Detect Review Manipulation by Leveraging Reviewer Historical Stylometrics in Amazon, Yelp, Facebook and Google Reviews

Nafiz Sadman
Silicon Orchard Ltd Dhaka, Bangladesh
nafiz@siliconorchard.com

Kishor Datta Gupta
University of Memphis Dhaka, Bangladesh
kgupta1@memphis.edu

Ariful Haque
Silicon Orchard Ltd Dhaka, Bangladesh
ariful@siliconorchard.com

Subash Poudyal
University of Memphis Dhaka, Bangladesh
spoudyal@memphis.edu

Sajib Sen
University of Memphis Dhaka, Bangladesh
ssen4@memphis.edu

ABSTRACT

Consumers now check reviews and recommendations before consuming any services or products. But traders try to shape reviews and ratings of their merchandise to gain more consumers. Seldom they attempt to manage their competitor's review and recommendation. These manipulations are hard to detect by standard lookup from an everyday consumer, but by thoroughly examining, customers can identify these manipulations. In this paper, we try to mimic how a specialist will look to detect review manipulation and came up with algorithms that are compatible with significant and well known online services. We provide a historical stylometry based methodology to detect review manipulations and supported that with results from Amazon, Yelp, Google, and Facebook.

CCS Concepts

•Computing methodologies →Artificial intelligence →Natural language processing →Lexical semantics

Keywords

Review manipulation, Stylometry, Natural language processing, Sentient analysis, Jaccard similarity, Fake review detection, HCI

1. INTRODUCTION

Review manipulation by traders for their own or competitor product is a well-known practice among them. It is a big headache for genuine business companies. Manipulated reviews include fake re- views, paid reviews, bot reviews, boosted reviews etc. Most com- panies depend on reviews for their reputation and boosting sales. Not only does these harm the competitive market, but also deceive a large portion of the crowd. Yelp is one of the biggest review-bank in the United States. So it is a high target for fake or paid reviewers and bots. Moreover, around 200 million people around the world visits Amazon per month [8]. The number keeps increasing expo- nentially for Google and Facebook users. Detection of such ma- licious act has become important now more than ever since sub- stantial amount of people are using the Internet. In this paper, we tried to identify these practices by using some stylometric analy- sis techniques. We developed a web service with a real-time user- friendly web-application to detect and analyze a reviewer, which will help its user to check any product reviews and rating are ma- nipulated or not. Our web services can effectively detect any paid or bot reviews(AI simulated reviews). Identifying these reviews as a fake, we later checked manually to measure the effectiveness of our methodology. We showed our method has better accuracy with significant advantages from other methods use for counterfeit review detection.

In this paper, section two describes the background needed to understand the methodology following a section of related works. In chapter 5, we express our methods with the pseudo-code. In chapter 5, we showed our experimental design based on our solution, and in the following sections, we have a detailed discussion about our results and analysis. We also talked about related works in this section. We concluded the paper with the limitations and our plans.

2. LITERATURE REVIEW

In this section, we will describe what review manipulation is, differences between real, paid, and Artificial reviews know as bot review. We will also discuss how different well know web services operated. In the third part of this section, we will describe some NLP methods, which are essentials to understand our methodology.

2.1 Review Manipulation

The concept of using sentiment analysis to determine motives has been in history since the 90s. Another closely related term used with sentiment analysis is known as opinion mining. Sentiments are generally categorized into positive, negative or neutral scores, upon which a task specific analysis is performed. Pang et. al in journal [11] has stated the importance and impact of sentiment analysis with increasing rate of data. The article covers critical issues of privacy, vulnerability to manipulation, and whether or not reviews can have measurable economic impact. Social media monitoring, brand monitoring, customer service, product analytic, market research are some popular application areas of sentiment

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.
ICEBA 2020, February 25–27, 2020, Kuala Lumpur, Malaysia
© 2020 Association for Computing Machinery.
ACM ISBN 978-1-4503-7735-5/20/02…$15.00
https://doi.org/10.1145/3387263.3387272

analysis. Among these a lot of researches in social monitoring and product analytic are getting the hype to combat fake reviews and scams.People review restaurants, contractors, sites, food, almost everything. Reviews make great impact in decision making process. Some people take advantage of it by posting fake, fabricated reviews to up vote or down vote a particular target. The term used to identify such actions is also well coined as fraud detection.

