A memory frontier for complex synapses
Subhaneil Lahiri and Surya Ganguli
Department of Applied Physics, Stanford University, Stanford CA

Background

Synaptic learning and memory

Learning and memory involve the interplay between neuronal activity and synaptic plasticity.

Neuronal activity

Synaptic efficacy

Depression

Plasticity

Synaptic efficacy

Additive weights, binary switch...

Negative attractors

Update sampling...

Spike rate, STDP...

Therorists frequently neglect the question of how plasticity is implemented. A synapse is often modeled as a single number: the synaptic weight.

Complex synapses

In reality, a synapse is a complex dynamical system. We will describe a synapse by stochastic processes on a finite number of states, M.

Potentiation and depression cause transitions between these states.

Storage capacity of synaptic memory

A classical perception, when used as a recognition-memory device, has a memory capacity o(N), the number of synapses.

However, this requires synapses' dynamic range to be also o(N).

If synaptic efficacies are linked to a fixed dynamic range, -- strong tradeoff between learning and forgetting -- due to new memories overwriting old.

If we wish to store new memories rapidly, then memory capacity is o(log N).

To circumvent this tradeoff, it is essential to enlarge our theoretical conception of a synapse as a single number.

Cascade and serial models

Two example models of complex synapses with different memory storage properties.

Synaptic state transition models

Assumptions:

- Candidate plasticity events occur independently at each synapse,
- Each synapse responds with the same state-dependent rules,
- Synaptic weight takes only two values.

Recognition memory

The synapses are given a sequence of patterns (potentiation & depression) to store.

Later: presented with a pattern. Has it been seen before?

Memory curve

Ideal observer approach: read synaptic weights directly -- upper bound on what could be read from network activity.

Measure overlap between \( \langle w(t) \rangle \), the A-vector element of synaptic strengths, and \( \langle w(t) \rangle \), the pattern we are testing.

Performance measured by signal-to-noise ratio, with mean recall time:

\[
\text{SNR} = \frac{\langle w(t) \rangle \cdot \langle w(t) \rangle}{\sqrt{\text{Var}(\langle w(t) \rangle)}}
\]

Proven upper bounds

Proven upper bounds on initial SNR and late time tail -- upper bound on memory curve at any time.

Initial SNR: deterministic binary synapse

Late times: serial model with "sticky" end states

The memory envelope

Proven upper bounds on initial SNR and late time tail -- upper bound on memory curve at any time.

Initial SNR: deterministic binary synapse

Late times: serial model with "sticky" end states

No model can ever go above this envelope. Is it achievable?

The memory Frontier for Complex Synapses:

- Comparing the upper bound (black line) to the empirical data (blue circles) reveals the potential for further improvement.
- The envelope is a useful tool for understanding the limits of memory storage.

Questions

- Can we understand the space of all possible synaptic models?
- How does the structure (topology) of a synaptic model affect its function (memory curve)?
- Can synaptic structure be tuned to store memories over different timescales?
- How does synaptic complexity (number of states) extend the frontiers of possibility for memory?
- Which synaptic state transition topologies maximize measures of memory?

Conclusions

Synaptic structures for different timescales of memory

Real synaptic structures are limited by the set of molecular building blocks, and they have a larger set of priorities. What can we conclude?

- Short timescales
- Intermediate timescales
- Long timescales

- Strong transitions
- Weak transitions

- Strong transitions
- Weak transitions

Experimental tests?

- Subject a synapse to a sequence of candidate plasticity events. Observe the change in synaptic efficacy.
- Use Expectation-Maximization algorithms to estimate transition probabilities.

Summary

- We have formulated a general theory of learning and memory with complex synapses.
- We find a memory envelope: a single curve that cannot be exceeded by the memory curve of any synaptic model.
- Synaptic complexity (M internal states) raises the memory envelope linearly in B for times > M.
- We understand which types of synaptic structure are useful for storing memories for different timescales.

References

- [Amit and Fusi (1992), Amit and Fusi (1994)]
- [Coba et al. (2009)]
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Timescales of memory

Memories stored in different places for different timescales

Different synapses have different molecular structures.

Also: Cerebellar cortex vs. cerebellar nuclei.

[Spezio and Alonso (1995), Robinson and Studholme (2002)]

[Naes and Sorensen (2012)]

Numeric envelope for memory curves

Find maximum memory curve at each time numerically:

At any timescale: best model has serial topology.

Earlier times: shorten the chain.

Later times: make end state "sticky".

[Netoff and Sorensen (2012)]

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