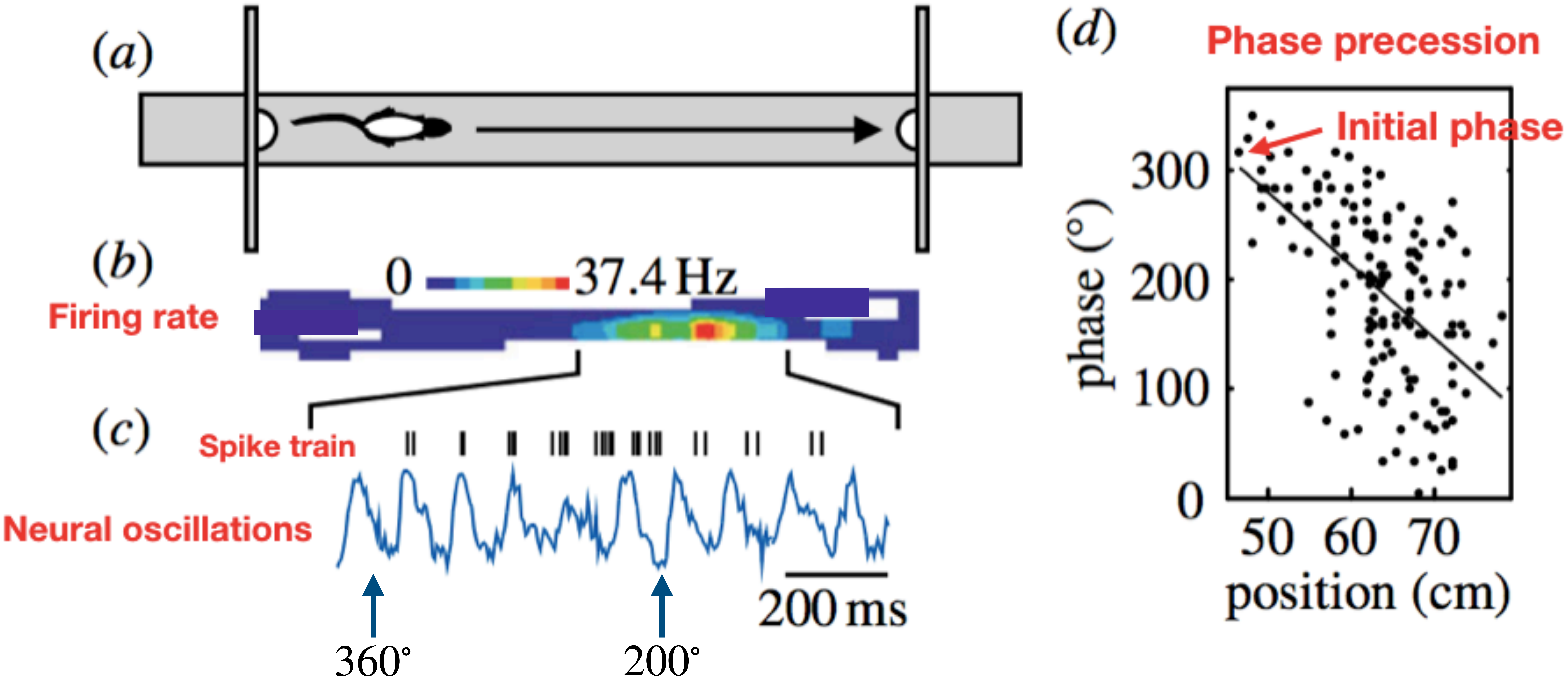
Successor representation in hippocampus

Presented by Yusi Chen

Background

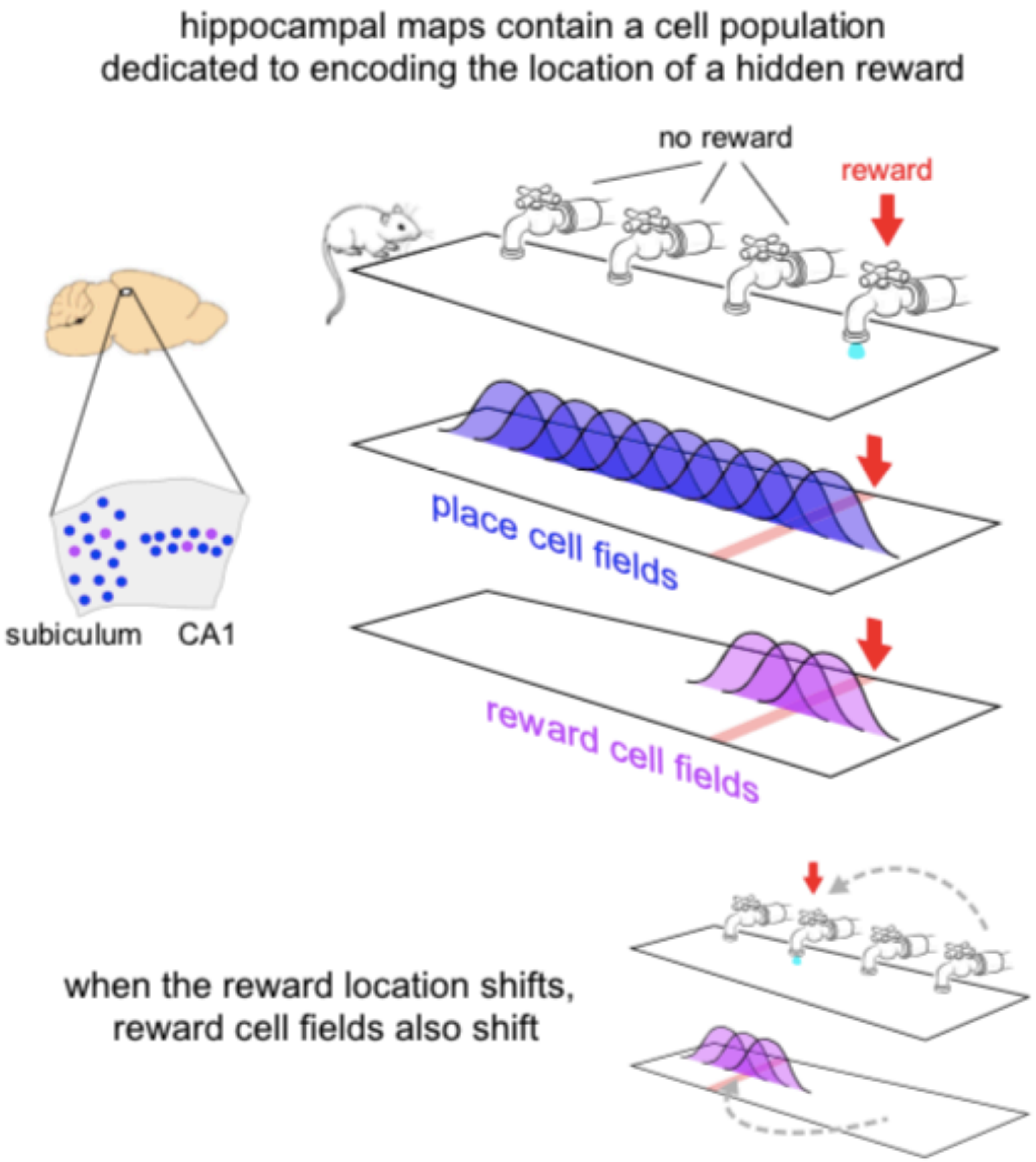
- Place cell: from spatial representation to successor representation (Tank lecture)
- Reinforcement learning: successor representation and temporal difference learning (Dayan_Neural Computation_1993)

Spatial representation of place cells

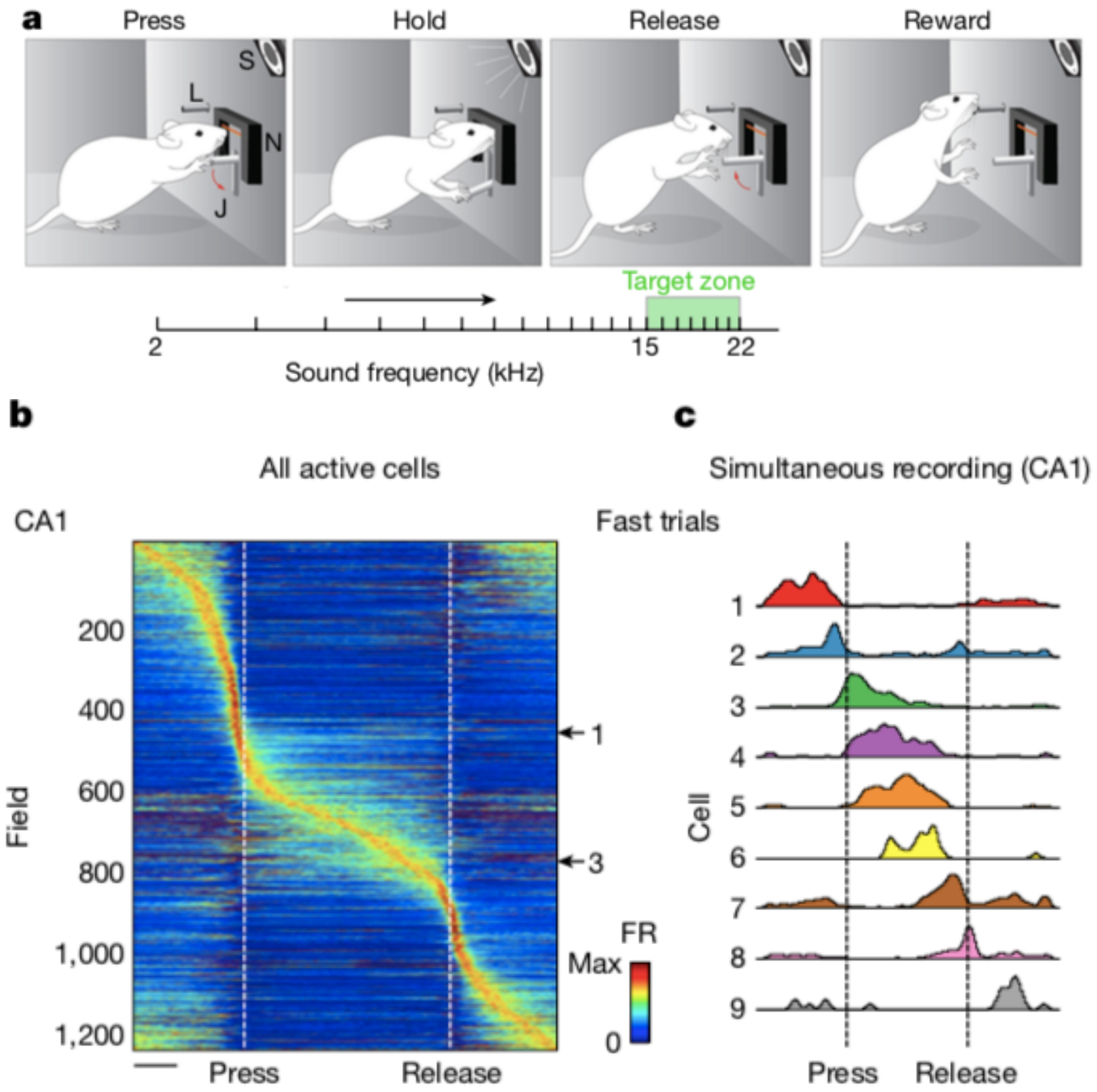


Hartley_2014

Non-spatial representation



Gauthier_Neuron_2018



Aronov_Nature_2017

- Results suggest grid cells and place cells build representations that represent adjacency in behavior; task performance, both in spatial navigation, and cognitive processes in general, activates a sequence of neural activity in the hippocampal formation in which firing fields are elicited parametrically with progress through behavior

