Week 6: Hebbian Learning

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Biological Modeling of Neural Networks

Week 6

Hebbian LEARNING and ASSOCIATIVE MEMORY

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EPFL, Lausanne, Switzerland

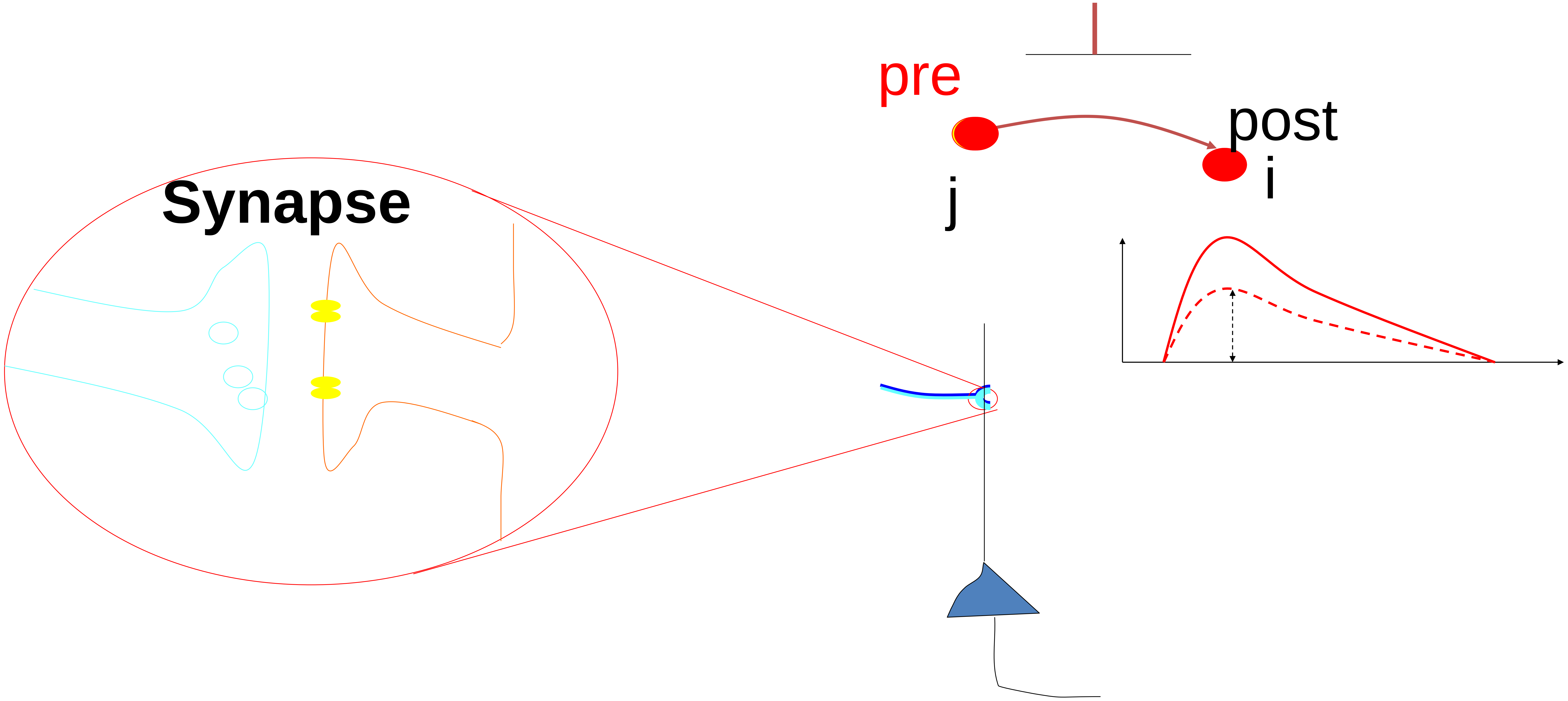
6.1 Synaptic Plasticity
- Hebbian Learning
- Short-term Plasticity
- Long-term Plasticity
- Reinforcement Learning

6.2 Models of synaptic plasticity
- Hebbian learning rules

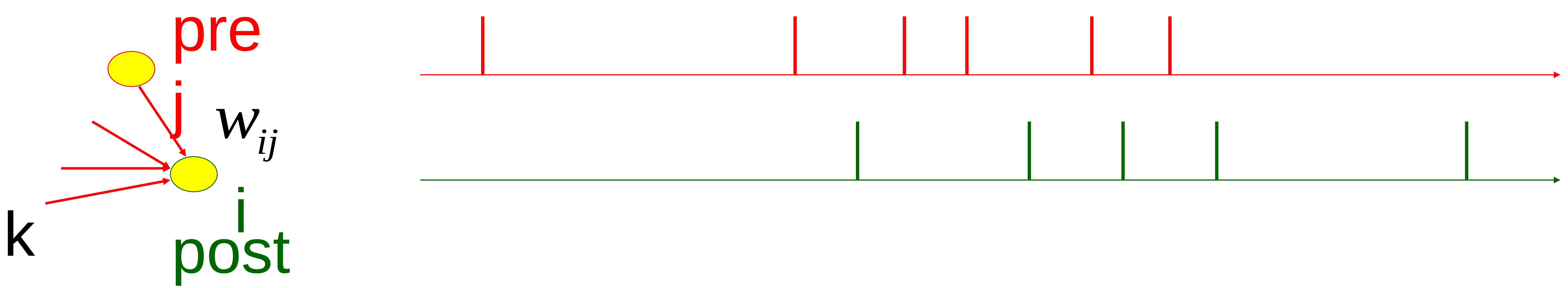
6.3
-
-

6.4

6.1 Synaptic plasticity



6.1 Synaptic plasticity: Hebbian Learning



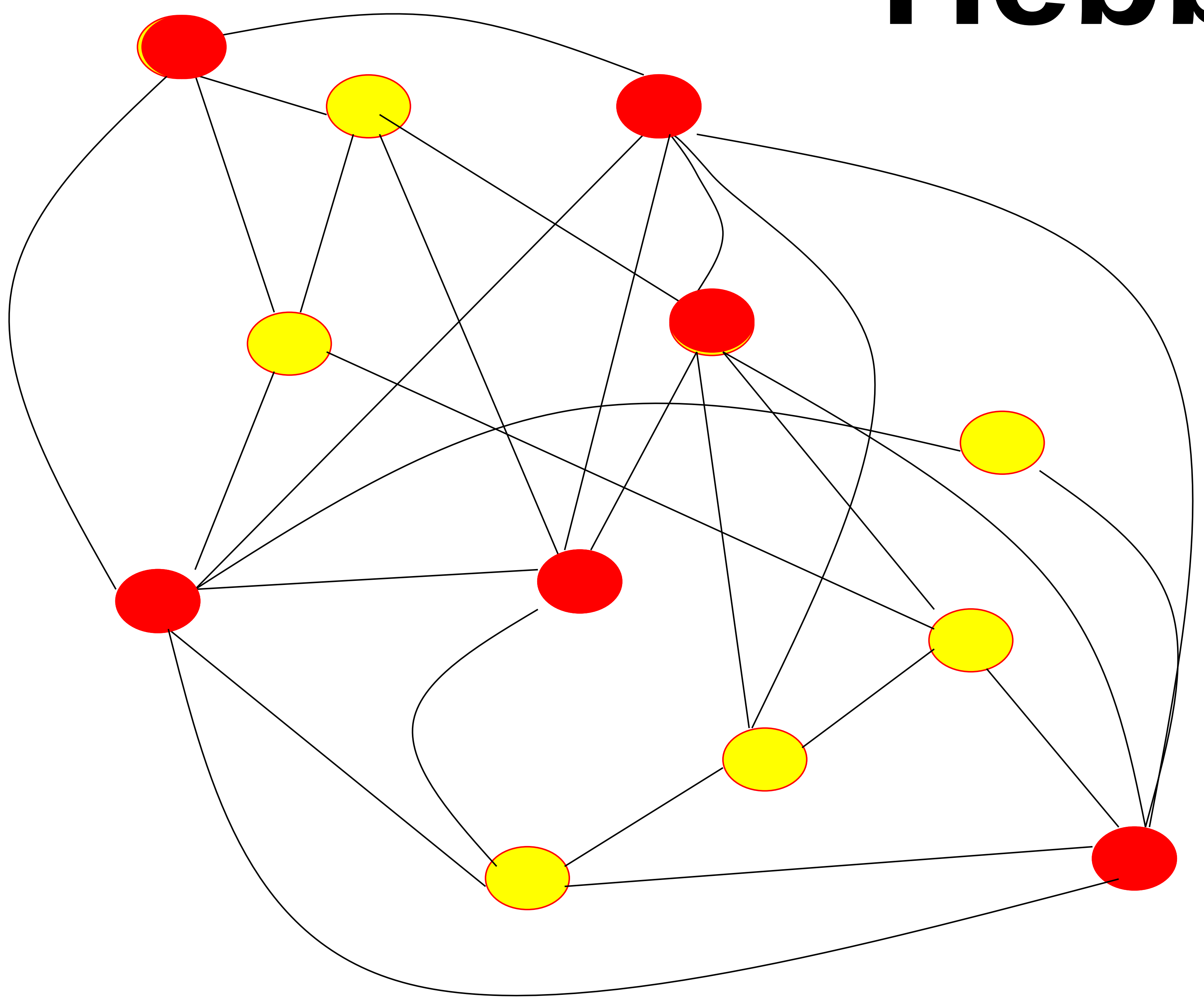
When an axon of cell **j** repeatedly or persistently takes part in firing cell **i**, then j's efficiency as one of the cells firing i is increased

Hebb, 1949

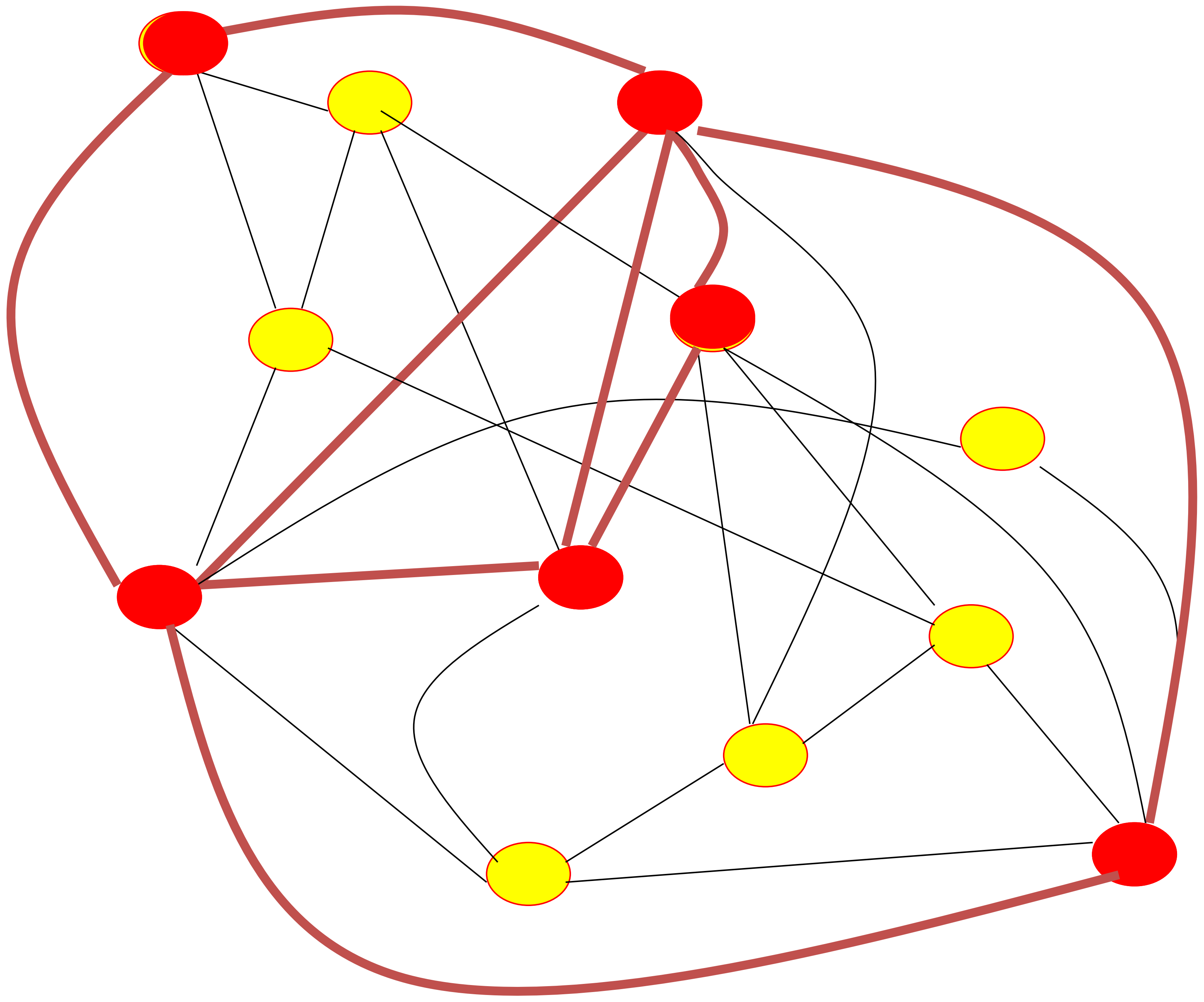
- local rule
- simultaneously active (correlations)

