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SENTIMENT ANALYSIS OF CUSTOMER REVIEW IN ONLINE FOOD DELIVERY INDUSTRY

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ABSTRACT: During the COVID-19 crisis, the fact that customers prefer to have foods delivery to their door instead of going in a restaurant has fueled the growing of Online Food Delivery (OFD). Nearly all restaurants like UberEats and DoorDash coming online and bringing OFD on board, online platform user reviews of a company's performance have grown in importance as a source of data. OFD organizations give great importance on collecting complaints from customer feedback and using data effectively to identify fields of development to increase customer satisfaction. Online reviews remain important during the COVID-19 pandemic as they help customers make safe food decisions. It is one of the basic needs of company managers to get customer opinions about the products and services provided by companies and to develop products and services. This work uses a Natural Language Processing (NLP) based approach. Sentiment Analysis is an area of study that uses user-shared emotions on websites and social networking sites to discover meaningful information. It is helpful to categorize emotions as positive, negative, or neutral using this type of analysis. We have performed experimentations using three modes i.e. Unigram, Bigram, and Trigram. The findings indicate that the main issues with the OFD company are primarily related to food delivery issues, and both organizations generally experience the same issues. The proposed method can be used as a guide for catering companies to evaluate customer satisfaction and complaints and develop marketing strategies to o acquire new customers and increase their market share.

Keywords: Sentiment analysis, NLP, Food Delivery Industry, Customer Complaint Categorization, Data Extraction, Data Management.

1. INTRODUCTION

Online food delivery (OFD) businesses have grown significantly during Covid-19, but each faced unique challenges and customer expectations. Restaurants remaining in the business world after the impact of Covid-19 saw the necessity of keeping up with the latest changes in the sector and providing OFD service in order to survive [1].
Although OFDs are successful segments, they have several barriers such as staff behavior and food quality [2] that affect customer usage intentions. Uber Eats has a significant increase in OFD orders following the no dine-in service [3]. In United States (US) restaurants, customer demand has drastically declined as restaurant demand begins to enter plumbing globally, with increasing cases of Covid-19 [4]. However increasingly more individuals were beginning to order food online from food delivery companies like DoorDash, Uber Eats and Grubhub in the US [5].

In 2020, DoorDash had revenue of $2.86 billion and $4.8 billion in 2021. The food delivery firm headquartered in the United States, the company operates in more than 7,000 cities. Additionally, Canada, Australia, Japan, and Germany offer DoorDash services [6].
Uber Eats, a startup that delivers meals, made $8.3 billion in sales in 2021. This figure represents a huge increase from the amount of 4.8 billion the year before [7].

OFD organizations have begun to collect complaints from consumer feedback and efficiently use data to identify fields of development to increase customer satisfaction. It can be noted that the best technique for assessing the sentiment of customer text is sentiment analysis. It is is a contextual text mining technique that pulls data from online sources to ascertain people's attitudes and opinions toward a business, brand, person, or event [8]. Sentiment research can give businesses a competitive advantage over their rivals by enabling them to evaluate the effectiveness of their marketing initiatives, the quality of their goods and services, and the ability to address issues before they become liabilities.

Table 1. The main third-party FDA's background information [9]

	DoorDash	Uber Eats
Set up year	2013	2014
Business Type	Private	Subsidiary (Parent company, Uber)
Area served	United States, Canada and Australia	32 countries including United States
Involved restaurants	340,00	600,000
Number of users	18 million	66 million
Revenue	$2.9 billion	$4.8 billion

The idea behind our study is to perform a sentiment analysis system that not only has the ability to predict emotions but can also categorize every complaint or recommendation. For this purpose, we used a Natural Language Processing (NLP) based approach Sentiment Analysis to categorize emotions as positive, negative, or neutral in OFD industry. We applied Unigram, Bigram, and Trigram.

Further, the sections of this study are arranged in the following order: Section 2 summarizes the related work. Section 3 explains the steps of data collection followed by data preprocessing, sentiment analysis and research methodology. Section 4 reviews the results and analysis and Section 5 concludes the research.

