

Optimal synaptic strategies for different timescales of memory

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What is a synapse?

What is a synapse?

Theorists

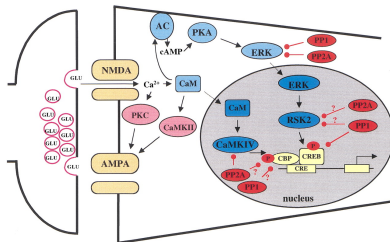
$$W_{ij}$$

What is a synapse?

Theorists

$$W_{ij}$$

Experimenters



[Klann (2002)]

Storage capacity of synaptic memory

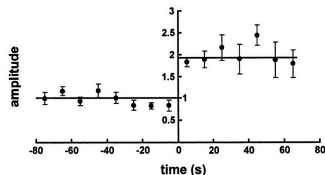
Hopfield, perceptron have capacity $\propto N$, ($\#$ synapses).

Assumes unbounded analog synapses

With discrete, finite synapses:

\implies memory capacity $\sim \mathcal{O}(\log N)$.

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



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

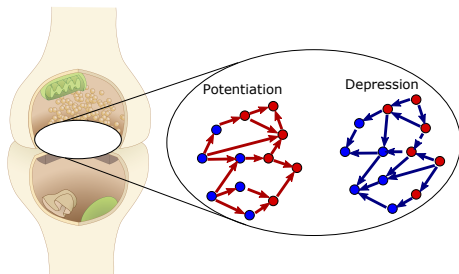
New memories overwrite old \implies stability-plasticity dilemma.

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

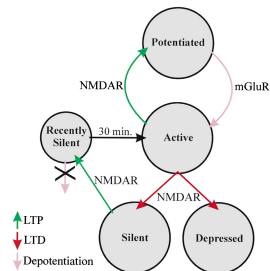
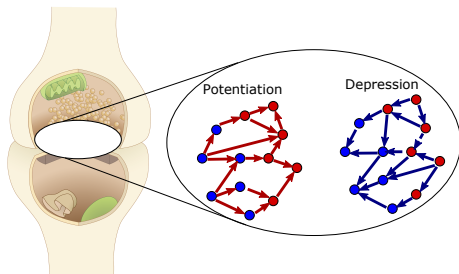


States: #AMPA, #NMDAR, NMDAR subunit composition,
CaMK II autophosphorylation, activating PKC, p38 MAPK,...

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

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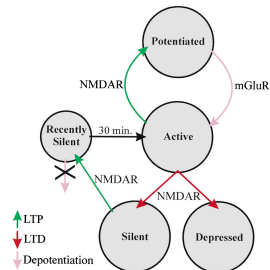
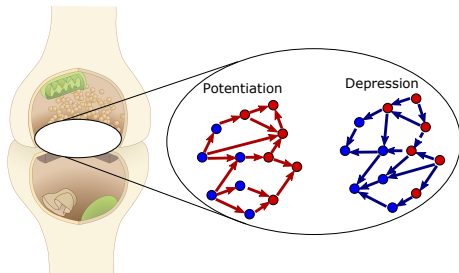
[Montgomery and Madison (2002)]

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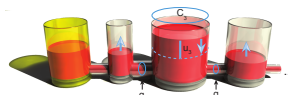
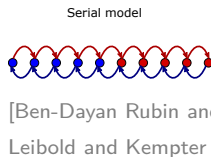
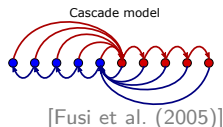
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Models of complex synaptic dynamics

