Rapid path planning and preplay in maze–like environments using attractor networks

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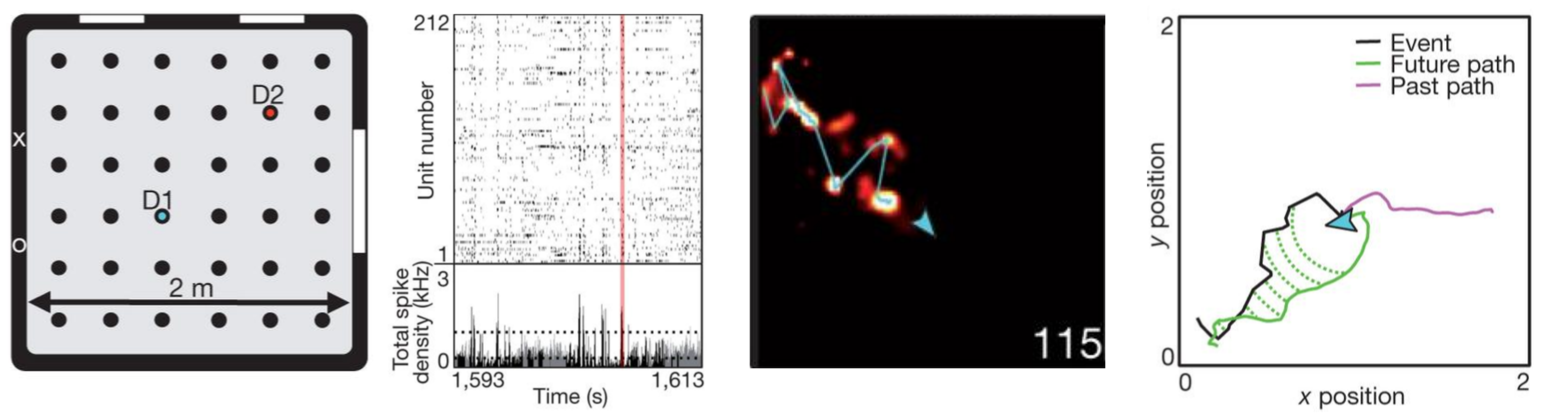
The hippocampus and rapid place learning

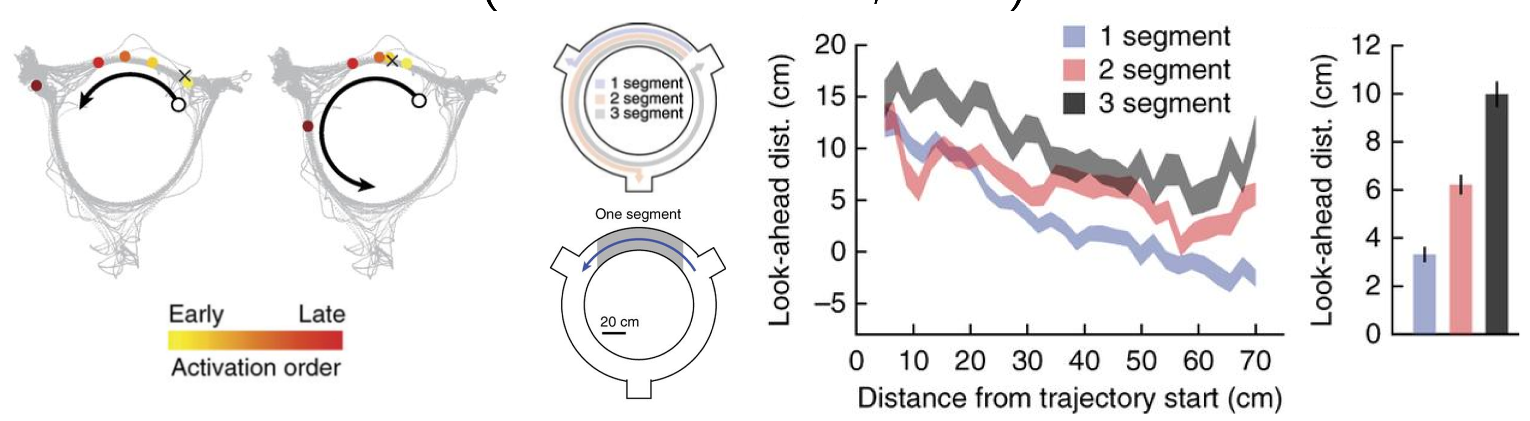
- "Place cells" in the hippocampal CA3 and CA1 regions fire when a rat visits a specific location in the environment, giving rise to the "cognitive map" theory of hippocampus (Keefe & Nadel, 1978).
- Animals navigating in a well–known environment can rapidly learn and revisit observed reward locations, often after a single trial.
- Rapid path planning critically depends on the intermediate hippocampus and on plasticity in the recurrently–connected CA3 region (Bast *et al.* , 2009; Nakazawa *et al.* , 2003).