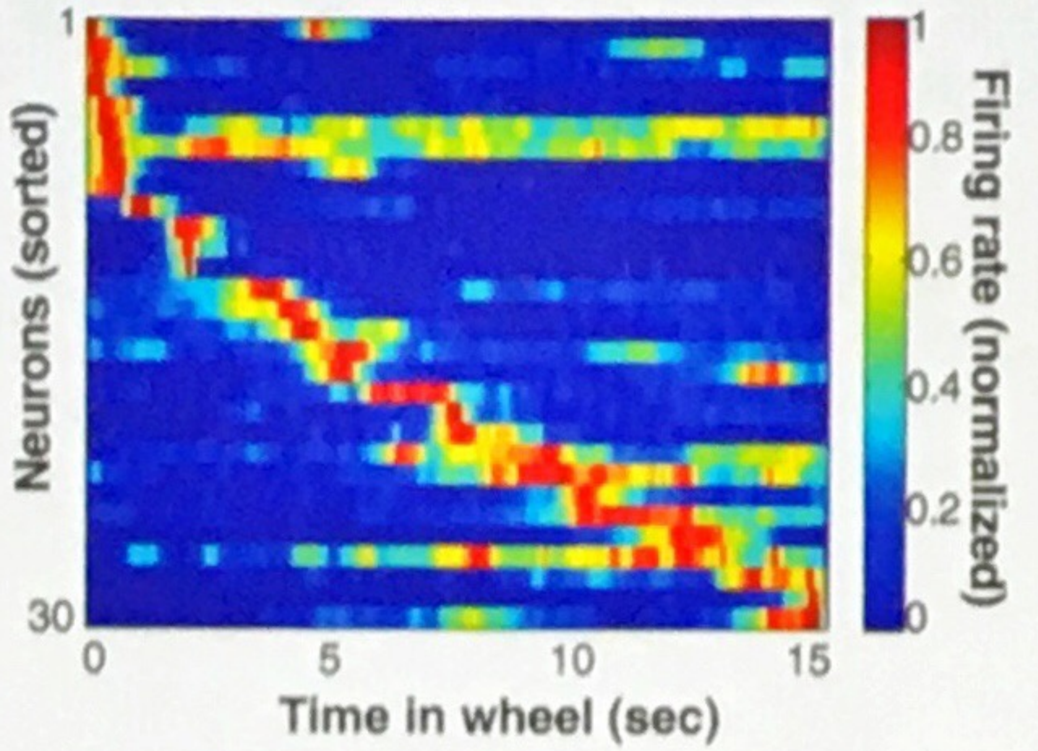
- Representation learning is very general and cells are repurposed between spatial and non-spatial tasks

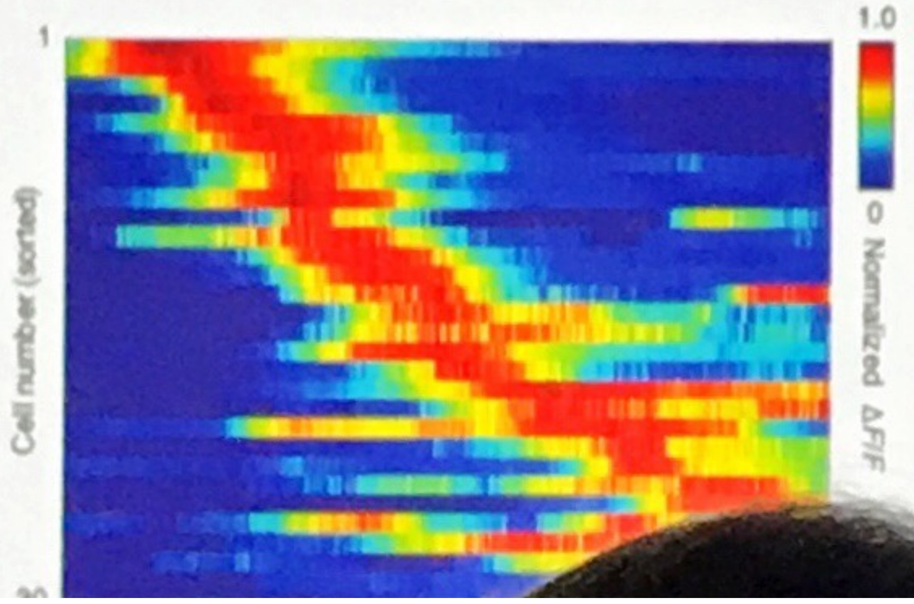
Representation of continuous variables

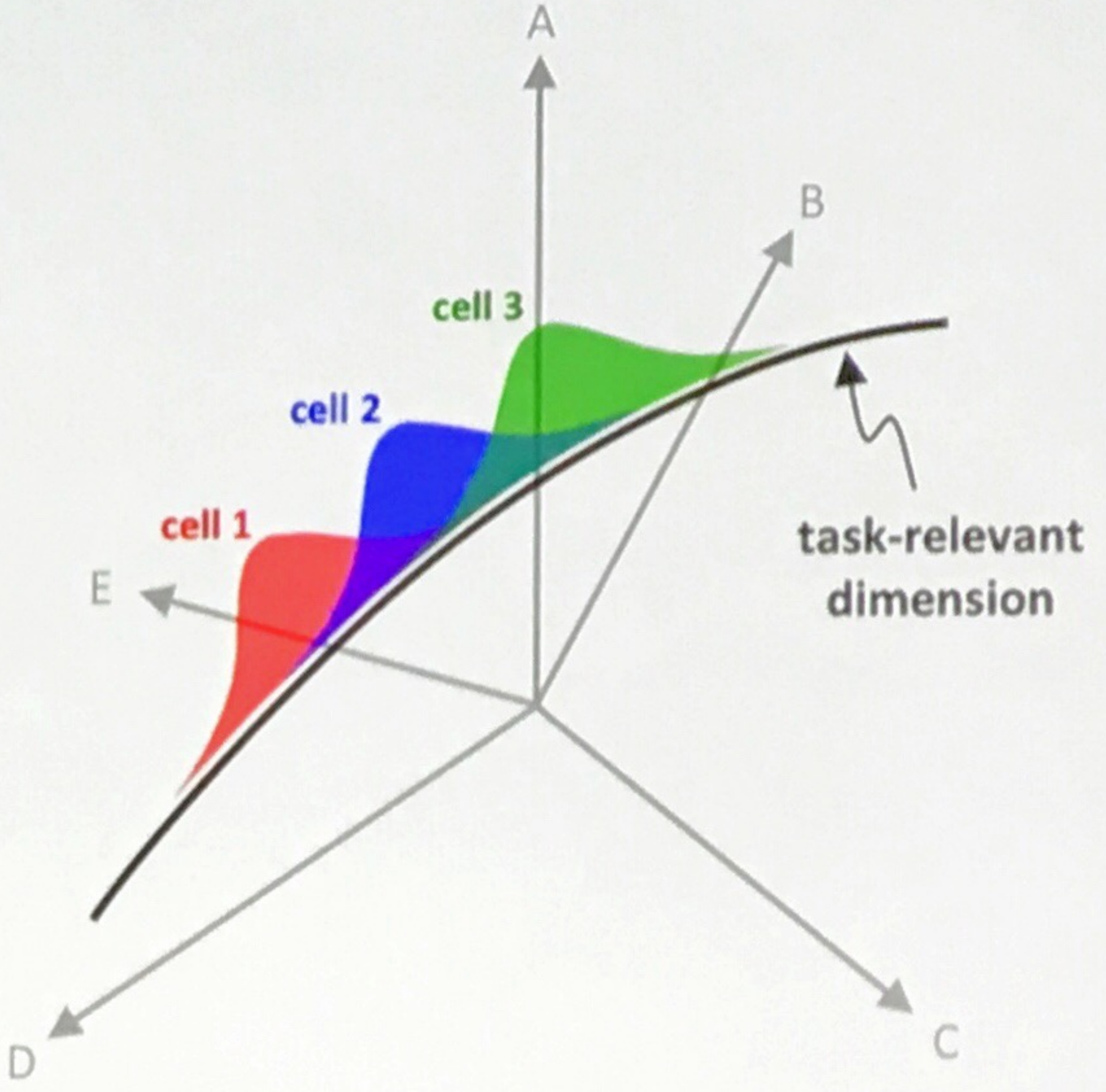
- **Time and Order, rodent and NHP**
  Manns, Howard, Eichenbaum (2007) odor sequences
  Pastalkova,…, Buzsaki (2008) episode sequences
  Naya, Suzuki (2011) time encoding between stimuli
  Heys, Dombeck (2018) elapsed time, MEC

- **Visual space, NHP**
  Killian, Jutras, Buffalo (2012)

- **Human (Social, Conceptual)**
  Tavares,…, Schiller (2015)
  Constantinescu, O'Reilly, Behrens (2016)







HIPPOCAMPUS 9:352–364 (1999)

Do Hippocampal Pyramidal Cells Signal Non-Spatial as Well as Spatial Information?

John O'Keefe*

Department of Anatomy and Developmental Biology, University College London, London, United Kingdom

ABSTRACT: It is generally agreed that the rat hippocampus is involved in spatial memory. Whether this is its sole or primary function, or merely one component of a broader function, is still debated. It has been suggested, for example, that the hippocampus stores information about flexible relations between stimuli, both spatial and non-spatial. In this paper, I reiterate the basic tenet of the cognitive map theory that the processing and storage of spatial information is the primary and perhaps the exclusive role of the hippocampus in the rat, and that data that appear to contradict this have been misinterpreted. These data are found in

map theory states that this is the sole function of the hippocampus in the rat, that the structure was designed to carry out this specific function, and that its components are wired up to achieve that purpose. It is, of course, possible to modify such a system to accomplish different or additional functions by adding components or by changing the data that is fed into it. For example,

Successor representation (SR)

Improving Generalisation for Temporal Difference Learning: The Successor Representation

Peter Dayan
Computational Neurobiology Laboratory
The Salk Institute
PO Box 85800, San Diego CA 92186-5800

Abstract

Estimation of returns over time, the focus of temporal difference (TD) algorithms, imposes particular constraints on good function approximators or representations. Appropriate generalisation between states is determined by how similar their successors are, and representations should follow suit. This paper shows how TD machinery can be used to learn such representations, and illustrates, using a navigation task, the appropriately distributed nature of the result.

- Successor representation: awarding similar representations to states that are nearby in some space
- Spatial space/frequency space/odor space
- Task/reward related states
- Theoretical basis of today's paper

nature neuroscience

The hippocampus as a predictive map

Kimberly L Stachenfeld[1,2], Matthew M Botvinick[1,3] & Samuel J Gershman[4]

A cognitive map has long been the dominant metaphor for hippocampal function, embracing the idea that place cells encode a geometric representation of space. However, evidence for predictive coding, reward sensitivity and policy dependence in place cells suggests that the representation is not purely spatial. We approach this puzzle from a reinforcement learning perspective: what kind of spatial representation is most useful for maximizing future reward? We show that the answer takes the form of a predictive representation. This representation captures many aspects of place cell responses that fall outside the traditional view of a cognitive map. Furthermore, we argue that entorhinal grid cells encode a low-dimensionality basis set for the predictive representation, useful for suppressing noise in predictions and extracting multiscale structure for hierarchical planning.

