Cognitive-narrative dynamics of self-perspective control across the lifespan

33rd IAPCT Conference
October 13, 2023

Joseph D. Monaco, Ph.D.
jdmonaco.com

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Prediction vs. control? Anchoring diachronic self-persistence to neural dynamics, emergent constraints, and process causality

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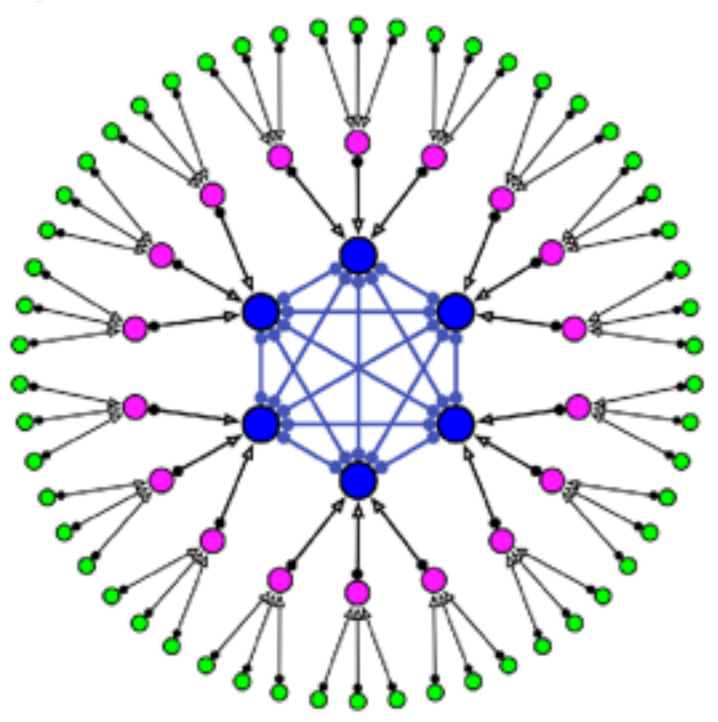
Toward a dynamical metastability process accounting of emergent autonomous control in living systems … ?

Relevant papers

• jdmonaco.com/pubs

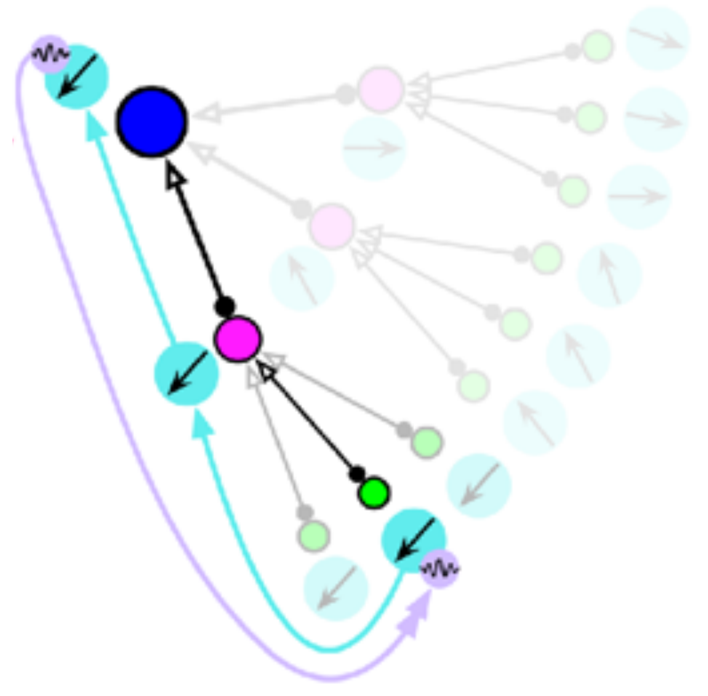
Dynamical principles for neuroscience, embodied cognition, and AI



Monaco JD and Hwang GM. (2022). Neurodynamical computing at the information boundaries of intelligent systems. *Cognitive Computation*. doi: 10.1007/s12559-022-10081-9

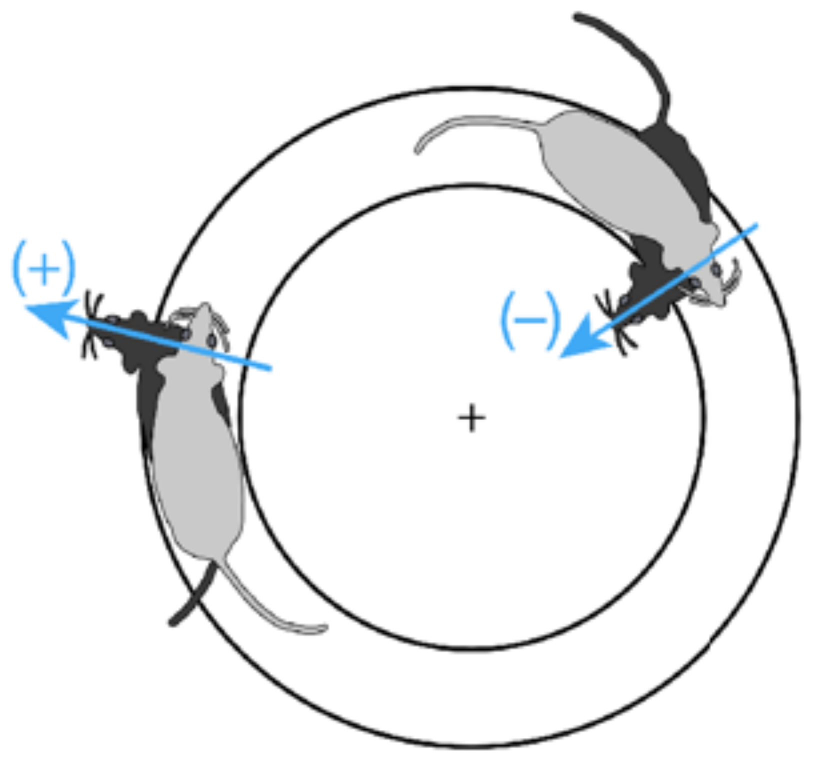
Monaco JD, Rajan K, and Hwang GM. (2021). A brain basis of dynamical intelligence for AI and computational neuroscience. *ArXiv Preprint*. arxiv:2105.07284

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

Head-scanning modifies place-field maps

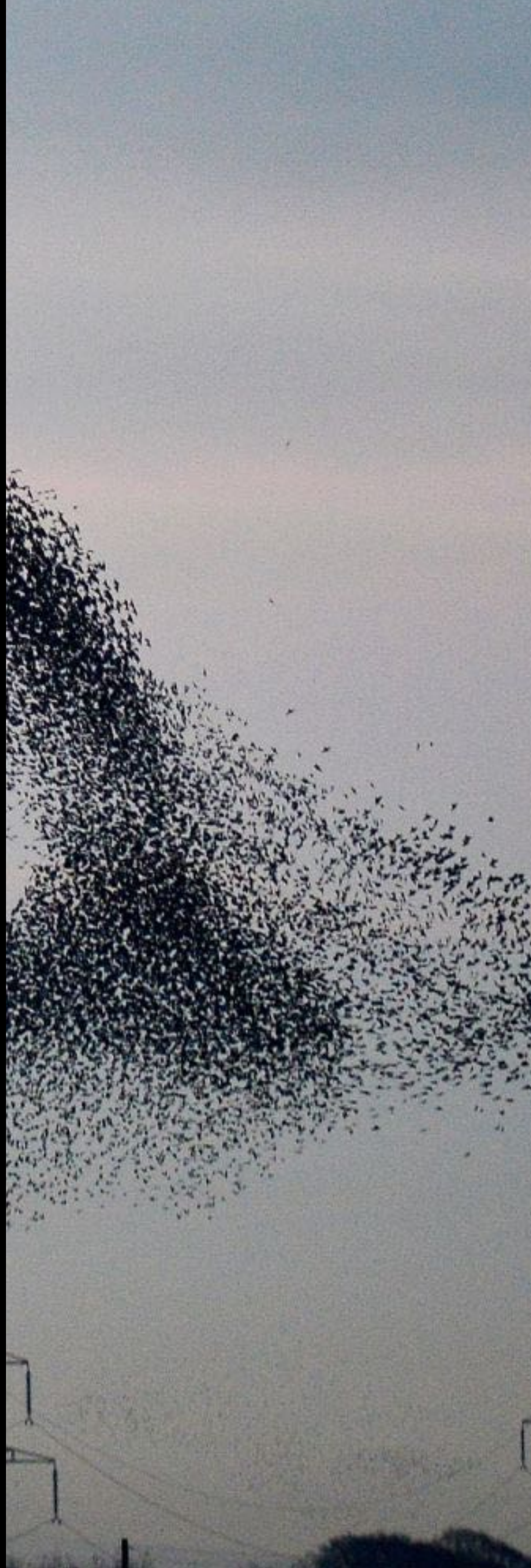


Monaco JD, Rao G, Roth ED, and Knierim JJ. (2014). Attentive scanning behavior drives one-trial potentiation of hippocampal place fields. *Nature Neuroscience*, 17(5), 725–731.
doi: 10.1038/nn.3687

Emergence of control

Moving beyond classical thermodynamical conceptions of energy transfer and cause–effect relations

- Efficient (force + particles) cause is not the only kind of cause
  - Aristotelian ‘in-formed’ types
  - Persistent unity-of-type in complex, evolvable systems
- History of physics
  - Helmholtz, Bayesian inference, Bayesian brain hypothesis, the free-energy principle, and active inference
- Embodied cognition
  - Autopoiesis implies ergodic system trajectories
  - Predictive processing framework implies autopoietic homeostasis



Embodied cognition

Progressive informational/entropic articulation vs. forward models

Embodiment-first theories invert our view of cognition as integrating isolated channels of sensory information into unified internal models, to one of articulating dynamical boundaries within existing global states that already reflect an organism's cumulative experience in its world (*umvelt*).

Monaco and Hwang. (2022). *Cognitive Computation*

External observer bias

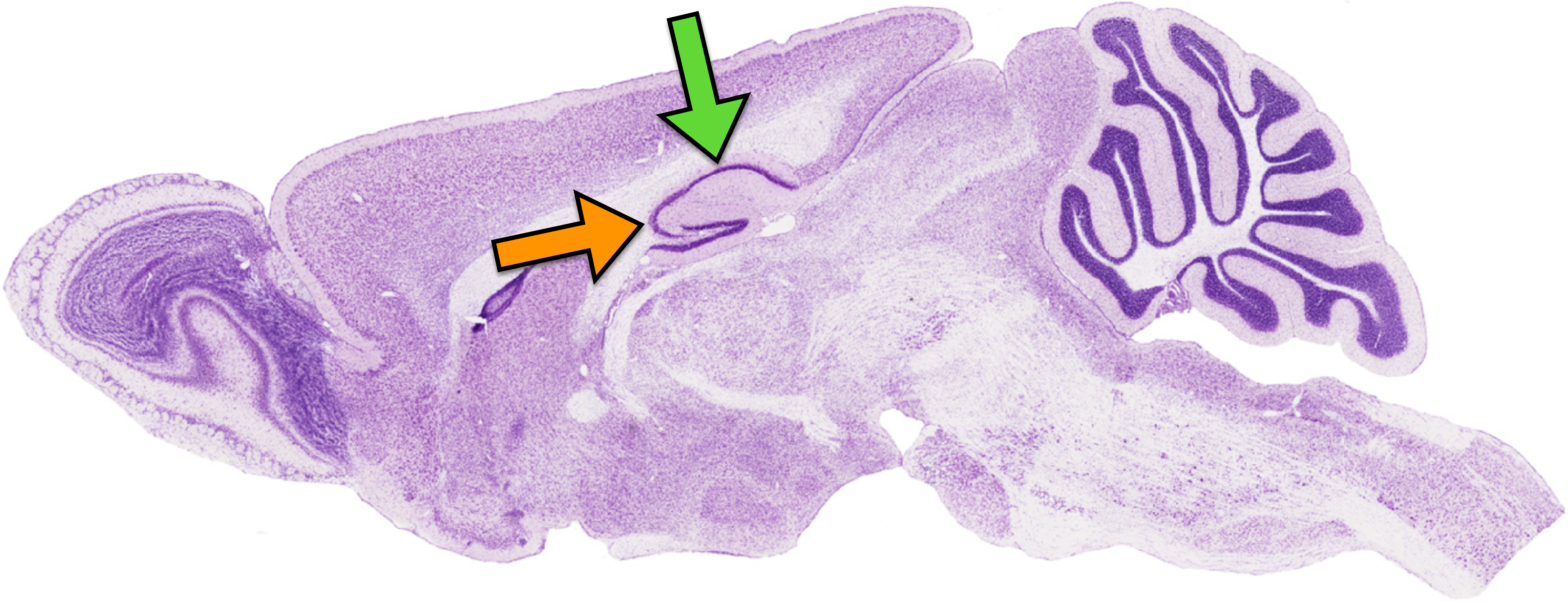
Inverting the input-output paradigm

1. Computational metaphors for the brain have entrenched the behaviorist bias that externally observable output is the endpoint of brain function

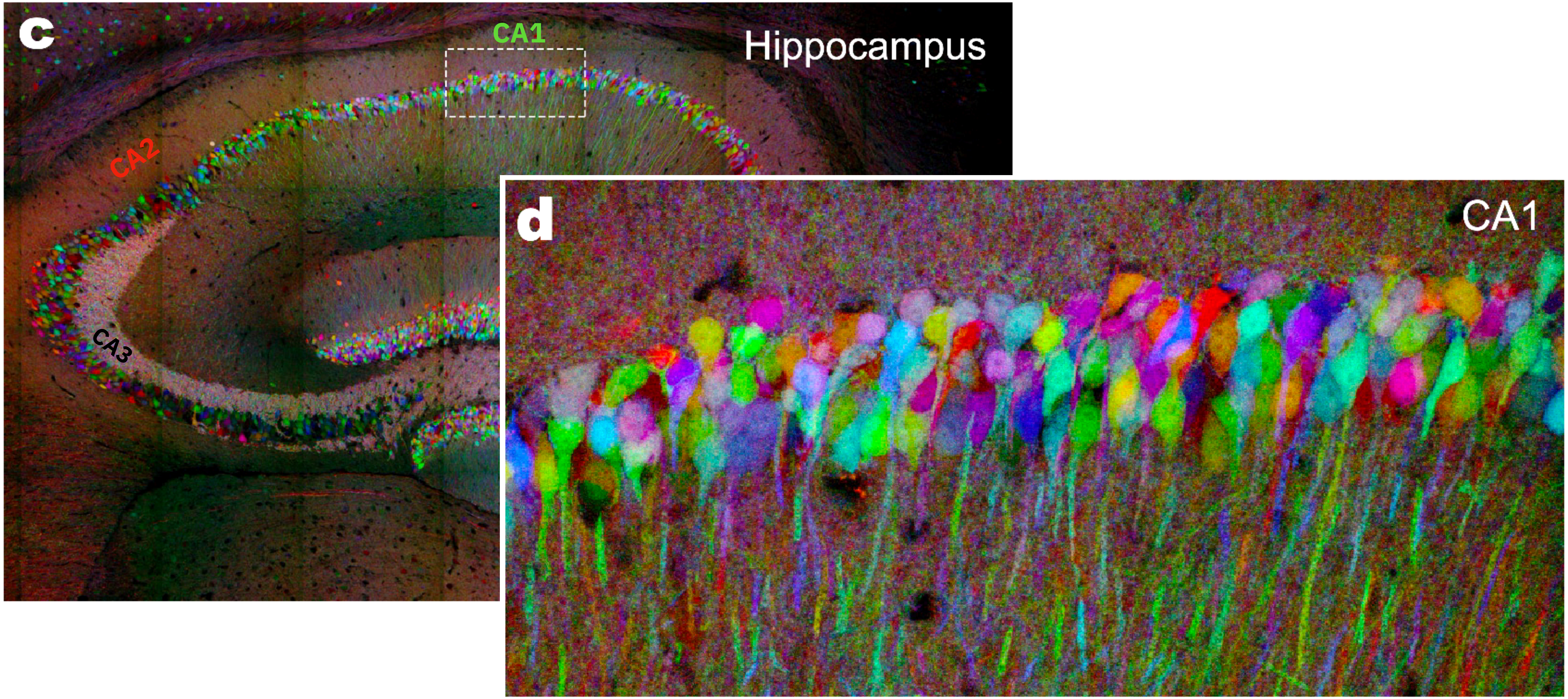
2. Neuroscience and AI have both embraced this bias, with either explicit or implicit input and output layers for computations

3. Implied control paradigm is one of building and evaluating forward (predictive/comparator) models

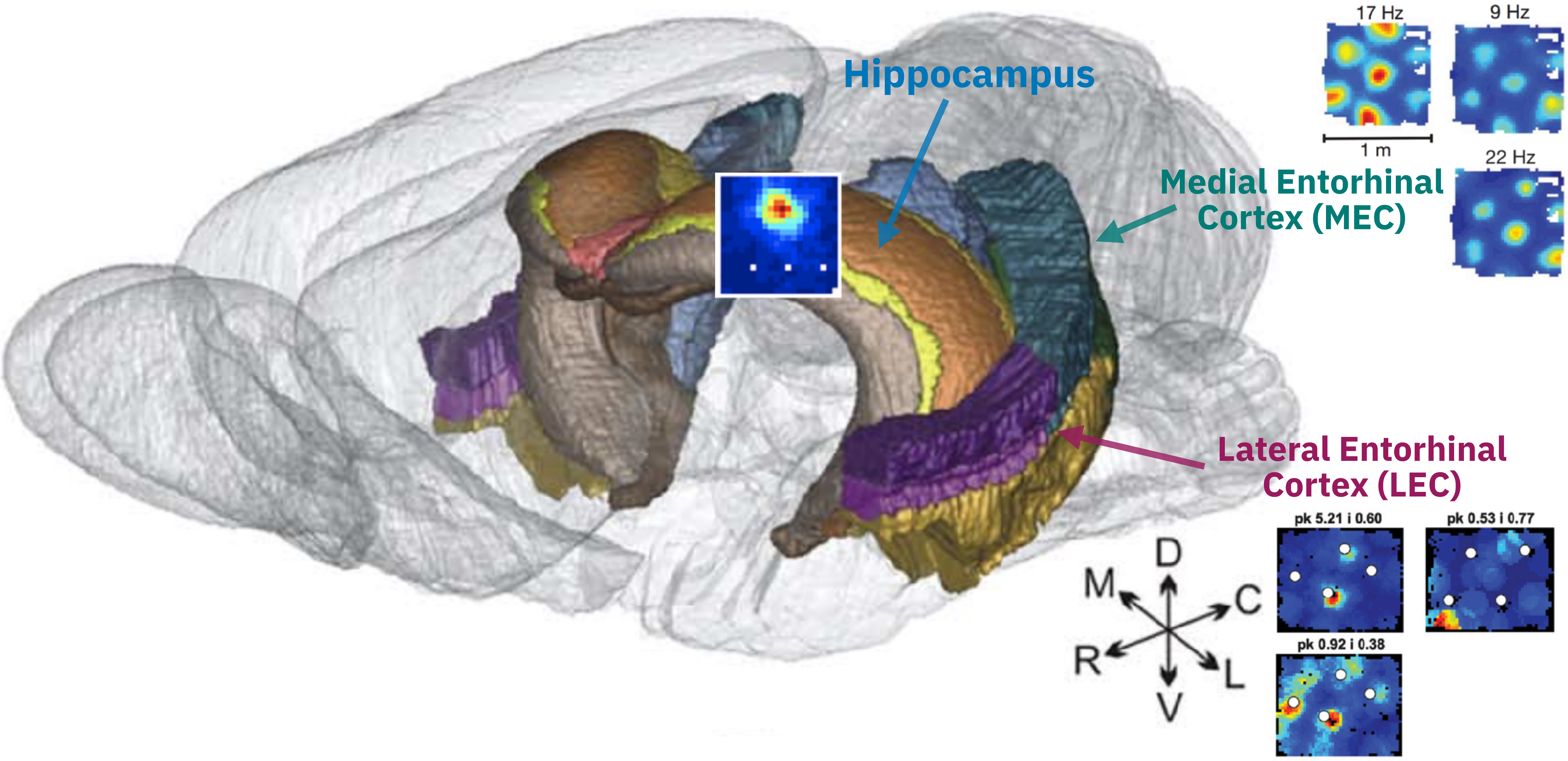
Image Credit: Glazer et al. (PEGASOS)



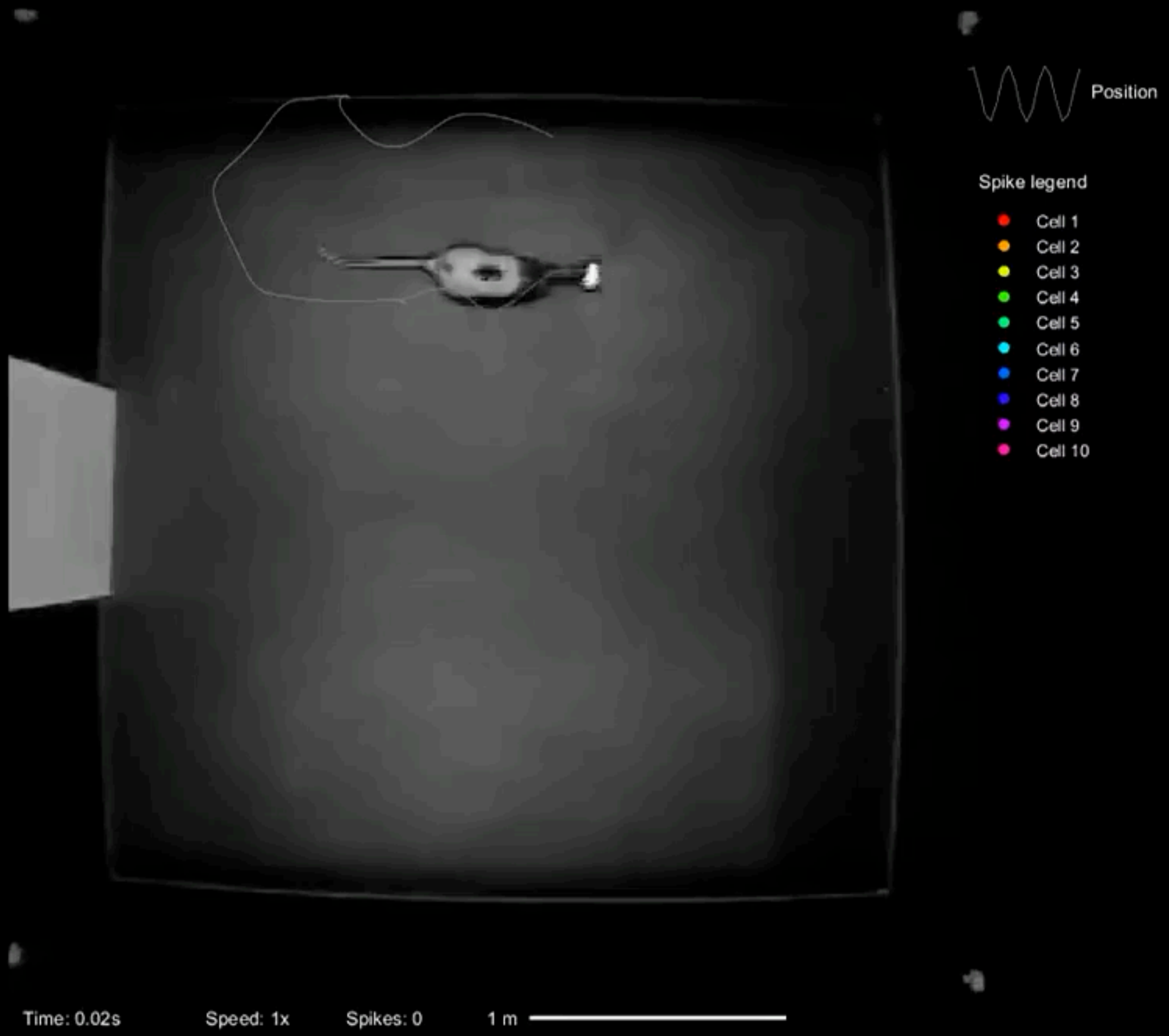
Credit: GENSAT Project, http://www.gensat.org/imagenavigator.jsp?imageID=60455



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

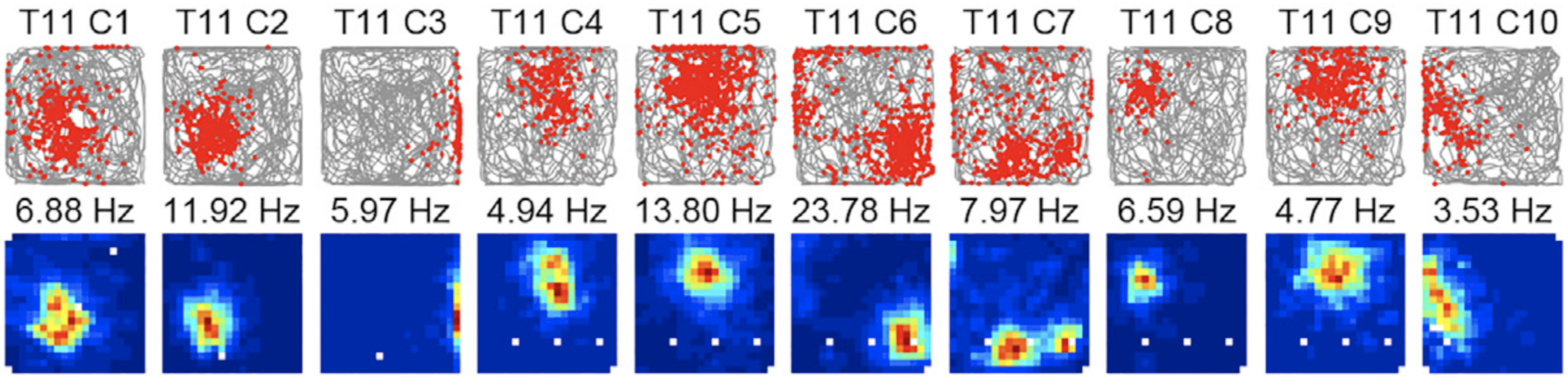


Boccara CN, *et al*. (2015). Hippocampus, 25: 838



Not Actual Speed

Video Credit: *R. Grieves*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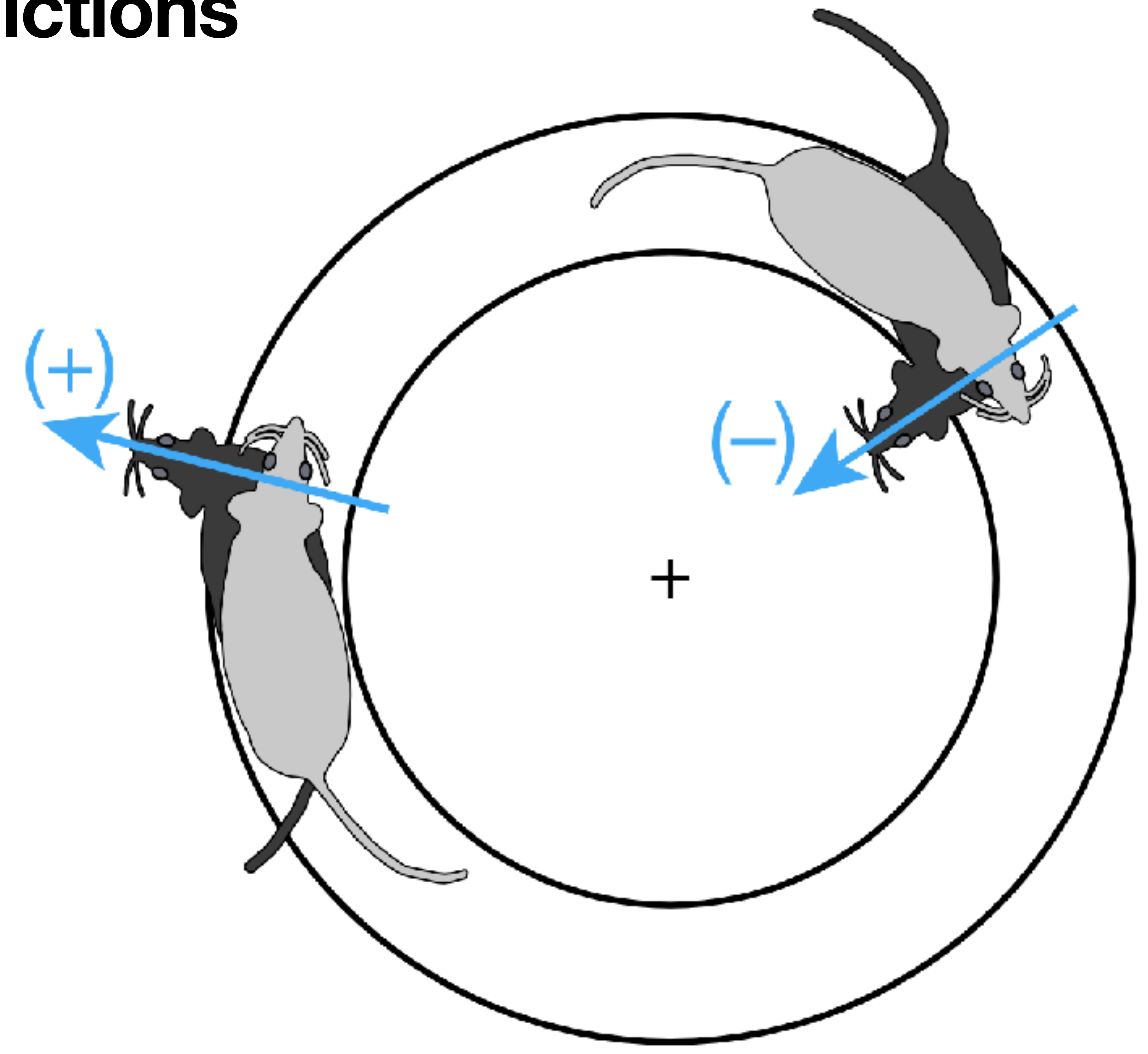
3.53 Hz

