

Modelling impaired and enhanced learning with enhanced plasticity

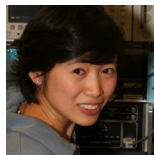
Subhaneil Lahiri, Barbara Nguyen-Vu, Grace Zhao, Aparna Suvrathan, Han-Mi Lee, Surya Ganguli, Carla Shatz and Jennifer Raymond

Stanford University

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 → impaired learning.

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

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

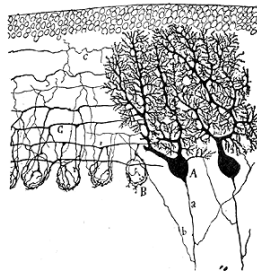
Simple synapses **cannot** explain behaviour. **Complex synapses** are required.
→ predictions for synaptic physiology.

Vestibulo-Occular Reflex training

VOR Increase Training



VOR Decrease Training



[Cajal]

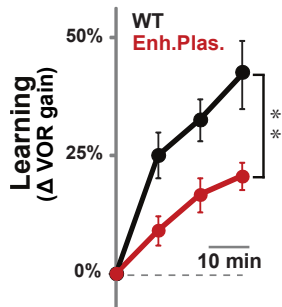
VOR increase: LTD in PF-Pk synapses.

[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.

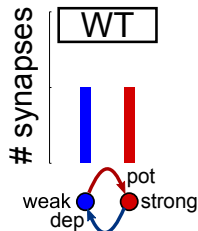
Knockout of MHC-I D^bK^b molecules in PF-Pk synapses

→ lower threshold for LTD

[McConnell et al. (2009)]

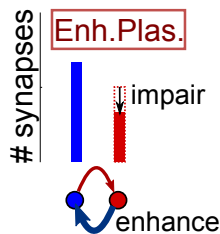
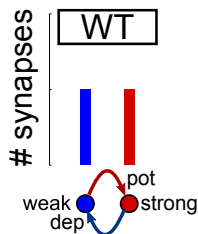
Depletion hypothesis

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



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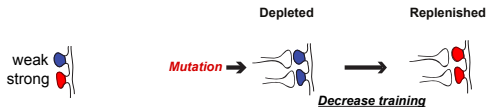


Question 1: depletion effect competes with enhanced intrinsic plasticity.
When is depletion effect stronger?

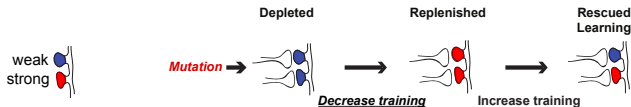
Replenishment by reverse-training



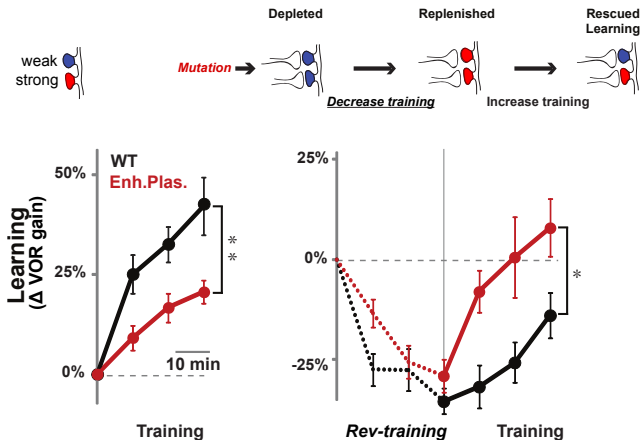
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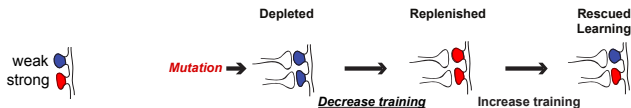
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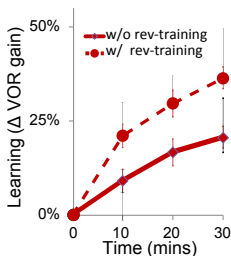
Replenishment by reverse-training



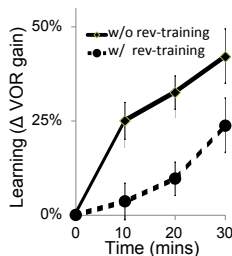
Replenishment by reverse-training



Enh. Plast.

