

Modelling impaired and enhanced learning with enhanced plasticity

based on work with: Barbara Nguyen-Vu, Grace Zhao, Aparna Suvrathan, Han-Mi Lee, Surya Ganguli, Carla Shatz and Jennifer Raymond

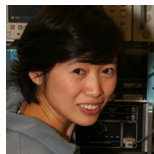
Subhaneil Lahiri

Stanford University, Applied Physics

March 1, 2014



Barbara Nguyen-Vu



Grace Zhao

Introduction

Learning requires synaptic plasticity.

Expect: enhanced plasticity \rightarrow enhanced learning.

[Tang et al. (1999), Malleret et al. (2001), Guan et al. (2009)]



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But often: enhanced plasticity \rightarrow impaired learning.

[Migaud et al. (1998), Uetani et al. (2000), Hayashi et al. (2004)]

[Cox et al. (2003), Rutten et al. (2008), Koekkoek et al. (2005)]



Introduction

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Mice with enhanced cerebellar plasticity can show both impaired and enhanced learning.

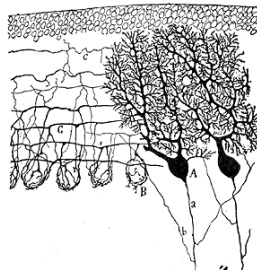
Simple synapses **cannot** explain behaviour. **Complex synapses** are required.
→ predictions for synaptic physiology.

Vestibulo-Occular Reflex training

VOR Increase Training

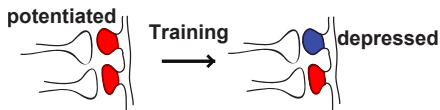


VOR Decrease Training



[Cajal]

Gain increase: LTD in PF-Pk synapses.

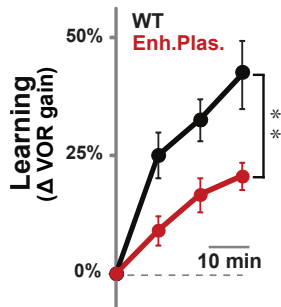


[du Lac et al. (1995), Boyden et al. (2004)]

Enhanced plasticity impairs learning

Expectation: enhanced LTD → enhanced learning.

**VOR Increase
Training**



Experiment: enhanced plasticity → impaired learning.

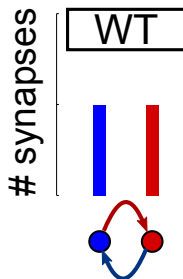
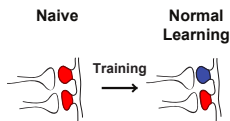
Knockout of MHC-I D^bK^b molecules in PF-Pk synapses

→ lower threshold for LTD

[McConnell et al. (2009)]

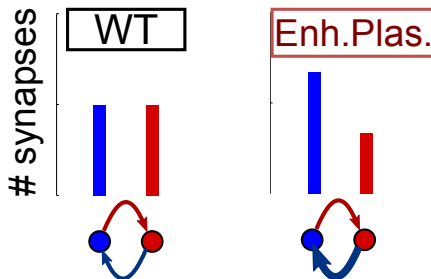
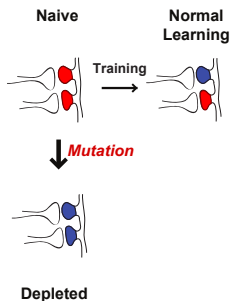
Depletion hypothesis

Learning rate \sim intrinsic plasticity rate \times # synapses available for LTD.



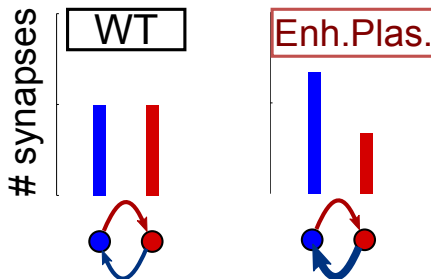
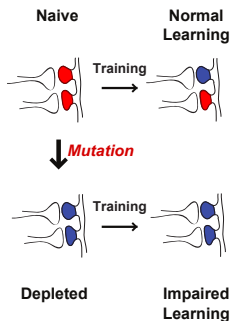
Depletion hypothesis

Learning rate \sim intrinsic plasticity rate \times # synapses available for LTD.



