Hippocampal Replay and Sleep's Hidden Language: Methods for Detecting Functional Connectivity from Spike Trains

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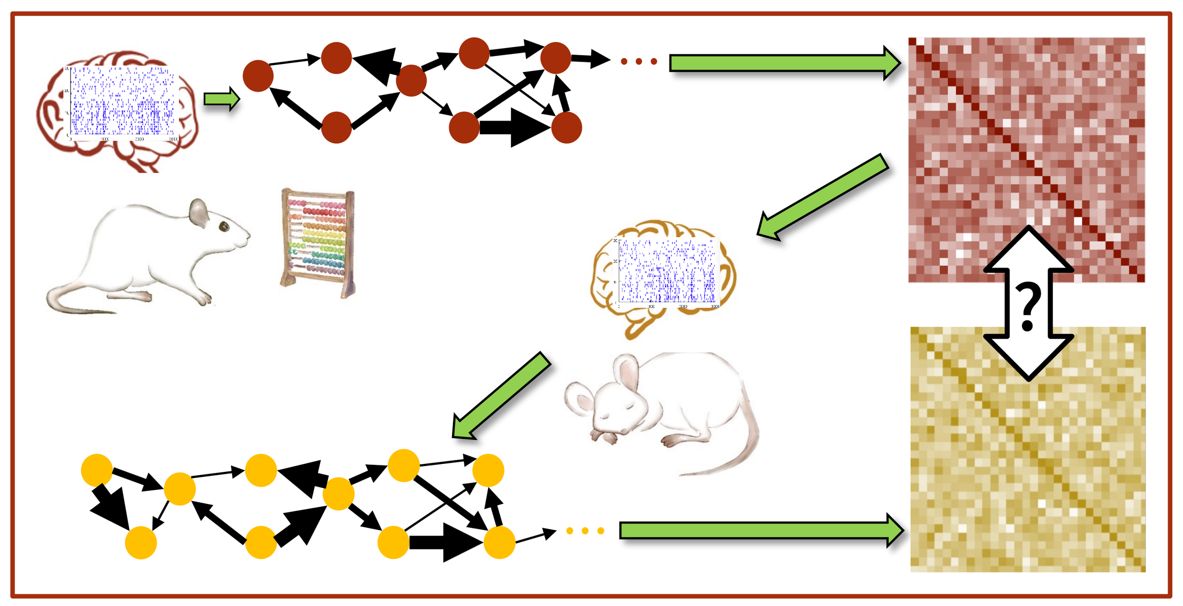
INTRODUCTION

- Hippocampal neurons reactivate during rest/sleep states.
- Spiking sequences 'resemble' those during preceding spatial navigation tasks.
- Important for memory consolidation and perhaps planning and decision making.
- Sequences may capture underlying functional causality structure established through learning and/or anatomical connections.
- **Detection of replay and replay structure needed for understanding neural coding and neural computation.**

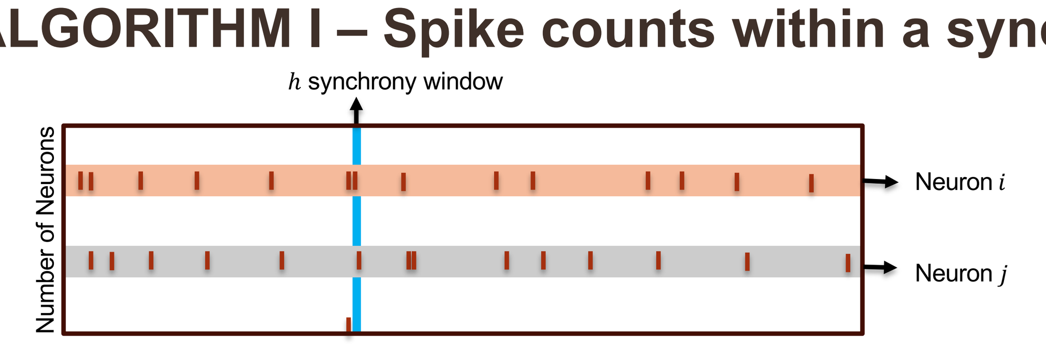


METHODS AND OBJECTIVES

- Simulating network activity of CA3 place cells using NEURON with single compartment multi-current pyramidal cell network and realistic AMPA and NMDA synapses.
- Ground truth: conductance of synaptic currents specified by connection matrix to impose a causality structure in selected subgroups of neurons.
- **Goal: Comparing methods for detecting functional connectivity from spike trains only.**

