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Detection of Fake News Using Deep Learning

[1]M. Kavitha, [2]Anees U.K.

[1]Assistant professor/Arifical Intelligence and Data Science Kathir College of Engineering Coimbatore
[2]Student, Computer Science and Engineering, Kathir College of Engineering, Coimbatore, Tamilnadu

ABSTRACT

Fake news and false information are big challenges of all types of media, especially social media. There is a lot of false information, fake likes, views, and duplicated accounts as big social networks such as Facebook and Twitter admitted. Most information appearing on social media is doubtful and in some cases misleading. The dimensions of the fake news datasets are proliferating, so to obtain a better result of detecting false information with less computation time and complexity, the dimensions need to be reduced. This study aims to apply natural language

processing (NLP) techniques for text analytics and train deep learning models for detecting fake news based on news titles or news content. For NLP techniques, text preprocessing such as regular expression, tokenization, lemmatization, and stop words removal are used before vectorizing them into N-gram vectors or sequence vectors using terms frequency-inverse document frequency or one-hot encoding respectively. Then we can choose the framework as tensor flow and it can be used with deep learning communities which is having a large number of libraries. It is necessary to build a deep learning neural network. The news needs less time to complete the training using the deep learning neural network and to achieve good performance. Also, the overall performance of models fed with N-gram vectors is slightly better than models fed with sequence vectors. On the one hand, the detection runtime process decreased. On the other hand, the classification accuracy increased because of the elimination of redundant features and the reduction of datasets dimensions.

Keywords: Fake news detection, social media. natural language processing, deep learning, neural network,

I. INTRODUCTION

Detecting fake news has become a new research topic in recent years as the continuous spread of false information has raised the need for assessing the authenticity of digital content. Fake news is mostly created to influence people's perceptions in order to distort consciousness and decision-making [1], [2]. Although the dissemination of false information on the Internet is not a new phenomenon, the extensive usage of social media increases its negative impact on society and also more creation of fake news media.These days, with the growth of technologies, information is distributed very quickly and its impact on social networks is incredible as it can be reinforced and affect millions of users remarkably in a few minutes [3]. Fact-checking, information validation, and verification is a long-term issue that influences all types of media.

Fake news is one of the biggest scourges in digital connected world. It is defined as a subject including news, data, report, and information that is wholly or partly false. The impact of fake news from personnel on society is huge and no longer limit to conflict. It is a wildfire and will influence many people every day. Fakes news created a threat to a country’s security, economy, prosperity, and individual. People might not aware of how fake news could impact matters surrounding them on how to handle it when it happens. Billions of articles are created every day on the web, people might be the helping hand by spreading this news without knowing whether this news is real or fake. A simple action has become a serious issue if there is no control gate to prevent fake news stories from being spread aggressively. News-related data are usually described with many features and it is possible that most of them are unrelated and redundant for the desired data mining. A large number of these unrelated features make a negative impact on fake news detection algorithm performance whilst the computational complexity is very high too.

Besides, minimizing the dimensions of the dataset by removing unrelated redundant features is a challenging task in data mining and machine learning. This paper is organized as follows. The second section reviews the previous works on fake news detection approaches. The third section describes the proposed method. Evaluation and analysis discussion of the proposed method is described in section four and finally, the last section gives the conclusion of this paper.

II. METHODS AND MATERIAL

Research in the area of news verification and debunking of false information on the web involves different activities in order to achieve the best results (Rashkin et al., 2017). Despite the rapid increase in its popularity, the subject is still in its infancy among researchers. While there has been an increase in the number of studies that focus on the analysis and study of fake news and/or rumor characteristics in order to properly identify and debunk false information, there is still enough room left for research in this direction since there is not a unified solution yet (Vosoughi et al., 2018). Spreading of fake news and misleading information can eventually cause confusion and rumors circulating around and the victims could be badly impacted, one of the worst impacts is committing suicide.

The existing system on the topics of deep learning for deception and fake news detection has been focusing on online reviews and public postings on social media. It is difficult to detect fake news because it can be existing in a variety of patterns and there's a huge leap in NLP frameworks to avoid misinformation and fake news spreading around, fake news detection is much needed, and this project proposes 4 similar neural network models are to be trained and each model is fed with different text vectors of news title and news content so to be compared on the model performance. The 4 similar neural network models to be trained are as follows:

1. Model 1: Fed with N-gram vectors of the news title
2. Model 2: Fed with N-gram vectors of news content
3. Model 3: Fed with sequence vectors of the news title
4. Model 4: Fed with sequence vectors of news content.