How can a map–based model of the CA3 region support **rapid, arbitrary goal encoding** and **path planning**?

Preplay activity reflects goals and future paths

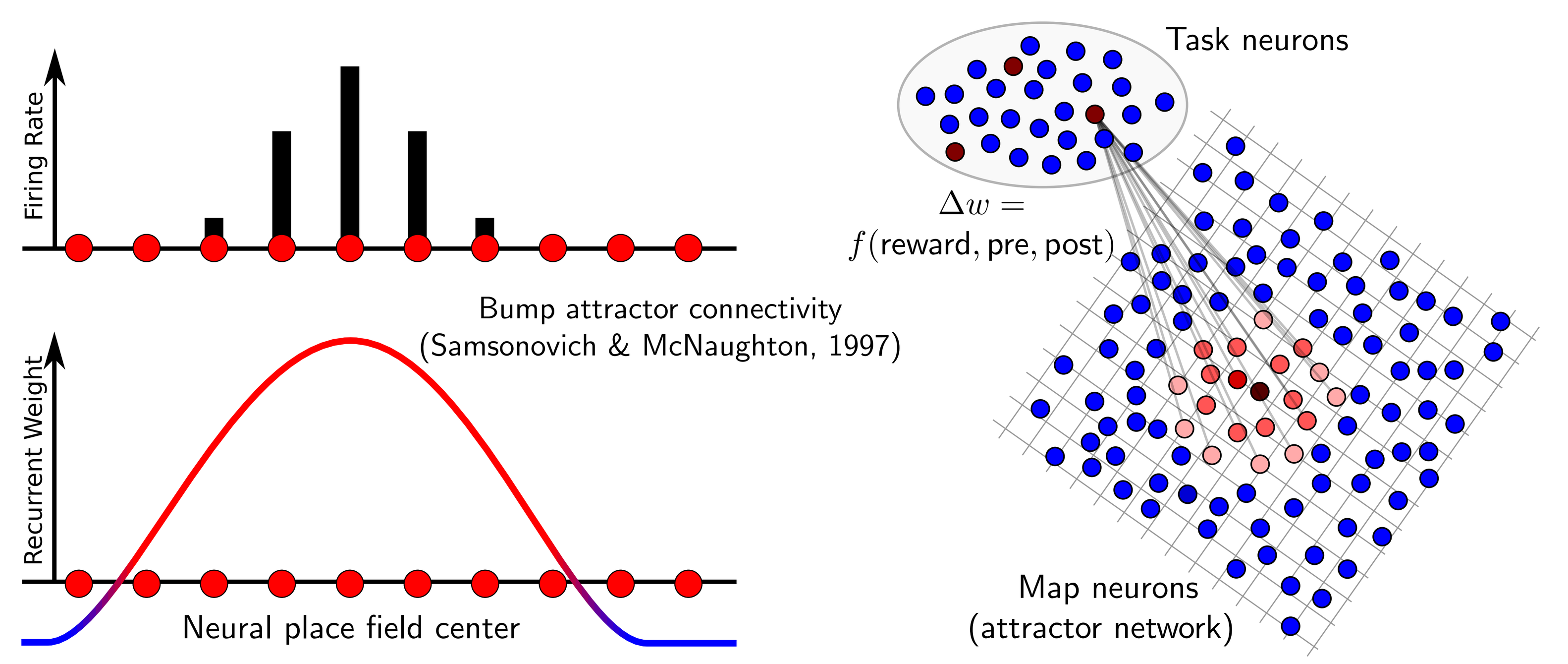


(Pfeiffer & Foster, 2013)



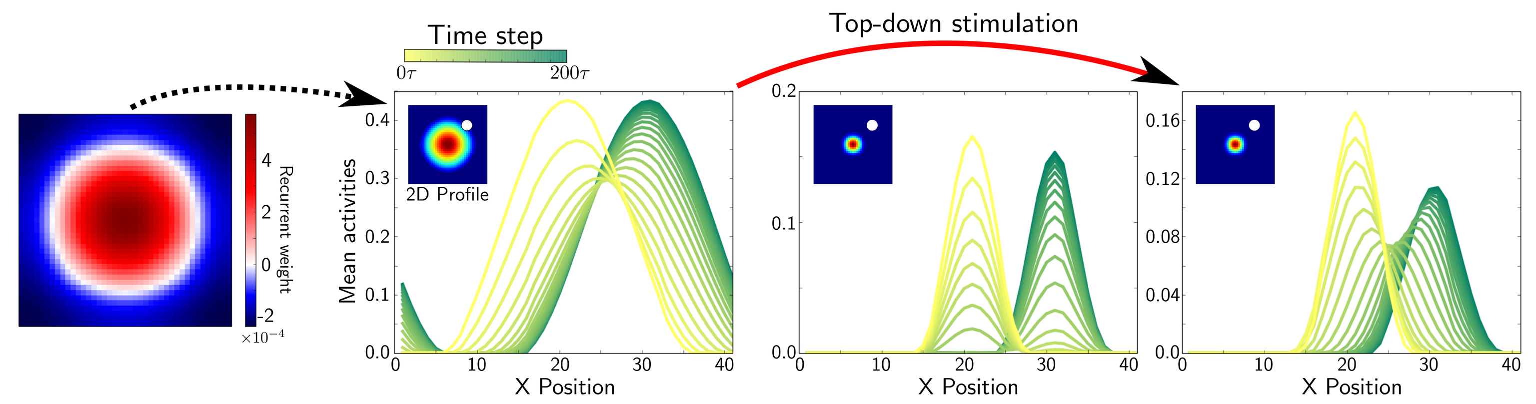
(Wikenheiser & Redish, 2015)

