Optimal synaptic strategies for different timescales of memory

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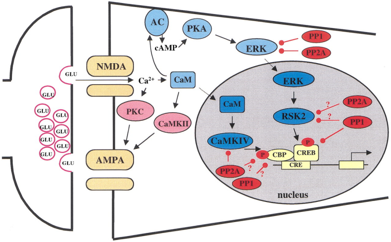
What is a synapse?

Experimenters



[Klann (2002)]

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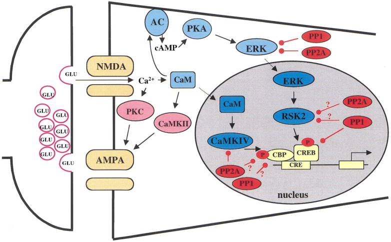


[Klann (2002)]

Theorists

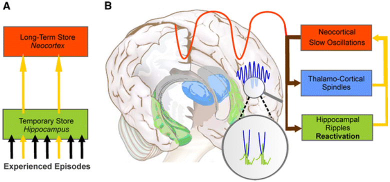
W_{ij}

Timescales of memory

Memories stored in different places for different timescales

[Squire and Alvarez (1995)]

[McClelland et al. (1995)]



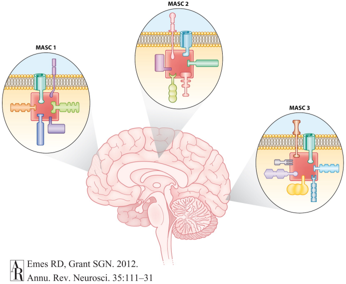
[Born and Wilhelm (2012)]

Also: Cerebellar cortex $\rightarrow$ nuclei.

[Attwell et al. (2002)]

[Cooke et al. (2004)]

Different synapses have different molecular structures.



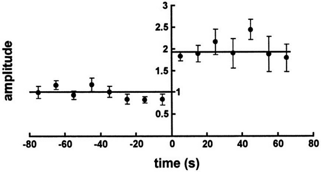
[Emes and Grant (2012)]

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



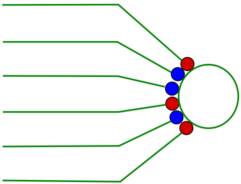
[Petersen et al. (1998), O'Connor et al. (2005)]

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



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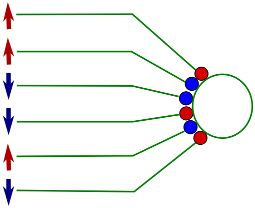

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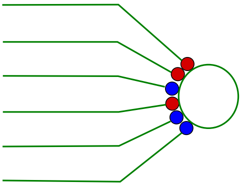

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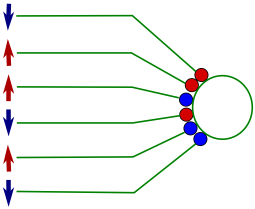

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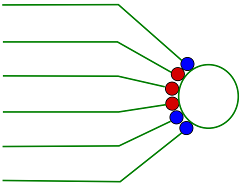

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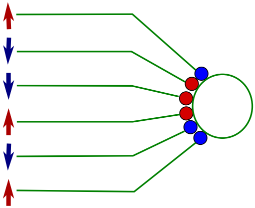

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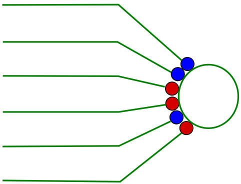

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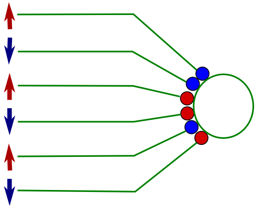

Later: presented with a pattern. Has it been seen before?

