

Computational Neuroscience: Neuronal Dynamics of Cognition



Neuronal Populations

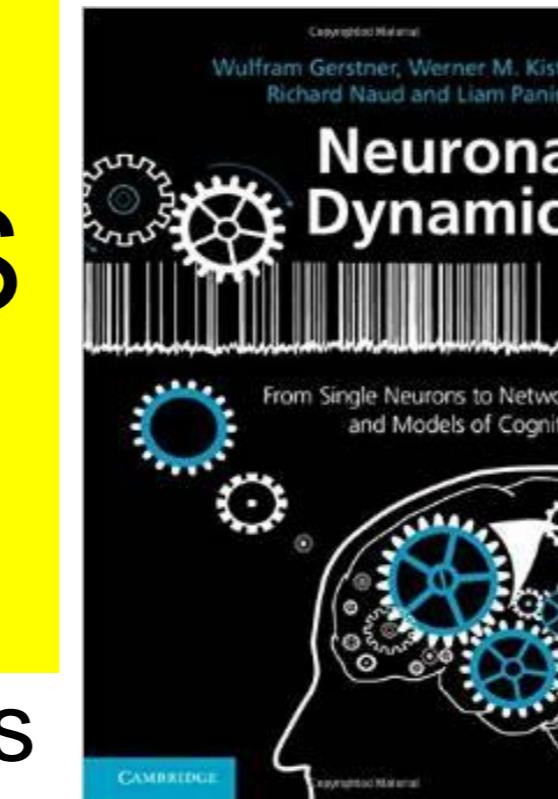
Wulfram Gerstner

EPFL, Lausanne, Switzerland

Reading:
NEURONAL DYNAMICS

- Ch. 12.1 – 12.4.3
(except Section 12.3.7)

Cambridge Univ. Press



1. Population activity

- definition and aims

2. Cortical Populations

- columns and receptive fields

3. Connectivity

- cortical connectivity
- model connectivity schemes

4. Mean-field argument

- input to one neuron

5. Stationary mean-field

- asynchronous state: predict activity

6. Random Networks

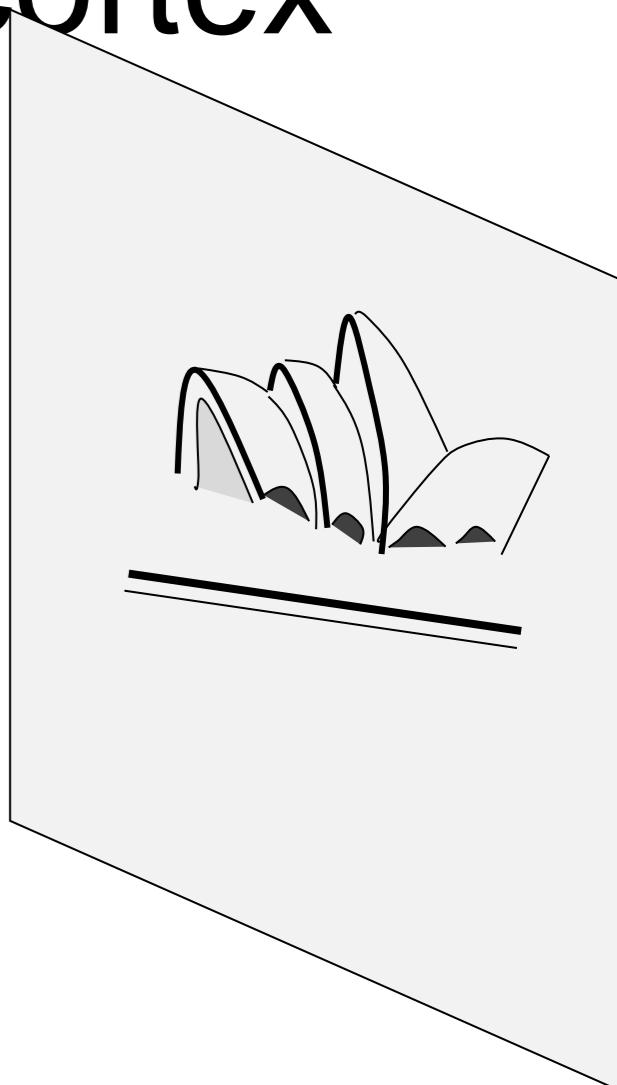
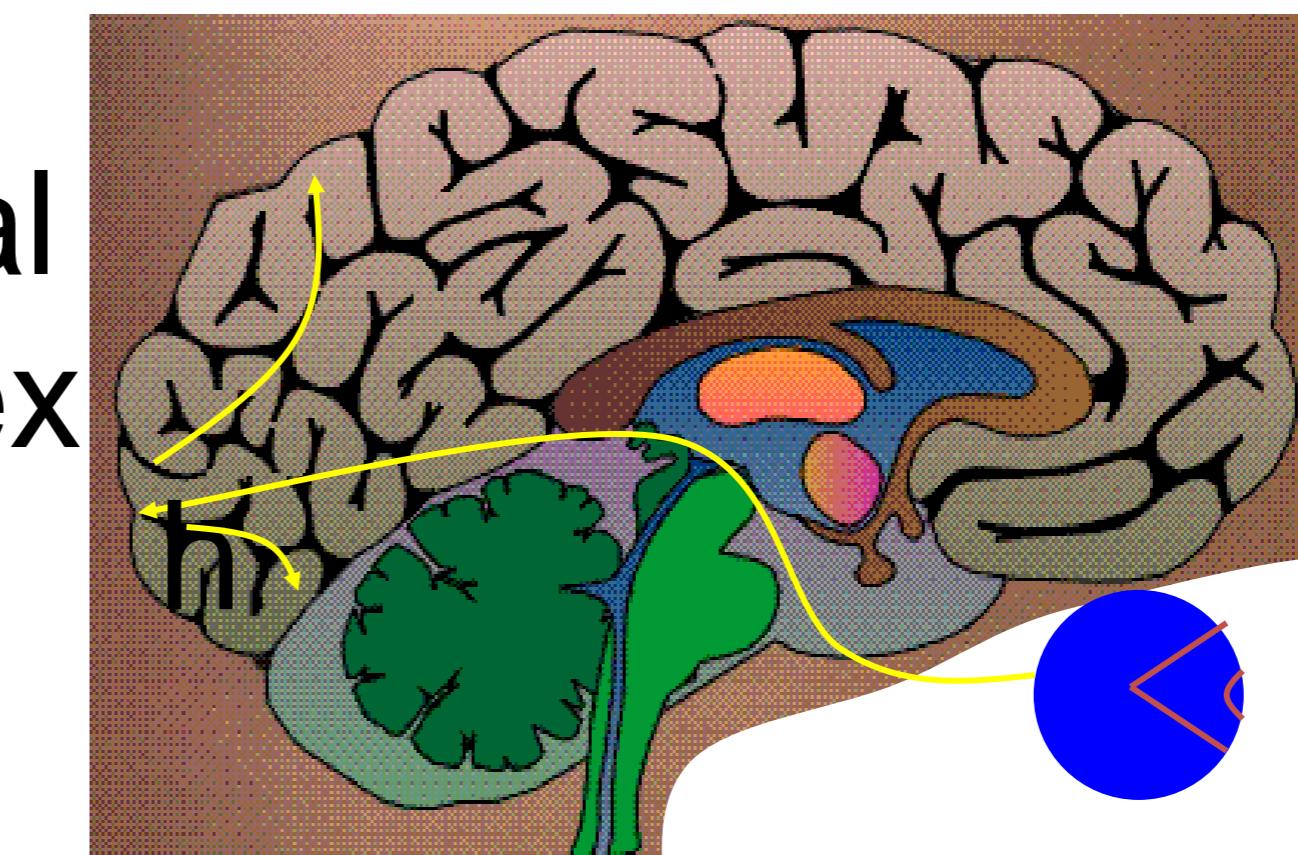
- Balanced state

1. review: the brain

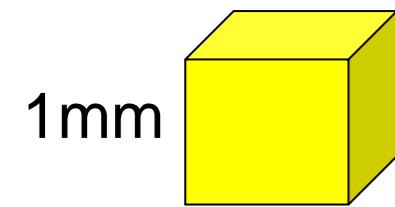
motor cortex

visual cortex

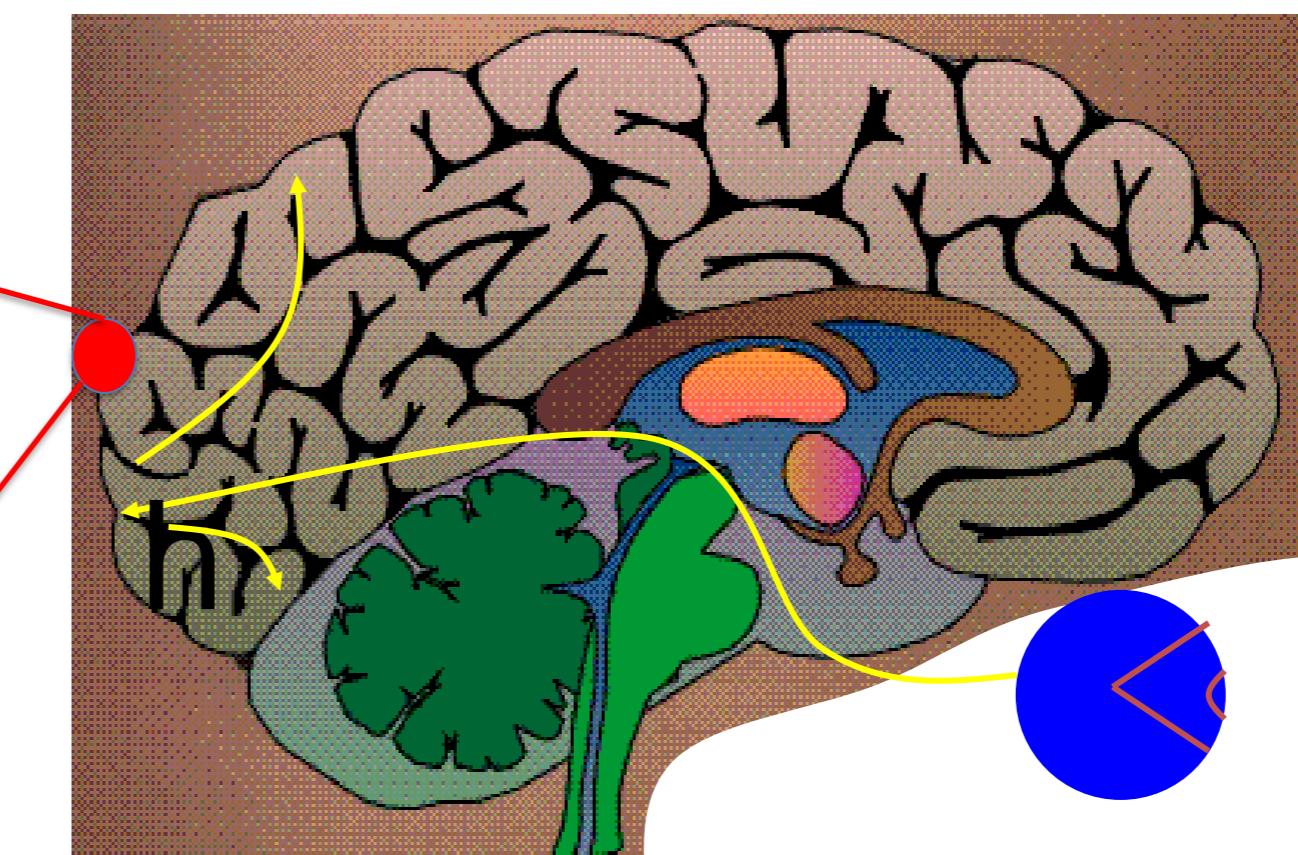
frontal cortex



1. review: the brain



10 000 neurons
3 km of wire



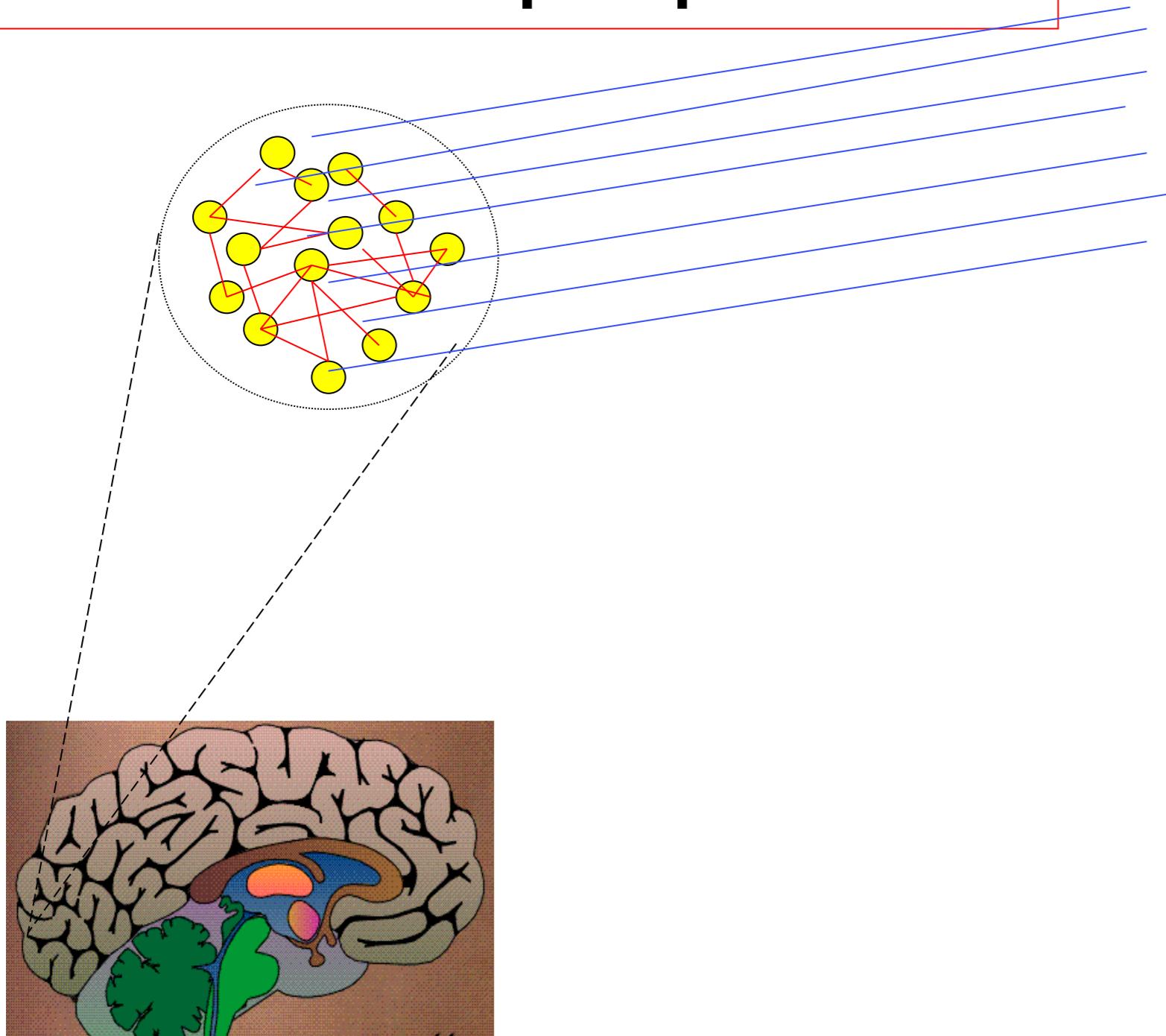
motor
cortex

frontal
cortex

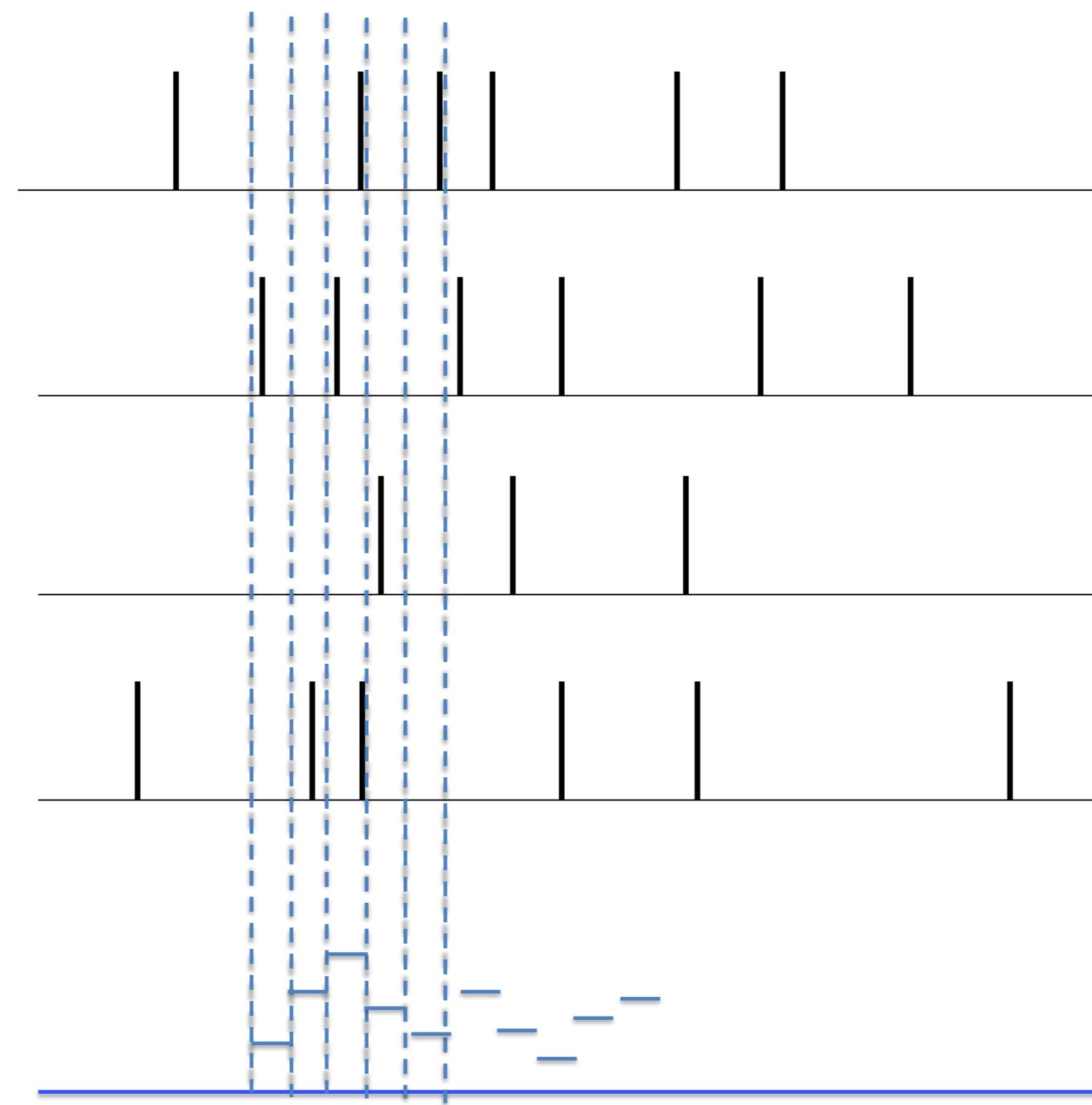
to motor
output

1. Population activity, definition

population of neurons
with similar properties



Brain



1. Population activity: definition

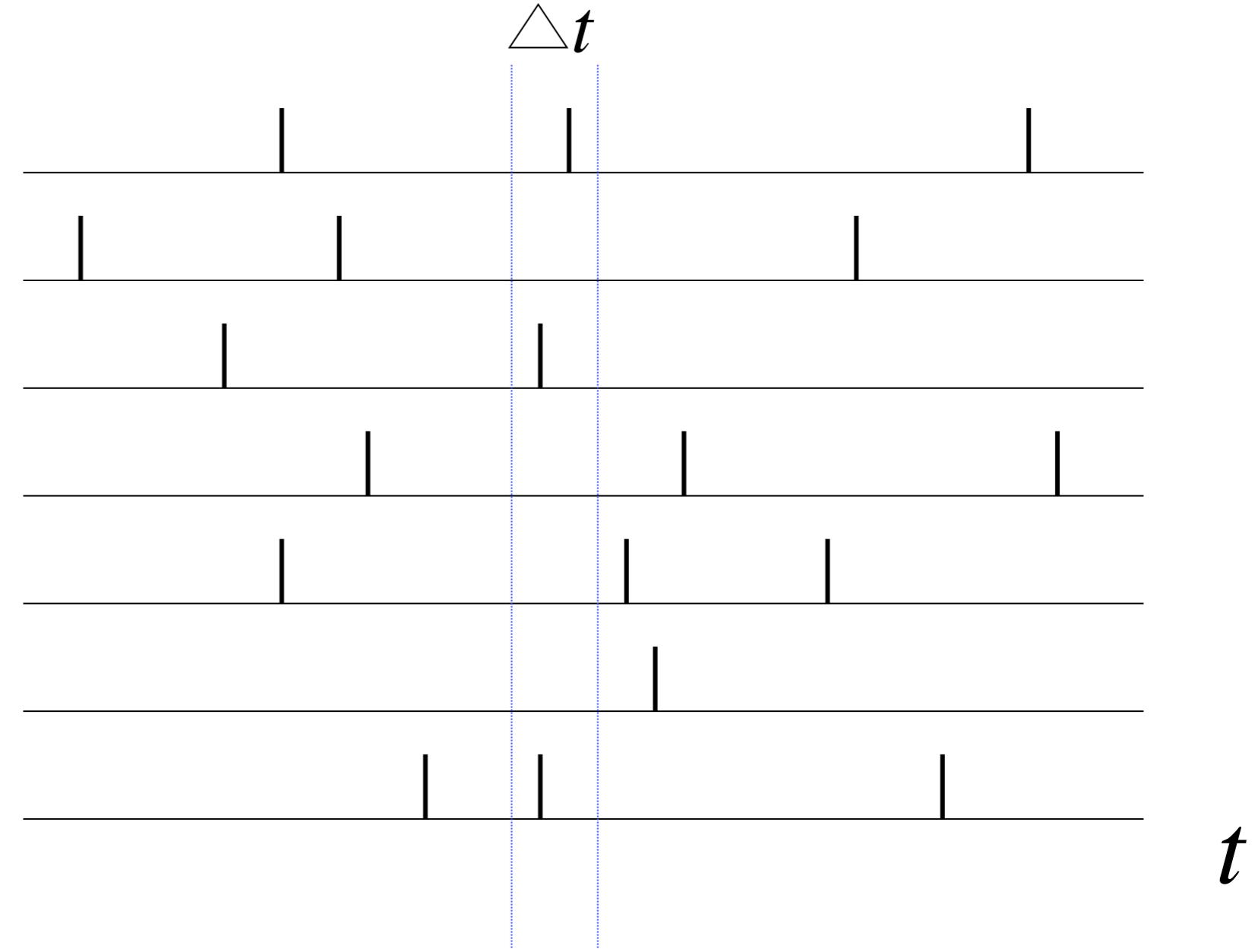
population activity - rate defined by population average

units?

invariances?

Time scale/averaging?

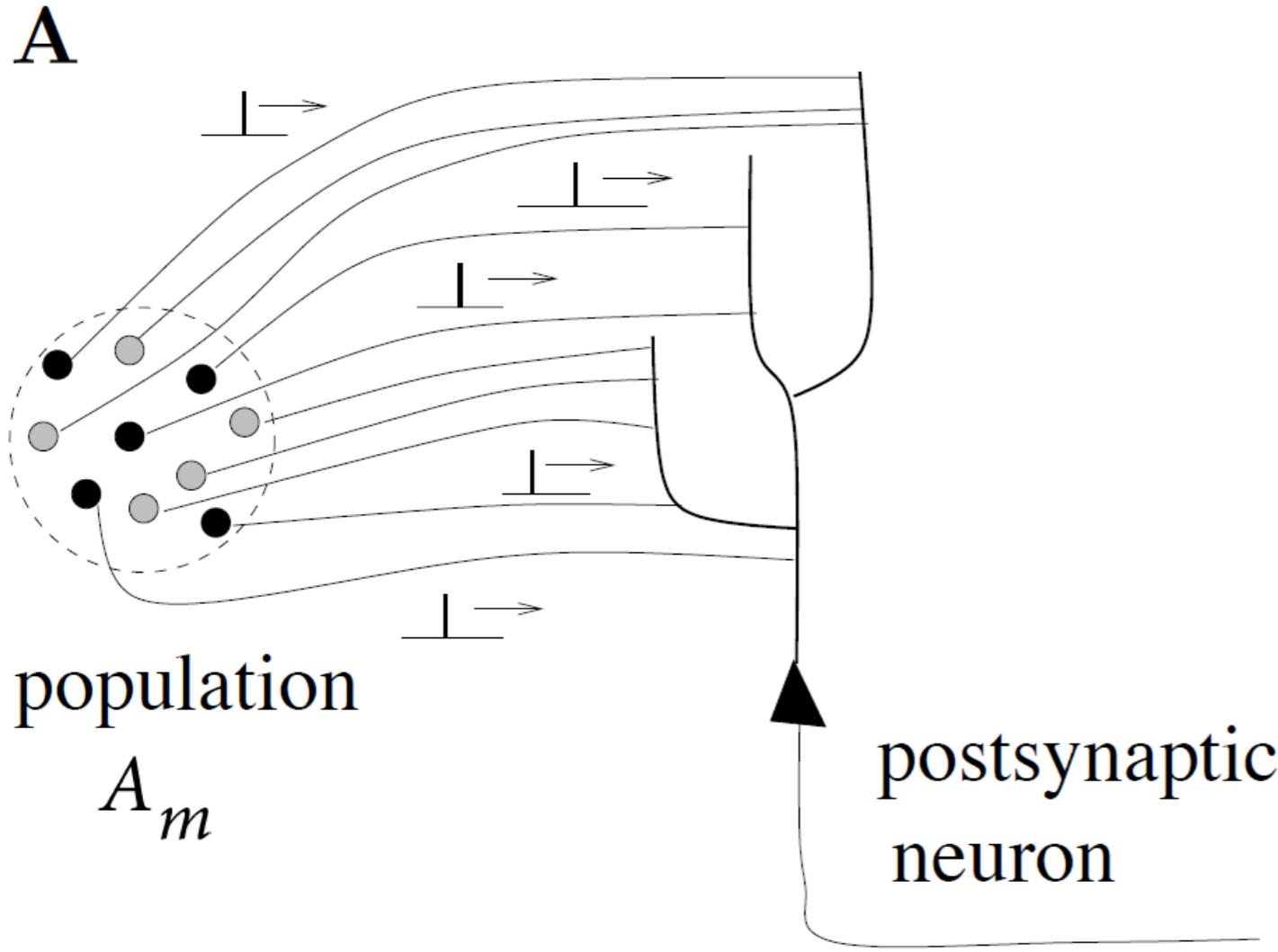
population
activity



$$A(t) =$$

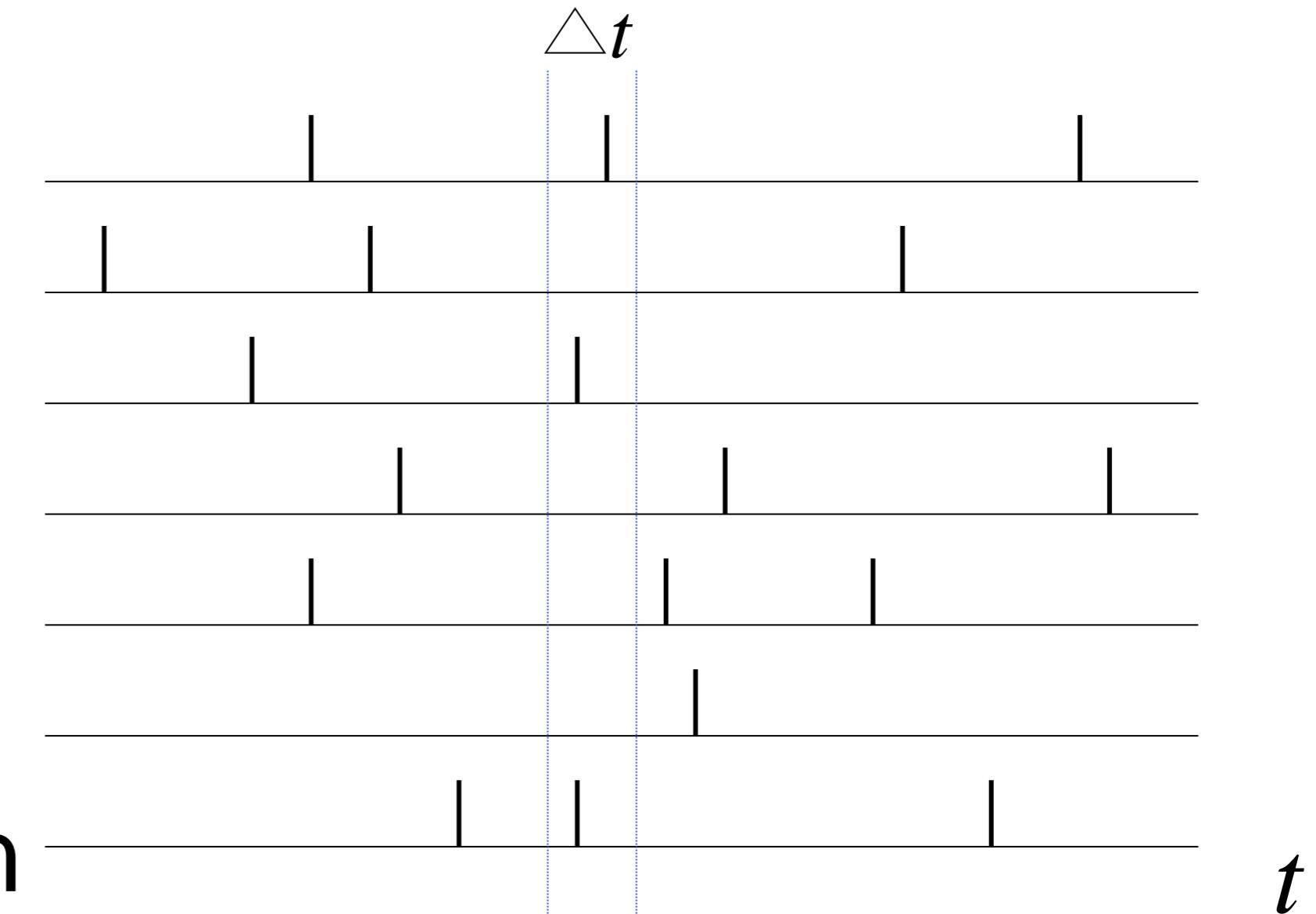
1. Population activity: definition

population activity - rate defined by population average



‘natural readout’