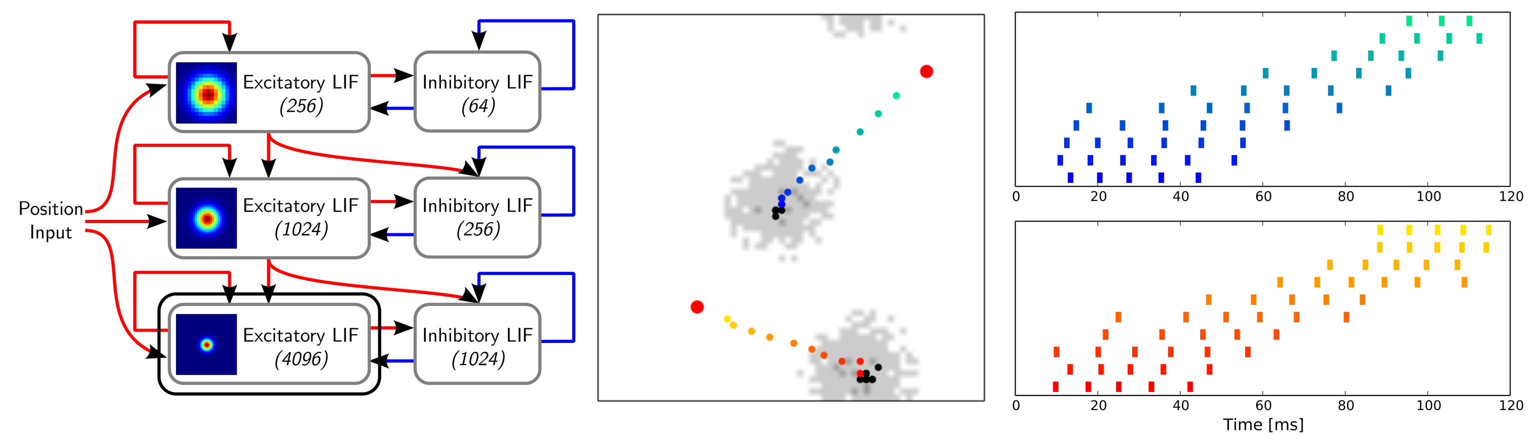
Encoding goals in feedforward activation



Large place fields allow for long–range sequences

- Here we consider large place fields, like those found in intermediate and ventral hippocampus (Kjelstrup *et al.* , 2008), with broad recurrent weight profiles.
- With this spatial map, stimulating the neurons active at a goal causes the bump to follow a continuous path to that location from the current position.
- A top–down bias from neurons with large place fields can induce sequential firing in neurons with smaller place fields, directed towards the goal.





Maze–like environments in attractor networks

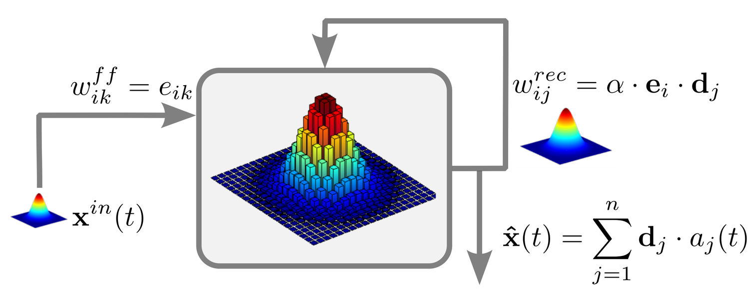
- Place fields in realistic environments, with walls and obstacles, appear to respect shortest–path distances around walls (Gustafson & Daw, 2011).
- We consider here a bump attractor network with large, geodesic place fields by using the pseudo–inverse method to determine appropriate recurrent weights (Conklin & Eliasmith, 2005; Eliasmith & Anderson, 2004).

