

Neurodynamical computing at the information boundaries of intelligent systems

APS/DBIO Neurodynamical Models of Cognition // March 8, 2023

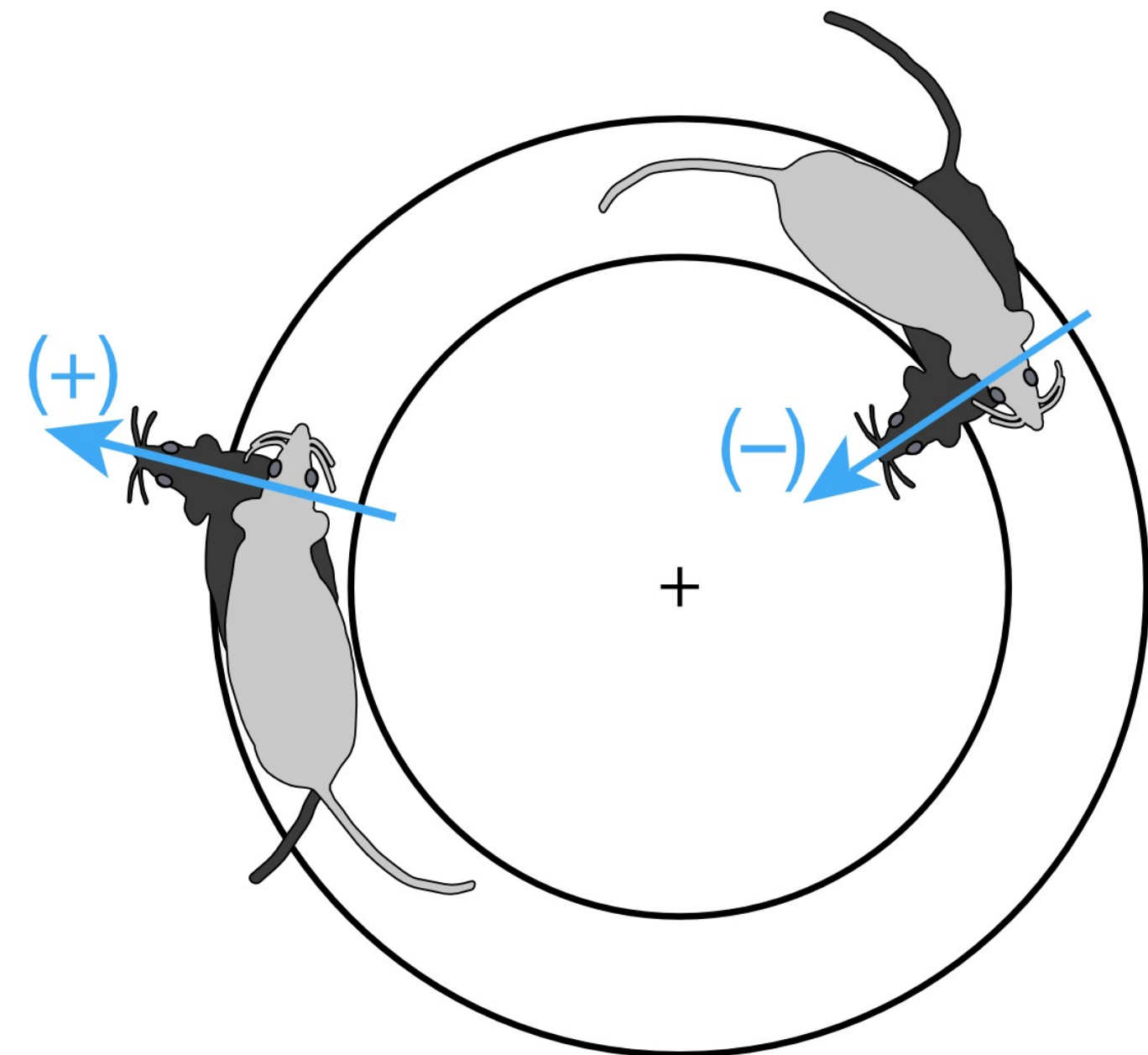
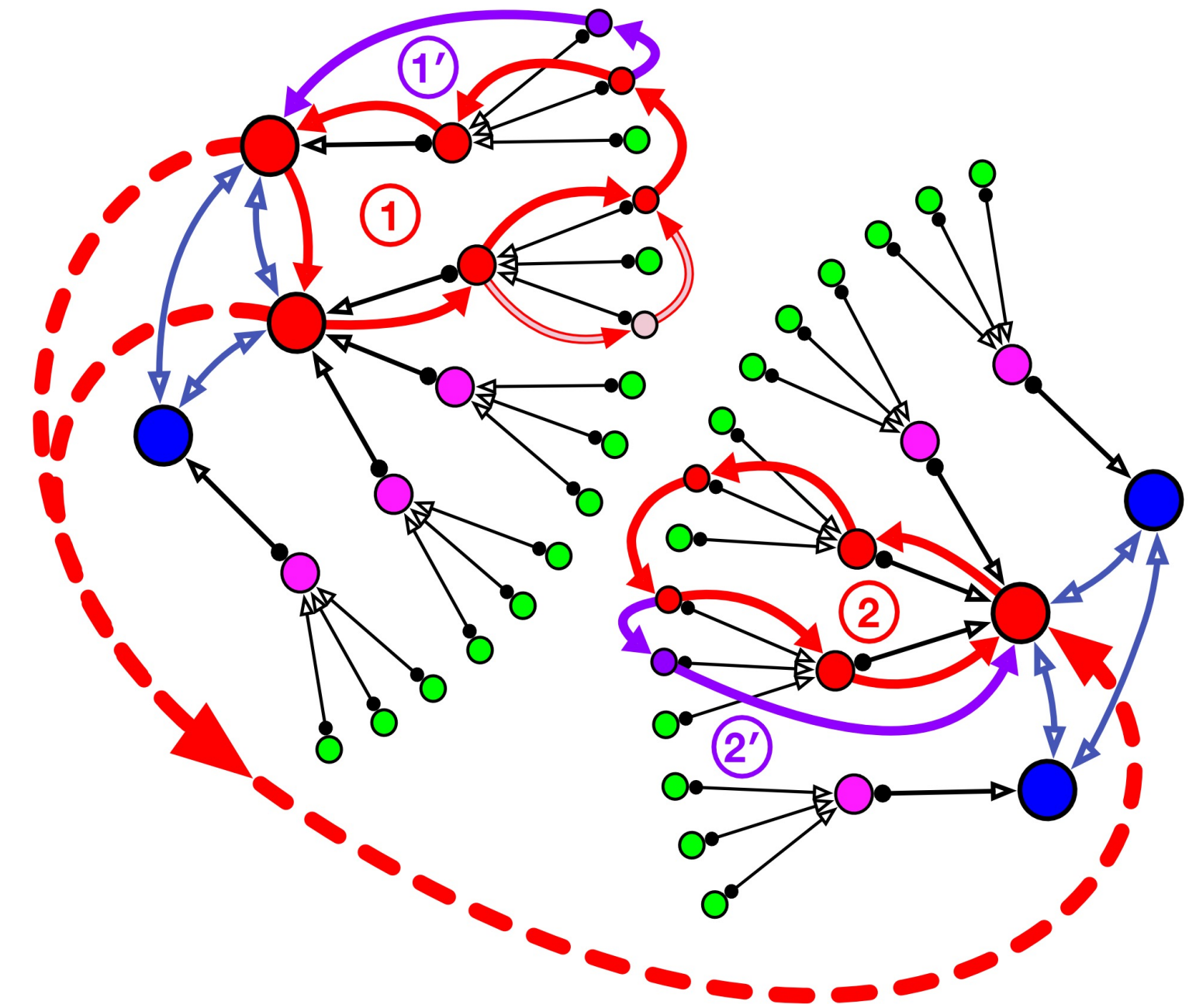
Joseph D. Monaco, SelfMotion Labs & National Institutes of Health

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Outline

Toward a nonreductive dynamical neuroscience of intelligence

1. Briefly review disciplinary approaches to formalizing biological intelligence
 - Highlight persistent gaps in concepts, theories, and hypotheses
2. Motivate a perceptual control framework for resolving external observer bias
 - Informational implications for cognitive computing with neural dynamics
3. Synthesize structure and temporal properties of mammalian hippocampal-cortical networks
 - Oscillations, dynamical articulation, and agency

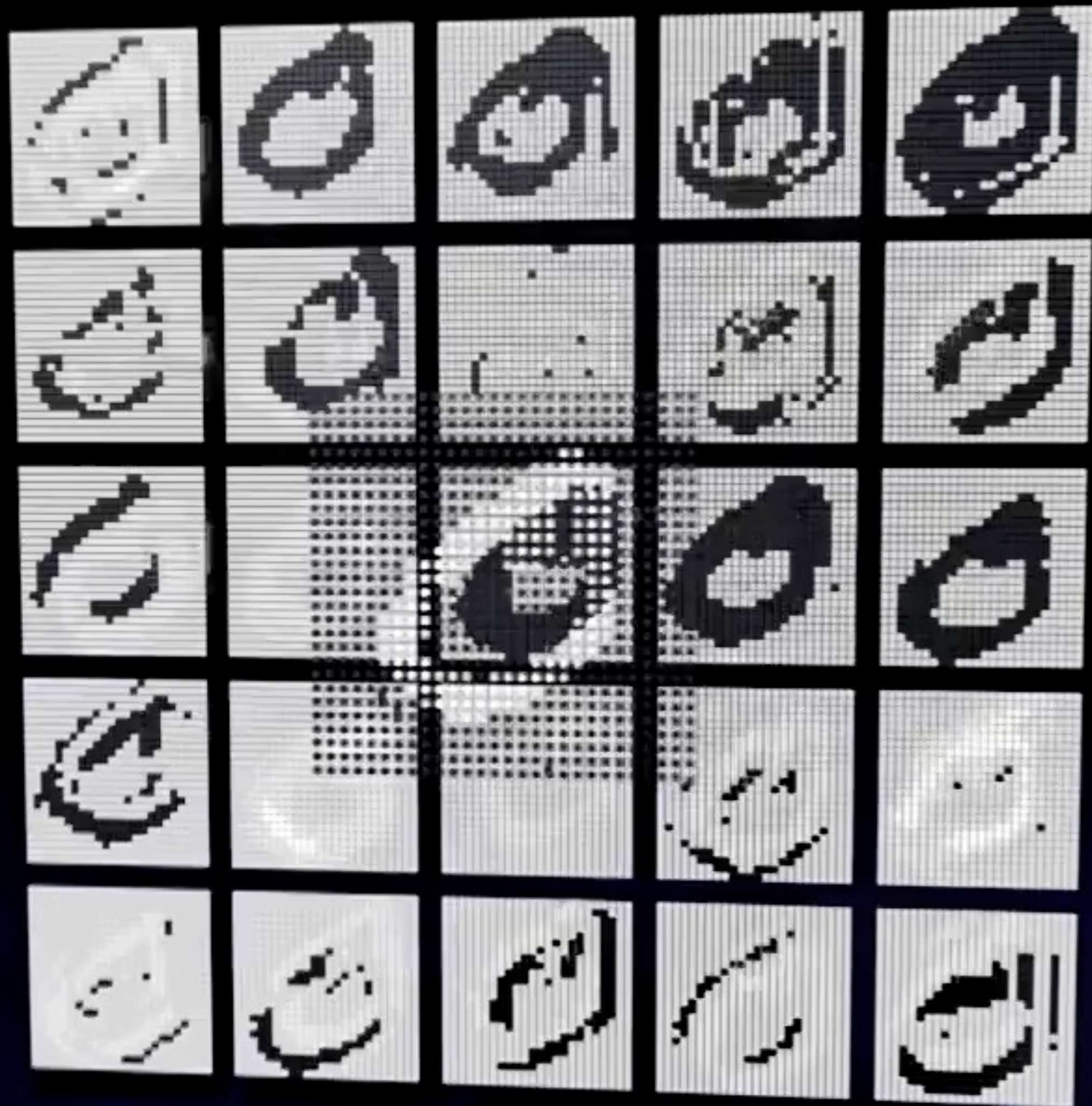


Three paths...

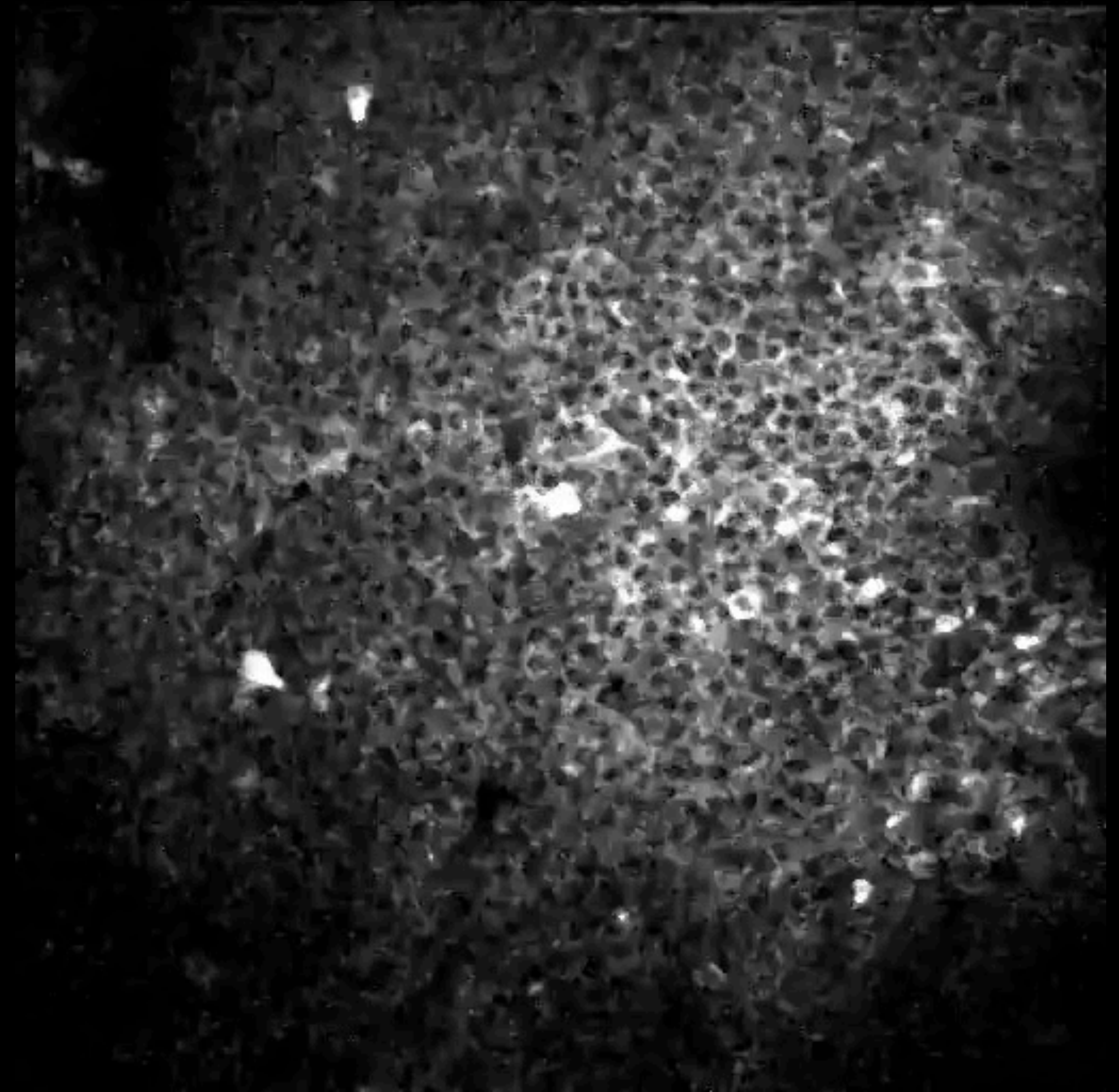
Framing an integrative (computational) neuroscience of intelligence