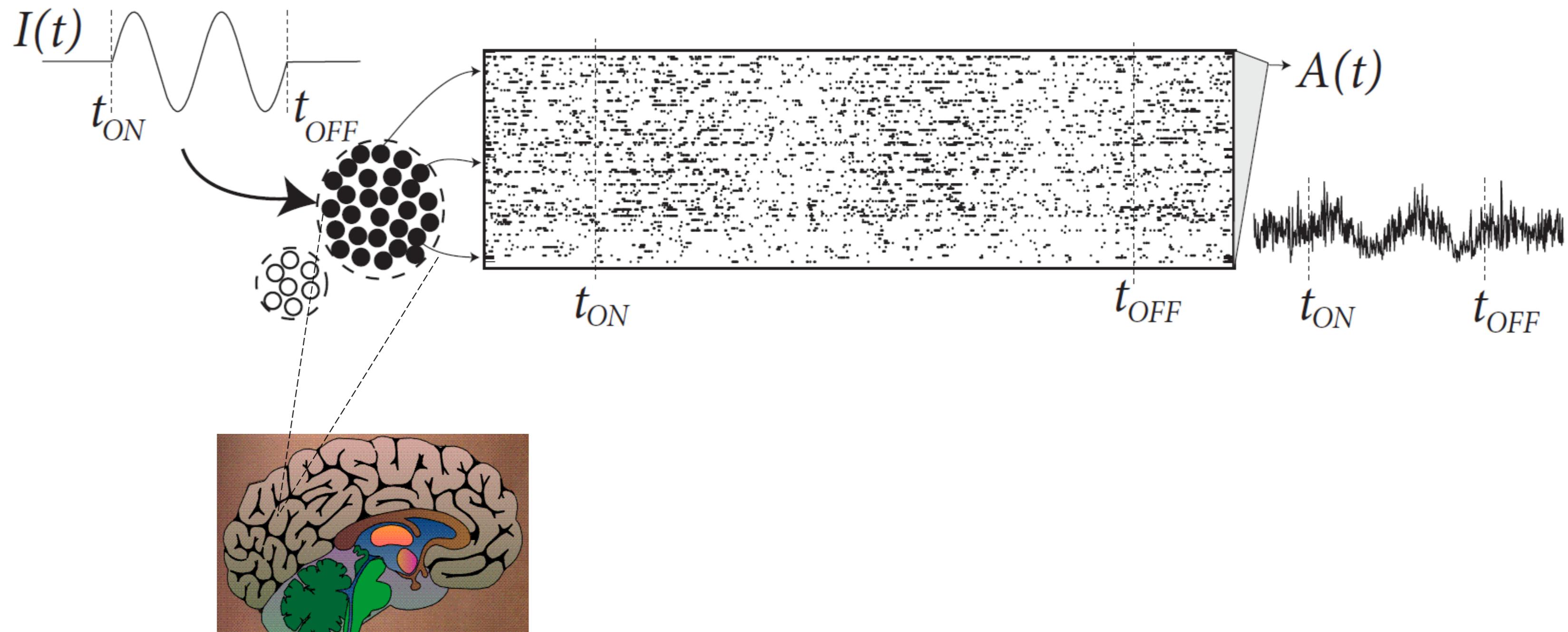
population
activity



$$A(t) = \frac{n(t; t + \Delta t)}{N\Delta t}$$

1. Population activity: example

population of neurons
with similar properties

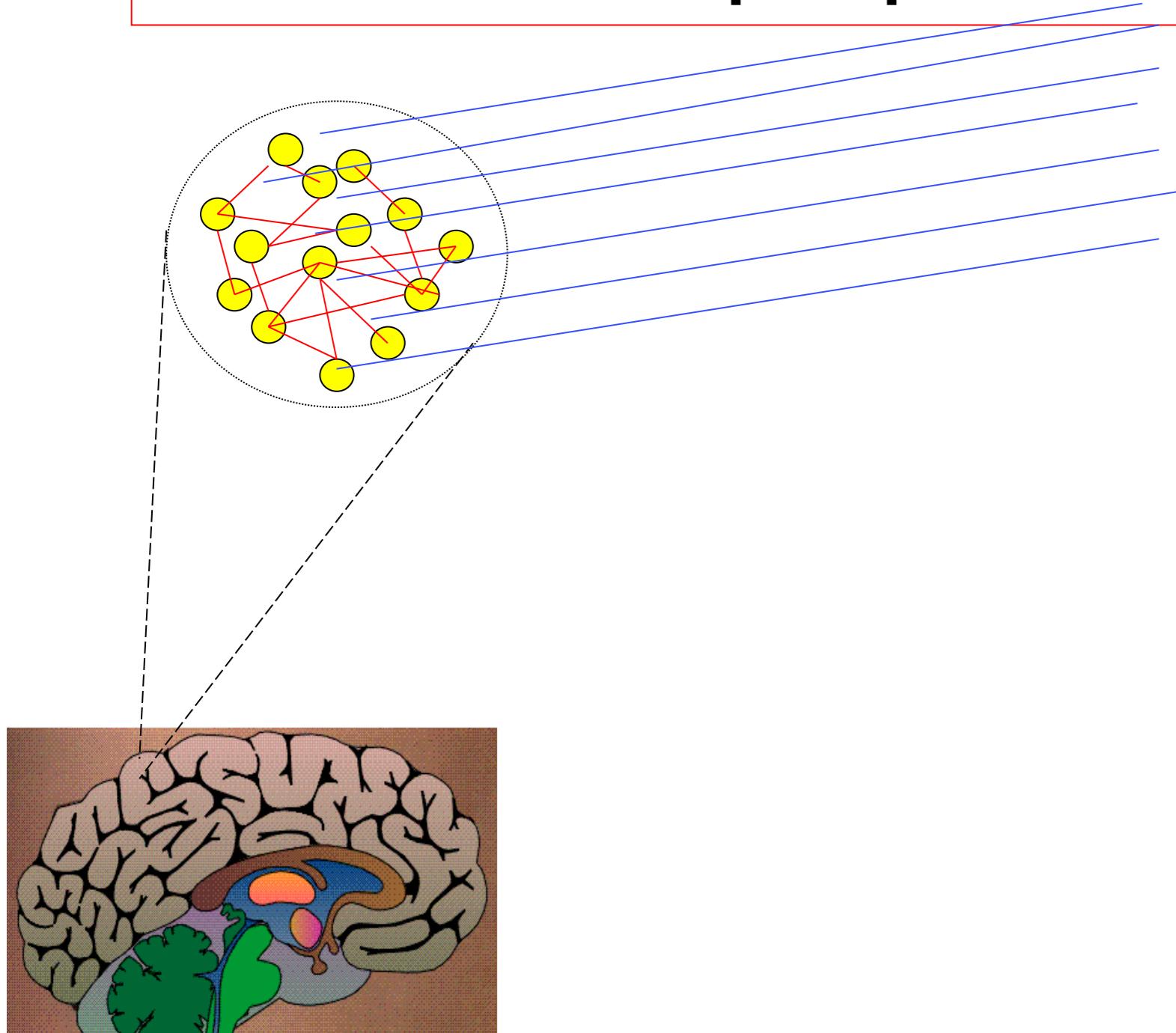


Brain

*Image: Neuronal Dynamics,
Gerstner et al.,
Cambridge Univ. Press (2014),*

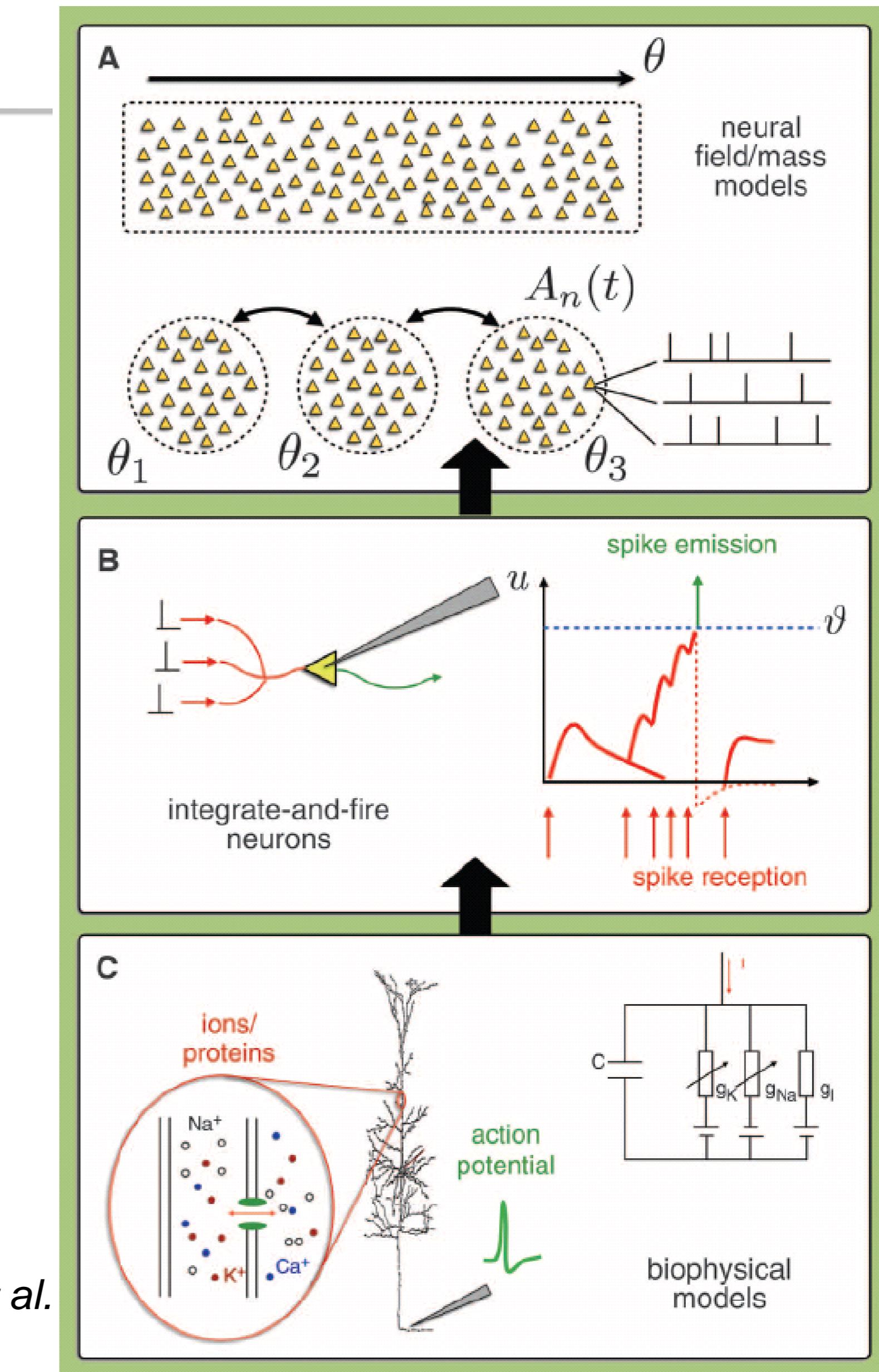
1. Scales of neuronal processes

population of neurons
with similar properties



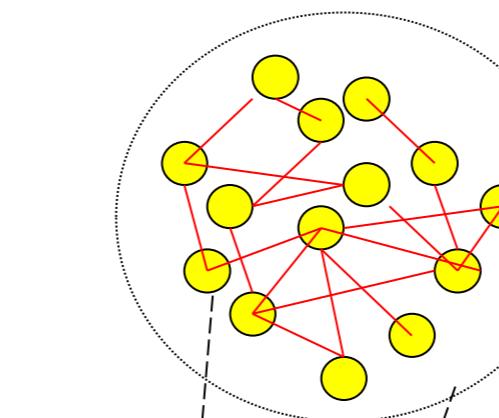
Brain

Image: Gerstner et al.
Science (2012),



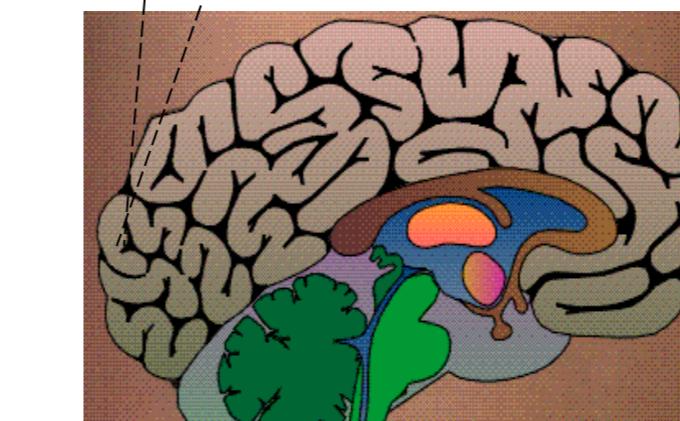
1. Population activity

population of neurons
with similar properties



population activity
→ $A(t)$

- do populations exist?
- how do they interact?
- can we predict $A(t)$?



Quiz 1, now

The population activity

- Is a firing rate
- Is a fast variable on the time scale of milliseconds
- Is proportional to the number of spikes
counted across a population in a short time window
- Is defined as the number of spikes
counted across a population in a short time window

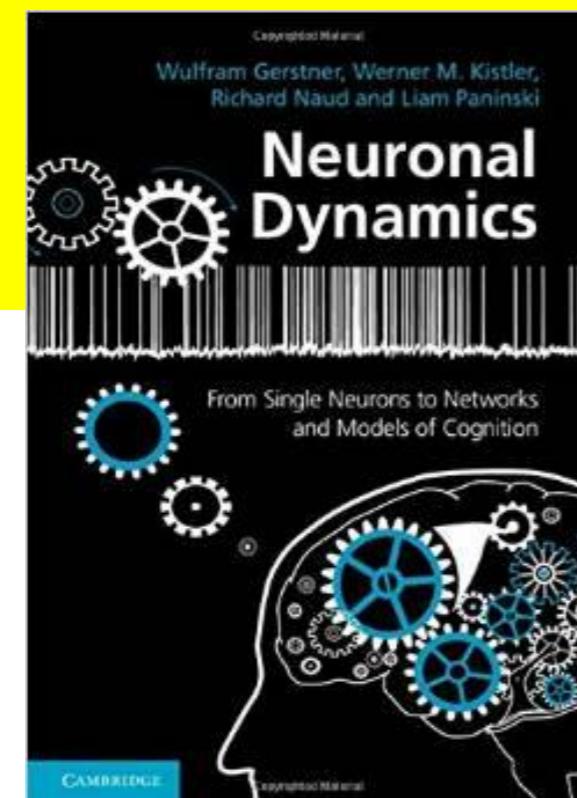
Additional information: Computational Neuroscience



Wulfram Gerstner
EPFL, Lausanne,
Switzerland

Background Reading: NEURONAL DYNAMICS

- Ch. 1.3.
- Ch. 12.1



Cambridge Univ. Press

Additional links to short MOOC - videos

<http://lcn.epfl.ch/~gerstner/NeuronalDynamics-MOOC1.html>

- Dirac delta-function in computational neuroscience

<https://www.youtube.com/watch?v=l3hvrx33IZc>

- Integrate-and-fire model, a first introduction

<https://www.youtube.com/watch?v=gU9UzFeg8f4>

Textbook also online:

<http://neuronal-dynamics.epfl.ch/>

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Neuronal Populations

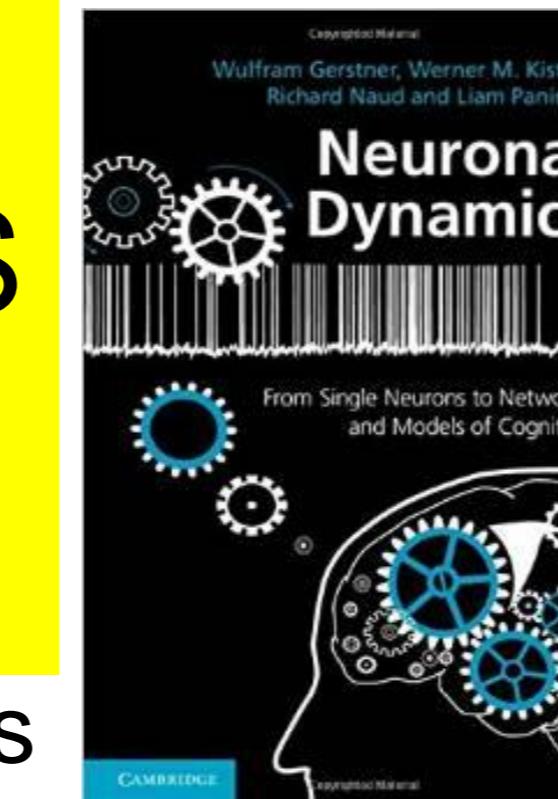
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Cambridge Univ. Press



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4. Mean-field argument

- input to one neuron

5. Stationary mean-field

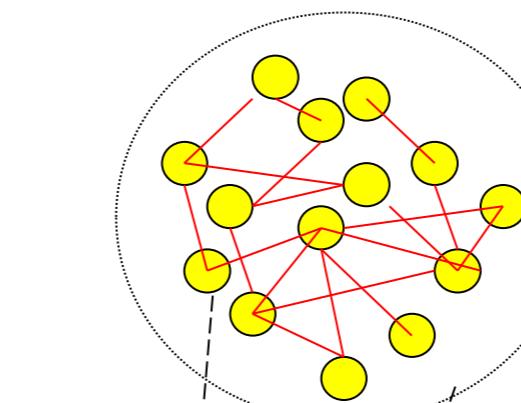
- asynchronous state: predict activity

6. Random Networks

- Balanced state

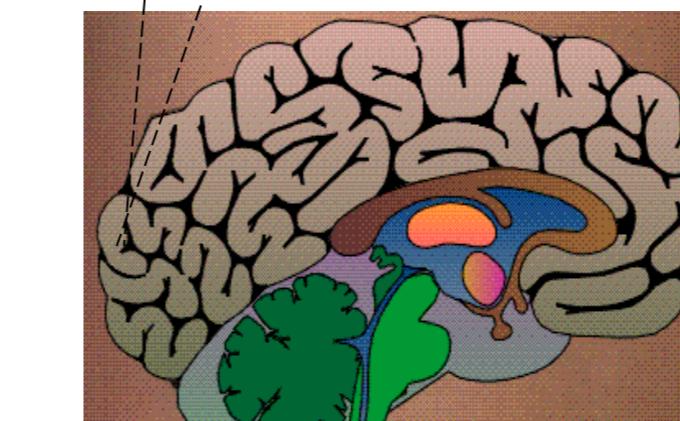
2. Population activity and cortical populations

population of neurons
with similar properties

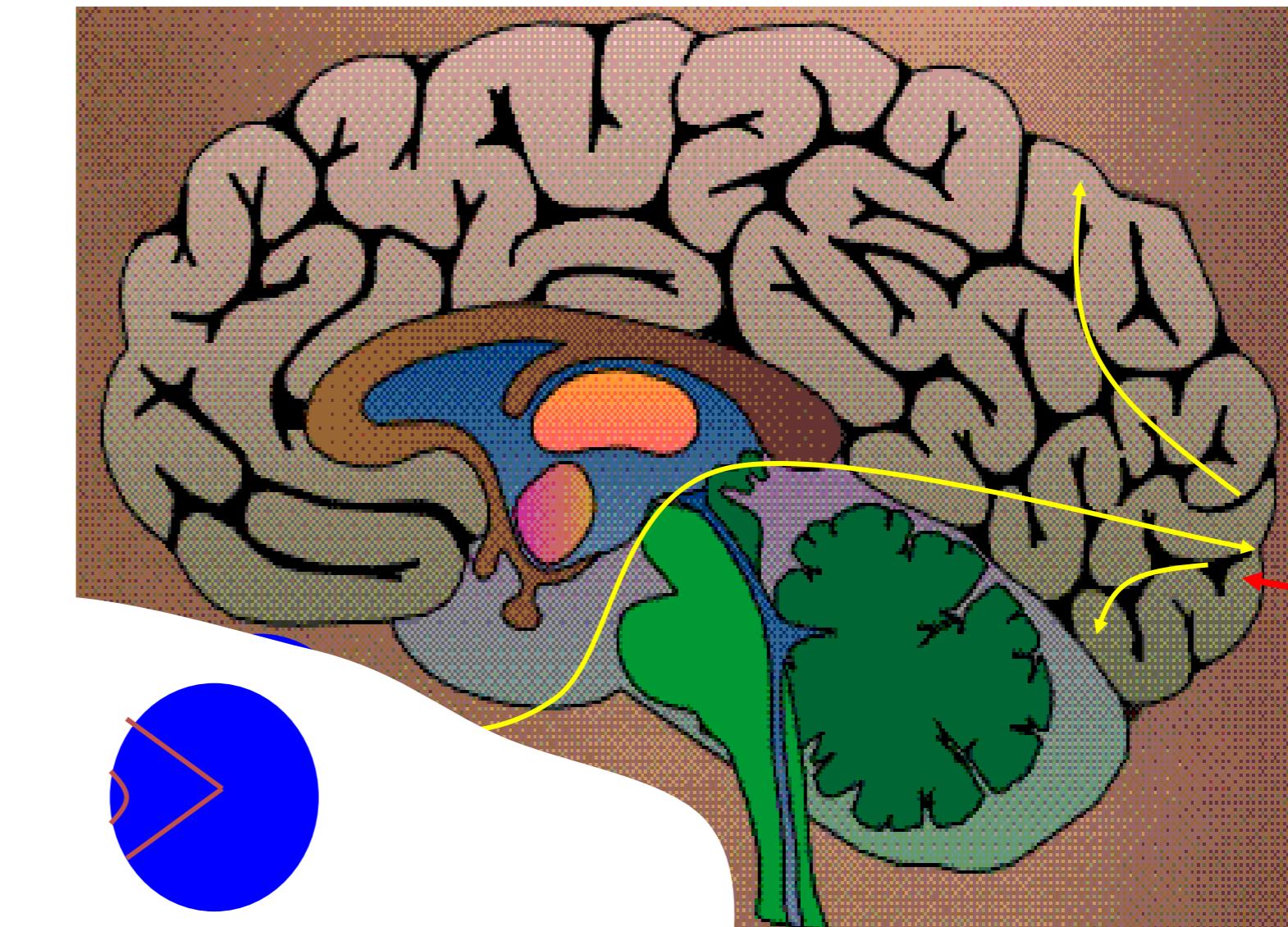
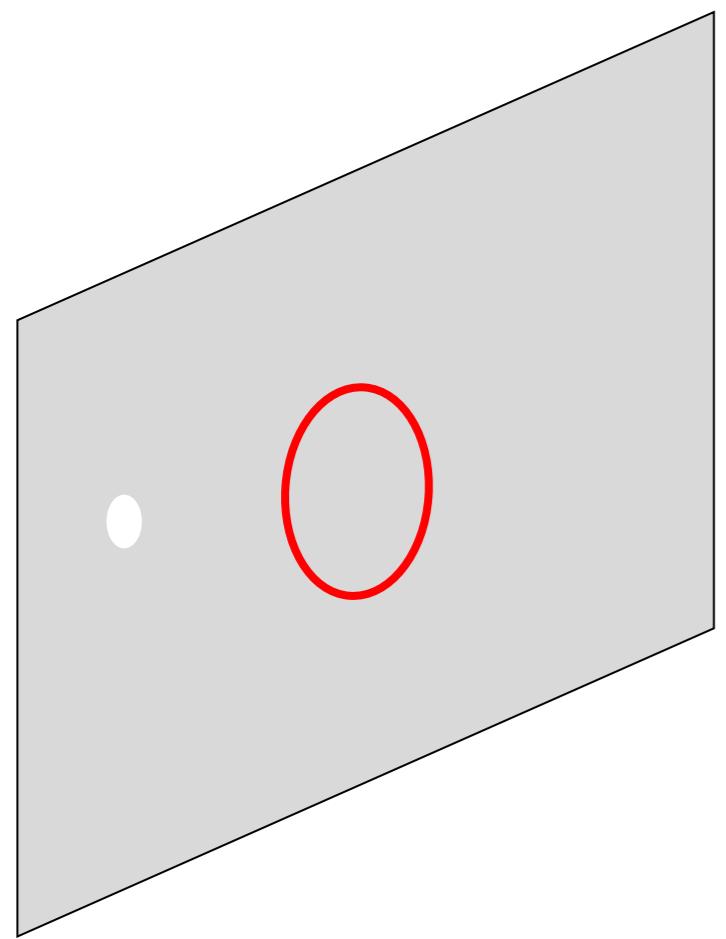


population activity
→ $A(t)$

- do populations exist?



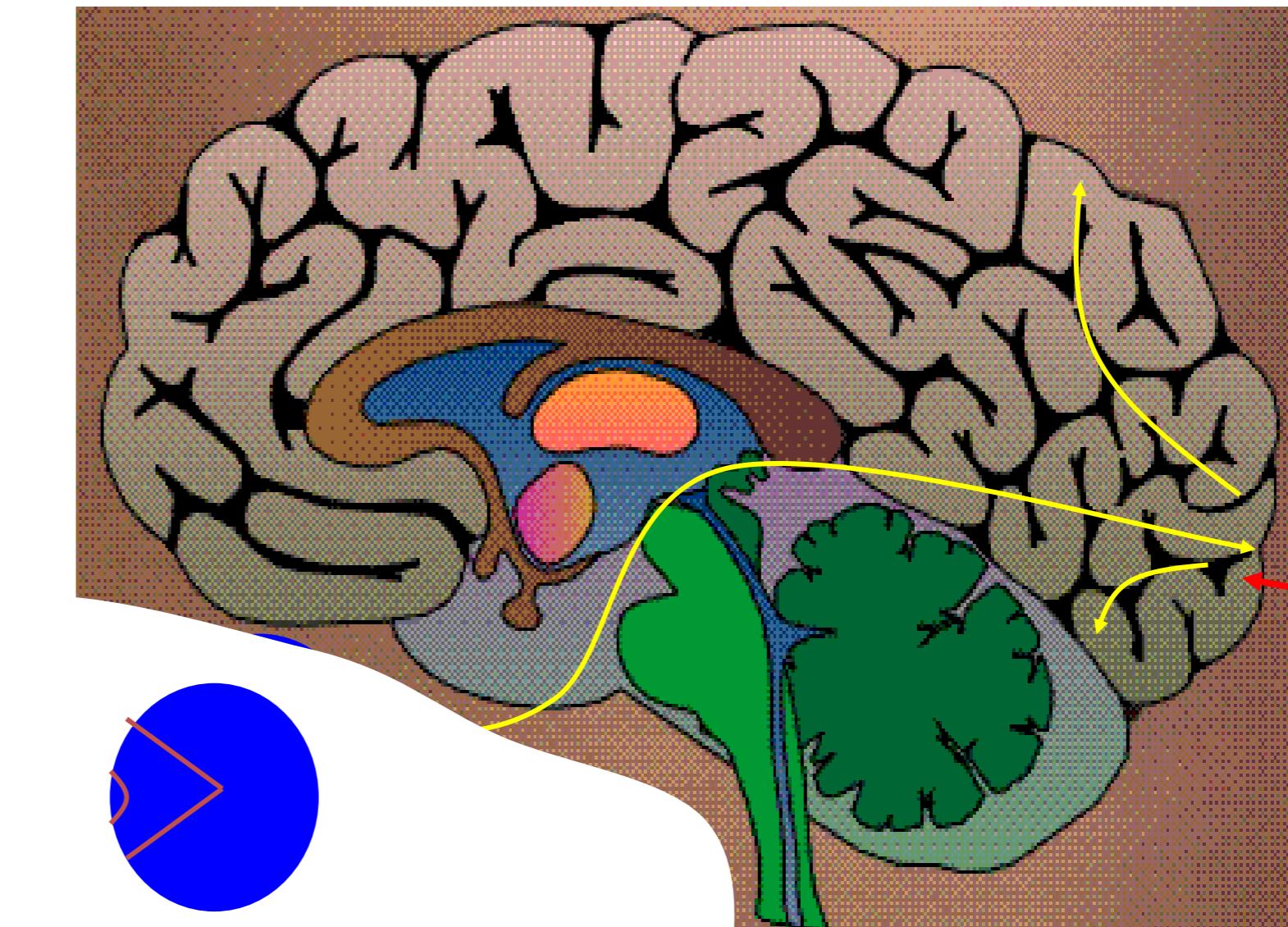
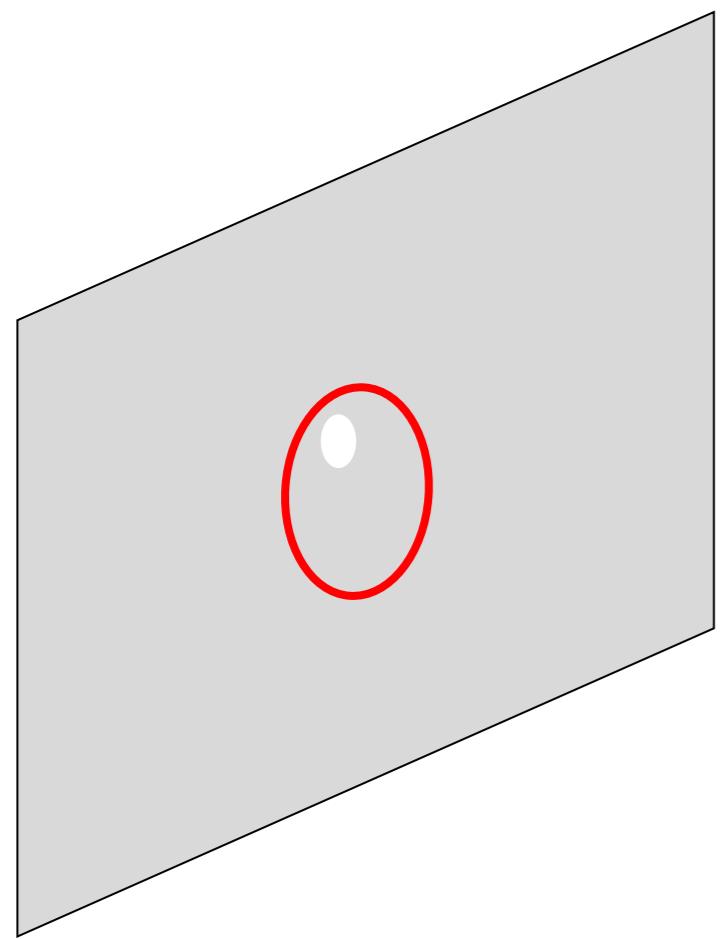
2. Receptive fields



visual
cortex

electrode

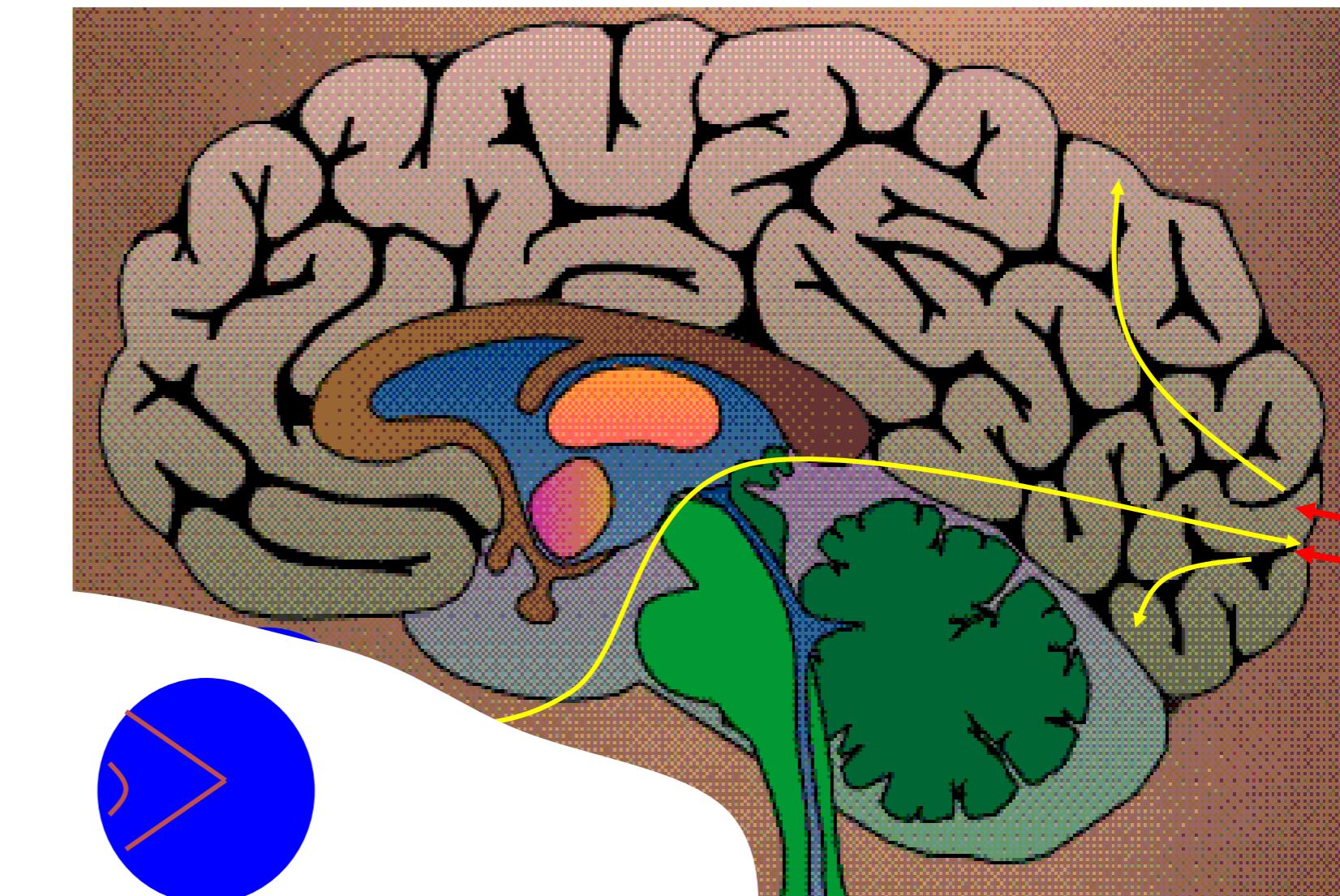
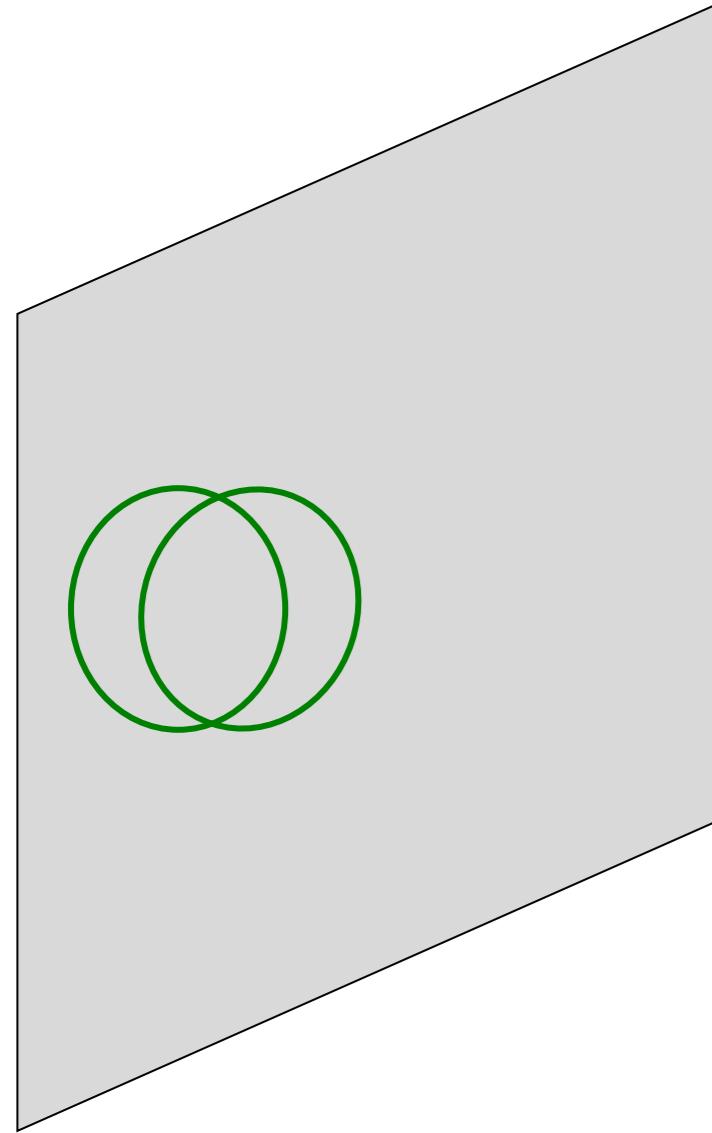
2. Receptive fields



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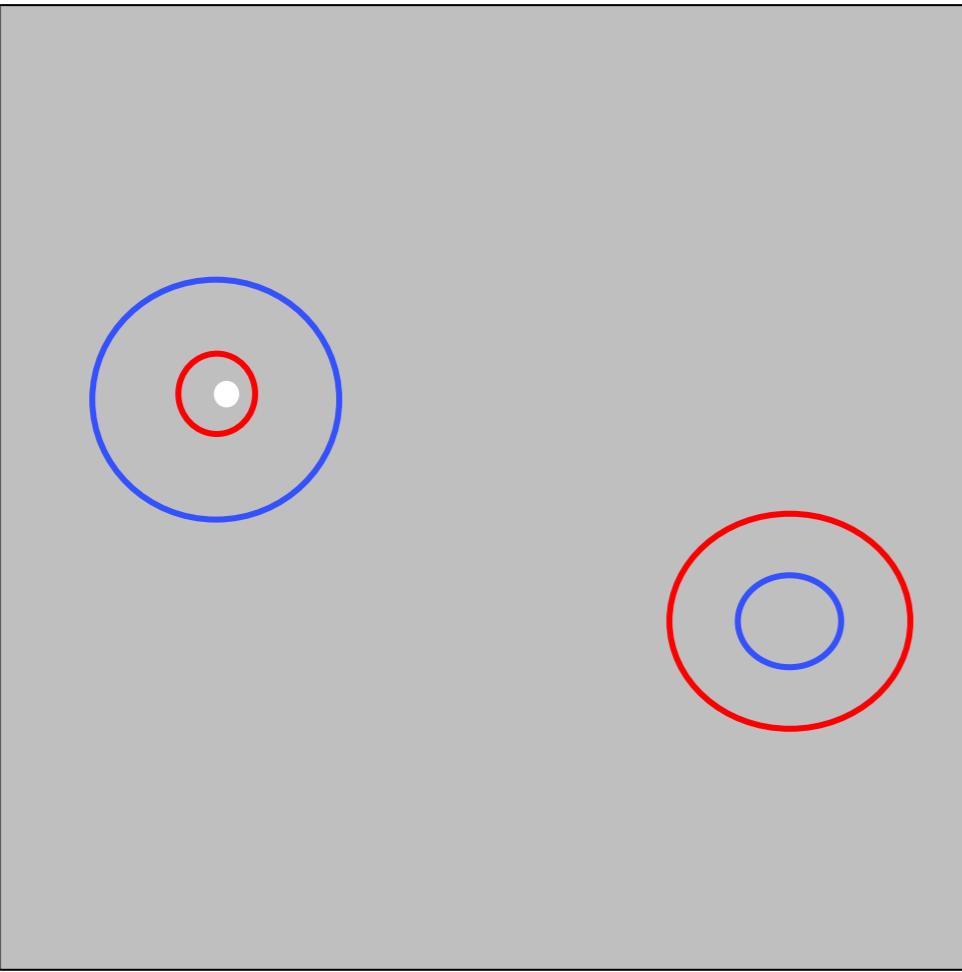
2. Receptive fields and Retinotopic Map



