Causality in Replay: Detecting Effective Connectivity from Spike Trains

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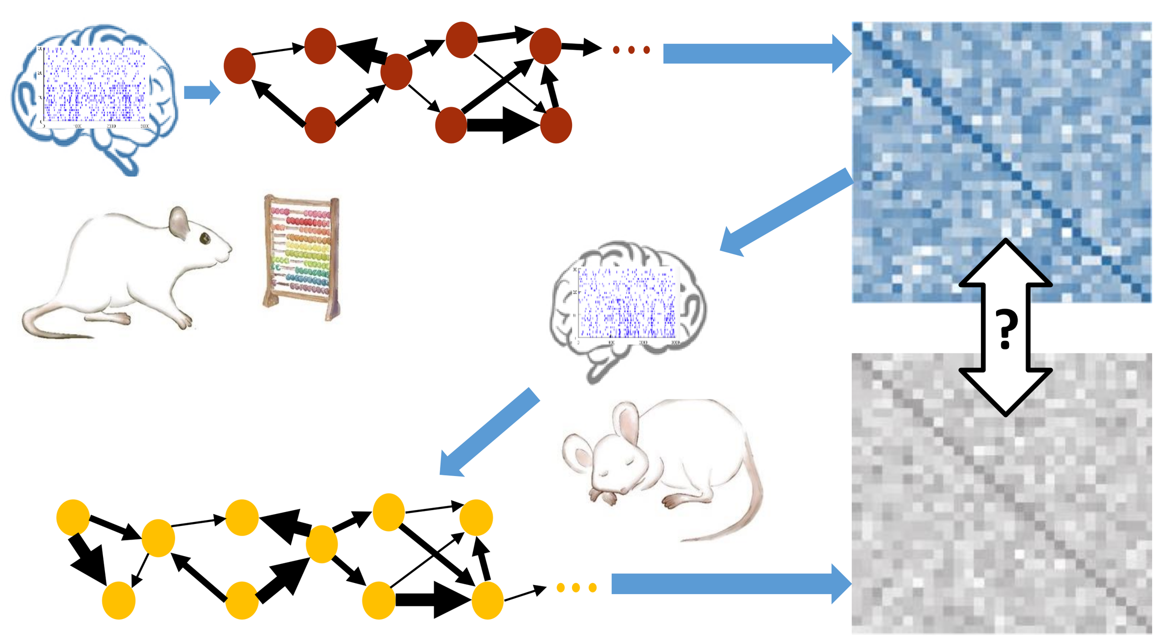
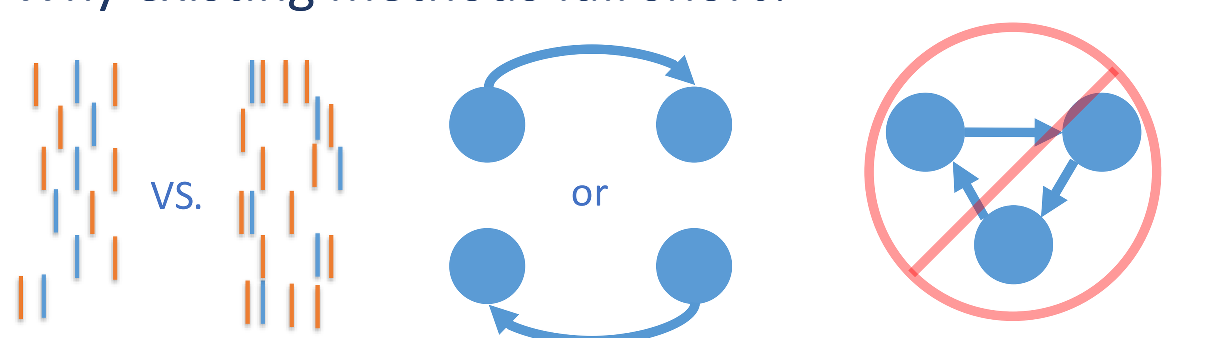
INTRODUCTION

- 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 ⇔ Causal influence [1]
- Detection of replay and its causal structure are important to understand neural computations



