Global Journal on Innovation, Opportunities and Challenges in AAI and Machine Learning
http://eurekajournals.com/IJIOCAAIML.html
ISSN: 2581-5156

Generation of Fake content using Machine Learning RNN Technique

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Abstract

A wider audience is being exposed to fake news than ever before. The proliferation of social networking sites and direct messaging systems is the primary culprit. The problem at hand is developing an algorithm using deep learning that can discern between real and fake news articles. In order to accomplish this, this research first examines a few datasets that allow for the coexistence of fake and true news. Then we review some of the existing research on deep learning algortihms and algorithms which are applied in fake news classification. This paper focuses on implementing an RNN algorithm with the minimum data preprocessing possible and achieving maximum accuracy.

Keywords: Fake news classification, Deep learning, Data Pre-processing, RNN, Accuracy.

Introduction

Fake news is untrue facts or rumours that have been altered and distributed on social media to harm a certain individual, business, or group. The greater accessibility of the wealth of information on the internet media in the form of books, films, audio, and many other formats is attracting a lot of attention from the general public in this digital age. Since information spreads like water, there is a good probability that you will encounter Fake News and be oblivious to it even after it has been proven to be false. A wider audience is being exposed to fake news than ever before. The main cause is the growth of direct messaging services and social media. It's like brandishing a two-edged sword when using social media for news.

For classifying different news we use different datasets containing the information in text, so we have to first apply some data pre-processing on the dataset. After this we apply tokenization to our data, the tokenisation will help us to divide the words into smaller units. Tokenization is required, as it helps our machine/computer to understand any text in their machine-level language. After the whole data pre-processing is done, we will classify our fake news using the program code and then give our accuracy mode of how much we have achieved.

Overall, fake news classification using deep learning is a complex and challenging task that requires a combination of expertise in natural language processing (NLP), machine learning, and deep learning. However, it has the potential to significantly improve our ability to detect and combat fake news in today's fast-paced media environment

Sequence data can be modeled using RNNs, a type of neural network architecture. Because RNNs are constructed from feedforward networks, their behavior is similar to that of human brains. Recurrent neural networks, in short, outperform other algorithms in the anticipation of sequential data.

The inputs and results of traditional neural networks are unrelated to one another. It's crucial to keep in mind the previous words since there are situations in which they are necessary, as when anticipating a sentence's following word. As a result, RNN was created, and it employed a Hiding Layer to resolve the problem. The most important component of an RNN is the Hidden state, which holds particular information about a sequence. RNNs maintain a record of all the data computations in their memory. For every input, it applies the same parameters since it performs the identical procedure on each input's visible or hidden layers to get the same outcome.

With some of the first documented examples dating back to the 16th century, the problem of fake news has been recognized and investigated for many years. However, the distribution and complexity of false news have increased with the development of digital media and virtual media platforms.

The U.S. presidential election in 2016 saw one of the earliest instances of fake news in the contemporary sense, with fraudulent information and articles being widely disseminated on social media. This raised interest in an investigation into the problem of fake news.

Since then, numerous organizations and scholars have been attempting to create instruments and tactics for identifying and thwarting false information. For instance, Facebook announced several efforts in 2017 to combat the spread of false information on its platform, including collaborating with external fact-checkers to identify and classify erroneous reports.

The issue of fake news and measures to prevent it are extensively covered in research papers, news pieces, and reports. The book "The Truth About Fake News" by Brian L. Ott and Greg Dickinson, the report "The Future of Truth and Misinformation Online," and the paper "The Science of Fake".

Literature Survey

According to J A Nasir et al., the most effective deep learning model for classifying false news is a unique hybrid model that blends recurrent and convolutional neural networks. The algorithm was successfully tested on two trolling dataset (ISO and FA-KES) with detection results significantly better than prior non-hybrid baseline techniques. This work became the first to suggest a broadening of models for identifying bogus news. This study demonstrates that while such models do not generalize well, they frequently perform well on a particular dataset. The globalization of false news detection programmers can open new possibilities. Overall, using artificial neural networks to detect bogus news is promising. In addition to CNN and RNN, additional complicated neural network architectures were considered in the analysis.

