339.623
Computational Neuroscience and Neuroinformatics

Prof. Marcus Kaiser

March 29, 2010

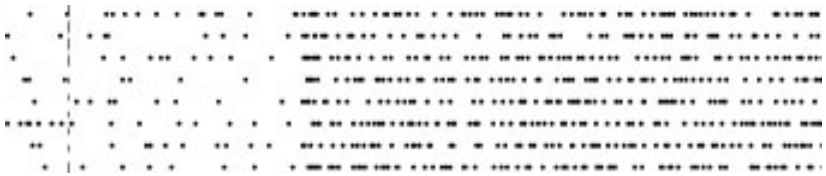
Week 5: Associators and synaptic plasticity
(textbook chapter 4)

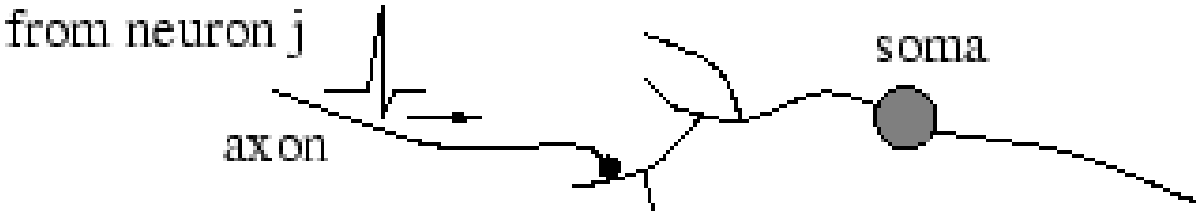
Seminar guidelines

- 20 minutes presentation + 10 minutes discussion (rule of thumb: #slides <= #minutes)

- Evaluation:
  - speaker: critical evaluation of the strengths and weaknesses of the presented work; own suggestions for improvement
  - speaker: quality of the slides and the presentation
  - participation in the discussion section

Neural activity



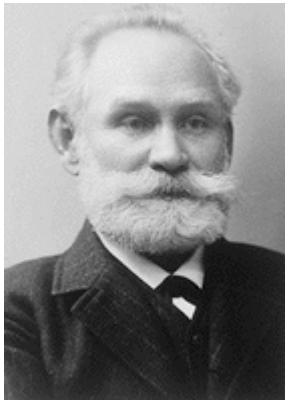


Learning at the organism level: Classical conditioning

<u>Before training:</u> Saliva production when food is presented (unconditioned reflex)

<u>Training:</u> Ringing a bell before presenting food (condition bell -> food)

After training: Ringing bell alone can lead to saliva production (conditioned reflex)



Ivan Pavlov, Nobel Prize 1904

Types of plasticity

- **Structural plasticity** is the mechanism describing the generation of new connections and thereby redefining the topology of the network.

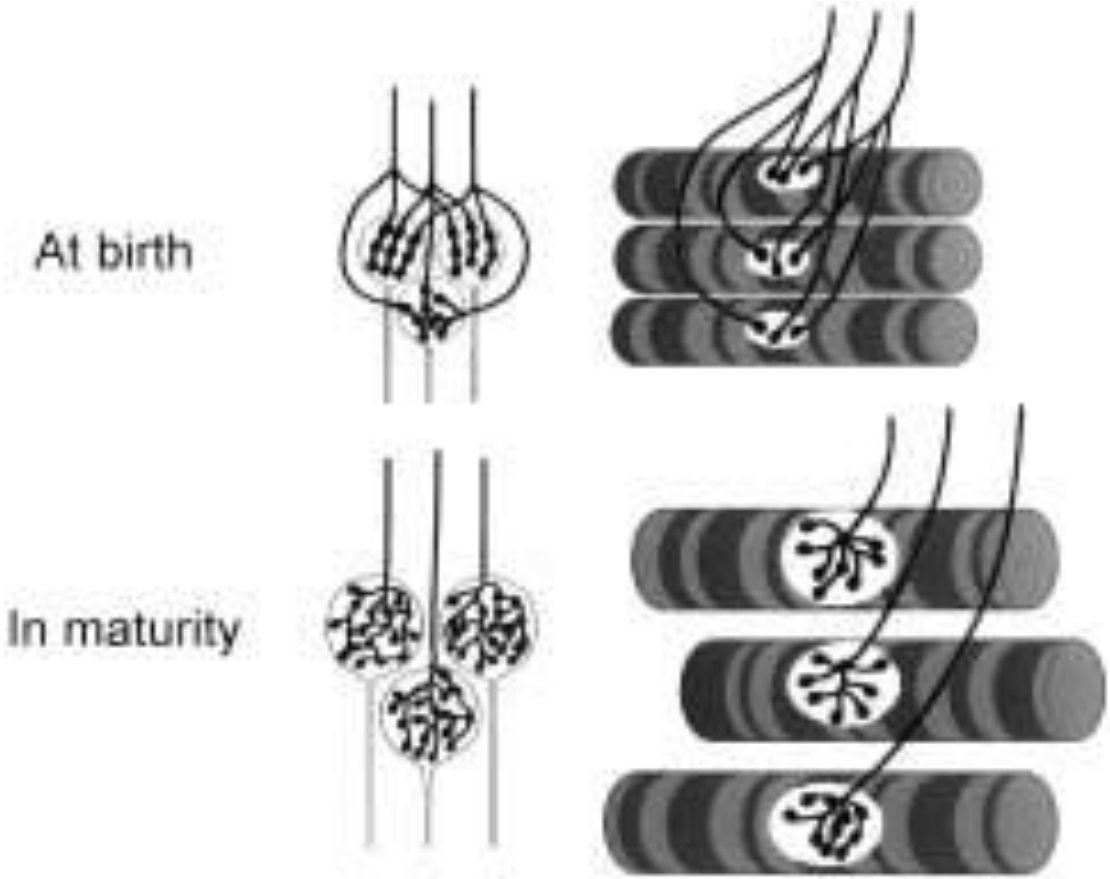
- **Functional plasticity** is the mechanism of changing the strength values of existing connections.

