Week 14 – Dynamics and Plasticity

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Biological Modeling of Neural Networks:

Week 14 – Dynamics and Plasticity

Wulfram Gerstner

EPFL, Lausanne, Switzerland

14.1 Reservoir computing
- Review:Random Networks
- Computing with rich dynamics

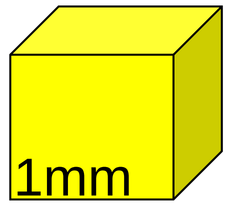
14.2 Random Networks
- stationary state
- chaos

14.3 Stability optimized circuits
- application to motor data

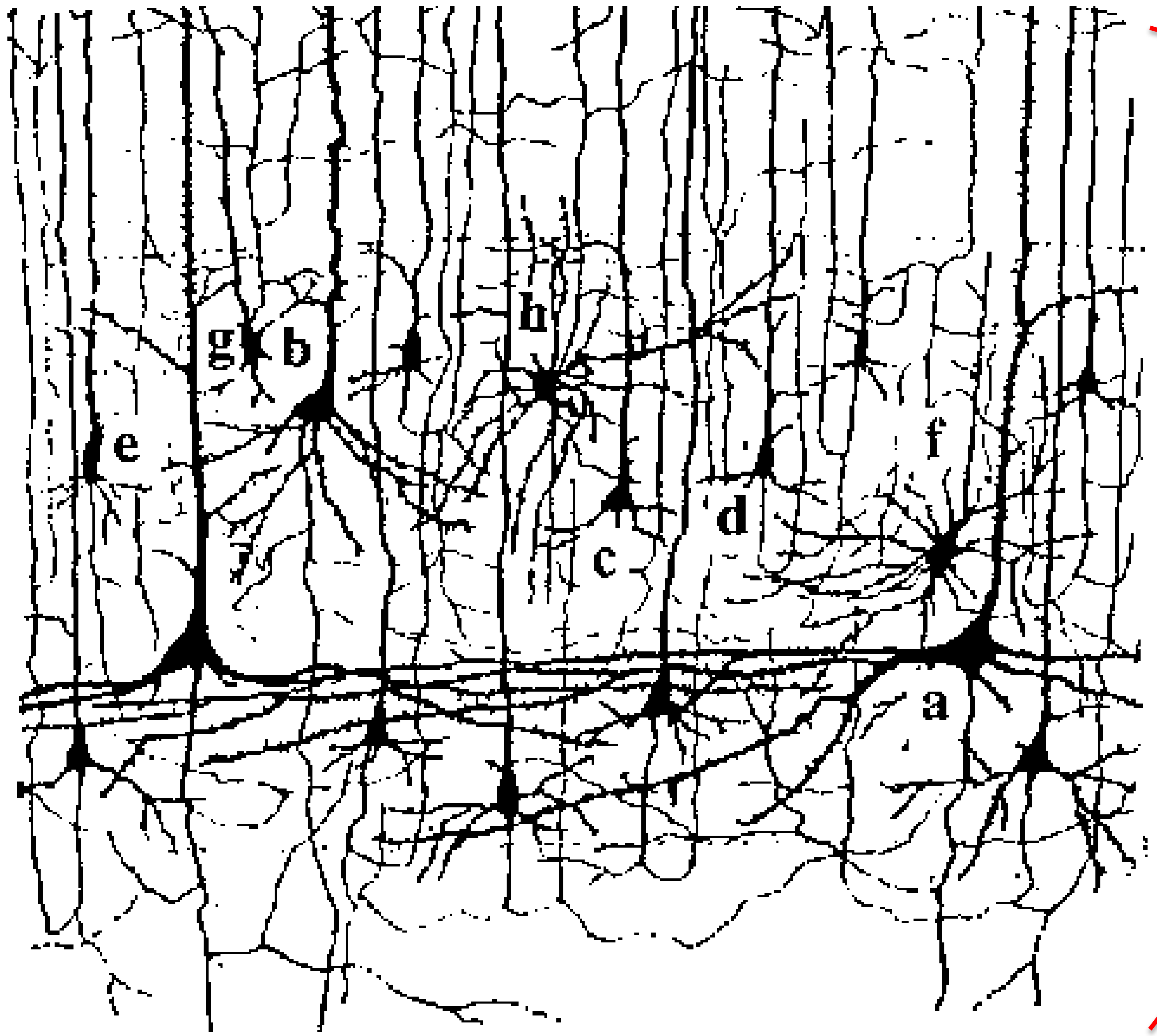
14.4. Synaptic plasticity
- Hebbian
- Reward-modulated

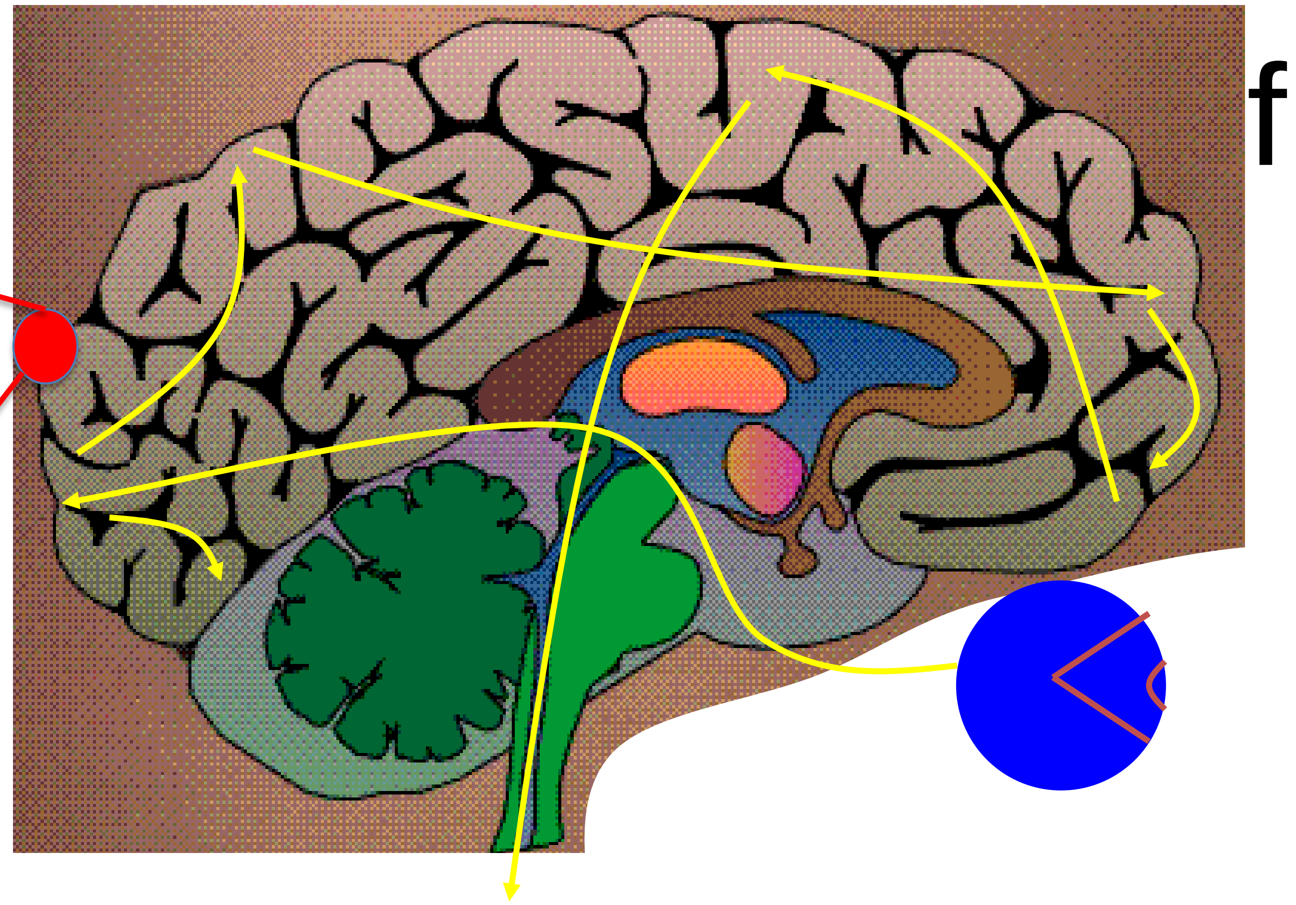
14.5. Helping Humans
- oscillations
- network states

Neuronal Dynamics – Brain dynamics is complex



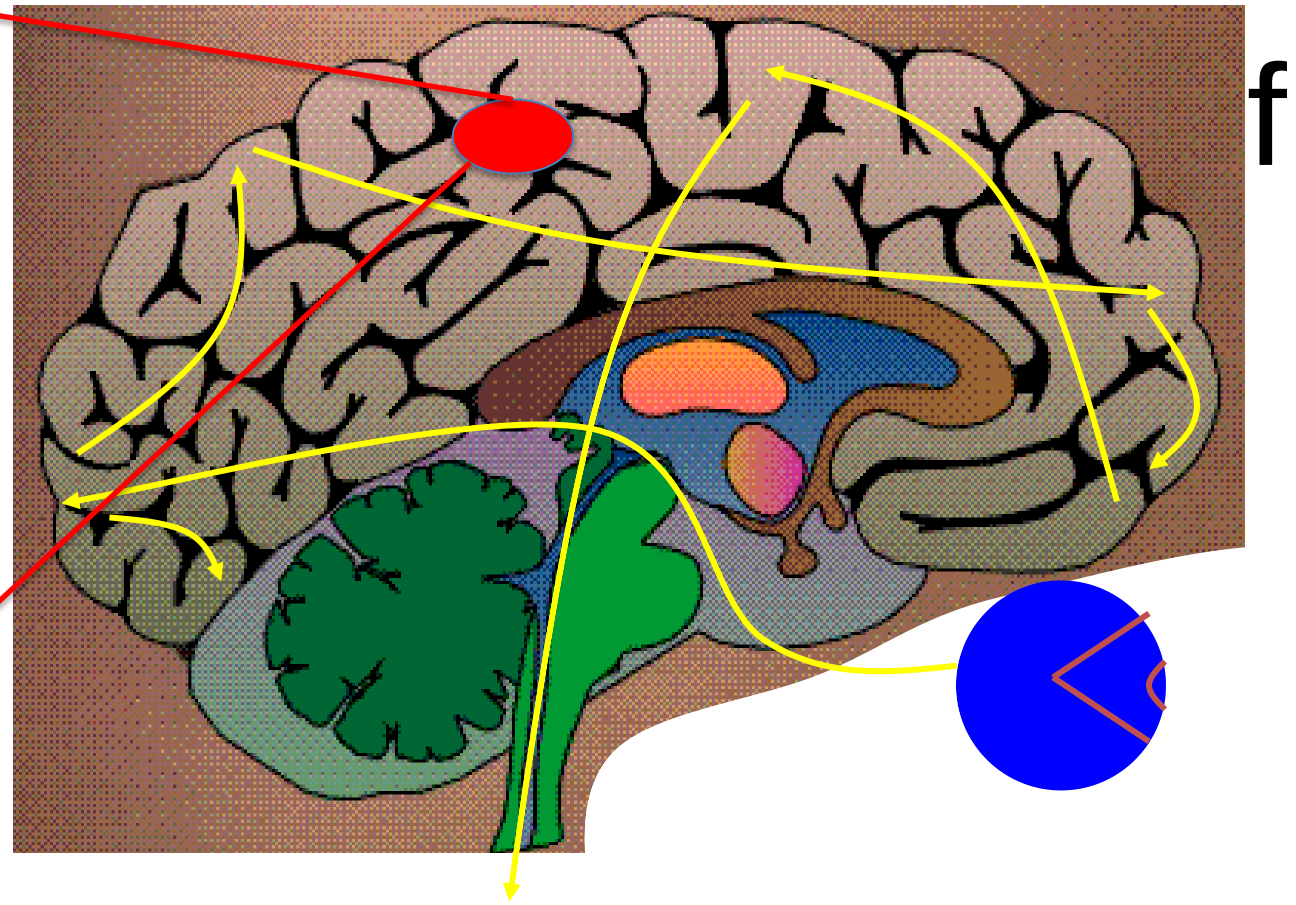
10 000 neurons
3 km wire





Neuronal Dynamics – Brain dynamics is complex

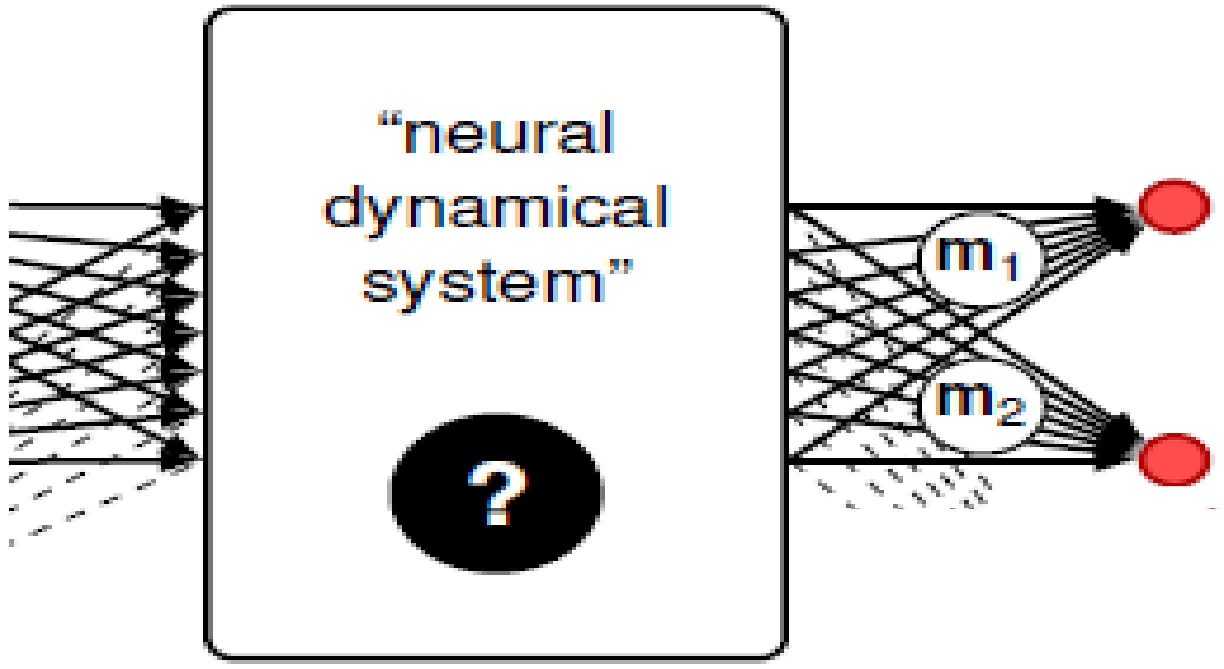
-Complex internal dynamics
-Memory
-Response to inputs
-Decision making
-Non-stationary
-Movement planning
-More than one 'activity' value



Liquid Computing/Reservoir Computing: exploit rich brain dynamics

Maass et al. 2002,
Jaeger and Haas, 2004
Review:
Maass and Buonomano,

Stream of sensory inputs



Readout 1

Readout 2

Week 14-part 1: Reservoir computing

See Maass et al. 2007

-'calculcate' $\nu_3 + \nu_4$

- if-condition on ν_1

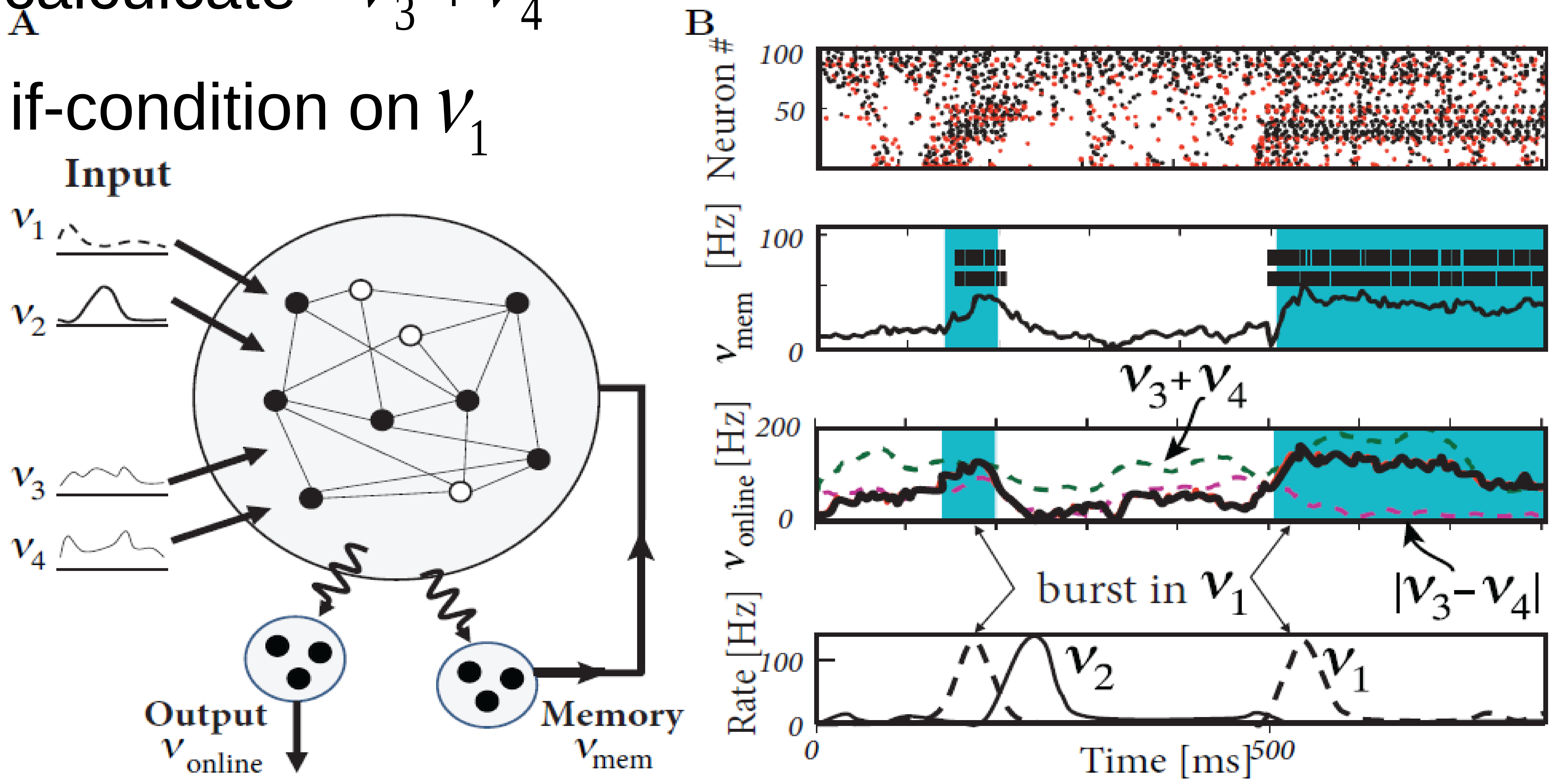
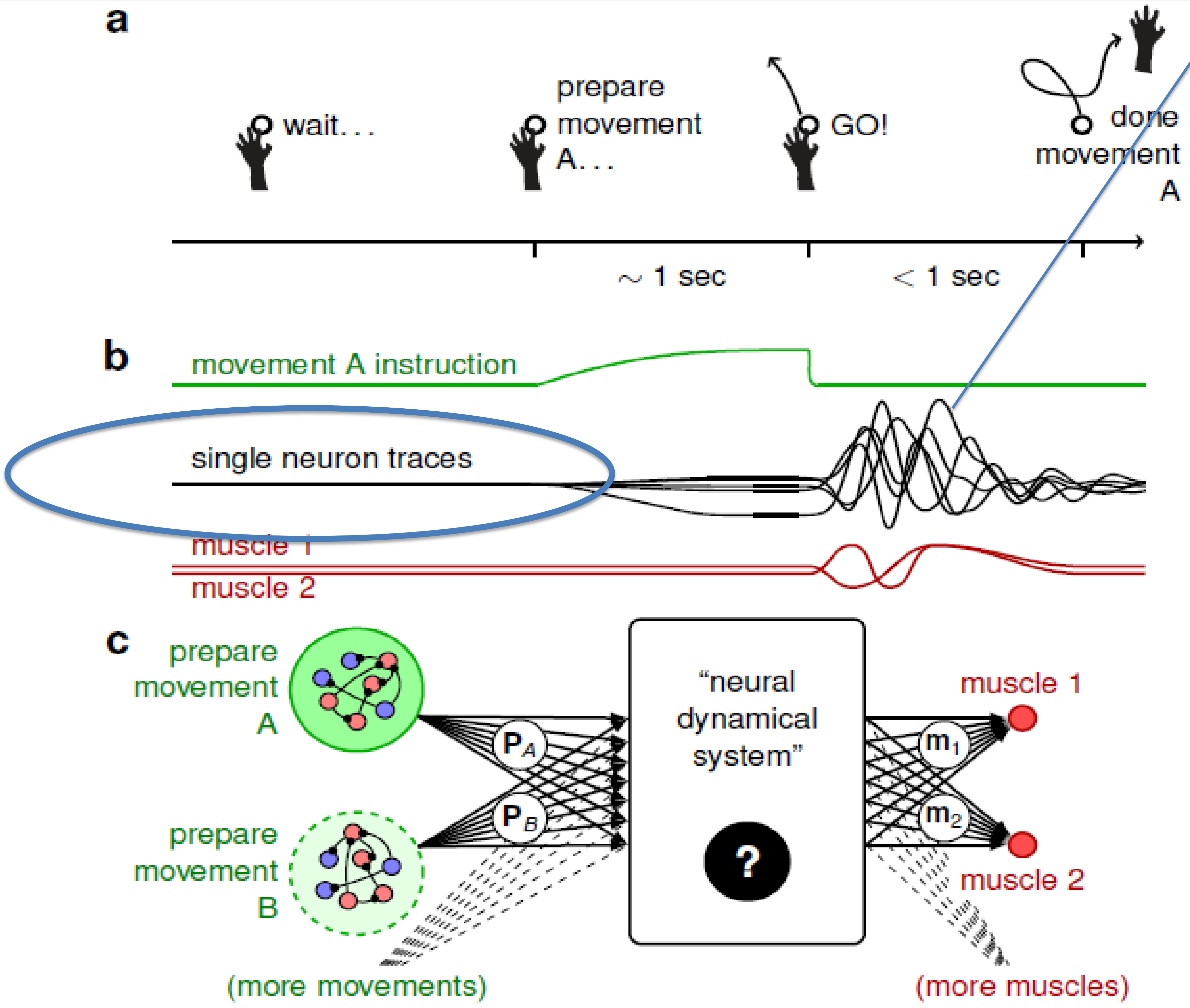


Fig. 20.1: Reservoir computing. **A.** A randomly connected network of integrate-and-

Week 14-part 1: Rich dynamics

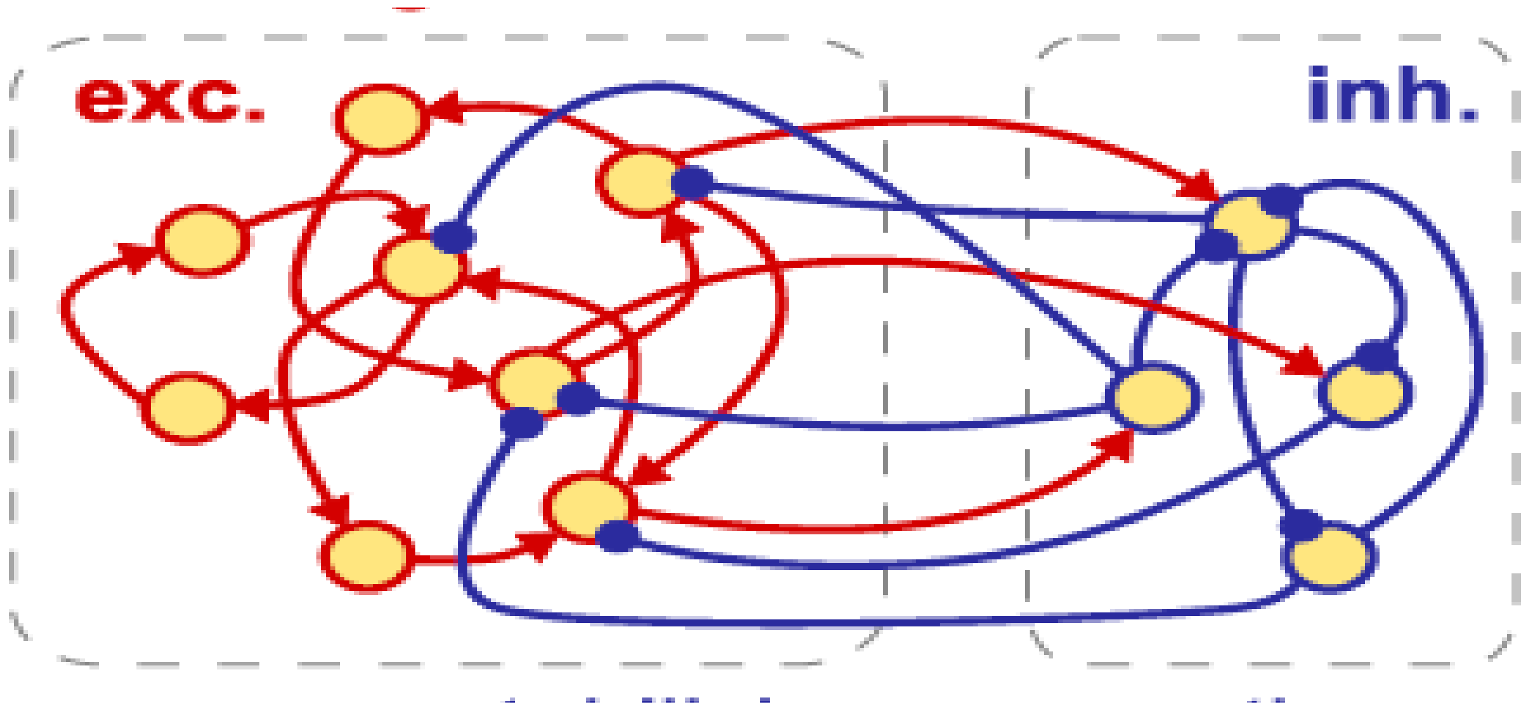
Rich neuronal dynamics



Experiments of
Churchland et al. 2010
Churchland et al. 2012
See also:
Shenoy et al. 2011

