Dynamic Graph Clustering with Graph Neural Networks

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Clustering dynamic graphs with high-dimensional attributes is a challenging task that requires jointly modeling attribute and stricture signals, while also accounting for temporal information. Graph neural networks (GNNs) have been successfully employed for downstream tasks including node regression, link prediction, and graph classification, and are currently in the state of the art for modeling networks where high-dimensional node or edge features are available. However, GNN-based models for learning on temporal graphs commonly rely on proxy objectives (e.g., reconstruction error) and memory-based mechanisms (such as recurrent units or long-short term memory) to capture temporal dependencies, without explicitly modeling community structure or temporal dynamics in a directly interpretable and optimized way. Moreover, their application for temporal node clustering (or community detection) remains considerably underexplored [7] – and although research in this direction has gained traction, problems with data scarcity, suitable benchmarks, and computational constraints remain active topics of discussion in the recent literature [5, 4].

In this work, we focus on the problem of dynamic graph clustering, where the goal is to identify evolving communities (node sets) in evolving graphs, and choose to extend an efficient deep learning framework [9, 6] to the temporal domain. Our contributions are as follows: we (**1**) derive a spectral relaxation of longitudinal modularity [1] – a recently introduced variant of the metric for continuous-time temporal graphs that avoids snapshot discretization and incentivizes contiguous community assignments over time – allowing for a differentiable form suitable for representation learning, that naturally recovers static modularity in the absence of temporal coupling. To model temporal interaction strength, we (**2**) introduce a Hawkes-based temporal decay embedded in the Laplacian operator of a modified graph encoder layer, enabling it to distinguish persistent structure from transient events. Although encoder-agnostic, we experiment with modern graph convolutional and attentional strategies [3, 2] to show that the proposed operator can be flexibly integrated into different convolutional schemes. We additionally (**3**) introduce an unpooling layer to retrieve discrete cluster assignments from event-level representations, allowing for a smoothness term in the objective to encourage persistent structures and temporal consistency in cluster assignments. Building on this foundation, we (**4**) instantiate a neural architecture for unsupervised node clustering that directly optimizes the proposed objective, allowing a model to exploit time-aware structural and attribute signals, as illustrated in Figure 1.

As far as we know, this is the first neural approach proposed to optimize a temporal version of modularity in an end-to-end fashion. The presented solution is designed to be efficient and scalable to large graphs, maintaining best-in-class scalability growing linearly with the number of edges. We will further experiment with additional regularization choices [8] and share our implementation online to foster research, ensure fairness and reproducibility, and properly assess the model's limitations w.r.t. varying detectability regimes on publication.

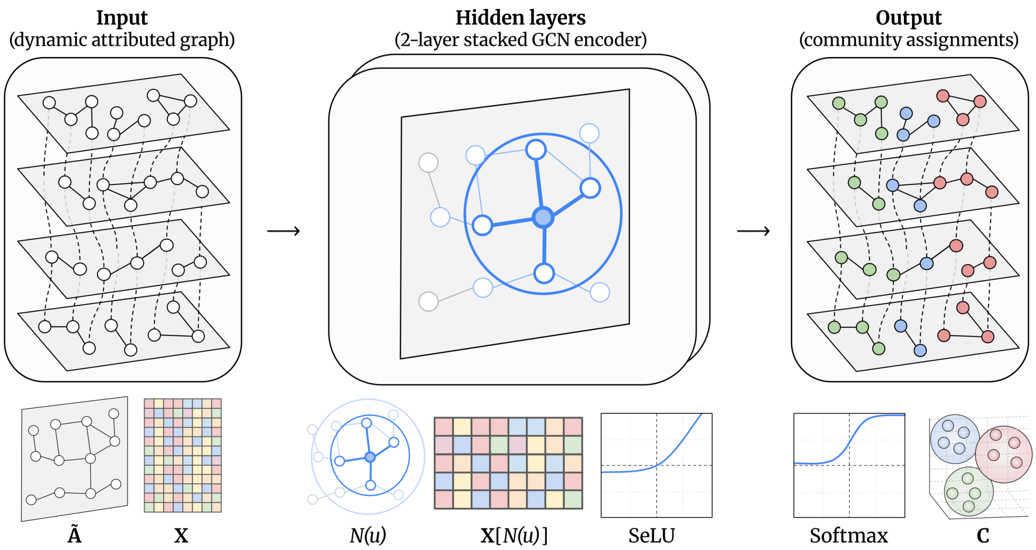

Figure 1: Illustrated architecture of the model. A temporal graph $\mathcal{G}$ is first processed to compute a normalized adjacency matrix $\tilde{\mathbf{A}}$ and a node feature matrix $\mathbf{X}$, and outputs dynamic clusters $\mathbf{C}$.

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