Modular networks with random projections for high-capacity associative pattern and sequence memory

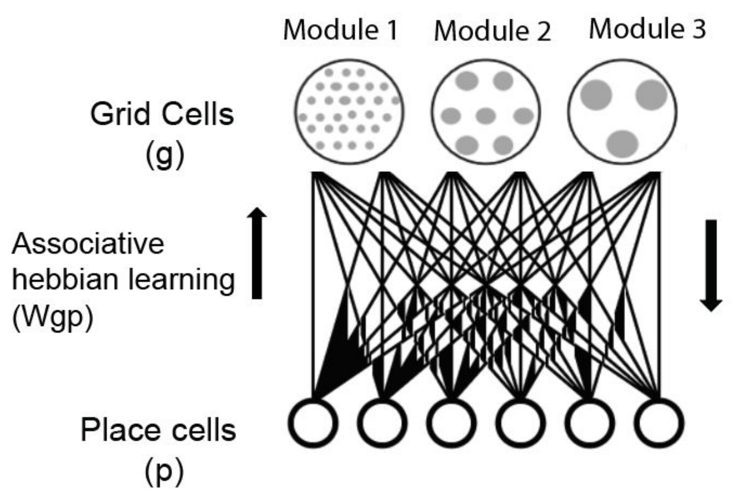
Sugandha Sharma, Sarthak Chandra, Rishidev Chaudhuri, Mirko Klukas, Ila R. Fiete

Background

How does hippocampus (HC), vastly outnumbered by the number of potential patterns in cortical neurons, store memories of experiences encoded by cortex?

- HC assumed to be associative memory, but classical models like Hopfield network store, robustly recall only ~N arbitrary patterns with N neurons.
- Input grid cell states are very large in number, but not auto-associative memory states. Can robust error correction be achieved by HC?
- We propose an entorhinal-HC (EC-HC) attractor network using the theme of modular input structures with random forward projections and learned return weights that exhibits exponentially many robust (large-basin) fixed points.

Grid-Place network



Multiple grid modules of different periods (λ) project randomly to a layer of binary place cells. Return projections: pairwise Hebbian plasticity.

$$W_{pg} \sim N(0,1)$$

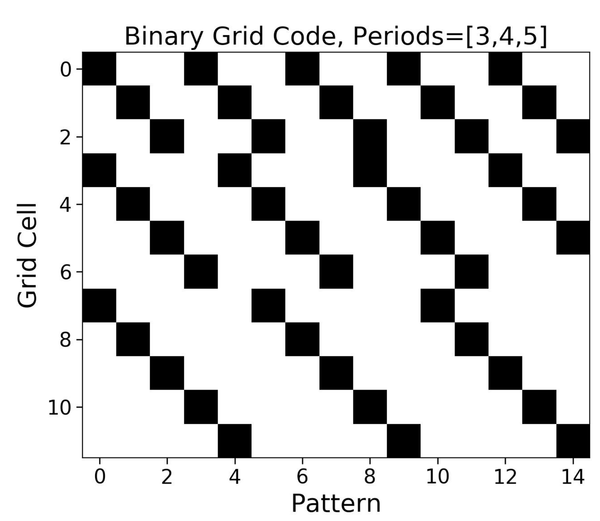
$$W_{gp} = (1/n)\sum_i^n g_i \cdot p_i^T$$

Dynamics:

