Financial Misinformation Detection via RoBERTa and Multi-channel Networks

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Abstract. Financial misinformation has been a potential threat to online social communities in the current era of macroeconomic conditions. However, there is less attention in this direction of research. This paper presents a new study for financial misinformation detection. A new model called `Fin-MisID` is introduced, consisting of input, `RoBERTa` in the embedding layer and multi-channel networks (CNNs, BiGRU, and attention layers). The performance of the proposed `Fin-MisID` model is investigated on a new financial misinformation-based dataset. It shows comparatively better results than two existing studies and several baseline methods.

Keywords: Online social media · Misinformation detection · Financial misinformation detection · Information retrieval · Multi-channel Networks

1 Introduction

In the last two decades, the rapid growth of user-generated information (UGI) has remarkably increased [1]. It has become the giant source for online social interaction and propagate non-literal information, like humor, sarcasm, fake news, etc. [2,3]. However, such UGI is also used to mislead people globally. Such dubious information has immense potential to create false suspicion and uncertainty. It is available in varied forms, including satire, parody, fake content, hoax, spam, rumor, etc. Furthermore, a huge amount of such misleading content originated and propagated using UGI, which has reflected a possible threat to online communities. It gives a negative impact on numerous online activities, like e-commerce shopping, stock price movement, and financial purchases [4].

The financial market surveillance provides the efficient flow of the finance-based business and solutions [5]. The available online data has been perceived as a valuable source to spread unverified financial information massively, like the spread of false rumors, financial fake news, etc. [6]. Also, the manual verification of online financial misinformation is tedious and time-consuming tasks. Therefore, identification of financial misinformation is the need of the hour for proper functioning of the financial activities which is less explored by researchers.

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1.1 Our Contributions

The extraction of semantic and syntactic information in line with context is crucial for any particular domain, like finance [6]. Considering this, we investigate a new study for financial misinformation detection. To the best of our knowledge, this is a first study towards the financial misinformation detection, wherein a new relevant dataset is created and a novel deep learning-based model called `Fin-MisID` is introduced to perform classification task. `Fin-MisID` constitutes an input layer, `RoBERTa` in embedding layer followed by multi-channel networks. Each channel consists of convolutional neural network (CNN) to extract semantic and syntactic information with respect to the different window sizes, kernel values, etc., bidirectional gated recurrent unit (BiGRU) to obtain latent contextual sequences, and attention layer which is used to emphasise important and relevant financial and misinformation tokens in the input data. The combined output generated from the summation of each channel is passed to the dense and output layers, wherein classification is done via *sigmoid*. The key contributions are given below:

– Proposed a new financial misinformation detection problem.
– Created a new dataset based on the financial misleading texts.
– Development of a new `Fin-MisID` model to detect financial misinformation.
– Performed an empirical evaluation of the proposed model and compared the results with existing studies and baselines methods.

The remaining portion of this study is presented as follows: Section 2 presents the existing studies. Section 3 presents the problem description and dataset preparation. Section 4 presents the proposed model. Section 5 presents the experimental setup and evaluation results. Lastly, Sect. 6 presents the conclusion of this study and future works.

2 Related Work

This section presents the existing studies for misinformation detection (MID) problem on online content. In [7], authors extracted word-based features for MID and obtained less recall due to unwanted tags in fake contents. In [8], authors extracted 23 features and used graph kernel-based hybrid machine learning-based classifier to detect rumor. In [9], authors applied recurrent neural network (RNN) to capture the contextual information of rumors posts on two real-world datasets.

In [10], authors proposed hierarchical recurrent convolutional neural network to learn contextual information. In [11], authors proposed deceptive review identification using recurrent CNN to identify the deceptive text. In [12], authors presented a system for hoax detection in mail system by taking benefit of intelligent automation. In [13], authors proposed hoax detection framework for prior diagnosis of available hoaxes in digital social media. In [15], authors proposed fake news detection and applied CNN and LSTM models in financial domain. In [14], authors authors proposed satire detection and they extracted lexical and feature groups.

3 Problem Description and Dataset Preparation

This section presents the problem description and preparation of a newly created dataset.

3.1 Problem Description

The online Cambridge dictionary defines misinformation as "wrong information, or the fact that people are misinformed"[1]. This study presents the financial misinformation detection as a two-class problem. Hence, a portion of textual data is classified either as financial misinformation (FMI) or true financial information (TFI).

3.2 Dataset Preparation

This section presents the dataset collection and data pre-processing steps.

Dataset Collection. In this study, data is collected from `Politifact`[2], a popular fact-check website using `BeautifulSoup4`[3] wrapper/html parsing tool. We consider key financial topics from [5] work which is given in Table 1 to collect financial misinformation only. Also, each data is labelled as either *half true*, *true*, *mostly true*, *pants on fire*, *false*, *mostly false*.

