

COMS30127: Computational Neuroscience

Synaptic plasticity (part 1):

Rules

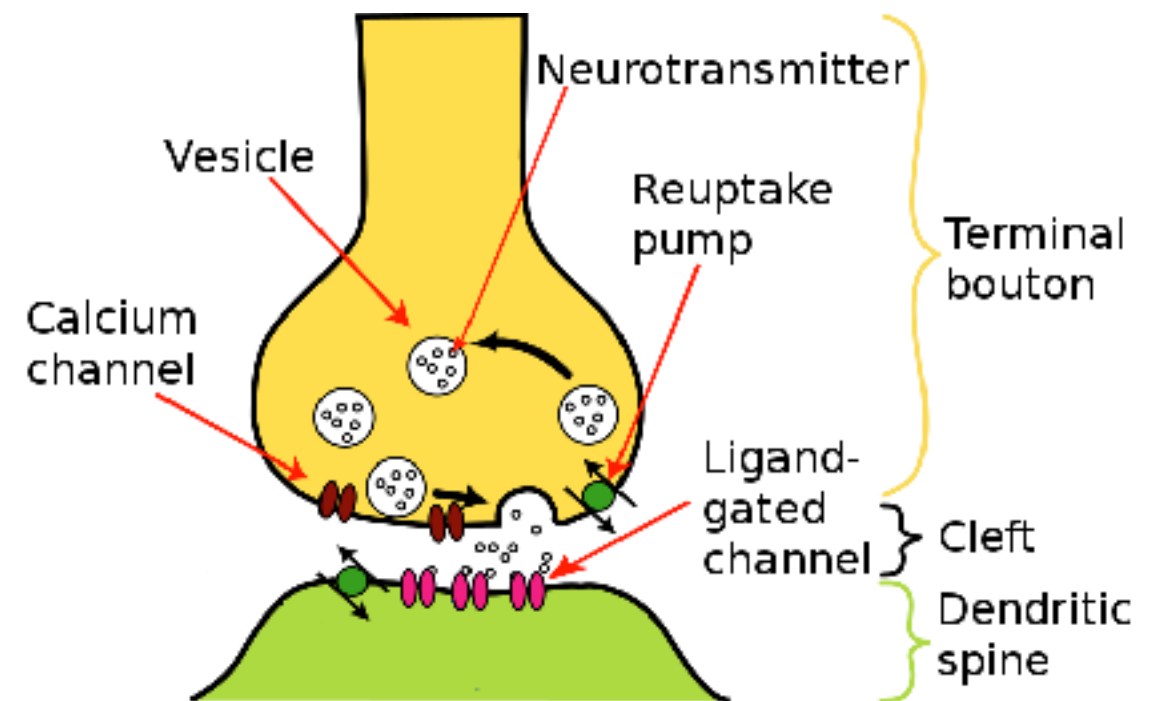
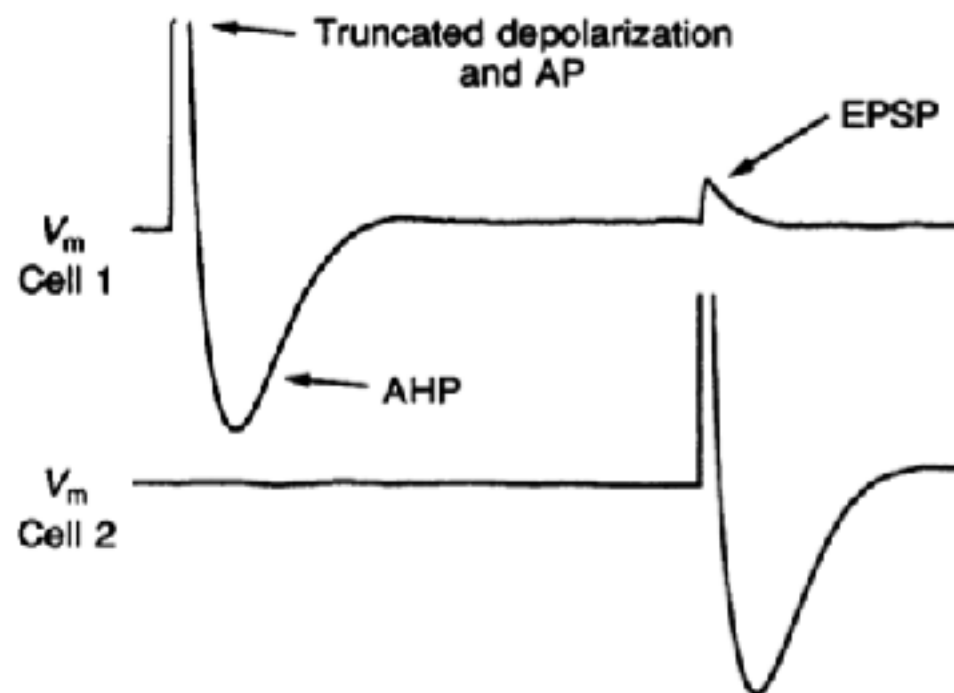
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What we covered in the previous lecture

- What is a synapse?
- How do synapses work?
- How can we computationally model synapses?



What we will cover next

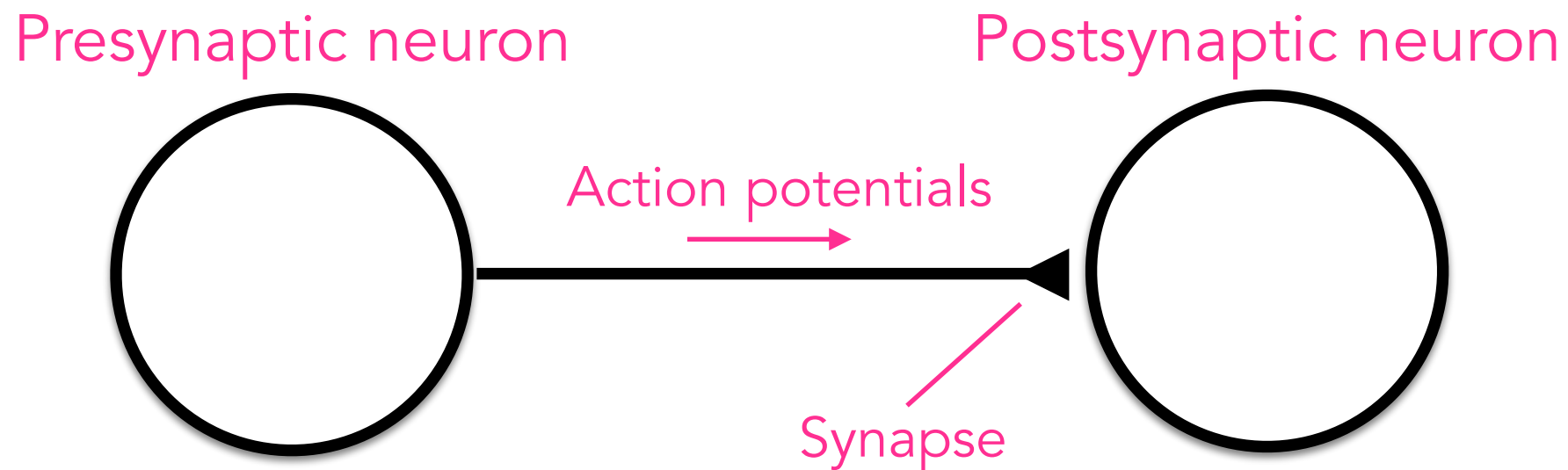
- What is synaptic plasticity?
- How might synaptic plasticity underlie learning and long-term memory?
- What are the rules of synaptic plasticity?
- What are the mechanisms of synaptic plasticity?
- What have we learned from models of learning?

