Webology (ISSN: 1735-188X)
Volume 18, Number 4, 2021

Detecting Fake Reviews Through Multinomial Naive Bayes Algorithm With Deep Learning Techniques

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Abstract— Nowadays online data generation and consumption plays an important role in the field of information technology. Customer has to purchase any product through online needs the past history and review result for achieving better reliability. Traditionally various kind of recommendation systems are available with single source and specific form of review. The impact of online reviews on businesses has grown dramatically over the past years, it is important to determine business success in a variety of sectors, from restaurants, hotels to e-commerce. Unfortunately, some users use illegal means to improve their online reputation by writing fake reviews for their businesses or competitors. Previous studies have focused on the detection of fraud in many domains, such as product or business reviews in restaurants and hotels. However, despite its economic interest, the background of the electronic consumer business has not been well-studied. This article proposes a theoretical framework for detecting false reviews that have been explored in the consumer retail domain. The contributions are threefold:

1. Definition of a feature framework for fake review detection,
2. Development of a fake review classification method based on the proposed framework,
3. Evaluation and analysis of the results for each of the site under study.

Keywords— e-commerce, fake review, reliability, recommendation

1. INTRODUCTION

Online consumer product reviews play an important role for customers, which include new types of word-of-mouth (WOM) information. Recent research shows that 52% of online consumers use the Internet for product information, while 24% of them use the Internet to browse products before purchasing. Consequently, online reviews have a strong impact on consumer decision-making in e-commerce, which affects highly relevant areas such as travel and accommodation, online retailers and entertainment, In addition, online reviews of the same product can be found in multiplicative information sources, which can be classified according to parties that host WOM information on internal WOMs (eg Amazon, Walmart, Best Buy, etc.) and external, independent product review providers hosted. Do (e.g. CNET, Yelp, Trip Advisor, Epinions, etc.).

However, only credible reviews have a significant impact on consumers' purchase decision. Moreover, product category can significantly affect the reliability of WOMs. The Consumer Retail product category is reviewed online based on a number of factors. On the one hand, consumer usually requires considerable investment and the more valuable and expensive an item is, the more it is investigated. According to one study [1], consumer retail is the most influential product of online reviews, affecting 24% of the products received in this category, and WOMs are the second most effective source of search engines in this product category. On the other hand, consumers do research on consumer retail products, as these products are changing very often, with new products and updates to existing ones. Therefore, consumers often rely on reviews to avoid making the wrong purchase decision As a result, Harrigan et al. [2] more than 50% of consumer retail buyers report contacting several WOMs before making a purchase decision. Therefore, in consumer retail, the retailer's internal WOM has a limited impact, while external WOM sources have a significant impact on retailer reputation and sales [3]. Therefore, consumer retailer more prone to the effects of external WOMs because they are not easy to operate on them.

As consumers and retailers are overwhelmed with the vast amount of feedback available on WOM internal and external resources, automatic natural language processing and sentiment analysis techniques are often applied. Review polarity classification, review summary , competitive intelligence acquisition and reputation monitoring are the most frequent application domains. Given the importance of business reviews and the difficulty of getting a good reputation on the Internet, several strategies have been used to improve online presence, including illegal content. Indexing is one of the most popular illegal methods available on sites like Yelp or Trip Advisor. However, according to Jindal and Liu [4], not all corrupt reviews are equally harmful. Negative fake reviews on good quality products are really hurting businesses, and more

With good illegal updates to low quality products, the result is also harmful to consumers. Misleading positive reviews on poor quality products are also detrimental to competitors who offer medium or poor-quality products but do not have a lot of reviews on it.

The purpose of this article is to analyze the issue of field review in the consumer in various sectors, to read businesses more accurately from major sites in the USA. No previous research has been done in this concrete sector, for retail online purchase are the most important cases. We want to prove that the problem of detecting fraudulent online consumer and fraud can be solved through deep learning and shows that the difficulty of achieving it depends on the location.

