

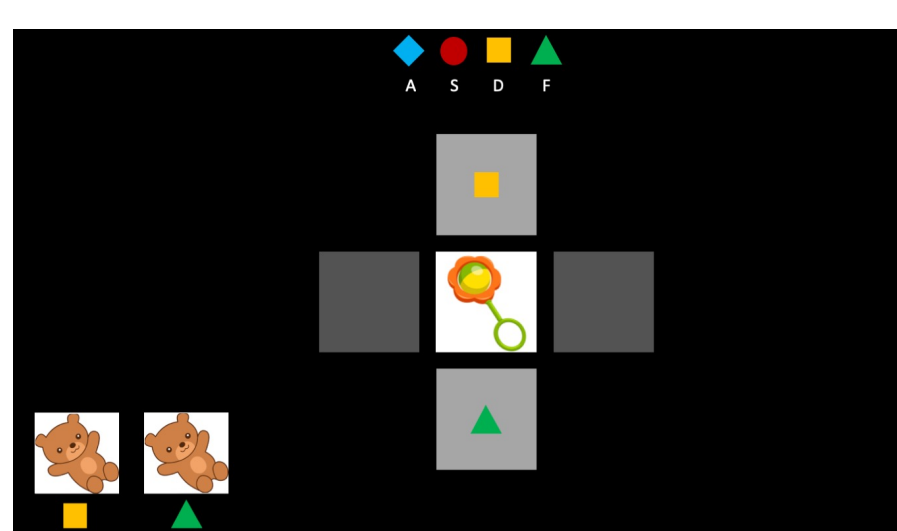
Question: How can we teach people a cognitive map most efficiently?

Introduction

Background

- Accurate spatial and non-spatial cognitive maps of our environment are crucial for our ability to plan flexibly and in line with goal demands
- We know a lot about the neural underpinnings of existing maps and potential computational mechanisms that help us utilise them
- We don't know how we can learn new maps in the most efficient way

Aim: find the best one-step curriculum for flexible multi-step planning

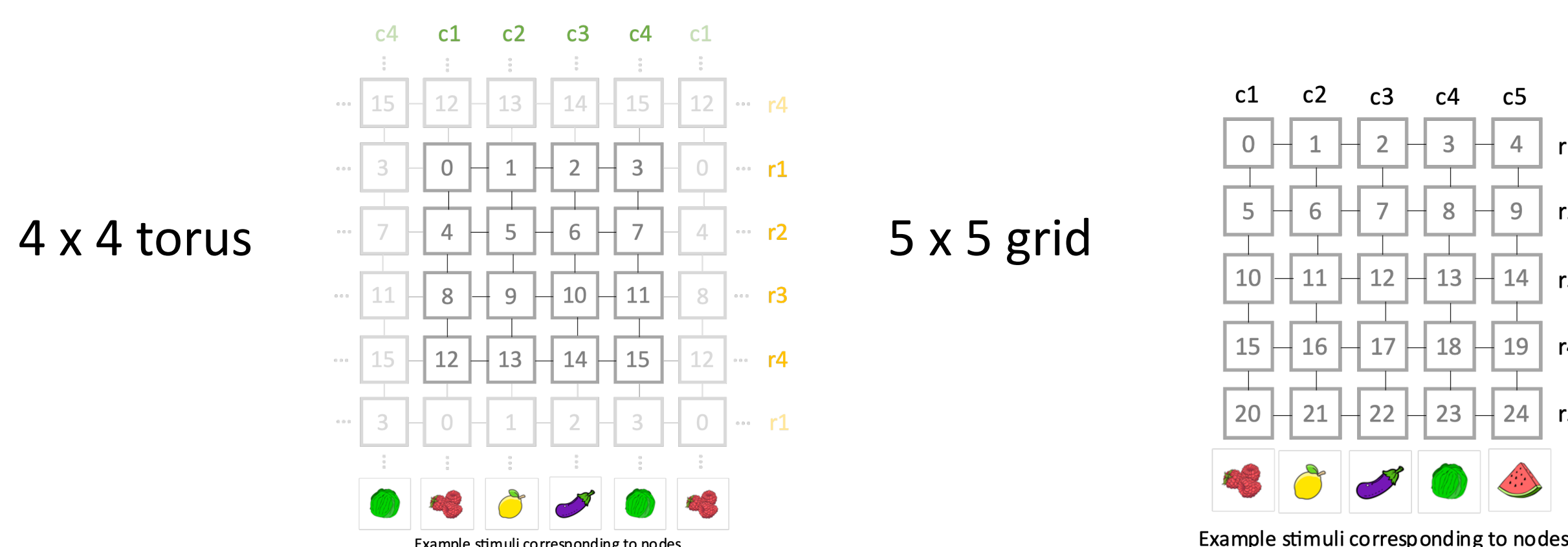


TBC

	c1	c2	c3	c4	c5	
r1	0	1	2	3	4	
r2	5	6	7	8	9	
r3	10	11	12	13	14	
r4	15	16	17	18	19	
r5	20	21	22	23	24	

Experimental manipulations

1. Map shape



2. Training: temporal spacing manipulation

LOCAL: which transitions are **within a block**

- Row/column: random walk along 1 row/col (8 transitions)
- Random: set of 8 randomly sampled transitions