$$g(t) = f\,[W_{gp} * p(t)]$$

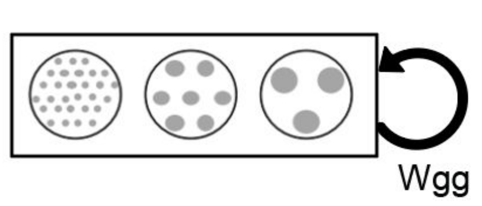
$$p(t+1) = sign\,[W_{pg} * g(t)]$$

where f enforces modular grid code



GC states used for training

Baseline model



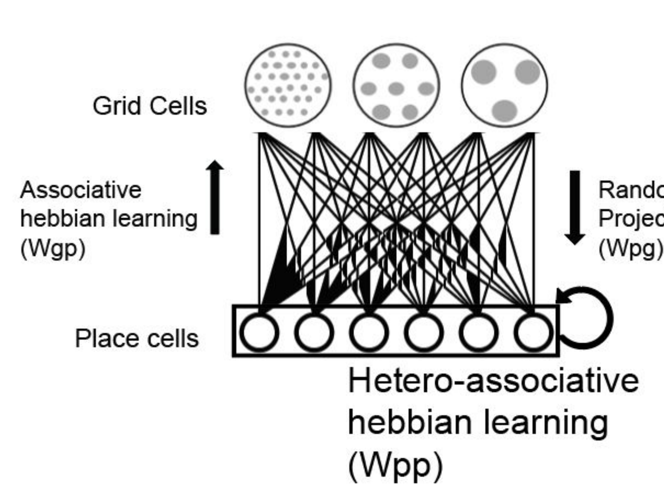
Wgp*Wpg in the Grid-Place network approximates Wgg in the baseline model that stores associations from a grid state to itself.

$$W_{gg} = (1/n)\sum_i^n g_i \cdot g_i^T \quad ; \quad g(t+1) = f\,[W_{gg} * g(t)]$$

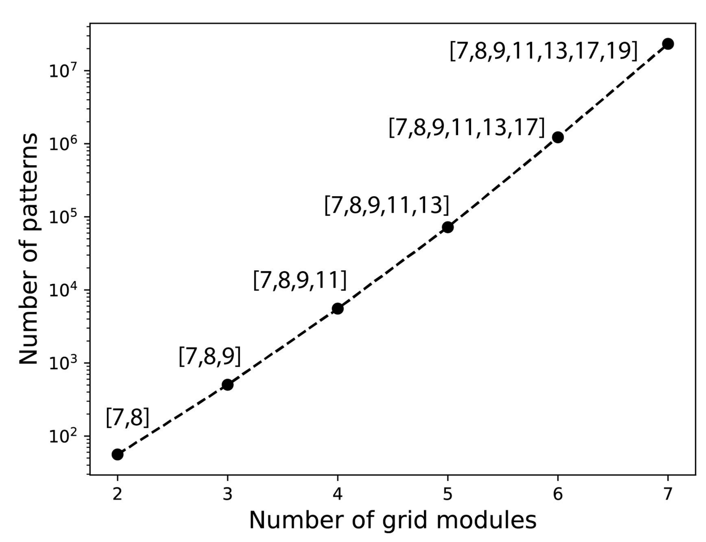
Sequence model

To learn 1D sequences, we introduce heteroassociative hebbian learning within place cells to learn the mapping from a given state to the next.

$$W_{pp} = (1/n)\sum_i^n p_i . p_{i-1}^T$$

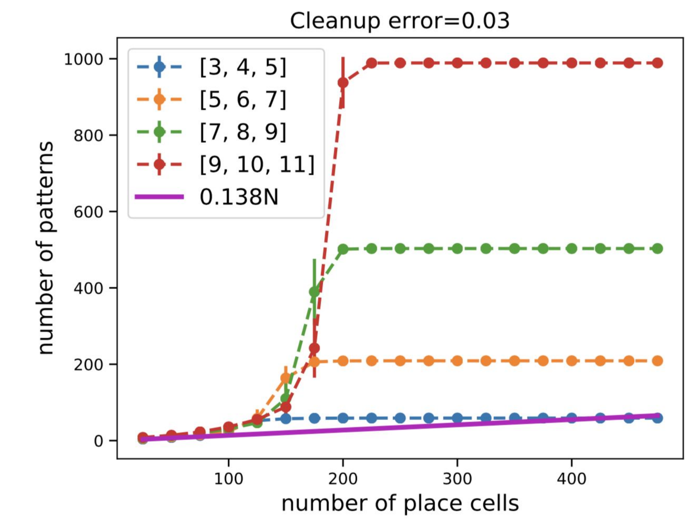


Binary Grid-Place network has high capacity

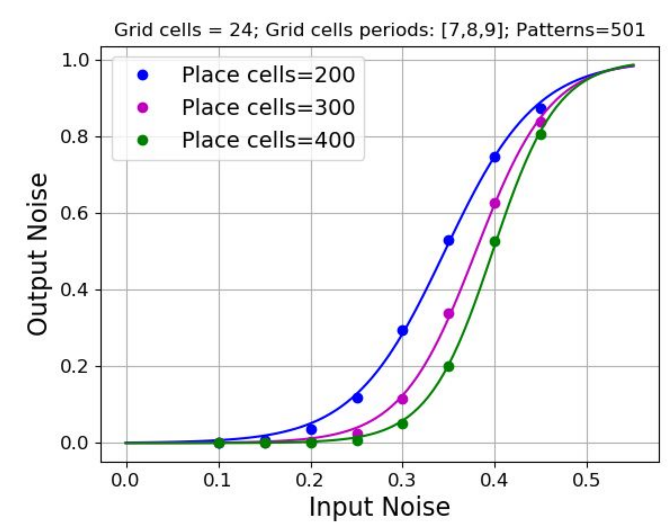


(Labels beside data points show module periods.)

