# Rumor Diffusion Model Based on Representation Learning and Anti-Rumor

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***Abstract*—The traditional rumor diffusion model primarily studies the rumor itself and user behavior as the entry points. The complexity of user behavior, multidimensionality of the communication space, imbalance of the data samples, and symbiosis and competition between rumor and anti-rumor are challenges associated with the in-depth study on rumor communication. Given these challenges, this study proposes a group behavior model for rumor and anti-rumor. First, this study considers the diversity and complexity of the rumor propagation feature space and the advantages of representation learning in the feature extraction of data. Further, we adopt the corresponding representation learning methods for their content and structure of the rumor and anti-rumor to reduce the spatial feature dimension of the rumor-spreading data and to uniformly and densely express the full-featured information feature representation. Second, this paper introduces an evolutionary game theory, which is combined with the user-influenced rumor and anti-rumor, to reflect the conflict and symbiotic relationship between rumor and anti-rumor. we obtain a network structural feature expression of the influence degree of users on rumor and anti-rumor when expressing the structural characteristics of group communication relationships. Finally, aiming at the timeliness of rumor topic evolution, the whole model is proposed. Time slice and discretize the life cycle of rumor is used to synthesize the full-featured information feature representation of rumor and anti-rumor. The experiments denote that the model can not only effectively analyze user group behavior regarding rumor but also accurately reflect the competition and symbiotic relation between rumor and anti-rumor diffusion.**

***Index Terms*—Rumor and anti-rumor, information diffusion, representation learning, deep learning, game theory.**

## I. Introduction

RUMOR refers to information and statements that have not been officially confirmed and are inconsistent with facts. For example, in January 2020, COVID-19 broke out in China, and a lot of rumors related to the epidemic spread on social networks. These rumors undoubtedly bring great panic to people and pose a threat to social stability. At the same time, in the academic world, SCIENCE published two online rumor articles describing the essence and harm of fake news in cyberspace [1]–[3]. Especially, [3] was ranked as $2^{th}$ in the Altmetirc top 100 papers of 2018 [4]. The new generation of social information dissemination technology promotes rapid information sharing and large-scale information cascading [5], [6]. Online rumors can quickly spread their influence and can even spread faster and more widely than real information because of their concealment, suddenness, and dispersion. Therefore, the analysis of the internal propagation laws of online rumors have great significance in guiding correct public opinion, serving social stability, and managing social networks. The research on rumor propagation is becoming a hotspot in social network and service management.

Recently, scholars have extensively studied the spread of rumor topics on social networks [7]–[9]. Some researchers use the framework of infectious disease models to analyze the information transmission dynamics in social networks, subdivide the state of users in social networks, and denote the information transmission process among users through state transfers and changes between nodes [10]–[12]. Other scholars use machine learning, deep learning, and other methods to study the topic propagation rules after extracting user behavior characteristics [13]–[15].

In this rumor study, we found an interesting phenomenon. When a rumor topic erupts in a social network, the corresponding rumor incidental information will be generated. The worthiest of our attention is the anti-rumor message that competes with rumors. The anti-rumor report refers to the clarification and feedback made by the relevant departments through the official media. Fig. 1 shows an example of the rumor topic spread. When the message "Redivevir is a specific for COVID-19" appears, the message "Redivevir is still in research Drugs. Its safety and effectiveness have not yet been determined." also appears, simultaneously. This is a typical "rumor and anti-rumor" relationship. It can be seen that studying the spread mechanism of rumors from the multi-information perspective of "rumor and anti-rumor" can more truly and comprehensively discover the spread rules of online rumors. Although research on rumor propagation has achieved remarkable results, some challenges remain, and they are as follows.

1. The complexity, high dimensionality, and timeliness of the rumor topics. A problem that should solved is how to adequately express social relations and interests among users under rumor topics.

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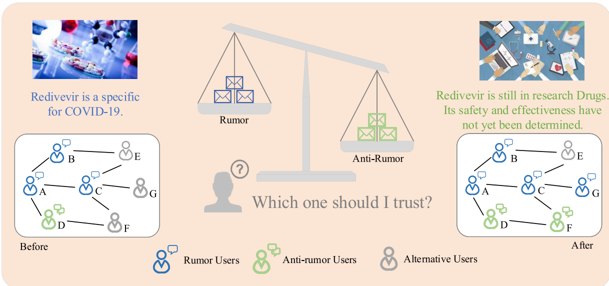



Fig. 1. A simple Rumor and Anti-rumor interaction propagation example.

2. The diversified nature of the message under the rumor topic. Some rumor propagation models do not consider the impact of incidental messages on rumors in social networks. The rumor that exhibits a competitive relation with rumor news will slow the spread of rumors; quantifying this influence is a novel challenge.

3. The imbalance of actual useful data during the spread of rumors. In a single rumor topic, the rumor and anti-rumor message data samples are sparse, which results in an imbalance in the proportions of different sample data tags, complicating the study of rumor communication.

In response to the aforementioned challenges, this study proposes a dynamic rumor and anti-rumor information dissemination group behavior method based on representation learning and CNN-GCN. We use a full-featured representation strategy based on representation learning from two aspects: user social structure and historical behavior in the rumor topic communication space. This paper considers the symbiosis and competition between rumor and anti-rumor, introduces an evolutionary game theory to describe the real relations between users, and establishes a predictive model of user group behavior with respect to rumors. The deep learning model is integrated with the traditional dynamic model, and a new training method is designed to mitigate adverse effects caused by the sparse target data samples. Finally, we use the real data obtained from Weibo to verify the effectiveness of the proposed method. The contributions of this study can be summarized as follows.

1. This paper proposes a representation strategy based on representation learning, rumor, and anti-rumor feature space. Based on the social content and relation structure, the user is adequately influenced by the rumor topic. The user's feature attributes are learned and are represented by low-dimensional vectors, using different learning methods because of the complexity of different information spaces.

2. This paper proposes a method based on the evolutionary game theory to quantify the relation between rumor and anti-rumor. Based on the symbiosis and competition between the rumor and anti-rumor messages, a combination of the evolutionary game theory and multiple linear regression methods is used to initially measure the influence of rumor and anti-rumor and subsequently integrate them into the topological matrix of rumor topic propagation. Thus, the structure of real rumor topic communication relations is accurately represented.

3. This paper proposes a dynamic rumor and anti-rumor information dissemination group behavior model based on representation learning and CNN-GCN and designs a new training method to mitigate adverse effects caused by the imbalance of the data sample proportions. The proposed model comprehensively considers the non-Euclidean structure characteristics of the rumor topic propagation space structure and performs time slicing and time discretization processing on the life cycle of the rumor topic. The model not only dynamically predicts the user's participation behavior in rumors but also realistically describes the development trend of rumor and anti-rumor.

The remainder of this paper is organized as follows. Section II introduces the work related to this paper. Section III provides relevant definitions and formulates the problems, and Section IV describes the proposed method and related learning algorithms. Further, Section V presents and analyzes the experimental results using real data sets. Finally, Section VI outlines the avenues for future research.

## II. Related Work

Recently, scholars have studied the information dissemination direction of online rumors from various perspectives and have obtained considerable research results from the field of social networks. This section highlights the achievements of scholars in recent years and focuses on the three challenges that have been mentioned in previous section and the research status of game theory in social networks.

One challenge currently faced by the rumor communication researchers is related to the complexity and high dimensionality of the rumor topics. Some scholars use machine learning and deep learning methods to analyze the individual information and behavioral characteristics of users, thereby establishing a forwarding model. Zhang *et al.* [16] focused on the impact of the user network forwarding behavior on friends and predicted the forwarding behavior of the user through a custom logistic regression classifier that affects the local function. Chen *et al.* [17] confirmed a recurrent cascades convolutional networks model, which proved that the forward task can be appropriately completed. Zhao *et al.* [18] proposed the Influence Beta-Poisson Factorization model to mine the influencing factors that affect the user forwarding decisions. Zhang *et al.* [19] embedded features into a fixed feature vector to predict the forwarding behavior, and proposed an attention-based neural network forwarding prediction model. Jiang *et al.* [20] proposed a multidimensional forward prediction model based on context-aware coupling matrix tensor factorization. All the aforementioned studies extract the mixed feature information from the social network, but do not provide a reasonable representation of the full picture or consider the non-Euclidean structure of the social network.

