

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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1. Acknowledge Barbara and Grace

1. It does help in some cases

One might expect enhanced plasticity to enhance learning. But often it actually causes impairment.

We argue that this impaired learning is due to basal activity biasing the synapses prior to learning, leaving fewer synapses available for further plasticity.

By analysing several models of complex synapses, we see that the behaviour of enhanced LTD mice in a motor learning task can constrain the synaptic structure.

- 1 VOR learning and the cerebellum
- 2 The effects of enhanced plasticity and saturation
- 3 Modelling approach
- 4 Modelling results

2013-07-11

Saturation by enh. plasticity impairs learning

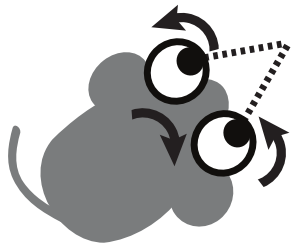
Outline

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- 1 VOR learning and the cerebellum
- 2 The effects of enhanced plasticity and saturation
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Saturation by enh. plasticity impairs learning
└ VOR learning and the cerebellum

VOR learning and the cerebellum



Eye movements compensate for head movements to maintain fixation.

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

Needs to be adjusted as eye muscles age, etc.

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

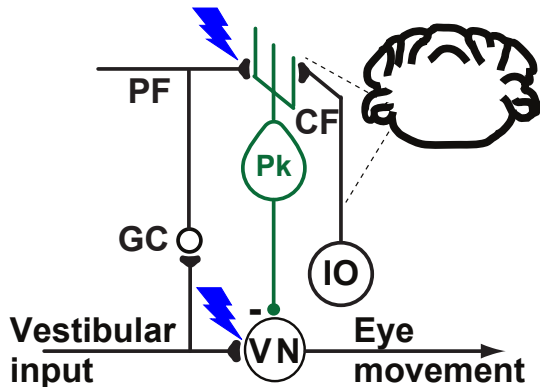


VOR training

VOR Increase Training



VOR Decrease Training



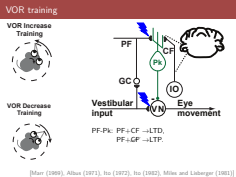
PF-Pk: PF+CF \rightarrow LTD,
PF+CF \rightarrow LTP.

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Saturation by enh. plasticity impairs learning

└ VOR learning and the cerebellum

└ VOR training



1. trick brain into thinking VOR gain needs adjusting my moving visual stimulus
2. anti-phase \rightarrow increase gain
3. in phase \rightarrow decrease gain
4. Gain change involves cerebellum
5. Marr-Albus-Ito: Pf-Pk synapses
6. Lisberger-Miles: Vestibular input-VN synapses
7. Different mechs for different freq, head angle, gain up/down.
8. Different Pk cells have different tunings.
9. Gain up in case of interest: LTD in Pf-Pk in flocculus
10. Gain down: uses different mech for behaviour, but does reverse LTD in Pf-Pk in flocculus

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Saturation by enh. plasticity impairs learning
└ The effects of enhanced plasticity and saturation

Section 2

The effects of enhanced plasticity and saturation

Section 2

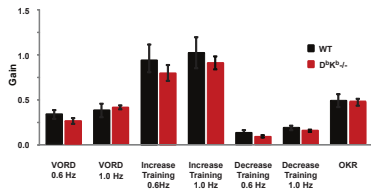
The effects of enhanced plasticity and saturation

MHC-I D^bK^b -/- knockout

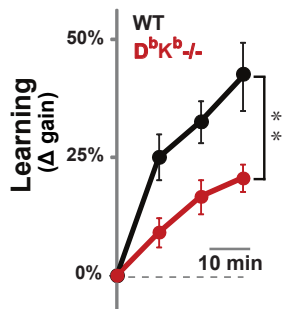
Knockout of molecule lowers threshold for LTD in PF-Pk synapses.

[McConnell et al. (2009)]

Baseline



Gain increase at 1.0 Hz



Saturation by enh. plasticity impairs learning

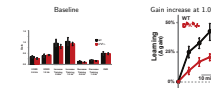
└ The effects of enhanced plasticity and saturation

└ MHC-I D^bK^b -/- knockout

1. Easier LTD → expect better learning
2. No difference at baseline
3. Impairment of learning

Knockout of molecule lowers threshold for LTD in PF-Pk synapses.

