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Abstract: The popularity and development of social media has made it more and more convenient to spread rumors, and it has become especially important to detect rumor information from massive amounts of information. Most of the traditional rumor detection methods use content characteristics or propagation structure to mine rumor characteristics, ignoring the fusion characteristics of content and structure and their interaction characteristics. Therefore, a novel rumor detection method based on heterogeneous convolutional networks is proposed. Firstly, this paper constructs a heterogeneous map of joint rumor content and propagation structure to explore the interaction between content and propagation structure during rumor propagation and obtain rumor representation. On this basis, this paper uses the deep residual graph convolutional neural network to construct the content and structure interaction information of the current network propagation model. Finally, this paper uses the two datasets of Twitter15 and Twitter16 to verify the proposed method. Experimental results show that the proposed method has higher detection accuracy than the traditional rumor detection method.

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1. Introduction

A major feature of the information age is the influx of information, including a massive amount of false information. This false information affects people's decision-making and causes social conflicts. False information is often used as an important tool for fraud and phishing, and is often used to spread rumors and slander. This poses a significant threat to individual and social safety and interests, making detection of false information increasingly important.

The application scenarios of false information detection are very extensive, involving multiple fields such as news media, social networks, and e-commerce. In the news media field, false information detection can help news organizations and reporters distinguish and block fake news, improve the credibility and credibility of news reporting. In the social network field, false information detection can help social network platforms to timely discover and delete false information, maintain the health and order of the network space. In the e-commerce field, false information detection can help consumers identify fake goods and false advertising, safeguard the rights and interests of consumers.

In false information detection tasks, there are many research results available for reference. For example, Ma proposed a method for rumor detection using a tree-structured recursive neural network, and the research results show that the proposed method has excellent early detection of rumors [1]. However, this method may have some difficulties in processing long texts and complex syntax structures. Vu proposed a new model based on graph convolutional network and propagation embedding for rumor detection in social media, and conducted sufficient experiments on real datasets to prove the effectiveness of the method [2]. However, this method is aimed at text propagation in social networks, and may not be suitable for cases involving visual or other non-textual information in the propagation process. In addition, Monti proposed a new type of automatic fake news detection model based on geometric deep learning, and experiments showed that social network propagation and structure are important features for highly accurate detection of fake news [3]. However, this method may be affected by the sparseness and incompleteness of the data. Social media data often have high dynamicity and noise and lack complete information labels, which may lead to a decline in the performance of the model.

Compared with existing methods, this article proposes a rumor detection method for the interaction characteristics of joint content and structure named GCRES, which can combine content and propagation patterns to characterize rumors, The residual structure based on graph convolutional network is used to model the content structure correlation of heterogeneous graphs, thus solving the problem of indistinguishable effects of adjacent neighbor nodes in the rumor propagation process and effectively realizing rumor classification. Specifically, the main contributions of this article include the following three points:

(1) This article constructs a heterogeneous graph to obtain the representation of rumors by combining post content and rumor propagation pattern, which includes textual information of rumors and initial propagation information.

(2) This article proposes a residual structure based on graph convolutional network. This structure uses a skip connection method to effectively overcome the problem of indistinguishable effects of adjacent nodes in the rumor propagation process and can obtain the interaction characteristics of heterogeneous graph.

(3) This article uses Twitter15 and Twitter16 datasets widely used in rumor detection for experimental verification. The experimental results show that compared with traditional rumor monitoring methods, the proposed GCRES method can achieve a higher rumor detection accuracy.

2. Related Work

Traditional methods for detecting fake information can be categorized into two types: rule-based methods and machine learning-based methods. Rule-based methods classify real and fake information by using the difference between them, such as using features like keywords, sentence structures, and sentiment polarities in the text [4]. On the other hand, machine learning-based methods classify real and fake information by building models, such as using support vector machines, random forests, or other algorithms to train and classify data. Ma et al. first used deep learning models to detect rumors on Weibo [5]. In subsequent studies, they proposed two recursive neural network models based on top-down and bottom-up tree structures to better capture rumor structures and text features. The results showed that this model had a higher effect in detecting early propagating rumors [1].

Since introducing deep learning methods, the accuracy and efficiency of fake information detection have significantly improved. Among them, graph neural networks, as a powerful representation learning method, have a wide range of applications in fake information detection. Graph neural network-based fake information detection methods usually fall into two categories: node-based methods and graph-based methods.

