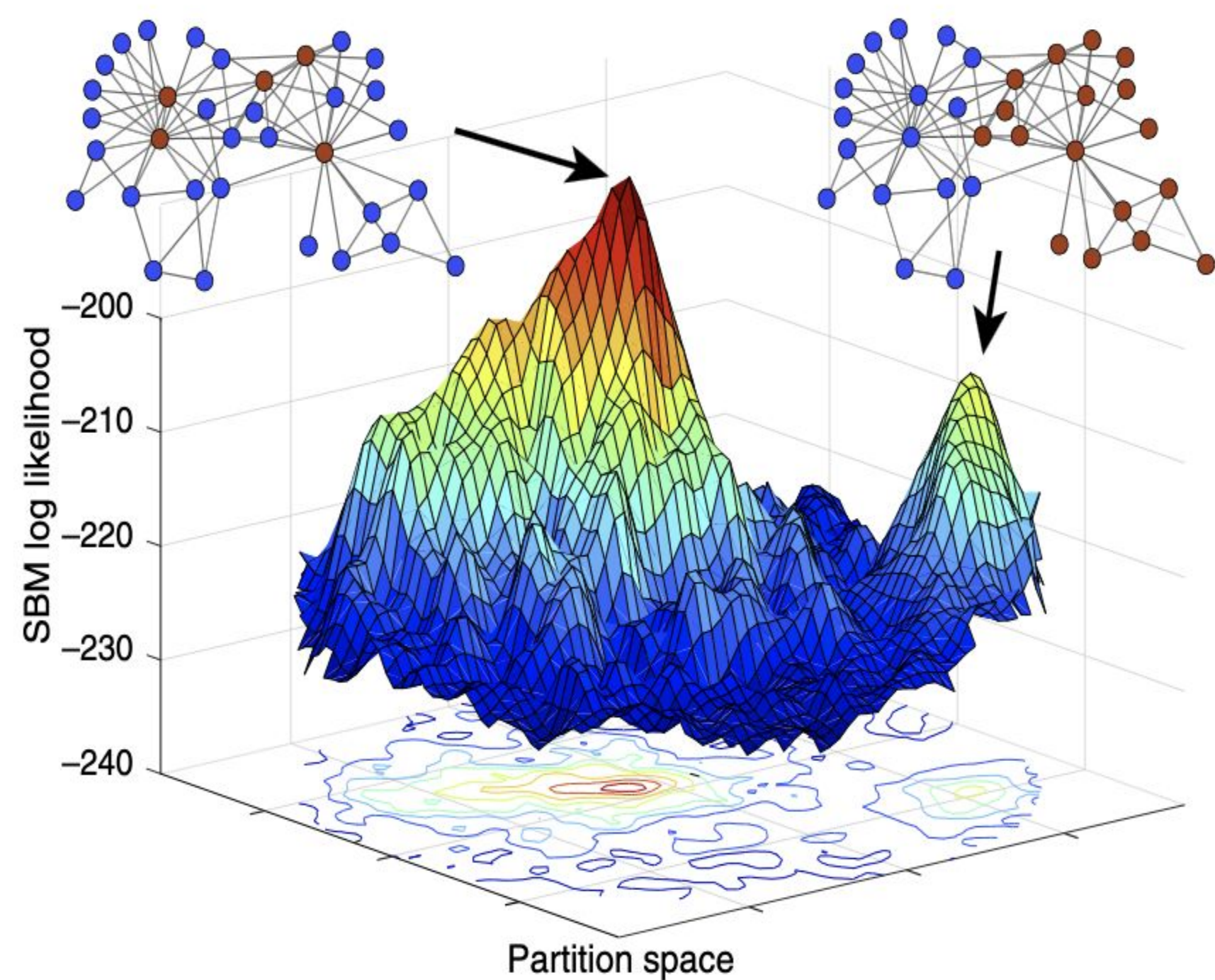


Efficient 'Neural' Community Detection on Temporal Graphs: Challenges, Advancements and Opportunities

Nelson Aloysio Reis de Almeida Passos

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**.

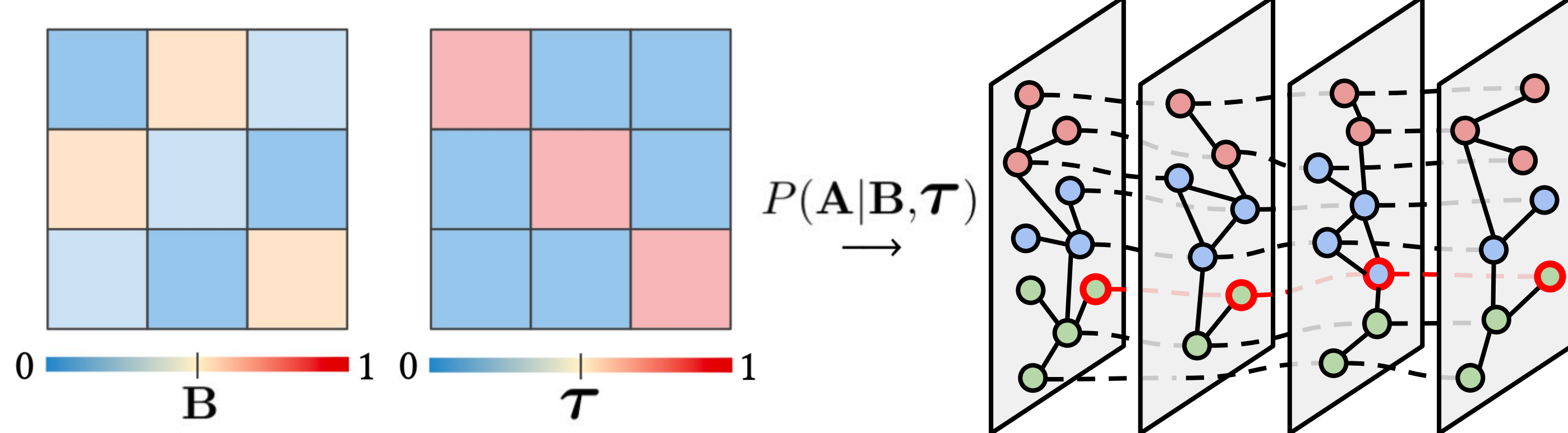
Fig. 1. SBM log-likelihood surface for bipartitions of the Karate Club network [2]. In this example, the graph partitioning matching the known ground truths (communities) correspond to a **local** maximum.