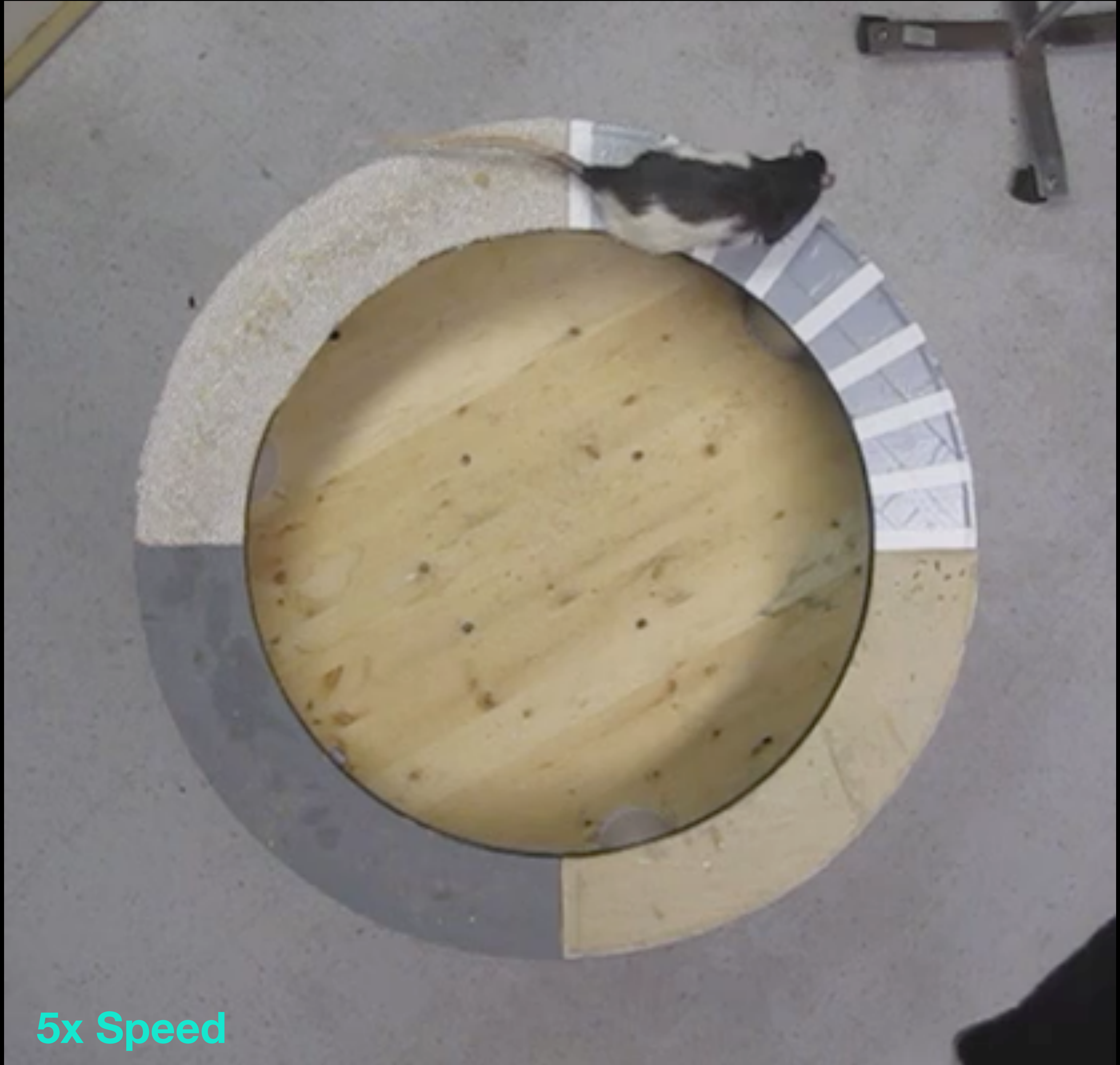
Active Inference

The generative–variational role of sensory predictions

- *<u>Predictive processing</u>* suggests that feedback-driven generative models require *<u>active inference</u>*: actions that maximize model evidence by balancing internal active-state (self) entropy with external sensory-state (nonself) entropy.
    - *Autonomous agents learn massively distributed internal feedback models by adaptively balancing entropy/negentropy accumulation in information streams arising at the self–nonself boundary.*

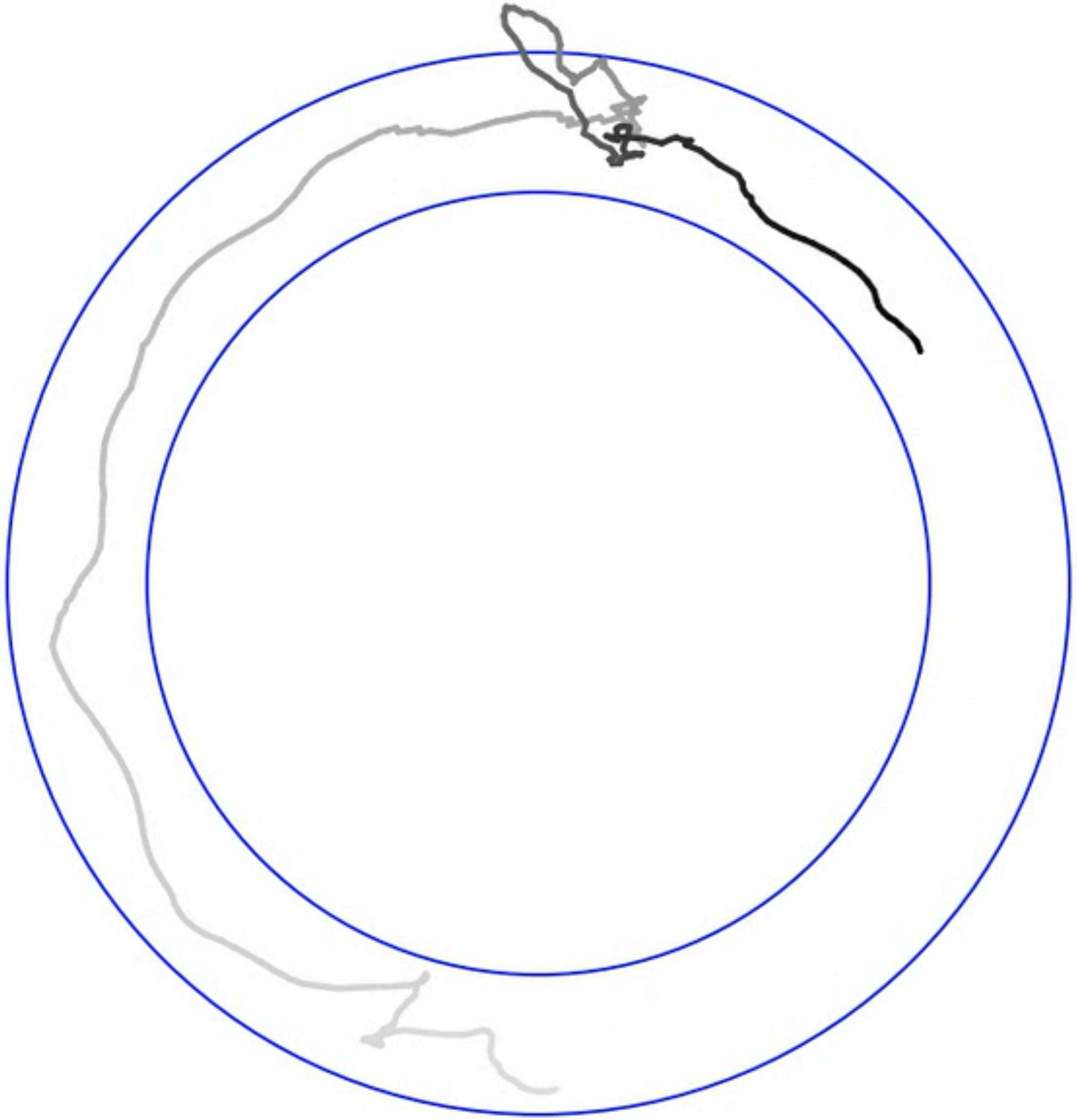


Friston K. Hierarchical models in the brain. PLOS Comput Biol. 2008;4: e1000211
Friston K. What is optimal about motor control? Neuron. 2011;72:488–98.



Video Credit: G. Rao

Active inference — Head scanning and place fields



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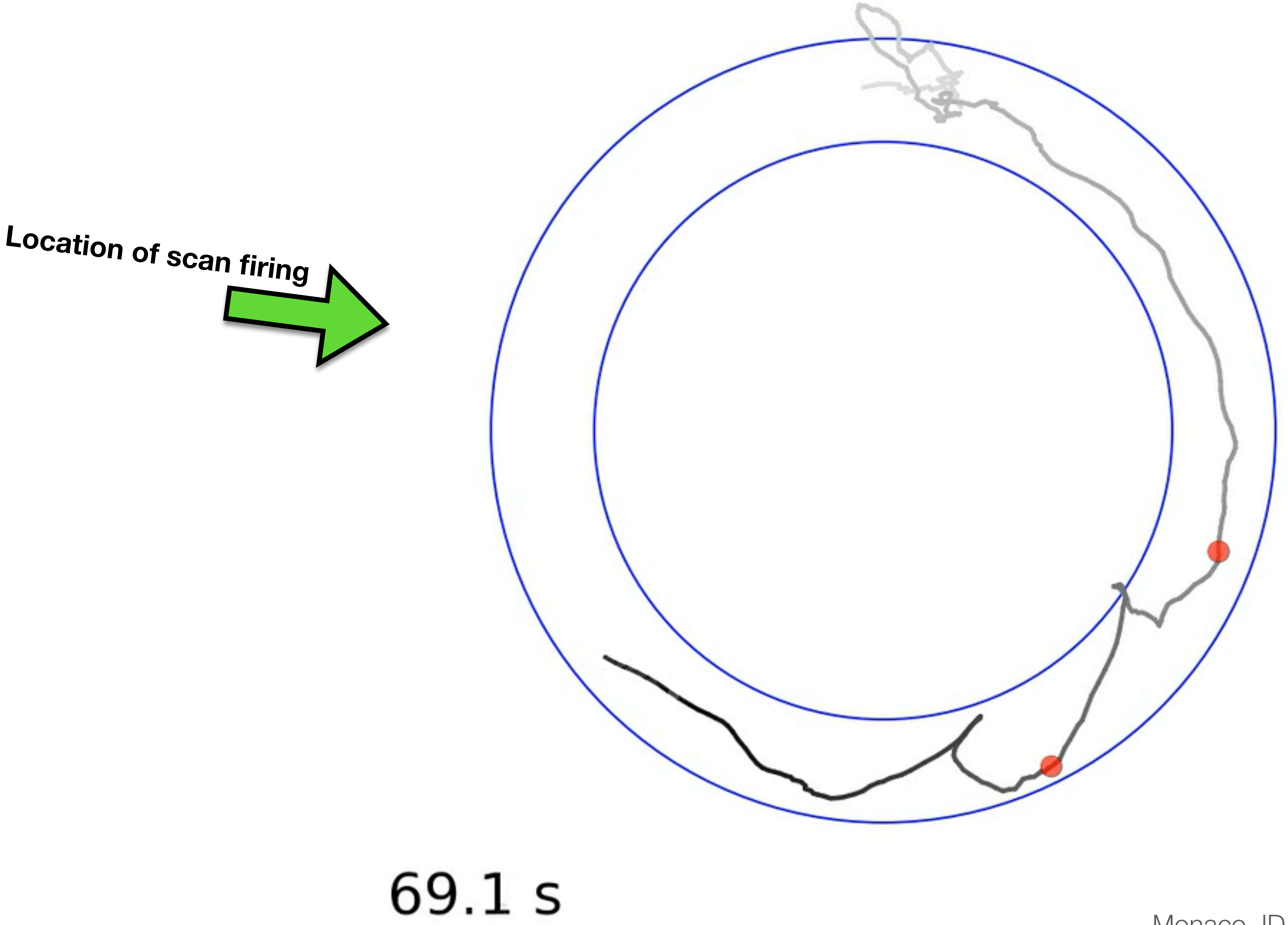
Monaco JD, *et al*. (2014). Nature Neuroscience, 17: 725

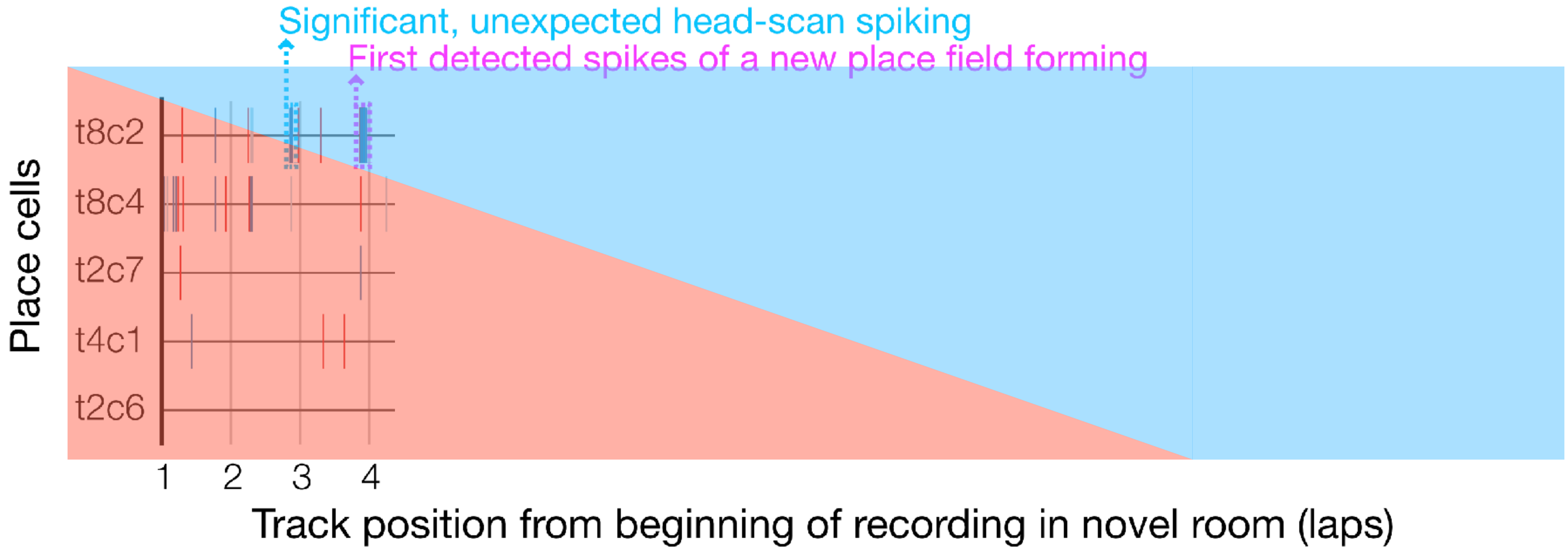
Active inference — Head scanning and place fields



Monaco JD, *et al*. (2014). Nature Neuroscience, 17: 725

Active inference — Head scanning and place fields

Cognitive map-building driven by autonomous head-scan sampling



Monaco JD, *et al*. (2014). Nature Neuroscience, 17: 725

Reorganizing the control flow

Perceptual control internalizes input, output, and goals (purposiveness)

- Goal-setting autonomy recognizes the agency inherent in embodied living systems
  - Animals have goals and those goals govern their behavior
- Environmental control is established through internal perceptual control of corresponding sensory perceptions constructed by perceptual input functions

Mansell (ed.). (2020). *International Handbook of Perceptual Control Theory*

Reorganizing the control flow

Perceptual control internalizes input, output, and goals (purposiveness)

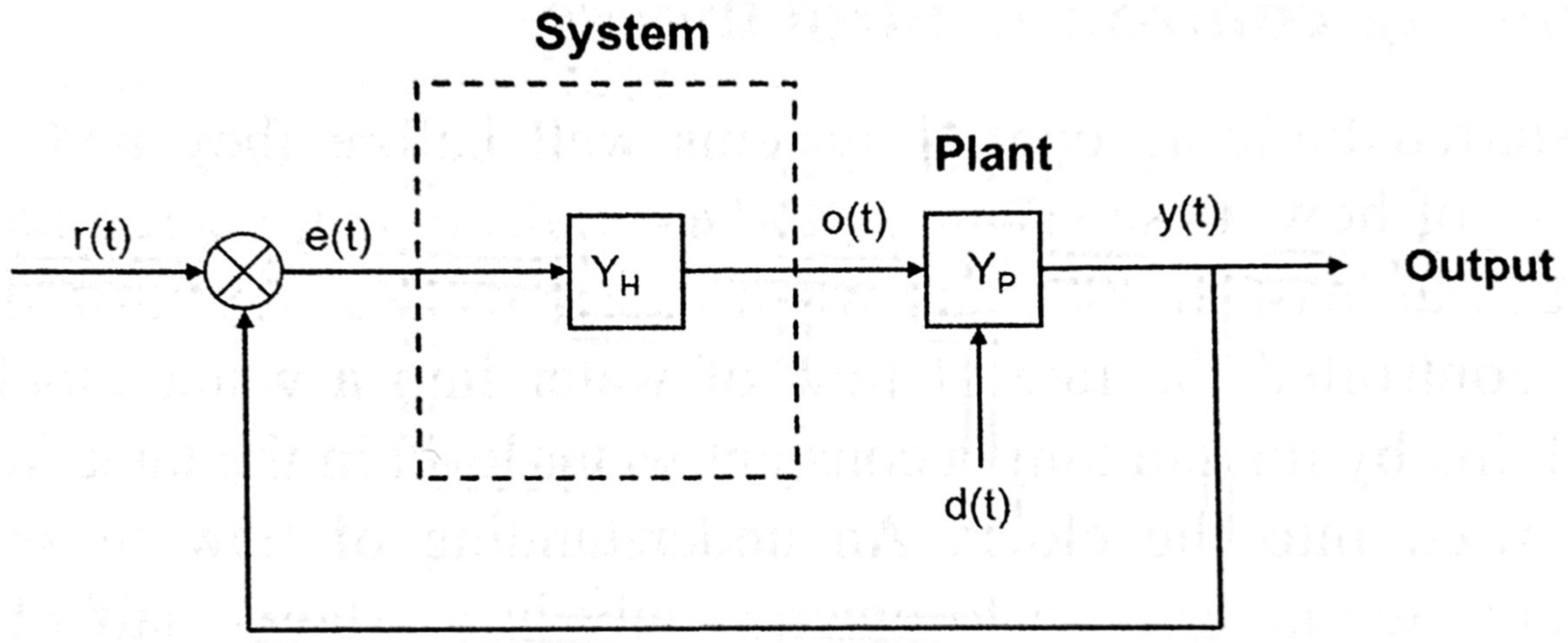


FIG. 2.1 Diagram of a negative feedback control system.[21]

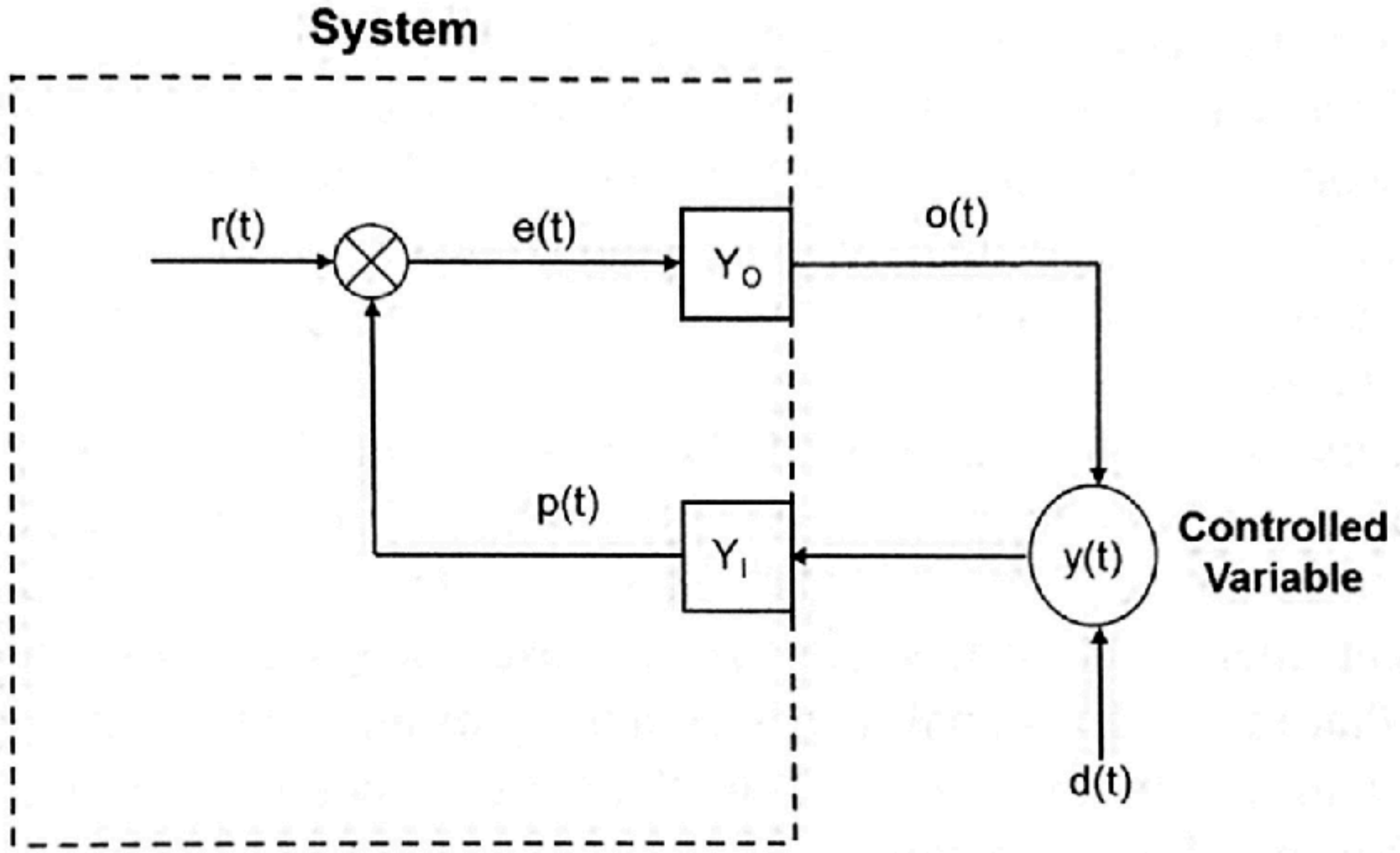


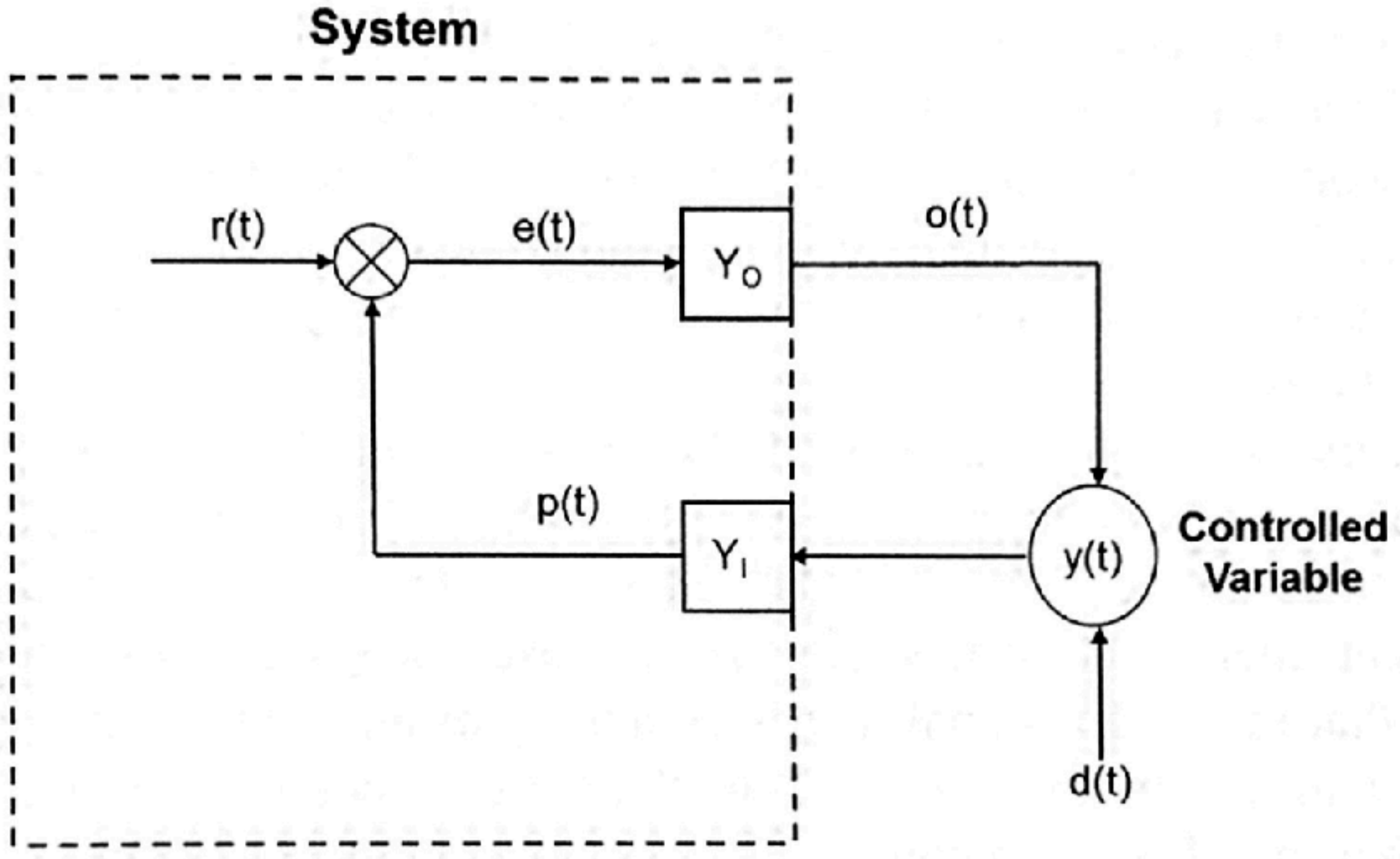
FIG. 2.2 PCT model of a control system; control theory for psychologists.