PART 1

PART 2
PART 3

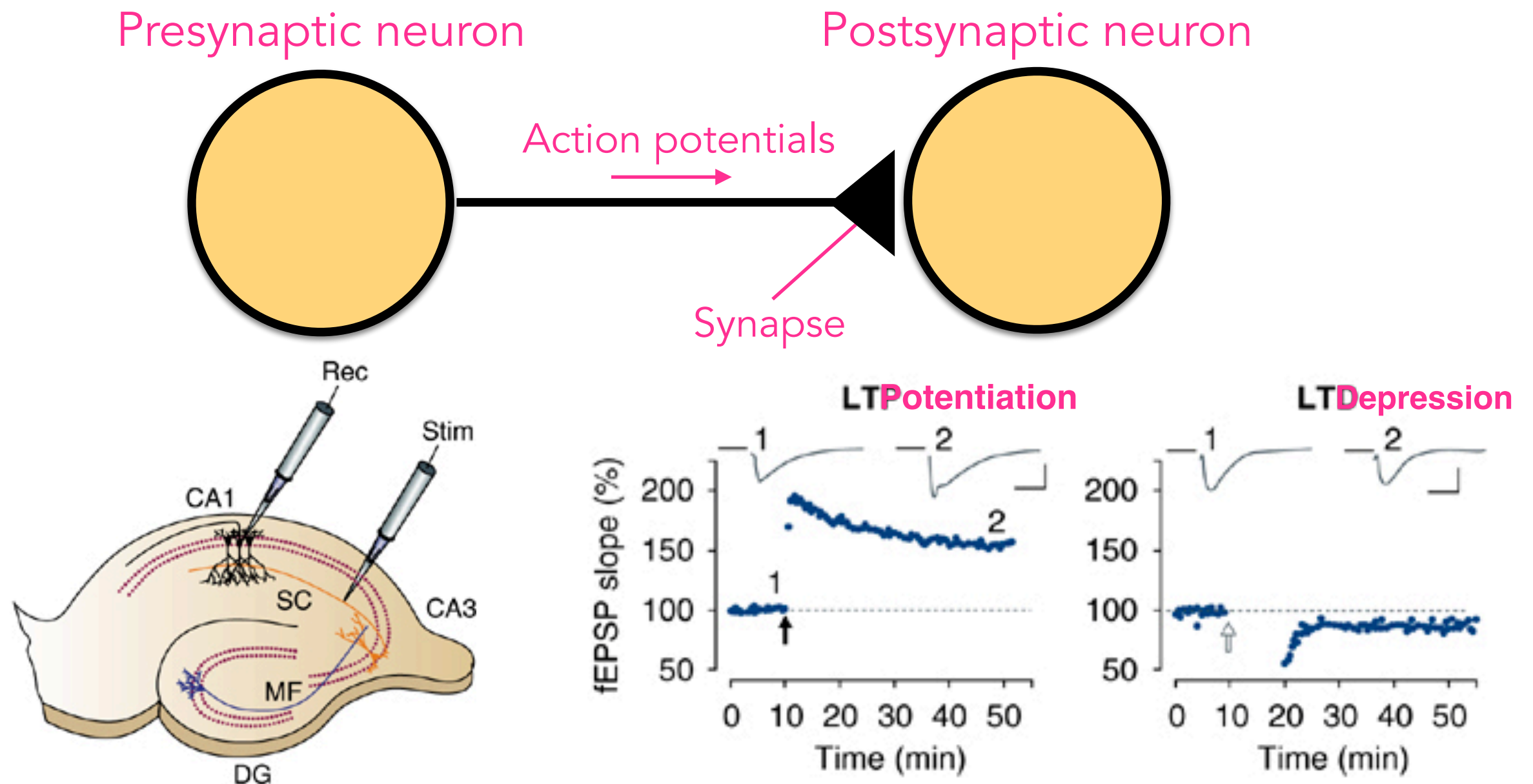
What is synaptic plasticity?

Synaptic plasticity is a (activity-dependent) semi-permanent change in the strength of the connection from one neuron to another.

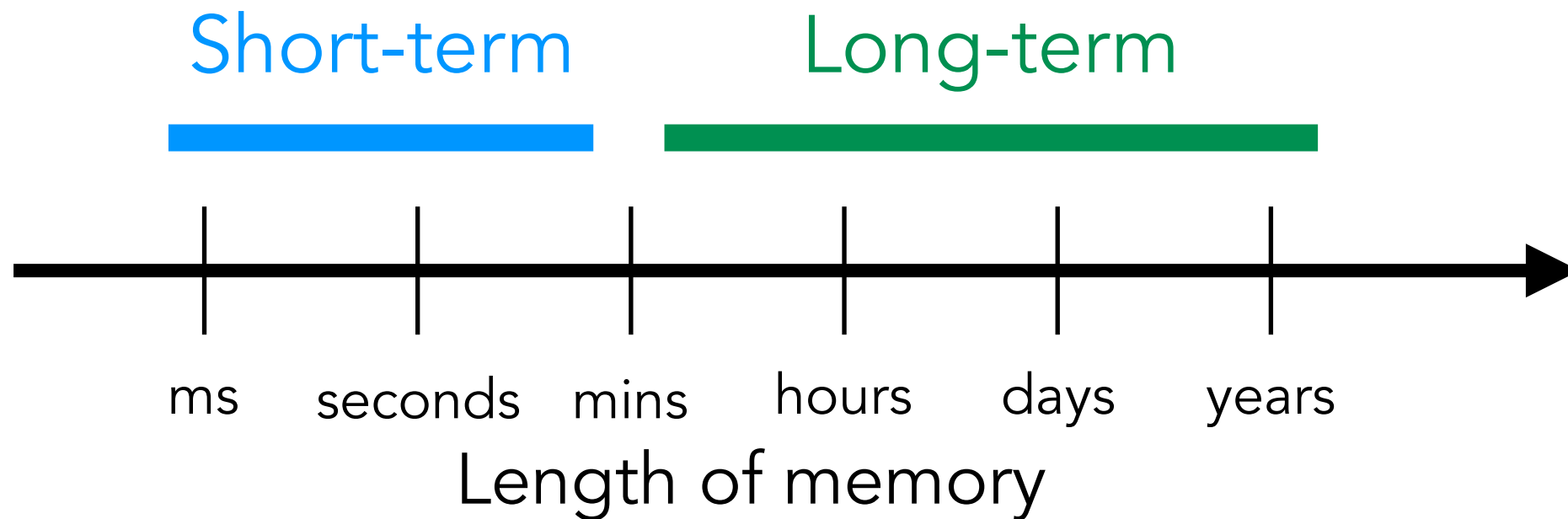


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What is long-term memory?



