Rumor detection technology based on ubiquitous relationship

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Keywords: Rumor detection, Ubiquitous relationship, Propagation model, Graph convolutional neural network.

Abstract. This paper addresses the limitations of existing rumor detection methods that heavily rely on single or local features, which restrict their ability to capture comprehensive and detailed characteristics of rumors. The main objective of this study is to enhance the efficiency of rumor detection. To achieve this, we propose a novel approach that integrates user attributes, comment structure, and propagation models, introducing the concept of ubiquitous relationships for messages in social networks. We construct a Tweet-word-user ubiquitous relationship network using a propagation model and further leverage the Graph Convolutional Neural Network (GCN) to enhance semantic features. Consequently, we present a novel rumor detection model, the Ubiquitous Relationship-based Graph Convolutional Neural Network (U-GCN), which effectively combines user, text, and comment features within a unified framework, while also enhancing semantic features from the source post for comprehensive detection. Extensive experiments are conducted on two publicly available Twitter Datasets. The results demonstrate that our proposed U-GCN model achieves an accuracy rate of above 0.9, outperforming methods that solely consider single or local features. Our findings highlight the effectiveness of leveraging ubiquitous relationships in rumor detection.

1 Introduction

Initially, traditional approaches to rumor detection relied on labor-intensive manual annotation methods, which proved to be inefficient and limited in scope. As research in the fields of Machine Learning (ML), Data Mining (DM), and Natural Language Processing (NLP) progressed, new perspectives on rumor detection emerged. Serena et al. [1] applied NLP techniques to analyze comments on individual tweets, utilizing collective intelligence for rumor detection. Addressing the issue of temporal delays in comments and retweet information, Ge et al. [2] proposed a detection model based on sentiment features and rumor types. However, their analysis solely relied on the semantic analysis of the text,

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overlooking the broader aspects of rumor propagation, such as the global structural dynamics of the information, user attributes, user comments, and associated user attributes that contribute to the representation of rumors. Additionally, the historical tweets of users and associated users can provide valuable insights into the likelihood of spreading rumors, which is relevant for rumor judgment. By incorporating user historical data alongside semantic and collective intelligence, we break free from the limitations of users' tendencies to share inaccurate information, speculations, and unverified evidence on social media. Even if user comments are inaccurate or propagate misinformation, such tendencies can be revealed through the associated features in user's historical data.

The focus of this work is to integrate the aforementioned features for rumor detection, aiming to obtain a more stable, accurate, and generalizable rumor detection model. To achieve this, we introduce the concept of "ubiquitous networking," defining a set of attributes that may establish connections between messages as ubiquitous relationships, including the structural propagation of messages, user historical attributes, user associations, and comment properties during the dissemination process. Building upon this concept, we construct a ubiquitous relationship network based on the propagation structure of messages, and utilize Graph Convolutional Neural Network (GCN) to simulate the global propagation process of rumors, including retweets, likes, comments, and cross-level interactions. The model focuses on constructing and integrating the relevant attributes of messages during the propagation process, analyzing low-dimensional features and advanced representations of comment text and source tweet between Tweet and user nodes. Additionally, recognizing the significant role of textual semantics as a primary detection feature in rumor detection tasks, we cyclically introduce textual features from the source tweet to enhance its content representation. Finally, experimental validation on public datasets verifies the stability and accuracy of the model.

2 Related word

In 2018, Liu et al. [3] proposed a rumor detection method that combines RNN and CNN, which to some extent allows for the analysis of the temporal sequence characteristics of user rumor propagation. Shu et al. [4] first proposed the interpretable detection model dEFEND in 2019, utilizing news sentences and user comments to provide explanations through the weights of co-attention. In 2020, based on the propagation tree proposed by Ma et al. [5], T-Bian et al. [6] used a bidirectional GCN network for rumor detection. This work captures the global features of the propagation structure and achieves good detection results, but it is limited to representing rumor propagation as a static graph and lacks interpretability research. Lu et al. [7] proposed the GCAN model in 2020 to solve the difficulties in constructing information propagation trees and the weak interpretability of models. The GCAN model models the information source and information propagation tree and uses Co-attention to explain the key users and key information in the decision-making process, but the model's generalization ability is insufficient. Dong et al. [8] proposed a GCN-based model that can identify the source of rumors without prior knowledge of the underlying propagation model. Although different models have been used in rumor detection, these models have not been able to utilize deep learning models to integrate the structural information of user graphs and comment graphs. In this paper, we utilize the message propagation structure for ubiquitous relationship modeling, providing a new approach to further improve the generalization ability of rumor detection. Moreover, it is precisely because the ubiquitous relationship network allows nodes to have different attributes that the interaction between nodes becomes diverse, thereby increasing the complexity representation of graph data and the flexibility of model theory to be applied in different scenarios.

