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Attention-based explainable friend link prediction with heterogeneous context information

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ABSTRACT

Friend link prediction is an important research problem in recommender systems. Existing network embedding and knowledge embedding methods mainly consider the structural relationships of entities, ignoring the explanatory role of text contents. In this paper, we present an explainable friend link recommendation method that leverages direct and indirect similarity of user pairs via fusion embedding of heterogeneous context information. In social networks, while considering user content interests, first, a fusion user embedding method was developed by incorporating external knowledge semantics. Second, for a user pair, we calculate their direct similar relationship using fusion user embeddings. Additionally, based on intermediate neighbors, we compute their indirect similar relationship by using an attention mechanism, which explains neighbors' bootable and transitive influences for learning the social relationship of user pairs. Then, a hybrid personalized and neighbor attention model for friend link prediction was proposed by considering direct and indirect factors. Finally, experiments were conducted on the Sina Weibo datasets, which indicates that the proposed method effectively predicts the friends of users and provides a good interpretation for link prediction recommendation results.

1. Introduction

With the development of information technology, huge amounts of structured and unstructured data are produced on social media every day. Particularly, heterogeneous social resources such as texts, tags, reviews, posts and follow relations appear on social media, which give rich and diverse information. How to leverage heterogeneous context resources to improve the performance of recommender systems has become an essential challenge in this field [45]. Conventional recommender systems model users' preferences and make friend recommendation based on collaborative filtering (CF) and hybrid strategies [48]. Existing friend recommendation methods mainly focus on enhancing the accuracy of recommender systems, while ignoring the explainable ability of recommendation results [39]. To address this problem, heterogeneous context information can be used to improve the explanation of recommendation results and enhance the usability of recommender systems [1], especially in microblog social media networks.

In microblog social networks, when a user cares about something, he or she will follow the related people, called followees. Most users are used to maintaining interests about topics, and are familiar with a followee. Followees' microblog contents and behaviors can reveal the relationships of user pairs. How to model the social following relation between user

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pairs is a promising problem. For a given user pair (u, v), if u has followed user t and t has followed user v, it could be said that t is an intermediate neighbor followee of user pair (u, v). Thus, the activities of intermediate followees can be used to interpret user pairs' intention relationships. That is, intermediate followees' activities can be used to predict the following relations of user pairs. The intermediate followees can build a bridge to connect relationships of user pairs from collaborative transitive influences. In the process of following relation diffusion, intermediate followees can play various roles because of their different interest similarities with user pairs. Many deep neural networks have been suggested to incorporate similar users' influences to make social friend recommendations. The attention mechanism has exhibited significant effects in most fields, such as sentiment classification, recommendation systems, machine translation, and computer vision [32]. As intermediate followees produce different influences for linkage relation modeling, we can exploit the attention mechanism to explain various roles of mediators in the prediction of user pairs' following behaviors.

To make it easier to understand the influence contributions of intermediate followees on the following relation prediction of user pairs, we need to model the intermediate users' embeddings based on their posted/reposted microblogs. Generally, users' microblogs contain rich semantic text information, and users with similar interests are more likely to follow each other. This can explain the following relations of user pairs from the perspective of content interest. Thus, according to one's posted/reposted content, users' content embedding (CE) is modeled to explore their explicit behavioral similarity relationship. Simultaneously, due to the characteristics of short texts, a piece of microblog incorporates just one or two topic concepts. Hence, insufficient concept subjects in short text encounter difficulty in capturing users' implicit relationships. In most cases, different microblogs may have semantic relevance in concept-specific spaces. For instance, if one user posted a microblog with the word "basketball" while another user reposted that associated with the word "football", the two words are semantically related to the aspect of "sports". As an ontology knowledge base can extend rich and hierarchical information for origin microblog text subjects, extracting conceptual entities from the knowledge base to exploit deep semantics is necessary. Thus, we can model users' semantic embedding (SE) to mine implicit similar relationships in terms of an extended tree concept set. Based on the aforementioned idea, considering users' CE and SE, we model fusion user embedding (FUE) to explore users' similar relationships.

To the best of our knowledge, traditional methods mainly focus on learning user profile embedding while ignoring its explanatory function on link prediction. In this paper, a hybrid personalized and neighbor attention model (HPNAM) is proposed to predict and explain the following relations of user pairs. First, based on users' microblog contents and external knowledge base, CE and SE are learned to supplement users' descriptions. By combining two types of embeddings, we generate FUE to model behavior intentions among users. Then, based on user pairs' FUEs, we calculate their direct similar relationship. Considering the different contributions of intermediate neighbor followees, we utilize the attention mechanism to compute their indirect similar relationship from collaborative perspectives. Both direct and indirect similar relationships are used to predict the following relation of user pairs. Finally, through extensive experiments, we validate the efficacy of the proposed method over state-of-the-art friend recommendation methods and visually interpret the predicted results.

To sum up, the major contributions of this paper are as follows: (1) A fusion user embedding method is proposed by leveraging heterogeneous contextual text contents and an external knowledge base. The fusion strategy is beneficial to enriching the semantic description of user embedding. (2) A neighbor-based attention mechanism is designed to develop collaborative bootable and transitive embeddings. The collaborative embeddings help understand the transitive influences of mediators from the source and target perspectives. (3) A hybrid personalized and neighbor framework is presented to predict the following relation of user pairs. The framework can explain the different roles of intermediate followees on user pairs' following relation.

The rest of this paper is organized as follows. Section 2 introduces related work, including the state of the art of friend link recommendation. In Section 3, the FUE process and overview framework of the proposed HPNAM for friend link prediction are presented. Section 4 provides the generating process of FUE with heterogeneous context information. Section 5 presents the HPNAM friend recommendation process. Section 6 reports the experimental results and evaluation analysis. Finally, Section 7 concludes this work.

2. Related work

Multiple recommendation methods have been proposed to leverage the relationships among users. In this section, three kinds of strategies related to our friend recommendation model, namely, link-based, interest-based, and explainable recommendations are summarized.

2.1. Link-based recommendation

Recently, network representation learning has been widely used in many fields, such as classification, link prediction and recommender systems. These methods mainly learn latent embedding of nodes in a low-dimensional space [3]. Early methods constructed the correlation matrix of networks and learned top-k eigenvectors to represent the node. Such methods include locally linear embedding [28], Laplacian eigenmaps [35], and directed graph embedding [4]. With the widespread application of deep learning, neural networks have been utilized to model the node representations from link structures among nodes. Embedding representation methods mainly consider the local structure of nodes, such as DeepWalk [24], Line

[34], Node2vec [13], and SDNE [38]. These methods optimize network parameters and exhibit better performance than eigenvector methods. In heterogeneous social networks, nodes often contain different attribute information and types, which cause them to have various heterogeneous structures. Thus, learning an efficient representation with rich semantic information is a critical problem in the task of network analysis [36]. Often, graph embedding has been used to learn the node representation for networks. Kipf et al. [17] applied convolutional neural networks to graphs that can effectively learn the nodes' hidden embeddings while preserving their local graph structure and features. Velickovic et al. [37] designed a graph neural attention network by leveraging different weights to neighboring nodes, efficiently learning different neighborhood features for node classification. Furthermore, Hamilton et al. [14] proposed a GraphSAGE method that learns node embeddings by sampling and aggregating features from local neighborhoods. Based on user and item interactions, Wang et al. [40] utilized a graph network and suggested a unified collaborative filtering framework for capturing the correlations between users. Xiao et al. [43] considered both the network structure and user text to propose a link prediction method based on an attentional convolutional neural network, which improves the performance of link prediction. Although these node user embedding methods achieve successful accurate performance in relation extraction, they do not fully take advantage of the user interest profile.

2.2. Interest-based recommendation

Traditional recommendation methods can be divided into three categories: memory-based methods, matrix factorization models, and hybrid approaches [20]. Matrix factorization-based models such as probabilistic matrix factorization [23], Bayesian probabilistic matrix factorization [29], and general probabilistic matrix factorization [31] consider global characteristics to learn latent factors for computing latent relations between users and items [18], which have achieved great success. However, existing models still face problems of cold start and data sparsity. Recently, deep learning has been integrated into matrix factorization to implement the use of hybrid recommendations by considering other information, such as social tags, social relations, and contextual information [25]. By integrating a convolutional neural network (CNN) with probabilistic matrix factorization, Kim et al. [16] considered the document context and statistics of items to develop a deep hybrid recommender system. By considering a multiplex network of Twitter and Foursquare, Jalili et al. [15] designed a meta-path-based method to investigate the connections between users for link prediction. By exploiting the ego-social features of multiplex links in social networks, Rezaeipanah et al. [27] considered the structural and interactive features to make the link prediction through a classification method. Zhou et al. [49] exploited personalized full-path recommendation in terms of long short-term memory (LSTM) network. Zhang et al. [44] exploited structural information, text information, and image information to propose a collaborative knowledge base embedding method for promoting the quality of recommender systems. Devooght et al. [8] utilized RNN to make short-term and long-term recommendations especially in CF methods. Although the text/review contents enrich the descriptions of users and items, the networks do not fully consider users' potential semantic interests. Generally, users' interest is periodic and hierarchical, and the text within a vertical domain has great relevance in semantics. Different concept keywords from different sentences have semantic relevance in the same domain, for example, "sports" and "basketball" in different sentences can be viewed as a kind of semantic relevance. In our paper, based on one's microblogs, we adopt the BiLSTM to capture content embedding, and learn semantic embedding in terms of extended concepts with an external knowledge base.

