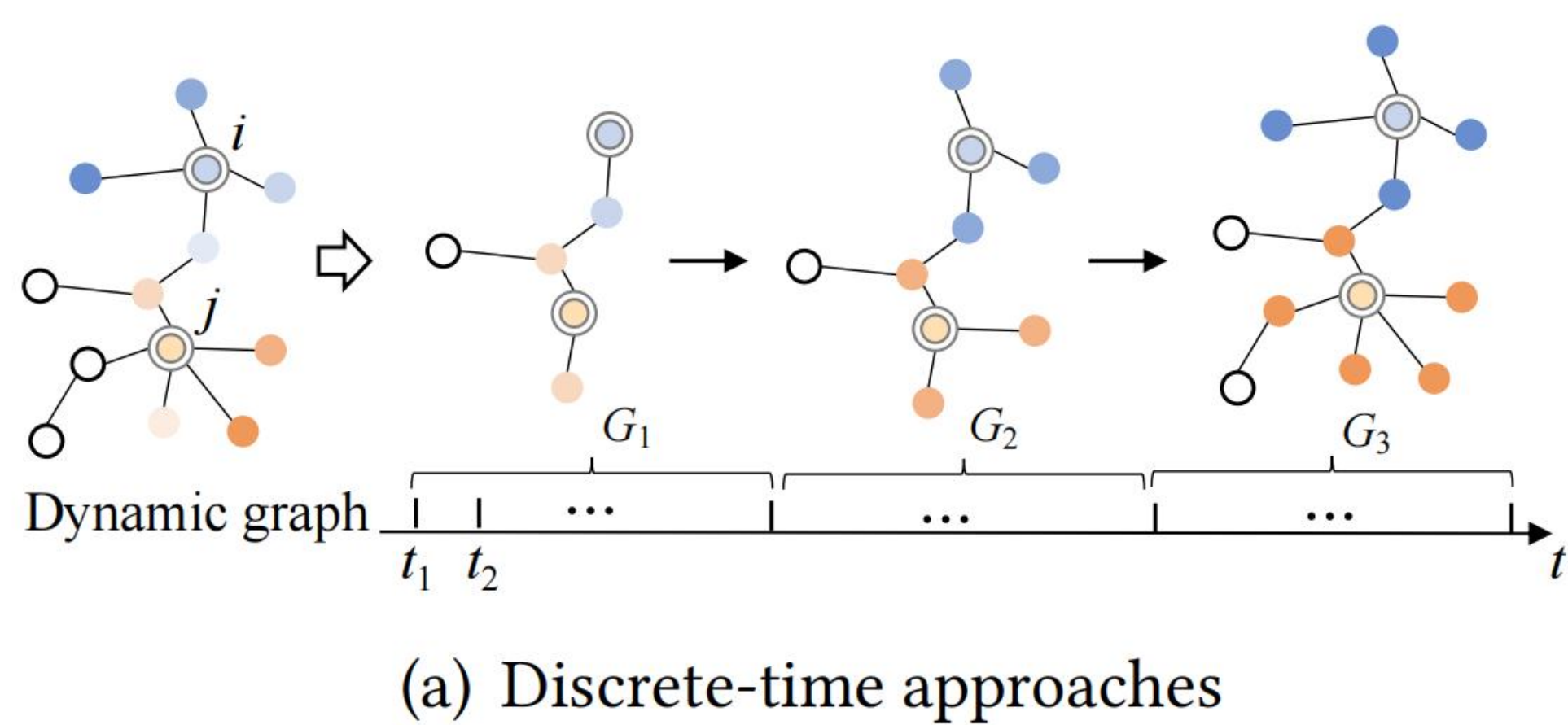


On the Feasibility of Simple Transformer for Dynamic Graph Modeling