2.2 Online Recommendation Services

One of the major massive 'review-bank' site known as Yelp consists reviews from people residing mostly all over United States and are categorised under few categories such as home services, restau- rants, contractors, etc. The Yelp fact sheet [1] states that many businesses depend on yelp reviews for their popularity and driving more sales.As of 2018, around 172 million reviews are posted in al- most every type of business. Around 45% of consumers are likely to check Yelp reviews before availing a service or product. Even though Yelp holds strict restrictions on fake or boosted reviews, detection of such reviews has become challenging as technologies update every now and then. Amazon.com, Inc. is a B2B and B2C e-commerce platform with over 200 million users per month. With time the company has expanded immensely, delivering products all over the world. Even the products are original most of the times, boosting of products by owners is an existing problem in context of authenticity of the products. Sometimes defected or fake prod- ucts get boosted by reviews and people often rely on these reviews when purchasing a product. Google is by default the most used web search engine in the world till date. From searching word meanings to looking up products, the boundaries are limitless. Google too has review pages of place, products, restaurants, celebrities etc. Google also pulls up relevant suggestions. People post their opinion or reviews in these pages. With vast number of people using Google everyday, it is important to detect manipulated reviews in Google. Facebook is the social-media giant and the most relied form of com- munication for people. There are no limitations on opening an ac- count or a page other than having an email ID and required age.

Therefore it is the easiest target of Internet misuse. This misuse is detected after getting reported by people. But most of the times, the deception is convincing, therefore goes undetected. There are nu- merous manipulated reviews/opinions in Facebook pages regard- ing some products or promotions [2].

2.3 Naltural Language Processing Techniques

Natural Language Processing (NLP) is a specialized field of Artifi- cial Intelligence. NLP is concerned with understanding the human language. Speech and texts processing are sub-domain of NLP. In this paper, we work with textual data, extracting and analyzing them with two well known techniques: Vader Sentiment Analysis and Jaccard Similarity Coeffi cient measurement. One interesting application of NLP is the stylometric analysis. Stylometry refers to the style and pattern of a language. A particular author or writer tends to follow a certain pattern of writing. Stylometry is the clas- sification of the writers according to their style of writing.

3. RELATED WORKS

Opinion mining and opinion spam detection are important field of research with many numerous contributions. But most of them rely on a labeled data set and focuses on restricted domain. In [5], Jindal et. al introduced significant existence of opinion spam in on- line sites like Amazon and demonstrates detailed techniques for detection. They use pre-labeled data for one of their three categories for spam detection and use supervised learning techniques. But their study was limited to amazon reviews (2006). In [6] Li et. al studied Diangping.com and talked about their algorithm is limited to abnormality in reviews and reviewers with no text processing for classification. The site claims to accurately detect fake reviews, but not sure if other reviews are completely genuine. [6] used text processing and detection with PU learning with a labeled data set focused on restaurant. However, an assumption was made that the fake review in their test data set represents all the fake reviews in the site. In [9] Mukherjee et. al performed supervised learning on Yelp's filtered data set. They observe that Yelp's fake review detection algorithm perform reasonably well in detecting abnormality in spams and classifying them as spams. They have studied word frequency distribution among reviews and concluded that fake reviewers tend to use some or few common words in their reviews.Peng et. al in [12] used sentiment analysis to detect spam reviews by shallow dependency parser, and observed abnor- mality in reviews. They used a pre-trained data set from "reseller- ratings.com" and showed that spam detection based on ratings are not reliable and that sentiment analysis can provide more believ- able results. In [7] Lin et. al have introduced the concept of using 'personal content similarity' in reviews, and used jaccard similarity along with other similarity measurement techniques.

