Modelling impaired and enhanced learning with enhanced plasticity

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

Stanford University

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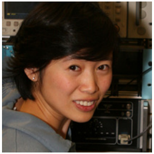
Barbara Nguyen-Vu



Grace Zhao

Introduction

Learning requires synaptic plasticity.
Expect: enhanced plasticity $\rightarrow$ enhanced learning.

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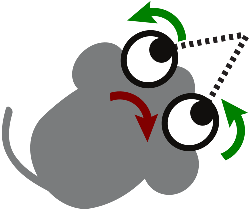
Mice with enhanced cerebellar plasticity can show both impaired and enhanced learning.

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

Vestibulo-Occular Reflex



Eye movements compensate for head movements
$\implies$ stabilise image on retina.

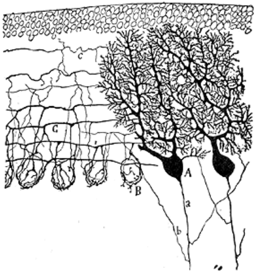
Requires control of VOR gain $= \frac{\text{eye velocity}}{\text{head velocity}}$.

Needs to be adjusted as eye muscles age, etc.

Vestibulo-Occular Reflex training

VOR Increase Training

VOR Decrease Training



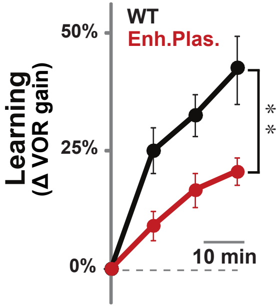
[Cajal]

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.

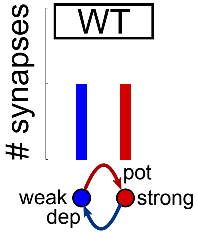


Experiment: enhanced plasticity → impaired learning.

Knockout of MHC-I K^bD^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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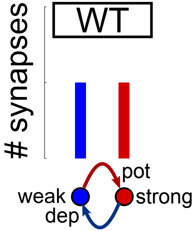
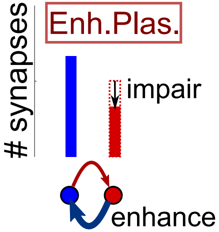
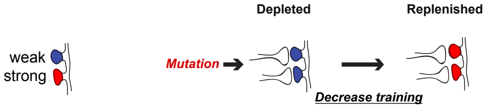




Question 1: depletion effect competes with enhanced intrinsic plasticity.
When is depletion effect stronger?

Replenishment by reverse-training

Replenishment by reverse-training



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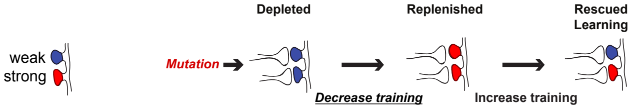

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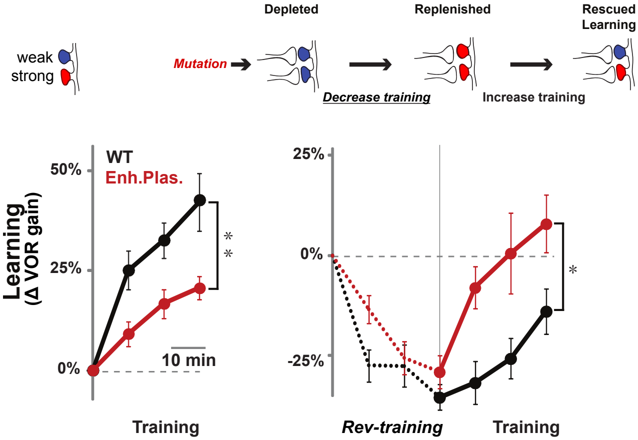

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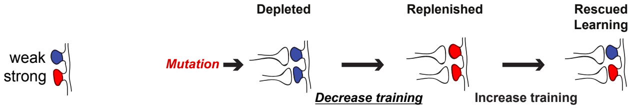
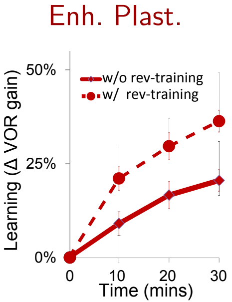
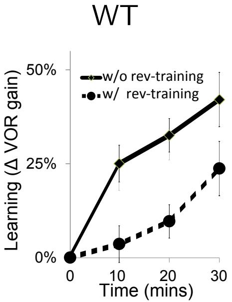
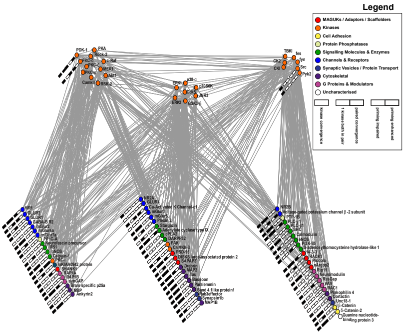




