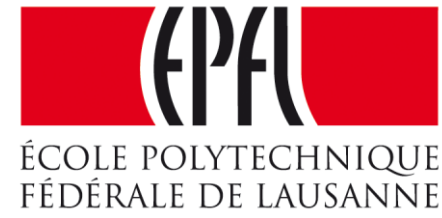


Week 15 – Integral Equation for population dynamics



Biological Modeling of Neural Networks:

Week 15 – Population Dynamics: The Integral –Equation Approach

Wulfram Gerstner

EPFL, Lausanne, Switzerland

15.1 Populations of Neurons

- review: homogeneous population
- review: parameters of single neurons

15.2 Integral equation

- aim: population activity
- renewal assumption

15.3 Populations with Adaptation

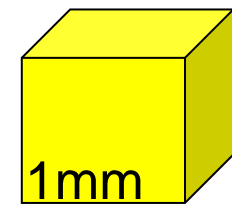
- Quasi-renewal theory

15.4. Coupled populations

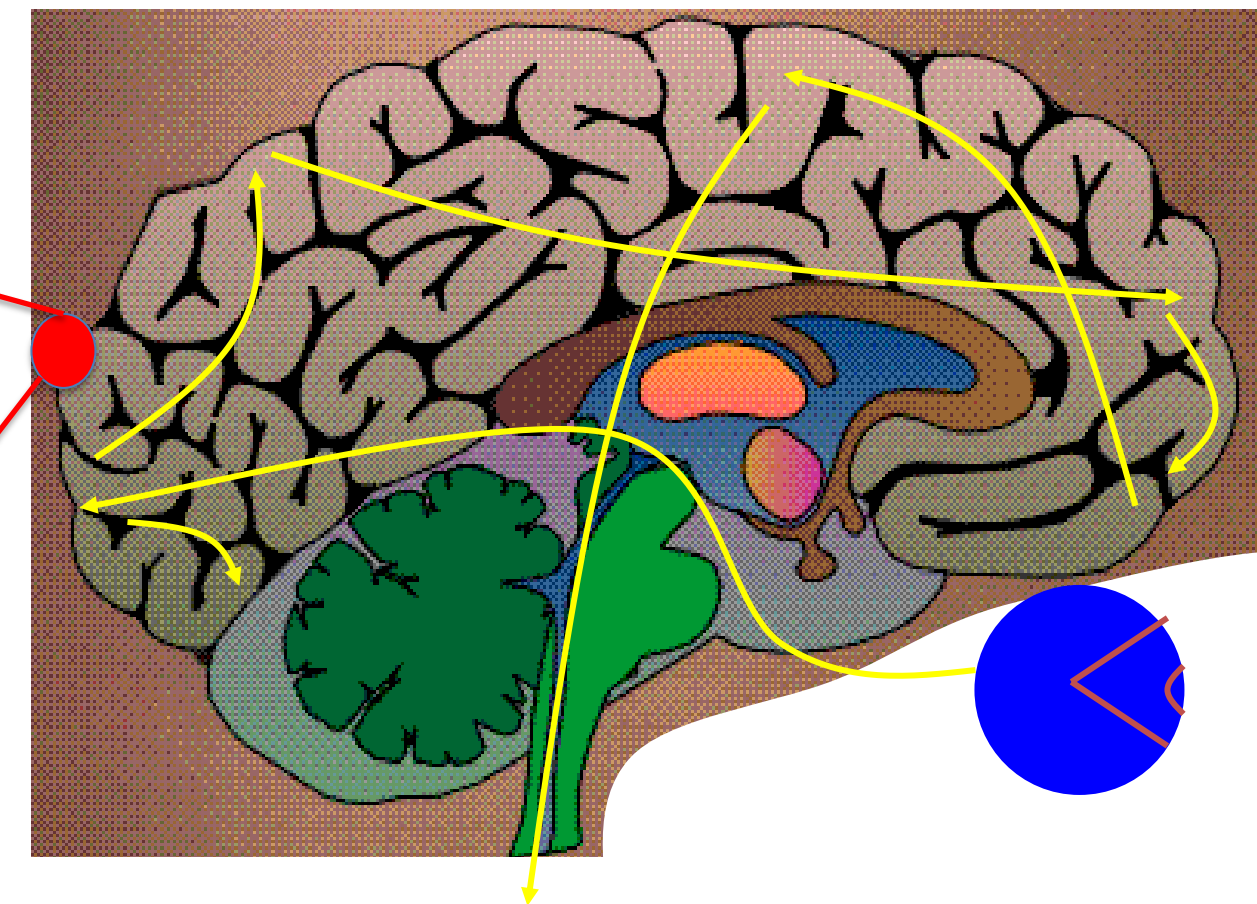
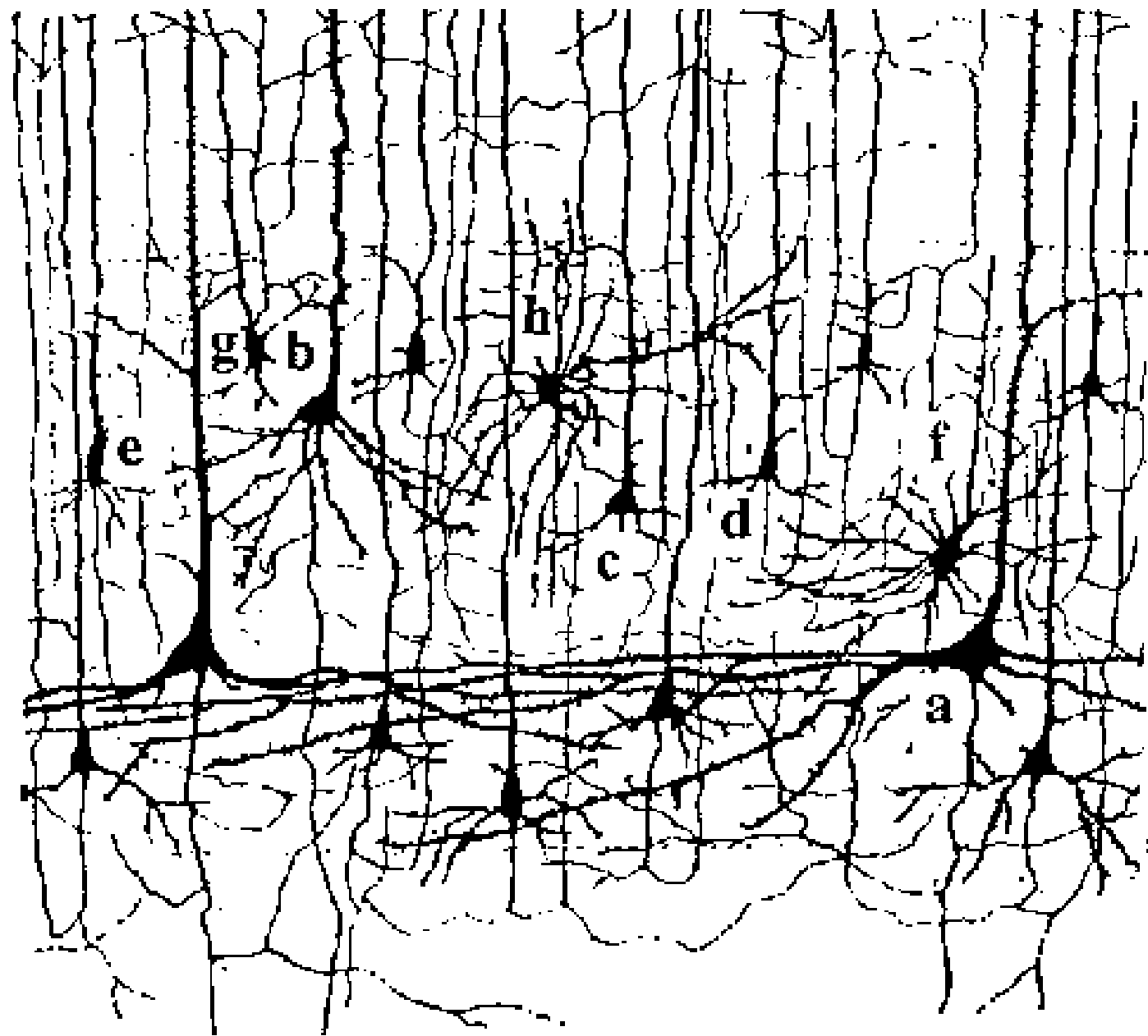
- self-coupling
- coupling to other populations

Week 15-part 1: Review: The brain is complex

Neuronal Dynamics – Brain dynamics is complex



10 000 neurons
3 km of wire

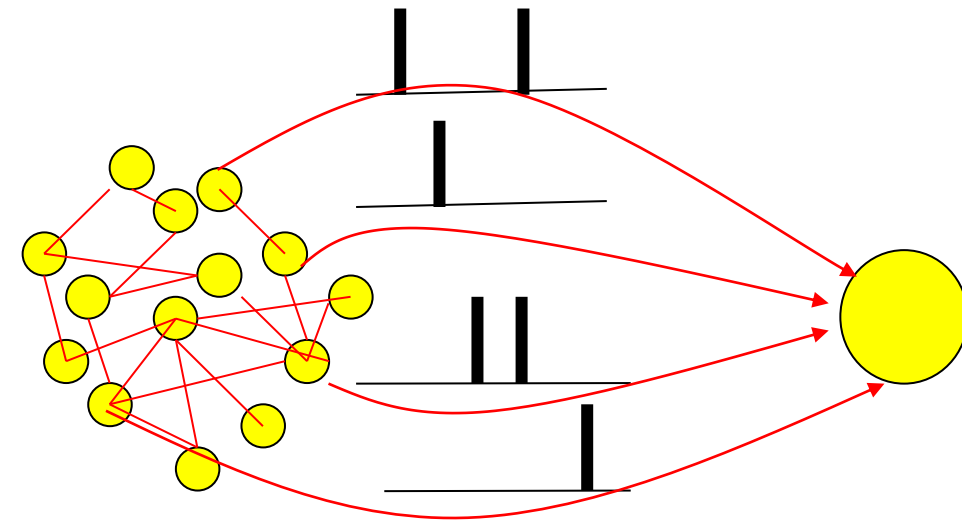


motor
cortex

frontal
cortex

to motor
output

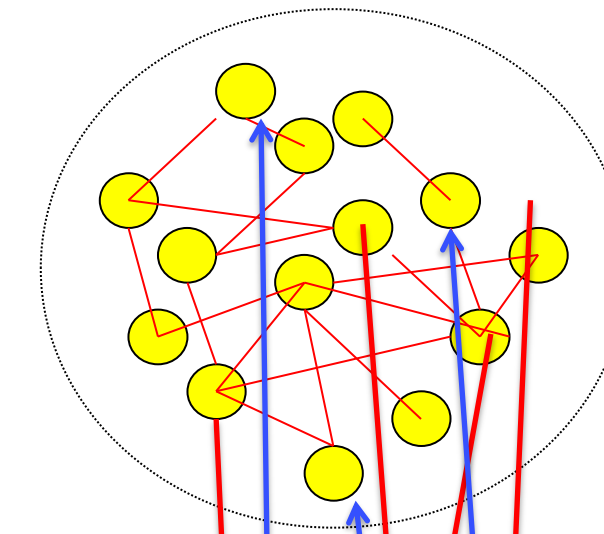
Week 15-part 1: Review: Homogeneous Population



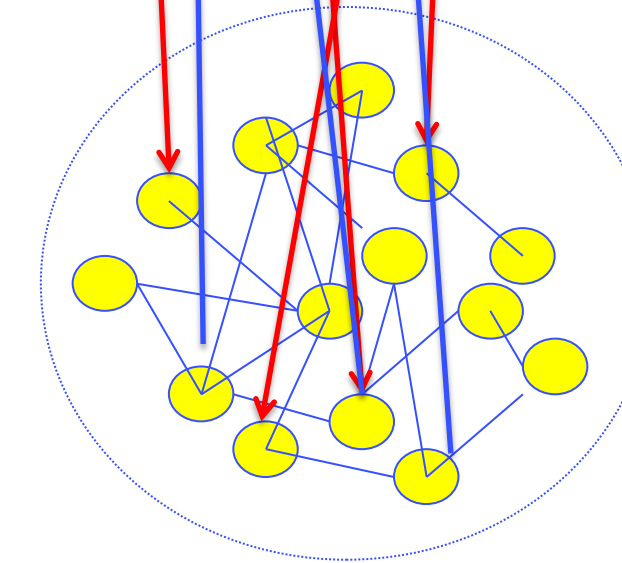
Homogeneous population:

- each neuron receives input from k neurons in the population
- each neuron receives the same (mean) external input (could come from other populations)
- each neuron in the population has roughly the same parameters

Example: 2 populations

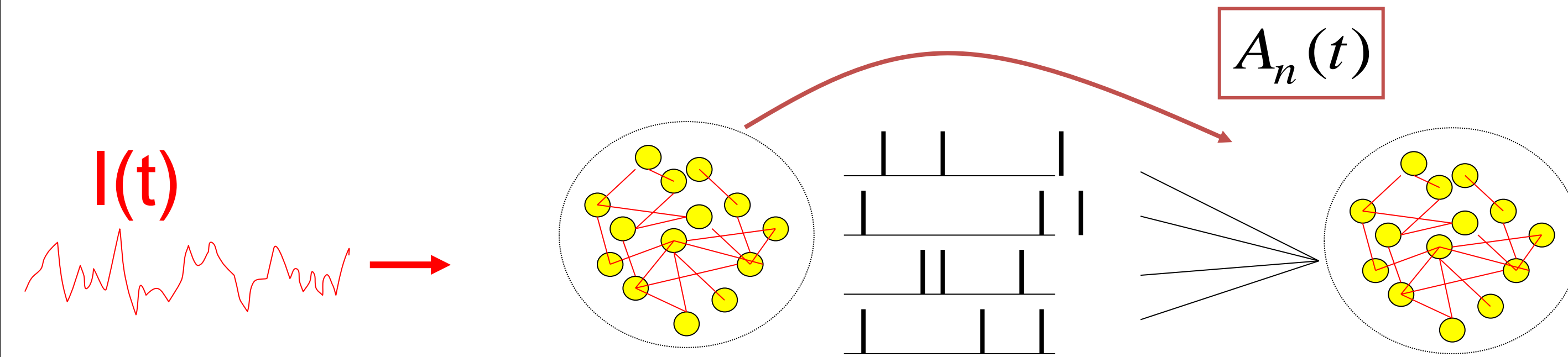


excitation



inhibition

Week 15-part 1: Review: microscopic vs. macroscopic



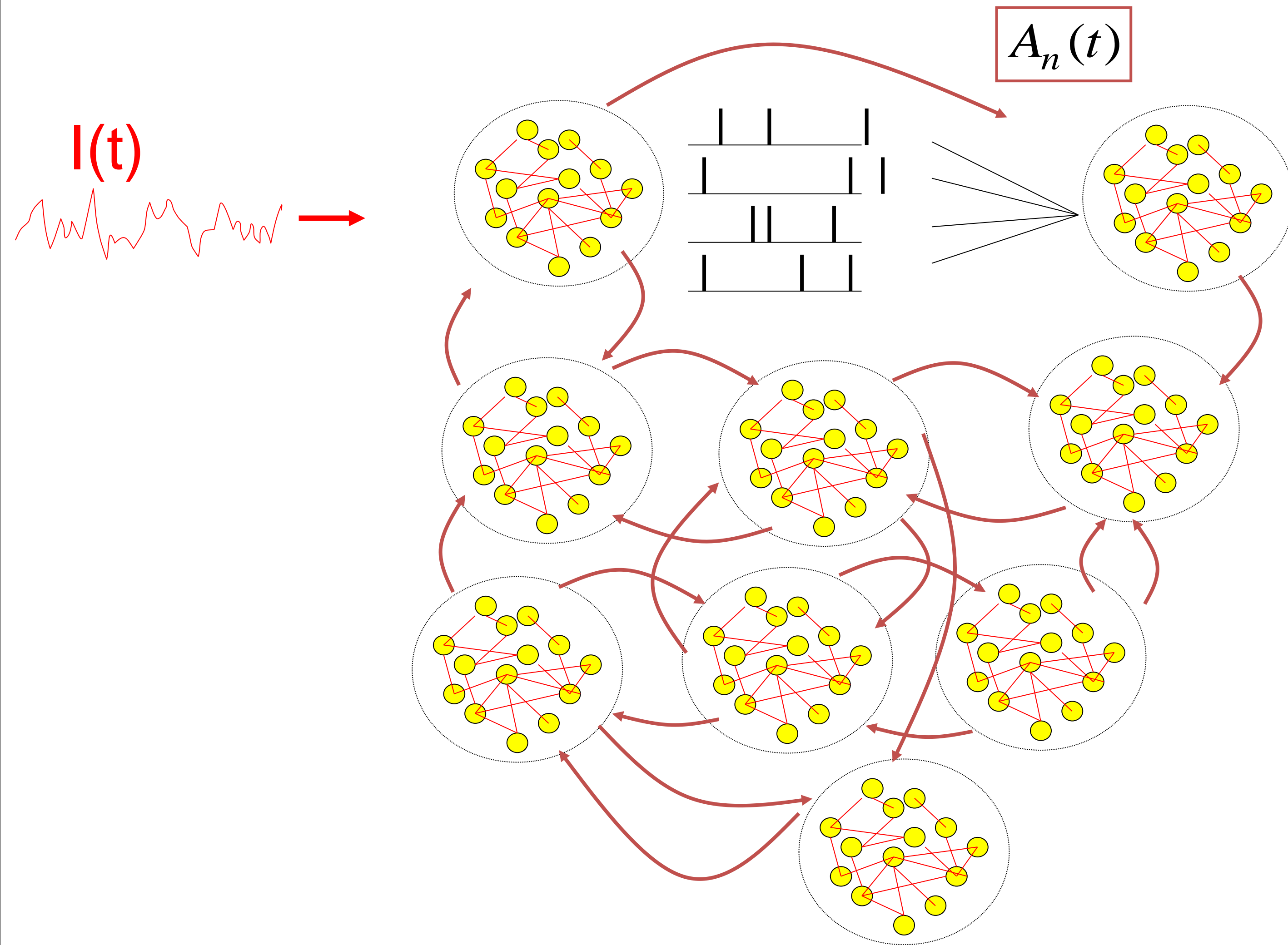
microscopic:

- spikes are generated by individual neurons
- spikes are transmitted from neuron to neuron

macroscopic:

- Population activity $A_n(t)$
- Populations interact *via* $A_n(t)$

Week 15-part 1: Review: coupled populations



Week 15-part 1: Example: coupled populations in barrel cortex

Neuronal Populations

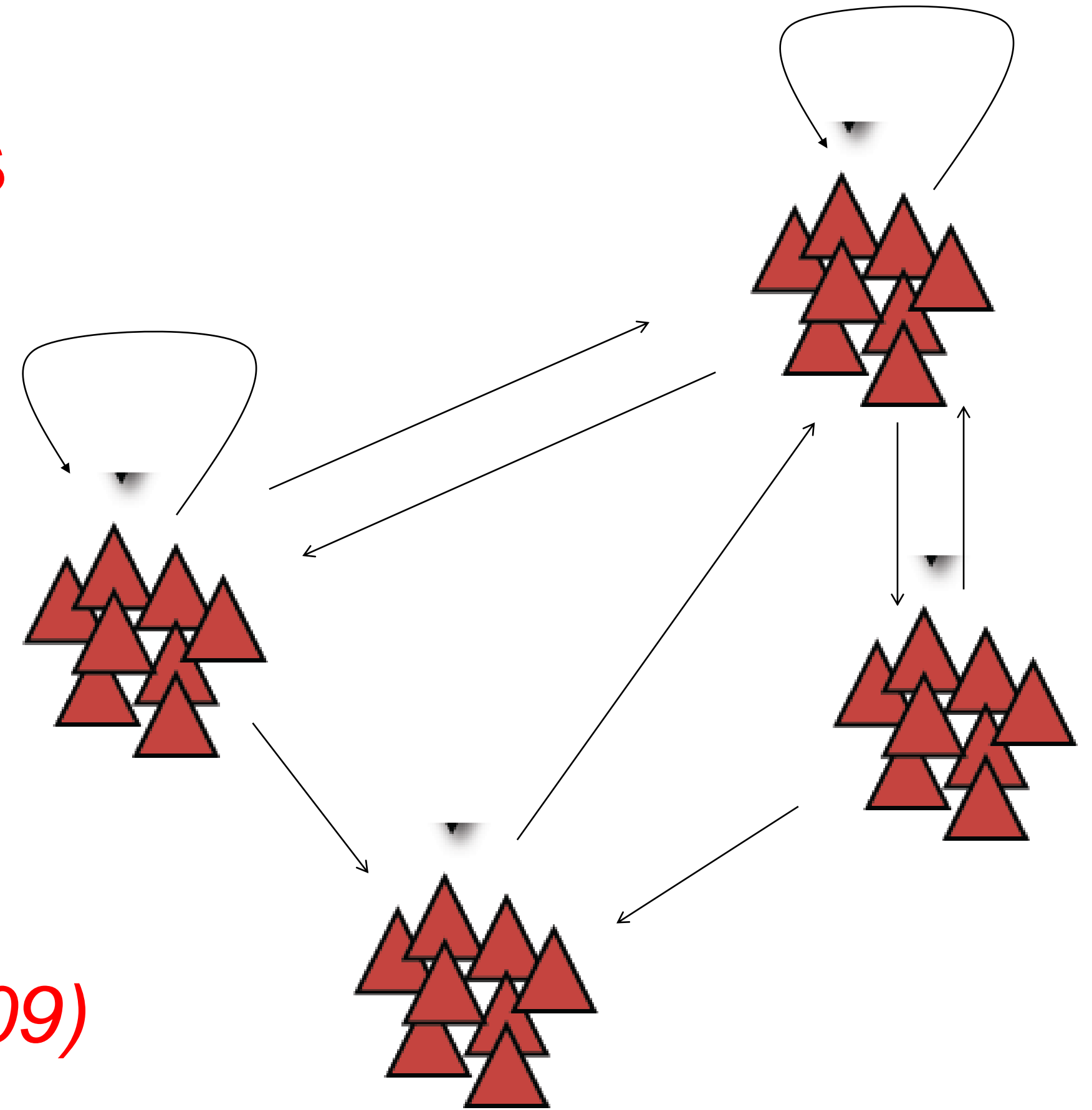
= a homogeneous group of neurons
(more or less)

Populations:

- pyramidal neurons in layer 5 of barrel D1
- pyramidal neurons in layer 2/3 of barrel D1
- inhibitory neurons in layer 2/3 of barrel D1

100-2000 neurons

per group (*Lefort et al., NEURON, 2009*)

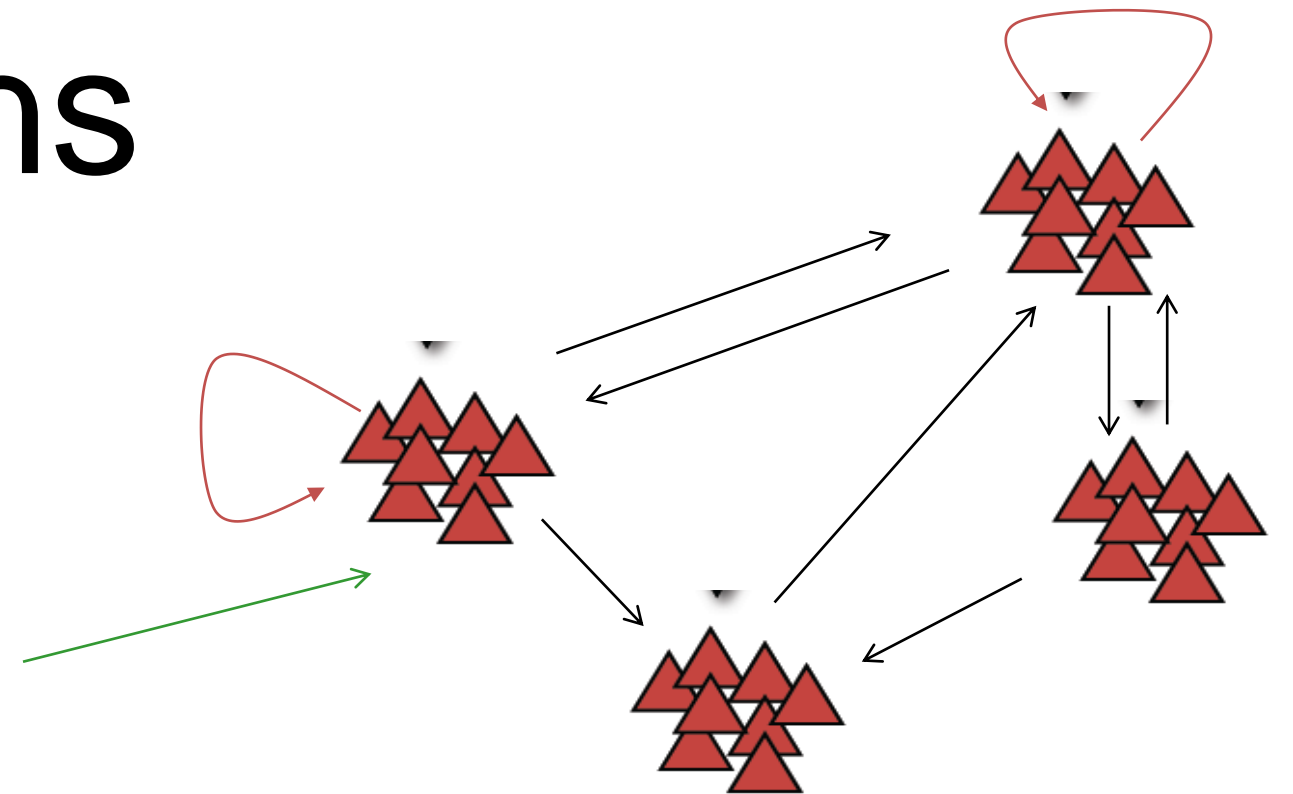


different barrels and layers, different neuron types → different populations

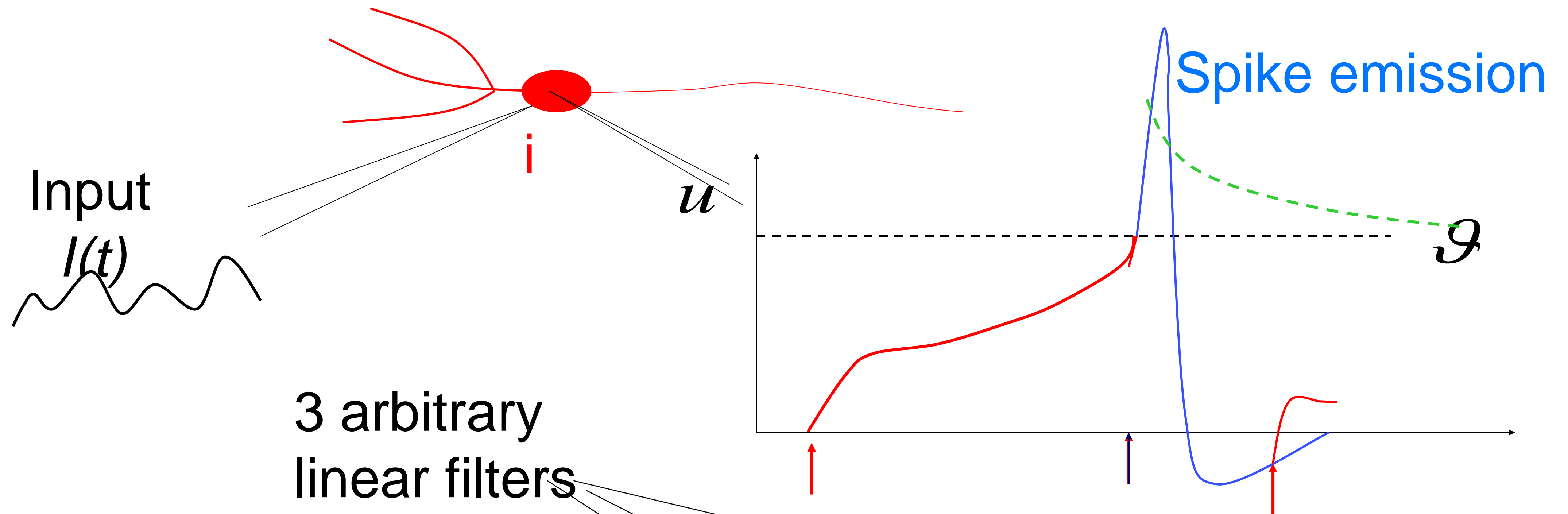
Week 15-part 1: Global aim and strategy

- Extract parameters for SINGLE neuron
(see NEURONAL DYNAMICS, Chs. 8-11; review now)
- Dynamics in one (homogeneous) population
Today, parts 15.2 and 15.3!
- Dynamics in coupled populations
- Understand Coding in populations
- Understand Brain dynamics

Sensory input



Week 15-part 1: Review: Spike Response Mode (SRM)



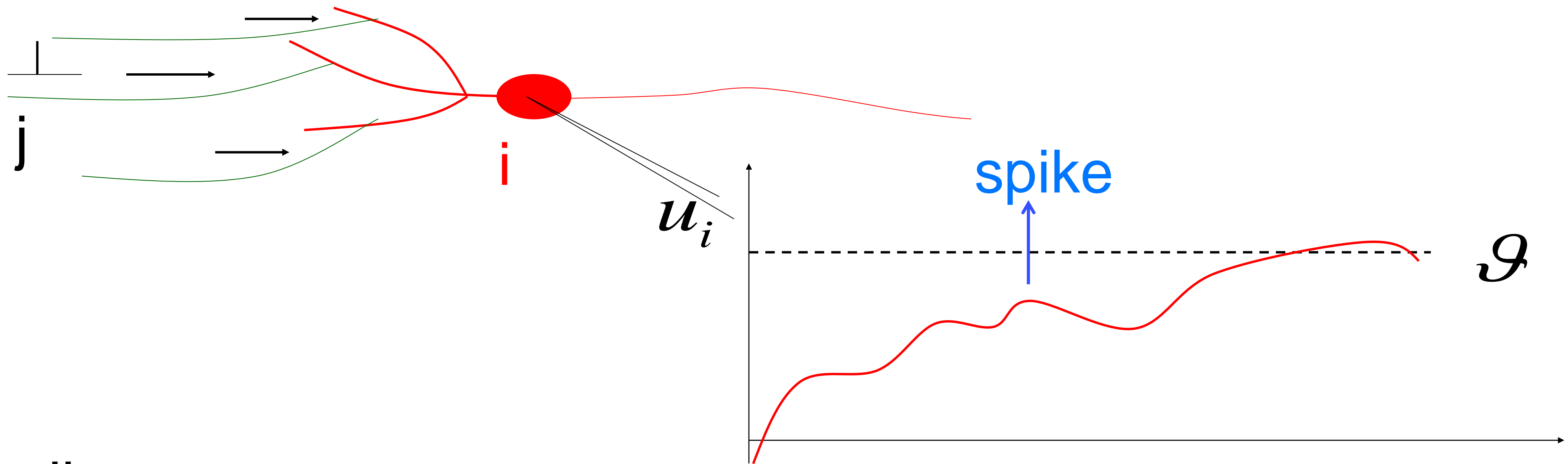
potential

$$u(t) = \sum_{\hat{t}} \eta(t - \hat{t}) + \int_0^\infty \varepsilon(s) I(t - s) ds + \dots$$

threshold

$$\mathcal{G}(t) = \mathcal{G}_0 + \sum_{t'} \theta(t - t')$$

SRM +escape noise = Generalized Linear Model (GLM)



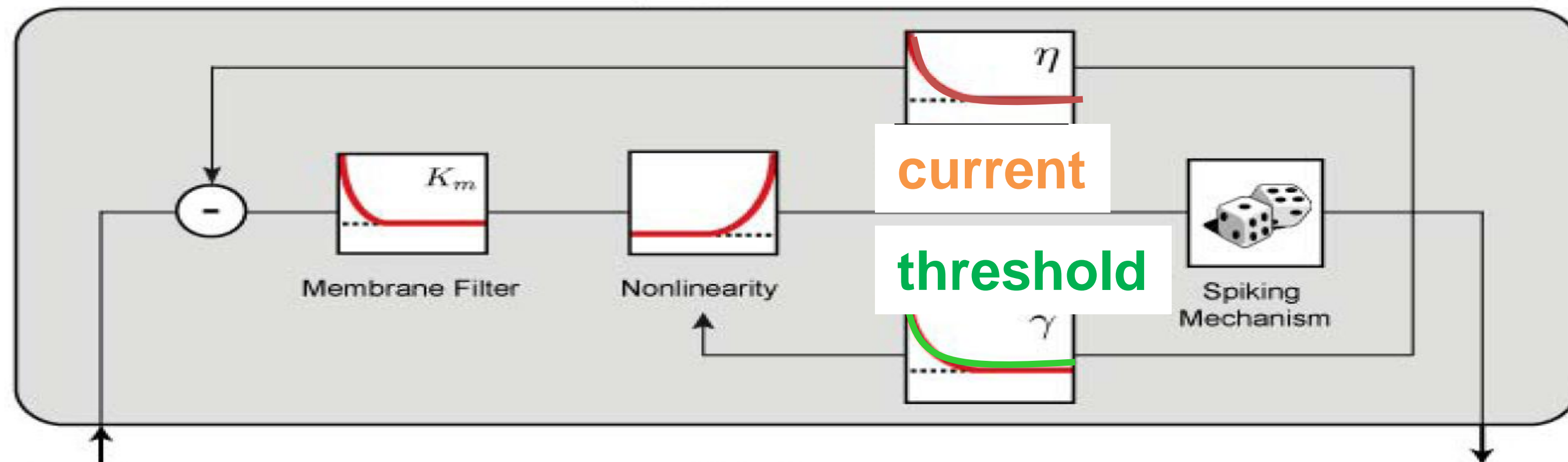
- spikes are events
- spike leads to reset/adapt. currents/increased threshold
- strict threshold replaced by escape noise:

$$\Pr \{ \text{fire in } [t; t + \Delta t] \} = \lambda(t) \Delta t = f[u(t) - \mathcal{G}(t)] \Delta t$$