In existing research, GCN is able to extract graph structure information and better describe the neighborhood features of nodes. Multiple graph convolutional layers (GCL) are defined to iteratively aggregate the neighborhood features of each node, and can be represented as a simple message passing framework. Based on such developments, the research on rumor detection has also been deeply influenced by GCN. Similarly, for the processing of Twitter data, the research on graph embedding is also indispensable. Representing nodes in a graph as a low-dimensional vector space while preserving the network's topological structure and node information enables existing machine learning algorithms to be directly applied to subsequent graph analysis tasks, transforming the entire corpus into a homogeneous or heterogeneous graph through modeling.

3 Method

3.1 Problem definition

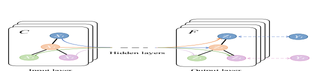
Typically, rumor detection is considered as a multi-classification task, aiming to learn classifiers from training data. The research in this paper focuses on determining whether a given source tweet is a rumor by analyzing a series of information generated from the continuous retweeting of the source tweet, as well as the historical tweets of the source tweet user and related users.

In formal terms, the objective can be stated as follows: Let $\mathbf{C}=\{c_1,c_2,c_3,\ldots,c_m\}$be the Datasets for rumor detection,consisting of m events, with c_i representing the i-th event. Let $c_i=\{r_i,xi\ 1,ci\ 2,\ldots,ci\ n\text{-}1,G_i\}$, r_i denote the source tweet (representing the source tweet user), and $xi\ j$ represent the j-th related retweet (representing the j-th associated user). The propagation structure is denoted as $\mathbf{G_i}=<V_i,E_i>$, with nodes $V_i=\{r_i,xi\ 1,ci\ 2,\ldots,ci\ n\text{-}1\}$ and $E_i=\{ei\ st|\mathbf{s},t=0,\ldots,n_i\text{-}1\}$ representing a set of directed edges from the corresponding response tweet to the respective retweet. Let $A_i\in\{0,1\}^{n_i\times n_i}$ be the adjacency matrix of the graph, with an initial value defined as follows:

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

Furthermore, each event c_i is assigned a basic fact label $y_i\in\mathbf{Y}$, where $\mathbf{Y}$ represents a fine-grained class including four labels{**N**,**F**,**T**,**U**}: **N** for non-rumor, **F** for false rumor, **T** for true rumor, and **U** for unverified rumor. When the Datasets is provided, f:$\mathbf{C}\rightarrow\mathbf{Y}$ is used to predict the labels of rumor events using user features, text features, and relevant propagation features constructed with the source tweet.

In a set of graph data, there exists **N** nodes with unique node features. The features of these **N** nodes can be combined to form an $\mathbf{N}\times\mathbf{D}$-dimensional matrix, while the relationships between the nodes can be represented as an $\mathbf{N}\times\mathbf{N}$-dimensional matrix **A**. In this context, **X** represents the input feature matrix, and **A** represents the adjacency matrix. When **X** and **A** are used as inputs, the layer-wise propagation rule for GCN can be defined as:



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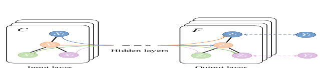
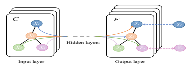


(3)

Initializing node representations through text features, where $\boldsymbol{H^{(l)}}$ is the hidden feature matrix at the layer. Here, $\tilde{\mathbf{A}}$=**A**+$\boldsymbol{I}$ is the undirected graph adjacency matrix with self-connections added for each node. To avoid overly large vector values after multiple convolutions, **A** matrix needs to be normalized, leading to the following equation:



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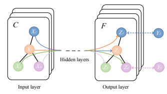

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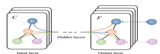
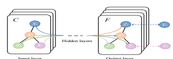
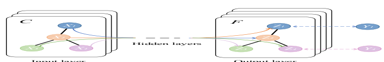


(6)

Taking the example of the two-layer GCN model set up in this experiment, the ***Softmax*** and ***Relu*** activation functions are used respectively. The prediction formula is as follows:

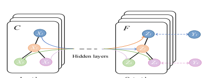


(7)



(8)

The loss function is:



(9)

Where $\boldsymbol{y}$ is the set of nodes with class labels, and $\boldsymbol{f}$ is the number of classes.