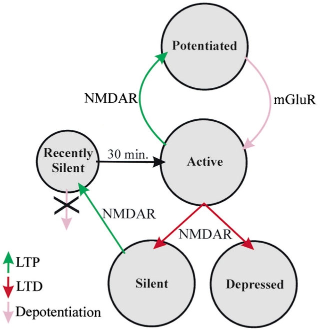


Question 2: How can replenishment *ever* impair learning?

Synapses are complex

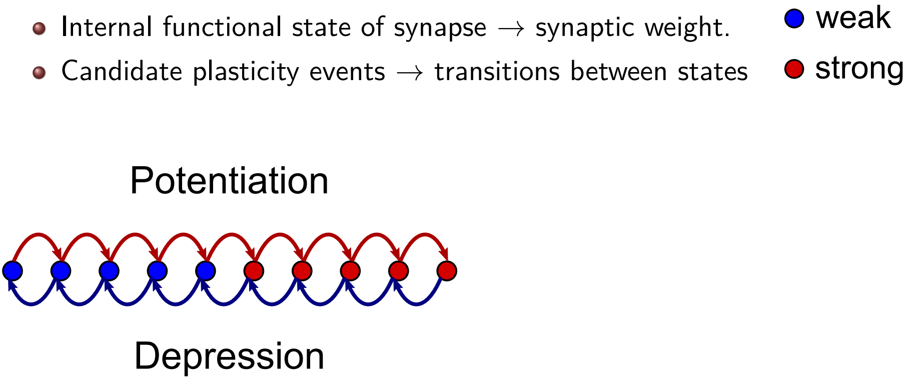


[Coba et al. (2009)]



[Montgomery and Madison (2002)]

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



[Fusi et al. (2005), Fusi and Abbott (2007), Barrett and van Rossum (2008)]
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Models of complex synaptic dynamics

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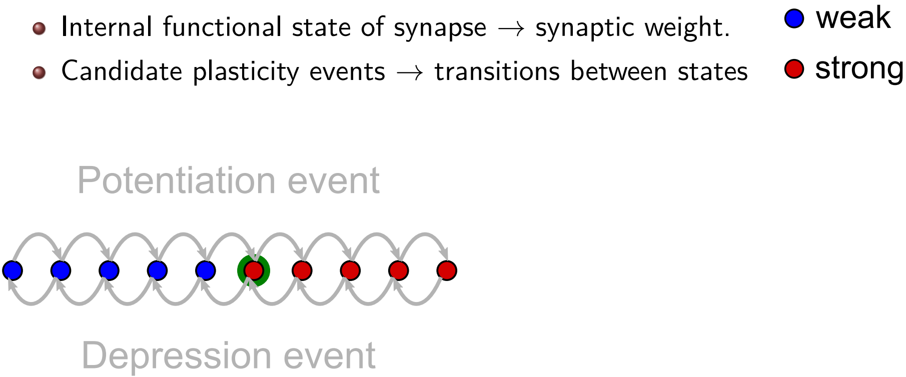

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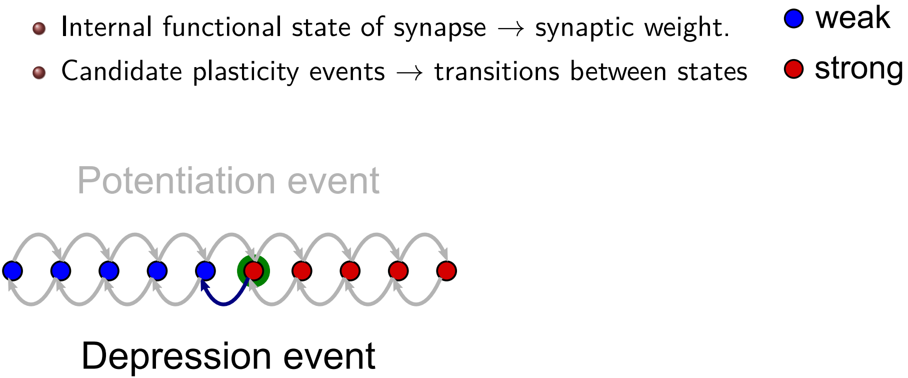