Modeling
Hennequin et al. 2014,
See also:
Maass et al. 2002,
Sussillo and Abbott, 2009
Laje and Buonomano, 2012
Shenoy et al., 2011

Week 14-part 1: Rich neuronal dynamics: a wish list



-Long transients

-Reliable (non-chaotic)

-Rich dynamics (non-trivial)

-Compatible with neural data (excitation/inhibition)

-Plausible plasticity rules

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- Review:Random Networks
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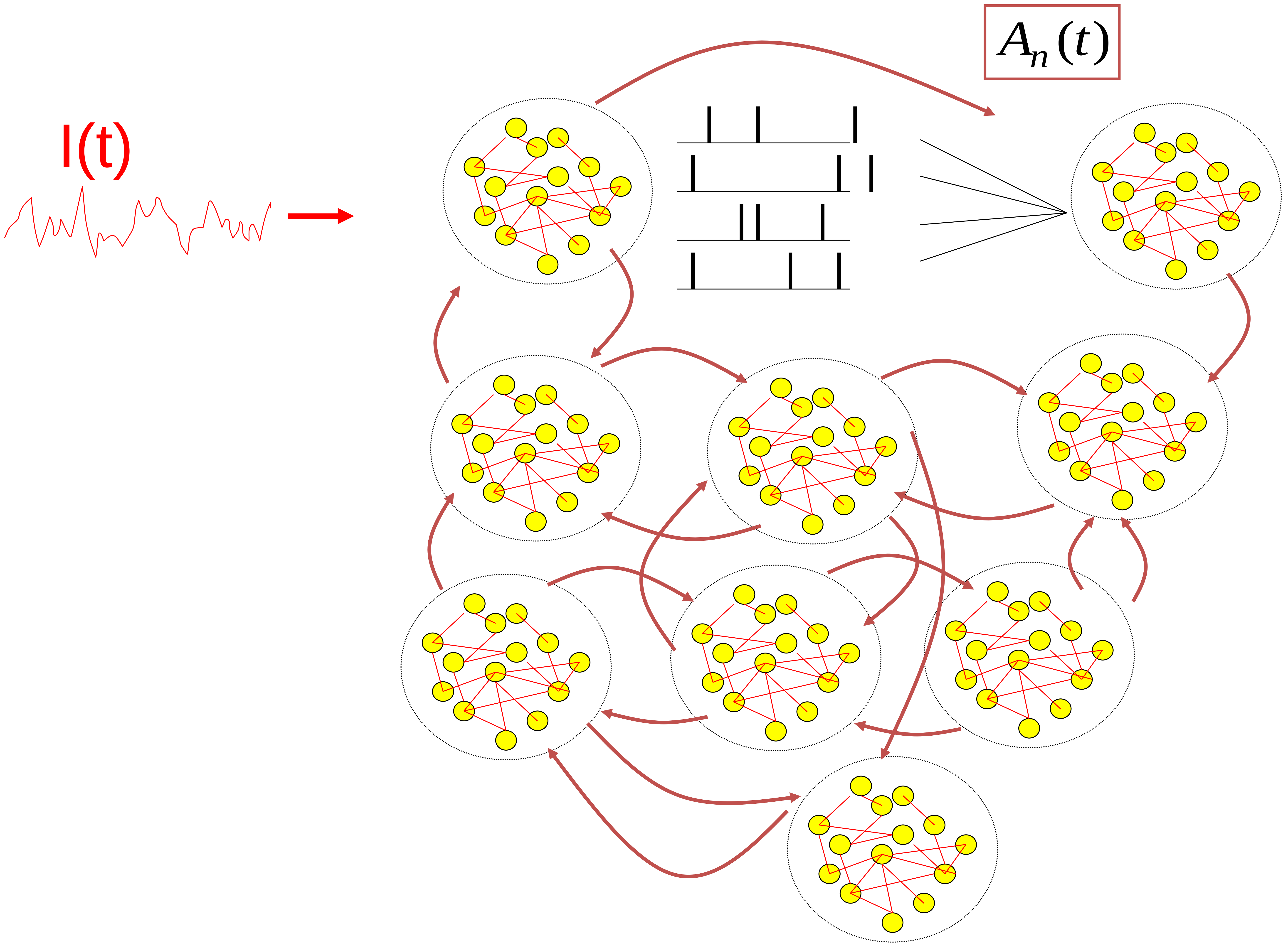
14.2 Random Networks
- rate model
- stationary state and chaos

14.3 Hebbian Plasticity
- excitatory synapses
- inhibitory synapses

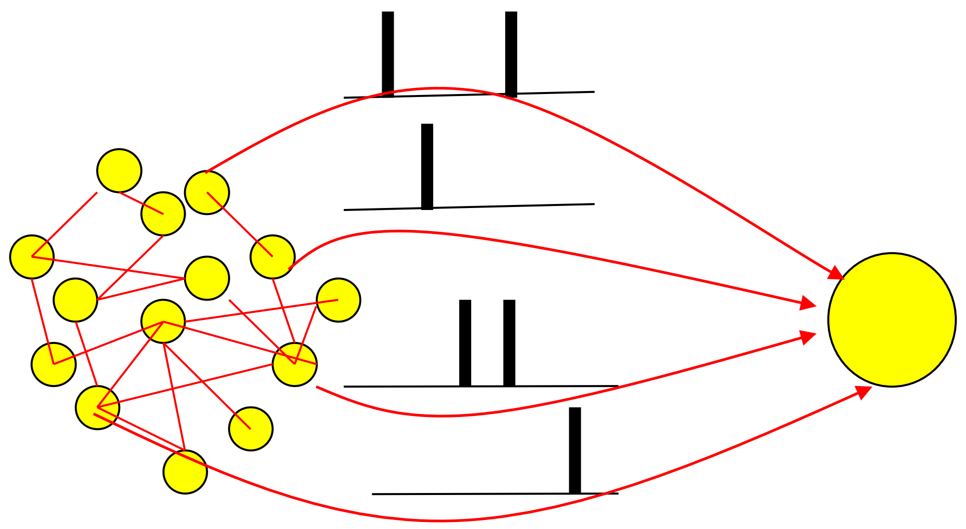
14.4. Reward-modulated plasticity
- free solution

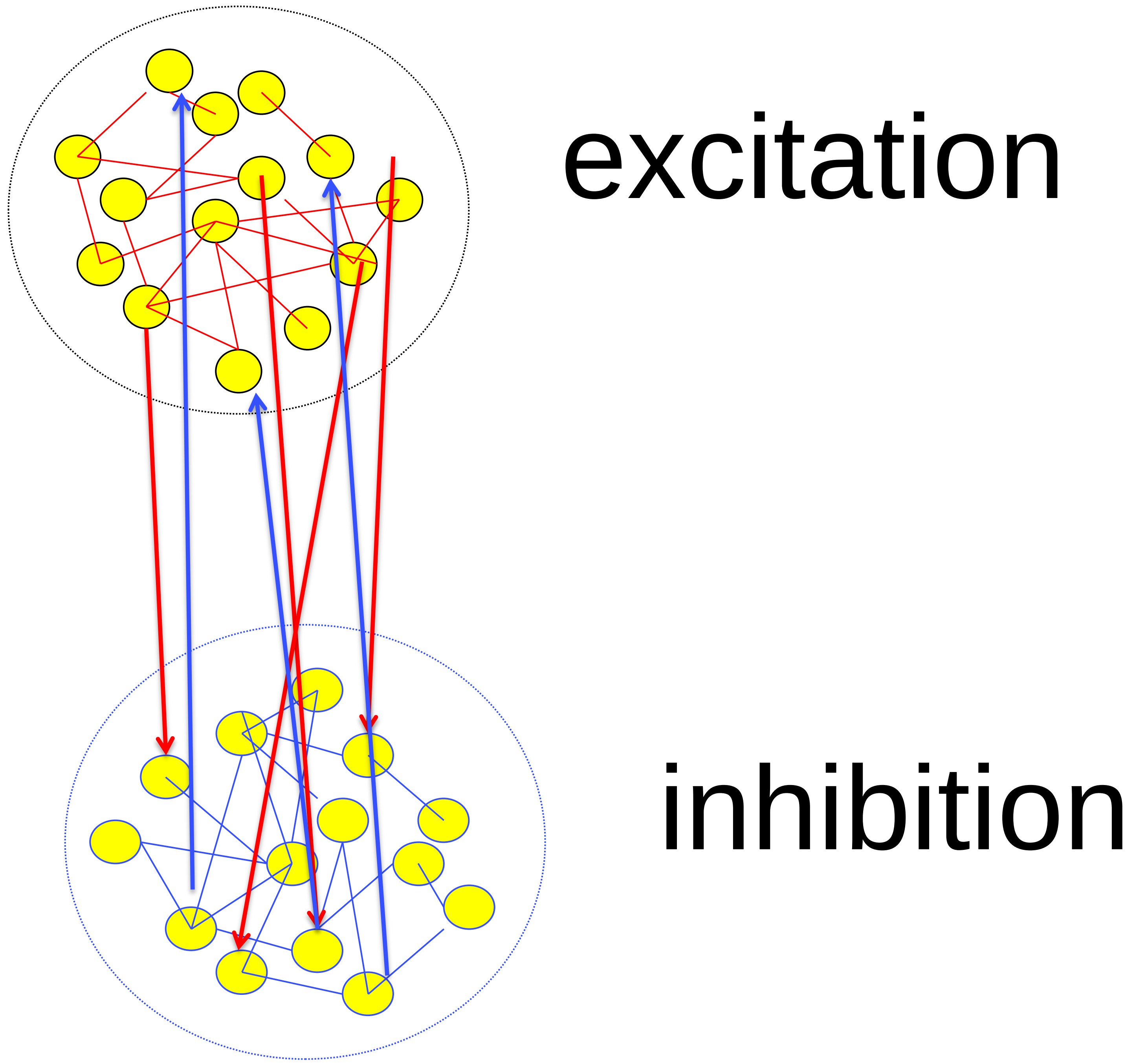
14.5. Helping Humans
- time dependent activity
- network states

Week 14-part 2: Review: microscopic vs. macroscopic



Week 14-part 2: Review: Random coupling



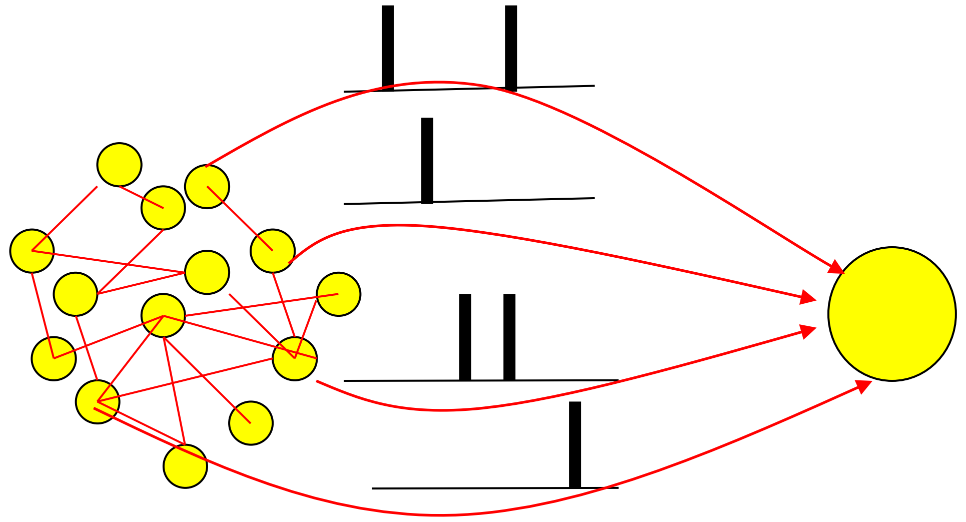


Homogeneous network:

-each neuron receives input from k neurons in network

-each neuron receives the same (mean) external input

Week 14-part 2: Review: integrate-and-fire/stochastic spike arrival



Stochastic spike arrival:

excitation, total rate R_e

inhibition, total rate R_i

Synaptic current pulses

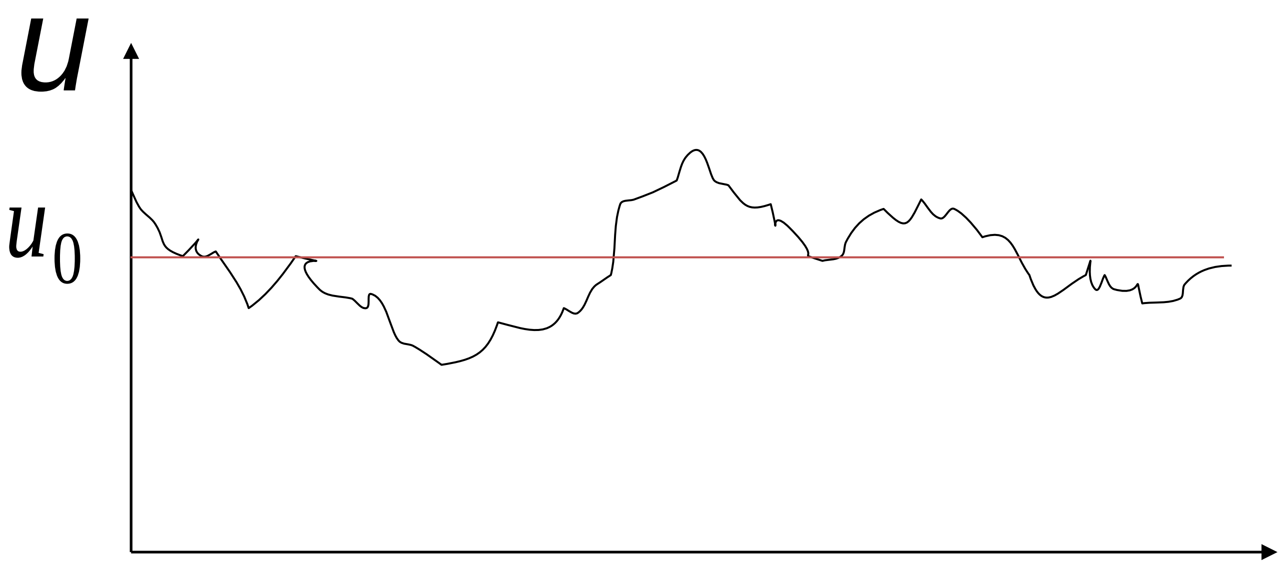
$$\tau \frac{d}{dt}u = -(u-u_{eq}) + R\left\{ \sum_{k,f} q_e \delta(t-t_k^f) - \sum_{k',f'} q_i \delta(t-t_{k'}^{f'}) \right\}$$

EPSC

IPSC

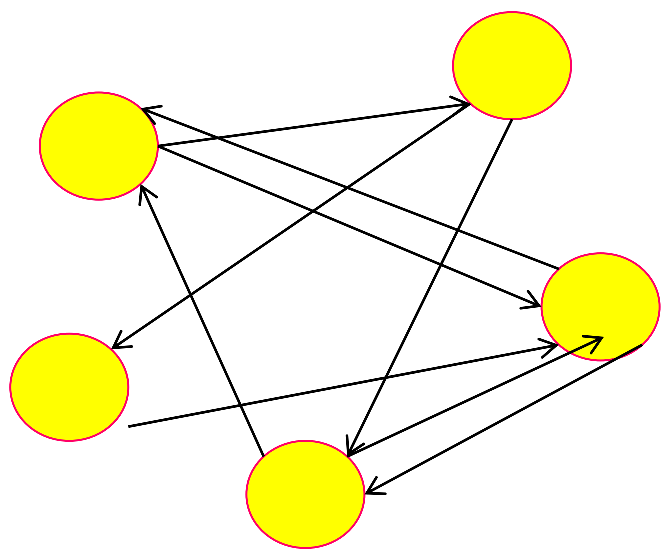
Firing times:
Threshold crossing

$$\tau \frac{d}{dt}u = -(u-u_{eq}) + R\, I^{mean}(t) + \xi(t)$$



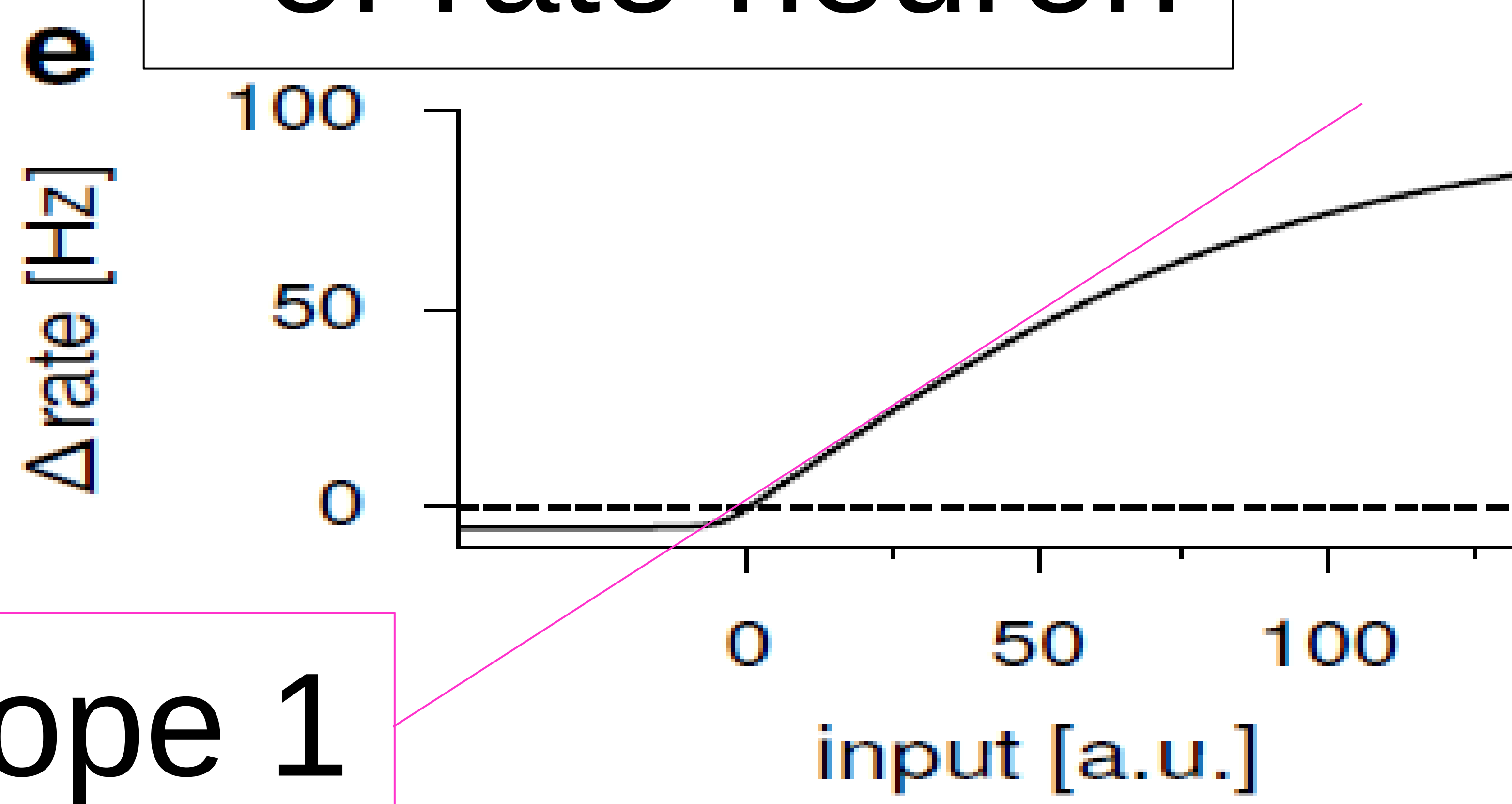
Langevin equation,
Ornstein Uhlenbeck process
→ Fokker-Planck equation

Week 14-part 2: Dynamics in Rate Networks



$$\frac{d}{dt} r_i = -r_i + F\left(\sum_j w_{ij} r_j\right)$$

F-I curve
of rate neuron



Slope 1

Fixed point with F(0)=0 →

$$r_i = 0$$

stable

unstable

Suppose:

$$1 = F'(0) = \frac{d}{dx} F(x=0)$$

Suppose 1 dimension

$$\frac{d}{dt} x = -x + F(wx)$$

Exercise 1: Stability of fixed point

$$\frac{d}{dt}x = -x + F(wx)$$

Next lecture: 9h43

Fixed point with F(0)=0 →

$$x = 0$$

Calculate stability, take *w* as parameter

Suppose:

$$1 = F'(0) = \frac{d}{dx}F(x=0)$$

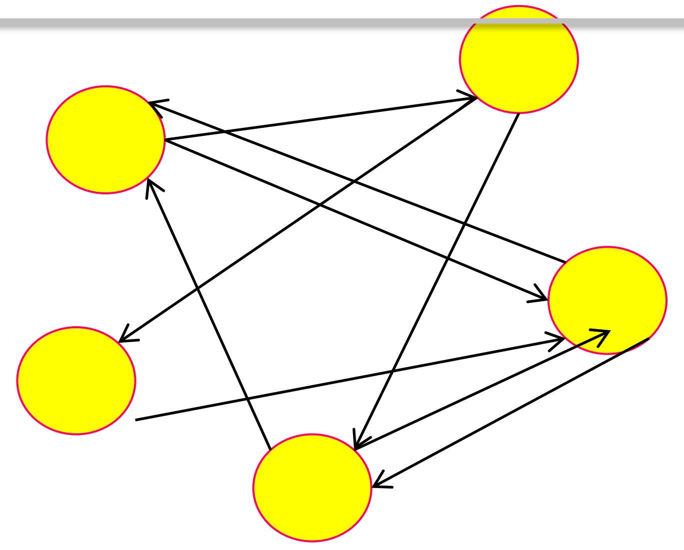
Suppose 1 dimension

$$\frac{d}{dt}x = -x + F(wx)$$

Week 14-part 2: Dynamics in Rate Networks

Blackboard:
Two dimensions!

$$\frac{d}{dt} r_i = -r_i + F\Big(\sum_j w_{ij} r_j\Big)$$



Fixed point with F(0)=0 $\rightarrow$

$$r_i = 0$$

stable
w<1

unstable
w>1

Suppose:

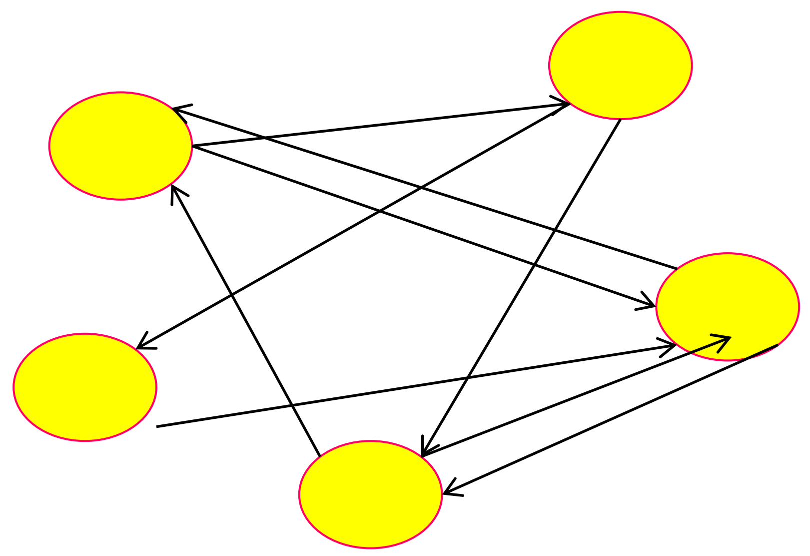
$$1 = F'(0) = \frac{d}{dx} F(x=0)$$

Suppose 1 dimension

$$\frac{d}{dt} x = -x + F(wx)$$

Week 14-part 2: Dynamics in RANDOM Rate Networks

$$\frac{d}{dt} r_i = -r_i + F\left(\sum_j w_{ij} r_j\right)$$



Random,
10 percent connectivity

$$1 = F'(0) = \frac{d}{dx} F(x=0)$$

Fixed point:

$$r_i = 0$$

stable

$$\mathrm{Re}(\lambda) < 1$$

unstable

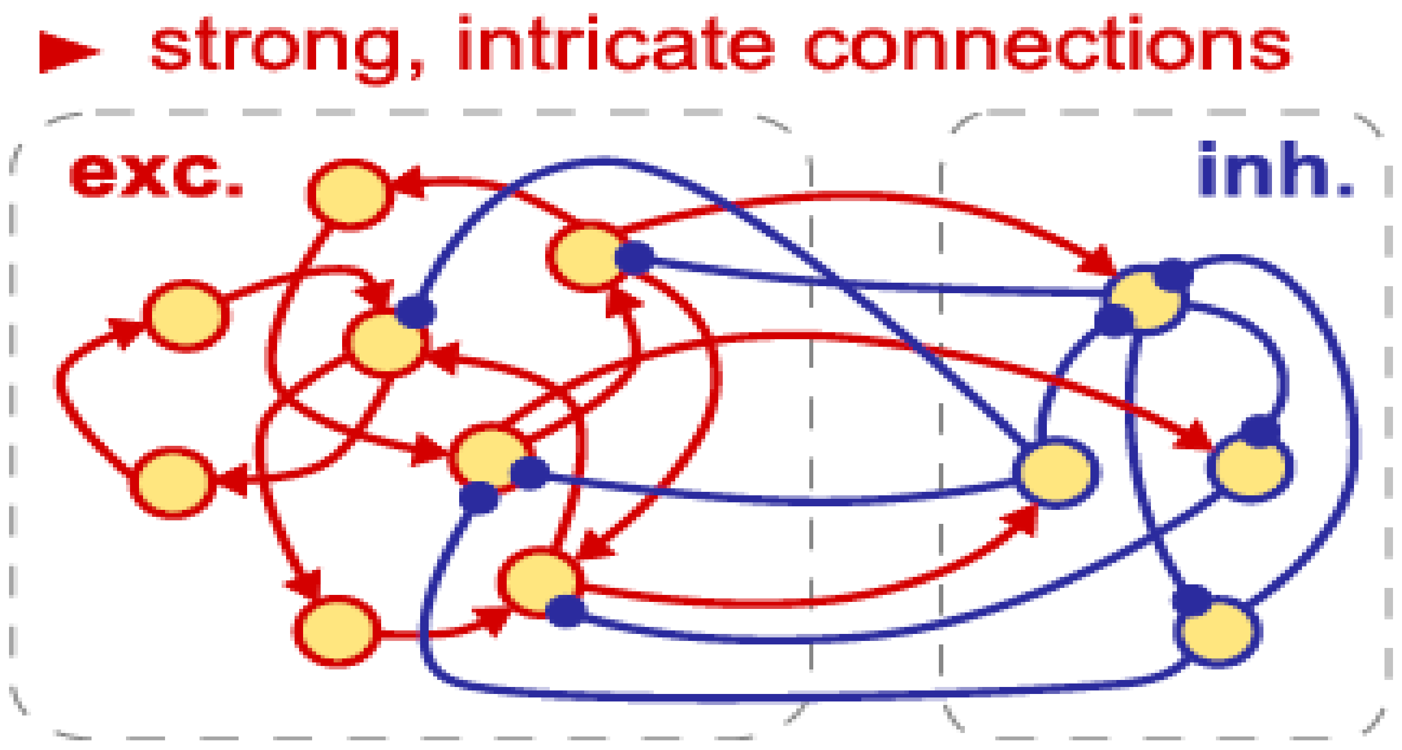
$$\mathrm{Re}(\lambda) > 1$$

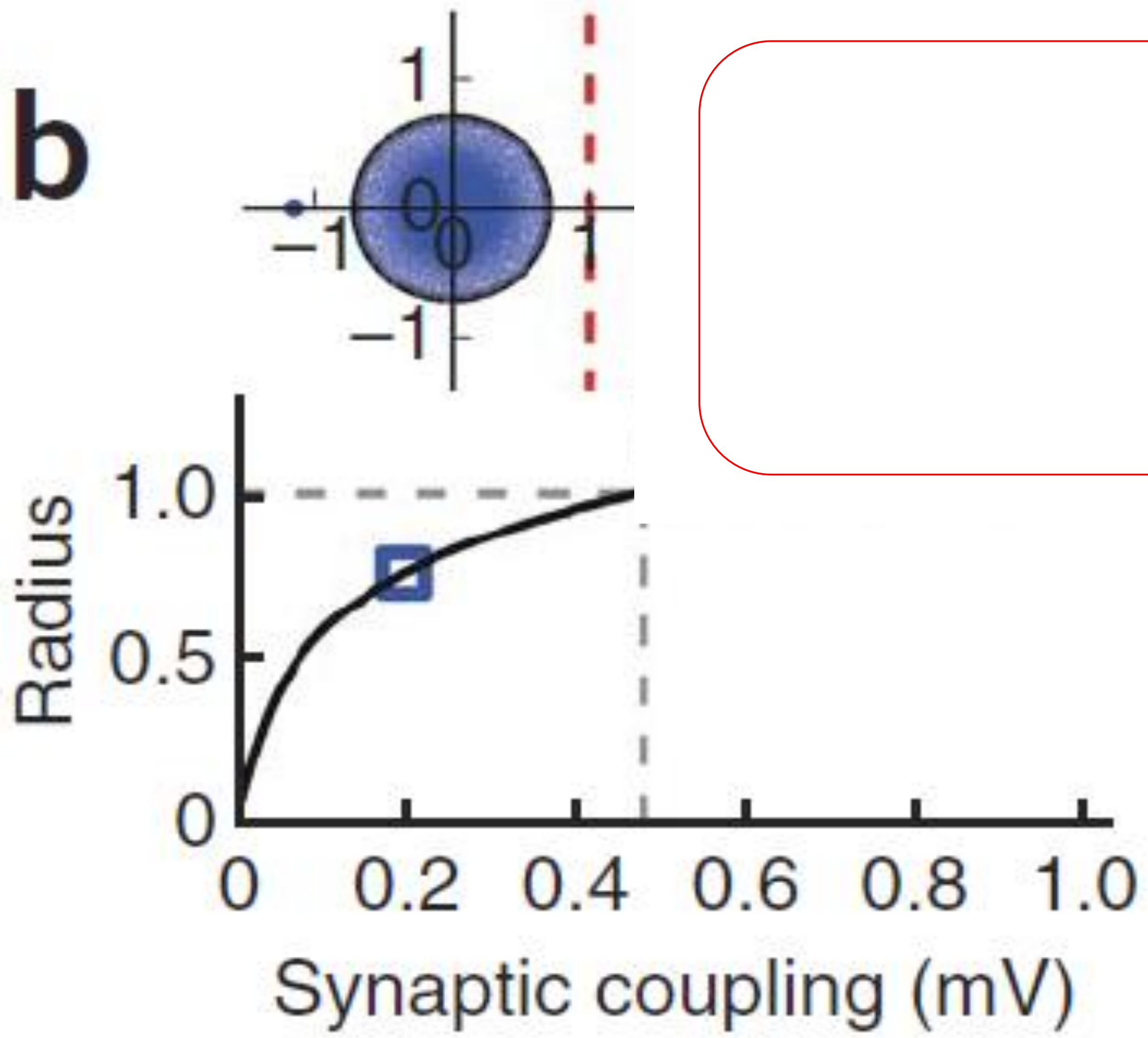
Chaotic dynamics:

Sompolinksy et al. 1988
(and many others:
Amari, ...

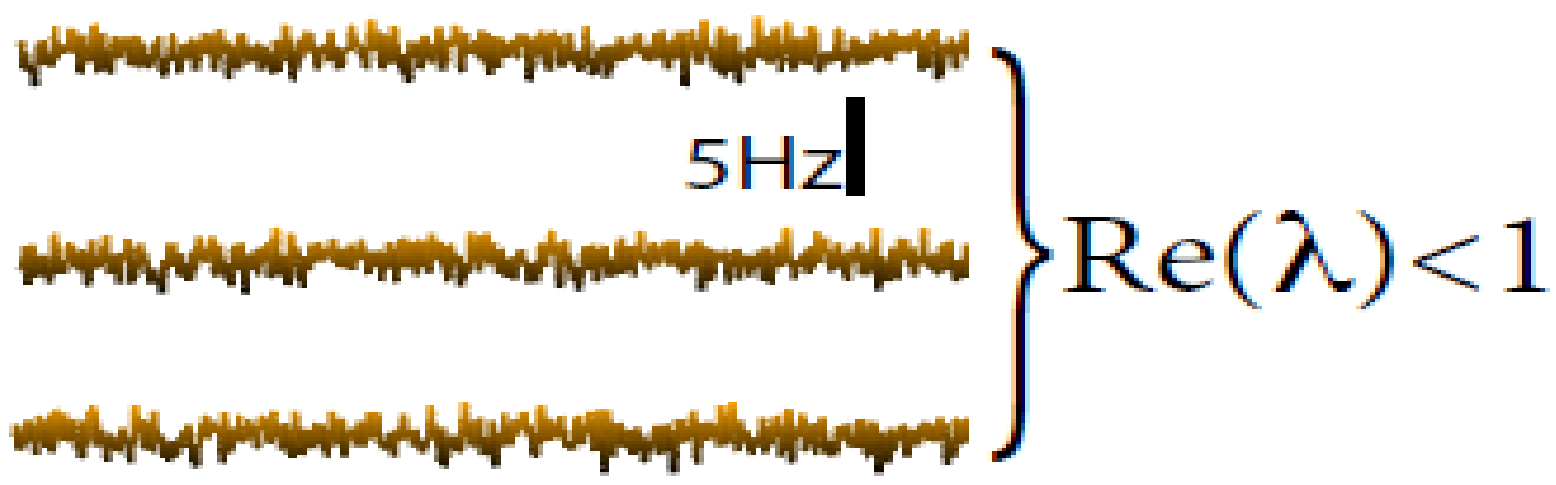
Unstable dynamics and Chaos

$$\frac{d}{dt} r_i = -r_i + F\left(\sum_j w_{ij} r_j\right) + \cancel{\xi_i}(t)$$





chaos



Rajan and Abbott, 2006
Image: Ostojic, Nat.Neurosci, 2014

Image:
Hennequin et al. Neuron, 2014

Week 14-part 2: Dynamics in Random SPIKING Networks

$$\frac{d}{dt}u_i = -u_i + \sum_j \sum_f w_{ij} \; \delta(t - t_j^f)$$

Firing times:
Threshold crossing

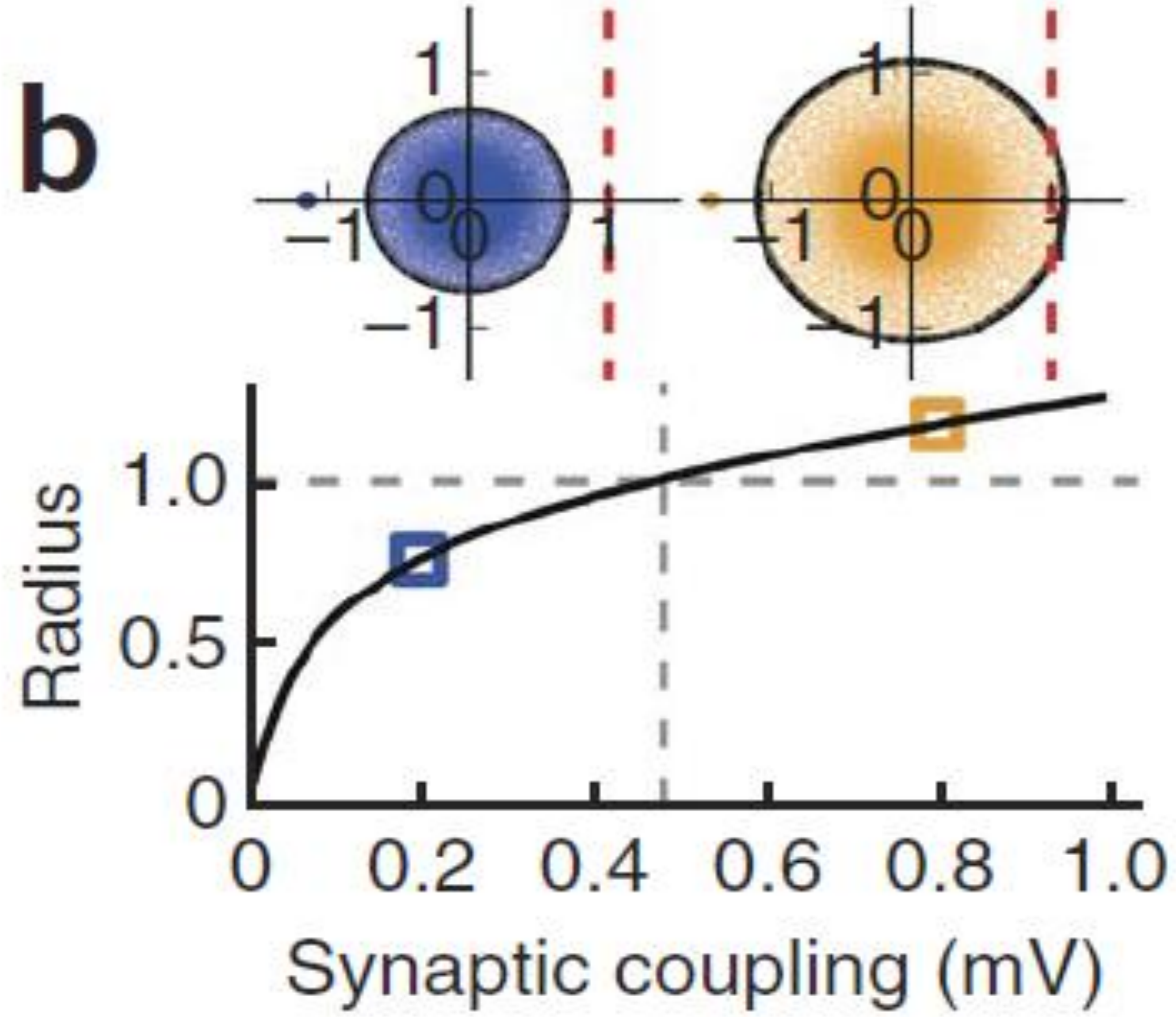
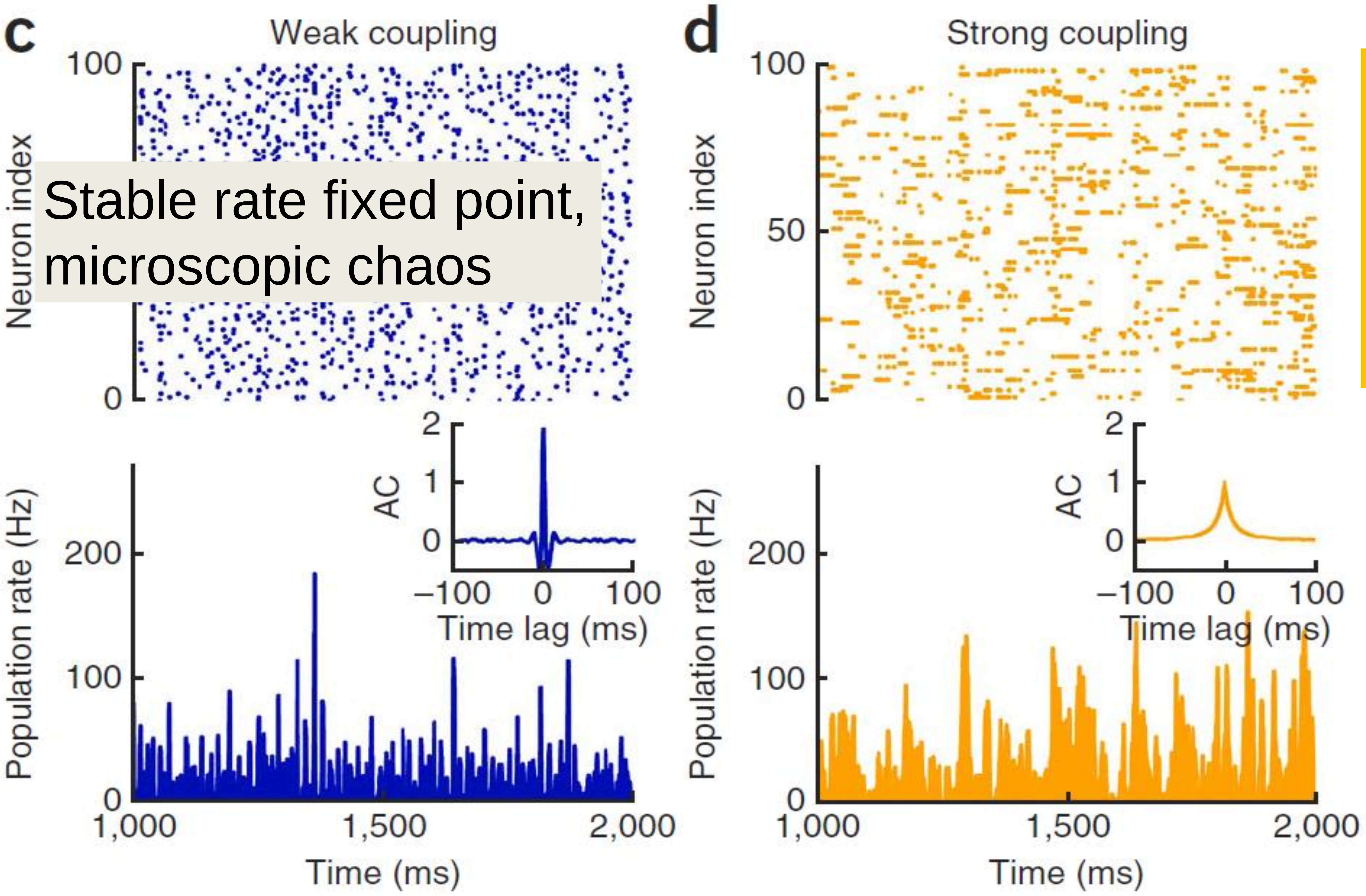


Image: Ostojic, Nat.Neurosci, 2014

Week 14-part 2: Stationary activity: two different regimes



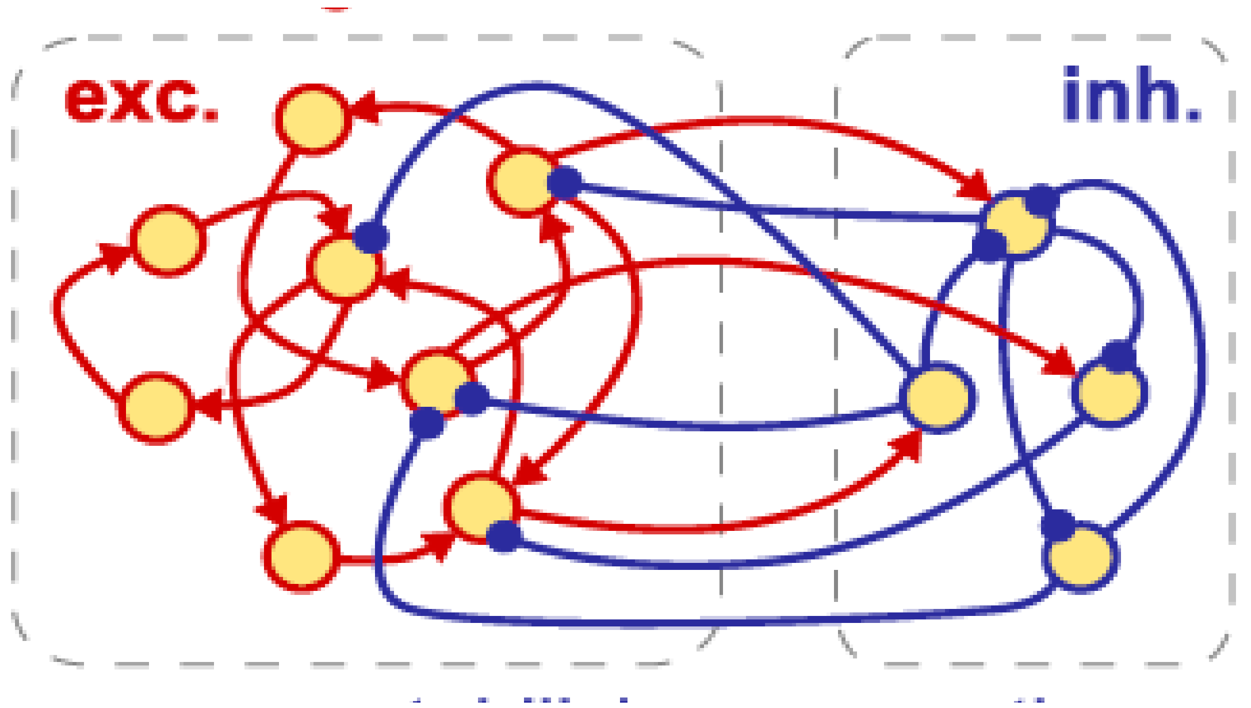
Stable rate fixed point,
microscopic chaos

Switching/bursts →
long autocorrelations:
Rate chaos

$$\mathrm{Re}(\lambda) > 1$$

Ostojic,
Nat.Neurosci, 2014

Week 14-part 2: Rich neuronal dynamics: a wish list



-Long transients

-Reliable (non-chaotic)

-Rich dynamics (non-trivial)

-Compatible with neural data (excitation/inhibition)

-Plausible plasticity rules

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Week 14-part 3: Plasticity-optimized circuit

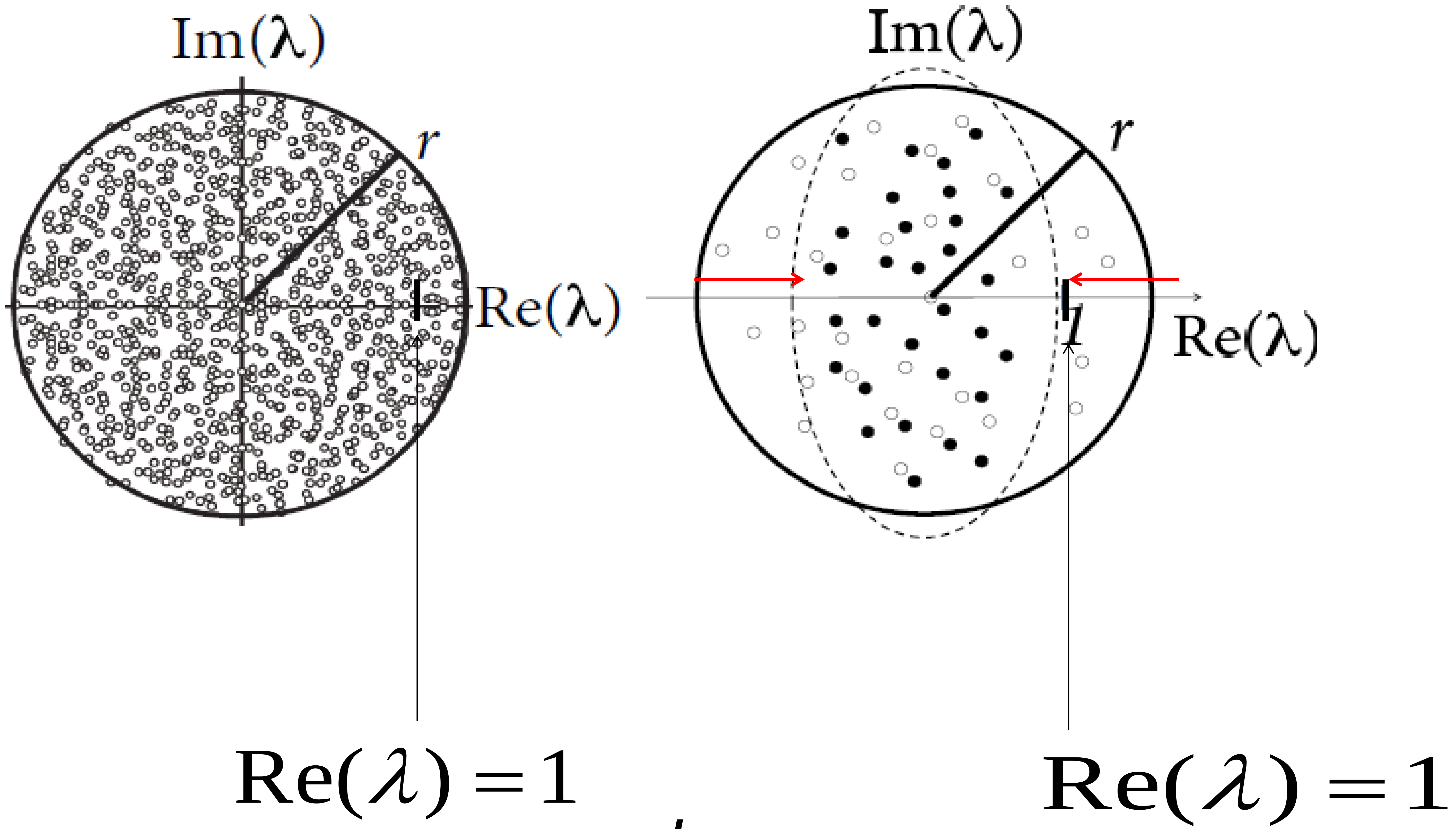
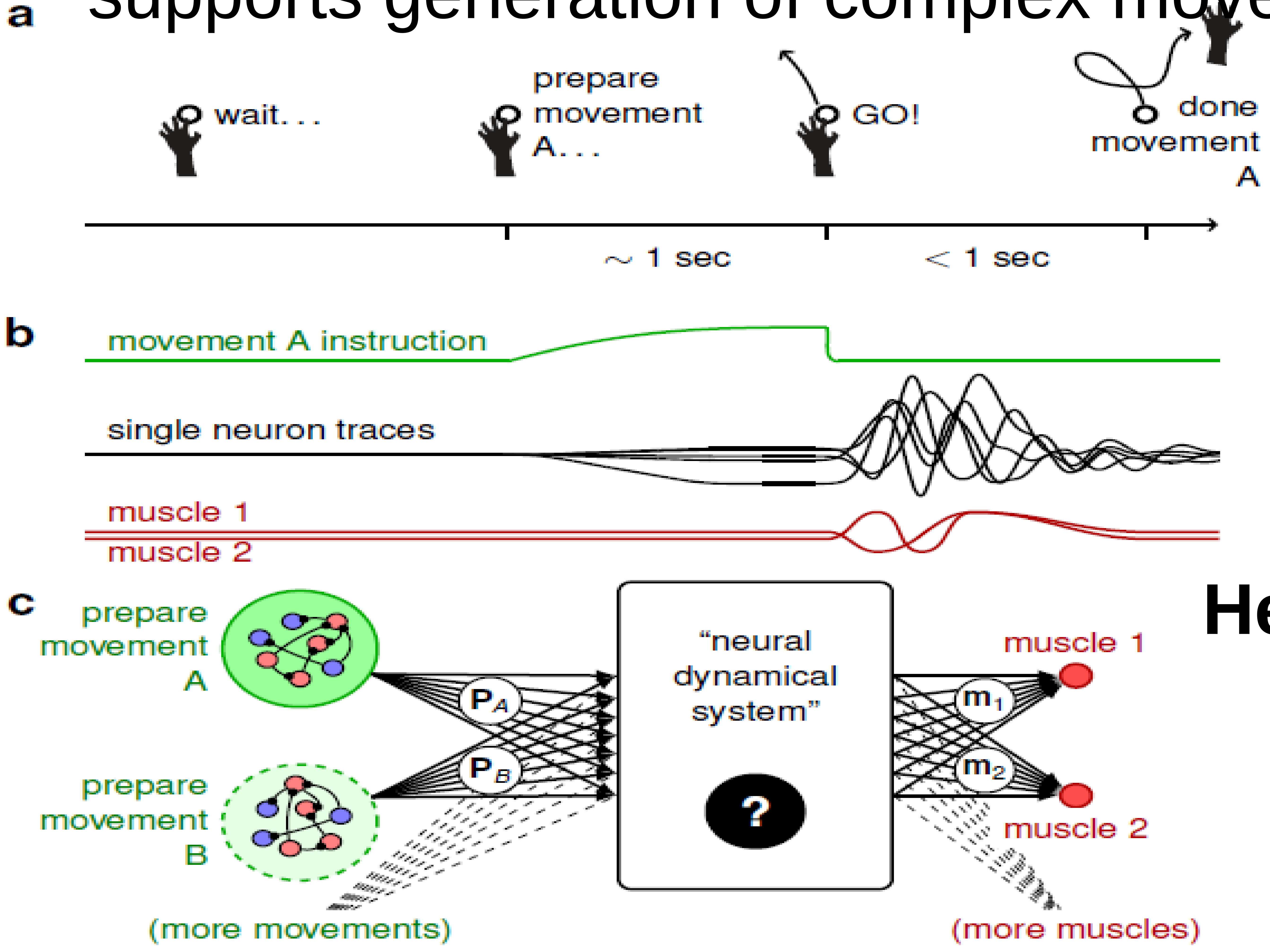