Capacity is exponential in the number of grid cell modules.

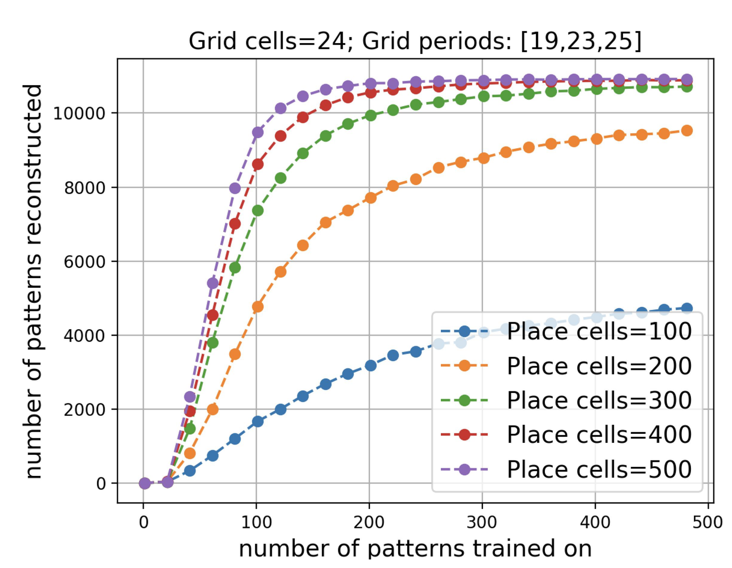


Network has a high capacity (pink: hopfield net). Given a critical number of place cells, the network stores all patterns for arbitrarily large grid periods.



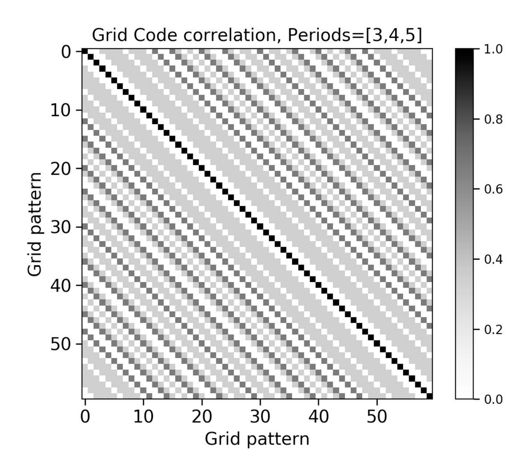
Despite storing a large number of patterns, the network reconstructs all states with high accuracy from highly corrupted initial HC states.

Grid-Place network generalizes its stored inputs to unseen states



Network creates stable EC-HC states around every pattern in the grid coding space despite training over its small subset. In the limit of a large number of place cells, the size of this subset is $m \times \lambda_{max}$.

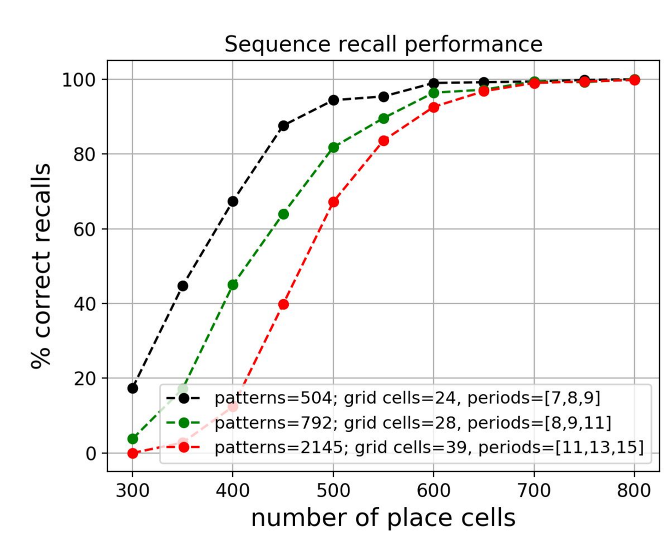
In the baseline model, Wgg converges after training on $m \times \lambda_{max}$ states due to periodic and translational invariant properties of the grid code.