Reinforcement learning framework

- ***V(s)**: the value of a current state **s**, equals to expected discounted sum of the reward at each future state* s_t

$$V(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t) \mid s_0 = s\right]$$

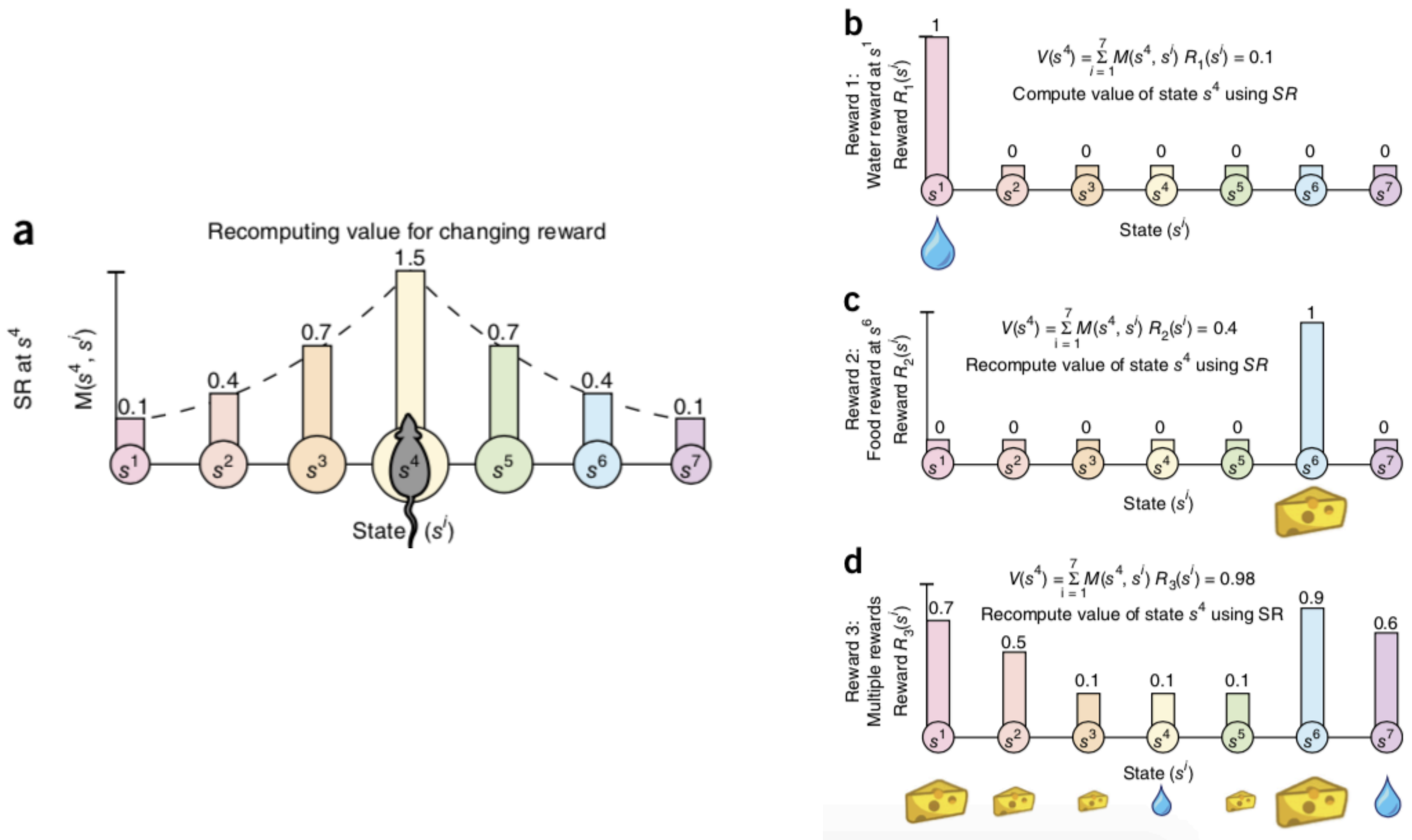
- **V(s)** could be factorized into successor representation matrix (**M**) and direct reward function (**R**)

$$V(s) = \sum_{s'} M(s, s') R(s'),$$

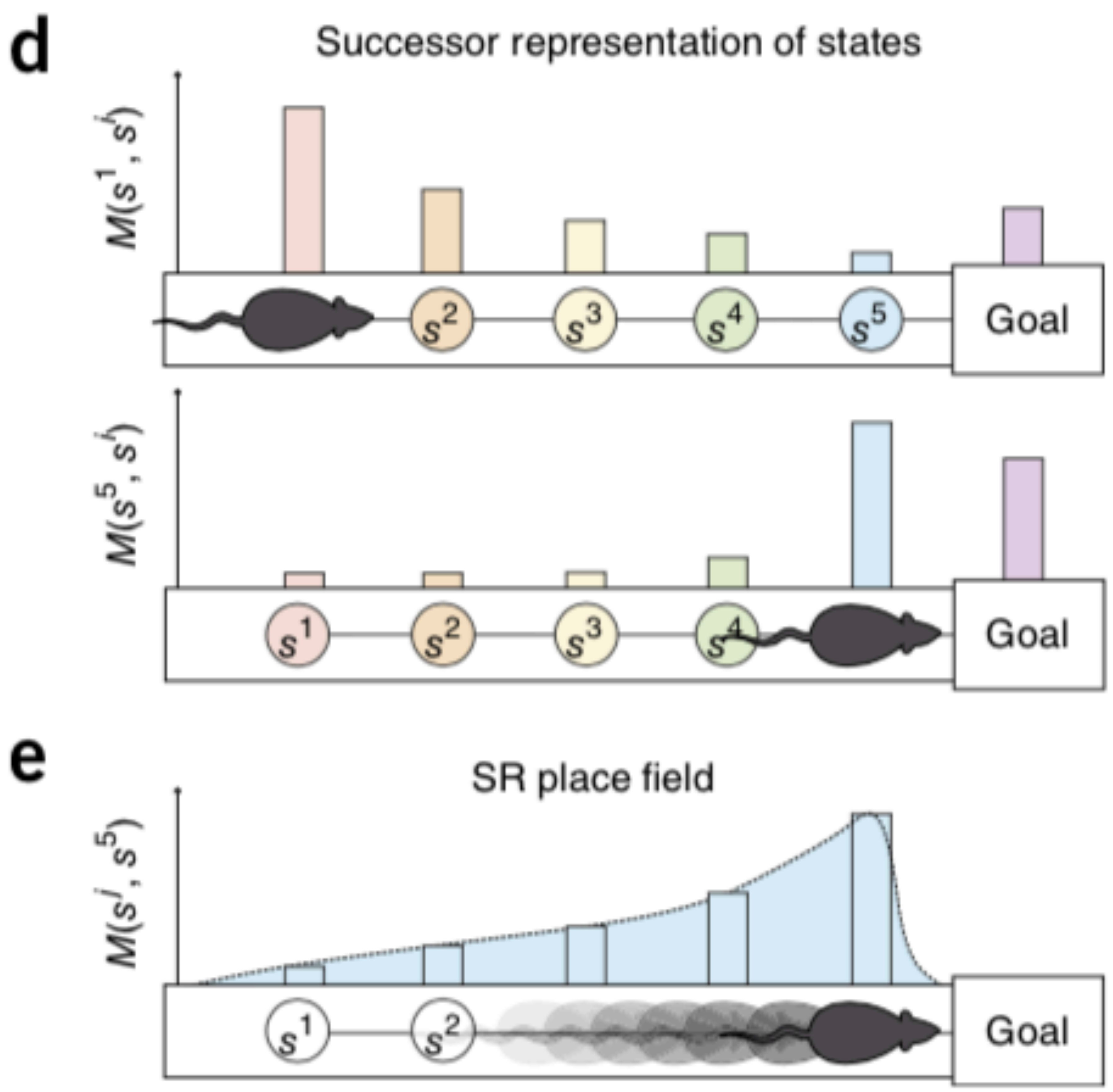
- ***M(s,s')**: the expected number of times a single encoded location **s'** will be visited under current policy, starting from state **s***

$$M(s, s') = \mathbb{E}\left[\sum_{t=0} \gamma^t \mathbb{I}\left(s_t = s'\right) \mid s_0 = s\right]$$

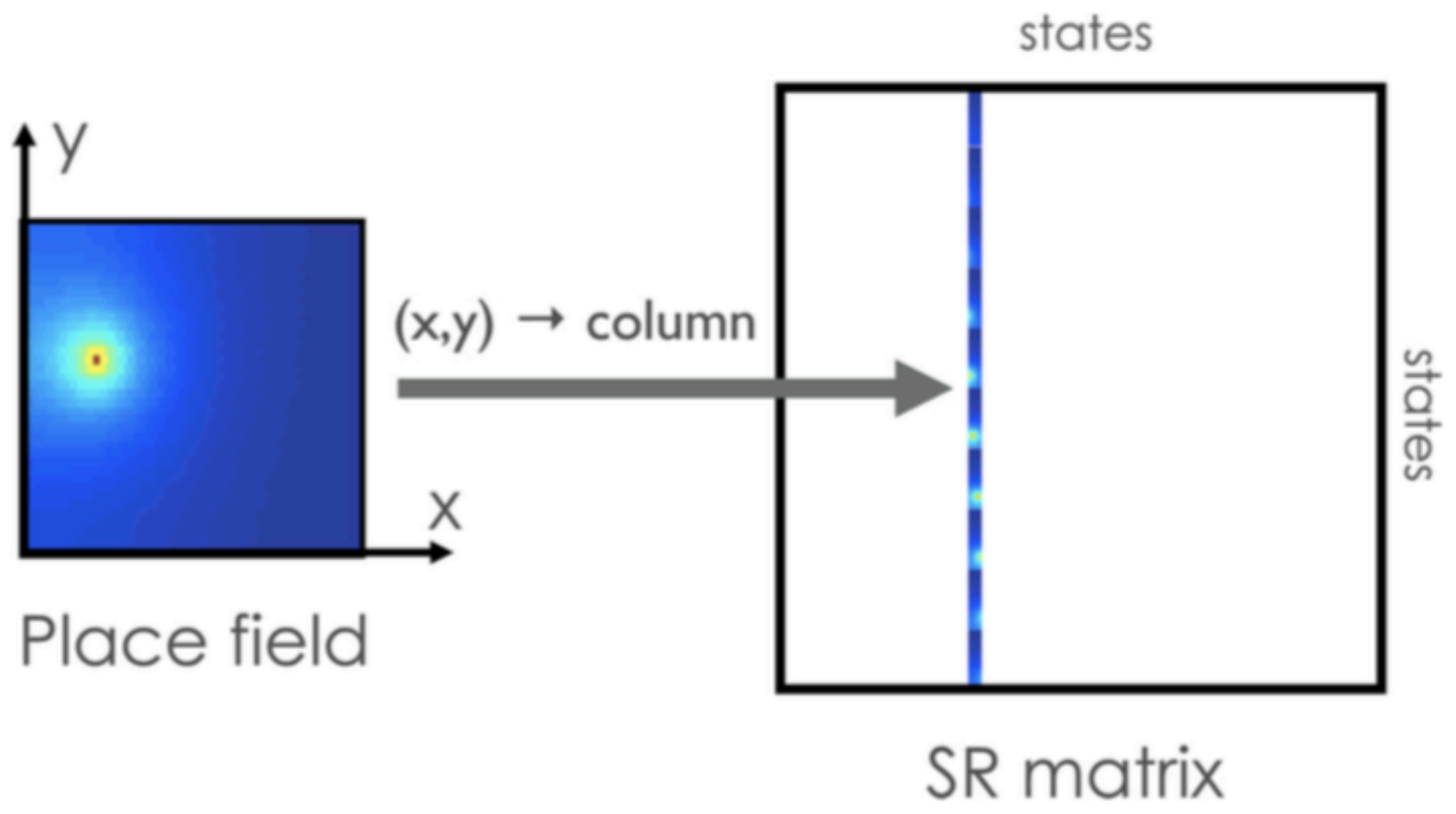
Updating value using SR



Successor representation of a place cell



- ***M(s,s')**: the expected number of times a single encoded location **s'** will be visited under current policy, starting from state **s***
- M(:,s'): successor representation of one place cell indexed as **s'**