EXISTING METHODS

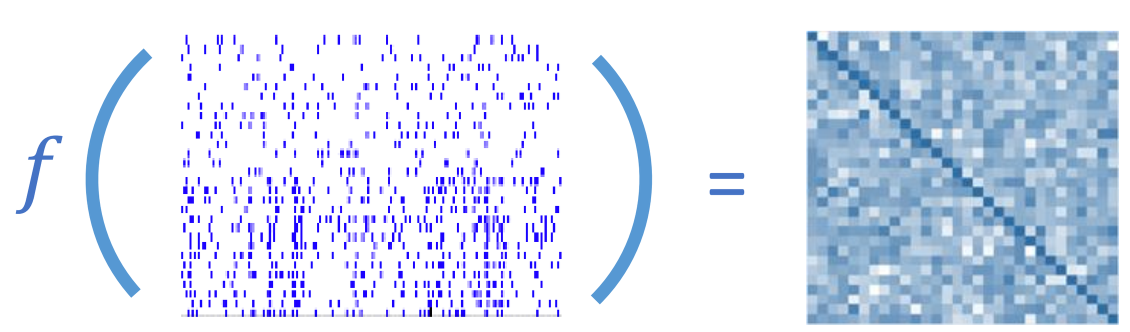
Why existing methods fall short?



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:

- Robustly handles sparse spiking
- Recovers diverse network topologies
- Makes no linearity assumptions
- Scales efficiently and accurately to large networks under realistic firing rates (10-20 Hz)

METHODS

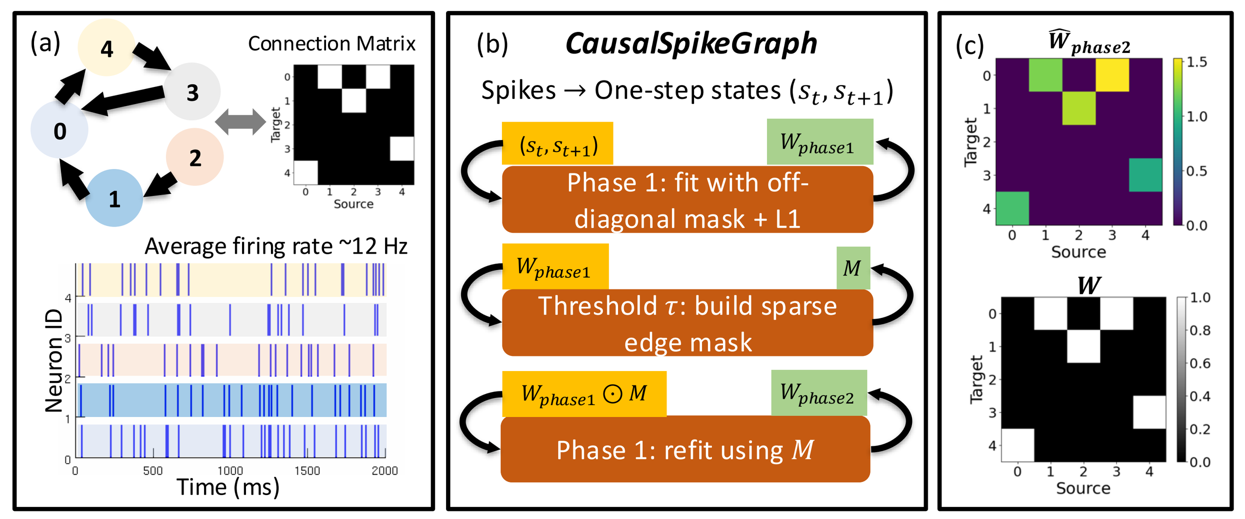
Data Generation

I. Fully Synthetic Spikes

- Known influence 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)

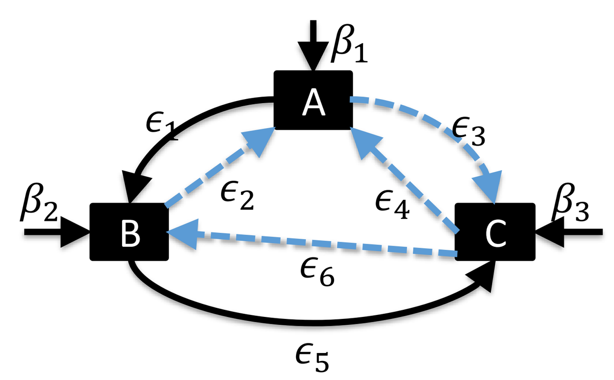
- Single compartment multi-current pyramidal cell network of CA3 place cells (binarized)



