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Research Article

FAKE NEWS STANCE DETECTION USING DEEP NEURAL NETWORK

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ABSTRACT

With the advancement of technology, fake news is more widely exposed to users. Fake news may be found on the Internet, news sources and social media platforms. The spread of the fake news has harmed both individuals and society. The way to observe fake news using the stance detection technique is the focus of this paper. Given a set of news body and headline pairs, stance detection is the task of automatic detection of relationships among pieces of text. Pre-trained GloVe word embedding is used for the word to vector representation as it can capture the inter-word semantic information. The LSTM neural network had been shown efficient in deep learning applications because it can capture sequential information of input data. In this paper, it is found that the LSTM-based encoding decoding model using pre-trained GloVe word embedding achieved 93.69% accuracy on the FNC-1 dataset.

Keywords—Fake News, Stance Detection, Encoder-Decoder model, LSTM

I. Introduction

News is a very effective technique for disseminating information. It is an excellent source of information. It is also one of the most effective ways for individuals to communicate with one other and with the rest of the world.

Fake News represents false news or propaganda comprising disinformation transmitted via classical media outlets like newspapers and television in addition to modern media sources such as social media [1]. Fake news is characterized by two points: credibility and intent. Credibility assumes that fake news contains false facts and can be verified and intent, implying that the false data was written to confuse the reader. The word of the year was also dubbed "Fake news" by the Macquarie Dictionary in 2016, taking into account the existence of these phenomena [2]. Digital news is becoming more readily available to people around the world, which leads to the spreading of hoaxes and misinformation online. Fake news can be found in popular platforms like social media and the Internet which may deceive the users. There have been a variety of solutions and attempts to spot false news, including artificial intelligence methods. However, fake news intends to convince the reader to believe false information which deems these articles difficult to perceive.

The rate of production of digital news is large and quick, running daily at every second, thus it is challenging for machine learning to effectively detect fake news. The processing area of natural language is changing from mathematical approaches to neural network methods. The language model demand to deal with the nuances tangled in conveying messages via text to better categorization of fake news. For several factors, identifying fake news is tough. Detecting fake news manually is also a very subjective and tedious task. Evaluating the veracity of a news article, also for professional experts, is a complicated task. News, no longer only circulated via traditional media channels, but also through the new platforms of social media. So, the automated approach requires an understanding of the complicated and dynamic nature of natural language processing and generation. This makes the classification of text as fake news a challenging job. So, to overcome the automated fake news classification, it needs the task of stance detection.

The growing rise in the production and circulation of false news poses an urgent need for such twisted news stories to be tagged and identified automatically. Automated identification of false news, however, is a difficult task to achieve as it allows the model to comprehend nuances in natural language. It needs the ability of the model to consider how the published news is related or unrelated as opposed to the real news. Fake news now covers a wide area of cyberspace around the world. To achieve the desired result, fake news is often generated and distributed via social media. On the other hand, it may also require the telling of a true tale that has been exaggerated. Identifying the vocabulary that is used to mislead readers is the essential task of identifying fake news. A difficult challenge is a concept of classifying fake news through learning word-level context. Therefore, the way to observe fake news is using the stance detection technique, which will be the objective of this paper. Given a set of news body and headline pairs, stance detection is the task of automatic detection of relationship among pieces of text. The stances between them can be described as 'agree', 'disagree', 'discuss', or 'unrelated' depending on the relation between the body and headline of the news.

II. Literature Review

In NLP (Natural Language Processing), stance detection is a well-known and well-researched topic. It is characterized as deciding whether the audience is for, against, or neutral about the goal from the text [3]. Many activities, such as fake news detection [4], claim validation [5], and statement quest [6], depend on the stance detection. On 1 December 2016, the first fake news stance identification challenge was launched. The FNC-1 stance detection task was motivated by the work of [7], in which they classified the stance of a single sentence in a news headline against a particular argument. The FNC-1 challenge (Fake News Challenge) dataset was partially named and was based on the Emergent dataset [7]. The stance is de-emphasized in FNC-1. The stance is detected at the document level in FNC-1, which classifies the entire news body relation with a headline. The top-performer team in FNC-1 is called SOLAT in the SWEN [8] and was created by the Talos Research Intelligence team. Previous fake news detection research has focused on target-specific stance prediction, which decides the stance of a text entity related to a subject or a named entity. Target-specific stance prediction for tweets is used in many studies. A news article is made up of a collection of words. As a result, several authors have proposed text mining and machine learning methods to evaluate news textual data to forecast news authenticity in the past. Many of the current fake news detection methods highly rely on feature extraction. The authors also suggested methods in [9] and [10] which are feature extraction machine learning-based models.

