Curriculum learning for cognitive map formation for human navigation

Leonie Glitz
(leonie.glitz@psy.ox.ac.uk)
Department of Experimental Psychology
University of Oxford, UK

Helen C. Barron
(helen.barron@merton.ox.ac.uk)
MRC Brain Network Dynamics Unit
University of Oxford, UK

Christopher Summerfield
(christopher.summerfield@psy.ox.ac.uk)
Department of Experimental Psychology
University of Oxford, UK

Abstract:

Cognitive maps are complex associative mental structures that allow us to plan and navigate flexibly. Testing over 500 participants, we investigated how learning curricula impact the acquisition of cognitive maps. We found that the temporal spacing of spatially adjacent paired associate pairs during learning is a crucial factor in deciding how well humans learn new cognitive maps. Greater temporal spacing was associated with better navigation performance, both when spacing happened at the local (within block) and the global (across blocks) scale. We hypothesise that interference between adjacent paired associate pairs is driving this effect and propose a computational model to support this hypothesis.

Keywords: cognitive map; planning; navigation; curriculum.

Introduction

Cognitive maps help us plan and make decisions under rapidly changing goal demands (Behrens et al., 2018). We know little, however, about how maps are learned. Based on recent work (Dekker, Otto & Summerfield, 2022; Flesch et al., 2018), we set out to investigate the effect of different orderings of spatially adjacent paired associates (curricula) on cognitive map acquisition. Across two studies, we generated maps consisting of discrete objects arranged in a lattice (grid) or torus (wraparound grid). We trained participants on paired associates (directed transitions between adjacent states) under curricula that varied whether transition training was (1) locally structured, i.e. whether trials in a block were paired associates from the same row/column, and (2) globally structured, i.e. whether participants learned first one half of the paired associates and then the other. We then tested participants on multi-step navigation that required them to take several steps from a start to a goal state.

Exp. 1: global structure (3 steps)

In each of two separate experiments (Exp. 1a-b, N=437 total), we trained two groups of participants on paired associations drawn from a map (1a 4x4 torus; 1b 5x5 lattice). In each block of training, both groups experienced 1-step transitions drawn from a single row or column of the torus/lattice. In the fixed half condition (n = 153 torus, n = 73 lattice), all row blocks were experienced before column blocks or vice versa. In the interleaved (n = 136 torus, n = 75 lattice) condition, row and column blocks occurred alternatingly.

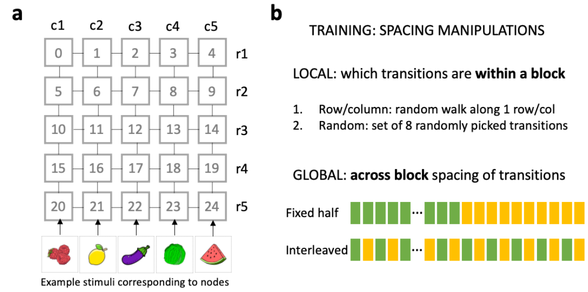

Figure 1. Task design. (a) Lattice layout. (b) Illustration of spacing manipulations.

In a subsequent test phase, we measured the accuracy of navigation to goals that were a knight's move (three steps) away from a starting location. We found an effect of our global manipulation in the torus but not the lattice: while the torus fixed half condition group performed better on three-step navigation than the torus interleaved group (U = 12324.0, p = .007; Fig 2a), there was no difference between the lattice cohorts (U = 2867.5, p > .05; Fig 2b).

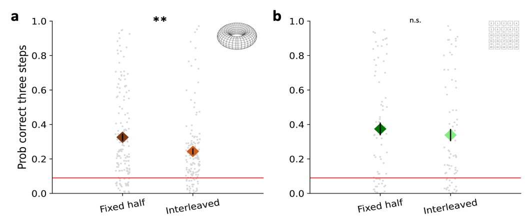

Figure 2. Fixed half condition participants are better at three step navigation than interleaved participants in the torus (a), but not the lattice (b; ** p<.01)

Exp 2.: global and local structure (2 steps)

A salient feature Exp1 is that participants found the 3-step navigation task very hard. To increase navigation accuracy and investigate the effect of local temporal spacing (in the lattice condition), we modified the layout of the training task and the duration of training. We ran two within-subjects experiments, now training each participant on two 5x5 grids in succession (Fig 1a). We crossed local and global factors in a 2 x 2 mixed design. Each cohort (n ~ 50), learned one map per level of the local manipulation (Fig 1b; map A: single rows/columns per block; map B: randomly drawn across the grid; within-subjects). We trained two cohorts, one which learned both maps in a split half fashion and one which learned both maps in an interleaved fashion (global manipulation; between-subjects). The experiment lasted three days, with participants learning one map a day and then completing a refresher and test on day 3. A mixed ANOVA revealed a significant main effect of our local manipulation on two-step navigation accuracy ($F(1,93) = 10.97$, $p = .001$), with the random condition outperforming the row/column condition in both fixed half and variable half settings (Fig 3b). Interestingly, this effect was reversed during training, with participants being significantly better in row/column than random training ($F(1,93) = 69.65$, $p<.001$, Fig 3a). Replicating Exp.1b, we saw no effect of the global (fixed vs. variable halves) curriculum on the lattice in this study.

