Causality in Replay: Detecting Effective Connectivity from Spike Trains

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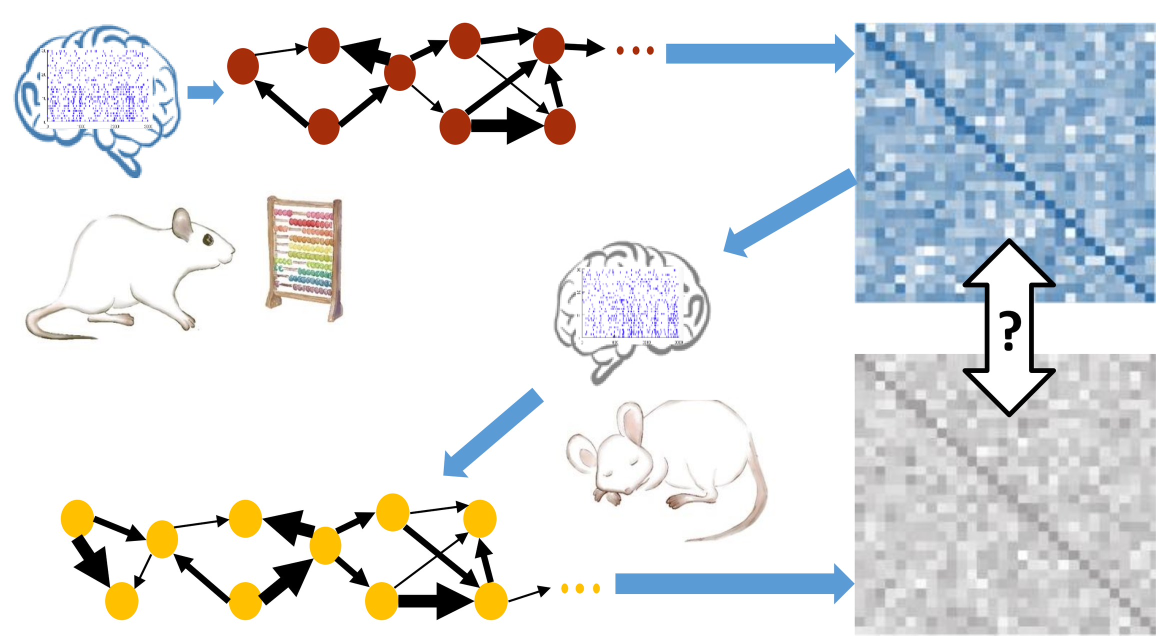
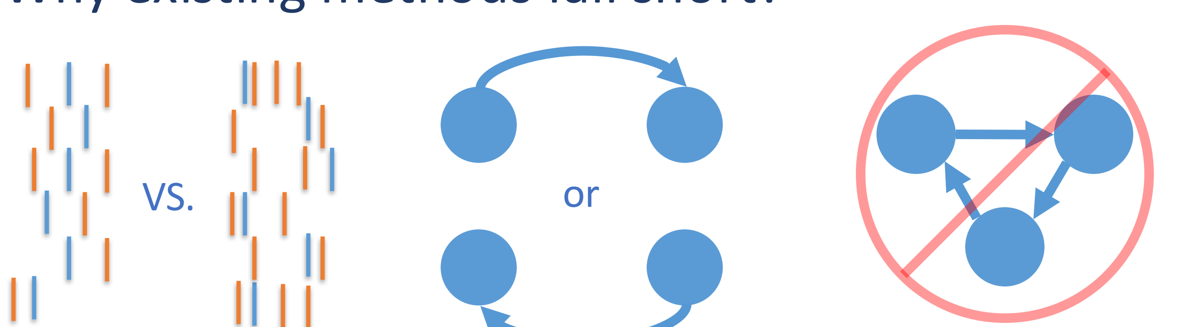
INTRODUCTION

- Neural reactivation during sleep/rest resembles preceding tasks (replay, memory consolidation)
- Replay of spike sequences may capture underlying causal functional relationships between neurons
- Effective connectivity ⇔ Directed causal influence [Friston, 2011]
- Detection of replay and its causal structure are important to understand neural computations



