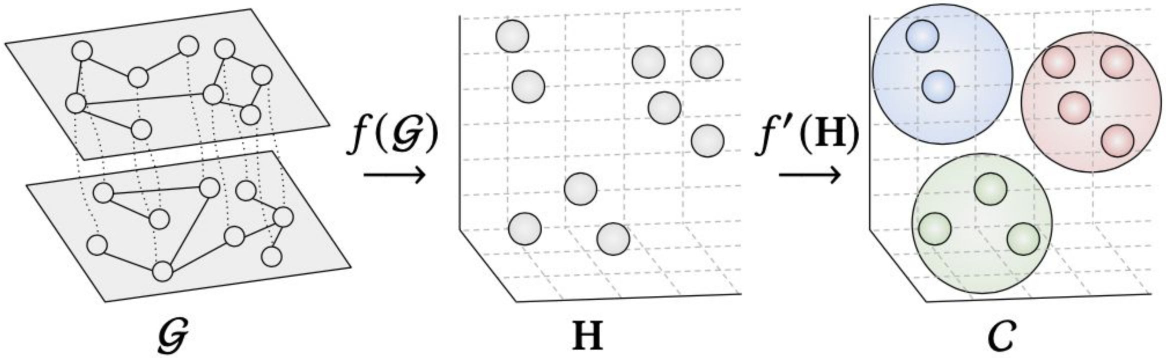
# Why “neural” community detection?

- Graph representation learning models allow exploiting a graph’s (i) topology, (ii) temporal dynamics, and (iii) attribute features to obtain node, edge, or graph-level embeddings.




- This joint exploration potentially improves on the community detectability thresholds, and the obtained functions (models) may be used to predict unseen (future/past) information.

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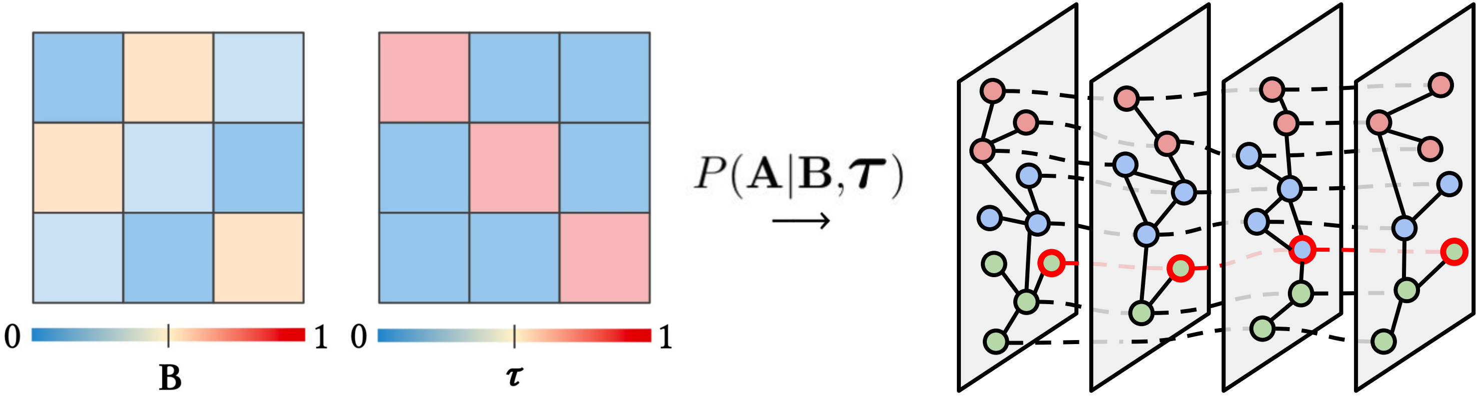
# How to evaluate such models?

- *Not a trivial task!* → Real-world temporal graph data is scarce and of limited scope, and synthetic generators often do not simulate time, attributes, and communities altogether.

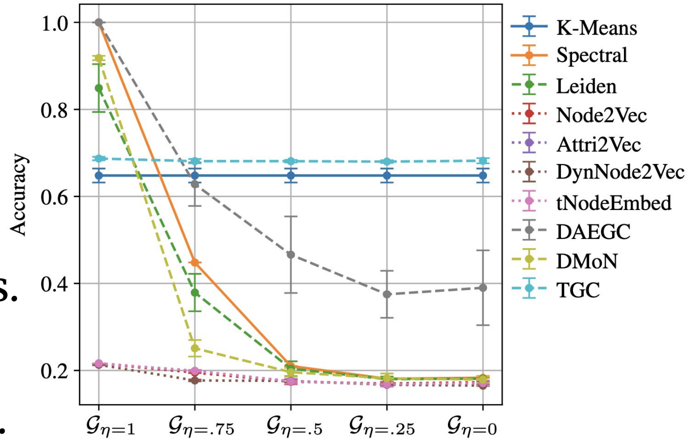
- We introduce **TADC-SBM**: a Time-varying, Attributed, Degree-Corrected Stochastic Block Model (2025), based on the work of Tsitsulin et al. (2020) and Ghasemian et al. (2014).



# Benchmarking the SOTA...

## ...with a transition matrix $\boldsymbol{\tau} := \eta\,\mathbf{I} + (1-\eta)\,\dfrac{\mathbf{J}-\mathbf{I}}{k-1}$ :

- Traditional (*algorithmic*) approaches performed better or as good as neural solutions in most simulated scenarios.
- The same observation also applied for real-world graph benchmarks in a separate experiment (Passos et al., 2024).
- In sum: ‘Neural Community Detection Is *Not* All You Need’!




# Limitations and future work:

- Extending the TADC-SBM model for mixed memberships;
- Dynamically generating (node and edge-level) features;
- More robust frameworks for graph learning benchmarks.

Preprint and code at:
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