2.3. Explainable recommendation

Most recommendation algorithms do not provide users with better interpretability for recommendation results [32]. Interpretability has become a hot topic in recommender systems. Explainable recommendation approaches mainly involve matrix factorization, topic modeling, and deep learning models. Using phrase-level sentiment analysis on users' textual reviews, Chen et al. [6] built the user-item-feature cube and designed a tensor matrix factorization algorithm to learn user preferences. To the best of our knowledge, textual sentences can directly reflect user's interest. Most models have designed explainable recommendation results in terms of different types of texts. Tan et al. [33] modeled user and item representation into the same semantic space with a factorization framework by considering review information. Additionally, the latent topics can be used to explain the recommended items. Using concept, topic, and sentiment labels of users' reviews, Ren et al. [26] utilized a topic model to explain the social relation of users. Deep learning techniques for explainable recommendation mainly involve CNN [30], RNN/LSTM [7], GRU [21], and attention mechanisms [5] and so on. Chen et al. [5] designed a novel neural architecture for explaining recommendation results by highlighting the key regions of images and user review information. By incorporating rich information in the knowledge graph, Wang et al. [41] constructed a knowledge-aware path recurrent network to implement reasoning on paths in terms of an attention mechanism, which can discriminate the strengths of different paths. By leveraging the features operating for different network topological structures, Engelen et al. [9] utilized useful categories of feature sets to make link predictions and thereby improved the explainability of the results. Ge et al. [10] proposed an intelligent friend recommendation in online social networks, which mainly investigated the characteristics of network structure and users' interest preference for node representation. Additionally, some researchers have considered global and local relations of entities to learn node embedding [2,42,19]. Existing works mainly explain product recommendation results based on the relevant aspects of users' texts and reviews. Limited research has focused on the explanation of social friend relations. Thus, inspired by the attention idea, attention-based neighbor embedding has been developed to address explanations of the following behaviors of user pairs by considering transitive social influences of intermediate users.

3. Friend prediction framework based on HPNAM

An explainable friend relation prediction framework for social networks based on hybrid personalized and neighbors' semantic similarities were presented. First, FUE was modeled in terms of user content embedding and external knowledge-based semantic embedding. Fig. 1 shows the detailed steps of the FUE modeling process dealing with heterogeneous context information. Then, based on users' FUEs, a hybrid personalized and neighbor attention prediction method was designed. Fig. 2 presents the framework of HPNAM. In the following, we introduce the steps of modeling a user's FUE, and then predict the following relation of a user pair, respectively.

In Fig. 1, the FUE is obtained from contextual CE and external knowledge-based SE. First, the user's contextual CE by leveraging the vectors of documents is learned. The microblogs of users can be viewed as a document to learn CE. The word embedding of documents is viewed as a cell of the input layer. By using the Bi-LSTM, we learn the contextual relationship of sentence content, which is called CE. The CE models a user's stable interest representation from the aspect of the local relevance of microblog contents. Some users have fewer documents for the CE because they rarely post or repost microblogs. Then, by introducing an external knowledge base, some parent concepts for the origin entities of the user's document were extended. This can help enrich the semantic interest description of users. Meanwhile, an expanded interest concept tree is built for the target user. Considering the word embeddings of extended subjects, the $tf-idf$ mechanism is utilized to weigh the global importance of the semantics of various subjects, called SE. Finally, FUE was modeled by concatenating the two different embedding vectors.

Based on the FUEs, given a user pair (u, v), we can predict their following relation in terms of their personalized and intermediate neighborhood similarities. As shown in Fig. 2, the framework includes two stages: direct and indirect prediction modules. The direct module learns explicit similarity from source user u to target user v based on their FUEs. Then, the indirect module models bootable contributions of intermediate neighbor followees for source user u with an attention mechanism, which generates a weighted sum embedding of neighbors. Further, the transitive contributions of the intermediate neighbor followees to target user v are also computed. Based on the attention roles of neighbor followees, the indirect similarity between users u and v is computed. This can implicitly help model the linkage of user u and v. Last, by jointly learning two kinds of similarity with nonlinear function, the direct and indirect parts from u to v were combined to predict their following relation score $\hat{y}(u, v)$.

4. Fusion user embedding with heterogeneous context information

In this section, the modeling method of FUE was presented on the basis of heterogeneous context information, including contextual CE and external knowledge-based SE.

4.1. Content embedding

In social networks, users' personal content intuitively reflects their preferences and hence can be used to learn rich representations of user profile descriptions.

Given a user u, let $D_u = \{s_1, s_1, \dots, s_k\}$ be u's microblog document set. Each sentence s can be defined as a set of words $s = \{w_1, w_2, \dots, w_n\}$. Sentences in the document are explored to learn one's CE. Bi-LSTM is widely used for text embedding due to its excellent performance in capturing relations of context for sequence documents [12]. Wu et al. [47] adopted a hierarchical structure to learn document representation, including word-level representation and sentence-level representation. Fig. 3 shows the architecture of Bi-LSTM [11].

In Fig. 3, the basic LSTM unit uses three gates to implement the maintenance and update of semantic information for each neuron [49]. The states of each LSTM unit are formalized as follows [11,12,49].

$$\mathbf{i}_t = \sigma(\mathbf{W}_i[\mathbf{h}^w_{t-1}, \mathbf{w}_t] + \mathbf{b}_i), \tag{1}$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_f[\mathbf{h}^w_{t-1}, \mathbf{w}_t] + \mathbf{b}_f), \tag{2}$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_o[\mathbf{h}^w_{t-1}, \mathbf{w}_t] + \mathbf{b}_o), \tag{3}$$

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c[\mathbf{h}^w_{t-1}, \mathbf{w}_t] + \mathbf{b}_c), \tag{4}$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \tag{5}$$

$$\mathbf{h}^w_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t), \tag{6}$$

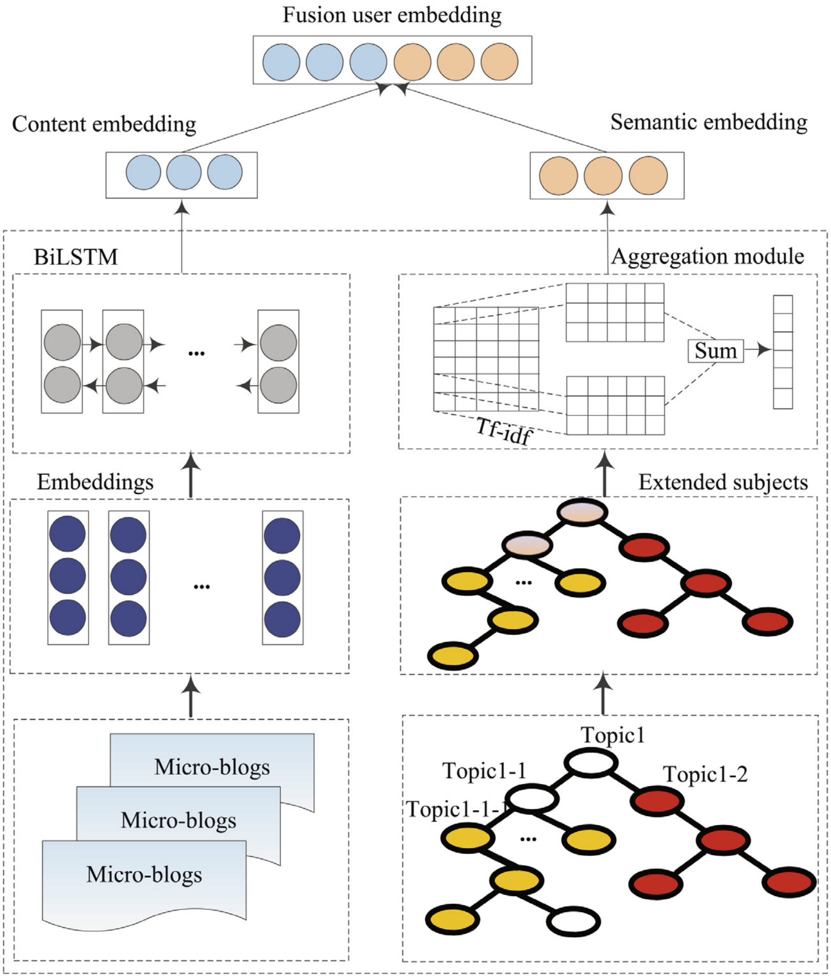

Fig. 1. FUE based on the integration of heterogeneous context information.

where $\mathbf{i}_t, \mathbf{f}_t$, and $\mathbf{o}_t$ are the input gate, forget gate and the output gate, respectively. σ is the sigmoid function, and $\odot$ defines the element matrix multiplication.

