Social Media Rumor Detection Based on Multi-Channel Graph Convolutional

Meng LI, Mengyuan Liu, Lulu He

***Abstract*— The emergence of social media also speeds up the speed of information dissemination. At the same time, the development of social network platform also leads to the rapid spread of rumors, which has a great negative impact on social life. The research field of social media rumor detection has become a hot spot at present. The existing rumor detection methods can not effectively pay attention to the spread characteristics and breadth spread characteristics of social media rumors. To solve this problem, a new rumor detection method based on multi-channel graph Convolutional Network (MA-GCN) was proposed. The model mainly combines the textual features, propagation features and structural features of the event to judge whether the event is a rumor. The model explores the two characteristics of rumor propagation and dissemination through the operation of the top-down and bottom-up transmission modes of rumors, uses the bidirectional graph structure to learn the rumor propagation mode and capture the rumor propagation structure, uses the undirected graph to capture the global information for prediction, and introduces the multi-head attention mechanism for information fusion. The effectiveness of the proposed MA-GCN method is verified by experiments on twitter public datasets.**

***Index Terms*—Social Media Rumor Detection, Graph Convolutional Networks, Multi-channel Mechanism, Multi-head Attention.**

I. INTRODUCTION

As of April 2023, the number of Internet users in the world has reached 8.5 billion, of which 1.067 billion in China, an increase of 35.49 million over March 2023, and the Internet penetration rate has reached 75.6%. From the above data, it can be seen that the number of users of social media is increasing day by day, and social media has become the main means of current information dissemination. Among the numerous information disseminated, network rumors also account for a large part, and the spread of network rumors has a great impact on the current social stability. For example, since August 18, 2022, a rumor of Zhejiang's collective production of growth hormone caused the market value of Changchun High-tech to evaporate 25 billion [1], causing investors to suffer serious losses. In daily life, there are also many rumors, causing panic to the normal life of residents, such as "citrus soaked with preservative, harmful to health?" [2] Such rumors emerge in an endless stream, which affect everyone's normal life, mislead public opinion, and even damage the image of the government and cause social unrest. Based on the above problems, the task of social media rumor detection research is imminent.

The existing social network rumor detection is mainly divided into three categories: manual detection methods, machine learning-based detection methods and deep learning based detection methods [3]. The manual detection method has high accuracy, but it has obvious lag in processing a large amount of data. The rumor detection method based on machine learning relies on manual extraction and selection of features, which is time consuming and labor-intensive, and the robustness of the obtained feature vector [4] is not robust enough. The deep learning-based rumor detection method makes up for the above shortcomings by mining the text content and transmission structure of rumors, but the accuracy of rumor detection is not satisfactory. Literature [5] proposes a rumor detection method based on RNN, which for the first time applies deep learning technology to false news detection. This method learns to capture the hidden representation of contextual information of related posts changing over time according to the relevance of posts. Literature [6] proposes a rumor detection method based on convolutional neural networks, which vectorizes rumor events, improves the traditional convolutional layer filtering operation, and uses CNN for rumor detection. Literature [7] proposes a rumor detection model based on Bi-LSTM hierarchical social attention network, which mainly uses social features and text information to judge whether an event is a rumor.

Driven by deep neural networks, in order to process a large number of graph structured data, graph neural network GNN model [8] came into being. Graph neural network GNN draws on the ideas of convolutional networks, cyclic networks and deep auto encoders. Graph neural network is a very broad concept, which can be simply understood as: Graph neural network = graph + neural network, graph neural network can solve the current traditional neural network can not deal with causal reasoning, interpretability and a series of bottleneck problems, is the future focus of the field of neural networks. There is an important variant of GNN called Graph Convolutional network GCN[9], which has a similar function to CNN and can extract features, but the extraction object of GCN is graph data. Features extracted from graph data by GCN can be used to complete many tasks such as node classification, node prediction, edge prediction and graph classification. It can be seen that GCN has a wide range of uses and is constantly developing. At present, some researches have adopted deep learning methods to discover

Manuscript received Feb 11, 2024

Meng Li, School of computer science and technology, Tiangong University, Tianjin, China.
Mengyuan Liu, School of computer science and technology, Tiangong University, Tianjin, China.
Lulu He, School of computer science and technology, Tiangong University, Tianjin, China.

rumors by the way they spread. However, these deep learning methods only consider the mode of deep propagation, and ignore the structure of widespread propagation in rumor detection, which affects the effect of rumor detection. To solve this problem, a rumor detection model based on multi-channel graph convolutional network is proposed. Experiments show that this model can detect rumors effectively.

