Detecting Replay in Multi-Unit Spike Data

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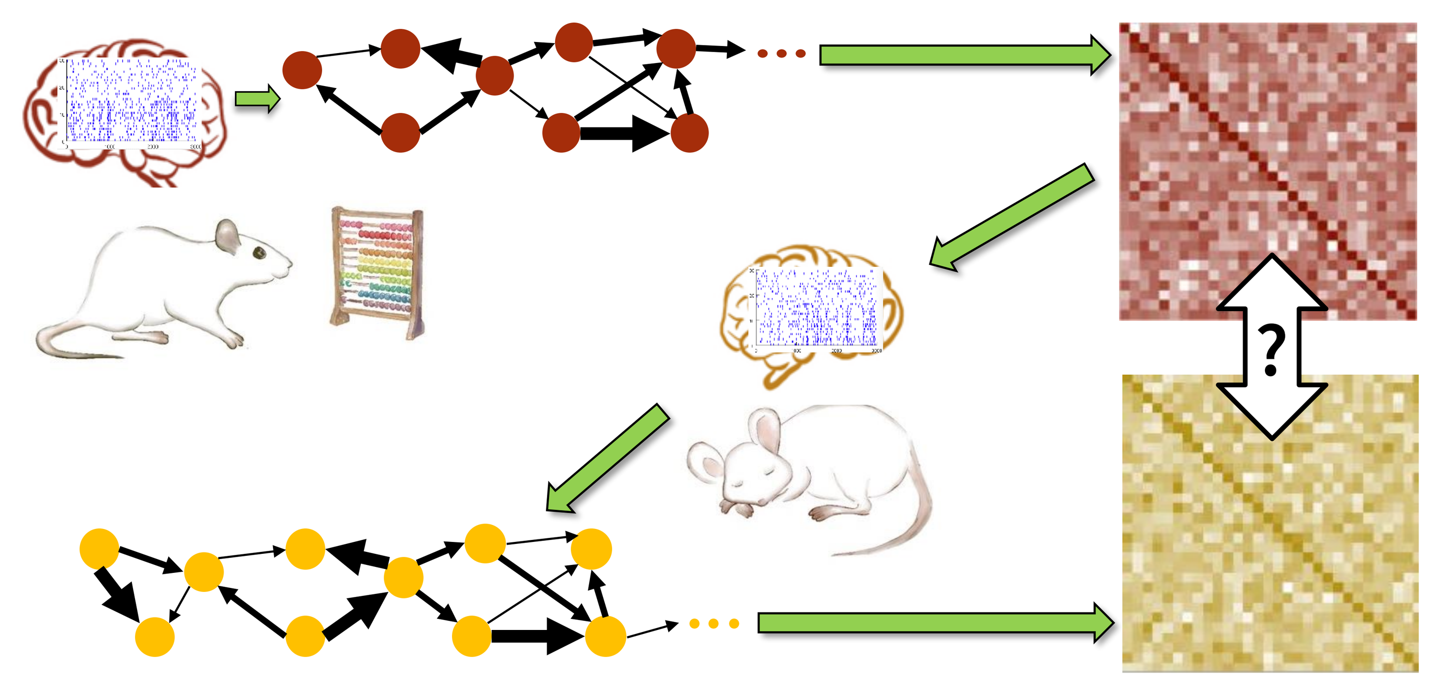
INTRODUCTION

- Hippocampal replay of neural activity during sleep facilitates memory consolidation and retrieval
- Interpreting hippocampal replay is facilitated by the detection of causality (functional connectivity) between recorded neurons



Replay contains information about the functional connectivity of a network of neurons that can be mathematically extracted to make inferences about learning.

