COMS30127/COMSM2127
Computational Neuroscience

Lecture 9: Models of the Hippocampus (e)

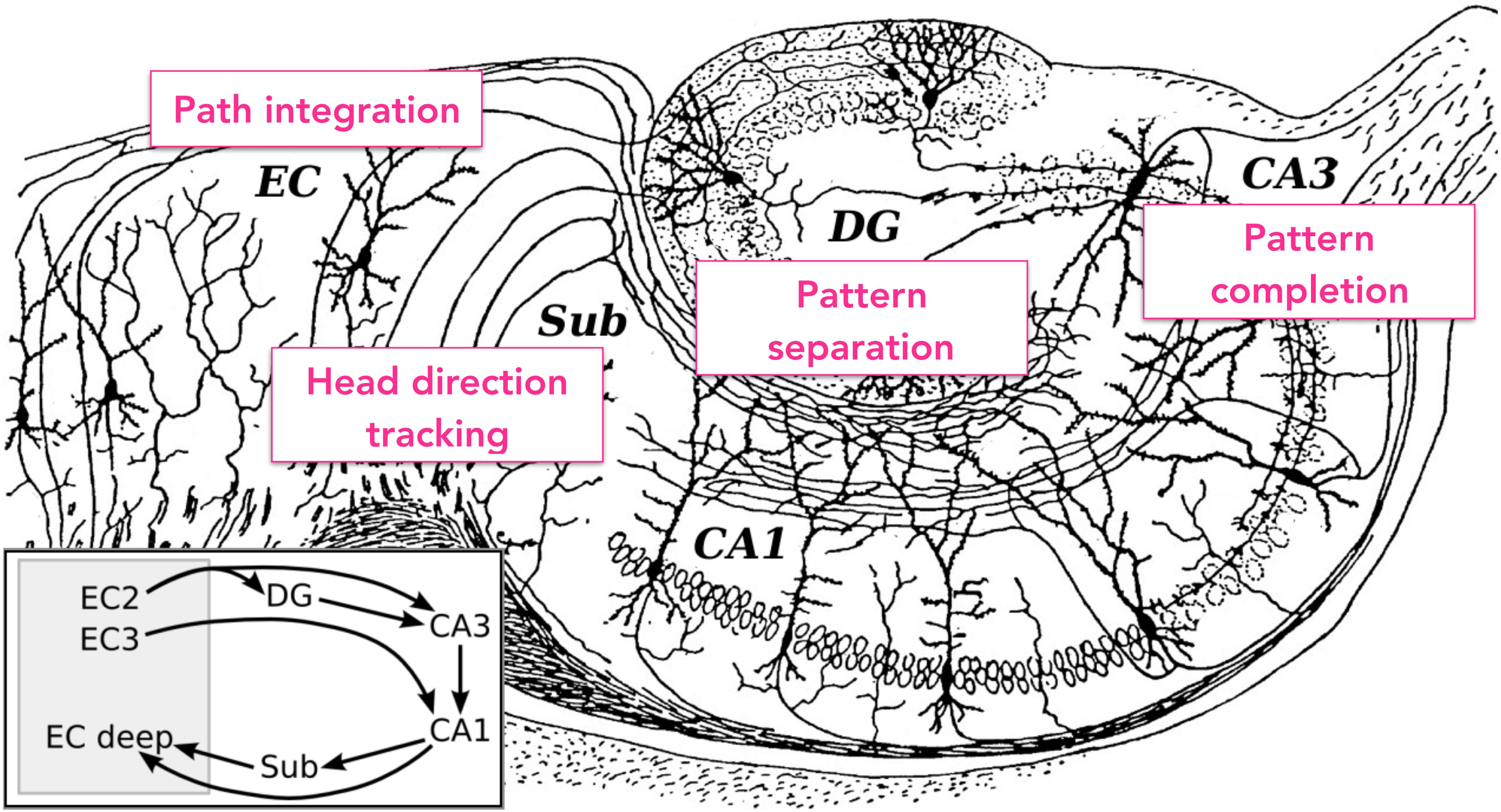
Dr. Cian O’Donnell

cian.odonnell@bristol.ac.uk

What we will cover today

- Attractor networks in the hippocampus:
  - Point attractors for memory recall (CA3 and DG).
  - Ring continuous attractors for tracking head direction (subiculum)
  - Torus continuous attractors for path integration (entorhinal cortex).

Computations of the hippocampus



Original drawing by Ramon y Cajal (circa 1900)
https://en.wikipedia.org/wiki/Hippocampus#/media/File:CajalHippocampus_(modified).png

