Modelling impaired and enhanced learning with enhanced plasticity
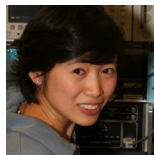
Subhaneil Lahiri, Barbara Nguyen-Vu, Grace Zhao, Aparna Suvrathan, Han-Mi Lee, Surya Ganguli, Carla Shatz and Jennifer Raymond

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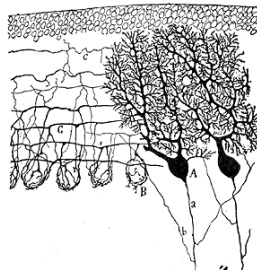Mice with enhanced cerebellar plasticity can show both impaired and enhanced learning.

Simple synapses cannot explain behaviour. Complex synapses are required.
$\rightarrow$ predictions for synaptic physiology.
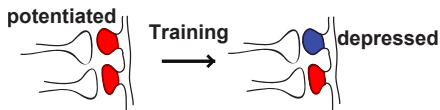
Vestibulo-Occular Reflex training

VOR Increase Training

VOR Decrease Training
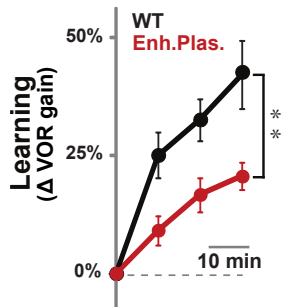

[Cajal]

Gain increase: LTD in PF-Pk synapses.

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

Expectation: enhanced LTD → enhanced learning.

**VOR Increase
Training**

Experiment: enhanced plasticity → impaired learning.
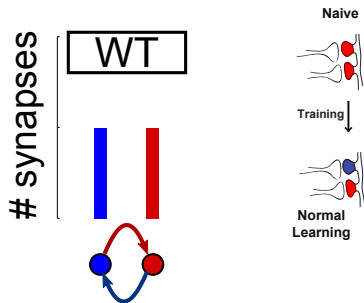
Knockout of MHC-I D^bK^b molecules in PF-Pk synapses
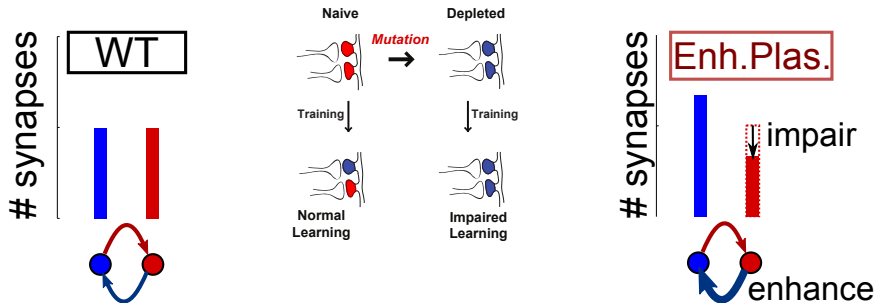→ lower threshold for LTD   [McConnell et al. (2009)]

Depletion hypothesis

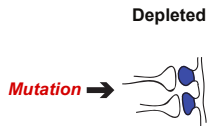Learning rate $\sim$ intrinsic plasticity rate $\times$ # synapses available for LTD.

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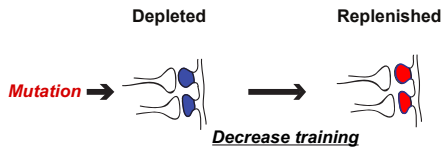

