

Optimal synaptic strategies for different timescales of memory

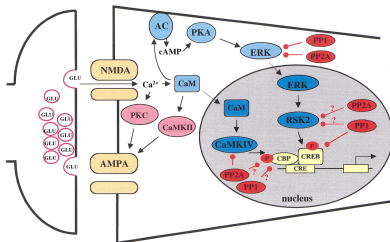
Subhaneil Lahiri and Surya Ganguli

Stanford University, Applied Physics

February 26, 2016

What is a synapse?

Experimenters

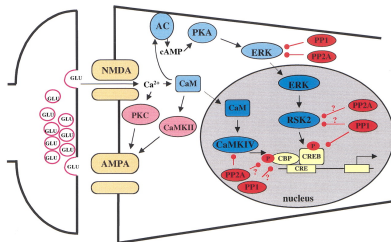


[Klann (2002)]

What is a synapse?

Experimenters

Theorists



W_{ij}

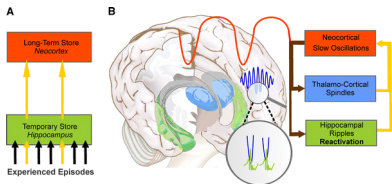
[Klann (2002)]

Timescales of memory

Memories stored in different places
for different timescales

[Squire and Alvarez (1995)]

[McClelland et al. (1995)]



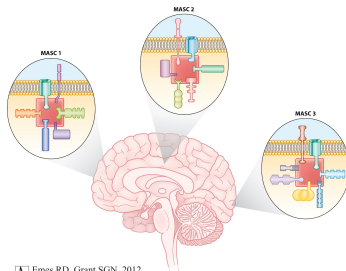
[Born and Wilhelm (2012)]

Also: Cerebellar cortex → nuclei.

[Attwell et al. (2002)]

[Cooke et al. (2004)]

Different synapses have different
molecular structures.



[Emes RD, Grant SGN, 2012.
Annu. Rev. Neurosci. 35:111–31]

[Emes and Grant (2012)]

Storage capacity of synaptic memory

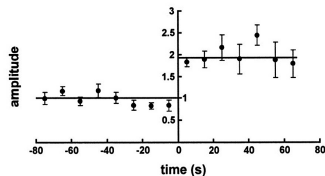
A classical perceptron has a capacity $\propto N$, ($\#$ synapses).

Requires synapses' dynamic range also $\propto N$.

With discrete, finite synapses:

\implies new memories overwrite old,

\implies stability-plasticity dilemma.



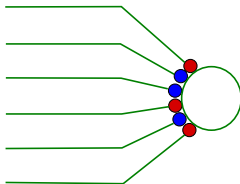
[Petersen et al. (1998), O'Connor et al. (2005)]

When we store new memories rapidly, memory capacity $\sim \mathcal{O}(\log N)$.

[Amit and Fusi (1992), Amit and Fusi (1994)]

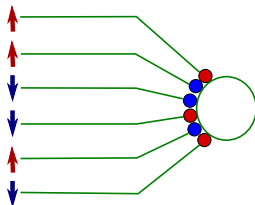
Recognition memory

Synapses given a sequence of patterns (pot & dep) to store



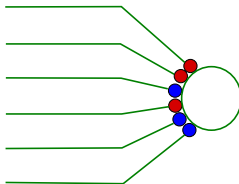
Recognition memory

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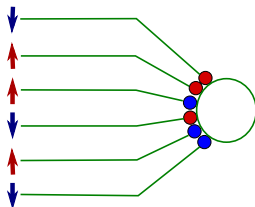
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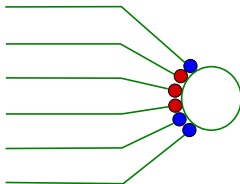
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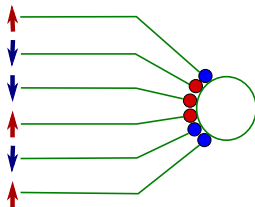
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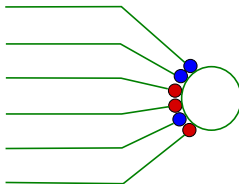
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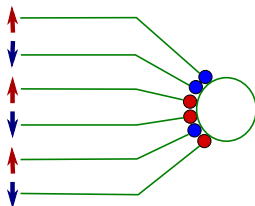
Recognition memory

Synapses given a sequence of patterns (pot & dep) to store



Recognition memory

Synapses given a sequence of patterns (pot & dep) to store



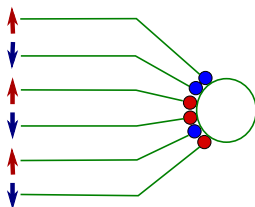
Later: presented with a pattern. Has it been seen before?