Awais Yasin et al. classified the news based on the source and all previous history with combined CNN and LSTM. Their approach classifies trustworthy news stories from dependable news sources with an 99.7% correctness on training data and 97.5% accuracy on test data. We determined that using CNN and LSTM, which are among the top models for text data coupled with the embedding layer, is ideal when working with text data and needing to perform sentiment analysis. Due to the LSTM's processing of the entire data stream and discovery of the pattern, the final output is the result.

Abhishek Koirala discussed the classification of fake news articles related to COVID-19 using deep learning. The experiments demonstrated that deep learning outperforms baseline models in terms of text classification. However, selecting an accurate model is also important. The inconsistent data may be to blame for the lower-than-expected accuracy bar. Koirala stated that one approach to this might be to subclassify news articles according to their type and create hybrid models for the final classification.

S. S. Chauhan et al. presented a deep learning algorithm, BerConvoNet, to classify the received news text into fake or real with maximum accuracy and minimum error. This model first created news embedding representations from news articles, after which the suggested convolutional neural network was fed the embedding for classification. The provided model was analysed in comparison to other cutting-edge models. On several performance criteria, it was demonstrated that BerConvoNet outperforms other models.

According to T. Chauhan, there are a number of methods for spotting false information on social media, but artificial brains have been shown to be the most successful. The deep learning framework utilized by the suggested model makes use of short-term memory architecture and neural networks. The notion of stopwords was used for data preprocessing before training the model, which improved accuracy and allowed for 99.88% accuracy.

Methodology

The methodology of implementing RNN for fake news classification includes the following steps:

A. Data collection and preparation

First the datasets are collected and loaded and the text data is preprocessed by being cleaned, noise is removed, and the text is tokenized into words or characters.

B. Data pre-processing

Then we create a numerical representation of the preprocessed text data that is appropriate for the RNN model. The words are represented as continuous dense vectors by using word embeddings to ensure that the sequences are of similar length as input to the RNN model, we pad or truncate them.

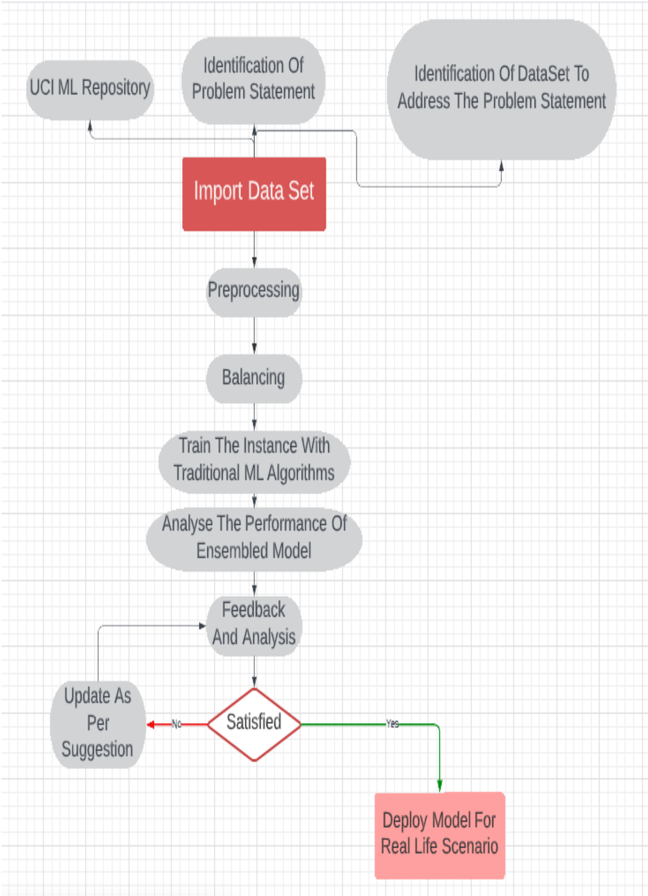

Figure 1: Proposed Methodology

C. Designing model architecture for RNN

We create the RNN model's architecture, utilising LSTM.