The main contributions of this paper are as follows:

- This paper proposes a new social media rumor detection method based on multi-channel graph convolutional networks, which has a significant improvement over other methods on multiple data sets.
- A new multi-channel propagation path design is proposed, which combines the graph neural network model of top-down, bottom-up and bidirectional propagation flows to fully explore the path of rumor detection and traceability, and solve the problem that other methods are often based on one-way propagation path modeling, which leads to incomplete traceability.
- A prediction module based on multi-head attention is proposed. Through modeling the attention of different channels, the dynamic weight combination of information of different transmission paths is obtained, so as to improve the overall prediction effect of the model.

II. Related Works

In recent years, social media rumor detection has attracted widespread attention.Traditional detection methods mainly use artificially designed features, such as user characteristics, text content and propagation patterns, to train supervised classifiers.For example, decision trees [10],SVMs [11].There are also some studies that apply more effective features, such as temporal structure features [12], user comments, and the emotional attributes of posts.However, these methods mainly rely on feature engineering, which is time-consuming and labor-intensive.And these artificially designed features usually lack high-order representations extracted from rumor propagation and dissemination.

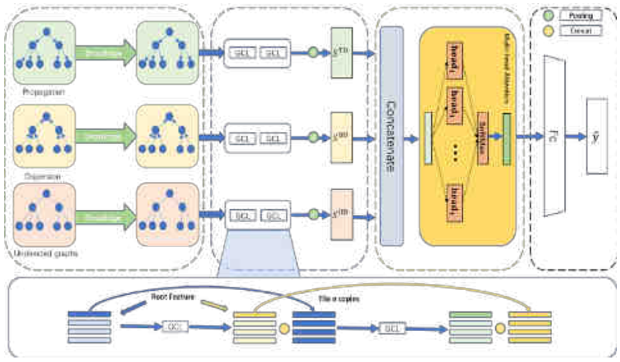
Recently, many rumor detection methods based on deep learning models have been proposed in order to mine high-order representations for rumor recognition. [13]Recurrent neural networks (RNNs) are used to capture hidden representations from temporal content features. [14]This method is improved by combining attention mechanisms and RNNs to focus on text features with different attentions. [15] has been improved a convolutional neural network (CNN) based method is proposed to learn key features scattered in input sequences and form high-level interactions between important features. [16]RNNs and CNNs are combined to obtain time-series-based user features. Recently, [17] an adversarial learning approach was used to improve the performance of rumor classifiers, where a discriminator served as the classifier and a corresponding generator improved the discriminator by generating conflicting noise.In addition, [18] a tree-structured recurrent neural network (RvNN) was established to capture hidden representations from both propagation structure and textual content.However, these methods are too inefficient to learn features from propagation structure and also ignore the global structural features of rumor propagation.

Compared with the deep learning models mentioned above, GCN is better at capturing global structural features from graphs or trees.Inspired by the success of CNN in the field of computer vision, GCN has shown extremely advanced performance in various tasks using graphical data, using GCN as a special transitive model for undirected or directed graphs.Later, [19] presented a theoretical analysis of undirected graph convolution methods based on spectral graph theory. Subsequently, [20] developed a method called Chebyshev spectral CNN (ChebNet) and used Chebyshev polynomials as filters.Following this work, [21] proposed a first-order approximation of ChebNet (1stChebNet), where the information of each node is aggregated from the node itself and its adjacent nodes.

III. Method

The overall framework of the Multi-channel attention graph convolutional network (MA-GCN) model proposed in this paper is shown in Figure.1.

Fig. 1. General framework diagram.



This model mainly combines the textual features, transmission features and structural features of the event to judge whether the event is a rumor. Firstly, the causality and structural features of rumors in the process of transmission are represented by a directed graph. In this way, the composition and relationship graph between the original text and the comment can be constructed, and features other than the text can be introduced to judge whether the event is a rumor. Bi-GCN is used to connect the source post with other comment features. The undirected graph is used to capture the global information, capture the complete process, and introduce the context learning relationship, because the rumor may start somewhere in the middle and have an impact on the downstream and the source simultaneously through influential nodes.

