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Gated Feature Fusion based Multi-view Graph Attention for Social Rumor Classification

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Abstract: The widespread use of the Internet and the rapid development of social media have greatly facilitated people's lives, but they have also significantly promoted the spread of rumors, even causing social unrest. Therefore, rumor detection has become a global public challenge. Although traditional machine learning methods have certain practicality, they often require manual extraction of data features and focus only on text analysis, ignoring the increasingly complex structure of rumors. Deep learning models can further effectively extract rumor features, but they ignore the importance of different features. In recent years, graph neural networks have shown great potential in rumor detection tasks, but existing models still have significant limitations in capturing long-range dependencies and integrating heterogeneous information. To address these issues, we propose a multi-view attention network named GFF-MGA based on the gated feature fusion mechanism. GFF-MGA simultaneously constructs two topological views: the tweet propagation subgraph and the user-tweet interaction subgraph. The tweet propagation subgraph is used to model the forwarding, reply, and propagation links between tweets, reflecting the rumor diffusion path. The user-tweet subgraph describes the publishing and forwarding behaviors between users and tweets. These two subgraphs can respectively capture content propagation features and user behavior features, compensating for the representation deficiencies caused by the lack of information in a single view topology. We conducted experiments on the Twitter15 and Twitter16 datasets, and the results showed that our method outperformed the current baseline models, achieving an accuracy improvement of 1.4% and 0.2% on the two datasets.

Keywords: Rumor Classification; Graph Attention Network; Gate Mechanism; Multi-view.

1. Introduction

With the increasing digitization of mass media, new news dissemination models have emerged. These new models have significantly changed the way the public obtains news and information. In the process of competing with rivals to seize the initiative, journalists sometimes sacrifice the principles of traditional journalism, prioritizing the speed of dissemination, and striving to attract attention, increase likes, comments, and shares by generating content quickly, thus achieving "viral dissemination". This new approach focuses on meeting the needs, behavioral patterns, and interest preferences of users. [1] Although social media provides a convenient platform for extensive communication, it also brings the risk of exacerbating the spread of rumors. For example, the 2016 US presidential election[2], the COVID-19 pandemic event[3], and the war in Ukraine[4]. Understanding the various factors that lead to the spread of rumors is crucial for formulating effective response strategies. Therefore, identifying such misleading information remains a key and ongoing challenge, which prompts the need for people to adopt automated, data-driven methods.[5]

Traditional data mining and machine learning have been widely applied in rumor classification. Granik et al.[6] proposed a fake news detection method based on a naive Bayes classifier. The main idea is to independently consider each word in the news, by calculating the conditional probability of specific words in the news, to determine the truthfulness of the news. However, this model is relatively simple. When the model first encounters a word that does not appear in the training set, it is difficult to accurately classify the given news. Rubin et al.[7] analyzed the rhetorical structure, discourse components, and coherence relationships of true and false news, and then applied the vector space model to cluster news based on the similarity of discourse features. However, the evidence extracted through text similarity may not be related to the facts expressed in the news, thus misleading the classifier. To compensate for the shortcomings of the method of calculating text similarity from a single aspect, Wang et al.[8] proposed a double similarity calculation method, generating event summaries from both semantic and textual aspects, and measuring content differences through a fine-grained difference calculation method, and then using the sentence weights formed by content differences to obtain an effective news representation, thereby achieving high-quality fake news detection. Jin et al.[9] utilized "collective wisdom" and used the topic model method to mine conflicting viewpoints in microblog news, construct a news credibility propagation network that supports or opposes, and generate the final evaluation result of the news through iterative reasoning on this network. However, these methods often require manual extraction of features and have low detection efficiency.