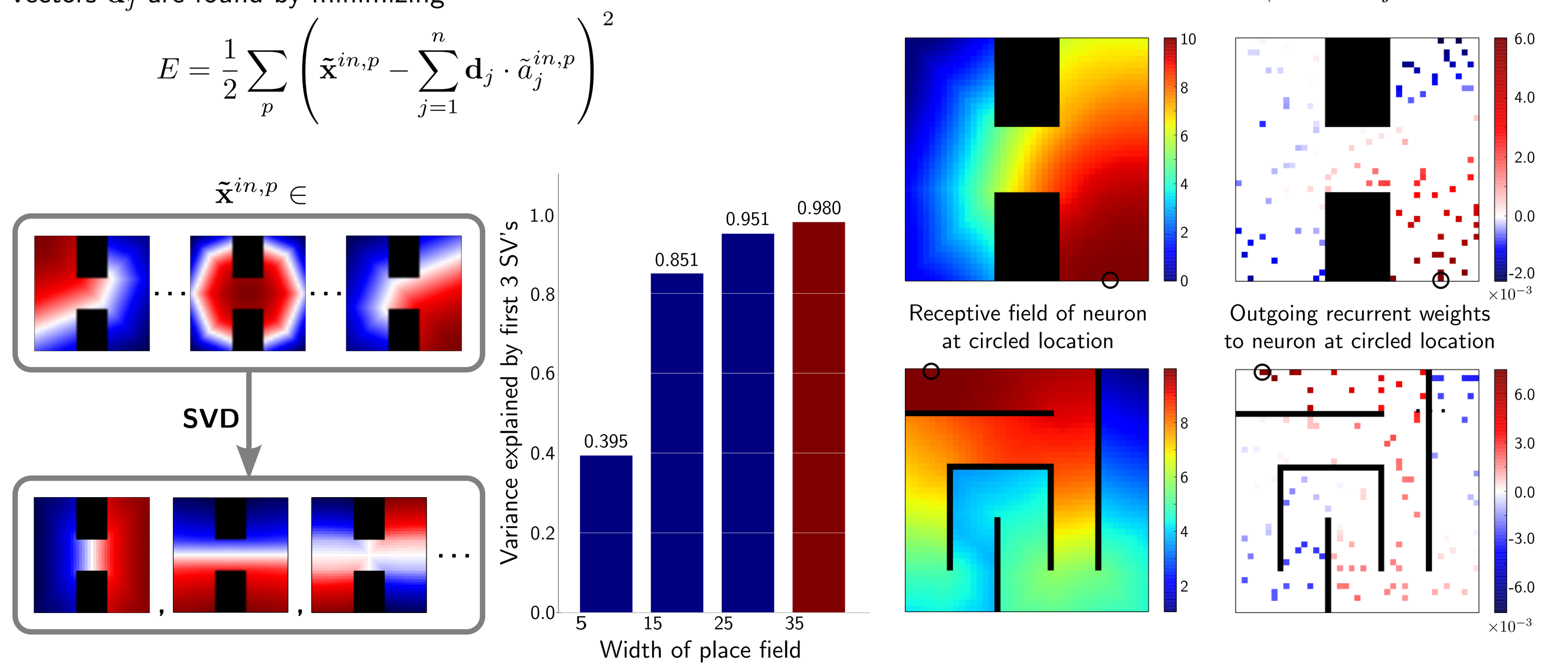
Neuron model:

$$\tau \frac{da_i(t)}{dt} = -a_i(t) + \left[\sum_{j=1}^{n} w_{ij}^{rec} a_j(t) + \sum_{k=1}^{m} w_{ik}^{ff} x_k^{in}(t)) \right]_+$$

with weights $w_{ik}^{ff} = e_{ik}$ and $w_{ij}^{rec} = \alpha \cdot \mathbf{e}_i \cdot \mathbf{d}_j$. Given steady–state activities $\tilde{\mathbf{a}}_j^{in,p}$ in response to example inputs $\tilde{\mathbf{x}}^{in,p}$, the vectors $\mathbf{d}_j$ are found by minimizing

