Brain oscillations: From cortical computing to the existential nonduality of conscious agents

QuEST Brown Bag

Air Force Research Lab
Aug 26 2022

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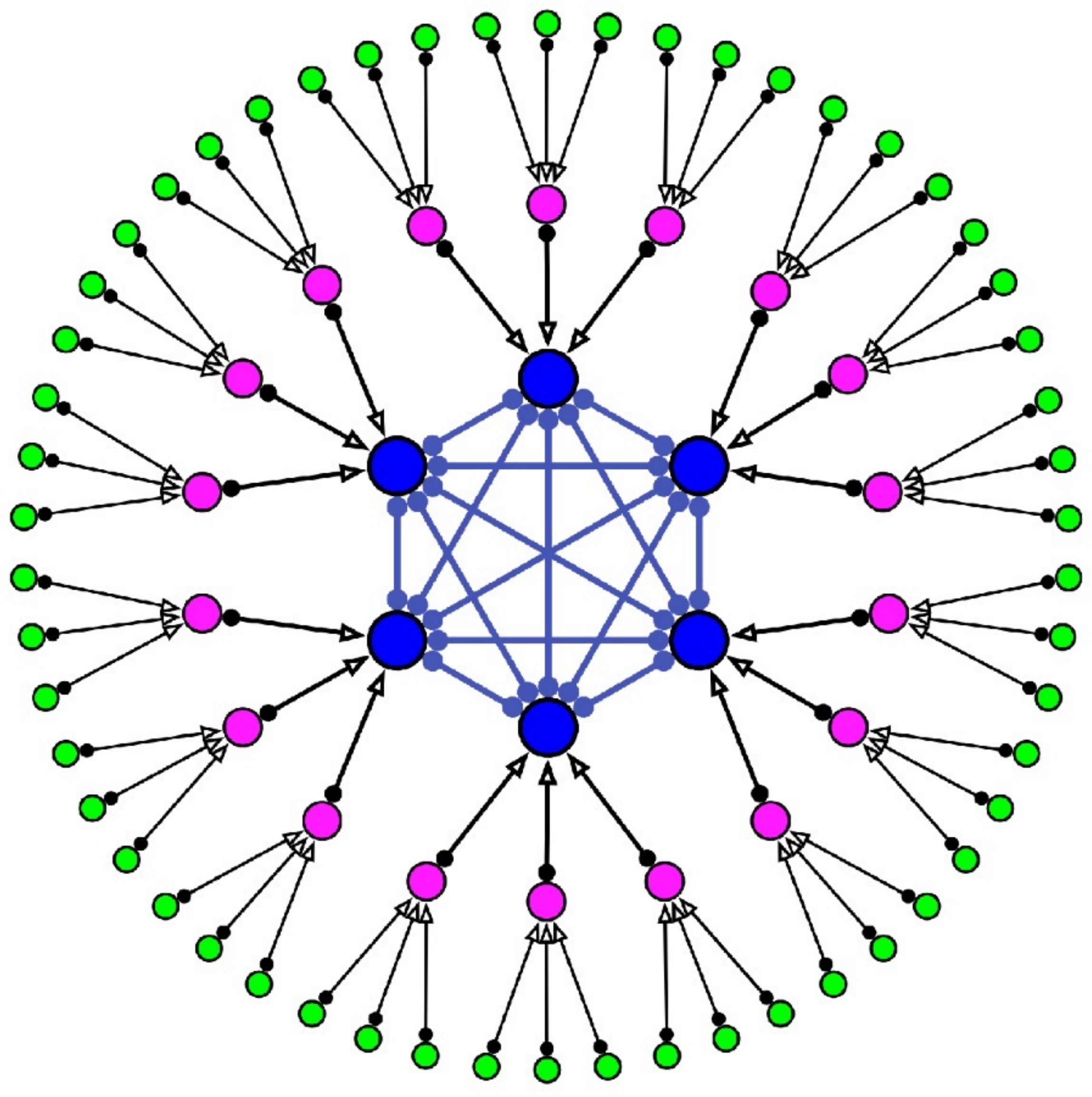
jdmonaco.com

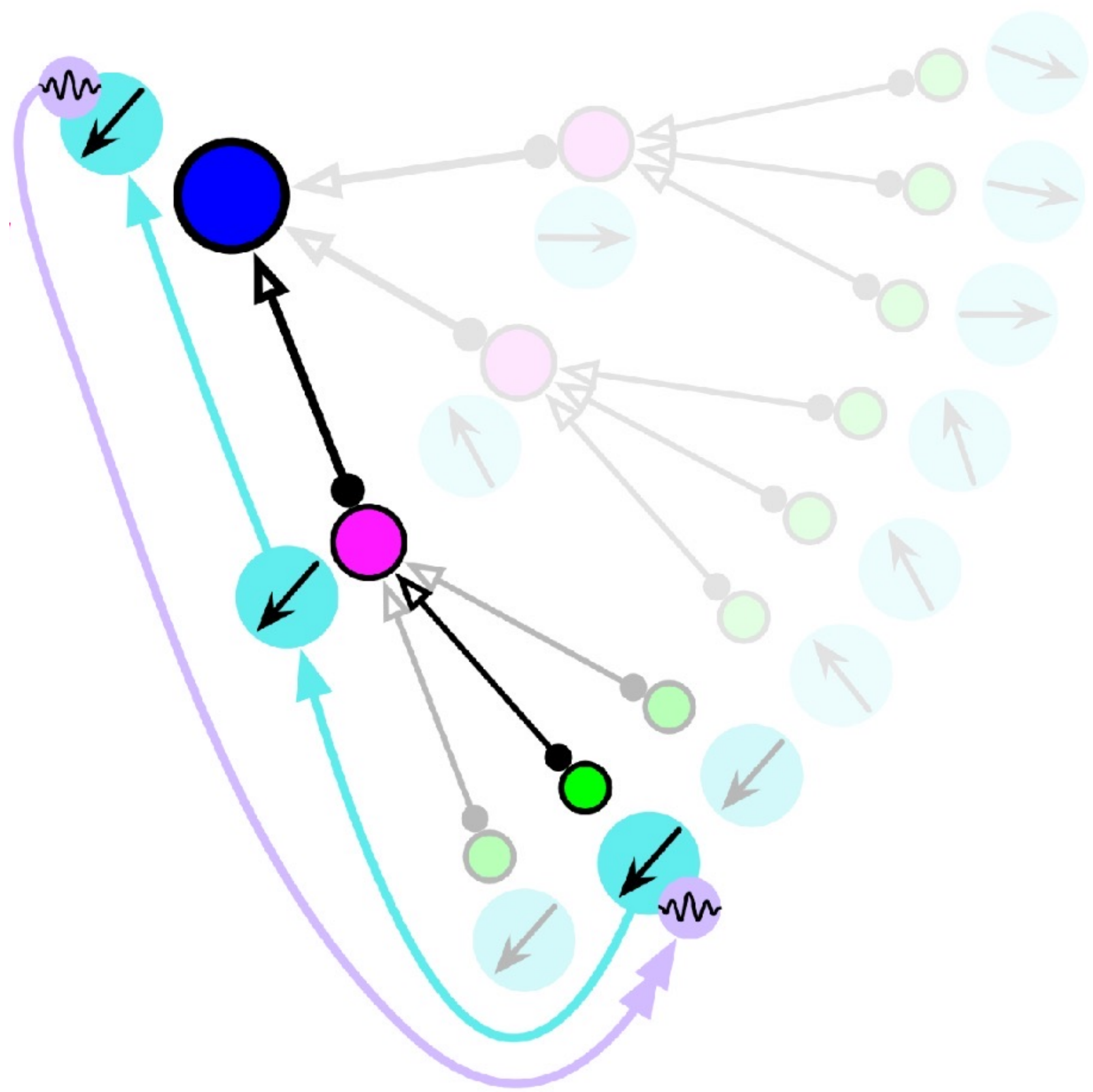
Presented work performed while at JOHNS HOPKINS SCHOOL of MEDICINE

Neurodynamical Computing: Selection and Interaction

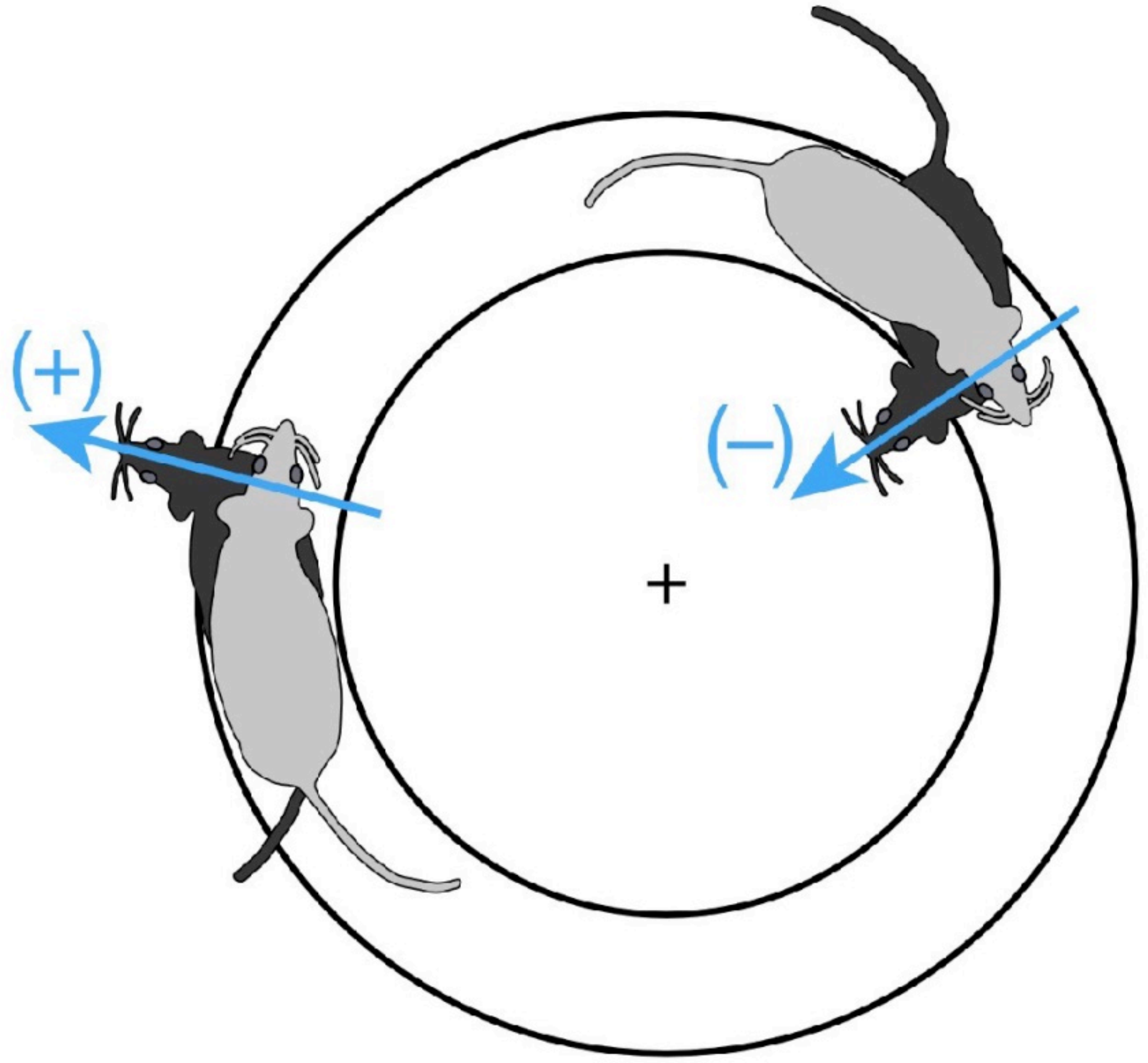
(1) Structural heterarchy



(2) Oscillatory coupling



(3) Agential interaction



What kinds of models are needed to advance this framework for cognitive flexibility?

Monaco, Rajan, and Hwang (2021) ArXiv Preprint. arxiv:2105.07284

Neurodynamical Computing: Selection and Interaction

(1) Network structure:

- Hippocampal/cortical networks can be viewed as sparsely connected ‘heterarchies’ (i.e., allowing some violations of strict hierarchy)
- Sparse heterarchies can emerge from simple developmental processes and/or network learning rules
  - Aggregate log-skewed distributions of *generalist* vs. *specialist* cells (cf. Buzsaki, 2019, *The Brain from Inside Out*)

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(2) Temporal dynamics:

- The “spectral connectome” provides a spatiotemporal structure of oscillations (generally conserved across mammals) for phase-based control of message routing
- Timing and synchrony (incl. nonoscillatory) interact with recurrence-mediated dynamics underlying attractors, heteroclinic cycles, etc.

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(3) Agential interaction:

- Local affordances, constrained singular p.o.v., and limited self-guided interactions with the environment provide the foundation for sample-efficient lifelong learning

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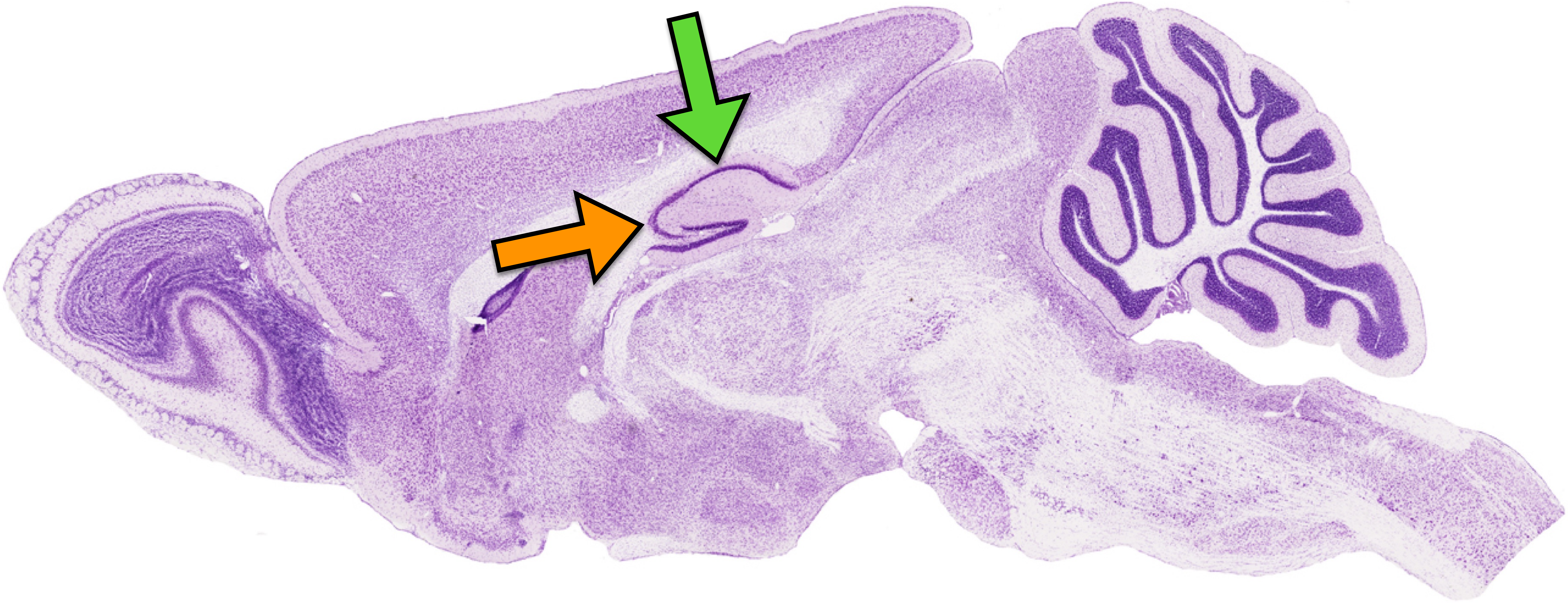
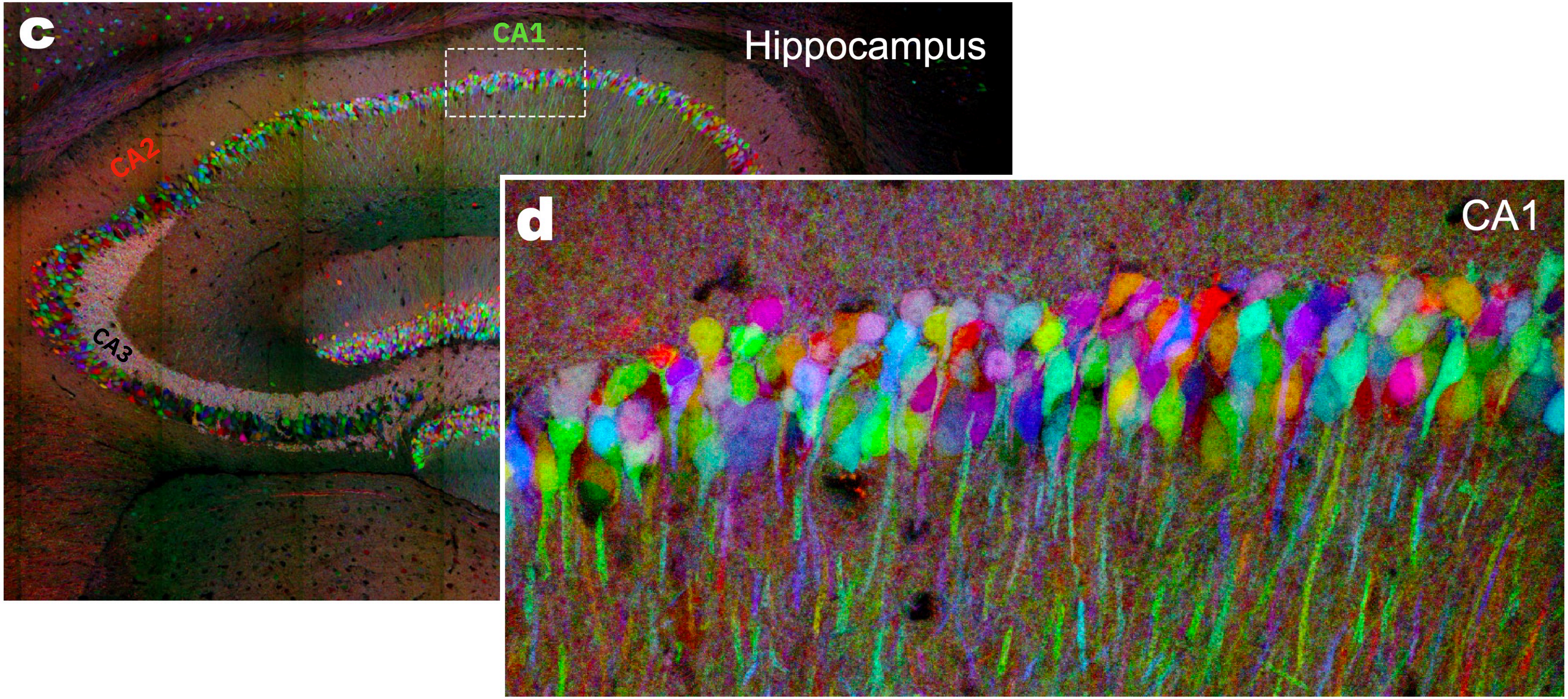
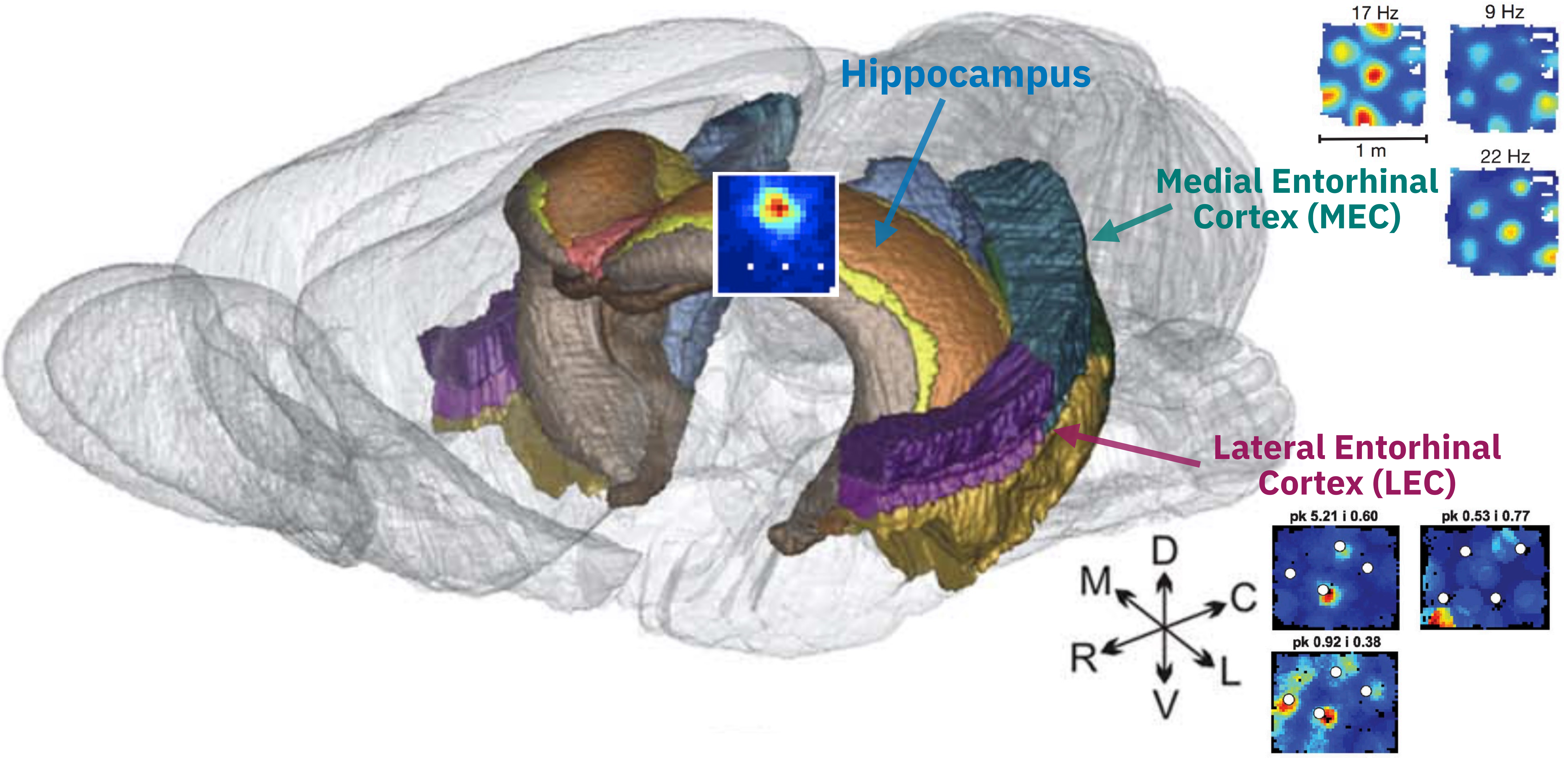


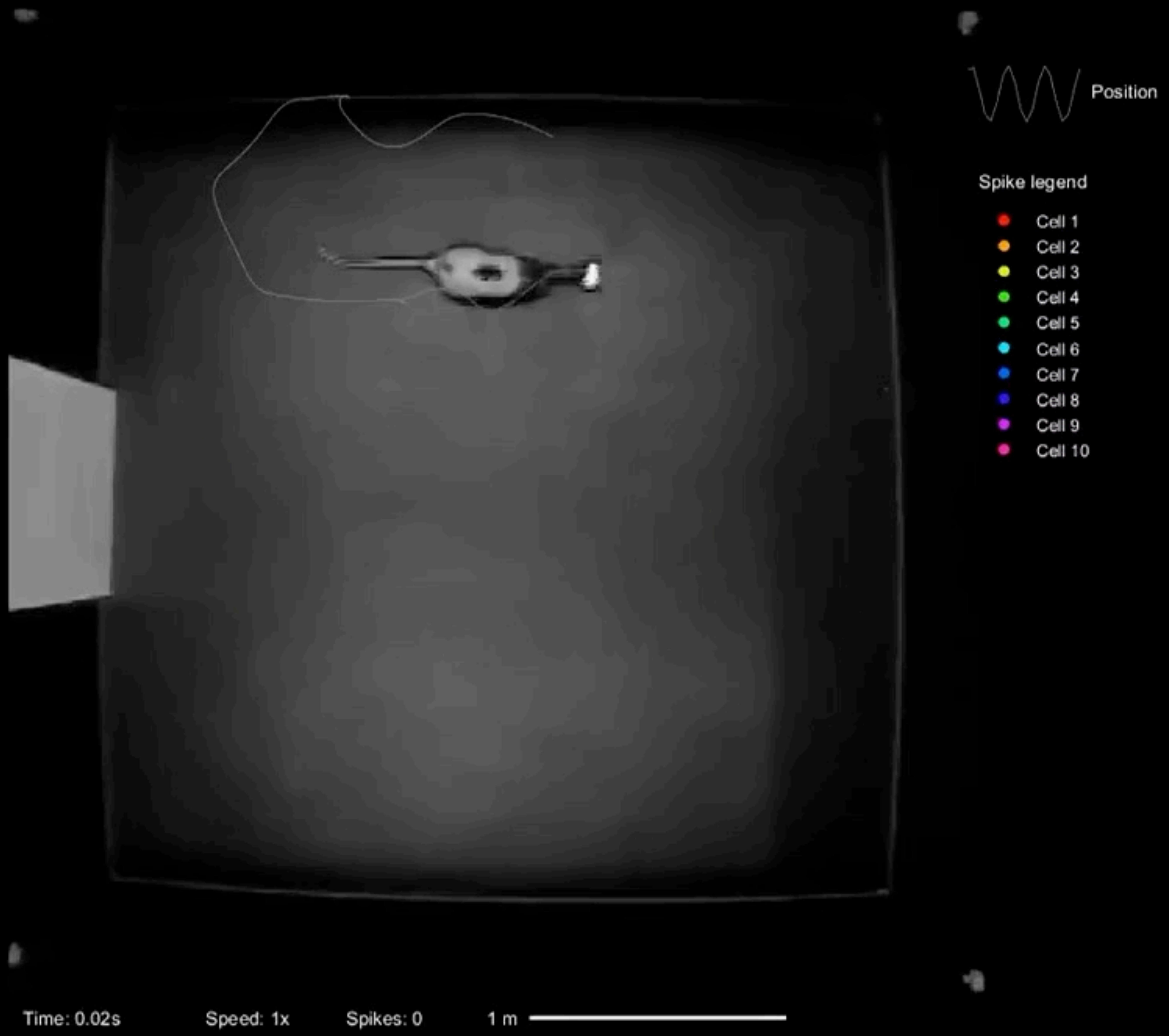
Credit: GENSAT Project, http://www.gensat.org/imagenavigator.jsp?imageID=60455



Livet J, *et al.* (2007) Nature, 450, 56

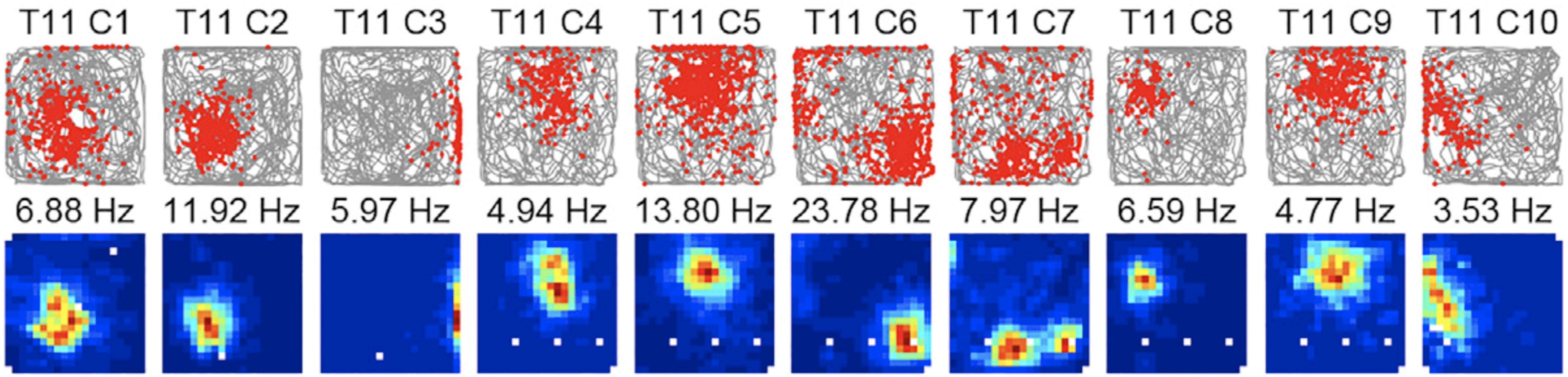


Boccara CN, *et al*. (2015). Hippocampus, 25: 838



Not Actual Speed

Video Credit: R. Grieves


T11 C1
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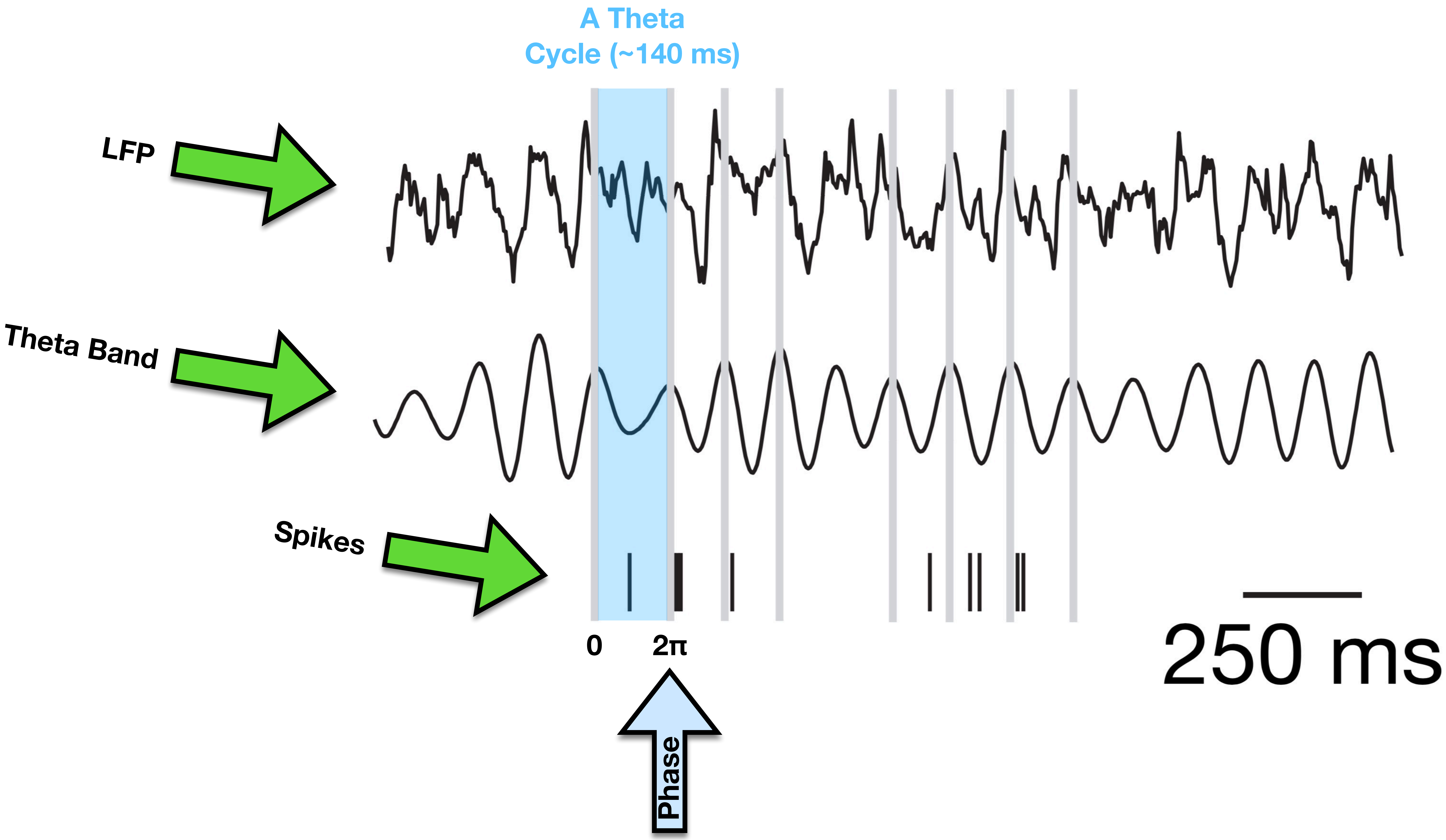
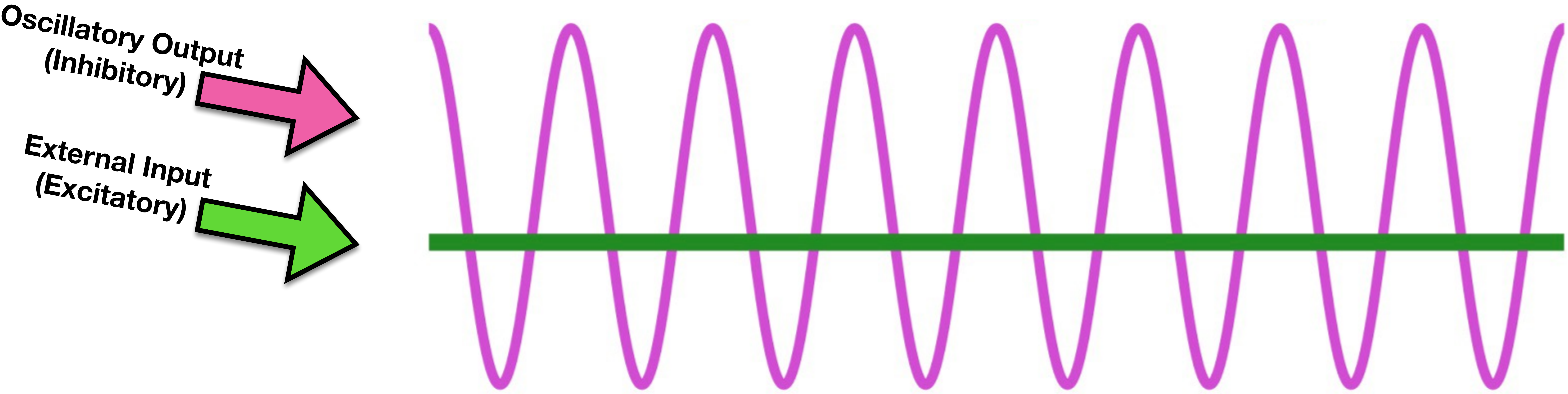
T11 C4
T11 C5
T11 C6
T11 C7
T11 C8
T11 C9
T11 C10
6.88 Hz
11.92 Hz
5.97 Hz
4.94 Hz
13.80 Hz
23.78 Hz
7.97 Hz
6.59 Hz
4.77 Hz
3.53 Hz

The Hippocampal Theta Rhythm



Trace image: Hafting T, *et al*. (2008). Nature, 453: 1248

How to Make an Oscillator



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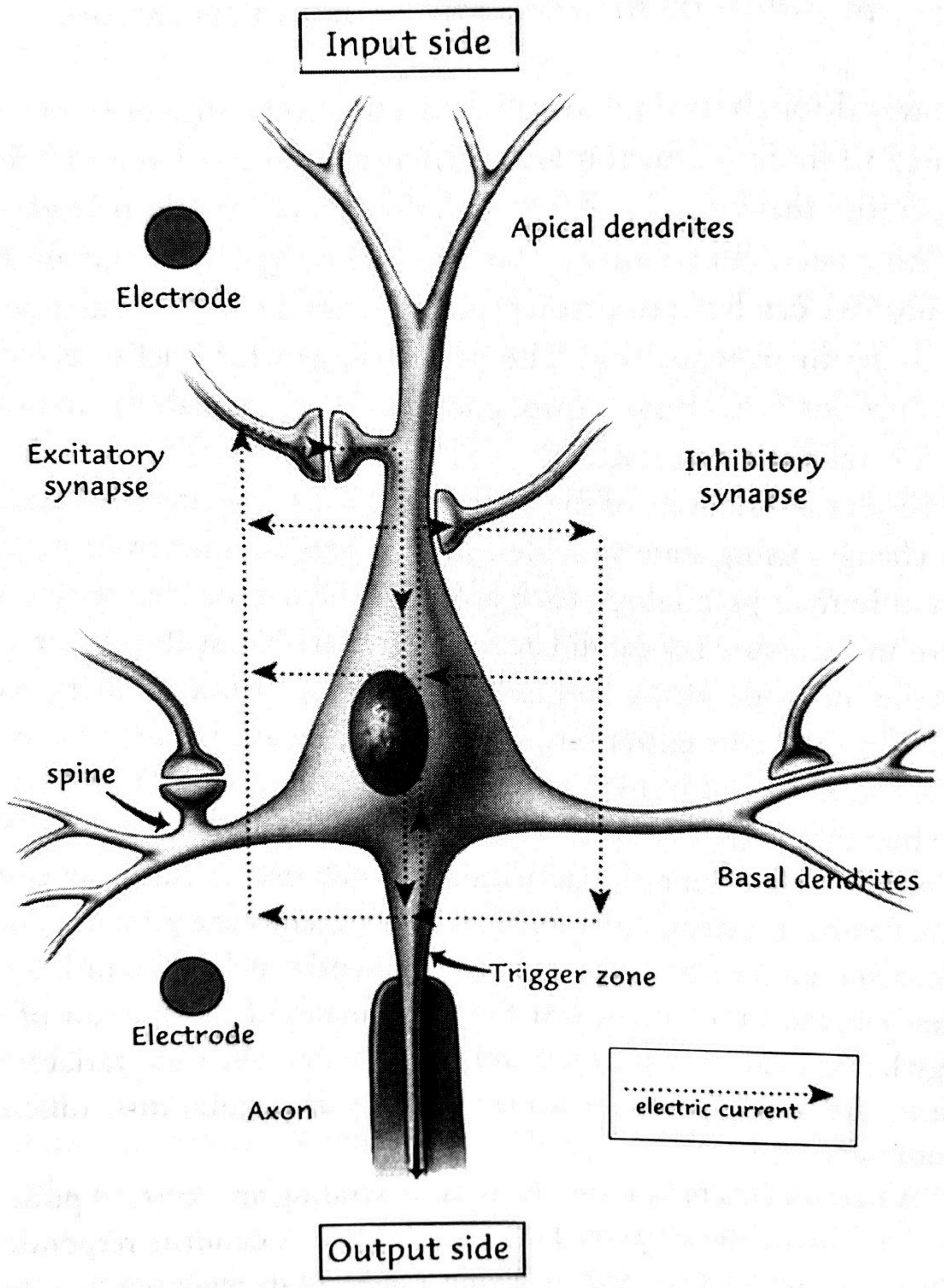
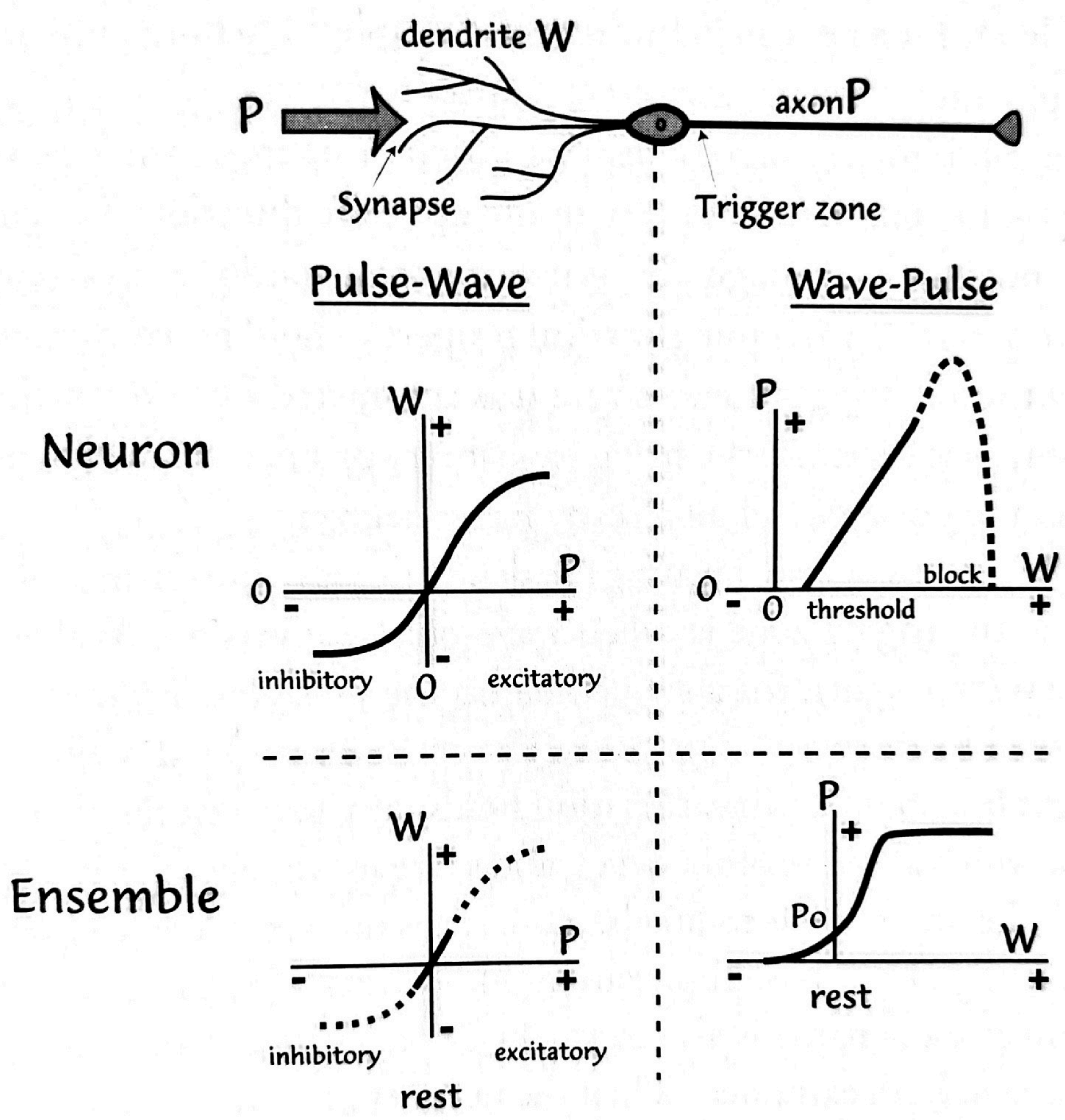
How to Make a (Neuronal) Oscillator