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

Recognition memory

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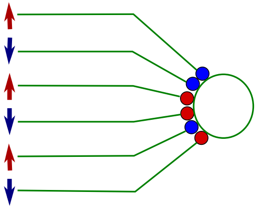

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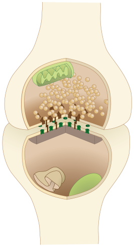
$$\mathsf{SNR}(t) = \frac{\langle \vec{s}\cdot\vec{w}(t)\rangle - \langle \vec{s}\cdot\vec{w}(\infty)\rangle}{\sqrt{\mathsf{Var}(\vec{s}\cdot\vec{w}(\infty))}}, \qquad \overline{\mathsf{SNR}}(\tau) = \int \mathrm{d}\tau \, \frac{\mathrm{e}^{-t/\tau}}{\tau} \, \mathsf{SNR}(t).$$

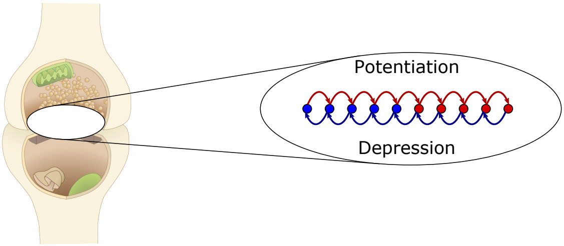
Models of complex synaptic dynamics



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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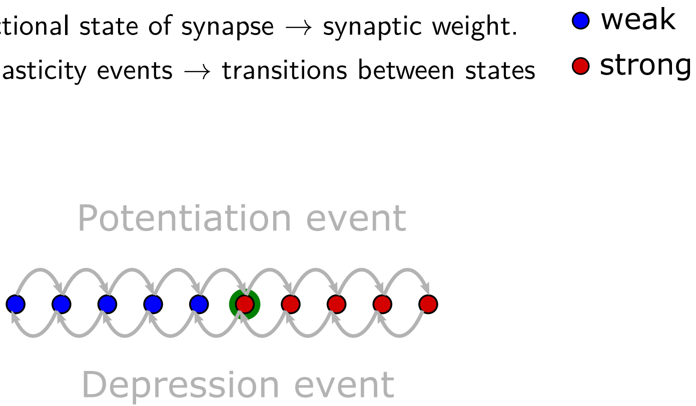

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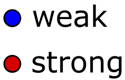

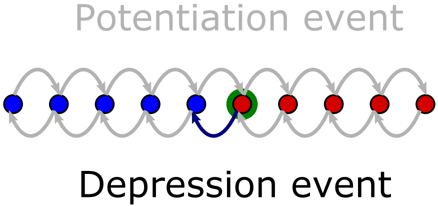

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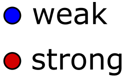
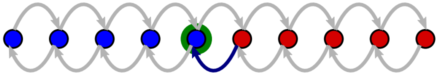


Potentiation event



Depression event

Models of complex synaptic dynamics

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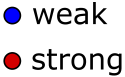

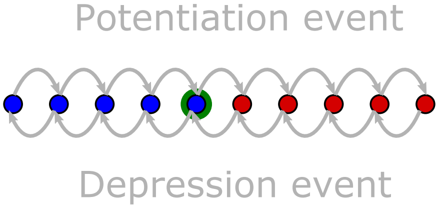

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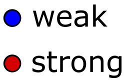

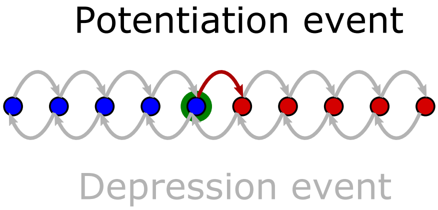

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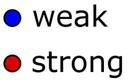

