e-ISSN 2320 –7876 www.ijfans.org
Vol.11, S Iss.1, 2022
  UGC CARE Listed (Group -I) Journal

Spotting Fake Reviews Using Multifaceted Representation And Detailed Aspects Strategy

Shaik Mohd Hamed [1] Md. Ateeq Ur Rahman[2] and Ganesh Mani[3]

[1]Research Scholar, Dept. of Computer Science and Engineering, Shadan college of Engineering and Technology, Hyderabad, Telangana, India – 500086.

[2]Professor, Department of Computer Science and Engineering, Shadan College of Engineering and Technology, Hyderabad, Telangana, India – 500086.

[3]Professor, Department of Computer Science and Engineering, Shadan College of Engineering and Technology, Hyderabad, Telangana, India – 500086.

Abstract - Due to the rapid growth of network data, the authenticity and reliability of network information have become increasingly important and have presented challenges. Most of the methods for fake review detection start with textual features and behavioral features. However, they are time-consuming and easily detected by fraudulent users. Although most of the existing neural network-based methods address the problems presented by the complex semantics of reviews, they do not account for the implicit patterns among users, reviews, and products; additionally, they do not consider the usefulness of information regarding fine-grained aspects in identifying fake reviews. In this paper, we propose an attention-based multilevel interactive neural network model with aspect constraints that mines the multilevel implicit expression mode of reviews and integrates four dimensions, namely, users, review texts, products and fine-grained aspects, into review representations. We model the relationships between users and products and use these relationships as a regularization term to redefine the model's objective function. The experimental results from three public datasets show that the model that we propose is superior to the state-of-the-art methods; thus showing the effectiveness and portability of our model.

Index Terms — Fake reviews detection, multidimensional representations, relationship modeling, fine-grained aspects.

I. INTRODUCTION

Currently, the Internet is not only a tool by which people acquire knowledge but also a platform on which people can express their views and disseminate information. In the realm of e-commerce, review information has a significant impact on both users' purchasing decisions [1] and enterprises' development on online platforms. According to the latest data from the social commerce platform Bazaarvoice, more than 50% of users discontinue their purchasing behavior and lose trust in brands after discovering fake reviews of a product. Fake reviews may not only damage the entire online review system, but ultimately cause a loss of credibility [2]. Therefore, it is important to automatically identify fake reviews on online platforms and provide users with more truthful information.

The early work on this subject focused on manual design features in combination with machine learning methods. For example, semantic features of the text include the length of the review text [4], [5], its lexical features [6],

 ,

and its affective polarity [7]. Users' behavioral features include the number of good or bad reviews that they publish [4] and the frequency of these reviews [8]. Driven by profits, spammers are enhancing and disguising their schemes in accordance with the corresponding detection methods. During recent years, along with the development of deep learning, a number of fake review detection methods based on deep learning have been developed [9]–[11], [19], [20]. Compared to feature-based methods, these methods have a greater ability to automatically capture semantic information implicit within text without a manual design and have a stronger domain adaptable and effective. The existing methods have achieved good results, but most of them are only from a single perspective, such as that of review texts or users; additionally, they ignore some user implicit expression patterns and the influences among users, products and texts [11]. In addition, we find when users express their true feelings, whether their reviews are positive or negative, their descriptions will include some details (such as the taste of a dish in a resturant) that enhance their emotional expression. Their expression are far more descriptive. However, a spammer cannot describe a product in detail because he or she is not describing a personal experience or an actual use. Fine-grained aspect is a set of terms used to describe a topic in a related domain, which can be the features of a product or attributes of a service [12], that is the ''details'' mationed above. Thus, we assume that fine-grained aspects can be used as a plan to detect fake reviews

II. SYSTEM ANALYSIS

Problem Statement:

Currently, the Internet is not only a tool by which people acquire knowledge but also a platform on which people can express their views and disseminate information. In the realm of e-commerce, review information has a significant impact on both users' purchasing decisions [1] and enterprises' development on online platforms. According to the latest data from the social commerce platform Bazaarvoice, more than 50% of users discontinue their purchasing behavior and lose trust in brands after discovering fake reviews of a product. Fake reviews may not only damage the entire online review system, but ultimately cause a loss of credibility [2]. Therefore, it is important to automatically identify fake reviews on online platforms and provide users with more truthful information.