6.1 Synaptic plasticity: Hebbian Learning

Hebbian Learning



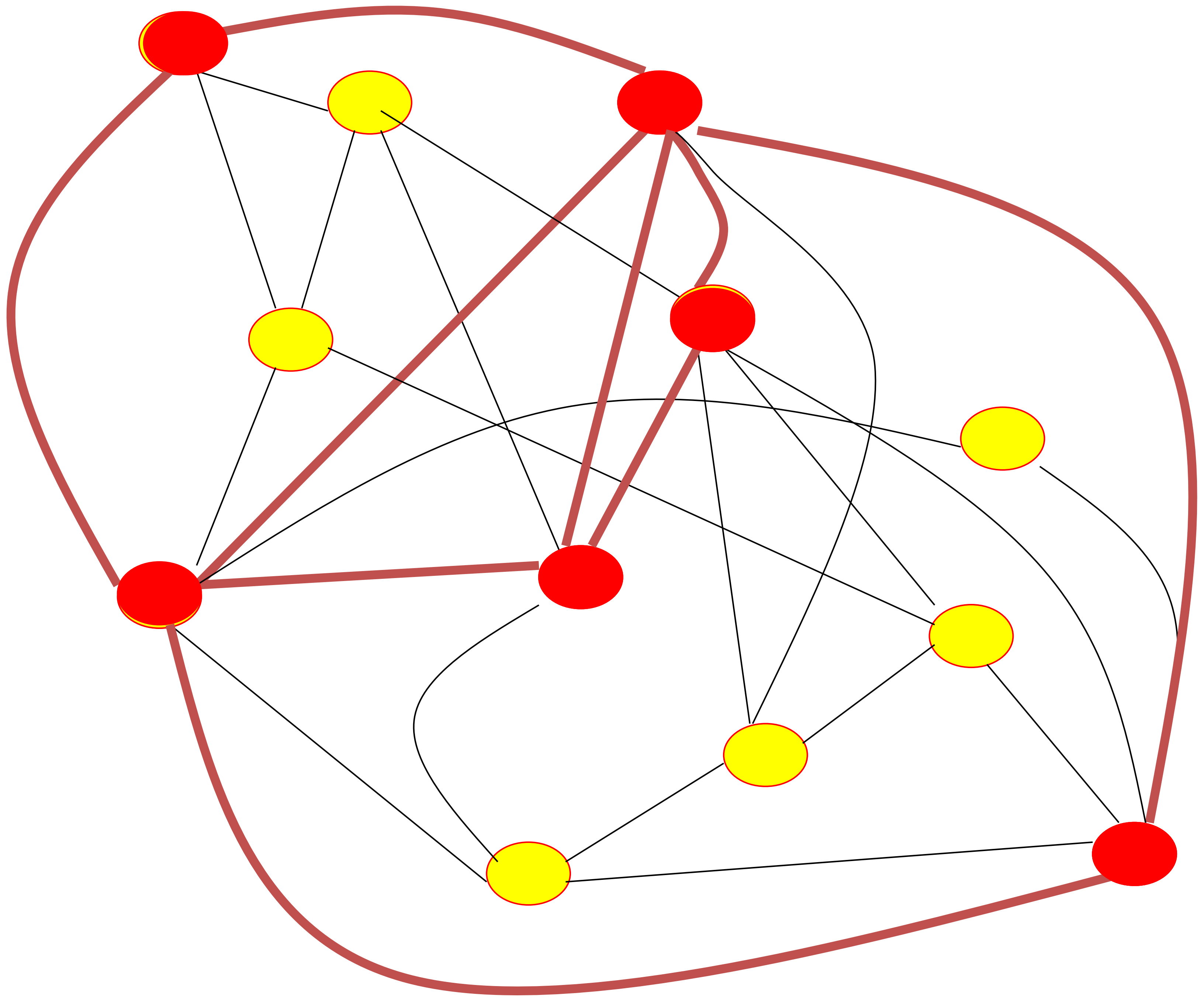
6.1 Synaptic plasticity: Hebbian Learning



item memorized

6.1 Synaptic plasticity: Hebbian Learning

Recall:
Partial info



item recalled

6.1 Synaptic plasticity

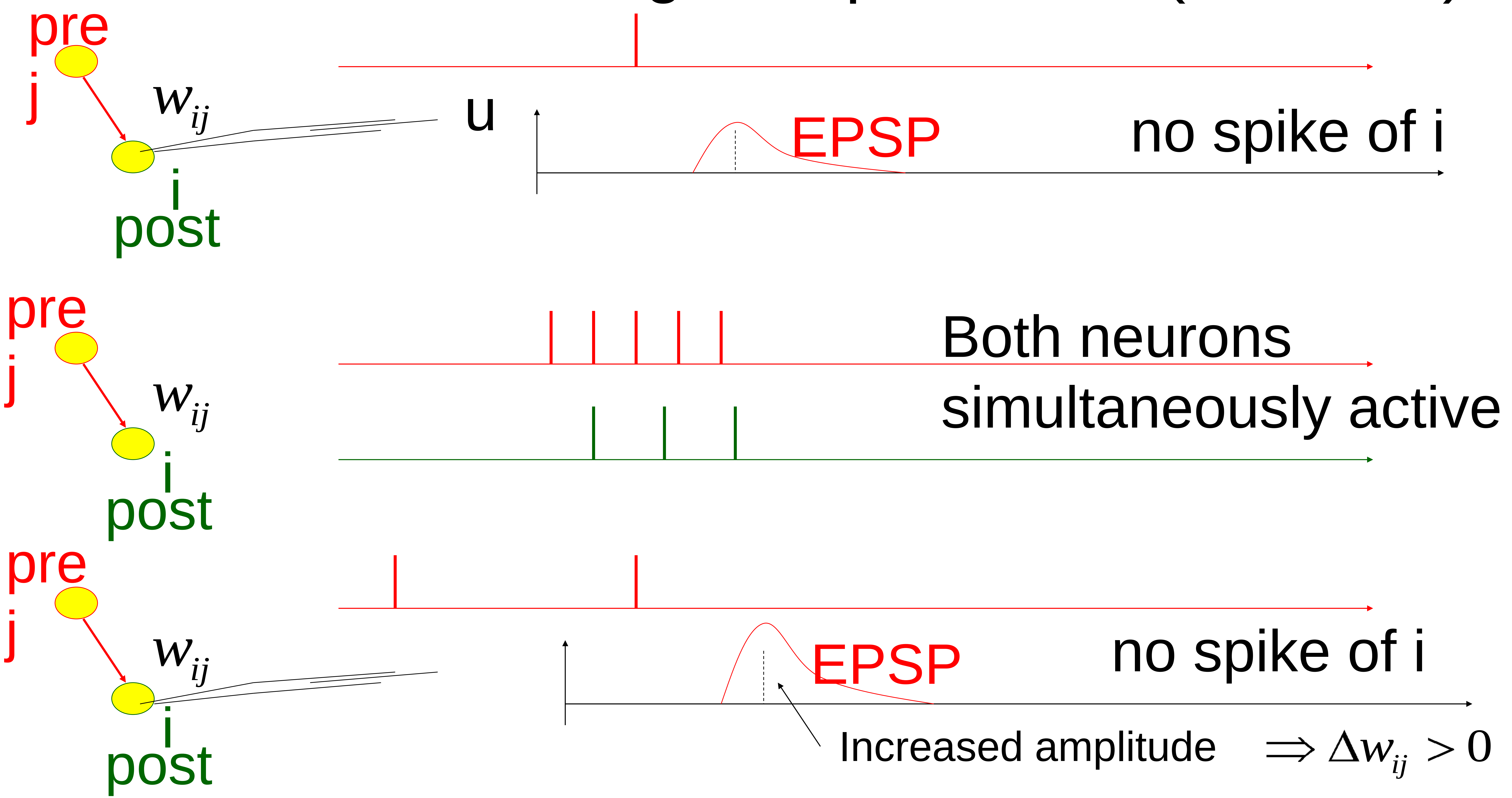
-Hebbian Learning

- Experiments on synaptic plasticity

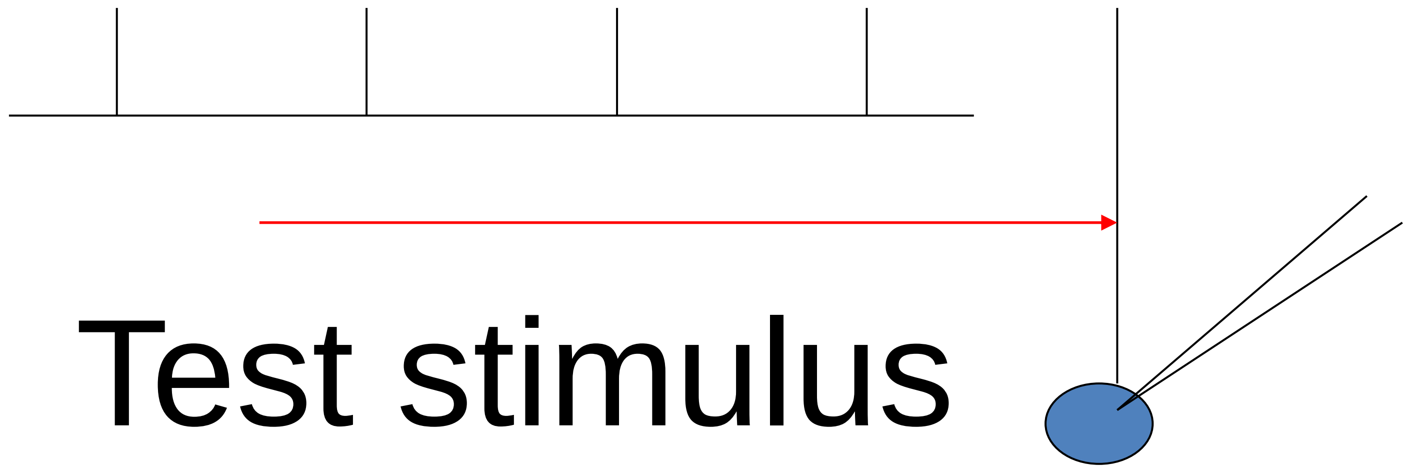
-Formulations of Hebbian Learning

6.1 Synaptic plasticity

Hebbian Learning in experiments (schematic)