2. OVERVIEW

Existing approaches are based on manual discrete features, which can capture linguistic and psychological cues. However, such features fail to encode the semantic meaning of a document from the discourse perspective, which limits the performance. In this paper, we empirically explore a deep learning model to learn document-level representation for detecting deceptive opinion spam. In particular, given a document, the model learns sentence representations with a convolution neural network, which are combined using a gated recurrent neural network with attention mechanism to model discourse information and yield a document vector. Finally, the document representation is used directly as features to identify deceptive opinion spam. Experimental results on various domains show that our proposed method outperforms state-of-the-art methods.

3. LITERATURE REVIEW

Spam detection is still extensively investigated in Web-Web and E-mail domains (Gyo¨ngyi et al., 2004; Ntoulas et al., 2006) [5], while research has recently been expanded into the domain of customer reviews. Different types of indicator signals have been investigated. For example, trained Jindal and Liu [4] models use content-based features to review, review, and the product itself. Yoo and Gretzel (2009) [6] compiled a review of 40 authentic and 42 fake hotels and manually compared the language differences between them.

Ott et al. (2011) [7] created a database of ratings by recruiting Turkers to write false reviews. Their data are accepted by the line of work that follows (Ott et al., 2012 [8]; Feng et al., 2012 [9]; Feng and Hirst, 2013) [10]. For example, Feng et al. (2012) [9] looked at syntactic materials from Context Free Grammar (CFG) cleaning trees to improve performance. Feng and Hirst (2013) [10] create hotel profiles from clusters of reviews, measures the relevance of customer reviews on a hotel profile, and uses it as a feature of spam detection. Recently, Li et al. (2014) [11] created a broad integration benchmark, which included data from three domains (Hotel, Restaurant, and Surgeons), and explored common ways of identifying spam for viewing ideas online. We accept this data for our experiments because of its large size and integration.

Existing methods use traditional syntactic elements, which can be small and fail to incorporate semantic information from complete speech. In this paper, we propose to study the representation of the neural levels of a document to better identify spam ideas. To the best of our knowledge, we are the first to investigate the intensive education of spam detection of delusional ideas.

There is some work to do without the content of the review itself. In addition to Jindal and Liu (2008) [4], Mukherjee et al. (2013) [12] examined factors from customer behavior to detect fraud. Based on factual reviews and numerous unlisted reviews, Ren et al. (2014) [13] proposed a supervised learning approach, and created an intuitive classifier to detect deceptive updates. Kim et al. (2015) [14] introduced an independent semantic-based feature based on FrameNet. Experimental results indicate that semantic independent features can improve classification accuracy.

Neural network models have been misused to study the dense feature representation for a variety of NLP functions (Collobert et al., 2011 [15]; Kalchbrenner et al., 2014 [16]; Ren et al., [17]. Distributed word returns (Mikolov et al., 2013) [18] have been used as a basic building block with many NLP models. Numerous methods have been proposed to study the introductions of phrases and large sections of texts from the vocabulary distribution. For example, Le and Mikolov (2014) [19] introduced a vector of categories to read document presentations, extending the word embedding methods of Mikolov et al. (2013) [18]. Socher et al. (2013) [20] introduced a family of recur alive neural recompilation networks to represent a semantic level category. Subsequent research includes a multidimensional network of neural and global feedback.

4. PROPOSED SYSTEM

The built system can classify the ecommerce Dataset into deceptive and truthful review using the Multinomial Naive Bayes Algorithm with deep learning. The conceptual diagram of the proposed method is shown in figure 1.