- Cybernetics → Cognitive Science
- GOFAI → “Third Wave” AI learning and reasoning
- Behaviorist Psychology → Mainstream neuroscience
- Physics of neural systems → Computational neuroscience





WWW.CV



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

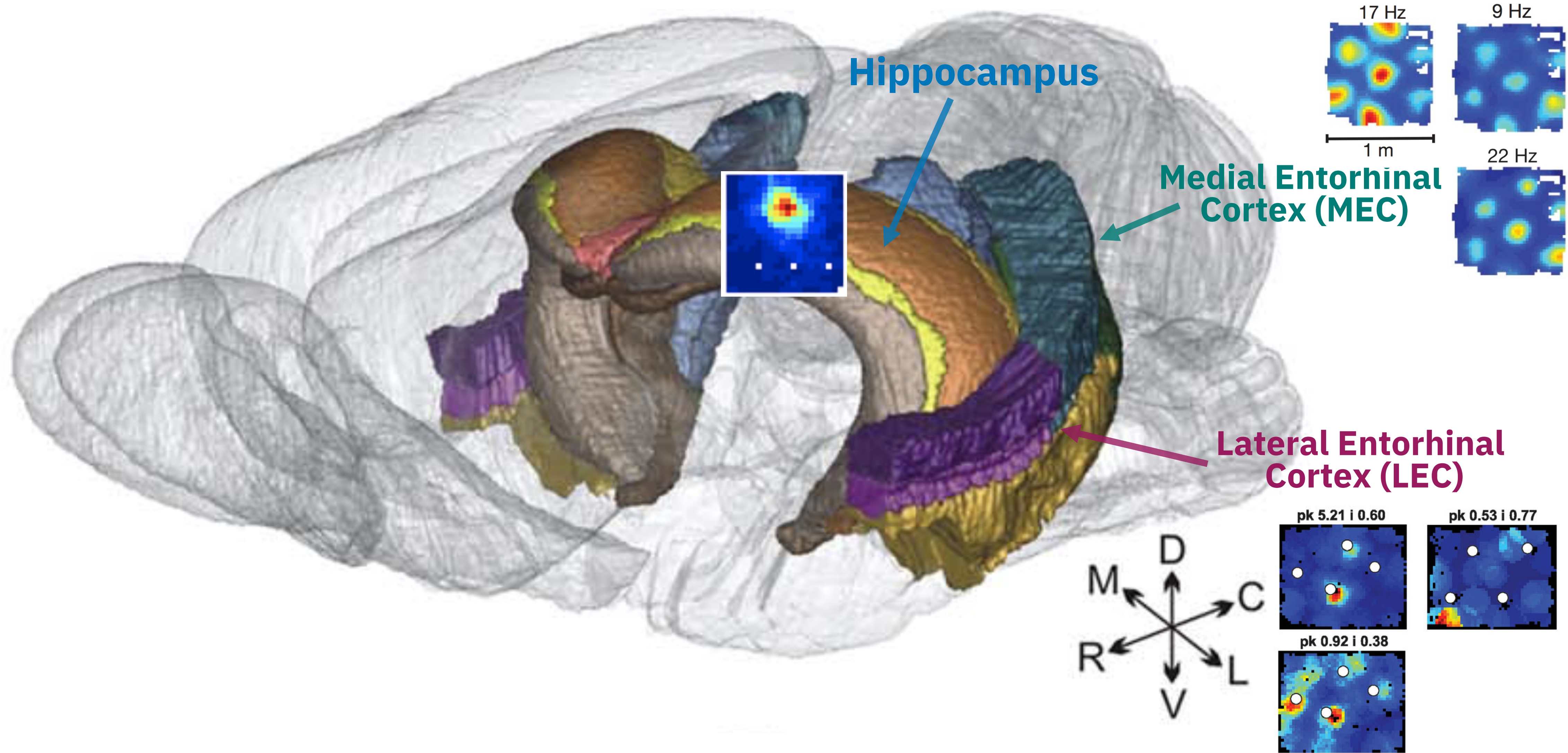
Video Credit: J. Taxidis

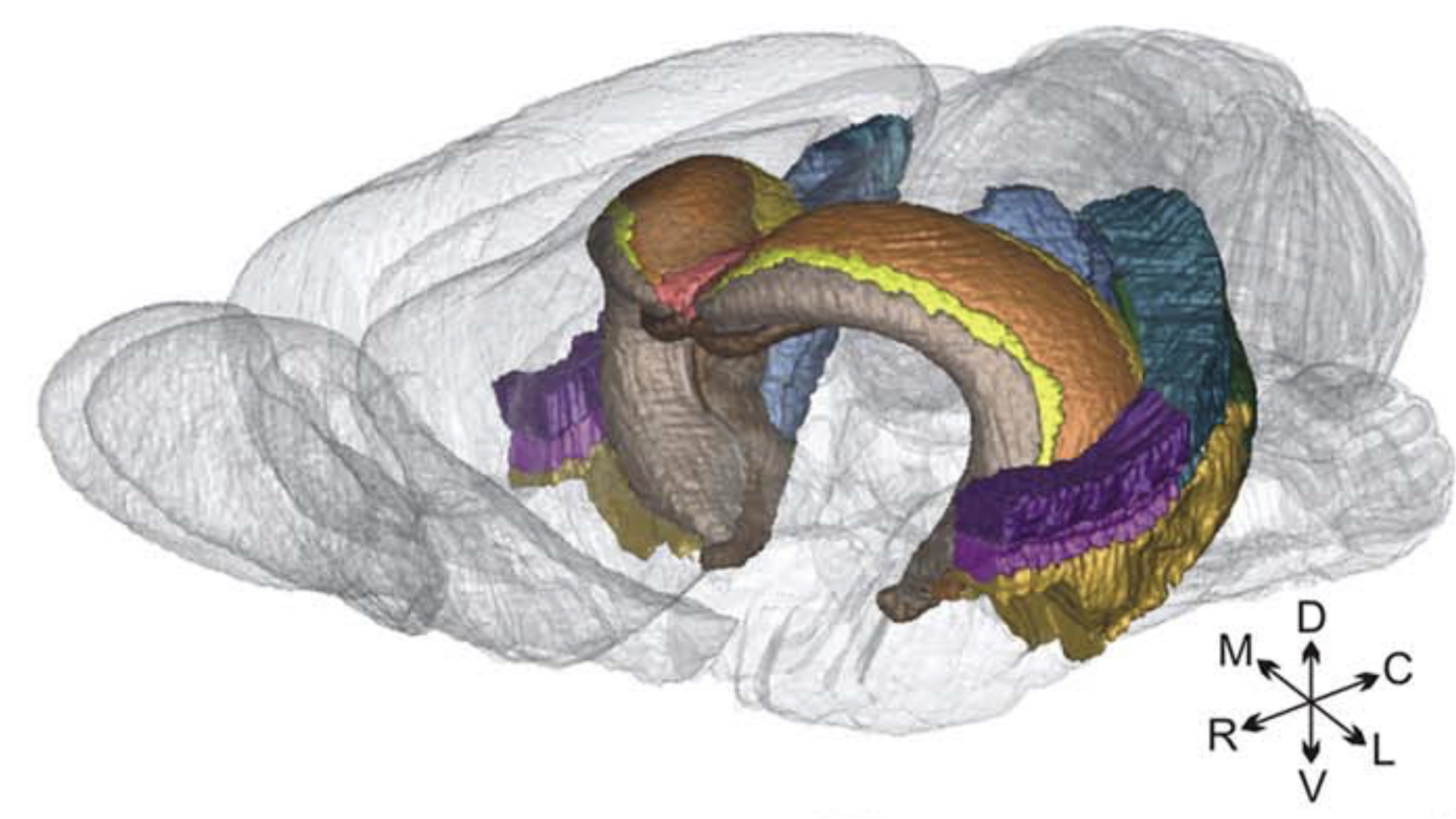
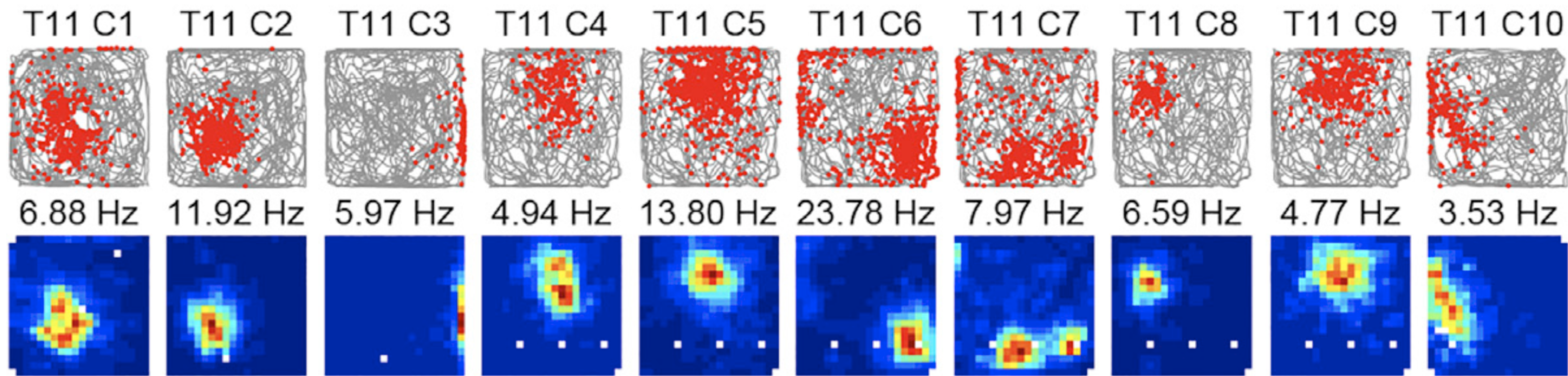
External observer bias

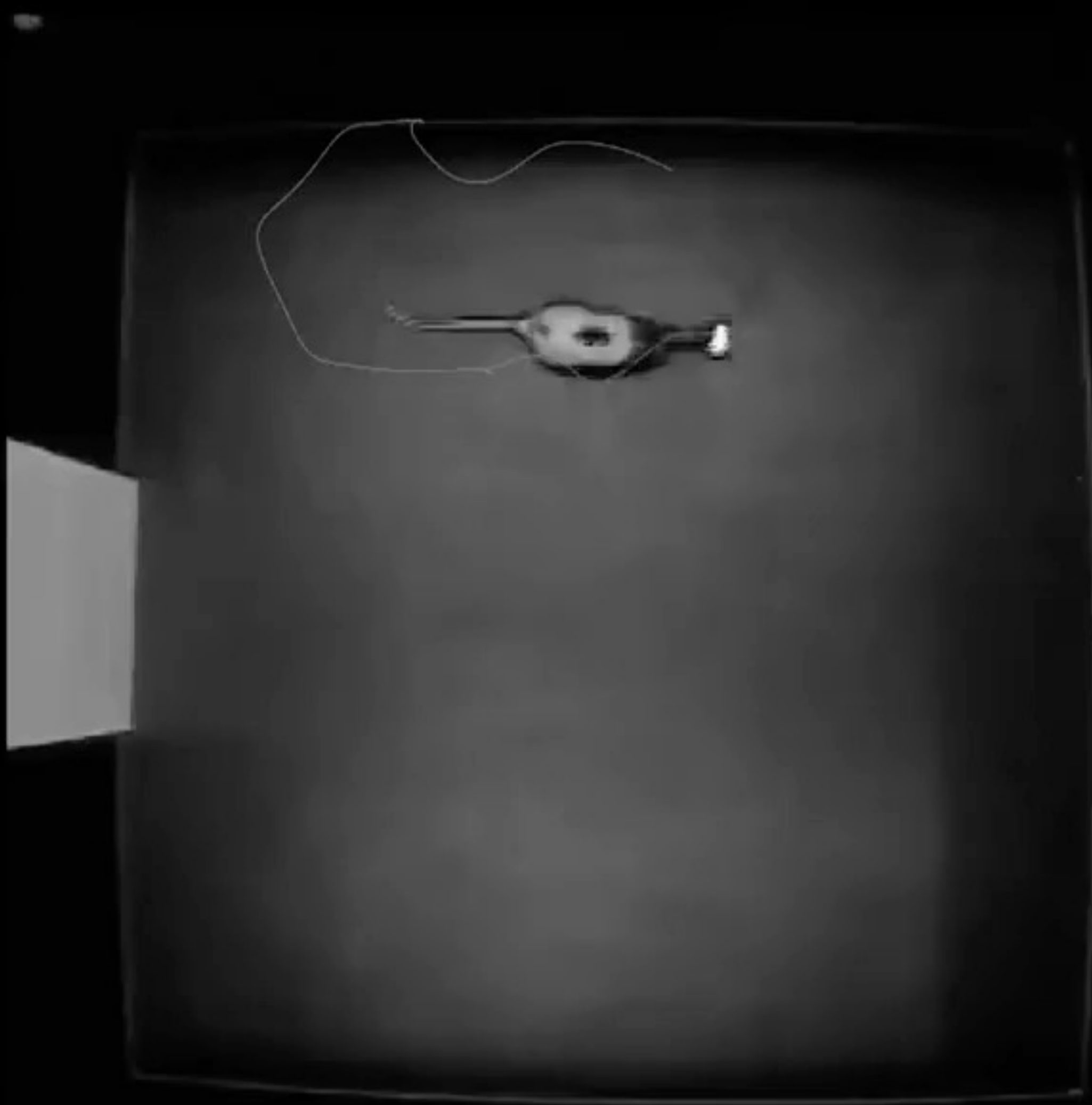
Inverting the input-output paradigm

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 forward (predictive) models










 Position

Spike legend

- Cell 1
- Cell 2
- Cell 3
- Cell 4
- Cell 5
- Cell 6
- Cell 7
- Cell 8
- Cell 9
- Cell 10