In recent years, more and more deep learning techniques have been applied to detect rumors. Brasoveanu et al.[10] proposed a semantic-based fake news detection method, which directly extracts relationships such as emotions, entities or facts from news texts. By calculating semantic features and syntactic features and applying various deep learning classifiers to identify fake news, such as long short-term memory, convolutional neural networks, capsule networks, etc. However, the news semantic-based method only explores the deep features of the news, resulting in a significant loss of shallow effective information. To address this issue, Jing et al.[11] proposed the Progressive Fusion Network for multimodal false information detection. This

network captures the feature representations of each modality of the news at different levels and establishes strong connections between different levels and layers through a mixer to achieve modality fusion. Deep learning techniques focus on text content detection, but rumors have become increasingly diverse in form and deep fake in nature. Rumors often involve different sources and user information, and extracting only text content features is difficult to cope with the complexity of rumors and cannot further improve the accuracy of rumor classification. Therefore, more researchers have turned to building graph neural networks for rumor classification. Yang[12] mapped the false news detection problem to a semi-supervised classification task on a graph. Firstly, based on news similarity, a text graph was constructed, and then a graph neural network was used to classify news as true or false. This model is relatively simple and only utilizes news text information, without involving additional information such as comments. Hu et al.[13] considered that false news detection is related to the topic and enriched the feature representation of news by combining the topic, proposing an end-to-end graph neural network model. Zhao et al.[14] proposed a multi-source information heterogeneous graph model, which extracts information from multiple sources, such as rumor content, user information, propagation process, and diffusion structure. Through graph convolution networks, it extracts higher-order semantic representations of rumor content and integrates local relationship attention mechanisms to strengthen key semantics. At the same time, rumors and users are constructed as heterogeneous graphs to capture the propagation and diffusion structure of rumors. Finally, we introduce a global relationship attention mechanism to measure the importance of sub-modules. Based on this, Zhao et al.[15] further proposed a dual-channel graph convolution attention network with a dynamic feature fusion model. This network builds a heterogeneous graph to model the semantic information between source tweets and vocabulary, as well as the propagation structure information between source tweets and users. Then, using the designed dual-channel graph convolution network, it simultaneously captures the semantic information and propagation structure information of news. On this basis, the graph attention mechanism is further integrated to learn the importance of tweet nodes, user nodes, and vocabulary nodes in the heterogeneous graph. Finally, the dynamic feature fusion mechanism is adopted to extract semantic features and propagation features. However, when performing feature fusion, the personalized features of different rumors were not fully considered. Only simple feature concatenation was carried out, and the contributions of different view features were not fully considered.

To address these issues, we proposed a multi-view attention network based on gated feature fusion, which is abbreviated as GFF-MGA. The main contributions of this work are as follows, respectively addressing the limitations of existing rumor classification models and demonstrating the innovativeness of our model:

a. Construct a dual-view social topology subgraph to depict the feature of rumors from two different perspectives. Most of the existing rumor classification methods only construct tweet propagation reply graphs, focusing only on the forwarding and reply relationships between tweets, while ignoring the interaction behavior information between users and tweets. We simultaneously constructed two topological views: the tweet-word graph and the tweet-user propagation graph. The tweet-word graph models the semantic features of tweets, while the tweet-user graph models the publishing and forwarding behaviors between users and tweets. The introduction of the user behavior topology reflects the diffusion path of rumors. These two subgraphs can respectively capture the content semantic features and the propagation structure features, compensating for the representation deficiencies caused by the insufficiency of topological information in a single view.

b. Based on the multi-head graph attention network, the topological representations of the two views are learned separately. For the two heterogeneous subgraphs, the multi-head graph attention mechanism is utilized to conduct independent graph representation learning for each view. With the multi-head attention mechanism, the importance of different neighboring nodes can be adaptively learned. Moreover, we focus on mining the key tweets on the forwarding and reply chains of the propagation subgraph to identify the influence of the key tweets. We also adaptively recognize high-risk users and suspicious forwarding behaviors in the user-tweet subgraph.

c. Introduce the input control integration mechanism to achieve adaptive fusion of dual-view features. Most traditional multi-view models usually achieve the fusion of different view features through simple concatenation or direct averaging, without distinguishing the contributions of each view. They are unable to dynamically balance the importance of semantic topology and propagation topology for rumor classification. Therefore, we designed a gated feature fusion module, which uses learnable gating weights to adaptively allocate the proportion of the output features from the two views. The model automatically selects to focus more on semantic information or propagation path information based on the sample's own situation, achieving dynamic fusion of the two view features, reducing the interference caused by invalid view information, improving the final node representation quality, and enhancing the rumor classification effect.