Question 1: depletion effect competes with enhanced intrinsic plasticity. Which effect is stronger?
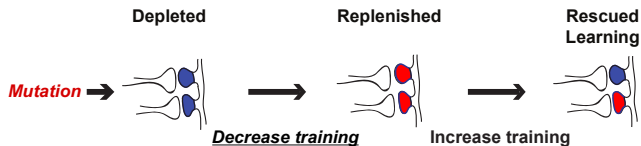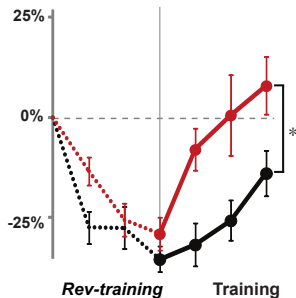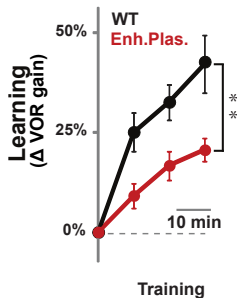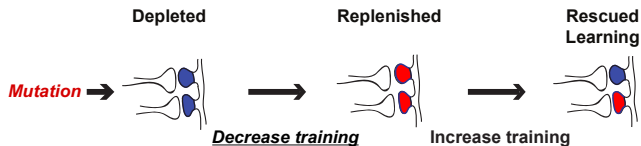
Replenishment by reverse-training

Depleted

Mutation ➡

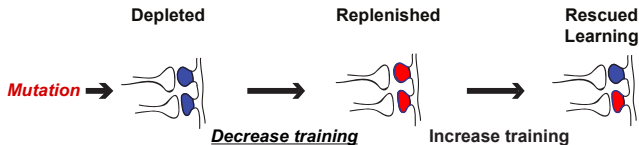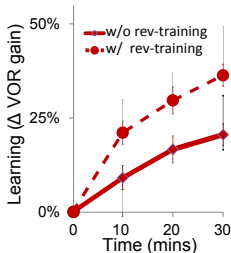# Replenishment by reverse-training

Replenishment by reverse-training

Depleted   Replenished   Rescued Learning

Mutation ➔

Decrease training   Increase training

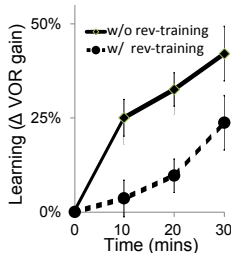# Replenishment by reverse-training
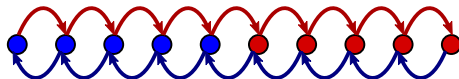
Question 2: How can *too much* replenishment impair learning?

Models of complex synaptic dynamics

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

Potentiation

Depression

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

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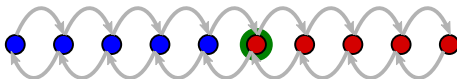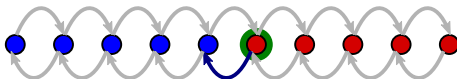

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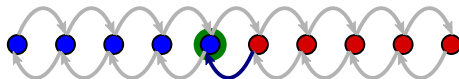
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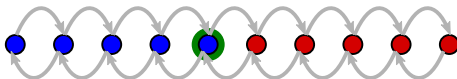

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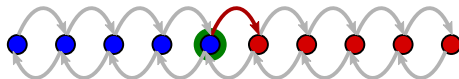
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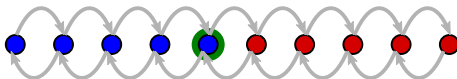
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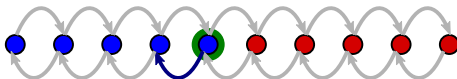
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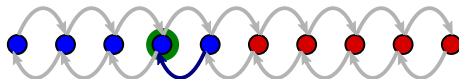

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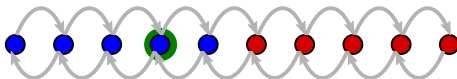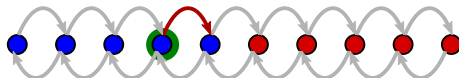
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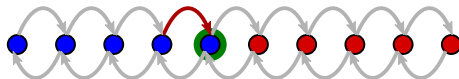- Candidate plasticity events $\rightarrow$ transitions between states

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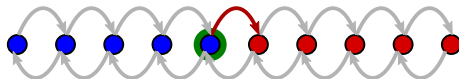
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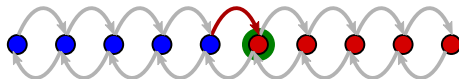
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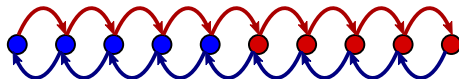
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Potentiation

Depression

Mutation: trans. probs.