2. LITERATURE REVIEW

We summarized related work in the literature. Meena and Kumar [10] used social media data to examine the performance of OFD companies and customer expectations in the COVID-19 pandemic period. The results showed that consumer in India were more satisfied with OFD companies int the COVID-19 pandemic period compared to consumers in the US. Trivedi and Singh [11] presented that Zomato received a 26% positive opinion, more favorable than the other two companies, Swiggy (25%) and UberEats (24%). Negative reviews for Zomato were low compared to Swiggy and UberEats. Consumer Reports evaluated DoorDash, Grubhub, Postmates, and Uber Eats as the top four third-party FDA players, according to Roberts [12]. The findings showed that several customers were worried about the following app-related issues: service and delivery costs imposed; and suggestions for ordering.

In order to predict client sentiment in the area of FDS, Adak et al. [13] looked at deep learning, machine learning, and explainable artificial intelligence methodologies. According to a survey of the literature, dictionary-based and ML approaches are frequently used to forecast emotions from customer feedback in FDS. However, there aren't many research using DL approaches because the judgments made aren't easily interpreted by the model or explicable. The argument for explainability and system trust can be made by organizations, however 77% of models are intrinsically unintelligible. McCainy et al. [14] analyzed guest comments about the Uber Eats food delivery application (FDA) in the USA period of the COVID-19 pandemic quarantine period with the text mining technique. Performance in practice, product quality, and service quality, which affect customer satisfaction, were evaluated with the FDA. The most important dimension regarding their perception of FDA was service quality (40.02%), and then FDA's performance dimension (39.43%) and product quality dimension (20.54%). There were many negative reviews: FDAs (P/N=0.728), product quality (P/N=5 0.60) and service quality (P/N=5 0.865). Valera and Patel's study [15] took consumers' comments on the top-rated products on the Amazon website to measure the positive and negative feelings of users with the highest-rated products. Their study showed a comparative analysis of the top-rated products on the Amazon website with competing products. The study [16] presented seven concerns with online retail services in online shipping using text mining techniques: product, store advertising, delivery, payment, communication, return/refund, and price. The emotional extremes of internet shoppers' posts are the subject of the problems. The findings indicate that these two groups' sensitivity to goods and payment varies. Negative emotions (such as wrath, sadness, and fear) differ between the two groups in terms of delivery, communication, and return/return. [17] discovered a strong relationship between customer ratings and the sentiment polarity (i.e., positive, negative, or neutral emotion) of customer reviews. [18] discovered a favorable correlation between customer opinions expressed on Twitter and the company's brand image. A food delivery service’s strong brand reputation influences customers’ behavioral intention to use OFD services favorably [19].

None of the above studies use data from pissedconsumers.com where customers forward their complaints, experiences and recommendations to OFD companies. Companies can better grasp client expectations with this data. This study differs from other studies in that it categorizes negative emotions in terms of complaints. This article reviews of OFD companies by collecting consumer data about two US OFD companies and using sentiment analysis.

3. METHODS

3.1. Sentiment Analysis

Sentiment analysis, known as sentiment analysis, is basically a text processing method. It is used to analyze the meaning of a word, sentence or text [20]. Basically, three different results can be obtained as positive, negative and neutral [21]. Generally, positive and negative classes are used in sentiment analysis, but in some studies, thinking that thinking can be neutral, studies were carried out on three classes.

The examination of information that has been extracted to characterize responses, attitudes, context, and emotions is known as sentiment analysis. For instance, the phrases "happy, sweet, surprise" and "boiling, worried, clumsy" have positive and negative connotations, respectively. Using the dictionaries from the Nebraska Literary Lab and NRC, sentiment analysis was carried out. Eight fundamental emotions (angry, fear, anticipation, confidence, surprise, sadness, joy, and disgust) and two additional emotions are included in the list of English terms and connotations provided by the NRC Emotion Lexicon technique (negative and positive).

