

Fake Product Review Monitoring and Removal using Opinion Mining

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Abstract:

Online product review on shopping experience in social media has promoted user to provide feedback. Nowadays, many e-commerce sites allow the customer to write their review or opinion on the product which they have bought from that site. The review given by the customer can build the good name of the product or make the product famous. Due to this reason, in some product the customer reviews about the product are included by the item organization individuals itself so as to make so as to deliver false positive item reviews and also one can demote a product by giving the false negative review about the product. In this paper, we will propose a framework to detect fake product reviews or spam reviews by using Opinion Mining. The Opinion mining is also known as Sentiment Analysis. In Sentiment analysis, we try to figure out the opinion of a customer through a piece of text. We first take the review and check whether the review is positive or negative or neutral using sentimental analysis. We use Spam dictionary to identify the spam words in the reviews. In Text Mining we will apply Naïve Bayes classifier and SVM classifier and compare their result that which one is more accurate and on the basis of these algorithms we get the specific results.

Keywords:

Sentimental analysis, SVM Classifier, Naive Bayes Classifier, Tokenization, Bag-of words model.

1. INTRODUCTION

As the majority of the people require survey about an item before spending their money on the item. So, individuals will go for the product review to know positive and negative sides of the product that were added by the people who had bought the product earlier. In some e-commerce websites some good reviews are added by the product company people itself in order to make the product famous or boost up the sells of their product. Client won't most likely find out whether the review is certifiable or fake. To find out fake review in the site this "Fake Product Review Monitoring and Removal using Opinion Mining" framework is presented. This framework will find out fake surveys made by social media optimization team by opinion mining or sentimental analysis. For sentiment analysis we will use two algorithm Naïve Bayes algorithm and SVM classifiers, and then we will compare the result to find which one is more accurate.

1.1 Objective: The objective of paper named "Fake Product Review Monitoring and Removal using Opinion Mining" is to identify the cheating in reviews about the product. Data mining mechanisms will be used to find out the fake reviews. The proposed system will save their efforts and time by helping the users and business organizations identify spams from different opinions quickly and also help in purchasing their valuable products from a trustworthy site.

1.2 Scope: Now any people can write any opinion text or review, this can draw the individual's attention and organizations to give undeserving spam opinions to promote or to discredit some target products. So there is a need to develop a smart system which automatically mine opinions and classify them into spam and non-spam category. Proposed opinion spam analyzer will automatically classify user opinions into spam or non-spam. This automatic system can be useful to business organization as well as to customers. Business organization can monitor their product selling by analysing and understand what the customers are saying about products. Customers can make decision whether he/she should buy or not buy the products. This can be helpful for the people to purchase valuable product and spend their money on quality products.

2. LITERATURE SURVEY

Opinion Mining has attracted to a great deal of research earlier. However, not a great amount of work has been done in this field. Review Spam is very hard to detect unless read manually. Here are the some of the work proposed and implemented earlier. Paper [1] proposes three types of new features like review density, semantic, and emotion and gives the model and algorithm to construct each of these features. Although, it is not a good metric and the reduction is not substantial. Paper [2] have used linguistic features like unigram presence, unigram frequency, bigram presence, bigram frequency and review length to build a model and find fake reviews. Although, the main problem is data scarcity and it requires both linguistic features and behavioural features. Paper [3] proposes behavioural approach to detect review spammers who try to manipulate the ratings on some target products. an aggregated behaviour scoring methods for rank reviewers is derived. Paper [4] proposes to employ categories of lexical semantic and linguistic features in the detection of online spam reviews. In Paper [5] we found that spotting the individual fake reviews was quite a difficult task but spotting

the groups was comparatively easier one frequent item set mining (FIM) method is used to analyse the dataset. Paper [6] first performed a comparison using real-life filtered (fake) and unfiltered (non-fake) reviews in Yelp. The results showed that the real-life data is much harder to classify, with an accuracy of only 67.8%. In paper [7] find the difference between normalized rating and sentiment score and detect 111 fake reviews out 300 reviews. But they have to increase their efficiency. In paper [8] they detect the fake review by identify the same IP address of the user ID multiple times. In paper [9] Spam detection technique using J48 Algorithm is used to check for spams in the reviews and find J48 algorithm have more accuracy over Naïve Classifier. In paper [10] Used Naïve Bayesian classifier which resulted in very low error rate. In paper [11] they used Naïve Bayesian classifier which resulted in very low error rate. In paper [12] Evaluation of the utilized Multiplayer Perceptron (MLP) classifier displayed high accuracy on detecting review spam based on content. MLP can be effectively used in review text categorization as spam or genuine. In paper [13] they used SVM with a small no of support vectors that can have good generalization, even when the dimensionality of the data is high. In paper [14] they used POS tagging to reads text and determine the part of speech for each token and then the sentiment score is used to shows a review's sentiment polarity with 57.2% accuracy. In paper [15] Scraping processing is used to build the data set from yelp and then Fake Feature Framework for organizing the extraction and characterization of features in fake detection. Their framework is composed of two main types of features: review centric and user centric. Review centric features are only related to the text of the review and User centric features show how the user behaves within the site.