The information diversity associated with the rumor topics is the second challenge for the rumor communication researchers. Some scholars have employed the mathematical modeling of infectious diseases to understand rumor communication. Dong and Huang [21] proposed a SIS rumor-spreading model based on transmission dynamics and population dynamics. This model considered the impact of changing the number of online social network users and user activity. Zhang *et al.* [22] introduced the protection effect into the SIR model and dynamically captured the rumor propagation process. Han *et al.* [23] proposed the SIDR rumor propagation model, containing additional states to describe a situation in which the persuader became a communicator. Wang and Wang [24] studied the influence of the difference in network node recognition ability on rumor propagation and proposed a new SIR model based on the average field theory. All the aforementioned studies were modeled based on a single rumor message. Their research object was considerably monotonous and did not consider the impact of other messages on the spreading of rumors. Wang *et al.* [25] integrated negative information based on positive information dissemination, studied the dynamic diffusion process of positive and negative information, and controlled the spread of negative news in a timely manner. Xu *et al.* [26] analyzed infectious disease models with immune mechanisms in mobile social networks. Kong *et al.* [27] proposed a method to predict problems in the popularity stage from the micro and macro aspects and considered the contribution of different dynamic factors at the micro level to infer the evolution stage of the topic in the future. Wang *et al.* [28] proposed a dynamic rumor influence minimization model, which is based on user experience, and a dynamic Ising propagation model, which is based on rumors with global popularity and individual attraction. Zhang *et al.* [29] proposed an anti-rumor mechanism, which is based on the rumor dynamics, and analyzed the dynamics of the model using real data. All the aforementioned studies denoted the influence of anti-rumor on the spread of rumors; however, they ignored the symbiosis and competition between rumor and anti-rumor.

The third major challenge associated with the study of rumor communication is the imbalance of different classification data with respect to the topic of rumors. Some scholars attempted to use the representation learning method to mitigate adverse effects caused by data sparsity. Chen *et al.* [30] and Kong *et al.* [31] solved the problem of sparse data in the recommendation system via network representation learning. Fu *et al.* [32] proposed a new representation learning framework (i.e., HIN2Vec) for heterogeneous information networks to solve the problem of inaccurate predictions caused by data sparseness in link prediction applications. These researchers have effectively mitigated adverse effects caused by data sparseness; however, this approach is not applicable to the user participation behavior prediction model under the rumor and anti-rumor social network structure.

Finally, some scholars use game theory to study the interactions between users in social networks, and then predict individual behavior. Wang *et al.* [33] proposed a simple but effective EGT-based mechanism, VPEF (Voluntary Principle and round-based Entry Fee), to drive the networking environment into cooperative. Wang *et al.* [34] proposed an incentive evolutionary game model for stimulating cooperation among nodes. This model can suppress the bad impact on the network from those abnormal nodes. Jiang *et al.* [35] proposed an evolutionary game theoretic framework to model the dynamic information diffusion process in social networks. These studies all use evolutionary game theory to study user relationships in social networks. However, under the rumor and anti-rumor social network structure, the competitive relationship between rumor and anti-rumor is worthy of attention and research. In summary, this study designs a dynamic, predictive group behavior model, which is based on representation learning and CNN-GCN for rumor and anti-rumor topic space, and designs a new training method to mitigate adverse effects caused by data imbalance.

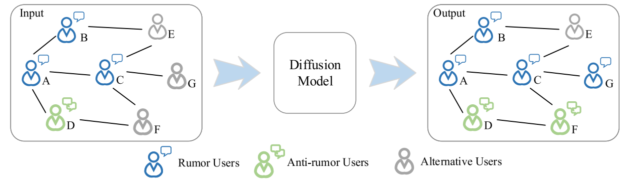



Fig. 2. Problem overview.

## III. Problem Definition

### A. Related Definitions

The primary objective achieved in this paper is to predict whether potential users in the rumor topic will forward the rumor message or forward the anti-rumor message, and at the same time predict the development trend of rumor topics. We do this by analyzing the participating users of the rumor message and the anti-rumor message. The specific description is presented in Fig. 2. Here, rumor refers to information and statements that have not been officially confirmed and are inconsistent with facts, anti-rumor refers to the clarification and feedback made by the relevant departments through the official media. In particular, in order to facilitate the discussion and prediction of this article, the potential users will not be infected again after being infected as rumor user or anti-rumor users.

*Definition 1:* Participating users $U^t \subset (R^t \cup A^t)$ and the network of participating users ${G_U}^t = (U^t, E_{U^t})$ $U^t$ indicates the participating users of the rumor topic in the time period *t*. $R^t$ is the rumor participating user and refers to a user who participated in the dissemination of rumor message. $A^t$ is the anti-rumor participating user and refers to a user who participated in the dissemination of anti-rumor message. ${G_U}^t = (U^t, E_{U^t})$ represents the participating users and thier network with respect to the topic of rumors in time period *t*. $E_{U^t} \subset U^t \times U^t$ represents the side set of the rumor topic participating users $U^t$ in time period *t*.

*Definition 2:* Alternative users $V^t$ and the network of alternative users ${G_V}^t = (V^t, E_{V^t})$ $V^t$ represents the potential users of the rumor topic in the time period t, including rumor potential users and anti-rumor potential users, such as fans of the current rumor topic participating with the user. ${G_V}^t = (V^t, E_{V^t})$ represents the potential users and their network with respect to the rumor topics in time period *t*. $E_{V^t} \subset V^t \times V^t$ represents the side set of the rumor topic's potential users in time period *t*.

TABLE I
THE SYMBOLS IN PROBLEM DEFINITION

| Symbol | Description |
|---|---|
| $U$ | The participating users |
| $V$ | The potential users |
| $R$ | The participating users of rumor |
| $A$ | The participating users of anti-rumor |
| $HS$ | User's history social content |
| $UP$ | User's basic property collection |
| $u$ | Single user in the topic of rumors |
| $t$ | The time period of the rumor topic |
| $s$ | Single user's history content collection |
| $p$ | Single user's basic property collection |

*Definition 3:* User's basic properties $UP = \{(u_i, p)|u_i \in (R \cup A \cup V)\}$ $p$ indicates that the basic attributes of each user $u_i$ in the rumor topic include the internal and external factors of the user. They include the user activity $Act(u_i)$, user's history forwarding rate $Ret(u_i)$, user's information perception rate $Pre(u_i)$, and the influence of the user's friend on the user set $Fri(u_i)$. Thus, $p = [Act(u_i), Ret(u_i), Pre(u_i), Fri(u_i)]$.

*Definition 4:* User's historical social content is set as $HS = \{(u_i, s)|u_i \in (R \cup A \cup V)\}$ $S$ indicates all the historical microblog text information of a single user $u_i$, including the original Weibo content and the forwarding Weibo content, in the rumor topic communication space. We treat each Weibo content published by the user as a sentence and form a paragraph with the same topic in a specific period of time to create a user's historic Weibo information in the form of an article.

*Definition 5:* Information popularity *Pop*($t$). The spread of rumor information in social networks usually has a considerable time limit. Some rumors will become a popular topic in a short period of time; however, this popularity will rapidly decrease after reaching its peak. This process is similar to the half-life of elements [36]. We use the propagation rate function *InfoNum*($t$) $-$ *InfoNum*($t-1$) to represent the strength of the rumor topic at the current moment and introduce the half-life function $(\frac{1}{2})^{\frac{t-t'}{w}}$. Therefore, the influence of the information transmission of the rumor topic can be defined as follows.

$$Pop(t) = (InfoNum(t) - InfoNum(t-1)) \times \left(\frac{1}{2}\right)^{\frac{t-t'}{w}} \quad (1)$$

where $t$' indicates the moment when the rumor first appeared, *InfoNum*($t$) indicates the amount of forwarding of the rumor topic up to the current time $t$, and *InfoNum*($t-1$) indicates the amount of forwarding of the rumor topic up to the previous moment $t-1$. $w$ is the regularization factor, $w = 1000$ in this study.