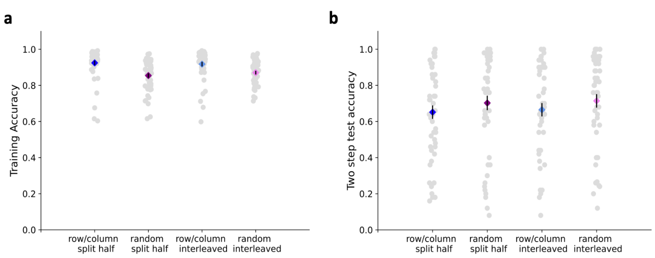

Figure 3. (a) Row/column training accuracy is higher (b), but the random condition is associated with better two-step navigation performance (local manipulation)

Computational Model

Finally, we sought to capture these effects in a computational model. Our model combines a state-action-state (SAS') model and a state-state association network (SS') to simulate multi-step planning.

SAS' model. The SAS' model is an MLP with one hidden layer (60 units), 2*N two-hot (start and goal) input units and 2 output units, which learns to map two object states (random vectors) onto a vector describing their relative position in the map (heading direction, bounded between 1 and -1).

SS' model. The SS' map is initialised to small random weights. For trial t from node i to node j

$$SS_{i,j,t} = SS_{i,j,t} - 1 + \alpha * (R - SS_{i,j,t} - 1)$$

Importantly, $R \in [0,1]$ is an upper bound on association strength. It is modulated by interference provided as a function of the trial history

$$R = 1 - \frac{\sum_{k=24}^{k=0} E_{i,k} + \sum_{k=24}^{k=0} E_{j,k}}{4}$$

where E is an NxN matrix in which $E_{i,j}$ is set to 1 on trial t and which decays uniformly with decay rate λ. Thus, S-S learning is subject to more interference when a state has many recent associates. Navigation choices can be made by heading towards the goal (repeatedly calling the SAS network) or by retrieving which adjacent state is closest to the goal from the SS model, and heading in that direction. Thus, our model allows for purely vector based (SAS') and association based (SS' + SAS') navigation (e.g. Edvardsen, Bicanski & Burgess, 2020).

We find that SS' based navigation can capture both local and global interference (Fig 4a, c). However, we posit that SS' based navigation is more useful in torus (Fig 4b) than lattice (Fig 2d, 4b) because pure heading direction is misleading in the former case. Our model can thus capture the effects of both Exp1 and Exp2.

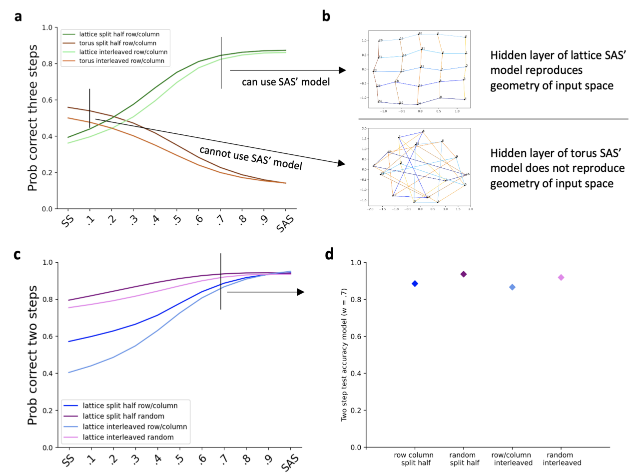

Figure 4. Simulated navigation performance across a range of integration values between SS' and SAS' based navigation (a) replicates global effect in lattice and torus, (d) both (global+local) effects in lattice. (b) Input space reproduced in SAS' hidden layer in lattice but not torus, which affects the usefulness of the SAS' model during navigation (see Fig 4a). (d) Figure 3b is replicated with an integration value of .7.

Discussion

We show two curriculum effects in the learning of cognitive maps. Firstly, when learning to navigate in a torus, we see a global benefit for training all rows before all columns or vice versa, relative to interleaving blocks. Secondly, in a lattice we see a local benefit in training random transitions rather than blocks of rows and columns. These apparently contradictory findings can be captured by a computational model that combines transition- and vector-based navigation, but assumes that temporally local interference limits associative learning between states in an SS' transition function.

Acknowledgments

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