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FAKE NEWS CLASSIFICATION WITH MACHINE 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. 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. It became easier for consumers to acquire the latest news at their fingertips. Facebook referrals account for 70% of traffic to news websites. 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 and in other cases for creating biased opinions, manipulating mindsets, 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. 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 science. One such area affected by fake news is the financial markets, where a rumour can have disastrous consequences and may bring the market to a halt.

Keywords: Fake news, social media platforms, machine learning.

1. INTRODUCTION

In today's scenario, the fast and extensive growth of social media has witnessed, and a spike is created. News from social media is prevalent these days and people do rely on social media for the latest updates, trending stories, and mutual information. This demonstrates the lack of professional competence with traditional news platforms nowadays. Although distinguish the fake news and anomalous information from the online truthful signals is yet a challenging issue. It became an obstacle for the advanced computing technologies to deal with the variety of information and different meaning of the context. On the other end, much of the social media platforms are flooded with fake news that affects the news ecosystem, people's opinions, and stock markets. False/Fake news is basically rumouring, canard (hoaxes), dismembered news that hides or unravel the truthfulness of the news. Because of little knowledge of actual data young minds get attracted to satire/comedy sites and hence, get influenced by fake sources. Fake news put down your credibility. Throwing a shed light towards fake news is much more important for the sake of a peaceful society. Digital natives and Cybernauts are used to see viral posts, news, content, and images that can affect or change their mindset as well as community opinion. Their trust towards fake news became a disturbing manifestation to weaken the country's democratic process. Indeed, fake news can't help to make the world a better place but real news can benefit for growth. The prime purpose of click farm groups is to bump up the news in the popularity list. This has become a practice to use satire, shady means in content to commit fake/fraudulent news.

The concept of fake news has been in existence even before the emergence of Internet and other computational technologies. Dissemination of fake news and misleading information has always been used as a weapon to fulfil immoral objectives since ages. The advancement of Internet and web technologies has made it very easy for anyone to post anything in online platforms like blogs, comments to news articles, social media, etc. The advancement of technologies has enabled convenient access to authentic and falsified information even faster posing a real challenge. The involvement of social media replacing the traditional media has an even more catalytic effect, where both fake and authentic news are spread extremely rapidly. The spread of such fake news has extremely negative impact on target individuals and also the society at large. Consequently, it also creates an impression among readers such that the general perception and responses towards authentic news also gets diluted hampering the balance of news ecosystem. One of the startling examples is the US 2016 presidential election wherein fake news were purposely spread through Facebook and twitter at a larger scale in comparison to authentic information.

In the past few years, various social media platforms such as Twitter, Facebook, Instagram, etc. have become very popular since they facilitate the easy acquisition of information and provide a quick platform for information sharing. The availability of unauthentic data on social media platforms has gained massive attention among researchers and become a hot-spot for sharing fake news. Fake news has been an important issue due to its tremendous negative impact; it has increased attention among researchers, journalists, politicians and the general public. In the context of writing style, fake news is written or published with the intent to mislead the people and to damage the image of an agency, entity, person, either for financial or political benefits.

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. It became easier for consumers to acquire the latest news at their fingertips. Facebook referrals account for 70% of traffic to news websites. 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 and in other cases for creating biased opinions, manipulating mindsets, and spreading satire or absurdity. The phenomenon is commonly known as fake news.

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2. LITERATURE SURVEY

Saqib Hakak et. al [1] proposed a machine-learning based fake news detection model using a supervised approach. They used the ensemble approach for training and testing purposes consisting of decision tree, random forest, and extra tree classifiers. The aggregation of outputs was done using the bagging approach and compared to the state-of-the-art, our model achieved better results.

Kaliyar et. al [2] propose a BERT-based (Bidirectional Encoder Representations from Transformers) deep learning approach (FakeBERT) by combining different parallel blocks of the single-layer deep Convolutional Neural Network (CNN) having different kernel sizes and filters with the BERT. Such a combination is useful to handle ambiguity, which is the greatest challenge to natural language understanding. Classification results demonstrate that our proposed model (FakeBERT) outperforms the existing models with an accuracy of 98.90%.

Somya Ranjan Sahoo et. al [3] proposed a fake news detection approach for Facebook users using machine learning and deep learning classifiers in chrome environment. Our approach analyses both user profile and news content features. In this proposed work, they have developed a chrome extension that uses crawled data extracted by our crawler. Also, to boost up the performance of chrome extension, they have used deep learning algorithm called Long Short-Term Memory.