Node-based methods mainly focus on node features and contextual information, while graph-based methods use the entire graph as input and utilize graph neural networks to learn graph representations. In node-based methods, the commonly used approach is to use the social and content attributes of nodes for fake information detection. For example, by using features such as user information, text content [6,7], and time information to determine whether the node is spreading fake information. Y Liu et al. used recurrent and convolutional networks to construct a time series classifier to capture global and local variations in user features on the propagation path, thus detecting

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fake news [8]. This method is the first to model the news dissemination path on social media as multi-dimensional time series and practice fake news detection through a sequence classifier. Ling Sun et al. discussed a novel joint learning model called HG-SL for early detection of fake news. This model uses hyper-GNN to embed the global relationships of users and multi-head self-attention modules to simultaneously learn local contexts (local context in specific news) during propagation, in order to comprehensively capture the differences between true and false news. The introduction of global node centrality and local propagation status further highlights user influence and news dissemination ability. The experiments show that HG-SL is significantly better than the SOTA models in early detection of fake news [9]. In addition, some studies also consider the propagation behavior of nodes as one of the node features, such as the forwarding and like counts of nodes [10,11].

In graph-based methods, the main approach is to learn the representation of the entire graph through graph neural networks and then perform fake information detection. For example, Tian Bian et al. proposed a novel bidirectional graph convolutional network (Bi-GCN) model, which uses a rumor propagation directed graph with a top-down structure to learn the propagation patterns of rumors and a rumor propagation graph with a reverse direction to capture the structure of rumor propagation. The influence of the original post of the rumor is enhanced in the graph structure and achieved excellent results in fake information detection [12]. K Tu et al. proposed a framework for rumor representation learning and detection. This framework uses joint text and propagation structure representation learning to improve rumor detection performance ,and proposes a joint graph concept to integrate the propagation structure of all tweets to alleviate the sparsity issue of propagation structure in the early stage [13]. Some researchers also combine graph neural networks with attention mechanisms to learn graph representations more accurately. For instance, Qi Huang et al. proposed a meta-path-based heterogeneous graph attention network framework. The heterogeneous graph is decomposed into tweet word and user subgraphs according to tweet words and tweet user paths, and node representations are learned using subgraph attention networks to capture global semantic relationships of text content and fuse information involved in source tweet propagation for rumor detection [14]. Chunyuan Yuan et al. proposed a novel global-local attention network (GLAN) for rumor detection on social media. This method combines local semantic relationships with global structural information, uses multi-head attention mechanisms to integrate semantic information of relevant retweets into the source tweet, generates a better integrated representation, and then establishes a heterogeneous graph using global structural information to capture complex global information between different source tweets and uses global attention for rumor detection. Experimental results show that GLAN is significantly better than existing models in rumor detection and early detection [15]. In addition, Ma et al. used statistical features in three aspects of rumor content language characteristics, user characteristics participating in rumor transmission, and propagation network structure to build a feature graph, and integrated entity recognition, sentence reconstruction, and ordinary differential equation networks into a unified framework called ESODE, which improved the performance of rumor detection [16].

3. Solution Design

3.1. System Model

A Rumor Detection Dataset $X = \{x_1, x_2, \dots x_n\}$, Where $x_i$represents the i-th event, where n represents the total number of events. Each event x_i Contains Two Independent Sets: Content and Propagation Structure. That is $x_i = \{P_i, G_i\}$,Where P_i and G_i Represent the Content and Propagation Structure of x_i, Respectively. The Propagation Structure G_i is Composed of a Set of Nodes $C_i = \{c_{i0}, c_{i1}, \dots, c_{iN}\}$ and a Set of Connections $E_i = \{e_{st} \mid s, t = 0, 1, \dots, N\}$, Where c_{i0} Represents the Original Post and c_{ij} Represents the j-th Response Post. Let $A \in \{0,1\}^{N \times N}$ be the adjacency matrix, where A_{st}=1 if there exists an edge from node c_{is} to node c_{it}, and A_{st}=0 otherwise. Moreover, Let A' be the adjacency matrix of the heterogeneous graph that combines both content and propagation

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structure. In this paper, we model the rumor detection task as a supervised classification problem, where each event has a true label y_i, with a value set of $\{NR, FR, TR, UR\}$, representing non-rumors, falsehood rumors, true rumors and unverified rumors, respectively. Our goal is to train a classifier $f : x_i \rightarrow y_i$ to accurately predict the label of the content and propagation structure of a given post.