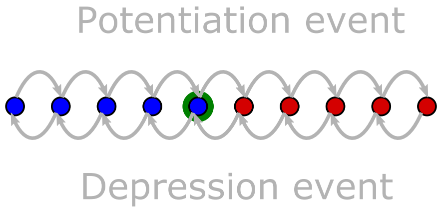

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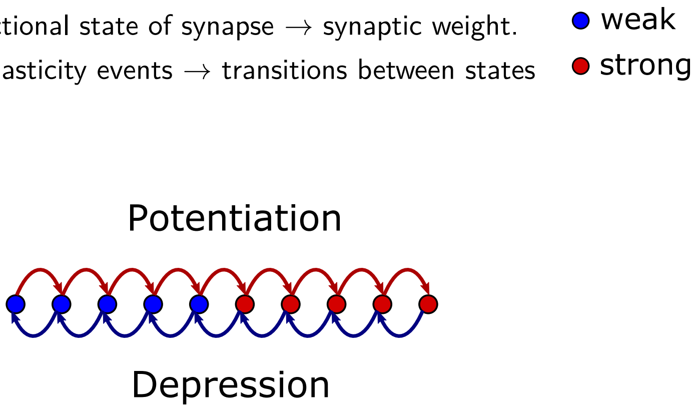
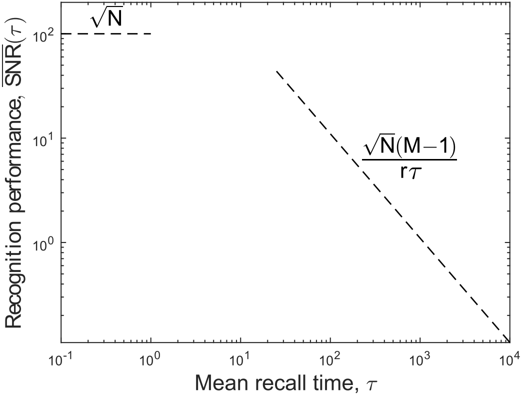
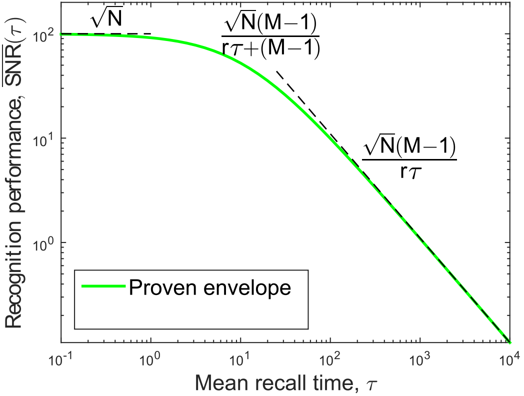


Proven envelope: memory frontier



Proven envelope: memory frontier

Upper bound on memory curve at *any* timescale.



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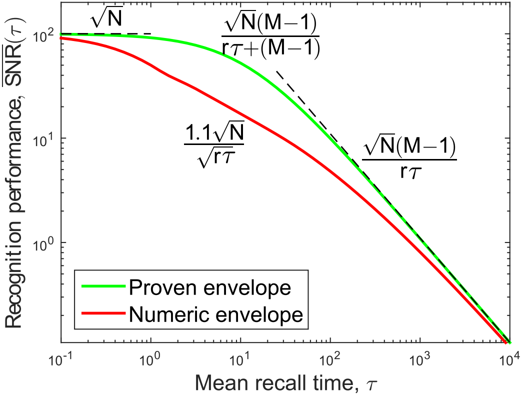
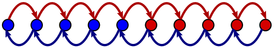
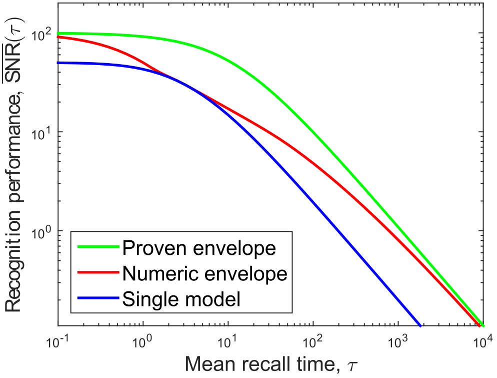
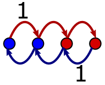


Serial topology:



Models that maximise memory for one timescale





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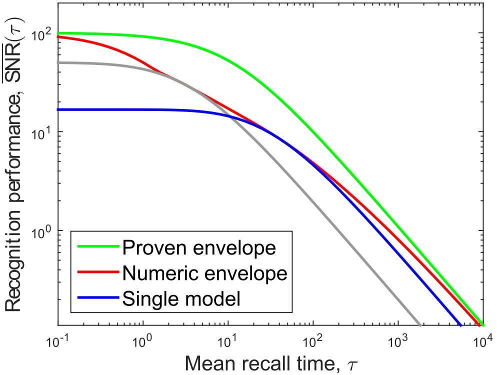

