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Fake Financial News Detection with Deep Learning: Evidence from China

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Abstract

Although fake news detection has become an emerging research attracting much attention, research in financial sector is very limited. Particularly in China, no public dataset of fake financial news is available. This paper focuses on Chinese financial market and constructs a unique dataset from clarification announcements targeting for financial news with Internet sources. Besides content features and contextual features, financial features are typically added to the feature set due to unique characteristics of financial news. Based on our sample, a deep learning approach is proposed to detect fake financial news, which demonstrates superior performance to several other baseline models, with accuracy of 94.38% and f1-score of 87.67%.The ablation experiment indicates that content features contained in the article itself contribute strongly to detect fake financial news. Finally, Shapley value is used to explain the characteristics of fake financial news compared with real ones in Chinese financial market.

Keywords: fake financial news; detection; deep learning; China

1. Introduction

In the face of rapidly changing and complex financial markets, financial news provides essential reference for most investors to make investment decisions. However, the quick development of social media in recent years has enabled the wide spread of fake news, which has the potential for extremely negative impacts on individuals and society. Thereby, fake news detection has become an emerging research attracting much attention. Specifically, fake

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financial news will bring damage to interests of investors and even disrupt the stability of the financial market. Detecting fake financial news is critical to protect investors and mitigate its negative impact on financial markets. However, most of the studies about fake news detection are concerned with political and social domains [1,2], while few of them are concerned with financial sector. Existing studies related to fake financial news focus on its impact on investor attention and market reaction instead of detection.

Furthermore, although a few public datasets of fake news are available, sample for fake financial news is very limited. Kogan et al [3] obtain a small sample of identified fake articles from a Securities and Exchange Commission (SEC) investigation: 171 articles covering 47 companies with verified false content. While in China, no such a dataset can be found. This paper focuses on Chinese financial market and obtains the sample of fake financial news from listed companies' clarification announcements targeting for financial news with Internet sources. In recent several years, scholars have utilized various machine learning and deep learning approaches to detect fake news. Based on our sample, a deep learning approach is proposed to detect fake financial news, which demonstrates superior performance to several other baseline models. Finally, Shapley value is used to explain the characteristics of fake financial news compared with real ones in Chinese financial market.

2. Related work

Fake news can be defined as "news articles that are intentionally and verifiably false and could mislead readers" [1].For research in fake news detection, a reliable dataset is required and the accuracy of the annotation needs to be guaranteed. Labelling needs to be accomplished by human experts or through crowdsourcing, both of which are costly in terms of time and manpower. Therefore, not many public datasets are available. Existing datasets contain fake news mainly from political and social domains, e.g., the FakeNewsNet dataset contains news articles from fact-checking websites such as PolitiFact and GossipCop, and the LIAR dataset consists of short political statements from PolitiFact annotated with their sources. To detect fake news, content features and contextual features need to be extracted and analysed. Content features are basic features to detect fake news, and usually include syntax features, lexical features, and semantic features [4]. Contextual features characterize other relevant information about the news, such as the source of the news and the time of publication.

Scholars have utilized various methods using machine learning and deep learning to improve the performance of fake news detection. Imbwagaet al [5]select Logistic Regression, Decision Tree, Gradient Boosting and Random Forest due to their excellent performance on binary classification problems. Hakaket al [6]propose an ensemble machine learning approach combining Decision Tree, Random Forest and Extra Tree Classifier to detect fake news by feature extraction. Some scholars point out the limitation of machine learning approaches and the improvement direction by implementing deep learning. Deep learning can automatically extract hidden high-dimensional features of news texts, while machine learning cannot. Some deep learning models have already shown superior performance to traditional machine learning models for fake news detection. Kaliyaret al [7] propose a deep Convolutional Neural Network (CNN) using three parallel convolutional layers with different kernel sizes in order to contain more information in the form of a different set of word vectors during training. Aslam et al [8] propose an ensemble-based deep learning model using LIAR dataset, in which a Bi-LSTM-GRU-dense deep learning model and a dense deep learning model are used for textual attribute and remaining attributes. Amer et al [9]conducted experiments with4 machine learning classifiers (RF, DT, SVM, NB) and 3 deep learning models (LSTM,GRU, BERT),the results show that LSTM and GRU outperformed other models.

