Deep community detection on attributed dynamic graphs with a Spatio-Temporal Graph Neural Network

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Summary: *Real-world networks are rarely static, presenting temporal dynamics intead that are often difficult to consider for analysis and visualization purposes. This work aims to exploit the temporal dimension of networks modeled as dynamic graphs to improve on existing community detection methods with deep learning, by introducing a novel Spatio-Temporal Graph Neural Network model geared toward the node-level clustering of temporal networks.*

Introduction

Identifying mesoscale patterns in large graphs allows the study of increasingly complex networks, further the understanding of its dynamics. The task of community detection is understood as one of the most relevant in the field of Network Science [1] and has been a thriving research topic for decades, during which a plethora of methods have been introduced [2–13]. Only a relatively small part, however, focuses on the issue of dynamic graphs, with continuously changing nodes and edges, even though real-world networks are rarely static.

Graph Neural Networks (GNNs) are an effective framework for learning on non-Euclidean domains and have recently achieved the state of the art for semi-supervised node-level clustering of attributed graphs [14, 15], relying on both its topology (structure) and attributes (features). In summary, they usually rely on a paradigm known as message passing [16], in which equivariant functions that disregard a specific node ordering are responsible for aggregating information from each node's $n-$hop neighborhood, being n equal to the number of layers defined in its architecture. This has been proved to efficiently allow a model to learn the nodes' representations and perform node-level, edge-level, or (sub-)graph-level predictions. Notwithstanding, there is a perceived gap in the state of the art w.r.t. models for node-level clustering of dynamic graphs [17], though similar works have successfully applied them in other contexts, e.g., traffic prediction [18] and recommendation systems [19].

This work therefore aims to exploit both the spatial and temporal dimensions of networks modeled as dynamic graphs, plus nodes and edges' features, in case of attributed graphs, to improve on existing methods for their mesoscale analysis. To tackle this objective, we seek to introduce a Spatio-Temporal Graph Neural Network (STGNN) model geared for the node-level clustering of attributed temporal graphs, which we discuss in the next section.

Discussion

This research is currently in experimental stage and the following discussion is the result of a one year study, part of the Ph.D. program in Artificial Intelligence at the University of Pisa. We are currently in the process of comparing distinct model architectures to arrive at a robust method and present a comprehensive evaluation of our first results in the near future.

Graph input: algorithms for dynamic community detection usually rely on depicting a temporal network as a sequence of discrete graphs (*snapshots*), based on a preselected time interval, while it may sometimes be more appropriately represented as a sequence of observation points (*events*) instead. Such a choice leads to distinct algorithmic solutions and is understood in the recent literature as a useful taxonomy criterion for STGNNs [17].

Although our model currently expects snapshot-based temporal graphs as input, we foster the hypothesis that considering a network's temporal dynamics as observation points — i.e., abstracting from sequences of snapshots and modeling the dataset as an event-based temporal graph instead — may bring significant advantages for node-level clustering tasks,

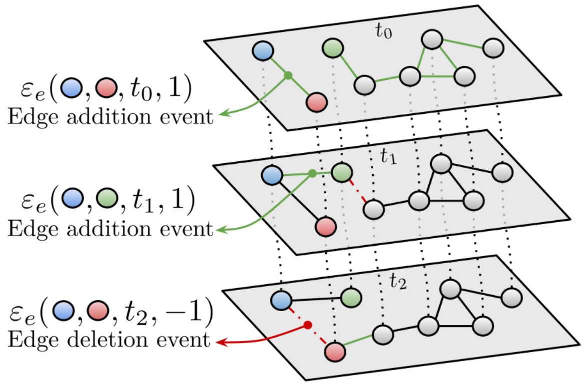

Fig. 1. A temporal graph depicted as three snapshots, with arrows pointing to edge addition and deletion events among colored nodes, and dotted lines to identical node couplings. Notice how blue node's neighborhood change over time, in a way that an interval $\Delta t = 2$ leads to information loss.

as it would allow a STGNN to better capture its dynamics without being bound to any arbitrary intervals, as well as avoid information "squashing", as depicted in Figure 1.

Architecture: to learn on spatio-temporal signals, a model requires both spatial and temporal layers in its architecture, for which we are comparing distinct configurations.

The spatial aggregation performed by a STGNN is identical to that of static GNNs, which is based, e.g., on graph convolutional [20–24], spectral graph convolutional [25–28], and attentional message-passing layers [29, 30], in which "messages" from each node's neighbor consider either a constant — defined by the graph's adjacency matrix or Laplacian matrix, in case of spectral graph convolutional layers — or an attention function to compute its importance. Meanwhile, the temporal aggregation usually relies either on attentional functions [31–33], Long-Short Term Memory (LSTM) [34], or Gated Recorrent Units (GRU) [34–36], effectively allowing it to make future or past predictions based on already seen data.

Our **current implementation** couples identical nodes (see dotted lines in Fig. 1) in distinct snapshots and combines graph attentional and convolutional layers for spatial aggregation from their temporal neighborhoods, allowing the prediction of static clusters considering the temporal domain, which we aim to extend for temporal prediction with GRUs or LSTM.

Datasets: for preliminary tests, we modeled a snapshot-based temporal graph from the online social network Twitter, obtained from the now-unavailable Academic API (V2) [37]. It comprises 781.993 edges (retweets) among 333.237 nodes (profiles) over a period of seven days, in which nodes' and edges' attributes are the users' and tweets' information. This dataset was selected for preliminary testing purposes due to its assortative mixing (homophily) property and embedded temporal information, although subsequent tests may prioritize larger-scale networks and include artificial generators for dynamic community detection evaluation [38]. We highlight that there is a lack of standardized temporal graph data sets for node-level clustering tasks, although the recently released Temporal Graph Benchmark [39] for edge-level prediction tasks is an important step in this direction.

Evaluation: our baseline methods consider approaches that use only attribute features (e.g., K-Means), topological information [9, 40–43], or a combination of both [14, 44–46]. Meanwhile, tracking dynamic communities may rely on the comunity similarity function introduced by [47], due to it being a parameter-free approach that will ensure a straightforward comparison against other methods for deep and non-deep community detection.

Final thoughts

Given the empirical-focused approach we observe in the existing literature for proposing new task-oriented GNNs, our next steps will be in the direction of implementing, experimenting, and comparing distinct model architectures. Lastly, we expect to open source our implementation when we present our preliminary results in the near future, with the aim of integrating it with existing technologies [48] for learning on spatio-temporal graph signals.

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