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Learning and Clustering on Temporal Graphs: **Principles, Primitives, and Pooling**

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Outline

1. Introduction
Complex systems, temporal networks

2. Principles
Graph operators, detectability thresholds

3. Primitives
Algorithms, accelerated eigensolvers

4. Pooling
Clustering or detecting communities

5. Final Remarks
Takeaways – and where to go from here?

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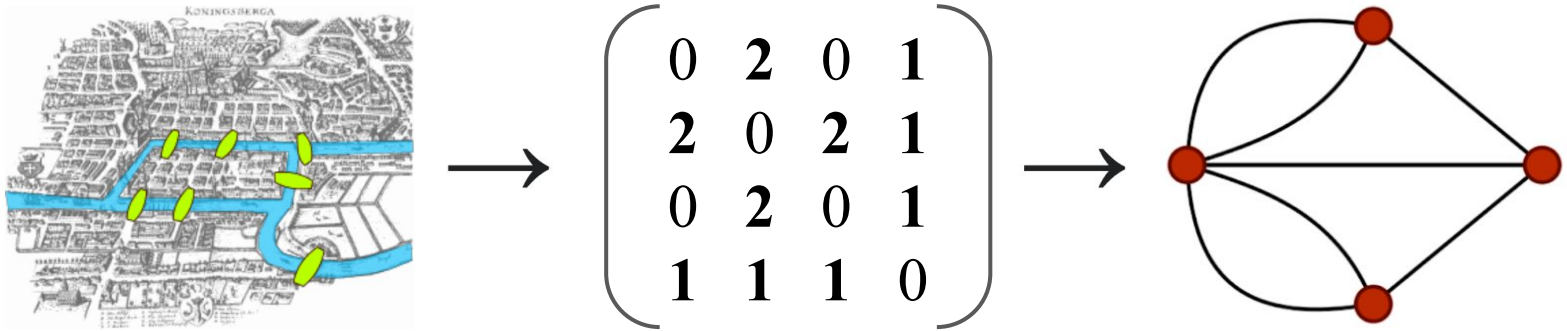
1. Introduction

Complex systems, temporal networks

- Many real-world systems can be modeled and studied as **networks** (or **graphs**).
- Elements are **nodes**, connections are **edges** – *often* mathematically constructed as **matrices**.



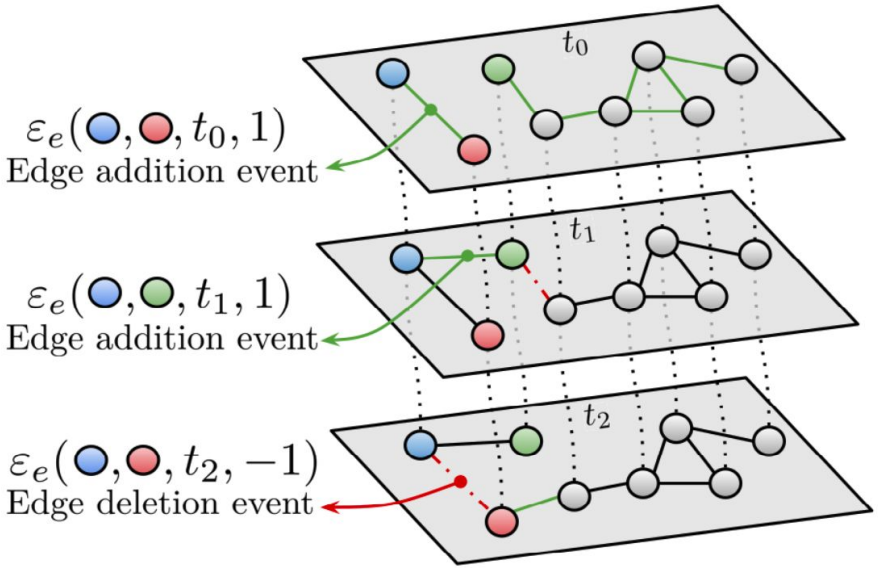
- But the systems we observe are rarely fixed *(static)* in time; instead, they *change* or *evolve.*
- A **temporal network** can be modeled as a **dynamic graph** – with *time-varying* nodes and edges.

Seven Bridges of Königsberg. Wikipedia (2026).

1. Introduction

Complex systems, temporal networks

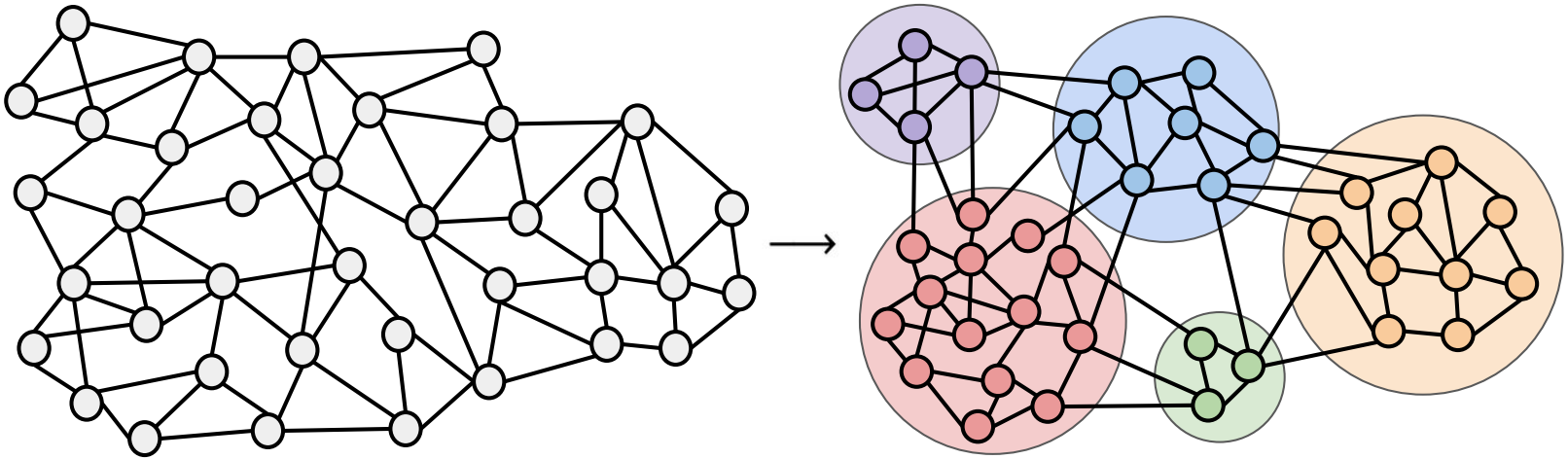
- A dynamic or temporal graph consists of temporal node and edge sets – as *snapshots* or *events*:



1. Introduction

Complex systems, temporal networks

- But complex networks are often *too large* to analyze; we need to 'aggregate' them first; by *clustering (computer science), community detection* (network *science),* or ***pooling*** *(graph ML).*

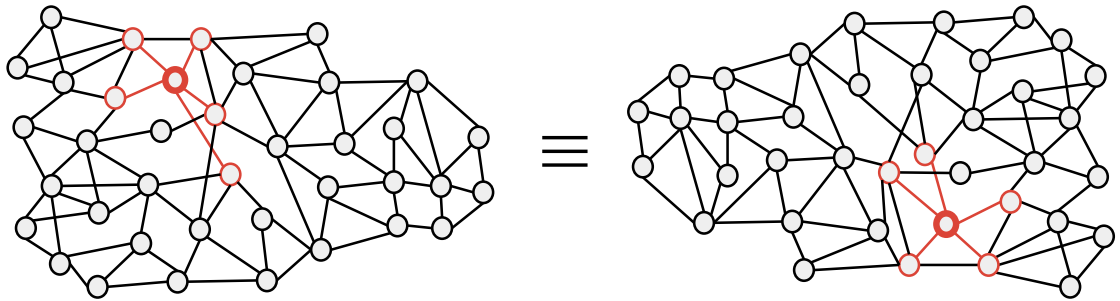


- **But *how*, when the graph changes over time and is associated with additional metadata?**

1. Introduction

Complex systems, temporal networks

- Machine learning models are very good in approximating (*learning* from) lots of data.
- **But** classical ML models can not learn from relational (*non-Euclidean*) datasets directly...



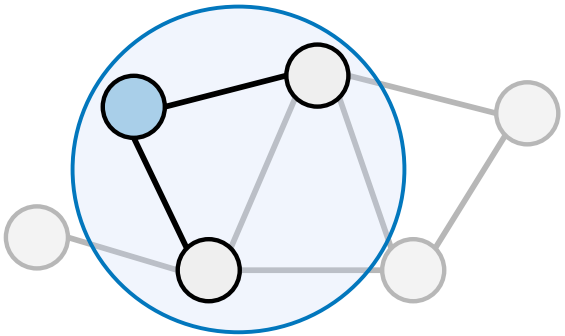
...unless first *mapped* to a real-dimensional (*Euclidean*) space – the sort of space *we live in*.

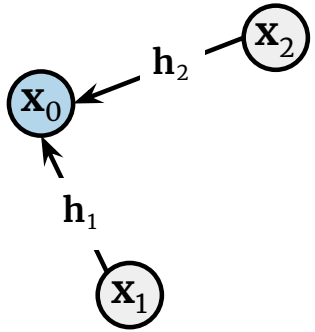
1. Introduction

Complex systems, temporal networks

- **State of the art**: community detection is done with **algorithms** or **neural** models *for graphs*.
  - **Algorithms**: *spectral clustering, heuristic optimization, statistical inference...*
  - **Neural models**: *graph neural networks (GNNs)*, which can learn on graphs by ***message passing.***

Methods from both approaches have been adapted **from static to dynamic** settings.





$$\mathbf{m}_i^{(\ell)} = \bigoplus_{j \in \mathcal{N}(i)} \phi\left(\mathbf{h}_i^{(\ell)}, \mathbf{h}_j^{(\ell)}, \mathbf{e}_{ij}\right)$$

$$\mathbf{h}_i^{(\ell+1)} = \psi\left(\mathbf{h}_i^{(\ell)}, \mathbf{m}_i^{(\ell)}\right)$$

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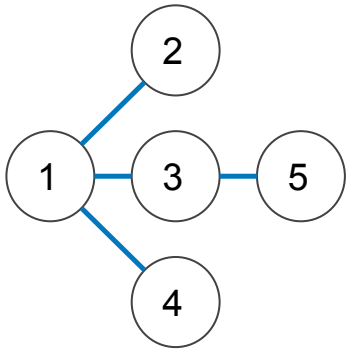
2. Principles

Graph operators, detectability thresholds

- Many methods for node clustering exist – usually split in *descriptive* or *inferential* ones.
- But there is 'no free lunch' for node clustering – as is true for other optimization tasks.
- There is a fundamental limit for detection – the **detectability threshold** , λ being the *community signal*, *c* the *mean community degree*, and *k* the number of communities.
- In SBM graphs, it is known that at $c\lambda^2 = 1$, a *phase transition* (Almeida-Thouless line) occurs, and no algorithm can recover community structure better than chance (Kesten-Stigum bound).
- **But** if there are $k \geq 4$ communities, **those two thresholds diverge**; a new bound appears where algorithms ***may*** recover them better than chance, but is not yet known how to do it ***efficiently***.
- Our work targets it by means of neural approximation of spatio-temporal and metadata signals.

3. Primitives

Algorithms, accelerated eigensolvers



G

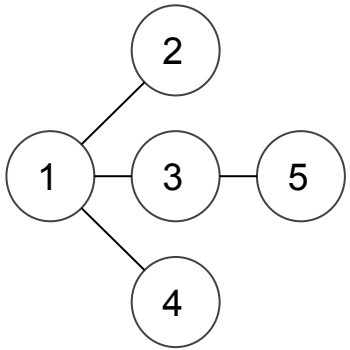
$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\mathbf{D} = \begin{bmatrix} 3 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\rightarrow \mathbf{D} - \mathbf{A} = \mathbf{L} = \begin{bmatrix} 3 & -1 & -1 & -1 & 0 \\ -1 & 1 & 0 & 0 & 0 \\ -1 & 0 & 2 & 0 & -1 \\ -1 & 0 & 0 & 1 & 0 \\ 0 & 0 & -1 & 0 & 1 \end{bmatrix}$$

3. Primitives

Algorithms, accelerated eigensolvers



G

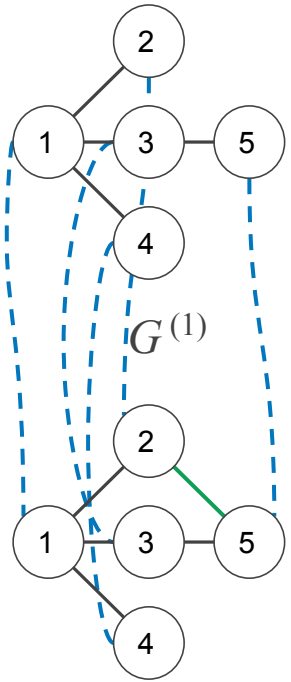
$$\mathbf{L}_{\text{norm}} := \begin{cases} 1 & \text{if } i = j \text{ and } \deg(v_i) \neq 0 \\ -\dfrac{1}{\sqrt{\deg(v_i)\deg(v_j)}} & \text{if } i \neq j \text{ and } v_i \text{ is adjacent to } v_j \\ 0 & \text{otherwise.} \end{cases}$$