To improve the clarity of this section, the symbols in problem definition are described in Table I.

### B. Problem Formulation

To express the problem to be solved in this paper in a scientifically formal manner, let $G^t{}_{U\cup V}$ denote the hybrid network under the rumor topic within the time period $t$. First, the participating user relation network $G^t{}_U$ and the potential user relation network $G^t{}_V$ have to be obtained. Next, the social relations and social content of the participating and potential users in time period $t$ are learned and represented by two low-dimensional vectors. Finally, these vectors are inputted into the prediction model to forecast whether the potential users will forward the rumors in the next time period and, if they are forwarded, to judge whether they are rumor or anti-rumor, represented by $Y^{t+1}$. The problem definition can be expressed as follows.

$$\left.\begin{array}{r} G^t_{U\cup V} \to G^t_U, G^t_V \\ UP = \{(u_i, p)|u_i \in (R \cup A \cup V)\} \\ HS = \{(u_i, s)|u_i \in (R \cup A \cup V)\} \end{array}\right\} \Rightarrow G^{t+1}_U = Y^{t+1}. \quad (2)$$

*1) Problem Input:* Based on the definitions and descriptions presented in Section III-A, the input to the model can be determined in the following order:

1. The mixed network of participating and potential users in the rumor and anti-rumor information $G^t{}_{U\cup V}$.

2. The user's historical social content $HS = \{(u_i, s)|u_i \in (R \cup A \cup V)\}$.

3. The user's basic attributes $UP = \{(u_i, p)|u_i \in (R \cup A \cup\ V)\}$.

*2) Problem Output:* According to the above description, the outputs in this study can be given as follows:

1. The multidimensional feature vector $F^x{}_u$ of the corresponding attribute of a single user $u$. $f : (X_u) \to F^x{}_u, (X, x) \in ((G, a), (HS, b), (UP, c))$. We cannot use the collected social network raw data to directly predict user behavior. The features of data that can be recognized by a computer are extracted from the original data. In this study, the extracted user attribute features are expressed differently to obtain it.

2. The rumor and anti-rumor influence adjacency matrix $W^M_{U\cup V}$. The worthiest of our attention in the rumor topic is the competitive relationship between rumor and anti-rumor. We need to use a suitable method to align the model. We consider the user internal factors and external factors and uses the multiple linear regression algorithm to construct the information influence function $Inf(u_i, u_j)$, which represents the influence of user $u_j$ on user $u_i$. In addition, we introduce evolutionary game theory to construct the rumor and anti-rumor interaction power model.

3. The model outputs $Y$. In order to accurately predict the behavior of user groups under the topic of rumors, and to get a more realistic reflection of the competition and symbiotic relationship of rumor and anti-rumor in the spread process. This paper establishes the CNN-GCN model by combining the CNN and GCN models. It indicates whether the user $u$ will participate in the topic of the rumor and judges whether it spreads rumor or anti-rumor.

## IV. Proposed Method

To solve the aforementioned problems, a dynamic rumor and anti-rumor information dissemination group behavior prediction model is proposed based on representation learning and CNN-GCN. The model is mainly divided into three

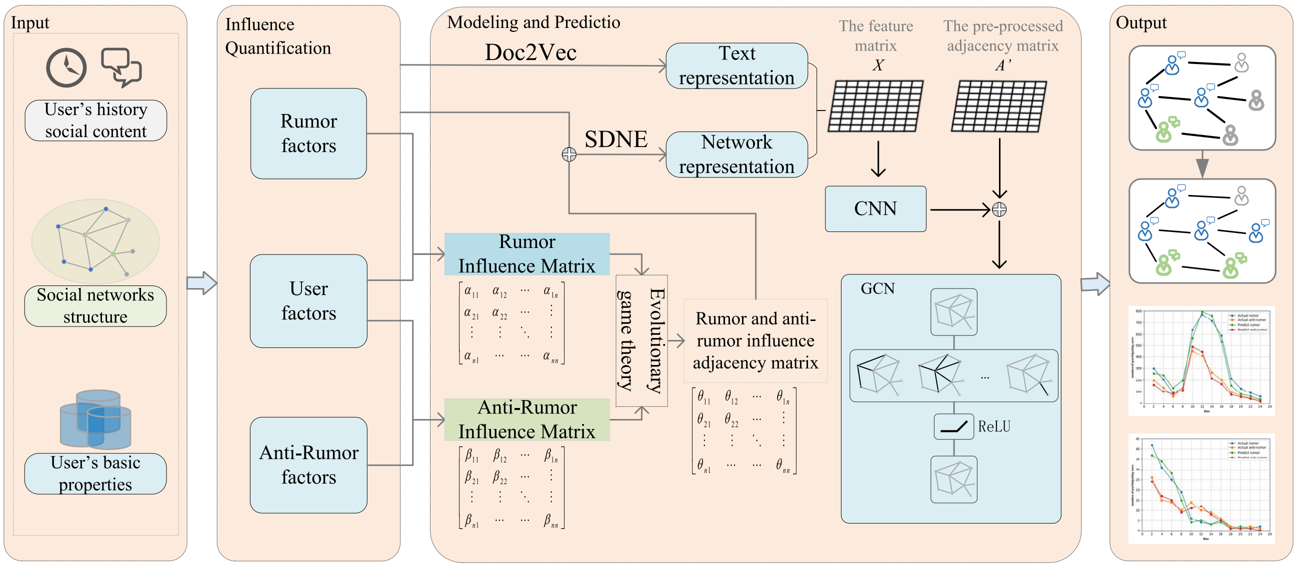



Fig. 3. Model framework.

stages, i.e., user's feature representation under a rumor topic, the quantitative representation of rumor and anti-rumor, and forwarding prediction model design, as shown in Fig. 3. In the first stage, different representation learning methods are used to represent the social structure and historical behavior of the user. In the second stage, the influence of rumor and anti-rumor on the forwarding behavior of the user is comprehensively considered. Further, the influence between rumor and anti-rumor is quantified based on the evolutionary game theory and multiple linear regression and is incorporated into the network representation learning of the user's social structure. The third stage discretizes and serializes the rumor topic to obtain the entire life cycle of the topic and establishes a prediction model based on representation learning and CNN-GCN for obtaining the rumor and anti-rumor information dissemination behavior and the spread of rumor and anti-rumor.

### A. Representation of the Rumor Topic Features

In this section, we understand the manner in which the model learns two aspects of the user's social structure and historical behavior with respect to rumor topic and propose a holistic rumor and anti-rumor communication feature space representation theory. In case of the user's social structure, the SDNE algorithm is used to represent vectors that can preserve the local and global structural features. In the user's historical behavior, the Doc2vec algorithm is used to represent the feature vector that represents the user's interest in a particular content.

*1) Representation of the Structural Characteristics of Social Networks:* Shallow models are used by many network representation methods. However, shallow models often cannot capture highly nonlinear network structures because of the complexity of the social network structure, and the obtained results are not the best network representation. This paper uses the SDNE method for network representation learning to effectively capture the structure of social networks and maintain global and local structural features. This method uses a self-encoder structure, which is robust with respect to the representation of sparse social networks, to optimize first and second-order similarity.

The overall optimization objectives of the model should be defined to train the SDNE model. First, we define the second-order similarity optimization objective. Its loss function can be written as follows.

$$L_{2nd} = \sum\nolimits_{i=1}^{n} \|\hat{x}_i - x_i\|_2^2 \tag{3}$$

The rumor and anti-rumor influence adjacency matrix $A$ is used as the model input, which will be explained in Section IV-B. Any user $i$ has $x_i = w_i$, and each $w_i$ contains the user structure information for user $i$; however, owing to the sparsity of the social network, the non-zero elements in the adjacency matrix $W^M{}_{U\cup V}$ are considerably less than the zero elements. This will make it easier for the model to reconstruct the zero elements in matrix $W^M{}_{U\cup V}$. To solve this problem, the weighted loss function is used for optimization, and the non-zero element has a higher penalty coefficient, as shown below.

$$L_{2nd} = \sum\nolimits_{i=1}^{n} \|\hat{x}_i - x_i \odot \mathrm{b}_i\|_2^2 \tag{4}$$

where $\odot$ is the Hadamard product, $\mathrm{b}_i = \{b_{i,j}\}_{j=1}^{n}$; if $w_{i,j} = 0$, then $b_{i,j} = 1$; otherwise, $b_{i,j} = \beta > 1$.