3. PROPOSED METHODOLOGY

Step1. Research and Survey:

We studied the previous work done in this topic and try to analyze the thesis, the existing procedure in spam detection, identifying the drawback in the existing approaches, we prepare the strategies and solution on how to proceed or extend in order to be overcome in our research.

Step2. Data Acquisition:

In this step, we prepare a data set of reviews and reviewers using human collected from online e-commerce websites or application like Amazon, Flipkart with different characteristics and sizes. The records are chosen randomly from any of the records or any of the products that are available on the website. From the data set we choose one data set for training the model and one data set for testing the model. For training the model we will use 80% of the data and for training the model we will use 20% of data.

Step3. Data Integration:

In this step, we combine the data from multiple review source data sets into a coherent form.

Step4. Spam Identification Labeling:

In this step, we look for various types of the spam in the data integrated set, and labeled each record as spam and non-spam manually.

Step5. Pre-processing:

In this step, we use various types of pre-processing techniques to handle the missing, noisy and inconsistent data. There are a number of pre-processing techniques such as case folding dam character erase, tokenization, bag of word model, stop word elimination.

Step6. Tokenization:

The process of breaking a stream of text up into phrases, words, symbols, or other meaningful elements called tokens. The goal of the tokenization is the exploration of the words in a sentence. Tokenization relies mostly on simple heuristics in order to separate tokens by following a few steps:

- A. Tokens or words are separated by whitespace, punctuation marks or line breaks.
- B. White space or punctuation marks may or may not be included depending on the need.
- C. All characters within contiguous strings are part of the token. Tokens can be made up of all alpha characters, alphanumeric characters or numeric characters only.

Tokens themselves can also be separators. For example, in most programming languages, identifiers can be placed together with arithmetic operators without white spaces. Although it seems that this would appear as a single word or token, the grammar of the language actually considers the mathematical operator (a token) as a separator, so even when multiple tokens are bunched up together, they can still be separated via the mathematical operator.

Step7. Stop-word Elimination:

The most common words that are not going to help text mining such as prepositions, articles, and pro-nouns can be considered to be stop words. Since every text document deals with these words which are not necessary for application of text mining. All these words are eliminated.

Step8. Bag-of-words Model:

The bag-of-words model is one of the simplest language models used in NLP. It makes an unigram model of the text by keeping track of the number of occurrences of each word. This can later be used as a feature for Text Classifiers. In this bag-of-words model you only take individual words into account and give each word a specific subjectivity score. We make the list of unique words in the text corpus called vocabulary. Then, we can represent each sentence or document as a vector with each word represented as 1 for present and 0 for absent from the vocabulary. Another representation can be count the number of times each word appears in a document.

Step9. Training the classifier:

We are training the classifier using the Features Extracted using the Bag-of-words model. The Features of both the training and test dataset are compared. And this will give the classifier to predict on the test data.

Step10. Sentimental Analysis:

For sentimental analysis we are using the Naïve Bayes and SVM classifiers. We also see which classifier has the most accuracy. We will be using the classifier to classify the words and label them into negative and positive. This system will help us to carry out fake product review removal and when the same person is giving reviews on the same product multiple times; our system will make sure that only the recent comment of the user is shown. The analysis of spam reviews by detecting the fake or fraudulent reviews. Those reviews with spam words can be removed to recover a fair item evaluation system. The flowchart for the proposed methodology is shown in Fig. 3.1.

