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Rumor detection on social media through mining the social circles with high homogeneity

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A R T I C L E   I N F O

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A B S T R A C T

The massive spread of rumors on social media has become a major global challenge, increasing the urgent demand for rumor detection. Although social circles are ubiquitous in social networks and have the property of describing users' behavioral preferences, they have not been explicitly considered in rumor detection models. Meanwhile, information diffusion studies have shown that social circles have a significant impact on the speed, scope, and content of rumor propagation. Motivated by this important absence, we validate the significant difference between the social circles of rumor and non-rumor sources, and propose a new rumor detection algorithm. The algorithm explores a new feature space by extracting social circles with high homogeneity from user context, and combines it with social interaction to automatically detect rumors. Experimental results obtained on three real-world datasets support that the proposed approach outperforms state-of-the-art methods and displays a superior capacity for detecting rumors at early stages. The code of this work is made publicly available to foster any further research.[1]

1. Introduction

Social media, such as Twitter and Weibo, are becoming more integrated into people's lives. Users are no longer just recipients of information, but active participants in its creation. Compared to newspapers and television, information spreads faster and more widely on social networks. This provides opportunities for exposure to all kinds of content and contributes to the rapid spread of rumors [1,2]. Especially with the emergence of COVID-19, a large number of rumors have flooded online networks, which not only created many obstacles to epidemic prevention, but also disturbed public order in society [3]. Therefore, there is an urgent requirement for effective methods to detect rumors on social media.

Among various rumor detection approaches, manual labeling rumors on social networks is an impractical and costly process in the era of big data. In contrast, automatic rumor detection methods based on deep learning occupy a significant position due to their powerful semantic characterization capabilities [4–6]. For example, graph neural networks (GNNs) represented by graph convolutional networks (GCNs) and graph attention networks (GATs), and their various variants can effectively capture the structural representations of rumor propagation [4,7]. Attention-based models such as Transformer and BERT are capable of learning the deep semantics of rumor content [8,9]. Most works capture signals of rumor deception primarily from textual content and propagation

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[1] Code is available at: https://github.com/Coder-HenryZa/RDMSC.

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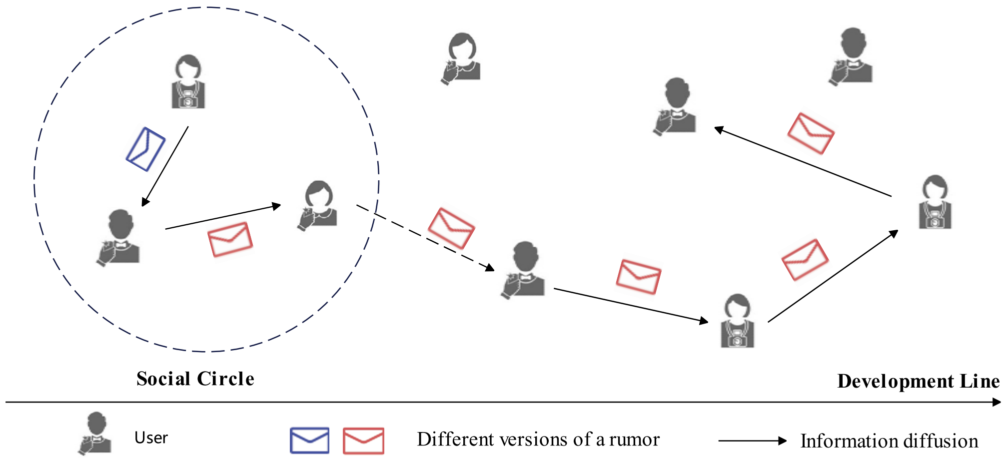


Fig. 1. Information diffusion process during the rumor-generation phase.

structure, while ignoring the fact that users are the fundamental determinant of whether a rumor is spread. To this end, recent researches evaluate the credibility of rumor sources by analyzing their static profiles [10,11]. However, the influence of social circles on rumor diffusion is not considered.

A social circle refers to a specific group of users with close relationships, shared interests, and frequent interactions, which is driven by homogeneity. The presence of homogeneity promotes mutual attraction and interaction between members in social circles [12]. Although social circles have the property of describing users' behavioral preferences, no rumor detection model has explicitly considered the influence of social circles on rumor diffusion. As shown in Fig. 1, we observe that during the rumor generation phase, a rumor initially spreads within the social circle in several different variants and usually iterates through multiple content versions before spreading widely to social networks. For example, the highly concerned "Kavanaugh Hearings" event [13] was not only widely reported in the news ecosystem, but also spread through social networks with different narrative content. Many claims about the event were proven false, including seven different rumors that were repeatedly fabricated by members of two conspiratorial social circles. Information diffusion researches [14,15] have theorized the influence of social circles on message propagation and applied it to the fields of social network analysis [16] and personalized recommendation [17].

To further explore whether social circles contribute to rumor detection, we utilize users' attributes and historical tweets as proxies and find significant differences between the social circles of rumor and non-rumor sources. For example, compared to non-rumor social circles, tweets in rumor social circles have a higher subjective expression, and members in these circles have a lower authentication rate. Therefore, capturing the differences among social circles can improve the signal of rumor detection. However, these rich user contexts are not explicitly considered. This may be due to the massive size of social networks. Mining social circles of information sources on a global scale would consume enormous resources and reduce the usability of social networks [18]. An egocentric network is a local social network that focuses on the central user and his neighboring users. Compared with the global network, it can more deeply depict the internal structure of the social circle and the connections between members [19]. In addition, egocentric networks can better protect user privacy. This is because, in contrast to the global network, an egocentric network only contains information about the users who are connected to the central user. Sociological studies [20–22] have leveraged egocentric networks to effectively discover users' social circles. Thus, for rumor detection, when the research focuses on claim sources, choosing egocentric networks to mine their social circles is an appropriate choice.

