TrustGNN: Graph Neural Network-Based Trust Evaluation via Learnable Propagative and Composable Nature

Cuiying Huo, Dongxiao He, Chundong Liang, Di Jin, Member, IEEE, Tie Qiu, Senior Member, IEEE, and Lingfei Wu, Member, IEEE

Abstract—Trust evaluation is critical for many applications such as cyber security, social communication, and recommender systems. Users and trust relationships among them can be seen as a graph. Graph neural networks (GNNs) show their powerful ability for analyzing graph-structural data. Very recently, existing work attempted to introduce the attributes and asymmetry of edges into GNNs for trust evaluation, while failed to capture some essential properties (e.g., the propagative and composable nature) of trust graphs. In this work, we propose a new GNN-based trust evaluation method named TrustGNN, which integrates smartly the propagative and composable nature of trust graphs into a GNN framework for better trust evaluation. Specifically, TrustGNN designs specific propagative patterns for different propagative processes of trust, and distinguishes the contribution of different propagative processes to create new trust. Thus, TrustGNN can learn comprehensive node embeddings and predict trust relationships based on these embeddings. Experiments on some widely-used real-world datasets indicate that TrustGNN significantly outperforms the state-of-the-art methods. We further perform analytical experiments to demonstrate the effectiveness of the key designs in TrustGNN.

Index Terms—Graph neural networks (GNNs), social networks, social trust evaluation, trust chains.

I. INTRODUCTION

WITH the evolution of communication technology and the widespread popularity of the Internet, the number of social network users is growing rapidly. Online social networks such as Facebook, LinkedIn, and Twitter have become an integral part of their user’s daily life. However, due to the inherent openness of online social networks, anyone can join these networks, which inevitably provides an opportunity for malicious users to spread incorrect or illegal information [1], [2]. Therefore, evaluating social trust, which plays a crucial role in the functionality and operation of social networks, has become an important topic in online social network analysis.

Trust is the extent by which one user (trustor) expects that another user (trustee) performs a given action [3]. Trust evaluation is to evaluate the pairwise trust relationship between two users who are directly or indirectly connected within online social networks. As shown in Fig. 1, trust-based online social networks usually contain multiple types of social trust relationships. The trust relationship is usually asymmetric, that is, there may be two trust relationships in opposite directions between two users. There are many different attempts proposed to evaluate the social trust in online social networks [4], [5], [6], [7], [8], e.g., the subjective logic-based methods [9], [10], [11], which follow the assumptions of cognitive recognition and introduce the uncertainty inference process for the subjective nature of trust. The probability statistics-based methods [12], [13], [14], rely on statistical distributions to represent and model social trust relationship in a computational way. The machine learning-based methods [3], [15], [16], [17], use some machine learning techniques such as matrix factorization to model the trust evaluation task as a learnable problem. However, these existing approaches usually have high computational complexity or poor performance because they do not consider the user’s attribute information.

In recent years, with the great success of deep learning, graph neural networks (GNNs) [18], [19], [20], as powerful tools for processing graph data, have shown superior performance on various network analysis tasks, such as node classification [21], [22], [23], link prediction [24], [25] and recommendation [26], [27]. The essence of GNNs is the process of information propagation and aggregation guided by graph structure. These GNN-based methods obtain meaningful representation of nodes/edges in a network by integrating the neighborhood information of nodes/edges. On the other hand,
an online social network based on social trust can be thought of as a trust graph where the nodes are social users and the edges are the trust relations between them. The edge in the graph can represent the trust relationship between two nodes. Therefore, it is significant to utilize the powerful representation learning capabilities of GNN for trust evaluation tasks.

To our best knowledge, there has been only one attempt to apply GNNs to trust evaluation in online social networks, i.e., Guardian [28], presented very recently. Guardian divides the neighbor nodes into the set of in-degree neighbor nodes and the set of out-degree neighbor nodes, and uses a graph convolutional network (GCN) [29] layer for information aggregation, respectively. It uses a mean aggregator to aggregate the information of different first-order neighbors, and aggregates high-order neighbor information by stacking multiple GCN layers. But the design of Guardian does not take full account of the nature of social trust in social networks, e.g., the propagative and composable nature, which are however essentially important for trust evaluation. To sum up, in order to better apply GNNs to trust evaluation, there are three main challenges as follows.

1) The propagative nature indicates that trust can be passed between users along a chain, so we can obtain the trust value between any two users who are indirectly connected through the chain. Guardian fails to explicitly consider the role of the social trust chain, which will result in redundancy or lack of effective information. In this context, the first challenge is how we can explicitly integrate the trust chain into GNN frameworks in order to better model the propagative nature.

2) Due to the asymmetry of the trust relationship, the directionality of trust propagation also needs to be considered. Simply grouping neighbor nodes based on in-degree and out-degree is not suitable for trust chains. Therefore, the second challenge is how to define a directional propagation pattern for trust chains.

3) The composable nature indicates us that when there are multiple trust chains between two users, the trust value needs to be aggregated by considering the interaction between these chains. The mean aggregator of Guardian cannot distinguish the information from different chains. Thus, the third challenge is how to assign different weights according to the importance coefficients of neighbor nodes to consider the composable nature more comprehensively.

Facing the above challenges, we propose a GNN-based trust evaluation method that comprehensively utilizes the nature of social trust, namely TrustGNN. Since there are usually multiple types of trust relationships in online social networks, we first define multiple specific trust chains according to the trust types. The trust chain is composed of multiple users and trust relationships. Inspired by knowledge graph embedding (KGE) methods, we define the propagative pattern of information on chains by considering the interaction between users and trust relationships in a chain, as well as the directionality of social trust. By doing so, the propagative nature and the asymmetry of social trust can be obtained. Moreover, in online social networks, a target node usually needs to aggregate information from multiple trust chains, i.e., the composable nature of social trust. Considering that different types of trust chains have different impact on the target node, we adopt a learnable attention [30], [31] to learn their contributions for better capturing the composable nature of online social networks.

To summarize, the main contributions of this article are as follows. First, we discuss and clarify what is essentially necessary for GNN to deal with trust evaluation. And then, we introduce that GNN, as an effective tool for processing graph-structured data, can be used for trust evaluation in a more natural way. Second, we propose a GNN-based online social network trust evaluation method (TrustGNN), which more comprehensively and essentially integrates the propagative, composable, and asymmetric nature of social trust into the same GNN framework. Third, extensive experiments and analyses on two online social networks demonstrate the superiority of the proposed method over the state-of-the-art methods.

The rest of this article is organized as follows. Section II discusses the related work. Section III gives the problem definitions and analysis. Section IV proposes the new approach TrustGNN. Finally, we conduct extensive experiments in Section V and conclude in Section VI.