Mansell (ed.). (2020). *International Handbook of Perceptual Control Theory*

Reorganizing the control flow

Perceptual control internalizes input, output, and goals (purposiveness)

- Behavior is no longer the *output* of the neural system
    - Outputs (Y_0) are cascading internal reference signals
    - The lowest control levels form the self–nonself boundary that interacts with the environment
- Internal perceptions of controlled environmental variables are controlled, not behavior



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Reorganizing the control flow

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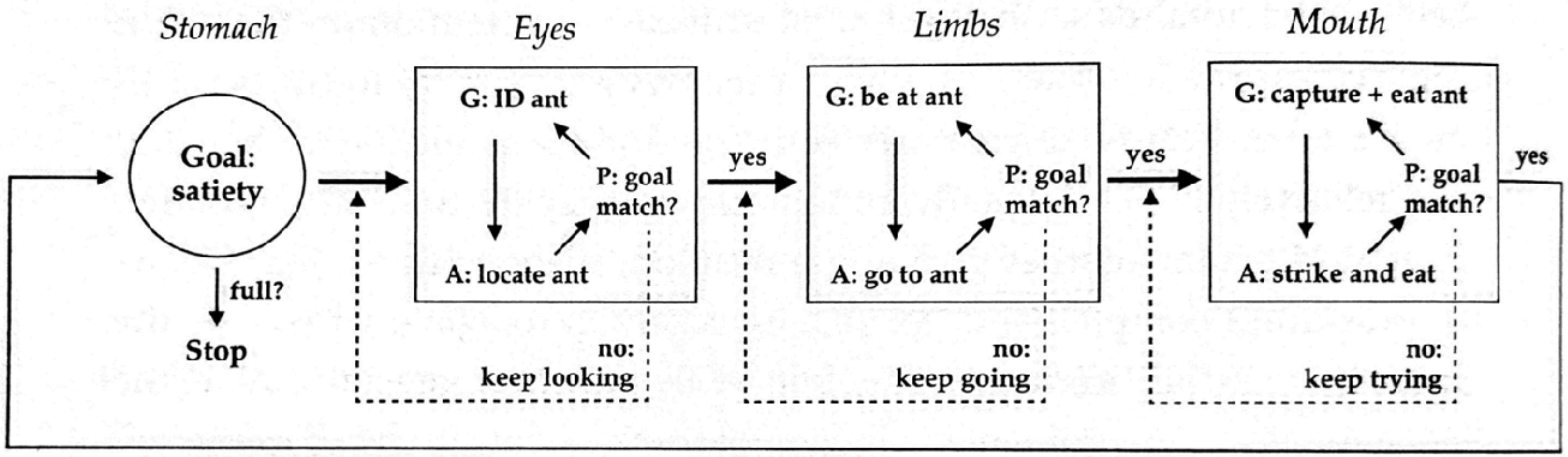
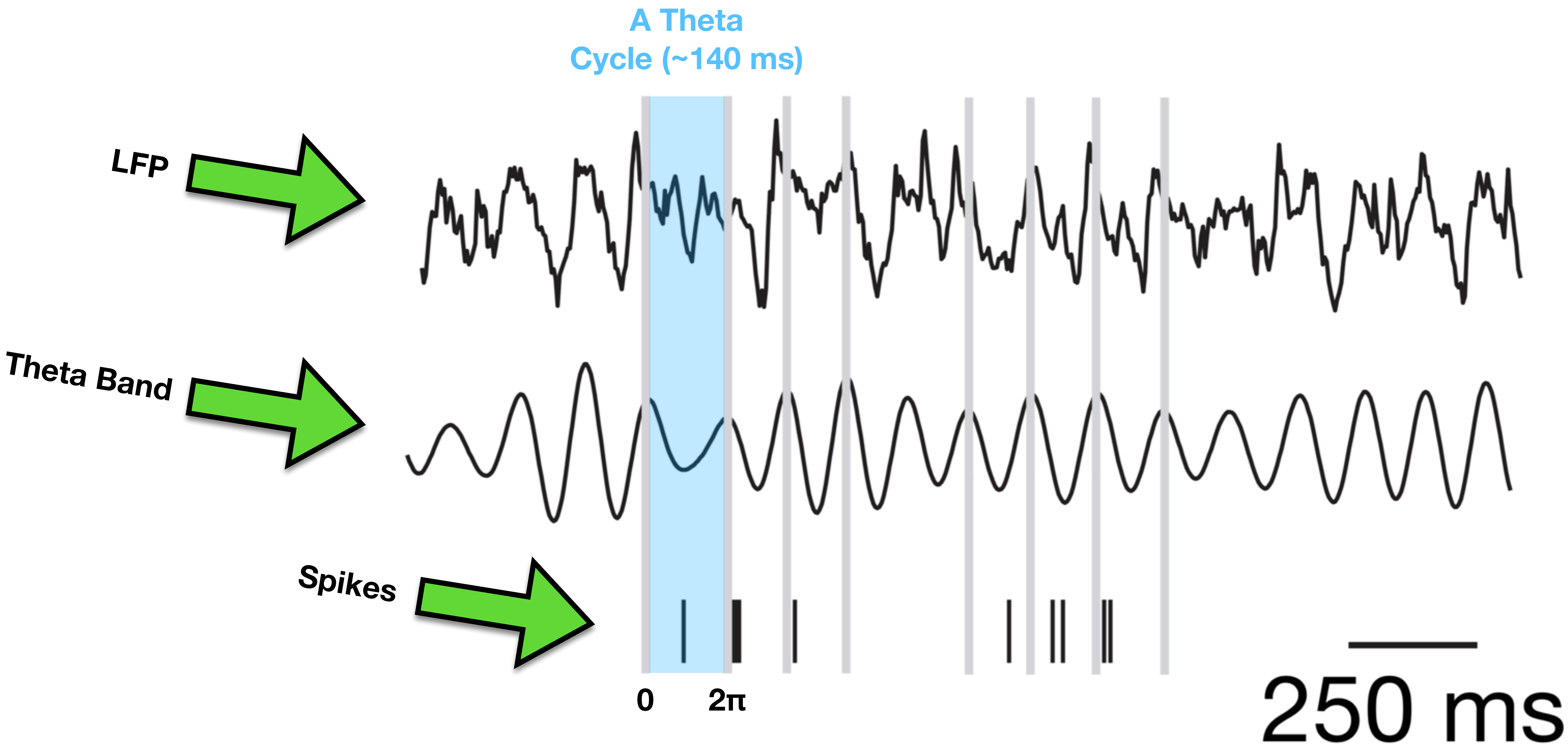


Figure 3.3
Highly simplified sequence of feedback control systems comprising a lizard's foraging for an ant efficiently and flexibly. *G* = goal; *A* = action; *P* = perception (to see if actual situation matches goal situation). Each box actually represents a hierarchy of submechanisms (e.g., moving limbs to locomote, opening mouth to eat, etc.).

The Hippocampal Theta Rhythm



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

‘Theta flickering’ of hippocampal maps

Cyclic rebuilding of internal context → entropy management?

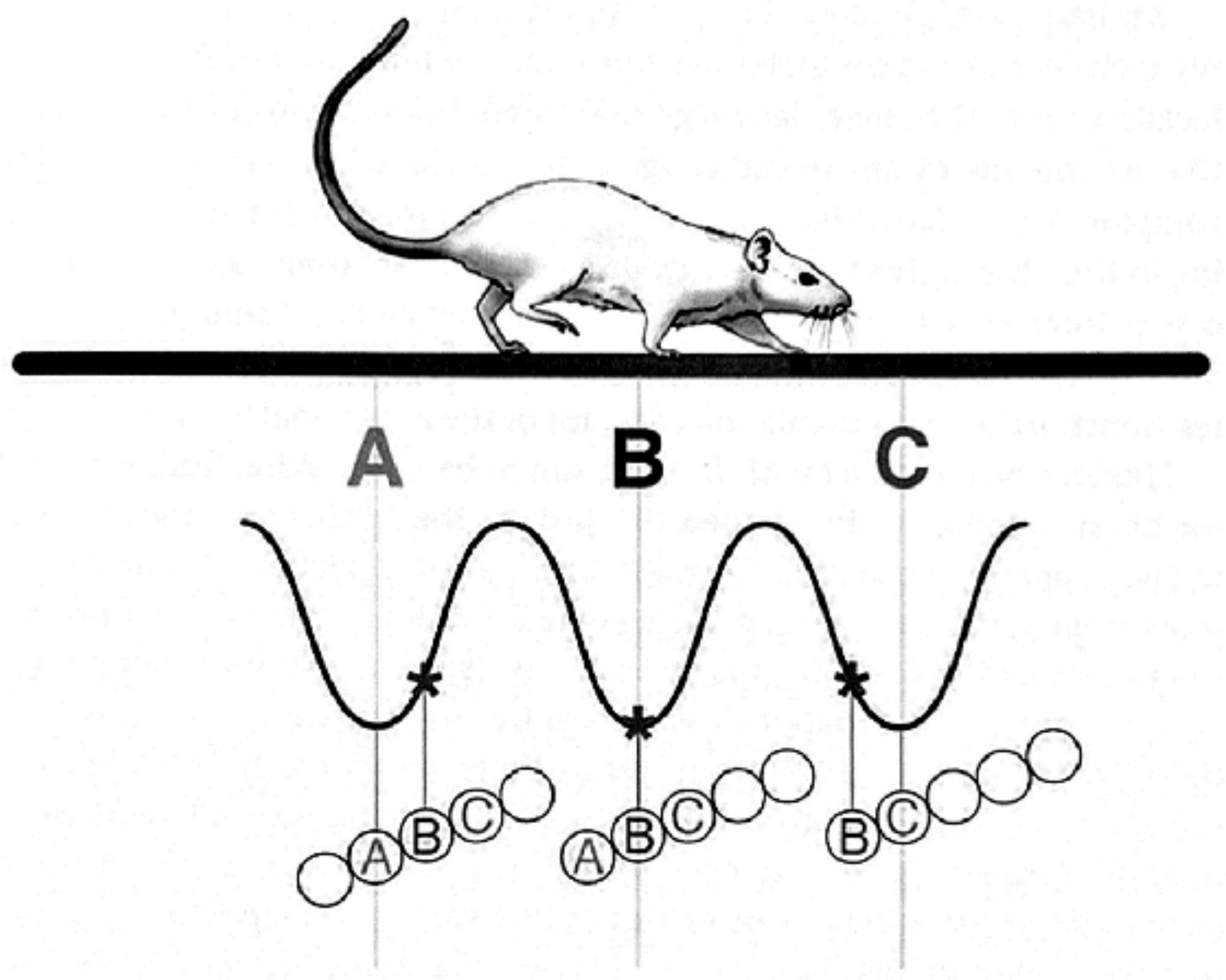
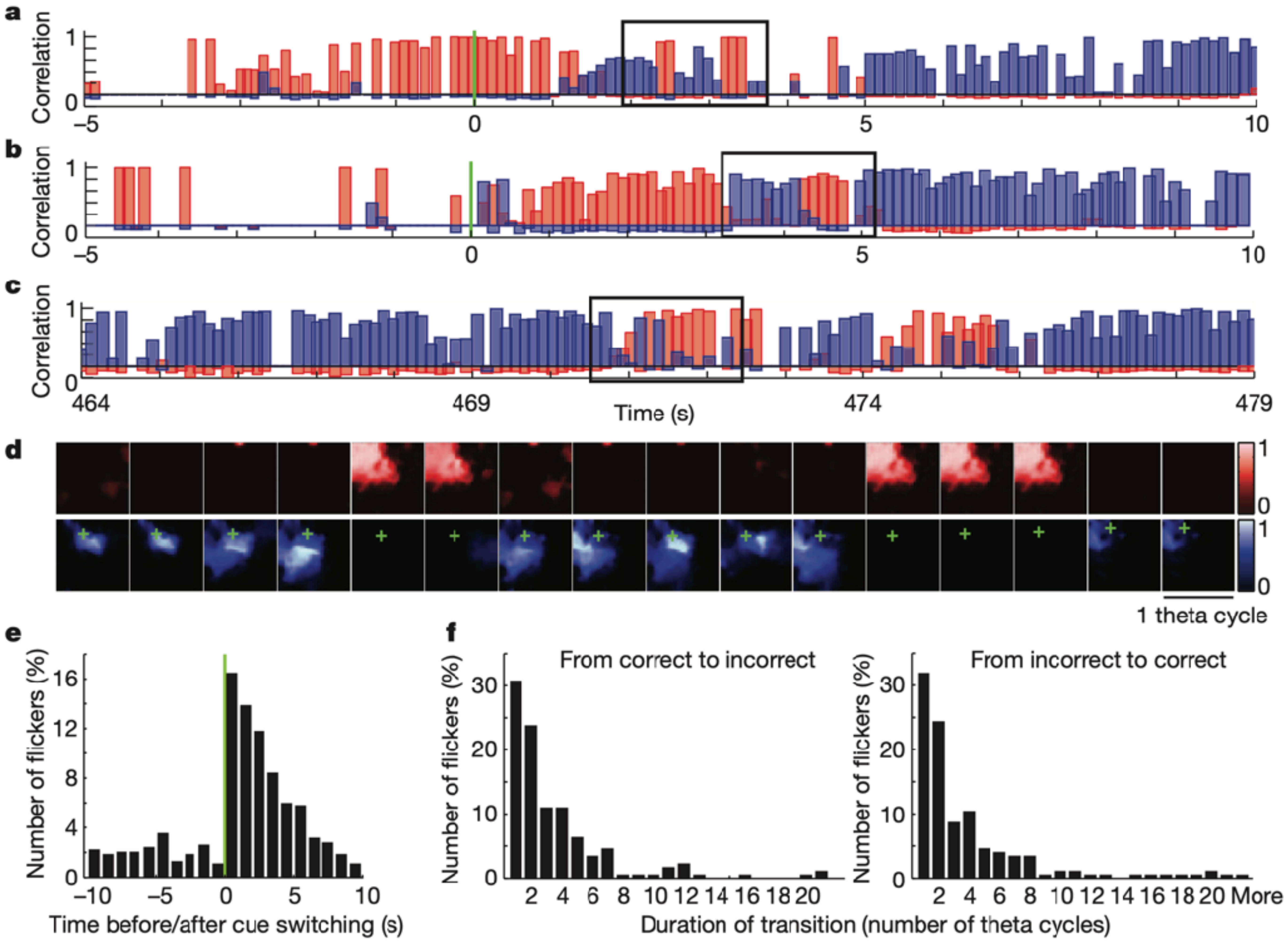


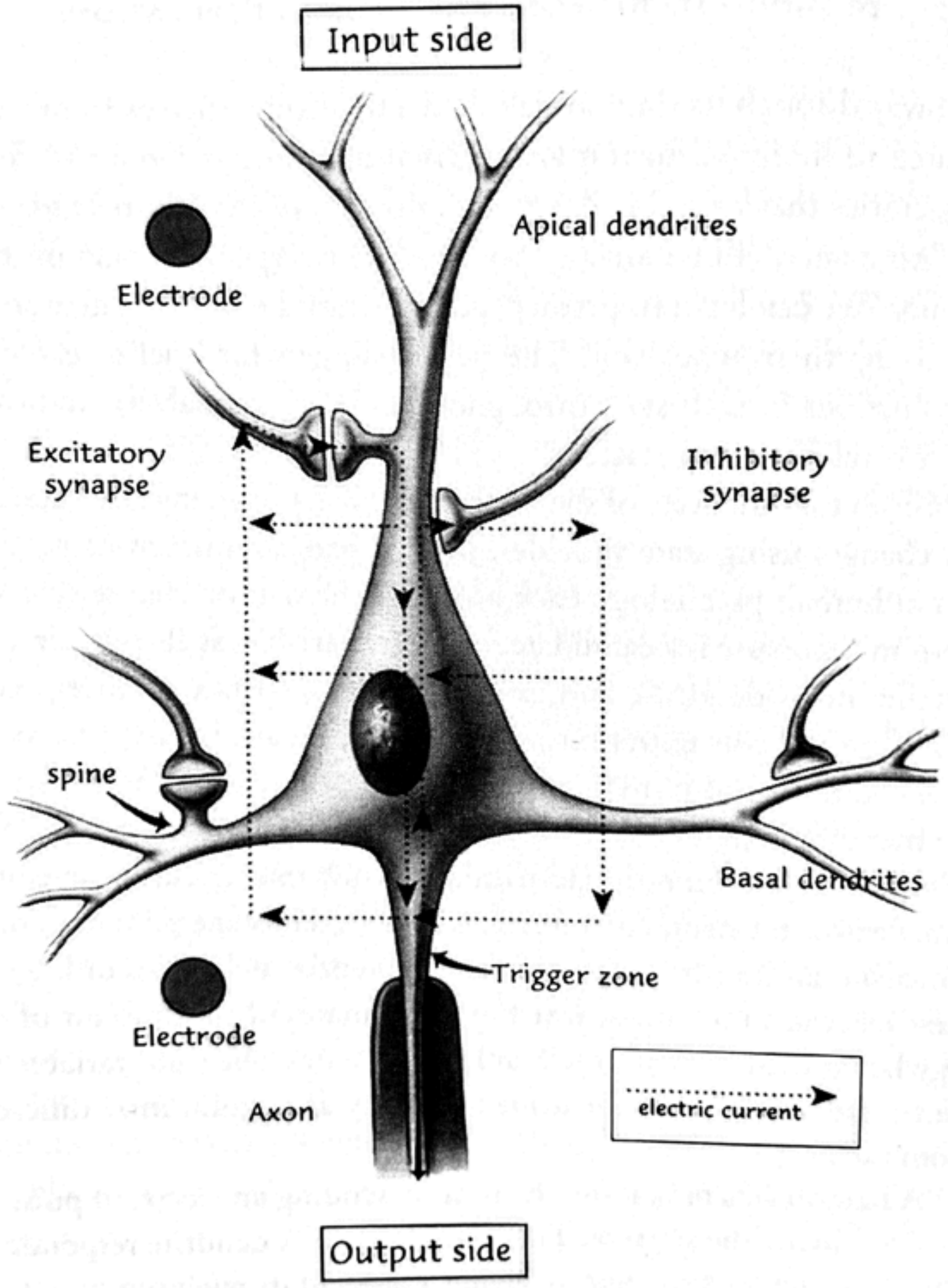
Figure 3a.1
Place cell B fires at different times relative to the background theta-wave as the rat moves from locations A through C. Reprinted from Buckner (2010) with permission.

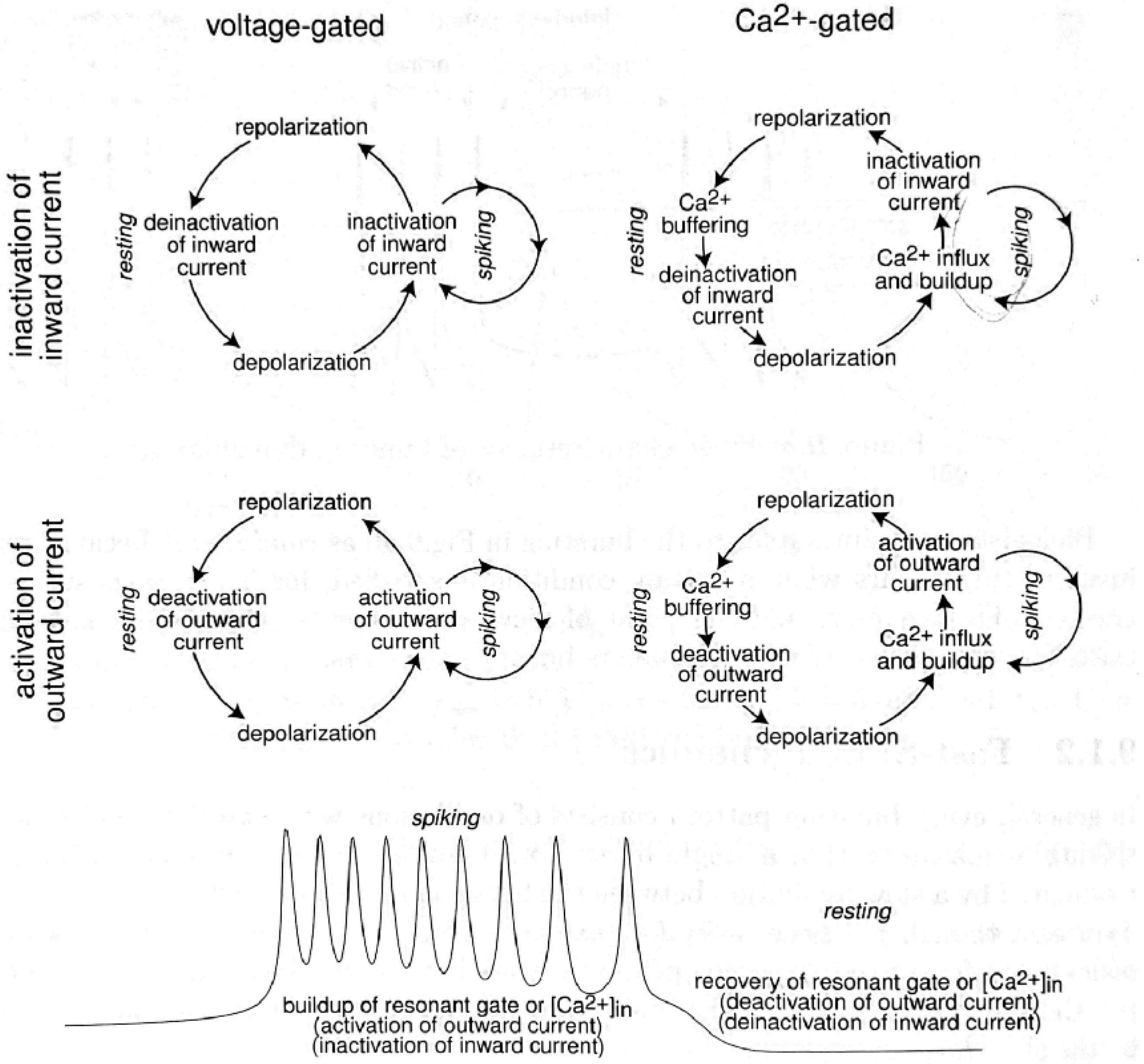


Anderson. (2014) *After Phrenology*

Jezek, *et al*. (2011). *Nature*

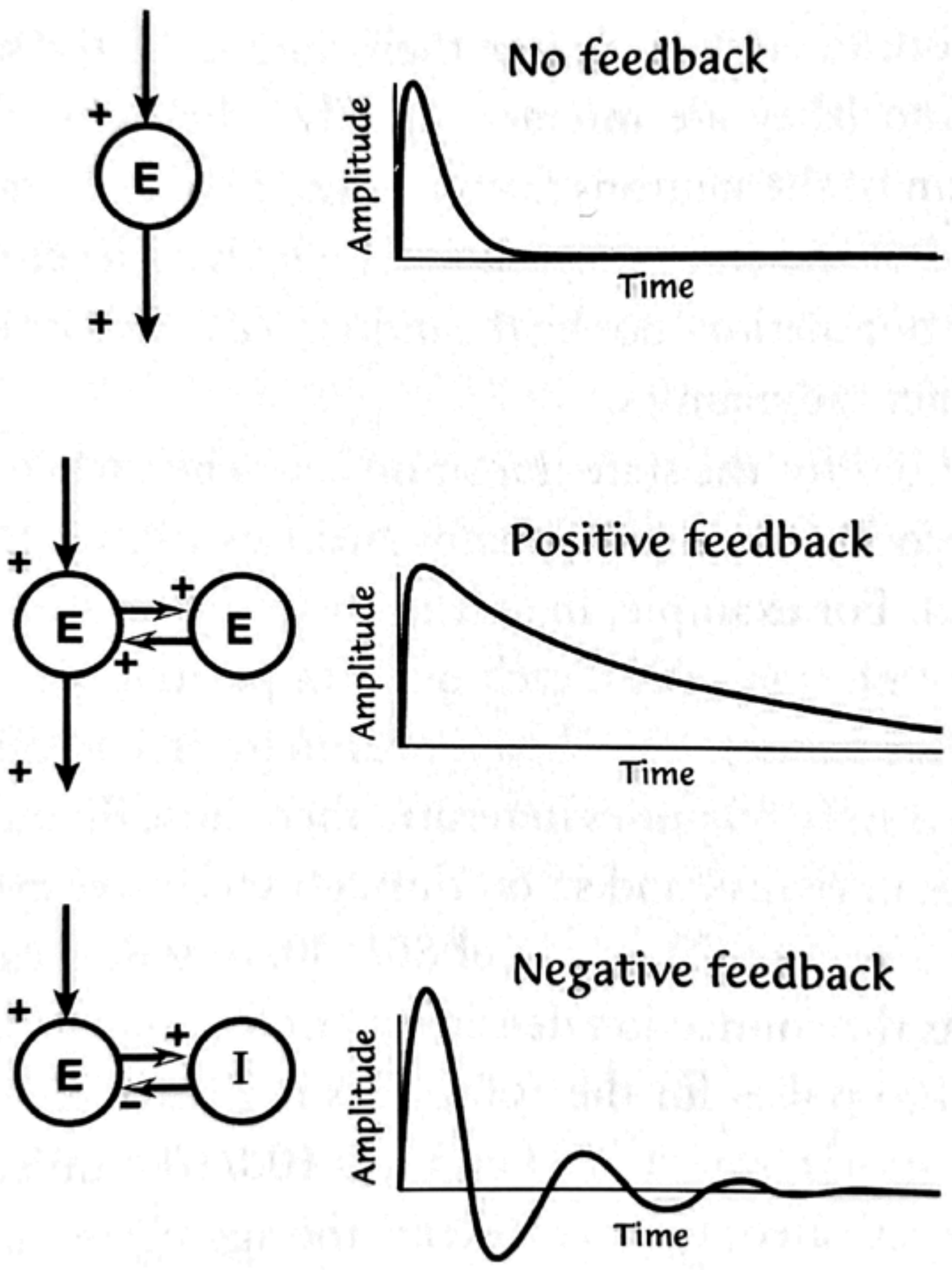
Neural dynamics emerge from interdependent ionic gates