Accordingly, we propose a novel model called Rumor Detection through Mining the Social Circles (RDMSC), which explores a new feature space by extracting the social circles from user context, and combines it with social interaction to automatically detect rumors. Specifically, RDMSC consists of three main components. First, we design an unsupervised clustering algorithm to mine users' social circles from their egocentric networks based on interest distribution, communication frequency, and overlapping relationship. Second, to model the propagation structure, we construct interaction trees and present a root-edge enhancement strategy to capture long-range information interactions. Finally, dual GCN encoders and an attention mechanism are employed to learn and fuse these two features for classification. The main contributions of this work are summarized as follows:

- We propose and verify that the social circle signals are distinctive between rumor and non-rumor sources. And an unsupervised clustering algorithm is developed to mine social circles from egocentric networks.
- We design a unified framework for rumor detection that not only considers the social circles of rumor sources, but also models the social interactions of rumors and captures the correlation between them with an attention alignment module.
- To represent realistic interaction scenarios, we propose a root-edge enhancement strategy that captures the long-range information interaction between the root node and non-adjacent nodes.
- We evaluate our proposed model on three real-word datasets. The results demonstrate that RDMSC significantly outperforms state-of-the-art methods. Furthermore, these results reveal the effectiveness of RDMSC for the early detection of rumors.

Table 1
The list of symbols.

Symbol	Description
G_i^I	The social interaction graph of claim c_i
G_i^N	The egocentric network of claim source u_i
s^I	The similarity of interest distribution between users
s^F	The similarity of communication frequency between users
s^O	The similarity of overlapping relationship between users
$\boldsymbol{A}$	The adjacency matrix of a topology graph
$\boldsymbol{H}$	The node feature matrix of a topology graph
$\boldsymbol{h}$	The graph-level feature vector
$\hat{\boldsymbol{y}}_i$	The prediction vector output by our model for claim c_i
$\mathcal{L}$	The cross-entropy loss utilized to train our model

2. Related works

2.1. Rumor detection methods

The assumption behind content-based approaches is that rumors are often composed of special textual content designed to trigger more dissemination and deceive the public, such as emotional features [23], thematic features [24], and entity features [25]. Zhang et al. [26] extracted publisher and social emotions from the text content and revealed the relationship between emotional signals and news authenticity. Zhu et al. [27] designed a de-biasing framework based on entity, content, and news authenticity by causal inference, thus improving the generalization ability of rumor detection. With the development of neural networks, many researchers have represented text as graph topology to explore deceptive signals [28,29]. Vaibhav et al. [30] constructed sentences in form of graphs to exploit the characteristics of their interactions. A graph neural network was utilized as a classifier for rumor detection. Hu et al. [31] presented heterogeneous document graphs containing topics and entities for each text to capture topic-rich textual and contextual entity representations. Content-based methods are highly dependent on linguistic features, while social media tweets are short and unstructured. In addition, textual content in different domains often has different writing styles, which affects the transferability of these methods.

Propagation-based approaches, which focus on user interactions, such as replies and comments, are considered to be one of the valid research directions at present [32,33]. The intuition behind these approaches is that users will share their doubts and speculations about inaccurate information. Bian et al. [7] proposed a bi-directional graph convolution network model for learning high-level representations of top-down and bottom-up propagation graphs. Sun et al. [34] applied graph contrast adversarial learning to represent rumor propagation structures in complex conversational environments. At the same time, recent work has found that modeling the propagation structure with other knowledge, such as user profiles and spatiotemporal information, can improve detection performance. Dou et al. [35] collected users' historical posts to mine their preferences and fused exogenous context to predict news credibility. Sun et al. [36] extracted dynamic information on propagation structure and contextual knowledge in a unified framework. However, these methods ignore the influence of users' social circles on the dissemination of rumors.

2.2. Social circle discovery

Traditional social circle discovery algorithms, similar to community detection, implement clustering based on statistical inference from the perspective of network topology, such as the Louvain algorithm [37] and PageRank algorithm [38]. However, the large size of social networks makes mining at the global level will consume enormous resources. For this reason, many researchers have focused on mining users' social circles in egocentric networks. Wang et al. [39] proposed a method for assessing link similarity based on structural and attributional information to identify overlapping social circles in egocentric networks, but ignored interactions between users, such as retweets and replies. Lan et al. [20] designed a spectral clustering approach to identify social circles in terms of structure and information transfer. Most social circle discovery algorithms are applied to specific datasets. At the same time, social networks have huge amounts of data and are characterized by diversity and interactivity, allowing users to participate in the information dissemination. These characteristics make it difficult to directly adapt existing social circle discovery algorithms to the task of rumor detection.

3. Problem formulation

Formally, let $E = \{e_1, e_2, e_3, \ldots, e_n\}$ denotes the datasets, where e_i represents the i-th event and n represents the total number of events. $e_i = \{c_i, G_i^I, G_i^N\}$, where c_i is a claim, G_i^I represents the interaction graph, and G_i^N represents the egocentric network of the claim source u_i. Specifically, $G_i^I = (V_i^I, E_i^I)$, in which each node in V_i^I represents a tweet and c_i is the root node. Interactions between tweets, such as comments and replies, form the edge set E_i^I. $G_i^N = (V_i^N, E_i^N)$, where each node in V_i^N represents a user, and the following or follower relationships between users form the edge set E_i^N.

Each event e_i is assigned a fact label $y_i \in Y$. Our goal is to learn a classifier W that can automatically assign identity labels to unknown events, which is $f(e_i) \rightarrow y_i$. The symbols used in this paper are listed in Table 1.

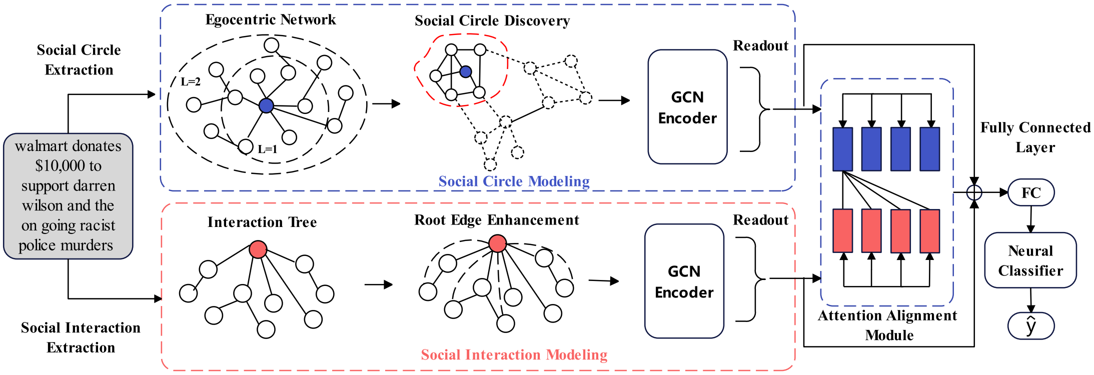


Fig. 2. An overview of our rumor detection model RDMSC. Given an input of news content, we mine a social circle from the source's egocentric network, and construct an interaction tree from social interactions. Then, we apply dual GCN encoders to compute the representations of the social circle and the interaction tree separately, and capture their correlations using an attention alignment module. Finally, multiple feature vectors are concatenated to train the model.