II. RELATED WORK

A. Trust Evaluation

Due to the significance of trust in online social networks, trust evaluation has been widely studied and reviewed [4], [5], [6], [7], [8]. Traditional trust evaluation methods mainly use the experience of direct and indirect interactions between trustees and trustees to assess trust. For example, MoleTrust [32] starts from the source node, captures the input trust edges by walking, and discards those trust edges whose trust score of a user is lower than a specific threshold. Finally, a user’s trust score is the average of all the accepted incoming trust edge values, weighted by the trust score of the user who has issued the trust statement. TNA-SL [9] formalizes trust relationships as subjective trust measures. It simplifies the complex trust graph to a series-parallel graph by deleting the most uncertain path to obtain a canonical graph. Trust measures are expressed as beliefs, and subjective logic is used to calculate the trust between any parties in the network. AssessTrust [10] assumes social trust among users is determined by the objective evidences, and define interpersonal trust as a trinary event (belief, distrust, neutral). It distinguishes the posteriori and priori uncertainties existing in trust, and the difference between distorting and original opinions, and uses Dirichlet distribution to model opinion vectors to assess multihop interpersonal trust. OpinionWalk [11] models social trust based on subjective logic and uses an opinion matrix to model the topology of the trust graph. Each entry in the matrix is a direct opinion of two corresponding users. They then devised multiple matrix-like operations by using discounting and combining operations instead of traditional multiplication and summation. In this matrix-like operations, the discounting and combining operations are adopted to model trust propagation and fusion. Itrust [13] quantifies interpersonal trust by analyzing the frequency of social interactions
between users and their friends on Facebook. They adopt bidirectional interaction relationships in online social networks to deconstruct users’ social behaviors and apply principal component analysis to estimate interpersonal trust. In addition, there are some classic traditional trust evaluation methods for other types of networks [33], [34], [35], [36]. For example, TIDTM [37] models traffic data trust for vehicular ad hoc networks. It models trust information based on Dempster–Shafer theory, and finds malicious nodes by evaluating the trust of vehicles to solve the traffic congestion problem. Alnasser and Sun [38] propose a trust model based on fuzzy logic to protect the smart grid network from malicious network attacks. It uses predefined fuzzy logic rules to model the uncertain relationship of trust and develops an adaptive trust evaluation strategy. Dai et al. [39] proposes an entropy-based trust modeling and evaluation method for wireless sensor networks (WSNs). It uses directional graph to describe trust in WSN, and proposes an entropy-based trust evaluation method based on the definition of entropy, so as to obtain the relative credibility between any two nodes.

Very recently, many trust evaluation methods based on machine learning technology are also constantly being proposed. For example, Matri [3] is a multiaspect trust inference model using matrix factorization. It views the trust evaluation problem as a recommendation task, then borrows the rich methodologies from collaborative filtering. NeuralWalk [15] first designs a neural subunit named WalkNet to model the propagation and fusion of direct trust in trust social networks. Then, the unknown multihop trust relationship between users is calculated by iterating this subunit continuously. iSim [16] is an integrated and time-aware similarity-based collaborative filtering approach, which integrates vector space similarity, matrix factorization, and propagated trust for trust prediction. AtNE-Trust [17] obtains user representations by capturing the properties of trust network structures and multiview user attributes, and jointly optimizes the representation learning module and the trust evaluation module. Especially, with the success of deep learning, GNN-based model Guardian [28] has been proposed. Guardian divides the neighbor nodes directly connected to the target node into in-degree neighbor nodes and out-degree neighbor nodes, and uses the convolutional layer for information aggregation, respectively. Then it obtains high-order neighbor information by stacking multiple convolutional layers.

B. Graph Neural Networks

GNNs [18] have been proved to be an effective tool for analyzing graph-structural data. Most GNNs learn node representations by aggregating message from neighboring nodes based on the guidance of graph topology. GNNs are first applied to homogeneous graphs. For example, GCN [29] simplifies spectral graph convolutions [40] by using a localized first-order approximation. GAT [30] considers that different neighbors of the target node may have different importance, and integrates the importance coefficients into the aggregation function. GraphSAGE [41] aggregates the neighbor information of the target node in a learnable manner, and learns node representations in an inductive manner by using node-level sampling methods. R-GCN [42] designs multiple convolution operations in units of edge types to model the impact of different types of edges on the target node. GIN [43] aims to study the expressive power of GNNs by studying the ability to distinguish any two graphs, and proposes a new framework, which is shown to have the same expressive power as Weisfeiler-Lehman. Beyond homogeneous graphs, there are also some GNNs for heterogeneous graphs. Heterogeneous graphs contain more than one type of nodes or edges, which can better model real-world systems. In heterogeneous GNNs, the most important design is using discriminate operations to distinguish the role of different types of nodes/edges in the GNN framework. For example, HAN [44] and MAGNN [45] use attention mechanism to learn the weights for information with different semantic. HetSANN [46] and HGT [47] propose a type-aware attention layer to model the relationships between different types of nodes without directly adopting traditional convolutional layers. In addition, GNNs have also been continuously extended to computer vision [48], natural language processing [49], [50], [51] and other fields [18], and have achieved great success.

Despite the great success of previous work, there is seldom GNN-based work for trust evaluation tasks. A trust graph can be seen as a heterogeneous graph but it has more field-related properties. In this article, we show our insights about trust graph and design a new GNN-based trust evaluation method by integrating trust properties into the GNN framework.

C. Knowledge Graph Embedding

KGE focus on learning low-dimensional embeddings for entities and their relations in knowledge graph (KG) [52], [53]. The learned embeddings can be used for KG tasks such as KG alignment [54], [55] and relation predictions [53], [56]. KGE methods can be viewed as modeling (head entity, relation, tail entity) triples. Concretely, a scoring function is defined to measure the plausibility of triplets given embeddings and help update the representation of the training data. The scoring functions have many designing criteria, such as translation relation [57], rotational relation [58], inner product [59], and others [60], [61]. For example, RotatE [58] is a recent proposed method. It maps the entities and relations in a KG to complex vector space, and defines the relations between entities as rotations from source entities to target entities. The interaction between entities and relations in score functions maintains the semantic relationships between entities and relations, and also can be applied to model trust relationships. In this article, we extend design principles in KGE to model the propagative nature of trust, not only for triplets but also for more complex interaction, e.g., multiple user and relationships in a trust chain.

