Synaptic Plasticity - Spike-Timing

The impact of a synapse onto its postsynaptic neuron (amplitude of EPSPs/IPSPs) is termed the *weight* (efficacy) of a synapse.

This weight undergoes dynamics on a variety of time scales

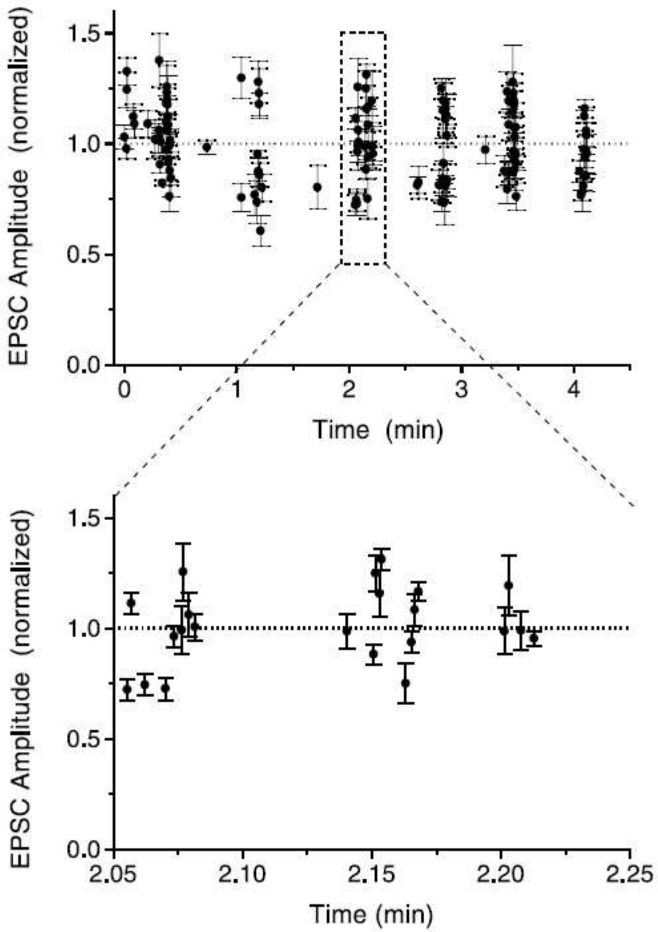
Phenomenon	Duration	Locus of Induction
Short-term Enhancement		
Paired-pulse facilitation (PPF)	100 *msec*	Pre
Augmentation	10 *sec*	Pre
Post-tetanic potentiation	1 *min*	Pre
Long-term Enhancement		
Short-term potentiation (STP)	15 *min*	Post
Long-term potentiation (LTP)	> 30 *min*	Pre and post
Depression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

Table 12.1. Different forms of synaptic plasticity

Dynamic Synapses

All spikes have an approximately equal shape.

However, the PSPs of a synapse vary deterministically in the range of several 100 % in general.



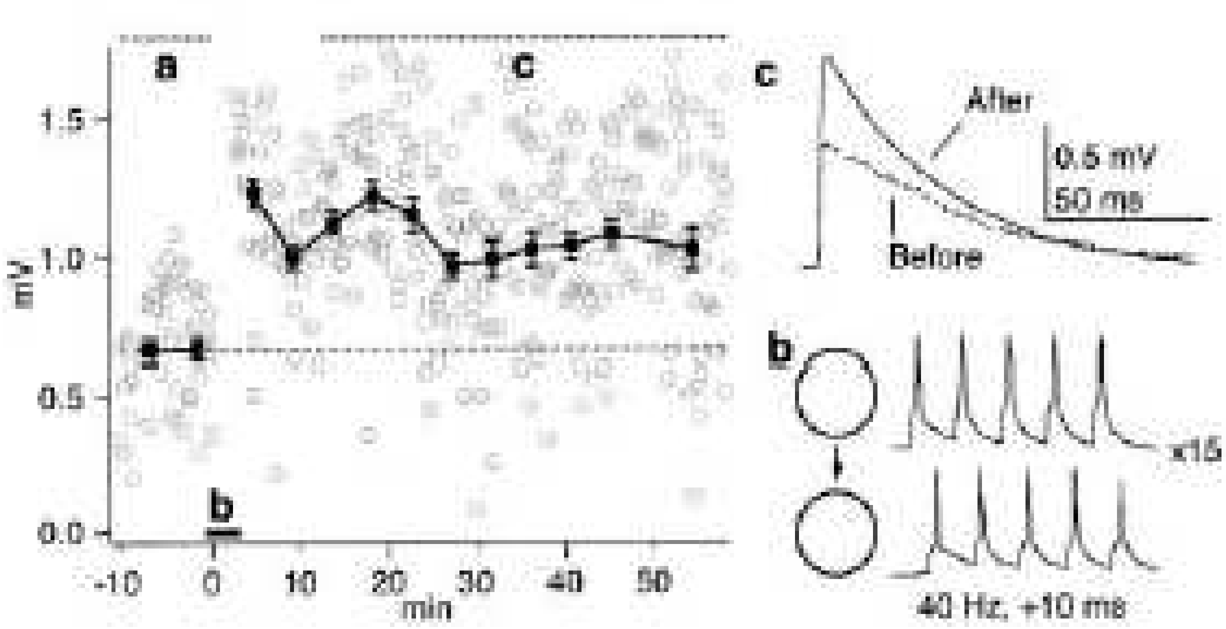
The variation in $w(t)$ can be described as follows:

$$w(t) = w \cdot D(t) \cdot (1 + F(t))$$

$D(t) \in \{0, 1\}$, depression term
$F(t) \geq 0$, facilitation term

Examine not only rates of pre- and postsynaptic neurons, but precise spike times.