2. The Proposed Model

In order to fully utilize the multi-source information contained in the tweets and thereby learn distinguishable features, we uniformly model the rich information included in the tweets, such as rumor text information and dissemination information. We constructed two subgraphs from two dimensions, namely the tweet-word subgraph and the tweet-user subgraph. The word nodes represent the words contained in the tweets, while the user nodes represent the users who posted, forwarded, or commented on the tweets. The user nodes are provided in the form of a propagation tree and do not include the user's meta-attribute information. Then, we utilized the multi-head attention mechanism to adaptively learn the importance of nodes in different views. On this basis, we further introduced the gated fusion mechanism to achieve dynamic fusion of the features of the two views and perform rumor classification based on the learned final features. The model we constructed is shown in Figure 1.

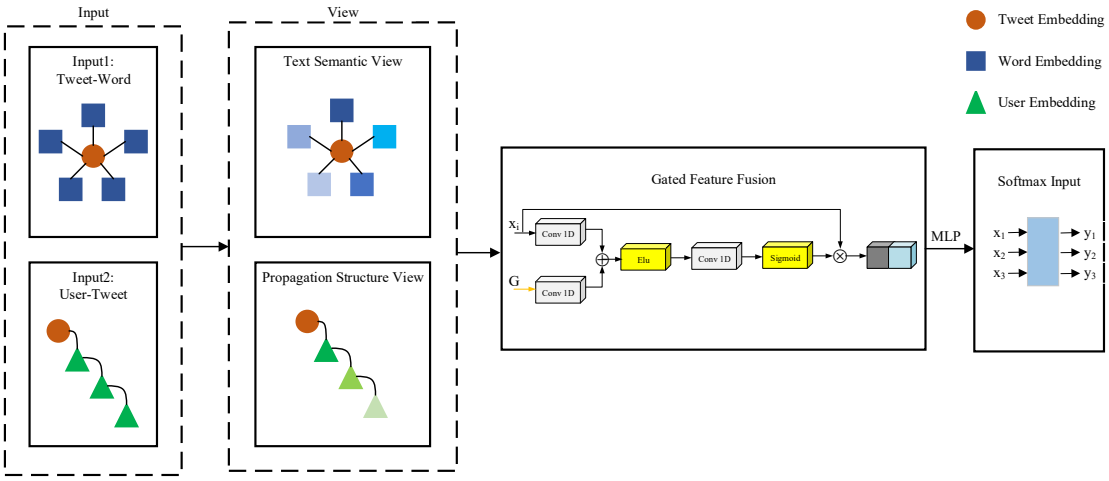


Fig 1. The architecture of our model GFF-MGA

2.1. Construction of Graph

We uniformly model the tweets, words, and users in the rumors into a heterogeneous graph, represented as $G = (V, E)$, where $V = \{T, W, U\}$, and $E = \{E_{tw}, E_{tu}, E_{ww}\}$ represent the node set and edge set respectively. The node set includes the tweet set T, the word set W, and the user set U. The tweet set $T = \{t_1, t_2, t_3, \ldots, t_n\}$ represents a series of tweets in the dataset, with n being the number of tweets. For each post t_i, the source post and the forwarded or commented posts are distinguished, that is, $t_i = \{t_i, s_1^i, s_2^i, \ldots, s_j^i, \ldots, s_{m_i}^i\}$, indicates that a tweet contains the original tweet and its sequence of retweet comments. $W = \{w_1, w_2, w_3, \ldots, w_l\}$ represents the number of words contained in the tweet, where l denotes the total number of words. $U = \{u_1, u_2, u_3, \ldots, u_k\}$ represents all the users in the dataset, where k is the number of users. The edge set contains three types of edges: E_{tw}, E_{ww}, and E_{tu}, which respectively represent tweet-word, word-word, and tweet-user edges. Edge Etw describes the containment relationship between tweets and words, by modeling the words in the tweets, it represents the semantic content information of the tweets. The edge weights are calculated based on the TF-IDF (term frequency-inverse document frequency) values of the words, where the term frequency is the frequency of the word's occurrence in the tweet, and the inverse document frequency is the ratio of the total number of tweets to the number of tweets containing that word. The purpose is to highlight important words. Edge E_{ww} describes the co-occurrence information of words in tweets. Usually, words that frequently appear together can express a specific context and reflect a specific event, which is helpful