Freeman (2000) *How Brains Make Up Their Minds.* Columbia University Press

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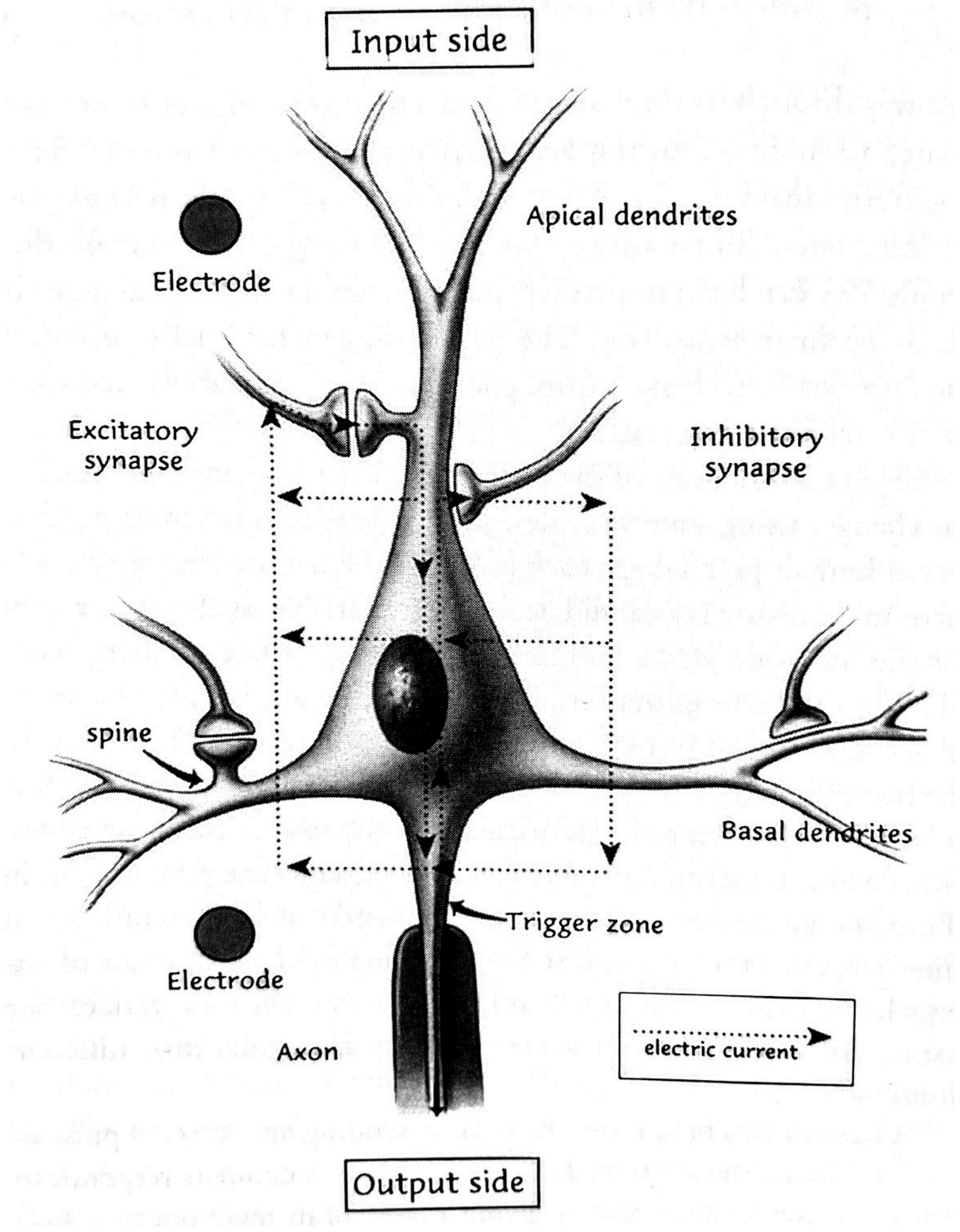

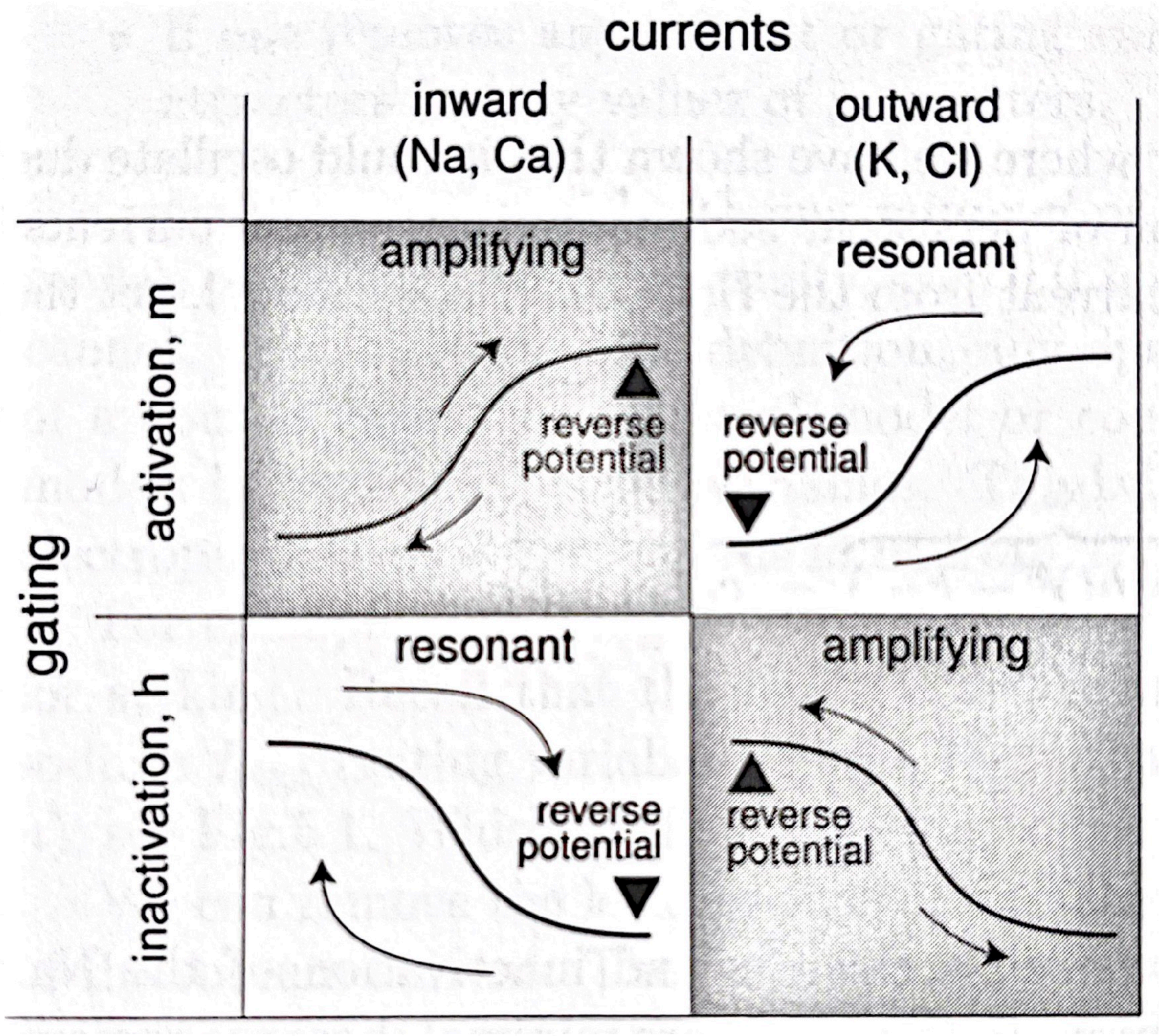

Izhikevich (2007) *Dynamical Systems in Neuroscience.* MIT Press
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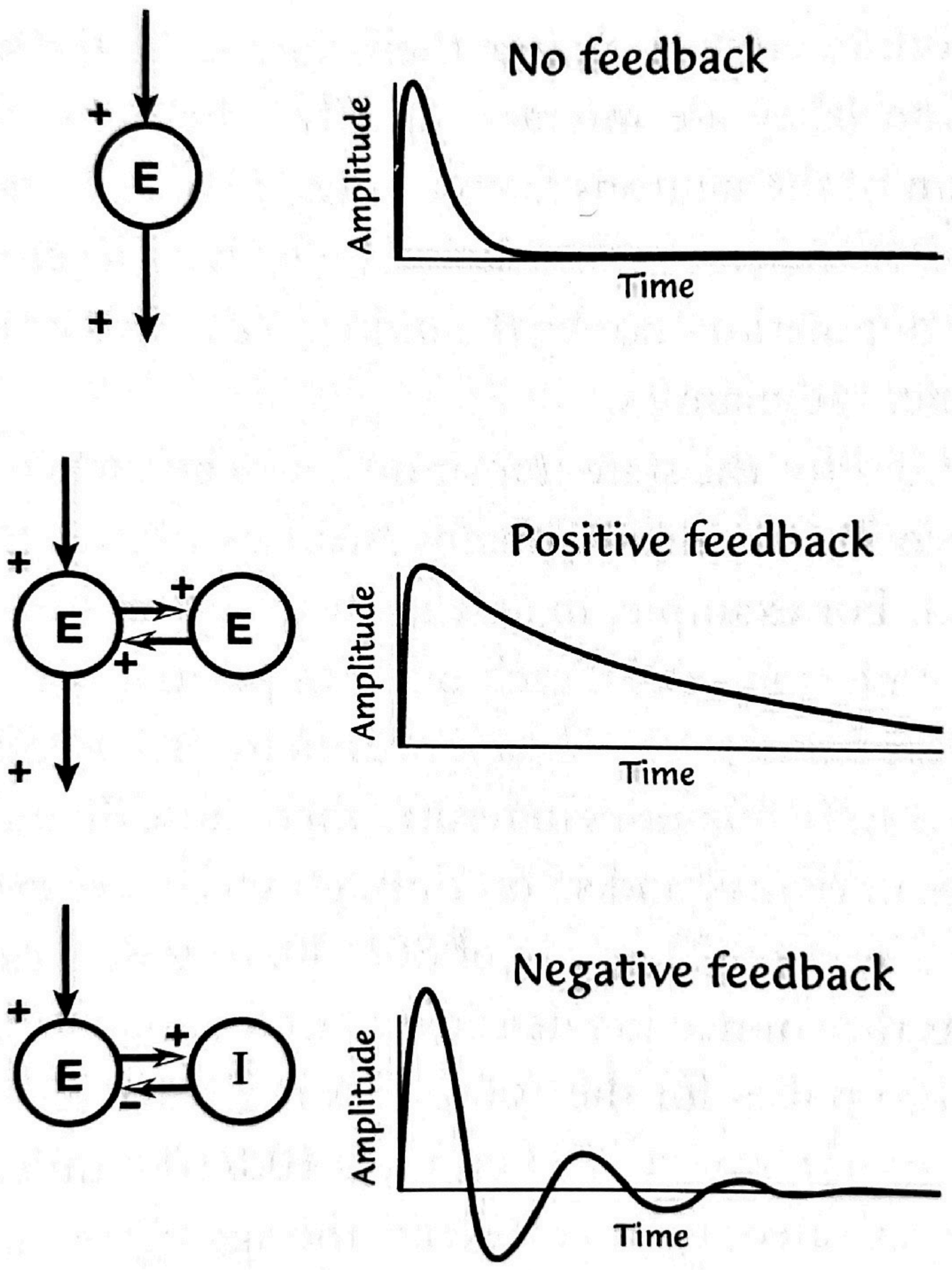

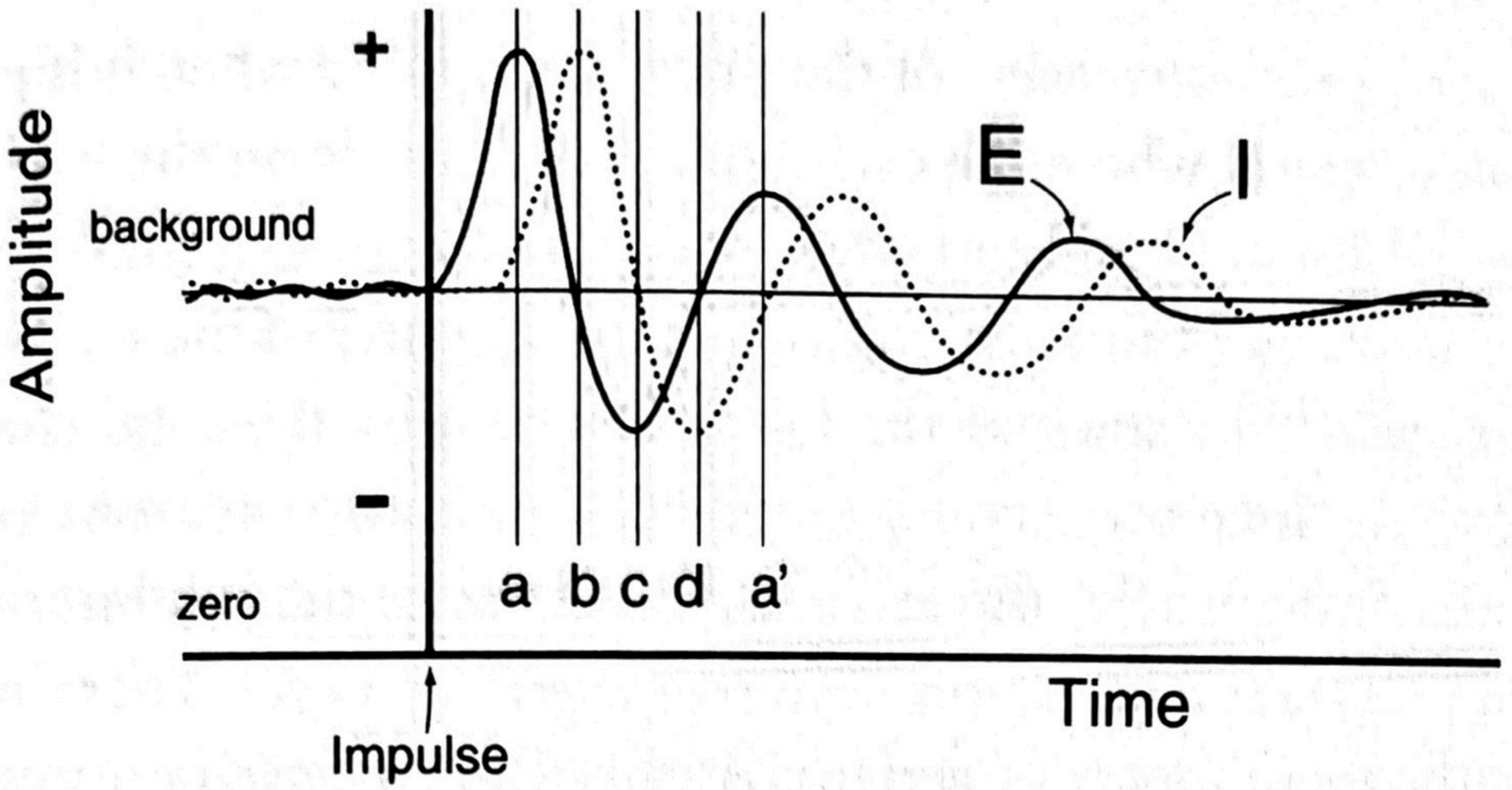

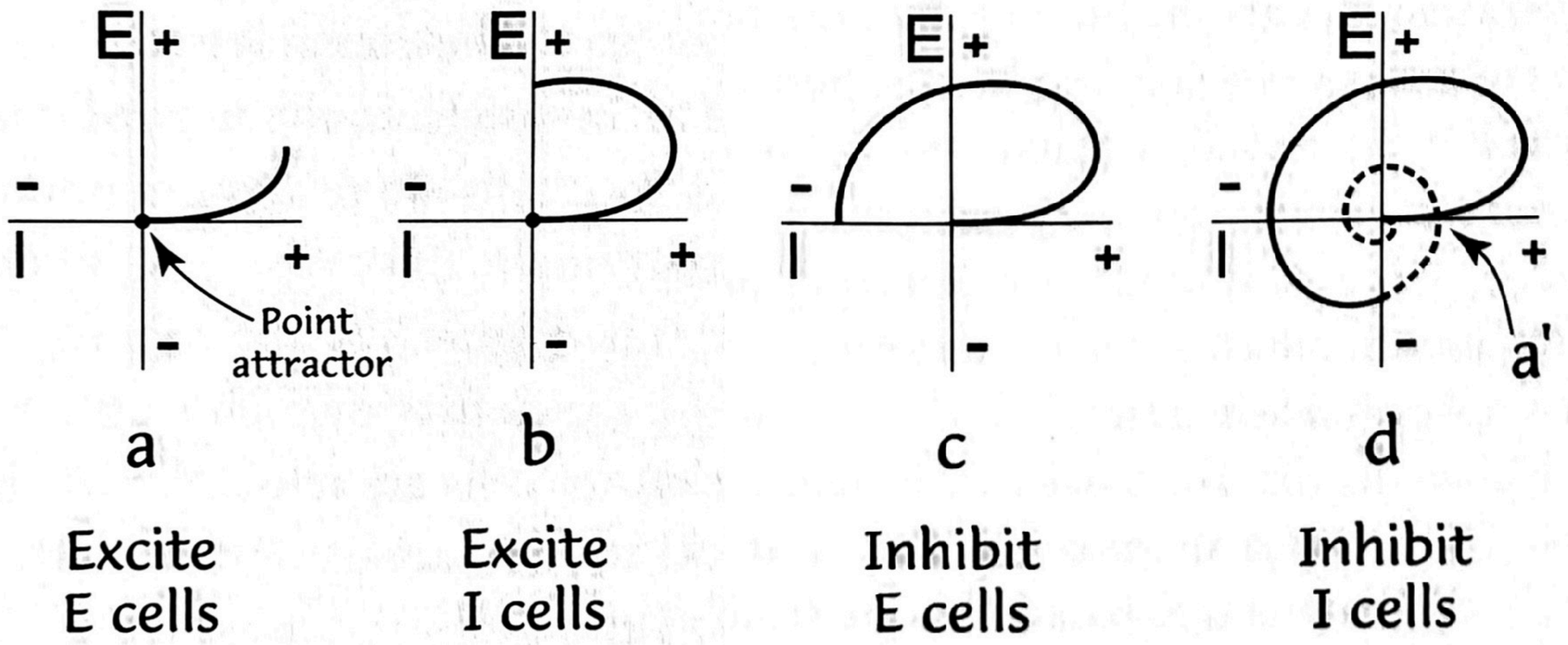

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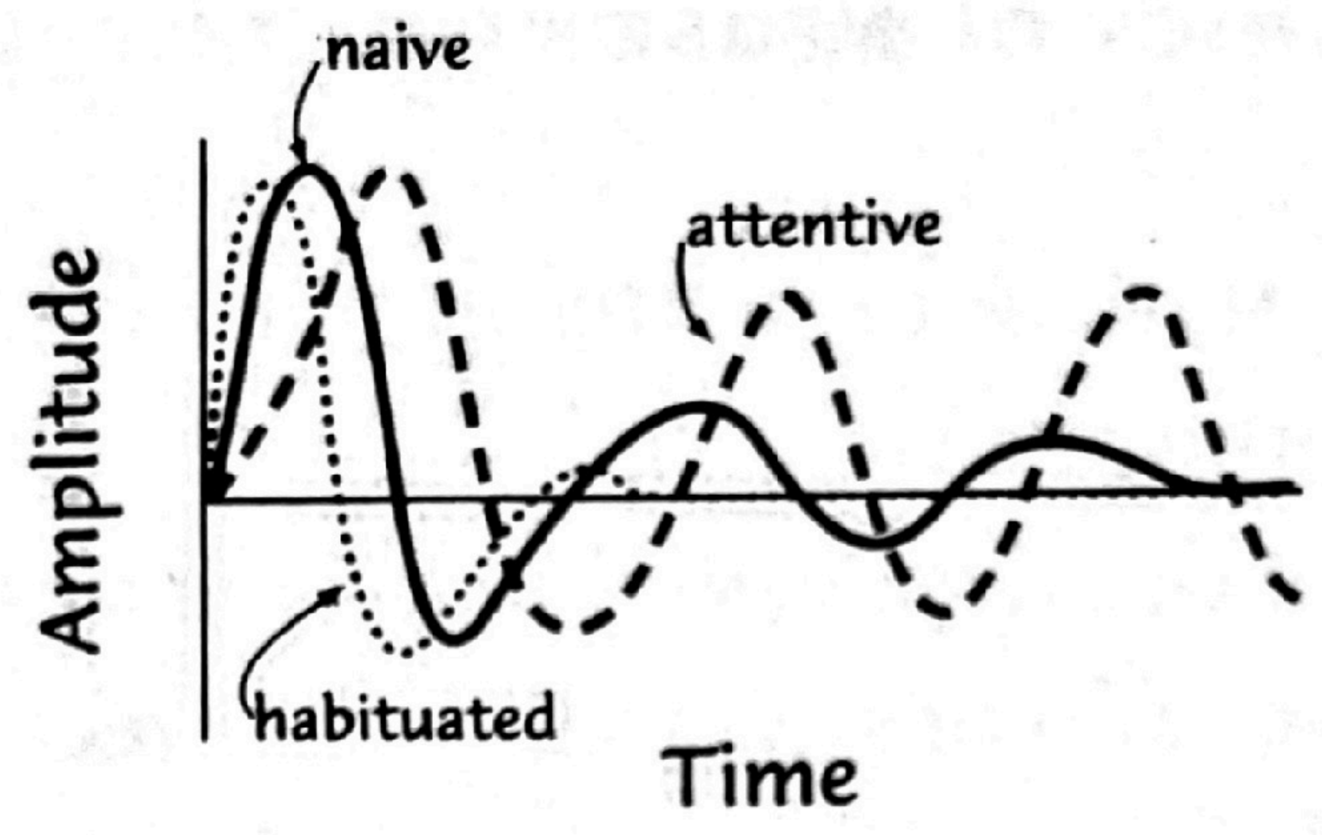

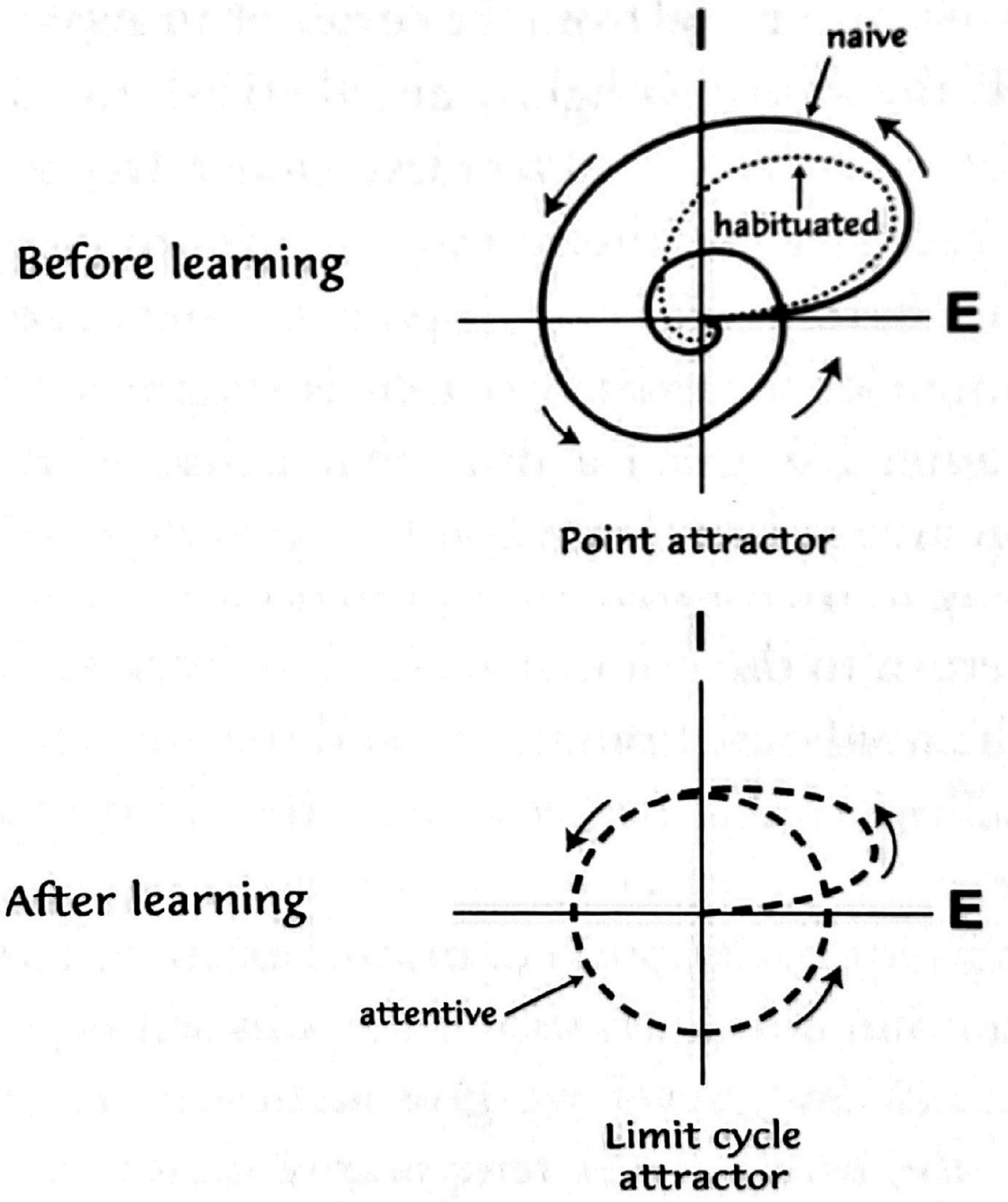

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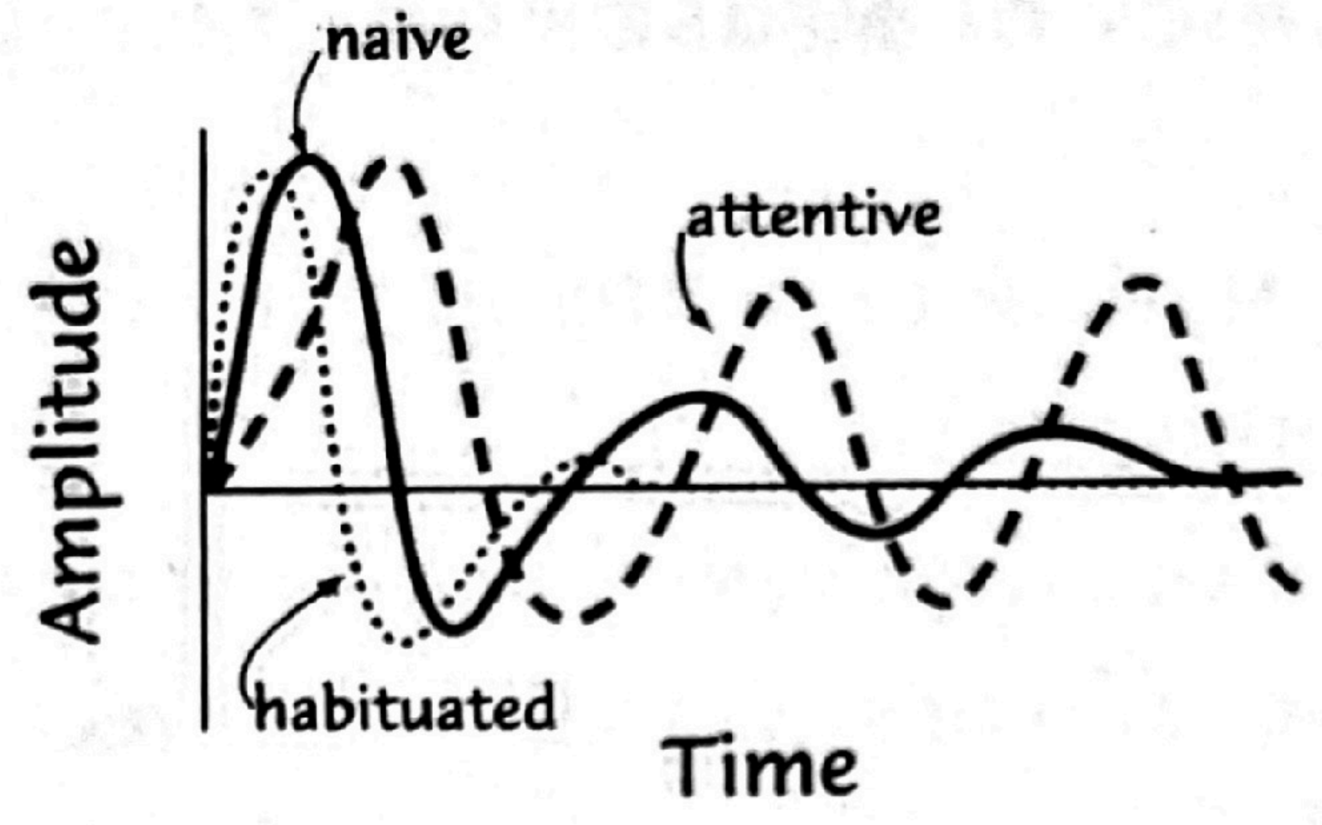

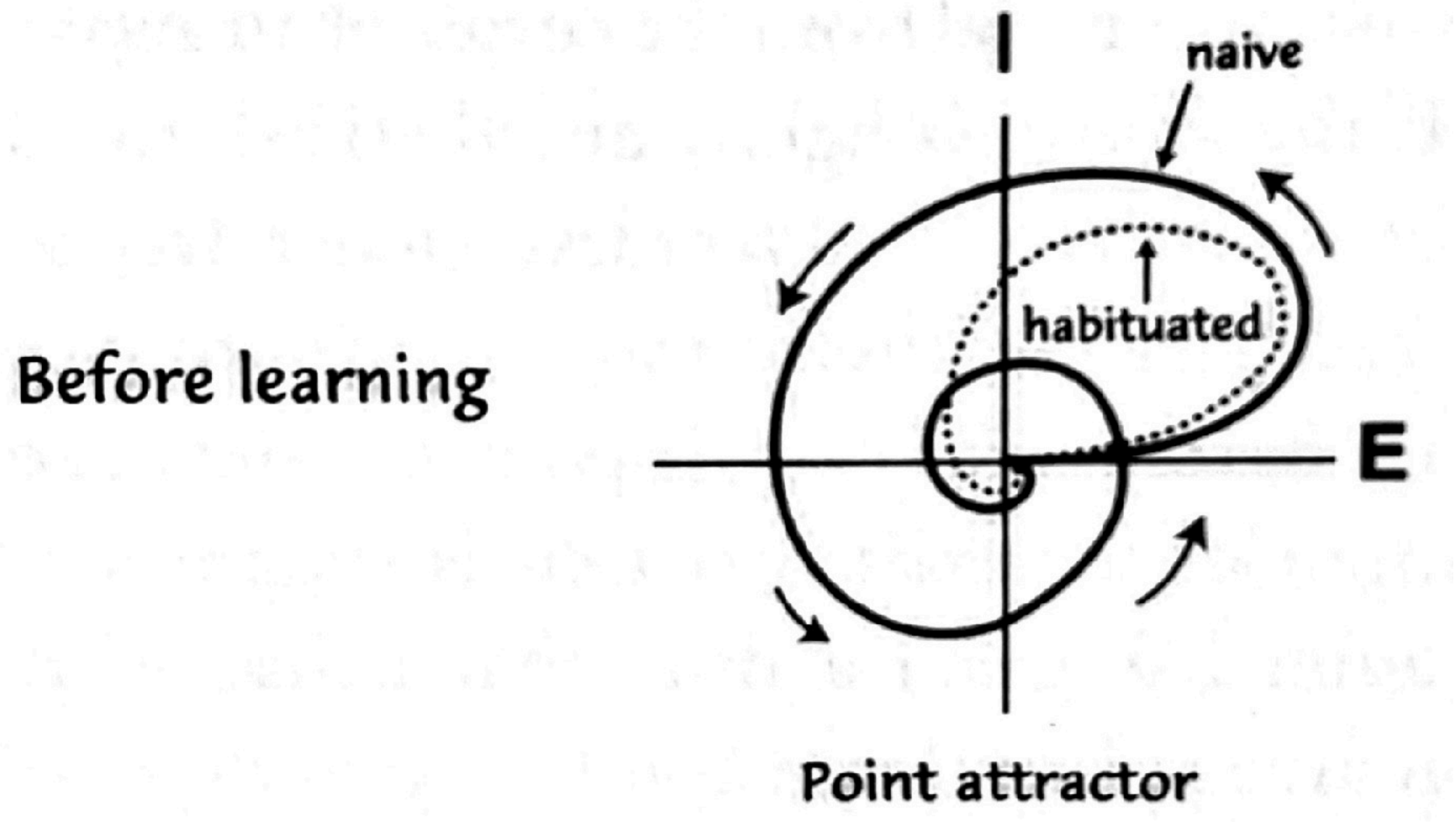

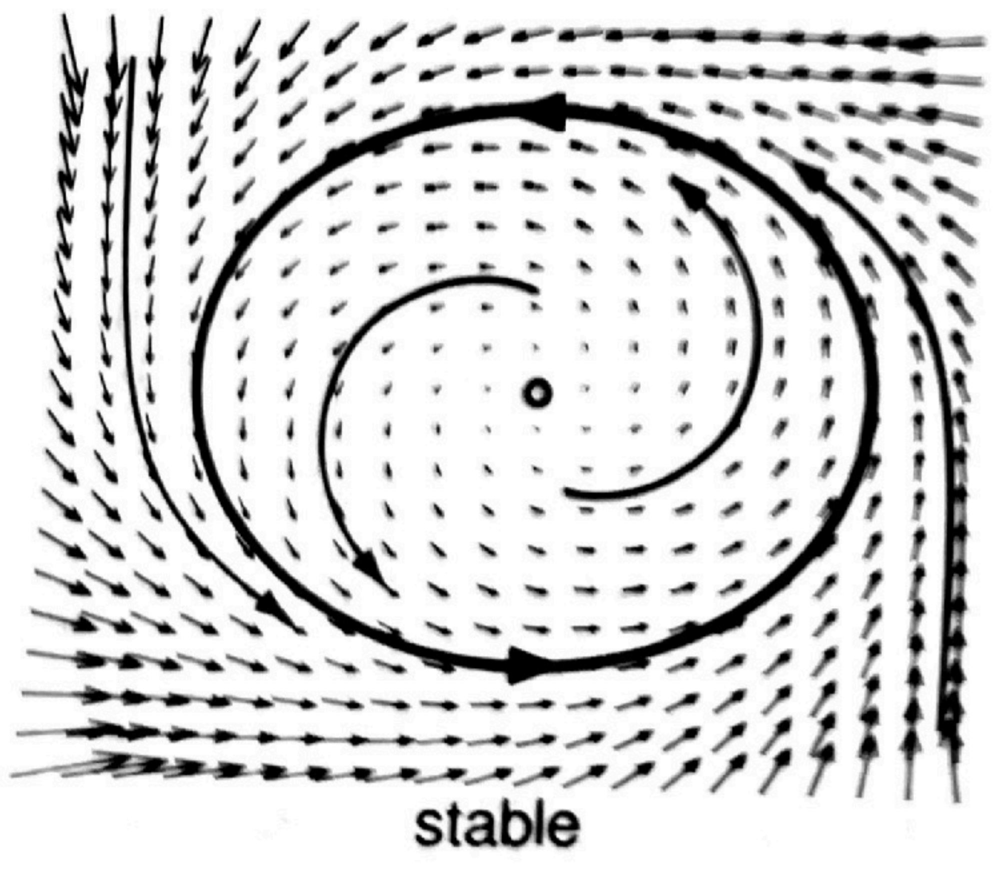

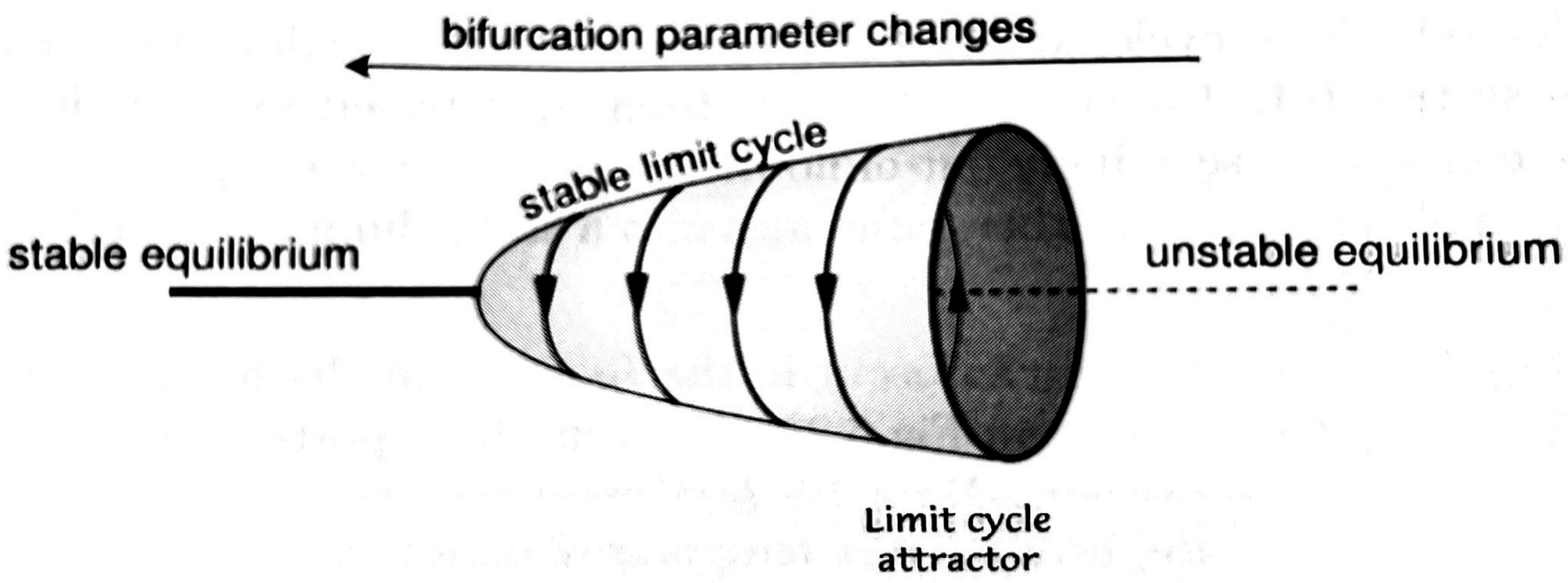

Izhikevich (2007) *Dynamical Systems in Neuroscience.* MIT Press

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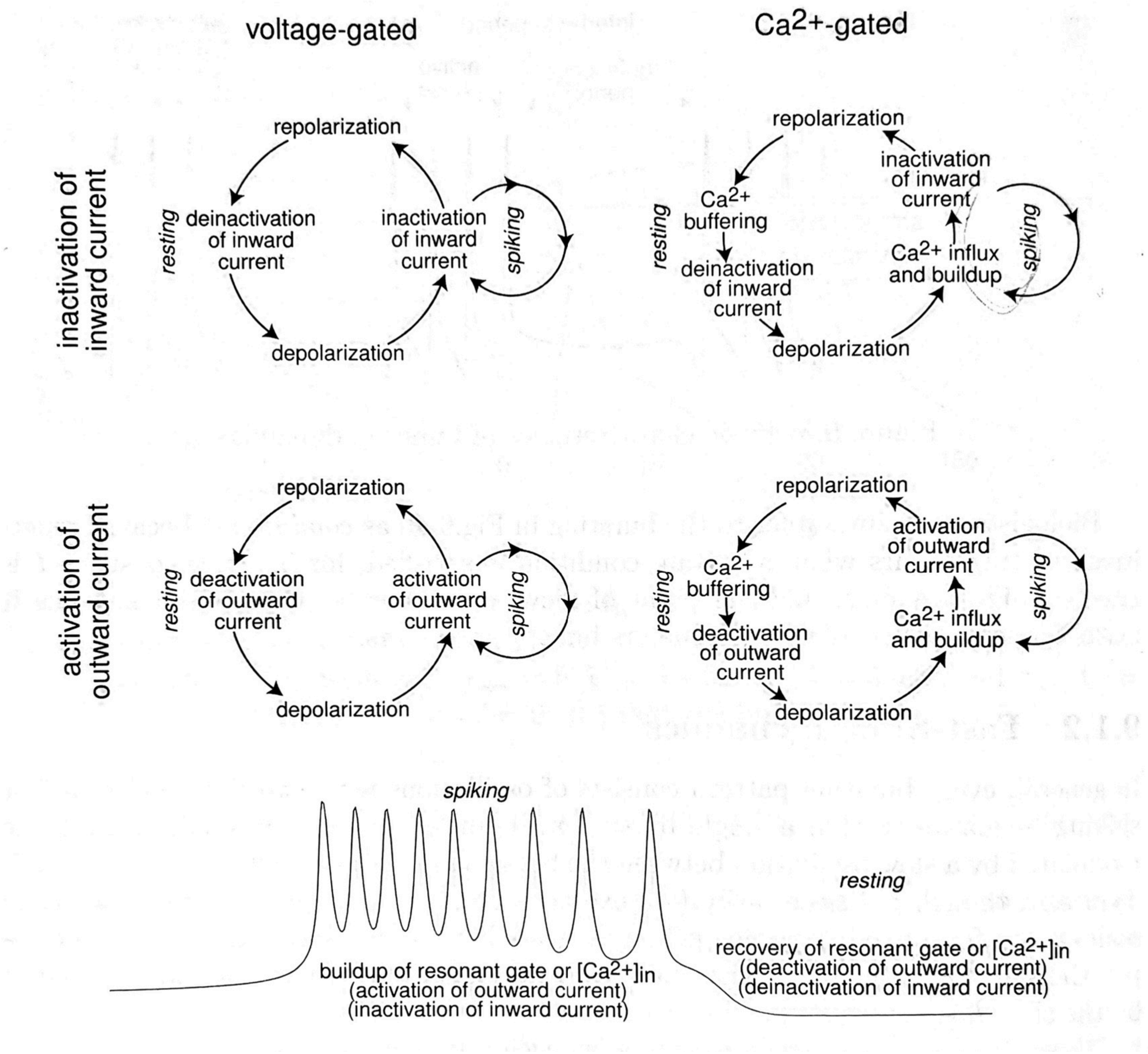
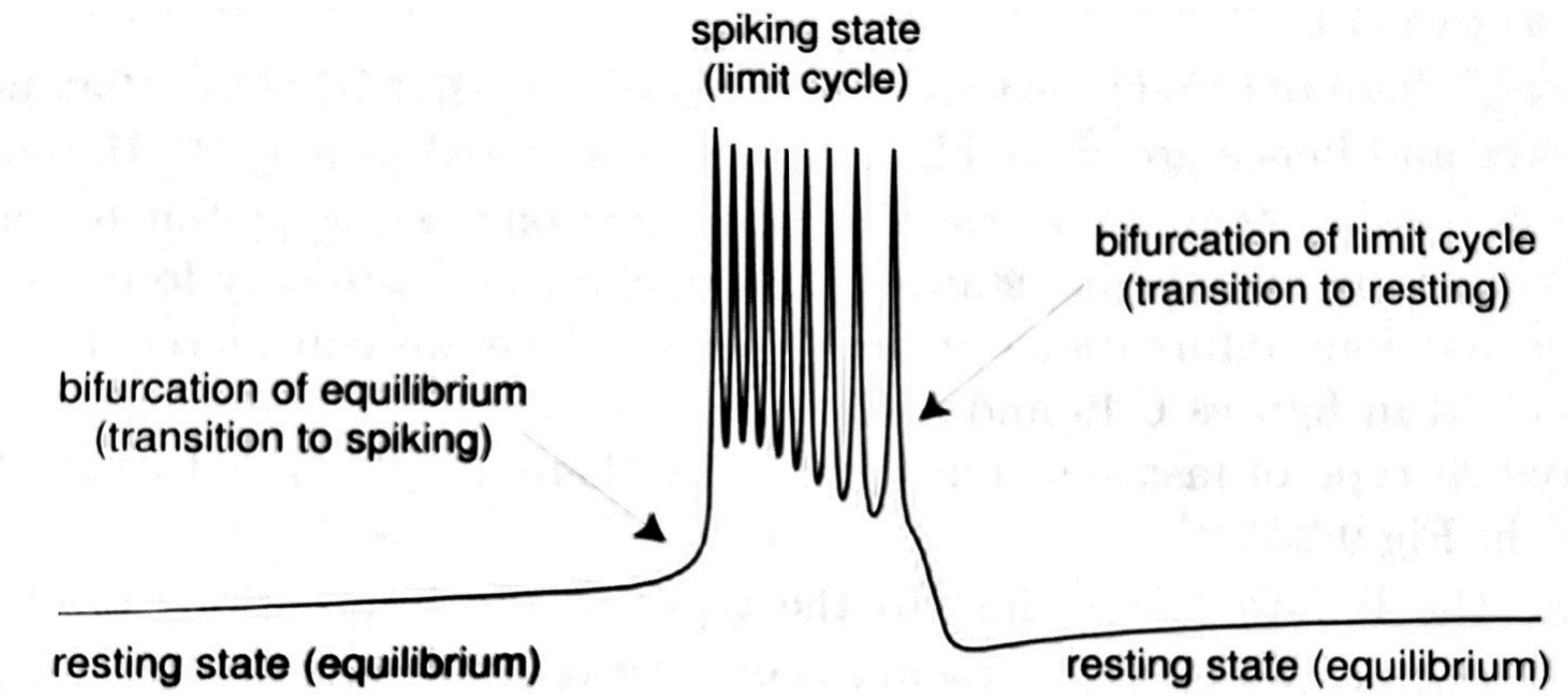
Nested Spiking/Bursting Oscillations