Compare $\vec{s} \cdot \vec{w}(t)$ to threshold.

[Sommer and Dayan (1998)]

Recognition memory

Synapses given a sequence of patterns (pot & dep) to store



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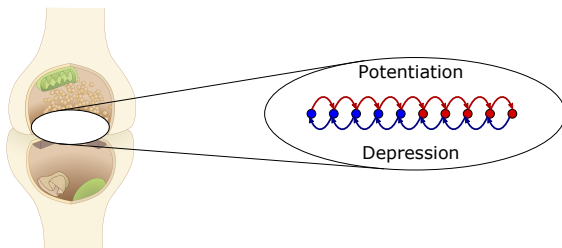
$$\text{SNR}(t) = \frac{\langle \vec{s} \cdot \vec{w}(t) \rangle - \langle \vec{s} \cdot \vec{w}(\infty) \rangle}{\sqrt{\text{Var}(\vec{s} \cdot \vec{w}(\infty))}}, \quad \overline{\text{SNR}}(\tau) = \int d\tau \frac{e^{-t/\tau}}{\tau} \text{SNR}(t).$$

Models of complex synaptic dynamics



Models of complex synaptic dynamics

- Internal functional state of synapse \rightarrow synaptic weight.
 - Candidate plasticity events \rightarrow transitions between states
- weak
● strong

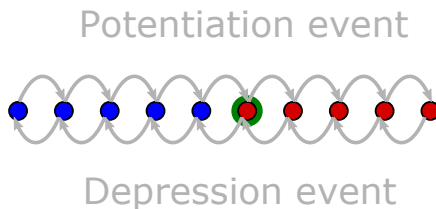


States: #AMPA, #NMDAR, NMDAR subunit composition,
CaMK II autophosphorylation, activating PKC, p38 MAPK,...

[Fusi et al. (2005), Fusi and Abbott (2007), Barrett and van Rossum (2008)]

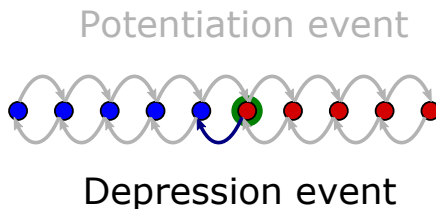
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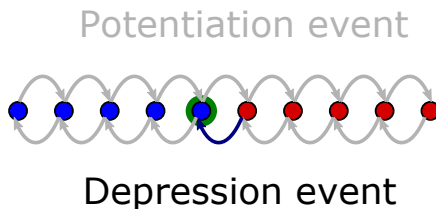
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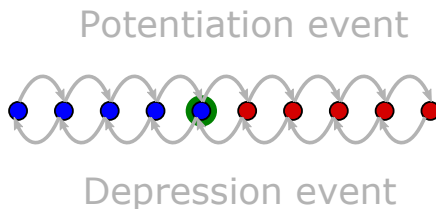
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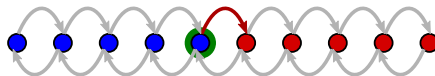
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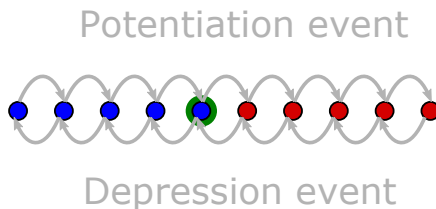
Potential event



Depression event

Models of complex synaptic dynamics

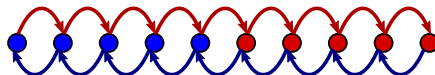
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Models of complex synaptic dynamics