Table 1. A list of finance-based topics

A list of finance-based topics
'income', 'debt', 'loan', 'mortgage', 'economy', 'job', 'poverty', 'salary', 'money', 'bank', 'savings', 'fund', 'payroll' 'earning', 'wage', 'revenue', 'payoff', 'wealth'

Data Pre-processing. After data collection, we have done several cleaning steps to receive pre-processed textual data which can be used further for classification tasks. To this end, we have removed numbers, comma, exclamations, quotation, full-stop, punctuation marks, etc. Lastly, convert the raw data into its lower-case form.

4 Proposed Model

This section presents the layer-wise complete description of the proposed `Fin-MisID` model, as given in Fig. 1.

1 https://dictionary.cambridge.org/dictionary/english/misinformation.
2 https://www.politifact.com/.
3 https://beautiful-soup-4.readthedocs.io/en/latest/.

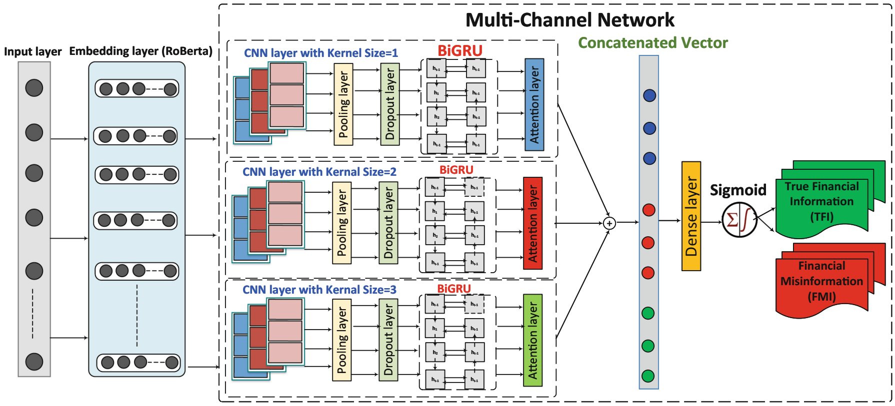

Fig. 1. Work-flow of the proposed `Fin-MisID` model

4.1 Input Layer

The input layer receives pre-processed text as an input text and that tokenizes each word from it, accordingly. Each token is assigned a number as an index. It results in a dictionary and finally converted into a numeric vector n as per the index value of the dictionary. Each numeric vector is of different size due to the varying length. Hence, a fixed-length f of 100 is taken as a padding value for each input vector and it is considered as a padded vector p such that $|p| = f \geq |n|$. The fixed-length of the resulting vector as $p \in R^{1\times f}$ is passed to the succeeding layer.

4.2 Embedding Layer

In the study, `RoBERTa`[4] is used in embedding layer. The resultant input vector is received by the embedding layer to retrieve relevant contextual financial misinformation in both directions. In this line, we have taken 768-dimensional word vector representation to cover contextual information in bidirectional mode using `Transformer`. The encoded representation from `RoBERTa` gives a relevant and enrich contextual representation. Finally, the vector generated from this layer is forwarded to the next layer (i.e., multi-channel network).

4.3 Multi-channel Networks

This section briefly describe the multi-channel networks. Each channel is consisted of a CNN with varying kernel sizes, pooling and dropout, followed by BiGRU, and attention layers. A detailed description of each layer is given below:

[4] https://huggingface.co/docs/transformers/model_doc/roberta.

Multi-channel CNN Layer. In this study, the proposed `Fin-MisID` model considers a one-dimensional convolution layer with kernel sizes of 1, 2, and 3 and several filters, f to each network in a multi-channel environment. Mathematically, for channel x, filters of kernel size, k is $f^x \in R^{kd}$, where d is the `RoBERTa` dimension. The matrix generated from the embedding layer for channel c via maximum sequence length p is $m^c \in R^{pd}$. Further, the role of the pooling layer is to receive the extracted features-map. The max pooling extracts the key semantic financial misinformation-based feature and reduces the feature-map size accordingly. The dropout value of 0.2 is used in the dropout layer.

