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EDITED BY
Jiang Zhu,
Netskope Inc., United States

REVIEWED BY
Xiu-Xiu Zhan,
Hangzhou Normal University, China
Yukie Sano,
University of Tsukuba, Japan

*CORRESPONDENCE
Mengfan Zhao,
zhaomengfan@tju.edu.cn

†These authors share first authorship

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Jointly multi-source information and local-global relations of heterogeneous network for rumor detection

Xiaohong Han[1†], Mengfan Zhao[1,2*†], Yutao Zhang[1,2] and Tingzhao Zhao[3]

[1]School of Information and Electrical Engineering, Hebei University of Engineering, Handan, China, [2]College of Intelligence and Computing, Tianjin University, Tianjin, China, [3]Science College, Shijiazhuang University, Shijiazhuang, China

The widespread rumors on social media seriously disturb the social order, and we urgently need practical methods to detect rumors. Most existing deep learning methods focus on mining news text content, user information, and propagation features but ignore the rumor diffusion structural features. Rumors spread in a vertical chain and diffusion in a horizontal network. Both are essential features of rumors. In addition, existing models need more effective methods to extract higher-order features of multiple resource information. To address these problems, we propose a multi-source information heterogeneous graph model in this paper, called jointly Multi-Source information and Local-Global relationship of heterogeneous network model named MSLG. It extracts multi-source information such as rumors content, user information, propagation, and diffusion structure. Firstly, we extract the higher order semantic representation of rumors content by graph convolution network and integrate local relational attention to strengthen the critical semantic. At the same time, we construct the rumors and users as heterogeneous graphs to capture the propagation and diffusion structure of the rumors. We are finally fusing global relational attention to measure submodules' importance. Experiments on two real-world datasets show that the proposed method achieves state-of-the-art results in fake news detection.

KEYWORDS

multi-source information, propagation diffusion structure, attention mechanism, heterogeneous graph, rumor detection

1 Introduction

The convenience of social media provides an opportunity for the generation and propagation of fake news. When a public event happens, the public still has a limited understanding of it, so all rumors catering to public psychology take advantage of the space. Some users lack verification when retweeting news, which makes them helpful for rumor spreading. In the mobile Internet era, users can express their opinions freely. The concealment of information makes it easier for fake news and spread faster and harder to trace and control its source. The propagation of rumors not only brings trouble to the person concerned but also affects the order of the Internet and reduces the media's credibility. Therefore, we urgently need an efficient method for rumor detection.

We classify existing rumor detection methods into five categories which are a knowledge-based method, rumor content-based method, propagation structure-based method, source-based method, and mixed method. When detecting fake news from a knowledge-based perspective, the aim is to verify the authenticity of the news by comparing the knowledge extracted from the news content with the known facts. The manual fact-checking method relies on domain experts to verify the authenticity of given news. This method is time-consuming, laborious, and inefficient. With the increased quantity of information, the scalability is extremely poor. Furthermore, because of people's subjectivity, it is also highly subjective to judge the authenticity of the news. To address these problems, existing research has developed from manual verification methods to automated verification. Some researchers obtain existing knowledge from the open network and use knowledge triples to realize fake news detection [1, 2]. Knowledge-based methods mainly assess the veracity of a given news story, while style-based methods focus on analyzing the content features of rumors. They can assess news intent, i.e., whether they intentionally mislead the public [3]. It is helpful for us to detect rumors by mining features of rumors content. However, when users intentionally publish rumors for a specific purpose, they use ambiguous words to circumvent the conditions that the model determines as rumors. Therefore, content-based methods do not cover comprehensive information when detecting rumors, which limits the improvement of detection accuracy. The propagation-based methods start from the forwarding path of rumors and mining the features of rumor propagation by constructing tree structure [4, 5], graph structure [6, 7], or hierarchical structure [8, 9] to realize rumor detection. With the development of technology, some researchers have incorporated the source of rumors into their models. Here, we regard the source as a general concept, i.e., the source includes three aspects. Firstly, create sources of news stories, such as news writers. Secondly, the sources that publish news reports, such as news publishers or news publish platforms. Thirdly, the sources that spread the news, such as social media accounts [3]. Early news detection is achieved by detecting news sources to judge whether they are true or false. However, this detection method is one-sided, which seriously limits the effect of the model. Although these methods are effective for fake news detection, they cannot be used alone to improve detection accuracy further. Therefore, some hybrid methods [10, 11] come into being. By combining news content, propagation structure, social context, and source information for fake news detection, news features are fully characterized, greatly improving the detection effect. However, the hierarchical structure constructed by these hybrid methods cannot extract the higher-order feature representation of news, which is an urgent problem to be solved.

By investigating the spread of rumors on social media, we found differences in the propagation structure of true and false rumors. Consistent with previous research results [12], compared with true rumors, false rumors spread faster, cascade deeper, are more comprehensive, and are more popular. In fact, propagation and diffusion are two key characteristics of a rumor. The deep vertical propagation features represent the causal characteristics of rumors spread along the relationship chain, and reflect the interaction between users' attention, comments and forwarding. The horizontal diffusion characteristics of rumors represent the structural characteristics of rumors in the community. It reflects the common relationship between users who forward or comment on the same news, but there is no direct interaction between these users. By observing the characteristics of users, we found that true and fake users and users with different preferences would present apparent cluster distribution. For example, for a user who often publishes or retweets rumors, the news that the user retweets again are likely to be fake. Users on social media tend to connect with like-minded people, so fake users form clusters, thus creating information cocoons. Figure 1 shows the propagation of rumors on social media. After the source user publishes a piece of news, different users will retweet or comment. We observe that users 1-5 are more interested in political news, users 6–10 are more interested in medical science, and users 11 and 12 are more interested in the medical and health fields. However, user13 participates in news forwarding in medical science and medical health, indicating that the two fields cover some similar news. For the news in the three fields, users who retweet or comment on this news show an apparent clustering phenomenon, which also conforms to our cognition. In order to improve the accuracy of rumor detection, many models extract rumor information by constructing a graph structure [13–15]. However, these models do not utilize the various information contained in rumors, the extracted information features are not comprehensive, and the excessive noise information contained limits the improvement of detection accuracy. To address these problems, we fully use all the information contained in rumors, such as content, propagation and user information, *etc.* Different from previous hierarchical models, we construct heterogeneous graphs for this multi-source information to extract higher-order features of rumors. Specifically, based on the constructed multi-source information heterogeneous graph, we design a semantic content feature module to extract higher-order content information of rumors. Moreover, we design a propagation diffusion feature module to extract higher-order structural features of rumor propagation and diffusion. Furthermore, a feature dynamic fusion module achieves a weighted fusion of two parts of features.

