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Application of deep learning models in the identification and screening of fake news

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Abstract. As data sets and data streams continue to expand, traditional machine learning is becoming less effective in predicting fake news. This paper is a review of deep learning in fake news detection and prevention. Author takes the model based on convolutional neural network as an example to illustrate the principle and application of deep learning in fake news detection, including OPCNN-FAKE, Dual-channel Convolutional Neural Networks with Attention-pooling (DC-CNN) model which is completely based on Convolutional Neural Network (CNN), and Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) model which combines convolutional neural network with long-short time model. These models have obvious advantages in accuracy over traditional machine learning models. This paper then points out the problems of deep learning in the field of fake news identification: it does not have good scalability and slow training speed. The author proposes possible solutions, and widely uses transfer learning and uses distributed computing platforms, such as spark, to train models. Hope this review can help the research on fake news prediction using deep learning.

Keywords: deep learning, neural network, fake news.

1. Introduction

Fake news is a subset of information which are deliberately and strategically constructed lies that are presented as news articles and are intended to mislead the public [1]. An early enough example of how fake news or misinformation to influence human communication is Octavian's propaganda campaign against Antony in the Roman era, which aimed to discredit him by smearing his private life [2]. This kind of false propaganda with strong political overtones is common. With the development of the Internet, the carriers of fake news are no longer limited to books and newspapers, social media has also become one of the main channels for spreading fake news. According to a survey by Andrea Moscadelli, during the covid-19 epidemic, there were more than two million clicks on links to fake news on Italian social media, accounting for 23.1% of the total number of clicks on links related to covid-19 [3]. This range of fake news undoubtedly reduces the efficiency of people obtaining effective information and increases the time cost of obtaining real information. Hence, it is important to identify which information is fake news and remind the public to be vigilant against it.

The development of technology has not only facilitated the spread of fake news, but also helped in combating fake news. Today, researchers are using various data mining methods to improve the model's ability to identify fake. For instance, Shu et al divides the feature extraction of fake news into two categories, 'news content feature' and 'social context features' [4]. Modeling based on news content can be categorized into two types: fact-based modeling and style-based modeling, which focuses on the author's style. Additionally, modeling based on social context can be segmented into modeling that considers the author's position and modeling that assesses the dissemination potential of the article. Using these four classification methods, the classification algorithm for fake news is constantly improved. As an emerging technology, deep learning has been proven to be more effective than traditional machine learning in predicting fake news [5] due to its superior feature extraction capabilities in processing high-dimensional and complex data. These capabilities are exactly what is needed for fake news prediction.

Based on this reality, the four classification methods mentioned above have made new technological breakthroughs after the introduction of deep learning. In terms of modeling based on factual information, Xu et al. used graph neural networks to model long-distance semantic relationships in news and evidence [6]. In terms of modeling based on pattern information, Altheneyan et al. created a stacked ensemble model to detect the stance of article titles [7]. At the same time, Sheng et al. proposed the Pref-FEND model, attempting to achieve joint detection of "pattern information-based" and "factual information-based" through graph convolutional neural networks and attention modules [8].

Given the recent important progresses made in this field, this paper aims to summarize the recent deep learning techniques for fake news detection. In the rest of this paper, Section 2 will list the deep learning models and methods used by different researchers. Section 3 will compare and analyze the advantages and disadvantages of different models, as well as explain potential future research directions. Finally, Section 4 will summarize the paper.

2. Method

2.1. Introduction of deep learning

Deep learning is a type of machine learning. Unlike traditional machine learning, deep learning does not require different vector extractors for different tasks, but instead combines simple but nonlinear modules, each of which transforms one level of representation into a higher, more abstract representation [9]. Taking a traditional Artificial Neural Network (ANN) shown in Figure 1 as an example, after the features are passed into the input layer, they are processed by multiple hidden layer functions, and the final result is calculated by the hidden function of the data layer to obtain the final result.

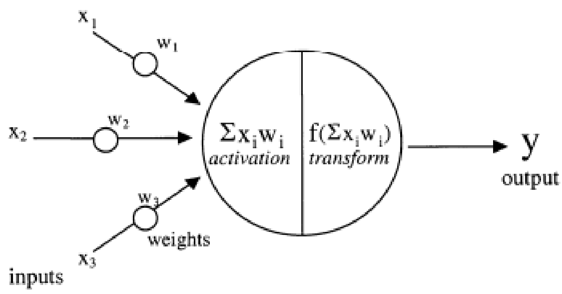

Figure 1. The model of the neural network [10].

After continuous improvement and optimization, deep learning has evolved into different branches to meet different needs. It can be roughly divided into ANN, Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Graph Neural Networks (GNN), and Recurrent Neural Networks (RNN) according to their structure and application. In natural language recognition, the Long Short-term Memory (LSTM) network improved from the recurrent neural network is a commonly used model. LSTM can capture long-term dependencies by introducing forget gates, input gates, and output gates.