GLOBAL: **across block** spacing of transitions



Methods

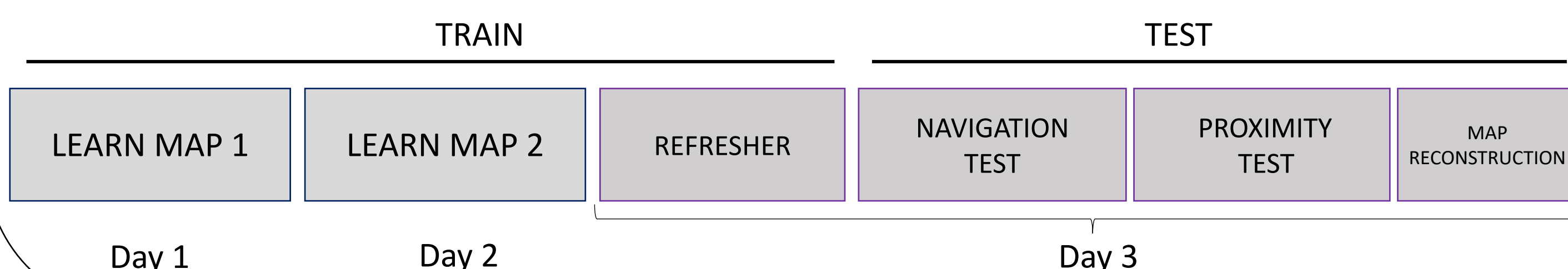


DESIGN	Between subjects factor (GLOBAL)	Fixed half row/column	Fixed half random
		Interleaved row/column	Interleaved random

Within subjects factor (LOCAL)
(one random and one row/column map per participant)

N_{GRID, FIXED HALF} = 49
N_{GRID, INTERLEAVED} = 43

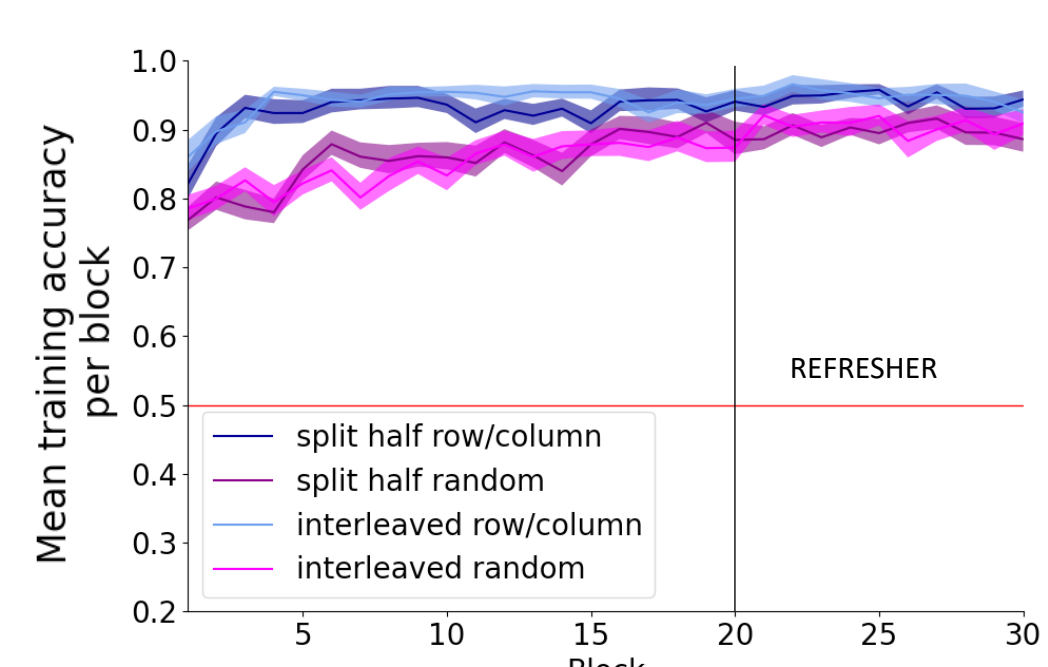
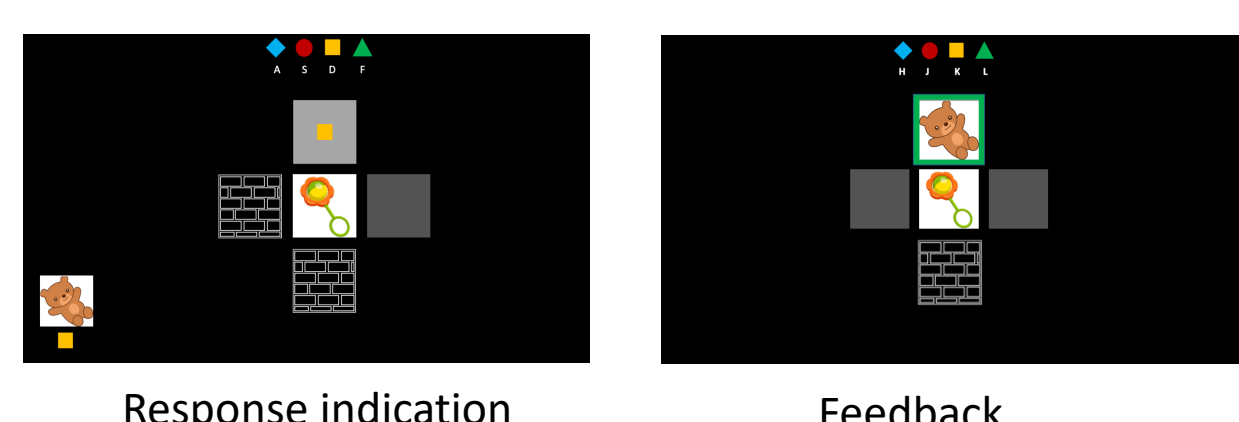
N_{TORUS, FIXED HALF} = 46
N_{TORUS, INTERLEAVED} = 44