OBJECTIVES

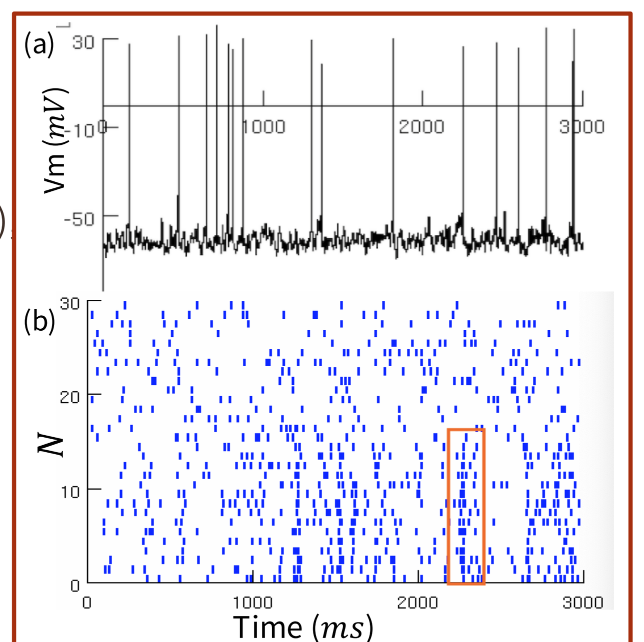
Statistical learning facilitates highly repetitive and structured cognitive functions such as learning and decision-making (Sherman et al. 2020). We:

- Create *an algorithm* that detects the functional connectivity within a network of neurons from their spike trains
- Determine *a similarity metric* to compare detected connectivity and ground truth from the simulations
- Study the metric's *robustness* with changes in ***the total number of neurons***, ***synaptic strength***, and ***sparsity of connection between neurons***

METHODS

NEURON Simulation Environment

- One compartment, leak, INa, IKdr, IAHP, ICa, Ca pump, and diffusion
- AMPA and NMDA probabilistic synapses (facilitation depression) scaled to adjust synaptic strengths
- Excitatory and Inhibitory Ornstein Uhlenbeck processes (Destexhe et al, 2001) *in-vivo* like background synaptic inputs



Voltage plot (a) and rastergram with replay in orange (b) against time in ms.

Algorithm

1) **Uniform connectivity**: N total number of neurons, $\boldsymbol{W_U}$

   Sparsity levels: $S \in \{25, 50, 70, 80, 90, 100\}$ %

2) **Realistic non-uniform connectivity**: $\boldsymbol{W_R} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{I_\epsilon})$

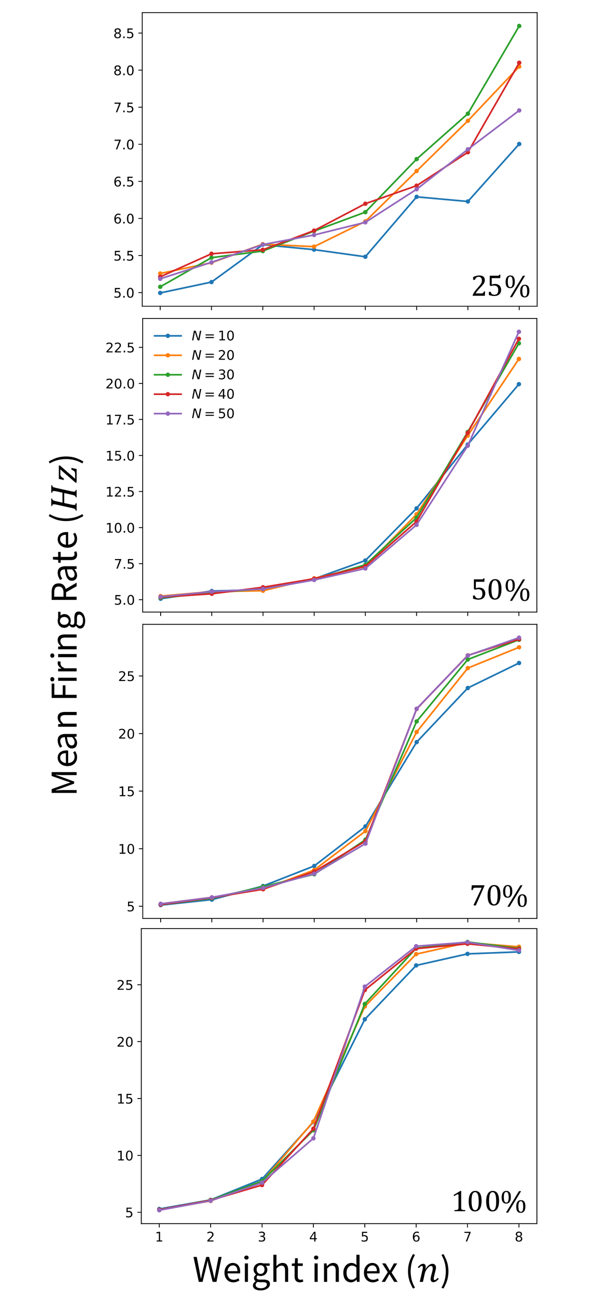
   $\boldsymbol{\mu}$: mean conductance scaling