Aim of the Project:

The main of the project is to identify fake reviewson online platforms based on fine grained details. We have used the Deceptive Opinion Spam Corpusdata set which is an open source dataset on Kaggle. This corpus consists of truthful and deceptive hotel reviews of 20 Chicago hotelsand fed it to the proposed model that is built using advanced machine learning techniques.

Scope of the Project:

The scope of the project is limited to the compute the accuracy of the proposed model and identify fake reviews. The admin of the system trains the proposed model with training data. The test data can be given to the model to find if the review is fake or not. Maintenance of user accountsdoes not fall under the scope of the project.

Proposed System:

During recent years, along with the development of deep learning, a number of fake review detection methods based on deep learning have been developed [9]–[11], [19], [20]. Compared to feature-based methods, these methods have a greater ability to automatically capture semantic information implicit within text without a manual design and have a stronger domain adaptable and effective.In addition, we find when users express their true feelings, whether their reviews are positive or negative, their descriptions will include some details (such as the taste of a dish in a restaurant) that enhance their emotional expression. Their expression are far more descriptive. However, a spammer cannot describe a product in detail because he or she is not describing a personal experience or an actual use. Fine-grained aspect is a set of terms used to describe a topic in a related domain, which can be the features of a product or attributes of a service [12], that is the ‘‘details’’ mentioned above. Thus, we assume that fine-grained aspects can be used as a plan to detect fake reviews.

Advantages:

- High accuracy
- Can be extended to real time environments.

III. PROPOSED MODULAR IMPLEMENTATION

The Algorithm/ Technique used:

1. Identification of Dataset
2. Data preprocessing
3. N-gram analysis of reviews
4. Fine-grained aspect extraction
5. Creation of Model
6. Testing the model.

Below is the proposed modular implementation of the project. It consists of two modules:

1. Admin
2. User

Below is the proposed modular implementation of the project. It consists of modules:

3. Admin
4. User

Admin Module:

The admin of the system is responsible for the activities like:

1. Uploading the dataset
2. Analysis of Deceptive Reviews Dataset.
3. Comparison of various machine learning algorithms on the deceptive corpus.
4. Build model for Fake Review Detection.
5. Review the performance of the algorithms on the given dataset
6. Test the model for fake reviews using test data.

User Module:

The user can login and test the model by entering the review. The review is given as input to the model and the model shall predict if the review is truthful or deceptive.

IV. PROJECT EXECUTION

Home page:

This is the starting page of the application when the application is executed on Pycharm, the application is hosted on a web server and URL is generated to access the application once the user clicks on the URL the below page is opened on the browser.

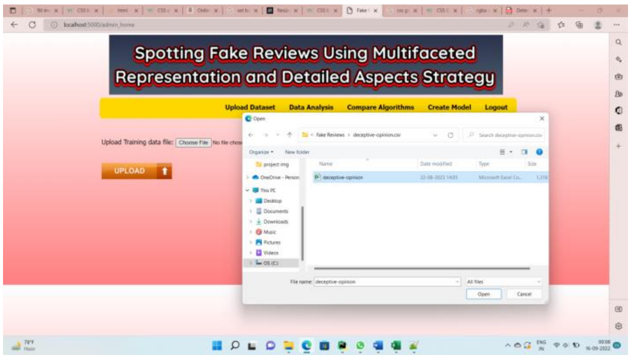
Admin Login:

