

Lagrangian dynamics of dendritic microcircuits enables real-time backpropagation of errors

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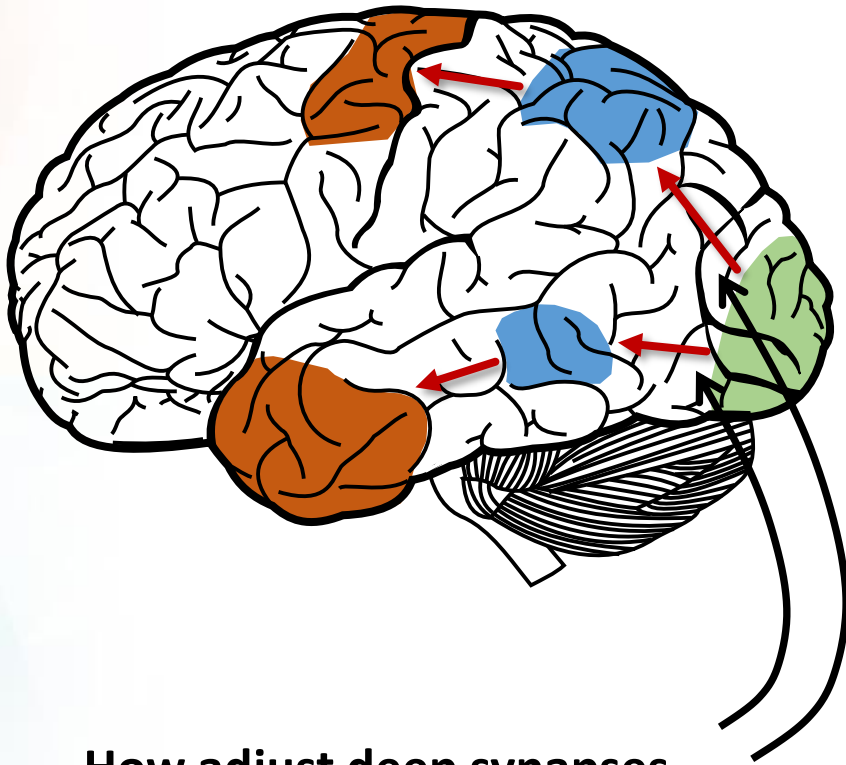
² Kirchhoff-Institute for Physics, Heidelberg.

³ Institute of Neuroinformatics, UZH/ETH Zurich.

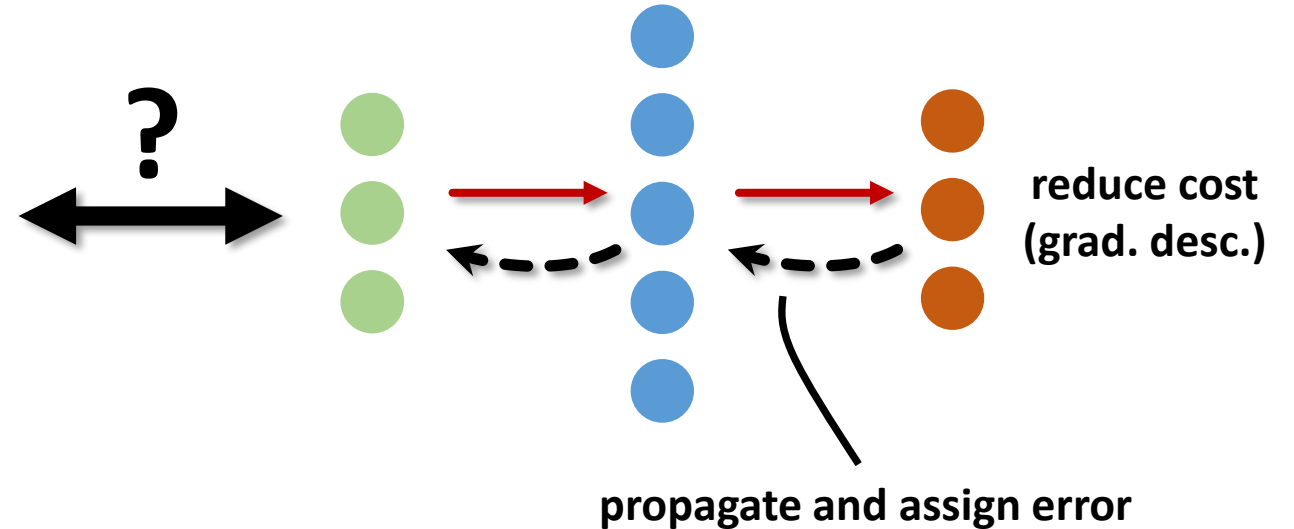
⁴ Department of Neurology, Inselspital, Bern.