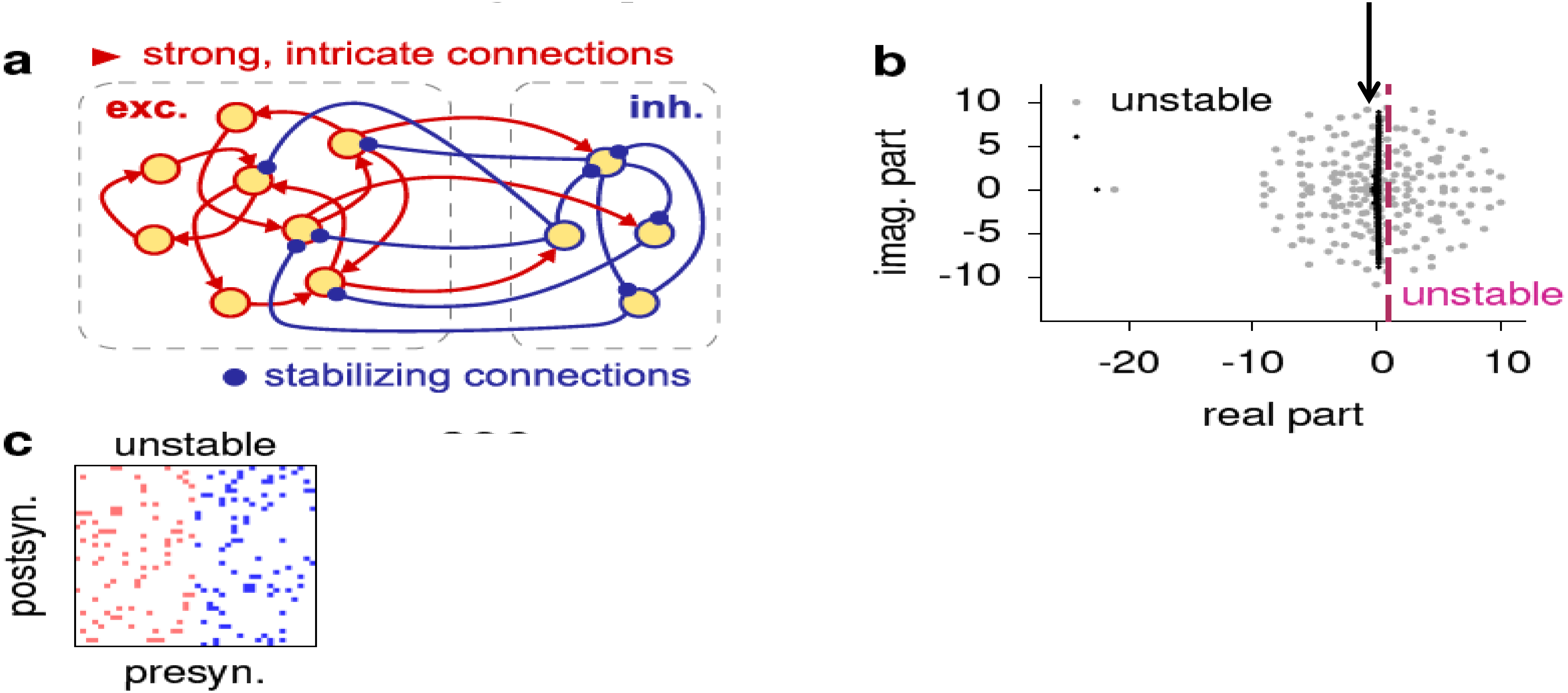
Image:
Hennequin et al. Neuron, 2014

Optimal control of transient dynamics in balanced networks supports generation of complex movements



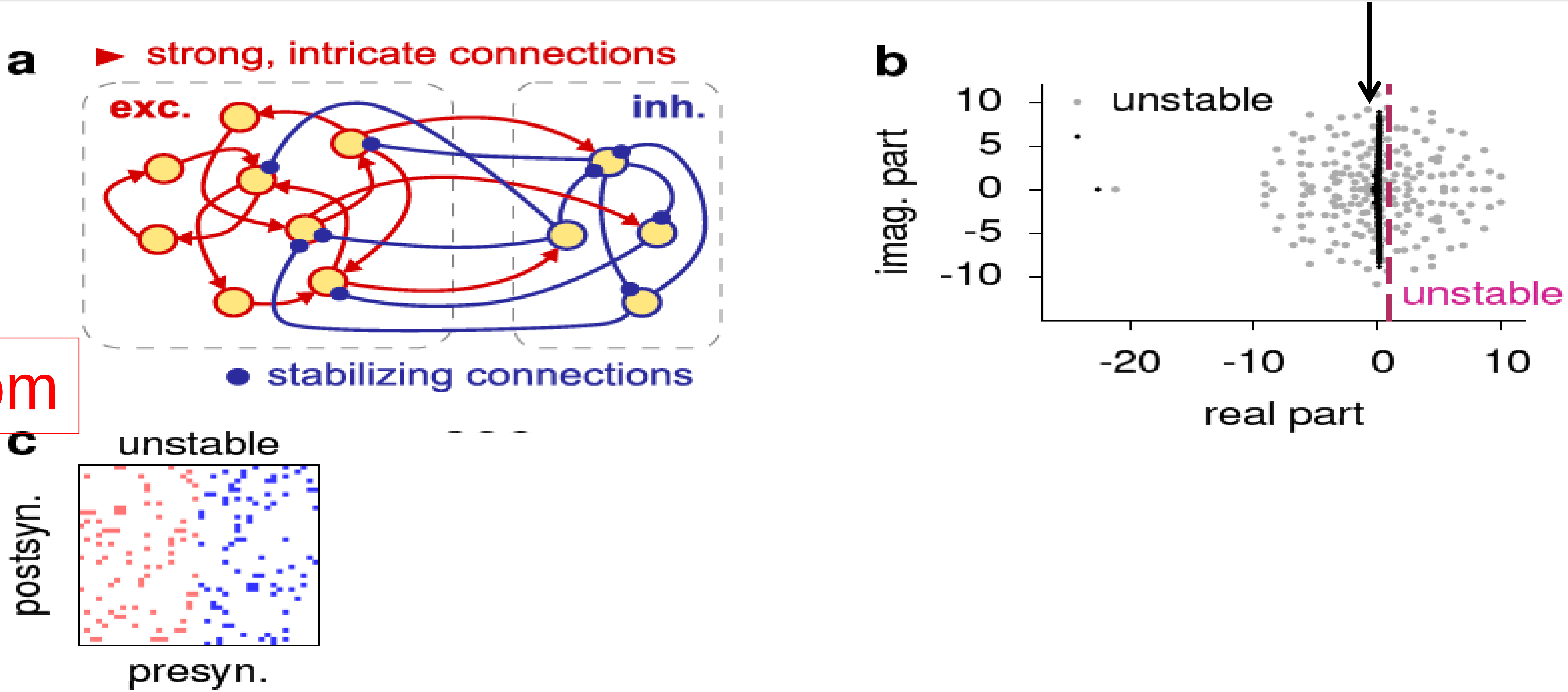
Hennequin et al. 2014,

Random



Random connectivity

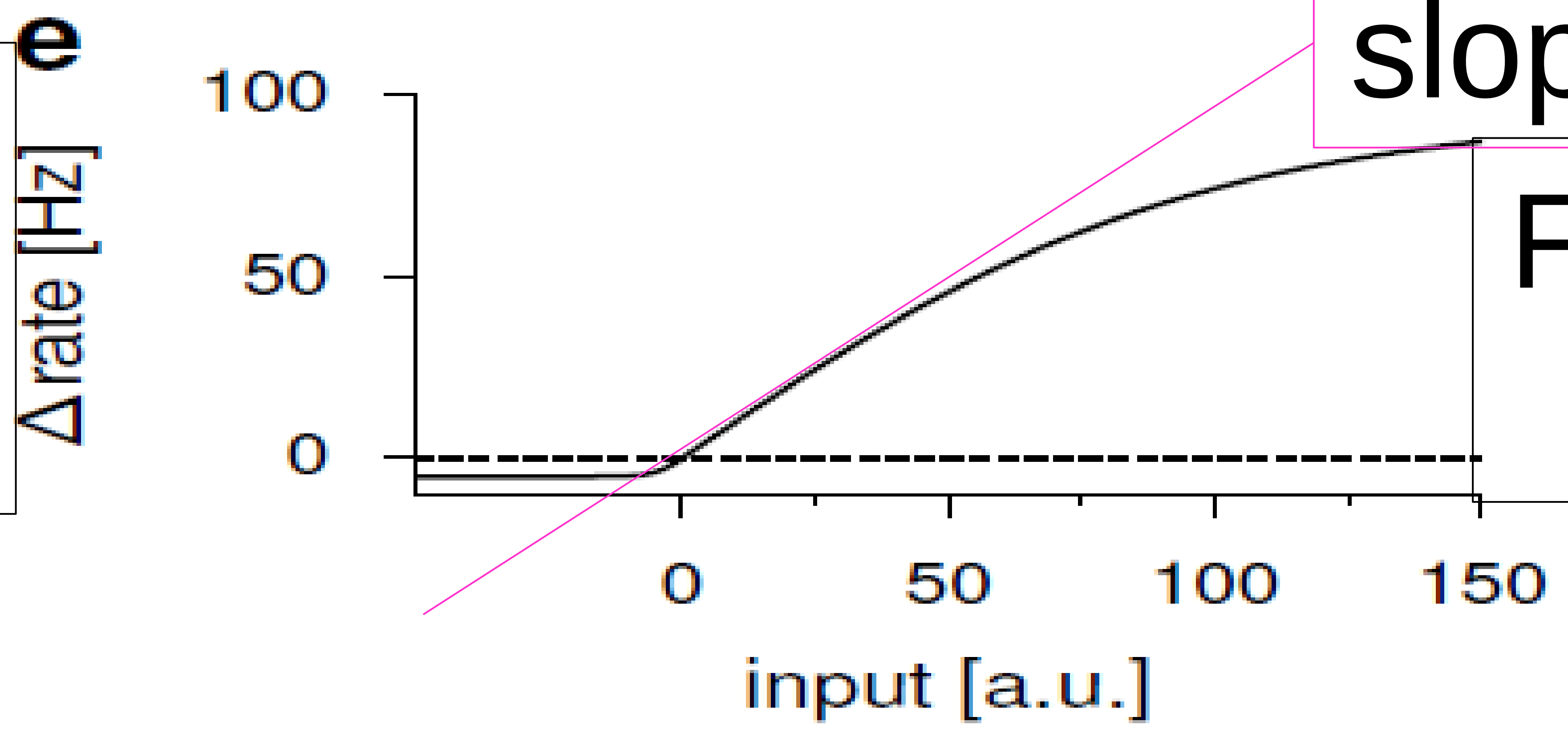
Week 14-part 3: Random Plasticity-optimized circuit



Random

Week 14-part 3: Random Plasticity-optimized circuit

a_1= slowest
= most amplified

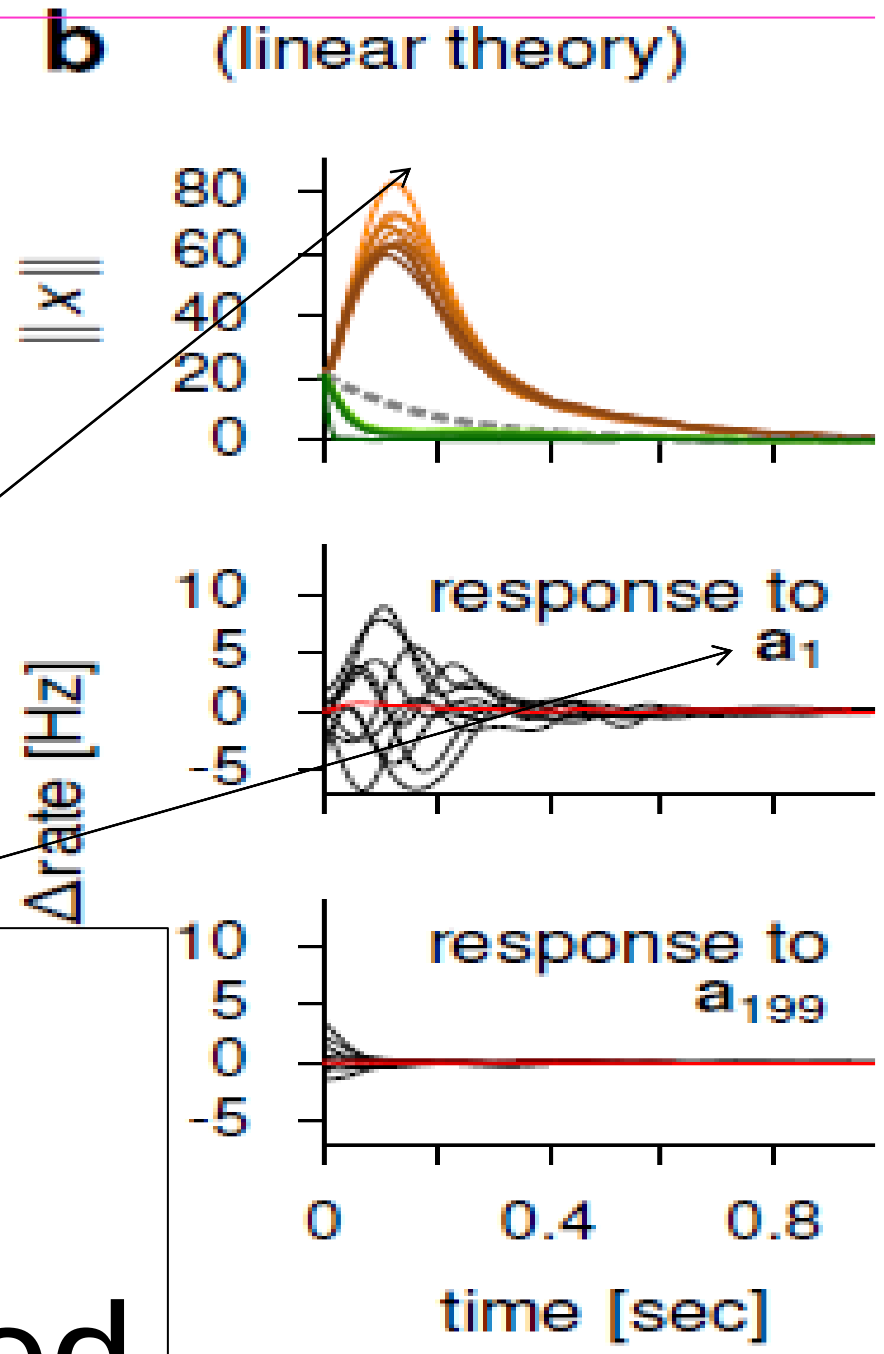


slope 1/linear theory

F-I curve
of rate neuron

Week 14-part 3: Random Plasticity-optimized circuit

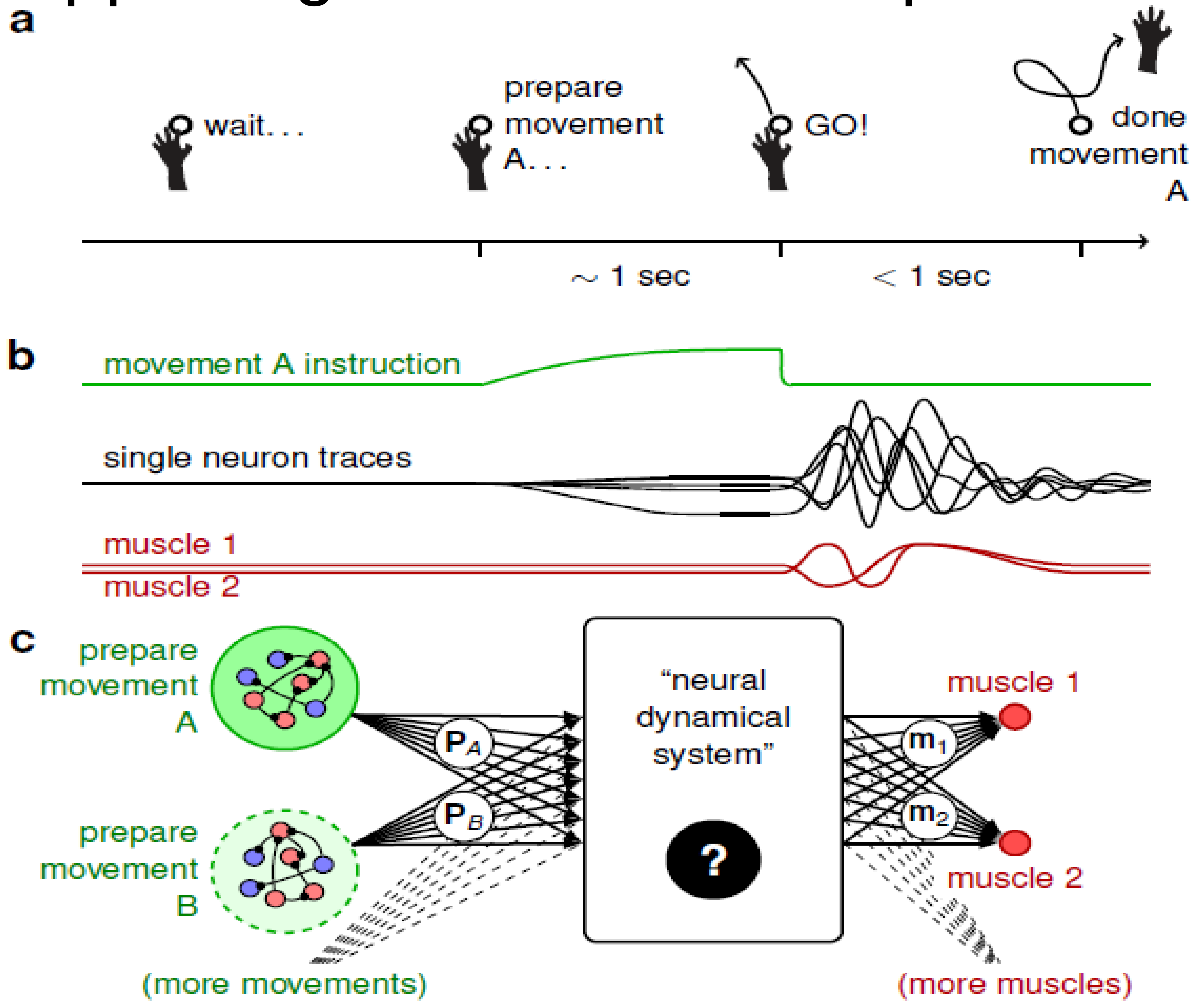
slope 1/linear theory



a1= slowest

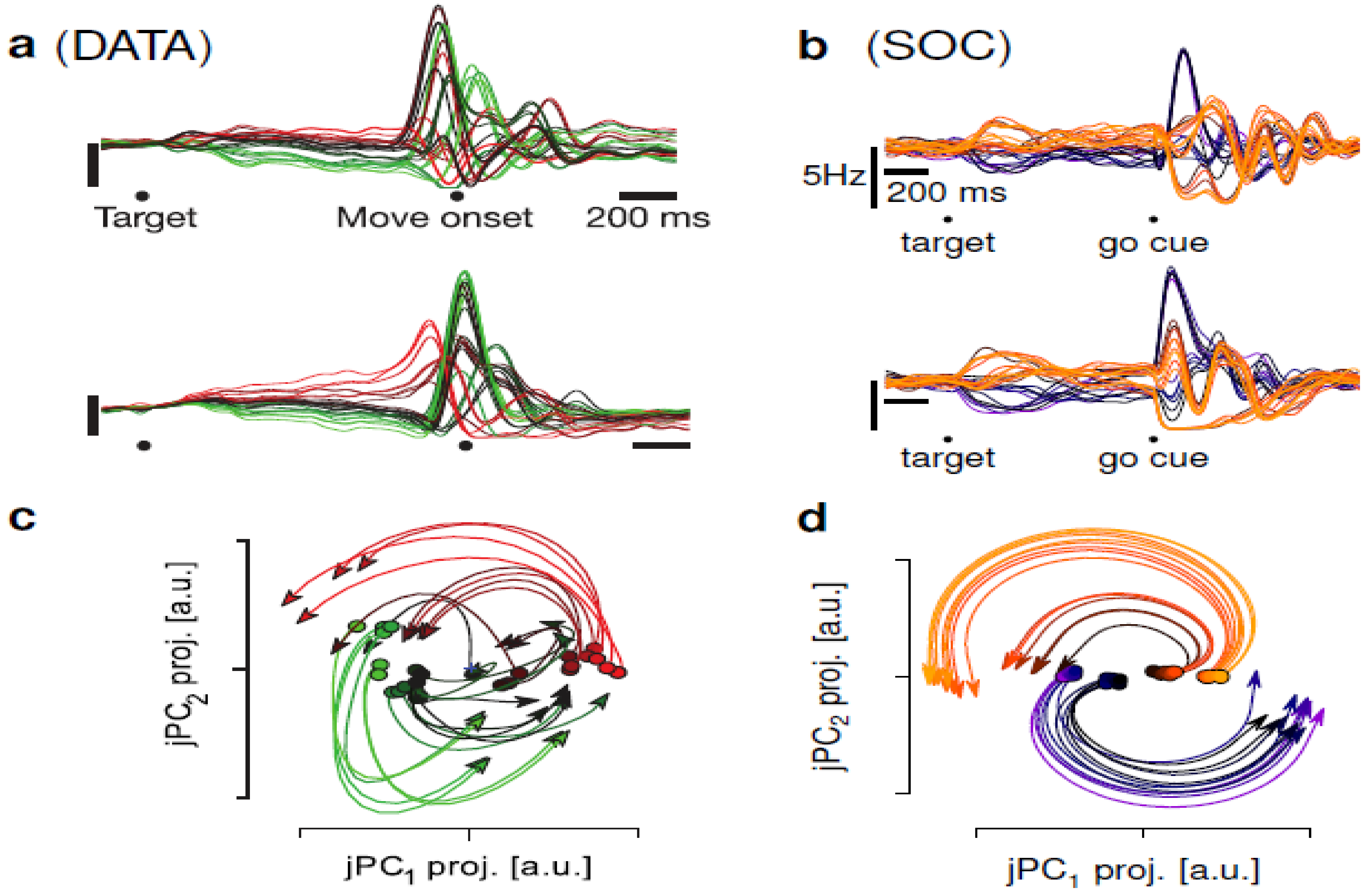
= most amplified

Optimal control of transient dynamics in balanced networks supports generation of complex movements



Hennequin et al. NEURON 2014,

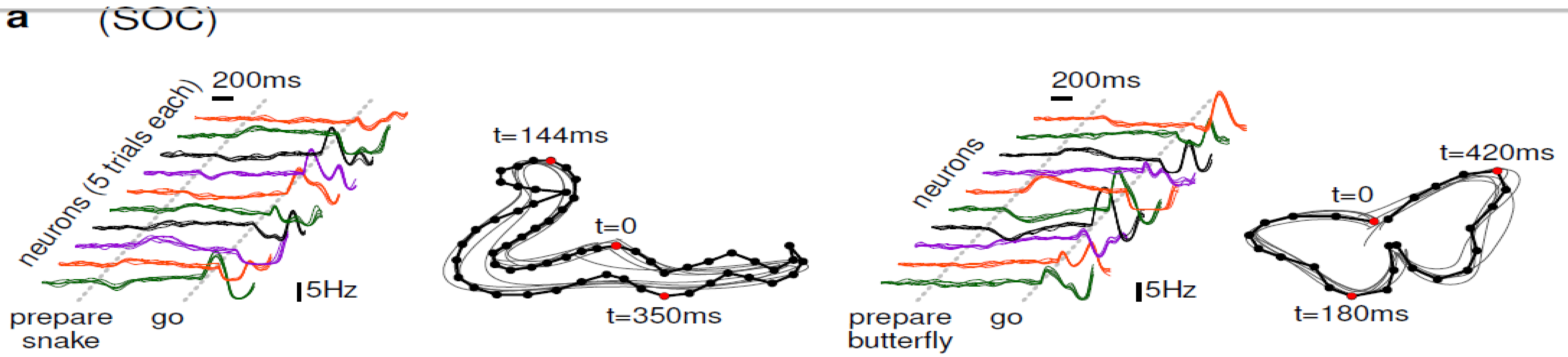
Week 14-part 3: Application to motor cortex: data and model