Probabilistic Model: *CausalSpikeGraph (CSG)*

- One-Step Transition Max Likelihood Estimation
- Transition probabilities from $\boldsymbol{s_t}$ to $\boldsymbol{s_{t+1}}$:

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



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

Example: Let $\epsilon_1 = \epsilon_5 = 2.5$ and $\beta_n = -2$

Phase 1 Weights (Target × Source)

Target \ Source	A	B	C
A	0.00	0.06	0.09
B	2.40	0.00	0.36
C	0.20	2.39	0.00

$\geq \tau$ → Prune

Binary Mask M

Target \ Source	A	B	C
A	0	0	0
B	1	0	0
C	0	1	0

→ Refit

Phase 2 Weights

Target \ Source	A	B	C
A	0.00	0.00	0.00
B	2.51	0.00	0.00
C	0.00	2.53	0.00

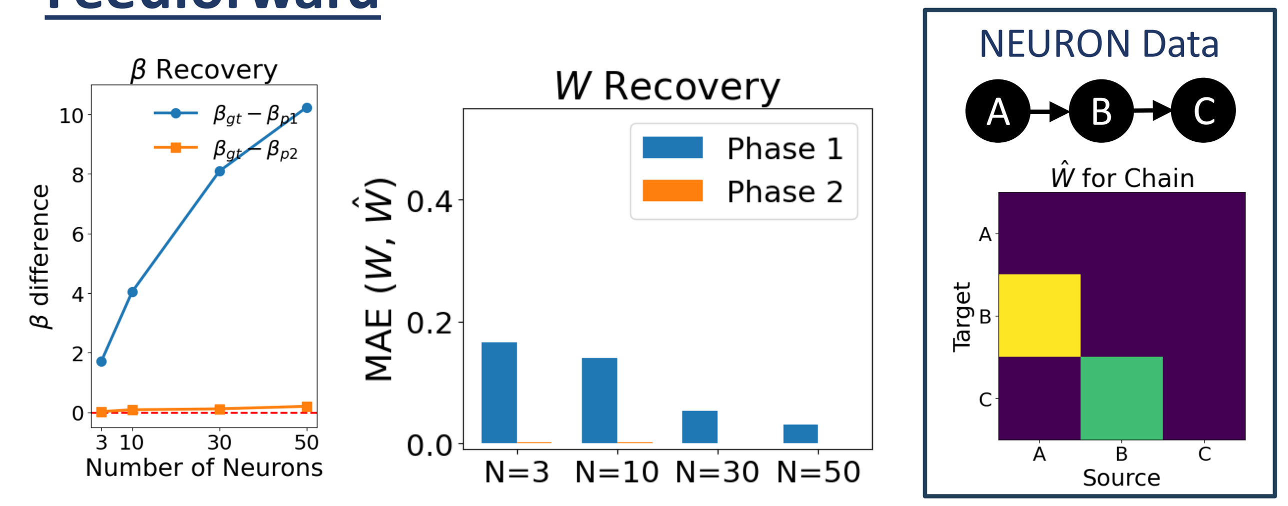
Loss functions for optimization

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

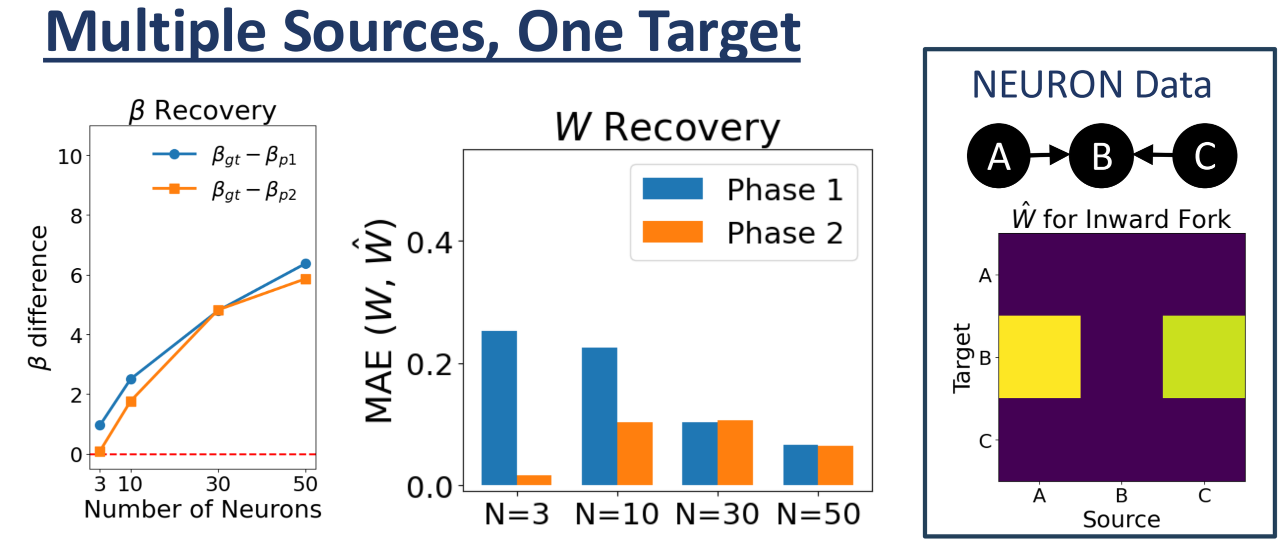
$$L_{Phase2} = -\sum_{(s_{t+1}, s_t)} \log p(\boldsymbol{s_{t+1}} \mid \boldsymbol{s_t}; \boldsymbol{W} \odot \boldsymbol{M}, \boldsymbol{\beta})$$