⁵ MILA, Montreal.

Can backprop be implemented in the brain?



**How adjust deep synapses
to improve final output...?**



Towards bio-plausible backprop?

A theoretical framework for backprop, Y. le Cun (1988)

Feedback alignment, T. Lillicrap et al. (2016)

Equilibrium Propagation, B. Scellier & Y. Bengio (2016)

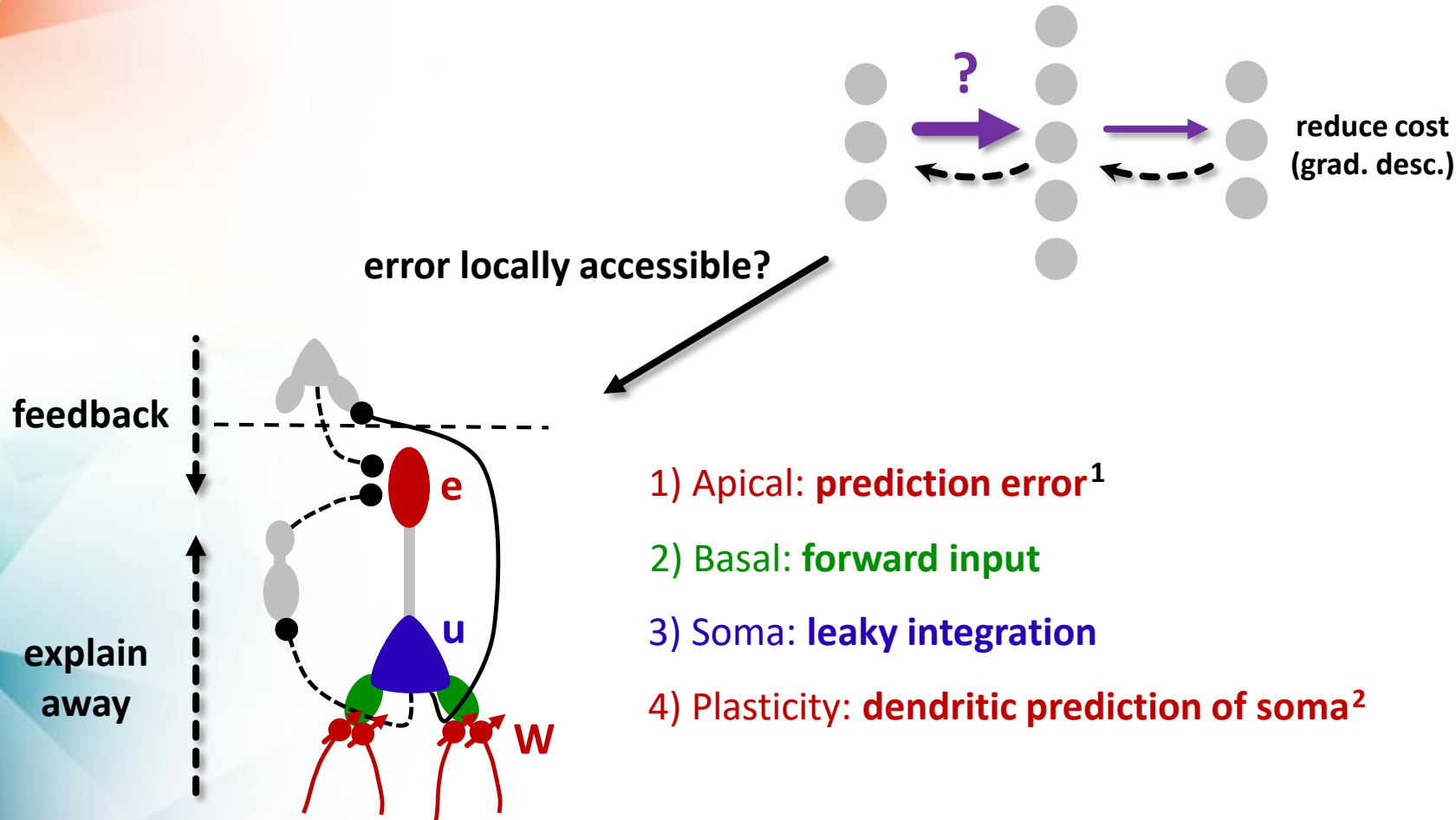
Dendritic backprop, J. Sacramento et al. (2018)

