TemporalGAT: Attention-Based Dynamic Graph Representation Learning

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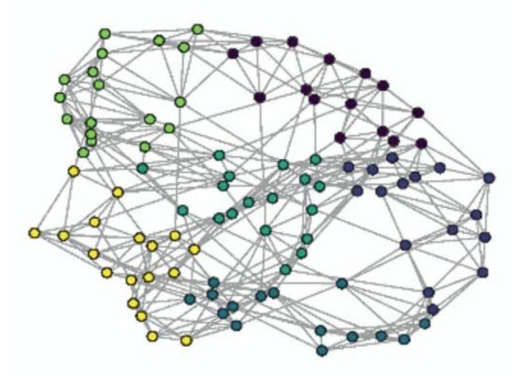
Ahmed Fathy and Kan Li. “TemporalGAT: Attention-Based Dynamic Graph Representation Learning”.

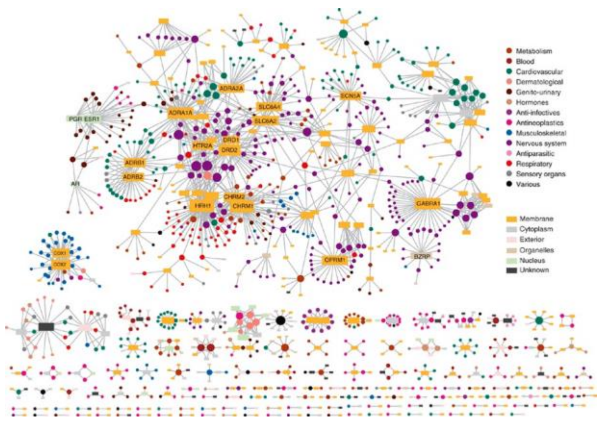
Real-world Graphs are in Continuous Evolution

- Real-world dynamic graphs are continuously evolved.
- New nodes and edges are added or removed during graph evolution.

Social networks



Collaboration networks



Drug-protein networks

Dynamic Graph Representation Learning

- Finds the most informative *low-dimensional representation* of the data that preserves the structural, temporal and other network information.

Why is it important?

- Dynamic Information networks are becoming more prevalent in our daily lives such as social networks and citation networks, etc.
- It has extensive real-world applications such as friendship prediction, and user recommendation.

Research Questions

- How to integrate network **topology structure**, **node features**, and **temporal information** in the representation learning process?

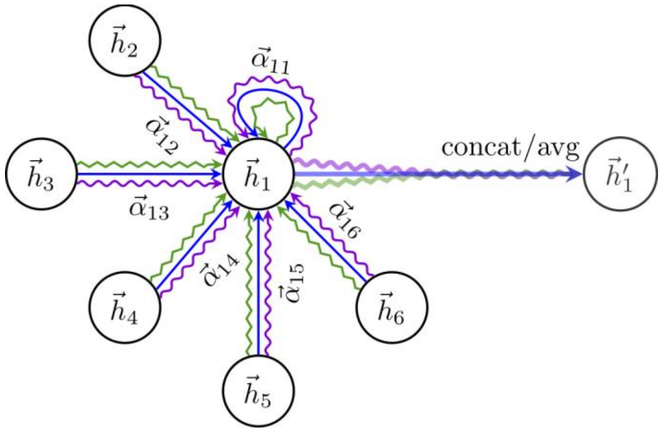
- How to learn meaningful graph representations using state-of-the-art **graph neural networks** and **deep learning** methods?

Related Work: Static Graph Representation Learning

Learn effective node representations for static graphs

- Network Structure:
  - DeepWalk (Perozzi et al., 2014)
  - LINE (Tang et al., 2015)
  - …

- Network Structure and Node Features:
  - Graph Convolutional Networks – GCN (Kipf et al., 2016)
  - Graph Attention Networks – GAT (Veličković et al., 2018)
  - …



Graph Attention Network

Pros and Cons of Static Graph Representation Learning Methods

Pros

- Learn superior node representations for static graphs
- Effective in several network analytic tasks such as:
  - Node classification
  - Link prediction
  - Network visualization

Cons

- Unable to model the evolving nature of dynamic graphs
- Model training and inference on dynamic graphs are difficult, due to the evolving nature of graph structures