This is the login page for the admin module. The admin need to login into the system with his credentials in order to perform operations like uploading the dataset, Training the dataset, Exploratory data Analysis of the dataset, Feeding the dataset to different Machine learning Algorithms to find the Algorithm that can meet the best accuracy and Create a model that can be hosted on the Flask Application to be used by the users.

e-ISSN 2320 –7876 www.ijfans.org
Vol.11, S Iss.1, 2022
  UGC CARE Listed (Group -I) Journal

Upload Dataset:

On this page, the administrator of the system can upload datasets that are used for training the machine learning models. The admin has to select the file by clicking on the Choose file button and click on the upload button to upload the file to the server. Once the upload is complete, a success message would be displayed that the file is successfully uploaded. For this project we are using test_data_4_students, training_data_2_csv_UTF reviews as a dataset.

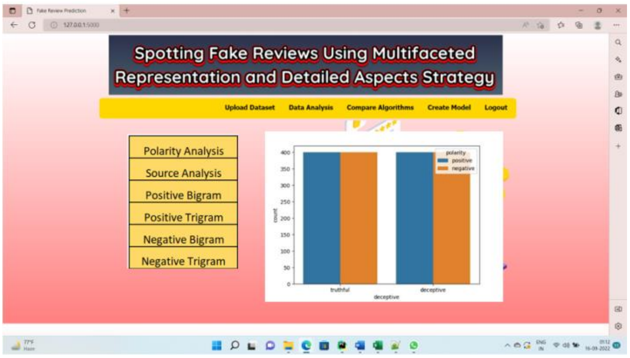


Data Analysis:

Exploratory Data Analysis is performed on the dataset inorder to clean the dataset for any missing data, identify patterns, identify the relationships of various parameters of the outputs with the help of graphs, statistics etc.

PolarityAnalysis:

The below graph shows the polarity analysis of reviews

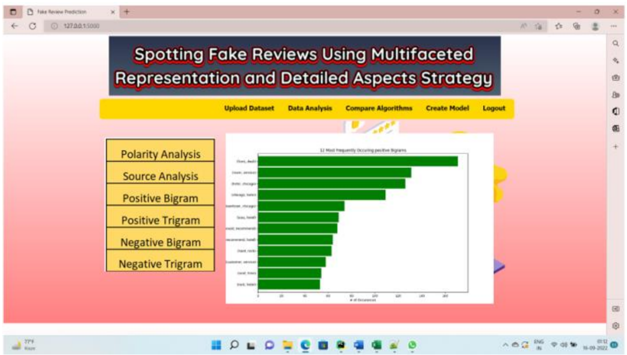


SourceAnalysis:

The below graph shows the Source analysis of reviews

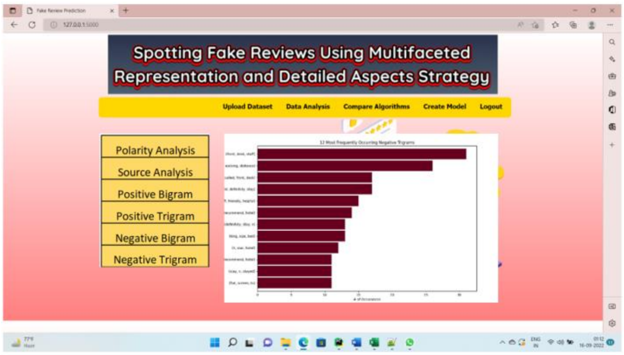
Positive Bi-gramAnalysis:

The below graph shows the 12 most frequently occurring bi-grams in the review dataset.



Negative Trigram Analysis:

The below graph shows the 12 most frequently occurring negative tri-grams in the review dataset.

