WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Identification of Fake Review using Machine Learning

D.ChinnaMoulali, K. Rajasekhar, D. N. L Rangaiah, D. Imam Vali

Students of Dept of CSE, Santhiram Engineering College, Nandyal, Nandyal

A B S T R A C T

The continuous of purchasing online products, For the buy of any product, we must see the reviews of that product after that we purchase the products. Review places the main role in online purchasing the product. Mainly positive reviews make customers buy a product online, similarly, the negative reviews make confusion about whether the customer buys a product or not. The product seller wrote a fake review to satisfy the customer. Thus, identifying fake reviews is a faithful and ongoing research area. Identifying a fake review depends on key features of the review but also it depends on behave of the reviews. This paper proposes a Machine learning accession to the identification of fake reviews. In addition to the features eradication process of the reviews. This paper appeal to some features engineering techniques to essence various behave of the reviews. This paper equates the performance of some trail runs on a real dataset of online shopping reviews with and without features estimations of users' behavior. In both cases, we compare the performance of some classifiers: K-Nearest Neighbor (KNN), Navy Bayes, Logistic Regression, and Random Forest algorithm.

Keywords: Fake reviews Identification; data mining; Machine learning;

I. INTRODUCTION

Without any trustworthy external oversight, user created content is becoming more and more popular on social media platforms, making it impossible to determine which user-generated content is credible or which source is genuine. Spreading such false information has serious repercussions that hurt both users and businesses. The numerous subsets of traits, or qualities, that are frequently taken into account by various methodologies related to reviews and reviewers as well as to the network structure connecting various entities on the review-site in an exam The primary goal of this study is to analyse the key review and review-centric features that have been suggested to identify phoney reviews,

II. RELATED WORKS

Textual and behavioral indicators are used to detect bogus review research. Textual features are the review activity's verbal characteristics. Thus, textual properties are influenced by the words of the reviews. The nonverbal aspect of the reviews is characterised by behavioural characteristics. They typically depend on how reviewers behave, including writing styles, facial expressions, and how frequently they write evaluations. Despite the difficulty and importance of assigning textual elements, behavioural features are as important and cannot be disregarded because of their substantial significance on the effectiveness of the phoney review identification procedure. Textual characteristics have improved significantly.

* *Corresponding author.*
E-mail address: 18x51a0545@srecnandyal.edu.in

III. Literature survey

Analyzing user-generated content (UGC), the traits of the writers, and the fundamental structure of social media platforms—that is, the social ties tying the concerned parties together—are all factors in determining the reliability of information on the Social Web. These characteristics, or features, can include simple linguistic features that are connected to the UGC's text, additional meta-data features that are, for example, associated with the content of reviews or tweets, behavioural features that are gleaned from user behaviour in social media, or features that are connected to the user profile (if available). In addition, other techniques have examined product-based aspects, like in the case of review sites where items and/or services are evaluated, or have considered social features, which use

IV. Proposed methodology

We give a comprehensive explanation of the several features that can be used to spot phoney reviews. These two classes will be taken into account because the most successful systems in the literature are typically supervised and take into account review- and reviewer-centric features.

A. Features Focused on Reviews

The first class of features that have been taken into consideration consists of those that are connected to a review. They can be taken out of both the text that makes up the review—textual features—and the meta-data that is associated with the review—meta-data features. A significant portion of reviews are singletons, meaning that a given reviewer only writes one review in a certain amount of time. To accommodate this type of review, particular features must be created.

1) Textual Features, first Natural language processing techniques can be used to extract basic textual features from the text, as well as to employ word-related statistics and sentiment estimates as features. Numerous strategies use both unigrams and bigrams as textual features.

Meta-data features include: They can be produced by analysing the cardinality of the review in relation to the reviewer and the thing under consideration. These features include: • Basic features like • Review rating; • Rating deviation, which is the difference between the evaluation provided in the review and the entity's average rating; • Singleton feature; and • Burst features, which can be caused by either the sudden popularity of the entities reviewed or spam attacks.

B. Features aimed at reviewers

These qualities pertain to the reviewer's conduct and make up this category of features. By taking into account user behaviour as a whole while submitting reviews, it is feasible to look beyond the content and meta-data linked with a review, which are restricted for classification.

2) Rating attributes

They are based on an analysis of the ratings data for each reviewer that is taken into consideration.

• The overall count of reviews.

• Ratios, such as the proportion of unfavourable, favourable, and "extreme" evaluations.

• Standard deviation from the entity's mean.

Temporal characteristics

They are founded on the temporal data that explains the distribution of the ratings over time in more detail.

• The user's activity time is the difference between the timestamps of the most recent and oldest reviews for a certain reviewer.

Maximum rating per day; Data entropy, the number of days between successive pairs of reviews; and Maximum rating per day.

The implementation of the supervised machine learning methodology for classification, data balance, and classifier testing uses the following methods.