Different mechanisms, different parts of the brain.

Short-term: Reverberating electrical activity in neural circuits.

Long-term: Semi-permanent changes in the strengths of synaptic connections between neurons.

3 stages of memory

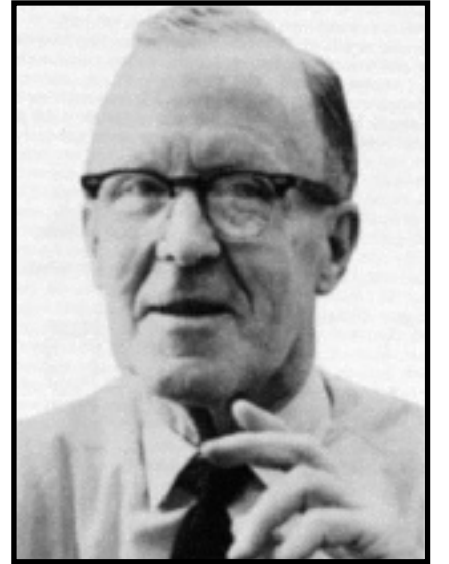


Learning and memory via synaptic plasticity

- Synaptic plasticity is generally believed to be the primary basis of long-term memory in the brain.
- Other neural components are also plastic (intrinsic excitability, neural morphology, etc), but their role in learning and memory is poorly understood. We will not cover them in this unit.
- Synapses increase or decrease their strength according to certain 'rules of plasticity'.
- Linked to learning and memory in the following way:
 - Neural activity during learning triggers synaptic strength changes.
 - Synaptic strength changes alters the propensity for neurons to fire.
 - Next time the same neural circuit receives an input, it responds in a different fashion than it otherwise would have. **That's memory.**

What are the rules of synaptic plasticity?

Hebbian plasticity



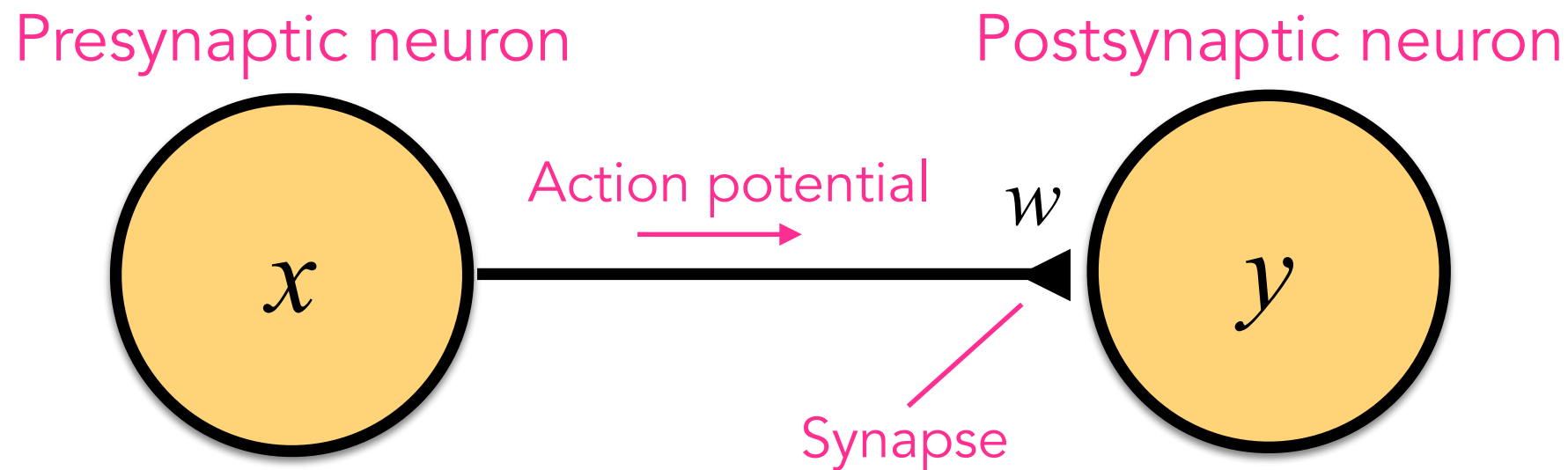
Donald Hebb

"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."

— Donald Hebb (1949)

a.k.a. "neurons that fire together wire together."