To the best of our knowledge, there are no research work done combining jaccard similarity with sentiment analysis and using time-frame data for the detection of fake reviews on online sites.

4. OUR SOLUTION

In this section, we will describe our brief hypothesis and our method- ology, which we used to verify our hypothesis.

4.1 Hypothesis

If any product/item/services reviews are manipulated there will be some signs of these reviews such as

- If a significant percentage of review posted time is in a concise period, and all of these reviews contain overly positive or overly negative, then there was a review manipulation for that product/services.
- If reviewers all reviews have overly positive sentiment or negative sentiment, he is a paid reviewer. If, for a product/services, most of the reviewers identified as paid, there was a review manipulation for that product/services.
- If reviewers all reviews have overly use of similar words and expressions and also always excessively positive or excessively negative, It is a Bot reviewer. If for a product/services, most of the reviewers identified as Bot, there was a review manipulation.

4.2 Methodology

In this paper we propose a real-time user-friendly web-application devised with a statistical machine learning approach to classify au- thenticity of reviewer registered in the recommendation sites. We use vader sentiment analysis since it can capture and consider var- ious expressions such as emojis and symbols. Vader is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. We use jaccard similar- ity to understand word to word similarity of each of the reviews. Based on a standard average score, we introduced a probability of a reviewer being authentic, and being fake or manipulator. We have used Django framework for the web-application, and we have de- ployed it using the AWS EC2 server to maintain highest priority for user safety.

As example, for amazon products or yelp restaurants have similar algorithm like algorithm 1

Algorithm 1 Amazon product review manipulation check

Amazonp roducti d = Ap
reviewers reviewed AP = RAP
number of reviewer N = RAP
count = 0

each Reviewer Ri ∈ RAP check
all Review TR i ∈ Ri

if TR i < threshold of Vader Ri is paid

TR i < threshold of jaccard

Ri is a bot

else

Ri is real

count + +

count ∗ 100 > Thresholdr eal

Ap review es are mostly authentic.

Figure 1 demonstrates the logical process for our proposed solution. Details of each component of the flowchart is listed below. The methodology is a general view in common to both Yelp, Ama- zon, Google and Facebook. For Google and Facebook, we analyze whether a search result (page or product) is authentic or boosted depending on the pattern of reviews and similarities within a short time frame. For Amazon and Yelp, we analyze reviews by accessing each reviewer's profile and calculating the probability of authen- ticity. Using vader sentiment analysis and jaccard similarity, we analyze the reviewer's profile which includes the reviews posted, the date and the ratings. We observe the stylometric pattern of the reviews, the contextual similarities and any unusual pattern in the reviews.

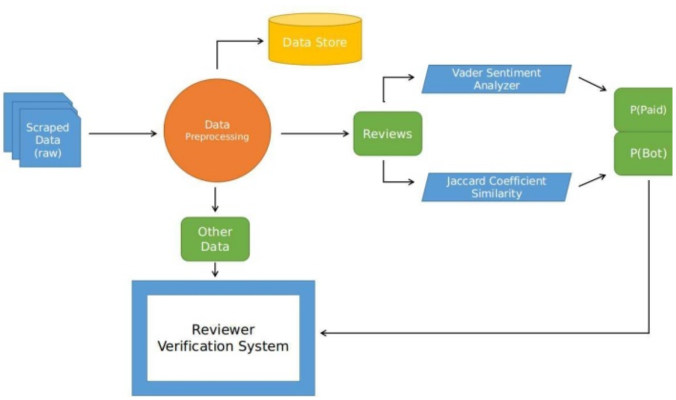

Figure 1. Methodology flowchart

4.2.1 Scraped Data (raw)

Initially, we scrape our required data from the internet using two scraping mechanisms. They are 'Se- lenium' and 'Scrapy'. Yelp is a static website, therefore Scrapy is best suitable for information extraction. On the other hand, Google, Facebook and Amazon are all dynamic-content websites, which re- quires Selenium to scrape the data.