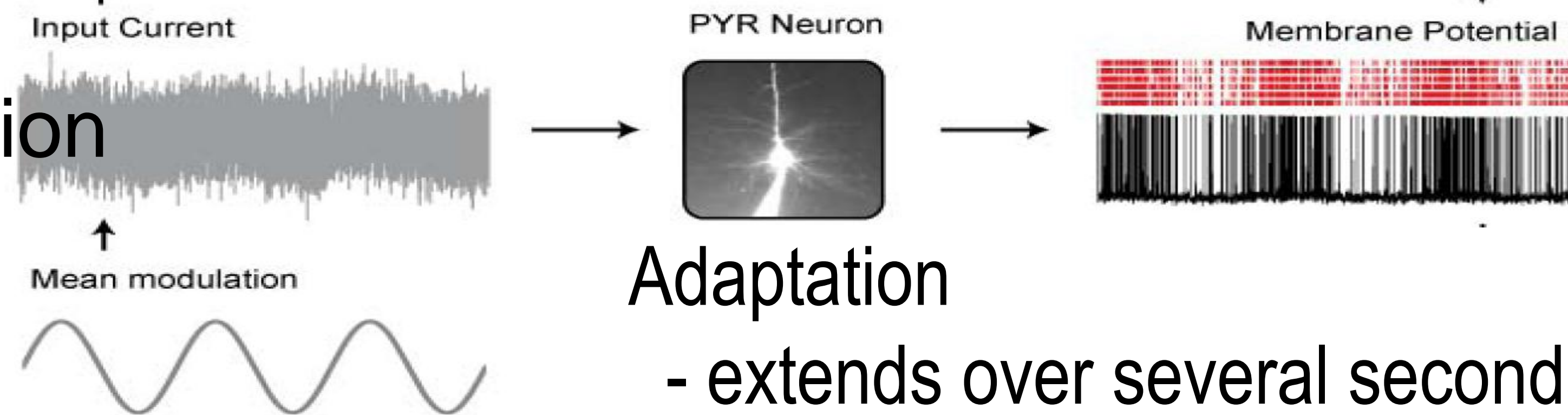
exp

Jolivet et al., J. Comput. NS, 2006

Spiking Neuron Model



Input current:
-Slow modulation
-Fast signal



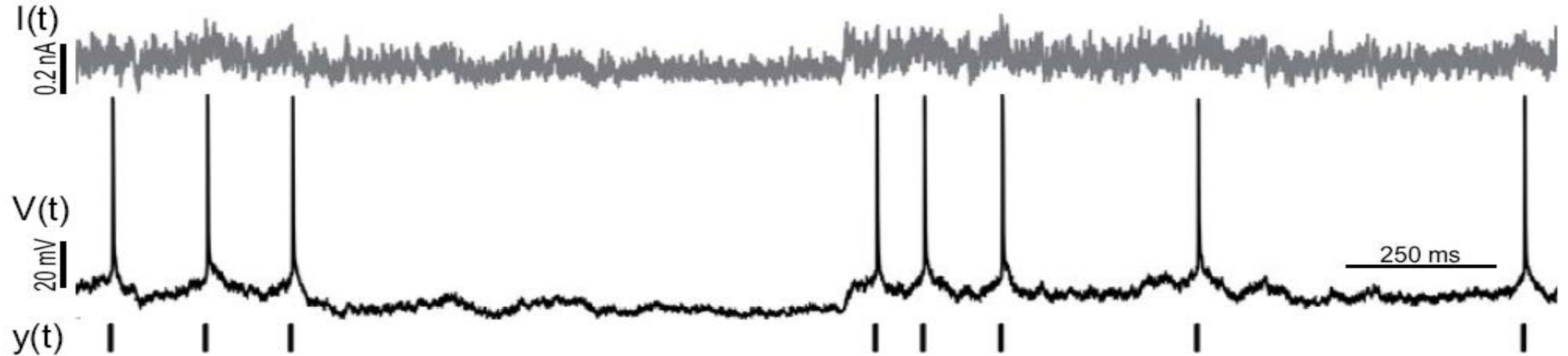
Adaptation

- extends over several seconds
- power law

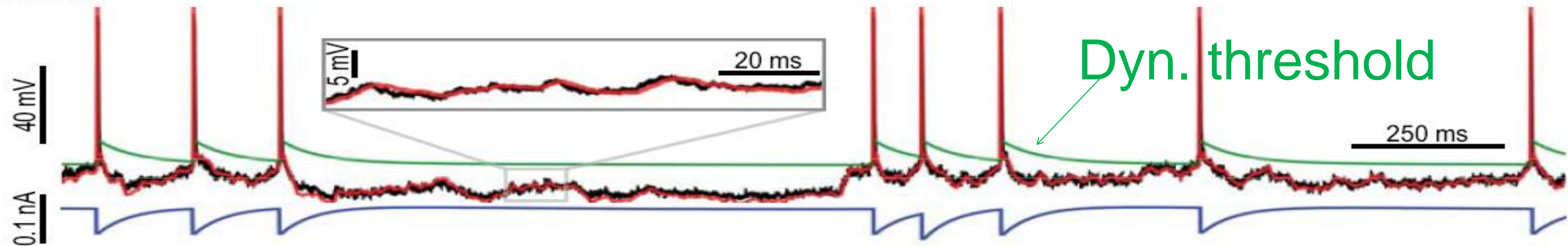
Pozzorini et al.
Nat. Neuros,
2013

Week 15-part 1: Predict spike times + voltage with SRM/GLM

A Experimental data set

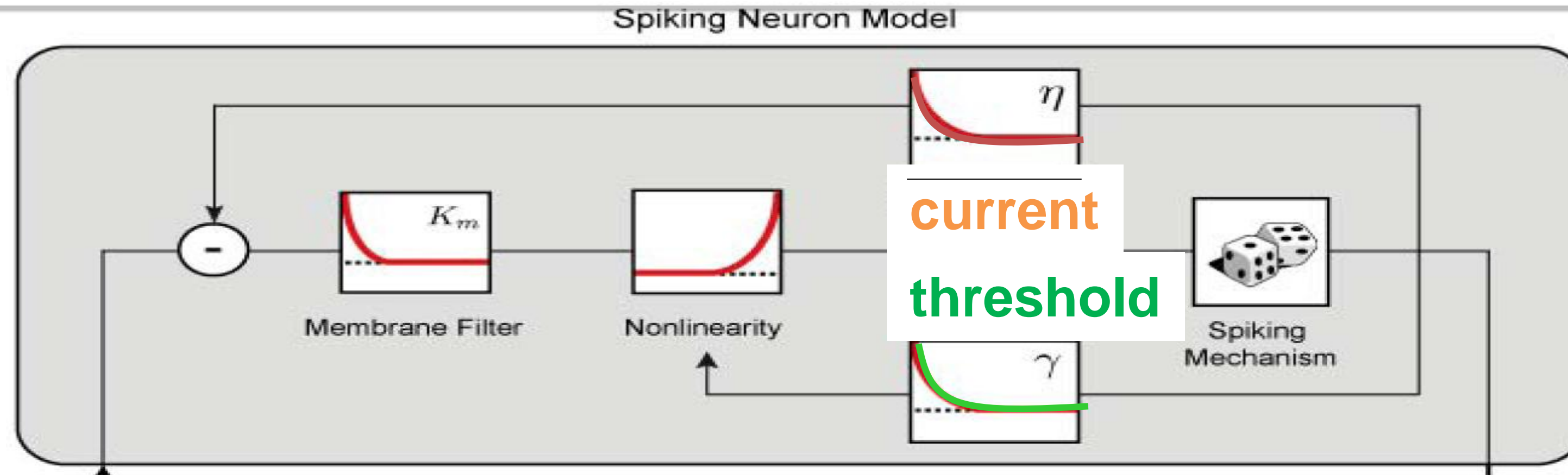


C Model



*Mensi et al. 2012,
Jolivet et al. 2007*

Week 15-part 1: Extract parameter for different neuron types



*Mensi et al.
2011*

Dynamic threshold

Pyramidal N.
Dyn. Threshold
VERY IMPORTANT

Fast Spiking
Dyn. Threshold
unimportant

Non-fast Spiking
Dyn. Threshold
important

Different neuron types have different parameters

Week 15-part 1: Summary and aims

- We can extract parameters for SINGLE neuron

(see NEURONAL DYNAMICS, Chs. 8-11)

- Different neuron types have different parameters

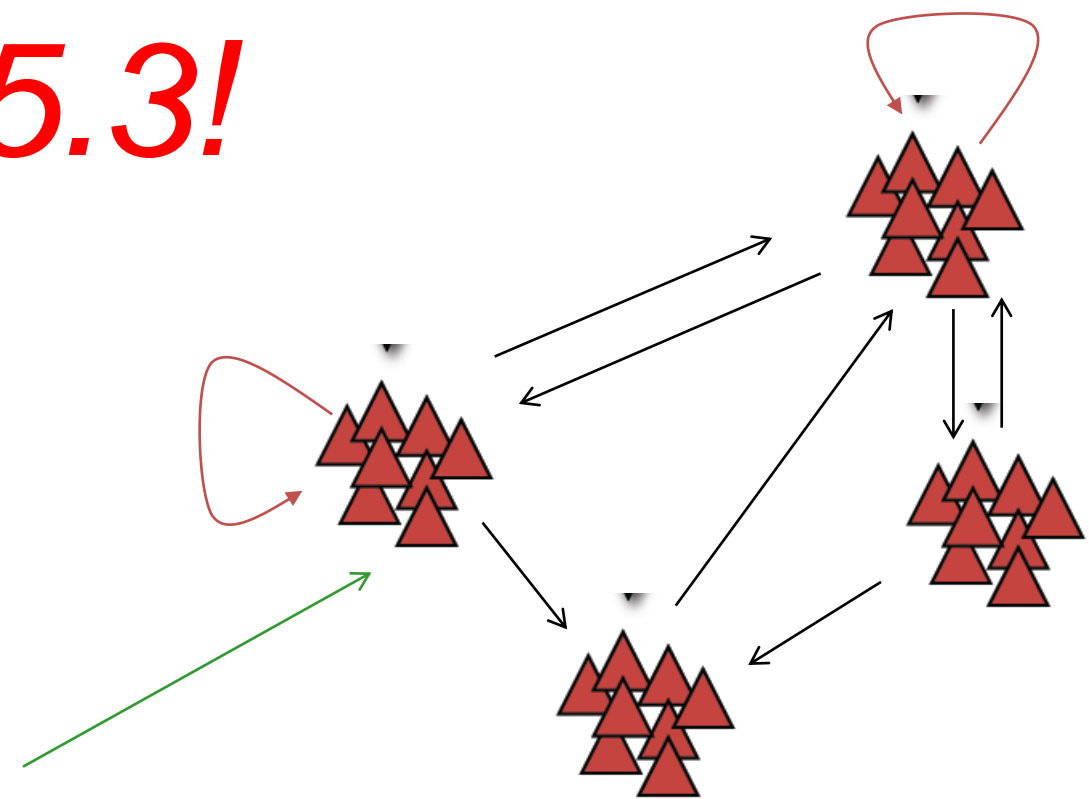
- Model Dynamics in one (homogeneous) population

Today, parts 15.2 and 15.3!

- Couple different populations

Today, parts 15.4!

Sensory input



Eventually: Understand Coding and Brain dynamics

Week 15 – Integral Equation for population dynamics



Biological Modeling of Neural Networks:

Week 15 – Population Dynamics: The Integral –Equation Approach

Wulfram Gerstner

EPFL, Lausanne, Switzerland

15.1 Populations of Neurons

- review: homogeneous population
- review: parameters of single neurons

15.2 Integral equation

- aim: population activity
- renewal assumption

15.3 Populations with Adaptation

- Quasi-renewal theory

15.4. Coupled populations

- self-coupling
- coupling to other populations

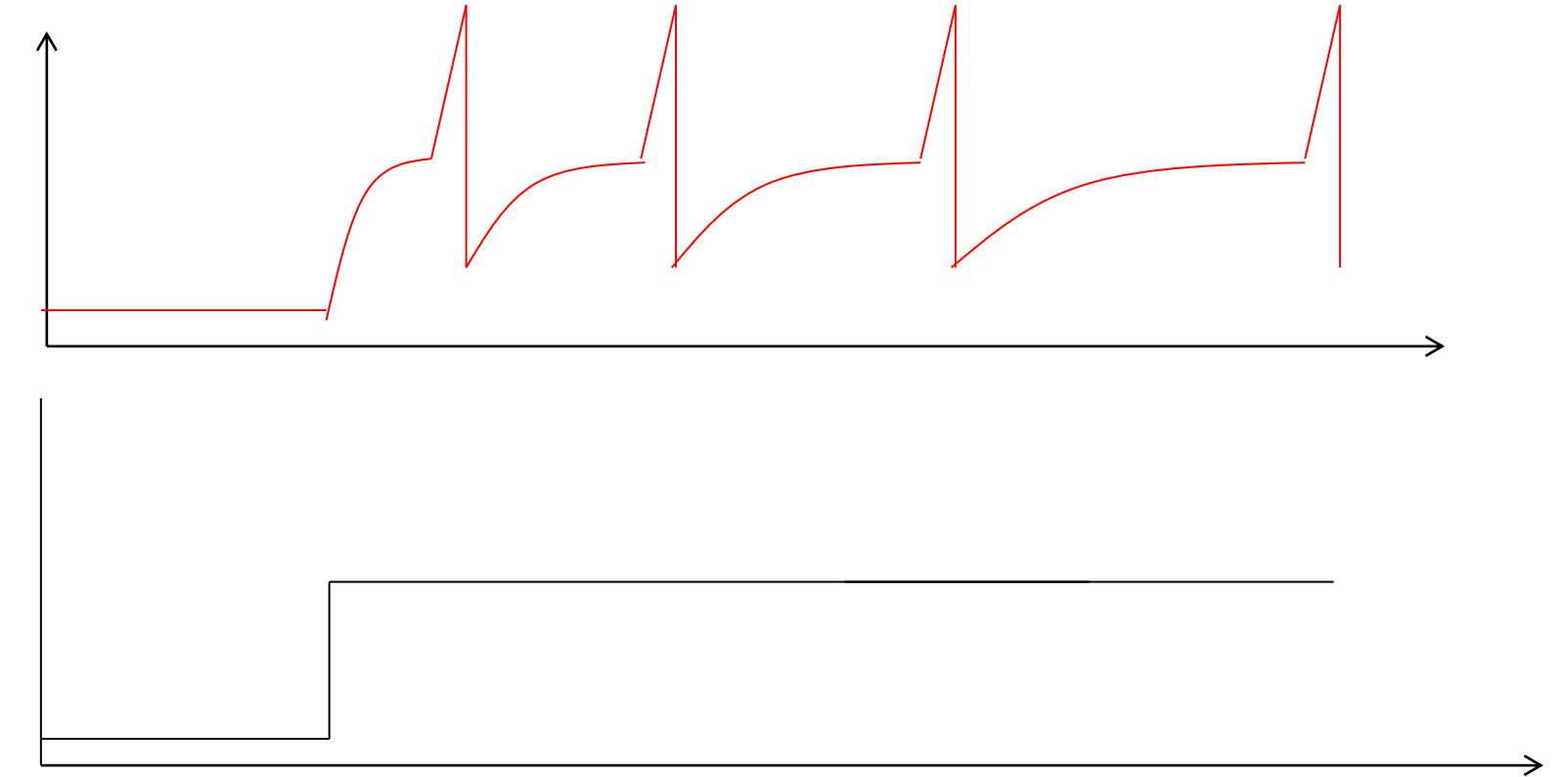
Week 15-part 2: Aim: from single neuron to population

Single neurons

- model exists
- parameters extracted from data
- works well for step current
- works well for time-varying current