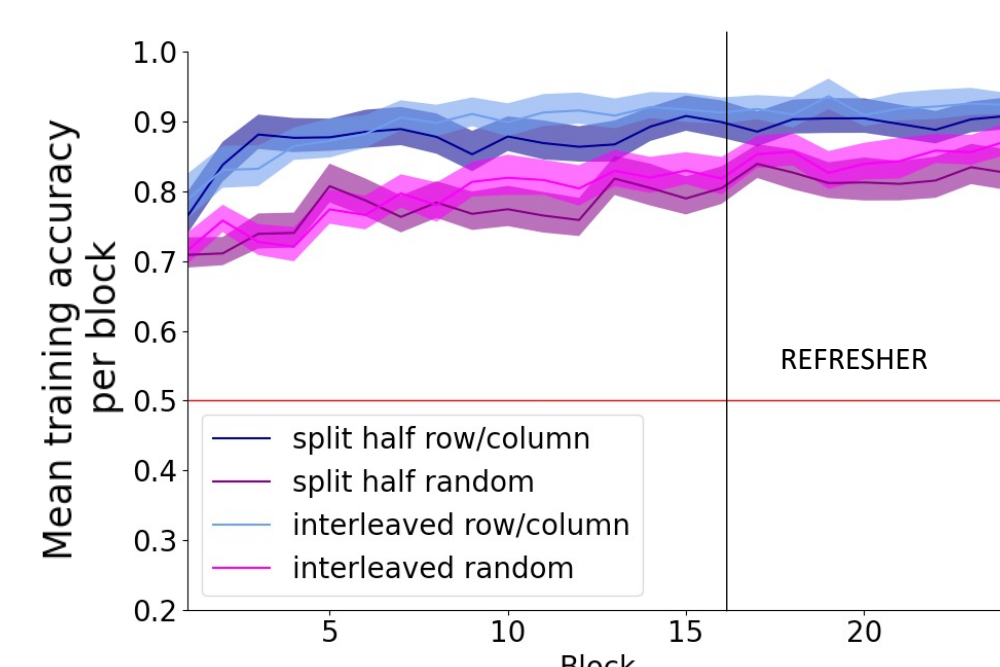
Results I: training

First day of training: all blocks experienced *twice*; 4 repeats per transition per block
Refresher: all blocks experienced *once*; 4 repeats per transition per block

5 x 5 GRID



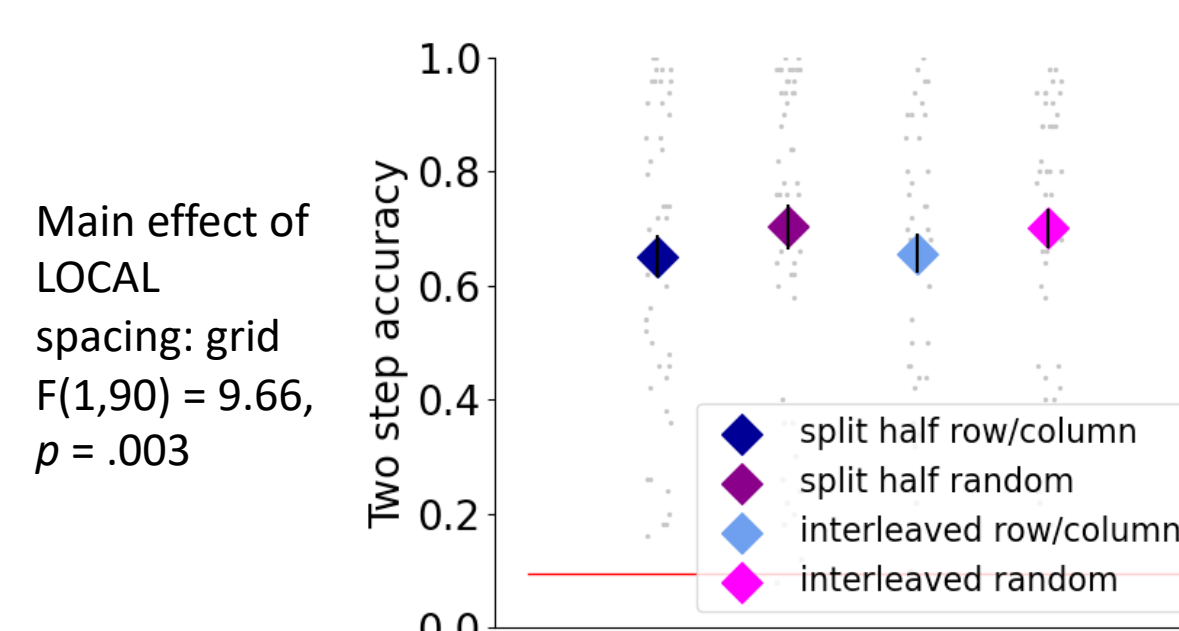
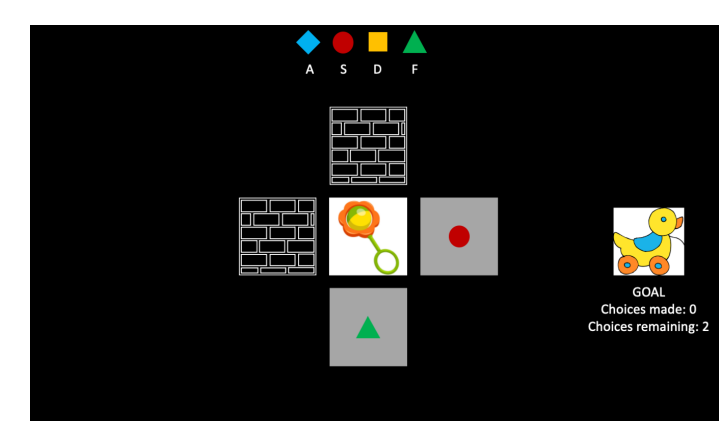
4 x 4 TORUS