4. Model design

4.1. Overview of the framework

The complete architecture of our proposed approach is shown in Fig. 2, which consists of four parts: social circle modeling, social interaction modeling, attention alignment module, and rumor classification. Next, we will detail the process of model construction and representation learning.

4.2. Social circle modeling

4.2.1. Social circle construction

We explore the social circles where the claim sources are located according to the principle of homogeneity. Extracting such information can be complicated, since gathering social information on a large scale can be costly and noisy. Instead, we utilize egocentric networks to mine social circles with high homogeneity, focusing on those users who are more similar to the sources.

First, we define the social relationships between users. For a claim source u_i, its egocentric network is expressed as $G_i^N = \{V_i^N, E_i^N\}$, each node in the graph represents a user. There are three types of relationships between users: [follower, following, follower and following]. In comparison, the third relationship has the strongest connection and is not easily manipulated. Therefore, only the third relationship is chosen to construct the social circle. The adjacency matrix $A \in \mathbb{R}^{n\times n}$ is used to represent the connection relationship between u_i and its neighbor user u_j:

$$A(i,j) = \begin{cases} 1 & \text{if } [\mathrm{u_i}, \mathrm{u_j}] \text{ is the third relation} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

After selecting the third relationship, we can obtain the set of neighboring users that are bidirectionally connected to source u_i, denoted as $N(u_i) = \{u_j \in V_i | A(i,j) = 1\}$.

Our goal is to mine users who are closely related and more similar to u_i, so as to construct a social circle with high homogeneity. Next, we will elaborate the process of mining users from $N(u_i)$ in terms of interest distribution, communication frequency, and overlapping relationship.

Interest Distribution. Two users are likely to have identical interests if they post tweets with a similar topic distribution. Users typically post information in short-form on social platforms, which limits the length of the content and encourages users to express their views and emotions more concisely. To avoid the problem of sparse data due to the small size of a single tweet, we aggregate the tweets published by a user into a large document. The topic distributions in the documents are analyzed so as to find similar interests among users. We utilize a modified LDA [40] to automatically obtain the topic distribution probability of each document from the document set. The topic probability matrix $\boldsymbol{DT} \in \mathbb{R}^{m\times t}$ can be calculated by the LDA, where m represents the total amount of documents and t indicates the number of topics. $\boldsymbol{DT}_{ij}$ captures the probability that document m_i has potential topic t_j. Adopting the Jensen-Shannon Divergence [41], the interest similarity between users u_i and u_j can be calculated as:

$$s_{ij}^I = 1/\sqrt{JSD(i,j)} \tag{2}$$

where $JSD(i,j)$ represents the Jensen-Shannon Divergence, which describes the divergence between the user topic probability distributions $\boldsymbol{DT}_{i\cdot}$ and $\boldsymbol{DT}_{j\cdot}$, and is defined as:

$$JSD(i,j) = \frac{1}{2}(D_{kl}(\boldsymbol{DT}_{i.}||\boldsymbol{M}) + D_{kl}(\boldsymbol{DT}_{j.}||\boldsymbol{M})) \tag{3}$$

where $\boldsymbol{M} = \frac{1}{2}(\boldsymbol{DT}_i. + \boldsymbol{DT}_j.)$, and D_{kl} represents the Kullback-Leibler Divergence which can be calculated by $D_{kl}(\boldsymbol{P}||\boldsymbol{Q}) = \sum_i \boldsymbol{P}(i) log \frac{\boldsymbol{P}(i)}{\boldsymbol{Q}(i)}$.

Communication Frequency. It describes the frequency between two users in retweeting and mentioning. If two users constantly contact each other, they have higher homogeneity. We define the communication frequency between u_i and u_j as follows:

$$s_{ij}^F = \frac{S_{both}}{\sqrt{|R_i|}\sqrt{|R_j|}} + \frac{r_{ij} + r_{ji}}{|R_i|\,|R_j|} \tag{4}$$

where r_{ij} represents the times u_i retweets or mentions u_j. $|R_i|$ represents the number of users retweeted and mentioned by u_i, and S_{both} is the number of users retweeted and mentioned by both u_i and u_i.

Overlapping Relationship. Similar to traditional clustering methods, we explore the homogeneity of overlapping relationships from the network topology, including common friends and followers. The homogeneity of overlapping relationships between user u_i and user u_j is defined as:

$$s_{ij}^O = \frac{S_{friend}}{\sqrt{|Fr_i|}\sqrt{|Fr_j|}} + \frac{S_{follower}}{\sqrt{|Fl_i|}\sqrt{Fl_j}} \tag{5}$$

In the above equation, S_{friend} and $S_{follower}$ represent the number of mutual friends and followers of two users. $|Fr_i|$ and $|Fl_i|$ represent the number of users followed by u_i and the number of users following u_i, respectively.

With the above metrics, we can calculate the homogeneity intensity between users. Before the aggregation operation, each metric needs to be normalized. Then, we adopt the entropy method to determine the weights of each metric. The homogeneity intensity between u_i and u_j is ultimately defined as:

$$s_{ij} = \lambda_1 s_{ij}^I + \lambda_2 s_{ij}^F + \lambda_3 s_{ij}^O \tag{6}$$

$$\lambda_k = \frac{1 - q_k}{\boldsymbol{M} - \sum\limits_{k=1}^{M} q_k} \quad (0 \le \lambda_k \le 1, \sum_{k=1}^{M} \lambda_k = 1) \tag{7}$$

where λ_1 represents the weight of interest distribution and M is the number of metrics. $q_k = -\ln(L)^{-1} \sum_{l=1}^{L} p_{lk} \ln p_{lk}$ refers to the information entropy of k-th metric, in which L is the number of neighbor nodes in an egocentric network, p_{lk} represents the weight of the l-th node of the k-th metric.