3.2. Rumor Detection Framework

As shown in Figures 1 and 2, we propose a rumor detection framework based on the interaction characteristics of heterogeneous graphs, named GCRES. The framework consists of three parts: rumor representation, interaction representation learning , and rumor classification. Firstly, we construct a graph model based on the content and propagation structure for rumor representation. Specifically, we first use the TF-IDF model to extract the representation information of the rumor content [17]. Then, we encode the propagation node vectors using the adjacency matrix, combine the content and propagation information, and finally embed the joint graph into a low-dimensional space. Secondly, we use a graph convolutional network (GCN) to learn the initial state of the heterogeneous graph. At the same time, we use interaction representation learning technology to obtain the interaction features of the heterogeneous graph. Finally, We use an average pooling layer to cascade features of heterogeneous maps and make predictions of rumor categories.

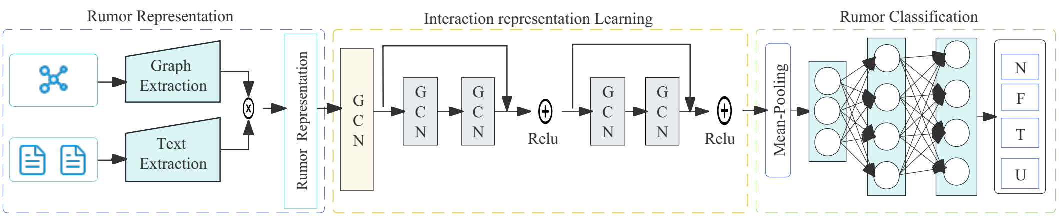

Figure 1. Rumor Detection Framework.

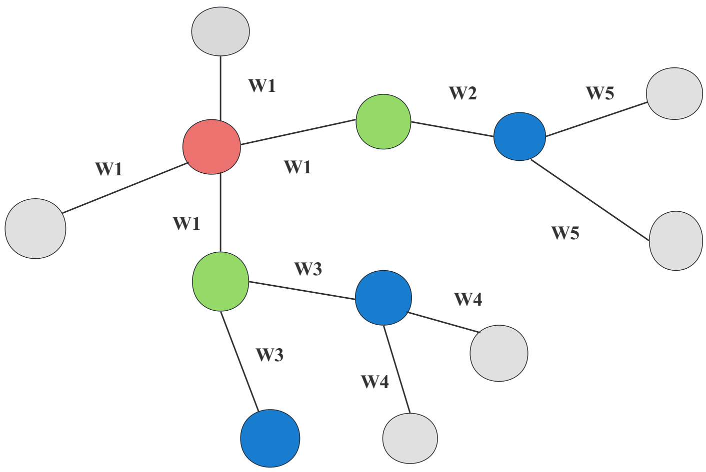

Figure 2. Heterogeneous Graph Combining Rumor Content and Propagation Structure.

3.3. Rumor Representation

As shown in Figure 1, we constructed a heterogeneous graph to characterize rumors by combining the content and propagation structure. Specifically, we used the TF-IDF method to obtain the representation of the content in each post. First, we filtered out stop words and constructed a corpus. Then, the word frequency can be represented as:

$$tf_{ij} = \frac{n_{ij}}{\sum_k n_{ik}} \tag{1}$$

In the equation, n_{ij} represents the number of times the i-th vocabulary appears in the j-th post. At the same time, inverse document frequency can be represented as:

$$idf_i = \frac{\log|D|}{1 + |k : t_i \in p_k|} \tag{2}$$

Where $|D|$ represents the total number of posts in the corpus, $|k : t_i \in p_k|$ represents the number of posts containing the vocabulary t_i. Then, the weight of the vocabulary t_i can be represented as:

$$t_i = tf_{ij} \times idf_i \tag{3}$$

Therefore, the content representation of the j-th post is $p_j = \left[t_1, t_2, \ldots, t_{|W|}\right]$, where $|W|$ is the total number of vocabulary in the corpus.

On the other hand, since the representation of p_j is high-dimensional and sparse, we use an embedding layer to map it to a low-dimensional space to obtain dense real-valued vectors as the content representation of the j-th post:

$$v_j = W_j p_j \tag{4}$$

Where W_j represents the weight of the embedding layer.

Based on the above framework, we further construct the propagation structure of the rumor $G_j = \{C_j, E_j, A\}$. Since the adjacency matrix $A \in \{0,1\}^{N \times N}$ reflects the transmission path of the rumor, the adjacency matrix of the joint rumor content and propagation path can be obtained from A and v_j:

$$A'_{st} = A_{st} v_j \tag{5}$$

Where A_{st} represents the weight of the edge from node c_{js} to node c_{jt}. Based on this, the initial representation of the rumor r_j can be represented as:

$$r_j = \frac{1}{M} \sum_{c_{js}, c_{jt} \in C_j} A'_{st} \tag{6}$$

Where M is the number of edges occupied by the j-th post in the propagation structure.

