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RESEARCH ARTICLE

Topic-Aware Fake News Detection Based on Heterogeneous Graph

LIJUAN SUN AND HONGBIN WANG

Faculty of Information Engineering and Automation, Kunming University of Science and Technology, Kunming 650500, China
Key Laboratory of Artificial Intelligence in Yunnan Province, Kunming University of Science and Technology, Kunming 650500, China

Corresponding author: Hongbin Wang (whbin2007@126.com)

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ABSTRACT In recent years, fake news has had a bad impact on individuals and society, which has aroused widespread concern about fake news detection. The existing heterogeneous graph-based fake news detection model (CompareNet) mainly focuses on the semantic consistency analysis between news content and external knowledge, which out-performs traditional content detection models in terms of its efficiency and scalability. However, we found that the framework ignores the fact that the node content of heterogeneous graphs is mostly in the form of short text, and such methods often have difficulty in extracting effective features due to the sparsity problem of short text data. In addition, previous studies have not considered the structural relationship between different writing styles of fake news. Aiming at the above problems this paper proposes a topic-aware fake news detection (FND) method based on heterogeneous graphs, the model investigates the effect of news topics on fake news detection and enhances the discriminative ability of fake news detection. Our model introduces semantically enhanced topic node information in the fake news detector, which fully utilizes three types of information: external knowledge (Wikipedia), news content, and news topics. Therefore, it can better enhance the fake news detection performance.

INDEX TERMS Fake news detection, heterogeneous graph, topic-aware, double-layer heterogeneous graph attention network.

I. INTRODUCTION

With the booming development of the Internet and various digital technologies, the cyberspace has become extremely complex. It is difficult to distinguish between true and false, with the massive amounts of online information growing by the second. This leads to a large variety of false news widely spread on many different platforms, impacting the authority and credibility of the mainstream media, thus bringing negative impacts on the society and triggering harmful public opinion. For example, in the 2016 US. presidential election, fake news spread on various social media platforms, seriously affected the judgment of voters, and eventually social media overcame the mainstream media [1]. Therefore, how to automatically detect different types of fake news from various fields and avoid the adverse impact of malicious fabrication on society is an urgent problem and a challenging task in current social media public opinion work.

In order to effectively detect fake news, the traditional methods mainly focus on finding the typical features of fake news from the given data for detection. Due to the insufficient feature representation capability, the long-distance semantic dependency of text is difficult to be captured in the face of a wide range of types as well as long text fake news, leading to poor detection. With the emergence of graph neural networks, methods based on graph structures, such as GAT+Attn [2], have been proposed to classify news by segmenting a long news article into a fully connected sentence graph. Fake news detection based on graph structure has achieved significant results in the field of fake news detection. Existing heterogeneous graph-based approaches, such as end-to-end CompareNet, help to determine whether news is credible or not by capturing semantic consistency through a network of entity comparisons that compare news to external knowledge (Wikipedia) [3]. However, existing

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work relies heavily on entity knowledge for detection. When the number of entities increases, it is difficult for the model to extract key features if an entity is incorrectly linked to an incorrect entity. On the other hand, the emergence of hot events often triggers the creation of fake news, leading to a certain dynamism in its formation. Fake news is also written in a style increasingly similar to real news, and some extracted features may lose their descriptiveness [4]. This suggests that structural relationships in news content may both facilitate and confound the fake news detection task, limiting the efficiency of the model in different styles of fake news detection. For example, if an algorithm is able to detect fake news in the style of ''satire'', it will rely on features extracted from the training set that are more or less ''satire''. Therefore, it is difficult to use the trained model to detect various types of fake news. The detection effect is not good when the news content is short and the diversity of fake news styles increases.

Therefore, the existing heterogeneous graph-based fake news detection methods have the following problems in social media fake news detection. First, previous methods mainly rely on entities and external knowledge to detect them, which suffers from the problem of entity polysemy. Secondly, most of the news graphs constructed using heterogeneous graphs are in the form of short text, which suffers from the problems of data sparsity and insufficient semantic features [5], leading to difficulties in extracting accurate and critical sample features during detection. In order to solve the problems of existing methods, this paper proposes a topic-aware fake news detection method FND based on heterogeneous graphs. FND introduces topic node information from the heterogeneous graph into the fake news classifier. Topic nodes acquire news topics carrying contextual information through a two-layer heterogeneous graph attention mechanism, which serves as the basis for news credibility inference and enhances the semantic representation of news. Enabling the model to extract accurate and critical sample features using semantically enhanced news topic relevance in the presence of short text as well as increased heterogeneous graph entities as a way to improve model detection performance. This is because, at a higher level, the fake news detection task and topic detection are highly correlated, and topic credibility is positively correlated with article authenticity [6]. In addition, we considered the variability of features resulting from the structural relationship between different writing styles of fake news. FND has designed different feature fusion mechanisms as a way to improve the detection efficiency of the model. In summary, the main contributions of our work are as follows:

- We propose a topic-aware approach based on heterogeneous maps to alleviate the problem of short texts in heterogeneous maps that fail to capture effective features. The detection capability of traditional CompareNet is improved by incorporating semantically enhanced news topics into a fake news classifier.
- We consider the problem of different features brought about by the structural variability of fake news with different writing styles, and design different feature fusion mechanisms in the fake news classifier as a way to improve the detection efficiency of the model.
- We demonstrate the effectiveness of FND through comparative experiments and heterogeneous graph node effectiveness analysis. FND achieves better performance compared to state-of-the-art heterogeneous graph-based models.