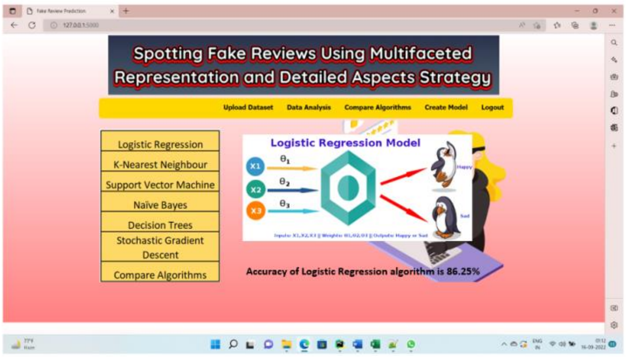


Compare Algorithms:

On this page, the admin can feed the dataset to various Algorithms to train them and get the test accuracy for each algorithm.

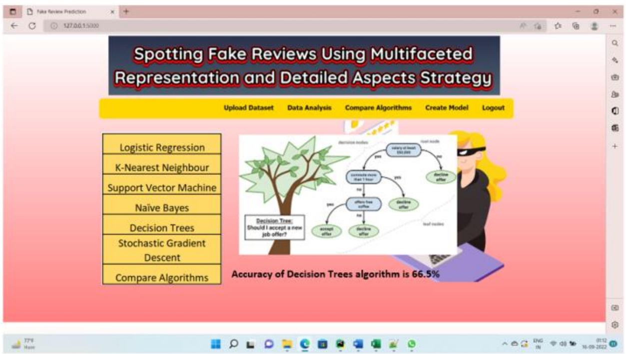
Logistic Regression:

When the dataset is feed to Logistic regression algorithm we observe that the test accuracy is 0.86.



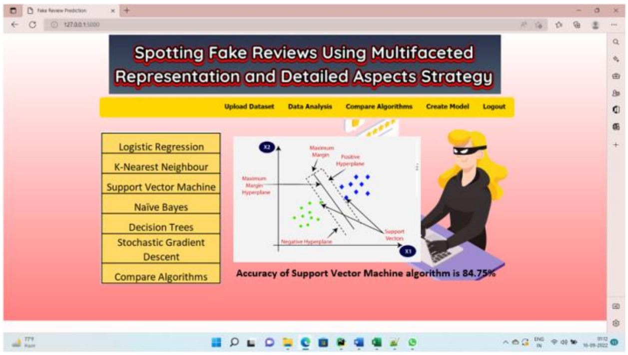
Decision Trees:

When the dataset is feed to Decision Trees algorithm we observe that the test accuracy is 66.5%



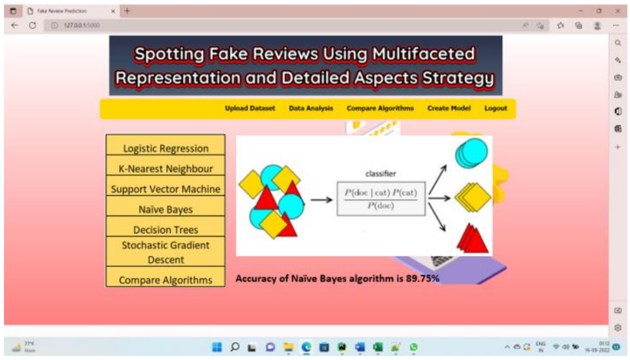
Support Vector Machine:

When the dataset is feed to Support Vector Machine algorithm we observe that the test accuracy is 84.75%



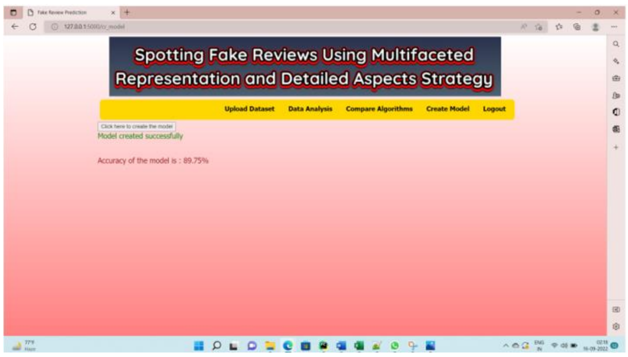
Naive Bayes Algorithm:

When the dataset is feed to Naive Bayes algorithm we observe that the test accuracy is 89.75%.



