Computational Neuroscience: Neuronal Dynamics of Cognition

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

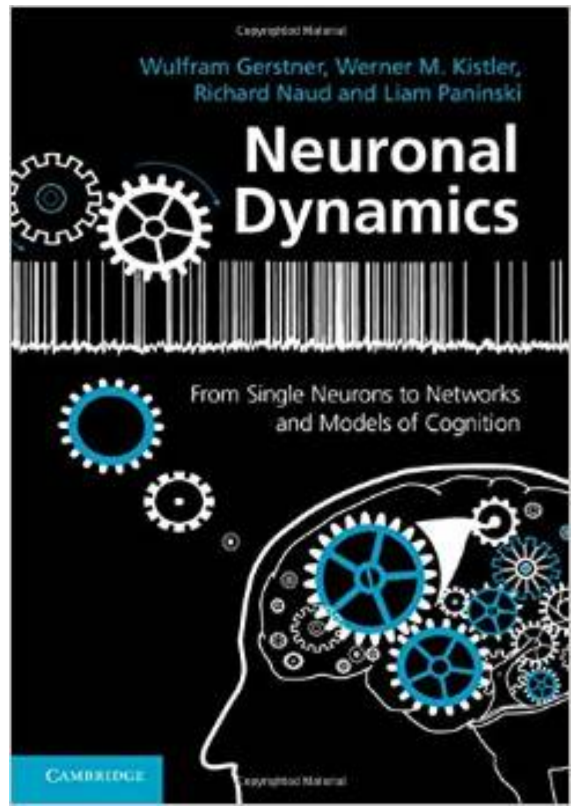
Synaptic Plasticity and Learning

Wulfram Gerstner

EPFL, Lausanne, Switzerland

Reading for plasticity:
NEURONAL DYNAMICS
- Ch. 19.1-19.3

Cambridge Univ. Press



1. Synaptic plasticity
motivation and aims

2. Classification of plasticity
- short-term vs. long-term
- unsupervised vs. reward modulated

3. Model of short-term plasticity

4. Models of long-term plasticity
- Hebbian learning rules
- Bienenstock-Cooper-Munro rule

5. Spike-Timing Models of plasticity

6. From spiking models to rate models

7. Triplet STDP model

8. Online learning of memories

1. Behavioral Learning – and Memory

Learning actions:

→ riding a bicycle

Remembering facts

→ previous president of the US

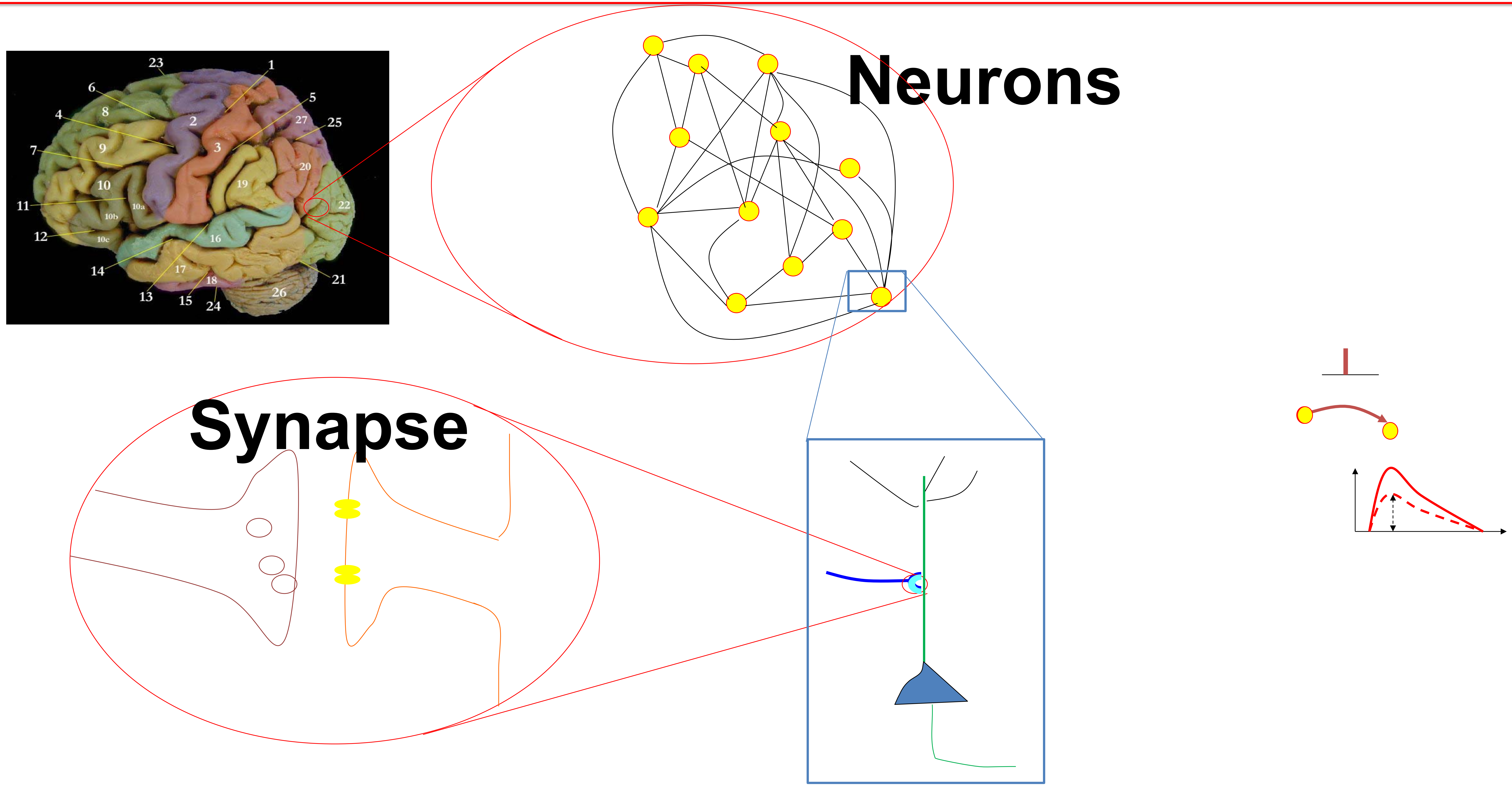
→ name of your mother

Remembering episodes

→ first day at EPFL

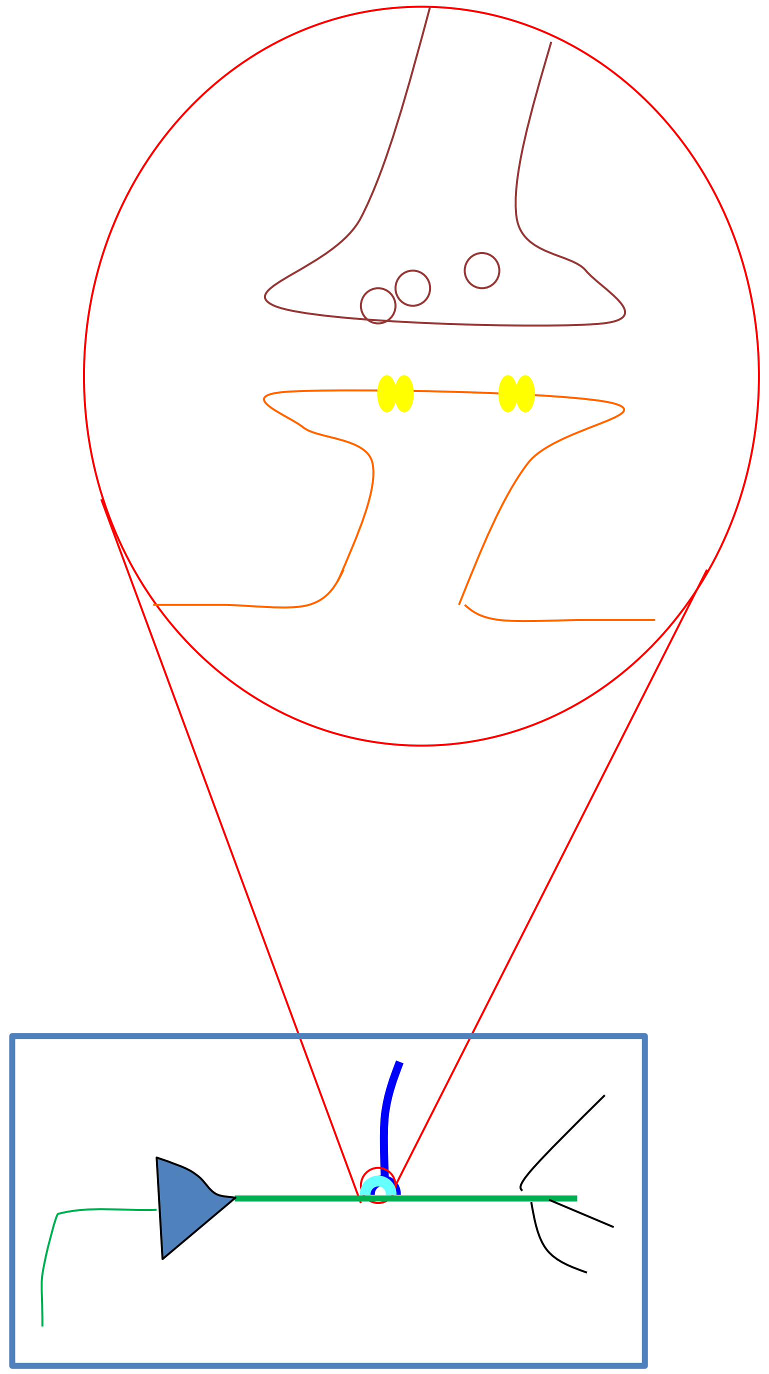
which parking spot?

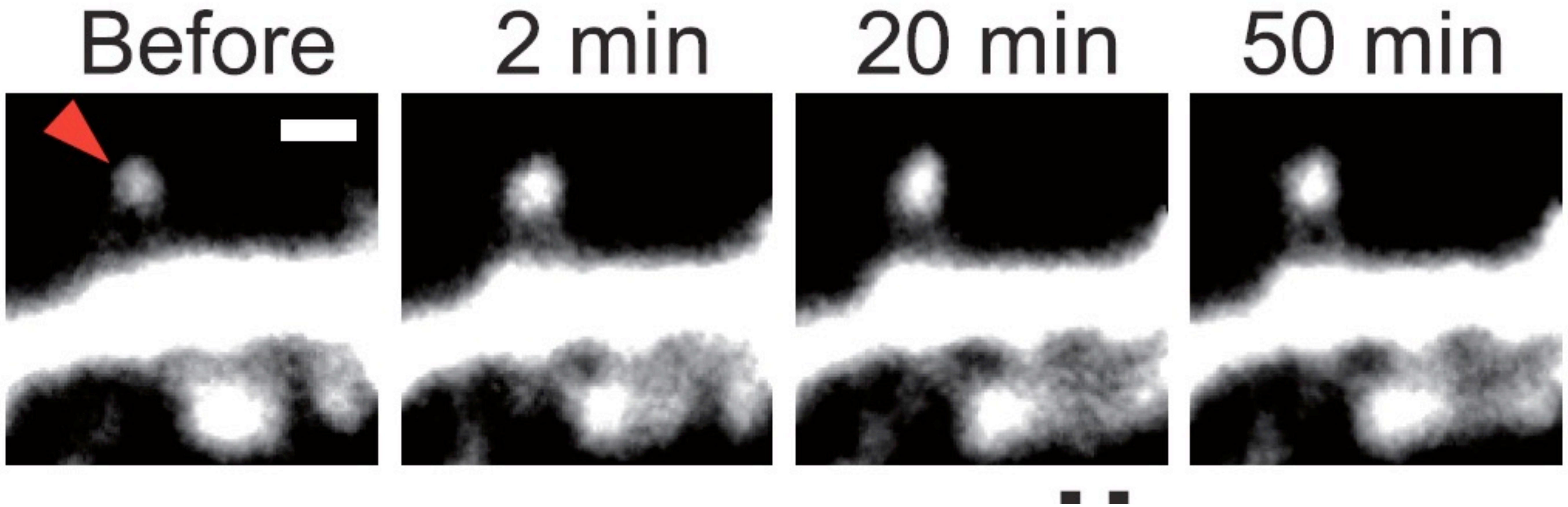
1. Behavioral Learning – and synaptic plasticity



Synaptic Plasticity =Change in Connection Strength

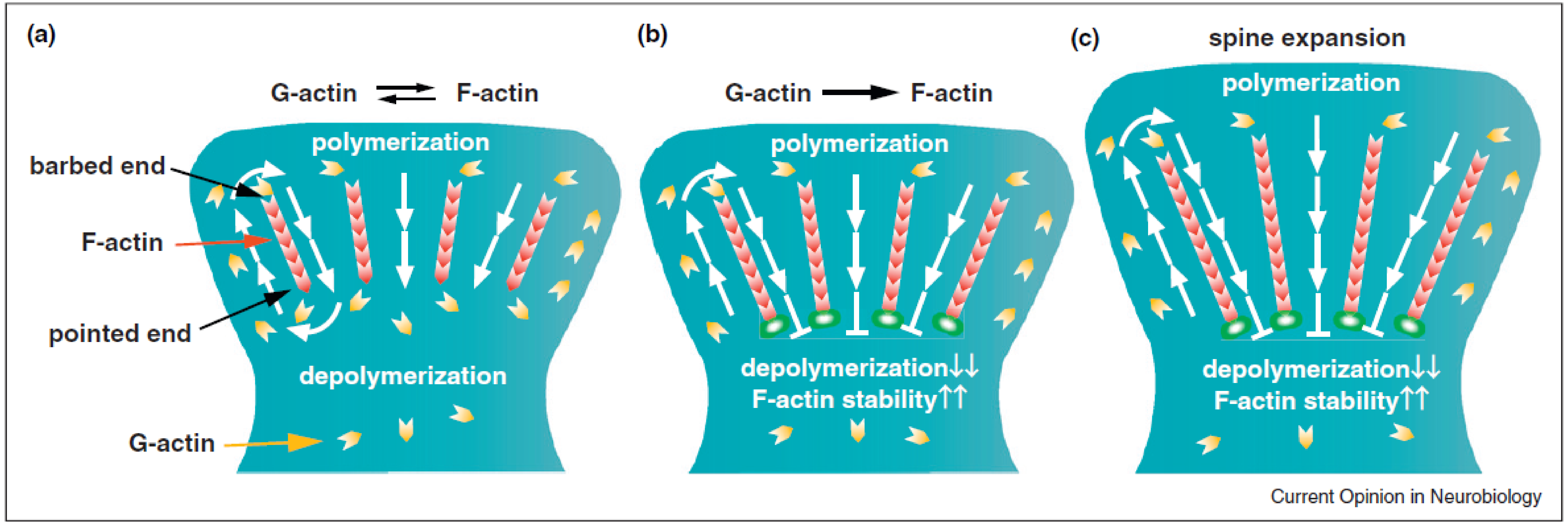
1. Synaptic plasticity – structural changes