Word embeddings

RNN layers are typically combined with word embeddings to represent the input text. Word embeddings convert words into vector representations that are dense and capture word semantic links.

Reversed-path RNN

In false news classification, bidirectional RNN layers—which comprise two RNNs, one of which processes the input sequence forward and the other of which processes it backwards—are frequently employed to gather contextual information from the past and the future. This enables the model to include data from textual terms that are both past and future.

Retention and discontinuation

The RNN layers can be subjected to regularization methods like dropout to avoid overfitting. During training, dropout arbitrarily turns a portion of the unobserved components to zero, which lessens the model's dependence on particular connections and improves its capacity for generalization.

Output layer and classification

Usually, a the SoftMax activation function is applied after one or more fully linked layers have processed the result of the RNN layers.

D. Model Training

Thereafter, evaluation, training, and test sets are created from the labeled datasets. We trained the RNN model on the training set of data using gradient descent and backpropagation through time (BPTT). The neural network (RNN) model is developed with labeled data, and its objective is to minimize a suitable loss function (binary cross-entropy, for example).

E. Model Evaluation

On the test dataset, we gauge the performance of the trained RNN model. Evaluation criteria including precision, recall, accuracy, and the F1-score were utilized to evaluate the RNN model's performance.

Result

In machine learning and statistics, metrics like recall, precision, accuracy, and F1 score are frequently employed to assess how well categorization models perform. These metrics are useful for evaluating how well a model predicts the future, particularly when there are concerns about imbalanced classes or various kinds of errors.

F. Precision

A model's accuracy in making positive predictions is measured by precision, which is also referred to as positive predictive value. It provides an answer to the query, "How many of all the instances that were predicted as positive were actually positive?"

$$\text{Precision} = \frac{\text{True Positives}}{\text{Total } \textit{Predicted} \text{ Positives}}$$

G. Accuracy

The general accuracy of an algorithm's predictions, taking into account all actual favourable and true negative expectations as they relate to the entire dataset, is measured by its accuracy.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{All Samples}}$$

H. F1 score

An impartial means of assessing a model's performance is through its F1 score, which is a harmonic average of precision and recall. It integrates the recall and precision trade-off, particularly when a balance between these two measures is required.

$$\text{F1 Score} = \frac{2 \text{ x } (\text{Precision x Recall})}{\text{Precision + Recall}}$$

I. Recall

Recall gauges how well the model can locate all pertinent occurrences of the positive class; it is also referred to as sensitivities or true positive rate. "Of all the actually affirmative instances, what proportion were accurately anticipated as positive?" is the question it answers.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

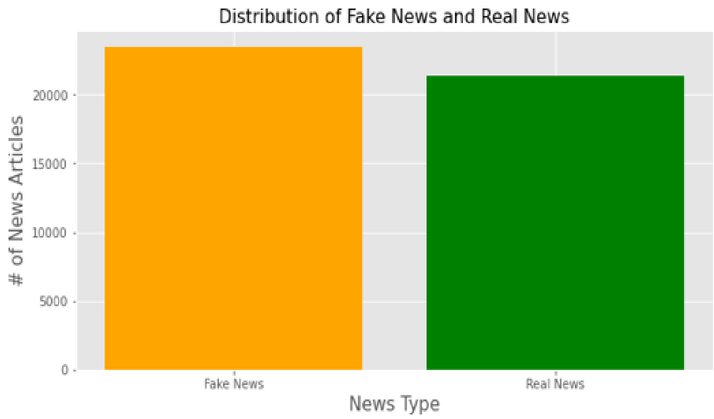

Figure 2: Distribution of Fake News and Real News

The Evaluation metrics used to assess the performance of the RNN model, such as accuracy, precision, recall, and F1-score are:

