Causality in Replay: Comparing Methods to Detect Effective Connectivity from Spike Trains

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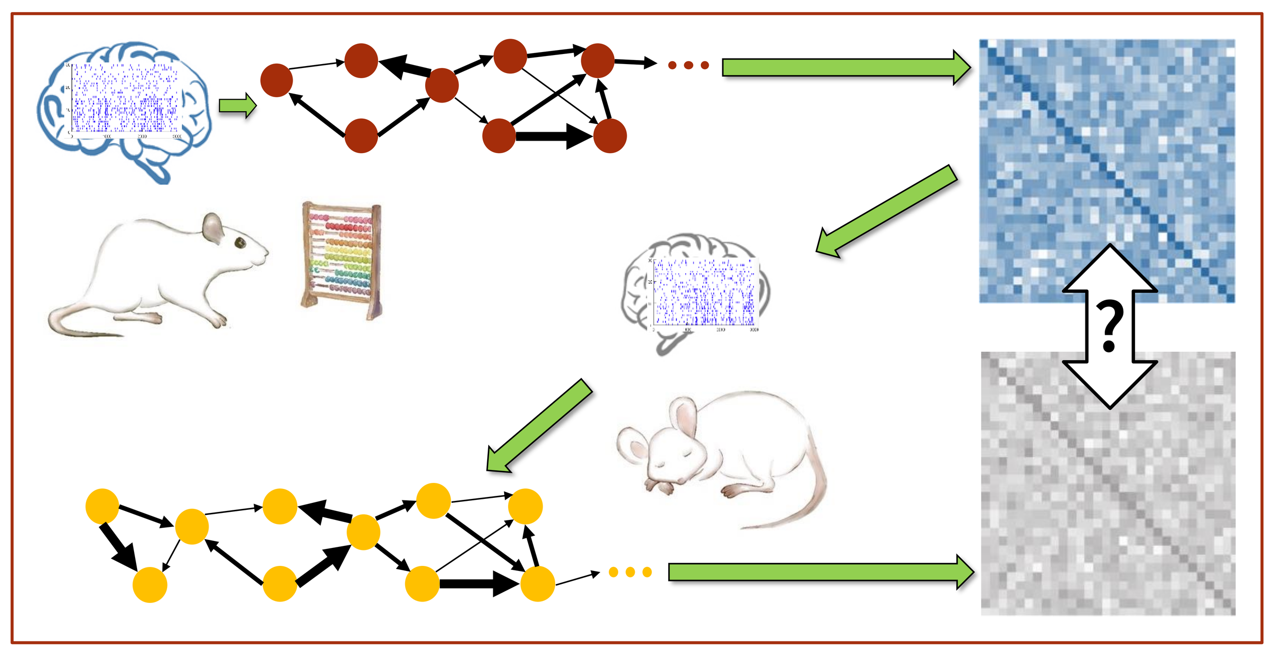
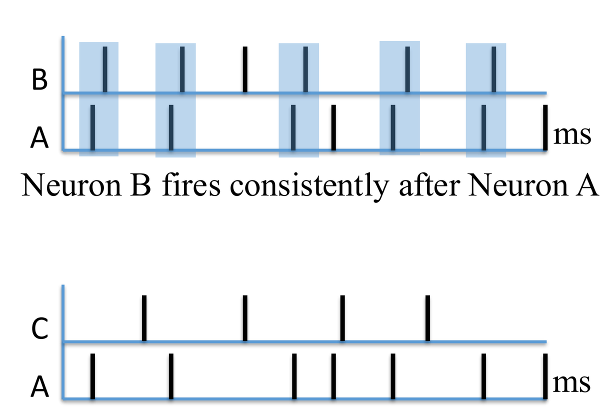
INTRODUCTION

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



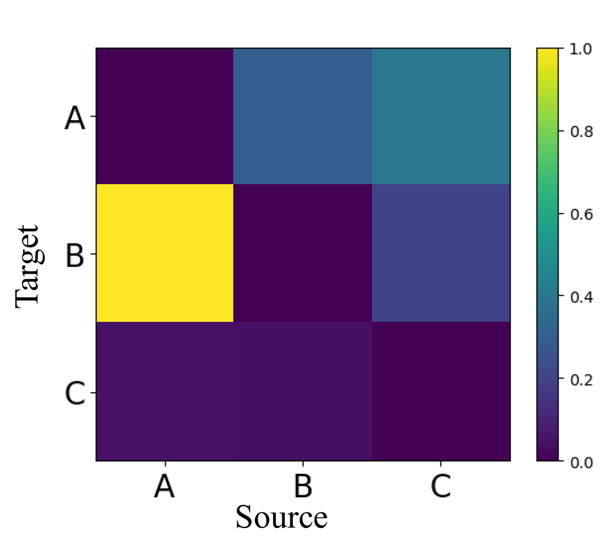
OBJECTIVES

- Simulate biophysical **network activity of interconnected CA3 place cells** using NEURON
- Implement specific **causal structures as ground truth (gt)** by building synaptic connection matrices
- Evaluate and compare methods for **detecting effective connectivity** from spike trains alone



