Optimal synaptic strategies for different timescales of memory

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What is a synapse?

What is a synapse?

Theorists

$$W_{ij}$$

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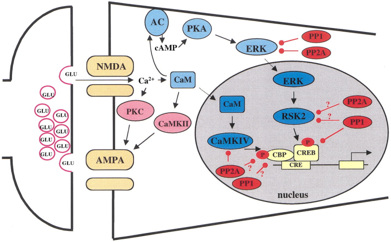
$$W_{ij}$$

Experimenters

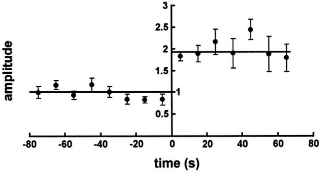


[Klann (2002)]

Storage capacity of synaptic memory

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

Assumes unbounded analog synapses

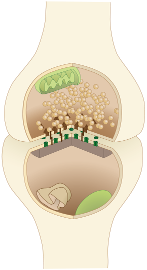


[Petersen et al. (1998), O'Connor et al. (2005)]

With discrete, finite synapses:
$\implies$ memory capacity $\sim \mathcal{O}(\log N)$.
[Amit and Fusi (1992), Amit and Fusi (1994)]

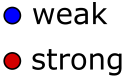
New memories overwrite old $\implies$ stability-plasticity dilemma.

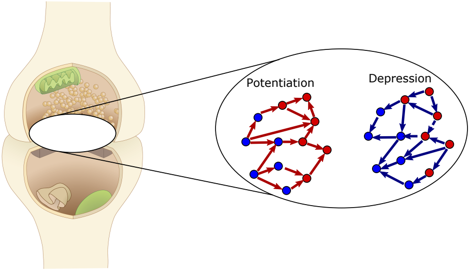
Models of complex synaptic dynamics



Models of complex synaptic dynamics

- Internal functional state of synapse → synaptic weight.
- Candidate plasticity events → transitions between states





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

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

Models of complex synaptic dynamics

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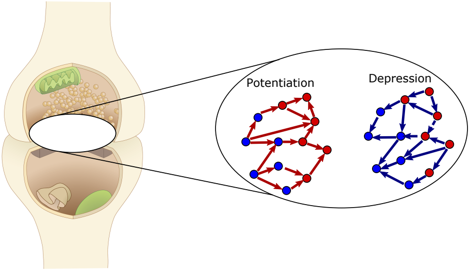
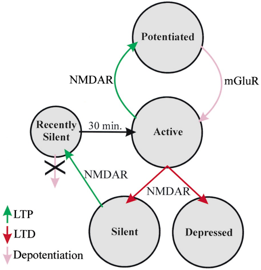
● weak
● strong





[Montgomery and Madison (2002)]

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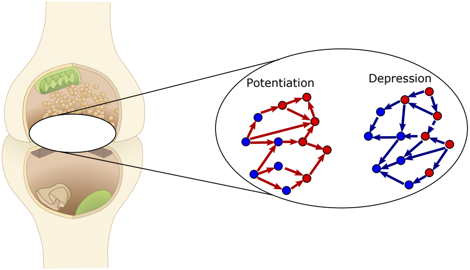
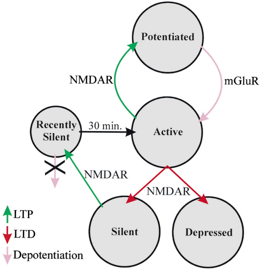
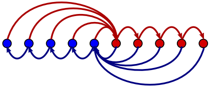




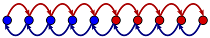
[Montgomery and Madison (2002)]

Cascade model

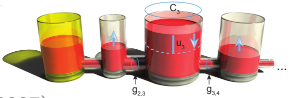


[Fusi et al. (2005)]

Serial model

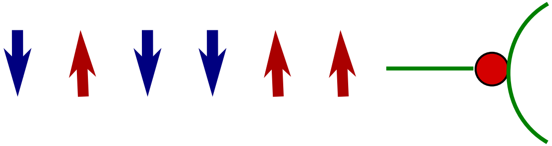


[Ben-Dayan Rubin and Fusi (2007), Leibold and Kempter (2008)]

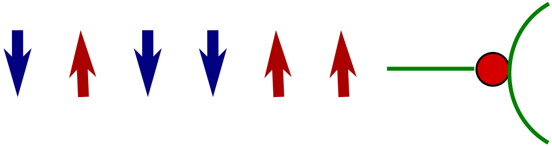


[Benna and Fusi (2015)]

Synaptic memory curves



Synapses store a sequence of memories.



