Temporal GNN

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Graph Neural Networks and Applications

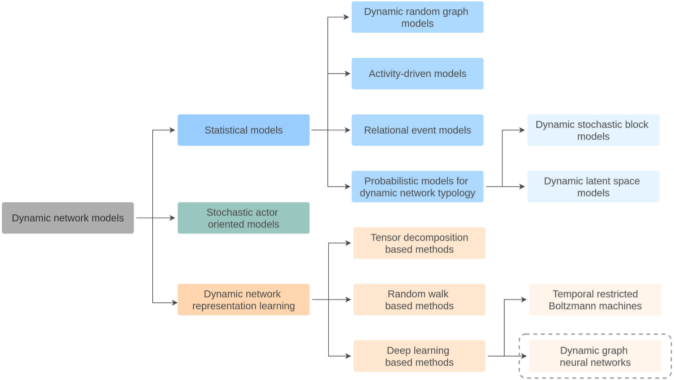
Topics

1. Categorization
2. Temporal Graph Embeddings
3. Temporal & Spatial Aggregation and Attention

Taxonomy of Temporal Models

Foundations and modeling of dynamic networks using dynamic graph neural networks

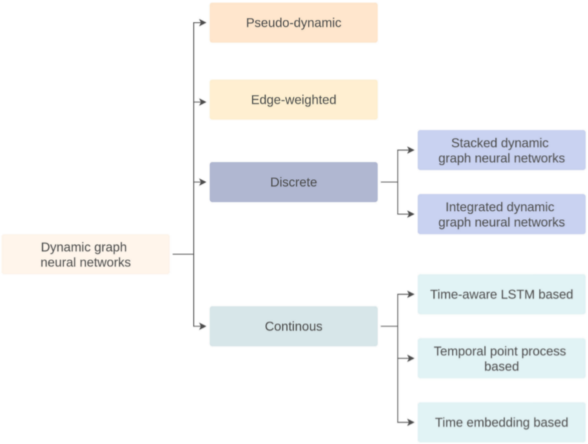
- Statistical, Representation Learning, Stochastic Agent-based



from Musial et al., 2021

Foundations and modeling of dynamic networks using dynamic graph neural networks

- Network type, and Discrete or Continuous models



from Musial et al., 2021

Simple Models

TemporalNode2vec: Temporal Node Embedding in Temporal Networks

1. Compute PPMI (Positive Pointwise Mutual Information) over temporal window ω
2. Factorize PPMI with regularization tricks and temporal consistency

$$PPMI_t(v_1,\, v_2) = max\left(0,\, log\left(\theta\, \frac{|v_1,\, v_2|_t^w \cdot |V|}{|v_1|_t \cdot |v_2|_t}\right)\right)$$

$$\forall (v_1,\, v_2 \neq v_1,\, t) \in V^2 \times [\![1,\, T]\!]$$

$$\begin{aligned} L &= L_{St} + \tau\, L_{Sm} + \lambda\, L_{LR} \\ &= \sum_{t=1}^{T} \left\| PPMI_t - U_t\, U_t^T \right\|_F^2 + \tau \sum_{t=2}^{T} \|U_t - U_{t-1}\|_F^2 + \lambda \sum_{t=1}^{T} \|U_t\|_F^2 \end{aligned}$$