BiGRU Layer. BiGRU is a special kind of GRU which consists of two gates. It is applicable in two opposite directions that gives latent semantic feature sequences. It is operational in forward direction as $\overrightarrow{gru_f}$ to retrieve latent semantic representation of misinformation-based on financial tokens as forward sequences (f_t to f_{32}). On the other hand, GRU operational in backward direction as $\overleftarrow{gru_b}$ to retrieve latent semantic representation of misinformation-based on financial tokens as backward sequences (f_{32} to f_t). The final hidden representation of GRU is obtained by combining the outcome of both forward and backward directions of GRU, as given in Eq. 1, and it is passed further to the next layer.

$$gru_i = [\overleftarrow{gru_b}, \overrightarrow{gru_f}] \tag{1}$$

Attention Layer. In this study, the attention layer is employed to apply varying weights for tokens in the input text to highlight the important financial misinformation-related keyword-based features. It also minimizes the effect of normal keywords in parallel. The latent representation, u_t, received using $tanh(.)$, is given in Eq. 2. The normalized similarity α_t is given in Eq. 3 for u_t via `softmax`. Lastly, Eq. 4 measures the resultant vector s_i.

$$u_t = \tanh(W_w f_c + gru_i) \tag{2}$$

$$\alpha_t = \frac{\exp(u_t)}{\sum_t(\exp(u_t))} \tag{3}$$

$$s_i = \sum_{i=1}^{t} \alpha_t f_c \tag{4}$$

4.4 Concatenated Layer

This layer refers to the concatenated vector which is obtained by combining all vectors received across multi-channel networks. The resultant concatenated vector is forwarded to the dense and output layers for final classification steps.

4.5 Dense and Output Layers

The fully connected dense layer gives financial misinformation-related features set from the resultant concatenated vector from the previous layer and divisible into two classes as FMI and TFI. *Sigmoid* and *binary cross-entropy* are applied to perform the final classification of input data labeled as FMI or TFI.

5 Experimental Setup and Results

In this section, we discuss the experimental setup and evaluation results. We have taken `Intel Haswell` machine, Ubuntu-20.04 operative system, 32 GB RAM, and `NVIDIA Tesla A100` GPU as hardware components. The proposed `Fin-MisID` model is implemented in `Keras` with `Python` 3.7. The neural network-based parameter settings used in this study include 100 batch-size, 30 padding, 0.4 spatial dropout at BiGRU, 25 epoch with early stopping, $1e-5$ learning rate, and `Adam` as optimizer.

5.1 Dataset

As discussed in Subsect. 3.2, we have prepared a financial misinformation dataset, wherein only *true* and *false* labels are taken and replace them as *TFI* and *FMI*, respectively. We have called this newly created dataset as `FMID` dataset, as shown in Table 2.

Table 2. Final statistics of the newly created `FMID` dataset

Actual labels	Final labels	Total
True	TFI	1791
False	FMI	3179

5.2 Evaluation Results and Comparative Analysis

The performance evaluation results of the proposed `Fin-MisID` model are given in Table 3. It shows that the proposed `Fin-MisID` model receives impressive results as *f-score* of 0.85, *training accuracy* of 0.88, and *test accuracy* of 0.83, respectively. It also compares the evaluation results of the `Fin-MisID` with recent studies. It shows that the `Fin-MisID` outperforms as compared to the existing studies. `Fin-MisID` performs 13.33%, 10.00%, and 10.66% better than [15] work in terms of *f-score*, *training accuracy*, and *testing accuracy*, respectively. It also compares the results with several baseline methods based on neural networks and `Fin-MisID` shows better results. It can be seen that the performance of BiGRU is better across several baseline methods. `Fin-MisID` performs 21.42% better than

Table 3. Performance evaluation results on newly created `FMID` dataset

Methods ↓	Precision	Recall	F-score	Train Acc.	Test Acc.
Fin-MisID	**0.82**	**0.88**	**0.85**	**0.88**	**0.83**
Zhi et al. [15]	0.73	0.77	0.75	0.80	0.75
Raza and Ding [16]	0.71	0.75	0.72	0.71	0.70
CNN	0.65	0.69	0.67	0.72	0.68
GRU	0.64	0.65	0.65	0.74	0.70
LSTM	0.65	0.63	0.64	0.68	0.64
BiGRU	0.68	0.72	0.70	0.69	0.74
BiLSTM	0.67	0.60	0.63	0.61	0.70
CNN+BiGRU	0.61	0.67	0.64	0.65	0.68
CNN+BiLSTM	0.66	0.63	0.64	0.61	0.67
BERT	0.78	0.74	0.76	0.78	0.74

BiGRU in terms of *f-score*. Likewise, `Fin-MisID` performs 18.91% better than GRU in terms of *training accuracy* and 12.16% better than BiGRU in terms of *testing accuracy*. The proposed model also performs better than BERT.

These results indicate that the proposed `Fin-MisID` model shows impressive results with fine-grained new labeled dataset. It shows that contextual information and extraction of semantic features using several multi-channel layers also play a significant role in classification performance.

6 Conclusion and Future Works

This study has presented a new problem for financial misinformation detection. A new labeled dataset based on financial information/misinformation has created for experimental evaluation. We have proposed a new model called `Fin-MisID` for financial misinformation detection mainly based on a contextualize embedding followed by multi-channel networks. The proposed model shows impressive results and outperforms in comparison to the existing studies and baseline methods. The inclusion of multi-modal settings and multi-lingual data could be an interesting research direction for this work.

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