Structural plasticity

Pruning during development

Brain cells make too many connections at first, and then trim away the incorrect ones by a process of ‘pruning’

Neural Darwinism:
“Use it or loose it”
(Connections which are not used are removed)

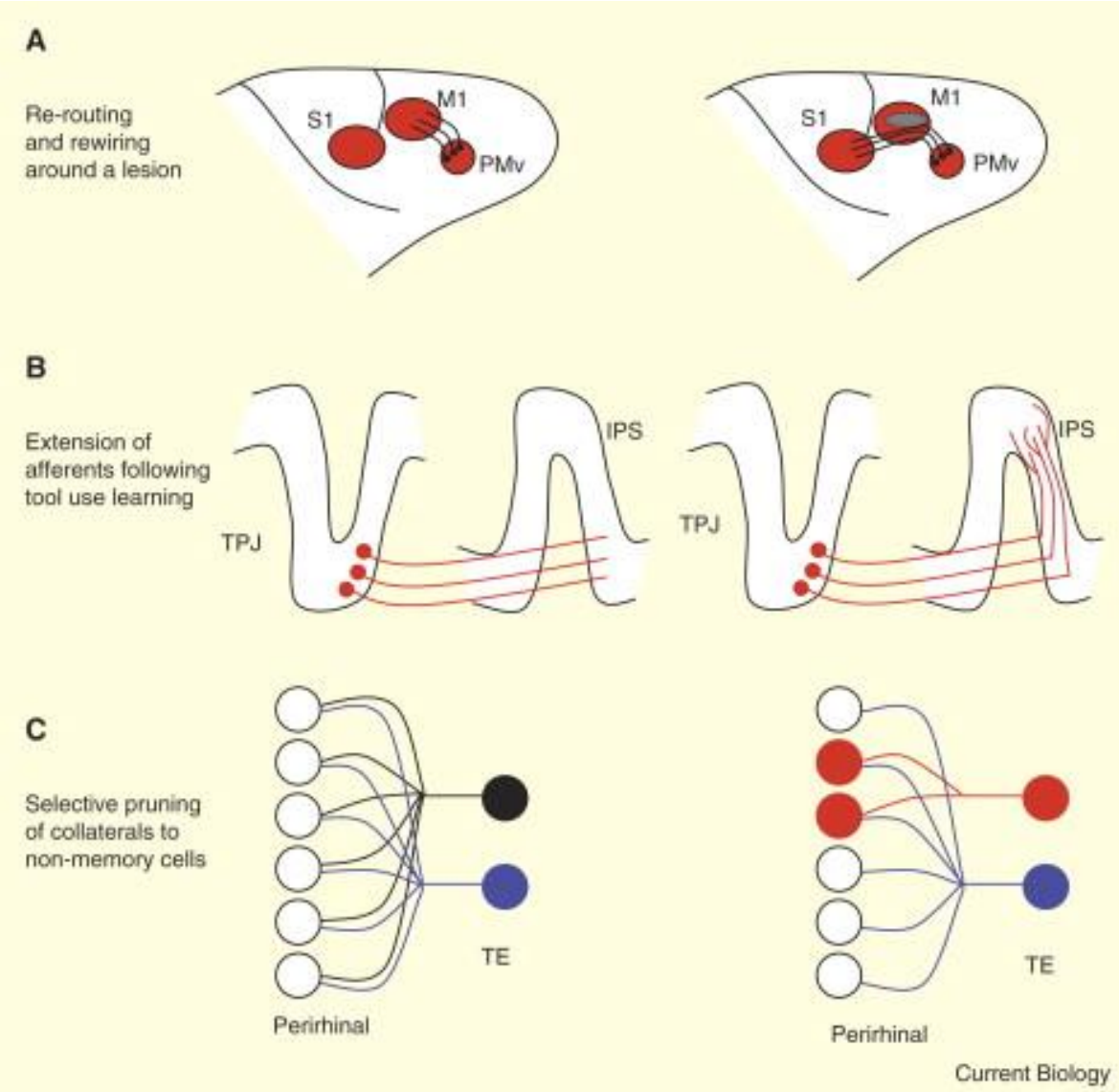


Examples from the PNS

Purves *et al*. Trends in Neurosciences, 1996

Structural plasticity in adults!

rewiring after lesions or learning in monkeys



Heidi Johansen-Berg. Current Biology, 2007

Functional plasticity

Learning at the neuron level: Hebbian plasticity

"When an axon of a cell A is near enough to excite cell B or repeatedly or persistently takes part in firing it, some growth or metabolic change takes place in both cells such that A's efficiency, as one of the cells firing B, is increased."

or “what fires together wires together”
(meaning functional plasticity = weight changes)

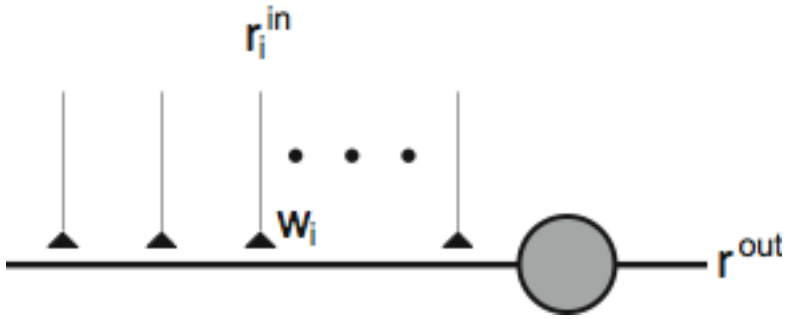
Also: If cells A and B fire at *different* times, the weight of that connection is decreased.