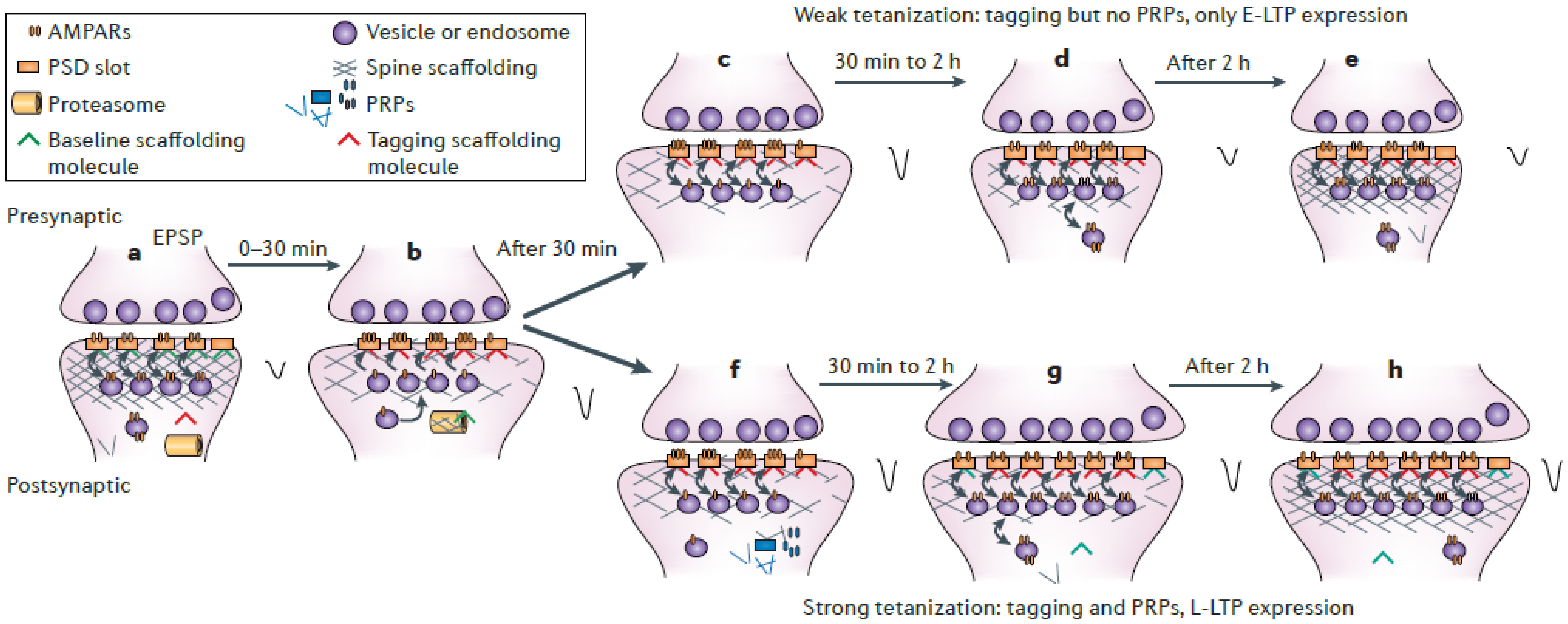


Yagishita et al.
Science, 2014

1. synaptic plasticity – molecular changes

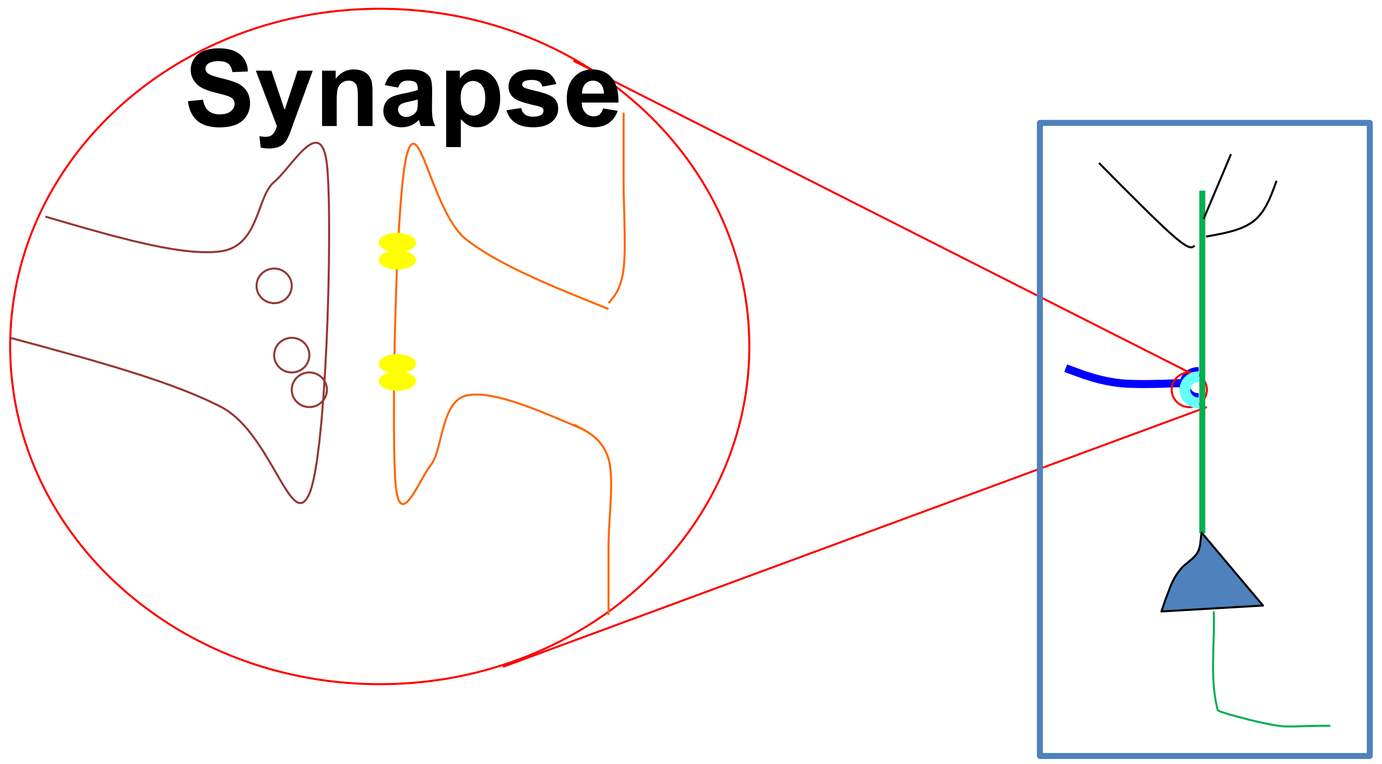


Bosch et al. 2012, Curr. Opinion Neurobiol.



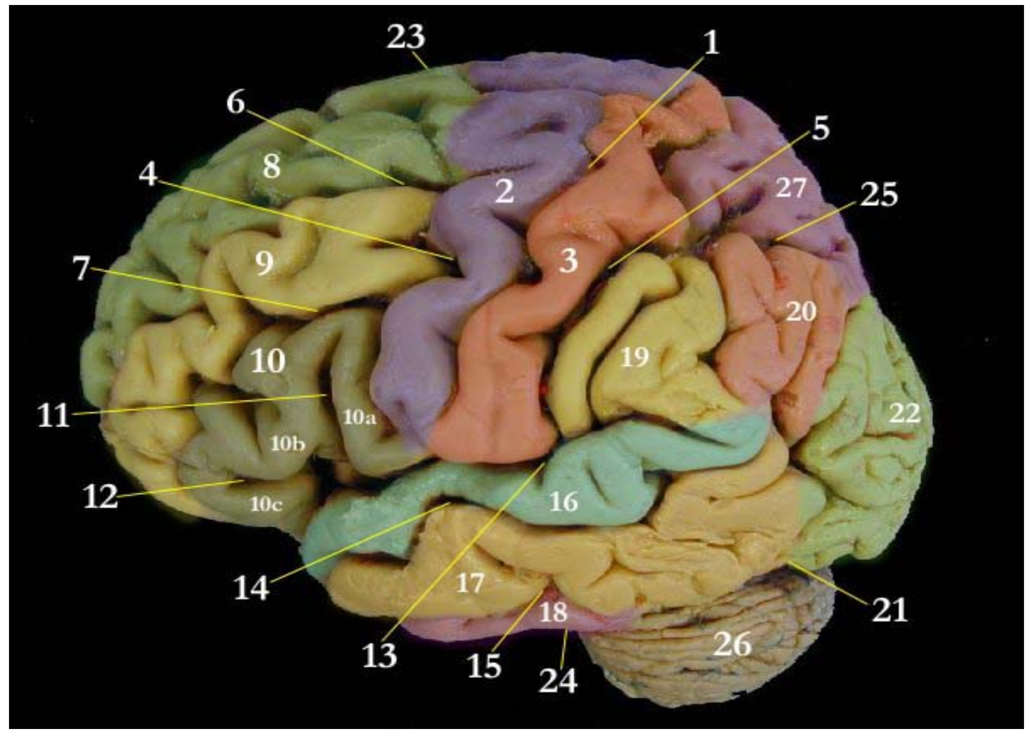
Redondo and Morris 2011, Nature Rev. Neurosci.

1. synaptic plasticity – connections change



More space in cortex allocated
- musicians vs. non-musicians

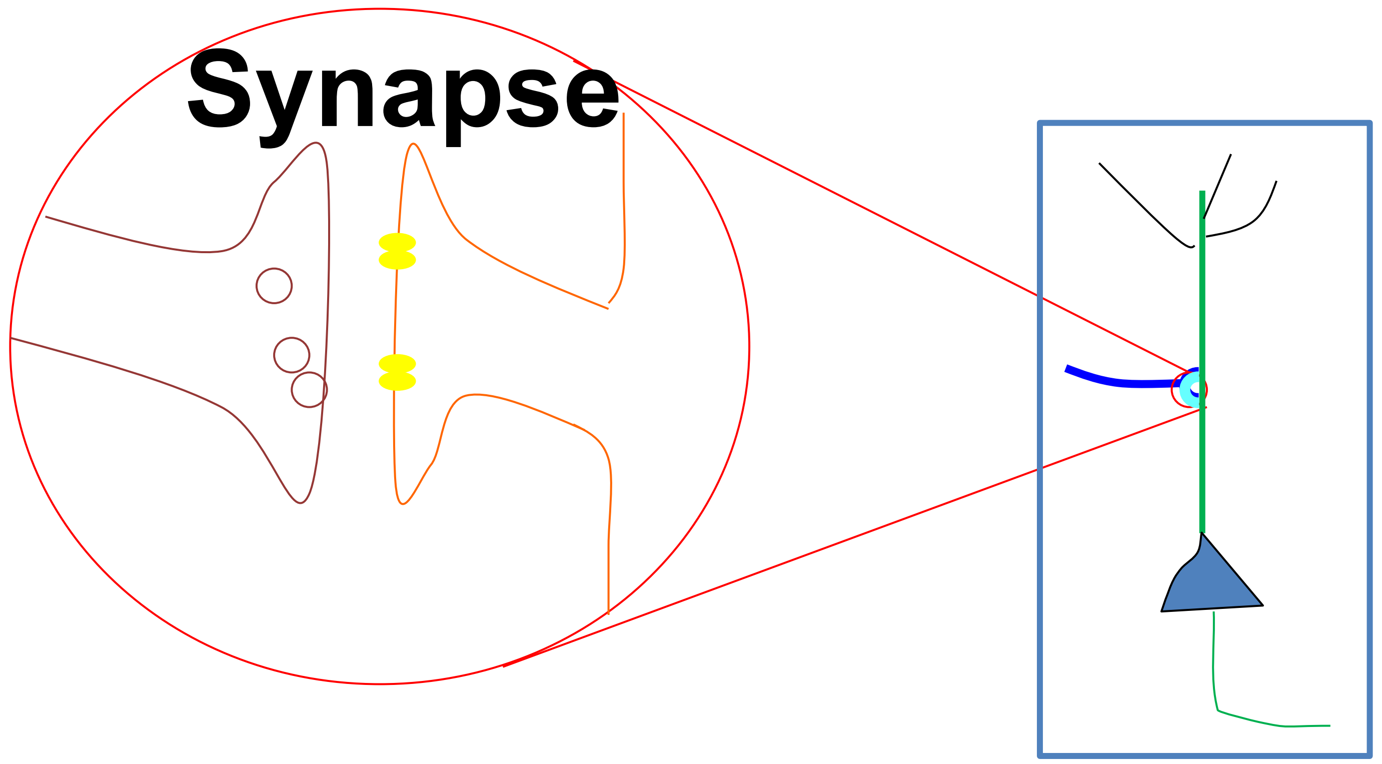
Amunts et al. Human Brain Map. 1997
Gaser and Schlaug, J. Neuosci. 2003