$u(t)$

$I(t)$



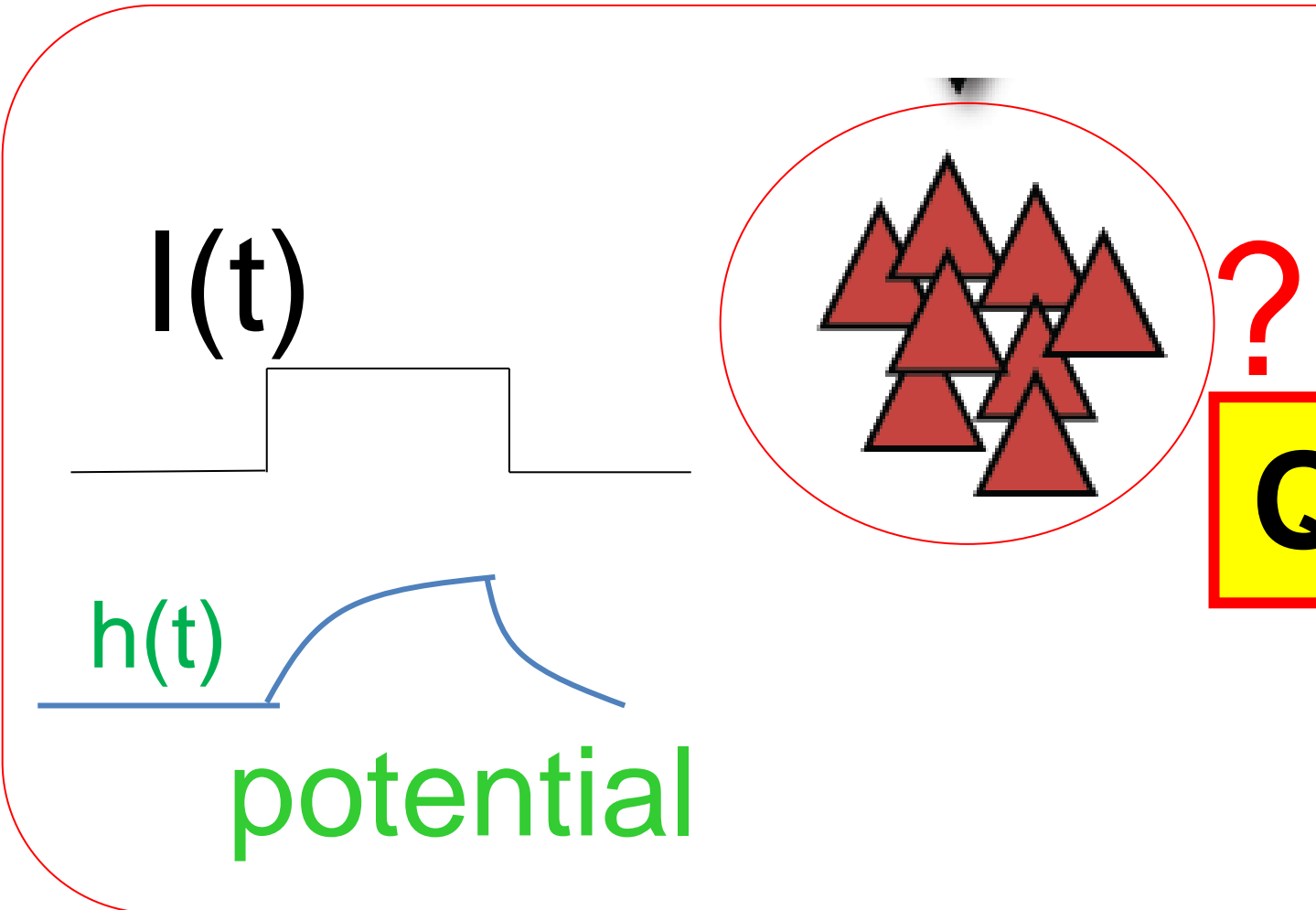
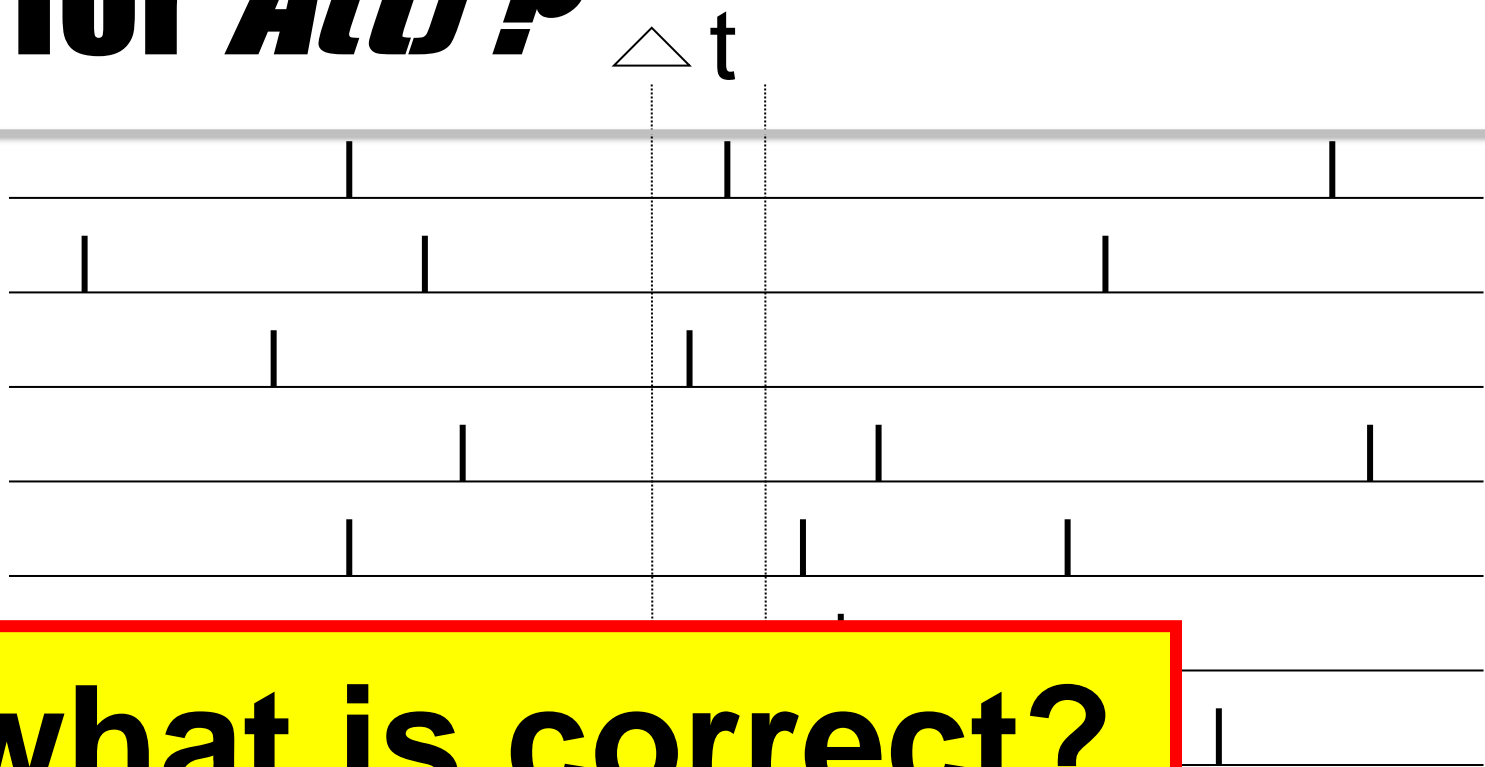
Population of Neurons?



Population equation for $A(t)$

- existing models
- integral equation

Week 15-part 2: population equation for $A(t)$?



Question: – what is correct?

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

$A(t)$ ~~Wilson-Cowan~~ $\tau \frac{d}{dt} A(t) = -A(t) + f(h(t))$

$A(t)$ ~~LNP~~ ~~Ostojic-Brunel~~ $A(t) = f(h(t)) = f(\int \varepsilon(s) I(t-s) ds)$

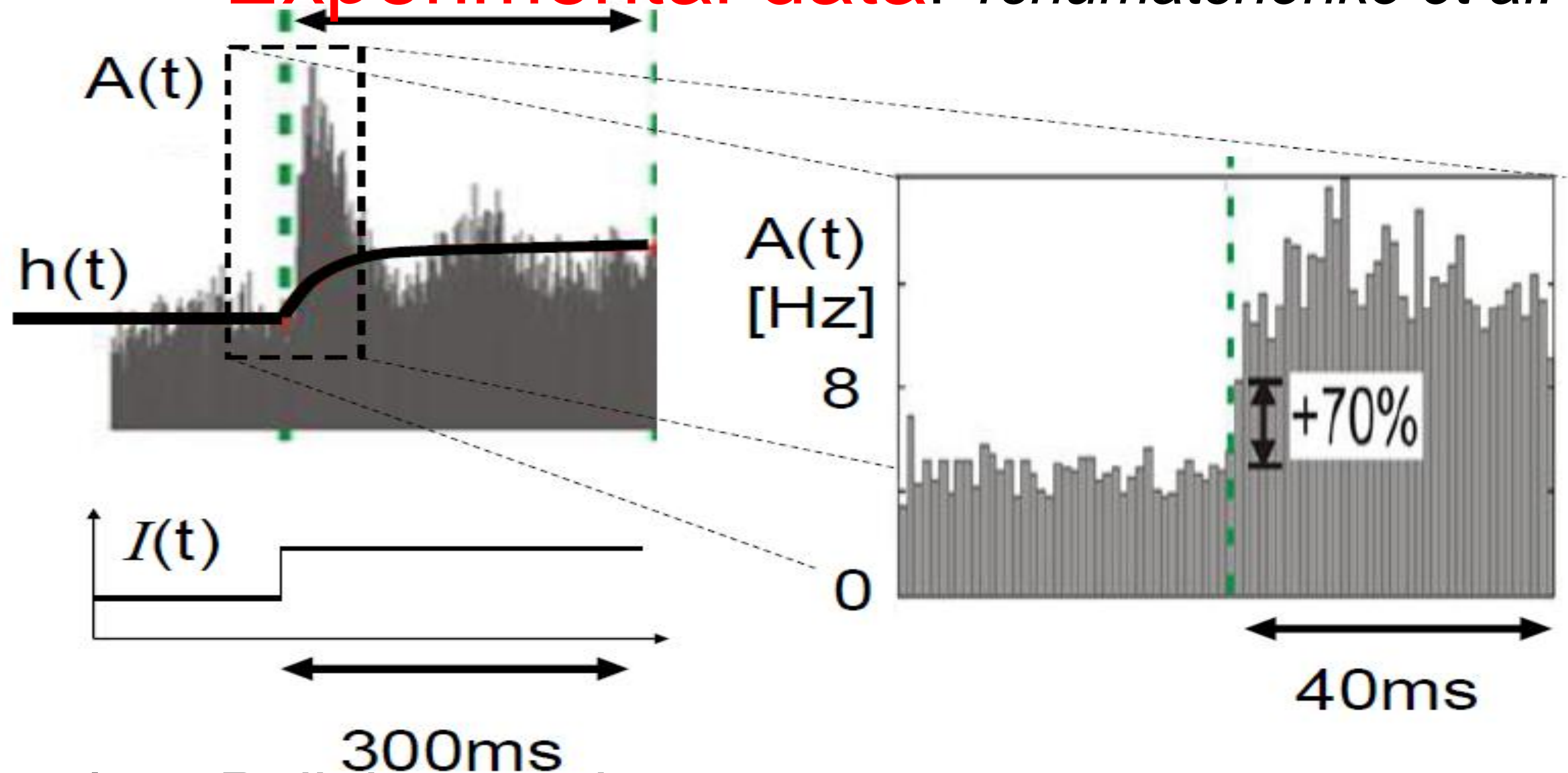
$A(t)$ ~~current~~ $A(t) = g(I(t))$

Poll!!!

$A(t)$ ~~Benda-Herz~~ $A(t) = g(I(t) - \int G(s) A(t-s) ds)$

Week 15-part 2: $A(t)$ in experiments: step current, (*in vitro*)

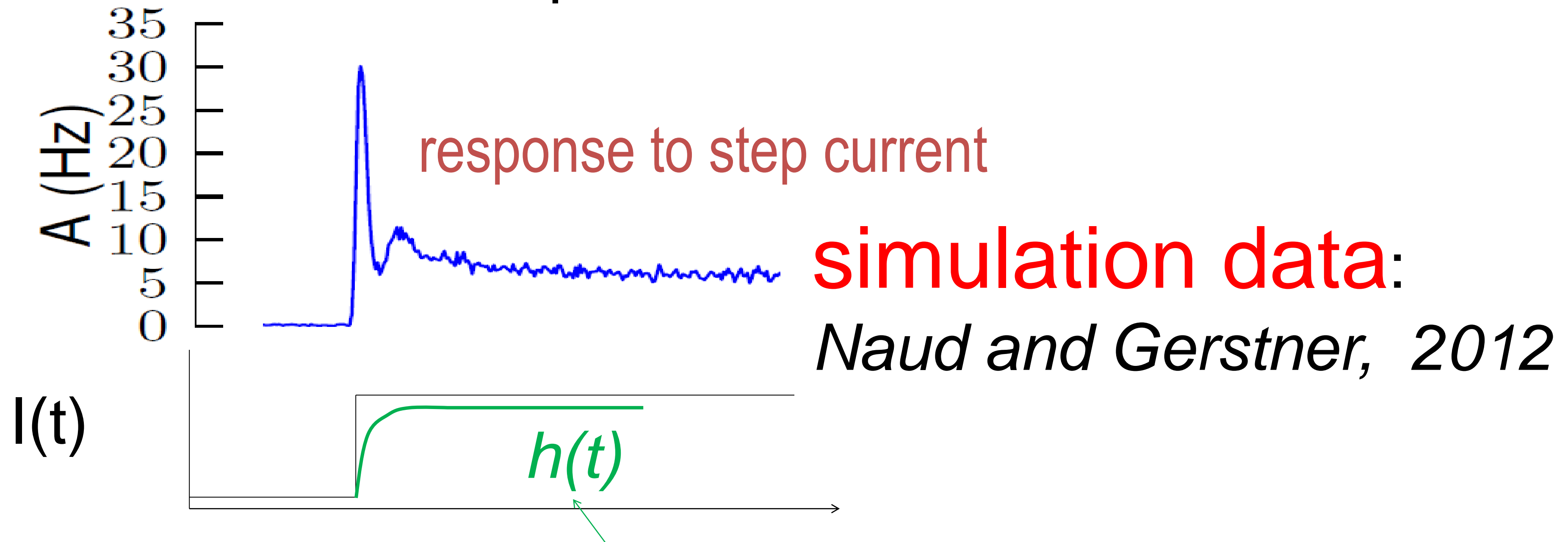
Experimental data: *Tchumatchenko et al. 2011*



See also: *Poliakov et al. 1997*

Week 15-part 2: $A(t)$ in simulations : step current

25000 identical model neurons (GLM/SRM with escape noise)
parameters extracted from experimental data



potential

$$u(t) = \sum_{t'} \eta(t - t') + \int_0^\infty \underbrace{\varepsilon(s) I(t - s) ds}_{h(t)} + \dots$$

Week 15-part 2: *A(t)* in theory: an equation?

Can we write down an equation for *A(t)* ?

Simplification: Renewal assumption

Potential (SRM/GLM) of one neuron

$$u(t) = \sum_{t'} \eta(t - t') + \int_0^\infty \varepsilon(s) I(t - s) ds$$

~~Sum over all past spikes~~

Keep only last spike

→ time-dependent renewal theory

h(t)

Week 15-part 2: Renewal theory (time dependent)

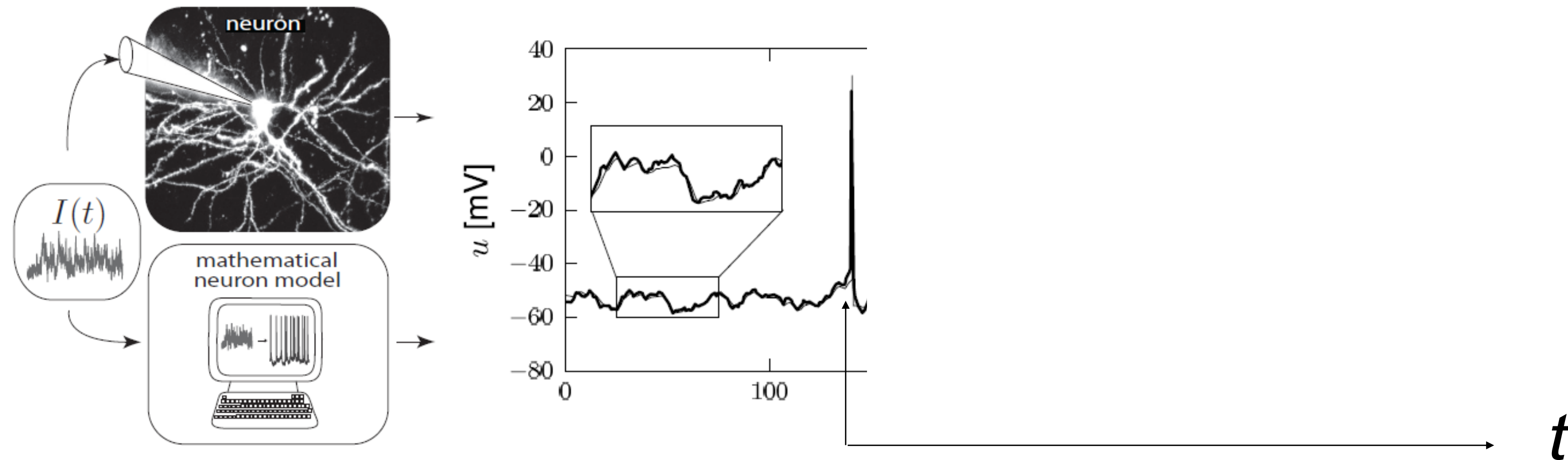
Keep only last spike → time-dependent renewal theory

