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AN ALGORITHM OF DYNAMIC HETEROGENEOUS NETWORKS LINK PREDICTION

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By considering the evolution of networks over time and the rich semantic and structural characteristics of heterogeneous networks, DyMDGCN model is proposed in this paper. The model uses multi-channel partition to deal with heterogeneous networks, and then combines RNN and time attention capture evolution mode to obtain the final node embedding vector from and apply it to link prediction. In order to verify the effectiveness of this method, this paper selects two real dynamic heterogeneous network data sets of Twitter and EComm for experiments, and compares the AUC index with the traditional algorithm. The results show that this method can deal with heterogeneous network information and capture the dynamic evolution information of the network, and has a certain improvement in accuracy compared with the traditional algorithm.

Keywords: dynamic network, heterogeneous network, link prediction, dyMDGCN, time attention, AUC.

1. Introduction

A dynamic heterogeneous network link prediction method based on network representation learning is proposed in this paper, which is roughly shown as follows:

1. In order to deal with the heterogeneous network while being able to obtain deep relationships, this paper selects the MDGCN method, which divides the heterogeneous network by using the multi-channel division method, using meta-paths as channels and processing each channel by graph convolution to obtain the node feature relationships, and to obtain the deep relationships, the method also uses the Graph Inception model to construct a hierarchy from simple To obtain deep relationships, the method also uses the Graph Inception model to construct a hierarchical structure from simple to complex, so by combining the two, a more accurate and comprehensive node-relationship feature vector can be derived.

2. In order to obtain the evolutionary patterns of the network considering the dynamics of the network, this paper combines the RNN with the attention mechanism. Firstly, RNN learns the evolutionary patterns of the network snapshots, and the most generalized LSTM and GRU methods are selected in this paper; then, unlike the traditional methods, this paper does not choose to stitch all the vectors but instead, the temporal self-attentive model is used to The final node vector of the last snapshot is used for the downstream task.

2. DyMDGCN model

2.1. Basic ideas of the DyMDGCN model

The main task of dynamic heterogeneous network embedding is how to capture both heterogeneous information and temporal evolution patterns on a dynamic network. In this paper, we propose a new approach for dynamic heterogeneous network embedding, which uses the MDGCN model to capture the heterogeneity of snapshots and uses the temporal attention RNN model to learn the evolutionary patterns in evolutionary time.The proposed model DyMDGCN (Dynamic Multi channel Deep Graph Convolutional Network) The whole framework of this paper is shown in Fig. 1.

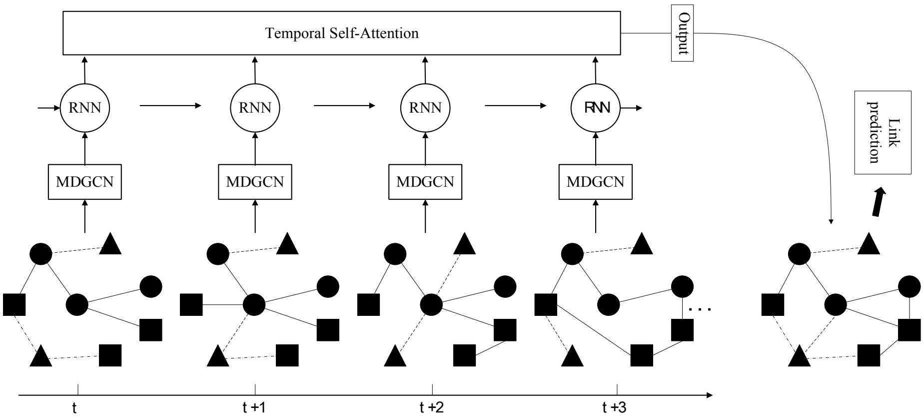

Fig. 1. DyMDGCN framework diagram

2.2. Heterogeneous network information learning

The MDGCN model was chosen to deal with complex heterogeneous networks, using a multi-channel approach to divide the heterogeneous network based on meta-paths, followed by node embedding using graph convolution, and finally stitching the resulting vectors to capture the heterogeneous information in a static heterogeneous network snapshot.