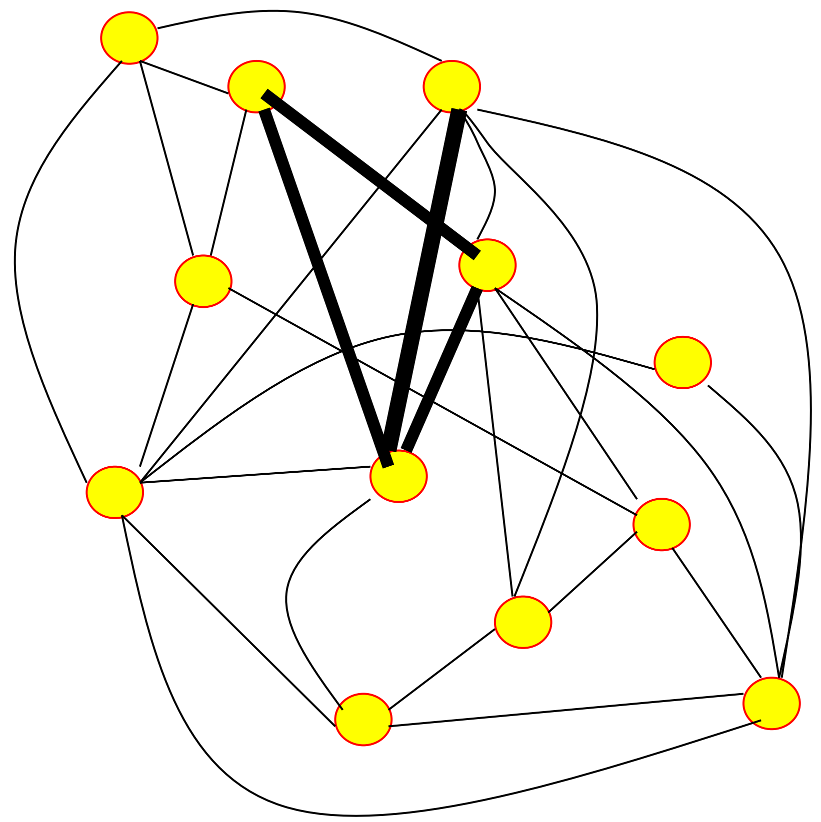


More space in hippocampus allocated
- London taxi driver vs bus driver

Macquire et al. Hippocampus 2006

1. Synaptic plasticity





Should enable **Learning**

- adapt to the statistics of task and environments (receptive fields, allocate space etc)
- memorize facts and episodes
- learn motor tasks

Should avoid:

- blow-up of activity
- unnecessary use of energy

homeostasis

Aim: models that capture the essence

1. Synaptic plasticity: program for this week

Hebbian learning

- Experiments on synaptic plasticity
- Mathematical Formulations of Hebbian Learning
- Mathematical models of Spike-Timing Dependent Plasticity
- Back to Attractor Memory Models

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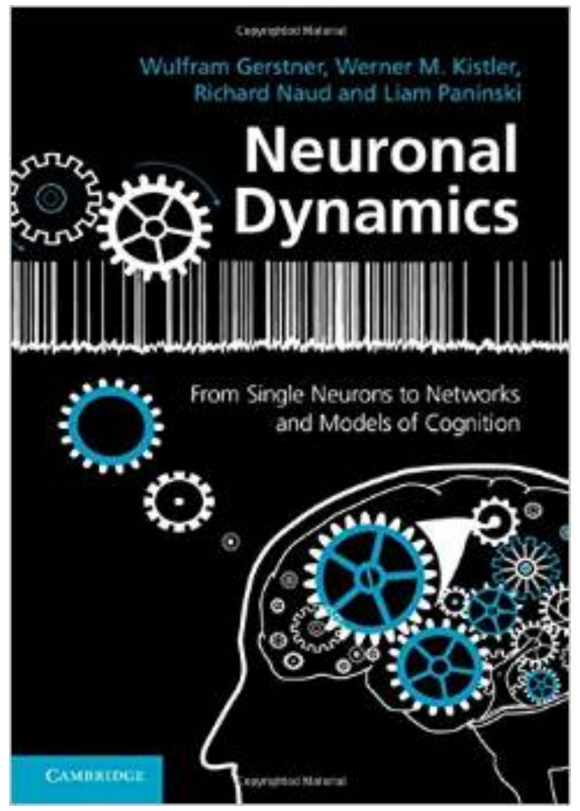

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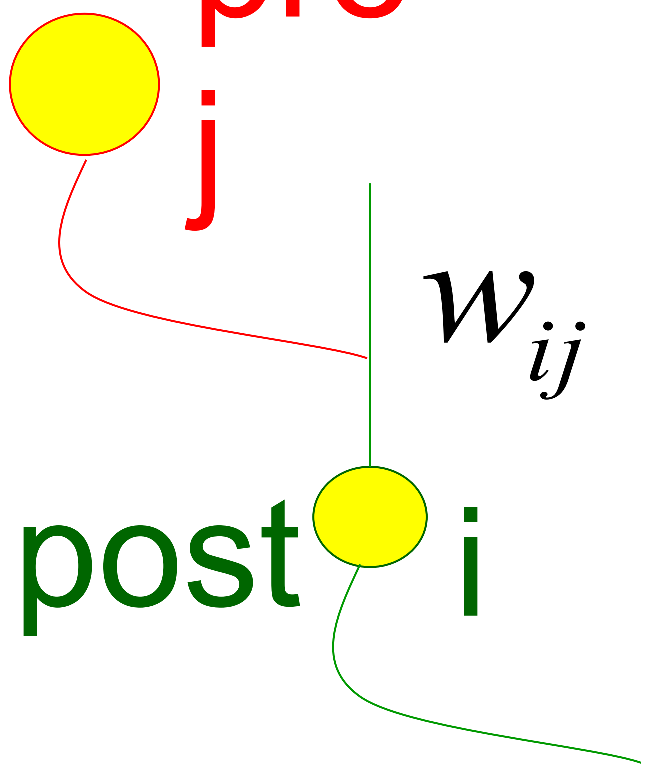
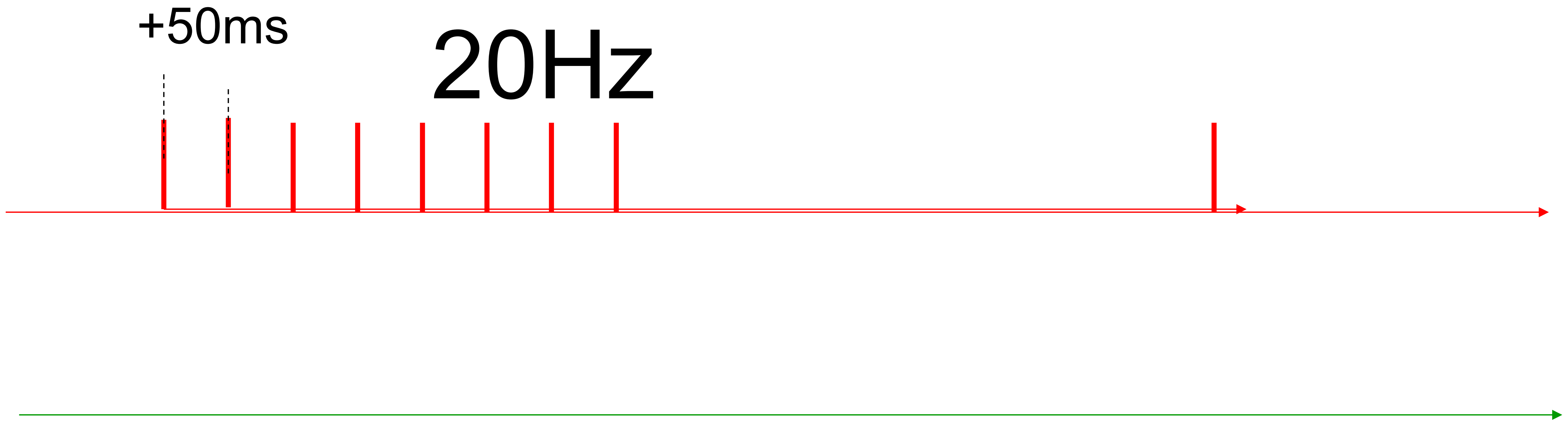
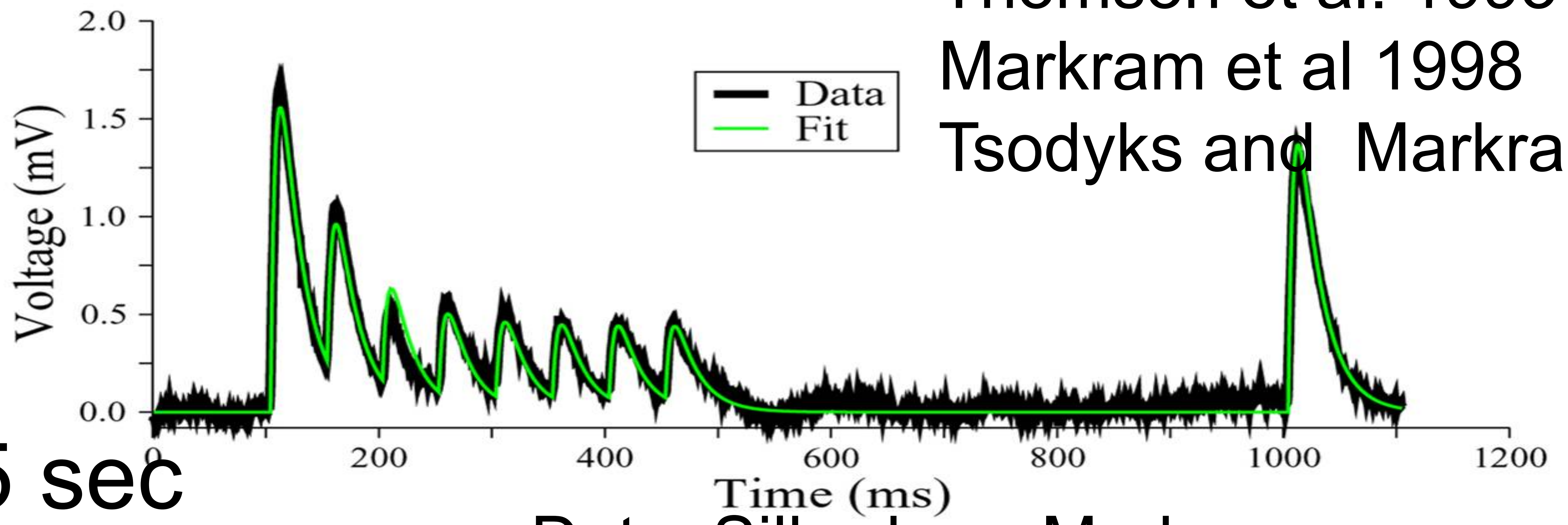
2. Classification of synaptic changes: Short-term plasticity





Short-term plasticity/fast synaptic dynamics

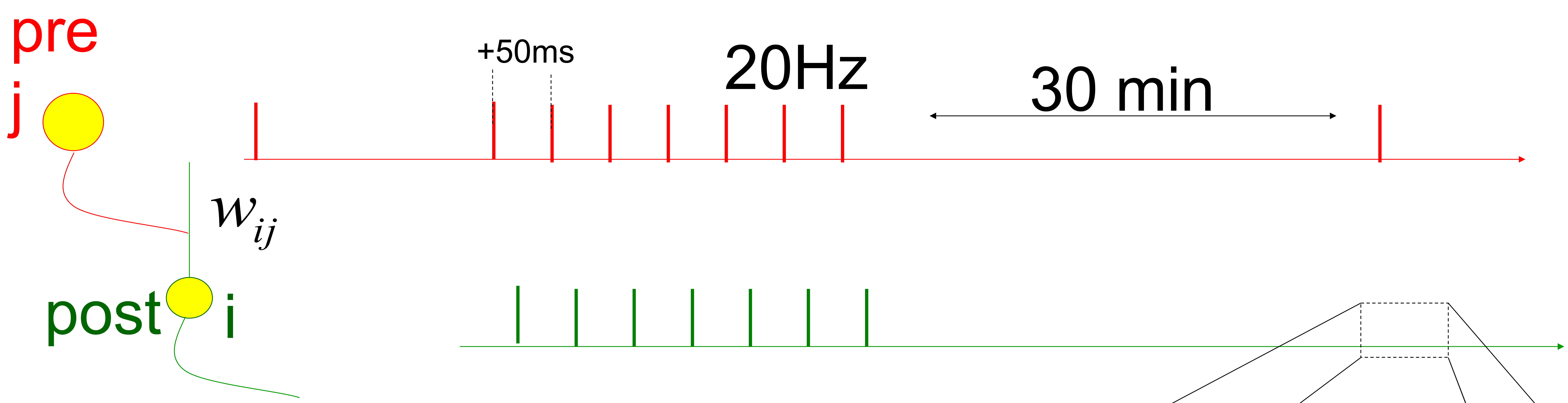
Thomson et al. 1993
Markram et al 1998
Tsodyks and Markram 1997



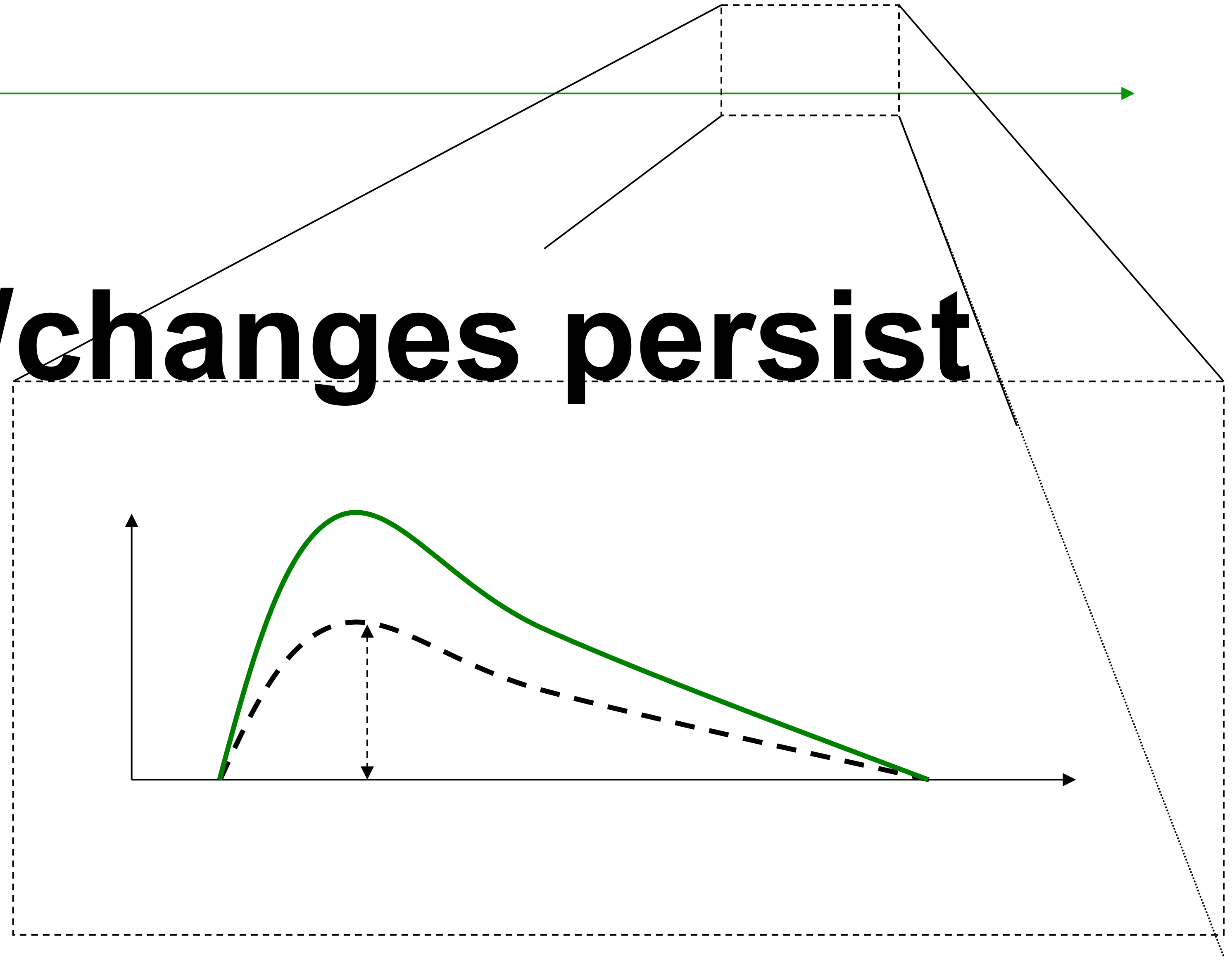
Changes
- induced over 0.5 sec
- recover over 1 sec