Review by Whittington & Bogacz (2019)

...

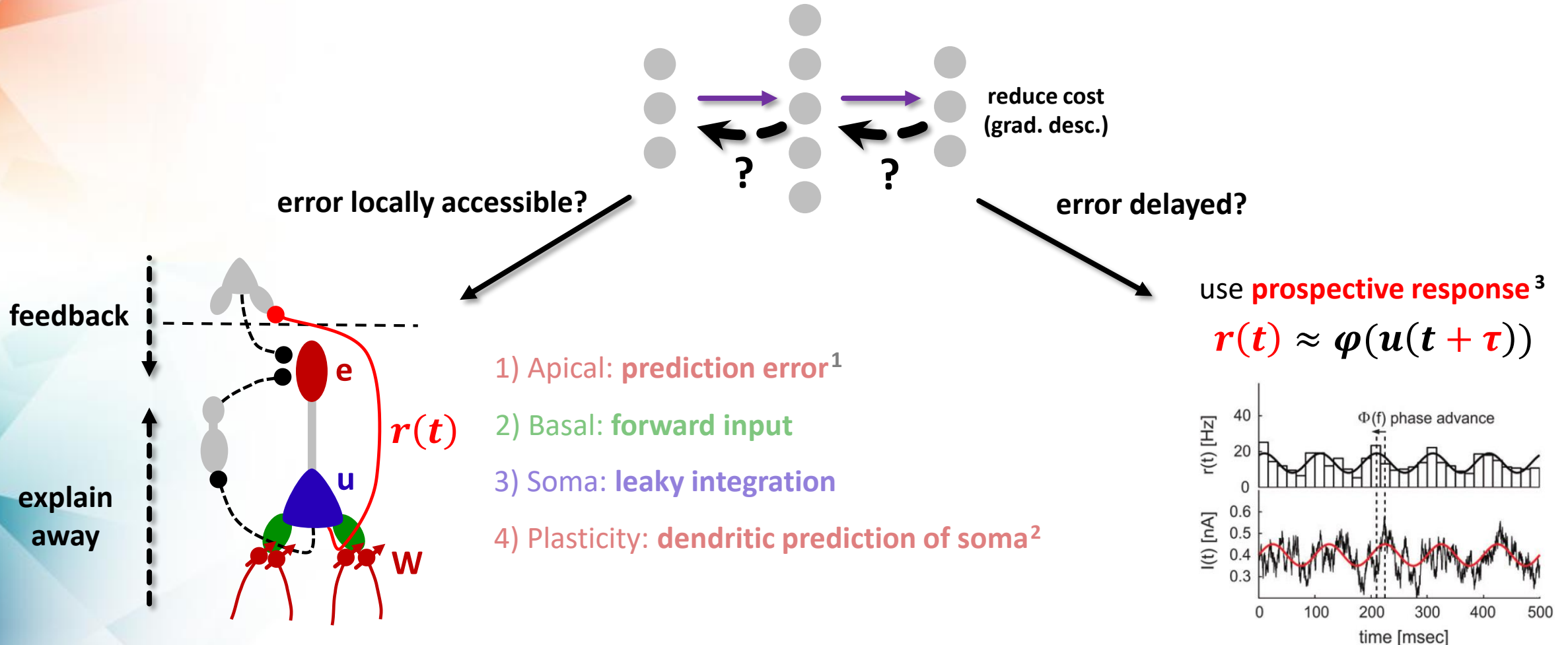
Image adjusted from https://commons.wikimedia.org/wiki/File:Brain_Surface_Gyri.SVG

