PhD in Artificial Intelligence - XXXVIII Cycle

FAIR Future Artificial Intelligence Research

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Efficient 'Neural' Community Detection on Temporal Graphs:

Challenges, Advancements and Opportunities

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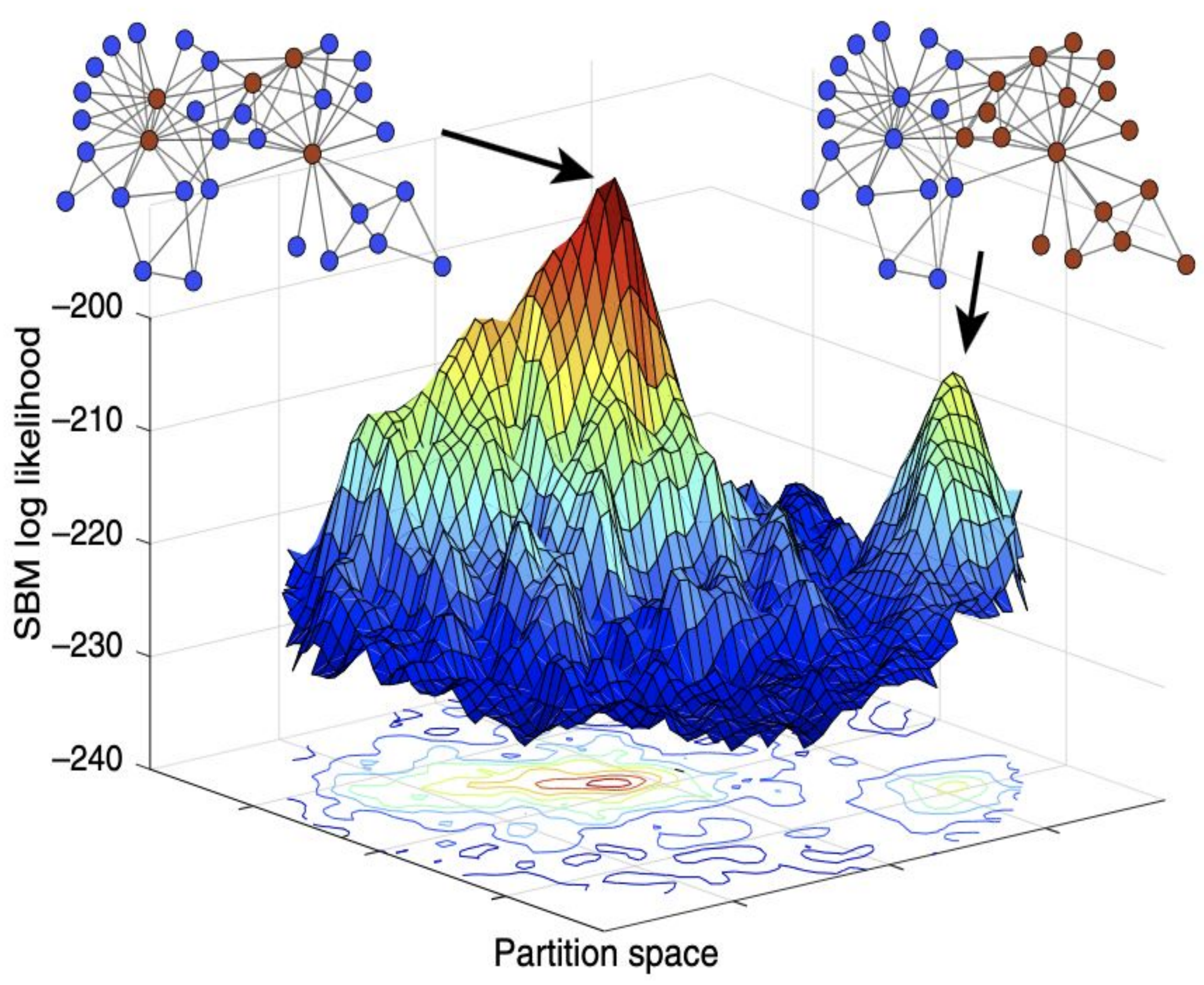
Challenges



The task of dividing a network's components (nodes) in groups (communities) is not trivial: **the definition of a community is contested** among researchers, and in case of attributed graphs, their topological properties may not at all match their features.

Neural networks for graphs present a promising approach for the task, as they may improve the detectability thresholds of communities **[1]**. But their highly non-convex loss landscapes can make optimization challenging and lead to **suboptimal solutions**.