The rest of this paper is organized as follows. Section II reviews the related research in the field of fake news detection. Section III presents the architecture of the proposed model. Section IV analyzes and discusses the experiments performed. Finally, the conclusion and future works are drawn in Section V.

II. RELATED WORK

In this part, we briefly introduce the recent developments of fake news detection.

A. CONTENT-BASED FAKE NEWS DETECTION

News content-based detection methods focus on extracting various features of news content, including text, images, videos and the writing style of news in the news. In the complex social media environment, the traditional method based on manually produced features cannot cover the potential features in the new scenario, so Jin et al. [7] for the first time used convolutional neural network (CNN) to extract the news text features, and the obtained embedding vectors were inputted into a classifier to obtain the classification results. Pan et al. [8] proposed to use the knowledge graph to detect the fake news based on the news content, but the detection effect of this method largely depends on the quality of knowledge graph construction. With the rise of deep learning, some work began to turn to extracting image features in news to detect fake news. Qi et al. [9] compared fake news images with real news images at the physical level, and judged the true and false news through the spectrum; both text-based and image-based information to detect are effective, whether we can consider combining the information of the two to detect them. Singhal et al. [10] designed a text-based feature extractor and visual feature extractor model, using VGG to extract visual features, using XLNET to extract text features, and splicing the two to input into the classifier to classify fake news.

B. SOCIAL CONTEXT-BASED FAKE NEWS DETECTION

Fake news on social media is often intentionally written to mislead readers into believing false information. Therefore, it is not enough to rely only on news content to detect it. Lu et al. [11] developed a novel neural network model GCAN, which utilizes user trustworthiness to predict the authenticity of source tweets. Social media facilitates users to learn about real-time news, but the low cost and non-authentication allow fake news to spread widely and rapidly due to malicious accounts. Jiang et al. [12] proposed to construct a homogeneous network consisting of news distribution and user social networks to detect fake news by combining news and user embedding as network features. Previous approaches based on homogeneous graphs have certain limitations, and some studies have begun to consider modeling based on heterogeneous graphs. The social context of the news dissemination process on social media creates an inherent triadic relationship i.e., between publishers, news clips, and users, which has the potential to improve the detection of fake news. Shu et al. [13] proposed a three party relationship embedding framework TriFN, which simultaneously models the publisher-news relationship and the user-news interaction and this three sourced combination is modelled for fake news classification. Kang et al. [14] considered the relationship between news in terms of release time, topic relationship, content relationship, and source relationship, and designed a new heterogeneous graph neural network HDGCN to get the embedding representation of news and applied it to the news classification task. Sun et al. [15] used a global interaction learning module based on hypergraphs to detect fake news by utilizing the global relationship between the user and the news as well as the propagation relationship of the news.

C. FACT CHECKING-BASED FAKE NEWS DETECTION

Fact checking is mainly done by searching large knowledge bases such as Wikipedia and Baidu Encyclopedia to find relevant evidence to determine the authenticity of the news. Dun et al. [16] proposed a new knowledge-aware attention network, KAN, which utilizes the transformer model as well as the knowledge graph to introduce external validation knowledge for fake news detection. Xu et al. [17] proposed a unified graph-based semantic structure mining framework GET, which utilizes multiple evidences to detect the authenticity of news. Sheng et al. [18] proposed to integrate schema-based and fact-based models into a framework that learns the respective preferences of schema-based and fact-based models for joint detection. Wang et al. [19] proposed a novel knowledge-driven multimodal graph convolutional network KMGCN by jointly modelling textual information, knowledge concepts and visual information into a unified fake news detection framework for detection.

The above three different perspectives of fake news detection research have made considerable progress in identifying fake news. But it does not take into account the interaction between sentences in the document and make full use of the external knowledge base. To solve this problem, Hu et al. [3] proposed an end-to-end model, CompareNet, to detect fake news through a entity comparison network. However, most heterogeneous graphs are in the form of short text. If the detection is mainly based on entity and external knowledge, there may be data sparsity and insufficient semantic features, and it is difficult to extract accurate and key sample features.

III. PROPOSED METHOD

Aiming at the limitations of existing research methods, this paper proposes a fake news detection model based on topic perception. The overall framework of the model is shown in Figure 1, which is mainly composed of four parts: 1) News heterogeneous graph construction: each news is partitioned into a set of sentences, and a directed heterogeneous graph is constructed with sentences, topics and entities as nodes. 2) Node feature extraction: for the three types of nodes in the heterogeneous graph, LSTM is used to initialize the sentence after coding, one-hot coding is used to initialize the topic, and the structured triad of entities and unstructured entity description in KB (Wikipedia) are used to learn the KB-based entity representation to initialize entity nodes, respectively. Then, a two-layer heterogeneous graph attention network is introduced in the heterogeneous convolutional layer to learn the feature representation of the three types of nodes. 3) Entity comparison: comparing the news item with external knowledge-based entities to obtain semantic consistency. 4) Fake news classification: After the heterogeneous graph attention network obtains the feature representation of the three types of nodes, then, according to the feature variability of fake news; the different writing styles are integrated into the topic representation in each different way. The fused features are then fed into the classifier for training. This paper will introduce each part in detail in the following subsections.

A. TASK FORMULATION

Topic-aware fake news detection based on heterogeneous graph is a classification task, where the model is required to output the prediction of news veracity. Specifically, each news is preprocessed into three types of nodes: sentences $S = \{s_1, s_2, \cdots, s_m\}$, topics $T = \{t_1, t_2, \cdots, t_k\}$, and entities $E = \{e_1, e_2, \cdots, e_n\}$. The input are each news which containing three types of nodes, the output is the predicted accuracy probability. The FND goal is to train the fake news detection task by simultaneously uniting news content, topics, entities, and external knowledge.

