helpful to know what aspects of the business the customers are dissatisfied about. This insight can be obtained by analyzing customer reviews posted on various online websites (Nie et al., 2020).

It is easier to leave a review on Facebook as customers are already using this social media app in their day to day lives. This means that if asked for a review, it is easier to leave one on Facebook than on Yelp. For Yelp, customers need to create a profile specifically in order to leave a review. Whereas on the other hand, on Facebook customers have a casual approach while posting a review, meaning they do not visit Facebook specially to write up a business review, they usually use Facebook to connect with friends and share life updates. However, on Yelp, people focus only on reviews, which means that if a person visits Yelp, he or she either looks for other peoples' reviews or to write up his/her experience of a business. This leads to the hypothesis that Yelp as a platform dedicated to reviews, is more reliable and should be more focused on while analyzing a restaurant performance.

2. LITERATURE REVIEW

In a recent research report published by the experts at Website Builder, approximately 61 percent of customers have read online reviews about restaurants. People tend to read online reviews prior to visiting a particular restaurant to dine or hosting an event, it is also worth pointing out that around 34 percent of diners currently choose restaurants based solely on information offered on peer review websites. This means that most diners disregard the restaurant's website or social media pages, preferring to rely on data present on review sites, further increasing their importance and influence on the market. Another interesting fact is that approximately 53 percent of the coveted 18 to 34-year-old demographic reported that online reviews play an important role into their dining decisions.

In research for improving restaurant recommendations on Yelp, authors leveraged two approaches in building the model, a direct and indirect approach. In the direct approach they build a K means model from the corpus of reviews which provide user ids, business ids and ratings. Here they may directly identify the businesses that users like or dislike and create clusters of users with similar affinities. In the indirect approach they assume that there exist multiple latent variables represented as topics, which define the characteristics of a given user preference for businesses. Then it has been used LDA in conjunction with the star rating to extract topics from the review from which they may generate user and business profiles (Li et al., 2019).

Before moving to the next steps, it is important to take a look at Figure 2 that shows an insight on what makes people most likely to write a review about a certain restaurant.

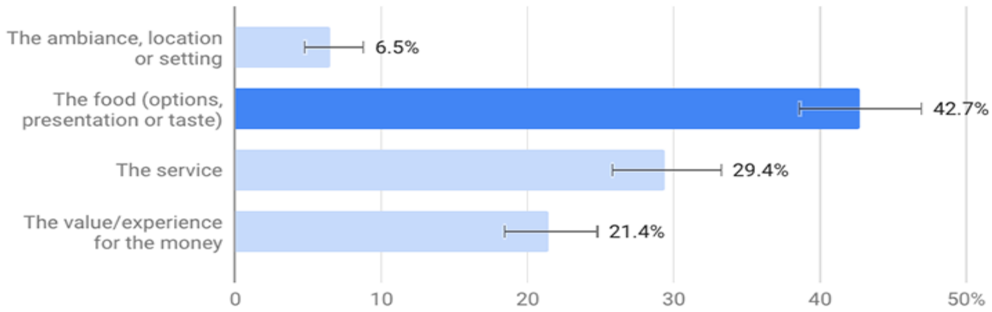

Figure 2: Restaurant aspects focused while writing a review (Weiche, 2018)

As observed, food (options, presentation or taste) comes first. However, the next important aspect of a restaurant business is service which is the primary reason 29.4% of the reviews.

3. DATASET AND METHODOLOGY

The web has huge dumps of unstructured text data that can be used to gain insights about various topics. Reviews help businesses determine what keeps their customers happy so through using the given dataset and by using the LDA model that describes the most mentioned topics it provided to be helpful for the owners to keep a track of the customers view towards their business.