2.3. Multi-channel division

Meta-paths are pathways between two nodes, which can represent the semantic information between such nodes, and different meta-paths can represent different meanings of network information. In this paper, we use a multi-channel partitioning approach, which treats different meta-paths as different channels to achieve the acquisition of heterogeneous network information.

2.4. Graph convolution to obtain node embeddings

The graph convolution operation under a heterogeneous network is then implemented by applying a multichannel network. Since the neighbouring nodes of the nodes on each channel are not the same, the filter selected for each channel is chosen differently; at the same time, in order to reduce the dimensionality of the obtained node embedding, a feature mapping is used in this paper for the dimensionality reduction operation.

As there are many deep relational features in the heterogeneous network, learning the shallow layer alone cannot fully reflect the information of the heterogeneous network, so the MDGCN model uses the Graph Inception model for deep convolution

2.5. Dynamic Evolutionary Information Learning

Nodes and edges are added and deleted in time-evolving patterns as time changes. the MDGCN model of DyMDGCN can effectively capture the heterogeneity of static snapshots, but cannot model patterns that evolve over time. Recently, recurrent neural networks (RNNs) have been introduced into dynamic network embedding methods and good performance has been achieved. Thus, in this paper, we extend the existing RNN model and propose a temporal attention RNN model to capture deeper evolutionary patterns in continuous timestamps. The proposed temporal attention RNN model consists of two main parts, i.e., recurrent neural network and temporal self-attention model.

2.6. Use of Time Self-Attention

Compared with the traditional RNN that joins all feature vectors together as the final embedding to predict the dynamic links in the last snapshot, this paper employs a temporal self-attentive model to further capture the evolutionary patterns on the dynamic network. Firstly, the node embeddings of static snapshots of node i at different moments t can be obtained by RNN $\{s_i^1, s_i^2, ..., s_i^T\}$, then this paper adopts Scaled Dot-Product Attention to learn the node embeddings under different snapshots, and finally use the final acquired snapshot embeddings for link prediction. Its formula is shown in (1):

$$Z_i = \tau_i \cdot V_i = soft\max\left(\frac{(S_i W_q)(S_i W_k)^T}{\sqrt{D'}} + M\right)(S_i W_u) \tag{1}$$

Among them. W_q, the W_k and W_u are trainable parameters, D is the dimensionality of the output embedding vector and M is the mask matrix.

According to the above equation, the final embedding of node i can be derived as $\{z_i^1, z_i^2, ..., z_i^T\}$, i. e., the final embedding choice is z_i^T.

3. Experimental results and analysis

In this paper, two real heterogeneous dynamic network datasets Twitter and EComm are selected, and the information of the heterogeneous network is first learned by DyMDGCN model.

The comparison algorithms selected in this paper are metapath2vec, DynamicTriad, dyngraph2vec and DHNE, which are classical algorithms for static network, static heterogeneous network, dynamic network and dynamic heterogeneous network, respectively, and their AUC results are shown in Table 1.

Table 1

AUC values under different data sets

	Tiwteer	**EComm**
metapath2vec	0.686	0.599
DynamicTriad	0.785	0.688
dyngraph2vec	0.724	0.509
DHNE	0.649	0.626
DyMDGCN-lstm	0.802	**0.732**
DyMDGCN-gru	**0.805**	0.729

4. Summary

In this paper, a DyMDGCN model is proposed to improve the previously proposed MDGCN model to make it applicable to dynamic networks while processing heterogeneous networks. TheDyMDGCN model uses MDGCN to process heterogeneous networks to obtain node embedding vectors of static snapshots, and then uses a temporal attention model combined with RNN to obtain evolutionary patterns of dynamic networks to obtain the final node embedding and complete the link prediction. Finally, the validity of the DyMDGCN model is demonstrated through experiments.