Row/column > random during training in grid ($F(1,90) = 108.20, p < .001$) and torus ($F(1,88) = 77.92, p < .001$)

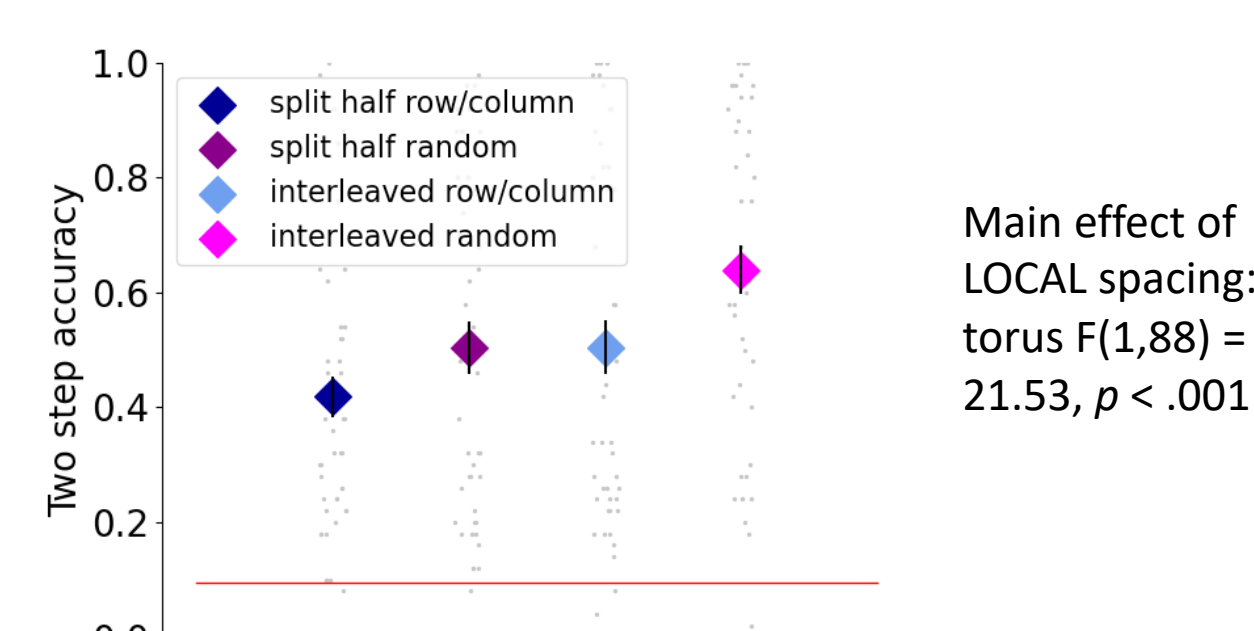
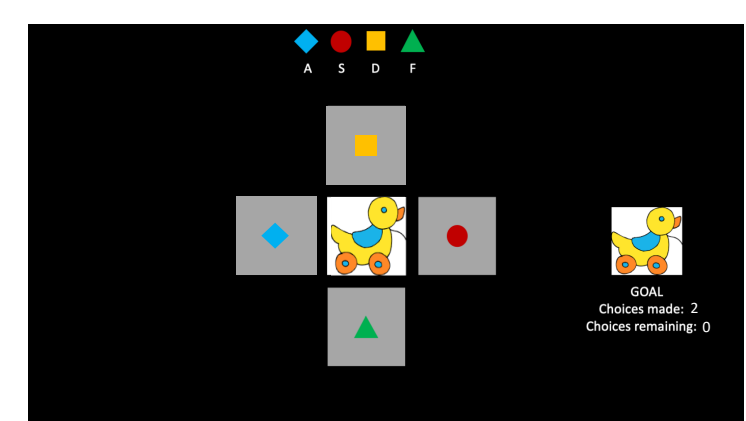
Results II: two-step navigation and proximity

5 x 5 GRID



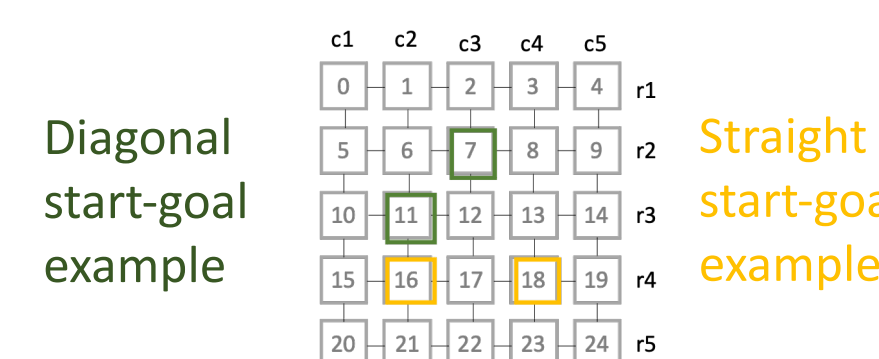
Main effect of LOCAL spacing: grid
 $F(1,90) = 9.66, p = .003$

