Neural Temporal Walks: Motif-Aware Representation Learning on Continuous-Time Dynamic Graphs

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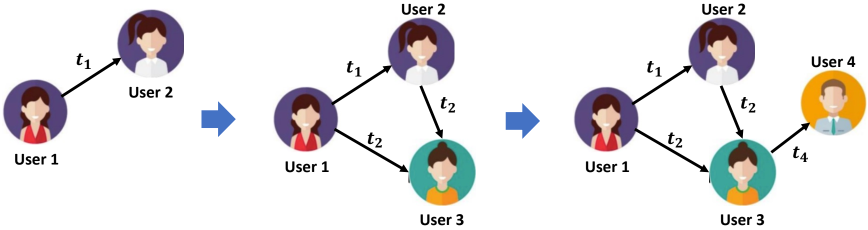
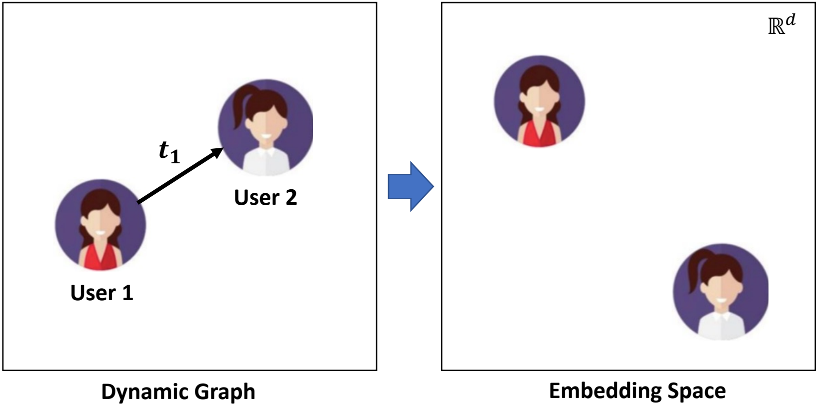
Code is available at:
https://github.com/KimMeen/Neural-Temporal-Walks

Temporal Interaction Network

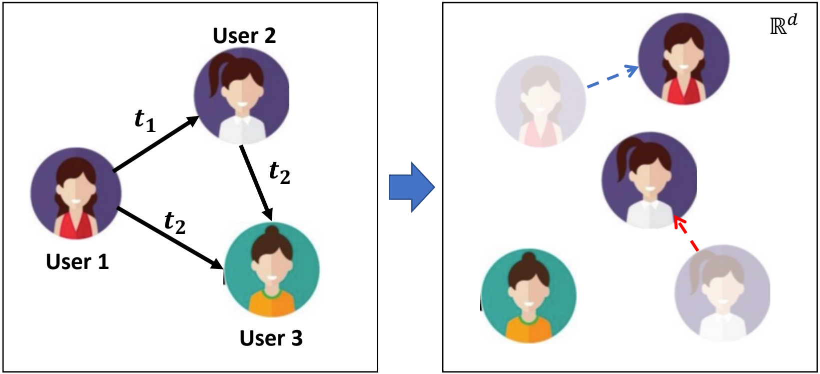
- It is also known as Continuous-Time Dynamic Graph (CTDG)



Dynamic Graph Representation Learning



Dynamic Graph Representation Learning



Dynamic Graph

Embedding Space

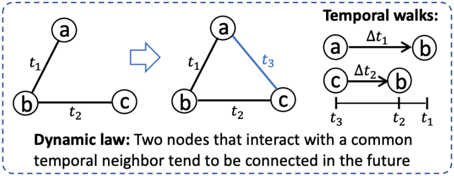
Challenges

- The entangled spatial and temporal dependencies in real-world dynamic graphs need a *specific paradigm* to model

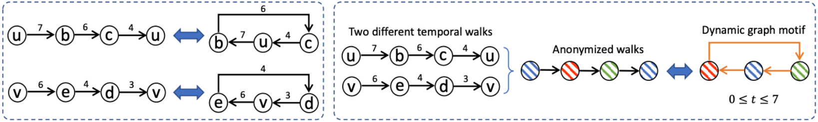
- Temporal events in CTDGs occur *irregularly*, resulting in a significant challenge in modeling temporal dependencies

