Synaptic Plasticity

Kris Wu

Advanced Topics in Theoretical Neuroscience

Outline

Hebbian learning (LTP and LTD)

Homeostatic plasticity (metaplasticity, synaptic scaling, and intrinsic plasticity)

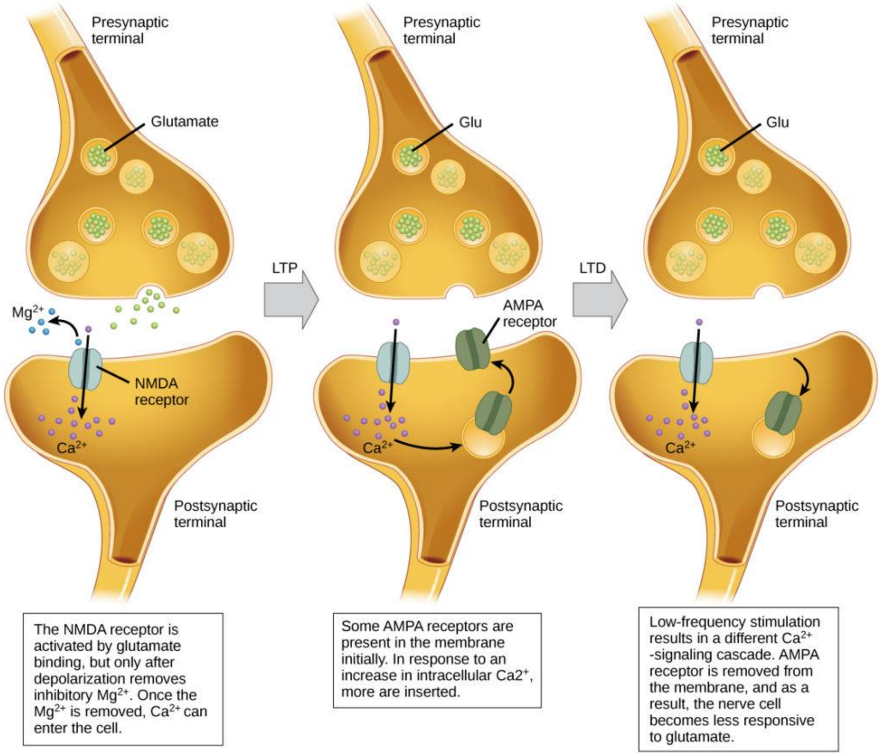
Spike timing dependent plasticity and calcium-based plasticity

Inhibitory plasticity and cell-type-specific plasticity

Modern approaches to study synaptic plasticity

Other forms of plasticity mechanisms (short-term plasticity, etc.)

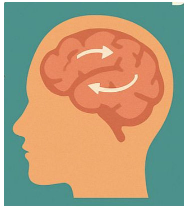
Synaptic plasticity



OpenStax

Importance of studying plasticity in the brain

Learning and memory



Neurological disorders

Development

Aging

Image generated by OpenAI

Hebb’s postulate of learning

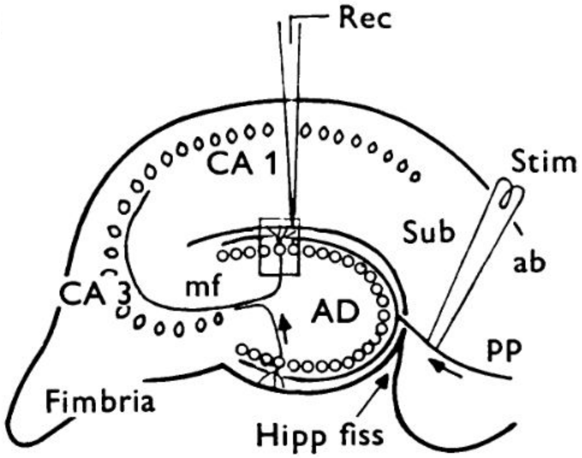
A NEUROPHYSIOLOGICAL POSTULATE

Let us assume then that the persistence or repetition of a reverberatory activity (or “trace”) tends to induce lasting cellular changes that add to its stability The assumption * can be precisely stated as follows *When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A’s efficiency, as one of the cells firing B, is increased*

“cells that fire together, wire together”

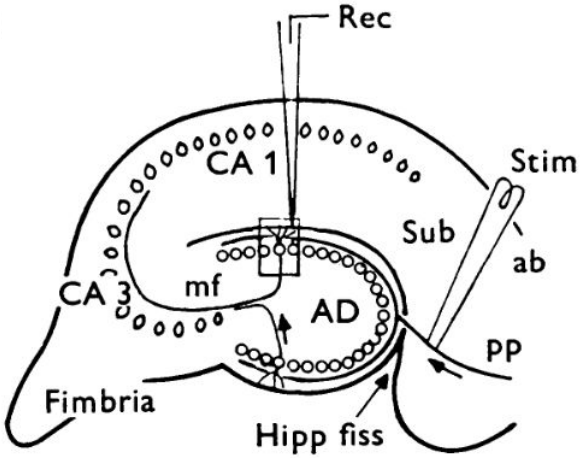
Hebb 1949, The Organization of Behaviour: A Neuropsychological Theory

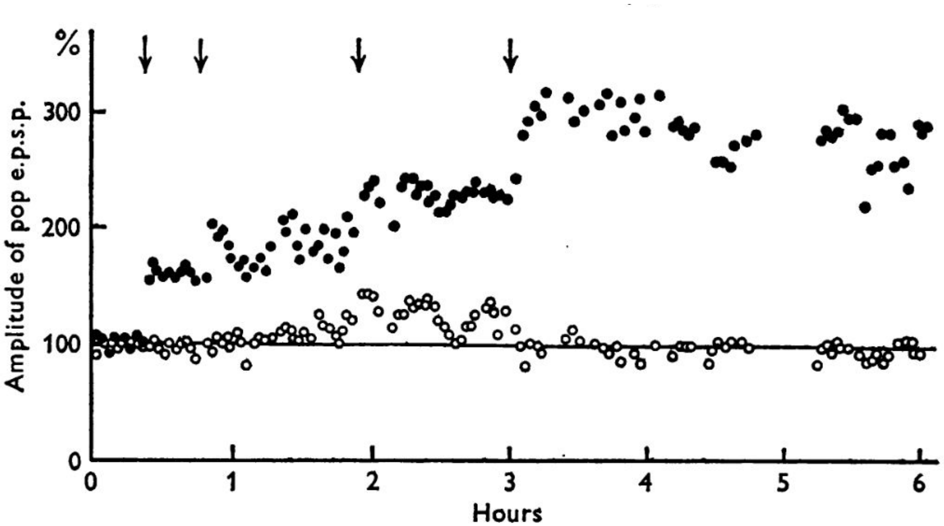
Long-term potentiation - experiments



Bliss & Lømo 1973, Journal of Physiology

Long-term potentiation - experiments

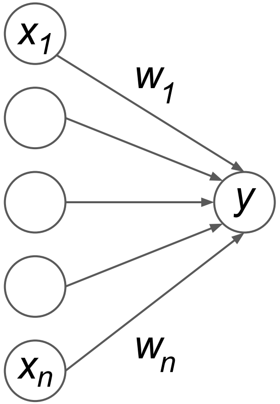




Bliss & Lømo 1973, Journal of Physiology

Long-term potentiation - experiments

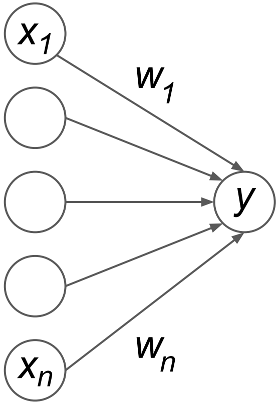
Hebbian learning - models



We consider a single postsynaptic neuron receiving input from n presynaptic neurons. Let:

- $\boldsymbol{x} \in \mathbb{R}^n$: input (presynaptic activity vector),
- $\boldsymbol{w} \in \mathbb{R}^n$: synaptic weight vector,
- $y = \boldsymbol{w}^\top \boldsymbol{x}$: postsynaptic output (linear neuron).

Hebbian learning - models



A classical rate-based Hebbian learning rule is defined as:

$$\frac{d\boldsymbol{w}}{dt} = \eta\, y \boldsymbol{x} = \eta\, (\boldsymbol{w}^\top \boldsymbol{x})\boldsymbol{x}$$

Taking the average over the input distribution:

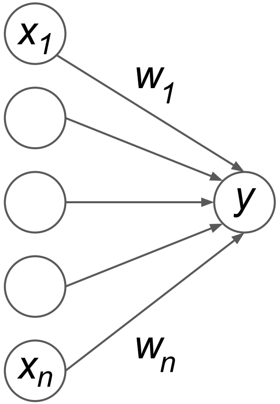
$$\left\langle \frac{d\boldsymbol{w}}{dt} \right\rangle = \eta\, \left\langle (\boldsymbol{w}^\top \boldsymbol{x})\boldsymbol{x} \right\rangle = \eta\, \left\langle \boldsymbol{x}\boldsymbol{x}^\top \right\rangle \boldsymbol{w} = \eta\, \boldsymbol{C}\boldsymbol{w}$$

where $\boldsymbol{C}$ is the input covariance matrix.

Then we obtain:

$$\boldsymbol{w}(t) = e^{\eta \boldsymbol{C} t}\, \boldsymbol{w}(0)$$

Hebbian learning - models



Let $\lambda_1, \dots, \lambda_n$ be the eigenvalues of $\boldsymbol{C}$, and $\boldsymbol{u}_1, \dots, \boldsymbol{u}_n$ the corresponding orthonormal eigenvectors. Any initial weight vector $\boldsymbol{w}(0) \in \mathbb{R}^n$ can be decomposed as:

$$\boldsymbol{w}(0) = \sum_{i=1}^{n} \alpha_i \boldsymbol{u}_i$$

Then we have,

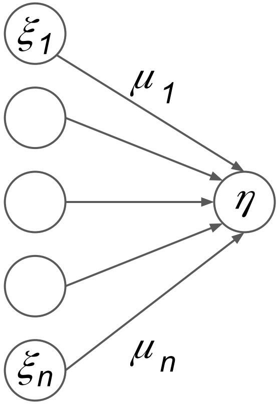
$$\boldsymbol{w}(t) = e^{\eta \boldsymbol{C} t} \boldsymbol{w}(0) = \sum_{i=1}^{n} \alpha_i e^{\eta \lambda_i t} \boldsymbol{u}_i$$

Since $\boldsymbol{C}$ is positive semi-definite, all $\lambda_i \geq 0$. If any $\lambda_i > 0$, the corresponding component of $\boldsymbol{w}(t)$ grows exponentially as $t \to \infty$.

Oja's learning rule - models

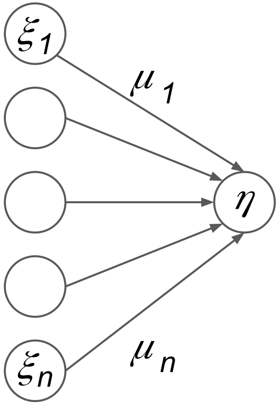
$$\eta = \sum_{i=1}^{n} \mu_i \xi_i.$$

$$\mu_i(t+1) = \frac{\mu_i(t) + \gamma\eta(t)\xi_i(t)}{\{\sum_{i=1}^{n} [\mu_i(t) + \gamma\eta(t)\xi_i(t)]^2\}^{1/2}},$$



Oja 1982, Journal of Mathematical Biology

Oja's learning rule - models



$$\eta = \sum_{i=1}^{n} \mu_i \xi_i. \qquad \mu_i(t+1) = \frac{\mu_i(t) + \gamma\eta(t)\xi_i(t)}{\{\sum_{i=1}^{n} [\mu_i(t) + \gamma\eta(t)\xi_i(t)]^2\}^{1/2}},$$

Let

$$w_i = \mu_i(t) + \gamma\eta(t)\xi_i(t),$$

then we have

$$\|\boldsymbol{w}\| = \left(\sum_{i=1}^{n} w_i^2\right)^{1/2} = \left(\sum_{i=1}^{n} [\mu_i(t) + \gamma\eta(t)\xi_i(t)]^2\right)^{1/2} = \left(\sum_{i=1}^{n} \left[\mu_i^2(t) + 2\gamma\eta(t)\mu_i(t)\xi_i(t) + \gamma^2\eta^2(t)\xi_i^2(t)\right]\right)^{1/2}$$

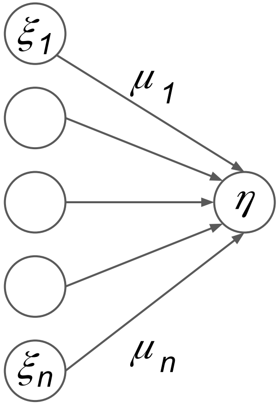
$$\|\boldsymbol{w}\| = \left(\|\boldsymbol{\mu}(t)\|^2 + 2\gamma\eta(t)\sum_{i=1}^{n} \mu_i(t)\xi_i(t) + \gamma^2\eta^2(t)\|\boldsymbol{\xi}(t)\|^2\right)^{1/2}$$

Assuming $\|\boldsymbol{\mu}(t)\| = 1$, we have:

$$\|\boldsymbol{w}\| = \left(1 + 2\gamma\eta^2(t) + \gamma^2\eta^2(t)\|\boldsymbol{\xi}(t)\|^2\right)^{1/2}$$

Oja 1982, Journal of Mathematical Biology

Oja's learning rule - models



$$\eta = \sum_{i=1}^{n} \mu_i \xi_i.$$

$$\mu_i(t+1) = \frac{\mu_i(t) + \gamma\eta(t)\xi_i(t)}{\{\sum_{i=1}^{n} [\mu_i(t) + \gamma\eta(t)\xi_i(t)]^2\}^{1/2}},$$

Assuming $\|\boldsymbol{\mu}(t)\| = 1$, we have:

$$\|\boldsymbol{w}\| = \left(1 + 2\gamma\eta^2(t) + \gamma^2\eta^2(t)\|\boldsymbol{\xi}(t)\|^2\right)^{1/2}$$

Using the Taylor expansion $(1+\epsilon)^{1/2} \approx 1 + \frac{1}{2}\epsilon$ for small γ, we get:

$$\|\boldsymbol{w}\| \approx 1 + \gamma\eta^2(t) + O(\gamma^2)$$

$$\mu_i(t+1) = \frac{\mu_i(t) + \gamma\eta(t)\xi_i(t)}{1 + \gamma\eta^2(t) + O(\gamma^2)}$$

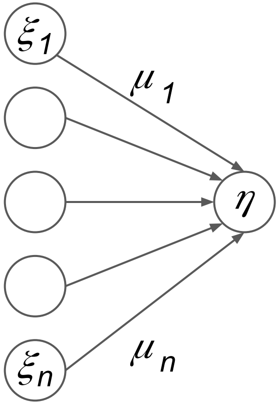
Use the expansion $\frac{1}{1+\epsilon} \approx 1 - \epsilon$ for small ϵ:

$$\mu_i(t+1) \approx [\mu_i(t) + \gamma\eta(t)\xi_i(t)]\left[1 - \gamma\eta^2(t)\right] = \mu_i(t)(1 - \gamma\eta^2(t)) + \gamma\eta(t)\xi_i(t)(1 - \gamma\eta^2(t))$$

$$\mu_i(t+1) \approx \mu_i(t) - \gamma\eta^2(t)\mu_i(t) + \gamma\eta(t)\xi_i(t) + O(\gamma^2) = \mu_i(t) + \gamma\eta(t)[\xi_i(t) - \eta(t)\mu_i(t)] + O(\gamma^2)$$

Oja 1982, Journal of Mathematical Biology

Oja's learning rule - models



$$\eta = \sum_{i=1}^{n} \mu_i \xi_i.$$

$$\mu_i(t+1) = \frac{\mu_i(t) + \gamma\eta(t)\xi_i(t)}{\{\sum_{i=1}^{n} [\mu_i(t) + \gamma\eta(t)\xi_i(t)]^2\}^{1/2}},$$

$$\mu_i(t+1) \approx \mu_i(t) - \gamma\eta^2(t)\mu_i(t) + \gamma\eta(t)\xi_i(t) + O(\gamma^2) = \mu_i(t) + \gamma\eta(t)\left[\xi_i(t) - \eta(t)\mu_i(t)\right] + O(\gamma^2)$$

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Oja 1982, Journal of Mathematical Biology

Oja's learning rule - models

$$\eta = \sum_{i=1}^{n} \mu_i \xi_i. \qquad \mu_i(t+1) = \frac{\mu_i(t) + \gamma\eta(t)\xi_i(t)}{\{\sum_{i=1}^{n} [\mu_i(t) + \gamma\eta(t)\xi_i(t)]^2\}^{1/2}}, \qquad \mu_i(t+1) = \mu_i(t) + \gamma\eta(t)[\xi_i(t) - \eta(t)\mu_i(t)] + O(\gamma^2).$$

Oja's rule introduces a normalization term to the classic Hebbian learning rule:

$$\frac{d\boldsymbol{w}}{dt} = \eta\, y\boldsymbol{x} - \eta\, y^2\boldsymbol{w} = \eta(\boldsymbol{w}^\top\boldsymbol{x})\boldsymbol{x} - \eta(\boldsymbol{w}^\top\boldsymbol{x})^2\boldsymbol{w}$$

Taking the expectation over the input distribution:

$$\left\langle \frac{d\boldsymbol{w}}{dt} \right\rangle = \eta\left\langle (\boldsymbol{w}^\top\boldsymbol{x})\boldsymbol{x} \right\rangle - \eta\left\langle (\boldsymbol{w}^\top\boldsymbol{x})^2 \right\rangle \boldsymbol{w} = \eta\left(\boldsymbol{C}\boldsymbol{w} - (\boldsymbol{w}^\top\boldsymbol{C}\boldsymbol{w})\boldsymbol{w}\right)$$

$$\|\boldsymbol{w}\|^2 = \boldsymbol{w}^\top\boldsymbol{w}$$

$$\frac{d}{dt}(\|\boldsymbol{w}\|^2) = \frac{d}{dt}(\boldsymbol{w}^\top\boldsymbol{w}) = 2\boldsymbol{w}^\top\frac{d\boldsymbol{w}}{dt} = 2\boldsymbol{w}^\top\eta\left(\boldsymbol{C}\boldsymbol{w} - (\boldsymbol{w}^\top\boldsymbol{C}\boldsymbol{w})\boldsymbol{w}\right) = 2\eta(\boldsymbol{w}^\top\boldsymbol{C}\boldsymbol{w})(1 - \|\boldsymbol{w}\|^2)$$

Oja 1982, Journal of Mathematical Biology

Oja's learning rule - models

$$\eta = \sum_{i=1}^{n} \mu_i \xi_i. \qquad \mu_i(t+1) = \frac{\mu_i(t) + \gamma\eta(t)\xi_i(t)}{\{\sum_{i=1}^{n} [\mu_i(t) + \gamma\eta(t)\xi_i(t)]^2\}^{1/2}}, \qquad \mu_i(t+1) = \mu_i(t) + \gamma\eta(t)[\xi_i(t) - \eta(t)\mu_i(t)] + O(\gamma^2).$$

$$\frac{d}{dt}(\|\boldsymbol{w}\|^2) = \frac{d}{dt}(\boldsymbol{w}^\top \boldsymbol{w}) = 2\boldsymbol{w}^\top \frac{d\boldsymbol{w}}{dt} = 2\boldsymbol{w}^\top \eta \left(\boldsymbol{C}\boldsymbol{w} - (\boldsymbol{w}^\top \boldsymbol{C}\boldsymbol{w})\boldsymbol{w}\right) = 2\eta(\boldsymbol{w}^\top \boldsymbol{C}\boldsymbol{w})(1 - \|\boldsymbol{w}\|^2)$$

Let $\lambda = \boldsymbol{w}^\top \boldsymbol{C}\boldsymbol{w} \geq 0$, since $\boldsymbol{C}$ is positive semi-definite. Then:

- If $\|\boldsymbol{w}\|^2 < 1$, the norm increases.
- If $\|\boldsymbol{w}\|^2 > 1$, the norm decreases.
- If $\|\boldsymbol{w}\|^2 = 1$, the norm remains constant.