   $\boldsymbol{\epsilon}$: noise

Parameters
- $N \in \{10, 20, 30, 40, 50\}$
- Synchrony within h ms
- $\boldsymbol{W_U}$ or $\boldsymbol{W_R}$

→ **Simulation and Rastergram Analyses**
- $\boldsymbol{M_C}$: Spike coincidence counts
- $\boldsymbol{M_S}$: **Shuffled** spike coincidence counts

→ **Thresholding**
- Threshold, t=mean $(\boldsymbol{M_C})$
- Binarized $\boldsymbol{M_C}$ and $\boldsymbol{M_S}$



For different N, an increase in weights according to $\Omega(n)$ achieves the same firing rate. Our approach focuses on the partial synchrony of spikes rather than the changes in firing rates.

RESULTS

Firing Rate versus Synchrony

- Weight index $n \in \{1, 2, 3, 4, 5, 6, 7, 8\}$
- $\Omega(n)$ describes the weight scaling factor

$$\Omega(n) = \begin{cases} \dfrac{(n-1)}{40N} & n \in [1, 5] \\ \dfrac{33n - 64}{1000N} & n \in [6, 8] \end{cases}$$

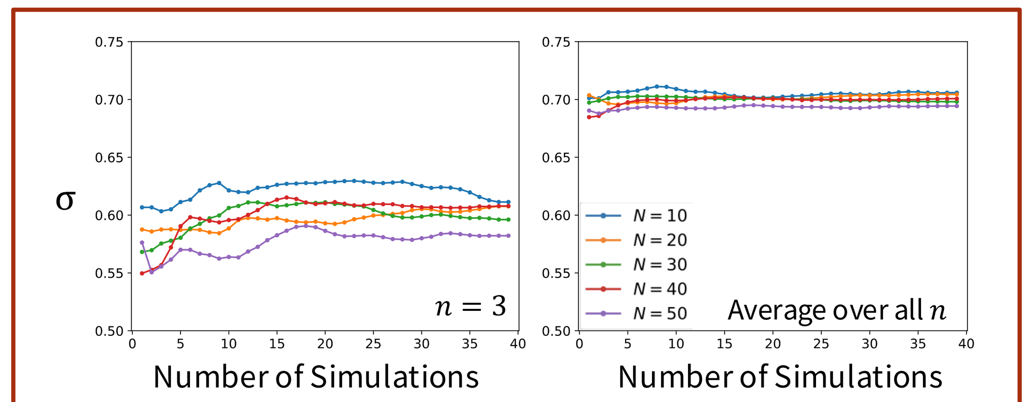
Similarity measure

- Similarity metric, σ, between binarized M_X and ground truth, G_Y

$$\sigma = \frac{\sum_i^n \sum_j^n \mathbb{I}\,(M_X[i][j] = G_Y[i][j])}{N^2},$$

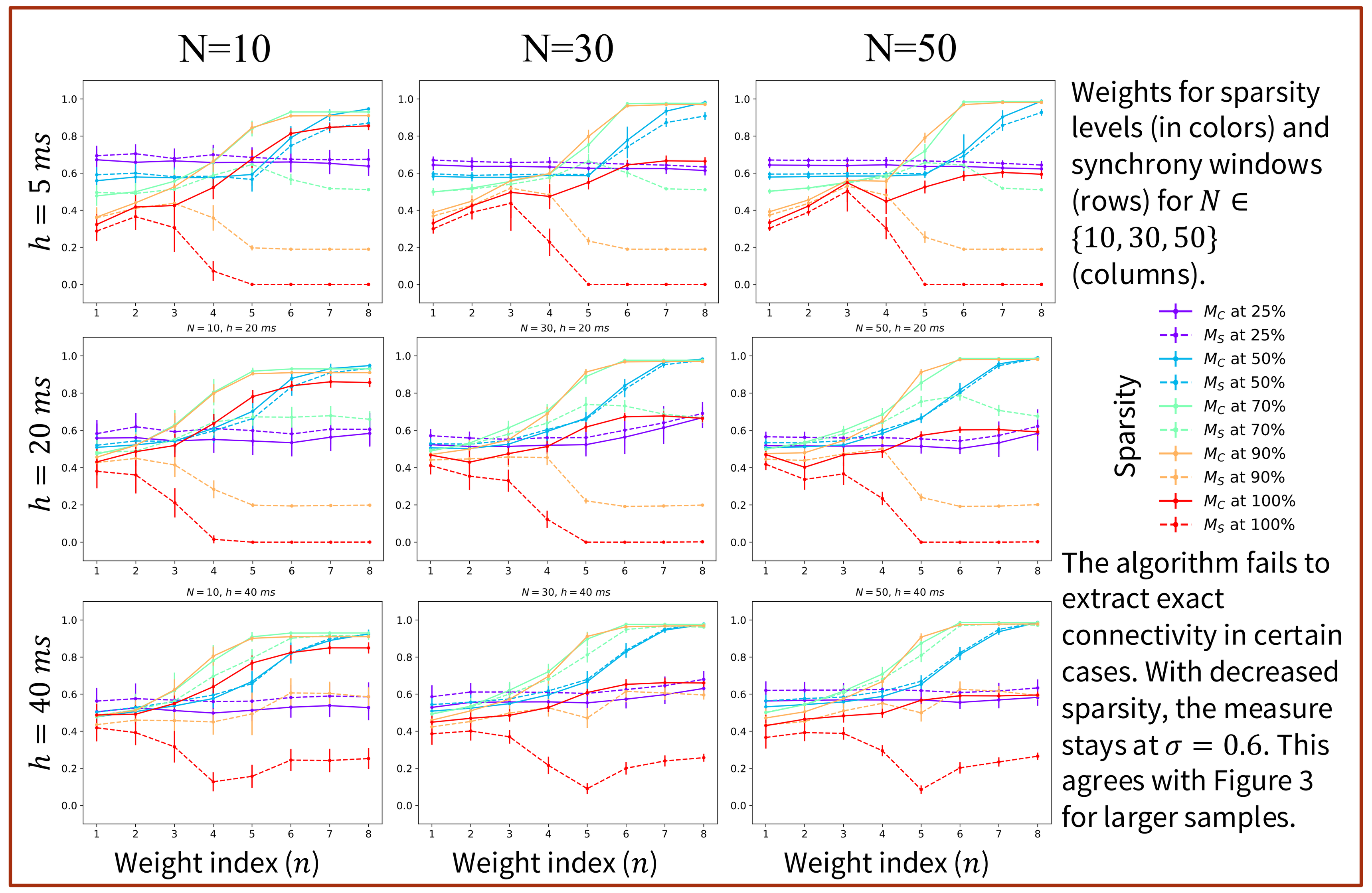
where $X \in \{C, S\}$ for types of spike coincidence and $Y \in \{T, V\}$ for types of connection weights.