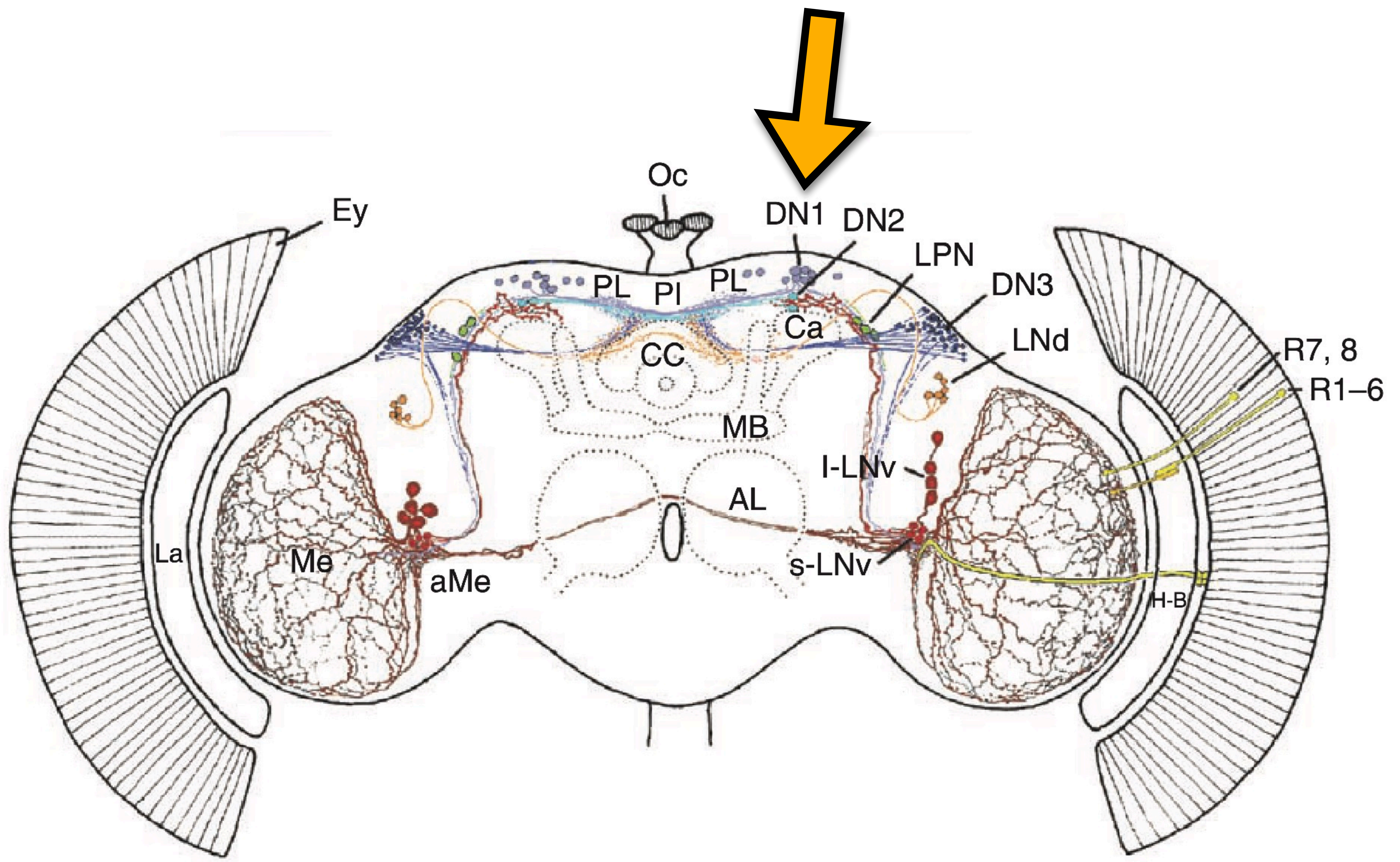




Izhikevich (2007) *Dynamical Systems in Neuroscience.* MIT Press

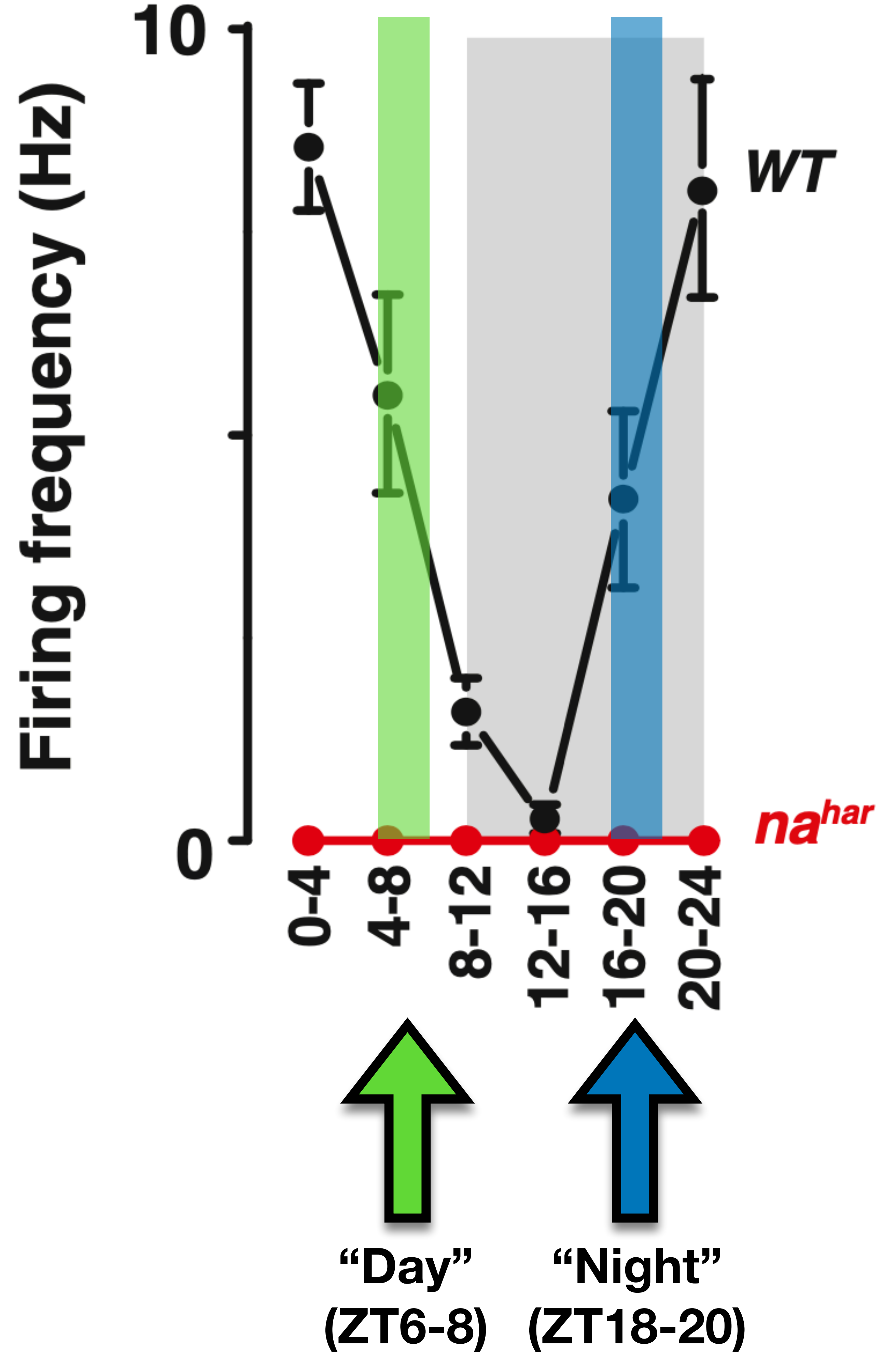
Optic Lobe Dorsal Clock Neurons (DN1p): Day vs. Night Firing Rates

Dorsal Clock Neurons (Gap-Junction Coupled Networks)



Lim C & Allada R. (2013). Nature Neuroscience, 16: 1544

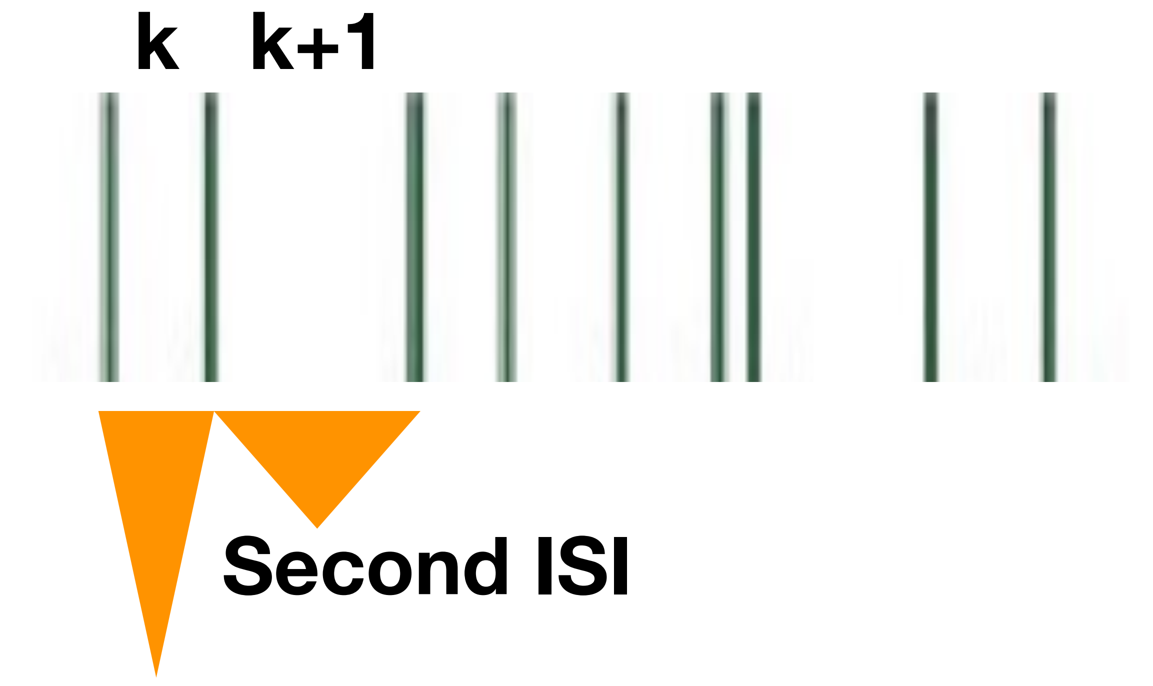
Circadian Rhythmic Modulation of DN1p Firing Rate

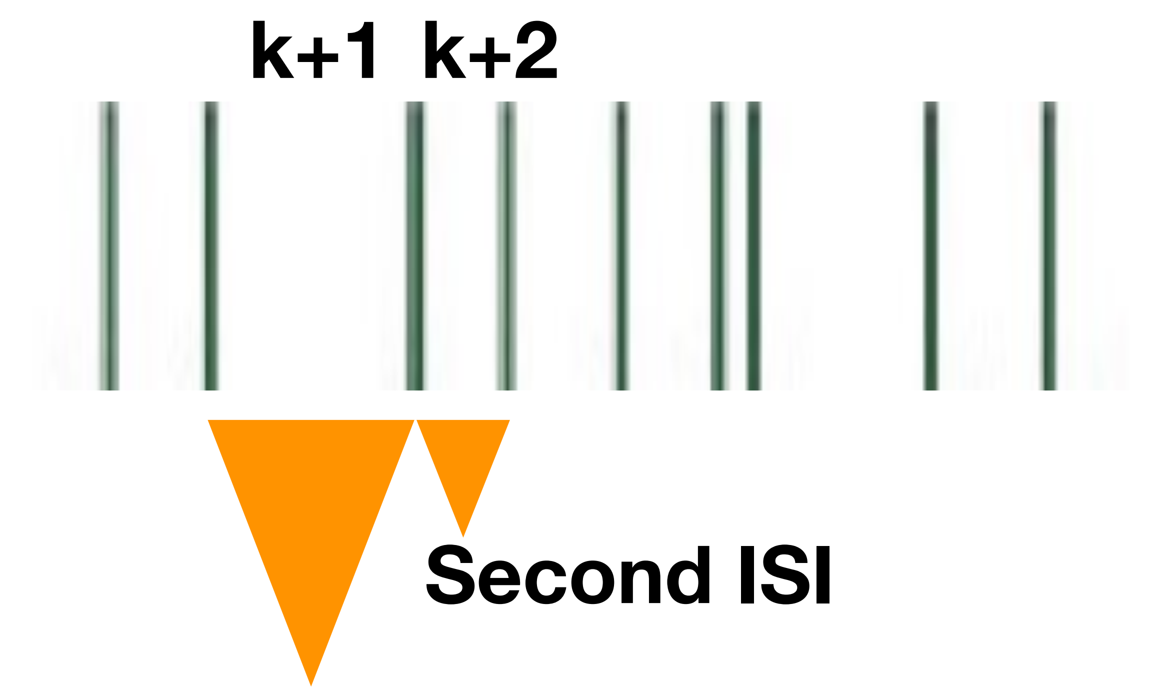


Flourakis, *et al*. (2015) Cell,162: 836

Statistical Model: Gaussian Mixture Captures Spike Timing

• <u>Second-order timing</u>: Normalize inter-spike intervals (ISIs) for each experiment to mean 1 and take the log to analyze adjacent intervals





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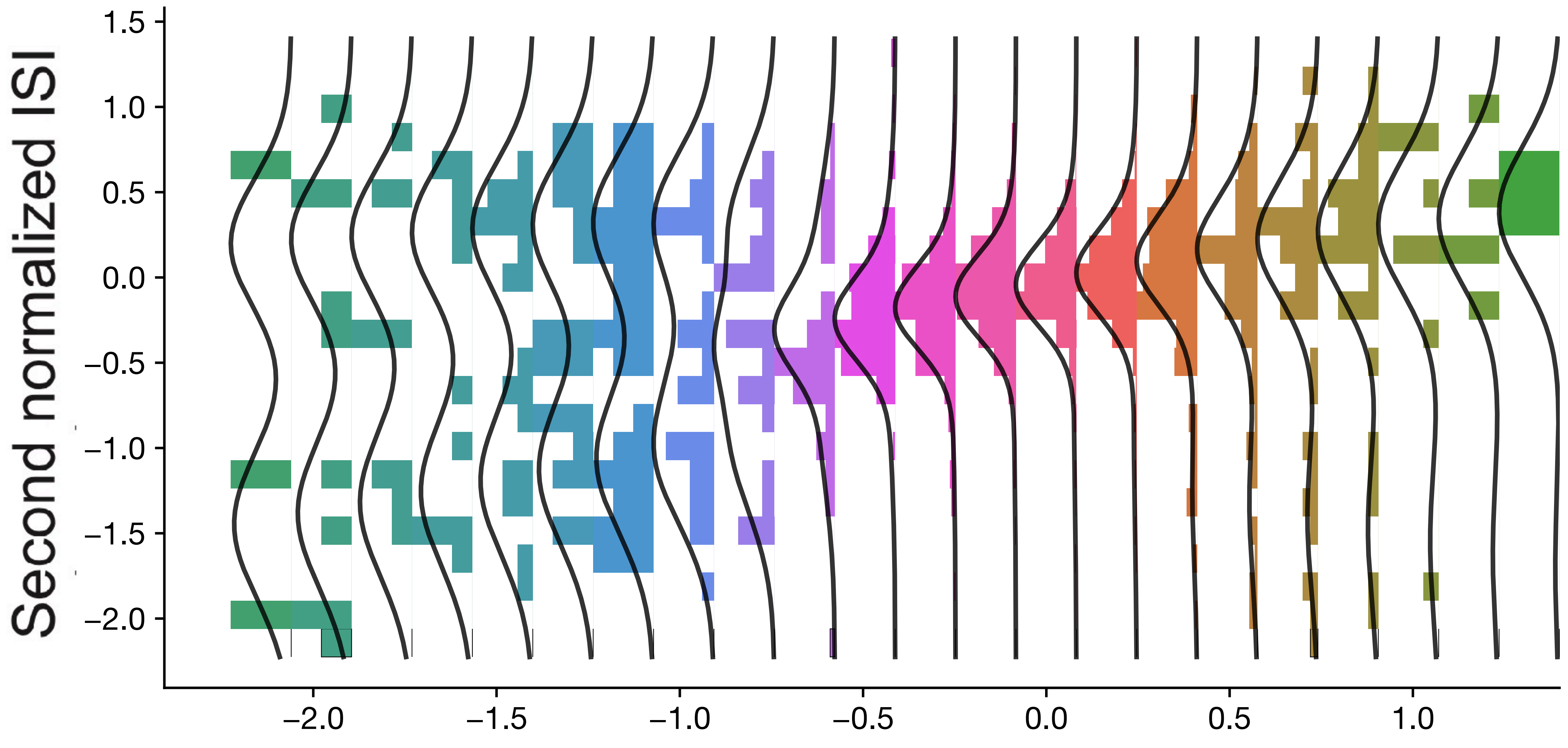
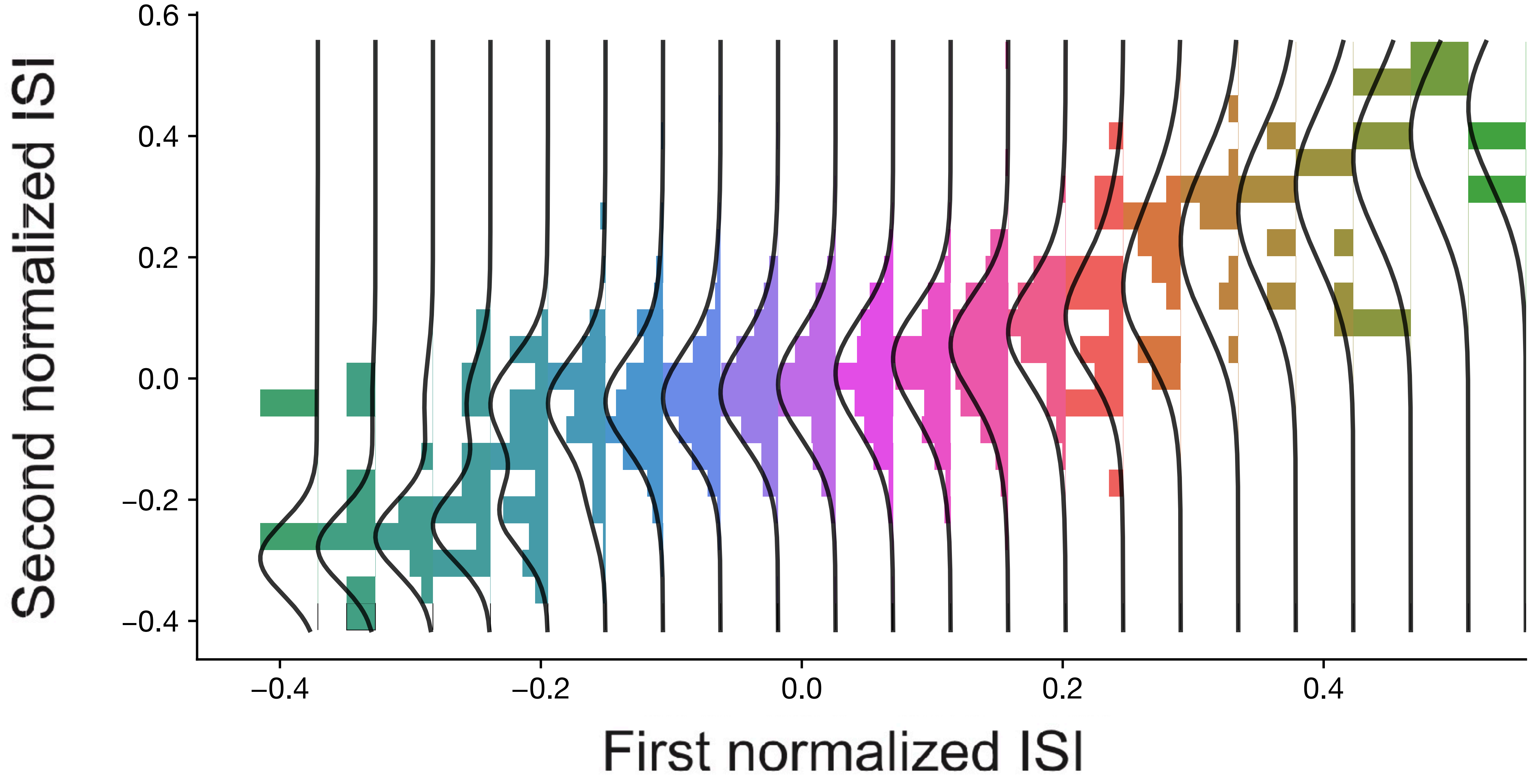
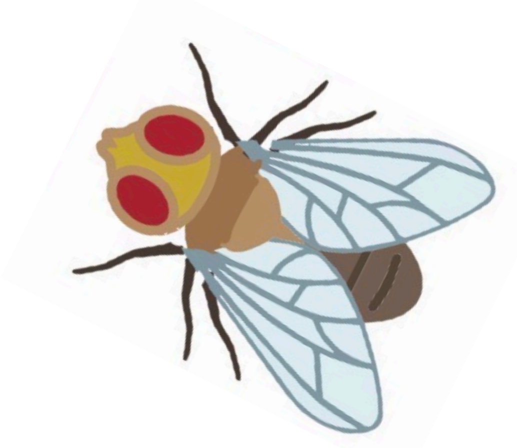
“Day” (ZT6-8)



“Night” (ZT18-20)

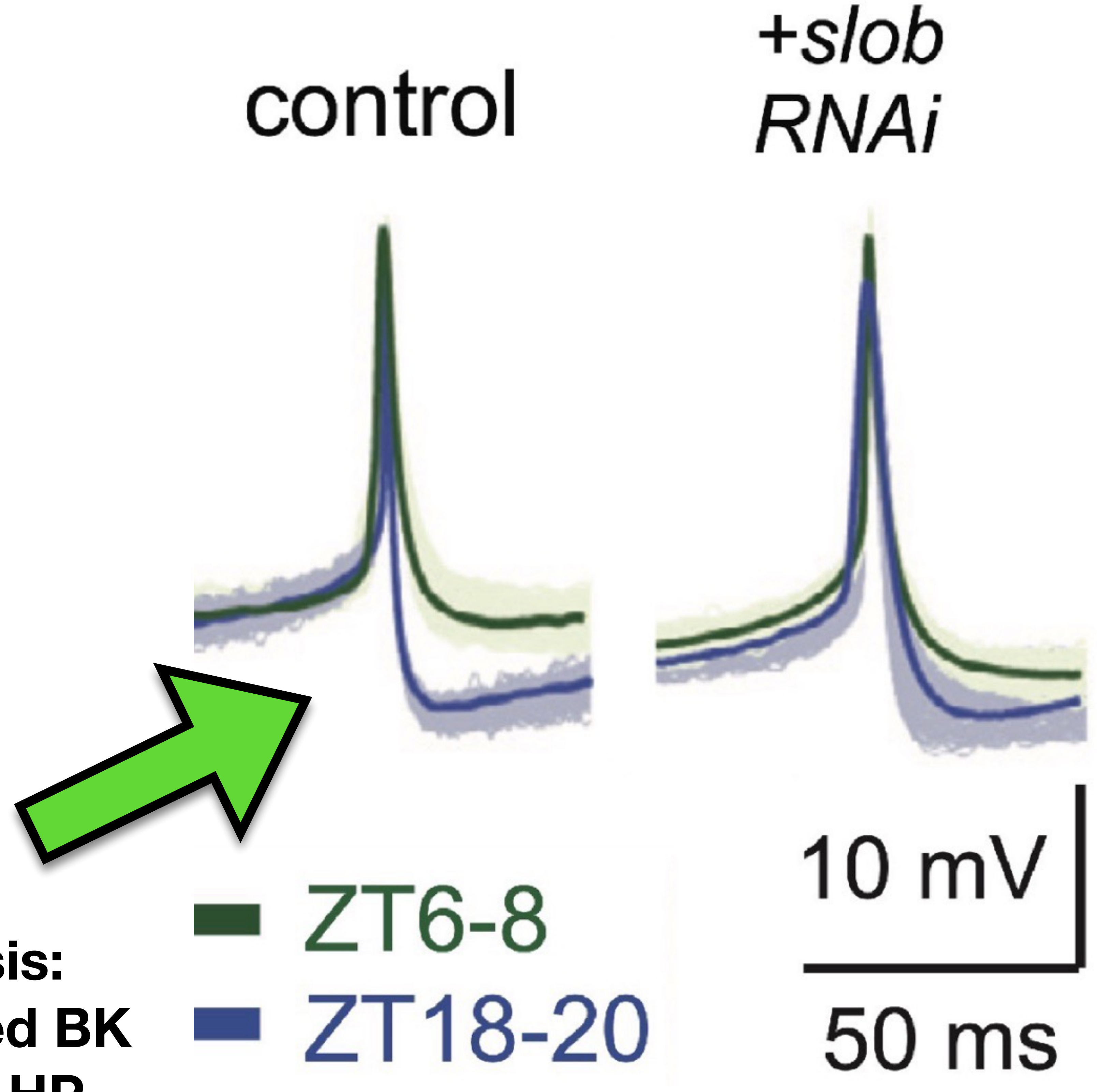


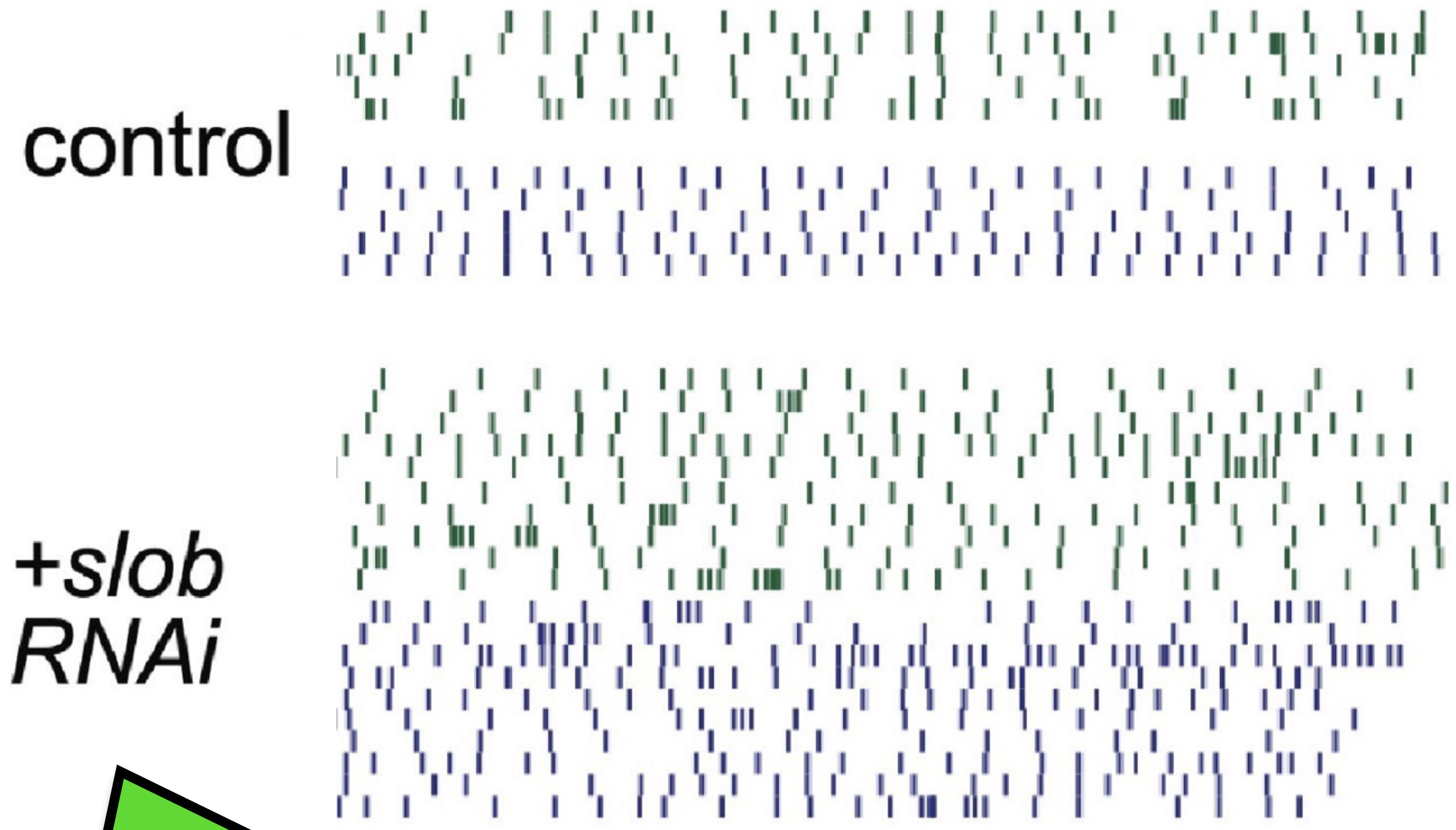
• <u>Conditional Probabilities</u>: Validate conditional second-order densities from mixture model against conditional timing data histograms



Tabuchi, Monaco, *et al*. (2018). Cell, 175: 1213

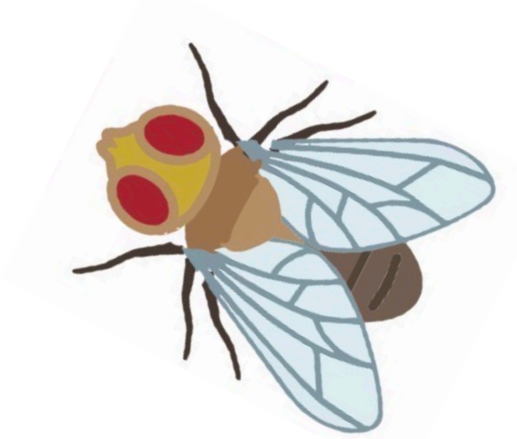
Biophysical Neuron Model: Spike Waveforms→Firing Regularity





- **Hypothesis: Slob-mediated BK enhances AHP amplitude and duration at night**

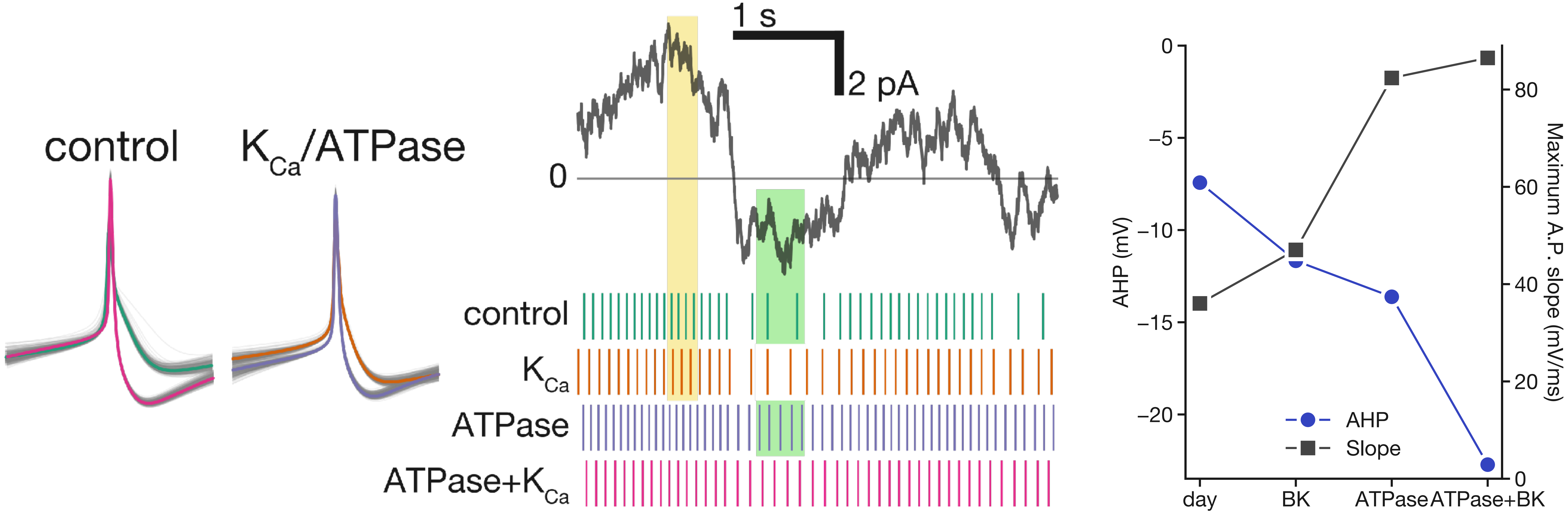
- **Slob regulates a large-conductance calcium-activated potassium (BK) channel in *Drosophila***



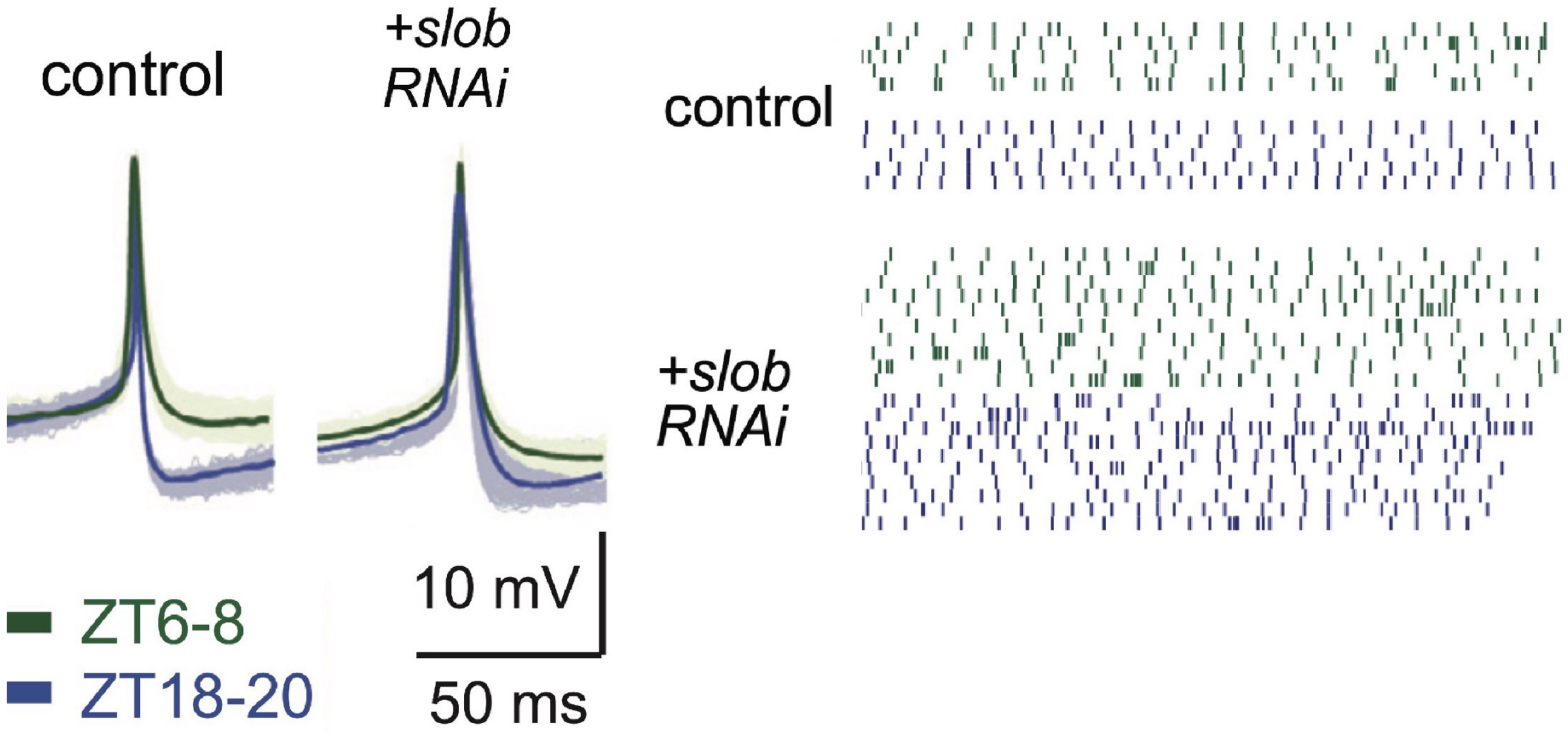
Tabuchi, Monaco, *et al*. (2018). Cell, 175: 1213

Biophysical Neuron Model: Spike Waveforms→Firing Regularity

- **Hodgkin-Huxley clock neuron model to demonstrate effects of diurnal modulation of K_{Ca} (BK) and Na^+/K^+ ATPase activity (via reversal potentials)**

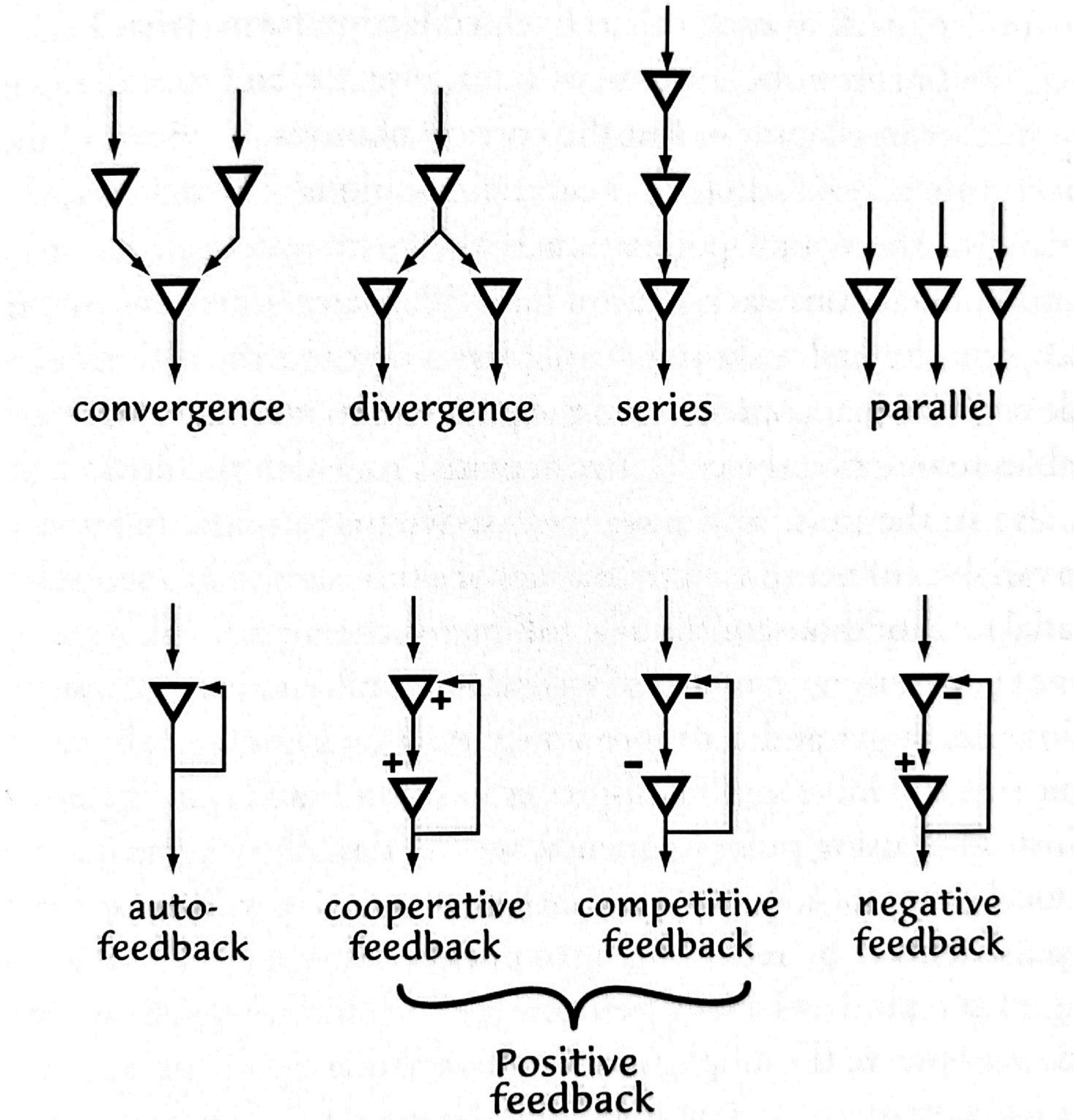


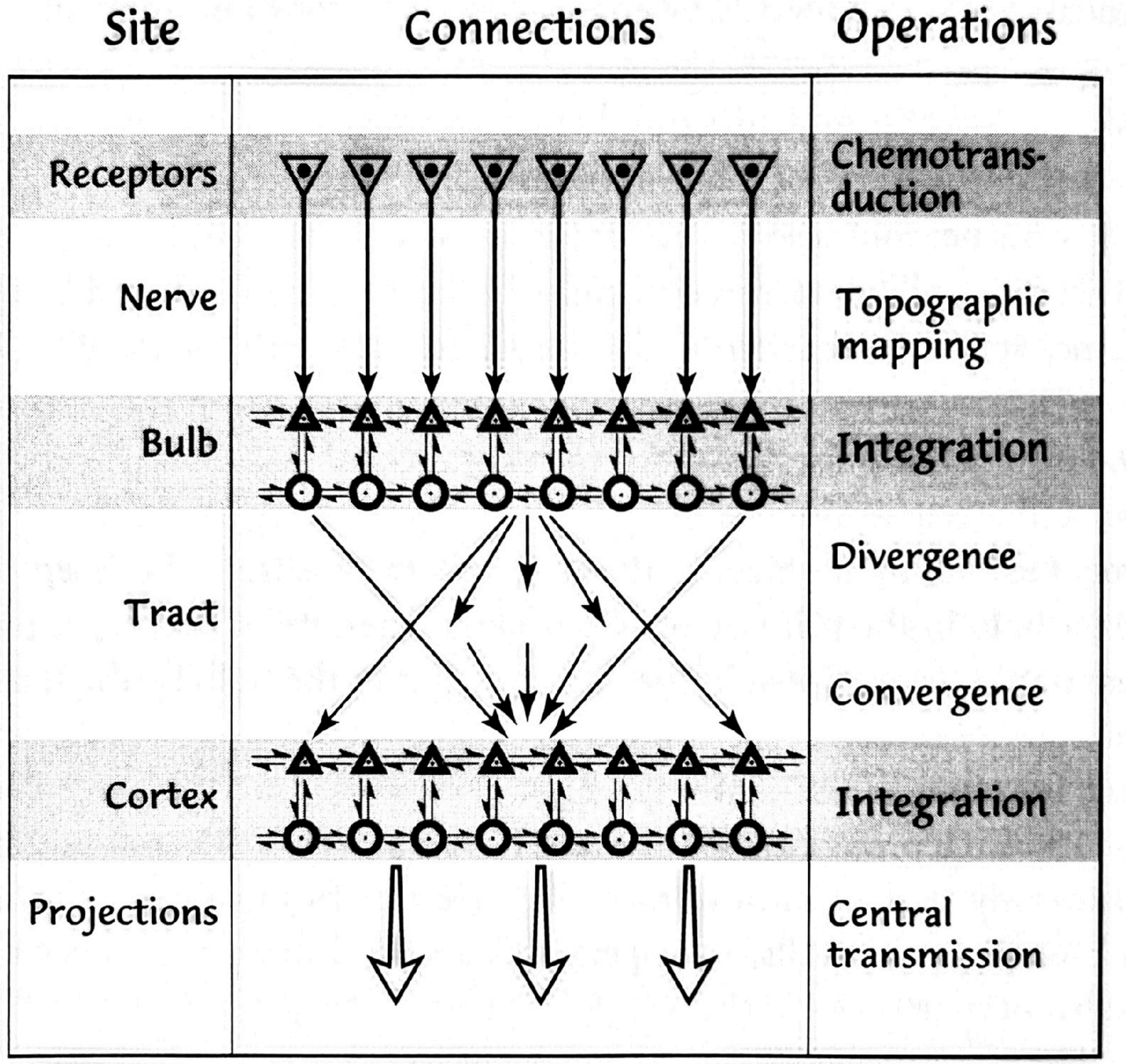
- **In vivo spike waveforms and spike-timing rasters during Day (green) and Night (blue) epochs**