for the model to classify rumors. By setting a fixed-sized sliding window in the tweet to collect the global co-occurrence information of words, its edge weight is calculated based on the word correlation, that is, the point-wise mutual information value[16]. Edge E_{tu} reflects the interaction between tweets and users, that is, users posting, forwarding or commenting on tweets, describing the structural relationship of tweet dissemination and diffusion. Its edge weight is initialized as the reciprocal of the time when the user posts, forwards or comments on the tweet. Formally, for nodes i and j, the adjacency matrix A_{ij} can be obtained as shown in Equation 1:

$$A_{ij} = \begin{cases} TF - IDF_{ij} & i \in T, j \in W \\ PMI & i, j \in W \\ \frac{1}{t+1} & i \in T, j \in U \\ 1 & i = j \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

Where t represents the time elapsed after user j posts, forwards or comments on tweet i.

2.2. Multi-view Feature Extraction Module

The tweet-word heterograph we constructed is used to extract the semantic features of the text. Therefore, the initial feature representation of the word set W is $X_W = \{x_{w_1}, x_{w_2}, x_{w_3}, \ldots, x_{w_l}\}$, where $x_{w_i} \in R^N$ and x_{w_i} is the feature embedding of the word w_i, and N is the dimension of the word embedding. The feature representation of the tweet set T is $X_T = \{x_{t_1}, x_{t_2}, x_{t_3}, \ldots, x_{t_n}\}$, where $x_{t_i} \in R^N$ and x_{t_i} is the feature representation of the tweet t_i that contains the comment information. The feature representation of each tweet is calculated as the average of the word embeddings contained in that tweet, that is, $x_{t_i} = \frac{1}{|w|}\sum_{w_j \in t_i} x_{w_j}$, where $|w|$ is the number of words contained in the tweet t_i. By connecting the node feature vectors in the graph, we can obtained the semantic feature $X_{sc} = \{x_{t_1}, x_{t_2}, x_{t_3}, \ldots, x_{t_n}, x_{w_1}, x_{w_2}, x_{w_3}, \ldots, x_{w_l}\}$, $x_{t_i} \in X_T$, $x_{w_i} \in X_W$.

To distinguish the importance of different nodes, we incorporate the attention mechanism to focus on the important words in the tweets and the important information in the tweet comments, as shown in Equation 2:

$$\boldsymbol{a}_1 = soft\,max(\,tanh(X_{sc} \cdot \mathbf{W}_1) \cdot \boldsymbol{w}_2) \quad (2)$$

Where $\boldsymbol{a}_1 \in \boldsymbol{R}^l$ is the attention distribution of l words or comments. However, the semantics of a tweet may be generated by multiple parts of the tweet, so the multi-head attention mechanism is utilized to expand the vector $\boldsymbol{w}_2$ into a matrix $\mathbf{W_2} \in \boldsymbol{R}^{a_1 \times h_1}$ to capture the different semantic contributions of words or comments, where h1 is the number of attention heads. At this point, modify Equation 2 to 3:

$$\boldsymbol{A}_1 = soft\,max_{col}(\,tanh(X_{sc} \cdot \mathbf{W}_1) \cdot \mathbf{W}_2) \quad (3)$$