Futher, we define the first-order similarity optimization target whose loss function can be given as follows.

$$L_{1st} = \sum\nolimits_{i,j=1}^{n} w_{i,j} \left\| y_i{}^{(K)} - y_j{}^{(K)} \right\|_2^2 \tag{5}$$

If two similar users are located away after space mapping, they will be penalized to ensure that the final output neighboring user nodes are very close in the mapping space.

After combination, the minimum objective function can be obtained as follows.

$$L_{mix} = L_{2nd} + \alpha L_{1st} + \nu L_{reg} \tag{6}$$

$L_{reg}$ is the regularization term defined to prevent the model from over-fitting. $\alpha$ is the parameter that controls the first-order loss, and $\nu$ is the parameter that controls the regularization term.

Finally, the model with the smallest $L_{mix}$ is trained, and its output is expressed as the user's network structure feature vector as follows.

$$S = n \times F^a \tag{7}$$

Here, $n$ is the number of network nodes that is, i.e., it represents the number of users with respect to the rumor topic. $F^a$ is a social structure feature representation vector corresponding to a user.

*2) Representation of the Historical Behavioral Characteristics:* The social content posted by the users can indicate the user's interest and opinion in different time segments to a certain extent. We can consider the social content posted by the users in a particular period of time as an article and divide the time period into shorter time segments according to the changes in popular topics. The social content posted by the users in this time segment is a paragraph in the article. Each paragraph has a clear theme. Furthermore, each short text form of the microblog content posted by the user can be considered to be a sentence. Thus, we can use the Doc2vec algorithm to learn the historical social content of the user and represent it in a vector that reflects the social interests of the user.

If the fixed-length sliding window is directly used to obtain the context of the target word, there is a problem caused by the particularity of Chinese grammar. Therefore, we have introduced some improvements. First, the user-published Weibo content is used to perform Chinese word segmentation and part-of-speech tagging to eliminate useless words and stop words. Thus, candidate keywords are obtained with respect to the Weibo content of the user. The TF-IDF algorithm is used to calculate the weight of each candidate keyword, and the information center keyword of the social content of the user is extracted, which eliminates noise from the social content and retains the main social interest of the user.

The Doc2vec algorithm is used to perform representation learning on a keyword sequence representing the historical social content of the user. The output, i.e., the feature vector of the historical behavior of the user can be given as follows.

$$D = n \times F^b \tag{8}$$

Here, $n$ is the number of users with respect to a rumor topic and is a vector that represents the historical social content interest feature of the corresponding user.

## B. Quantitative Model of the Influence Between Rumor and Anti-Rumor

*1) Information Influence:* The information influence function comprises the internal and external factors of a user. The internal influence factors comprise the user activity and user historical forwarding rate, whereas the external factors are friend and information transmission influences. These factors will be separately explained. Users exhibiting high user activity are more likely to participate in information forwarding. The activity of user $u_i$ can be given as follows.

$$Act(u_i) = \sigma * Num[orig(u_i)] + Num[retw(u_i)] \tag{9}$$

$Num[orig(u_i)]$ indicates the number of published Weibo content, and $Num[retw(u_i)]$ indicates the number of forwarded Weibo content within a specified time period before the spreading of rumors. This model adds a custom weakening factor before the published Weibo content because it predicts the probability that the user will participate in the rumor topic.

The proportion of the Weibo content forwarded by the user to the total number of Weibo content obtained by users reflects the probability that the users will forward new topics, and the Weibo content obtained by the users mainly originate from friends. Therefore, the history forwarding rate of the user can be given as follows.

$$Ret(u_i) = \frac{retwNum(u_i)}{getRetNum(u_i)} \tag{10}$$

Here, $getRetNum(u_i)$ represents the total number of Weibo content obtained from the user's friends.

The user's information perception rate $Pre(u_i)$ reflects the probability of the user selecting the rumor topic.

$$Pre(u_i) = \frac{Fol(u_i)}{Fol_{ave}(net)} \tag{11}$$

Here, $Fol(u_i)$ denotes the attention of user $u_i$ and $Fol_{ave}(net)$ is the average attention of all the social network users.

With respect to rumor topics, a particular user is often affected by the communication behavior and participation of all the social network users in spreading a certain rumor. Different users have different motivations. We construct a multidimensional vector to show the influence of different users on user $u_i$.

$$w_{u_i}^{Fri} = \left[a_1^{Fri}, a_2^{Fri}, \ldots, a_n^{Fri}\right] \tag{12}$$

Here, *n* is the number of participating users and potential users in a rumor topic and ${a^{Fri}}_j$ represents the influence of user $u_j$ on user $u_i$ and can be constructed as follows.

$$a_j^{Fri} = \frac{e^{\overline{retwedNum(u_j)}}}{\left(\sum_{k=0}^{n} \overline{retwedNum(u_k)}\right)/n} \tag{13}$$

$\overline{retwedNum(u_k)}$ represents the average number of users $u_i$ forwarding Weibo content to user $u_k$ Weibo. If $\sum_{k=0}^{n} \overline{retwedNum(u_k)} = 0$ or user $u_j$ is not a friend of user $u_i$, then ${a^{Fri}}_j = 0$.

We construct the internal influence factor $f_{in}(u_i)$ from three aspects, i.e., the user activity, historic forwarding rate of the user, and information perception rate of the user. The external influence factors are constructed based on friend influence and information communication influence. They can be given as follows.

$$f_{in}(u_i) = Act(u_i) \times Ret(u_i) \times Pre(u_i) \tag{14}$$

$$f_{\text{out}}(u_i, u_j) = a_j^{Fri} \times Pop(t) \tag{15}$$

Finally, we synthesize the internal and external factors of user behavior via multiple linear regression algorithms to construct the influence function of rumor and anti-rumor.

$$Inf_R(u_i, u_j) = \rho_0 + \rho_1 \times f_{in}(u_i) + \rho_2 \times f_{out}^1(u_i, u_j) \tag{16}$$
$$Inf_A(u_i, u_j) = \rho_0 + \rho_1 \times f_{in}(u_i) + \rho_2 \times f_{out}^2(u_i, u_j) \tag{17}$$

$\rho_0$, $\rho_1$, and $\rho_2$ are the partial regression coefficients trained using multiple linear regression algorithms. $f_{out}^1(u_i, u_j)$ represents the external influence factor of user $u_j$ on user $u_i$ in rumor, whereas $f_{out}^2(u_i, u_j)$ represents the external influence factor of user $u_j$ on user $u_i$ in anti-rumor.

*2) Model of Rumor and Anti-Rumor Based on Evolutionary Game Theory:* In social networks, users tend to trust only one type of information because rumor and anti-rumor are antagonistic. Therefore, rumor and anti-rumor information will compete for the attention and support of potential users. We should consider the impact of rumored news when predicting the user behavior. This paper introduces an evolutionary game theory to (i) propose the rumor and anti-rumor influence model, (ii) quantify the influence of rumor and anti-rumor under a particular rumor topic on users, and (iii) obtain the rumor and anti-rumor influence adjacency matrix ${W^M}_{U\cup V}$.