Donald O. Hebb, The organization of behavior, 1949

see also Sigmund Freud, Law of association by simultaneity, 1888

Donald Hebb

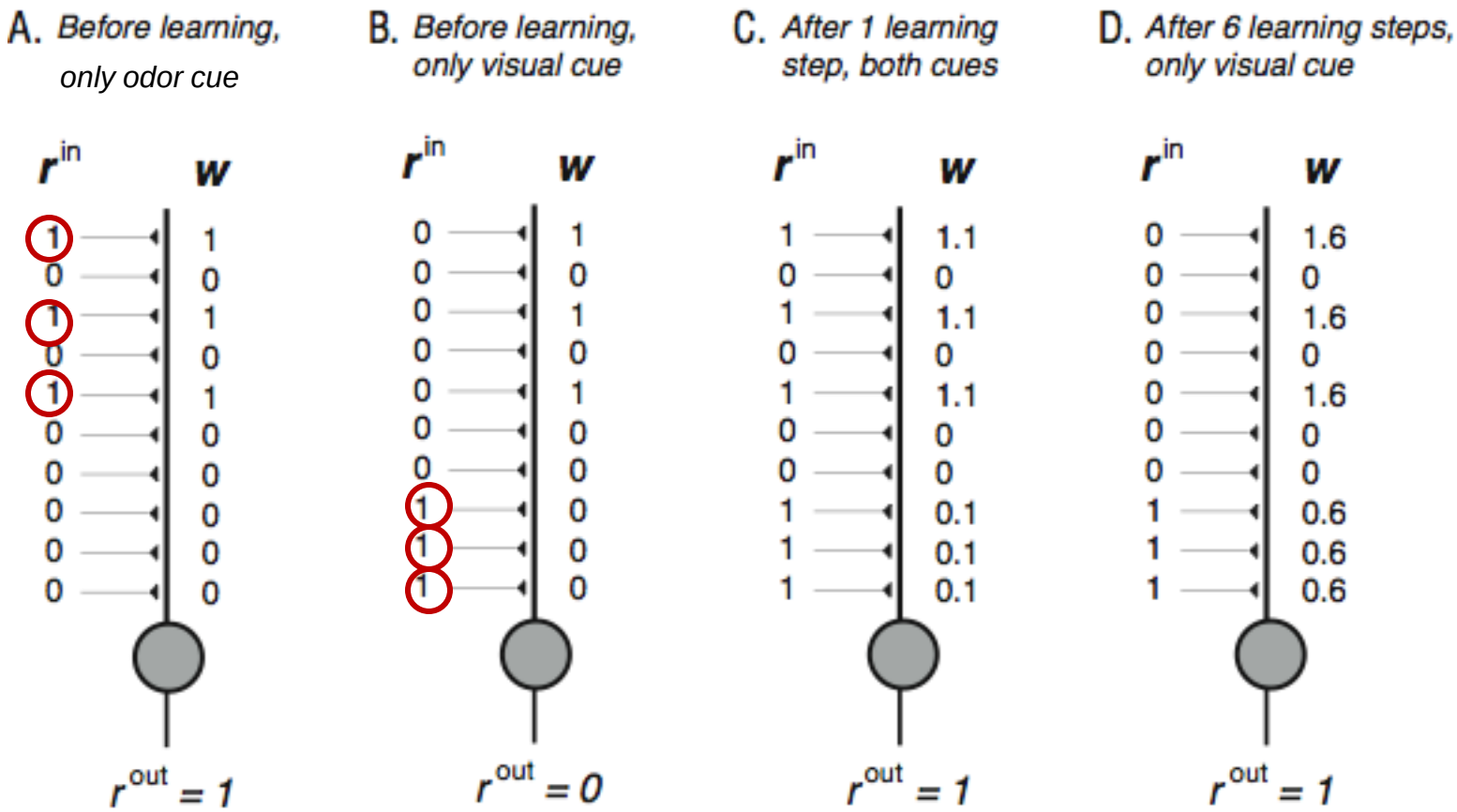
Association



Neuron model: In each time step the model neurons fires if $\sum_i w_i r_i^{in} > 1.5$

Learning rule: Increase the strength of the synapses by a value $\Delta w = 0.1$ if a presynaptic firing is paired with a postsynaptic firing.