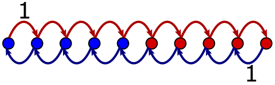

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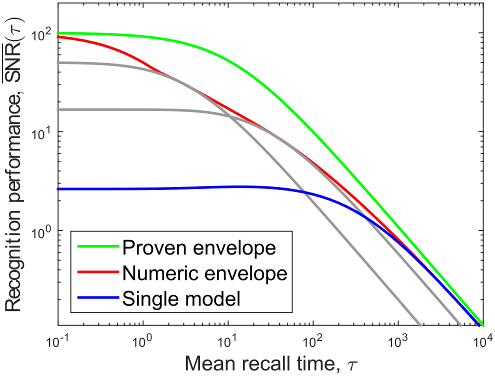
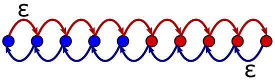
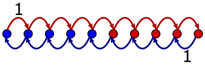




Synaptic structures for different timescales of memory

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

$\longrightarrow$



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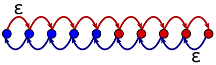

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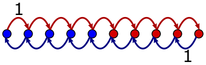

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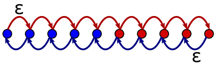

short topology $\longrightarrow$ long topology

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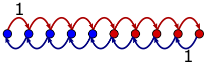

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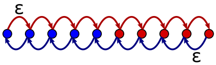


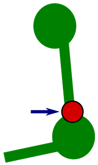
short topology $\longrightarrow$ long topology

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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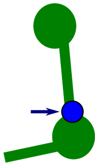

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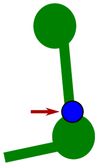

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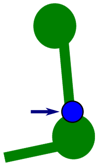

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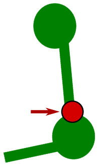

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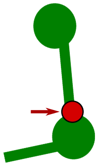

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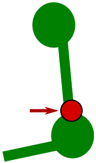
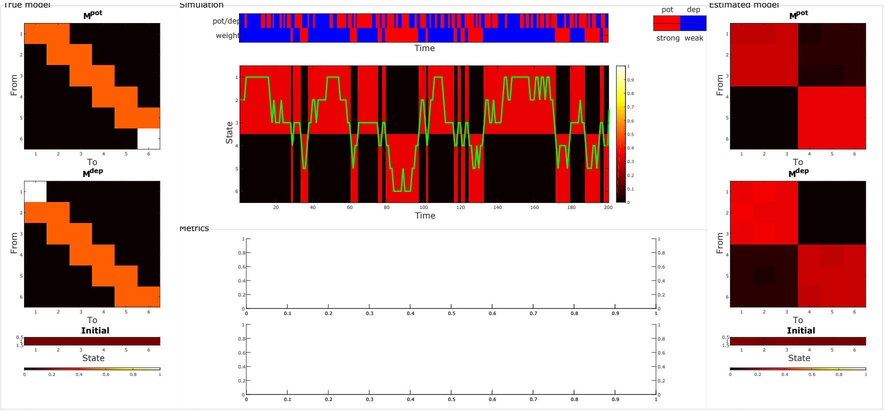


EM algorithms:

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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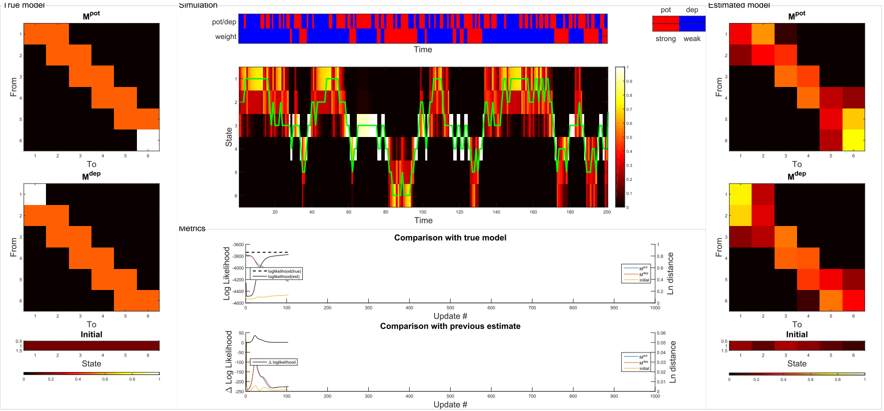