Gershman_JfN_2018

SR computation

1. Policy optimization

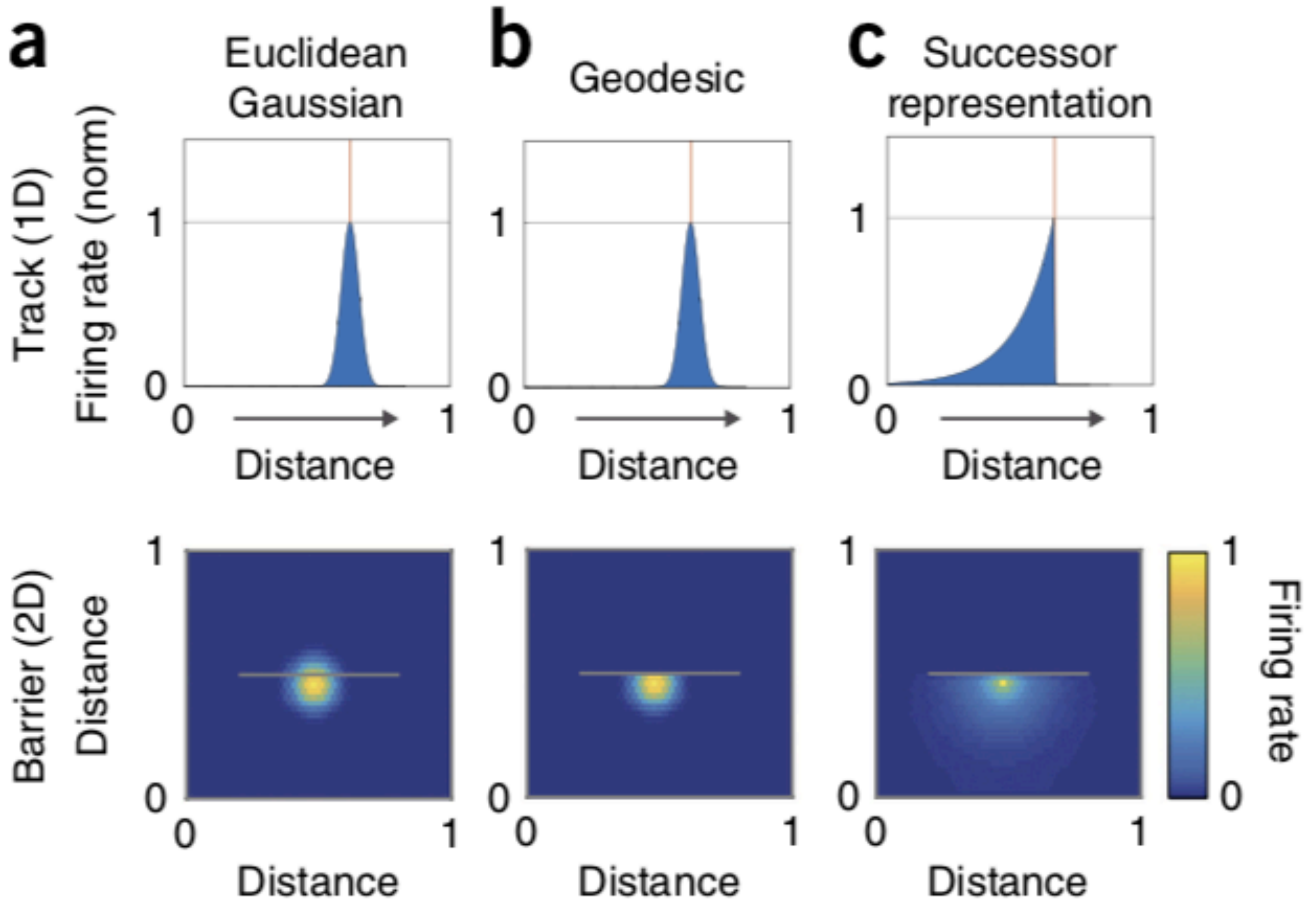
2. Transition matrix computation $T(s,s') = \sum_a \pi(a \mid s) P(s' \mid s, a)$

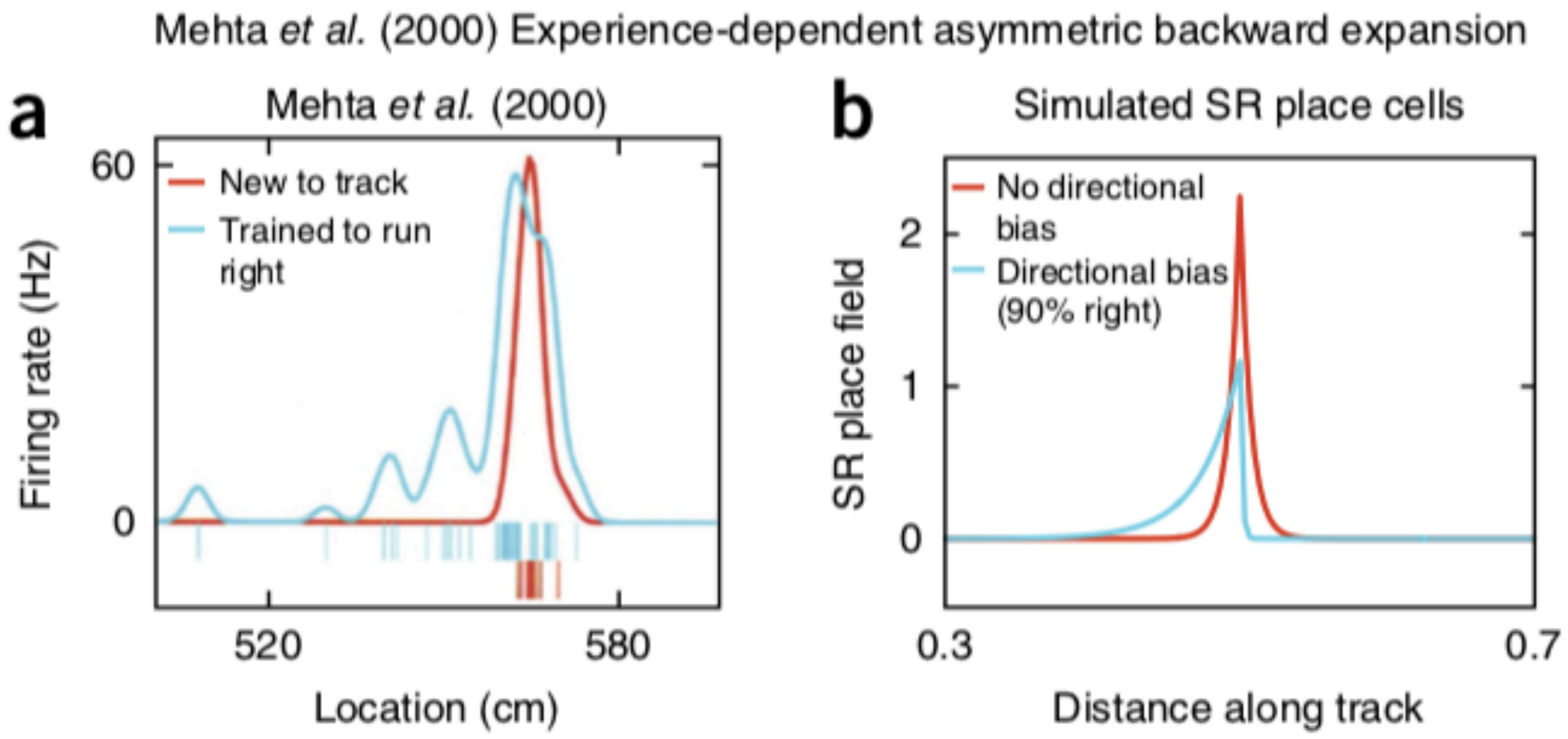
3. SR could be computed analytically or through online learning using temporal difference update rule

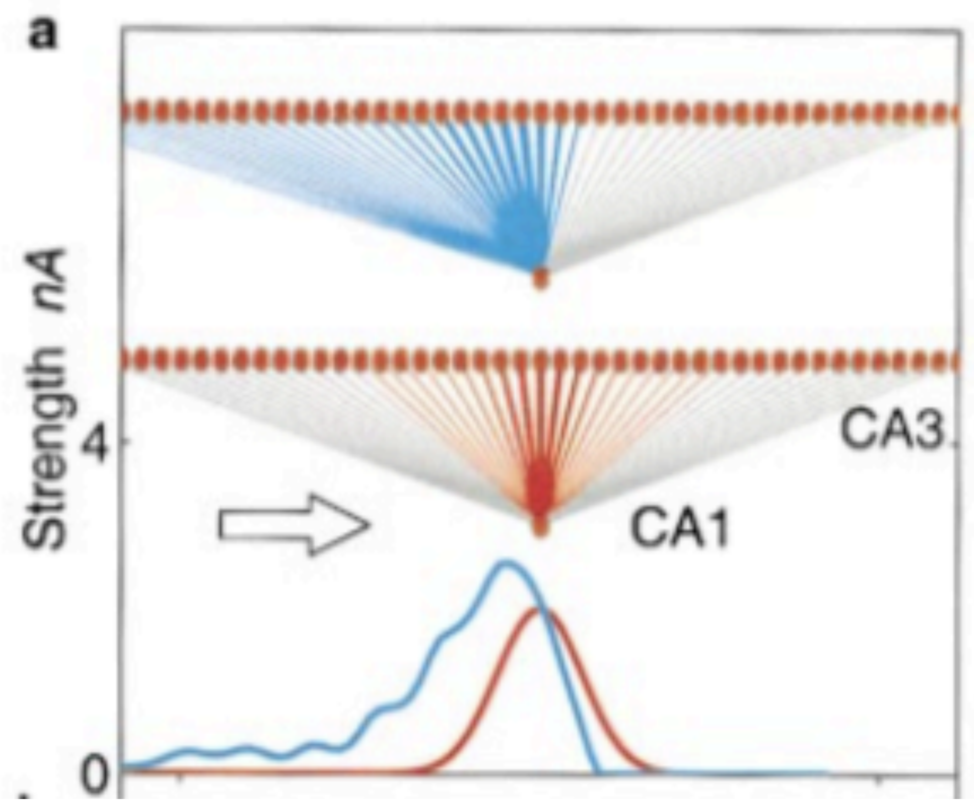
$$M = \sum_{t=0}^{\infty} \gamma^t T^t = (I - \gamma T)^{-1}$$

$$\hat{M}_{t+1}(s_t, s') = \hat{M}_t(s_t, s') + \eta \left[\mathbb{I}(s_t = s') + \gamma \hat{M}_t(s_{t+1}, s') - \hat{M}_t(s_t, s') \right]$$

