GAN-LSTM : LONG SHORT TERM MEMORY BASED GRAPH ATTENTION NETWORK TOWARDS DETECTION, PREVENTION AND CLASSIFICATION OF FAKE REVIEWS IN FOOD ECOMMERCE APPLICATIONS

Dr. N. Hamsaleka, Asst. Professor, Department of CS, A.V.P. College of Arts and Science, Tirupur, Tamilnadu, India.

Dr. V. Kathiresan Principal, A.V.P. College of Arts and Science, Tirupur, Tamilnadu, India

Abstract

Food E commerce Applications is increasing rapidly across all parts of the world due to digital technology evolution and lifestyle of human beings both urban and rural regions. Food E commerce Applications like Swiggy, Uber eats and zomato has been adopted across many peoples in the world due to its fast acquisition of food products to its delivery to consumers. However food review has become increasingly important in making purchase decision by unfamiliar consumers. Unfortunately fake reviewers often utilize advantage of the online review to provide fake review to promote or demote the certain food products and its brands. Incorporation of Natural Language processing tools like BERT and LSTM along artificial intelligence architecture types such as Machine learning and Deep learning architecture were employed to detect and prevent propagation of the fake review. Despite of various advantageous of those tools still it requires major improvement in increasing the prediction accuracy to detect, prevent and classify fake review with reduced processing time. In this article, Graph Attention Network is employed along the Bidirectional Long Short Term Memory to process the review data of the food e commerce applications in form of graph structures. Organizing the review data on graph structure increases computation accuracy and efficiency. Next attention coefficient is incorporated to gather the behavioral changes of the reviewer to various food product on processing their historical review and current reviews. LSTM model is incorporated to process the sentiment associated with reviews. Attention score is calculated for the different opinions of the reviewer to various products and various brands on the multiple context. Particular attention score is processed in the softmax function which uses Support Vector Machine classifier to classify the reviews of the product or brand. Experimental analysis of proposed architecture is carried out using Amazon food review dataset which is popular as e commerce application. On analysis, proposed model proves that it is high capable in detecting, preventing and classifying the fake review of the product. Performance analysis of proposed model represents increased prediction accuracy while compared to state of art approaches.

Keywords : Food Quality, Fake Review Detection , Fake Review Classification , Fake Review Prevention , Graph Attention Network, Natural Language Processing, Deep Learning

1. Introduction

Food quality is nowadays a important constraint in both developed and developing countries. In order to maintain adequate food quality, many types of preservative and food colors were employed to prevent food contamination and food taste. However preservative and food colors may causes many health hazards. In order to avoid these complications, strong food standards has imposed but still many industries were violating these standards. Especially growth of social media and digital technologies has been used to create awareness regarding the food safety standards to increase the knowledge of the people in food quality analysis[1].

Nowadays, food e commerce is been used by people across the world to purchase food items due to lifestyle changes. In India, Food E commerce Applications like Swiggy, Uber eats and zomato has been adopted due to food acquisition and delivery models to consumers. Unfamiliar consumer uses the food review system to make the purchase decision. Unfortunately fake reviewers often utilize advantage of the online review to provide fake review to promote or demote the certain food products and its brands. Incorporation of Natural Language processing tools like BERT and LSTM along artificial intelligence architecture types such as Machine learning and Deep learning architecture were employed to detect and prevent propagation of the fake review. Despite of various advantageous of

those tools still it requires major improvement in increasing the prediction accuracy to detect, prevent and classify fake review with reduced processing time[2].

In this article, Graph Attention Network is employed along the Bidirectional Long Short Term Memory to process the review data of the food e commerce applications in form of graph structures[3]. Organizing the review data on graph structure increases computation accuracy and efficiency. Next attention coefficient is incorporated to gather the behavioral changes of the reviewer to various food product on processing their historical review and current reviews. LSTM model[4] is incorporated to process the sentiment associated with reviews. Attention score is calculated for the different opinions of the reviewer to various products and various brands on the multiple context. Particular attention score is processed in the softmax function which uses Support Vector Machine classifier to classify the reviews of the product or brand[5].

The remaining part of the article is sectioned as follows, section 2 provides the review of existing architectures towards fake review detection in detail and section 3 provides architecture design of the proposed graph attention network to detect, prevent and classify the fake food reviews on association with LSTM model. Section 4 provides the experimental and performance analysis of the proposed architecture against state of art language model using Amazon dataset. Finally article has been summarized with its achievements in section 5.

