

Learning and memory with complex synapses

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Background

Storage capacity of Hopfield networks

- Hopfield capacity $\propto N$ requires unbounded synaptic strengths.
- Bounded synapses \implies capacity $\propto \log N$.
- Trade-off between learning & remembering.
- Can be ameliorated by using metaplasticity in complex synapses

Complex synapses

Not just a synaptic weight.

Take into account state of molecular network.

Cascade and multistate models

Two models of metaplasticity in complex synapses

Framework

Markov processes

We have two Markov processes describing transition probabilities for potentiation and depression.

Memory curve

Reconstruction error.

Upper bounds on performance

Area bound

We can show that the area under the SNR curve is bounded:

$$A \leq \sqrt{N}(n-1).$$

This leads to a bound on the lifetime of a memory:

$$\text{SNR}(\text{lifetime}) = 1 \implies A \geq \text{lifetime}.$$

This is saturated by a molecular network with the multistate topology.

Ordering the states

Let \mathbf{T}_{ij} be the mean first passage time from state i to state j .
Kemeny's constant

$$\eta = \sum_j \mathbf{T}_{ij} \mathbf{p}_j^\infty,$$

is independent of the initial state i .

[Kemeny and Snell (1960)]

We define:

$$\eta_i^+ = \eta = \sum_{j \in \text{strong}} \mathbf{T}_{ij} \mathbf{p}_j^\infty, \quad \eta_i^- = \eta = \sum_{j \in \text{weak}} \mathbf{T}_{ij} \mathbf{p}_j^\infty.$$

These measure “distance” to the strong/weak states. They can be used to put the states in order (increasing η^- or decreasing η^+).

Envelope memory curve

References

 J.G. Kemeny and J.L. Snell, *Finite markov chains*. Springer, 1960.