Users with the same color indicate that they share some common behavioral characteristics and are pulled close together in space.

In summary, the proposed model has the following contributions.

1) We build multi-source information into a heterogeneous graph, which enhances the representation ability of information and facilitates the model to learn comprehensive features in the future.
2) We design a content extraction module and a propagation extraction module to extract rumors' content information and propagation structure. Furthermore, our model considers rumors' vertical propagation structure and rumors' horizontal diffusion structure, which effectively complements the deficiencies of current research.
3) Integrate the local and global attention mechanism to realize the adaptive dynamic fusion of features and reduce the influence of noise information.
4) Experiments on two real-world datasets demonstrate the effectiveness of the proposed model.

The remaining paper is structured as follows: Related work introduces the methods, defects, and research progress of rumor detection. The model describes the proposed model in detail. Experiments introduces our datasets, baselines, experimental results, ablation experiments, and rumor early detection. The conclusion summarizes our research results and discusses future research directions and emphasis.

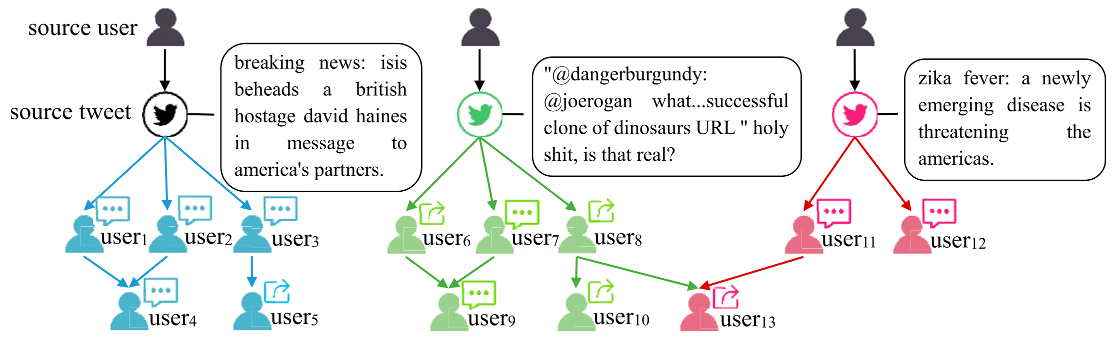

FIGURE 1
An example of news dissemination structures in social networks.

2 Related work

2.1 Knowledge-based methods

In order to detect fake news with knowledge, it is necessary to construct a knowledge base or graph. Here, knowledge-based methods are divided into those that use external knowledge bases and those that do not. Using an external knowledge base needs to introduce an external knowledge base and use existing knowledge to assist rumor detection. The method that does not use an external knowledge base analyzes a rumor by extracting knowledge triples (subject, predicate, object) from the rumor content. Hu et al. [16] propose a new end-to-end graph neural model, which compares news with a knowledge base (KB) through entities to detect fake news. However, external knowledge graphs are often required in the limited work of knowledge-based fake news detection, which may bring additional problems. It is common for entities and relationships, especially new concepts, to be missing from existing knowledge graphs. Han et al. [17] research fake news detection without any external knowledge and transform the problem of fake news detection into a subgraph classification problem. Entities and relations are extracted from each news to form a knowledge graph, where a subgraph represents each news.

Introducing an external knowledge base in rumor detection has low time efficiency. It is difficult to be effectively promoted due to the need to search for knowledge from external web pages. When we do not use the external knowledge base to detect rumors, it is necessary to construct the content of rumor text into knowledge triples. However, due to rumors' unstable writing style and incomplete subject-predicate, it is challenging to construct knowledge triples effectively.

2.2 Content-based methods

In the early stage of rumors detection, many researchers detected rumors by mining potential features in news content. According to research in forensic psychology [18], statements based on real experiences are very different from fictional statements in both content and quality. Przybyla P [19] designs a neural network and a model based on style features to distinguish true and false news by identifying sensational words. The emotions contained in the news can help us make judgments. Kumari R et al. [20] propose a deep multi-task learning model, which jointly performs novelty detection, emotion recognition, emotion prediction, and fake news detection, proving that these tasks are related.

Advances in fake news detection technology have, in turn, led to changes in the form of fake news. In order to achieve a specific purpose, many rumors will highly imitate real news to mislead the judgment of the model. Therefore, more than relying on news content alone is needed to improve the accuracy of fake news detection further.

2.3 Propagation-based methods

The propagation information of rumors can characterize the propagation path and cascade depth of rumors. For rumor detection, propagation features are critical. Bian et al. [4] capture the propagation structure features by constructing top-down and bottom-up propagation trees for rumors and using a bidirectional graph convolution network to learn the propagation patterns of rumors. Silva et al. [21] use the graph structure to predict the complete propagation network by embedding part of the propagation network and only use the propagation information of the news without using the news content features to realize the early detection of fake news. In order to understand the correlation between news propagation networks and fake news, Shu et al. [8] build a hierarchical propagation network for fake news and real news. Furthermore, comparing and analyzing the features of the propagation network between fake news and real news from the perspective of structure, temporal, and linguistics proves the potential of using these features to detect fake news.

Most existing propagation-based methods only dig the cascade propagation information of rumors, ignoring the diffusion characteristics of rumors and the cluster characteristics of users. In fact, rumors' vertical propagation and diffusion characteristics are crucial, and the users' follow-follower characteristics can help us detect rumors.

2.4 Source-based methods

Generally speaking, for users who often publish or retweet fake news, the news they publish or retweet again may also be fake.