B. NEWS HETEROGENEOUS GRAPH CONSTRUCTION

Since the heterogeneous graph allows different types of edges or nodes to have different dimensions of features or attributes, it contains more comprehensive information and richer semantics. Therefore, in this paper, each news article is constructed as a directed news heterogeneous graph $G(\nu, \varepsilon)$, as shown in Figure 2.

There are three kinds of nodes in the graph: topics $T = \{t_1, t_2, \cdots, t_k\}$, sentences $S = \{s_1, s_2, \cdots, s_m\}$, and entities $E = \{e_1, e_2, \cdots, e_n\}$, $\nu = T \cup S \cup E$. The edge ε set represents the relationship between sentences, entities, and topics. The news is first segmented into a set of sentences in a heterogeneous graph where sentences are connected to each other in both directions and each sentence is treated as a pseudo-document. Then, an unsupervised topic mining method, LDA [20], is utilized to mine potential topics T

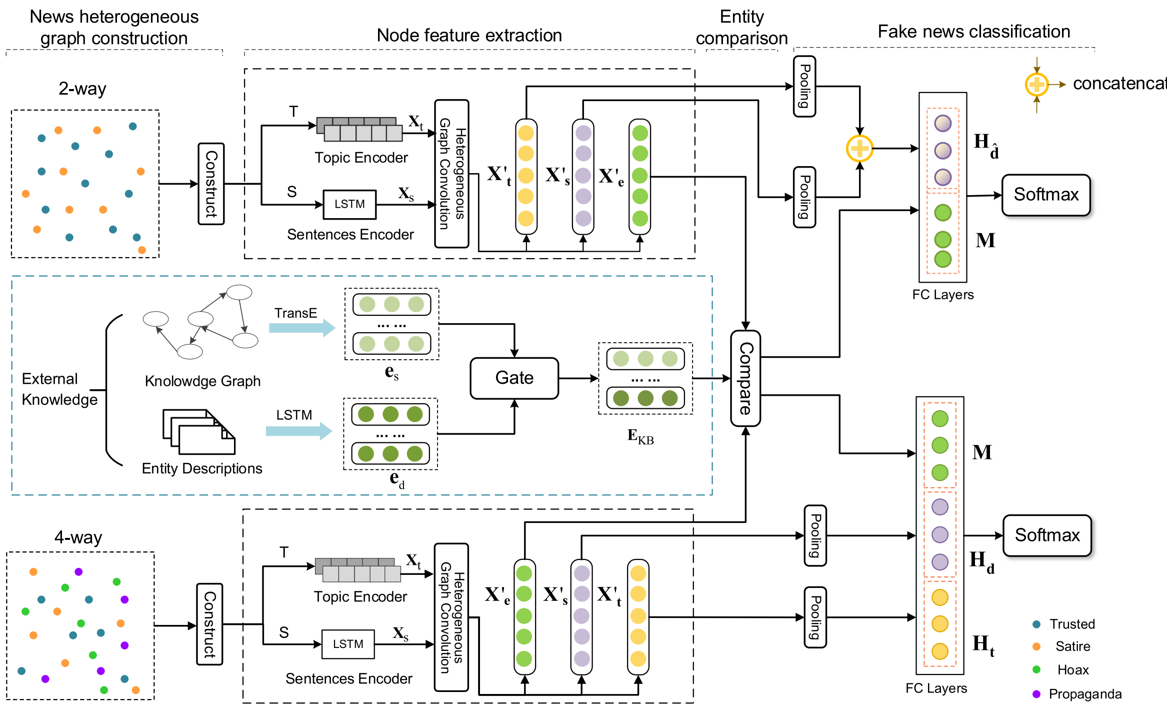

FIGURE 1. **Topic-aware fake news detection model based on heterogeneous graph.**

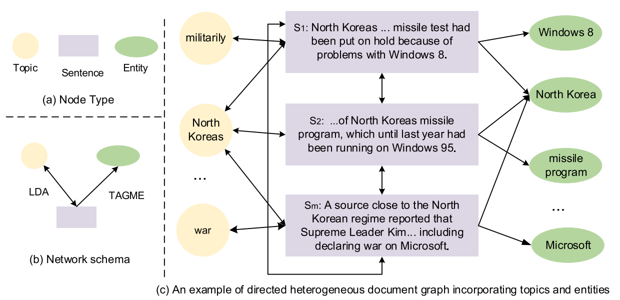

FIGURE 2. **(a) Three types of nodes; (b) Network model; (c) Example of a heterogeneous document graph.**

from all sentences, and each topic t is represented by the top 2 words with the highest probability. Finally, each sentence is bidirectionally connected to the top two relevant topics with the highest probability, allowing topics to learn contextual information. For entity E in document d, map it to Wikipedia via the entity linking tool TAGME.[1] If a sentence s contains an entity e, a directed edge from the sentence to the entity is constructed in the graph. In this way, information can only propagate from sentences to entities, avoiding direct integration of real entity knowledge into news representations and misleading the detection of fake news.

C. NODE FEATURE EXTRACTION

In node feature extraction, in order to extract accurate and critical sample features. This part is mainly used to obtain semantically rich node representations through heterogeneous graph convolution.