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

2. Classification of synaptic changes: Long-term plasticity



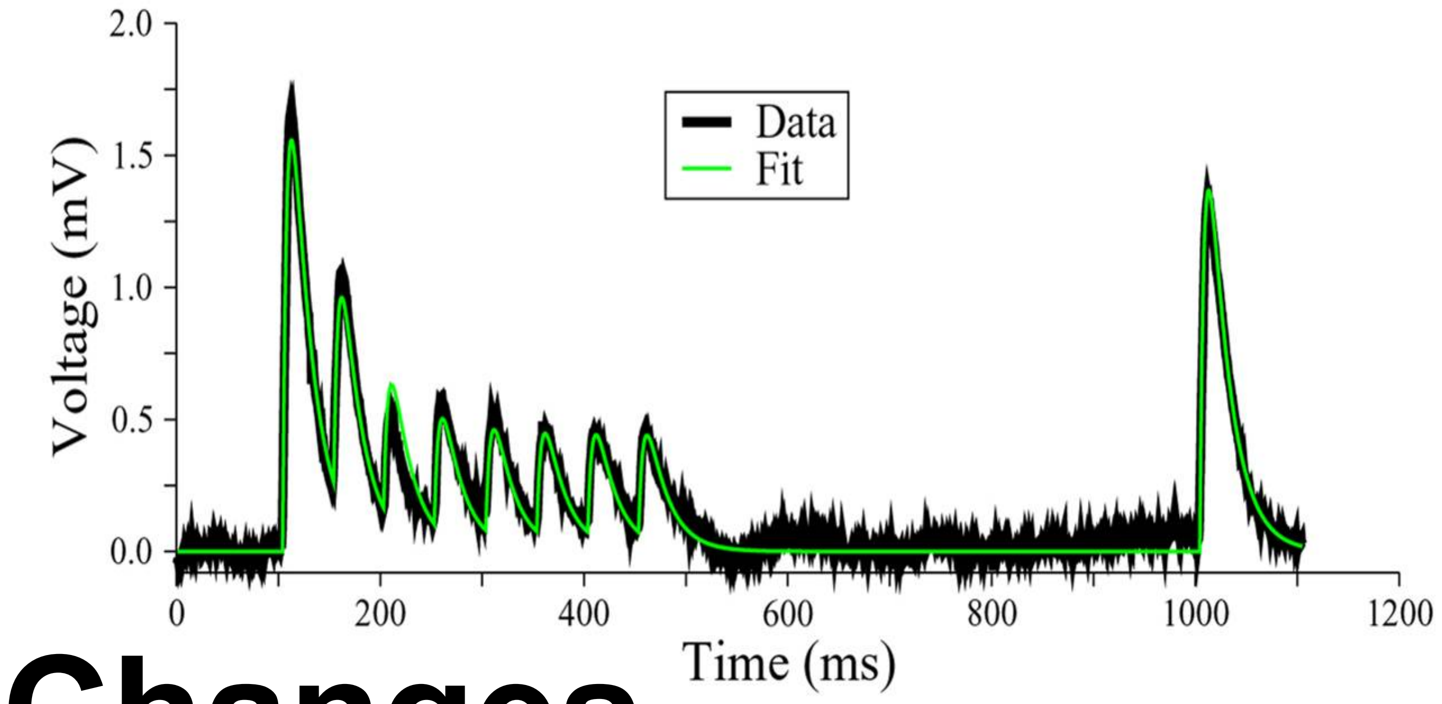
Long-term plasticity/changes persist



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

2. Classification of synaptic changes

Short-Term vs/ Long-Term



Changes

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

Protocol

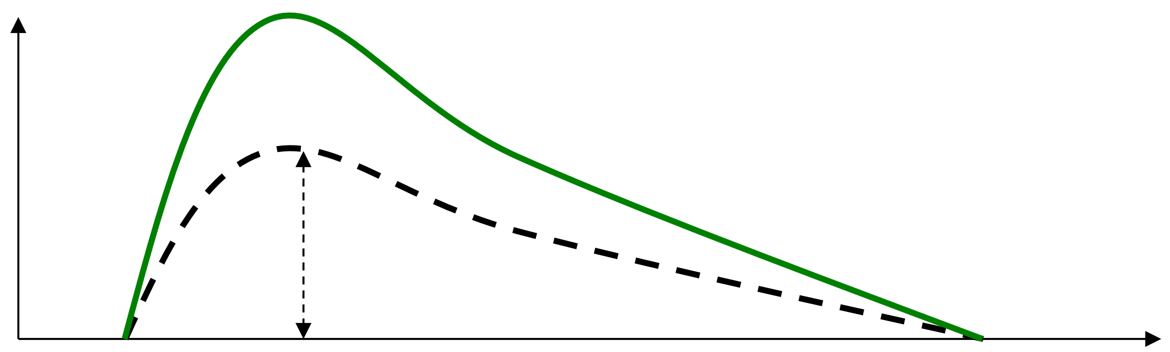
- presynaptic spikes

Model

- well established

(Tsodyks, Pawelzik, Markram Abbott-Dayan)

LTP/LTD/Hebb



Changes

- induced over 0.5-10sec
- remains over hours

Protocol

-presynaptic spikes + …

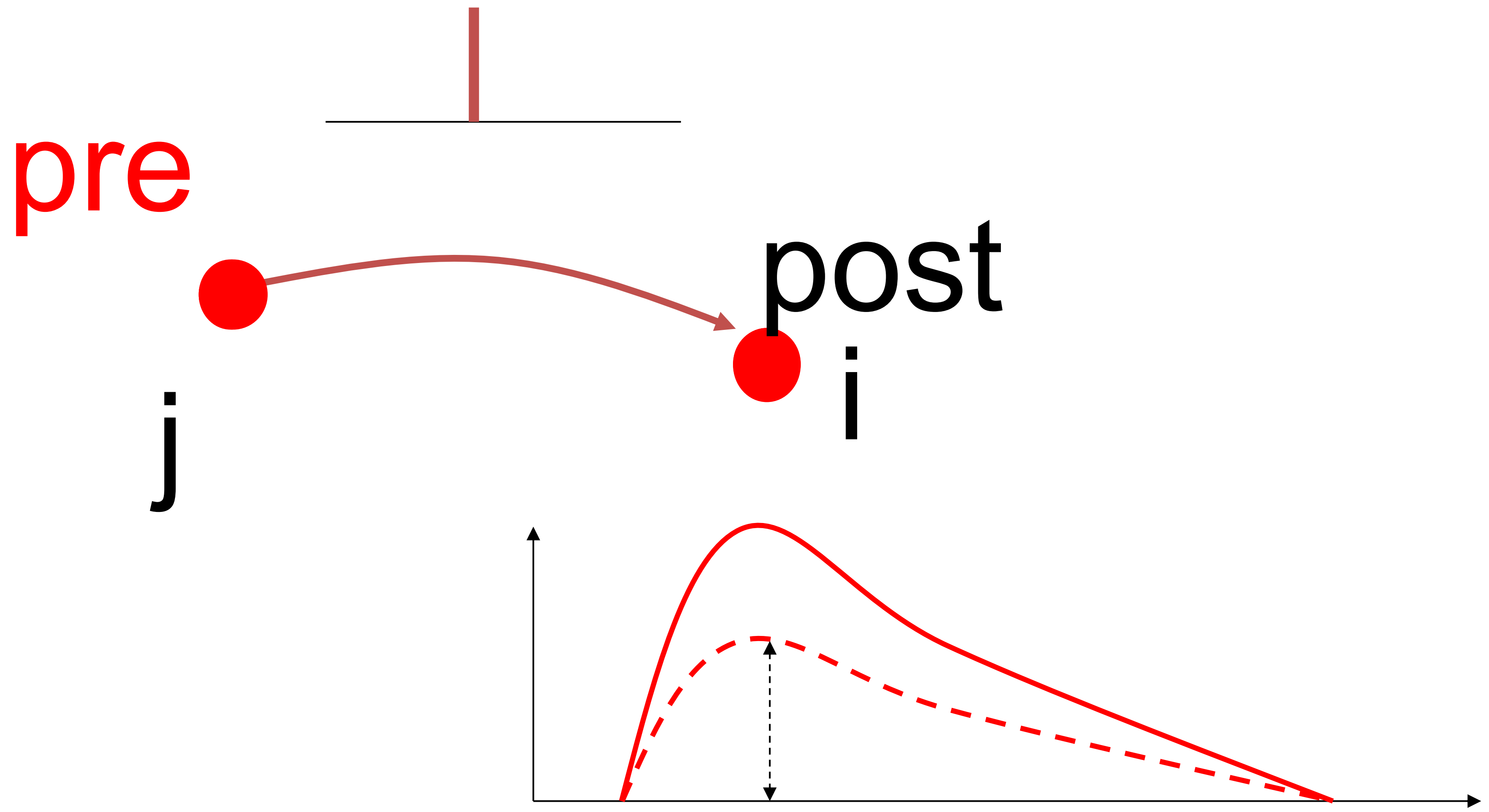
Model

- we will see

2. Classification of synaptic changes

Induction of changes

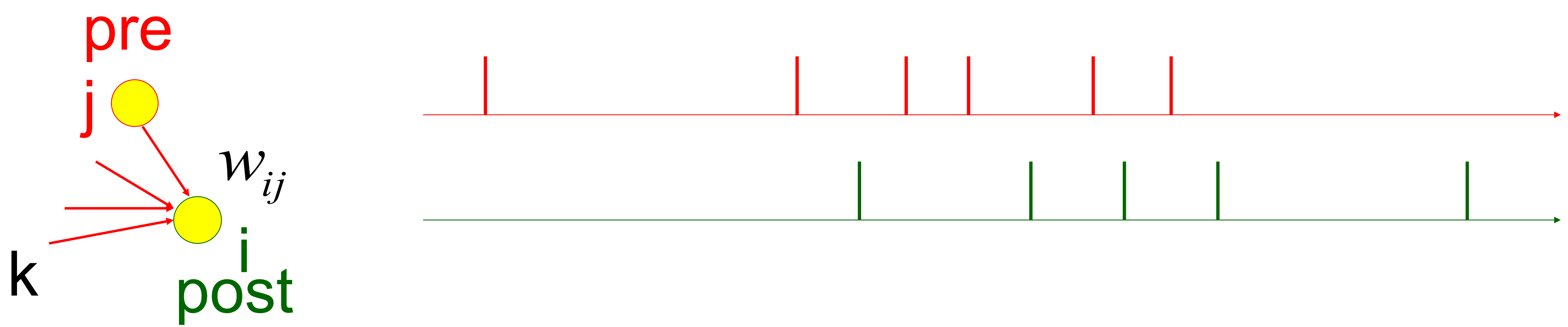
- fast (if stimulated appropriately)
- slow (homeostasis)



Persistence of changes

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

2. Review: Hebb rule



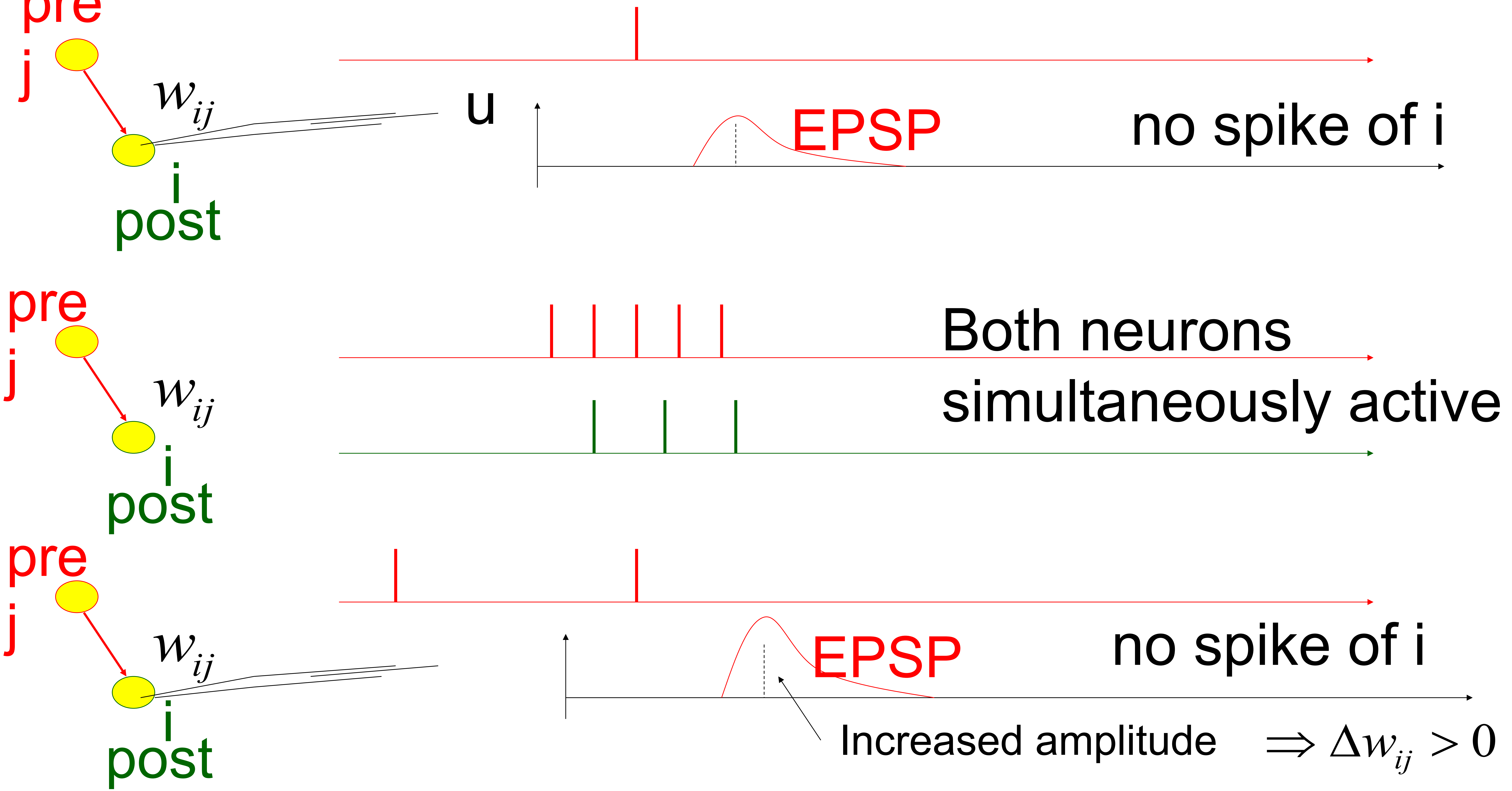
When an axon of cell **j** repeatedly or persistently takes part in firing cell **i**, then j's efficiency as one of the cells firing i is increased