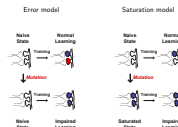
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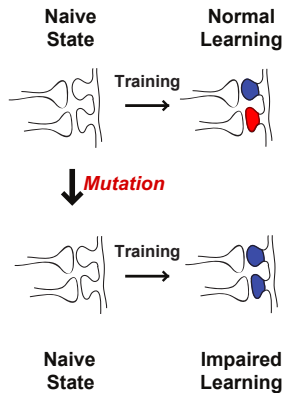
Saturation hypothesis

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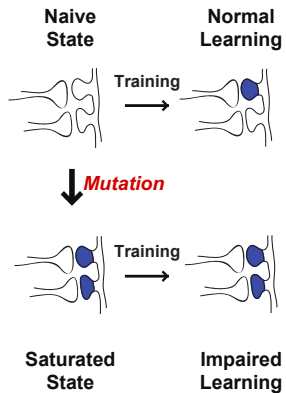
Saturation by enh. plasticity impairs learning
 └ The effects of enhanced plasticity and saturation
 └ Saturation hypothesis



Error model

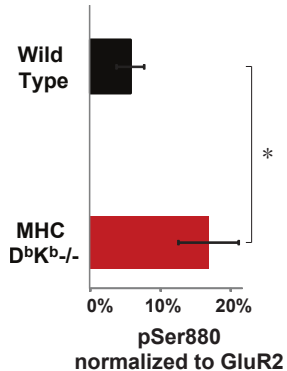


Saturation model



1. Older explanation: error model
2. Our model: baseline activity → saturation → less depression possible

Evidence: level of depression



Basal level of GluR2 phosphorylation at serine 880 in AMPA receptor.

Biochemical signature of PF-Pk LTD.

Shows that # depressed synapses in flocculus is larger in KO than WT.

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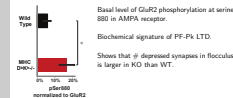
Saturation by enh. plasticity impairs learning

└ The effects of enhanced plasticity and saturation

└ Evidence: level of depression

1. Predicted by saturation hypothesis

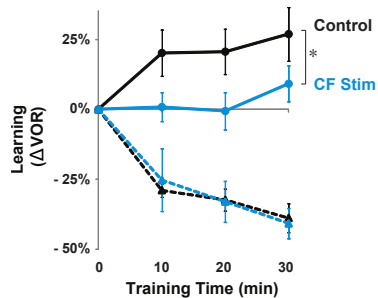
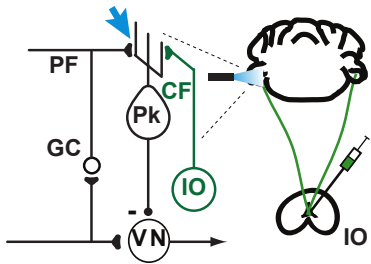
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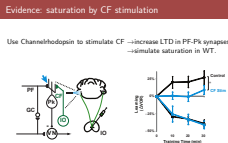
Evidence: saturation by CF stimulation

Use Channelrhodopsin to stimulate CF → increase LTD in PF-Pk synapses
→ simulate saturation in WT.

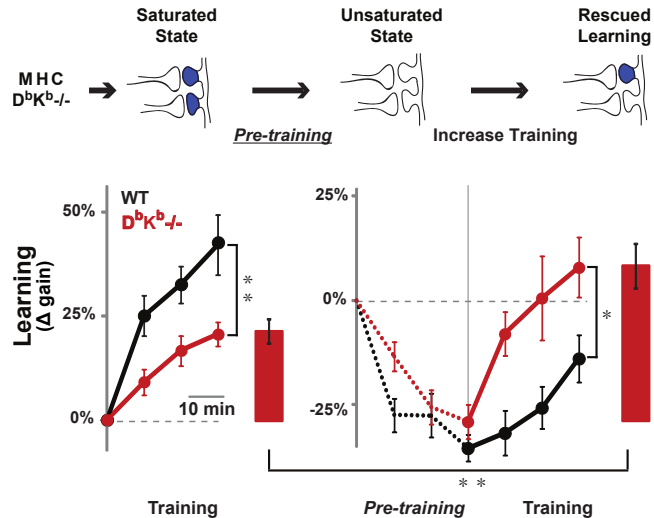


Saturation by enh. plasticity impairs learning
└ The effects of enhanced plasticity and saturation
└ Evidence: saturation by CF stimulation

1. should result in similar behaviour to KO



Evidence: desaturation by gain-decrease pretraining

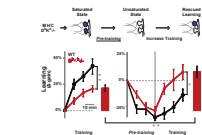


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Saturation by enh. plasticity impairs learning