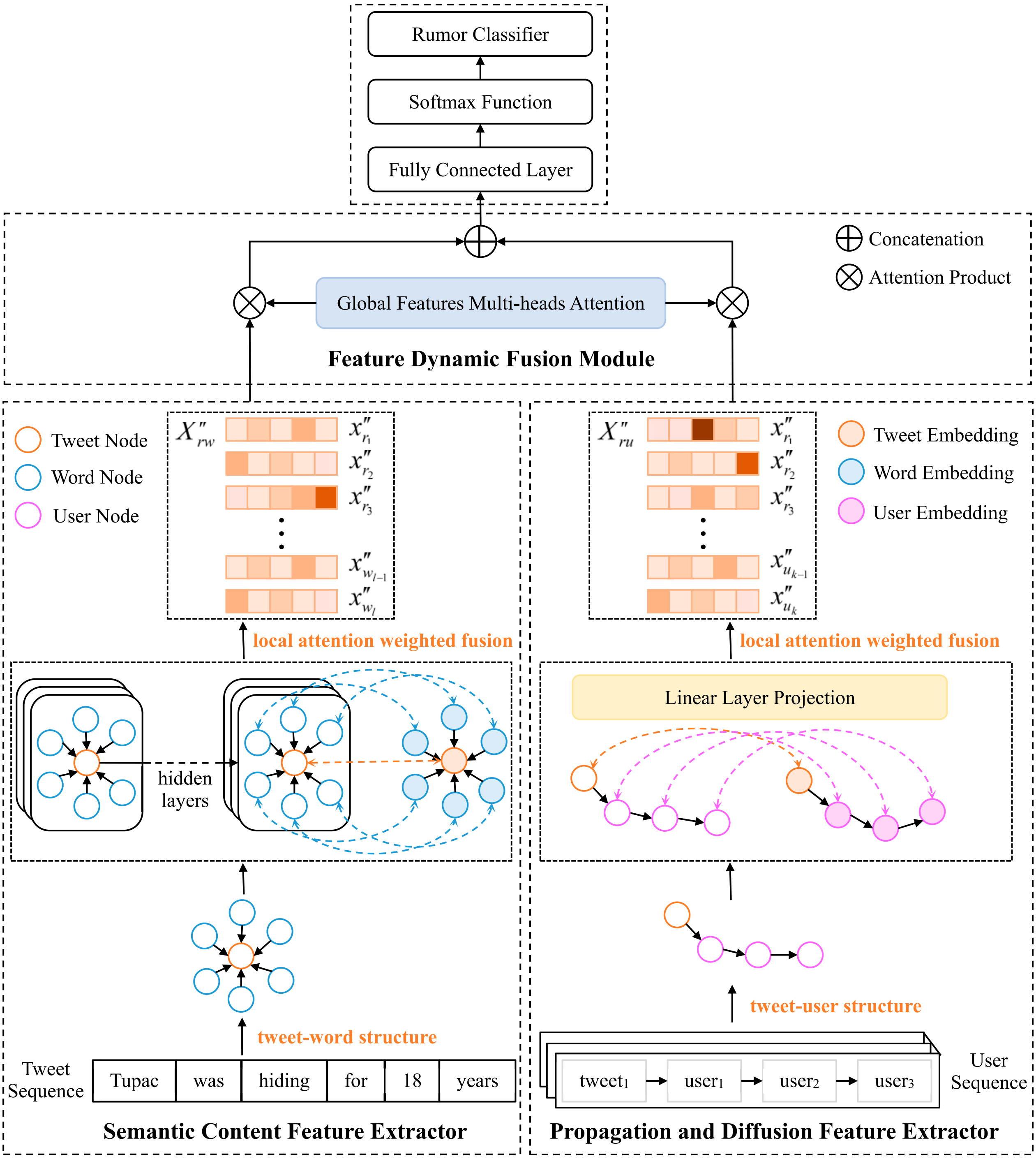

FIGURE 2
The architecture of the local-global attention model MSLG for rumor detection.

Similarly, for news publishers, platforms that routinely disseminate fake news are less credible than official media platforms, which proves that news sources can help us detect fake news. Karimi H et al. [22] introduce information from multiple sources and used a convolutional neural network (CNN) and long short-term memory network (LSTM) to realize fake news detection. Sitaula et al. [23] construct a news author collaboration network in which nodes represent the authors and edges indicate the two authors collaborate in writing one or more news articles, and fake news detection is carried out through the user homogeneity network.

Source-based methods follow a rule of thumb, so they can only play an auxiliary role and cannot replace the features of rumors themselves. Moreover, the detection methods are one-sided, and using them alone cannot improve detection accuracy.

TABLE 1 Statistics of the datasets.

Statistic	Twitter15	Twitter16
source tweets	1,490	818
Tweets	331,612	204,820
Users	276,663	173,487
true rumors	372	205
false rumors	370	205
non-rumors	374	205
unverified rumors	374	203

TABLE 2 Confusion matrix.

Ground truth	Predicted results	
	Positive	Negative
Positive	TP (True Positive)	FN (False Negative)
Negative	FP (False Positive)	TN (True Negative)

2.5 Mixed methods

Recent studies have widely used mixed methods for rumor detection and demonstrated excellent performance. Lu et al. [24] predict the truth of news according to news content, user propagation sequence, and user profile. News content features are extracted by a graph convolution network (GCN), and news propagation features are captured by a convolutional neural network (CNN) and gate recurrent unit (GRU). Shu et al. [25] develop a sentence-comment co-attention network to exploit news content and user comments to jointly capture check-worthy sentences and user comments for fake news detection. Silva et al. [10] find that news records from different domains have significantly different word usage and propagation patterns. Therefore, the constructed model retains the knowledge of a specific domain to detect fake news from different domains effectively.

However, the hierarchical structure constructed by these hybrid methods cannot extract the higher-order feature representation of news, which is an urgent problem to be solved.

3 The proposed model

In this section, we will detail our constructed model MSLG. As shown in Figure 2, the model consists of four main parts. Firstly, we build the rich information in the dataset into a graph structure. Secondly, based on the constructed multi-source information heterogeneous graph, we can effectively extract the semantic information of news by semantic content feature extraction module. Then we use the feature extraction module of dissemination and diffusion to characterize the structure of news dissemination and diffusion. Finally, we design the weight measurement module for dynamic feature fusion to achieve accurate rumor classification.

Our goal is to have the model learn a classification function that maps a rumor r_i to a category L_i, where $L_i \in$ {non-rumor, false rumor, true rumor, unverified rumor}.

