Event-to-Event Variability in Autoassociative Spiking Dynamics During Ripples

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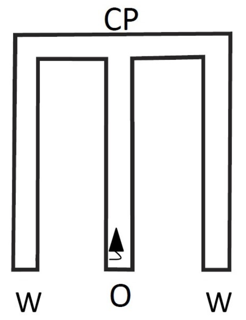
Introduction

- Human intelligence is characterized by its extreme cognitive flexibility—the ability to transfer past learning to new contexts and to form abstract thoughts, such as analogies and inferences, to guide behaviors.
- One crucial prerequisite of this flexibility is the ability to remember past experiences at different levels of specificity.
- Current theories suggest that memories of past experiences are stored when specific patterns of neural activity cause changes in the connections among neurons, and they are retrieved when these patterns are reinstated during hippocampal sharp wave-ripples (SWRs).
- However, the underlying mechanisms involved in flexibly storing and retrieving memories in varying degrees of detail remain elusive.
- Recent advances in reinforcement learning demonstrate that artificial agents that operate at different levels of temporal abstraction by using "multi-level hindsight experience replay" can learn tasks more quickly.
- Could the hippocampal circuits employ a similar strategy?

Clusterless decoding and classification of SWR representational content from tetrode recordings in the hippocampus of a rat performing a spatial memory task



- Briefly, we characterizes the instantaneous probability of observing a spike with mark $\vec{m}$ at time t as a function of some underlying internal state variable $x(t)$, such as an animal's location in space, that varies across time, using the joint mark intensity function $\lambda(t, \vec{m}|H_t)$ where H_t is the history of the spiking activity up to time t:

$$\lambda(t, \vec{m}|H_t) = \lim_{\Delta \to 0} \frac{\Pr(\text{a spike with mark vector } \vec{m} \text{ in } (t, t+\Delta]|H_t)}{\delta} = g(x(t), \vec{m}|H_t).$$

- In the case of tetrode recordings, the mark is a length-four vector of the maximum amplitudes on each of the four electrodes at every spike time. Our decoding algorithm, using discrete-time state-space adaptive filters, computes, at each time point, the unnormalized posterior distribution of the state variable given observed marked spiking activity.

$$p(x_k|\Delta N_k, \vec{m}_k, H_k) \propto p(\Delta N_k, \vec{m}_k|x_k, H_k) \cdot \int p(x_k|x_{k-1}) p(x_{k-1}|\Delta N_{k-1}, \vec{m}_{k-1}, H_{k-1}) dx_{k-1}.$$