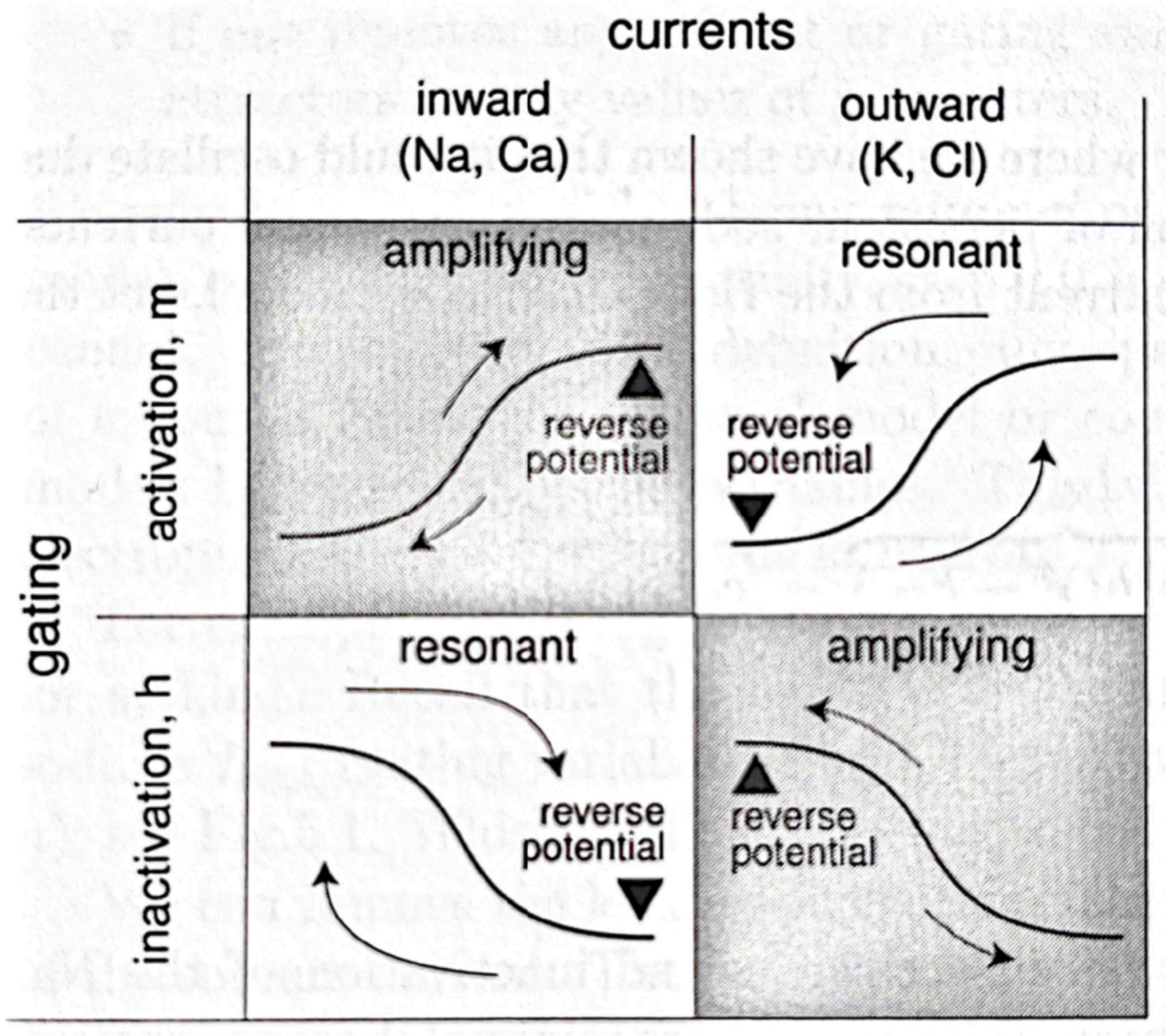




Izhikevich (2007) *Dynamical Systems in Neuroscience.* MIT Press

How to Make a (Neuronal) Oscillator





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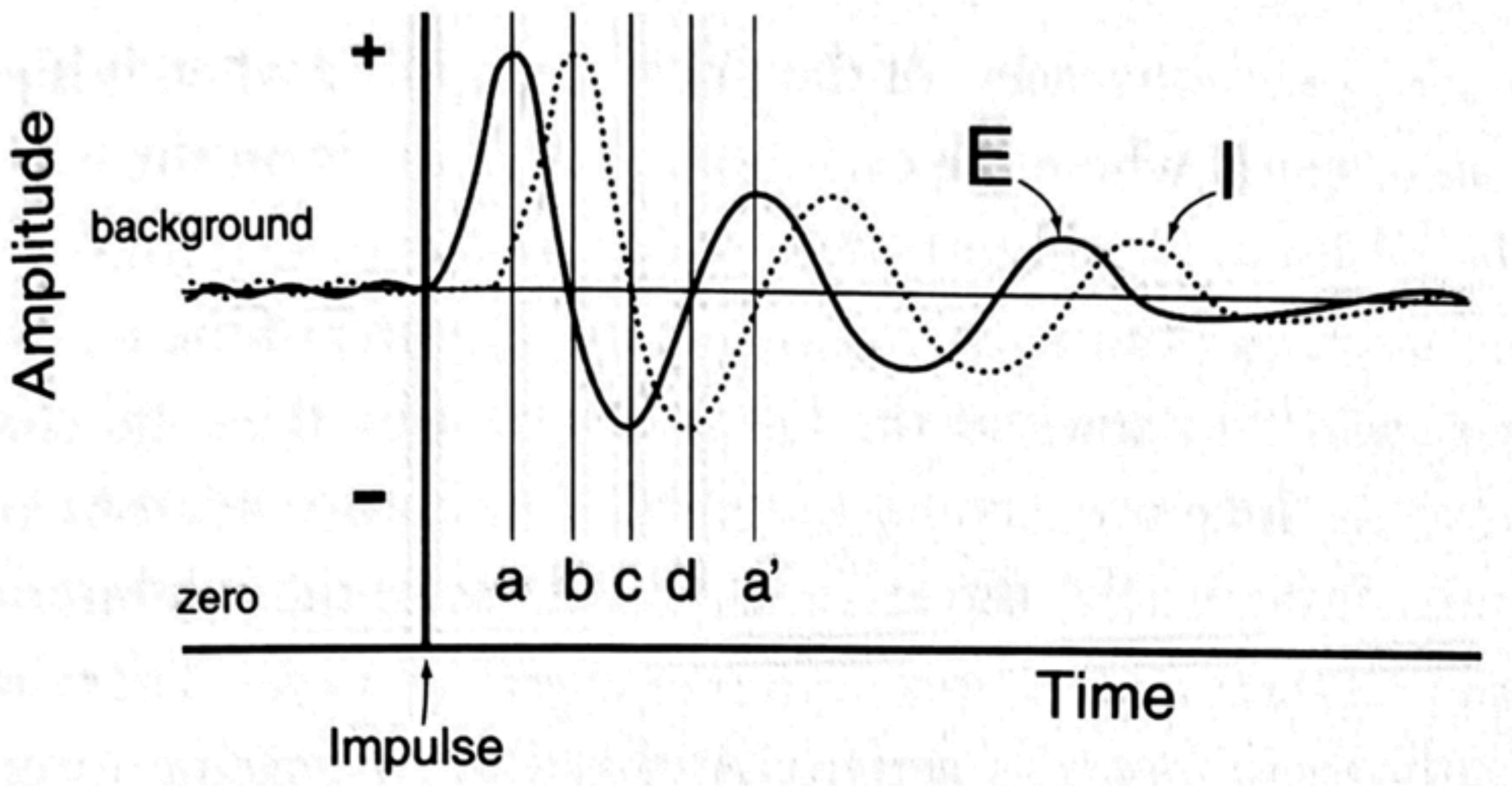
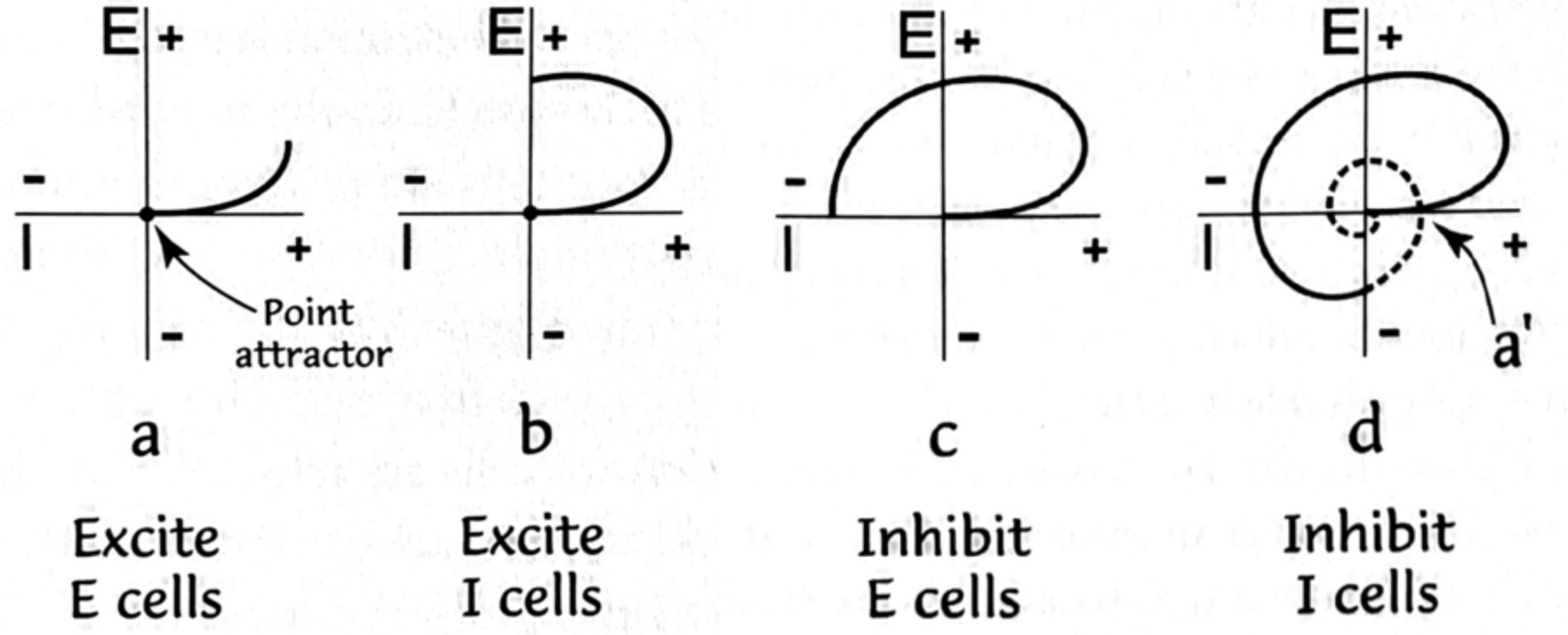
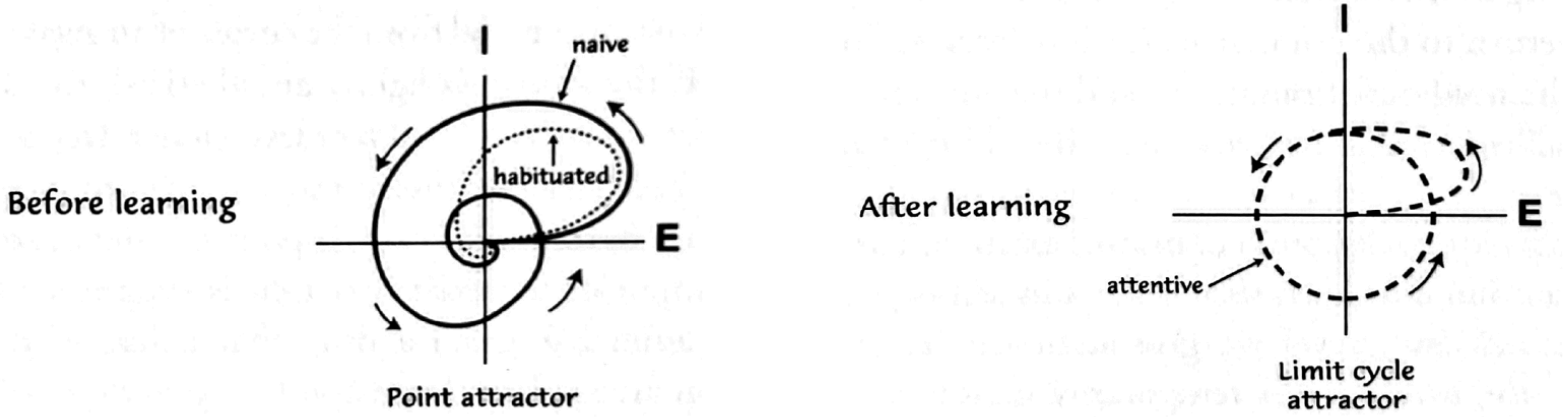
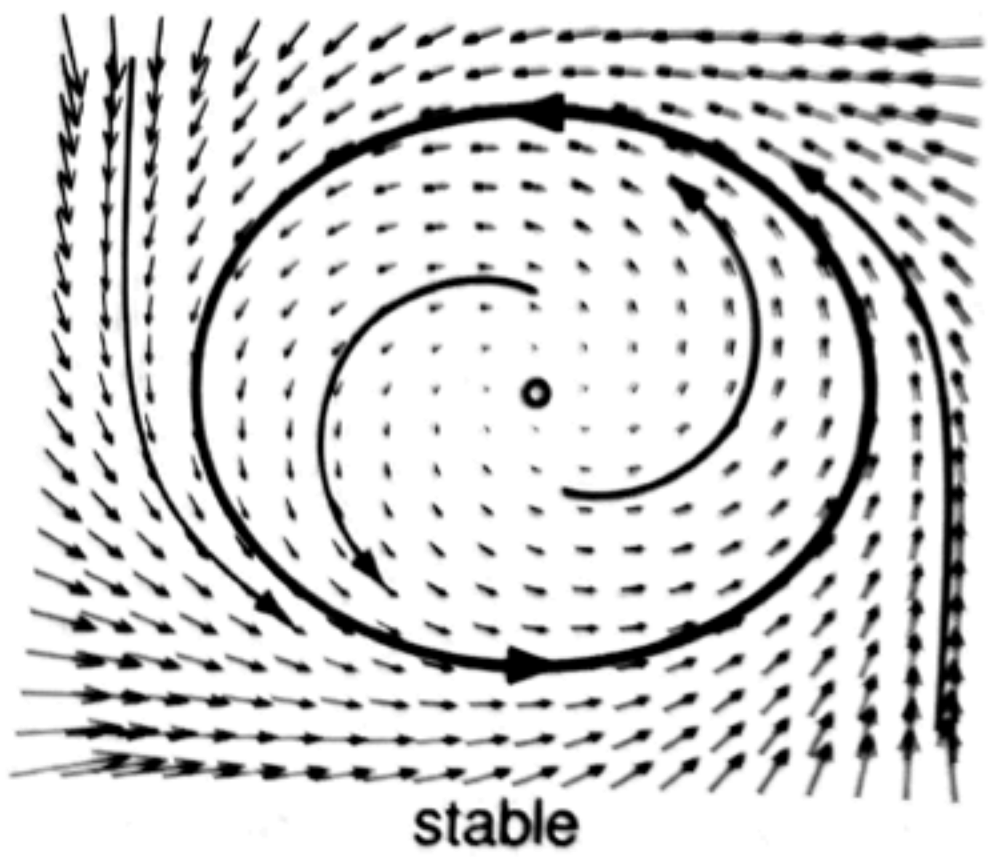


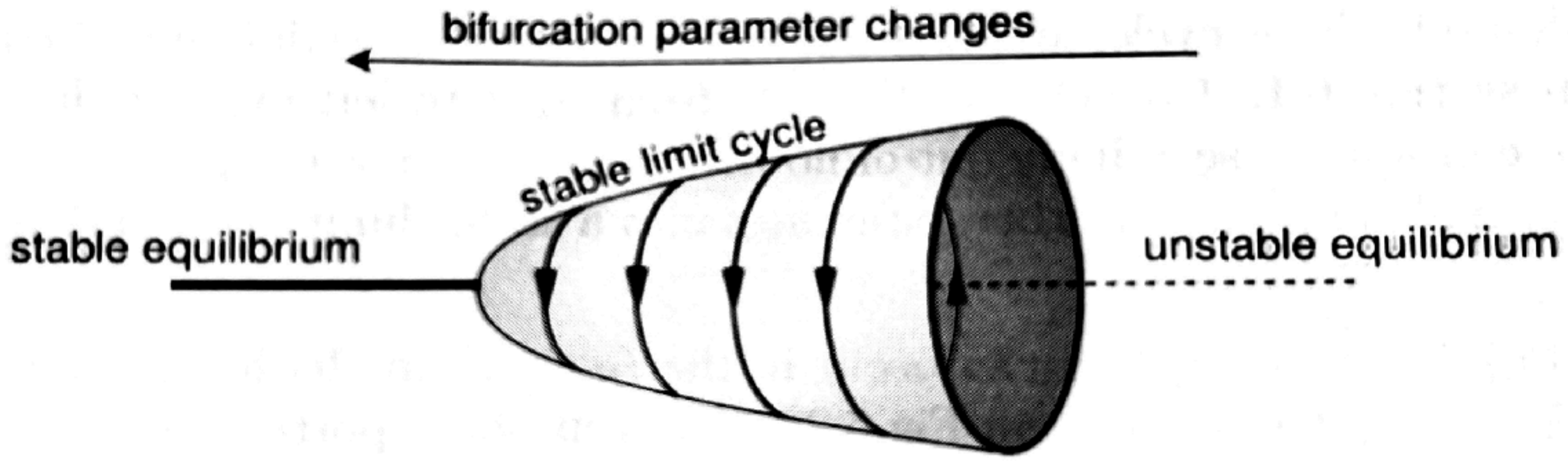


Freeman (2000) *How Brains Make Up Their Minds.* Columbia University Press

How to Make a (Neuronal) Oscillator







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

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

Communication Through Coherence (Fries, 2005)

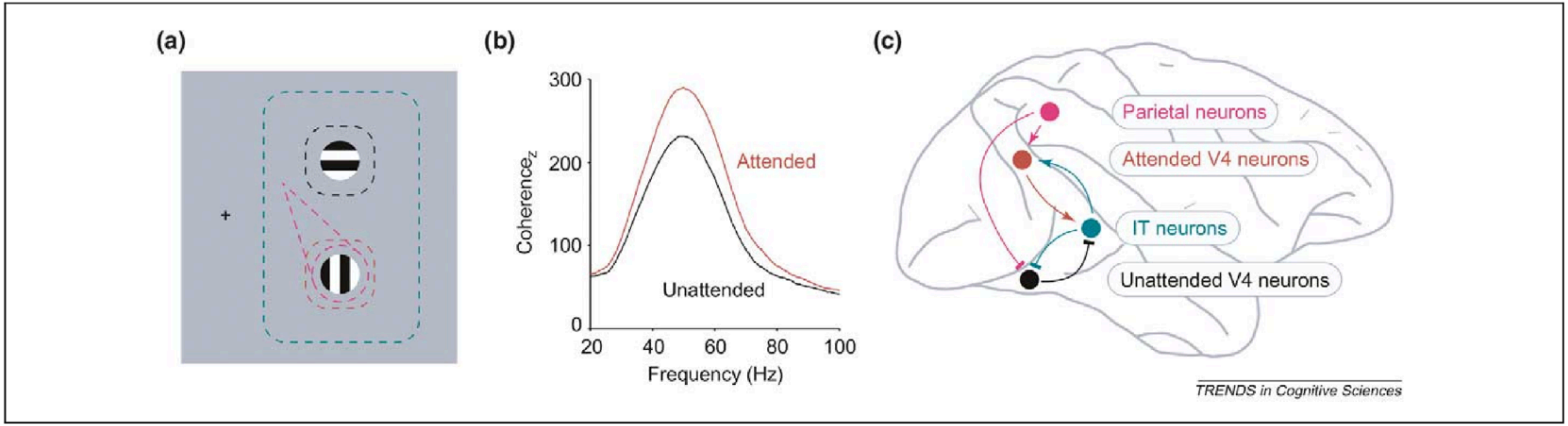
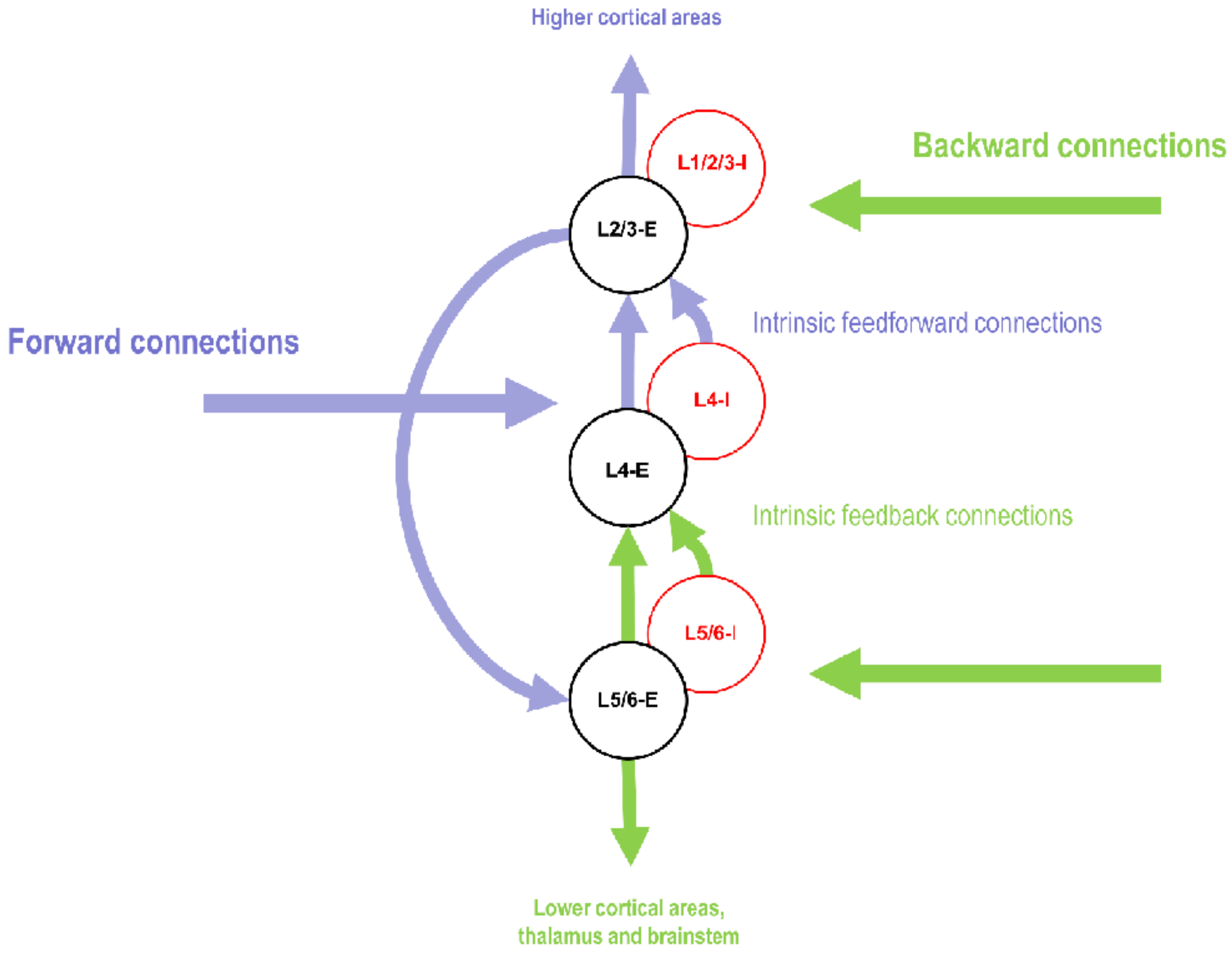
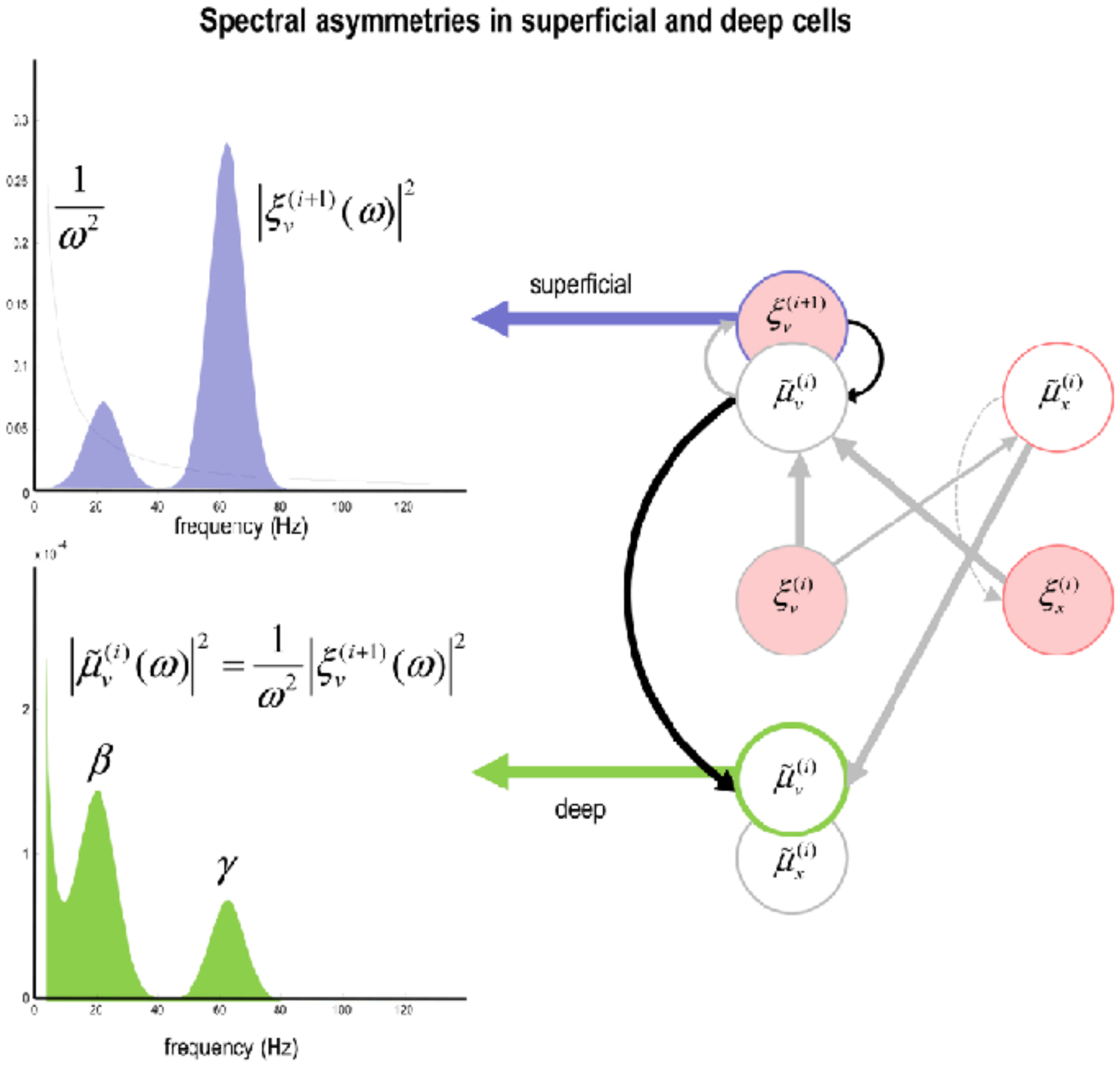


Figure 5. Coherence and competition. **(a)** Stimulus configuration used in a selective visual attention experiment [22]. The lower patch of grating falls into the receptive field of a neuronal group in V4 indicated in red (and black for the upper patch). Both grating patches fall into the receptive 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.