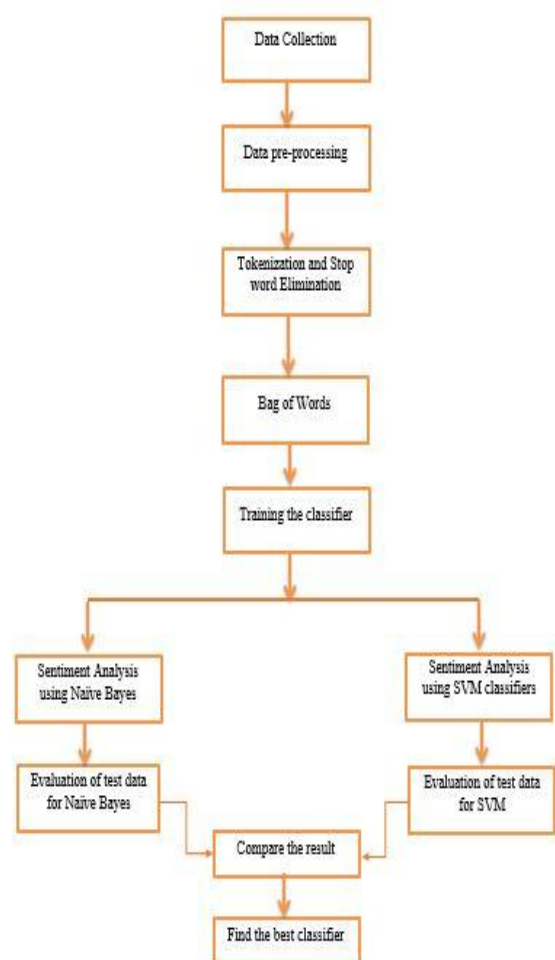


Fig. 3.1: Flow chart for the proposed methodology

4. ALGORITHM FOR SENTIMENTAL ANALYSIS

4.1 Naïve Bayes Theorem

It is the probability of an event happening from the probability of another event that just happened. The expression for the hypothesis is

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$$

$$P(c|x) = P(x_1|c) \times P(x_2|c) \times \dots \times P(x_n|c) \times P(c)$$

In this equation probability of c with respect to x i.e. $P(c|x)$ is the posterior probability of class (c , target) given predictor (x attributes). $P(c)$ is the prior probability of class c . $P(x|c)$ is the likelihood which is the probability of predictor given class. Then $P(x)$ is the prior probability of the predictor.

4.1.1 Posterior probability: It is the probability that an event will happen after all evidence or background information has been taken into account.

4.1.2 Prior probability: It is the probability that an event will happen before you taken any new evidence into account.

$$\text{Posterior probability} = \text{Prior probability} + \text{Likelihood}$$

4.1.3 Naive assumption

Now, we will put a naive assumption to the Bayes' theorem, which is, independence among the features. So now, we split evidence into the independent parts. If any of two event A and B are independent, then we can write the naive equation as $P(A,B) = P(A)P(B)$ Hence, we reach to the result:

$$P(y - x_1, \dots, x_n) = \frac{P(x_1|y)P(x_2|y) \dots P(x_n|y)P(y)}{P(x_1)P(x_2) \dots P(x_n)}$$

We can express the above equation as:

$$P(y - x_1, \dots, x_n) = \frac{P(y)^{Q_{n+1}} P(x_i|y)}{P(x_1)P(x_2) \dots P(x_n)}$$

Now as the denominator remain constant for a given input, we can remove that term:

$$P(y - x_1, \dots, x_n) \propto P(y)^{Q_{n+1}} P(x_i|y)$$

Now we need to create a classifier model. For this we find the probability of given set of inputs for all possible values of the class variable y and pick up the output with maximum probability. This can be expressed mathematically as:

$$y = \text{argmax}_y P(y)^{Q_{n+1}} P(x_i|y)$$

So, finally we are left with the task of calculating $P(y)$ and $P(x_i|y)$.

Please note that $P(y)$ is also called probability and $P(x_i|y)$ is called conditional probability.

4.2 SVM Classifier

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating the datum by a hyper plane. The main objective of the SVM is to find out a

maximum marginal hyper plane that based divide the data set into class as shown in Fig. 4.1.

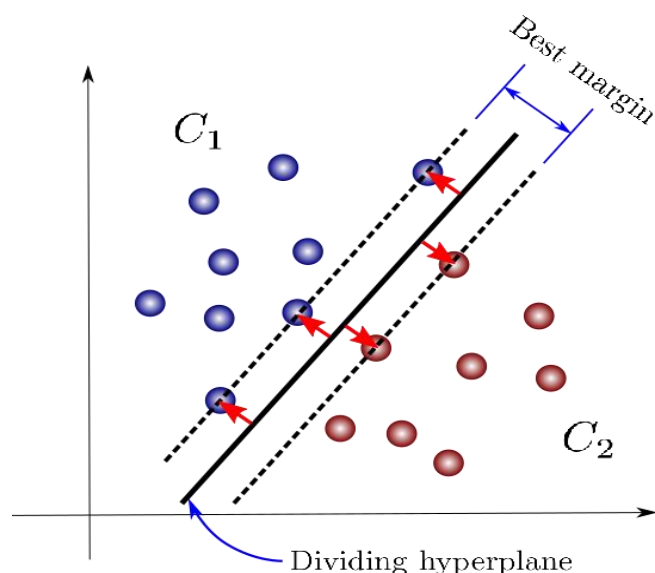


Fig. 4.1: Data set representation on SVM classifier

4.2.1 Support Vector: Support vector can be defined as those data point which are close to the hyper plane. The support vector defines the separating line by calculating margin.