[1] https://sobigdata.d4science.org/group/tagme/

1) EXTERNAL KB-BASED ENTITY REPRESENTATION

In this paper, we learn entity representation based on external KB through structured triples of entities in KB (Wikipedia) with textual descriptions of unstructured entities. For each entity in a news article, the first paragraph of the corresponding Wikipedia page is used as the text description of the entity, and the text embedding e_d is encoded using LSTM. Then, the gate mechanism is used to adaptively fuse the useful information in the preprocessed entity structured triples e_s and entity text descriptions e_d.

$$\boldsymbol{E}_{KB} = g_e \odot e_s + (1 - g_e) \odot e_d \tag{1}$$

where, g_e is a gating vector, $\odot$ denotes elementwise multiplication, assign the gate value to the e_s and e_d, e_s and e_d are summed with different weights for each dimension. Finally a door-aware entity embedding e_{KB} is generated, the Sigmoid function is used to calculate the value of the gate g_e that represents the feature level importance.

$$g_e = \sigma(\tilde{g_e}) \tag{2}$$

where, $\tilde{g_e}$ is a real-valued vector obtained through training learning, σ is the activation function of the gate.

The final fused entity representation is the entity representation E_{KB} based on the external KB, and the entities in the news heterogeneous graph are initialized, if an entity in the news heterogeneous graph does not exist in the KB, the node will be discarded during node initialization.

2) HETEROGENEOUS GRAPH CONVOLUTION

Since most of the nodes in the news heterogeneous graph G are in the form of short texts, this paper introduces a

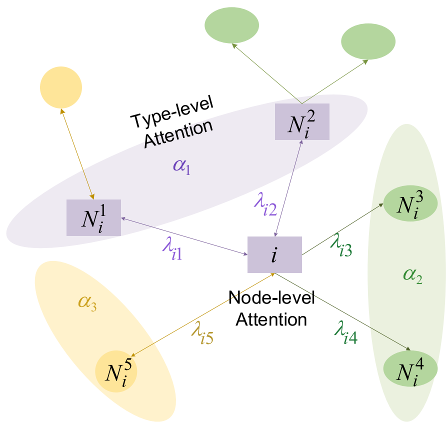

FIGURE 3. Two-layer heterogeneous graph attention mechanism for extracting node features.

two-layer heterogeneous graph attention mechanism including node-level and type-level to obtain the characteristics of each node in the heterogeneous graph, as shown in Figure 3. This mechanism can understand the importance of different neighboring nodes and different node (information) types to the current node. Therefore, the topic nodes can learn the contextual information through this mechanism and acquire semantically enhanced news topics.

There are three types of nodes in the constructed news heterogeneous graph $\phi = (\varphi_1, \varphi_2, \varphi_3)$. For sentence node S, LSTM is used to encode the sentence to obtain its feature vector x_s. For a topic node T, the topic is initialized with a one-hot coded vector x_t. For entity node T, the entity is initialized using an external KB-based entity representation E_{KB}.

For a graph $G(v, \varepsilon)$ consisting of news content, topics, and entities, where v, ε denotes the set of nodes and edges of the graph. $X \in \mathbb{R}^{|v| \times M}$ is the matrix containing nodes and their features $x_v \in \mathbb{R}^M$. The heterogeneous convolutional layer updates the node representation $H^{(l+1)}$ by aggregating the features of different types φ of neighboring nodes $H_\varphi^{(l)}$. Initially, $H^{(0)} = X$.

$$H^{(l+1)} = \sigma(\sum_{\varphi \in \phi} \beta_\varphi \cdot H_\varphi^{(l)} \cdot W_\varphi^{(l)}) \tag{3}$$

where, $\sigma(\cdot)$ denotes the ReLU activation function, and different types φ of nodes have different transformation matrices $W_\varphi^{(l)}$. The transformation matrix $W_\varphi^{(l)}$ takes into account the differences between the different feature spaces and projects them into an implicit common space. $\beta_\varphi \in \mathbb{R}^{|v| \times |v_\varphi|}$ is an attention matrix whose rows represent all nodes and columns represent neighboring nodes of type φ, and the element $\lambda_{vv'}$ in row v and column v' s calculated as follows:

$$\lambda_{vv'} = Softmax(\sigma(\gamma^T \cdot \alpha_\varphi[h_v, h_{v'}])) \tag{4}$$

where, γ is the attention vector, h_v, $h_{v'}$ denotes the current node embedding and its neighboring node embeddings respectively, α_φ is the type-level attention weight. Finally, apply the Softmax function to normalize all the node-level attention weights, and finally obtain the node-level attention weights.

The formula for calculating the type-level attention weight α_φ based on the current node embedding h_v and type embedding h_φ is as follows:

$$\alpha_\varphi = Softmax_\varphi(\sigma(\mu_\varphi^T \cdot [h_v, h_\varphi])) \tag{5}$$

where, μ_φ is the attention vector of type φ, $h_\varphi = \sum_{v'} \tilde{A}_{vv'} h_{v'}$ is the weighted sum representation of the embeddings h'_v of neighboring nodes of type φ. The weight matrix $\tilde{A} = D^{-\frac{1}{2}}(A + I)D^{-\frac{1}{2}}$ is the normalized adjacency matrix with the addition of self-connections. A is the adjacency matrix, and D is the degree matrix. Finally, the Softmax function is applied to normalize all types of attention weights.

After L-layer heterogeneous graph convolution, all node representations aggregating the neighborhood semantics can be finally obtained as sentence embedding x'_s, topic embedding x'_t, and entity context embedding x'_e. The three types of nodes are maximally pooled to obtain the topic-enhanced news representation $H_d \in \mathbb{R}^N$, the entity representation $e_c \in \mathbb{R}^N$ with contextual semantic information, and the semantically-enhanced topic representation $H_t \in \mathbb{R}^N$.