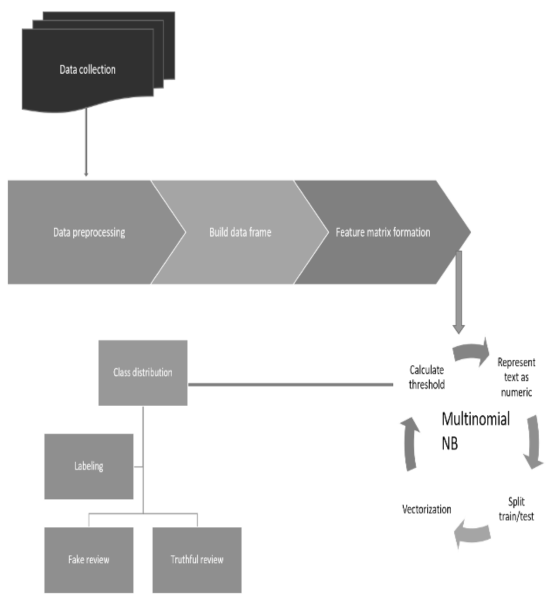


Figure1. Conceptual Diagram

Data Collection:

The Data Set used is a list of over 71,045 reviews from 1,000 different products provided by Data finiti's Product Database. The dataset includes the text and title of the review, the name and manufacturer of the product, reviewer metadata, and more.

Data Preprocessing:

This Data Set contains 25 columns of information. We require the id and review text data to find the deceptive and truthful review so we extracted that information from the collection and used as our dataset.

We have a csv file containing reviews. Each row in the dataset contains the text of the review, and whether the tone of the review was classified as positive (1), or negative (0). We want to predict whether a review is negative or positive given only the text. We have used NLTK (natural language tool kit) and Tex Blob to predict the polarity of the review.

In order to do this, we'll train an algorithm using the reviews and classifications in train.csv, and then make predictions on the reviews in test.csv. We'll then be able to calculate our error using the actual classifications in test.csv.

Data Frame:

Feature are known as predictors, inputs or attributes .In this phase for each row the features such as id, review text, polarity of the review are formed in the formed in matrix format. After preprocessing, the selected features will be stored in the Bag of words. The example of forming a Bag of words in a text document is described in table 3, where d1 and d2 represent the review.

Doc1: This is creamy white chocolate

Doc2: This matcha is so creamy

Doc	creamy	white	chocolate	this	is	matcha	so
Doc1	1	1	1	1	1	0	0
Doc2	1	0	0	1	1	1	1

Table1. The Example of forming bag of words

In order to build a model,

- Features must be numeric
- Machine Learning models conduct mathematical operations so this is necessary
- Every observation must have the same features in the same order
- Rows must have features with the same order for meaningful comparison

Multinomial Naive Bayes

A Pipeline class was used to make the vectorizer => transformer => classifier easier to work with. Such hyper-parameters as n-grams range, IDF usage, TF-IDF normalization type and Naive Bayes alpha were tuned using grid search. The performance of the selected hyper-parameters was measured on a test set that was not used during the model training step.

Step 1: Calculate prior probabilities. These are the probability of a document being in a specific category from the given set of documents.

P (Category) = (No. of documents classified into the category) divided by (Total number of documents)

P(class a) = (No of documents classified into class a)divided by (Total number of documents) = 2/5 = 0.4

P (class b) = 2/5 = 0.4

P (class c) = 1/5 = 0.2

Step 2: Calculate Likelihood. Likelihood is the conditional probability of a word occurring in a document given that the document belongs to a particular category.

P (Word/Category) = (Number of occurrence of the word in all the documents from a category+1) divided by (All the words in every document from a category + Total number of unique words in all the documents)

P (Saturn/Class a) = (Number of occurrence of the word “SATURN” in all the documents in “CLASS A”+1) divided by (All the words in every document from “CLASS A” + Total number of unique words in all the documents)

= (1+1)/(6+13) = 2/19 = 0.105263158

The tables below provide conditional probabilities for each word in Class a, class b, and class c.