Finally, based on the measure of homogeneity intensity between users, we design an unsupervised clustering method. In particular, for the claim source u_i, we mine its social circle with high homogeneity through three main steps: (1) Take u_i as the clustering center. Calculate the homogeneity intensity s_{ij} with neighbor nodes $u_j \in N(u_i)$ in turn, and select not more than m nodes from them to maximize the value of $T(u_i) = \sum s_{ij}$ as the one-level neighbor nodes $N'(u_i)$. (2) The one-level neighbor nodes $N'(u_i) = [u_1, u_2, \cdots, u_k]$ are taken as clustering centers, and as in the first step, the homogeneity intensity of their neighbor nodes is calculated to obtain the two-level neighbor nodes $N''(u_i)$. (3) According to the connectivity relationships among nodes, the two-level social circle G_i^S is constructed, accompanied by the adjacency matrix $\boldsymbol{A}_i^S \in \mathbb{R}^{n_i \times n_i}$.

4.2.2. Social circle encoding

Graph convolutional networks have achieved an impressive performance in graph-based domains with the ability to learn embeddings of nodes in graphs by message transfer. Each node iteratively aggregates information about itself and its neighbors through the graph convolution layer. Inspired by this, we utilize a GCN to encode social circles.

For a claim source u_i, the social circle $G_i^S = (V_i^S, E_i^S)$ can be constructed through the unsupervised clustering algorithm. Let its initial feature matrix be $\boldsymbol{H}_i^{S(0)} \in \mathbb{R}^{n_i \times d_0}$, where d_0 is the dimension of the feature vector and n_i represents the number of nodes. We apply a two-layer GCN to update the features of nodes, which is defined as:

$$\boldsymbol{H}_i^{S(1)} = \sigma(\widehat{\boldsymbol{A}}_i^S \boldsymbol{H}_i^{S(0)} \boldsymbol{W}_1^S + \boldsymbol{b}_1^S) \tag{8}$$

$$\boldsymbol{H}_i^{S(2)} = \sigma(\widehat{\boldsymbol{A}}_i^S \boldsymbol{H}_i^{S(1)} \boldsymbol{W}_2^S + \boldsymbol{b}_2^S) \tag{9}$$

where $\boldsymbol{W}_1^S$ and $\boldsymbol{b}_1^S$ are the parameter matrix and vector. σ indicates a nonlinear activation function, e.g. a ReLU. $\widehat{\boldsymbol{A}}_i^S$ represents the normalized symmetric adjacency matrix and is defined as:

$$\widehat{\boldsymbol{A}}_i^S = (\widetilde{\boldsymbol{D}}_i^S)^{-\frac{1}{2}} \widetilde{\boldsymbol{A}}_i^S (\widetilde{\boldsymbol{D}}_i^S)^{-\frac{1}{2}} \tag{10}$$

In the above equation, $\widetilde{\boldsymbol{A}}_i^S = \boldsymbol{A}_i^S + \boldsymbol{I}_{n_i}$, in which $\boldsymbol{I}_{n_i}$ is a unit matrix with the dimension of n_i. $\widetilde{\boldsymbol{D}}_i^S$ is a degree matrix with the elements $\widetilde{\boldsymbol{D}}_{iu}^S = \sum_v \widetilde{\boldsymbol{A}}_{iuv}^S$ on the diagonal.

Although graph convolution is effective at aggregating information from neighboring nodes, it still has some limitations. For example, suppose a GCN has many layers and a central node has a lot of neighboring nodes. In this case, the average aggregation operation of the features will significantly dilute the original features of the central node, making the features indistinguishable between nodes. Therefore, we improve the generalization ability of the encoder using jump knowledge [42], which means obtaining an enhanced feature matrix of a L-th layer GCN:

$$\boldsymbol{H}^{(L)} = \text{CONCAT}(\{\boldsymbol{H}_i^{S(l)} | l = 1, 2, ..., L\}) \tag{11}$$

where CONCAT$(\cdot)$ refers to the concatenate function. Through Eq. (9) and Eq. (11), we can obtain the node representations:

$$\widehat{\boldsymbol{H}}_i^{S(2)} = \text{CONCAT}(\boldsymbol{H}_i^{S(2)}, \boldsymbol{H}_i^{S(1)}) \tag{12}$$

$$\boldsymbol{H}_i^S = \text{ReLU}(\boldsymbol{W}^S \widehat{\boldsymbol{H}}_i^{S(2)} + \boldsymbol{b}^S) \tag{13}$$

where $\boldsymbol{W}^S$ and $\boldsymbol{b}^S$ are trainable parameters. $\boldsymbol{H}_i^S \in R^{n_i \times d}$ denotes the node representations of G_i^S.

We regard the rumor detection task as a graph classification problem. To aggregate the node representations in the social circle, we utilize a readout function to form the final representation:

$$\boldsymbol{h}_i^S = \text{MEAN}(\boldsymbol{H}_i^S) \tag{14}$$

where MEAN$(\cdot)$ refers to the mean-pooling aggregation function and $\boldsymbol{h}_i^S \in \mathbb{R}^{1 \times d}$ refers to the graph-level feature vector of G_i^S.

4.3. Social interaction modeling

4.3.1. Interaction tree construction

For a claim, the interaction between users in a social network can be modeled as a tree structure. The root node represents the claim to be detected, while the other nodes represent the tweets of interactions, such as comments and replies. An edge refers to a comment or reply relationship between users. The fundamental principle behind interaction trees is that users on social media are likely to share their opinions, guesses, and evidence about inaccurate information, which can be captured for rumor detection. To model top-down propagation patterns and bottom-up diffusion structures, we construct bi-directional interaction trees.

Interaction trees can graphically represent the process of rumor spreading in social networks. However, existing work ignores the fact that in a natural interaction scenario, a user posting a replay may be replaying to the entire claim thread, rather than to a specific user. To this end, we propose a root edge enhancement strategy to capture long-range interactions between the root node and non-adjacent nodes. In particular, the interaction tree of a claim c_i can be defined as $G_i^I = (V_i^I, E_i^I)$. Let $v_r \in V_i^I$ denote the root node, and e_{rj} denote an edge between nodes v_r and v_j. The tree structure can be represented by an adjacency matrix $\boldsymbol{A}_i^I \in [0,1]^{m_i \times m_i}$ with $\boldsymbol{A}_i^I(r,j) = 1$ if $e_{rj} \in E_i^I$ and $\boldsymbol{A}_i^I(r,j) = 0$ if $e_{rj} \notin E_i^I$. As shown in Fig. 2, we establish connection relationships between the root node and non-adjacent nodes to update the adjacency matrix $\boldsymbol{A}_i^I$, making $\boldsymbol{A}_i^I(r,j) = 1$ for any $v_j \in V_i^I$.