D. COMPARISON OF ENTITIES

Due to the fact that the entity in the news document may have polysemy problem, which leads to the inconsistency between the entity and the entity description in the KB. Therefore, in this paper, we compare the news document with KB for inter-entity comparison as a way to obtain the semantic consistency between the news content and KB (Wikipedia). The main method is to compute the comparison vector $e_c \in \mathbb{R}^N$ between each entity in the news and its corresponding entity $E_{KB} \in \mathbb{R}^N$ based on the external KB based on the entity. The formula is as follows:

$$m_i = f_c(e_c, W_e, E_{KB}) \tag{6}$$

where, $f_c()$ denotes the comparison function, $W_e \in \mathbb{R}^{N \times 2N}$ is the transformation matrix, the comparison function is calculated as follows.

$$f_c(x, y) = W_c[x - y, x \odot y] \tag{7}$$

where, $W_c \in \mathbb{R}^{N \times 2N}$ is the transformation matrix, the final comparison vector $M \in \mathbb{R}^N$, is obtained by maximally pooling the alignment vectors $A = [\boldsymbol{a}_1, \boldsymbol{a}_2, \cdots, \boldsymbol{a}_n]$, of all the entity representations $E = [e_1, e_2, \cdots, e_n]$ in the news document.

E. FAKE NEWS CLASSIFICATION

In this paper, we consider the feature variability brought by the structural relationship of different writing styles of fake news, so the fake news classifier is mainly divided into two parts to improve the efficiency of fake news detection with different feature fusion mechanisms.

1) 2-WAY CLASSIFICATION

For a single type of fake news, its features are more targeted, and the subject representation is connected to the news representation and then integrated into the fully connected layer. After obtaining the features in the same dimension space by maximum pooling, the news representation H_d, and the topic representation H_t, are connected to obtain the feature-enhanced news representation $H_{\hat{d}}$.

$$H_{\hat{d}} = H_d + H_t \tag{8}$$

Then, the final news representation vector $H_{\hat{d}}$ is connected to the entity comparison vector M and fed into a Softmax layer for fake news classification.

$$N_2 = Softmax(W_0[H_{\hat{d}}, M] + b_0) \tag{9}$$

where, W_0, b_0 is the parameter matrix and scalar of a linear transformation, N_2 denotes a prediction for the final 2-way classification.

2) 4-WAY CLASSIFICATION

For multi-type fake news detection, which contains many different fake news features, in order to promote the interaction between the features, the fully connected layers are deepened to improve the nonlinear expressive ability of the model. After obtaining the comparison vector M, the final news representation H_d and the topic representation H_t, they are connected and input to the Softmax layer for fake news classification.

$$N_4 = Softmax(W_1[H_d, M, H_t] + b_1) \tag{10}$$

where, W_1, b_1 is the parameter matrix and scalar of a linear transformation, N_4 denotes a prediction for the final 4-way classification.

3) MODEL TRAINING

During 2-way and 4-way model training, the objective function is the cross-entropy loss function commonly used in classification in order to minimize the loss value, the objective function is shown below.

$$\mathcal{L} = -\sum_{i \in D} \sum_{j=1} Y_{ij} \cdot logN_{ij} + \eta \|\Theta\|_2 \tag{11}$$

where, D denotes the overall training corpus, Y is the corresponding label indication matrix, Θ is a model parameter, η is the L2 regularization coefficient, and a gradient descent algorithm is used for model optimization.

IV. EXPERIMENTS

In this section, this paper first introduces the datasets LUN, SLN used in the experiments, the corresponding parameter settings, and then demonstrates the performance of the proposed method in this paper, comparing it with some advanced fake news detection methods.

A. EXPERIMENTAL CONFIGURATIONS

1) DATASET

In order to evaluate the effectiveness of this method, this paper conducts experiments on LUN [21] and SLN [22] datasets, the LUN dataset contains four types of news, namely Trusted, Satire, Hoax, and Propaganda, and the SLN dataset contains two types of news, namely Trusted and Satire, and the details of the datasets are shown in Table 1.

For single-type fake news (containing only articles of trusted and satire types), the satirical and credible news articles in the LUN-train dataset are used to train the model, the LUN-test dataset is used as the validation set, and the SLN dataset is used as the test set. For multi-type fake news (containing articles of trusted, satire, hoax, and propaganda types), the LUN-train training set is divided into training and validation sets at a ratio of 4:1, and the LUN-test dataset is used as the test set.

2) PARAMETER SETTINGS

The hyperparameter settings are chosen based on the best experimental results on the validation set. The heterogeneous convolutional layer in the model is 1 layer, the LSTM hidden dimension and sentence embedding dimension are both 100, the maximum sentence length is 50, the maximum length of the sentence in the document is set to 10000, the batchsize is set to 16, the number of training iterations is set to 15, the learning rate is 0.001, and in order to prevent overfitting, the dorpout mechanism is used in the model, with a rate of 0.5, using ReLU as the nonlinear activation function, pooling operations are used to maximize pooling. In the experiment, we fixed the random number seed to make the comparison more scientifically sound as the two cases are in the same randomized situation. The loss function used in this paper is the cross-entropy loss function, in order to improve the robustness of the fake news detection model and to prevent overfitting, the Adam with a weight decay rate of 1E-6 is used as the optimizer of the objective function.