To express the problem to solve in a more formal way; given as a news article defined by a set of own characteristics (ie. title, text, photos, newspaper, author, ...), a function is sought such as

$$f(a) = \begin{cases} 0 & \text{if a is fake} \\ 1 & \text{if a is true} \end{cases}$$

This section presents an overview of the dataset, preprocessing techniques, and a description of the deep learning model used for classification. Figure 1 represents the proposed study methodology. The dataset contains two types of features such as short textual features, i.e., statements,s, and other features like speaker job title, subject, and venue. Therefore, the features were initially divided according to the category. For the statement attribute, several NLP techniques like tokenization, lemmatization, and stop word removal were used. However, for the other category of features, different data preprocessing techniques were applied that will be discussed further in the preprocessing section.

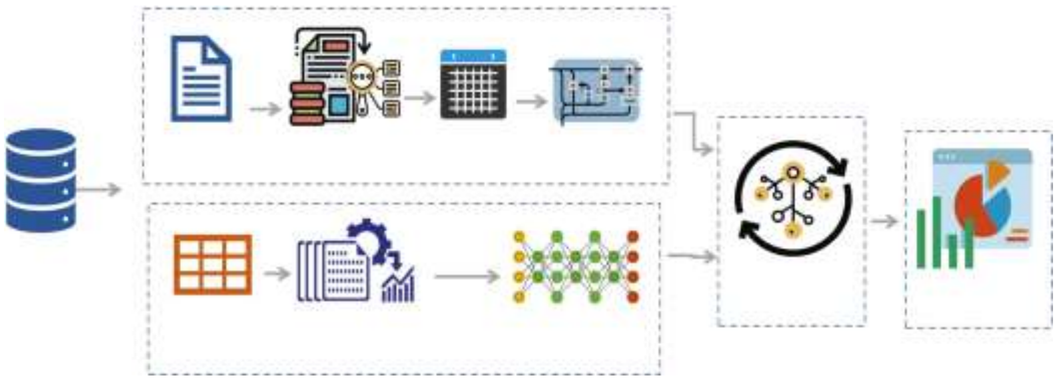

Fig 1: Block diagram of the proposed study methodology.

III RESULTS AND DISCUSSION

Data set description

The study used "LIAR" dataset [4] that contains 12.8 K human-labeled short statements from POLITIFACT.COM, and each statement is checked for its truthfulness by a POLITIFACT.COM editor. It has six categories for the label to rate accuracy, which are pants fire, false, mostly true, half true, mostly true, and true. The dates for the statements are primarily from 2007 to 2016.

The speakers include a combination of democrats and republicans, and for each speaker, there is a rich collection of metadata that includes historical counts of false statements for each speaker. Such statements are sampled from different contexts/venues, and also the speakers are discussing a diverse set of subjects. Table 1 shows the description of the dataset. The statistical analysis of the historical counts of inaccurate statements for each speaker is also presented in the table. For the numeric variable mean (μ), standard deviation (σ), and range are used. However, a categorical variable number of categories has been used. The table also contains the number of missing values per attribute. In the dataset, only three attributes have missing values, namely, the speaker's job title, state info, and the context. The study used the records with the class label true and false with a total number of records of 4557. The number of news records with true class labels is 2053 and with a false class, the label is 2504, respectively.

Table 1: Description of the LIAR dataset.

Model for Fake News Detection

Table 1

Description of the LIAR dataset.

No.	Feature name	Datatype	Missing values	Mean (μ) ± Std (σ)	Range	No. of categories
1	ID of the statement	Object	—	—		
2	Label	Object	—	—		2
3	Statement	Object	—	—		4007
4	Subject(s)	Object	—	—		1823
5	Speaker	Object	—	—		9
6	Speaker's job title	Object	1184	—		656
7	State info	Object	926	—		
8	Party affiliation	Object	—	—		4
9	Barely true counts	Int (64)	—	11.59 ± 18.98	0–70	
10	False counts	Int (64)	—	13.36 ± 24.14	0–114	
11	Half true counts	Int (64)	—	17.19 ± 35.85	0–160	
12	Mostly true counts	Int (64)	—	16.50 ± 36.17	0–163	
13	Pants on fire counts	Int (64)	—	6.25 ± 16.18	0–70	
14	The context (venue/location of the speech or statement)	Object	52			

4.1. Preprocessing

Several preprocessing techniques were applied to the dataset. Initially, the dataset consists of 14 attributes. Three attributes have missing values, namely, state_info, speaker job title, and venue. State info was removed from the study due to the low relevance of the attribute. However, the other two attributes with missing values, namely, speaker's_job title and venue were included for further analysis. In the speaker's job title and venue, attribute missing values were replaced with the unique category unknown. The party affiliation feature consists of 24 categories and is converted into four categories, namely, republican, democrat, unknown, and other, respectively. The category none is replaced with unknown while all other 19 categories are replaced with other except republican and democrat. Normalization was performed on four columns, namely, barely true counts, false counts, half true counts, mostly true counts, and pants on fire counts, respectively. The data were normalized in the range (0-1).