III. Deep Neural Network

A neural network (NN) is a set of algorithms that attempts to detect underlying relationships in a piece of data using a technique that is similar to how the human brain works.

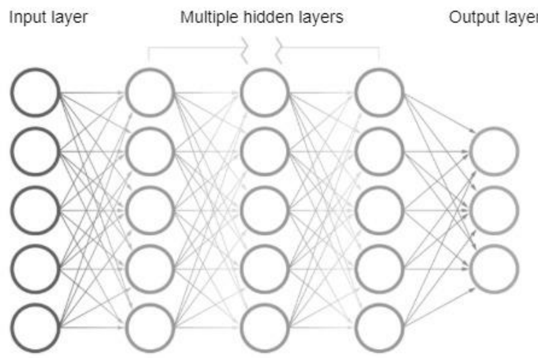

Fig. 4. Layers in deep neural network.

A neural network contains an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, is connected to the others and has a weight and threshold associated with it. If a node's output exceeds a certain threshold value, the node is activated, and data is sent to the next layer of the network. Otherwise, no data is sent on to the network's next layer. The artificial neurons are connected to one another by weight connections. These units then calculate the weighted sum of the inputs and determine the output using squashing or activation functions. The output of a neuron is produced using an activation function. It is also known as a squashing function since it reduces (limits) the output signal's amplitude range to a limited value.

The term "deep" in the context of deep neural networks simply refers to the number of layers in a neural network. The deep neural network is a neural network with more than one hidden layers.

Recurrent Neural Network (RNN) is a type of deep neural network that focuses on utilization of sequential information. It processes input through a feedback loop, allowing the networks to remember what they have already done. RNN, in comparison to other neural networks, execute the same function for each element of a sequence, but the network is recurrent, meaning the output data is sent back into the network. Recurrent Neural Networks are particularly well suited to situations in which the sequence is more essential than the individual elements. The output of a recurrent neural network is determined not only by the current inputs, but also by the neuron state of the preceding phase. For sequential data, recurrent neural networks are common because each unit can remember the state of the previous unit.

Traditional RNN, on the other hand, has trouble retrieving information from the distant past due to the long-term dependence problem. The vanishing gradient problem and the expanding gradient problem are problems with RNN.

IV. Methodology

A. Data Collection

Fake News Challenge [11] publishes the FNC-1 dataset, as the initial step for the Fake News detection task for the public competition, on 1 February 2017. The data used for this competition was taken from Craig Silverman's Emergent Dataset. The dataset contains the news body, the news headline, and the stance label for the relationship between the news body and the headline pair. The data include details on 1683 news stories and 49,972 different pairs of news articles and headlines. There are 4 different categories of stance: agree, disagree, discuss, and unrelated.

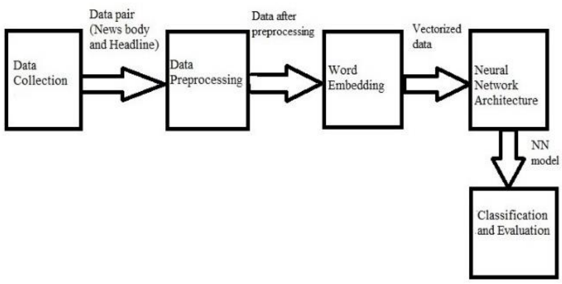

Fig. 2. Method Implemented in Fake News Stance Detection System.