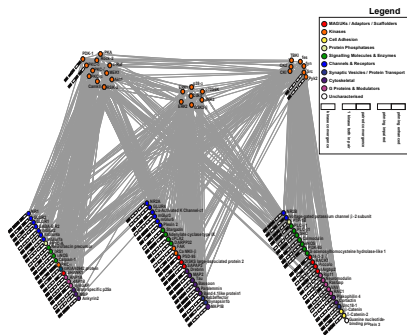


WT

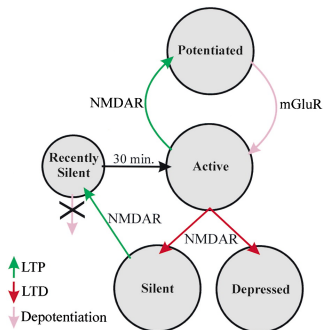


Question 2: How can replenishment ever impair learning?

Synapses are complex



[Coba et al. (2009)]

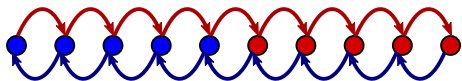


[Montgomery and Madison (2002)]

Models of complex synaptic dynamics

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

Potential



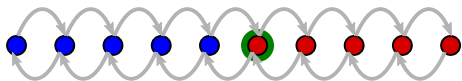
Depression

[Fusi et al. (2005), Fusi and Abbott (2007), Barrett and van Rossum (2008)]
[Smith et al. (2006), Lahiri and Ganguli (2013)]

Models of complex synaptic dynamics

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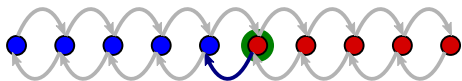
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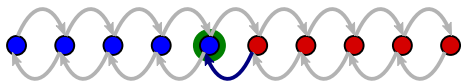
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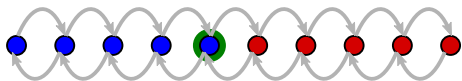
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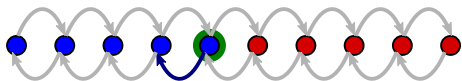
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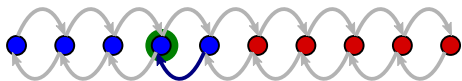
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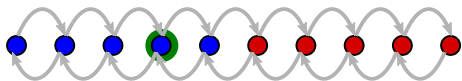
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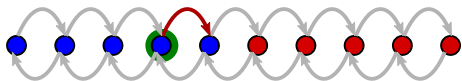
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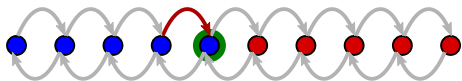
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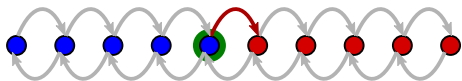
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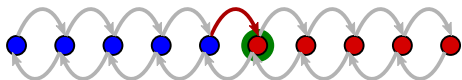
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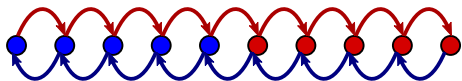
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Potential



Depression

Mutation: trans. probs.

Training: freq. of pot/dep events

Learning: synaptic weight

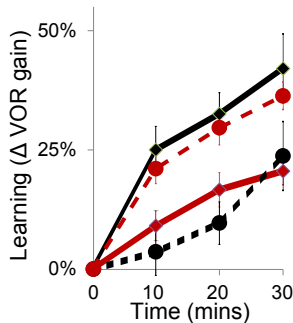
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Simple synapses cannot explain the data

Multistate synapse

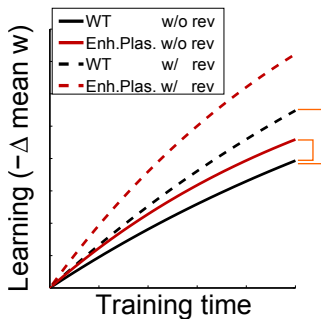
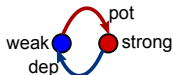


VOR Increase Training

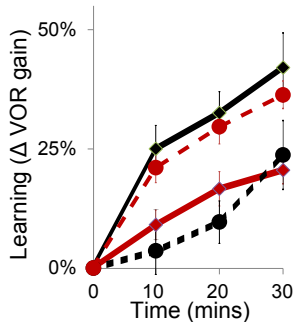


Simple synapses cannot explain the data

Binary synapse

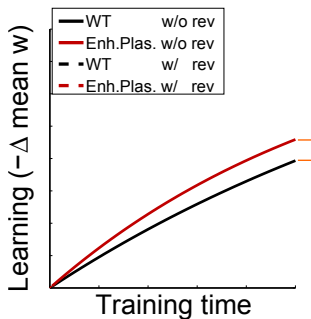
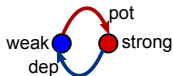