Rules of synaptic plasticity



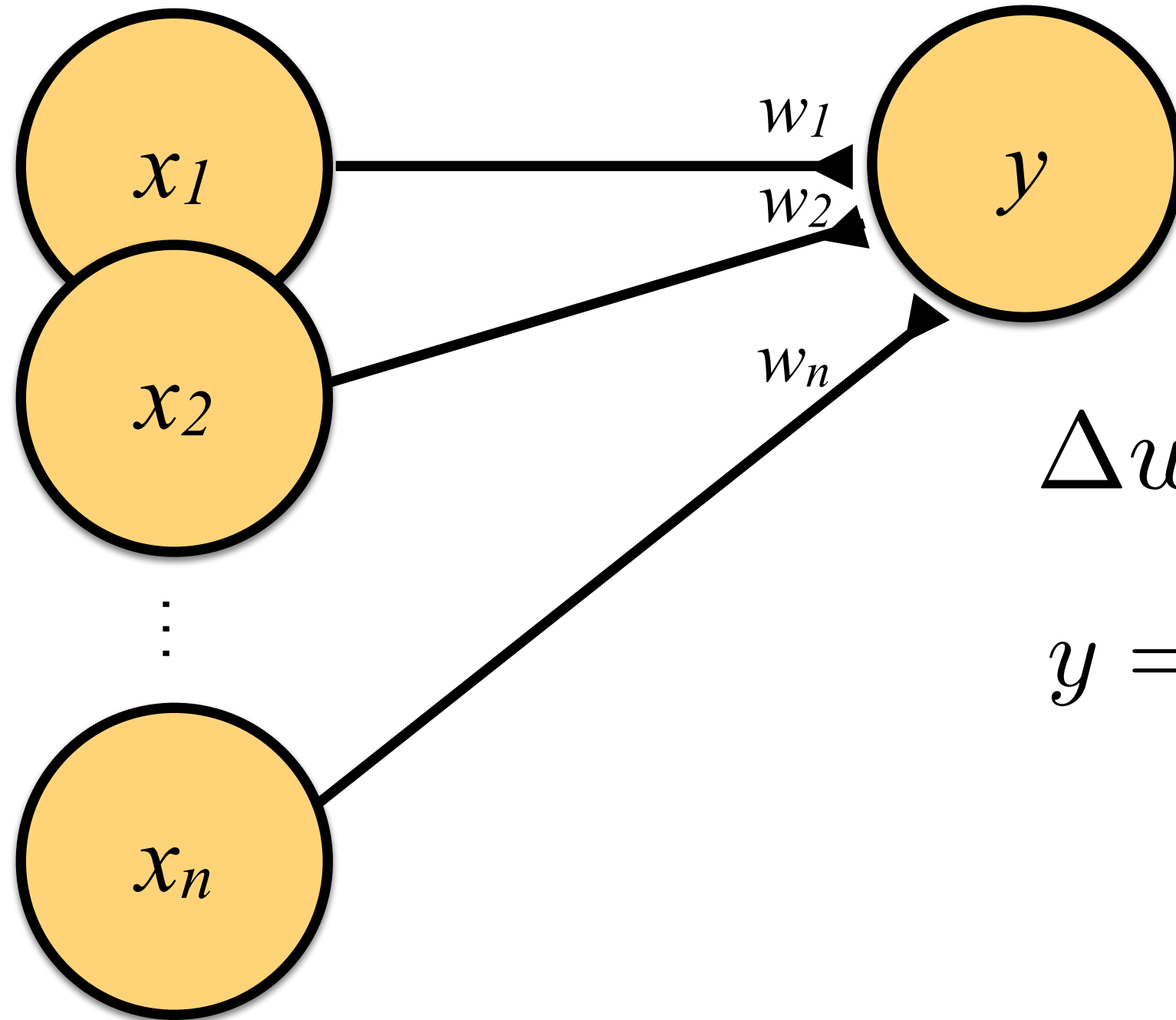
$$\Delta w = f(x, y) = ???$$

A Hebbian rule: $\Delta w = \eta xy$

Rules of synaptic plasticity

Presynaptic neuron

Postsynaptic neuron



$$\Delta w_i = \eta x_i y$$

$$y = \sum_i x_i w_i$$

A linear Hebbian rule

- Linear, rate-based neuron model:
- Simple, dynamical Hebbian plasticity rule:
- Average over an ensemble of input \mathbf{x} 's:
- The weight of each incoming synapse grows at a rate proportional to its input unit's average correlation with all other inputs.
- Explains Pavlov's dogs!
- Note that the dynamics are unstable: \mathbf{w} and hence y grow without bound.

$$y = \sum_i x_i w_i = \mathbf{x}\mathbf{w}$$

$$\frac{d\mathbf{w}}{dt} = \eta \mathbf{x} y$$

$$\begin{aligned} \frac{d\mathbf{w}}{dt} &= \eta \langle \mathbf{x} y \rangle \\ &= \eta \langle \mathbf{x} (\mathbf{x}\mathbf{w}) \rangle \\ &= \eta \mathbf{Q} \mathbf{w}, \quad \mathbf{Q} = \langle \mathbf{x} \mathbf{x} \rangle \end{aligned}$$

What about weakening synapses?

- Let's modify the previous rule to make potentiation happen only if the postsynaptic activity is above some threshold, and depression happen when it's below:

$$\frac{d\mathbf{w}}{dt} = \eta \mathbf{x} (y - \theta_y)$$

- An alternative choice would be to put the threshold on the presynaptic activity:

$$\frac{d\mathbf{w}}{dt} = \eta (\mathbf{x} - \theta_{\mathbf{x}}) y$$

- These seemingly similar models imply very different plasticity outcomes:
 - in the first case, all active synapses will increase or decrease together (homosynaptic pot/dep).
 - in the second case, inactive synapses will weaken if $y > 0$ (heterosynaptic depression).

BCM rule

- Similar plasticity rule as first on previous slide, but multiplied by y to stop inactive synapses changing:
- Their key idea was to add a second rule that let the threshold vary depending on activity:
- This sliding threshold has two effects:
 - It stabilises plasticity and hence activity.
 - It introduces competition between the synapses.

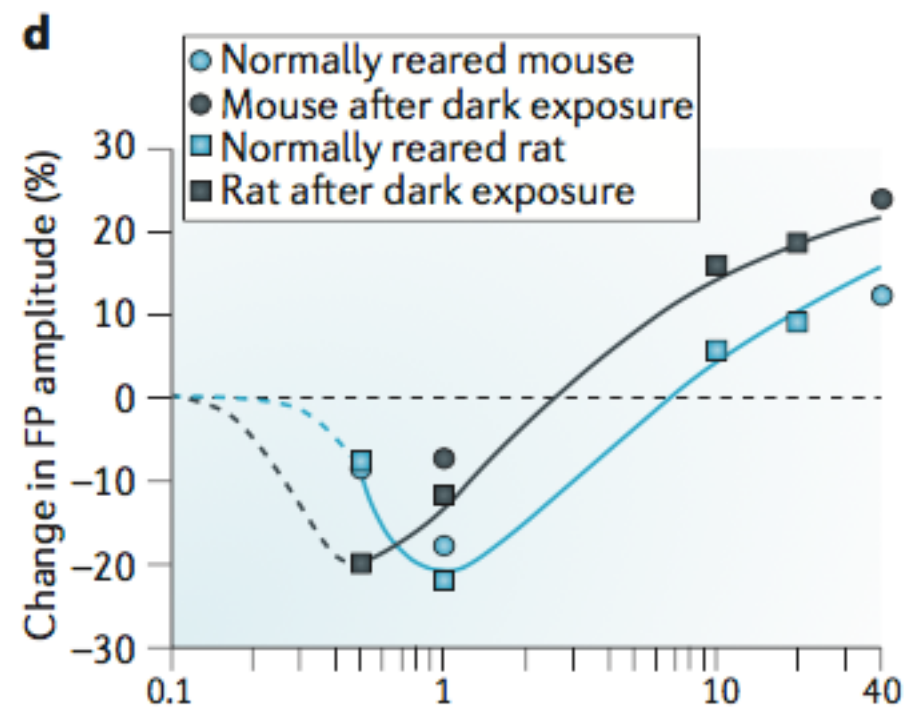
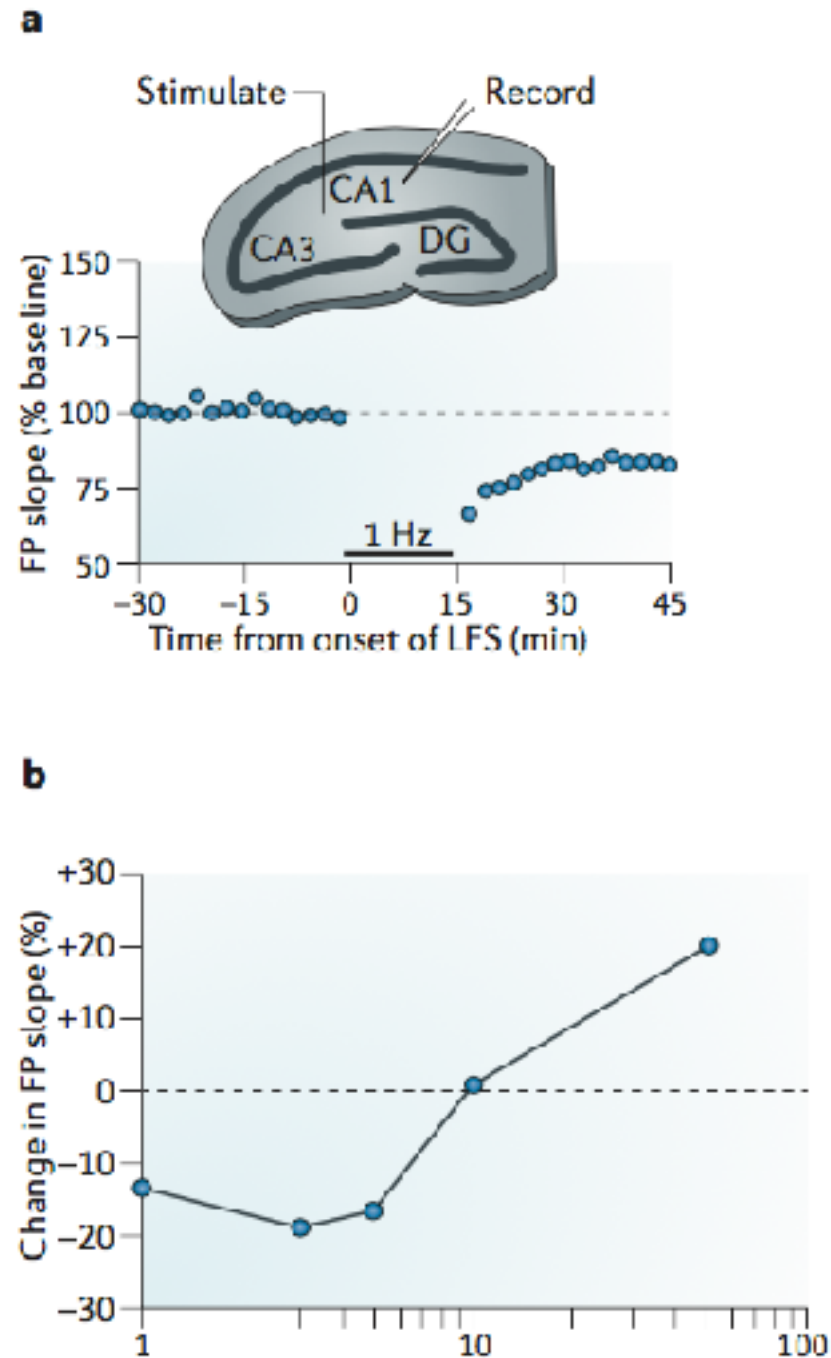
$$\frac{d\mathbf{w}}{dt} = \eta_w \mathbf{x}y(y - \theta_y)$$