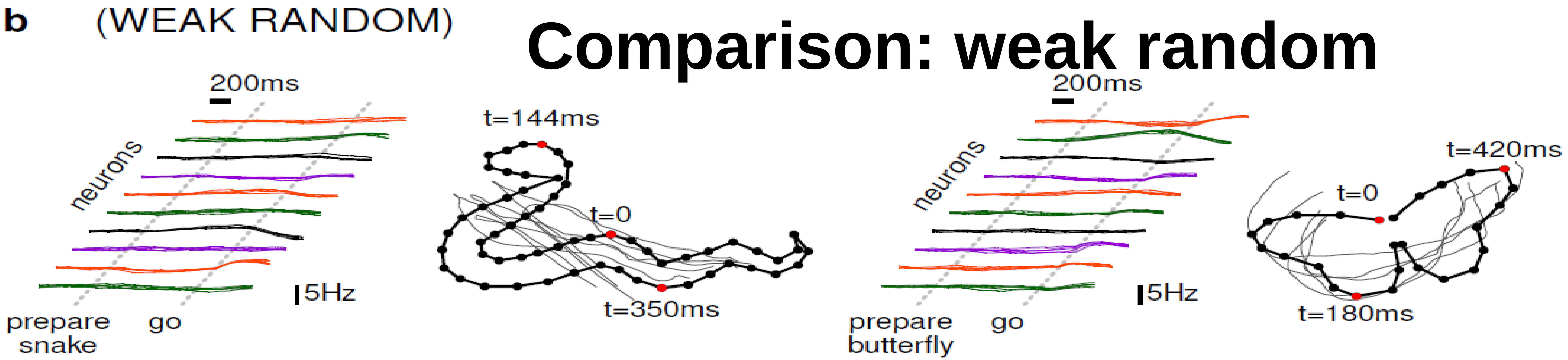


Churchland et al. 2010/2012

Hennequin et al. 2014

Week 14-part 3: Random Plasticity-optimized circuit





Comparison: weak random

Hennequin et al. 2014

Week 14-part 3: Stability optimized SPIKING network

Classic sparse random connectivity (Brunel 2000)

Random connections, fast

Stabilizy-optimized random connections

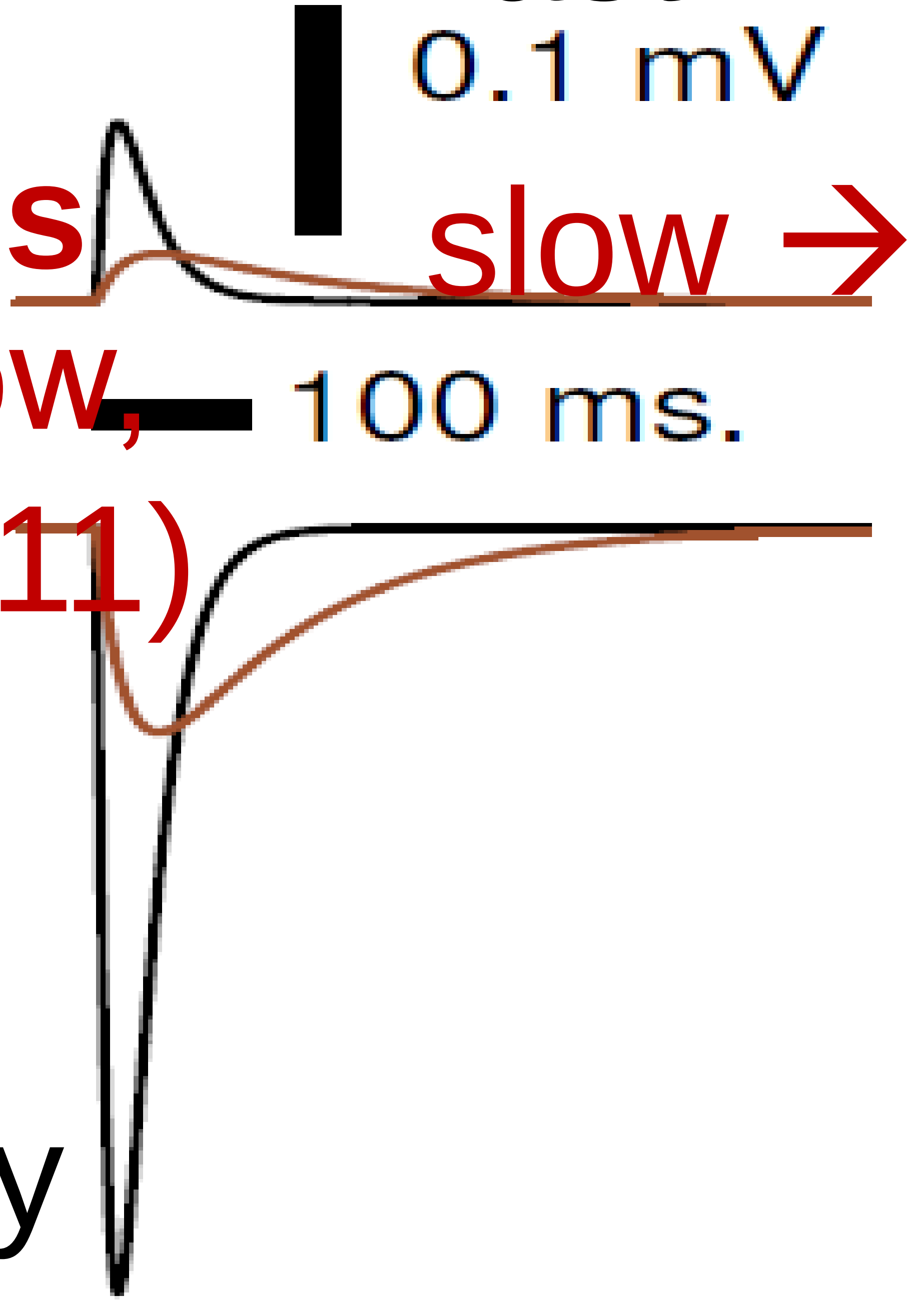
'distal' connections, slow,

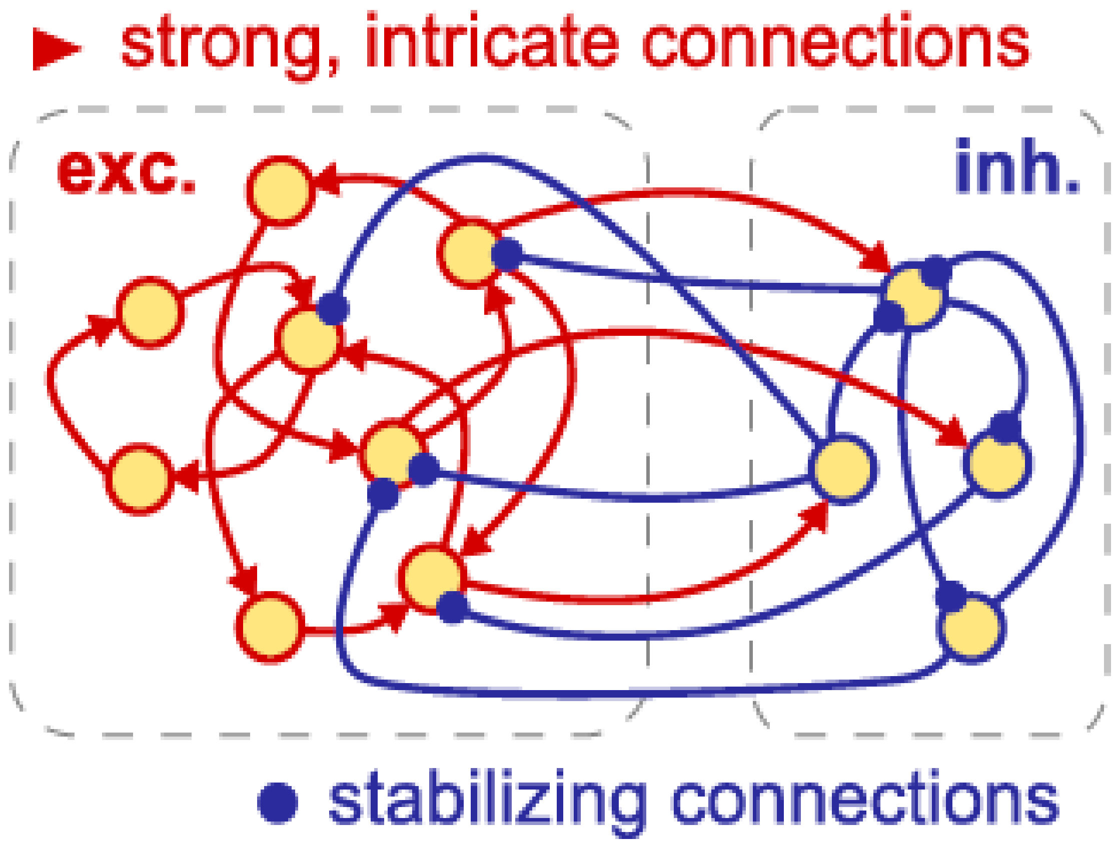
(Branco&Hausser, 2011)

structured

Fast → AMPA

slow → NMDA





Overall:

20% connectivity

12000 excitatory LIF = 200 pools of 60 neurons

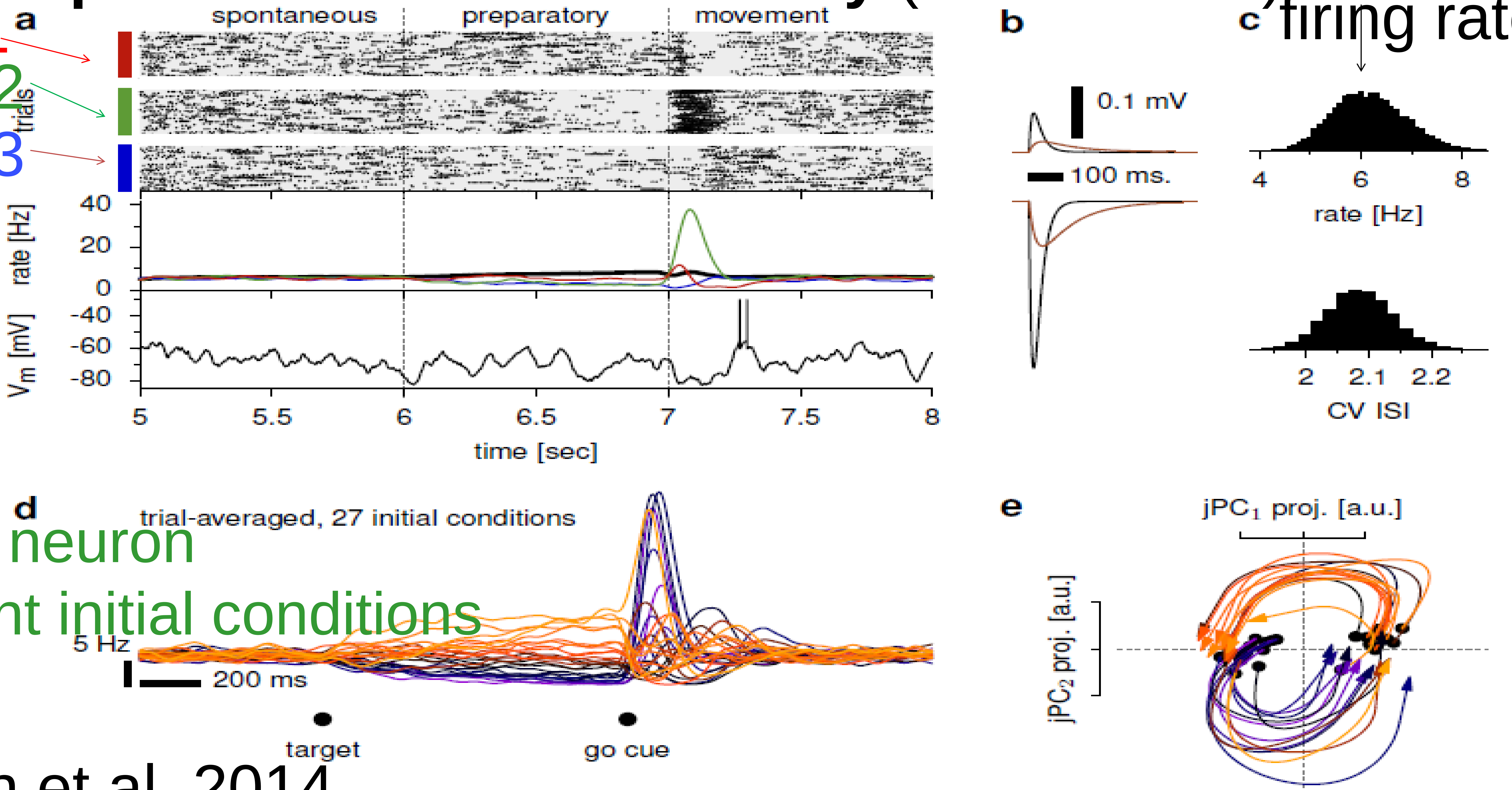
3000 inhibitory LIF = 200 pools of 15 neurons

Week 14-part 3: Stability optimized SPIKING network

Classic sparse random connectivity (Brunel 2000)

Spontaneous firing rate

Neuron 1
Neuron 2
Neuron 3



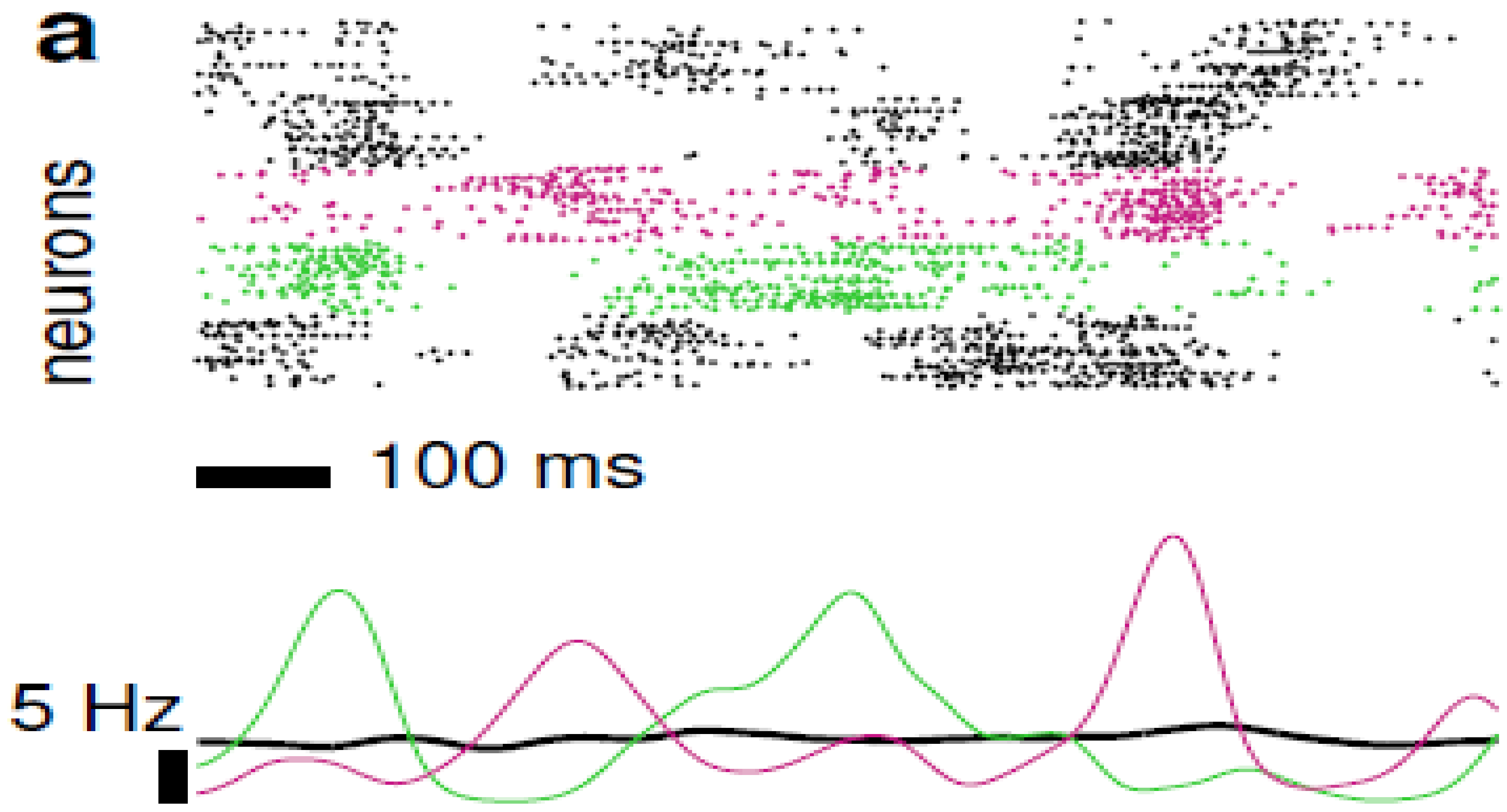
Single neuron
different initial conditions

Hennequin et al. 2014

7: Transient dynamics in a spiking SOC. (a) The network is initialized in a mixture of its to

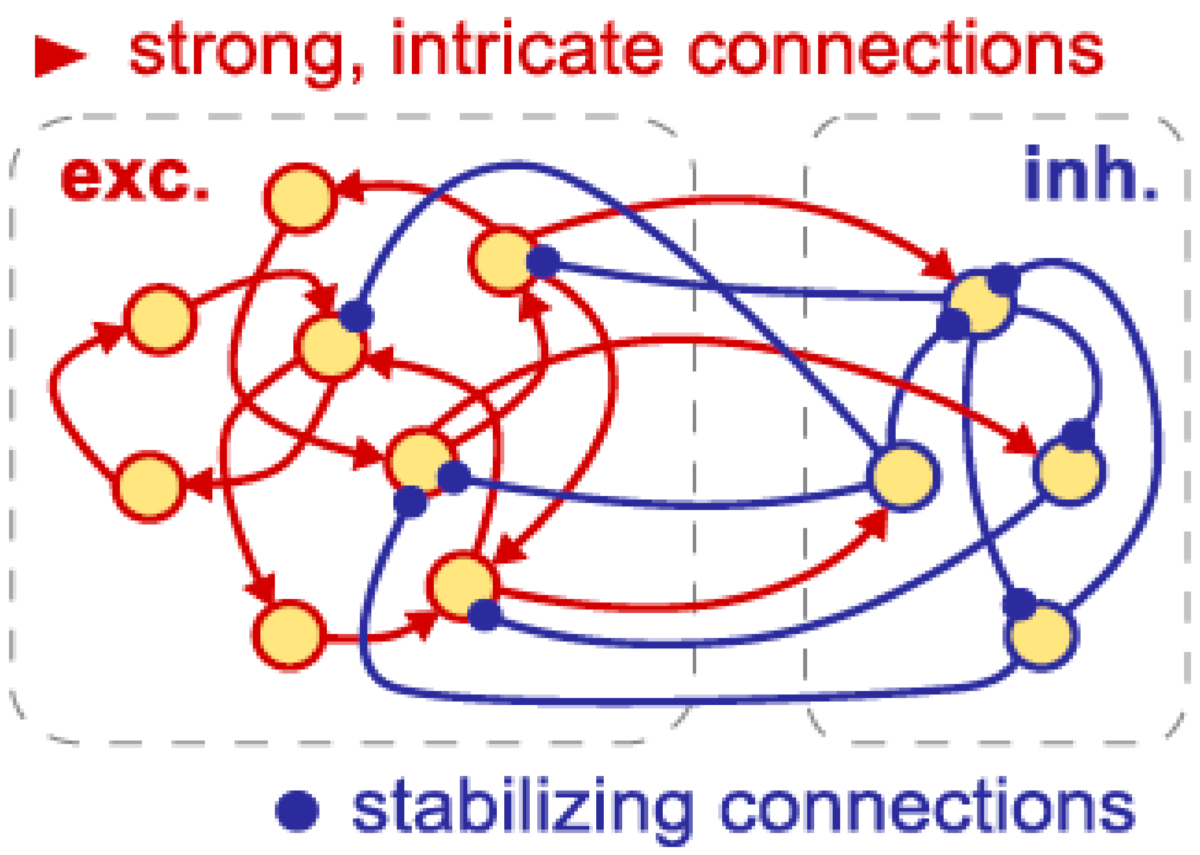
Week 14-part 3: Stability optimized SPIKING network

Classic sparse random connectivity (Brunel 2000)



Hennequin et al. 2014

Week 14-part 3: Rich neuronal dynamics: a result list



- ✓ -Long transients
- ✓ -Reliable (non-chaotic)
- ✓ -Rich dynamics (non-trivial)
- ✓ -Compatible with neural data (excitation/inhibition)
- -Plausible plasticity rules