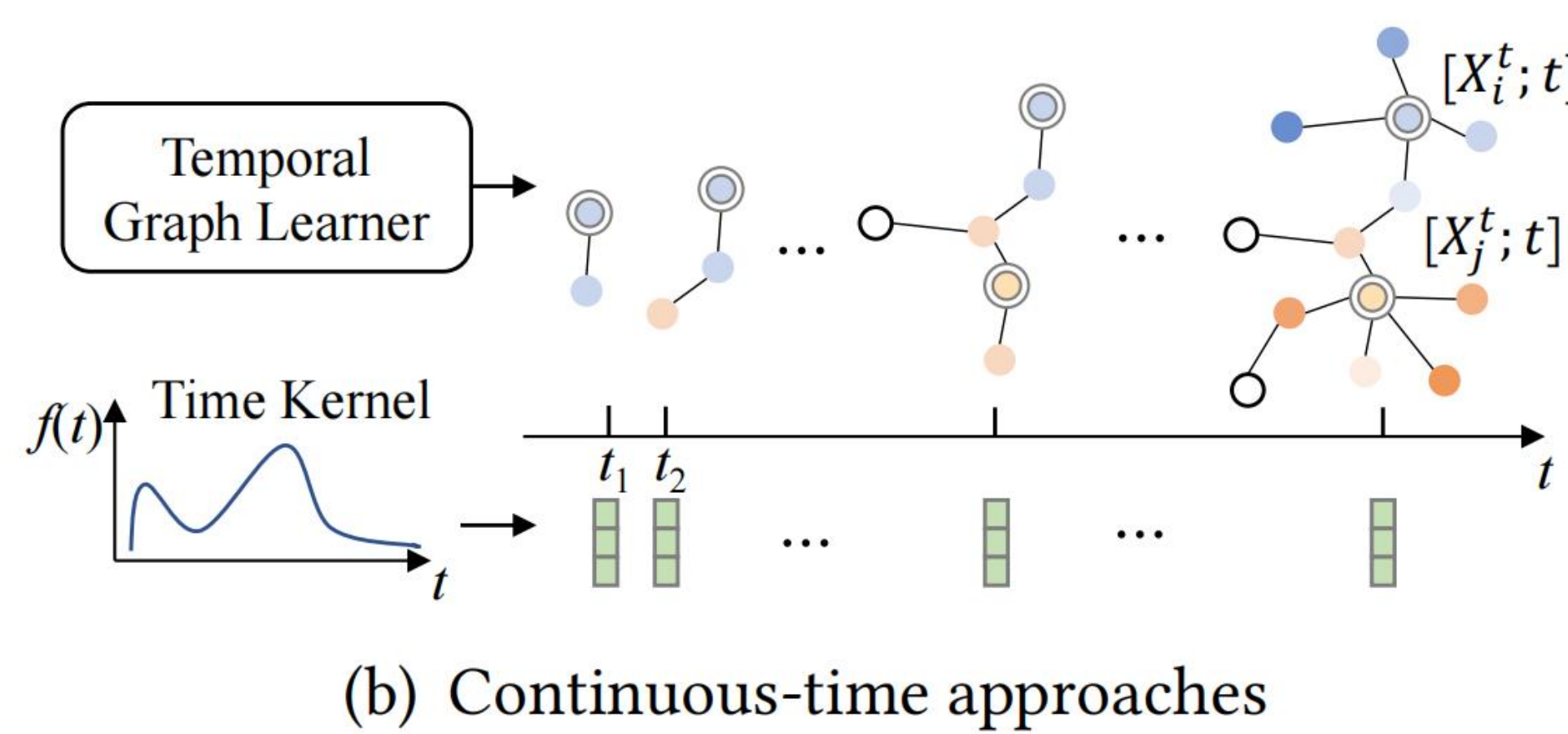
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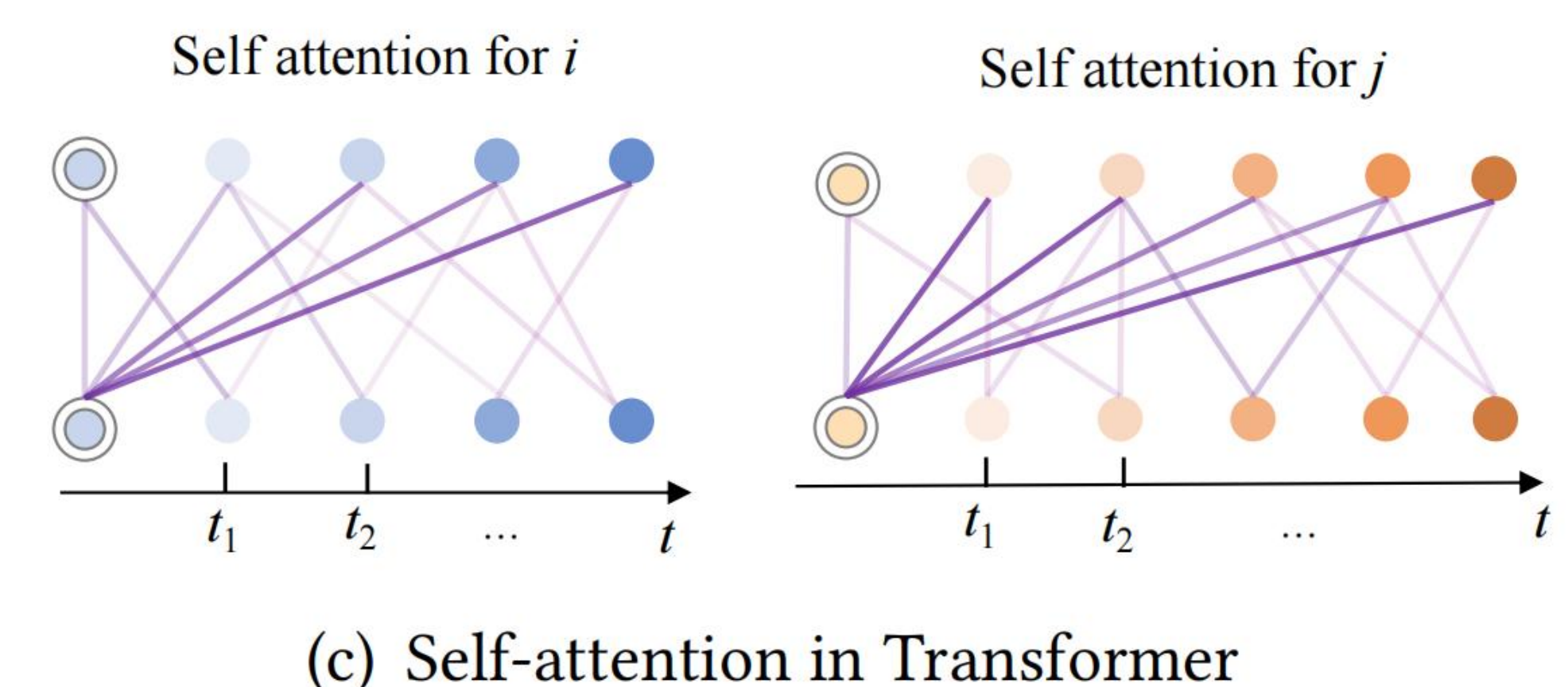
Motivation