Benchmark with other models





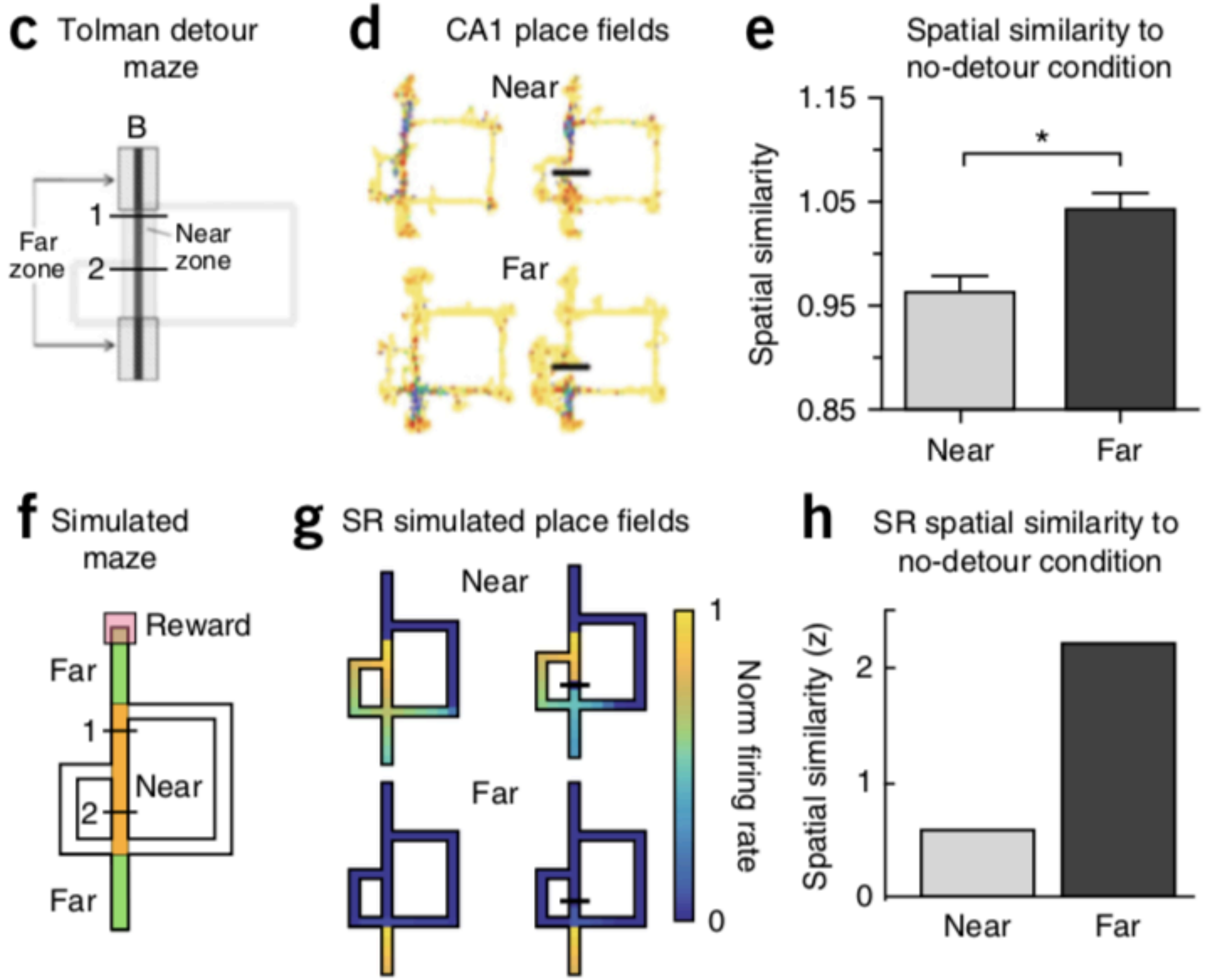


STDP evolution of asymmetry in Euclidean model

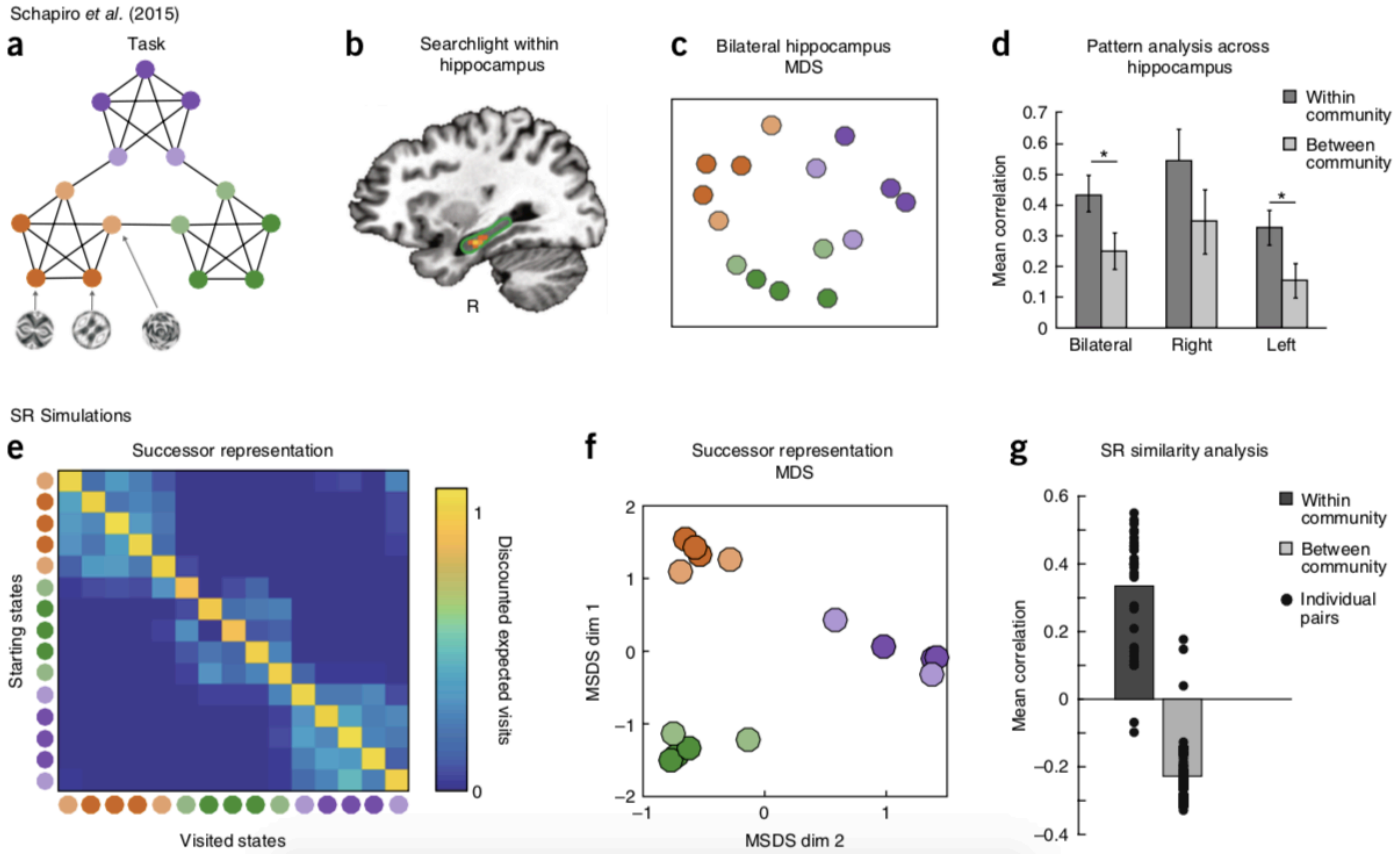
Mehta_NN_2000

Policy-dependent place field remapping

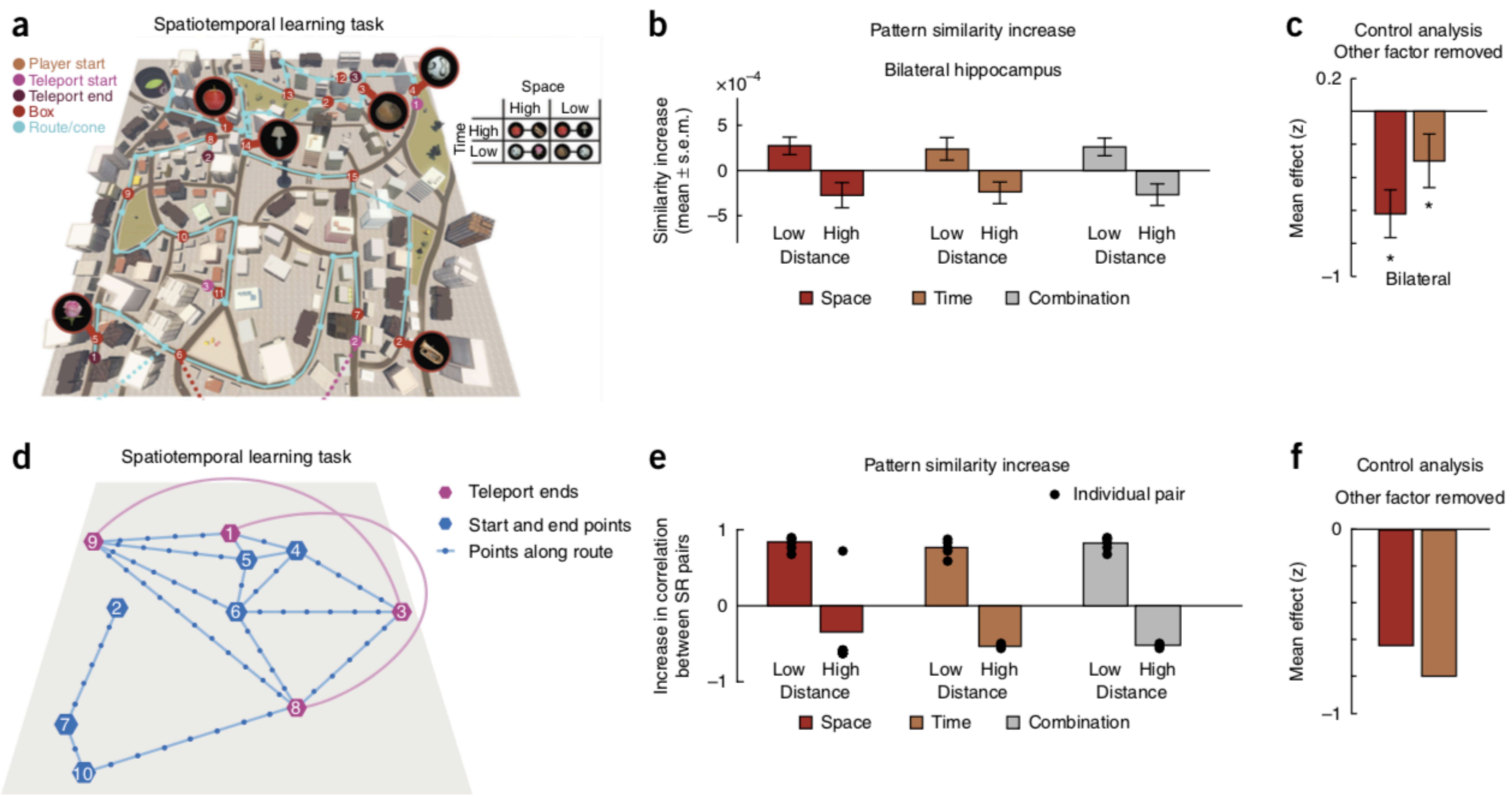
Alvernhe *et al.* (2011) recordings from Tolman detour maze