Tabuchi, Monaco, *et al*. (2018). Cell, 175: 1213

How to Make an Oscillatory Neural Pathway





Freeman (2000) *How Brains Make Up Their Minds.* Columbia University Press

Theta-Phase Precession of Place Cell Spikes

Discovery

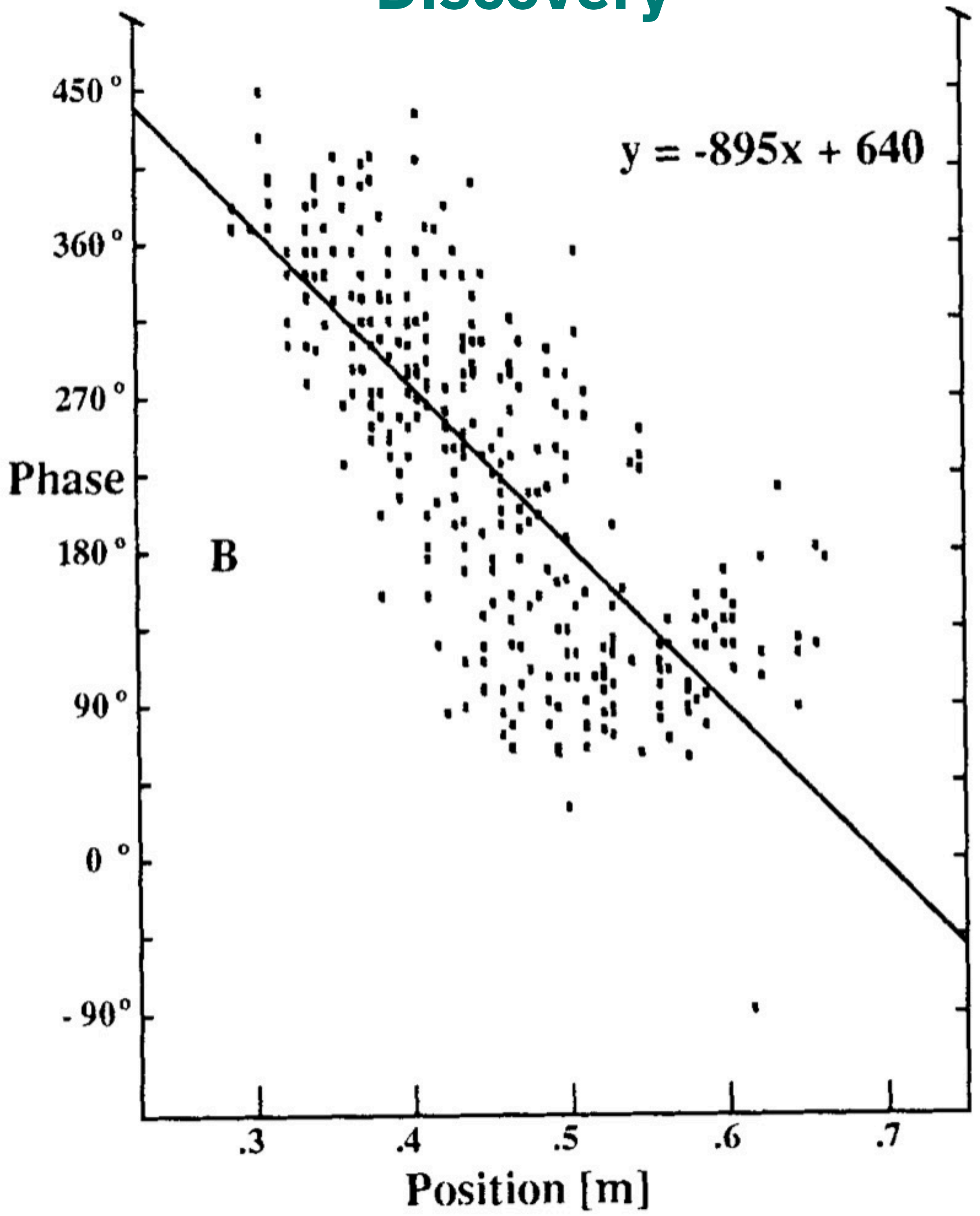
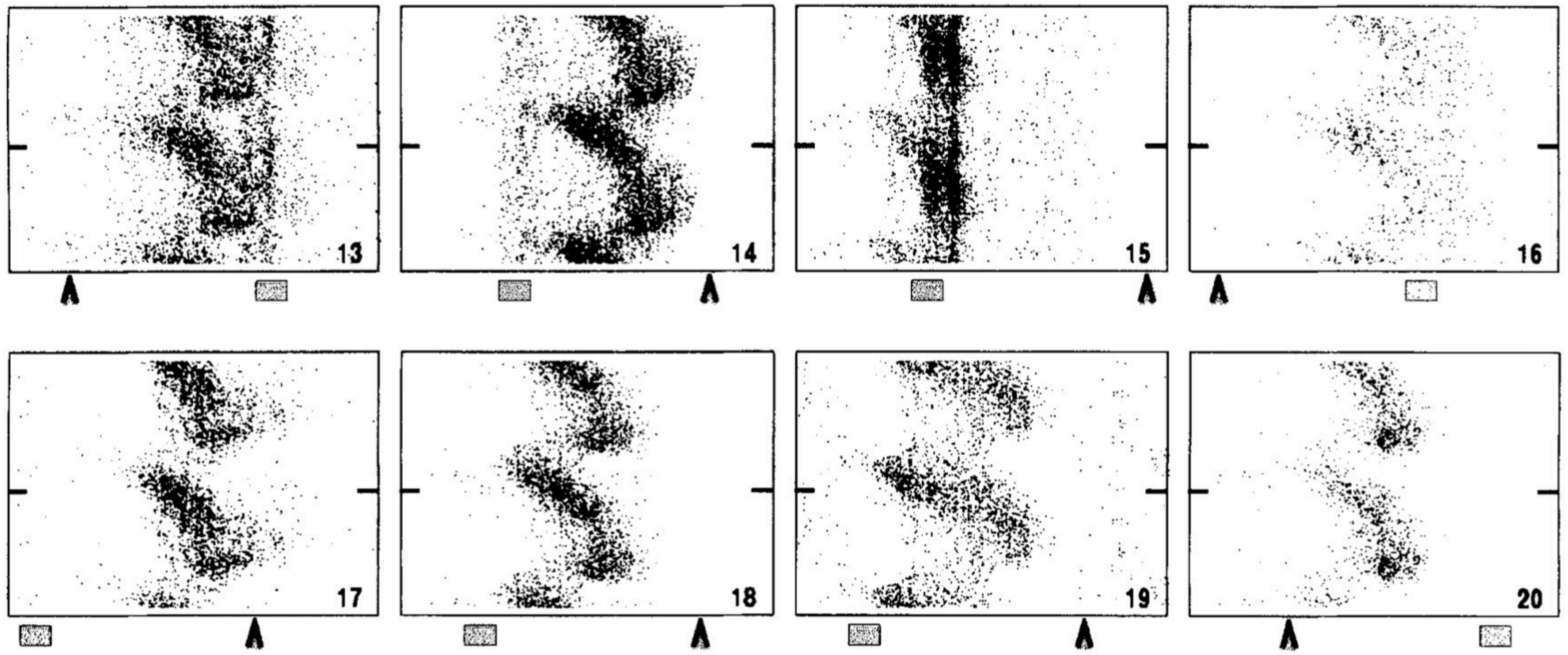
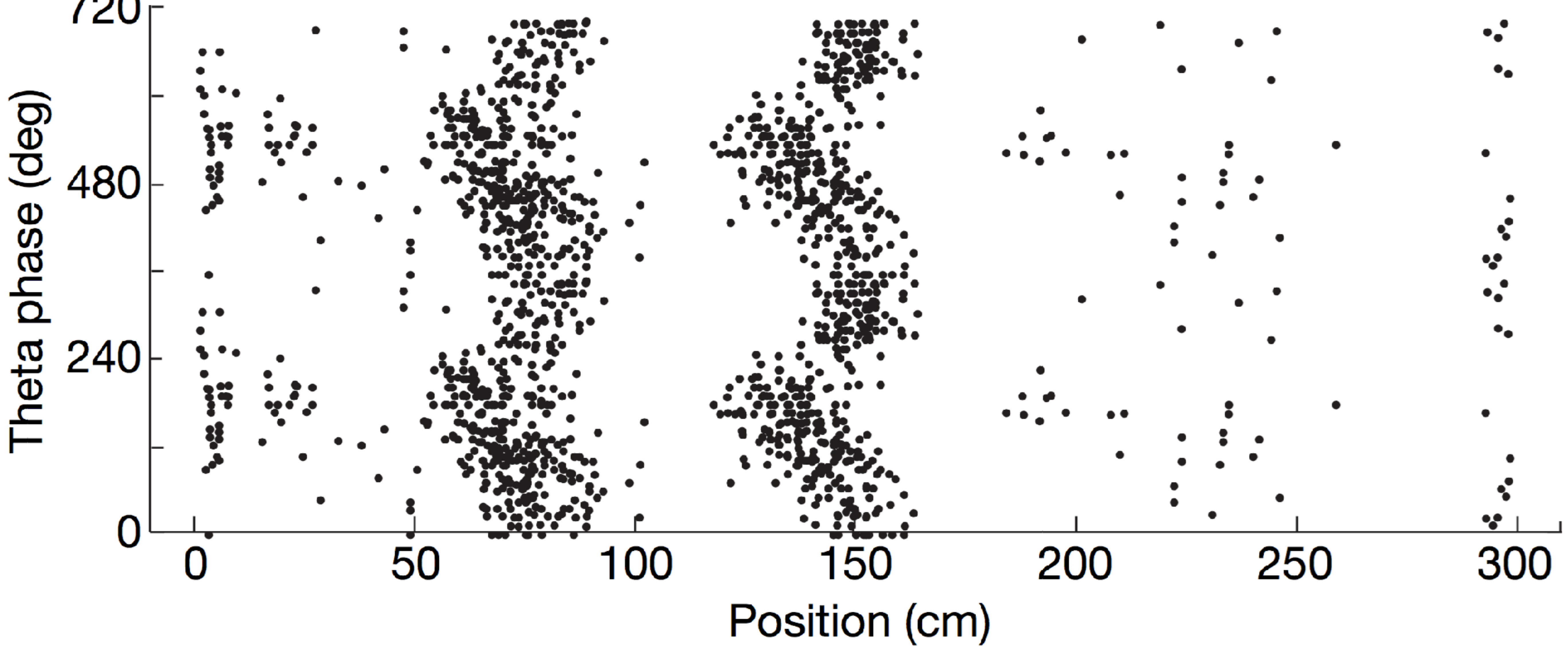


Fig. 3. Demonstration of the effect of the data mapping procedure to find the best-fit line to periodic phase data for cell 8. (A) Each spike location plotted against the phase of the theta wave. The spikes at the beginning of the field between 0.3 and 0.4 m on the track have clearly wrapped around the 0°/360° line and fall in the lower phase range. (B) Data pattern that results from the application of the unwrapping program. Imagine that the graph of A has been cut along the dotted line and rolled into a unit cylinder. The cylinder is rotated until a single straight line can be drawn through the data points. Many of the points in the left lower quadrant of the graph have been wrapped to the left upper quadrant, and it is clear that a straight line provides a good fit to these data.

Temporal Compression



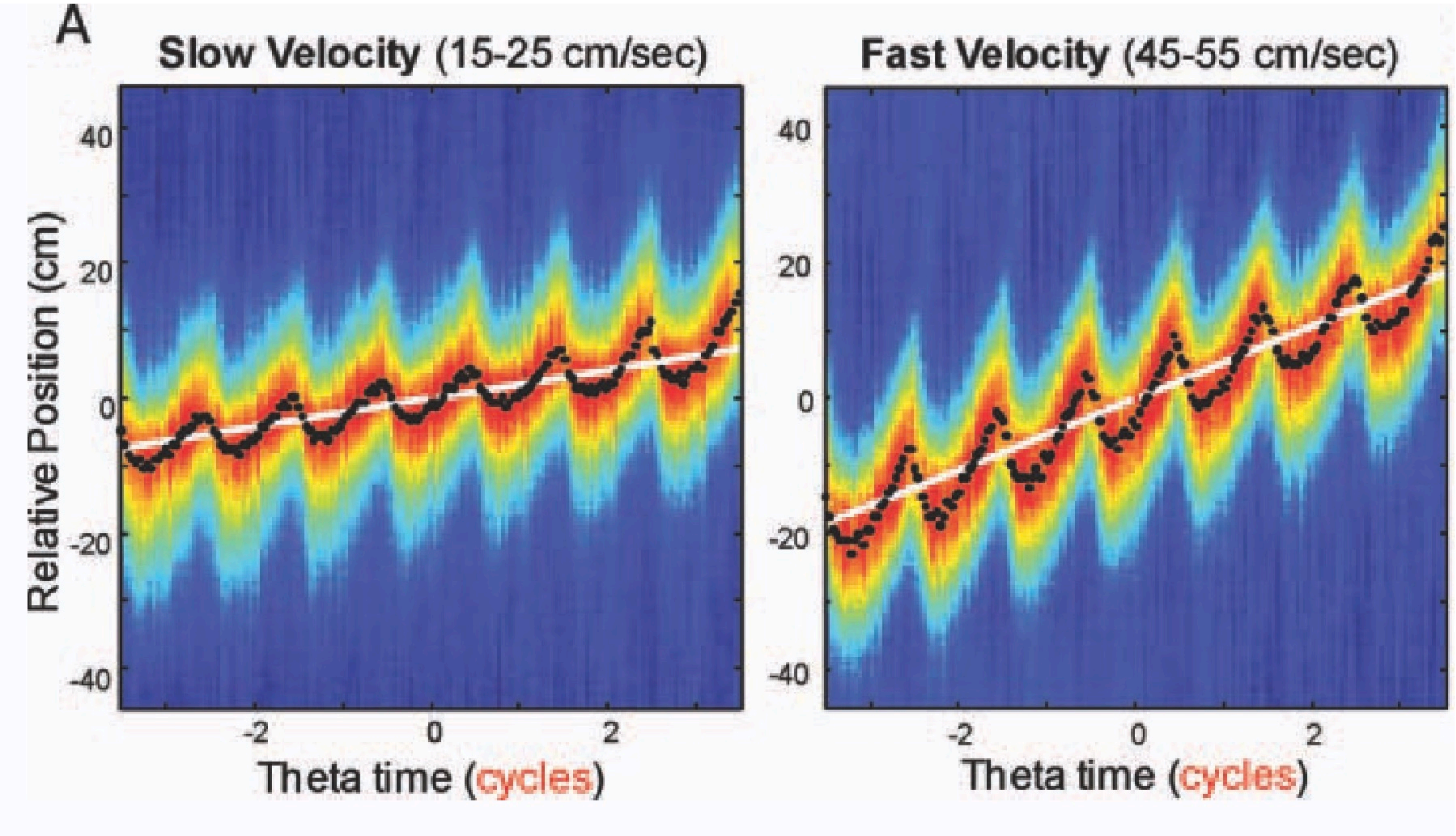
Grid Cell in MEC



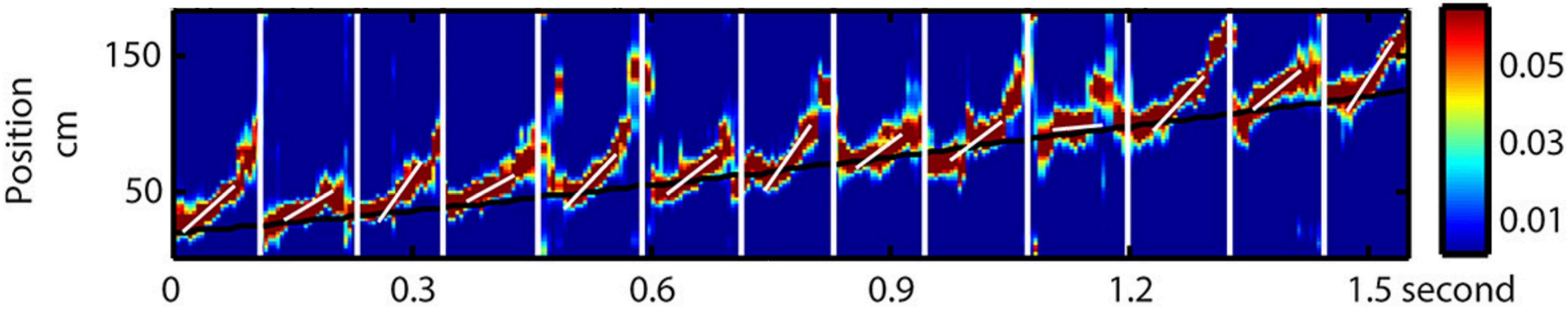
O'Keeffe & Recce (1993); Skaggs et al. (1996); Hafting et al. (2008)

What is the Function of Theta-Phase Precession?

Periodic “look-ahead” to anticipate future positions

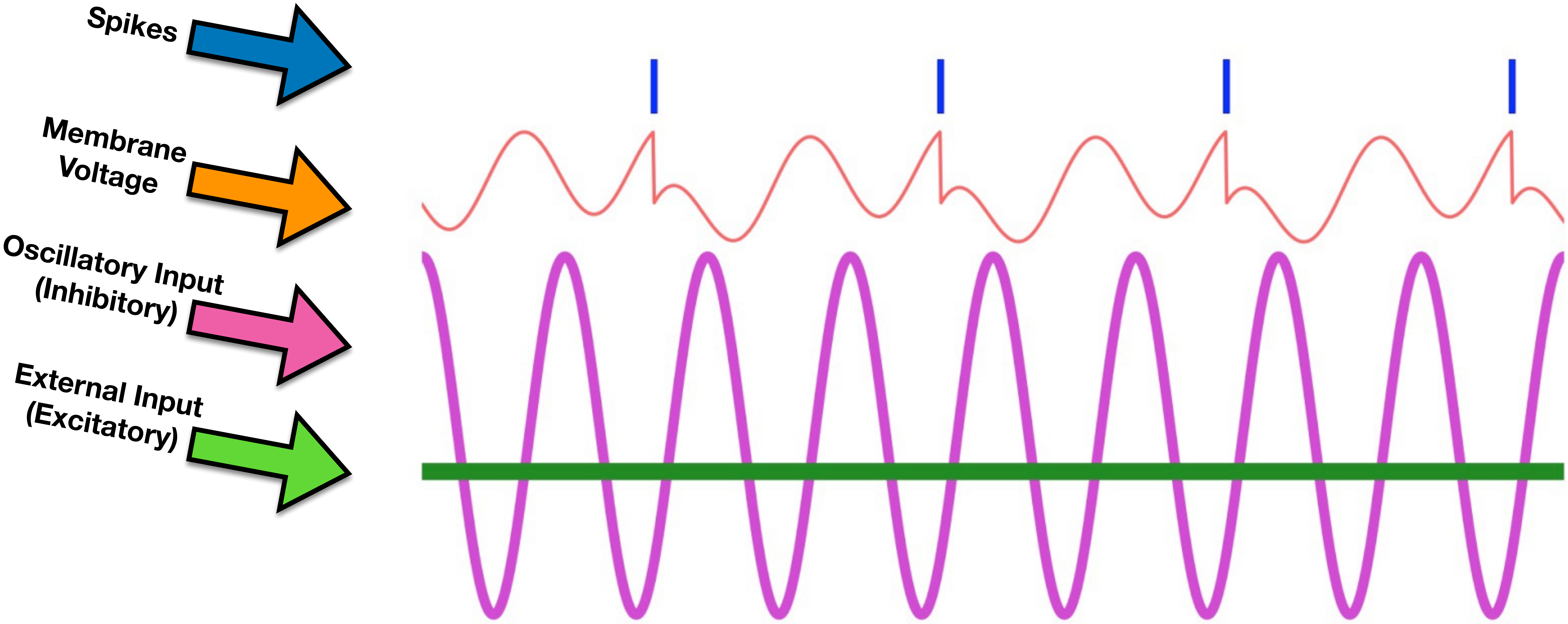


Construction of sequences of “cell assemblies” that preserve the temporal ordering of experience for learning and memory



Maurer et al. (2012); Feng, Silva, & Foster (2015)

How to Make a Spike-Field Phase Code



Monaco, *et al*. (2019) PLOS Computational Biology, 15: e1006741

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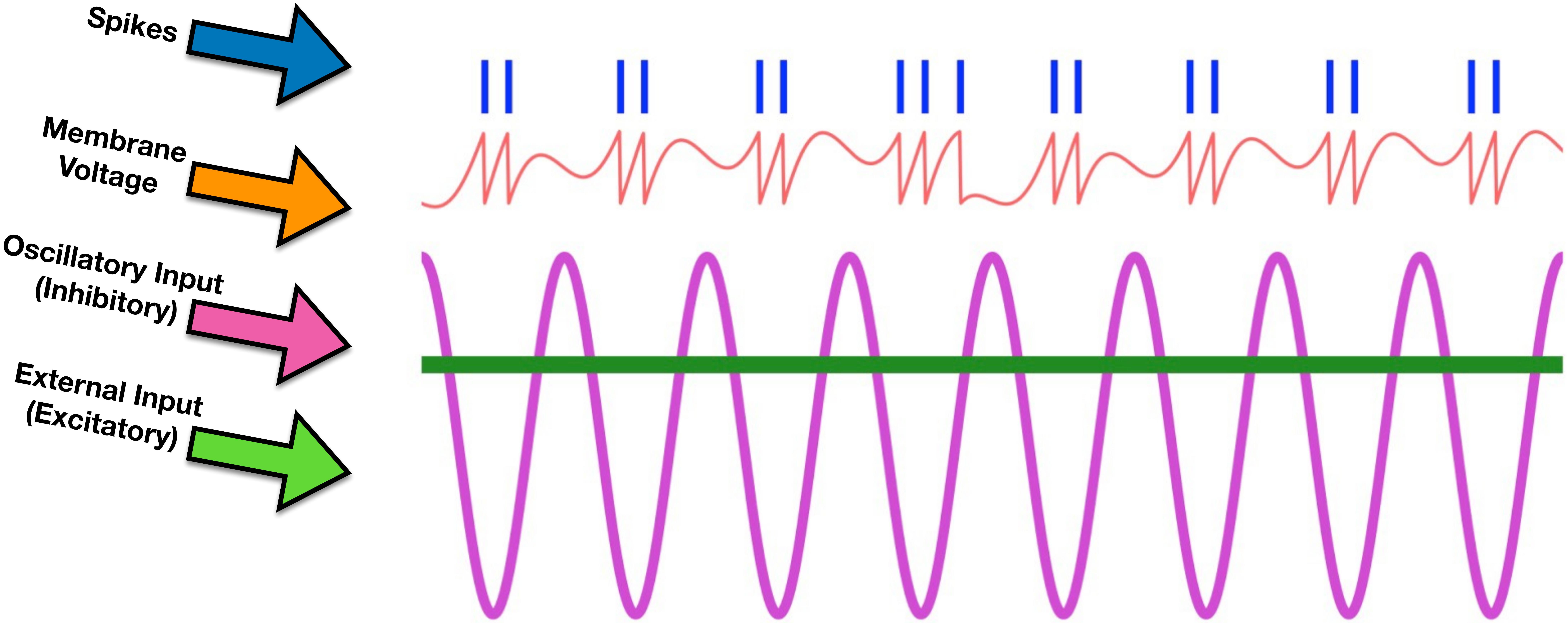

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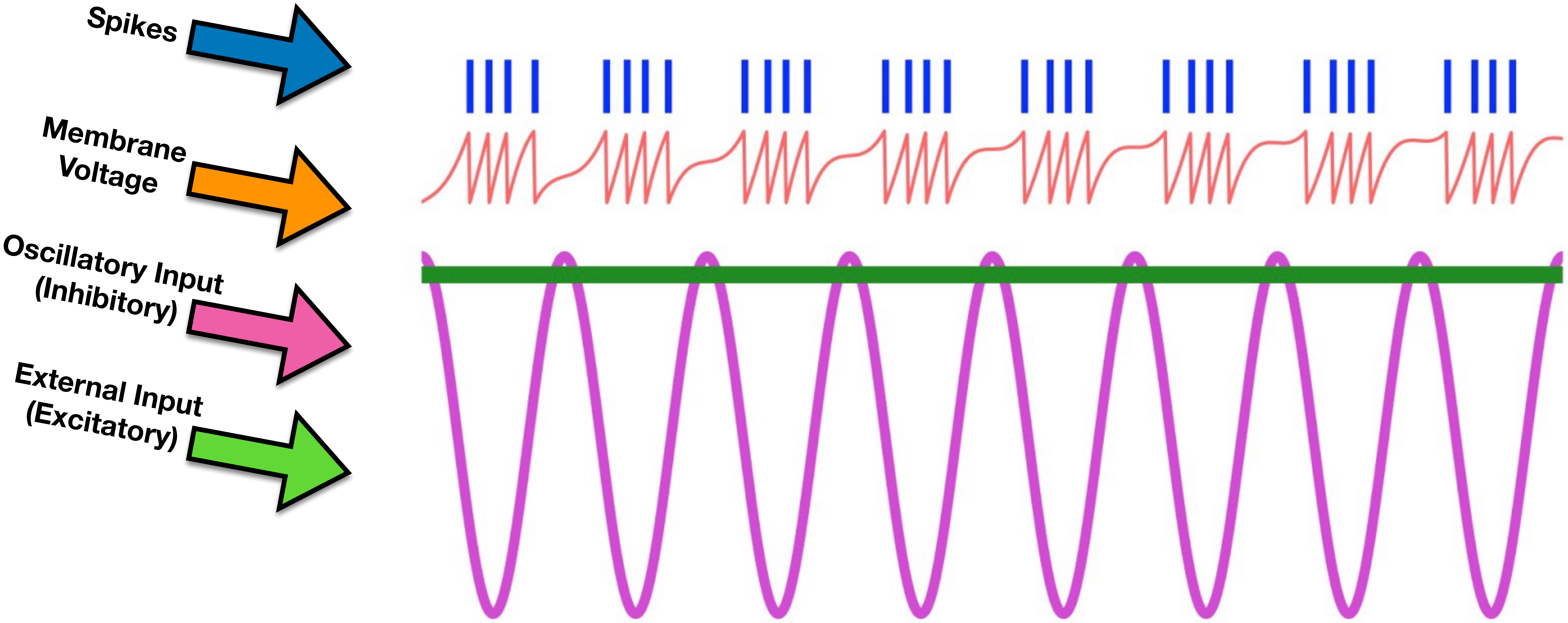

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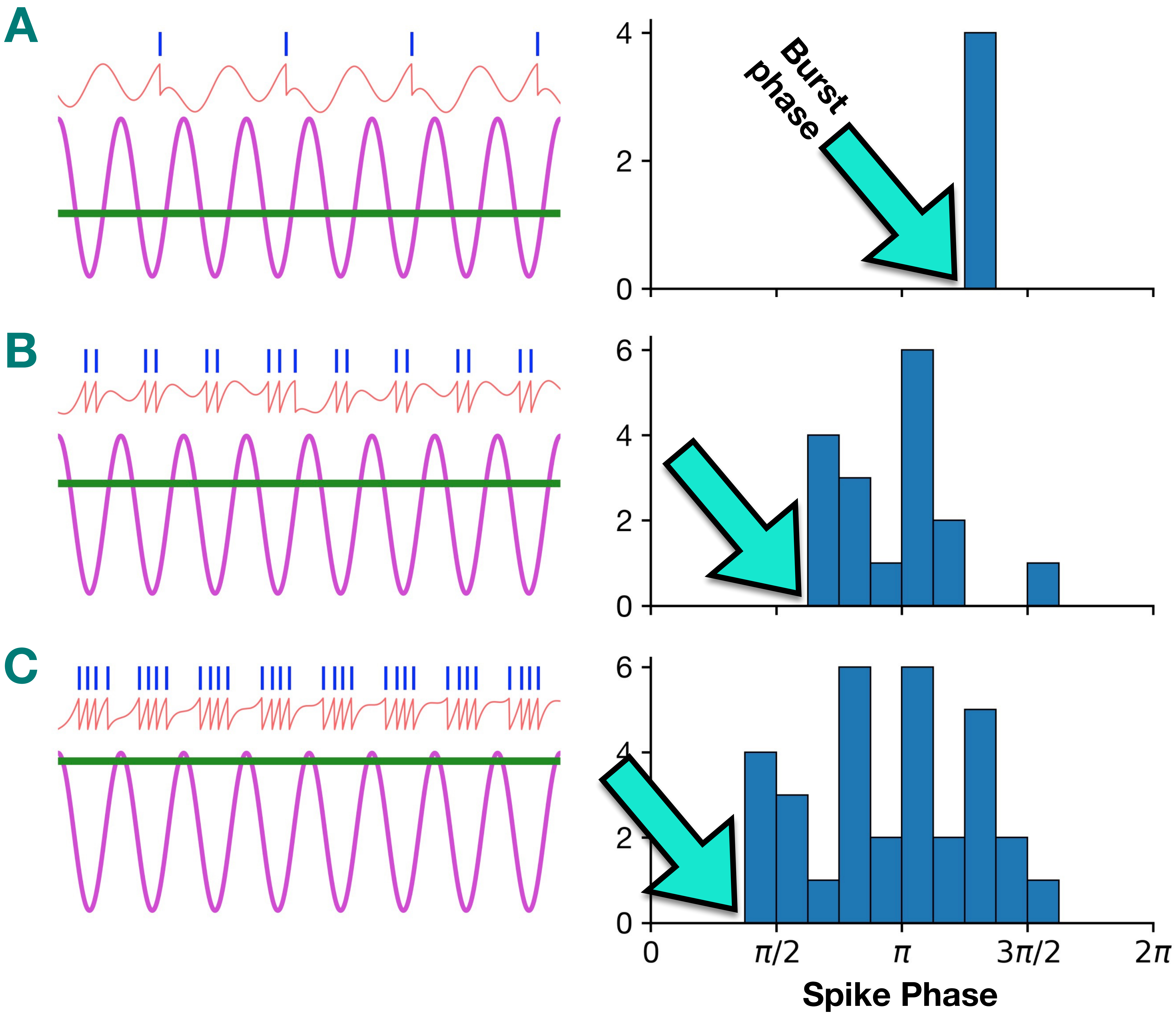
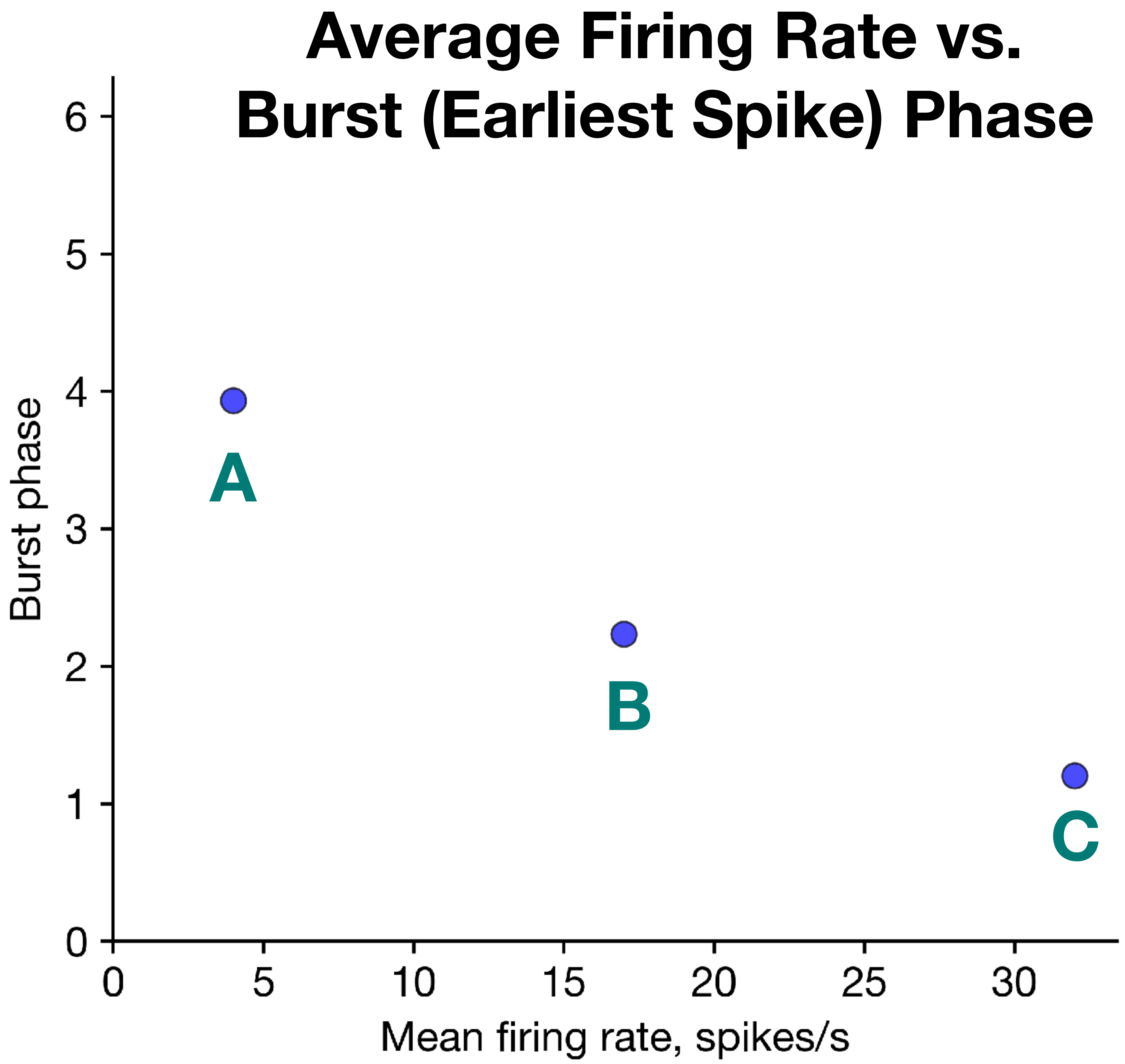
How to Make a Negative Rate-Phase Correlation





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Navigation Between Waypoints: The Problem of Path Integration

- Path integration — A computation of spatial position and orientation from internal heading & velocity signals (e.g., vestibular, proprioceptive, optic flow)
  - Complementary to absolute orientation according to landmarks
- Self-motion is integrated over time, but so are errors: thus, path integration must be corrected, or reset, to the absolute frame of reference

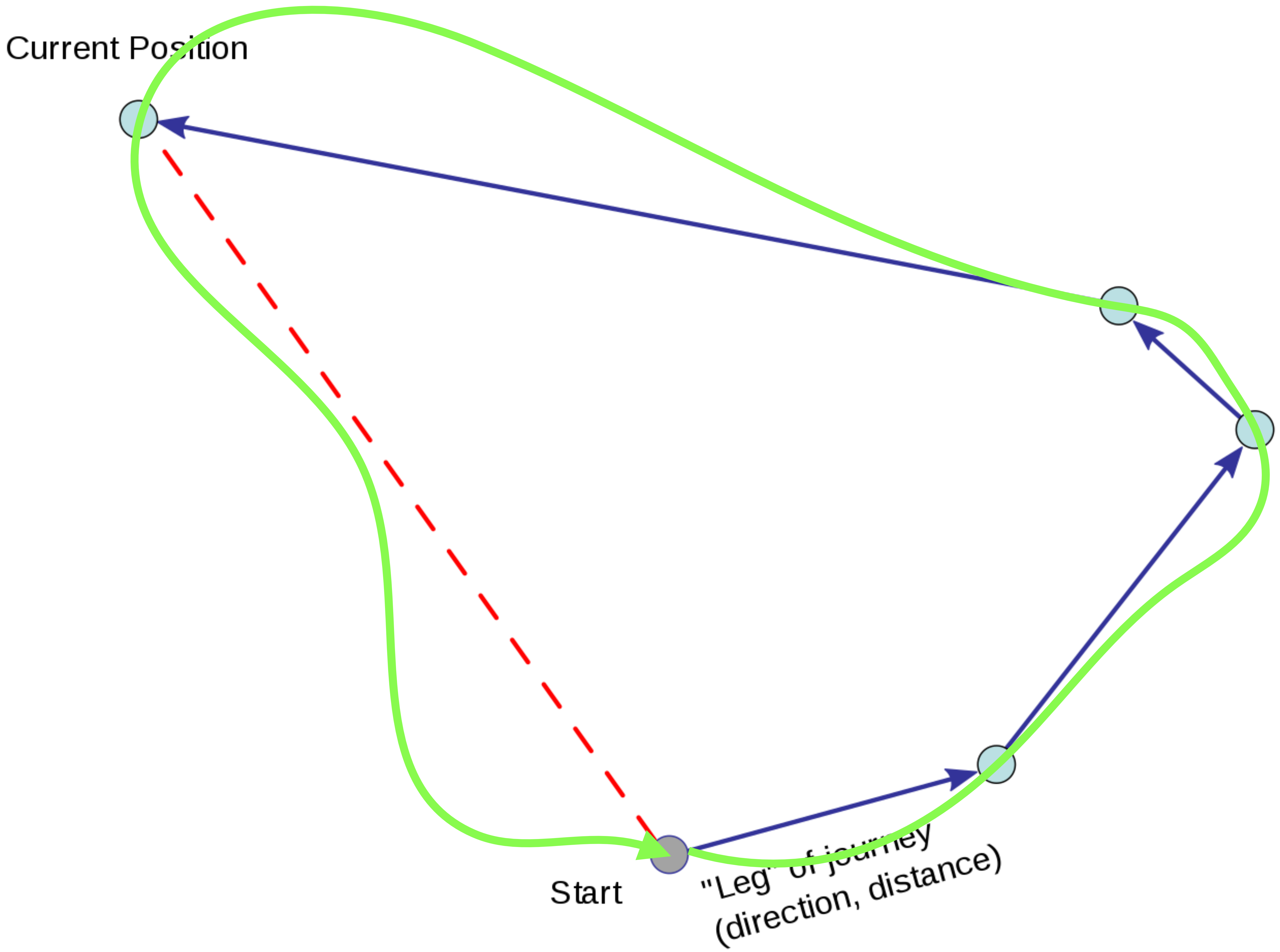
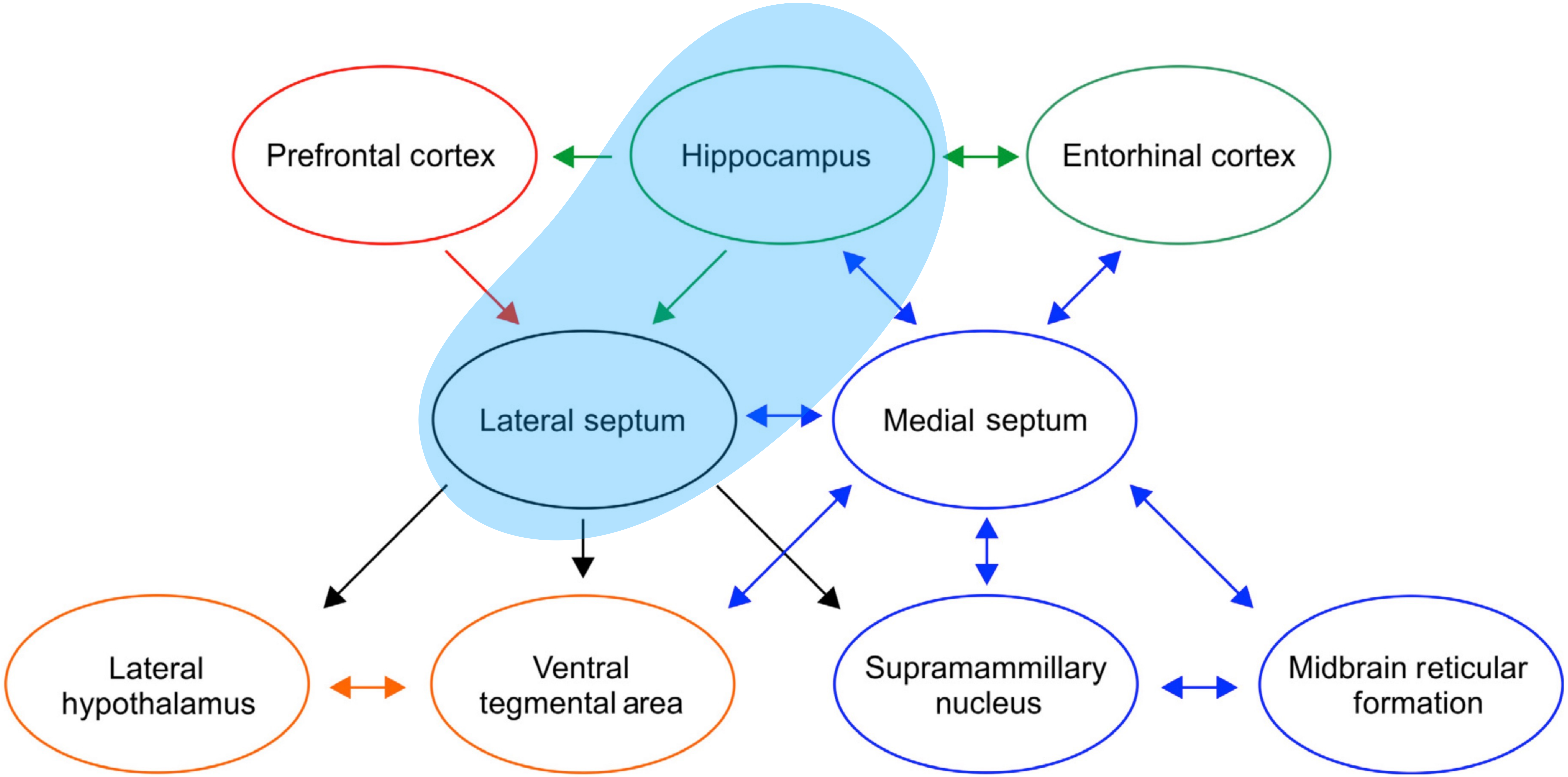