4.2.2 Hyper Plane: Hyper Plane can be defined as a decision plane which separates the given set of object into different classes based on the membership value.

4.2.3 Working methodology of SVM: While designing a SVM the main objective is to segregate the given data set through a hyper plane with the maximum possible margin between the support vectors in the given data set

5. RESULT

5.1 Naïve Bayes Classification: Naïve Bayes algorithm performs quite well in our field. We have applied Naïve Bayes classifier over 21,000 amazon product reviews for analysis these reviews weather they are fake or real. And the result we have obtained is shown in fig. 5.1.

Mean of cross-validations (Accuracy, Precision, Recall, F1score): [0.9602381 0.99457864 0.91977984 0.9446458]

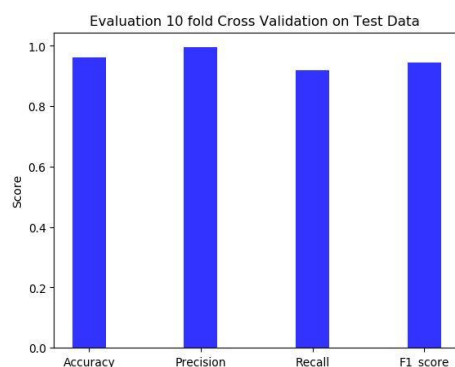


Fig. 5.1: Evolution of test data for Naïve Bayes classifier

For the Naïve Bayes classifier we get 96% accuracy, 99.45% precision, 91.97% recall and 94.46% F1 score.

5.2 SVM classification: SVM classifier also perform quite well in our field but not good as Naïve Bayes classifier. We have applied SVM classifier on the same amazon dataset to analyse the reviews. And the result obtained is shown in fig. 5.2.

accuracy: 0.825
Precision: 0.8259852751883645
Recall: 0.8246312145477109
f1-score: 0.824729493222959

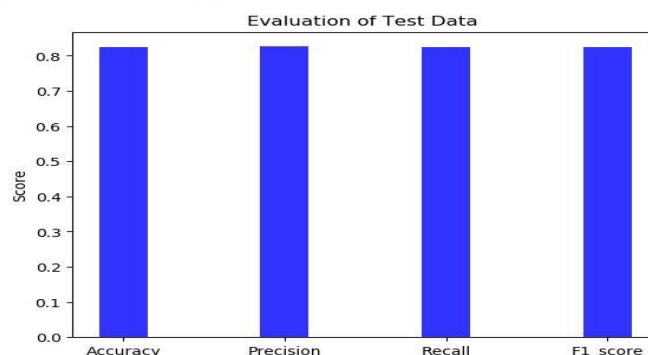


Fig. 5.2: Evolution of test data for SVM classifier

So, for the SVM classifier we get 82.50% accuracy, 82.59% precision, 82.46% recall and 82.47% F1 score.

5.3 Comparison Result:

The comparison between the result of Naïve Bayes classifier and the SVM classifier is shown in Table 5.1 and their comparison graph is shown in Fig. 5.3.

Table 5.1: Comparison table between Naïve Bayes and SVM classifier

Algorithm Name	Accuracy	Precision	recall	F1 score
Naïve Bayes	96%	99.45%	91.97%	94.46%
SVM	82.50%	82.59%	83.46%	82.47%

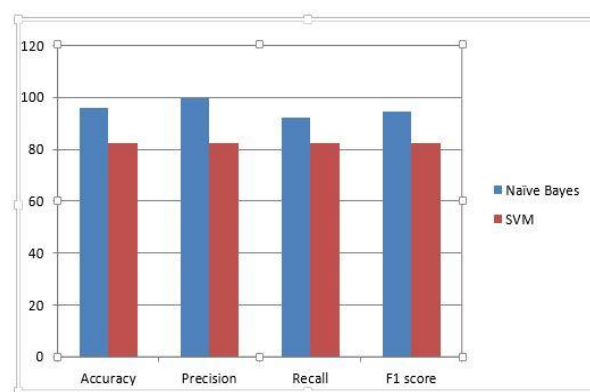


Fig. 5.3: Comparison graph between Naïve Bayes and SVM classifier

6. CONCLUSION AND FUTURE WORK

In this paper we have used sentimental analysis for detecting the spam in the product reviews. Sentiment analysis play vital role to make business decision about the product/services. As we applied two machine learning algorithms for analysing the amazon product reviews we have found that Naïve Bayes classifier have more accuracy over the SVM classifier. Major challenges in Sentiment Analysis includes feature weighting which plays a crucial role for good classification. In future we will apply some other machine learning algorithms for sentimental analysis and compare their result to find the best algorithm.

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