Where $\mathbf{A}_1 \in \boldsymbol{R}^{l \times h_1}$, and each column of $\mathbf{A}_1$ has been normalized by the softmax function. Intuitively, $\mathbf{A}_1$ represents the h_1 different attention head distributions of l words in a piece of news, helping the model capture different aspects of the tweet's semantics. Then, the final semantic

representation of the tweet can be obtained as $X'_{sc} = \{x'_{t_1}, x'_{t_2}, x'_{t_3}, \ldots, x'_{t_n}, x'_{w_1}, x'_{w_2}, x'_{w_3}, \ldots, x'_{w_l}\}$, where the x'_{t_i} part contains the user comment information.

The constructed tweet - user heterograph is used to extract the structural features of the propagation process. To distinguish the importance of different nodes, we still incorporate the attention mechanism, as shown in Equation 4:

$$\boldsymbol{a}_2 = soft\,max(\,tanh(X_{pd} \cdot \mathbf{W}_3) \cdot \mathbf{w}_4) \quad (4)$$

Where $\boldsymbol{a}_2 \in \boldsymbol{R}^k$ is the attention distribution of k users or comments. However, the structural characteristics of the tweets' dissemination and diffusion may be generated by multiple users or comments of the news. Therefore, the joint multi-head attention mechanism expands the vector $\mathbf{w}_4$ into a matrix $\mathbf{W_4} \in \boldsymbol{R}^{a_2 \times h_2}$ to distinguish the weights of different users and dissemination paths. Specifically, the multi-head propagation diffusion attention mechanism applies h_2 different attention heads. At this point, the modified Equation 4 becomes Equation 5:

$$\mathbf{A}_2 = soft\,max_{col}(\,tanh(X_{pd} \cdot \mathbf{W}_3) \cdot \mathbf{W}_4) \quad (5)$$

Where $\mathbf{W}_3 \in \boldsymbol{R}^{k \times a_2}$ and $\mathbf{W}_4 \in \boldsymbol{R}^{a_2 \times h_2}$. Matrix $\mathbf{A}_2$ is a collection obtained by applying h_2 different attention head distributions to k users involved in a piece of news, and each column of it is normalized using the softmax function. With the obtained attention weights, at this point, the diffusion structure of the news can be represented as $X'_{pd} = \{x'_{t_1}, x'_{t_2}, x'_{t_3}, \ldots, x'_{t_n}, x'_{u_1}, x'_{u_2}, x'_{u_3}, \ldots, x'_{u_k}\}$, $x_{t_i} \in X'_T$, $x_{u_i} \in X'_U$.

2.3. Gated Feature Fusion Module

The information contained in the text semantic view and the propagation structure view is different, and their contributions to rumor classification are also different. To accurately identify rumors, we have constructed a gated feature fusion module to learn the weights of features from different views. The learning process is shown as Equation 6-7:

$$g = \sigma(W_g[H_1||H_2]) + b_g \quad (6)$$

$$H_{fused} = g \odot H_1 + (1 - g) \odot H_2 \quad (7)$$

Where W_g is the gating layer weight matrix, b_g is the bias vector, and σ is the Sigmoid activation function.

Finally, we input the tweet features obtained into a multi-layer perceptron network with softmax function normalization, thereby obtaining the predicted probability distribution of the rumor, as shown in Equation 8:

$$y_i = \mathrm{softmax}(\mathrm{MLP}(x_i)) \quad (8)$$

Where L_i is the news category label, t_i is the i-th news item and θ is the model parameter.

In our model, the parameters of the model are trained using cross-entropy loss and regularization terms. The specific training process is shown in Equation 9:

$$L_i = -\sum_{i \in T} y_i f + \lambda||\theta||_2^2 \quad (9)$$

Where y_i represents the true label vector of the i-th news, λ is the coefficient, and $||\cdot||_2^2$ is the L_2 regularization term, which is mainly used to prevent the model from overfitting.