EXISTING METHODS

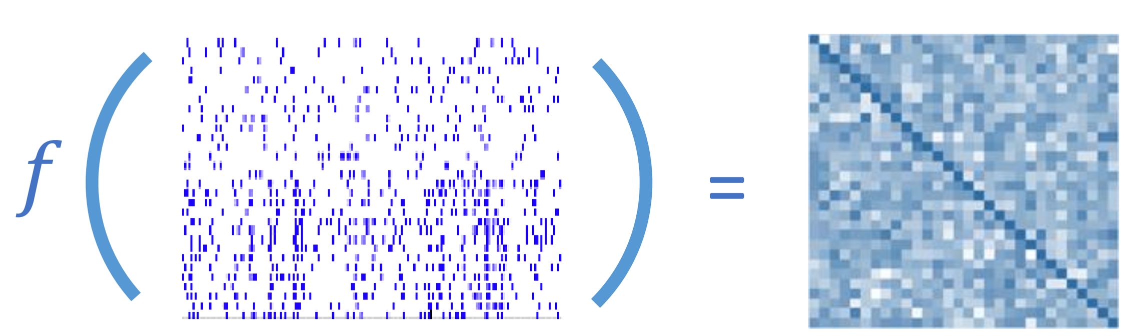
Why existing methods fall short?



fail for high signal-to-noise ratio

catch synchrony but not direction

fail to capture recurrent relationships



assume f is linear, oversimplifying the interactions between neurons

OBJECTIVES

Develop a model that is
- robust to **sparse spiking**,
- applicable to **diverse underlying topologies**,
- is **non-parametric** (assumes **non-linearity**)

METHODS

Data Generation

I. Fully Synthetic Spikes
- Known weight matrix $\boldsymbol{W}$ and bias terms $\boldsymbol{\beta}$
- Simulate trajectories of binary states $s_t \in \{-1,+1\}^N$ for N neurons using $\boldsymbol{W}$ and $\boldsymbol{\beta}$
- -1: no spike, $+1$: spike

II. NEURON (Biophysically realistic spikes)
- Single compartment multi-current pyramidal cell network of CA3 place cells (binarized)

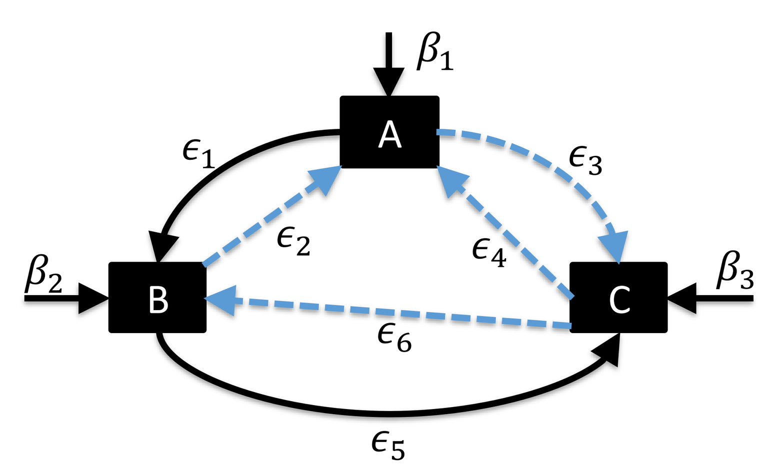
Probabilistic Model: *CausalSpikeGraph*

Build a $2^N \times 2^N$ transition probability matrix

$$p(s_{t+1,n} = +1 \mid \boldsymbol{s_t}) = \sigma(\beta_n + \boldsymbol{W_n} \cdot \boldsymbol{s_t})$$