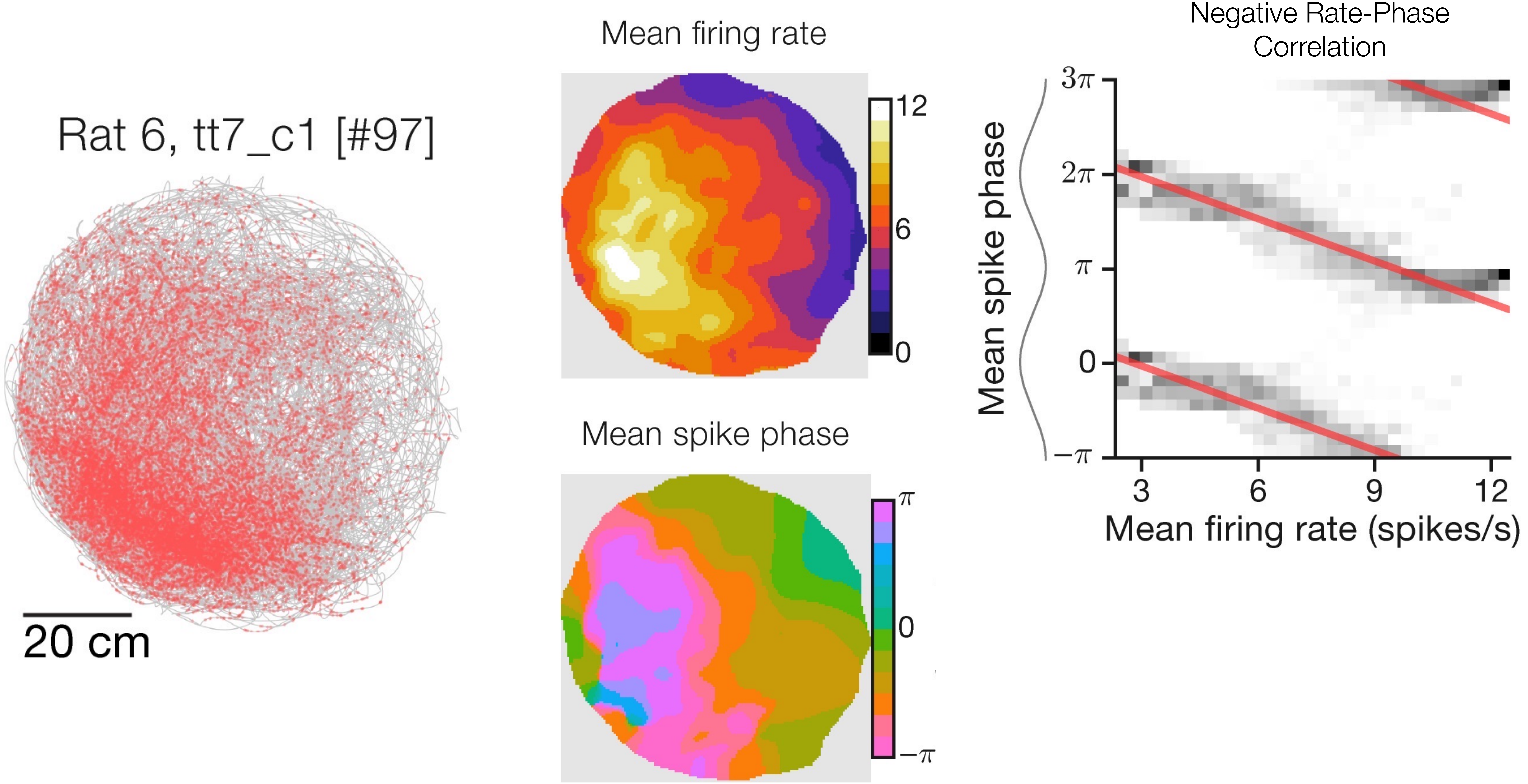
Image Credit: WikiMedia Commons

Subcortical Data from Theta-Rhythmic Brain Areas



Limbic system diagram: Tsanov M. (2017). Eur J Neurosci, 48: 2783

Discovery of Lateral Septal ‘Phaser Cells’



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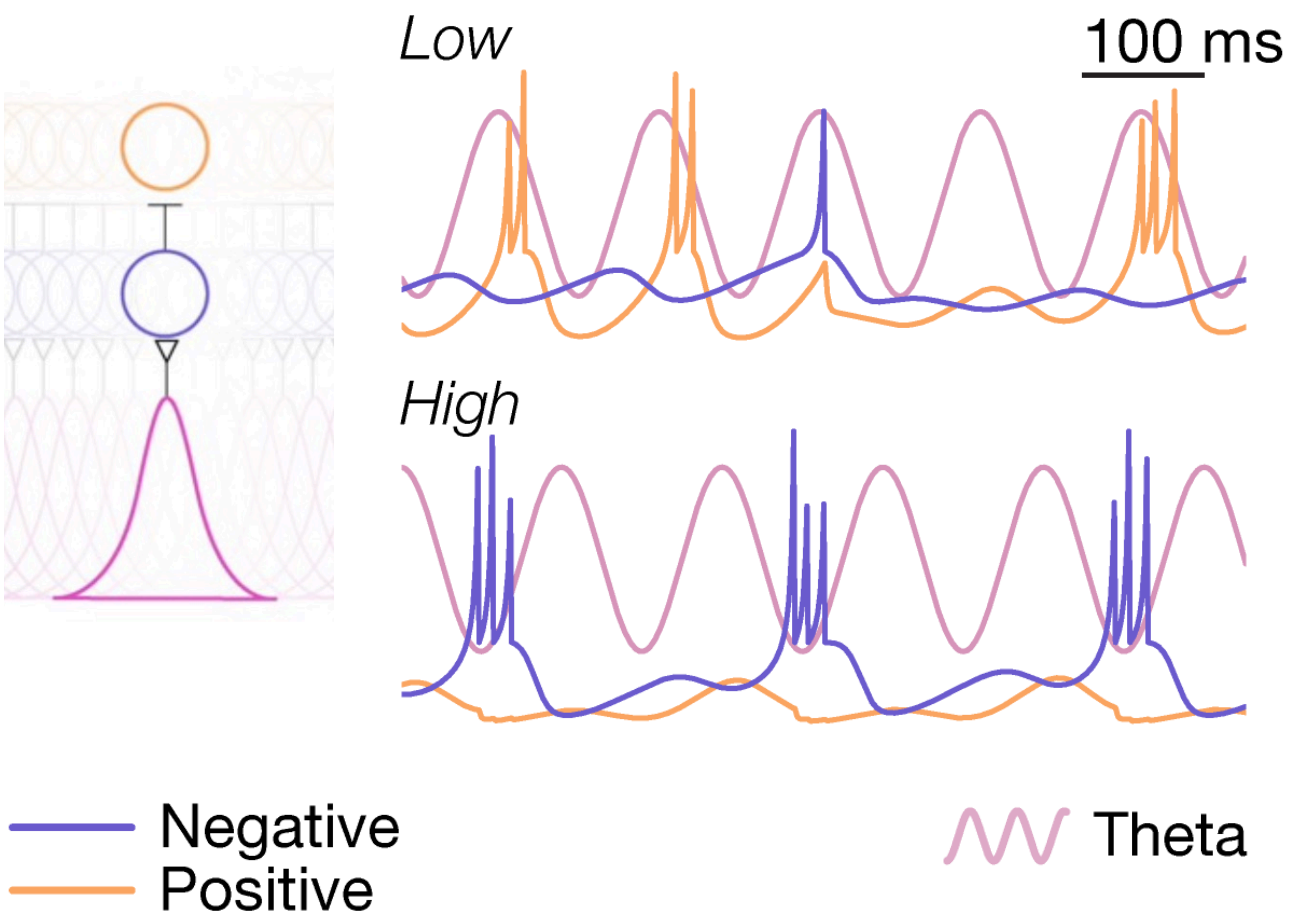
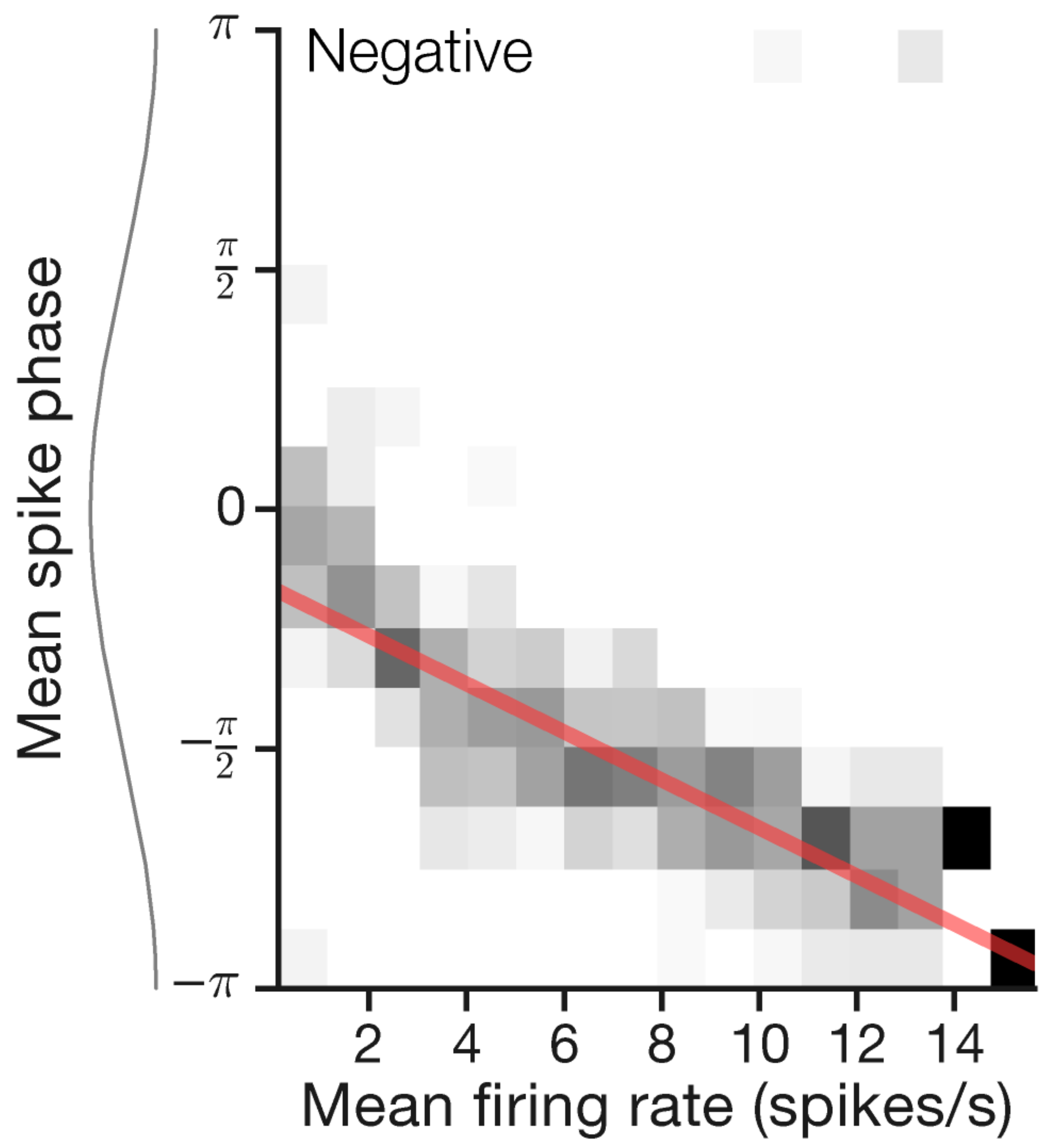
Dynamical Data-Driven Phaser Cell Models

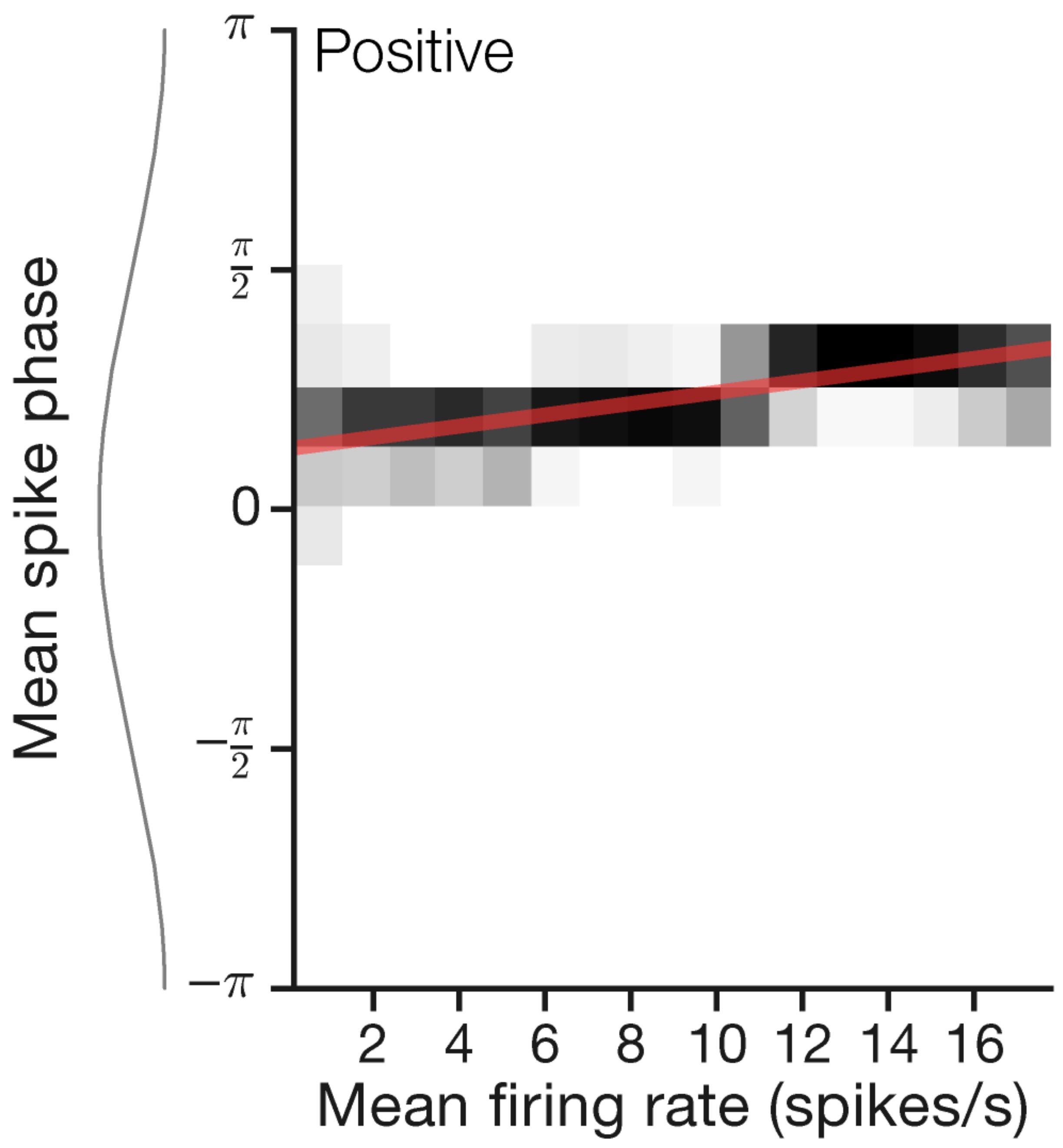
Bursting neuron models with spatial input and feedforward inhibition



Negative Phaser Cell Model

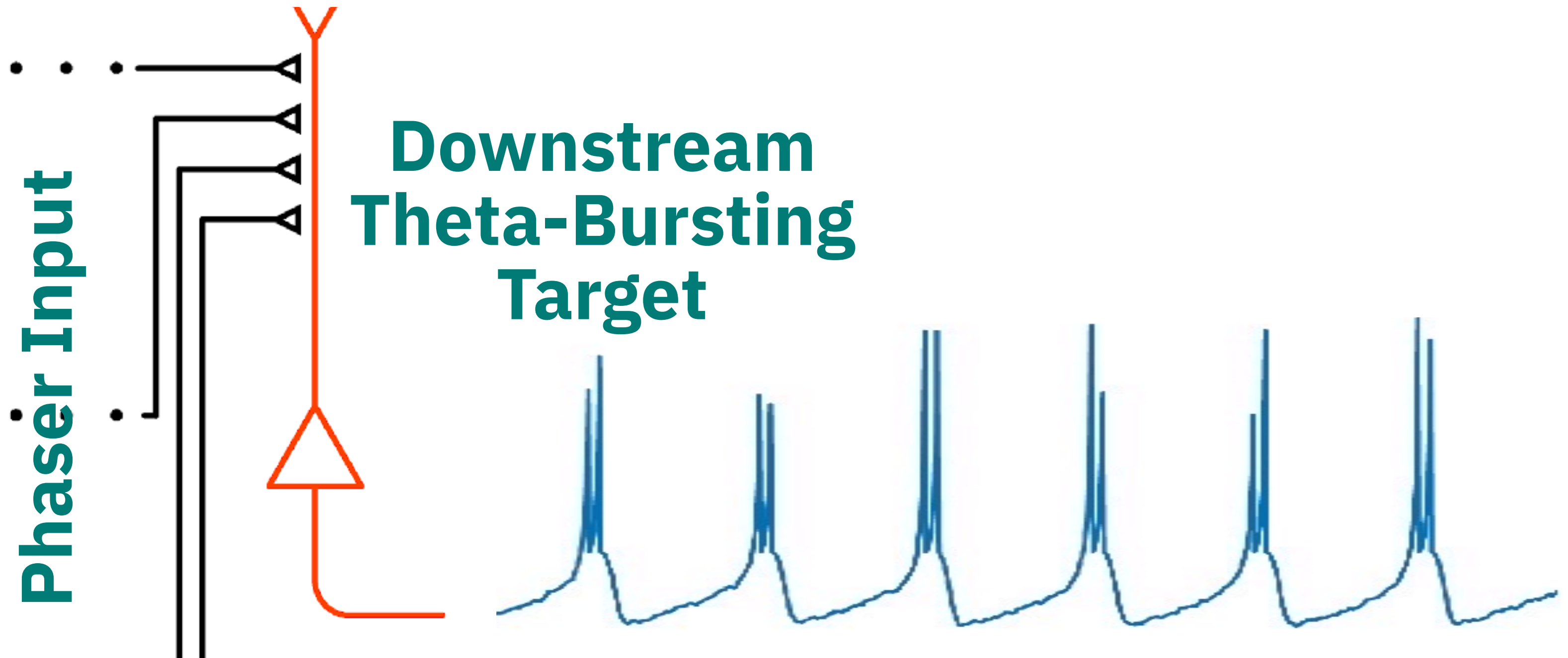


Positive Phaser Cell Model



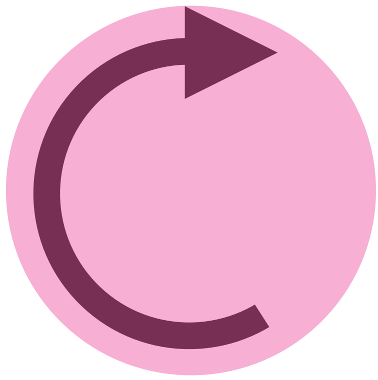
Monaco, *et al*. (2019) PLOS Computational Biology, 15: e1006741

Downstream Functional Decoding of Model Phaser Cells

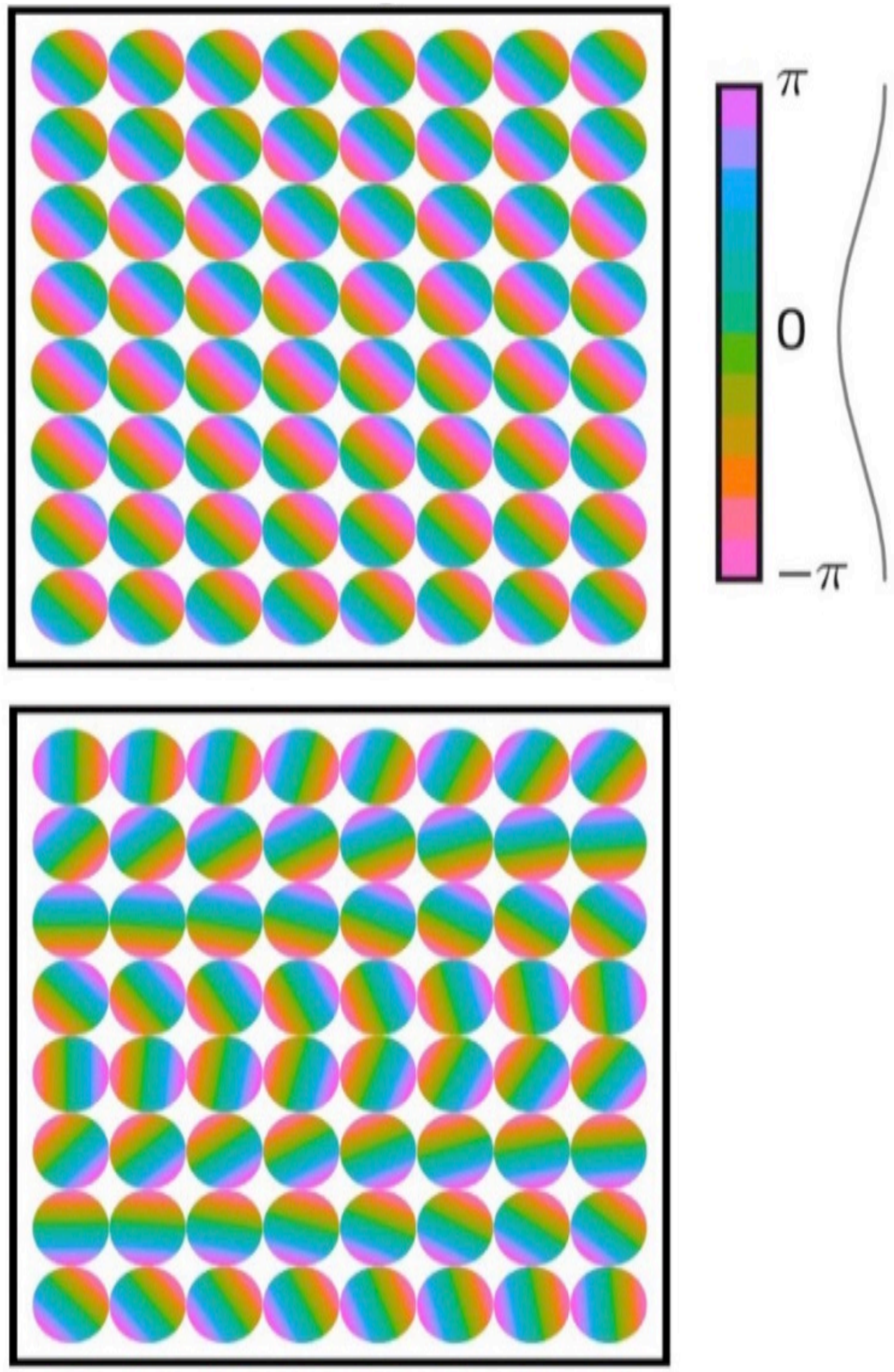


Same preferred direction, Different spatial offsets

Different preferred directions, Same spatial offset

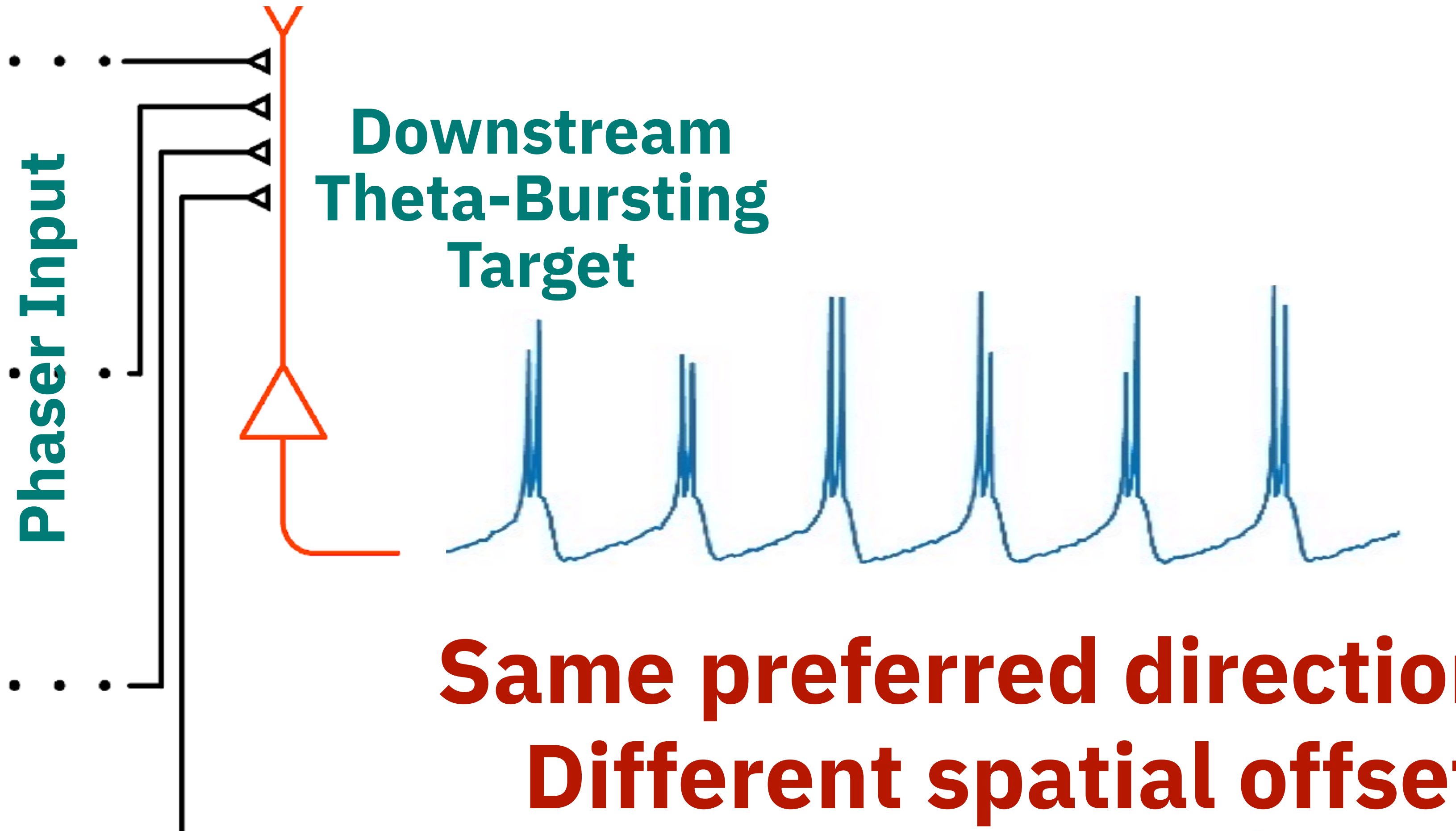


Spatial Phase Patterns Learned by 64 Target Neurons



Monaco, *et al*. (2019) PLOS Computational Biology, 15: e1006741

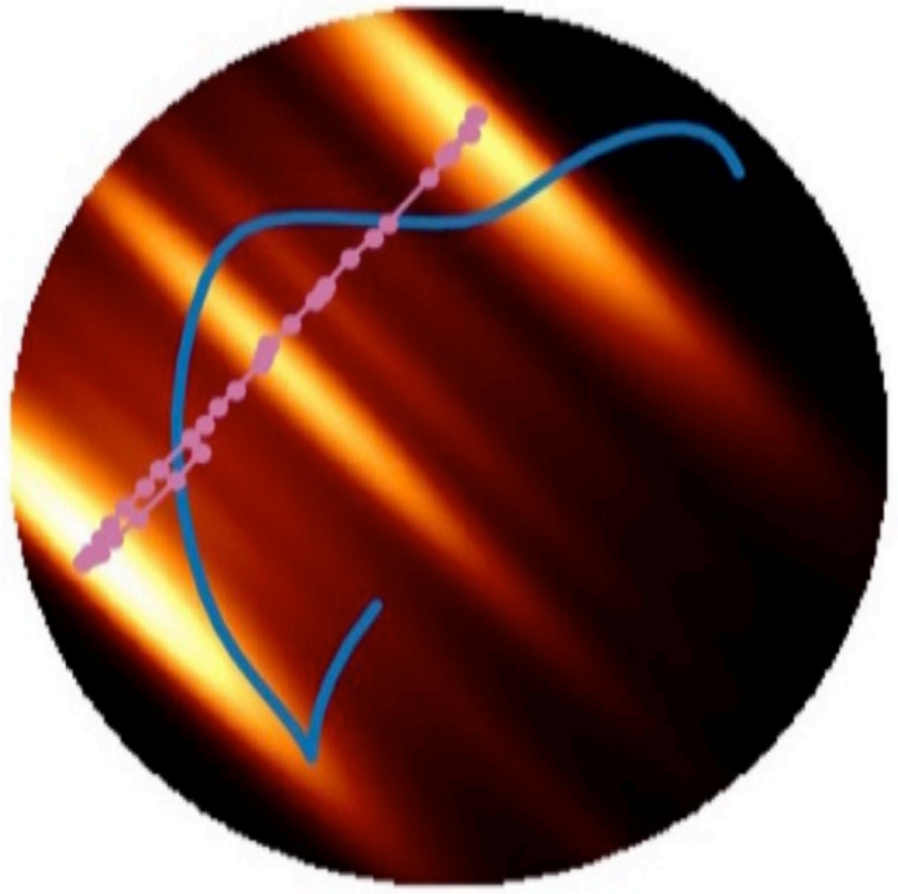
Downstream Functional Decoding of Model Phaser Cells



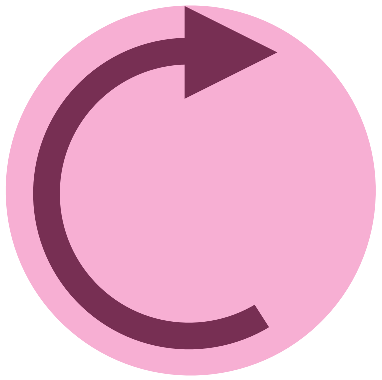
Same preferred direction,
Different spatial offsets

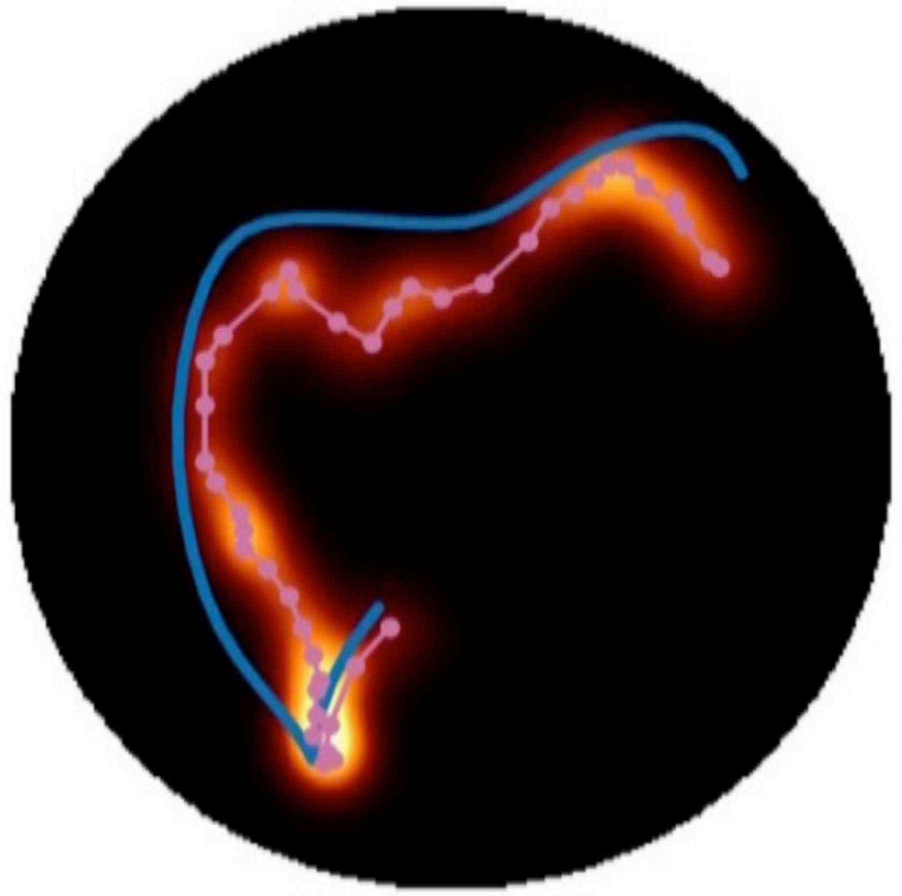
Spatial Phase Patterns Learned by 64 Target Neurons

Phase Decoding of Target Population for Sample Trajectory



Different preferred directions,
Same spatial offset

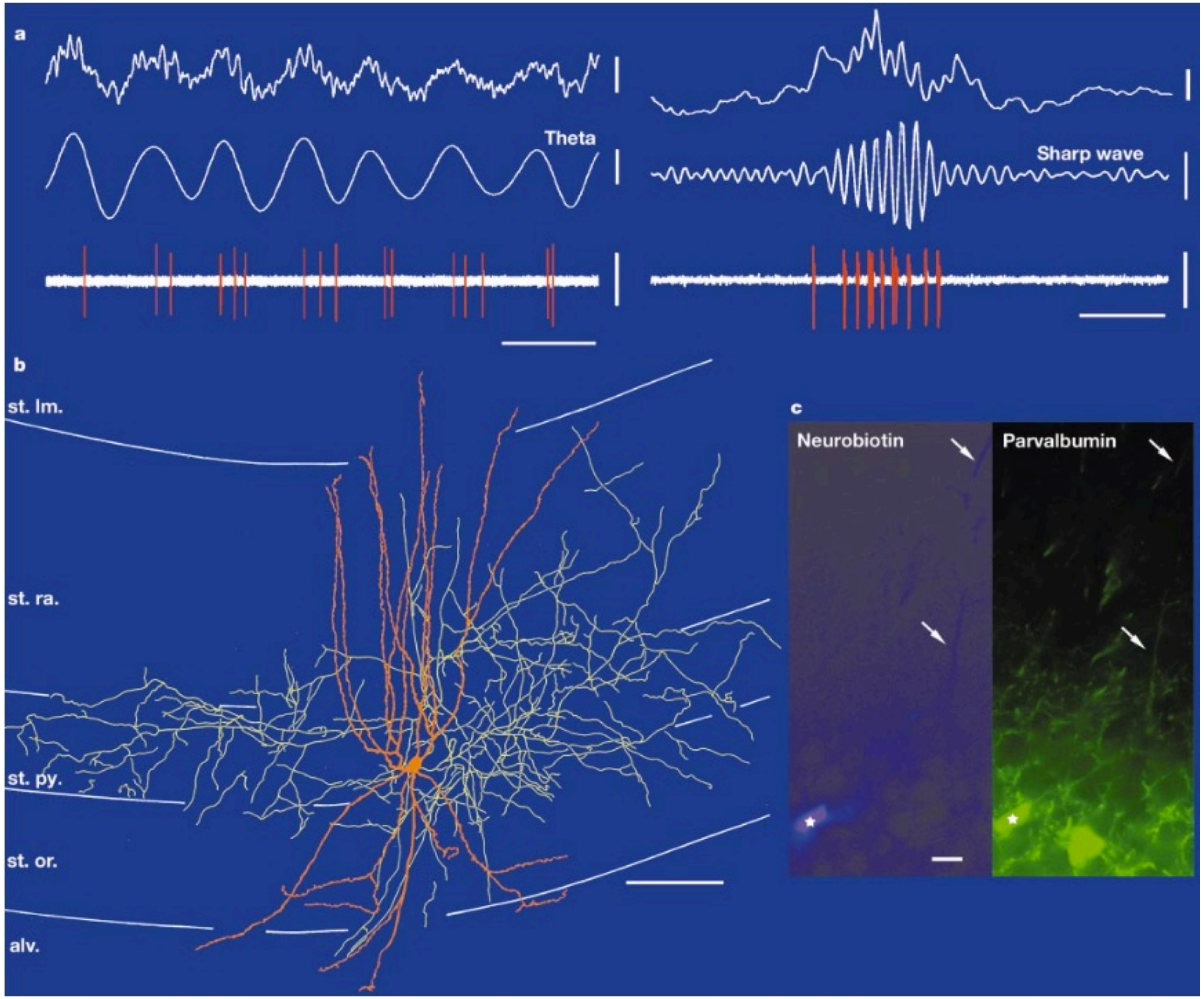




Monaco, *et al*. (2019) PLOS Computational Biology, 15: e1006741

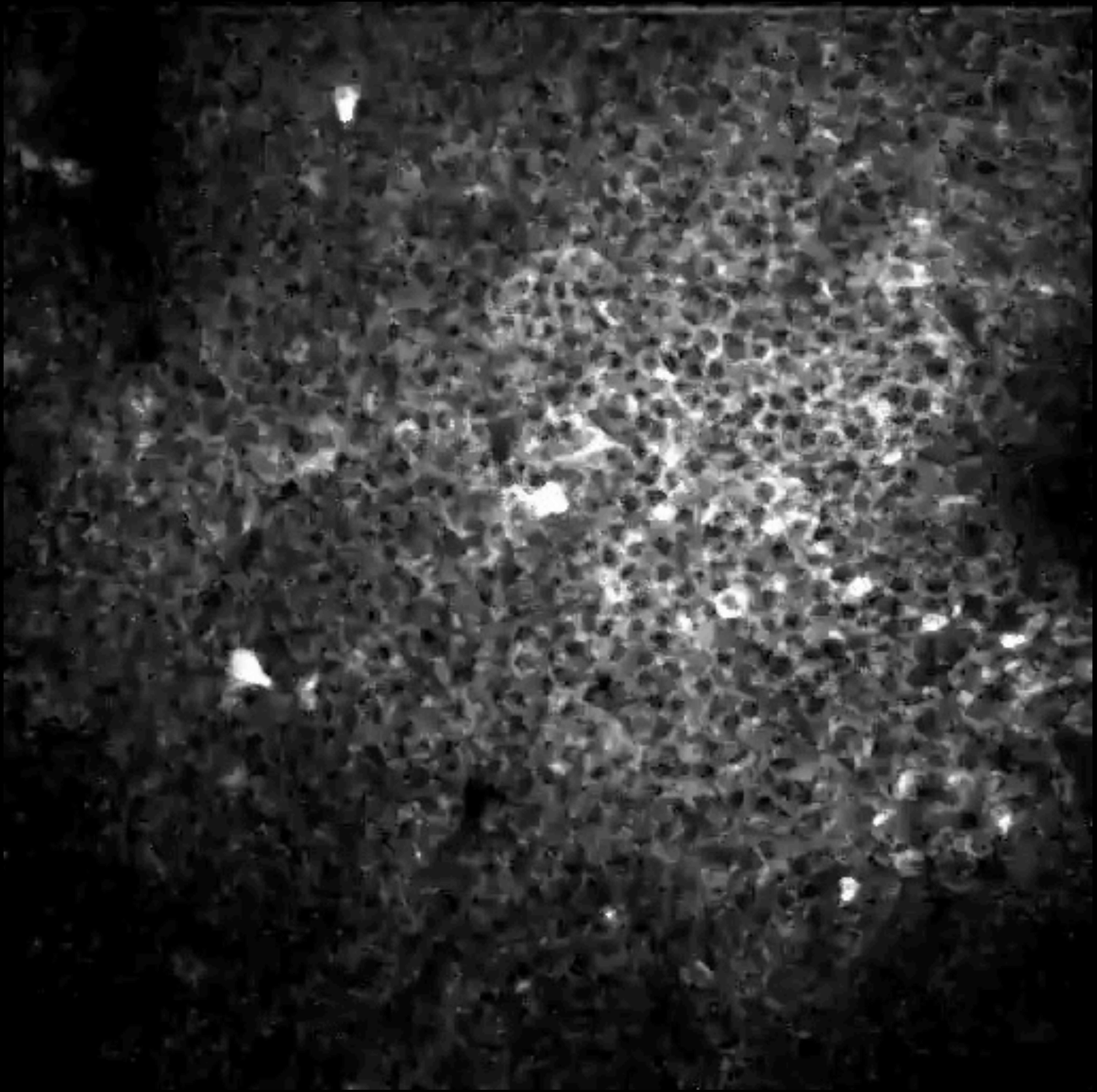
From theta to fast “ripple” transient oscillations

- **In vivo recordings of parvalbumin-positive basket cells, with perisomal innervation of pyramidal neurons (i.e., place cells)**



Klausberger et al. (2003)

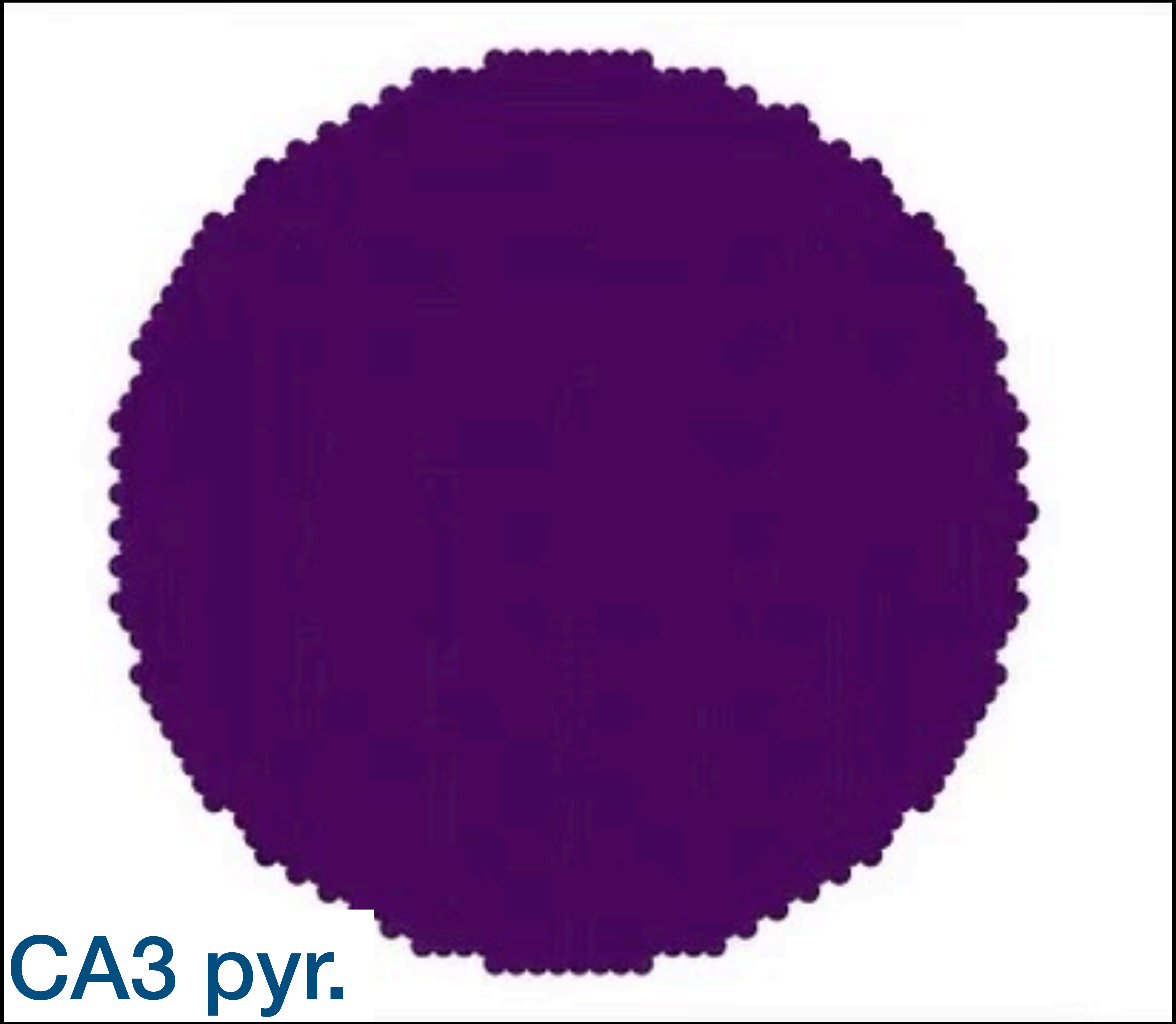
Hippocampal In Vivo 2P Calcium Imaging



500x500 μm f.o.v. over mouse CA1 of synapsin-driven GCaMP6f during training in an olfactory working-memory task.