Hippocampal representation in non-spatial task

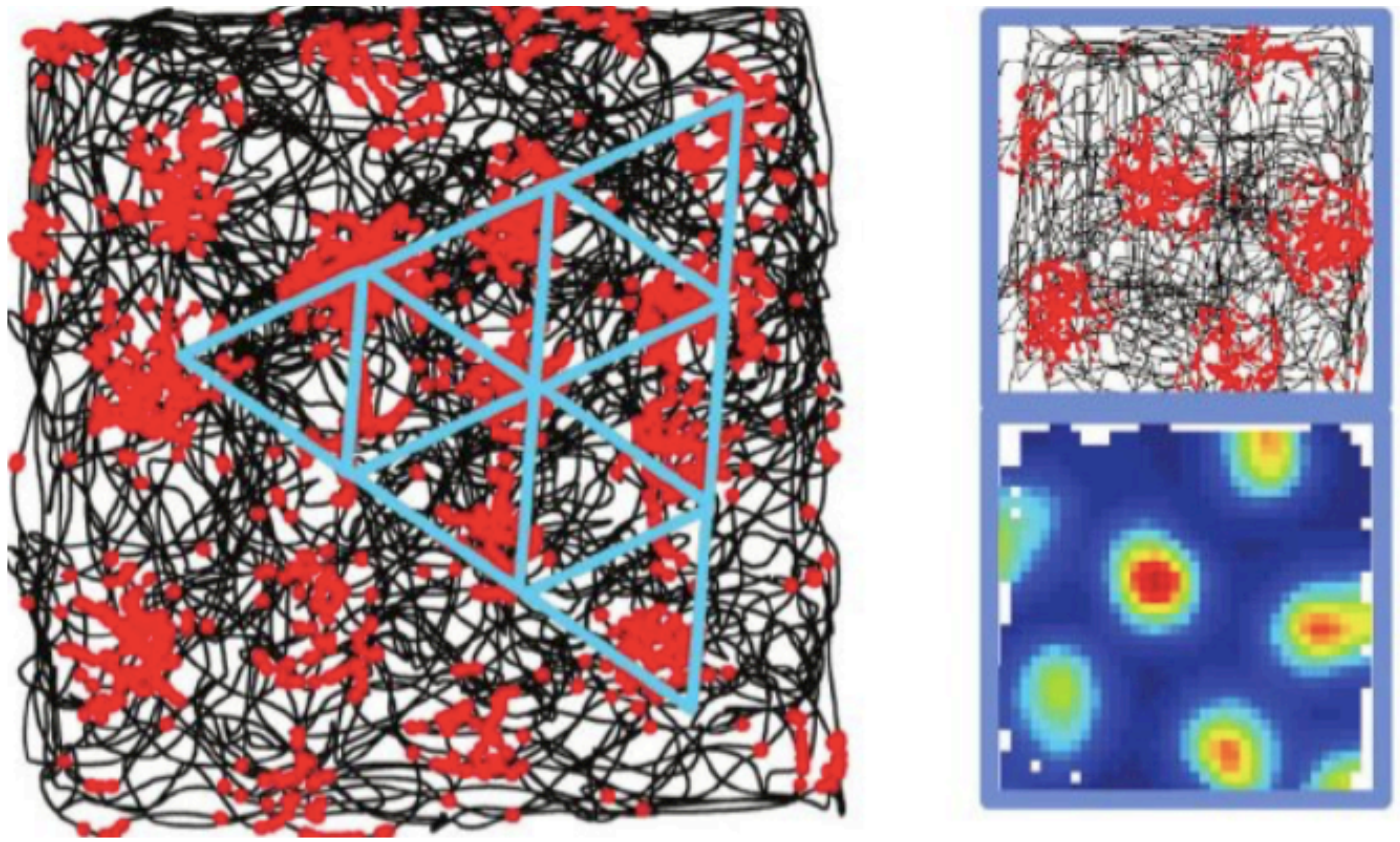


In a spatiotemporal task



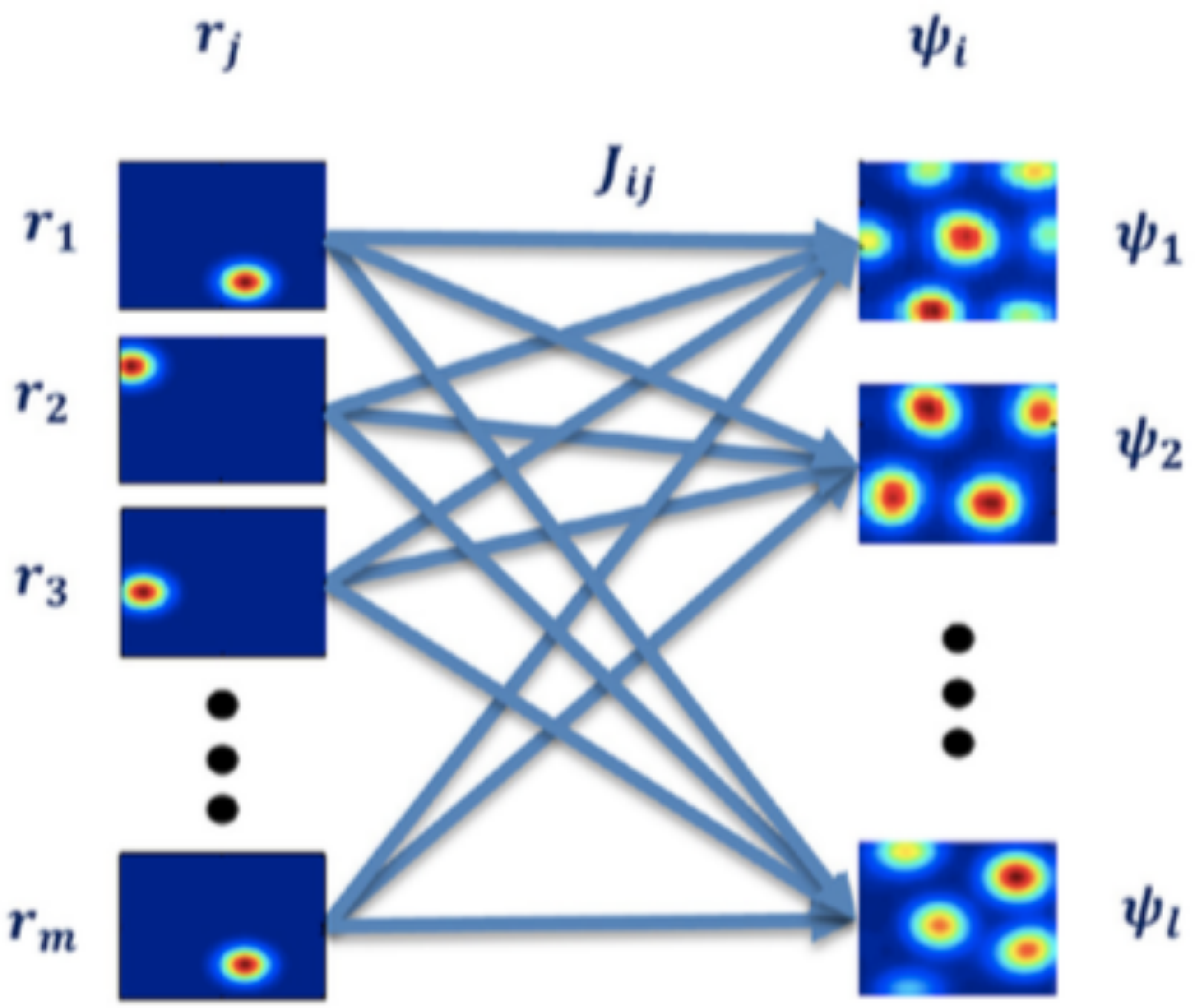
Grid cell representation

Entorhinal-hippocampal spatial circuit



- Allocentric grid cell: based on spatial relationships
- Idiothetic place cell: relative location from an arbitrary reference point
- Egocentric head direction cell: relative to body part axis

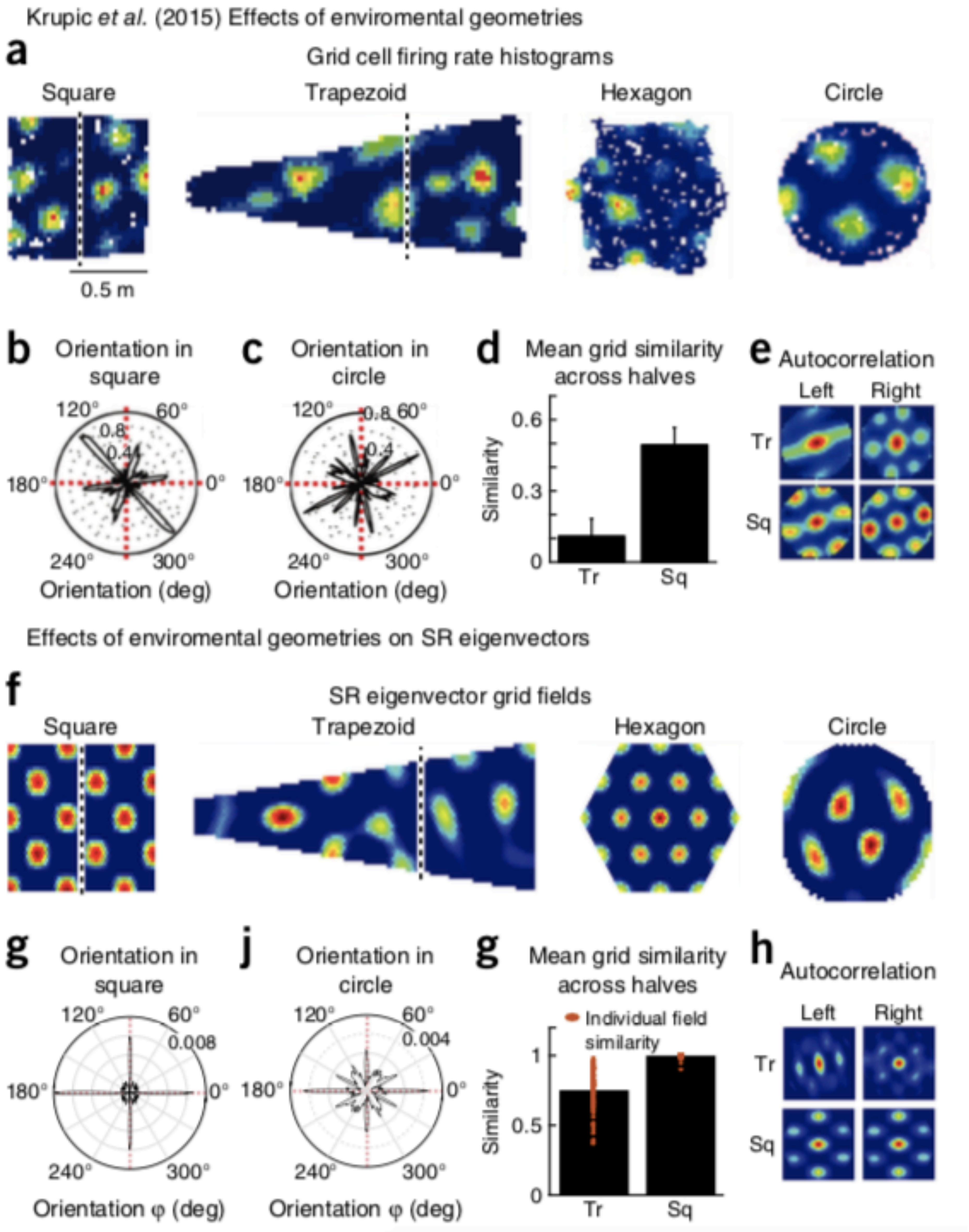
Theoretical model: from place cell to grid cell

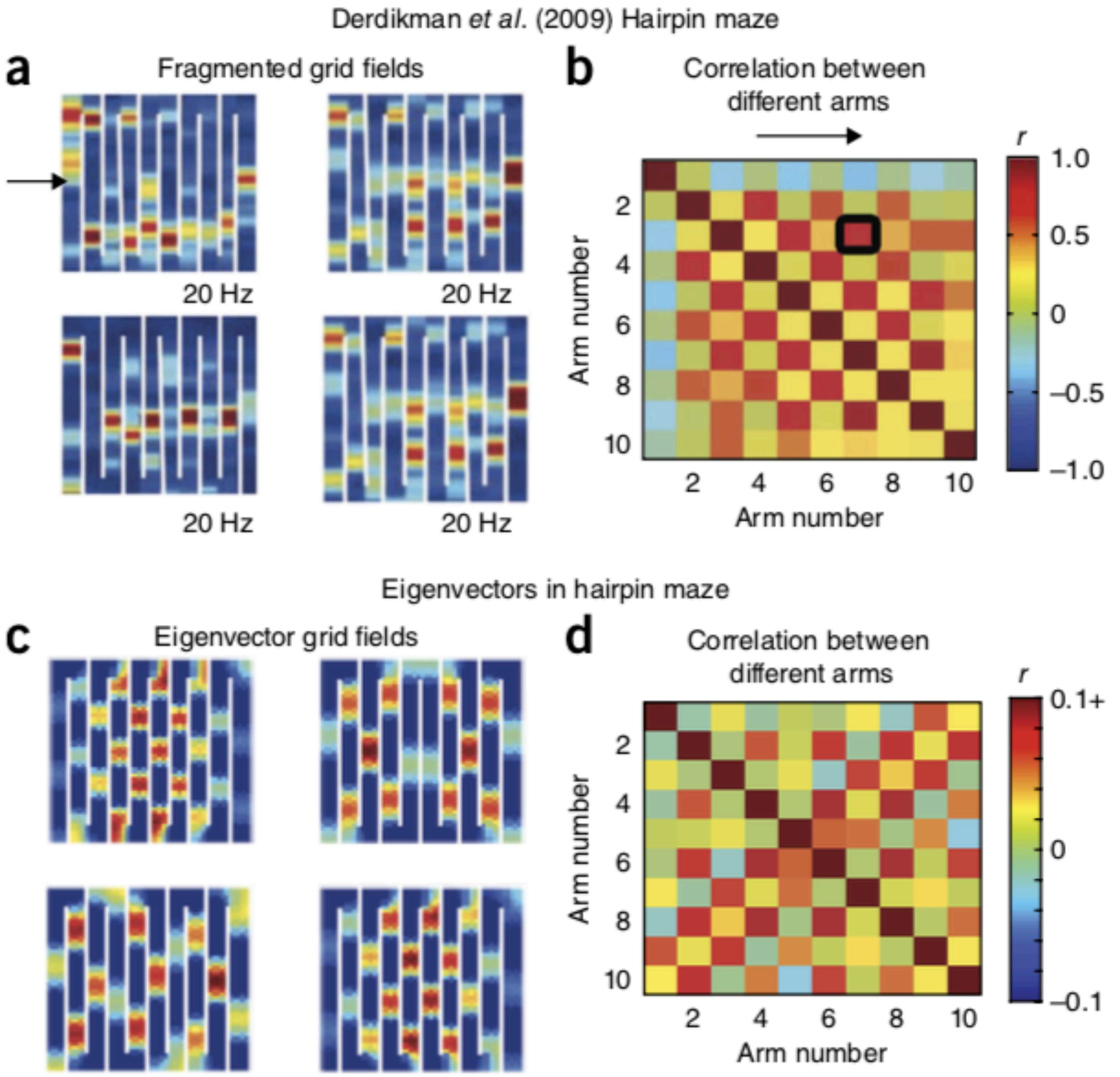


- Feedforward network with generalized Hebbian learning (PCA)
- Grid pattern is the eigenvector of place cell patterns