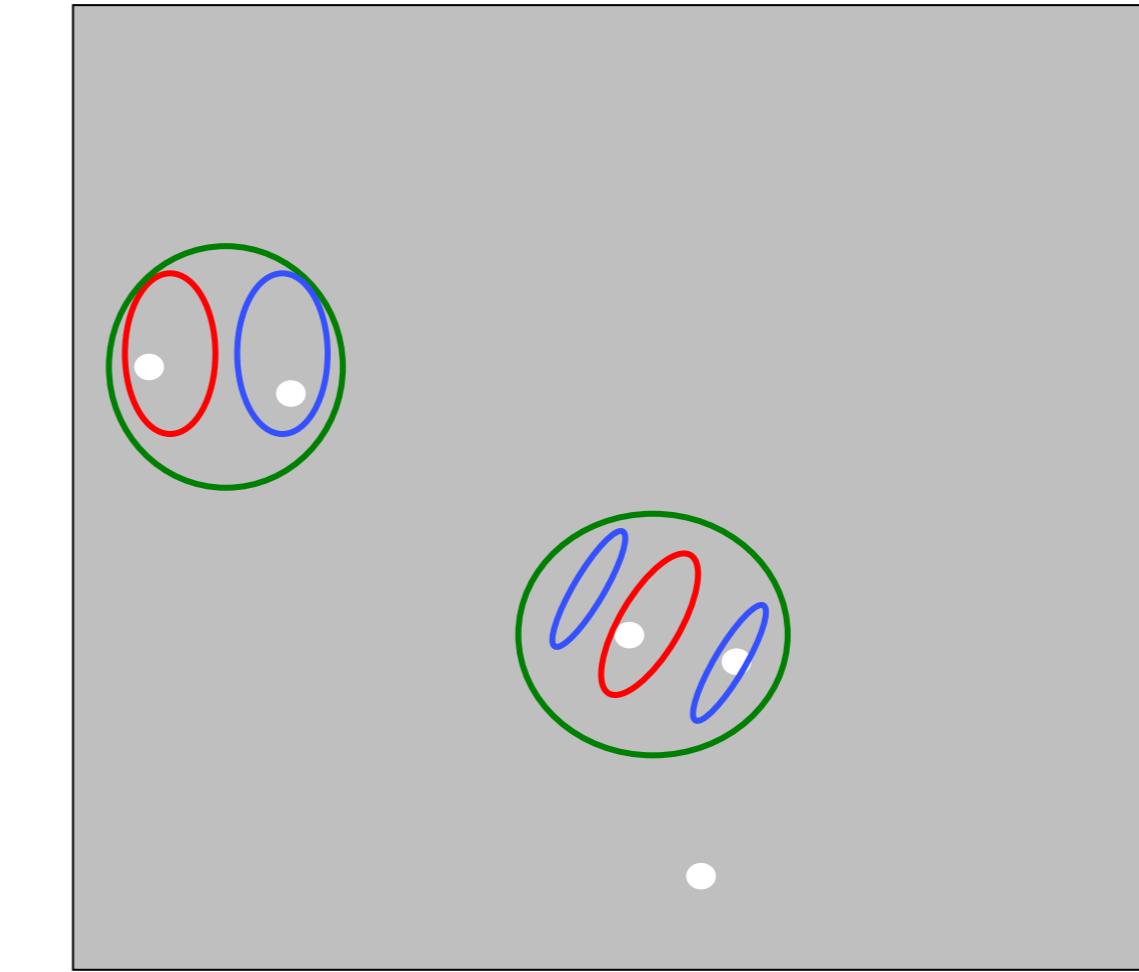
Neighboring cells
in visual cortex
have similar preferred
center of receptive field

2. Receptive fields with Orientation Tuning

Receptive fields:
Retina, LGN



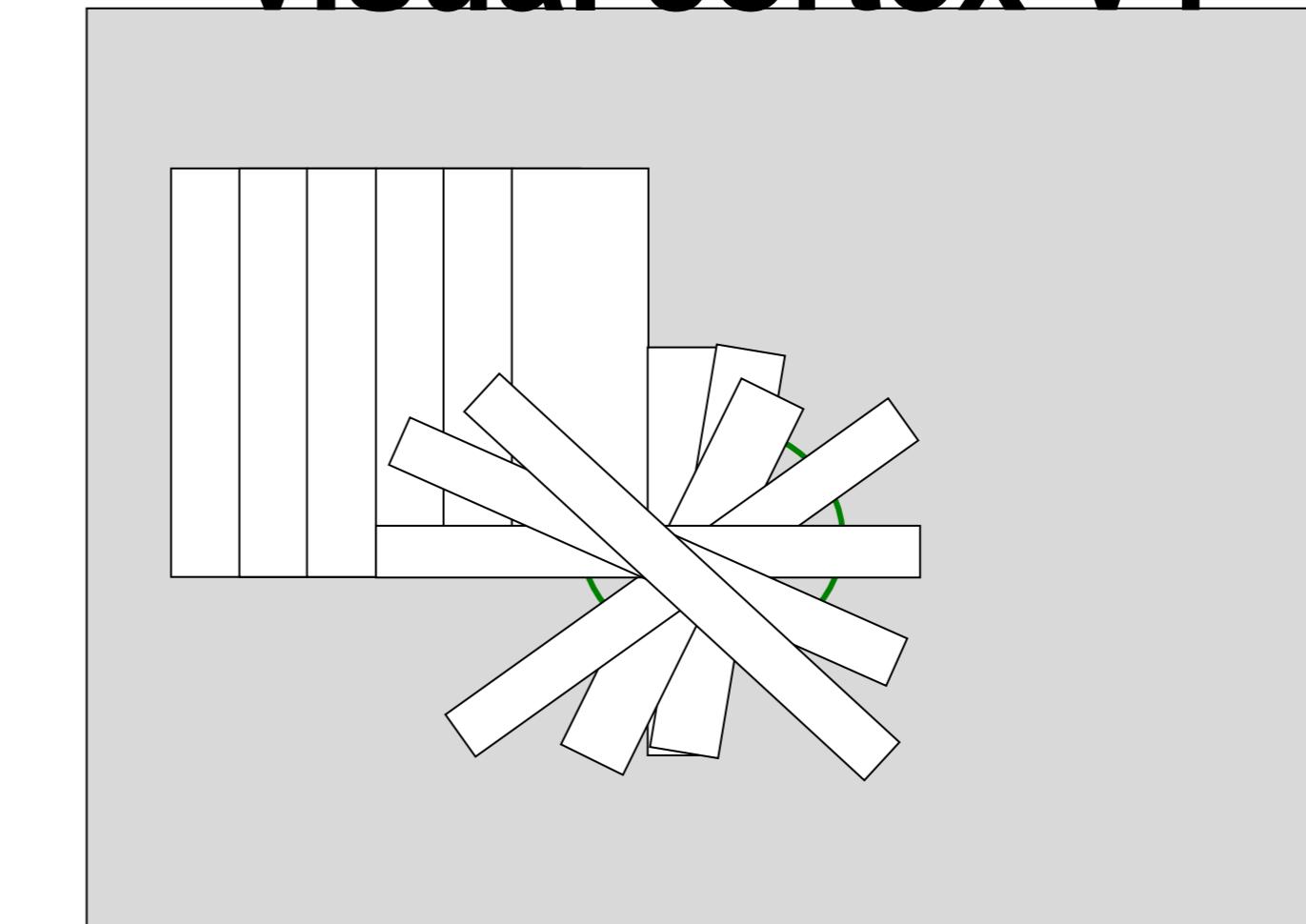
Receptive fields:
visual cortex V1



Orientation
selective

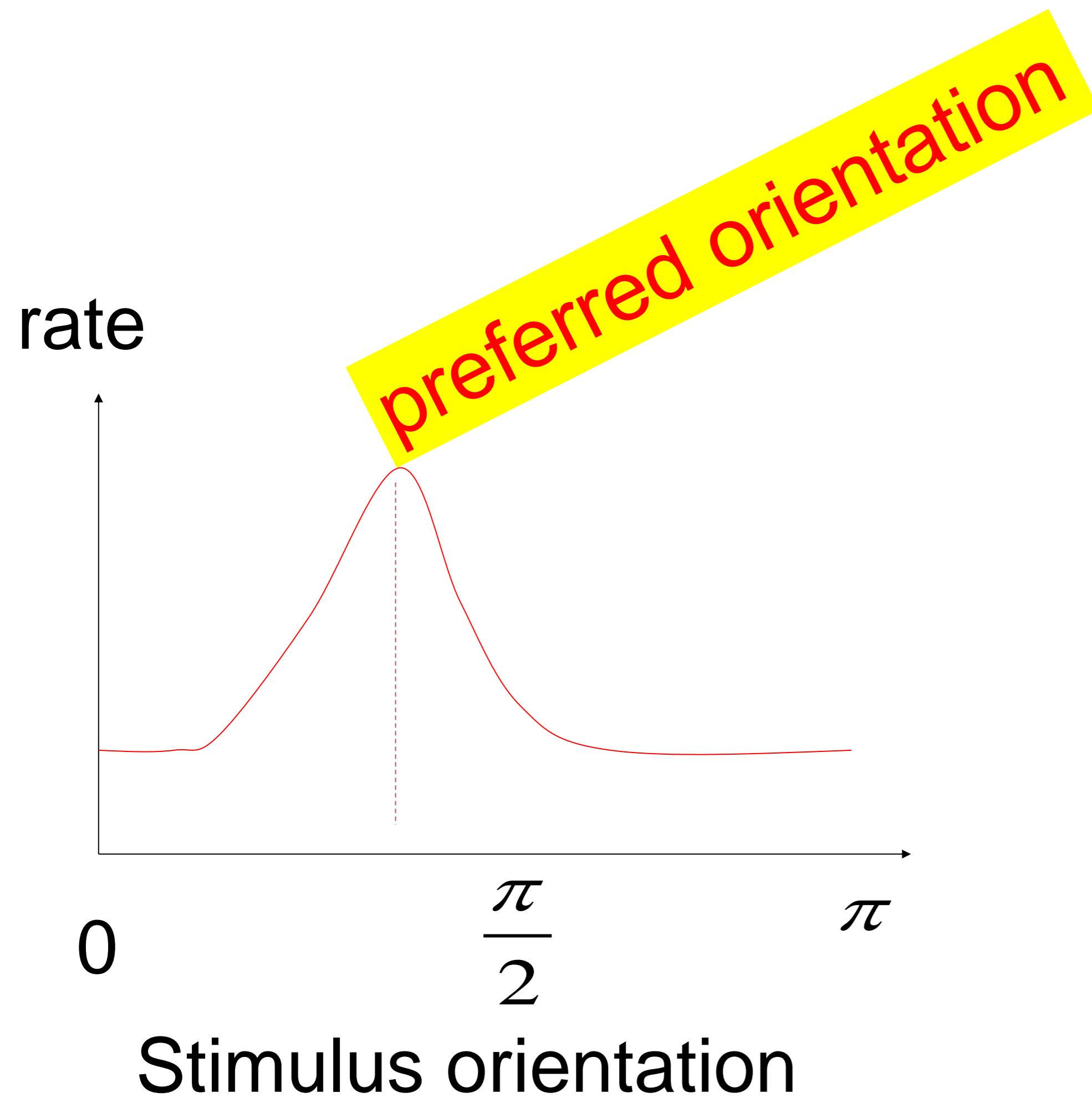
2. Receptive fields with Orientation Tuning

Receptive fields:
visual cortex V1

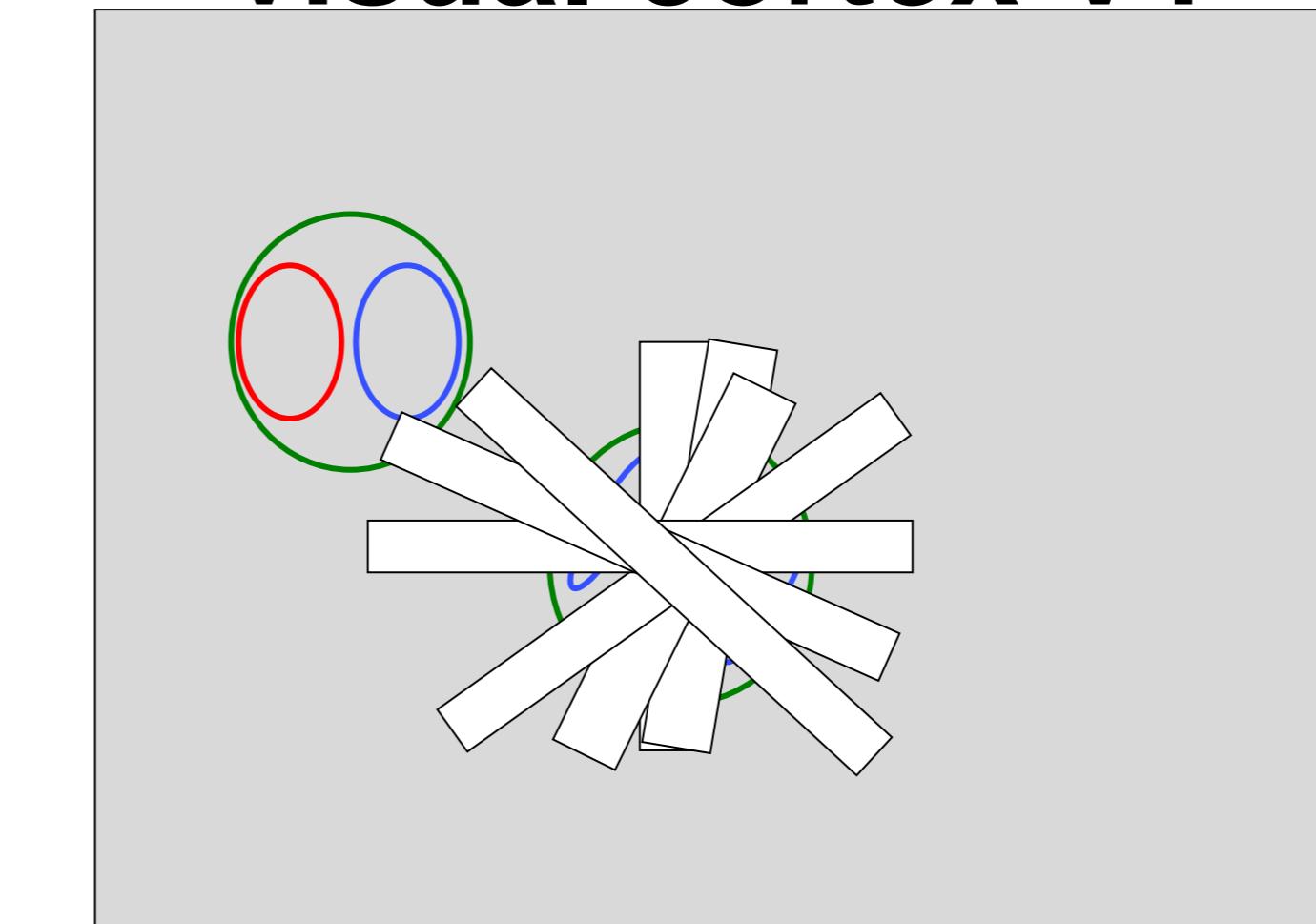


Orientation selective

2. Receptive fields with Orientation Tuning



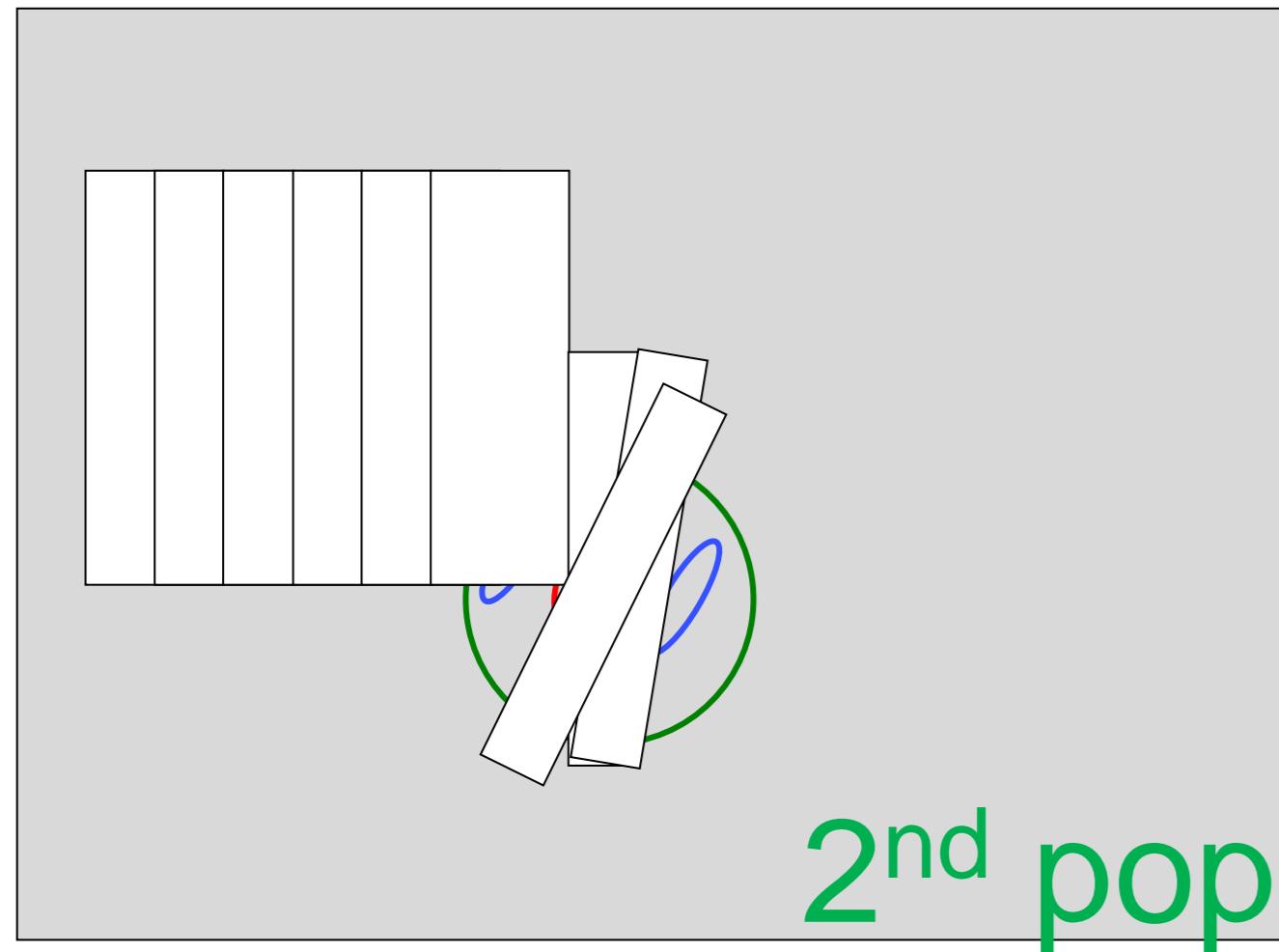
Receptive fields:
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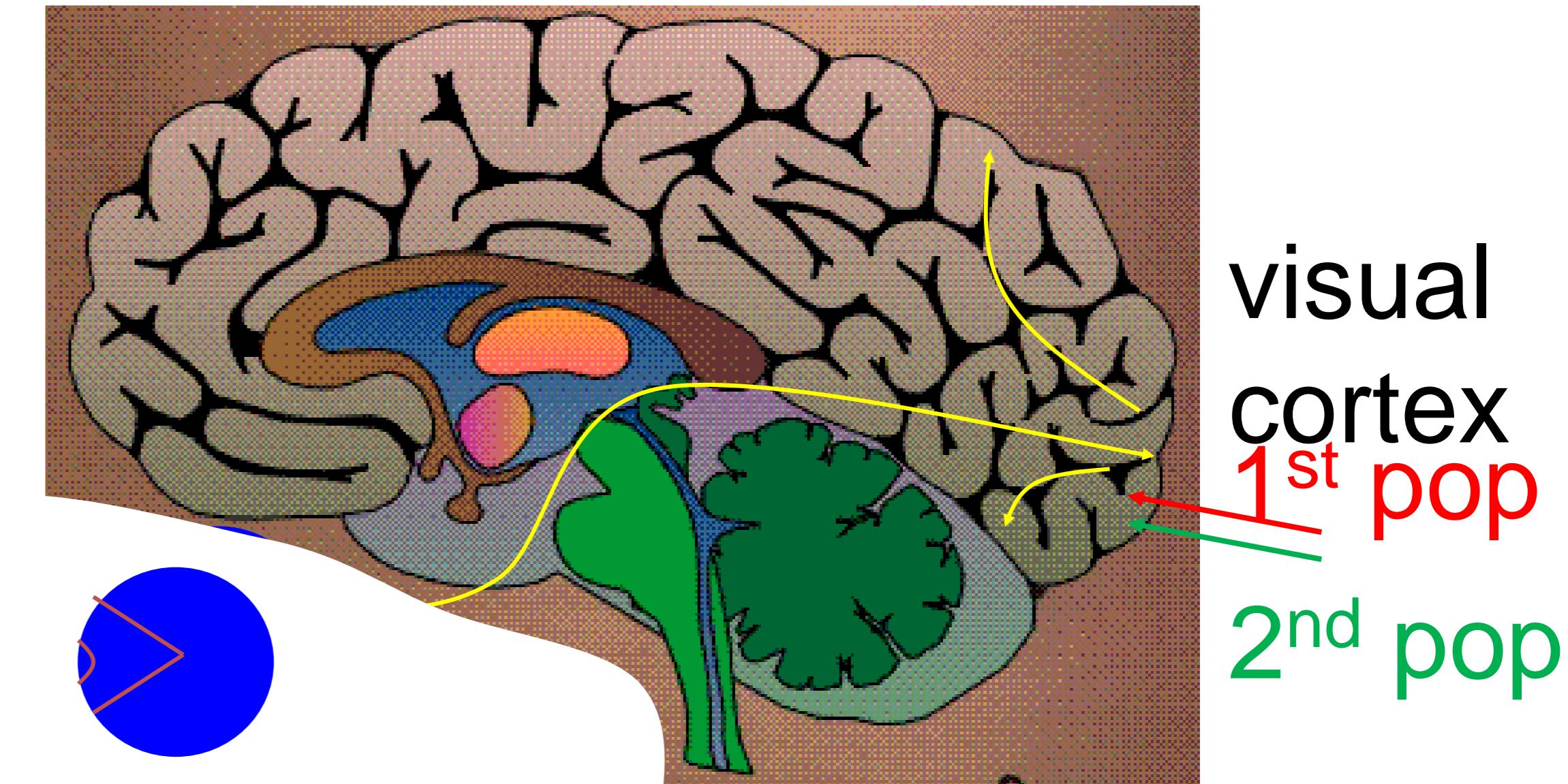
Orientation selective

2. Orientation Tuning and Orientation Maps

Receptive fields:
visual cortex V1

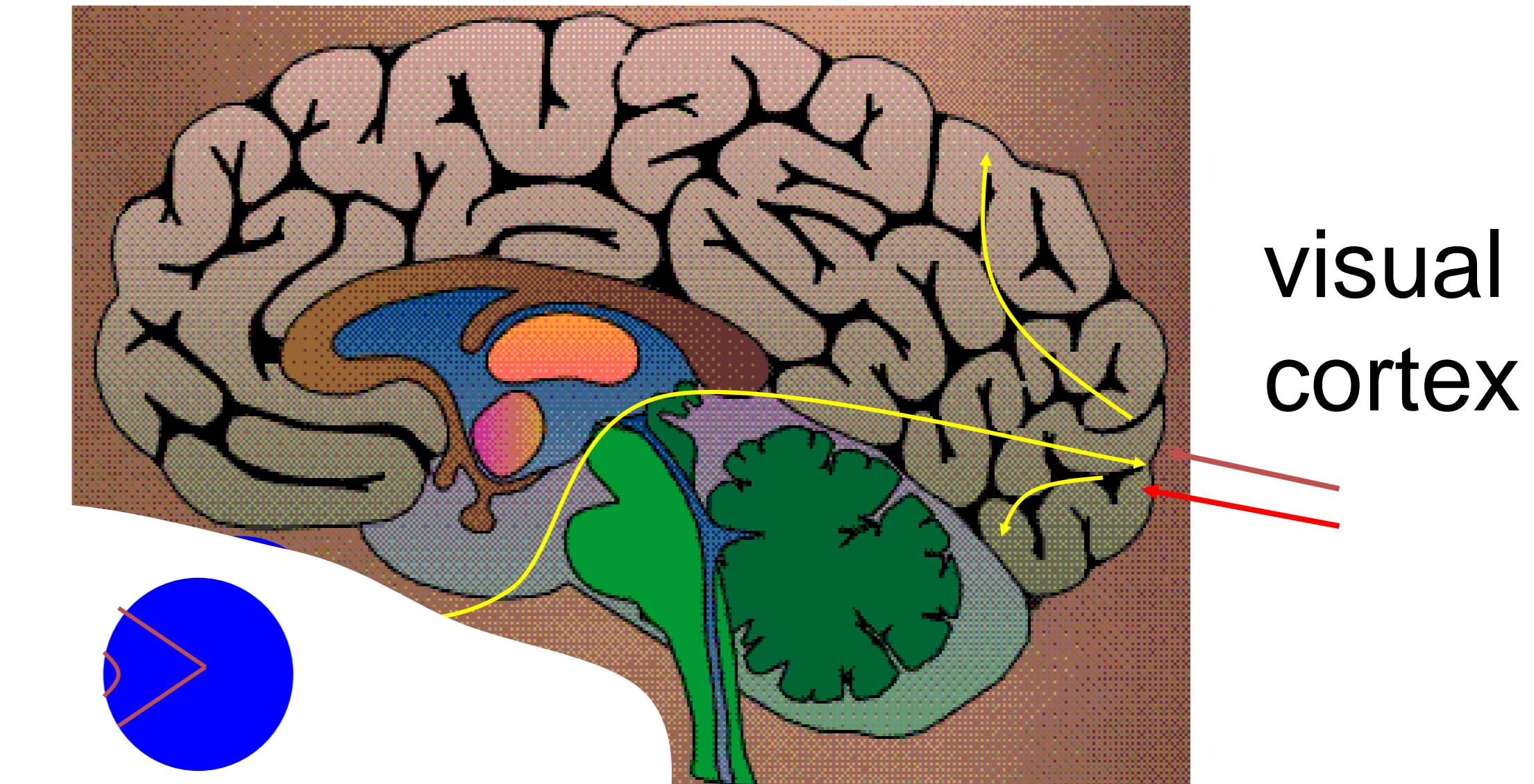
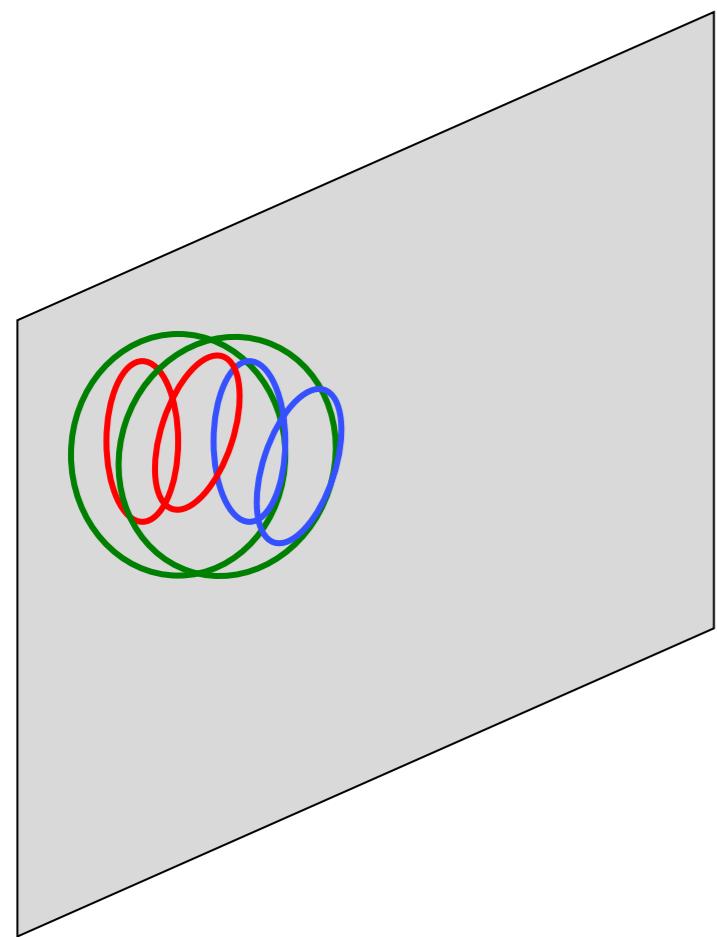


Orientation selective



**Neighboring neurons
have similar properties**

2. Orientation Map



Neighboring cells in visual cortex
Have similar preferred orientation:
cortical orientation map

*Hubel and Wiesel 1968; Bonhoeffer&Grinvald, 1991;
Bressloff&Cowan, 2002; Kaschube et al. 2010*

2. Orientation Map

Receptive field

- set of stimulus features to which a neuron responds
- for visual neurons: location, orientation, color, ...

Neighboring cells in visual cortex

- similar preferred orientation
- similar location of receptive field

→ candidate of ‘neuronal population’

Quiz 2, now

The receptive field of a visual neuron refers to

- The localized region of space to which it is sensitive
- The orientation of a light bar to which it is sensitive
- The set of all stimulus features to which it is sensitive

The receptive field of a auditory neuron refers to

- The set of all stimulus features to which it is sensitive
- The range of frequencies to which it is sensitive

The receptive field of a somatosensory neuron refers to

- The set of all stimulus features to which it is sensitive
- The region of body surface to which it is sensitive

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Neuronal Populations

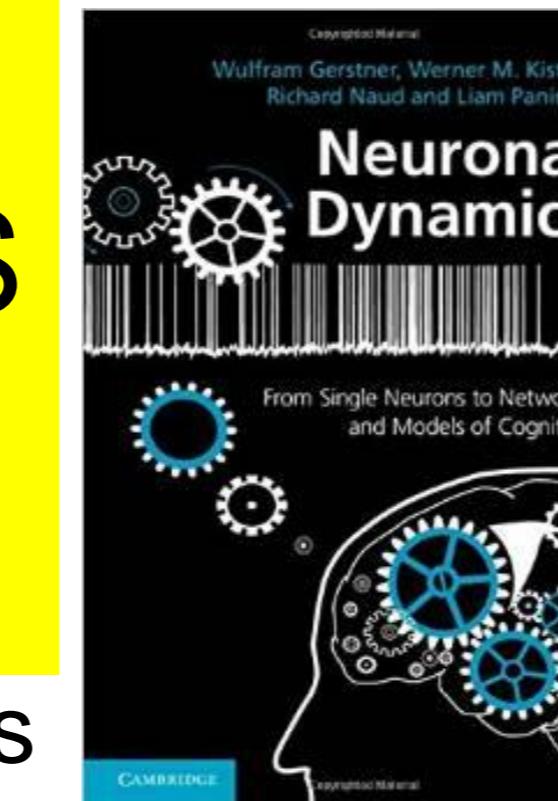
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NEURONAL DYNAMICS

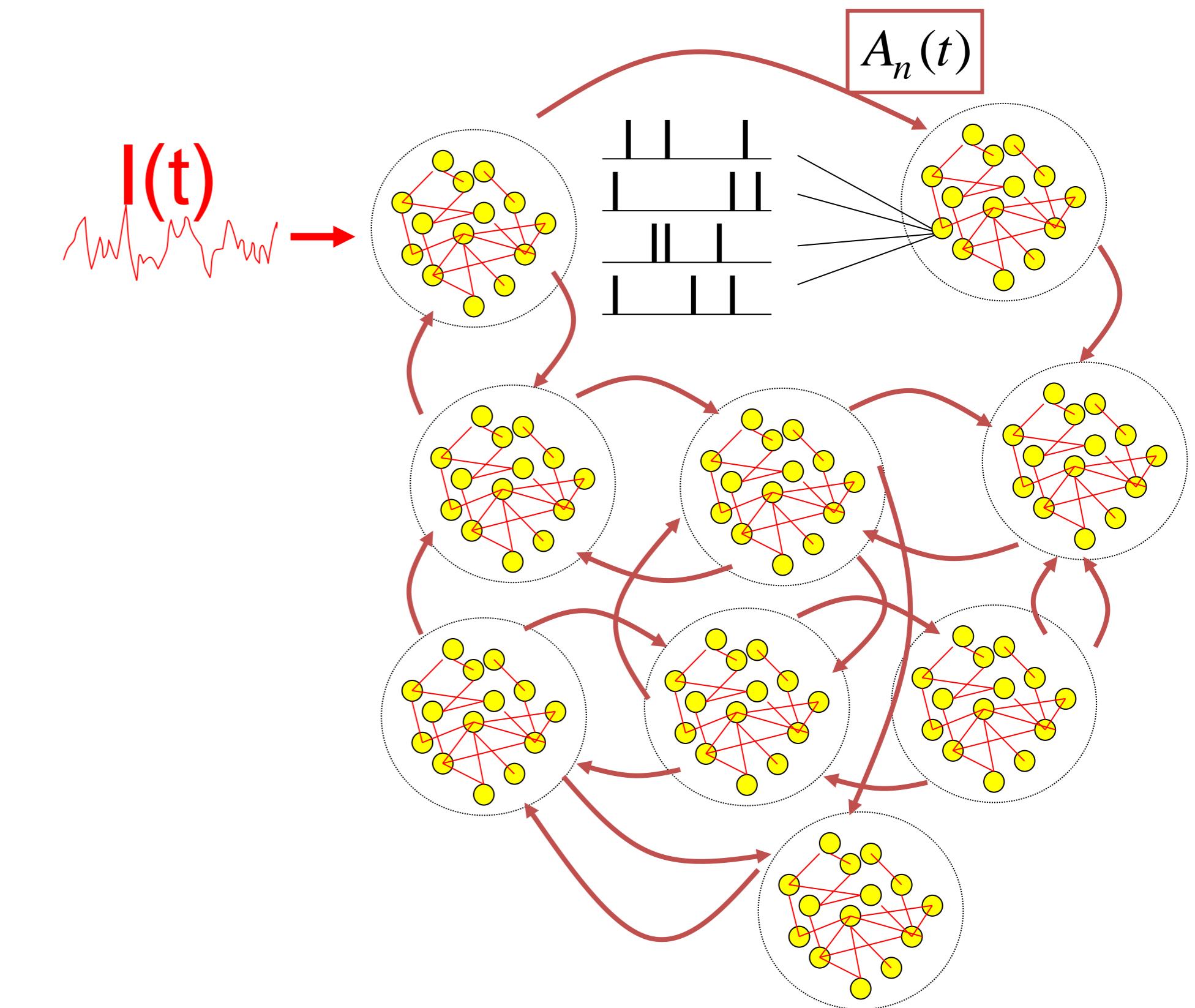
- Ch. 12.1 – 12.4.3
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Cambridge Univ. Press



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 - definition and aims
- 2. Cortical Populations**
 - columns and receptive fields
- 3. Connectivity**
 - cortical connectivity
 - model connectivity schemes
- 4. Mean-field argument**
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- 5. Stationary mean-field**
 - asynchronous state: predict activity
- 6. Random Networks**
 - Balanced state

3. Interacting Populations in models



What are these populations?
How are they connected?