$$\mathbf{L} = \begin{bmatrix} \mathbf{3} & \mathbf{-1} & \mathbf{-1} & \mathbf{-1} & 0 \\ \mathbf{-1} & \mathbf{1} & 0 & 0 & 0 \\ \mathbf{-1} & 0 & \mathbf{2} & 0 & \mathbf{-1} \\ \mathbf{-1} & 0 & 0 & \mathbf{1} & 0 \\ 0 & 0 & \mathbf{-1} & 0 & \mathbf{1} \end{bmatrix} \rightarrow \mathbf{L}_{\text{norm}} = \begin{bmatrix} 1 & -1/\sqrt{3} & -1/\sqrt{6} & -1/\sqrt{3} & 0 \\ -1/\sqrt{3} & 1 & 0 & 0 & 0 \\ -1/\sqrt{6} & 0 & 1 & 0 & -1/\sqrt{2} \\ -1/\sqrt{3} & 0 & 0 & 1 & 0 \\ 0 & 0 & -1/\sqrt{2} & 0 & 1 \end{bmatrix}$$

3. Primitives

Algorithms, accelerated eigensolvers

— Static edge — Temporal edge ··· Inter-slice coupling



$$\mathbf{A}^{(1)} = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\mathbf{A}^{(2)} = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix}$$

$$\mathbf{I} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{A}^{\text{supra}} = \begin{pmatrix} \mathbf{A}^{(1)} & \omega\mathbf{I} & \cdots & \mathbf{0} \\ \omega\mathbf{I} & \mathbf{A}^{(2)} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^{(T)} \end{pmatrix}$$

$$\rightarrow \mathbf{L}_{\text{norm}} = \ldots$$

2. Principles

Graph operators, detectability thresholds

- The most common method for node clustering across domains is *modularity optimization* [3,4].

- Modularity is a ‘quality’ function of the ‘goodness’ of a graph partitioning, which measures the proportion of edges within communities against the expected amount in a null (random) graph:

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \gamma \frac{d_i^{\text{out}} \, d_j^{\text{in}}}{2m} \right) \delta(c_i, c_j)$$

i, j: nodes *d*: degree
m: total edges in graph
c: community/cluster
γ: resolution param

- It has since been adapted to **temporal** graphs as well, such as the **multislice modularity** variant:

$$Q_{\text{MS}} = \frac{1}{2\mu} \sum_{s,r} \sum_{i,j} \left[\left(A_{ij}^{(s)} - \gamma_s \frac{d_{is}^{\text{out}} \, d_{js}^{\text{in}}}{2m_s} \right) \delta_{sr} + \delta_{ij} \omega_{jsr} \right] \delta\left(c_i^{(s)}, c_j^{(r)} \right)$$

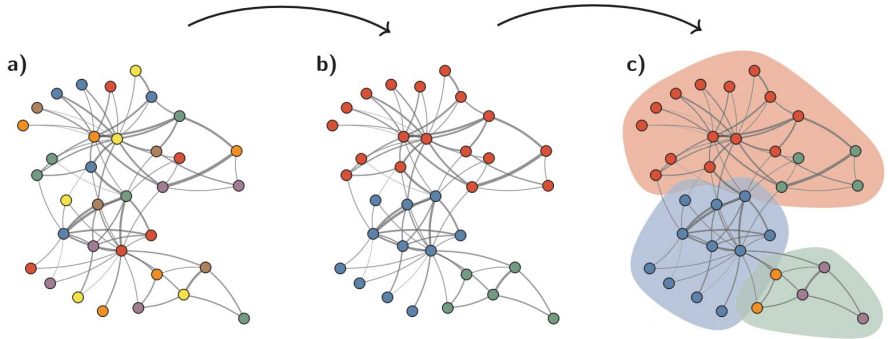
s, r: snapshots (slices)
μ: intra + inter-slice edges
ω: inter-slice weight param

[1] TADC-SBM: a Time-varying, Attributed, Degree-Corrected Stochastic Block Model. Passos, N.A.R.A. et al. (2026). In Proceedings: IEEE ISCC 2025.
[2] Graph Clustering with Graph Neural Networks. Tsitsulin, A. et al. (2023). Journal of Machine Learning Research (JMLR).

2. Principles

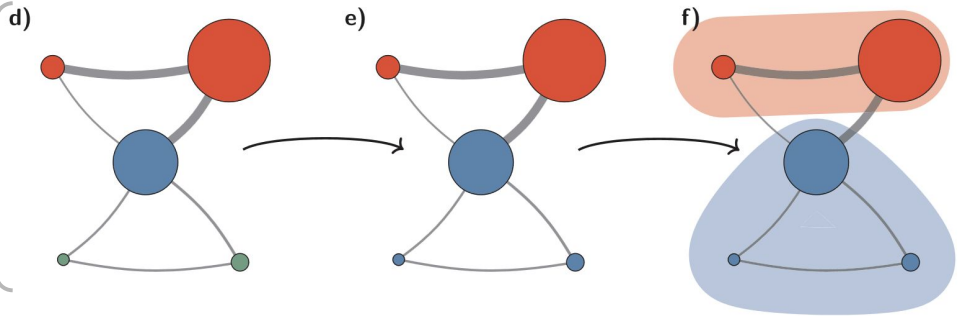
Graph operators, detectability thresholds

- **Leiden** is a refinement over **Louvain** for 2-step greedy optimization of quality functions [5,6].



Level 1 (*node aggregation and refinement*)

Level 2 (*supra-node aggregation and refinement*)



