Neuroinformatics

April 6, 2017

Lecture 6: Synaptic plasticity and Hebb's rule

Learning what is is?

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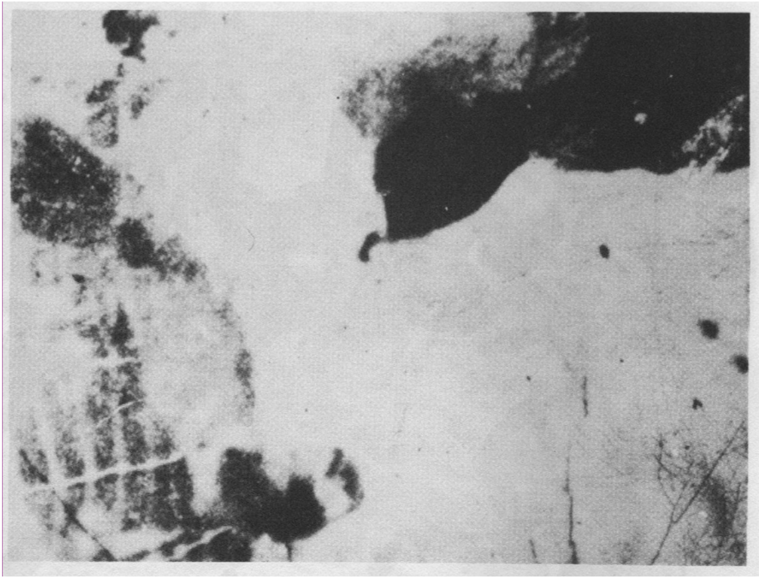
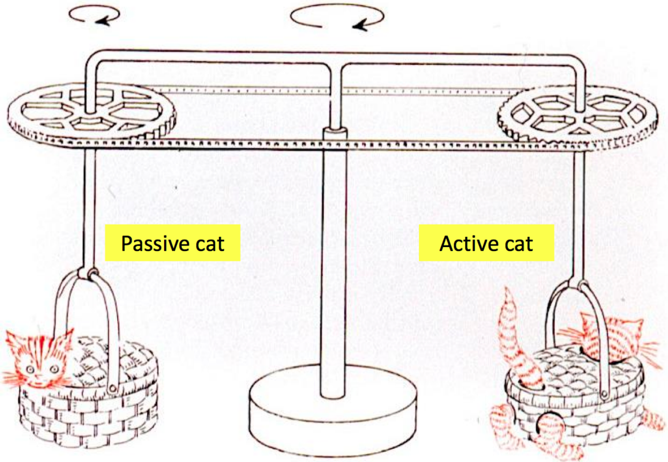


Action-perception loop



Held R, Hein A (1963)

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.

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."

Donald O. Hebb, **The organization of behavior**, 1949
See also Sigmund Freud, **Law of association by simultaneity**, 1888
Santiago Ramn y Cajal - memories might instead be formed by strengthening the connections between existing neurons to improve the effectiveness of their communication, 1894

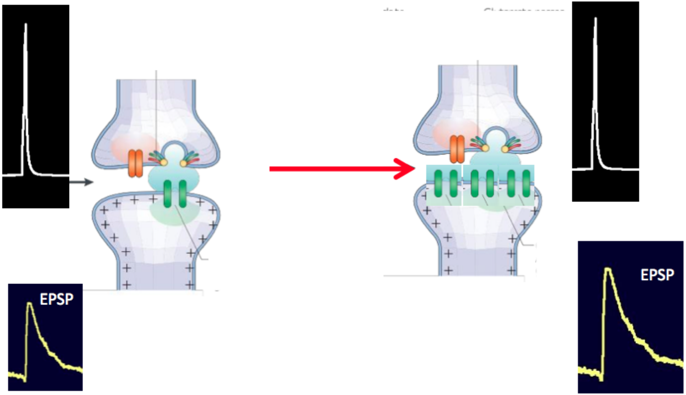
Possible neuronal mechanisms sub-serving learning and memory

New nerve cells grow - new functional neural networks are formed .1
for exhibiting new learned items- structural plasticity

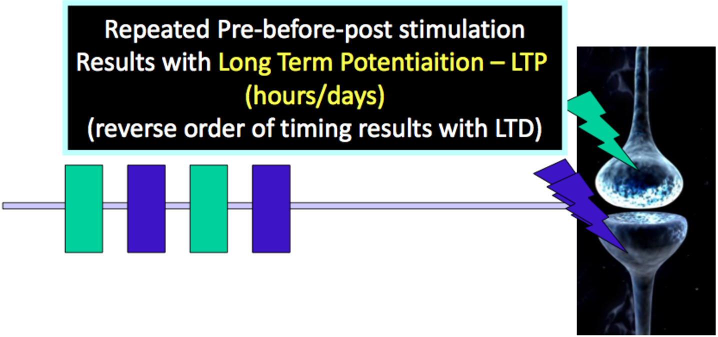
New synaptic connections (new functional neural networks) are .2
formed - structural plasticity - (*Ramon Y. Cajal)*