3 stages of long-term memory

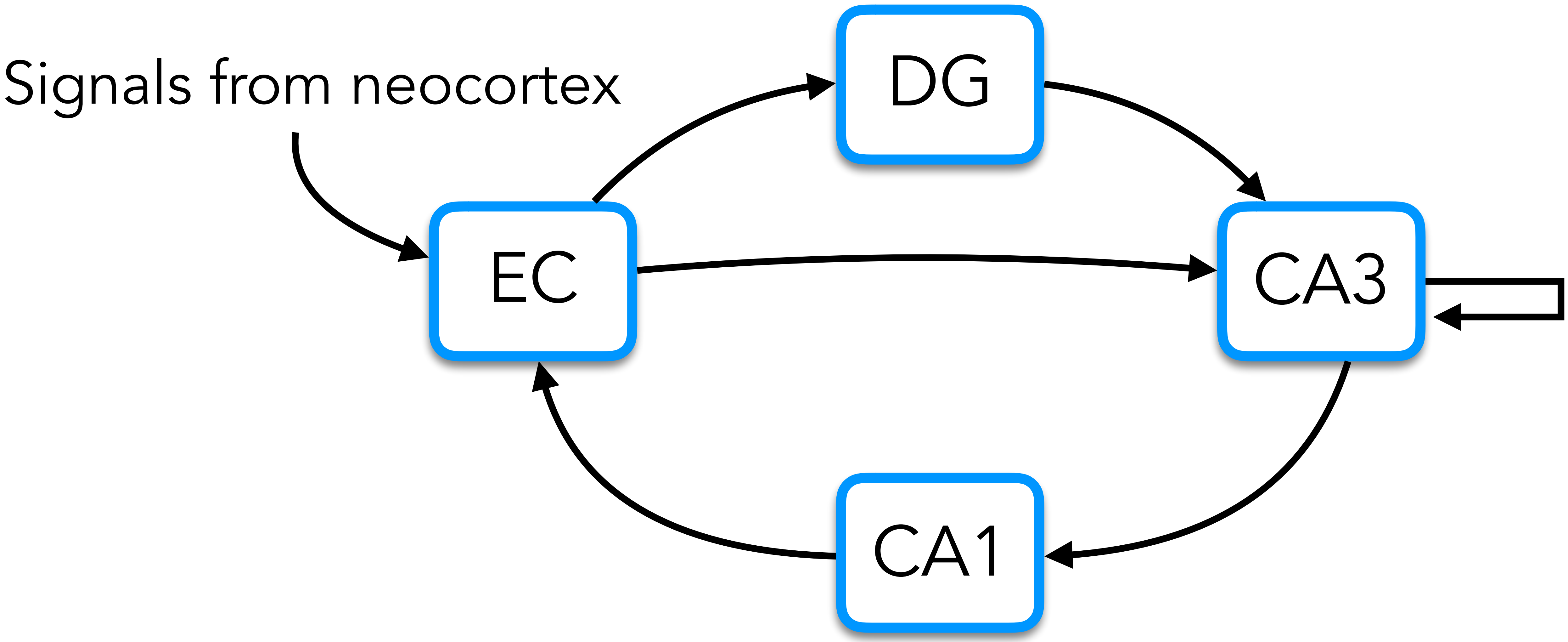
Encoding → Storage → Recall

Computational models of hippocampal memory encoding and recall

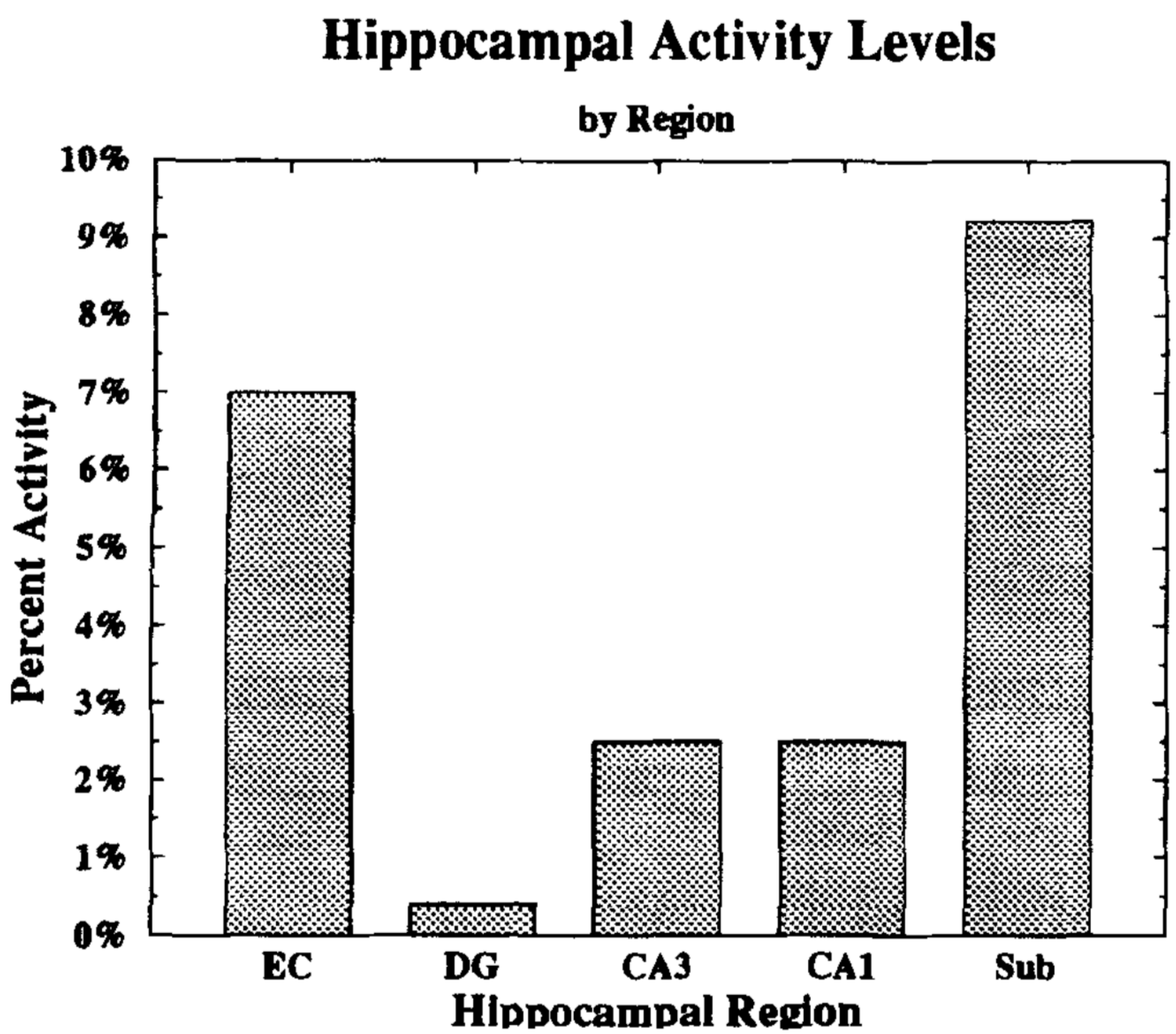
- A leading theory (O'Reilly and McClelland, 1994) is that distinct episodic memories are stored as attractors in CA3.
- During encoding of a new memory, we want to create a new attractor. This allocation is done at random, via a pattern separation mechanism implemented by the dentate gyrus (DG).
- The DG acts as a kind of teacher, activating some random set of neurons in CA3. Encoding then involves Hebbian plasticity both in the EC→CA3 synapses, and in the recurrent CA3→CA3 synapses.
- During memory recall the external cue signal is routed via EC, completed by CA3, then read out by CA1 (synaptic plasticity is not involved in recall).
- Note that this implies content-addressable memory (can recall an item based on partial information of the item itself, rather than by knowing a location in memory as in human-made computers).

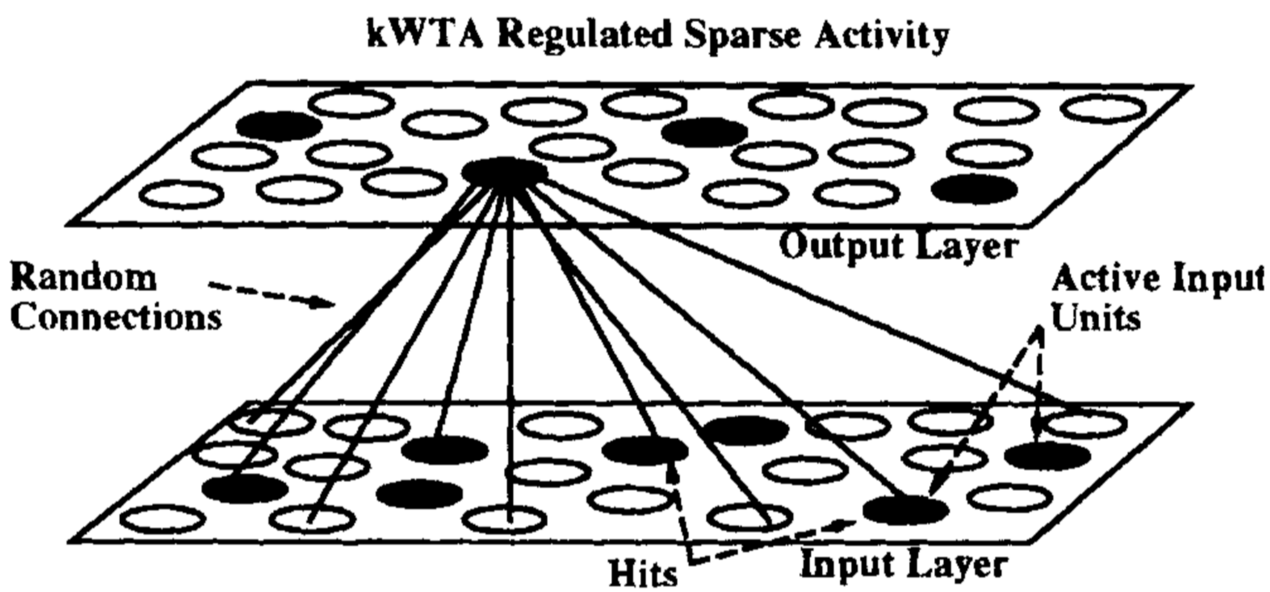
O'Reilly, R.C., McClelland, J.L. *Hippocampus* (1994) 4, 661–682

Computational models of hippocampal memory encoding and recall



Computational models of hippocampal memory encoding and recall





What is the pattern overlap at the output layer as a function of the overlap in the input layer?

