A THEORY OF MEMORY STABILITY IN HIPPOCAMPUS AREA CA3

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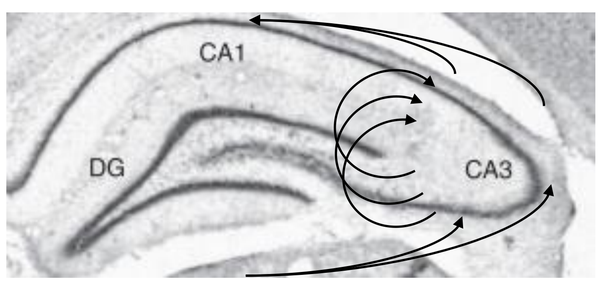
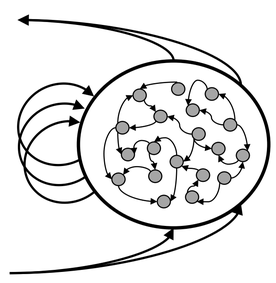
Hippocampal area CA3 has been suggested to implement auto-associative memory [1-6].





We provide a new analysis of the conditions for high-capacity storage of stable memories using biologically plausible recall dynamics.

network dynamics

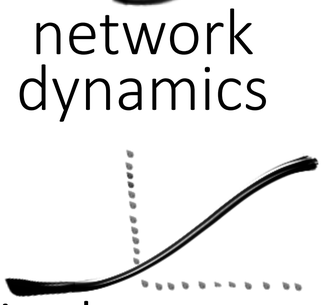
A network with nonlinear voltage dynamics:

$$\dot{\boldsymbol{v}} = -\boldsymbol{v} + W g(\boldsymbol{v}) - \theta$$

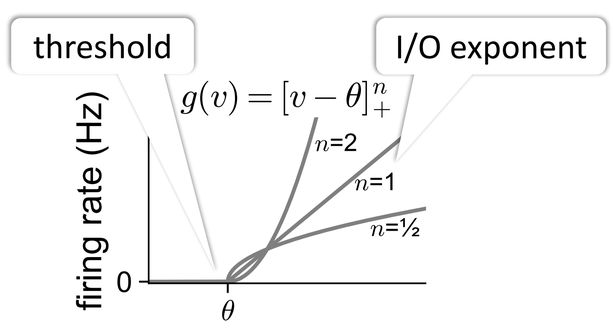
Memories are stable fixed points of the dynamics:

$$\boldsymbol{r}^{\mu} = g(W\boldsymbol{r}^{\mu} - \theta)$$

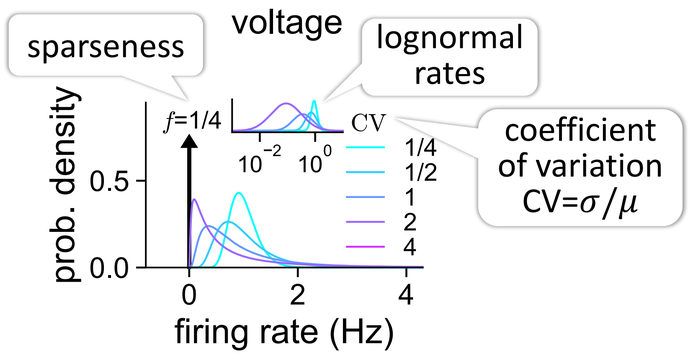
How do single-neuron properties support stable recall of memories?