However, most of the studies about fake news detection are concerned with political and social domains [1,2]. Despite the widespread of fake financial news, few studies are concerned with it, probably due to the lack of available dataset and the difficulty of collecting data. Recent several studies start to focus on the impact of fake financial news on investor attention and market reaction. Clarke et al [10] collect data from Seeking Alpha (the world's largest crowdsourcing investing community), which consists of 383 fake news articles and other legitimate news articles published during the same time period. Fong [11] identifies the 2019 Chinese ADR Delisting Treat as a specific example of fake news and uses event study methodology to analyse its market reactions. Specifically, Zhang et al [12]use the same 383 fake news articles as in [10] and develop a machine learning system to detect financial disinformation, in which feature selection is conducted through recursive feature elimination with cross-validation. Chung et al [13]collect financial social media messages about four U.S. high-tech company stocks and develop a deep learning approach to detect financial disinformation by discovering abnormal returns of stocks and producing human-validated labels of disinformation.

According to related work, research about fake financial news detection is very limited. Particularly in China, no public dataset of fake financial news is available, and it's hard to determine and label a financial news article as "fake" or "real". In this paper, we construct a unique dataset from clarification announcements of listed companies. Considering unique characteristics of financial news, we typically add financial features to the feature set. In order to deal with diverse features, we propose a model integrating two deep neural sub-networks in which one is used for content features and the other is used for contextual features and financial features. The experimental results show that our model outperforms other five baseline models.

3. Methodology

3.1 Data Collection and Processing

Listed companies' clarification announcements targeting for fake news often contain information about the fake news that has been disproved. Cninfo is the information disclosure website for listed companies designated by the China Securities Regulatory Commission (SEC). We first collect clarification announcements targeting for fake financial news from Cninfo. Then according to the related information contained in the clarification announcements, we search the fake news from Internet. Since disproved news are often removed by publishing source, only some of the fake news articles can be found. Thus 160 fake news articles are obtained with Internet source, spanning from Jan. 2019 to Dec. 2022. Since fake financial news often disrupt the market and bring damage to both investors and the related company, we assume that financial news that is not clarified by the related company is real news. We randomly select 480 real news articles from Wind database, which are three times larger than the sample of fake news. Temporal distribution of real news is also consistent with that of fake news during the same period. Thus, our dataset totally includes640 articles in which160 are fake news and 480 are real ones.

For each news article, its original text and title are collected as content features. For contextual features, we collect source of publication, text length, and text sentiment. To measure text sentiment, we use the Chinese financial sentiment dictionary constructed by Jiang [14],which is expanded through manual filtering and the word2vec algorithm based on the Loughran MacDonald's dictionary [15].The sentiment scores for the headline and the body text are calculated separately and added together as the sentiment score of the article. Due to unique characteristics of financial news, financial features of the related company concerned in the news are also collected from its annual report or third quarterly report which can be found in Resset or Wind databases. For example, return on assets and operating profit margin reflect the company's profitability, total asset turnover measures the company's operating capacity, and the non-current assets to assets ratio reveals the company's capital structure.

3.2Model Construction

In order to make effective use of different types of feature inputs, we propose a model integrating two deep neural sub-networks to perform the task of financial news detection. Figure 1 illustrates the architecture of our model.