Anshika Choudhary et. al [4] proposed a solution to fake news detection and classification. In the case of fake news, content is the prime entity that captures the human mind towards trust for specific news. Therefore, a linguistic model is proposed to find out the properties of content that will generate language-driven features. This linguistic model extracts syntactic, grammatical, sentimental, and readability features of particular news.

Language driven model requires an approach to handle time-consuming and handcrafted features problems in order to deal with the curse of dimensionality problem. Therefore, the neural-based sequential learning model is used to achieve superior results for fake news detection. The results are drawn to validate the importance of the linguistic model extracted features and finally combined linguistic feature-driven model is able to achieve the average accuracy of 86% for fake news detection and classification. The sequential neural model results are compared with machine learning based models and LSTM based word embedding based fake news detection model as well. Comparative results show that features based sequential model is able to achieve comparable evaluation performance in discernable less time.

Aphiwongsophon et. al [5] proposes the use of machine learning techniques to detect Fake news. Three popular methods are used in the experiments: Naive Bayes, Neural Network and Support Vector Machine. The normalization method is important step for cleaning data before using the machine learning method to classify data. The result show that Naive Bayes to detect Fake news has accuracy 96.08%. Two other more advance methods which are Neural Network and Support Vector Machine achieve the accuracy of 99.90%.

Georgios Gravanis et. al [6] proposed a model for fake news detection using content-based features and Machine Learning (ML) algorithms. To conclude in most accurate model, they evaluate several feature sets proposed for deception detection and word embeddings as well. Moreover, they test the most popular ML classifiers and investigate the possible improvement reached under ensemble ML methods such as AdaBoost and Bagging. An extensive set of earlier data sources has been used for experimentation and evaluation of both feature sets and ML classifiers. Moreover, they introduce a new text corpus, the "UNBiased" (UNB) dataset, which integrates various news sources and fulfills several standards and rules to avoid biased results in classification task. Our experimental results show that the use of an enhanced linguistic feature set with word embeddings along with ensemble algorithms and Support Vector Machines (SVMs) is capable to classify fake news with high accuracy.

Umer et. al [7] proposed to employ the dimensionality reduction techniques to reduce the dimensionality of the feature vectors before passing them to the classifier. To develop the reasoning, this work acquired a dataset from the Fake News Challenges (FNC) website which has four types of stances: agree, disagree, discuss, and unrelated. The nonlinear features are fed to PCA and chi-square which provides more contextual features for fake news detection. The motivation of this research is to determine the relative stance of a news article towards its headline. The proposed model improves results by ~4% and ~20% in terms of Accuracy and F1−score. The experimental results show that PCA outperforms than Chi-square and state-of-the-art methods with 97.8% accuracy.

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Vasu Agarwal et. al [8] discusses the approach of natural language processing and machine learning in order to solve this problem. Use of bag-of-words, n-grams, count vectorizer has been made, TF-IDF, and trained the data on five classifiers to investigate which of them works well for this specific dataset of labelled news statements. The precision, recall and f1 scores help us determine which model works best.

Junaed Younus Khan et. al [9] presented an overall performance analysis of 19 different machine learning approaches on three different datasets. Eight out of the 19 models are traditional learning models, six models are traditional deep learning models, and five models are advanced pre-trained language models like BERT. They find that BERT-based models have achieved better performance than all other models on all datasets. More importantly, we find that pre-trained BERT-based models are robust to the size of the dataset and can perform significantly better on very small sample size. They also find that Naive Bayes with n-gram can attain similar results to neural network-based models on a dataset when the dataset size is sufficient. The performance of LSTM-based models greatly depends on the length of the dataset as well as the information given in a news article. With adequate information provided in a news article, LSTM-based models have a higher probability of overcoming overfitting.

Reis et. al [10] presented a new set of features and measure the prediction performance of current approaches and features for automatic detection of fake news. Our results reveal interesting findings on the usefulness and importance of features for detecting false news. Finally, they discuss how fake news detection approaches can be used in the practice, highlighting challenges and opportunities.

3. PROPOSED SYSTEM

We propose a scalable community-based probabilistic framework to model the spreading of news about events in online media. Our approach exploits the latent community structure in the global news media and uses the affiliation of the early adopters with a variety of communities to identify the events widely reported in the news at the early stage of their spread. The time complexity of our approach is linear in the number of news reports. It is also amenable to efficient parallelization. To demonstrate these features, the inference algorithm is parallelized for message passing paradigm and tested on the Rensselaer Polytechnic Institute Advanced Multiprocessing Optimized System, one of the fastest Blue Gene/Q supercomputers in the world. Thanks to the community-level features of the early adopters, the model gains an improvement of 20% in the early detection of the most massively reported events compared with the feature-based machine learning algorithm. Its parallelization scheme achieves orders of magnitude speedup.