If users participate in the rumor topic, they will choose to forward the rumor or anti-rumor. There are two game strategies, i.e., "forwarding rumor" and "forwarding anti-rumor." The proportions of forwarding rumor and forwarding anti-rumor in the adjacent user groups of the target user *x* are represented as $P_1$ and $P_2$, respectively. The adjacent users of user $u_i$ may not participate in these two strategies; however, because such users have little influence on the target users under the current rumor topic, they are not considered. Therefore, $P_1 + P_2 = 1$. The profit function of the two strategies can be given as follows.

$$Pro_R(u_i, u_j) = P_1 \times Inf_R(u_i, u_j) \tag{18}$$
$$Pro_A(u_i, u_j) = P_2 \times Inf_A(u_i, u_j) \tag{19}$$

In addition, we use the evolutionary game theory to measure rumor and anti-rumor:

$$Mut_R(u_i, u_j) = \frac{e^{(Pro_R(u_i,u_j) - Pro_A(u_i,u_j))}}{1 + e^{(Pro_R(u_i,u_j) - Pro_A(u_i,u_j))}} \tag{20}$$
$$Mut_A(u_i, u_j) = \frac{e^{(Pro_A(u_i,u_j) - Pro_R(u_i,u_j))}}{1 + e^{(Pro_A(u_i,u_j) - Pro_R(u_i,u_j))}} \tag{21}$$

where $Mut_R(u_i, u_j)$ and $Mut_A(u_i, u_j)$ indicate the influence of user $u_j$ on the rumor propagation behavior of user $u_i$ under a rumor message and the influence of user $u_j$ on the rumor propagation behavior of user $u_i$ under an anti-rumor message, respectively, after the application of the evolutionary game theory.

Finally, the rumor and anti-rumor influence adjacency matrix is obtained based on the basis of the competitive nature of rumor and anti-rumor.

$$W^M_{U\cup V} = \begin{bmatrix} m_{(u_1,u_1)} & m_{(u_1,u_2)} & \cdots & m_{(u_1,u_n)} \\ m_{(u_2,u_1)} & m_{(u_2,u_2)} & & m_{(u_2,u_n)} \\ \vdots & & \ddots & \vdots \\ m_{(u_n,u_1)} & m_{(u_n,u_2)} & \cdots & m_{(u_n,u_n)} \end{bmatrix} \tag{22}$$

In general, $m_{(u_i,u_j)} = Mut_R(u_i, u_j) - Mut_A(u_i, u_j)$. If $i = j$, then $m_{(u_i,u_j)} = 0$.

### C. Rumor Forwarding Model

*1) CNN-GCN Model Design:* The social network is a typical non-Euclidean structure data, and the graph convolutional neural network begins from the theoretical framework of the map and implements the convolution operation on the graph [37]. In the previous section, the user's feature attribute vectors extracted by representation learning method were used. If they are directly spliced, the model input becomes considerably long, which is not conducive to the training of the model. The CNN layer is added before the GCN model, and the user feature vector is convoluted. This paper proposes a dynamic and predictive model based on representation learning and CNN-GCN for rumor and anti-rumor topic space group behavior.

The task of the predictive model is to predict whether the potential user node will participate in spreading the rumor topic. If the user participates, the model determines that the user forwards the rumor or anti-rumor; then, the model can convert it into a three-category task.

The model input can be given as follows.

1. The feature matrix $Input = n \times F^{(a,b)}$, where *n* is the number of users in the rumor topic propagation network. The input feature dimension of each node in the network is $F^{(a,b)} = (F^a, F^b)^T$. The features are the two types of social topic features after learning and processing in Section IV-A.

2. The adjacency matrix *B*, which represents the connection information between nodes in the rumor topic propagation hybrid network.

In this model, the CNN layer is used to convolve the feature matrix for the first time. Next, the output of the CNN layer and the pre-processed adjacency matrix $\hat{A}$ are input into the double-layer graph convolutional network with a dropout middle layer. Finally, the SoftMax function is used to convert the output of the graph convolution network into probability values having different classifications for different nodes. The model specific formula can be expressed as shown in (23).

$$Z = softmax\left(\hat{A} ReLU\left(\hat{A}\left(r_j^0 \times cnn\_model\left(H^0\right)\right) W^0\right) W^1\right) \tag{23}$$

Here, $ReLU(x) = max(0, x)$, $r_j^i \sim Bernoulli(p)$, and $softmax(x_i) = \frac{exp(x_i)}{\sum_i exp(x_i)}$. The weight matrix corresponding to the *i*-th layer network in the graph convolutional network is $W^i$. $\hat{A} = \hat{D}^{-\frac{1}{2}} \tilde{A} \hat{D}^{-\frac{1}{2}} = \hat{D}^{-\frac{1}{2}} (A + I) \hat{D}^{-\frac{1}{2}}$.

The output of the entire model is $Z = P(r, a, d|u_i)$, because this paper discusses a three-category problem. The specific definition can be given as follows.

$$Y = \begin{cases} 1, & P(r|u_i) = max(P(r,a,d|u_i)) \\ 0, & P(d|u_i) = max(P(r,a,d|u_i)) \\ -1, & P(a|u_i) = max(P(r,a,d|u_i)) \end{cases} \tag{24}$$

If $Y = 1$, the potential user $u_i$ is judged to be forwarding the rumor in the next time period. If $Y = -1$, the potential user $u_i$ is judged to be forwarding the anti-rumor in the next time period. Otherwise, the potential user $u_i$ will not participate in the rumor topic in the next time period.

*2) Training Program:* The data sparseness of rumor and anti-rumor with respect to rumor topic has resulted in an uneven ratio of different tag data samples. The trained model is prone to over-fitting and poor generalization. Therefore, we designed a new model training program to mitigated adverse effects.

In general, deep learning model training, we usually select 80% of the data as the training set, 10% of the data as the test set, and 10% of the data as the verification set. If we train the model using this approach, model over-fitting will occur. Therefore, the training set should be selected according to the labels so that the ratio of rumor users, anti-rumor users, and non-participating users is 1:1:2. To accomplish this, we find one of the two types of rumor and anti-rumor, consider 80% of the data as the training set of this class, and use this as a benchmark to calculate the training set selection rate for the remaining two types of users so as to select the label ratio as 1:1:2. After completing the model training, another rumor topic is considered to be the test and verification sets for optimizing and finalizing the model.

## D. Learning Algorithm

The inputs to the algorithm include the hybrid networks of participating and potential users in the rumor and anti-rumor topic $G^t{}_{U \cup V}$, the historical social content of the users $HS = \{(u_i, s)|u_i \in (R \cup A \cup V)\}$, and the basic attributes of the users $UP = \{(u_i, p)|u_i \in (R \cup A \cup V)\}$, as described in Section III.

The output of the algorithm is based on the data at time *t*, which predicts the potential user participation behavior of the rumor topic at time $t + 1$. The experiment is mainly divided into two parts, one part is the rumor and anti-rumor influence algorithm (algorithm 1), whereas the other part is the rumor topic forwarding algorithm (algorithm 2). The specific learning algorithm can be given as follows.

Suppose *N* is the number of users in the entire rumor topic. The time c0omplexity of the rumor and anti-rumor influence algorithm is $O(N^2)$ because any two different users must calculate their influence with respect to rumor and anti-rumor.

Here, the time complexities of the Doc2vec algorithm, SDNE algorithm, and CNN-GCN prediction model are $O(log_2 N)$, $O(N^2)$, and $O(N^2)$, respectively. By combining both the algorithms, the overall time complexity of the prediction algorithm is $O(N^2)+O(N^2)+O(log_2 N)+O(N^2) \sim O(N^2)$. It needs to be explained here that although the time complexity of the algorithm reaches $O(N^2)$, the algorithm is feasible in actual experiments. There are three main reasons: first, the adjacency matrix of users is a sparse matrix in the rumor topic. There is no direct follow relationship between many users, which greatly eases the problem of time complexity. Second, there are many zombie fans and commercial robot users in actual social networks, rumors topic is also the same case. In the actual processing, we preprocessed the data. Finally, a characteristic of information dissemination is that the information is almost snowballed. In other words, when we predicting the problem of k layer propagation, data training will only occur at the k-1 layer. The difference in this layer is actually much smaller in the scale of the problem.