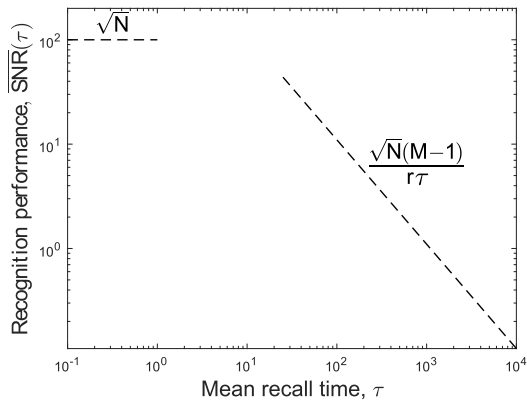
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Potentiation



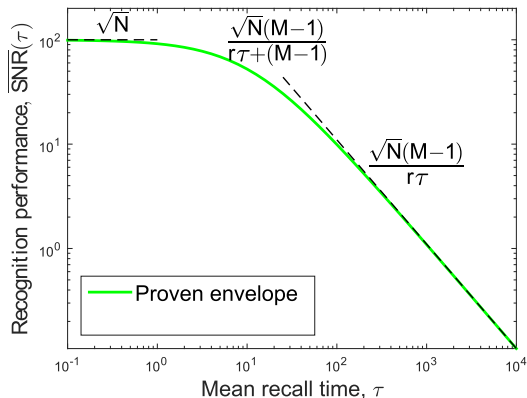
Depression

Proven envelope: memory frontier



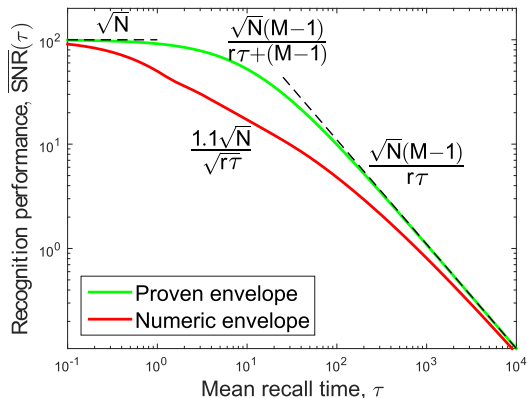
Proven envelope: memory frontier

Upper bound on memory curve at *any* timescale.

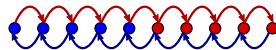


Proven envelope: memory frontier

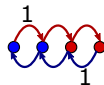
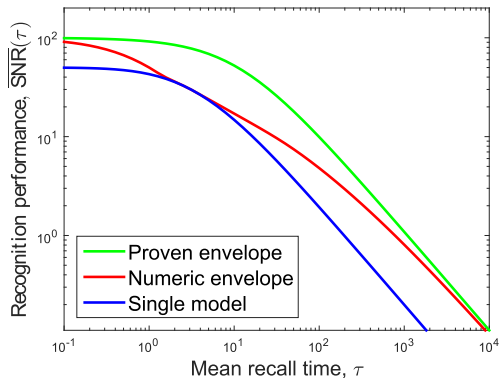
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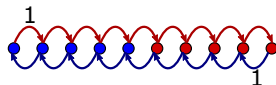
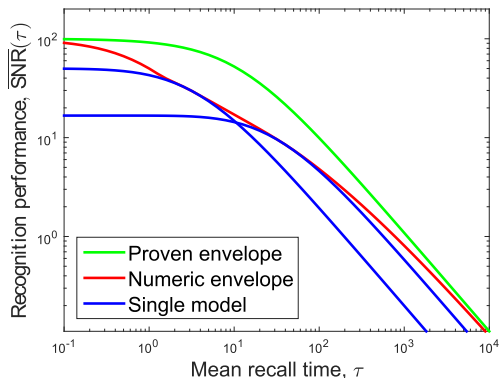
Serial topology:



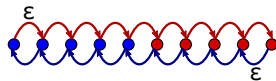
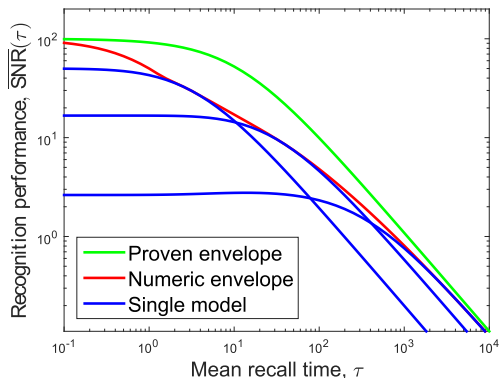
Models that maximise memory for one timescale