4 x 4 TORUS

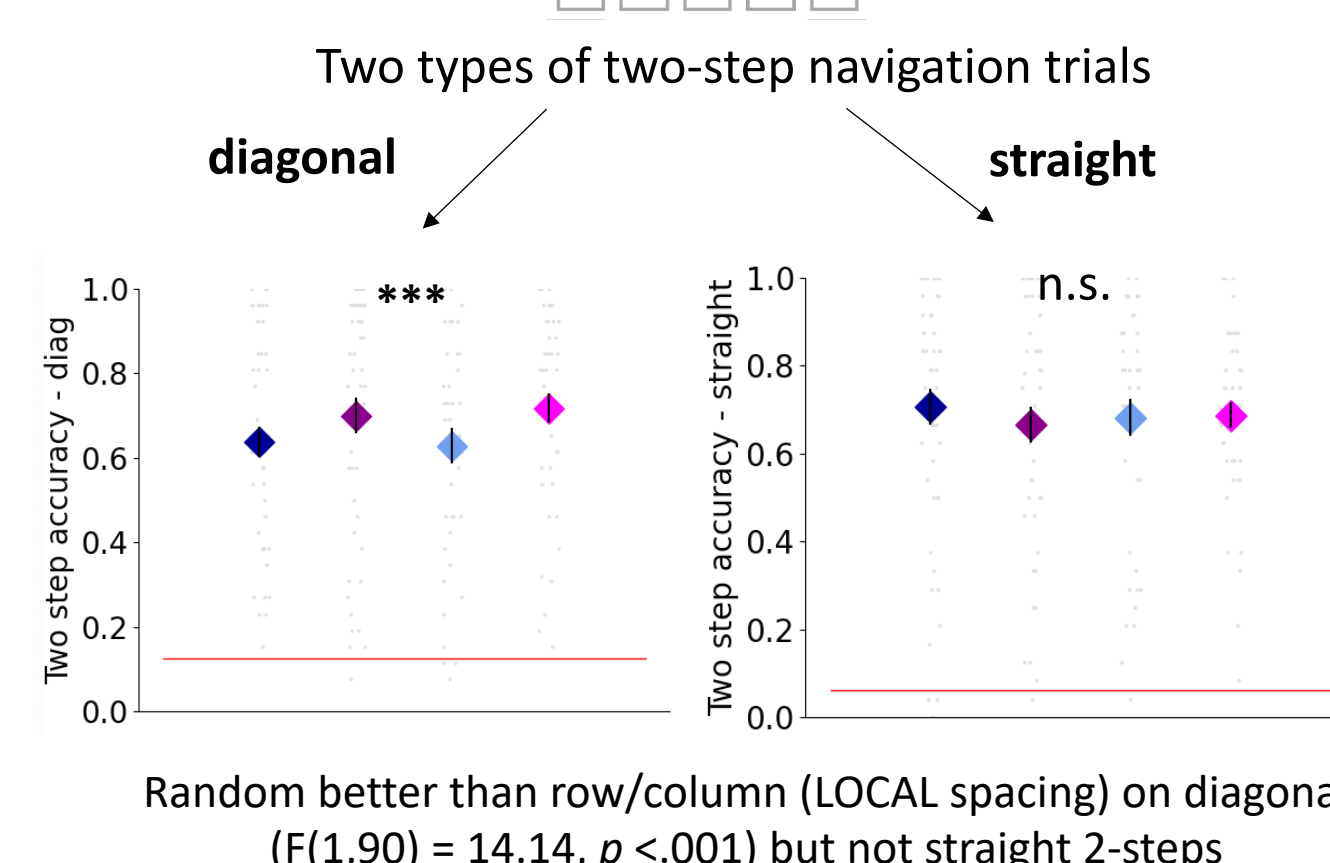


Main effect of LOCAL spacing: torus
 $F(1,88) = 21.53, p < .001$

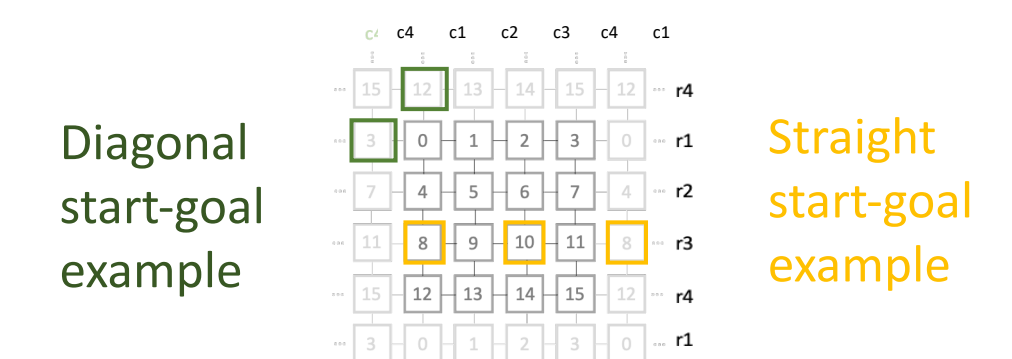
Random training associated with better 2-step navigation performance