Training: plast. event rates
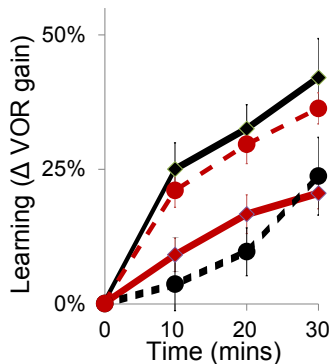
Learning: synaptic weight

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Simple synapses cannot explain the data
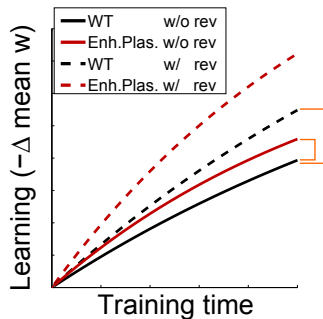
Multistate synapse

VOR Increase Training
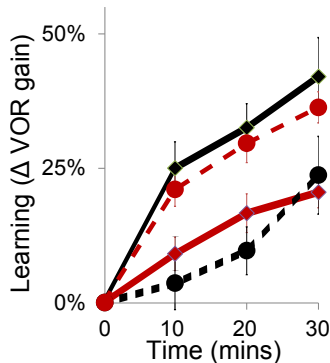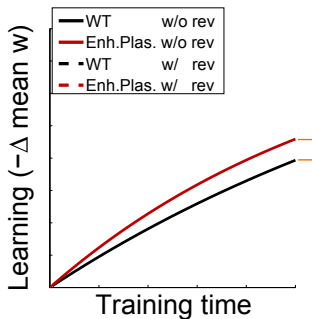
Simple synapses cannot explain the data

Simple synapses cannot explain the data

Binary synapse

VOR Increase Training

WT w/o rev
Enh.Plas. w/o rev
WT w/ rev
Enh.Plas. w/ rev

Learning (−Δ mean w)

Training time

Learning (Δ VOR gain)

50%

25%

0%

0   10   20   30
Time (mins)

Binary synapse

Initial distribution

State probability

Enh.Plas.
w/o rev-training
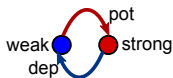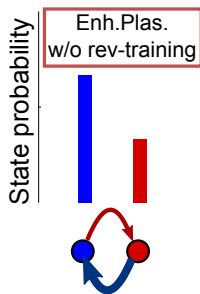
depletion effect
$<$
enhanced plasticity

$\implies$ enhanced learning

Simple synapses cannot explain the data
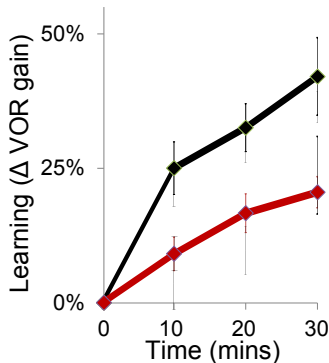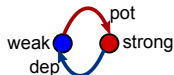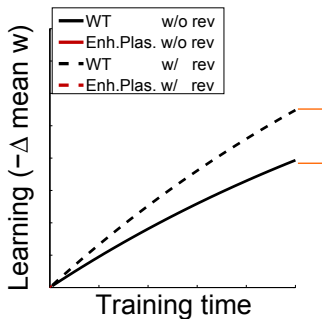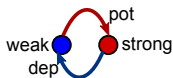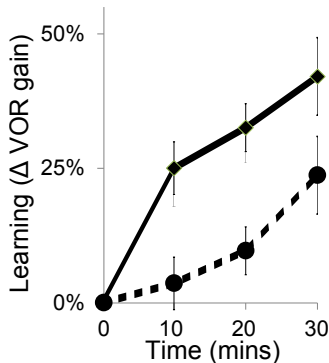