2.2. OPCNN-FAKE

OPCNN-FAKE is a specialized CNN model for fake news prediction [11]. It extracts high-level and low-level features from news texts through a combination of multiple convolutional layers and pooling layers. The model consists of six main layers. The embedding layer embeds each word of the news text into a vector space, where each row of the vector corresponds to a word. The input dimension represents the size of the vocabulary, and the output dimension represents the dimension of the word vector; the dropout layer is used for regularization to prevent the model from overfitting, and the model dropout ratio is set to 0.5 for the best; the convolution layer is used for feature extraction, and the Rectified Linear Unit (ReLU) activation function is used to identify features; the pooling layer reduces the number of features through the maximum pooling operation, retaining only the most important features; the flattening layer converts the multi-dimensional feature map into a one-dimensional array; and the output layer generates the final result. After the model is built, hyperopt is used for hyperparameter optimization to select the best parameter combination.

2.3. DC-CNN

The Dual-channel Convolutional Neural Networks with Attention-pooling (DC-CNN) model effectively improves the accuracy of fake news detection by combining multi-channel convolutional neural networks and attention pool optimization mechanisms [12]. The embedding layer of this model uses the DWtext method to generate word embeddings and generates context-related word vectors through word segmentation and data cleaning. In the process of data clarification, DWtext can filter out irrelevant information and retain useful classification features. DWtext ensures that words with the same context have similar semantics by predicting context word vectors. This method can also handle new words and derivative words at the same time; the convolution layer uses a variety of convolution kernels to extract text features and capture local dependencies between adjacent words; the dual-channel pooling layer extracts local and global features through Max-pooling and Attention-pooling respectively, among which the Max-pooling layer: is mainly used to extract local features, reduce redundant features, and improve the robustness of the model; the Attention-pooling layer uses a multi-head attention mechanism to capture long-distance dependencies and enhance the learning of global semantics; the classifier inputs the extracted features into the fully connected layer for classification and outputs the fake news detection results.

2.4. CNN-LSTM

This model is a hybrid neural network that combines the two basic models of CNN and RNN [13]. The model is mainly divided into five parts. The embedding layer converts the input news title and topic into word vectors and converts each word into a 100-dimensional vector. The number of input features is 5, 000, and the output is a 5, 000×100 matrix; the convolution layer extracts local features of the input text and uses 64 filters of different sizes for convolution operations; the maximum pooling layer reduces the feature dimension and retains important features; the LSTM layer processes sequence data and captures long-distance dependencies; the fully connected layer uses the softmax activation function for multi-classification output. In order to improve the efficiency and performance of the model, this model uses two feature selection and dimensionality reduction methods, Principal Component Analysis (PCA) and chi-square test (Chi-Square).

3. Discussion

Based on the above and similar studies, the identification of fake news has made great progress due to the introduction of deep learning. However, there are still some shortcomings and challenges in the current research.

The important thing to consider is the scalability of the model dataset. Currently, many fake news identification models have good performance on the given small data. However, whether the accuracy can reach the same level as that of the small dataset when migrating to a larger dataset remains to be

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verified. Model developers often consider migrating the model to a larger dataset as a future work direction [11].

Similar, the models generally lack cross-language and cross-cultural generalization capabilities. When training the model, it is often only trained on texts in a single language, mainly English. Due to differences in culture and writing habits, a model trained in one language is difficult to effectively recognize articles in another language. In fact, due to the characteristics of some languages, such as Chinese and Japanese, there are no white spaces between words [14], so some models trained in non-language languages cannot be applied at all.

At the same time, model training speed is also a very thorny issue. Taking the CNN-LSTM model mentioned as an example, it takes 3 hours to train a training set of 50,000 samples based on 2 Intel Xeon 8-core 2.4GHz processors and 32GB DDR4 memory [11]. 3 hours of training time are a reasonable time for this task and model, but considering the training configuration, the training time of a machine with ordinary configuration will be longer. For actual application scenarios, this time may still need to be optimized.

Based on the above problems, a possible solution is to use transfer training to train new models based on existing related tasks, reduce the need for large-scale labeled data in the target domain, and improve the performance of the model in the target domain by adjusting the differences in features and data distribution between the original domain and the target domain [15, 16]. In the work of fake news prediction, for models of language style and sentiment analysis, transfer learning methods can be used to resolve differences between different data by reweighting instances in the source domain or discovering potential common feature spaces, so as to achieve the goal of not having to completely retrain the model.

Another possible method is to conduct model training based on distributed computing platforms, such as spark. Spark has the characteristics of memory computing, distributed computing, integration, etc. It can rely on memory to process data in parallel on the cluster, which can significantly improve the computing speed [17]. Spark also provides a wealth of high-level libraries (such as SparkSQL, GraphX), which simplify data preprocessing, feature extraction and other processes.

4. Conclusion

This work summarizes the recent innovations and applications of deep learning in fake news identification. This article focuses on three deep learning models used in fake news identification: OPCNN-FAKE, DC-CNN, and CNN-LSTM. Compared with general machine learning, they have better prediction accuracy. At the same time, in the field of fake news prediction, the scalability and training speed of the model are issues worthy of attention. To solve these two problems, this paper proposes two possible solutions: transfer learning and distributed computing, which can be considered the effective solutions for these issues.

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