4.2.2 Data Prepossessing.

After the data is collected, we filter out stop-words and tokenize each review. We do not remove any punc- tuation marks nor convert them to all lower cases, as sentiment analysis uses these as features to produce polarity scores.

4.2.3 Data Store

The cleaned data is stored in Comma-Separated Values (CSV) file for future references. This CSV is kept well pro- tected in the AWS Server. The other reason for storing information is to reduce latency, and scraping time as previously scraped data will not be extracted again.

4.2.4 Reviews

The collected reviews are used to analyze the sen- timents. For the purpose of detecting fake/paid reviews, we use vader sentiment analyzer. For the purpose of detecting reviews posted by 'bots', we use a jaccard similarity coeffi cient. Both of these two techniques are talked about in details in the next subsec- tion. The scores calculated are displayed in the Reviewer Verifica- tion System as probabilities.

4.2.5 Vader Sentiment Analysis

Vader sentiment provides a faster performance and can capture punctuation marks, word-shape, emoti- cons, acronyms, and many more. In [4], Hutto et. al mentions that vader performs comparatively much better than 11 other high per- forming sentiment algorithms. The vader sentiment produces 4 scores; positive, negative, neutral, and compound. The compound score is the cumulative of the valence scores of each lexicon words, and then normalised between -1 and +1. Score closest to -1 is con- sidered to be most negative, and closes to +1 is considered to be most positive. We have considered the compound score. If the score is less than -0.99 or more than 0.99, we assign a value of 1. If the score is less than -0.8 or more than 0.8, we assign a value of 0.75. If the score is less than -0.60 or more than 0.60, we assign a value of 0.5. Else we assign 0.The probability is then calculated using the formula:

$$\text{probability(fake)}=\frac{n(1)}{\sum n}$$

which means the probability is the ratio of total number of 1 scores divided by the summation of all the scores. This is probability of a reviewer posting fake reviews. The probability of the reviewer be- ing authentic is calculated by subtracting the previous value from 1. The pseudo code for this algorithm is as follows:

object_from_vader =

SentimentIntensityAnalyzer()

userDataFrame = apply sentiment to extract

compound score from comment on yelp-user

dataframe sentiment_score = []

for s in userDataFrame['compound']: # when sentiment is too positive or negative

if s < -0.99 or s > 0.99: sentiment_score.append(1.0)

when sentiment is very positive or negative

elif s < -0.8 or s > 0.8: sentiment_score.append(0.75)

when sentiment is just positive or negative

elif s < -0.6 or s > 0.6: sentiment_score.append(0.5)

when sentiment is neutral else:

sentiment_score.append(0.0) userDataFrame['sentiment_score'] = sentiment_score

Probability Calculate

d = dict(userDataFrame.sentiment_score. value_counts())

if 1 in d:

probabilityOfPaid = d[1]/sum(d.values())

else:

probabilityOfPaid = 0.0

probabilityOfHuman = 1- probabilityOfPaid

4.2.6 Jaccard Similarity

Jaccard similarity measures similarity co- effi cient between pairs to identify which elements are common to both the pairs, in this case, reviews. Jaccard similarity can be used to detect reviews produced by bots. Bots are usually automated softwares which are given some predetermined instructions. Most of the time they are built to either promote a business by posting plethora of positive reviews, or sink a target by posting negative reviews. These reviews are usually constructed using similar con- texts and words. Moreover, bots respond unusually faster within a short time frame. In [10], Niwattanaku et. al used jaccard similar- ity to compare the performance in measuring similarity between data sets. The paper states that jaccard similarity coeffi cient per- forms well when measuring similarities between words. The for- mula used to calculate the jaccard similarity for two review

$$JSR1, R1 = P (R1 \cap R2)|P (R1 \cup R2) \quad (1)$$

We calculate the jaccard similarity by passing two reviews R1 and R2, where each review is paired with the rest of the reviews. We then calculate the average of these values. This is the probability that the reviewer could be a bot. The pseudo code for this algorithm is as follows:

def jaccardSimilarity(review1, review2):

intersection = set(review1).