Learning example



UCS CS

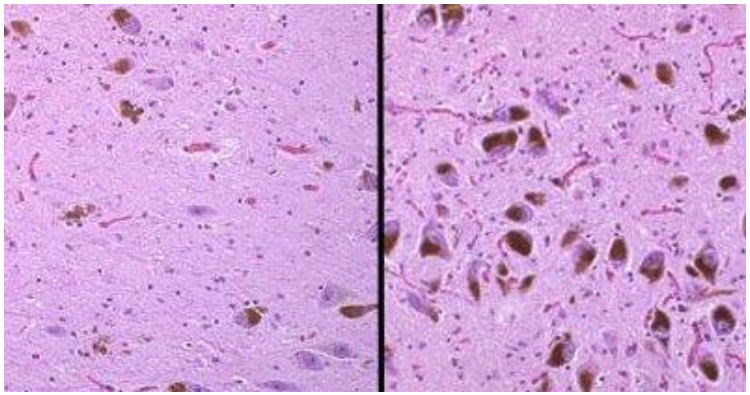
$\Delta w = 0.1$ threshold = 1.5

Features of associators and Hebbian learning

- Pattern completion (incomplete input) and generalization (similar input)
- Prototypes and extraction of central tendencies (representation of average stimulus features)
- Graceful degradation and fault tolerance (pattern recognition even after loss of many neurons)

Examples for graceful degradation (robustness)

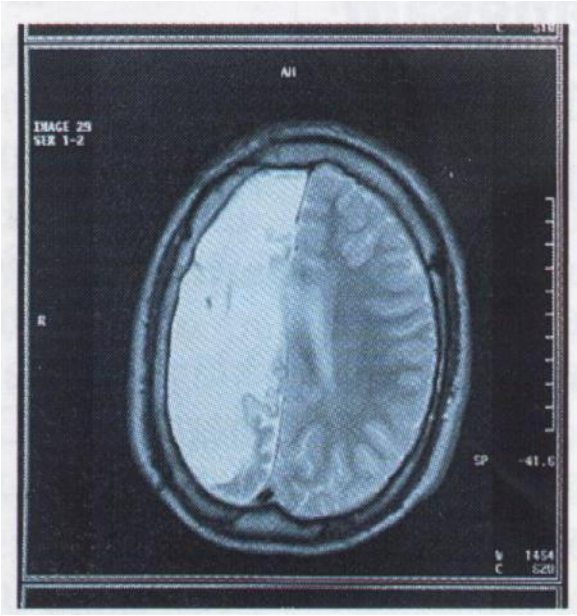
Parkinson: death of pigmented cells in the substantia nigra (pars compacta)



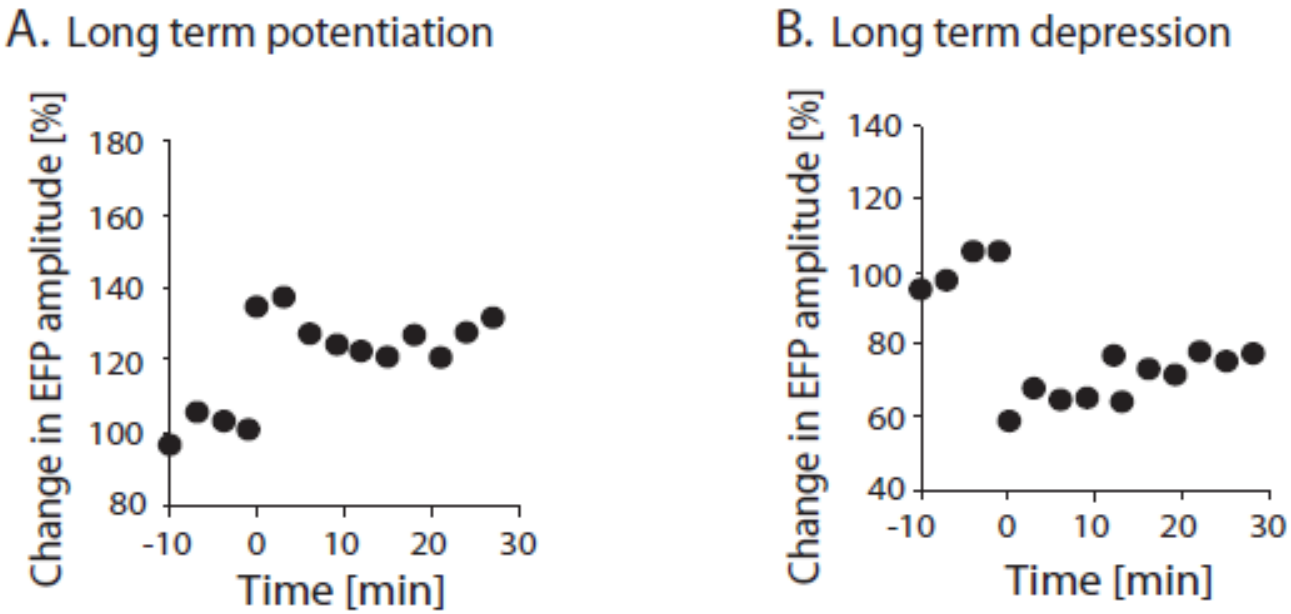
Parkinson patient Healthy subject

Disease only becomes visible (e.g. tremor) after 2/3 of the neurons are dead!