B. Data Preprocessing

In order to apply deep learning methods to textual data, text preprocessing is required. When dealing with text in Natural Language Processing, text pre-processing is an important initial step. Different approaches are used to convert text data into a form that is appropriate for modeling. Both the headlines and the news stories have to apply the data preprocessing measures. Tokenization, lower casing, stop word removal, stemming are preprocessing steps used in our fake news detection system.

Tokenization is the step which take the sentence and breaking it down into words. Using white spaces and punctuation symbols as delimiters, the text is broken down into single words or tokens. Lower casing is the step of changing to the lower case of a word in English language. Words like BOOK and book have the same meaning, but in the vector space model, they are represented as two separate words if they are not transformed to lower case, which results in more dimensions. Lowercasing is one of the most basic and effective text preprocessing techniques, which also greatly improves desired output consistency. The common words in any natural language are stopwords. These stopwords can not add much value to the context of the document when interpreting text data and constructing NLP models. Stop words include articles, prepositions, conjunctions, and certain pronouns. Some common words in a document are; the, is, in, about, where, at, to and so on.

TABLE V. Stance Category In Dataset

Stance	Description	Percentage
Agree	The headline agrees with the news article.	7.36%

Disagree	The headline disagrees with the news article.	1.68%
Discuss	The headline addresses the same subject as the news story but does not agree.	17.83%
Unrelated	The headline didn't discuss the topic as in a news article.	73.13%

C. *Word Vector Representation*

Word vector representation is used to give the numerical vector for words that can represent the meaning of the word. It is very difficult to use the text to model from the body and title of the news story. So, this includes translating the raw text into computational functions to achieve text analytics. Text vectors or word embedding representations are sometimes referred to as the method of describing words as vectors. In comparison to the amount of news published every day, the dataset given for the challenge is very limited. As a result, a model trained on such a limited vocabulary could underperform on a dataset that has never been seen before. So, we used word embeddings that have been pre-trained over broad datasets to allow our model to account for new vocabulary in test data.

The 100-dimensional pre-trained GloVe word embedding [12] is used for the word vector representation. The GloVe is an unsupervised learning algorithm that generates word vector representations. The resulting representations highlight fascinating linear substructures of the word vector space, and training is based on aggregated global word-word co-occurrence statistics from a corpus. This is accomplished by mapping words into a meaningful space in which the distance between words is equal to the semantic similarity. The objective of using word embeddings are;

- To reduce dimensionality.
- To use a word to predict the words around it.
- To capture the inter-word semantics.

D. *LSTM (Long Short-Term Memory)*

LSTM networks are a revised form of RNN (Recurrent Neural Network). LSTM uses the combined method of real-time recurrent learning and back-propagation through time. LSTMs are explicitly designed to avoid the vanishing gradient problem and the expanding gradient problem in the previous recurrent neural network. LSTMs have a chain-like structure like in classical RNN, but the repeated module is distinct.

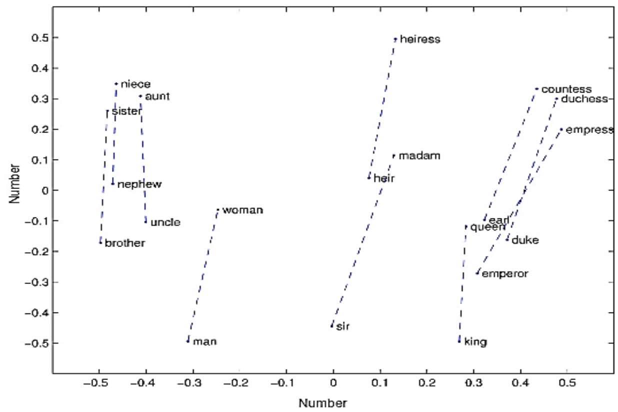

Fig. 3. An example for linear visualization of GLoVe Embedding.

There are three different gates in an LSTM cell:

- Forget Gate: The first stage in the LSTM algorithm is to determine which data should be erased from the memory cell. This choice is made by the forget gate. This layer computes a number between 0 and 1 for each number in the memory cell C_{t-1} based on the previous state h_{t-1} and the current input x_t.