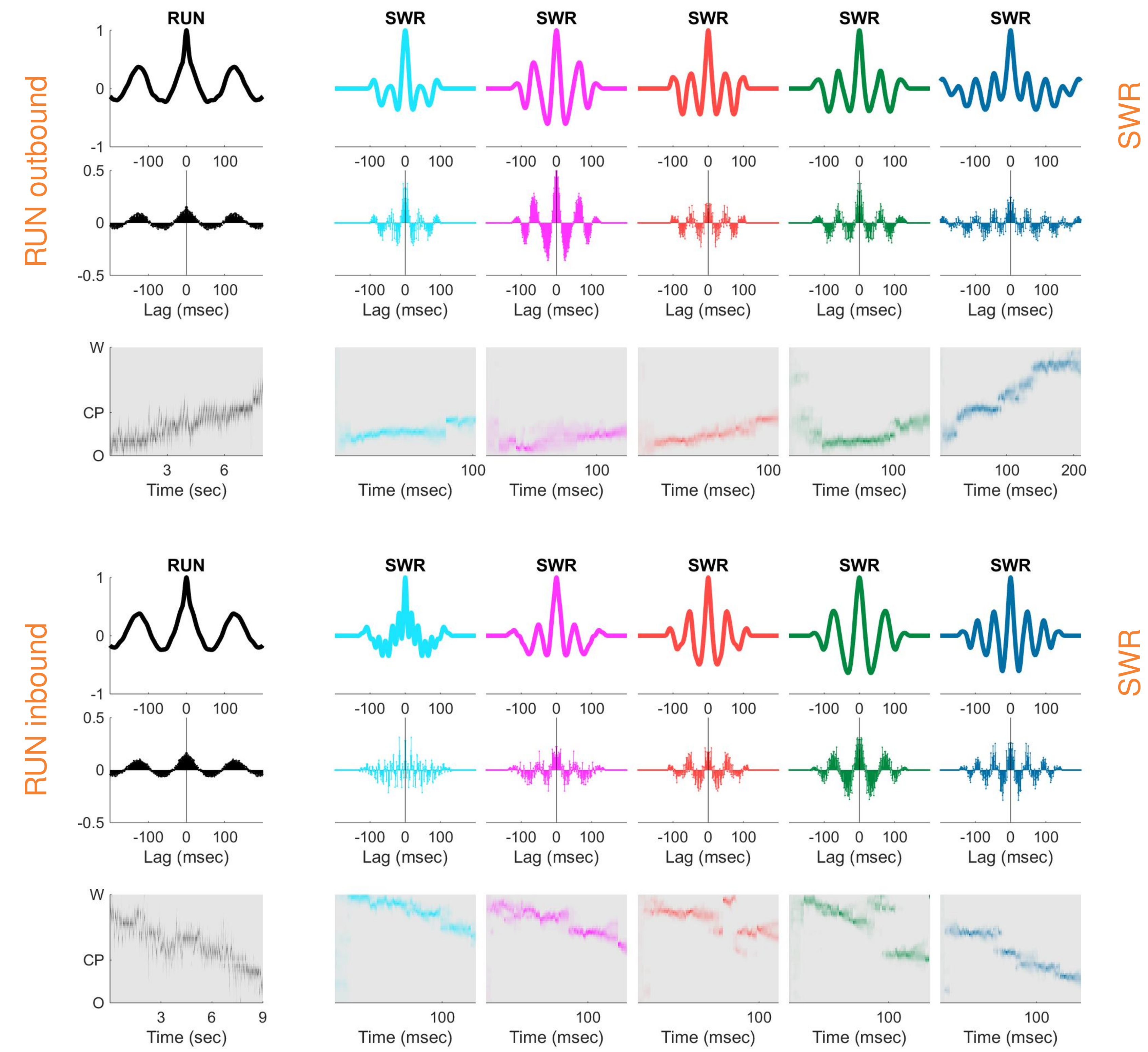
- The $p(\Delta N_k, \vec{m}_k|x_k, H_k)$ term is the likelihood or observation distribution at time t_k:

$$p(\Delta N_k, \vec{m}_k|x_k, H_k) \propto \begin{cases} \exp[-\Delta_k \Lambda(t_k|H_k)], & \Delta N_k = 0; \\ \prod_{i=1}^{\Delta N_k} [\lambda(t_k, \vec{m}_{k_i}|H_k)\Delta_k] \exp[-\Delta_k \Lambda(t_k|H_k)], & \Delta N_k > 0. \end{cases}$$