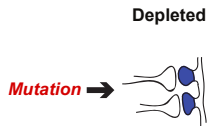
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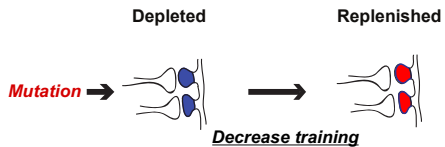


Question 1: depletion effect competes with enhanced intrinsic plasticity.
Which effect is stronger?

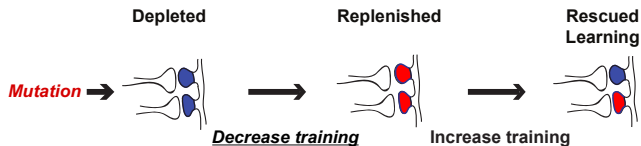
Replenishment by reverse-training



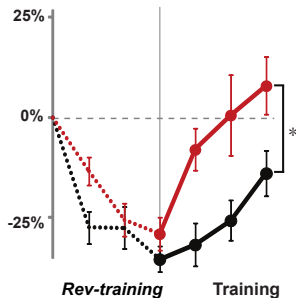
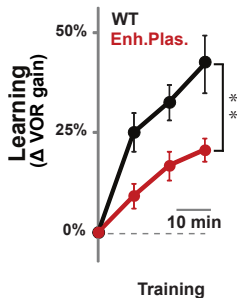
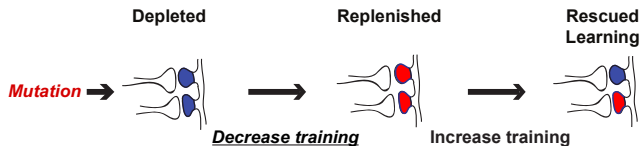
Replenishment by reverse-training



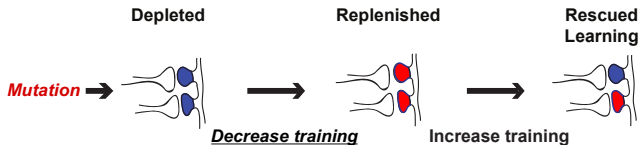
Replenishment by reverse-training



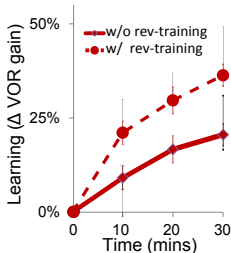
Replenishment by reverse-training



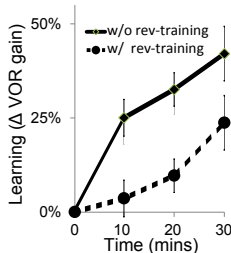
Replenishment by reverse-training



Enh. Plast.



WT

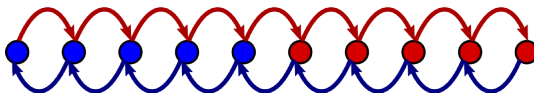


Question 2: How can *too much* replenishment impair learning?

Models of complex synaptic dynamics

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

Potential

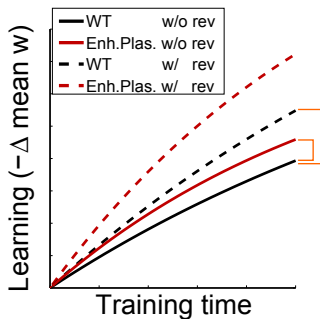
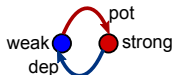


Depression

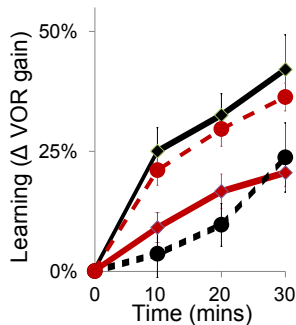
[Fusi et al. (2005), Fusi and Abbott (2007), Barrett and van Rossum (2008)]
[Smith et al. (2006)]

Simple synapses cannot explain the data

Binary synapse

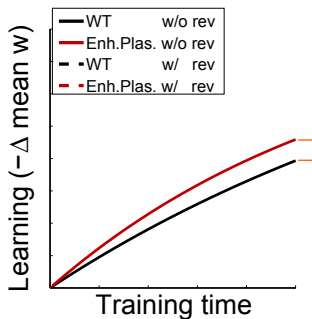
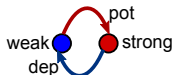


