## **Improving Temporal Link Prediction via Temporal Walk Matrix Projection**

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## **Background: Temporal Link Prediction**

➢ Aims at predicting future links based on historical observations.



➢ Crucial for temporal graph learning and real-world applications.



- ➢ Relative Encodings
	- Indispensable module for effective temporal link prediction.
	- Additional node features (conditioned on the link to be predicted) to inject

the pairwise information that can not be capture by the message passing.



Timestamps:



Link  $\overline{A}$ B C F D  $[0,0]$  $(D, F, t_3)$  $[0,0]$  $[0,0]$  $[0,0]$  $[1,1]$  $[0,0]$  $(D, A, t_3)$  $[0,0]$  $[0,0]$  $[0,1]$  $[0,0]$  $[1.0]$  $[0,0]$ 

a) Message passing on the temporal graph can not capture the pairwise information.

b) Relative encoding  $r_w^{(u,v,t)} = [g(u,w,t), g(v,w,t)],$ where  $g(a, b, t) = \{$ 1,  $b \in \mathcal{N}_a(t)$ 0, otherwise

## **Problems of Existing Relative Encodings**

**1) Concept**. Existing relative encodings are derived from different heuristics. The connections between different relative encodings are unclear.

2) **Method Design**. Most existing relative encodings are constructed based on structural connectivity, where the temporal information is ignored.

**3) Computation.** Constructing existing relative encodings always relies on timeconsuming graph queries, making it the computational bottleneck.

## **A Unified View of Relative Encodings**

**Relative Encoding.** Given an observed graph  $\mathcal{G}_t$  and a link  $(u, v)$  to be predicted, the relative encoding for node w is the concatenation of two similarity features  $r^{w|u}$  and  $r^{w|v}$ , which is  $r^{w|(u,v)} = [r^{w|u}$  ,  $r^{w|v}$ ].

Unified View of the Similarity Feature. Existing similarity features  $r^{w|u}$  can be unified into the function of temporal walk matrices. Formally,  $r^{w|u} \in \mathbb{R}^k$  can be represented as

$$
r^{w|u} = g\left(\left[A_{u,w}^{(0)}(t), A_{u,w}^{(1)}(t), \cdots, A_{u,w}^{(k-1)}(t)\right]\right), \qquad A_{u,w}^{(i)}(t) = \sum_{W \in M_{u,w}^i} s(W),
$$

A 4-step temporal walk from  $B$  to  $F$ 

 $[(B, t), (C, t_1), (A, t_2), (D, t_2), (F, t_1)]$ 

Where  $M_{u,w}^i$  is the set of i-step temporal walks from u to w and  $s(\cdot)$  is a score function that maps a temporal walk to a scalar.

Timestamps:  $t_1 < t_2 < t_3 < t_4 < t$ 

Temporal Graph  $G_t$ 

**A New Temporal Walk Matrix**. We propose a new temporal walk matrix based on time decay effect, which simultaneously consider the temporal and structure information.

**An Incremental Maintenance Algorithm**. We propose an incremental algorithm to maintain the random projections of the proposed temporal walk matrices, which provably preserve the inner product between different rows of the matrices.

**A Temporal Graph Network**. We propose an effective and efficient temporal graph neural network, which construct relative encodings without time-consuming graph queries.

## **Experimental Results**

### SOTA performance on 13 benchmark datasets  $\overline{33} \times$  speedup compared to SOTA baseline

#### Table 1: Transductive results for different baselines under the random negative sampling strategy. **blod** and underline highlight the best and second best result respectively.







#### Code and tutorial

https://github.com/lxd99/TPNet

# **Thanks for listening !**