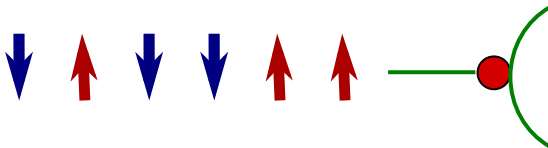
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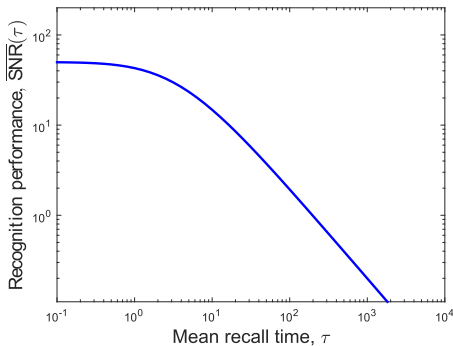
[Montgomery and Madison (2002)]



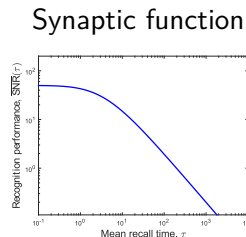
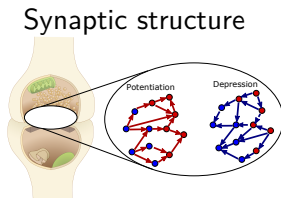
Synaptic memory curves



Synapses store a sequence of memories.



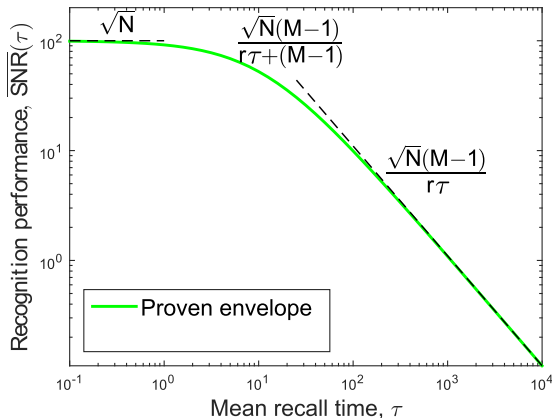
General principles relating structure and function?



- What are the fundamental limits of memory?
- Which models achieve these limits?
- What are the theoretical principles behind the optimal models?

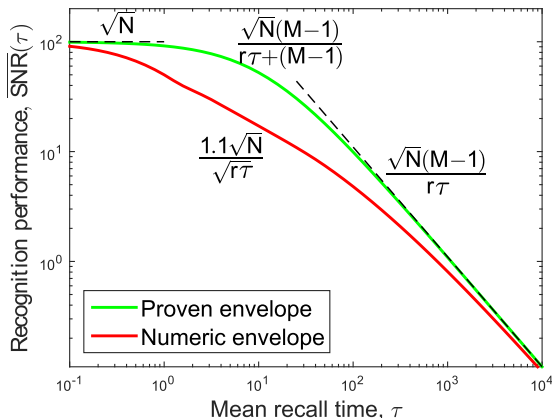
Proven envelope: memory frontier

Upper bound on memory curve at *any* timescale.