C. Implementation and classifier selection

Most supervised classifiers used to address the problem of detecting opinion spam are based on Nave Bayes or Support Vector Machines (SVM). Python has been selected to create the classifier since it is widely used by developers and provides a wide range of tools and modules for use in many contexts.

D. Choosing a dataset

The Yelp classification has been utilised as a basis for comparison, with recommended reviews correlating with "real" reviews and not recommended reviews correlating with "false" ones. These databases' advantages include

• The large amount of reviews per user, which enables taking into account each user's behavioural characteristics

• The variety of entities examined, including

E. Data balancing

One of the main problems that must be resolved while performing supervised classification is imbalanced data. If the unbalanced nature of the training data is not taken into account, there is a chance that the classifier will learn mostly from the largest class of labelled data, ignoring the minority class. Considered is the oversampling approach, which entails boosting the minority class to balance it with the largest.

V. Block diagram

Our framework is divided into three main sections:

• Data Collection: This module completes duties linked to compiling data for the intended use.

a web crawler that pulls every link off the page. The data is parsed and then placed in the MySQL database.

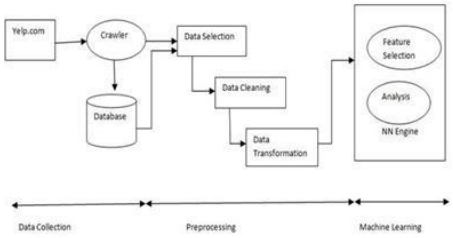

Fig. 1. The framework's modules

• Data pre-processing: Since the data being collected is not consistent, it must be trained using different machine learning methods and provided in a certain format.

• Machine Learning: In this module, multiple feature sets are taken into account and analysed in order to draw conclusions.

VI. Conclusion

The methods for detecting false reviews are based on data-driven techniques that take into account a number of attributes related to reviews, reviewers, and the social network's network structure that can be used to categorise reviews in terms of their reliability. In general, supervised classifiers perform better and frequently use reviewer-centric features. Although unsupervised approaches are typically less successful, they do have the advantage of not requiring labelled training data. Contrarily, supervised systems have demonstrated their efficacy with regard to narrow subsets of features and too small or review site dependent labelled datasets.

REFERENCES

[1] R. Barbados, O. Araque, and C. A. Iglesias, “A framework for fake review detection in online consumer electronics retailers,” Information Processing & Management, vol. 56, no. 4, pp. 1234 – 1244, 2019.

[2] S. Tadelis, “The economics of reputation and feedback systems in eCommerce marketplaces,” IEEE Internet Computing, vol. 20, no. 1, pp.12–19, 2016.

[3] M. J. H. Mughal, “Data mining: Web data mining techniques, tools, andalgorithms: An overview,” Information Retrieval, vol. 9, no. 6, 2018.

[4] C. C. Aggarwal, “Opinion mining and sentiment analysis,” in MachineLearning for Text. Springer, 2018, pp. 413–434.

[5] A. Mukherjee, V. Venkataraman, B. Liu, and N. Glance, “What yelpfake review filter might be doing?” in Seventh international AAAIconference on weblogs and social media, 2013.

[6] N. Jindal and B. Liu, “Review spam detection,” in Proceedings of the16th International Conference on World Wide Web, ser. WWW ’07,2007.

[7] E. Elmurngi and A. Gerbi, Detecting Fake Reviews through SentimentAnalysis Using Machine Learning Techniques. IARIA/DATA ANALYTICS, 2017.

[8] V. Singh, R. Piryani, A. Uddin, and P. Waila, "Sentiment analysisof movie reviews and blog posts," in Advance Computing Conference(IACC), 2013, pp. 893–898.

[9] A. Molla, Y. Biadgie, and K.-A. Sohn, "Detecting Negative DeceptiveOpinion from Tweets." in International Conference on Mobile andWireless Technology. Singapore: Springer, 2017.

[10] S. Shojaee et al., "Detecting deceptive reviews using lexical andsyntactic features." 2013.

[11] Y. Ren and D. Ji, "Neural networks for deceptive opinion spamdetection: An empirical study," Information Sciences, vol. 385, pp. 213–224, 2017.

[12] H. Li et al., "Spotting fake reviews via collective positive-unlabeledlearning." 2014.

[13] N. Jindal and B. Liu, "Opinion spam and analysis," in Proceedings ofthe 2008 International Conference on Web Search and Data Mining,ser. WSDM '08, 2008, pp. 219–230.

[14] D. Zhang, L. Zhou, J. L. Kehoe, and I. Y. Kilic, "What online reviewerbehaviors matter? effects of verbal and nonverbal behaviors ondetection of fake online reviews," Journal of Management InformationSystems, vol. 33, no. 2, pp. 456–481, 2016.

[15] E. D. Wahyuni and A. Djunaidy, "Fake review detection from a productreview using a modified method of iterative computation framework."2016.