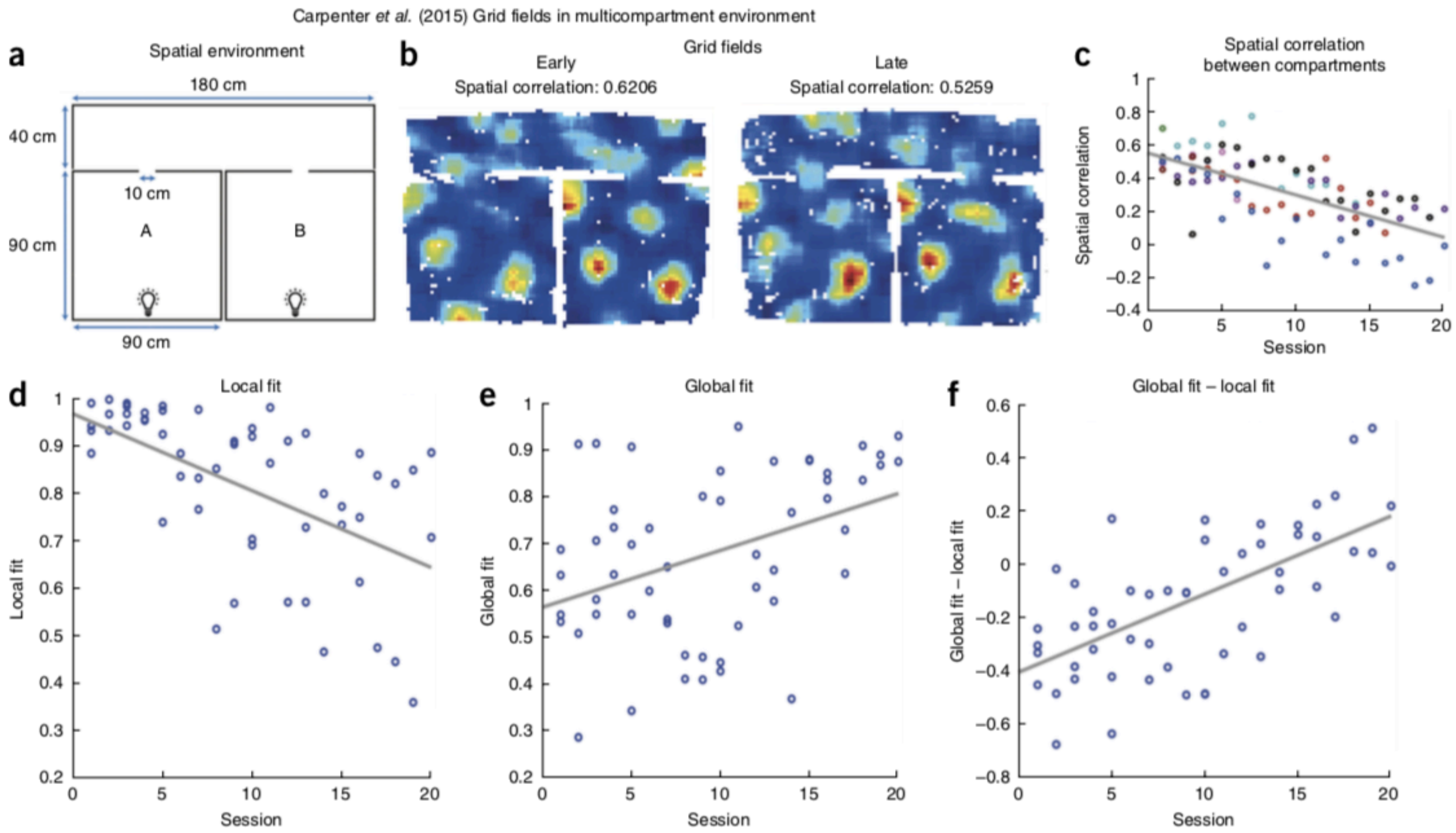
Dordek_Elife_2015

Boundary sensitivity and effect of fragmentation

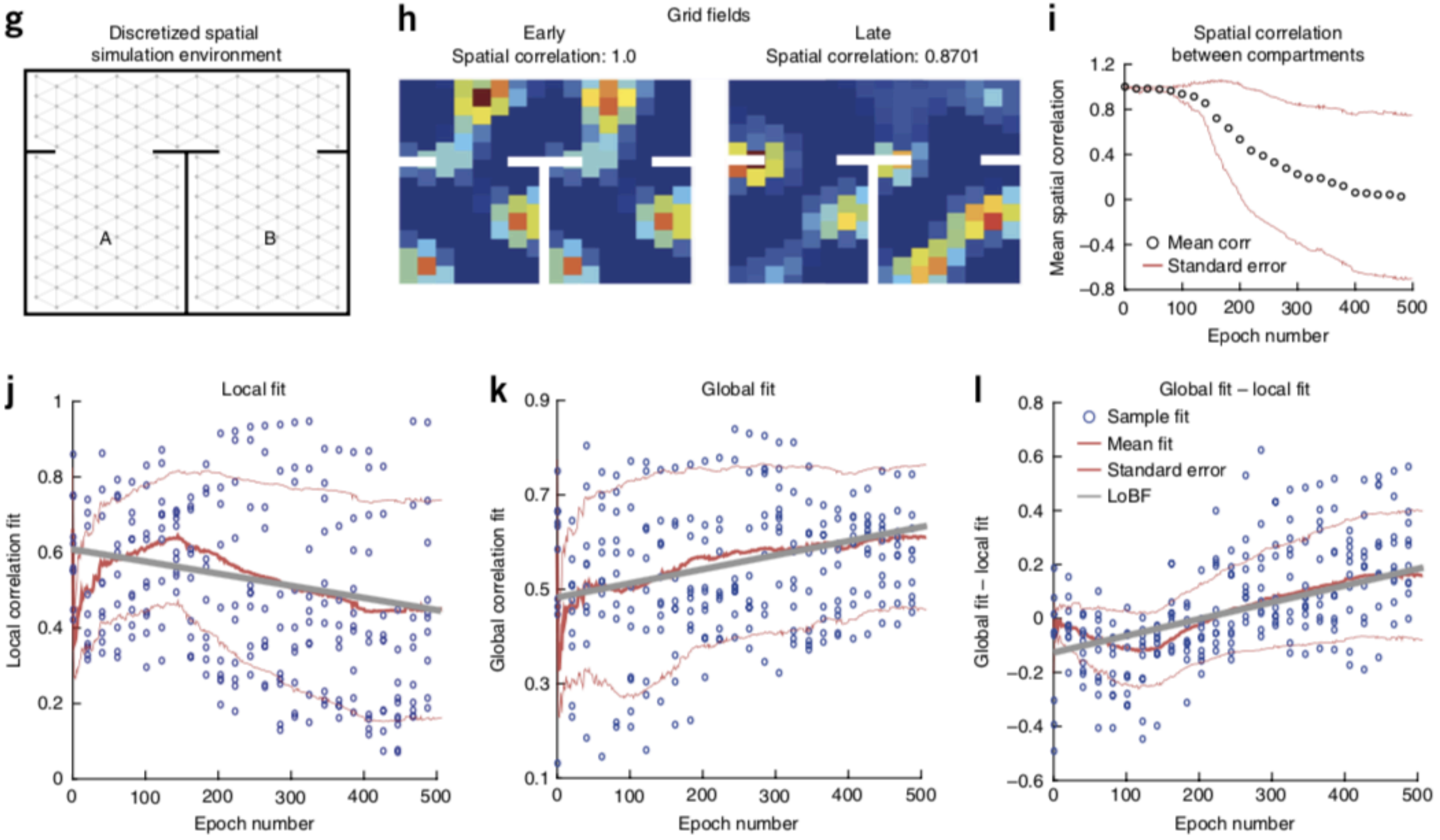




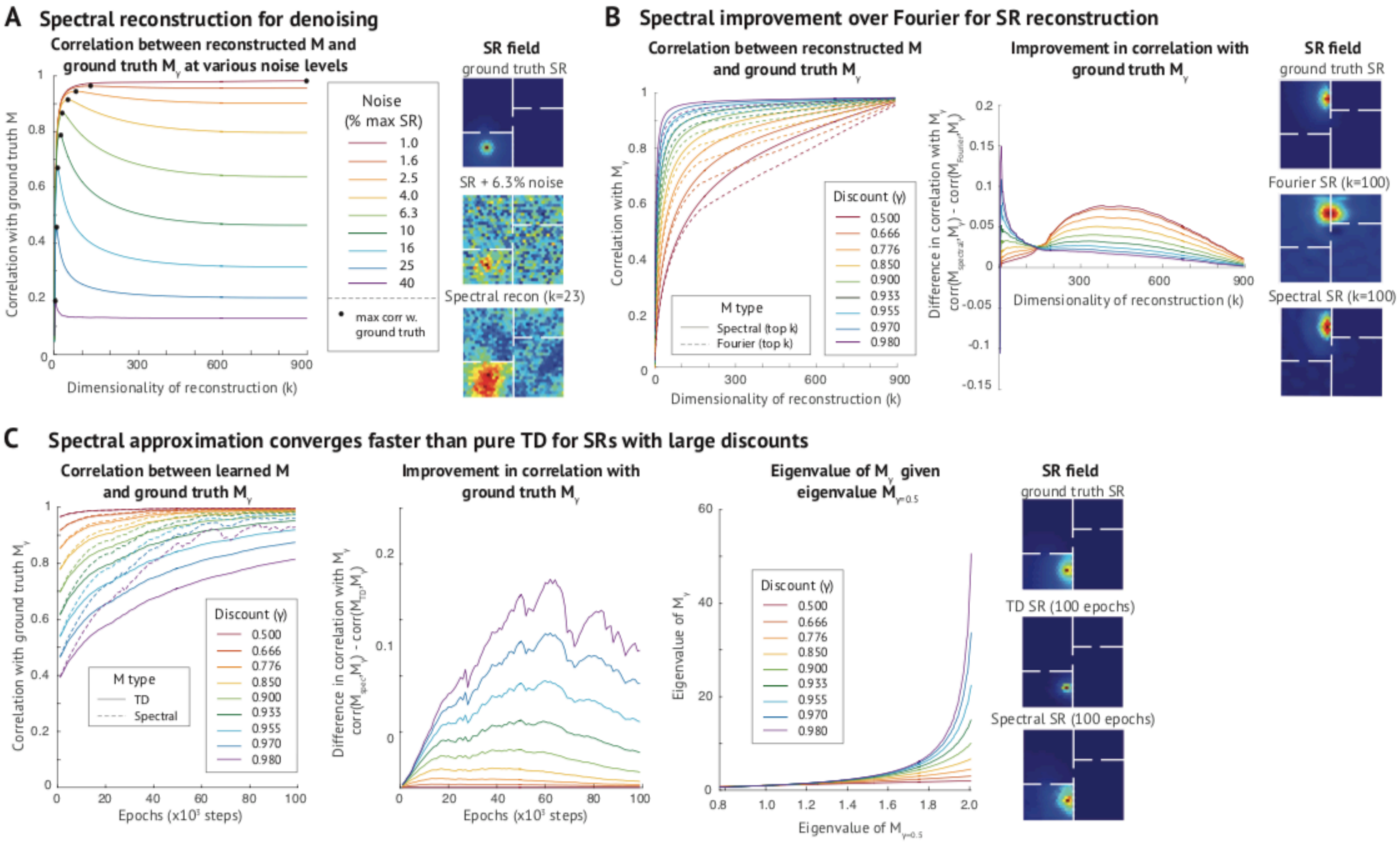
Simulation of spatial learning



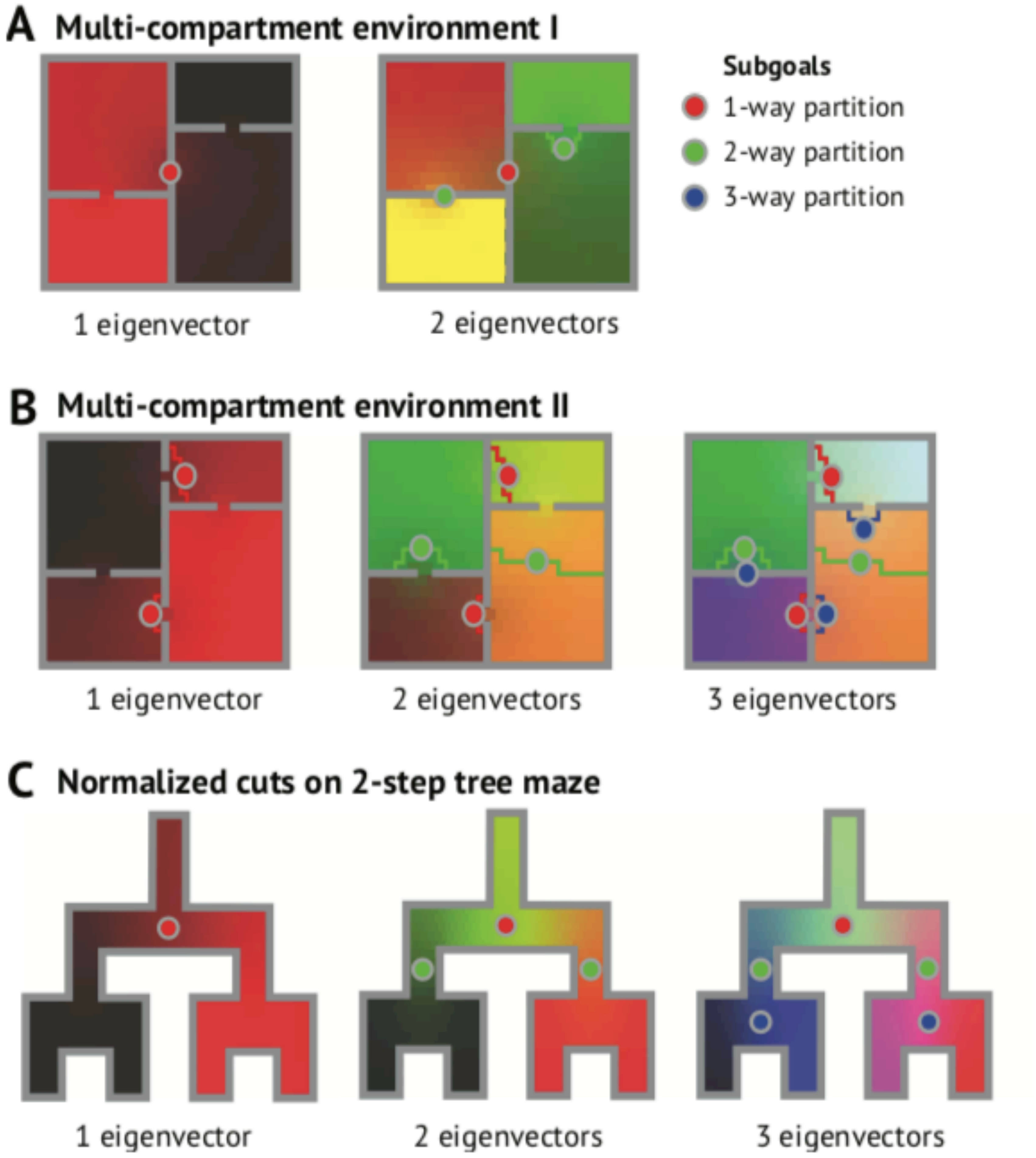
Eigenvector grid fields learned in multicompartment environment



De-noised reconstruction from grid cells