Mohammad and Turney [22], 2013 from the National Resource Council, created this strategy. The method was based on associating with words, not simply adding the sentiment values for each word. The associations of words result in different emotion categories such as anger, fear, disgust (negative emotion), and the word achieved is associated with joy (positive emotion). While performing the sentiment analysis, a training data set is first created. In the training data set, the data whose class is determined positive, negative or neutral are used. Then, these data are pre-processed with various data mining methods and cleaned and made suitable for classification. Some of these pre-processes are cleaning the symbols and punctuation marks in the text, separating the text into individual words and creating term lists by finding the roots of each word with various methods, removing stop words formed by prepositions, conjunctions and pronouns in the text, term frequencies (TF) and inverse document frequencies (TDF) to create the vector model. Among the methods used in vector space models, n-gram, binary, inverse document frequency, term frequency methods can be counted [20].

3.2. Data Collection

The data in this study is extracted from reviews of users of the Pissed Consumers website for food industry companies Doordash, Ubereats. This data includes text from reviews of food and beverage customers. Data was extracted from the first 1000 pages for each company and approximately 15,000 reviews (15001 Ubereats, 14985 DoorDash) for each company. Two online app-based food delivery companies such as UberEats and DoorDash were included in this study. Figure 1 presents the sample data from row dataset.

	date	url	complaint
0	Sep 05, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n Unbelievable!!! After many, many bad experiences with Doordash, I finally gave up on them. I went onto my account to delete it and found out that there is no way to do so. I believe that this practice of not allowing a customer to delete their account borders on fraud.... \n
1	Sep 07, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n Not received my refund yet and um tired of waiting on my money when I first started ordering from door dash it was my favorite app now I don't know what to say about you all I am really upset. User's recommendation: Not to order to much confusion.\n
2	Jul 19, 2017	https://doordash.pissedconsumer.com/1/RT-P.html	\n Will have to wait and hope refund is forthcoming sooner than later. Driver failed to deliver food order from Panera. Delivery location was an easy to find hi-rise building right on the corner. Not sure what caused the lapse in understanding on the part of the driver. User's recommendation: Poorly understood directions by Doordash.\n
3	Jun 18, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n Chargers I didnt make for the past few months Ive noticed $9.99 being charged to my account and I havent used DoorDash for anything lately need my money refund back to my account as soon as possible if not Ill be contacting my attorney dont know whos making these purchases but its definitely not me please contact me and let me know what you find out
4	Sep 07, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n They did not compensate me. Bad reputation with dashers. The dasher stole my food worth $51. I will never use this app again and I do not recommend anyone use these services. They did not even give me door dash credit. I called corporate. I filed a police report. I reported the dasher. They told me to check my texts for picture where he supposed left my food no texts no photos all lies. User's recommendation: Do not use DoorDash.\n

Figure 1. Sample data from row dataset.

We extracted 3 columns from the "pissedconsumers.com" that is presented in Figure 1. First column represents the date when the complaint is entered to the website. The second field URL represents consist of website link of the where the comment is placed. The third column complaint has the raw text of the complaint.

Figure 2 presents data after cleaning and Figure 3 indicates some examples of reviews that are labeled as positive, negative and neutral.