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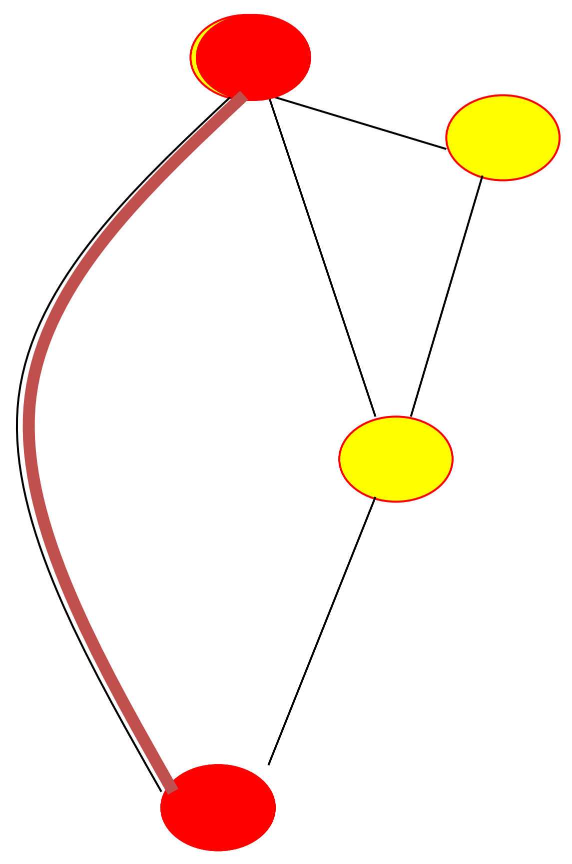
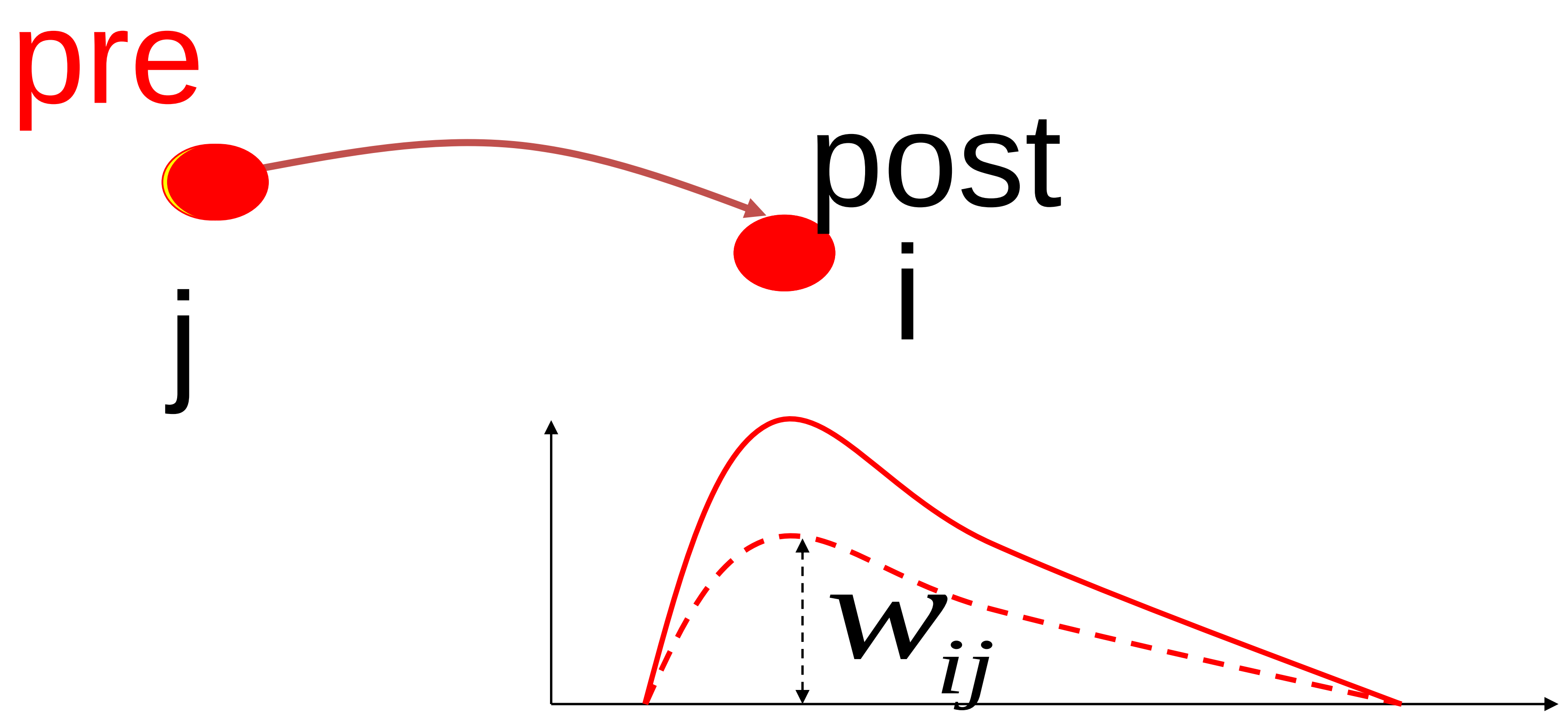
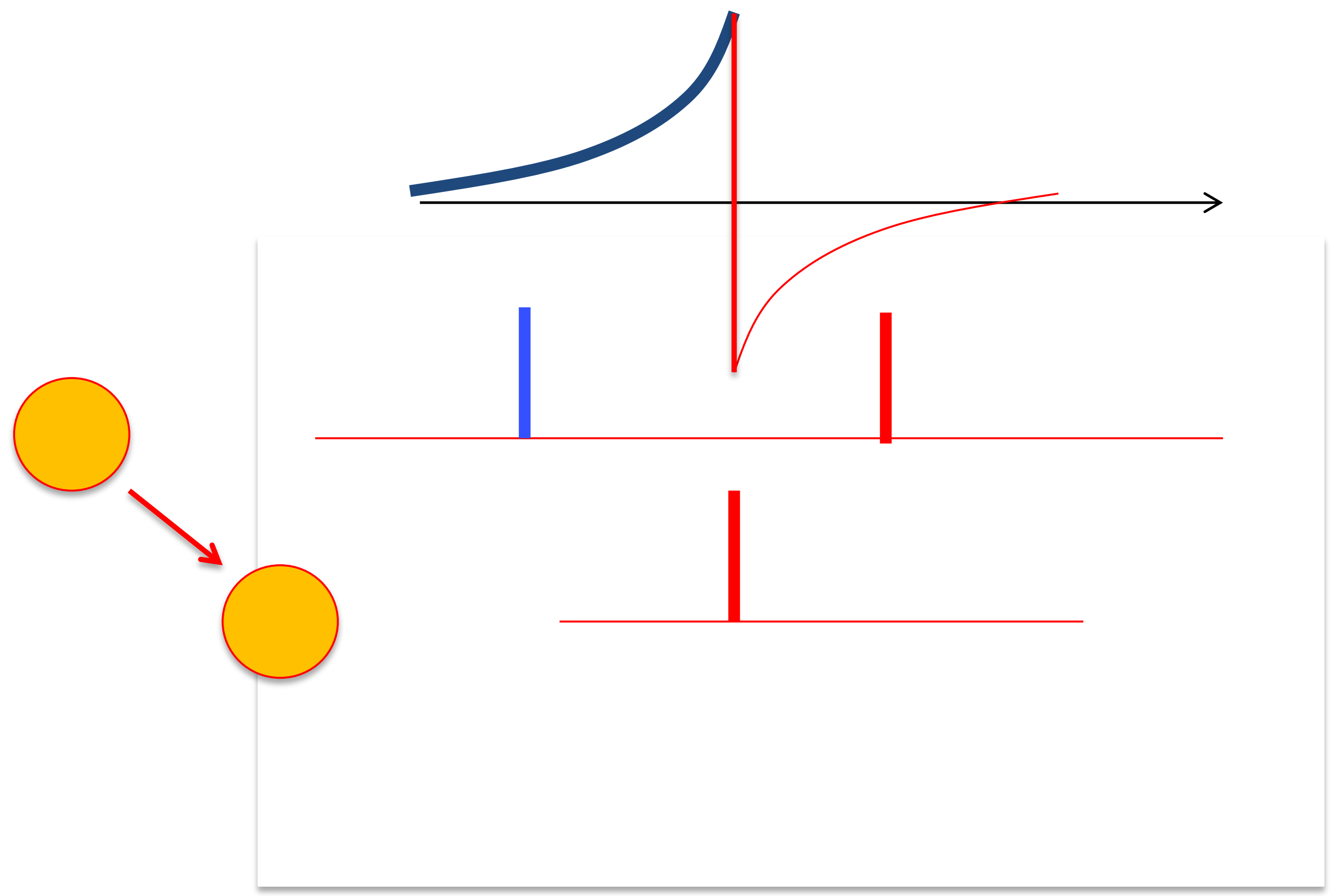
Hebbian Learning
= all inputs/all times are equal





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

 STDP = spike-based Hebbian learning

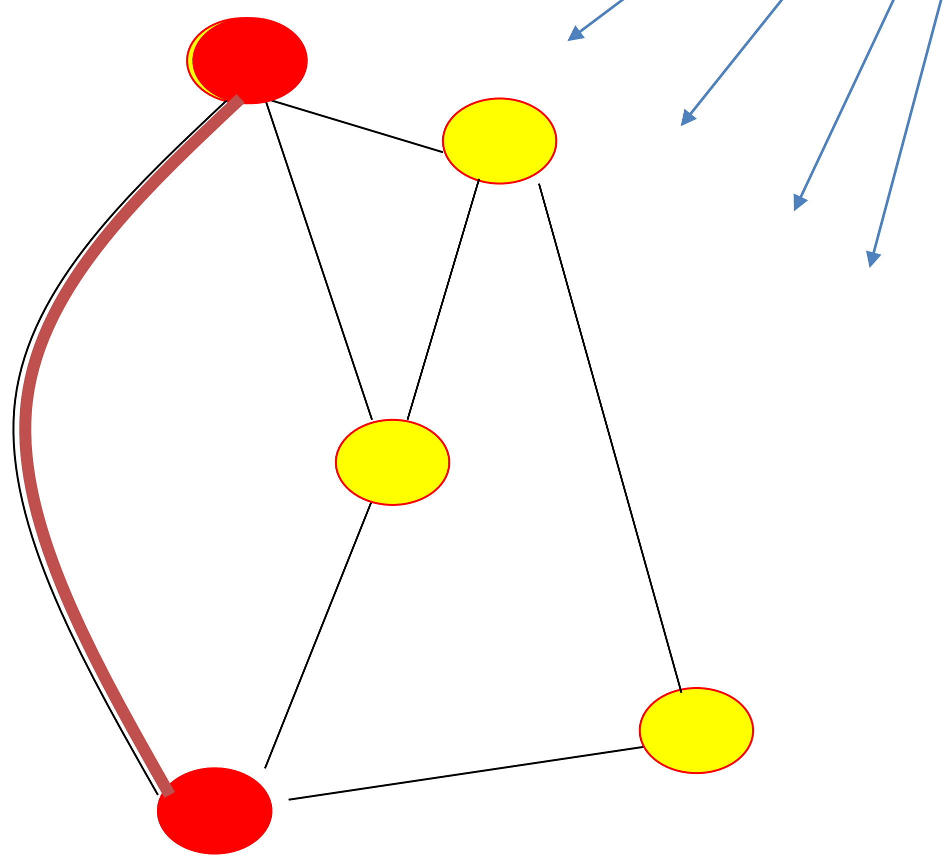


Pre-before post: potentiation of synapse

Pre-after-post: depression of synapse

Modulation of Learning
= Hebb+ confirmation

confirmation



Functional Postulate

Useful for learning the important stuff

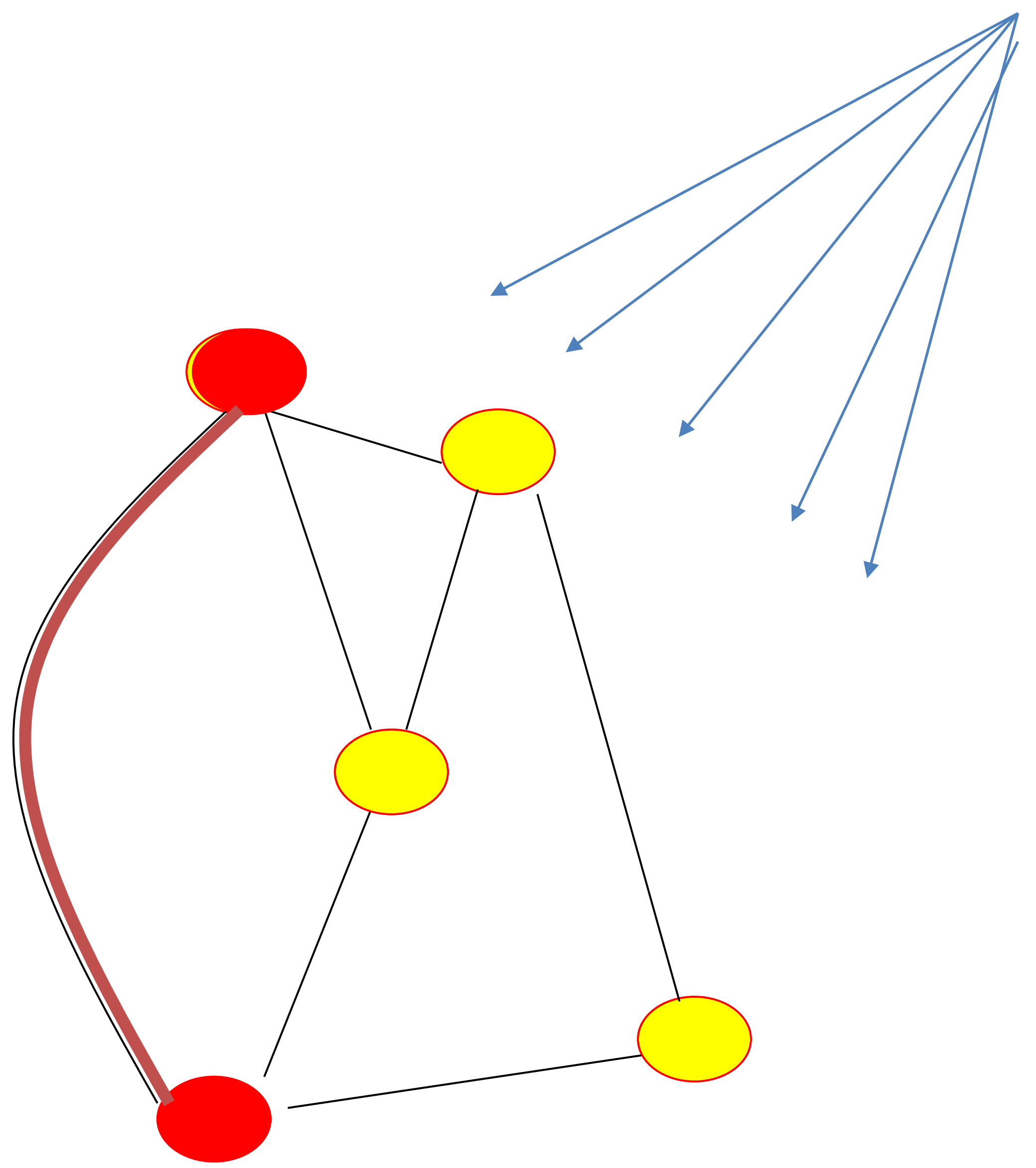
$$\Delta w_{ij} \propto F(pre, post, CONFIRM)$$

local global

Many models (and experiments) of synaptic plasticity do not take into account Neuromodulators.

Except: e.g. Schultz et al. 1997, Wickens 2002, Izhikevich, 2007; Reymann+Frey 2007; Moncada 2007, Pawlak+Kerr 2008; Pawlak et al. 2010

Consolidation of Learning



Success/reward

Confirmation

-Novel

-Interesting

-Rewarding

-Surprising

Neuromodulators dopmaine/serotonin/Ach

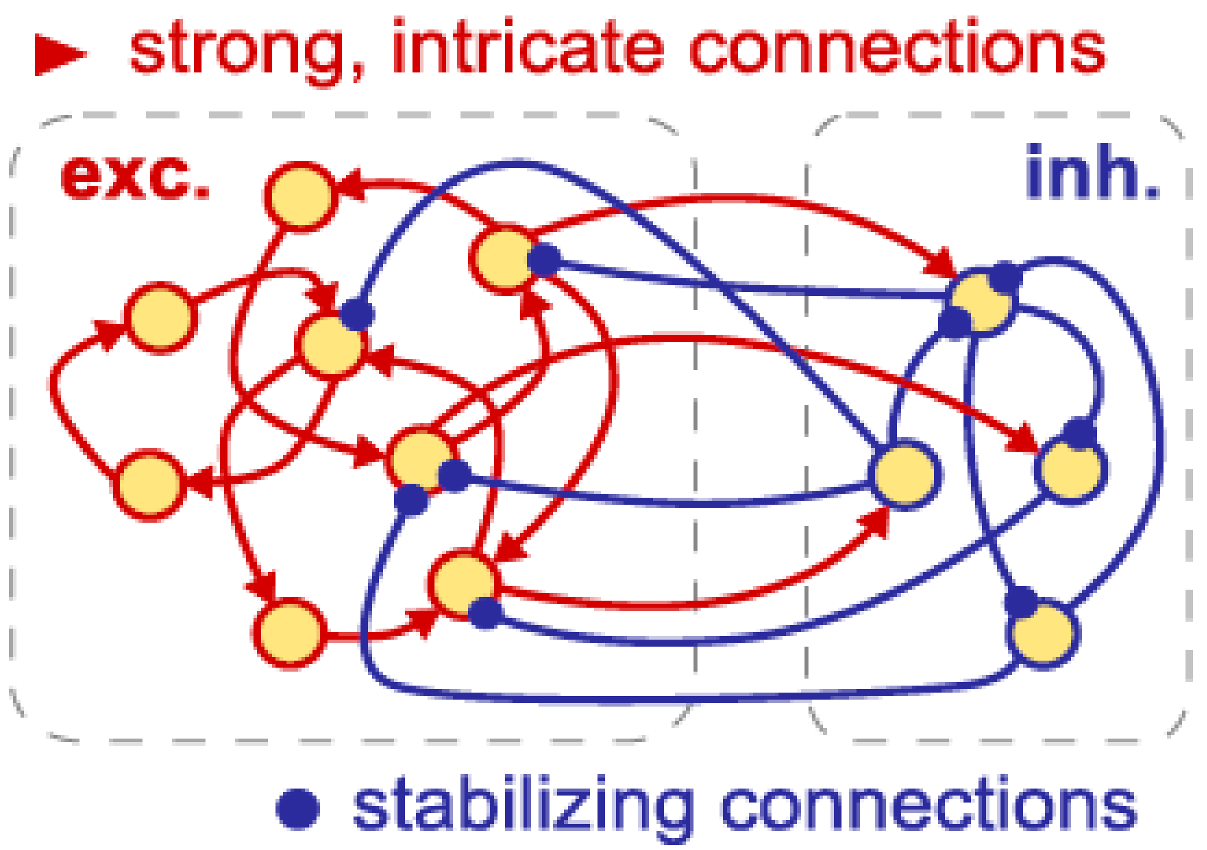
Crow (1968),
Fregnac et al (2010),
Izhikevich (2007)

'write now' to long-term memory'

Plasticity

Stability-optimized curcuits

- here: algorithmically tuned

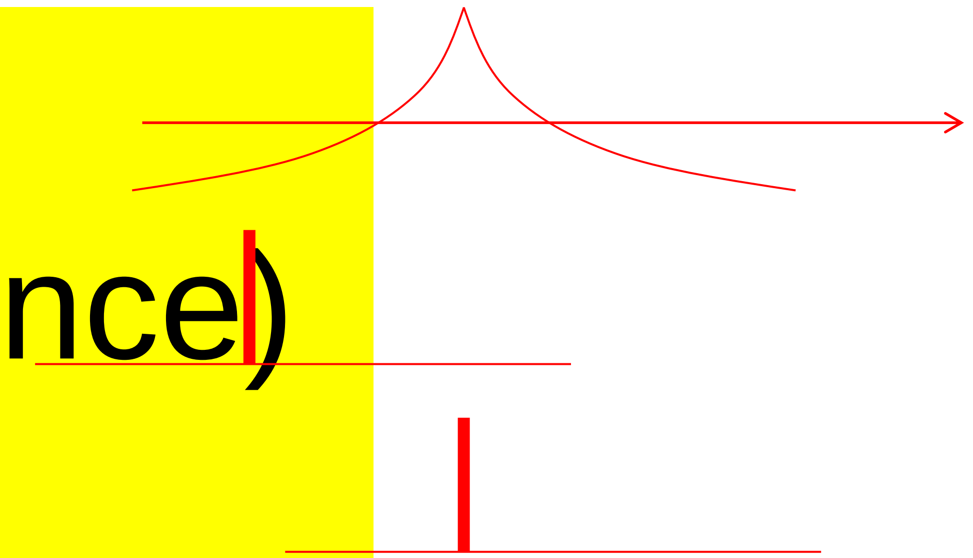


BUT

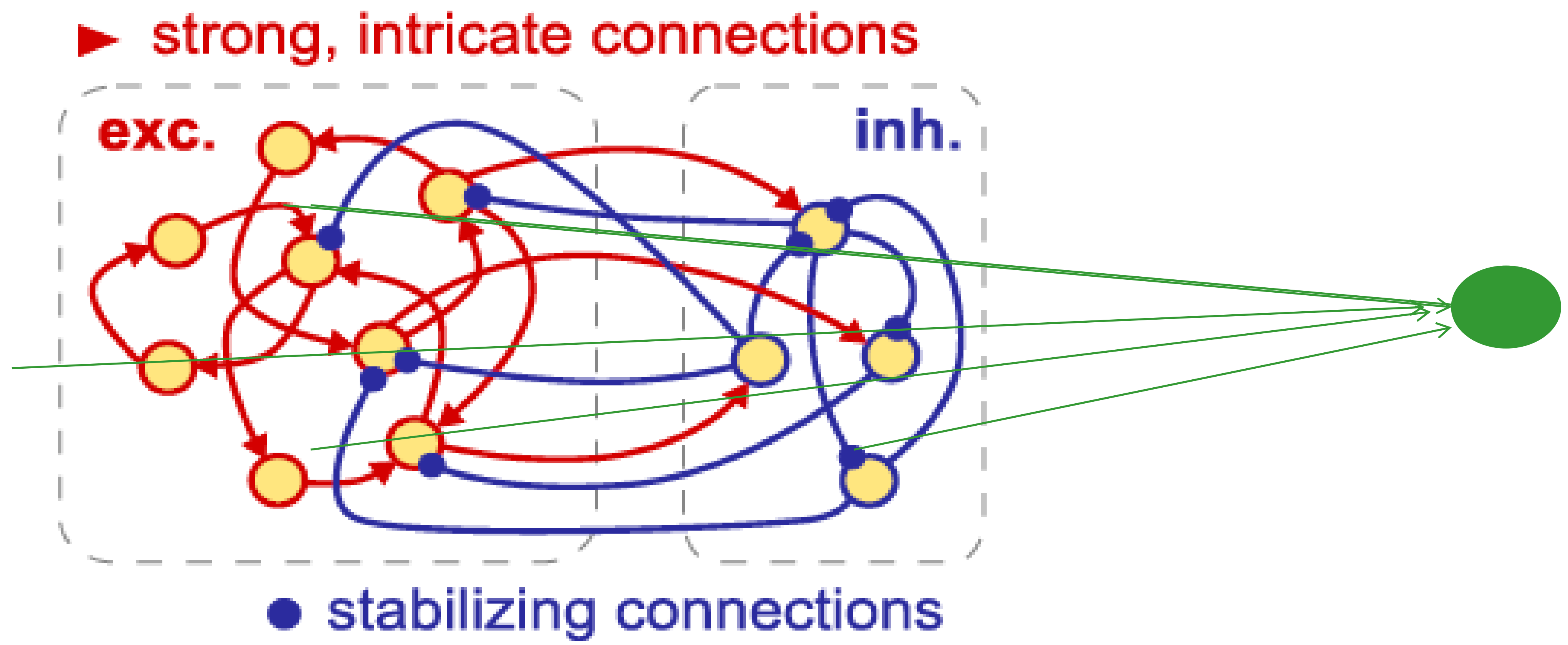
- replace by inhibitory plasticity

Vogels et al.,
Science 2011

→ avoids chaotic blow-up of network
→ avoids blow-up of single neuron (detailed balance)
→ yields stability optimized circuits