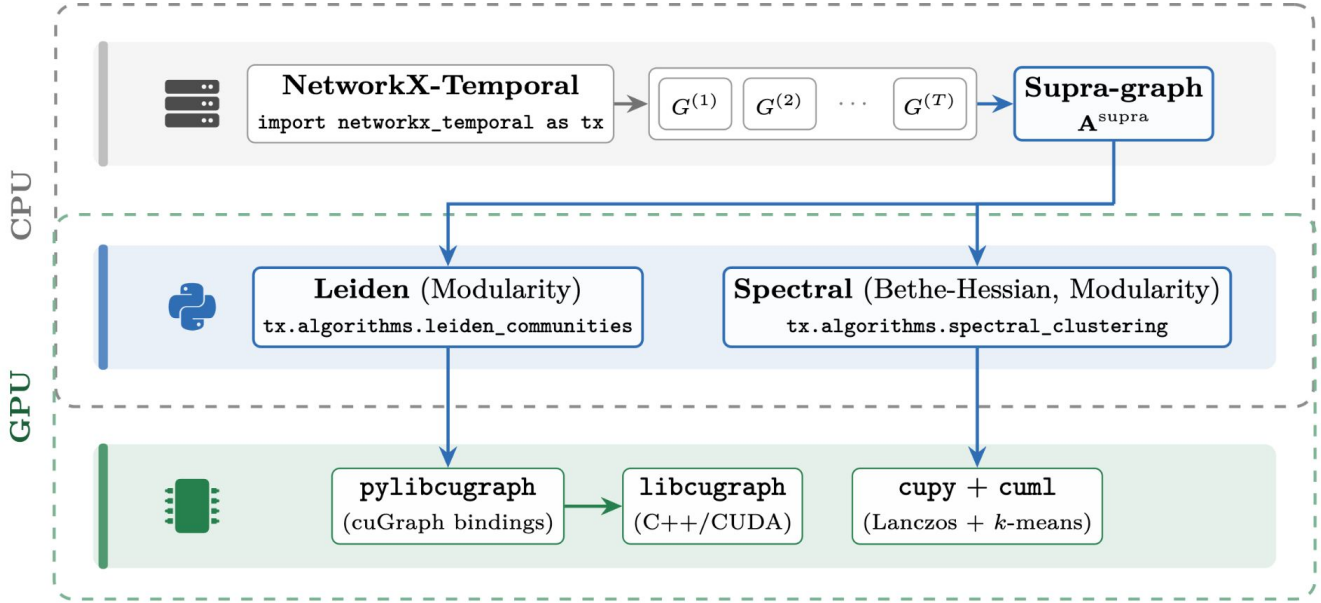
[5] Traag, V. et al. (2019). From Louvain to Leiden: guaranteeing well-connected community. Scientific Reports.

[6] Blondel, V. et al. (2008). Fast unfolding of community in large networks. Journal of Statistical Mechanics: Theory and Experiment.

2. Principles

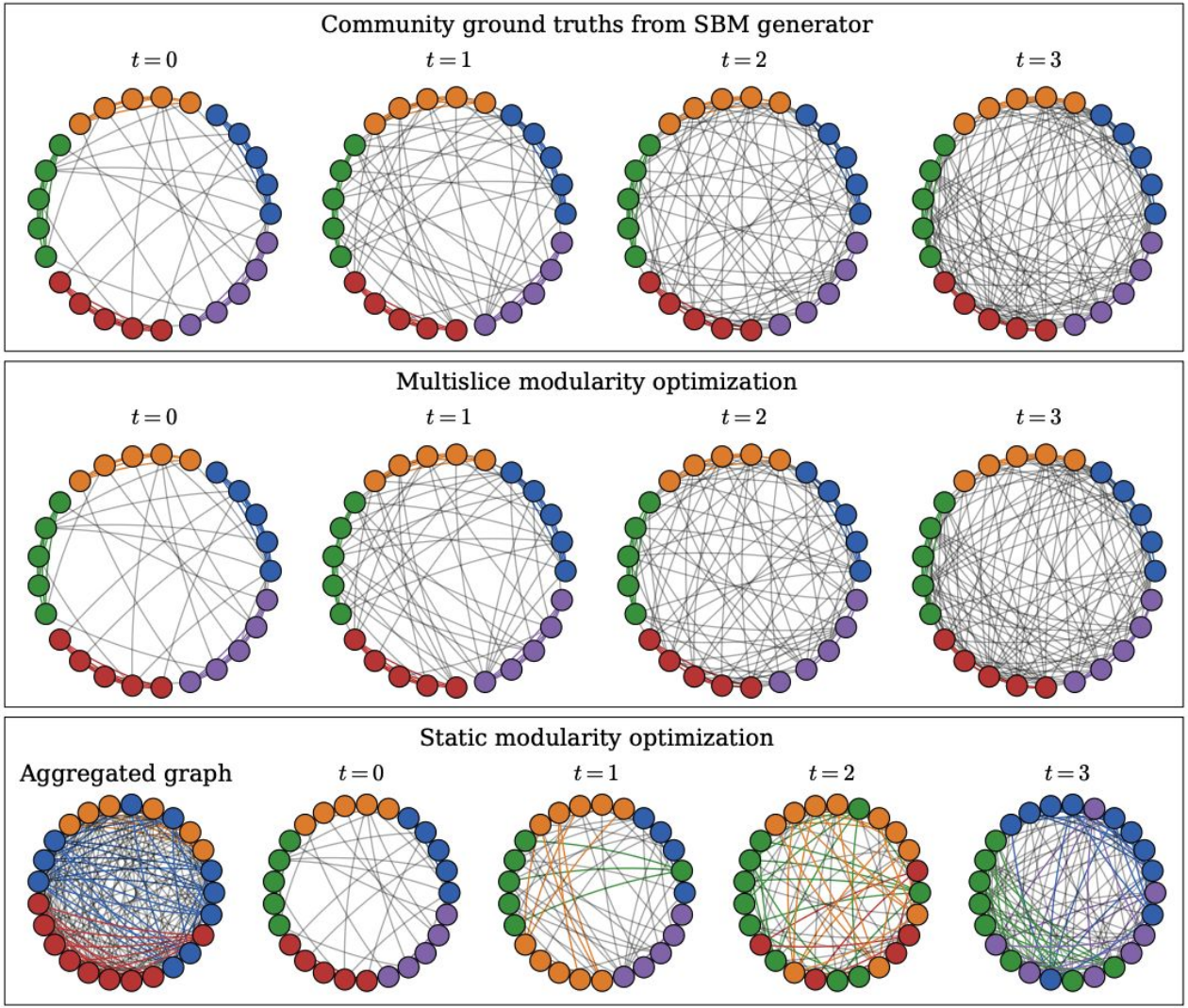
Graph operators, detectability thresholds

- NetworkX-Temporal: implemented on CPU and GPU (NVIDIA CUDA and AMD ROCm) devices, with a single environment variable **`NX_GPU_AUTOCONFIG=1`** enabling acceleration by default.



2. Princ

Graph operators



2. Principles

Graph operators, detectability thresholds

- However, heuristic optimization of functions like modularity is **not optimal**.

  → It brings *no guarantees* that the results (the *detected* communities) are the ‘best’ we may find.

- Another way of using modularity for community detection is employing its **spectral** version.

- **The spectrum of a graph** is obtained by a **matricial operation** (*eigendecomposition*) and preserves its most fundamental properties; so **spectral modularity** is therefore an alternative:

$$\mathbf{M} = \mathbf{A} - \gamma \frac{\mathbf{d}_{\text{out}} \mathbf{d}_{\text{in}}^{\top}}{m}, \quad Q = \frac{1}{2m} \text{Tr}(\mathbf{C}^{\top} \mathbf{M} \mathbf{C})$$

M: modularity matrix
C: community matrix
Tr: trace (sum of diags)

- But modularity is **not needed** for spectral decomposition – other graph operators may be used.