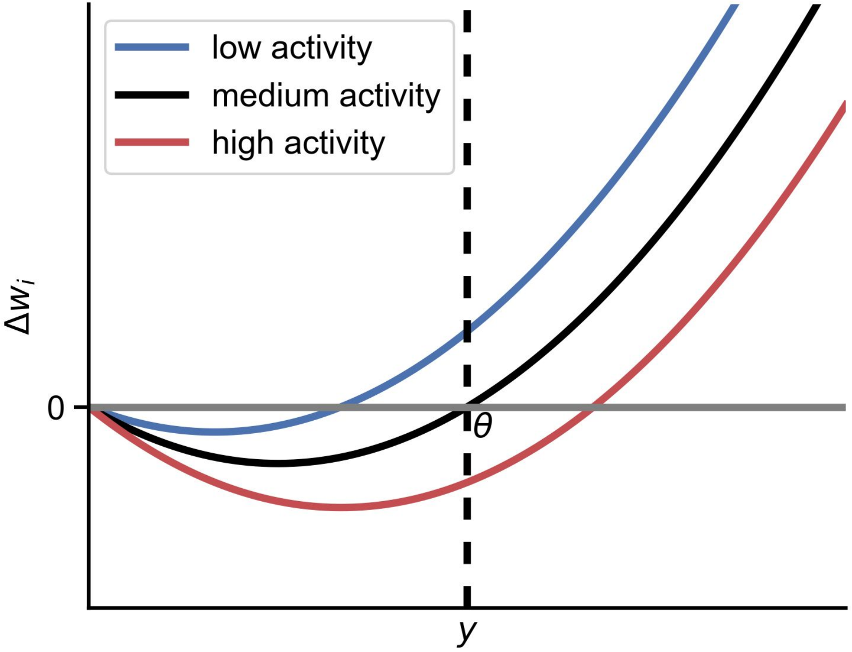
This implies that $\|\boldsymbol{w}\| \to 1$ over time, meaning the weight vector becomes norm-stable. Therefore, Oja's rule stabilizes Hebbian learning by preventing unbounded growth.

Oja 1982, Journal of Mathematical Biology

BCM (Bienenstock, Cooper, and Munro) learning rule - models

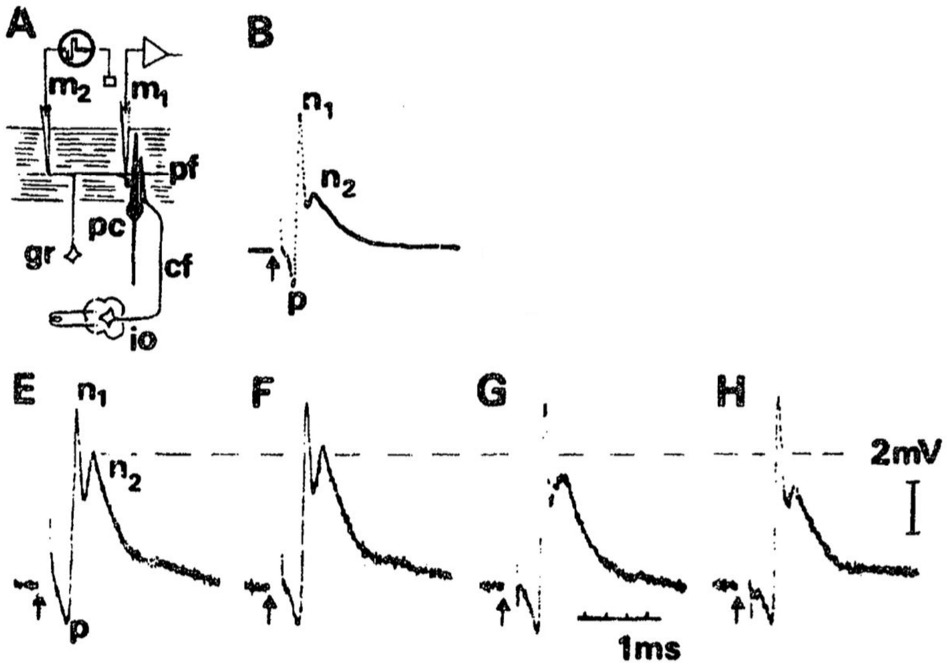
$$\frac{d\boldsymbol{w}}{dt} = \eta y(y - \theta)\boldsymbol{x}$$

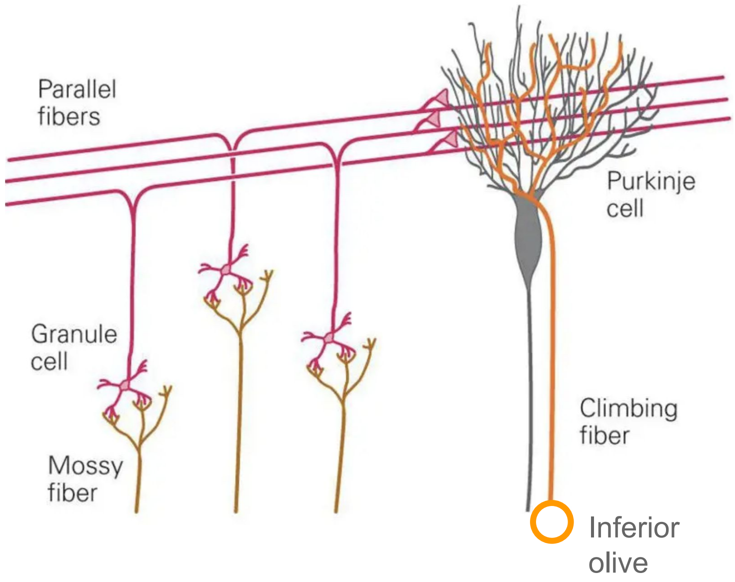
$$\frac{d\theta}{dt} = \frac{1}{\tau}\left(y^2 - \theta\right)$$