3.1 Dataset

The research was focused on three restaurants, two of them being TS restaurants (Kimo's and Leilani's) while the third is a competitor restaurant (Relish oceanside restaurant from the Westin resorts and spa). Kimo's is a relaxed seafood spot with harbor views featuring local seafood, prime rib & famous Hula Pie dessert. Leilani's is a beachside eatery known for its seafood-driven menu, tropical drinks & family-friendly vibe. Relish Oceanside is a restaurant of Burgers, a breakfast buffet & island-inspired cocktails served in a bright hotel courtyard setting. Customer reviews of these restaurants has been retrieved from Facebook and Yelp that consists of more than 30 features each.

Facebook dataset of Kimo's restaurant is from January 2010 to October 2017. This dataset contains 3301 instances. The dataset of Leilani's restaurant is from October 2011 to September 2017. This dataset contains 765 instances. The dataset of Relish Oceanside is from November 2009 to September 2017. The dataset contains 1986 instances.

Yelp dataset of Kimo's restaurant is from August 2005 to September 2017. This dataset contains 2080 instances. The dataset of Leilani's restaurant is from January 2006 to September 2017. This dataset contains 1624 instances. The dataset of Relish Oceanside is from March 2015 to September 2017. The dataset contains 76 instances.

However, the focus of this research lies towards the review text from both the datasets. Textual reviews are important not only because prospective customers do read them before making purchase decisions (Chevalier & Mayzlin, 2006), but also because textual reviews are at least equally important in affecting the customers' purchase decisions. To understand the sentiments and to extract the topics that are most discussed among the customers, text analysis techniques has been performed on the textual reviews.

3.1.1 Data Pre-processing

The first step to implementation is to convert text from human language to machine readable format for further processing. After removing null values, performed the text specific processing techniques. After text is obtained, text normalization that includes the five main steps as mentioned in Figure 3.

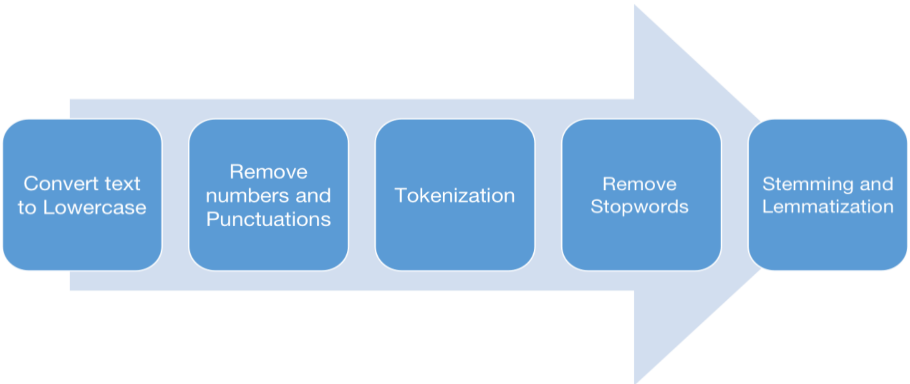

Figure 3: Data Pre-processing Flow

3.2 Methodology

Research methodology is the specific procedure or techniques used to identify, select, process, and analyze information about a topic. In a research paper, the methodology section allows the reader to critically evaluate a study's overall validity and reliability.

3.2.1. Modeling

Modeling refers to the process of training the model to deliver the desired results. One of the techniques in the field of text mining is Topic Modeling. As the name suggests, it is a process to automatically identify topics present in a text object and to derive hidden patterns exhibited by a text corpus. Thus, assisting better decision making (Gan et al., 2016). Topic modeling is different from rule-based text mining approaches that use regular expressions or dictionary-based keyword searching techniques. It is an unsupervised approach used for finding and observing the bunch of words (called "topics") in large clusters of texts. Topics can be defined as "a repeating pattern of co-occurring terms in a corpus". A good topic model should result in – "health", "doctor", "patient", "hospital" for a topic – Health care, and "farm", "crops", "wheat" for a topic – "Farming" (Saad Andaleeb & Conway, 2006).