3.2 A semantics-integrated ubiquitous-relationship-based rumor detection model

In order to achieve better performance in rumor detection compared to traditional methods, this paper fully considers the information generated by rumors during the propagation process and proposes a rumor detection method based on ubiquitous relationships that integrates semantics. The method constructs a Graph Convolutional Neural Network (GCN) model based on ubiquitous relationships, called U-GCN. The model focuses on the ubiquitous relationship graph of Tweet-word-user, decomposed into propagation subgraphs based on comments related to the source post and users associated with the source post. GCN is introduced to enhance the semantic features of the source post. Then, the two types of features obtained for the source post are fused through pooling, concatenation, and other operations to achieve rumor detection for that post. This model not only considers the textual semantics but also takes into account the ubiquitous relationships involved in the post's propagation process, including relevant content, reposted comments, and user attributes. The specific model construction is illustrated in Figure 1.

The first part in Figure 1 is the Ubiquitous Relationship Representation layer, which decomposes it into the Tweet-word and Tweet-user subgraphs. The second part consists of the Semantics-enhanced GCN layer and B-GCN layer, which learn from the subgraphs obtained in the previous step. The third part is the Concatenation and Classification layer, which concatenates the features represented in the two networks and performs classification to achieve comprehensive detection.

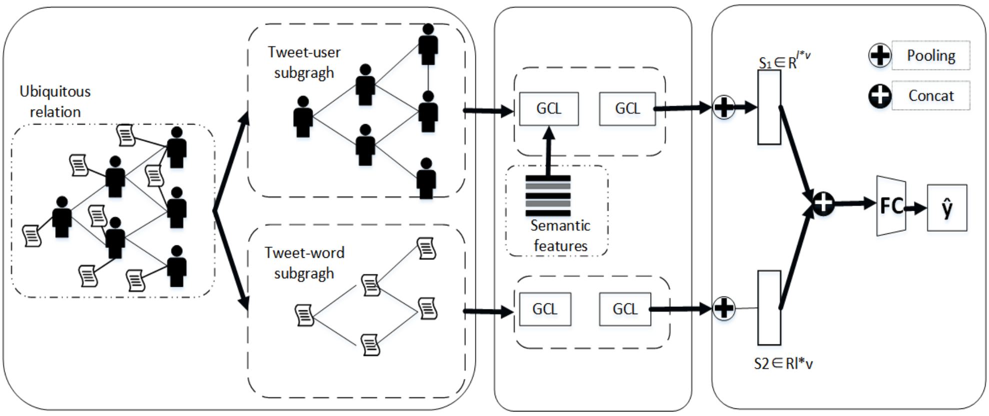


Fig. 1. A semantics-integrated ubiquitous-relationship-based rumor detection model.

3.2.1 Ubiquitous relationship construction

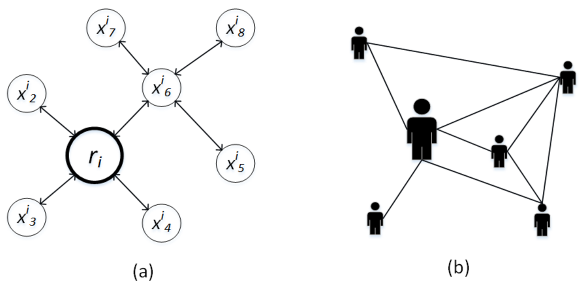


Fig. 2. Tweet-word-user.

