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LSTM Encoder Decoder Model for Fake News Detection

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Abstract
With the advancement of technology, fake news is more widely exposed to users globally. Fake news can be found through popular platforms like social media and the Internet. There have been multiple solutions and efforts in the detection of fake news where it even works with artificial intelligence tools. The way to observe the fake news is using stance detection technique, is the focus of this paper. Given a set of news body and headline pair, 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'. In this paper, it is found that LSTM-based encoding decoding model using pre-trained GloVe word embeddings achieved 93.69% accuracy on FNC-1 dataset.

Keywords
Fake news; Stance detection; NLP; LSTM

1. Introduction

Data, increasing to become the richest asset that anyone can own, needs to be transmitted and exchanged and becomes much more important as becomes information. News and posts, both in physical and digital form, are one of the most common methods of knowledge sharing. With genuine knowledge helping to make us a more evolved species, the entire meaning will destroyed by fake news [1].
Fake News represents false news or propaganda comprising disinformation transmitted via classical media outlets like newspapers and TV in addition to modern media sources such social media [2]. Fake news is characterized by two points: credibility and intent. Credibility assumes that fake news contains false facts and can be verified and intent implies that the false data was written in order 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 this phenomenon [3].
To achieve the desired result, fake news is often generated and distributed via social media. Identifying the vocabulary that is used to mislead readers is the essential task of identifying fake news. 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.
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 in order to better categorization of the fake news.A difficult challenge is the concept of classifying fake news through learning word-level context. Therefore, the way to observe the fake news is using stance detection technique will be the objective of our paper. Given a set of news body and headline pair, stance Detection is the task of automatic detection of relationship among pieces of text.

1.1 Dataset

Fake News Challenge [4] publishes the FNC-1 dataset, as the initial step for 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 [5]. The dataset contains the news story article, 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 category of stance: Agree, Disagree, Discuss and Unrelated.

Table 1: Stance Category in dataset.

Stance	Description	Percentage
Agree	Headline agrees with the news article.	7.36%
Disagree	Headline disagrees with the news article.	1.68%
Discuss	Headline addresses the same subject as the news story, but does not agree completely.	17.83%
Unrelated	Headline didn't discuss the topic as in a news article.	73.13%

2. Methodology

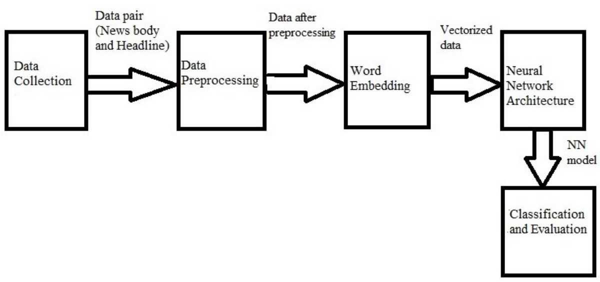

Figure 1: Method for fake news stance classification.

In order to apply deep learning methods on them, text data requires special preprocessing. We must first define the words that make up a string of characters before process natural language. As a result, tokenization is the most fundamental step in the NLP process (text data). This is significant since the text's meaning can be easily deduced by examining the words in the text. The total vocabulary size of given dataset is 27,873.
Out of 49,972 pairs of headline and news,the dataset is first splitted into two groups as training dataset and testing dataset in the ratio 80:20.After this, training dataset again splitted into training dataset and validation dataset in the ratio of 80:20. For this purpose,python library scikit learn is used.
Word vector representation is use to give the numerical vector for words that can represent meaning of word. It is very difficult to use the text to model from the body and title of the news story. So, this includes translating raw text into computational functions in order to achieve text analytic. Text vectors or word embedding representations are sometimes referred to as the method of describing word 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 employed pre-trained word embeddings to allow our model to account for new vocabulary in test data. The 100 dimensional pretrained GloVe embedding (Wikipedia 2014 + Gigaword 5) [6] for the word vector representation is used.
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 terms into a meaningful space in which the distance between words is equal to the semantic similarity. The objective of using word embeddings are;

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

2.1 Network Architecture

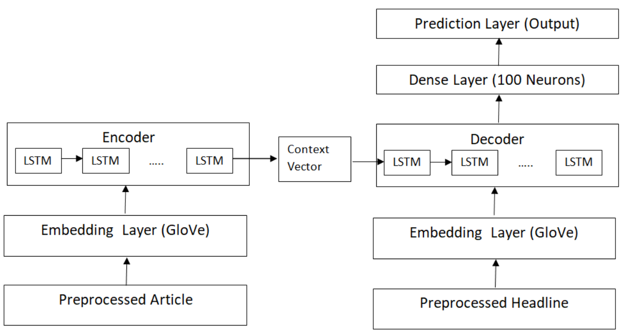

Figure 2: Network Architecture for Fake News Detection System

Embedding layer gives the 100 dimensional vector representations for the each token in the headlines and news body, then creating an embedding matrix. The

LSTM layer is sequence to sequence encoder decoder model. The Encoder Decoder architecture is the most popular architecture used to create Seq2Seq models. For sequential data, recurrent neural networks are common because each unit can remember the state of the previous unit. This is especially useful in natural language processing because it aids in language comprehension. RNNs consist of an input layer, an output layer, and a set of hidden recurrent units with memory gates. LSTMs also have chain-like structure like in classical RNN, but the repeated module is distinct. Instead of a having single neural network layer, there are four, each of which interacts in a special way.