Models that maximise memory for one timescale



Models that maximise memory for one timescale



Synaptic structures for different timescales of memory

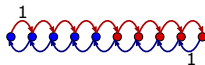
Short timescales



short & wide



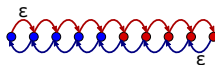
Intermediate timescales



long & thin

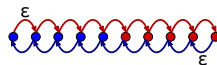
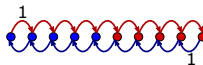


Long timescales



Synaptic structures for different timescales of memory

Short timescales \longrightarrow Intermediate timescales \longrightarrow Long timescales



short & wide



long & thin

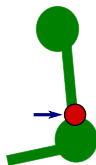
strong transitions



weak transitions

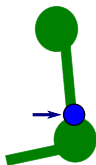
Proposed Experimental design

Subject a synapse to a sequence of candidate plasticity events.
Observe the changes in synaptic efficacy.



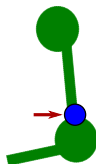
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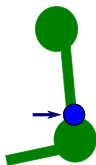
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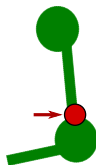
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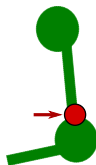
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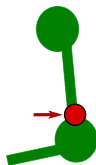
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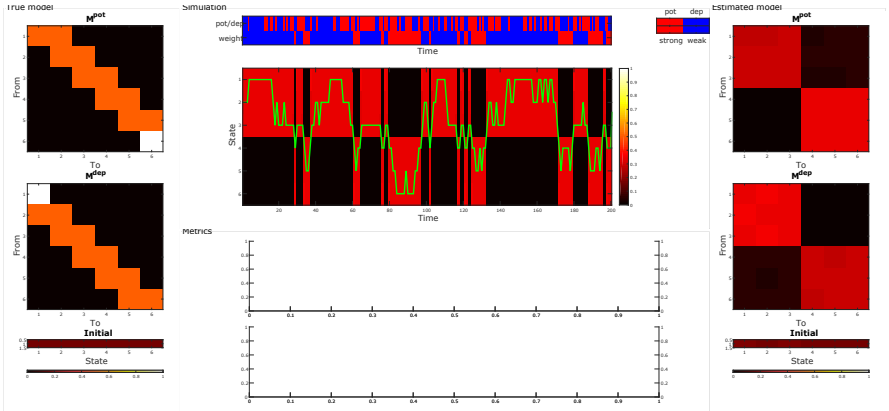
EM algorithms:

Sequence of hidden states \rightarrow estimate transition probabilities

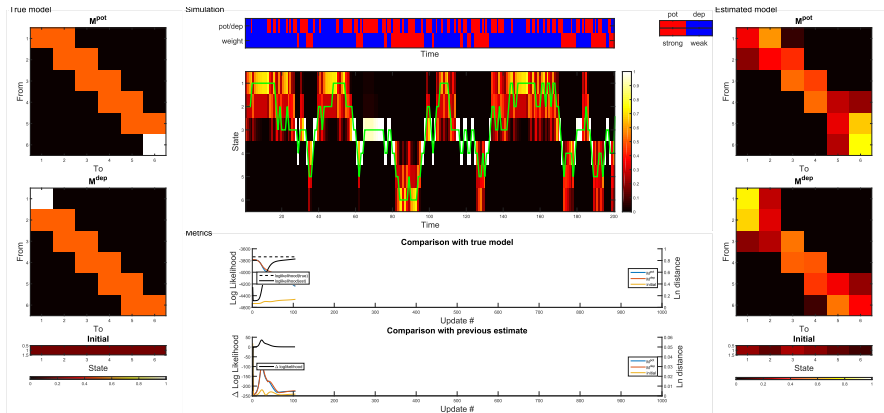
Transition probabilities \rightarrow estimate sequence of hidden states

[Baum et al. (1970), Rabiner and Juang (1993), Dempster et al. (2007)]