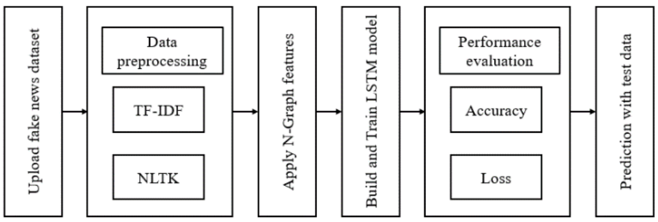

Fig. 1: Block diagram of proposed system.

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TF-IDF Feature extraction

TF-IDF which stands for Term Frequency – Inverse Document Frequency. It is one of the most important techniques used for information retrieval to represent how important a specific word or phrase is to a given document. Let's take an example, we have a string or Bag of Words (BOW) and we have to extract information from it, then we can use this approach.

The tf-idf value increases in proportion to the number of times a word appears in the document but is often offset by the frequency of the word in the corpus, which helps to adjust with respect to the fact that some words appear more frequently in general. TF-IDF use two statistical methods, first is Term Frequency and the other is Inverse Document Frequency. Term frequency refers to the total number of times a given term t appears in the document doc against (per) the total number of all words in the document and The inverse document frequency measure of how much information the word provides. It measures the weight of a given word in the entire document. IDF show how common or rare a given word is across all documents. TF-IDF can be computed as tf * idf

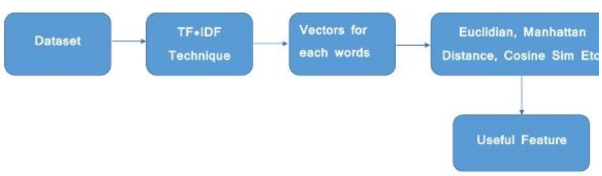

Fig. 2: TF-IDF block diagram.

TF-IDF do not convert directly raw data into useful features. Firstly, it converts raw strings or dataset into vectors and each word has its own vector. Then we'll use a particular technique for retrieving the feature like Cosine Similarity which works on vectors, etc.

Terminology

t — term (word)

d — document (set of words)

N — count of corpus

corpus — the total document set

Step 1: Term Frequency (TF): Suppose we have a set of English text documents and wish to rank which document is most relevant to the query, "Data Science is awesome!" A simple way to start out is by eliminating documents that do not contain all three words "Data" is", "Science", and "awesome", but this still leaves many documents. To further distinguish them, we might count the number of times each term occurs in each document; the number of times a term occurs in a document is called its term frequency. The weight of a term that occurs in a document is simply proportional to the term frequency.

$$tf(t,d) = count\ of\ t\ in\ d\ / number\ of\ words\ in\ d$$

Step 2: Document Frequency: This measures the importance of document in whole set of corpora, this is very similar to TF. The only difference is that TF is frequency counter for a term t in document d, whereas DF is the count of occurrences of term t in the document set N. In other words, DF is the number of documents in which the word is present. We consider one occurrence if the term consists in the document at least once, we do not need to know the number of times the term is present.

$$df(t) = occurrence\ of\ t\ in\ documents$$

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Step 3: Inverse Document Frequency (IDF): While computing TF, all terms are considered equally important. However, it is known that certain terms, such as “is”, “of”, and “that”, may appear a lot of times but have little importance. Thus, we need to weigh down the frequent terms while scale up the rare ones, by computing IDF, an inverse document frequency factor is incorporated which diminishes the weight of terms that occur very frequently in the document set and increases the weight of terms that occur rarely. **The** IDF is the inverse of the document frequency which measures the informativeness of term t. When we calculate IDF, it will be very low for the most occurring words such as stop words (because stop words such as “is” is present in almost all of the documents, and N/df will give a very low value to that word). This finally gives what we want, a relative weightage.

$$idf(t) = N/df$$

Now there are few other problems with the IDF, in case of a large corpus, say 100,000,000 , the IDF value explodes , to avoid the effect we take the log of idf . During the query time, when a word which is not in vocab occurs, the df will be 0. As we cannot divide by 0, we smoothen the value by adding 1 to the denominator.

$$idf(t) = log(N/(df + 1))$$

The TF-IDF now is at the right measure to evaluate how important a word is to a document in a collection or corpus. Here are many different variations of TF-IDF but for now let us concentrate on this basic version.

$$tf - idf(t, d) = tf(t, d) * log(N/(df + 1))$$

Step 4: Implementing TF-IDF: To make TF-IDF from scratch in python, let’s imagine those two sentences from different document:

first_sentence: “Data Science is the sexiest job of the 21st century”.

second_sentence: “machine learning is the key for data science”.