3. Experiments

3.1. Datasets

We conduct experiments on two real datasets, Twitter15 and Twitter16[23]. Twitter15 and Twitter16 are English datasets and belong to short text datasets. The news in the datasets is divided into four categories: true Rumors(TR), false Rumors(FR), non-rumors(NR), and unverified rumors(UR). Users in the dataset include all users who publish, re-tweet and reply to news, and posts include all news items that retweet and reply to the source tweet. We randomly select 10% of the data as the validation set during the experiments. And the rest of the data is divided into training set and testing set according to the ratio of 3:1. The details of the datasets are shown in Table 1.

Table 1. Statistics of the Twitter datasets

Statistic	Twitter15	Twitter16
Tweets	1,490	818
Posts(comments or retweets)	331,612	204,820
Users	276,663	173,487
True rumors	372	207
False rumors	370	205
Non-rumors	374	205
Unverified rumors	374	201
Propagation path	37,339	17,543
Average cascade length	223	251

3.2. Baseline Models

We compared the methods and models used in current research on rumor classification, including the proposed GFF-MGA model, as well as several cutting-edge methods and baseline approaches. These methods provided a foundation for evaluating the effectiveness of our proposed model. The details of the relevant models are as follows:

(1) Models based on traditional machine learning:

DTC[17]: A method based on decision trees, which detects fake news by extracting relevant features from news texts.

RFC[18]: Develop three classifiers based on decision tree, random forest and SVM, and utilize temporal, structural and linguistic features to distinguish between true and false rumors in a given set of tweets related to a specific topic.

DTR[19]: A model based on decision trees, which searches for information query phrases through regular expressions, clusters tweets related to controversial topics, and identifies rumors by ranking the clusters.

SVM-RBF[20]: An SVM (Support Vector Machine) classifier with an RBF (Radial Basis Function) kernel, which classifies by extracting various news features.

SVM-TS[21]: An SVM classifier that captures temporal features of social context through time series of rumor lifecycle.

SVM-HK[22]: A hybrid SVM classifier based on graph kernel, which can extract semantic features such as the topic and sentiment of news, as well as the propagation mode.

SVM-TK[23]: A method called propagation tree kernel, which models the propagation structure of microblog posts

using propagation trees and captures the propagation patterns of different types of rumors by evaluating the similarity between the propagation tree structures.

(2) Model based on deep learning:

GRU-RNN[24]: A model based on recurrent neural networks (RNN), which achieves fake news detection by capturing the hidden representations of the context information of related posts that change over time.

BU-RvNN and TD-RvNN[25]: Two recursive neural models based on bottom-up and top-down tree structures were proposed for rumor representation learning and classification.

PPC[26]: By classifying the news dissemination paths, a time series classifier was constructed, which combines recurrent networks and convolutional networks, respectively capturing the global and local changes of user features along the dissemination path, to detect fake news.

PLAN[27]: A post-level attention model, using multi-head attention mechanisms to model long-distance interactions between tweets.

PPA-WAE[28]: A lightweight propagation path aggregation (PPA) neural network for rumor embedding and classification, and using the neural topic model in the Wasserstein autoencoder (WAE) framework to capture event-insensitive posture patterns that do not include the source post in the response propagation tree.

(3) Model based on Graph Neural Network:

GLAN[29]: By jointly encoding the local semantic and global structural information of rumors, it first integrates the semantic information of tweets with the attention mechanism to generate better integrated representations for each source tweet. Then, it models the global relationships among all source tweets, retweets, and users as a heterogeneous graph to capture the rich structural information for rumor detection.

Bi-GCN[30]: A bidirectional homogeneous graph model that utilizes a top-down and bottom-up propagation directed graph to explore the two characteristics of rumor propagation and diffusion, achieving effective rumor detection.

HGATRD[31]: A heterogeneous graph attention network framework based on meta-paths, used to capture the global semantic relationships of text content and the global structural information of source tweet propagation, for rumor detection.