III. PROBLEM DEFINITION AND ANALYSIS

Trust Graph. In this article, we define trust relationships in the online social network as a directed trust graph \( G = (V, E, \mathcal{R}, \phi) \), where node set \( V \) represents users and edge set \( E \) represents trust relationships among users. The trust type set \( \mathcal{R} \) enumerates all trust relationship types in
the graph $\mathcal{G}$. The mapping function $\phi : \mathcal{E} \rightarrow \mathcal{R}$ maps observed edges to trust relationship types, so each edge strictly corresponds to a specific trust relationship. Moreover, the trustworthiness is different in different application domains. For example, trustworthiness can be simply classified into two types, i.e., $\mathcal{R} = \{\text{Distrust, Trust}\}$. But in some more complicated situations such as in Advogato $^1$ and Pretty-Good-Privacy $^2$ (PGP), the trust relations have four types, i.e., $\mathcal{R} = \{\text{Observer, Apprentice, Journeyer, Master}\}$.

**Trust Evaluation.** The trust evaluation task is to predict the unobserved trust relationships in a trust graph $\mathcal{G}$. Specifically, given a trust graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{R}, \phi)$, the goal is to train a model $f(\cdot)$. For nodes $u \in \mathcal{V}$, $v \in \mathcal{V}$, and edge $(u, v) \notin \mathcal{E}$, the model $f(\cdot)$ can predict the trust relationship for the two nodes, i.e., $f((u, v)) \rightarrow \mathcal{R}$. Note that trust relationships are directed, and the trust relationship from node $u$ to node $v$ does not equal to the relationship from node $v$ to node $u$. Therefore, $f((u, v)) \neq f((v, u))$.

**Properties in Trust Graph.** Before discussing the proposed method, we first show some insights about trust graphs and analyze some properties which are used in our method. For any two nodes $u$ and $v$, there will be a kind of trust relationship from node $u$ to node $v$ if $(u, v) \in \mathcal{E}$. We define $u$ as the trustor and $v$ the trustee. The two common-used properties in trust evaluation are the propagative nature and composable nature of social trust $[28]$. Specifically, the propagative nature of social trust means that trust can be passed among nodes, creating trust chains that connect two nodes who are indirectly connected in the graph. For example, in Fig. 2(a), node $u$ trusts node $a$ with a trust value of 2 and node $a$ trusts node $v$ with a trust value of 1. There is a trust chain between node $u$ and node $v$, which can be taken as evidence to create trust relationship from node $u$ to node $v$. The composable nature of social trust means that there may be several trust chains between two nodes, and these chains interact to provide evidence for us to create a new trust relationship between these two nodes [see Fig. 2(b)].

**Trust Chain.** In the trust graph, a trust chain is defined as a path $v_1 \xrightarrow{r_1} v_2 \xrightarrow{r_2} \ldots \xrightarrow{r_l} v_{l+1}$ with trust types $r_1, r_2, \ldots, r_l \in \mathcal{R}$, simplified as $r_1r_2\ldots r_l$, which represents the link path created when trust is passed from one node ($v_l$) to another ($v_{l+1}$).

In this article, we define two nodes connected by a trust chain as neighbor nodes. In particular, the head node $u$ is the trust chain based trustor neighbor of the tail node $v$, while the tail node $v$ is the trust chain based trustee neighbor of the head node $u$.

**Graph Neural Networks.** GNNs $[18]$ are powerful tools for analyzing graph-structural data. A GNN can be interpreted as smoothing local information through propagation and aggregation operations in a graph, and finally learning node representations that can be applied to various downstream tasks. After $k$ iterations of propagation and aggregation, a node’s representation can capture topology and attribute information within its $k$-hop neighborhood in the graph. Formally, in the $k$th layer, the representation $h_u^{(k)}$ of node $u$ is

$$a_v^{(k)} = \text{Prop}^{(k)}(h_v^{(k-1)}), \quad v \in \mathcal{N}(u) \quad (1)$$

$$h_u^{(k)} = \text{Agg}^{(k)}(h_u^{(k-1)}, \{a_v^{(k)} : v \in \mathcal{N}(u)\}) \quad (2)$$

where $\mathcal{N}(u)$ is the set of the direct neighbors of node $u$, Prop$^{(k)}(\cdot)$ and Agg$^{(k)}(\cdot)$ are two functions implemented by neural networks in the $k$th GNN layer. Prop$^{(k)}(\cdot)$ corresponds to the node representation transformation in the propagation process and Agg$^{(k)}(\cdot)$ aggregates the transformed neighbor node representations and its own representation.

In this work, we use the GNN framework to learn node embeddings and evaluate trust relationships between two nodes based on their embeddings. The key novelty here is that we design a new GNN to simultaneously model propagative and composable nature of trust graphs. Intuitively, different trust chains should have different effects for creating trust. Therefore, there should be different propagation rules on different trust chains in GNNs. In this way, the propagative nature in trust graphs can be well learned. Moreover, when GNNs aggregate neighbor information from different trust chains, it should distinguish the contribution of information from different chains and generate node representations based on their contributions. This is because a trust chain composed of relationships with high value is more helpful to create a new trust relationship. Thus, GNNs can capture the composable nature in trust graphs and learn comprehensive node embeddings for trust evaluation.

In the following, we will show the proposed model based on the ideas discussed above. All notations that we used in this article and their explanations are provided in Table I.

---

1http://trustlet.org/datasets/advogato/
2http://networkrepository.com/arenas

**TABLE I**

| Notations | Explanations |
|-----------|--------------|
| $x_{node}$ | The attributes of a node. |
| $x_{edge}$ | The attributes of an edge. |
| $p$ | A trust chain. |
| $P_j$ | The $j$-th type of trust chains. |
| $h_{v_l, H}$ | The latent representation of node $v_l$'s all nodes. |
| $r_i$ | The latent representation of the $i$-th edge type. |
| $z_{v, Z}$ | The final node embedding vector of node $v$'s all nodes. |
| $q$ | The attention vector. |
| $w_{P_j}$ | The importance of chain type $P_j$. |
| $\alpha_{P_j}$ | The normalized weight of chain type $P_j$. |
| $W, b$ | The parameters of neural networks. |
| $Y$ | The predicted trust relationships. |
| $\tilde{Y}$ | The ground truth. |

---
IV. METHOD

A. Overview

In this section, we present our TrustGNN. Since the propagative and composable nature is the basis for creating new trust, we integrate these two properties into the GNN framework, and capture them in a learnable manner. The overview of TrustGNN is illustrated in Fig. 3, which consists of four components. (i) TrustGNN first initializes the attributes of nodes and edges and projects them into a latent space, i.e., attribute transformation. (ii) The information is propagated along trust chains. Here TrustGNN extends KGE methods to GNN to better model the propagative pattern of trust, and further considers the asymmetry of trust, i.e., trust chain-based propagation. (iii) TrustGNN identifies the information propagated from different chains and aggregates the information in a discriminative way, and finally generates node embeddings, i.e., trust chain based aggregation. (iv) TrustGNN uses a multilayer perceptron (MLP) layer to predict trust relationships based on node pair embeddings, i.e., the predictor layer.