We introduce **L-DMoN: Longitudinal Deep Modularity on Networks**

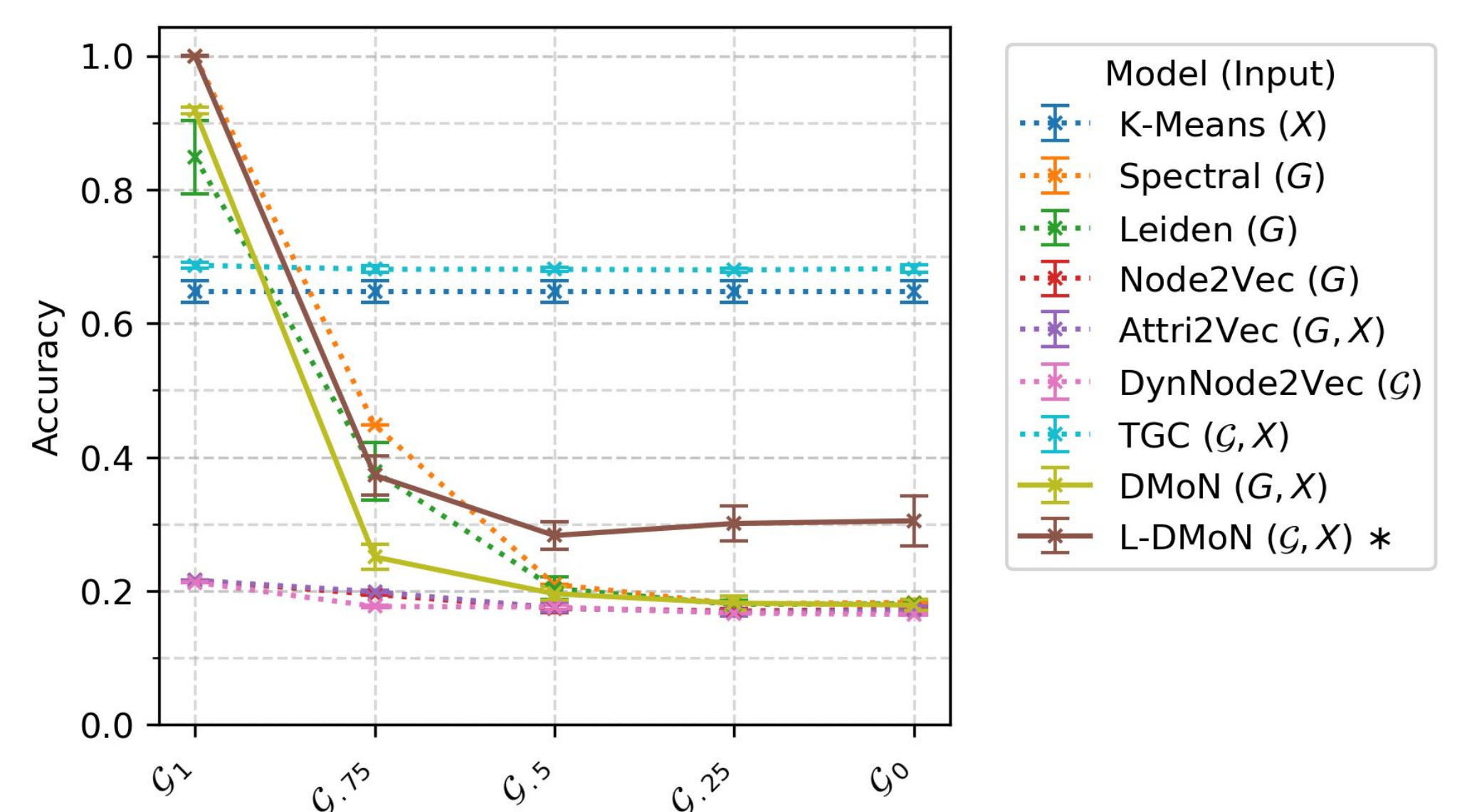
[3], an end-to-end differentiable module for unsupervised node clustering. The chosen objective is the optimization of longitudinal modularity - a graph-theoretic 'quality' metric for dynamic graphs.

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.



Advancements



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 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.