Secondly, the effectiveness of the model is improved by concatenating the features of each graph convolution layer of GCN. In addition, the method of root feature enhancement is used in the graph convolution layer, that is, the hidden features between the original text and the comments are connected to increase the expression of text semantics, so as to enhance the accurate representation of nodes in each layer. By adding multi-head attention mechanism, the diversity of information extraction is increased, and information is extracted from multiple dimensions. Then softmax function is used to fuse the feature information of the three groups of nodes obtained from different graphs, and finally the prediction is made.

A. *Definitions*

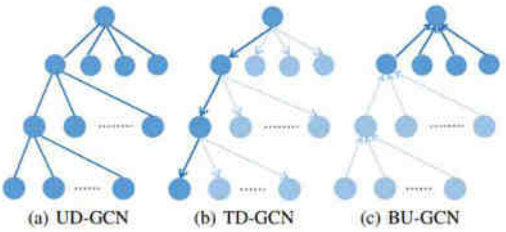


Figure 2: (a) the undirected graph with only node relationships; (b) the deep propagation along a relationship chain from top to down; (c) the aggregation of the wide dispersion within a community to an upper node.

Let $C = \{c_1, c_2, \ldots, c_m\}$ be the rumor detection dataset, where c_i is the i-th event and m is the number of events. $c_i = \{r_i, w_1^i, w_2^i, \ldots, w_{n_{i-1}}^i, G_i\}$, where n_i refers to the number of posts in c_i , r_i is the source post, each w_j^i represents the j-th relevant responsive post, and G_i refers to the propagation structure. Specifically, G_i is defined as a graph $\langle V_i, E_i \rangle$ with r_i being the root node, where $V_i = \{r_i, w_1^i, w_2^i, \ldots, w_{n_{i-1}}^i\}$, and $E_i = \{e_{st}^i | s, t = 0, \ldots, n_i - 1\}$ that represents the set of edge from responded posts to the retweeted posts or responsive posts, as shown in Figure 2(b). For example, if w_2^i has a response to w_1^i , there will be an directed edge $w_1^i \rightarrow w_2^i$, e_{12}^i. If w_1^i has a response to r_i , there will be an directed edge $r_i \rightarrow w_1^i$, e_{01}^i. Denote $A_i \in \{0,1\}^{n_i * n_i}$ as an adjacency matrix where

$$a_{ts}^i = \begin{cases} 1, & if\ e_{st}^i \in E_i \\ 0, & otherwise \end{cases}$$

Denote $X_i = \left[{x_0^i}^T, {x_1^i}^T, \ldots, {x_{n_{i-1}}^i}^T \right]^T$ as a feature matrix extracted from the posts in c_i , where ${x_0^i}^T$ represents the feature vector of r_i and each other row feature ${x_j^i}^T$ represents the feature vector of w_j^i . Moreover, each event c_i is associated with a ground-truth label $y_i \in \{F, T\}$ (i.e., False Rumor or True Rumor). In some cases, $y_i \in \{N, F, T, U\}$ (i.e., Non-rumor, False Rumor, True Rumor, and Unverified Rumor). Given the dataset, the goal of rumor detection is to learn a classifier $f: C \rightarrow Y$, where C and Y are the sets of events and labels respectively, to predict the label of an event based on text contents, user information and propagation structure constructed by the related posts from that event.

B. *Graph Convolutional Networks*

The application of convolution to graphs has attracted the attention of scholars, among which GCN is one of the most effective convolution methods. The convolution operation of GCN can be regarded as a message passing structure:

$$H_k = M(A, H_{k-1}; W_{k-1}), \quad \#(1)$$

where $H_k \in \mathbb{R}^{n * v_k}$ is the hidden layer feature matrix calculated by the k − th Graph Conventional Layer (GCL) and M is the message propagation function, which depends on the adjacency matrix A, the hidden feature matrix H_{k-1} and the trainable parameters W_{k-1}.