B. Attribute Transformation

In a complete trust graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{R}, \phi)$, there are homogeneous nodes and heterogeneous edges, and nodes and edges both have their attributes. These nodes and edges may have different attribute vector dimensions. Even though they happen to have the same dimension, they may still be in different vector spaces. Therefore, we need to transform these attributes into a common vector space to feed to the GNN framework.

TrustGNN uses a linear transformation to transform all node attributes. For each node $v \in \mathcal{V}$, there is

$$h_v = W_{\text{node}} \cdot x_v$$

(3)

where $x_v$ is the attribute vector of node $v$, $h_v$ the transformed representation of node $v$ and $W_{\text{node}}$ a learnable parameter matrix. TrustGNN has different linear transformations corresponding to different types of edges. For the $i$th type of edge, there is

$$r_i = W_{\text{edge}^i} \cdot x_{\text{edge}^i}$$

(4)

where $x_{\text{edge}^i}$ is the attribute vector of the $i$th edge type, $W_{\text{edge}^i}$ a learnable parameter matrix specific to the $i$th edge type, and $r_i$ the transformed representation of the $i$th edge type.

Note that not all datasets have completed attributes for nodes and edges. For the datasets missing node or edge attributes, we initialize these missing attributes as random vectors and treat these vectors as a part of learnable parameters in neural networks.

C. Trust Chain Based Propagation

In trust graphs, the trust may be passed from one node to another along a trust chain so that two nodes at the head and tail of a trust chain can create a new trust relationship, in which the head node is a trustor and the tail node is a trustee. The message passing in GNNs is a similar propagative pattern with trust propagation in a trust graph. Therefore, we can integrate trust chains into GNNs and make GNNs propagate information along trust chains. However, the length of a trust chain can be infinite and there can be infinite types of trust chains in a trust graph. In TrustGNN, we limit the maximum length of the trust chain to the preset hyperparameter $K$, which is reasonable because trust will decrease in the propagation process and a too long trust chain is not beneficial to creating new trust.

Consider a trustee node $v$ and a trust chain $p$ of length $k$ ($k \leq K$): $u \xrightarrow{r_1} \cdots \xrightarrow{r_k} v$, the node $v$ should receive the information from node $u$ as well as edges $\{r_1, \ldots, r_k\}$ in the chain. Here, TrustGNN uses a RotatE-like method [58] to compose the attributes of node $u$ and edges $\{r_1, \ldots, r_k\}$ in the
complex plane

\[ h_v^p = u \circ r_1 \circ \cdots \circ r_k \]  

(5)

where \( u, r_1, \ldots, r_k \in \mathbb{C}^d \), \( \mathbb{C}^d \) denotes the complex plane, the modulus \(|r_i| = 1\) and \( \circ \) is Hadamard (elementwise) product. Due to the propagation property of RotatE, the Hadamard product among edges \((r_1 \cdots \circ r_k)\) can be seen as the new type of composed relationship specific to the trust chain \( p \), and \( h_v^p \) is the information that node \( v \) receives on the chain \( p \).

Trust is asymmetric. It is worth noting that node \( v \) also serves as a trustor node in a trust graph, and a comprehensive node embedding should contain information from its trustee role and trustor role. Thus, for the same trust chain \( p \) with node \( v \) being the head \((p: v \overset{\rightarrow}{\leftrightarrow} \cdots \overset{\rightarrow}{\leftrightarrow} u)\), TrustGNN computes

\[ \tilde{h}_v^p = u \circ \tilde{r}_1 \circ \cdots \circ \tilde{r}_1 \]  

(6)

where \( \tilde{r}_i \) is conjugate with \( r_i \) in formula (5). Due to the inversion property of RotatE, the conjugate vector \( \tilde{r}_i \) can present the inverse relationship of \( r_i \) (trust and trusted), and \( \tilde{h}_v^p \) is the information that node \( v \) receives when node \( v \) serves as a trustor node in chain \( p \).

Discussions: First, for the nodes in a trust chain, TrustGNN only considers the attributes of the head/tail node but ignores the nodes in between. This is because we just want to capture the trust relationship between head and tail nodes through a trust chain. Other nodes in the chain may be the head/tail node in other chains and thus can be computed to create trust relationships in other propagation processes. Second, RotatE [58] is a KG embedding method. It maps each entity and relation in a KG to the complex vector space and defines each relation as a rotation of the source entity to the target entity. The propagation property of RotatE means that two relations can be composed (Hadamard product) to generate a new type of relations, which can be thought of as a new rotation in a complex plane. TrustGNN extends RotatE to compose multiple relations (edges) to generate more complex relations. The inversion property of RotatE means that two relations with opposite semantics can be represented by conjugate vectors in the complex plane. TrustGNN uses the inversion property to compute propagative information from views of both trustor and trustee of a node. Moreover, when TrustGNN computes formulas (5) and (6) from left to right, the intermediate results exactly correspond to the representation of intermediate nodes of a chain. This is another reason why we can ignore the nodes inner a chain.

D. Trust Chain Based Aggregation

There are often multiple different types of trust chains in a trust graph and these chains interact to provide evidence for us to create a new trust relationship between the two nodes. Accordingly, a node aggregates information from several chains with different types in our TrustGNN framework. TrustGNN uses a learnable attention score [30], [31] to distinguish the contribution of different types of chains. Before computing the attention score, TrustGNN first summarizes the information on the chains sharing the same type. Consider a node \( v \) and a set chains in the \( j \)th type, TrustGNN aggregates the information via a sum operation

\[ h_v^{P_j} = W_{P_j} \cdot \left( h_v + \sum_{\psi(p)=P_j} h_v^p \right) \]  

(7)

where \( \psi(\cdot) \) is a mapping function to indicate which type a trust chain is, \( P_j \) the \( j \)th type of trust chain, and \( W_{P_j} \), a learnable parameter matrix specific to \( P_j \), \( h_v^{P_j} \) is the representation of node \( v \) for the \( j \)th type chain. Correspondingly, we use \( H_{P_j} \) to represent all nodes. Here, a sum operation means TrustGNN treats chains with the same type equally, because chains with the same type have the same propagative process [see formula (5)] and thus should have equal contribution for node embeddings.