Video Credit: J. Taxidis

Hippocampal
In Silico
Model

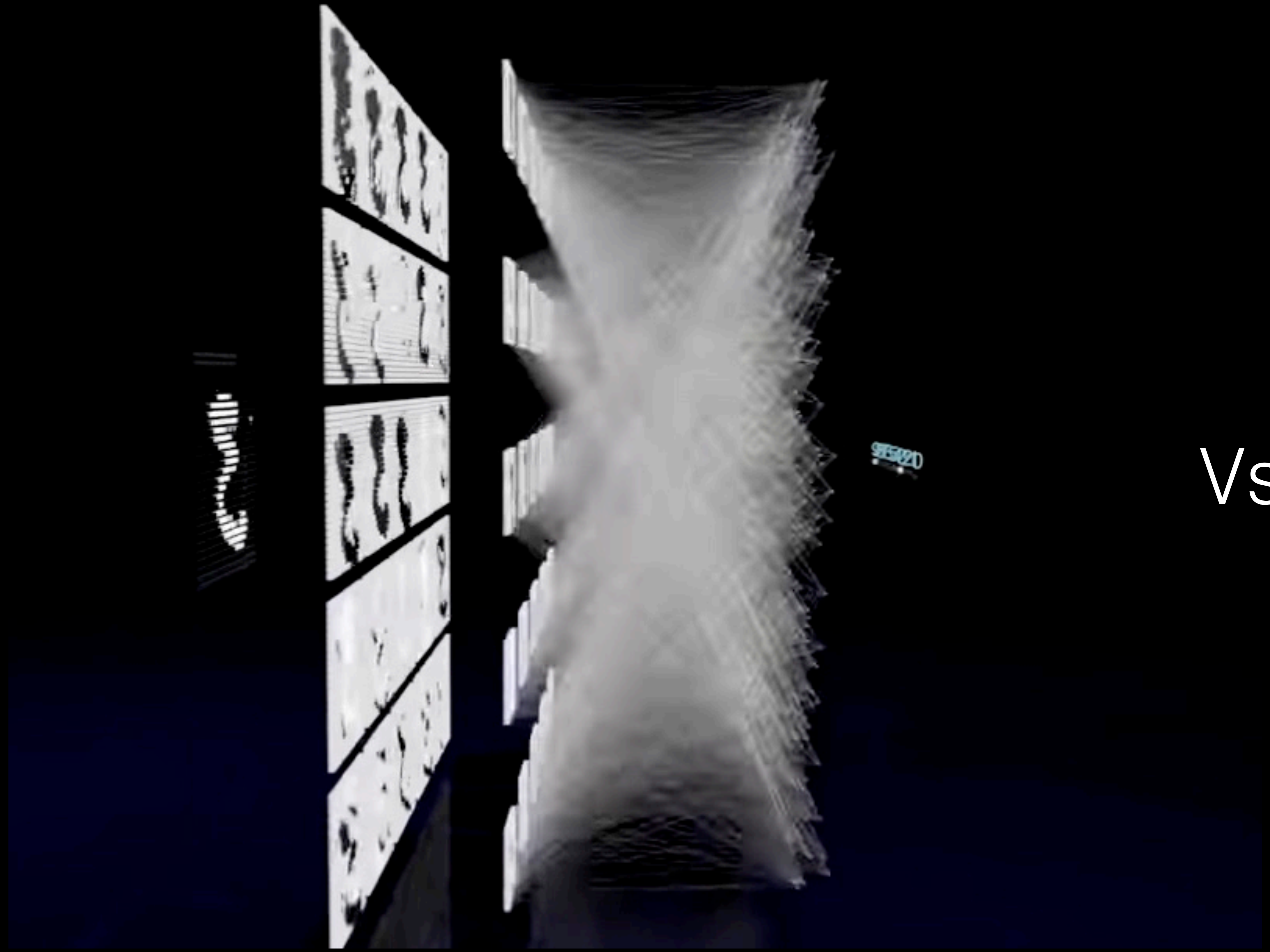


Detailed CA3 Microcircuit Model

Synchronous Sharp Waves and Fast Gamma Oscillations

(NIH) Monaco & Zhang

Convolutional Network (MNIST, Backprop)

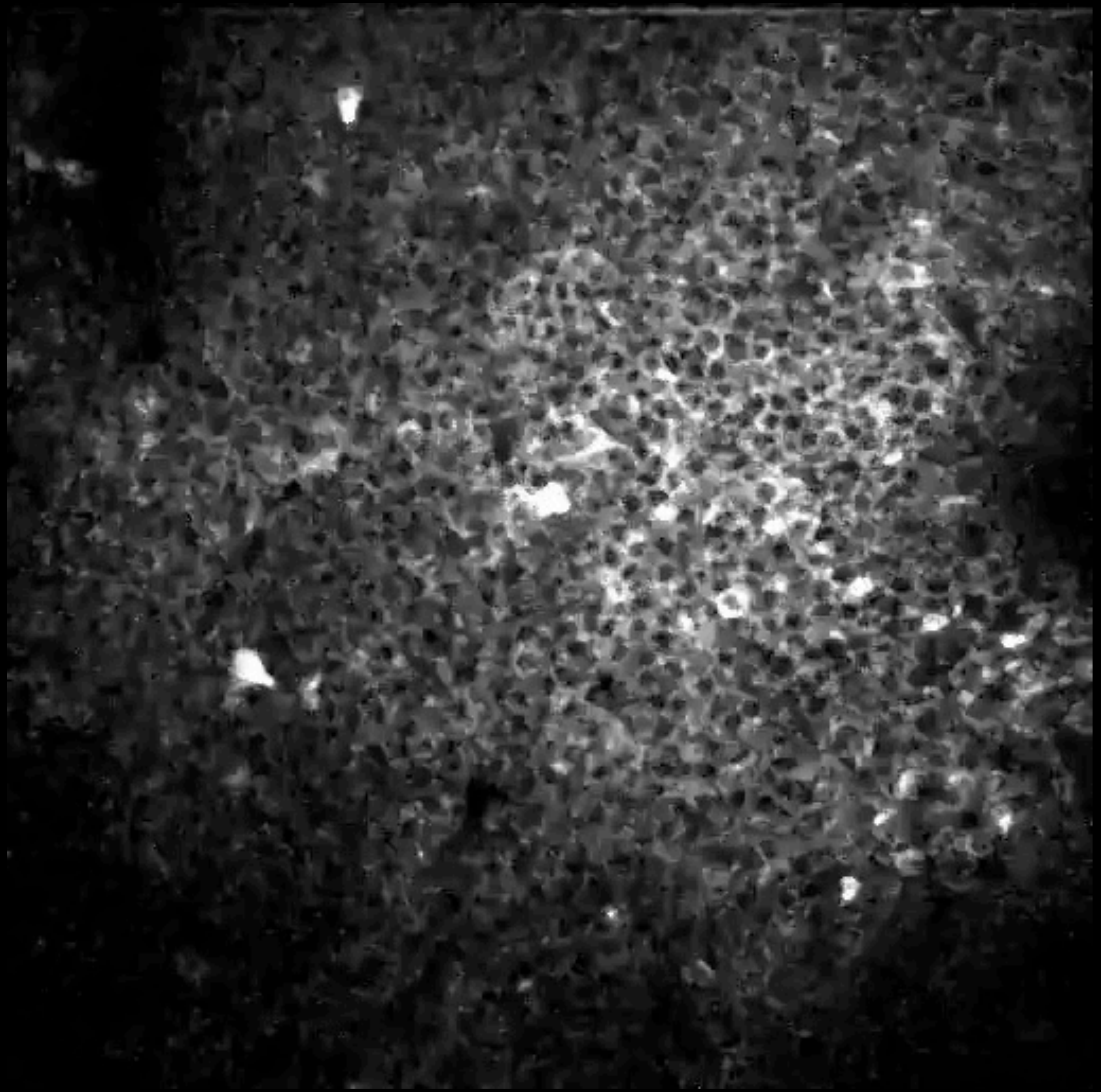


19,794 hidden neurons, 3.61M synapses (2% shown)

Credit: Dennis Dmitriev.
youtube.com/watch?v=3JQ3hYko51Y

Vs.

Mouse CA1 Hippocampus (Olfactory Task Learning)



500x500 μm f.o.v. over mouse CA1 of synapsin-driven GCaMP6f during training in an olfactory working-memory task

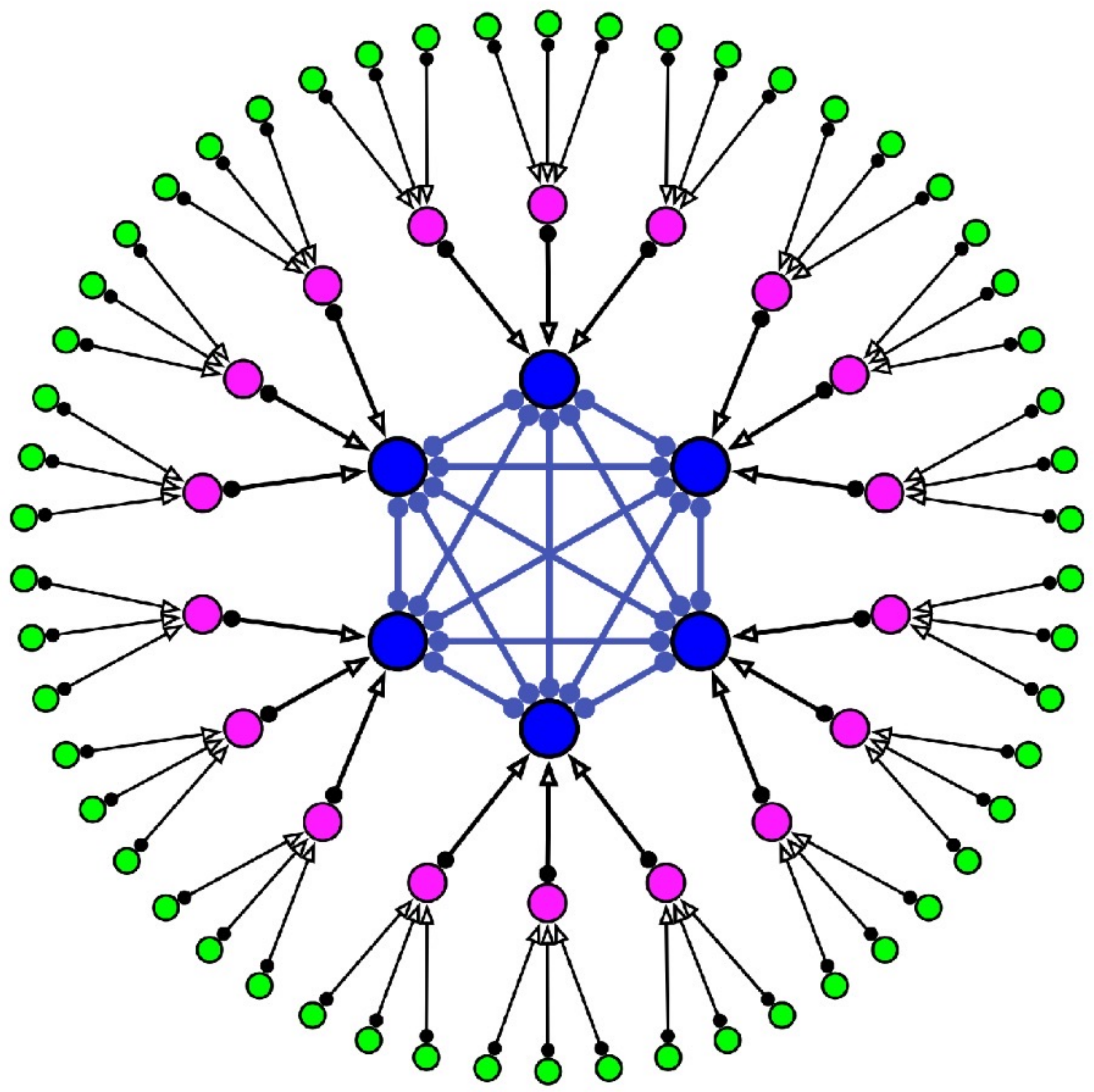
Credit: Jiannis Taxidis. **doi: 10.1101/474510**
twitter.com/JiannisTax/status/1216922110150373376

Modern AI Models vs. Biological Learning

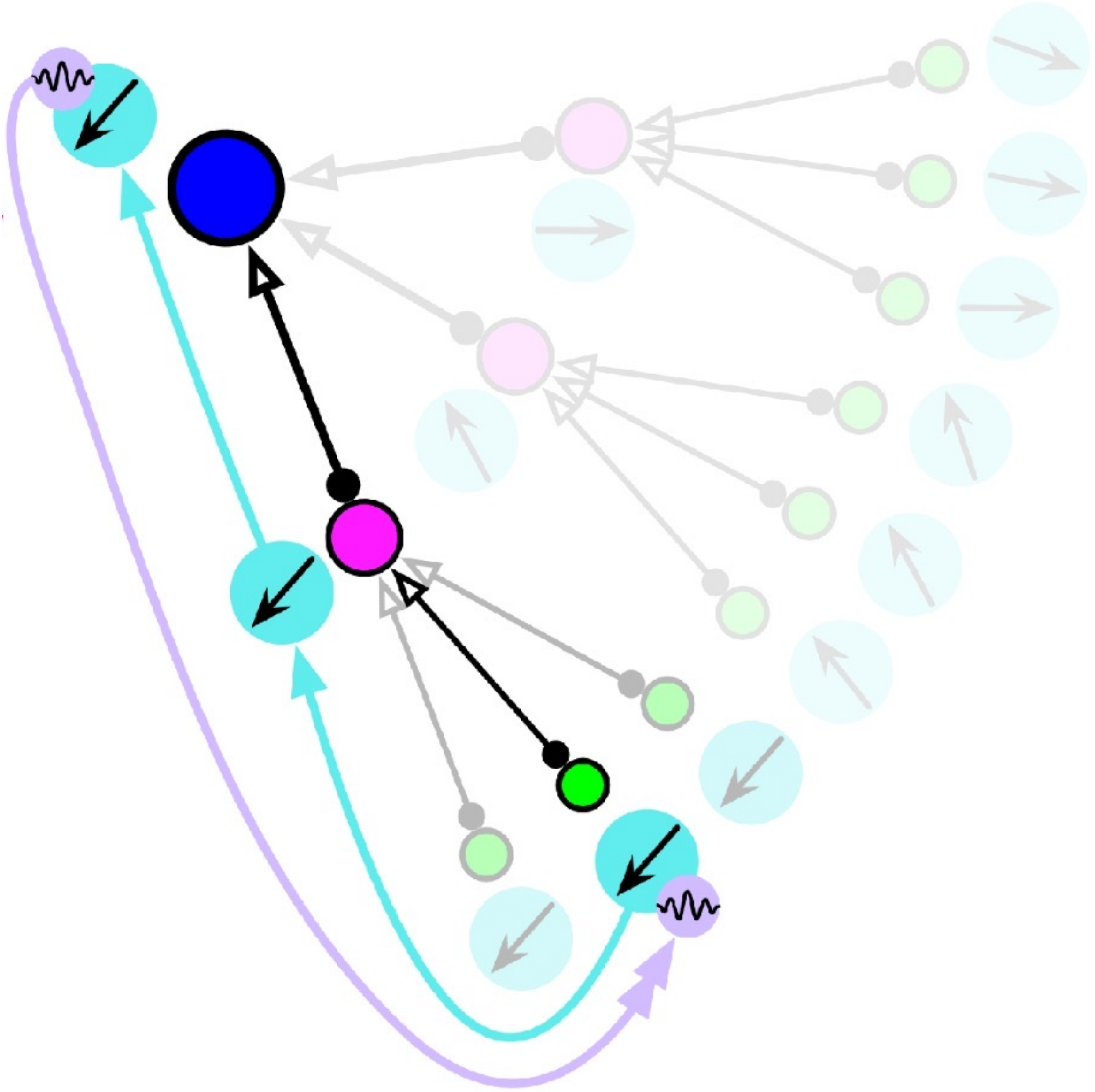
	Artificial Neural Networks	Animals & Brains
	Train/test splits, validation, convergence	Continual learning through experience
	Backpropagation is exact and *highly successful*	Global credit assignment unclear
	Massive (N >> p) single-domain datasets	Finite multimodal samples across the lifespan
	Noise helps! (E.g., dropout, float precision)	Noise vs. variability? (E.g., “spontaneous” activity)
(1)	Dense activation over forward passes	Sparse activation over hierarchies
	Singular goals, infinite time horizon	Many conflicting goals, overlapping timescales
(2)	Limited time dependence	Oscillations, synchrony, STDP, eligibility traces, etc.
	Recurrence out of favor (use transformers)	Recurrence and feedback dominate
	Global objective function	Local, modular processing
	Transfer learning nontrivial; o.o.d. samples bad	Zero/one/few-shot generalization is typical
	Input stimulus-driven operation	Continuous internal operation
(3)	Models require external interpreter (*tool*)	Brains construct their own meaning (*agent*)

Neurodynamical Computing: Selection and Interaction

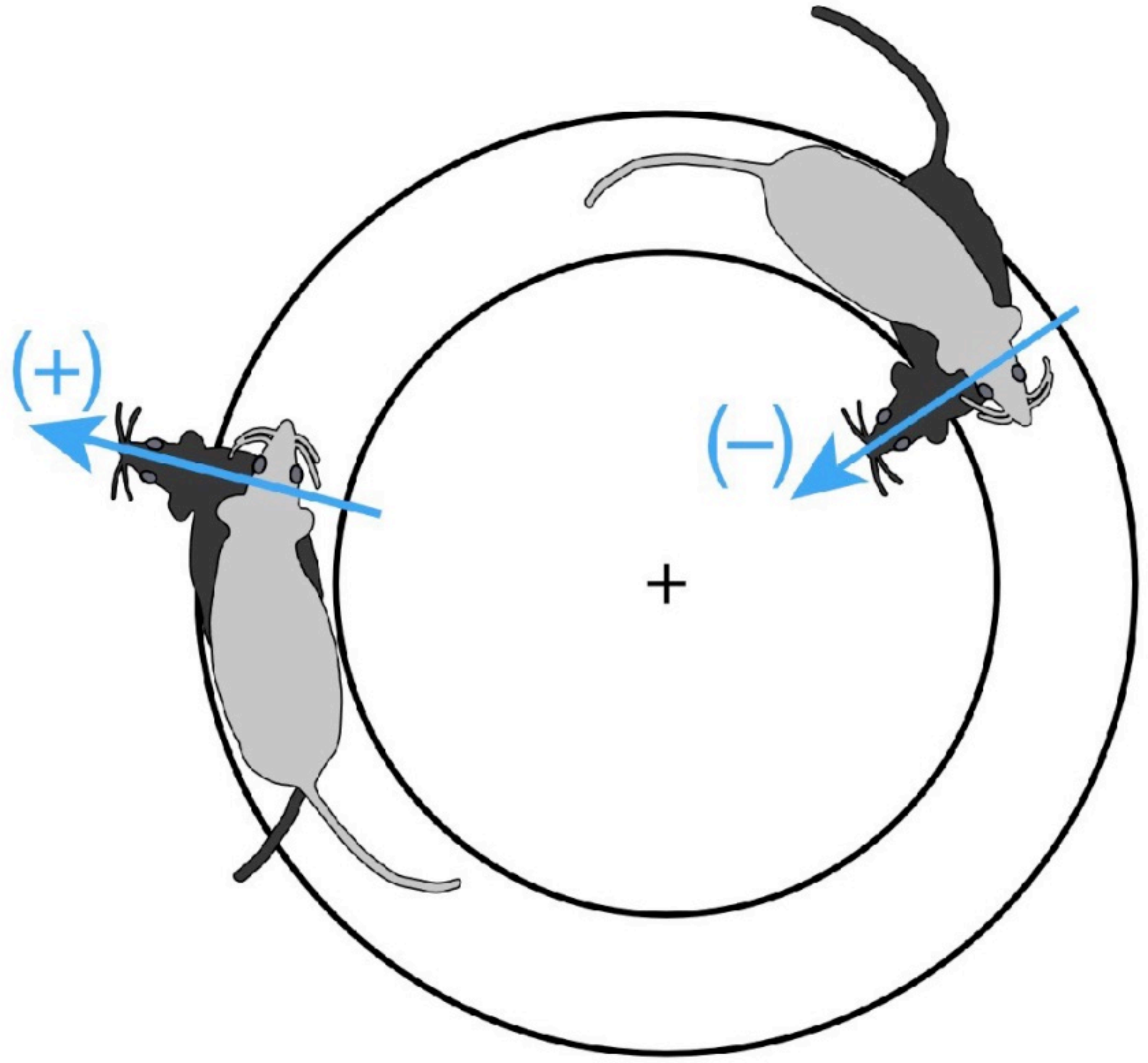
(1) Structural heterarchy



(2) Oscillatory coupling



(3) Agential interaction

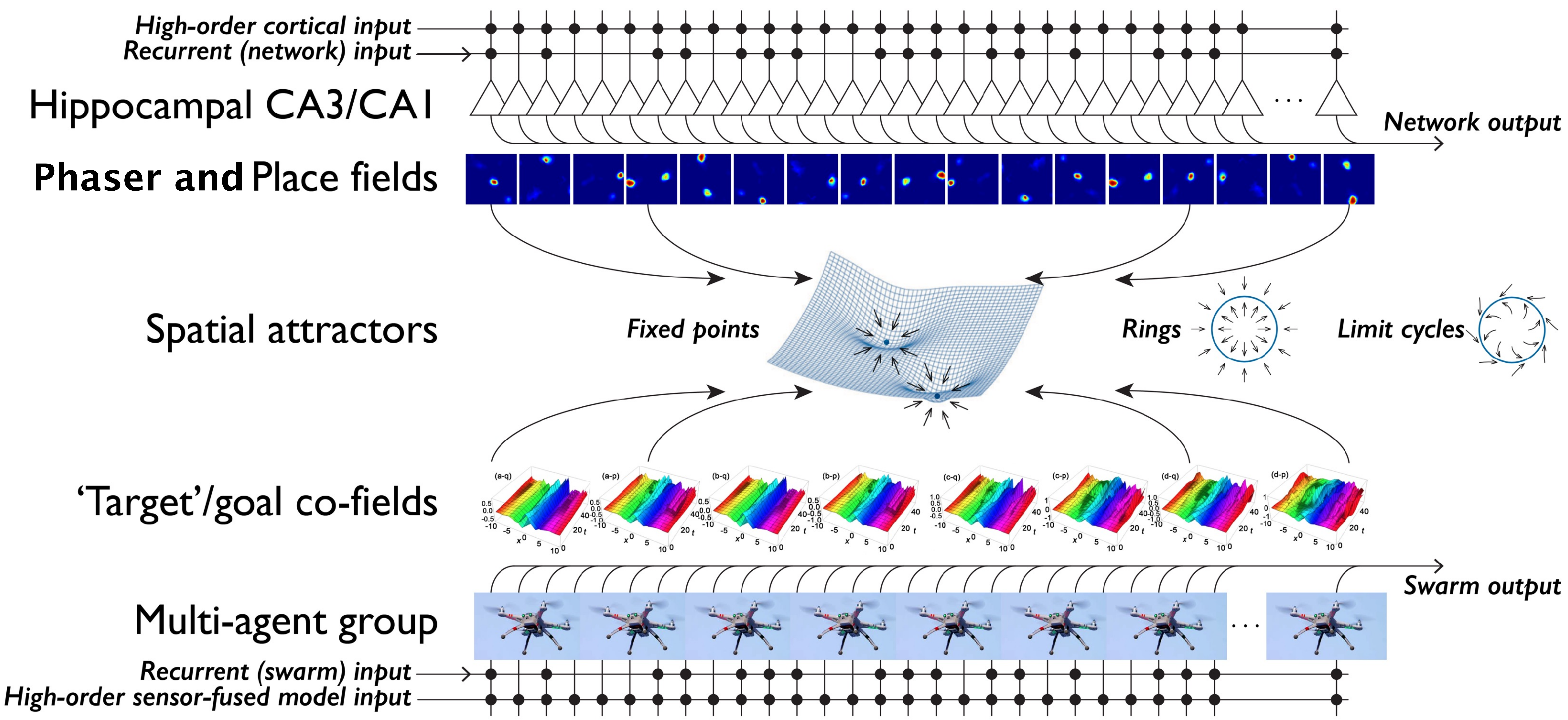


What kinds of models are needed to advance this framework for cognitive flexibility?

Monaco, Rajan, and Hwang (2021) ArXiv Preprint. arxiv:2105.07284


A murmuration of starlings

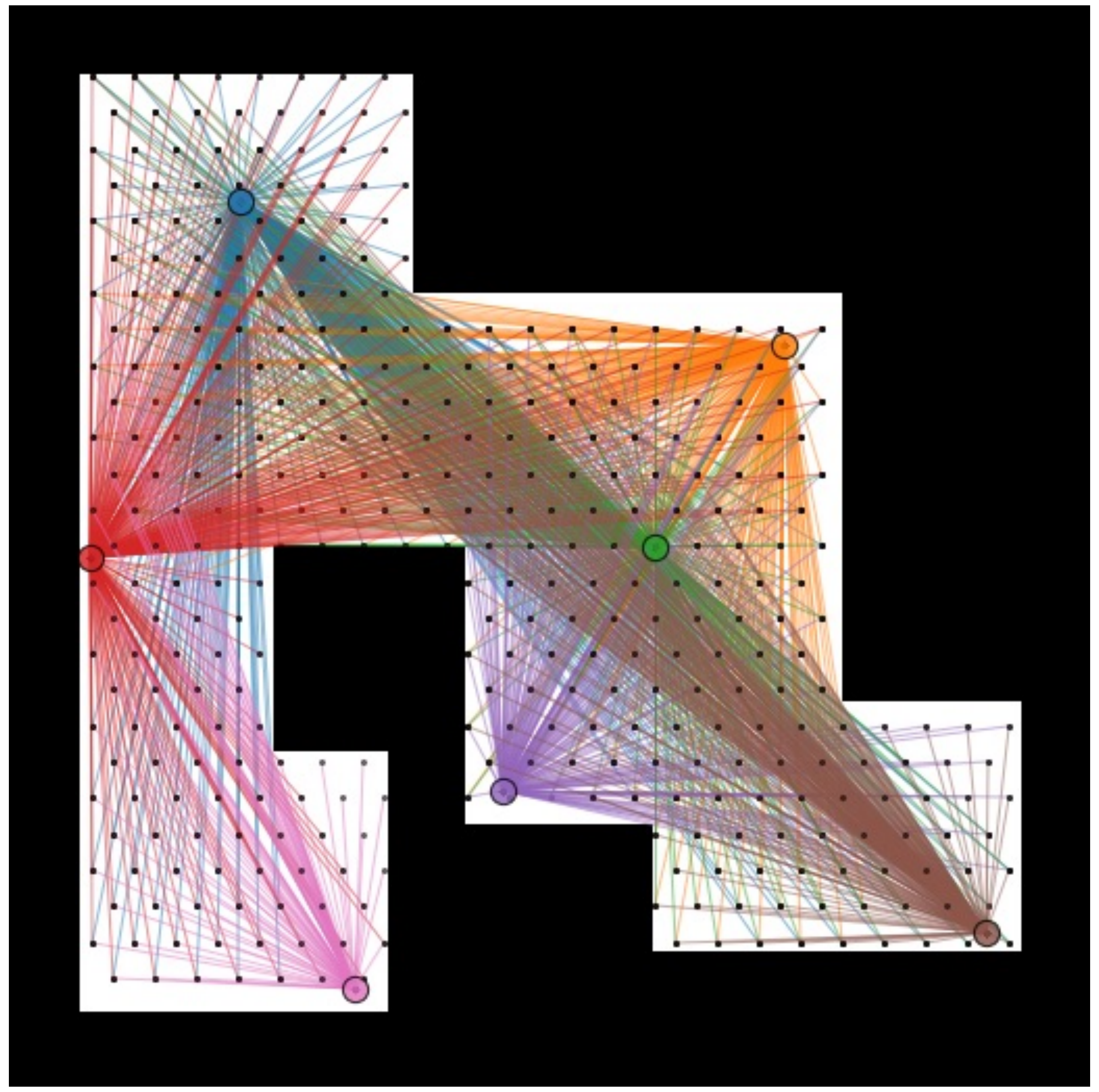
NeuroSwarms: Control by Phase-Organized Attractors



Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics. doi: 10.1007/s00422-020-00823-z

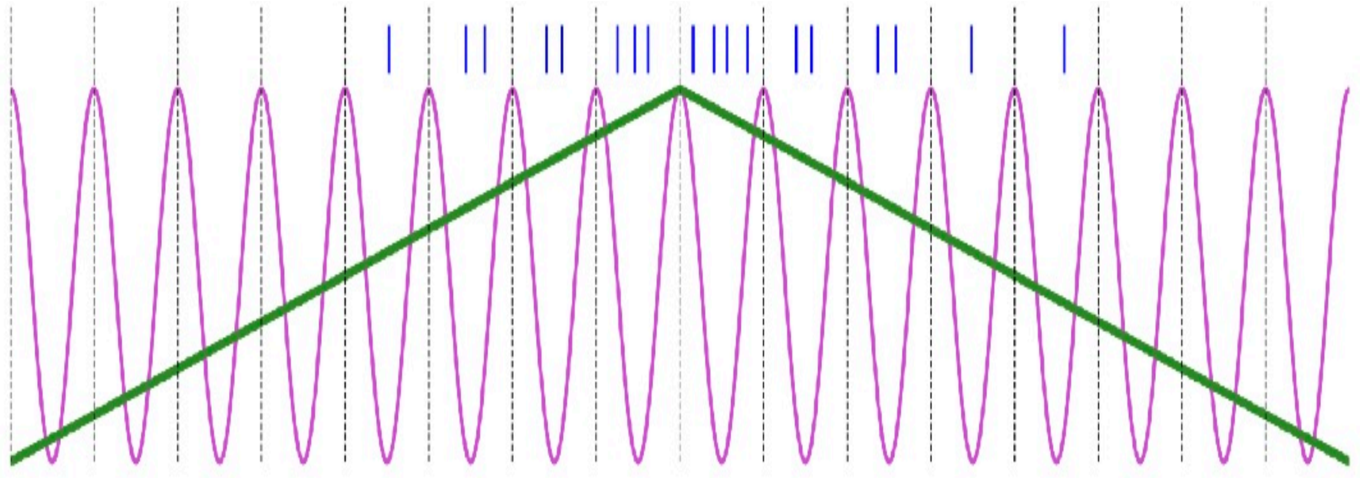
NeuroSwarms: Control by Phase-Organized Attractors

(1) Structural heterarchy



Inherit from spatial geometry

(2) Dynamical selection

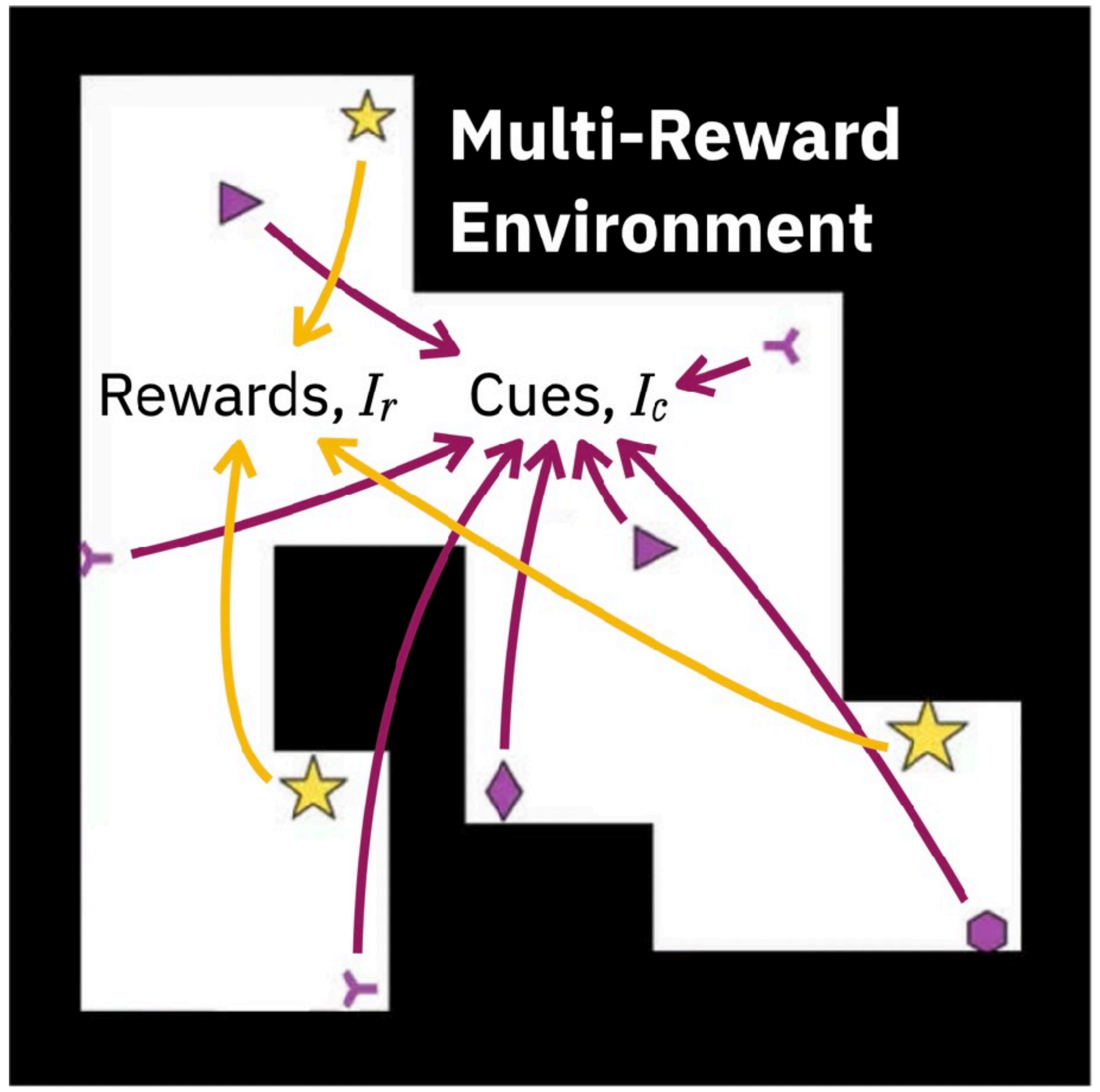


$$\tau_q \dot{q}_{ij} = V_{ij} \cos(\theta_j - \theta_i) - q_{ij}$$

Phase-Coupling Term

Spatial phase coding with interagent coupling

(3) Agential interaction



Visible cue input and reward approach

Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics. doi: 10.1007/s00422-020-00823-z

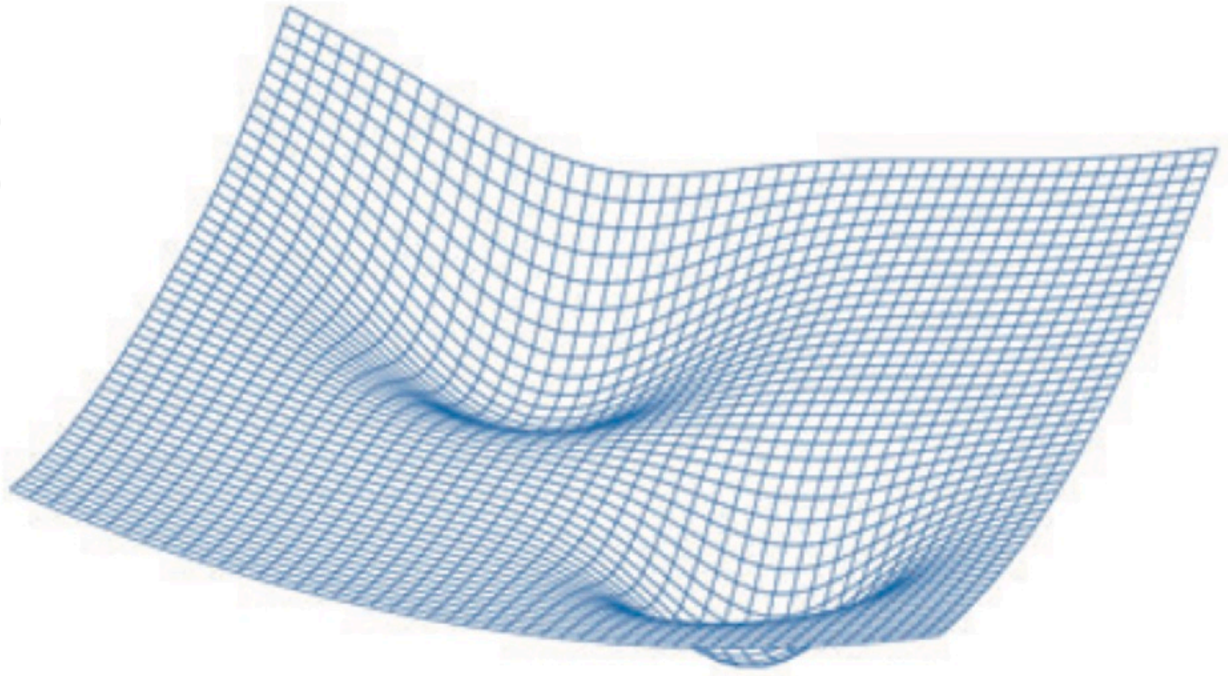
Multi-Agent Swarming as Learning & Memory

$$W_{ij} = V_{ij} \exp(-D_{ij}^2/\sigma^2) , \quad (3)$$

Distance kernels to create synaptic weights

A Gaussian kernel for distance constructs a spatial attractor map in the connections

$$W_{ik}^r = V_{ik}^r \exp(-D_{ik}^r/\kappa) ,$$



Knierim & Zhang (2012)

Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

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Multi-Agent Swarming as Learning & Memory

for reward k and integration time-constant τ_r. Unlike sensory cues, all agents respond equally to rewards when visible. We define recurrent inputs $\boldsymbol{q} \in \mathbb{R}^{N_s \times N_s}$,

$$\tau_q \dot{q}_{ij} = V_{ij} \cos(\theta_j - \theta_i) - q_{ij} \, , \tag{7}$$

Phase-Coupling Term

to agent i from agent j with integration ime-constant τ_q and internal tphase $\boldsymbol{\theta}$. We chose to implement the phase-coupling of the recurrent swarming input in (7) as the cosine of phase differences between pairs of agents (cf. O'Keeffe et al., 2017). The cosine provides an even and circularly periodic function of phase similarity for synchrony-driven attraction (via positive

Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

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Multi-Agent Swarming as Learning & Memory

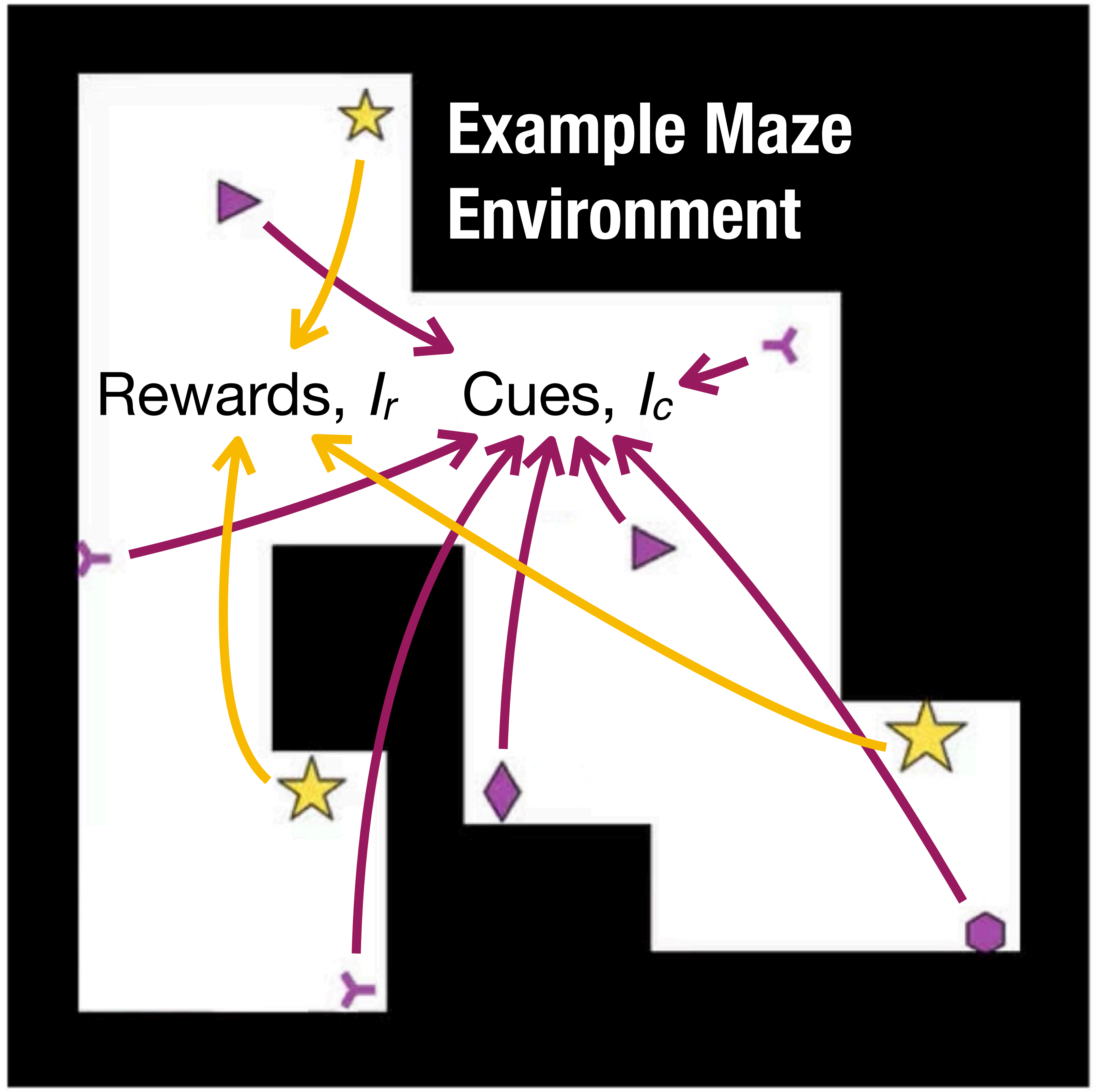
Neural Activation

Total Recurrent Swarming Input

$$\boldsymbol{p} = [I_c + I_r + I_q]_+ \,, \qquad \tau_q \dot{q}_{ij} = V_{ij} \cos(\theta_j - \theta_i) - q_{ij}$$

Phase-Coupling Term

$$\dot{\boldsymbol{\theta}} = \boldsymbol{\omega}_0 + \omega_I \, \boldsymbol{p} \,,$$



Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

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Multi-Agent Swarming as Learning & Memory

Instead, after updating agent activations via equation (11), we compute updated weights W' as

$$W'_{ij} = W_{ij} + \Delta t\, \eta V_{ij}\, p_i (q_{ij} - p_i W_{ij})\,, \qquad (13)$$

with simulation time-step Δt and learning rate η, which effectuates a pre-synaptic normalization according to Oja's rule (Oja, 1982). Similarly, the updated feedforward weights $W^{r\prime}$ are computed for reward k as

$$W^{r\prime}_{ik} = W^r_{ik} + \Delta t\, \eta_r V^r_{ik}\, p_i (r_{ik} - p_i W^r_{ik})\,. \qquad (14)$$

The normalization effected by equations (13) and (14) is due to a subtractive term, quadratic in the post-

'Postsynaptic' Activation

'Presynaptic' Activity

Hebbian Learning via Oja's Rule

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Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