3.1 Multi-information heterogeneous graph construction

We unify the dataset's rumors, words, and users into the graph model. Specifically, given graph $G = (V, E)$, where $V = \{R, W, U\}$, $E = \{E_{rw}, E_{ru}, E_{ww}\}$, denote node sets and edge sets, respectively. The node set includes the rumor set R, the word set W, and the user set U. The set $R = \{r_1, r_2, r_3, ..., r_n\}$ represents a series of rumors in the dataset, where r_i is the i-th rumor in the dataset, and n is the number of rumors. For each rumor r_i, we distinguish between the source rumors (the first tweet) and the retweet or comment rumors (user response). Namely $r_i = \left\{s_i, t_1^i, t_2^i, ..., t_j^i, ..., t_{m_i}^i\right\}$, which means that a rumor post contains the source rumor and its retweet comment sequence, where t_j^i indicates the j-th retweeted rumor, and m_i is the number of retweeted rumors in the rumor sequence. $W = \{w_1, w_2, w_3, ..., w_l\}$ denotes the words in the rumor, where w_l is the l-th word and l is the number of words. $U = \{u_1, u_2, u_3, ..., u_k\}$ represents all users in the dataset, where u_k is the k-th user and k is the number of users. The edge set contains three types of edges, E_{rw}, E_{ww} and E_{ru} represent rumor-word, word-word, and rumor-user edges, respectively. Specifically, we link the rumor with its words as the rumor-word edges. A word is connected to other words at a fixed distance as word-word edges, and the sliding window size is fixed at five. The rumor is connected to its associated users as the rumor-user edges.

For the constructed heterogeneous graph, we first initialize the weight matrix. E_{rw} describes the semantic content information of the rumor. The weight of the edges E_{rw} is calculated by the TF-IDF (Term Frequency-inverse Document Frequency) value of the word, where the term frequency is the frequency of the word, and the inverse document frequency is the ratio of the total number and the number of rumors that contain the word, our goal is to highlight important words. E_{ww} describes the co-occurrence relationship of words. Generally speaking, words that frequently appear together can express a specific context and reflect a specific event, which helps us to detect fake news. We collect word co-occurrence information through the sliding window, and calculate the weight by a popular measure of word association, point-wise mutual information (PMI) [26]. E_{ru} reflects the rumor-user and user-user interactions, and describes the structural relationship between rumor propagation and diffusion. The weight of edge E_{ru} is initialized as the reciprocal of the time that the user publishes or retweets a rumor. Formally, for node i and node j, we obtain the adjacency matrix as follows:

$$A_{ij} = \begin{cases} TF-IDF_{ij} & i \in R, j \in W \\ PMI & i, j \in W \\ \dfrac{1}{t+1} & i \in R, j \in U \\ 1 & i = j \\ 0 & otherwise. \end{cases} \tag{1}$$

where t is the elapsed time after users publish or retweet rumors.

TABLE 3 Performance on Twitter15 dataset. The results indicated with * are obtained from [14] (NR: Non-Rumor; FR: False Rumor; TR: True Rumor; UR: Unverified Rumor).

Categories	Models	Accuracy	F1			
			Nr	Fr	TR	Ur
Traditional machine learning-based models	SVM-TS*	0.544	0.796	0.472	0.404	0.483
	SVM-HK*	0.493	0.650	0.439	0.342	0.336
	SVM-TK*	0.667	0.619	0.669	0.772	0.645
Deep learning-based models	PPC	0.842	0.811	0.875	0.790	0.818
	PLAN	0.852	0.840	0.846	0.884	0.837
	PPA-WAE	0.873	0.899	0.881	0.869	0.843
Graph neural networks-based models	Bi-GCN	0.886	0.891	0.860	0.917	0.829
	GLAN	0.881	0.932	0.904	0.810	**0.881**
	HGATRD	0.905	0.940	0.905	0.909	0.864
Ours	MSLG	**0.920**	**0.953**	**0.922**	**0.922**	**0.881**

Bold values represent the optimal results for each indicator.

3.2 Semantic content feature extractor

The semantic content information of rumor itself is very important for rumor detection. Therefore, in the rumor-word heterogeneous graph, we first extract the initial feature vector of the rumor. The initial feature representation of the word set W is $X_w = \{x_{w_1}, x_{w_2}, x_{w_3}, ..., x_{w_l}\}, x_{w_i} \in R^N$, where x_{w_i} is the feature embedding of word w_i, and N is the dimension of word embedding. The feature representation of rumor set R is denoted as $X_R = \{x_{r_1}, x_{r_2}, x_{r_3}, ..., x_{r_n}\}, x_{r_i} \in R^N$, where $x_{r_i} = \{x_{s_i}, x^i_{t_1}, x^i_{t_2}, x^i_{t_3}, ..., x^i_{t_{m_i}}\}$ is the feature representation of each rumor x_{r_i}, indicating that the feature vector of each rumor contains the feature information of the forwarding and comment sequence. The feature representation of each rumor is calculated by the average of word embeddings contained in the rumor and the forwarding sequence, i.e., $x_{r_i} = \frac{1}{r_i} \sum_{w_j \in r_i} x_{w_j}$. Then we extract the higher order features of the rumor content by performing convolution operations on the constructed graph and map them into the vector space. Specifically, according to the constructed graph G and the initial feature vector X, higher order features are extracted layer by layer. We obtain the information of each layer by the weighted sum of the information of the previous layer and the neighbor nodes. At this point, we get the rumor content feature is denoted as $X'_{rw} = \{x'_{r_1}, x'_{r_2}, x'_{r_3}, ..., x'_{r_n}, x'_{w_1}, x'_{w_2}, x'_{w_3}, ..., x'_{w_l}\}$. The higher order feature extraction process is as follows:

$$H^1 = \left(\tilde{A} X W^0\right) \tag{2}$$

$$H^l = \sigma\left(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^{l-1} W^{l-1}\right) \tag{3}$$

where A is the adjacency matrix, $\tilde{A}$ denotes the self-connected adjacency matrix, namely $\tilde{A} = A + I_A$. $\tilde{D} = D + I_D$ indicates the degree matrix with self-connection. σ is the activation function.