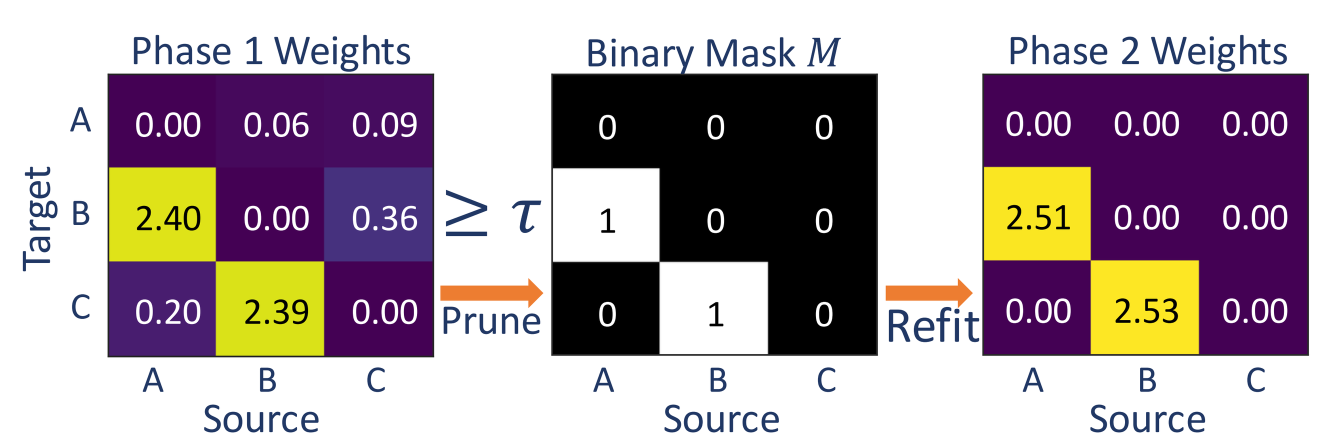
Goal: Recover W from observed paths $(\boldsymbol{s_{t+1}}, \boldsymbol{s_t})$

1) Optimize a dense model with L_1 regularization
2) Prune using chosen threshold τ and obtain mask M
3) Re-optimize survived edges for unbiased recovery.



	A	B	C
0	-1	-1	-1
1	-1	-1	+1
2	-1	+1	-1
3	-1	+1	+1
4	+1	-1	-1
5	+1	-1	+1
6	+1	+1	-1
7	+1	+1	+1

Let $\epsilon_1 = \epsilon_5 = 2.5$ and β_n = -2



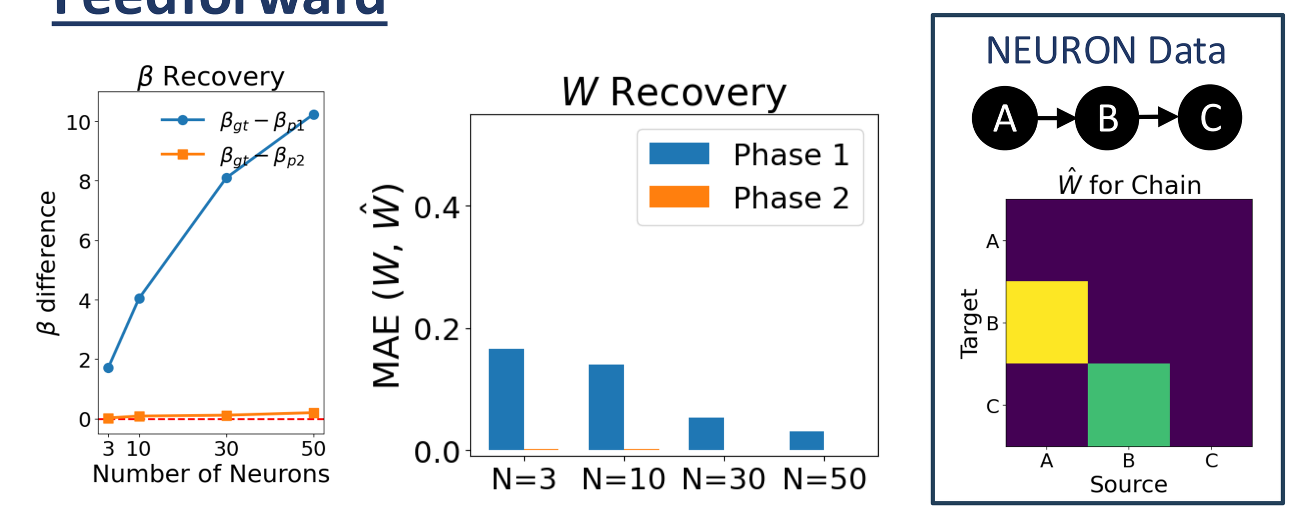
Loss functions for optimization

$$L_{Phase1} = -\sum_{(s_{t+1},s_t)} \log p(\boldsymbol{s_{t+1}} \mid \boldsymbol{s_t}; \boldsymbol{W}, \boldsymbol{\beta}) + \lambda \sum_{m \neq n} |W_{n,m}|,$$