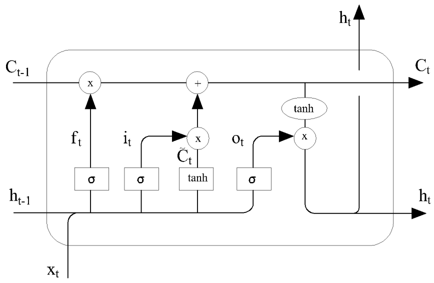

Fig. 4. LSTM repeating module.

- Input Gate: The input layer determines the amount of data kept in memory.
- Output Gate: The sigmoidal function is used to concatenate information. Then the tanh function is used to transmit information from the memory cell.

E. *Network Architecture*

The preprocessed headline and news body are separately fed to the GloVe embedding layer for the word to a vector representation. The embedding layer gives the 100-dimensional vector representations for each token in the headlines and news body then creates an embedding matrix. The LSTM layer is the sequence to sequence encoder-decoder model. Encoder and decoder both are LSTM models.

- The encoder takes the input sequence and summarizes it in internal state vectors (in the case of LSTM, hidden state, and cell state vectors). We only preserve the internal states of the encoder.
- The initial states of the decoder LSTM are set to the final states of the encoder LSTM.
- The decoder begins producing the output sequence using these initial states.

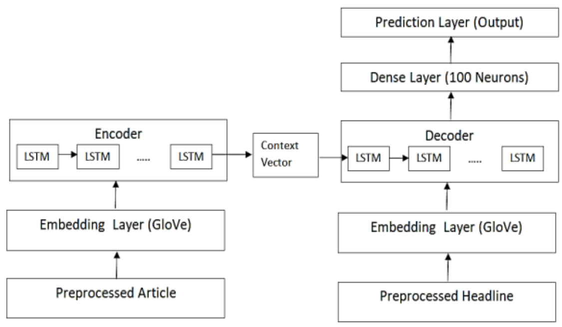

Fig. 5. Network Architecture for Fake News Stance Detection.

Encoder-decoder models have significantly pushed the state of art performance on a range of natural language related tasks, such as text summarization and machine translation. The encoder-decoder architecture is the most popular architecture used to create sequence to sequence(seq2seq) models. The encoder decoder model has the potential to train a single end-to-end model directly on input and target phrases, as well as the capacity to handle variable length input and output text sequences.

The encoder takes the input sequence from the article body embedding vector and summarizes it in internal context vectors, using an LSTM neural network model. Context vector is the final hidden state, generated by the encoder. This vector tries to capture all input element information to support the decoder in making correct predictions. In our study, we employ the decoder to take inputs as context vectors from the encoder and word embedding vector of the news headlines from the embedding layer. The decoder begins producing the output sequence based on the context vectors from the encoder and headline embedding vectors. So, the decoder tries to find the relatedness between the news article and the headline. The dense layer is that each layer's neurons are coupled to those in the previous layers. The hidden unit uses the relu as an activation function and the prediction layer uses the softmax activation function. The softmax function normalizes the output of a network into a probability distribution of each possible output.

Google Colab is used to implement the deep learning model. Colab is a cloud environment for jupyter notebooks that includes GPUs and TPUs for high computation. The experimental code is written using Python programming. The keras and tensorflow python library is used to implement the LSTM model in encoder-decoder architecture. For reading datasets and processing arrays, respectively, the pandas and numpy libraries are utilized. For the data preprocessing task, the NLTK package is used. The scikit-learn package is used to analyze the data, evaluate the results. For graph visualization, matplotlib is used.

V. RESULTS AND DISCUSSION

A stance detection of headlines and article body for fake news detection system has been developed. The confusion matrix for our model on the testing dataset is shown in Fig 6. The confusion matrix represents the number of true positive, true negative, false positive, and false negative on individual classes. It shows the accuracy on the FNC-1 testing dataset 93.69% using LSTM neural network on our encoder-decoder architecture. The FNC-1 dataset is unbalanced, so we also have to evaluate and analyze other evaluation metrics precision, recall, and F1-score.