In the first part of the model, the rumor Datasets is constructed into a ubiquitous relationship network called Tweet-word-user based on the ubiquitous relationship of the messages. This network includes the content of the source post, user comments, and directly or indirectly related users. The ubiquitous relationship network contains not only direct features related to textual semantics but also reflects multi-level explicit or implicit associations between various pieces of information. After introducing GCN, the network learns low-dimensional semantic representations while exploring the ubiquitous higher-level features within the information.However, the heterogeneous nature of the node and edge attributes in the ubiquitous relationship network makes it unsuitable to directly introduce into a homogeneous network like GCN. Doing so would result in noise during the aggregation of high-order neighbors or intermediate representations [9]. To address this, this paper decomposes the heterogeneous ubiquitous relationship network into two homogeneous propagation models based on node attributes, as shown in Figure 2. These models are (a) the Tweet-word subgraph, which focuses on the propagation of posts, and (b) the Tweet-user subgraph, which focuses on the propagation of users.

In the Tweet-word subgraph, the nodes represent relevant Twitter posts, and the edges represent comment relationships between nodes. Ri represents the source post i, and Xi represents comments about the source post, including both direct and indirect comments. In this subgraph, the source post features are introduced to enhance the semantic representation of the rumor features, which is the primary factor in enhancing the semantic representation of the source post. Additionally, the feature learning aims to explore the interaction development of rumors during the propagation process, taking into account the semantic changes in the message. Inspired by previous GCN-based methods [6], the Tweet-word subgraph, which focuses on comment and retweet content, should include both the spreading and diffusion directions of the rumor features.

In the Tweet-user subgraph, the nodes represent Twitter users, and the user features are based on the comprehensive semantic features of all the tweets they have posted. The edges represent connections between users, for example, if user 1 has commented on one or more tweets by user 2, there is a connection between user 1 and user 2. This subgraph primarily deals with the relationships between users, which involve historical and recent relationships, as well as explicit and implicit relationships. When mining user-associated features, the nodes do not need to introduce the semantic features of the source post again. Additionally, these features can provide evidence and explanatory support in reverse for rumor detection. Since the Tweet-user subgraph primarily considers the historical dependencies between associated users, this paper assumes a symmetric dependency relationship between parent nodes and child nodes, which is widely accepted in GCN-based methods [10].

3.2.2 GCN layer

Referring to the model structure of Bi-GCN proposed by Tian et al. [6] and the general model structure of GCN in semi-supervised classification based on graph convolutional networks suggested by Thomas et al. [11], we conducted experiments with both a two-layer Bi-GCN model and a three-layer GCN model. In the first layer of the Tweet-word subgraph, we introduced the source post text semantic features and applied stacked convolutional layers to recover a rich set of convolutional filter functions, achieving a filtering effect similar to high-order polynomial frequency response functions to some extent.The hidden layer representation of the Tweet-word subgraph in the Bi-GCN model is defined from top to bottom as:

$$H_{a1}^{TD} = \sigma[\hat{A}^{TD}(X + X_0)W_0^{TD}] \tag{10}$$

$$H_{a2}^{TD} = \sigma\left(\hat{A}^{TD} H_{a1}^{TD} W_1^{TD}\right) \tag{11}$$

$$\hat{A} = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} \tag{12}$$

In this case, where ***X*** represents the text semantic features, $\boldsymbol{X_0}$ represents the source post semantic features.

$$H_{a1}^{TD} \in R^{n \times v_1} \tag{13}$$

$$H_{a2}^{TD} \in R^{n \times v3} \tag{14}$$

$$W_1^{TD} \in R^{v_1 \times v_2} \tag{15}$$

The filtering parameter matrix for the two-layer BI-GCN is denoted as ***WTD 1***, where ***A*** represents the adjacency matrix, ***D*** represents the degree matrix, and ***ReLU*** is used as the activation function.

$$\tilde{A} = A + I_m \tag{16}$$

Ã represents the addition of self-loops and the enhancement of source-root features to obtain a new feature matrix, which can be expressed as follows:

$$\tilde{H}_{a2}^{TD} = concat[H_{a2}^{TD}, (H_{a1}^{TD})^{root}] \tag{17}$$

Similarly, the bottom-up feature matrix in BI-GCN can be obtained as follows:

$$\tilde{H}_{a2}^{UB} = concat[H_{a2}^{UB}, (H_{a1}^{UB})^{root}] \tag{18}$$

By utilizing the average pooling operation to aggregate the features of upper and lower class nodes, and further integrating the information, the node representation of Tweet-word in BI-GCN is obtained.