from Bedart et al., 2019

Node Embedding over Temporal Graphs

1. Recurrent snapshot model
2. Initialization by node2vec
3. Q_t as static embeddings rotated by R_t

$$f_{t+1}(v) = \sigma(Af_t(v) + BR_tQ_tv)$$

$$-\sum_t \sum_{v_t \in V_t} \log Pr(N(v_t)|Q_tv_t)$$

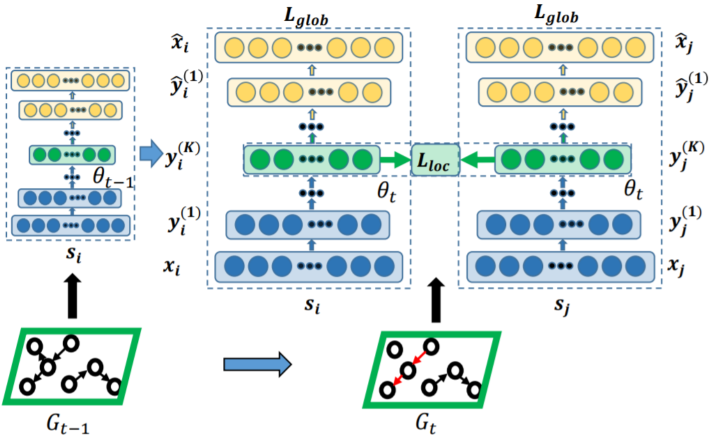
$$\sum_t \|R_{t+1}Q_{t+1} - Q_t\| + \lambda\|R_{t+1}^T R_{t+1} - I\|$$

$$R_{t+1} = \text{argmin}_{R \text{ s.t. } R^T R = I} \|RQ_{t+1} - Q_t\|$$

from Radinsky et al., 2019

DynGEM: Deep Embedding Method for Dynamic Graphs

1. Extension of SDNE graph autoencoders
2. Retraining with parameters from previous snapshots

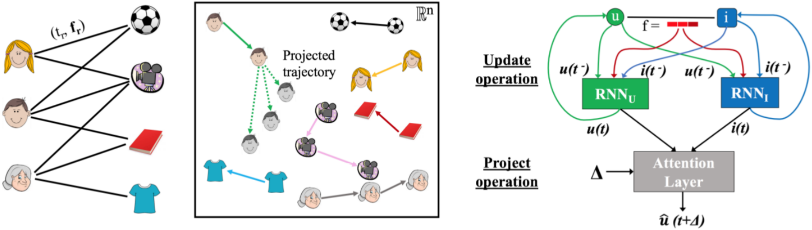


from Liu et al., 2019

Recommender Systems

Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks

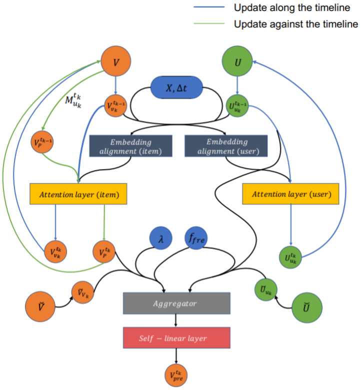
1. JODIE adapts user positions along sessions adapting current recommendations
2. RNN updates for user and item embeddings, while predicting user position for next point.



from Leskovec et al., 2019

Highly Liquid Temporal Interaction Graph Embeddings

1. Used-based and frequency-based windows for priority of updates
2. Dynamic and static embeddings, frequent previous nodes window, time decay and frequency factors.