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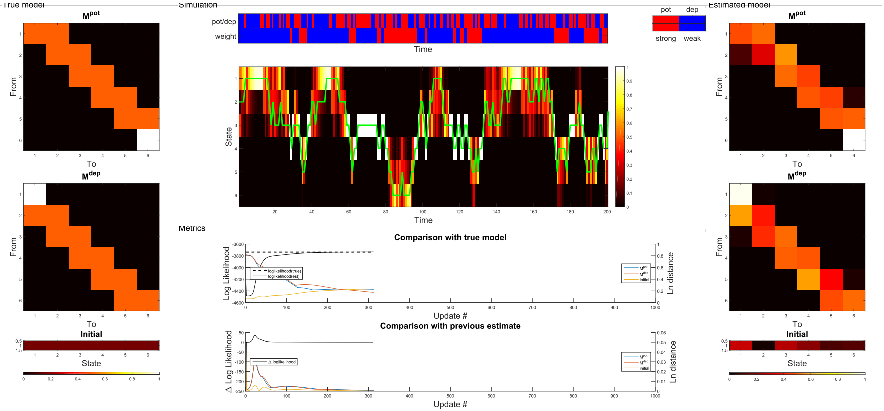

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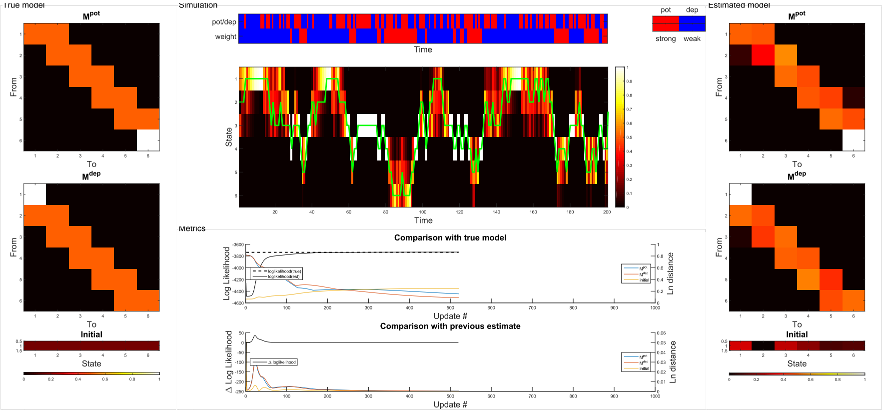

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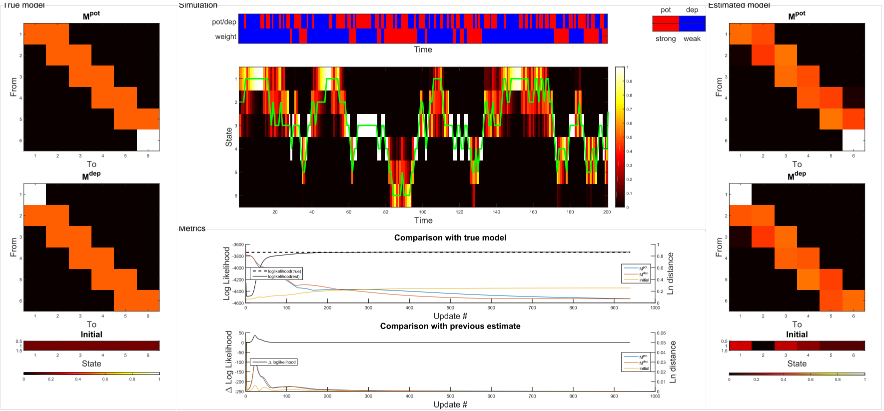

Summary

- 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
- Jascha Sohl-Dickstein

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References I

Eric Klann.

"Metaplastic Protein Phosphatases".

Learning and Memory, 9(4):153–155, (2002) ,
http://learnmem.cshlp.org/content/9/4/153.full.pdf+html.

