Enhancing Dynamic GCN for Node Attribute Forecasting with Meta Spatial-Temporal Learning (Student Abstract)

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Abstract

Node attribute forecasting has recently attracted considerable attention. Recent attempts have thus far utilized dynamic graph convolutional network (GCN) to predict future node attributes. However, few prior works have noticed the complex spatial and temporal interaction between nodes, which will hamper the performance of dynamic GCN. In this paper, we propose a new dynamic GCN model named meta-DGCN, leveraging meta spatial-temporal tasks to enhance the ability of dynamic GCN for better capturing node attributes in the future. Experiments show that meta-DGCN effectively models comprehensive Spatio-temporal correlations between nodes and outperforms state-of-the-art baselines on various real-world datasets.

Introduction

Node attribute forecasting is crucial in considerable graph fields such as traffic-flow prediction, disease transmission control, and web page access detection. The accurate and reliable dynamic node attribute forecasting help people control the development scale of dynamic graph and avoid catastrophic consequences. For example, we can provide guidance for vehicles and reduce traffic jams by monitoring the change in traffic flow on the road map. Similarly, we can speculate the infection rate according to the number of people infected with the disease so as to find the possible transmission path. Thus, exploring the dynamic graph influence and developing node attribute forecasting methods to reflect these variations is desired.

Recently, driven by the advances in graph convolutional network (GCN) (Kipf and Welling 2017), many attempts adopt GCN for node representation learning and combine the recurrent neural network (e.g., LSTM or GRU) to encode temporal evolution of dynamic graph. However, existing dynamic GCN methods ignore that the dynamic graph evolves over the whole time span and has frequent spatial-temporal interaction between nodes, revealing that the changes of node attributes are irregular, and these methods can hardly promise performance on node attribute forecasting in the future. To tackle the challenges, we propose meta-DGCN, employing meta-learning at both spatial and temporal tasks to enhance dynamic GCN for forecasting node attributes. Concretely, we design three modules, named encoding layer, task construction, and meta optimization. The encoding layer aims to obtain the node embeddings by leveraging GCN and a gating mechanism. In the task construction module, we construct support sets and query sets for both spatial and temporal tasks. Meta optimization reveals that we utilize the spatial and temporal tasks to update the parameters of tasks and meta-DGCN to better capture patterns of the dynamic graph, which enhances the performance of meta-DGCN to forecast the node attributes.

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Main Structural of Our Model

Our model consists of three modules, namely encoding layer, task construction, and meta-learning.

Encoding Layer. This section introduces how to encode the dynamic graph and obtain node embeddings. To simplify and describe the GCN layer, we have

$$\mathbf{X}' := GCN(\mathbf{X}) = \hat{\mathbf{D}}^{-1/2}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-1/2}\mathbf{X}\mathbf{\Theta}, \tag{1}$$

where $\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I}$ denotes the adjacency matrix with inserted self-loops and $\hat{D}_{ii} = \sum_{j=0} \hat{A}_{ij}$ its diagonal degree matrix. $\mathbf{X}$ is the initial node attribute matrix, and $\mathbf{\Theta}$ represents the multi-layer perceptron (MLP). Then we design a gating mechanism similar to LSTM to update node embeddings. Mathematically, we write

$$\mathbf{Z} := UPDATE(\mathbf{X}', \mathbf{H}) = \sigma(\mathbf{X}' + \mathbf{H}), \tag{2}$$

$$\mathbf{R} := RESET(\mathbf{X}', \mathbf{H}) = \sigma(\mathbf{X}' + \mathbf{H}), \tag{3}$$

$$\mathbf{H}' := STATE(\mathbf{X}', \mathbf{H}, \mathbf{R}) = \sigma(\mathbf{X}' + GCN(\mathbf{H} * \mathbf{R})), \tag{4}$$

$$\mathbf{H} := OUTPUT(\mathbf{Z}, \mathbf{H}, \mathbf{H}') = \mathbf{Z} * \mathbf{H} + (1 - \mathbf{Z}) * \mathbf{H}', \tag{5}$$

where we set initial node embeddings $\mathbf{H}$ as a zero matrix, and its shape is the same as $\mathbf{X}$. $\mathbf{h}$ represents single node embedding. σ denotes the activation function such as Relu.

Task Construction. Consider a dynamic graph, a spatial task $\mathcal{T}_s$ involves a support and a query set $(\mathcal{S}_s, \mathcal{Q}_s)$, defined as

$$\mathcal{T}_s = (\mathcal{S}_s = \{(u, v) \in \mathcal{E}\}, \mathcal{Q}_s = \{(p, q) \in \mathcal{E}\}) \quad s.t. \mathcal{S}_s \cap \mathcal{Q}_s = \emptyset, \tag{6}$$

where the support $\mathcal{S}_s$ and query $\mathcal{Q}_s$ contain edges e randomly sampled from the edge set $\mathcal{E}$ of the dynamic graph, and they are mutually exclusive. In like wise, a temporal task $\mathcal{T}_t$ also includes a support set and a query set $(\mathcal{S}_t, \mathcal{Q}_t)$, defined as

$$\mathcal{T}_t = (\mathcal{S}_t = \{v_i \in \mathcal{V}\}, \mathcal{Q}_t = \{v_j \in \mathcal{V}\}), s.t. \mathcal{S}_t \cap \mathcal{Q}_t = \emptyset. \tag{7}$$

We randomly select nodes v from the node set V to from the support $\mathcal{S}_t$ and query $\mathcal{Q}_t$, and they are also mutually exclusive. We learn the prior knowledge such that, after updating by gradient descent w.r.t. the loss on the support set, it optimizes the performance on the query set, which simulates the possible changes of the space-temporal relationship on the nodes in the future.