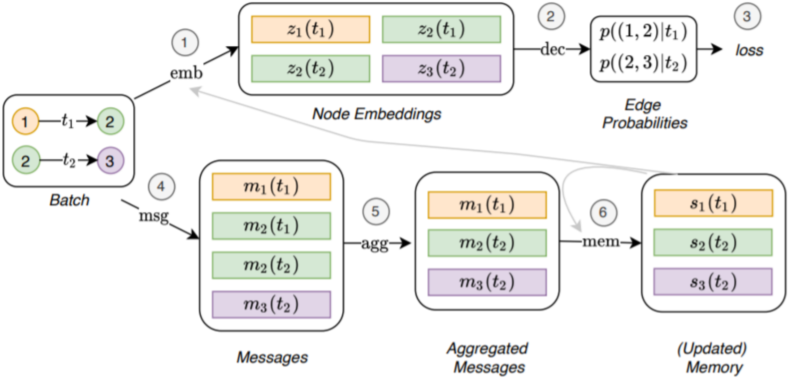


from Yu et al., 2021

General Framework

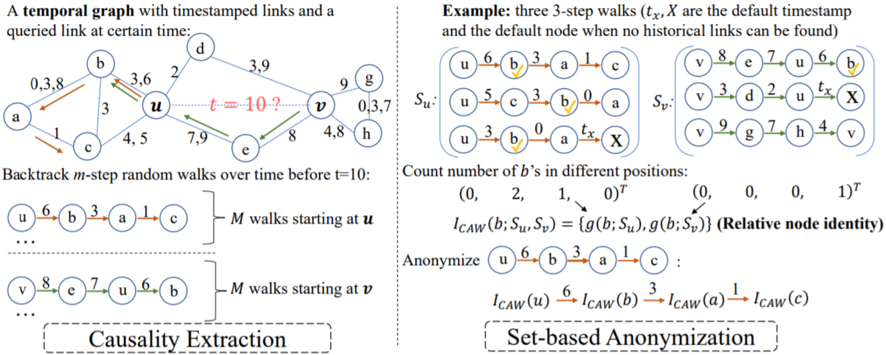
Temporal graph networks for deep learning on dynamic graphs

1. Universal framework for temporal graph processing
2. Embedding incorporates memory updates



from Bronstein et al., 2020

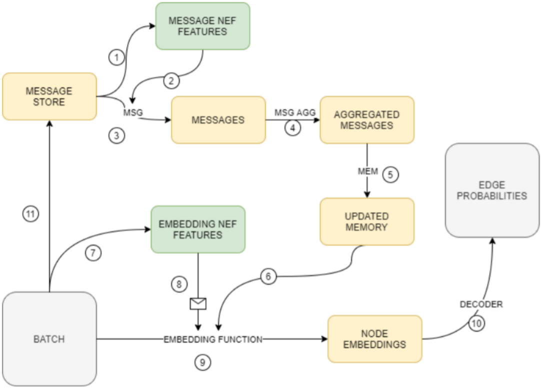
Inductive Representation Learning in Temporal Networks via Causal Anonymous Walks



from Li et al., 2021

Temporal Graph Network Embedding with Causal Anonymous Walks Representations

1. Efficient integration of CAW for LP and TGN for NC
2. Temporal Network Embedding benchmarking

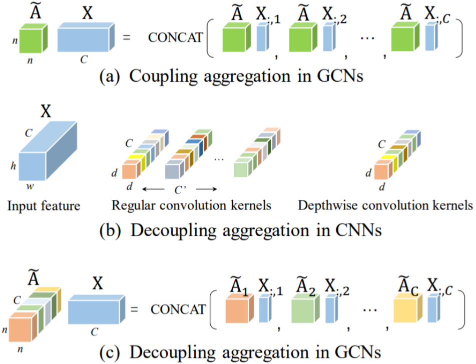


from Babaev et al., 2021

Decomposition-based Models

Decoupling GCN with DropGraph Module for Skeleton-Based Action Recognition

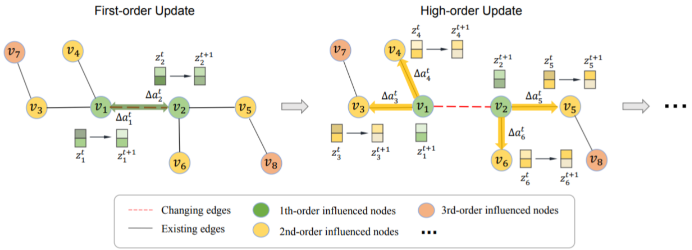
1. Decoupling aggregation patterns may help decomposing dynamic and static patterns



from Lu et al., 202

DyGCN: Dynamic Graph Embedding with Graph Convolutional Network

1. Iteratively propagate updates from temporal changes
2. Use historic and update decomposition in model training



from Ai et al., 2021

DyGCN: Dynamic Graph Embedding with Graph Convolutional Network

Algorithm 1 DyGCN

Input: $\mathcal{G}^t = \{\mathcal{V}^t, \mathcal{E}^t\}, G^{t+1} = \{\mathcal{V}^{t+1}, \mathcal{E}^{t+1}\}$: the graph at time t and $t+1$;
$Z_t = \{z_v^t, v \in \mathcal{V}^t\}$: the node embeddings at time t;
$\{W_0, W_1, W_2, ..., W_K\}$: the transformation matrices.