Predictive processing hierarchy and the “spectral connectome”



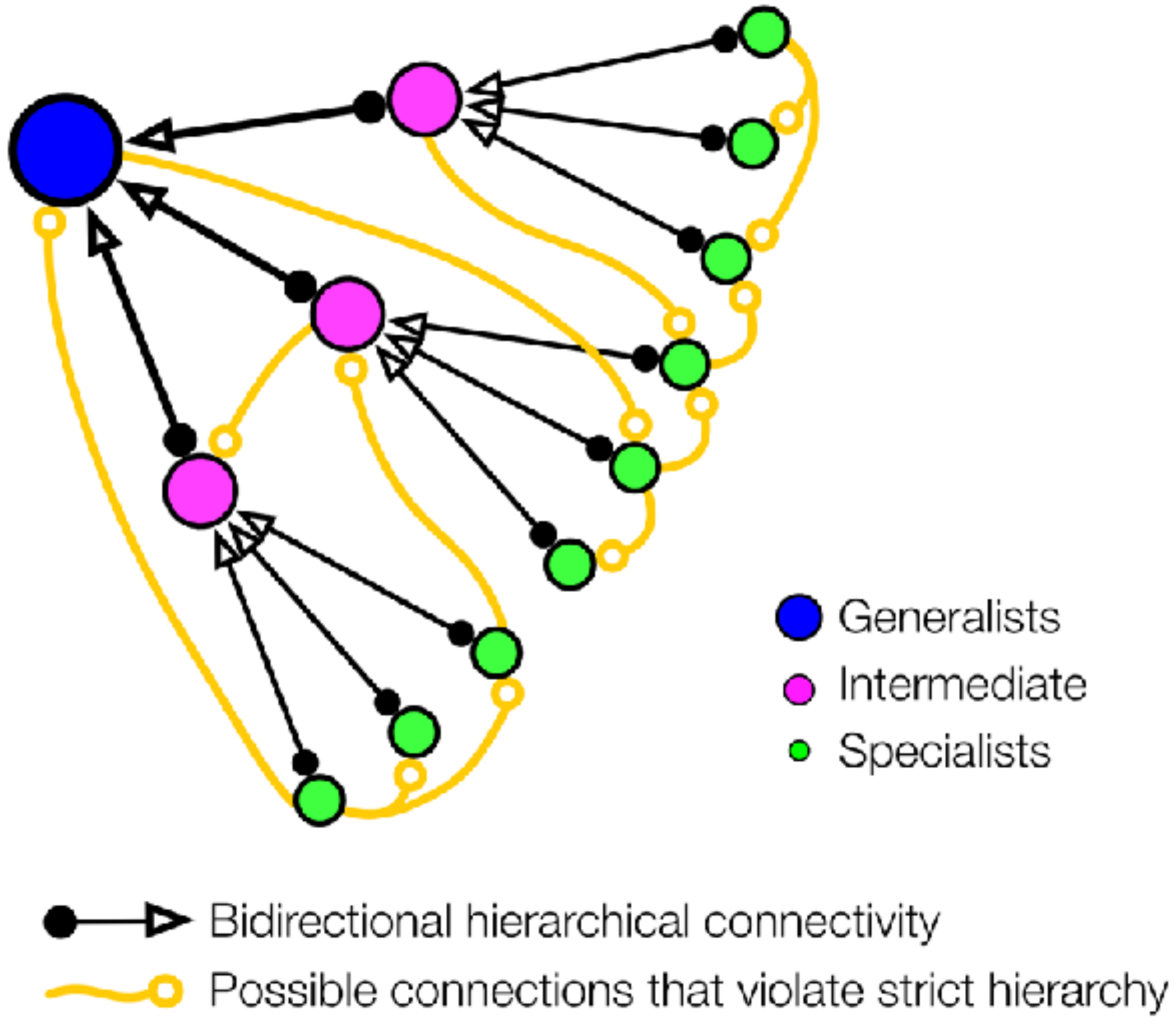


Bastos, …, Friston. (2012) Canonical Microcircuits for Predictive Coding. *Neuron, 76, 695.*

Integrative framework for neurodynamical cognition

(1) Network structure:

Sparse, distributed hierarchies are non-strict



(2) Temporal dynamics:

(3) Agentic interaction:

Monaco and Hwang. (2022). *Cognitive Computation*

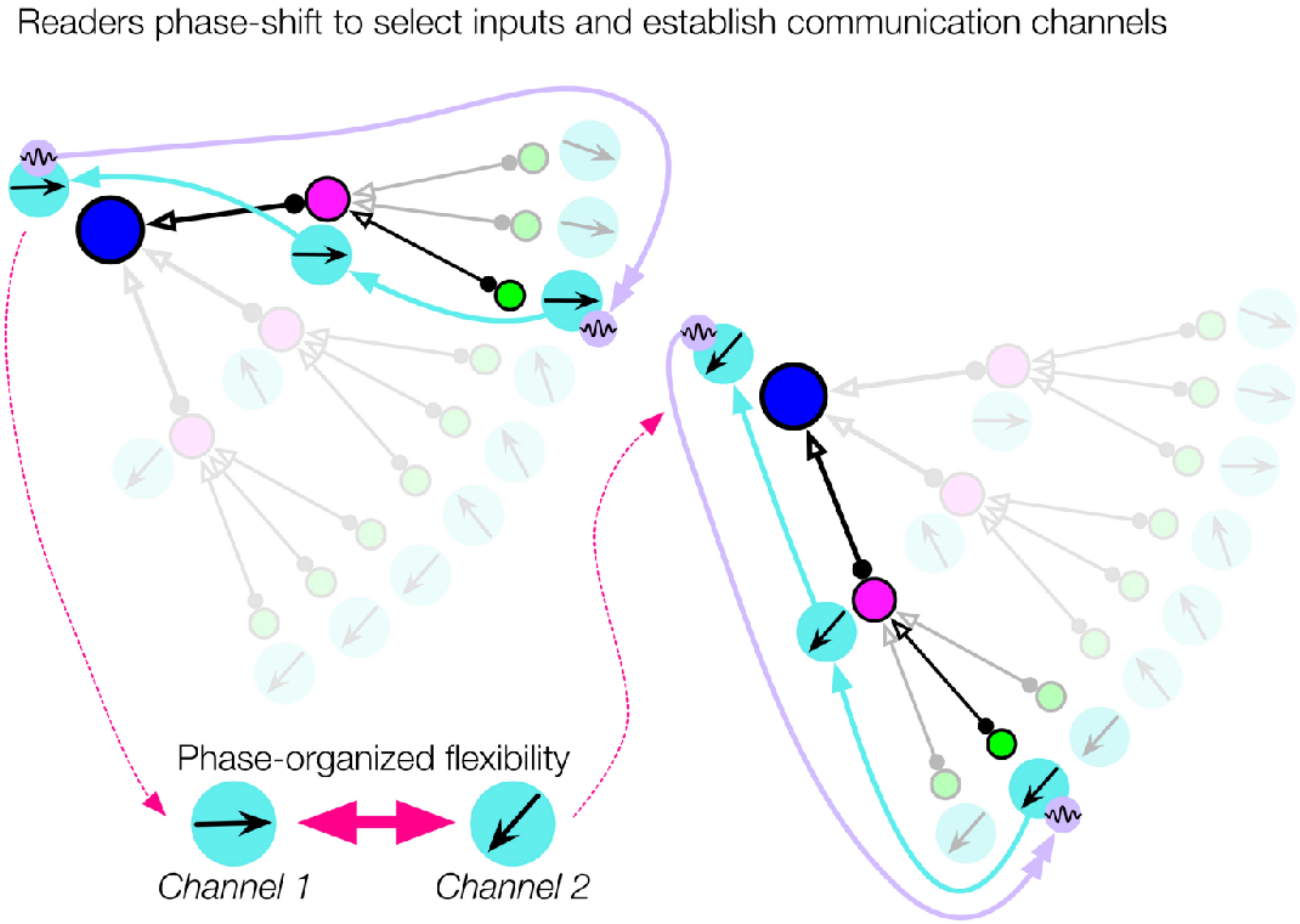
Integrative framework for neurodynamical cognition

(1) Network structure:

(2) Temporal dynamics:

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

(3) Agentic interaction:



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Integrative framework for neurodynamical cognition

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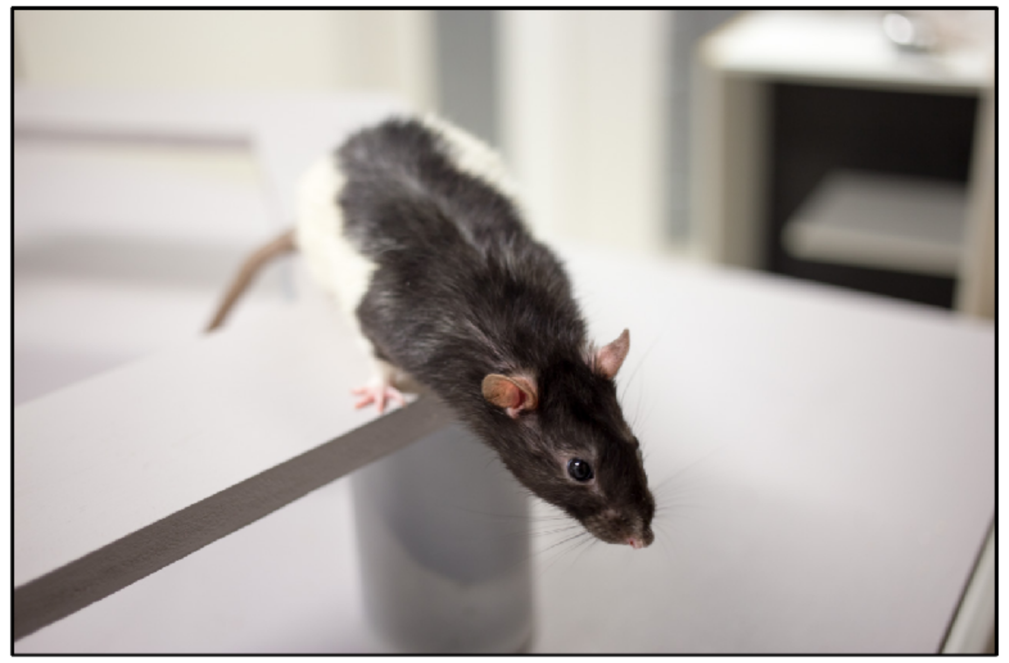
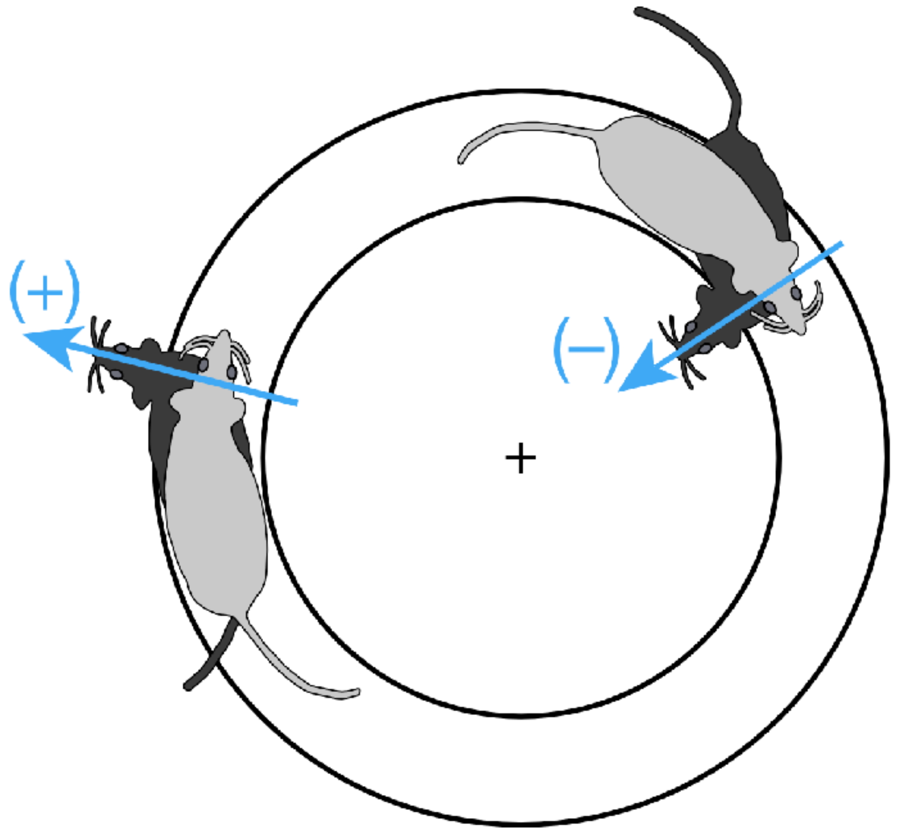
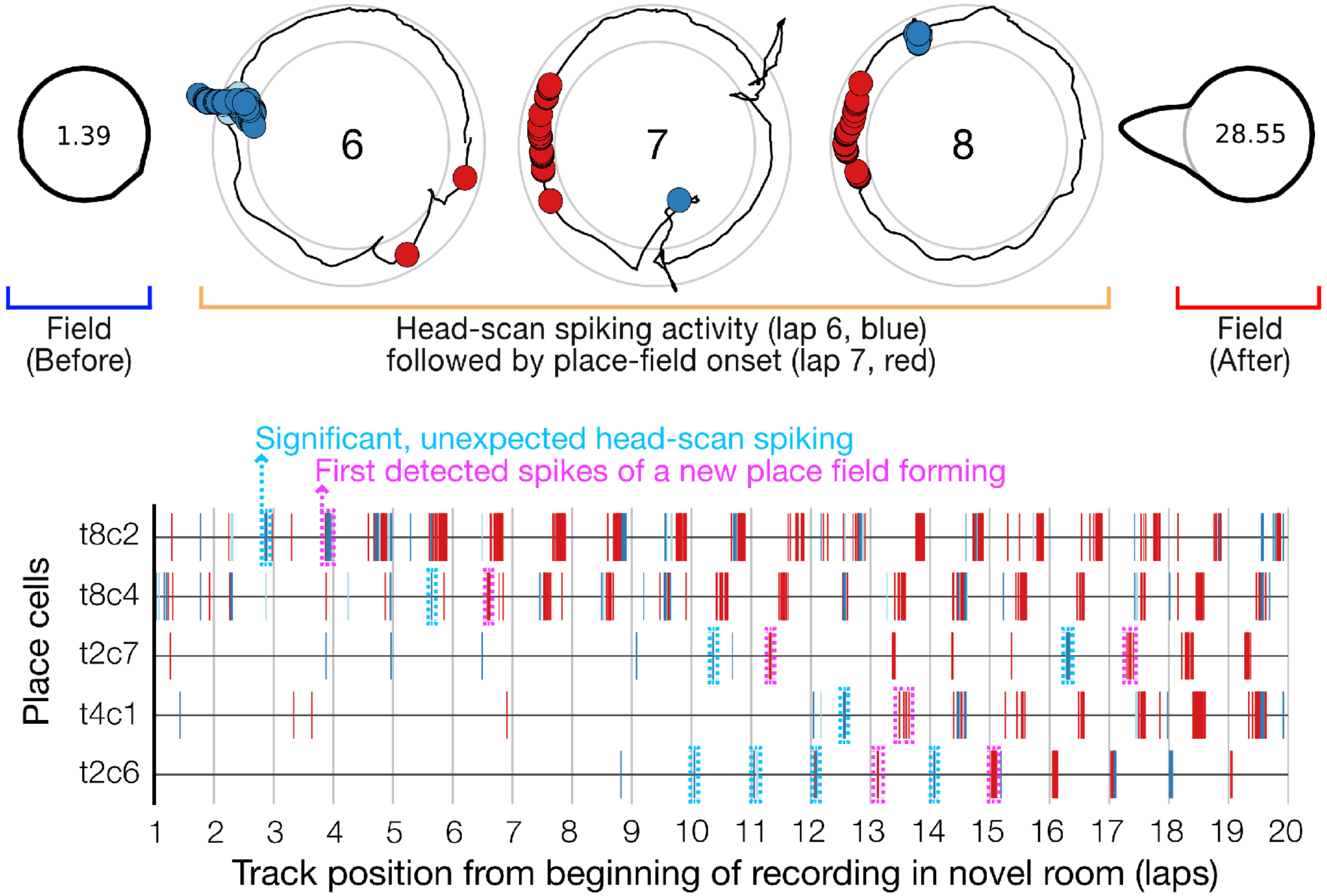


(2) Temporal dynamics:





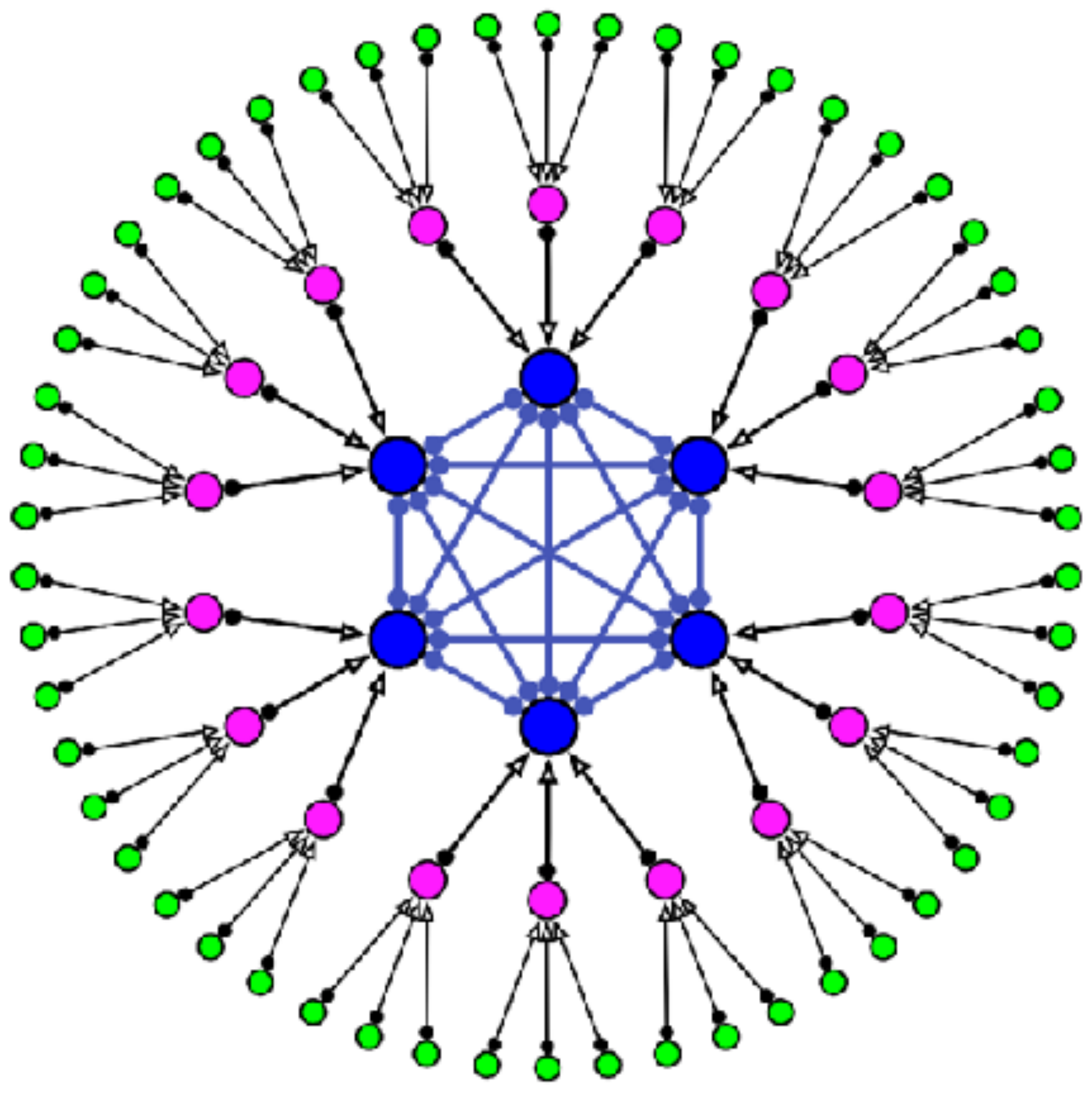
(3) Agentic interaction:

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

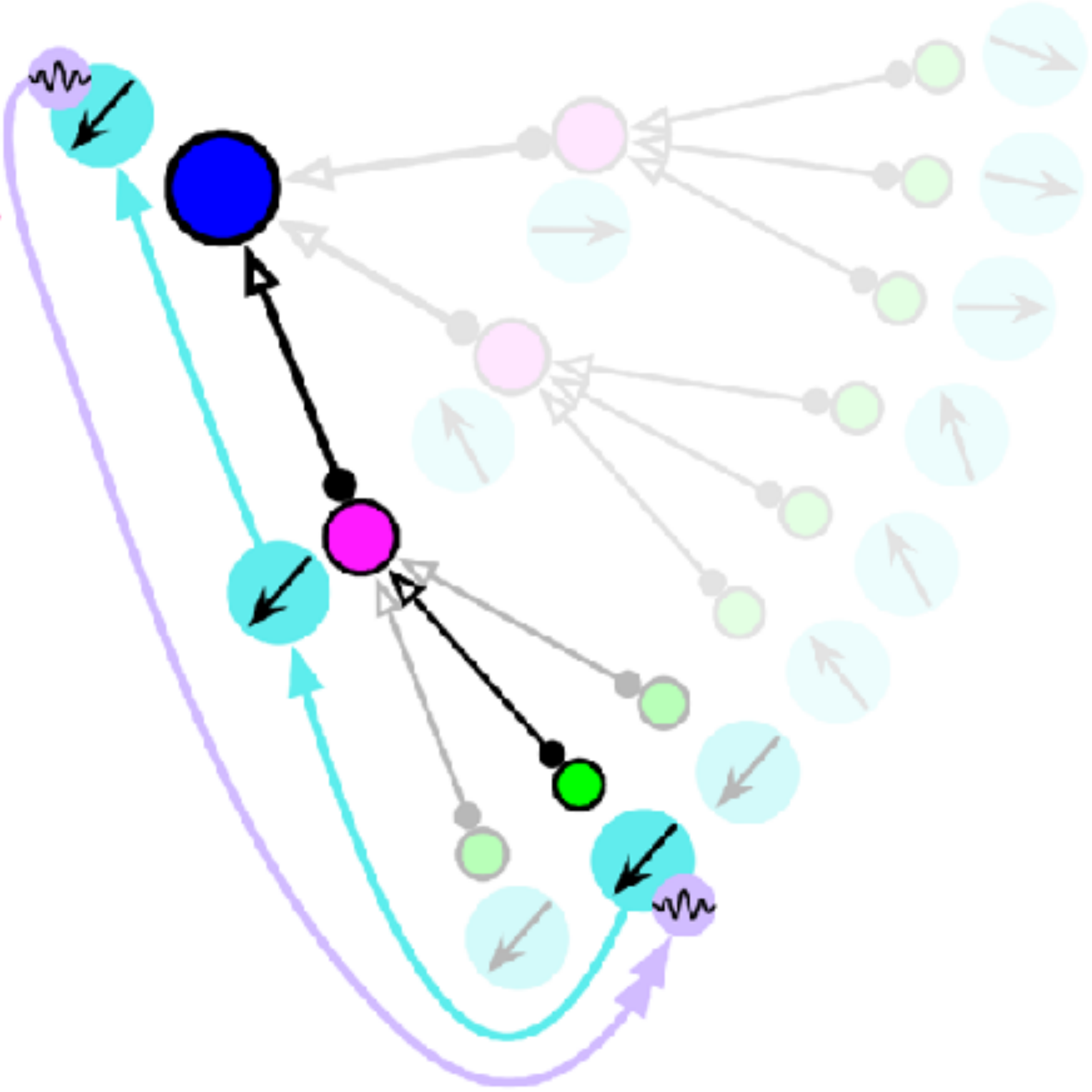
Monaco and Hwang. (2022). *Cognitive Computation*

Neurodynamical computing: Variation, selection, action

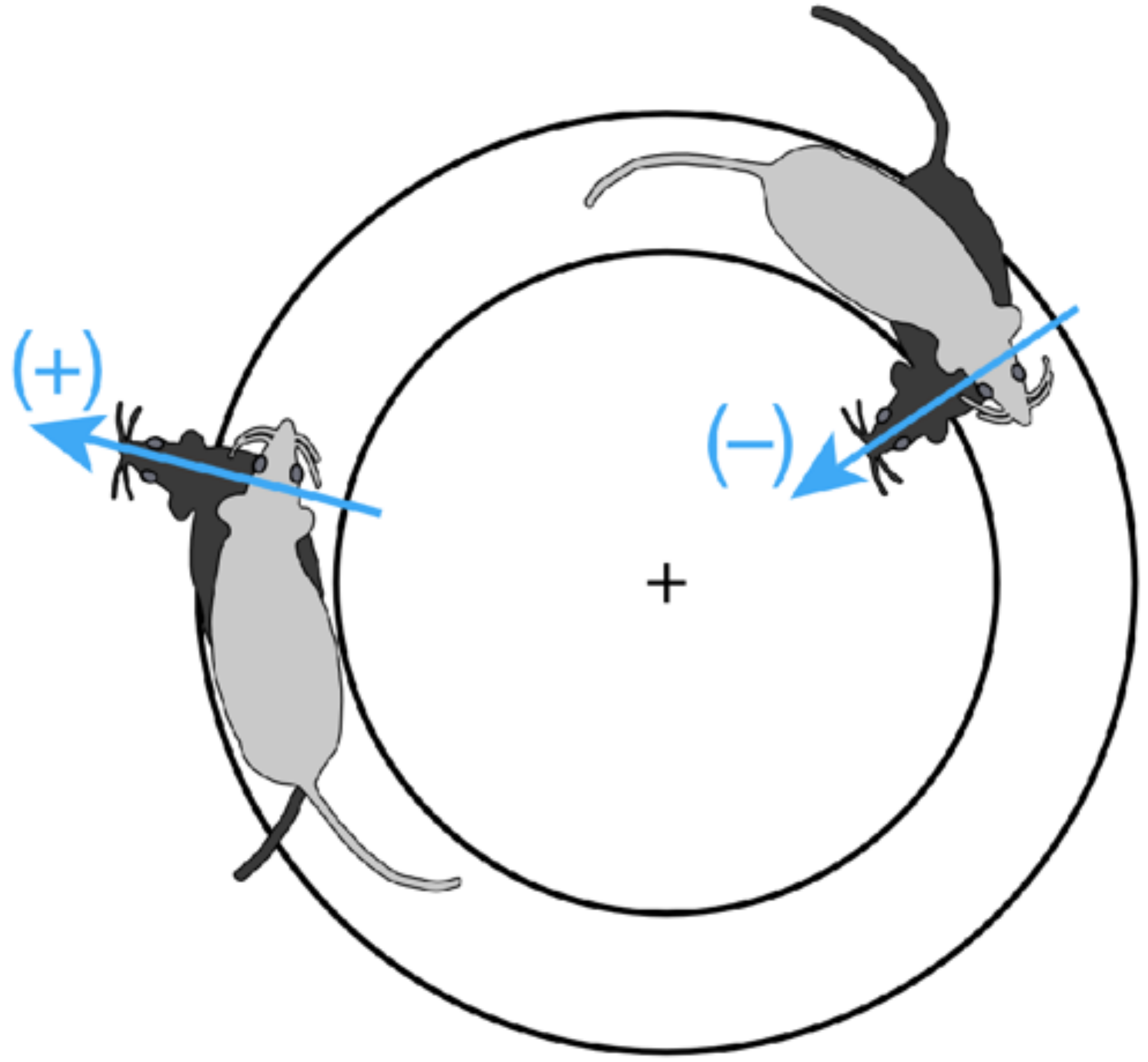
(1) Structural heterarchy



(2) Oscillatory coupling



(3) Agentic interaction



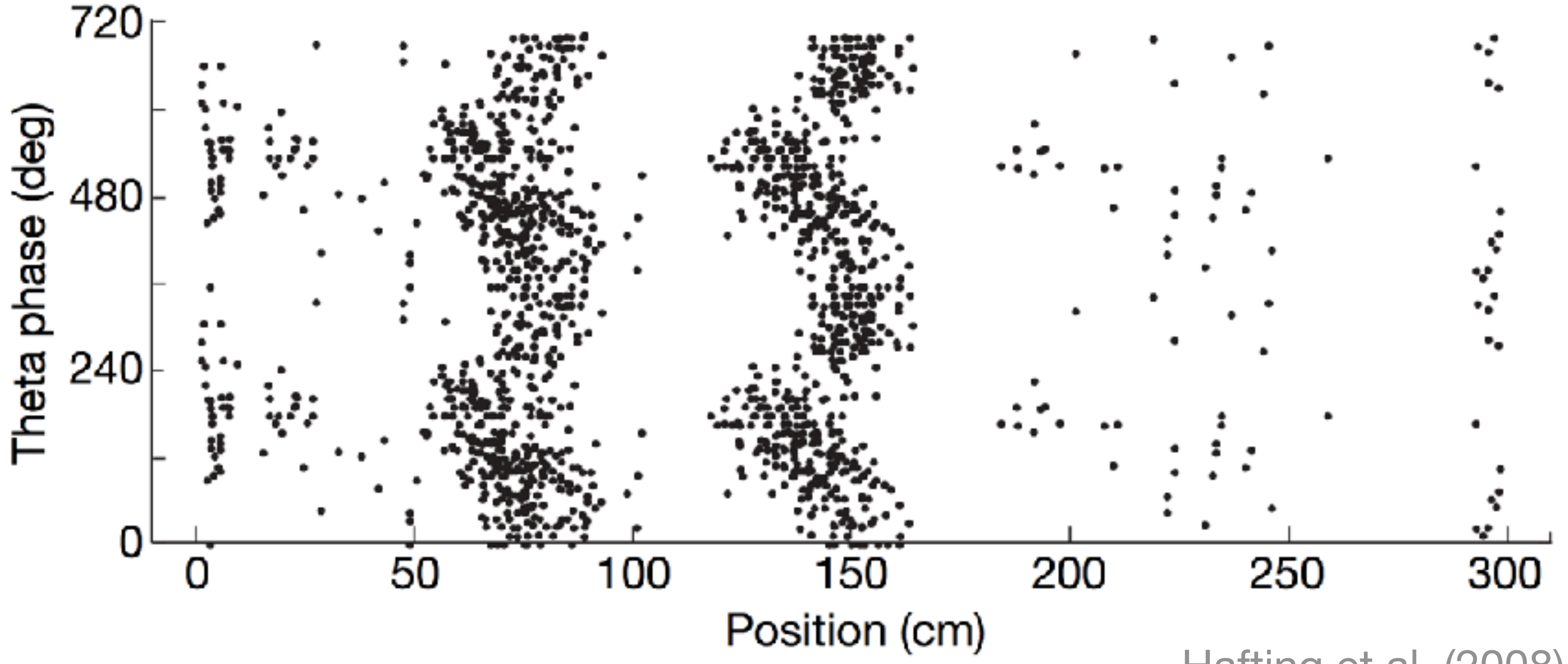
What kinds of models can advance this framework for emergent autonomy in complex systems?