	date	url	complaint	complaint_cleaned
0	Sep 05, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n Unbelievable!!! After many, many bad experiences with Doordash, I finally gave up on them. I went onto my account to delete it and found out that there is no way to do so. I believe that this practice of not allowing a customer to delete their account borders on fraud.... \n	unbelievable many many bad experiences doordash finally gave went onto account delete and found way believe practice not allowing customer delete account borders fraud
1	Sep 07, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n Not received my refund yet and um tired of waiting on my money when I first started ordering from door dash it was my favorite app now I don't know what to say about you all I am really upset. User's recommendation: Not to order to much confusion.\n	not received refund yet and um tired waiting money first started ordering door dash favorite app not know say really upset user recommendation not order much confusion
2	Jul 19, 2017	https://doordash.pissedconsumer.com/1/RT-P.html	\n Will have to wait and hope refund is forthcoming sooner than later. Driver failed to deliver food order from Panera. Delivery location was an easy to find hi-rise building right on the corner. Not sure what caused the lapse in understanding on the part of the driver. User's recommendation: Poorly understood directions by Doordash.\n	wait and hope refund forthcoming sooner later driver failed deliver food order panera delivery location easy find hi rise building right corner not sure caused lapse understanding part driver user recommendation poorly understood directions doordash
3	Jun 18, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n Chargers I didnt make for the past few months Ive noticed $9.99 being charged to my account and I havent used DoorDash for anything lately need my money refund back to my account as soon as possible if not Ill be contacting my attorney dont know whos making these purchases but its definitely not me please contact me and let me know what you find out	chargers didnt make past months ive noticed charged account and havent used doordash anything lately need money refund back account soon possible not ill contacting attorney dont know whos making purchases definitely not please contact and let know find
4	Sep 07, 2022	https://doordash.pissedconsumer.com/1/RT-P.html	\n They did not compensate me. Bad reputation with dashers. The dasher stole my food worth $51. I will never use this app again and I do not recommend anyone use these services. They did not even give me door dash credit. I called corporate. I filed a police report. I reported the dasher. They told me to check my texts for picture where he supposed left my food no texts no photos all lies. User's recommendation: Do not use DoorDash.\n	not compensate bad reputation dashers dasher stole food worth never use app and not recommend anyone use services not even give door dash credit called corporate filed police report reported dasher told check texts picture supposed left food texts photos lies user recommendation not use doordash

Figure 2. Sample data after data cleaning.

	index	complaint	complaint_cleaned	sentiment
0	250	\n When the gentleman pulled up he was very nice. I was not upset at all, I called because I was unsure how to add a tip. That has been taken care off. All is well	gentleman pulled nice not upset called unsure add tip taken care well	Positive

	complaint	complaint_cleaned	sentiment
0	\n Unbelievable!!! After many, many bad experiences with Doordash, I finally gave up on them. I went onto my account to delete it and found out that there is no way to do so. I believe that this practice of not allowing a customer to delete their account borders on fraud.... \n	unbelievable many many bad experiences doordash finally gave went onto account delete and found way believe practice not allowing customer delete account borders fraud	Negative
1	\n Not received my refund yet and um tired of waiting on my money when I first started ordering from door dash it was my favorite app now I don't know what to say about you all I am really upset. User's recommendation: Not to order to much confusion.\n	not received refund yet and um tired waiting money first started ordering door dash favorite app not know say really upset user recommendation not order much confusion	Negative
2	\n Will have to wait and hope refund is forthcoming sooner than later. Driver failed to deliver food order from Panera. Delivery location was an easy to find hi-rise building right on the corner. Not sure what caused the lapse in understanding on the part of the driver. User's recommendation: Poorly understood directions by Doordash.\n	wait and hope refund forthcoming sooner later driver failed deliver food order panera delivery location easy find hi rise building right corner not sure caused lapse understanding part driver user recommendation poorly understood directions doordash	Negative
3	\n Chargers I didnt make for the past few months Ive noticed $9.99 being charged to my account and I havent used DoorDash for anything lately need my money refund back to my account as soon as possible if not Ill be contacting my attorney dont know whos making these purchases but its definitely not me please contact me and let me know what you find out	chargers didnt make past months ive noticed charged account and havent used doordash anything lately need money refund back account soon possible not ill contacting attorney dont know whos making purchases definitely not please contact and let know find	Negative
4	\n They did not compensate me. Bad reputation with dashers. The dasher stole my food worth $51. I will never use this app again and I do not recommend anyone use these services. They did not even give me door dash credit. I called corporate. I filed a police report. I reported the dasher. They told me to check my texts for picture where he supposed left my food no texts no photos all lies. User's recommendation: Do not use DoorDash.\n	not compensate bad reputation dashers dasher stole food worth never use app and not recommend anyone use services not even give door dash credit called corporate filed police report reported dasher told check texts picture supposed left food texts photos lies user recommendation not use doordash	Negative

	index	complaint	complaint_cleaned	sentiment
0	45	\n I need my identity fixed so I can work for yall. Im not sure what happen. I do have drivers license and a car.	need identity fixed work yall im not sure happen drivers license and car	Neutral

Figure 3. Examples of reviews that are labeled as positive, negative and neutral.