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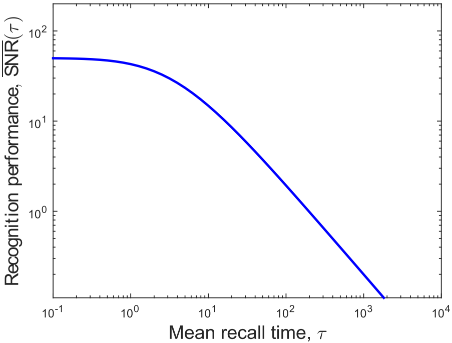
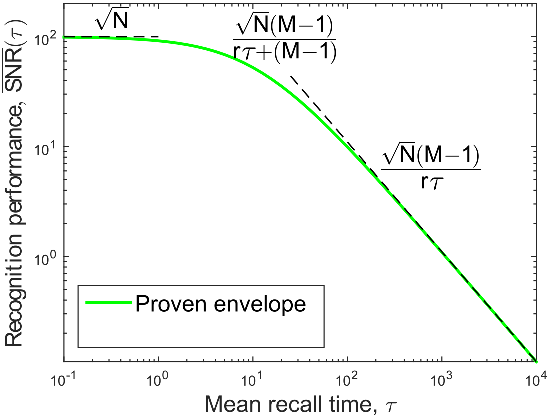


Questions

- What are the upper bounds?
- Which models achieve them?
- What are the theoretical principles behind them?

Proven envelope: memory frontier

Upper bound on memory curve at *any* timescale.



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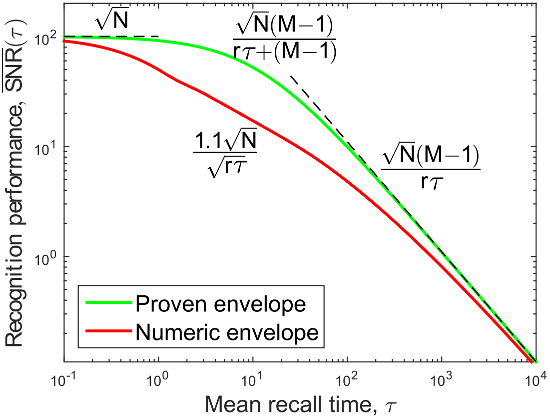
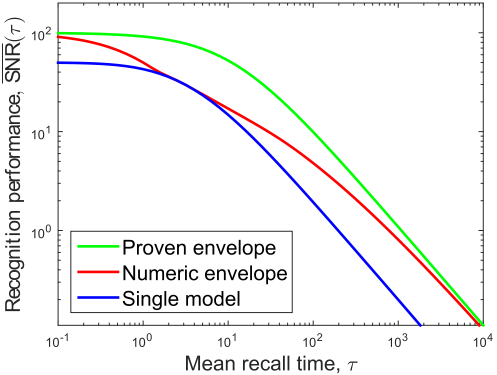
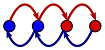


Models that maximize memory for one timescale





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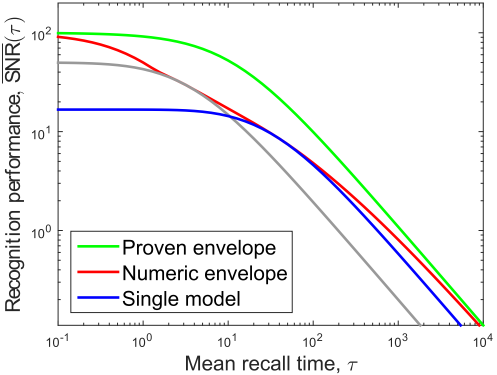