**Algorithm 1** The Rumor and Anti-Rumor Influence Algorithm

**Input:** Mixed network of 2 topic $G^t{}_{U \cup V}$;
The basic attribute set of the rumor topic node $UP = \{(u_i, p)|u_i \in (R \cup A \cup V)\}$;
**Output:** the rumor and anti-rumor influence adjacency matrix $W^M_{U \cup V}$

```
1: for each the rumor topic node do
2:   calculate the activity of user factor Act(u_i) from Eq (9);
3:   calculate the history forwarding rate of user Ret(u_i) from Eq (10);
4:   calculate the information perception rate of user Pre(u_i) from Eq (11);
5:   calculate different friends influence user w_{u_i}^{Fri} = [a_1^{Fri}, a_2^{Fri}, ..., a_n^{Fri}] from Eq (12);
6: end for
7: Establish information influence function Inf(u_i, u_j), Multiple linear regression algorithm is used to calculate regression coefficients ρ_0, ρ_1, ρ_2;
8: for each the rumor topic node do
9:   calculate the rumor and anti-rumor influence Mut_R(u_i, u_j), Mut_A(u_i, u_j) from Eq (18-21);
10: end for
11: construct W^M_{U∪V} from Eq (22)
12: return W^M_{U∪V}
```

# V. Experiment Analysis

## A. Experimental Settings

In this section, we will introduce the data used in the experiment, label and analyze the data, provide the baseline method used in the experiment, and introduce an evaluation index to evaluate the performance of the method.

*1) Experimental Data:* The dataset used in this article is derived from the Sina Weibo dataset compiled by the Aminer team at the Tsinghua University [38].

To evaluate our online rumor group behavior method, this paper sorts out four different microblogging rumors from the Sina Weibo dataset. They are “Wenzhou train chase” (topic A), “Han Han ‘three-door’ ghost” (topic B), “Chinese children try to eat genetically modified rice” (topic C), and “Kehua Zhou was not killed” (topic D). These topics are used as examples to obtain the Forecast model. The specific statistical data of different topics are presented in Table II.

**Algorithm 2** The User Behavior Algorithm in Rumor Topic

**Input:** Mixed network of 2 topic $G^t{}_{U \cup V}$;
Historical behavior set $HS = \{(u_i, s) | u_i \in (R \cup A \cup V)\}$;
The basic attribute set of the rumor topic node $UP = \{(u_i, p) | u_i \in (R \cup A \cup V)\}$;
The label matrix of the rumor topic node $Z \in R^{n \times y}$;
The number of iterations $Epoch$;
**Output:** $Z = P(r, a, d | u_i)$

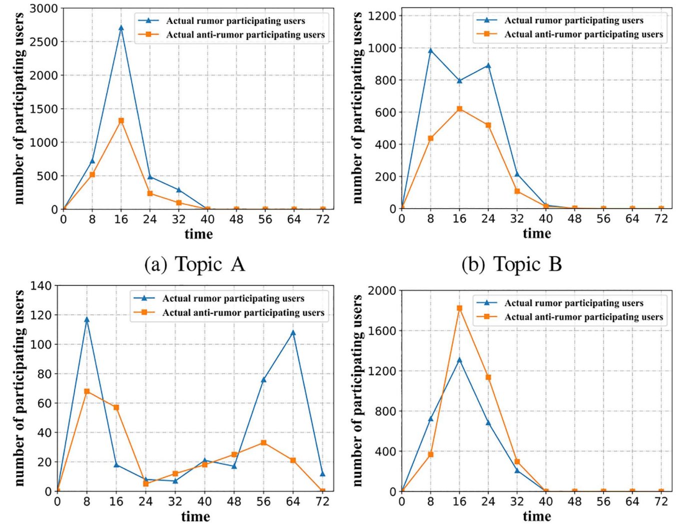
Random initialize Network parameter matrix $W^0$, $W^1$, initialization learning rate $\tau$
**for** each the rumor topic node **do**
  Represent the content feature vector of the rumor topic $X_a = N \times F^a$ by doc2vec algorithm;
  $W^M_{U \cup V}$ in Algorithm 1 is used to represent the structure feature of the topic rumor $X_b = N \times F^b$ by SDNE algorithm from Eq (3-7);
**end for**
**for** training data **do**
  convolve $H^1 = f(H^0, A) = ReLU(\tilde{A}(r_j^0 \times cnn\_model(H^0))W^0)$ from Eq(23);
  convolve $Z = f(H^1, A) = softmax(\tilde{A}H^1W^1)$ from Eq (23);
**end for**
**repeat**
  update $W^0, W^1$, calculate $\frac{\partial L}{\partial W^0}$ and $\frac{\partial L}{\partial W^1}$ by gradient descent method
**until** converge

TABLE II
EXPERIMENTAL DATA OF FOUR TOPICS

| Topic | The number of the rumor topic | The number of the anti-rumor topic | The number of following for all users of the topic |
|---|---|---|---|
| Topic A | 3680 | 2336 | 825234 |
| Topic B | 2392 | 1685 | 598542 |
| Topic C | 1815 | 2046 | 783182 |
| Topic D | 2599 | 3558 | 743591 |

Figure 4 (a–d) show the number of actual users who participate in spreading rumor, the number of actual users who participate in spreading anti-rumor, and the number of potential participating users; these numbers change over time for different rumor topics. There is a symbiotic relation between rumor and anti-rumor. As shown in Fig. 4 (c) "Hengyang Genetically Modified Rice Experiment" (topic C), a second outbreak of rumor occurred in the rumor after 48-72 h. As shown in Fig. 4 (d) "Kehua Zhou was not killed"(topic D), the official released the news of rumors in time. In most time periods after this rumor broke out, the increment of rumor spreading users was more than that of anti-rumor spreading users. Therefore, the analysis of anti-rumor exhibits a certain practical significance for studying rumor communication.

*2) Baseline Methods:* To evaluate the performance of the model proposed in this paper, the following methods are compared.




(a) Topic A (b) Topic B (c) Topic C (d) Topic D

Fig. 4. Distribution of participation of different users in the rumor topic.

SUA-ACNN [19]: SUA-ACNN is a classification depth neural network model based on the attention mechanism combined with the similarity of user interest as well as information and the characteristics of users and authors.

ODW-ELM [39]: The ODW-ELM proposed by researchers is the most advanced method for data imbalance in user behavior prediction. We take topic features as input and make rumor topic forward predictions.

Cloud-RBFNN [40]: The Cloud-RBFNN model has a good fit for the non-linear relationship between user attributes and forwarding behavior. We compare it as a predictive model.

Retweeting Prediction Method based on Tensor Decomposition(RPMTD) [41]: The RPMTD model is a retweeting prediction method for social hotspots based on tensor decomposition, using user information, relationship and behav-ioral data. The method can be used to predict the behavior of users and analyze the evolvement of topics.

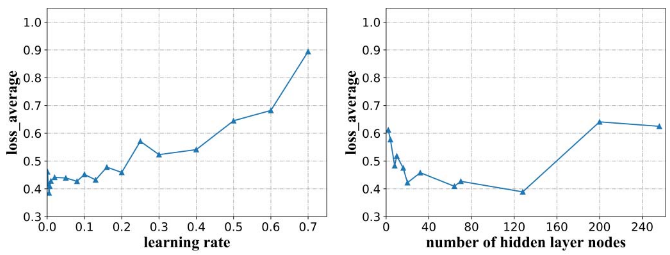
Other classifiers: We use several classic machine learning algorithms as classifiers to solve the problem of rumor forwarding prediction. The algorithms selected are logical regression and support vector machine.

*3) Evaluation Metrics:* In this paper, loss, macro-average (Macro-F1), and micro-average (Micro-F1) are used as the evaluation indicators for this model.

Loss embodies the accuracy of the forward prediction model with respect to the rumor topic. The smaller the value, the better will be the model. Macro-F1 and Micro-F1 calculate the F1-scores using their different classification data by employing their own confusion matrix. The confusion matrix is presented in Table III. Macro-F1 is the average of the F1-scores that can be used to directly obtain different categorical data. Micro-F1 is to calculate the different confusion matrices for each classification data, add the corresponding elements for all the confusion matrices, and calculate the F1-scores for this confusion matrix.

TABLE III
CONFUSION MATRIX FOR PREDICTION

| Actual class | Experimental result | |
|---|---|---|
| | Retweet | Not retweet |
| Retweet | TP | FN |
| Not retweet | FP | TN |



(a) Different learning rates. (b) Different numbers of hidden layer neurons.