Apical dendrite carries local prediction error



¹ Sacramento et al., NIPS 2018; ² Urbanczik & Senn, Neuron 2014

Prospective response enables just-in-time error



¹ Sacramento et al., NIPS 2018; ² Urbanczik & Senn, Neuron 2014; ³ Köndgen et al., Cereb Cortex 2008

Prospective coding and least-action principle

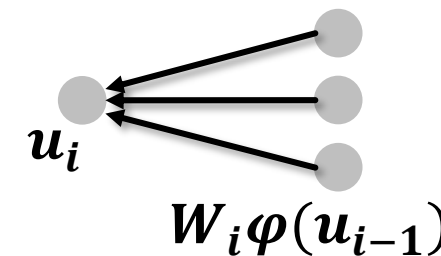
Energy function



Lagrange function

$$E(u) = \sum_i \underbrace{\|u_i - W_i \varphi(u_{i-1})\|^2}_{\text{prediction error } e_i} + \beta \cdot \text{cost}$$

↙ teacher strength



$$L = -E(\underbrace{\tilde{u}, \dot{\tilde{u}}}_{\text{prospective response}}, t)$$

Physics!

$$\delta \int L dt = 0$$

$$\dot{W} \propto \nabla_W L$$

Theorem 1 (real-time backprop)

$$e_i = W_{i+1}^T e_{i+1}, \quad \dot{W}_i \propto e_i \varphi(u_i)^T$$

Theorem 2 (real-time gradient descent)

$$\frac{d}{dW_i} \text{cost} = \lim_{\beta \rightarrow 0} \frac{1}{\beta} e_i^\beta \varphi^\beta(u_i)^T$$

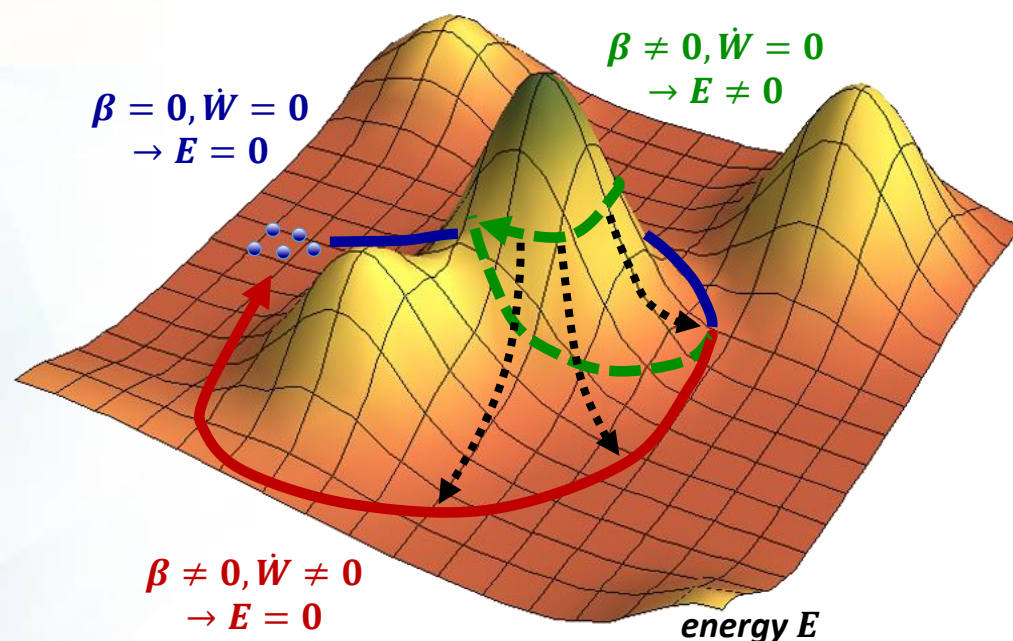
$$\frac{\partial L}{\partial \tilde{u}} - \frac{d}{dt} \frac{\partial L}{\partial \dot{\tilde{u}}} = 0$$