Neuron B fires consistently after Neuron A

Neuron A and Neuron C fire inconsistently



Data	**Simulation**
$D = \{S_i\}_{i=1}^{N}$	N: Size of the network $\{10, 30, 50\}$
N: Number of neurons	W: Synaptic strengths $\{1, 2, 3\}$
S_i: Spike trains for neuron i	

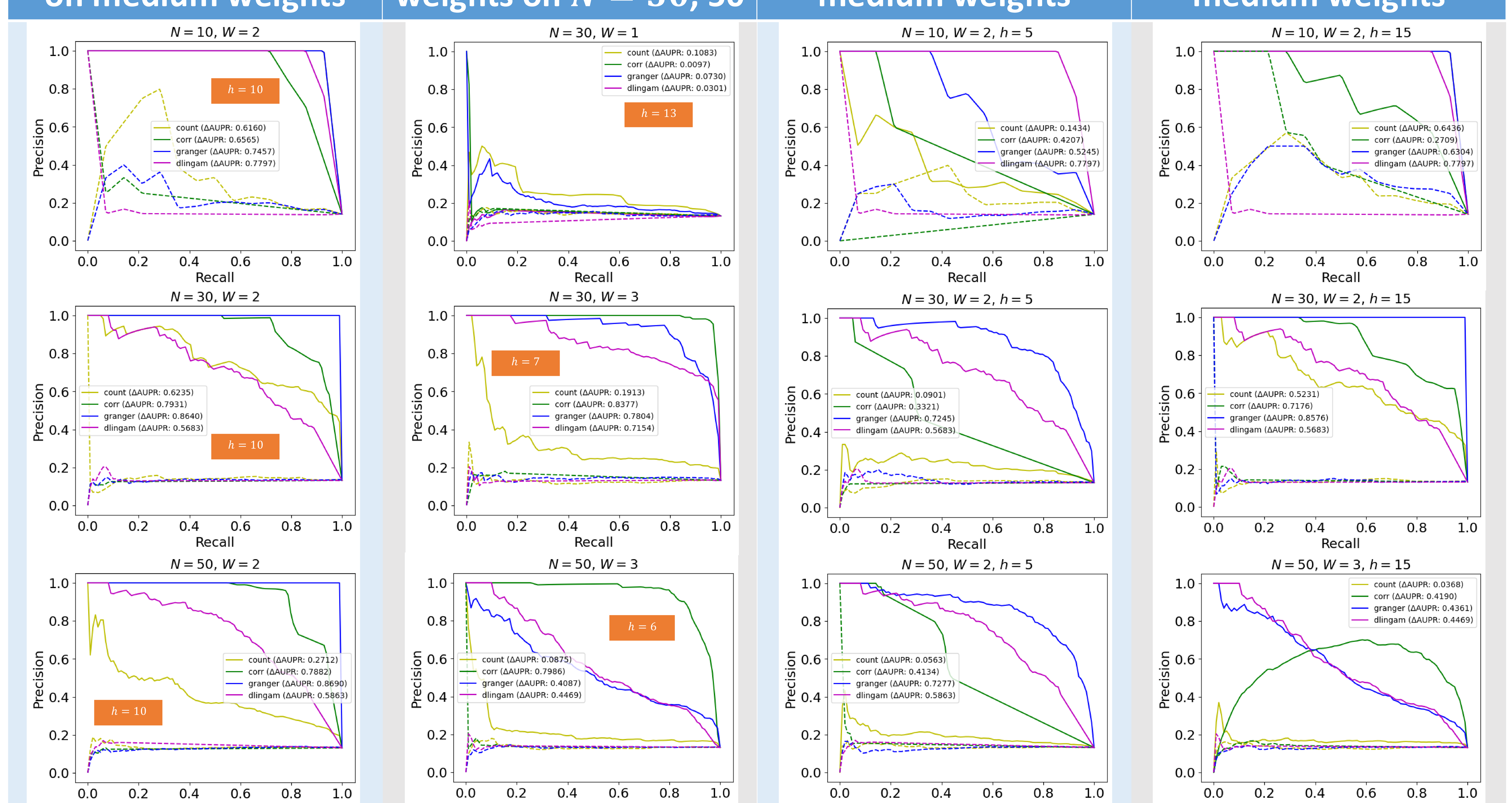
METHODS

	Spike-Count	Cross-Correlation	[1] Granger Causality	[2] DirectLiNGAM
Procedure	Identifies temporal spike relationships	Computes cross correlations	Predicts based on lagged regression	Discovers direct causal structure (DAG)
Directionality/Causal Interpretation; (Instantaneous Causality?)	Spike cooccurrence within h ms; (No)	Temporal alignment within h ms lag range; (No)	Past activity predicts future activity within h ms; (No)	Causal ordering from stats independence (no h window); (Yes)
Assumptions	Spike timing reflects influence; firing within h ms is meaningful	Strong correlation implies influence; fixed lag direction is meaningful	Linearity; stationarity; no hidden confounders; temporal lagged influence	Linearity; non-Gaussian independent noise; no hidden confounders; only acyclic structure
Data Requirements	Spike times	Binary trains	Binary trains	Binned trains