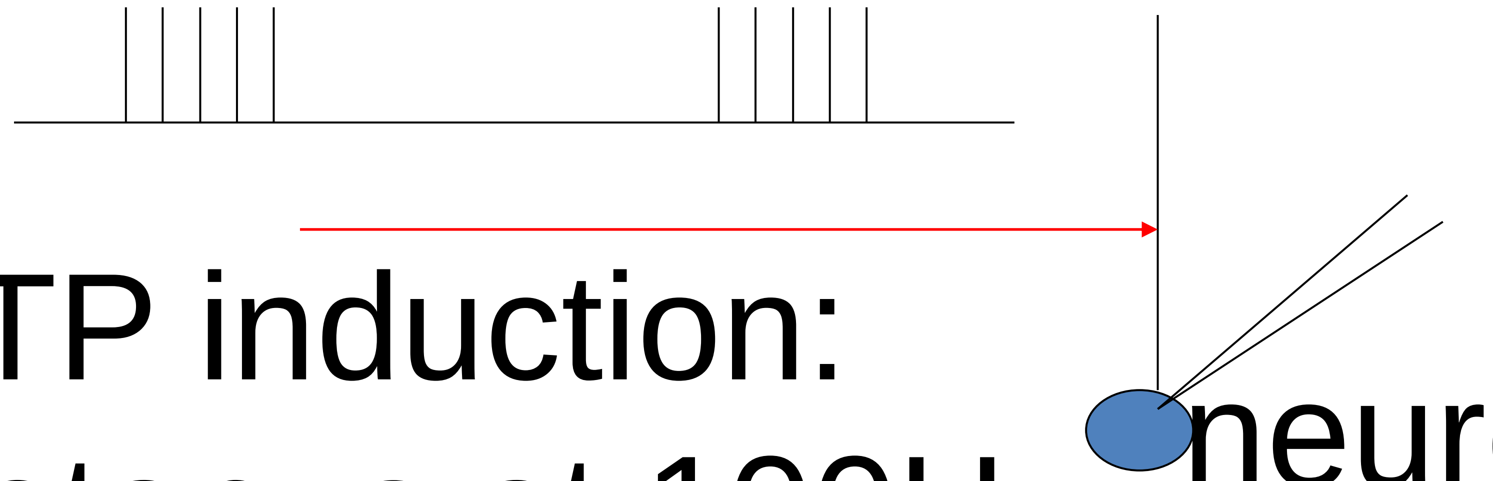


Classical paradigm of LTP induction – pairing



Test stimulus
At 0.1 Hz

neuron at -70mV



LTP induction:
tetanus at 100Hz

neuron depolarized
to -40mV

Standard LTP
PAIRING experiment

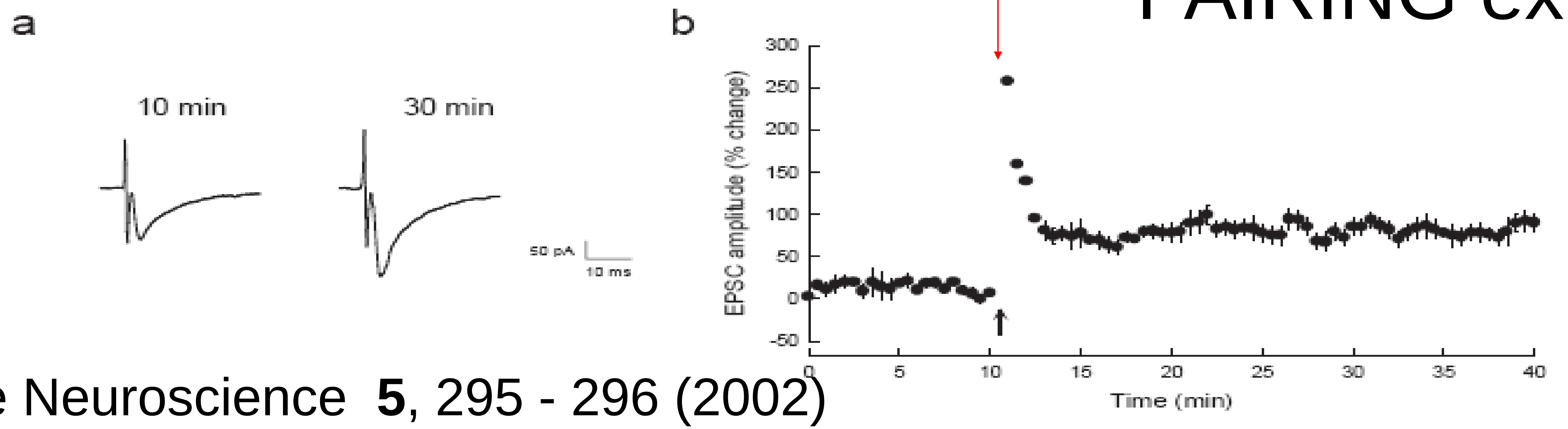
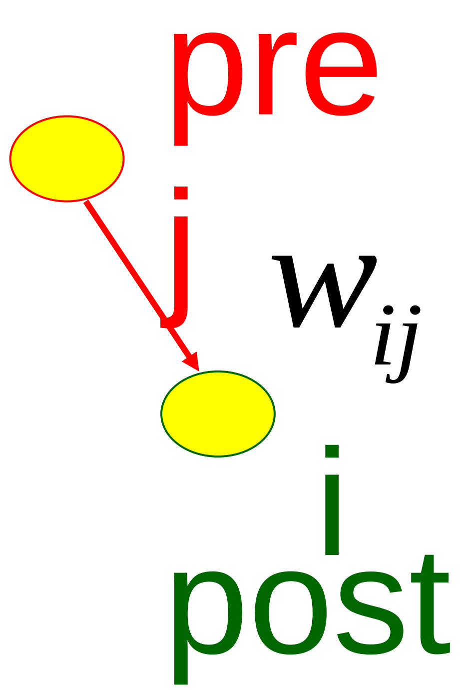
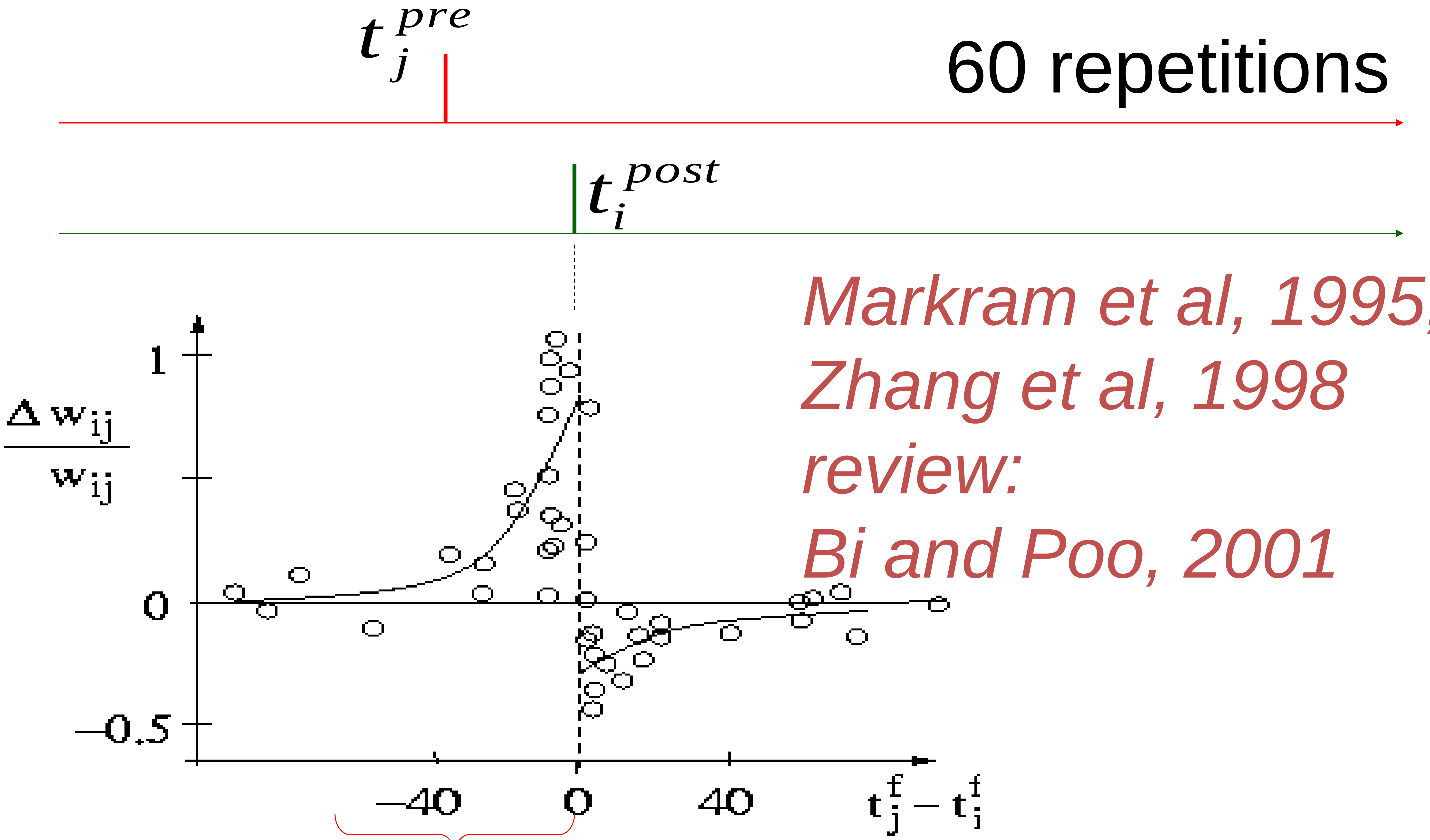


Fig. from Nature Neuroscience **5**, 295 - 296 (2002)
D. S.F. Ling, … & Todd C. Sacktor
See also: Bliss and Lomo (1973), Artola, Brocher, Singer (1990), Bliss and Collingridge (1993)

Spike-timing dependent plasticity (STDP)