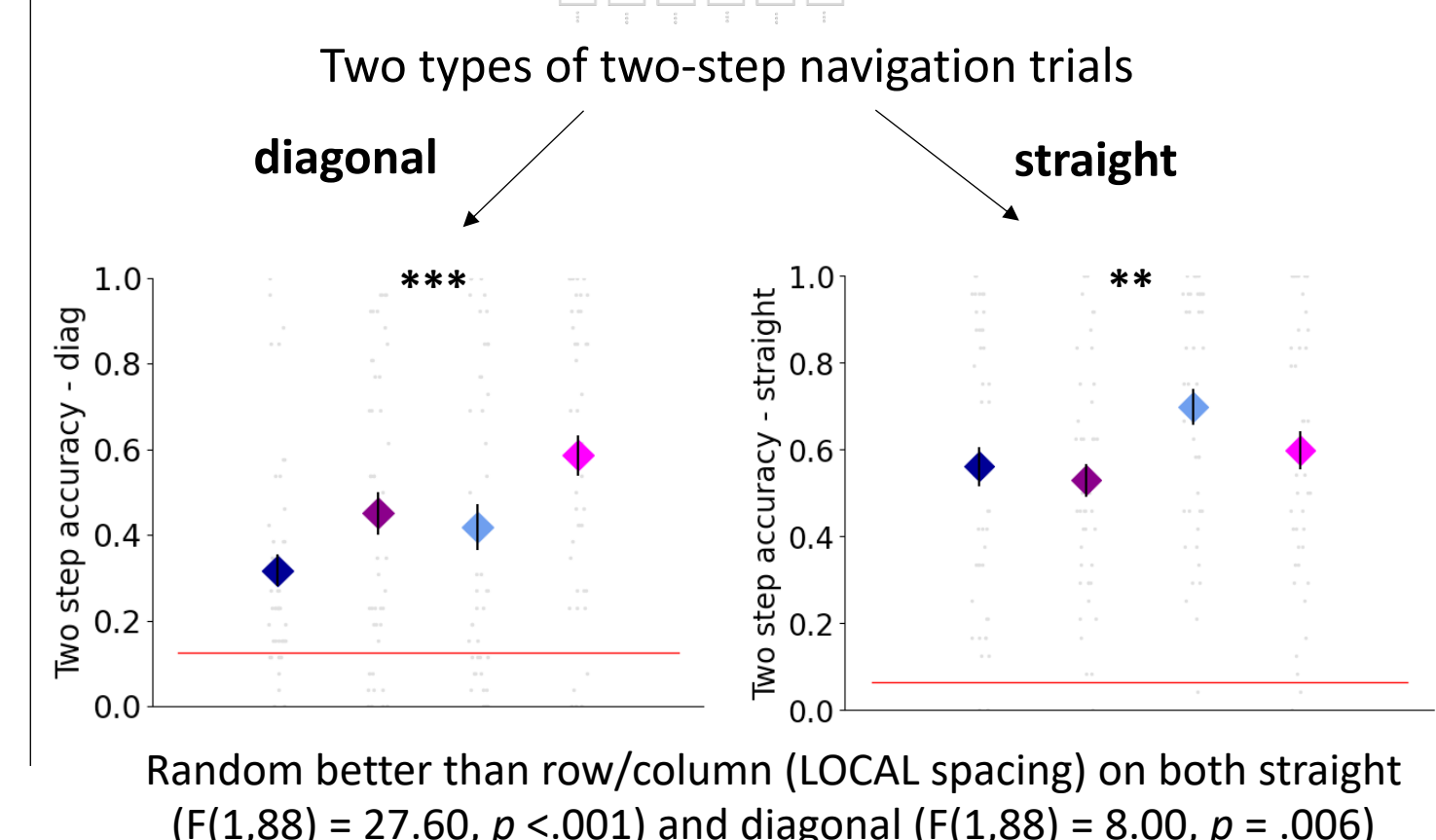
Straight start-goal example



Random better than row/column (LOCAL spacing) on diagonal ($F(1,90) = 14.14, p < .001$) but not straight 2-steps



