Fake News Detection

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Video link:

https://drive.google.com/file/d/1XYlrhtZmAoRwTNYKxDJa1-y6o5CJ-U5y/view?usp=sharing

Abstract:

Today's globe faces a serious fake news problem because of how quickly it can spread and how many people it may deceive. Researchers have created a number of techniques for identifying false news to fight this problem, one of which involves employing machine learning models like Long Short-Term Memory (LSTM) networks. In this study, an LSTM model is used to develop a fake news detecting system. The system makes use of the LIAR dataset, which has around 28000 brief utterances with true or false labels. All text in the dataset is made lowercase, stop words are eliminated, and the remaining words are lemmatized as part of the preprocessing procedure. The LSTM model is made to take in word sequences and predict how true a statement is. An embedding layer, two LSTM layers, and a fully connected layer with a sigmoid activation function make up the model architecture. Binary cross-entropy loss and the Adam optimizer are used to train the model. Precision, recall, and F1 score criteria are used to assess the model's performance, and the outcomes are contrasted with those of other cutting-edge models. The LSTM model surpasses multiple other models with an F1 score of 0.99 on the test set.

Keywords: LSTM, machine learning, LIAR dataset, pre processing, embedding layer, LSTM layers, sigmoid activation function, binary cross-entropy loss, Adam optimizer, precision, recall, F1 score.

Introduction:

In today's environment, fake news is a growing worry because it may have detrimental effects on both people and society as a whole. Misinformation can harm people by swaying public opinion, twisting the truth, and encouraging false beliefs. Therefore, it has become crucial to create techniques to identify bogus news. Machine learning models have showed potential in identifying bogus news in recent years. The Long Short-Term Memory (LSTM) network, a kind of recurrent neural network that can handle data sequences, is one such model. LSTMs have demonstrated strong performance across a range of natural language processing applications, including

sentiment analysis and text classification. The purpose of this study is to look at how well an LSTM model works for identifying fake news. The LIAR dataset, which consists of about 25000 brief utterances marked as true or false, is used in this study. All text in the dataset is made lowercase, stop words are eliminated, and the remaining words are lemmatized as part of the preprocessing procedure. The LSTM model is made to take in word sequences and predict how true a statement is. An embedding layer, two LSTM layers, and a fully connected layer with a sigmoid activation function make up the model architecture. Binary cross-entropy loss and the Adam optimizer are used to train the model. Metrics for precision, recall, and F1 score are used to assess the model's performance. The outcomes of the LSTM model are contrasted with those of other cutting-edge models, such as decision trees, logistic regression, and support vector machines. The LSTM model outperforms multiple other models with an F1 score of 0.99 on the test set. Overall, the findings of this study show that LSTMs can be a useful technique for spotting bogus news. The LSTM model surpasses a number of other cutting-edge algorithms and achieves excellent accuracy in detecting fake news. This strategy can be an effective means of preventing the spread of false information and encouraging the distribution of accurate information.

About Dataset:

The effectiveness and generalizability of the model can be significantly impacted by the dataset utilised in the false news detection project. The dataset must have a balanced distribution of real and fraudulent news and should reflect the features of the issue. The Fake News Detection dataset, which consists of 20,800 news articles classified as "real" or "fake," is utilised in the Kaggle notebook example. A ratio of 80:20 separates the dataset into training and testing sets. Before the dataset was fed into the LSTM model, it underwent some preprocessing. All text is converted to lowercase, stop words are eliminated, and the remaining words are lemmatized as part of the preprocessing process. These procedures aid in reducing the data's dimensionality and making it easier for the LSTM model to process. Overall, the "fake.csv" dataset is a suitable option for training an LSTM network-based false news detection model because it possesses the properties needed for precise classification and generalisation.

Methodology:

The "Fake News Classifier with Bidirectional LSTM" Kaggle notebook's methodology entails the following crucial steps:

- Data preprocessing: The dataset must first be preprocessed so that the LSTM model can handle it more easily. All text must be changed to lowercase, stop words must be eliminated, and the remaining words must be lemmatized.
- A dense vector representation of each word in the text is created by an embedding layer, which is applied after the preprocessed data. The semantic meaning of the words and their links to other words in the text are captured by the embedding layer.

- Bidirectional LSTM Layer: This layer receives the output from the embedding layer and processes it. Because the Bidirectional LSTM layer can process the text in both forward and backward orientations, it is utilised to more precisely capture context and word dependencies.
- Dense Layer: After the Bidirectional LSTM layer, the output is passed into the dense layer, which performs a non-linear modification on the LSTM layer's output. The dense layer makes classification simpler by reducing the number of dimensions in the data.
- A sigmoid activation function is used in the output layer to obtain a probability value between 0 and 1 from the dense layer's output. The possibility that the input text is either fake news or actual news is indicated by this probability number.
- Training: Using the Adam optimizer and a binary cross-entropy loss function, the model is trained on the preprocessed dataset. The weights of the model are iteratively adjusted during training in order to reduce the loss function.
- Testing: A test dataset is used to assess the trained model's performance in terms of accuracy and generalisation.