3. A single model population

population = group of neurons
with

- similar neuronal properties
- similar input
- similar receptive field
- similar connectivity



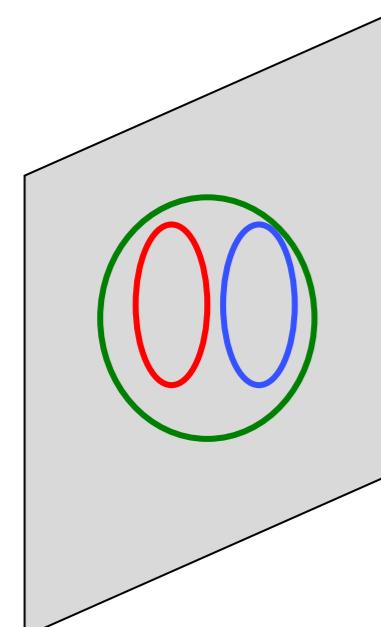
make this more precise

3. Cortical orientation map and cortical column

population = group of neurons with

- similar neuronal properties
- similar input
- similar receptive field
- similar connectivity

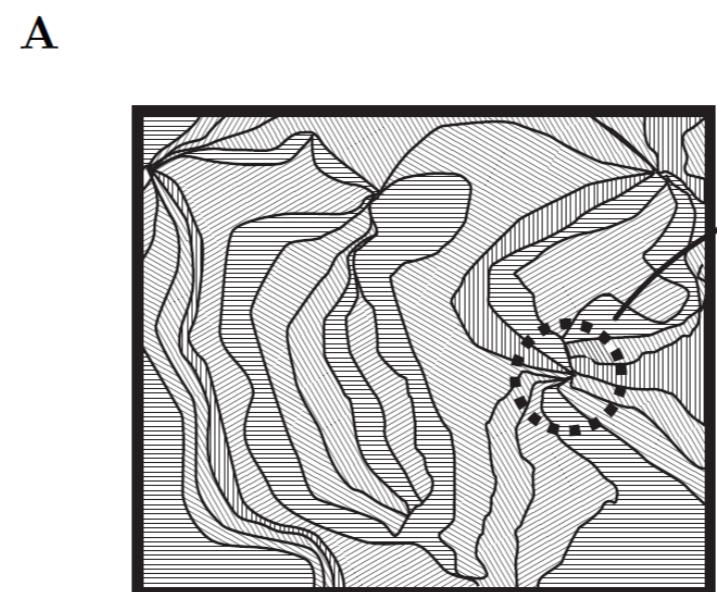
→ make this more precise



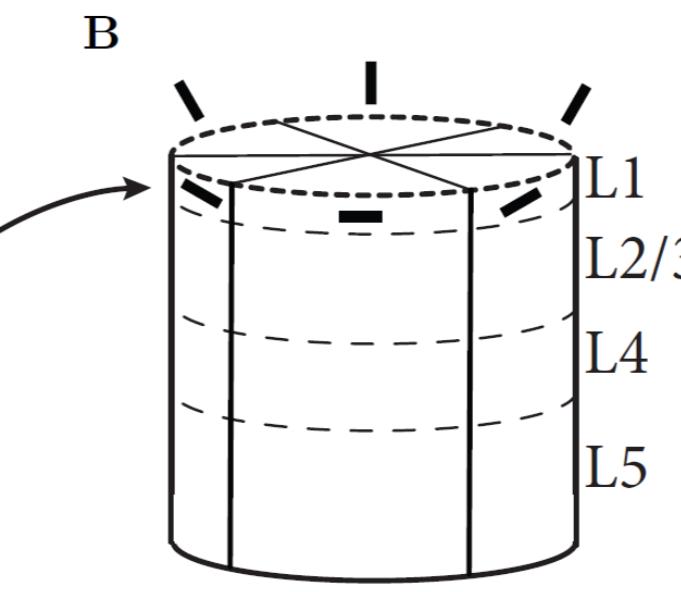
Rec. Field on Screen

cortical orientation map

Sheet of visual cortex cortical column



A

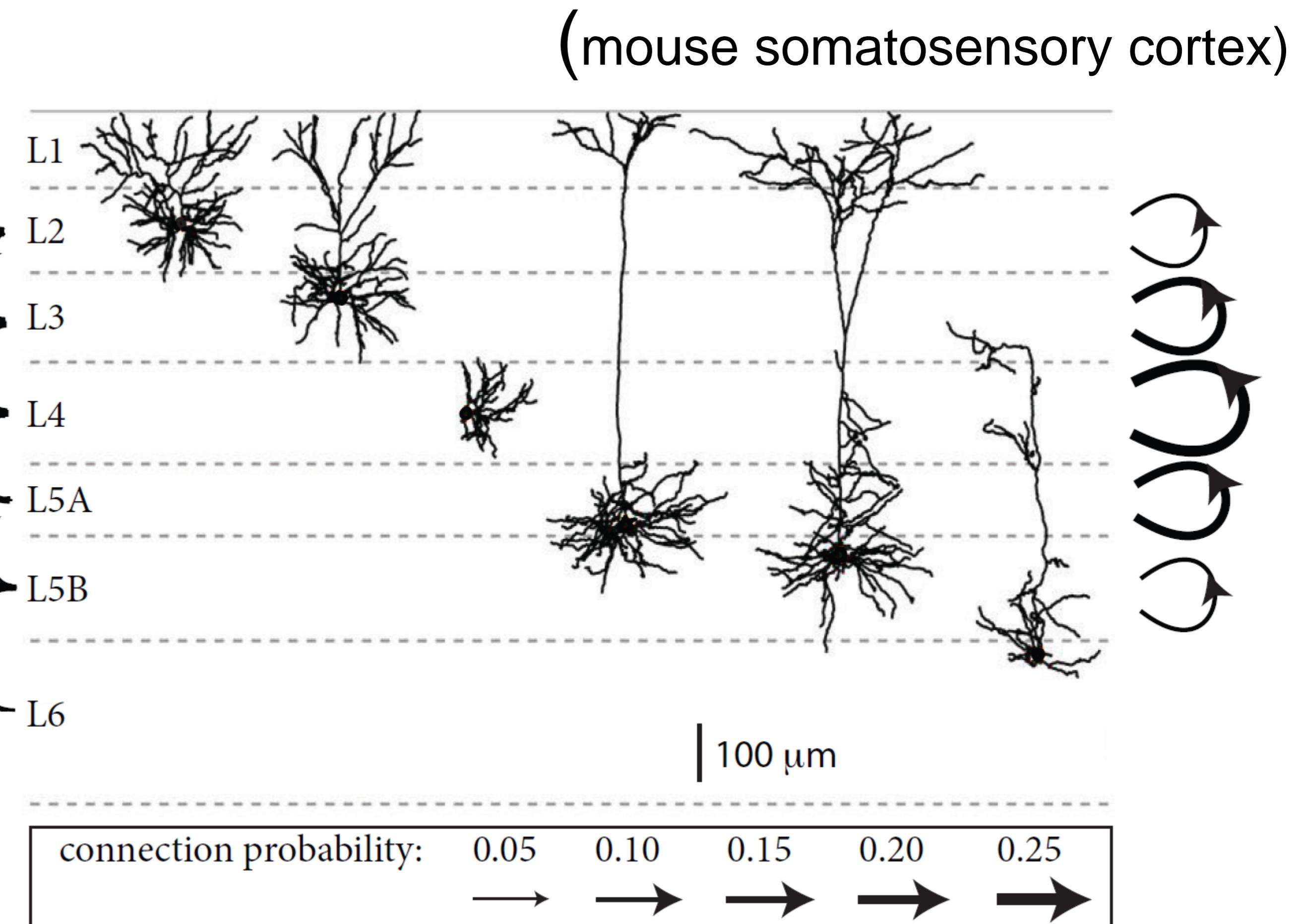
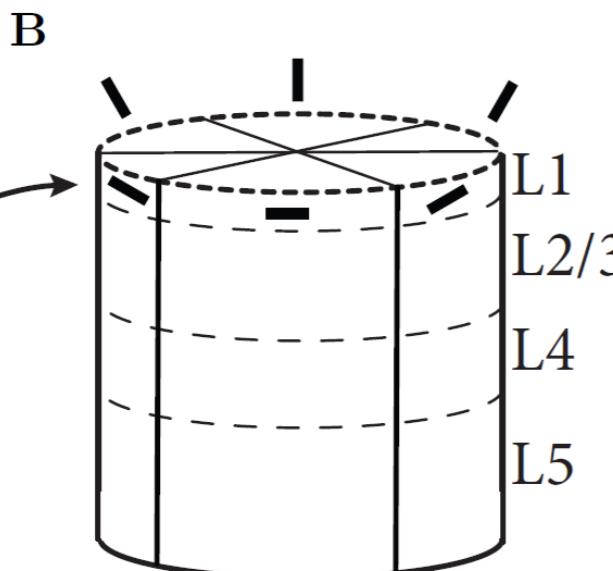
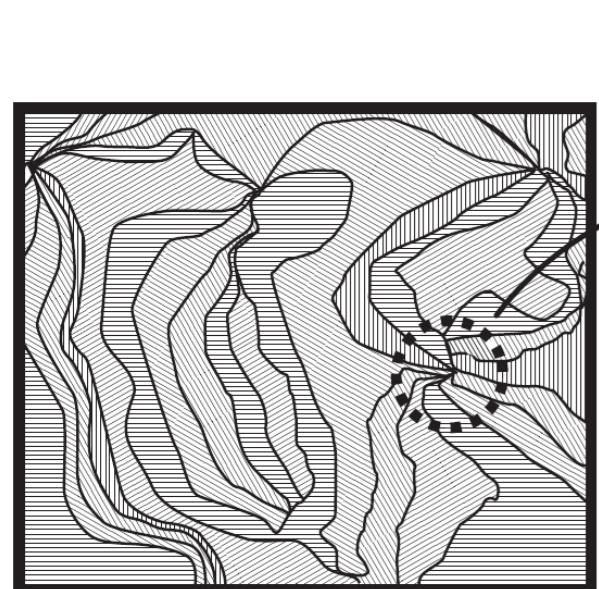


B

*Hubel and Wiesel 1968;
Bonhoeffer&Grinvald, 1991*

3 local cortical connectivity across layers

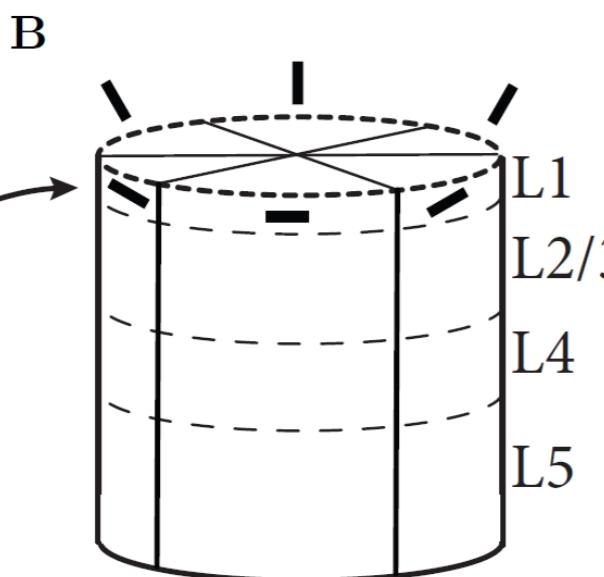
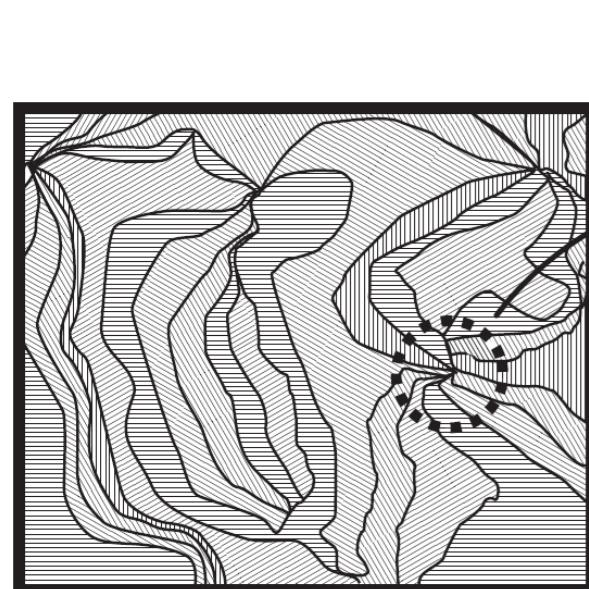
Here:
Excitatory neurons



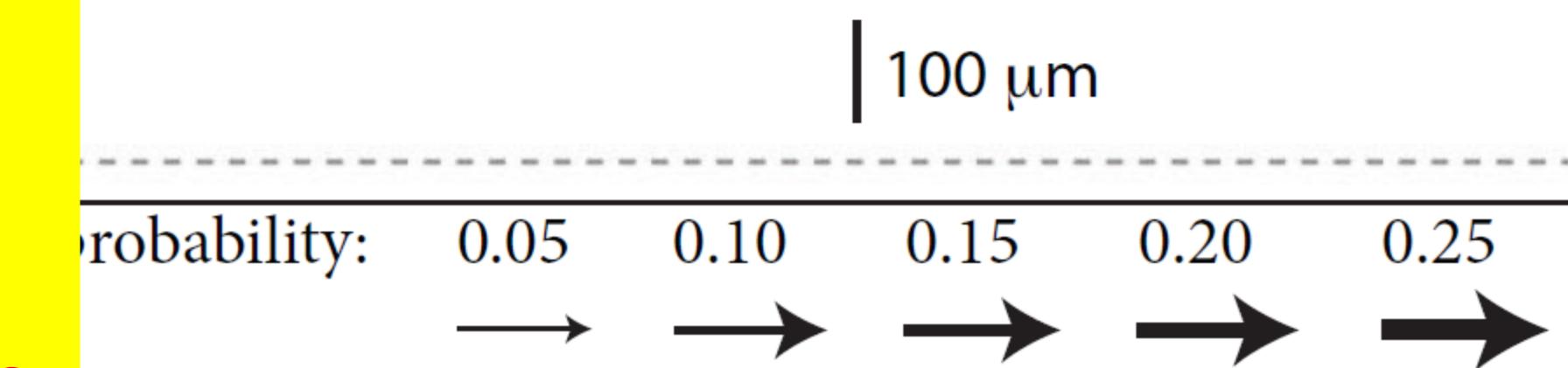
Lefort et al. NEURON, 2009

3 local cortical connectivity across layers

Here:
Excitatory neurons



1 population =
all neurons of given type
in one layer of same column
(e.g. excitatory in layer 3)



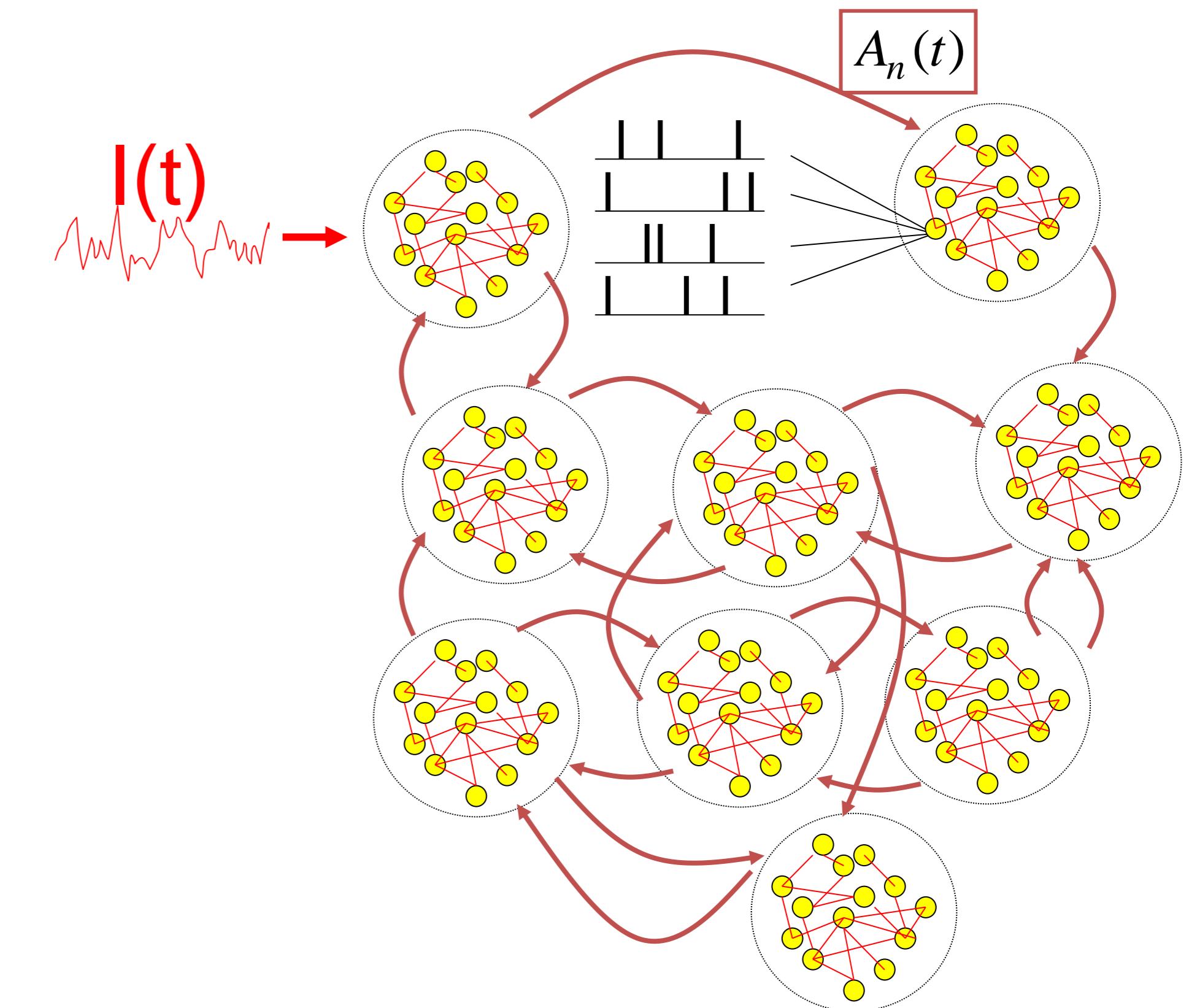
Lefort et al. NEURON, 2009

3. Interacting Populations in models

Connection probability:

- within population
- across population

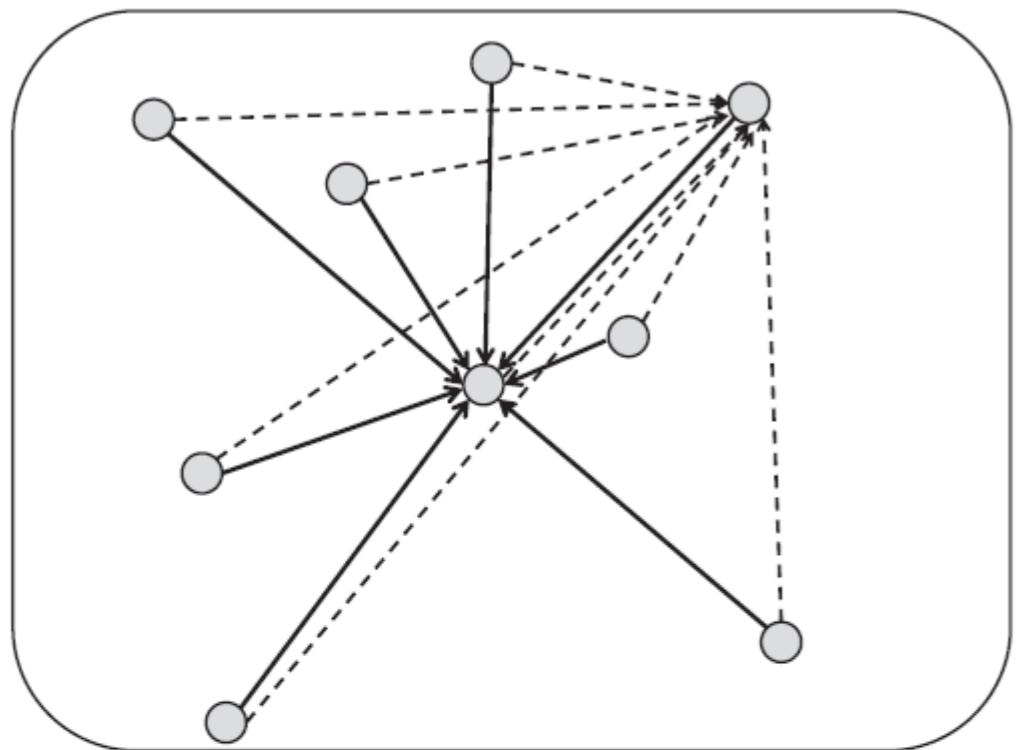
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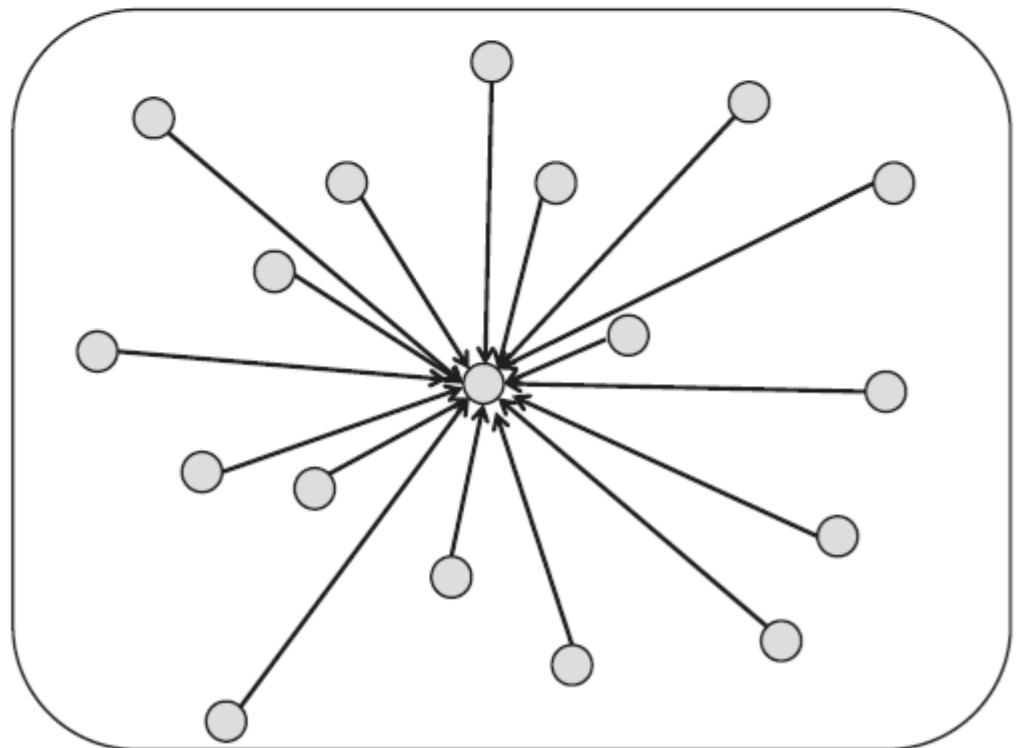
3. Connectivity schemes (models)

full connectivity
all-to-all

$N=5000$
neurons



$N=10000$
neurons



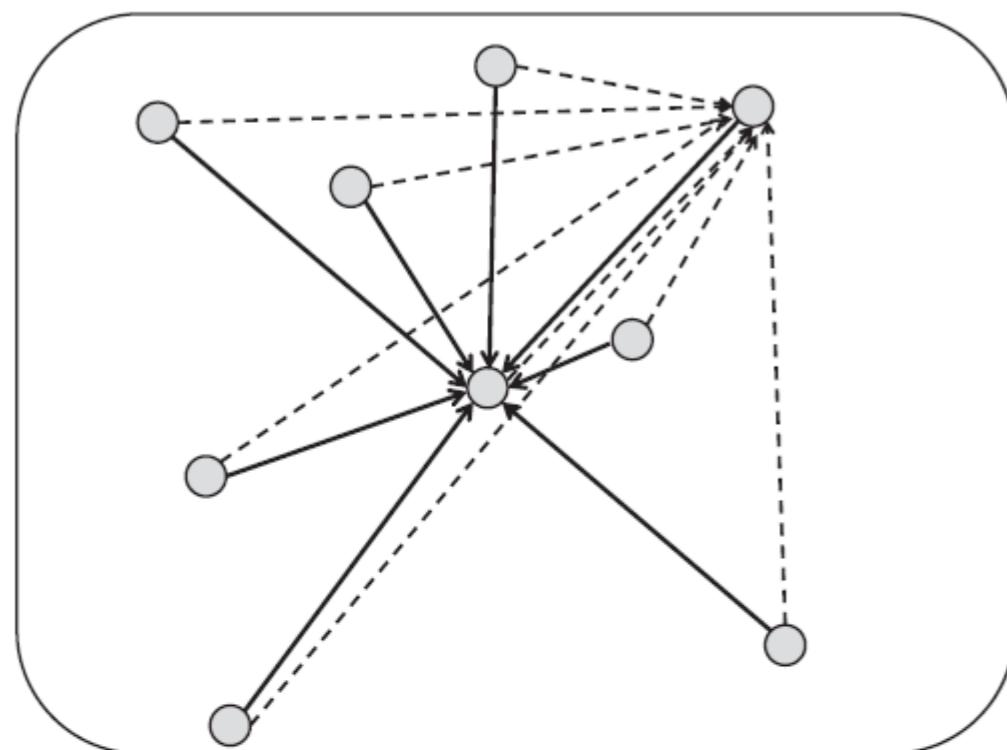
Each neuron receives
 N connections

*Image: Gerstner et al.
Neuronal Dynamics (2014)*

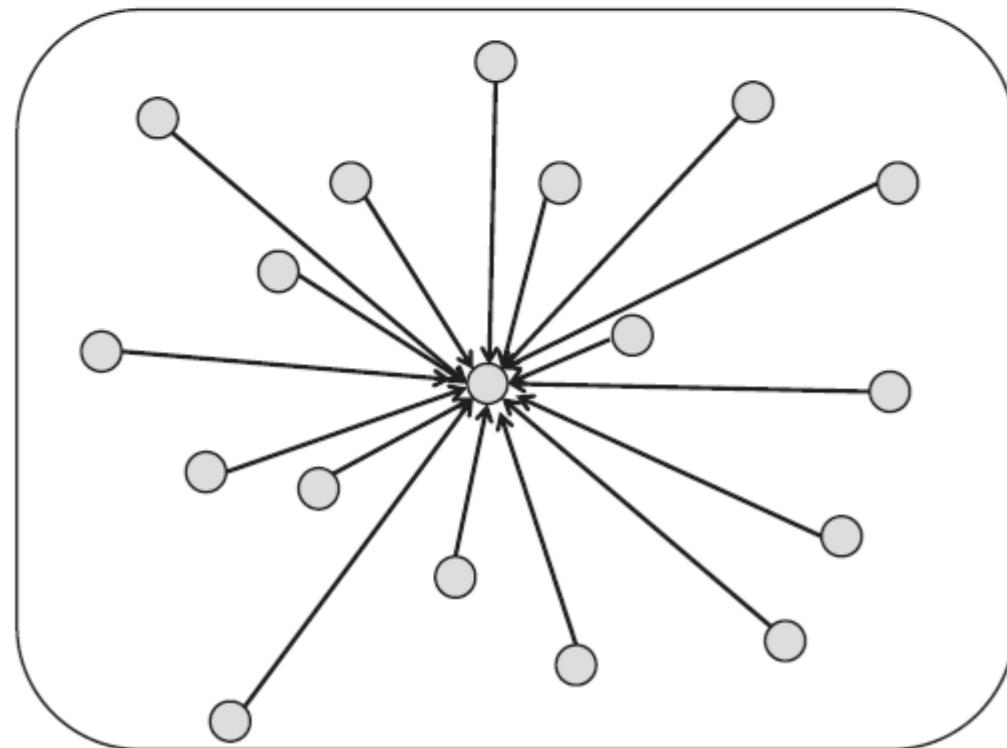
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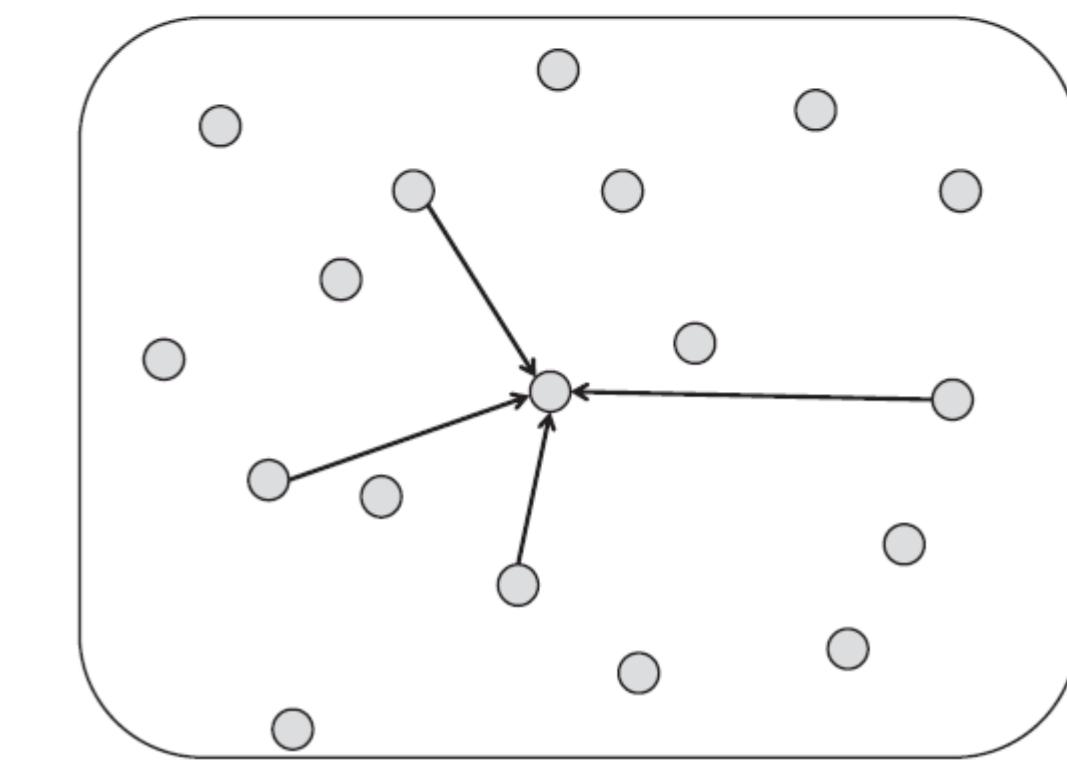
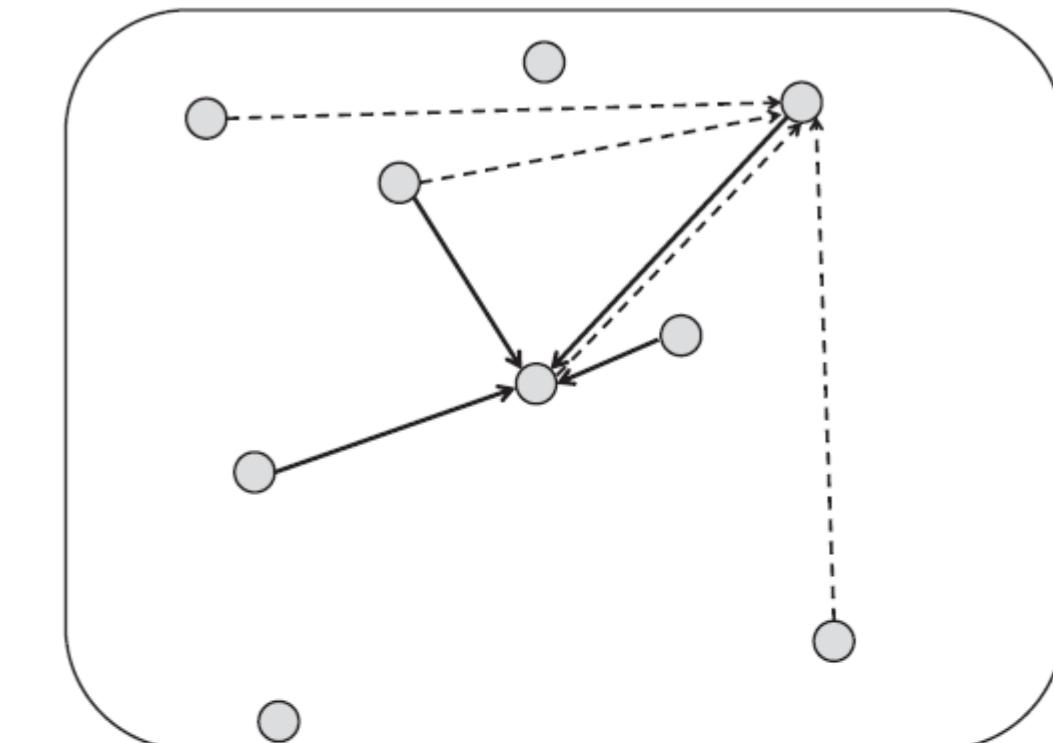


$N=10000$
neurons



Each neuron receives
 N connections

Random connectivity
w. number K of inputs fixed



*Image: Gerstner et al.
Neuronal Dynamics (2014)*

Each neuron receives
 K connections

3 Random connectivity – fixed number of inputs

random: number of inputs $K=500$, fixed

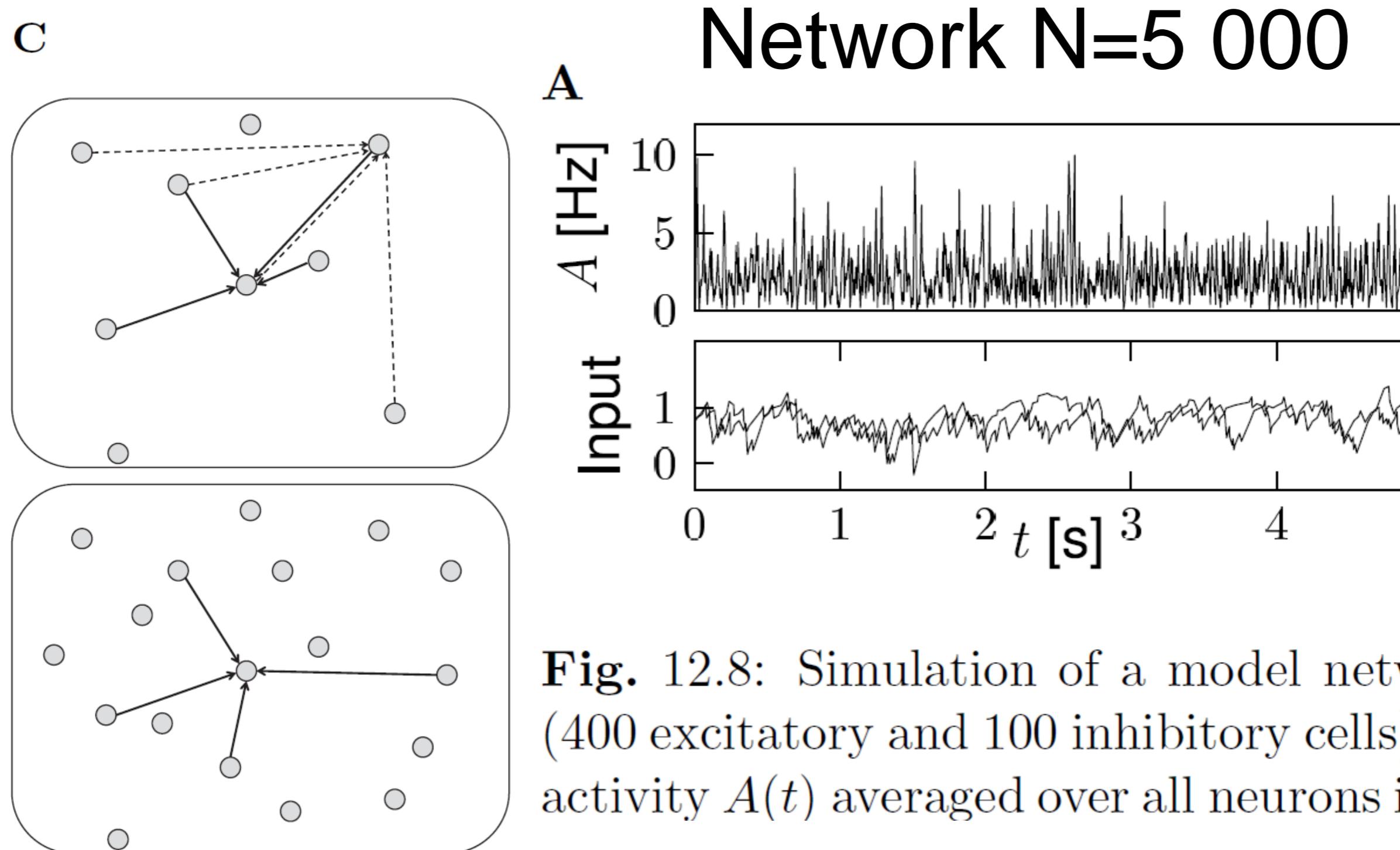


Fig. 12.8: Simulation of a model network with a fixed number of presynaptic partners (400 excitatory and 100 inhibitory cells) for each postsynaptic neuron. **A.** Top: Population activity $A(t)$ averaged over all neurons in a network of 4 000 excitatory and 1 000 inhibitory

