

Synaptic Plasticity

BENG/BGGN 260 - Neurodynamics

UCSD

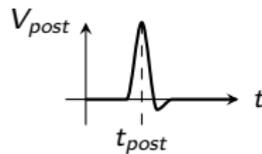
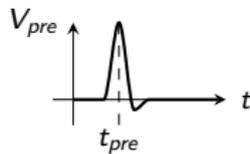
Week 5

Reading Materials

- C. Koch, *Biophysics of Computation*, Oxford Univ. Press, 1999, Ch. 13, pp. 308-329.
- P. Dayan and L. Abbott, *Theoretical Neuroscience*, MIT Press, 2001, Ch. 8, pp. 281-298.
- W. Gerstner and W. Kistler, *Spiking Neural Models: Single Neurons, Populations, Plasticity*, Cambridge Univ. Press, 2002, Ch. 10, pp. 351-385.
- Larry F. Abbott and Wulfram Gerstner, "Homeostasis and Learning Through Spike-Timing Dependent Plasticity", *Methods and Models in Neurophysics*, Elsevier Science, 2004.

Synaptic Plasticity

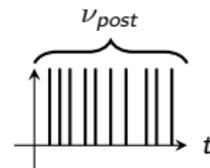
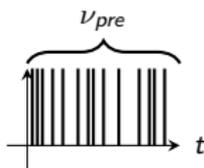
TIMING



synaptic "strength"

$$(\overline{g_{syn}} \propto n \cdot p \cdot q)$$

RATE



$$\nu_{post} \approx W \cdot \nu_{pre}$$

Adaptation:	STP, STD	short term potentiation/depression
Learning/Memory:	LTP, LTD	long term potentiation/depression
Rate-based:	$\frac{dW}{dt} = f(\nu_{pre}, \nu_{post}, W)$	Hebbian Learning
Timing-based:	$\frac{dW}{dt} = f(t_{pre}, t_{post}, W)$	Spike-Timing Dependent Plasticity (STDP)

Synaptic Plasticity at Various Time Scales

TABLE 13.1 Different Forms of Synaptic Plasticity

Phenomenon	Duration	Locus of Induction
<i>Short-term Enhancement</i>		
Paired-pulse facilitation (PPF)	100 msec	Pre
Augmentation	10 sec	Pre
Post-tetanic potentiation (PPT)	1 min	Pre
<i>Long-term Enhancement</i>		
Short-term potentiation (STP)	15 min	Post
Long-term potentiation (LTP)	>30 min	Pre and post
<i>Depression</i>		
Paired-pulse depression (PPD)	100 msec	Pre
Depletion	10 sec	Pre
Long-term Depression (LTD)	>30 min	Pre and post

Synaptic plasticity occurs across many time scales. This table lists some of the better studied forms of plasticity together with a very approximate estimate of their associated decay constants, and whether the conditions required for induction depend on pre- or on postsynaptic activity, or on both. This distinction is crucial from a computational point of view, since Hebbian learning rules require a postsynaptic locus for the induction of plasticity. Note that for LTP and LTD, we are referring specifically to the form found at the Schaffer collateral input to neurons in the CA1 region of the rodent hippocampus; other forms have different requirements.