There are many kinds of message transfer functions for GCN, among which the message propagation function defined in the first-order approximation of ChebNet (1stChebNet) is as follows:

$$H_k = M(A, H_{k-1}; W_{k-1}) = \sigma\left(\hat{A} H_{k-1} W_{k-1}\right). \#(2)$$

In the above equation $\hat{A} = \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}}$ is the normalized adjacency matrix, where $\tilde{A} = A + I_N$, the self-ring is added.

C. *DropEdge*

DropEdge is the article published in ICLR 2020 [22] to mitigate overfitting problems with GCN-based models. Each time the epoch is trained, some edges are randomly removed from the original plot at a certain rate. This method enhances the randomness and diversity of the input data, just like the random rotation and flipping of the picture.

Assuming that the total number of edges in the graph A is N_e and the dropping rate is , then the adjacency matrix after DropEdge, A', is calculated as follows:

$$A' = A - A_{drop}, \#(3)$$

where A_{drop} is constructed from the original edge set with $N_e * p$ random sampling bars.

IV. MA-GCN RUMOR DETECTION MODEL

In this paper, a rumor detection method based on multi-channel graph Convolutional network (MA-GCN) is proposed. The core idea of MA-GCN is to learn higher-order representations from rumor propagation and rumor dispersion. The two-layer 1stChebNet is used in the MA-GCN model as the basic GCN component. As shown in the figure1, the execution process of MA-GCN model is divided into the following four steps.

A. *Construct Propagation and Dispersion Graphs*

Based on the reply and forward relationship,we construct the propagation structure $\langle V, E \rangle$ for a rumor event c_i. Let $A \in \mathbb{R}^{n_i * n_i}$ is its adjacency matrix and X is the feature matrix of the rumor event based on the rumor propagation tree. Where A only include the contiguous edges from the upper node to the lower node. In each training epoch, p percentage of edges are dropped via Eq. (3) to form A', which avoid penitential overfitting issues. Based on A' and X, build the MA-GCN model.

The MA-GCN model consists of TD-GCN, BU-GCN and UD-GCN. These three components use different adjacency matrices. For TD-GCN, the adjacency matrix is $A^{TD} = A'$.For BU-GCN, the adjacency matrix is $A^{BU} = A'^{T}$. For UD-GCN, the adjacency matrix is $A^{UD} = A' + A'^{T}$. TD-GCN, BU-GCN and UD-GCN use the same feature matrix X.

B. Calculate the High-level Node Representations

After the DropEdge operation, we can use TD-GCN, BU-GCN and UD-GCN to get the top-down, bottom-up and up-down propagation characteristics respectively.

By changing Eq. (2), the hidden layer representation of two layers of TD-GCN is obtained:

$$H_1^{TD} = \sigma\left(\hat{A}^{TD} X W_0^{TD}\right), \#(4)$$

$$H_2^{TD} = \sigma\left(\hat{A}^{TD} H_1^{TD} W_1^{TD}\right), \#(5)$$

where $H_1^{TD} \in \mathbb{R}^{n*v_1}$ and $H_2^{TD} \in \mathbb{R}^{n*v_2}$ are the hidden layer feature representation of the two layers of TD-GCN. $W_0^{TD} \in \mathbb{R}^{d*v_1}$ and $W_1^{TD} \in \mathbb{R}^{v_1*v_2}$ are the convolution kernel parameter matrix of TD-GCN. Similar to the calculation in Eq. (4) and Eq. (5), the bottom-up hidden features, H_1^{BU} , H_2^{BU} , H_1^{UD} and H_2^{UD} of BU-GCN and UD-GCN can be obtained.

C. Root Feature Enhancement

The root post of the rumor event always contains enough information to have a wider range of impact. It is quite ne-cessary to make better use of the information in the root post and get a more accurate node representation from the relationship between the node and the source post.

In addition to the hidden layer features of TD-GCN, BU-GCN and UD-GCN, the enhancement of root cause features is proposed to improve the performance of the model for rumor detection.