Prospective coding and least-action principle

Energy function

$$E(u) = \sum_i \|u_i - W_i \varphi(u_{i-1})\|^2 + \beta \cdot \text{cost}$$

↙ teacher strength



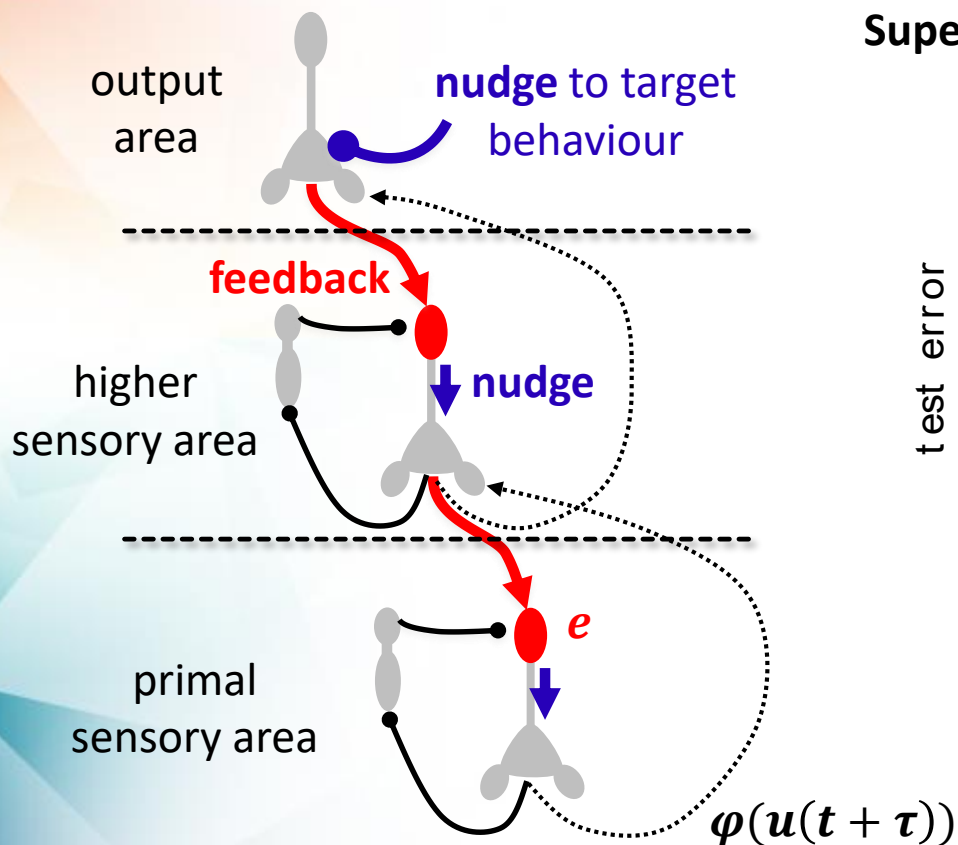
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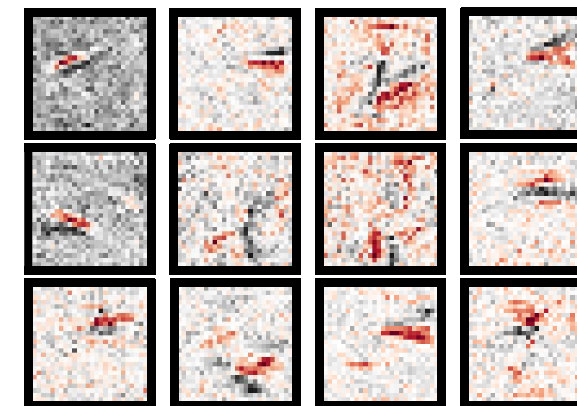
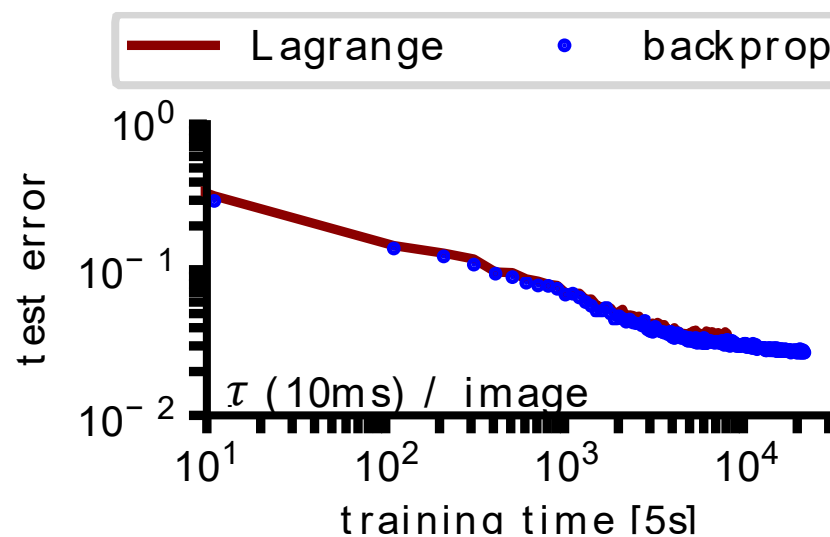
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Real-time error backpropagation in cortical circuits

