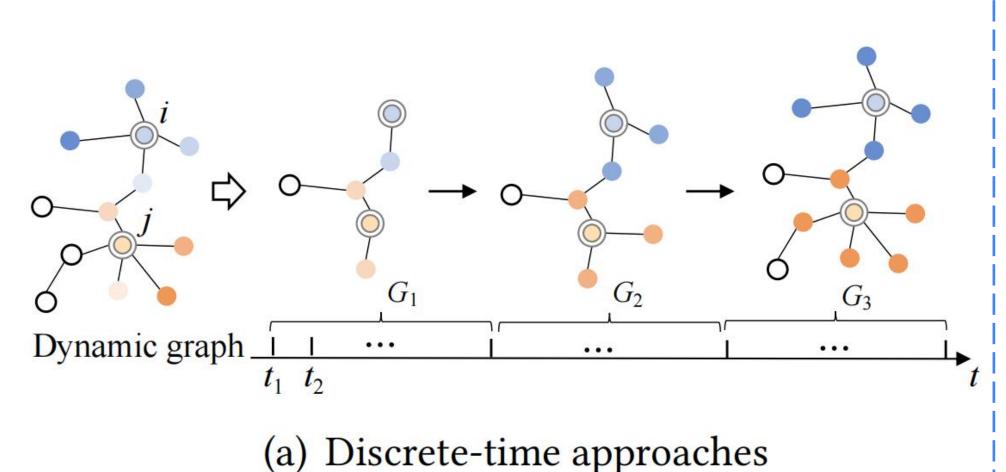
CONFERENCE

On the Feasibility of Simple Transformer for Dynamic Graph Modeling

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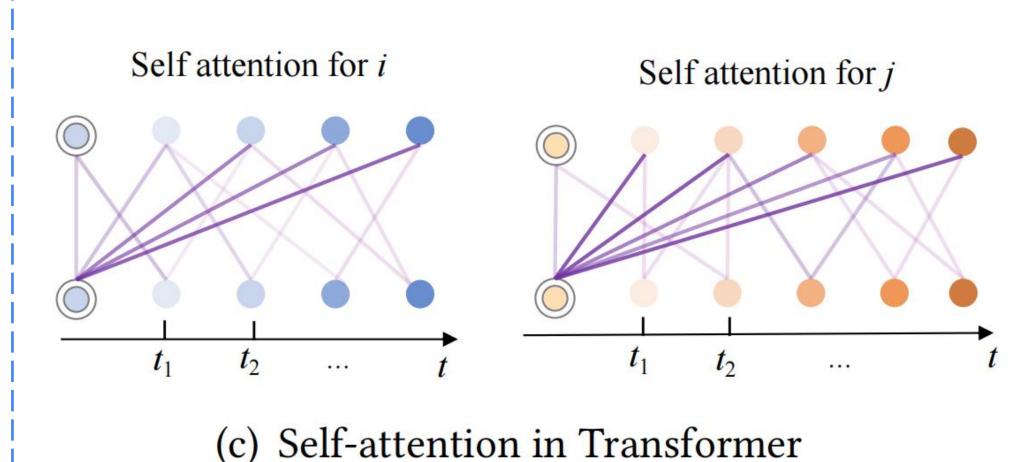
Motivation



Discard the fine-grained temporal information within the snapshot

Temporal f(t) Time Kernel Continuous-time approaches

Difficult for capturing long-term dependency within historical graph data

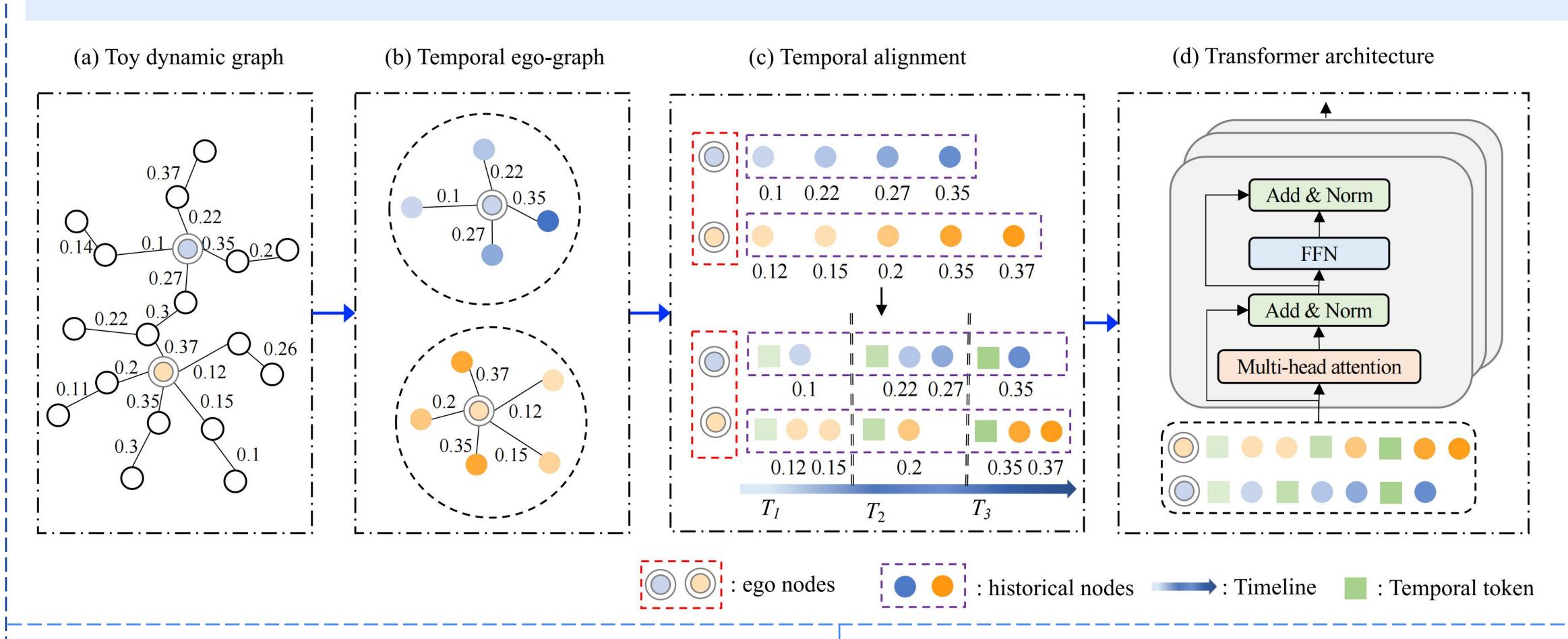


Naturally support continuous sequence Self-attention --> long-term dependency

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

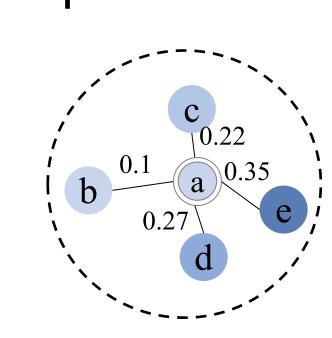
$$\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{T}, \mathcal{X})$$

 \mathcal{V} : nodes

 \mathcal{E} : edges

 \mathcal{T} : time domain

 χ : input feature matrix



Temporal Ego-graph

☐Temporal ego-graph for one node:

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

☐Training sample:

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

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

Temporal Alignment

□Segment the time domain into *T* time steps

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

☐Training sample:

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

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

Experiment

Datasets

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

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

Results

4#	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