Bienenstock et al., 1982 Journal of Neuroscience

Long-term depression - experiments

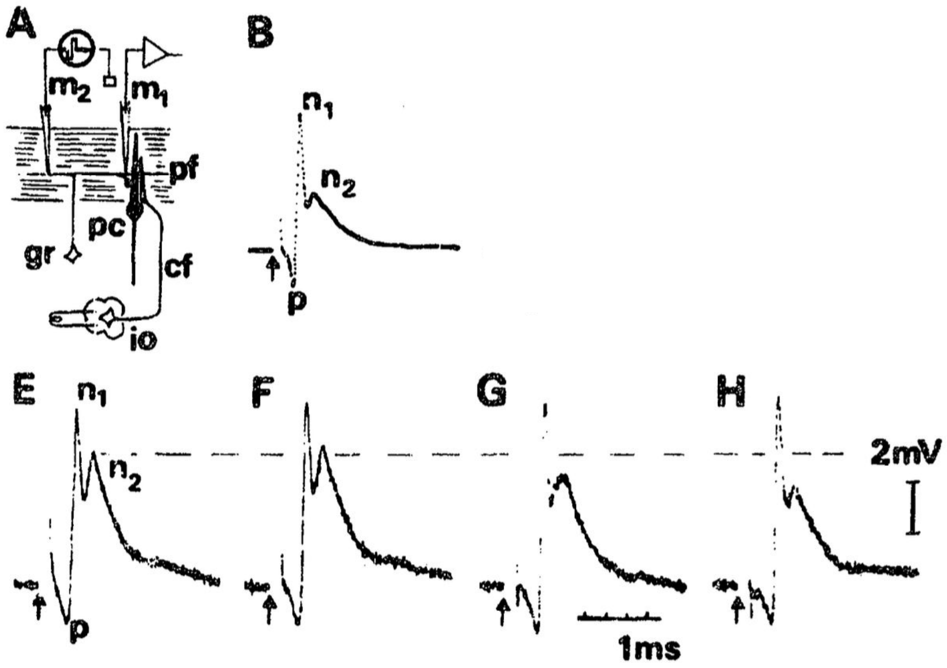


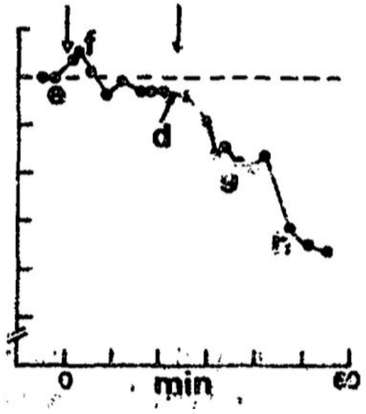


Ito and Kano 1982, Neuroscience Letters

Schematic from Neupsy Key

Long-term depression - experiments

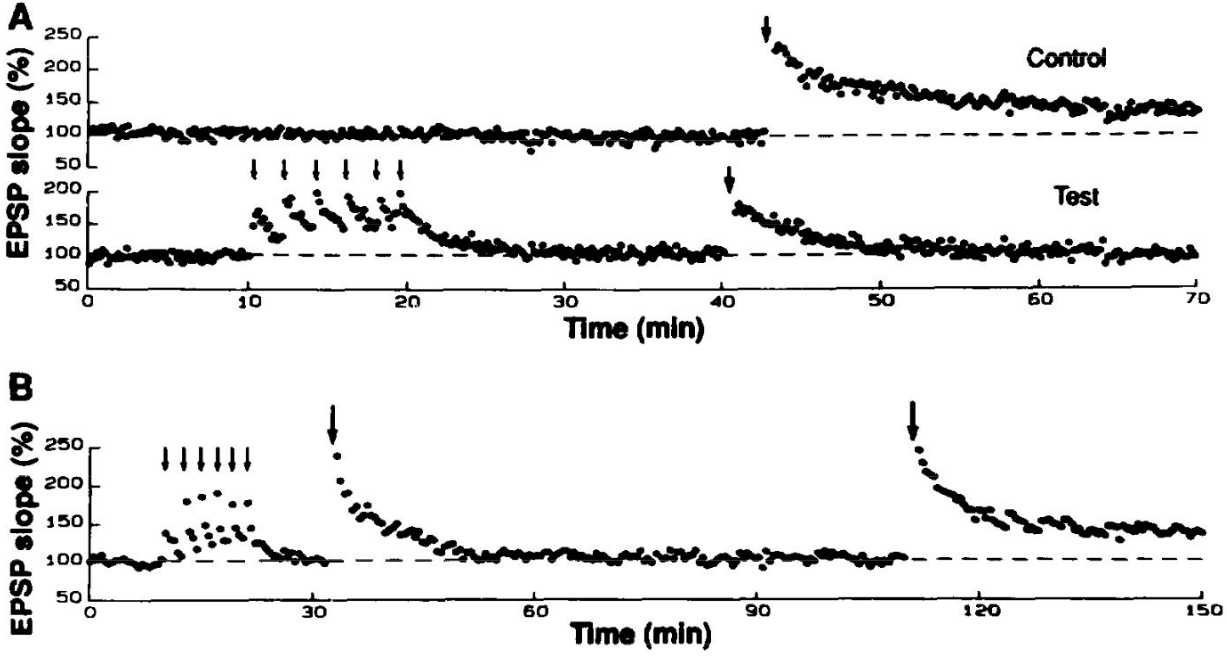




Ito and Kano 1982, Neuroscience Letters

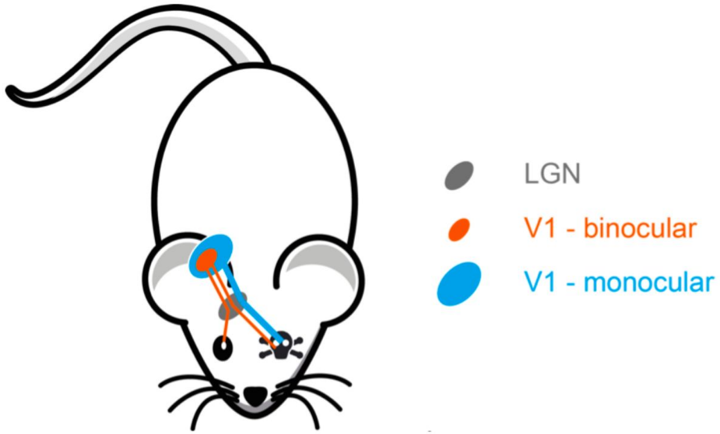
Metaplasticity - experiments

Metaplasticity: the plasticity of synaptic plasticity



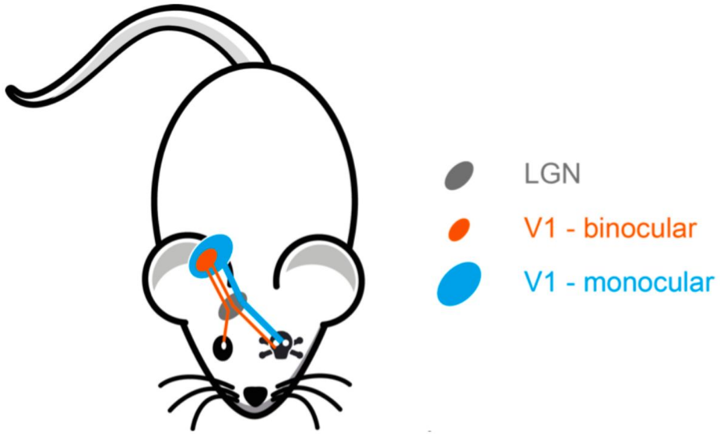
Abraham and Bear 1996, TINS

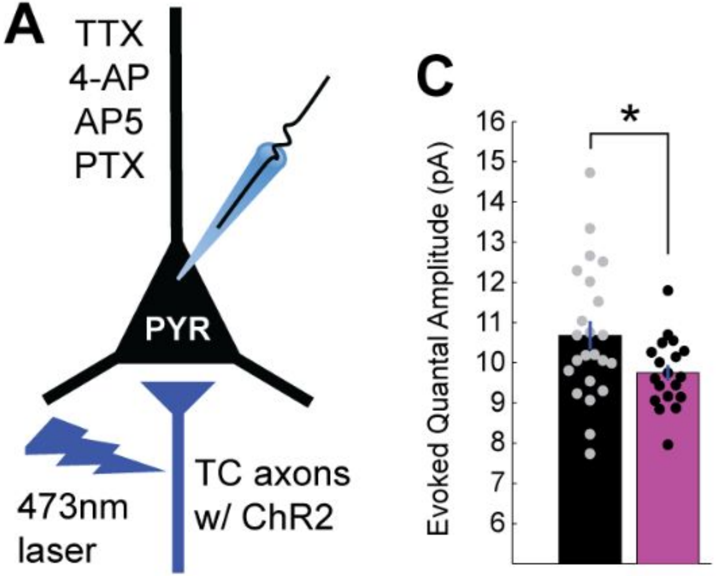
Metaplasticity - experiments



Miska et al., 2020 eLife

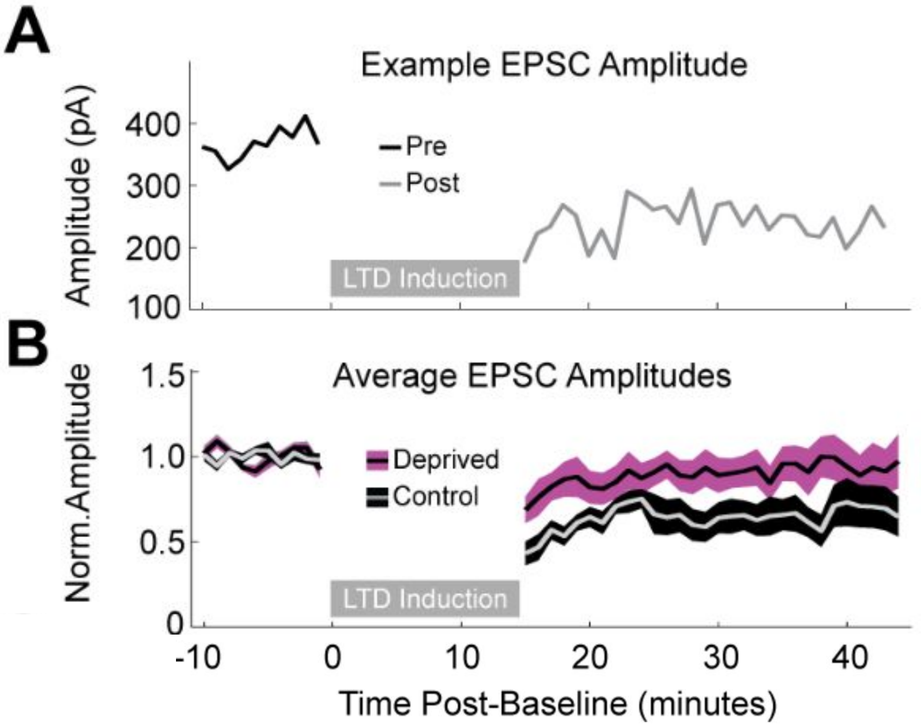
Metaplasticity - experiments





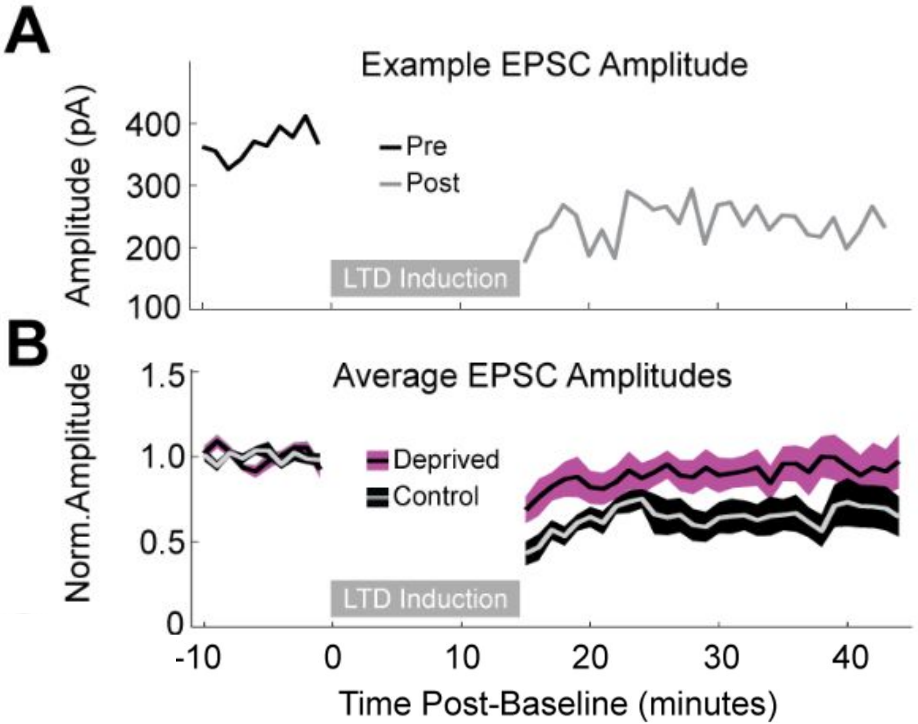
Miska et al., 2020 eLife

Metaplasticity - experiments



Miska et al., 2020 eLife

Metaplasticity - experiments

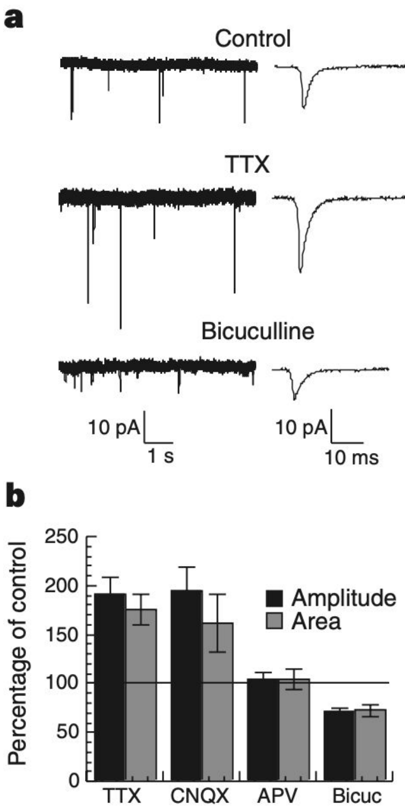


$$\frac{d\boldsymbol{w}}{dt} = \eta y(y - \theta)\boldsymbol{x}$$

$$\frac{d\theta}{dt} = \frac{1}{\tau}\left(y^2 - \theta\right)$$

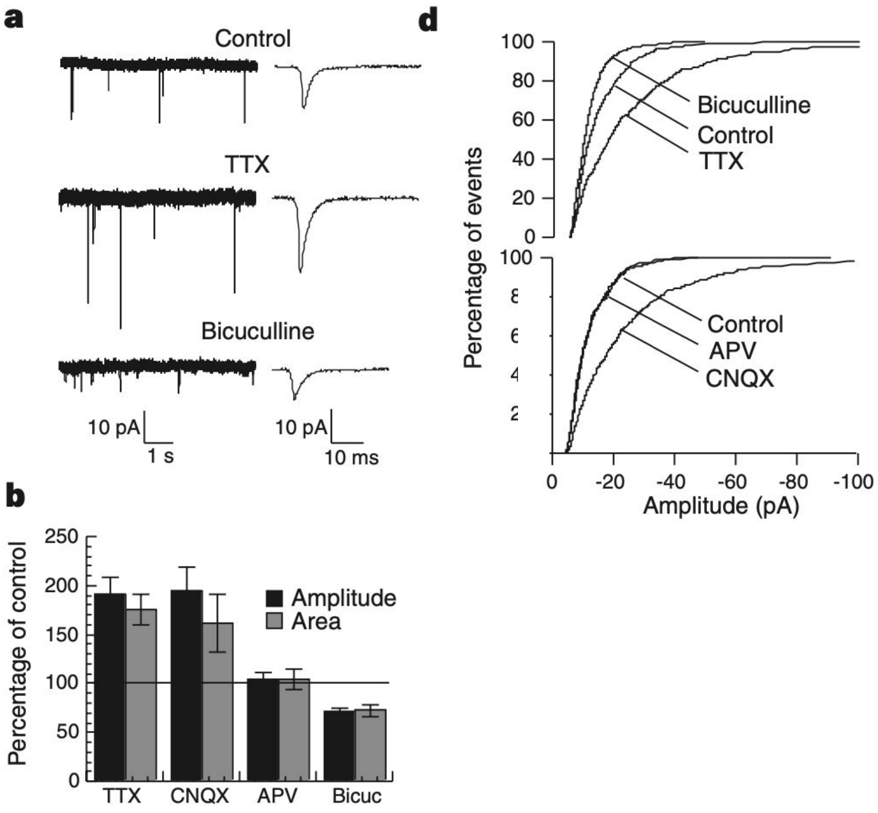
Miska et al., 2020 eLife

Synaptic scaling - experiments



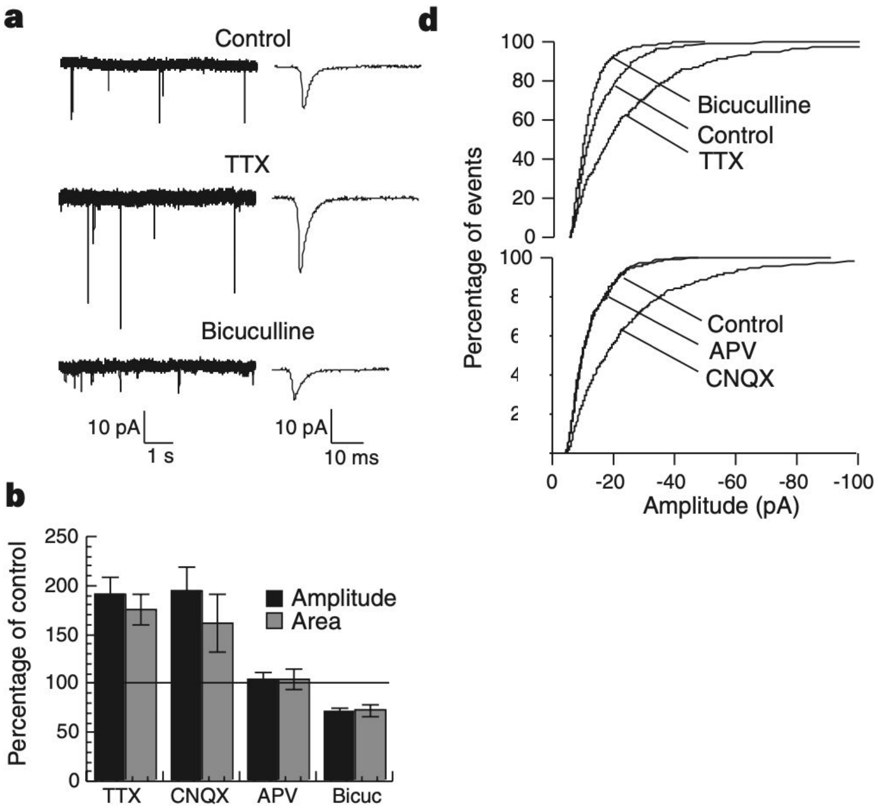
Turrigiano et al., 1998 Nature

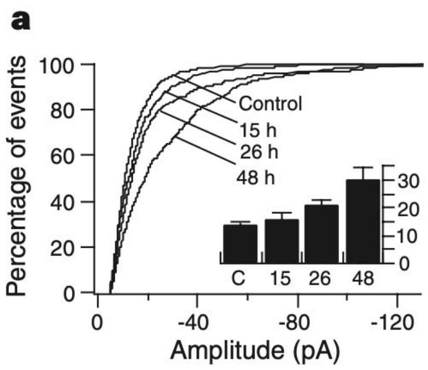
Synaptic scaling - experiments



Turrigiano et al., 1998 Nature

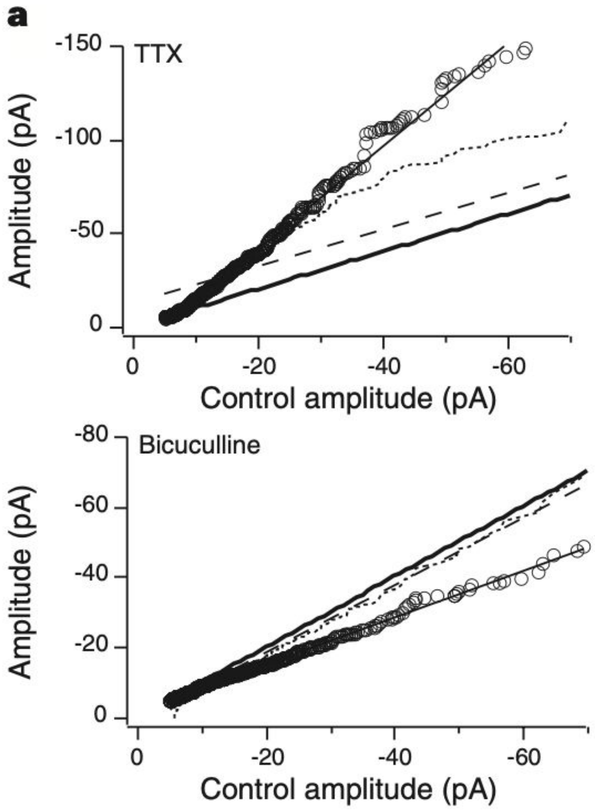
Synaptic scaling - experiments





Turrigiano et al., 1998 Nature

Synaptic scaling - experiments



Turrigiano et al., 1998 Nature

Synaptic scaling - models

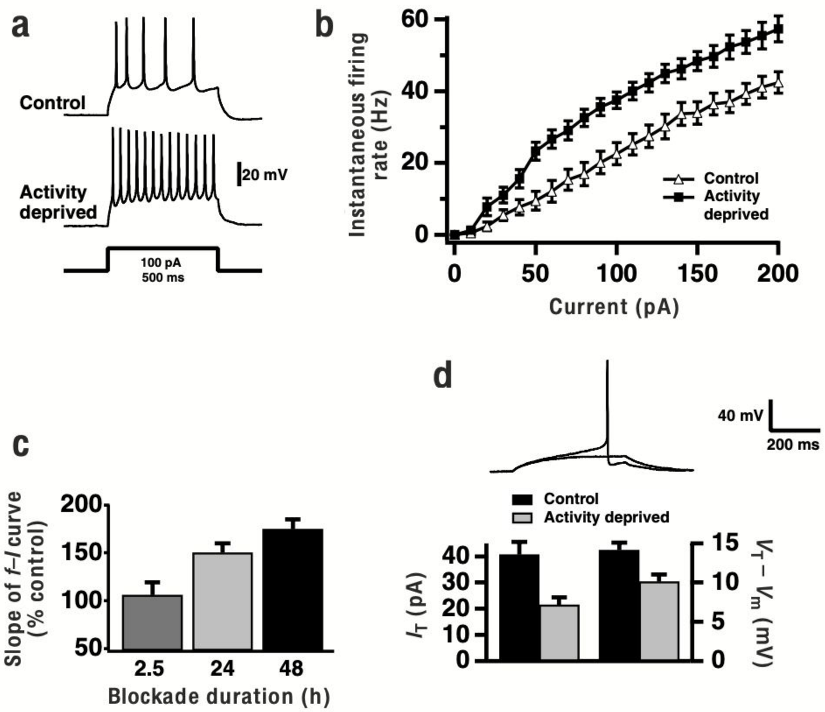
Activity-dependent scaling scales the weights to prevent too low or too high activity levels. The scaling is thought to be multiplicative and independent of presynaptic activity (Turrigiano et al., 1998; Turrigiano, 1999). A simple implementation would be to update the weights every time step according to:

$$\frac{dw(t)}{dt} = \beta w(t)[a_{goal} - a(t)],$$

where a_{goal} is the desired postsynaptic activity, set to 20 Hz, and β is a constant determining the strength of the scaling.

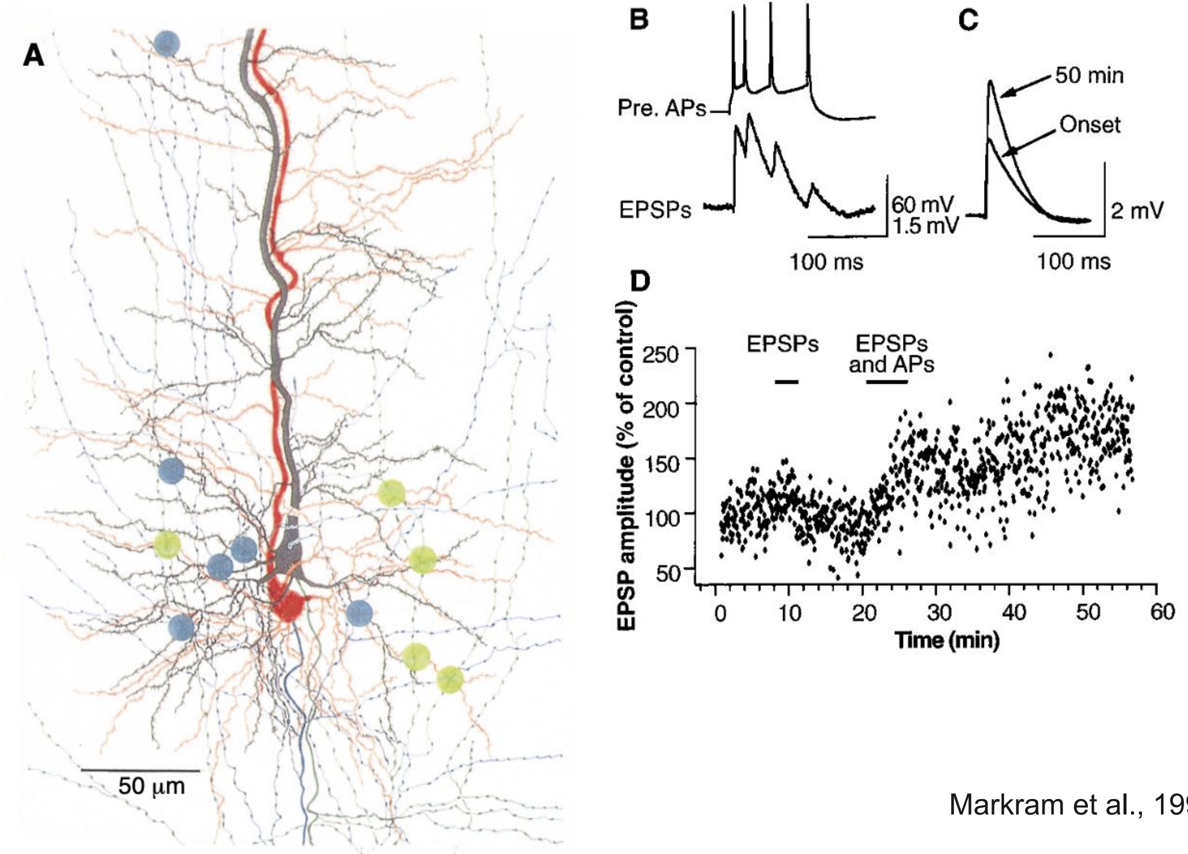
van Rossum et al., 2000 Journal of Neuroscience

