A saturation model for impaired learning with enhanced plasticity

based on work in preparation by: T.D. Barbara Nguyen-Vu, Grace Q. Zhao, Han-Mi Lee, SL, Surya Ganguli, Carla J. Shatz, Jennifer L. Raymond

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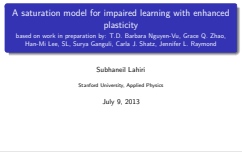

Outline

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VOR learning and the cerebellum
The effects of enhanced plasticity and saturation
Modelling approach
Modelling results

Section 1

VOR learning and the cerebellum

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Section 2

The effects of enhanced plasticity and saturation

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Questions

- Can we find a purely synaptic explanation of these results?
- Can the saturation effect overcome the enhanced plasticity?
- How can a little reverse bias help, but too much hurt?

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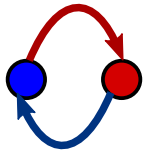
Section 3

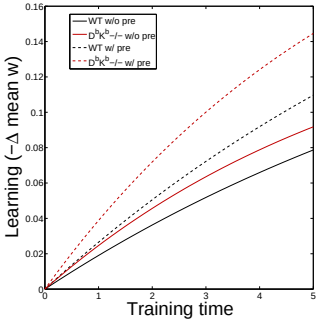
Modelling approach

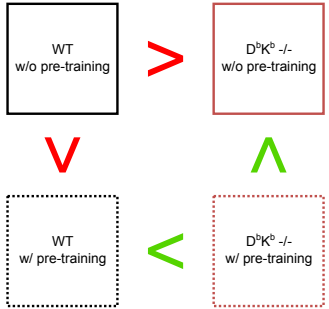
Section 4

Modelling results

Binary synapse







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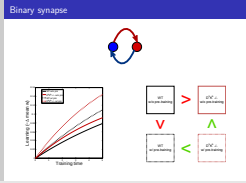
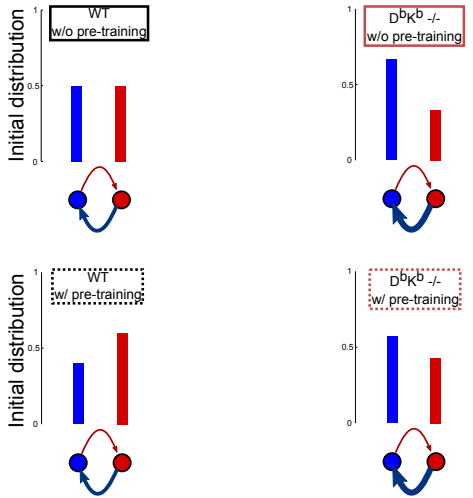


1. understand why next slide

Binary synapse: initial distributions



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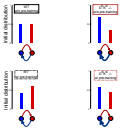

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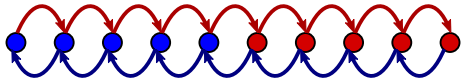
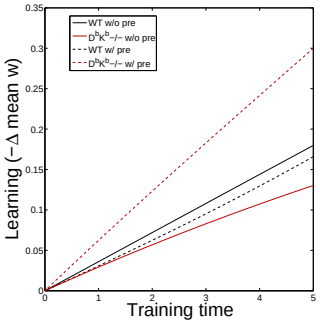
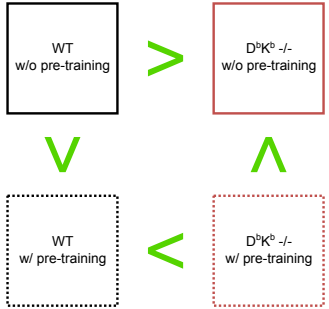
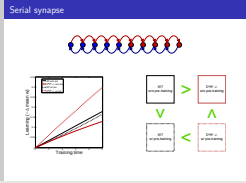
Serial synapse