Hebb, 1949

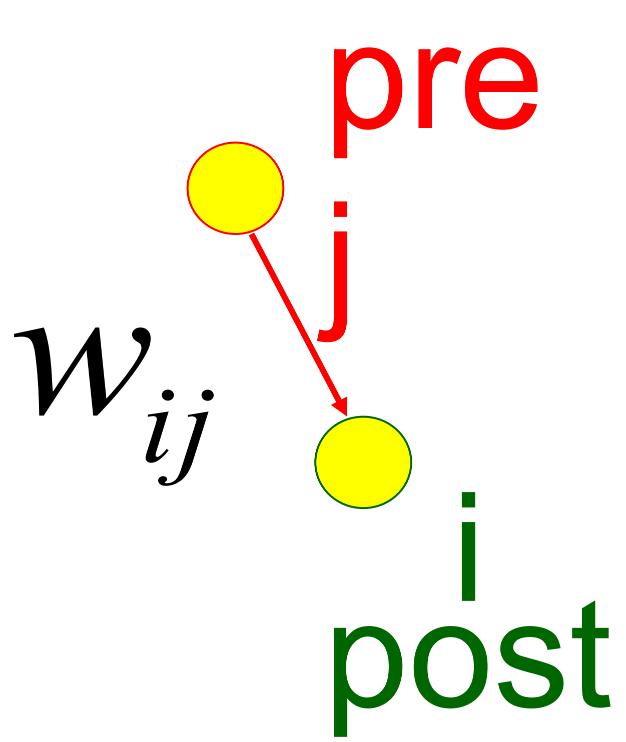
- local rule
- simultaneously active (correlations)

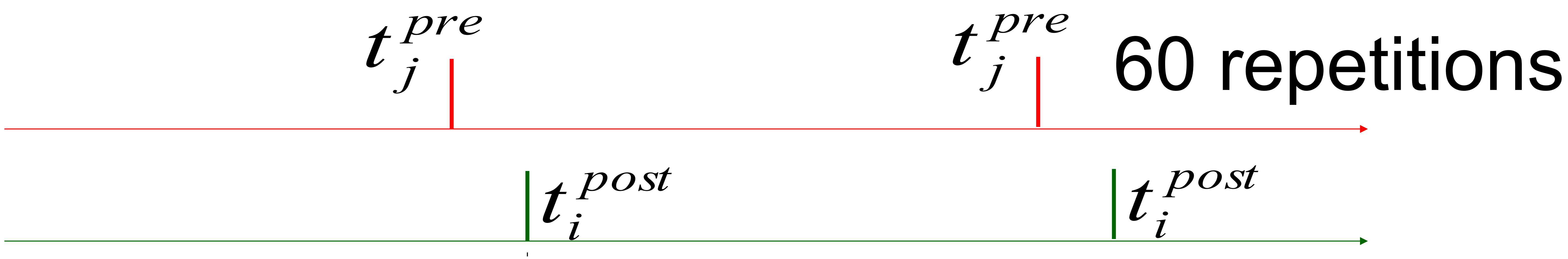
2. Synaptic plasticity: Long-Term Potentiation (LTP)

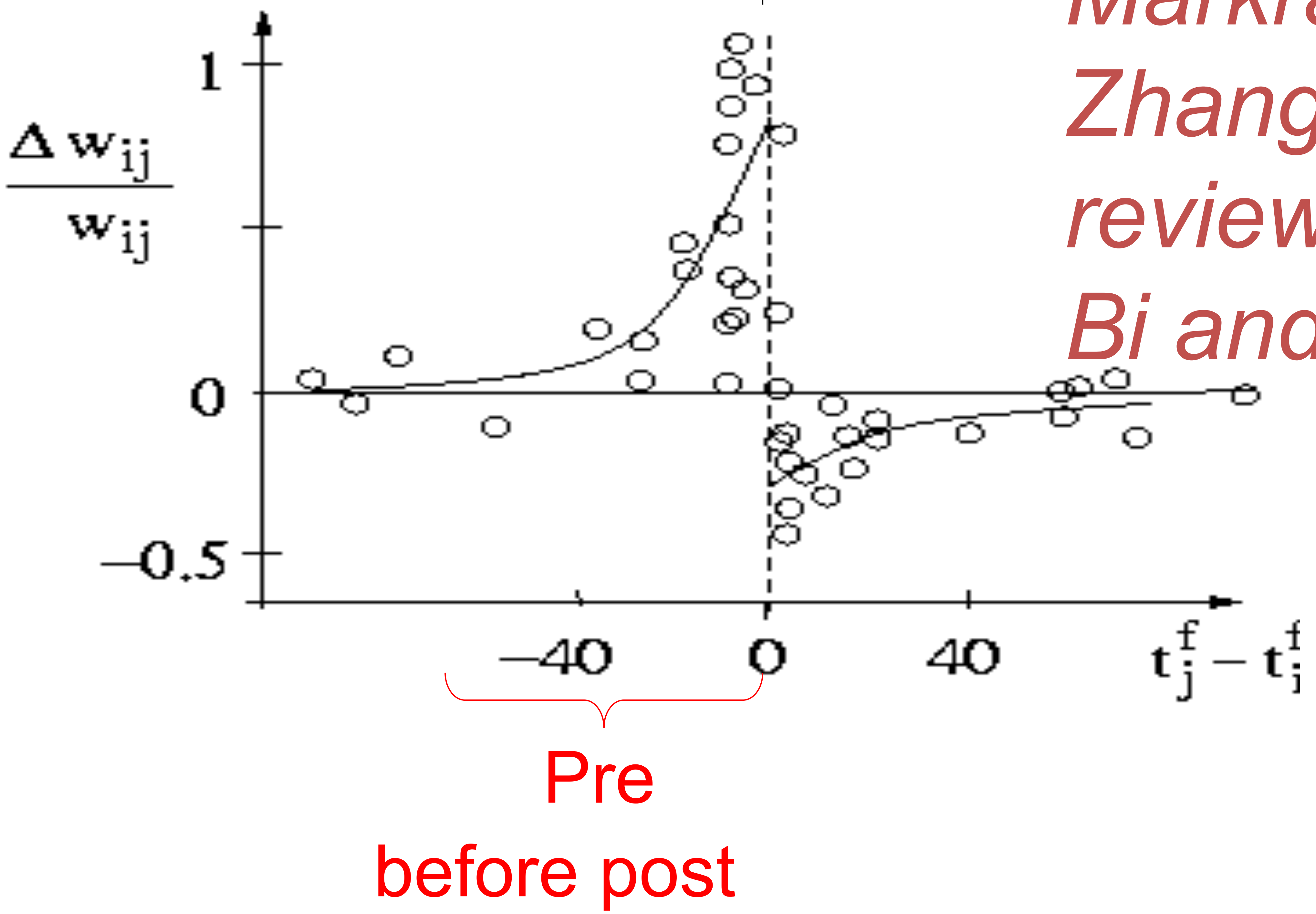
Hebbian Learning in experiments (schematic)



2. Spike-timing dependent plasticity (STDP)





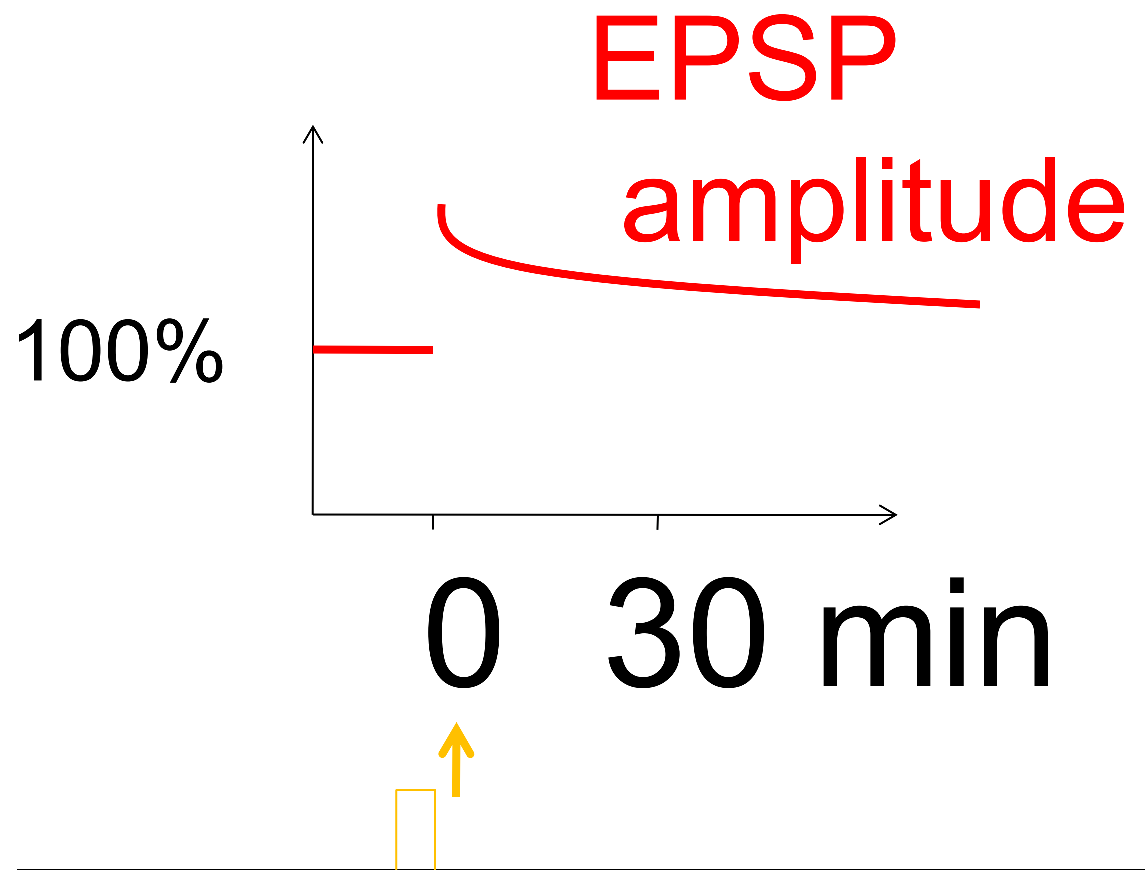


Markram et al, 1995,1997

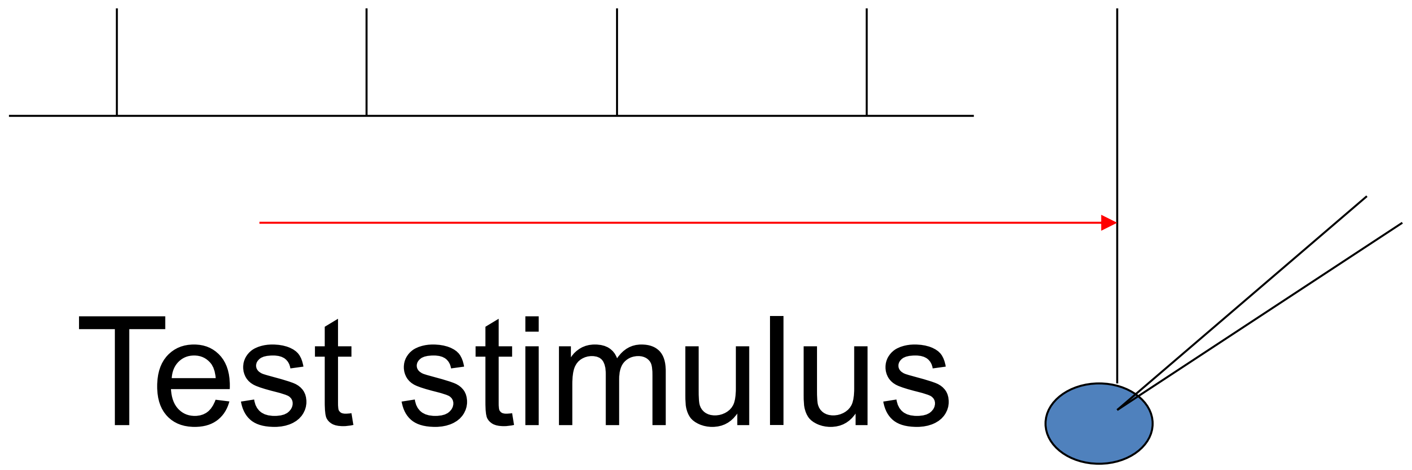
Zhang et al, 1998

review:

Bi and Poo, 2001



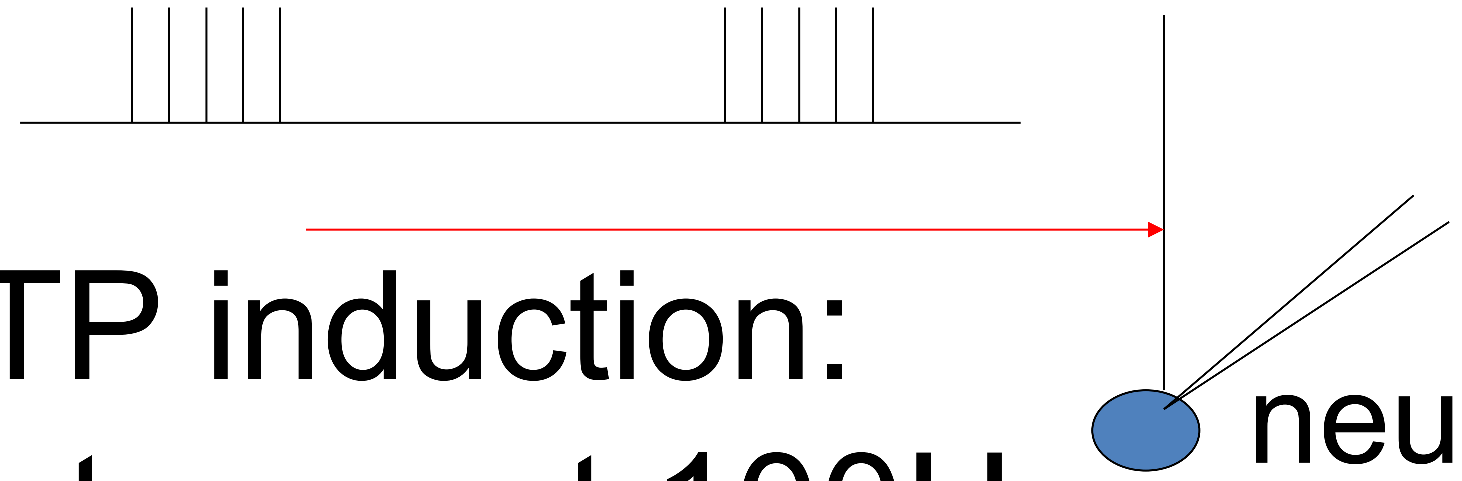
2. Classical paradigm of LTP induction – pairing



Test stimulus
At 0.1 Hz

neuron at -70mV

LTP induction:
tetanus at 100Hz



neuron depolarized to -40mV

Standard LTP
PAIRING experiment

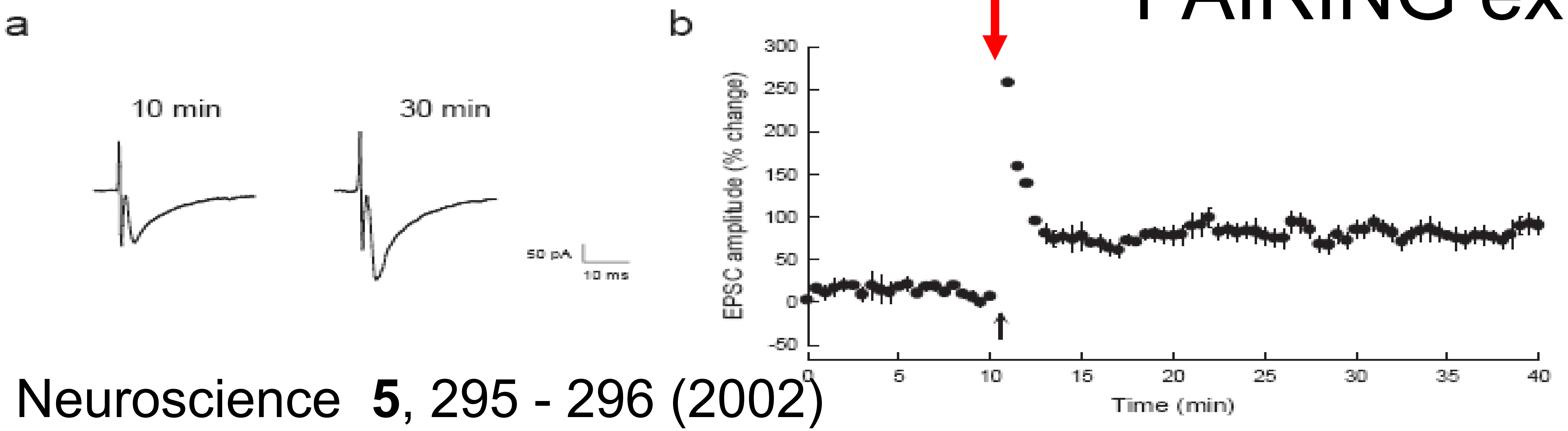
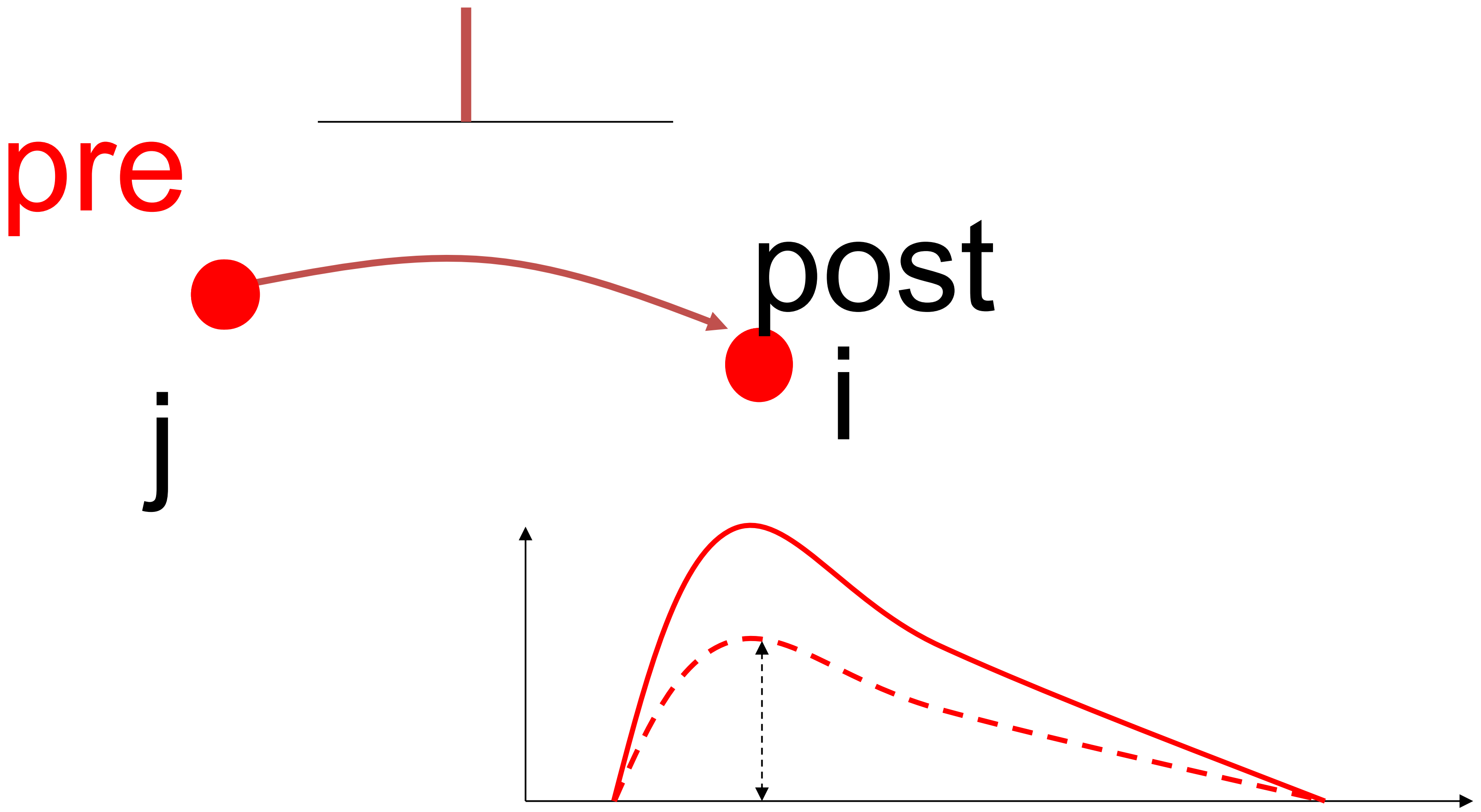


Fig. from Nature Neuroscience **5**, 295 - 296 (2002)
D. S.F. Ling, … & Todd C. Sacktor
See also: *Bliss and Lomo (1973), Artola, Brocher, Singer (1990), Bliss and Collingridge (1993)*

2. Classification of synaptic changes

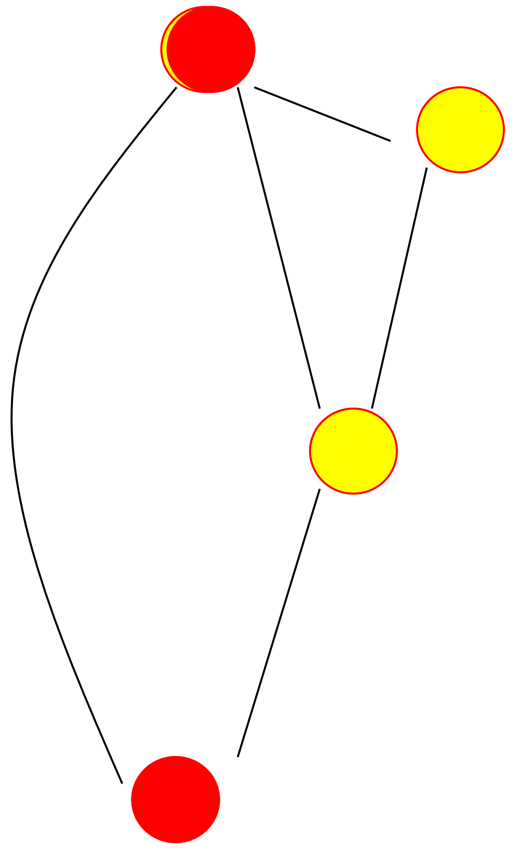
Induction of changes
- fast (if stimulated appropriately)
- slow (homeostasis)

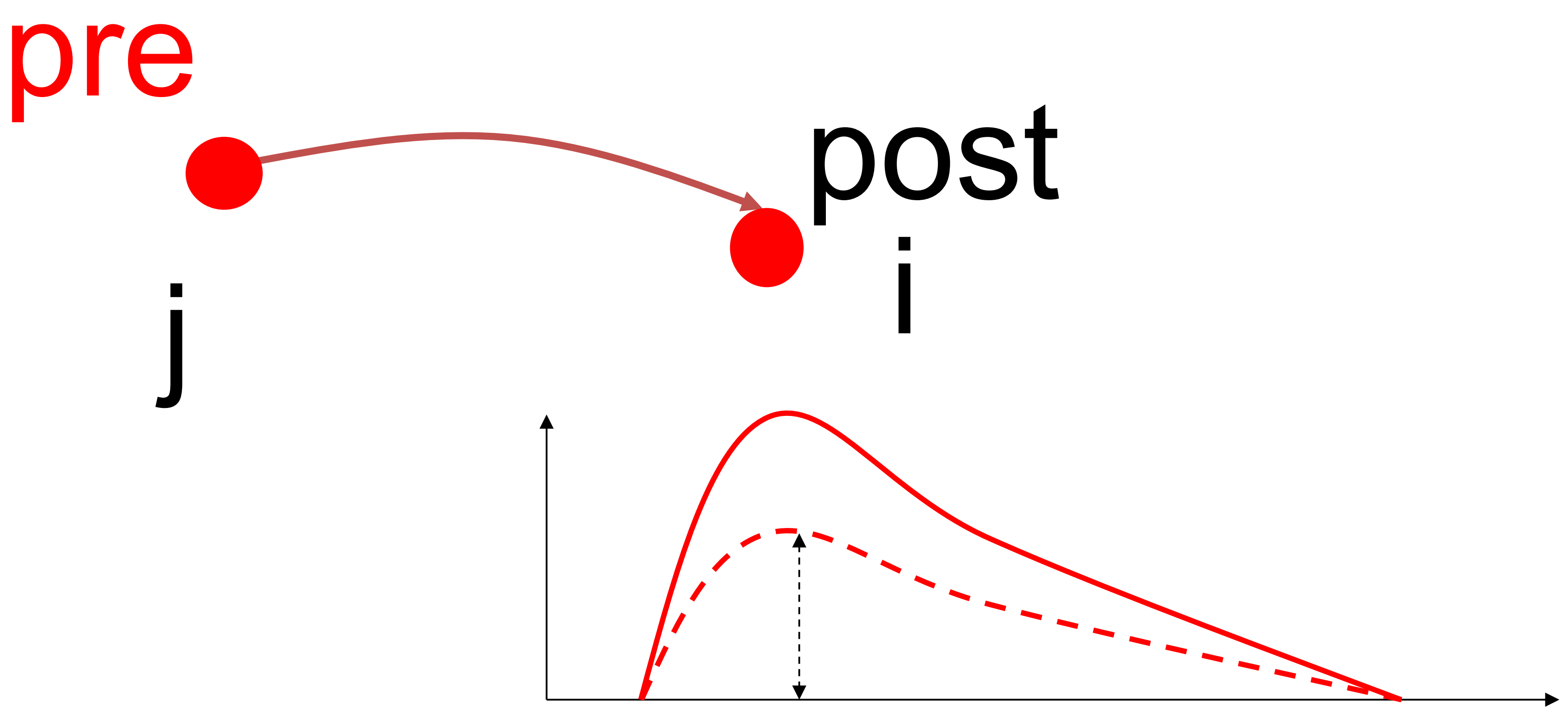


Persistence of changes
- long (LTP/LTD)
- short (short-term plasticity)

Functionality
- useful for learning a new behavior/forming new memories
- useful for development (wiring for receptive field development)
- useful for activity control in network: **homeostasis**
- useful for coding