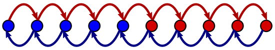

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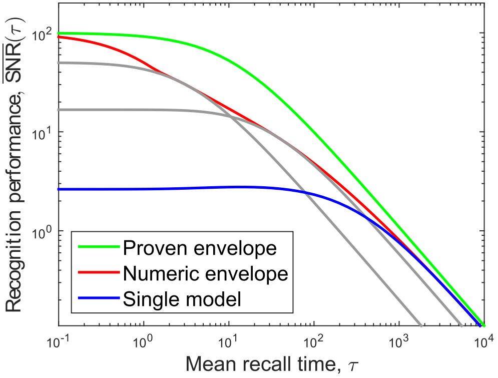
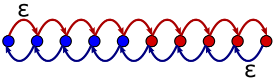
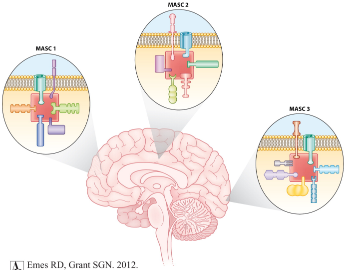




Different synapses have different molecular structures.



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

[Emes and Grant (2012)]

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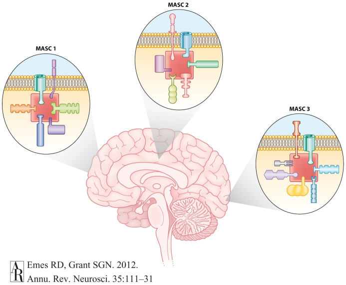
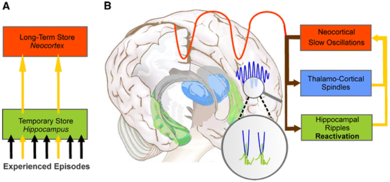


[Emes and Grant (2012)]

Memories stored in different places for different timescales

[Squire and Alvarez (1995)]

[McClelland et al. (1995)]



[Born and Wilhelm (2012)]

Also: Cerebellar cortex → nuclei.

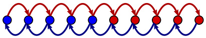
[Attwell et al. (2002)]

[Cooke et al. (2004)]

Synaptic structures for different timescales of memory

Short timescale $\longrightarrow$ Intermediate timescale $\longrightarrow$ Long timescale

$\longrightarrow$



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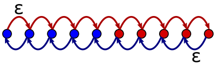

Synaptic structures for different timescales of memory

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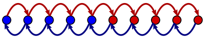
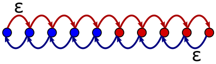
	$\longrightarrow$		$\longrightarrow$	
short topology	$\longrightarrow$	long topology		

Synaptic structures for different timescales of memory

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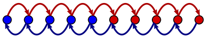

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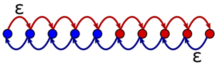
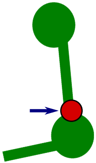


short topology $\longrightarrow$ long topology

deterministic synapse $\longrightarrow$ stochastic synapse

Proposed Experimental design

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



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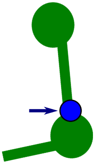

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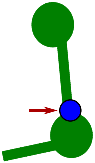

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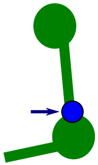

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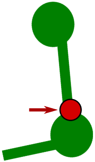

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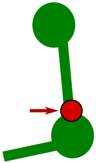

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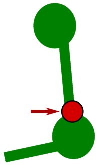

EM algorithms:

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)]

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.

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40

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)]

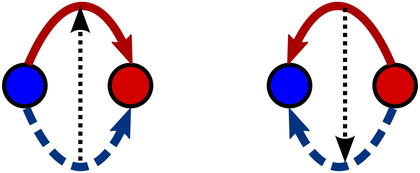
We define:

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

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