Time: 0.02s Speed: 1x Spikes: 0 1 m 

Not Actual Speed

Embodied cognition

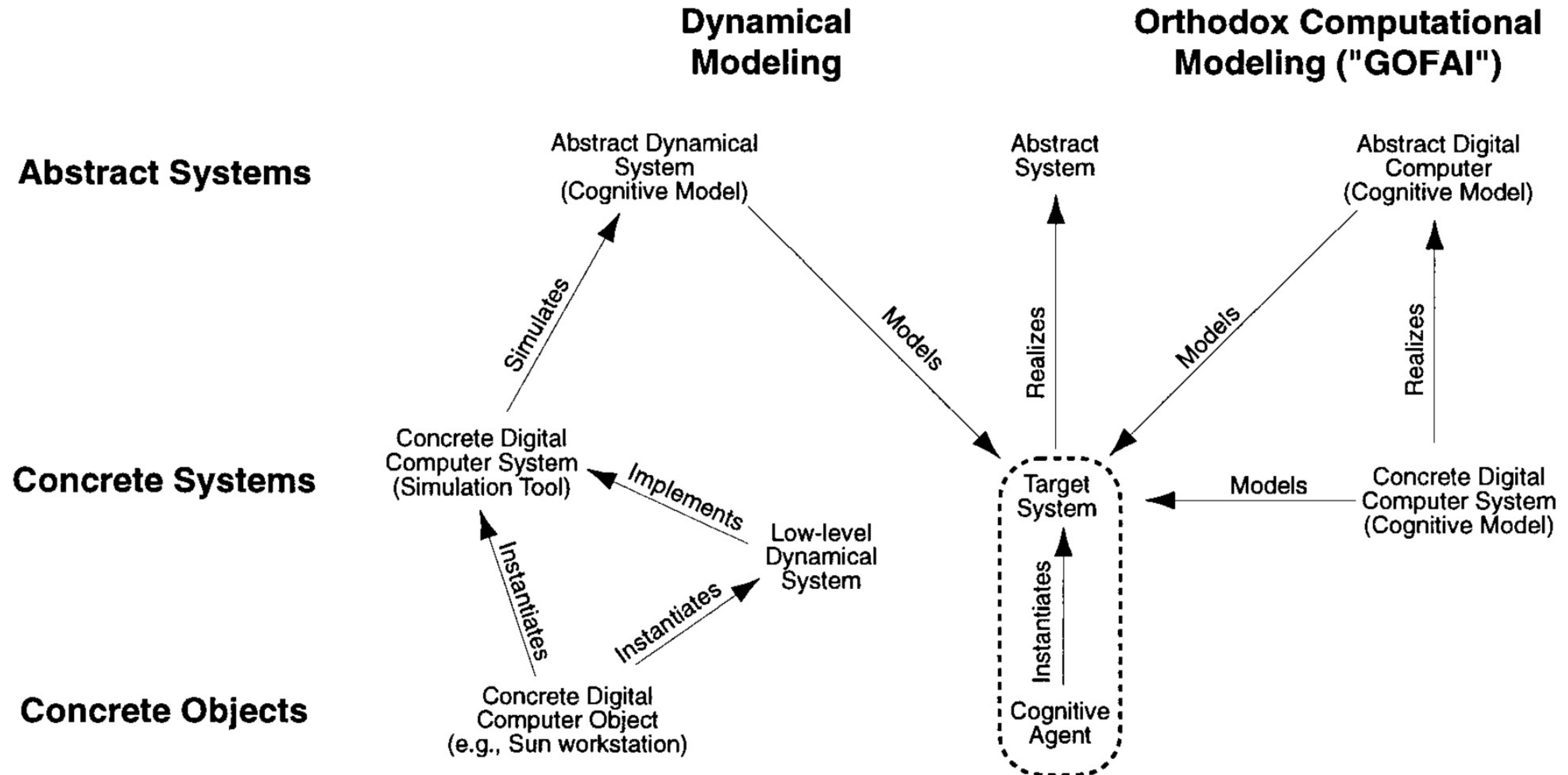
Progressive articulation vs. forward models

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 (*umwelt*).



Dynamical systems view of cognition

Temporal unfolding and the locus of agency



Reorganizing the control flow

Perceptual control internalizes input, output, and goals

- 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 input

Reorganizing the control flow

Perceptual control internalizes input, output, and goals

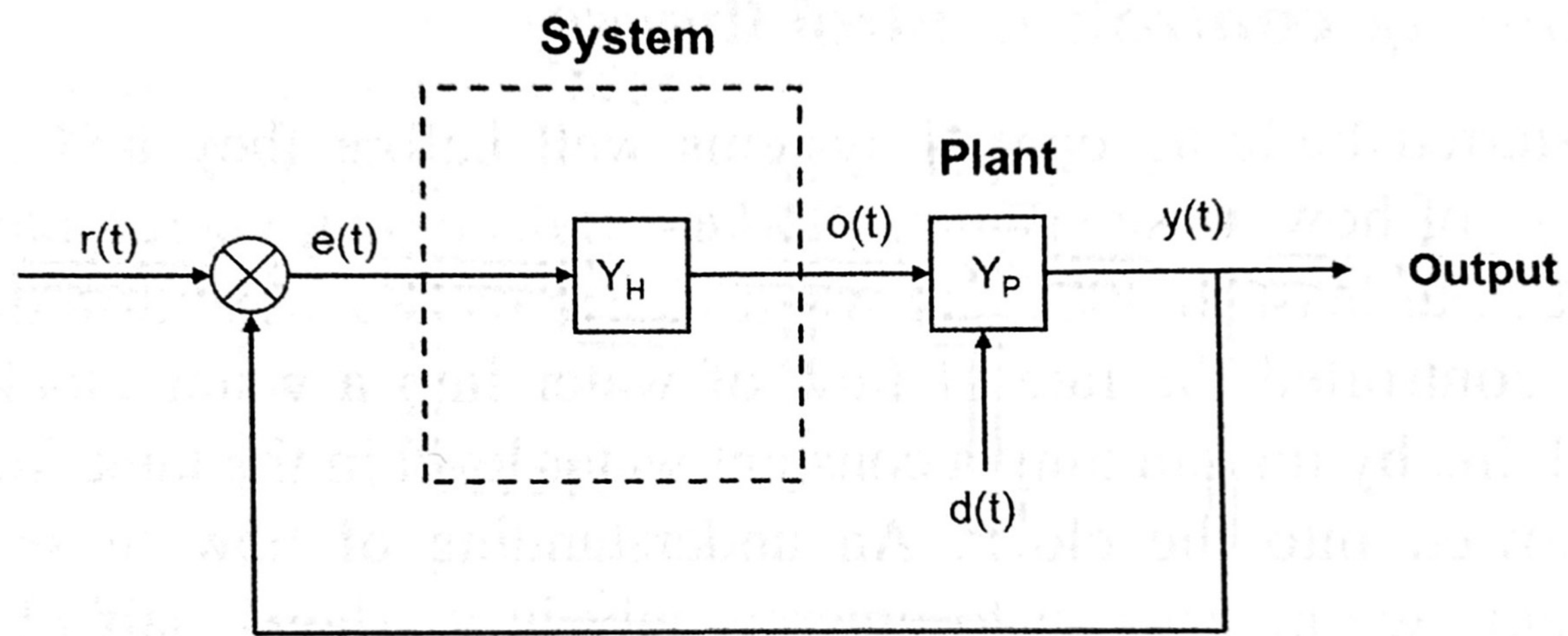


FIG. 2.1 Diagram of a negative feedback control system.²¹

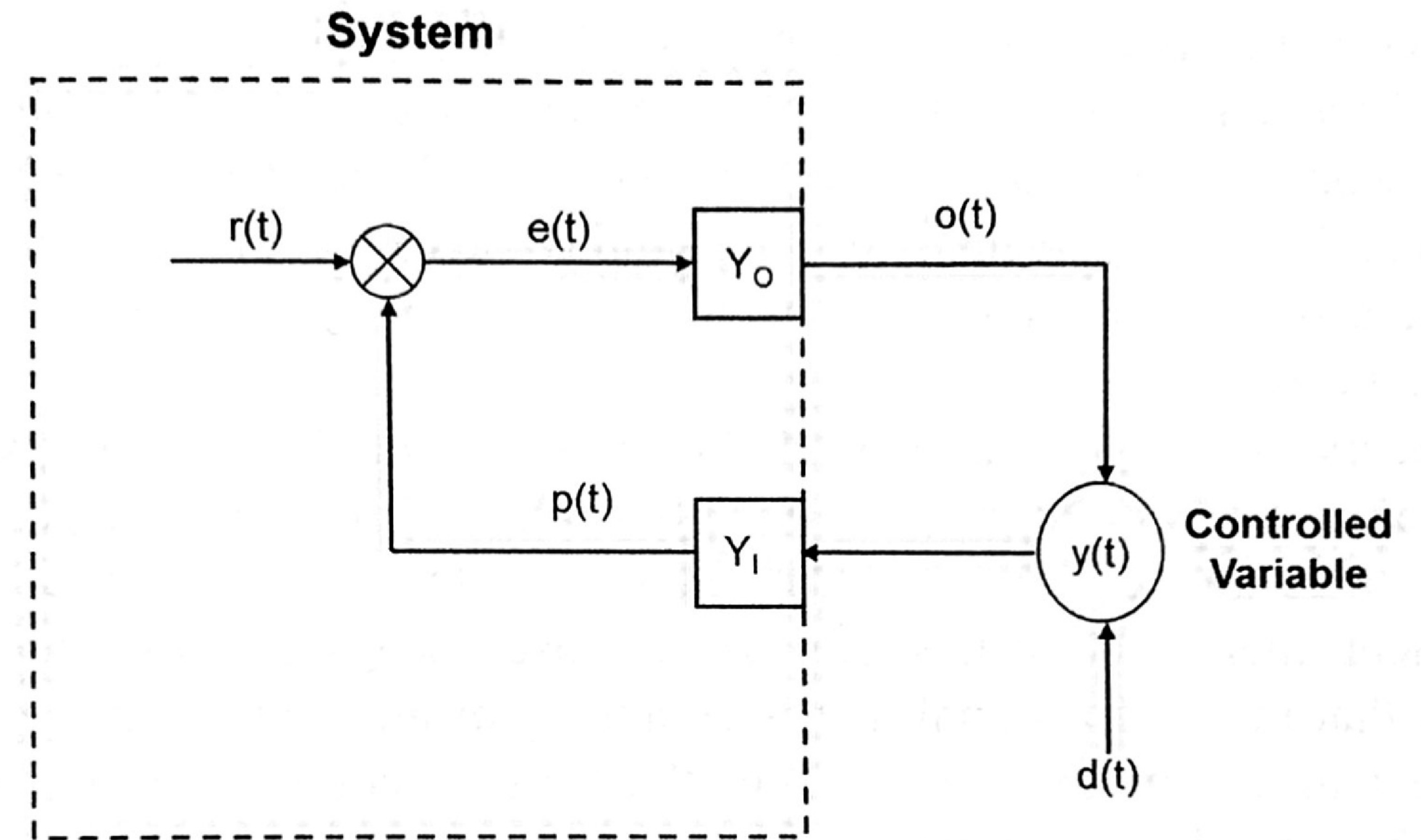


FIG. 2.2 PCT model of a control system; control theory for psychologists.

Reorganizing the control flow

Perceptual control internalizes input, output, and goals

- 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

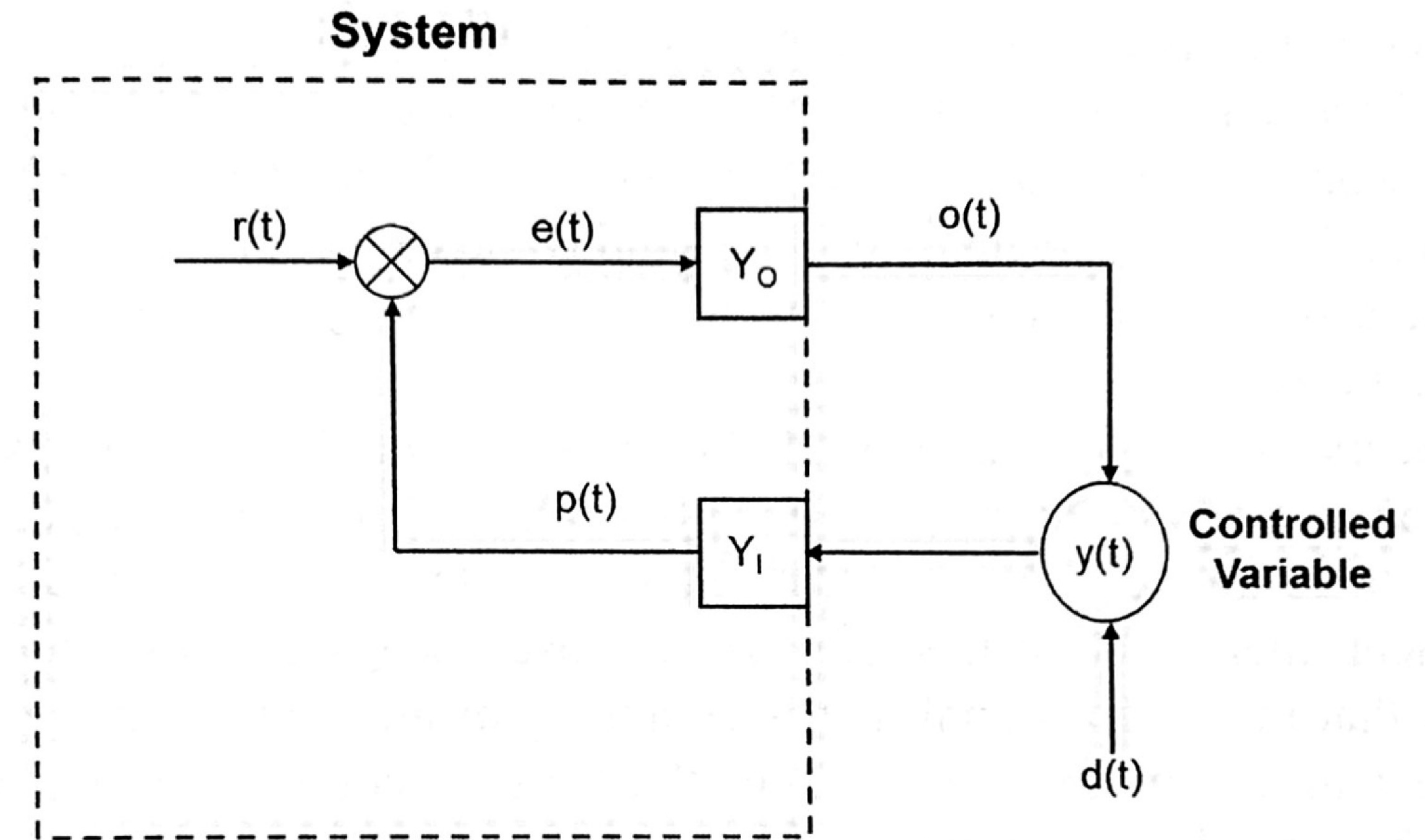
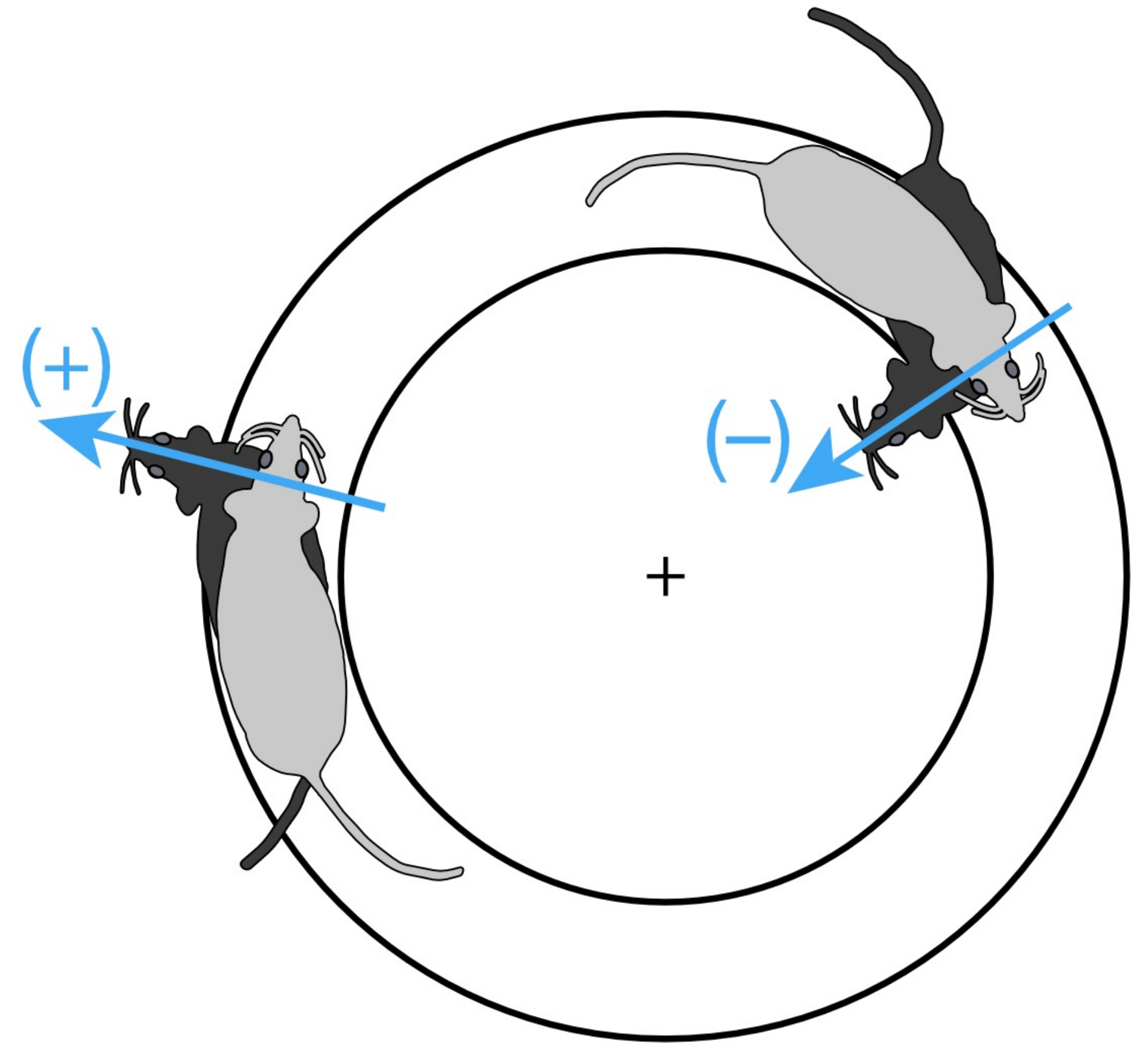