Topic Models are very useful for the purpose for document clustering, organizing large blocks of textual data, information retrieval from unstructured text and feature selection. For Example – New York Times are using topic models to boost their user – article recommendation engines. Various professionals are using topic models for recruitment industries where they aim to extract latent features of job descriptions and map them to right candidates. They are being used to organize large datasets of emails, customer reviews, and user social media profiles. Two such models that has been used for the data are: NMF (Gillis, 2014) and LDA (Blei & Jordan, 2006).

Given a set of documents, NMF identifies topics and simultaneously classifies the documents among these different topics. It is a deterministic algorithm which arrives at a single representation of the corpus. It is a technique for obtaining low rank representation of matrices with non-negative or positive elements. NMF is closely related to existing topic models, in particular probabilistic latent semantic analysis and indexing (Gillis, 2014). Since for the data, the better results were found using LDA than that found using NMF. The results obtained using LDA gave a better topic distribution, with less overlapping of topics and a fair document distribution (Blei & Jordan, 2006).

LDA is a generative statistical model that allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. LDA tries to infer the hidden topic structure from the documents by computing the posterior distribution, the conditional distribution of the hidden variables given the documents. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of text modeling, the topic probabilities provide an explicit representation of a document. A sample output of topics and words associated with each topic is as shown in Table 1.

Table 1: Sample Topic Modeling result - YELP Leilani's Reviews

Topic1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
drink	place	fish	food	cold	just	table	service	food	got
grill	food	tacos	downstairs	view	ordered	food	leilani	good	dry
going	minutes	food	service	went	got	just	food	stars	asked
don	grill	just	menu	came	eat	like	right	service	ordered
hula	service	good	good	worst	beach	wait	good	great	night
took	hula	didn	hour	asked	food	bad	place	restaurant	hour
came	wait	husband	waiting	hula	know	minutes	server	beach	wasn
like	order	really	restaurant	try	nice	restaurant	waiter	just	said
just	dinner	service	waited	come	didn	waited	went	menu	waitress
got	like	place	make	really	meal	ordered	really	like	just
did	worst	bad	did	didn	table	hostess	make	view	told
server	downstairs	location	maui	waiter	took	service	downstairs	didn	food
really	ordered	maui	experience	told	location	waiting	wasn	time	time
waitress	meal	time	minutes	place	service	really	table	try	nice
food	know	going	bad	experience	experience	time	came	place	dinner
downstairs	restaurant	like	eat	make	view	said	night	server	tacos
nice	try	did	wasn	restaurant	way	don	way	order	husband
wasn't	fish	came	took	did	great	hula	waitress	hostess	went
did	hour	come	wait	order	like	tacos	minutes	leilani	waited
husband	eat	dinner	hula	said	pretty	know	did	pretty	came

3.2.2 Distribution of Kimo's reviews

In the below Table 2.1, it is clearly mentioned that Facebook and Yelp has more positive reviews when compared to negative and neutral reviews. Facebook has 75 percent of positive reviews about the Kimo's and on Yelp its 93 percent of positive reviews about the Kimo's restaurant.

Table 2.1: Kimo's review distribution

	Facebook	Yelp
Positive %	75	93
Negative %	2	6
Neutral %	23	1

3.2.3 Distribution of Leilani's reviews

In the below Table 2.2, as shown most of the reviews are positive for both Facebook and Yelp. Moreover, Facebook and Yelp share 93% of the overall reviews.

Table 2.2: Leilani's review distribution

	Facebook	Yelp
Positive %	93	93
Negative %	3	6
Neutral %	4	1

3.2.4 Distribution of Relish Oceanside reviews

In the below Table 2.3, the reviews are mostly positive on Yelp and Facebook with a slightly more positive reviews on Facebook. But there are more negative reviews on Yelp, 12% of the reviews are negative on Yelp while only 7% are negative on Facebook.

Table 2.3: Relish Oceanside review distribution

	Facebook	Yelp
Positive %	90	88
Negative %	7	12
Neutral %	3	0

4. Results

In this section analytical results have been shared. Section 4.1 presents the results using Word Clouds which is followed by the next section 4.2 presenting topic modeling results.