Figure 2 represents the number of records per category for the party affiliation attribute. Venue attribute was reduced to 8 categories, namely, interview (1686 records), other (766 records), ad (685 records), news (427 records), social media (316 records), website (72 records), unknown (39 records), and show (20 records), respectively. The distribution of categories for the subject attributes is shown in Figure

3. Similarly, the speaker job title attribute was converted into 9 categories such as unknown (1089 records), other (968 records), state representative (730 records), president (469 records), US representative records, media (159 records), government (157 records), company (58 records), and office director (31 records), respectively. Figure 4 represents the number of records per category for subject attribute after reduction.

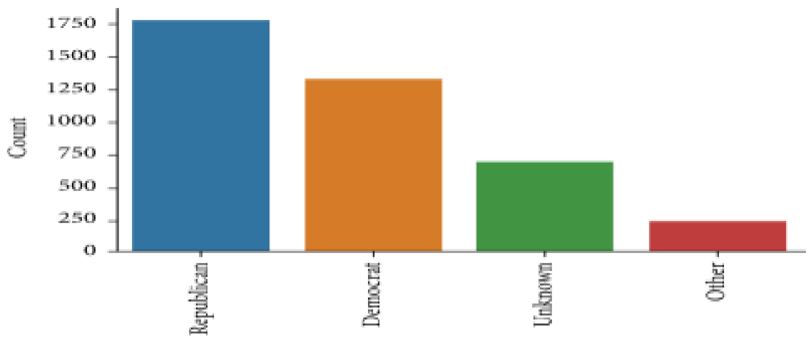

Figure 2: Number of records per category for party affiliation attribute.

Besides, models trained with news titles require relatively less computation time when compared to models trained with news content. This is also the key reason why training models with news titles instead of only training with news content can yield higher accuracy and recall rate. In social media applications such as WhatsApp, WeChat, and more which can be used for chatting and social networking, users tend to respond faster to incoming messages and fake news can be spread faster if anyone intended to do so. In this case, models with low computation time and high recall rate are much required. Therefore, models trained with news titles can eventually come in place to detect any fake news generated.

Despite longer computation time, models trained with news content can also be used in social media applications such as Facebook and Twitter where the fake news is coming from feeds. The fake news may not need to be detected as soon as it is published because users' feeds may not be updated so soon. But with higher accuracy and recall model which can accurately detect fake news, the feeds can be removed as soon as the model detects the fake news.

CONCLUSION

The primary goal of this paper is to reduce the drawback of social media, which is the fast spread of fake news that often misleads people, creates wrong perceptions, and has a negative influence on society. Therefore, an ensemble-based deep learning model is constructed to classify the news as fake or real. Several preprocessing techniques were applied initially to the dataset. Furthermore, NLP techniques were applied to statement attributes. Two deep learning models were used, the deep learning dense model for the other 9 attributes excluding statements and the Bi-LSTM-GRU-dense model for statement attributes. The results achieved by the proposed study are significant with an accuracy of 0.898 using the statement feature. This model performance surpassed the other studies on the same dataset, and it is very effective in detecting fake news. Finally, fake news detection using machine learning is still a new topic and challenging. Despite the significant results achieved by the proposed study, there is still room for improvement. The model needs to be investigated using other fake news datasets.

The best neural network model trained in this project work can achieve up to 90.3% accuracy with 97.5% recall that can accurately detect fake news with very low mistakes. Neural network models trained with N-gram vectors are performing slightly better than models trained with sequence vectors mainly because of N-gram vectors using TF-IDF which will not rely only on term frequency, but also on a weighted score that emphasizes more important terms. Models trained with news titles are suitable to be used in social media applications in that users would respond fast to any updates or incoming messages due to their fast computation time and high recall rate (low mistake rate). With fast computation, any message that sends out fake news can be stopped. On the other hand, for social media applications are having feeds updated from time to time, fast computation time is not very crucial and therefore, models trained with news content that would have higher accuracy and recall will be of a better choice to accurately detect the fake news and stop users from spreading it

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