Hebbian Learning
= unsupervised learning





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

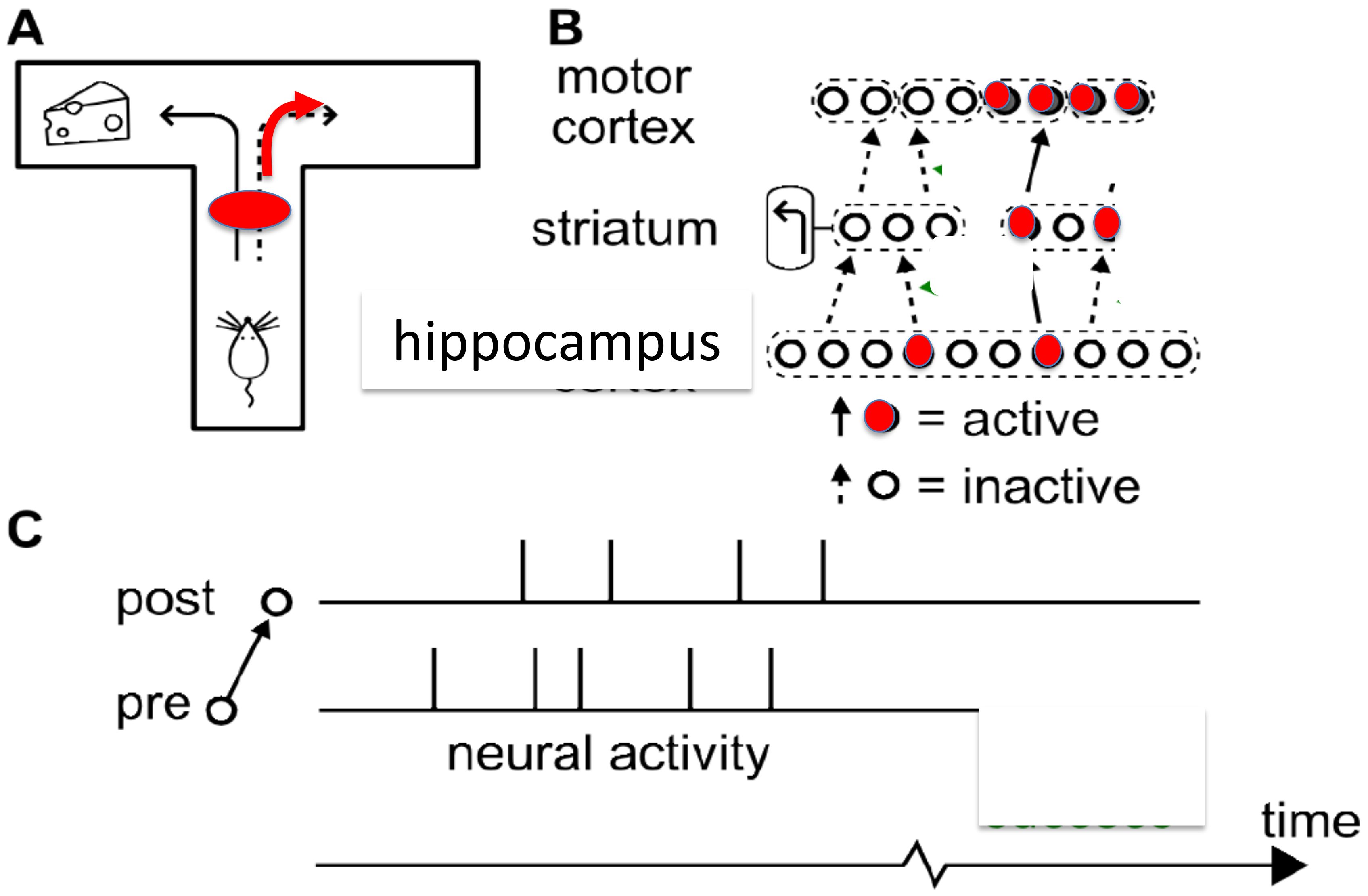
$$\Delta w_{ij} \propto F(pre, post)$$

2.Limits of unsupervised learning

Is Hebbian Learning sufficient?
No!

Image: Gerstner et al. NEURONAL DYNAMICS,

Eligibility trace:
Synapse keeps memory of pre-post Hebbian events



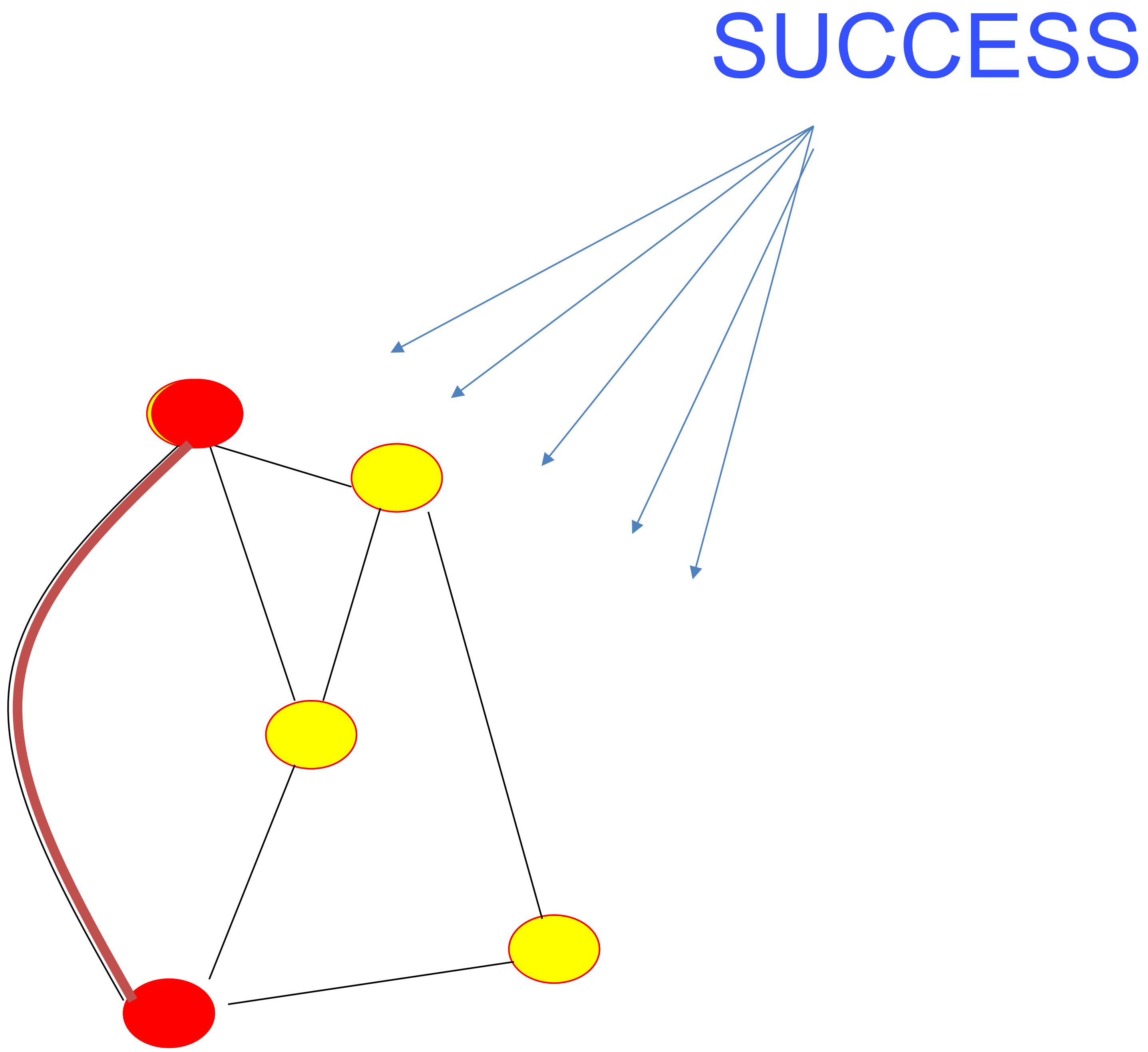
Dopamine: Reward/success

Schultz et al. 1997; Waelti et al., 2001;

→ Reinforcement learning: success = reward – (expected reward)

TD-learning, SARSA, Policy gradient (book: Sutton and Barto, 1997)

2. Classification of synaptic changes: Reinforcement Learning



Reinforcement Learning
= reward + Hebb

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

local global

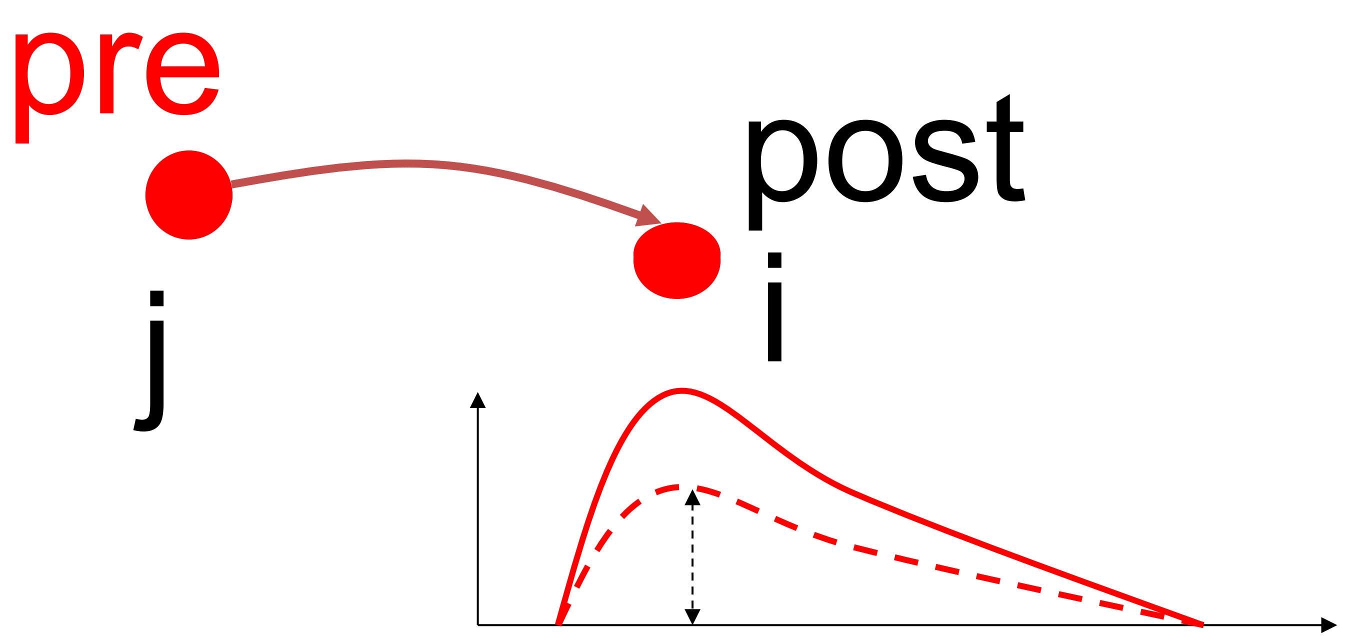
broadly transmitted signal:
neuromodulator

unsupervised vs reinforcement

LTP/LTD/Hebb

Theoretical concept

- passive changes
- exploit statistical correlations



Functionality

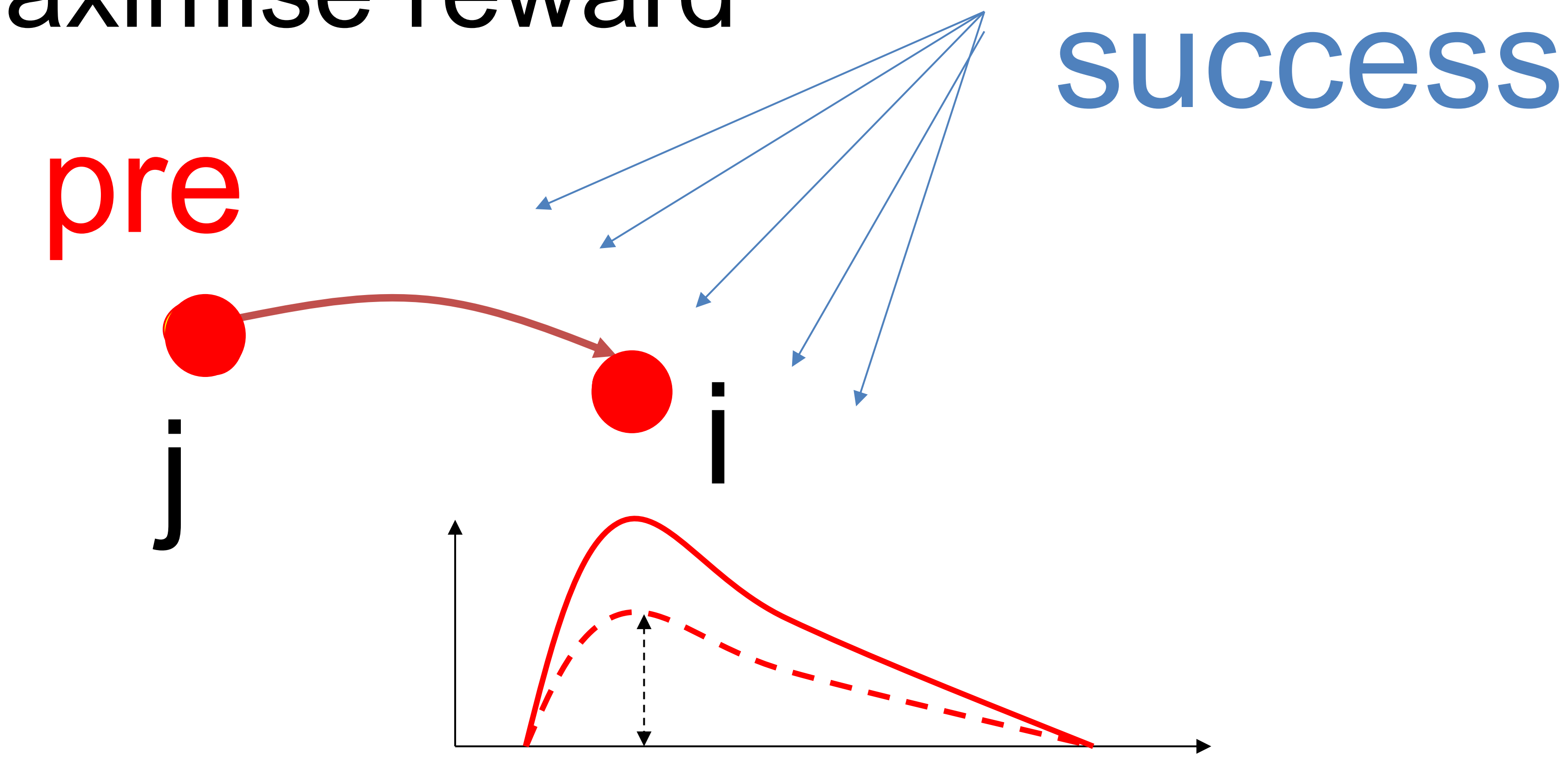
-useful for development

(wiring for receptive field)