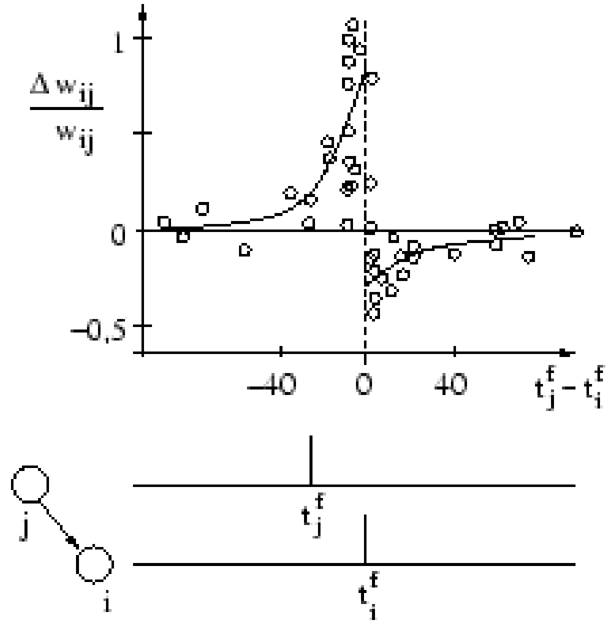
Experiment: Neurons A and B are forced to spike at times t_{pre} und t_{post} (pairing). The efficacy of the synapse changes as a function of $t_{pre} - t_{post}$.



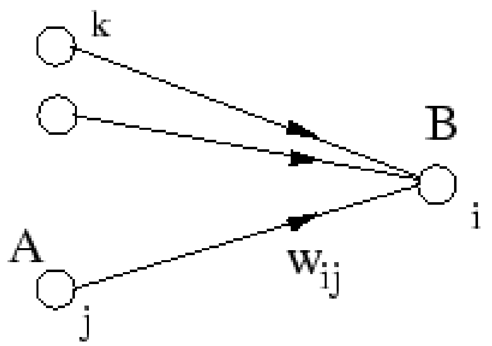
Spike-Timing Depenent Plasticity (STDP)

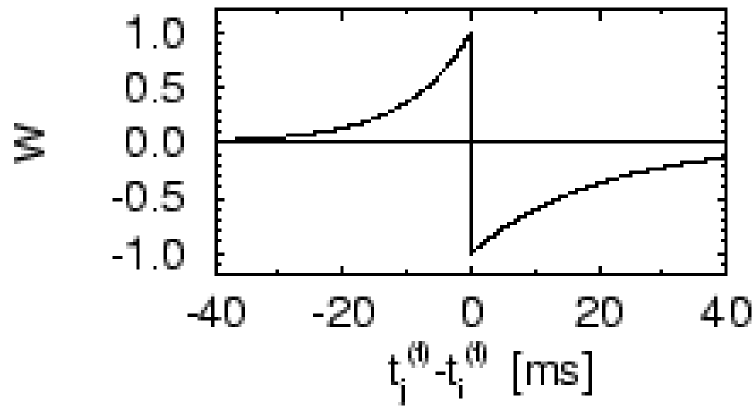
The synapse is *strengthened*, if the presynaptic neuron fired in a certain time window *before* the postsynaptic neuron.

The synapse is *weakened*, if the presynaptic neuron fired in a certain time window *after* the postsynaptic neuron.



The synapse gets information about t_{post} through an action potential backpropagating the dendritic tree.





Spike train of neuron i with $t_i^{(f)}$ as the f-th spike time:

$$S_i(t) = \sum_f \delta(t - t_i^{(f)}) \; .$$

The learning window W defines the dependence of weight changes on the timing difference between the pre- and postsynaptic spikes:

$$W(s) = \begin{cases} A_+ e^{s/\tau_1} & \text{for} \quad s < 0 \\ A_- e^{-s/\tau_2} & \text{for} \quad s > 0 \end{cases}$$

Analysis of STDP

Model for learning dynamics:

$$\frac{d}{dt}w_{ij}(t) = S_j^{pre}(t)\int_0^{\infty} W(s)S_i^{post}(t-s)ds + S_i^{post}(t)\int_0^{\infty} W(-s)S_j^{pre}(t-s)ds$$

Pre- and postsynaptic spike trains are drawn from a stochastic ensemble. Averages relatively to this ensemble are denoted by $\langle \cdot \rangle_E$.

We compute the expected weight change over some (long) time T:

$$\frac{\langle w_{ij}(t+T) - w_{ij}(t)\rangle_E}{T} \approx \int_{-\infty}^{\infty} W(s)\langle\langle S_i^{post}(t-s)S_j^{pre}(t)\rangle_E\rangle_T \, ds$$

$\langle f(t)\rangle_T \equiv T^{-1}\int_t^{t+T} f(t')\,dt'$ is a temporal average.

Analysis of STDP

$$\frac{\langle w_{ij}(t+T) - w_{ij}(t)\rangle_E}{T} \approx \int_{-\infty}^{\infty} W(s)\langle \nu_{ij}(t-s,t)\rangle_T ds$$

Joint firing rate of neurons i and j: $\quad \nu_{ij}(t,t') \equiv \langle S_i^{post}(t) S_j^{pre}(t')\rangle_E.$

- The mean weight change therefore depends on correlations between inputs and outputs.
- The output of the neuron is generated by the input.
- For simple neuron models, one can derive the weight changes given the statistics of the inputs (unsupervised learning).
- If the input is only weakly correlated with the output, the weight decreases.
- Groups of inputs which are strongly correlated (and drive the neuron) are strengthened.
- STDP tends to select inputs which are correlated on the timescale of the learning window.