Create Model:

The Model can be created using the Create Model button. Once the button is clicked, the model is created and appropriate success message is displayed. The accuracy of our model is 89.75%



Test Model:

The model can be tested using the below screen.

V. CONCLUSION

In this study, we focused on the task of identifying spam reviews. After analyzing the reviews in the datasets, we propose a hypothesis that fine-grained aspect information can be used as a new scheme for fake review detection and recon structed the representation of reviews from four perspectives: users, products, reviews text, and fine-grained aspects. We have applied NLP techniques on the fake review dataset, did the required n-gram analysis and fed the processed dataset to multiple machine learning algorithms to test their performance. We finaly built a machine learning model using multinomial Naive Bayes and its accuracy is about 90%. In this paper, the fine-grained aspect terms are for restaurants and hotels. When it comes to cross-domain issues, you only need to further obtain fine-grained aspects in the relevant domain. This is the current limitation of our proposed method, and it is also the content of our future research. Our futher work includes: (a) validate the performance of our proposed method on cross-domain datasets, (b) build a joint model that can automatically extract fine-grained aspects and identify fake reviews

REFERENCES

[1] R. Filieri and F. McLeay, ``E-WOM and accommodation: An analysis of
the factors that in_uence travelers' adoption of information from online
reviews," *J. Travel Res.*, vol. 53, no. 1, pp. 44_57, Jan. 2014.

[2] E. Kauffmann, J. Peral, D. Gil, A. Ferrández, R. Sellers, and H. Mora,
``A framework for big data analytics in commercial social networks: A
case study on sentiment analysis and fake review detection for marketing
decision-making," *Ind. Marketing Manage.*, vol. 90, pp. 523_537,
Oct. 2020.

[3] N. Jindal and B. Liu, ``Review spam detection," in *Proc. 16th Int. Conf.*
World Wide Web, 2007, pp. 1189_1190

[4] A. Mukherjee, V. Venkataraman, B. Liu, and N. S. Glance, ``What
yelp fake review _lter might be doing," in *Proc. ICWSM*, 2013,
pp. 409_418.

[5] S. Rayana and L. Akoglu, ``Collective opinion spam detection: Bridging
review networks and metadata," in *Proc. 21th ACM SIGKDD Int. Conf.*
Knowl. Discovery Data Mining, Aug. 2015, pp. 985_994.

[6] F. Li, M. Huang, Y. Yang, and X. Zhu, ``Learning to identify review
spam," in *Proc. IJCAI 22nd Int. Joint Conf. Artif. Intell.*, vol. 3, 2011,
pp. 2488_2493.

[7] X. Hu, J. Tang, H. Gao, and H. Liu, ``Social spammer detection with
sentiment information," in *Proc. IEEE Int. Conf. Data Mining*, Dec. 2014,
pp. 180_189.

[8] S. Kc and A. Mukherjee, ``On the temporal dynamics of opinion spamming:
Case studies on yelp," in *Proc. 25th Int. Conf. World Wide Web*,
Apr. 2016, pp. 369_379.

[9] Y. Ren and Y. Zhang, ``Deceptive opinion spam detection using neuralnetwork,"
in *Proc. 26th Int. Conf. Comput. Linguistics, Tech. Papers COLING*, Dec. 2016, pp. 140_150.

[10] X. Wang, K. Liu, and J. Zhao, ``Handling cold-start problem in review
spam detection by jointly embedding texts and behaviors," in *Proc. 55th*
Annu. Meeting Assoc. Comput. Linguistics (Long Papers), vol. 1, 2017,
pp. 366_376. [Online]. Available: https://www.aclweb.org/anthology/P17-1034.pdf