60 repetitions

Markram et al, 1995,1997
Zhang et al, 1998
review:
Bi and Poo, 2001

Pre
before post

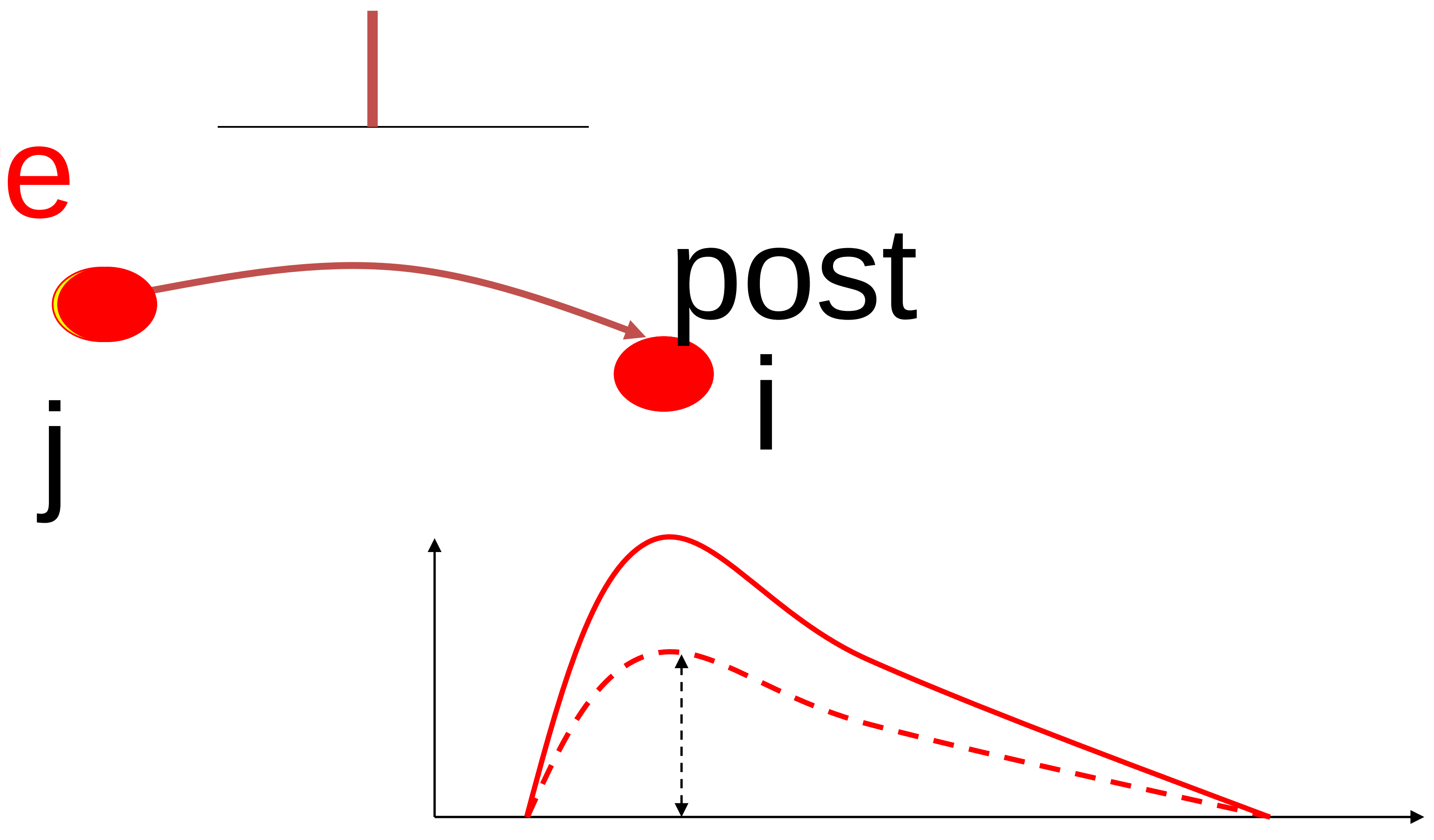
6.1 Classification of synaptic changes

Induction of changes

- fast (if stimulated appropriately)
- slow (homeostasis)

Persistence of changes

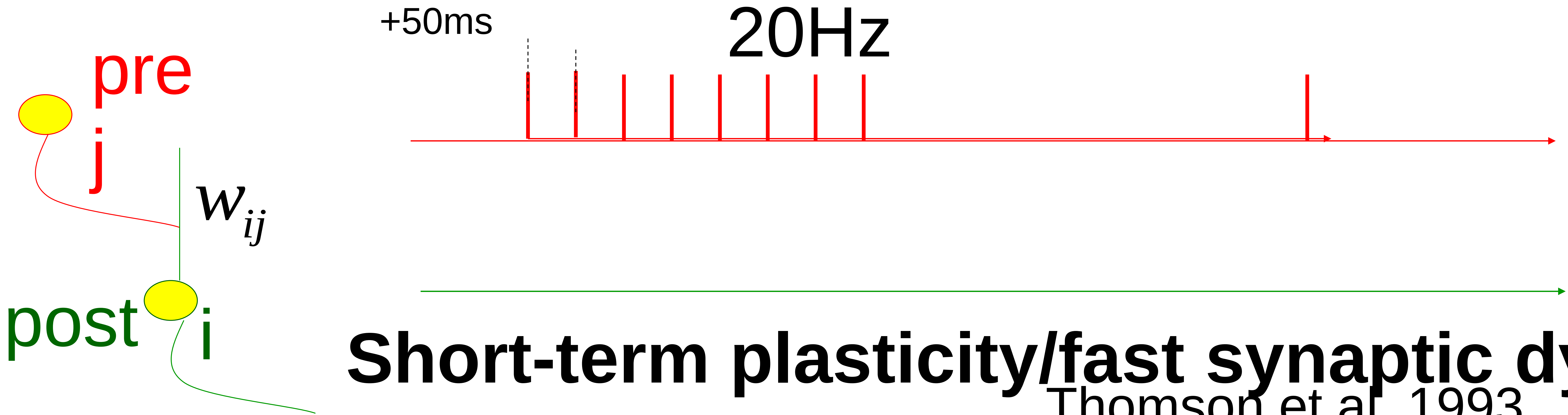
- long (LTP/LTD)
- short (short-term plasticity)



Functionality

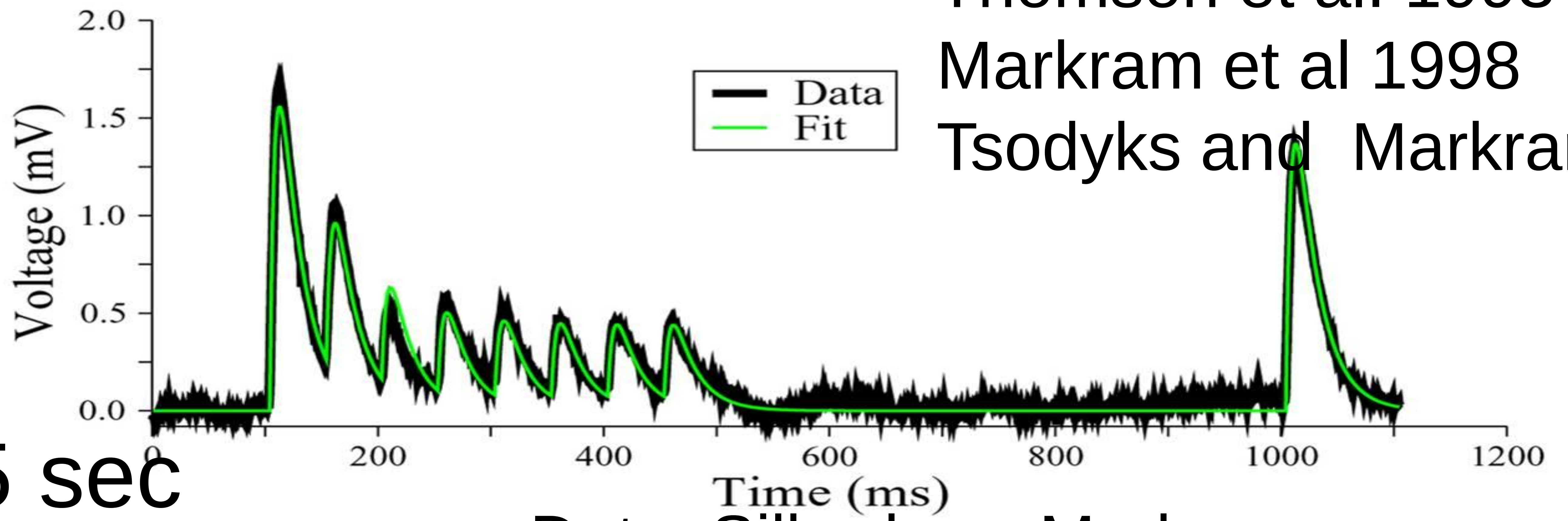
- useful for learning a new behavior
- useful for development (wiring for receptive field development)
- useful for activity control in network
- useful for coding

6.1 Classification of synaptic changes: Short-term plasticity



Short-term plasticity/fast synaptic dynamic

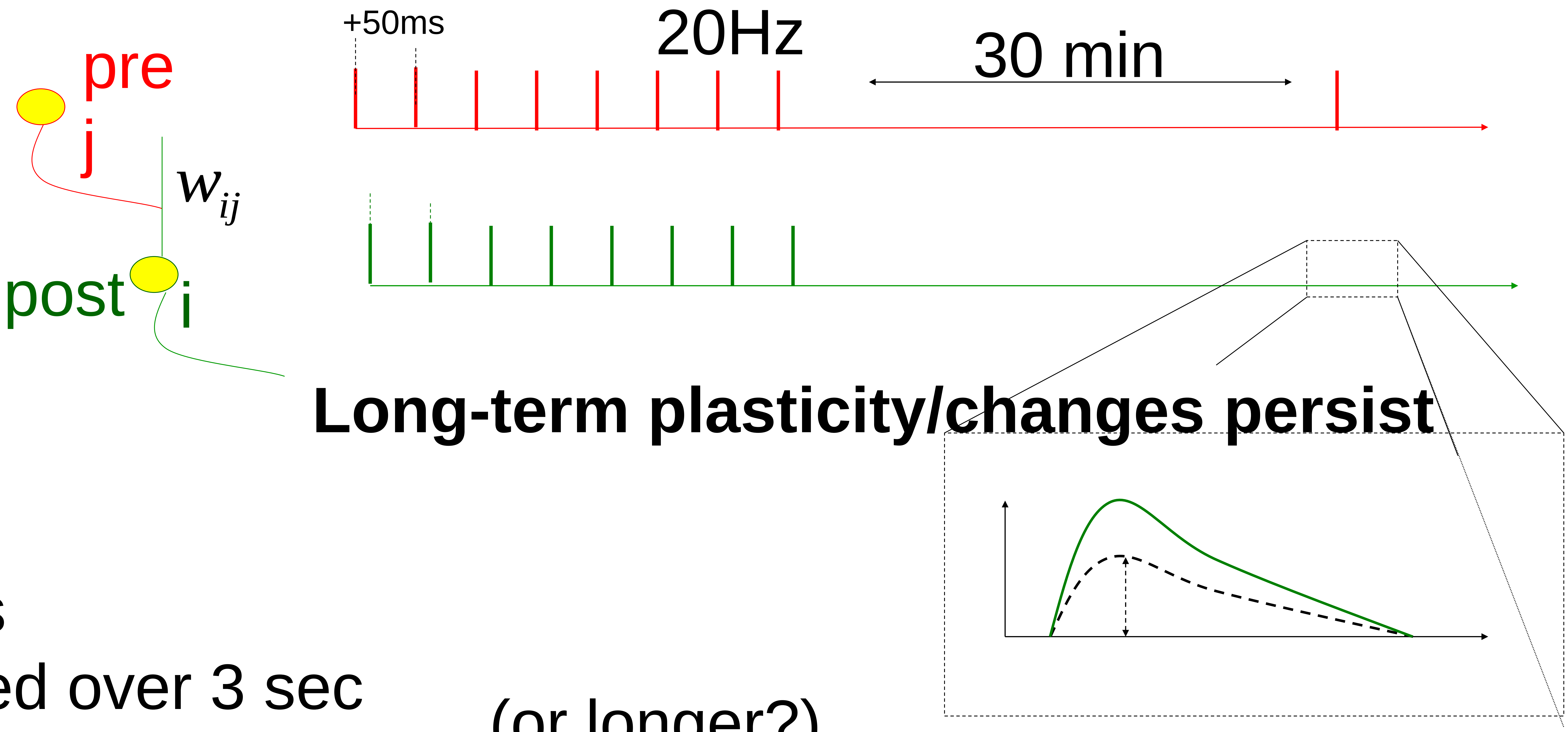
Thomson et al. 1993
Markram et al 1998
Tsodyks and Markram 1997



Data: Silberberg,Markram
Fit: Richardson (Tsodyks-Markram model)