*Image: Gerstner et al.
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3 Random connectivity – fixed number of inputs

random: number of inputs $K=500$, fixed

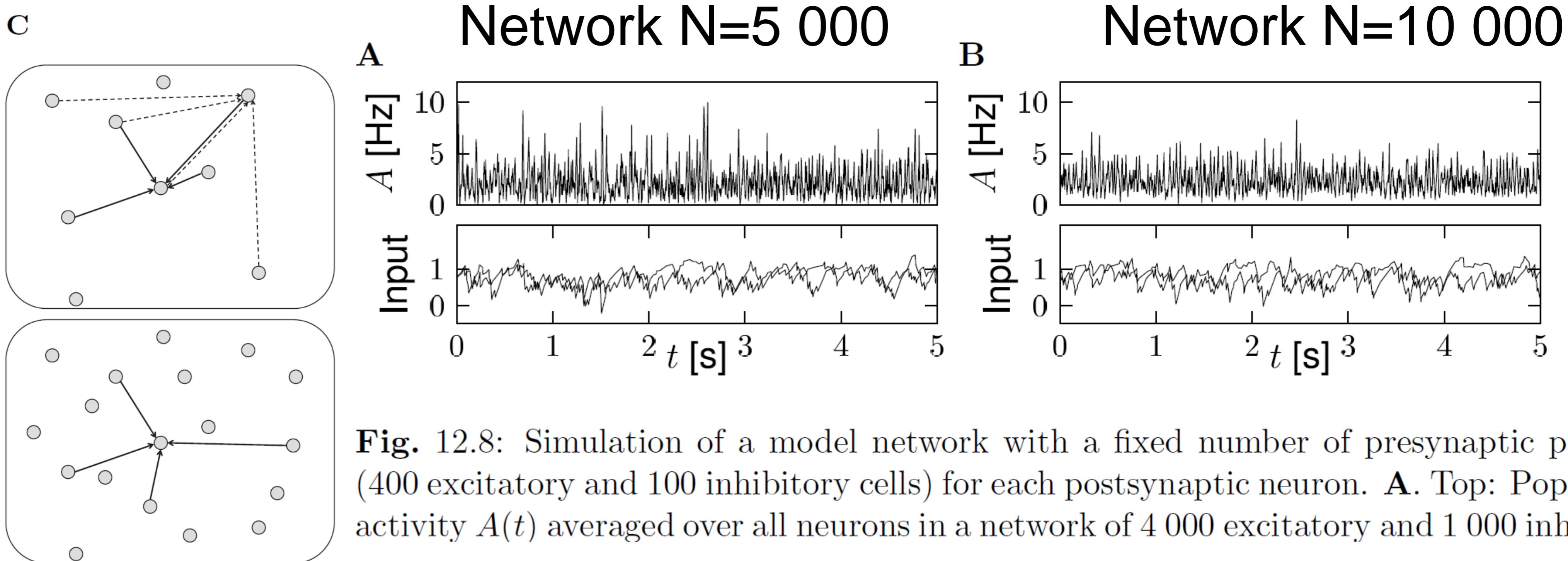
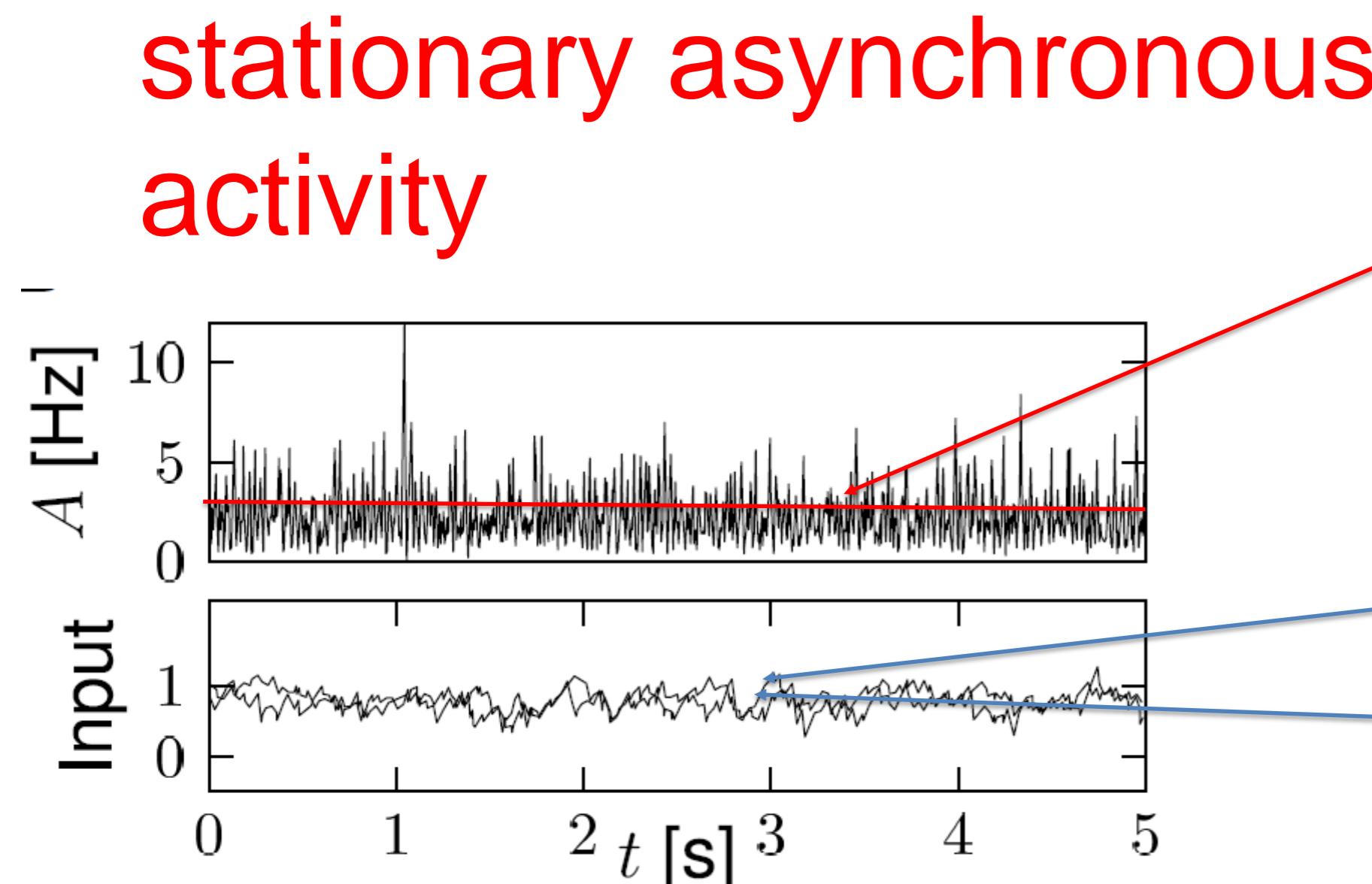


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*Image: Gerstner et al.
Neuronal Dynamics (2014)*

3. Random Connectivity: stationary asynchronous activity

Observations:



- $A(t)$ is nearly constant
- $A(t)=A_0$ independent of N

Input is nearly identical
for different neurons
(and nearly constant)

3. Random Connectivity network: population activity

Can we mathematically
predict the population activity?

given

- connection probability p and
- weight w_{ij}
- properties of individual neurons
- large population

Can we mathematically define
stationary asynchronous activity?

Quiz 3, now

You simulate a network of 5000 neurons or 10000 neurons. In both networks you have randomly selected 500 input connections for each neuron. You observe that the population activity fluctuations around a stationary value.

- [] The connectivity in the first network is 10 percent.
- [] The connectivity in the second network is 10 percent.
- [] Since there are twice as many neurons, the value of the stationary population activity increases by a factor of 2 when you compare the network of 10000 neurons with that of 5000 neuron.
- [] The value of the average input into one neuron increases by a factor of 2 when you compare the network of 10000 neurons with that of 5000 neuron.

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Neuronal Populations

Wulfram Gerstner

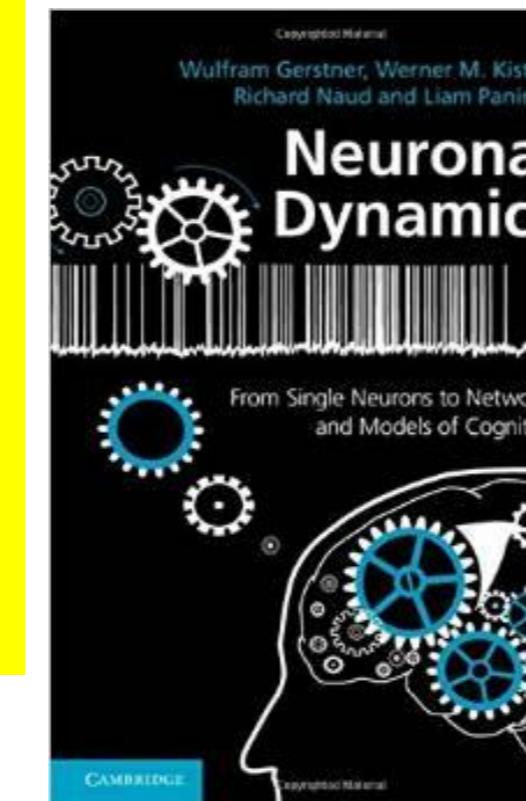
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Cambridge Univ. Press



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4. Review and aims

Can we mathematically predict the population activity?

given

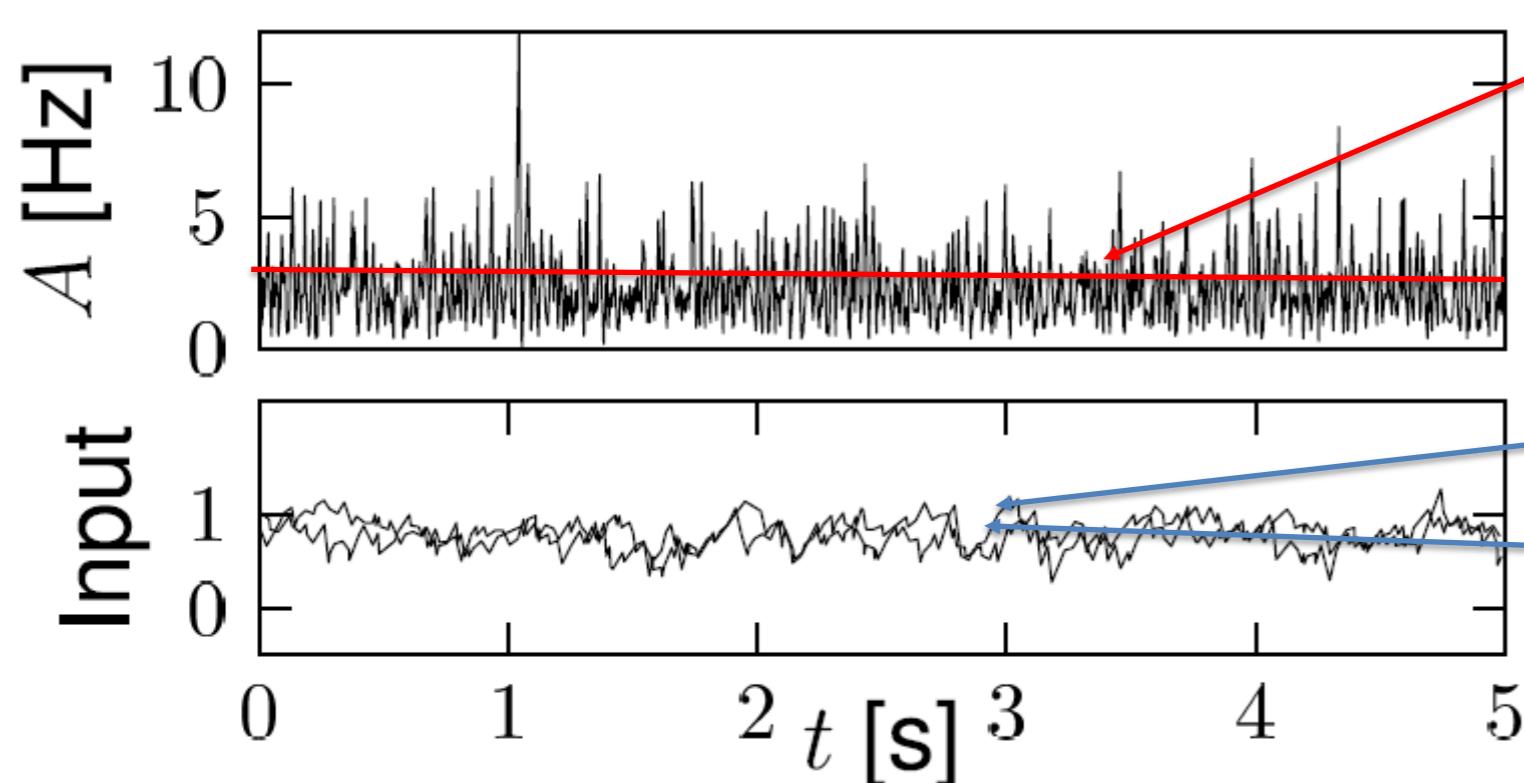
- connection probability p and
- weight w_{ij}
- properties of individual neurons
- large population

Can we mathematically define stationary asynchronous activity?

4. Review: stationary asynchronous activity

Observations:

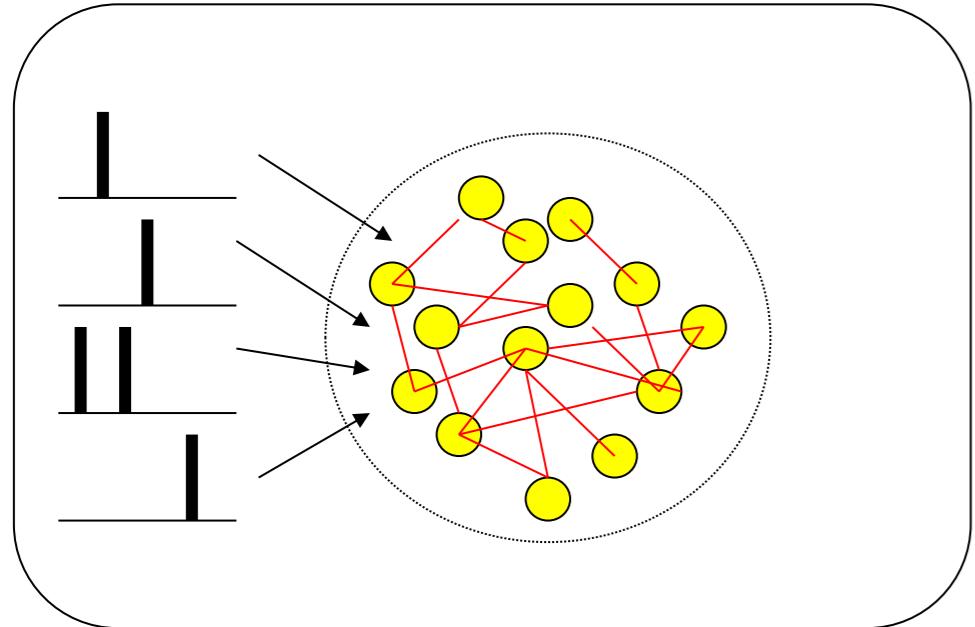
stationary asynchronous activity



- $A(t)$ is nearly constant
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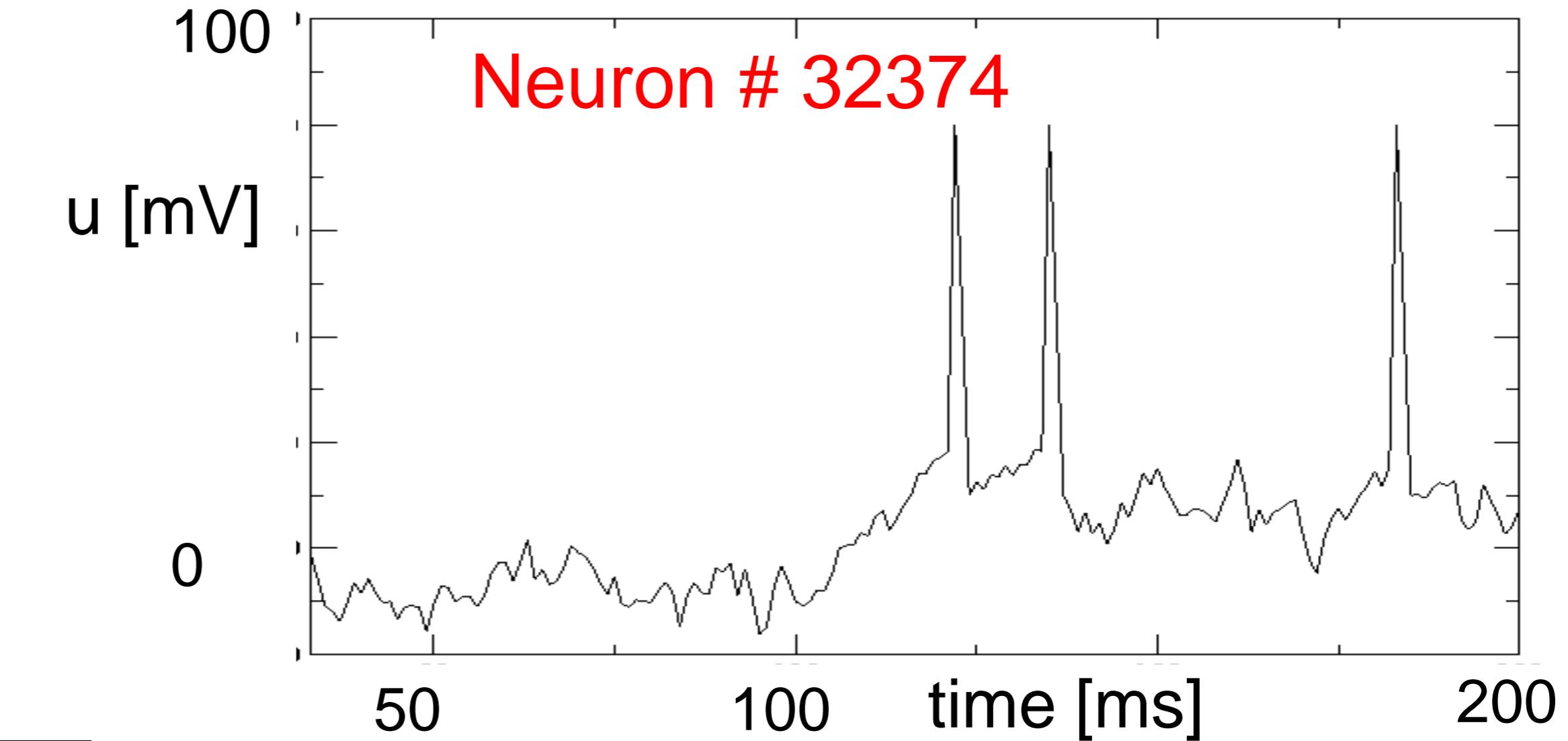
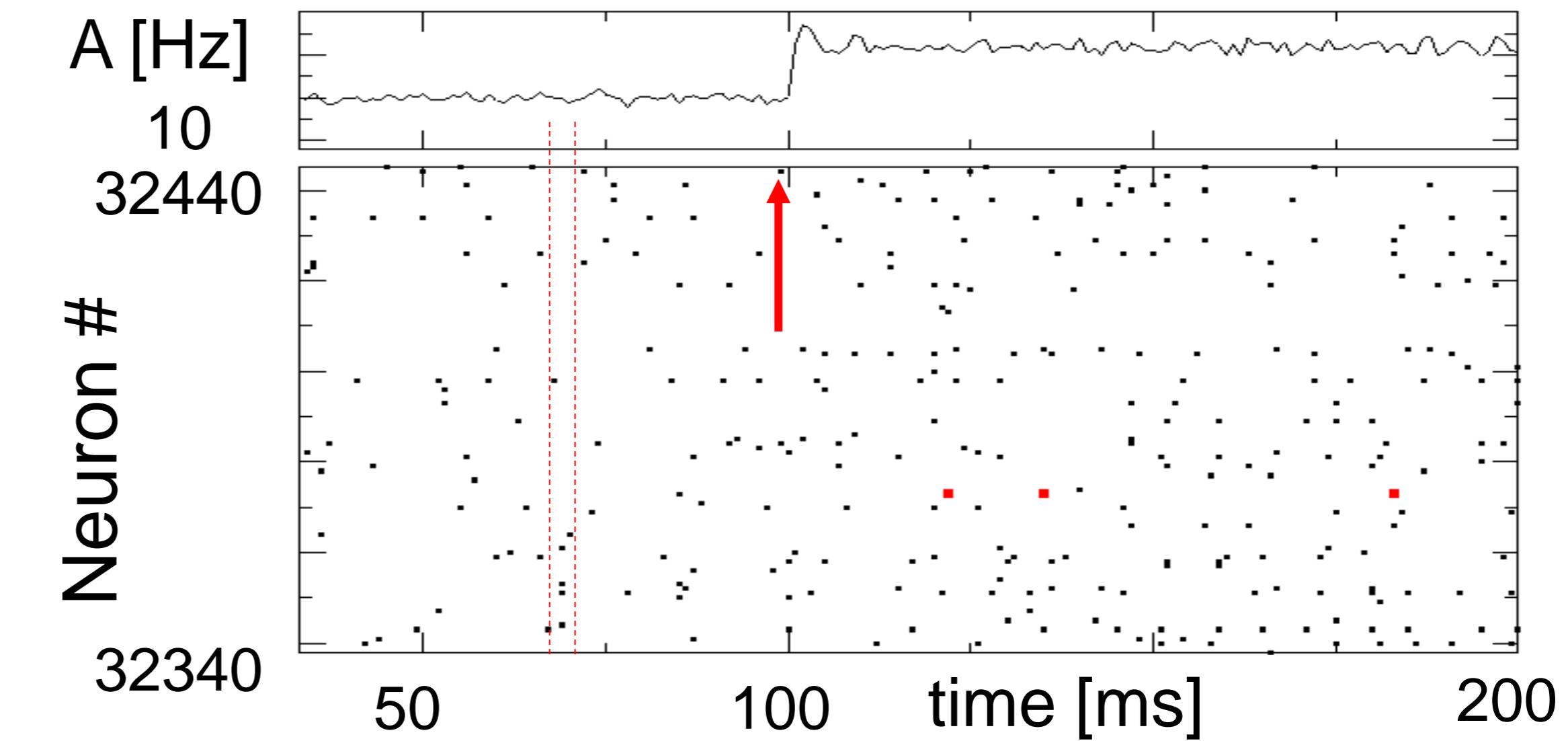
Input is nearly identical
for different neurons
(and nearly constant)

4. asynchronous firing / asynchronous state

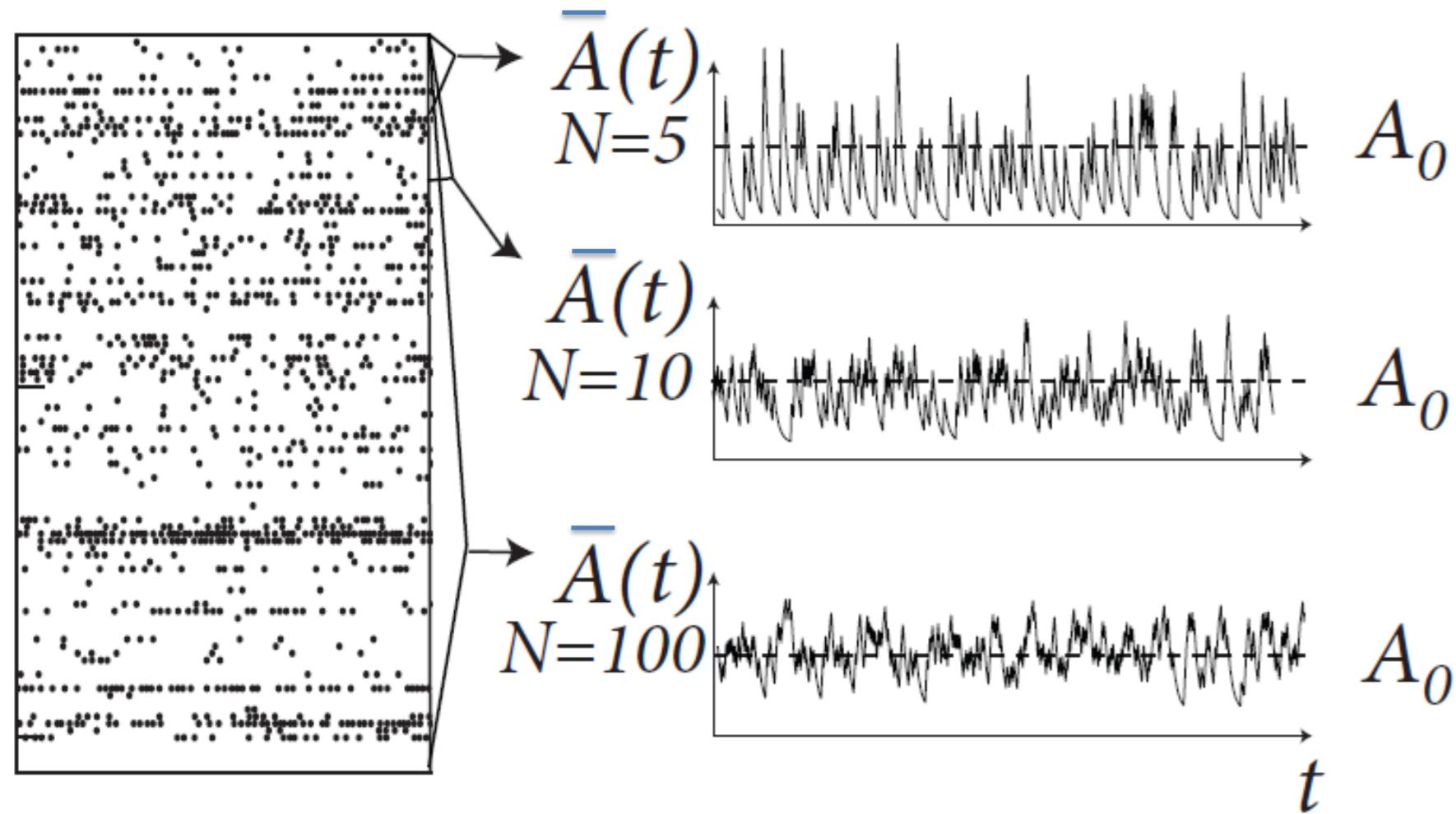


input {
low rate
- high rate

Population
- 50 000 neurons
- 20 percent inhibitory
- randomly connected



4. asynchronous state



- Definition of $A(t)$
- filtered $A(t)$
- $\langle A(t) \rangle$

Image: Gerstner et al.
Neuronal Dynamics (2014)

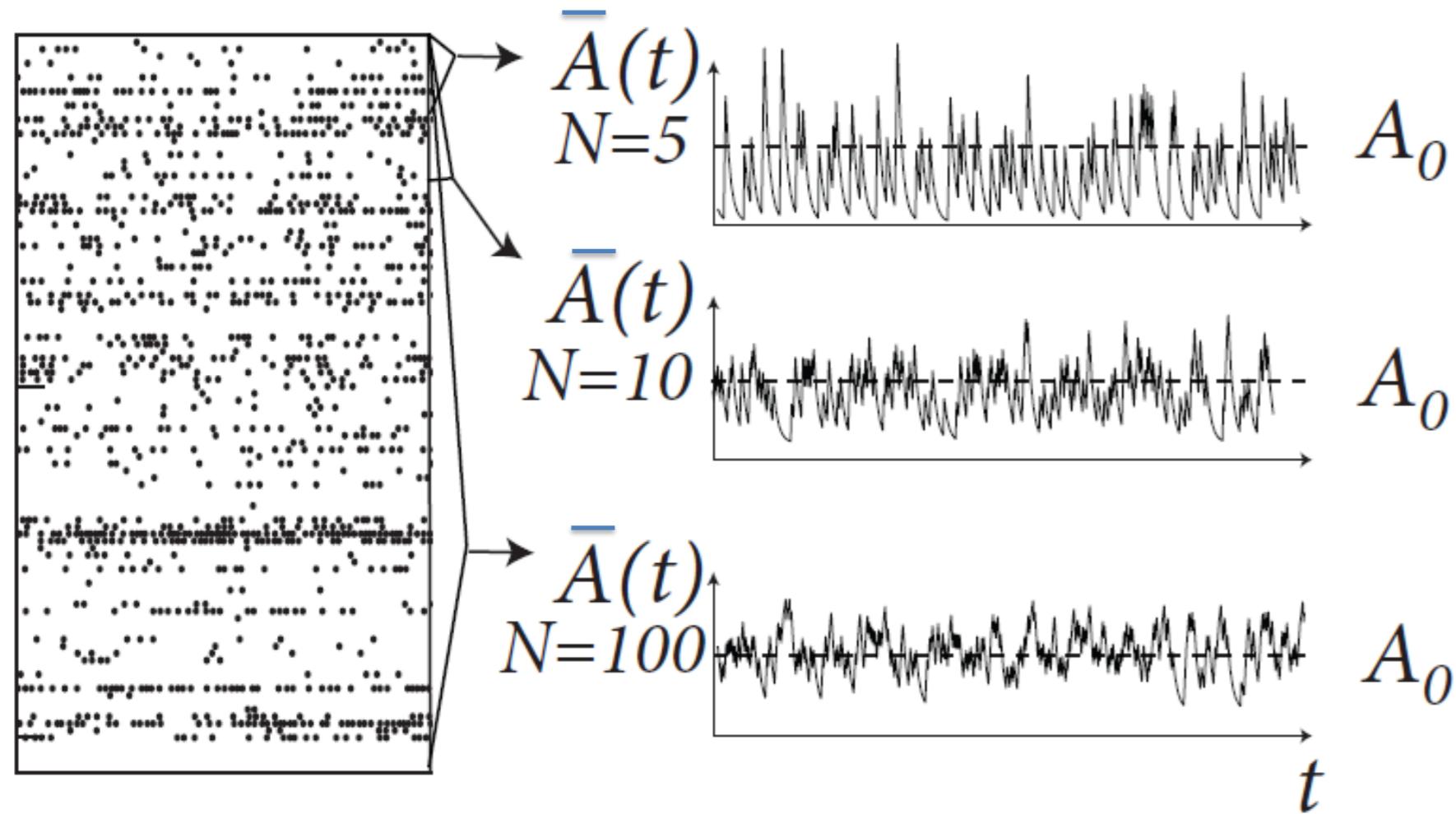
Asynchronous state

$\langle A(t) \rangle = A_0 = \text{constant}$

4. asynchronous state

Asynchronous state

$$\langle A(t) \rangle = A_0 = \text{constant}$$



- filtered $A(t)$
- convergence in weak sense

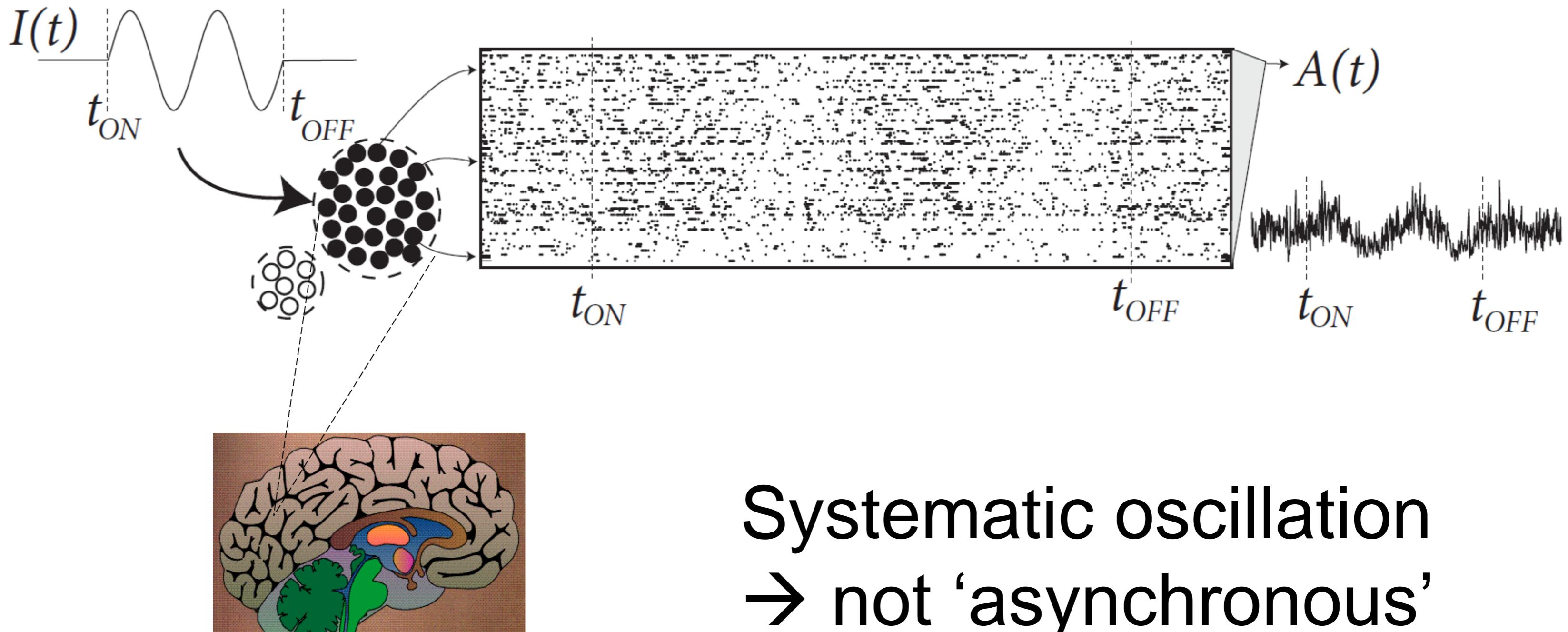
*Image: Gerstner et al.
Neuronal Dynamics (2014)*

Weak convergence in Hilbert space:

[https://en.wikipedia.org/wiki/Weak_convergence_\(Hilbert_space\)](https://en.wikipedia.org/wiki/Weak_convergence_(Hilbert_space))