Figure 3 illustrates clearly the transformations of the texts clearly after following our data cleaning methods from the section 3.3. As for labeling texts as Positive, Negative and Neutral, we use the TweetEVAL [23] algorithm for sentiment predictions. Firstly, positive prediction indicates that the complaint has a positive sentiment, the complaint is related a person who wishes to know how to make a tip to a well-mannered Doordash employee which referred as a gentleman. Secondly, in this complaint we can see that consumers need to know how to apply for a driver job in Doordash. This complaint does not have any positive or negative adjectives in order to affect the results on sentiment. Therefore, predicted as Neutral. Lastly, negative sentiment predictions show the complaint has many negative adjectives in their complaints, and therefore predicted as Negative. Even though, some customers used "pissed consumers" platform as a blog that they can share their experiences, raise questions and complaining about their bad experience. Each entry is accepted as a complaint and treated as such.

3.3. Data Cleaning

After obtaining textual data process, it should be cleaned. Data cleansing is the process of standardizing and removing irrelevant characters and text. To prepare the dataset containing text for modeling NLP (Natural Language Processing) Algorithms applications, data cleansing is a crucial part for the process. Clean data returns much better and accurate predictions compare to the dirty data, eventually garbage in garbage out. In this study, we performed the following operations for cleaning processes respectively.

First, the words are normalized. Joining text data is one of the most straightforward and efficient text preprocessing techniques. The majority of text extraction and natural language processing issues are solved using this phase, which greatly improves the projected output quality. Secondly, sparse words, URL’S, emojis and writing their emoji name (slightly smiling face etc.) and punctuations. We cleared a group of symbols such as [! ”# $%&’ () * +, -./: ≤>? @ [\] ^ _ ’{|} ~]. In some cases, sparse terms in textual data, such the username, must be removed. Thirdly, expanding contraction (decontraction) is made. For example, Won't is simply a contraction of the words will not. Don’t refers to do not. Fourth, alphanumeric data is separated. For instance, 123456asd converts into 123456 asd. Fifth, stop words are removed. Ineffective terms include "the," "on," "is," "all," and "a" are stop words in English. These words are extracted from textual data because they don't convey much semantic meaning and don't have a specific semantic load. Last process includes lowercasing all the texts. Consequently, data cleaning can impact the prediction and Bleu scores (Bilingual Evaluation Understudy) [24].

After data cleaning process we used [23] method. A standardized benchmark called TweetEval was developed for the comparative assessment of diverse datasets made available for Twitter.

3.4. System Overview

The methodology of research is presented in Figure 4. Some pre-processing was done before counting bigrams and trigrams in order to reveal the complaint evaluation of OFD companies. Stop words and some punctuation removed. Later, all letters were converted to lowercase. The usage numbers of bigrams and trigrams repeated two or more times were calculated.
After cleaning the data, we used TweetEVAL [23] algorithm for the prediction (classification) of the sentiments for the food Industry companies (Doordash, Ubereats). We extracted approximately 15.000 Review (15001 Ubereats, 14985 doordash, first 1000 page of the reviews) for each Company. The review of the sentiment is labeled as negative, neutral, and positive [21].
We have implemented all the classifiers in three modes i.e. Unigram, Bigram, and Trigram.
by applying word embeddings, including Unigram, Bigram, and Trigram as N-gram.