In fact, different graph nodes have different contributions to the rumor detection task, which requires our model to be able to distinguish between important and unimportant nodes, and give high weight to important nodes. Here we introduce the attention mechanism [27] to measure the weight of different nodes. Given the node pair (i, j), we learn the weight α^{rw}_{ij} of different nodes through the self-attention mechanism, which represents the importance of node i to node j. The calculation process is as follows:

$$\alpha^{rw}_{ij} = f\left(W_{x_i}, W_{x_j}\right),\ x_i, x_j \in X'_{rw} \tag{4}$$

Then we use the softmax function to normalize the weight coefficient and get the final attention coefficient β^{rw}_{ij}:

$$\beta^{rw}_{ij} = \mathrm{softmax}\left(\alpha^{rw}_{ij}\right) = \frac{e^{\sigma\left(\boldsymbol{o}^{(rw)\mathrm{T}} \cdot \left[W_{x_i} \| W_{x_j}\right]\right)}}{\sum_{k \in N_i} e^{\sigma\left(\boldsymbol{o}^{(rw)\mathrm{T}} \cdot \left[W_{x_i} \| W_{x_k}\right]\right)}} \tag{5}$$

where $\sigma(\cdot)$ donates the activation function, $\boldsymbol{o}^{rw}$ represents the weight vector, $\cdot^T$ donates the transpose operation, $\|$ is concatenation operation.

Next, we update the feature representation of node i by aggregating its neighbor nodes and corresponding weight coefficients. The aggregation process is as follows:

$$x^{(1)}_i = \sigma\left(\sum_{j \in N_i} \beta^{rw}_{ij} X'_{x_j}\right) \tag{6}$$

In order to stabilize the learning process and get more accurate feature representation, we perform K transformations on the aggregation process, and then we can get the final output of each rumor:

$$x''_i = \mathop{\Big\|}_{k=1}^{K} \sigma\left(\sum_{j \in N_i} \beta^{(rw)k}_{ij} X'^{k}_{x_j}\right) \tag{7}$$

We can obtain the final feature representation $X''_{rw} = \{x''_{r_1}, x''_{r_2}, x''_{r_3}, ..., x''_{r_n}, x''_{w_1}, x''_{w_2}, x''_{w_3}, ..., x''_{w_l}\}$ about semantic content information by connecting the learned representations.

3.3 Propagation and diffusion feature extractor

For a rumor, propagation and diffusion are two important structural features, which can play an auxiliary role in rumor

TABLE 4 Performance on Twitter16 dataset. The results indicated with * are obtained from [14] (NR: Non-Rumor; FR: False Rumor; TR: True Rumor; UR: Unverified Rumor).

Categories	Models	Accuracy	F1			
			Nr	Fr	TR	Ur
Traditional machine learning-based models	SVM-TS*	0.574	0.755	0.420	0.571	0.526
	SVM-HK*	0.511	0.648	0.434	0.473	0.451
	SVM-TK*	0.662	0.643	0.623	0.783	0.655
Deep learning-based models	PPC	0.863	0.820	0.898	0.837	0.843
	PLAN	0.874	0.853	0.839	0.917	0.888
	PPA-WAE	0.885	0.882	0.886	0.921	0.842
Graph neural networks-based models	Bi-GCN	0.880	0.847	0.869	0.937	0.865
	GLAN	0.897	0.876	0.854	0.864	**0.947**
	HGATRD	0.886	0.903	0.857	0.925	0.857
Ours	MSLG	**0.913**	**0.935**	**0.889**	**0.957**	0.870

Bold values represent the optimal results for each indicator.

detection. Therefore, in the rumor-user heterogeneous graph, we extract the initial features of the user as $X_u = \{x_{u_1}, x_{u_2}, x_{u_3}, ..., x_{u_k}\}$, $x_{u_i} \in R^M$, where x_{u_i} is the feature representation of user u_i and the dimension is M. The feature representation of the rumor set R is still $X_R = \{x_{r_1}, x_{r_2}, x_{r_3}, ..., x_{r_n}\}$, $x_{r_i} \in R^N$, where N is the dimension of rumor embedding. Since rumor feature embeddings and user feature dimensions are different, we cannot jointly extract the propagation structure information. Therefore, we first need to project rumor features and user features into the same feature space. Specifically, we design feature transformation matrices T_R and T_U for rumor nodes and user nodes, and the projection process is as follows:

$$X_R^{'} = Q_R \cdot (X_R + X_R^0) \tag{8}$$

$$X_U^{'} = Q_U \cdot (X_U + X_U^0) \tag{9}$$

where $X_R^0 \in R^{R\times N}$ and $X_U^0 \in R^{U\times M}$ are dynamic feature vectors whose values are updated with gradients. $X_{R(U)}$ and $X_{R(U)}^{'}$are the original feature vector and the feature representation obtained after projection, respectively.

At this point, we get the propagation diffusion structure feature expressed as $X_{ru}^{'}= \{x_{r_1}^{'}, x_{r_2}^{'}, x_{r_3}^{'}, ..., x_{r_n}^{'}, x_{u_1}^{'}, x_{u_2}^{'}, x_{u_3}^{'}, ..., x_{u_k}^{'}\}$, where $x_{r_i} \in X_R^{'}$, $x_{u_i} \in X_U^{'}$. In the rumor-user heterogeneous graph, the importance of different nodes is also different. Therefore, we design an attention mechanism to measure the weights of different nodes, which can effectively extract local relationship information when capturing the higher order structural relationship of rumor propagation and diffusion. Similar to the rumor-word heterogeneous graph processing, given a node pair (m, n), we learn the weights α_{mn}^{ru} of different nodes through the self-attention mechanism [27], representing the importance of node n to node m. Then we use the softmax function to normalize the weight coefficient and get the final attention coefficient β_{mn}^{ru}. The calculation process is as follows:

$$\beta_{mn}^{ru} = \mathrm{softmax}(\alpha_{mn}^{ru}) = \frac{e^{\sigma\left(\boldsymbol{o}^{(ru)\mathrm{T}}\cdot[W_{x_m}\|W_{x_n}]\right)}}{\sum_{k\in N_m} e^{\sigma\left(\boldsymbol{o}^{(ru)\mathrm{T}}\cdot[W_{x_m}\|W_{x_k}]\right)}} \tag{10}$$

where $\sigma(\cdot)$ donates the activation function, $\boldsymbol{o}^{ru}$ represents the weight vector, $\cdot^T$ donates the transpose operation, $\|$ is concatenation operation.

