FAKE NEWS DETECTION USING DEEP LEARNING

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Abstract - Due to the exponential growth of information online, it is becoming impossible to decipher the true from the false. Thus, this leads to the problem of fake news. This research considers previous and current methods for fake news detection in textual formats while detailing how and why fake news exists in the first place. This paper includes a discussion on Linguistic Cue and Network Analysis approaches, and proposes a three-part method using Naïve Bayes Classifier, Support Vector Machines, and Semantic Analysis as an accurate way to detect fake news on social media. This Project comes up with the applications of NLP (Natural Language Processing) techniques for detecting the 'fake news', that is, misleading news stories that comes from the non-reputable sources. Only by building a model based on a count vectorizer (using word tallies) or a (Term Frequency Inverse Document Frequency) tfidf matrix, (word tallies relative to how often they're used in other articles in your dataset) can only get you so far. But these models do not consider the important qualities like word ordering and context. It is very possible that two articles that are similar in their word count will be completely different in their meaning. The data science community has responded by taking actions against the problem. There is a Kaggle competition called as the "Fake News Challenge" and Facebook is employing AI to filter fake news stories out of users' feeds. Combatting the fake news is a classic text classification project with a straight forward proposition. Is it possible for you to build a model that can differentiate between "Real "news and "Fake" news? So a proposed work on assembling a dataset of both fake and real news and employ a Naive Bayes classifier in order to create a model to classify an article into fake or real based on its words and phrases.

1. INTRODUCTION

These days' fake news is creating different issues from sarcastic articles to a fabricated news and plan government propaganda in some outlets. Fake news and lack of trust in the media are growing problems with huge ramifications in our society. Obviously, a purposely misleading story is "fake news " but lately blathering social media's discourse is changing its definition. Some of them now use the term to dismiss the facts counter to their preferred viewpoints.The importance of disinformation within American political discourse was the subject of weighty attention, particularly following the American president election. The term 'fake news' became common parlance for the issue, particularly to describe factually incorrect and misleading articles published mostly for the purpose of making money through page views. In this paper, it is seeked to produce a model that can accurately predict the likelihood that a given article is fake news. Facebook has been at the epicenter of much critique following media attention. They have already implemented a feature to flag fake news on the site when a user sees's it; they have also said publicly they are working on to distinguish these articles *in* an automated way. Certainly, it is not an easy task. A given algorithm must be politically unbiased – since fake news exists on both ends of the spectrum – and also give equal balance to legitimate news sources on either end of the spectrum. In addition, the question of legitimacy is a difficult one. However, in order to solve this problem, it is necessary to have an understanding on what Fake News is. Later, it is needed to look into how the techniques in the fields of machine learning, natural language processing help us to detect fake news.

Fake news denotes a type of yellow press which intentionally presents misinformation or hoaxes spreading through both traditional print news media and recent online social media. Fake news has been existing for a long time, since the "Great moon hoax" published

In 1835 [1]. In recent years, due to the booming developments of online social networks, fake news for various commercial and political purposes has been appearing in large numbers and widespread in the online world. With deceptive words, online social network users can get infected by these online fake news easily, which has brought about tremendous effects on the offline society already. During the 2016 US president election, various kinds of fake news about the candidates widely spread in the online social networks, which may have a significant effect on the election results. According to a post-election statistical report [4], online social networks account for more than 41.8% of the fake news data traffic in the election, which is much greater than the data traffic shares of both traditional TV/radio/print medium and online search engines respectively.