4.3.2. Interaction tree encoding

Each node in the interaction tree represents a tweet. Tweets are typically composed of short, unstructured, and noisy texts. In particular, users like to express their semantics with new words or abbreviations, such as “I dunno” and “good 9t”. Therefore, we first preprocess text features with emoticon to text, lemmatization, and URL replacement, etc.

Then, similar to the approach of encoding social circles, we apply a two-layer GCN to capture the signals for rumor classification in interaction trees. For the interaction tree $G_i^I = (V_i^I, E_i^I)$, the initial feature matrix can be defined as $\boldsymbol{H}_i^{I(0)} \in \mathbb{R}^{m_i \times d_0}$, where m_i represents the number of nodes and d_0 represents the dimensionality of feature vector. The node features are updated in the following way:

$$\boldsymbol{H}_i^{I(1)} = \sigma(\widehat{\boldsymbol{A}}_i^I \boldsymbol{H}_i^{I(0)} \boldsymbol{W}_1^I + \boldsymbol{b}_1^I) \tag{15}$$

$$\boldsymbol{H}_i^{I(2)} = \sigma(\widehat{\boldsymbol{A}}_i^I \boldsymbol{H}_i^{I(1)} \boldsymbol{W}_2^I + \boldsymbol{b}_2^I) \tag{16}$$

where $\boldsymbol{W}_1^I$ and $\boldsymbol{b}_1^I$ are the parameter matrix and vector. σ represents a nonlinear activation function, e.g. a ReLU. $\widehat{\boldsymbol{A}}_i^I$ represents the normalized symmetric adjacency matrix and is defined as:

$$\widehat{\boldsymbol{A}}_i^I = (\widetilde{\boldsymbol{D}}_i^I)^{-\frac{1}{2}} \widetilde{\boldsymbol{A}}_i^I (\widetilde{\boldsymbol{D}}_i^I)^{-\frac{1}{2}} \tag{17}$$

In the above equation, $\widetilde{\boldsymbol{A}}_i^I = \boldsymbol{A}_i^I + \boldsymbol{I}_{m_i}$, in which $\boldsymbol{I}_{m_i}$ is a unit matrix with the dimension of m_i. $\widetilde{\boldsymbol{D}}_i^I$ is a degree matrix with the elements $\widetilde{\boldsymbol{D}}_{iu}^I = \sum_v \widetilde{\boldsymbol{A}}_{iuv}^I$ on the diagonal.

We adopt the jump knowledge to increase the size of the influence distribution by aggregating neighborhoods from the previous layer. The node representations of the interaction tree can be calculated:

$$\widehat{\boldsymbol{H}}_i^{I(2)} = \text{CONCAT}(\boldsymbol{H}_i^{I(2)}, \boldsymbol{H}_i^{I(1)}) \tag{18}$$

$$\boldsymbol{H}_i^I = \text{ReLU}(\boldsymbol{W}^I \widehat{\boldsymbol{H}}_i^{I(2)} + \boldsymbol{b}^I) \tag{19}$$

where $\boldsymbol{W}^I$ and $\boldsymbol{b}^I$ are trainable parameters. $\boldsymbol{H}_i^I \in \mathbb{R}^{m_i \times d}$ denotes the node representations of G_i^I.

The rumor detection task is viewed as a graph classification problem. We obtain the final representation of G_i^I through a mean-pooling readout function:

Table 2
Statistics of the datasets.

Statistic	Twitter15	Twitter16	PHEME
# claims	1490	818	3164
# True rumors	374	205	-
# False rumors	370	205	1564
# Non-rumors	372	205	1600
# Unverified rumors	374	203	-
# Tree-depth	2.80	2.77	3.12
# Users	47,615	23,227	36,443
# Tweets	57,368	27,652	78,859

$$\boldsymbol{h}_i^I = \mathrm{MEAN}(\boldsymbol{H}_i^I) \tag{20}$$

where $\boldsymbol{h}_i^I \in \mathbb{R}^{1\times d}$ refers to the graph-level feature vector of G_i^I.

4.4. Attention alignment module

After obtaining the social circle and the interaction tree representations, our goal is to highlight valuable shared features and facilitate deeper interactions between them. We apply an attention alignment module to capture their correlation features. In this module, the query vector is the interaction tree embedding. The key and value vectors are the social circle representation. Specifically, given the social circle representation $\boldsymbol{h}_i^S$, we calculate the attention embedding between $\boldsymbol{h}_i^S$ and the interaction tree embedding $\boldsymbol{h}_i^I$:

$$\boldsymbol{h}_i^{Attn} = \mathrm{Softmax}\left(\frac{1}{\sqrt{d}}\boldsymbol{h}_i^I \boldsymbol{W}_q (\boldsymbol{h}_i^S \boldsymbol{W}_k)^T\right)\boldsymbol{h}_i^S \boldsymbol{W}_v \tag{21}$$

where $\boldsymbol{W}_q$, $\boldsymbol{W}_k$ and $\boldsymbol{W}_v$ are learnable parameter matrices. $(\cdot)^T$ denotes the transposition operation. d is the feature dimension of the vector $\boldsymbol{h}_{attn}$. The probability of the weight distribution obtained by the Softmax function determines the importance of each social circle feature.

4.5. Rumor classification

To obtain the global features for rumor classification, we concatenate the high-level representations $\boldsymbol{h}_i^S$, $\boldsymbol{h}_i^I$ and $\boldsymbol{h}_i^{Attn}$ as follows:

$$\boldsymbol{h}_i^G = \mathrm{CONCAT}(\boldsymbol{h}_i^S, \boldsymbol{h}_i^I, \boldsymbol{h}_i^{Attn}) \tag{22}$$

The vector of predicted probabilities is calculated via a full connection layer and a Softmax function:

$$\hat{\boldsymbol{y}}_i = \mathrm{Softmax}\left(\mathrm{FC}(\boldsymbol{h}_i^G)\right) \tag{23}$$

Finally, we minimize the cross-entropy loss between the predicted probabilities and the ground truth distribution:

$$\mathcal{L} = -\sum_i \sum_c^C \boldsymbol{y}_i^c \log \hat{\boldsymbol{y}}_i^c + \eta\|\theta\|_2 \tag{24}$$

where C is the number of categories, η is the $L2$ regularization factor, and y_i^c represents the ground-truth probability under the category c. For model optimization, the gradient descent is adopted to train the model.