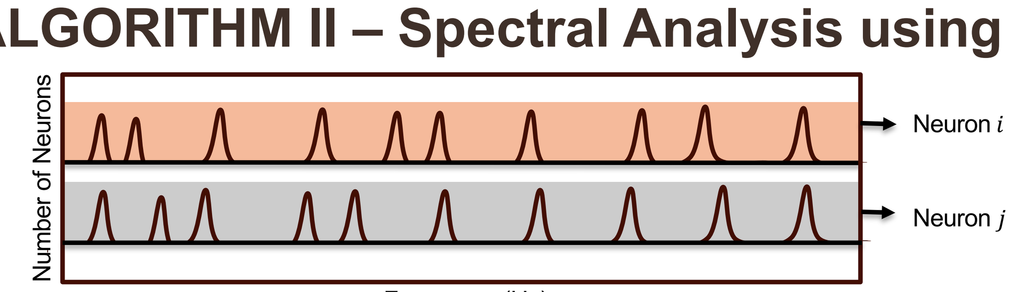
ALGORITHMS

ALGORITHM I – Spike counts within a synchrony window



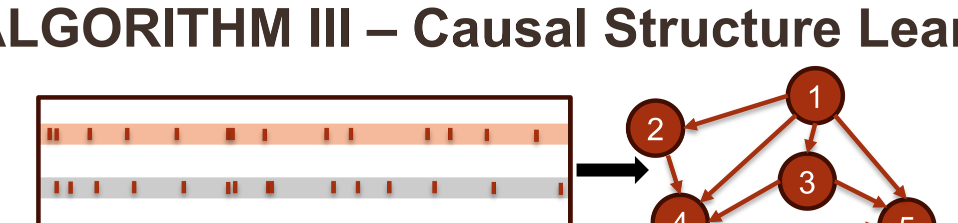
An $N \times N$ matrix, with (i, j) the number of times neurons i and j fired within h ms of each other

ALGORITHM II – Spectral Analysis using Fourier Transform



An $N \times N$ matrix with (i, j) the cross-correlation between frequency content of spike trains (i, j)

ALGORITHM III – Causal Structure Learning using LiNGAM[1]

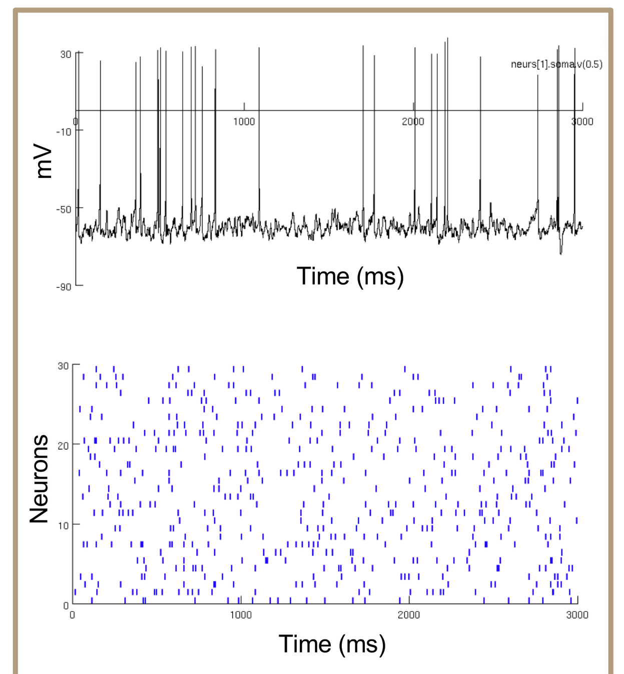


An $N \times N$ matrix, with (i, j) causal strength between neuron i and neuron j.

Linear, Non-Gaussian, Acyclic causal Models (LiNGAM) for Bayesian Network extraction.