Intrinsic plasticity - experiments



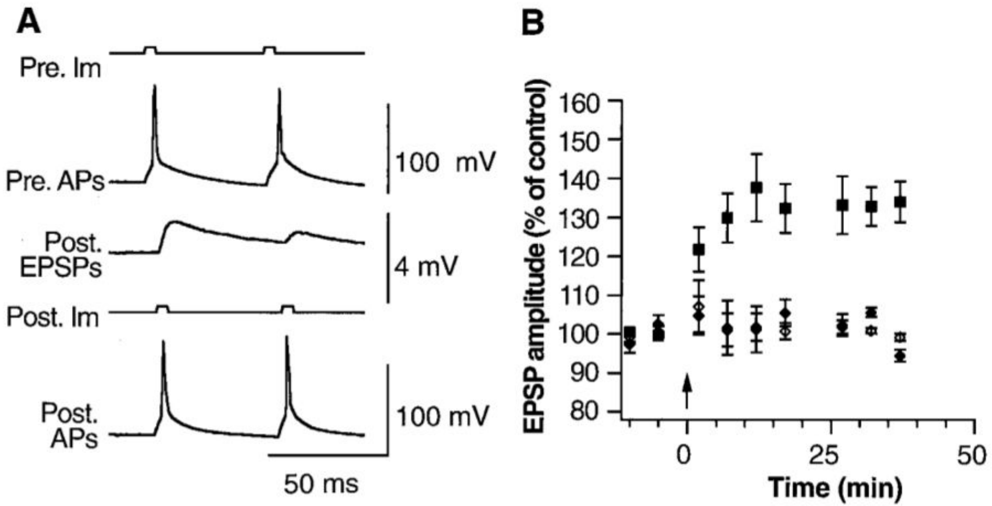
Desai et al., 1999 Nature Neuroscience

Spike-timing-dependent plasticity - experiments



Markram et al., 1997 Science

Spike-timing-dependent plasticity - experiments



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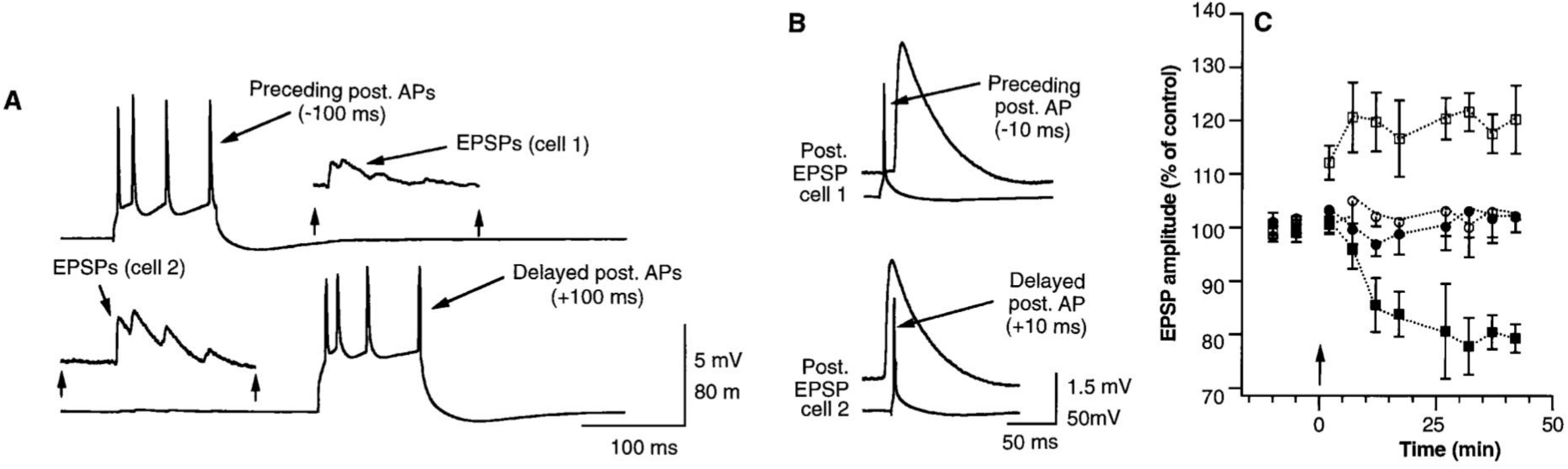

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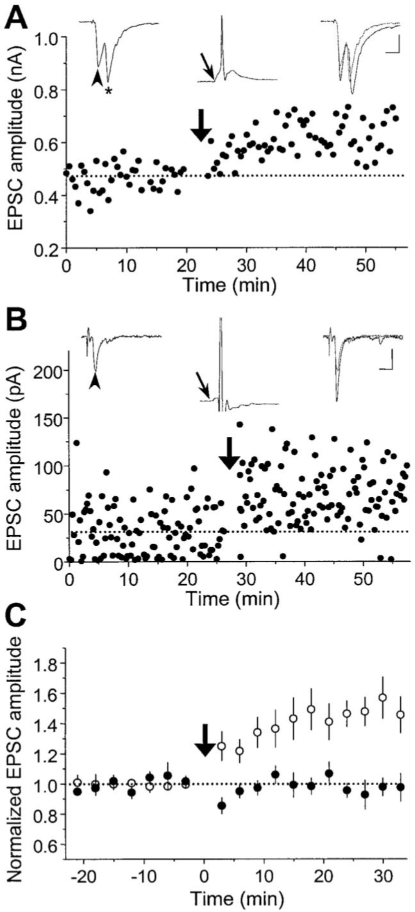
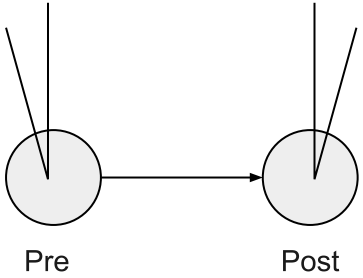
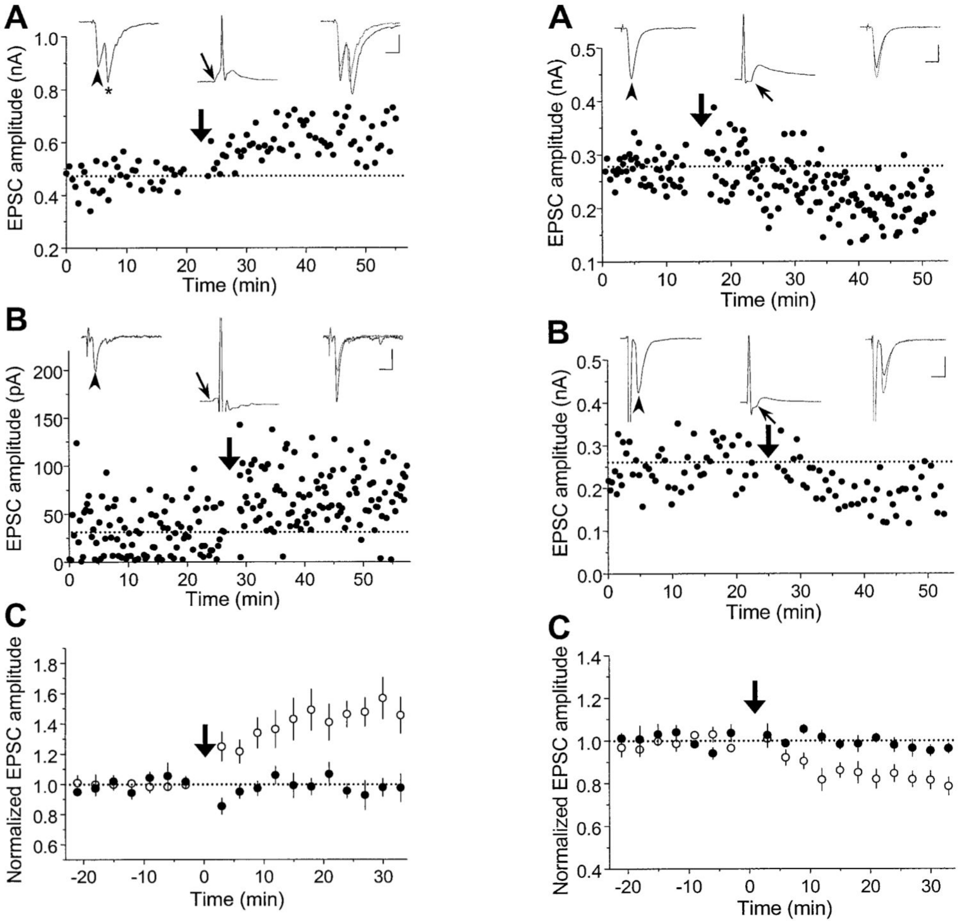




Bi and Poo 1998, Journal of Neuroscience

Spike-timing-dependent plasticity - experiments



Bi and Poo 1998, Journal of Neuroscience

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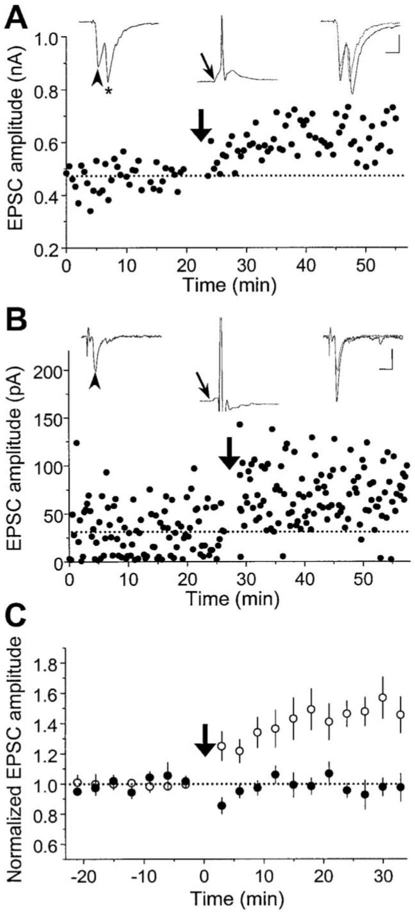
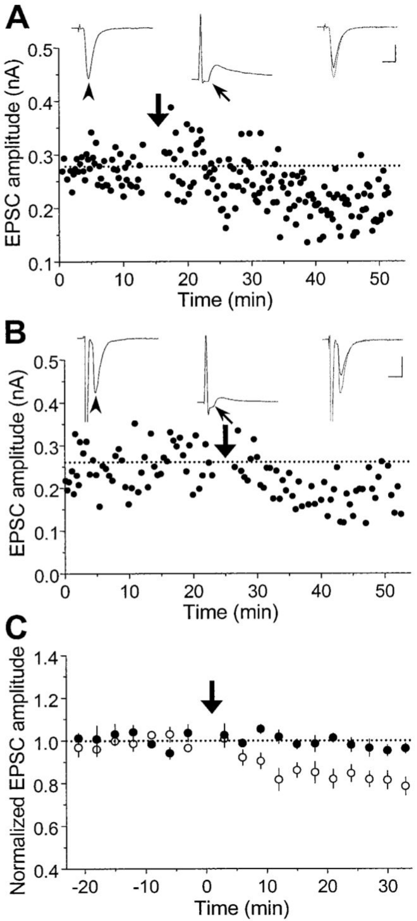
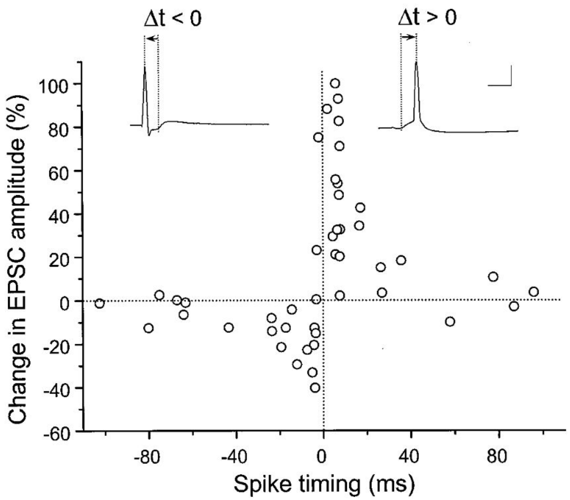






Bi and Poo 1998, Journal of Neuroscience

Spike-timing-dependent plasticity - pairwise STDP model

Let

$$\Delta t = t_{\text{post}} - t_{\text{pre}}$$

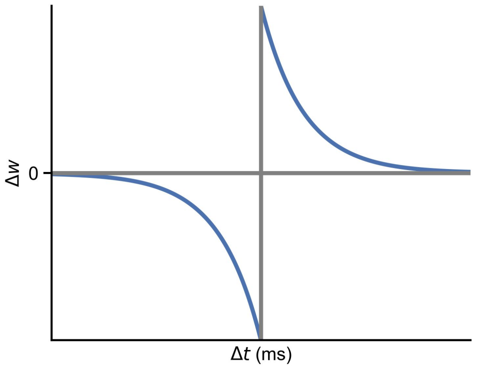
where t_{pre} is the time of a presynaptic spike, and t_{post} is the time of a postsynaptic spike.

The synaptic weight change Δw is given by:

$$\Delta w = \begin{cases} A_+ \cdot e^{-\Delta t/\tau_+}, & \text{if } \Delta t > 0 \quad \text{(LTP)} \\ -A_- \cdot e^{\Delta t/\tau_-}, & \text{if } \Delta t < 0 \quad \text{(LTD)} \end{cases}$$

where:

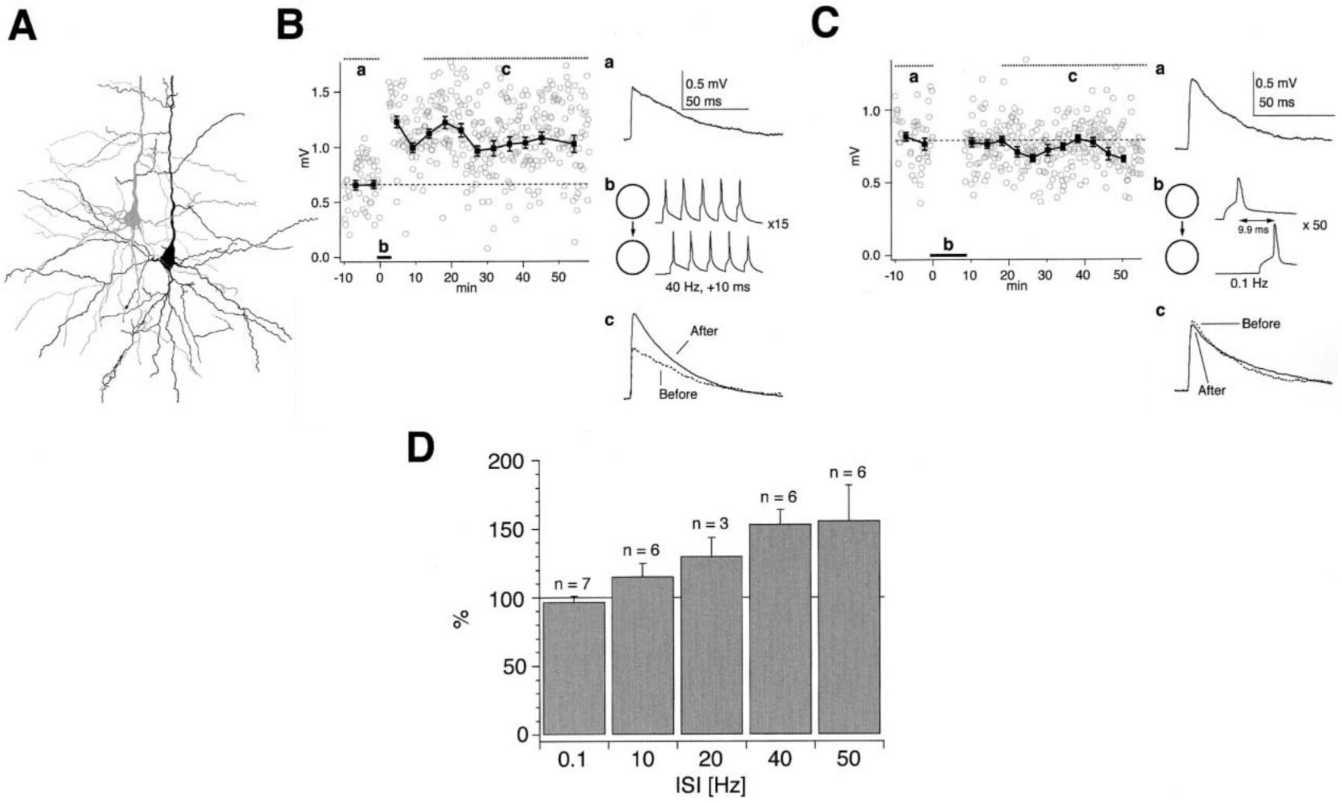
- A_+, A_- are the amplitude of the weight change whenever there is a pre-post pair or a post-pre pair,
- τ_+, τ_- are the corresponding time constants.



Gerstner et al., 1996 Nature
Kempter et al., 1999 PRE
Song et al., 2000 Nature Neuroscience

Rate and spike timing - experiments

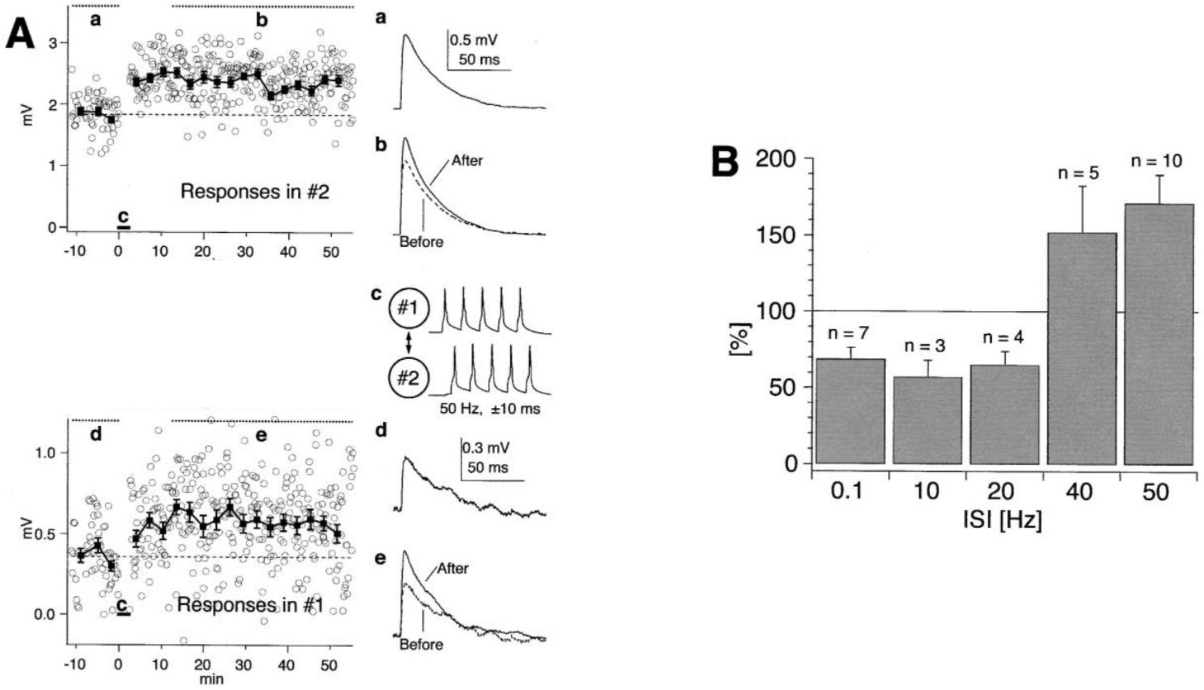
Rate, Timing, and Cooperativity Jointly Determine Cortical Synaptic Plasticity