$$\frac{d\theta_y}{dt} = \eta_\theta y^2 - \theta_y$$

$$\eta_\theta \gg \eta_w$$

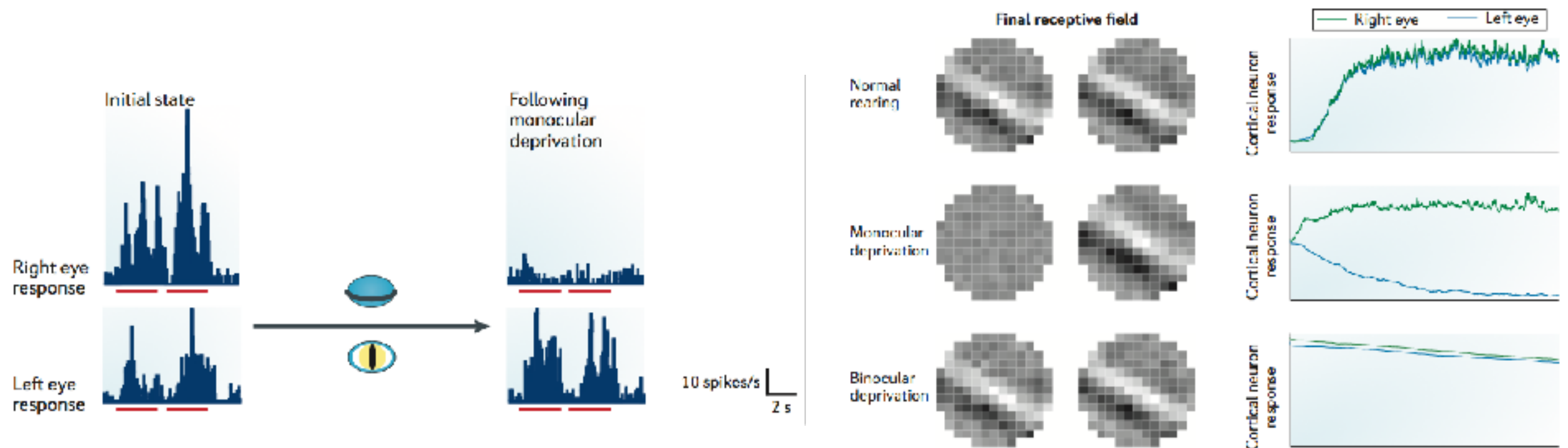
BCM rule

Evidence for the sliding threshold.



BCM rule

Can account for monocular deprivation experiments.