2. Principles

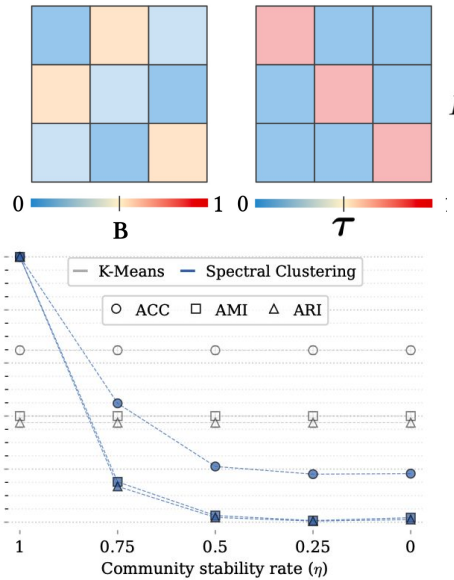
Graph operators, detectability thresholds

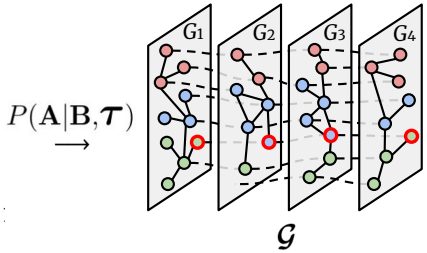
- In another vein, inference with stochastic block models (**SBMs**) also allows *reconstructing* a graph.
- **The *inverse* problem –** given a network, how was it generated? – allows a *clustering* form, i.e., communities, where the probabilities of nodes connecting is based on their (*prior*) affiliations.
- **SBMs** may also be used for *principled* model benchmarking with *attributed temporal graphs*.
- Artificially, we are able to escape two limitations of other model evaluation frameworks:
    - *Real-world data is messy:* **no guarantees** of community alignment with topology/attributes.
    - *Real-world data is scarce:* most datasets come from few application **domains** (e.g., citations).
- Result: controlling spatio-temporal (structural/time) and attribute (metadata) signal alignment.

2. Principles

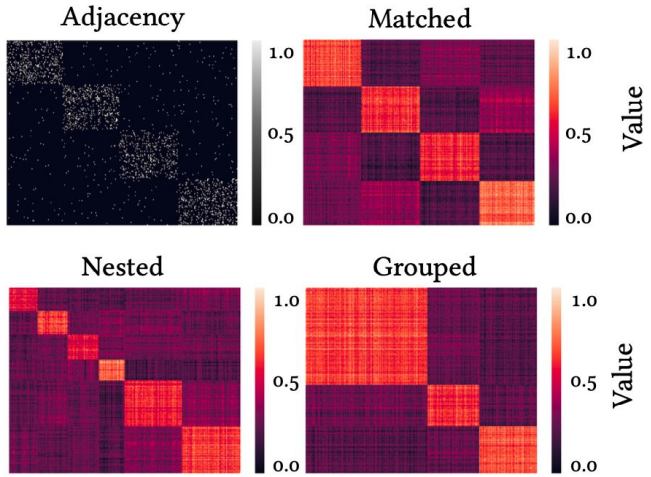
Graph operators, detectability thresholds

Benchmarking with TADC-SBM, a time-varying, attributed, degree-corrected SBM generator, allows to control and reproduce the exact known conditions for evaluating models under well-known settings.





Model	η	Accuracy
k-means	$*$	0.648 ± 0.016
Spectral	1	1.000 ± 0.000
	0.75	0.448 ± 0.000
	0.50	0.210 ± 0.000
	0.25	0.181 ± 0.000
	0	0.183 ± 0.000



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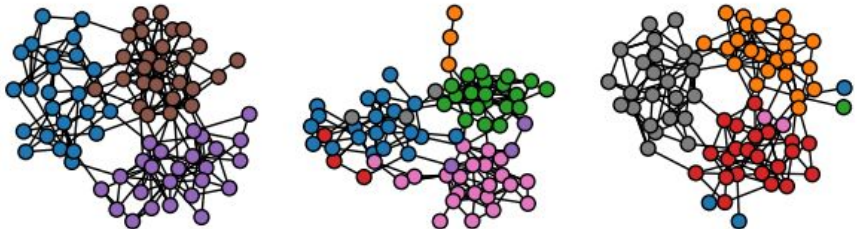
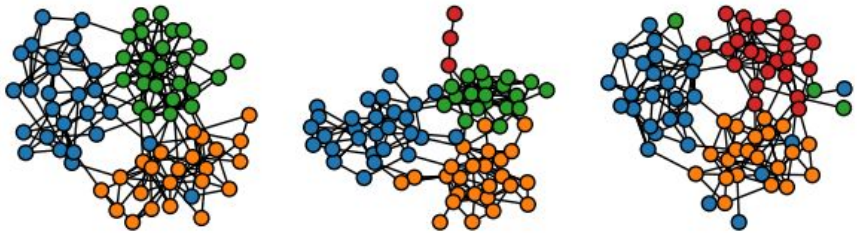
$$Q = \frac{1}{2m} \sum_{(i,j) \in V^2} \left[A_{ij} - \gamma \frac{d_i^{out} \, d_j^{in}}{2m} \right] \delta(c_i, c_j)$$

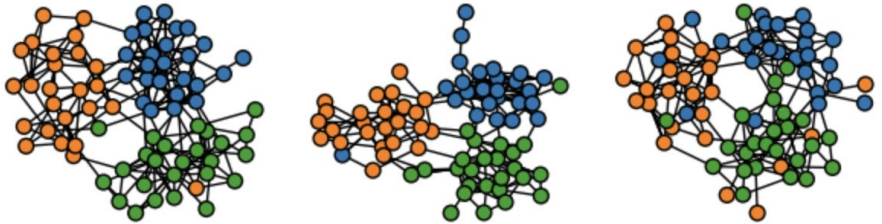
Static Modularity Optimization



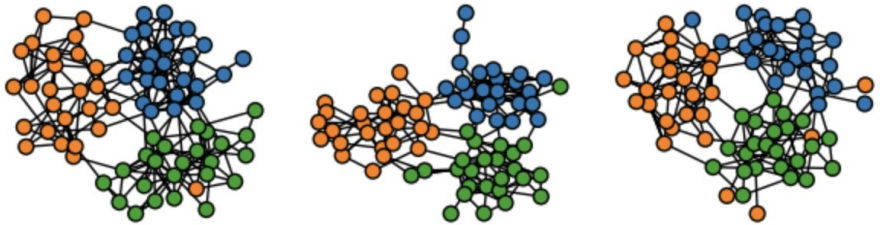
Static Modularity Optimization (Re-Weighted)