Sjöström et al., 2001 Neuron

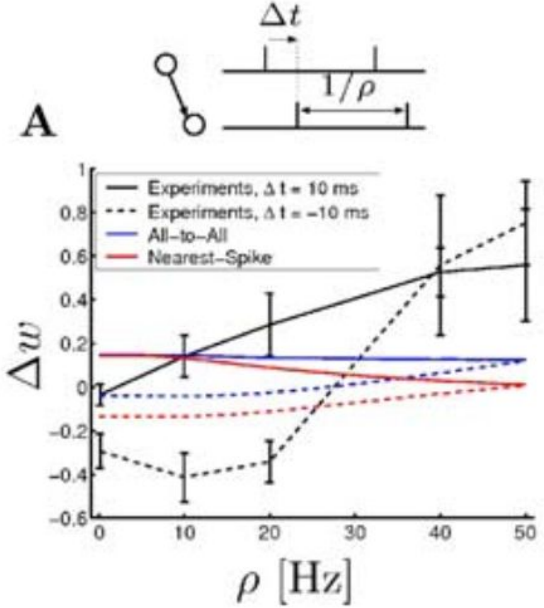
Rate and spike timing - experiments

Rate, Timing, and Cooperativity Jointly Determine Cortical Synaptic Plasticity



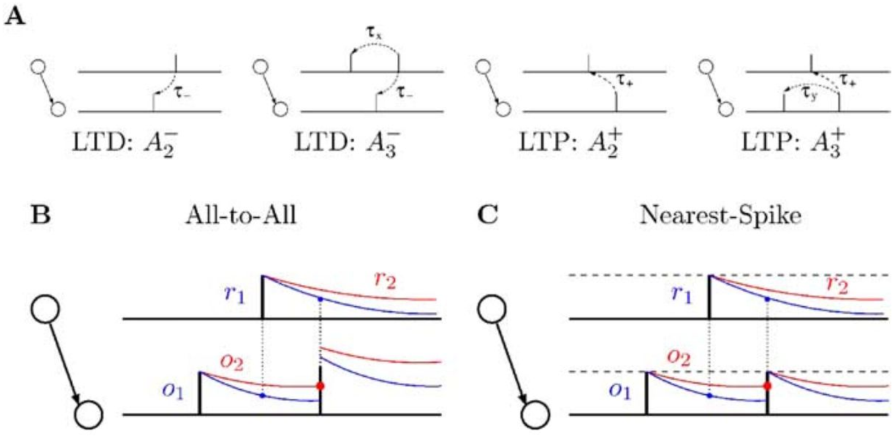
Sjöström et al., 2001 Neuron

Spike-timing-dependent plasticity - triplet STDP model



Pfister and Gerstner 2006, Journal of Neuroscience

Spike-timing-dependent plasticity - triplet STDP model



$$\frac{dr_1(t)}{dt} = -\frac{r_1(t)}{\tau_+} \quad \text{if } t = t^{\text{pre}}, \text{ then } r_1 \rightarrow r_1 + 1.$$

$$\frac{dr_2(t)}{dt} = -\frac{r_2(t)}{\tau_x} \quad \text{if } t = t^{\text{pre}} \text{ then } r_2 \rightarrow r_2 + 1$$

$$\frac{do_1(t)}{dt} = -\frac{o_1(t)}{\tau_-} \quad \text{if } t = t^{\text{post}} \text{ then } o_1 \rightarrow o_1 + 1$$

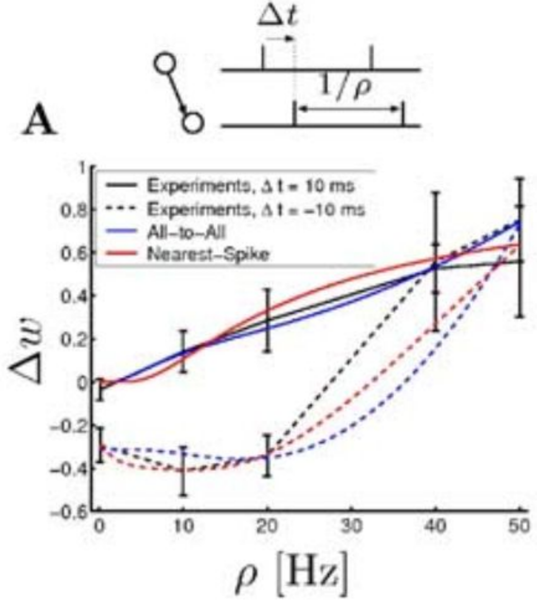
$$\frac{do_2(t)}{dt} = -\frac{o_2(t)}{\tau_y} \quad \text{if } t = t^{\text{post}} \text{ then } o_2 \rightarrow o_2 + 1.$$

$$w(t) \rightarrow w(t) - o_1(t)[A_2^- + A_3^- r_2(t - \epsilon)] \text{ if } t = t^{\text{pre}}.$$

$$w(t) \rightarrow w(t) + r_1(t)[A_2^+ + A_3^+ o_2(t - \epsilon)] \text{ if } t = t^{\text{post}}.$$

Pfister and Gerstner 2006, Journal of Neuroscience

Spike-timing-dependent plasticity - triplet STDP model



Pfister and Gerstner 2006, Journal of Neuroscience

Relate STDP to structural motifs

$$\Delta_{ij}^{\mathrm{STDP}} = \int_{-\infty}^{\infty} C_{ij}(\tau)F(\tau)d\tau . \quad C_{ij}(\tau) \equiv \left\langle S_i(t+\tau)S_j(t)\right\rangle$$

$$\tilde{C}(\omega) = 2\pi\delta(\omega)rr^T + [I - \tilde{a}(\omega)W]^{-1}D[I - \tilde{a}(-\omega)W^T]^{-1},$$

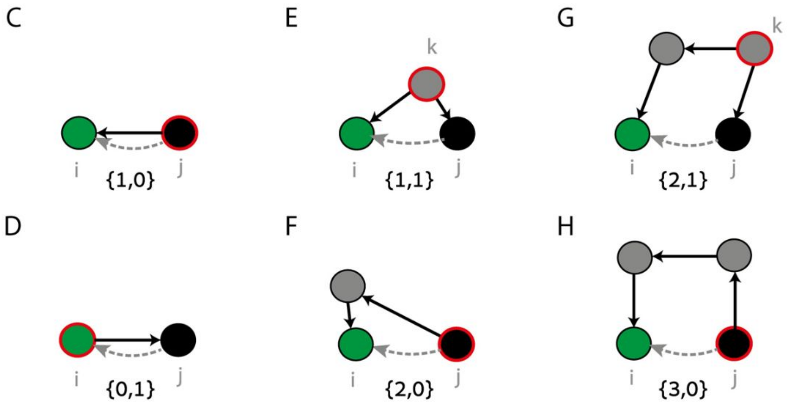
$$[I - A]^{-1} = \sum_{i=0}^{\infty} A^i .$$

$$\Delta^{\mathrm{STDP}} = f_0 rr^T + \frac{1}{2\pi}\int_{-\infty}^{\infty} d\omega\tilde{F}(-\omega)[I - \tilde{a}(\omega)W]^{-1}D[I - \tilde{a}(-\omega)W^T]^{-1} .$$

$$\Delta_{ij}^{\mathrm{STDP}} = f_0 r_i r_j + \sum_{\alpha\beta} f_{\alpha,\beta} \cdot \sum_k r_k (W^\alpha)_{ik}(W^\beta)_{jk},$$

$$f_{\alpha,\beta} = \frac{1}{2\pi}\int_{-\infty}^{\infty} \mathrm{d}\omega\tilde{F}(-\omega)\tilde{a}(\omega)^\alpha\tilde{a}(-\omega)^\beta$$

$$\Delta_{ij}^{\mathrm{STDP}} = f_0 r_i r_j + f_{1,0} r_j W_{ij} + f_{0,1} r_i W_{ji} + \ldots .$$



Tannenbaum and Burak 2016, PLOS CB
Montangie et al., 2020 PLOS CB
Hawkes 1971, Journal of the Royal Statistical Society
Trousdale et al., 2012 PLOS CB
Hu et al., 2013 Journal of Statistical Mechanics
Richardson 2008 Biological Cybernetics
……

Calcium-based plasticity - models

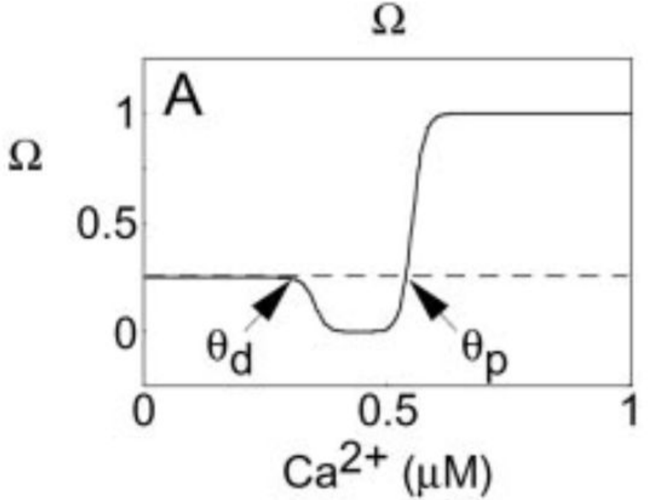
A unified model of NMDA receptor-dependent bidirectional synaptic plasticity

Harel Z. Shouval*†, Mark F. Bear*‡§, and Leon N Cooper*‡¶

Assumption 1: The Calcium Control Hypothesis. The hypothesis that different calcium levels trigger different forms of synaptic plasticity (12, 13, 18) can be formulated mathematically as:

$$\dot{W}_j = \eta\Omega([Ca]_j), \qquad \textbf{[1]}$$

where W_j represents the synaptic strength of synapse j, η is the learning rate, and the calcium level at synapse j is denoted by $[Ca]_j$. When the calcium level is below a lower threshold θ_d, no modification occurs. If $\theta_d < [Ca]_j < \theta_p$, W_j is depressed, and for $[\mathrm{Ca}]_j > \theta_p$, the synaptic strength is potentiated (Fig. 1*A*).



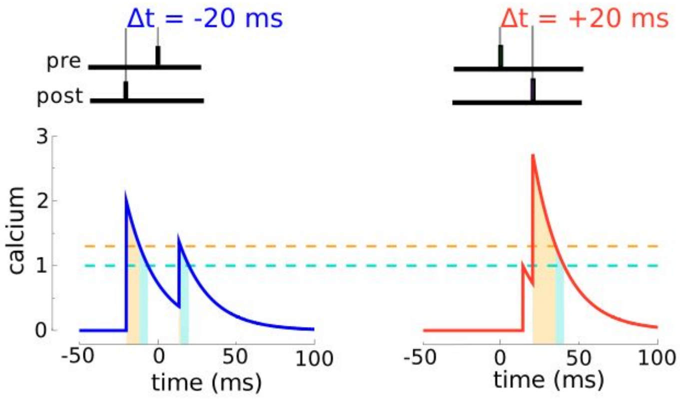
Shouval et al., 2002, PNAS

Calcium-based plasticity - models

Calcium-based plasticity model explains sensitivity of synaptic changes to spike pattern, rate, and dendritic location

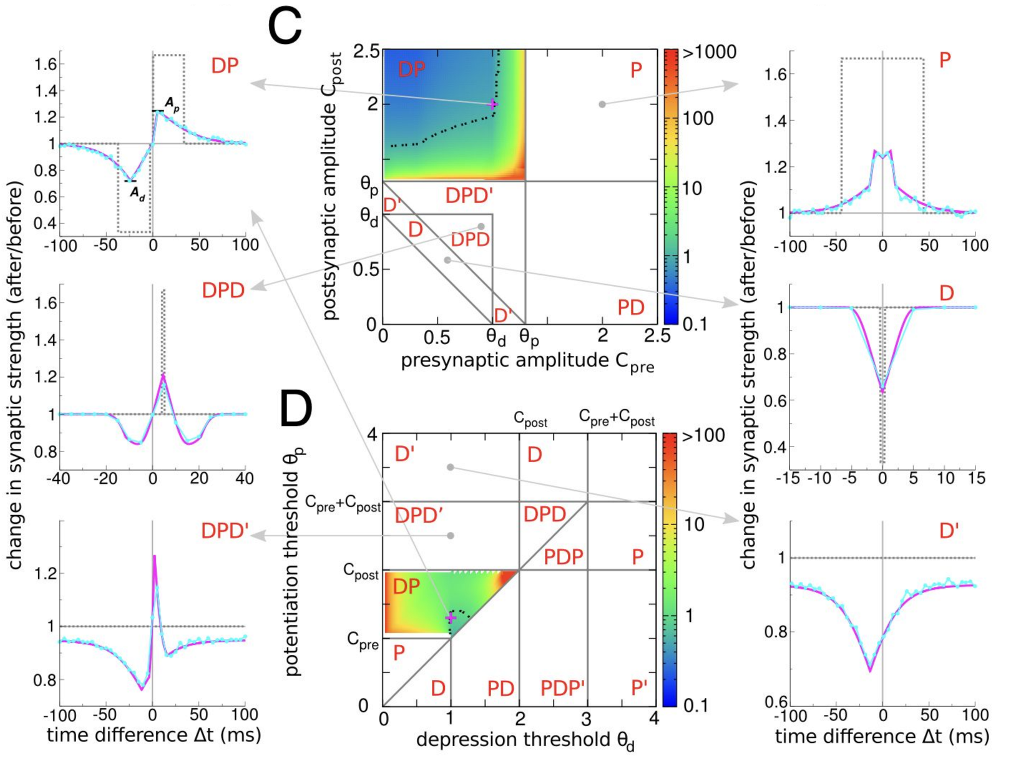
Michael Graupner[a,b,1] and Nicolas Brunel[a]

$$\tau \frac{d\rho}{dt} = -\rho(1-\rho)(\rho_\star - \rho) + \gamma_p (1-\rho)\Theta\left[c(t) - \theta_p\right]$$
$$-\gamma_d \rho \Theta[c(t) - \theta_d] + Noise(t).$$



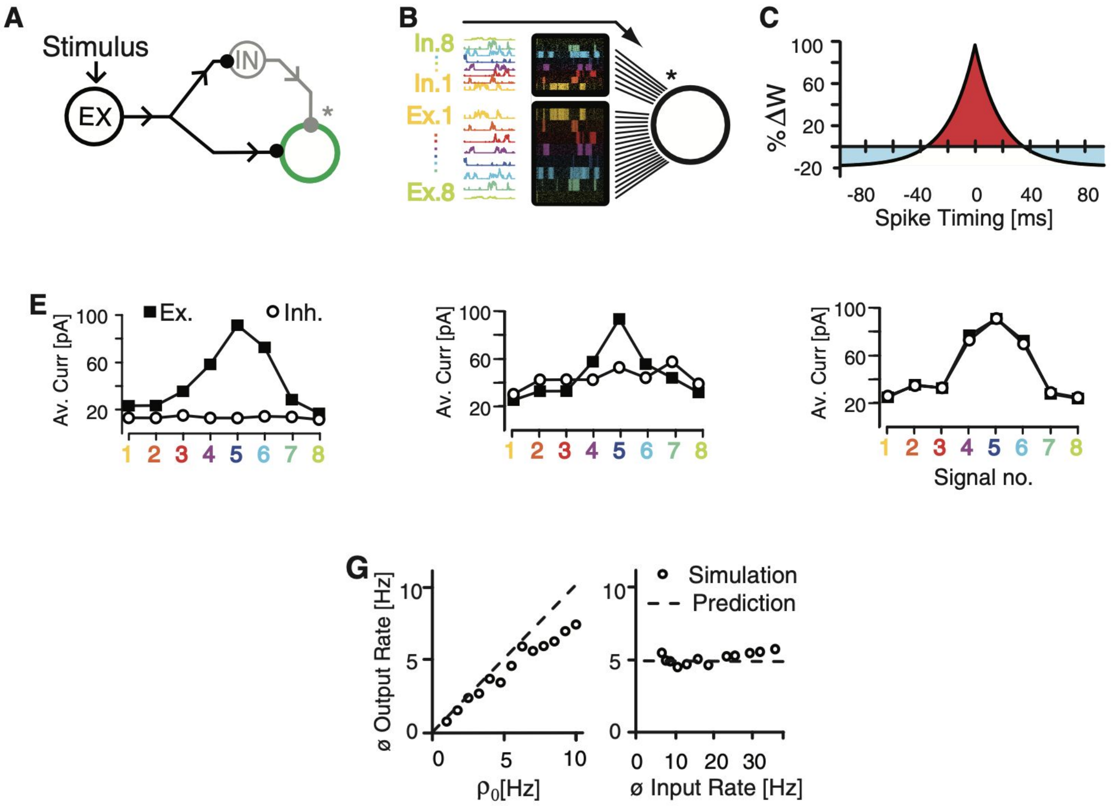
Graupner and Brunel 2012, PNAS

Calcium-based plasticity - models



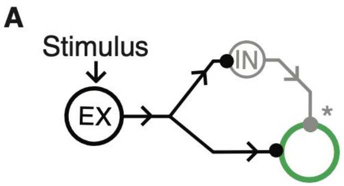
Graupner and Brunel 2012, PNAS
Also see Inglebert et al., 2020, PNAS

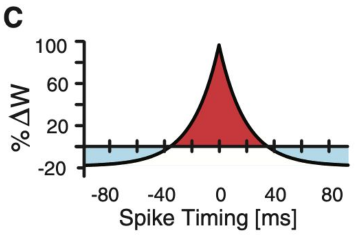
Inhibitory plasticity - models

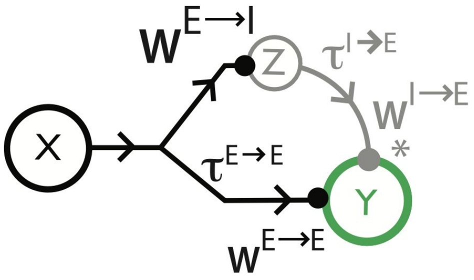


Vogels*, Sprekeler*, et al. 2011, Science

Inhibitory plasticity - models







$$\Delta W_j^{I\to E} = \eta \int_0^T \int_0^T L(t-t')Y(t')Z_j(t)\mathrm{d}t\,\mathrm{d}t' - \eta\rho_0 \int_0^T Z_j(t)\mathrm{d}t\,,$$

where $L(t) = [2\tau_{\mathrm{STDP}}]^{-1}e^{-|t|/\tau_{\mathrm{STDP}}}$ denotes a symmetric learning window with a coincidence time τ_{STDP}, η is a learning rate and ρ_0 is a constant that controls the relative strength of the non-Hebbian weight decrease in relation to the Hebbian weight increase.