$$H_a = concat[MEAN(\tilde{H}_{a2}^{TD}), MEAN(\tilde{H}_{a2}^{UB})] \tag{19}$$

In model GCN, the hidden layer representation of Tweet-user (i.e., graph (b)) is expressed as follows:

$$H_{b1} = \sigma[\widehat{A}\overline{X}W_0] \tag{20}$$

$$H_{b2} = \sigma(\widehat{A}H_{b1}W_1) \tag{21}$$

$$H_b = \sigma(\widehat{A}H_{b2}W_2) \tag{22}$$

$$\hat{A} = \tilde{D}^{-\frac{1}{2}}A\tilde{D}^{-\frac{1}{2}} \tag{23}$$

Then, combining the user information and post information, the expression for the combined representation is as follows, considering that both Tweet-word and Tweet-user matrices have the same dimensions after undergoing GCN operations:

$$S = concat\left(H_a, H_b\right) \tag{24}$$

Finally, by applying a fully connected layer followed by a softmax layer, the expression for the label can be obtained as:

$$\hat{y} = softmax\left(FC\left(S\right)\right) \tag{25}$$

The objective of training the model is to minimize the cross-entropy loss on the Twitter Datasets using the standard gradient descent algorithm. The corresponding function is defined as:

$$\min_{\Theta} L = -\sum_{j=1}^{n}\sum_{i=1}^{m} y_i^j \log \hat{y}_i^j + \lambda \|\Theta\|^2 \tag{26}$$

Θ represents all the trainable parameters of the model, while λ represents the coefficient of the **L2** regularization term.

4 Experimental

4.1 Experimental setup

In this study, we used two publicly available Datasets from the publications by Ma[5,12] in 2016 and 2017. The Datasets are referred to as Twitter15 Datasets and Twitter16 Datasets. Since events are caused by reports and replies to each source post, the number of events is equal to the number of source posts. The Dropout parameter in this study was set to 0.5, and the learning rate was set to 0.001 for training the model. The training process involved 200 iterations. The code execution would stop when the window size reached 10. In other words, if the validation loss rate did not decrease for 10 consecutive training iterations, the model training would be halted.

Table 1. Rumor detection results.

Method	Data	Acc	NR	FR	TR	UR	Data	Acc	NR	FR	TR	UR
			F1	F1	F1	F1			F1	F1	F1	F1
SVM-TS	Twitter15	0.544	0.796	0.472	0.404	0.483	Twitter16	0.574	0.755	0.420	0.571	0.526
RvNN		0.723	0.682	0.758	0.821	0.654		0.737	0.662	0.743	0.835	0.708
PPC_RNN+CNN		0.477	0.359	0.507	0.300	0.640		0.564	0.591	0.543	0.394	0.674
PLAN		0.764	0.742	0.744	0.840	0.699		0.719	0.746	0.708	0.760	0.646
Bi-GCN		0.790	0.749	0.784	0.837	0.776		0.768	0.773	0.781	0.783	0.721
U-GCN		0.901	0.883	0.899	0.895	0.854		0.913	0.904	0.902	0.897	0.899

4.2 Comparative study

Using the same Twitter15 and Twitter16 datasets, we compare the experimental results of this study with those of the baseline models. The baseline models include both handcrafted detection algorithms and deep learning detection algorithms, providing a comprehensive and scientific perspective for the experiment. In addition, we compare the experimental research methodology of this study with four other methods(SVM-TS[13], RvNN[14], PPC_RNN+CNN[15], PLAN[16], Bi-GCN[6]), aiming to demonstrate the performance of each model on the Twitter-based Datasets. The rumor detection results are presented in Table 1 and Figure 3.

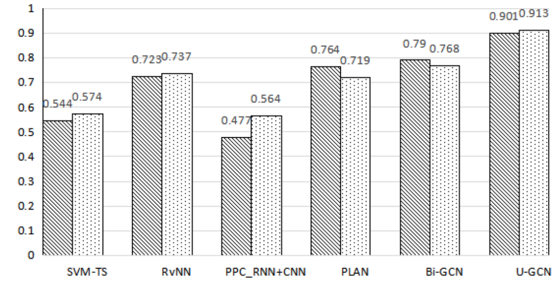


Fig. 3. Bar chart of rumor detection results.