Changes
- induced over 0.5 sec
- recover over 1 sec

6.1 Classification of synaptic changes: Long-term plasticity

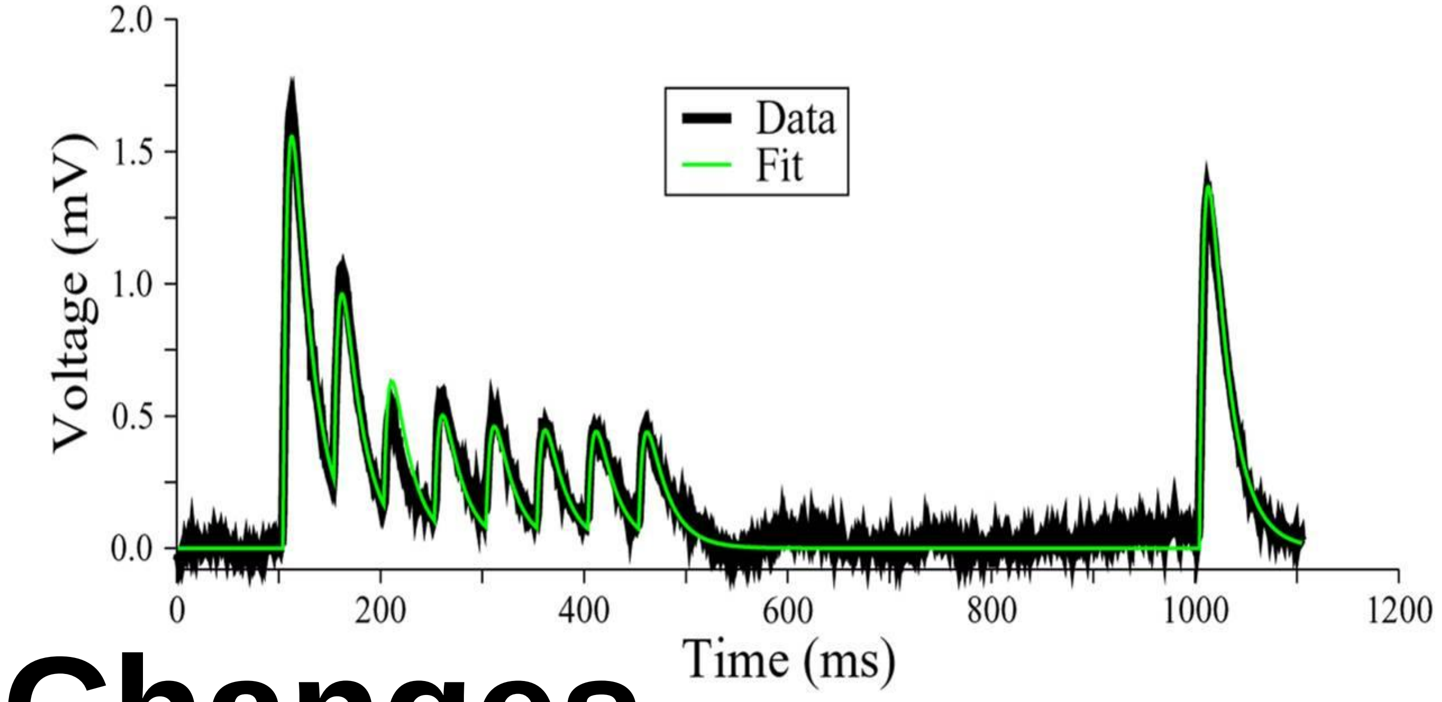


Long-term plasticity/changes persist

Changes
- induced over 3 sec
- persist over 1 – 10 hours (or longer?)

6.1 Classification of synaptic changes

Short-Term vs/ Long-Term



Changes

- induced over 0.1-0.5 sec
- recover over 1 sec

Protocol

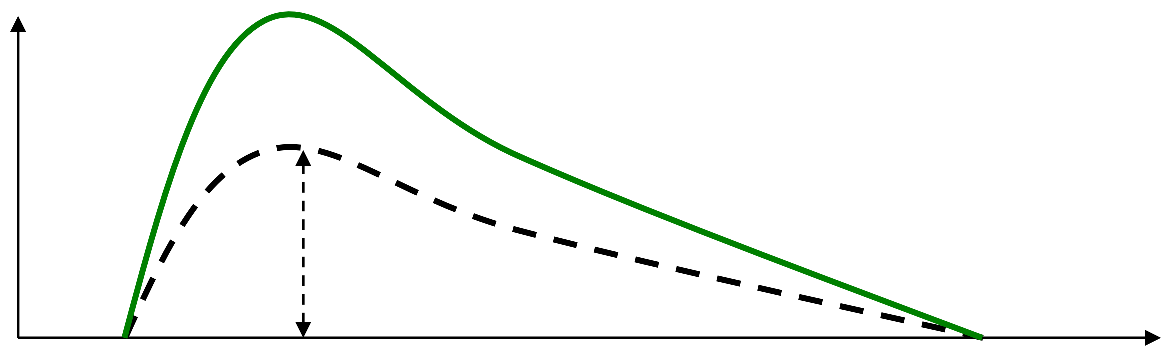
- presynaptic spikes

Model

- well established

(Tosdyks, Senn, Markram)