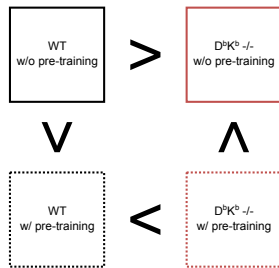
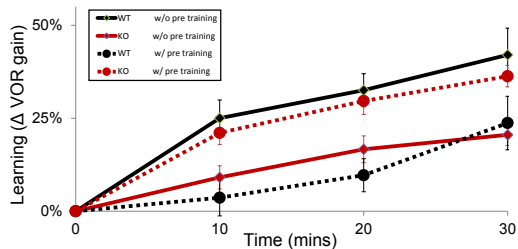
└ The effects of enhanced plasticity and saturation

└ Evidence: desaturation by gain-decrease pretraining



1. gain dec reverses LTD
2. but behaviour from elsewhere

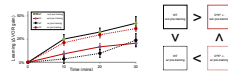
Summary of training results



Saturation by enh. plasticity impairs learning

- The effects of enhanced plasticity and saturation
- Summary of training results

1. Restricted to gain inc for comparison
2. Black: WT. Red: KO
3. Solid: no pre. Dashed: with pre
4. Horz and vert comparisons: conceptual
5. Diagonal comparisons: paramter fitting. Depend on size of KO vs. pretraining
6. KO hurts w/o, but helps w/
7. pre helps KO but hurts WT
8. top and left most restrictive



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

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Saturation by enh. plasticity impairs learning
└ The effects of enhanced plasticity and saturation

└ Questions

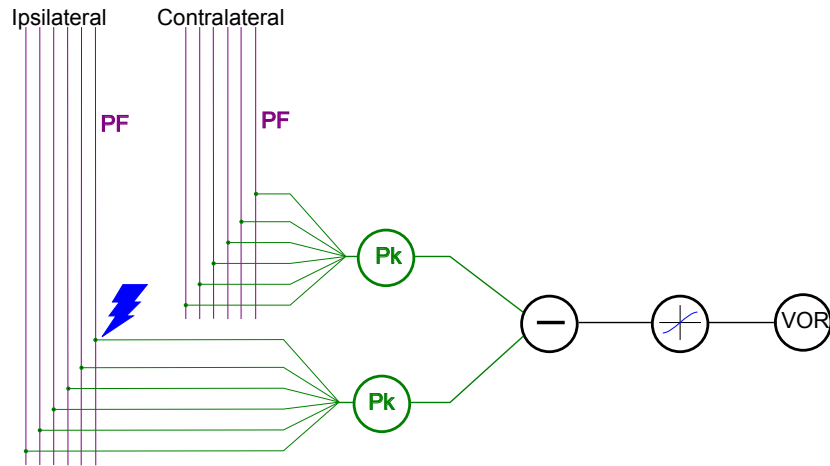
Questions

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

1. in competition
2. first makes sense, but second?
3. This is a question about synaptic populations after all.

Modelling approach

Model of circuit

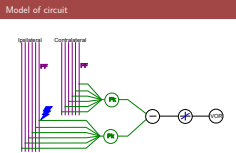


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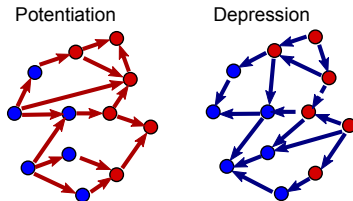
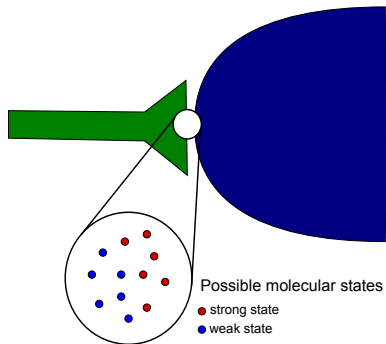
Saturation by enh. plasticity impairs learning

└ Modelling approach

└ Model of circuit



1. Contralateral baseline shift compensates for Our baseline shift
2. Gain increase due to LTD at lightning
3. Gain decrease due to plasticity elsewhere, but also reverses LTD at lightning
4. Nonlinearity here won't affect our questions, as long as it doesn't change
5. Nonlinearity before compensation could change things

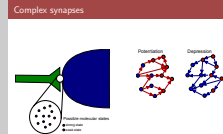


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Saturation by enh. plasticity impairs learning