Monaco and Hwang. (2022). *Cognitive Computation*

Temporal and Population Dynamics

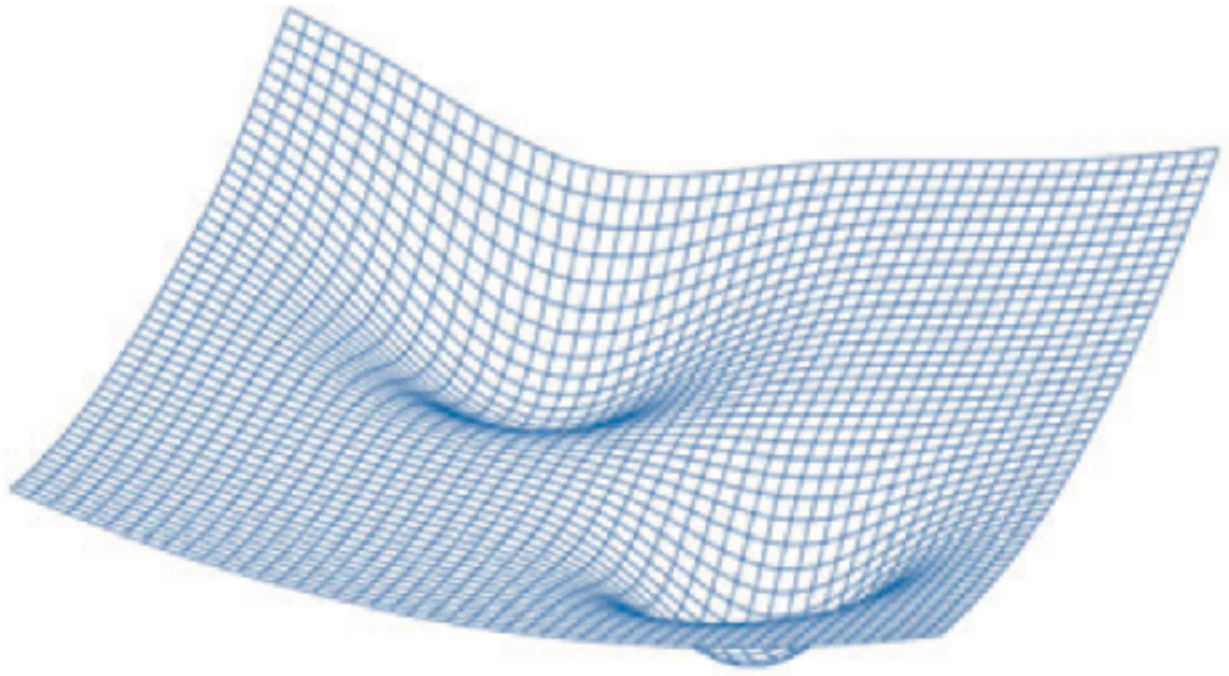
Key Building Blocks

- **Local oscillations and neuronal synchrony**
  - Temporal coding with oscillatory phase
  - O’Keefe & Recce (1993) — Theta-phase precession of hippocampal place-field firing

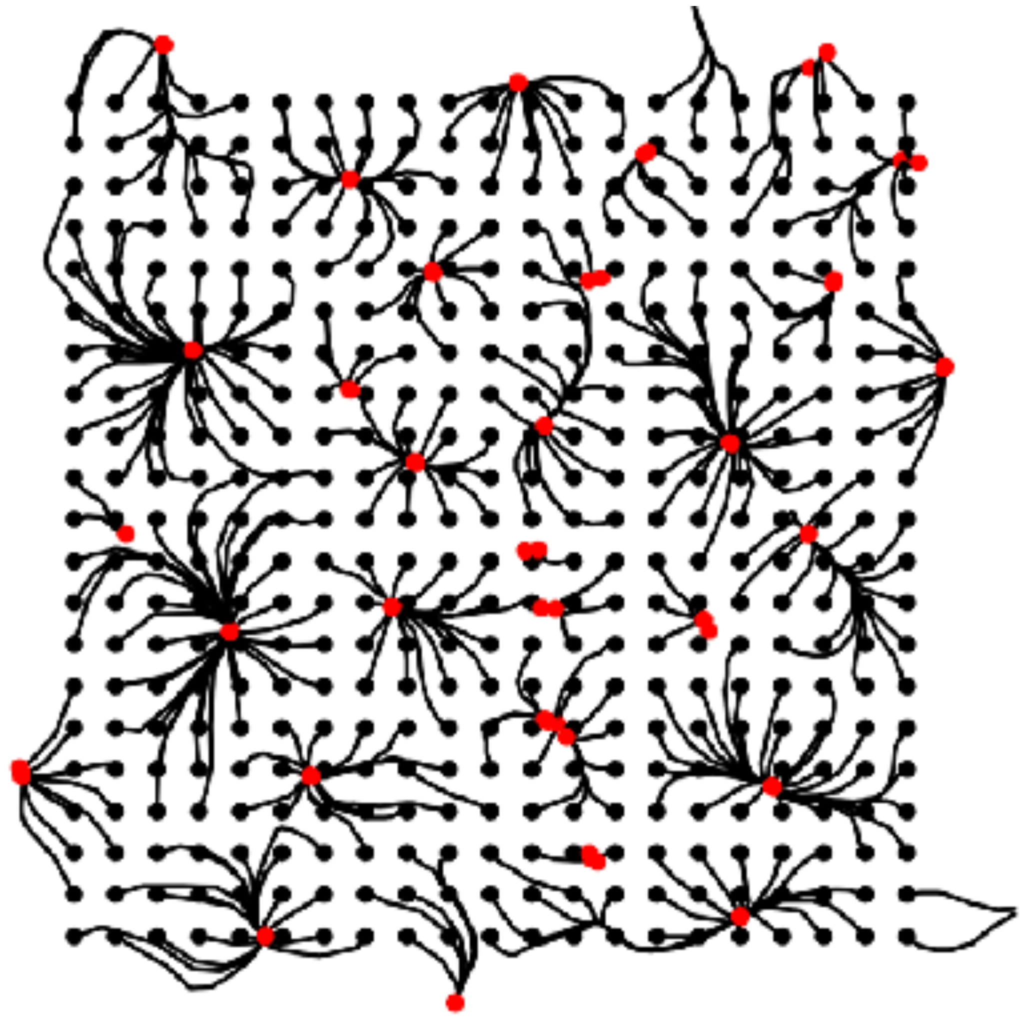


Hafting et al. (2008)

- **Emergent self-organizing states arising from recurrence and feedback in structured networks**
  - Hopfield networks (1982) — Pattern completion supports content-addressable memory with (limited) generalization
  - **Memory retrieval as a state-space trajectory that probes basins of attraction**



Knierim & Zhang (2012)



Hedrick & Zhang (2016)

Monaco and Hwang. (2022). *Cognitive Computation*

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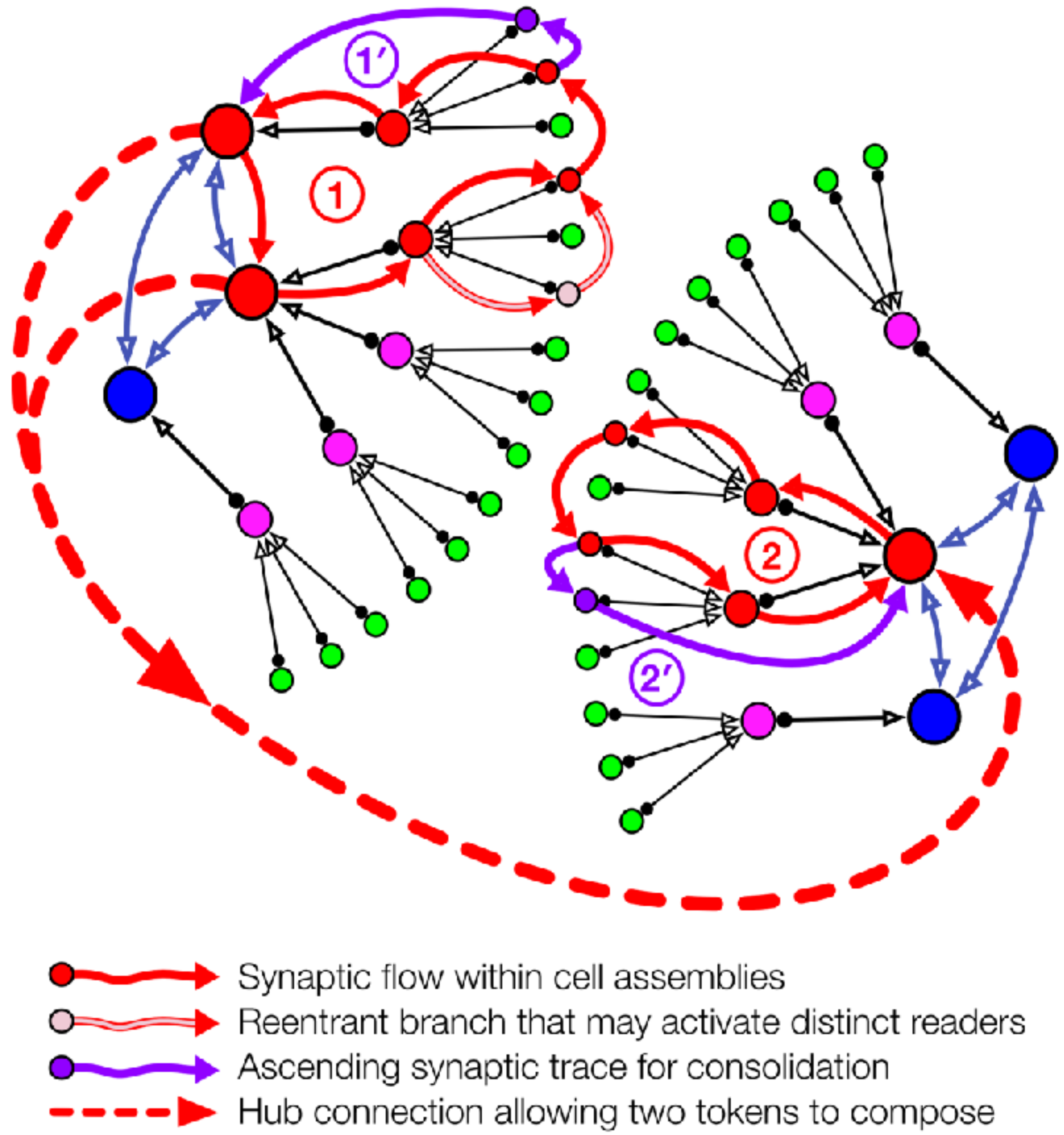
Cell assemblies, synaptic traces, and reentrant loops

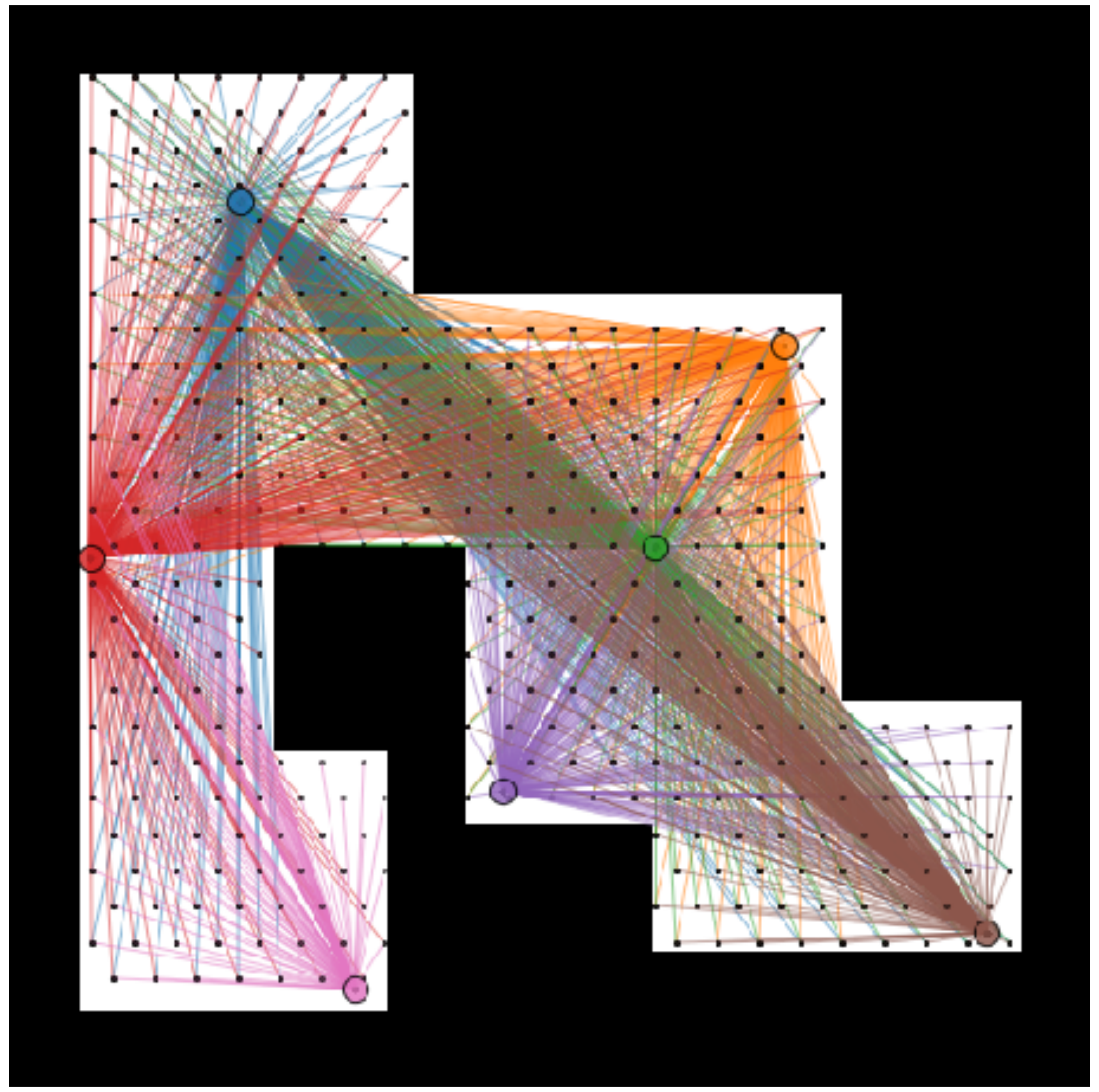


Monaco and Hwang. (2022). *Cognitive Computation*

A murmuration of starlings

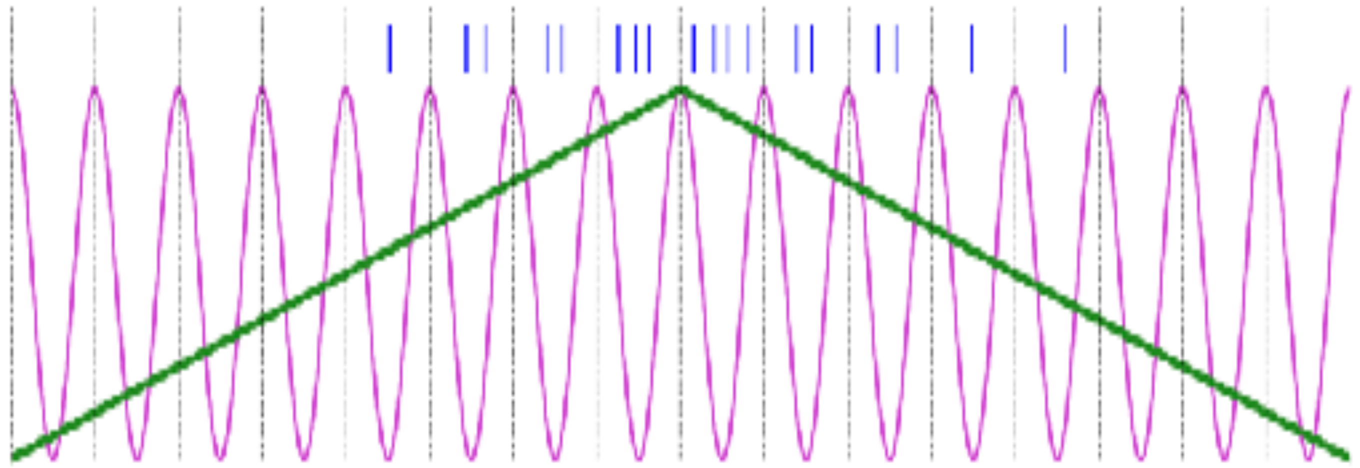
NeuroSwarms: Control by Phase-Organized Attractors

(1) Structural heterarchy



Inherit from spatial geometry

(2) Dynamical selection

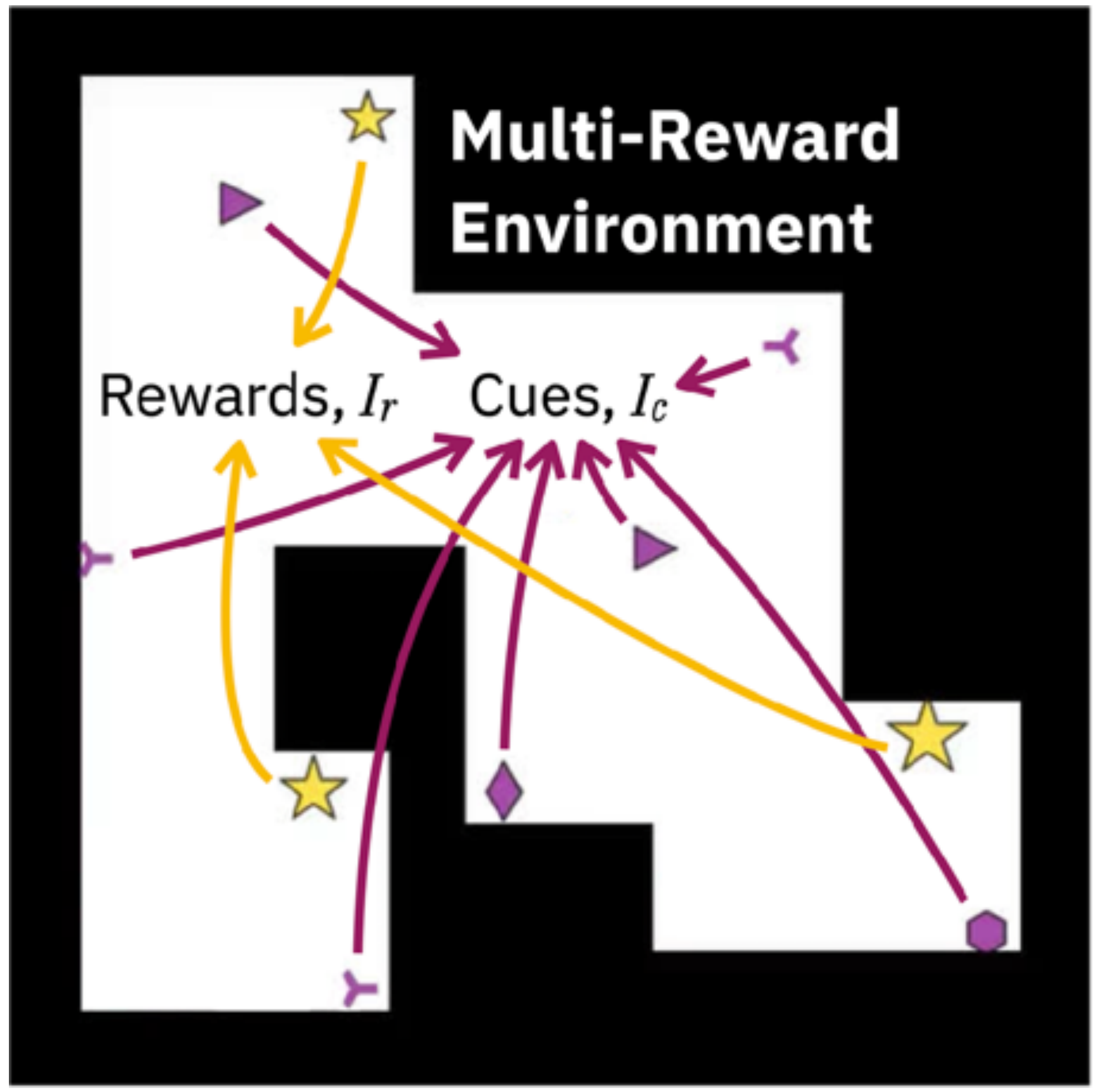


$$\tau_q \dot{q}_{ij} = V_{ij} \cos(\theta_j - \theta_i) - q_{ij}$$

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

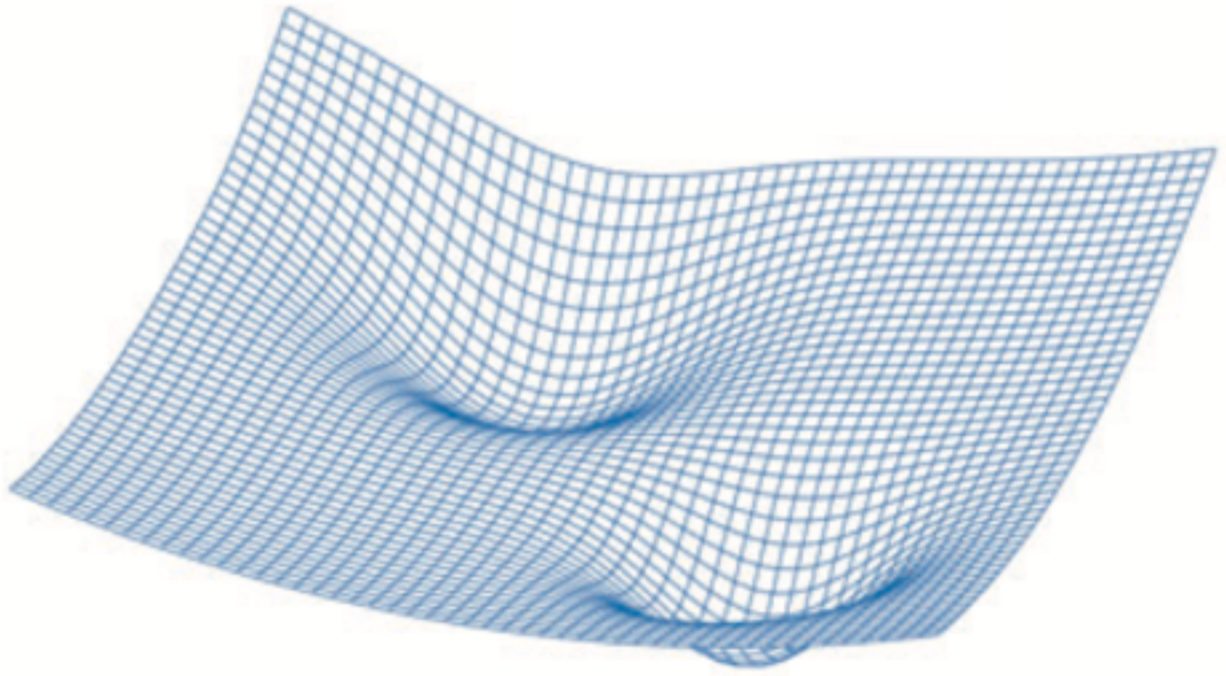
Multi-Agent Swarming as Learning & Memory

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

Distance kernels to create synaptic weights

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

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



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 $\boldsymbol{q} \in \mathbb{R}^{N_s \times N_s}$,

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

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

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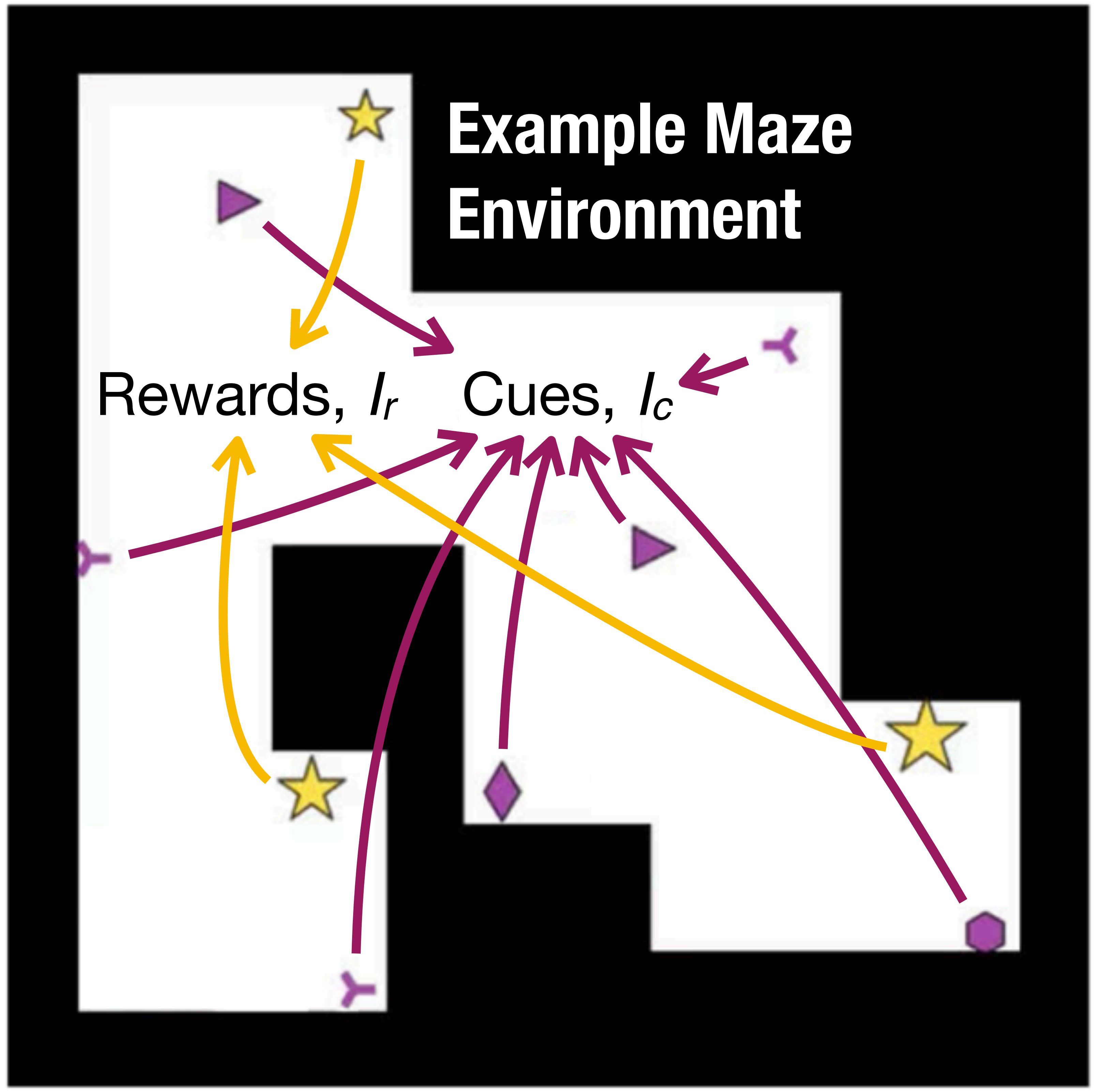
Multi-Agent Swarming as Learning & Memory

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

$$\dot{\boldsymbol{\theta}} = \omega_0 + \omega_I \boldsymbol{p} \,,$$



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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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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),

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

and the exponential reward kernel in (4),

Inverted distance kernels to calculate motion

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

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

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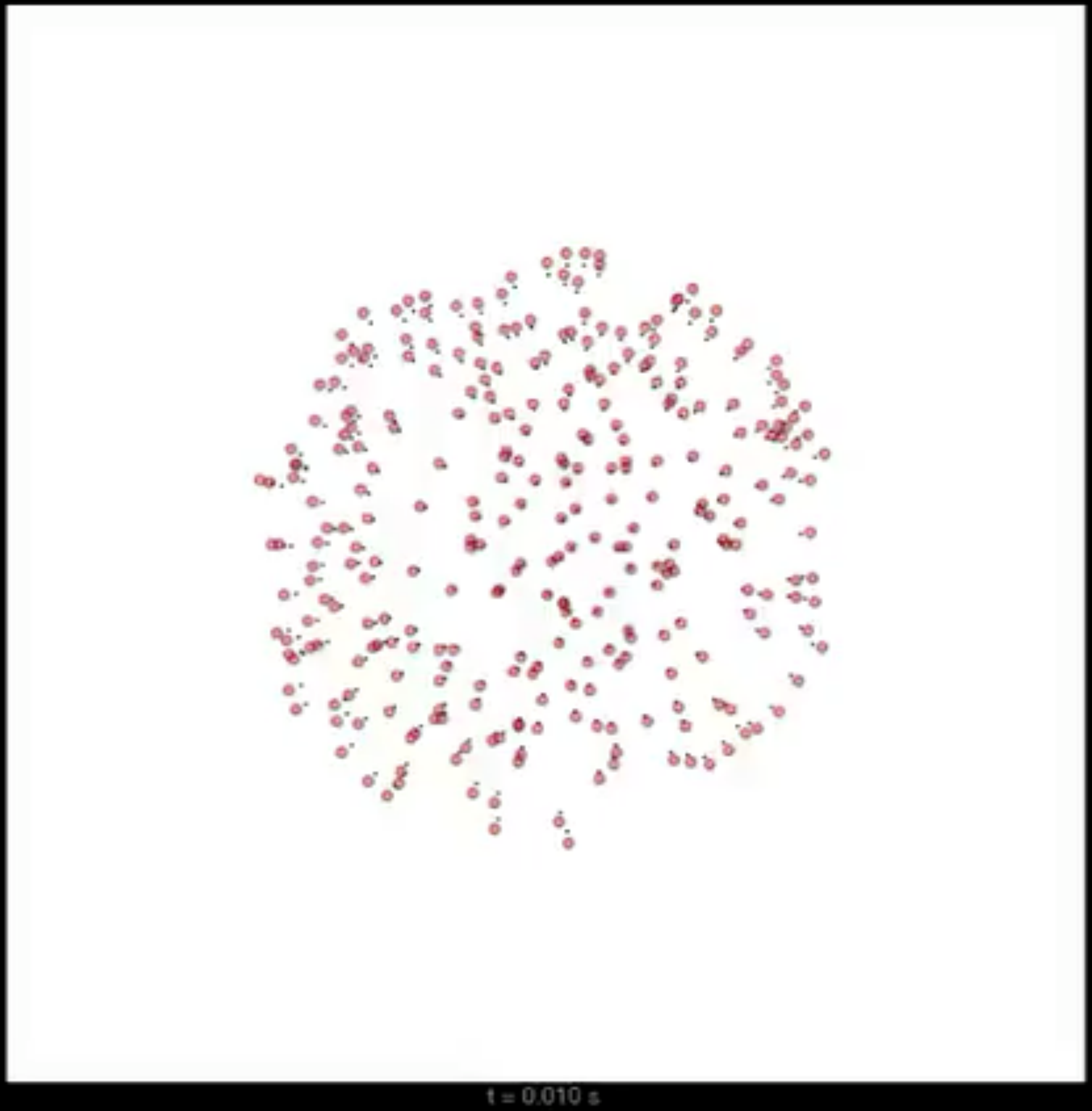
Cognitive Swarming:
With Attractor Learning but Without Phase Coupling