Step 3:
Calculate P(Category/Document) = P(Category) * P(Word1/Category) * P(Word2/Category) * P(Word3/Category)

P (Class a/D6) = P(Class a) * P(Engine/Class a) * P(Noises/Class a) * P(Car/Class a)

= (0.4) * (0.052631579) * (0.157894737)

= (0.00005831754)

P(Class b/D6) = 0.000174953

P(Class c/D6) = 0.00004882813

The most probable category for D6 to fall into is Class b, because it has the highest probability among its peers.

P (Class a/D7) = 0.00017495262
P (Class b/D7) = 0.0000583175

P (Class c/D7) = 0.00004882813

The most probable category for D7 to fall into is Class a, because it has the highest probability among its peers.

The Multinomial Naive Bayes technique is pretty effective for document classification.

Labeling:
Labeling will be done automatically on data using the reference of two labeling methods. The data will be labeled with the number 1 which means truthful and the number 0 which means deceptive.

5. ENVIRONMENTAL SETUP

Our model is tested with the data set derived from the Kaggle data set of e-commerce .We have used python and Keras API for deep learning to accrue hidden information in the review set..

6. RESULTS AND DISCUSSION

The derived dataset contains 500 documents with Amazon user reviews alone. In this 239 is having positive polarity remaining 241 are negative reviews are identified .We have use it frame 480 *2 of data frame. From that 208 review are classified as truthful .And 272 review are classified into deceptive reviews based on our model.F1 Score is achieved 0.8791

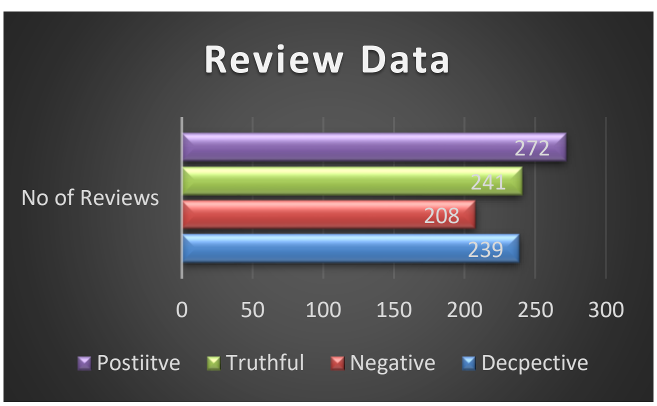


Figure2. Number of Reviews classified in the dataset

Performance is evaluated by considering the parameter such as precision and recall. Precision refers to the future prediction value of the particular data whereas recall is a value in which the data sensitivity is analyzed. Figure3 and Figure4 show that the comparison of precision and recall of the Amazon review. Figure 5 describes the comparison between precision and recall. Figure6 and Figure7 describes that the comparison of accuracy and F1 scores of the review. Figure8 show the overall performance for 7 simulations