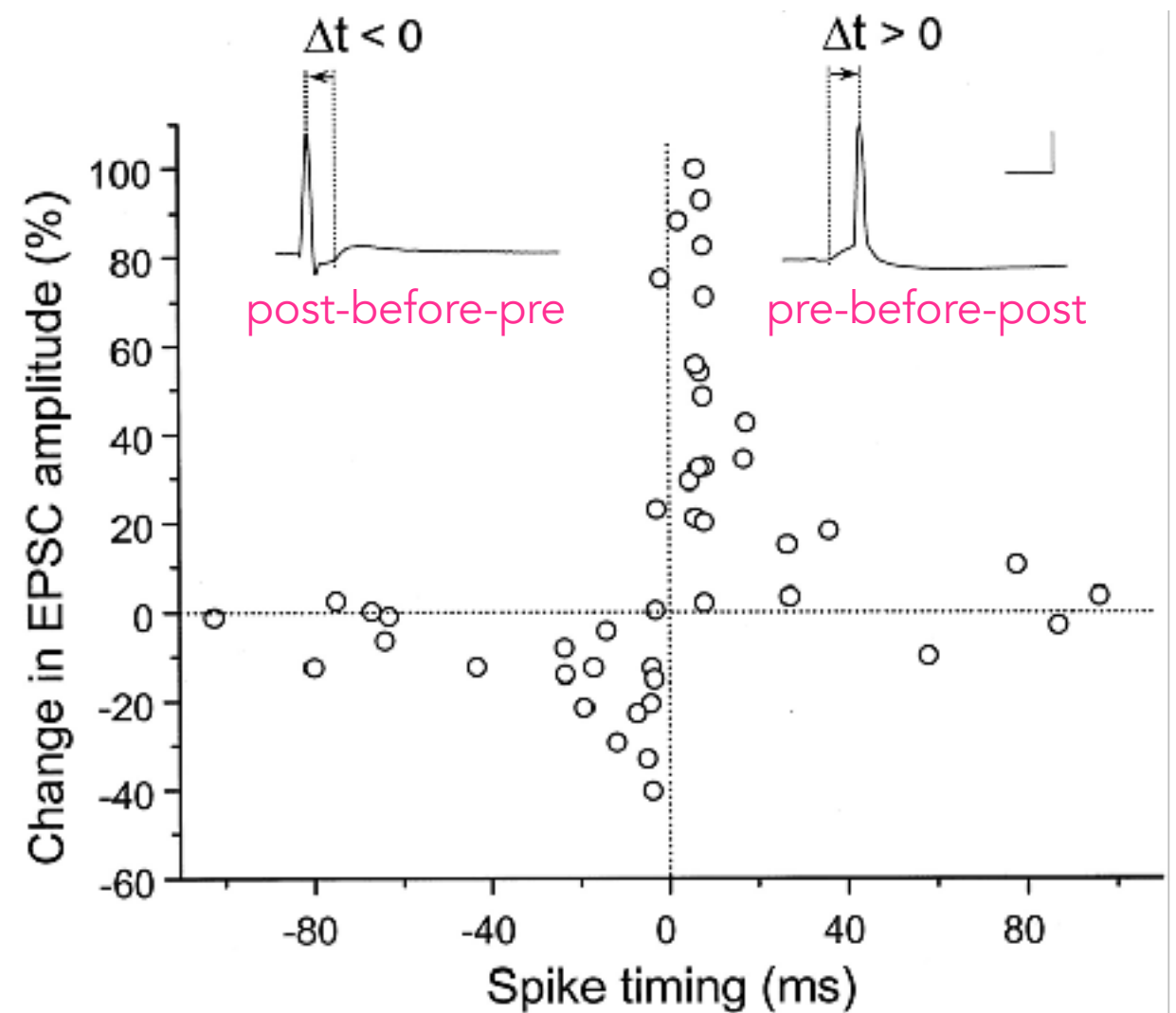
Summary

Rate-based plasticity rules

- Mostly based on Hebb's ideas.
- Basic rules consider potentiation only, and weights can learn to pick out correlations in the input signals.
- To avoid weights blowing up, we need also some mechanism for weakening synapses. Adding a threshold to the plasticity rules can do this, but leads to other effects.
- One alternative mechanism to stabilise weight and firing dynamics (that we did not discuss) is **homeostatic synaptic plasticity**.
There, weights are typically normalised multiplicatively on slow timescale.
- Were developed in an era when people thought the exact timing of spikes carried no additional information that was not already conveyed by the neuron's firing rate.

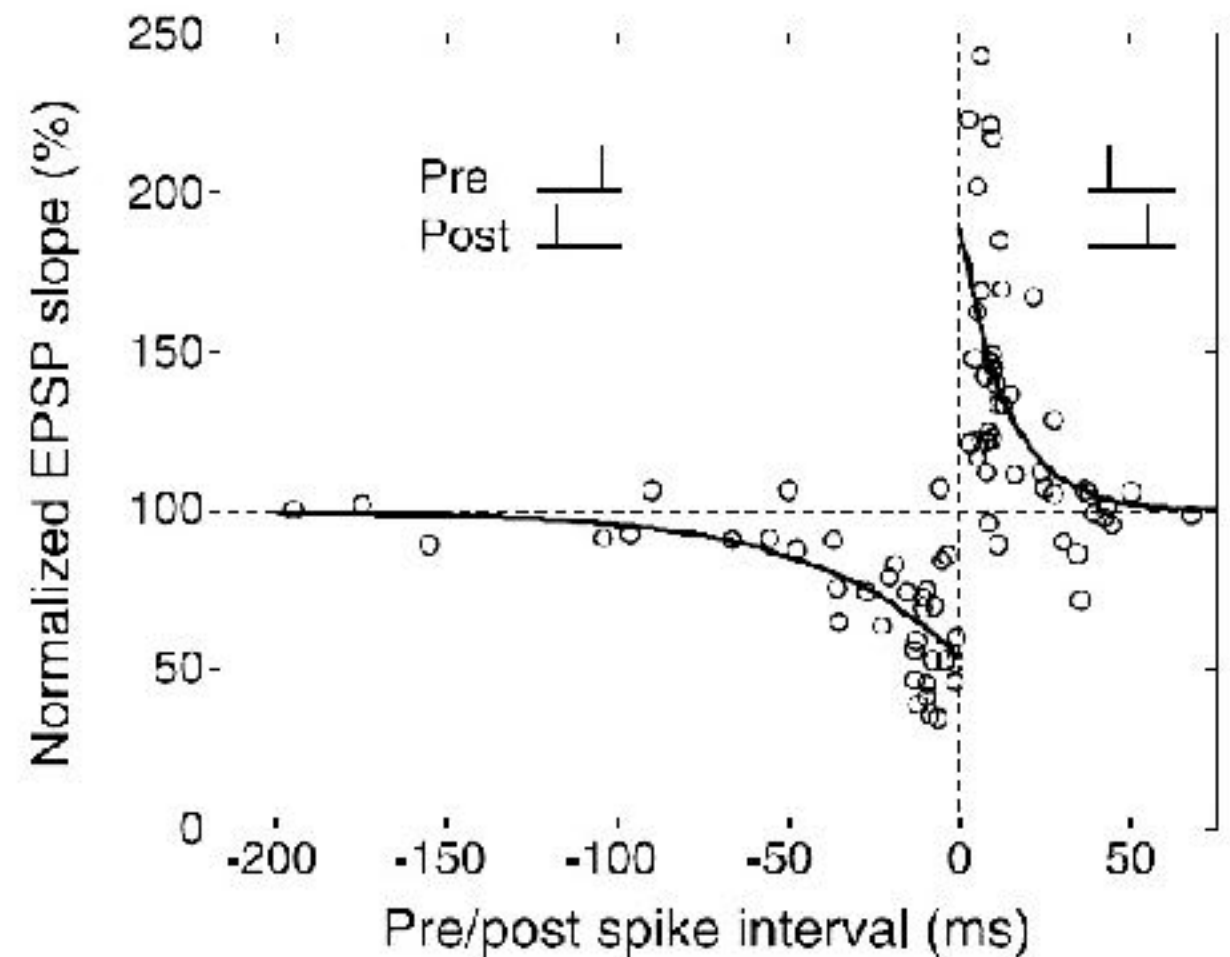
Spike-timing-dependent plasticity

- STDP (discovered in late 1990s) encapsulates the idea of causality implied by Hebb.
- Synapses can detect millisecond-level differences in spike timing when deciding whether to strengthen or weaken.
- When first discovered it was seen as the possible “atom of plasticity”.
- “Things turned out to be just as simple as we first thought”
— *No biologist, ever*