3.4. Acquiring the initial state

After obtaining the representation of the rumor, we use a GCN to obtain the initial state of the heterogeneous graph. Specifically, we first construct the operator $\tilde{A}$ of the GCN, defined as:

$$\Phi = \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}} \tag{7}$$

$$\tilde{A} = A' + I \tag{8}$$

Where A' and I are the adjacency matrix and identity matrix of the heterogeneous graph, respectively, and $\widetilde{D}$ is the degree matrix of $\tilde{A}$. Then, the initial state representation of the joint graph can be represented as:

$$H^{(0)} = \sigma\left(\Phi r_j W^{(0)}\right) \tag{9}$$

Where $H^{(0)}$ represents the initial state of the rumor propagation, $W^{(0)}$ is the weight matrix of the filter, and $\sigma(\cdot)$ is the ReLU activation function.

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3.5. Interaction representation learning

In order to obtain the interaction feature information of rumor content and propagation graph, we use interaction representation learning to learn the continuous temporal correlation in the propagation process.

Firstly, First, we assume that the hidden representations of all nodes are correlated, and we combine the GCN and residual network (ResNet) methods to learn the embedding representations of nodes. Specifically, we use a two-layer GCN network model to learn the representation of the propagation graph and extract potential relationships through the feature information of the nodes themselves and adjacent nodes. Each GCN layer first obtains the features of the current node and the adjacent nodes, and then uses aggregation functions to obtain local feature relationships, and finally trains through shallow learning to obtain high-dimensional features. The propagation relationship between layers can be represented as:

$$H^{(l+1)} = \sigma\left(\widetilde{D}^{-\frac{1}{2}}\tilde{A}\widetilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{10}$$

Where $\tilde{A} = A + I$, I is the identity matrix, $\widetilde{D}$ is the degree matrix of $\tilde{A}$, and $\sigma(\cdot)$ is the ReLU activation function.

On the other hand, this article uses a structure based on residual networks to cascade four GCN networks. As the number of model layers in GCN increases, it is prone to the problem of over-smoothing, which makes the effect differentiation of neighboring nodes in the rumor propagation process unclear. Therefore, a graph neural network incorporating residual networks is designed, adopting skip connection to improve and avoid this problem. As shown in Figure 1, the output of each residual block can be represented as:

$$y^{(l+1)} = h^{(l)}\left(x^{(l)}\right) + F\left(x^{(l)}, H^{(l)}\right) \tag{11}$$

3.6. Rumor Classification

We further use average pooling operation to aggregate the output of all GCNs, that is:

$$H = \frac{1}{L}\sum_{l=0}^{L} H^{(l)} \tag{12}$$

Where L is the number of GCNs. Then, we use fully connected layers and softmax layer for rumor classification, which is:

$$\hat{y} = \mathrm{softmax}\left(W_{FC}H + b_{FC}\right) \tag{13}$$

Where W_{FC} and b_{FC} are the weight and bias of the last hidden layer, $\hat{y}$ represents the predicted probability vector of rumors belonging to each category, and it is also the label for predicting rumor events. Finally, we train the model by minimizing the cross-entropy between $\hat{y}$ and the true distribution y, and adding L2 regularization to prevent overfitting.

4. Experiment

4.1. Dataset

We conducted experimental validation of the proposed method using two open-source datasets, Twitter15 and Twitter16. Both datasets consist of social media data, each with 1490 and 818 propagation graphs. The labeling of the propagation graphs includes four types: non-rumor, true rumor, false rumor, and unverified rumor. In addition, nodes in the graph represent users, and edges represent replies and forwarding. Table 1 provides statistical information on the two datasets.

Table 1. Twitter15 and Twitter16 datasets.

Statistical information	Twitter15	Twitter16
Total number of posts	331612	204820
Original post count	1490	818
Non-rumor count	372	205
True rumor count	374	203
False rumor count	370	205
Unverified rumor	374	205

4.2. Baseline method

We used the following seven baseline methods for rumor detection:

1) DTC [6]: This method uses decision tree classifiers and manually designed features to extract and analyze tweet information

2) RFC [18]: This method uses a random forest classifier to detect rumors by combining user features, language features, and news structure features.

3) SVM-TS [9]: This method is based on SVM classifier, using manually designed features to form a time series kernel to identify rumors.

4) SVM-HK [20] : This method uses graph kernel to measure the similarity of propagation structure and combines SVM classifier for rumor detection.