Koch 1999, p. 311

Hippocampus as Gateway of Memory and Learning

Transfer of Short-term Memory to Long-term Memory

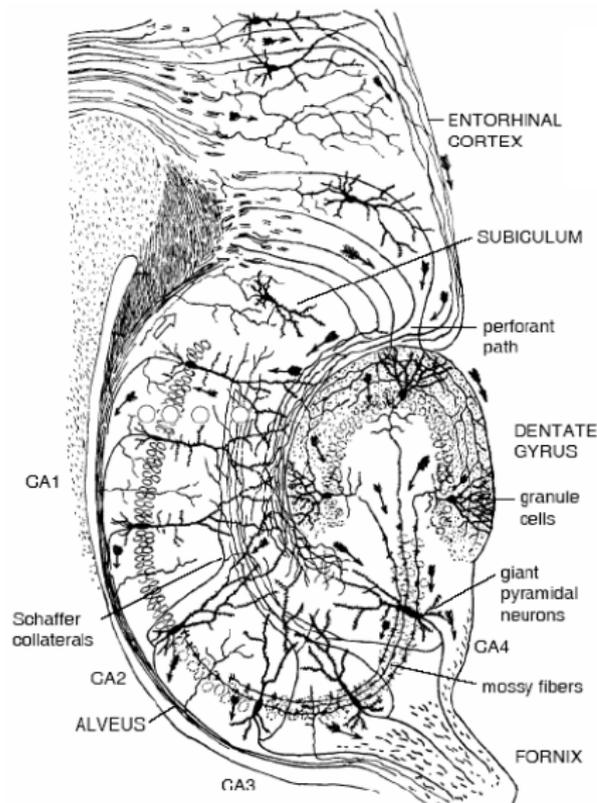


Figure 13.4: Hippocampal Circuitry

Neuronal elements of the hippocampal formation in rodents as drawn by Ramón y Cajal at the turn of the century (when it was called Ammon's Horn). This cortical structure is implicated in the transfer from short to long-term memory. Granule cells in the dentate gyrus send their output axons, so-called *mossy fibers*, to pyramidal cells in the CA3 region. These pyramidal cells in turn project, with so-called *Schaffer collaterals*, onto pyramidal cells in the CA1 region. The majority of LTP and LTD research has been carried out at either the mossy fiber-CA3 synapse or at the Schaffer collateral-CA1 synapse. This figure with the modern nomenclature is taken from Brown and Zador (1990).

Koch 1999, p. 314

Rate-Based Hebbian Learning

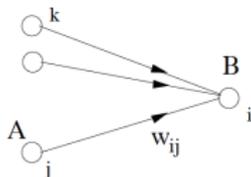


Fig. 3. The change at synapse w_{ij} depends on the state of the presynaptic neuron j and the postsynaptic neuron i and the present efficacy w_{ij} , but not on the state of other neurons k .

Table 1

post	pre	$\frac{d}{dt} w_{ij} \propto$				
i	j	$\nu_i \nu_j$	$\nu_i \nu_j - c_0$	$(\nu_i - \nu_\theta) \nu_j$	$\nu_i (\nu_j - \nu_\theta)$	$(\nu_i - \langle \nu_i \rangle) (\nu_j - \langle \nu_j \rangle)$
ON	ON	+	+	+	+	+
ON	OFF	0	-	0	-	-
OFF	ON	0	-	-	0	-
OFF	OFF	0	-	0	0	+

The change $\frac{d}{dt} w_{ij}$ of a synapse from j to i for various Hebb rules as a function of pre- and postsynaptic activity. 'ON' indicates a neuron firing at maximal rate ($\nu = \nu^{max}$), whereas 'OFF' means an inactive neuron ($\nu = 0$). From left to right: standard Hebb rule, Hebb with decay, pre- and postsynaptic gating, covariance rule. The parameters satisfy $0 < \nu_\theta < \nu^{max}$ and $0 < c_0 < (\nu^{max})^2$.

Rate-Based Hebbian Learning

Principal Component Analysis

$$\tau \frac{d}{dt} W_{ij} = -W_{ij} + \nu_i \nu_j$$

$$\nu_i = \sum_k W_{ik} \nu_k$$

$$\left\langle \tau \frac{d}{dt} W_{ij} \right\rangle = -W_{ij} + \sum_k \boxed{\langle \nu_k \nu_j \rangle} W_{ik}$$

Q_{kj} , input correlation

Principal axes (eigenvector-eigenvalue) decomposition:

$$\mathbf{Q} \mathbf{e}_n = \lambda_n \mathbf{e}_n, \lambda_n > 0$$

$$W_{ij}(t) = \sum_n \sum_k W_{ik}(0) e_{nj} e_{nk} \exp\left(\left(\lambda_n - 1\right) \frac{t}{\tau}\right)$$

Rate-Based Hebbian Learning

Weight Dynamics with Saturation

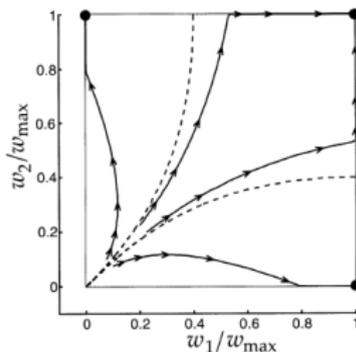


Figure 8.3 Hebbian weight dynamics with saturation.

The correlation matrix of the input vectors had diagonal elements equal to 1 and off-diagonal elements of -0.4 . The principal eigenvector, $\mathbf{e}_1 = (1, -1)/2^{1/2}$, dominates the dynamics if the initial values of the weights are small enough (below or to the left of the dashed lines). This makes the weight vector move to the corners $(w_{max}, 0)$ or $(0, w_{max})$. However, starting the weights with larger values (between the dashed lines) allows saturation to occur at the corner (w_{max}, w_{max}) . (Adapted from MacKay & Miller, 1990.)