RESULTS

Feedforward



Multiple Sources, One Target



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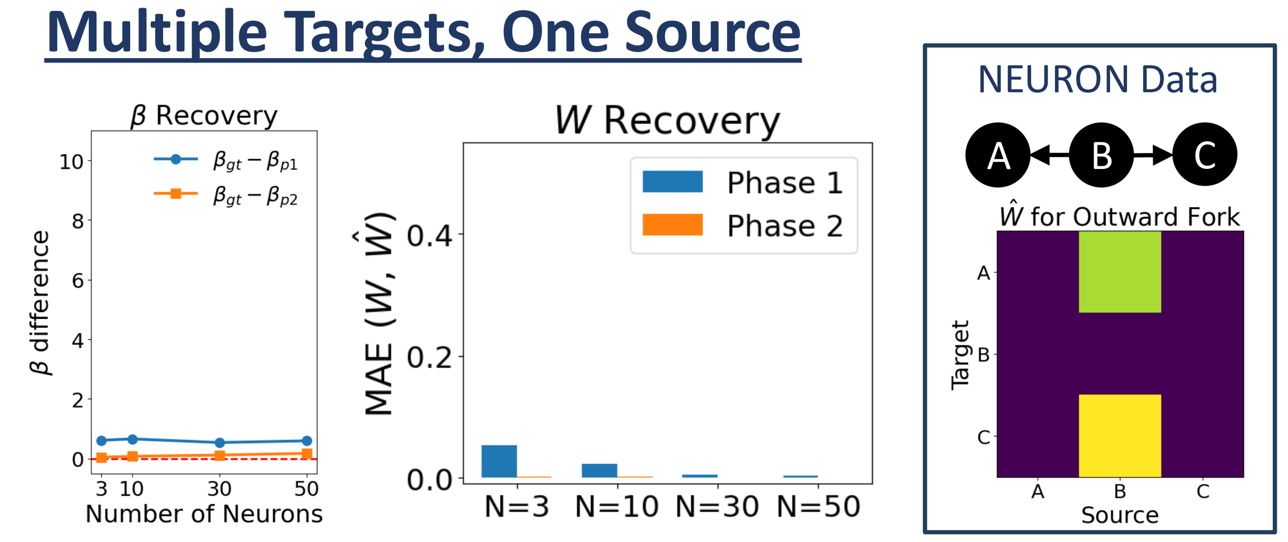
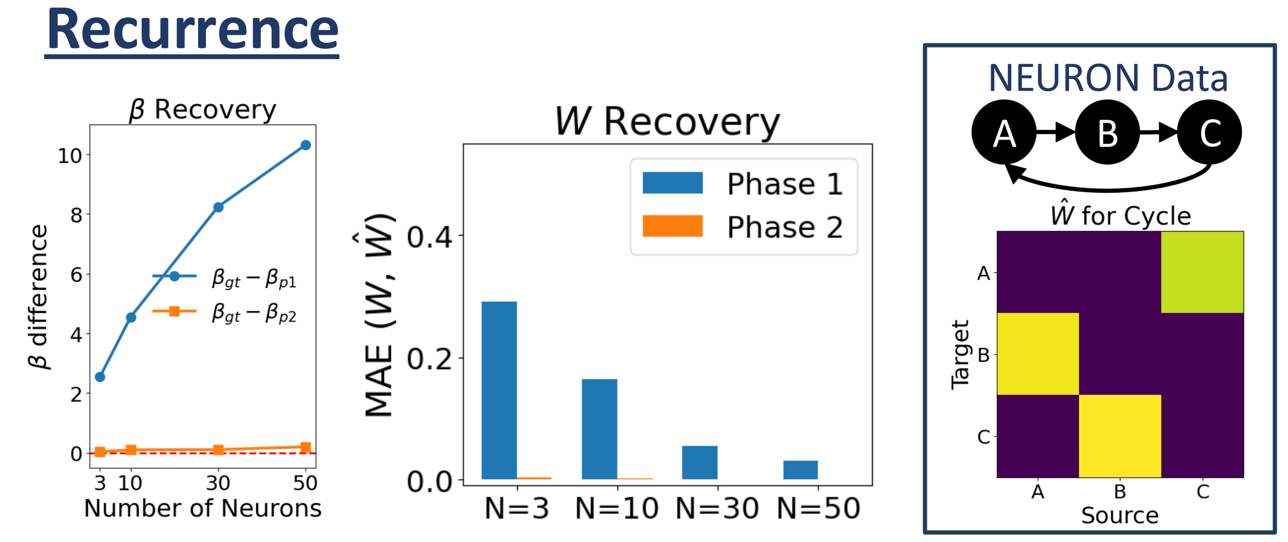
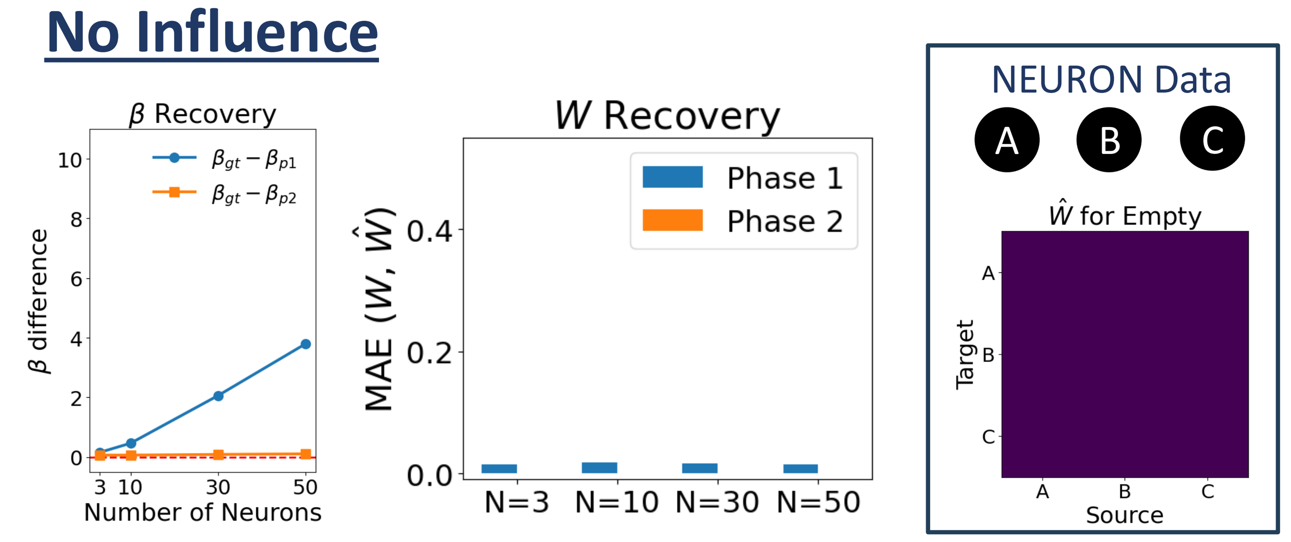