Meta Optimization. Meta-learning intends to learn a form of general knowledge across similar learning tasks so that the learned knowledge can be quickly adapted to new tasks (Peng 2020). In our work, we intend to explore the spatial interaction and temporal change rules of nodes in the dynamic graph and predict the future value of node attributes through meta-learning under limited current information. Concretely, we implement the spatial task to capture the spatial connections between nodes, formulated as

$$\mathcal{L}_s(\omega, \mathcal{S}_s) = \sum_{(u,v)\in\mathcal{S}_s} -\ln\sigma(\mathbf{h}_u\mathbf{h}_v^T) - \ln\sigma(-\mathbf{h}_u\mathbf{h}_{v'}), \tag{8}$$

where v' is a negative node sample that is not linked with u. The learnable parameters ω (i.e., $\mathbf{\Theta}$) for both space and temporal tasks represent meta-knowledge. Then, we design a temporal task to simulate the change happening on node attributes, formulated as

$$\mathcal{L}_s(\omega, \mathcal{S}_t) = \frac{1}{n}\sum_{v_i\in\mathcal{S}_t} (\sigma(\mathbf{h}_{v_i}) - y)^2, \tag{9}$$

where y is the target value of the node attribute in the future. Besides, we combine the spatial and temporal tasks to provide significant gain for capturing inherent evolving patterns in the dynamic graph. With the space and temporal adaptations on the query set, we can obtain a more scalable dynamic GCN model. The adaptation loss is formulated as

$$\theta \leftarrow \theta - \gamma\frac{\partial(\mathcal{L}_s(\mathcal{Q}_s) + \beta\mathcal{L}_t(\mathcal{Q}_t))}{\partial\theta}, \tag{10}$$

where the parameters θ (i.e., $\mathbf{\Theta}$) is optimized to quickly adapt the model to changes on node attributes in the dynamic graph. The γ is the learning rate of the model, and β denotes the balance coefficient between two task losses.

Experiment and Discussion

We conduct experiments on three real-world datasets, including WikiMaths, EnglandCovid, and PedalMe. We present a controlled comparison of our model against dynamic GCN methods, including GConvGRU, GConvLSTM, DCRNN, EvolveGCNH, and TGCN. All detailed information about datasets and baselines refer to (Rozemberczki, Scherer, and Yixuan He 2021). We evaluate the test performance with the mean squared errors (MSE). We repeat all experiments with 10 random seeds and report the mean with standard deviation.

Models	Datasets		
	WikiMaths	EnglandCovid	PedalMe
GCN	0.8211±0.03	0.9723±0.06	1.1512±0.09
GConvGRU	0.7931±0.02	0.9412±0.02	1.2016±0.07
GConvLSTM	0.7991±0.02	0.9541±0.03	1.2141±0.06
DCRNN	0.8061±0.01	0.8323±0.06	1.2213±0.05
EvolveGCNO	0.7783±0.02	0.9793±0.03	1.2013±0.09
TGCN	0.7875±0.02	0.8587±0.12	1.2515±0.08
meta-DGCN	**0.7650±0.01**	**0.5411±0.03**	**1.0106±0.03**

Table 1: Forecasting error is given by MSE on three real-world datasets. The bold denotes the best results.

The results of MSE show that our model performs comparably with state-of-the-art methods. We argue that meta-DGCN provides the fast and best result in node attribute forecasting for the following three main reasons: 1) We utilize the GCN layer, and a gating mechanism can obtain high-quality node embeddings, which has laid a good foundation for the calculation of the following meta space-temporal tasks. 2) The spatial-temporal interaction between nodes can be captured by the spatial and temporal tasks, which can well reflect the changes and development trends of the dynamic graph. 3) Meta optimization mechanism integrates spatial and temporal tasks into dynamic GCN, enabling the model to adapt to various dynamic changes.

Conclusions

This paper presents meta-DGCN, which utilizes meta-learning to enhance dynamic GCN for forecasting node attributes. We innovatively construct support sets and query sets to integrate spatial and temporal tasks into the dynamic GCN learning. Experiments demonstrate the superiority of meta-DGCN over the current advanced methods. Meanwhile, the research of meta-learning for dynamic GCN remains in its infancy, and its application in dynamic graphs is worthy of further exploration.

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