4.1 Word Cloud Results

Word clouds (also known as text clouds or tag clouds) work in a simple way: The more a specific word appears in a source of textual data (such as a speech, blog post, or database), the bigger and bolder it appears in the word cloud (Wang & Zhao & North, 2013). It is one of the most popular forms because it is easy to spot difference in word frequencies. They can be used to find trends and discover frequent topics which would otherwise be difficult to see in tabular format. Figure 4.

Figure 4a: Sample Word Cloud of Leilani's Negative reviews (Yelp)

Looking at the results in Figure 4a, customers posting reviews on Yelp talk more about service, slow, chicken and seat.

Figure 4b: Sample Word Cloud of Leilani's Negative reviews (Facebook)

Looking at the results in Figure 4b, customers on Facebook talk more about food like nachos, steak, salad and tasteless.

Before building a word cloud, apart from the text pre-processing techniques, customer reviews have been bifurcated into positive and negative ones by performing sentiment analysis on those reviews. However, if raw reviews are passed as input to word clouds, the words popped hold no specific meaning with respect to the sentiment of the customer. They emphasize frequency of the words, not necessarily the importance. They do not provide context of the review hence the meaning of individual words used could be lost, hence word clouds are suited best for exploratory purposes. Due to these limitations of word cloud, topic modeling technique has been performed to get a better understanding of the customer reviews.

4.2 Topic Modeling Results

After topic modeling has been performed, it was essential to know the meaning of each topic generated by the fitted model and the prevalence of each topic. It is also useful to know how each topic is related to other topics in the model output. Hence, LDAviz visualization system was developed that can helps to understand and analyze LDA results.

Using LDAViz package of python, the results of visualizing LDA results are as shown in Figure 5.1a and Figure 5.1b. It is designed to help users interpret the topics in the topic model. This package extracts information from a fitted LDA topic model to inform an interactive web-based visualization. The visualization is intended to be used within an IPython notebook but can also be saved to a stand-alone HTML file for easy sharing (PyLDAvis, 2021).

The visualization has two basic pieces. First, the left panel presents a global view of the topic model. In this view, it was plotted the topics as circles in the two-dimensional plane whose centers are determined by computing the distance between topics, and then by using multidimensional scaling to project the inter-topic distances onto two dimensions. Each topic's overall prevalence has been encoded using the areas of the circles, where the topics were sorted in decreasing order of prevalence (Sievert & Shirley, 2014).

Second, the right panel of the visualization depicts a horizontal bar chart whose bars represent the individual terms that are the most useful for interpreting the currently selected topic on the left, and allows users to answer question, "What is the meaning of each topic?". A pair of overlaid bars represent both the corpus-wide frequency of a given term as well as the topic-specific frequency of the term (Sievert & Shirley, 2014).