Vogels*, Sprekeler*, et al. 2011, Science

Inhibitory plasticity - models

$$\langle \Delta W_j^{I \to E} \rangle_{Z,Y|X} = \eta \int \big(y(t) z_j(t) - (\rho_0 + \rho_s W_j^{I \to E}) z_j(t) \big) \, \mathrm{d}t \, .$$

with $\rho_s := \int L(\tau)\epsilon(\tau)\mathrm{d}\tau.$

$$\Psi(\mathbf{W}^{I \to E}) = \frac{1}{2} \langle (y(t) - \rho_0)^2 \rangle_t + \frac{1}{2} \rho_s \sum_j \bar{z}_j(t) \left(W_j^{I \to E} \right)^2$$

Vogels*, Sprekeler*, et al. 2011, Science

Inhibitory plasticity - models

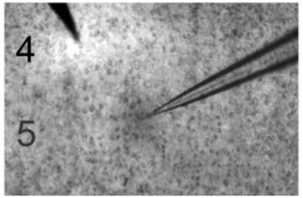
$$\frac{\partial}{\partial W_j^{I\to E}}\Psi = \langle (y(t)-\rho_0)\frac{\partial}{\partial W_j^{I\to E}} y(t)\rangle_t + \rho_s \langle z_j(t)\rangle_t W_j^{I\to E}$$
$$= -\langle y(t) z_j(t) - (\rho_0 + \rho_s W_j^{I\to E}) z_j(t)\rangle_t$$
$$= -\frac{1}{T}\int y(t) z_j(t) - (\rho_0 + \rho_s W_j^{I\to E}) z_j(t) \mathrm{d}t$$

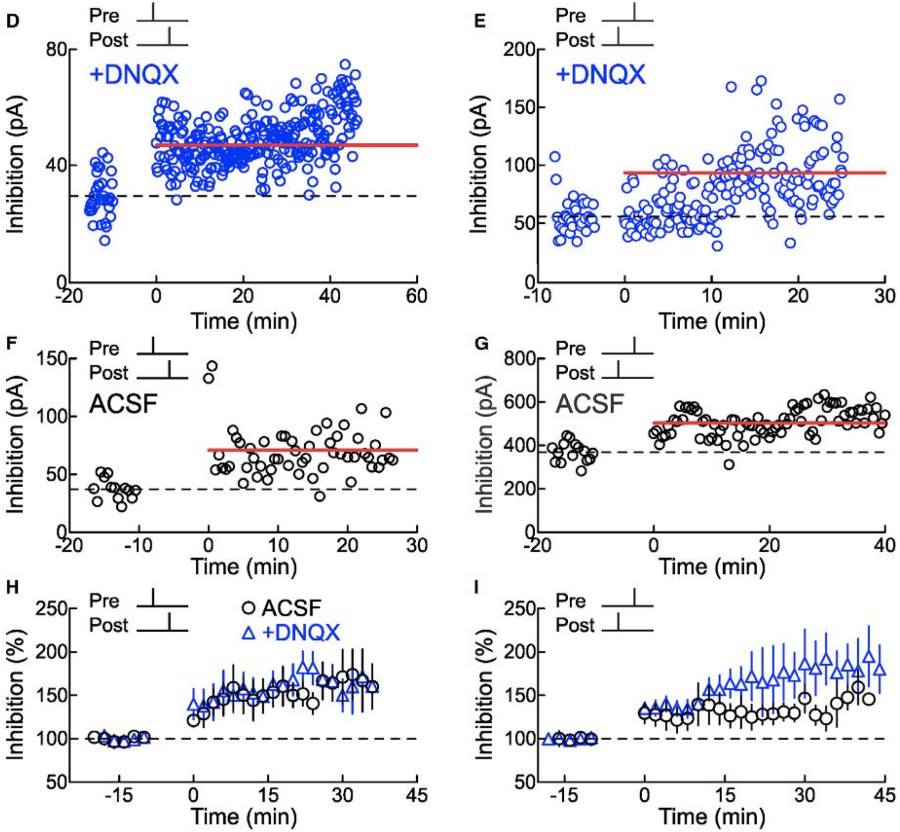
A comparison with Eq. 23 shows that the inhibitory plasticity rule is indeed a gradient descent on the energy function Ψ:

$$\langle \Delta W_j^{I\to E}\rangle_{Z,Y|X} = -\eta T \frac{\partial}{\partial W_j^{I\to E}}\Psi\,.$$

Vogels*, Sprekeler*, et al. 2011, Science

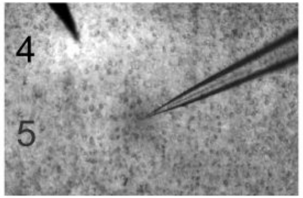
Inhibitory plasticity - experiments

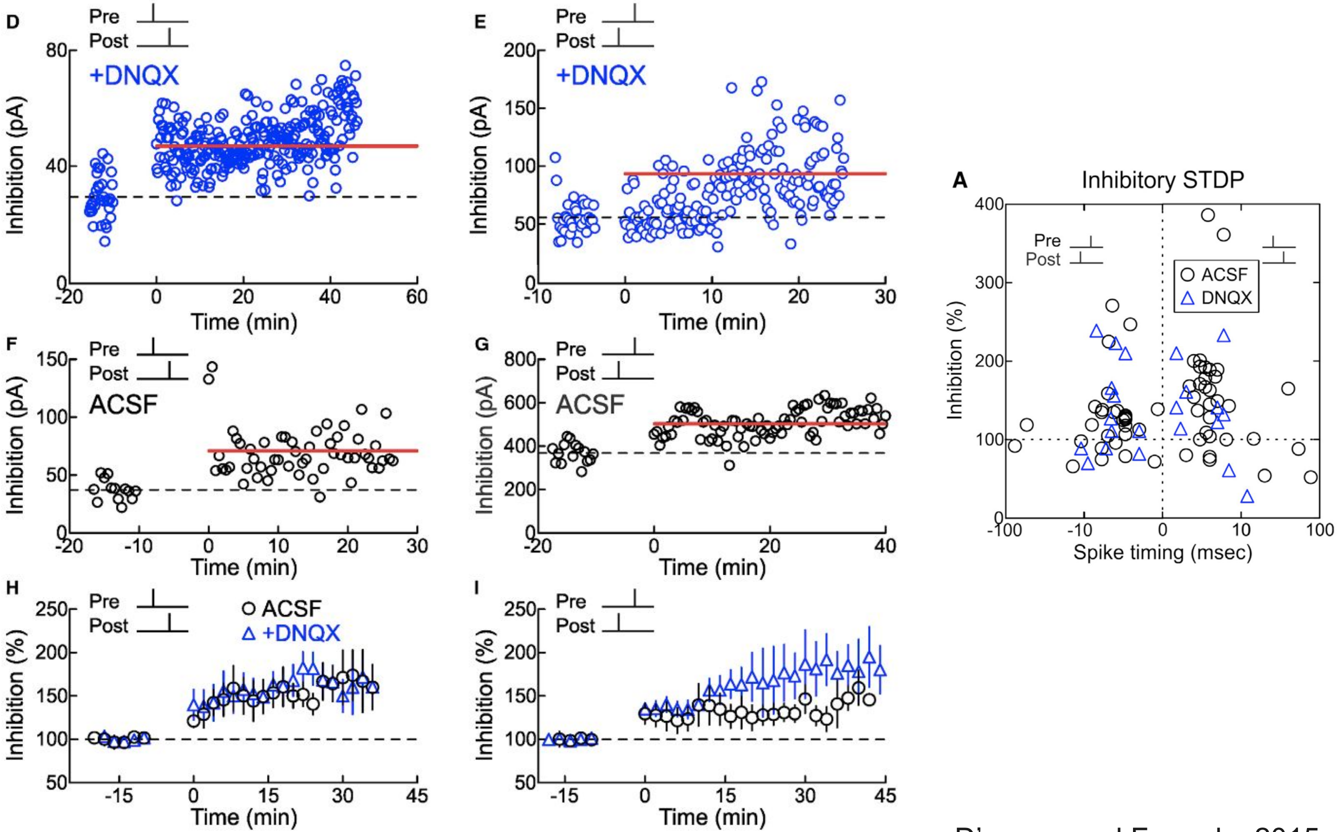




D’amour and Froemke 2015, Neuron

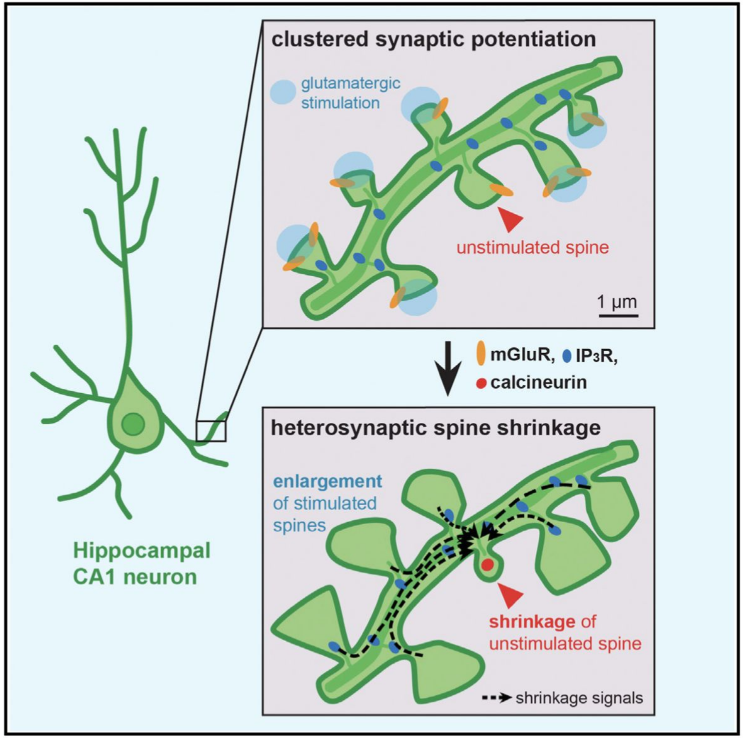
Inhibitory plasticity - experiments

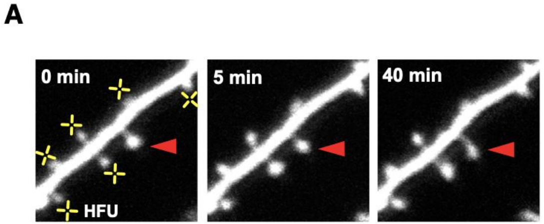


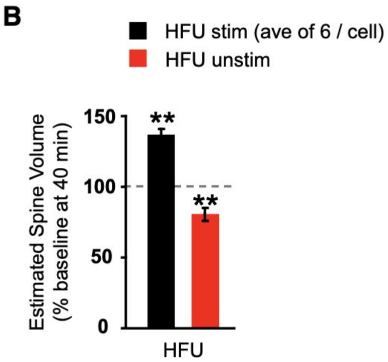


D’amour and Froemke 2015, Neuron

Heterosynaptic plasticity

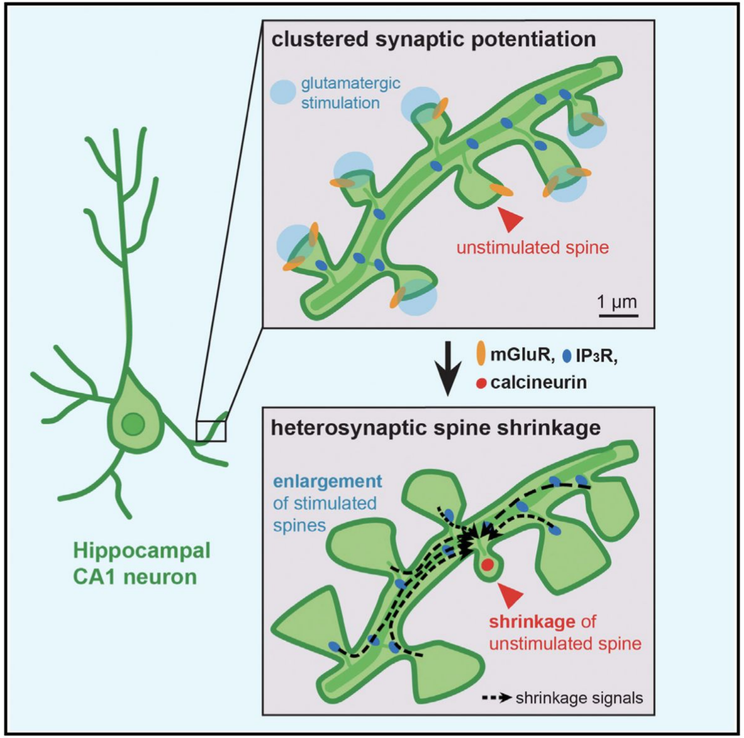


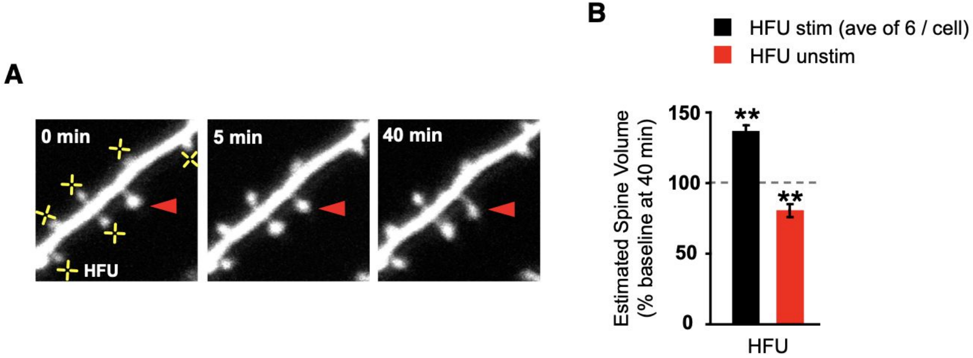


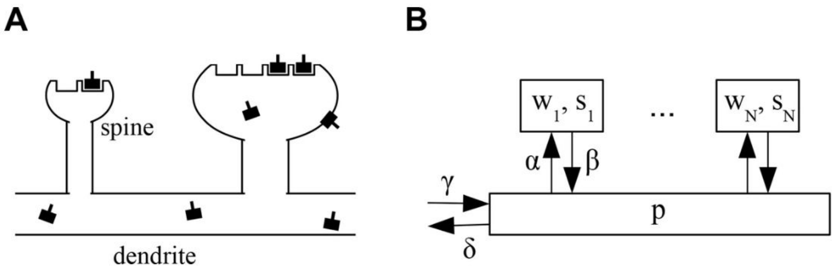


Oh et al., 2015 Cell Reports
Triesch et al., 2018 eLife

Heterosynaptic plasticity



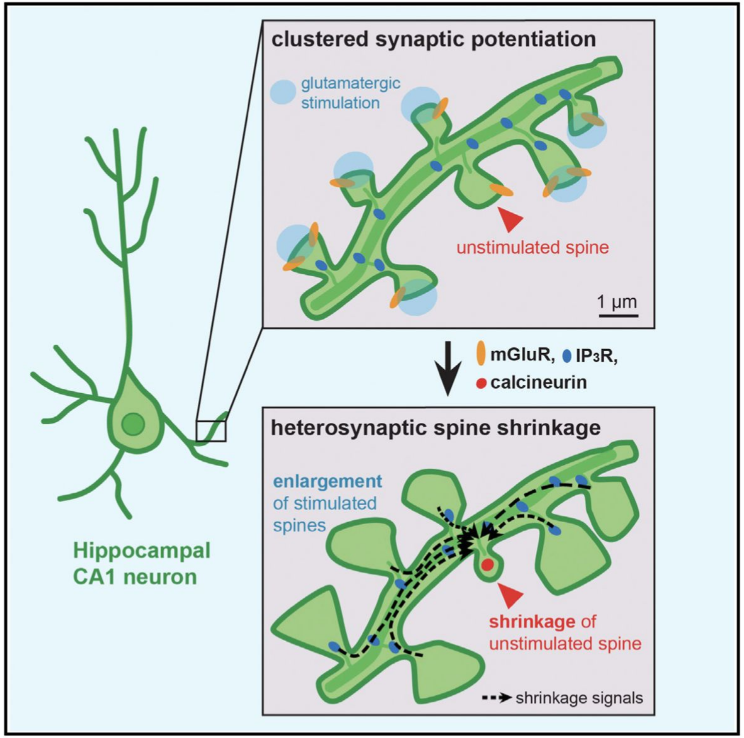


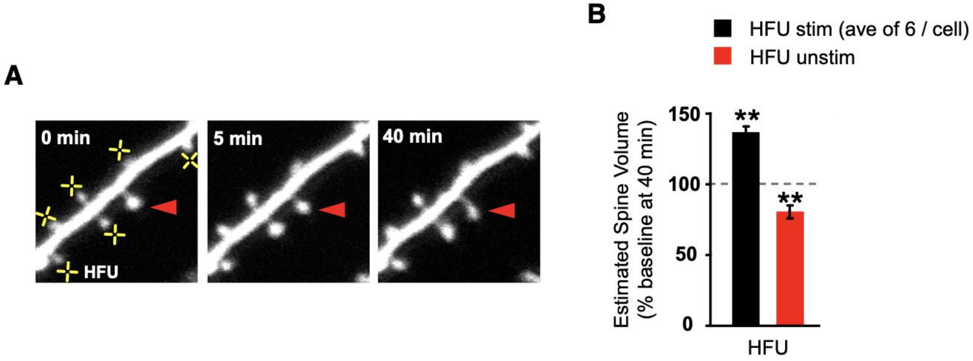


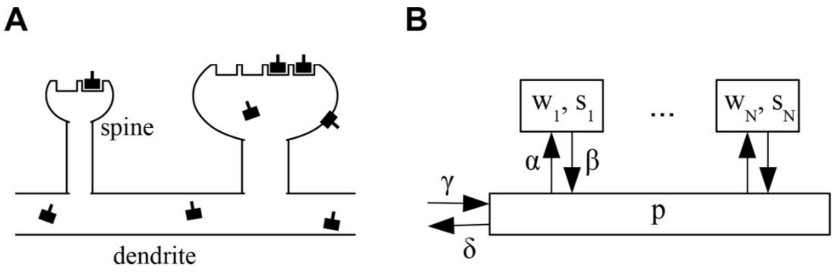
Oh et al., 2015 Cell Reports
Triesch et al., 2018 eLife