Accuracy - 0.99142538

Precision - 0.98934

Recall - 0.99426

F1 Score - 0.9917

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, None, 32)          320000
_________________________________________________________________
bidirectional (Bidirectional (None, None, 128)         49664
_________________________________________________________________
bidirectional_1 (Bidirection (None, 32)                18560
_________________________________________________________________
dense (Dense)                (None, 64)                2112
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 65
=================================================================
Total params: 390,401
Trainable params: 390,401
Non-trainable params: 0
```

Figure 3: Model Sequential

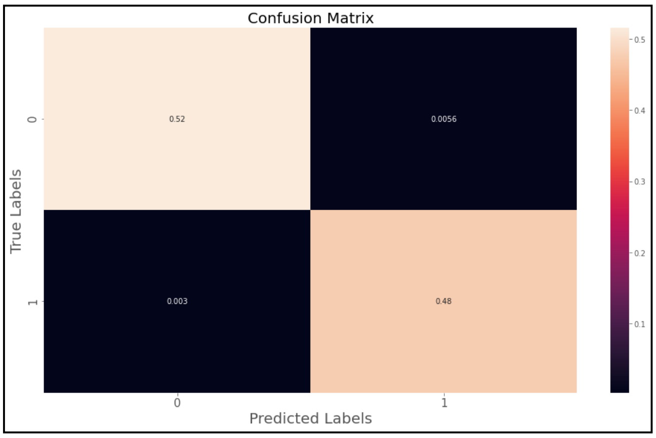

Figure 4: Confusion Matrix

The confusion matrix illustrates how well the model distinguishes between authentic and fraudulent news.

Conclusion and Future Scope

In conclusion, the categorization of fake news using RNN and Python deep learning algorithms is a promising method that might prove to be highly successful in identifying false information. It's important to keep in mind that neural networks might occasionally make mistakes and are not perfect. Furthermore, it's important to keep in mind that fake news is always being generated, which is why it's imperative to keep the RNN updated with breaking news.

These are some advantages of employing RNNs for fake news classification. RNNs are highly effective in tasks such as speech recognition and language processing due to their ability to recognize long-term features in text. RNNs may be developed from a large dataset of real and fake news articles to improve their accuracy. It is feasible to classify new items as genuine or fake news in real-time using RNN.

The following illustrates a few of the difficulties in classifying false news using RNNs. It might be challenging to compile a sizable and superior dataset of bogus and legitimate news stories. Since fake news stories are always being produced, it's critical to maintain the RNN current with breaking news. Since fake news pieces are frequently expertly written, it can be challenging to tell them apart from genuine news reports. Despite these challenges, RNNs might be a very helpful tool for spotting misleading material. They are becoming more and more popular and will likely play a major role in the fight against misinformation.

Some potential future research utilising RNN deep learning algorithms with Python for the categorisation of false news:

RNN model accuracy should be increased. Accuracy can still be improved in RNN models, which are continually being developed. Using a larger collection of both actual and false news stories is one technique to increase accuracy. Using a more complex RNN model is another method to increase accuracy. Create RNN models that are able to identify false information in many languages. At the moment, the majority of RNN models can only identify false information in English. Creating RNN models that are also capable of identifying false news in additional tongues would be advantageous. Create RNN models that are able to identify bogus news in a variety of forms. At the moment, the majority of RNN models can only identify false information in textual form. It would be useful to create RNN models that are also capable of identifying false news in other media, such as pictures and videos.

Create RNN models with real-time false news detection capabilities. At the moment, the majority of RNN models can only identify false information when it has been made public. Developing RNN models with real-time fake news detection capabilities might be helpful in preventing the spread of false information earlier it has had a chance to do damage.