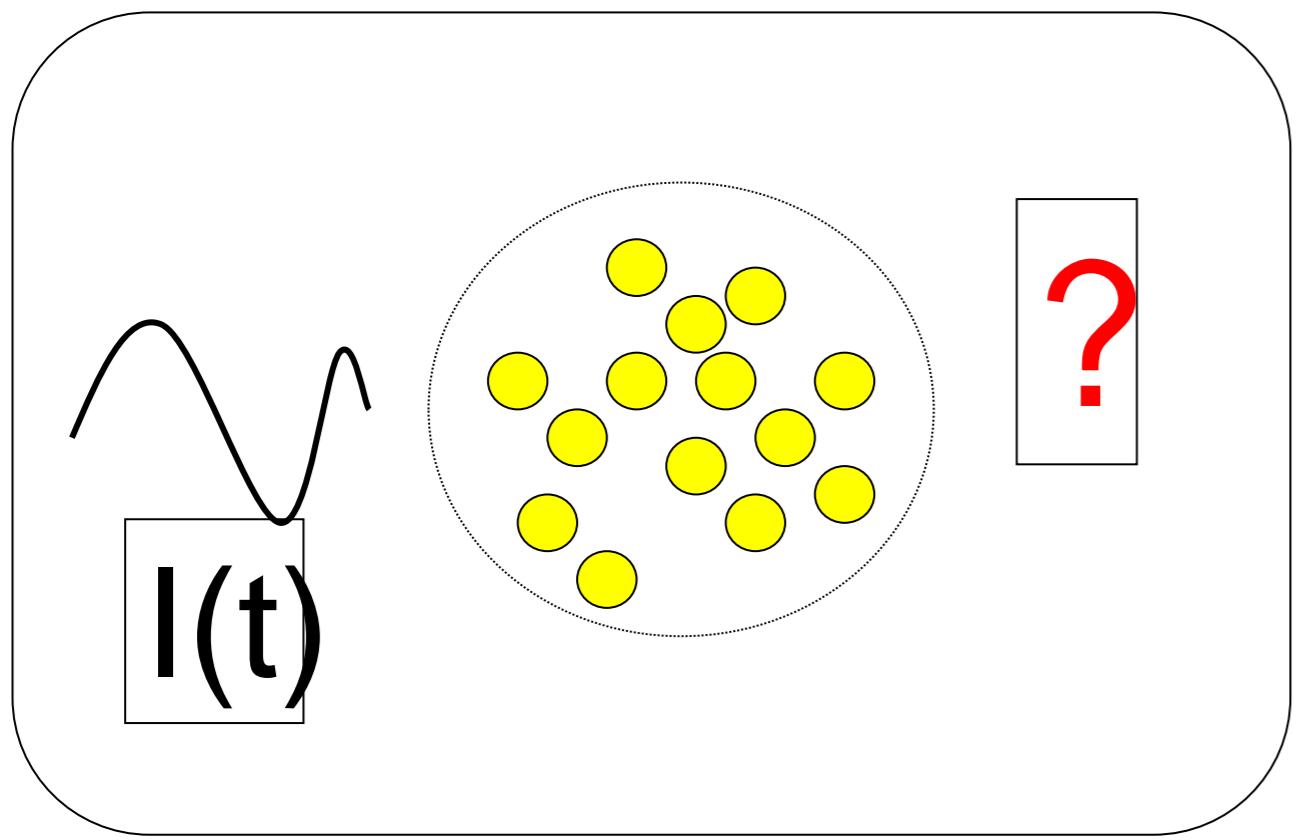
4. asynchronous state – counter examples, $\langle A(t) \rangle$ not constant

population of neurons
with similar properties



Brain

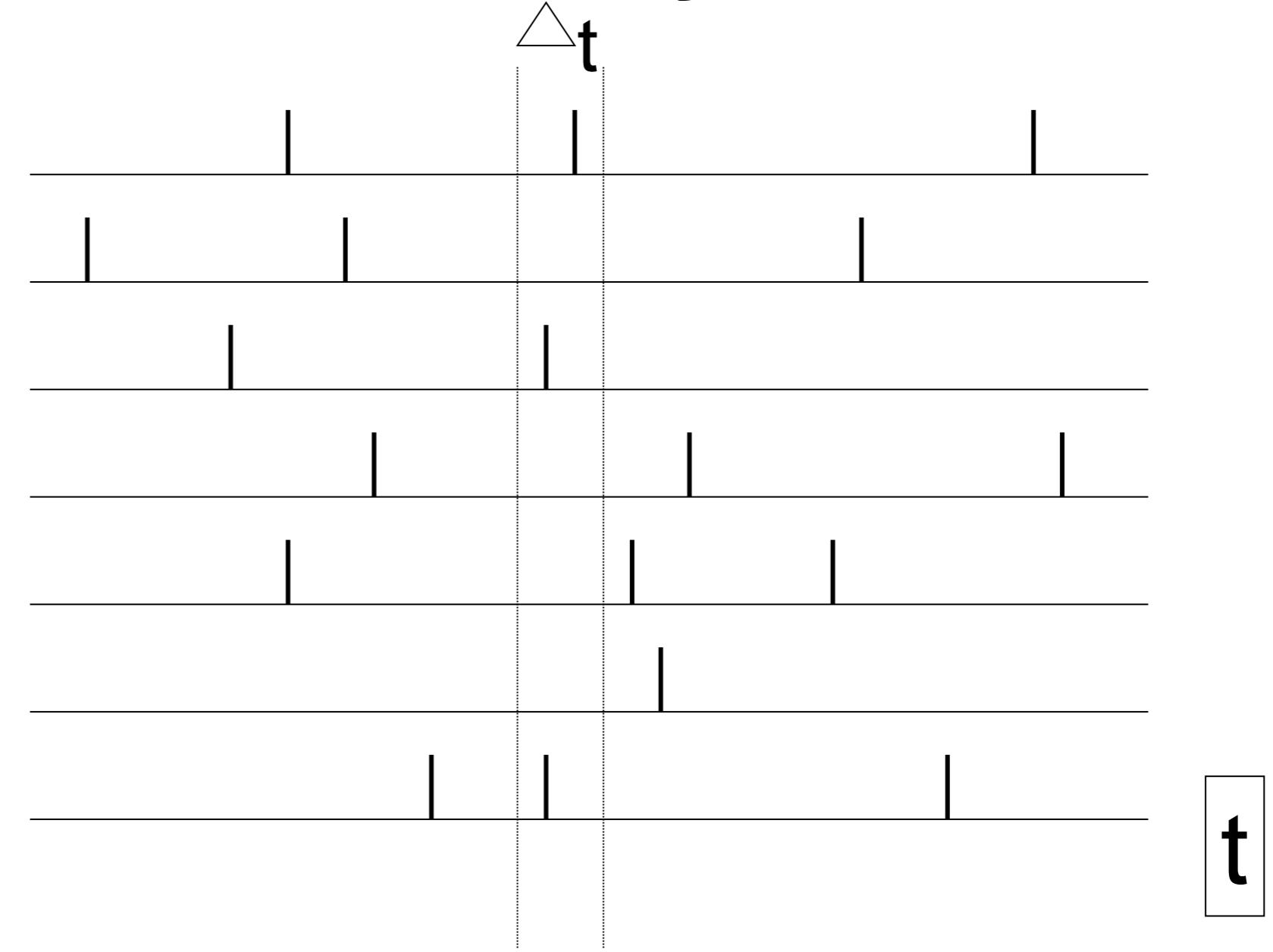
4. asynchronous state in a homogeneous network



Homogeneous network:

- all neurons are 'the same'
- all synapses are 'the same'
- each neuron receives input from k neurons in network
- each neuron receives the same (mean) external input

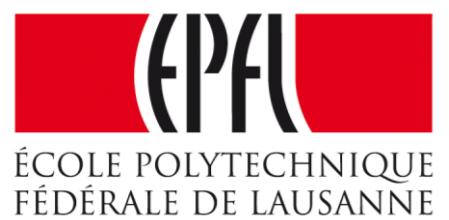
population activity?



population activity

$$A(t) = \frac{n(t; t + \Delta t)}{N \Delta t}$$

Computational Neuroscience: Neuronal Dynamics of Cognition



Neuronal Populations

Wulfram Gerstner

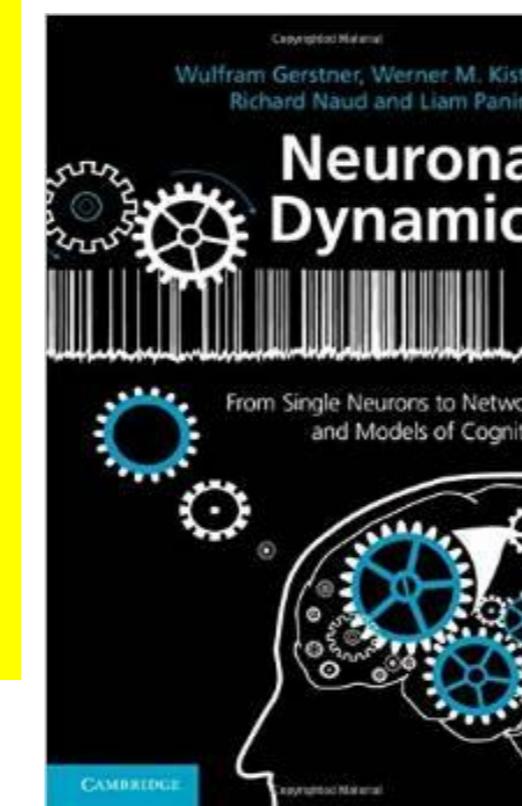
EPFL, Lausanne, Switzerland

Reading:

NEURONAL DYNAMICS

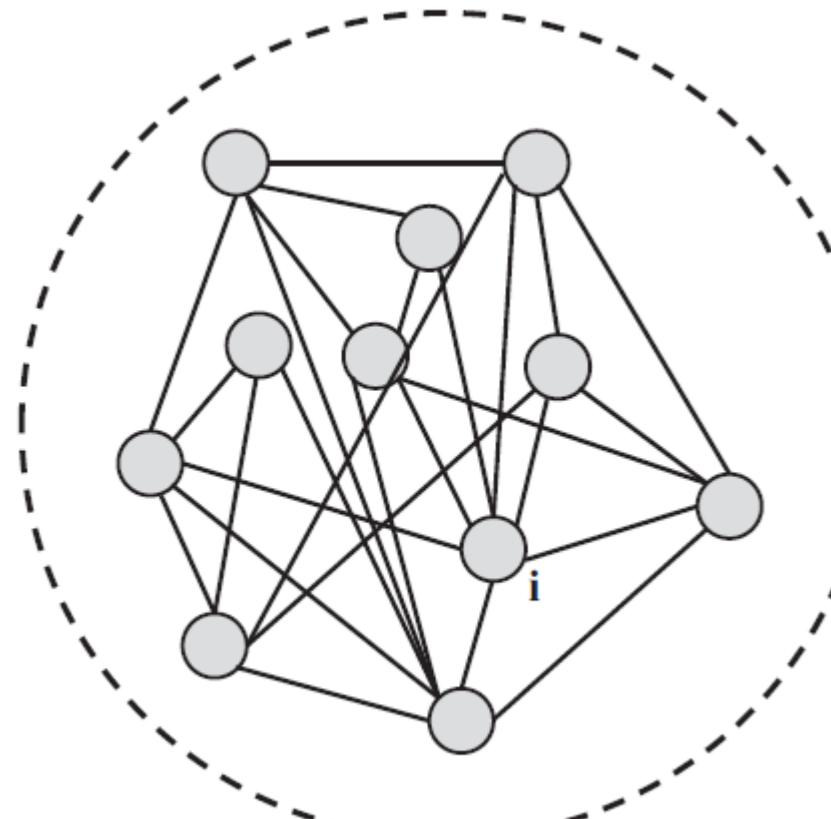
- Ch. 12.1 – 12.4.3
(except Section 12.3.7)

Cambridge Univ. Press

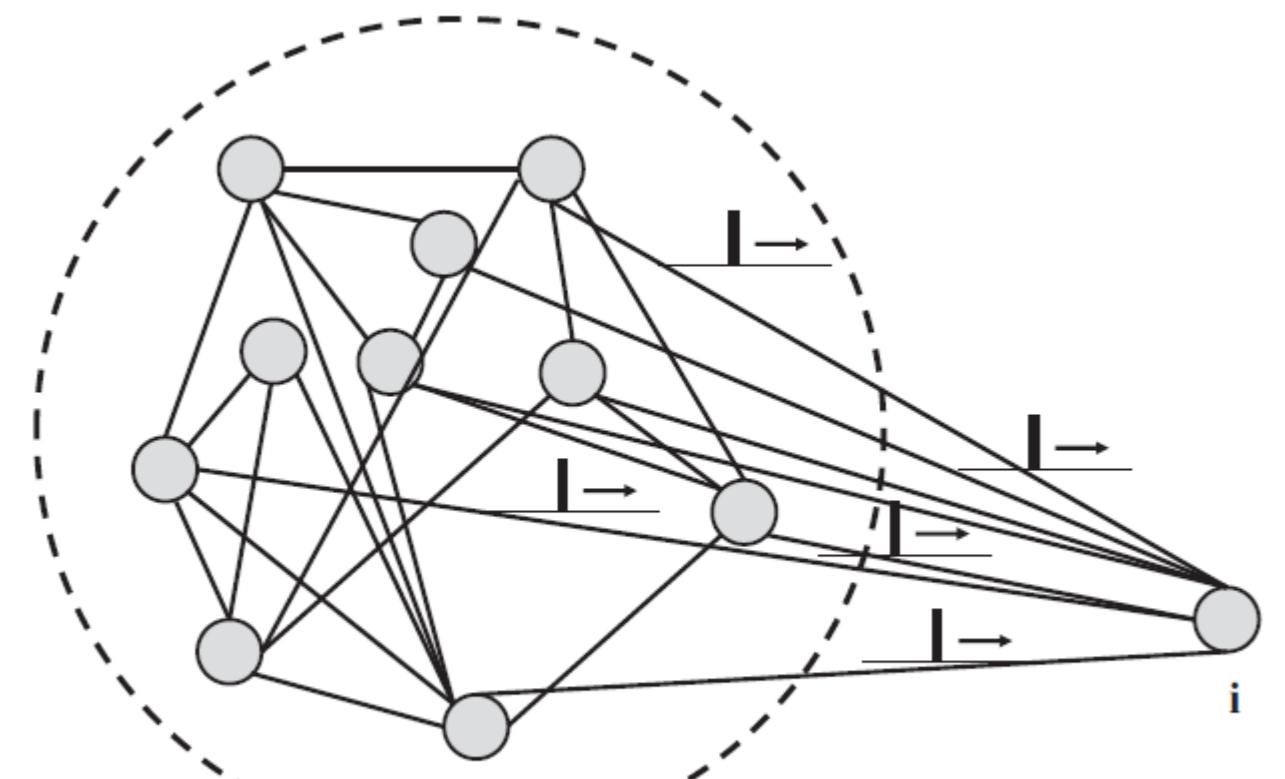


- 1. Population activity**
 - definition and aims
- 2. Cortical Populations**
 - columns and receptive fields
- 3. Connectivity**
 - cortical connectivity
 - model connectivity schemes
- 4. Mean-field argument**
 - stationary asynchronous activity
 - input to one neuron
- 5. Stationary mean-field**
 - asynchronous state: predict activity
- 6. Random Networks**
 - Balanced state

4. mean-field arguments (full connectivity)

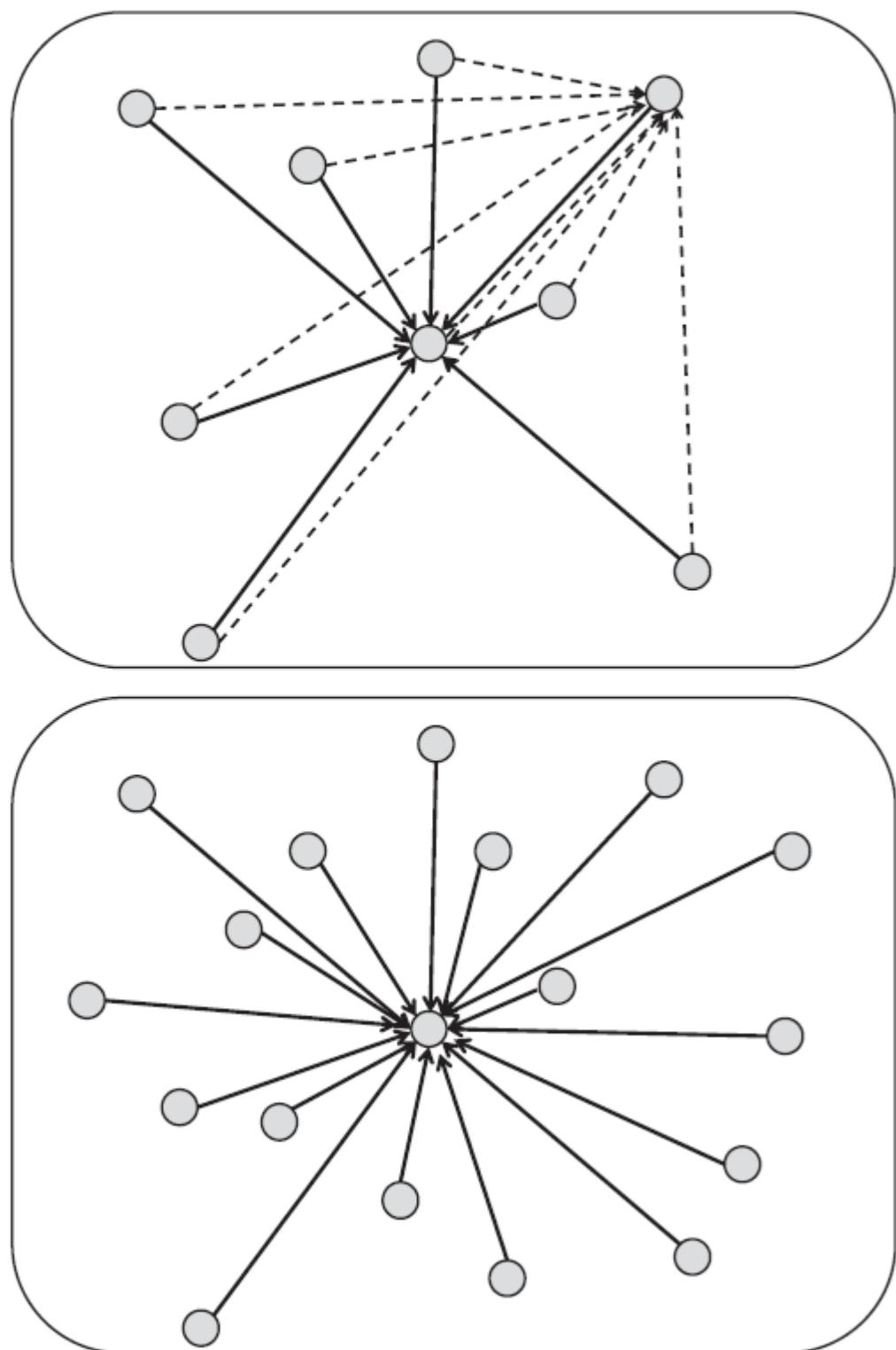


Input to neuron i



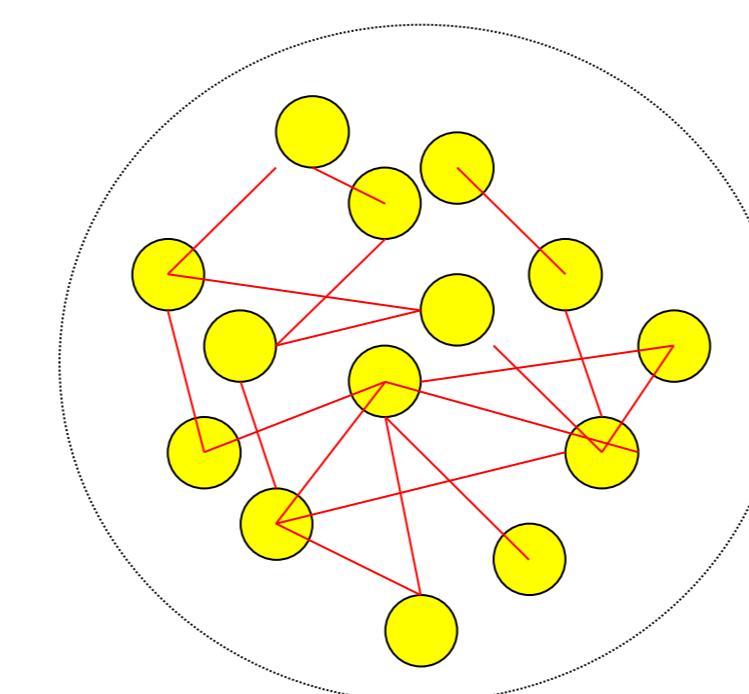
4. mean-field arguments (full connectivity)

A



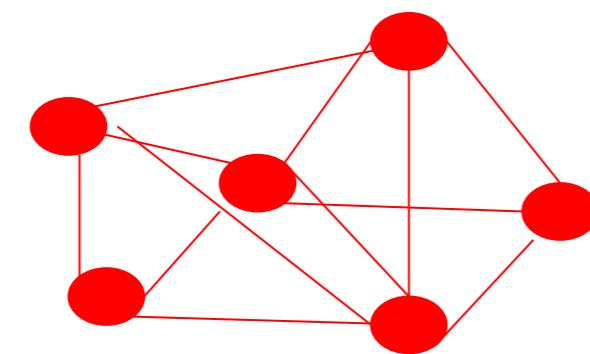
B

Full connectivity



4. mean-field arguments (full connectivity)

Fully connected network



fully
connected
 $N \gg 1$

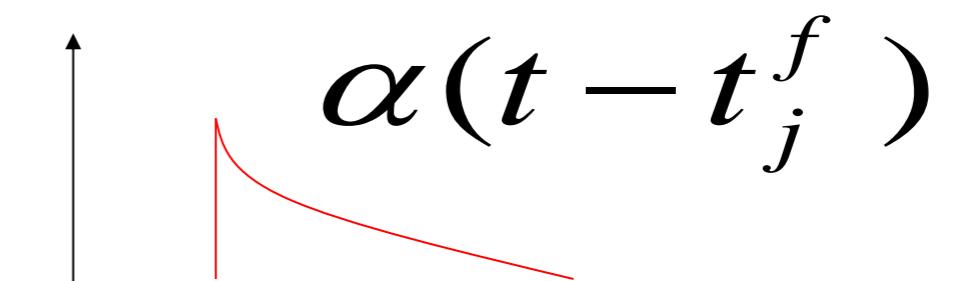
Synaptic coupling

$$w_{ij} = w_0$$

$$I(t) = I^{ext}(t) + I^{net}(t)$$

$$I^{net}(t) = \sum_j \sum_f w_{ij} \alpha(t - t_j^f)$$

All spikes, all neurons



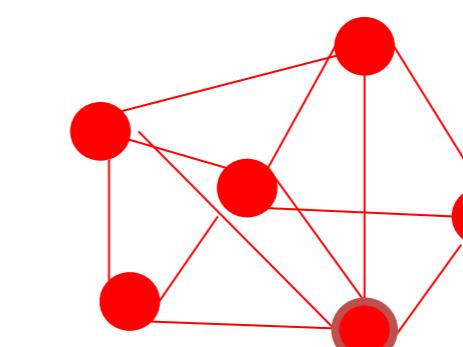
4. mean-field arguments (full connectivity)

All neurons receive the same total input current
(‘mean field’)

$$I_i(t) = J_0 \int \alpha(s) A(t-s) ds + I^{ext}(t)$$

Index i disappears

$$w_{ij} = \frac{J_0}{N}$$



fully
connected

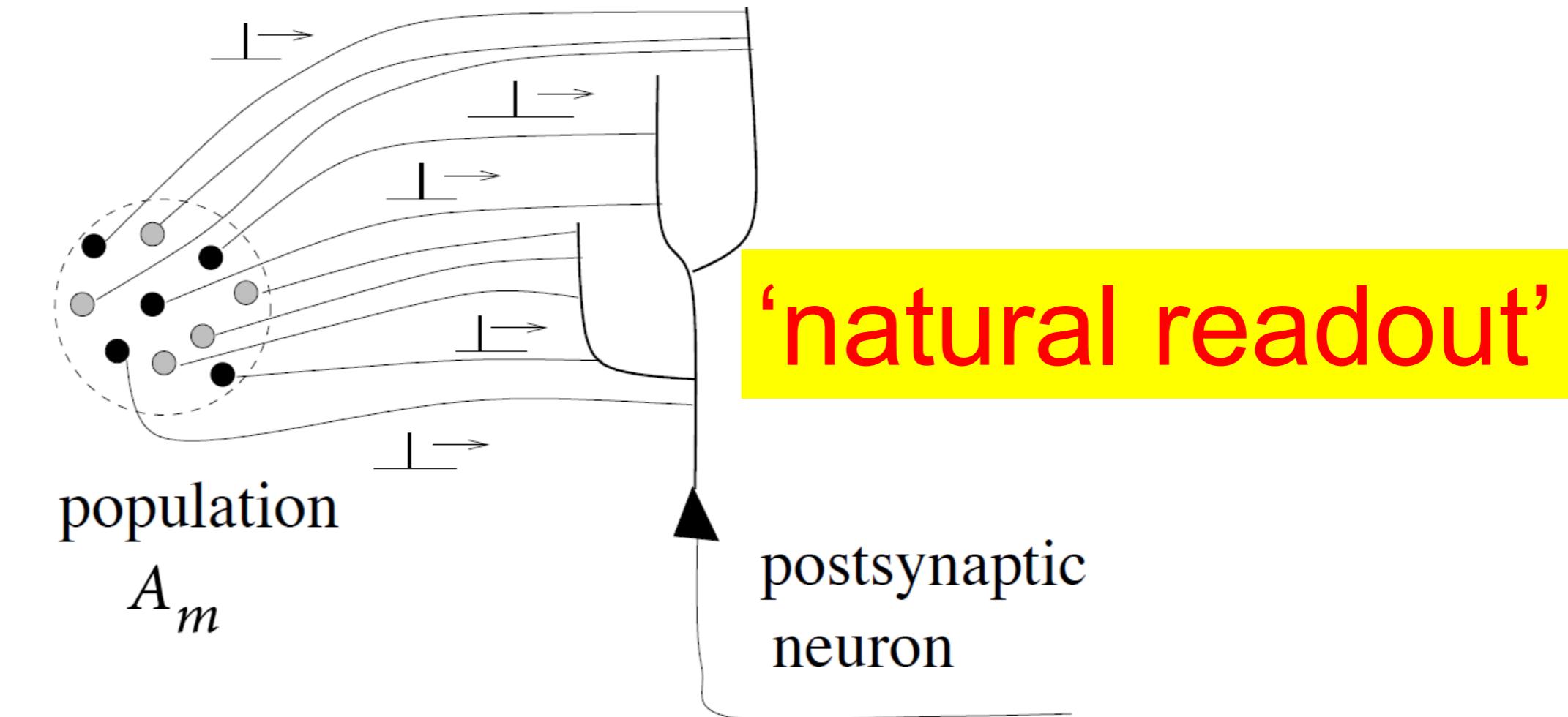
$$I^{net}(t) = \sum_j \sum_f w_{ij} \alpha(t - t_j^f) + I^{ext}(t)$$

All spikes, all neurons

4. mean-field arguments (full connectivity)

All neurons receive the same total input current
(‘mean field’)

$$I_i(t) = J_0 \int \alpha(s) A(t-s) ds + I^{ext}(t)$$



Quiz 4, now

In a fully connected homogeneous network of 5000 neurons, the total input into neuron $i=10$

- [] is the same as the input into its neighbors ($i=9$ and $i=11$)
- [] is the same as the input into the neuron $i=3564$
- [] depends on the population activity of the network
- [] is always constant

Computational Neuroscience: Neuronal Dynamics of Cognition



Neuronal Populations

Wulfram Gerstner

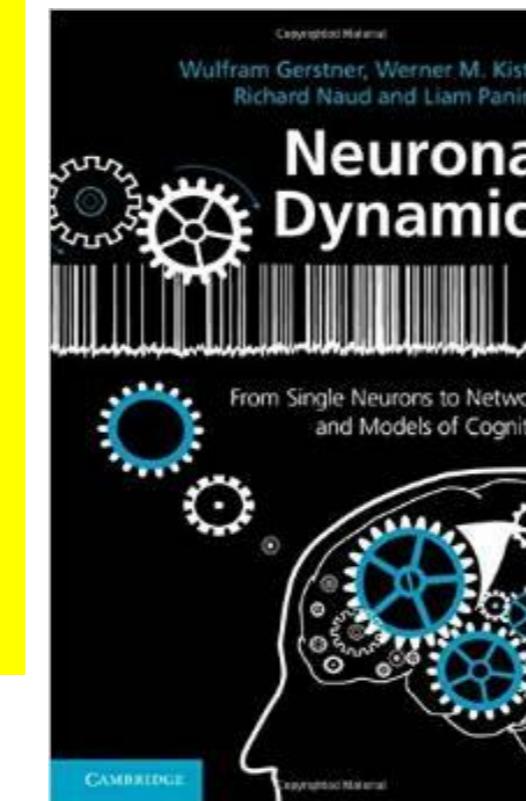
EPFL, Lausanne, Switzerland

Reading:

NEURONAL DYNAMICS

- Ch. 12.1 – 12.4.3
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1. Population activity

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- input to one neuron

5. Stationary mean-field

- asynchronous state: predict activity

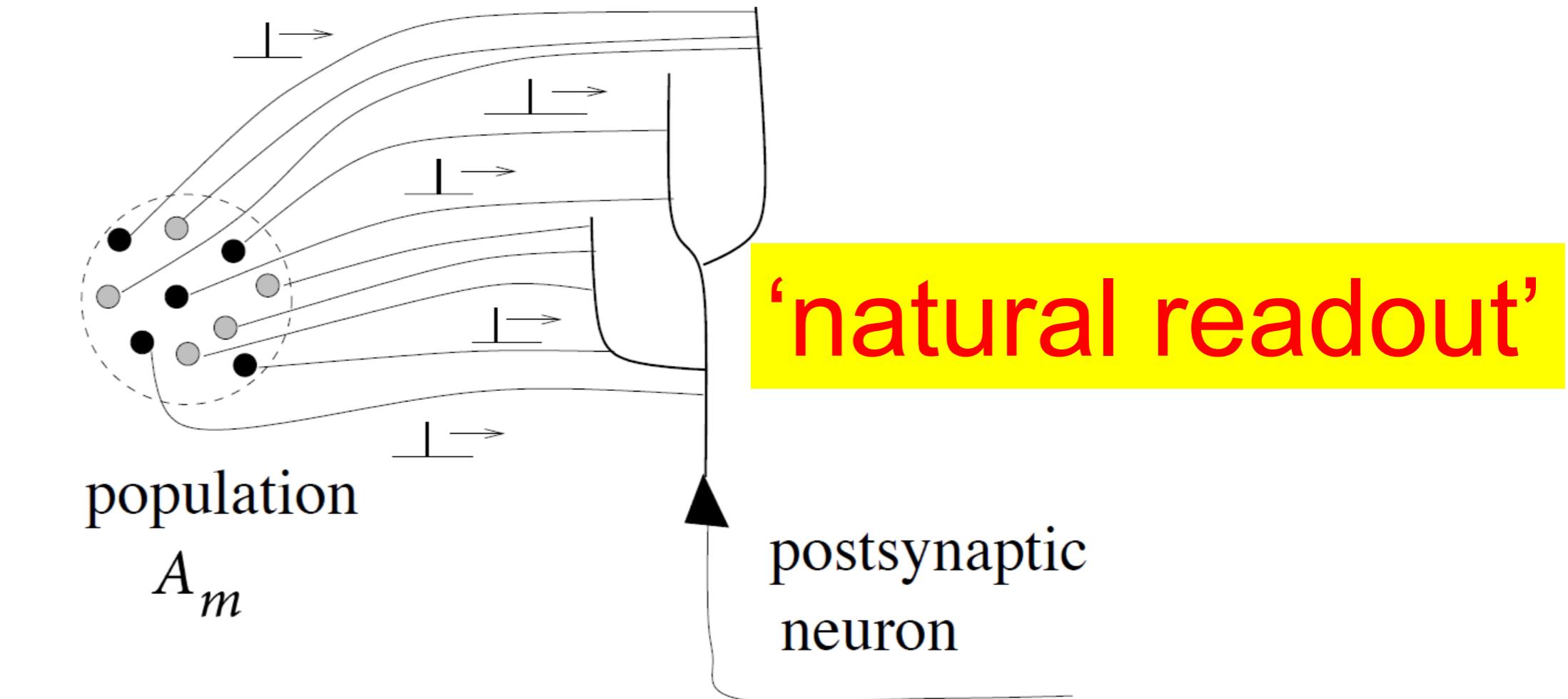
6. Random Networks

- Balanced state

5. Review and aims: predict activity

- all neurons receive the same input current
- population activity drives input

→ Predict population activity?



5. mean-field arguments: asynchronous state

Assume all variables are constant in time:

Stationary state

$$I_i(t) = J_0 \int \alpha(s) A(t-s) ds + I^{ext}(t)$$



$$(1) \quad I_0 = [J_0 q A_0 + I_0^{ext}]$$

Firing rate? Population rate?

5. mean-field argument: f-I curve of single neuron

$$I_0 = [J_0 q A_0 + I_0^{ext}]$$

Firing rate?