LTP/LTD/Hebb



Changes

- induced over 0.5-5sec
- remains over hours

Protocol

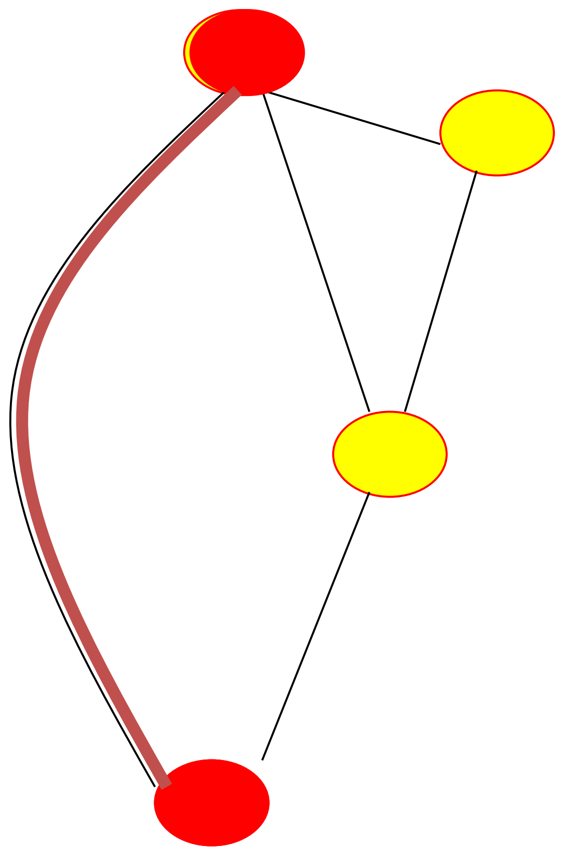
-presynaptic spikes + …

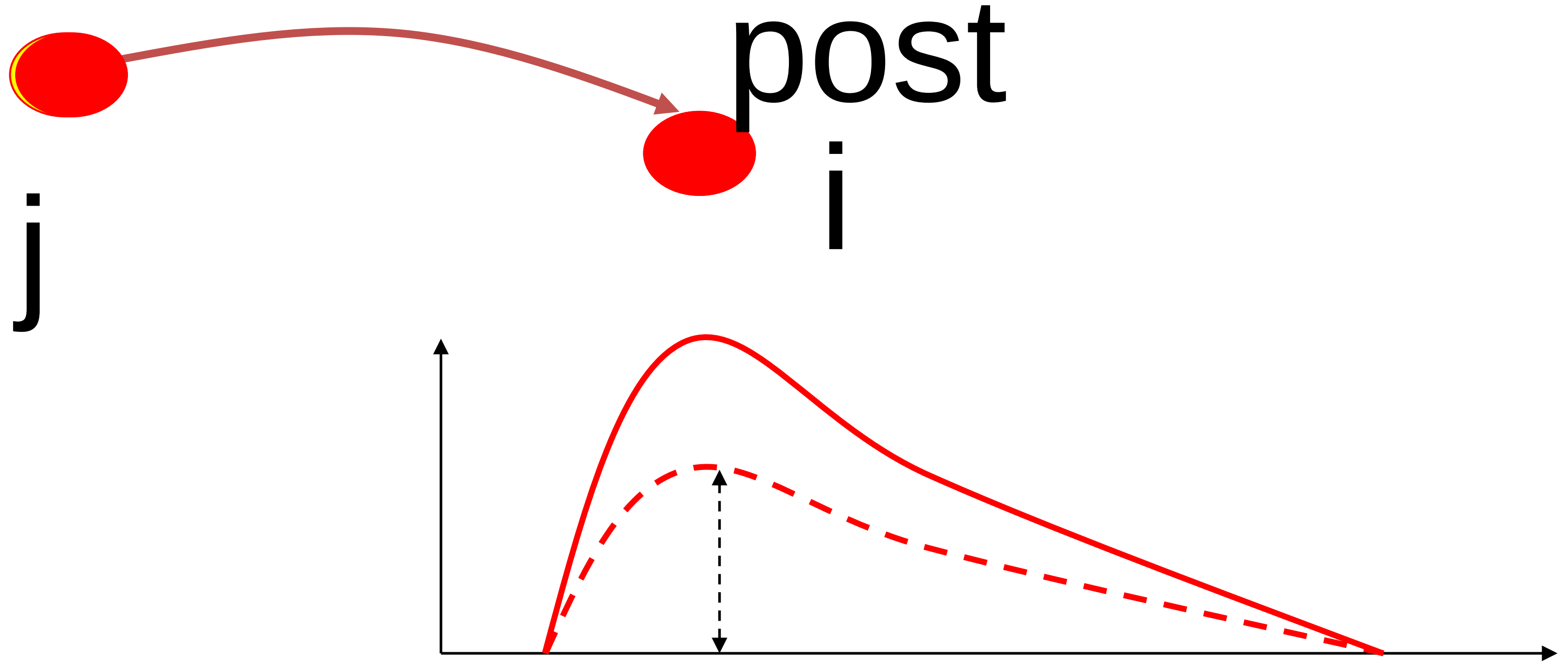
Model

- we will see

6.1 Classification of synaptic changes: unsupervised learning

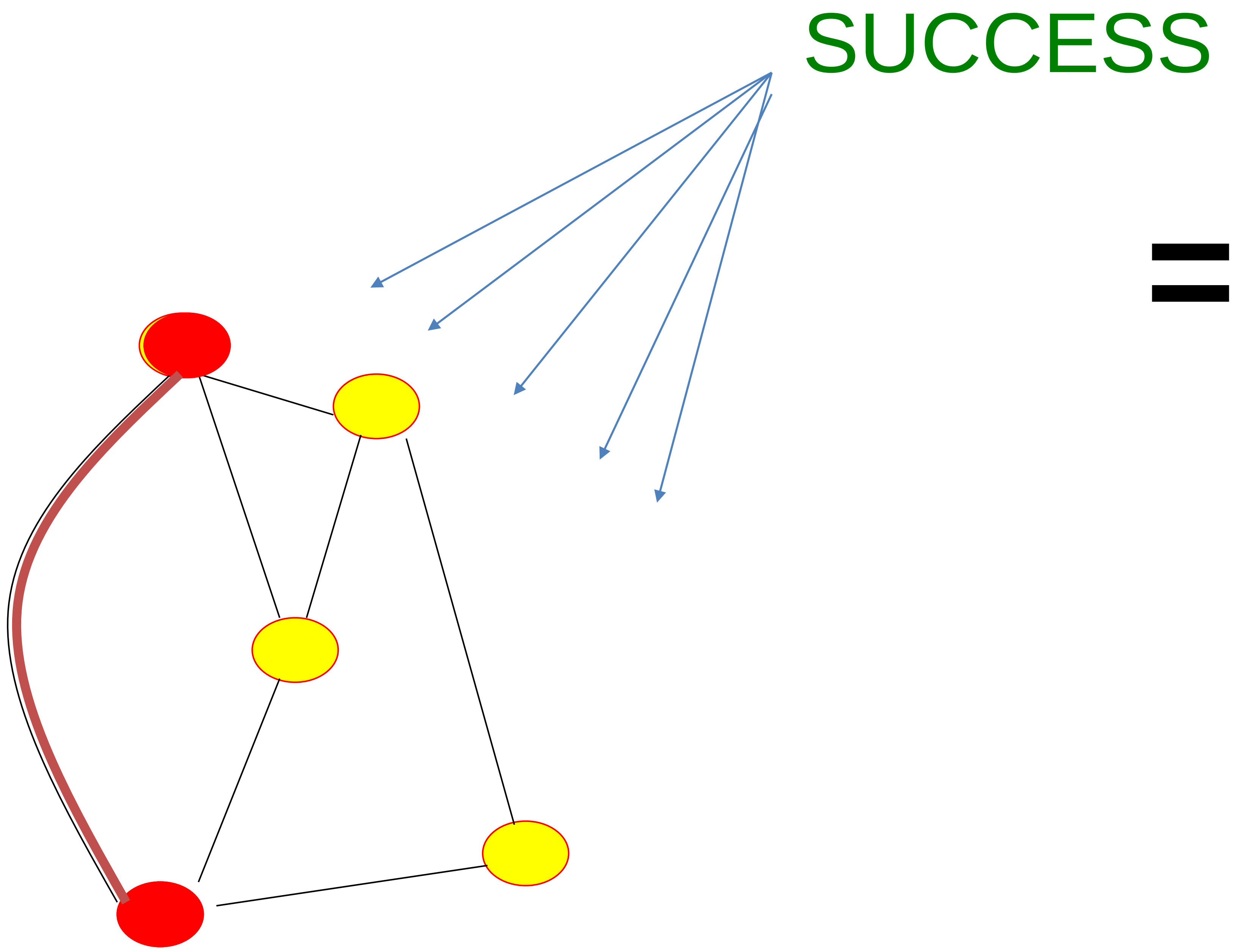
Hebbian Learning
= unsupervised learning





$w_{ij}\,\varepsilon\,(\,-t_j^f$

$$\Delta w_{ij} \propto F(pre, post)$$



Reinforcement Learning
= reward + Hebb

$$\Delta w_{ij} \propto F(pre, post, SUCCESS)$$

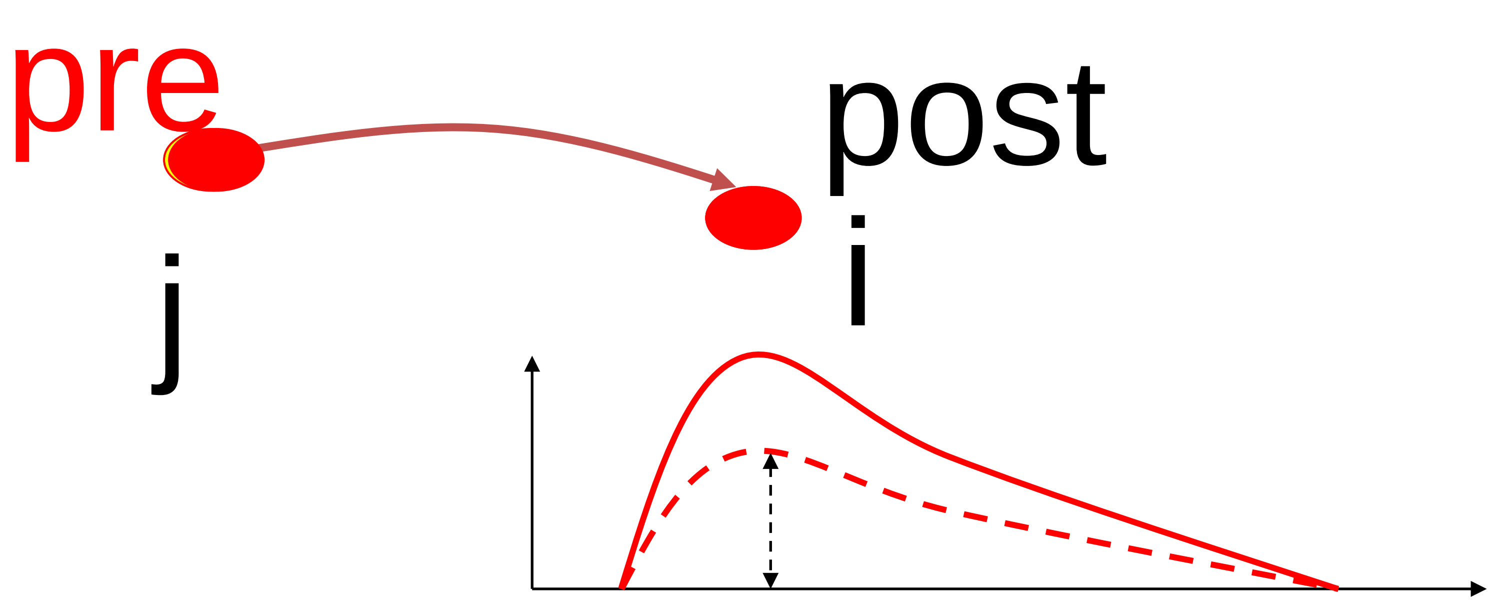
local global

6.1 Classification of synaptic changes

unsupervised vs reinforcement

LTP/LTD/Hebb
Theoretical concept

- passive changes
- exploit statistical correlations

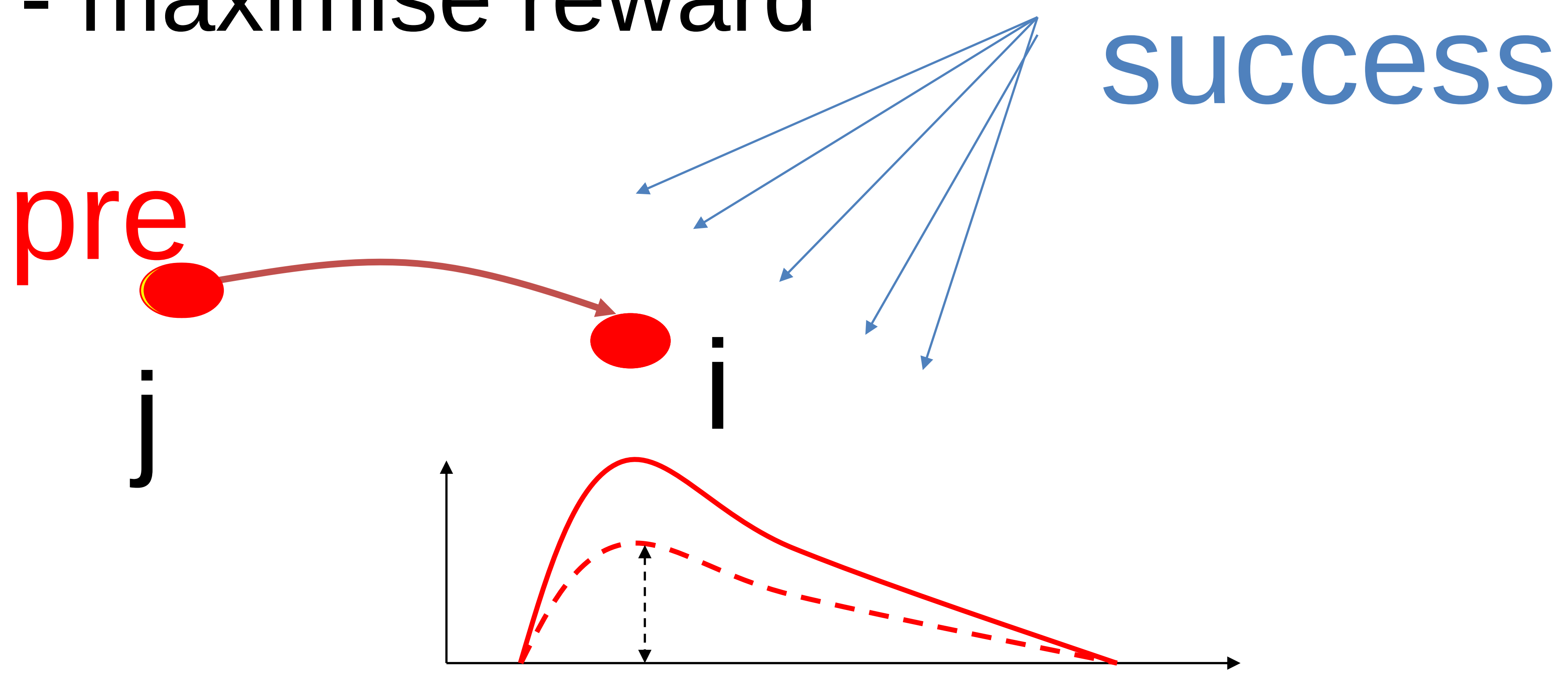


Functionality

-useful for development
(wiring for receptive fields)