MGAT[32]: An end-to-end multi-channel graph attention network without an event sharing module, achieving rumor detection by mining the structural features of tweet propagation.

MGAT-ESM[32]: An end-to-end multi-channel graph attention network with an event sharing module, achieving rumor detection by aggregating the propagation structural information and event invariant features.

MSLG[14]: A multi-source heterogeneous information graph model, which can extract multi-source information such as rumor content, user information, propagation paths, and diffusion structures.

GETAE[1]: A two-part model architecture that integrates both textual data and the spread of information on social media to improve the detection of fake news.

3.3. Rumor Classification Performance

Tables 2 and 3 present the results of our model on two datasets. It can be observed that our model outperforms the baseline model in both cases. From the results in the tables, it can be seen that traditional machine learning models have the poorest performance, while the performance of deep learning models has improved to some extent, such as PPC, PLAN, and PPA-WAE. The performance of the graph neural network-based model has reached the current best level, which also proves that the graph structure can effectively capture the high-order features of rumors.

The model we proposed achieved an accuracy rate of 87.8% on the Twitter15 dataset, which was 0.5% higher than the best PPA-WAE model in the baseline model. On the Twitter16 dataset, our model reached an accuracy rate of 91.8%, which was 0.2% higher than the best MGAT-ESM model in the baseline model. This result was achieved because the heterogeneous graph we constructed could fully capture the text semantic features and propagation structure features of rumors, and the dynamic gating mechanism could effectively integrate the features of different views of rumors.

Table 2. Rumor classification results on Twitter15

Category	Models	Accuracy	F1
Based on traditional machine learning models	DTC	0.454	0.455
	RFC	0.565	0.544
	DTR	0.409	0.412
	SVM-RBF	0.318	0.234
	SVM-TS	0.544	0.539
	SVM-HK	0.493	0.442
	SVM-TK	0.667	0.676
Based on the deep learning models	GRU-RNN	0.641	0.644
	BU-RvNN	0.708	0.709
	TD-RvNN	0.723	0.729
	PPC	0.842	0.824
	PLAN	0.852	0.852
	PPA-WAE	0.873	0.873
Based on the graph neural network models			
	Bi-GCN	0.864	0.864
	GETAE	0.825	0.827
Ours	GFF-MGA	**0.878**	**0.877**

Table 3. Rumor classification results on Twitter16

Category	Models	Accuracy	F1
Based on traditional machine learning models	DTC	0.465	0.465
	RFC	0.585	0.569
	DTR	0.414	0.410
	SVM-RBF	0.321	0.324
	SVM-TS	0.574	0.568
	SVM-HK	0.511	0.502
	SVM-TK	0.662	0.676
Based on the deep learning models	GRU-RNN	0.633	0.609
	BU-RvNN	0.718	0.718
	TD-RvNN	0.737	0.737
	PPC	0.863	0.850
	PLAN	0.874	0.874
	PPA-WAE	0.887	0.887
Based on the graph neural network models	GLAN	0.897	0.885
	Bi-GCN	0.879	0.877
	HGATRD	0.886	0.886
	MGAT	0.910	0.910
	MGAT-ESM	0.916	0.916
	GETAE	0.897	0.896
	MSLG	0.913	0.913
Ours	GFF-MGA	**0.918**	**0.918**

4. Conclusion

Although models based on graph neural networks have achieved the best results so far, most current models only consider the second-order structural features of rumors. In fact, rumors not only contain textual information but also involve the users who post the rumors, as well as the friendship relationships among users. Therefore, there are still challenges in effectively integrating complex and multi-source information. In our model, we constructed a heterogeneous graph that integrates the text information of rumors and the propagation structure information, and introduced a dynamic gating mechanism to effectively distinguish the contributions of the two views. The effectiveness and advancement of this model have also been demonstrated on two real datasets.

In future research, we will further develop the hypergraph model, integrate more features of the rumor views, and extract the meta-attribute information of the rumor users, in order to achieve early detection of rumors and effectively curb the spread rate before the rumors become widespread.

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