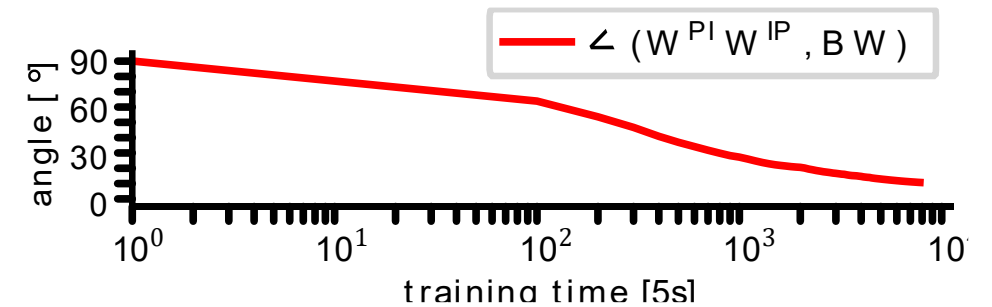
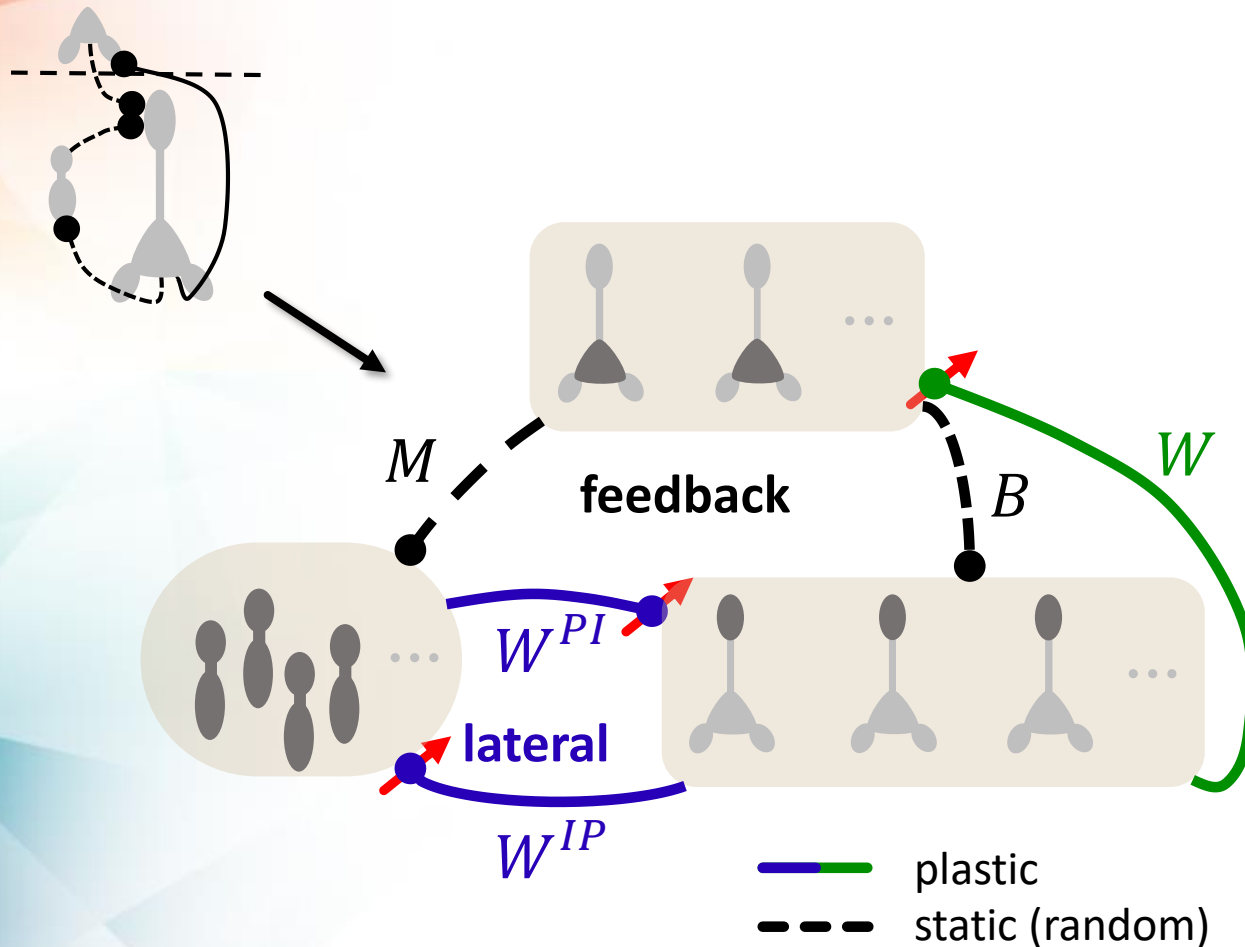