Compare outputs against ground truth $N \times N$ connection matrix

DATA SIMULATION AND MODEL EVALUATION



CA3 place cell network activity simulated using NEURON.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad \text{Recall} = \frac{TP}{TP+FN}$$

Precision-Recall Curves

	Positive (Predicted)	Negative (Predicted)
Positive (Target)	True Positives (TP)	False Negatives (FN)
Negative (Target)	False Positives (FP)	True Negatives (TN)

Size of the network

$$N = \{10, 30, 50\}$$

Sparsity of the network

$$C = \{25, 50, 75\}\%$$

Synaptic strengths

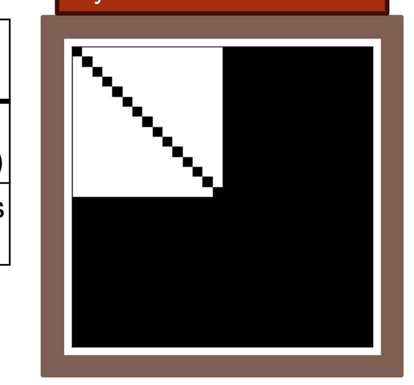
$$W = \{1, 2, 3\}$$

for 'low', 'medium', and 'high' weights

Spike train duration in seconds

$$T = \{3, 10\}$$

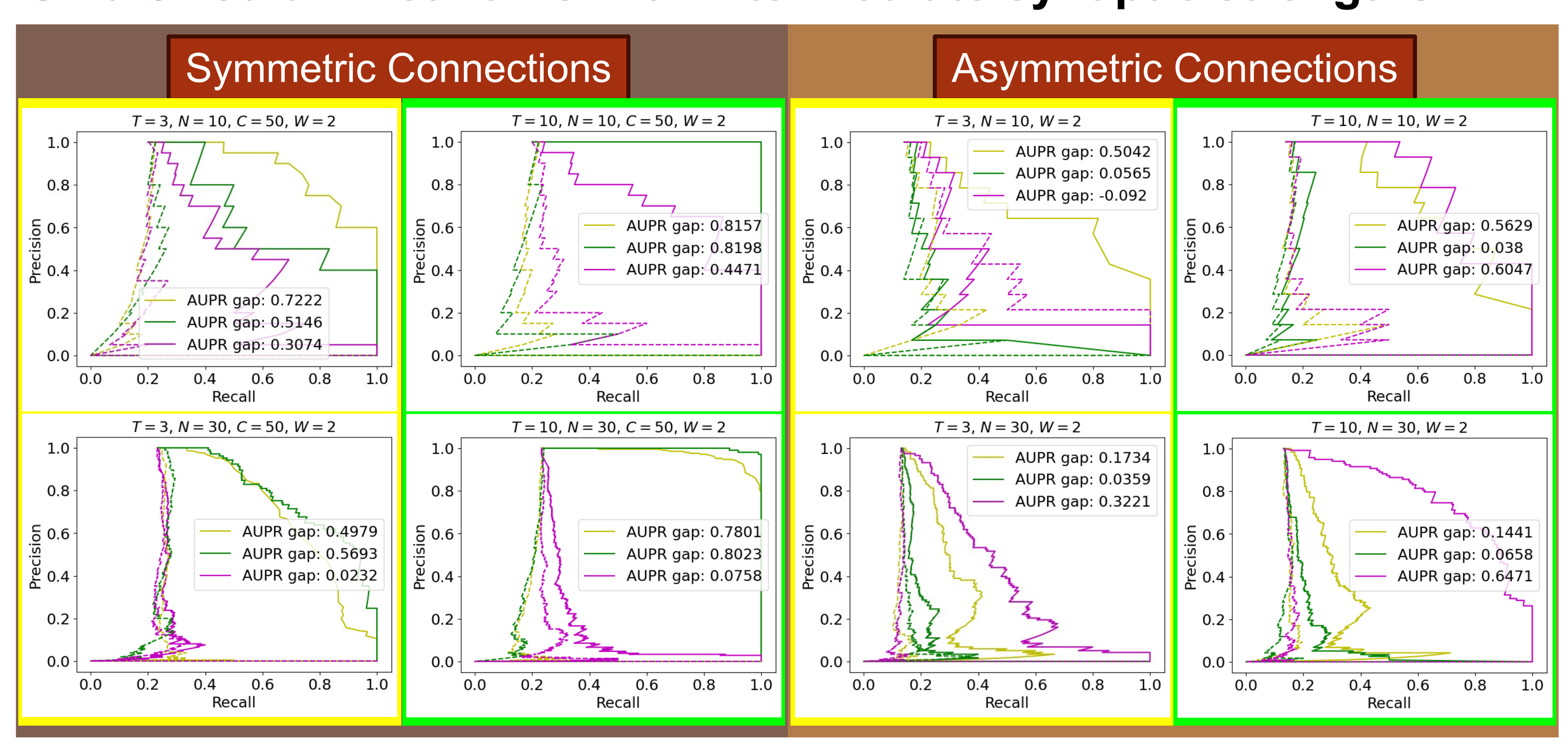
Symmetric Connections



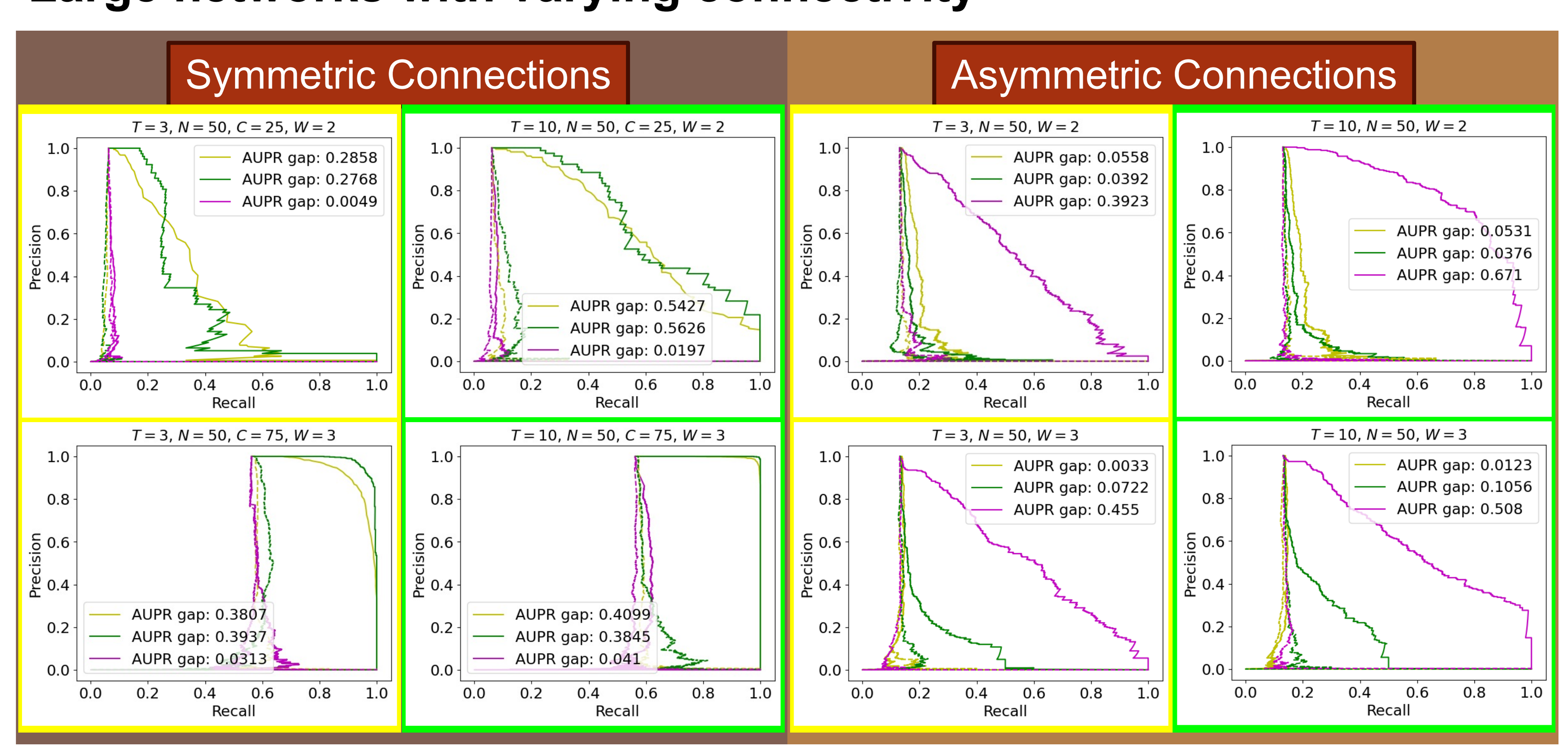
Asymmetric Connections