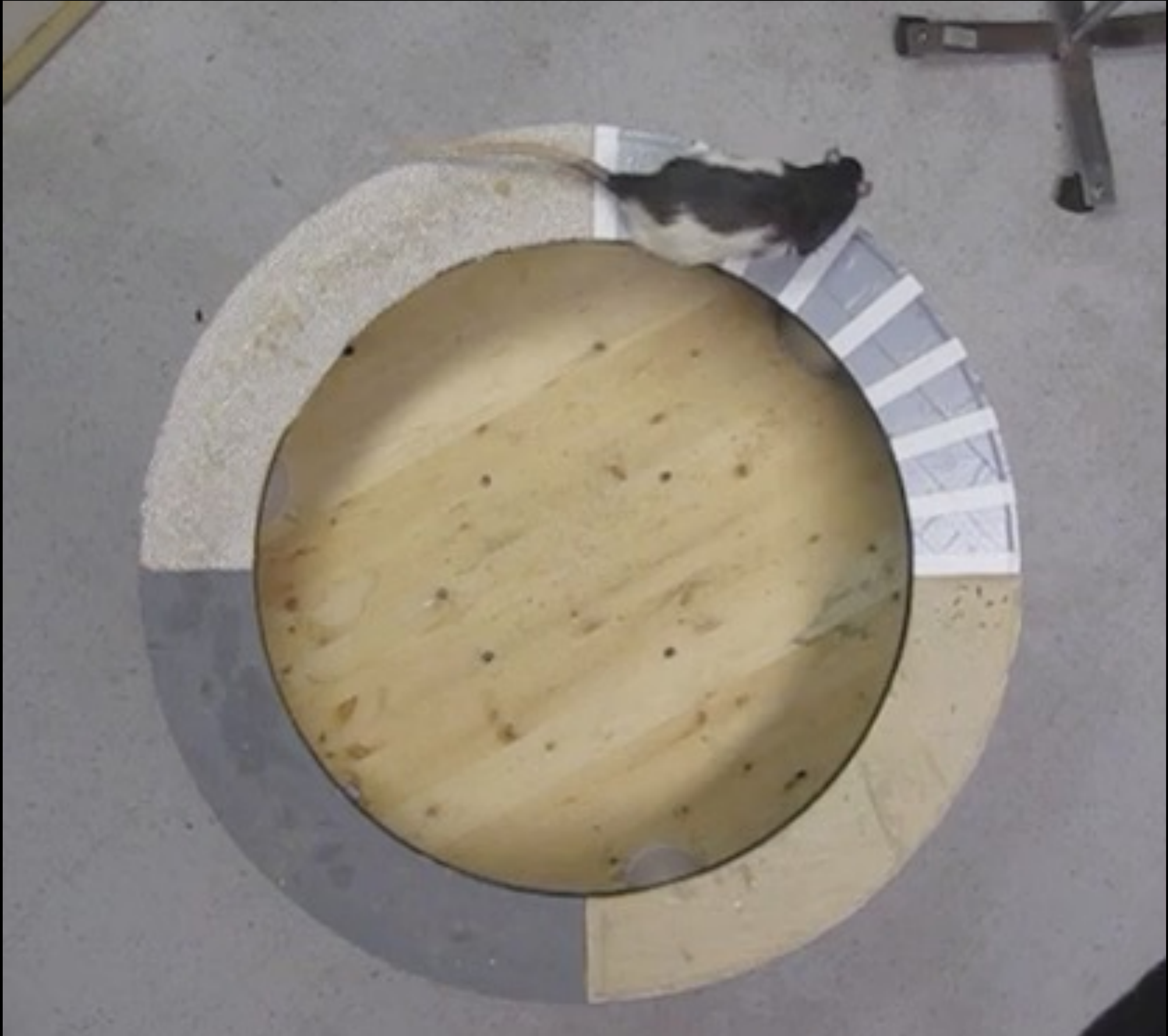
FIG. 2.2 PCT model of a control system; control theory for psychologists.

Active inference

The generative role of behavior

- Optimal (Bayesian) inference in feedback-driven generative models require *active inference*: actions that maximize model evidence by balancing internal active-state (self) entropy with external sensory-state (nonself) entropy.
- *Agents learn massively distributed internal feedback models by adaptively balancing information streams arising at the self–nonself boundary.*