Reinforcement Learning
Theoretical concept

- conditioned changes
- maximise reward



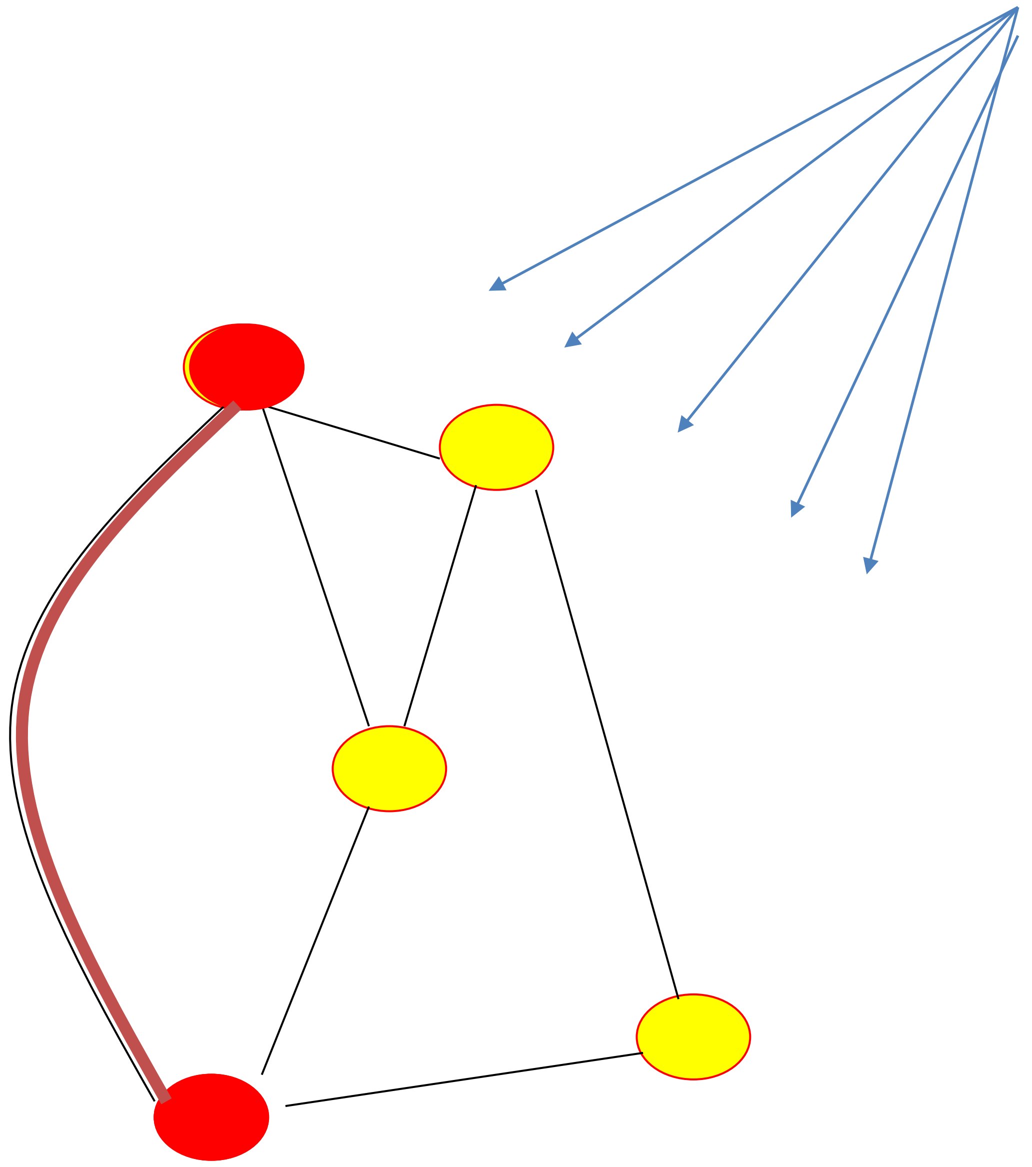
Functionality

- useful for learning
a new behavior

Modulated Hebbian Learning

= neuromodulator + **Hebb**

Neuromodulator: Interestingness, surprise; attention; novelty



$$\Delta w_{ij} \propto F(pre, post, MOD)$$

local global

Quiz 6.1: Synaptic Plasticity and Learning Rules

Long-term potentiation

[ ] has an acronym LTP
[ ] takes more than 10 minutes to induce
[ ] lasts more than 30 minutes
[ ] depends on presynaptic activity, but not on state of postsynaptic neuron

Short-term potentiation

[ ] has an acronym STP
[ ] takes more than 10 minutes to induce
[ ] lasts more than 30 minutes
[ ] depends on presynaptic activity, but not on state of postsynaptic neuron

Learning rules

[ ] Hebbian learning depends on presynaptic activity and on state of postsynaptic neuron
[ ] Reinforcement learning depends on neuromodulators such as dopamine indicating reward

Week 6: Hebbian Learning and Associative Memory

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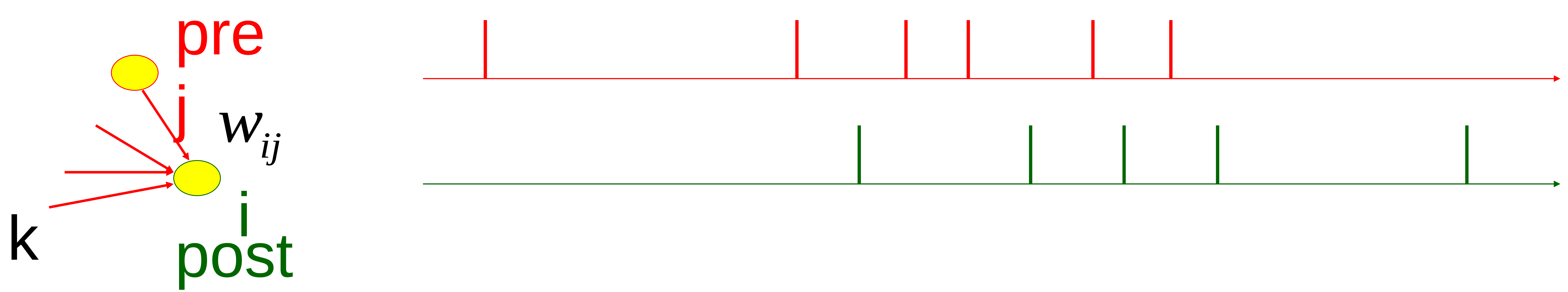
6.2 Models of synaptic plasticity
- Hebbian learning rules

6.3 Hopfield Model
- probabilistic
- energy landscape

6.4 Attractor memories

6.2 Hebbian Learning (rate models)



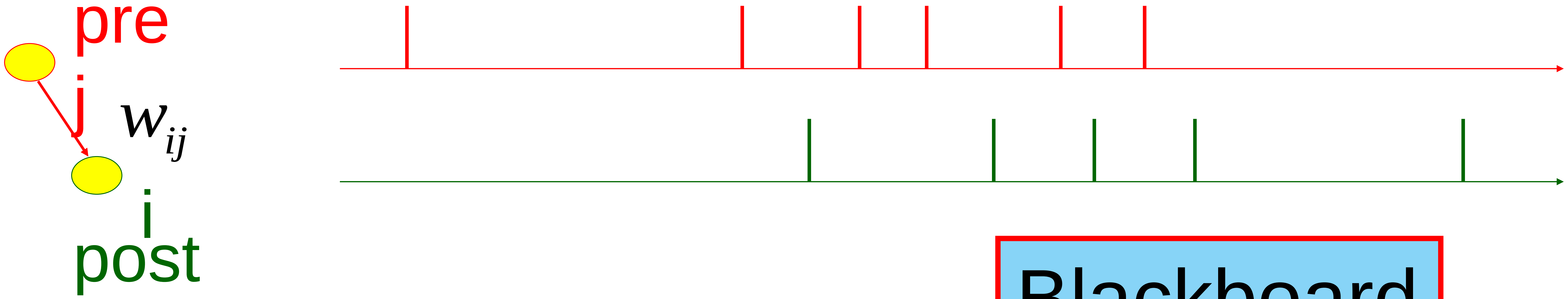
When an axon of cell j repeatedly or persistently takes part in firing cell i, then j's efficiency as one of the cells firing i is increased

Hebb, 1949

- local rule
- simultaneously active (correlations)

Rate model:
active = high rate = many spikes per second

6.2 Rate-based Hebbian Learning

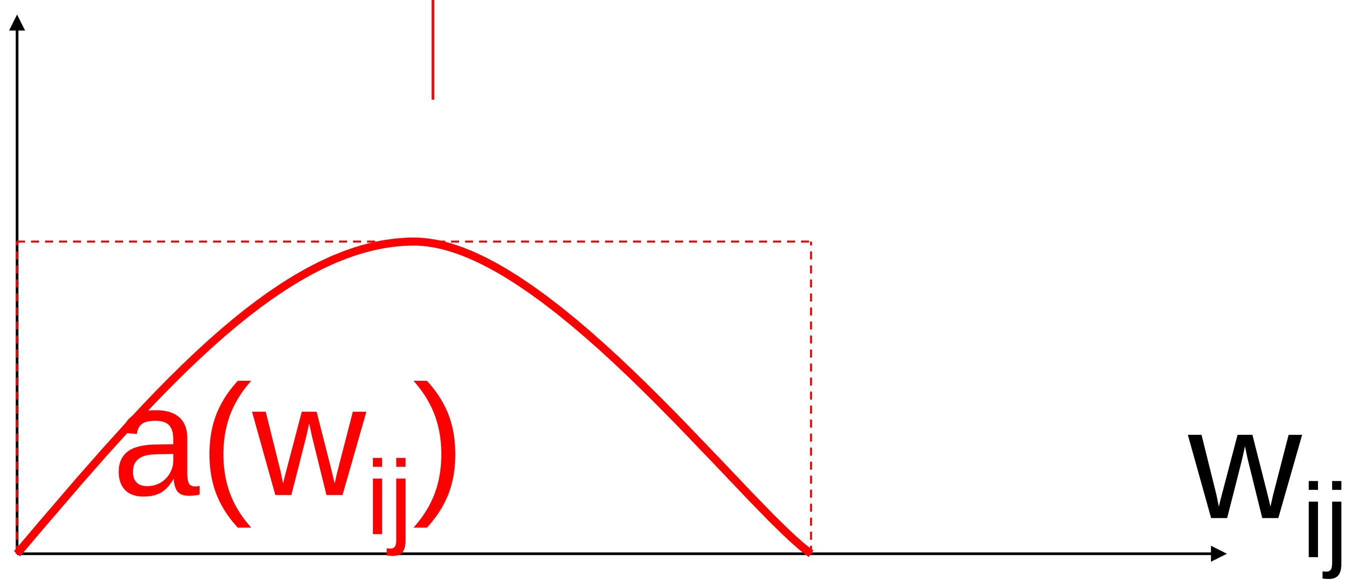


Blackboard

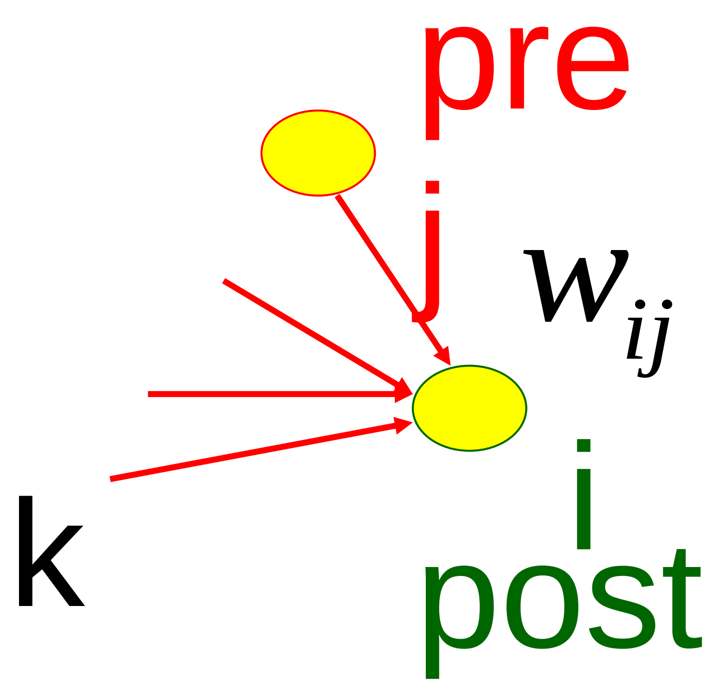
$$\frac{d}{dt} w_{ij} = F(w_{ij}; \nu_j^{pre}, \nu_i^{post})$$

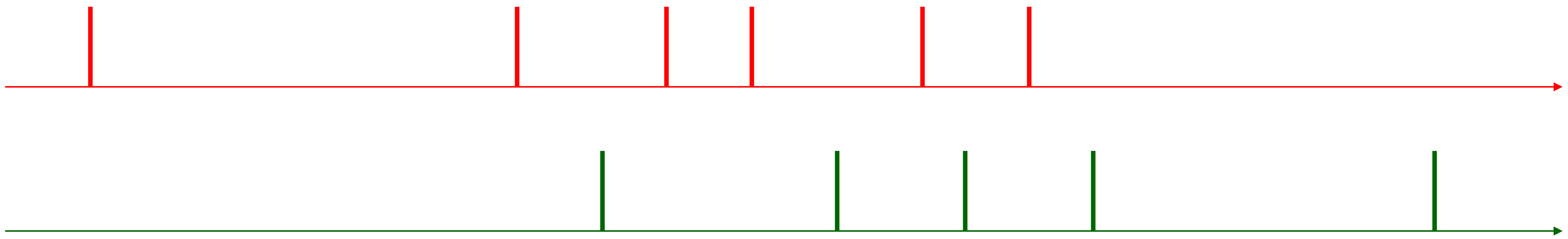
$$\frac{d}{dt} w_{ij} = a_0 + a_1^{pre} \nu_j^{pre} + a_1^{post} \nu_i^{post} + a_2^{corr} \nu_j^{pre} \nu_i^{post} + \dots$$