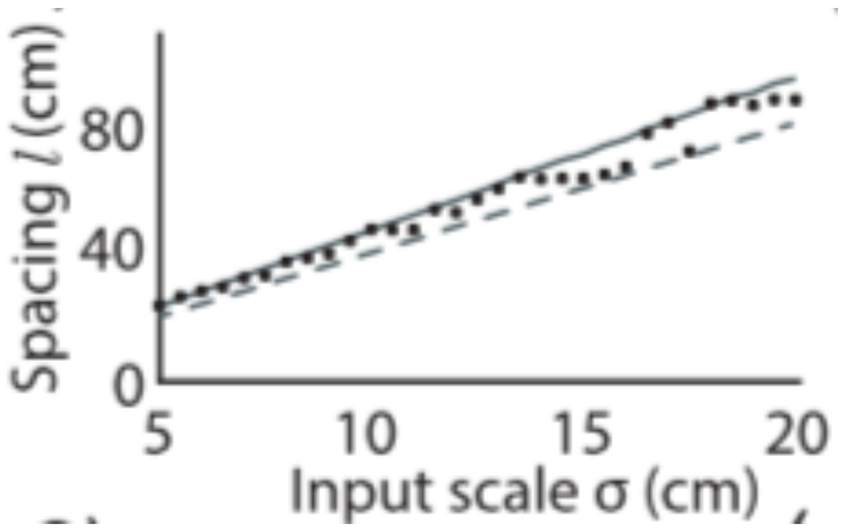


Hierarchical planning



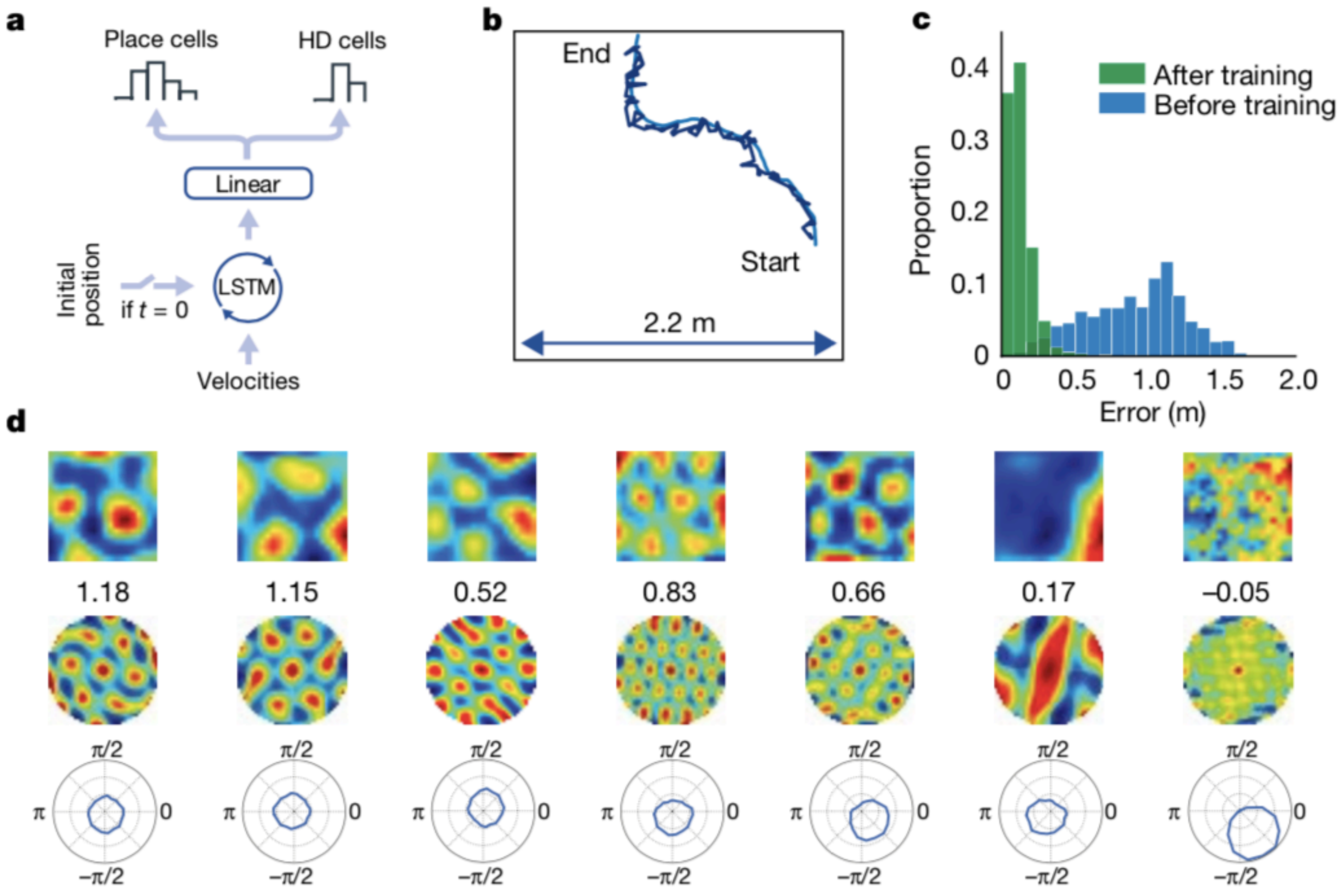
Furthermore

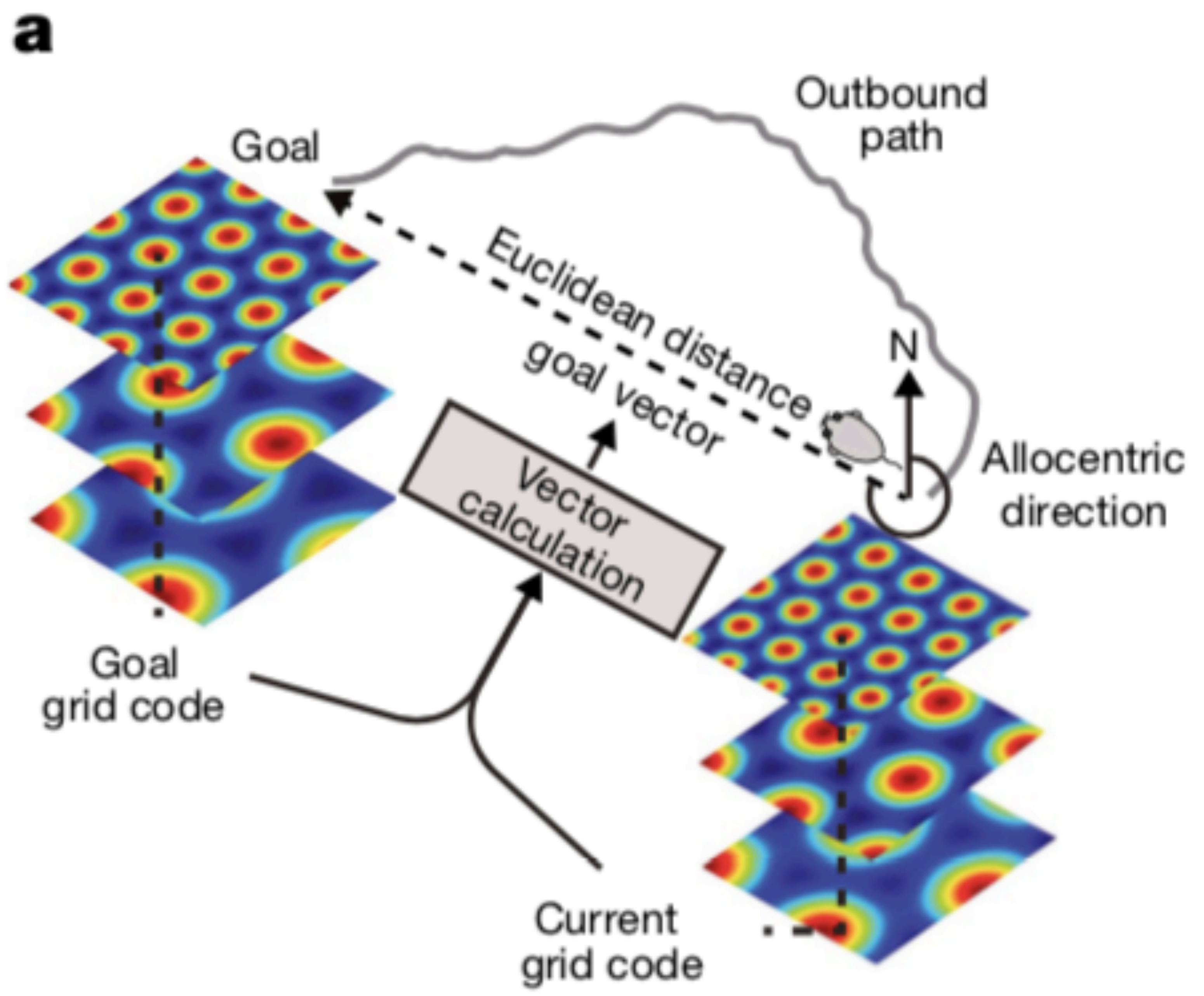
- Phase precession (Drieu_Science_2018)
- Size of place field and grids (Mercado_PRL_2017)
- Navigation system (Banino_Nature_2018)



Hippocampus-based navigation system

- RL framework
- Vector-based navigation





Banino_Nature_2018