# Benchmarking Algorithmic and Neural Approaches for Temporal Community Detection

N. A. R. A. Passos[12], E. Carlini[2], and S. Trani[2],

1. University of Pisa, Italy
2. National Research Council, Italy

This work presents an experimental evaluation of algorithmic and neural community detection methods for temporal graphs [1], comparing more established approaches with newly introduced deep learning models designed for node-level clustering. We devise a novel stochastic block model-based approach [2, 3] to generate time-varying attributed temporal graphs with community ground truths, and employ it to compare the performance of distinct state-of-the-art solutions. In this framework, node features are kept fixed, while community structures are dynamic — allowing to study how well differing solutions are able to jointly exploit the feature space and the temporal dynamics of the generated graphs to improve on the detectability threshold of communities and allow better recovering the hidden community structure of the generated networks. In addition, we assess the performance of the models on a set of diverse real-world datasets of various scales, focused on a transductive learning setting, and extending to an inductive learning setting when possible.

The main motivation behind this work are the recent advances in network representation learning, which have also sparked a renewed interest in the improvement and development of new strategies for learning on spatio-temporal signals. Despite the popularity of Graph Neural Networks (GNNs), which have become the state of the art for applications like traffic forecasting and recommendation systems, most specialized solutions for node-level clustering, i.e., community detection, are still designed for static graphs — while real-world networks are rarely fixed and continuously evolve over time instead [4]. Moreover, most neural approaches for the this are evaluated in a transductive learning setting only — mostly due to a lack of real-world datasets with node-level attribute features and community ground truths — therefore leaving a significant gap to be filled in order to understand how well they generalize in inductive learning settings.

Hence, we here aim to close this gap by providing a useful benchmarking framework that relies on a principled approach for synthetic graph generation. We showcase our solution by employing it to compare several state-of-the-art approaches for community detection on attributed temporal graphs. The obtained results show that deep learning models for community detection do not consistently outperform more established methods on this task, although temporal GNNs seem especially resilient to changes in the community structure over time. Furthermore, we observe that spectral techniques recognized to be asymptotically optimal down to the detectability threshold of communities in graphs, considering only the (static) graph's topology, achieved higher performance than temporal GNN-based models that jointly exploit the graph's structure, temporal dynamics, and attribute features of during learning — therefore hinting at interesting research opportunities and a large room for further improvements of neural methods for community detection.

[1] N. A. R. A. Passos, E. Carlini, S. Trani (2024). Deep Community Detection in Attributed Temporal Graphs: Experimental Evaluation of Current Approaches. In Proceedings of the 3rd GNNet Workshop on Graph Neural Networking Workshop.
[2] A. Ghasemian, P. Zhang, A. Clauset, C. Moore, L. Peel (2016). Detectability Thresholds and Optimal Algorithms for Community Structure in Dynamic Networks. Physical Review X 6(3).
[3] A. Tsitsulin; B. A. Rozemberczki, J. Palowitch, B. Perozzi (2021). Synthetic Graph Generation to Benchmark Graph Learning. In Workshop on Graph Learning Benchmarks.
[4] A. Longa, V¿ Lachi, G. Santin, M. Bianchini, B. Lepri, P. Lio, F. Scarselli, A. Passerini (2023). Graph Neural Networks for Temporal Graphs: State of the Art, Open Challenges, and Opportunities. Transactions on Machine Learning Research.
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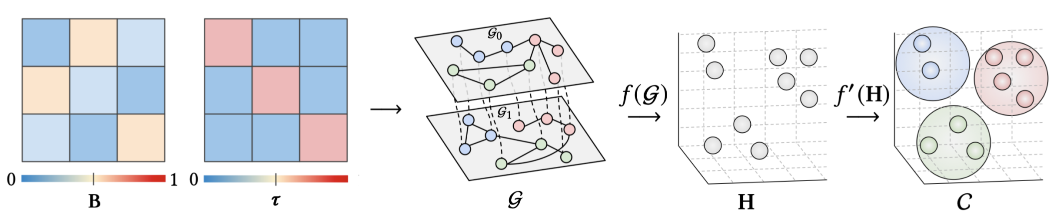


Figure 1: Illustration of a graph generation from a stochastic block matrix $\mathbf{B}$ and a transition matrix $\boldsymbol{\tau}$. A function $f$ then obtains node embeddings $\mathbf{H}$ from the temporal graph $\mathcal{G}$ and a second function is used to cluster and evaluate them.