$a = a(w_{ij})$



6.2 Rate-based Hebbian Learning



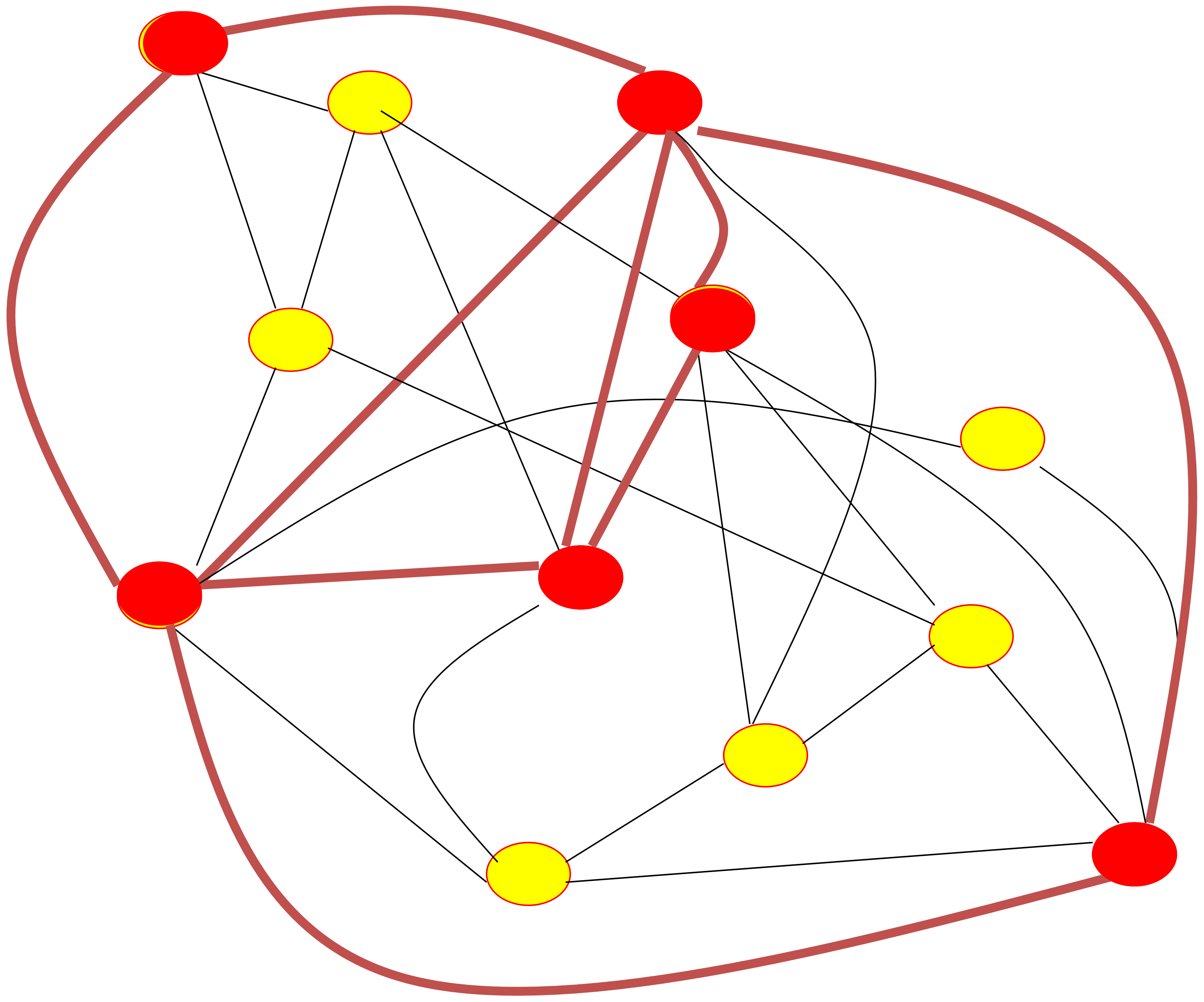


pre	on	off	on	off
post	on	on	off	off
	+	0	0	0

$$\frac{d}{dt} w_{ij} = a_2^{corr} \nu_j^{pre} \nu_i^{post}$$

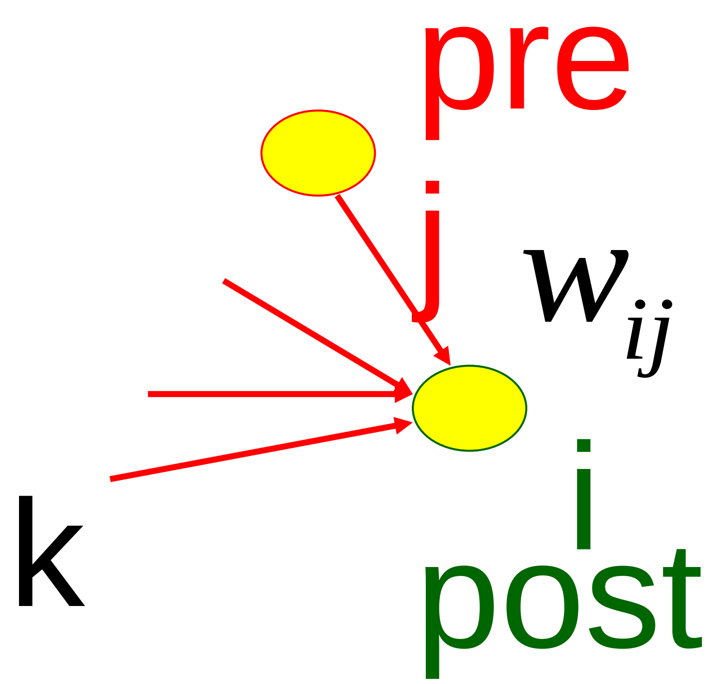
Hebbian Learning

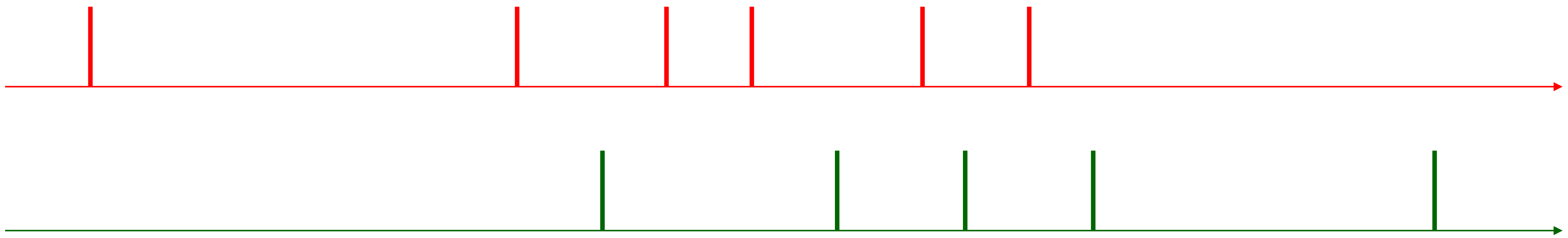
Recall:
Partial info



item recalled

6.2 Rate-based Hebbian Learning

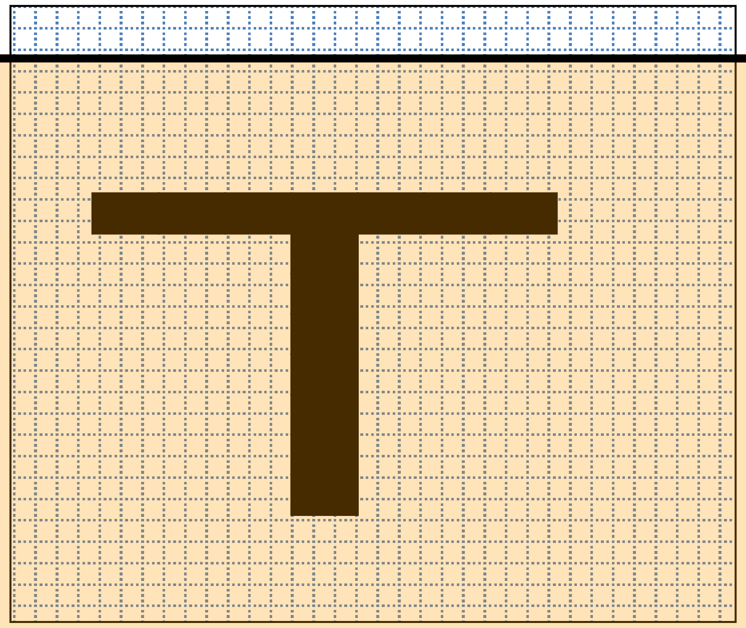


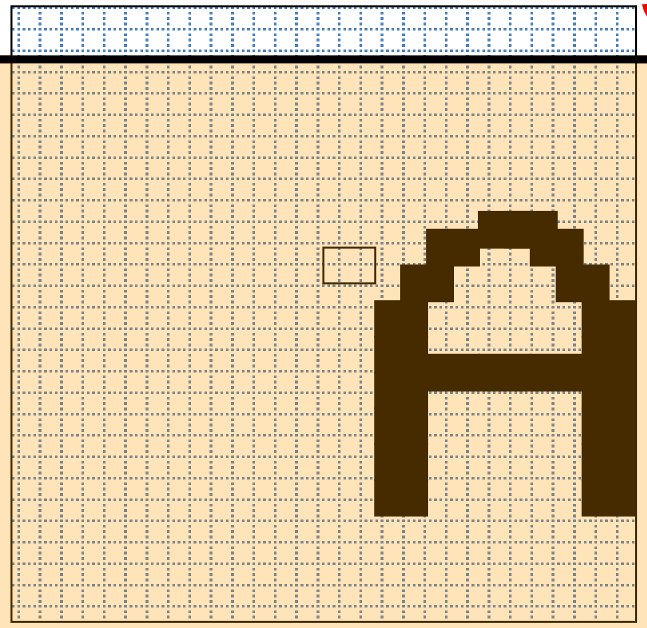


pre	on	off	on	off
post	on	on	off	off
$\frac{d}{dt} w_{ij} = a_2^{corr} \nu_j^{pre} \nu_i^{post}$	+	0	0	0
$\frac{d}{dt} w_{ij} = a_2^{corr} \nu_j^{pre} \nu_i^{post} - c$	+	-	-	-
$\frac{d}{dt} w_{ij} = a_2^{corr} \nu_j^{pre} (\nu_i^{post} - \vartheta)$	+	0	-	0
$\frac{d}{dt} w_{ij} = a_2^{corr} (\nu_j^{pre} - \vartheta)(\nu_i^{post} - \vartheta)$	+	-	-	+

Exercise 1 now: learning of prototypes

Prototype $\vec{p}^1$





Prototype $\vec{p}^2$

interactions

(1) $$w_{ij} = \sum_{\mu} p_i^{\mu} p_j^{\mu}$$

Sum over all prototypes

a) Show that (1) corresponds to a rate learning rule

(2) $$\frac{d}{dt} w_{ij} = a_2^{corr} (\nu_j^{pre} - \vartheta)(\nu_i^{post} - \vartheta)$$

Next lecture 10:15

Assume that weights are zero at the beginning;

Each pattern is presented (enforced) during 0.5 sec (One after the other).

note that $p_j^{\mu} = \pm 1$ but $\nu_j \geq 0$

b) Compare with: $\frac{d}{dt} w_{ij} = a_0 + a_1^{pre} \nu_j^{pre} + a_1^{post} \nu_i^{post} + a_2^{corr} \nu_j^{pre} \nu_i^{post} + \ldots$

c) Is this unsupervised learning?

The end