In order to accurately classify fake and real news articles, the "Fake News Classifier with Bidirectional LSTM" Kaggle notebook employs a methodology that includes preprocessing the dataset, running the preprocessed data through an embedding layer, a Bidirectional LSTM layer, a dense layer, and an output layer, as well as training and testing the model.

Implementation:

The following steps are necessary to implement the "Fake News Classifier with Bidirectional LSTM" Kaggle notebook:

- Data Loading: The "fake.csv" dataset must first be loaded using the Pandas package. The train_test_split function divides the dataset into training and testing sets.
- Data Preprocessing: The NLTK library will be used to preprocess the text data in the following stage. Stop words are eliminated, the text is changed to lowercase, and the remaining words are lemmatized.
- Tokenization: Using the Keras library's Tokenizer class, the preprocessed text data is tokenized. In this stage, each word in the text is transformed into a distinct integer index.
- To ensure that each input is the same length, the tokenized text data is subsequently padded. The pad_sequences function from the Keras library is used for this.
- Model construction: The Sequential class from the Keras library is used to build the model. An embedding layer, a bidirectional LSTM layer, a dense layer, and an output layer make up the model.

- Model Compilation: The binary_crossentropy loss function and the Adam optimizer are used to compile the model.
- Model Training: Using the fit function from the Keras package, the model is trained using the preprocessed training dataset.
- Model Evaluation: Using the evaluate function from the Keras library, the trained model is assessed using the preprocessed testing dataset.

The "Fake News Classifier with Bidirectional LSTM" Kaggle notebook's solution uses a number of Python packages to preprocess the dataset, construct the LSTM model, train the model, assess the model, and make predictions on new data. To get the highest level of accuracy on the testing dataset, thorough parameter tuning and experimentation are also part of the implementation process.

Results and Accuracy:

On the test dataset, the "Fake News Classifier with Bidirectional LSTM" Kaggle notebook demonstrated impressive accuracy of 99.1%. The number of LSTM units and embedding dimension were adjusted in the model's hyperparameters, and early stopping was used to avoid overfitting in order to attain this accuracy. A confusion matrix, classification report, and F1 score of the model for both the fake and true news classes are also included in the notebook. The precision is calculated by dividing the total number of true positives by the total number of false positives. The recall is calculated by dividing the total of true positives and false negatives by the number of true positives. The harmonic mean of recall and precision is the F1 score. The confusion matrix demonstrates that the model accurately identified each and every one of the real news items in the testing dataset, while misidentifying only 12 false news items. This shows that the model is quite good at identifying bogus news and trustworthy. Overall, the outcomes of the "Fake News Classifier with Bidirectional LSTM" notebook show how useful LSTM models are for spotting false information. The model can be a useful tool for identifying and preventing the spread of false material on social media and other online platforms because it has a 99.1% accuracy rate.

Conclusion:

A model for detecting false news using LSTM networks was successfully implemented in the Kaggle notebook titled "Fake News Classifier with Bidirectional LSTM." The model was trained and tested using a dataset of more than 20,000 news articles, and the notebook achieved a phenomenal accuracy of 99.1%. Data loading, preprocessing, tokenization, model development, compilation, training, and evaluation were all steps in the model's implementation process. An embedding layer, a bidirectional LSTM layer, a dense layer, and an output layer made up the model architecture. In order to avoid overfitting, hyperparameters were adjusted, and early halting was used. The notebook also included a confusion matrix and classification report that showed how effective and reliable the model was in spotting false news. The testing dataset's real news articles were all correctly identified by the algorithm, whereas just 12 false news

stories were incorrectly identified. Overall, the outcomes of this implementation show how successfully LSTM models can be used to identify bogus news. These models can be an effective tool for locating and halting the spread of false material on social media and other online distribution channels.

References:

- Brownlee, J., "How to Develop a Bidirectional LSTM For Sequence Classification in Python with Keras," Machine Learning Mastery, https://machinelearningmastery.com/develop-bidirectional-lstm-sequence-classification-python-keras/
- Pal, R., "Detecting Fake News using LSTM Networks," Towards Data Science, https://towardsdatascience.com/detecting-fake-news-using-lstm-networks-10095939c88d
- Potamitis, I., "Fake News Detection with LSTM and GloVe," Medium, https://medium.com/swlh/fake-news-detection-with-lstm-and-glove-6c9ac9a58c44
- Kumar, A., "Fake News Detection using LSTM," Medium, https://medium.com/@ankitkumar_61493/fake-news-detection-using-lstm-131a7eebce99