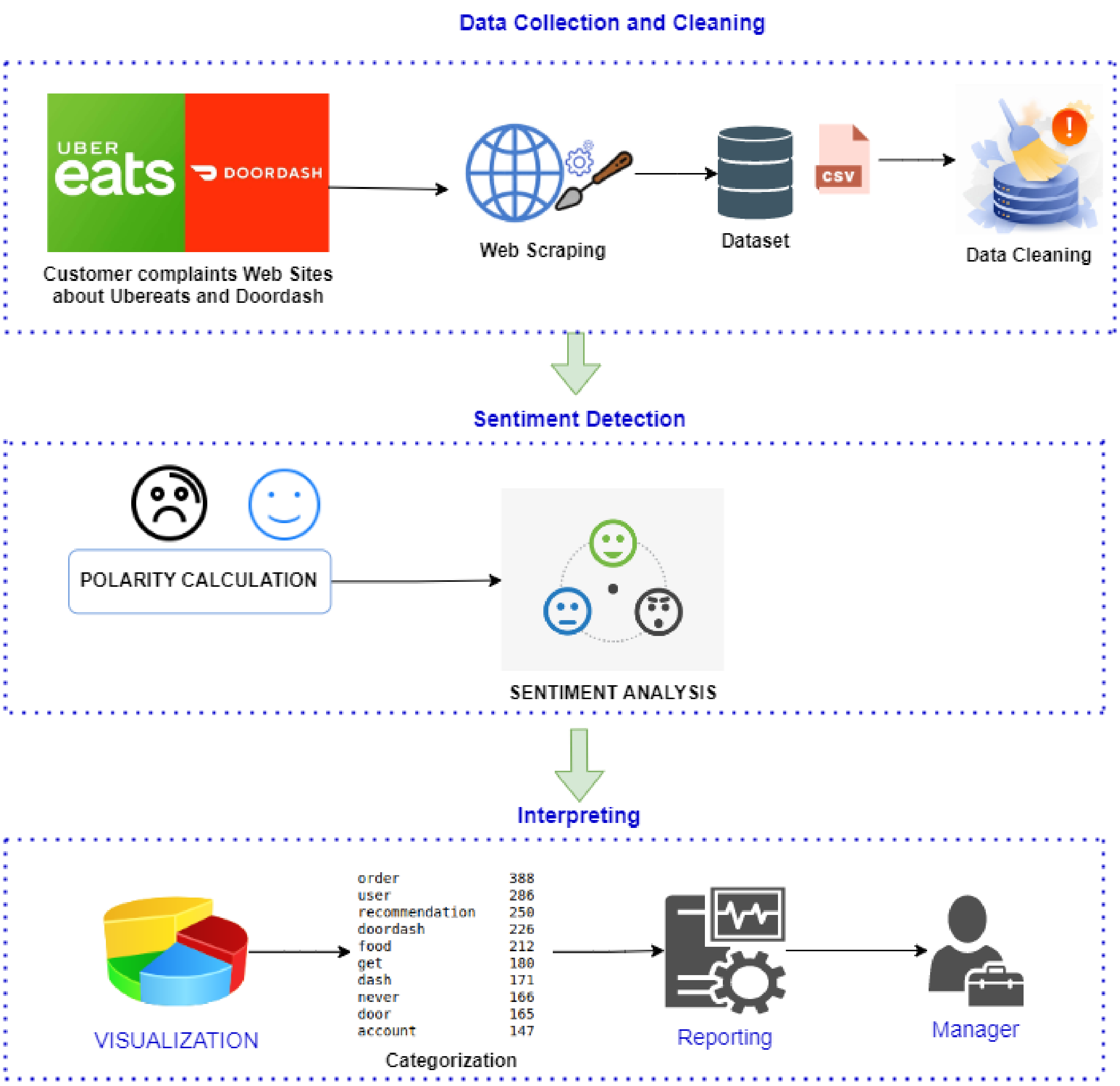
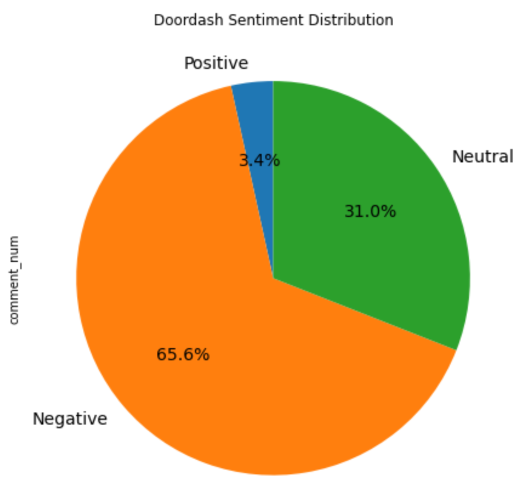


Figure 4. Methodology of Research.