5) GRU-RNN [5]: This method relies on a recurrent neural network with GRU units to capture the contextual changes of relevant posts over time for rumor detection.

6) BU-RvNNand TD-RvNN [21]: The method adopts a bidirectional tree-structured recursive neural model, which includes top-down and bottom-up tree-structured neural networks, combined with GRU units, to learn and analyze rumor information.

7) Rumor2vec [13]: The method uses a CNN-based model to combine the textual content with the propagation structure to achieve joint representation learning for rumor detection.

4.3. Experimental setup

We use a TF-IDF model based on 5000 vocabulary words to represent the content of the post. The node and hidden layer embedding sizes are searched in $\{32, 64, 128, 256\}$. The embedding size of the model and the number of samples selected for each training are both set to 64. At the same time, we divide each dataset into five parts and perform five-fold cross-validation to ensure the robustness and fairness of the experimental results. We use accuracy for the four categories and F1 value for each category as performance indicators. In addition, we use the Adam algorithm for model optimization. The learning rate is 0.005, and the number of iterations is 100 epochs. Finally, in order to prevent overfitting, we stop training early when the validation stops decreasing for 10 epochs.

4.4. Performance comparison

Table 2 shows the test results of the proposed method and seven baseline methods on Twitter15 and Twitter16. From the table, it can be seen that compared with methods using manually designed features (DTC, RFC, SVM-TS and SVM-HK), methods based on deep learning (GRU-RNN, BU-RvNN, Rumor2vec) and the proposed method can achieve higher accuracy and F1 value. This is because deep learning technology can learn effective highdimensional features of rumors. This result proves that deep learning technology can effectively improve the performance of rumor detection.

On the other hand, the proposed method has the highest accuracy on both datasets. Specifically, the proposed method achieved accuracies of 84.6% and 88.9% on Twitter15 and Twitter16, respectively, which is 5% and 3.7% higher than the baseline method Rumor2vec. This is because CNN cannot handle data with dynamic features, making it difficult for Rumor2vec to capture the interaction characteristics of rumor propagation. This result demonstrates that incorporating interaction features can effectively improve the performance of rumor detection. It is worth noting that for the non-rumor category, Rumor2vec outperforms the proposed method. This is because non-rumor posts are often posted or replied by more authoritative and credible users, so the propagation path and content of non-rumor posts are more fixed. Therefore, the interaction characteristics of non-rumor posts have little impact on the detection performance.

Table 2. Comparison experiment results.

Method	Acc.	NR F1	FR F1	TR F1	UR F1
Twitter15 dataset					
DTC	0.454	0.733	0.355	0.317	0.415
RFC	0.565	0.810	0.422	0.401	0.543
SVM-TS	0.544	0.796	0.472	0.404	0.483
SVM-HK	0.493	0.650	0.439	0.342	0.336
GRU-RNN	0.641	0.684	0.634	0.688	0.571
BU-RvNN	0.708	0.695	0.728	0.759	0.653
TD-RvNN	0.723	0.682	0.758	0.821	0.654
Rumor2vec	0.796	**0.883**	0.746	0.836	0.723
GCRES	**0.846**	0.803	**0.857**	**0.903**	**0.811**
Twitter16 dataset					
DTC	0.473	0.254	0.080	0.190	0.482
RFC	0.585	0.752	0.415	0.547	0.563
SVM-TS	0.574	0.755	0.420	0.571	0.526
SVM-HK	0.511	0.648	0.434	0.473	0.451
GRU-RNN	0.633	0.617	0.715	0.577	0.527
BU-RvNN	0.718	0.723	0.712	0.779	0.659
TD-RvNN	0.737	0.662	0.743	0.835	0.708
Rumor2vec	0.852	**0.857**	0.769	**0.927**	0.850
GCRES	**0.889**	0.767	**0.832**	0.907	**0.878**

5. Conclusion

By utilizing the dynamic changes in rumor content, propagation structure, and propagation heterogenous graph, this paper proposes a novel interaction rumor detection method based on graph convolutional network called GCRES. First, a novel heterogenous graph is proposed by combining rumor content and propagation structure to obtain accurate rumor representation. Secondly, a residual module consisting of four cascaded graph convolutional networks is designed using the powerful ability of graph convolutional networks in dealing with heterogenous graphs for representation learning, thus fully mining the interaction characteristics of the heterogenous graph. Experimental results show that compared with traditional rumor detection methods, the GCRES method exhibits better detection performance on both the Twitter15 and Twitter16 datasets.

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