2. Related work

In this section, existing deep learning model using sentimental analysis towards detection of online fake review is analyzed as follows

2.1. Deep Sentiment Analysis Architecture for Fake Review Detection

In this architecture, review related features are extracted as linguistic features, Part-of-Speech features and sentiment analysis features. Those features are integrated as feature vector and it is processed in the dense convolution neural network to detect and classify it. Initially feature vector processed to generate feature map after normalization finally it is applied to softmax function to classify the fake reviews [6].

3. Proposed model - Graph Attention Network

In this section, a detailed design of the proposed deep learning model and sentiment analysis model is carried out to detect, prevent and classify the fake food review in the food e- commerce applications.

3.1. Graph Representation -Long Term Short Memory

Graph Attention Network is organizes the review data in form of graph structure. Graph contains set of vertices and edge to represent the review data of each user. Further graph vertex[7] is represented with review and edge is represent the user. Graph partition data into groups. Graph with objective function is mentioned as follows

G = (V, E)

V ={ Review 1, review 2, Review 3...Review N}

 $E = \{User 1, User 2, User 3... User N\}$

LSTM model is incorporated to process the sentiment associated with reviews. Sentiment feature is computed on basis of lexicons and sentiment is calculated to various interest in this layer. LSTM model contains various gate to store these sentiment information[8].

3.2. Attention Mechanism

Initially feature vector is computed on graph processing. Next Attention Mechanism assigns different weights to its vertex and edges as attention coefficient to gather the behavioral changes of the reviewer to various food product on processing their historical review and current reviews. Weight Function is used to compute the attention score

Attention score $A_s = \sum_{n=0}^{N} (a(G(v)^t - G(v)^{t-1}))$

Attention score is calculated for the different opinions of the reviewer to various products and various brands on the multiple context. Figure 1 represents the architecture of the proposed model.

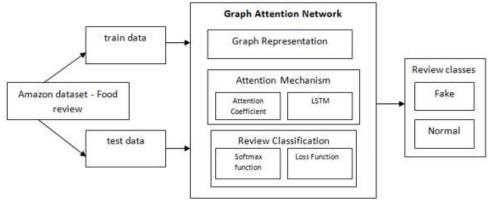


Figure 1: Architecture of the proposed model

3.3. Output Layer

Particular attention score is processed in the softmax function which uses Support Vector Machine[9] classifier to classify the reviews of the product or brand. Softmax classifier classifies the review on basis of the margin. Margin is set as threshold to attention score. It determines the original and fake review of the user easily. Further it helps the application to train the system to prevent the fake review from posting in real time using this architecture as analysis model.

Algorithm : Fake Review classification Input : Product Reviews

Output: Review classes {Authentic review, Fake Review} Process () Graph Attention Network() Graph Representation (Reviews) G(V,E)V is set of reviews E is set of user LSTM () Compute latent features LF = (LF1, LF2, ..., LF3)Compute sentiment feature SF = (SF1, SF2, ..., SF3)**Compute Context Feature** $CF = \{CF1, CF2...CF3\}$ Attention Mechanism (SF+AF+CF) Assign Coefficient to each category of features **Compute Attention Score** Weight Function (Attention Coefficient of each category of features) Attention Score $A_s = \{w1, w2, w3...wn\}$ Output layer () Softmax function (SVM) Set Margin = Attention Score Threshold Margin(Attention Score> Threshold) Authentic Review Attention Score<Threshold Fake Review

4. Experimental Analysis

Experimental analysis of the proposed graph attention network is carried out using amazon food review dataset[10]. Experiment is done in python environment . Dataset is partitioned into training data and testing data. Model training is done using training data and model validation is achieved using cross fold validation. Model is evaluated on basis of its effectiveness in detecting and

classifying the fake reviews in review collections. Further model accuracy is computed using following metric

• Precision : It is defined as ratio of review classified as fake among all the reviews of the model. It is computed using confusion matrix as it provides true positive, true negative, false positive and false negative value on cross validation.

Tuble 21 I enternance Evaluation of Face review detection architectures			
Metric	Class	DCNN +BERT – Existing	GAN+LSTM
Precision Analysis	Fake Opinion Class	96.15	99.98
	Normal Opinion Class	98.33	99.78
Recall Analysis	Fake Opinion Class	94.52	97.28
	Normal Opinion Class	96.58	97.26
F Measure Analysis	Fake Opinion Class	98.19	99.45
	Normal Opinion Class	99.78	99.78

• Table 2: Performance Evaluation of Fake review detection architectures

Figure 2 represents the precision analysis of the deep learning model against fake review detection and classification.

