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Fake News Detection with Deep Learning

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Abstract:-The advent of the World Wide Web and the rapid adoption of social media platforms (such as Facebook and Twitter) paved the way for information dissemination that has never been witnessed in the human history before. With the current usage of social media platforms, consumers are creating and sharing more information than ever before, some of which are misleading with no relevance to reality. Automated classification of a text article as misinformation or disinformation is a challenging task. Even an expert in a particular domain has to explore multiple aspects before giving a verdict on the truthfulness of an article. In this work, we propose to use machine learning ensemble approach for automated classification of news articles. Our study explores different textual properties that can be used to distinguish fake contents from real. By using those properties, we train a combination of different machine learning algorithms using various ensemble methods and evaluate their performance on 4 real world datasets. Experimental evaluation confirms the superior performance of our proposed ensemble learner approach in comparison to individual learners.

Keywords: Machine Learning, Neural Networks, Deep Learning, LSTM (RNN), Deep Learning and Tensorflow.

INTRODUCTION

The rise of fake news during the 2016 U.S. Presidential Election highlighted not only the dangers of the effects of fake news but also the challenges presented when attempting to separate fake news from real news. Fake news may be a relatively new term but it is not necessarily a new phenomenon. Fake news has technically been around at least since the appearance and popularity of one-sided, partisan newspapers in the 19th century. However, advances in technology and the spread of news through different types of media have increased the spread of fake news today. As such, the effects of fake news have increased exponentially in the recent past and something must be done to prevent this from continuing in the future.

The advent of the World Wide Web and the rapid adoption of social media platforms (such as Facebook and Twitter) paved the way for information dissemination that has never been witnessed in the human history before. Besides other use cases, news outlets benefitted from the widespread use of social media platforms by providing updated news in near real time to its subscribers. The news media evolved from newspapers, tabloids, and magazines to a digital form such as online news platforms, blogs, social media feeds, and other digital media formats [1].

It became easier for consumers to acquire the latest news at their fingertips. Facebook referrals account for 70% of traffic to news websites [2]. These social media platforms in their current state are extremely powerful and useful for their ability to allow users to discuss and share ideas and debate over issues such as democracy, education, and health. However, such platforms are also used with a negative perspective by certain entities commonly for monetary gain [3, 4] and in other cases for creating biased opinions, manipulating mind sets, and spreading satire or absurdity. The phenomenon is commonly known as fake news.

There has been a rapid increase in the spread of fake news in the last decade, most prominently observed in the 2016 US elections [5]. Such proliferation of sharing articles online that do not conform to facts has led to many problems not just limited to politics but covering various other domains such as sports, health, and also science [3]. One such area affected by fake news is the financial markets [6], where a rumour can have disastrous consequences and may bring the market to a halt.

Our ability to take a decision relies mostly on the type of information we consume; our world view is shaped on the basis of information we digest. There is increasing evidence that consumers have reacted absurdly to news that later proved to be fake [7, 8]. One recent case is the spread of novel corona virus, where fake reports spread over the Internet about the origin, nature, and behaviour of the virus [9]. The situation worsened as more people read about the fake contents online. Identifying such news online is a daunting task.

Fortunately, there are a number of computational techniques that can be used to mark certain articles as fake on the basis of their textual content [10]. Majority of these techniques use fact checking websites such as "PolitiFact" and "Snopes." There are a number of repositories maintained by researchers that contain lists of websites that are identified as ambiguous and fake [11]. However, the problem with these resources is that human expertise is required to identify articles/websites as fake. More importantly, the fact checking websites contain articles from particular domains such as politics and are not generalized to identify fake news articles from multiple domains such as entertainment, sports, and technology.

The World Wide Web contains data in diverse formats such as documents, videos, and audios. News published online in an unstructured format (such as news, articles, videos, and audios) is relatively difficult to detect and classify as this strictly requires human expertise. However, computational techniques such as natural language processing (NLP) can be used to detect anomalies that separate a text article that is deceptive in nature from articles that are based on facts [12]. Other techniques involve the analysis of propagation of fake news in contrast with real news [13].

More specifically, the approach analyses how a fake news article propagates differently on a network relative to a true article. The response that an article gets can be differentiated at a theoretical level to classify the article as real or fake. A more hybrid approach can also be used to analyse the social response of an article along with exploring the textual features to examine whether an article is deceptive in nature or not.

A number of studies have primarily focused on detection and classification of fake news on social media platforms such as Facebook and Twitter [13, 14]. At conceptual level, fake news has been classified into different types; the knowledge is then expanded to generalize machine learning (ML) models for multiple domains [10, 15, 16]. The study by Ahmed et al)

According to the research, as the number of increased in-grams calculated for a particular article, the overall accuracy decreased. The phenomenon has been observed for learning models that are used for classification. Shu et al. [12] achieved better accuracies with different models by combining textual features with auxiliary information such as user social engagements on social media. The authors also discussed the social and psychological theories and how they can be used to detect false information online. Further, the authors discussed different data mining algorithms for model constructions and techniques shared for features extraction. These models are based on knowledge such as writing style, and social context such as stance and propagation.

RNN:-An RNN remembers each and every information through time. It is useful in time series prediction only because of the feature to remember previous inputs as well. This is called Long Short Term Memory. Recurrent neural network are even used with convolutional layers to extend the effective pixel neighbourhood.

