Optimal synaptic strategies for different timescales of memory

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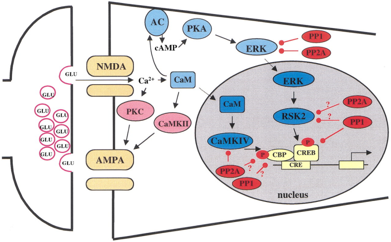
Stanford University, Applied Physics

February 26, 2016

What is a synapse?

Experimenters



[Klann (2002)]

What is a synapse?

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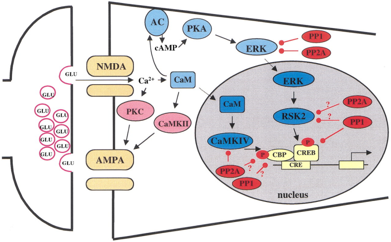


[Klann (2002)]

Theorists

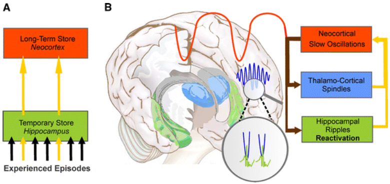
W_{ij}

Timescales of memory

Memories stored in different places for different timescales

[Squire and Alvarez (1995)]

[McClelland et al. (1995)]



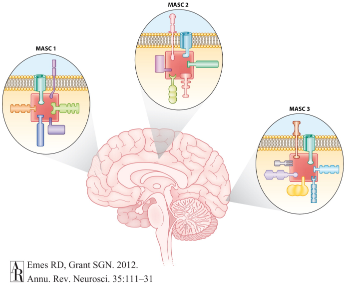
[Born and Wilhelm (2012)]

Also: Cerebellar cortex $\rightarrow$ nuclei.

[Attwell et al. (2002)]

[Cooke et al. (2004)]

Different synapses have different molecular structures.



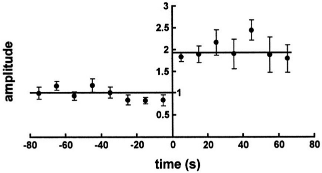
[Emes and Grant (2012)]

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:
$\Longrightarrow$ new memories overwrite old,
$\Longrightarrow$ stability-plasticity dilemma.



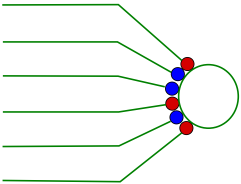
[Petersen et al. (1998), O'Connor et al. (2005)]

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



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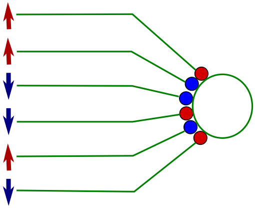

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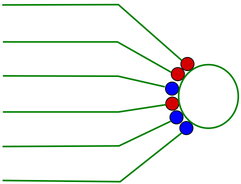

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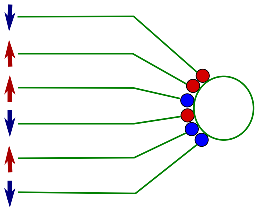

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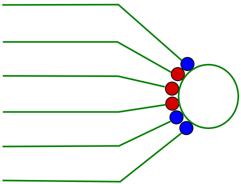

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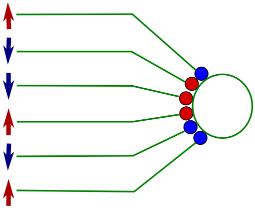

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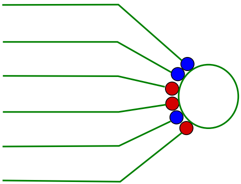

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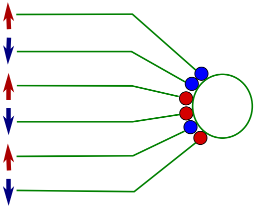

Later: presented with a pattern. Has it been seen before?