RESULTS

Small/Medium networks with intermediate synaptic strengths

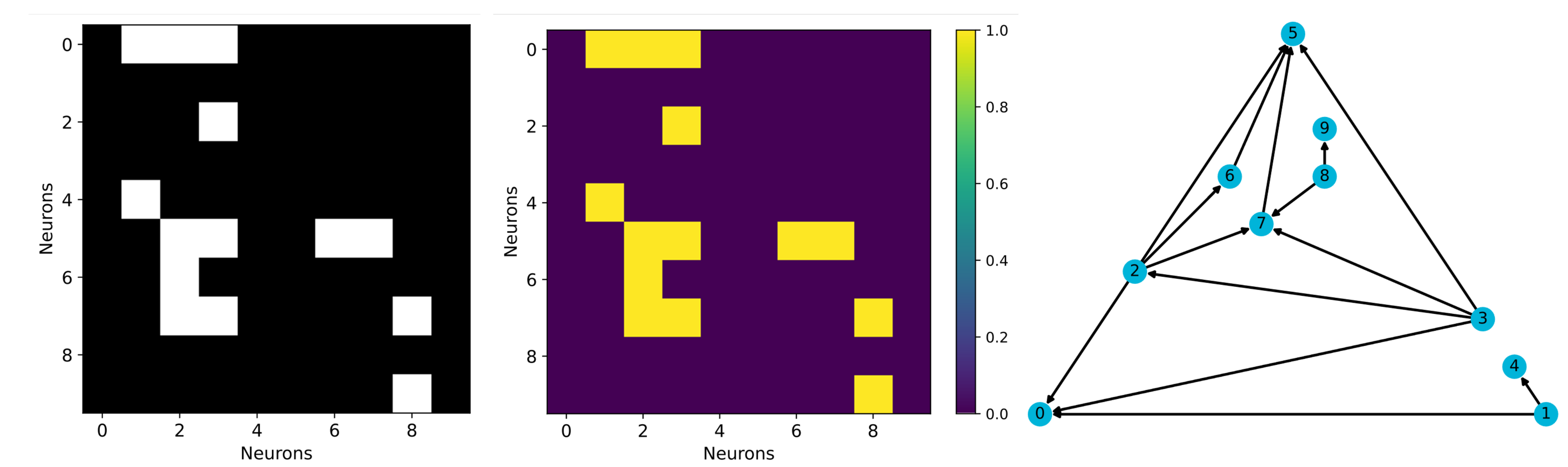


Large networks with varying connectivity



Replay order

Ground Truth (Left), Predicted (Middle) using LiNGAM, Inferred order of replay (Right)



CONCLUSIONS

Algorithms strengths and *weaknesses*

- N is the number of neurons and M is the average length of a spike

Algorithm I – $O(N^2M^2)$	
Best performance for symmetric data for shorter duration and small networks Reasonable performance for all settings	*Weak performance for asymmetric data* *Worst run time*

Algorithm II – $O(N^2 M \log M)$	
Best overall performance for symmetric data for all sized networks and durations	*Fails for asymmetric data for small and medium sized networks*

Algorithm III – $O(N^3)$	
Best performance for asymmetric data for both durations Best at capturing the ground truth for larger networks at larger durations Easy extraction of the order of replay under asymmetric setting	*Fails for symmetric data*

- Identification of replay and underlying causality depends on the asymmetric properties of the underlying networks
- Need new measures to estimate causal asymmetry from spike trains

Future directions

- Assess order of replay and its role in learning and decision-making in complex environments
- Compare the three methods for experimental data as the rats solve complex navigation tasks in megaspace

REFERENCES

[1]T. Ikeuchi, M. Ide, Y. Zeng, T. N. Maeda, and S. Shimizu. **Python package for causal discovery based on LiNGAM**. *Journal of Machine Learning Research*, 24(14): 1–8, 2023.

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