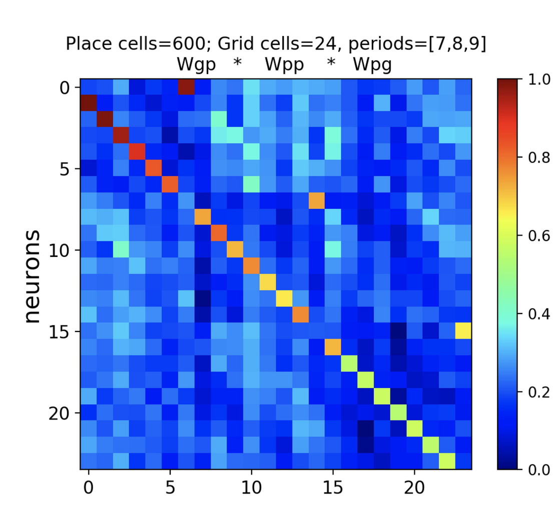
Grid code is Translationally Invariant (TI)

$$g(x) = W^x g(0)$$
$$d(x,\ x+\Delta x) = constant$$
W is grid state transition matrix

Sequence model learns 1D sequences

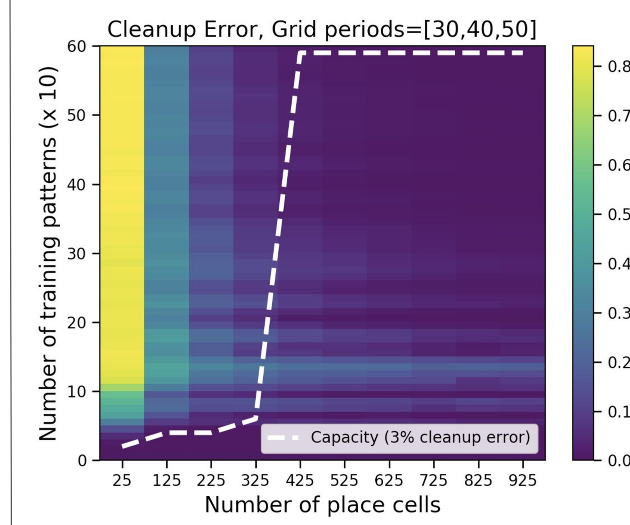


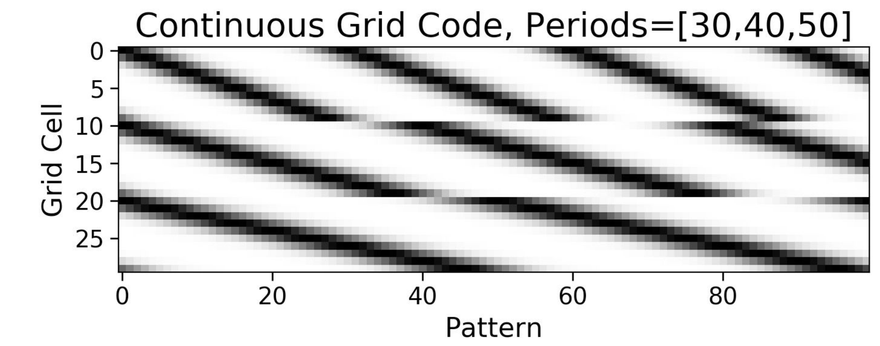
The model recovers arbitrarily long 1D sequences given a critical number of place cells