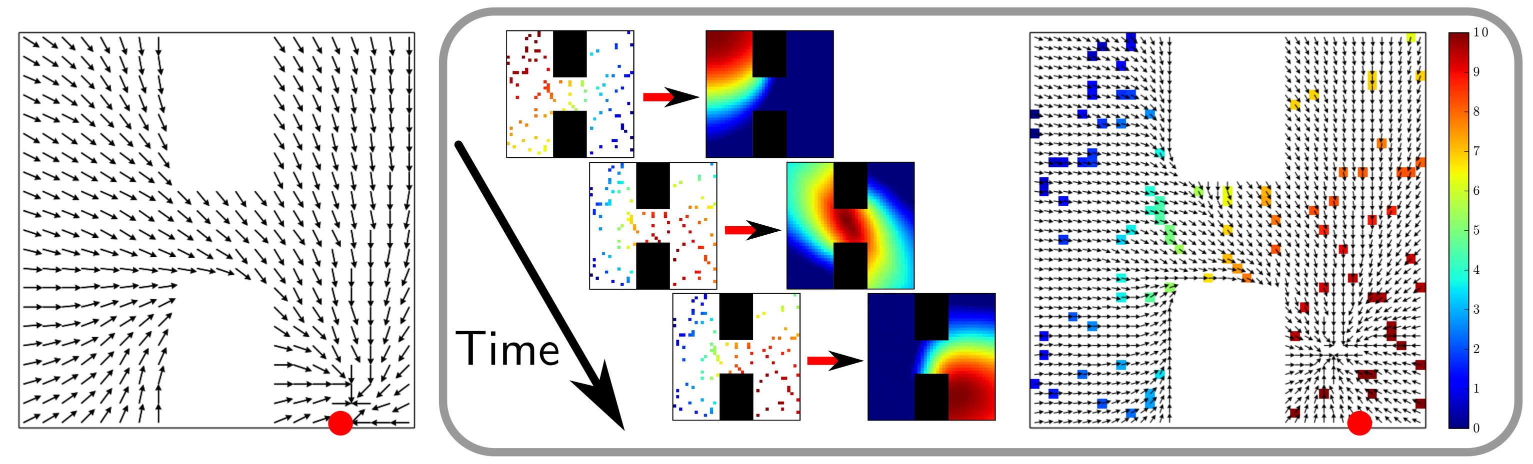
$$E = \frac{1}{2} \sum_p \left(\tilde{\mathbf{x}}^{in,p} - \sum_{j=1}^{n} \mathbf{d}_j \cdot \tilde{a}_j^{in,p} \right)^2$$