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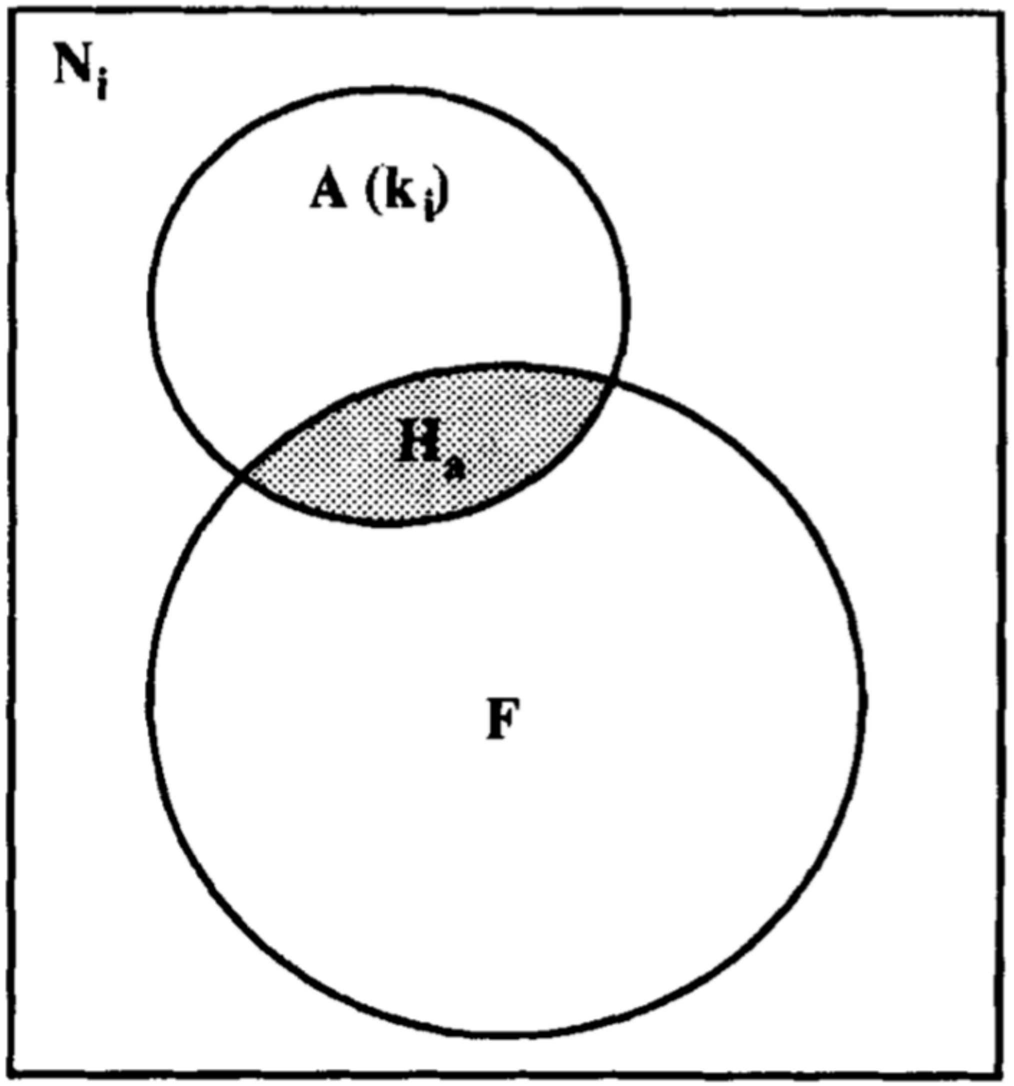
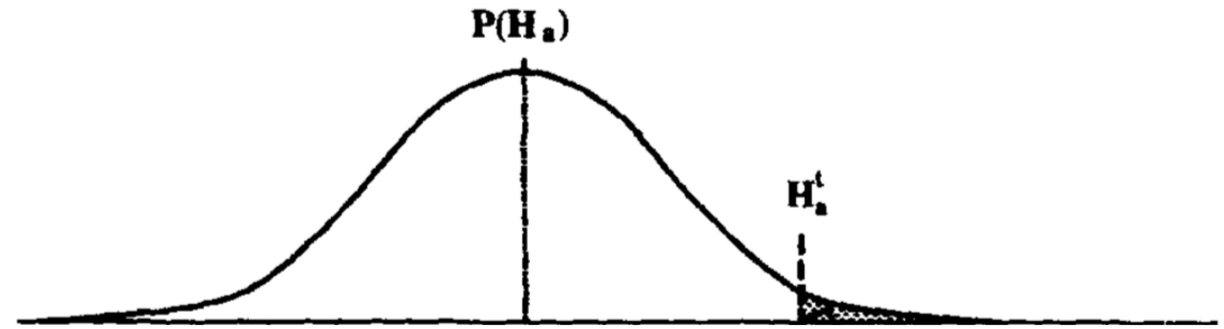
Computational models of hippocampal memory encoding and recall





$$P(H_a \mid k_i, F, N_i) = \frac{\binom{k_i}{H_a}\binom{N_i - k_i}{F - H_a}}{\binom{N_i}{F}}$$

N_i is total number neurons in input layer.
Pattern A activates k_i of these neurons.
A single neuron in the output layer receives inputs from a subset F of the N_i neurons.
H_a is the number of “hits” or active neurons seen by the second layer neuron.

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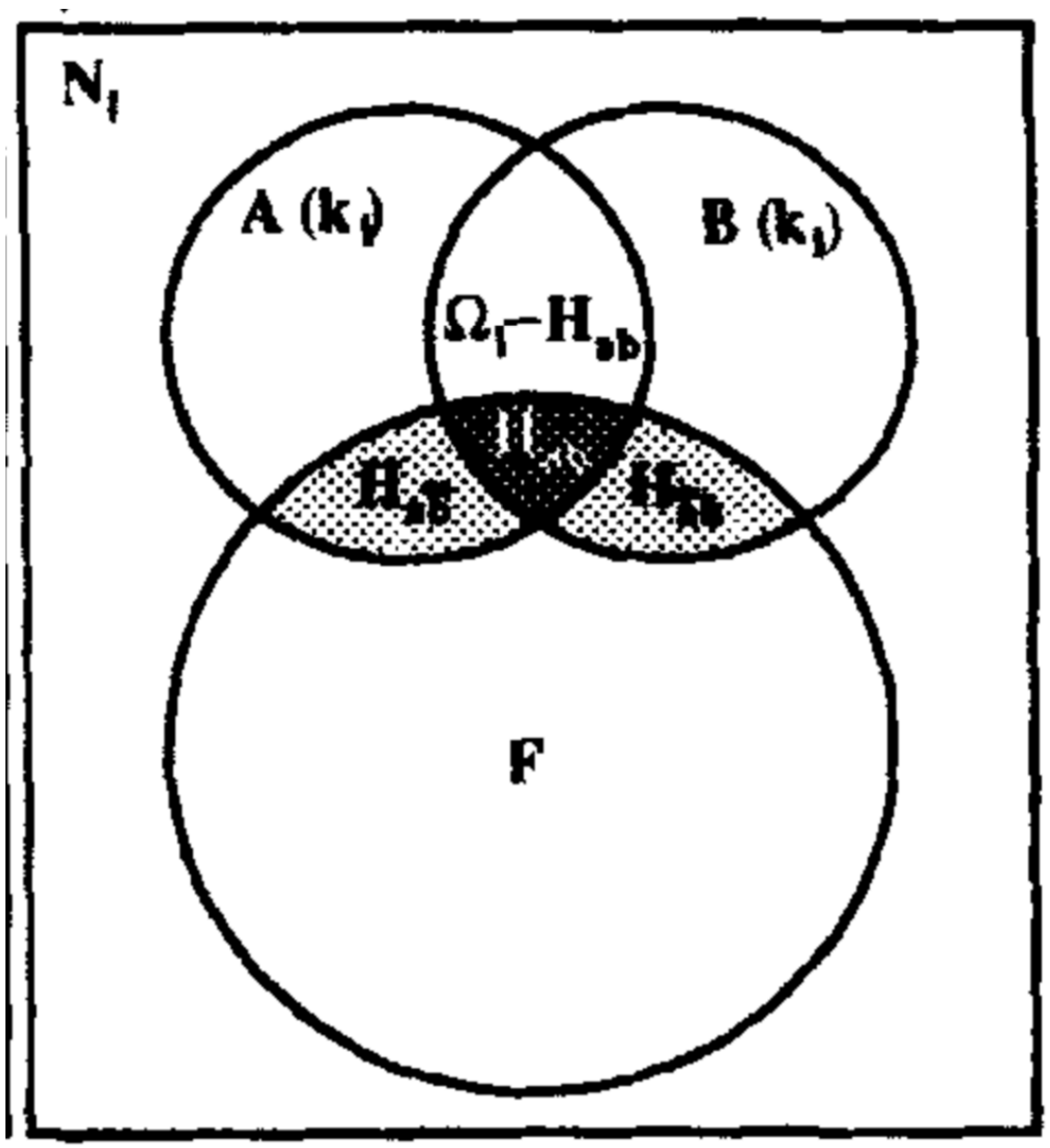
Computational models of hippocampal memory encoding and recall