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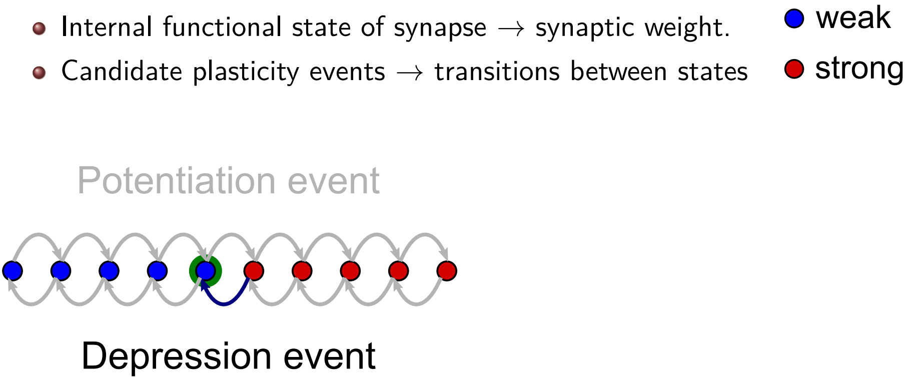

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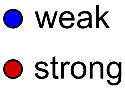

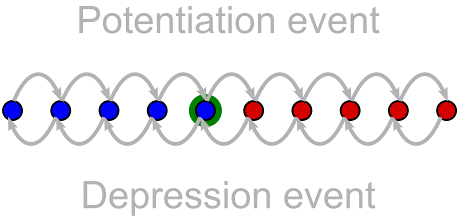

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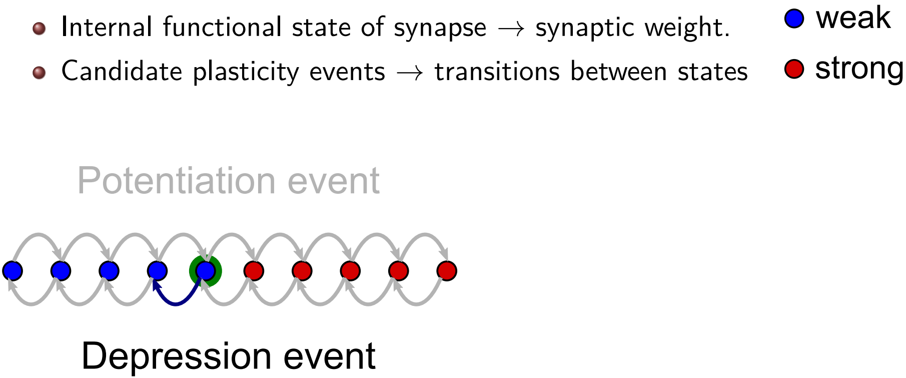

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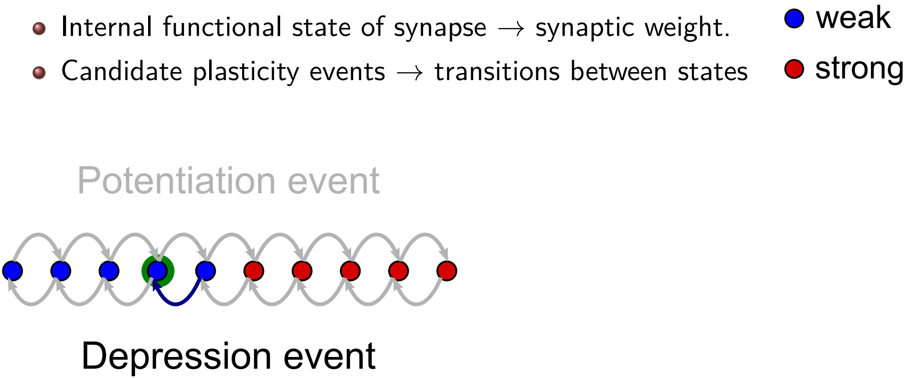