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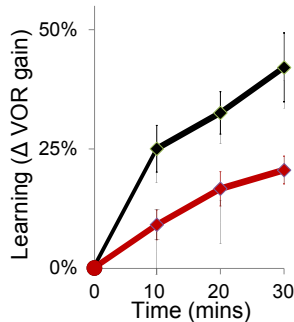


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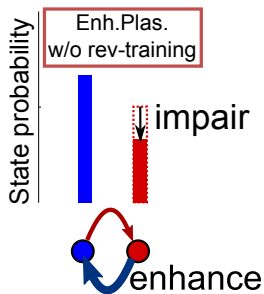


Simple synapses cannot explain the data

Binary synapse



Initial distribution



depletion effect

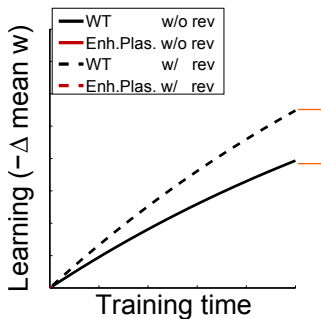
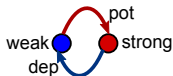
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enhanced plasticity

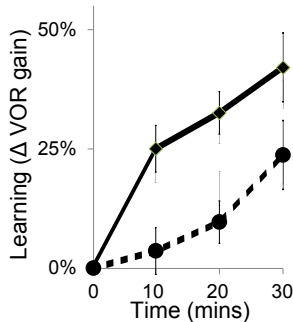
⇒ enhanced learning

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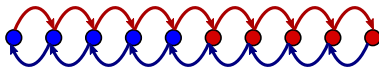


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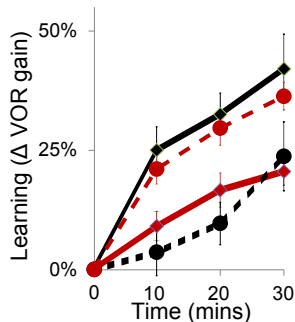
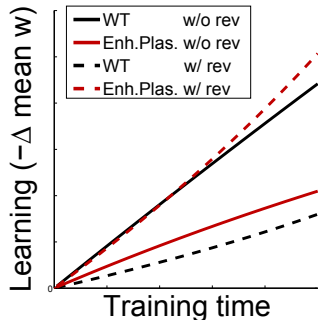


Complex metaplastic synapses can explain the data

Serial synapse



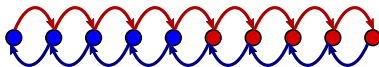
VOR Increase Training



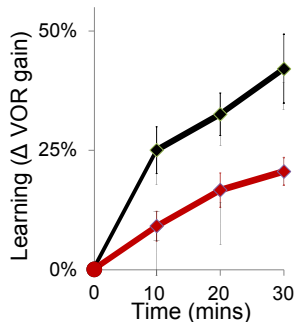
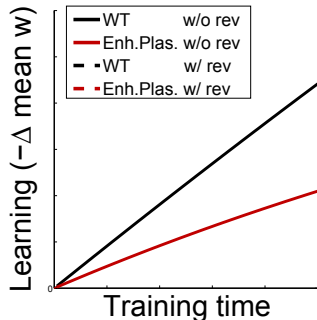
[Leibold and Kempter (2008), Ben-Dayan Rubin and Fusi (2007)]

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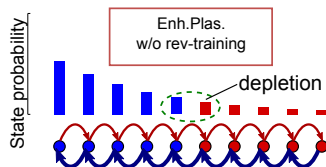
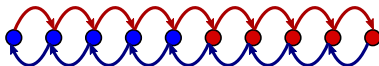
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amplified depletion

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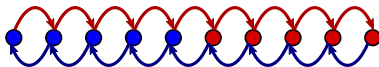
enhanced plasticity