4. EXPERIMENTS AND EVALUATION

4.1. DoorDash



	labels	comment_num
0	Positive	517
1	Negative	9829
2	Neutral	4640

Figure 1. Sentiment Analysis of DoorDash.

The findings from Figure 5 indicate DoorDash's Sentiment Analysis as 517 positive, 9829 negative and 4640 neutral. As expected, the results were extracted from the Pissed Consumers website were mainly negative comments. 65.6% of reviews for Doordash are negative, followed by 31% Neutral and 3.4% Positive.

Then, we used Ngrams for the text classification in order to find the most problematic categories for the both companies. We used unigrams, bigrams, and trigrams for the analysis however bigrams are the ones that help us classify texts. Ngram size 1 referred to as unigram, Ngram size 2 is referred to as bigram as Latin numerical prefixes.

Table 2. The most used bigram for DoorDash

No	Bigram	Number
1	User recommendation	249
2	Door dash	139
3	Customer service	64
4	Recommendation use	44
5	Money back	36
6	Never received	28
7	Would like	27
8	Never got	26
9	Use doordash	25
10	Phone number	22

It is evident from Table 2 that the most used bigram for Doordash is the word “user recommendation”. Other bigrams most frequently used in customer complaints are "door dash", "customer service", "recommendation use" and "money back", respectively.
Table 3 illustrates the most used trigrams for DoorDash.

Table 3. The most used trigrams for DoorDash

No	Trigram	Number
1	User recommendation use	44
2	Use doordash	14
3	Review posted user	14
4	Original review posted	14
5	Recommendation use doordahs	13
6	Ever ever ever	13
7	Trash trash trash	13
8	User recommendation order	12
9	Never got order	11
10	User recommendation go	10

Table 4. The most used unigram for Doordash

No	Unigram	Number
1	Order	388
2	User	286
3	recommendation	250
4	doordash	226
5	Food	212
6	Get	180
7	Dash	171
8	Never	166
9	Door	165
10	account	147

Table 3 illustrates the most used unigram for Doordash. When we examine the unigrams of the Doordash, Table 4 depicted that order, user, recommendation, doordash, food has more occurrences than other words. As expected, the most used word is order from the Doordash.

4.2. Ubereats

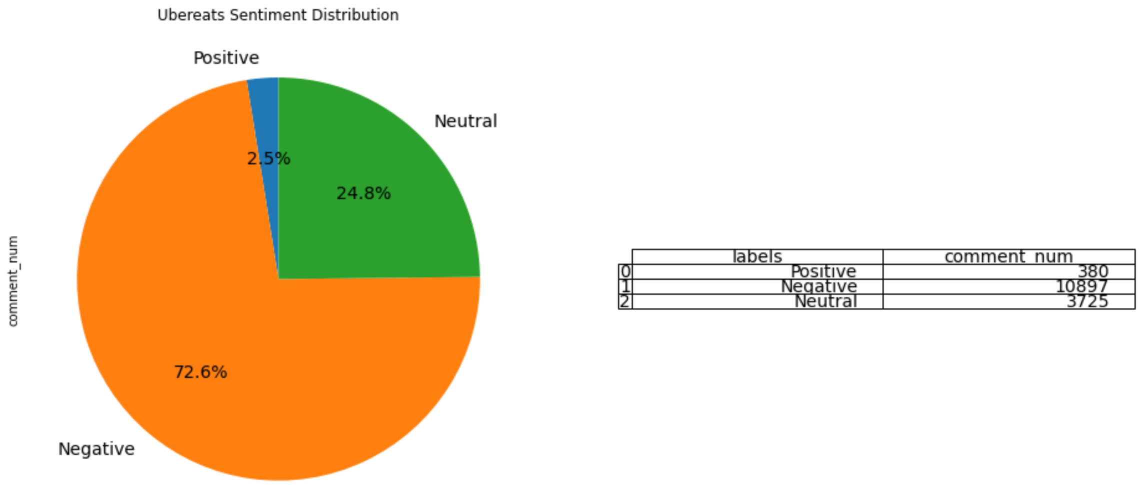


Figure 2. Sentiment Analysis of Ubereats.