Heterosynaptic plasticity

$$\frac{d\boldsymbol{w}}{dt} = \eta(\boldsymbol{w}^\top \boldsymbol{x})\boldsymbol{x} - \eta(\boldsymbol{w}^\top \boldsymbol{x})^2 \boldsymbol{w}$$







Oh et al., 2015 Cell Reports
Triesch et al., 2018 eLife

Interactions between different plasticity mechanisms in recurrent neural networks

Formation and maintenance of neuronal assemblies through synaptic plasticity

Ashok Litwin-Kumar & Brent Doiron

Nature Communications **5**, Article number: 5319 (2014) | Cite this article

Diverse synaptic plasticity mechanisms orchestrated to form and retrieve memories in spiking neural networks

Friedemann Zenke, Everton J. Agnes & Wulfram Gerstner

Nature Communications **6**, Article number: 6922 (2015) | Cite this article

Homeostatic mechanisms regulate distinct aspects of cortical circuit dynamics

Yue Kris Wu, Keith B. Hengen, Gina G. Turrigiano, and Julijana Gjorgjieva Authors Info & Affiliations

Edited by Terrence J. Sejnowski, Salk Institute for Biological Studies, La Jolla, CA, and approved August 04, 2020 (received for review October 20, 2019)

September 11, 2020 | 117 (39) 24514-24525 | https://doi.org/10.1073/pnas.1918368117

Synapse-type-specific competitive Hebbian learning forms functional recurrent networks

Samuel Eckmann, Edward James Young, and Julijana Gjorgjieva Authors Info & Affiliations

Edited by Terrence Sejnowski, Salk Institute for Biological Studies, La Jolla, CA; received April 4, 2023; accepted April 25, 2024

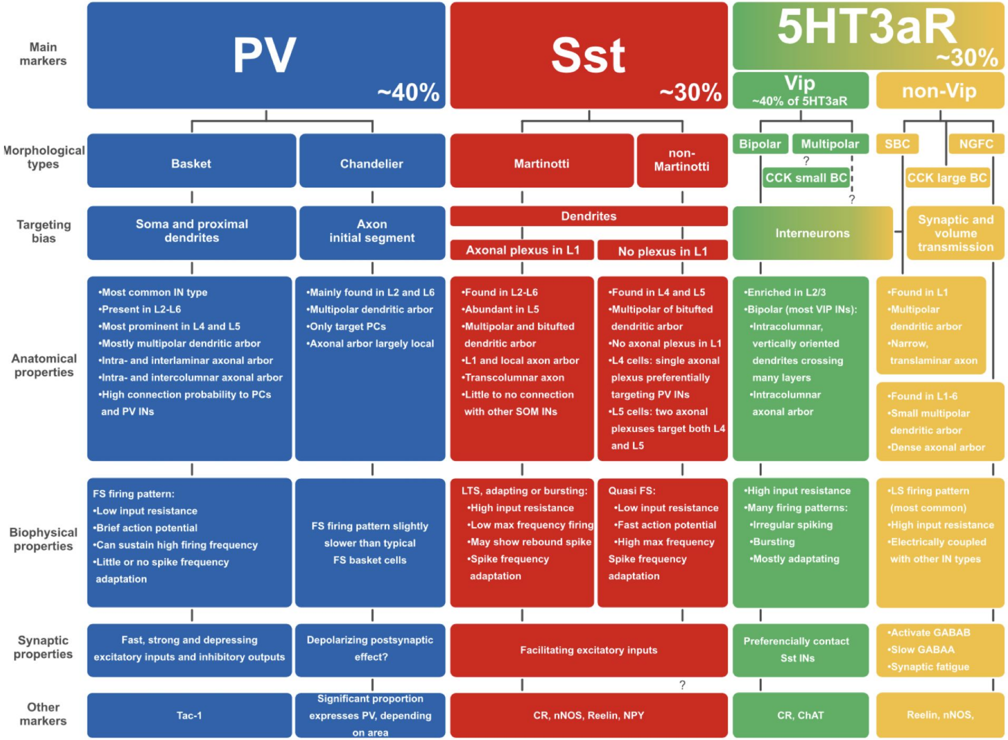
June 13, 2024 | 121 (25) e2305326121 | https://doi.org/10.1073/pnas.2305326121

Co-dependent excitatory and inhibitory plasticity accounts for quick, stable and long-lasting memories in biological networks

Everton J. Agnes & Tim P. Vogels

Nature Neuroscience **27**, 964–974 (2024) | Cite this article

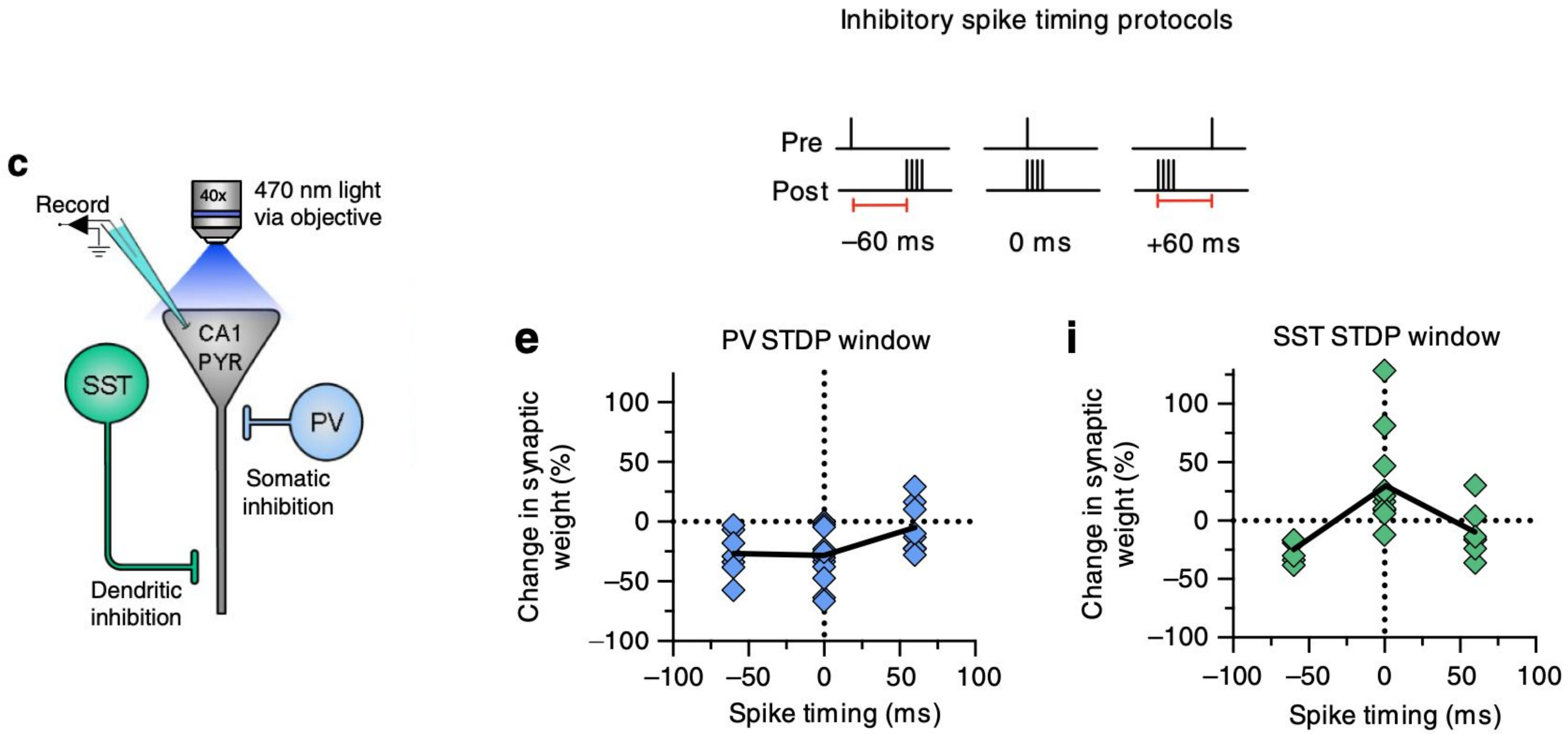
Interneuron cell types



Pfeffer et al., 2013 Nature Neuroscience

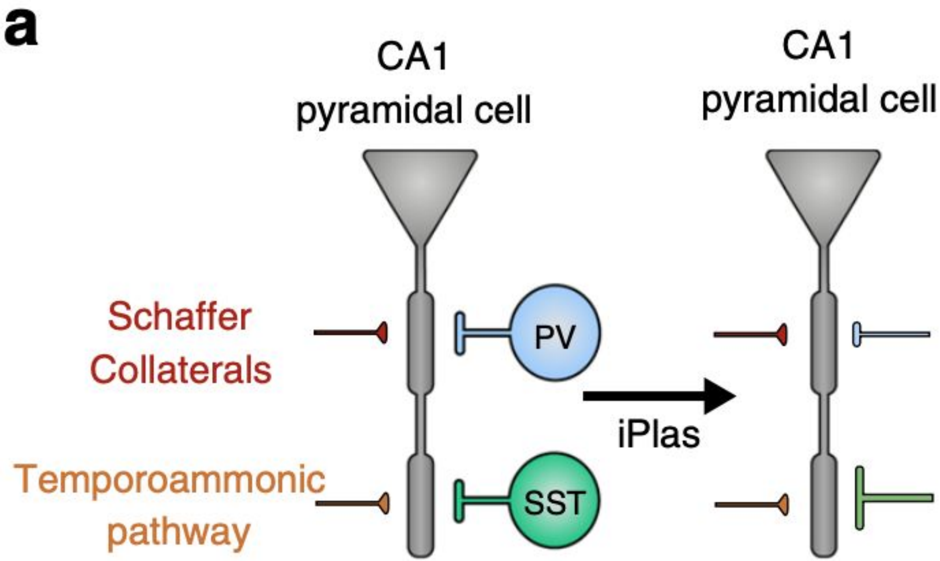
Tremblay et al., 2016 Neuron

Interneuron-specific plasticity



Udakis et al., 2020 Nature Communications

Interneuron-specific plasticity



Udakis et al., 2020 Nature Communications

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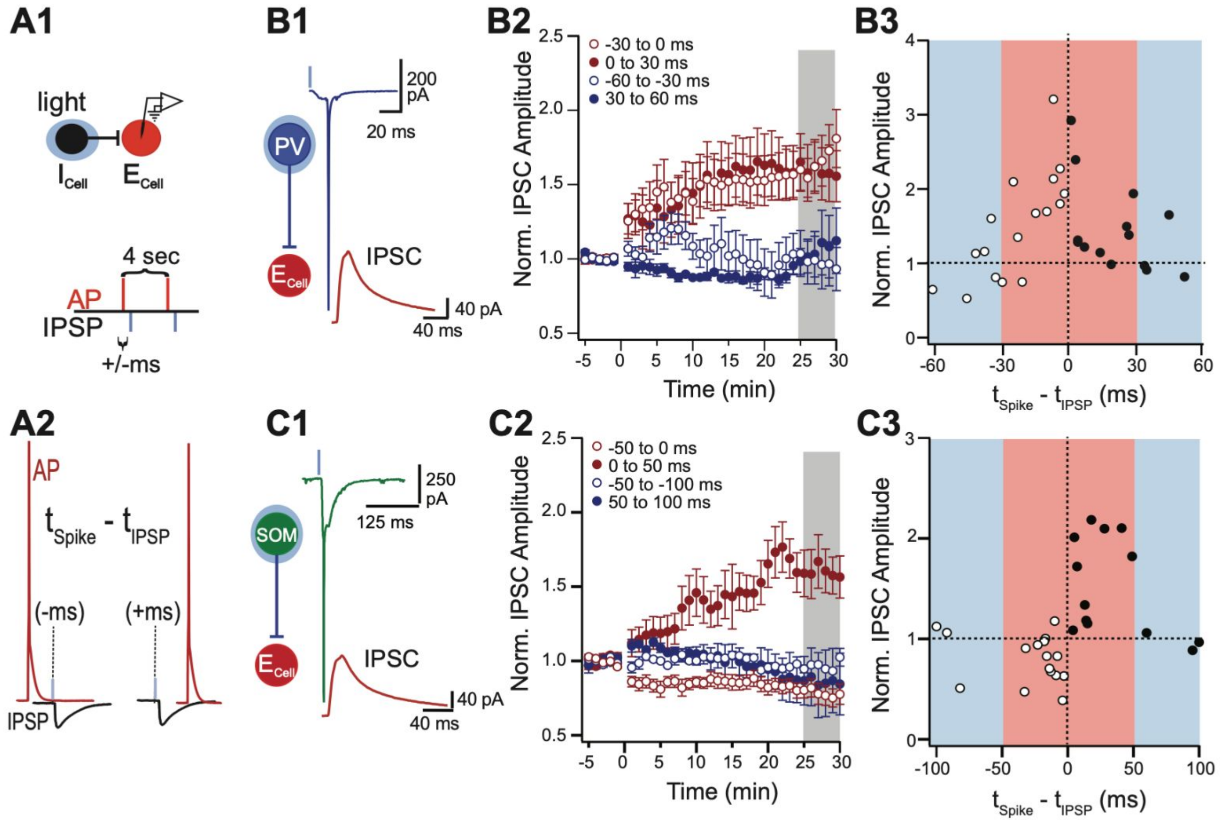


Lagzi et al., bioRxiv 2021

Plasticitome

similar to genome, transcriptome, and connectome.

Review Article | Published: 30 December 2022

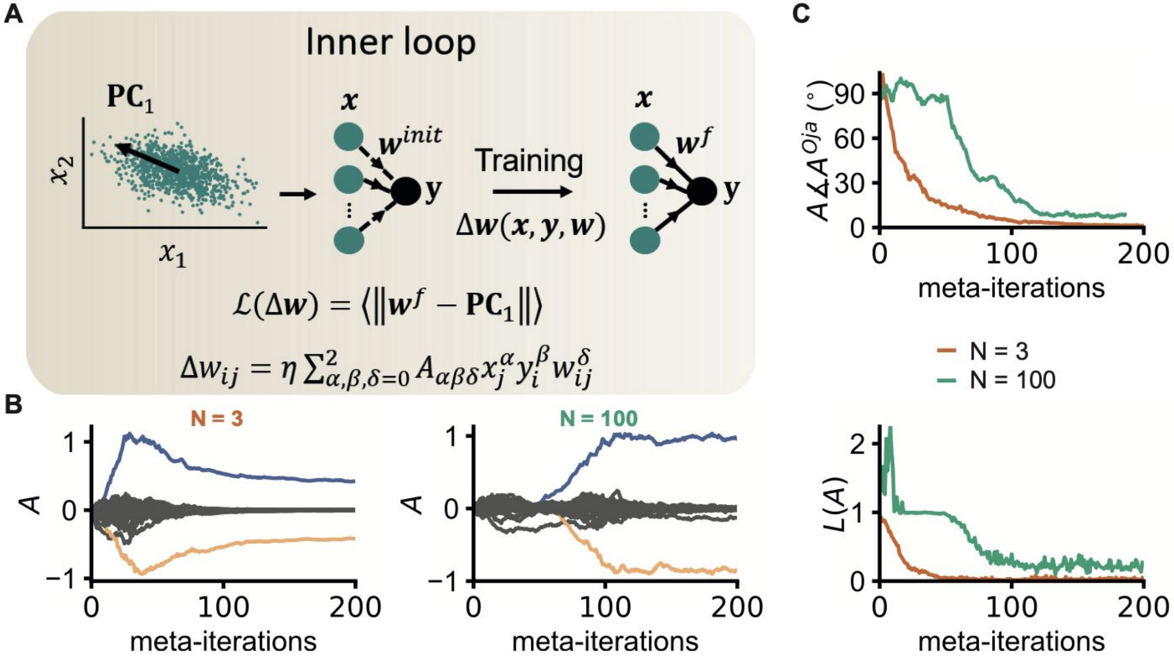
The plasticitome of cortical interneurons

Amanda R. McFarlan, Christina Y. C. Chou, Airi Watanabe, Nicole Cherepacha, Maria Haddad, Hannah Owens & P. Jesper Sjöström

Nature Reviews Neuroscience **24**, 80–97 (2023) | Cite this article

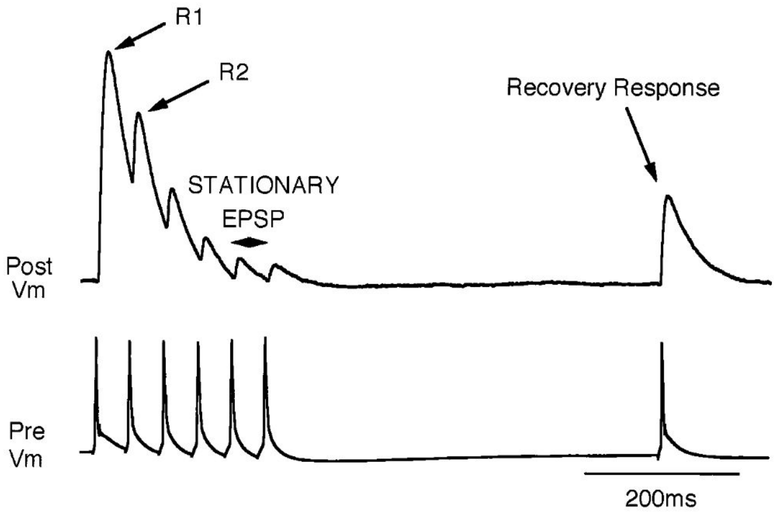
Machine learning approach to study plasticity

$$A^{\mathrm{Oja}}_{\alpha\beta\delta} = \begin{cases} 1, & \text{if } \alpha = 1, \beta = 1, \delta = 0 \\ -1, & \text{if } \alpha = 0, \beta = 2, \delta = 1 \\ 0, & \text{otherwise.} \end{cases}$$