Based on the idea in Wu [47], hierarchical attention network information was adopted to obtain a document vector. The Bi-LSTM considers the forward and backward sequences for each entity word to obtain a better output. The forward hidden state $\mathbf{h}_t^{wf}$ and backward hidden state $\mathbf{h}_t^{wb}$ of each word can be concatenated to define the hidden information state of word x_t, i.e., $\mathbf{h}_t^w = \left[\mathbf{h}_t^{wf}; \mathbf{h}_t^{wb}\right]$. For all words in s_i, an average pooling layer was applied to their hidden states $[\mathbf{h}_1^w, \mathbf{h}_2^w, .., \mathbf{h}_l^w]$ and get the contextual sentence embedding representation $\mathbf{s}_i$. For all sentences in D_u, their sentence embedding representation $[\mathbf{s}_1, \mathbf{s}_2, .., \mathbf{s}_k]$ was inputted into Bi-LSTM to get hidden information state of each sentence s_t, i.e., $\mathbf{h}_t^s = \left[\mathbf{h}_t^{sf}; \mathbf{h}_t^{sb}\right]$. Based on all sentences' representation, an average pooling layer on all hidden states $[\mathbf{h}_1^s, \mathbf{h}_2^s, .., \mathbf{h}_l^s]$ was conducted to get the final CE representation $\mathbf{c}(u)$ of user u.

CE depicts a user's features from the documents' local semantic structure of interest words in documents. The context information of documents and sentences can effectively model the sequence semantics of interest words, which can be used to discover explicit semantic similarities between user profiles.

4.2. Semantic embedding

Although CE is conducive to modeling explicit interest relationships between users, it is powerless when microblog documents and sentences from two users have less similar content. In most cases, the features of short texts in microblog social networks make it challenging to mine implicit semantic relationships of users.

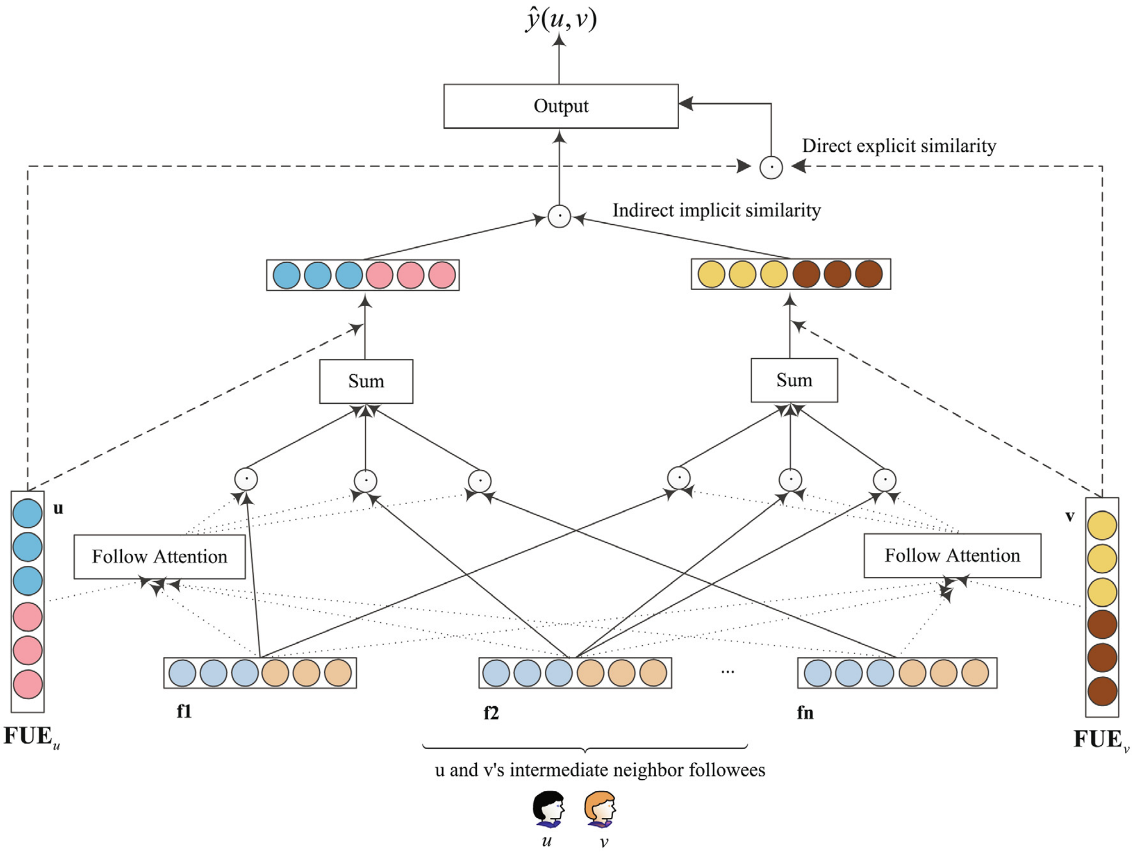

Fig. 2. Friend following relation prediction based on HPNAM.

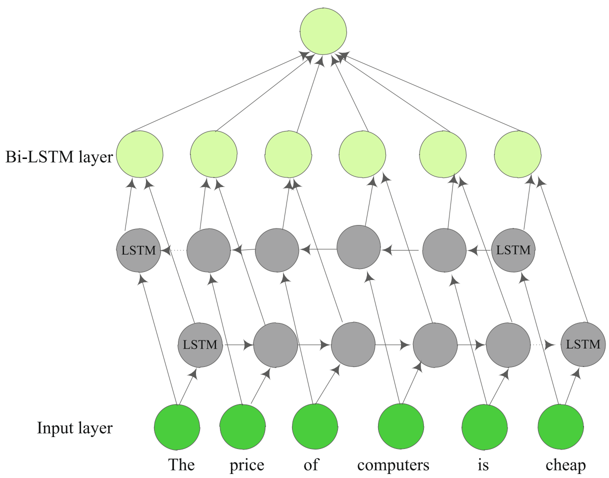

Fig. 3. Architecture of Bi-LSTM.

As is known, microblog contents generally contain different words in the same domain. Many words may be associated with a coarse-granularity concept of a specific domain. Therefore, it is meaningful to establish a connection between two words in terms of related coarse-granularity concepts. An ontology knowledge base can give a structured relationship between domain concept words. In this paper, based on ontological structured relationships, some concept words are expanded to supplement the origin interest words of the users. Additionally, the frequency of words in the document reflects the interest degree of users, which can strengthen their semantic profile description. In the following, we describe how to compute the interest degree of concept words and learn the semantic embeddings of users.

For each word w in the user's microblog corpus S, its tf-idf weight can be computed as follows.

$$tfidf_w = \frac{freq_w}{\max_l(freq_l)} \times \log\frac{N_S}{n_w}, \tag{7}$$

where $freq_w$ is the raw term frequency of w in corpus S and $\max_l(freq_l)$ is the frequency of word l that has the maximum frequency in S. N_S is the total number of microblog sentences, and n_w is the number of microblogs that contain w. The tf-idf weight describes the relative importance of a term in representing the sentence from the aspect of document's global content.

Then, considering users' related microblogs, we can calculate the interest degree of word w for user u as follows.

$$Cid_u(w) = \frac{tfidf_w}{\sum_{w_i \in D_u} tfidf_{w_i}}, \tag{8}$$

where D_u is the microblogs corpus set posted by u. Generally, there are fewer the same interest subjects between user pairs, making it challenging to calculate their semantic similarity. Thus, we extend coarse-grained aspects of subjects for users to enhance one's semantic interest by a predefined knowledge base C. The knowledge base C includes some predefined topics, such as society, sports, economics, culture, IT, and tourism, from the Baidu encyclopedia. Fig. 4 shows part of the hierarchical structure related to many topics.

By matching words in microblogs with the ontology knowledge base, origin explicit interest word subjects that user u is interested in can be obtained. Based on explicit interest word subjects, an origin interest tree is created for user u, as shown in Fig. 5(a), where colored objects are the explicit interest words. When a user is interested in the word subject "NBA," it was assumed that he or she must be interested in the word "basketball." Thus, in Fig. 5(a), the gray circle subjects can be extended to the user's interest from its direct children nodes with the bold dotted line. The extended interest tree is shown in Fig. 5(b), where the pink circles represent new interest subjects, and the other hollow circles represent subjects that the user is not interested in.

In Fig. 5(b), for the new extended ancestral nodes s_{22}, s_{11}, s_{12} and s, we can mark their word subjects as w_{22}, w_{11}, w_{12} and w_0. Then, their interest degree can be defined as recursive transmission of the interest degree of the original child nodes, shown in the following equation:

$$Cid_u(w) = \sum_{w_i \in Child(w)} Cid_u(w_i), \tag{9}$$

where $Child(w) = \{w_i | w_i \rightarrow w\}$ is the set of child nodes who have parent node w. For the other hollow word subjects, their interest degree is assigned as 0.