The lack of interpretability for high-dimensional relational data is also a shortcoming, and as resulting partitionings all correspond to posterior distributions of a stochastic block model, the benefits neural-based strategies may bring on the long run in favor of principled approaches grounded in rigorous statistical theory are **unclear at best**.

Fig. 1. SBM log-likelihood surface for bipartitions of the Karate Club network **[2]**. In this example, the graph partitioning matching the known ground truths (communities) correspond to a **local** maximum.

Advancements

We introduce **L-DMoN**: Longitudinal Deep Modularity on Networks **[3]**, an end-to-end differentiable module for unsupervised node clustering. The chosen objective is the optimization of longitudinal modularity - a graph-theoretic 'quality' metric for dynamic graphs.

This choice allows for the mesoscale **description** of a graph based on its set of 'neural' communities, wherein node and edge features, topological properties, and temporal dynamics are all accounted for.

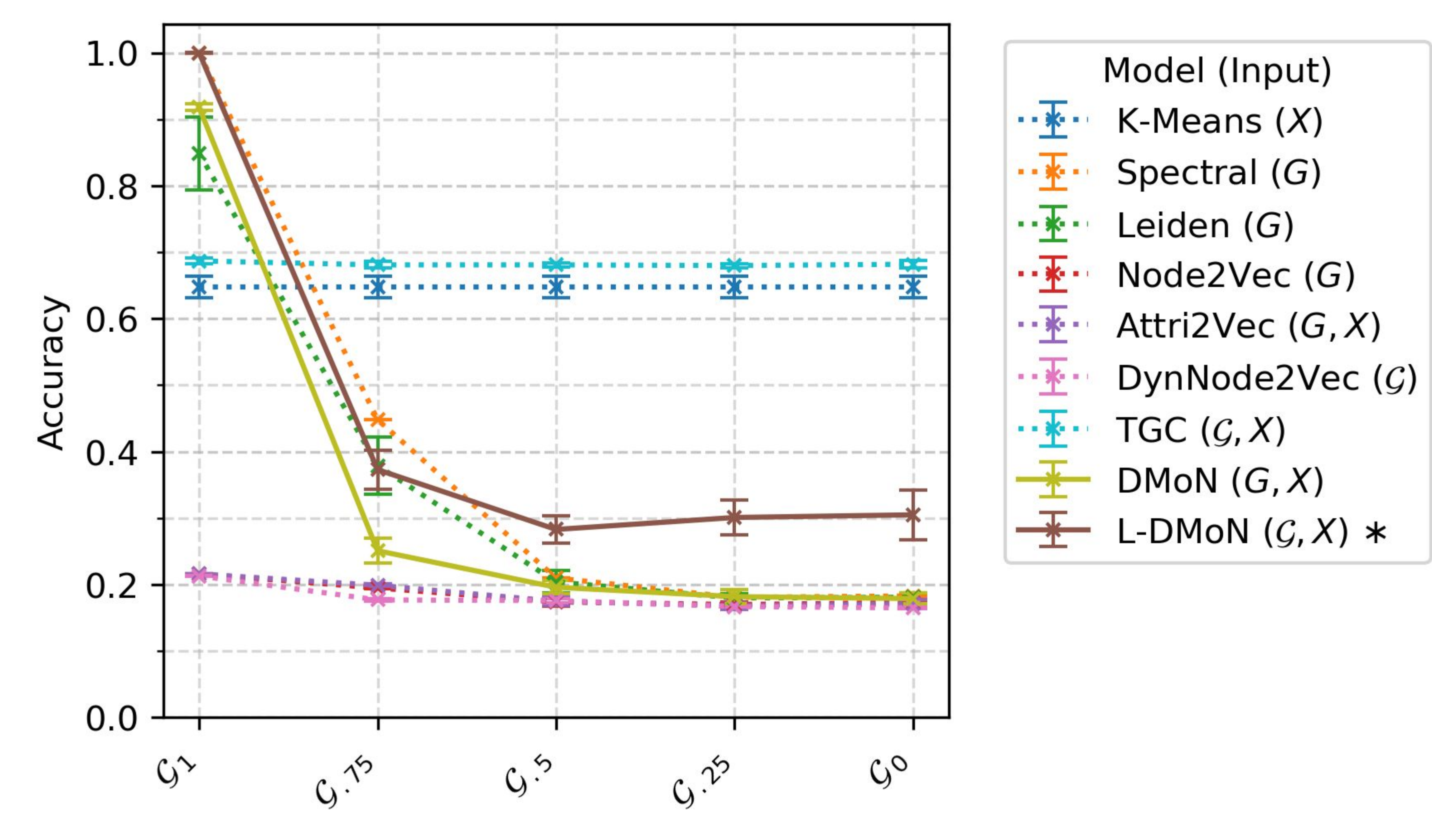
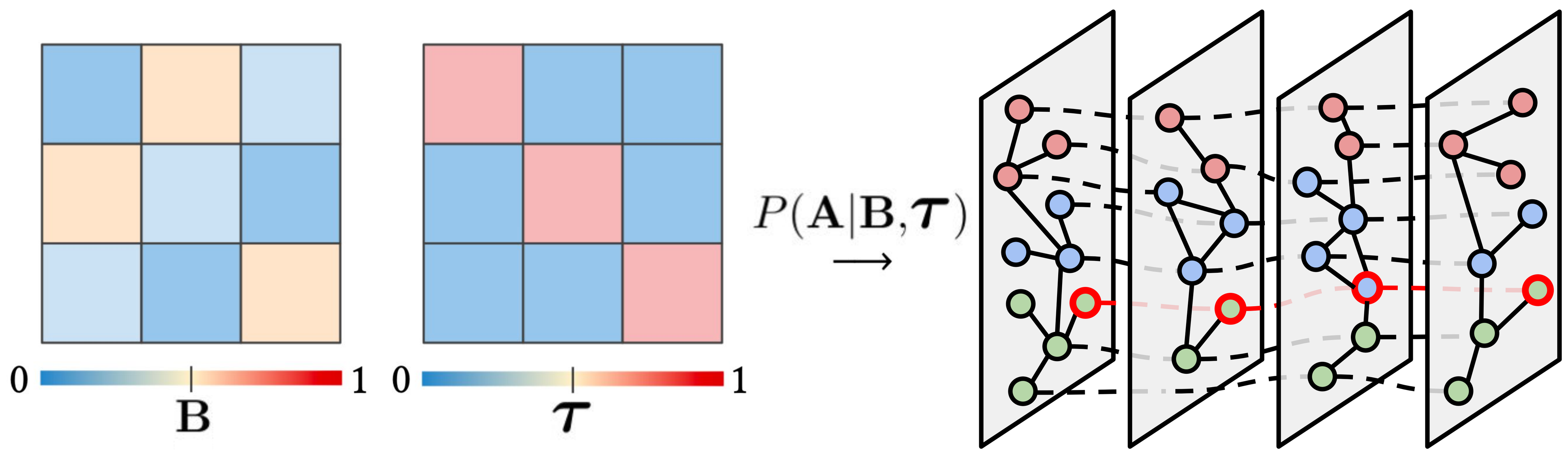