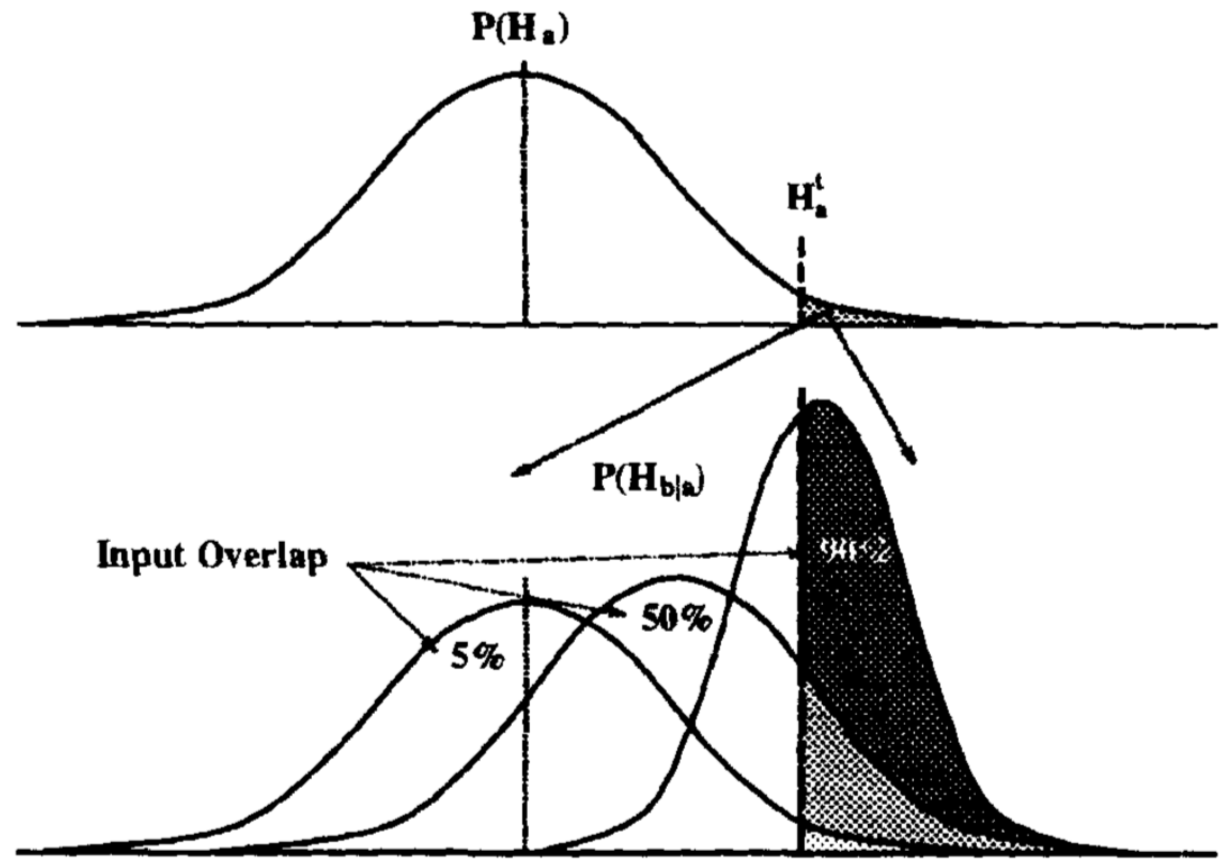


Fig. 4. Representation of the effect of increasing input overlap on the probability distribution $P(H_{b|a})$, which is derived from the tail of the distribution $P(H_a)$. As input overlap increases, the distributions get narrower and the mean shifts upward toward the threshold. These changes interact with the concave shape of the distribution to produce a level of output overlap that is lower than the input overlap, resulting in pattern separation. Actual distributions shown are based on the hypergeometric model described in the text.

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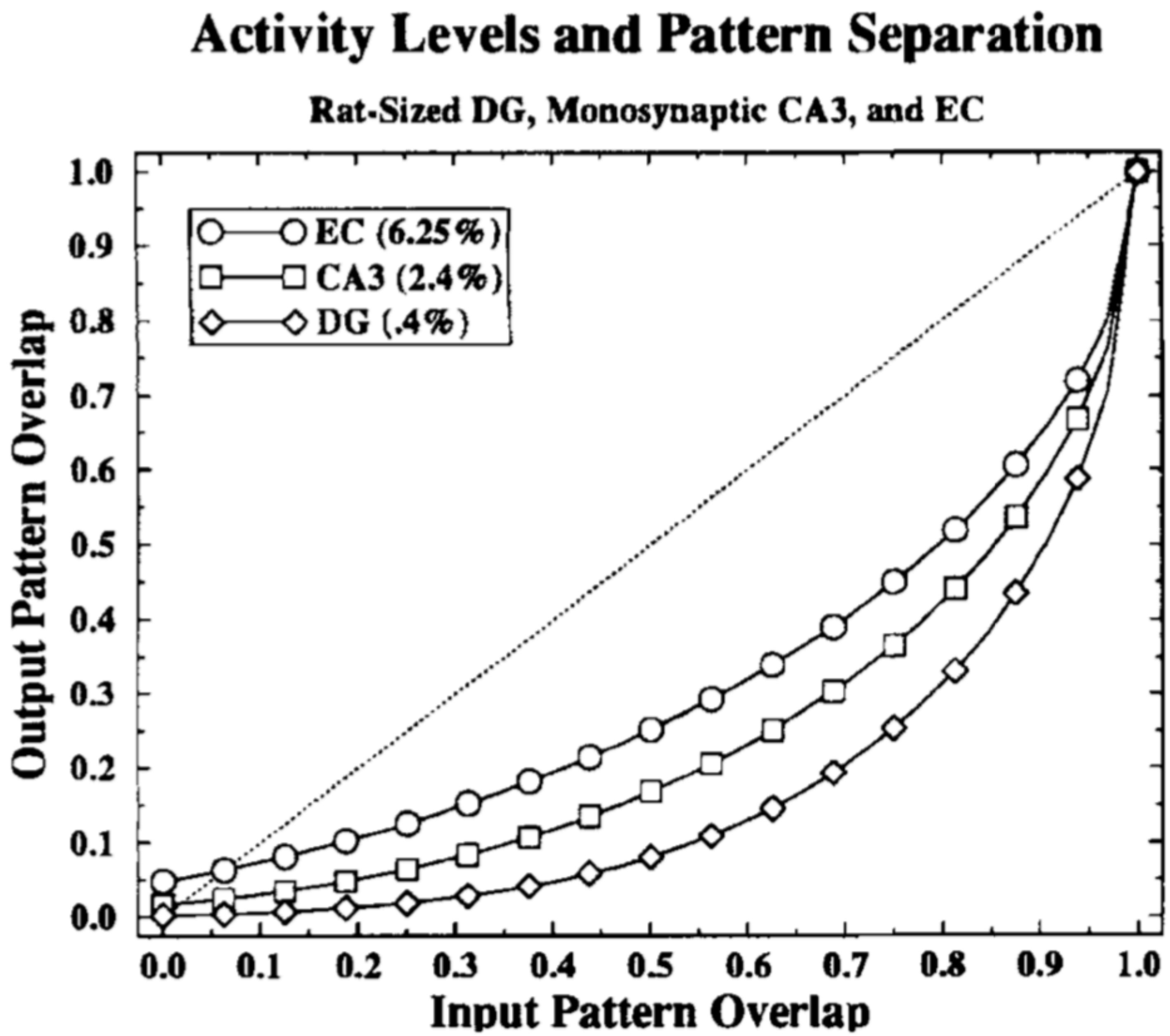
Computational models of hippocampal memory encoding and recall



A sparse, random feedforward network generically does pattern separation.

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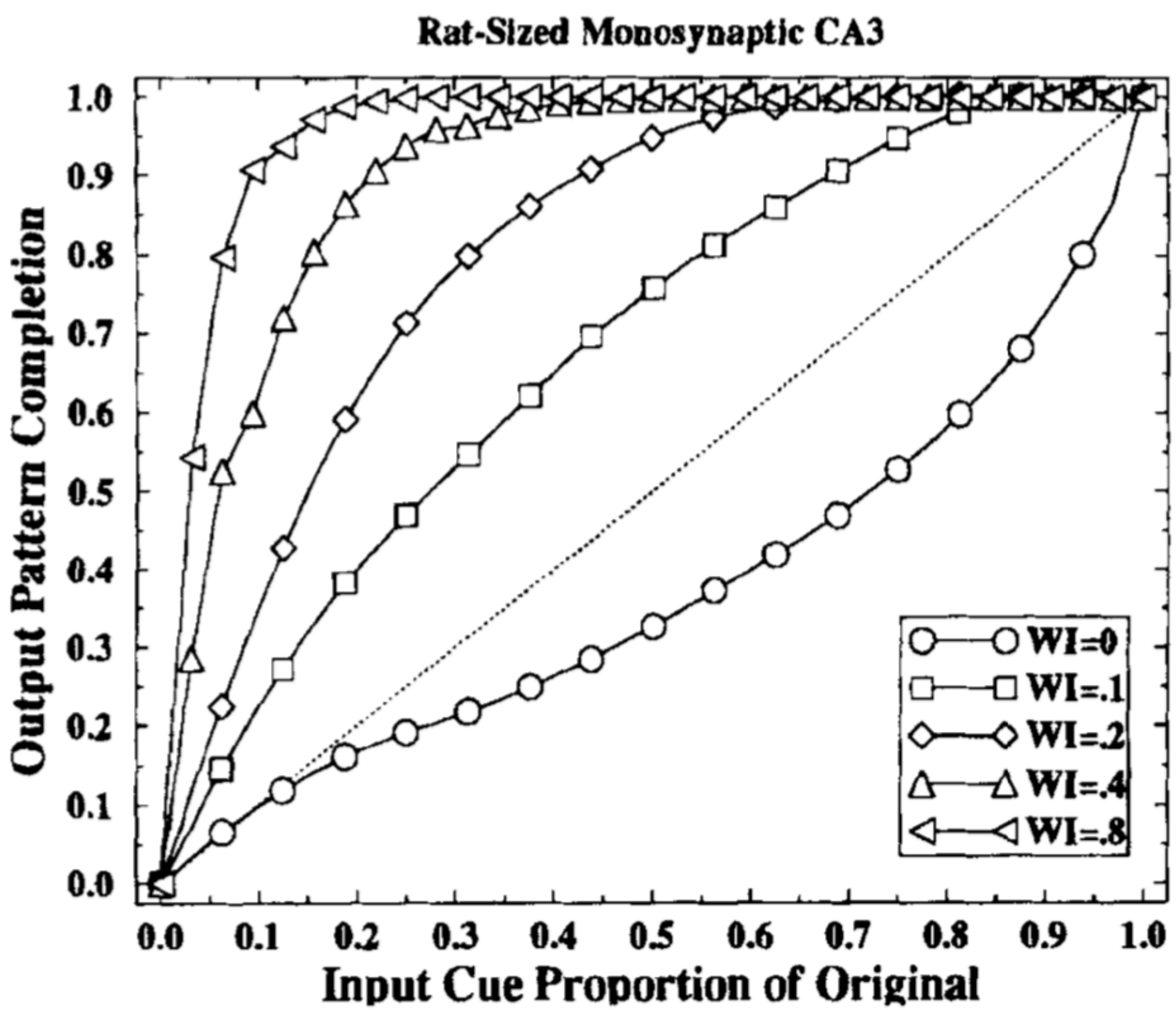
Computational models of hippocampal memory encoding and recall



Strengthening activated feedforward synapses can lead to pattern completion.

