Dynamic Network Link Prediction Based on Characterization of Temporal Attributes

Extended Abstract

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ABSTRACT

The core challenge of dynamic network link prediction lies in capturing link uncertainty and the temporal evolution characteristics of node attributes. Existing methods mostly focus on node spatiotemporal dynamics while ignoring temporal changes in attributes, leading to insufficient extraction of structural and semantic information. This paper proposes the Gaussian-distributed Dynamic Time Embedding (GDTE) algorithm and the GDTEformer model: GDTE models network embeddings as a Gaussian distribution to jointly learn dynamic representations of nodes and attributes; the model integrates the Transformer architecture, distinguishes link importance through spatial position encoding, and addresses temporal nonlinear sparsity. Experiments on four real-world datasets show that GDTEformer significantly outperforms mainstream methods such as Transformer and TGAT in AUC and Precision metrics, with strong robustness.

KEYWORDS

Link prediction; Network representation learning; Gaussian distribution; Variational inference; Transformer

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1 INTRODUCTION AND MOTIVATION

Most real-world data can be naturally modeled as dynamic networks, where node interactions evolve over time [6]. As a fundamental task, link prediction requires learning low-dimensional embeddings that jointly capture both structural dependencies and temporal dynamics. However, existing continuous-time dynamic graph learning methods suffer from two key limitations. They typically model temporal node representations independently, overlooking correlations among nodes and the temporal evolution of node attributes [1, 4, 7, 8]. In addition, they lack topology-aware positional encoding, which restricts their ability to capture both local and global structural patterns [2, 3]. To overcome these limitations, this paper proposes the GDTEformer model, which jointly addresses temporal attribute modeling and structural information learning within a unified framework.

2 MODEL DESIGN

2.1 Overall Framework

GDTEformer consists of an encoder and a decoder. The inputs are the node matrix and attribute matrix generated by GDTE, which reformulates dynamic link prediction as a matrix generation problem, as shown in Eq. (1). Feature fusion is achieved by stacking multiple layers of multi-head self-attention mechanisms and spatial position encoding as shown in Fig. 1

$$I^{(N_t+F_t)\times D} = \Phi((Z_t^V)^{N_t\times D}, (Z_t^A)^{F_t\times D}) \quad (1)$$

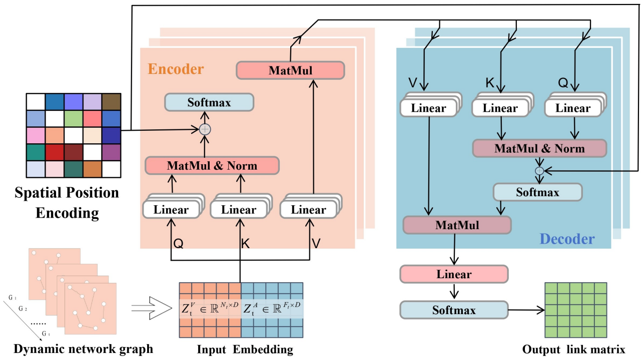

Figure 1: Framework of GDTEformer. "MatMul" and "Norm" are matrix multiplication and layer normalization. $\oplus$ is the addition of matrices.

2.2 Core Innovative Components

GDTE Algorithm: Defines node and attribute embeddings as functions of time, describes dynamic changes through ordinary differential equations as Eq. (2), and models them as Gaussian distributions as Eq. (3). The variance captures embedding uncertainty, initial

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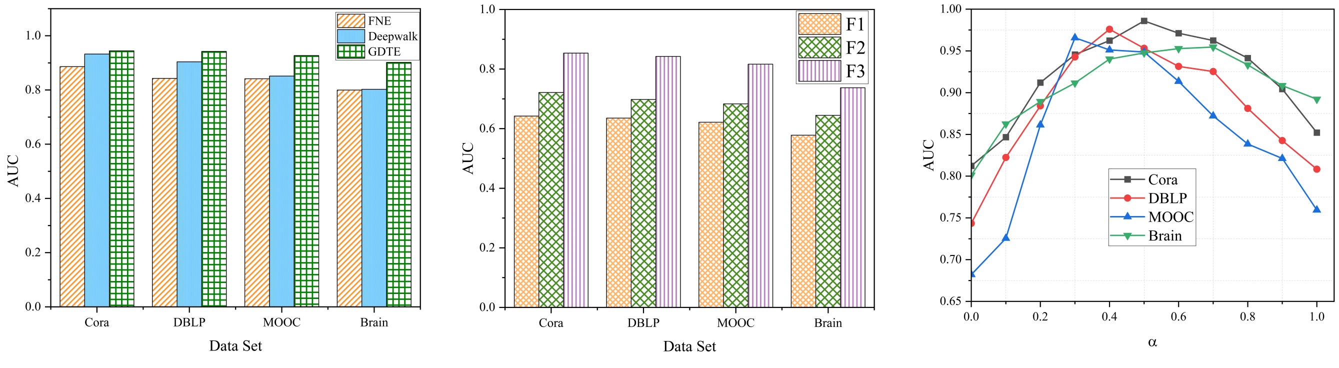