Reinforcement Learning

Theoretical concept

- conditioned changes
- maximise reward



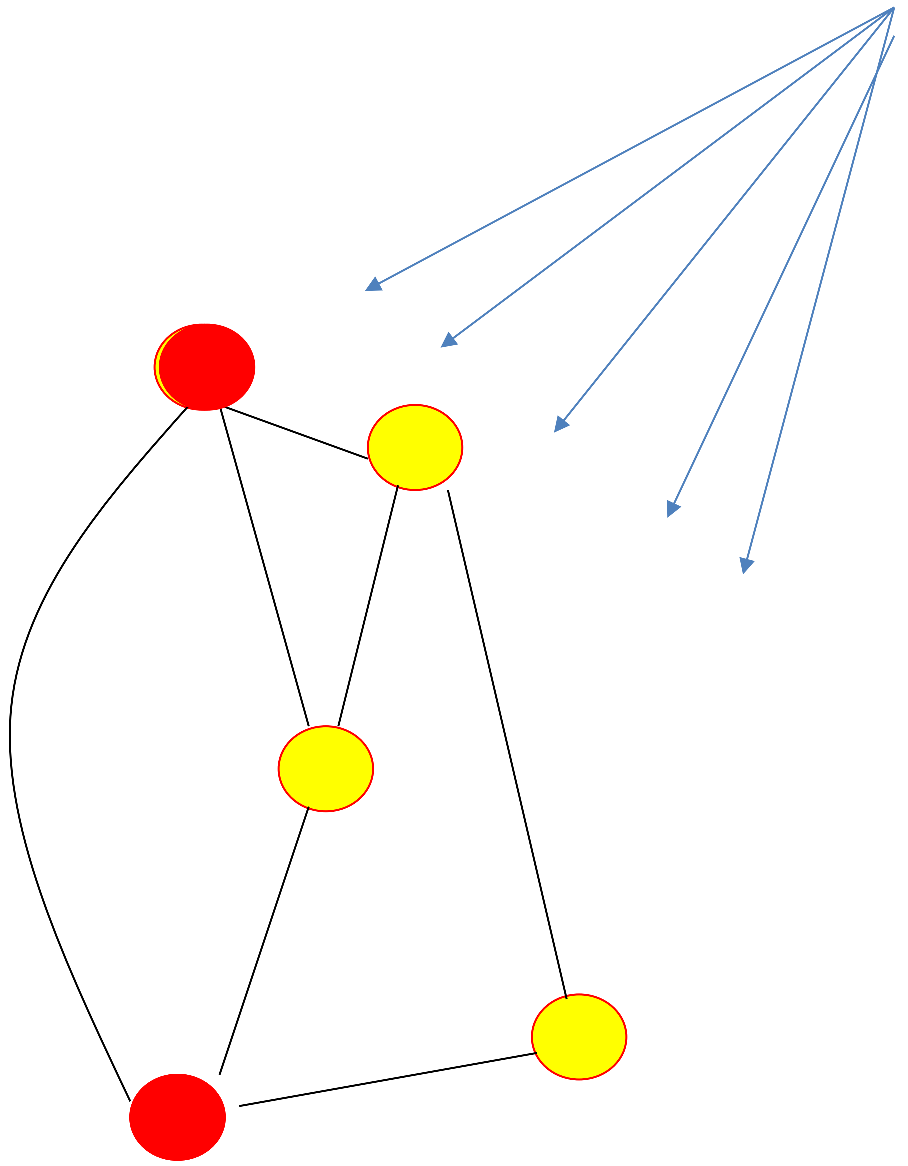
Functionality

- useful for learning a new behavior

2. Three-factor rule of Hebbian Learning

= Hebb-rule gated by a neuromodulator

Neuromodulators: Interestingness, surprise; attention; novelty



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

local global

Neuromodulator projections

- 4 or 5 neuromodulators
- near-global action

Dopamine/reward/TD:
Schultz et al., 1997,
Schultz, 2002

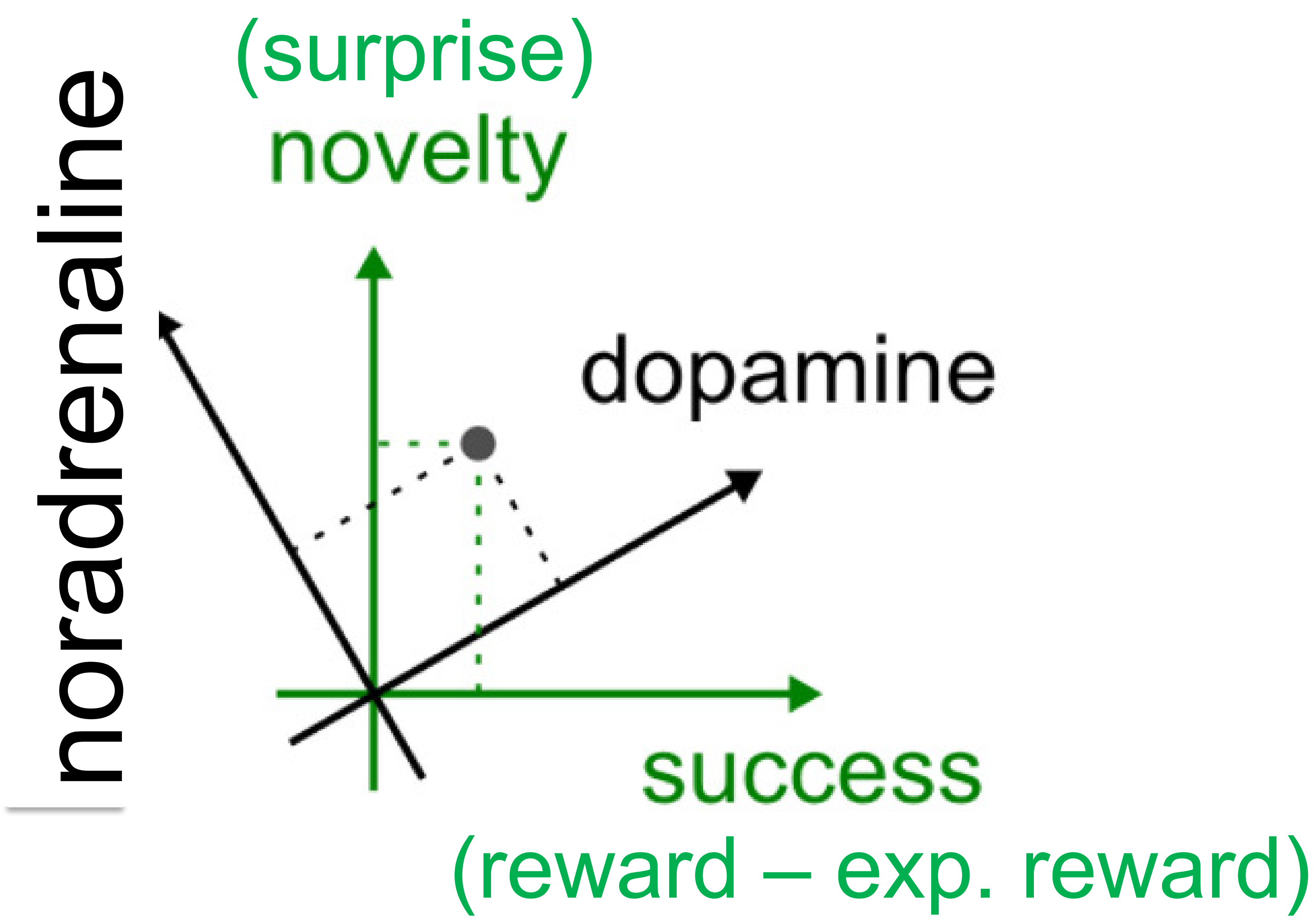
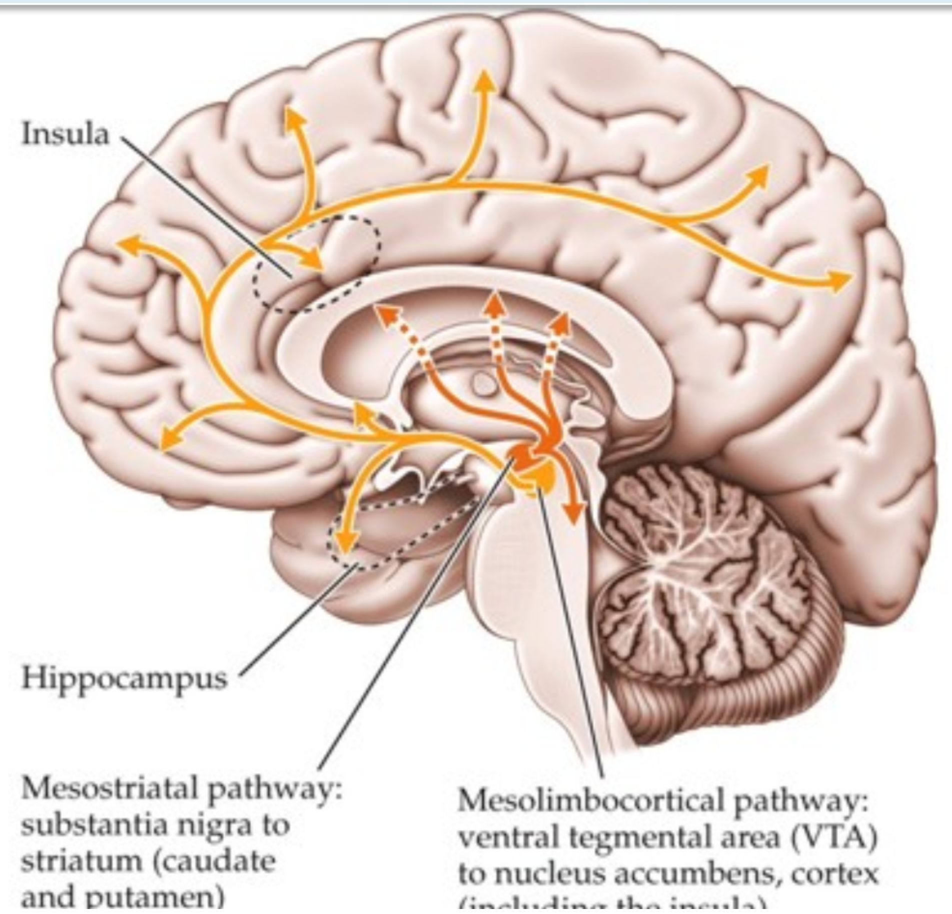


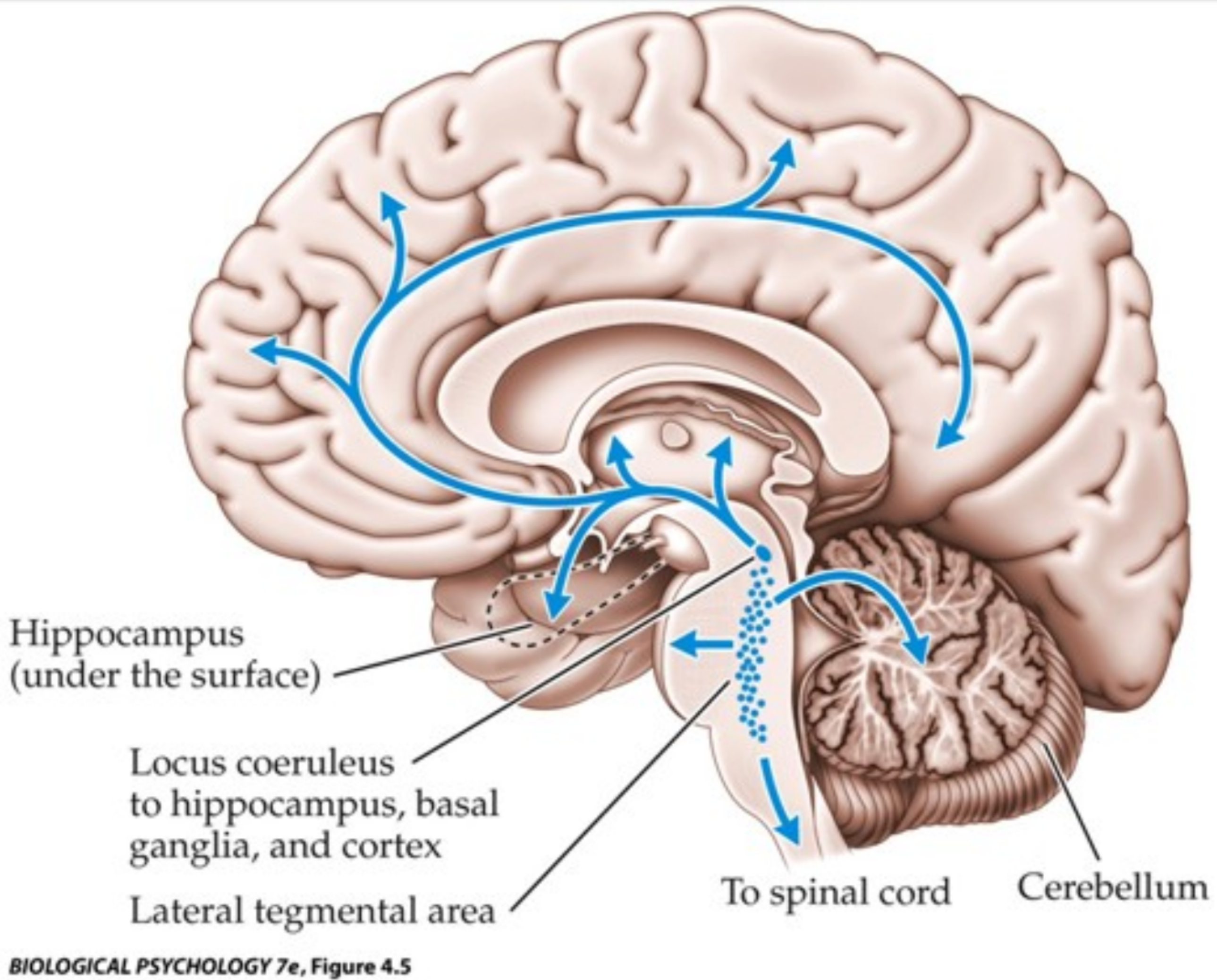
Image:
Fremaux and Gerstner, Frontiers (2016)

Image: Biological Psychology, Sinauer

Dopamine



Noradrenaline



Quiz 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