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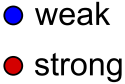
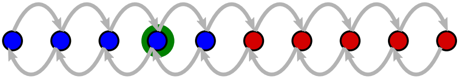


Potentiation event



Depression event

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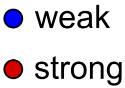

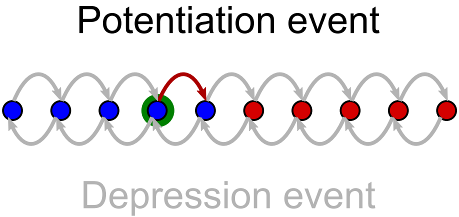

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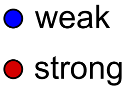

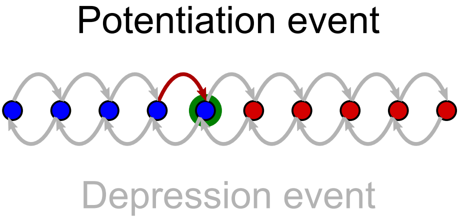

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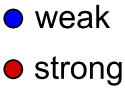

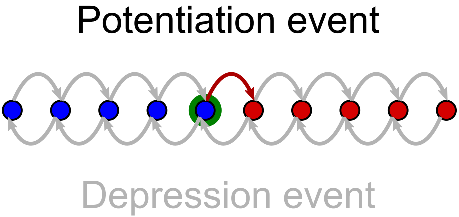

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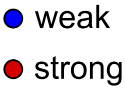

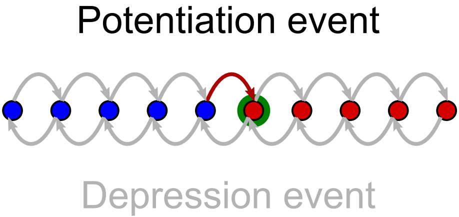

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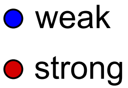

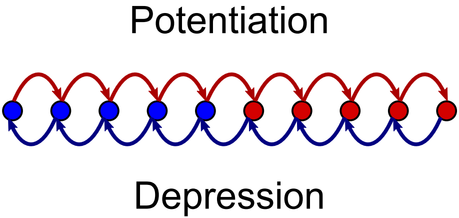

Mutation: transition probabilities

Training: rates of pot/dep events

Learning: synaptic weight

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

Depletion effect competes with enhanced intrinsic plasticity.

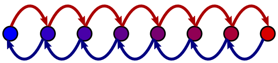
Question 1: When is the depletion effect stronger?

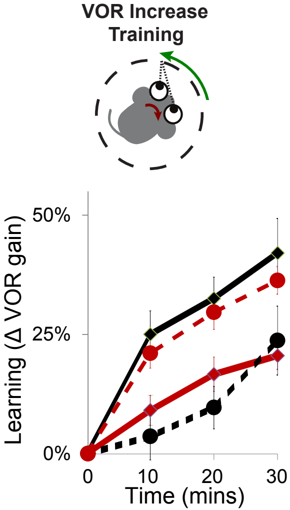
Reverse training impairs learning in wild-type.

Question 2: How can replenishment *ever* impair learning?

Simple synapses cannot explain the data

Multistate synapse





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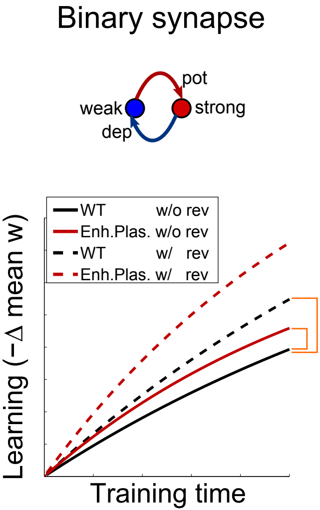
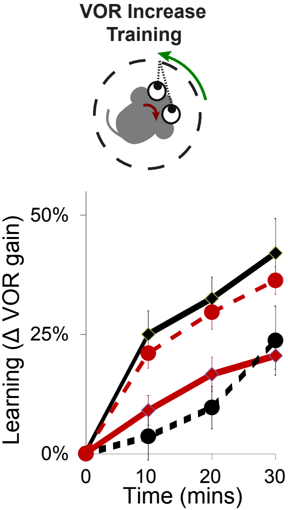
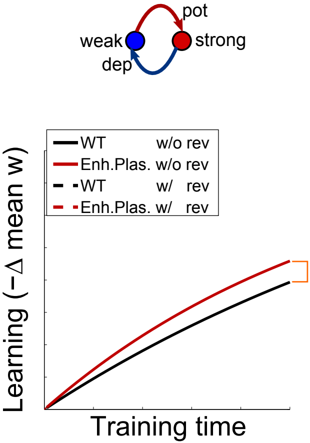