How many simulations are needed?



A weight with index $n = 3$ and average over 8 weight settings show that it takes about 35 simulations to reach a stable similarity measure for all N.

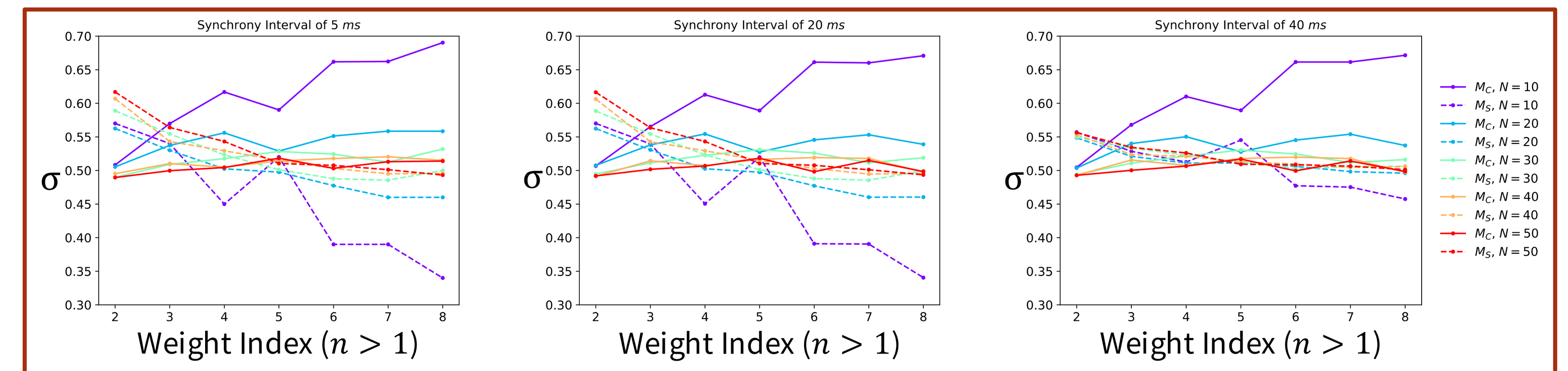
Extracted Connectivity Structure: *Uniform Weights*



Weights for sparsity levels (in colors) and synchrony windows (rows) for $N \in \{10, 30, 50\}$ (columns).

The algorithm fails to extract exact connectivity in certain cases. With decreased sparsity, the measure stays at $\sigma = 0.6$. This agrees with Figure 3 for larger samples.

Extracted Connectivity Structure: *Non-uniform weights*



For realistic parameter settings, connectivity structure can be better detected for smaller networks.

CONCLUSIONS

Results

- Algorithm performs better for smaller networks and higher weights
- Sparser connectivity shows minimal differences between the actual and shuffled spike coincidence counts

Summary

Our analyses extracted the functional connectivity from the spike train dataset. We:

- Showed that 35 simulations were sufficient to reliably estimate the connectivity structure
- Confirmed that for different numbers of neurons and connection strengths, the firing rate is similar for all weights considered to ensure the focus on synchrony, not on firing rate
- Compared the results and the ground truth using a binarized similarity measure
- Established the limits of the algorithm as simulation parameters were varied

Future Work

- Use a probabilistic graphical approach to analyze patterns of connections (instead of pairwise comparisons) to better infer connectivity
- Introduce Hebbian synaptic plasticity during replay for increased biological relevance

Bayesian Networks (BN)

- Vital probabilistic framework to capture causality between variables
- Edges in the BN will represent replay order between neurons (nodes)
- We hypothesize that BN will facilitate learning of unknown parameters in spike train data that will explain the underlying causality structure in real data

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