3) EVALUATION METRICS

In this paper, the evaluation metrics Micro-f1 and Macro-f1, which are commonly used in fake news detection tasks, are used to evaluate the performance of all models. The calculation methods of various metrics are as follows:

$$P_i = \frac{TP_i}{TP_i + FP_i}, \quad R_i = \frac{TP_i}{TP_i + FN_i} \tag{12}$$

where, TP is the number of correctly identified fake news, TN is the number of incorrectly identified fake news, FP is the number of incorrectly identified real news and FN is the number of correctly identified real news.

The micro-average precision P_{Micro} and micro-average recall R_{Micro} are calculated as follows:

$$P_{Micro} = \frac{\sum_{i=1}^{k} TP_i}{\sum_{i=1}^{k}(TP_i + FP_i)} \tag{13}$$

TABLE 1. Dataset statistics.

Dataset	Trusted (#Docs)	Trusted (#Satire)	Trusted (#Hoax)	Propaganda (#Docs)
LUN-train	GN except 'APW' and 'WPB'(9995)	The Onion(14047)	American News(6942)	Activist Report(17870)
LUN-test	GN only 'APW' and 'WPB'(750)	The Borowitz Report, Clickhole(750)	DC Gazette(750)	The Natural News(750)
SLN	The Toronto Star,The NY Times(180)	The Onion, The Beaverton(180)	-	-

$$R_{Micro} = \frac{\sum_{i=1}^{k} TP_i}{\sum_{i=1}^{k}(TP_i + FN_i)} \tag{14}$$

The macro average precision P_{Macro} and macro average recall R_{Macro} are calculated as follows:

$$P_{Macro} = \frac{\sum_{i=1}^{k} P_i}{k} \tag{15}$$

$$R_{Macro} = \frac{\sum_{i=1}^{k} R_i}{k} \tag{16}$$

The performance of multicategorization tasks is usually evaluated by Micro-f1 and Macro-f1, which are calculated as follows:

$$M_i - f_1 = \frac{2P_{Micro} \times R_{Micro}}{P_{Micro} + R_{Micro}} \tag{17}$$

$$M_a - f_1 = \frac{2P_{Macro} \times R_{Macro}}{P_{Macro} + R_{Macro}} \tag{18}$$

B. COMPARISONS WITH BASELINE

In order to validate the effectiveness of the present method, this paper compares it with two types of baseline models - traditional deep learning classification models, classification models based on graph neural networks.

In the comparison experiments with traditional deep learning classification models, this paper chooses BERT, LSTM as the comparison model. In general, BERT has very high accuracy in text classification and performs robustly on a variety of learning tasks [23]. LSTM has a wide range of applications in the field of text categorization because of its ability to learn dependencies in larger time lags as well as its powerful feature selection capability [24]. In addition, several graph neural network-based approaches are used in this paper for comparison, including graph convolutional network GCN, graph attention network GAT [7], end-to-end CompareNet [4] model based on heterogeneous graphs.

- **BERT** directly for document encoder.
- **BERT+LSTM** [3] BERT for sentence encoder and then LSTM for document encoder.
- **GAT+Max, GAT+Attn** [3] segmenting news into a set of sentences and using the sentences to construct a fully connected graph, GAT learns news document representations based on an undirected fully connected sentence graph using attention pooling or max pooling.
- **CompareNet** [4] the model constructs each news story as a directed heterogeneous document graph, and then designs an Entity Comparison Network to detect fake news by comparing contextual entities with external knowledge to capture the semantic consistency between news content and KB.

C. EXPERIMENTAL RESULTS AND ANALYSIS

1) COMPARISON OF EXPERIMENTAL RESULTS ANALYSIS

In order to comprehensively evaluate the proposed method, this paper conducts experiments for single-type fake news and multi-type fake news respectively. The experimental results of the baseline method and the method proposed in this paper on the two datasets are shown in Table 2.

As can be seen from Table 2, compared with the best baseline model, the method proposed in this paper improves on both datasets because it emphasizes the information learned by the topics in the heterogeneous graph. In this case, the Micro-F1 metric in 4-way classification improves 1.85% and the Macro-F1 metric improves 1.87%, while the Micro-F1 metric in 2-way classification improves 0.83% and the Macro-F1 metric improves 0.88%. At the same time, we can see that the performance of the graph neural network-based method is better than the traditional deep learning method, which is because the traditional deep learning algorithm mainly extracts information from objects encoded in some fixed structure. While the graph structure representation of data can extract more valuable information from entities and entity-relationship representations, which can be used to capture the interdependencies between instances.

The results of the above comparison experiments show that the CompareNet method and the method proposed in this paper perform better than the GCN and GAT methods. Because it employs heterogeneous graphs to represent a variety of data with greater relevance, it contains more comprehensive information and richer semantics. In contrast, FND performed slightly better than the best baseline model, CompareNet. Under the same training environment, regardless of 2-way classification or 4-way classification, FND detection model is faster than traditional CompareNet model. Because the introduction of semantically enhanced topic information in the fake news classifier provides more useful information for the fake news detection task and helps the model to extract the key sample features to quickly target the fake news. In order to intuitively understand the advantages of adding semantically enhanced news topics to the fake news detector, this paper uses heatmaps to visualize the classification results. The classification results of the baseline model CompareNet are shown in Figure 4. After using the proposed method, as shown in Figure 5, we can see that the four news categorization divisions are more obvious. The detected real news and fake news are both increased compared to CompareNet, indicating that the method proposed in this paper leads to better performance in fake news identification.

TABLE 2. The results of different methods on LUN and SLN datasets.