Potential (SRM/GLM) of one neuron

$$u(t) = \eta(t - \hat{t}) + h(t)$$

last spike

Week 15-part 2: Renewal model –Example



deterministic part of input

$$I(t) \rightarrow u(t)$$

noisy part of input/intrinsic noise

\rightarrow *escape rate*

Example:
nonlinear integrate-and-fire model

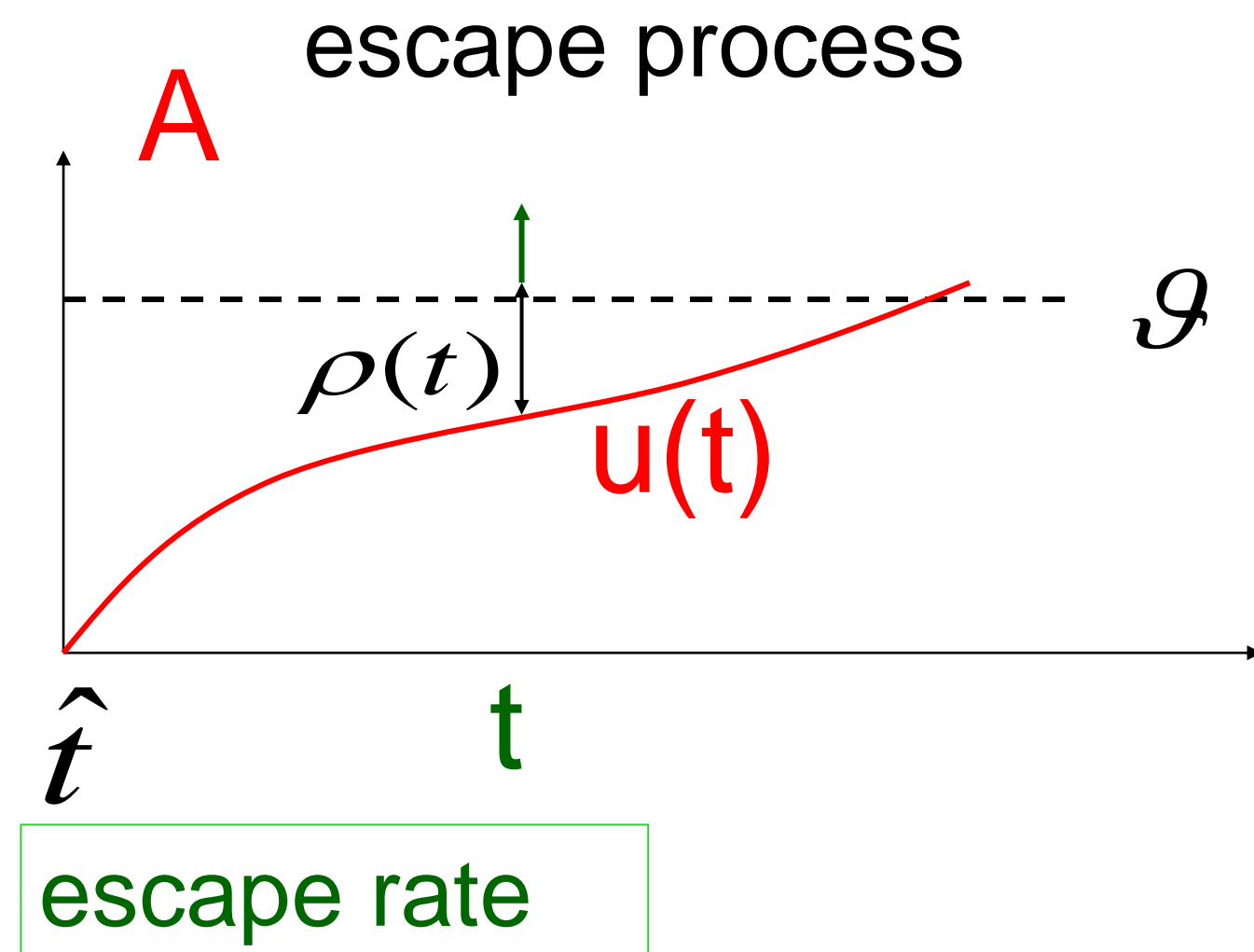
$$\tau \cdot \frac{d}{dt} u = F(u) + RI(t)$$

$$\text{if spike at } t^f \Rightarrow u(t^f + \delta) = u_r$$

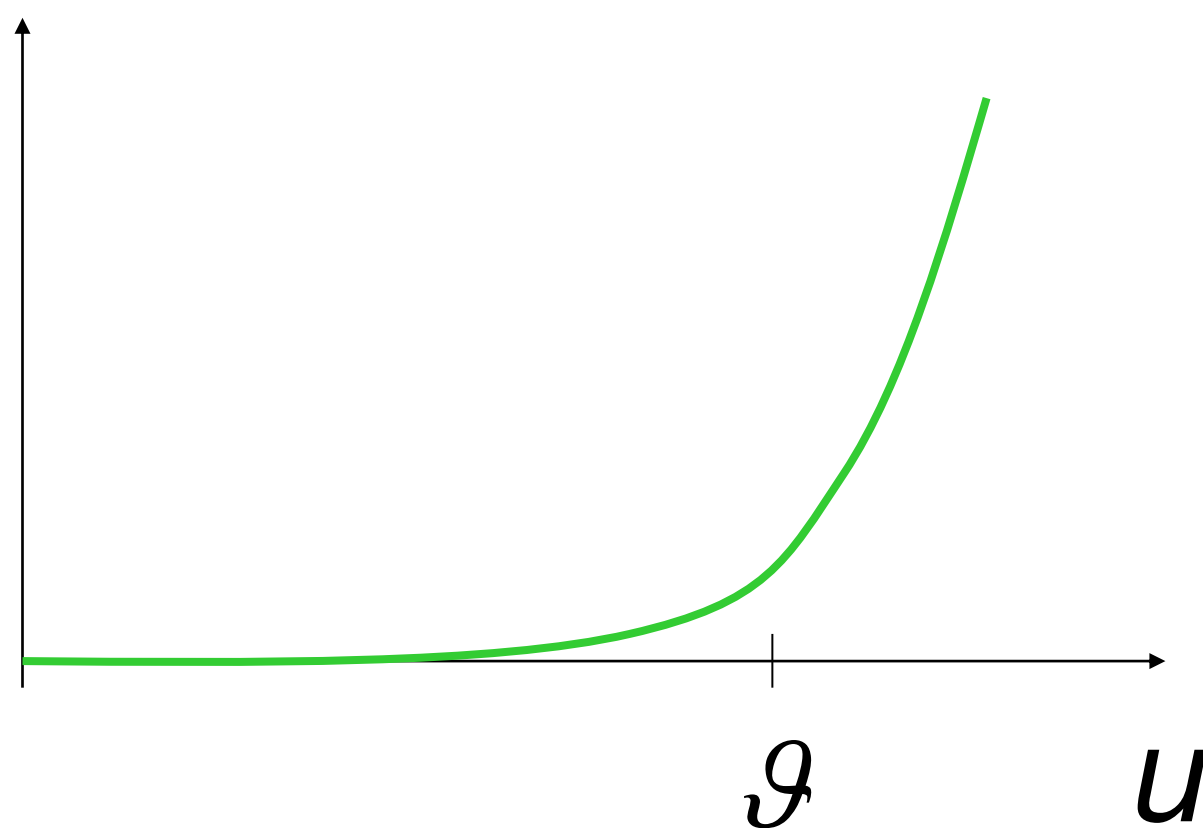
Example:
exponential stochastic intensity

$$\rho(t) = f(u(t)) = \rho_g \exp(u(t) - \mathcal{G})$$

Week 15-part 2: Renewal model - Interspike Intervals



$$\rho(t) = f(u(t) - \mathcal{G})$$



Survivor function

$$\frac{d}{dt} S_I(t|\hat{t}) = -\rho(t) S_I(t|\hat{t})$$

$$S_I(t|\hat{t}) = \exp\left(-\int_{\hat{t}}^t \rho(t') dt'\right)$$

Interval distribution

$$P_I(t|\hat{t}) = \underbrace{\rho(t)}_{\text{escape rate}} \cdot \underbrace{\exp\left(-\int_{\hat{t}}^t \rho(t') dt'\right)}_{\text{Survivor function}}$$

Week 15-part 2: Renewal model – Integral equation

population activity

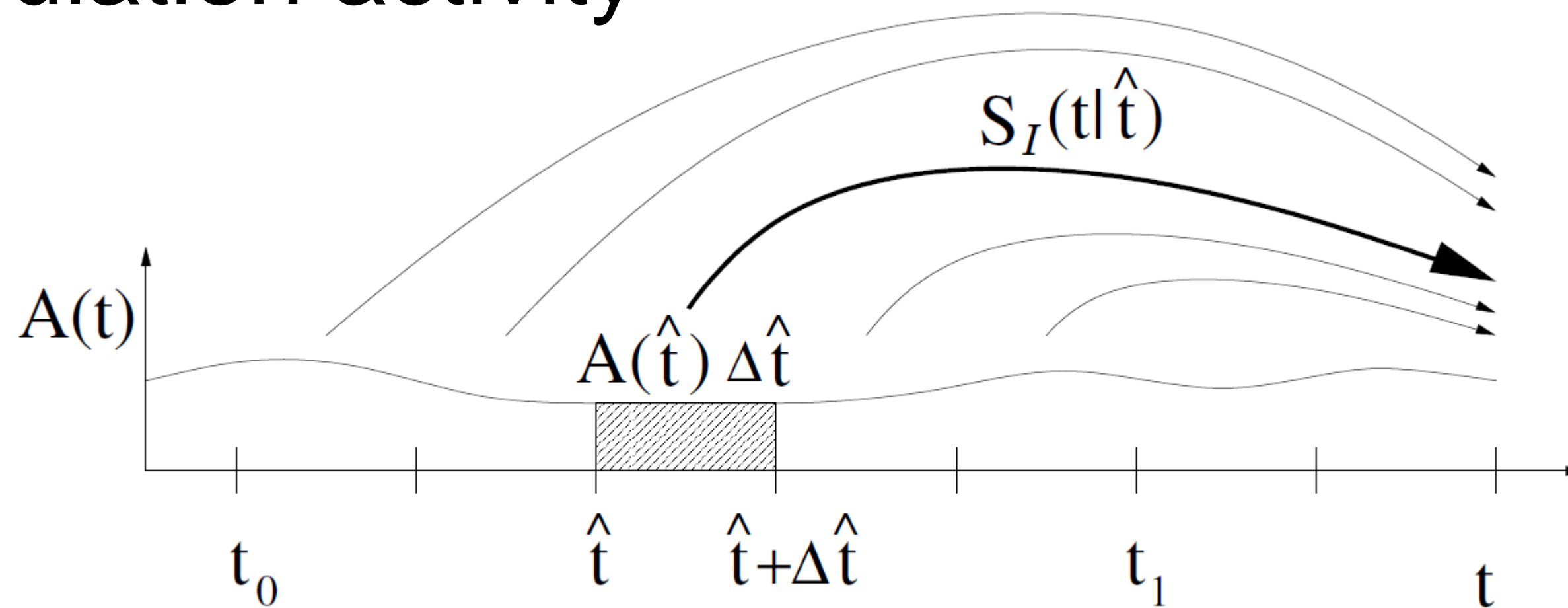


Image:

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

Blackboard!

$$A(t) = \int_{-\infty}^t P_I(t | \hat{t}) A(\hat{t}) d\hat{t}$$

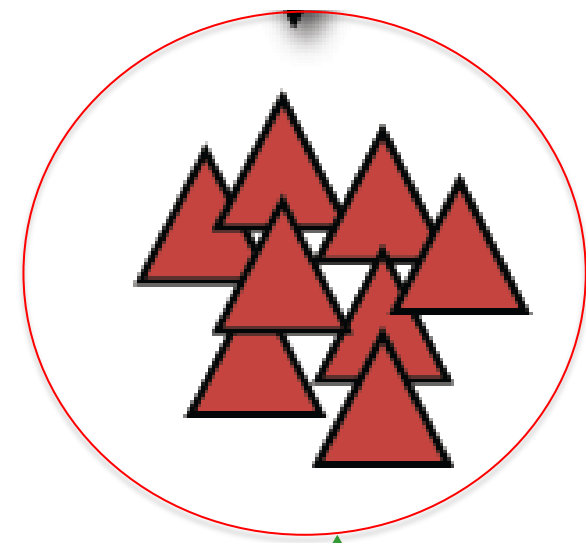
Interval distribution

$$P_I(t | \hat{t}) = \underbrace{\rho(t)}_{\text{escape rate}} \cdot \exp\left(-\underbrace{\int_{\hat{t}}^t \rho(t') dt'}_{\text{Survivor function}}\right)$$

Gerstner 1995, 2000; Gerstner&Kistler 2002
See also: Wilson&Cowan 1972

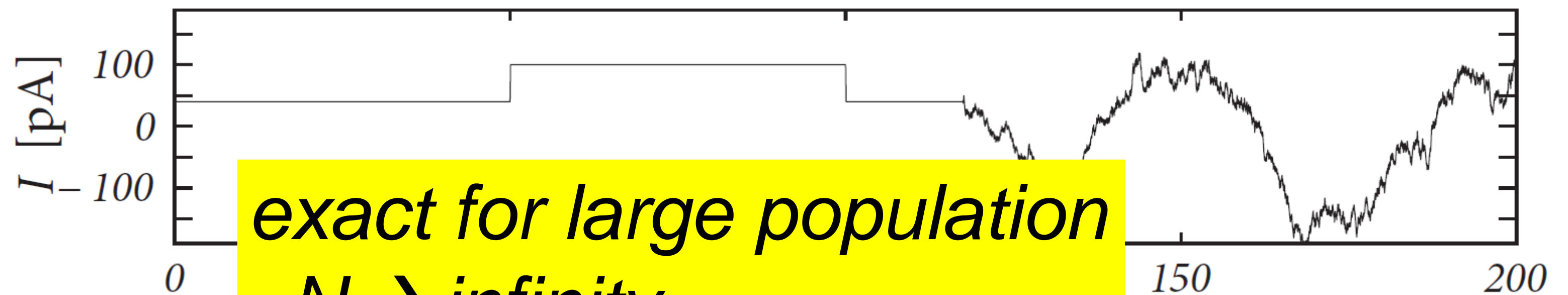
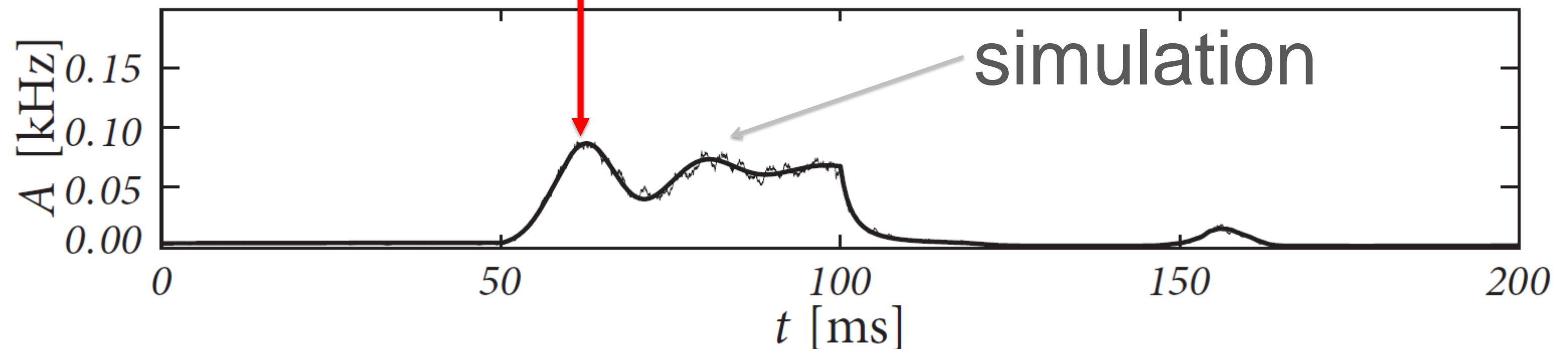
Week 15-part 2: Integral equation – example: LIF

population of
leaky integrate-and-fire
neurons w. escape noise



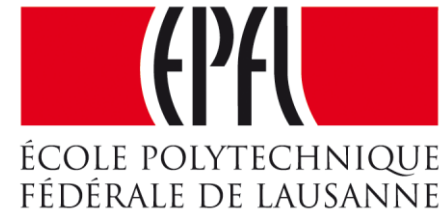
input

$$A(t) = \int_{-\infty}^t P_I(t|\hat{t}) A(\hat{t}) d\hat{t}$$



*exact for large population
 $N \rightarrow \text{infinity}$*

Week 15 – Integral Equation for population dynamics



Biological Modeling of Neural Networks:

Week 15 – Population Dynamics: The Integral –Equation Approach

Wulfram Gerstner

EPFL, Lausanne, Switzerland

15.1 Populations of Neurons

- review: homogeneous population
- review: parameters of single neurons

15.2 Integral equation

- aim: population activity
- renewal assumption

15.3 Populations with Adaptation

- Quasi-renewal theory

15.4. Coupled populations

- self-coupling
- coupling to other populations

Week 15-part 3: Neurons with adaptation

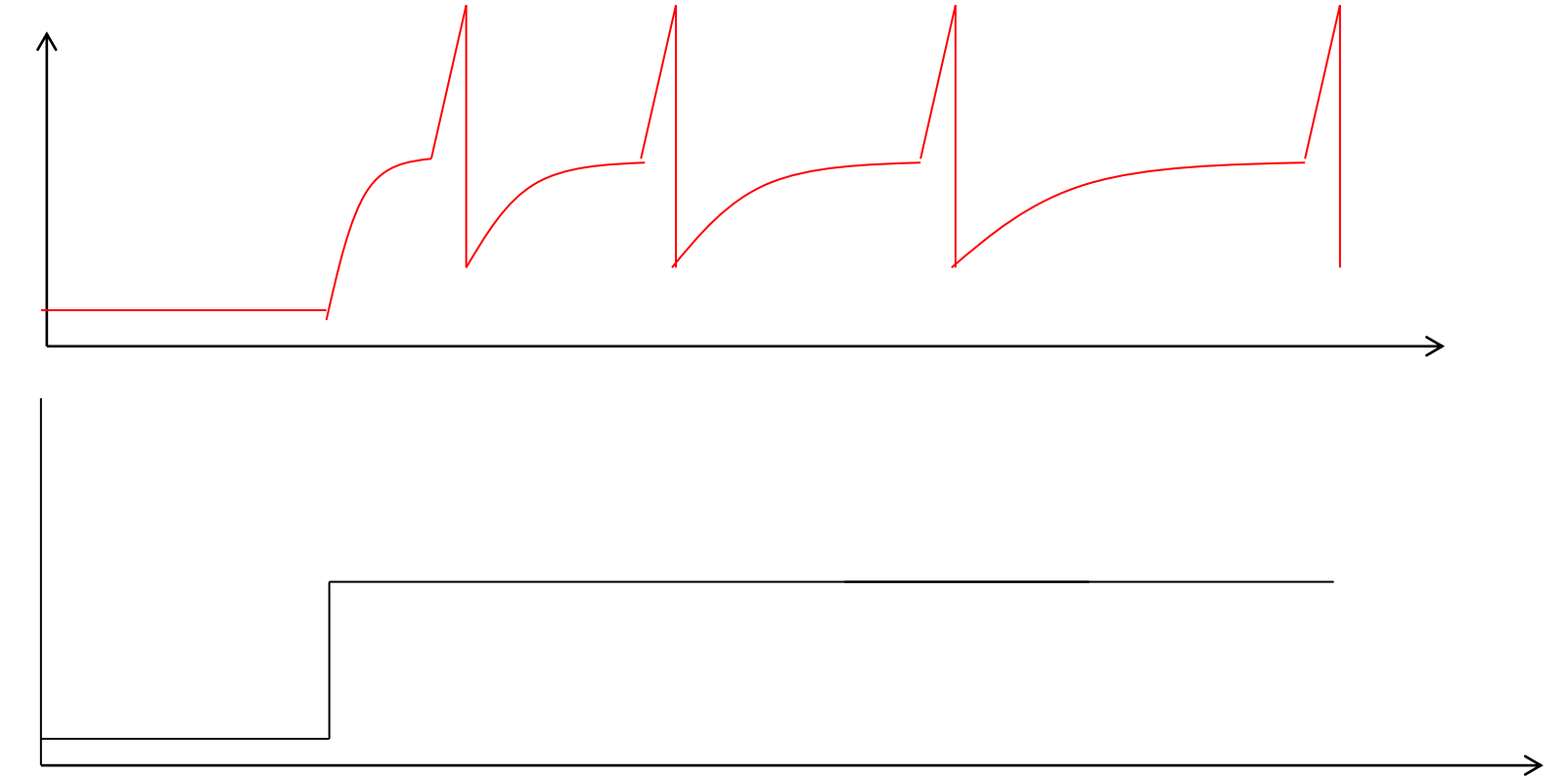
Real neurons show **adaptation** on multiple time scales