└ Modelling approach

└ Complex synapses



1. functional states, not molecules
2. synaptic weight depends on state
3. many states can have same weight
4. stochastic transitions

Simplifying assumptions

- No spatial/temporal correlations in plasticity events.
 - Potentiating/depressing plasticity events \sim Poisson processes.
 - Potentiation and depression are described by Markov processes.
- [Fusi et al. (2005), Fusi and Abbott (2007), Barrett and van Rossum (2008)]

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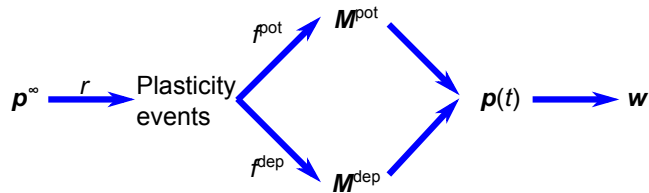
Saturation by enh. plasticity impairs learning

- Modelling approach

- Simplifying assumptions

1. allows us to concentrate on synapse, not neuron/network
2. No filing system
3. don't care if STDP...

There are N identical synapses with M internal functional states.



$$\frac{d\mathbf{p}(t)}{dt} = r\mathbf{p}(t)\mathbf{W}^F, \quad \mathbf{W}^F = f^{\text{pot}}\mathbf{M}^{\text{pot}} + f^{\text{dep}}\mathbf{M}^{\text{dep}} - \mathbf{I},$$

$$\mathbf{p}^\infty \mathbf{W}^F = 0.$$

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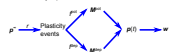
Saturation by enh. plasticity impairs learning

└ Modelling approach

└ Synaptic dynamics

Synaptic dynamics

There are N identical synapses with M internal functional states.



$$\frac{d\mathbf{p}(t)}{dt} = r\mathbf{p}(t)\mathbf{W}^F, \quad \mathbf{W}^F = f^{\text{pot}}\mathbf{M}^{\text{pot}} + f^{\text{dep}}\mathbf{M}^{\text{dep}} - \mathbf{I},$$

$$\mathbf{p}^\infty \mathbf{W}^F = 0.$$

1. stoch process has steady state.
2. Prior activity puts it in this state. row vec.
3. plasticity events at rate r
4. fraction pot/dep
5. probs changed by Markov matrices, prob $i \rightarrow j$
6. Readout: synaptic weight vec when in each state.
7. Memory at $t = 0$, keep track of pot/dep
8. subsequent: average over pot/dep

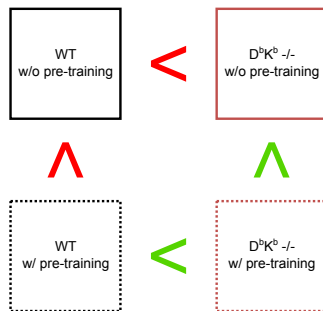
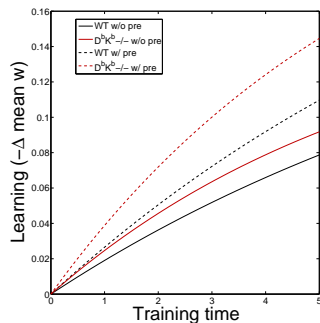
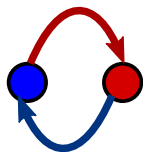
Mutation: Changes mechanism of LTD \implies change $\mathbf{M}^{\text{dep.}}$

Training: Changes statistics of LTP/LTD \implies change $r, f^{\text{pot}}, f^{\text{dep.}}$

Learning: Change in VOR gain \implies fn. of decrease in $\langle \mathbf{w} \rangle$.

1. lower threshold \rightarrow increase off-diagonal elements.
2. Only parameters we have. Don't care about r .
3. Same PF+CF input \rightarrow same $r, f^{\text{pot}}, f^{\text{dep.}}$ in each case.
4. Only output we have. Don't keep track of synaptic identity.
5. Input to Pk, some linear combination of \mathbf{w} 's.