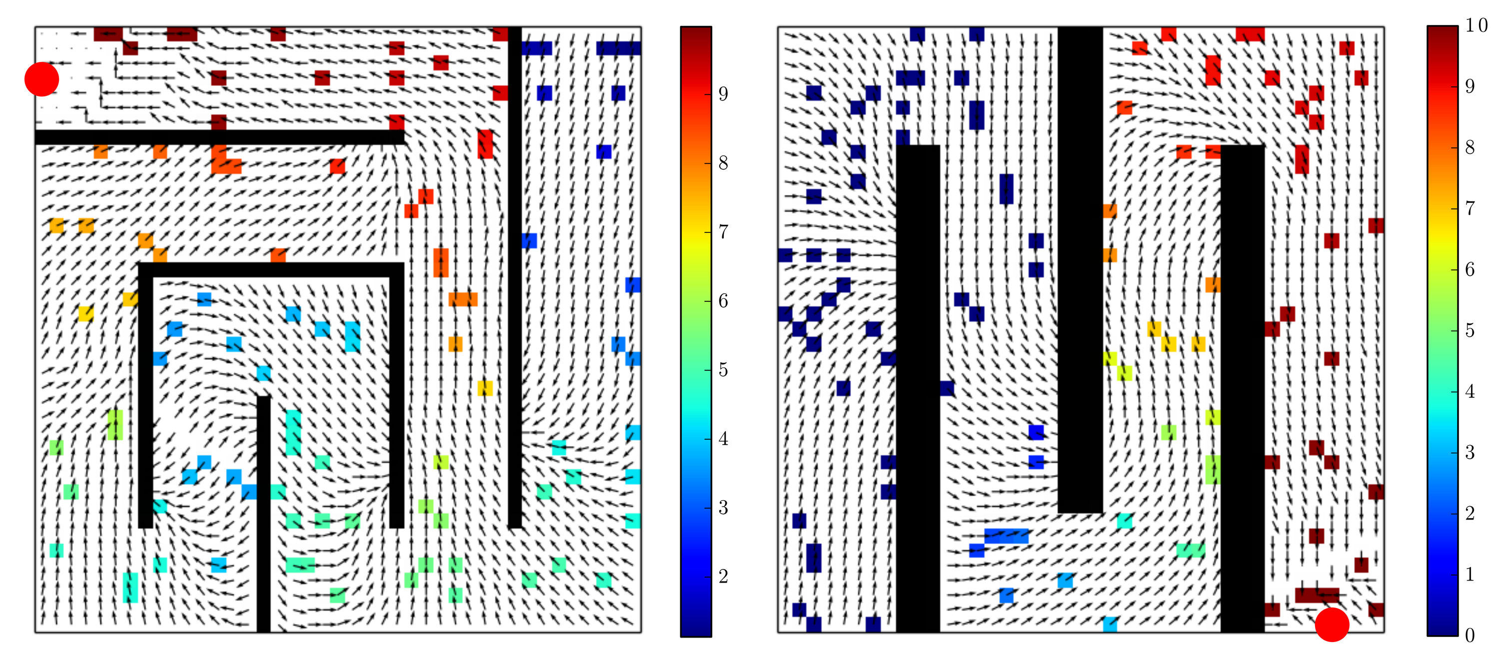


Results

- The activity profile moves around obstacles towards the stimulated location, from an arbitrary start point.



- The same small attractor network can be used for pathfinding in multiple maze–like environments, i.e. a "multichart" attractor (Samsonovich & McNaughton, 1997).



Conclusions

- Bump attractor networks incorporating neurons with large place fields can support long–distance goal–directed sequential activity, as seen in experimental data.
- Attractor networks can represent maze–like environments with walls and obstacles, where sequential activity may contribute to non–trivial path planning.
- **Prediction:** Removal of the intermediate and ventral hippocampal regions will interrupt not only pathfinding ability (Bast *et al.* , 2009), but also long–distance sequential activity in the dorsal hippocampus.

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References

Bast, Tobias, Wilson, Iain A, Witter, Menno P, & Morris, Richard GM. 2009. From rapid place learning to behavioral performance: a key role for the intermediate hippocampus. *PLoS biology*, **7**(4), e1000089.

Conklin, John, & Eliasmith, Chris. 2005. A controlled attractor network model of path integration in the rat. *Journal of computational neuroscience*, **18**(2), 183–203.