intersection(set(review2))

union = set(review1).union(set(review2)) return len(intersection)/len(union)

BOT DETECTION JACCARD SIMILARITY

userDataFrame['comment'] = userDataFrame['comment'] sum = 0

count = 0

corpus = userDataFrame['comment'] length = len(corpus)

for i in range(length-1): for j in corpus[i+1:]:

sum += jaccardSimilarity(corpus[i],j) count+= 1

bot_score(avg) = sum/count

In [3], Hu et. al have established the economic impact of such manipulative reviews. These misleading or deceiving actions are diffi cult to trace as ’paid human reviewers’ as well as bots are get- ting smarter everyday. To detect, we need to consider a signifi- cant number of possible parameters, such as duplication of reviews, time period of posting, reactions of other people on those reviews, etc.The pattern of fake reviews are independent of time, but do consists some common features. Some common features include contextual similarities between the reviews, a dominant pool of positive or negative ratings, misspelled and nonconstructive sen- tences. Wang et. al in [13] introduced anomaly detection in data, one of the markers of fraud detection. The misuse of internet has become inevitable and rate of such malpractices have risen over the past few years.

4.2.7 Other Data

Other data includes name of the entity the re- viewer has reviewed, the ratings and the date of postings. These are displayed in the Reviewer Verification System and also used to calculate star-date correlation.

The source codes used for each analysis will be open sourced in github for contribution after the application is patented.

5. EXPERIMENTAL SETUP

5.1 Application Design

In this section we will talk about our web-application that we have used to achieve our purpose. We have used Django (version 2.0) as our web-based framework. Django is a robust framework that incorporates python with HTML easily. Since most machine learning models are built with python, Django is more suitable. We have kept the application as user friendly as possible with simple design. There are 4 options for users to choose from and provide input ac- cordingly. The input can be a full URL or just the unique identifier. For example: *https://www.yelp.com/user _details?userid=vUt_WLW6– JVtraCN8dl9g’ or ’_WLW6– JVtraCN8dl9g*

The verify button will follow the methodology stated in section III-A. The data will be scraped, cleaned, pre-processed, analyzed and returned to the user in a different page. One sample case is shown in Figure 2 and 3.

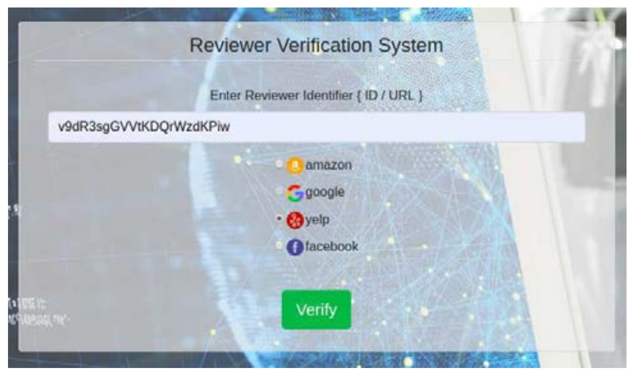

Figure 2. Yelp selection

5.2 Data Management

In this section, we will talk about how we collected data from the various platform and processed them.

5.2.1 Data Collection

The data was collected using Scrapy and Selenium, two well known python scrapper frameworks which are faster, reliable and accurate with reduced ip-block rates than the traditional scraping techniques. In Yelp and Amazon, for a particu- lar user, we have extracted the user name, user ID provided, name of entity the user has rated, ratings of each review and the cor- responding reviews, as well as the date of the review. In case of Google and Facebook, we scraped reviewer’s ratings and reviews. The constraints of scraping was limited to the Internet bandwidth, and processing capability of the computer.