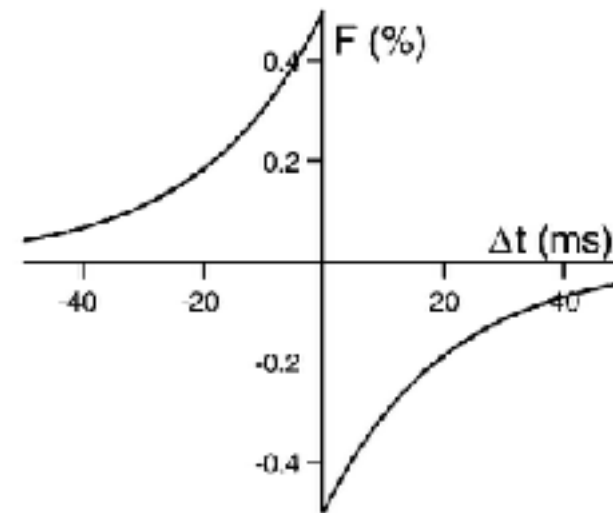
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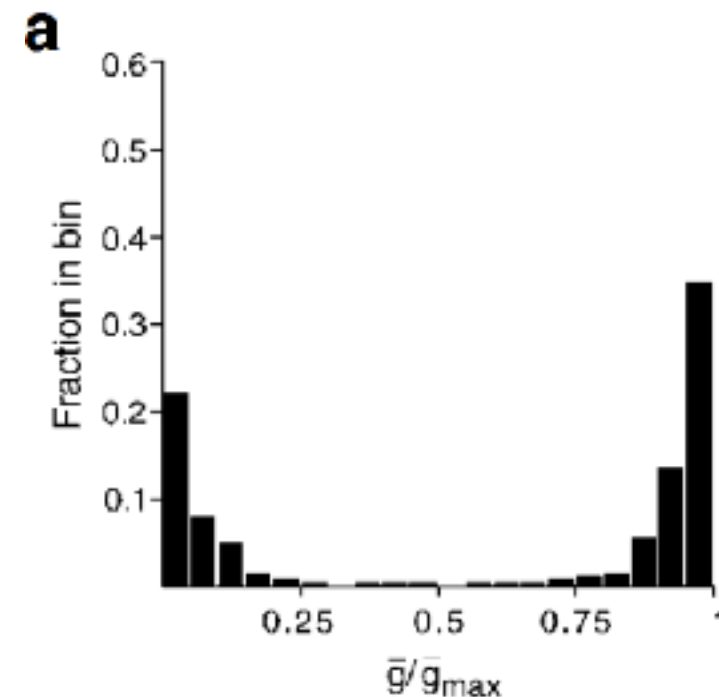


Competitive Hebbian learning via STDP

- A simple computational model of STDP demonstrated that it can induce competition between the inputs.
- The group of synaptic inputs with the strongest correlations 'wins'.
- Synaptic weight dynamics are unstable, and must be artificially capped. The resulting weight distribution is bimodal.

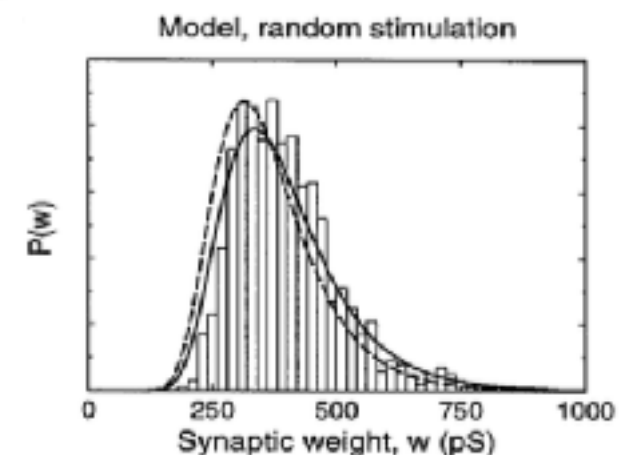
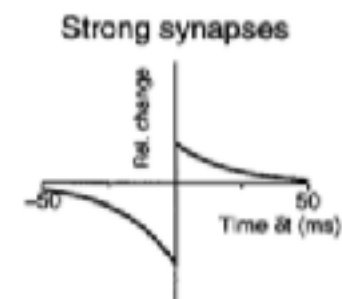
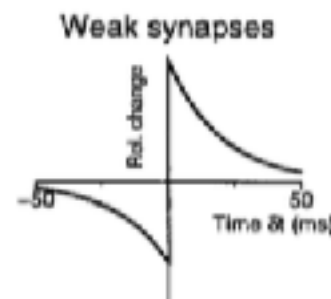
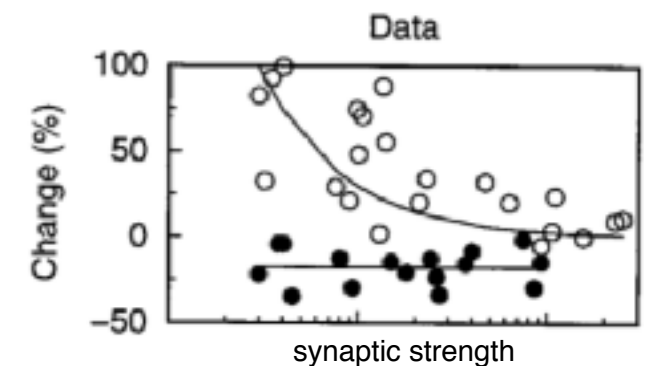
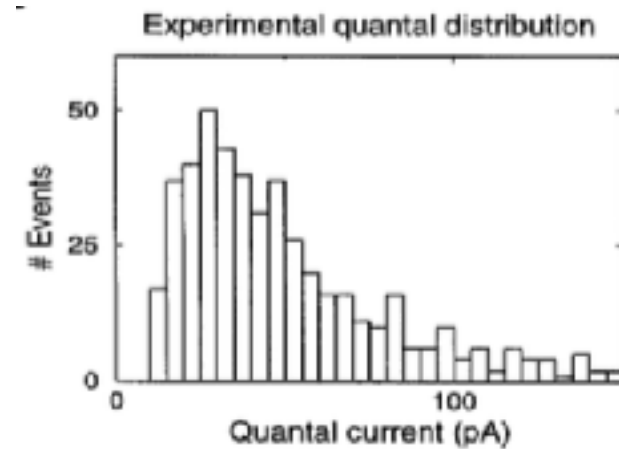


$$F(\Delta t) = \begin{cases} A_+ \exp(\Delta t / \tau_+) & \text{if } \Delta t < 0 \\ -A_- \exp(-\Delta t / \tau_-) & \text{if } \Delta t \geq 0 \end{cases}$$



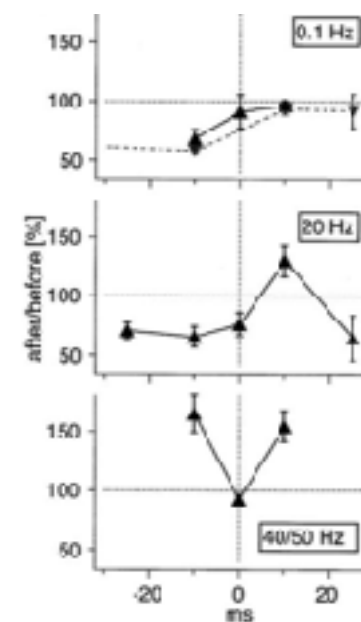
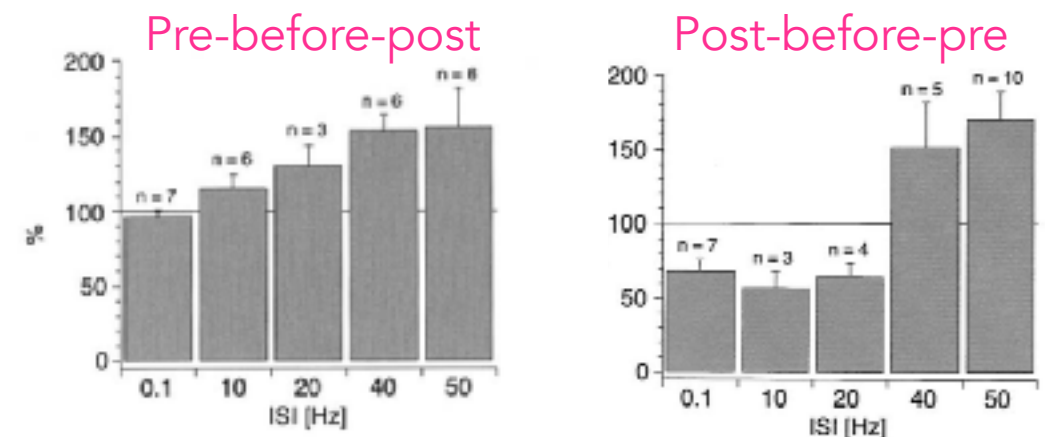
Stability and weight-dependence in STDP

- The bimodal weight distribution seen on previous slide is not observed experimentally.
- The data show that weak synapses potentiate more than strong synapses.
- Computational models that include a weight-dependence can however account for the unimodal distribution.
- This seems to come at the cost of fast memory forgetting due to overwriting (more on this effect in later lectures).