An important goal in improving the trustworthiness of information in online social networks is to identify the fake news timely, which will be the main tasks studied in this paper. Fake news has significant differences compared with traditional suspicious information, like spams [70], [71], [20], [3], in various aspects: (1) impact on society: spams usually exist in personal emails or specific review websites and merely have a local impact on a small number of audiences, while the impact fake news in online social networks can be tremendous due to the massive user numbers globally, which is further boosted by the extensive information sharing and propagation among these users [39], [61], [72]; (2) audiences' initiative: instead of receiving spam emails passively, users in online social networks may seek for, receive and share news information actively with no sense about its correctness; and (3) identification difficulty: via comparisons with abundant regular messages (in emails or review websites), spams are usually easier to be distinguished; meanwhile, identifying fake news with erroneous information is incredibly challenging, since it requires both tedious evidence-collecting and careful fact checking due to the lack of other comparative news articles available. These characteristics aforementioned of fake news pose new challenges on the detection task. Besides detecting fake news articles, identifying the fake news creators and subjects will actually be more important, which will help completely eradicate a large number of fake news from the origins in online social networks. Generally, for the news creators, besides the articles written by them, we are also able to retrieve his/her profile information from either the social network website or external knowledge libraries, e.g., Wikipedia or government-internal database, which will provide fundamental complementary information for his/her background check. Meanwhile, for the news subjects, we can also obtain its textual descriptions or other related information, which can be used as the foundations for news subject credibility inference. From a higher-level perspective, the tasks of fake news article, creator and subject detection are highly correlated, since the articles written from a trustworthy person should have a higher credibility, while the person who frequently posting unauthentic information will have a lower credibility on the other hand.

Similar correlations can also be observed between news articles and news subjects. In the following part of this paper, without clear specifications, we will use the general fake news term to denote the fake news articles, creators and Problem Studied: In this paper, we propose to study the fake news detection (including the articles, creators and subjects) problem in online social networks. Based on various types of heterogeneous information sources, including both textual contents/profile/descriptions and the authorship and article subject relationships among them, we aim at identifying fake news from the online social networks simultaneously. We formulate the fake news detection problem as a credibility inference problem, where the real ones will have a higher credibility while unauthentic ones will have a lower one instead. The fake news detection problem…

1.1 EXISTING SYSTEM

There exists a large body of research on the topic of machine learning methods for deception detection, most of it has been focusing on classifying online reviews and publicly available social media posts. Particularly since late 2016 during the American Presidential election, the question of determining 'fake news' has also been the subject of particular attention within the literature.

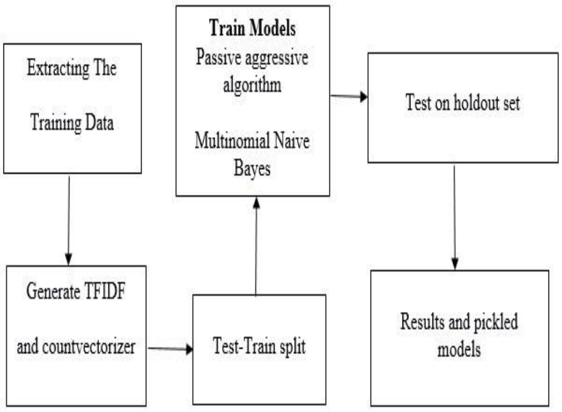
- Conroy, Rubin, and Chen [1] outlines several approaches that seem promising towards the aim of perfectly classify the misleading articles. They note that simple content-related n-grams and shallow parts-of-speech (POS) tagging have proven insufficient for the classification task, often failing to account for important context information. Rather, these methods have been shown useful only in tandem with more complex methods of analysis. Deep Syntax analysis using Probabilistic Context Free Grammars (PCFG) have been shown to be particularly valuable in combination with n-gram methods. Feng, Banerjee, and Choi [2] are able to achieve 85%-91% accuracy in deception related classification tasks using online review corpora.

DATASET DETAILED ANALYSIS:

Article Credibility Analysis with Textual Content: In Figures 1(a)-1(b), we illustrate the frequent word cloud of the true and false news articles, where the stop words have been removed already. Here, the true article set covers the news articles which are rated "True", "Mostly True" or "Half True"; meanwhile, the false article set covers the news articles which are rated "Pants on Fire!", "False" or "Mostly False". According to the plots, from Figure 1(a), we can find some unique words in True-labeled articles which don't appear often in Figure 1(b), like "President", "income", "tax" and "american", ect.; meanwhile, from Figure 1(b), we can observe some unique words appearing often in the false articles, which include "Obama", "republican" "Clinton", "obamacare" and "gun", but don't appear frequently in the True-labeled articles. These textual words can provide important's.