Then, for the summarized information \( H_{P_1}, H_{P_2}, \ldots, H_{P_j} \), TrustGNN aggregates them with different weights as chains with different types have a different impact on creating trust and, moreover, there is usually a complex interaction between different types of chains. TrustGNN learns weights through a discriminative attention mechanism [30], [31] to model the composable nature in trust graphs. Specifically, TrustGNN first transforms chain-type-specific representation \( (h_v^{P_j}) \) through a nonlinear transformation, and then measures the score of the chain-type-specific representation as the similarity of transformed representation with a chain-type-level attention vector \( q \). Furthermore, TrustGNN averages the score of all the chain-type-specific node representations, which can be explained the importance of each chain type

\[ w_{P_j} = \frac{1}{|\mathcal{V}|} \sum_{v \in \mathcal{V}} q^T \cdot \tanh \left( \mathbf{W}_{\text{attn}} \cdot h_v^{P_j} + b \right) \]  

(8)

where \( \mathbf{W}_{\text{attn}} \) is a learnable parameter matrix, \( b \) a bias vector, \( q \) the chain-type-level vector of attention. The parameter \( \mathbf{W}_{\text{attn}} \) and \( b \) are shared for all chain types. Then, the softmax function is adopted to normalize the score

\[ \alpha_{P_j} = \frac{\exp(w_{P_j})}{\sum_{k=1}^{k} \exp(w_{P_k})} \]  

(9)

which can be interpreted as the contribution of the chain type \( P_j \). The higher the weight of \( P_j \), the more contribution \( P_j \) provides in the composable nature. TrustGNN aggregates these chain-type-specific representations to obtain the embeddings

\[ Z = \sum_{j=1}^{k} \alpha_{P_j} \cdot H_{P_j}. \]  

(10)

Note that in Section IV-C, TrustGNN computes node representations from two aspects: the trustee role and the trustor role. The embedding \( Z \) only aggregates the information about the trustee role. Therefore, TrustGNN needs to compute an embedding \( \tilde{Z} \) for the trustor role and combines the two to get a more comprehensive node embedding

\[ \tilde{Z} = \sum_{j=1}^{k} \tilde{\alpha}_{P_j} \cdot \tilde{H}_{P_j}. \]  

(11)

where \( \tilde{H}_{P_j} \) is the node representations about the trustee role on the \( P_j \) chain type, and \( \tilde{\alpha}_{P_j} \) is the corresponding weight.
computed by formula (9). Note that $\tilde{\alpha}_P$ and $\alpha_P$ are irrelevant because TrustGNN uses another parameters to compute $\tilde{\alpha}_P$, i.e., $\tilde{\bar{W}}_{\text{attr}}$ and $\bar{b}$. This means that a chain will have different contributions when it serves for embeddings about different roles (trustee or trustor). To fully preserve the information of the node as both trustor and trustee, TrustGNN finally concatenates $Z$ and $\tilde{Z}$ to obtain the final embedding

$$Z_{\text{final}} = W \cdot (Z \parallel \tilde{Z})$$  \hspace{1cm} (12)

where $\parallel$ is the concatenation operation and $W$ a learnable parameter matrix to transform the embeddings into a low-dimensional space.

E. Predictor Layer

TrustGNN is a trust evaluation model based on node embeddings. Specifically, given two nodes $u$ and $v$ as a trustor-trustee pair, TrustGNN predicts their trust relationships based on their embeddings

$$\tilde{y}_{u-v} = \sigma(\text{MLP}(z_u \parallel z_v))$$  \hspace{1cm} (13)

where $z_u$ and $z_v$ are node embeddings (two vectors in $Z_{\text{final}}$), $\parallel$ is the concatenation operation, $\text{MLP}(\cdot)$ is a multilayer perceptron, and $\sigma(\cdot)$ is an activation function. Note that because of asymmetric property of trust relationships in trust graphs, $\tilde{y}_{u-v} \neq \tilde{y}_{v-u}$. As the number of trust types in trust graphs is limited, the trust evaluation task is equivalent to the classification task based on embedding pairs. TrustGNN is a semisupervised model and it minimizes cross-entropy between the predicted values and ground-truth values as the loss function

$$\mathcal{L} = \text{cross\_entropy}(Y, \hat{Y})$$  \hspace{1cm} (14)

where $Y$ is the observed categorical values in the trust graph and $\hat{Y}$ the predicted result by TrustGNN. TrustGNN is an end-to-end model, as the parameters in a predictor layer and that in embedding module are updated together via backpropagation, under the guidance of this unified objective function.

V. EXPERIMENTS

In this section, we first provide the experimental setup, including dataset description, baselines for comparison, and parameters and model settings. Then we show the comparison results with baseline methods and finally give the ablation experiments and parameter analysis.

A. Experiment Setup

1) Datasets: We adopt two widely-used, real-world datasets for model evaluation (as done in most related works such as Guardian [28], NeuralWalk [15] and OpinionWalk [11]). The statistics of the two datasets are shown in Table II.

| Datasets | Advogato | PGP | Ciao | Epinions |
|----------|----------|-----|------|----------|
| Nodes    | 6,541    | 38,546 | 4409 | 8174     |
| Edges    | 51,127   | 317,979 | 177,298 | 449,178 |

2) Baselines: We compare the proposed TrustGNN with four state-of-the-art methods, corresponding to four popular types of trust evaluation methods, i.e., a matrix factorization-based method, a walk-based method, a deep neural network-based method, and a GNN-based method.

1) Guardian [28] applies GNN to the trust evaluation task for the first time. It designs a trust convolutional layer to model trust interactions in social networks. The method is also designed to incorporate the two trust relationships of popularity and engagement into the model learning process, respectively. It finally predicts the trust relationship of each trustor-trustee pair based on the representations. Note that our proposed TrustGNN is also a GNN-based method, while TrustGNN better models the propagative nature and composable nature of trust among users to achieve better performance.

2) NeuralWalk [15] is a deep neural network-based method. It first models the propagation and fusion of direct trust among users in the trust social network by designing a neural network module named WalkNet. Then, with WalkNet as the neural subunit, the multihop social trust among users in the network is captured in the form of iterative neural subunits. This approach is the state-of-the-art modeling scheme for trust evaluation, but it typically requires greater computational and memory complexity than other approaches.

---

1. http://www.cse.msu.edu/~tangjili/trust.html
3) OpinionWalk [11] uses random walk to model the trust relationship between users. The method uses the breadth-first search method to create the trust relationship for every two users who do not have a direct trust relationship, uses Dirichlet distribution to model the data distribution, and expresses the direct trust value between users in the form of a matrix.

4) Matri [3] uses matrix factorization to infer trust relationships between users. It utilizes locally generated trust relationships to characterize multiple complex latent factors between each trustor and trustee, and further introduces prior knowledge and trust propagation to improve prediction accuracy. The trust relationship between each node pair is captured by computing the similarity between the trustor’s latent vector and the trustee’s latent vector in a learnable latent space.