Next, we update the feature representation of the node by aggregating the neighbor nodes of node m and the corresponding weight coefficients. The aggregation process is as follows:

$$x_m^{(1)} = \sigma\left(\sum\nolimits_{n\in N_m} \beta_{mn}^{ru} X_{x_m}^{'}\right) \tag{11}$$

In order to stabilize the learning process and get more accurate feature representation, we perform K transformations on the aggregation process, and then we can get the final output of each rumor:

$$x_m^{''} = \mathop{\Big\|}_{k=1}^{K} \sigma\left(\sum\nolimits_{n\in N_m} \beta_{mn}^{(ru)k} X'^{k}_{x_m}\right) \tag{12}$$

Finally, we can get the final characteristic representation $X_{ru}^{''}= \{x_{r_1}^{''}, x_{r_2}^{''}, x_{r_3}^{''}, ..., x_{r_n}^{''}, x_{u_1}^{''}, x_{u_2}^{''}, x_{u_3}^{''}, ..., x_{u_k}^{''}\}$ of rumor propagation and diffusion.

3.4 Feature dynamic fusion module

After obtaining the semantic content features and propagation diffusion features of rumors, we need to fuse these two features. These two features have different contributions when judging the category of rumor. Therefore, we design the global attention to capture the feature of rumors. The learning process is as follows:

$$(\varphi_{rw}, \varphi_{ru}) = attention_{global}\left(X_{rw}^{''}, X_{ru}^{''}\right) \tag{13}$$

Specifically, firstly, we transform the feature representation of the nodes in the heterogeneous graph. Then we take the similarity between the transformed representation and the attention vector $\boldsymbol{o}$ as the importance of the nodes. Finally, we can obtain the importance of the features by averaging the weight of the obtained nodes. The two parts' feature weights are calculated as follows:

TABLE 5 Ablation experiment results on Twitter15 dataset.

Method	Accuracy	F1			
		Nr	Fr	TR	Ur
MSLG	0.920	0.953	0.922	0.922	0.881
$MSLG_{-nc}$	0.652	0.870	0.604	0.629	0.453
$MSLG_{-ds}$	0.827	0.756	0.844	0.877	0.829

TABLE 6 Ablation experiment results on Twitter16 dataset.

Method	Accuracy	F1			
		Nr	Fr	TR	Ur
MSLG	0.913	0.935	0.889	0.957	0.870
$MSLG_{-nc}$	0.712	0.792	0.711	0.702	0.627
$MSLG_{-ds}$	0.842	0.744	0.845	0.920	0.847

$$\chi_{rw(ru)} = \frac{1}{X''_{rw(ru)}} \sum\nolimits_{x_i \in X''_{rw(ru)}} \boldsymbol{o}^{\mathrm{T}} \cdot \tan h\left(W_{rw(ru)} x_i\right) \tag{14}$$

where tanh $(\cdot)$ is a nonlinear transformation, $W_{rw(ru)}$ is the node weight of the semantic content (propagation diffusion structure) feature. After obtaining the importance of semantic content features and propagation diffusion features. Furthermore, we normalize them with the softmax function. The final weights of the two parts of the features are denoted as ω_{rw} and ω_{ru}, respectively:

$$\omega_{tw(tu)} = \frac{e^{\chi_{rw(ru)}}}{\sum e^{\chi_{rw(ru)}}} \tag{15}$$

Finally, using the learned feature weights and joint graph node representation, we can obtain the final rumor representation:

$$X_n = \{x_1, x_2, x_3, ..., x_n\} \tag{16}$$

$$x_i = \sum \omega_{tw(tu)} \cdot x_{r_i}, x_{r_i} \in X''_{tw(tu)} \tag{17}$$

where n is the number of rumors, and x_{r_i} represents the local-global rumor representation with semantic content and propagation structure features.

Then we input the obtained rumor feature representation to the fully connected layer for rumor classification. The classification process is as follows:

$$f = p(L_i|r_i, G; \theta) = softmax(FNN(x_i) + b) \tag{18}$$

where b is the bias.

To train the model parameters, we use the cross-entropy loss function for loss minimization, which can be formalized as follows:

$$L = -\sum\nolimits_{i \in R} y_i f + \lambda \|\theta\|_2^2 \tag{19}$$

where y_i represents the ground truth label of the rumor, λ donates the weight coefficient, $\|\theta\|_2^2$ is the regularization term, here we use the L_2 regularization to prevent overfitting.

4 Experiments

4.1 Datasets

To confirm the performance of MSLG in the rumor detection task, we conducted experiments on Twitter15 and Twitter16 datasets collected by Ma et al. [28]. The two datasets contained 1,490 and 818 rumors, respectively. Each rumor and its corresponding reply and retweet are provided as a spreading tree. Each news item is labeled as a true rumor, false rumor, non-rumor, unverified rumor. Since the original datasets do not include user information, nor do they contain all the text of retweets or comments, we call Twitter API to crawl the features of all users related to tweets. Furthermore, we crawl all the reply texts according to the reply IDs. To ensure the fairness of the comparison, we selected 10% of the datasets as the validation set. The remaining is divided into the training set and test set according to the ratio of 3:1. Detailed statistics for the two datasets are shown in Table 1.

4.2 Confusion matrix and evaluation metrics

In essence, fake news detection is a classification task, so our evaluation metrics follow the existing research and use accuracy and F1 score in each category to evaluate the model's performance. Since our task is a four-category problem, each category corresponds to a confusion matrix. According to the confusion matrix, we can calculate each category's accuracy and F1 score. The confusion matrix is shown in Table 2. The calculation method of accuracy and F1 score is shown as follows.

$$\text{Accuracy} = \frac{\text{correct classification}}{\text{all samples}} \tag{20}$$

$$P = \frac{TP}{TP + FP} \tag{21}$$

$$R = \frac{TP}{TP + FN} \tag{23}$$

$$F1 = \frac{2 \times P \times R}{P + R} \tag{24}$$

4.3 Baselines

We compare the proposed model with the following nine models, and we divide these baselines into three categories: traditional machine learning-based models, deep learning-based models, and graph neural networks-based models. Relevant models are introduced as follows:

Traditional machine learning-based models:

SVM-TK [28]: A kernel-based approach called propagation tree kernel captures high-order patterns that distinguish different types of rumors by evaluating the similarity between spread tree structures.