5. mean-field argument: population rate = single neuron rate



5. mean-field arguments: population activity (asynchr. state)

Input is constant and identical for all neurons

$$(1) \quad I_0 = [J_0 q A_0 + I_0^{ext}] \quad q = \int \alpha(s) ds$$

frequency (single-neuron gain function)

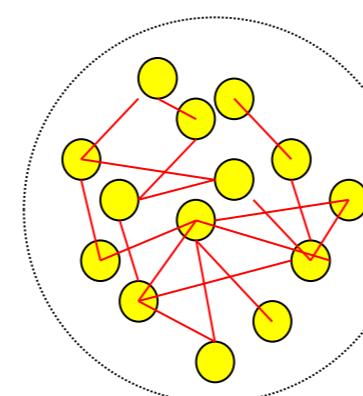
$$(2) \quad \nu = g(I_0)$$

Homogeneous network

All neurons are identical,

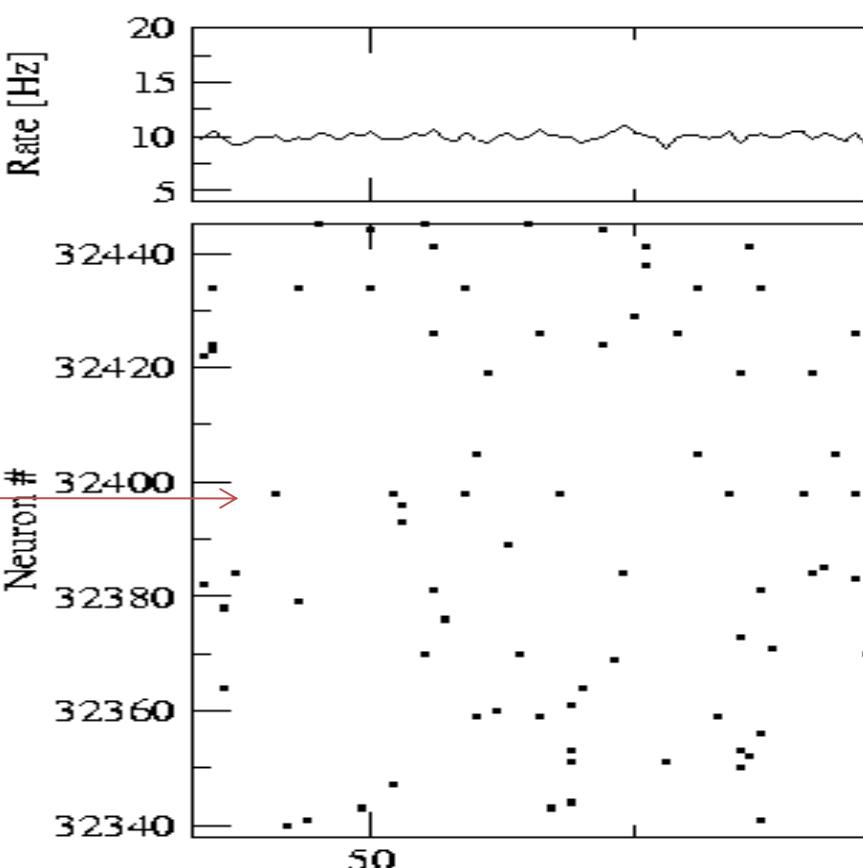
Single neuron rate = population rate

$$(3) \quad \nu = A_0$$



Single
neuron

$$A(t) = A_0 = \text{const}$$



5. stationary solution: population activity (asynchr. State)

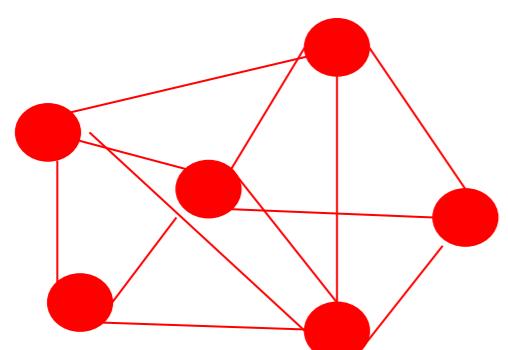
Stationary solution

=asynchronous state

$$(1) \quad I_0 = [J_0 q A_0 + I_0^{ext}]$$

$$(2) \quad \boxed{\nu = g(I_0)}$$

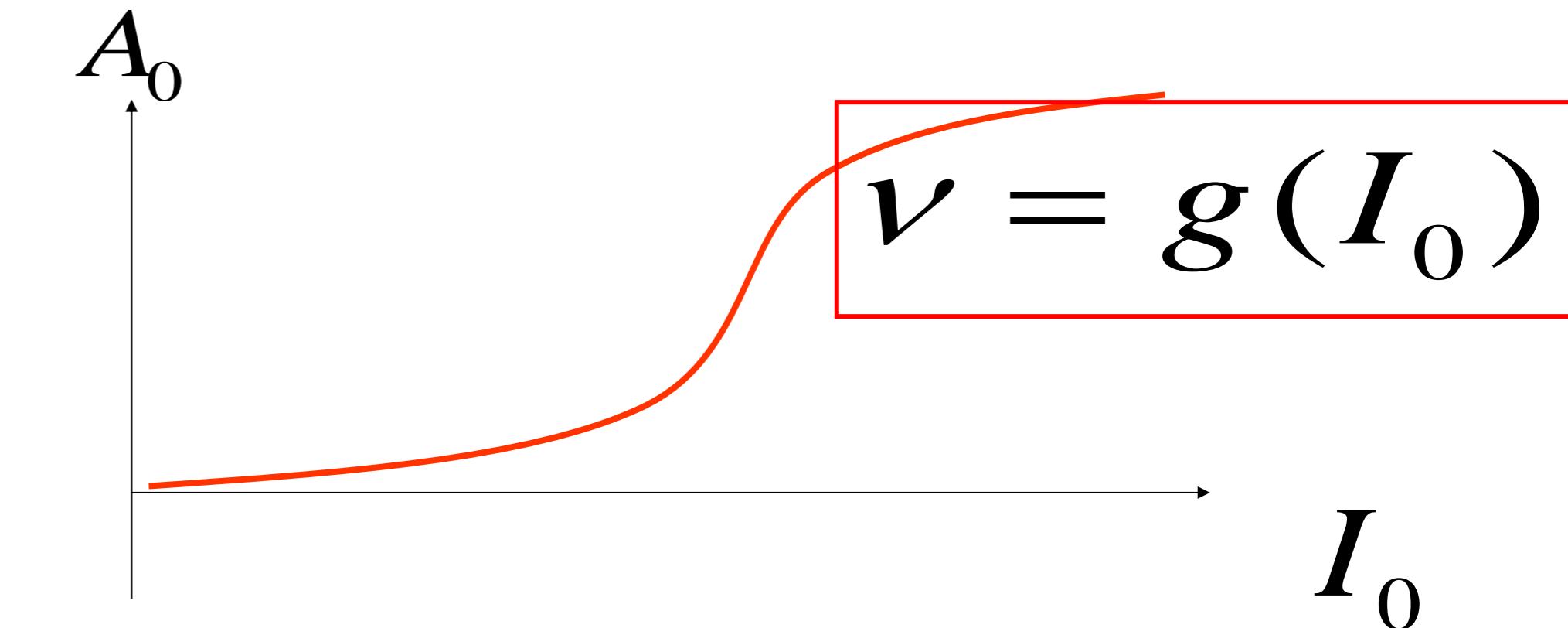
$$(3) \quad \boxed{\nu = A_0}$$



fully
connected

$N \gg 1$

$$\boxed{\nu = g(I_0) = A_0}$$



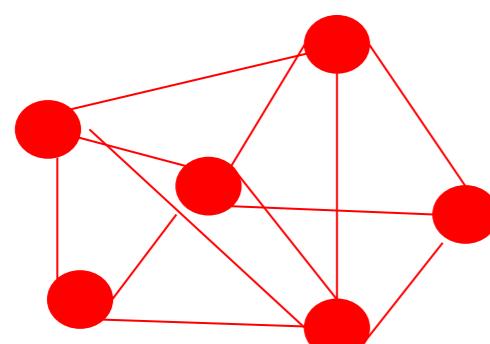
5. stationary solution: population activity (asynchr. state)

Stationary solution
=asynchronous state

$$(1) \quad I_0 = [J_0 q A_0 + I_0^{ext}]$$

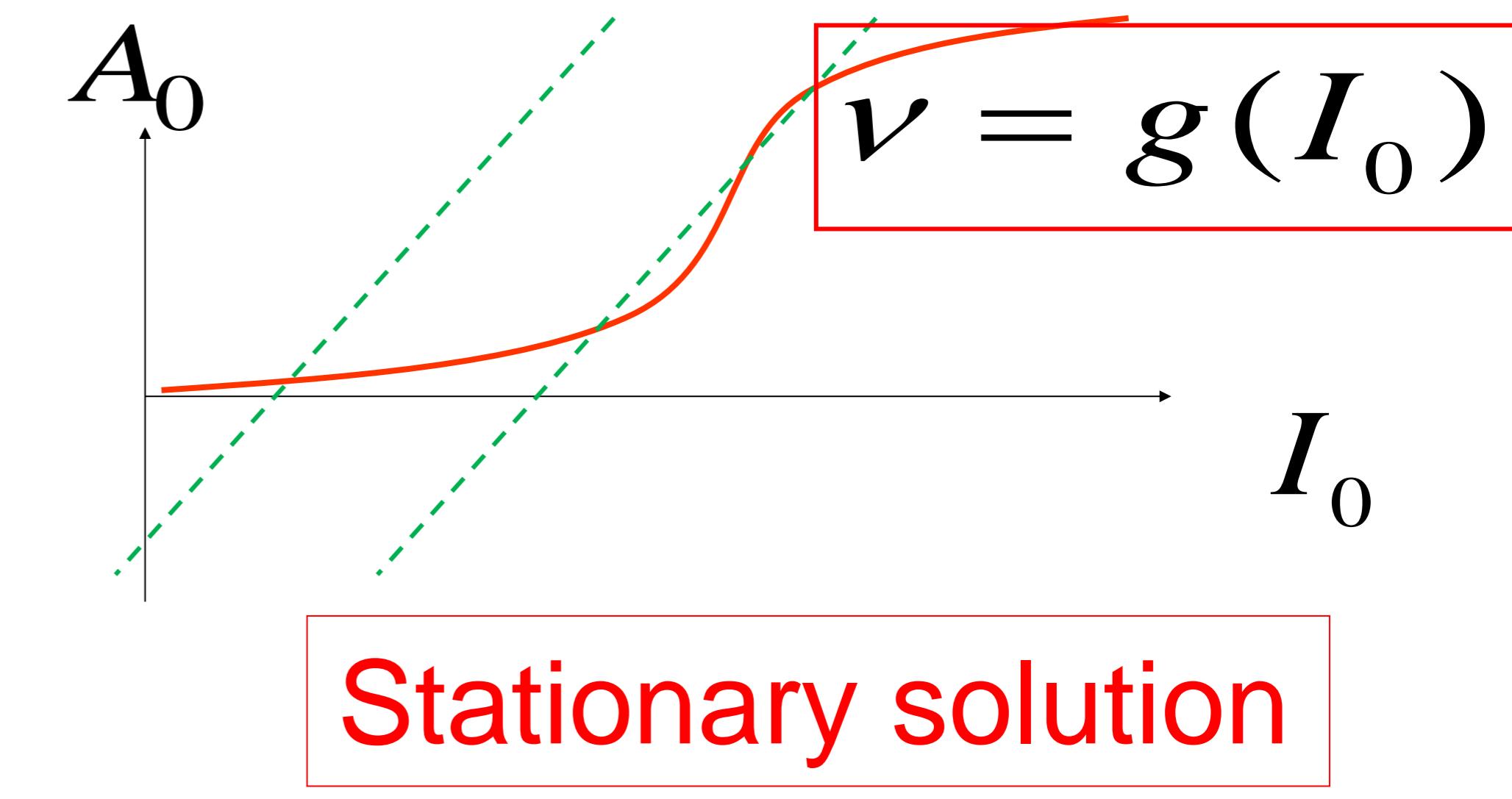
$$(2) \quad \nu = g(I_0)$$

$$(3) \quad \nu = A_0$$



fully
connected
 $N \gg 1$

Homogeneous network, stationary,
All neurons are identical,
Single neuron rate = population rate



5. stationary solution: population activity (asynchr. state)

Single Population

- homogeneous
- full connectivity
- stationary state/asynchronous state

Single neuron rate = population rate

$$A_0 = \nu = g(I_0) = g(J_0 q A_0 + I_0^{ext})$$

5. stationary solution: population activity (asynchr. state)

Single Population

- homogeneous
- full connectivity
- stationary state/asynchronous state

Single neuron rate = population rate

$$A_0 = \nu = g(I_0) = g(J_0 q A_0 + I_0^{ext})$$



What is this function g ?

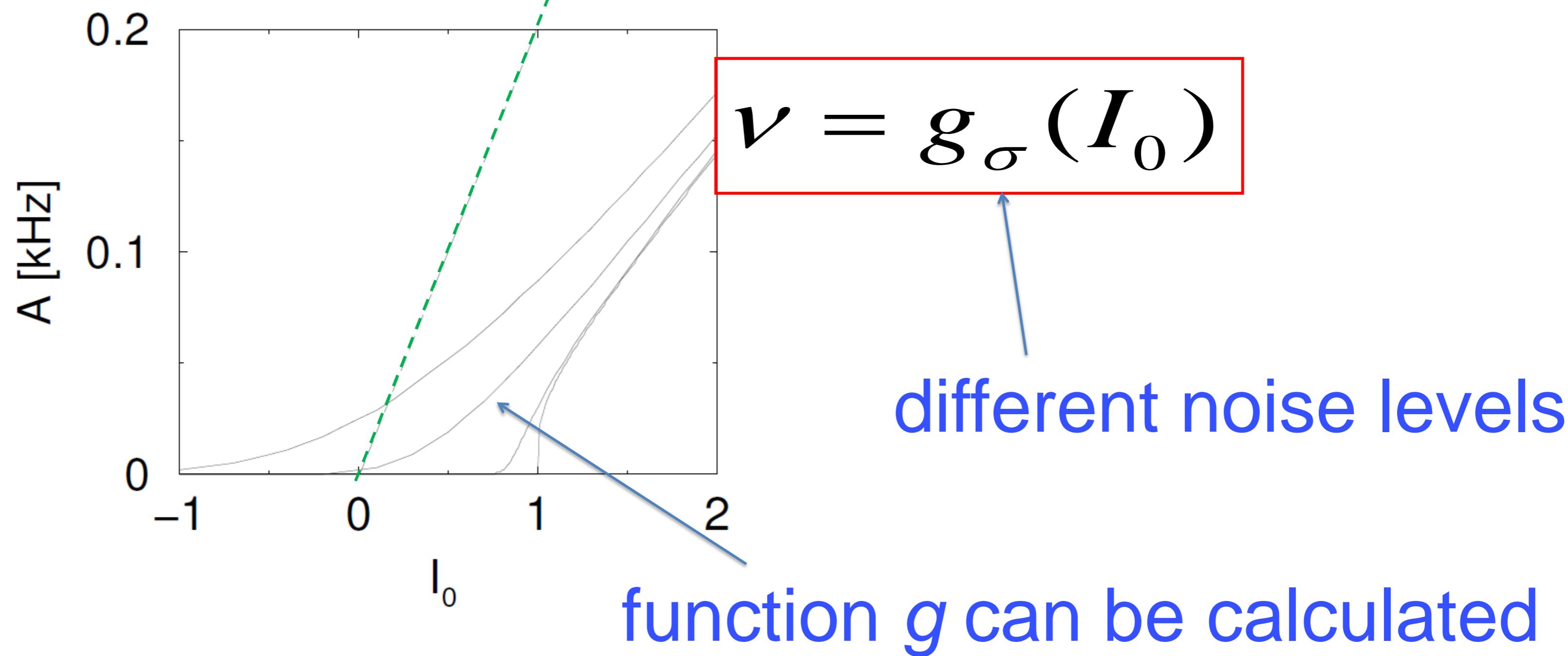
Examples:

- leaky integrate-and-fire (with noise)
- Spike Response Model (with noise)
- Hodgkin-Huxley model

5. stationary solution: integrate-and-fire neurons

$$I_0 = J_0 q A_0 + I_0^{ext}$$

$$[I_0 - I_0^{ext}] / J_0 q = A_0$$



5. gain function is noise-dependent

Gain-function g =frequency-current relation = f-I curve

function g can be calculated analytically or measured in
single-neuron simulations/single-neuron experiments

$$\nu = g_\sigma(I_0)$$

different noise levels

5. stationary solution: population activity (asynchr. state)

Single Population

- homogeneous
- full connectivity
- stationary state of asynchronous firing

Single neuron rate = population rate

$$A_0 = \nu = g(I_0) = g(J_0 q A_0 + I_0^{ext})$$

Gain function for constant input

- available for many neurons
- available for many neuron models

Limited to stationary state.

Computational Neuroscience: Neuronal Dynamics of Cognition



Neuronal Populations

Wulfram Gerstner

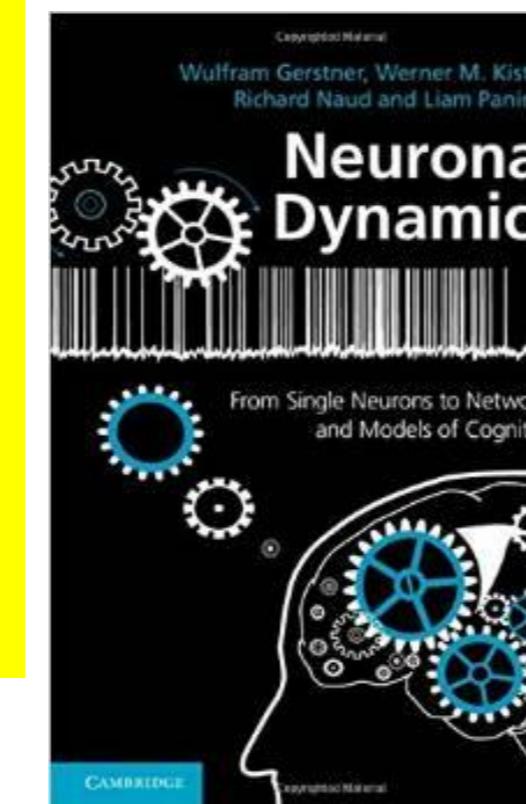
EPFL, Lausanne, Switzerland

Reading:

NEURONAL DYNAMICS

- Ch. 12.1 – 12.4.3
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Cambridge Univ. Press



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6. mean-field arguments (random connectivity)

**So far:
Full connectivity**

**More realistic:
random connectivity**

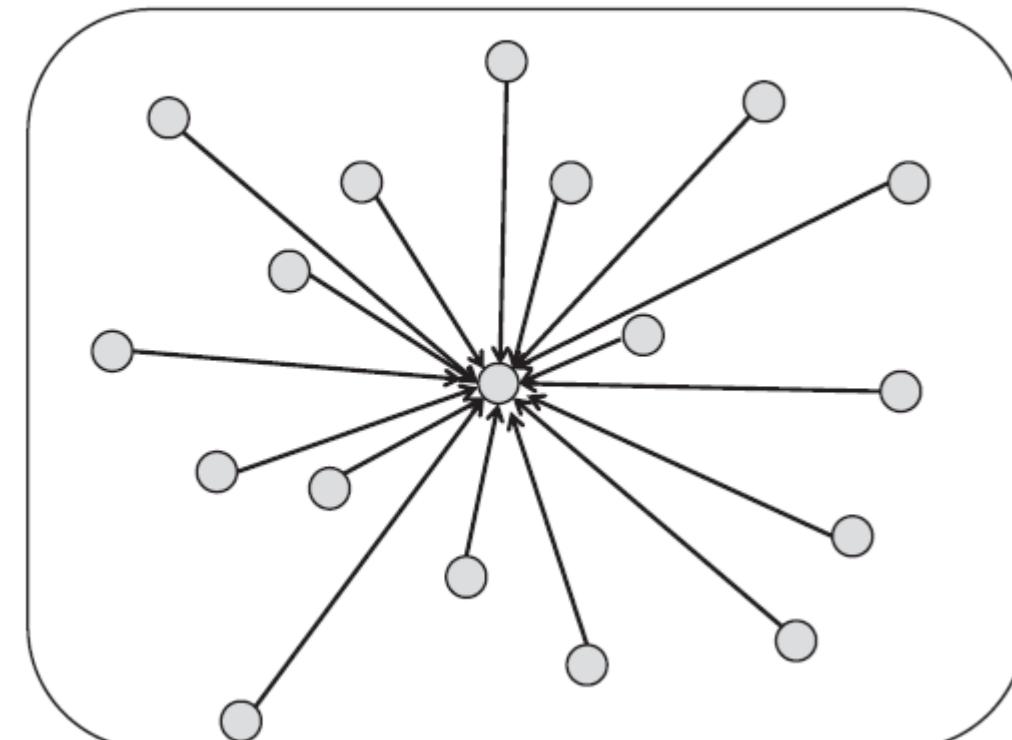
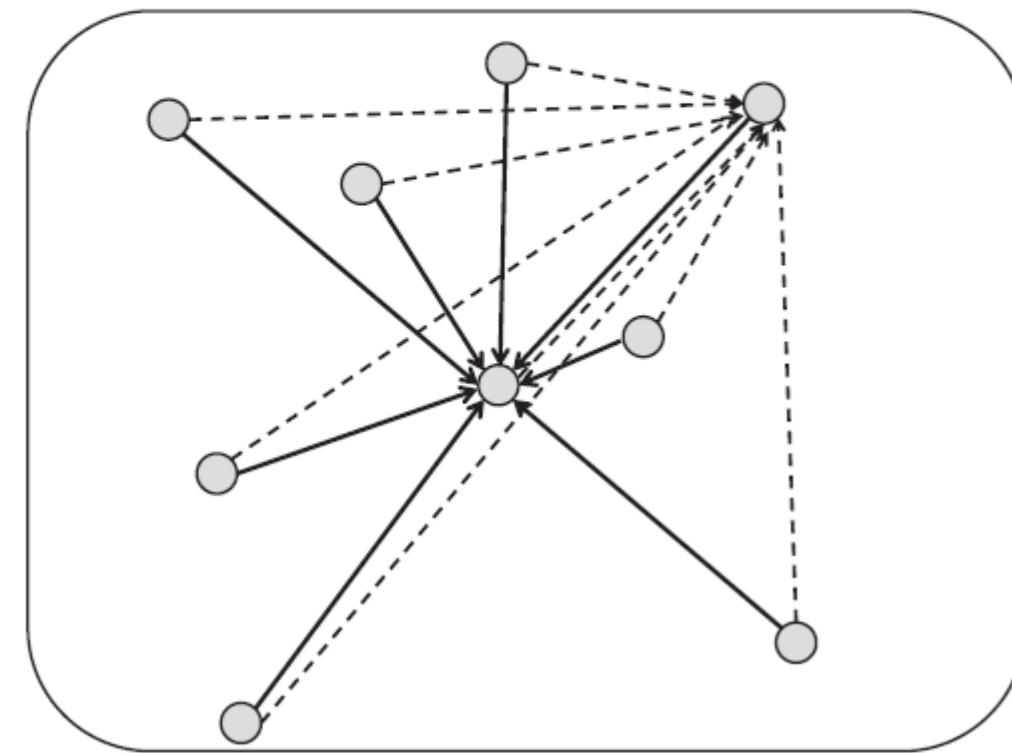
Can we repeat the
mean-field arguments?

6. mean-field arguments (random connectivity)

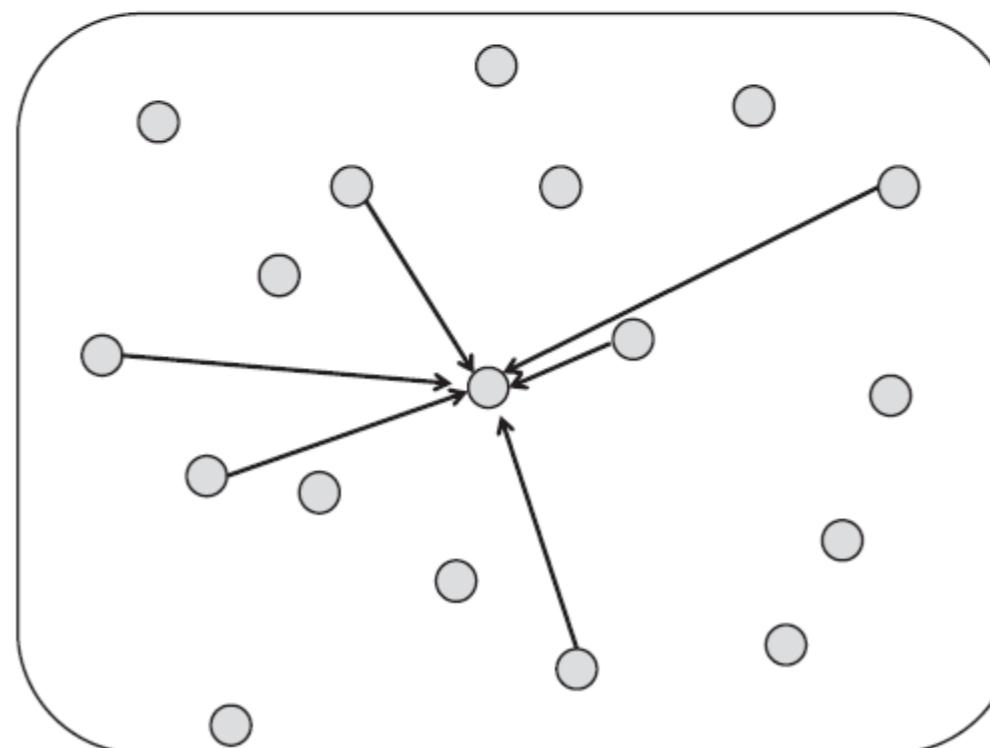
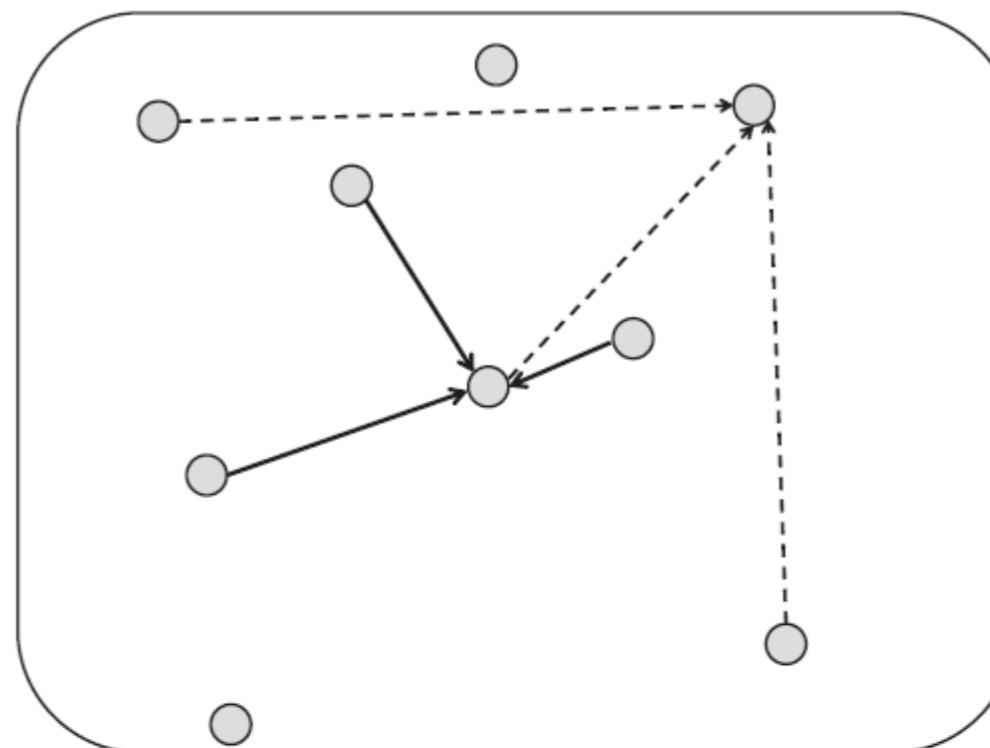
random connectivity

full connectivity

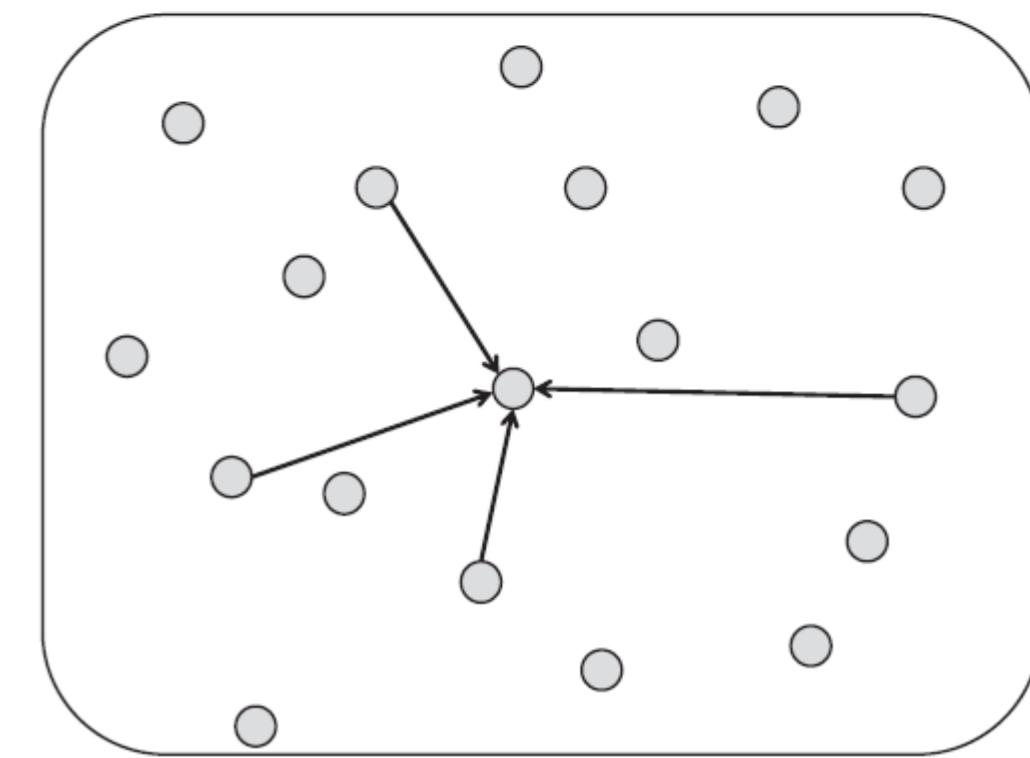
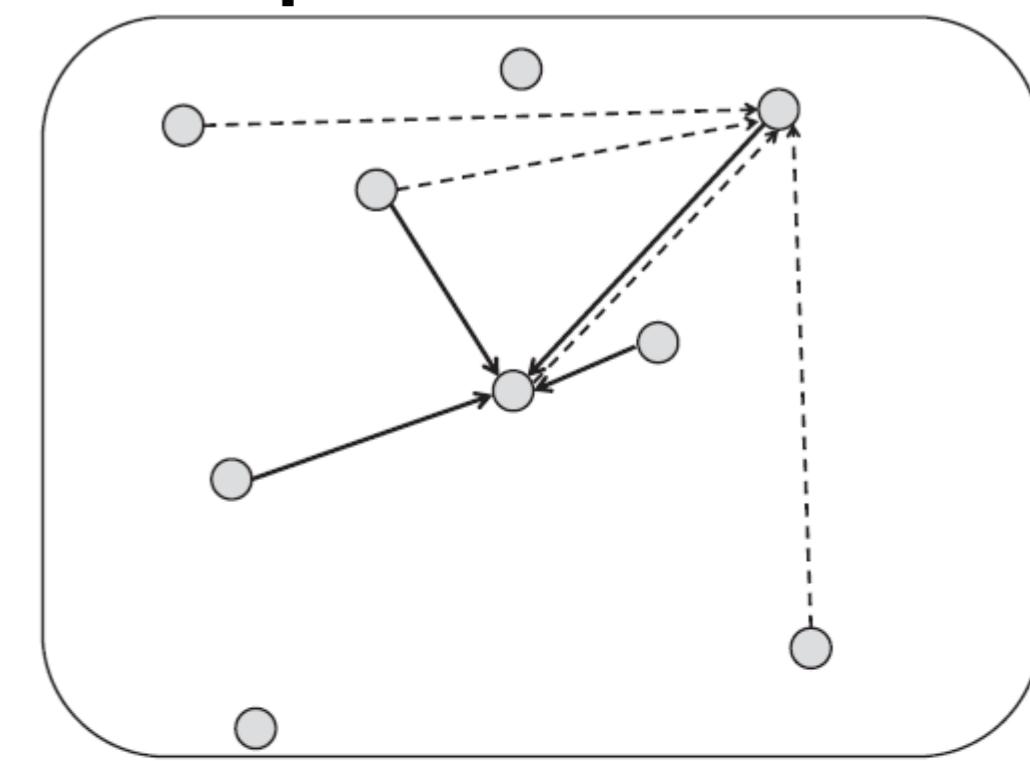
A



random: prob p fixed



random: number K
of inputs fixed

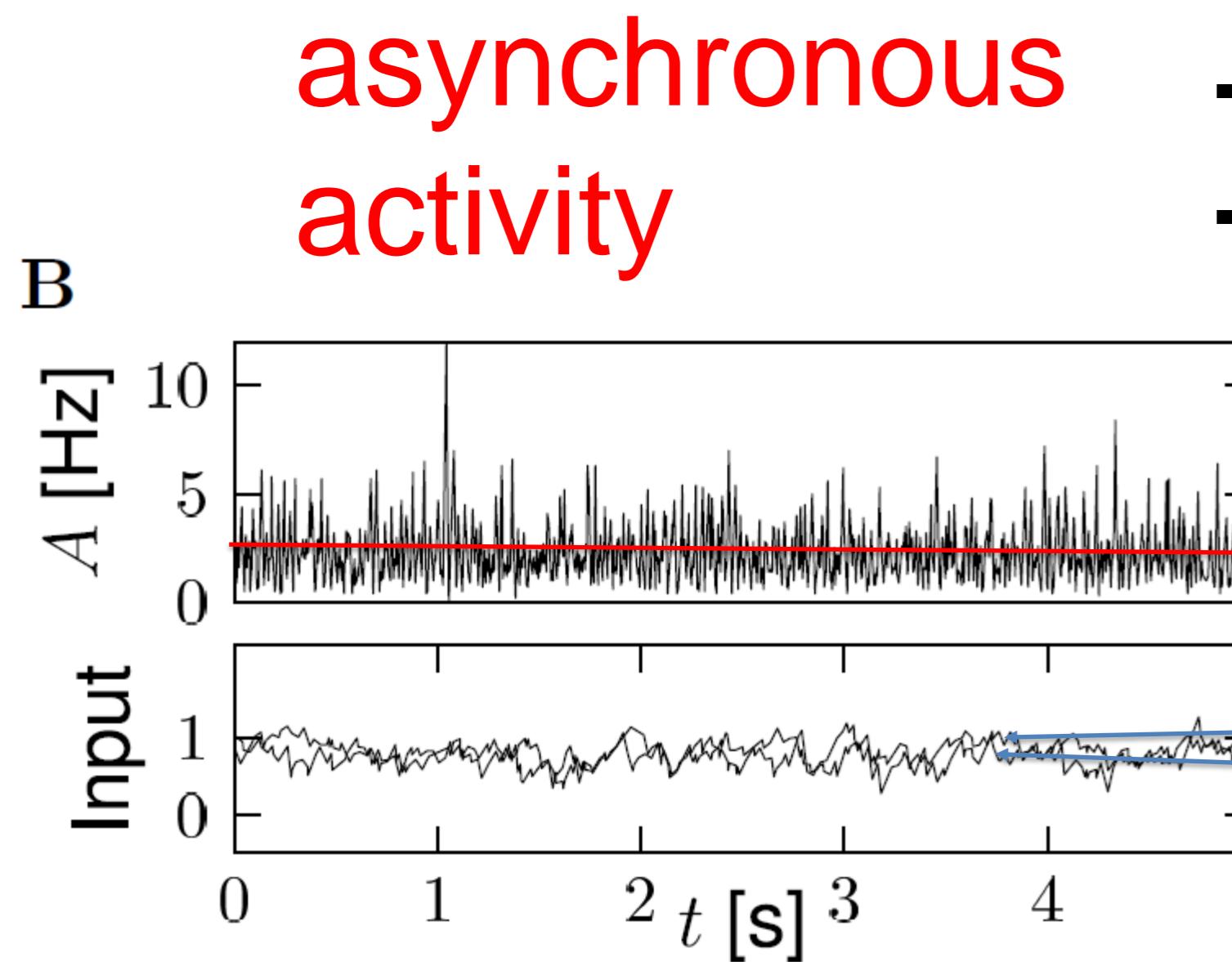


6. Review - Random Connectivity: fixed p

Can we mathematically predict the population activity?

given

- connection probability p and weight w_{ij}
- properties of individual neurons
- large population



Input is nearly identical for different neurons

6. Integrate-and-Fire neurons

Integrate-and-fire with
stochastic spike arrival

For any arbitrary neuron in the population

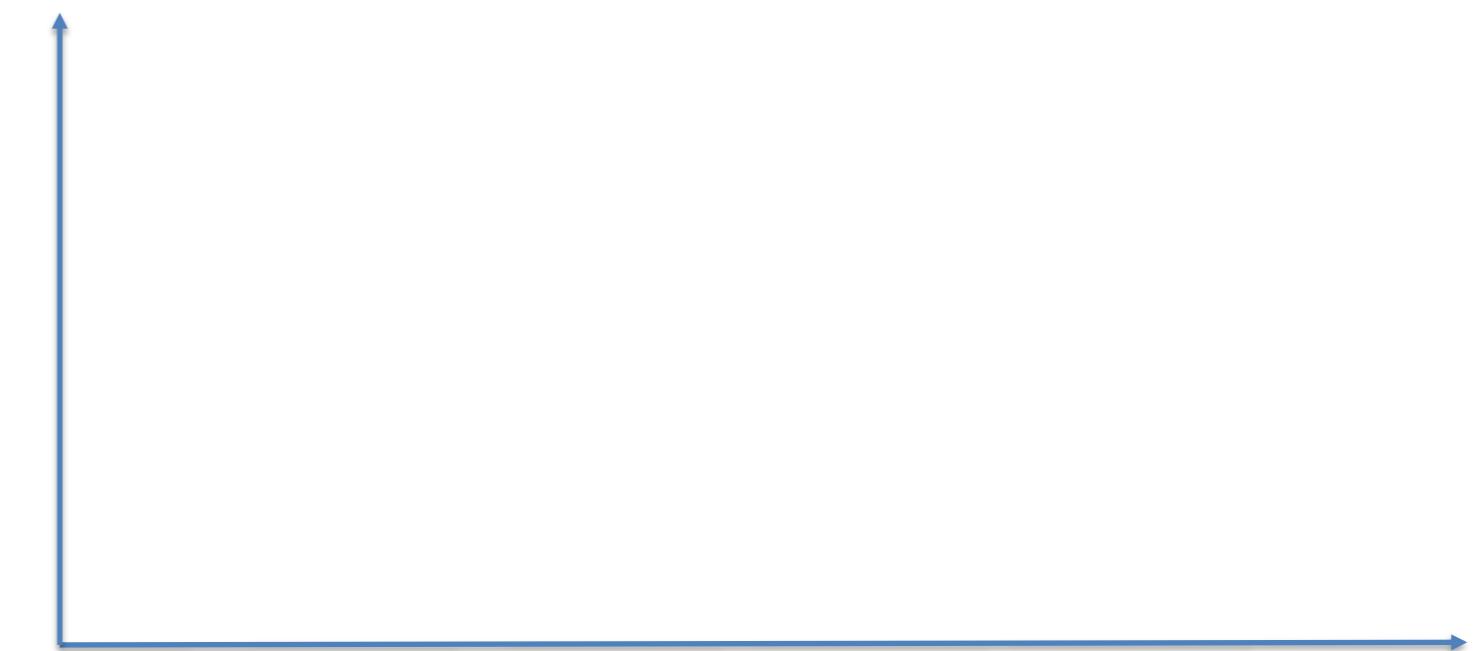
$$\tau \frac{d}{dt} u_i = -u + I_i$$

if $u_i = \vartheta$: "reset"

$$I_i = \sum_{k,f} w_{ik} \alpha(t - t_k^f)$$

EPSC

excitatory input spikes



6. Network of integrate-and-fire neurons (random connectivity)

Integrate-and-fire neurons with stochastic spike arrival

For any arbitrary neuron in the population

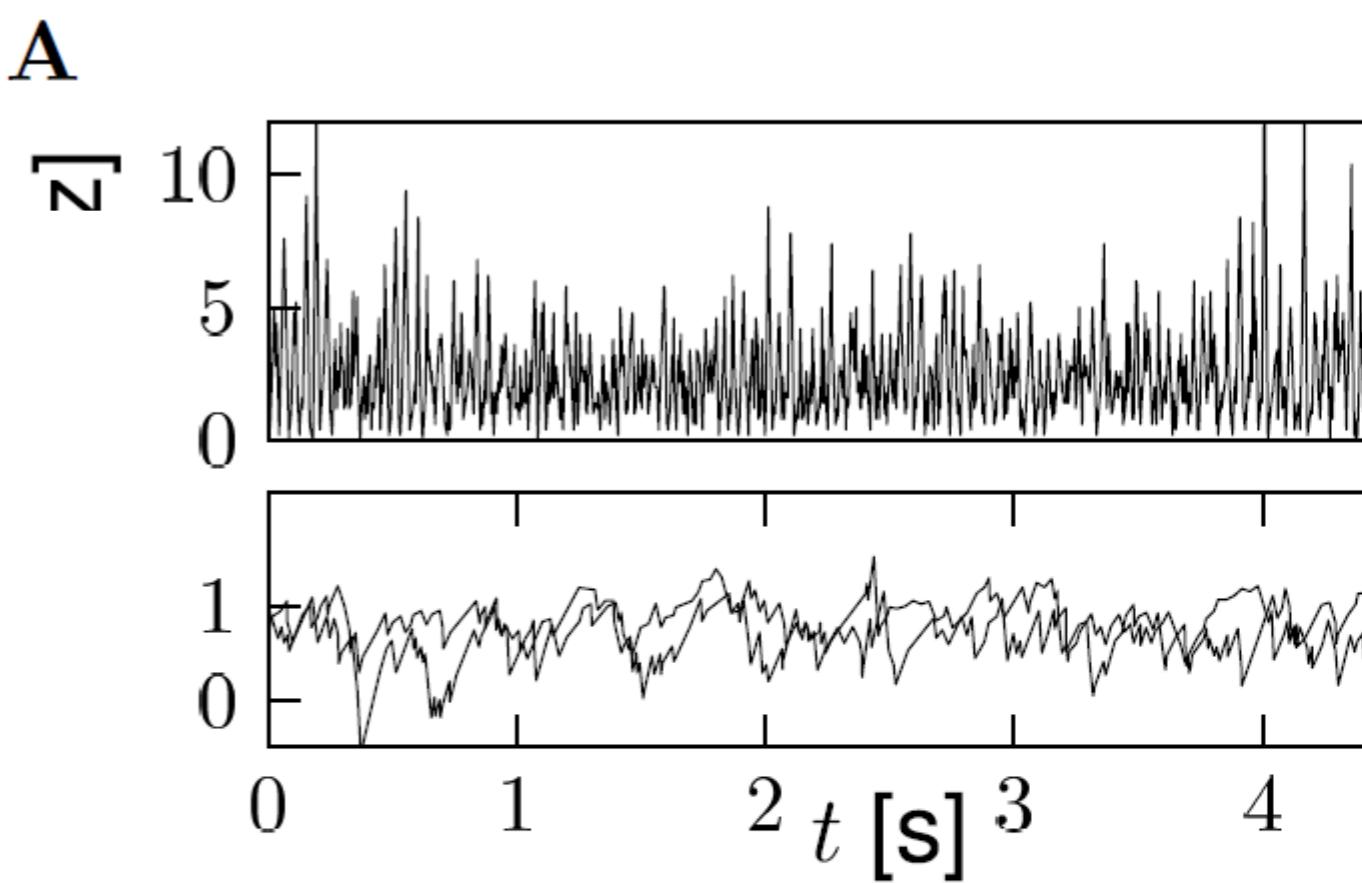
$$\tau \frac{du_i}{dt} = -u_i + I_i$$

if $u_i = \vartheta$: "reset"

$$I_i = \sum_{k,f} w_{ik} \alpha(t - t_k^f)$$

EPSC

excitatory input spikes



Can we predict the mean current?