5) AssessTrust [10] distinguishes the uncertainties existing in trust. It assumes social trust among users is determined by the objective evidences, and defines interpersonal trust as a trinary event. Leveraging on this new definition of trust, it designs the discounting and combining operations on opinions, and uses Dirichlet distribution to model opinion vectors to assess multihop interpersonal trust.

6) MoleTrust [32] proposes a personalized way to compute the trustworthiness of a particular user. It starts from the source node, captures the input trust edges by walking, and discards those trust edges whose trust score of a user is lower than a specific threshold. Finally, a user’s trust score is the average of all the accepted incoming trust edge values, weighted by the trust score of the user who has issued the trust statement.

3) Evaluation Metrics: Follow the metrics used in Guardian [28], we adopt two popular metrics to evaluate the effectiveness of the new proposed method, including Micro-F1 and mean absolute error (MAE). In the experiments, we run each method 20 times and take the average of these results as the final result. Note that larger Micro-F1 values indicate better prediction performance, whereas smaller MAE values indicate better prediction performance. For the split of the datasets, since OpinionWalk, AssessTrust, and MoleTrust are deductive, we conduct experiments with randomly selected 1000 trustor-trustee pairs for both datasets. As for other baselines as well as our TrustGNN, we randomize the two datasets into 80% trustor-trustee pairs to form the training set and the rest for the test set. When computing Micro-F1, we map the predicted relationship into categorical values, i.e., \{Observer: 0, Apprentice: 2, Journeyer: 3, Master: 4\} and \{Distrust: 0, Trust: 1\}. When computing MAE, we follow the Matri [3] and Opinion [11] to map the relationship into scalar values, i.e., \{Observer: 0.1, Apprentice:0.4, Journeyer: 0.7, Master: 1\} and \{Distrust: 0, Trust: 1\}. When computing Micro-F1, we follow the Matri [3] and Opinion [11] to map the relationship into scalar values, i.e., \{Observer: 0.1, Apprentice:0.4, Journeyer: 0.7, Master: 1\} and \{Distrust: 0, Trust: 1\}.

4) Parameter Settings: For the baselines, we adopt their default parameter settings as they often lead to the best results. For our TrustGNN, we use cross-validation to set the parameters, and all parameters have been optimized on the Advogato dataset and are then reused in the remaining datasets. We set the learning rate to 0.005, the dimensions of nodes and edge attributes to 1024, and the dimension of the attention vector \((q, r, z)\) to 128. We set the maximum length of trust chains \(K\) to 2 since it is typically sufficient to model trust relationships in online social networks. And when \(K\) is too large, there will be additional computational cost and more noise may be introduced. We implemented our proposed method using Python-3.7\(^5\) and Pytorch-1.6.\(^6\) All the experiments were conducted on the same machine with a Linux system (Ubuntu 5.4.0), Intel Xeon CPU E5-2680, 128-GB RAM and two NVIDIA 1080Ti GPUs.

### B. Performance Comparisons

We evaluate the performance of TrustGNN on four datasets. The experimental results are provided in Table III where the best results are in bold. The proposed TrustGNN outperformed all baselines. Compared to the second best results from Guardian or NeuralWalk, TrustGNN improves by an average of 0.9% on four datasets in terms of Micro-F1. Correspondingly, the error rate reduces by 4.1% on average.

| Methods | Advogato | PGP | Ciao | Epinions |
|---------|----------|-----|------|----------|
|         | Micro-F1 | MAE | Micro-F1 | MAE | Micro-F1 | MAE | Micro-F1 | MAE | Micro-F1 | MAE |
| TrustGNN | 74.4%   | 0.081 | 87.2% | 0.083 | 72.8% | 0.050 | 81.8% | 0.032 |
| Guardian | 73.0%   | 0.087 | 86.7% | 0.086 | 71.2% | 0.056 | 80.5% | 0.039 |
| NeuralWalk | 74.0% | 0.082 | – | – | 71.5% | 0.051 | 78.1% | 0.048 |
| OpinionWalk | 63.3% | 0.232 | 66.8% | 0.251 | 59.6% | 0.198 | 67.7% | 0.243 |
| Matri | 65.0% | 0.141 | 67.3% | 0.136 | 62.3% | 0.154 | 64.9% | 0.281 |
| AssessTrust | 63.9% | 0.230 | – | – | 57.8% | 0.212 | 68.4% | 0.223 |
| MoleTrust | 58.4% | 0.309 | 64.0% | 0.332 | 58.2% | 0.200 | 65.7% | 0.256 |

\(^5\)https://www.python.org/  
\(^6\)https://pytorch.org/
of improvements made by TrustGNN over the top two baseline methods (Guardian and NeuralWalk) utilizing paired t-test. When the significance test results are less than 0.05, it can be proved that the proposed method is significantly better than the baseline, and the smaller the test result, the stronger the significance advantage. As shown in Table IV, the significance test results of TrustGNN over two comparison baselines are far less than 0.05 on different datasets. These results show that TrustGNN has statistically significant improvements compared with these SOTA methods. Also of note is that, because of the huge computational and memory complexity of NeuralWalk, it fails to get the results on PGP dataset. In contrast, TrustGNN is lightweight and can meanwhile achieve the best performance.

Besides, as shown in Table III, there is a great gap between neural network-based methods (TrustGNN, Guardian, NeuralWalk) and the others (Opinion, Matri, AssessTrust, and MoleTrust). This means that the powerful learning ability of neural networks allows it to better solve the trust evaluation task. In the above three neural networks-based methods, the newly proposed TrustGNN has more elaborate designs. TrustGNN follows the principle of KGE to propagate information on chains, which can better model the propagative nature of social trust. It also applies attention mechanism between different types of chains, which is better to capture the composable nature to distinguish the contributions of different type of chains when creating new trust relationships.

We also evaluate TrustGNN on these four datasets with different training and testing splits. Specifically, we set the portions of training set as 40%, 60%, 80% and report the performance in terms of Micro-F1 and MAE. We select Guardian and Matri as comparison algorithms. The results are shown in Table V. Obviously, TrustGNN achieves best result across all splits on all datasets. This further demonstrates the robustness and stability of TrustGNN model.