SVM-TS [29]: A method to capture the temporal characteristics of social background based on the time series of rumors' lifecycle, which applies time series modeling techniques to integrate various social background information.

SVM-HK [30]: A hybrid SVM classifier based on graph kernel captures higher-order propagation patterns in addition to semantic features such as topics and sentiments.

Deep learning-based models:

PPC [31]: A time series classifier combining recurrent and convolutional networks for fake news detection by capturing global

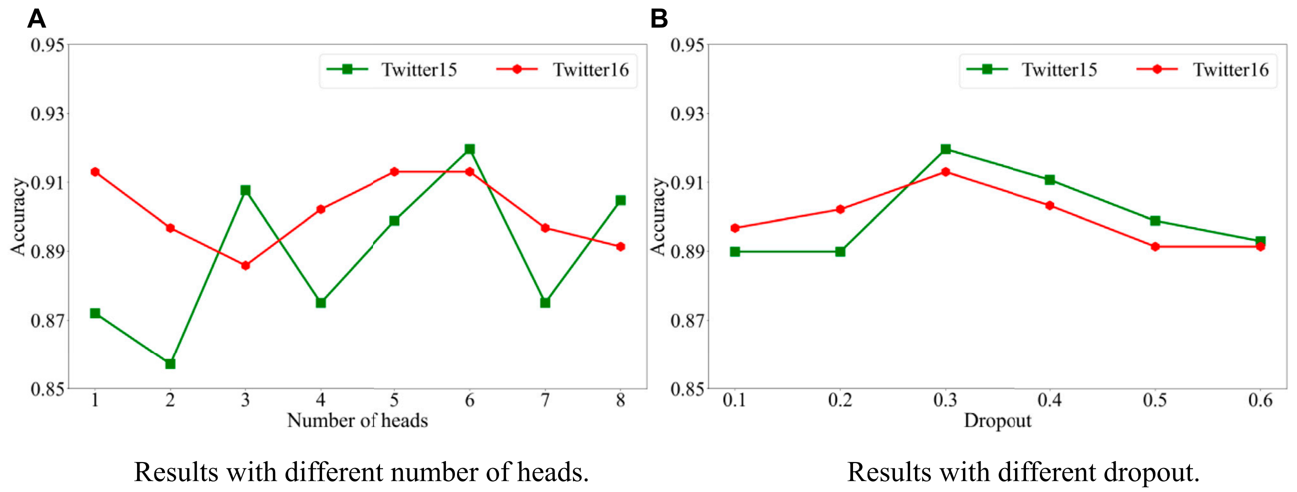

FIGURE 3
The performance of models with different parameters on two datasets.

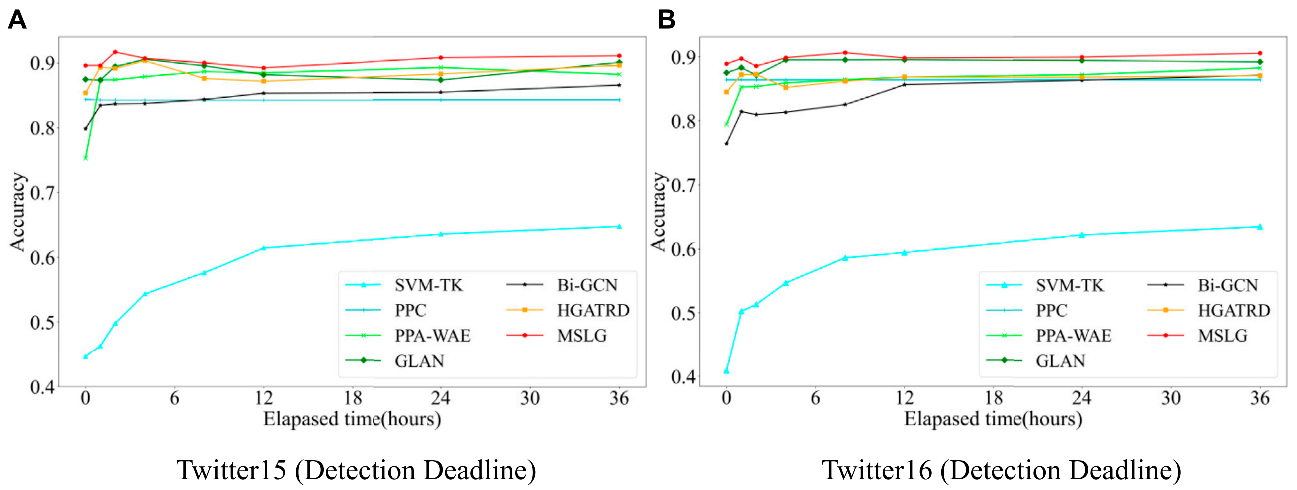

FIGURE 4
The performance of early rumor detection on two datasets.

and local user feature changes along the propagation path, respectively.

PLAN [32]: A post-level attention model. This model uses the multi-head attention mechanism in a transformer network to model long-distance interactions between tweets.

PPA-WAE [33]: A lightweight propagation path aggregation neural network for rumor embedding and classification. Furthermore, the neural topic model in the Wasserstein autoencoder framework is used to capture the event-insensitive stance patterns that do not contain the source post in response propagation trees.

Graph neural networks-based models:

Bi-GCN [4]: A homogeneous bidirectional graph convolution network model explores these two propagation characteristics by operating top-down and bottom-up propagation of rumors.

GLAN [13]: A global-local attention network for rumor detection jointly encodes local semantic and global structural information.

HGATRD [14]: A meta-path-based heterogeneous graph attention network framework is used to capture the semantic relationship of text content and the structure information of source tweet propagation for rumor detection.

4.4 Results and analysis

Tables 3 and Tables 4 show that our model achieves state-of-the-art results on both datasets compared to other baseline models. As we observe from the results in the table, traditional machine learning methods have the worst performance, such as SVM-TS, SVM-HK, and

SVM-TK. Moreover, the performance of deep learning models (such as PPC, PLAN, and PPA-WAE) has been improved to a certain extent. Graph neural network-based methods, such as Bi-GCN, GLAN, and HGATRD, have achieved better performance. These results are because the constructed graph structure can effectively capture the higher-order relations of news to obtain a more comprehensive feature representation.