Removal of one hemisphere for 11 year-old epilepsy patient



Classical LTP/LTD

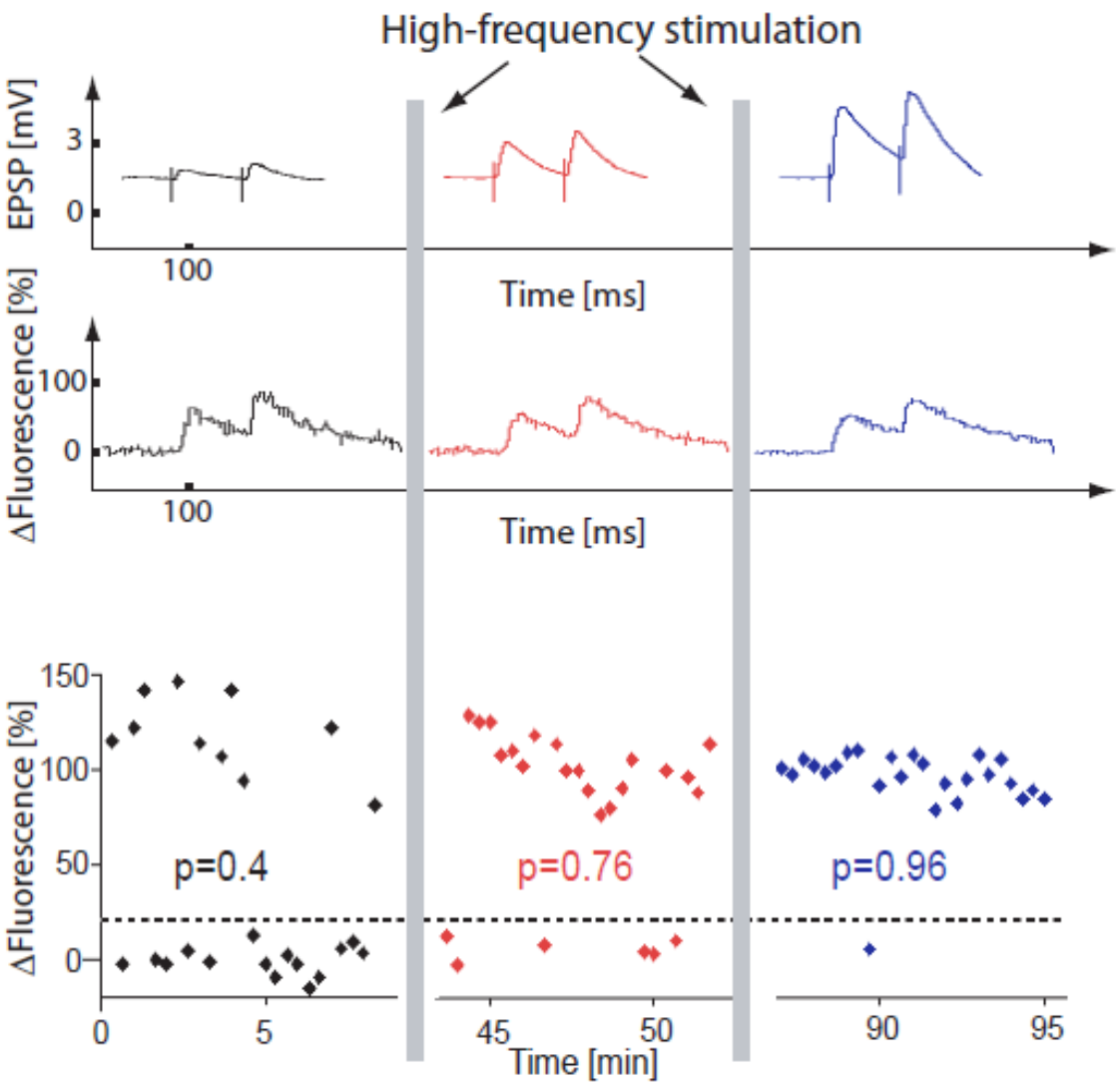


Evoked field potential (EFP) with a high-frequency stimulation at $t = 0$

-> Neuron remembers stimulations over a long time period (memory)

