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Fake Review Product Detection Using Opinion Mining

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Abstract: *In e-commerce, customer evaluations may have a substantial impact on an organization's income. Before purchasing any goods or service, online customers rely on reviews. As a result, the trustworthiness of online evaluations is critical for organisations and may have a direct impact on their reputation and revenue. That is why some companies pay spammers to write phoney reviews. These phoney reviews take advantage of customer purchasing decisions. Before making a purchase, the company's items were trusted. As a result, the fake review problem must be handled so that significant E-commerce sectors such as Flipkart, Amazon, and others can solve the issue and eradicate phoney reviewers and spammers, preventing people from losing faith in online buying platforms. This model may be used by websites and applications with a few thousands of users to forecast the validity of the review, allowing website owners to take appropriate action. The Nave Bayes and random forest approaches were used to create this model.*

Keywords: Fake review, fake review detection, opinion mining, sentiment analysis, text mining

I. INTRODUCTION

The sophistication of online review posting has risen at a quicker rate, with individuals purchasing nearly anything online and having it delivered to their door. As a result, because individuals are unable to personally check the product while purchasing online, they must rely on the evaluations of other purchasers, which must be as accurate as possible so that the buyer is not repeatedly deceived by phoney reviewers or spammers. The problem is straightforward, but it is time-consuming to go through/read every review and identify it as a bogus or confusing category. This must be done methodically to get to the bottom of the issue. A spam review or the use of several customer ids can be used to fraudulently filter reviews of the product in order to obtain a high rating for the product. This may be filtered by flagging the usage of terms like "amazing," "so good," "great," and so on. Because they prefer to promote the goods or try to imitate real reviews by repeating the same terms to make an impression on the consumer. As a result, spam filtering requires a large amount of data to train and be effective with additional domain knowledge such as sarcasm sentences used by users to express their dissatisfaction with the product, the product is good but not the delivery or packing, which affects the review classification. Instead of misclassification to a bad review, like in sentiment analysis, an NLP approach is utilised to detect such reviews. Data pre-processing is used to eliminate unnecessary or obsolete product reviews.

The goal of this research is to create an environment of online E-commerce industry where consumers build trust in a platform where the products they purchase are genuine and feedbacks posted on these websites/applications are true, are checked on a regular basis by the company where the number of users is increasing day by day, thus companies like Twitter, WhatsApp, Facebook use sentiment analysis to check fake news, harmful/derogatory posts and banning such users/organizations. Similarly, the E-commerce (Flipkart, Amazon) industries, hotel booking (Trivago), logistics, tourism (Trip Advisor), job search (LinkedIn, Glassdoor), food (Swiggy, Zomato), and other industries use algorithms to combat fake reviews and spammers who deceive consumers into purchasing subpar products/services.

II. RELATED WORK

The preceding analysis is done on the stated views through text, blogs, reviews, feedbacks, and so on as user opinions that are unique to calculate, research, and collect useful information, which is nothing more than sentiment analysis. Exiting research employed a two-step strategy, employing an SVM classifier for tweet classification. Other others utilised emoticons, smileys, and hashtags to categorise labels. The other researcher employed emoticons to train an SVM classifier.

2.1 Existing Systems

- Lexicon-based approaches: Twitter-based methods based on measuring the number of positive and negative words in a phrase.
- Methods based on rules: According to syntactic norms, for example, [query] is pos-adj - Tweet feel
- Machine learning-based methods: Twitter sentiment is based on a classifier constructed on training data.

The issue of detecting bogus reviews The researchers created strategies to solve the issue of detecting false reviews. New models, such as the ICF++ model, which includes honesty value, have affected accuracy and enhanced it by 49 percent. To identify/classify phoney reviews and delete them, a VADER and Polarity-based strategy was utilised to label the reviews as true, false, suspicious categories, and give polarity +1, -1, and 0.

III. METHODS

3.1 Dataset

The dataset utilised is "amazon academic review," which includes reviews, useful votes, ratings, user id, and a variety of other variables. The useful parameters for feature engineering are obtained. The dataset comprises thousands of authentic and false reviews that have been blended together to quickly test the correctness of the model that is being applied using this dataset. The academic challenge Yelp dataset provides information about 11,537 companies. There are 8,282 check-in sets, 43,873 users, and 229,907 reviews for these companies in this dataset. The dataset is difficult to work with since it comprises a big number of different reviews and parameters for training any algorithm.

3.2 Pre-processing

Pre-processing is the initial stage in analysing any dataset, and it consists of deleting extraneous characteristics, punctuation, stop words, missing words, redundant words, and so on in order to clean the dataset for training purposes. This guarantees that the model is properly trained.

3.3 Sampling of Data

Because the dataset contains a large number of reviews, the data is sampled before being supplied to the classifier. The sampling is performed to reduce the weight on the classifier, which loads the data in chunks. Different labels are used to authenticate the bogus reviews, and the data frame is returned after concatenating two columns after labelling.

IV. WORKING

The openness with which consumers express and use their comments has contributed to problems with websites carrying customer evaluations. Social media (Twitter, Facebook, etc.) allows anybody, at any moment, to openly express criticism or critiques of any organisation. As a result of the lack of limits, certain businesses use social media to unjustly promote their items, brands, or shops, or to unfairly criticise those of their competitors.