Compare $\vec{s} \cdot \vec{w}(t)$ to threshold. [Sommer and Dayan (1998)]

Recognition memory

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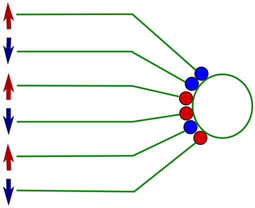

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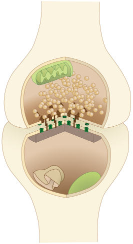
$$\mathrm{SNR}(t) = \frac{\langle \vec{s}\cdot\vec{w}(t)\rangle - \langle \vec{s}\cdot\vec{w}(\infty)\rangle}{\sqrt{\mathrm{Var}(\vec{s}\cdot\vec{w}(\infty))}}, \qquad \overline{\mathrm{SNR}}(\tau) = \int \mathrm{d}\tau \, \frac{\mathrm{e}^{-t/\tau}}{\tau} \, \mathrm{SNR}(t).$$

Models of complex synaptic dynamics

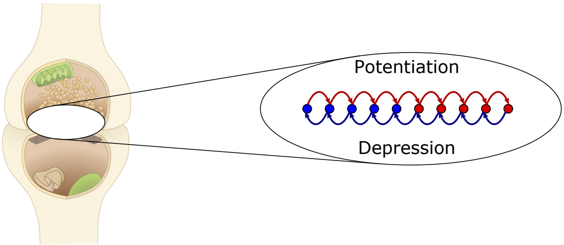


Models of complex synaptic dynamics

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

weak

strong



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)]

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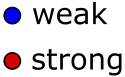

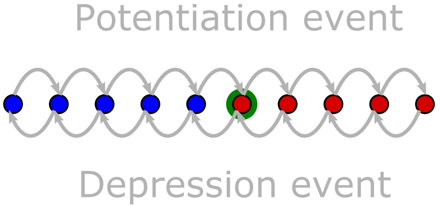

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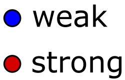

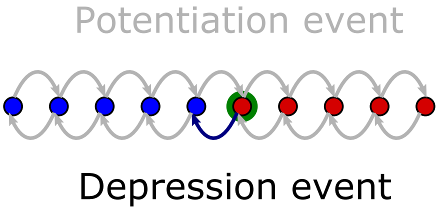

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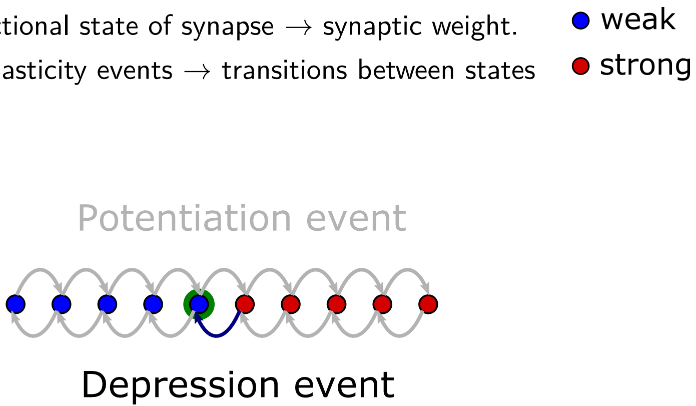

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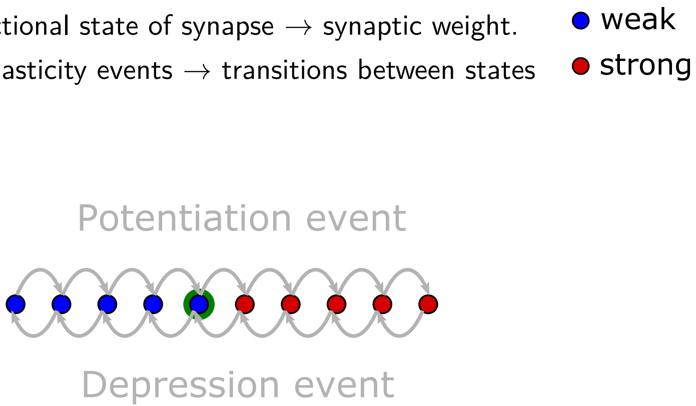

Models of complex synaptic dynamics

- Internal functional state of synapse → synaptic weight.
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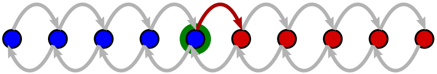
● weak
● strong

Potentiation event



Depression event

Models of complex synaptic dynamics

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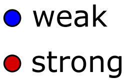