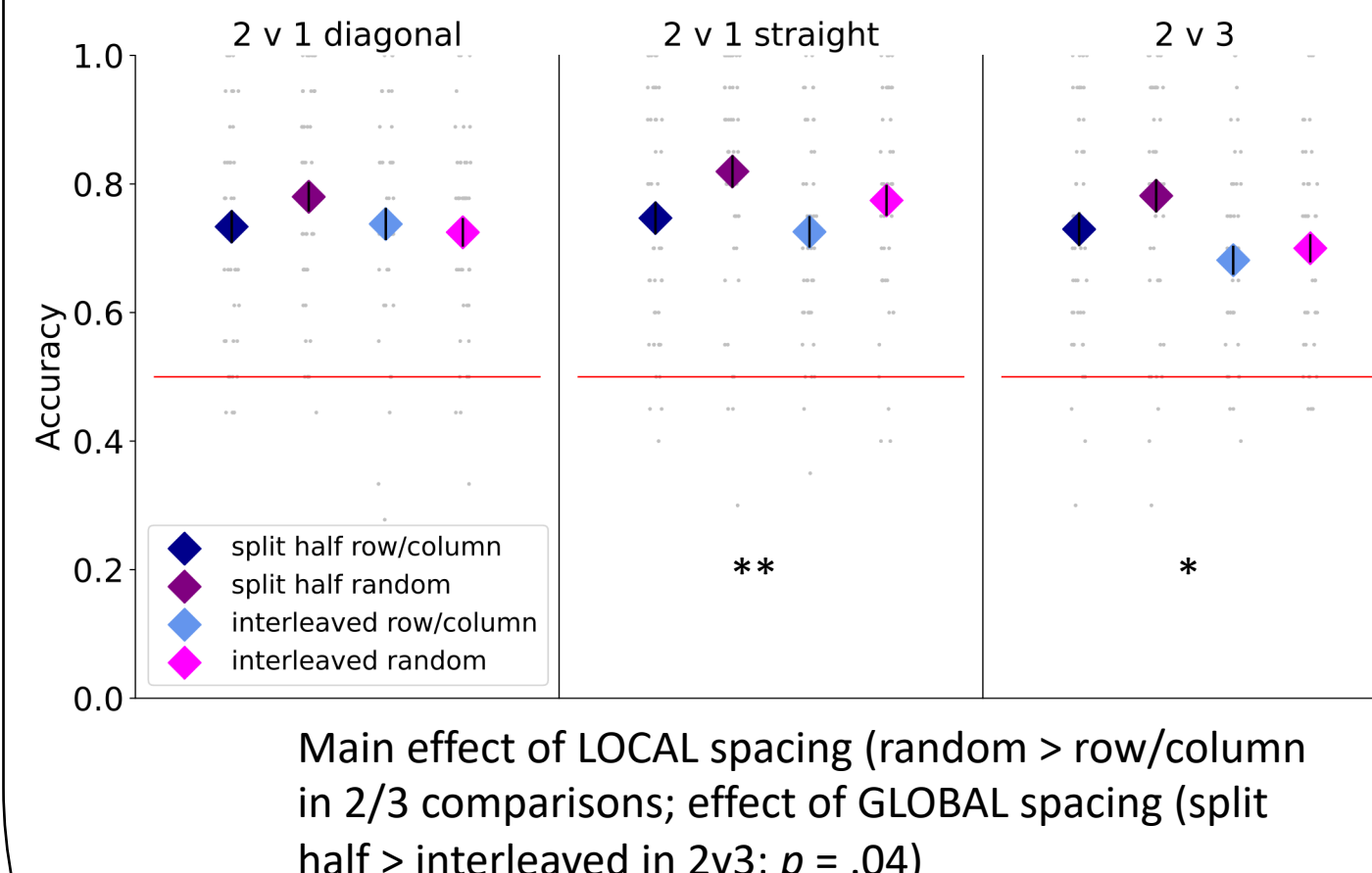
Straight start-goal example



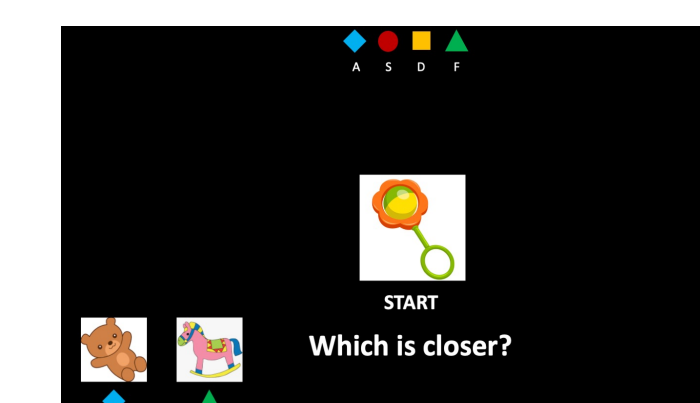
Random better than row/column (LOCAL spacing) on both straight ($F(1,88) = 27.60, p < .001$) and diagonal ($F(1,88) = 8.00, p = .006$)