4.1 A Naive Bayes Calculation

Naive Bayes algorithm was utilized to assemble a double arrangement model that would anticipate if the survey's conclusion was positive or negative. A Naive Bayes classifier expects that the estimation of a specific component is free of the estimation of some other element, given the class variable. It utilizes the preparation information to compute the likelihood of every result dependent on the highlights.

$$p\left(\frac{a}{b}\right) = \frac{p\left(\frac{b}{a}\right)p(a)}{p\,(b)}$$

$$Posterior = \frac{prior * livelihood}{excellence}$$

$$p\left(\frac{x_i}{y}\right) = \left(\frac{1}{\sqrt{2\pi\sigma^2{}_y}}\right)\exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma^2{}_y}\right)$$

Fig 1: Naïve Bayes algorithm

4.2 The Random Forest Classifier

It is a supervised learning algorithm for training and testing machine learning models. The term "forest" refers to a collection of decision trees trained using the "bagging" approach. In this case, decision trees are integrated to improve the model's performance and learning in order to get good overall outcomes. It simply integrates many decision trees to improve the random forest's performance and provide a more accurate forecast.

a) Accuracy= TP+TN/ FP+FN+TN
b) Precision= TP/TP+FP
c) Recall (sensitivity) = TP/TP+FN
d) F1_score= 2*(Recall*Precision)/ (Recall + Precision)

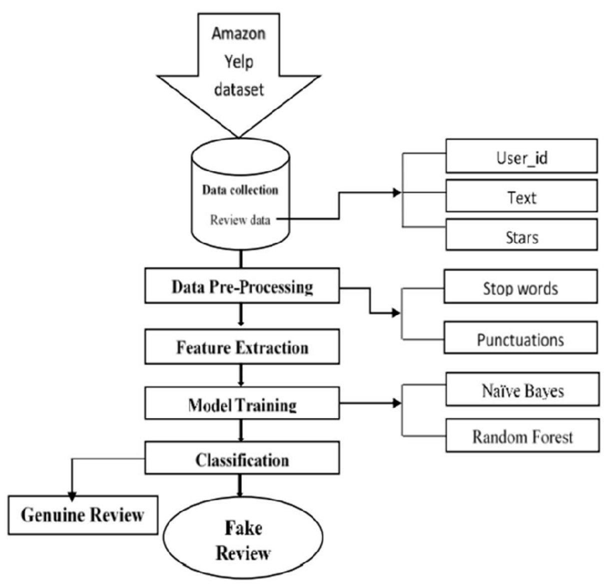

Fig 2: Model diagram for fake review detection

The flowchart in "Fig 2" explains that the issue solution process begins with dataset collecting, which requires attention to pick the suitable dataset to determine whether it is binary or categorical. I loaded the reviews in the Yelp academic dataset review. Json file to receive the data in the proper format for developing the model. Later, for brevity, just those traits that will be helpful in future occurrences were nominated. Feature extraction is performed and utilised to train Random Forests and Nave Bayes models, which record the associations between various characteristics and subsequently use them for classification.

4.3 Detection of a Spammer Group

According to the literature, identifying the spammer group is an important element of detecting fraudulent reviews (Mukherjee, et al., 2012). The large number of spammers results in the spread of bogus reviews at specified real-time intervals. As a result, they observed great accuracy in fake review identification by analysing research that focus on burst patterns. Future research should focus on the exploration of burst patterns utilising new approaches to detect spammers.

4.4 A Model for Detecting Fake Reviews

That Can Be Explained. Deep learning played an important part in natural language processing, producing great results. However, it is regarded as a "Black Box," as it lacks declarative information for further interpretations of the results. All of the deep learning algorithms for detecting false reviews are uninterpretable. As a result, trusting the model's performance and outcomes is challenging.

4.5 Dealing with the Concept Drift Issue

Existing approaches may not be suitable for detecting false reviews in real-world applications when the characteristics of the reviews vary over time due to the dynamic nature of the reviews. Furthermore, in real-world applications, the prediction model must be updated on a regular basis. As a result, an efficient model that can manage the idea drift problem in real-world circumstances is required.

V. RESULT

S. No	Parameter	Naïve Bayes (in %)	Random Forests (in %)
1.	Accuracy Score	79.007	**89.487**
2.	Precision Score	70.224	**85.577**
3.	Recall Score(Sensitivity)	99.099	94.389
4.	F1 Score	82.169	**89.768**

Fig 3: Accuracy Table

According to the above table, the two models performed quite well, with the random forests classifier outperforming the others. As a result, random forests have higher accuracy, precision, and F1 scores. It is concluded that a random forest classifier may be employed for the monitoring and eradication of false product reviews. When compared to models for various purposes, they perform well in certain categories and incompatible in others, resulting in their the application requires some prior knowledge.

VI. CONCLUSION

The results described in this article are a comparison of two models designed to justify the model performance for this "Amazon's yelp" dataset and its applicability to real-time applications. Hence The Random Forests model outperformed the Nave Bayes method by a wide margin. The topic of fake review detection is treated properly and provides a fair look into its legality and need; the goal is to pick an algorithm to complete the mission of false review identification and eradication. In future study, hybrid models and novel models for false review identification can be tested. The research can accelerate the execution process by utilising Google co-lab and NVIDIA graphics GPU.

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