TABLE VI. PARAMETER AND VALUES IN MODEL BUILDING

Parameter	Value
No. of headline and article pair for the training dataset	31981
No. of headline and article pair for the validation dataset	7996
No. of headline and article pair for the testing dataset	9995
Epoch	15
Optimizer	rms prop
Loss Function	Categorical cross-entropy
Batch size	64

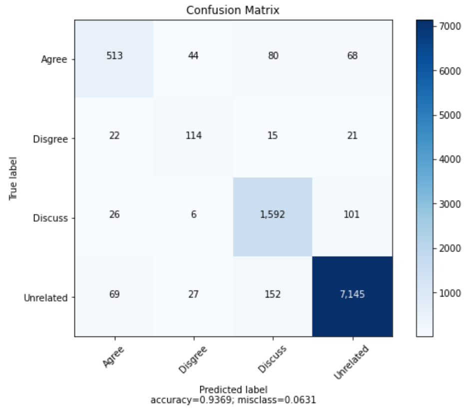

Fig. 6. Confusion matrix of Fake News Stance Detection.

- Accuracy: The accuracy of a model is a metric that sums up how well it performs across all classes. When all of the classes are equally essential, accuracy is beneficial. The ratio between the number of right predictions and the total number of predictions is used to compute the accuracy.
- Precision: Precision is defined as the ratio of properly predicted positive observations to total expected positive observations.
- Recall: Recall is defined as the proportion of properly predicted positive observations to all observations in the actual label.
- F1-score: The harmonic mean between recall and precision is the F1-score. As a result, this score takes both false positives and false negatives into account. F1-score is more useful than accuracy when the class distribution is unbalanced.

From the classification report, it is found that the F1-score in disagree class is 62.6% and in unrelated class the F1-score is 97%. A training learning curve is a learning curve extracted from the training dataset that shows how much the model is learning and a validation learning curve is the learning curve derived from a validation dataset in the model building process. The training accuracy curve for both training and validation datasets during the model training process is shown in Fig 7. The increase in accuracy shows the model is in the learning process.

TABLE VII. CLASSWISE EVALUATION METRICS OF MODEL

Stance	Accuracy	Precision	Recall	F1-score
Agree	96.9	81.4	72.7	76.9
Disagree	98.6	59.7	66.2	62.6
Discuss	96.1	86.6	92.3	89.3
Unrelated	95.6	97.4	96.6	97

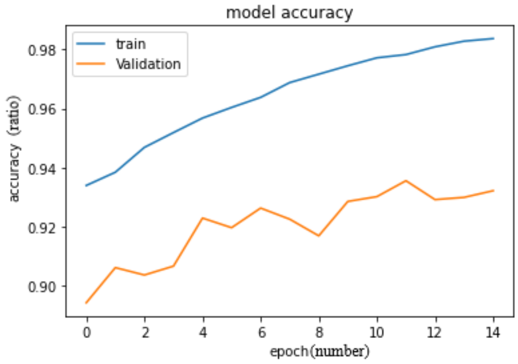

Fig. 7. Training – validation accuracy curve.

VI. Conclusion

Fake news is usually created to confuse and attract audiences for commercial and political benefit. Fake news may be found on the Internet, news sources and social media platforms. The spread of the fake news has harmed both individuals and society. The way to observe fake news using the stance detection technique is the focus of this paper. Given a set of news body and headline pairs, stance detection is the task of automatic detection of relationships among pieces of text. The stances between them can be described as 'agree', 'disagree', 'discuss', or 'unrelated'. The LSTM-based neural network model in encoder-decoder architecture was successfully trained and tested on multiclass FNC-1 fake news dataset. LSTM networks can perform better on the sequential data because it processes the input through a feedback loop, allowing the networks to remember what they have already done. For the word embedding, 100-dimensional pre-trained GloVe word embedding is used. The Glove embedding is used to capture semantic and syntactic information from the dataset. In this paper, it is found that LSTM based encoding decoding model using pre-trained GloVe word embeddings achieved 93.69% accuracy on the FNC-1 dataset. Hence, it is concluded that our model can perform in multiclass classification task for the fake news stance detection.

VII. Acknowledgment

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