Fig. 5. Training loss value under various conditions.

## B. Performance Analysis

In this section, the prediction results are analyzed and compared using the following four sets of comparative experiments: (i) perform model parameter analysis experiments on the CNN-GCN model; (ii) analyze and compare the performances of feature representation learning; (iii) analyze the effectiveness of rumor discrimination; and (iv) evaluate the ability to predict models by comparing them with the baseline methods.

*1) Design Parameters of the CNN-GCN Model:* The experimental data are divided into three groups, i.e., training set, verification set, and test set in a ratio of 8:1:1. Each person's feature representation is learned as a vector, and the network topology is used as an input to the model by the methods proposed in Sections IV-A and IV-B. The model outputs a potential user behavior probability matrix.

First, we do not consider the CNN part and use the GCN learning and training steps to gradually optimize the parameters of GCN, to mainly compare the learning rate and the number of hidden nodes. We calculate the average loss of different learning rates (from 0.001 to 0.7) and the number of different implicit nodes (from 2 to 256) in 150 epochs while maintaining the remaining parameters constant. The test results are presented in Fig. 5.

In Fig. 5, when the prediction model reaches the lowest loss value, the learning rate is 0.05, and the number of hidden layer nodes is 128. We use the same method to obtain different optimal algorithm parameters. The specific algorithm parameters are shown in Table IV. The experiments in the following sections use these parameters unless otherwise specified.

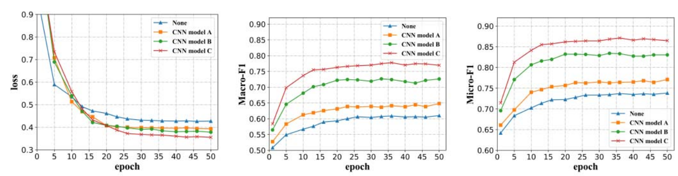
Here, we fixed some parameters of the GCN model and selected different CNN structures for conducting comparison experiments to select an appropriate CNN structure. When designing different CNN structures, we should consider the need to convolve two features of the same person having same and different meanings. Thus, the two vectors belonging to the same person are combined into a vector, which is different. The CNN structure is shown in Table V.

TABLE IV
PREDICTIVE MODEL TRAINING PARAMETERS

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| The number of GCN layer | 2 | dropout | 0.5 |
| The number of hidden layer nodes | 64 | Learning rate $\tau$ | 0.01 |
| The number of output layer nodes | 1 | L2 regularization | $5e^{-4}$ |
| Max Epoch | 50 | Network parameters $W^{(0)}$, $W^{(1)}$ | (0, 1)) |

TABLE V
SIZE OF THE CNN LAYERS

| Model name | None | CNN model A | CNN model B | CNN model C |
|---|---|---|---|---|
| convolution (kernel size) | – | 1*2*3 | 8*2*5 | 16*2*3 |
| stride | – | 2*1 | 2*1 | 2*1 |
| convolution (kernel size) | – | – | 1*1*1 | 1*1*1 |
| stride | – | – | 1*1 | 1*1 |



(a) Loss. (b) Macro-F1. (c) Micro-F1.

Fig. 6. Training loss value under various conditions.

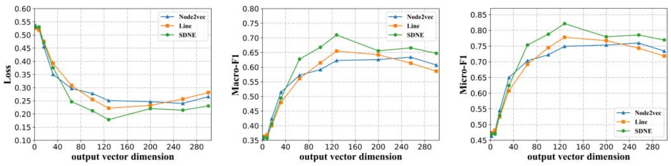
The None model indicates that it does not join the CNN model and contrasts with other groups. CNN model A chooses to use a single-layer CNN network to directly roll the input into the output needed for the next step. CNN model B and CNN model C add a 1*1 convolution kernel on the basis of A to realize information integration across channels. Their first layer uses different convolution kernels for comparison. Through training, the performance of different models is obtained with respect to the test set, as shown in Fig. 6.

From Fig. 6, denotes that the performance of the CNN model C is better than that of the remaining models. From the loss value of the prediction model, the loss of the None model decreases the fastest because the model parameters are relatively small; however, all the models exhibit a similar final loss. On the basis of the three indicators of loss, macro-F1, and micro-F1, the CNN model C exhibits the optimal performance. Therefore, the final prediction model training parameters are designed, as presented in Table VI.

*2) Representation Learning Method Analysis:* In Section IV-A, the user's feature representation part of the rumor topic, social network structure, and historical behavior are characterized. The SDNE and Doc2vec algorithms are selected Other representation learning methods are

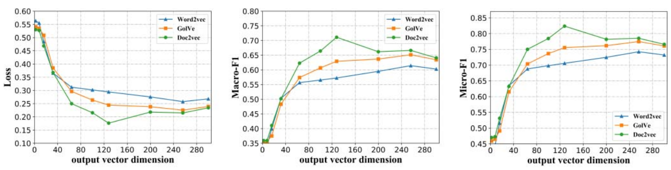
TABLE VI
CNN MODEL TRAINING PARAMETERS

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Convolution (kernel size) 1 | 16*2*3 | CNN stride 1 | 2*1 |
| Convolution (kernel size) 2 | 1*1*1 | CNN stride 2 | 1*1 |




(a) Loss. (b) Macro-F1. (c) Micro-F1.

Fig. 7. Different network representation learning algorithms.




(a) Loss. (b) Macro-F1. (c) Micro-F1.

Fig. 8. Different representation learning algorithm.

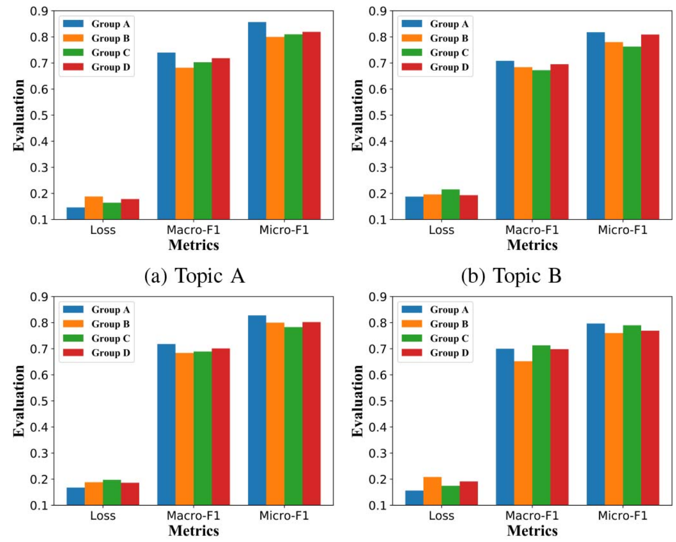
selected and compared to evaluate the prediction effects of the two representation learning methods.

In the previous section, the predictive model training parameters are selected. Further, the Node2vec, Line, and SDNE algorithms are used to train the user feature vector and the vector trained by the Doc2vec algorithm as the input of the reference model. Then, we attempt to train the feature vectors having different dimensions to compare and select the optimal output dimension. The specific experimental results are presented in Fig. 7.

Based on this, we can observe that the performance of SDNE is slightly better than that of the remaining spatial representation learning algorithms; the comprehensive effect of the prediction model is optimal when the output dimension is 128.

In the user historical behavior feature representation part, this paper employs the method of extracting keywords using TF-IDF and uses the Doc2vec algorithm to represent the text as a vector. In this section, we use Word2vec and the GolVe algorithm to convert keywords into vectors. Next, we use the concept of YoutubeNet network to weight and sum all the keyword vectors in the same paragraph and use a sigmoid function to map to (0, 1). In the interval, the corresponding text vector is obtained, and it is combined with the feature vector output using the SDNE as the model input. The experimental results are presented in Fig. 8.