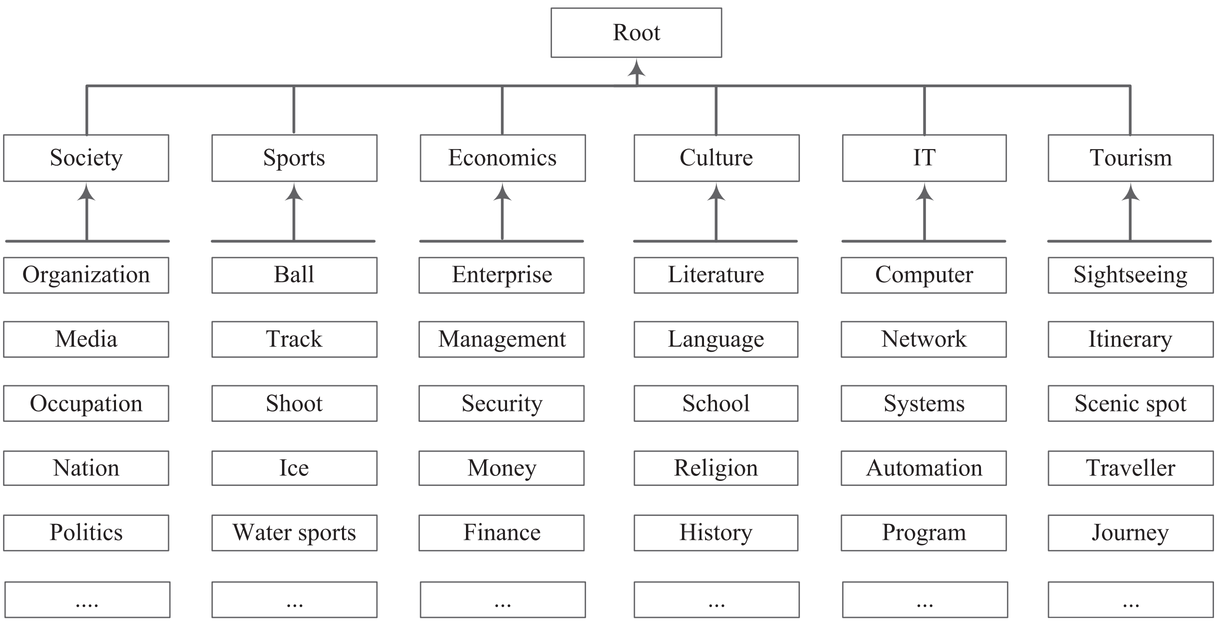

Fig. 4. A portion of the hierarchical structure related to many topics.

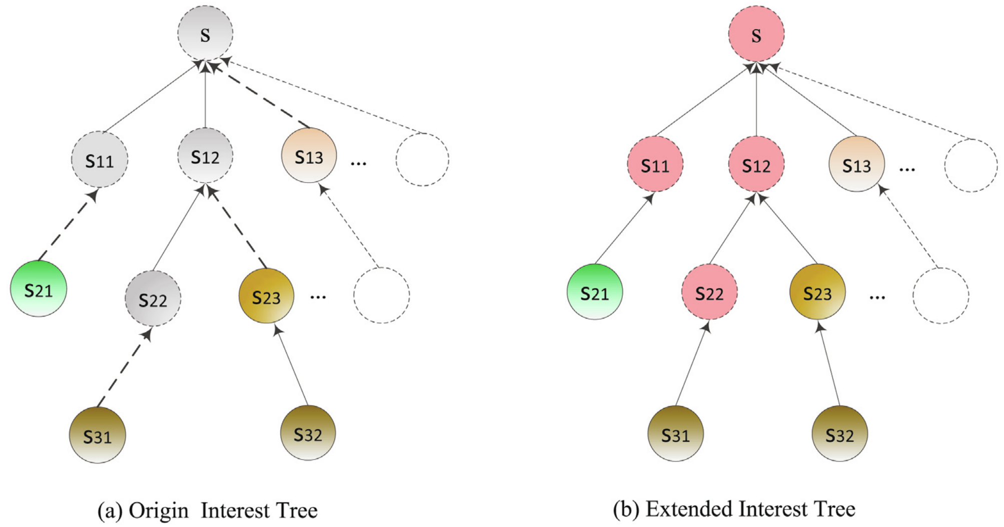

Fig. 5. An example of an original interest tree and extended interest tree for a user.

Based on the above idea, a potential interest subject set for a user can be obtained. For a given user u and one's interest subject $S_u = \{w_i | Cid_u(w_i) > 0\}$, the softmax function was adopted to normalize the interest degree of each word subject w as $\overline{Cid}_u(w) = e^{Cid_u(w)} / \sum_{w_i \in S_u} e^{Cid_u(w_i)}$. Then, the word embedding of each interest subject can be weighted by the normalized interest degree. This will describe the global importance of semantics interest of different subjects.

For an extended interest tree, by considering all the interest word subjects and their normalized interest degree, the SE of user u can be aggregated and defined as follows:

$$\mathbf{s}(u) = \sum_{w \in S_u} \overline{Cid}_u(w) * \mathbf{V}_w, \tag{10}$$

where S_u is the set of subjects that user u is interested in and $\mathbf{V}_w$ is the word vector of subject w. The SE describes users' implicit interesting features by the category structure of the external knowledge base, which helps analyze and discover the similar behavior tendency of users.

4.3. Fusion user embedding

According to the preceding presentations of CE and SE, a user profile can be described using comprehensive embedding. To the best of our knowledge, many feature fusion technologies are used to implement final embedding representation [46]. In our paper, different user embedding forms can be concatenated to obtain an overall description for a user since it has been proven successful in semantic interest description [16].

Given a user's CE $\mathbf{c}(u)$, SE $\mathbf{s}(u)$, the FUE can be defined as $\mathbf{r}(u) = [\mathbf{c}(u); \mathbf{s}(u)]$. The FUE gives a user's representation from the aspect of local content interest and global semantic interest. The overall description helps investigate the following relation of users. The detailed FUE generating process is shown in Algorithm 1.

Algorithm 1:Fusion user embedding generating process.

Input:
Users' microblogs and ontology knowledge base.
Output:
Fusion user embedding of user u, $\mathbf{r}(u)$.
1: Calculating the content embedding of user u as $\mathbf{c}(u)$ by one's microblog contents with Bi-LSTM;
2: Obtaining the semantic embedding of user u as $\mathbf{s}(u)$ based on one's extended subjects and their word vectors by Eq. (10);
3: Generating the fusion user embedding as $\mathbf{r}(u) = [\mathbf{c}(u); \mathbf{s}(u)]$ by aggregating the representations of content embedding and semantic embedding;
4: Return $\mathbf{r}(u)$.

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5. Attention-based friend link prediction with a hybrid strategy

In this section, we design a hybrid personal and neighbor-based attention model to predict users' following relation.

Given a user pair (u, v), their following relationship can be explored from two users' direct and indirect similar factors. In microblog social networks, one user often follows many users, i.e., followees. For example, if source user u's followees have followed target user v, it can be assumed that these intermediate neighbor followees socially link the two users. Particularly, when all the intermediate neighbor followees pay attention to the target user, the two users have a significant possibility of having the following relation. Thus, intermediate neighbor followees can be an important bridge for linking source and target users. In our study, intermediate neighbor followees are leveraged to study the flow of following relationships between user pairs.

5.1. Attention-based collaborative neighbor embedding

For a user pair (u, v), based on their FUEs, we can compute their direct similar relationship as $\mathbf{r}(u) \odot \mathbf{r}(v)$. Furthermore, the user pair's intermediate neighborhood set can be defined as $F = \{t | u \to t, t \to v\}$. That is, for $t \in F$, if t is similar to the source user u, and similar to the target user v, we can infer that t provides a certain contribution on the follow relation of u to v. Therefore, by analyzing attentional effects of intermediate neighbor followees, we can compute indirect similar relationship of user pairs. As FUE describes a user profile from serialized concept words and external contexts, FUEs of intermediate neighbor followees can provide complementary interpretation for the relation prediction of user pair (u, v).

Given a user pair (u, v) and an intermediate user $t \in F$, the function $g(\mathbf{r}(u), \mathbf{r}(t))$ is used to model the bootable contribution of t on the flow of following relation, where $g(\mathbf{r}(u), \mathbf{r}(t)) = \mathbf{h}^T \tanh\left(\mathbf{W}(\mathbf{r}(u) \odot \mathbf{r}(t)) + \mathbf{b}^c\right)$. Here, $\mathbf{W} \in \mathbb{R}^{d \times m}, \mathbf{h} \in \mathbb{R}^d, \mathbf{b}^c \in \mathbb{R}^d$ are the learned parameters, and m is the dimension of FUE. Then, considering all the mediators in F, the softmax function is utilized to normalize the bootable importance weight of user t as follows.

$$\gamma_t^u = \frac{\exp(g(\mathbf{r}(u), \mathbf{r}(t)))}{\sum_{f \in F} \exp(g(\mathbf{r}(u), \mathbf{r}(f)))}. \tag{11}$$

Thus, the intermediate neighbor followees' collaborative bootable contributions on source u can be calculated as the weighted sum in Eq. 12.

$$\mathbf{e}_u(F) = \sum_{t \in F} \gamma_t^u \mathbf{r}(t). \tag{12}$$

Considering the bootable role of the source user, the collaborative neighbor embedding and source user embedding can be aggregated to obtain neighbors' bootable embedding $\mathbf{r}_b(F)$. Some operations can be used to complete the concatenation of vectors. Here, we adopt the $\mathbf{r}(u) \odot \mathbf{e}_u(F)$ to conduct the bootable interaction. Similarly, intermediate neighbor followees also provide a propagating contribution on the target user v of (u, v). Based on the same attention mechanism, we can get the propagating influence weight of followee user t on user v as follows.

$$\beta_t^v = \frac{\exp(g(\mathbf{r}(v), \mathbf{r}(t)))}{\sum_{f \in F} \exp(g(\mathbf{r}(v), \mathbf{r}(f)))}. \tag{13}$$

The value of β_t^v reflects the degree of intermediate user t on transmitting following relation to target user v. Considering all the mediators in F, the collaborative transitive contribution on the target user v can be defined as follows.

$$\mathbf{e}_v(F) = \sum_{t \in F} \beta_t^v \mathbf{r}(t). \tag{14}$$

Then, we can obtain the neighbors' transitive embedding $\mathbf{r}_t(F) = \mathbf{e}_v(F) \odot \mathbf{r}(v)$ for the target user. Finally, considering the bootable and transitive roles, the collaborative indirect similarity relationship can be obtained by aggregating the interaction of embeddings as $\mathbf{r}_b(F) \odot \mathbf{r}_t(F)$. The intermediate neighbors' bootable and transitive embeddings can efficiently analyze the significant contributions of mediators in the relation maintaining process of user pairs.