Multi-Agent Swarming as Learning & Memory

Gazi and Passino, 2011). The weights W' and $W^{r\prime}$ can be converted to desired distances D' and $D^{r\prime}$ by inverting the Gaussian swarming kernel of (3),

$$D'_{ij} = \sqrt{-2\sigma^2 \log W'_{ij}}, \tag{15}$$

and the exponential reward kernel in (4),

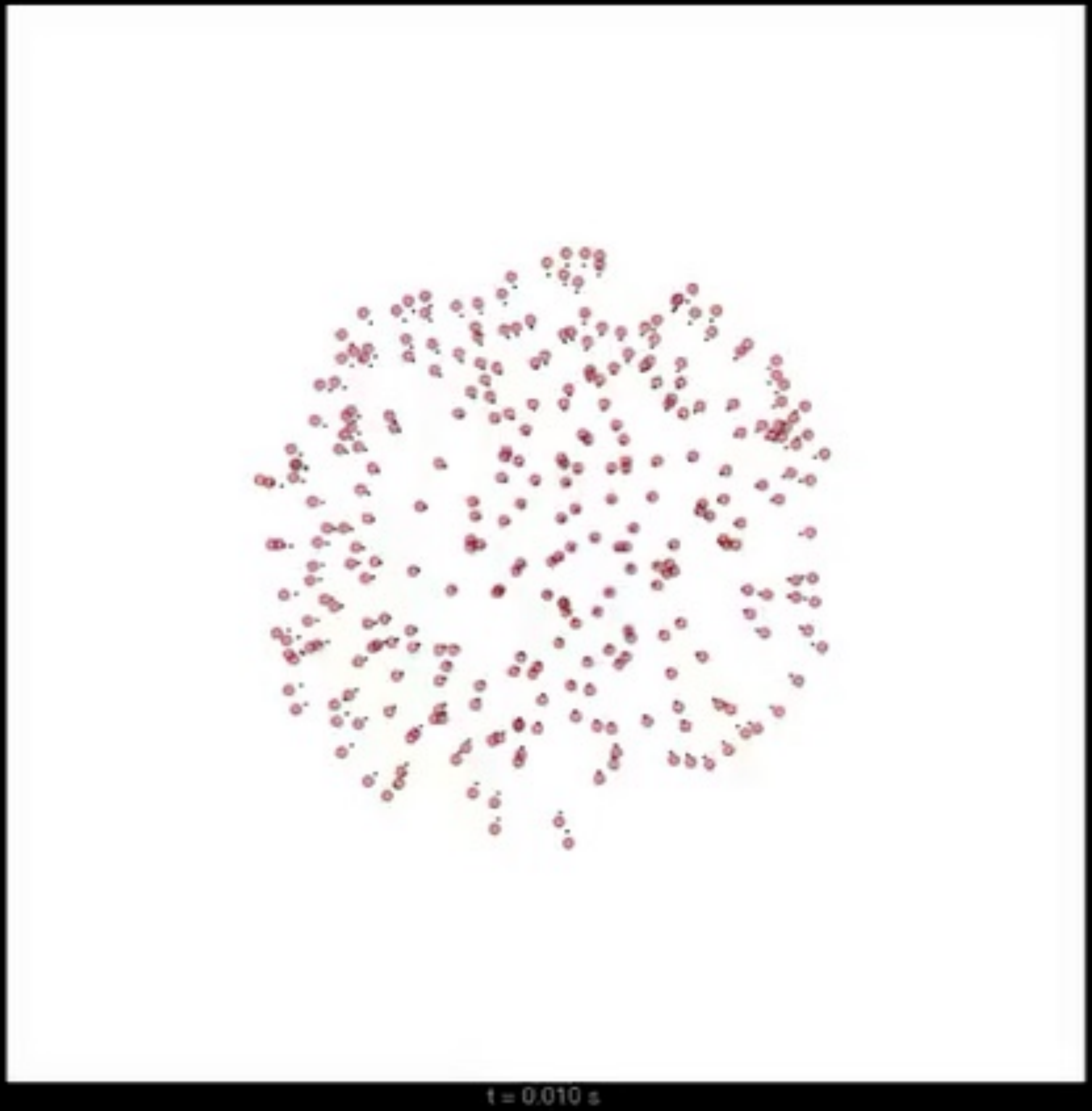
$$D^{r\prime}_{ij} = -\kappa \log W^{r\prime}_{ij}, \tag{16}$$

Inverted distance kernels to calculate motion

respectively. To compute the resultant swarm motion, the desired positional offset of agent i is averaged across its visible neighbors, i.e.,

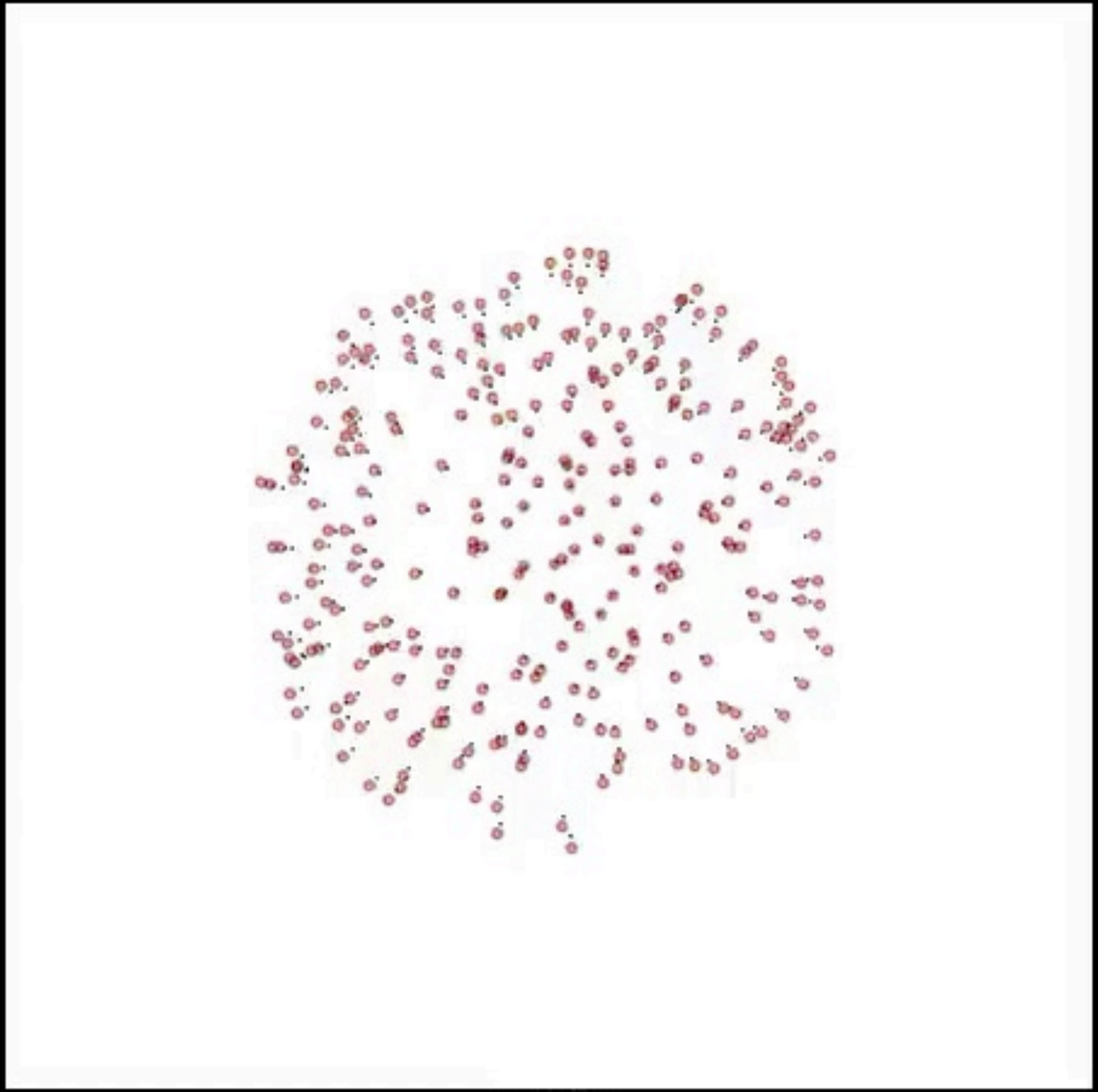
Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

Cognitive Swarming:
With Attractor Learning but Without Phase Coupling



Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

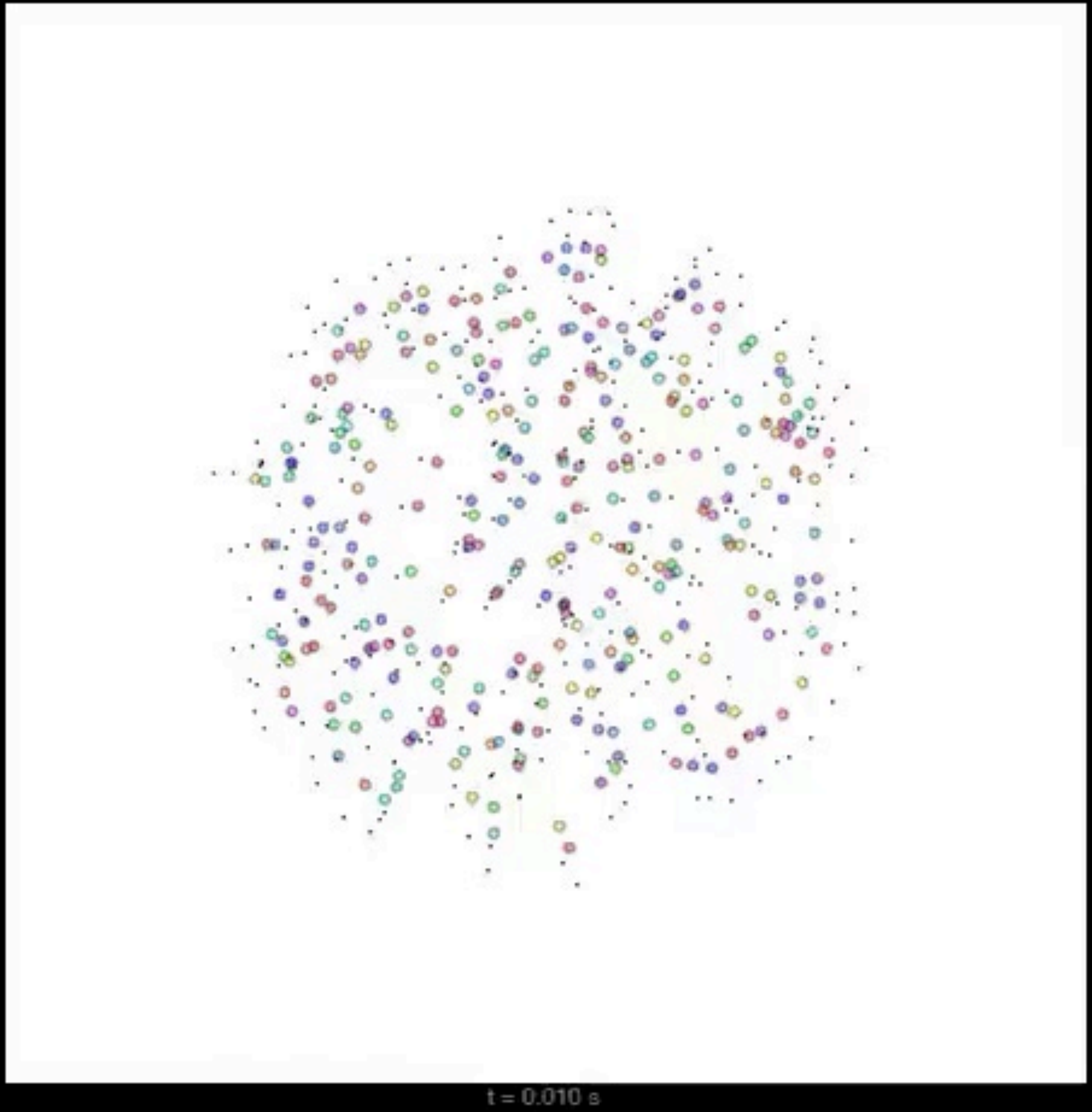
Cognitive Swarming:
With Phase Coupling and Identical Phase Initialization



t = 0.010 s

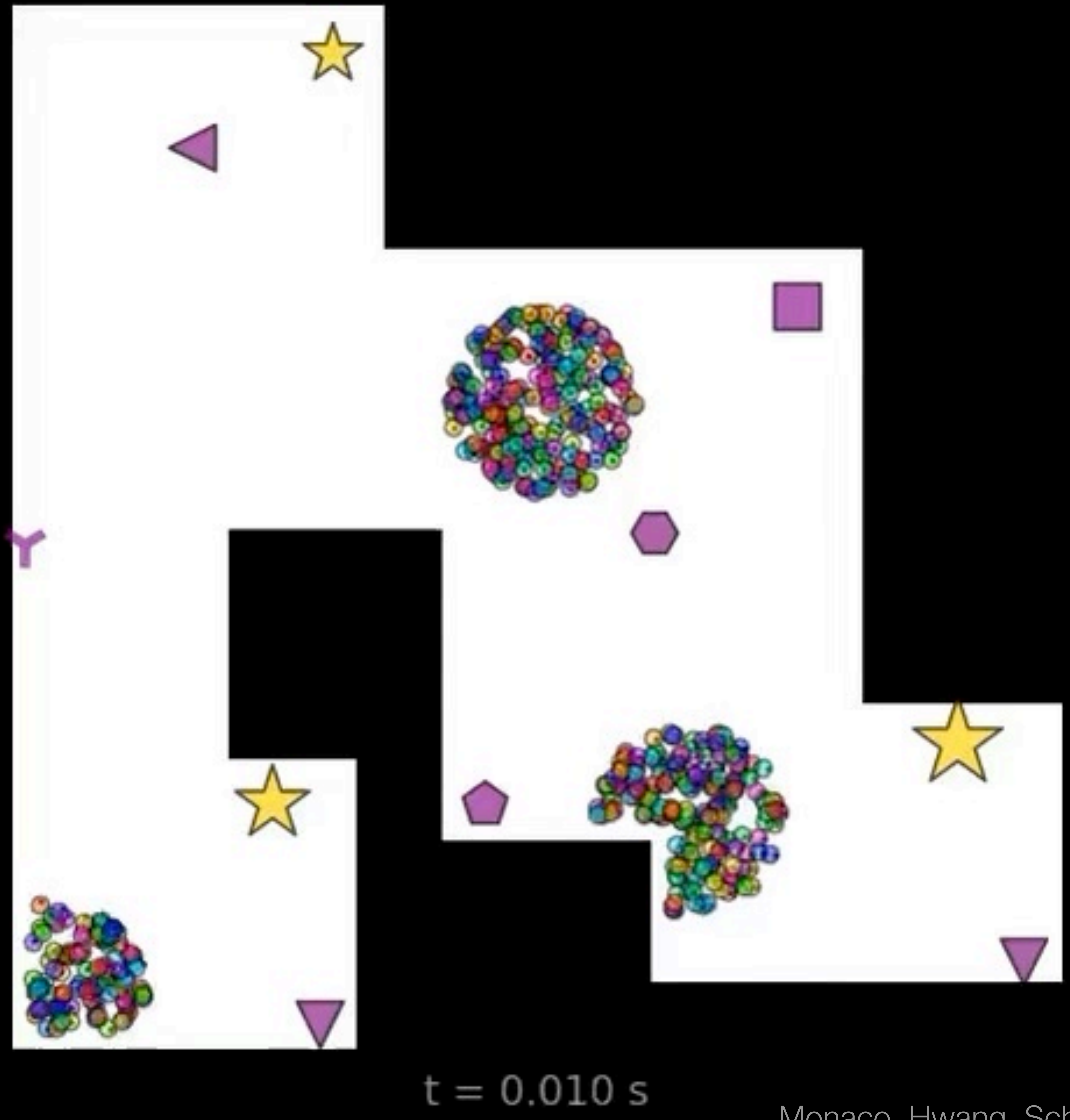
Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

Cognitive Swarming: With Phase Coupling and Random Phase Initialization



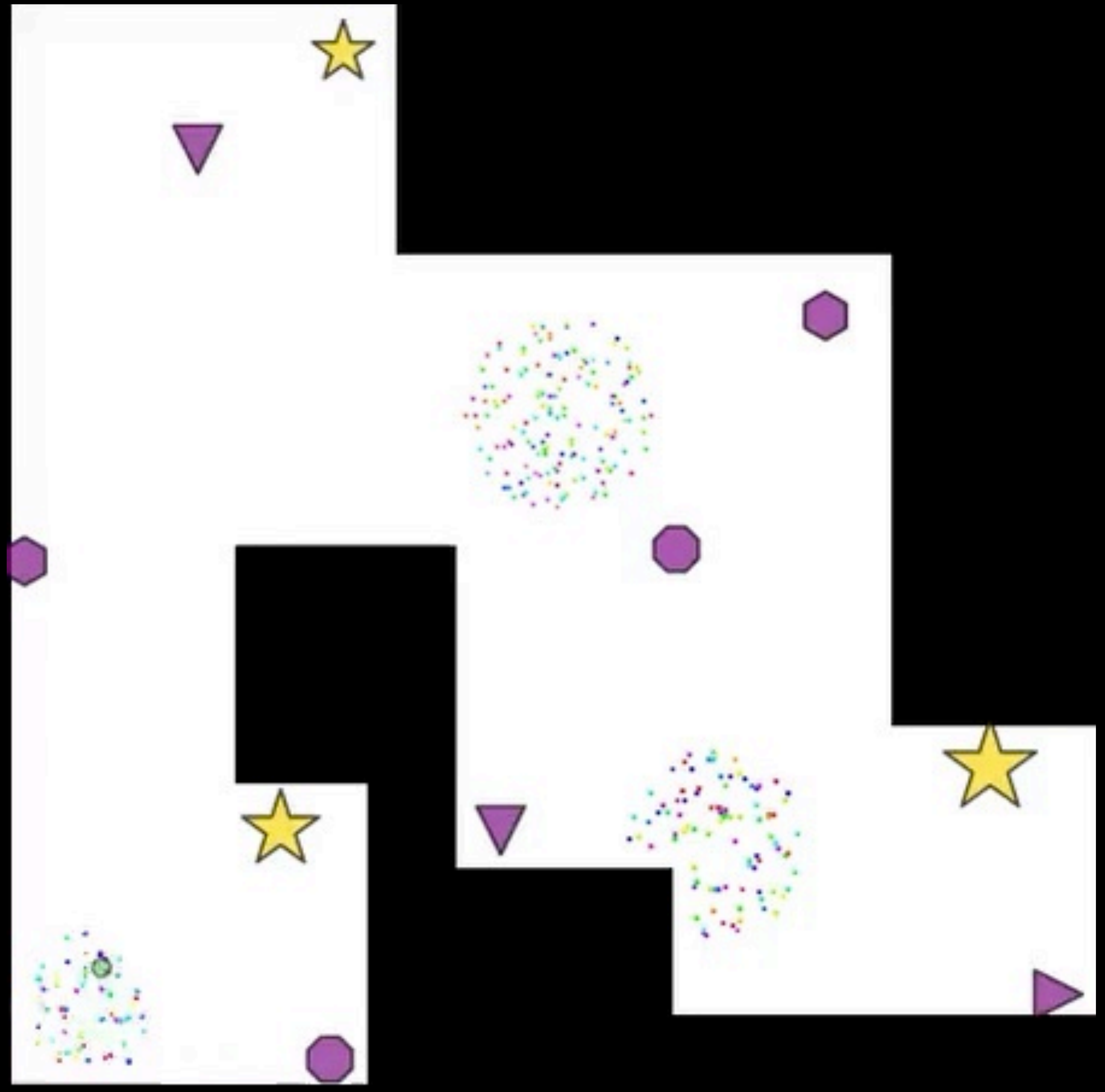
Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

Cognitive Swarming:
With Phase Coupling, Balanced Swarming and Reward Learning, and Multiple Rewards in a Complex and Irregular Maze



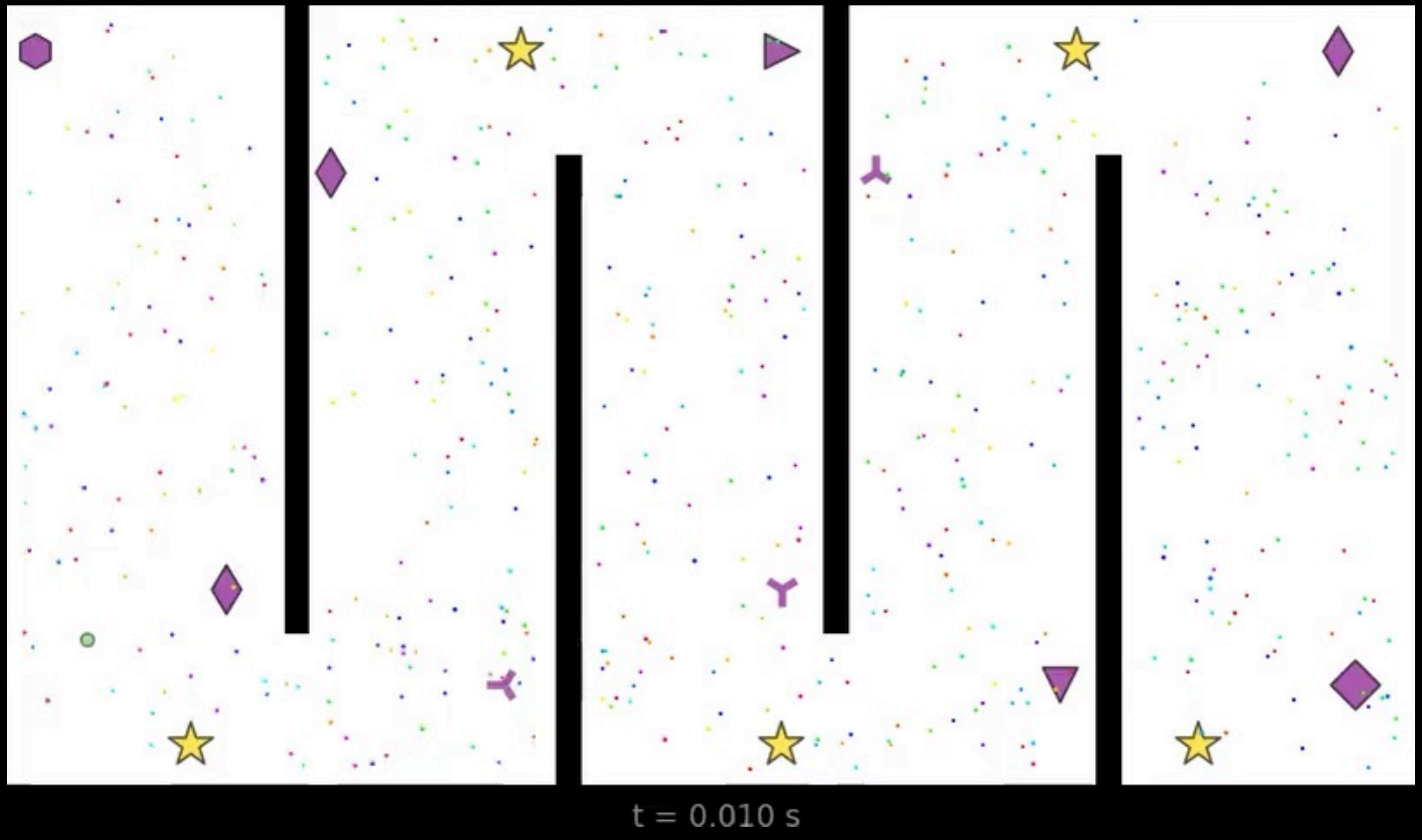
Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

Single-Agent Swarm:
Virtual Particle Swarm Guides a Single Agent (Green Circle) to Capture Multiple Rewards in an Irregular Maze



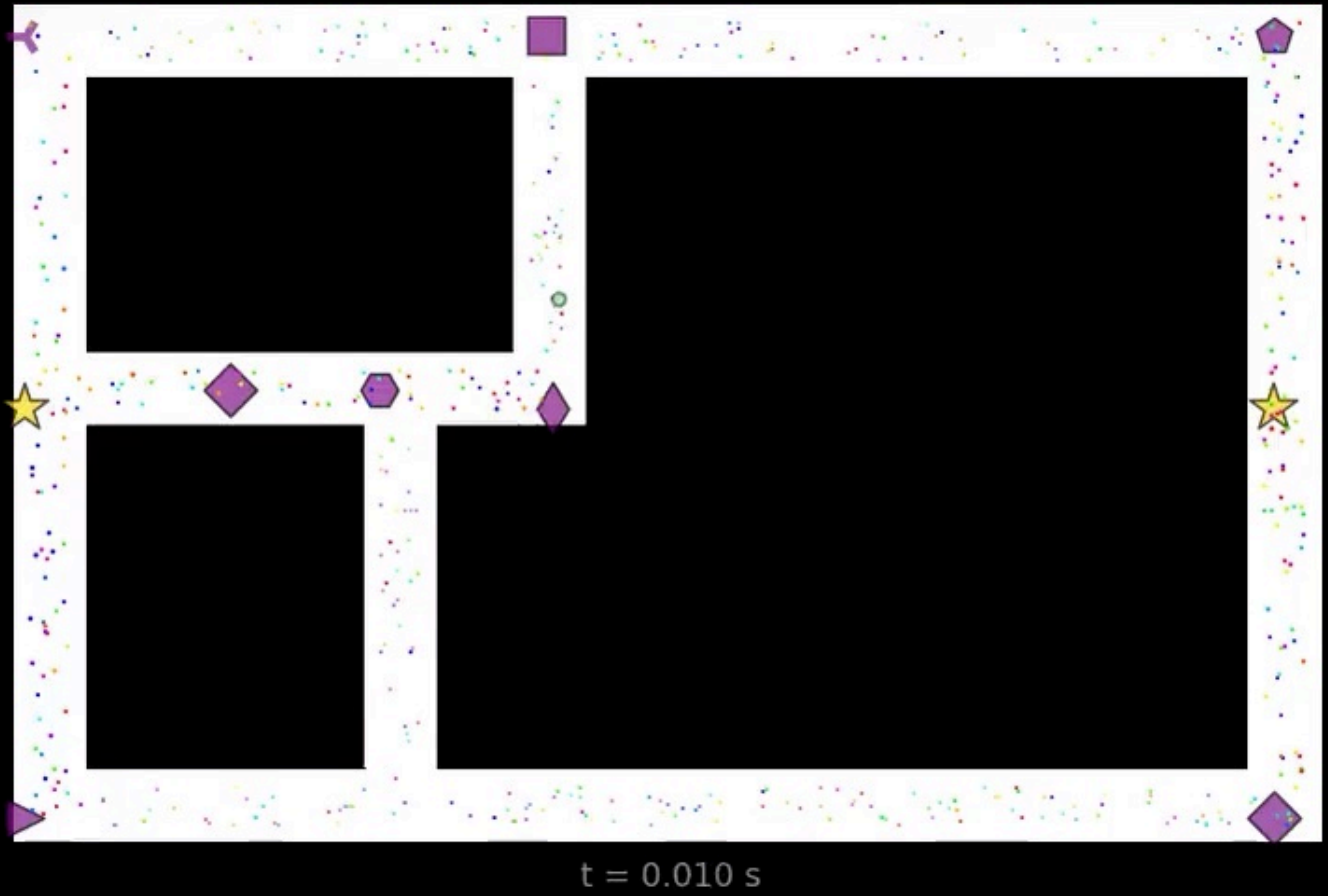
Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics. doi: 10.1007/s00422-020-00823-z

Single-Agent Swarm:
Virtual Particle Swarm Guides a Single Agent (Green Circle) to Rewards in a Large and Fragmented Hairpin



Monaco, Hwang, Schultz, & Zhang (2020) Biological Cybernetics

Single-Agent Learning-as-Swarming: Double-T Maze



Monaco, Hwang, Schultz, & Zhang. (2020). Biological Cybernetics, 114: 269

NSF announces next topics for the Emerging Frontiers in Research and Innovation (EFRI) program

PROGRAM SOLICITATION
NSF 21-615

April 7, 2021

The NSF Directorate for Engineering plans two new topic areas for the Emerging Frontiers in Research and Innovation (EFRI) program in fiscal year (FY) 2022. These topics were developed with input from the research community during fall 2020.

Brain-Inspired Dynamics for Engineering Energy-Efficient Circuits and Artificial Intelligence
New neuroscience discoveries have led to insights about the fundamental challenges facing artificial intelligence (AI) and engineered learning systems more generally, including how to achieve the unparalleled energy efficiency, computational flexibility, and robustness of biological intelligence, how to achieve continuous learning necessary for adaptive autonomy, and how to extract rich semantic information from only a few data points.

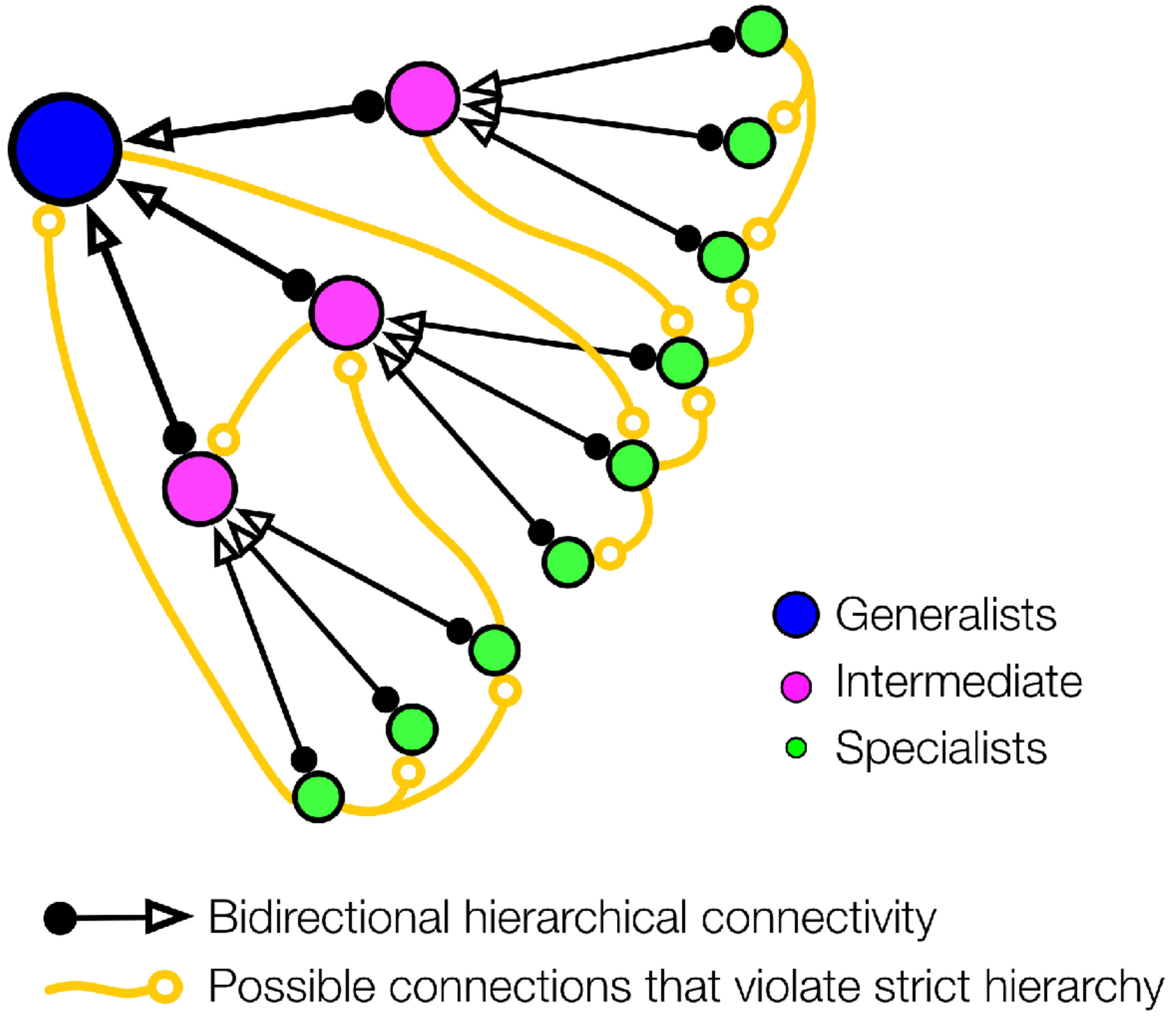
The Brain-Inspired Dynamics for Engineering Energy-Efficient Circuits and Artificial Intelligence (BRAID) EFRI topic will build on recent advances in neuroscience to stimulate and transform innovations in AI and engineered learning systems. The anticipated capabilities arising from this program will include features of intelligence associated with humans and other complex living systems not achievable using current machine learning solutions.

The BRAID topic will encompass three focus areas — theoretical neuroscience, brain-inspired circuit design, and algorithmic learning — that will reciprocally, cooperatively, and ethically advance foundational knowledge for future advances in engineered learning systems.

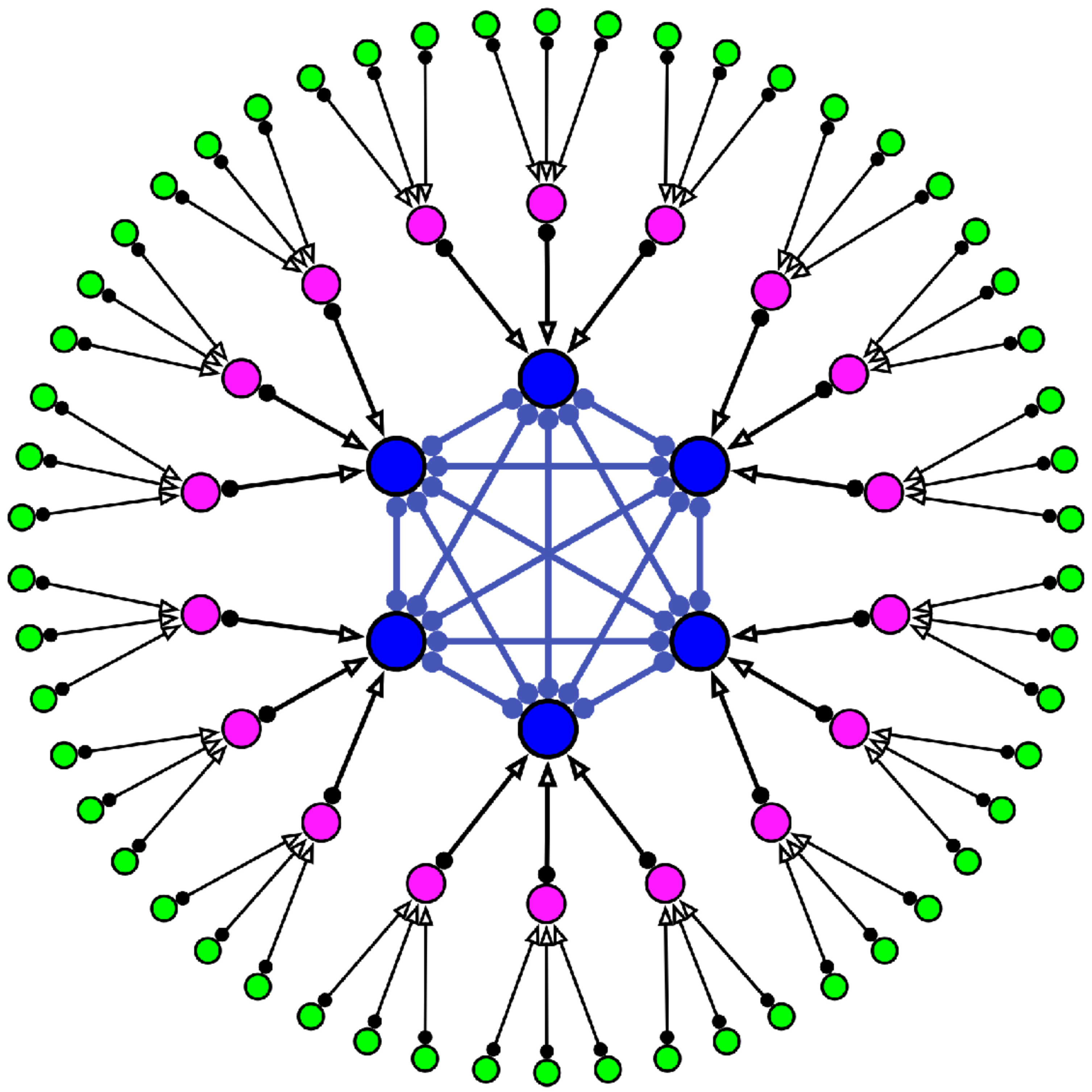
Neurodynamical Computing: Selection and Interaction

(1) Network structure:

Sparse, distributed hierarchies are non-strict



Sparse, bidirectional network with robust core



(2) Temporal dynamics:

(3) Agentic interaction:

Monaco, Rajan, and Hwang (2021) ArXiv Preprint. arxiv:2105.07284

Neurodynamical Computing: Selection and Interaction

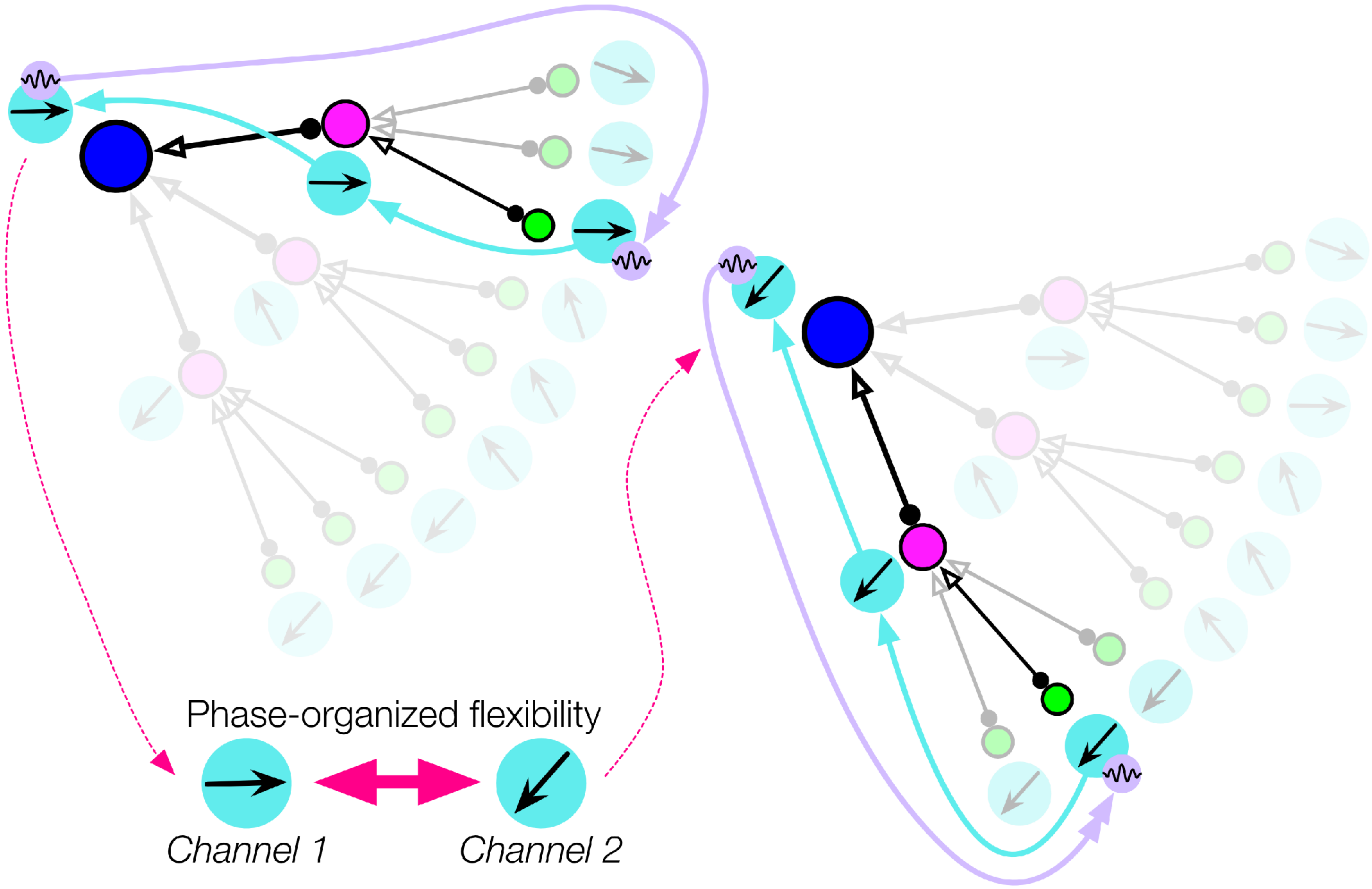
(1) Network structure:

(2) Temporal dynamics:

- Example: Nested oscillations with phase-amplitude coupling between levels of the pseudohierarchy

(3) Agentic interaction:

Readers phase-shift to select inputs and establish communication channels



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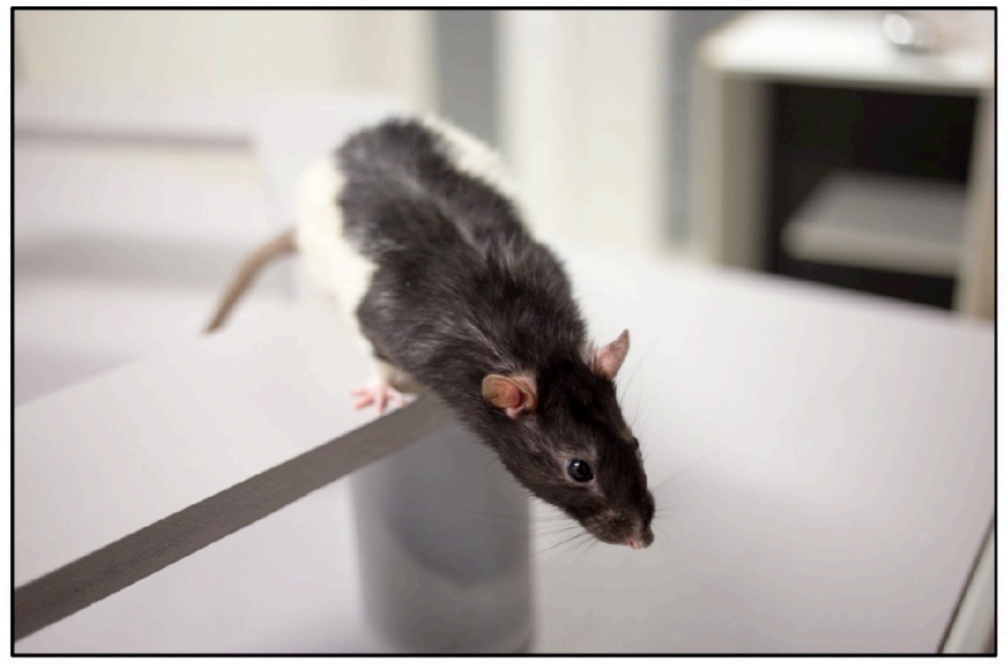
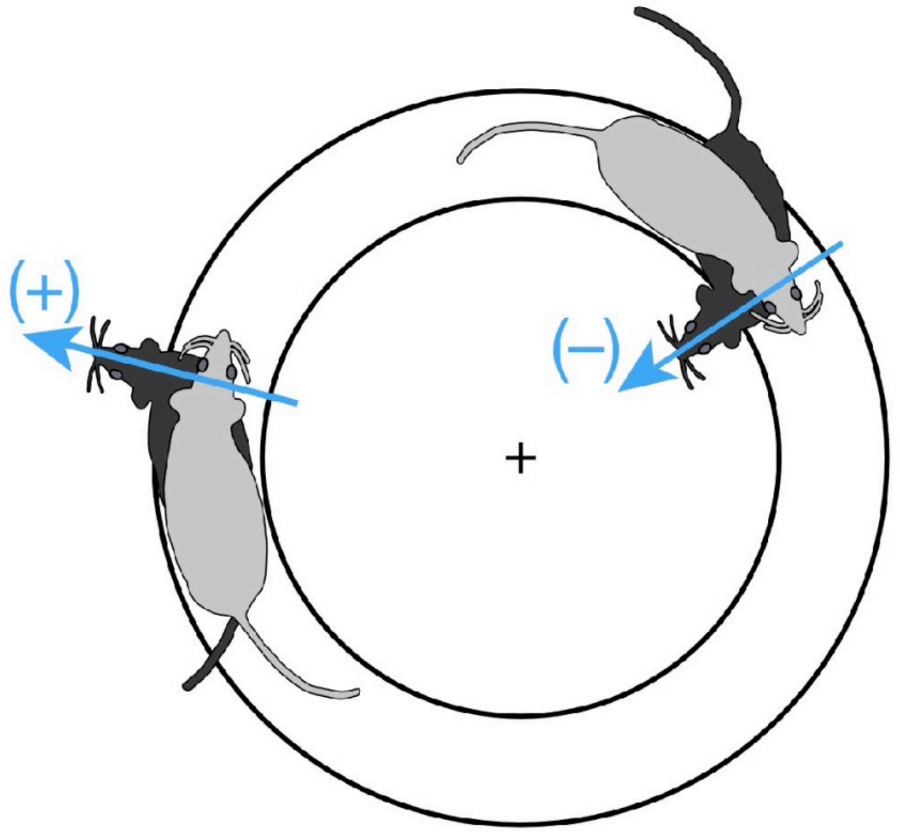
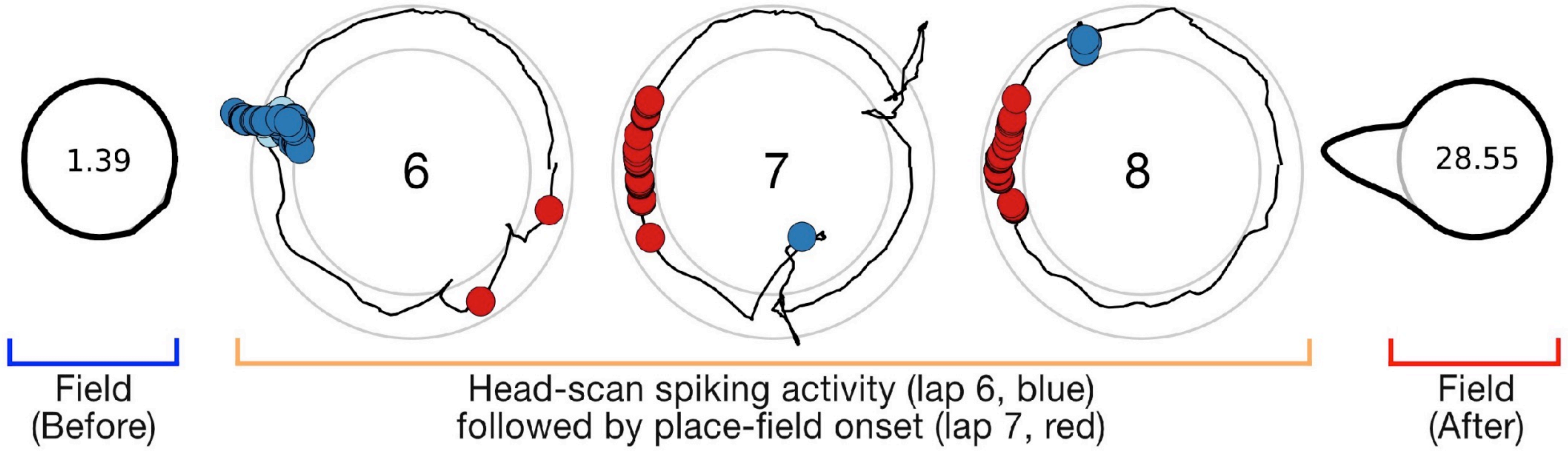
Neurodynamical Computing: Selection and Interaction

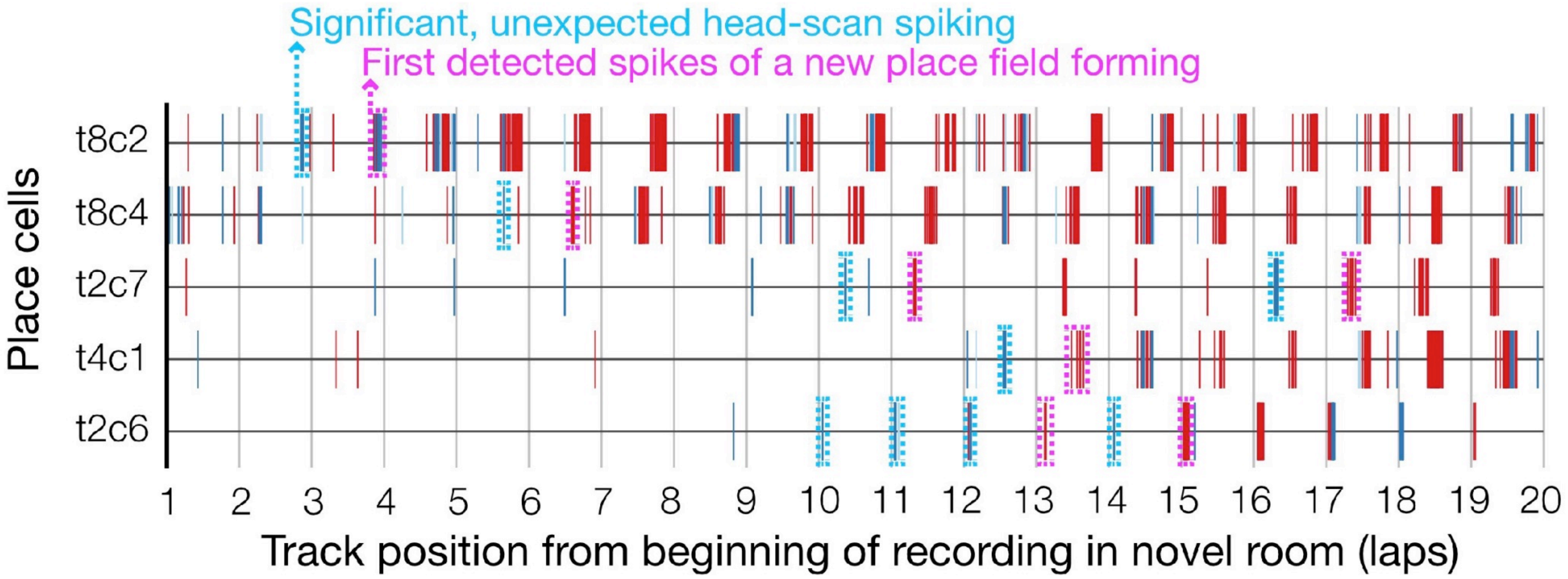
(1) Network structure:



(2) Temporal dynamics:





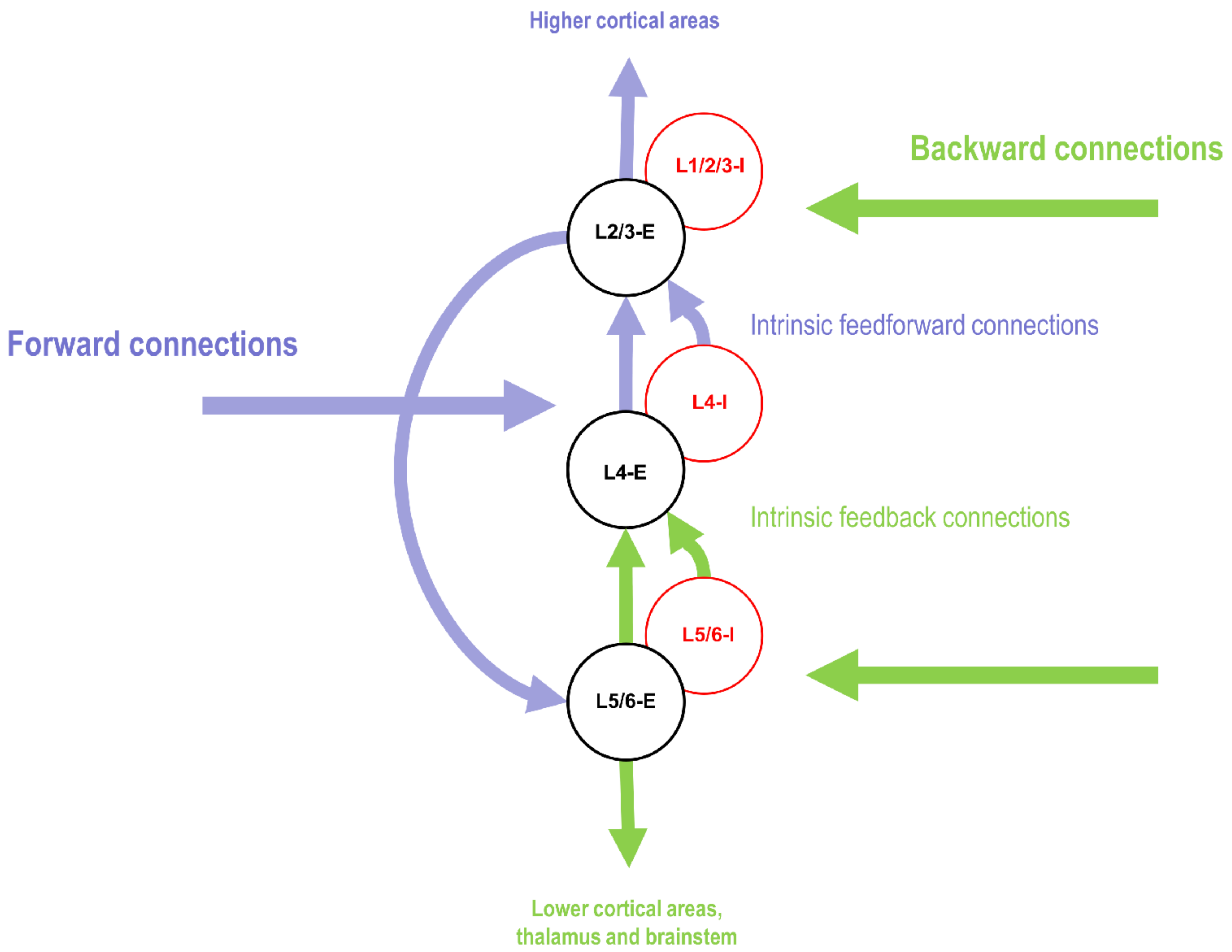


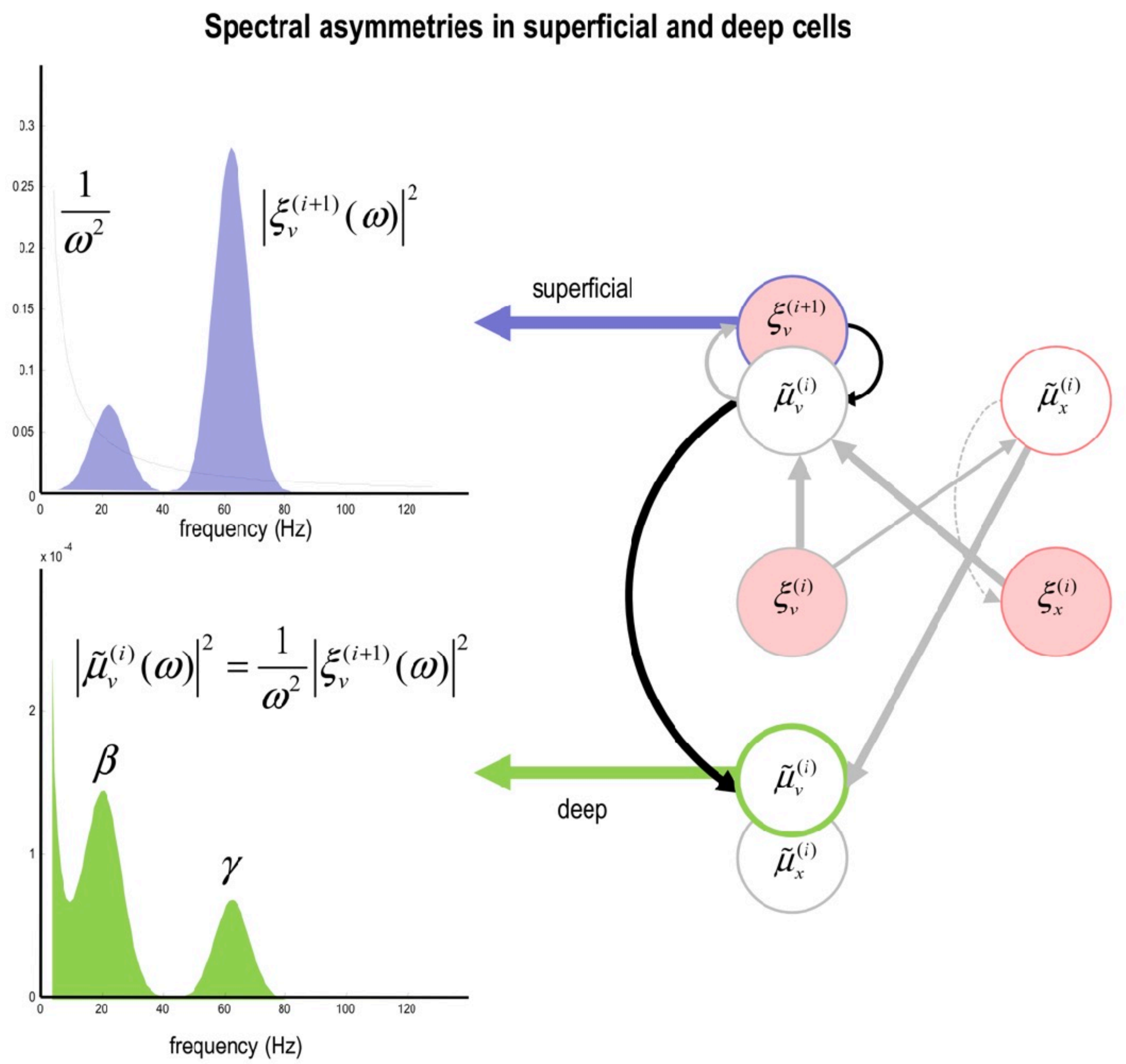
(3) Agentic interaction:

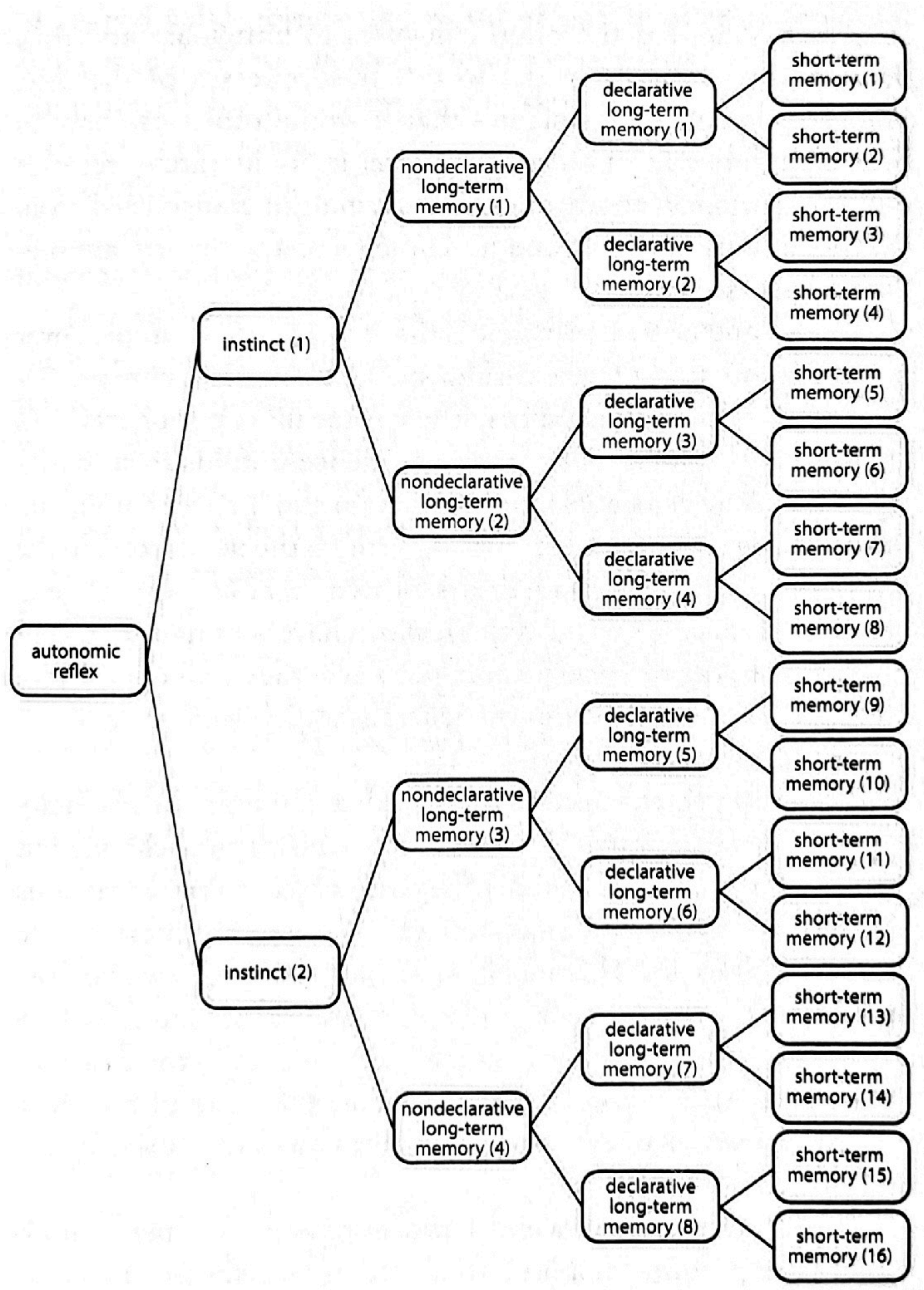
- Example: Attentive head-scanning behavior (Monaco et al., 2014)

Monaco, Rajan, and Hwang (2021) ArXiv Preprint. arxiv:2105.07284

Hierarchical Generative Models and the “Spectral Connectome”

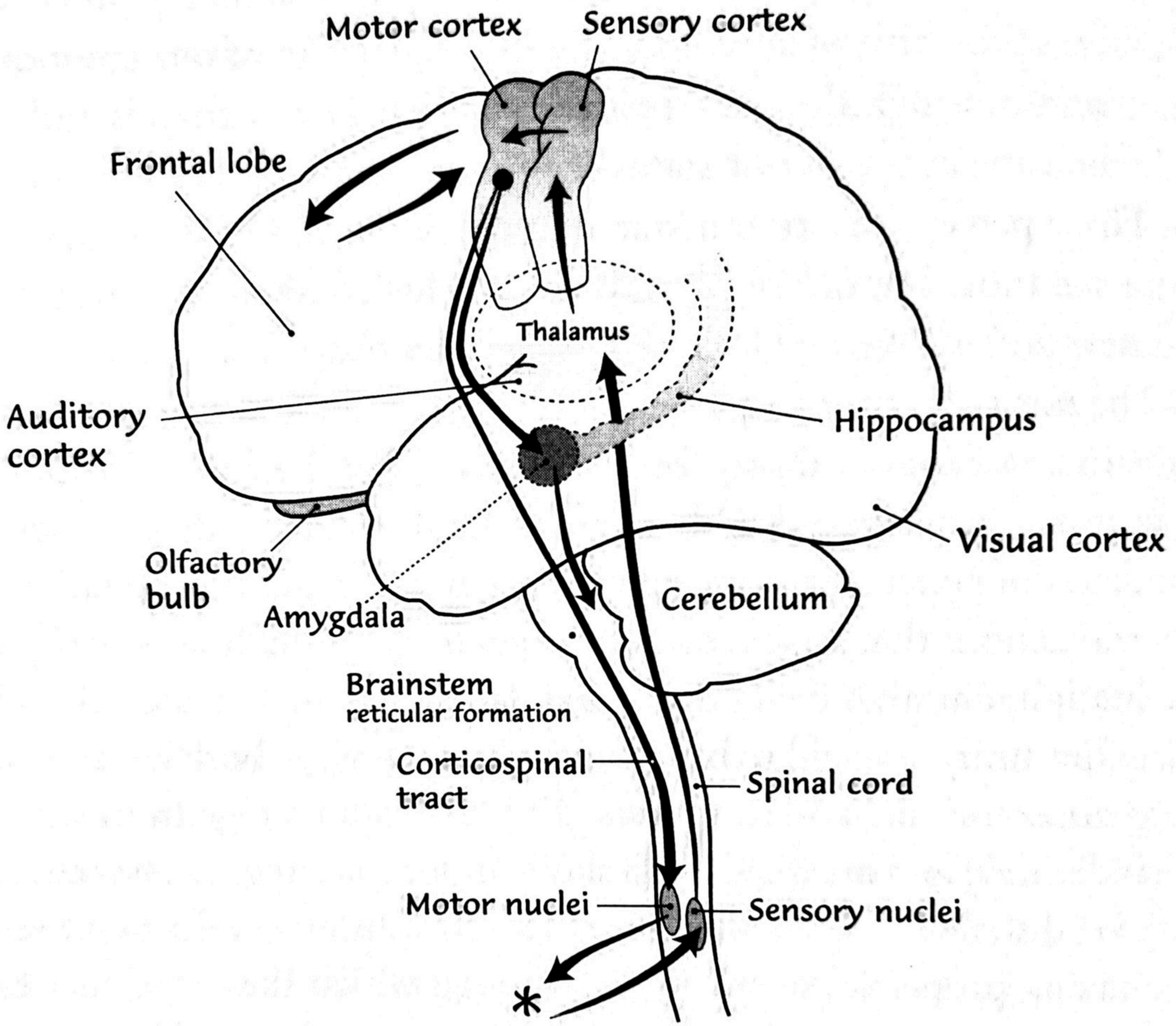


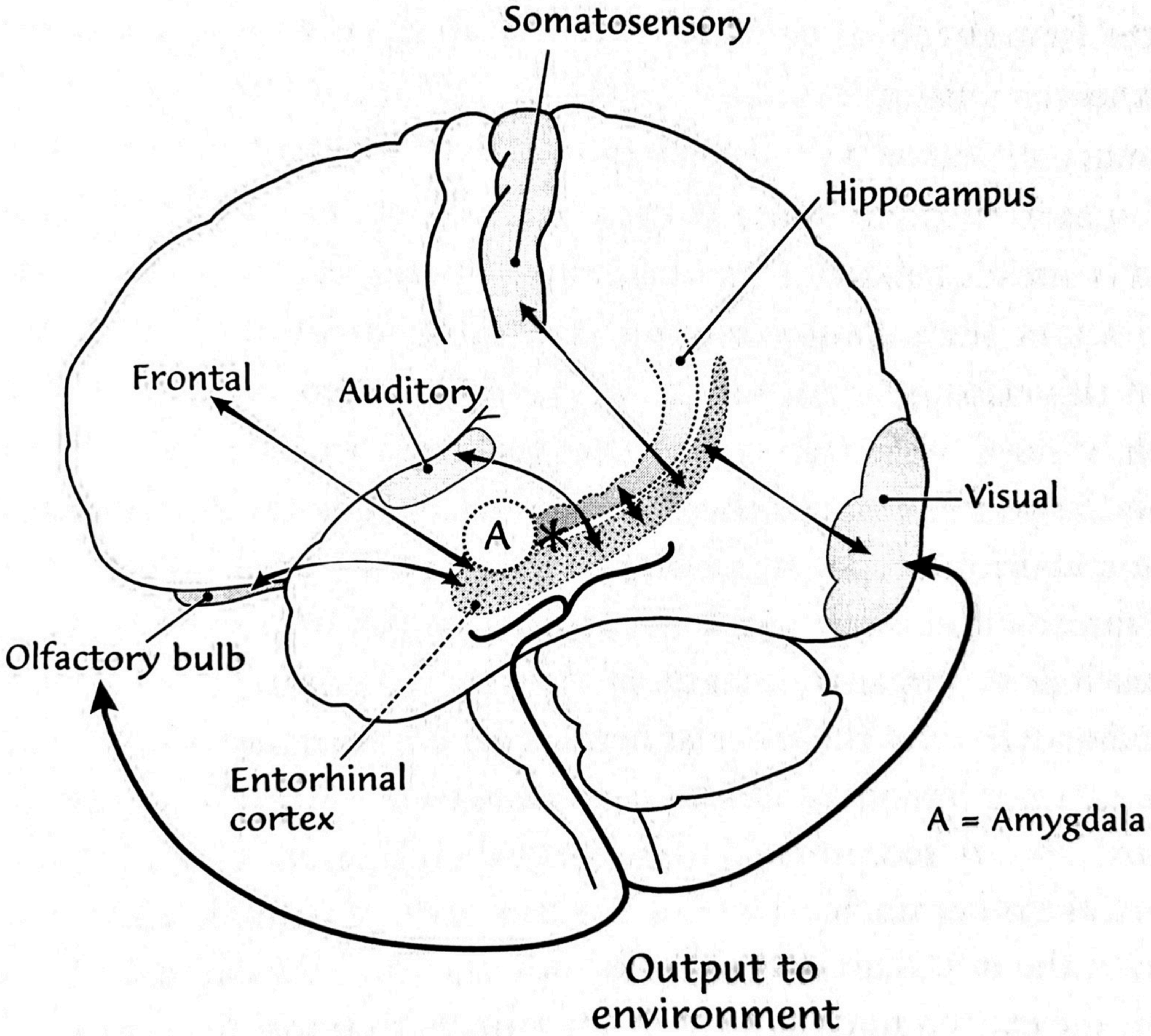




(Left) Bastos, …, Friston. (2012) Canonical Microcircuits for Predictive Coding. *Neuron, 76, 695.*
(Right) Holms. (2021) *The Hidden Spring.* W. W. Norton & co.

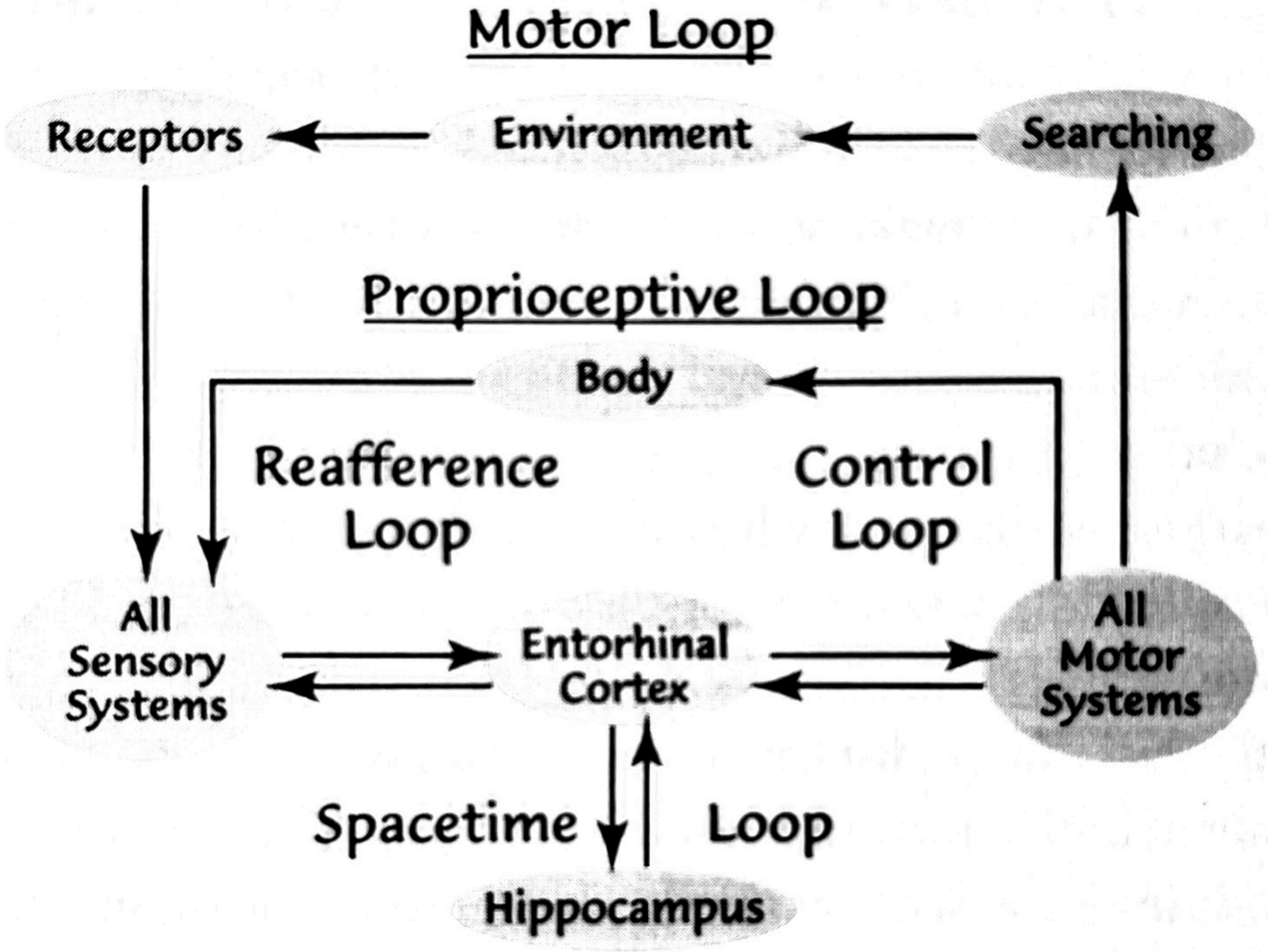
Inverting the Input-Output Sensorimotor Paradigm

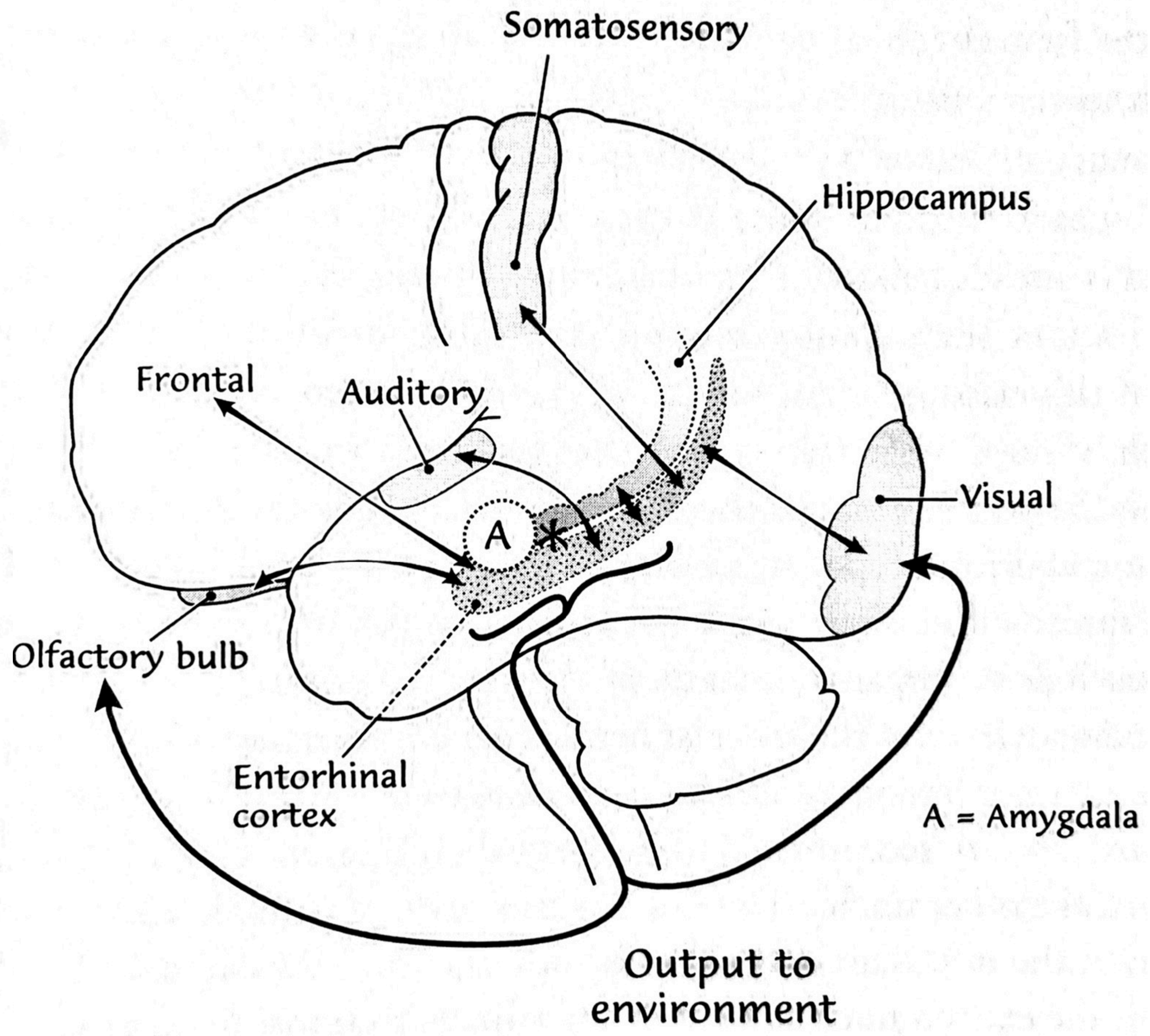




Freeman (2000) *How Brains Make Up Their Minds.* Columbia University Press

Inverting the Input-Output Sensorimotor Paradigm





Freeman (2000) *How Brains Make Up Their Minds.* Columbia University Press

Communication Through Coherence (CTC) (Fries, 2005)

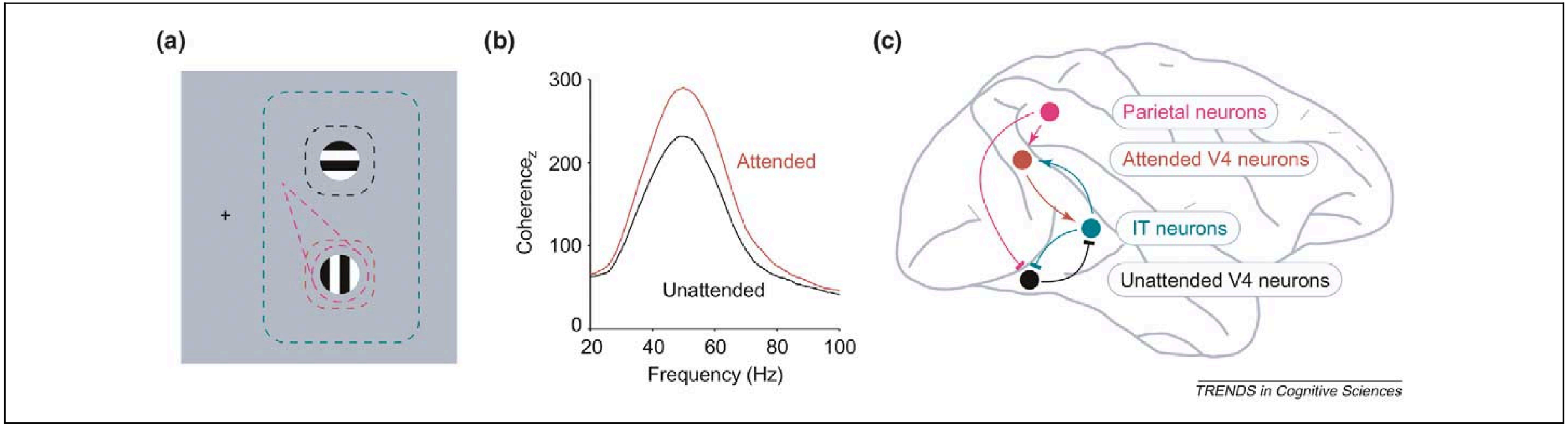


Figure 5. Coherence and competition. **(a)** Stimulus configuration used in a selective visual attention experiment [22]. The lower patch of grating falls into the receptive field of a neuronal group in V4 indicated in red (and black for the upper patch). Both grating patches fall into the receptive field of a neuronal group in IT cortex (green). The purple 'spotlight' indicates that spatial selective attention is directed to the grating patch contained in the red receptive field. **(b)** Although the firing rates of the attended V4 neurons are only slightly enhanced, they show a strong enhancement of gamma-band coherence. (Data from [22]; new analysis of spike-field coherence, z-transformed and pooled across pairs of recording sites). **(c)** The different neuronal groups in V4 and IT that are activated by the stimuli shown in (a). Experimental evidence suggests that the attended V4 neurons communicate effectively with the IT neurons but the unattended V4 neurons fail to do so. This is indicated with pointed and blunt arrowheads, respectively. This might be the result of modulatory input from parietal cortex that gives a competitive bias towards the attended V4 neurons.

P. Fries. (2005) A mechanism for cognitive dynamics: neuronal communication through neuronal coherence. *TICS*, 9, 474.

Papers & Preprints

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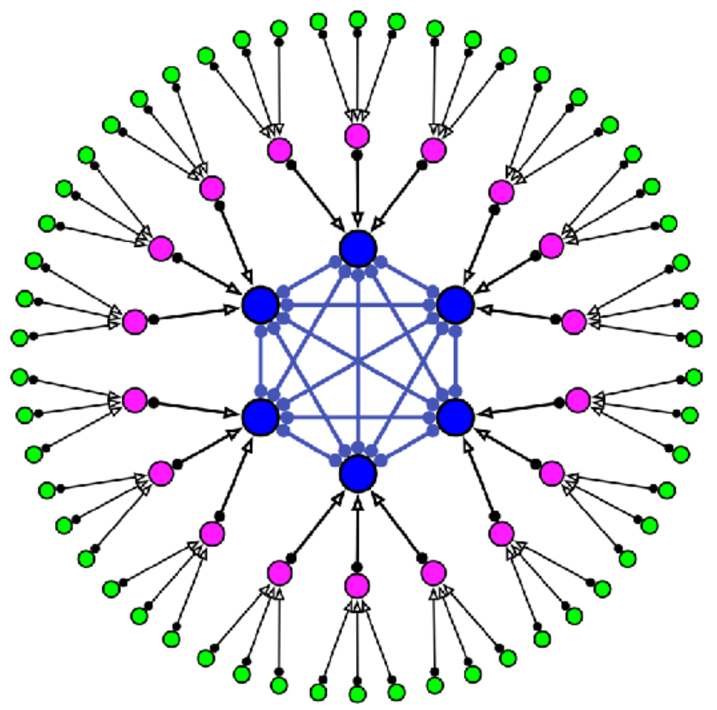
Dynamical principles for neuroscience and AI

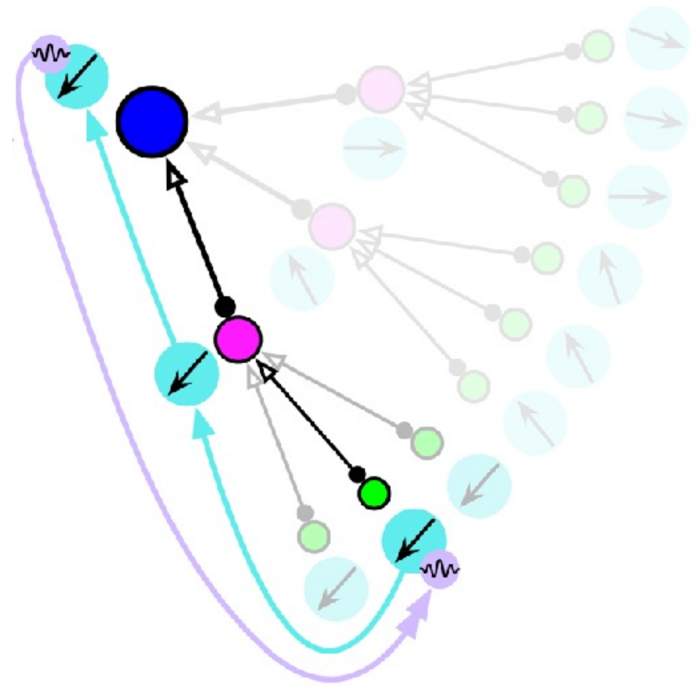
Monaco JD, Rajan K, and Hwang GM. (2021). A brain basis of dynamical intelligence for AI and computational neuroscience. *ArXiv Preprint*. arxiv:2105.07284



Cognitive swarming for multi-agent control

Monaco JD, Hwang GM, Schultz KM, and Zhang K. (2020). Cognitive swarming in complex environments with attractor dynamics and oscillatory computing. *Biological Cybernetics*, 114, 269–284.
doi: 10.1007/s00422-020-00823-z
https://rdcu.be/b3lem
arxiv:1909.06711

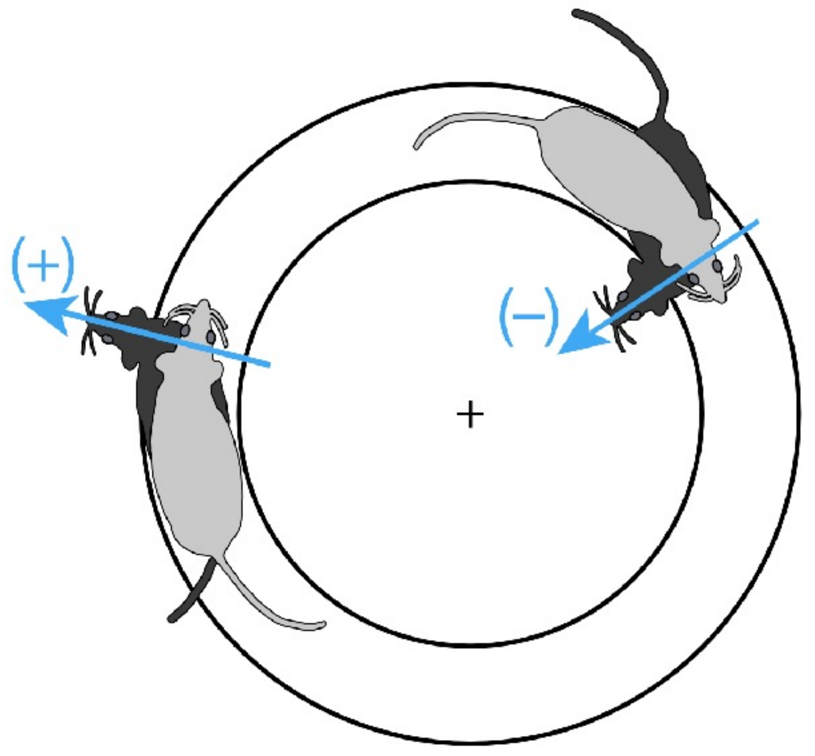
Hadzic A, Hwang GM, Zhang K, Schultz KM, and **Monaco JD**. (2022). Bayesian optimization of distributed neurodynamical controller models for spatial navigation. *Array*, 15, 100218.
doi: 10.1016/j.array.2022.100218



Spatial ‘phaser cells’ in the lateral septum

Monaco JD, De Guzman RM, Blair HT, and Zhang K. (2019). Spatial synchronization codes from coupled rate-phase neurons. *PLOS Computational Biology*, 15(1), e1006741.
doi: 10.1371/journal.pcbi.1006741

- Above work supported by NSF Award No. 1835279 “NCS-FO: Spatial Intelligence for Swarms Based on Hippocampal Dynamics”



Head-scanning modifies place-field maps

Monaco JD, Rao G, Roth ED, and Knierim JJ. (2014). Attentive scanning behavior drives one-trial potentiation of hippocampal place fields. *Nature Neuroscience*, 17(5), 725–731.
doi: 10.1038/nn.3687