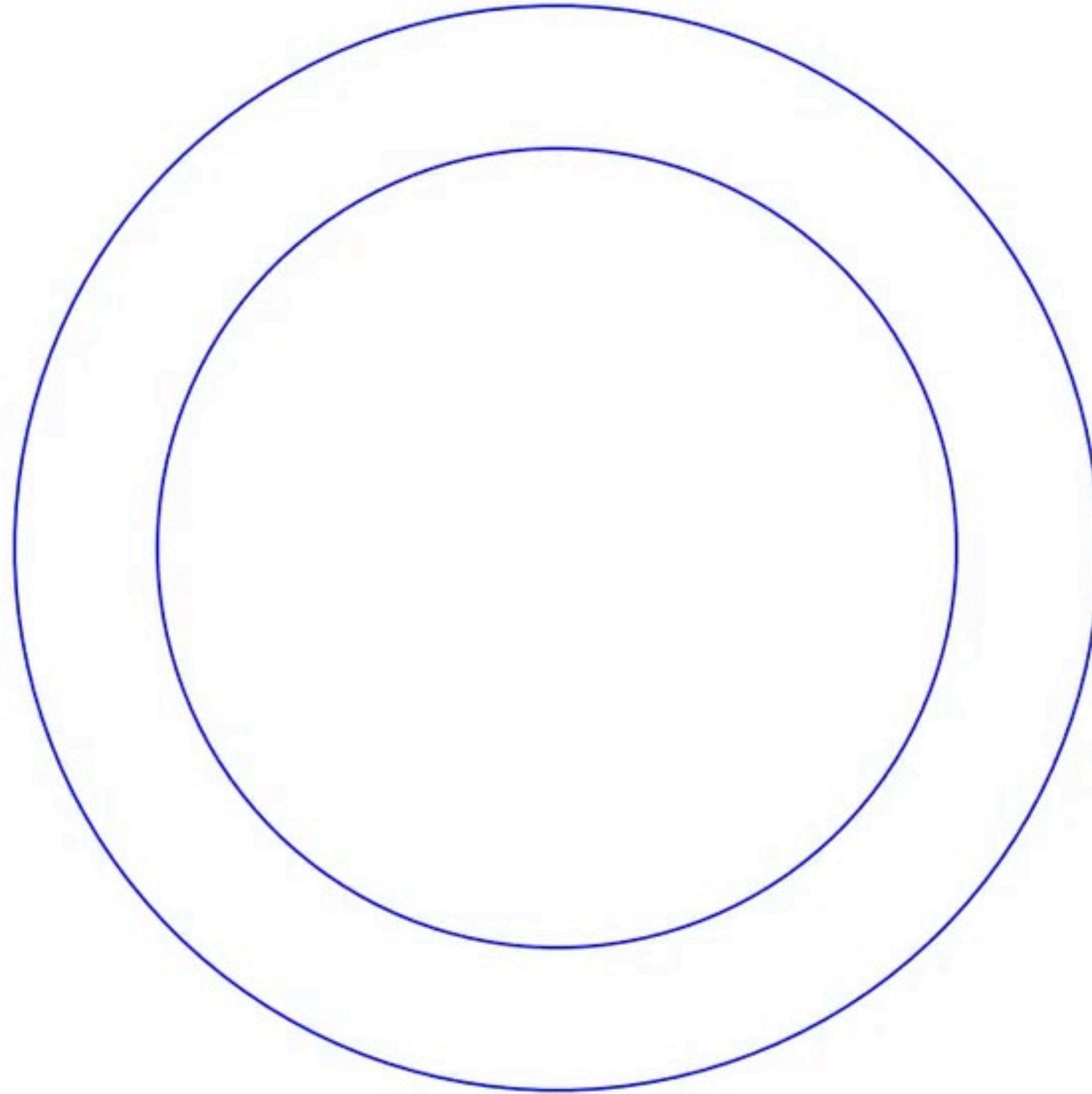




5x Speed


Video Credit: G. Rao

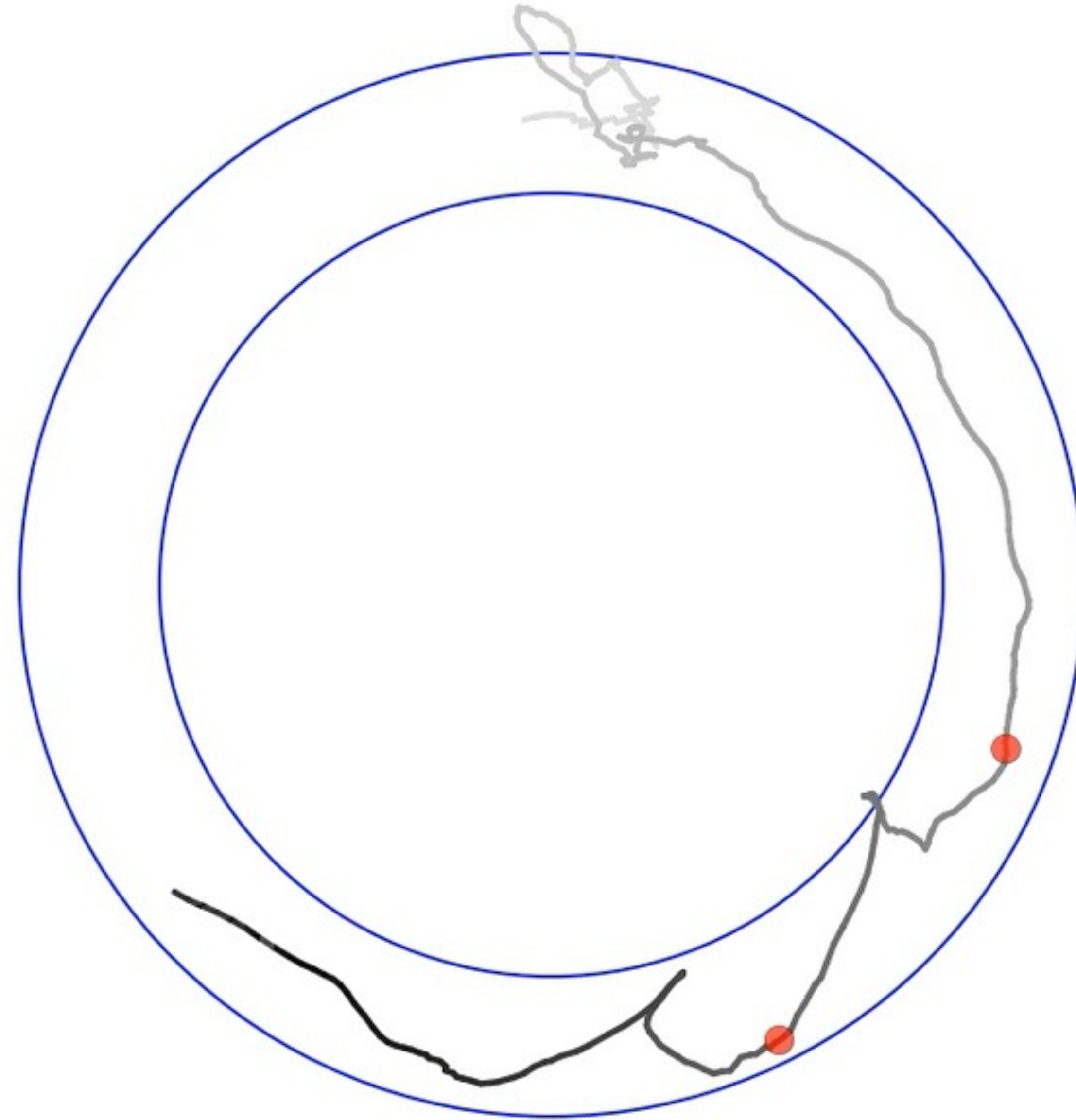
Example



0.0 s

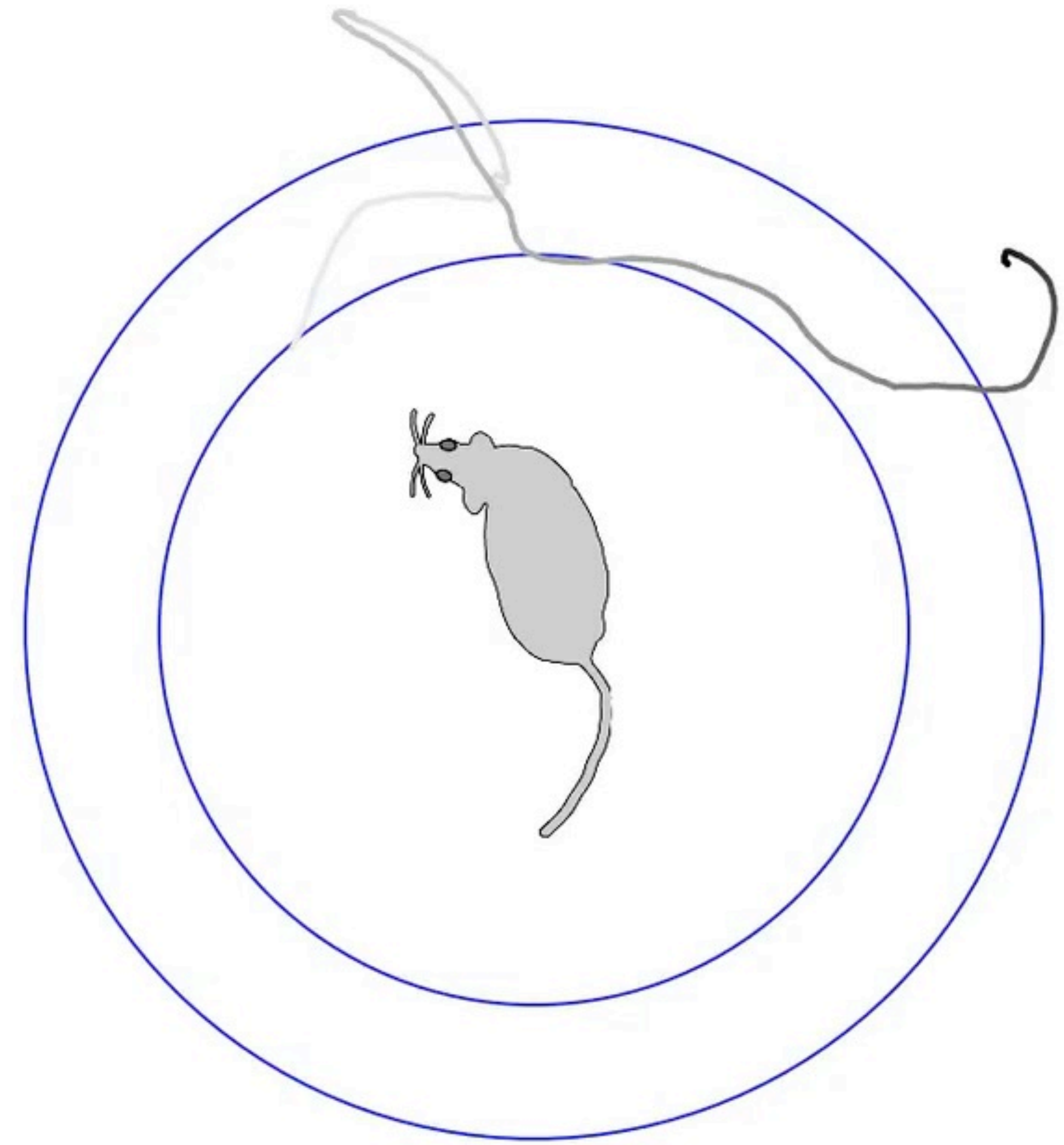
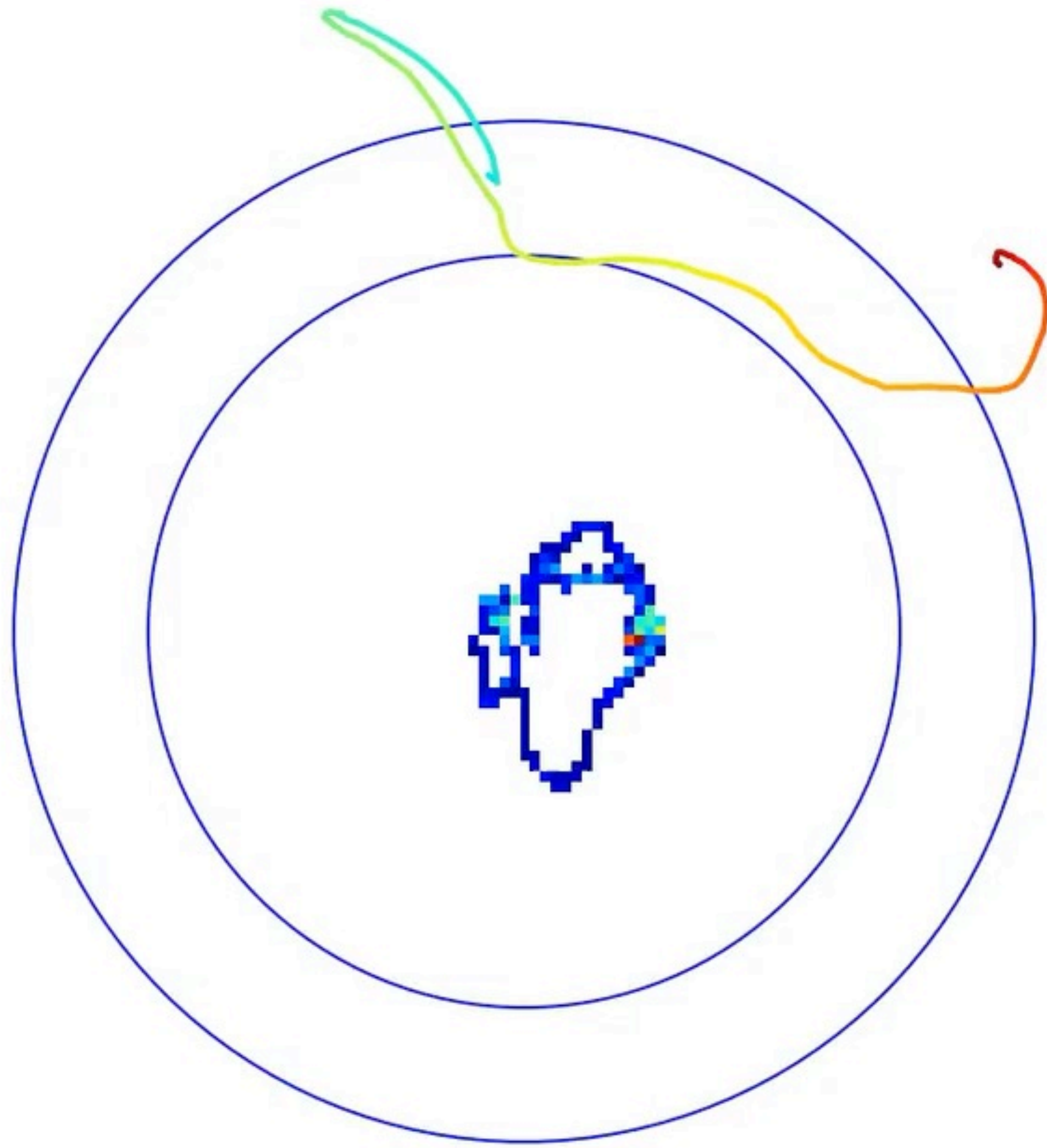
Example

Location of scan firing 



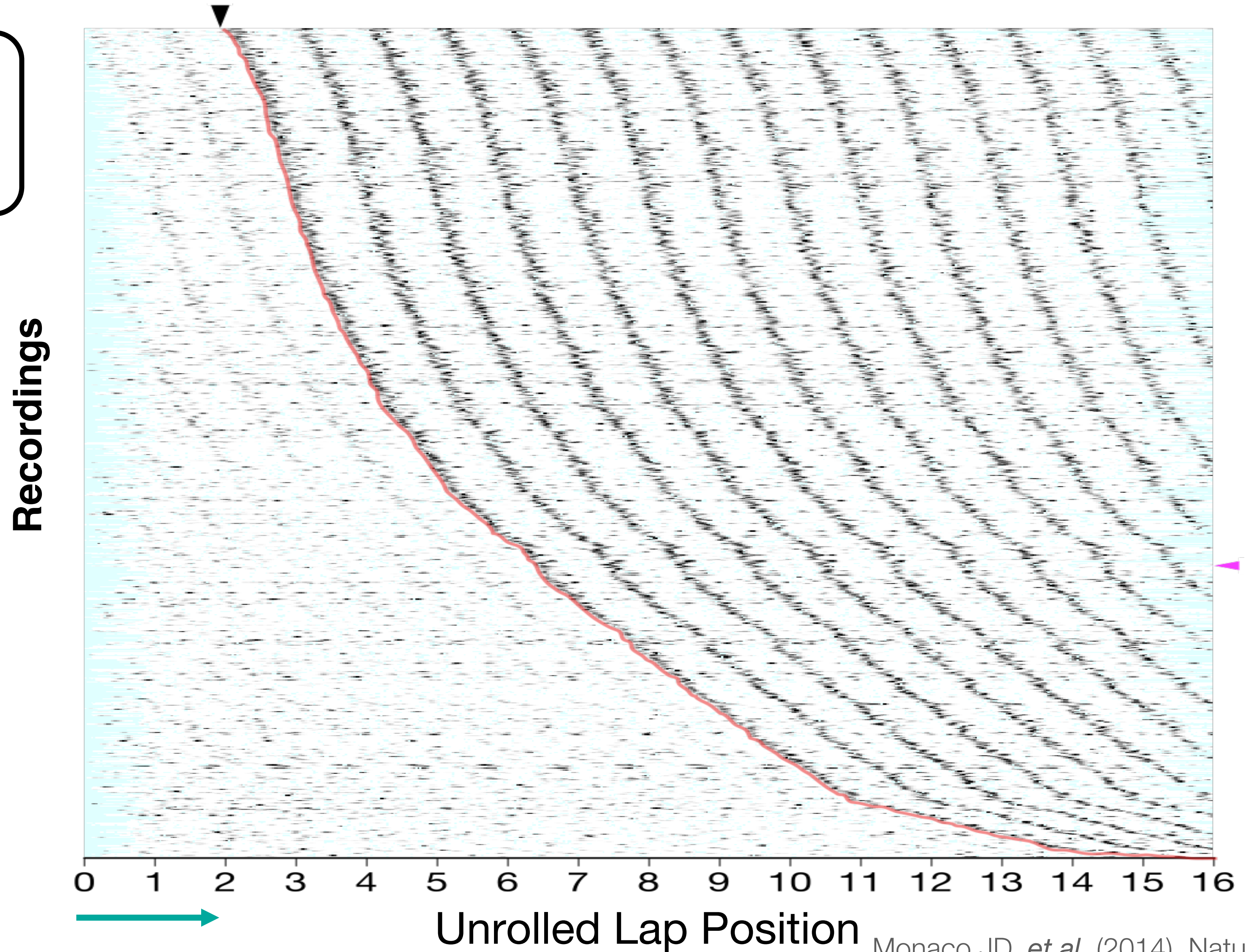
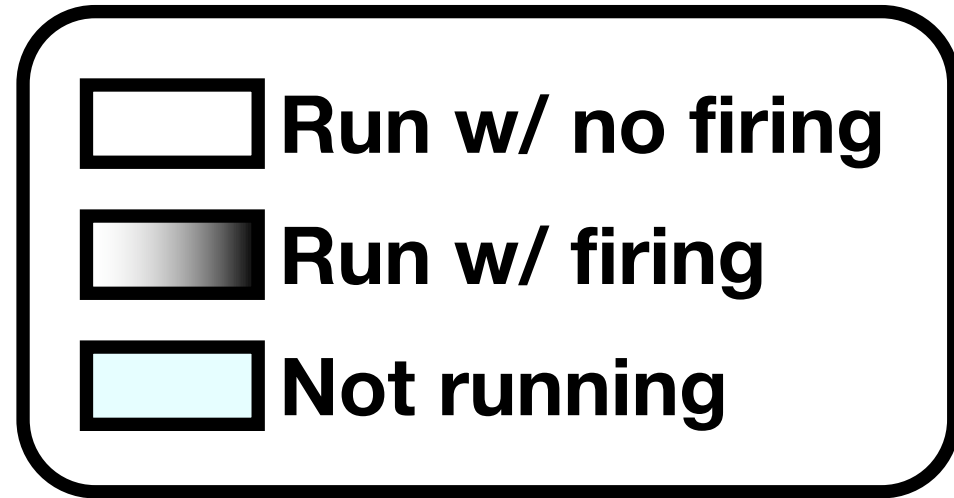
69.1 s