Strength of existing (synaptic) connections change - (new functional .3
neural networks) - functional plasticity (Donald Hebb)

Synaptic mechanism



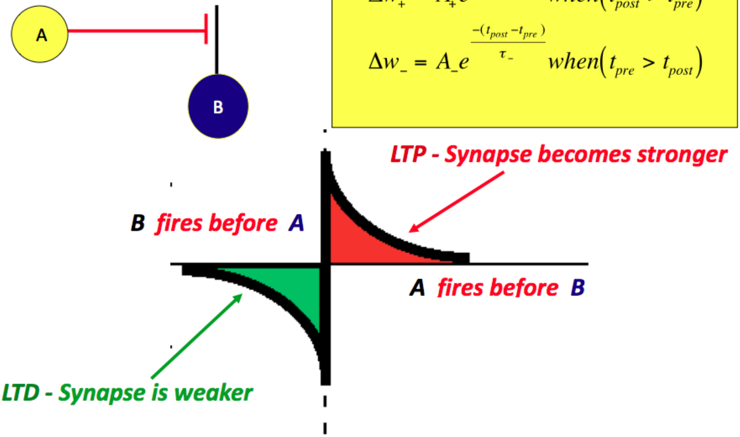
Long term potentiaition



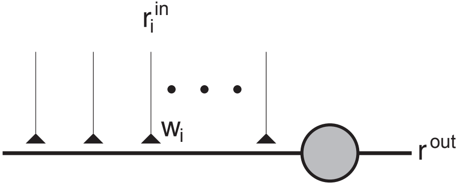
Hebbian model

$$\Delta w_+ = A_+ e^{\frac{-(t_{post} - t_{pre})}{\tau_+}} \quad when\left(t_{post} > t_{pre}\right)$$

$$\Delta w_- = A_- e^{\frac{-(t_{post} - t_{pre})}{\tau_-}} \quad when\left(t_{pre} > t_{post}\right)$$

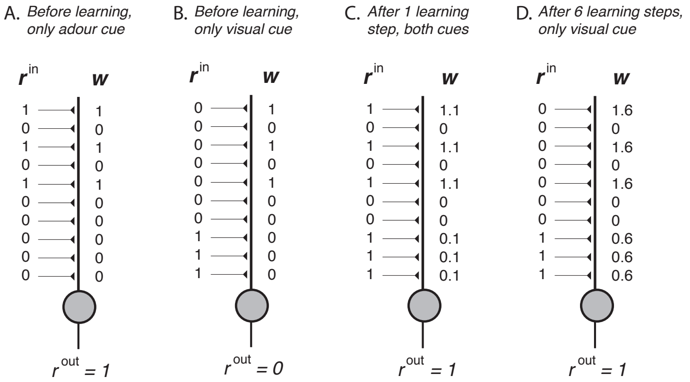


Association



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

Associative learning

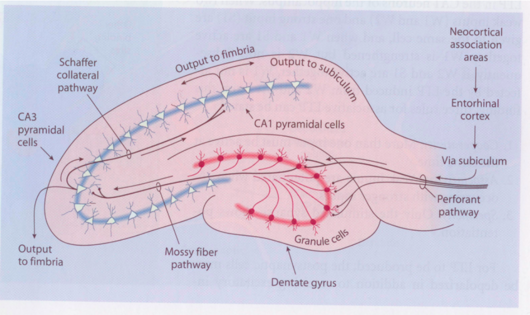


Features of associators and Hebbian learning

- Pattern completion and generalization, recall from partial input, overlap between input and trained pattern (recognition of noisy numbers)
- Prototypes and extraction of central tendencies, training on many similar but not equivalent examples (individual face, many common features in all faces)
- Graceful degradation and fault tolerance (loss of synapses or whole neurons)