For the k-layer GCL of TD-GCN, we concatenate the hidden layer feature vector of each node and the hidden layer feature vector of the root node of the (k-1)-layer GCL to form a new feature matrix:

$$\widetilde{H}_k^{TD} = concat(H_k^{TD}, \ (H_{k-1}^{TD})^{root}), \#(6)$$

with $H_0^{TD} = X$. We express TD-GCN with the root feature enhancement by replacing H_1^{TD} in Eq. (5) with $\widetilde{H}_1^{TD}$ and then get $\widetilde{H}_2^{TD}$ as follows:

$$H_2^{TD} = \sigma\left(\hat{A}^{TD} \widetilde{H}_1^{TD} W_1^{TD}\right), \#(7)$$

$$\widetilde{H}_2^{TD} = concat(H_2^{TD}, \ (H_1^{TD})^{root}), \#(8)$$

Similar to Eq. (7) and Eq. (8), we calculate the hidden feature metrics $\widetilde{H}_1^{BU}$, $\widetilde{H}_2^{BU}$, $\widetilde{H}_1^{UD}$ and $\widetilde{H}_2^{UD}$ for BU-GCN and UD-GCN.

D. Representations of Propagation and Dispersion for Rumor Classification

Node representations in TD-GCN, BU-GCN and UD-GCN are aggregated respectively to get the representations of propagation and diffusion. The mean-pooing operation is used to aggregate the three sets of node representations in the following form:

$$S^{TD} = MEAN\left(\widetilde{H}_2^{TD}\right), \#(9)$$

$$S^{BU} = MEAN\left(\widetilde{H}_2^{BU}\right), \#(10)$$

$$S^{UD} = MEAN\left(\widetilde{H}_2^{UD}\right), \#(11)$$

Then, the representations of propagation and diffusion are spliced to fuse their information:

$$\mathrm{S} = \mathrm{concat}(\mathrm{S}^{\mathrm{TD}}, \mathrm{S}^{\mathrm{BU}}, \mathrm{S}^{\mathrm{UD}}). \#(12)$$

After GCL, three vectors of S^{TD} , S^{BU} and S^{UD} are obtained. At this time, the number of channels is three, and the information is more diversified. Considering the interaction of multiple dimensions, multi-head attention mechanism is introduced to increase the diversity of information extraction.

Finally, the label of the event $\hat{y}$ is calculated via several full connection layers and a softmax layer. where $\hat{y} \in \mathbb{R}^{1*C}$ is a vector of probabilities for all the classes used to predict the label of the event.

$$\mathrm{M_k} = \mathrm{W_k^1}\left(\mathrm{W_k^0 S} + \mathrm{b_k^0}\right) + \mathrm{b_k^1}, \#(13)$$

$$\alpha_k = \frac{\exp(W_k^A S)}{\sum_{i=1}^{K} \exp(W_i^A S)}, \#(14)$$

$$\mathrm{M}_F = \sum_{k=1}^{K} \alpha_k M_k , \#(15)$$

$$\hat{y} = Softmax\left(FC(M_F)\right). \#(16)$$

V. EXPERIMENTATION

A. Datasets

The model proposed in this experiment is verified on Twitter datasets: Twitter15 and Twitter16 datasets. Twitter datasets have been widely used in the field of rumor detection.

Based on these datasets, the model is trained. Where, nodes represent users, edges represent forwarding and replying relationships, and features are top-5000 words extracted according to TF-IDF values.

The Twitter15 and Twitter16 datasets include four labels: Non-rumor (N), False Rumor (F), True Rumor (T), and Unverified Rumor (U). Table I represents the statistics for the datasets:

Table I
Statistics of the datasets

Statistic	*Twitter15*	*Twitter16*
# of posts	331,612	204,820
# of Users	276,663	173,487
# of events	1490	818
# of True rumors	374	205
# of False rumors	370	205
# of Unverified rumors	374	203
# of Non-rumors	372	205
Avg. time length / event	1,337 Hours	848 Hours
Avg. # of posts / event	223	251
Max # of posts / event	1,768	2,765
Min # of posts / event	55	81

B. Experimental Setup

We use the following methods for comparison:

- DTR : Zhao et al. (2015) proposed a rumor detection model based on decision tree, which uses phrases extracted from rumors to identify trend rumors and automatically identify the credibility of posts. Specifically, the features extracted from it classify posts into two states: credible or untrustworthy. Weibo posts related to the topic of "trend" are explained by using the publishing and forwarding behavior from users, the text of posts and the function of quoting to external sources [23].