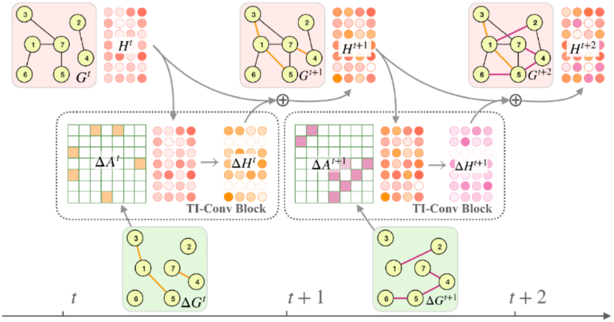
Output: $Z^{t+1} = \{z_v^{t+1}, v \in \mathcal{V}^t\}$, the node embeddings at time $t+1$.

```
// The update of first-order influenced nodes
for v ∈ V_1^t do
    Δa_v^t = Σ_{u∈N^{t+1}(v)∪v} z_u^t − Σ_{u∈N^t(v)∪v} z_u^t;
    z_v^{t+1} = σ(W_0 z_v^t + W_1 Δa_v^t);
end for
// The update of high-order influenced nodes
for k ∈ [2, ..., K] do
    for v ∈ V_k^t do
        Δa_v^t = Σ_{u∈N^{t+1}(v)∪v} (z_u^{t+1} − z_u^t);
        z_v^{t+1} = σ(W_0 z_v^t + W_k Δa_v^t).
    end for
end for
```

from Ai et al., 2021

TI-GCN: A Dynamic Network Embedding Method with Time Interval Information

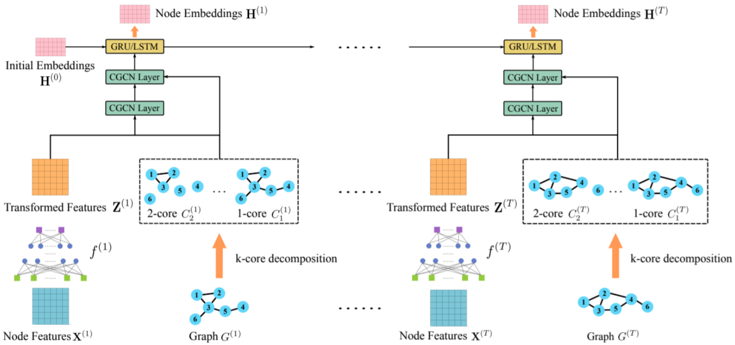
1. Pink backgrounds are network snapshots
2. Green are the changed networks
3. Orange lines mean edges appear during t and t + 1, purple ones means edges appear during t + 1 and t + 2



from Zhu et al., 2020

K-Core based Temporal Graph Convolutional Network for Dynamic Graphs

1. Preserving local proximity and global similarity
2. Feature transformation and feature aggregation for temporal case

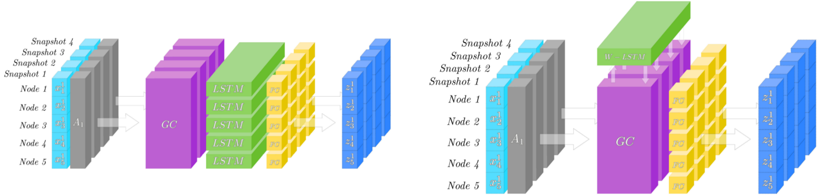


from Song et al., 2020

Combinations of GCN and LSTM

Dynamic Graph Convolutional Networks

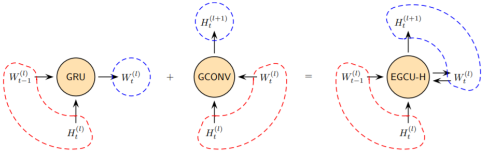
1. Combine Long Short-Term Memory networks and Graph Convolutional Networks to learn long short-term dependencies together with graph structure.