5.2. Score prediction

Given a user pair (u, v), we can consider direct and indirect similar relationships to predict their following relation. According to the FUEs of u and v, the similar score of user pair (u, v) is calculated as follows.

$$\hat{\mathbf{y}}(u, v) = \mathbf{h}_c^T \tanh\Big(\mathbf{W}^{dir}(\mathbf{r}(u) \odot \mathbf{r}(v)) + \mathbf{W}^{indir}(\mathbf{r}_b(F) \odot \mathbf{r}_t(F)) + \mathbf{b}\Big), \tag{15}$$

where $\mathbf{W}^{dir}, \mathbf{W}^{indir} \in \mathbb{R}^{d\times m}; \mathbf{h}_c, \mathbf{b} \in \mathbb{R}^d$ are the learned parameters; and $\odot$ is the pairwise product. The proposed considers the relative importance of two parts, including the direct explicit factor from the user pairs and the indirect implicit factor from the intermediate neighbor followees. In this way, the model can provide internal and external link explanations.

Furthermore, the cross-entropy loss between ground truth relation distribution and the prediction score distribution can be defined as follows.

$$Loss = -\sum_{(u,v)\in V}\sum_{f\in R} y_f(u,v)\cdot\log(\hat{y}_f(u,v)), \tag{16}$$

where $y_f(u,v)$ is the golden value of user pair (u,v) with following relation label $f\in R$. $R=\{0,1\}$ is the set of follow relation types.

To further observe the performance of prediction ability, we utilized a softmax classifier to the direct and indirect parts, respectively. The loss function for the direct part in the model prediction is calculated as follows.

$$\hat{\mathbf{y}}^{dir}(u,v) = \mathbf{h}_{dir}^T \tanh\left(\mathbf{W}^{dir}(\mathbf{r}(u)\odot\mathbf{r}(v)) + \mathbf{b}^{dir}\right), \tag{17}$$

$$Loss^{dir} = -\sum_{(u,v)\in V}\sum_{f\in R}\mathbf{y}_f^{dir}(u,v)\cdot\log\left(\hat{\mathbf{y}}_f^{dir}(u,v)\right), \tag{18}$$

where $\mathbf{h}_{dir}, \mathbf{b}^{dir} \in \mathbb{R}^d$ are the learning parameters of the direct part and $\hat{\mathbf{y}}_f^{dir}$ is the predicted relation distribution from the direct part for the user pair. Similarly, the loss for the indirect part is shown in the following equations.

$$\hat{\mathbf{y}}^{indir}(u,v) = \mathbf{h}_{indir}^T \tanh\left(\mathbf{W}^{indir}\mathbf{r}_b(F)\odot\mathbf{r}_t(F) + \mathbf{b}^{indir}\right), \tag{19}$$

$$Loss^{indir} = -\sum_{(u,v)\in V}\sum_{f\in R}\mathbf{y}_f^{indir}(u,v)\cdot\log\left(\hat{\mathbf{y}}_f^{indir}(u,v)\right), \tag{20}$$

where $\mathbf{h}_{indir}, \mathbf{b}^{indir} \in \mathbb{R}^d$ are the learning parameters of indirect part, and $\hat{\mathbf{y}}_f^{indir}$ is the predicted relation distribution of user pair (u,v) with intermediate neighbor followees. Thus, the final loss L can be defined as the following:

$$L = Loss + Loss^{dir} + Loss^{indir}. \tag{21}$$

The $Loss^{dir}$ and $Loss^{indir}$ are used to adjust the prediction ability of direct and indirect parts for the user pair's following relation. We can minimize the loss L by a batch gradient descent (BGD) algorithm instead of stochastic gradient descent. The BGD method can provide a globally optimal solution. Specifically, in our study, we predict a user pair's following relation according to the relation distribution $\hat{\mathbf{y}}(u,v)$. The detailed relation prediction process for the user pair (u,v) is shown in Algorithm 2.

Algorithm 2:Follow relation prediction process.

Input:
User pair (u,v) and their intermediate followees.
Output:
Follow relation prediction score $\hat{\mathbf{y}}(u,v)$.
1: Generating FUEs for u, v and their intermediate followees;
2: Computing the direct similarity part of user pair by $\mathbf{r}(u)\odot\mathbf{r}(v)$ in Eq. (17);
3: Computing the indirect similarity part of user pair by $\mathbf{r}_b(F)\odot\mathbf{r}_t(F)$ in Eq. (19);
4: Learning the weight matrices of direct and indirect similarity parts $\mathbf{W}^{dir}, \mathbf{W}^{indir}$ by Eq. (21);
5: Computing the prediction score of user pair as $\hat{\mathbf{y}}(u,v)$.

According to Algorithm 2, we can utilize the first-order direct similar relationship and second-order indirect similar relationship between user pairs to predict their social following relation. The hybrid personal and neighbor attention effect based on context information can help explain the motivation of following relation. Meanwhile, the attentional iterations among users can spread semantic information to multi-order neighbors, which is conducive to enhancing the embeddings of high-order neighbor nodes. Thus, during the experimental stage, we can first utilize the first-order and second-order information of HPNAM to model users' following relations, and then strengthen the higher-order neighbor information of nodes through graph neural networks. Based on user embeddings with higher-order neighbor information, we can again update the HPNAM model and conduct the following relation prediction in the process of model optimization.

6. Experimental evaluation and analysis

In this section, we conduct several experiments to test the validity of the FUE method and verify the effectiveness of the HPNAM method on friend link recommendation.

6.1. Experiment datasets

In our experiment, we illustrate the effectiveness of the proposed HPNAM method on two Weibo datasets. Table 1 provides detailed information for two datasets. For the NLPIR dataset, we select 167,838 posted/reposted microblogs of 334 users from November 18, 2011 to February 9, 2012 to learn their FUEs, and utilize their 2,931 following relations to perform explainable link prediction. The NLPIR dataset comes from the NLPIR website [1]. For the CSDN dataset, we collect 11,457 posted/reposted microblogs for 1,035 users from April 29, 2014 to May 12, 2014 to model their FUEs. In addition, 5,552 following relations from these users were selected to make friend link recommendation. The dataset is from the CSDN website [2]. For the two datasets, we split them into three sets: training set (80%), validation set (10%) and testing set (10%). The validation set is used to optimize the hyper-parameters of the model, and the testing set is used to verify the effect of various models. Our experiments are conducted on a computer with a 3.6-GHz Intel i7-8565U CPU and 16 GB of RAM.

6.2. Baselines

Friend link prediction recommendation has become one of the main challenges in recommender systems. In our experiment, we select several network embedding methods to compare against our proposal. DeepWalk [24] is a network representation learning method that generates random walk sequences on networks and applies skip-gram [22] for learning node representation. Based on the first-order and second-order proximities of the network, Line [34] optimizes the joint and conditional probabilities of edges to preserve both local and global network structures. Node2vec [13] maximizes the likelihood of network neighborhood architecture of nodes to learn mappings of nodes into low feature representations. Meanwhile, some knowledge embedding methods are used to learn relations between entities, which have been applied into sentiment analysis, recommender system, and link prediction tasks. Bordes et al. [2] presented the transE method with translation mechanism for learning both entities and relations. Wang et al. [42] proposed transH knowledge embedding method to exploit some mapping properties of relations in continuous embedding space, such as reflexive, one-to-many, many-to-one, and many-to-many relations. Considering different entity aspects and different relations, Lin et al. [19] proposed a novel transR method for learning the entity and relation embeddings in separate semantic space. Kipf et al. [17] utilized graph convolutional neural networks to learn the nodes' hidden embeddings for classification tasks. Velickovic et al. [37] designed a graph neural attention network to learn different features of neighborhoods for node classification. Hamilton et al. [14] presented a graphSAGE method by sampling and aggregating features of local neighborhoods to learn the node embeddings.

6.3. Experiment setting and evaluation metric

In our experiment, two evaluation metrics were adopted to verify the ranking performance of top-k friend recommendations. Hits@k measures the proportion of correct user entities in the top-k ranked recommendation list. The larger the values of hits@k are, the better the performance of the models. MeanRank considers the mean rank of correct entities for the top-k ranked recommendation list. The smaller the value is, the better the performance of the models. For the proposed HPNAM method, the attention embedding size is set to 128 for the two datasets. The batch size is set to 64. For the fusion user embedding, the embedding size of the user entity is set to 128.