Discard the **fine-grained** temporal information within the snapshot



Difficult for capturing **long-term dependency** within historical graph data

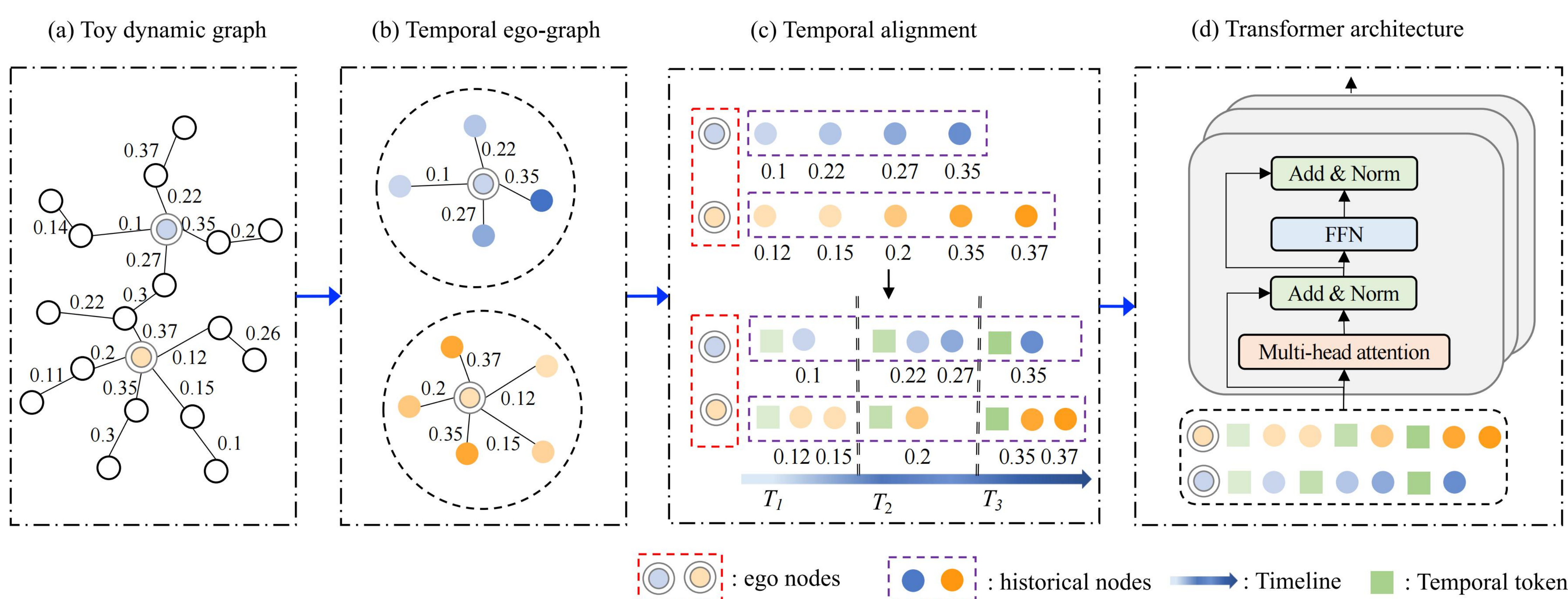


Naturally support **continuous sequence**
Self-attention --> **long-term dependency**