Recurrence

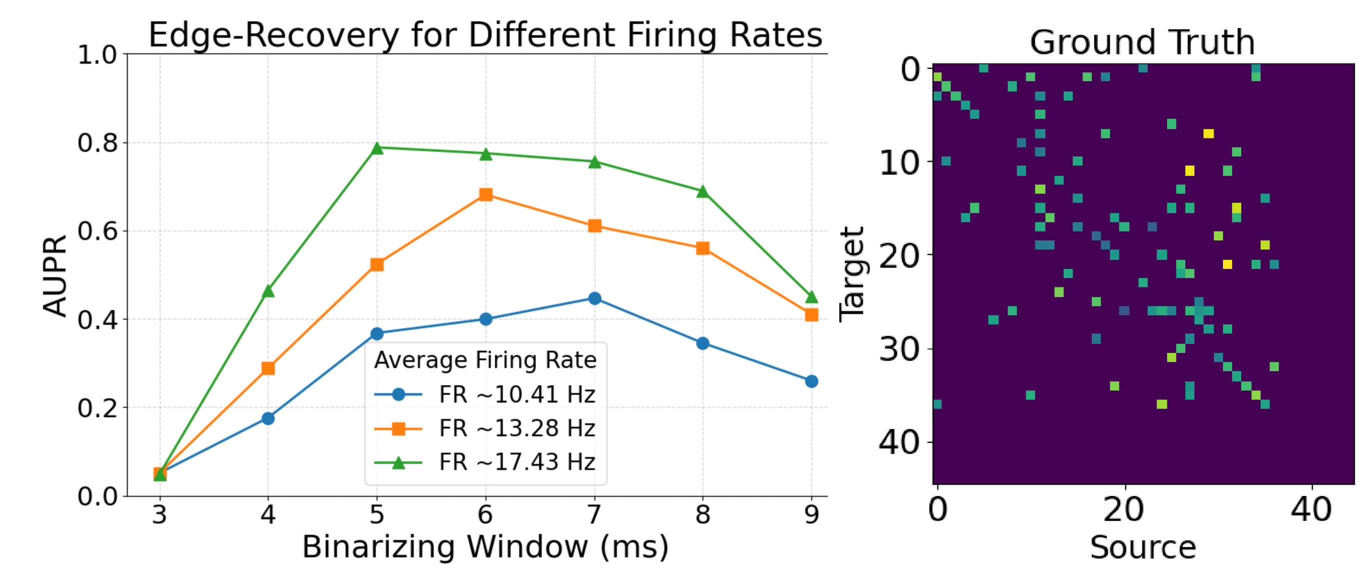


No Influence



Realistic (NEURON) & Multiple Motifs

- Area Under Precision-Recall (AUPR) of recovered connections vs binning window
- 45-neuron networks with motifs; firing-rate regimes from ~10–17 Hz



CONCLUSIONS

Introduced a causal structure method 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 a binning window
- Evaluate CSG's performance on more realistic datasets and against new reactivation detection methods [2]

REFERENCES

[1] Friston KJ. **Functional and effective connectivity: a review**. *Brain Connectivity*. 2011;1(1):13, 2011

[2] Tatsuno M, Fellous JM. **Long-term reactivation of multiple sub-assemblies in the hippocampus and prefrontal cortex**. *bioRxiv* preprint, 2024

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