Quantifying Lateral Head-Scan Behaviors

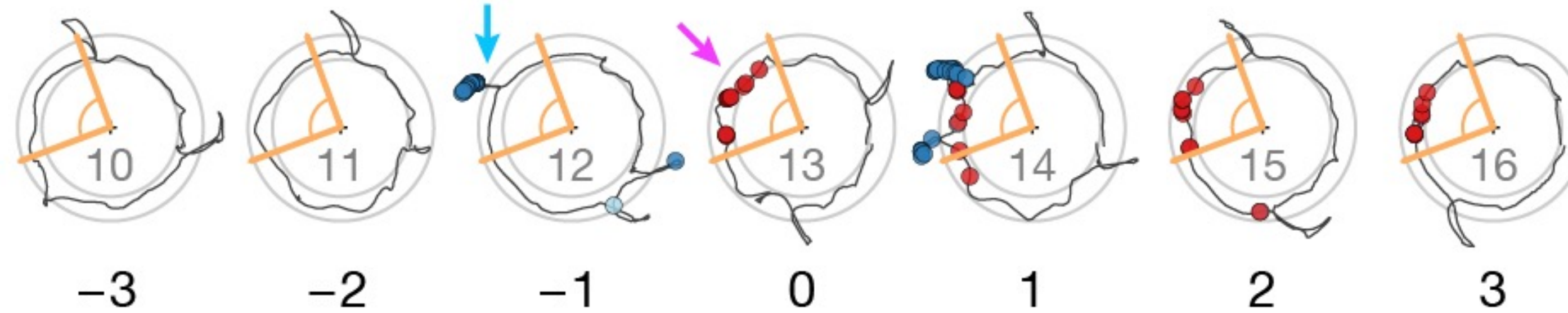


60.0 s

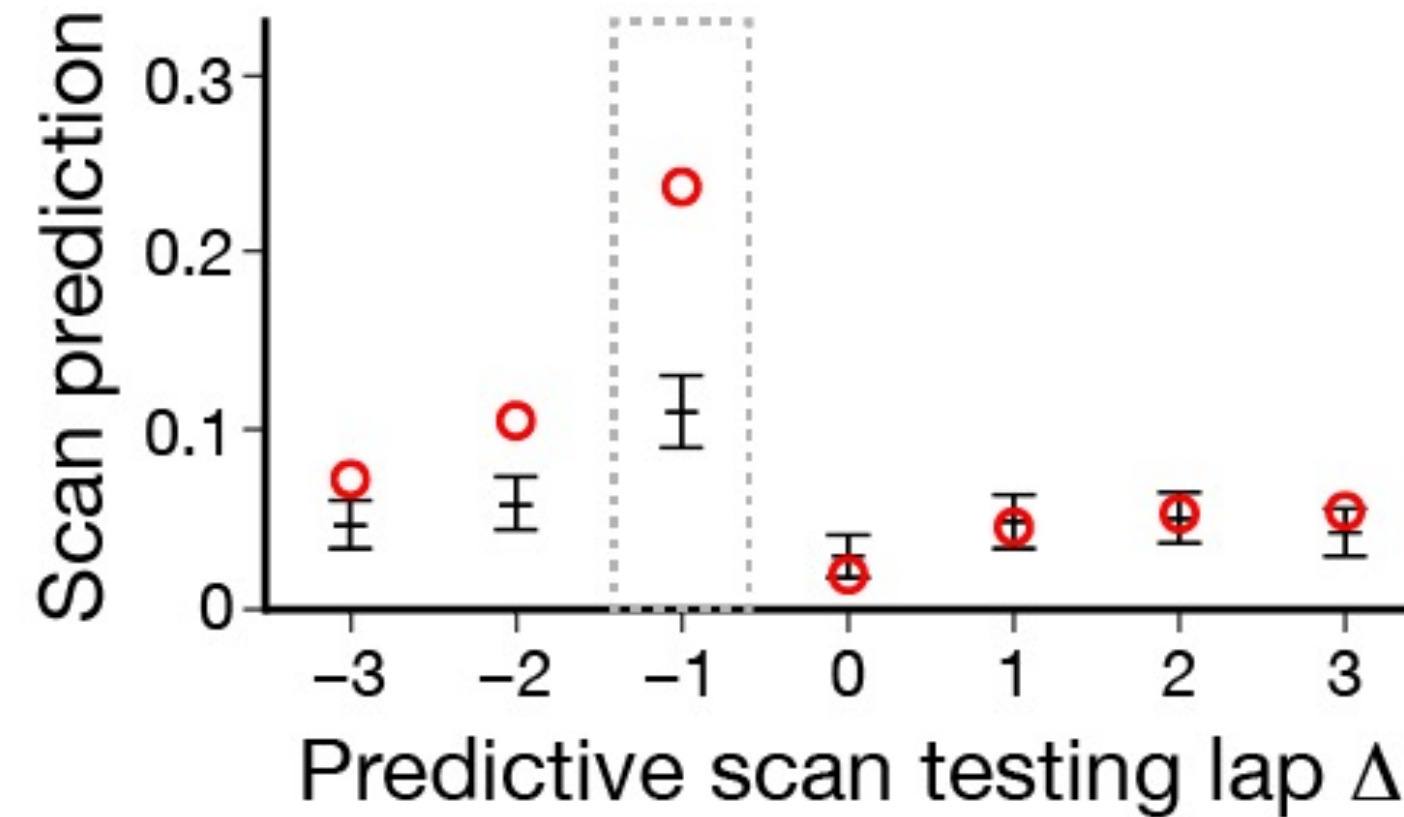
Place-Field Firing



Significant Predictive Value: Scan Firing → Place-Field Event

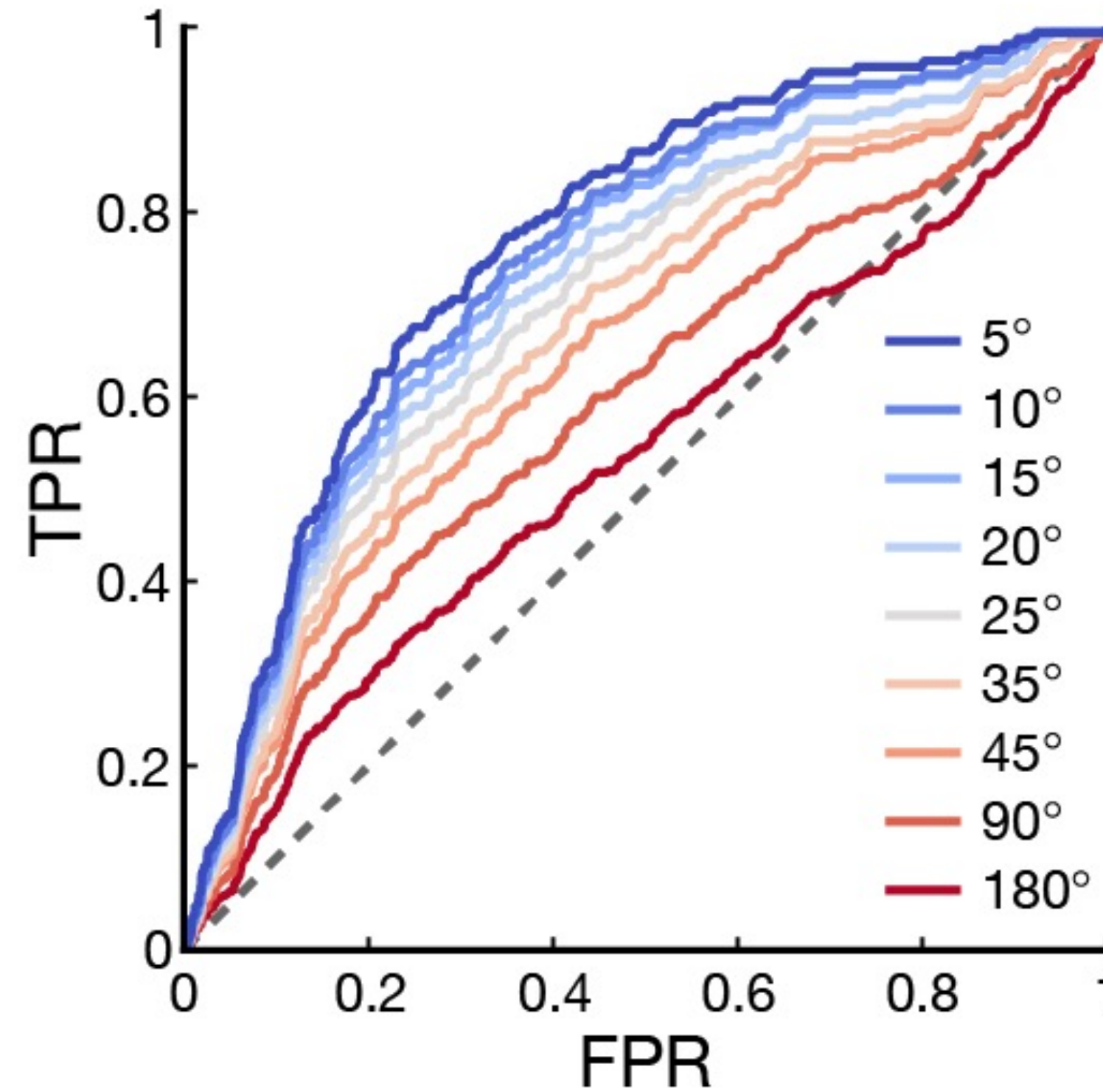
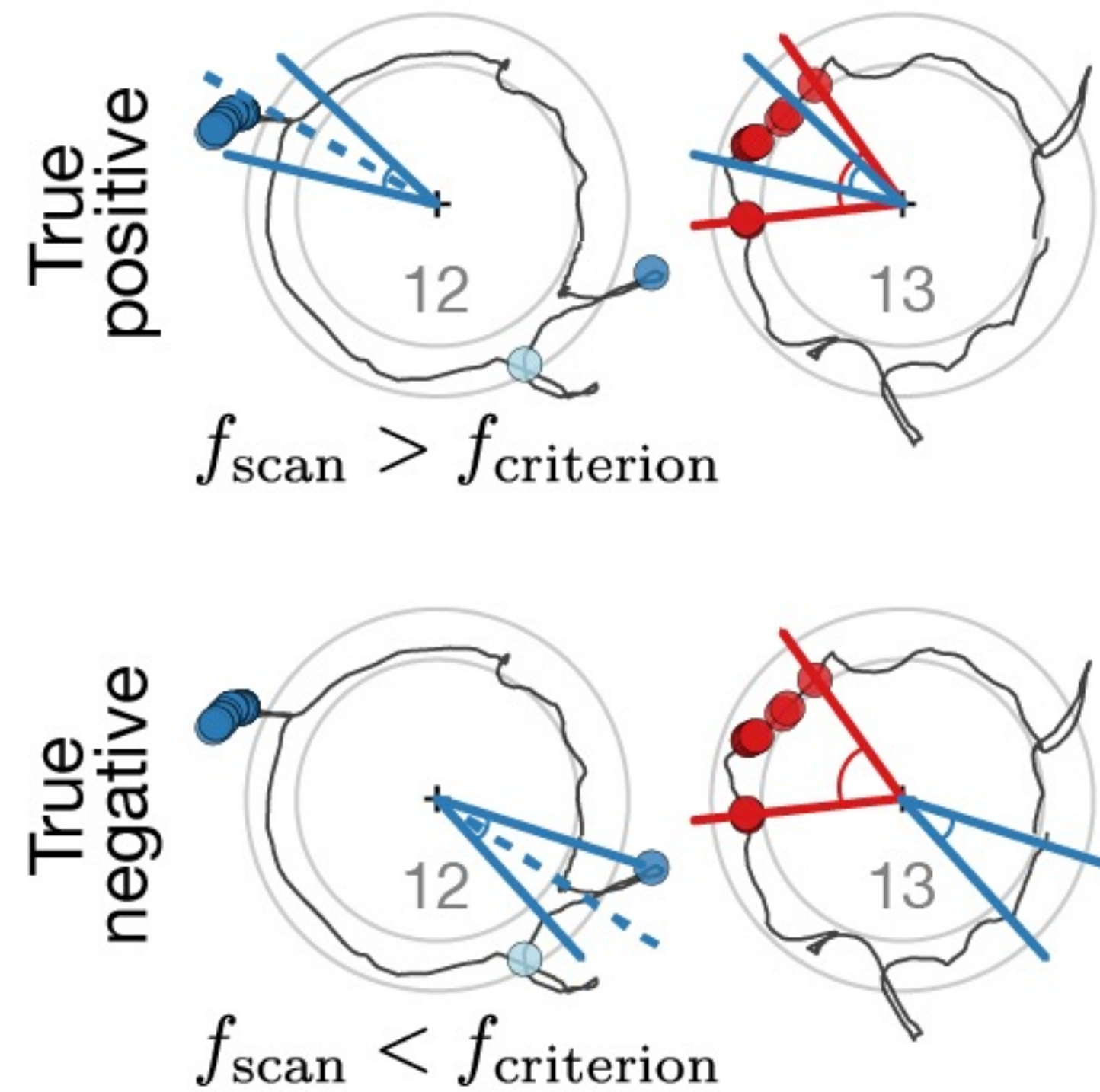


• **Scan Predictive Value:**
Fraction of criterion scan-firing events that fall within the track-angle bounds of a new or potentiated place field on the lap prior to the event ($\Delta=-1$)



• **Overall Result:**
Computed over all criterion scan-firing events in all animals ($n=36$), subregions (CA3, CA1), experiments (novelty vs. double rotation), training days, and session number (up to 5).

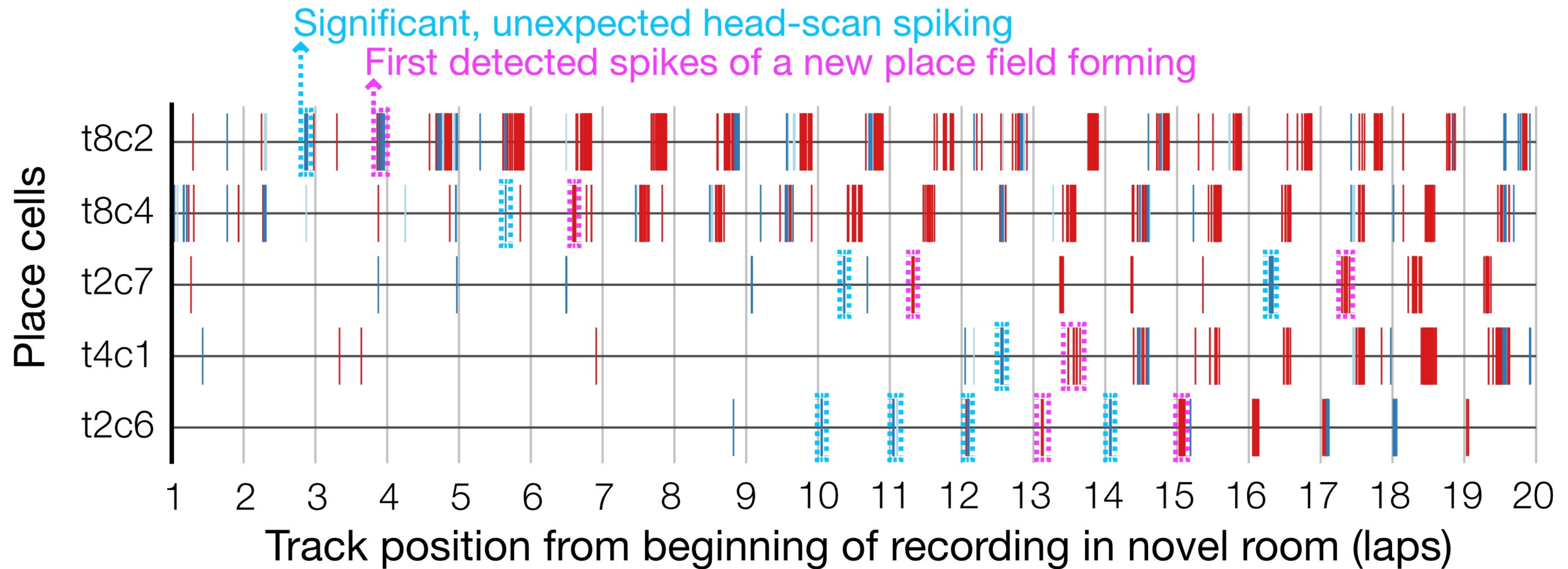
ROC Analysis: Place-Field Event → Prior Co-Localized Head Scan



- Abrupt place-field changes were diagnostically associated with significant high-firing head scans on the previous lap, with the association increasing to 75% AUC as the specificity of spatial co-localization approached $\pm 5^\circ$