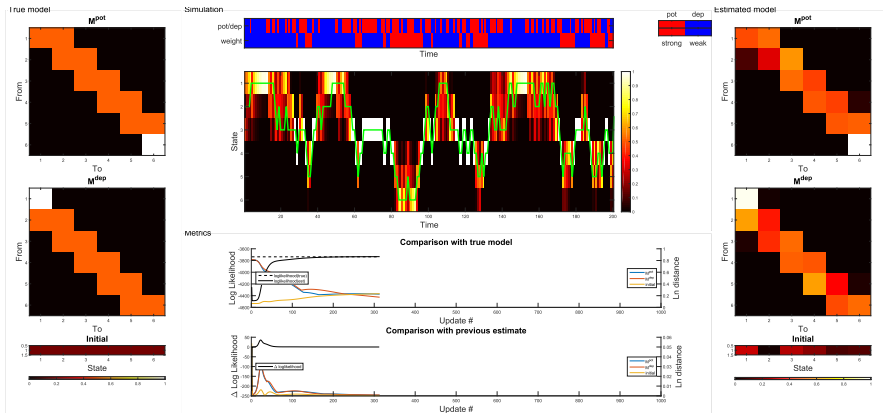
Simulated experiment



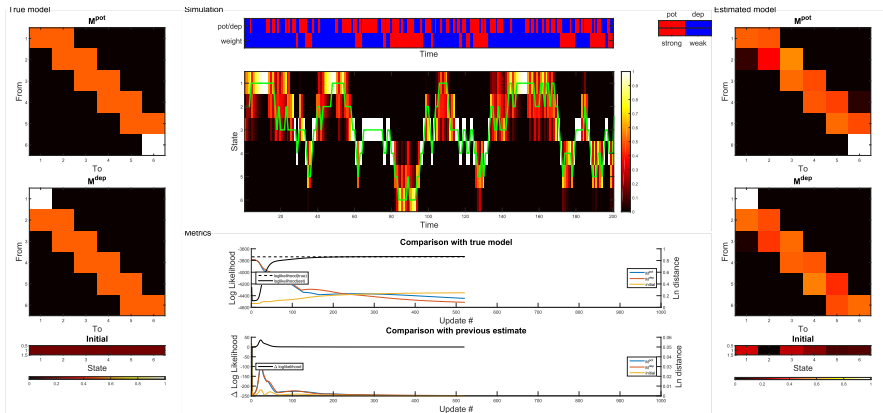
Simulated experiment



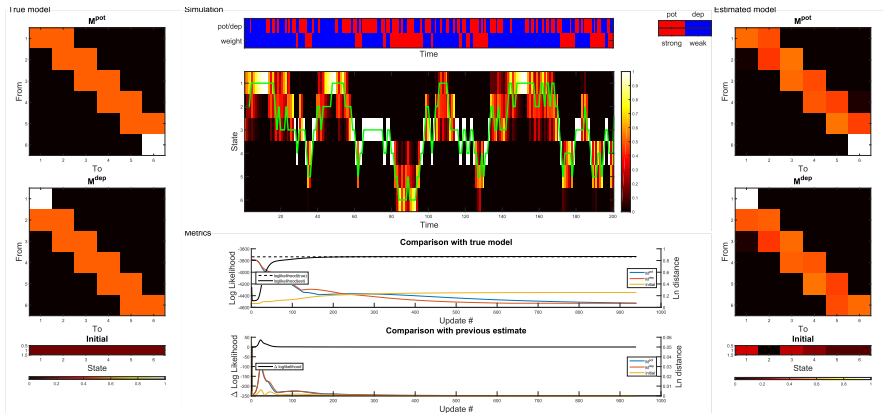
Simulated experiment



Simulated experiment



Simulated experiment



- 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.
- We understood which types of synaptic structure are useful for storing memories for different timescales.

Acknowledgements

Thanks to:

- Surya Ganguli
- Stefano Fusi
- Marcus Benna
- David Sussillo
- Jascha Sohl-Dickstein

Funding:

- Swartz foundation
- Stanford Bio-X
- Genentech

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Technical detail: ordering states

Let \mathbf{T}_{ij} = mean first passage time from state i to state j . Then:

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

is independent of the initial state i (Kemeney's constant).

[Kemeny and Snell (1960)]

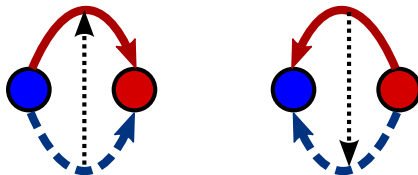
We define:

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

They can be used to arrange the states in an order (increasing η^- or decreasing η^+). [back](#)

Technical detail: upper/lower triangular

With states in order:



Endpoint: potentiation goes right, depression goes left.

[back](#)