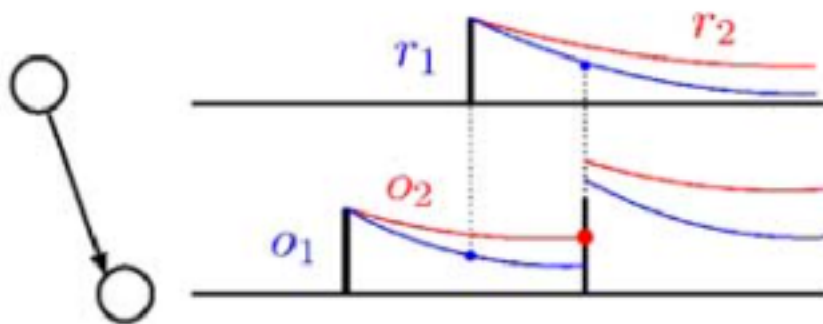
The effect of stimulation rate

- All of the STDP models discussed so far are linear, in the sense that the effects of separate spike pairs simply add up.
- However, experiments found that the rate of presentation of spike pairings has an effect on the direction of plasticity.
- Theorists have devised variants of the STDP rules with additional slow variables that provide information about the stimulation frequency, e.g. Clopath et al, *Nat Neurosci* (2010).

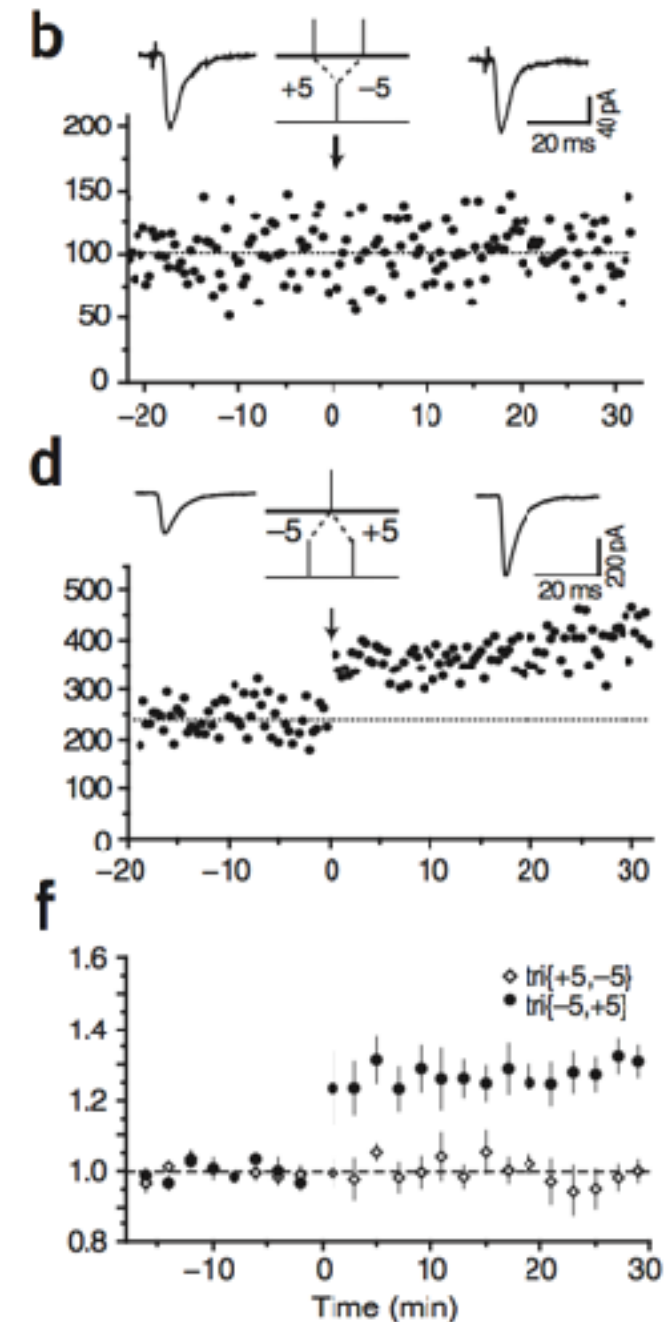


The triplet experiments

- Under the basic STDP model, the net effect of a *pre-post-pre* stimulation pattern should be identical to a *post-pre-post*.
- However that turned out not to be the case experimentally.
- Pfister & Gerstner (2006) proposed a modified 'triplet' STDP rule to account for this phenomenon.
- It involved introducing four dynamical variables: two that get increased when there is a presynaptic spike (one fast, one slow), and two more that get increased when there is a postsynaptic spike (also one fast, one slow).



Pfister & Gerstner, *J Neurosci* (2006)



Wang et al., *Nat Neurosci* (2005)

Further problems with STDP

- Current models have difficulty accounting for the cooperativity of LTP between incoming synapses.
- Synapses can't directly observe postsynaptic spikes at the faraway soma (rely on 'back-propagation' of the action potential).
- 'Always on' nature of the rule implies that information can't be read out without altering the synaptic strength.
- We will probably need to think more carefully about the actual biological mechanisms in future STDP models.

Summary

Synaptic plasticity part 1

- Synaptic plasticity the semi-permanent **changes in the strengths of the connections** between neurons.
- It's thought to be the primary **basis for learning and memory** (information storage) in the brain.
- **Rate-based** synaptic plasticity rules can give insight into synaptic weight dynamics and learning.
- **Spike-timing-dependent** plasticity rules have the potential to capture more fine-grained temporal information, but have so far had difficulty reproducing many aspects of the experimental data.

Further reading

- **Simple rate-based plasticity models:**
Dayan and Abbott book (2001), chapter 8.
- **BCM review:**
Cooper, L.N., and Bear, M.F. (2012). The BCM theory of synapse modification at 30: interaction of theory with experiment. *Nat Rev Neurosci* 13, 798–810.
- **STDP:**
Feldman, D.E. (2012). The spike-timing dependence of plasticity. *Neuron* 75, 556–571.
- **Problems with STDP:**
Lisman, J., and Spruston, N. (2005). Postsynaptic depolarization requirements for LTP and LTD: a critique of spike timing-dependent plasticity. *Nat Neurosci* 8, 839–841.

Synaptic plasticity part 2: What are the mechanisms?

End