C. Visualization and Interpretation

We visualize the weight of each type of trust chains in TrustGNN, i.e., \( \alpha \) in formula (9). TrustGNN uses attention mechanism to compute contribution of each type of chains. In the experiments, we limit the length of chains to 2. Here we use Advogato dataset as an example, which has four different types of relationships. Therefore, the number of chain types is \( 4 \times 4 = 16 \). We visualize the top five chain types in Fig. 4(a). We use scalars to represent different types of relationships \{Observer: 1, Apprentice:2, Journeyer: 3, Master: 4\} so that large values indicate strong trust relationships. From Fig. 4(a) we can see that the top five types of chains contain relationships with large values. This is reasonable because strong trust relationships are often more helpful to creating new trust relationships. Moreover, TrustGNN accurately assigns the highest weight for the chain type with two strongest relationships (4 \( \rightarrow \) 4). This demonstrates that TrustGNN is consistent with the laws of reality and has good interpretation. Note that there are also some relationships with small values in the top five types of chains. This may be because trustworthiness is
imbalance in trust graphs. As shown in Fig. 4(b), the number of relationships with values of 1 and 2 is much larger than relationships with values of 3 and 4. The model may be biased due to imbalance data, but in general, TrustGNN can learn high weight for chains with strong trust relationships.

D. Analysis of Attribute Initialization Methods

As some datasets may not have raw attributes, we need to define the attributes of nodes and edges in advance. In Guardian [28], they use node2vec [62] embeddings and one-hot vectors as node/edge attributes. We follow the Guardian’s setting to study what types of attributes are more suitable for our TrustGNN. In this experiment, node attributes are defined as embeddings pretrained from node2vec or initialized as a set of learnable parameters of the neural networks. Edge attributes are defined as one-hot vectors or initialized as a set of learnable parameters of the neural networks. We test all the cases and report the Micro-F1 and MAE score in Table VI. From Table VI we can find that TrustGNN achieves the best results when node and edge attributes are both initialized as learnable parameters. This may be because the learning ability of neural networks can learn good attributes for nodes and edges. We also noticed that using node2vec embeddings will reduce the performance while using one-hot vectors has little impact on the performance. The one-hot vectors assign discriminative attributes for different types of edges so that it can still distinguish the role of different types of trustworthiness. On the other hand, because node2vec is proposed for a graph with homogeneous edges, it may not be so suitable for trust graphs with multirelations.

E. Ablation Study

Similar to most deep learning methods, TrustGNN consists of several different components that may have an important impact on the model performance. To provide intuitive understanding of the model’s components, we perform experiments comparing TrustGNN with its four variants. The variants are defined as follows. (1) In the trust chain-based propagation process (see Section IV-C), a node will receive two kinds of information corresponding to its two roles. Here we ignore the trustor role of nodes and make a node only receive the information from its trustee role, named TrustGNN-1. (2) We also ignore the trustee role of nodes and make a node only receive the information from its trustor role, named TrustGNN-2. (3) In trust chain-based aggregation, we employ a sum operation instead of discriminative aggregation, named TrustGNN-3. (4) Instead of trust propagation based on the trust chain, we only propagate trust through direct neighbors and capture the information of high-order neighbors by stacking multiple convolutional layers, named TrustGNN-4. We report the average Micro-F1 on four datasets for comparison.

As shown in Fig. 5, we can draw four conclusions. (1) TrustGNN consistently outperforms all its variants on four datasets, illustrating the effectiveness of simultaneously considering two different roles of target nodes, trust propagation based on trust chains, and discriminative aggregation of different trust chains. (2) TrustGNN-1 and TrustGNN-2 have different performance advantages in different datasets, which further illustrates the necessity of comprehensively considering two different roles of target nodes. (3) TrustGNN-3 is consistently significantly lower than TrustGNN, which illustrates the rationality of aggregation considering the importance of different trust chains and can more fully capture the composable nature of trust. (4) TrustGNN-4 is also consistently significantly lower than TrustGNN, which shows that the propagation mechanism based on trust chain can model the propagation nature of network trust more accurately.

F. Parameter Analysis

We further analyzed how model parameters affected TrustGNN performance. The most important hyperparameters of TrustGNN are the maximum length of trust chain $K$ and the attribute dimension of edge/node. Here we report the average Micro-F1 on four datasets.

1) Maximum Length of Trust Chain: In order to analyze the influence of the maximum length of trust chain $K$ on the model performance, we test the performance when $K = 1, 2, 3$ and $4$ on four datasets, respectively. As shown in Fig. 6, the model performance first increases and then decreases with an increase of $K$ on four datasets. This observation is reasonable because trust chains that are too short cannot adequately capture the propagative nature of trust, while trust chains that are too long may introduce noise of low trust as trust will decrease in the propagation process.

In addition, the most time-consuming process in TrustGNN is the propagation and aggregation based on the trust chain, i.e., formulas (5) and (8), which are related to the size of $K$. For all nodes, the time complexity of the propagation mechanism is $O(F(|E_1| + |E_2| + \cdots + |E_K|))$, and the time complexity of the aggregation mechanism is $O(|V|F'(F + T)^k)$, where $|E_k|$ represents the number of trust chains with length $k (k \leq K)$, $|V|$ and $T$ the number of nodes and trust types, and $F$ and $F'$ the dimensions of input and hidden features. These two complexities are closely related to the properties of the dataset (number of nodes and edges, trust type, feature dimension), but both increase with the increase of $K$. However, as shown in Fig. 6, too long trust chains will lead to performance degradation of the model, which indicates that TrustGNN can achieve significant performance with less computational overhead.

2) Attribute Dimension: We also analyze the impact of attribute dimension when TrustGNN initializes node and edge attributes as learnable parameters. We perform a grid search
| Node Attributes | Edge Attributes | Advogato | PGP | Ciao | Epinions |
|----------------|----------------|---------|-----|------|---------|
| Parameter      | Parameter      | 74.4%   | 87.2% | 72.8% | 81.5%   |
| Parameter      | One-hot        | 74.2%   | 87.1% | 72.3% | 80.7%   |
| Node2vec       | Parameter      | 72.4%   | 83.3% | 71.2% | 78.9%   |
| Node2vec       | One-hot        | 72.4%   | 82.0% | 70.7% | 77.1%   |

**TABLE VI**

RESULTS OF TRUSTGNN WITH DIFFERENT TYPES OF ATTRIBUTES

Fig. 6. Parameter analysis of maximum length of trust chain $K$ on four datasets. (a) Advogato. (b) PGP. (c) Ciao. (d) Epinions.

Fig. 7. Parameter analysis of attribute dimensions of nodes and edges on four datasets. (a) Advogato. (b) PGP. (c) Ciao. (d) Epinions.

by searching the attribute dimensions of nodes and edges in $\{64, 128, 256, 512, 1024, 2048\}$. The analysis result of the node attribute dimension and that of the edge attribute dimension are both shown in Fig. 7. They show the same trend. The performances first rise and then fall and TrustGNN achieves the best performance when dimensions of nodes and edges are both around 1024. This may be because when the dimension is too small, e.g., 64, the expressive ability of the model will be weak due to the overly small number of parameters. When the dimension is too large, it is difficult for the model to converge to a good state due to the overly large number of parameters.