5. Experiments

5.1. Datasets

We evaluate the performance of our proposed model on three real-world datasets: Twitter15 [32], Twitter16 [32], and PHEME [43], all of which are collected from Twitter, the most popular social media platform in the US. Twitter15 and Twitter16[2] contain 1,490 and 818 claims, respectively, divided into four classes: False Rumor (F), True Rumor (T), Non-Rumor (NR), and Unverified Rumor(U). PHEME[3] contains claims related to five breaking news, and each claim is annotated with its veracity label, either False Rumor (F) or Non-Rumor (NR). Due to the unbalanced distribution of categories in PHEME, as in the previous work [44], we balance the number of instances in the two categories to ensure the validity and fairness of the experiment. The statistics of the resulting datasets are given in Table 2.

[2] https://www.dropbox.com/s/7ewzdrbelpmrnxu/rumdetect2017.zip?dl=0.
[3] https://figshare.com/articles/dataset/PHEME_dataset_of_rumours_and_non-rumours/4010619.

5.2. Experimental setup

We compare the proposed model with several state-of-the-art baselines that are highly representative and relevant to the work in this paper, including:

- **SVM-TK** [32]: A tree-kernel based SVM classifier for capturing high-level representations of rumor propagation patterns.
- **RvNN** [45]: A top-down and bottom-up framework that explores the structural characteristics of propagation trees from two perspectives.
- **StA-PLAN** [8]: A post-level attention model that flattens propagation trees and simulates long-distance interactions between twitters using Transformer's multi-headed attention.
- **PRC-RNN+CNN** [11]: A time series classifier based on recurrent and convolutional networks that detects false information by capturing global and local changes of users along the propagation path.
- **UPFD** [35]: The method models the endogenous preferences of users and the exogenous social context of rumors to build an end-to-end detection framework.
- **BiGCN** [7]: A bidirectional graph neural network based model which learns the propagation characteristics of rumors by top-down and bottom-up patterns.
- **RDLNP** [46]: A rumor hybrid feature learning model, which integrates the diffusion structure of the response and the contextual features of rumors.
- **GACL** [34]: The model is based on graph contrast learning, which improves the quality of representations by capturing commonalities between the same class instances.

The proposed model RDMSC is implemented by PyTorch.[4] We divide each of the three datasets into five parts and apply 5-fold cross-validation. Meanwhile, for Twitter15 and Twitter16, we apply the Accuracy (Acc.) to the four categories and calculate the F1 Score (F_1) on each category. For PHEME, we use Accuracy (Acc.), Precision (Prec.), Recall (Rec.), and macro F1 Score (F_1) to evaluate the model.

5.3. Model configuration

In our experiments, the initial learning rate 5×10^{-4} is utilized for training the model, which is optimized with a weight decay factor 1×10^{-4}. The batch size is set to 128. The early stop mechanism with patience epochs 10 is used to control the optimal number of iterations, which avoids overfitting on training datasets. The layer of the graph convolutional network is set as 2 with the droupout rate [0.2,0.4]. The hidden dimension is set as 128. The activation function is unified with ReLU. For interaction trees, the initial feature matrices are extracted in terms of TF-IDF values. For social circles, the maximum number of nodes at each layer is set as 60, and the initial feature matrices are extracted from the users' profiles with the normalized operation.

5.4. Experiment results and analysis

Tables 3 and 4 show the performance of all models on the three publicly real-world datasets, with the bolded parts indicating the best results. Our proposed model RDMSC achieves the best performance compared to all baselines. For Twitter15, RDMSC improves 3.2% on F1 score of False Rumor compared to the best baseline. For Twitter16, RDMSC achieves at least 3.4% and 2.0% improvements on the accuracy and F1 score of Unverified Rumor, respectively, compared to the state-of-the-art models. For PHEME, RDMSC outperforms the best baseline by 3.1% accuracy and 1.5% precision. These results confirm the advantages of incorporating the social circle representations of claim sources into the rumor detection task.

GCN-based models, such as BIGCN, RDLNP, and GACL, show excellent performance on three datasets. The advantage of GCN in structure and feature learning leads to the selection of GCN as encoders in this paper. BIGCN and RDLNP encode global structural information by analyzing the propagation relationships over time in rumor interaction trees. GCAL incorporates contrastive adversarial learning to improve the robustness of the model. GCN extracts high-level representations of node features by aggregating information from neighboring nodes and is able to capture the global structure, thus helping to improve the prediction accuracy.

According to the organization of the features, PRC-RNN+CNN, UPFD, and RDLNP are feature fusion models that are used as important baselines to verify the superiority of RDMSC. RDLNP introduces both nonlinear structure learning and linear sequence learning to propose a dual propagation model, but it does not take into account the intrinsic characteristics that users decide whether or not to spread rumors. PRC-RNN+CNN and UPFD learn the features of users along the path of rumor propagation. However, the low homogeneity among users creates a lot of noise.

The model presented in this paper is superior to all baselines, either the four-classified Twitter15 and Twitter16, or the two-classified PHEME. This is because RDMSC mines social circle representations with high homogeneity of claim sources in terms of user attributes and network topology from their egocentric networks. Moreover, when constructing the interaction trees, RDMSC utilizes an edge enhancement strategy to capture long-range information interactions. And, RDMSC takes into account not only the user context but also the interaction characteristics of rumors, making it possible to capture signals of various deceptions more comprehensively and accurately.

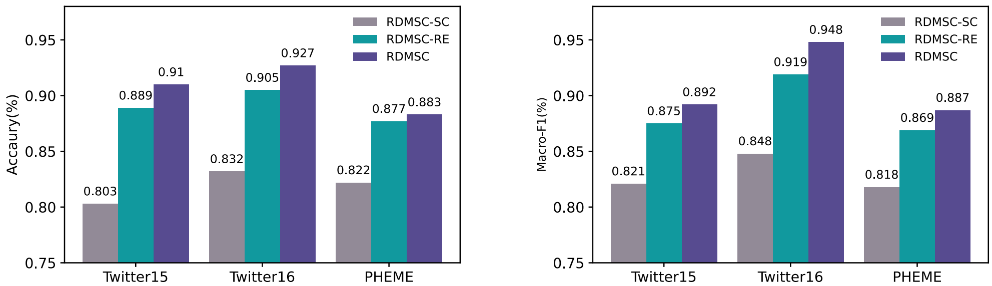
[4] https://pytorch.org/.