Temporal Modularity Optimization

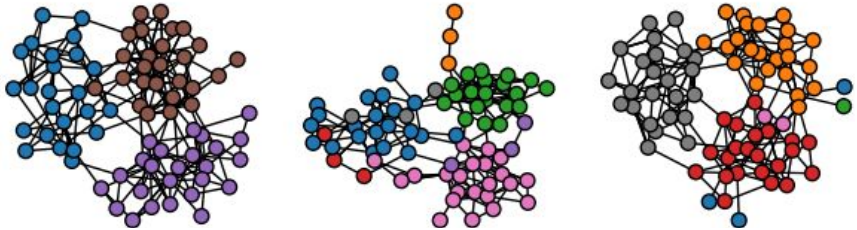


Temporal Modularity Optimization (parallelized)

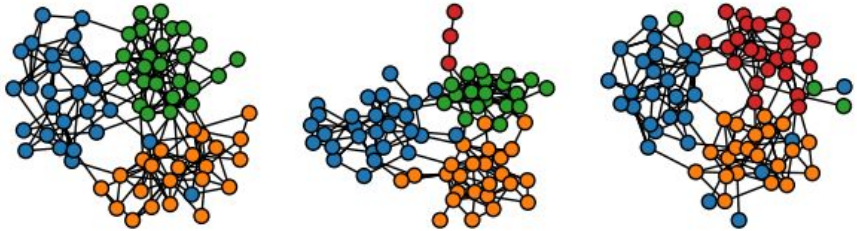


$$Q_{\mathrm{MS}} = \frac{1}{2\mu} \sum_{s,r} \sum_{i,j} \left[\left(A_{ij}^{(s)} - \gamma_s \frac{d_{is}^{\mathrm{out}} \, d_{js}^{\mathrm{in}}}{2m_s} \right) \delta_{sr} + \delta_{ij} \omega_{jsr} \right] \delta\left(c_i^{(s)}, c_j^{(r)} \right)$$

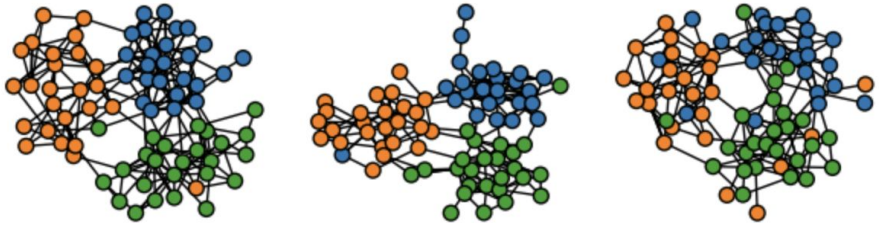
Static Modularity Optimization



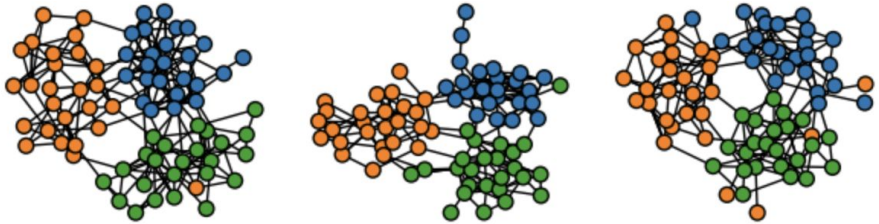
Static Modularity Optimization (Re-Weighted)



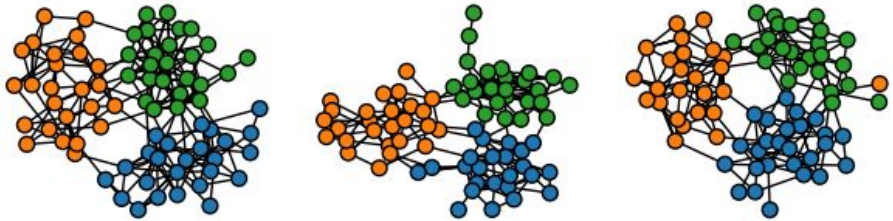
Temporal Modularity Optimization



Temporal Modularity Optimization (parallelized)



Spectral Clustering (Laplacian eigendecomposition + k-means)



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3. Primitives

Algorithms, accelerated eigensolvers

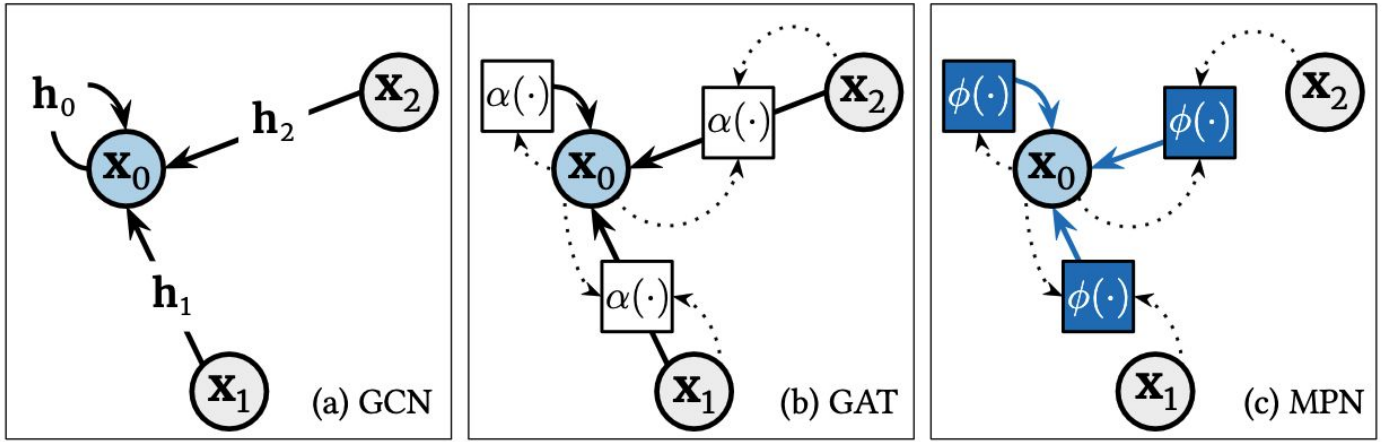
- This is where the state of the art for **community detection** with **spectral** algorithms fall short.
- It is, therefore, currently limited by both **theory** and **practice**:
  - **Theory:** unknown symmetrization without spectrum shift (e.g., the Bethe-Hessian)
  - **Practice:** missing GPU primitives of sparse asymmetric eigensolvers (for the Hashimoto)
- But spectral graph theory also has important implications for ***learning*** *on graphs*.
- Graph convolutional operations (e.g., in GCNs) can be understood as a node filtering operation where the graph signal is represented in a Fourier domain. Such graph *operations* require a graph *operator* – a matrix transformation – which usually considers the **Laplacian**.