**VI. CONCLUSION**

In this article, we proposed TrustGNN, a new GNN-based method for trust evaluation in online social networks. In TrustGNN, we for the first time, explicitly integrated the propagative and composable nature into the GNN framework to learn comprehensive embeddings for better trust evaluation. We defined trust chains to model the propagative pattern of trust and extended KGE methods to model the interaction among nodes and relationships in each trust chain. We further used attention mechanism to learn the importance coefficients of different types of chains, in order to distinguish the contributions of different propagative processes. Experimental results on widely-used real-world datasets have demonstrated the superiority of the new proposed TrustGNN. The ablation studies also showed the effectiveness of key designs in TrustGNN.

TrustGNN aims to fully describe the propagative and composable nature of social trust, but it is still not perfect. For example, in this work we only concatenate the representations of nodes from the trustor and trustee roles to get the final node representation. In the future, we plan to explore more mathematical manner to model the relationship between trustor and trustee roles in order to make the model more powerful. Currently, social interaction in online social networks may be time-varying, while TrustGNN is only for static networks, so it will be interesting to analyze the dynamic behavior of our model. Therefore, we would like to theoretically analyze the evolution of social trust in the process of dynamic behavior, and effectively model the propagative and composable nature of time-varying social trust. Furthermore, TrustGNN uses the classic graph convolutional neural network to model social trust. In the future, we would also like to explore more deep learning techniques and apply them effectively to trust evaluation in social networks.
Cuiying Huo received the B.S. degree from the School of Software, Yanshan University, Qinhuangdao, China, in 2019. She is currently pursuing the Ph.D. degree with the College of Intelligence and Computing, Tianjin University, Tianjin, China.

She has authored articles in the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS (TNNLS), AAAI, and WWW. Her main research interests include graph neural networks, heterogeneous graph analysis, and their applications.

Dongxiao He received the Ph.D. degree in computer science from Jilin University, Changchun, China, in 2014.

He was a Post-Doctoral Research Fellow with the Department of Computer Science, Dresden University of Technology, Dresden, Germany, from 2014 to 2015. She is currently an Associate Professor with the College of Intelligence and Computing, Tianjin University, Tianjin, China. She has authored more than 40 top-tier journal articles and conference papers. Her current research interests include the analysis of complex networks, graph data mining, and GNNs.

Chundong Liang received the B.S. degree from the School of Artificial Intelligence, Hebei University of Technology, Tianjin, China, in 2019. He is currently pursuing the M.S. degree with the College of Intelligence and Computing, Tianjin University, Tianjin.

He has authored articles in the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS (TNNLS), AAAI, and WWW. His research interests mainly include social networks, data mining, and deep learning.

Di Jin (Member, IEEE) received the Ph.D. degree in computer science from Jilin University, Changchun, China, in 2012.

He was a Research Scholar with the Data Mining Group (DMG), University of Illinois Urbana-Champaign (UIUC), Champaign, IL, USA, from 2019 to 2020. He is currently an Assistant Professor with the College of Intelligence and Computing, Tianjin University, Tianjin, China. He has authored over 50 research papers in international journals and conferences, such as the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS (TNNLS), IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING (TKDE), TYCB, NeurIPS, IJCAI, AAAI, and WWW. His research interests mainly include graph machine learning and graph data mining, especially on community detection, GNNs, and network embedding.

Tie Qiu (Senior Member, IEEE) received the Ph.D. degree in computer science from the Dalin University of Technology, Dalian, China, in 2012.

He held an assistant professor position in 2008 and an associate professor position in 2013 with the School of Software, Dalin University of Technology. He was a Visiting Professor in electrical and computer engineering with Iowa State University, Ames, IA, USA, from 2014 to 2015. He is currently a Full Professor with the School of Computer Science and Technology, Tianjin University, Tianjin, China. He has contributed to the development of three copyrighted software systems and invented 14 patents. He has authored/coauthored nine books and more than 100 scientific papers in international journals and conference proceedings.

Dr. Qiu is a Senior Member of the China Computer Federation (CCF) and ACM. He serves as the general chair, the program chair, the workshop chair, the publicity chair, the publication chair, or a TPC Member for a number of international conferences. He serves as an Associate Editor for the IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: SYSTEMS; an Area Editor for Ad Hoc Networks (Elsevier); an Associate Editor for IEEE ACCESS Journal, Computers and Electrical Engineering (Elsevier); and Human-Centric Computing and Information Sciences (Springer); and a Guest Editor for Future Generation Computer Systems. There are ten papers listed as ESI highly cited papers.

Lingfei Wu (Member, IEEE) received the Ph.D. degree in computer science from the College of William and Mary, Williamsburg, VA, USA, in 2016.

He was a Research Staff Member at the IBM Thomas J. Watson Research Center, Yorktown Heights, NY, USA, and led a 10+ research scientist team for developing novel graph neural networks methods and systems, which leads to the one AI Challenge Project in IBM Research and multiple IBM Awards, including three-time Outstanding Technical Achievement Award. He was a Principal Scientist at the JD.COM Silicon Valley Research Center, Mountain View, CA, USA, leading a team of 30+ machine learning/natural language processing scientists and software engineers to build intelligent e-commerce personalization systems. He is an Engineering Manager with the Content and Knowledge Graph Group, Pinterest, New York, NY, USA, where they are building the next-generation Knowledge Graph to empower Pinterest recommendation/research systems across all major surfaces, including Homefeed, Search, and Ads. He has authored one book (in GNNs) and more than 100 top-ranked conference papers and journal articles. He is a Co-Inventor of more than 40 filed U.S. patents. Because of the high commercial value of his patents, he has received eight invention achievement awards and has been appointed as IBM Master Inventors, class of 2020.

Dr. Wu was a recipient of the Best Paper Award and Best Student Paper Award of several conferences, such as IEEE IC’19, AAAI workshop on DLGMA’20, and KDD workshop on DL’19. He has co-organized more than ten conferences, such as KDD, AAAI, and IEEE BigData, and is the founding Co-Chair for the Workshops of Deep Learning on Graphs (with AAAI’21, AAAI’20, KDD’21, KDD’20, KDD’19, and IEEE BigData’19) and Deep Learning on Graphs for Natural Language Processing (with ICLR’22 and NAACL’22). He has currently served as an Associate Editor for the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS and ACM Transactions on Knowledge Discovery from Data.