Table 3
Rumor detection results on Twitter15 and Twitter16.

Method	Twitter15					Twitter16				
	Acc.	F F_1	T F_1	U F_1	NR F_1	Acc.	F F_1	T F_1	U F_1	NR F_1
SVM-TK	0.667	0.669	0.772	0.645	0.619	0.662	0.623	0.783	0.655	0.643
RvNN	0.723	0.758	0.821	0.654	0.682	0.737	0.743	0.835	0.708	0.662
StA-PLAN	0.852	0.846	0.884	0.837	0.840	0.868	0.927	0.888	0.826	0.833
PRC-RNN+CNN	0.842	0.875	0.790	0.818	0.811	0.863	0.898	0.837	0.843	0.820
UPFD	0.883	0.863	**0.942**	0.894	0.817	0.891	0.846	0.926	0.882	0.913
BiGCN	0.871	0.867	0.913	0.836	0.860	0.885	0.899	**0.932**	0.882	0.829
RDLNP	0.878	0.868	0.916	0.862	**0.893**	0.891	0.869	0.895	0.924	0.854
GACL	0.882	0.853	0.890	0.902	0.878	0.893	0.870	0.878	0.932	0.912
RDMSC	**0.910**	**0.907**	0.905	**0.928**	0.892	**0.927**	**0.899**	0.923	**0.952**	**0.948**

Table 4
Rumor detection results on PHEME.

PHEME				
Method	Acc.	Prec.	Rec.	F_1
SVM-TK	0.704	0.724	0.675	0.699
RvNN	0.775	0.754	0.733	0.779
StA-PLAN	0.756	0.755	0.721	0.747
PRC-RNN+CNN	0.781	0.763	0.796	0.784
UPFD	0.834	0.841	0.874	0.751
BiGCN	0.824	0.861	0.832	0.756
RDLNP	0.852	0.847	0.875	0.864
GACL	0.850	0.801	**0.901**	0.882
RDMSC	**0.883**	**0.876**	0.893	**0.885**



(a) Accuracy (b) Macro-F1 on Non-rumor

Fig. 3. Ablation studies on proposed model.

5.5. Ablation study

5.5.1. Proposed framework variants

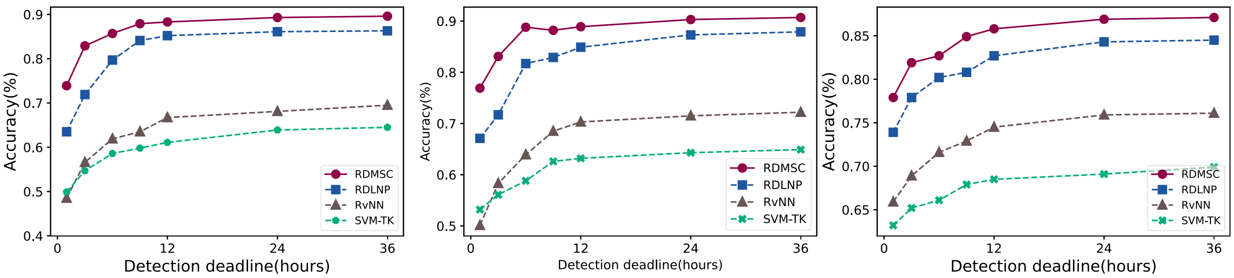
To verify the effectiveness of RDMSC components for rumor detection, we separate the functional modules and evolve the model into two variants: removing the social circle representations (RDMSC-SC) and removing the root edge enhancement strategy (RDMSC-RE). The results of the experiments are shown in Fig. 3. In terms of accuracy, RDMSC improves by 10.7%, 9.5%, and 6.1% compared to RDMSC-SC on Twitter15, Twitter16, and PHEME, respectively, which fully illustrates the effectiveness of mining social circles with high homogeneity from user context. Moreover, the root edge enhancement strategy can capture long-range interactions to portray realistic interaction scenarios, and contributes to the effectiveness of rumor detection. Compared with RDMSC-RE, RDMSC improves the Macro-F1 score on non-rumor by 1.7%, 2.9%, and 1.8% on the three datasets, respectively. With the experimental results, we conclude that each module of the proposed approach is indispensable, demonstrating the effectiveness of the framework.

5.5.2. Clustering algorithm variants

We design a clustering algorithm to mine users' social circles from egocentric networks. To evaluate the performance of the clustering algorithm, we split the clustering metrics and evolve the clustering algorithm into three variants to compare with the original algorithm. As shown in Table 5, we evaluate the performance of the egocentric network clustering algorithm (EgoCluster) after removing clustering metrics, including interest distribution (ID), communication frequency (CF), and overlapping relationship

Table 5
Ablation studies on proposed clustering algorithm.

Dataset	Method	Acc.	F F_1	T F_1	U F_1	NR F_1
Twitter15	EgoCluster	0.910	0.907	0.905	0.928	0.892
	- w/o ID	0.885	0.859	0.919	0.875	0.891
	- w/o CF	0.896	0.882	0.909	0.892	0.873
	- w/o OR	0.884	0.891	0.898	0.876	0.851
Twitter16	EgoCluster	0.927	0.909	0.923	0.952	0.948
	- w/o ID	0.912	0.892	0.927	0.903	0.909
	- w/o CF	0.911	0.899	0.928	0.915	0.896
	- w/o OR	0.905	0.898	0.907	0.926	0.872
PHEME	EgoCluster	0.883	0.881	-	-	0.885
	- w/o ID	0.873	0.869	-	-	0.876
	- w/o CF	0.874	0.877	-	-	0.867
	- w/o OR	0.865	0.869	-	-	0.862



(a) Twitter15 Dataset (b) Twitter16 Dataset (c) PHEME Dataset

Fig. 4. Performance of early rumor detection on three datasets.

(OR). We find that removing ID will bring an average decrease of 1.6% in accuracy. If we remove OR, the F1 Score on False Rumor decreases by at most 1.6%. Removing CF will bring a slight decrease in accuracy, 1.4%, 1.6%, and 0.9% on the three datasets, respectively. The experimental results show the superiority of our elaborate clustering algorithm on social networks.