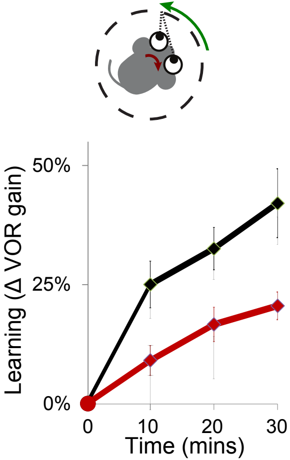


Simple synapses cannot explain the data

Binary synapse



VOR Increase Training



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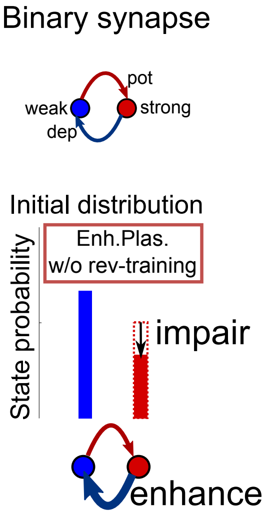


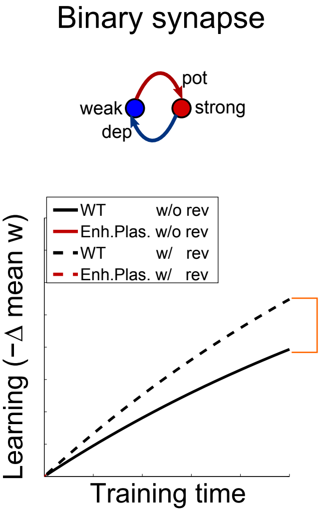
depletion effect

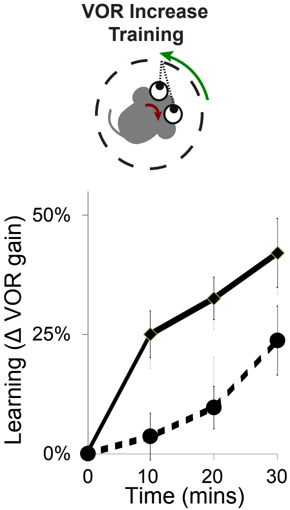
$<$

enhanced plasticity

$\Longrightarrow$ enhanced learning

Simple synapses cannot explain the data





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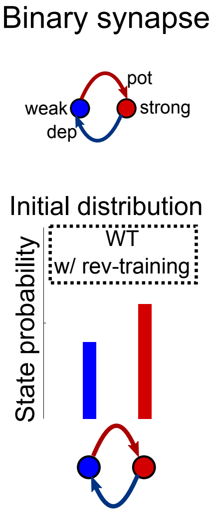