Eliasmith, Chris, & Anderson, C Charles H. 2004. *Neural engineering: Computation, representation, and dynamics in neurobiological systems*. MIT Press.

Gustafson, Nicholas J, & Daw, Nathaniel D. 2011. Grid cells, place cells, and geodesic generalization for spatial reinforcement learning. *PLoS computational biology*, **7**(10), e1002235.

Keefe, John O, & Nadel, Lynn. 1978. *The hippocampus as a cognitive map*. Clarendon Press Oxford.

Kjelstrup, Kirsten Brun, Solstad, Trygve, Brun, Vegard Heimly, Hafting, Torkel, Leutgeb, Stefan, Witter, Menno P, Moser, Edvard I, & Moser, May-Britt. 2008. Finite scale of spatial representation in the hippocampus. *Science*, **321**(5885), 140–143.

Nakazawa, Kazu, Sun, Linus D, Quirk, Michael C, Rondi-Reig, Laure, Wilson, Matthew A, & Tonegawa, Susumu. 2003. Hippocampal CA3 NMDA receptors are crucial for memory acquisition of one-time experience. *Neuron*, **38**(2), 305–315.

Pfeiffer, Brad E, & Foster, David J. 2013. Hippocampal place-cell sequences depict future paths to remembered goals. *Nature*, **497**(7447), 74–79.

Samsonovich, Alexei, & McNaughton, Bruce L. 1997. Path integration and cognitive mapping in a continuous attractor neural network model. *The Journal of Neuroscience*, **17**(15), 5900–5920.

Wikenheiser, Andrew M, & Redish, A David. 2015. Hippocampal theta sequences reflect current goals. *Nature neuroscience*.

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