This can be enhanced by recurrent attractor dynamics in CA3.

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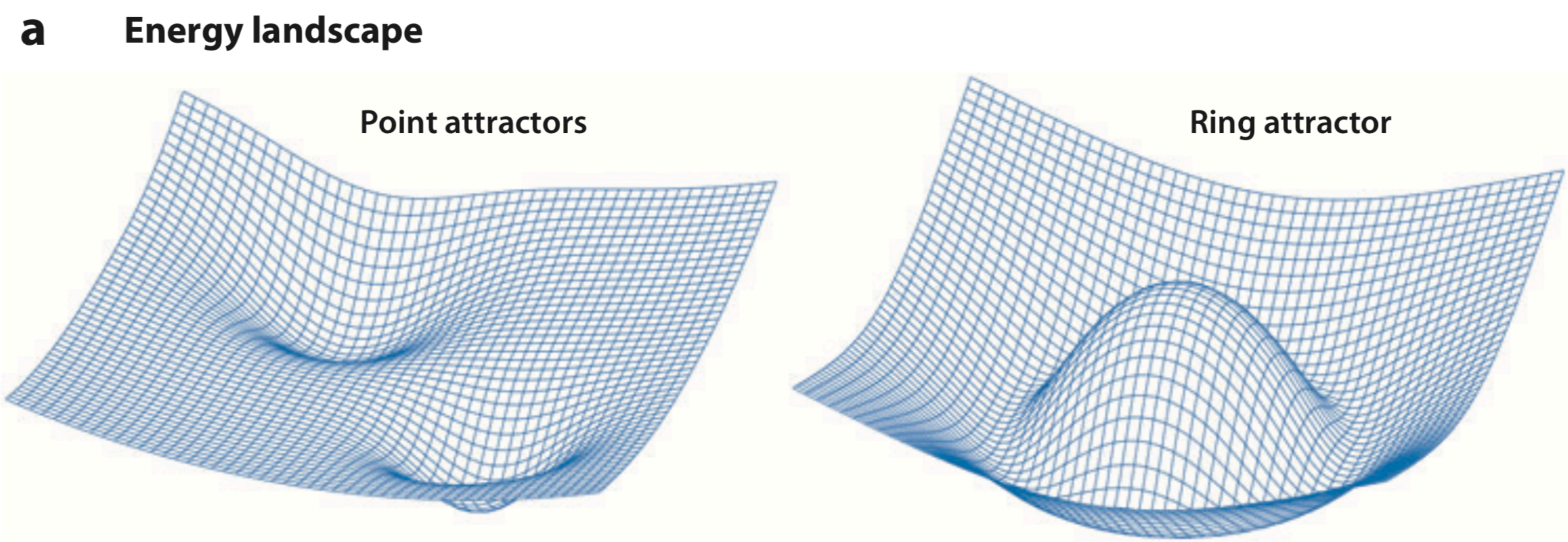
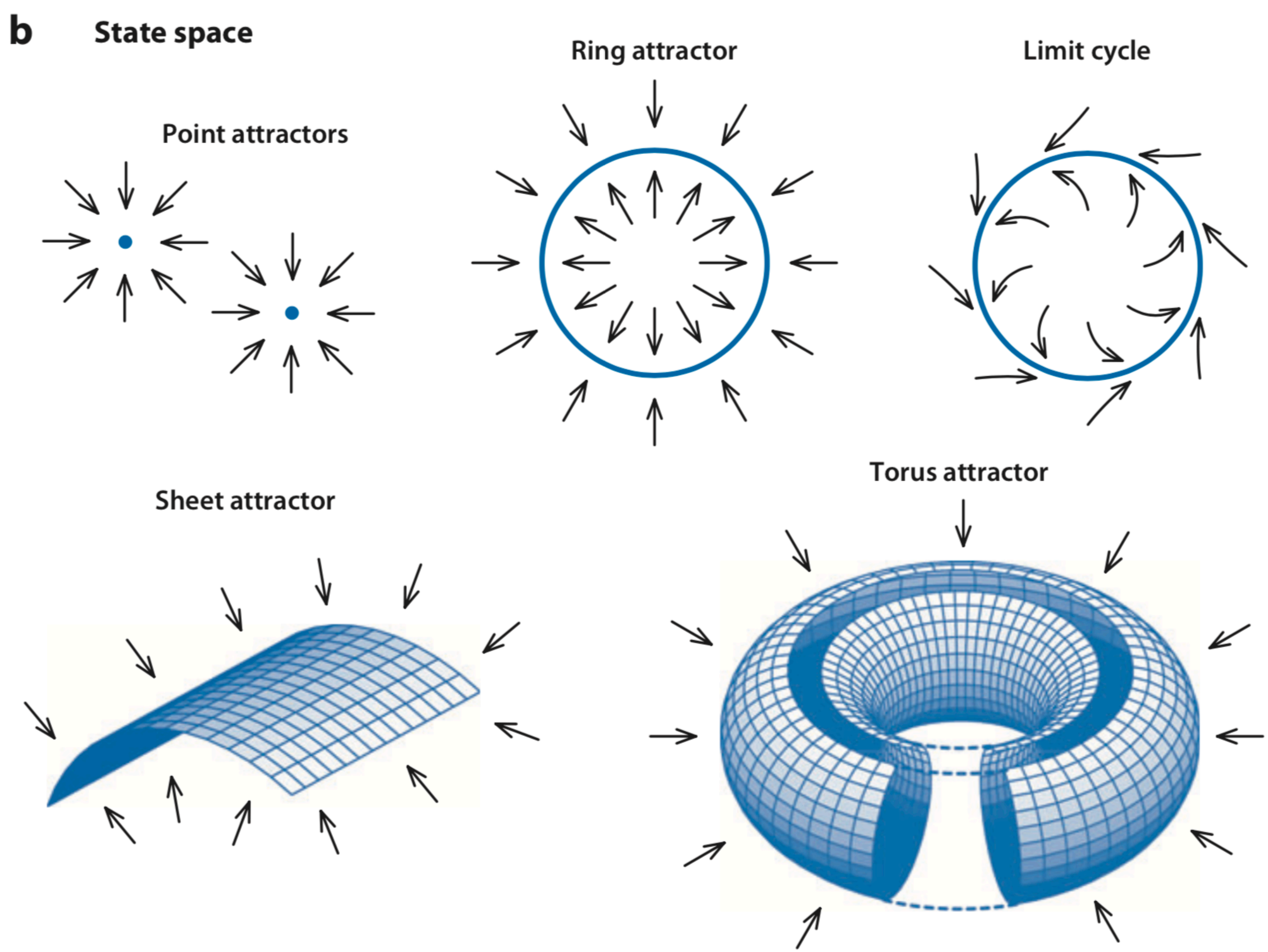
Attractor networks

- Attractor networks are recurrent neural networks where the internal dynamics evolves towards a stable pattern.



Knierim, J.J., Zhang, K., 2012. Annu. Rev. Neurosci. 35, 267–285.