reverse training

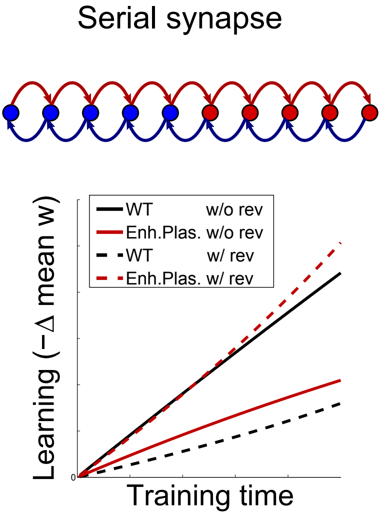
$\Longrightarrow$

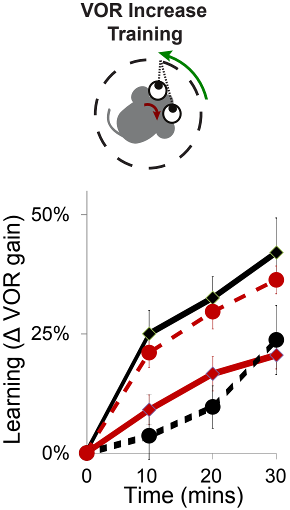
replenishment

$\Longrightarrow$

enhanced learning

Complex metaplastic synapses can explain the data





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

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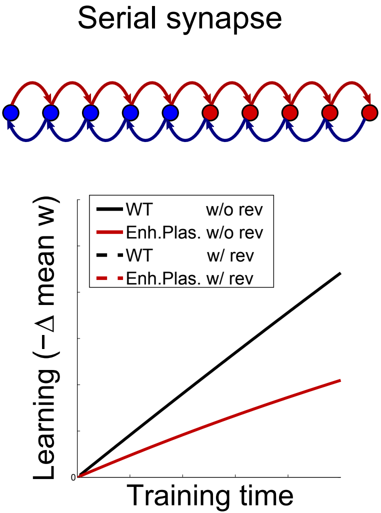

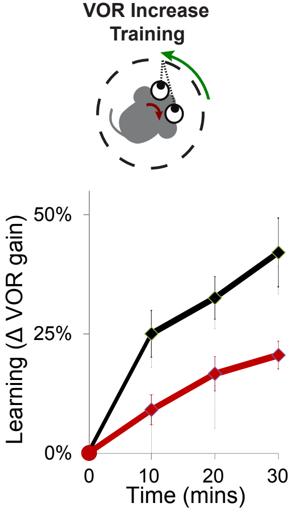

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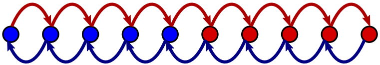
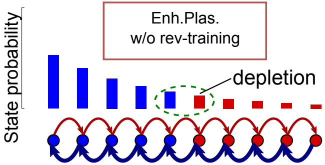
Complex metaplastic synapses can explain the data

Serial synapse





amplified depletion

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enhanced plasticity

$\Longrightarrow$ impaired learning

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

Complex metaplastic synapses can explain the data

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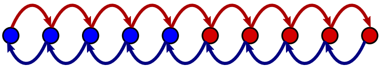

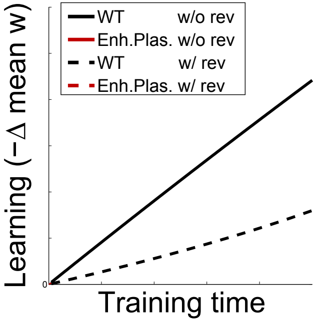

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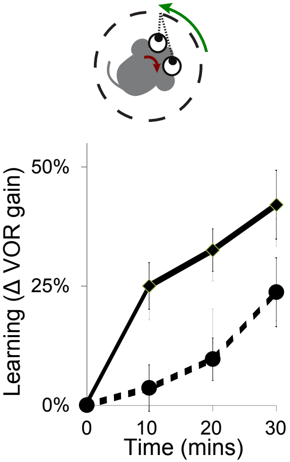

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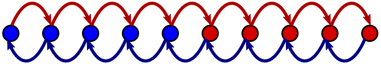
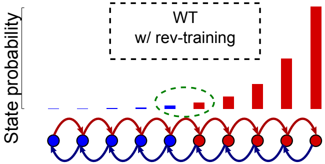




reverse training

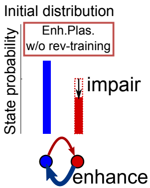
$+$

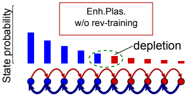
"stubborn" metaplasticity

$\Longrightarrow$ impaired learning

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

Enhanced plasticity can enhance or impair learning



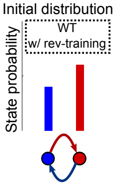


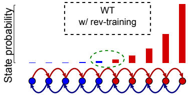
Intrinsic plasticity dominates depletion
↓
enhanced plasticity enhances learning

Depletion dominates intrinsic plasticity
↓
enhanced plasticity impairs learning

Key feature 1: Synaptic complexity that amplifies depletion effect.

Reverse-training can impair or enhance learning



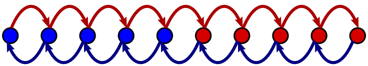


reverse-training
repopulates boundary
$\downarrow$
enhanced learning

reverse-training
depopulates boundary
$\downarrow$
impaired learning

Key feature 2: "Stubborn" metaplasticity.