Binary synapse

VOR Increase
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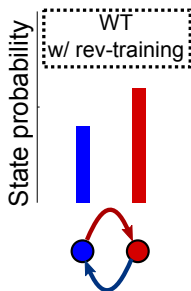
reverse training
$\Longrightarrow$
replenishment
$\Longrightarrow$
enhanced learning
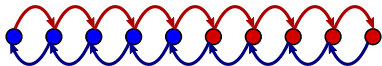
Serial synapse

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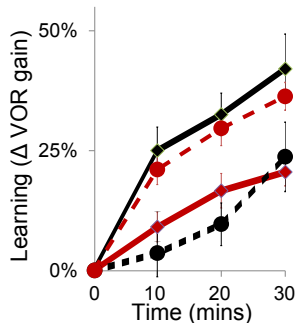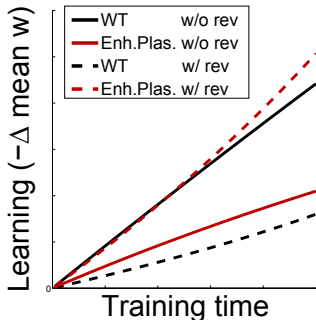
[Leibold and Kempter (2008), Ben-Dayan Rubin and Fusi (2007)]

Complex metaplastic synapses can explain the data

Serial synapse

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Serial synapse

State porobability

Enh.Plas.
w/o rev-training
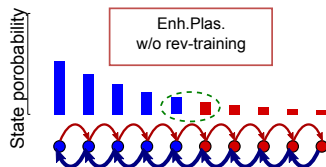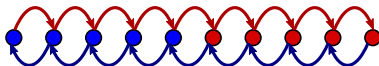
amplified depletion
$>$
enhanced plasticity

$\implies$ impaired learning

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

Serial synapse

VOR Increase Training

Learning ($-\Delta$ mean w)

- —— WT   w/o rev
- —— Enh.Plas. w/o rev
- - - WT   w/ rev
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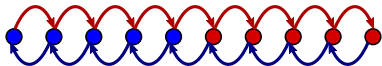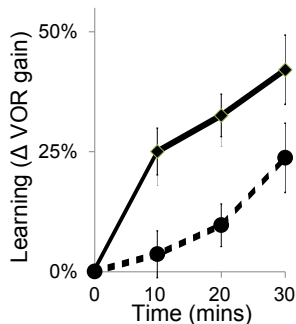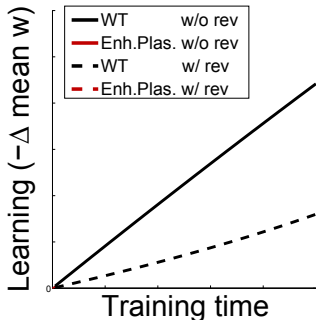
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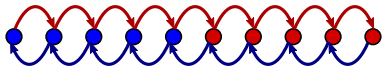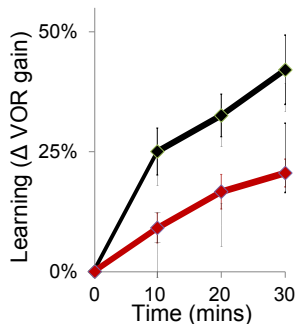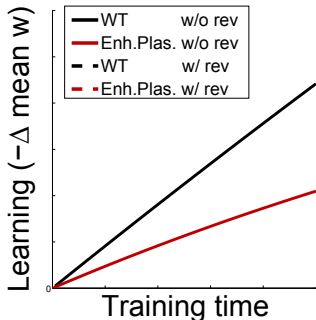
Complex metaplastic synapses can explain the data

Serial synapse
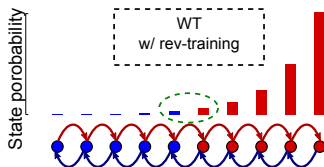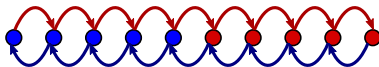
reverse training
+
"stubborn" metaplasticity