- Encoder and decoder, both are LSTM models.
- The encoder takes the input sequence and summarizes it in internal state vectors (in case of LSTM, hidden state and cell state vectors). We only preserve the internal states of 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.

3. Results and Discussion

A stance detection of headlines and article body for fake news detection system has been developed.

Table 2: Parameter and Value in Model building.

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

Confusion matrix is a tabular representation of the prediction model's results. The number of observations made by the model where it categorized the groups correctly or incorrectly is expressed by entry in a confusion matrix. The confusion matrix has peculiar table organization which helps the output to be visualized, usually supervised learning.It shows not only a predictive model's results, but also which groups are correctly predicted, which are incorrectly predicted, and what types of errors are being made. Figure 3 shows the confusion matrix on testing

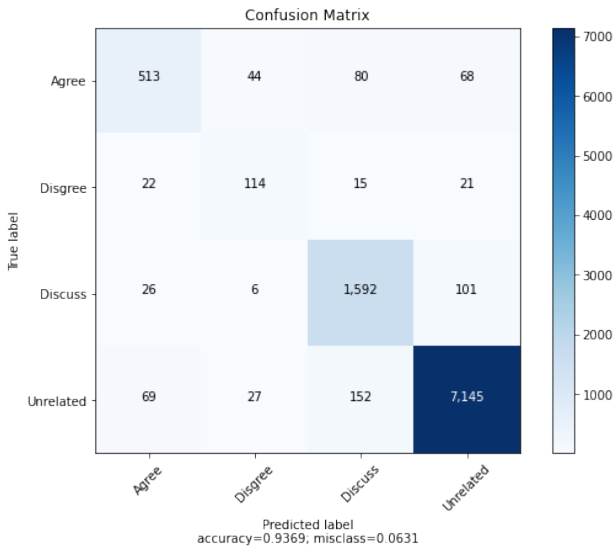

Figure 3: Confusion matrix on Testing Dataset.

dataset. The confusion matrix represents the number of true positive, true negative, false positive and false negative. It also shows the accuracy on testing dataet is achieved to 93.69% and misclassification of 6.31%. The detail of classwise different parameter and evaluation metrics are tabulated in classification report.

3.1 Classwise Evaluation Report

A) 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. It is calculated using the ratio between the number of correct predictions and the total number of predictions.

$$Accuracy = \frac{Total\, no.\, of\, accurate\, predictions}{Total\, no.\, of\, predictions\, made}$$

B) Precision: The ratio of correctly predicted positive observations to overall predicted positive observations is known as precision.

$$Precision = \frac{TP}{TP+FP}$$

C) Recall: The proportion of correctly predicted positive observations to all observations in the actual label is known as recall.

$$Recall = \frac{TP}{TP+FN}$$

D) F1-Score: The harmonic mean between Precision and Recall is the F1 Score. As a consequence, this score considers both false positives and false negatives. F1 is generally more useful than accuracy, particularly if the class distribution is unbalanced.
Precision consists of positive responses that are determined accurately divided by outcomes that have positivity consisting inaccurate recognition. Recall consists of positive results recognized accurately divided by positively recognized outcome.

$$F1-Score = \frac{2*Recall*Precision}{Recall+Precision}$$

Table 3: Classification Report of fake news detection system

Stance	Accuracy	Precision	Recall	F1-Score
Agree	0.969	0.814	0.727	0.769
Disagree	0.986	0.597	0.662	0.626
Discuss	0.961	0.866	0.923	0.893
Unrelated	0.956	0.974	0.966	0.97

The dataset is unbalanced on the four different class. So,it need to be analyze the F1-Score of individual classes. From the classification report, it is found that the F1-Score with least number of labels in testing dataset is disagree class, achieved 62.6%. And, the higher number of labels in testing dataset is unrelated class, achieved the F1-score of 97%.

3.2 Learning Curve

Training learning curve is a learning curve extracted from the training dataset that shows how much the model is learning. Validation learning curve is the learning curve derived from a validation dataset in model building process. The accuracy curve are plotted for both training and validation process in Figure 4. The increase in accuracy value shows the model is in learning process.

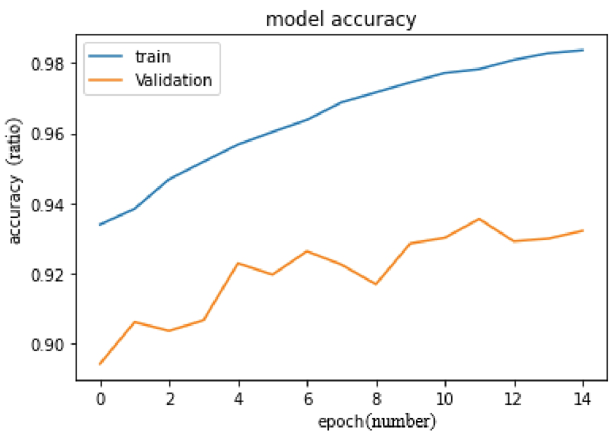

Figure 4: Train Validation Accuracy Curve

4. Conclusion

Fake news is usually created to confuse and attract audiences for commercial and political benefit. The way to observe the fake news is using stance detection technique, is the focus of this paper. Given a set of news body and headline pair, 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.

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