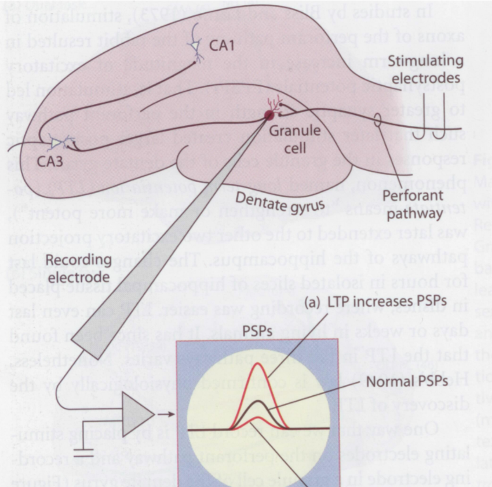
Hippocampus

- Hippocampus: centre of memory storage, The dentate gyrus is thought to contribute to the formation of new memories. It is notable as being one of a select few brainstructures currently known to have high rates of neurogenesis in adult rats
- Neurons must be plastic
- Experiment: isolated slices of hippocampal tissue placed in dishes



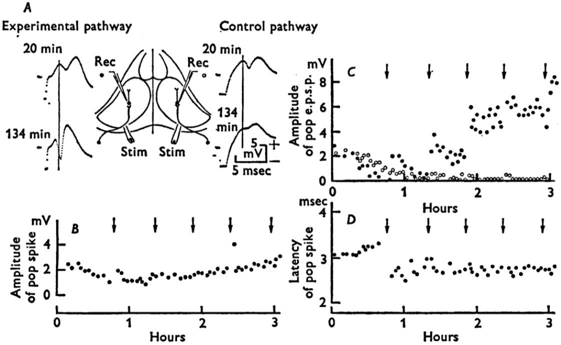
LTP experiment

- EXPERIMENTAL confirmation of Hebb's rule (1949)
- i) single pulse is presented ii) stimulation with burst of pulses: 100 pulses/sec ii) After LTP induced, single pulse stimulation
- Postsynaptic cells must be depolarized to LTP be produced AND receiving excitatory input - see Associative learning slide.

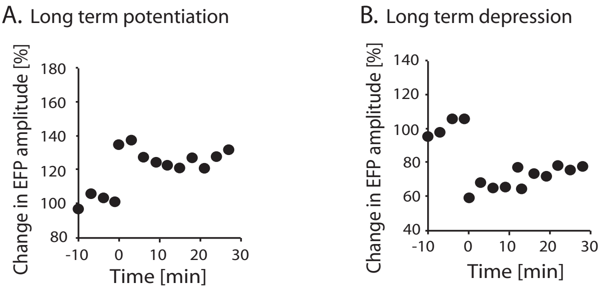


Original LTP by Bliss and Lomo, 1973

- Long-lasting changes of synaptic response characteristics
- High frequency-stimulus is applied (plasticity-induced tetanus) $\rightarrow$ long-term potentiation(to strengthen, make more potent) (LTP) average amplitude of EPSP increased
- Long frequency stimulus $\rightarrow$ long-term depression (LTD)

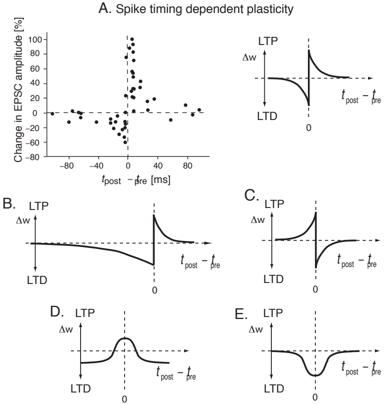


Classical LTP and LTD



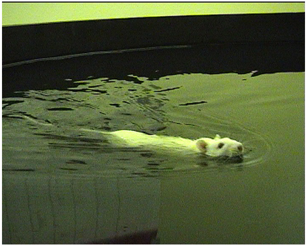
Spike timing dependent plasticity (STDP)

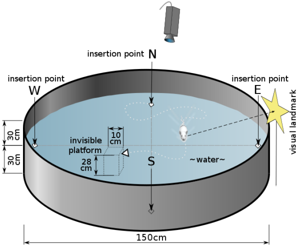
- Bi-Poo experiments: voltage clamp for hippocamal cells in vitro, $\rightarrow$ Excitatory PostSynaptic Current (EPSP) $\rightarrow$ critical time window $\Delta t = 40$ms
- critical window width is much larger, asymmetrical and symmetrical (for bursting neurons) form of Hebbian plasticity, inverse correlation in Purkinje cells (inhibitory) in the cerebellum



Morris Water Maze - spatial memory

- i) mice training ii) Chemical blocking of LTP by AP5 impair spatial learning, keep control group iii) AP5-treated mice significantly impaired
- i) slices of the hippocampus were taken from both groups ii) LTP was easily induced in controls, but could not be induced in the brains of APV-treated rats
- Alzheimer's disease → cognitive decline seen in individuals with AD may result from impaired LTP ??