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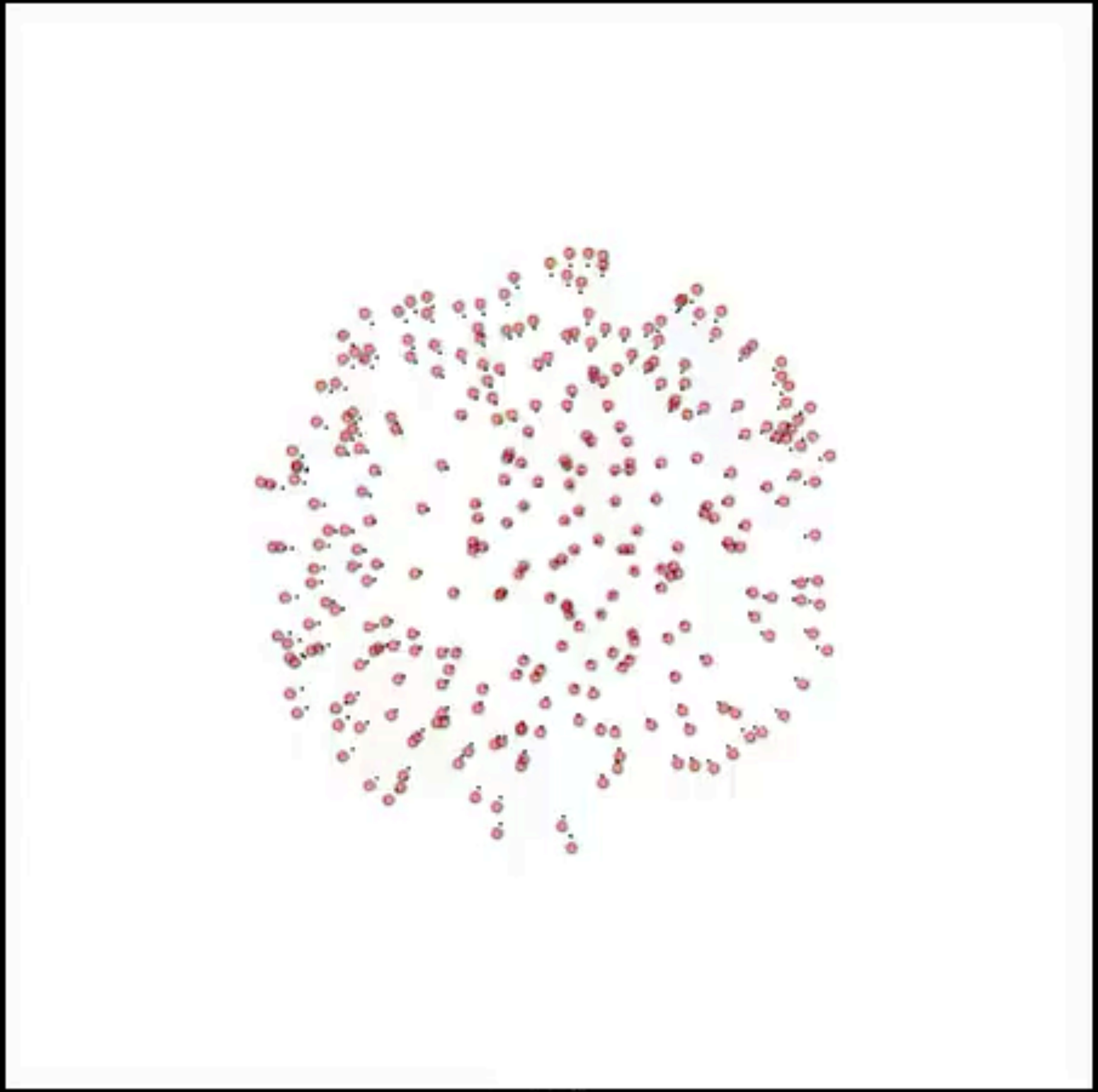
Cognitive Swarming: With Phase Coupling and Identical Phase Initialization



t = 0.010 s

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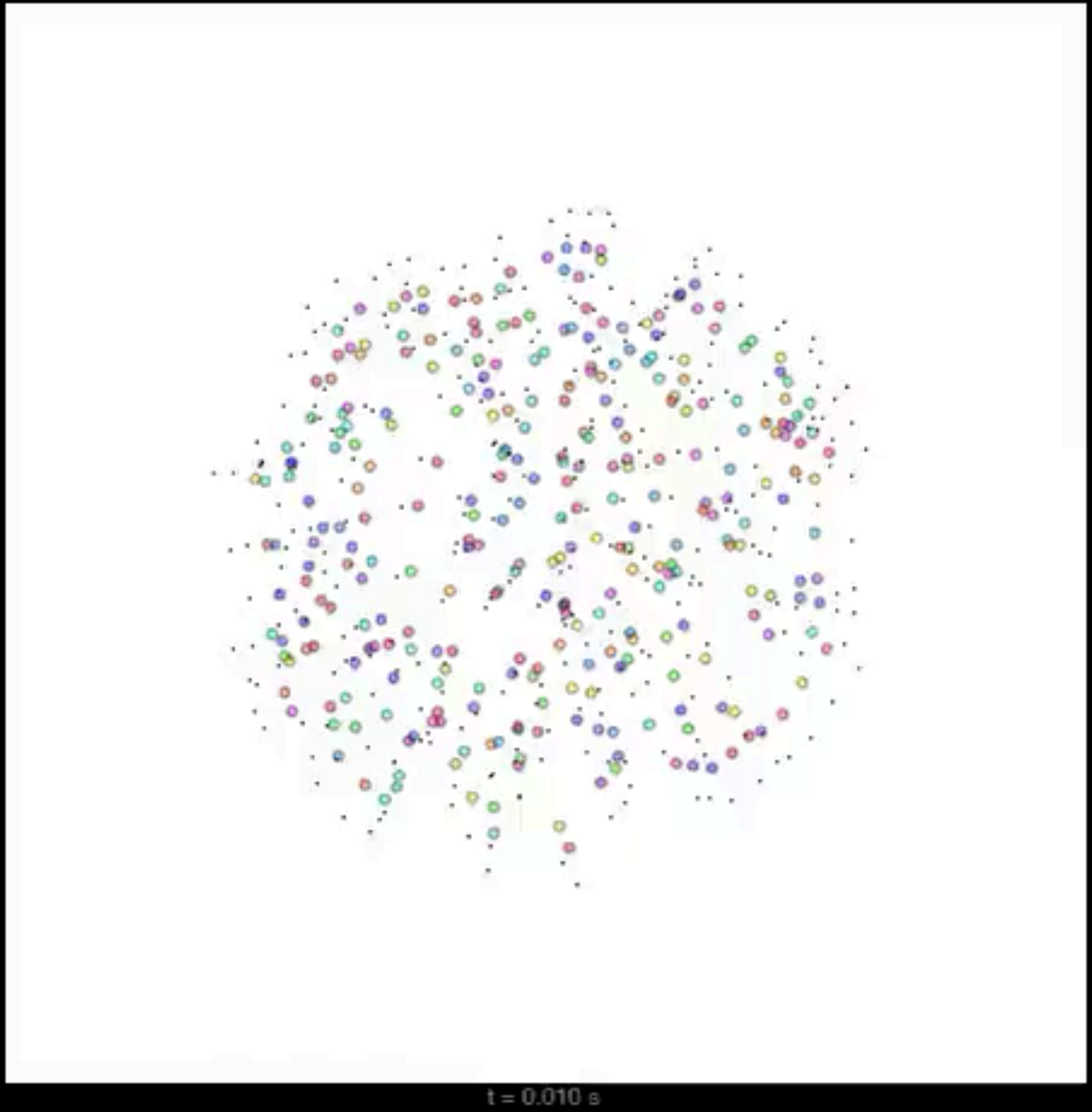
Cognitive Swarming:
With Phase Coupling and Random Phase Initialization



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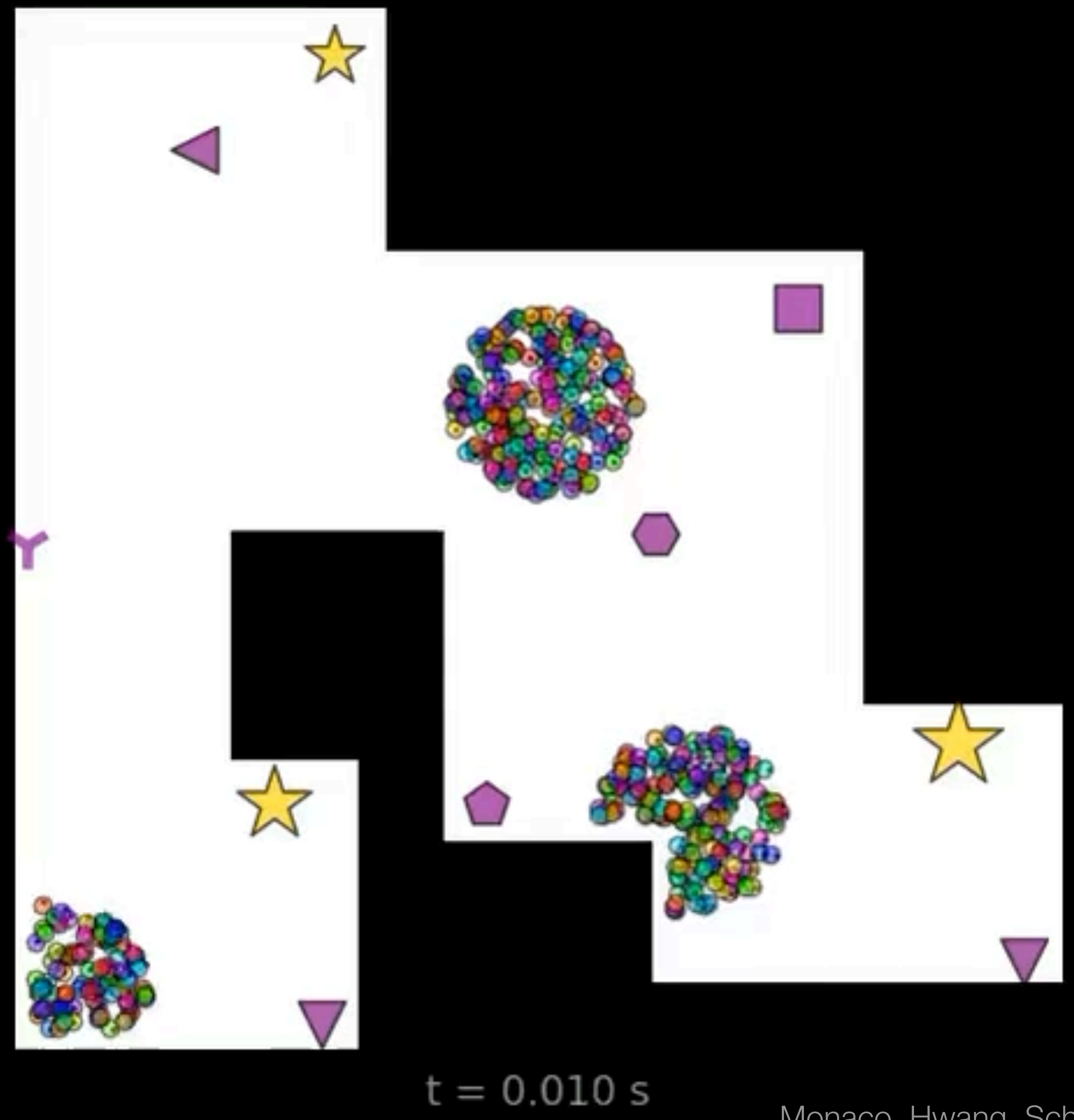
Cognitive Swarming:
With Phase Coupling, Balanced Swarming and Reward Learning, and Multiple Rewards in a Complex and Irregular Maze



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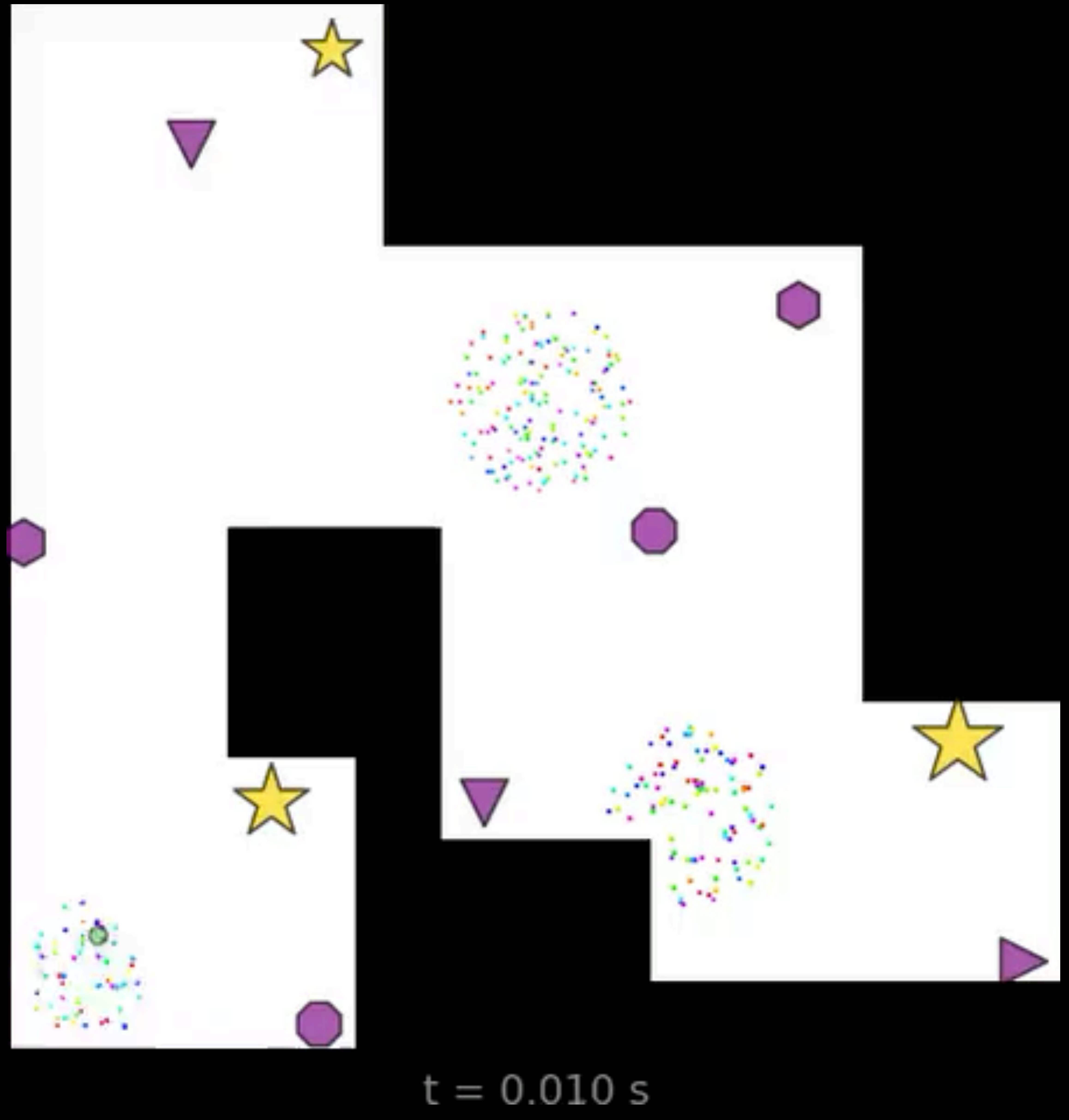
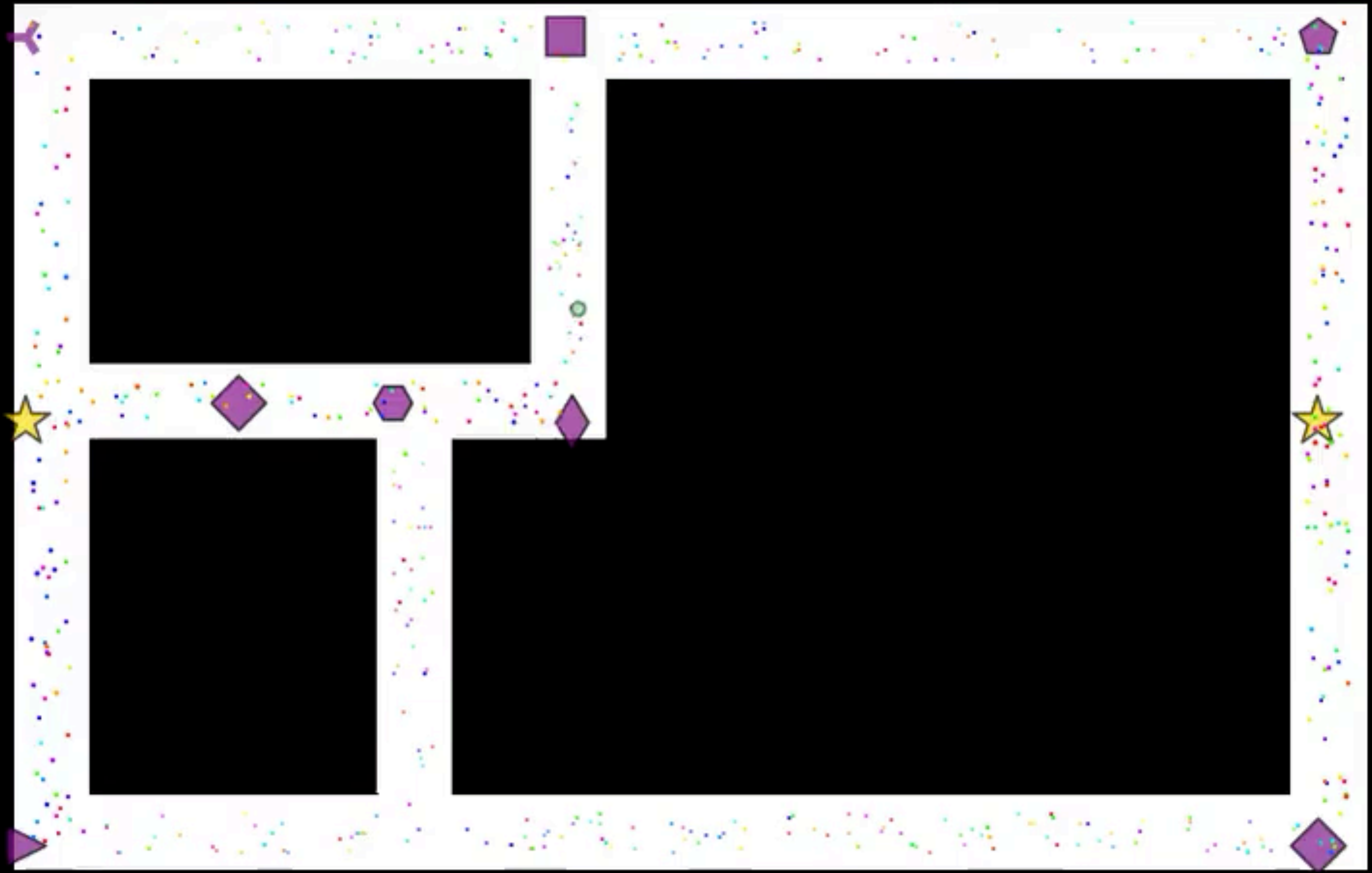
(2020) Biological Cybernetics

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 Learning-as-Swarming: Double-T Maze


t = 0.010 s

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Theories of consciousness

There are many…

Table 1 | **A selection of theories of consciousness**

Theory	Primary claim	Key refs
Higher-order theory (HOT)	Consciousness depends on meta-representations of lower-order mental states	31,46
Self-organizing meta-representational theory	Consciousness is the brain's (meta-representational) theory about itself	34,140
Attended intermediate representation theory	Consciousness depends on the attentional amplification of intermediate-level representations	141,142
Global workspace theories (GWTs)	Consciousness depends on ignition and broadcast within a neuronal global workspace where fronto-parietal cortical regions play a central, hub-like role	47–49
Integrated information theory (IIT)	Consciousness is identical to the cause–effect structure of a physical substrate that specifies a maximum of irreducible integrated information	57,59,60
Information closure theory	Consciousness depends on non-trivial information closure with respect to an environment at particular coarse-grained scales	143
Dynamic core theory	Consciousness depends on a functional cluster of neural activity combining high levels of dynamical integration and differentiation	144
Neural Darwinism	Consciousness depends on re-entrant interactions reflecting a history of value-dependent learning events shaped by selectionist principles	145,146
Local recurrency	Consciousness depends on local recurrent or re-entrant cortical processing and promotes learning	65,71
Predictive processing	Perception depends on predictive inference of the causes of sensory signals; provides a framework for systematically mapping neural mechanisms to aspects of consciousness	67,73,79
Neuro-representationalism	Consciousness depends on multilevel neurally encoded predictive representations	84
Active inference	Although views vary, in one version consciousness depends on temporally and counterfactually deep inference about self-generated actions	76; see also 91
Beast machine theory	Consciousness is grounded in allostatic control-oriented predictive inference	13,75,77; see also 90
Neural subjective frame	Consciousness depends on neural maps of the bodily state providing a first-person perspective	24
Self comes to mind theory	Consciousness depends on interactions between homeostatic routines and multilevel interoceptive maps, with affect and feeling at the core	23,147
Attention schema theory	Consciousness depends on a neurally encoded model of the control of attention	148
Multiple drafts model	Consciousness depends on multiple (potentially inconsistent) representations rather than a single, unified representation that is available to a central system	149
Sensorimotor theory	Consciousness depends on mastery of the laws governing sensorimotor contingencies	88
Unlimited associative learning	Consciousness depends on a form of learning which enables an organism to link motivational value with stimuli or actions that are novel, compound and non-reflex inducing	150
Dendritic integration theory	Consciousness depends on integration of top-down and bottom-up signalling at a cellular level	151
Electromagnetic field theory	Consciousness is identical to physically integrated, and causally active, information encoded in the brain's global electromagnetic field	152
Orchestrated objective reduction	Consciousness depends on quantum computations within microtubules inside neurons	18

Our selection of theories includes those that are either neurobiological in nature or potentially expressible in neurobiological terms.

Seth. (2022). *Theories of consciousness.* NRN

Intelligence vs. conscious experience

Interoceptor theory of consciousness and narrative dynamics across the lifespan

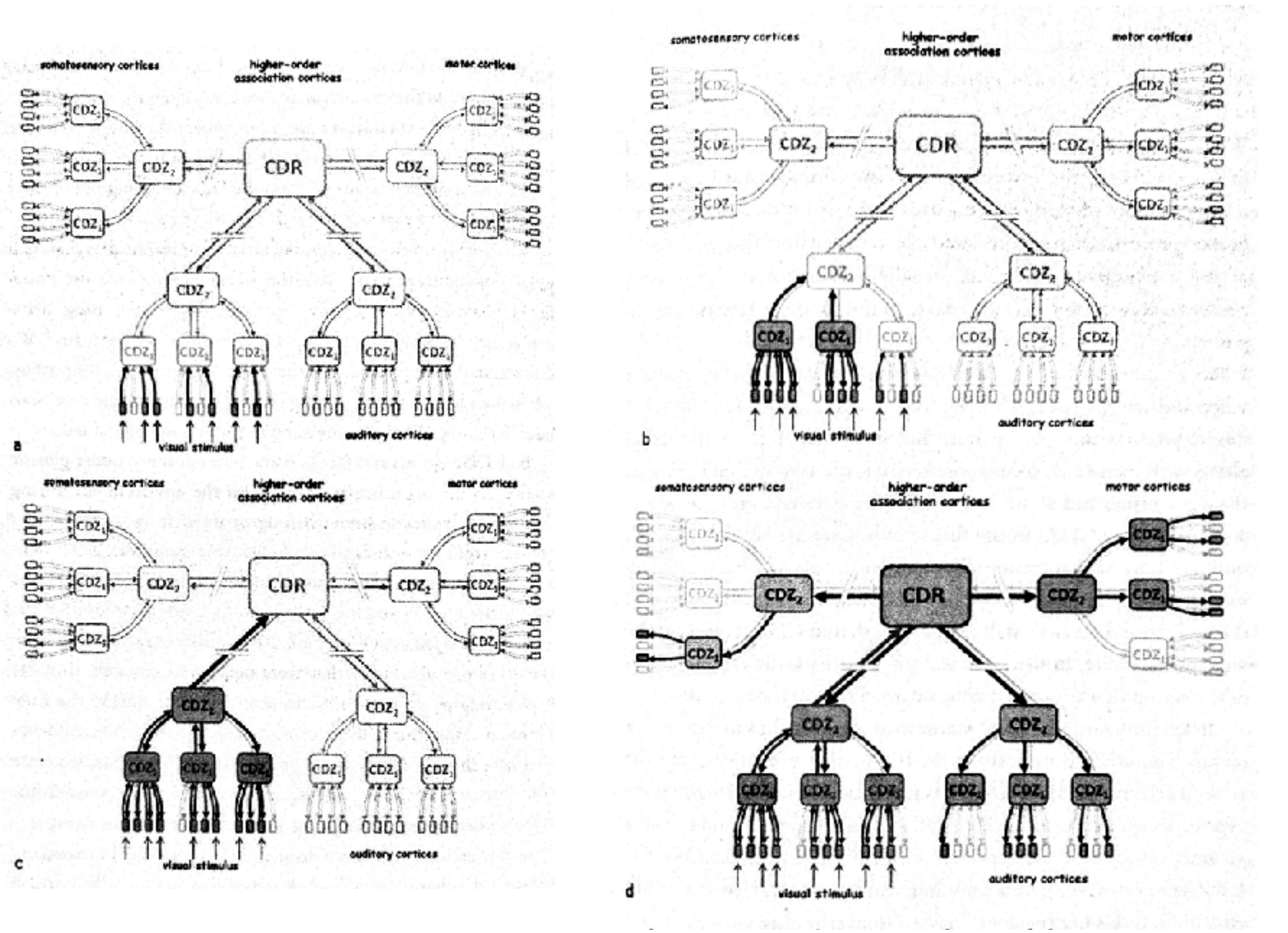
- The BIG questions…
  - What is intelligence and what is it for?
  - What is consciousness and what is it for?

- These are *real* questions, but are they *hard*?

What is sufficient for conscious states?