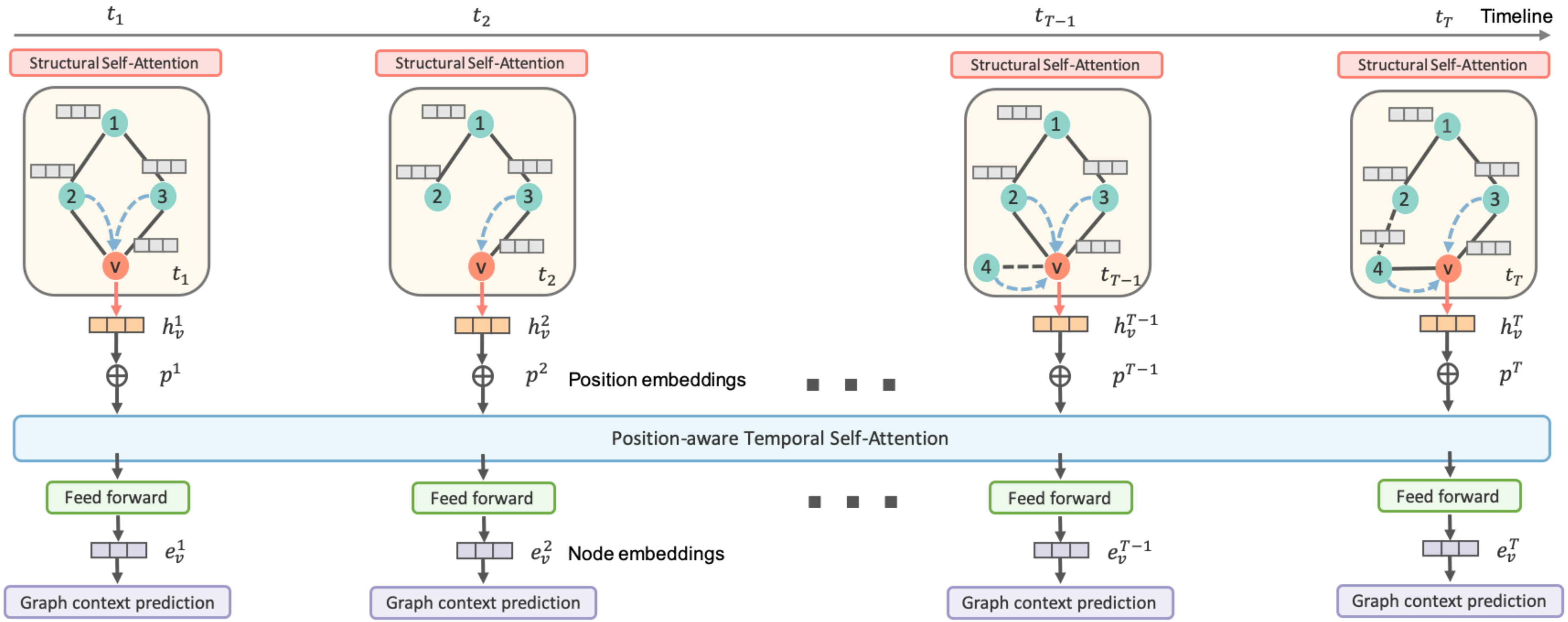
Related Work: Dynamic Graph Representation Learning

Examples:

- DANE (Li et al., 2017)
  - Updates the eigenvectors of graph Laplacian matrix over time series.
- DynGEM (Goyal et al., 2017)
  - Applies an autoencoder model to learn incremental node representations across time steps.
- DySAT (Sankar et al., 2018)
  - Captures structural properties separately using GAT, and applies temporal attention layers to capture the variations in the generated representations.

Related Work:

DySAT: Dynamic graph representation learning via self-attention networks



Pros and Cons of Dynamic Graph Representation Learning Methods

Pros

- Inspired by static graph representation methods.
- Capture the temporal evolutionary patterns of dynamic graphs.

Cons

- Several methods be considered as an *extension* of static methods.
- Tend to learn representation for each graph snapshot separately, and update the embedding weights according to snapshot position.

Can we do better?

TemporalGAT: Attention-Based Dynamic Graph Representation Learning

- Inspired by recent work, DySAT (Sankar et al., 2018).
- Towards combining structural and temporal information.
- Applies self-attention mechanism along structural neighborhoods over temporal dynamics.
- Leverage **temporal convolutional network** (TCN).