Single neurons

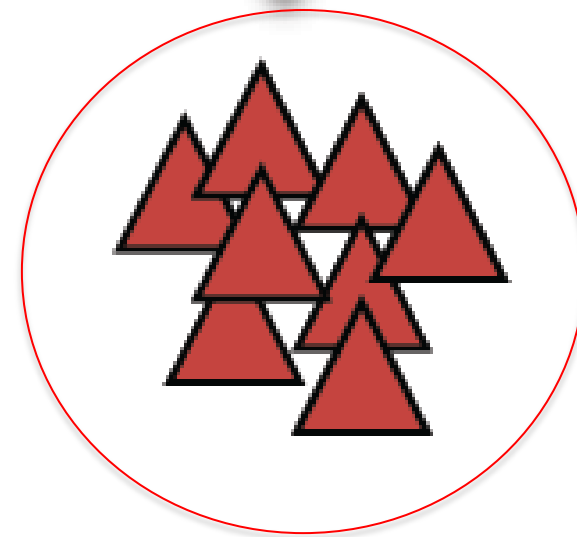
- model exists
- parameters extracted from data
- works well for step current
- works well for time-varying current

$u(t)$

$I(t)$



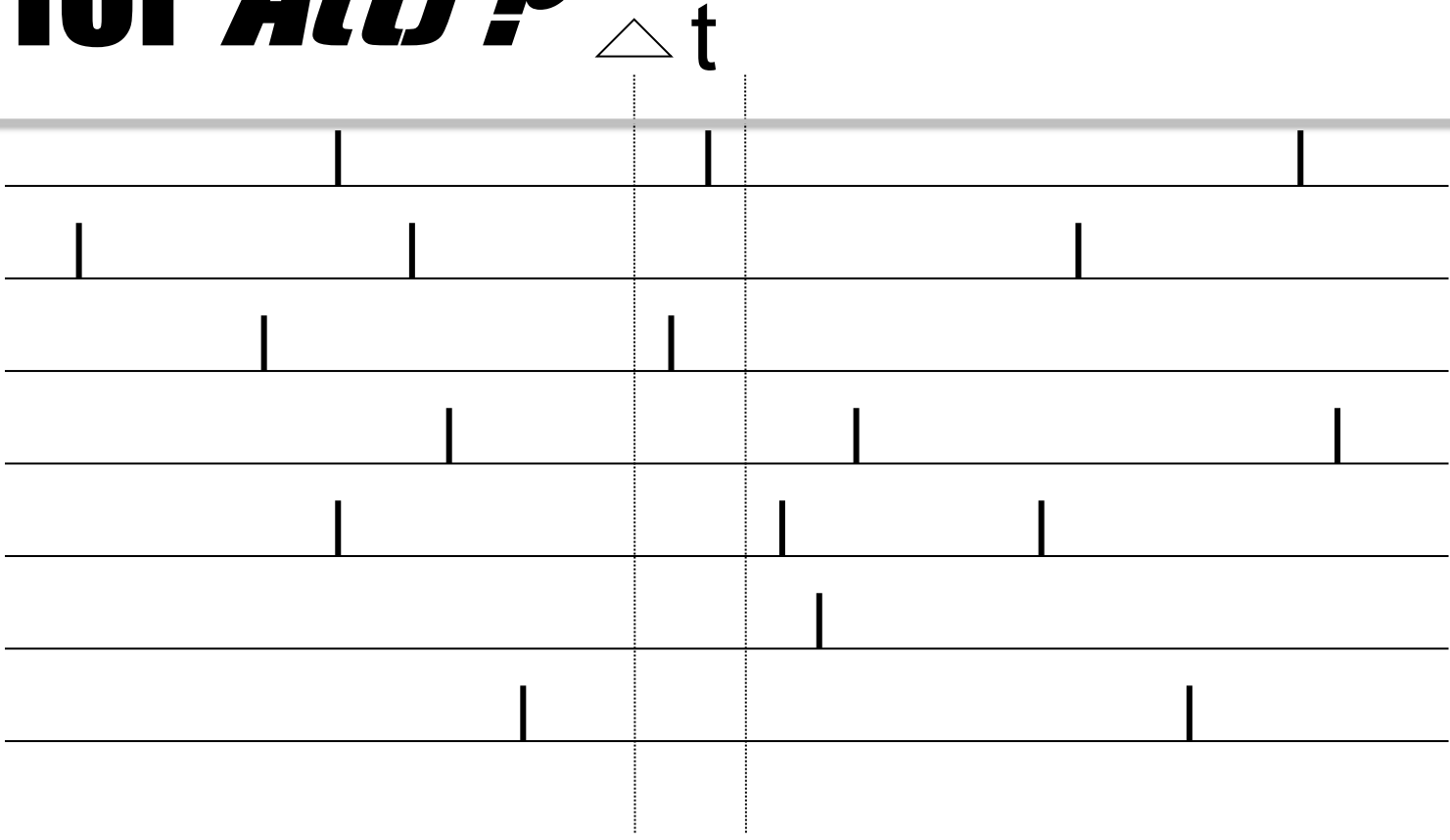
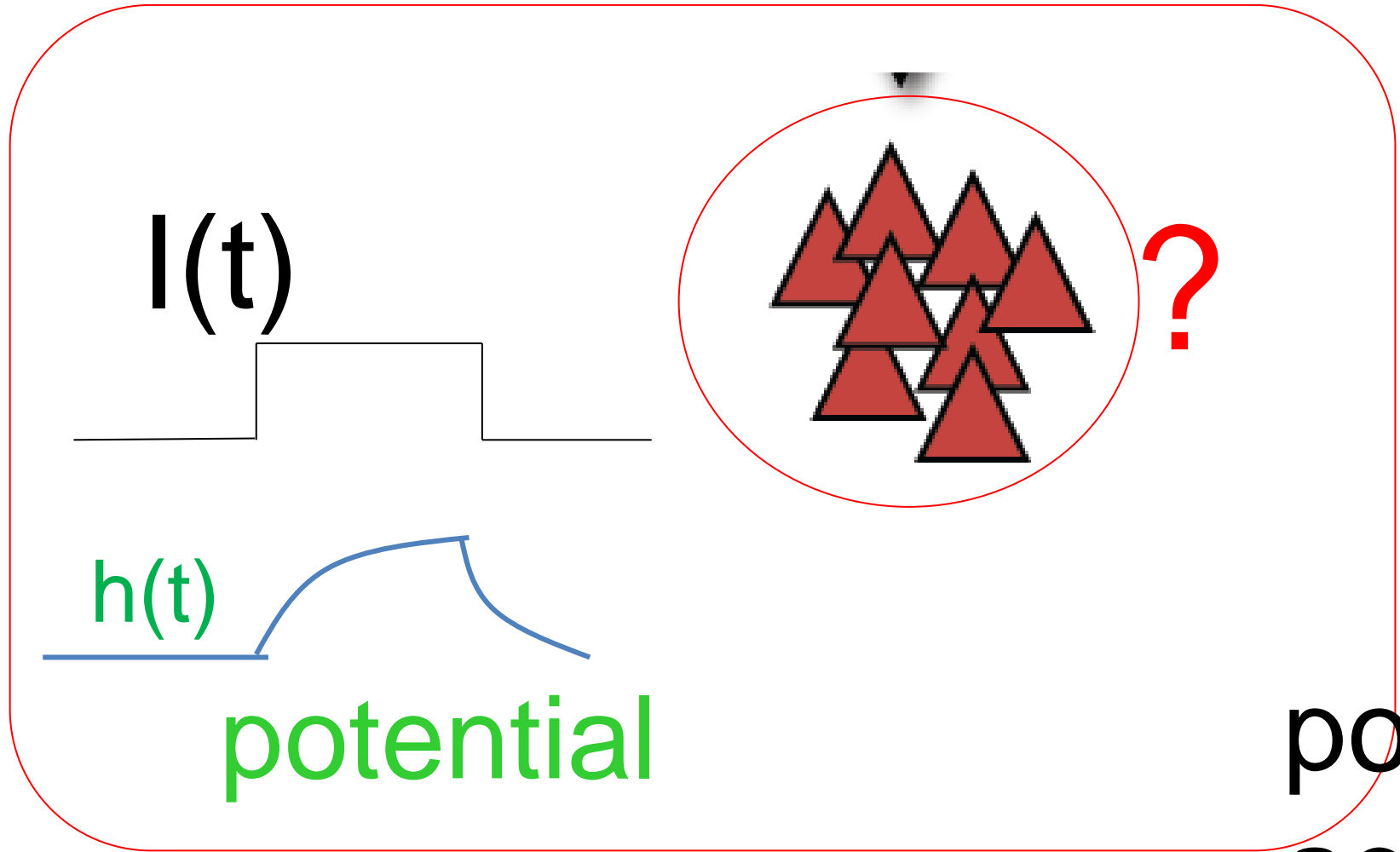
Population of **adapting** Neurons?



Population equation for $A(t)$

- existing modes
- integral equation

Week 15-part 3: population equation for $A(t)$?



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

- $A(t)$

Wilson-Cowan
- $A(t)$

LNP
- $A(t)$

current
- $A(t)$

Benda-Herz
- $$\tau \frac{d}{dt} A(t) = -A(t) + f(h(t))$$
- $$A(t) = f(\underline{h(t)}) = f(\int \varepsilon(s) I(t-s) ds)$$
- $$A(t) = g(I(t))$$
- $$A(t) = g(I(t) - \int G(s) A(t-s) ds)$$

Week 15-part 3: neurons with adaptation – $A(t)$?

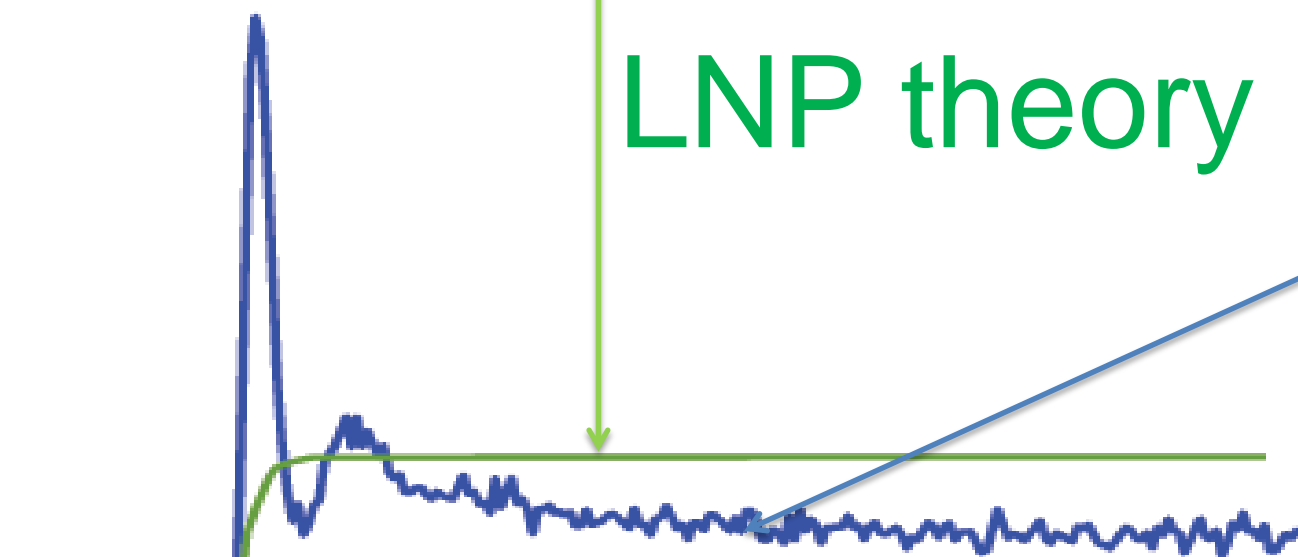
1) LNP

$I(t)$



$$A(t) = f(h(t)) \sim e^{h(t)}$$

$A(t)$

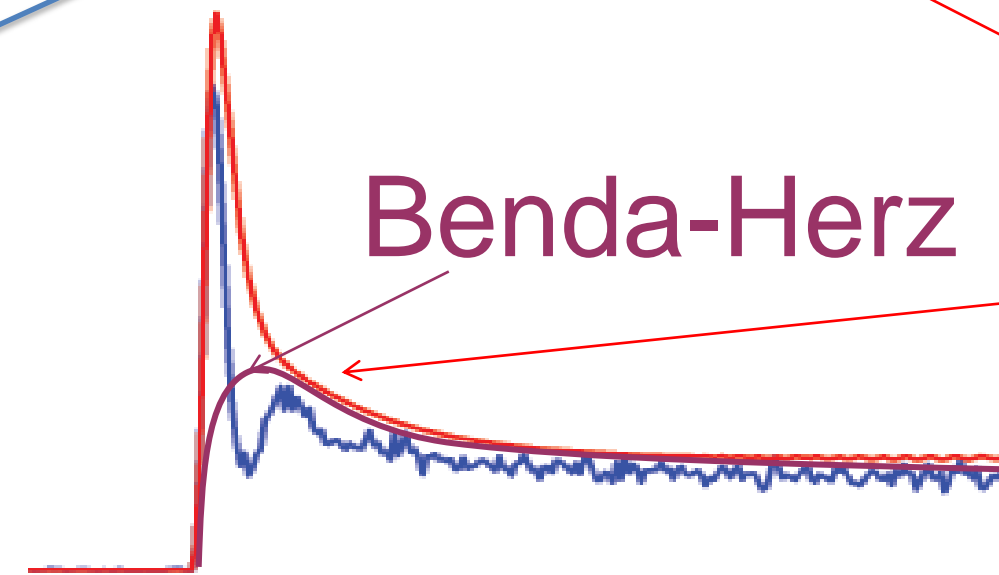


LNP theory

2) Rate adapt.



$$e^{h(t) - [g * A](t)}$$



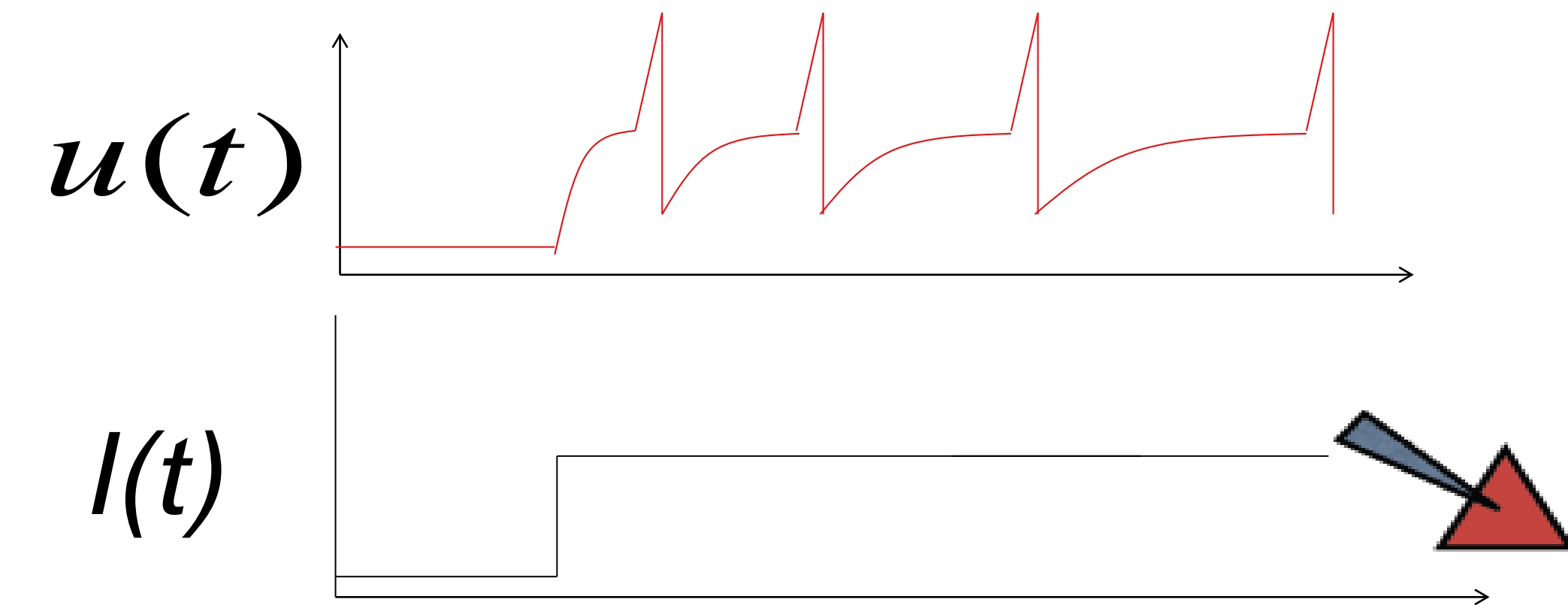
Benda-Herz

Naud and Gerstner 2012

simulation

optimal filter
(rate
adaptation)

Week 15-part 3: population equation for **adapting** neurons?