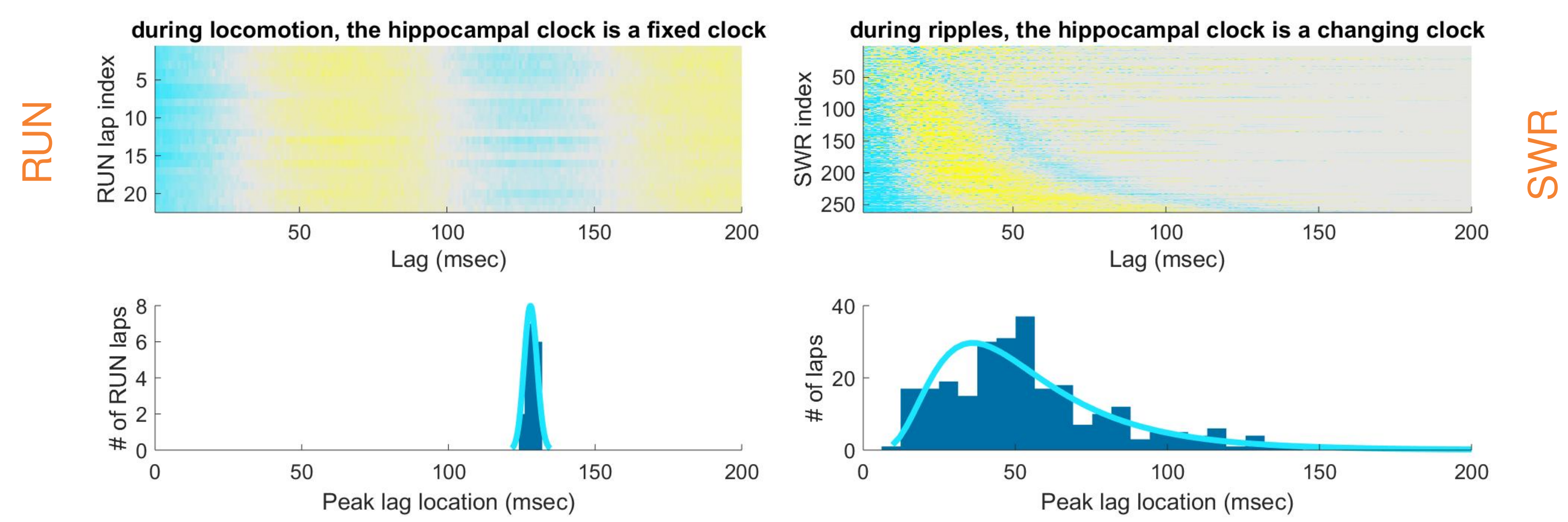
- The $\prod_{i=1}^{\Delta N_k} [\lambda(t_k, \vec{m}_{k_i}|H_k)\Delta_k]$ term characterizes the distribution of firing ΔN_k spikes, such that the mark value of the ith spike in the interval $(t_{k-1}, t_k]$ is m_{k_i}, where $i = 1, \ldots, \Delta N_k$. The probability of observing a spike regardless of the mark values is denoted by $\Lambda(t|H_t) = \int_{\mathcal{M}} \lambda(t, \vec{m}|H_t) d\vec{m}$.
- We extended the state variable in the clusterless decoder to jointly include a discrete decision state, I, that identifies whether each SWR event represents an outbound or inbound trajectory as well as whether the temporal order of activity occurs forward or backward in time. We categorized the representational content of example replay events using weighted parallel marked point process filters:

$$p(I, z_k|\Delta N_k, \vec{m}_k, H_k) \propto \begin{cases} p_{I=0}(\Delta N_k, \vec{m}_k|x_k, H_k) \int p_{I=0}(z_k|z_{k-1}) \cdot p_{I=0}(z_{k-1}|\Delta N_{k-1}, \vec{m}_{k-1}, H_{k-1}) dz_{k-1}; \\ p_{I=1}(\Delta N_k, \vec{m}_k|z_k, H_k) \int p_{I=1}(z_k|z_{k-1}) \cdot p_{I=1}(z_{k-1}|\Delta N_{k-1}, \vec{m}_{k-1}, H_{k-1}) dz_{k-1}; \\ \cdots \end{cases}$$

Population spiking underlying individual SWRs are rhythmic and exhibits high event-to-event variability



Speed of SWR-associated hippocampal clock follows an approximate lognormal distribution