RESULTS

Output matrix averaged over all samples before comparison to the ground truth

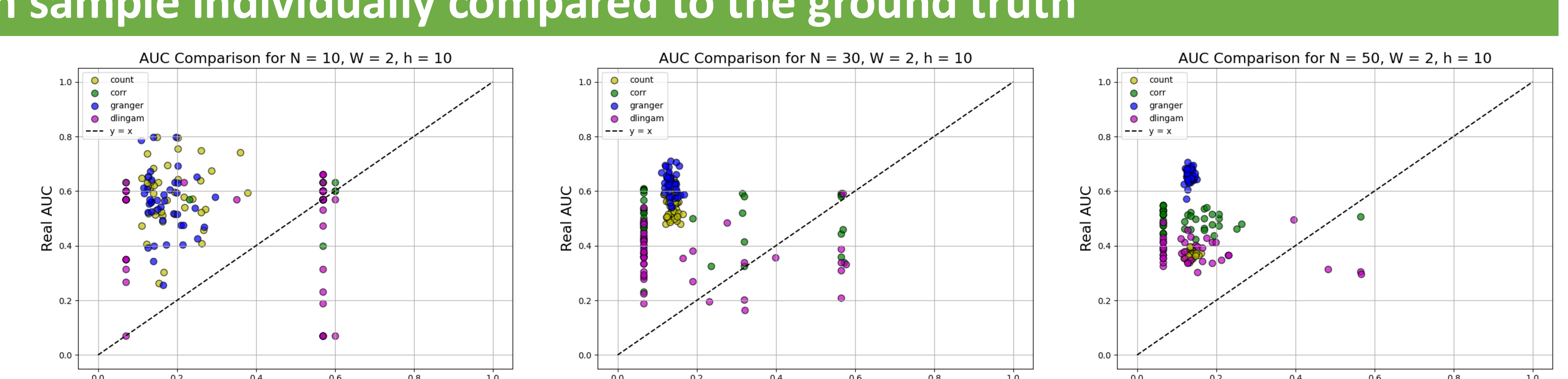
Optimal h (sc, cc, gc) on medium weights	Medium vs. other weights on $N = 30, 50$	Decreased h ms on medium weights	Increased h ms on medium weights



Each sample individually compared to the ground truth

Change in precision; Variability across samples

Similar behavior observed for (sc, gc) and (cc, dl)



N	W	h	sc	cc	gc	dl
10	1	13	0.0512 / **0.0221**	0.1506 / 0.4177	**0.0237 / 0.0298**	0.9093 / 0.1133
10	2	10	**0.0000 / 0.0493**	0.0873 / **0.0036**	**0.0000 / 0.0024**	0.0713 / **0.0108**
10	3	10	**0.0000** / 0.2098	**0.0000 / 0.0004**	**0.0000 / 0.0341**	**0.0000 / 0.0246**
30	1	13	**0.0044 / 0.0221**	0.6035 / 0.4177	**0.0044 / 0.0298**	0.5459 / 0.1133
30	2	10	**0.0000 / 0.0493**	**0.0000 / 0.0036**	**0.0000 / 0.0024**	**0.0000 / 0.0108**
30	3	7	**0.0000** / 0.2098	**0.0000 / 0.0004**	**0.0000 / 0.0341**	**0.0000 / 0.0246**
50	1	12	**0.0000 / 0.0221**	0.8952 / 0.4177	**0.0000 / 0.0298**	0.3738 / 0.1133
50	2	10	**0.0000 / 0.0493**	**0.0000 / 0.0036**	**0.0000 / 0.0024**	**0.0000 / 0.0108**
50	3	6	**0.0000** / 0.2098	**0.0000 / 0.0004**	**0.0000 / 0.0341**	**0.0000 / 0.0246**

Paired t-test p-values between AUCs of real and control: per-sample output vs. gt / average output vs. gt (grouped by W). Bolded values indicate statistically significant differences.

CONCLUSIONS

sc	Better on smaller networks with low/medium synaptic strengths; Moderate sample variability; Sensitive to h (the causal time window length within which spikes are counted)
cc	Best at high synaptic strengths; good at medium but only when h optimized; High variability; highly sensitive to h (time lag)
gc	Best overall performance; robust without h optimization; Low variability; Robust to h (time lag)
dl	Near-best performance without h optimization; Independent of h; high variability

Next Steps: We are currently investigating a Decision Flow framework, based on Markov Decision Processes, that models causality through modified transition probabilities.

REFERENCES

[1] Seabold, S., & Perktold, J. (2010). *Statsmodels: Econometric and statistical modeling with Python*. In *Proceedings of the 9th Python in Science Conference*.

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

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