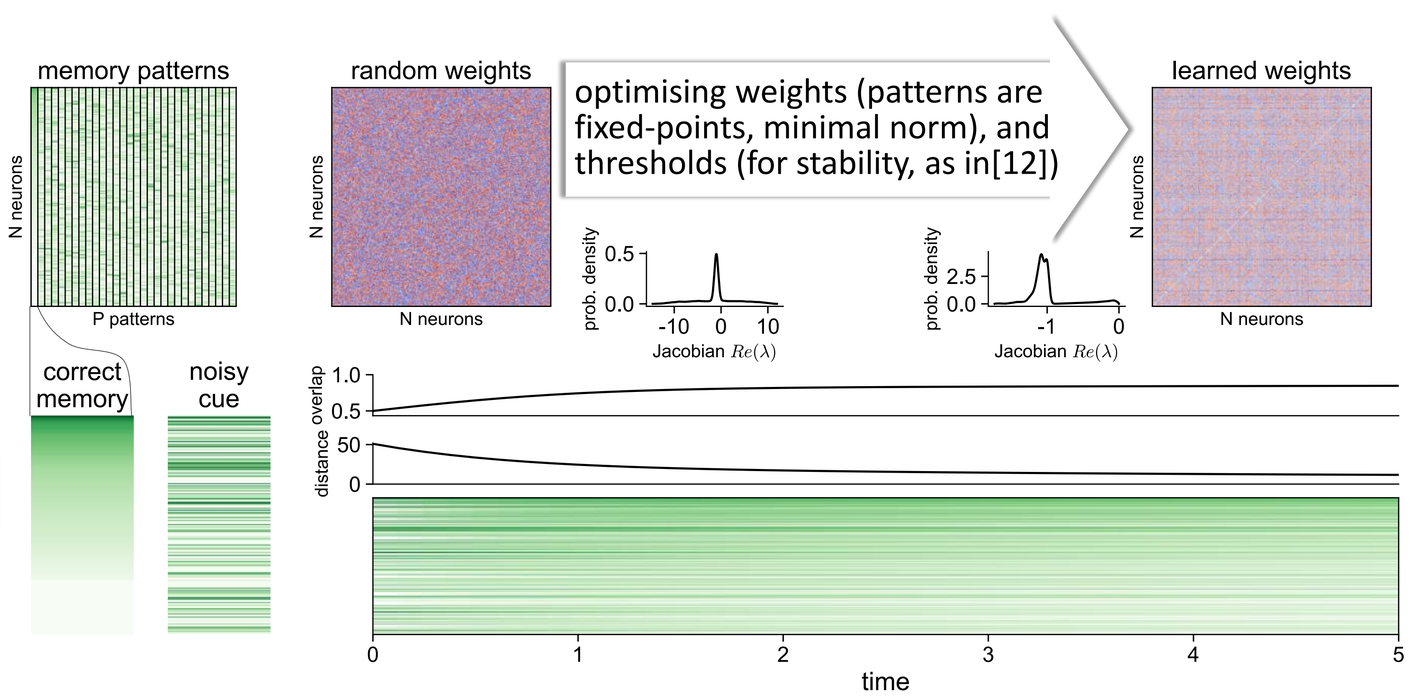


single-neuron nonlinearity



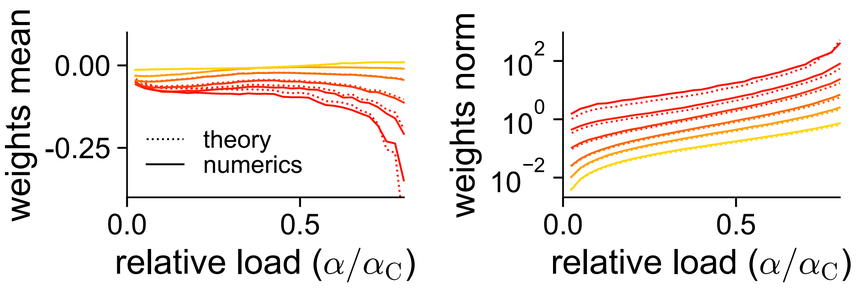
memory patterns





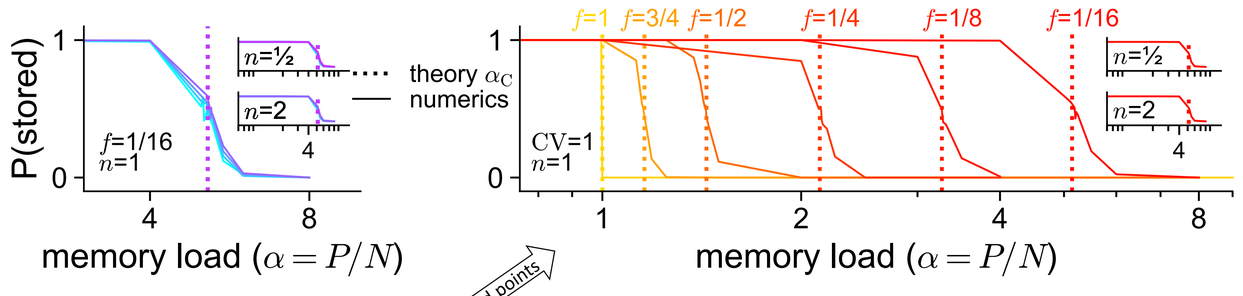
mean-field theory

Mean-field theory (à la [13-15]) fully describes the ability to store patterns as fixed-points.

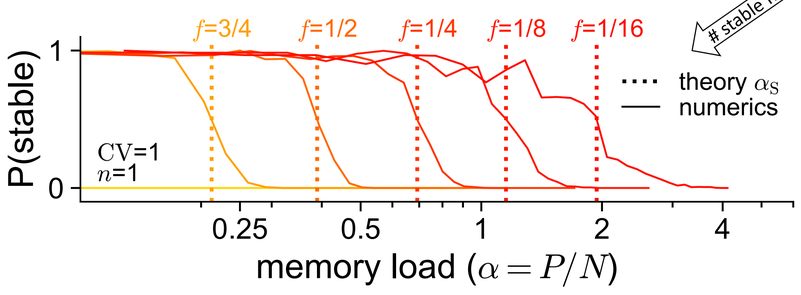


Number of fixed-points is invariant to CV and single-neuron non-linearity, depends only on sparseness (extending [15]).

Non-trivial stable memories regime; e.g., no stable fixed points for $n \geq 1$ and $\theta \geq 0$.