3. Primitives

Algorithms, accelerated eigensolvers

- The **Laplacian** operator is the one most graph neural networks perform message passing on: node signal **x** is projected to the spectral domain as $\hat{\mathbf{x}} = \mathbf{U}^\top \mathbf{x}$, with **U** the Laplacian eigenbasis.

  So a learned filter acts as $\mathbf{y} = \mathbf{U} g_\theta(\mathbf{\Lambda}) \mathbf{U}^\top \mathbf{x}$; graph convolutions become localized polynomial approximations of K-hop neighborhood aggregation without explicit eigendecomposition.



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4. Pooling

Clustering or detecting communities

- So a *practical* alternative is employing machine learning methods for *pooling* a graph.
    - **Advantage:** jointly modeling **structure** (topology), **attributes** (metadata), and **time**.
    - Disadvantage: expensive to compute, and *usually* not consistent (that is, not *optimal*).
- It has been empirically shown that considering metadata and time can **improve** detection.
- If a GNN learns a *graph-theoretical objective* that is *consistent* with detectability theory, and if **structure, metadata, and time are aligned**, additional signals → stronger detectability.
- For graphs with high-dimensional attributes, this naturally opens an interesting venue of exploration with machine-learning based methods such as **graph neural networks** (GNNs).

4. Pooling

Clustering or detecting communities

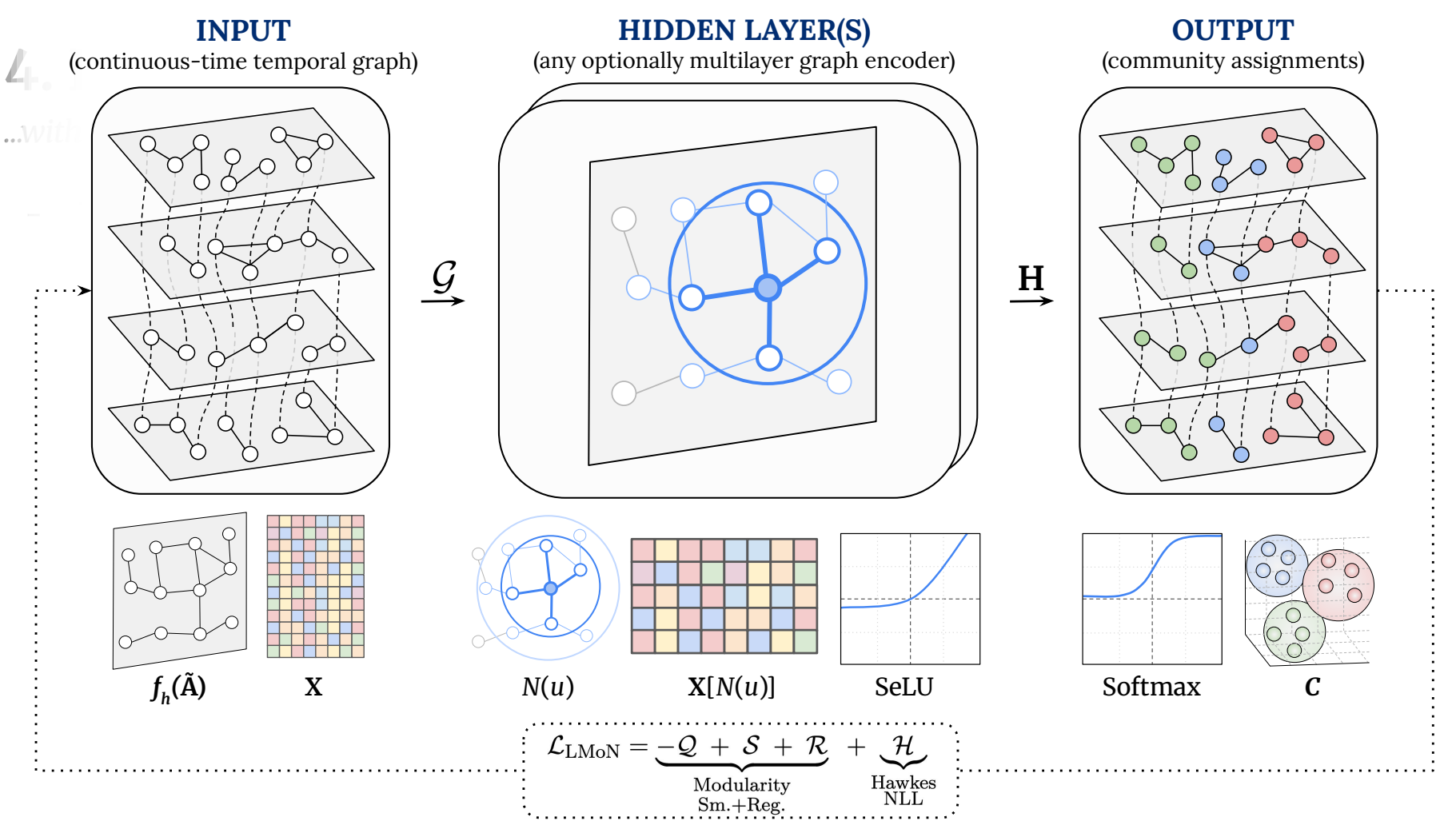
- **However**, few GNNs are *designed* for community detection, especially on *temporal* graphs.
  - *Not graph-theoretic:* they do not learn to approximate a *consistent* community objective.
  - *Not end-to-end differentiable*: additional post-processing steps are required for clustering.
  - *Not interpretable:* temporality is introduced by gating and memory encoder mechanisms.
- So a question appears: *can we employ GNNs for this task in a consistent and efficient way?*
- We introduce 🍋 **LMoN** – an *encoder-agnostic* Longitudinal Modularity optimization Network.

4. Pooling

Clustering or detecting communities

- **LMoN** builds upon a SOTA model (**DMoN**) and maintains its best-in-class scalability $O(d^2n+m)$.
    - *Graph-theoretic:* the objective is built specifically for community detection in graphs.
    - *End-to-end differentiable*: no additional post-processing steps are required for clustering.
    - *Interpretable:* temporality introduced by a *learned* Hawkes function (time-decaying edges).
- Result: we know the adjacency matrix (*re-weighted Laplacian*) and can *visualize it* after train.
- In addition, our architecture is **encoder-agnostic** – advancements in the state of the art for GNNs are transferable to LMoN's architecture by simply *swapping the encoder* (hidden layers).

  The two main components LMoN introduces – Hawkes-Laplacian operator and spectral optimization of longitudinal modularity – are independent of the encoder's expressiveness.