6.4. Experimental results

To verify the validity of the proposed HPNAM method, friend link prediction experiments were conducted by comparing with network embedding and knowledge embedding methods. Tables 2 and 3 show the evaluation results of hits@k and MeanRank metrics for different methods. These tables show that hits@k values of the FUE + HPNAM method achieves higher performance than those of other methods, including both network embedding and knowledge embedding methods. Meanwhile, the meanrank values of FUE + HPNAM are small. This explains a phenomenon that recommended friends by FUE + HPNAM ranks at the top of the recommendation list compared with other methods. The propsoed FUE + HPNAM method helps predict similar followees accurately. Specifically, on the CSDN dataset, compared with DeepWalk, Line, and Node2vec methods, our approach increases by 7.5%, 8.5%, and 6.3% on hits@10 values, respectively. MeanRank values have dropped by 288.98, 320.57, and 286.65, respectively. The reason is that the FUE + HPNAM method considers both the collaborative structure roles of intermediate neighbor users and rich semantic interest relevance, which is beneficial to calculate the comprehensive similarity between users. The accurate semantic relevance between user pairs is conducive to predicting the fol-

[1] http://www.nlpir.org/
[2] https://download.csdn.net/download/xmt1139057136/10973780

Table 1
Detailed information of Microblog datasets for friend link prediction.

Data sets	NLPIR	CSDN
Number of users	334	1,035
Number of Weibos	167,838	11,457
Number of follow relations	2,931	5,552
Number of follow relations in training set	2,344	4,441
Number of follow relations in validation set	293	555
Number of follow relations in testing set	294	556

Table 2
Friend link prediction results of compared methods on NLPIR dataset.

Models	Hits@5	Hits@10	Hits@15	MeanRank
DeepWalk	0.017	0.033	0.042	149.44
Line	0.012	0.027	0.039	146.97
Node2vec	0.021	0.034	0.047	173.61
TransE	0.086	0.228	0.444	18.43
TransR	0.063	0.219	0.390	19.53
TransH	0.074	0.197	0.419	19.67
FUE + HPNAM	**0.265**	**0.471**	**0.631**	**17.02**
GCN	0.267	0.492	0.605	18.78
GAT	0.275	0.503	0.611	18.08
GraphSAGE	0.281	0.509	0.616	17.85
FUE + HPNAM + GCN	0.291	0.516	0.629	16.97
FUE + HPNAM + GAT	0.302	0.525	0.637	16.02
FUE + HPNAM + GraphSAGE	0.310	0.535	0.642	14.83

Table 3
Friend link prediction results of compared methods on CSDN dataset.

Models	Hits@5	Hits@10	Hits@15	MeanRank
DeepWalk	0.049	0.079	0.108	401.87
Line	0.046	0.069	0.105	433.46
Node2Vec	0.049	0.091	0.119	399.54
TransE	0.047	0.111	0.181	128.28
TransR	0.055	0.115	0.177	129.83
TransH	0.052	0.122	0.180	127.57
FUE + HPNAM	**0.101**	**0.154**	**0.219**	**112.89**
GCN	0.095	0.151	0.196	112.29
GAT	0.101	0.162	0.208	107.38
GraphSAGE	0.117	0.168	0.217	102.64
FUE + HPNAM + GCN	0.121	0.170	0.212	91.07
FUE + HPNAM + GAT	0.129	0.181	0.225	88.75
FUE + HPNAM + GraphSAGE	0.135	0.188	0.222	83.59

lowing relations among users. Moreover, compared with knowledge embedding methods, such as transE, transH, and transR, our method improves hits@10 values by 4.3%, 3.2%, and 3.9%, respectively, reducing the meanrank metric by 15.39, 14.68 and 16.94. The reason is that knowledge embedding-based methods only utilize the information of head entity and tail entity to predict the relation. In contrast, our approach considers indirect effects of the intermediate neighbor users and the direct relationship between users, which can significantly improve the performance of friend link prediction.

Meanwhile, from the tables, we can see that the proposed model is slightly poorer than the baselines of graph neural networks in link prediction. For example, on the CSDN dataset, the GraphSAGE method achieves improvements of 1.6%, 1.4% on Hits@5 and Hits@10 metrics than the FUE + HPNAM method. This is because that the information diffusion of higher-order neighbor information in the graph neural network methods helps enrich the semantic representation of nodes to a certain extent, which captures more comprehensive semantic information and shows better results than the proposed model. However, the proposed HPNAM model makes full use of first-order and second-order information among nodes, which can enhance the semantic propagation intensity of multi-order neighbors and improve the node representation capability of graph neural network methods. Thus, by integrating the first-order and second-order information of proposed HPNAM with graph neural network methods, we update the node embedding representation and make following relation prediction. On two datasets, the node embeddings by combining the high-order neighbor information from graph neural networks have achieved the best results, which are superior to the performance of HPNAM and graph neural network methods. For example, the hits@10 values of FUE + HPNAM + GCN, FUE + HPNAM + GAT and FUE + HPNAM + GraphSAGE methods achieve improvements of 2.4%, 2.2%, and 2.6% for the NLPIR dataset, while 1.9%, 1.9%, and 2.0% for the CSDN dataset by comparing against those of GCN, GAT, and GraphSAGE methods. These results show that the first-order and second-order information of the proposed HPNAM model can enhance the node representation ability of graph neural network, and improve the accuracy of link prediction. In addition, by comparing with the FUE + HPNAM method, the higher-order information can supplement the semantic representation of nodes and play a certain role in the prediction of following relation. It can be seen that results of FUE + HPNAM + GCN, FUE + HPNAM + GAT and FUE + HPNAM + GraphSAGE methods are significantly better than the FUE + HPNAM method on hits@10 metric by 4.5%, 5.4%, and 6.4% on the NLPIR dataset, and 1.6%, 2.7%, and 3.4% on the CSDN dataset.

In addition, to better verify the effectiveness of the fusion embedding method and intermediate neighbor users for predicting head–tail entity relationships, the experimental results are presented by combining CE, SE with direct and indirect predictions, respectively. Tables 4 and 5 show experimental results for different link prediction methods with different user embeddings. The tables show that the FUE + HPNAM method is significantly better than other methods, especially when compared to the individual CE and SE methods. Meanwhile, FUE + HPNAM's prediction results achieve better performance in hits@k and meanrank metrics than those of direct FUE + PM and indirect FUE + NAM methods. For example, on the NLPIR dataset, it can be observed that the hybrid FUE + HPNAM method improves by 9.4% and 15.4% compared with the direct and indirect methods on hits@10 values, while dropping 13.34 and 15.41 on meanrank, respectively. These results show that the direct and indirect factors play different roles on the following relation prediction and better improve the relation prediction of user pairs. In addition, considering the fusion user embedding, the HPNAM method improves 7.3% and 6.5% compared with the CE + HPNAM and SE + HPNAM methods in hits@10 values, respectively. These results indicate that comprehensive context information help predict similar relations between users.

6.5. Ablation study

To verify the performance of the proposed HPNAM method, we observed the results by subtracting the direct or indirect similarity part in Eq. (21). Tables 6 and 7 indicate the contribution of node embedding representation of HPNAM through some ablation experiments. The experimental results are shown as follows.

According to the tables, it can be seen that the hits@k and meanrank values of FUE + HPNAM method are relatively better than those of the other methods on two datasets, which shows that the node representation of hybrid strategy can effectively predict the relation between user pairs. Particularly, compared with the results subtracting the direct or indirect part, the FUE + HPNAM model can obtain obvious improvements. When the direct part is removed, the link prediction of the model decreases significantly. However, by subtracting the indirect part, the model can also be slightly affected. For example, on the CSDN dataset, FUE + HPNAM achieves improvements of 12.8% and 2.5% on hits@10 by comparing with the - Dir and - Indir methods. These results are reasonable because the direct similar relationship and the indirect similar relationship between user pairs' context information can provide rich semantic information to predict social following relations.

Table 4
Friend link prediction results of fusing embedding method for HPNAM on NLPIR dataset.

Models	Hits@5	Hits@10	Hits@15	MeanRank
FUE + HPNAM	**0.265**	**0.471**	**0.631**	**17.02**
FUE + PM	0.214	0.377	0.473	30.36
FUE + NAM	0.155	0.317	0.430	32.43
CE + PM	0.166	0.309	0.481	29.60
CE + NAM	0.204	0.397	0.550	29.32
CE + HPNAM	0.207	0.398	0.535	22.39
SE + PM	0.195	0.374	0.501	30.84
SE + NAM	0.111	0.237	0.321	25.73
SE + HPNAM	0.222	0.406	0.552	21.38

Table 5
Friend link prediction results of fusing embedding method for HPNAM on CSDN dataset.

Models	Hits@5	Hits@10	Hits@15	MeanRank
FUE + HPNAM	**0.101**	**0.154**	**0.219**	**112.89**
FUE + PM	0.073	0.123	0.167	127.97
FUE + NAM	0.028	0.073	0.082	289.81
CE + PM	0.066	0.113	0.157	132.95
CE + NAM	0.022	0.043	0.093	297.49
CE + HPNAM	0.075	0.130	0.170	126.09
SE + PM	0.060	0.087	0.110	273.83
SE + NAM	0.033	0.074	0.078	324.71
SE + HPNAM	0.055	0.090	0.115	275.78

Table 6
Friend link prediction results of ablation study for HPNAM on NLPIR dataset.