Dang et al. PNAS, 2006

Synaptic neurotransmitter release probability



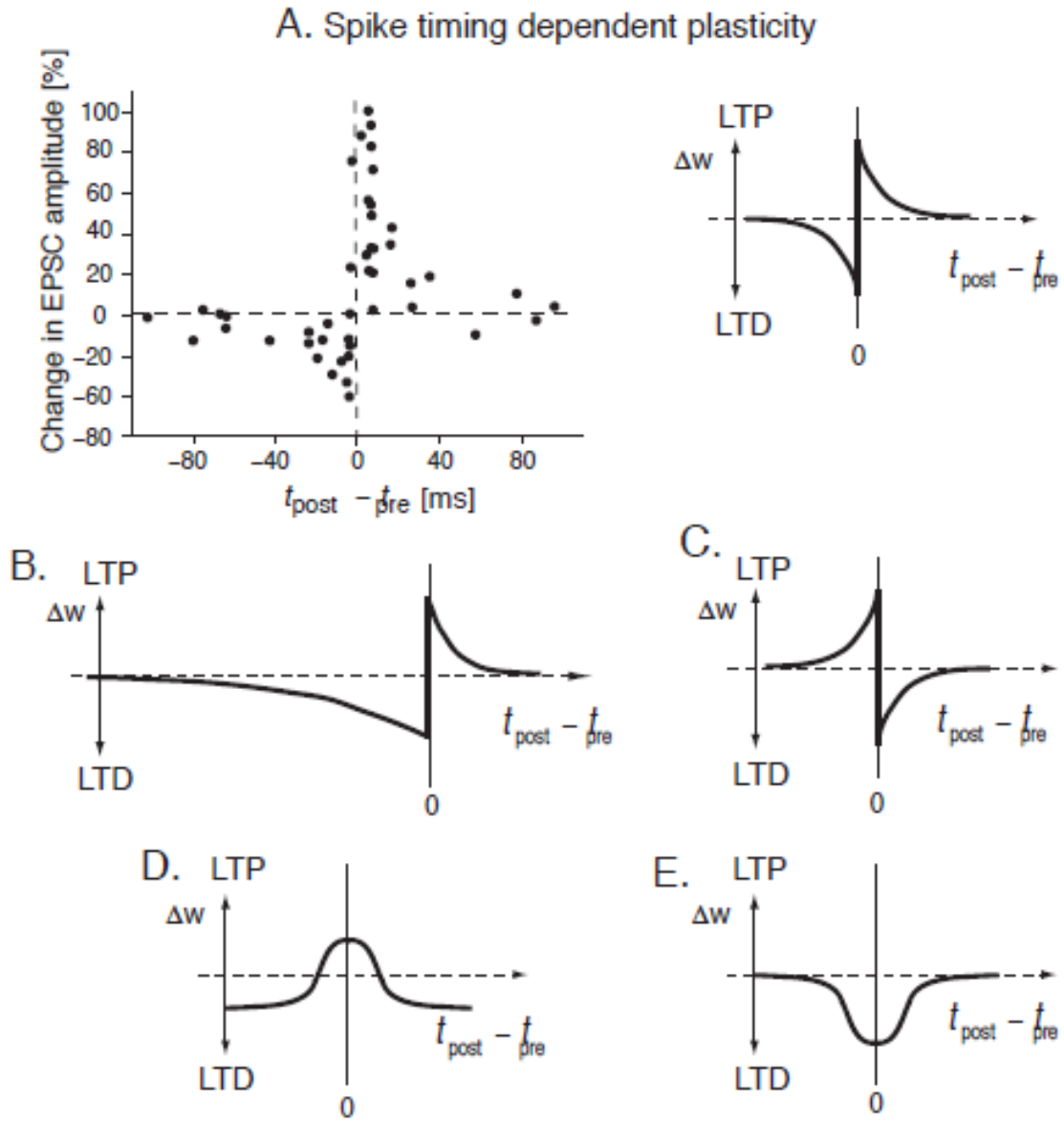
EPSP

single synapse

single synapse
(long time scale)

-> Learning through changed neurotransmitter release probability

Spike timing dependent plasticity (STDP)

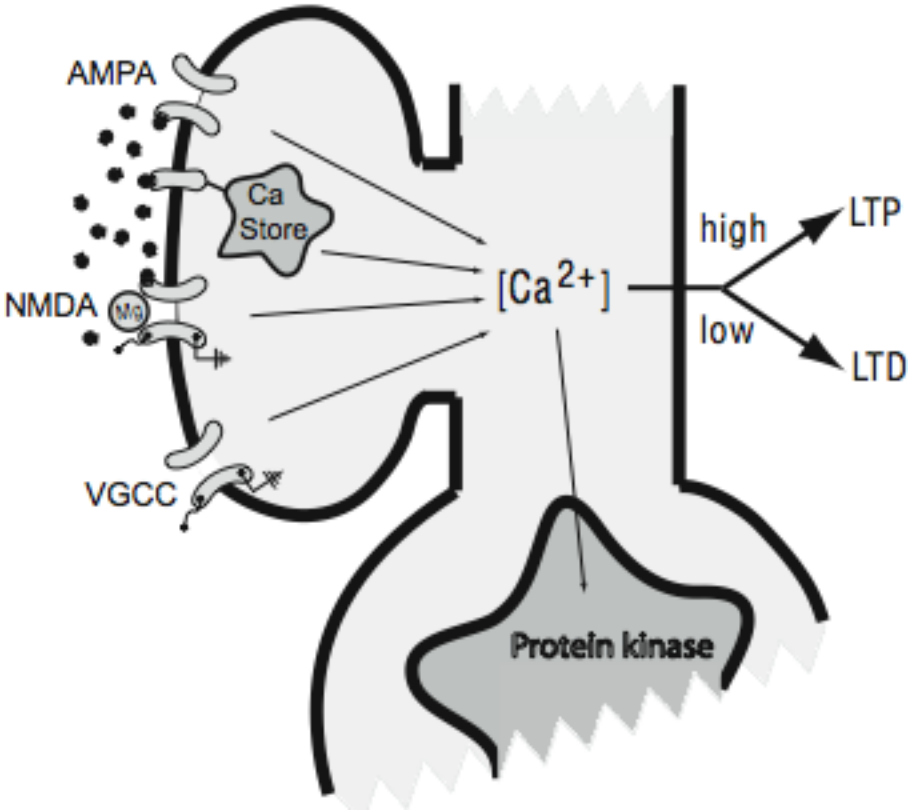


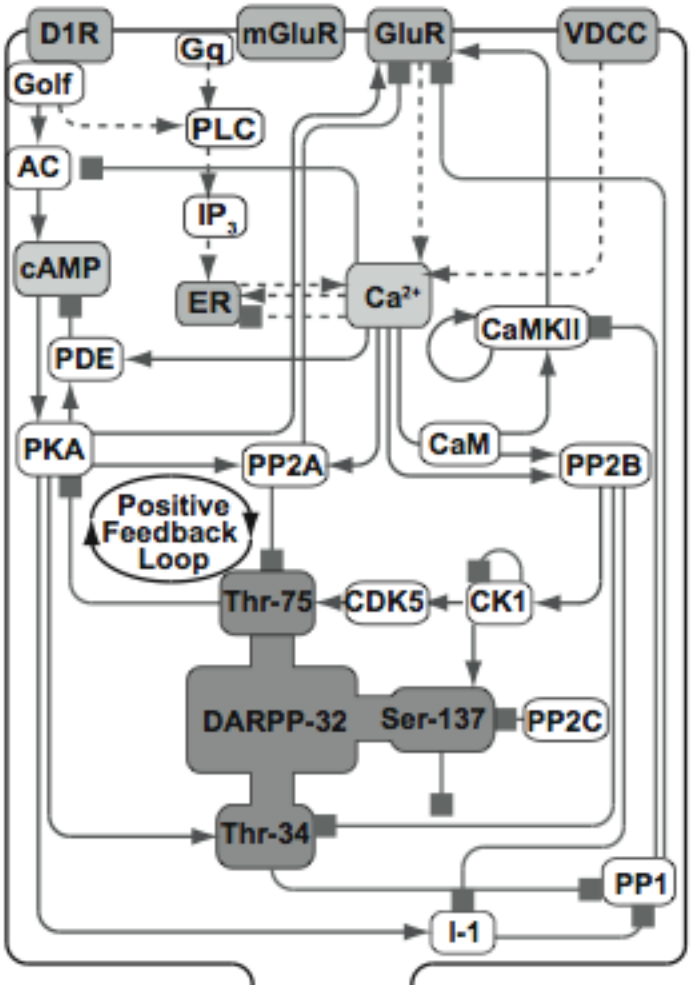
Whether input causes LTP or LTD after target neuro firing depends on the relative time between both events.