(1) The poor performance of the PPC_RNN+CNN model in rumor detection can be attributed to the inability of RNN and CNN algorithms to handle graph data. Additionally, the RvNN algorithm only utilizes the hidden feature vectors of leaf nodes, disregarding the features of the root node, which limits the range of rumor detection.

(2) Compared to the classical SVM-TS model, the U-GCN model demonstrates a significant improvement in the F1 score and overall accuracy for rumor detection in different types of messages, including NR, FR, TR, and UR. This confirms the enhanced classification capabilities of deep learning models, represented by the GCN model, compared to traditional models represented by SVM.

(3) Compared to the RNN model that learns advanced representations hidden within the propagation structure, the PPC_RNN+CNN model that learns user features using RNN and CNN, the Bi-GCN model that learns global propagation conclusions and diffusion structures using GCN, and the PLAN model that focuses on user comments using swarm intelligence, the U-GCN model achieves superior detection results. This reflects the fact that models considering multiple relevant features and attributes, such as propagation structure, user comments, and user features, outperform those that only consider single or partial features. In other words, the broader the scope of features learned by a model and the richer the details, the better the detection performance. This provides theoretical support and explanatory basis for rumor detection based on content-rich ubiquitous relationships.

(4) For the two Twitter datasets, we evaluated the performance of the models by calculating the accuracy (Acc). As shown in Figure 4, the experimental results on both real datasets indicate that the U-GCN model used in this study achieved accuracy rates above 0.9, significantly outperforming other baseline models and demonstrating high precision.

4.3 Ablation study

This paper conducts a set of disruptive experiments on the ubiquitous relationship model of messages. Table 2 present the experimental results based on the Twitter15 Datasets and Twitter16 Datasets, respectively. The experiments focus on the detection of individual users, individual posts, and comprehensive information.

Table 2 present rumor detection on the Twitter16 Datasets from three different perspectives. The experimental results demonstrate that across the five attribute data points of Acc, NR, FR, TR, and UR, the rumor detection results based on Tweet-word and Tweet-user are lower than those based on Tweet-word-user. This indicates that the approaches of solely modeling Twitter subgraphs for rumor detection, as well as solely modeling Twitter user subgraphs for rumor detection, are both one-sided and have certain limitations in detecting rumor features.

Table 2. Experimental results of the twitter15 datasets.

Method	Data	Acc	NR	FR	TR	UR	Data	Acc	NR	FR	TR	UR
			F1	F1	F1	F1			F1	F1	F1	F1
Tweet -word	Twitter15	0.813	0.708	0.857	0.864	0.813	Twitter16	0.810	0.698	0.787	0.836	0.809
Tweet -user		0.560	0.812	0.430	0.544	0.446		0.690	0.772	0.651	0.697	0.632
All		0.901	0.883	0.899	0.895	0.854		0.913	0.904	0.902	0.897	0.899

5 Conclusion

Building upon the neural network concepts of CNN, RNN, and others, this paper introduces, for the first time in existing rumor detection methods, the definition of ubiquitous relationships among messages. Based on this definition, a heterogeneous graph called

Tweet-word-user is constructed. The U-GCN model is further proposed and experimentally studied, precisely because it effectively combines the global characteristics of ubiquitous relationships and semantic features, achieving excellent performance in rumor detection. The experimental results on the Twitter Datasets indicate that the U-GCN model adopted in this paper has good effectiveness. However, during the experiments, the use of the GCN model requires certain memory configuration and imposes certain demands on computer performance. The model may also require a longer running time. Additionally, the issue of over-smoothing needs to be considered. When the number of GCN layers increases to a certain extent, the representation vectors of the nodes become approximately the same, making it difficult to distinguish between them. Moreover, after multiple iterations, the feature vectors tend to converge, leading to a decline in the model's performance. In future developments, deep learning algorithms will continue to be further researched. Sufficient attention should be paid to how to use the GCN model to handle unstructured and semi-structured data.

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