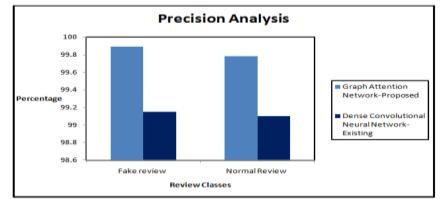


Figure 2: Precision analysis

• **Recall**: It is defined as specific classes which classifies all reviews correctly among other classes. Figure 3 represents the recall analysis of the deep learning model against fake review detection and classification

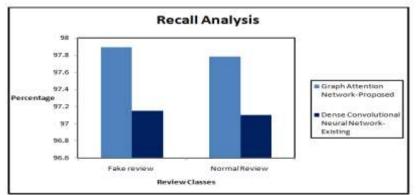


Figure 3: Recall Analysis

• **F Measure** : It is average of precision and Recall. Figure 4 represents the f measure analysis of the deep learning model against fake review detection and classification. Table 2 provides the performance evaluation results of the fake review detection architectures.

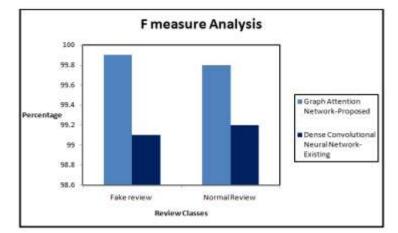


Figure 4: F-measure Analysis

Conclusion

In this work, Graph Attention Network along Long Short Term Memory is designed and experimented to process the review data to classify it into fake review and authentic review. Initially review data is organized in graph structure. Next attention coefficient is incorporated to gather the behavioral changes of the reviewer to various food product on processing their historical review and current reviews. LSTM model is incorporated to extract the sentiment features, context feature and latent features associated with reviews. Attention score is calculated for the different opinions of the reviewer to various brands on the multiple context and its sentiment. Particular attention score is processed in the softmax function which uses Support Vector Machine classifier to classify the reviews of the product or brand into fake or normal. Finally experimental analysis and performance analysis of proposed architecture is carried out using Amazon food review dataset . It is proved that proposed model represents increased prediction accuracy while compared to state of art approaches

References

- 1. Jindal, N.; Liu, B. Analyzing and Detecting Review Spam. In Proceedings of the Seventh IEEE International Conference on Data Mining (ICDM 2007), Omaha, NE, USA, 28–31 October 2007; pp. 547–552.
- Jindal, N.; Liu, B. Review Spam Detection. In Proceedings of the 16th International Conference on World Wide Web, WWW'07, Banff, AB, Canada, 8–12 May 2007; Association for Computing Machinery: New York, NY, USA, 2007; pp. 1189–1190.
- 3. Jindal, N.; Liu, B. Opinion Spam and Analysis. In Proceedings of the 2008 International Conference on Web Search and Data Mining, WSDM'08, Palo Alto, CA, USA, 11–12 February 2008; Association for Computing Machinery: New York, NY, USA, 2008; pp. 219–230.
- 4. Ott, M.; Cardie, C.; Hancock, J. Estimating the Prevalence of Deception in Online Review Communities. In Proceedings of the 21st International Conference on World Wide Web, WWW'12, Lyon, France, 16–20 April 2012; Association for Computing Machinery: New York, NY, USA, 2012; pp. 201–210
- 5. Ullrich, S.; Brunner, C.B. Negative online consumer reviews: Effects of different responses. J. Prod. Brand Manag. 2015, 24, 66–77.
- 6. Zhang, Y.; Jin, R.; Zhou, Z.H. Understanding bag-of-words model: A statistical framework. Int. J. Mach. Learn. Cybern. 2010, 1, 43–52.
- 7. Sudhakaran, P.; Hariharan, S.; Lu, J. A framework investigating the online user reviews to measure the biasness for sentiment analysis. Asian J. Inf. Technol. 2016, 15, 1890–1898. [Google Scholar]
- 8. Wu, Y.; Ngai, E.W.; Wu, P.; Wu, C. Fake online reviews: Literature review, synthesis, and directions for future research. Decis. Support Syst. 2020, 132, 113280.
- 9. Qiu, X.; Sun, T.; Xu, Y.; Shao, Y.; Dai, N.; Huang, X. Pre-trained models for natural language processing: A survey. Sci. China Technol. Sci. 2020, 63, 1872–1897.
- 10. Devlin, J.; Chang, M.W.; Lee, K.; Toutanova, K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv 2018, arXiv:1810.04805.