⇒ impaired learning

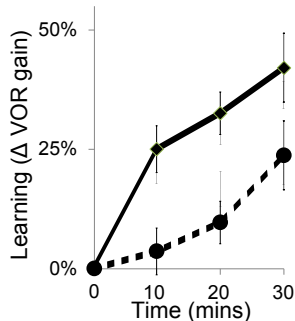
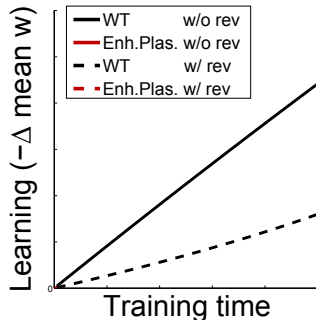
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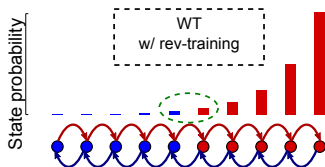
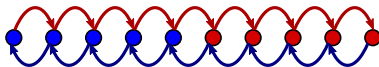
VOR Increase Training



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

Complex metaplastic synapses can explain the data

Serial synapse



reverse training
+
“stubborn” metaplasticity
⇒ impaired learning

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

Conclusions

- Diverse behavioural patterns:
Enhanced plasticity → enhance/impair learning (prior experience).
Reverse-training → enhance/impair learning (plasticity rates).
- enhanced LTD vs. depletion → learning outcome.
- 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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Barbara Nguyen-Vu

Grace Zhao

Aparna Suvrathan

Carla Shatz

Han-Mi Lee

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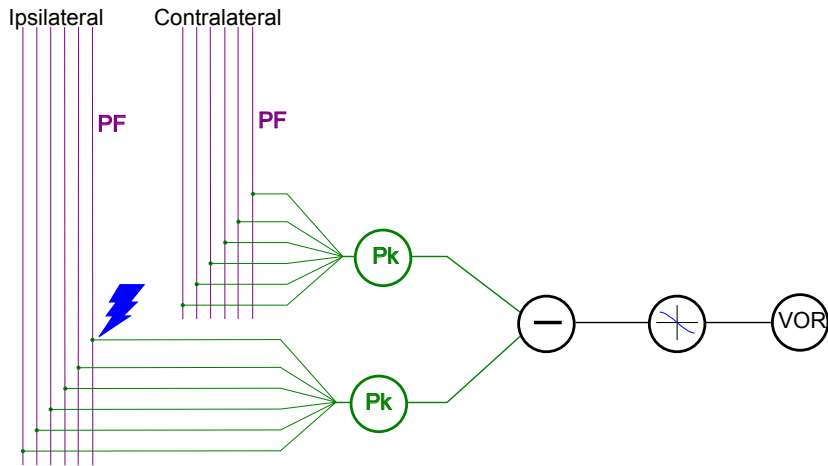


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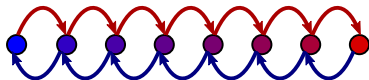
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Model of circuit

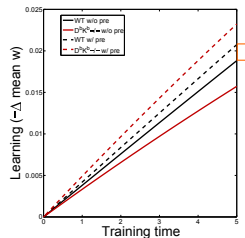
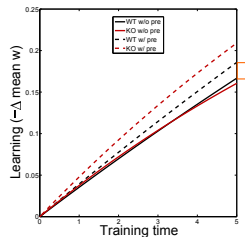
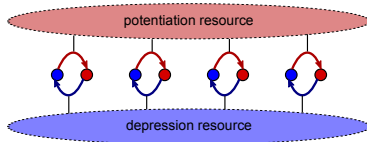


Other models that fail

Multistate synapse



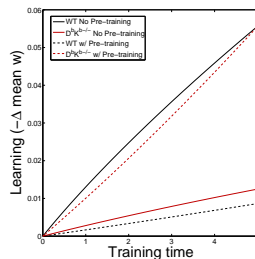
Pooled resource model



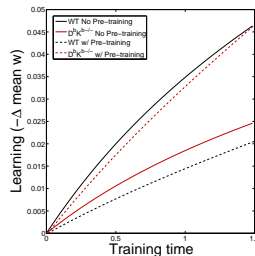
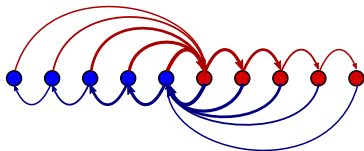
[Amit and Fusi (1994)]

Other models that work

Non-uniform multistate model

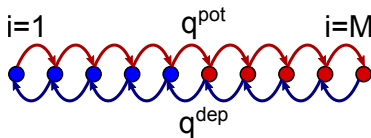


Cascade model



[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.