Acknowledgments & References

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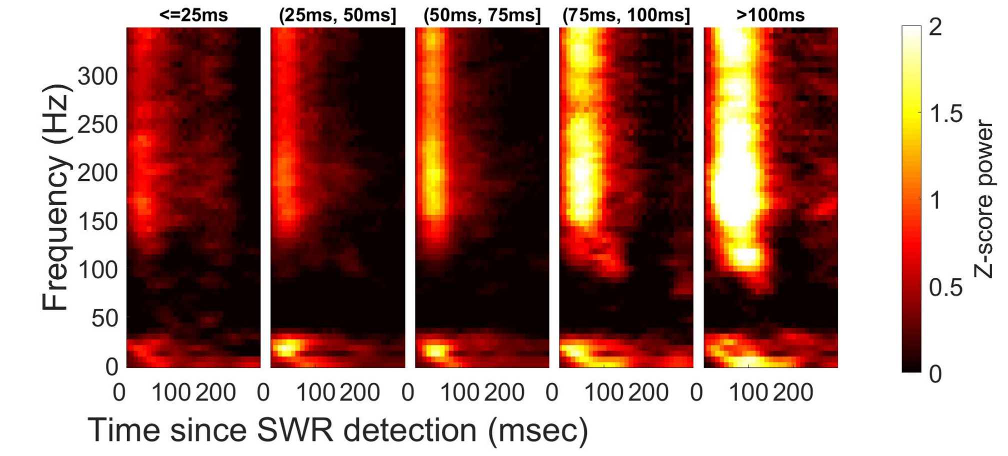
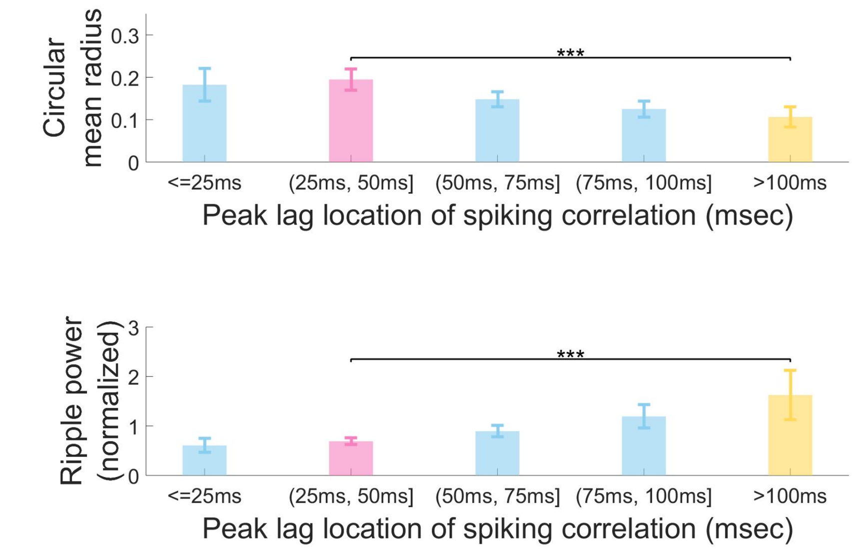
Speed of SWR-associated hippocampal clock correlates with strength of gamma phase locking and local field ripple power