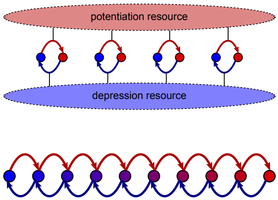
Essential features



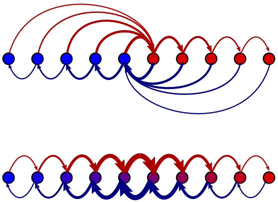
The success of the serial model relies on two features:

- Complexity - needed to amplify the effect of depletion,
- Metaplasticity – repeated potentiation impairs subsequent depression.

Fail:



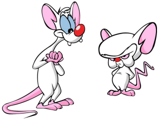
Succeed:



[Amit and Fusi (1994), Fusi et al. (2005)]

Conclusions

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



- enhanced LTD vs. depletion $\rightarrow$ learning outcome.

- Predictions for synaptic physiology:
  Synaptic complexity: necessary to amplify depletion.
  Synaptic stubbornness: repeated potentiation impairs future depression.

- We used behaviour to constrain the dynamics of synaptic plasticity

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Jay Sarkar		

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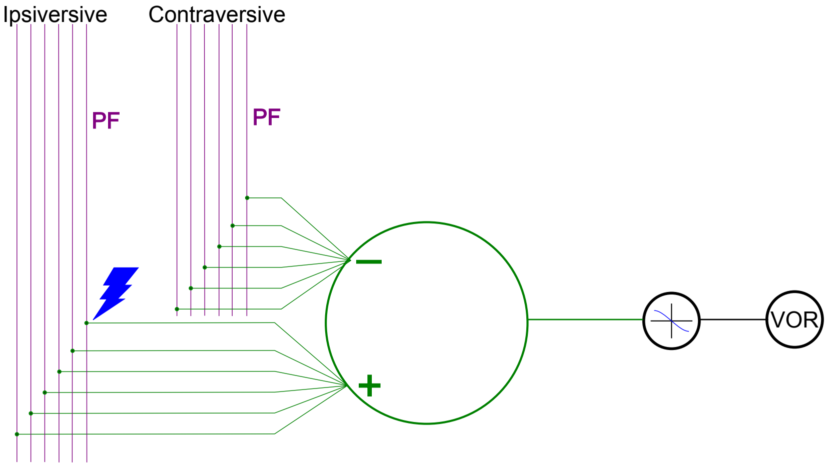
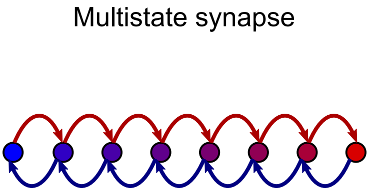
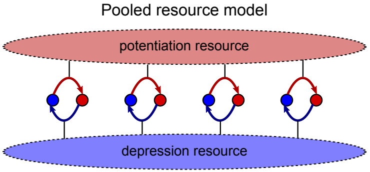
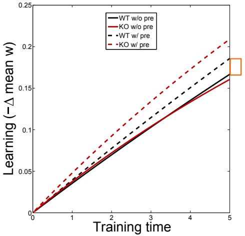
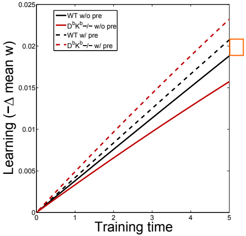
Model of circuit







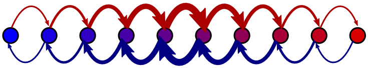


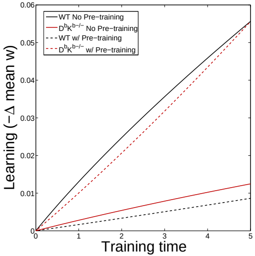


[Amit and Fusi (1994)]

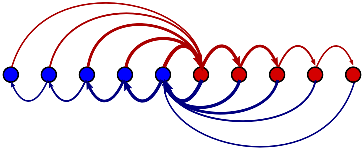
Other models that work

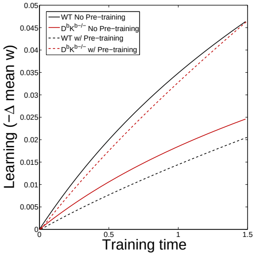
Non-uniform multistate model





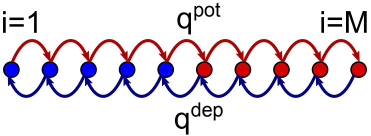
Cascade model





[Eusi 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.

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