Plasticity



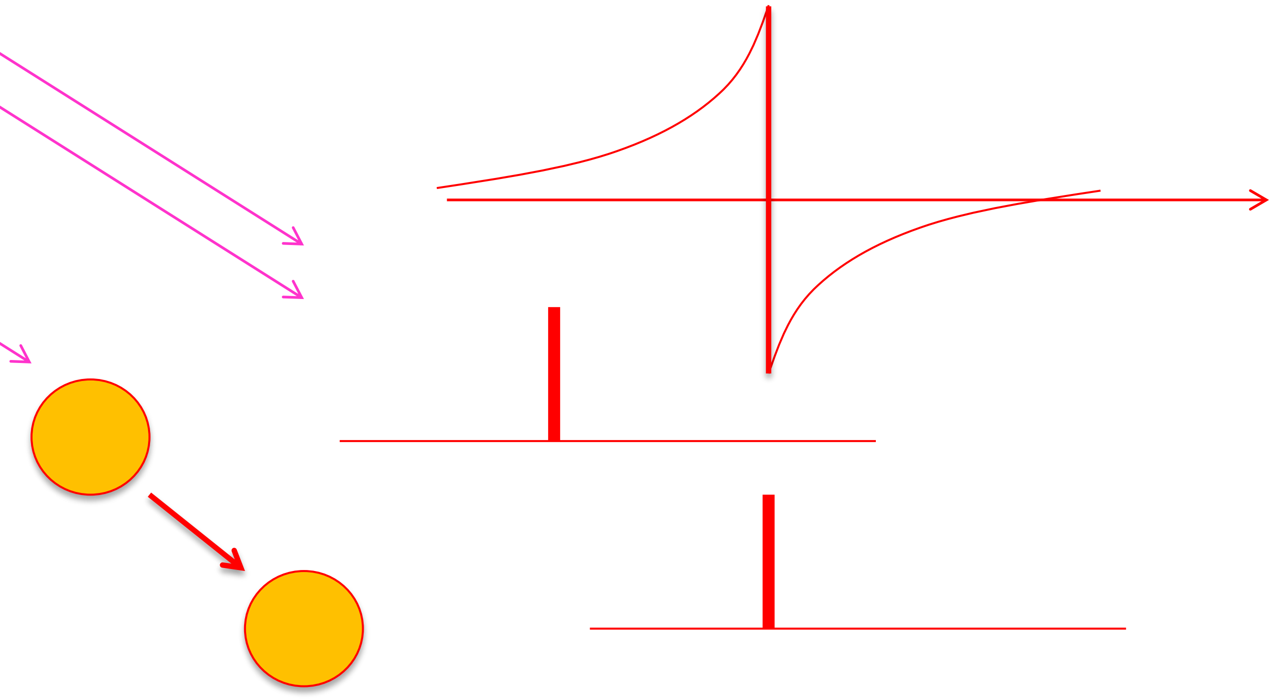
Readout

- here: algorithmically tuned

Izhikevich, 2007
Fremaux et al. 2012

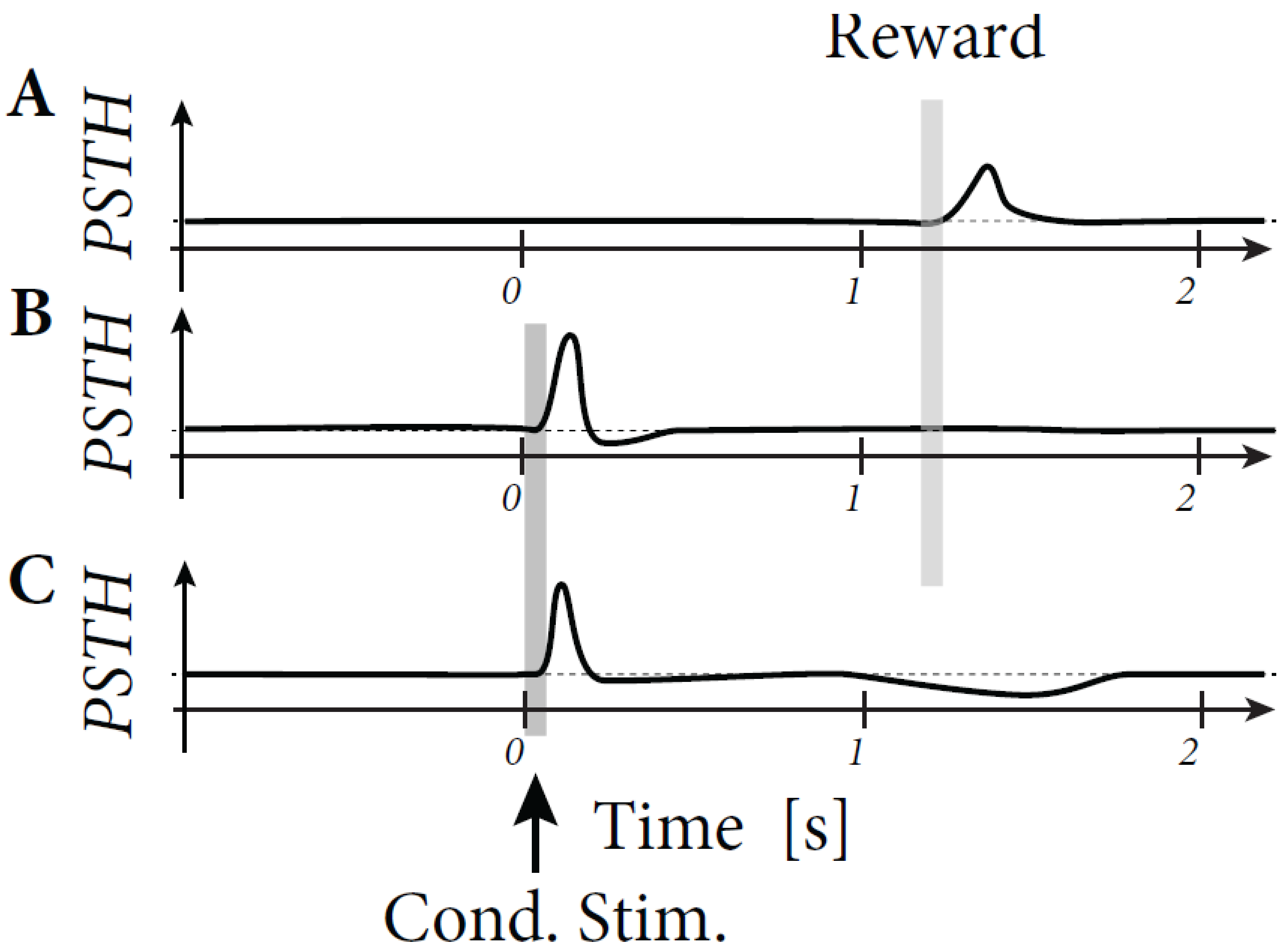
BUT

Success signal



- replace by 3-factor plasticity rules

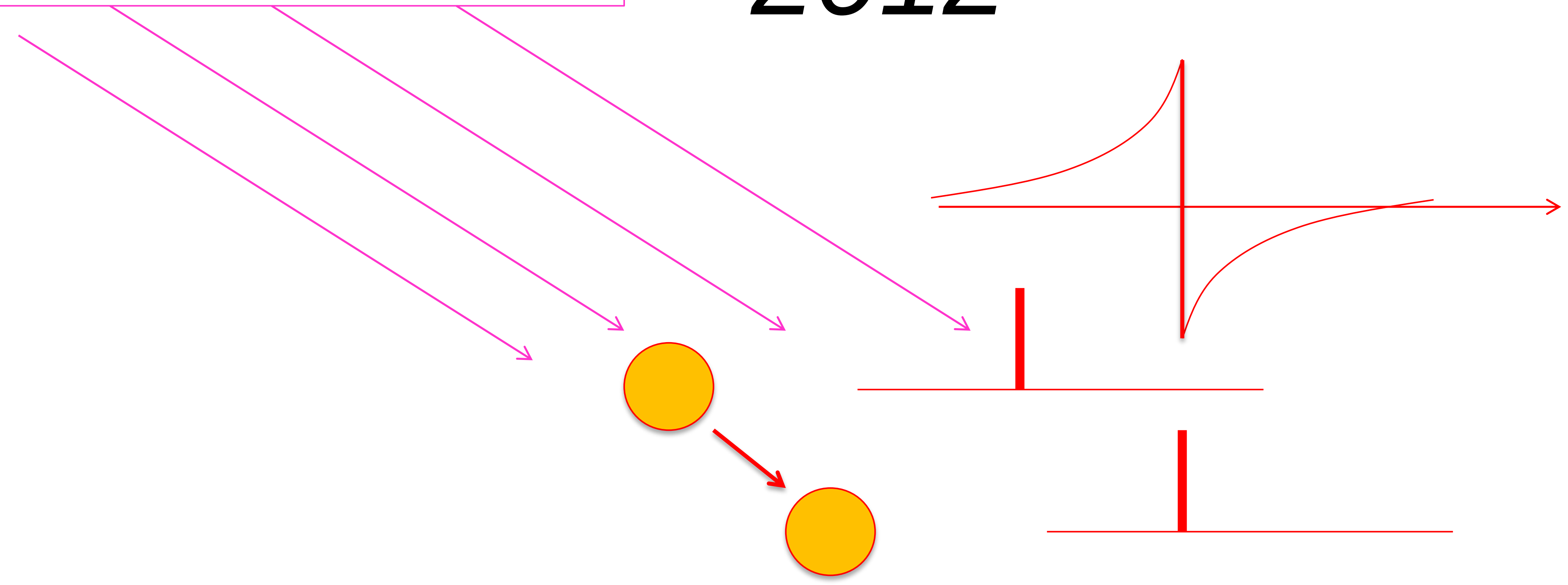
Week 14-part 4: Plasticity modulated by reward



Dopamine-emitting neurons:
Schultz et al., 1997

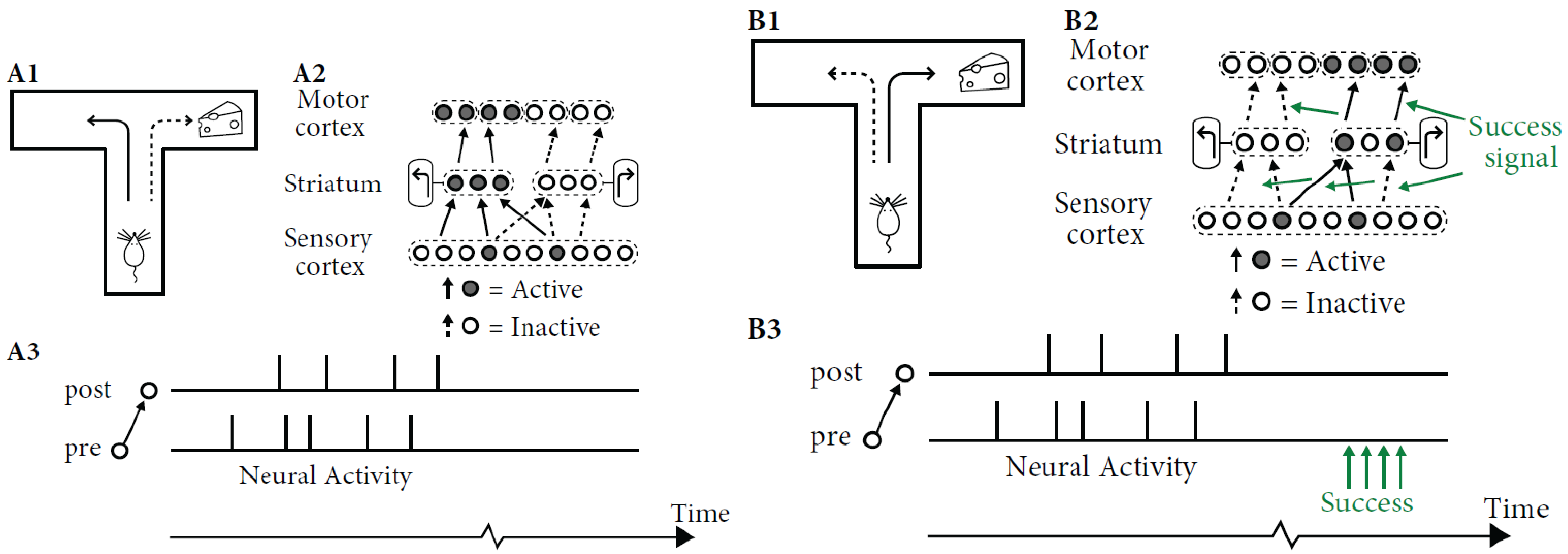
Izhikevich, 2007
Fremaux et al. 2012

Success signal

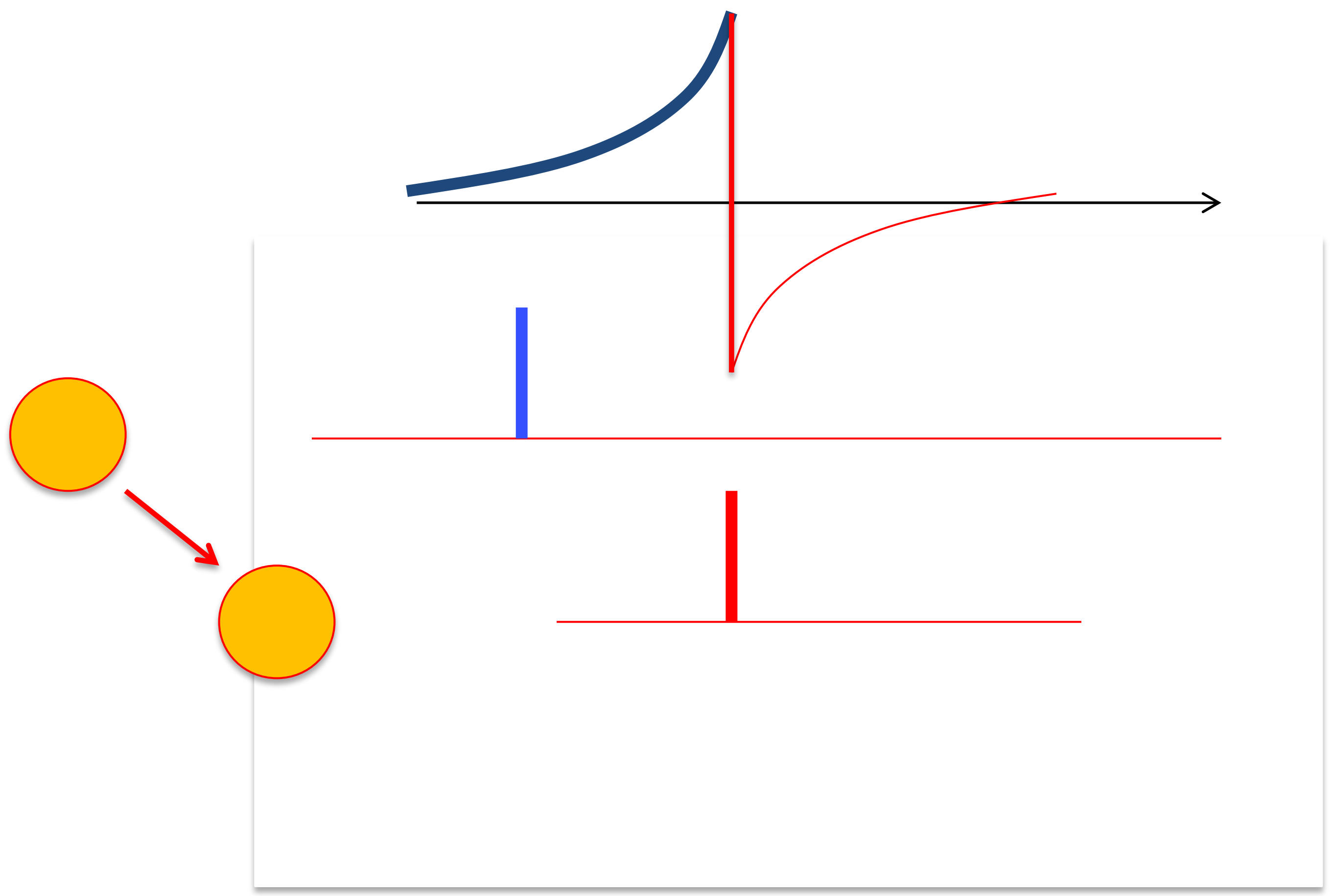


Dopamine encodes success=
reward – expected reward

Week 14-part 4: Plasticity modulated by reward



Week 14-part 4: STDP = spike-based Hebbian learning



Pre-before post: potentiation of synapse

Week 14-part 4: Plasticity modulated by reward

STDP with pre-before post: potentiation of synapse

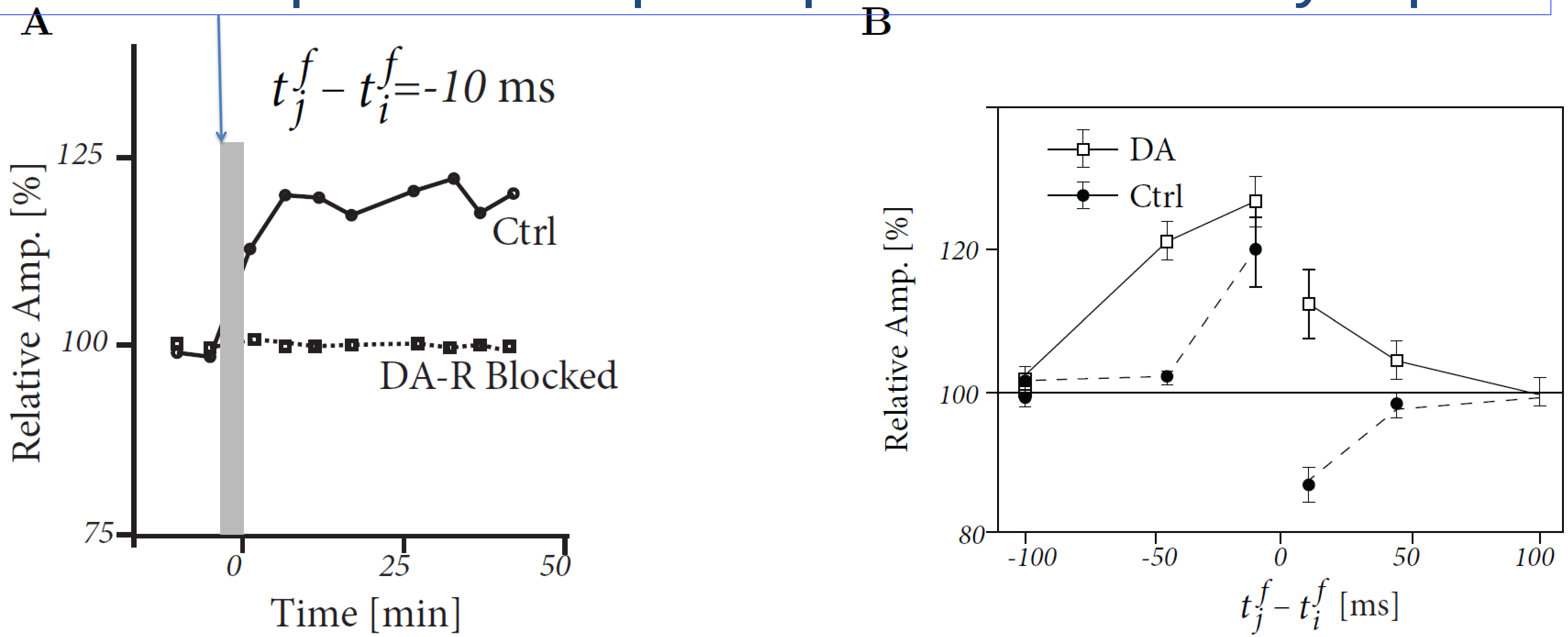
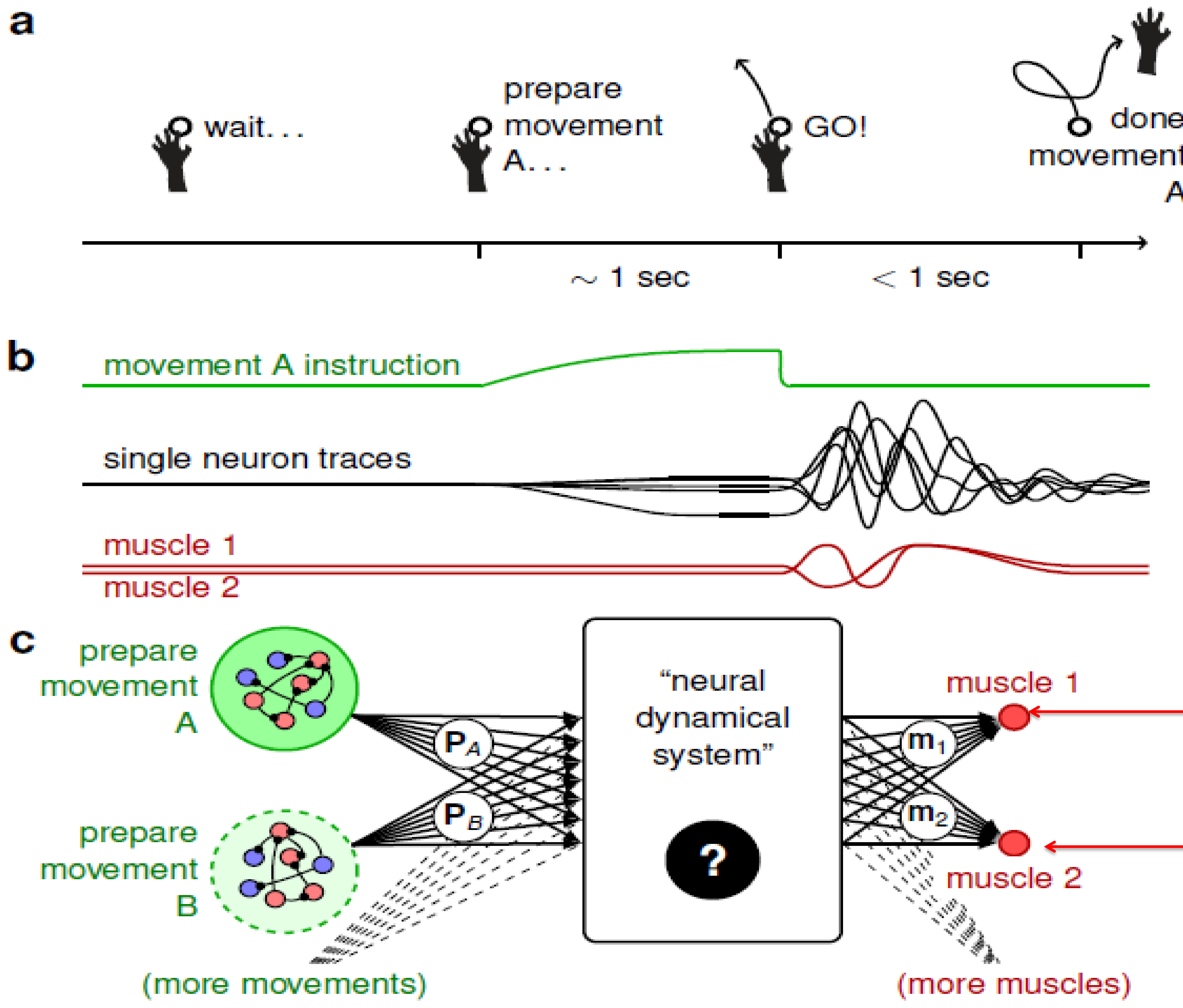


Fig. 19.16: Dopamine-modulated Hebbian learning. **A.** An STDP protocol normally gives rise to long-term potentiation (pre-before-post, solid black line as in Fig. 19.4D). However, if dopamine receptors are blocked, no change occurs (Schematic representation of experiments in Pawlak and Kerr (2008)). **B.** The STDP window in a control situation (dashed line and filled data points) changes if additional extracellular dopamine is present (solid lines, large open squares); adapted from Zhang et al. (2009).

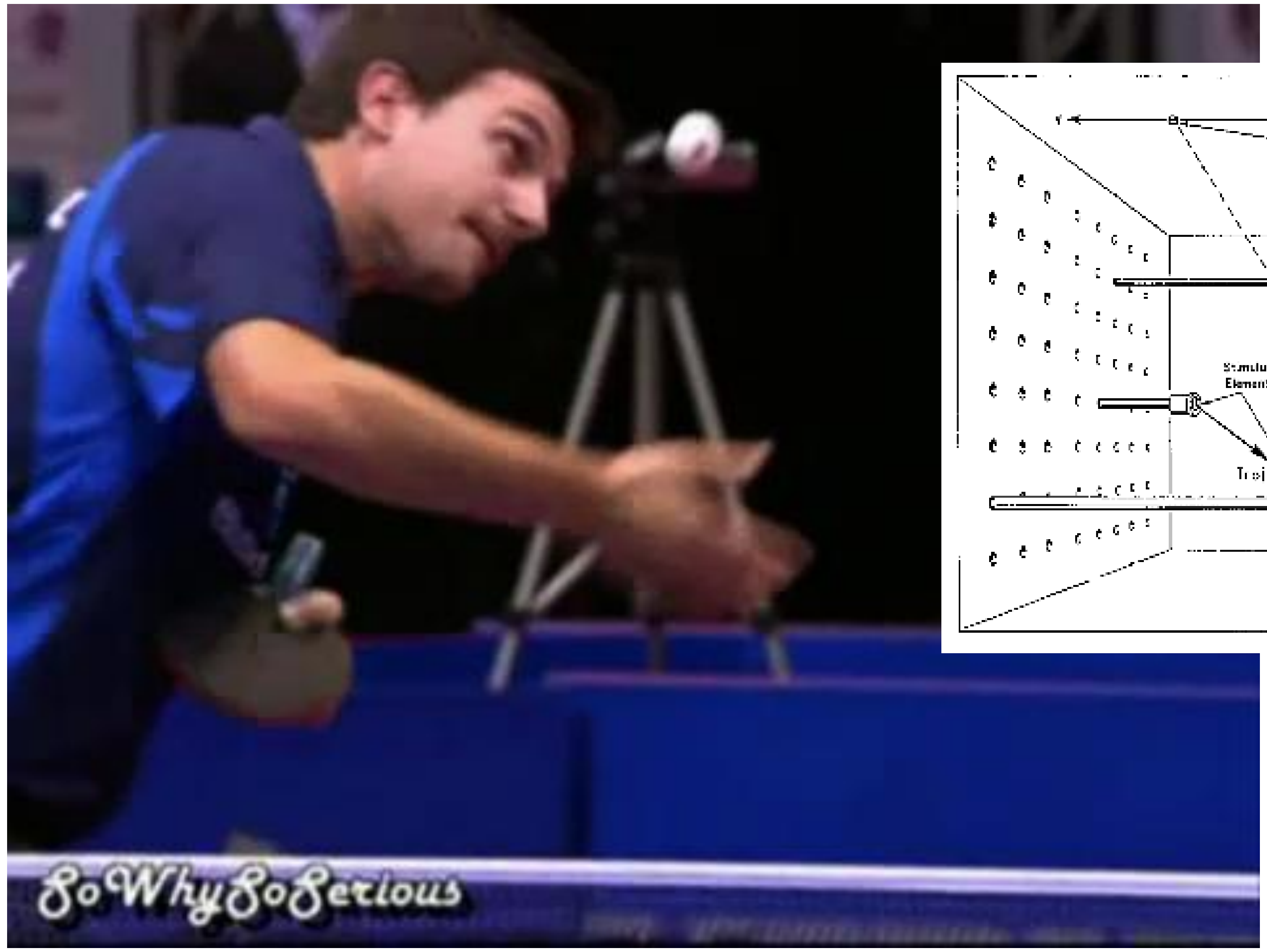
Week 14-part 4: from spikes to movement

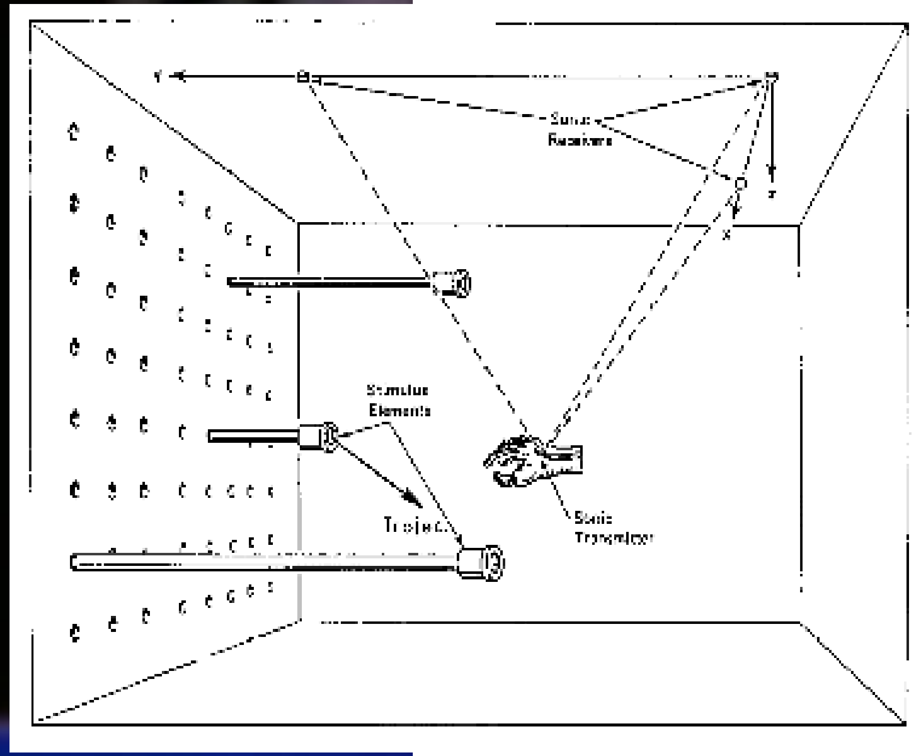


How can the readouts encode movement?