Modelling results



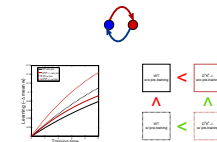
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Saturation by enh. plasticity impairs learning

└ Modelling results

└ Binary synapse

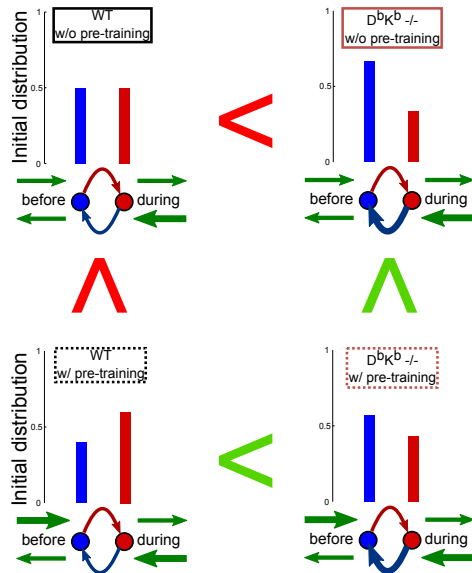
1. Compare solid curves
2. Compare black curves
3. understand why next slide



Binary synapse: initial distributions

Learning rate:

- ~ rate of events
- × prob. of transition
- × prob. ready for Δw
- × $(-\Delta w)$

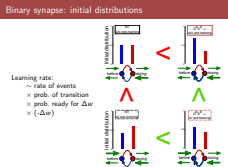


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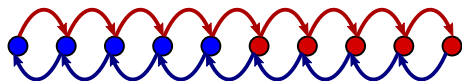
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└ Modelling results

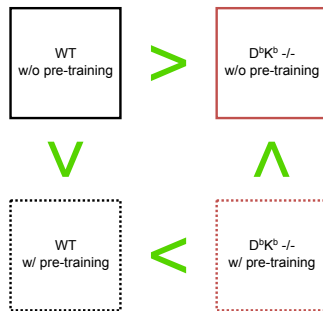
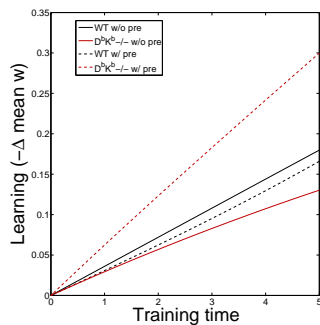
└ Binary synapse: initial distributions



1. WT: start with everything equal – just for illustration, not essential
2. WT: during training, increase f^{dep} (green arrow) → weakening.
3. KO: inc q^{pot} → bias
4. KO: competition between inc prob trans & dec prob ready
5. KO: first one wins. see why after next model
6. pre: reduces/reverses bias. always helps.



[Leibold and Kempster (2008)]

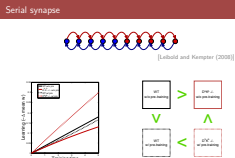


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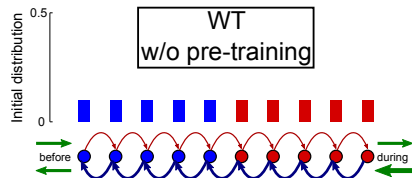
└ Modelling results

└ Serial synapse

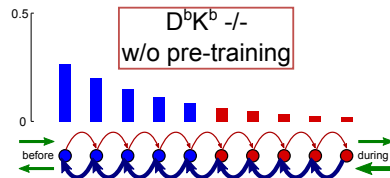


1. Still looks binary from outside. Hidden states (not essential).
2. Only see Δw at boundary.
3. understand why next slide

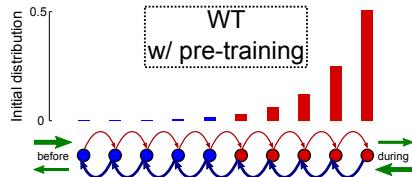
Serial synapse: initial distributions



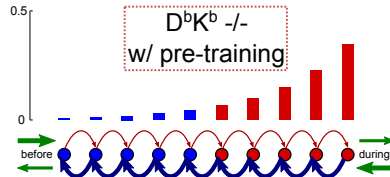
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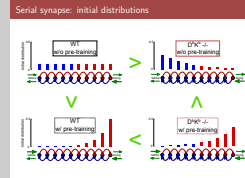


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Saturation by enh. plasticity impairs learning

└ Modelling results

└ Serial synapse: initial distributions



1. WT: start with everything equal – just for illustration, not essential
2. WT: during training, increase f^{dep} (green arrow) → weakening.
3. KO: inc q^{pot} → bias, now exponential
4. KO: comp. between inc prob trans & dec prob ready, now only at bndry
5. KO: second one wins, now exponential
6. pre: reduces/reverses bias.
7. pre: little reverse bias repopulates bndry, helps.
8. pre: too much reverse bias moves away from bndry, hurts.
9. maths next slide

Mathematical explanation

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Saturation by enh. plasticity impairs learning

- Modelling results

└ Mathematical explanation

Mathematical explanation

Serial synapse: $\mathbf{p}_i^{\text{sc}} \sim \mathcal{N}\left(\frac{\mathbf{g}^{\text{sc}}}{\sigma^2}\right)^i$.