LSTM (**Long Short Term Memory Network**):**-**

To solve the problem of Vanishing and Exploding Gradients in a Deep Recurrent Neural Network, many variations were developed. One of the most famous of them is the **Long Short Term Memory Network** (LSTM). In concept, an LSTM recurrent unit tries to "remember" all the past knowledge that the network is seen so far and to "forget" irrelevant data. This is done by introducing different activation function layers called "gates" for different purposes. Each LSTM recurrent unit also maintains a vector called the **Internal Cell State** which conceptually describes the information that was chosen to be retained by the previous LSTM recurrent unit. A Long Short Term Memory Network consists of four different gates for different purposes as described below:**-**

Forget Gate (f): It determines to what extent to forget the previous data**.**

Input Gate (I): It determines the extent of information be written onto the Internal Cell State.

Input Modulation Gate (g): It is often considered as a sub-part of the input gate and much literature on LSTM's does not even mention it and assume it is inside the Input gate. It is used to modulate the information that the Input gate will write onto the Internal State Cell by adding non-linearity to the information and making the information Zero-mean. This is done to reduce the learning time as Zero-mean input has faster convergence. Although this gate's actions are less important than the others and are often treated as a finesse-providing concept, it is good practice to include this gate in the structure of the LSTM unit.

Output Gate (o): It determines what output (next Hidden State) to generate from the current Internal Cell State.

Related Work

Mykhailo Granik ET. Al. in their paper [3] shows a simple approach for fake news detection using naive Bayes classifier. This approach was implemented as a software system and tested against a data set of Facebook news posts. They were collected from three large Facebook pages each from the right and from the left, as well as three large mainstream political news pages (Politico, CNN, ABC News). They achieved classification accuracy of approximately 74%. Classification accuracy for fake news is slightly worse. This may be caused by the skewness of the dataset: only 4.9% of it is fake news.

Himank Gupta et. al. [10] gave a framework based on different machine learning approach that deals with various problems including accuracy shortage, time lag (Bot Maker) and high processing time to handle thousands of tweets in 1 sec. Firstly, they have collected 400,000 tweets from HSpam14 dataset. Then they further characterize the 150,000 spam tweets and 250,000 non-spam tweets. They also derived some lightweight features along with the Top-30 words that are providing highest information gain from Bag-of- Words model. 4. They were able to achieve an accuracy of 91.65% and surpassed the existing solution by approximately18%.

Marco L. Della Vedova et. al. [11] first proposed a novel ML fake news detection method which, by combining news content and social context features, outperforms existing methods in the literature, increasing its accuracy up to 78.8%. Second, they implemented their method within a Facebook Messenger Chabot and validate it with a real-world application, obtaining a fake news detection accuracy of 81.7%. Their goal was to classify a news item as reliable or fake; they first described the datasets they used for their test, then presented the content-based approach they implemented and the method they proposed to combine it with a social-based approach available in the literature. The resulting dataset is composed of 15,500 posts, coming from 32 pages (14 conspiracy pages, 18 scientific pages), with more than2, 300, 00 likes by 900,000+ users. 8,923 (57.6%) posts are hoaxes and 6,577 (42.4%) are non-hoaxes.

Cody Buntain et. al. [12] develops a method for automating fake news detection on Twitter by learning to predict accuracy assessments in two credibility- focused Twitter datasets: CREDBANK, a crowd sourced dataset of accuracy assessments for events in Twitter, and PHEME, a dataset of potential rumours in Twitter and journalistic assessments of their accuracies. They apply this method to Twitter content sourced from BuzzFeeds fake news dataset. A feature analysis identifies features that are most predictive for crowd sourced and journalistic accuracy assessments, results of which are consistent with prior work. They rely on identifying highly retweeted threads of conversation and use the features of these threads to classify stories, limiting this works applicability only to the set of popular tweets. Since the majority of tweets are rarely retweeted, this method therefore is only usable on a minority of Twitter conversation threads.

In his paper, Shivam B. Parikhet. al. [13] aims to present an insight of characterization of news story in the modern diaspora combined with the differential content types of news story and its impact on readers. Subsequently, we dive into existing fake news detection approaches that are heavily based on text- based analysis, and also describe popular fake news datasets. We conclude the paper by identifying 4 key open research challenges that can guide future research. It is a theoretical Approach which gives Illustrations of fake news detection by analysing the psychological factors.

Proposed Work

After Analysing various algorithms and techniques, we found that RNN can be very effective in analysing the text data of any news. So we implemented the fake news detection model at application level. We built an web application of news which will work as OTT app and the content of the app is pre analysed. So that we can minimize the chance of fake news on the application.

Conclusion

In the 21st century, the majority of the tasks are done online. Newspapers that were earlier preferred as hard- copies are now being substituted by applications like Facebook, Twitter, and news articles to be read online. WhatsApp's forwards are also a major source. The growing problem of fake news only makes things more complicated and tries to change or hamper the opinion and attitude of people towards use of digital technology. When a person is deceived by the real news two possible things happen- People start believing that their perceptions about a particular topic are true as assumed. Thus, in order to curb the phenomenon, we have developed our Fake news Detection system that takes input from the user and classify it to be true or fake. To implement this, LSTMs and Other Machine Learning Techniques have to be used. The model is trained using an appropriate dataset and performance evaluation is also done using various performance measures. The best model, i.e. the model with highest accuracy is used to classify the news headlines or articles.

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