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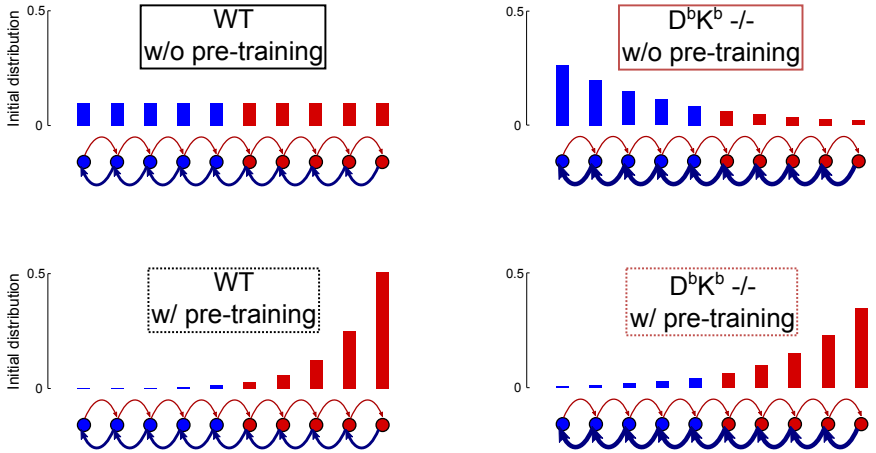

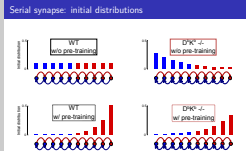

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Mathematics

Serial synapse: $\mathbf{p}_i^{\infty} \sim \mathcal{N}\left(\frac{q^{\text{pot}}}{q^{\text{dep}}}\right)^i$.

Learning rate $\sim \mathbf{p}_{M/2}^{\infty}\left(\frac{q^{\text{dep}}}{q^{\text{pot}}}\right) = \mathcal{N}\left(\frac{q^{\text{pot}}}{q^{\text{dep}}}\right)^{\frac{M}{2}-1}$.

For $M > 2$, larger $q^{\text{dep}} \implies$ slower learning.

For $M = 2$, larger $q^{\text{dep}} \implies$ larger $\mathcal{N} \implies$ faster learning.

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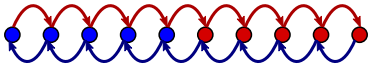
Essential features

The success od the serial model relies on two features:

- Enhancing the effect of saturation,
- Metaplasticity – repeated potentiation makes subsequent depression harder.

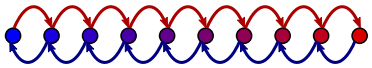


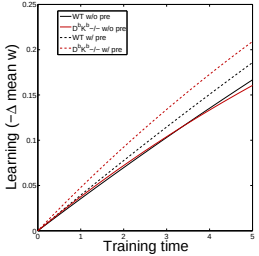
Essential features
The success od the serial model relies on two features:
Enhancing the effect of saturation,
Metaplasticity – repeated potentiation makes subsequent depression harder.

1. due to exponential decay
2. push away from boundary where signal generated
3. borne out by other models that fail/succeed

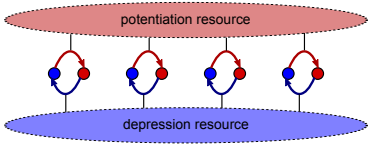
Other models that fail

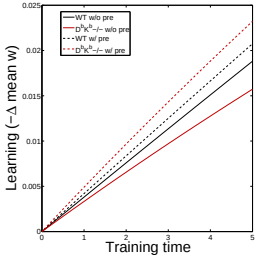
Multistate model



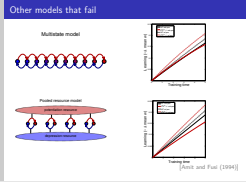


Pooled resource model



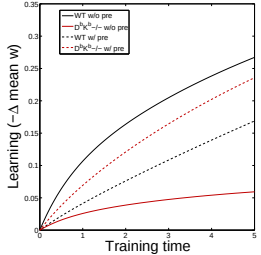


[Amit and Fusi (1994)]

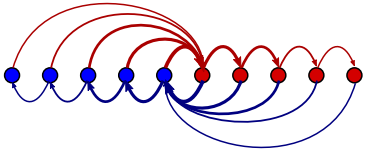


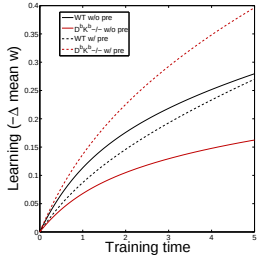
Other models that work

Non-uniform multistate model

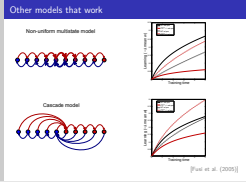


Cascade model





[Fusi et al. (2005)]



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