These are just a few potential future projects that use RNN deep learning algorithms and Python to classify false news. With the advancement of RNN technology, forthcoming fake news detection methods will likely be even more inventive and effective.

References

Jamal Abdul Nasir, Osama Subhani Khan, Iraklis Varlamis, “Fake news detection: A hybrid CNN-RNN based deep learning approach”, International Journal of Information Management Data Insights, Volume 1, Issue 1, 2021, 100007, ISSN 2667 - 0968, doi: 10.1016/j.jjimei.2020.100007.

Abdullah, & Yasin, Awais & Awan, Mazhar & Faisal Shehzad, Hafiz & Ashraf, “Fake NewsClassification Bimodal using Convolutional Neural

Network and Long Short-Term Memory”, International Journal of Emerging Technologies in Learning (iJET). 11. 209-212.

Abhishek Koirala, “COVID-19 Fake News Classification with Deep Learning”, Computer Science and Information Management Asian Institute of Technology, 2020 DOI: 10.13140/RG.2.2.26509.568.

Monika Choudhary, Satyendra Singh Chouhan, Emmanuel S. Pilli, Santosh KumarVipparthi, “BerConvoNet: A deep learning framework for fake news classification,” Applied Soft

Computing, Volume 110, 2021, 107614, ISSN 1568 4946, doi: 10.1016/j.asoc. 2021.107614.

Tavishee Chauhan, Hemant Palivela, "Optimization and improvement of fake news detection using deep learning approaches for societal benefit," International Journal of Information Management Data Insights, Volume 1, Issue 2, 2021, 100051, ISSN 2667-0968, doi:10.1016/j.jjimei.2021

Hiramath, Chaitra K., and G. C. Deshpande, "Fake news detection using deep learning techniques" In 2019 1st International Conference on Advances in Information Technology (ICAIT), pp. 411-415. IEEE, 2019.

T. Traylor, J. Straub, Gurmeet and N. Snell, "Classifying Fake News Articles Using Natural Language Processing to Identify In-Article Attribution as a Supervised Learning Estimator," IEEE 13th International Conference on Semantic Computing (ICSC), 2019, pp. 445-449.

A. Sen, K. Rudra and S. Ghosh, "Extracting Situational Awareness from Microblogs during Disaster Events," Social Networking Workshop, COMSNETS 2015, 2015.

Y. Bengio, P. Simrad and P. Franconi, "Learning Long-Term Dependencies with Gradient Descent is Difficult," IEEE Transactions on Neural Networks, Vol 5, No. 2, 1994, pp. 157-166.

D. P. Kingma and J. L. Ba, "ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION," 3rd International Conference for Learning Representations, San Diego arXiv:1412.6980, 2015.

T. Mikolov, I. Sutskever, K. Chen, G. Corrado and J. Dean, "Distributed Representations of Words and Phrases and their Compositionality," 2013, pp. 1-9.

R. Socher, J. Pennington, E. H. Huang, A. Y. Ng and C. D. Manning, "Semi-Supervised Recursive Autoencoders," EMNLP '11: Proceedings of the Conference on Empirical Methods in Natural Language Processing, 2011, pp. 151-161.

N. Kalchbrenner, E. Grefenstette and P. Blunsom, "A Convolutional Neural Network for Modelling Sentences," arXiv:1404.2188v1 [cs.CL], 2014.

K. Cho, B. v. Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk and Y. Bengio, "Learning Phrase Representations using RNN Encoder–Decoder," arXiv:1406.1078, 2014.

"Fake News Challenge," [Online]. Available: http://www.fakenewschallenge.org/.

M. Risdal, "Kaggle.com," [Online]. Available: https://www.kaggle.com/mrisdal/fake-news.

S. Hochreiter and J. ¨. Schmidhuber, "Long Short-Term Memory," in Neural Computation Vol. 9,8, https://doi.org/10.1162/neco.1997.9.8.1735, 1997, pp. 1735-1780.

S. Helmstetter and H. Paulheim, "Weakly Supervised Learning for Fake News Detection on Twitter," IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), 2018, pp. 274-277.

Barney, Nathan (May 9, 2018). "5 reasons why 'fake news' likely will get even worse". *USA Today*. Retrieved February 17, 2019.

Silverman, Craig (November 16, 2016). "This analysis shows how viral fake election news stories outperformed real news on Facebook". *BuzzFeed News*. Retrieved July 20, 2022.