2 3

Larry R Squire and Pablo Alvarez.

"Retrograde amnesia and memory consolidation: a neurobiological perspective".

Current Opinion in Neurobiology, 5(2):169–177, (April, 1995) .

4

James L McClelland, Bruce L McNaughton, and Randall C O'Reilly.

"Why there are complementary learning systems in the hippocampus and neocortex: Insights from the successes and failures of connectionist models of learning and memory.", 1995.

4

References II

Jan Born and Ines Wilhelm.
"System consolidation of memory during sleep.".
Psychological research, 76(2):192–203, (mar, 2012) .
4

Phillip J.E. Attwell, Samuel F. Cooke, and Christopher H. Yeo.
"Cerebellar Function in Consolidation of a Motor Memory".
Neuron, 34(6):1011–1020, (jun, 2002) .
4

Samuel F Cooke, Phillip J E Attwell, and Christopher H Yeo.
"Temporal properties of cerebellar-dependent memory consolidation.".
The Journal of neuroscience : the official journal of the Society for Neuroscience, 24(12):2934–41, (mar, 2004) .
4

References III

Richard D. Emes and Seth G.N. Grant.
"Evolution of Synapse Complexity and Diversity".
Annual Review of Neuroscience, 35(1):111–131, (2012) .
4

Carl C. H. Petersen, Robert C. Malenka, Roger A. Nicoll, and John J. Hopfield.
"All-or-none potentiation at CA3-CA1 synapses".
Proc. Natl. Acad. Sci. U.S.A., 95(8):4732–4737, (1998) .
5

Daniel H. O'Connor, Gayle M. Wittenberg, and Samuel S.-H. Wang.
"Graded bidirectional synaptic plasticity is composed of switch-like unitary events".
Proc. Natl. Acad. Sci. U.S.A., 102(27):9679–9684, (2005) .
5

References IV

D. J. Amit and S. Fusi.
"Constraints on learning in dynamic synapses".
Network: Computation in Neural Systems, 3(4):443–464, (1992) .
5

D. J. Amit and S. Fusi.
"Learning in neural networks with material synapses".
Neural Computation, 6(5):957–982, (1994) .
5

Friedrich T Sommer and Peter Dayan.
"Bayesian retrieval in associative memories with storage errors.".
IEEE transactions on neural networks / a publication of the IEEE Neural Networks Council, 9(4):705–13, (jan, 1998) .
6 7 8 9 10 11 12 13 14

References V

S. Fusi, P. J. Drew, and L. F. Abbott.
"Cascade models of synaptically stored memories".
Neuron, 45(4):599–611, (Feb, 2005) .
16

S. Fusi and L. F. Abbott.
"Limits on the memory storage capacity of bounded synapses".
Nat. Neurosci., 10(4):485–493, (Apr, 2007) .
16

A. B. Barrett and M. C. van Rossum.
"Optimal learning rules for discrete synapses".
PLoS Comput. Biol., 4(11):e1000230, (Nov, 2008) .
16

References VI

LE Baum, T Petrie, George Soules, and Norman Weiss.

"A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains".

The annals of mathematical statistics, 41(1):164–171, (1970) .

33 34 35 36 37 38 39

Lawrence R Rabiner and Biing-Hwang Juang.

Fundamentals of speech recognition, volume 14 of *Signal Processing*.

Prentice Hall, Inc., Upper Saddle River, NJ, USA, 1993.

ISBN 0-13-015157-2.

33 34 35 36 37 38 39

References VII

A. P. Dempster, N. M. Laird, and D. B. Rubin.

"Maximum Likelihood from Incomplete Data via the EM Algorithm".

Journal of the Royal Statistical Society. Series B (Methodological), (October, 2007) .

33 34 35 36 37 38 39

J.G. Kemeny and J.L. Snell.

Finite markov chains.

Springer, 1960.

54

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)]

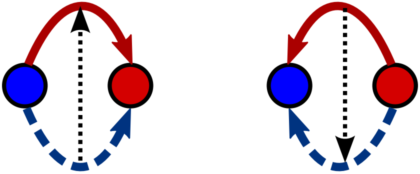
We define:

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

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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