Proximity judgements: 2AFC

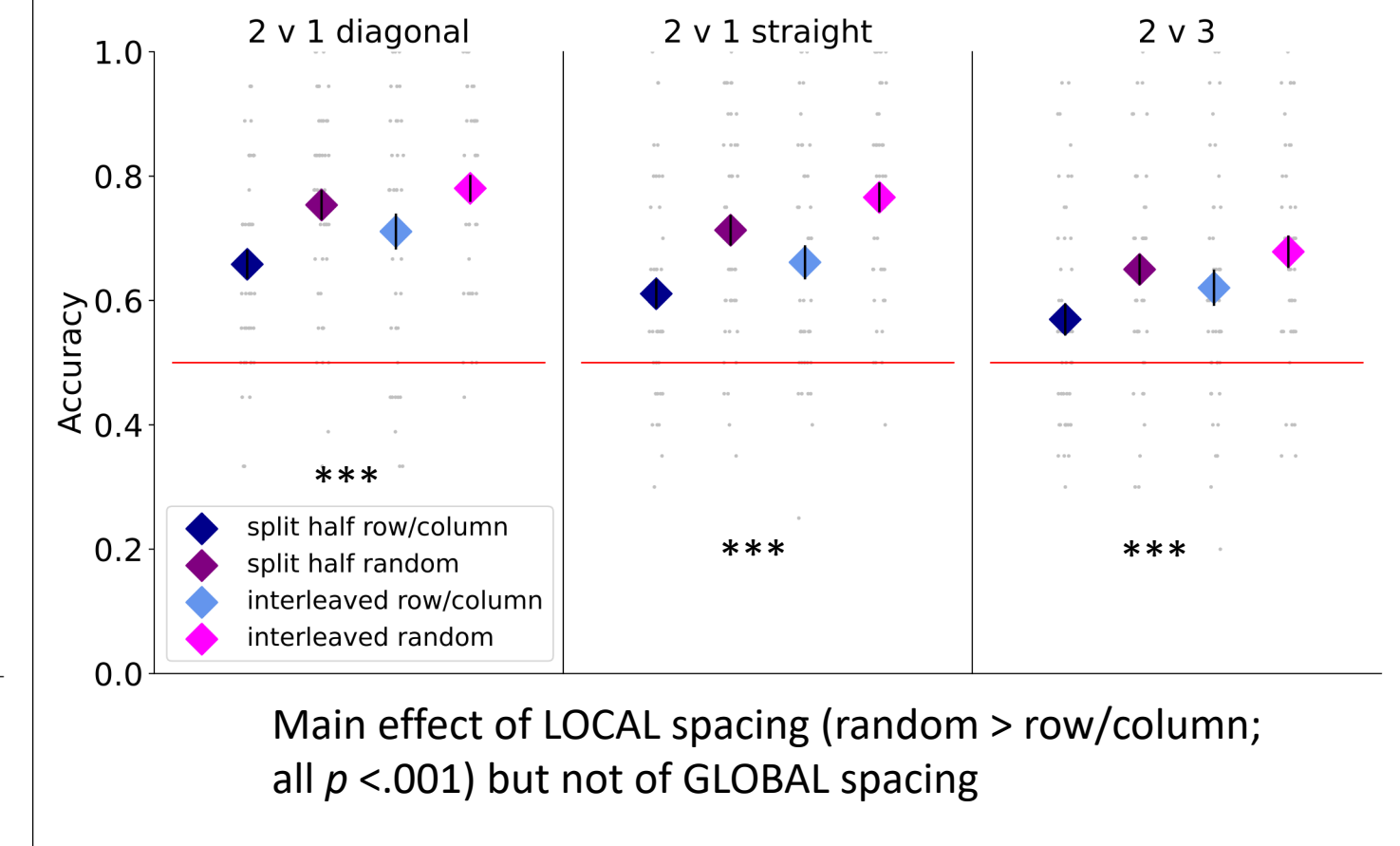
- 1 step away vs 2 steps straight
- 1 steps vs 2 steps diagonal
- 2 steps diagonal vs 3 steps diagonal



Main effect of LOCAL spacing (random > row/column in 2/3 comparisons; effect of GLOBAL spacing (split half > interleaved in 2v3; $p = .04$)



(no feedback)



Main effect of LOCAL spacing (random > row/column; all $p < .001$) but not of GLOBAL spacing

random training is associated with better map integration and more flexible deployment of learned information than row/column training (LOCAL manipulation) across tasks

Summary

- We manipulated both the content of a training block (LOCAL) and the order of training blocks (GLOBAL) when teaching people novel (spatial) cognitive maps
- The content of training blocks (LOCAL) had the biggest effect on learning
- Participants were better during training on the map where they were trained in a row/column (random walk) fashion in each block
- In contrast, navigation performance and proximity judgements were better in map with randomly sampled transitions in each training block
- This suggests that random walk type learning may *not* be the most efficient at teaching someone a flexible representation of a novel cognitive map

Future directions

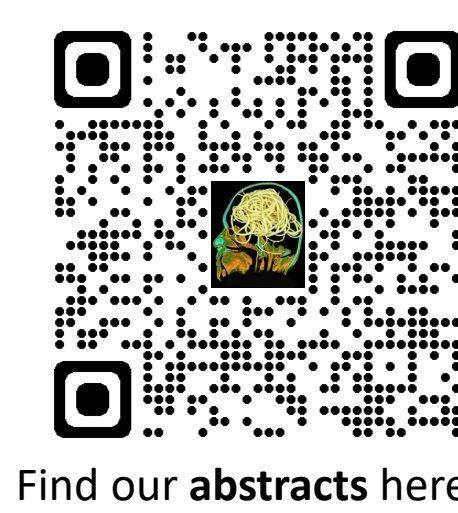
- Explain why learning disjointed transitions during training helps with flexible and robust cognitive map acquisition
- Use a neuroimaging version of the task (grid, fixed half) to help constrain the hypothesis space of what might underlie this effect and where in the brain it is implemented (presumably medial temporal lobe; N = 24/48 collected)

Acknowledgements

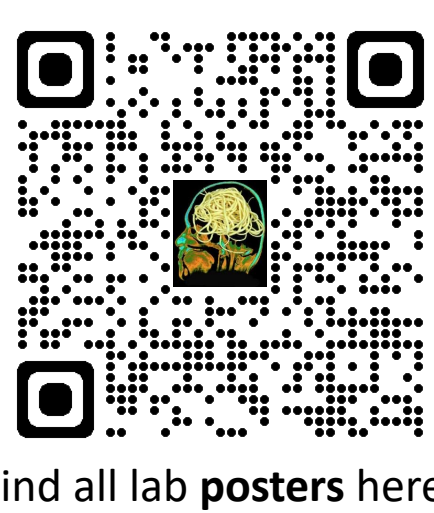
This work was supported by a Waverley Scholarship (The Queen's College) in collaboration with the Clarendon Fund to L.G., ERC award no. 725937 to C.S. and a UKRI Future Leaders Fellowship (MR/W008939/1) to H.C.B.



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