VOR Increase Training

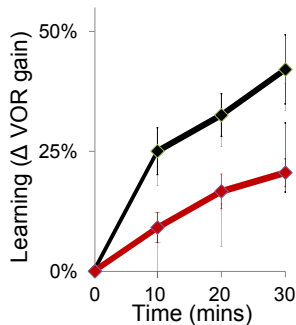


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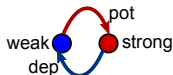


VOR Increase Training



Simple synapses cannot explain the data

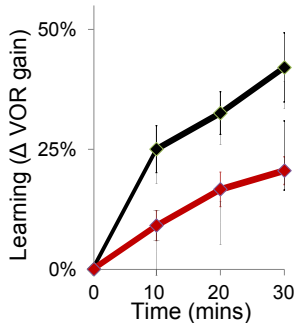
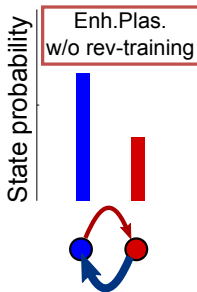
Binary synapse



VOR Increase Training

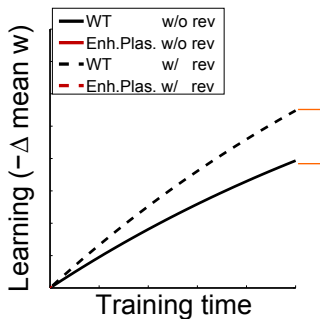
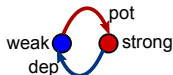


Initial distribution

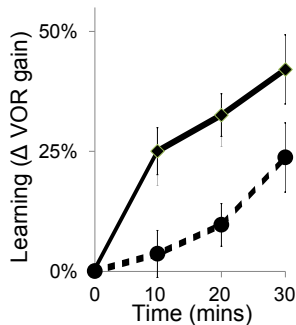


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Binary synapse

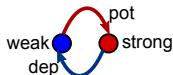


VOR Increase Training



Simple synapses cannot explain the data

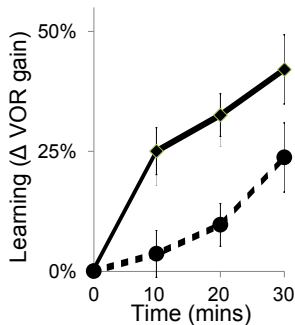
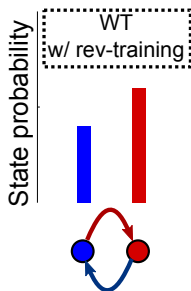
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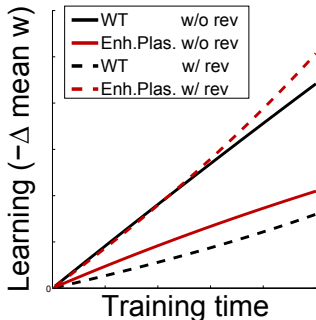
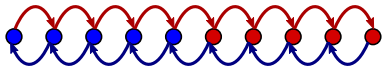


Initial distribution

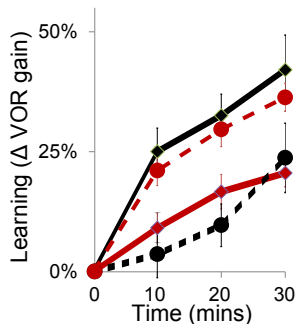


Complex metaplastic synapses can explain the data

Serial synapse



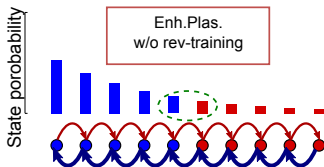
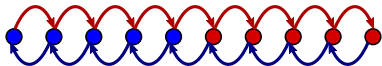
VOR Increase Training



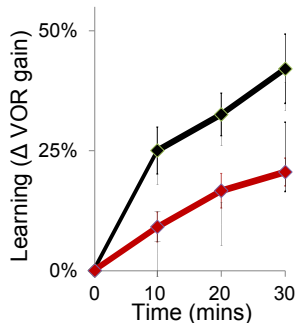
[Leibold and Kempter (2008)]