5.2.2 Data Cleaning and Processing

The scraped data was cleaned for further processing. Cleaning the data included removal of stop words and numbers. We kept duplicates as it is one of the markers to detect spam or fake review. The data was then tokenized and fed to the algorithms. We considered reviewers who had at least or more than 10 reviews. Less reviews meant less accuracy and over fitting of data.

5.2.3 Data Storage

The data is then stored in a Comma-Separated Values (CSV) file, and kept with write-protected in AWS server. This handles security risks of data loss or any sort of data alter- ation.

5.2.4 Data Design

In Yelp for each entry in the CSV file, the first column is the name of the reviewers, second column is the unique ID assigned by Yelp, the third column is the entity the reviewer has reviewed, the fourth column is the ratings, the fifth column is the review, the sixth column is the date of the ratings posted. We also kept a temporary 7th column as a validity indicator. The user can validate the information of our analysis. This helps us approach towards a semi-supervised data for further research. Figure 4 por- trays the sample design of the data storage in the CSV.

Figure 3. Data representation of Yelp analysis in user- end

	Name	ID	Entity	Rating	Comment	Date	S
0	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Studio 890 Salons & Spa	5.0	Oh my goodness I haven't been to Studio 890 fo...	10/16/2019	
1	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Stubby's Gastrogrub & Beer Bar	4.0	I've been to Stubby's a handful of times, most...	10/15/2019	
2	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Lou Malnati's Pizzeria	4.0	I'm not the biggest pizza eater, so I wouldn't...	10/14/2019	
3	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	The Merchandise Mart	5.0	I am in awe of The Merchandise Mart every time...	10/11/2019	
4	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Milwaukee Intermodal Station	5.0	The Amtrak Station is always such a seamless e...	10/10/2019	
5	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Shadowbox - Chicago	5.0	Had an awesome workout at Shadowbox this morni...	10/9/2019	
6	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Interval	5.0	I love this little corner cafe spot! My experi...	10/4/2019	
7	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Greige Patisserie	5.0	Love this little corner spot in Walker's Point...	10/3/2019	
8	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Pizza Studio	5.0	Pizza Studio all the way! Thanks so much for t...	10/2/2019	
9	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	DanDan	4.0	Stopped into DanDan on a Thursday night for my...	10/1/2019	
10	Jessica J.	v9dR3sgGVVtKDQrWzdKPiw	Simple Café	5.0	I've never, ever had a less than 5-star experi...	9/30/2019	

Figure 4. Yelp data sample

In Amazon for each entry in the CSV file, the first column is the URL to the queried product pages, second column is the name of the reviewers, the third column is the reviews given by the re- viewers , fourth column is a validity indicator. Figure 5 portrays a sample data we have used for amazon analysis.

In Facebook for each entry in the CSV file, the first column is the name of the reviewers, second column is the ratings, the third col- umn is the reviews given by the reviewers , fourth column is the date. Figure 6 portrays a sample data we have used for facebook analysis. In Google for each entry in the CSV file, the first column is the name of the reviewers, second column is the date, the third column is the reviews given by the reviewers , fourth column is the ratings. Figure 7 portrays a sample data we have used for Google analysis.