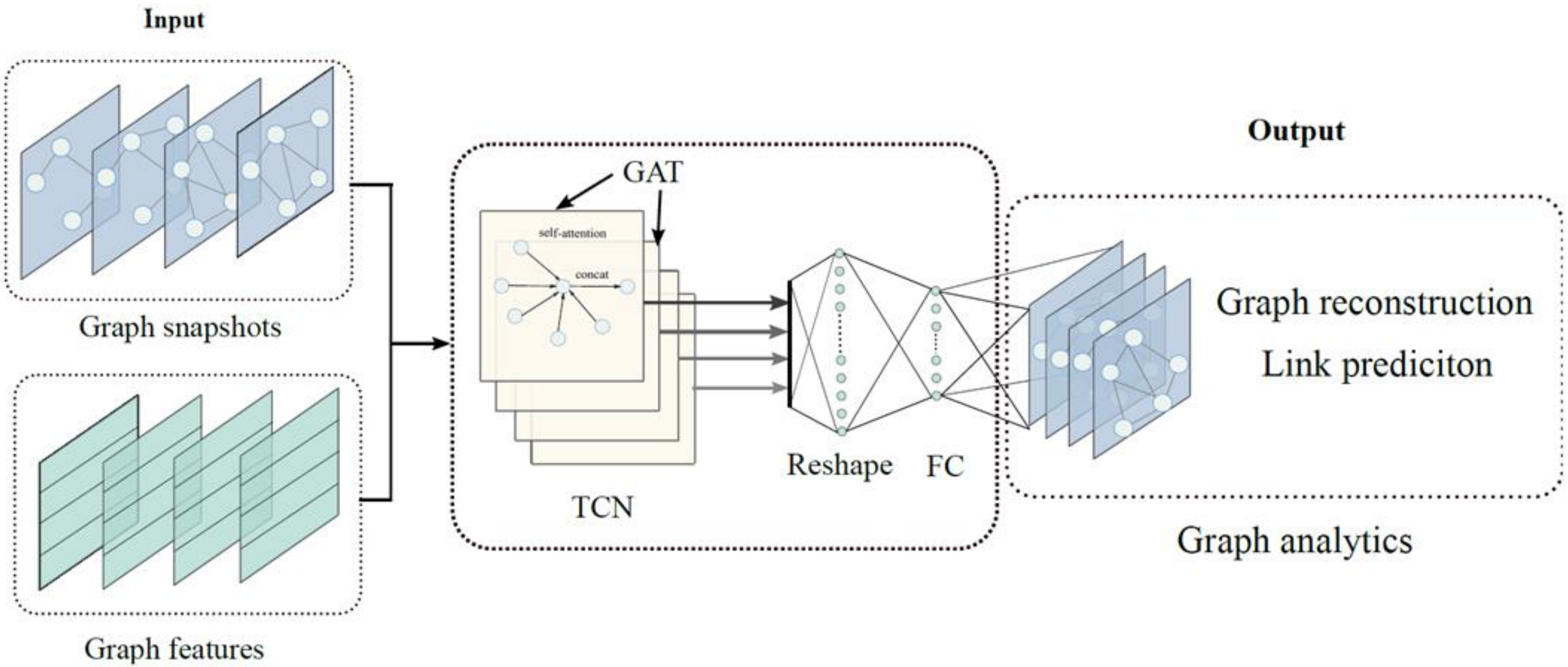
TemporalGAT: Method

- Apply multi-head graph attentions and TCNs as a special recurrent structure to improve model efficiency.
- The proposed GAT layer has **dilated convolutions** to ensure that ***no information leakage*** from future to past graph snapshots.