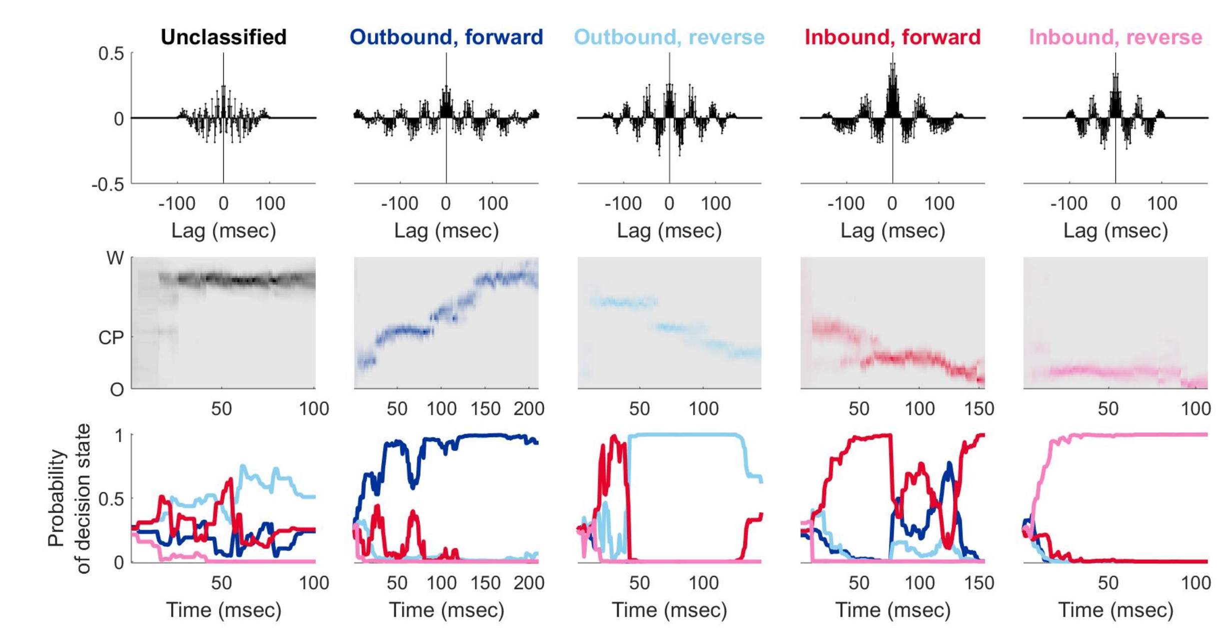


- LFP activity also suggests that there is a continuum of clock signal across SWR events.

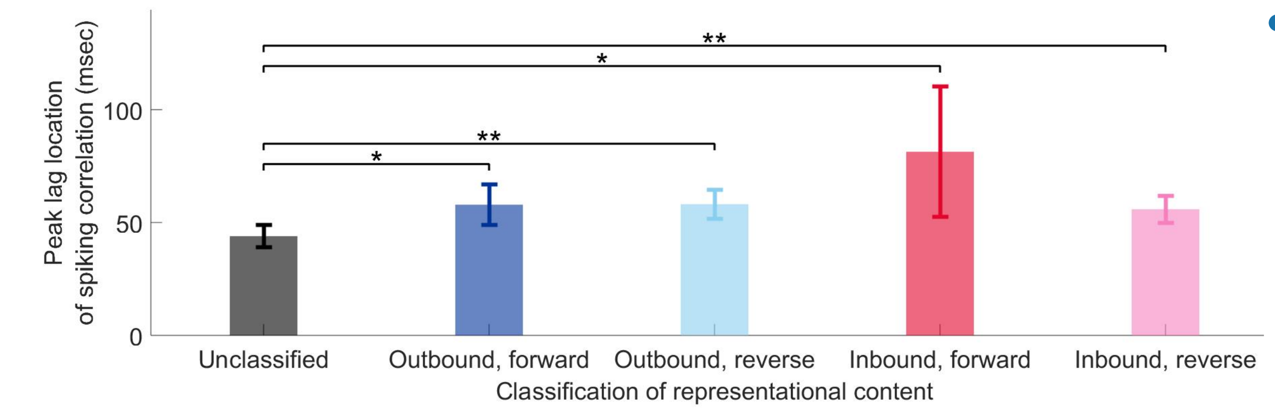


- SWRs with a stereotypical slow gamma clock with periodicity between 25 ms and 50 ms have stronger gamma phase locking than SWRs with a "long" clock.
- Even after accounting for event duration and mean firing rate, SWR clock speed remains significantly correlates with LFP ripple power.

Speed of SWR-associated hippocampal clock correlates with classifiability, but not types, of representational content



- Hippocampal circuits exploit the SWR structural variability for encoding purposes.



- Replay is not a simple, uniform compression of spatial experience, but rather an instantaneous, random sample.

Discussions

- Structural organization of internally generated hippocampal sequences is different between behavioral states
- Hippocampal clock as a potential mechanism for SWR initiation and termination
- A changing hippocampal clock could support flexible memory consolidation

"If you knew Time as well as I do, . . . , if you only kept on good terms with him, he'd do almost anything you liked with the clock."
— The Hatter in *Alice's Adventures in Wonderland*