Attractor networks



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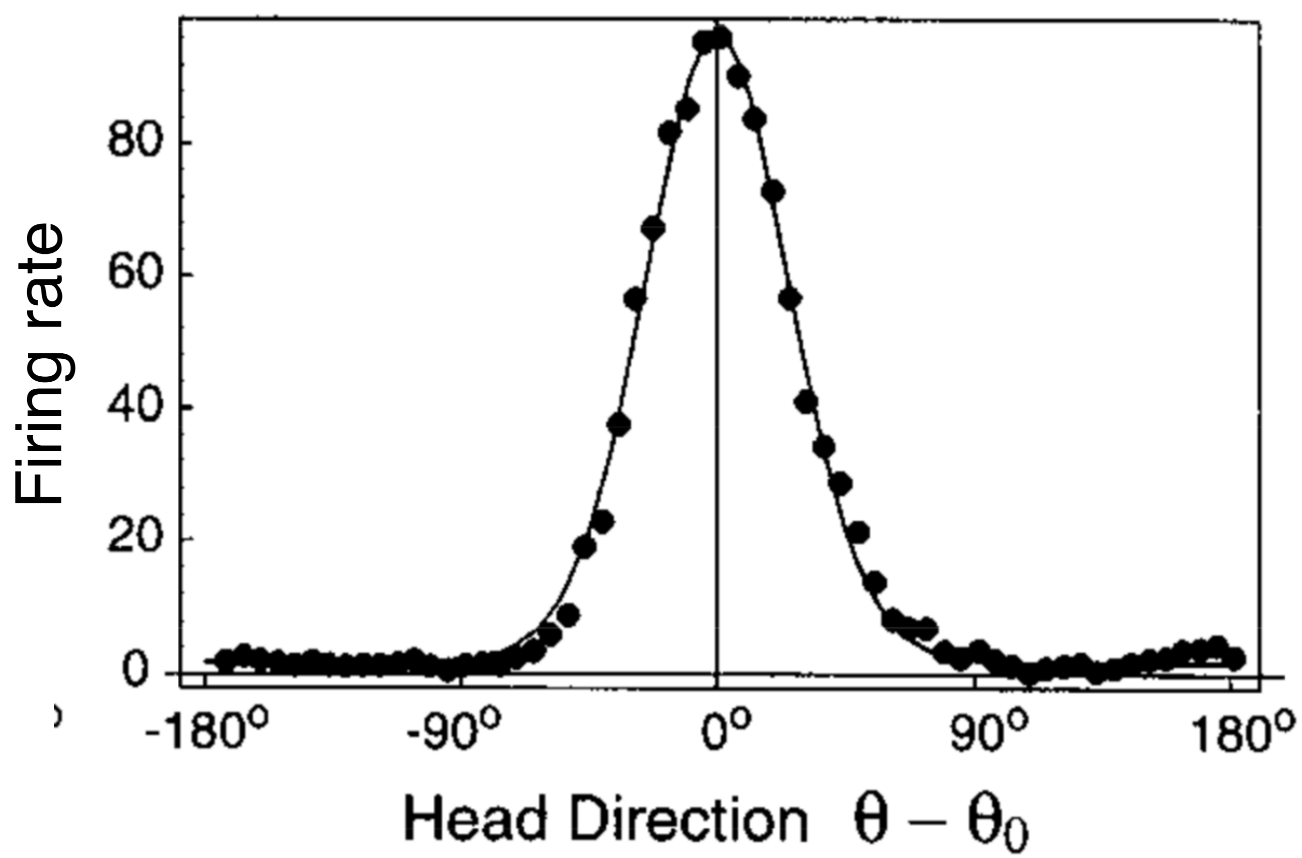
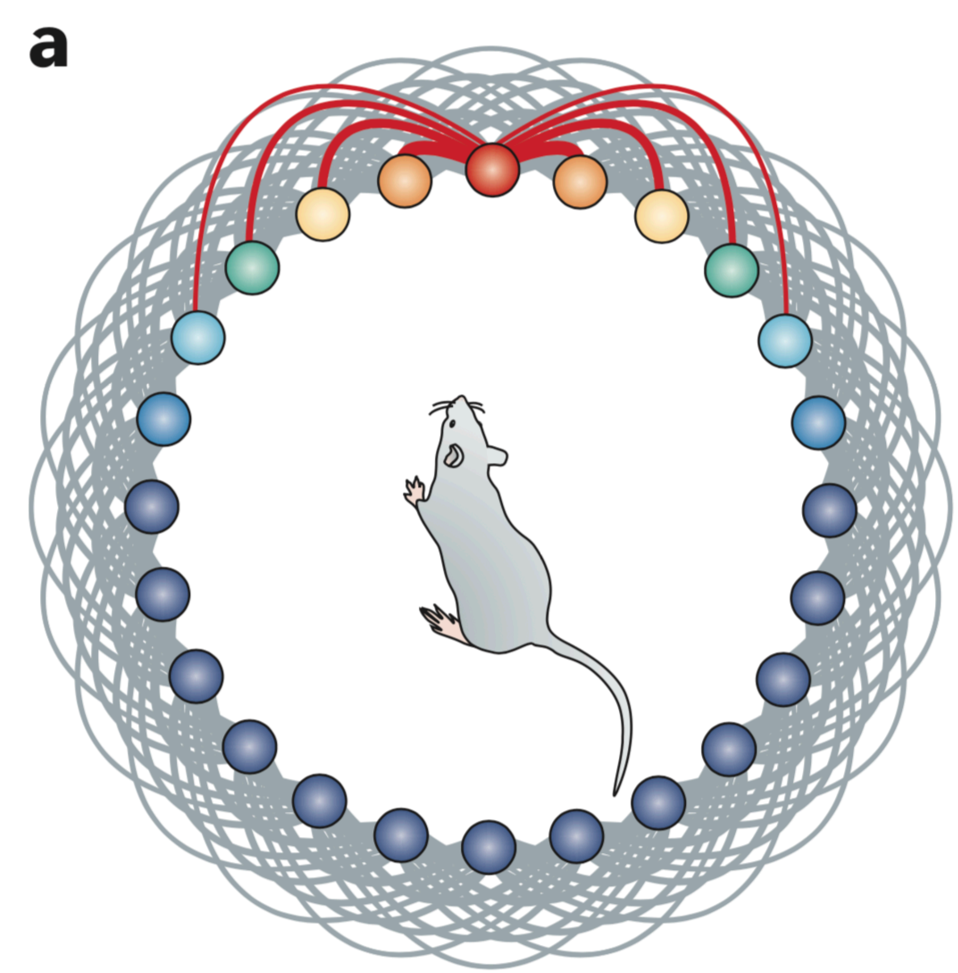
Continuous attractors in subiculum

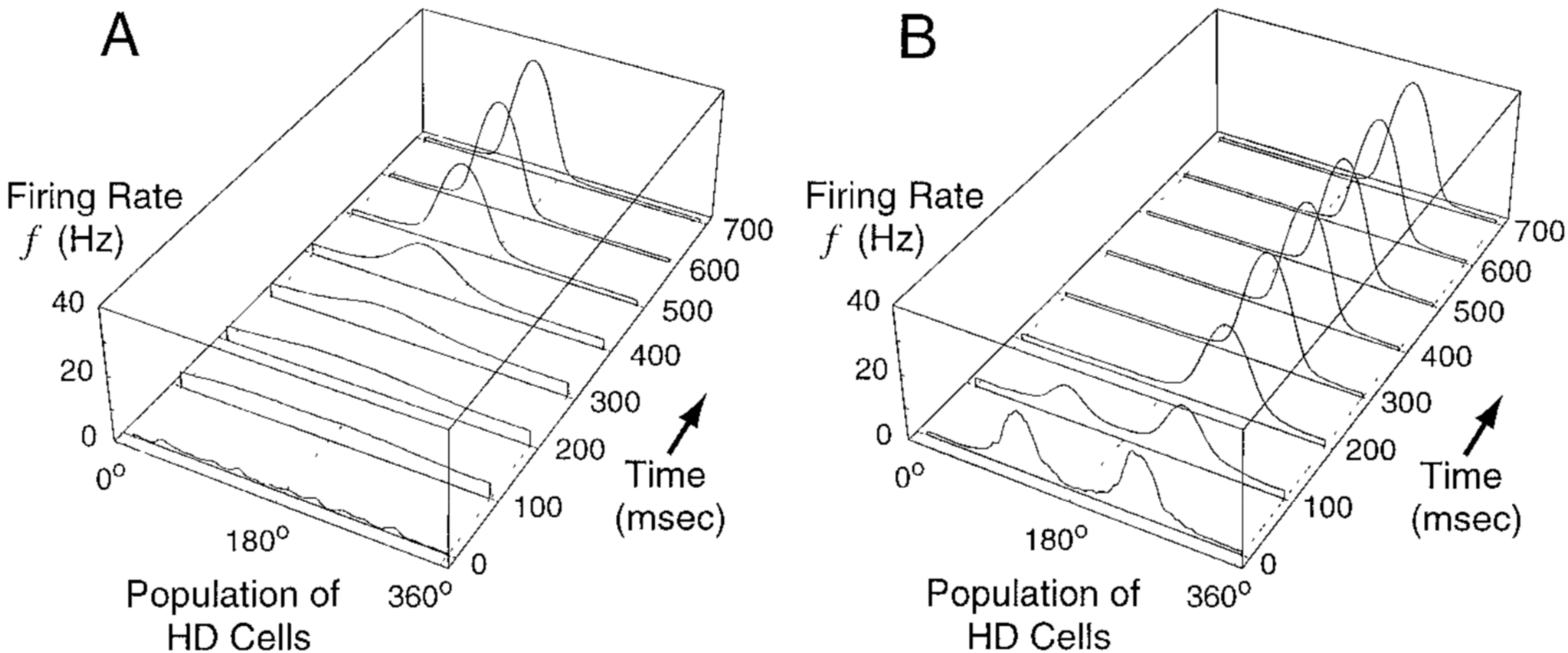




McNaughton, et al. (2006). Nat Rev Neurosci 7, 663–678

Zhang, K (1996). Journal of Neuroscience 16, 2112–2126.