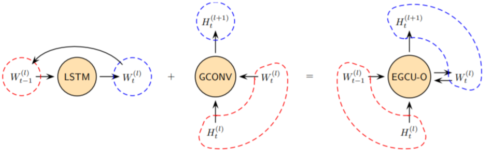
from Manzo et al., 2020

EvolveGCN: Evolving Graph Convolutional Networks for Dynamic Graphs

1. Left is a recurrent architecture; Middle is the graph convolution unit; Right is the evolving graph convolution unit.
2. Red region denotes information input to the unit and blue region denotes output information.



(a) EvolveGCN-H, where the GCN parameters are hidden states of a recurrent architecture that takes node embeddings as input.



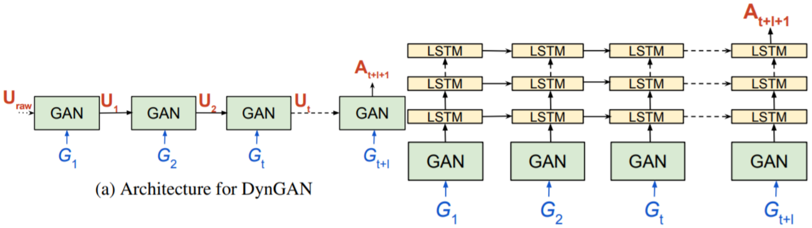
(b) EvolveGCN-O, where the GCN parameters are input/outputs of a recurrent architecture.

from Leiserson et al., 2020

Generative Models

DynGAN: Generative Adversarial Networks for Dynamic Network Embedding

1. GAN instead of temporal VGAE
2. Stacked LSTMs



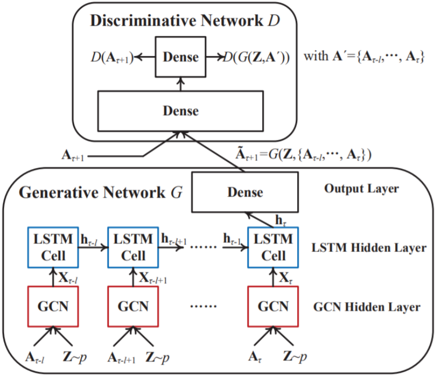
(a) Architecture for DynGAN

(b) Architecture for DynGAN-LSTM

from Ramakrishnan et al., 2019

GCN-GAN: A Non-linear Temporal Link Prediction Model for Weighted Dynamic Networks

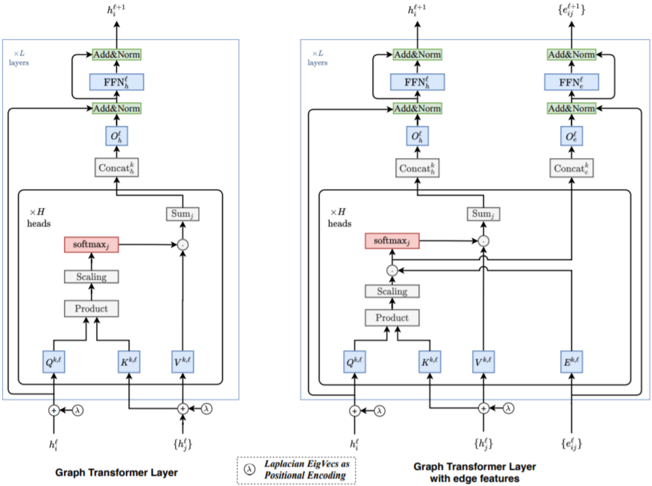
1. GCN-GAN temporal link prediction model
2. Generator is GCN stacked with LSTM and ourput FC
3. Discriminator is FC feedforward network.