Supervised learning (MNIST)



also applicable to
unsupervised learning and
reinforcement learning

Plastic microcircuit – no need for weight transport

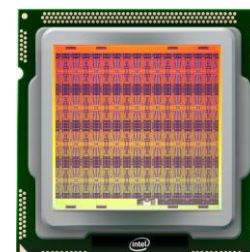


Neurosynaptic dynamics implement backprop

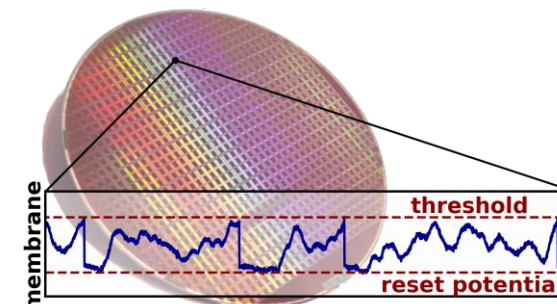
$$\delta \int L dt = 0$$
$$\dot{W} \propto \nabla_W L$$

“Learning by the
dendritic prediction
of somatic activity.”

Efficient learning for neuromorphic hardware

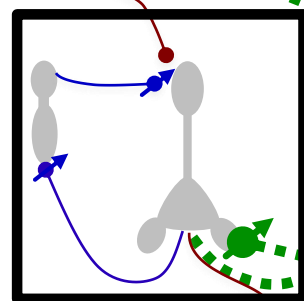


Intel Loihi



Uni Heidelberg BrainScaleS system

cortical
microcircuit



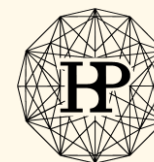
feed forward

feedback

“Local error minimization
is global cost reduction.”

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