Continuous attractors in subiculum



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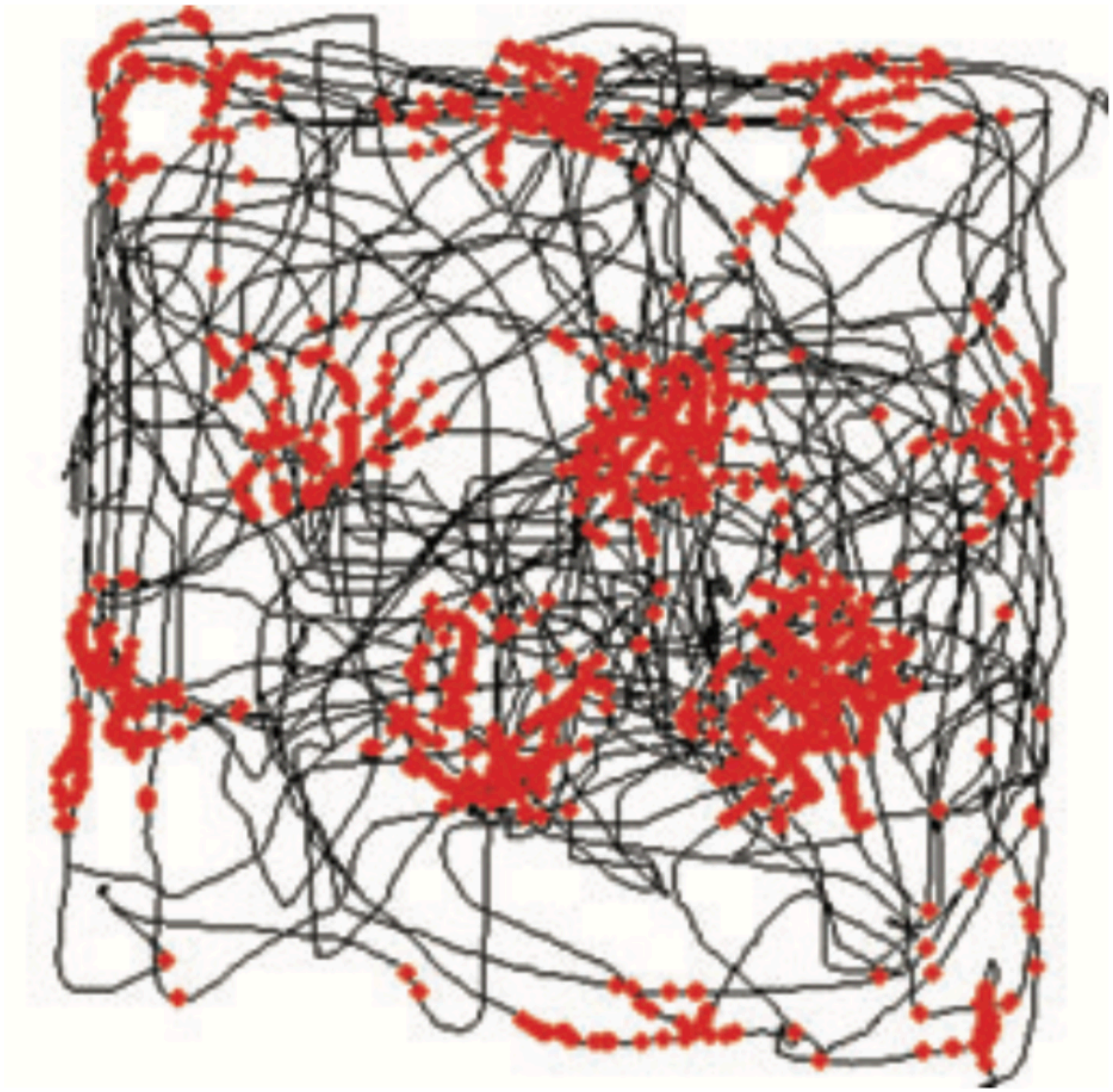
Continuous attractors in entorhinal cortex

Grid cell



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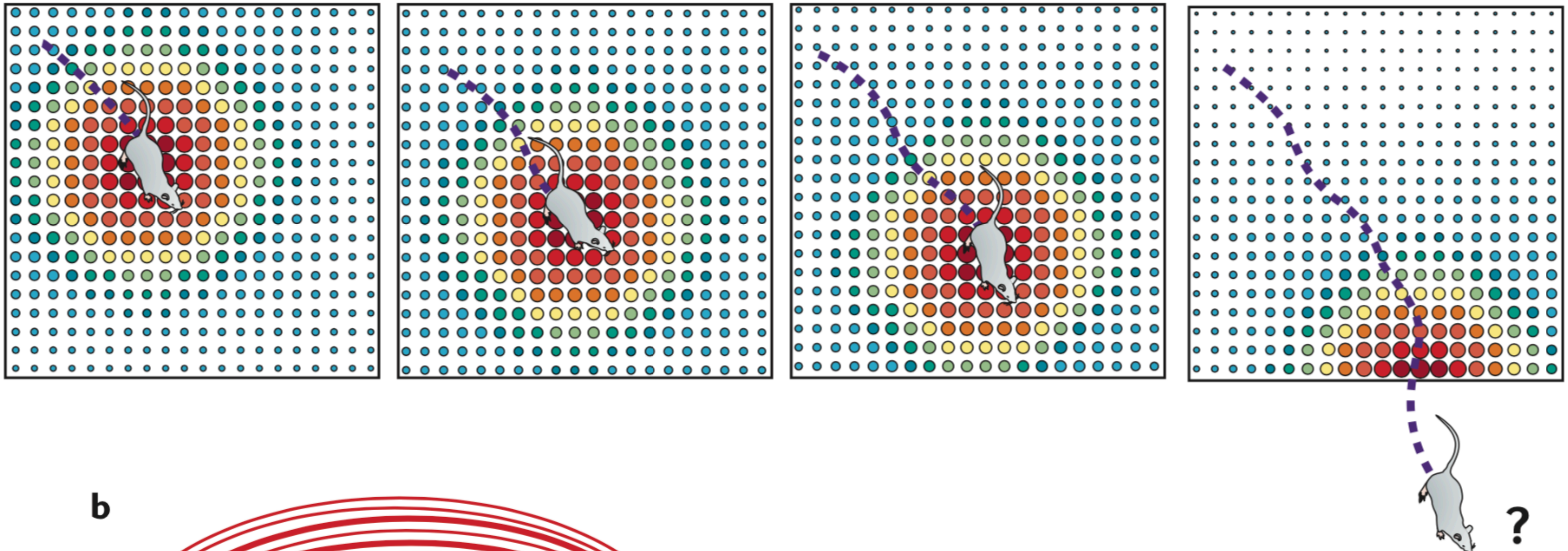
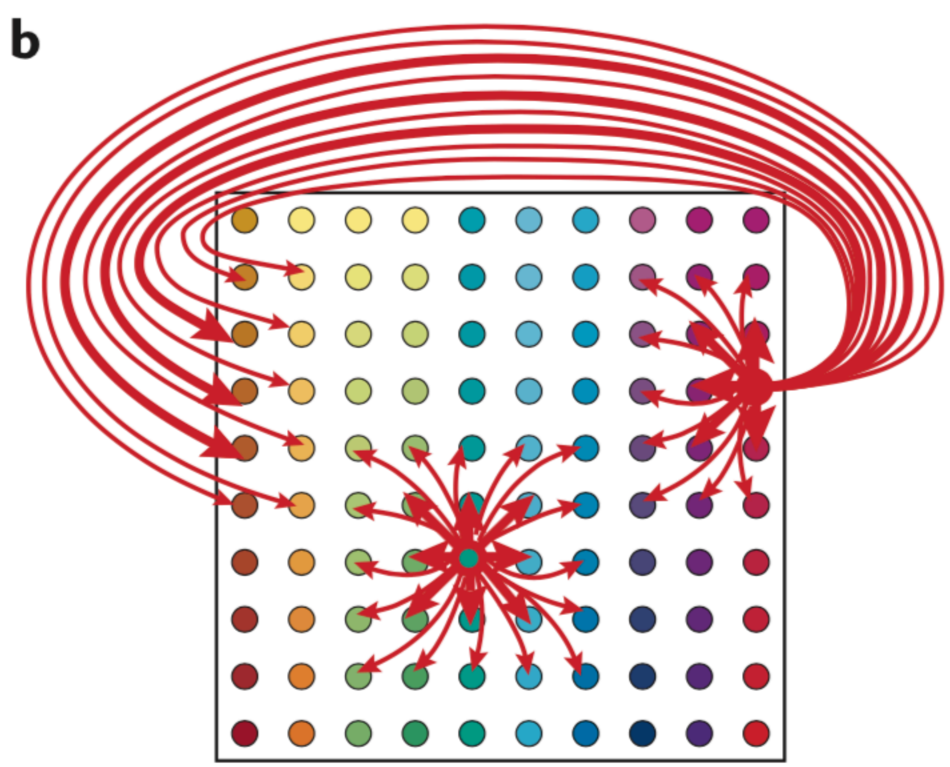
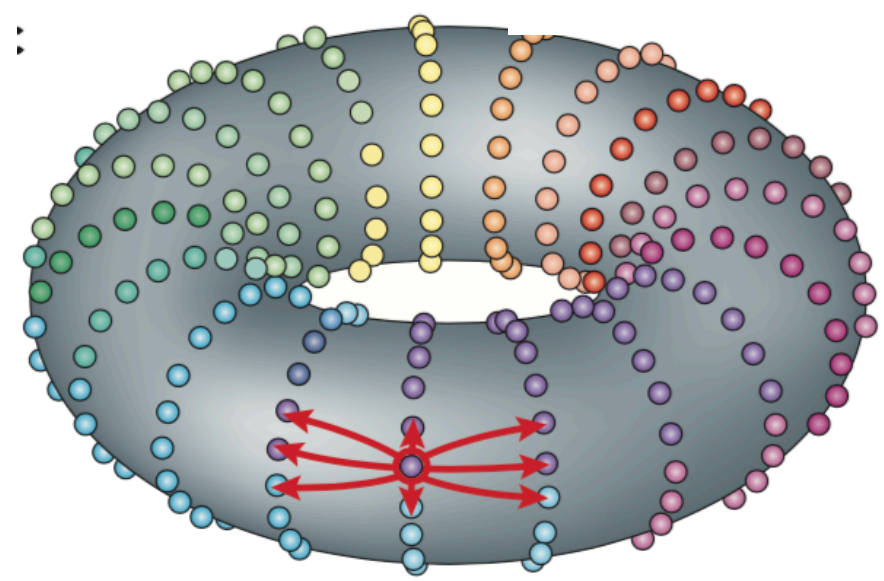
Continuous attractors in entorhinal cortex