5.6. Early rumor detection

Early detection is crucial for rumor detection, as the longer a rumor is spread, the more people are likely to believe it. For the early detection task, we select a series of deadlines relative to the original claim posted and utilize tweets before the deadlines to evaluate the performance of models. Fig. 4 displays the early rumor detection performance of our RDMSC model and other baselines. We observe that each model's performance improves as the deadline length increases. In addition, the proposed model RDMSC obtains an accuracy of more than 88% on Twitter16 at the six-hour mark. Also, the accuracy exceeds 85% on the PHEME dataset at a deadline of 12 hours. From the results of the experiments, we can conclude that RDMSC is superior and stable at all times, and it successfully outperforms other baselines. This is because the rich social circle information of claim sources is not dependent on the claim propagation, allowing the model to have more knowledge at an early stage.

5.7. Qualitative analysis of social circles

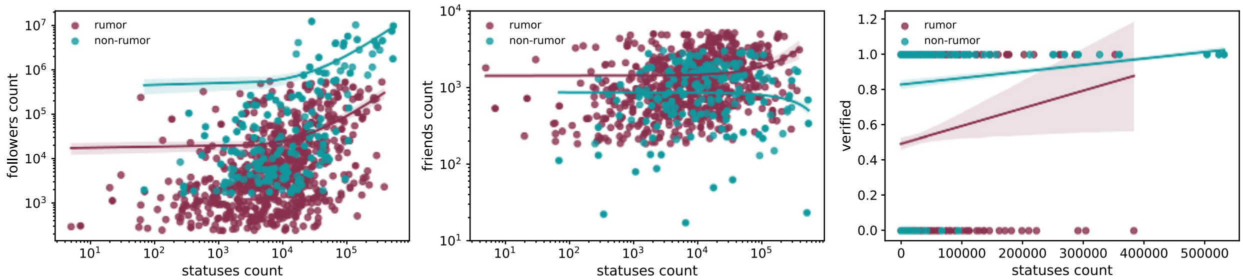
To illustrate the helpfulness of the mined social circles for rumor detection, we utilize quantitative analysis to explore the different characteristics of rumor social circles (RSC) and non-rumor social circles (NSC) in Twitter15 dataset. As shown in Table 6, the indicators used for the quantitative analysis include the mean value (Mean), standard deviation (Std), 50th percentile (50%), and maximum value (Max). We use TextBlob[5] to analyze the sentiment and subjectivity of users' historical tweets in the social circles. The Followers and Friends fields indicate the number of followers and friends of a user, respectively. The Lists field shows the number of public lists that a user is a member of, and the Favourites field refers to the number of tweets a user has liked in the account's lifetime.

From Table 6, we can conclude that the rumor social circles have significant attribute differences from the non-rumor social circles. For example, on average, texts published by members of the non-rumor social circles have twice the sentiment value and lower subjectivity than members from the rumor social circles. In addition, rumor social circle members have significantly more

[5] https://textblob.readthedocs.io/en/dev/.

Table 6
Quantitative analysis of rumor and non-rumor social circles.

Indicator	Category	Sentiment	Subjectivity	Followers	Friends	Lists	Favourites
Mean	RSC	0.039	0.314	4.72e+05	4269.60	2496.23	1.94e+04
	NSC	0.077	0.288	5.01e+06	1707.05	1.67e+04	1.24e+04
Std	RSC	0.229	0.320	1.87e+06	2.42e+04	9969.95	5.46e+04
	NSC	0.263	0.310	1.14e+07	5656.67	3.51e+04	2.92e+04
50%	RSC	0.000	0.252	4.64e+03	1021.00	70.00	4397.00
	NSC	0.000	0.230	3.32e+04	426.00	274.00	2091.00
Max	RSC	1.000	1.000	2.78e+07	6.49e+05	1.02e+05	8.89e+05
	NSC	1.000	1.000	4.85e+07	9.55e+04	1.43e+05	3.19e+05



(a) followers and statuses (b) friends and statuses (c) verified and statuses

Fig. 5. Attribute analysis of members from rumor and non-rumor social circles.

friends on average than non-rumor social circle members. These results fully demonstrate that the social circle features can effectively improve rumor detection performance.

5.8. Case study

Compared to other works, this paper mainly utilizes social circles of users to improve rumor detection. We statistically analyze the social circles of different categories of sources in PHEME to explain why the proposed model RDMSC is effective. In PHEME, we select the posters marked as “non-rumor” and “rumor” under the topic of the “Ottawa shooting”, and mine their corresponding highly homogeneous social circles to form two sets. These two sets represent the rumor and non-rumor social circles, respectively. Then, we analyze the basic attributes of users in each set. The results are shown in the Fig. 5, where red points indicate members from the rumor social circle and green points indicate members from the non-rumor social circle.

As shown in Fig. 5a, the horizontal coordinate denotes the number of posted statuses, and the vertical coordinate denotes the number of followers. We find that the number of followers is positively correlated with the number of their statuses. This trend is higher for members from the non-rumor social circle than members from the rumor social circle. Also, from Fig. 5b and Fig. 5c, we can observe that, on average, members from the non-rumor social circle follow fewer people and are more likely to have been verified. Thus, there are differences in the distribution of attribute features between rumor and non-rumor social circles, which can be utilized to improve the effectiveness of rumor detection.

6. Conclusion

In this paper, we propose a new rumor detection framework named RDMSC. First, we design an unsupervised clustering algorithm to mine users’ social circles from their egocentric networks. Second, to model the propagation structure, we construct interaction trees and present a root edge enhancement strategy to capture long-range information interactions. Finally, the GCN encoders and an attention mechanism are employed to learn and fuse the two types of features for classification. Experimental results show that our RDMSC method outperforms the state-of-the-art baselines on three real-world datasets and displays superior capability for early rumor detection. In future work, we will focus on few-shot learning and the interpretability of model decisions.

CRediT authorship contribution statement

Peng Zheng: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Zhen Huang:** Data curation, Supervision, Writing – review & editing. **Yong Dou:** Data curation, Formal analysis, Funding acquisition, Project administration, Software, Validation, Visualization, Writing – review & editing. **Yeqing Yan:** Data curation, Formal analysis, Software, Validation, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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