6. mean-field argument: random connectivity

$$w_{ij} = \frac{w_0}{pN}$$



$$A_0 = \nu = g(I_0) = g(J_0 w_0 A_0 + I_0^{ext})$$

6. mean-field arguments (random connectivity)

random: probability $p=0.1$ fixed, weights chosen as $w_{ij} = \frac{w_0}{pN}$

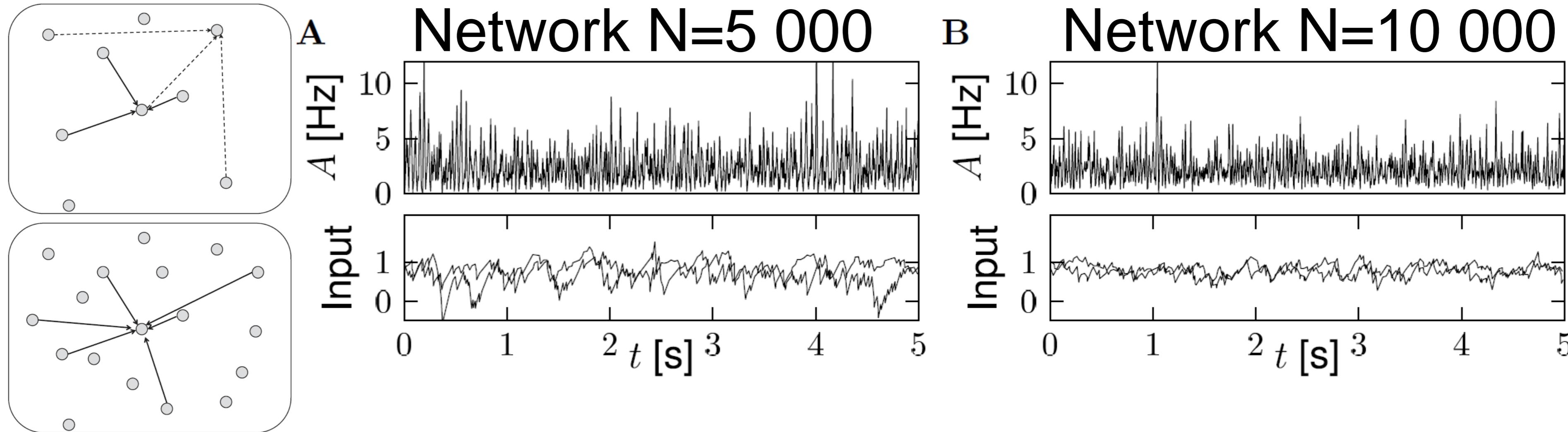


Fig. 12.7: Simulation of a model network with a fixed connection probability $p = 0.1$. A. Top: Population activity $A(t)$ averaged over all neurons in a network of 4 000 excitatory and 1 000 inhibitory neurons. Bottom: Total input current $I_i(t)$ into two randomly chosen

fluctuations of A decrease
fluctuations of I decrease

Image: Gerstner et al.
Neuronal Dynamics (2014)

6. Random connectivity – fixed number of inputs

random: input connections $K=500$ fixed, weights chosen as $w_{ij} = \frac{w_0}{K}$

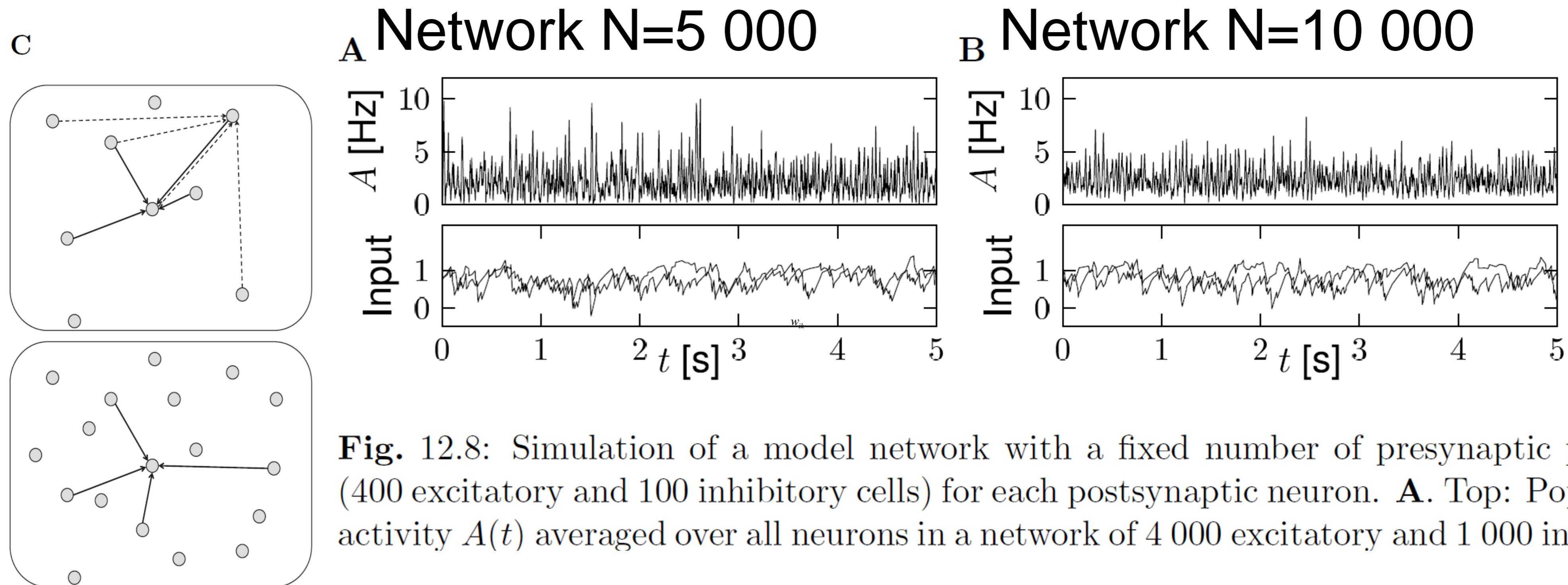


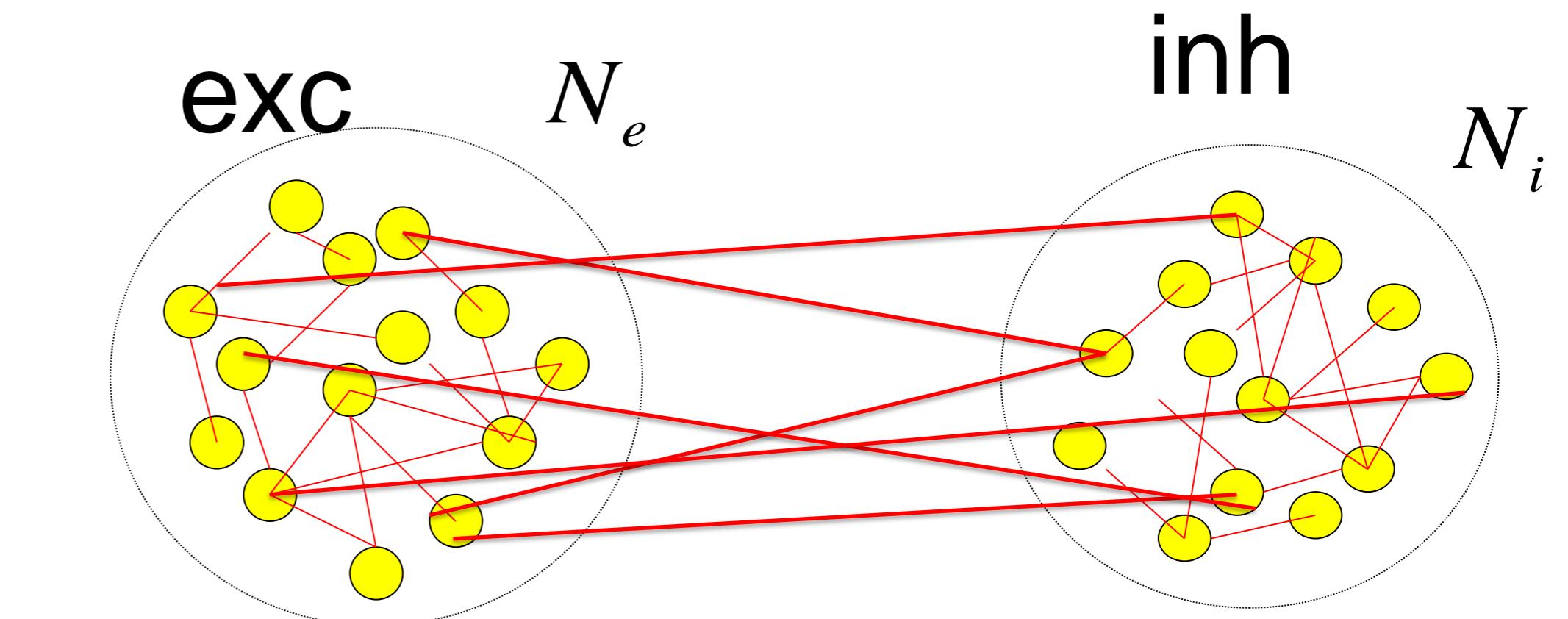
Fig. 12.8: Simulation of a model network with a fixed number of presynaptic partners (400 excitatory and 100 inhibitory cells) for each postsynaptic neuron. **A.** Top: Population activity $A(t)$ averaged over all neurons in a network of 4 000 excitatory and 1 000 inhibitory

Image: Gerstner et al.
Neuronal Dynamics (2014)

fluctuations of A decrease
fluctuations of I remain

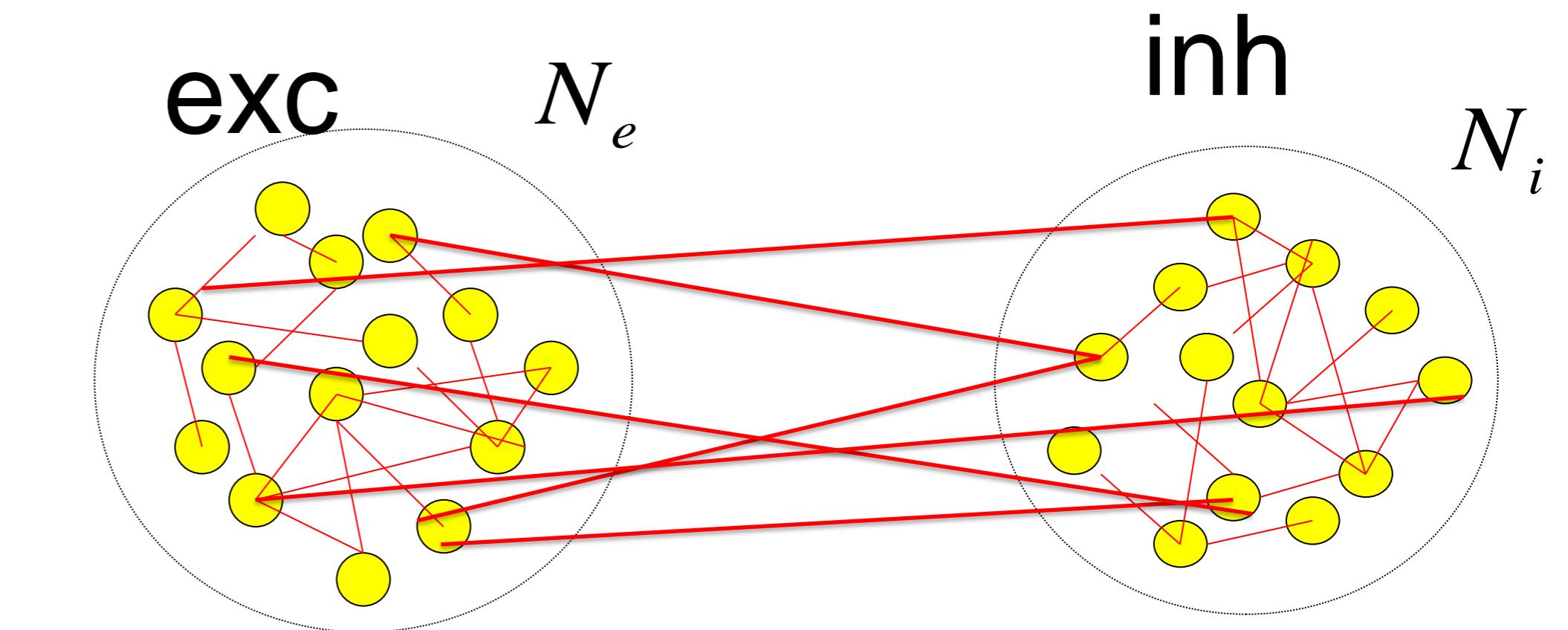
6. Connectivity schemes – random, fixed p, but balanced

$$I_i = \sum_{k,f} w_{ik} \alpha^{exc}(t - t_k^f) - \sum_{k,f} w_{ik} \alpha^{inh}(t - t_k^f)$$



6. Connectivity schemes – random, fixed p, but balanced

$$I_i = \sum_{k,f} w_{ik} \alpha^{exc}(t - t_k^f) - \sum_{k,f} w_{ik} \alpha^{inh}(t - t_k^f)$$



make network bigger, but
-keep mean input close to zero

$$p N_e J_e = -p N_i J_i$$

-keep variance of input

$$w_{ij} = \frac{J_e}{\sqrt{pN}}$$

$$w_{ij} = \frac{J_i}{\sqrt{pN}}$$

6. Connectivity schemes – random, fixed p , but balanced

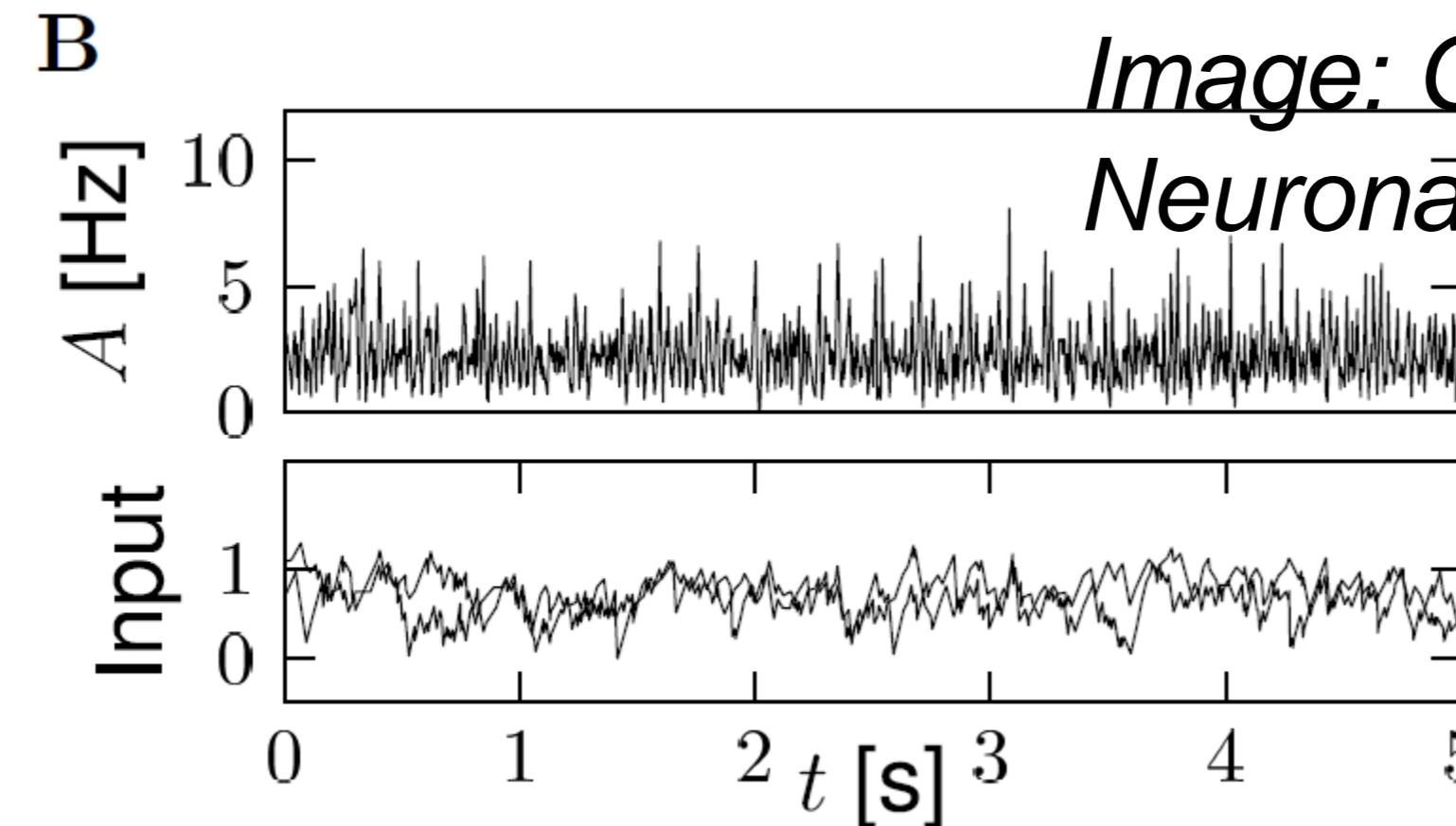
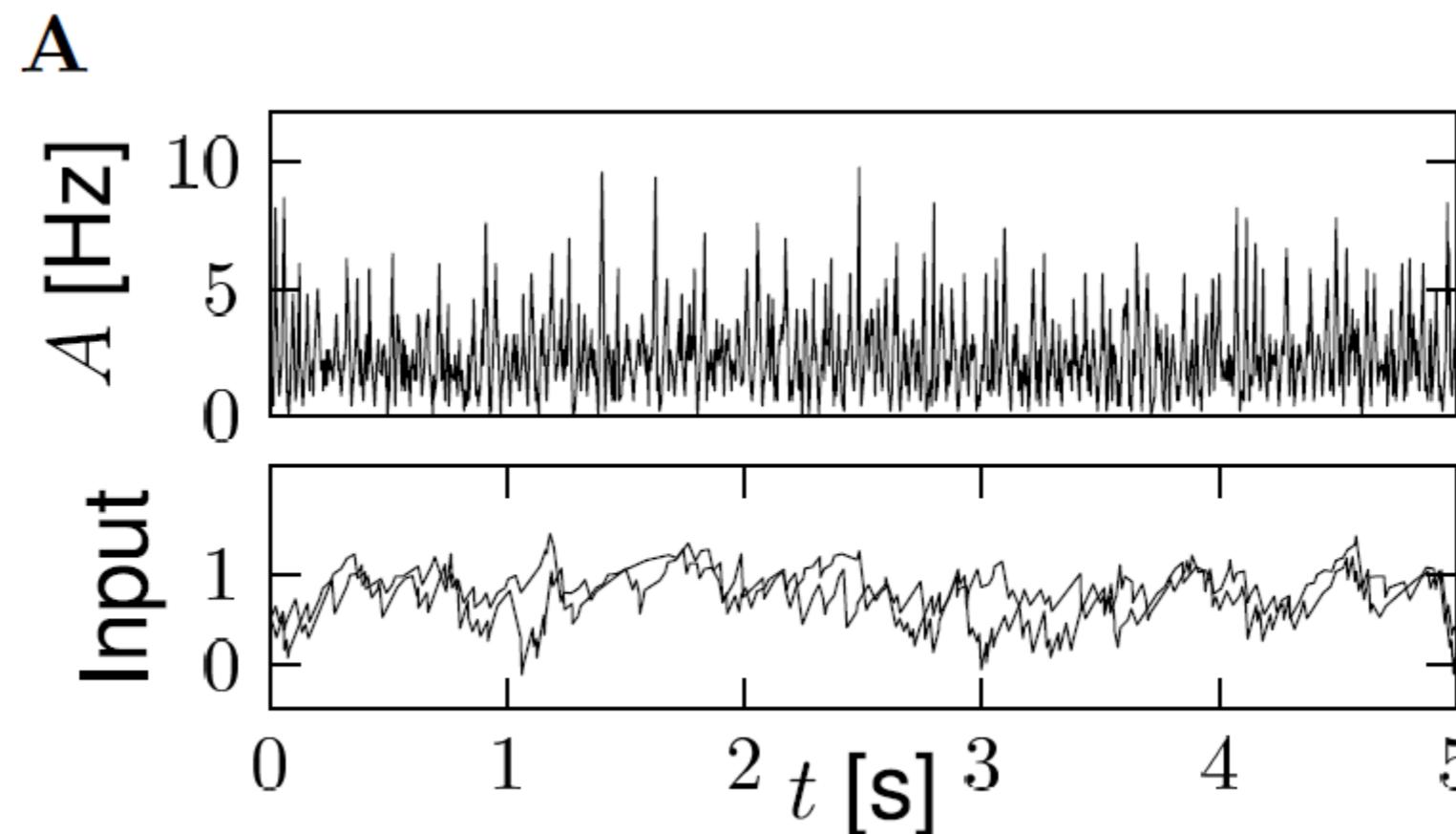


Fig. 12.9: Simulation of a model network with balanced excitation and inhibition and fixed connectivity $p = 0.1$ **A.** Top: Population activity $A(t)$ averaged over all neurons in a network of 4 000 excitatory and 1 000 inhibitory neurons. Bottom: Total input current $I_i(t)$ into two randomly chosen neurons. **B.** Same as A, but for a network with 8 000 excitatory and 2 000 inhibitory neurons. The synaptic weights have been rescaled by a factor $1/\sqrt{2}$ and the common constant input has been adjusted. All neurons are leaky integrate-and-fire units with identical parameters coupled interacting by short current pulses.

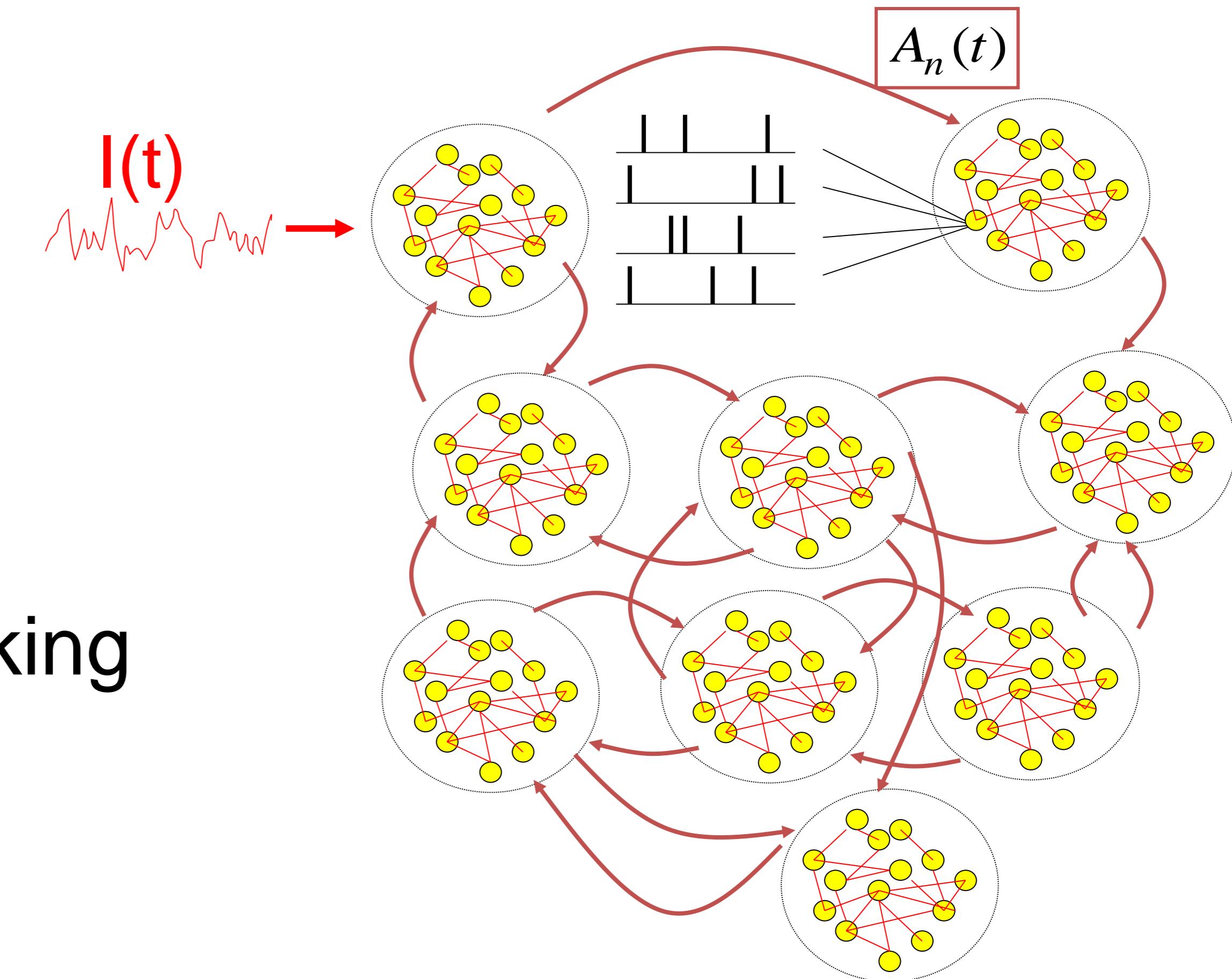
fluctuations of A decrease



fluctuations of I become ‘smoother’

6. Neuronal populations: outlook

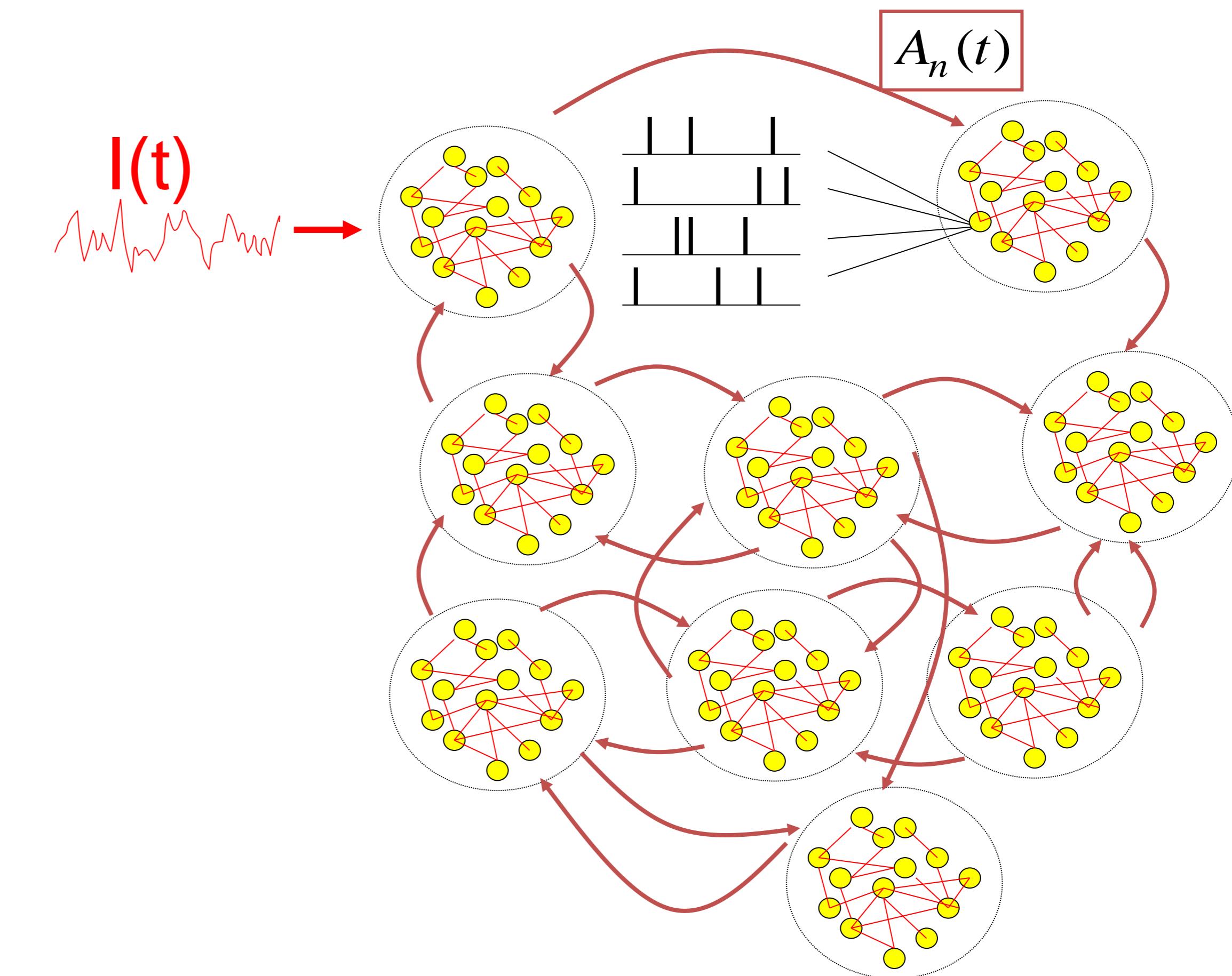
One population
→ multiple populations



Application to visual cortex
→ visual processing

Application to decision making
→ competitive networks

6. Summary: Neuronal Populations



6. Selected References: Neuronal Populations

Receptive fields, columns, and cortical connectivity

D. H. Hubel and T. N. Wiesel (1962) Receptive fields, binocular interaction and functional architecture in the cat's visual cortex.. *J. Physiol. (London)* 160, pp. 106–154.

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S. Lefort, C. Tomm, J.C.F. Sarria and C.C.H. Petersen (2009) The excitatory neuronal network of the c2 barrel column in mouse primary somatosensory cortex. *neuron* 61: 301-316.. *Neuron* 61, pp. 301–316.

Modeling populations

H. R. Wilson and J. D. Cowan (1972) Excitatory and inhibitory interactions in localized populations of model neurons.. *Biophys. J.* 12, pp. 1–24.

C. van Vreeswijk and H. Sompolinsky (1996) Chaos in neuronal networks with balanced excitatory and inhibitory activity. *Science* 274, pp. 1724–1726.

N. Brunel (2000) Dynamics of sparsely connected networks of excitatory and inhibitory neurons. *Computational Neuroscience* 8, pp. 183–208.

W. Gerstner (2000) Population dynamics of spiking neurons: fast transients, asynchronous states and locking. *Neural Computation* 12, pp. 43–89.

For those not familiar with the Dirac delta: <https://www.youtube.com/watch?v=l3hvrx33lZc>

More info on neuron models: <http://lcn.epfl.ch/~gerstner/NeuronalDynamics-MOOC1.html>

Computational Neuroscience: Neuronal Dynamics of Cognition



Neuronal Populations

The end

Documentation:

<http://neuronaldynamics.epfl.ch/>

Online html version available

Reading:

NEURONAL DYNAMICS

- Ch. 12.1 – 12.4.3
(except Section 12.3.7)

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