Neural Temporal Walks

- *Dynamic graph motifs* abstract important *dynamic laws* in a dynamic graph

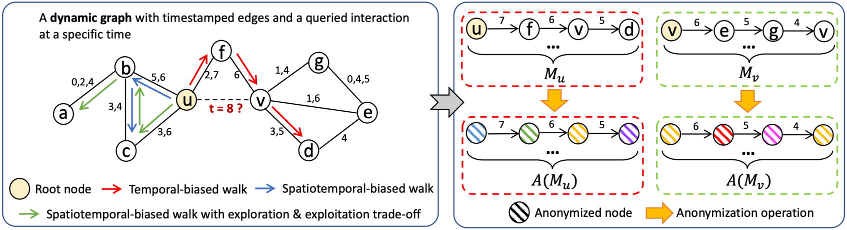


- A motif may have multiple instances, which are *temporal walks*



Neural Temporal Walks

- **Motif extraction:** We consider not only *temporal* but also *spatial* constrains when sampling walks



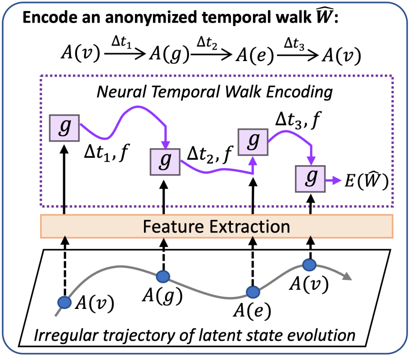
(a) Dynamic Graph Motif Extraction

(b) Walk Anonymization

- We also consider *tree traversal properties* to avoid sampling too much homogeneous motifs

Neural Temporal Walks

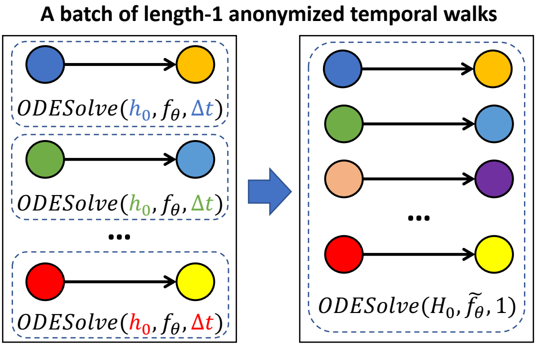
- **Motif encoding:** Interleaving the *continuous evolution* and *instantaneous activation* processes to learn the underlying spatiotemporal dynamics



- We aggregate the embedding of surrounding motifs as the representation of a temporal node or an interaction

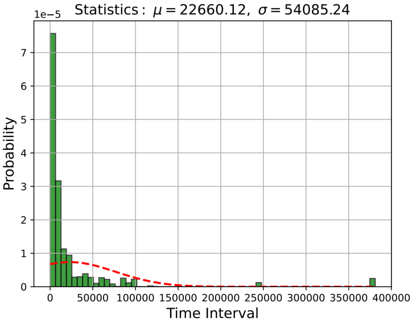
Batching for Scalability

- We employ a "substitute variable" trick

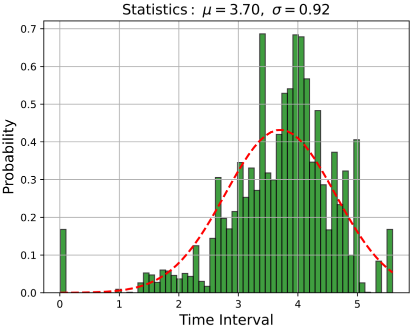


Time Interval Normalization

- We consider logarithmic transformations to make the solving tractable



(a) Distribution of raw time intervals in seconds



(b) Distribution of logarithmic scaled time intervals with the base 10

Results

- On six real-world dynamic graphs, our method **significantly and constantly outperforms state-of-the-art methods**
  - E.g., it surpasses the strongest baseline by up to **8%** in transductive or inductive temporal link prediction tasks
- Our walk sampling and encoding techniques bring around **3%** and **5%** improvements over the best available solutions
- Our method maintains good **interpretability** by learning motif-aware representations