Contribution:

- ❖ We explore the potential of the **Transformer** architecture for modeling **dynamic graphs**
- ❖ We propose a **simple yet effective** Transformer-based approach for dynamic graphs **without complex modifications**
- ❖ We introduce a **novel strategy** to map a dynamic graph into a set of sequences with **special tokens** to improve the scalability

Framework: SimpleDyG



Dynamic graph

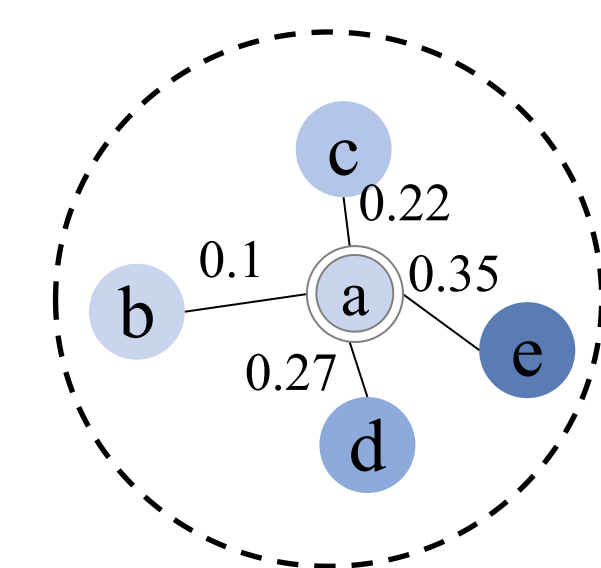
$$\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{T}, \mathcal{X})$$

\mathcal{V} : nodes

\mathcal{E} : edges

\mathcal{T} : time domain

\mathcal{X} : input feature matrix



Temporal Ego-graph

- Temporal ego-graph for one node:

$$w_i = \langle b, c, d, e \rangle$$

- Training sample:

• Input: $x_i = \langle |hist|, a, b, c, d, e, \langle |endofhist| \rangle \rangle$

• Output: $y_i = \langle |pred|, f, g, \dots, \langle |endofpred| \rangle \rangle$

Temporal Alignment

- Segment the time domain into T time steps

$$S_i^1 = \langle b \rangle \quad S_i^2 = \langle c, d \rangle \quad S_i^3 = \langle e \rangle$$

- Training sample:

• Input: $x'_i = \langle |hist|, a, \langle |time1| \rangle, b, \langle |time2| \rangle, c, d, \langle |time3| \rangle, e, \langle |endofhist| \rangle \rangle$

• Output: $y'_i = \langle |pred|, \langle |time4| \rangle, S_i^4, \langle |endofpred| \rangle \rangle$

Experiment

Datasets

Dataset	UCI	ML-10M
Domain	Social	Rating
# Nodes	1,781	15,841
# Edges	16,743	48,561

Dataset	Hepth	MMConv
Domain	Citation	Conversation
# Nodes	4,737	7,415
# Edges	14,831	91,986

Results

	UCI		ML-10M		Hepth		MMConv	
	NDCG@5	Jaccard	NDCG@5	Jaccard	NDCG@5	Jaccard	NDCG@5	Jaccard
DySAT [37]	0.010±0.003	0.010±0.001	0.058±0.073	0.050±0.068	0.007±0.002	0.005±0.001	0.102±0.085	0.095±0.080
EvolveGCN [32]	0.064±0.045	0.032±0.026	0.097±0.071	0.092±0.067	0.009±0.004	0.007±0.002	0.051±0.021	0.032±0.017
DyRep [40]	0.011±0.018	0.010±0.005	0.064±0.036	0.038±0.001	0.031±0.024	0.010±0.006	0.140±0.057	0.067±0.025
JODIE [20]	0.022±0.023	0.012±0.009	0.059±0.016	0.020±0.004	0.031±0.021	0.011±0.008	0.041±0.016	0.032±0.022
TGAT [49]	0.061±0.007	0.020±0.002	0.066±0.035	0.021±0.007	0.034±0.023	0.011±0.006	0.089±0.033	0.058±0.021
TGN [36]	0.041±0.017	0.011±0.003	0.071±0.029	0.023±0.001	0.030±0.012	0.008±0.001	0.096±0.068	0.066±0.038
TREND [44]	0.067±0.010	0.039±0.020	0.079±0.028	0.024±0.003	0.031±0.003	0.010±0.002	0.116±0.020	0.060±0.018
GraphMixer [6]	0.104±0.013	0.042±0.005	0.081±0.033	0.043±0.022	0.011±0.008	0.010±0.003	0.172±0.029	0.085±0.016
SimpleDyG	0.104±0.010	0.092±0.014	0.138±0.009	0.131±0.008	0.035±0.014	0.013±0.006	0.184±0.012	0.169±0.010