Fig. 2 (right): Performance comparison between models. Average from 5 runs without hyperparameter tuning; graphs with varying community stability levels.



In addition, we present **TADC-SBM**: a Time-varying, Attributed, Degree-Corrected Stochastic Block Model **[4]** for the generation of graphs and the comparison of models under controlled experimental conditions.

Fig. 3 (left): A temporal graph with four snapshots generated by TADC-SBM from a block matrix $\boldsymbol{B}$ and a transition matrix τ. The latter governs the community stability level of the graph.

Opportunities

The following model limitations will be addressed in future work. Beyond the scope of our contributions, advancements toward more **efficient** neural network models and **expressive** learning strategies are pressing needs for the task at hand.

- **Extend graph neural network model** (L-DMoN)
  Experiment with pooling strategies for dynamic node subsets, where communities are not fixed over time.
- **Extend synthetic graph generator** (TADC-SBM)
  Support mixed-membership scenarios (*soft clusters*), where nodes may simultaneously be in more than one community.

[1] Newman, M.E.J., Nadakuditi, R.R (2012). Graph Spectra and the Detectability of Community Structure in Networks. Phys. Rev. Letter. 108, 188701.
[2] Peel, L., Larremore, D. B., & Clauset, A. (2017). The ground truth about metadata and community detection in networks. Science Advances, 3(5).
[3] Passos, N.A.R.A. (2025). Efficient "Neural" Community Detection in Attributed Graphs with a Temporal Modularity Loss Function. (Under review)
[4] Passos, N.A.R.A., Carlini, E., Trani, S. (2025). TADC-SBM: a Time-varying, Attributed, Degree-Corrected Stochastic Block Model. In Proceedings of the 30th IEEE Symposium on Computers and Communications (ISCC'25). IEEE Computer Society, Los Alamitos, CA, USA, 1–6.

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