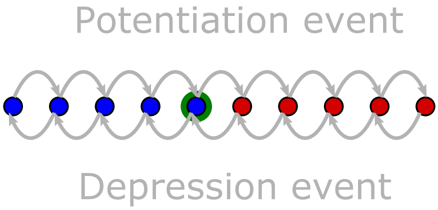

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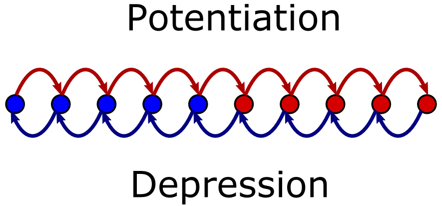
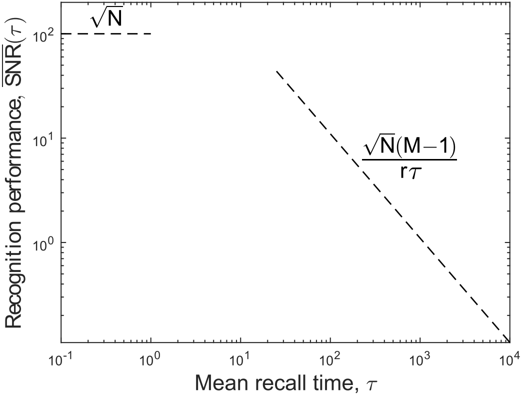
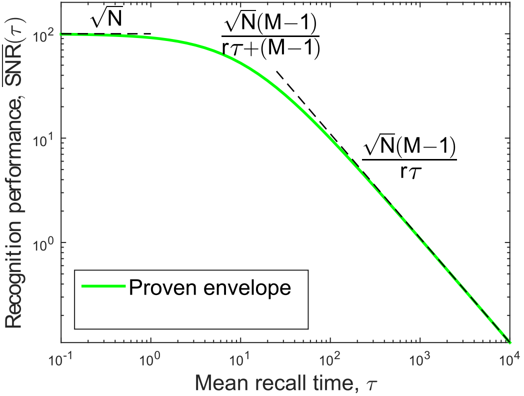


Proven envelope: memory frontier



Proven envelope: memory frontier

Upper bound on memory curve at *any* timescale.



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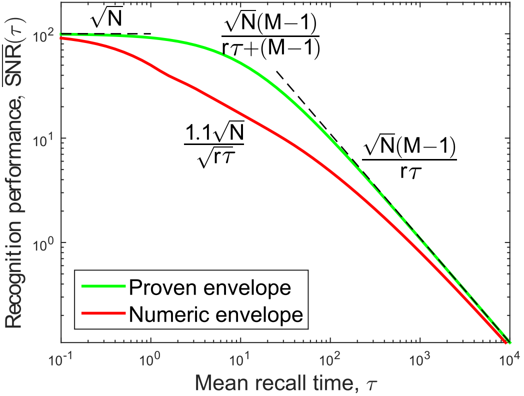
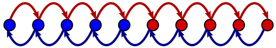
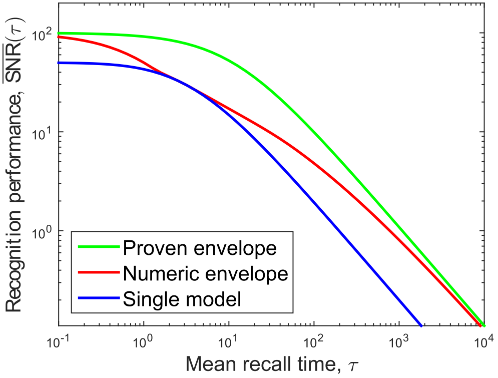
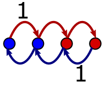


Serial topology:



Models that maximise memory for one timescale





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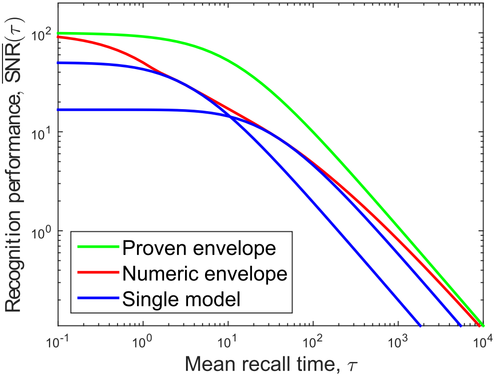