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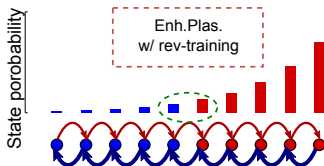
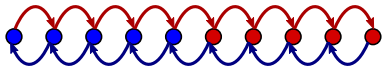
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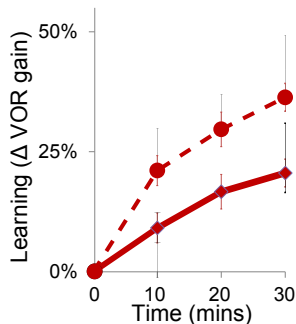
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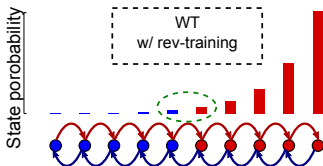
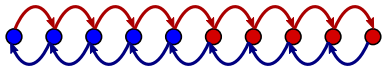
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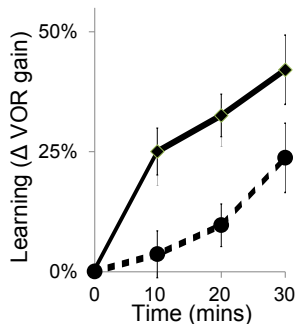
[Leibold and Kempter (2008)]

Complex metaplastic synapses can explain the data

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VOR Increase Training



[Leibold and Kempter (2008)]

- Diverse behavioural patterns:
Enhanced plasticity → enhance/impair learning (prior experience).
Reverse-training → enhance/impair learning (plasticity rates).
- Predictions for synaptic physiology:
Synaptic complexity: necessary to amplify depletion.
Synaptic stubbornness: repeated potentiation makes subsequent depression harder.
- We used behaviour to constrain the dynamics of synaptic plasticity

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Aparna Suvrathan

Carla Shatz

Han-Mi Lee

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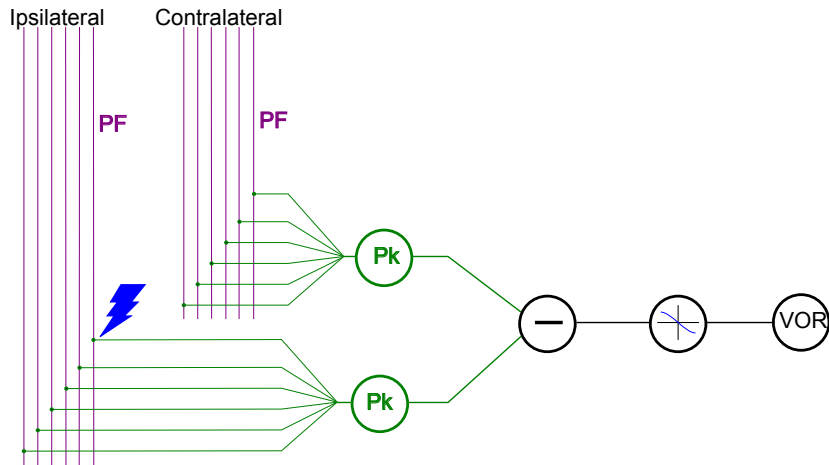
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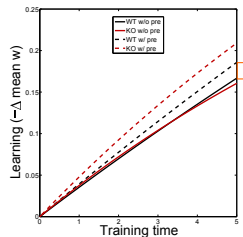
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Model of circuit

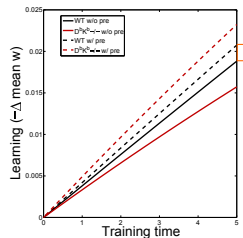
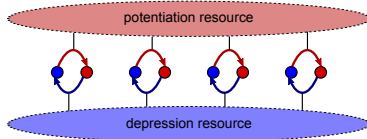


Other models that fail

Multistate model



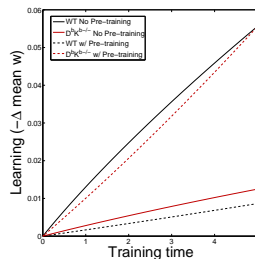
Pooled resource model



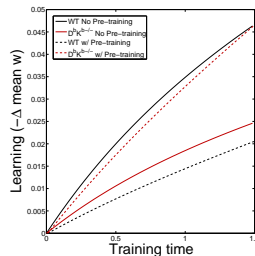
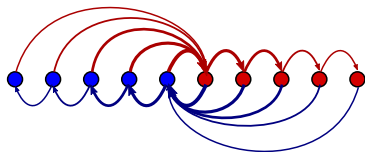
[Amit and Fusi (1994)]

Other models that work

Non-uniform multistate model

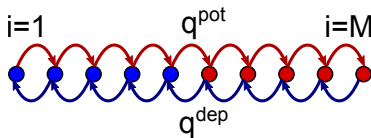


Cascade model



[Fusi et al. (2005)]

Mathematical explanation



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.