Mathematical formulation of Hebbian plasticity - spiking models

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

$$\Delta w_{ij}^{\pm} = \epsilon^{\pm}(w) K \pm (t^{\mathrm{post}} - t^{\mathrm{pre}})$$

Spike Timing Dependent Plasticity (SPDP)¿ (i) Exponential plasticity curve, (ii) Repeated spike pairings induced w UNBOUNDED growth $\rightarrow$ a weight dependent learning rate $\epsilon^{\pm}$

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

Additive rule with hard (absorbing) boundaries:

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

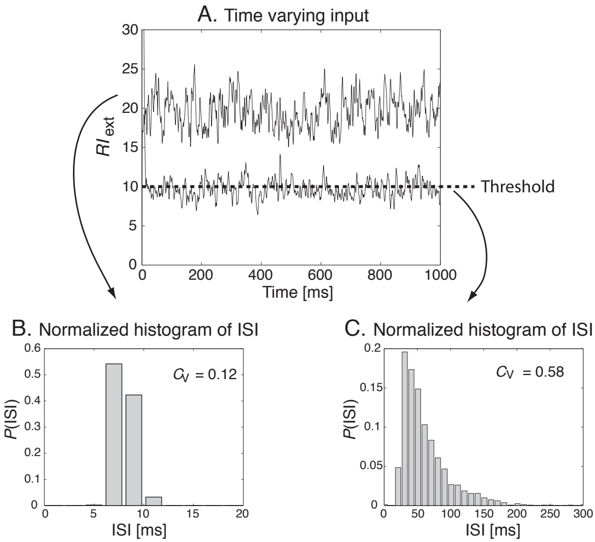
Multiplicative rule (soft boundaries):

$$\begin{aligned} \epsilon^{+} &= a^{+}(w^{\mathrm{max}} - w_{ij}) \\ \epsilon^{-} &= a^{-}(w_{ij} - w^{\mathrm{min}}). \end{aligned} \tag{1}$$

The LIF-neuron noise simulation I

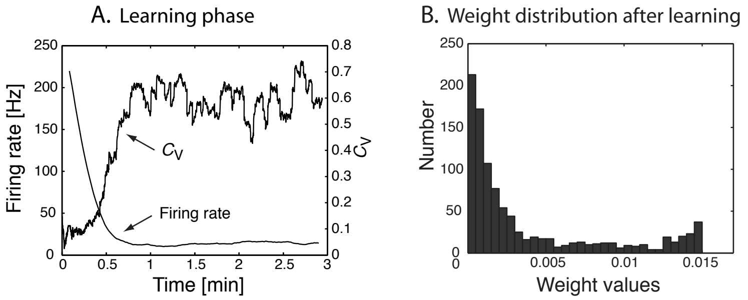
- real neuron with 5000 presynaptic neuron
- 10 % simulation $\rightarrow$ 500 Poisson-distributed spike trains (**??**) with refractory corrections
- mean firing rate = 20 Hz, after correction 19.3 Hz, refractory constant 2 ms.
- each presynaptic spike $\rightarrow$ EPSP in form of α function (**??**)
- $\omega = 0.5 \rightarrow$ regular firing, $C_V = 0.12$, average rate 118 Hz.
- $\omega = 0.25 \rightarrow$ irregular firing, $C_V = 0.58$, average rate 16 Hz. The $C_V >$ lower bound found in experiments

The LIF-neuron noise simulation II



Synaptic scaling and weight distributions

- IF neuron with 1000 excitatory synapses driven by presynaptic Poisson spike trains with average firing rate of 20 Hz, $\Delta w_{ij}^{\pm} = \epsilon^{\pm}(w)K\pm(t^{\text{post}} - t^{\text{pre}})$ applying additive rule and asymmetrical Gaussian plasticity windows
- (i) weights set to large values (ii) large frequency firing (see lec4) (iii) apply additive STDP rule with marginally stronger LTD than LTP
- increased CV, firing rate reduction, weight BINOMICAL distribution after 5 mins



after Song, Miller and Abbott 2000

Cross-correlation function

- $s(\Delta t)$, $s = 1$ if a spike occurs in Δt
- star line:$C(n) = 0$ for regular IF firing 270 Hz, $w = 0.015$, LTP occurs as much as LTD
- square line:after Hebb's learning, IF firing 18 Hz, some presynaptic spikes elicits post-synaptic spikes
- $C < 0$, if presynaptic spikes reduce postsynaptic (anti-correlation) and vice-versa

$$C(n) = \langle s^{pre}(t)s^{post}(t + n\delta t)\rangle - \langle s^{pre}s^{post}\rangle$$