INPUT
(continuous-time temporal graph)
HIDDEN LAYER(S)
(any optionally multilayer graph encoder)
OUTPUT
(community assignments)
$\mathcal{G}$
H
$f_h(\tilde{\mathbf{A}})$
X
$N(u)$
X[$N(u)$]
SeLU
Softmax
C
$\mathcal{L}_{\text{LMoN}} = \underbrace{-\mathcal{Q} + \mathcal{S} + \mathcal{R}}_{\text{Modularity Sm.+Reg.}} + \underbrace{\mathcal{H}}_{\text{Hawkes NLL}}$

4. Pooling

Clustering or detecting communities

- Longitudinal modularity abstract away *from snapshot* slicing, reducing modeling complexity.
- Moreover, if the graph is static, then our model **LMoN** *recovers* **DMoN** as a special case.
- At each epoch, the adjacency matrix of the graph is re-weighted...

$$\hat{A}_{ij}(t) = A_{ij}(t)\left(\mu_{ij} + \alpha \sum_{t_k \in T_{ij}:\, t_k < t} w_k\, \kappa(t - t_k)\right)$$

μ: baseline intensity
α: decay amplitude
κ: Hawkes kernel (e.g., exp.)
w: original edge weight

...so **pairwise interaction strength** is modeled as a function of time, e.g., exponentially decaying.

4. Pooling

Clustering or detecting communities

- But this is **not enough**: *principled* operators (e.g., the Bethe-Hessian) may still outperform GNNs.
- This has been empirically observed in benchmarks with both **real-world** and synthetic graphs.
- Moreover, several real-world systems (e.g., energy grids) are too **critical** to be left for heuristics.
- Considering *structure*, *attributes*, and ***time*** may allow us to improve on SOTA modeling/prediction.
- Graph eigendecomposition does not take into consideration additional attribute metadata — *enters machine learning* — but we know graph operators that are detectability-optimal.
- The question then becomes: *how to introduce **principled pooling primitives** for learning on graphs?*

Dataset	Model	Accuracy ↑	AMI ↑	ARI ↑	Cov. ↑	Cond. ↓
$SBM_{\eta=1.00}$	LMoN	**.894 ± .004**	**.766 ± .007**	**.776 ± .009**	**.471 ± .003**	**.530 ± .003**
	DMoN	.888 ± .015	.755 ± .022	.765 ± .027	.467 ± .010	.535 ± .010
$SBM_{\eta=.75}$	LMoN	**.249 ± .014**	**.056 ± .008**	**.038 ± .006**	.192 ± .002	.810 ± .003
	DMoN	.216 ± .008	.037 ± .004	.024 ± .003	**.193 ± .002**	**.808 ± .002**
$SBM_{\eta=.5}$	LMoN	**.194 ± .005**	**.020 ± .004**	**.012 ± .002**	.183 ± .002	.818 ± .002
	DMoN	.186 ± .005	.013 ± .002	.007 ± .001	**.185 ± .001**	**.816 ± .001**
$SBM_{\eta=.25}$	LMoN	**.177 ± .005**	**.009 ± .002**	**.005 ± .001**	.180 ± .001	.821 ± .001
	DMoN	**.177 ± .002**	.004 ± .002	.003 ± .001	**.182 ± .001**	**.819 ± .001**
$SBM_{\eta=0}$	LMoN	**.182 ± .010**	**.013 ± .007**	**.007 ± .004**	.180 ± .001	.820 ± .001
	DMoN	.169 ± .004	.003 ± .001	.002 ± .001	**.183 ± .001**	**.818 ± .001**

Evaluation on synthetic graphs: performance improves significantly as the temporal signal η gets stronger.

Dataset	Model	Accuracy ↑	AMI ↑	ARI ↑	Cov. ↑	Cond. ↓
$\mathrm{SBM}_{\eta=1.00}$	S(**H**)	**1.000 ± .000**	**1.000 ± .000**	**1.000 ± .000**	**.558 ± .000**	**.442 ± .000**
	LMoN	.894 ± .004	.766 ± .007	.776 ± .009	.471 ± .003	.530 ± .003
	DMoN	.888 ± .015	.755 ± .022	.765 ± .027	.467 ± .010	.535 ± .010
$\mathrm{SBM}_{\eta=.75}$	S(**H**)	**.454 ± .001**	**.158 ± .001**	**.141 ± .001**	**.295 ± .000**	**.705 ± .000**
	LMoN	.249 ± .014	.056 ± .008	.038 ± .006	.192 ± .002	.810 ± .003
	DMoN	.216 ± .008	.037 ± .004	.024 ± .003	.193 ± .002	.808 ± .002
$\mathrm{SBM}_{\eta=.5}$	S(**H**)	**.202 ± .003**	**.026 ± .002**	**.016 ± .001**	**.212 ± .001**	**.788 ± .001**
	LMoN	.194 ± .005	.020 ± .004	.012 ± .002	.183 ± .002	.818 ± .002
	DMoN	.186 ± .005	.013 ± .002	.007 ± .001	.185 ± .001	.816 ± .001
$\mathrm{SBM}_{\eta=.25}$	S(**H**)	**.192 ± .009**	**.015 ± .003**	**.010 ± .002**	**.205 ± .001**	**.796 ± .000**
	LMoN	.177 ± .005	.009 ± .002	.005 ± .001	.180 ± .001	.821 ± .001
	DMoN	.177 ± .002	.004 ± .002	.003 ± .001	.182 ± .001	.819 ± .001
$\mathrm{SBM}_{\eta=0}$	S(**H**)	**.190 ± .011**	**.020 ± .003**	**.012 ± .002**	**.203 ± .001**	**.798 ± .001**
	LMoN	.182 ± .010	.013 ± .007	.007 ± .004	.180 ± .001	.820 ± .001
	DMoN	.169 ± .004	.003 ± .001	.002 ± .001	.183 ± .001	.818 ± .001

Evaluation on synthetic graphs: spectral clustering of the Bethe-Hessian S(**H**) wins over LMoN as η gets stronger.

Outline

1. Introduction
Complex systems, temporal networks

2. Principles
Graph operators, detectability thresholds

3. Primitives
Algorithms, accelerated eigensolvers

4. Pooling
Clustering or detecting communities

5. Final Remarks
Takeaways – and where to go from here?

5. Final Remarks

Takeaways – and where do we go from here?

- **Conclusion:** model performance only **improves** if structure/attribute/time signals align.
- **Limitation:** when those signals do **not** align, then *principled* algorithms may outperform GNNs.
- Two **future directions** for research departing from this thesis:
  - ***Improving message passing:*** the Laplacian operator of GNNs is a bottleneck for clustering.
  - ***Principled pooling primitives:*** enabling applications such as *causal* learning *at scale*.
- Network science is an interdisciplinary field by excellence, and field hybridization contributes to the compendium of techniques it has accumulated – and much like statistics and machine learning in the past, notable advancements may be made possible through transdisciplinarity.

Thank you for your attention!

Learning and Clustering on Temporal Graphs: **Principles, Primitives, and Pooling**

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