- RFC: Random Forest Classifier, (Kwon et al., 2013). The spreading characteristics of rumors are studied from three aspects: time characteristics, structural characteristics and language characteristics. For time, a new time series model is used, which fully considers the daily click-and-forward changes and can detect the fluctuation of rumor detection in real time [24].
- SVM-TK and SVM-HK： SVM classifiers use tree kernel (Ma et al., 2017) and hybrid kernel (Wu et al., 2015) respectively. Both classifiers use kernel to model the propagation structure, and propose a new method to capture the time characteristics of these features based on the time series of rumor life cycle, and incorporate the time series modeling technology into various social context information to realize rumor detection.
- PPC_RNN+CNN: Combining the rumor detection model of RNN and CNN, learning the representation of rumors through the characteristics of users on the rumor propagation path.
- Bi-GCN: Rumor detection model based on GCN, using a two-way propagation structure[25].
- MA-GCN: Rumor detection model based on GCN, proposes a new multi-channel propagation path design and a prediction module based on multi-head attention to improve the overall prediction effect of the model.

C. Experimental Results

Table II show the comparative results of different methods on the Twitter datasets.

Table II

Rumor detection results on Twitter15 and Twitter16 datasets (N: Non-Rumor; F: False Rumor; T: True Rumor; U: Unverified Rumor)

Twitter15					
Method	Acc.	N	F	T	U
		F_1	F_1	F_1	F_1
DT-Rank	45.4	41.5	35.5	73.3	31.7
SVM-RBF	31.8	22.5	8.2	45.5	21.8
SVM-TS	54.4	0.796	0.472	0.404	0.483
SVM-TK	75.0	80.4	69.8	76.5	73.3
RvNN	72.3	68.2	75.8	82.1	65.4
PPC_RNN+CNN	47.7	35.9	50.7	30.0	64.0
Bi-GCN	81.2	75.2	84.3	87.4	77.0
MA-GCN	81.4	78.4	85.4	87.9	78.3

Twitter16					
Method	Acc.	N	F	T	U
		F_1	F_1	F_1	F_1
DT-Rank	47.3	25.4	8.0	19.0	48.2
SVM-RBF	55.3	67.0	8.5	11.7	36.1
SVM-TS	57.4	75.5	42.0	57.1	52.6
SVM-TK	73.2	74.0	70.9	83.6	68.6
RvNN	73.7	66.2	74.3	83.5	70.8
PPC_RNN+CNN	47.7	35.9	50.7	30.0	64.0
Bi-GCN	85.4	79.6	84.8	90.5	85.9
MA-GCN	86.2	75.8	85.1	91.6	87.1

First, it can be seen that deep learning-based approaches generally perform better than other approaches using artificial features. Deep learning methods can capture valid features and learn higher-order representations of rumors.

Secondly, the MA-GCN method proposed in this paper outperforms the PPC_RNN+CNN method in all indexes, which shows the effectiveness of the combined rumor diffusion structure for rumor detection. The RNN and CNN methods cannot deal with the data of graph structure, so they ignore the important structural features in rumor diffusion.

Finally, the rumor detection method based on multi-channel graph convolutional network is significantly superior to DT-Rank, SVM-RBF, SVM-TS, SVM-TK, RvNN, PPC_RNN+CNN and Bi-GCN methods in terms of accuracy. The MA-GCN method proposed in this paper, combined with a new multi-channel propagation path and multi-head attention prediction module, has remarkable results for rumor detection tasks.

VI. Conclusion

Rumor detection plays an important role in modern life. This paper proposes a new social media rumor detection method based on multi-channel graph convolutional network. GCN enables the model to process graph or tree structured data, and can learn higher-order representations that are more conducive to rumor detection. Ignoring the bidirectional propagation path of rumors, that is, rumors may start somewhere in the middle, and influence both downstream and source through influential nodes.

MA-GCN combines the graph neural network model of top-down, bottom-up and two-way propagation flows to comprehensively explore the ways of rumor detection and traceability. Solving the problem that other methods are often based on one-way propagation path modeling, which leads to incomplete traceability. For GCN embedding vectors with multiple channels, only one FC is used to predict the interaction characteristics between the multiple channels. In this paper, a three-channel graph network coding method is adopted, so the multi-channel attention is combined to obtain different interaction results between the multiple channels and improve the prediction performance. Experiments on Twitter datasets show that the accuracy of MA-GCN method for rumor detection tasks is significantly improved.

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