Relative timing of UCS and CS is important!

Pavlov: What happens if the bell rings after food presentation?

The calcium hypothesis and modeling chemical pathways





Mathematical formulation of Hebbian plasticity

$$w_{ij}(t+\Delta t) = w_{ij}(t) + \Delta w_{ij}(t_i^{\mathrm{f}}, t_j^{\mathrm{f}}, \Delta t; w_{ij}).$$

Δw : change in synaptic weight depends on the
(a) the firing times t_j of the presynaptic neuron *j*
and t_i the postsynaptic neuron *i*
(b) The length of the time step Δt and
(c) The current synaptic weight w

Note: for w_{ij} the first index i is always the target neuron and the second index j always the source neuron (i ← j)

Mathematical formulation of Hebbian plasticity

$$\Delta w_{ij}^{\pm} = \epsilon^{\pm}(w) e^{\mp \frac{t^{\text{post}} - t^{\text{pre}}}{\tau^{\pm}}} \; \Theta(\pm[t^{\text{post}} - t^{\text{pre}}]).$$

Additive rule with hard (absorbing) boundaries:

Learning rate

$$\epsilon^{\pm} = \begin{cases} a^{\pm} & \text{for } w_{ij}^{\min} \leq w_{ij} \leq w_{ij}^{\max} \\ 0 & \text{otherwise} \end{cases},$$

Multiplicative rule (soft boundaries):

$$\begin{aligned} \epsilon^{+} &= a^{+}(w^{\max} - w_{ij}) \\ \epsilon^{-} &= a^{-}(w_{ij} - w^{\min}). \end{aligned}$$

Why Boundaries? -> prevent that weight increases indefinitely

This can be used for neurons but also for populations!
Instead of firing times (spikes) firing rates can be used.

Hebbian learning in population and rate models

General: $\Delta w_{ij} = \epsilon(t, w)[f_{\text{post}}(r_i) f_{\text{pre}}(r_j) - f(r_i, r_j, w)]$

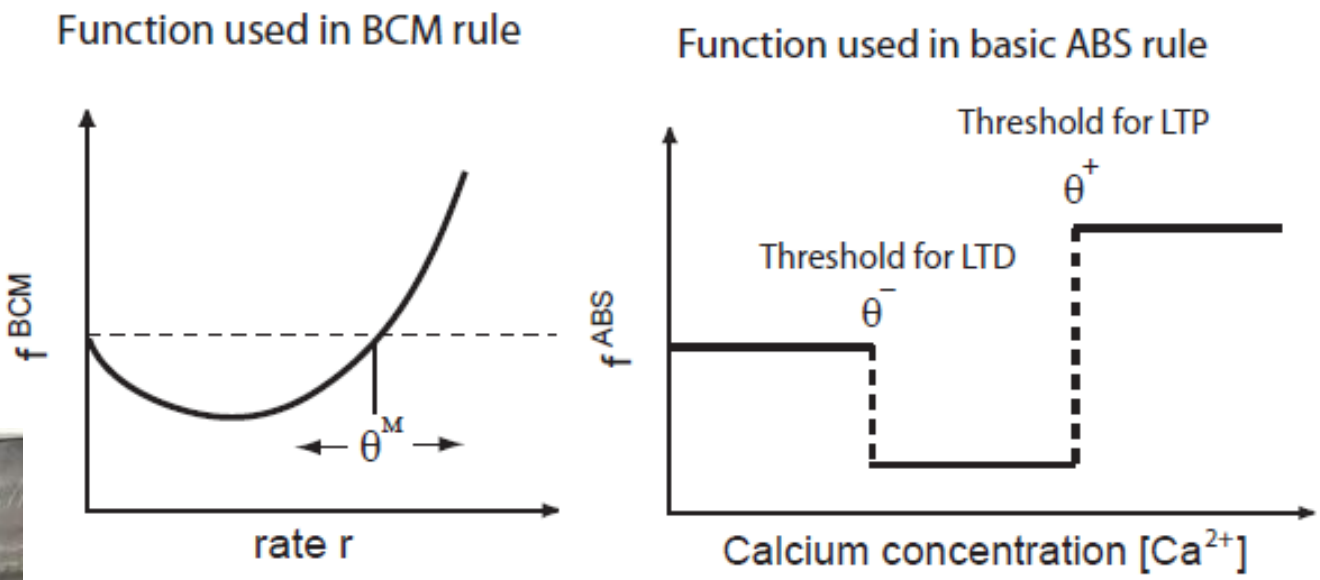
Mnemonic equation (Caianiello): $\Delta w_{ij} = \epsilon(w)[r_i r_j - f(w)]$