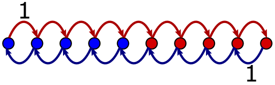

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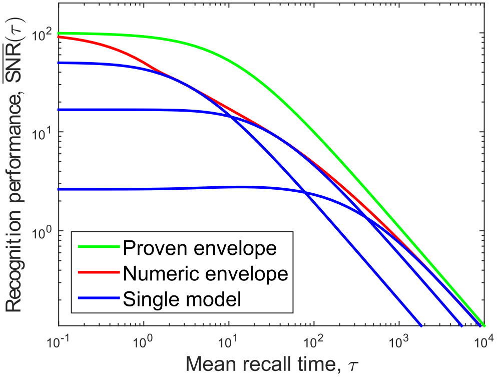
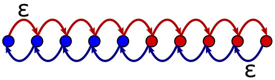
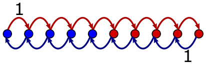




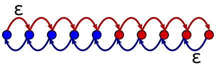
Synaptic structures for different timescales of memory

Short timescales $\longrightarrow$ Intermediate timescales $\longrightarrow$ Long timescales

$\longrightarrow$



$\longrightarrow$



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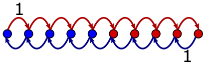

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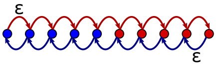

short topology $\longrightarrow$ long topology

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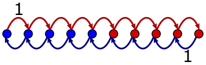

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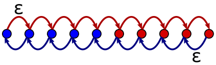
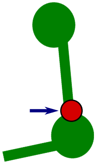


short topology $\longrightarrow$ long topology

strong transitions $\longrightarrow$ 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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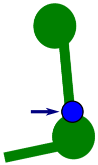

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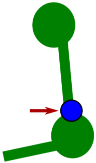

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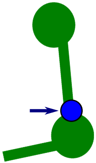

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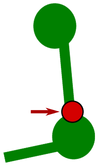

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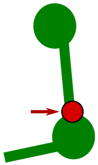

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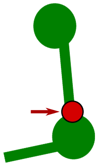
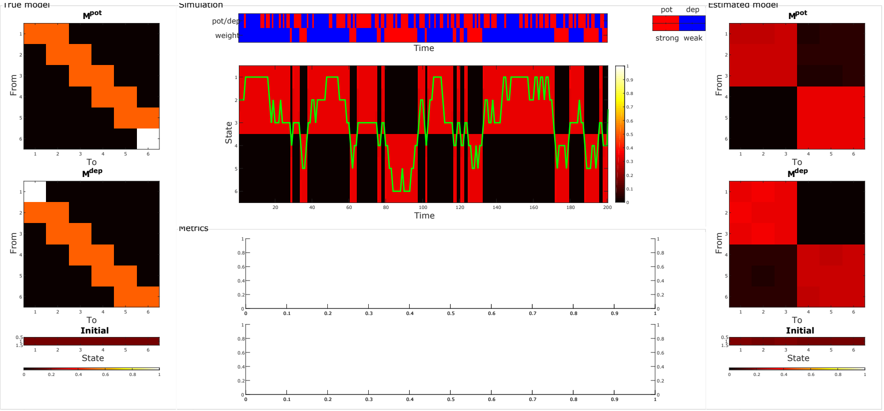


EM algorithms:

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



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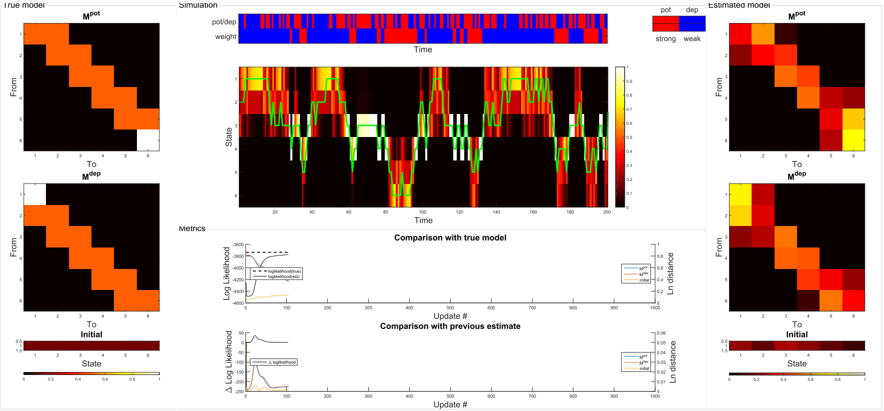