Spike-Timing Dependent Plasticity

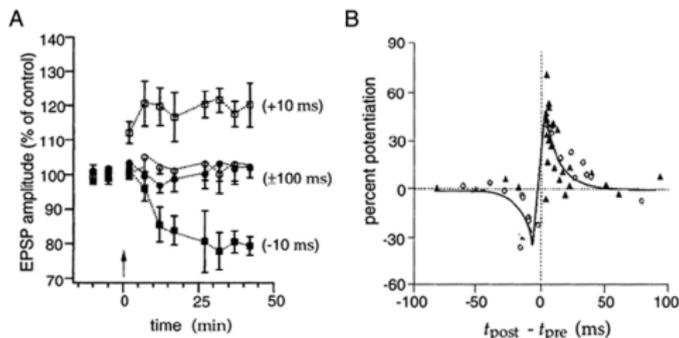


Figure 8.2 LTP and LTD produced by 50 to 75 pairs of pre- and postsynaptic action potential with various timings.

(A) The amplitude of the excitatory postsynaptic potential (EPSP) evoked by the stimulation of the presynaptic neuron plotted at various times as a percentage of the amplitude prior to paired stimulation. At the time indicated by the arrow, paired stimulations of the presynaptic and postsynaptic neurons were performed. For the traces marked by open symbols, the presynaptic spike occurred either 10 or 100 ms before the postsynaptic neuron fired an action potential. The traces marked by solid symbols denote the reverse ordering in which the presynaptic spike occurred either 10 or 100 ms after the postsynaptic spike. Separations of 100 ms had no long-lasting effect. In contrast, the 10 ms delays produced effects that built up to a maximum over a 5-to-10-minute period and lasted for the duration of the experiment. Pairing a presynaptic action potential with a postsynaptic action potential 10 ms later produced LTP, whereas the reverse ordering generated LTD. (B) LTP and LTD of retinotectal synapses recorded *in vivo* in *Xenopus* tadpoles. The percent change in synaptic strength produced by multiple pairs of action potentials is plotted as a function of their time difference. The filled symbols correspond to extracellular stimulation of the postsynaptic neuron, and the open symbols, to intracellular stimulation. The H function in equation 8.18 is proportional to the solid curve. (A adapted from Markram et al., 1997; B adapted from Zhang et al., 1998.)

Spike-Timing Dependent Plasticity

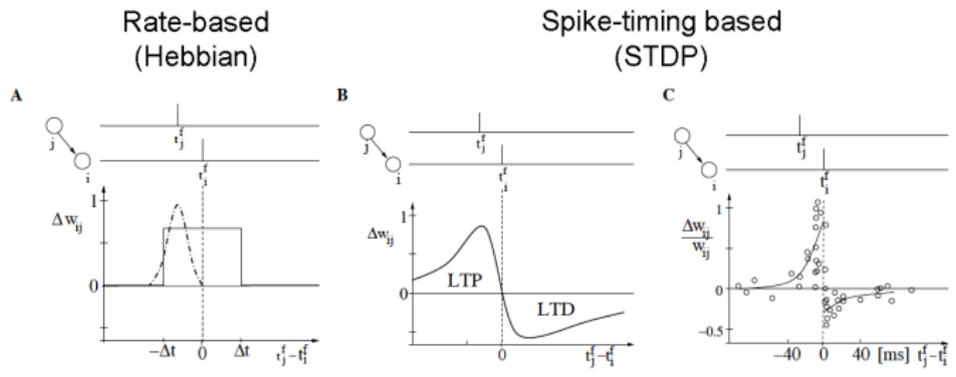


Fig. 4. Learning Window

The change Δw_{ij} of the synaptic efficacy depends on the timing of pre- and postsynaptic spikes. **A.** The solid line indicates a rectangular time window as is often used in standard Hebbian learning. The synapse is increased if pre- and postsynaptic neuron fire sequentially with an interspike interval smaller than Δt . The dot-dashed line shows an asymmetric learning window useful for sequence learning. The synapse is strengthened only if the presynaptic spike arrives slightly before the postsynaptic one and is therefore partially 'causal' in firing it. **B.** An asymmetric bi-phasic learning window similar to the one used in many modeling studies. A synapse is strengthened (long-term potentiation, LTP), if the presynaptic spike arrives slightly before the postsynaptic one, but is decreased (long-term depression LTD), if the timing is reversed. **C.** Experimental results have confirmed the existence of bi-phasic learning windows. Data points redrawn after the experiments of Bi and Poo (1998).