Models	Hits@5	Hits@10	Hits@15	MeanRank
FUE + HPNAM	0.265	0.471	0.631	17.02
- Indir	0.242	0.439	0.588	22.38
- Dir	0.020	0.061	0.127	66.40
- Dir - Indir	0.017	0.034	0.109	87.71

Table 7
Friend link prediction results of ablation study for HPNAM on CSDN dataset.

Models	Hits@5	Hits@10	Hits@15	MeanRank
FUE + HPNAM	0.101	0.154	0.219	112.89
- Indir	0.081	0.129	0.201	120.38
- Dir	0.008	0.026	0.045	186.38
- Dir – Indir	0.006	0.015	0.033	224.51

6.6. Hyper-parameter investigation

In our experiment, dimensions of FUE are crucial to the semantic interest representation of users. Different dimensions of user embedding lead to different results for link prediction tasks. Concretely, we obtained users' FUEs on different embedding dimension (ED) sizes, such as ED = 16, 32, 64, 128, 256; and then predicted the following relation between users. Fig. 6 shows the link prediction results under different ED sizes on two datasets. From the figures, we can see that the hits@k performance of the HPNAM model generally tends to increase with the increase of the embedding dimension size from 16 to 256. This indicates that high embedding dimension of semantics can successfully discover latent similar interests among users. In our experiment, we adopt the embedding dimension size ED = 128 to discover the semantic interest association of users for predicting following relations.

In addition, changes of attention embedding dimensions are also essential in selecting the best model. To explore the best performance of the model, experiments were conducted by setting different attention dimension (AD) sizes as AD = 16, 32, 64, 128, 256. Fig. 7 shows the influence results of different AD dimensions for the FUE + HPNAM model. From the results in the figures, it can be observed that the performance of the model improves with the increase of attention dimension size. However, when the attention dimension size has reached a certain level, it can cause overfitting, resulting in a performance decrease. These results indicate that the appropriate attention dimension can effectively explore the intermediate roles of neighbors, which is vital to predicting users' behavioral relations. Therefore, in our experiment, we set the attention embedding dimension size to 128 for two datasets.

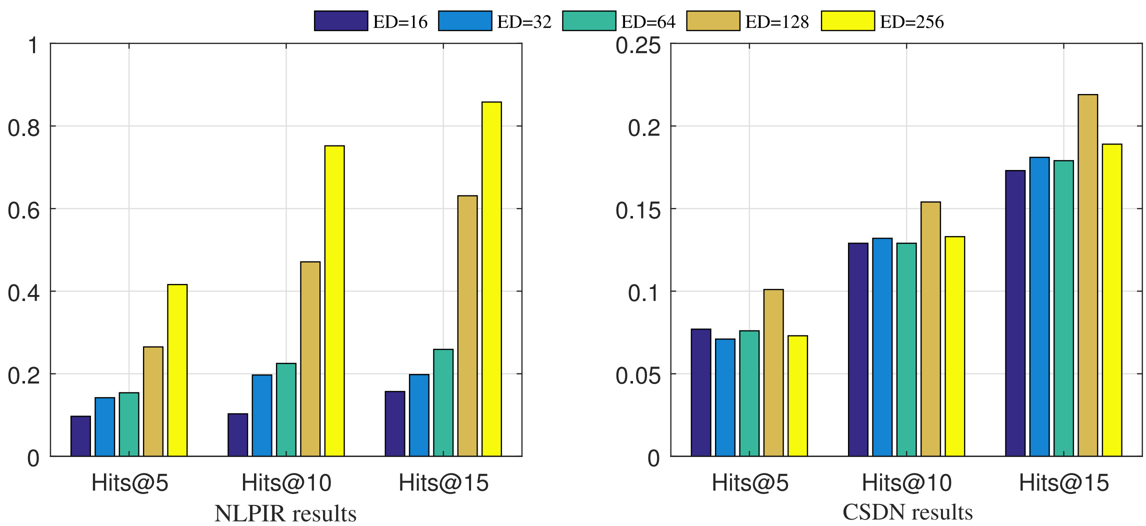

Fig. 6. Friend link prediction results with different fusion embedding dimensions for HPNAM on two datasets.

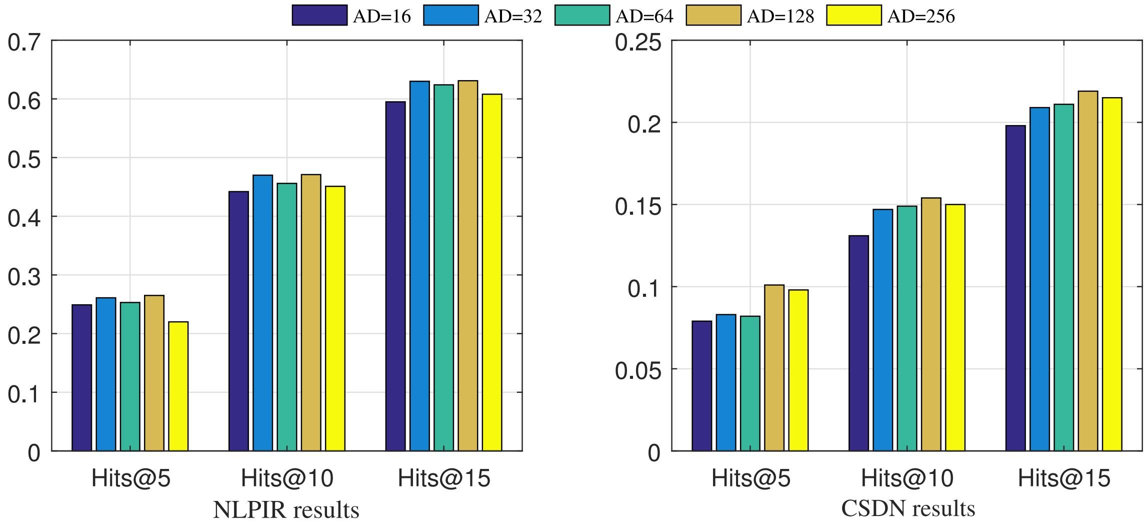

Fig. 7. Friend link prediction results with different attention embedding dimensions for HPNAM on two datasets.

Different dropouts can prevent the overfitting of the model. Fig. 8 shows the experimental results of different dropouts on two datasets. Taking the NLPIR dataset as an example, the model achieves the best performance when the dropout is set to 0.5. When the dropout is large, filtering out some representations of neighbor users can enhance the robustness of the model. The remaining representations can be more effective to model the relation between source and target users. In the experiments, we select the appropriate dropout to preserve representative neighbors and enhance the accuracy of friend link prediction.

6.7. Explainable case and visualization

In this subsection, the crucial roles of intermediate neighbor users on modeling user pairs' following relation were understood and explained with a visual style. In the NLPIR dataset, ten user pairs with following relations were selected, and their prediction scores $\hat{y}$ were computed by hybrid, direct, and indirect prediction methods, respectively. Fig. 9 gives prediction scores of different factors for 10 user pairs.

In the figure, for the user pairs numbered 1, 3, 5, and 7, although they have a low direct similarity prediction score, their following relation can be modeled through some neighbor users. The hybrid HPNAM can give a better score, which is higher than those of direct and indirect prediction methods. That is, when microblog contents of user pairs have a slight similarity, their relation can be explained through intermediate neighbor users. Thus, the intermediate neighbor users play a bridge role for the following relation prediction. Additionally, by observing the other user pairs, when the direct prediction score

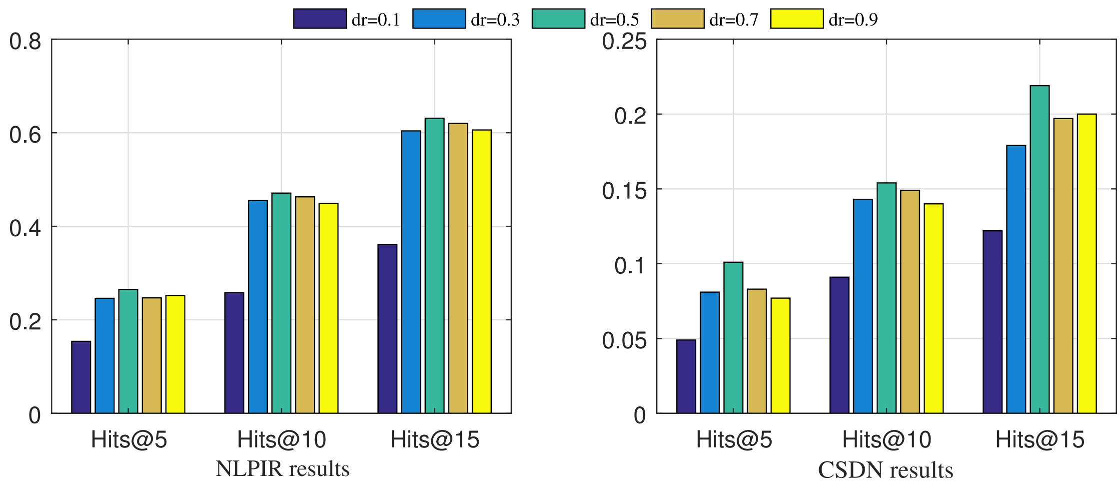

Fig. 8. Friend link prediction results with different dropout values for HPNAM on two datasets.