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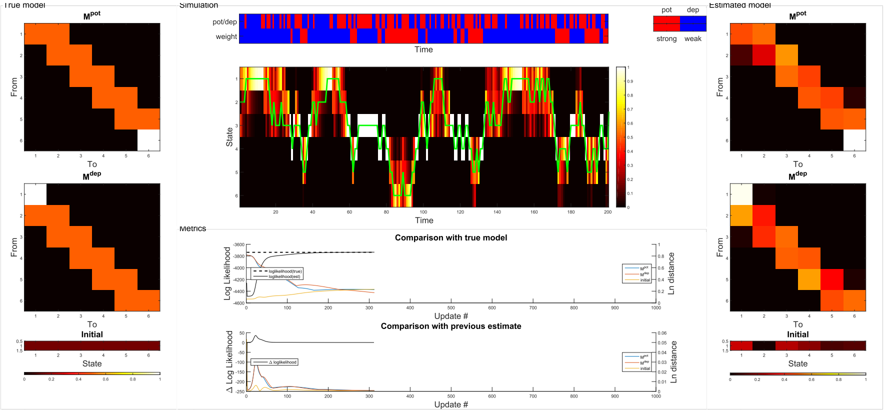

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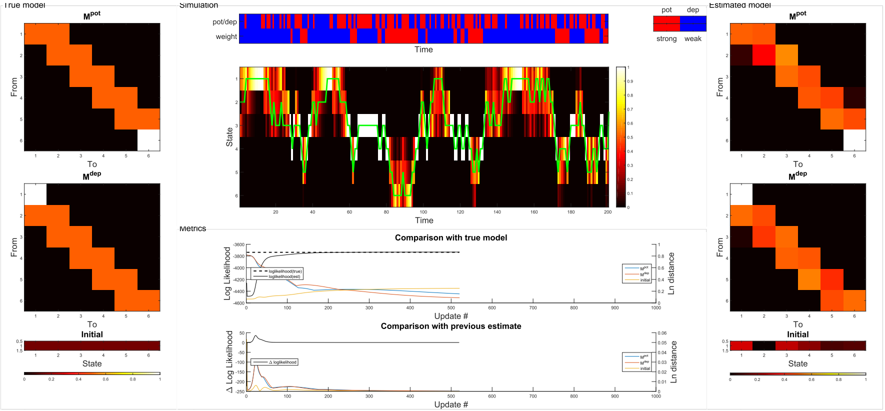

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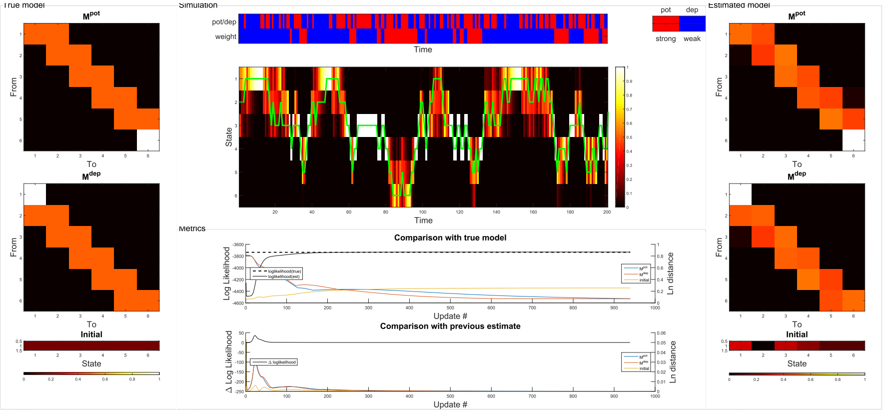

Summary

- 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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- Marcus Benna
- David Sussillo
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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)]

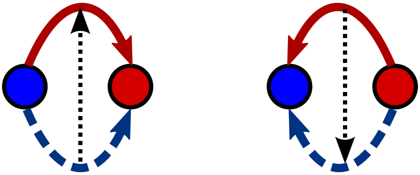
We define:

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

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.

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