Basic Hebb: $\Delta w_{ij} = \epsilon r_i r_j$

Covariance rule: $\Delta w_{ij} = \epsilon(r_i - \langle r_i \rangle)(r_j - \langle r_j \rangle)$

BCM theory: $\Delta w_{ij} = \epsilon(f^{\text{BCM}}(r_i; \theta^M)(r_j) - f(w))$

ABS rule: $\Delta w_{ij} = \epsilon(f_{\text{ABS}}(r_i; \theta^-, \theta^+)\text{sign}(r_j - \theta^{\text{pre}}))$



Eduardo Caianiello

Synaptic scaling: Limiting weight changes

Explicit normalization: $w_{ij} \leftarrow \frac{w_{ij}}{\sum_j w_{ij}}$

Basic decay: $\Delta w_{ij} = r_i r_j - c w_{ij}$

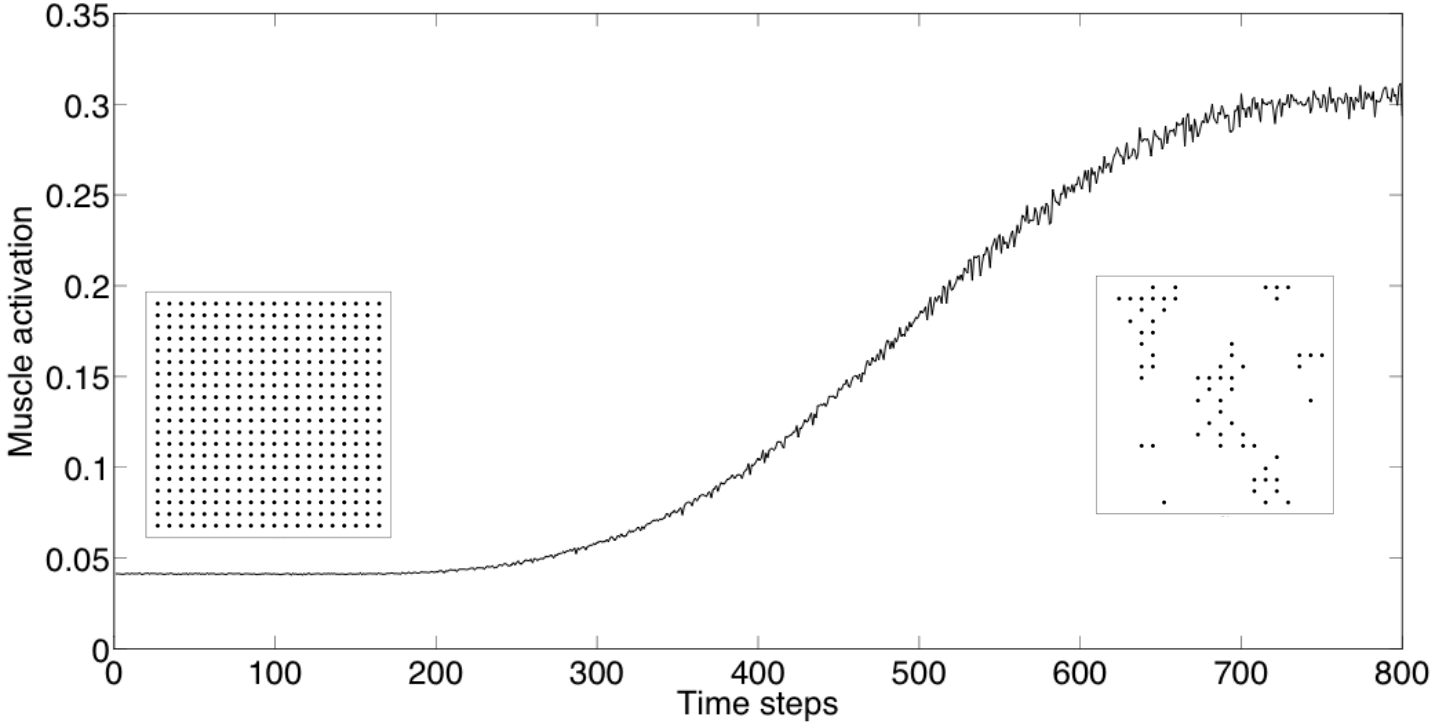
Willshaw rule: $\Delta w_{ij} = (r_i - w_{ij}) r_j$

Oja rule: $\Delta w_{ij} = r_i r_j - (r_i)^2 w_{ij}$

r: firing rates

for large weights w the weight increase slows down and finally stops

Example: Simulating the learning of muscle activation



Varier & Kaiser, Simulating lesions during child development.
in preparation

Summary

Structural plasticity: physical removal or addition of connections

Functional plasticity: change in synaptic weights

Hebbian learning: what fires together wires together

Synaptic level: LTP and LTD (long-term changes)

Spike-time dependent plasticity: event timing determines plasticity

Weight change depends on learning rate and existing weight

Synaptic scaling provides boundaries for synaptic weights

Further readings

Laurence F. Abbott and Sacha B. Nelson (2000), **Synaptic plasticity: taming the beast**, in **Nature Neurosci. (suppl.)**, 3: 1178–83.

Alain Artola and Wolf Singer (1993), **Long-term depression of excitatory synaptic transmission and its relationship to long-term potentiation**, in **Trends in Neuroscience** 16: 480–487.

Mark C. W. van Rossum, Guo-chiang Bi, and Gina G. Turrigiano (2000) **Stable Hebbian learning from spike timing-dependent plasticity**, in **J. Neuroscience** 20(23): 8812–21