The proposed model achieves 92.0% accuracy on the Twitter15 dataset, which is 2.5% higher than the best performance HGATRD model in baselines. This result is because the HGATRD model does not deeply extract the semantic features of news content, and the lack of semantic information extraction limits the performance improvement of the model. On the Twitter16 dataset, the best performance of all baseline models is GLAN, with an accuracy of 89.7%. The accuracy of our model is 91.3%, which is 1.6% higher than the model of GLAN. It is because our model not only extracts the global semantic information of rumors but also makes full use of the propagation structure information, thus achieving optimal performance.

Experimental results verify the effectiveness of our model in rumor detection. Our model's heterogeneous graph fully represents the dataset's information. The content information network we construct can extract the global semantic information of rumors. Through the propagation structure network, we extract information of high-order propagation and diffusion of rumors. Furthermore, the introduced node-level attention mechanism can enhance key nodes and networks' features and reduce noise information's weight. Finally, we fuse the two extracted features effectively to achieve high-quality rumor detection.

4.5 Ablation study

To verify the performance of each module of the model, we design two variants of the model MSLG, which are:

MSLG$_{\text{-nc}}$: We delete the news content network from the model, and the model only uses the propagation structure information.

MSLG$_{\text{-ds}}$: Deleting the propagation structure network in the model, and there is only news content information in the model.

Table 5 and Table 6 show the results of ablation experiments on the two datasets. Through the results in the table, we can observe that when we delete the news content network, model performance reduces rapidly. When we delete the propagation structure network, the model's performance is also lower to a certain degree. This result indicates that for the fake news detection task, the semantic information of the news itself is more important. In contrast, other information only plays an auxiliary role to a certain extent.

We performed a four-class classification task on these two datasets. For the non-rumor class, when we remove the news content network, the model accuracy decreases by 8.3% and 14.3% on the Twitter15 and Twitter16 datasets, respectively. When we delete the propagation structure information, the model accuracy decreases by 19.7% and 19.1% on the two datasets, respectively. This result shows us that the propagation structural information is essential. In contrast, for the other three categories, content information is more critical. This result is because, compared with real users, fake users have more obvious cluster behavior and specific communication structure for news comments and forwarding information. The propagation structure network will pay more attention to fake users' behavioral characteristics when we detect fake news. This result also conforms to our cognition.

4.6 Parameter analysis

This section analyzes the impact of different attention heads and dropout values on model performance. Figure 3 shows the visualized data results. As shown in Figure 3A, we can find that the model accuracy results show volatility when we use different attention heads. For the Twitter15 dataset, the model accuracy is highest when the number of attention heads is 6. For the Twitter16 dataset, the model has the highest accuracy when the number of attention heads is five or 6. As shown in Figure 3B, we can find that with different dropout values, the model performance is also different. We observe similar trends in both datasets when we apply different dropout values. The model's overall performance shows a trend of rising and then falling. When the dropout value is 0.3, the model achieves the best performance. These results indicate that the attention head and dropout selection are critical to the model.

4.7 Early detection of rumors

The early detection of rumors is a crucial goal of rumor detection. The longer it takes for a rumor to be published on social media, the more far-reaching its impact and the more difficult it is to dispel. Therefore, it is significant to realize the early detection of rumors. By studying the different propagation characteristics of real and fake news, Zhao et al. [34] realized fake news early detection is only based on the re-posting network topology between different users. However, there are only a few retweets or comments when a rumor is first published. At this time, we can only make full use of the text content of the source rumor for detection, which requires that the model constructed can fully extract the features of the text content of the rumor. To verify the performance of our model proposed in early rumor detection, we control the elapsed time after the source rumors have been published to represent different periods of rumor propagation. We reconstruct the semantic content feature extractor and propagation feature extractor by deleting comments and users after the deadline. Furthermore, we evaluate the performance of the different models. Figures 4A, B show the performance of each model on two datasets with different detection deadlines.

Figures 4A, B show that our model MSLG achieves relatively high accuracy early after the rumor is published. It proves that the MSLG model can effectively extract the semantic content information of the rumor. In addition, with the increase of time after the rumor is published, the accuracy of each model is improved. Furthermore, the performance of MSLG is better than SVM-TK and Bi-GCN, which indicates that the fusion of multi-source information is beneficial for long-term rumor detection and early rumor debunking.

From Figure 4A, we find that when the detection deadline varies from 4 to 12 h, the performance of our model decreases slightly, but it is still better than other models. This is because, with the spread of rumors, there is more rumors' semantic content and propagation structure, thus introducing noise information. As seen in Figure 4B, the performance of our model is always superior to other models, which indicates that the fusion of multi-source information is beneficial for long-term rumor detection and early rumor debunking. These results also indicate that our model is not sensitive to data and has good stability and robustness. In addition, semantic content and propagation information increased over time, increasing the accuracy of each model.

The experimental results on two real-world datasets prove that the proposed model can significantly improve the performance of rumor detection and realize the early detection of rumors.

5 Conclusion and future work

Most rumor detection methods based on graph neural networks have the problems of sparse features and excessive noise information. It is challenging to integrate complex multi-source information effectively. In addition, incomplete representation of the internal local relationship and external global relationship of rumors also limits the improvement of detection results. To address these problems, we extract various types of information from the dataset and design heterogeneous graph structures to represent the structure of multi-source information. Furthermore, we utilize a graph convolutional network to extract high-order feature representations of rumor content semantics and linear projection to extract propagation diffusion structure. Finally, we distinguish the importance of different nodes and different features by fusing local relational attention and global relational attention mechanisms, respectively. Experiments on two datasets verify the effectiveness of our method.

In future work, we consider designing a hypergraph structure to more comprehensively characterize rumors and further integrate user meta-attribute information to achieve fake news early detection. In addition, developing new datasets with pictures, audio, and video information is also a significant consideration. Fake news on social networks presents a multi-modal trend. A piece of news contains not only text information but also rich pictures and video information. This information is essential for fake news detection. Unfortunately, most of the datasets published so far only contain textual information. It results in many fake news detection methods being powerless in the face of multi-modal fake news.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XH reviewed the manuscript. MZ designed the model and verified the experiment results. YZ revised the first draft of the paper. TZ collected the data and realized the visualization of the parameter analysis. All authors read and approved the final draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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