1.2 PROPOSED SYSTEM

In this paper a model is build based on the count vectorizer or a tfidf matrix (i.e) word tallies relatives to how often they are used in other artices in your dataset) can help . Since this problem is a kind of text classification, Implementing a Naive Bayes classifier will be best as this is standard for text-based processing. The actual goal is in developing a model which was the text transformation (count vectorizer vs tfidf vectorizer) and choosing which type of text to use (headlines vs full text). Now the next step is to extract the most optimal features for countvectorizer or tfidf-vectorizer, this is done by using a n-number of the most used words, and/or phrases, lower casing or not, mainly removing the stop words which are common words such as “the”, “when”, and “there” and only using those words that appear at least a given number of times in a given text dataset.



2. NAIVE BAYES CLASSIFIER

In machine learning, naïve Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features. They are among the simplest Bayesian network models. The problem of judging documents as belonging to one category or the other (document categorization)(such as spam or legitimate, sports or politics, etc.) with word frequencies as the features. With appropriate pre-processing, it is competitive in this domain with more advanced methods including support vector machines. It also finds application in automatic medical diagnosis. Naïve Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers.

- There is not a single algorithm for training such classifiers, but a family of algorithms based on a common principle: all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable. For example, a fruit may be considered to be an apple if it is red, round, and about 10 cm in diameter. A naive Bayes classifier considers each of these features to contribute independently to the probability that this fruit is an apple, regardless of any possible correlations between the color, roundness, and diameter features.

- An advantage of naive Bayes is that it only requires a small number of training data to estimate the parameters necessary for classification.

- **SOFTWARE DESCRIPTION:**
- **if response_code == RPL_ENDOFNAMES:**
- **# Display the names**
- **print ‘\r\nUsers in %(channel)s:’ % irc**
- **for name in names:**
- **print name**
- **names = []**
- This tells Python that when the 366 response has been received, it should print out the now-complete list of names to the standard output before blanking the names list again. This last line—names = []—is important: without it, each time the loop runs it will add users’ names to the list even though they already exist from an earlier run. Finally, finish the program by entering the following lines:

  time.sleep(irc[‘namesinterval’])

  s.send(‘NAMES %(channel)s\r\n’ % irc)

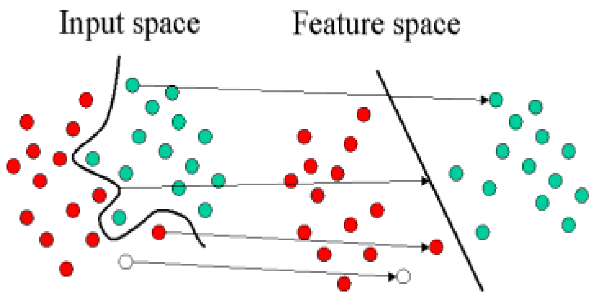


Fig -1: OUTPUT

3. CONCLUSION

In this paper, we have studied the fake news article, creator and subject detection problem. Based on the news augmented heterogeneous social network, a set of explicit and latent features can be extracted from the textual information of news articles, creators and subjects respectively. Furthermore, based on the connections among news articles, creators and news subjects, a deep diffusive network model has been proposed for incorporate the network structure information into model learning. In this paper, we also introduce a new diffusive unit model, namely GDU. Model GDU accepts multiple inputs from different sources simultaneously, and can effectively fuse these input for output generation with content “forget”and “adjust” gates. Extensive experiments done on a realworld fake news dataset, i.e., PolitiFact, have demonstrated the outstanding performance of the proposed model in identifying the fake news articles, creators and subjects in the network.IRJET sample template format ,Conclusion content comes here.

Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here Conclusion content comes here . Conclusion content comes here

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