Model	4-way(LUN Dataset)				2-way(SLN Dataset)			
	F1 − Mi	P − Ma	R − Ma	F1 − Ma	F1 − Mi	P − Ma	R − Ma	F1 − Ma
BERT	64.66	60.89	64.46	58.80	84.16	84.73	84.16	84.10
BERT+LSTM	55.56	57.45	57.45	57.45	75.83	76.62	75.83	75.65
GCN+Attn	67.08	68.60	67.00	66.42	85.27	85.59	85.27	85.24
GAT+Max	65.50	69.45	65.33	63.83	86.39	86.44	86.38	86.38
CompareNet	69.05	72.94	69.04	68.26	89.17	89.82	89.17	89.12
FND(ours)	**70.90**	72.18	70.90	**70.13**	**90.00**	90.08	90.00	**90.00**

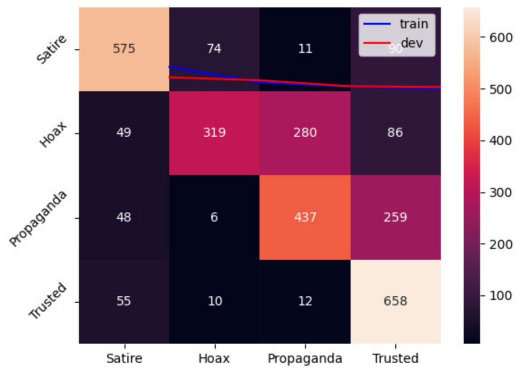

FIGURE 4. CompareNet.

FIGURE 5. FND(Ours).

2) HETEROGENEOUS GRAPH NODE VALIDITY ANALYSIS

In order to observe the contribution of the two main types of nodes, topic and entity, in the heterogeneous graph in recognizing fake news, and to explore the relationship between the truthfulness of news and its corresponding topic. In this paper, the proposed method is modified to present two heuristic models, which are compared with the optimal baseline model. The results on the LUN and SLN datasets are shown in Table 3 below. In order for the experiment to be free from other factors and to facilitate the comparison, the random numbers were fixed during the experiment.

- **FND** the news heterogeneous graph containing semantically enhanced topics, entities, and news article nodes.
- **w/o entity(FND)** the news heterogeneous graph contains two types of nodes: semantically enhanced topics, and news articles.
- **w/o topic** the news heterogeneous graph contains two types of nodes: entities and news articles.

From the experimental results in Table 3, it can be seen that entity nodes, semantically enhanced topic nodes all have an impact on the performance of the fake news classifier, especially in multi-categorization, the performance of the w/o topic model decreases more significantly. This shows that the contribution of news topics to recognize fake news is crucial in multi-type fake news. From the w/o entity(FND) model, it can be seen that the effect of entity nodes on multi-classification is not as high as single classification, which may be due to the increase of entities in multi-type news, and the feature extraction process has not extracted the effective entity features. It also shows that in the case of increased entities, the use of semantic enhancement of news topic relevance helps the model to extract accurate and critical sample features to quickly target fake news, thus improving the model's detection performance. In the case of 4-way classification, for example, the w/o entity(FND) model outperforms the w/o entity(CompareNet) model because the w/o entity(FND) model introduces semantically enhanced topic node information in the fake news classifier compared to the original CompareNet model. In addition, we find that in single classification, the performance of the model is more affected by entity nodes, because single type of fake news belongs to one style, and there is a similarity problem among news topics, and entity nodes are more capable of assisting the model to extract key sample features.

To further illustrate the advantages of topic nodes carrying contextual information in fake news recognition, this paper graphs the graph attention of heterogeneous graph nodes over their domains. As shown in Figure 6, take sentence S_4^m as an example, through the two-layer heterogeneous graph attention mechanism, although S_4^m can learn the information of its domain entities E_1^n, E_2^n and topic T_6^k, when the number of entities increases, the information of the entities learned by S_4^m may suffer from the problem of more than one but inaccurate. The attention mechanism allows us to know that sentences S_4^m, S_5^m have different relevance to the topic T_6^k, as a way to clarify the contribution of each sentence in the detection. Topic nodes are able to integrate additional in-formation and capture rich relationships between the source news to which they are connected. This mitigates

TABLE 3. The effectiveness of each node in the heterogeneous graph in fake news detection.

Model	4-way(LUN Dataset)				2-way(SLN Dataset)			
	F1 − Mi	P − Ma	R − Ma	F1 − Ma	F1 − Mi	P − Ma	R − Ma	F1 − Ma
FND(ours)	**70.90**	72.18	70.90	**70.13**	**90.00**	90.08	90.00	**90.00**
w/o entity(FND)	69.42	71.53	69.36	68.25	85.00	85.00	85.00	85.00
w/o entity(CompareNet)	67.46	70.38	67.43	66.35	-	-	-	-
w/o topic	66.52	68.46	66.56	65.96	86.39	86.44	86.39	86.38

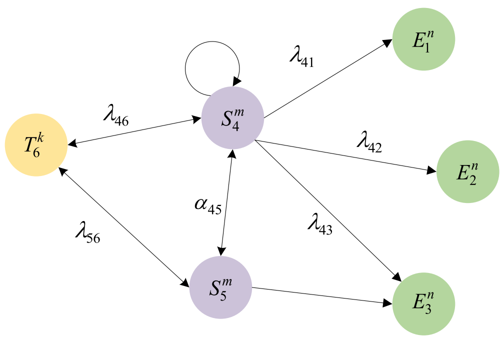

FIGURE 6. An illustration of graph attention by heterogeneous graph nodes on its neighborhood.