GDTE SPE SL

Figure 2: Effectiveness of different components on dynamic networks.

embeddings of new nodes adopt standard Gaussian distributions, and dynamic patterns of nodes and attributes are learned jointly.

$$\frac{dZ^V(t)}{dt} = g_\theta^V(Z^V(t), t) \tag{2}$$

$$p(Z_t^V | Z_{<t}^V; \theta) = \mathcal{N}(Z_0^V + \int_0^t g_\theta^V(Z^V(t), t), \delta_t I) \tag{3}$$

Spatial Position Encoding (SPE): Defines relative position weights based on the shortest path length between nodes as Eq. (4), and introduces learnable bias terms into attention scores as Eq. (5) to enhance sensitivity to local structures and relative node positions.

$$\eta(v_i, v_j) = \begin{cases} \frac{1}{spl(v_i, v_j)}, & \exists spl(v_i, v_j) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$A_{ij} = \frac{(v_i W_Q)\,(v_j W_k)^T}{\sqrt{d}} + b_{\eta(v_i, v_j)} \tag{5}$$

Structural Loss (SL): Combines cross-entropy loss L_1 with norm constraint of normalized Laplacian matrices L_2 to balance local prediction accuracy and global structural consistency as Eq. (6), effectively capturing global features such as node degree distribution and community structure.

$$L_{loss} = (1 - \alpha)L_1 + \alpha L_2 \tag{6}$$

3 EXPERIMENTAL RESULTS

3.1 Datasets and Setup

We compare four baseline methods: Transformer [9], TGAT [10], MTSN [8], and DNformer [5]. The data is divided chronologically, with 70% for training, 15% for validation, and 15% for testing. AUC and Precision are adopted as the evaluation metrics.

3.2 Key Results

Performance Advantage: GDTEformer achieves the best performance on all datasetsas as shown in Table 1.

Robustness: Maintains high AUC even when the training set ratio is as low as 30%, while significantly outperforming baseline methods as shown in Table 1.

Table 1: AUC comparisons across different datasets and training percentages.

Training Set Percentage	Method	Cora	DBLP	MOOC	Brain
70%	Transformer	0.7218	0.6618	0.6510	0.6400
	TGAT	0.9117	0.8717	0.8614	0.8459
	DNformer	0.9325	0.9025	0.8922	0.8743
	MTSN	0.9657	0.9357	0.9257	0.9201
	GDTEformer (ours)	**0.9859**	**0.9764**	**0.9657**	**0.9546**
60%	Transformer	0.6103	0.5736	0.5662	0.5462
	TGAT	0.8026	0.7764	0.7736	0.7495
	DNformer	0.8554	0.8247	0.8235	0.8056
	MTSN	0.9238	0.8932	0.8846	0.8742
	GDTEformer (ours)	**0.9702**	**0.9518**	**0.9368**	**0.9253**
50%	Transformer	0.5029	0.4889	0.4849	0.4568
	TGAT	0.6921	0.6732	0.6782	0.6421
	DNformer	0.7618	0.7195	0.7196	0.7108
	MTSN	0.8647	0.8126	0.8037	0.7965
	GDTEformer (ours)	**0.9426**	**0.9023**	**0.8745**	**0.8704**
40%	Transformer	0.4851	0.4081	0.4085	0.3786
	TGAT	0.5883	0.5831	0.5867	0.5307
	DNformer	0.6397	0.6127	0.6104	0.6027
	MTSN	0.7562	0.6984	0.6709	0.6792
	GDTEformer (ours)	**0.8641**	**0.8287**	**0.7992**	**0.7879**
30%	Transformer	0.4156	0.3916	0.3427	0.3045
	TGAT	0.5498	0.5249	0.5014	0.4264
	DNformer	0.5348	0.5137	0.5082	0.4869
	MTSN	0.5376	0.5034	0.5143	0.4997
	GDTEformer (ours)	**0.7469**	**0.7356**	**0.7213**	**0.6856**

Ablation Validation: The GDTE, SPE, and SL components are all indispensable. GDTE improves AUC by 0.0758 compared to DeepWalk on the MOOC dataset, and SPE effectively captures global network information as shown in Fig. 2.

4 CONCLUSIONS

The proposed GDTEformer model effectively improves dynamic network link prediction performance through Gaussian distribution modeling of attribute temporal evolution, spatial position encoding for structural feature capture, and structural loss balancing local and global optimization. Future work will optimize algorithm complexity and extend to large-scale dynamic network scenarios.

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