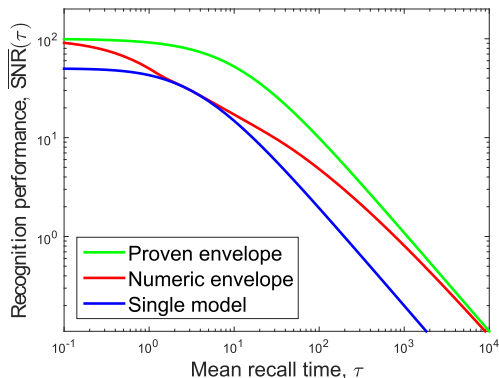


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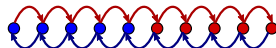
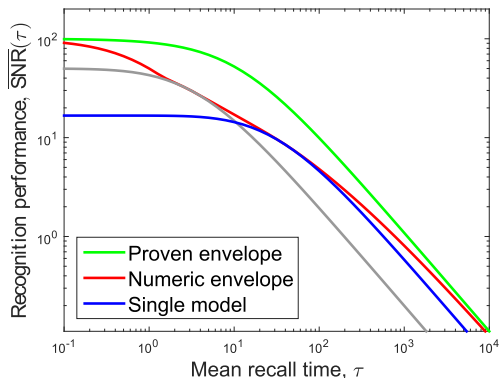
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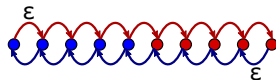
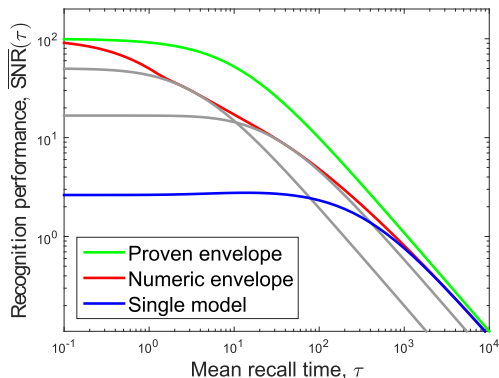
Models that maximize memory for one timescale



Models that maximize memory for one timescale

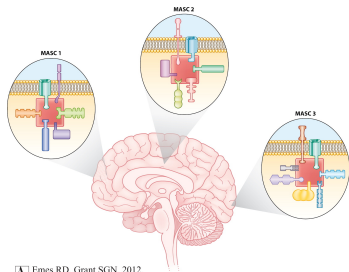


Models that maximize memory for one timescale



Synaptic diversity and timescales of memory

Different synapses have different molecular structures.

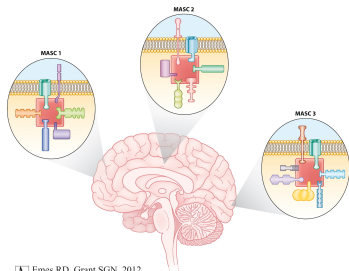


Emes RD, Grant SGN, 2012.
Annu. Rev. Neurosci. 35:111–31

[Emes and Grant (2012)]

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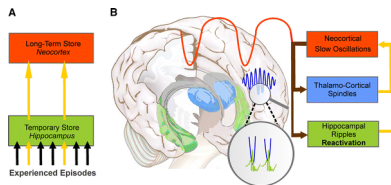
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[Emes and Grant (2012)]

Memories stored in different places for different timescales

[Squire and Alvarez (1995)]

[McClelland et al. (1995)]



[Born and Wilhelm (2012)]

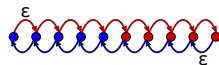
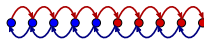
Also: Cerebellar cortex → nuclei.

[Attwell et al. (2002)]

[Cooke et al. (2004)]

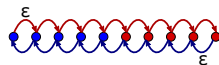
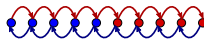
Synaptic structure and function: general principles

Short timescale \longrightarrow Intermediate timescale \longrightarrow Long timescale



Synaptic structure and function: general principles

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short topology



long topology

Synaptic structure and function: general principles

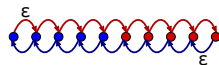
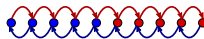
Short timescale



Intermediate timescale



Long timescale



short topology



long topology

deterministic synapse



stochastic synapse

Experimental tests?

Traditional experiments:



Experimental tests?

Traditional experiments:



To fit a model: long sequence of small plasticity events.
Observe the changes in synaptic efficacy.



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.
- We understood which types of synaptic structure are useful for storing memories for different timescales.
- We studied more than a single model. We studied *all possible models*, to extract general principles relating synaptic structure to function

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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)]

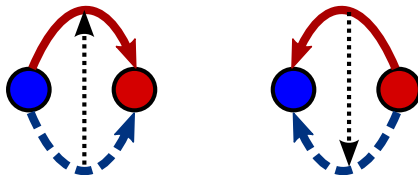
We define:

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

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](#)