Model approximates the grid state transition matrix

Analog Grid-Place network has high capacity



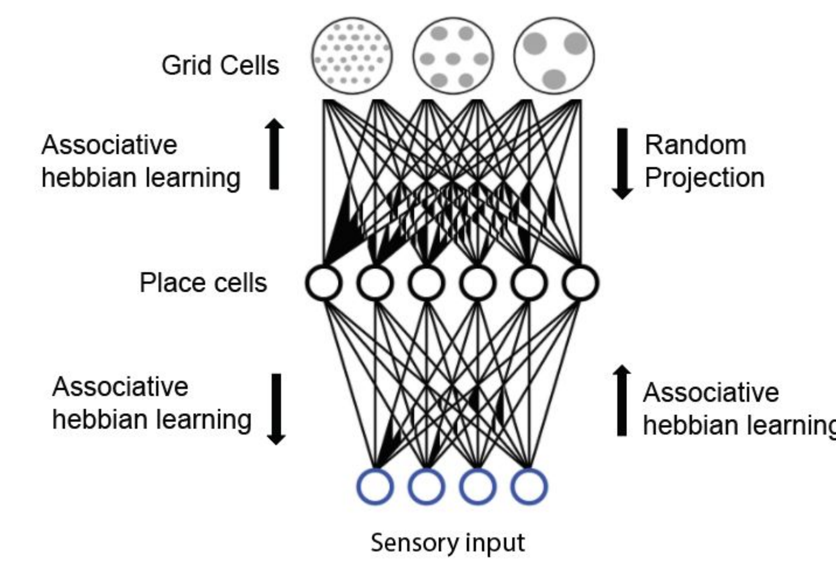


Network with analog grid code exhibits exponentially many robust fixed points similar to the binary grid-place network.

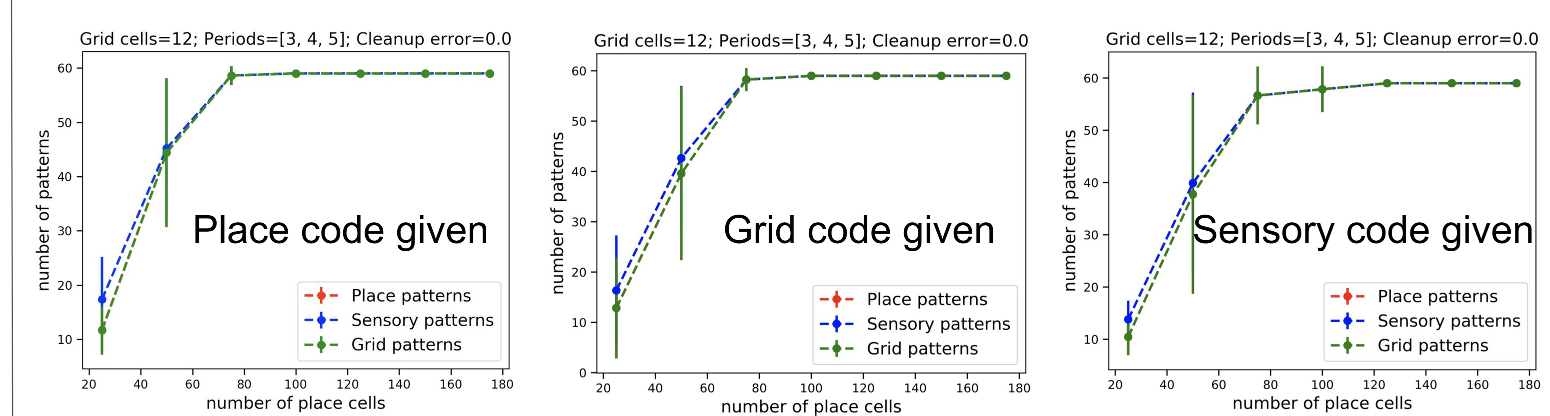
Adding sensory input to Grid-Place network enables storage of arbitrary states

Place cells construct conjunctions between sensory experience and spatial coordinates [4], so we add a one-hot sensory input stream to HC.

Dynamics are modelled such that place cells are recovered alternately from grid states and sensory states.



This architecture implements an error correction mechanism for grid coding states and sensory states. Place, grid and sensory states form fixed points of the network, and all stored states can be recovered given any one of them as shown below.



Summary

- The Grid-Place network is a high capacity system with robust error-correction of exponentially many states.
- Training HC to EC weights over small subset of contiguous grid states results in a large number of additional, large-basin HC fixed points.
- Addition of hetero-associative recurrent synapses within HC leads to learning of the grid state transition matrix and the potential for high-capacity sequence memory.
- The combination of structured grid states and sensory inputs in HC enables storage and robust recollection of a large number of grid, place and sensory states from partial cues.

Future work

- Characterize the information capacity of the network.
- Extend our model to 2D grid cells to enable learning of 2D trajectories.

References

[1] Hillar, C. J., & Tran, N. M. (2018).
[2] Chaudhuri, R., & Fiete, I. (2019). [3] Krotov, D., & Hopeld, J. J. (2016).
[4] Manns, J. R., & Eichenbaum, H. (2006). [5] Burak, Y., & Fiete, I. R. (2009)