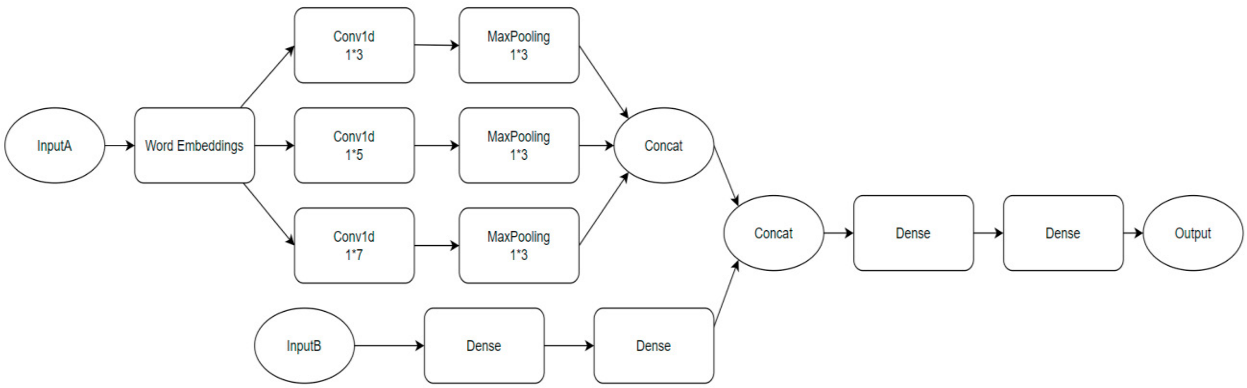

Fig. 1. Model Architecture

The article itself, including both the headline and the body, contains a large number of hidden features and provides the most important information to detect fake news. Therefore, we input the article (content features) separately into the first sub-network and try to explore deeper features hidden in it as fully as possible. For the input of the first sub-network, word embeddings of the article content are generated. Given the impressive performance of BERT in Natural Language Processing (NLP) tasks and the fact that our data is in Chinese, we adopt BERT-Chinese-wwm, a Chinese-oriented variant of BERT that incorporates traditional Chinese word separation. The word embedding representation obtained by BERT-Chinese-wwm is more informative in terms of syntax, lexis and semantics than Glove, which has been commonly used in previous studies. Furthermore, motivated by [8], we use three parallel CNN components to extract adequate features from word-embedding vectors. Each CNN component is composed of a convolutional layer and a pooling layer. The three convolutional layers have same parameters but different kernel sizes to capture local features at different granularities. The three pooling layers use max pooling to reduce the interference of invalid information in the article content. Then, the vectors obtained from the three parallel CNN components are joined together as the result of the first sub-network.

The second sub-network consists of two dense layers. We stitch together contextual features (source of publication, text length, text sentiment) and financial features into a feature vector as the input to this sub-network. Among them, source of publication is represented by a binary value, where 1 indicates official and 0 indicates individual. Subsequently, the outputs of the two sub-networks are concatenated together and passed to another two dense layers. The output of the model indicates whether the input article is fake news or not.

4. Experiments and Results Analysis

4.1Experimental Design

Our dataset consists of 160 fake financial news and 480 real ones spanning from Jan. 2019 to Dec. 2022 in China. Each item contains text, title, source of publication, text length, text sentiment, return on assets, operating profit margin, total asset turnover, and non-current assets ratio. For the 640 news items contained in the dataset, we use 75% of them as the training set and the remaining 25% as the test set.

Confusion matrix is commonly used to evaluate the effect of classification. In this study, the sample of fake news is set as P and the sample of real news is set as N. The confusion matrix is shown in Table 1. Using TP (True Positive), FP (False Positive), FN (False Negative), and TN (True Negative) values in the confusion matrix, the evaluation metrics of precision (TP/(TP+FP)), recall (TP/(TP+FN)), accuracy ((TP+TN)/(P+N)) and f1-score (2*precision*recall/(precision+recall)) can be calculated respectively.

Table 1. Confusion matrix

Category	Detection is Negative(N)	Detection is Positive(P)
Negative(real news)	TN (True Negative: real news)	FN (False Negative)
Positive(fake news)	FP (False Positive)	TP (True Positive: fake news)

As this study is based on a self-built dataset rather than a publicly available dataset, there are no studies using the same dataset for reference and comparison, so we adopt a progressive experimental approach. First, machine learning methods are used to examine the usability of the dataset. Specifically, we select several machine learning models that perform well in the fake news detection task, including Logistic Regression, Decision Trees, Random Forest and Naïve Bayes. The features obtained from the data processing are concatenated into feature vectors and serve as input to these machine learning models. Then we test the validity of deep learning methods on this dataset and compare with machine learning methods. We build a basic deep neural network model consisting of two dense layers and an output layer. Table 2 shows the hyperparameters for basic deep neural network. To test the performance of our proposed model, we input a vector of content features into BERT+CNN, and a vector of contextual features and financial features into a basic deep neural network. Table 3 shows the hyperparameters for our proposed model.

Uncomplicated network structure allows the model itself to learn from these raw feature vectors, so we try to reveal the contribution degree of different features and interpret how the features contribute to fake news detection by ablation experiments and Shapley value based on the basic deep neural network.