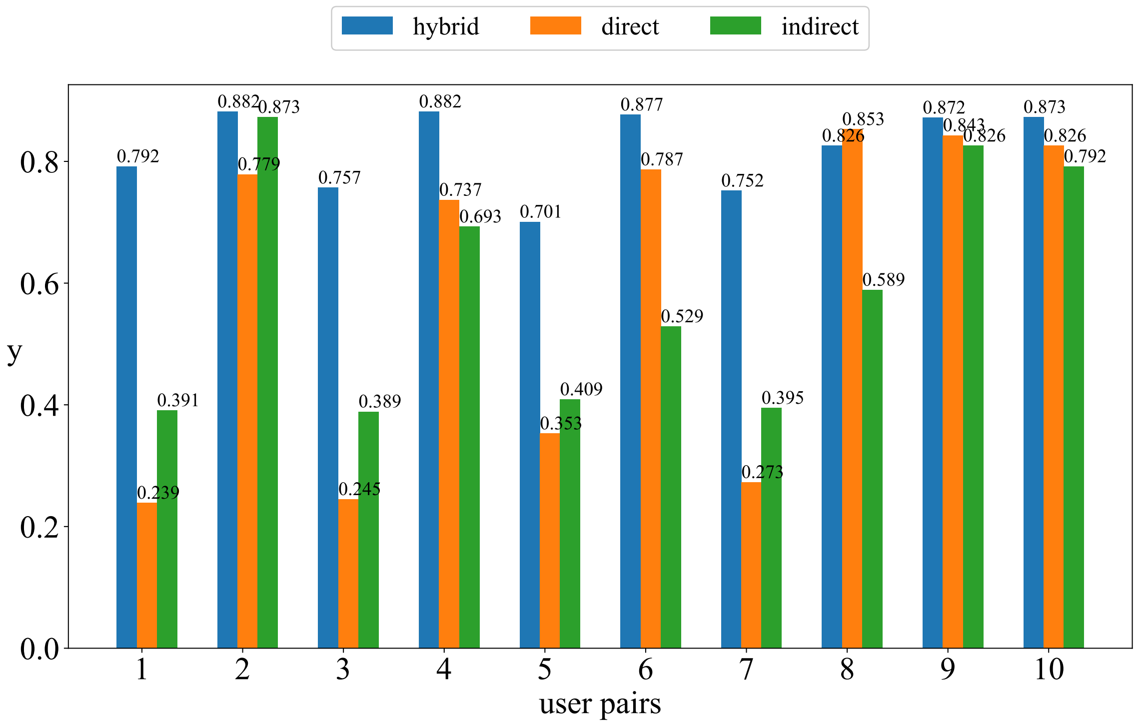

Fig. 9. Prediction scores of different factors for 10 user pairs on NLPIR dataset.

between the source and target user is high, we can directly explain their following relations. However, the hybrid HPNAM prediction score shows a significant improvement compared to direct and indirect methods. Therefore, the proposed HPNAM is also helpful to solve the link prediction problem of user pairs' following relations.

Further, to observe the influence roles of intermediate neighbor users, taking the 3rd and 7th user pairs in Fig. 9 as examples, Fig. 10 shows the attention weights of their neighbor users for the user pairs' following relation modeling. In the left figure, it could be found that the user pair has eight neighbors, and the corresponding attention weight values of neighbor

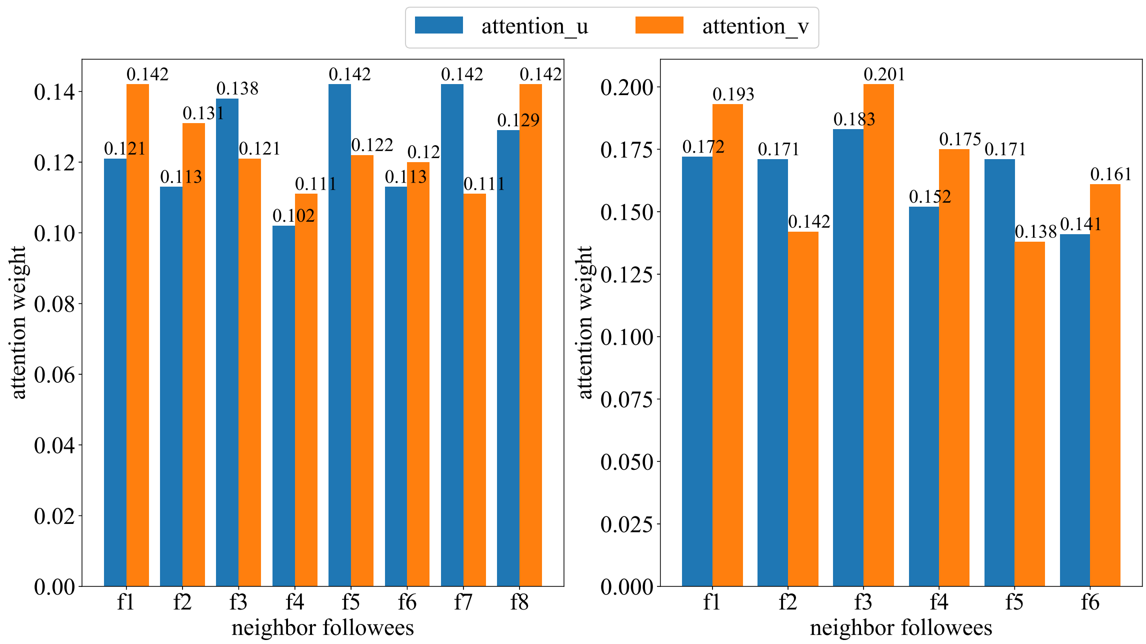

Fig. 10. Attention weights of intermediate neighbor users for two user pairs' follow relation prediction.

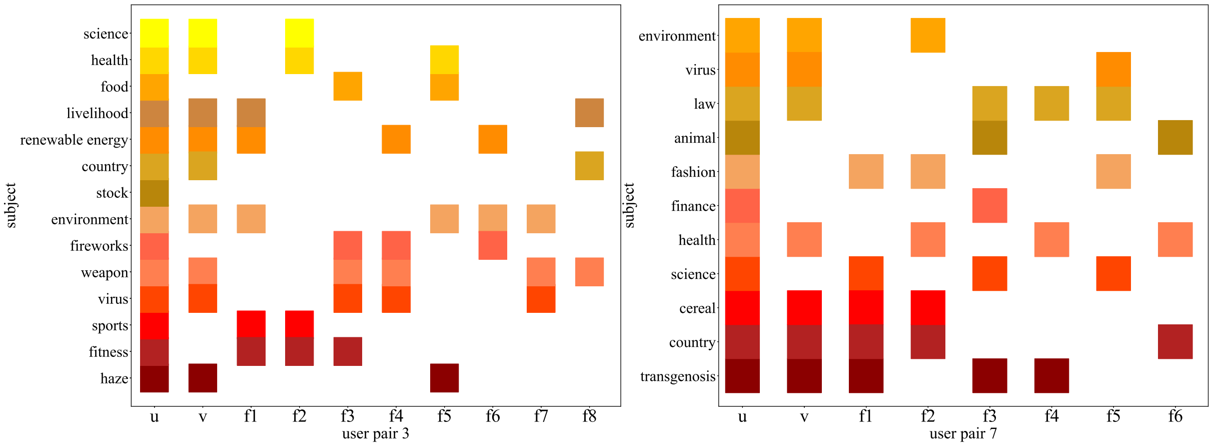

Fig. 11. Microblog subject distributions between user pairs and their intermediate neighbor users.

followees state the bootable and propagating contributions on the source and target users' following relation modeling. Different neighbor users play various intermediary roles. In the left figure, the 3rd and 5th neighbor users play large roles in the following relation modeling of user pair (u, v). More, Fig. 11 shows microblog subject distributions between two user pairs and their neighbor users. In the figure, most neighbor users have related or covered subjects with source and target users. For instance, in the left figure, by analyzing the microblog contents of the 3rd and 5th users, it was found that their microblog subjects are similar to those of source user and target user, which also states that both two neighbor users have large interest transitive contributions on the user pair's relation.

7. Conclusions

In this paper, we propose an explainable link prediction method based on the integration of heterogeneous context information. The major contribution of this paper is first to model a FUE by considering users' personal text contents and external knowledge base. Then, based on FUEs, direct and indirect following relation prediction scores are calculated in terms of collaborative neighborhood attention mechanism. Finally, explanations for link prediction results were provided with the prediction scores of direct and indirect factors. The critical observation is that semantic knowledge of fusion user embedding can better predict and explain the behavioral link relations between users. Interestingly, when the direct prediction between user pairs from text content is low, their following relation can be interpreted through the roles of intermediate neighbor users, which has a good potential for cold-start link prediction of text content.

As users' interests are dynamic and diverse, the user interest representation considering temporal factors can increase the accuracy of following relation prediction. In further work, we will address the challenging task of how to accurately predict the following relation of users through the changes of interest. Meanwhile, the following relation between users has a dynamic change effect. How to use the dynamic changes of intermediary neighbor users to generate explainable link prediction results is a promising research problem. In addition, users with similar interests can form interest communities. We will further take into account the higher-order propagation diffusion of interest subjects, and explain the following relations in groups of communities.

CRediT authorship contribution statement

Jianxing Zheng: Methodology, Investigation, Writing - original draft. **Zifeng Qin:** Investigation. **Suge Wang:** Writing - review & editing. **Deyu Li:** Methodology, 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.

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