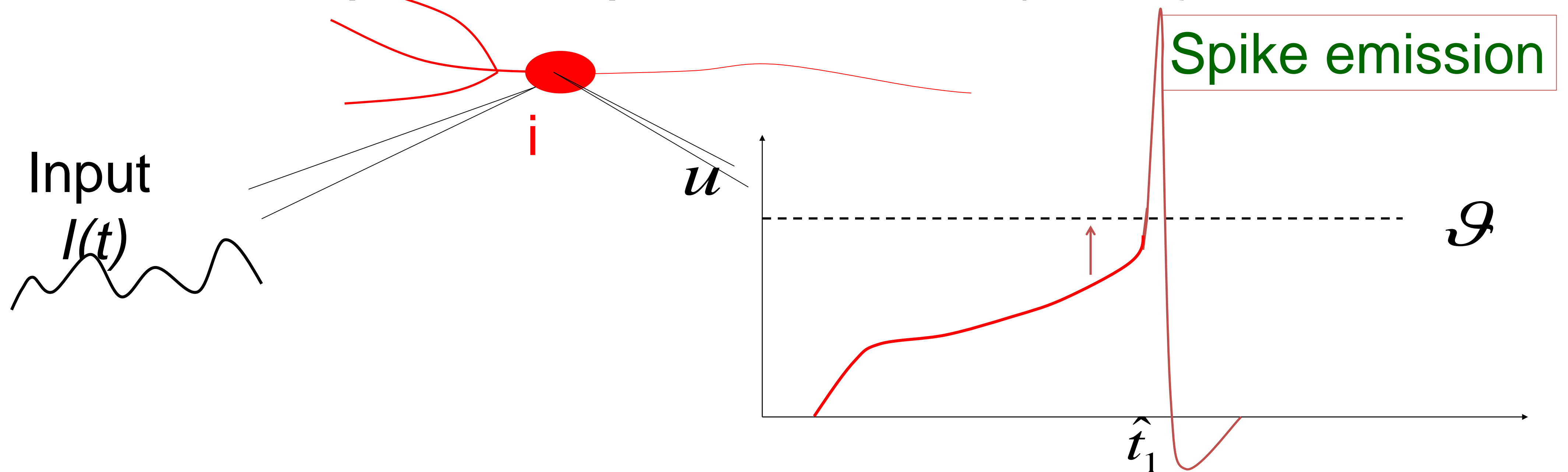


Population of
Adapting Neurons?



- 1) Linear-Nonlinear-Poisson (LNP): ***fails!***
- 2) Phenomenological rate adaptation: ***fails!***
- 3) Time-Dependent-Renewal Theory ?
→ Integral equation of previous section

Spike Response Model (SRM)



$$\text{potential } u(t) = \sum_{\hat{t}} \underline{\eta(t - \hat{t})} + \int_0^\infty \underbrace{\varepsilon(s) I(t - s) ds}_{h(t)} + \dots$$

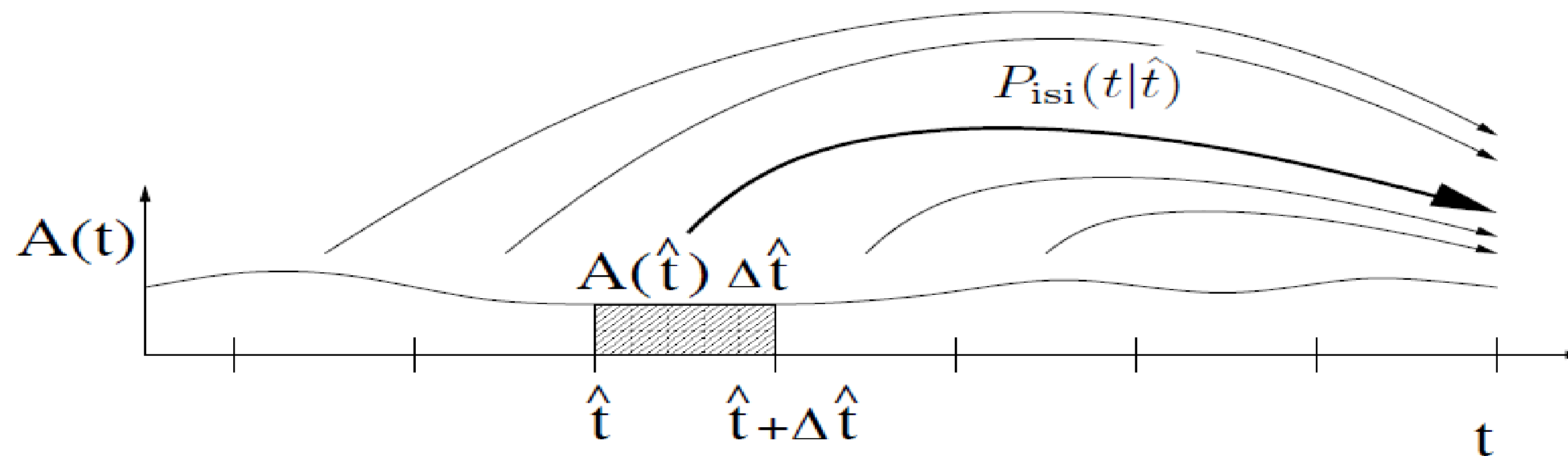
$$\Pr \{ \text{fire in } [t; t + \Delta t] \} = \lambda(t) \Delta t = f[u(t) - \mathcal{G}(t)] \Delta t$$

$$\lambda(t) = \lambda(t \mid h(t))$$

Time-dependent **Renewal** theory

Renewal assumption:

$$\lambda(t | h(t), \hat{t}_1, \hat{t}_2, \hat{t}_3, \dots) \approx \lambda(t | h(t), \hat{t})$$



last firing
time

$$A(t) = \int P_{isi}(t | h, \hat{t}) A(\hat{t}) d\hat{t}$$

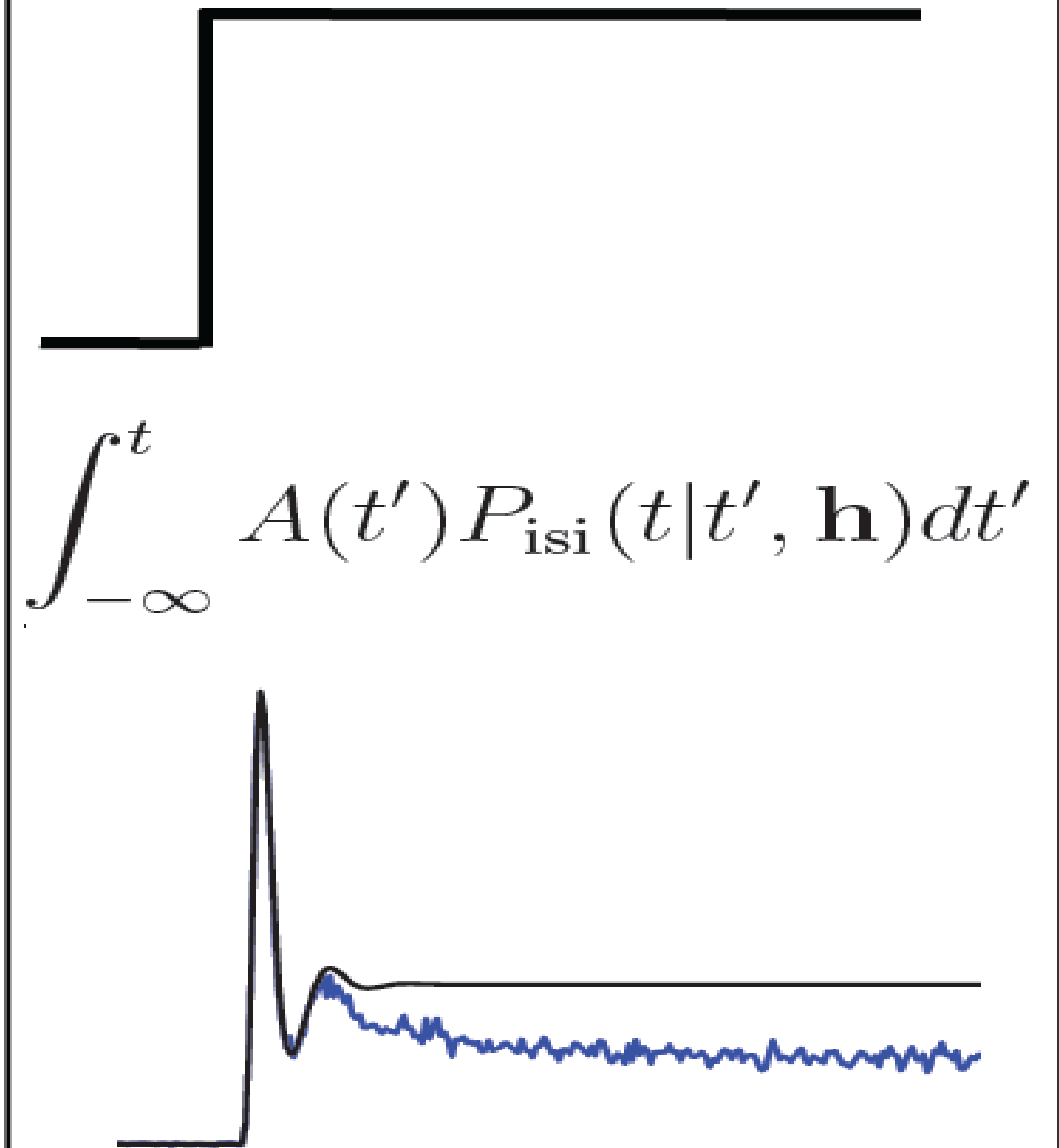
Gerstner 1995, 2000; Gerstner&Kistler 2002

See also: *Wilson&Cowan 1972*

interspike interval distribution

$$P_{isi}(t | \hat{t}) = \lambda(t | \hat{t}) e^{-\int_{\hat{t}}^t \lambda(x | \hat{t}) dx}$$

3) Renewal



Gerstner 1995

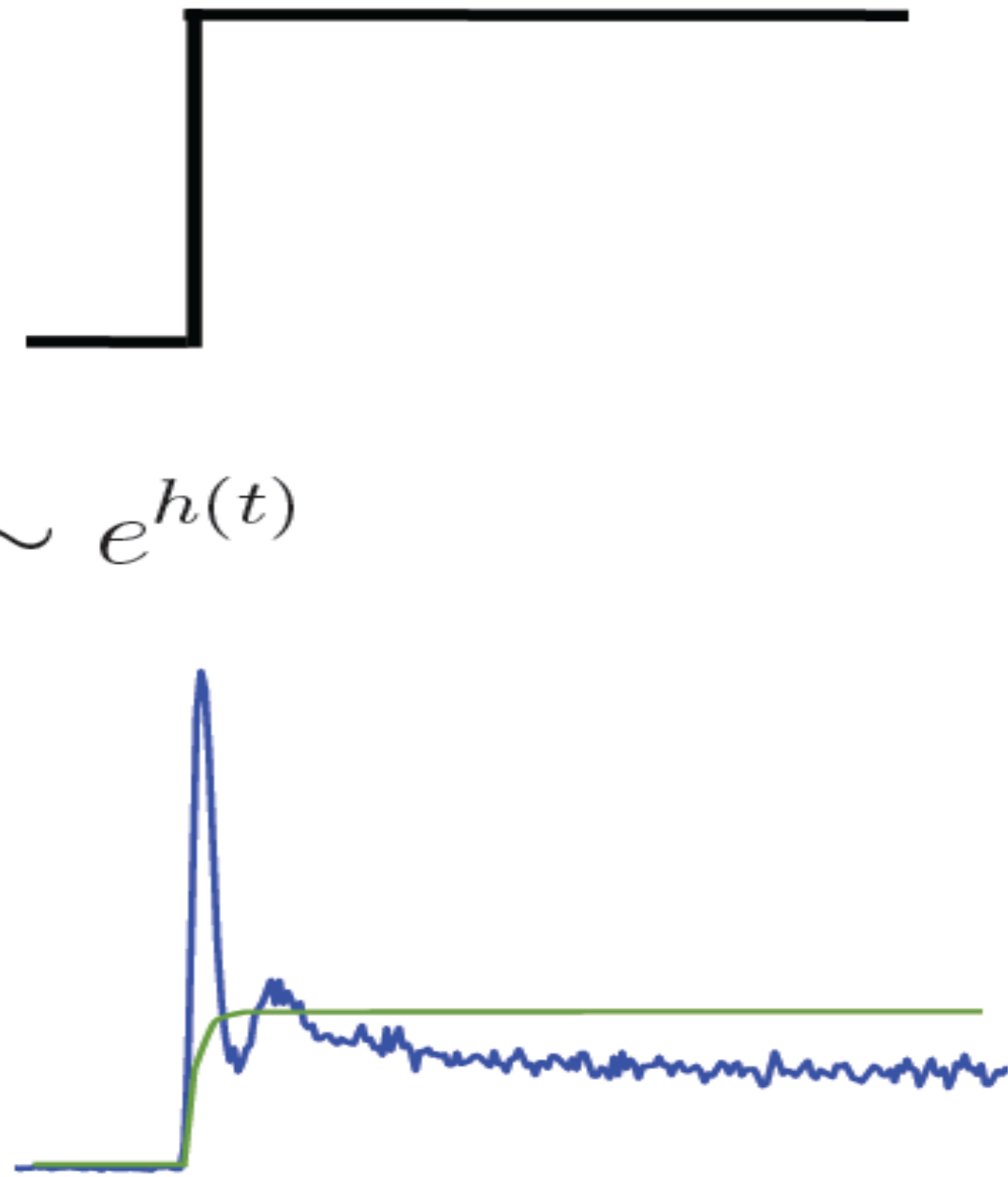
Week 15-part 3: population equation for **adapting** neurons?

1) LNP

$h(t)$

$$A(t) \sim e^{h(t)}$$

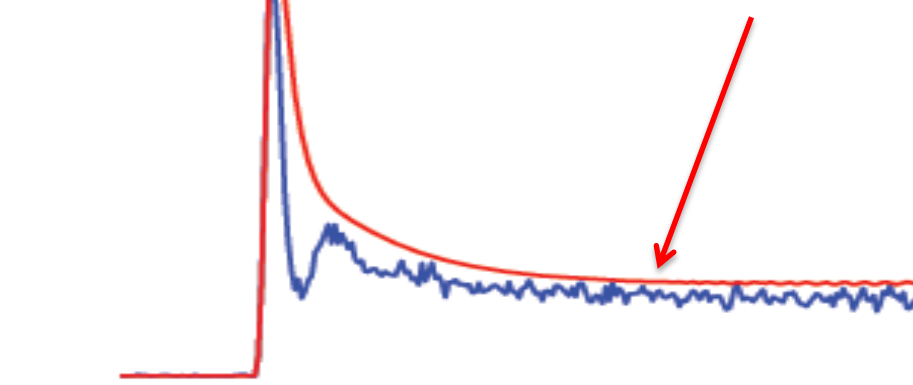
$A(t)$



2) Rate adapt.

$$e^{h(t) - [g * \mathbf{A}](t)}$$

OK in late phase



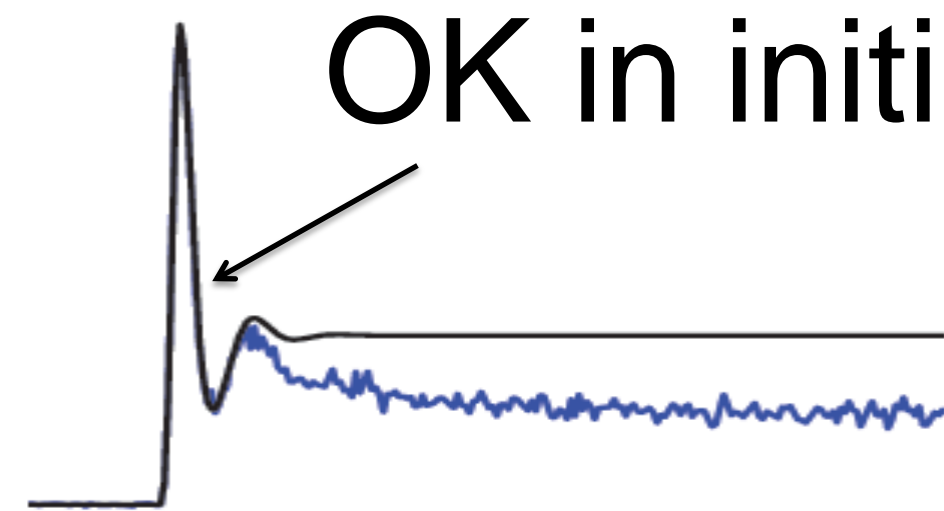
Benda and Herz 2003
Naud and Gerstner 2012