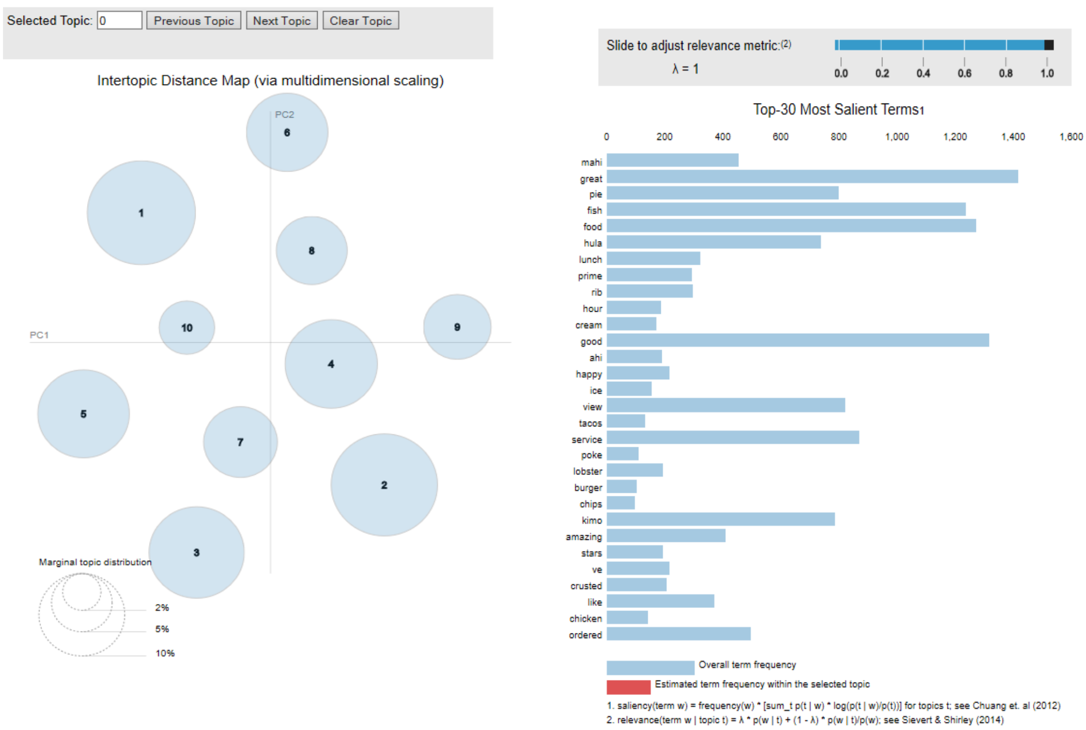

Figure 5.1 a: Sample LDA output (Yelp Kimo's positive reviews)

In Figure 5.1a and Figure 5.1b, each bubble represents the topic formed by LDA algorithm. They are indicated by the topic number based on bubble size. The area of the circle is based on the percentage of tokens in each topic over entire corpus. The topics were plotted Based on the Intertopic Distance Map (the distance between the topic clusters). The right panel in the figures describe 30 most discussed topics in the given corpus. It includes a relevance metric, using which led to change the lambda value and observe variations in the frequency of text.

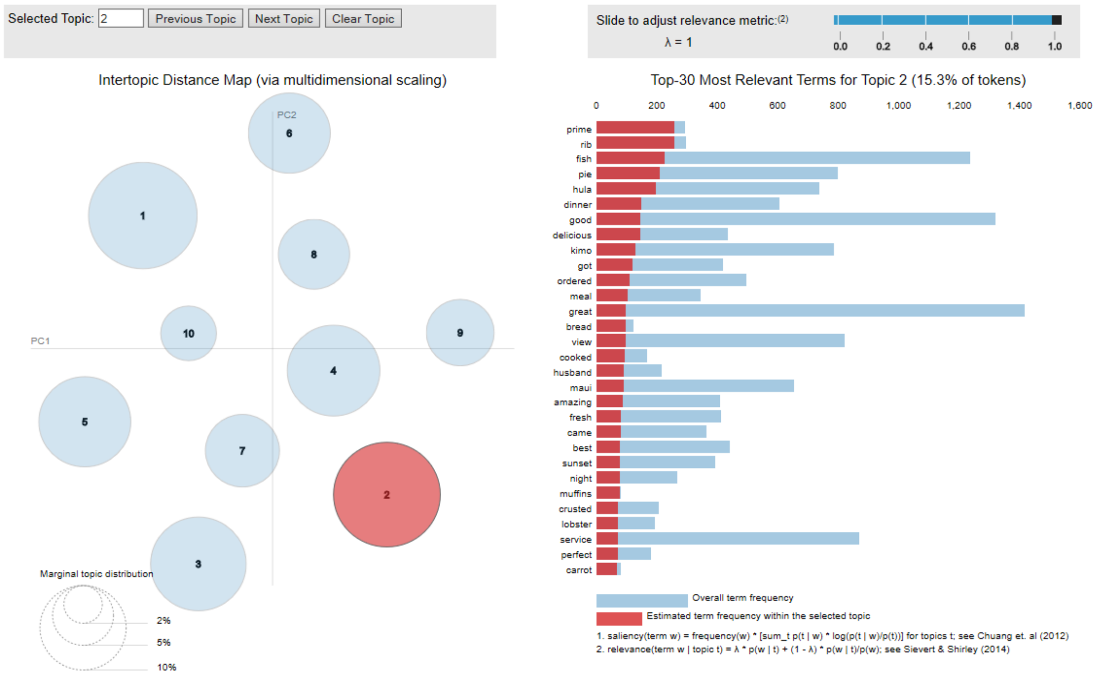

Figure 5.1 b: Sample LDA output (Yelp Kimos' Positive reviews)