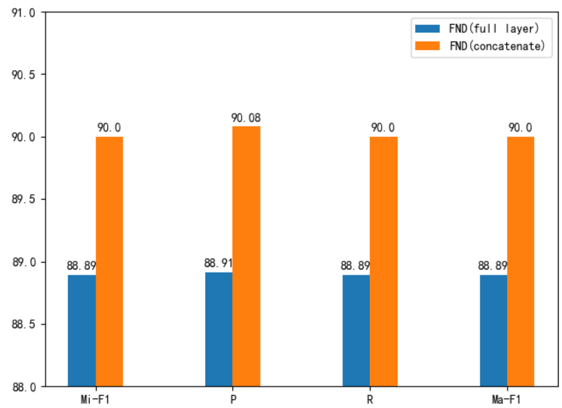

FIGURE 7. Influence analysis of 2-way classification fusion method.

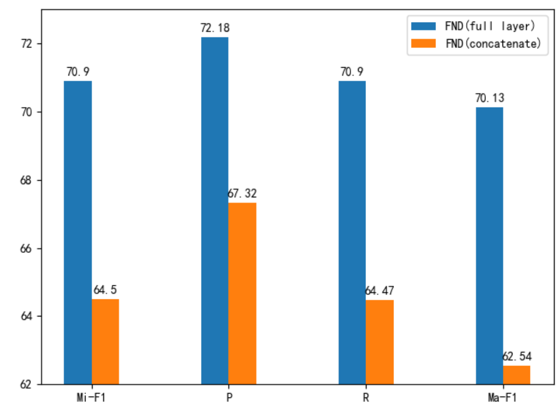

FIGURE 8. Influence analysis of 4-way classification fusion method.

the sparsity of short texts. Therefore, adding topic nodes into the fake news classifier is compared with adding only sentence and entity nodes in the baseline model. The former is more capable of clarifying whether the sentence's is the key feature for detection, and then selecting the key entity features, effectively combining the three types of features for fake news recognition. For example, if an entity error occurs for "Apple Inc." that links to the entity "Apple" in the Fruit category, then the entity description and knowledge graph for that entity also belongs to the Fruit category. Since the entities in the heterogeneous graph are initialized by external knowledge, the whole article captures semantic consistency by comparing the entities with the external entity knowledge, which captures very little valid information for short textbook news. The topic, on the other hand, is based on each sentence to extract the top two words with the highest probability, favoring the central idea that the whole article is trying to express. In response to the above occurrences, the information learned from the topic nodes can help the model to quickly identify the key features to be detected.

3) COMPARISON OF DIFFERENT INFORMATION FUSION METHODS

In the real world, different fake news authors may handle original content in different ways, so fake news tends to be of various styles [25], and the increase of news styles also affects the efficiency of fake news detection. In this paper, we investigate the fusion of single-type and multi-type topic information to prove the effectiveness of this paper's method. The single-type and multi-type theme information fusion methods are interchanged, and the experimental results are observed, as shown in Figure 7 and Figure 8.

The FND(full layer) model deepens the full connectivity layer by adopting the way of fusing multiple types of topic information and incorporating the topic layer, and it is found through Figure 7 found that both Macro-F1 and Micro-F1 have declined significantly. It shows that deepening the full connectivity layer is not applicable to the detection of single type of fake news, the features of single type of fake news are more targeted, and adopting the way of connecting the topic representation with the news representation and then integrating into the full connectivity layer is more helpful in highlighting the features of fake news for single type of fake news.

FND(concatenate) model by using a single type of topic information fusion way to connect the topic representation with the news representation, through Figure 8 found that both Macro-F1 and Micro-F1 have declined significantly, indicating that the way of feature fusion between the topic representation and the news representation is not applicable to the detection of multi-types of fake news, for multi-types of fake news, the full connectivity layer deepens to promote the interaction between the features, and it is more able to improve the model's nonlinear expressive ability.

V. CONCLUSION AND FUTURE WORK

In this paper, we address the problems of difficulty in extracting effective features from short texts and low efficiency in fake news detection based on heterogeneous maps. A topic-aware fake news detection method based on heterogeneous graph is proposed. The method obtains news topics carrying contextual information through a two-layer heterogeneous graph attention mechanism, and then integrates the semantically enhanced news topics into the fake news detection model to better enhance the semantic expression of the news and improve the detection performance; at the same time, taking into account the feature variability brought by the structural relationship of fake news in different writing styles, different feature fusion mechanisms are designed to improve the detection efficiency of the model. The effectiveness of this paper's method is confirmed by experiments on two real datasets. In our future work, we intend to further investigate the graph structure-based fake news detection, consider the relevance of topic information in more feature spaces, and achieve better detection by fusing feature information at more levels.

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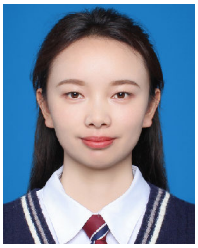
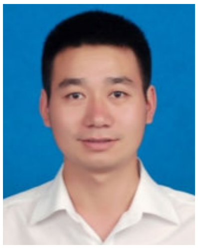


LIJUAN SUN was born in 1997. She received the B.E. degree from the Faculty of Mathematics and Information Technology, Yuxi Normal University, Yuxi, China, in 2020. She is currently pursuing the M.E. degree with the Faculty of Information Engineering and Automation, Kunming University of Science and Technology, Kunming, China. Her research interests include natural language processing and fake news detection.



HONGBIN WANG was born in 1983. He received the Ph.D. degree in computer science from Jilin University, Changchun, China, in 2013. He is currently an Associate Professor with the Faculty of Information Engineering and Automation, Kunming University of Science and Technology. His current research interests include intelligent information systems, natural language processing, and data analysis.