from Yang et al., 2019

Attention-based Models

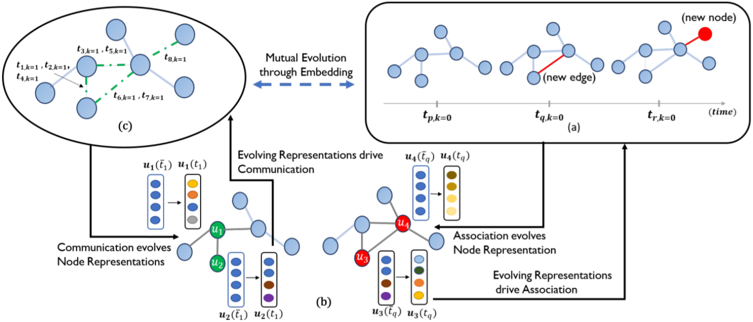
A Generalization of Transformer Networks to Graphs



from Bresson et al., 2020

DyREP: Learning representations over dynamic graphs

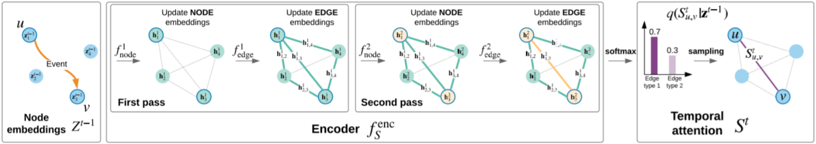
1. Deep temporal point process
2. Temporal-attentive representation network



from Zha et al., 2019

Learning Temporal Attention in Dynamic Graphs with Bilinear Interactions

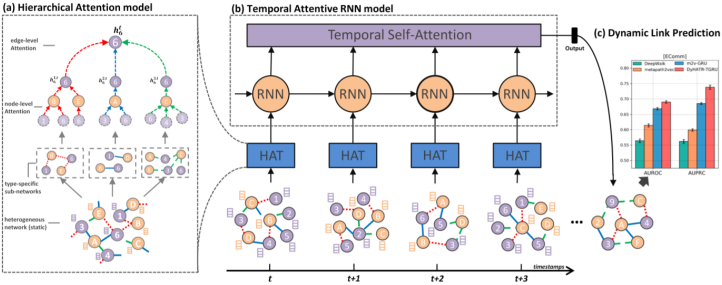
1. Temporal attention drives between-node feature propagation
2. Bilinear transformation layer for pairs of node features instead of concatenation



from Taylor et al., 2020

Modeling Dynamic Heterogeneous Network for Link Prediction using Hierarchical Attention with Temporal RNN

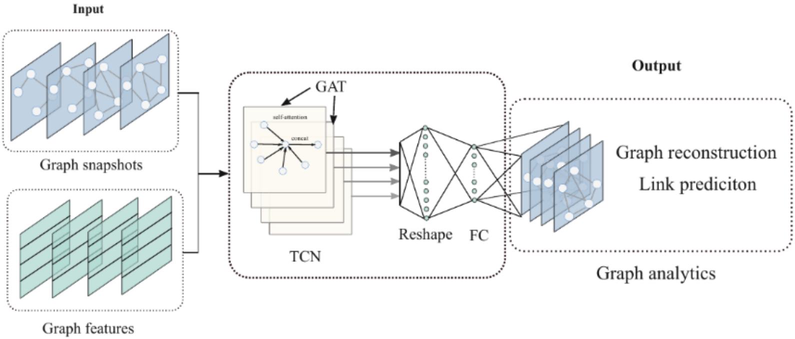
1. Hierarchical Attention model
2. Temporal Attentive RNN model
3. Dynamic Link Prediction



from Lin et al., 2020

TemporalGAT: Attention-Based Dynamic Graph Representation Learning

1. Decomposition into Snapshots with Spatial Attention
2. Temporal Convolutions for Dynamics



from Li et al., 2020

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