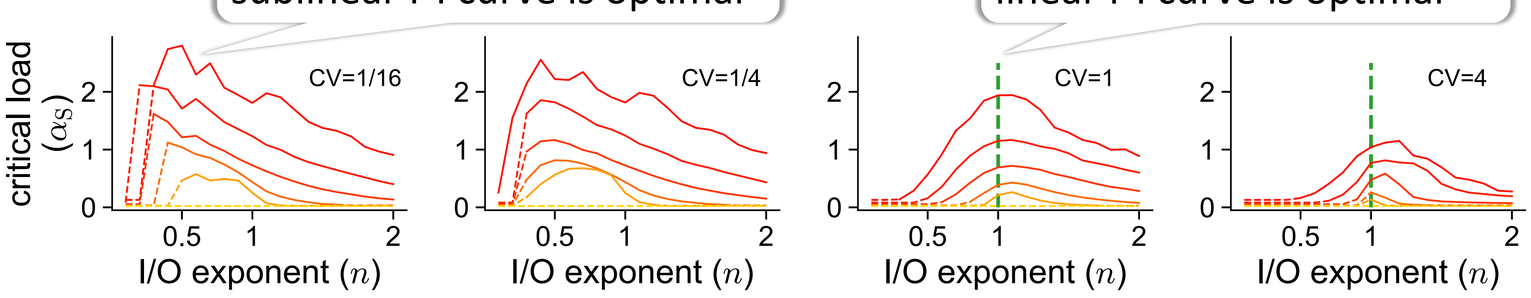
In the stable regime, memories are all stable up to a critical load.



stable fixed points ≠ # fixed points

At low firing rate CV, a sublinear f-I curve is optimal

At high firing rate CV, a linear f-I curve is optimal



technical novelty

The Hopfield model [7] and various extensions [8-11] all use *gradient-dynamics* to store stable memories in attractor networks: $\dot{r} \propto -\nabla E$

- ✓ stable low energy memories
- ✗ non-biological dynamics

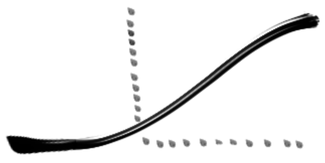
Our attractor networks has:

- ✓ biological plausible dynamics
- ✗ possibly unstable memories
- ✓ the regime where memories tend to be all stable provides new experimentally testable predictions

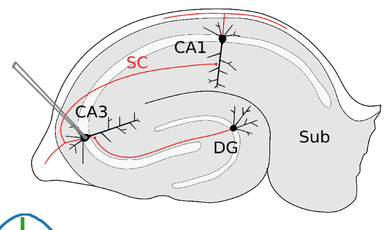
experimental data analysis

Due to its high-CV memory patterns, CA3 pyramidal neurons should have near-linear f-I curves, and negative threshold (i.e., should spontaneously fire if recurrent connections are suppressed)

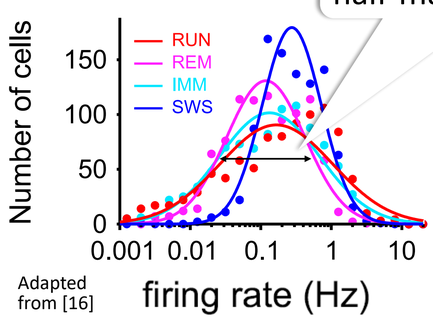
analysis of place cell activity in CA3 of freely moving rates [16-17]

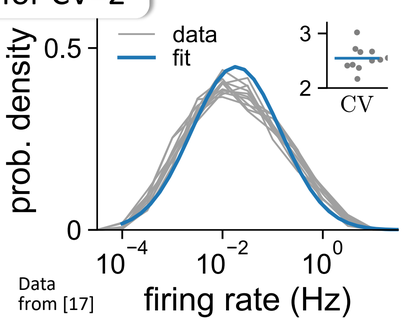


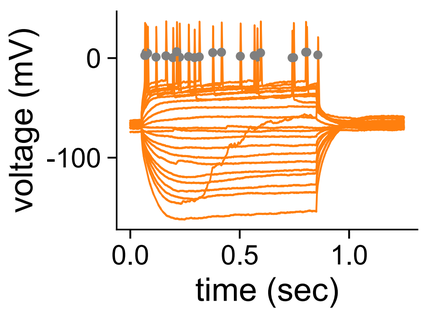
Recording activity from mice CA3 pyramidal neurons in in-vitro whole-cell experiments, we find near-linear f-I curves, and see similar results in existing in-vivo data [18].

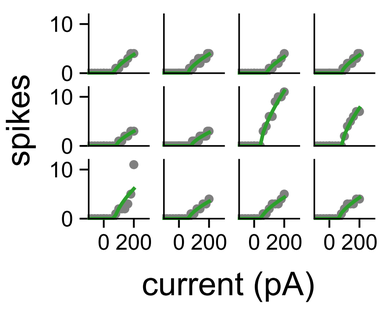


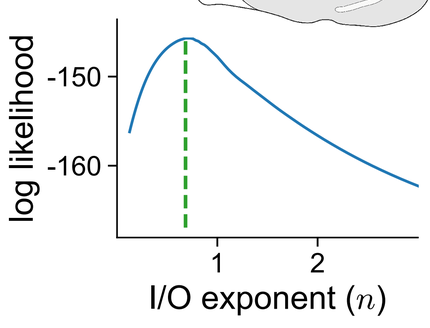
Expected full-width half-maximum for CV=2











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