Mental images must be grounded in (primordial) feeling

- An organism manages three sensoriums
    - Exteroception
    - Proprioception
    - Interoception
- All peripheral sensory activations construct neural patterns that pass through cortical and subcortical maps that impose a shared regimented order and structure
    - Neural patterns → mental “images”
    - Fingerprint of “ownership” and origin of self-perspective

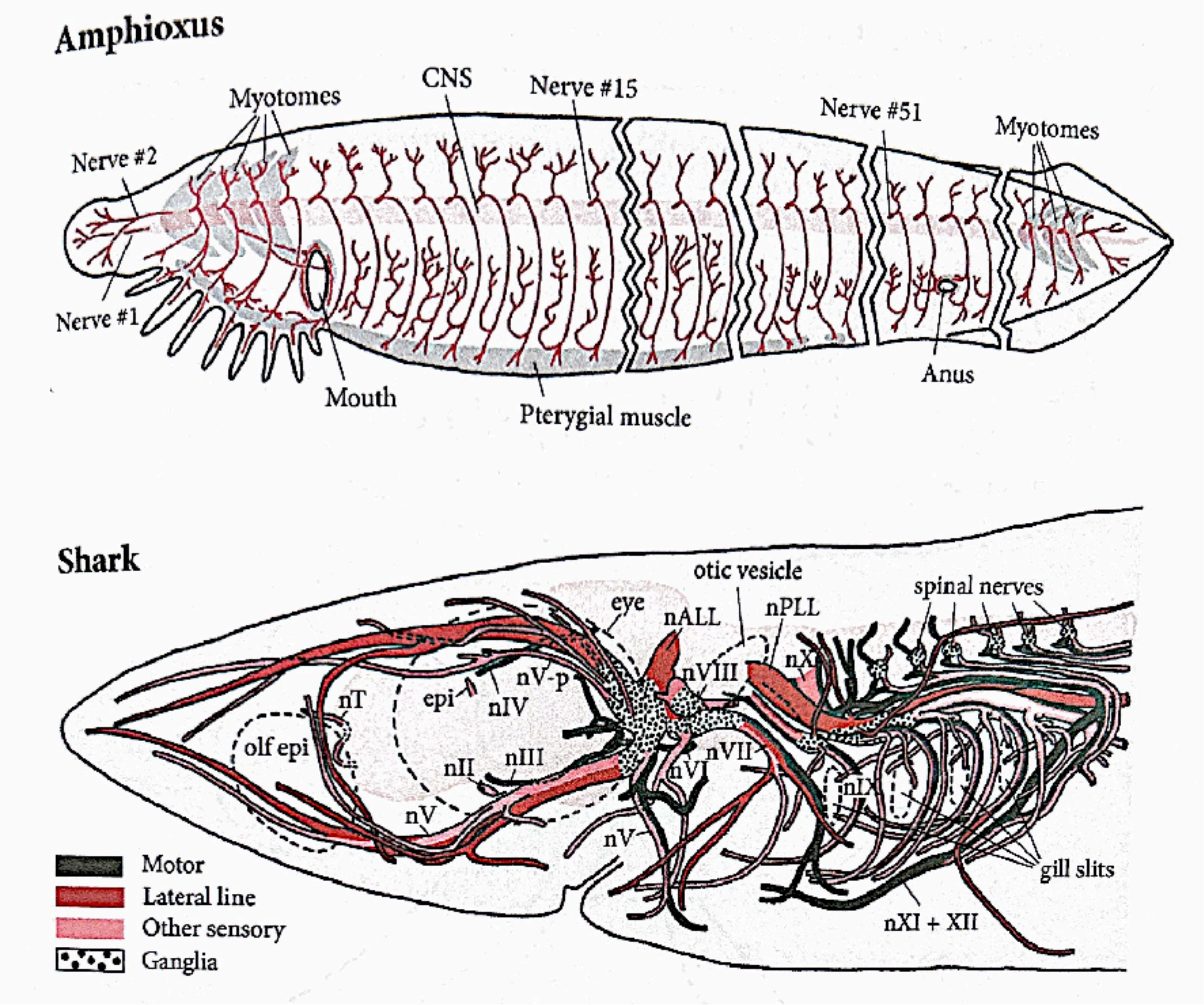


Damasio. *Self Comes to Mind*; Feeling & *Knowing*

Conserved affective-emotive construction

Direct visceral access to neural systems

- The visceral and peripheral milieu of bodies has direct access to peripheral ascending nerves
    - Unmyelinated, unlike exteroceptive and proprioceptive systems
    - Less precision, but direct and deeply integrated access

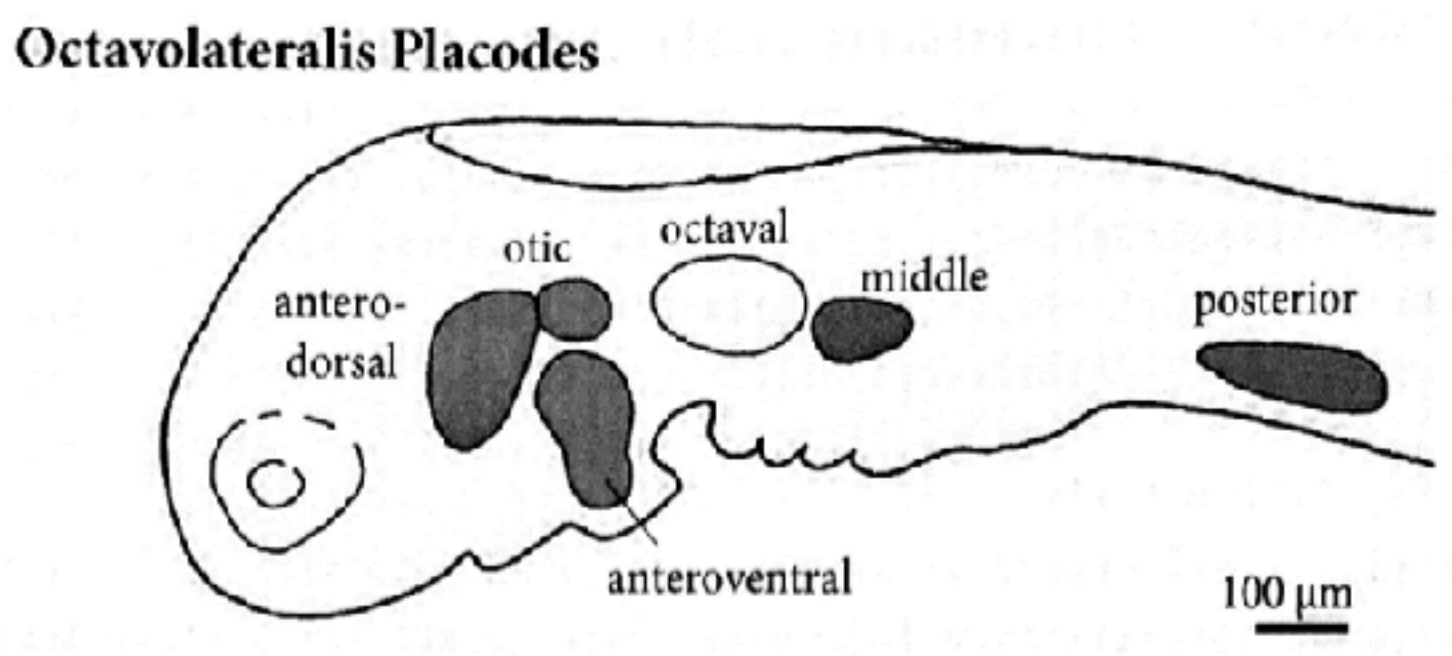


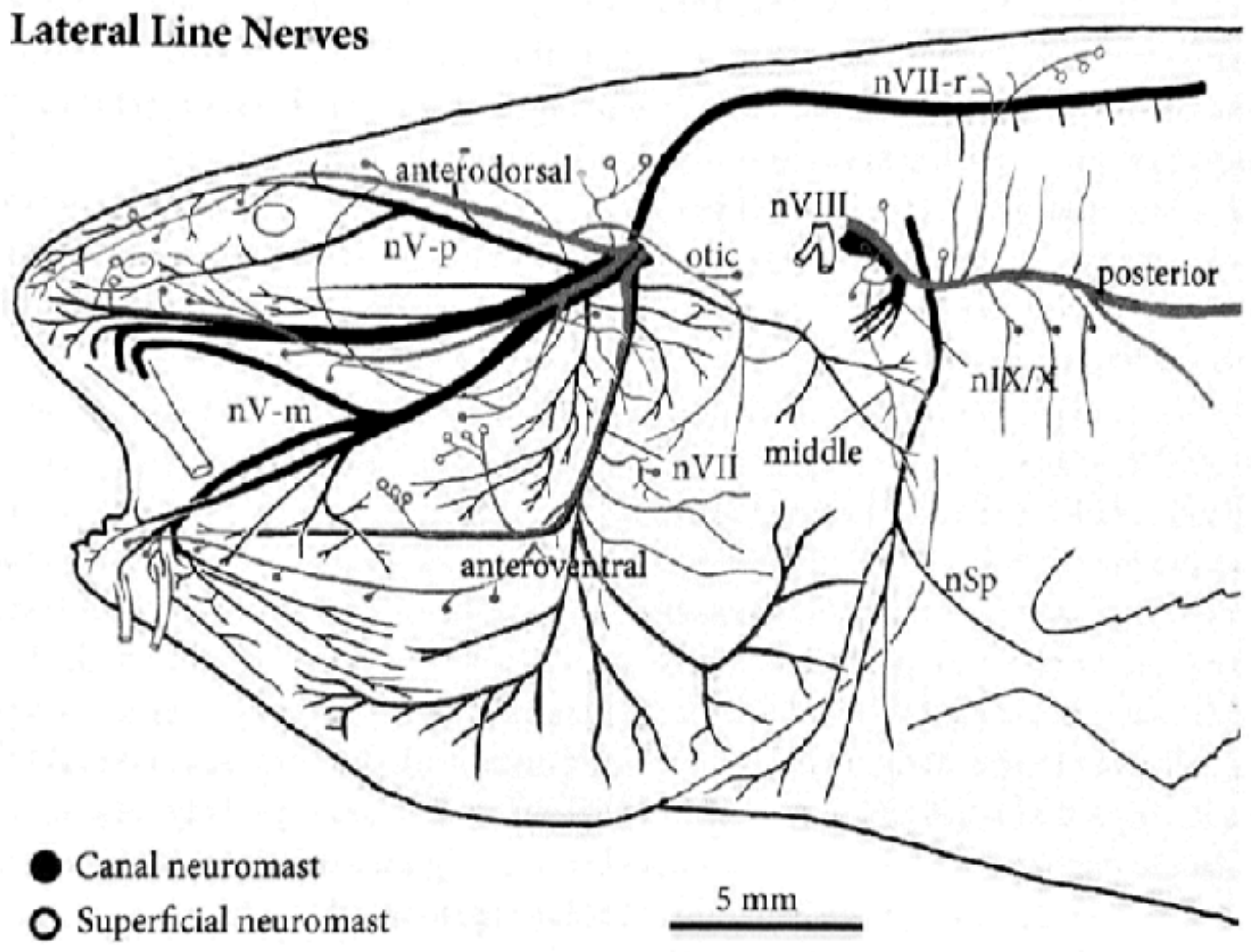
Striedter & Northcutt. *Brains Through Time*

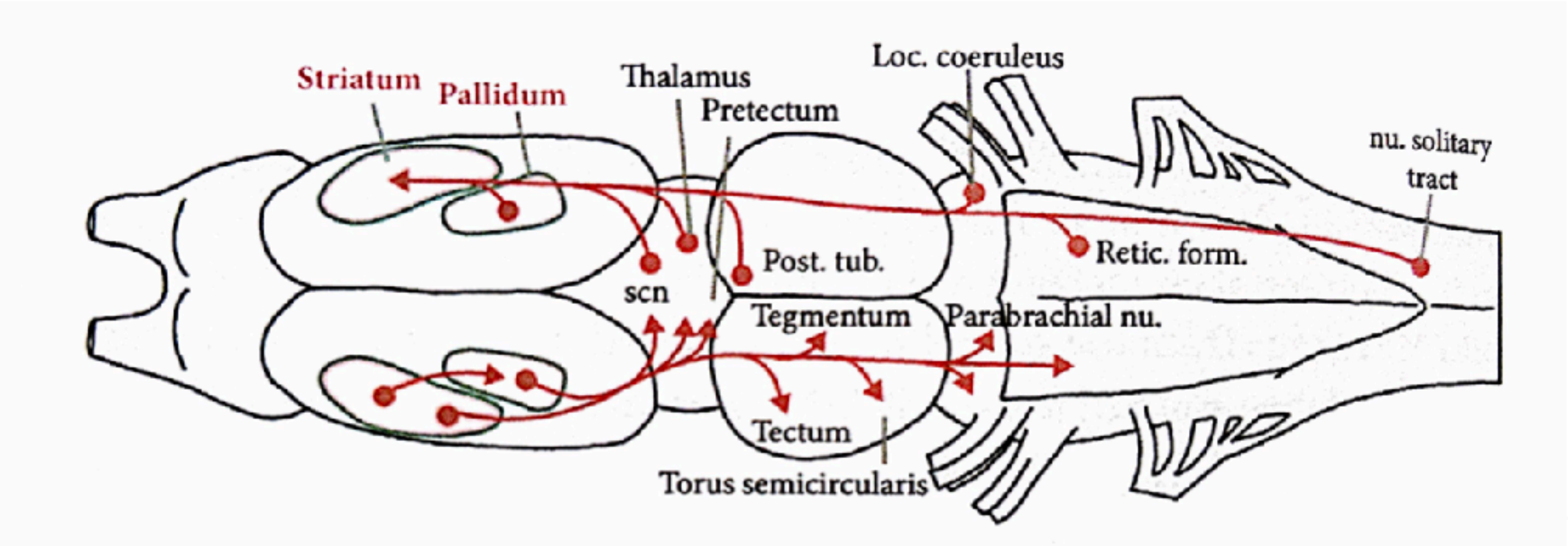
Conserved affective-emotive construction

Direct visceral access to neural systems

- Evolutionarily ancient system
  - Early fish (right) and amphibians (below)





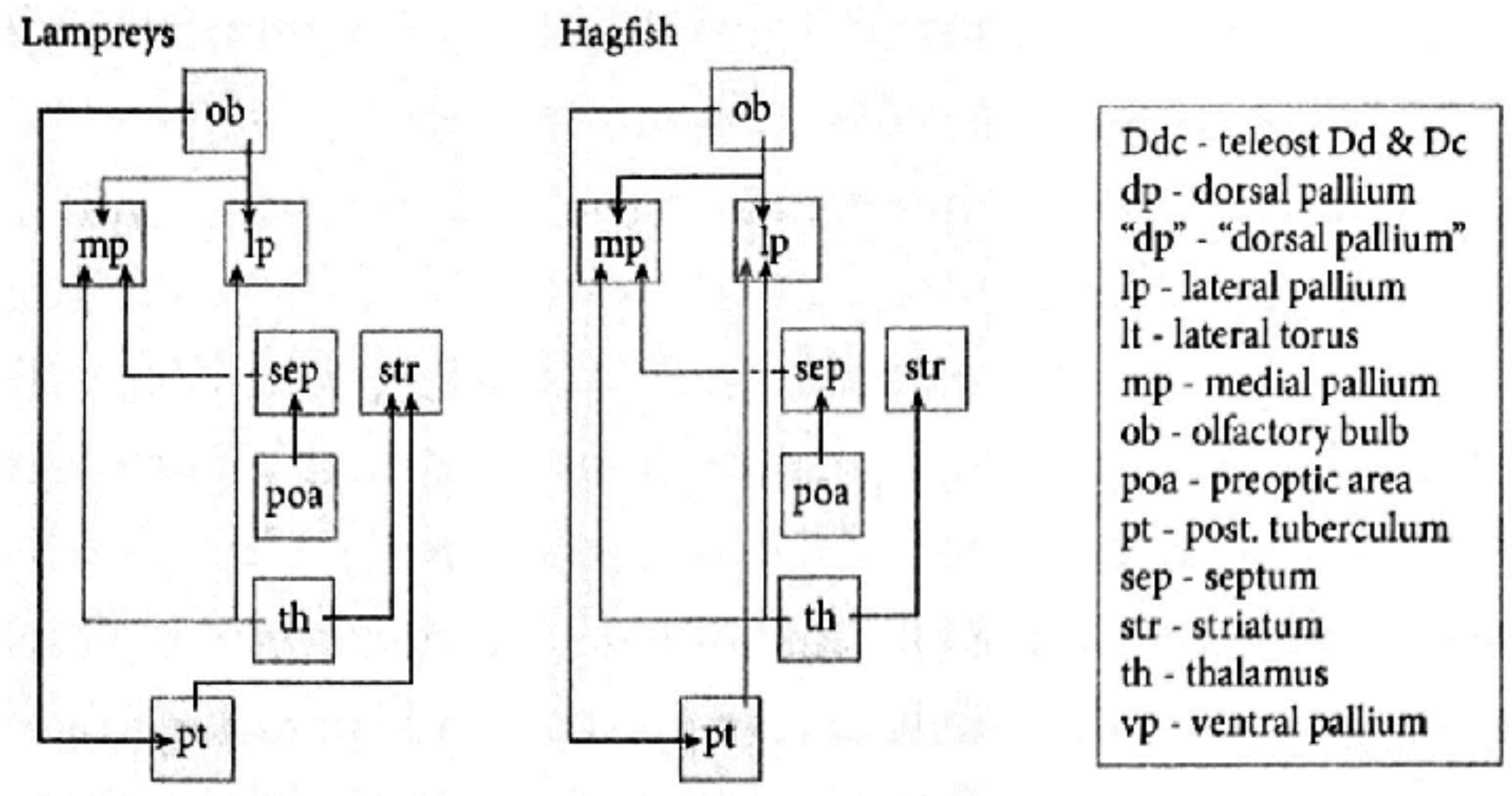


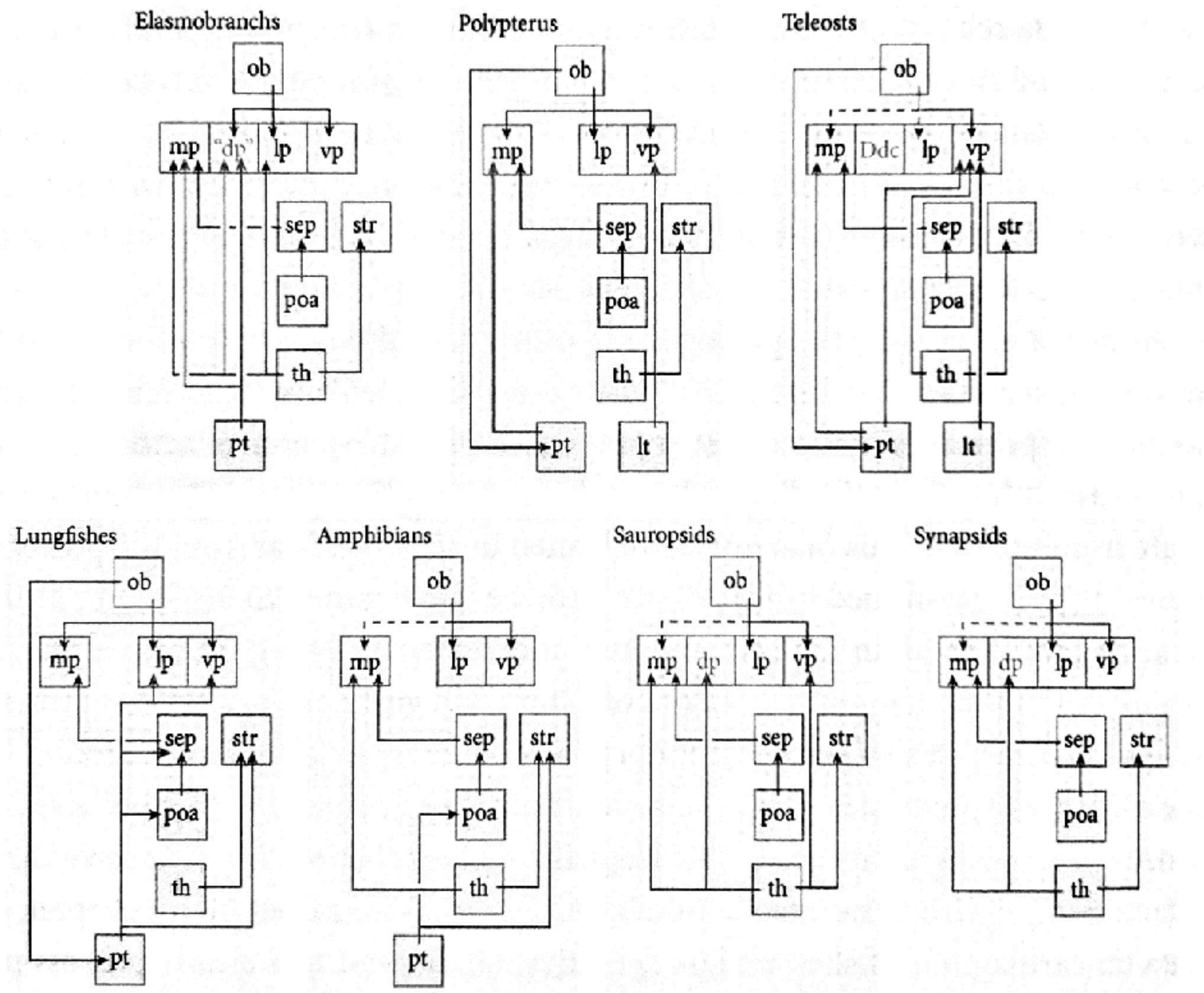
Striedter & Northcutt. *Brains Through Time*

Conserved affective-emotive construction

Direct visceral access to neural systems

- Interoceptive signals converge onto a small set of highly conserved brainstem nuclei



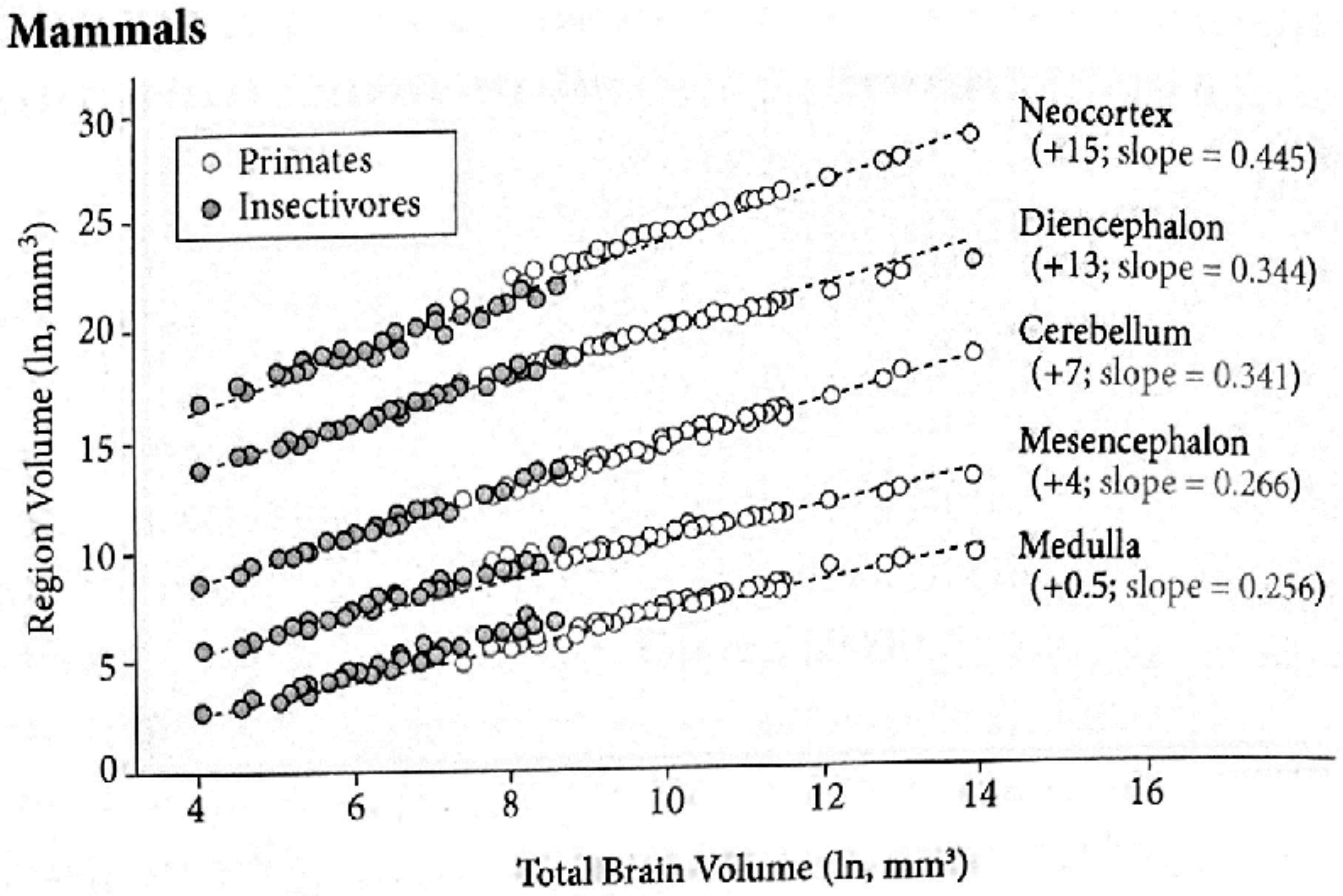


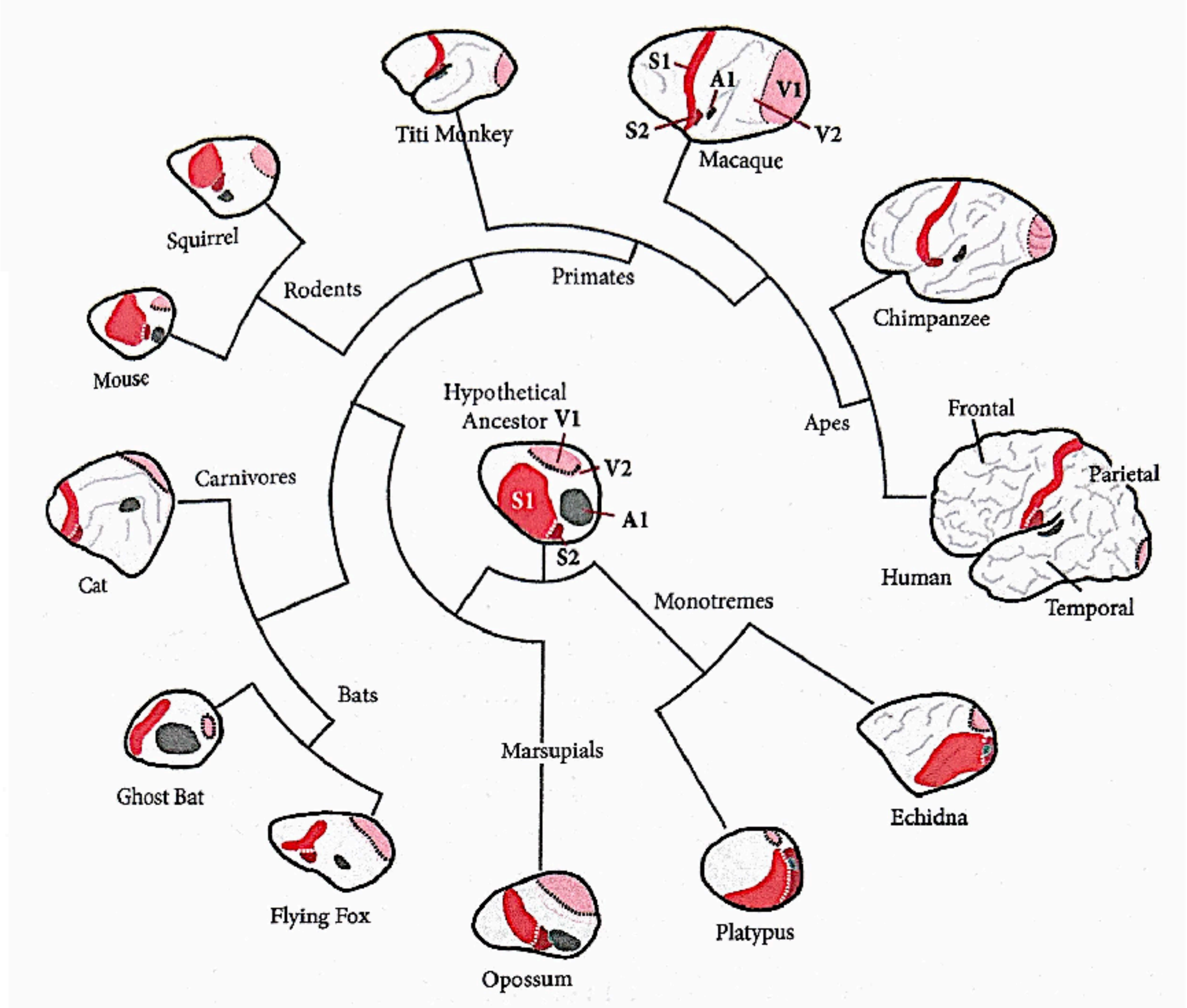
Striedter & Northcutt. *Brains Through Time*

Mental image-making and mapping cortices

Exteroceptive (body-in-world) and proprioceptive (brain-in-body) reference frames

- The “image-making” cortices are also highly conserved within mammalia, reflecting ~200 million years of selection





Striedter & Northcutt. *Brains Through Time*

Patrick Stewart as Macbeth

You have to care to be a “you”, and you have to feel to care

Affective-interoceptive origin of consciousness

“We would not only need a model of the brain functioning underlying coupled coping such as Freeman’s, but we would also need—and here’s the rub—a model of our particular way of being embedded and embodied such that what we experience is significant for us in the particular way that it is.”

Dreyfus. (2007). *Why Heideggerian AI failed…*