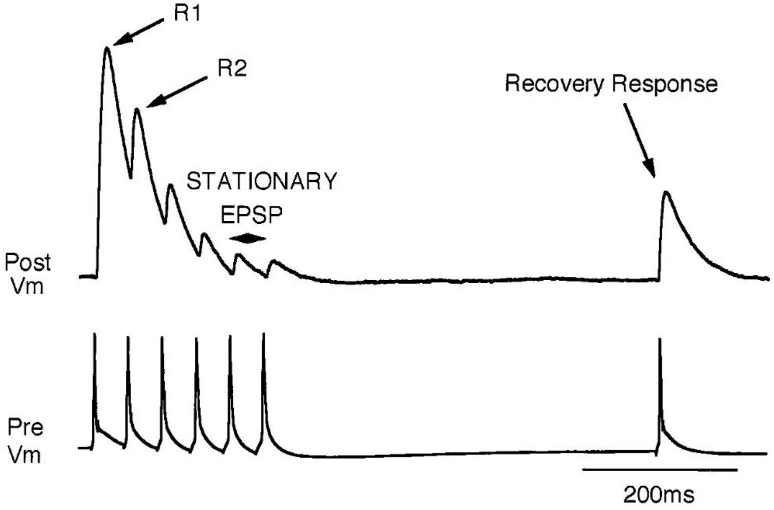
Confavreux et al., 2020 NeurIPS
Also see Ramesh et al., 2024 eLife

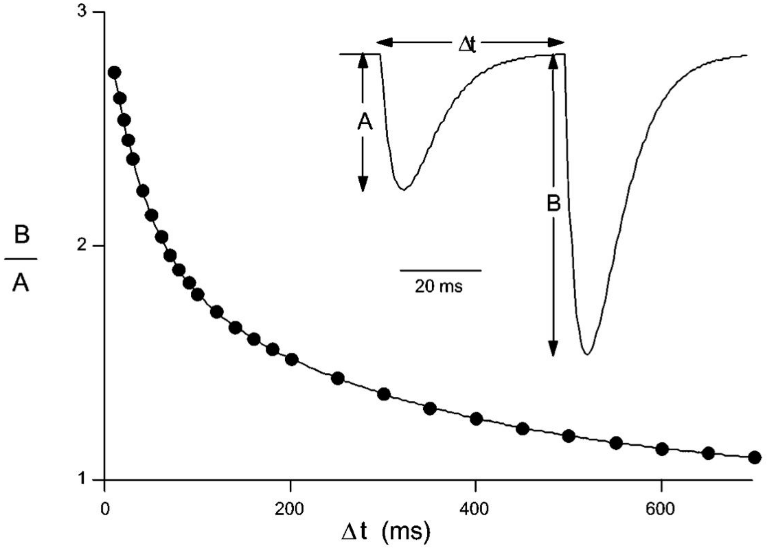
Short-term plasticity - experiments



Tsodyks and Markram 1997, PNAS

Short-term plasticity - experiments

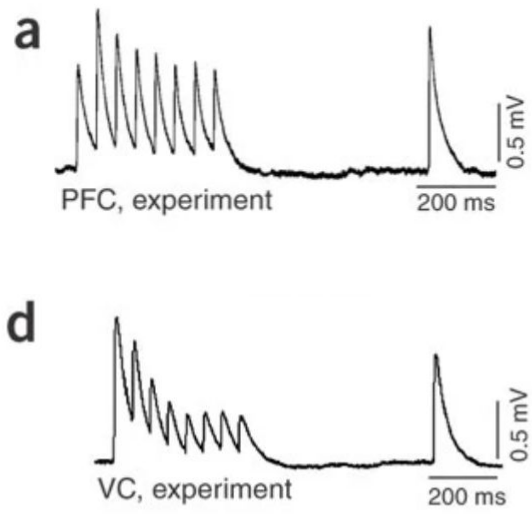




Tsodyks and Markram 1997, PNAS

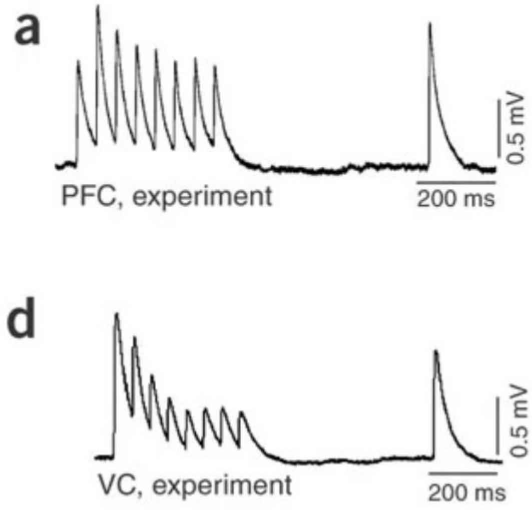
Zucker and Regehr 2002, Annu. Rev. Physiol.

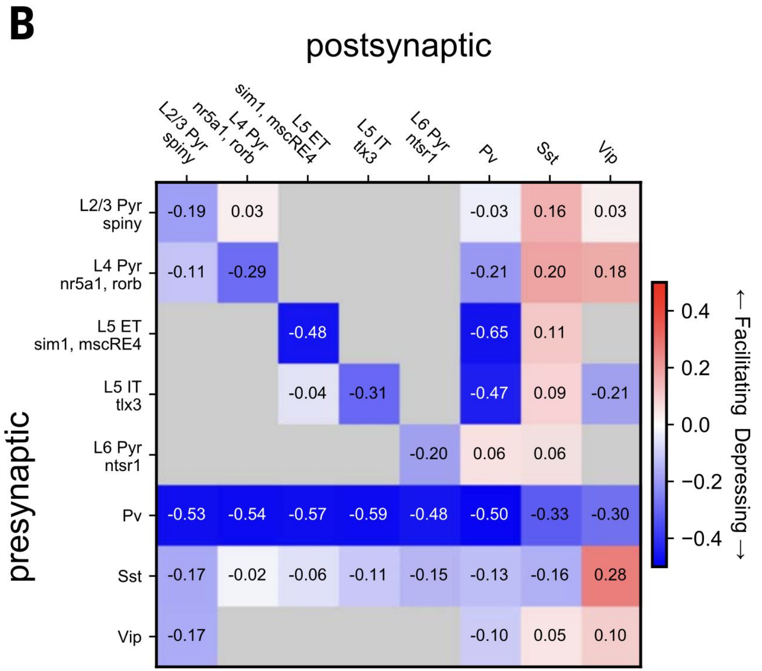
Short-term plasticity - experiments



Wang et al., 2006 Nature Neuroscience

Short-term plasticity - experiments

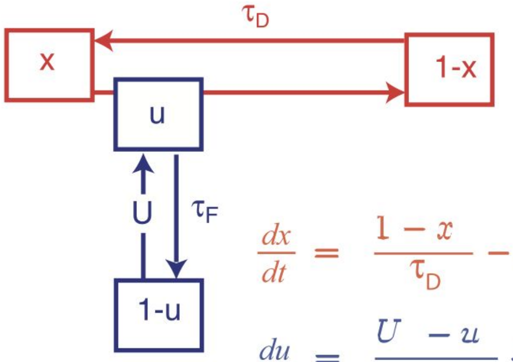




Wang et al., 2006 Nature Neuroscience

Campagnola et al., 2022 Science

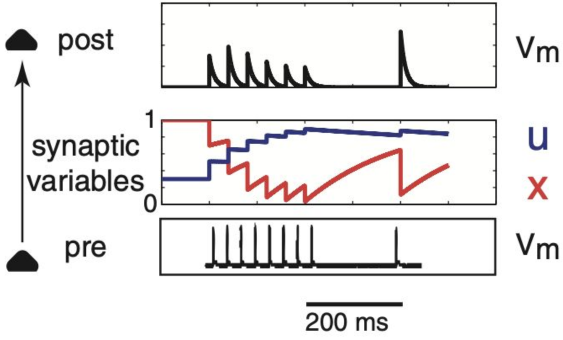
Short-term plasticity - models

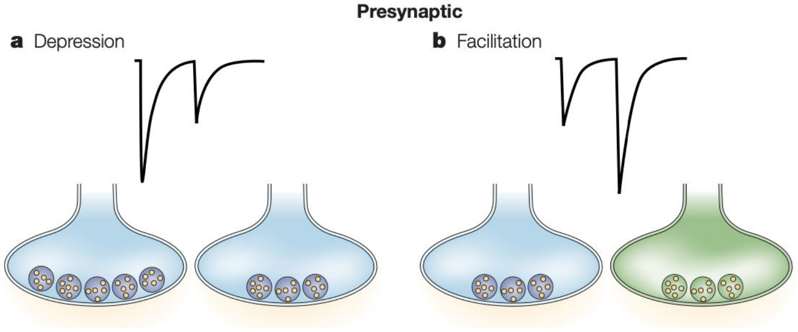


$$\frac{dx}{dt} = \frac{1-x}{\tau_D} - u\ x\ \delta(t-t_{sp})$$

$$\frac{du}{dt} = \frac{U-u}{\tau_F} + U\ (1-u\ )\ \delta(t-t_{sp})$$

$$\tau \frac{dE}{dt} = -E + g(JuxE + E_0)$$



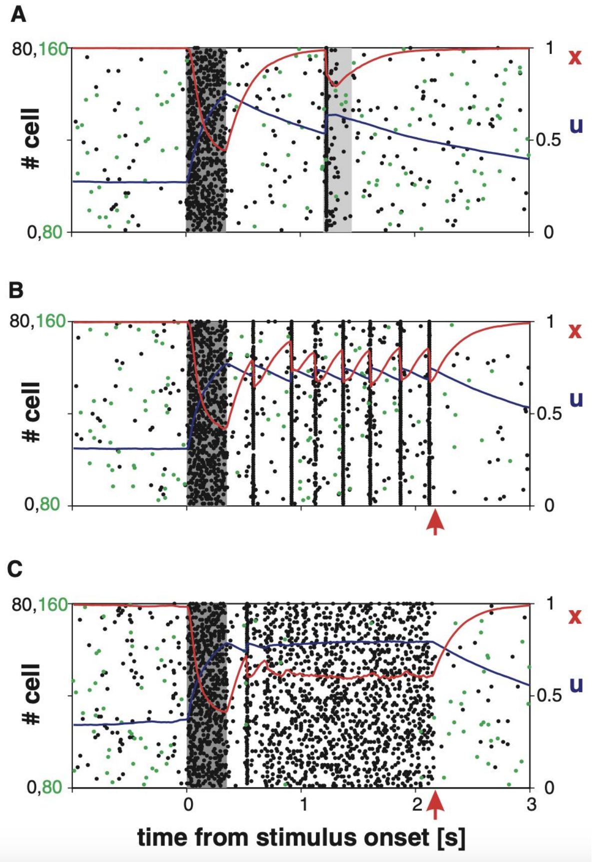


Tsodyks and Markram 1997, PNAS

Blitz et al. 2004, Nature Reviews Neuroscience

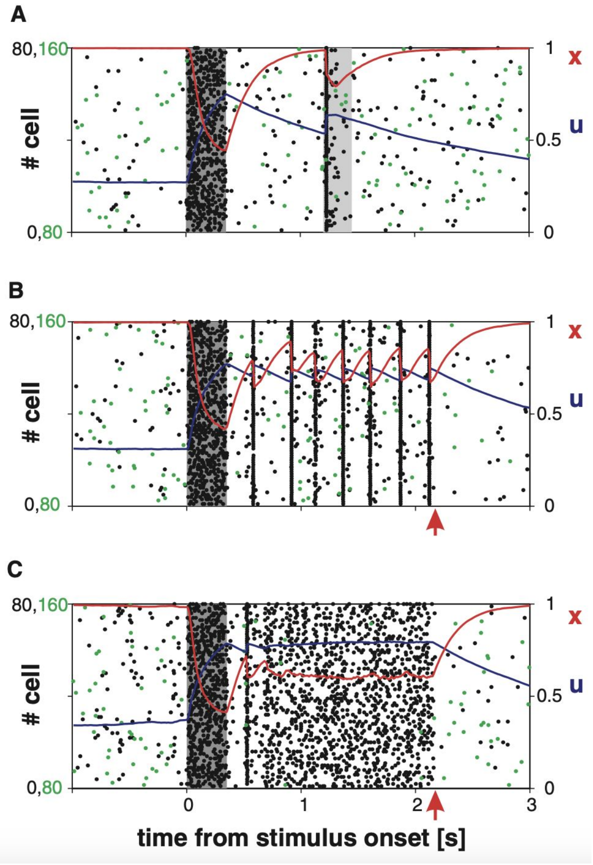
Mongillo et al., 2008 Science

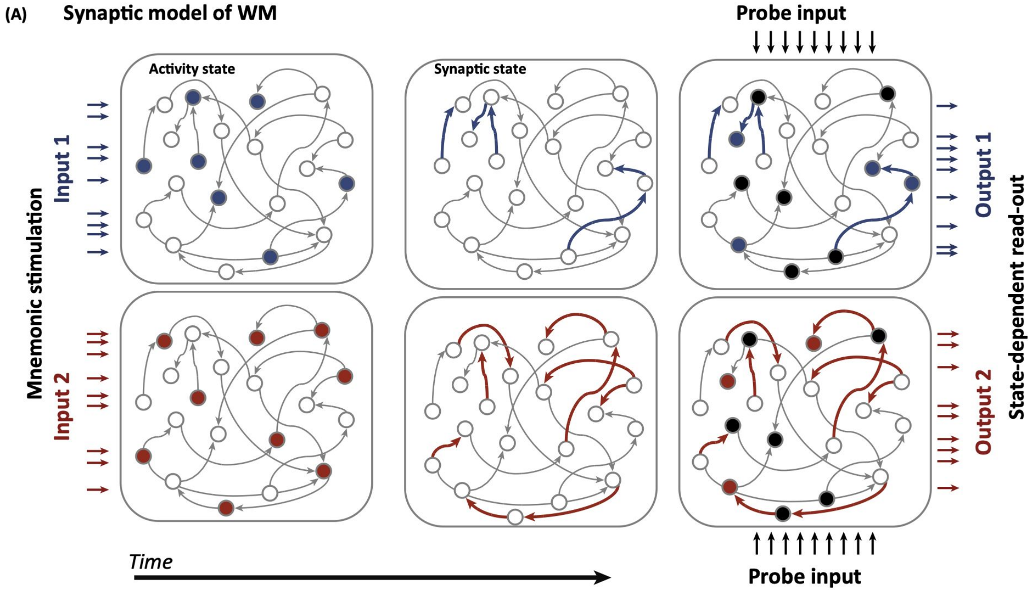
Short-term plasticity - computational implications



Mongillo et al., 2008 Science

Short-term plasticity - computational implications

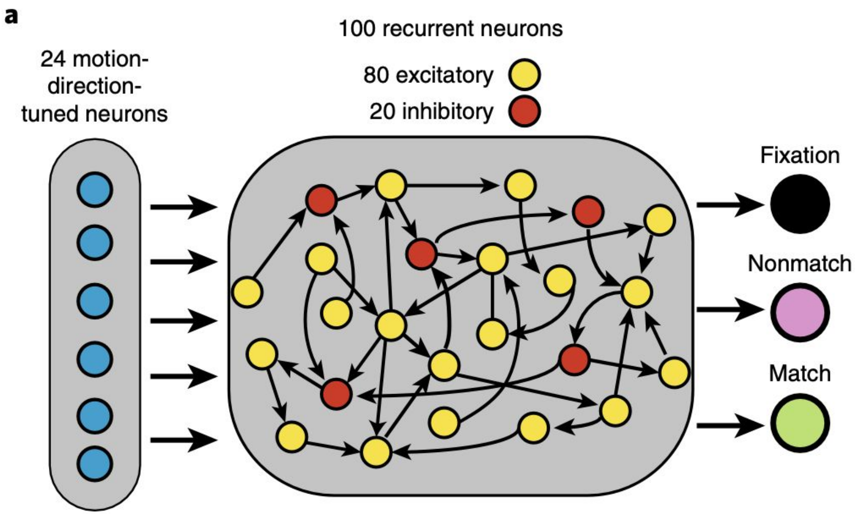


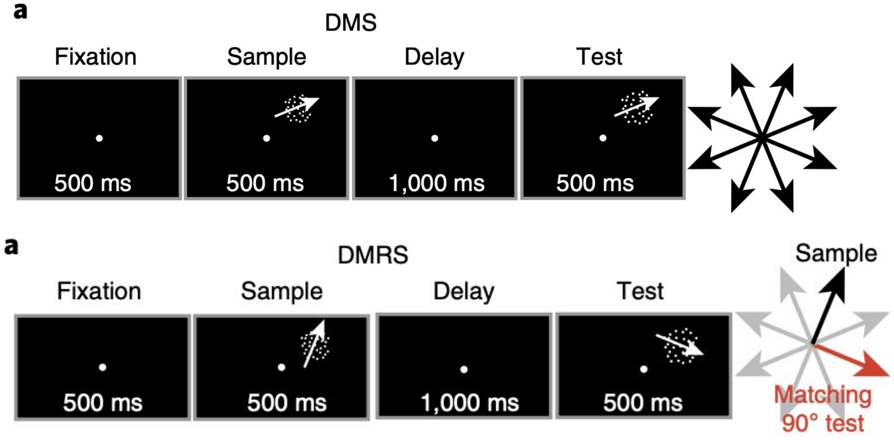


Mongillo et al., 2008 Science

Stokes 2015, Trends in Cognitive Sciences

Short-term plasticity - computational implications





Masse et al., 2019 Nature Neuroscience

Behavioral time scale synaptic plasticity (see Bittner et al., 2017 Science, Gonzalez et al., 2024 Nature)

Three factor learning rule (see review Gerstner et al., 2018 Frontiers in Neural Circuits)

State-dependent plasticity (see González-Rueda et al., 2018 Neuron, work by Tononi and Cirelli, etc.)