$\implies$ impaired learning

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

Conclusions

- Diverse behavioural patterns:
  Enhanced plasticity $\rightarrow$ enhance/impair learning (prior experience).
  Reverse-training $\rightarrow$ 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

Acknowledgements

Surya Ganguli   **Jennifer Raymond**   **Carla Shatz**
Madhu Advani   Barbara Nguyen-Vu   Han-Mi Lee
Peiran Gao   Grace Zhao
Niru Maheswaranathan   Aparna Suvrathan
Ben Poole
Jascha Sohl-Dickstein

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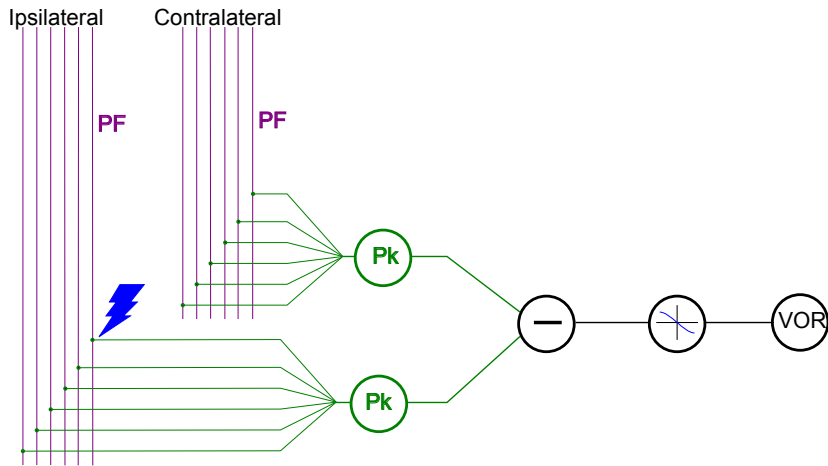*Frontiers in computational neuroscience*, 1(November):1–14, (2007) .
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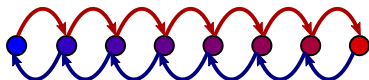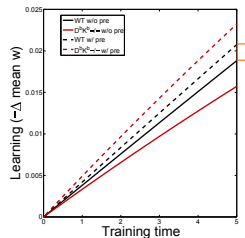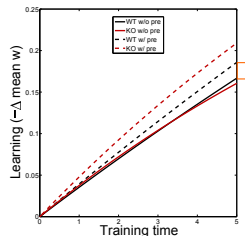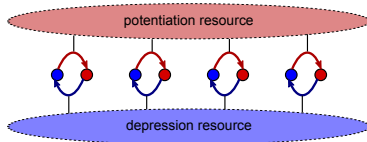*Neural Computation*, 6(5):957–982, (1994) .
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Model of circuit

Multistate synapse

Pooled resource model

potentiation resource

depression resource
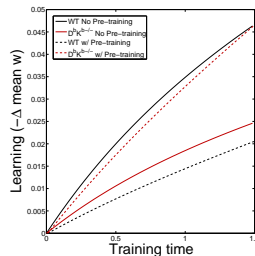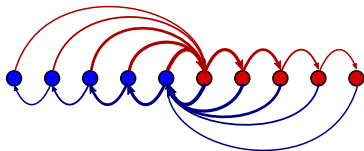
[Amit and Fusi (1994)]
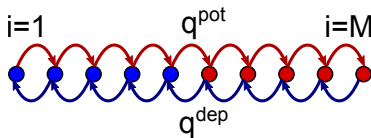
Non-uniform multistate model
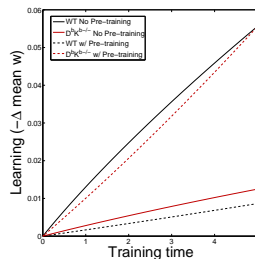
Cascade model

[Fusi et al. (2005)]

Mathematical explanation

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

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

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

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