Natural Language Toolkit

NLTK is a toolkit build for working with NLP in Python. It provides us various text processing libraries with a lot of test datasets. A variety of tasks can be performed using NLTK such as tokenization, lower case conversion, Stop Words removal, stemming, and lemmatization.

Tokenization

The breaking down of text into smaller units is called tokens. tokens are a small part of that text. If we have a sentence, the idea is to separate each word and build a vocabulary such that we can represent all words uniquely in a list. Numbers, words, etc. all fall under tokens.

Lower case conversion

We want our model to not get confused by seeing the same word with different cases like one starting with capital and one without and interpret both differently. So we convert all words into the lower case to avoid redundancy in the token list.

Stop Words removal

When we use the features from a text to model, we will encounter a lot of noise.

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These are the stop words like the, he, her, etc… which don't help us and just be removed before processing for cleaner processing inside the model. With NLTK we can see all the stop words available in the English language.

Stemming

In our text we may find many words like playing, played, playfully, etc… which have a root word, play all of these convey the same meaning. So we can just extract the root word and remove the rest. Here the root word formed is called 'stem' and it is not necessarily that stem needs to exist and have a meaning. Just by committing the suffix and prefix, we generate the stems.

Lemmatization

We want to extract the base form of the word here. The word extracted here is called Lemma and it is available in the dictionary. We have the WordNet corpus and the lemma generated will be available in this corpus. NLTK provides us with the WordNet Lemmatizer that makes use of the WordNet Database to lookup lemmas of words.

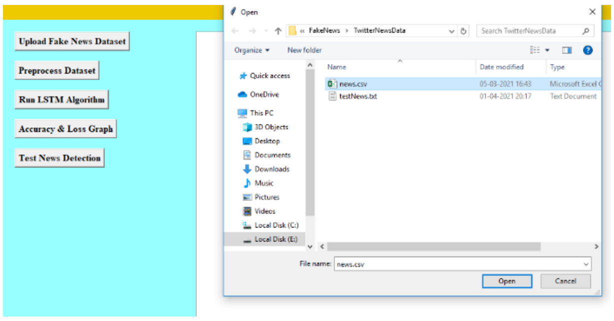
Advantage of proposed system

- TF-IDF is based on the bag-of-words (BoW) model, therefore it does not capture position in text, semantics, co-occurrences in different documents, etc.
- TF-IDF is only useful as a lexical level feature.
- Cannot capture semantics.
- Prediction is more.

4. RESULTS AND DISCUSSION

To run project double click on 'run.bat' file to get below screen

In above screen click on 'Upload Fake News Dataset' button to upload dataset



In above screen selecting and uploading 'news.csv' file and then click on 'Open' button to load dataset and to get below screen

In above screen dataset loaded and then in text area we can see all news text with the class label as 0 or 1 and now click on 'Preprocess Dataset & Apply NGram' button to convert above string data to numeric vector and to get below screen

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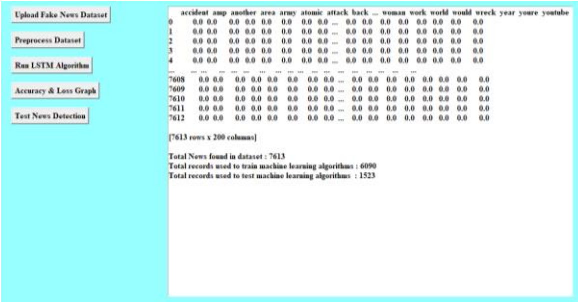
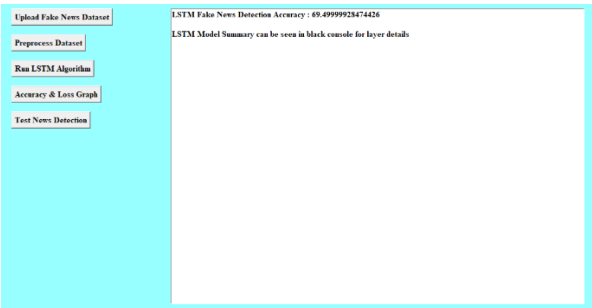
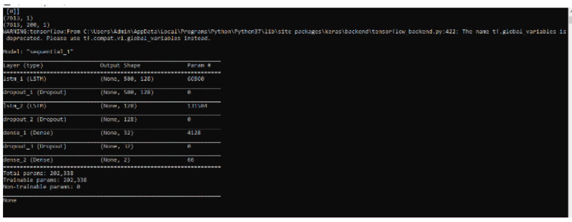