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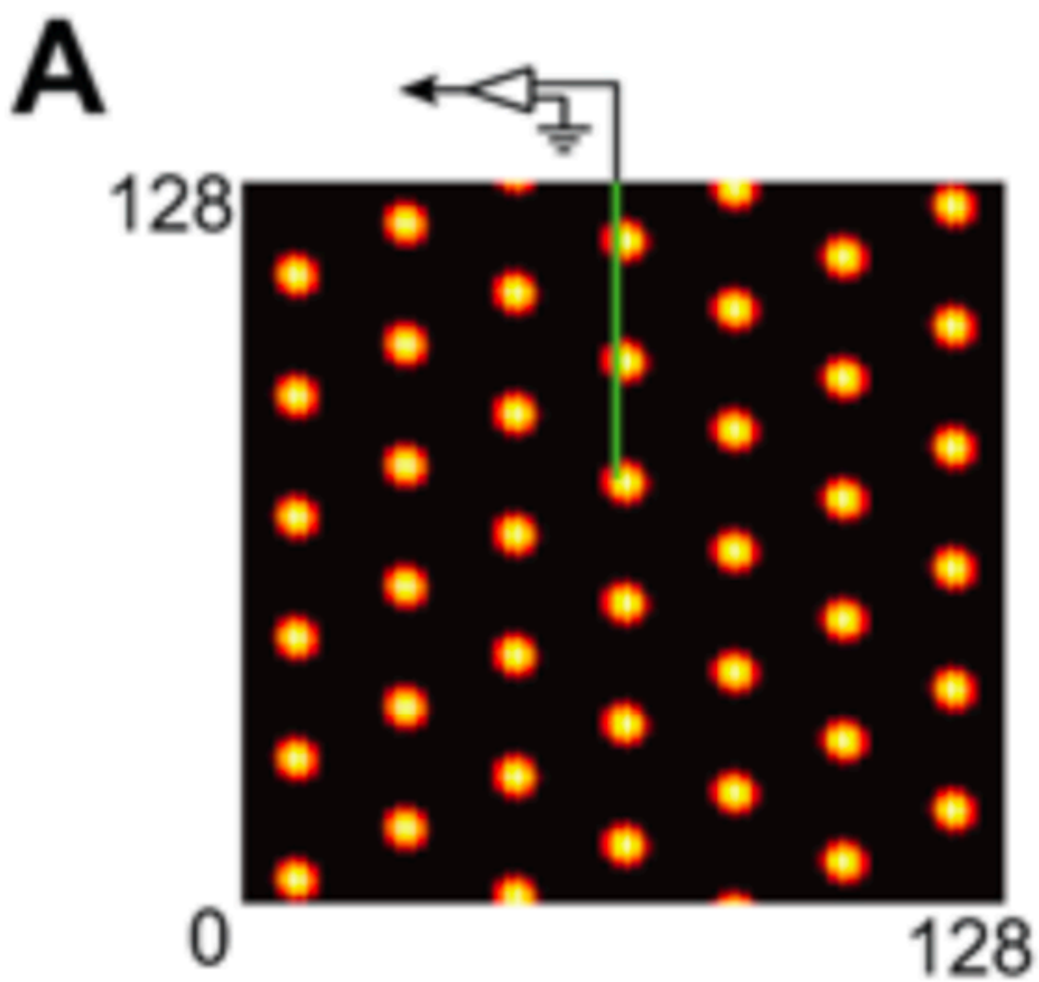
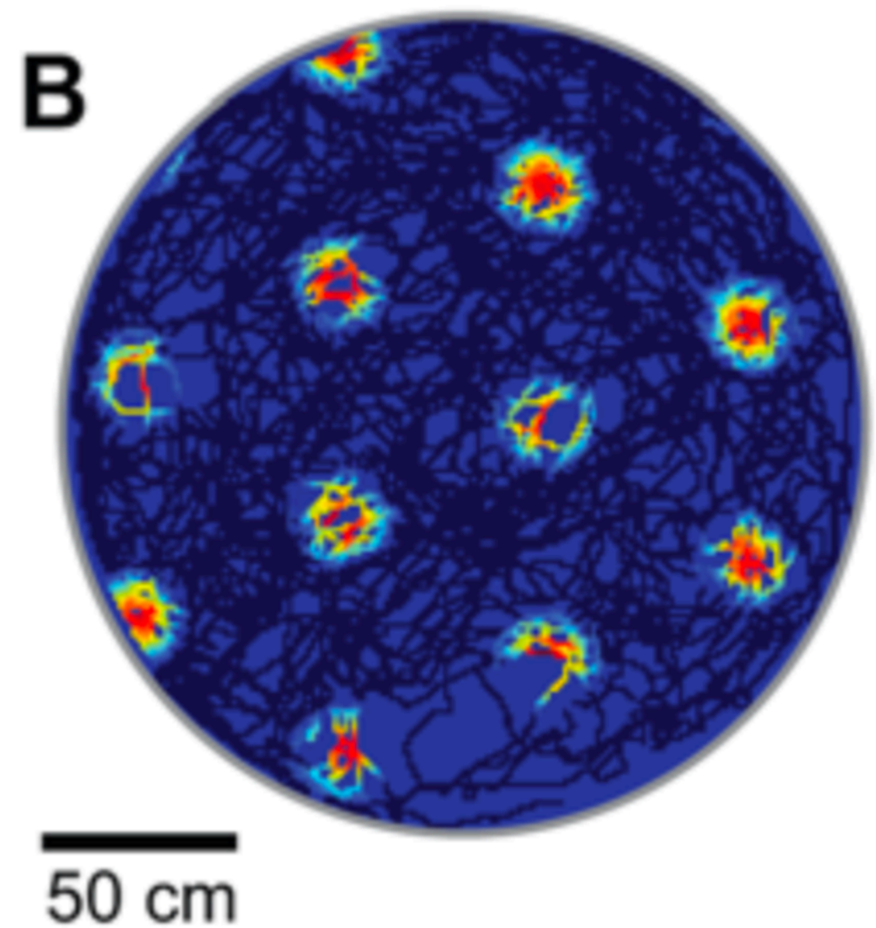
Continuous attractors in entorhinal cortex

Network activity

Single cell activity as a function of animal location





Burak and Fiete, PLoS Comput Biol (2009)

References

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