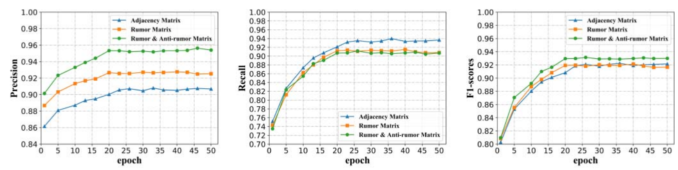
To select the optimal combination of features, this paper selects (1) SDNE, (2) Line, (3) Doc2vec, and (4) GolVe for a combination of the two models as the model input: Group A:(1) + (3); Group B:(1) + (4); Group C:(2) + (3); and Group D:(2) + (4). Experiments are conducted while ensuring that




(a) Topic A (b) Topic B

(c) Topic C (d) Topic D

Fig. 9. Different feature combination input models.




(a) Precision (b) Recall (c) F1-scores

Fig. 10. The predicted results of not participating users.

the remaining parameters are unchanged. The results obtained under different rumors are shown in Fig. 9.

The results of different combinations are similar with respect to different topics, but the effect of Group A is the best. Therefore, this study chooses Group A as the final representation learning algorithm combination.

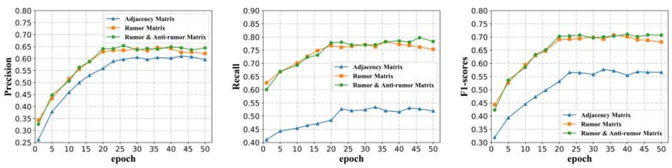
*3) Effectiveness of Influence Analysis:* In this section, the inputs of the model are the adjacency matrix (input A), the rumor influence matrix (input B), and the rumor and anti-rumor influence adjacency matrix $W^M_{U \cup V}$ (input C) when performing user network representation learning. These different inputs can be used to perform comparative tests to verify the impact of anti-rumor information on the forwarding behavior of the user.

In rumor topics, the number of users who participate in the topic (including rumor and anti-rumor) is far less than the number of users who do not participate in the topic. In order to more clearly reflect the difference between different inputs, we have selected different evaluation indicators for comparison in the previous section. We separately calculate the Precision, Recall, F1-scores of the three types of users who do not participate, rumor, and anti-rumor. The specific results for different types of users are shown in Figures 10-12.

Similar results are observed for three different inputs in Figure 10. The models with inputs A and B do not distinguish the users participating in spreading rumor and anti-rumor; therefore, their precision indicators are slightly lower than those of the model with input C. In Fig. 11, the recall and

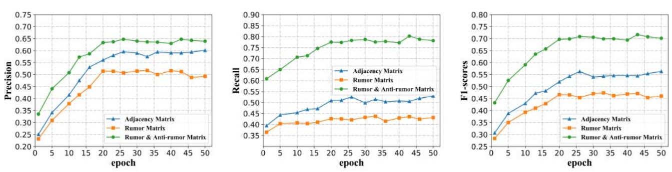
TABLE VII
COMPARISON OF EXPERIMENTAL RESULTS OF TOPICS A, B, C, AND D

| Method | Topic A | | | Topic B | | | Topic C | | | Topic D | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Loss | Macro-F1 | Micro-F1 | Loss | Macro-F1 | Micro-F1 | Loss | Macro-F1 | Micro-F1 | Loss | Macro-F1 | Micro-F1 |
| **CNN-GCN** | 0.143 | 0.741 | 0.856 | 0.177 | 0.692 | 0.823 | 0.162 | 0.710 | 0.837 | 0.164 | 0.803 | 0.835 |
| SUA-CNN | 0.200 | 0.641 | 0.799 | 0.276 | 0.565 | 0.723 | 0.217 | 0.643 | 0.782 | 0.245 | 0.699 | 0.754 |
| ODW-ELM | 0.232 | 0.730 | 0.767 | 0.229 | 0.735 | 0.770 | 0.220 | 0.743 | 0.779 | 0.199 | 0.768 | 0.801 |
| RBFNN | 0.257 | 0.708 | 0.742 | 0.255 | 0.710 | 0.744 | 0.243 | 0.722 | 0.756 | 0.246 | 0.722 | 0.753 |
| RPMTD | 0.268 | 0.695 | 0.731 | 0.271 | 0.692 | 0.728 | 0.247 | 0.692 | 0.752 | 0.241 | 0.719 | 0.758 |
| SVM | 0.279 | 0.566 | 0.720 | 0.381 | 0.444 | 0.619 | 0.277 | 0.550 | 0.722 | 0.314 | 0.635 | 0.685 |
| Logistic | 0.346 | 0.476 | 0.654 | 0.426 | 0.422 | 0.574 | 0.355 | 0.495 | 0.645 | 0.395 | 0.551 | 0.604 |



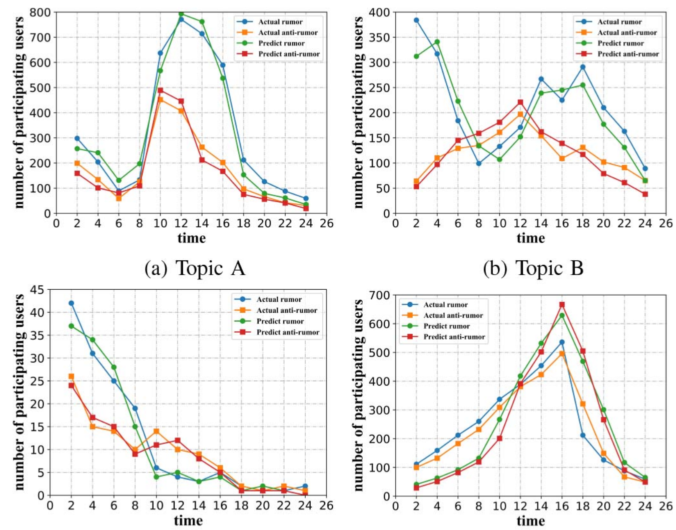

(a) Precision (b) Recall (c) F1-scores

Fig. 11. The predicted results of rumor participating users.




(a) Precision (b) Recall (c) F1-scores

Fig. 12. The predicted results of anti-rumor participating users.




(a) Topic A (b) Topic B

(c) Topic C (d) Topic D

Fig. 13. Development trend of different rumor topics.

F1-scores of the model with input A are lower than those of the remaining two models. This result is obtained because the adjacency matrix is directly used as the input; further, the influence between different users is considered to be not similar, which makes it impossible to accurately represent the relation between different users, worsening the prediction result.

In Fig. 12, we can clearly observe that the indicators of the models with inputs A and B are not as good as that of the model with input C because the models with inputs A and B do not consider the anti-rumor relation between users. In summary, comprehensive consideration of the influence of rumor and anti-rumor on the accuracy of forwarding predictions has been improved.

*4) Predict Performance Analysis:* In this section, the model performance is evaluated by comparing the experimental results of this study with those of the baseline method. We use different metrics to evaluate the predictions of different algorithms. The evaluation indicators for the prediction results of different models are presented in Table VII. The chart shows that the difference between the results of different algorithms is more pronounced. Combined with different evaluation indicators, the performance of the neural network model is basically better than that of Logistic. ODW-ELM has a better effect in dealing with the data on imbalanced user behavior. Considering different evaluation indicators, the CNN-GCN prediction model proposed in this study exhibits the optimal prediction effect.

To accurately describe the propagating trend of rumor topics, this paper performs time slicing on the active periods of three types of rumors and predicts the propagating trend of rumors in time slices. Fig. 13 shows the comparison of the predicted values of the model and the real values. The abscissa represents the time slice of the active period of the rumor topic, whereas the ordinate represents the number of participants in the rumor at different time slices. This paper effectively describes the development trend of rumors.

## VI. CONCLUSION

This paper constructs a rumor forwarding prediction model, which is based on representation learning, based on the user's network structure and historical behavior characteristics in the rumor topic communication space in social networks and predicts the user behavior in the next time slice based on the current time slice data. Considering the competition between rumor and anti-rumor, rumor and anti-rumor are integrated to reconstruct the user network structure when it is represented. Finally, the neural network, which is based on CNN-GCN, is used to predict the user behavior, and the discretization of the active time interval of the rumor topic can be used to obtain the development trend of the rumor topic. In future, we can study research the influence quantification mechanism in case of different users considering different rumors to improve the accuracy of forward prediction with respect to the rumor topic and the robustness of the prediction model.

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