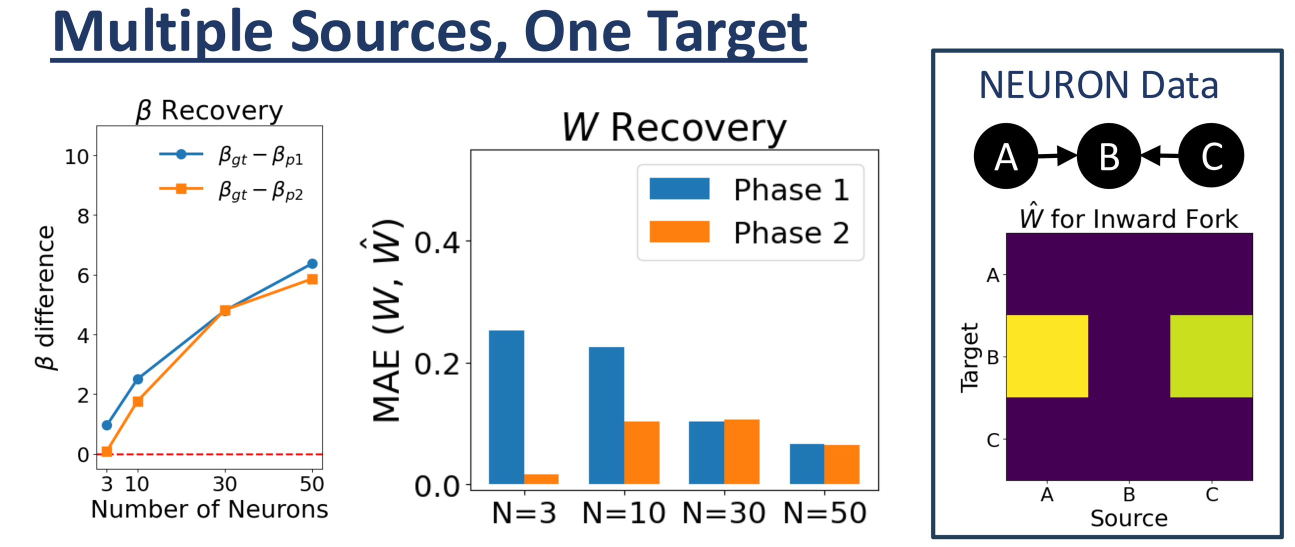
$$L_{Phase2} = -\sum_{(s_{t+1},s_t)} \log p(\boldsymbol{s_{t+1}} \mid \boldsymbol{s_t}; \boldsymbol{W} \odot \boldsymbol{M}, \boldsymbol{\beta})$$