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

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

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

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

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

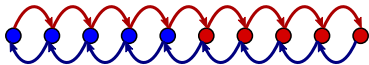
For $M > 2$: larger $q^{\text{dep}} \implies$ slower learning.

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

1. Detailed balance. Exponential decay.
2. for large enough M, q^{pot} , overcome \mathcal{N}
3. Other factor in \mathbf{p}^∞ smaller $\implies \mathcal{N}$ larger.

The success of the serial model relies on two features:

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



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Saturation by enh. plasticity impairs learning

└─Modelling results

└─Essential features

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

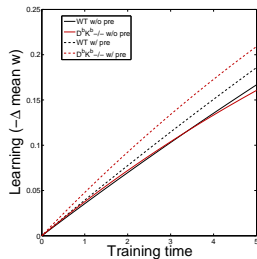
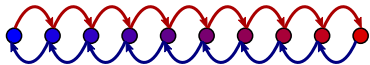
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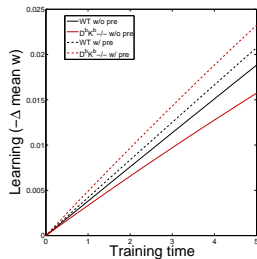
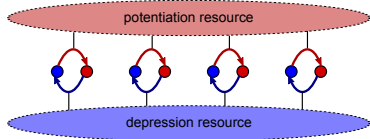


Other models that fail

Multistate model



Pooled resource model



[Amit and Fusi (1994)]



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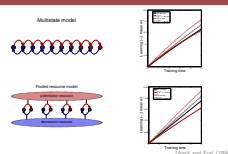
Saturation by enh. plasticity impairs learning

└ Modelling results

└ Other models that fail

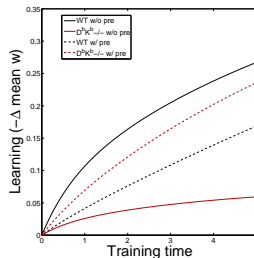
1. MS: linear weights, unlike serial.
2. like bunch of binary synapses in series.
3. solid curves: fails early on, but catches up quickly
4. black curves: fails badly
5. No real enhancement of saturation, no metaplasticity.
6. All transitions contribute: pushing to end has little effect.
7. Pooled: resource depleted by pot/dep. replenished by reverse.
8. solid curves succeed: enhanced saturation
9. black curves fail: opposite metaplasticity, pot makes dep easier

Other models that fail

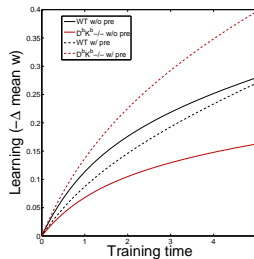
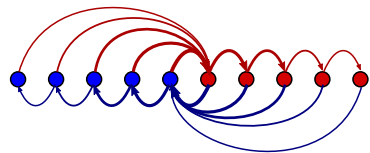


Other models that work

Non-uniform multistate model



Cascade model



[Fusi et al. (2005)]



2013-07-11

Saturation by enh. plasticity impairs learning

└ Modelling results

└ Other models that work

1. Both models, trans probs decay exponentially from centre.
2. Nonuni: linear weights. Cascade: binary weights.
3. Enhanced saturation and metaplasticity
4. Pushing to end makes pot and dep harder
5. Note: hidden states not necessary

Other models that work

Non-uniform multistate model



Cascade model



[Fusi et al. (2005)]

2013-07-11


- └ Modelling results

└ Conclusions and further questions


- The saturation effect overcome the enhanced plasticity, if it is enhanced. **Requires complexity**
- A little reverse bias can help, but too much hurts, if repeated potentiation makes depression harder. **Requires metaplasticity**
- We can find a purely synaptic explanation of VOR behaviour, iff the synapses have these features.
- We used behaviour to constrain molecular structure of synapses!
- Can we constrain it further with more experiments?

1. e.g. exponential decay, resource depletion,...
2. e.g. moving away from weight boundary, or weaker transitions.
3. Other explanations? Non-linearity in PK cell?


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