Figure 6 presents that there are 380 positive, 10897 negative and 3725 neutral comments. In the case of Ubereats, 72.6% of reviews were negative, followed by 24.8% Neutral and 2.5% Positive Reviews.

Table 5. The most used bigram for Ubereats

No	Bigram	Number
1	user recommendation	279
2	uber eats	180
3	customer service	104
4	recommendation use	51
5	money back	36
6	never received	34
7	user aug	26
8	use uber	25
9	recommendation order	22
10	make sure	22

Table 5 depicts the most used bigram for Ubereats. For Ubereats, the word "user recommendation" is the bigram most commonly used in customer complaints. Other bigrams most frequently used in customer complaints are "uber eats", "customer service", "recommendation use" and "money back", respectively.
Table 6 provides the most used trigrams for Ubereats.

Table 6. The most used trigrams for Ubereats

No	Trigram	Number
1	User recommendation use	51
2	Use recommendation order	22
3	Use uber eats	15
4	Original review posted	14
5	Order uber eats	15
6	User recommendation make	13
7	Want money back	12
8	Recommendation make sure	12
9	Called customer service	12
10	Review updated user	11
11	Update user aug	11

Table 7. The most used unigram for Ubereats

No	Unigram	Number
1	Order	487
2	User	313
3	Uber	283
4	Recommendation	279
5	Food	264
6	Eats	183
7	Service	168
8	Refund	167
9	Never	162
10	Get	162

Table 7 shows the most used unigram for Ubereats. Bigrams for Doordash the scope is slightly changed customers using recommendation, door dash, customer service, recommendation use, money back more than other word combinations.

4.3. Evaluation of Findings

At first glance, Doordash had slightly more positive frame for their reviews compare to the Ubereats. Doordash has 137 (+0.9%) more positive, 915 more neutral (+6.2%), 1068(-7%) less negative reviews.

Biggest challenge for Food Industries is food delivery, O2O market is rapidly growing in major countries [25]. In this Bigram Analysis we can clarify that customers need to get their refund for the non & late deliveries. User recommendation is Pissed Consumer's review block that allows user to give other customers an advice depends on their experience "Someone answered phone and just sat there saying nothing for 10 minutes. I cant get anyone on the phone to fix my issue. I want to delete payment methods on my account and cant nor can I get anyone to help me fix this issue. Going to delete my account if I cant get any help. Tired of the bs. User's recommendation: Check other options. Poor customer support." can be seen from the example. When Ubereats' unigrams were evaluated, the first two word is matching with each other, recommendation dropped the fourth place under Uber. Service, refund and get words used more in the Ubereats. Same pattern continued with the Ubereats as well, user recommendation, company name, customer service, recommendation use, money back, never received were the top used words together respectively. Even though doordash had slightly better sentiment distribution than Ubereats, when ngrams was examined, same pattern applied for the both companies. As explained previously, the major problem with the O2O (Online to Offline) business mainly deal with food delivery problems, pattern and the problems were relatively same for the both companies.

5. CONCLUSION

Online reviews, as a form of user-generated information, contain lots of useful and valuable feedback from customers who have used the products or experienced the service. In recent years, customer preference mining from online reviews that can help improve a company's performance has received increasing attention in the literature.

This study compares the consumer services and operations of OFD companies. We extracted consumer data for two OFD companies from DoorDash and Uber Eats. The consumer-level data were extracted from pissed consumer website. This study applied a Natural Language Processing (NLP) based approach Sentiment Analysis (SA).

This survey provides insight into customers' experiences with OFD businesses by using sentiment analysis. The findings from study indicated that problems faced for two companies are relatively same. The findings of the study provide many managerial insights.

It is planned to expand the analysis of this study for future studies. Besides the US companies, it will be exciting to examine people's emotions and define dimensions related to the performance of OFD companies in European markets. Also, another interesting study would be for OFD companies' delivery performance values, including financial variables such as profit and revenue.

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