In Figure 5.1b the red bars represent the frequency of a term in a given topic, and the blue bars represent a term's frequency across the entire corpus. On the left side, selection of a particular topic is available, for example topic 2, and the term frequencies of the cluster of words in topic 2 are available, also on the right side of the graph. In the given sample output, it is observed the aspect of service and fish coming up majorly in the entire corpus, but for the topic 2, it has seen that fish dominates followed by hula pie.

4.3 Overall Observed Results

Figure 6 shows the most discussed topics on both platforms for each restaurant under study.

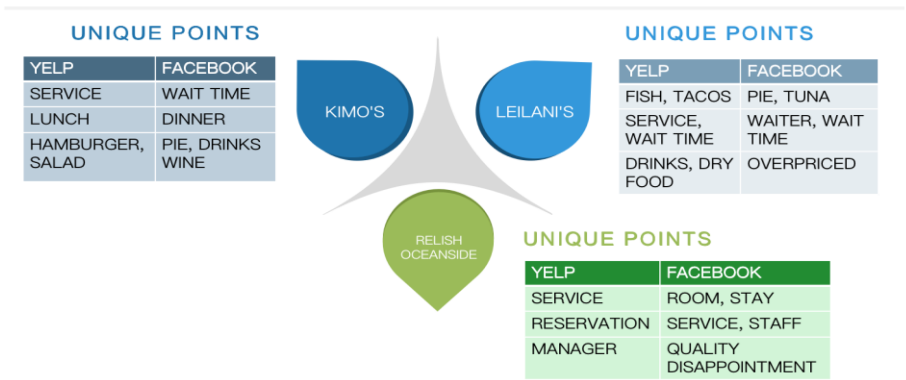

Figure 6: Unique aspects on each platform (Yelp and Facebook)

Based on the observed topics, Relish Oceanside needs to be more interactive with social media. Very a smaller number of reviews talk about the restaurant on Facebook, moreover, Yelp customers have expressed their views about the restaurant, but the number of reviews is less when it is compared with the TS restaurants. Both the TS restaurants face food quality and service issues that need to be worked upon.

5. CONCLUSION

Based on the research and analysis, many interesting insights were discovered. People on Facebook are more descriptive about their reviews that is, they put emotional aspect in their reviews, whereas people on Yelp talk about their experience in a way that just conveys the meaning by directly focusing on the good and bad aspects of the experience. The only descriptive reviews on Yelp belong to people who either are very happy with the experience or are extremely disappointed with it, which usually means the users that rate the restaurant with 5 star or 0-1 star. As a business owner, this research suggests that in order to build strategies for reputation management, negative review on Yelp should be the focus, because ratings and reviews on Yelp are more relevant to the user experience than on Facebook. A small change (such as half star rating) on Yelp affects the product sales directly, whereas on the other hand, more focus should be on getting and analyzing positive responses on Facebook. Facebook positive reviews are the backbone of business recommendations and as seen earlier, Facebook recommendations are more impactful than recommendations on Yelp.

6. FUTURE WORK

In this research, it has been concentrated on discovering topics and extracting most discussed aspects of the restaurant from customer reviews, however, it would be interesting to generate categories to compare the performance of the three restaurants. For example, several categories such as service, food, environment and ambiance, which can guide for a deeper understanding and a detailed analysis of the restaurant performance. The categories can be formulated by clustering the reviews into similar topic clusters and generating one category for each cluster, which then leads to comparing cluster wise restaurant performance.

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