	Product(URL)	Reviewer	Comment	Status
0	https://www.amazon.com/Outlander-Expandable-Ro...	Meggymoo	['I had this 2-1 cable less than a month and t...	0
1	https://www.amazon.com/Outlander-Expandable-Ro...	Trojansky	['Great little bottles to use for precise liki...	0
2	https://www.amazon.com/Outlander-Expandable-Ro...	RV	['Bought one year ago and working just fine. V...	0
3	https://www.amazon.com/Outlander-Expandable-Ro...	river_deb	[]	0
4	https://www.amazon.com/Outlander-Expandable-Ro...	David G. Lucas	["It's fine, but was hoping heavier like an ol...	0
5	https://www.amazon.com/Outlander-Expandable-Ro...	MSRP is a joke	["A few minutes of a fake news report to set u...	0
6	https://www.amazon.com/Outlander-Expandable-Ro...	C&C	['This product lasts FOREVER! We have been usi...	0

Figure 5. Amazon data sample

	Name	Rating	Comment	Date
0	Phil Hesbol	1	wonderful people everyone works toward the sam...	2018-07-31
1	Paul D. Oppedahl	5	feed my people food bank has been helping so m...	2017-12-10
2	Rita Rindahl	5	amazing facility and programming great to see ...	2014-03-27
3	Heather Tara	5	its free and help anyone that needs it	2019-02-08
4	Shannon Marie Shatley	5	we had an amazing experience at feed my people...	2019-09-20

Figure 6. Facebook data sample

	Name	Date	Comment	Star
0	Rafiqua Ferdousi	2019-07-15	daraz is complete rip off they are just frauds...	4.5
1	Mozammel Hoq	2019-10-13	the daraja began its operations in bangladesh...	4.0
2	MH SYAM	2019-07-15	the service is fairly good in many cases howe...	3.5
3	Rafiqua Ferdousi	2019-10-13	daraz is complete rip off they are just frauds...	3.0
4	Mozammel Hoq	2019-10-13	the daraja began its operations in bangladesh...	0.5
5	MH SYAM	2019-10-13	the service is fairly good in many cases howe...	NaN
6	ShadowStorm Gaming	2019-10-13	is not bad at all krpajanaka the distribution...	4.0
7	Kefayat Jahan Anika	2019-05-16	the first time was very unhappy and had to or...	4.0
8	Asraful Islam Rana	2019-04-16	loved this place actual loved this place	1.0
9	Kazi Khayrul Bashar	2019-09-13	boaring is too long delivery period after wee...	3.0
10	Pollob Plb	2019-03-17	the best online shopping sites actual more	3.0

Figure 7. Google data sample

Table 1. Result summary

Dataset	Items	Total Revi ews	Avg Review	Avg Rating	Acc(%)
Yelp	1000	50,000	50	4.32	93.33
Amazon	2000	40,000	20	3.92	90
Faceboo	k 1000	30,000	30	4.20	70
Google	1000	10,000	10	4.67	68

6. RESULT AND ANALYSIS

Referring to Table 1, we observe our algorithm achieves around 93% accuracy when detecting fake reviews and 90% for detecting boosted products in Amazon. Whereas the detection for fake Face- book pages and Google search queries produced 70% and 68% ac- curate responses. Some probable reasons are the missing reviews or disorganized reviews in Facebook. There are some reviews that are not written in standard English, and some are multilingual re- views. Same reason is applicable for Google as well. Filtering such reviews selectively will produce better results, but we wanted to observe the performance on the raw data. This can also be over- come by using Deep Neural Network techniques for NLP, which can be time consuming, and requires more processing capabilities. However, the accuracy strongly supports our hypothesis. With the vader sentiment analysis and jaccard similarities, we were able to detect presence of review manipulations in the giant e-commerce sites.

7. LIMITATION AND FUTURE WORK

Yelp and Amazon sites are scrape-friendly. Even though most web- sites block scrappers/crawlers, with certain precautions we were able to get our required data. In case of Facebook and Google, the data are much harder to scrape considering their continuous dy- namic environment. We were not always able to handle data ex- traction properly. For an instance, the format of the date was dif- ferent with respect to time. Moreover, the reviews are not well or- ganized, and there are no 'review' section for any user profiles. So it was harder to accumulate the reviews given by a particular user over the time period. For Yelp and Amazon, there were separate review sections on each user profiles. This is another reason Yelp and Amazon's accuracy surpassed that of Facebook and Google. Our proposed web-application is robust and provides real-time ser- vices with no pretrained data set. It does not use any heavy neural networks to perform computations, therefore requires few seconds of processing time with moderate computer hardware settings. In future, we will integrate all the platforms to stack the reviews and use unsupervised machine learning techniques for the detection processes. We will automate the process of recognizing the user search queries and provide in-depth analysis to the user. We will also open source our project for other researches and developers to contribute to our work.