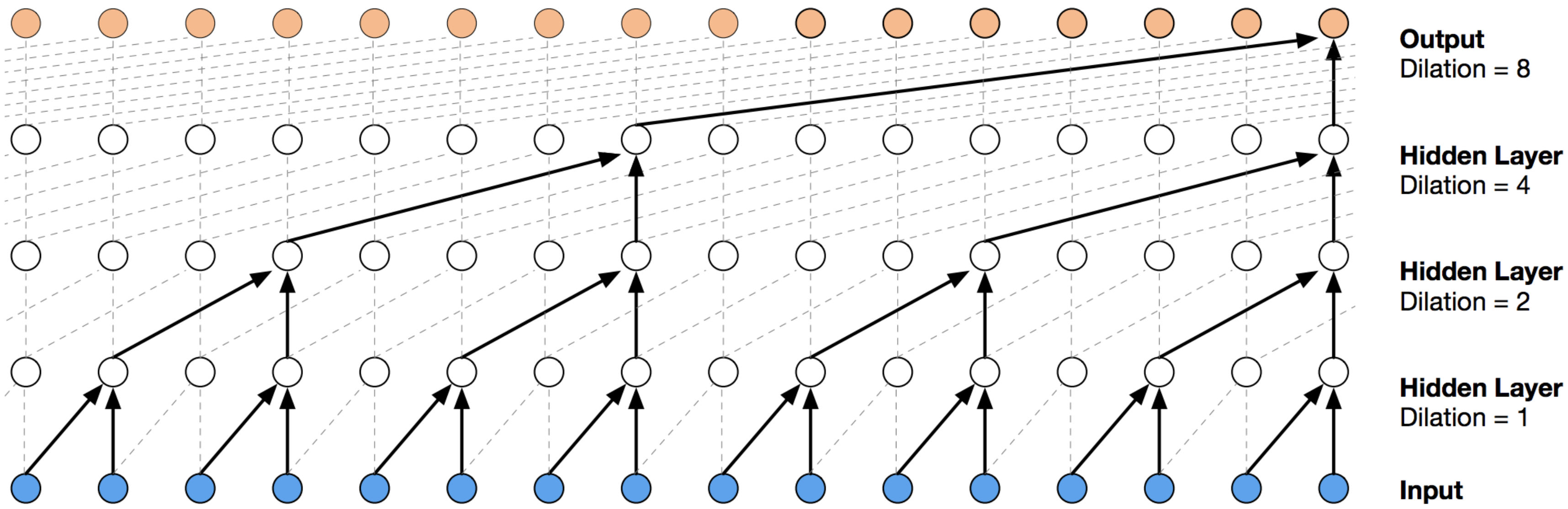
$$Conv_d(u) = (x *_d f)(u) = \sum_{i=0}^{k-1} f(i) \cdot x_{u-d\cdot i}$$

- Model weights are shared across graph snapshots.

TemporalGAT: Framework



TemporalGAT: Method



Stack of dilated causal convolutional layers (Wavenet, 2016)

Applications: Link Prediction

- Leverage structural and temporal information up to time step t and predict the existence of an edge between a pair of vertices at $t + 1$.
- Dynamic graph datasets used for performance evaluation:

Dataset	# Nodes	# Edges	# Time steps	Category
Enron	143	2,347	10	Communication
UCI	1,809	16,822	13	
Yelp	6,569	95,361	12	Rating

Results of Link Prediction

- State-of-the-art performance

Algorithm	Enron		UCI		Yelp	
	Micro	Macro	Micro	Macro	Micro	Macro
Node2Vec	83.7±0.7	83.1±1.2	80.0± 0.4	80.5±0.6	67.9±0.2	65.34±0.2
G-SAGE	82.5± 0.6	81.9±0.5	79.2± 0.4	82.9 ± 0.2	61.0±0.1	58.56±0.2
G-SAGE + GAT	72.5±0.4	73.3±0.6	74.0±0.4	79.8±0.2	66.2±0.1	65.1±0.2
GCN-AE	81.6±1.5	81.7±1.5	80.5±0.3	83.5±0.5	66.7±0.2	65.8±0.2
GAT-AE	75.7±1.1	76.0±1.4	80.0±0.2	81.9±0.3	65.9±0.1	65.4±0.1
DynamicTriad	80.3±0.8	79.0±0.9	77.6±0.6	80.3±0.5	63.5±0.3	62.7±0.3
Know-Evolve	61.6±1.1	62.3±1.5	71.2±0.5	80.9±0.2	56.9±0.2	59.7±0.2
DynGEM	67.8±0.6	69.7±1.3	77.5±0.3	79.8±0.5	66.0±0.2	66.0±0.2
DySAT	85.7±0.3	86.6±0.2	81.0±0.2	**85.8±0.1**	70.2±0.1	69.9±0.1
TemporalGAT	**86.4±0.4**	**86.8±0.3**	**82.7±0.2**	85.2±0.2	**71.9±0.3**	**70.3±0.2**

Summary

- Dynamic graph representation learning is a challenging research problem.
- TemporalGAT: towards combining structural information, node features and temporal evolutionary patterns during model training.
- Incorporating temporal information during training stage improves model capacity.
- State-of-the-art results on link prediction task.

Thank you