Active inference

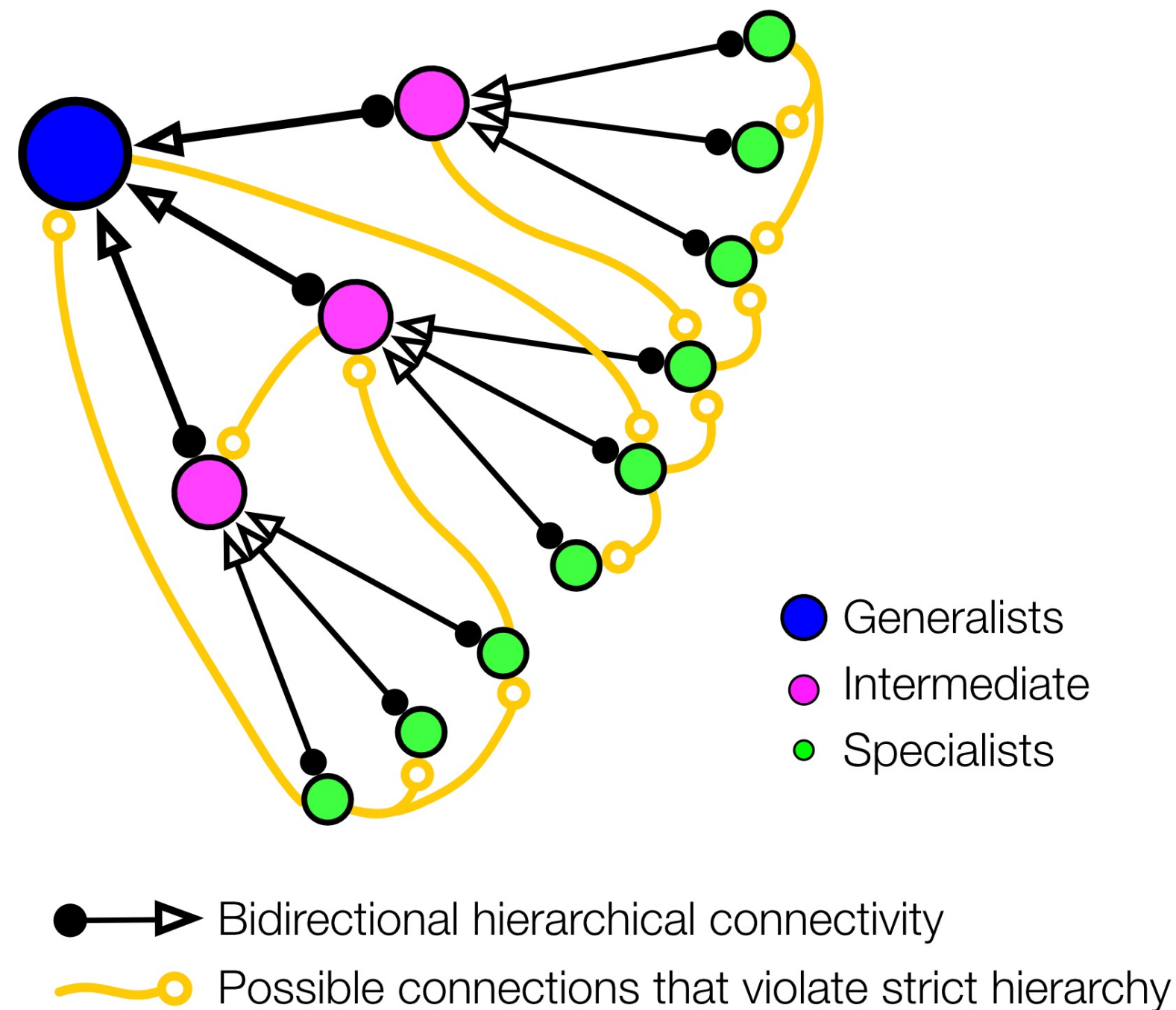
Cognitive map-building driven by autonomous head-scan sampling



Integrative framework for neurodynamical cognition

(1) Network structure:

Sparse, distributed hierarchies are non-strict



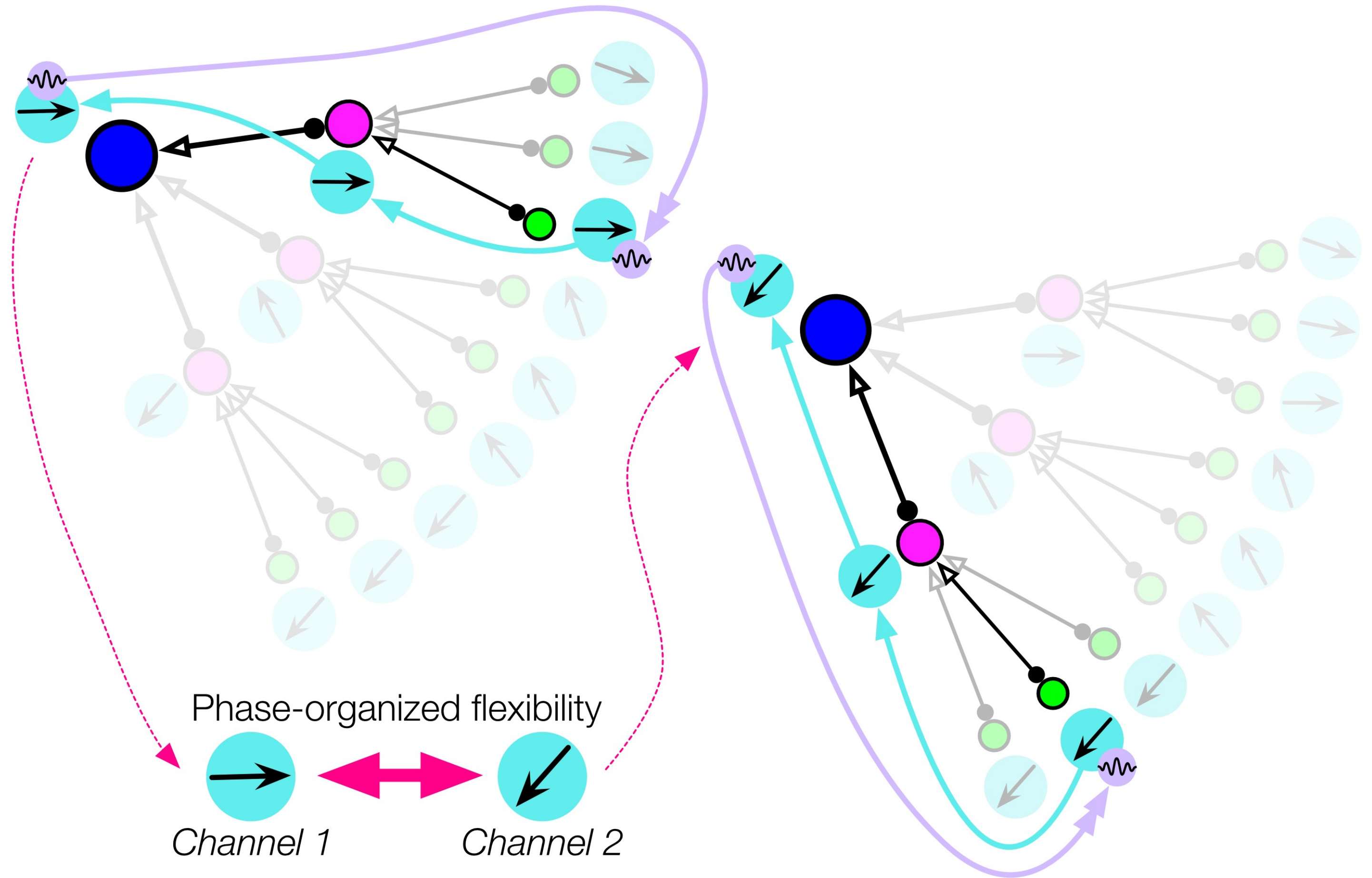
(2) Temporal dynamics:

(3) Agentic interaction:

Integrative framework for neurodynamical cognition

Readers phase-shift to select inputs and establish communication channels

(1) Network structure:



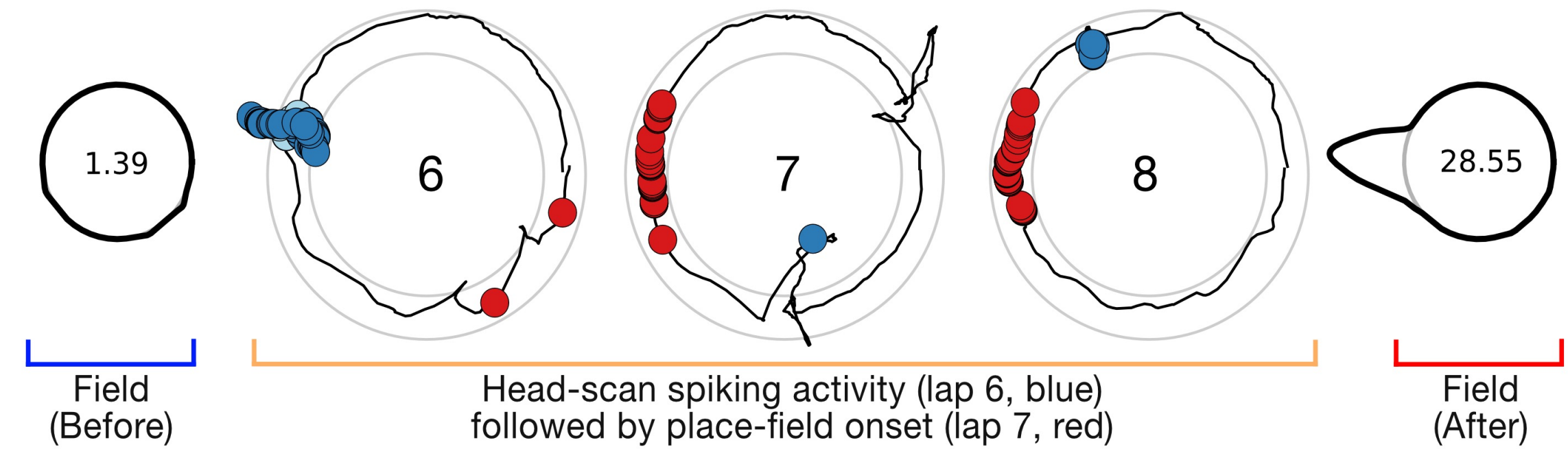
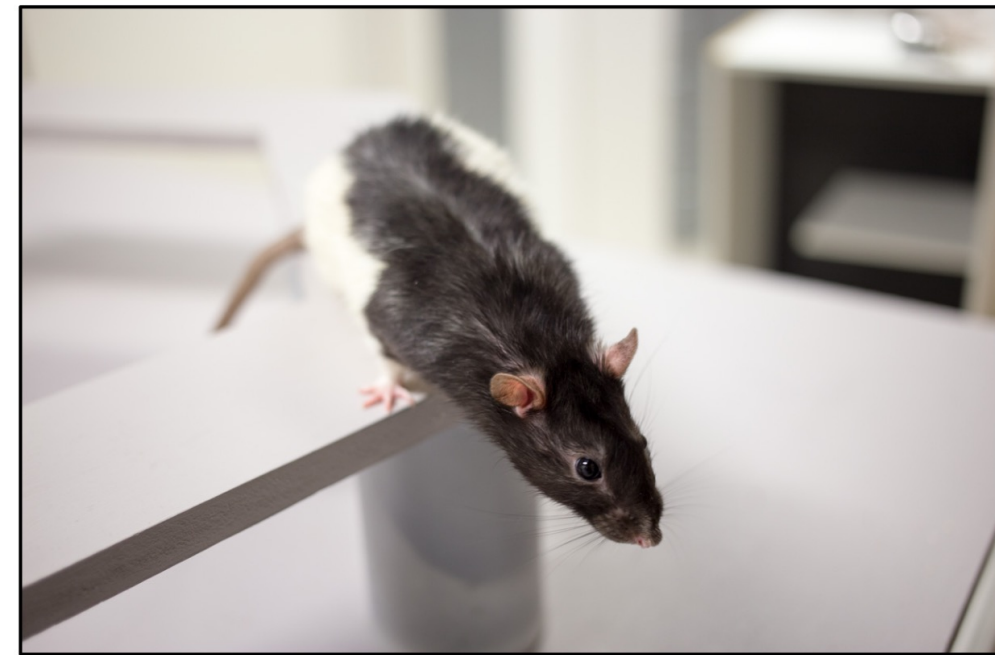
(2) Temporal dynamics:

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

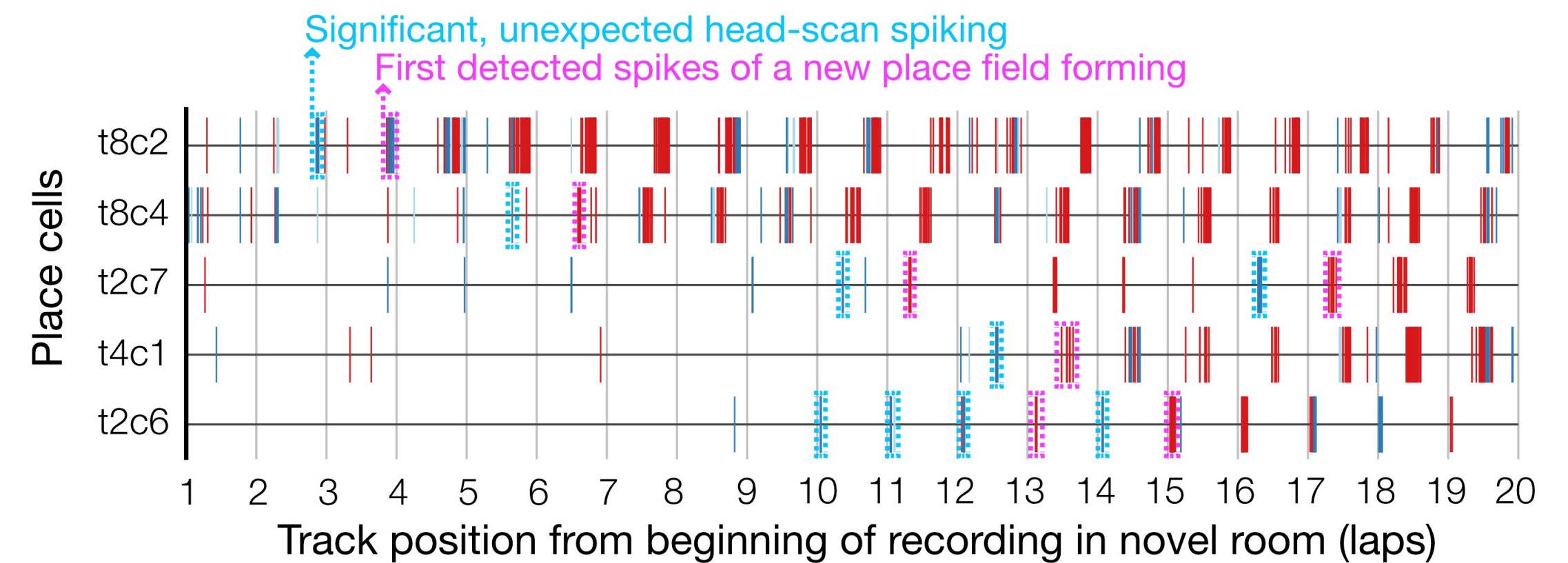
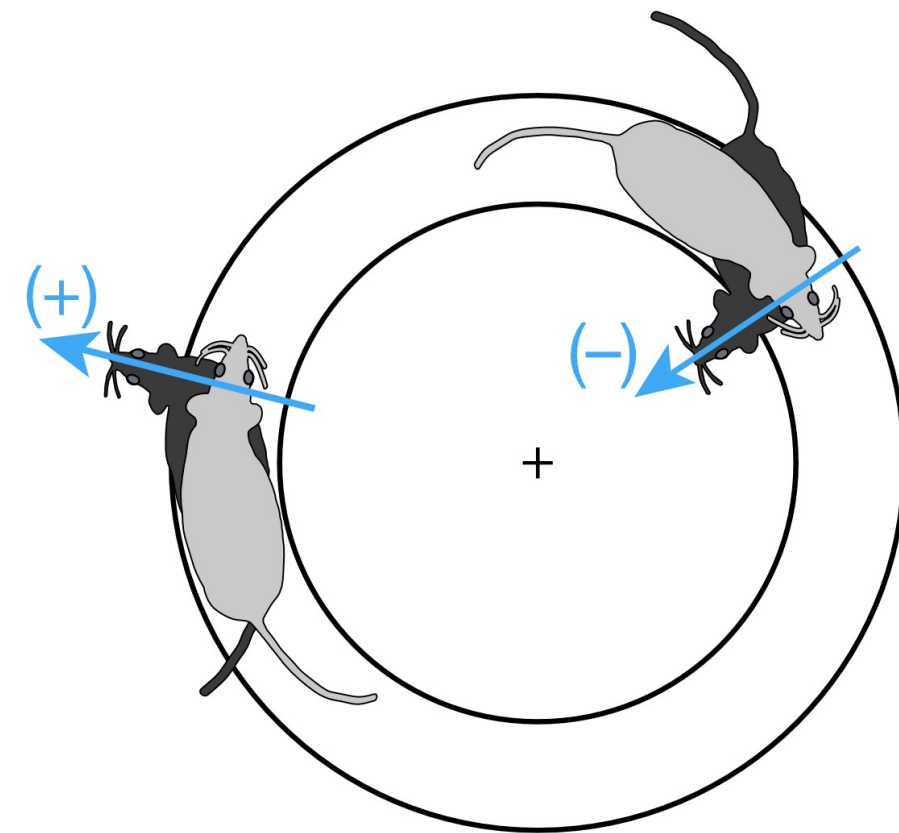
(3) Agentic interaction:

Integrative framework for neurodynamical cognition

(1) Network structure:



(2) Temporal dynamics:



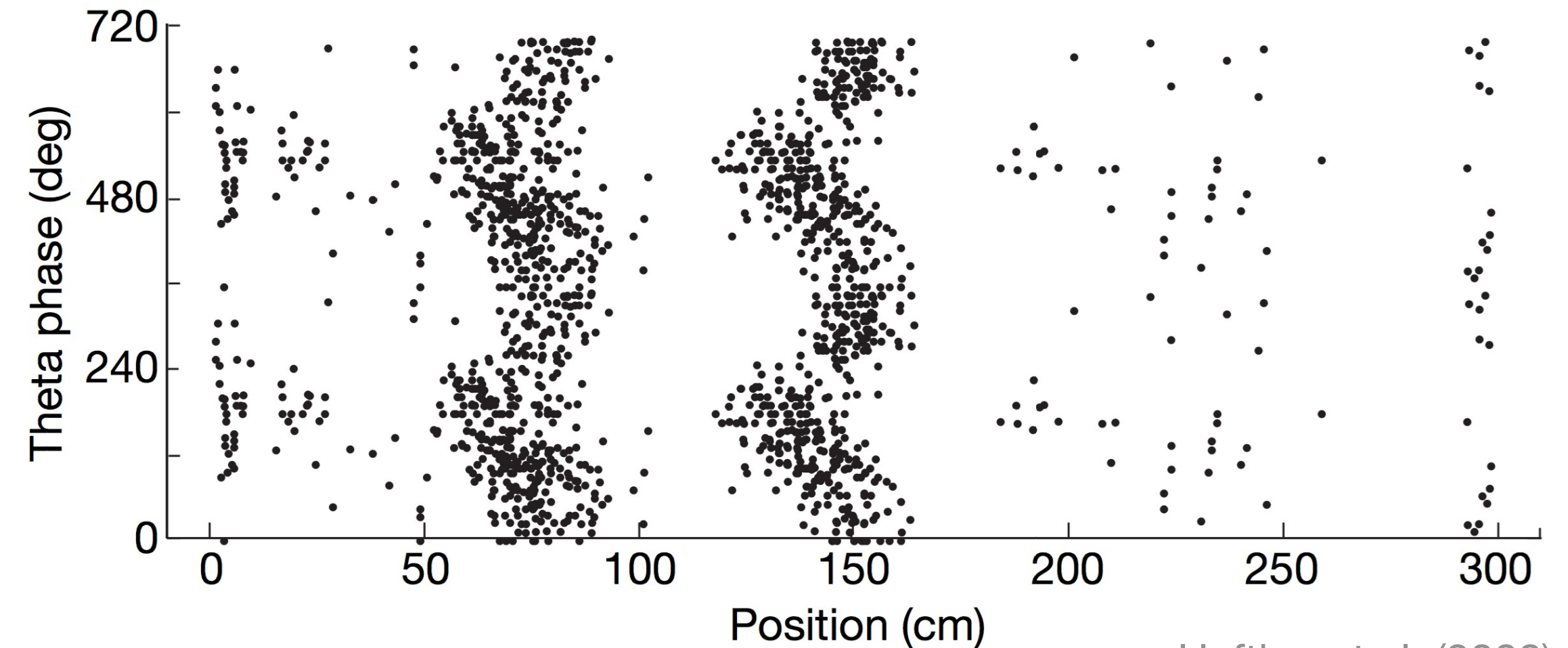
(3) Agentic interaction:

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

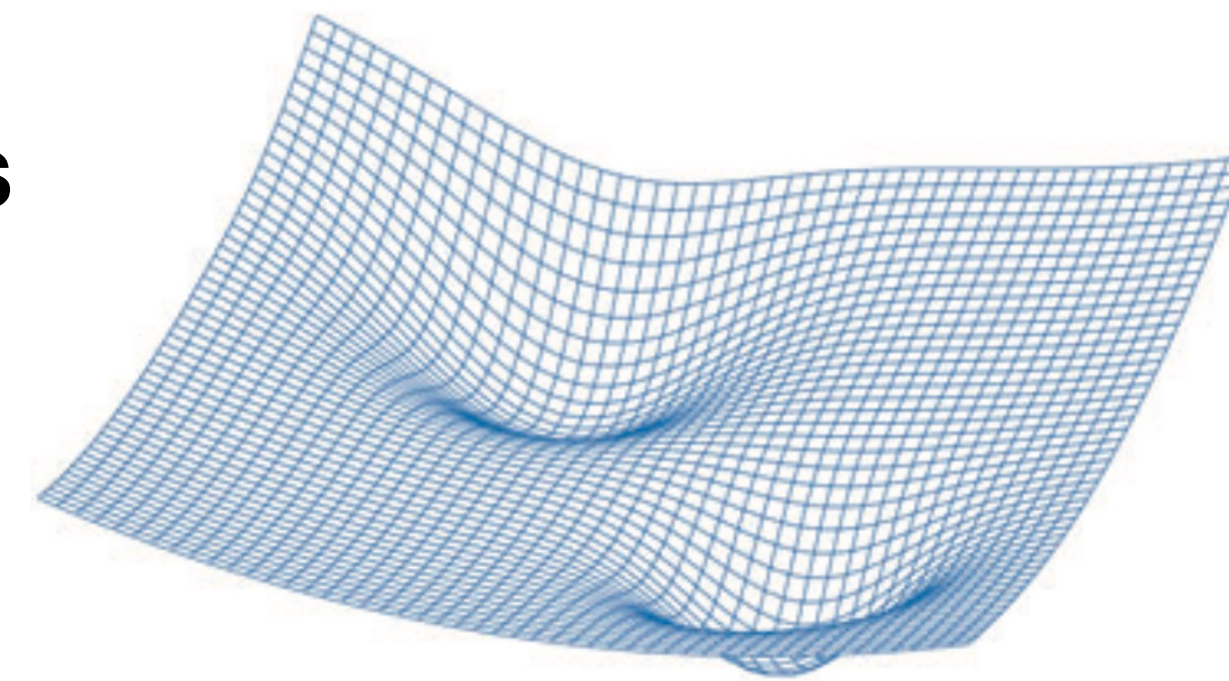
Temporal and Population Dynamics

Key Building Blocks

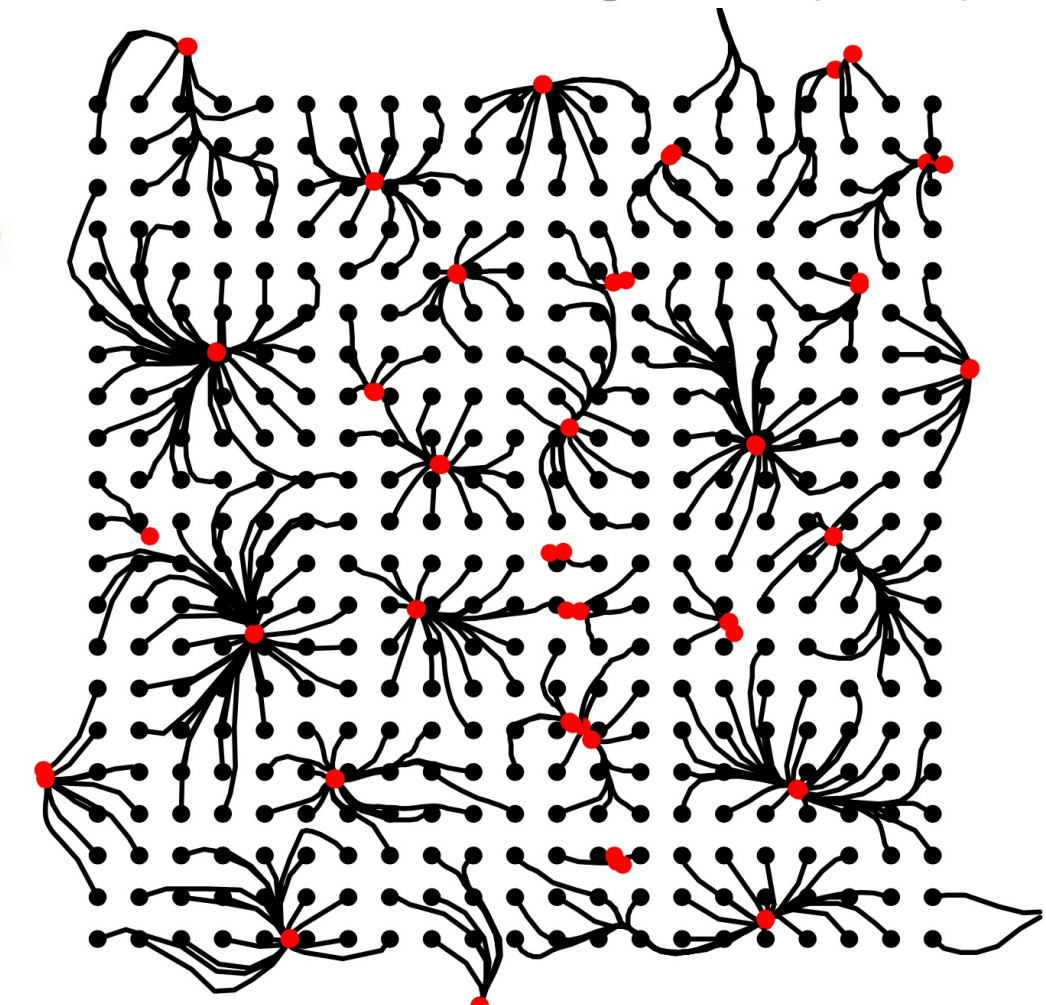
- **Local oscillations and neuronal synchrony**
 - Temporal coding with oscillatory phase
 - O'Keefe & Recce (1993) — Theta-phase precession of hippocampal place-field firing
- **Emergent self-organizing states arising from recurrence and feedback in structured networks**
 - Hopfield networks (1982) — Pattern completion supports content-addressable memory with (limited) generalization
 - **Memory retrieval as a state-space trajectory that probes basins of attraction**



Hafting et al. (2008)



Knierim & Zhang (2012)



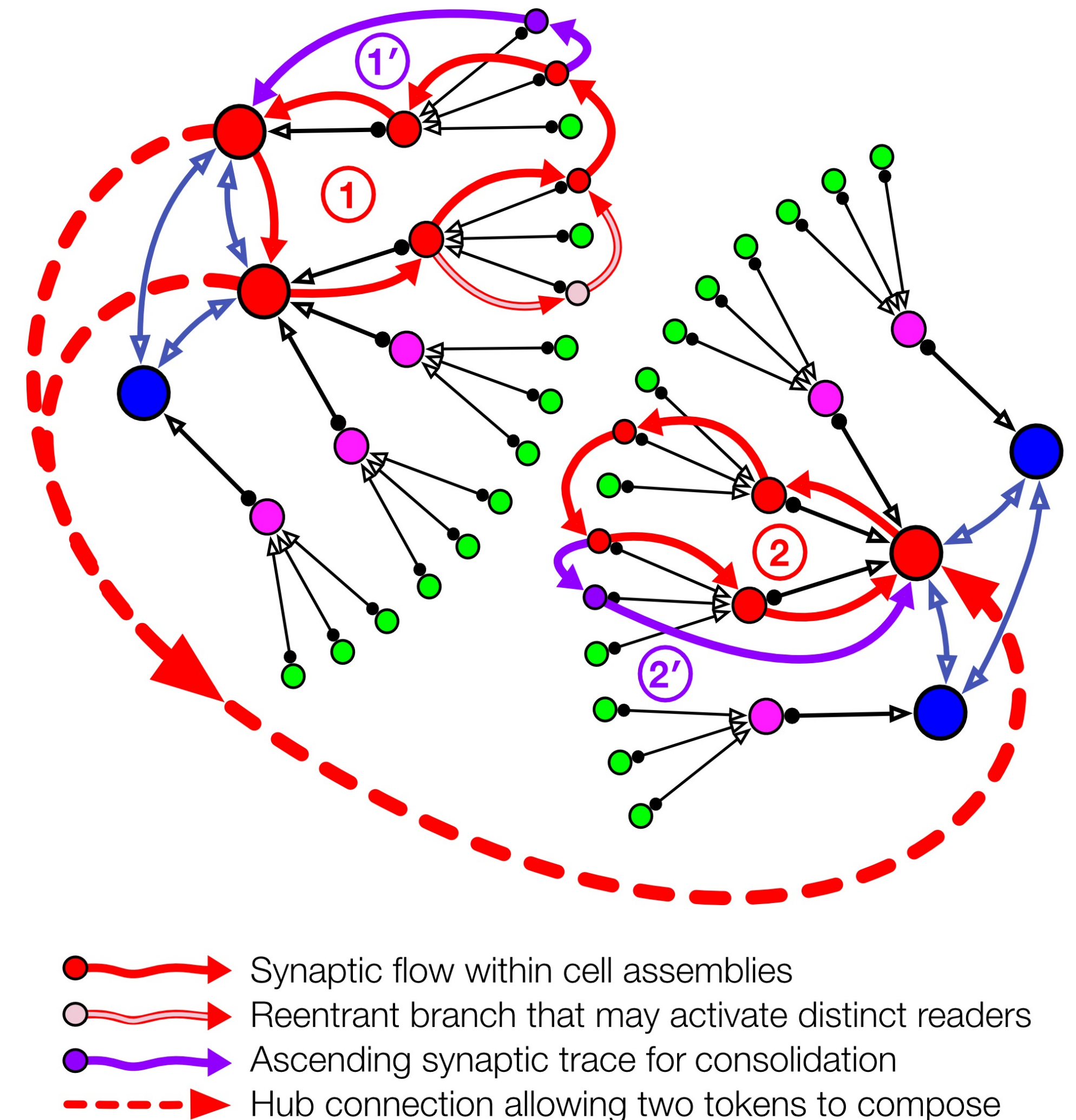
Hedrick & Zhang (2016)

Temporal and Population Dynamics

Key Building Blocks

- **Local oscillations and neuronal synchrony**
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 - **Memory retrieval as a state-space trajectory that probes basins of attraction**

Cell assemblies, synaptic traces, and reentrant loops



Papers

Neurodynamical principles for embodied intelligence

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

Head scanning modifies cognitive 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](https://doi.org/10.1038/nn.3687)

→ <https://jdmonaco.com/pubs>