RESULTS

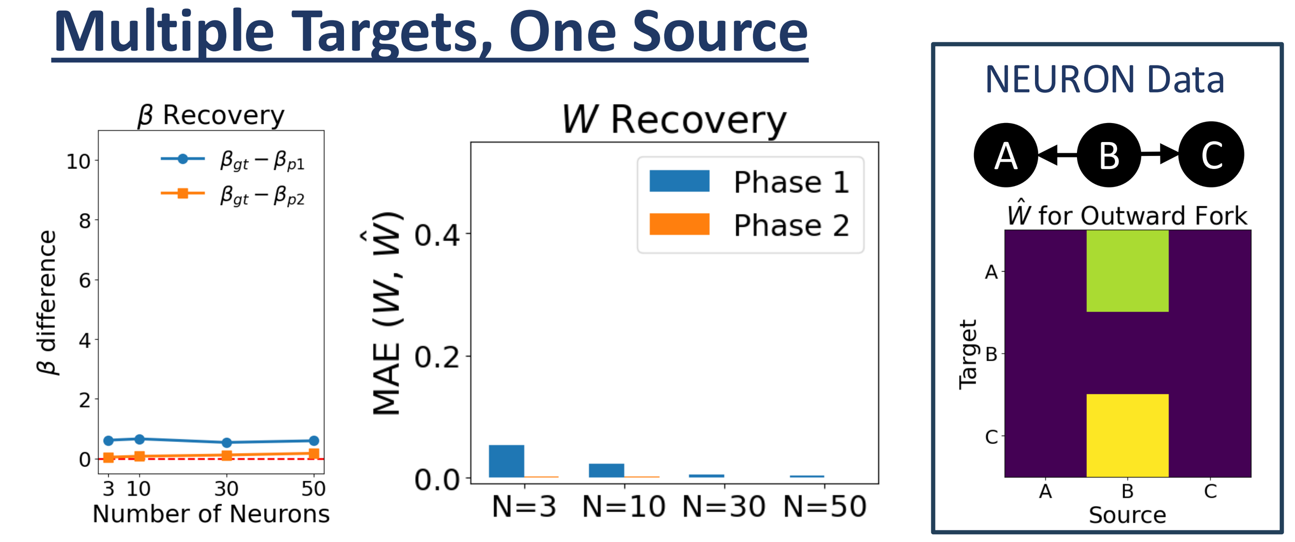
Feedforward



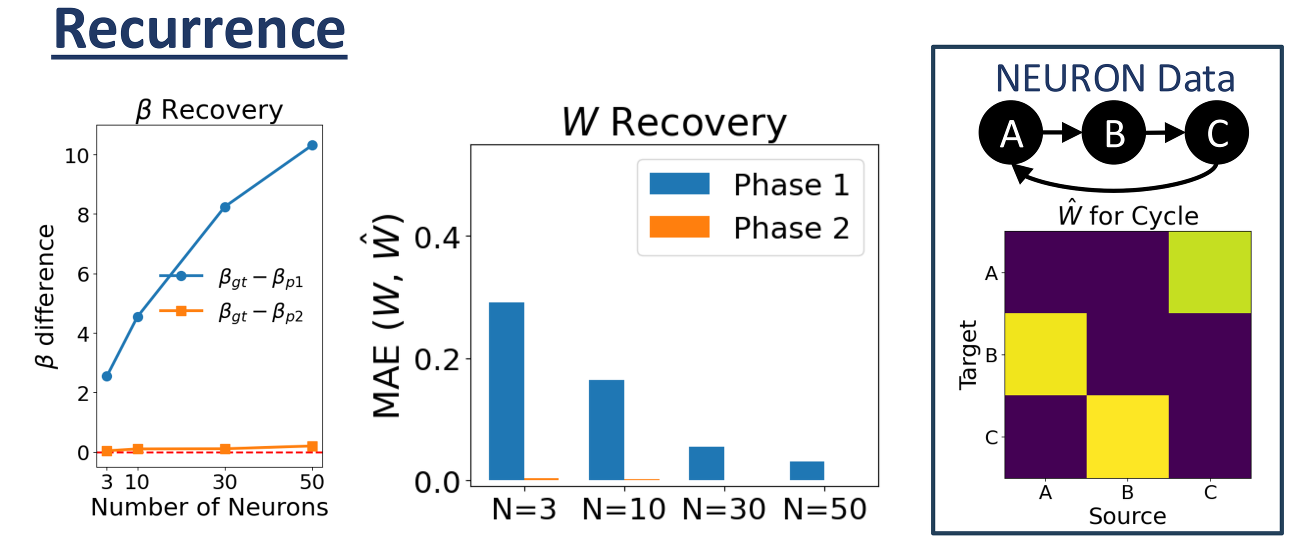
Multiple Sources, One Target



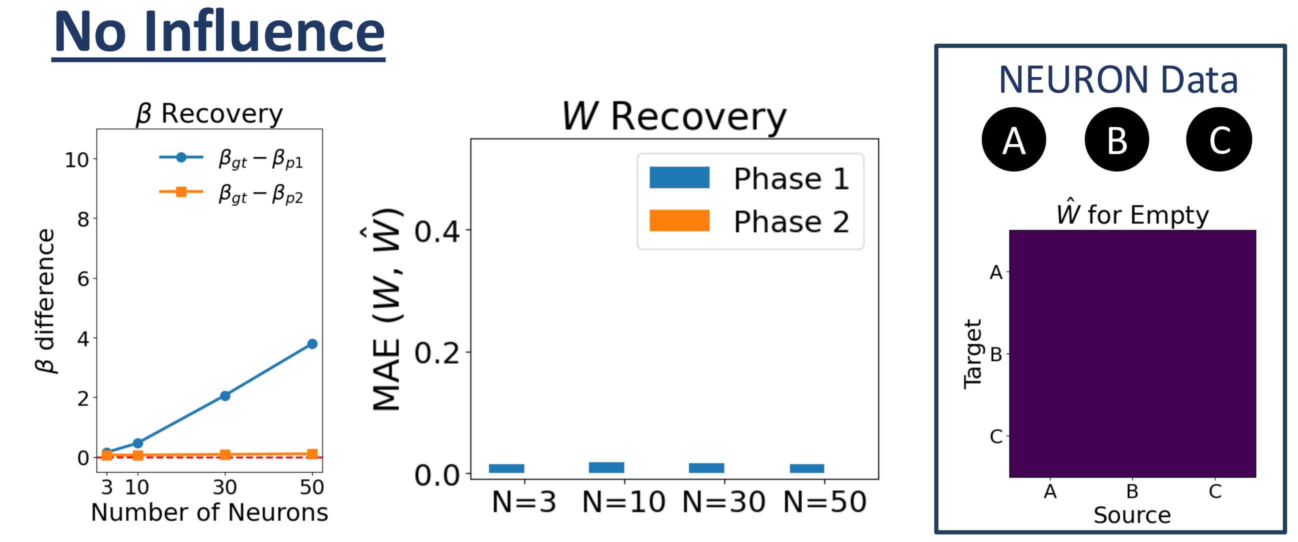
Multiple Targets, One Source



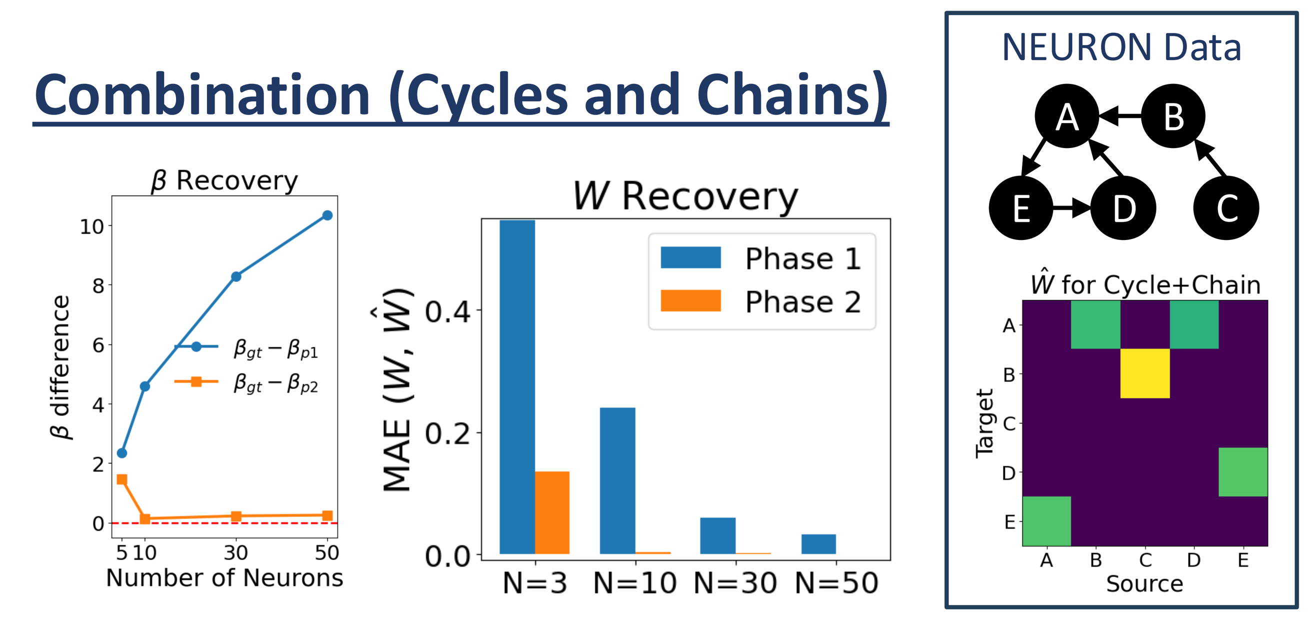
Recurrence



No Influence



Combination (Cycles and Chains)



CONCLUSIONS

Introduced a causal structure method called *CausalSpikeGraph* (CSG)
- Faithful discovery of all general topologies
- Reliable performance on NEURON data
- Does not assume linearity in data
- Does not depend on data lag, like Granger Causality, Cross-Correlation
- No pairwise comparisons
- No acyclicity, or other strong, assumptions like in Structural Equation Model DirectLiNGAM

Next Steps:
- Remove CSG's reliance on binning to binarize spike trains
- Test CSG on different levels of signal-to-noise ratio and more complex/larger topologies
- Evaluate CSG's performance on more datasets from NEURON and against new reactivation detection methods [Tatsuno and Fellous, 2024]

REFERENCES

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