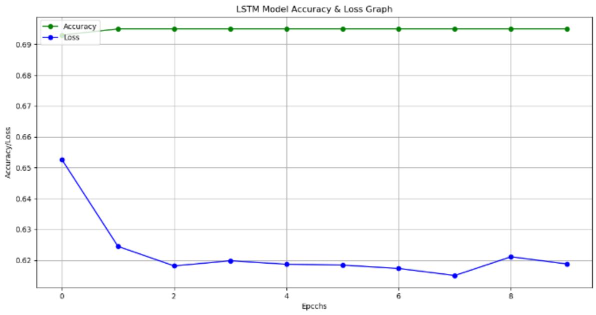
In above screen all news words put in column header and if that word appear in any row then that rows column will be change with word count and if not appear then 0 will be put in column. In above screen showing some records from total 7612 news records and in bottom lines we can see dataset contains total 7613 records and then application using 80% (6090 news records) for training and then using 20% (1523 news records) for testing and now dataset is ready with numeric record and now click on 'Run LSTM Algorithm' button to train above dataset with LSTM and then build LSTM model and then calculate accuracy and error rate



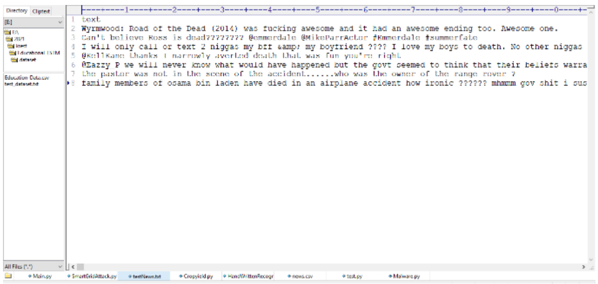
In above screen LSTM model is generated and we got its prediction accuracy as 69.49% and we can see below console to see LSTM layer details



In above screen different LSTM layers are created to filter input data to get efficient features for prediction. Now click on 'Accuracy & Loss Graph' button to get LSTM graph



In above graph x-axis represents epoch/iterations and y-axis represents accuracy and loss value and green line represents accuracy and blue line represents loss value and at each increasing epoch loss values get decrease and accuracy reached to 70%. Now click on 'Test News Detection' button to upload some test news sentences and then application predict whether that news is genuine or fake. In below test news dataset, we can see only TEXT data no class label and LSTM will predict class label for that test news



In above screen in test news, we have only one column which contains only news 'TEXT' and after applying above test news we will get prediction result

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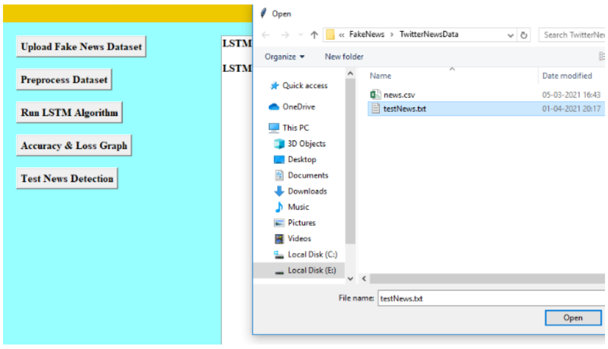
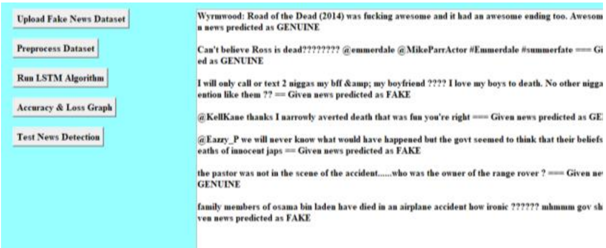


In above screen selecting and uploading 'testNews.txt' file and then click on 'Open' button to load data and to get below prediction result



In above screen before dashed symbols we have news text and after dashed symbol application predict news as 'FAKE or GENUINE'. After building model when we gave any news text then LSTM will check whether more words belong to genuine or fake category and whatever category get more matching percentage then application

5. CONCLUSION

We exploit the latent community structure in the global news network to improve the prediction of the viral cascades of news about events. The cascades which have early adopters in different communities have advantages in disseminating the contagion to these communities in parallel and therefore are more likely to result in the viral infections within a limited time period. Our model captures such property by inferring the community structure using the response times of nodes. Thus, we avoid using the explicit network topology which is often not known because the references to propagation sources are usually missing in the real data sets. Due to the size of the relevant data sets, we successfully parallelized the inference algorithm for distributed memory machines and tested this parallelization on the RPI AMOS achieving orders of magnitude speedup.

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