8. CONCLUSION

Manipulated reviews is a serious concern for businesses and for people relying on them before availing a service or product. In this paper, we proposed some detection techniques for such ma- nipulated reviews on online sites like Yelp, Amazon, Google and Facebook. We provided our algorithm for these techniques and demonstrated an example in a real-time web-framework which we built using Django. We showed that even after certain limitations, we were able to detect presence of manipulation and categorized them under fake or bot reviews without any pre-trained or labeled data.

9. REFERENCES

[1] Migs Bassig. 2018. Yelp Factsheet: Stats Your Business Needs to Know. Retrieved December 4, 2018 from https://www.reviewtrackers.com/blog/yelp-factsheet/

[2] Kishor Datta Gupta, Dipankar Dasgupta, and Sajib Sen. 2018. Smart Crowdsourc- ing Based Content Review System (SCCRS): An Approach to Improve Trustwor- thiness of Online Contents. In *International Conference on Computational Social Networks*. Springer, 523–535.

[3] Nan Hu, Indranil Bose, Noi Sian Koh, and Ling Liu. 2012. Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision support systems*. 52, 3 (2012), 674–684.

[4] Clayton J Hutto and Eric Gilbert. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Eighth international AAAI confer- ence on weblogs and social media.*

[5] Nitin Jindal and Bing Liu. 2008. Opinion spam and analysis. In *Proceedings of the 2008 international conference on web search and data mining*. ACM, 219–230.

[6] Huayi Li, Bing Liu, Arjun Mukherjee, and Jidong Shao. 2014. Spotting fake re- views using positive-unlabeled learning. *Computación y Sistemas,* 18, 3 (2014), 467–475.

[7] Yuming Lin, Tao Zhu, Hao Wu, Jingwei Zhang, Xiaoling Wang, and Aoying Zhou. 2014. Towards online anti-opinion spam: Spotting fake reviews from the review sequence. In *2014 IEEE/ACM International Conference on Advances in So- cial Networks Analysis and Mining (ASONAM 2014).* IEEE, 261–264.

[8] Matt. 2019. 20 EYE OPENING AMAZON STATISTICS FACTS FOR 2019. Retrieved August 22, 2019 from https://10under100.com/amazon-statistics-facts/

[9] Arjun Mukherjee, Vivek Venkataraman, Bing Liu, and Natalie Glance. 2013. What yelp fake review filter might be doing?. In *Seventh international AAAI con- ference on weblogs and social media.*

[10] Suphakit Niwattanakul, Jatsada Singthongchai, Ekkachai Naenudorn, and Su- pachanun Wanapu. 2013. Using of Jaccard coeffi cient for keywords similarity. In *Proceedings of the international multiconference of engineers and computer sci- entists,* Vol. 1. 380–384.

[11] Bo Pang and Lillian Lee. 2008. Opinion Mining and Sentiment Analysis. Foundations and Trends® in Information Retrieval, 2 1-–2 (2008), pp:1–135,. https://doi.org/10.1561/1500000011

[12] Qingxi Peng and Ming Zhong. 2014. Detecting Spam Review through Sentiment Analysis. *JSW,* 9, 8 (2014), 2065–2072.

[13] Zhaoxia Wang, Victor Joo, Chuan Tong, Xin Xin, and Hoong Chor Chin. 2014. Anomaly detection through enhanced sentiment analysis on social media data. In *2014 IEEE 6th International Conference on Cloud Computing Technology and Science*. IEEE, 917–922.