Table 2. Hyperparameter for basic deep neural network

Hyperparameter	Description or value
No. of dense layers	2
Loss function	Binary_crossentropy
Activation function	Relu
Optimizer	Adam
Number of epochs	50

Table 3. Hyperparameter for our proposed model

Hyperparameter	Description or value
No. of convolution layers	3
No. of max pooling layers	3
No. of dense layers	4
Loss function	Binary_crossentropy
Activation function	Relu
Optimizer	Adam
Number of epochs	30

4.2Experimental Results

A summary of the evaluation results for all models is shown in Table 4. Among the machine learning methods, the logistic regression model performs the best with f1-score of 76.87%. For the basic deep neural network model, f1-score improves by 2% and accuracy increases to 90.38%, which shows the superiority of deep learning method to machine learning methods. However, for all four machine learning methods and basic deep neural network, recall value is relatively low, which means these models are less capable of effectively detecting fake news in the sample of fake news. While for our proposed model, all four metrics improve significantly with accuracy of 94.38% and f1-score of 87.67%, which proves that the model has excellent performance in detecting financial fake news.

Table 4. Evaluation results

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	89.81%	83.45%	71.54%	**76.87%**
Decision Trees	83.88%	65.53%	68.38%	66.81%
Random Forest	88.38%	81.01%	67.03%	73.29%
Naïve Bayes	84.63%	68.88%	64.47%	66.52%
Basic Deep Neural Network	**90.38%**	83.46%	74.59%	78.74%
Proposed Model	**94.38%**	**86.49%**	**88.89%**	**87.67%**

Word embeddings (content features) and other features (contextual and financial) are successively excluded in ablation experiment based on basic deep neural network. Table 5 shows the ablation experimental results. Performance with only content features is almost the same as that with all features. However, when excluding content features, f1-score falls sharply. The ablation experiment indicates that content features contained in the article itself contribute strongly to detecting fake financial news.

Table 5. Ablation experimental results

Features	Accuracy	Precision	Recall	F1-score
All features	90.38%	83.46%	74.59%	78.74%
Excluding content features	85.62%	79.31%	57.50%	66.67%
Excluding contextual and financial features	88.12%	76.09%	81.40%	78.65%

Shapley value can be used to discover the characteristics of fake financial news. In our experiments, Shapley value of all contextual features and financial features are shown in Figure 2. According to the results, text length contributes greatly to detecting fake financial news, which means real financial news is usually shorter than fake financial news. As to source of publication, more fake news articles are published through individual sources than official sources. Text sentiment also plays an import role for detecting fake financial news, which usually shows negative emotions. For financial features, companies with weak profitability, high proportion of current assets, or high total asset turnover, tend to be targeted by fake financial news, which is consistent with profit motivation behind financial news.

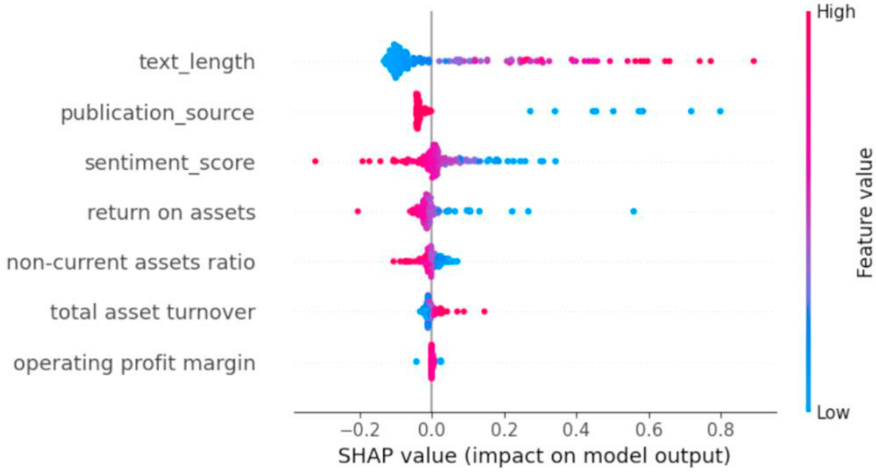

Fig. 2. Shapley value of contextual and financial features

5. Conclusion

In this paper, we propose a deep learning approach to detect fake financial news in China and conduct experiments on a unique self-built dataset with 160 fake news and 480 real ones. Besides content features and contextual features, financial features are also added to the feature set due to unique characteristics of financial news. The experimental results show that our model outperforms other five baseline models. The ablation experiment indicates that content features contribute strongly to detecting fake financial news. We also discover the characteristics of fake financial news, such as long text, individual sources, negative emotions, concerned company with weak profitability. For future research, more fake news and more features can be added to our unique dataset to obtain more valuable discoveries of fake financial news in China.

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