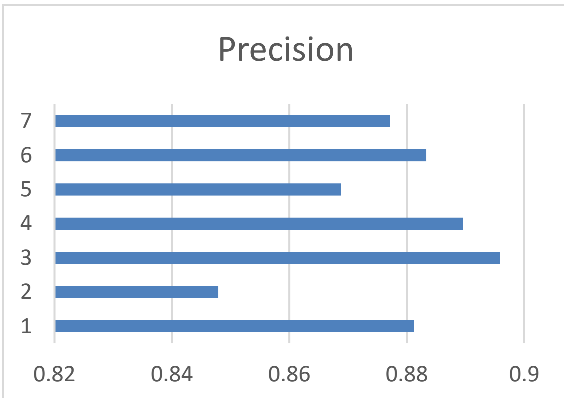


Figure 3. Precision

Figure 4. Recall

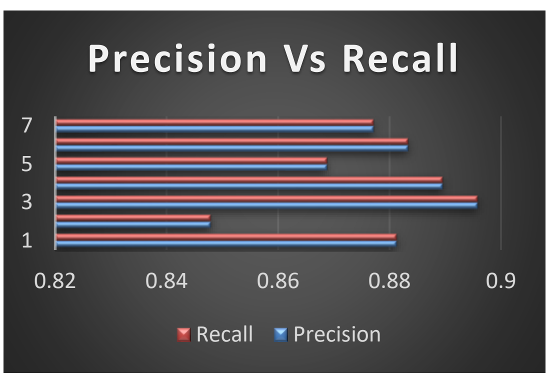


Figure 5. Precision Vs Recall

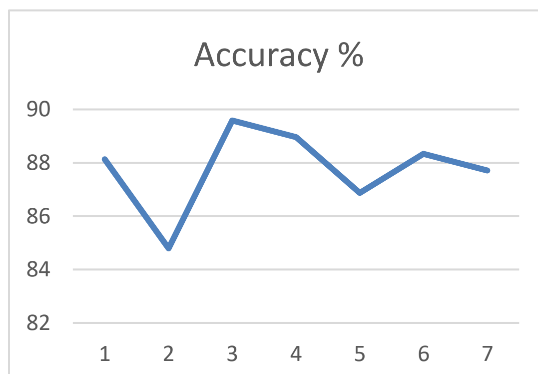
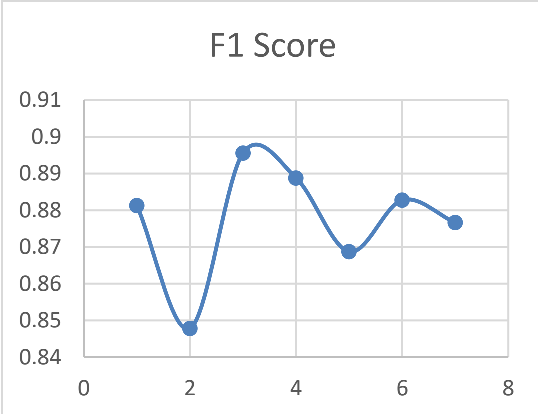


Figure 6. Accuracy



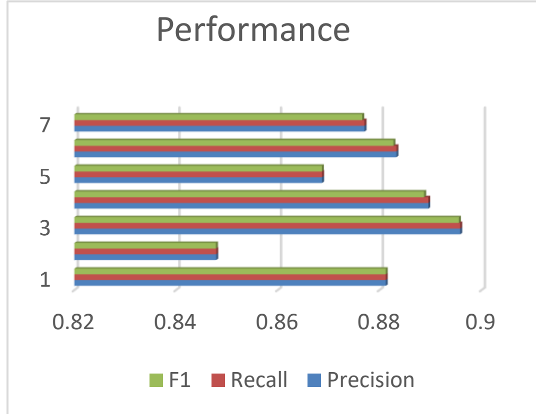


Figure 7. F1 Score

Figure 8. Performance

7. CONCLUSION

In our study, we took deep learning methods for review acquisition. We started with the methods Multinomial navies byes method and then we tried by word of mouth to vector the method in deep learning of the discovery of the truthful review.

We directed our work and got results. We have provided approximately 87% accuracy in obtaining MNB. In addition, we the Multi-layer Perception provided 88% accuracy in detection.

Our method found that all products contain more than 42% true reviews. The performance of our model is based on claims about three thirds of online reviews are false.

The result of system classification by implementing the method of labeling average and the use of feature selection by 20% which is implemented by using Multinomial Algorithm Naïve Bayes able to classify deceptive and truthful reviews .

8. FUTURE WORK:

The biggest challenge for e-commerce businesses is ensuring a superior customer service to shoppers. Helping those finds what they are looking for and guiding their shopping experience is what makes the process challengeable. In brick-and-mortar stores, you can always find savvy salespeople. They help to find what the shopper looks for and gives specific recommendations based on their preferences and wishes. To build such system the genunity of the review is very important aspect this model can be enhance with the recommendation system.

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