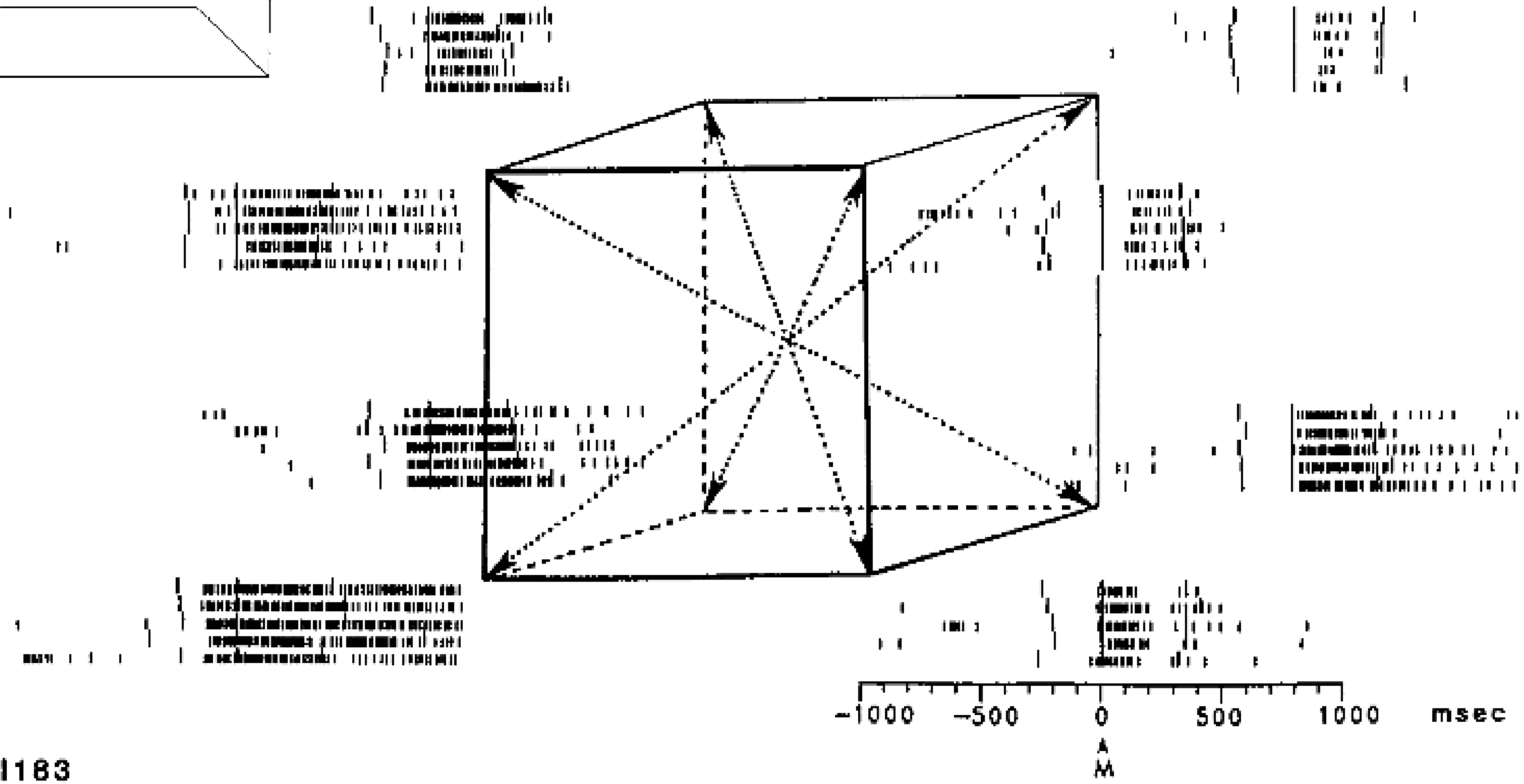
Week 14-part 5: Population vector coding

Population vector coding of movements





Schwartz et al. 1988



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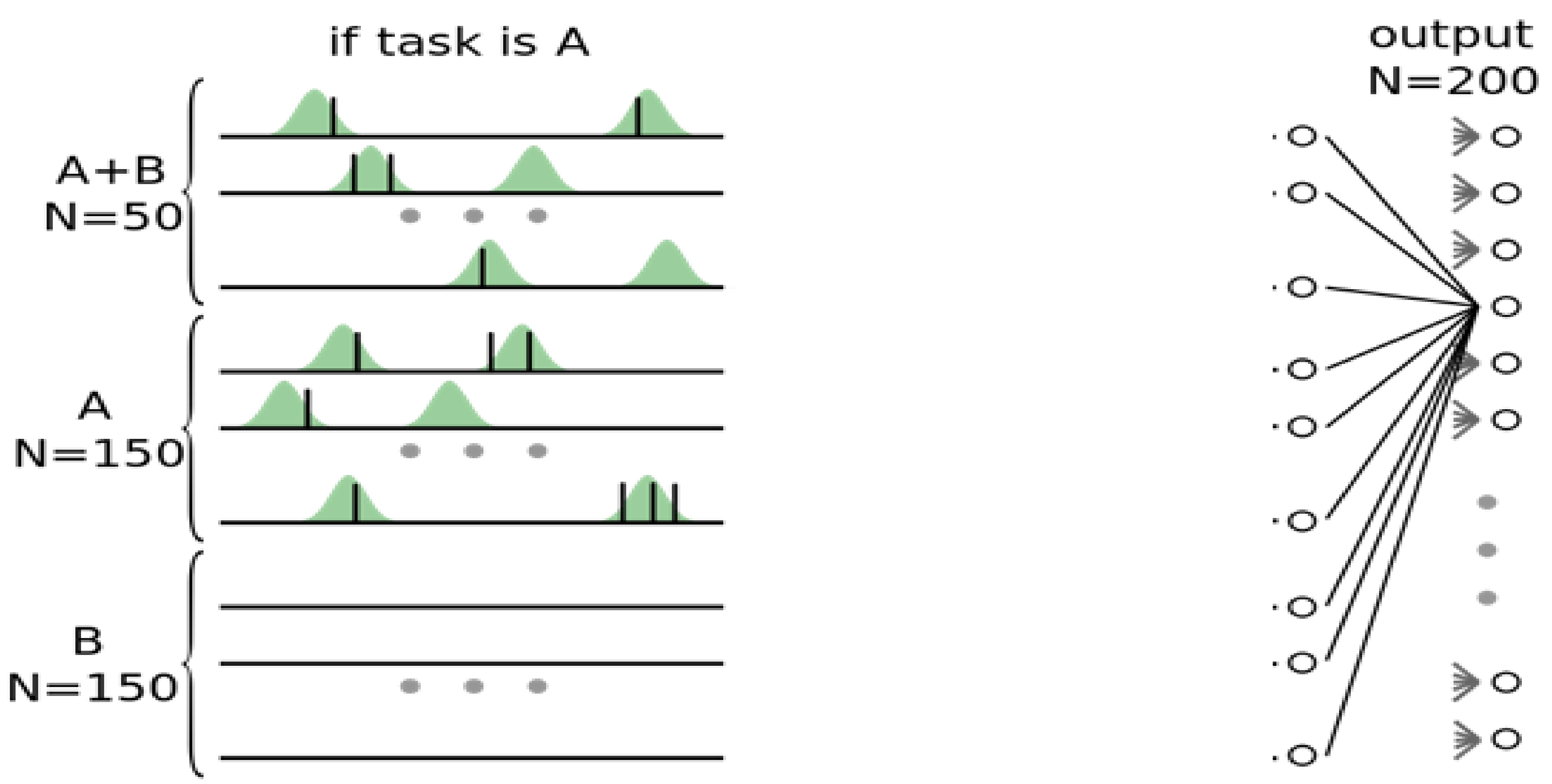
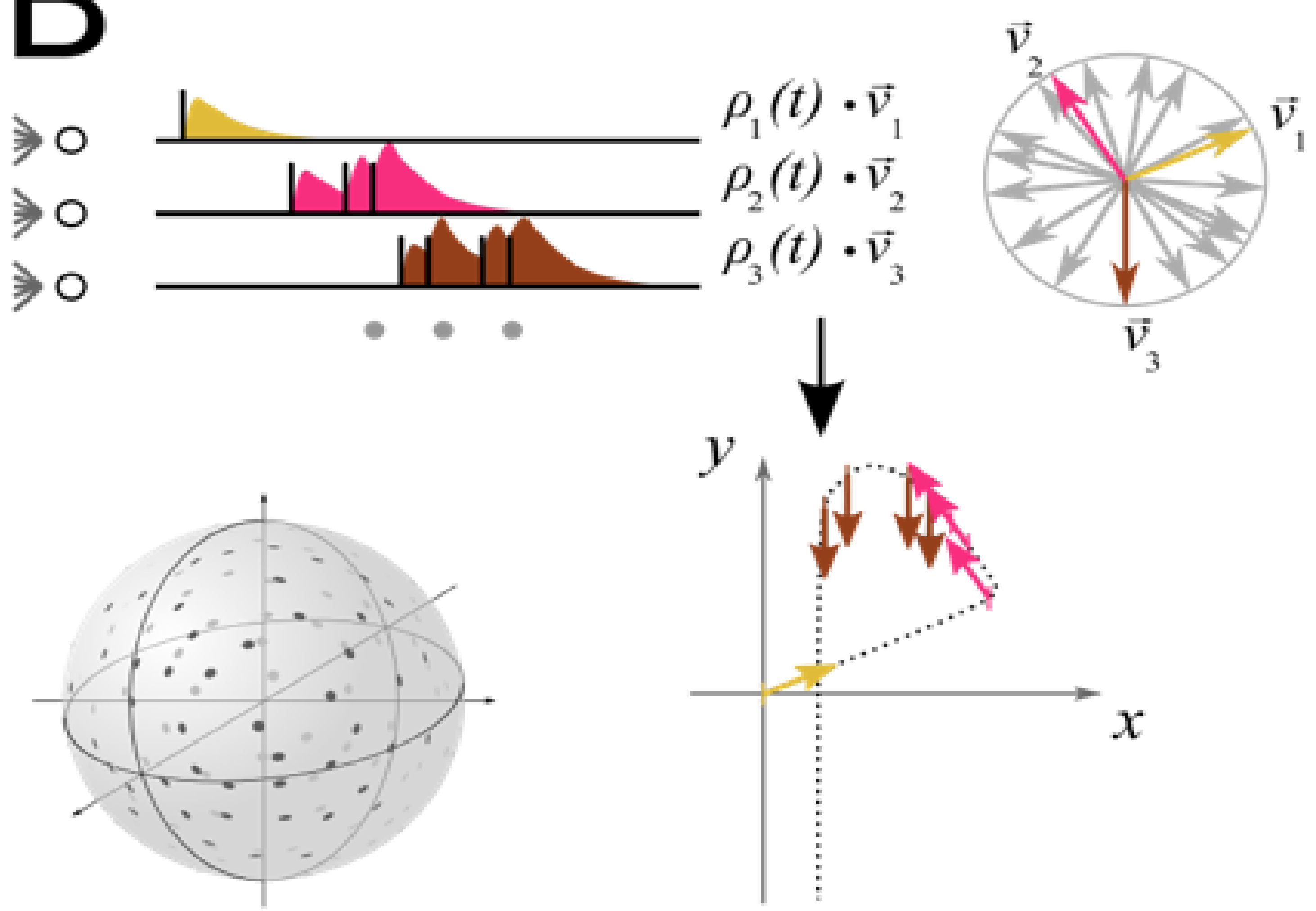
Week 14-part 4: Learning movement trajectories

Population vector coding of movements



B

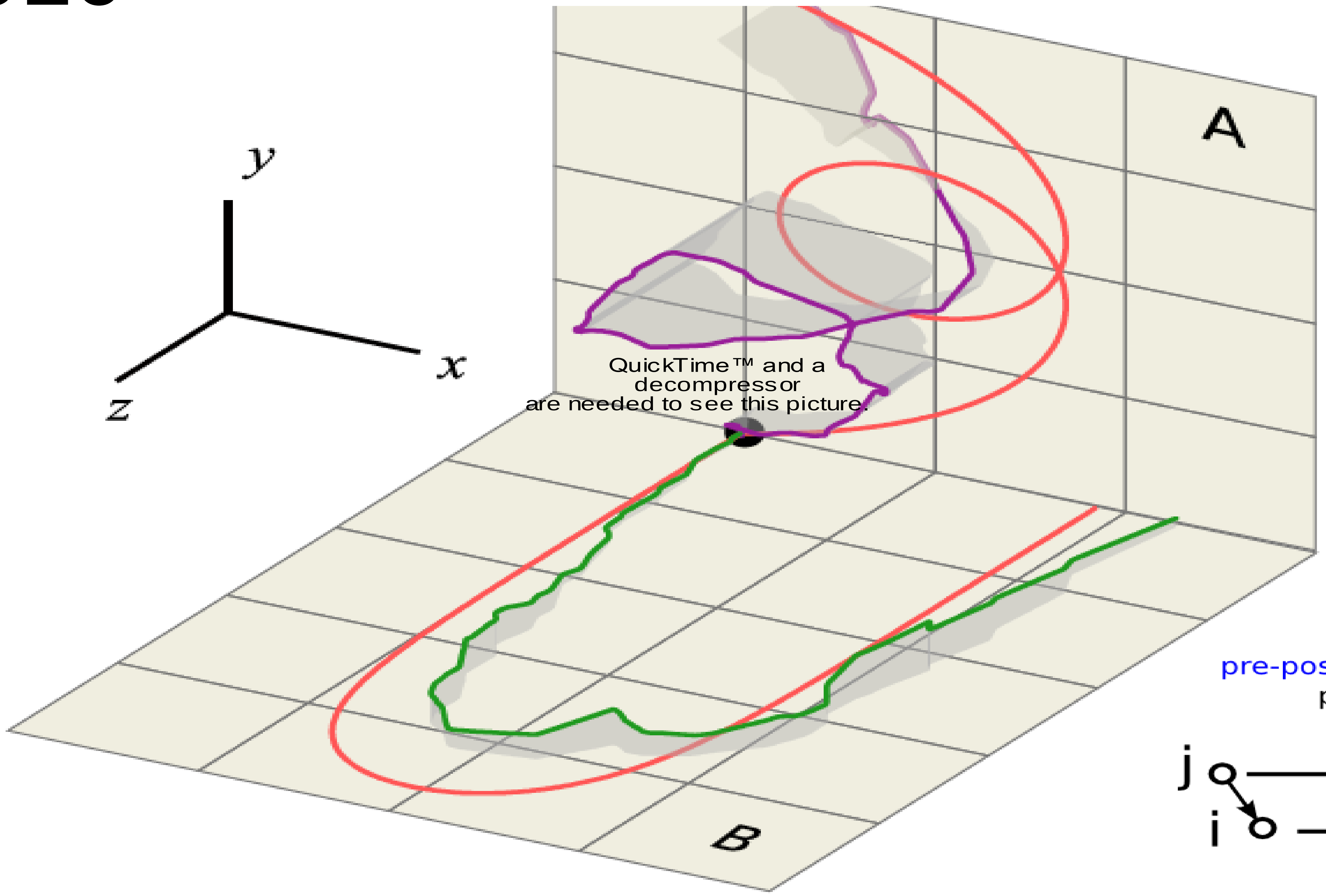


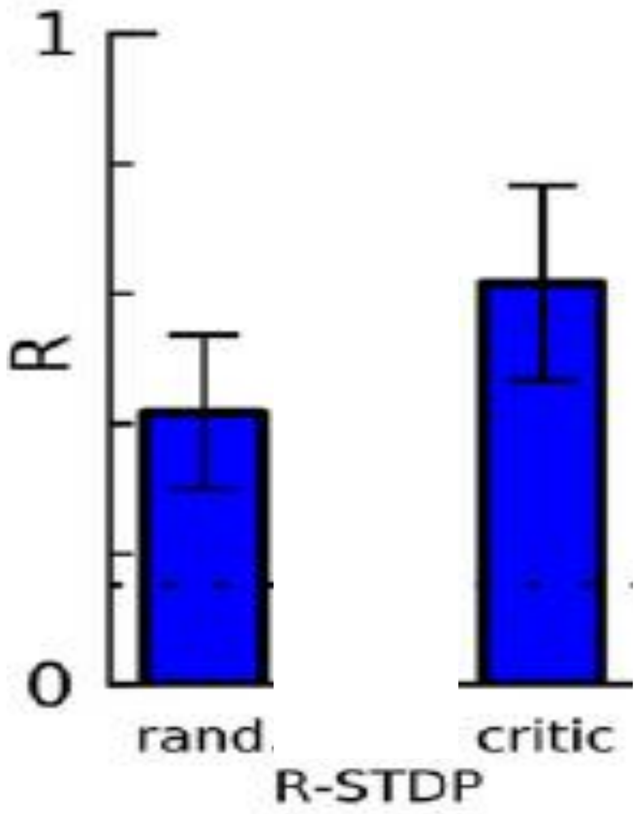
- 70’000 synapses
- 1 trial =1 second
- Output to trajectories via population vector coding
- Single reward at the END of each trial based on similarity with a target trajectory

Fremaux et al., J. Neurosci. 2010

Week 14-part 4: Learning movement trajectories

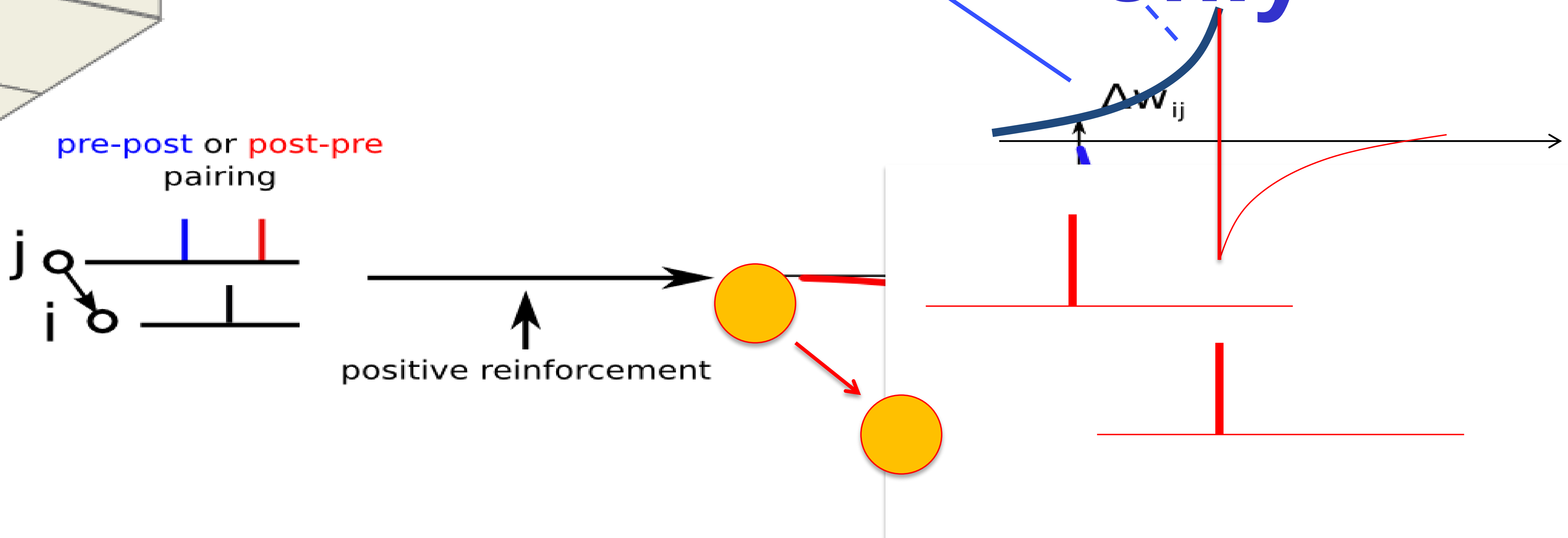
Fremaux et al. J. Neurosci. 2010





R-STDP

LTP-only

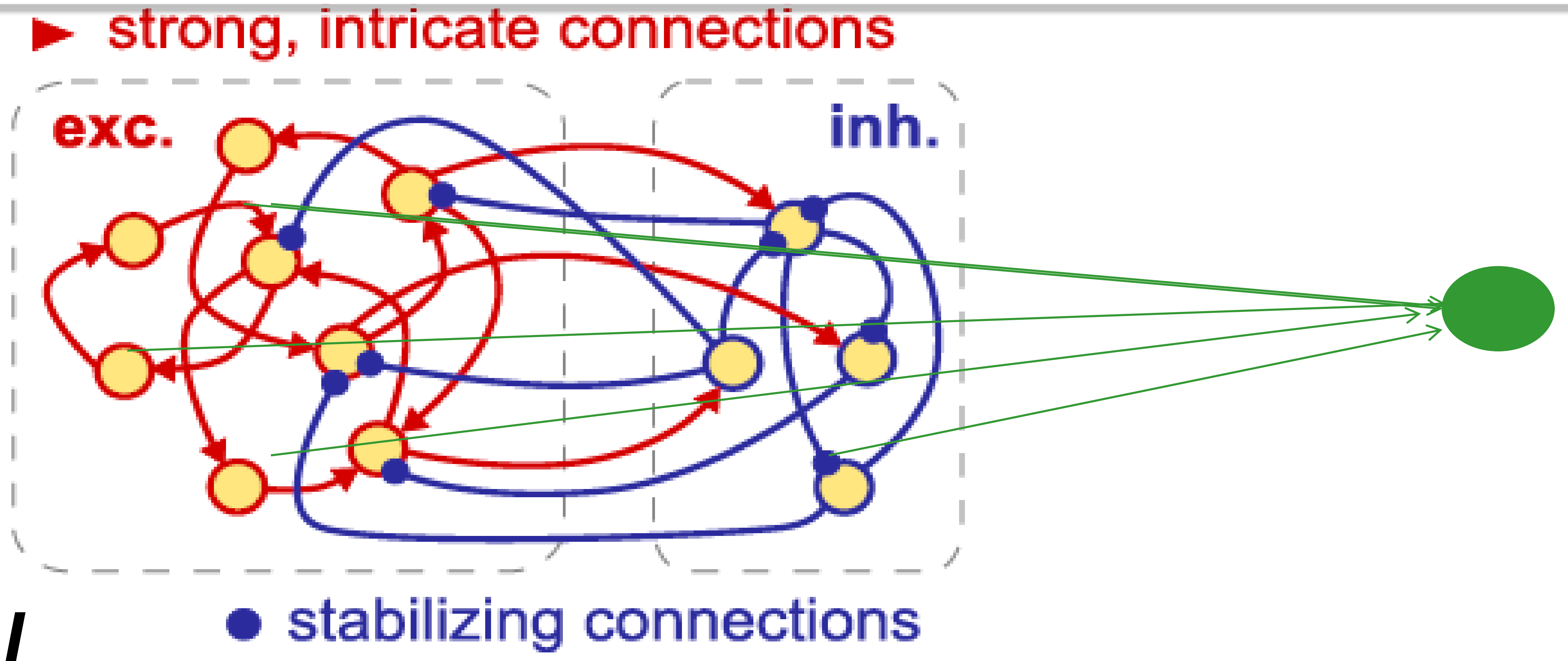


Week 14-part 4: Plasticity can tune the network and readout

Hebbian STDP

- inhibitory connections, tuned by 2-factor STDP, for stabilization

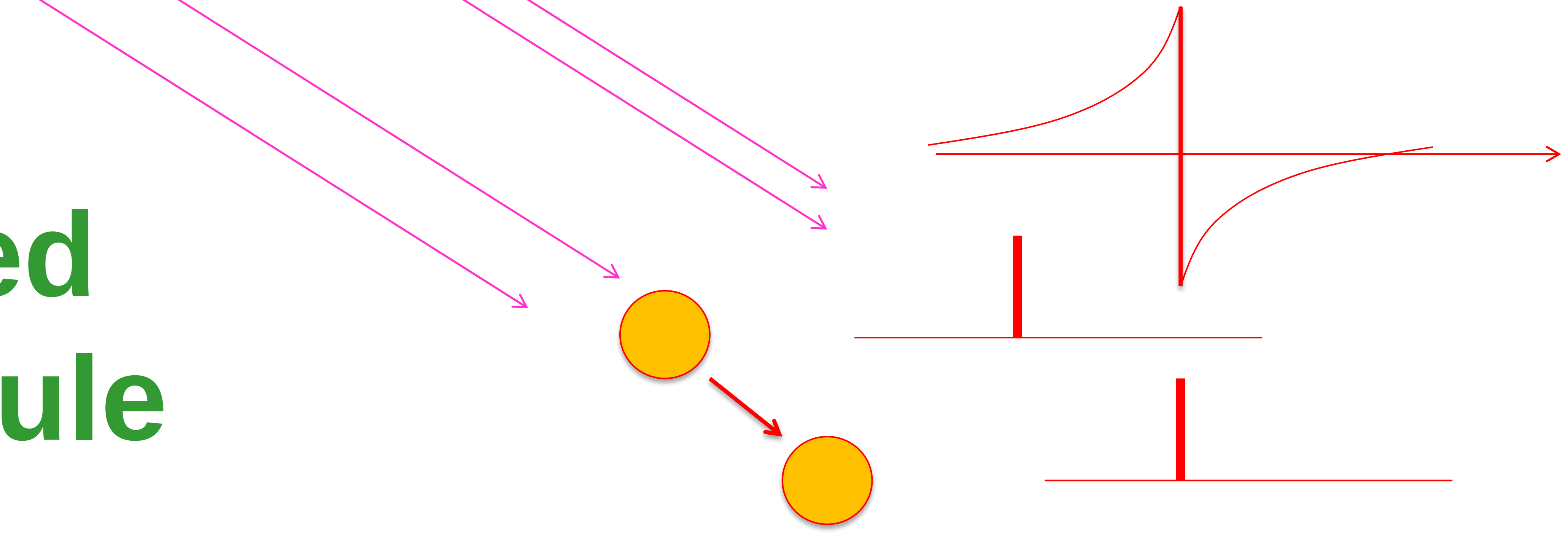
Vogels et al. 2011



Reward-modulated STDP for movement learning

Success signal

Fremaux et al. 2012



- Readout connections, tuned by 3-factor plasticity rule

Last Lecture TODAY

Exam:

- written exam 17. 06. 2014 from 16:15-19:00
- miniprojects counts 1/3 towards final grade

For written exam:

-bring 1 page A5 of own notes/summary

-HANDWRITTEN!

Nearly the end:
what can I improve for the students next year?

- Integrated exercises?
- Quizzes?
- Miniproject?
- Overall workload ?(4 credit course = 6hrs per week)
- Background/Prerequisites?
  - -Physics students
  - -SV students
  - -Math students
- Slides? videos?