CAUTION
RESTRICTED
AREA

3) Renewal

$$\int_{-\infty}^t A(t') P_{\text{isi}}(t|t', \mathbf{h}) dt'$$

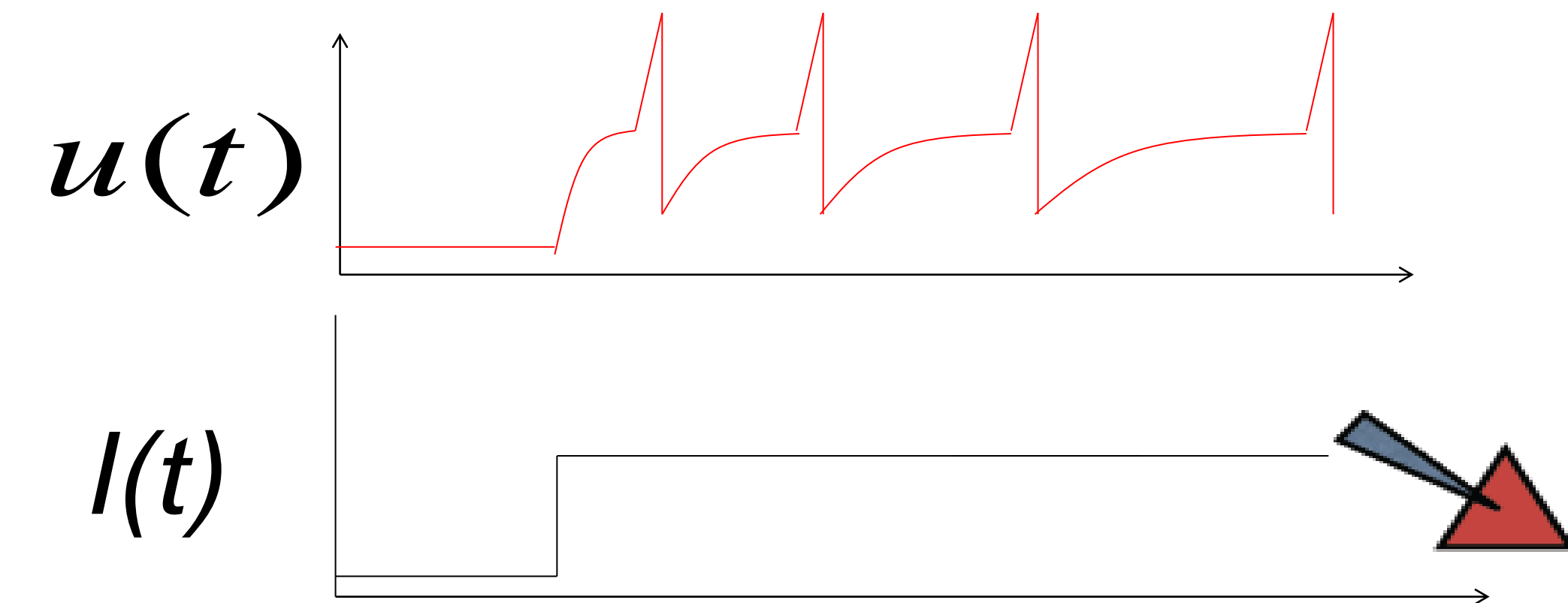
OK in initial phase



Gerstner 1995

CAUTION
RESTRICTED
AREA

Week 15-part 3: population equation for **adapting** neurons



Population of
Adapting Neurons



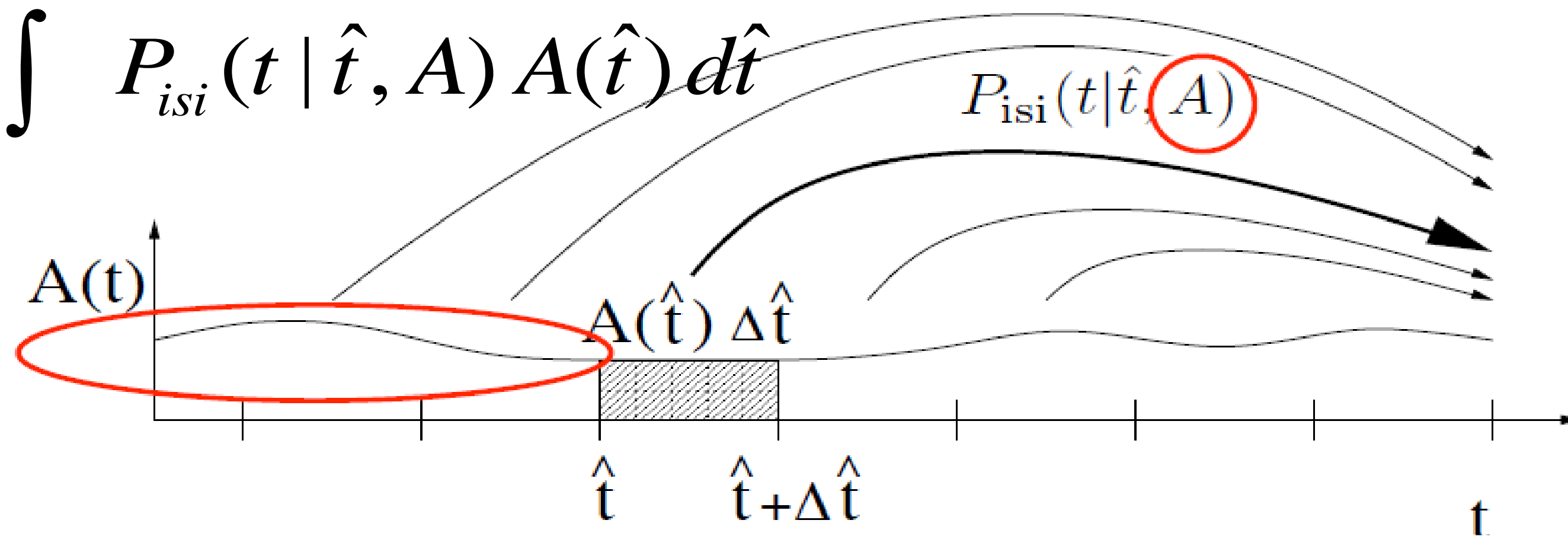
- 1) Linear-Nonlinear-Poisson (LNP): ***fails!***
- 2) Phenomenological rate adaptation: ***fails!***
- 3) Time-Dependent-Renewal Theory: ***fails!***
- 4) **Quasi-Renewal Theory!!!**

Week 15-part 3: Quasi-renewal theory

Quasi-Renewal assumption:

$$\lambda(t | h(t), \hat{t}_1, \hat{t}_2, \hat{t}_3, \dots) \approx \lambda(t | \hat{t}, A)$$

$$A(t) = \int P_{isi}(t | \hat{t}, A) A(\hat{t}) d\hat{t}$$



and
 $h(t)$

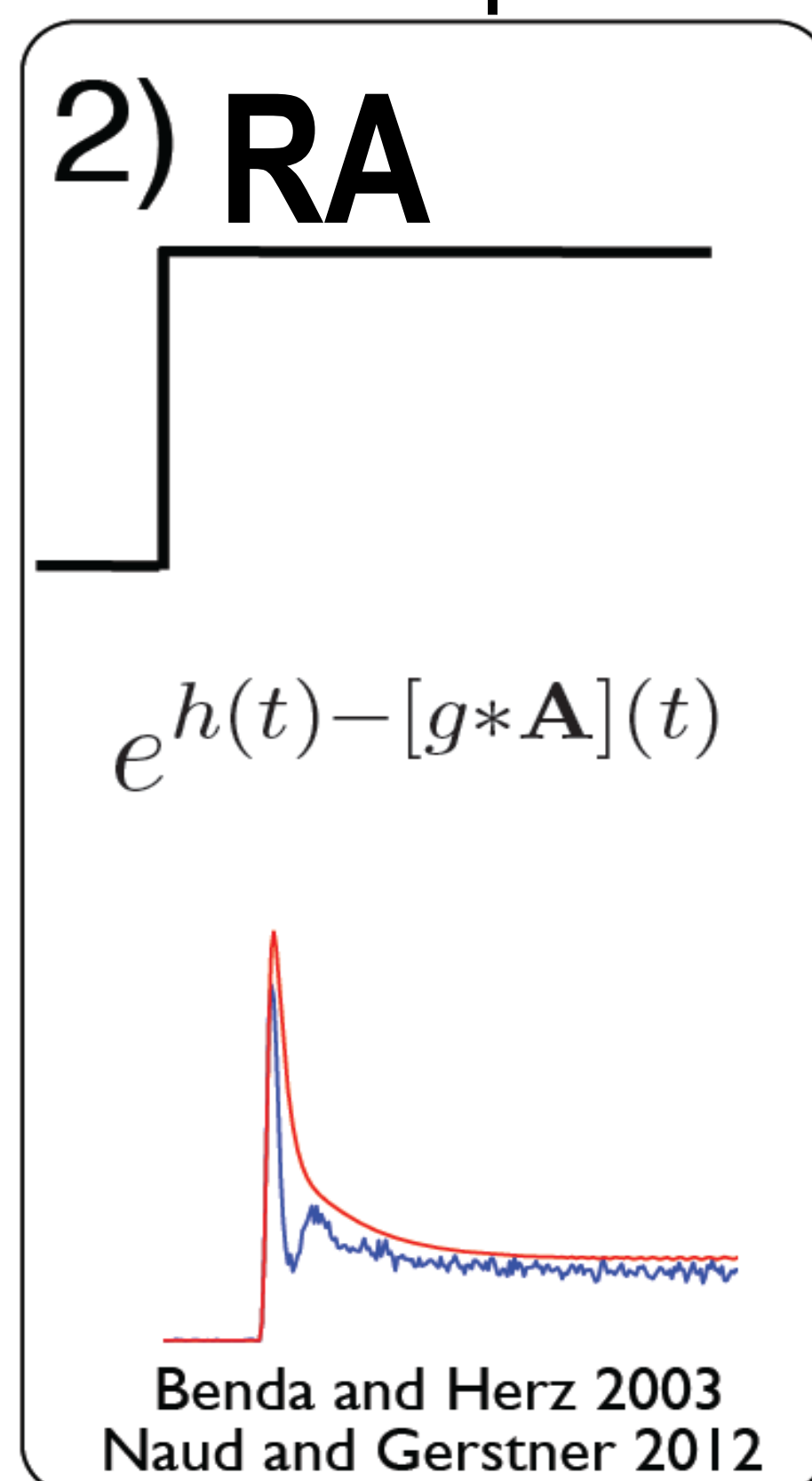
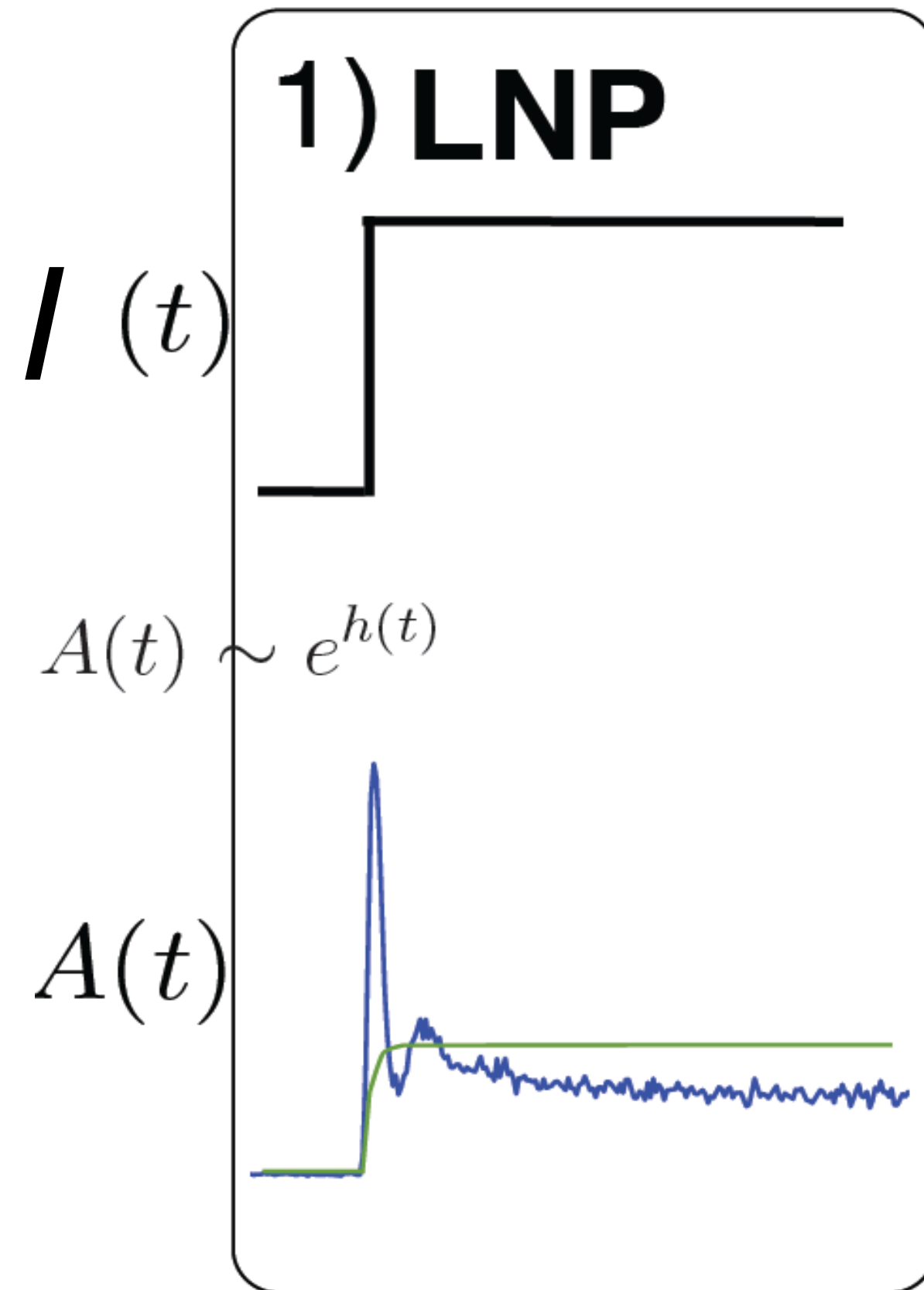
Expand the moment
generating functional

$$\lambda(t | \hat{t}, A) = \lambda_0 e^{h(t) + \eta(t - \hat{t}) - \int_{-\infty}^{\hat{t}} \underbrace{(1 - \exp(\eta(t - s)))}_{g(t-s)} A(s) ds}$$

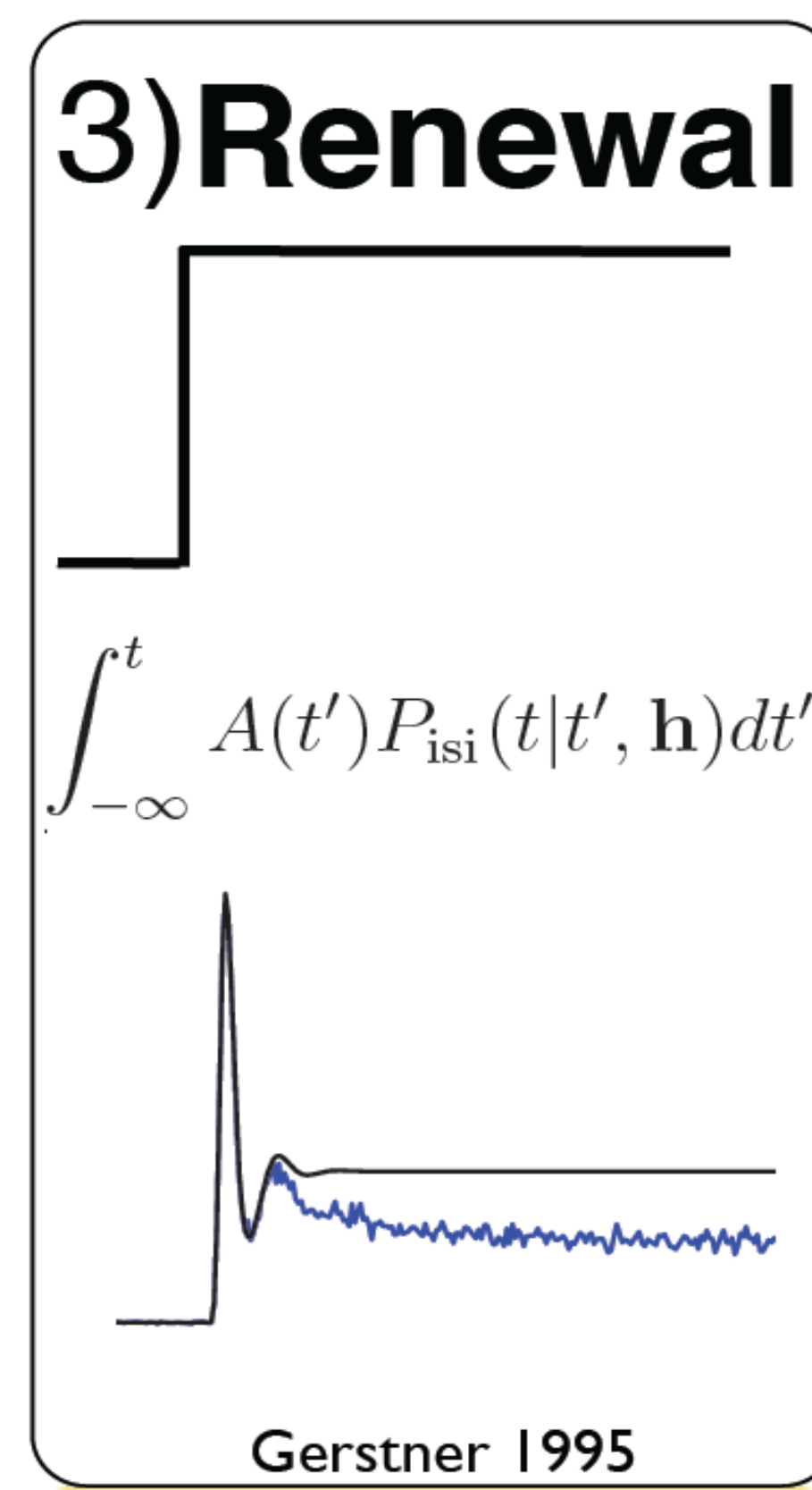
Blackboard!

Rate adapt.

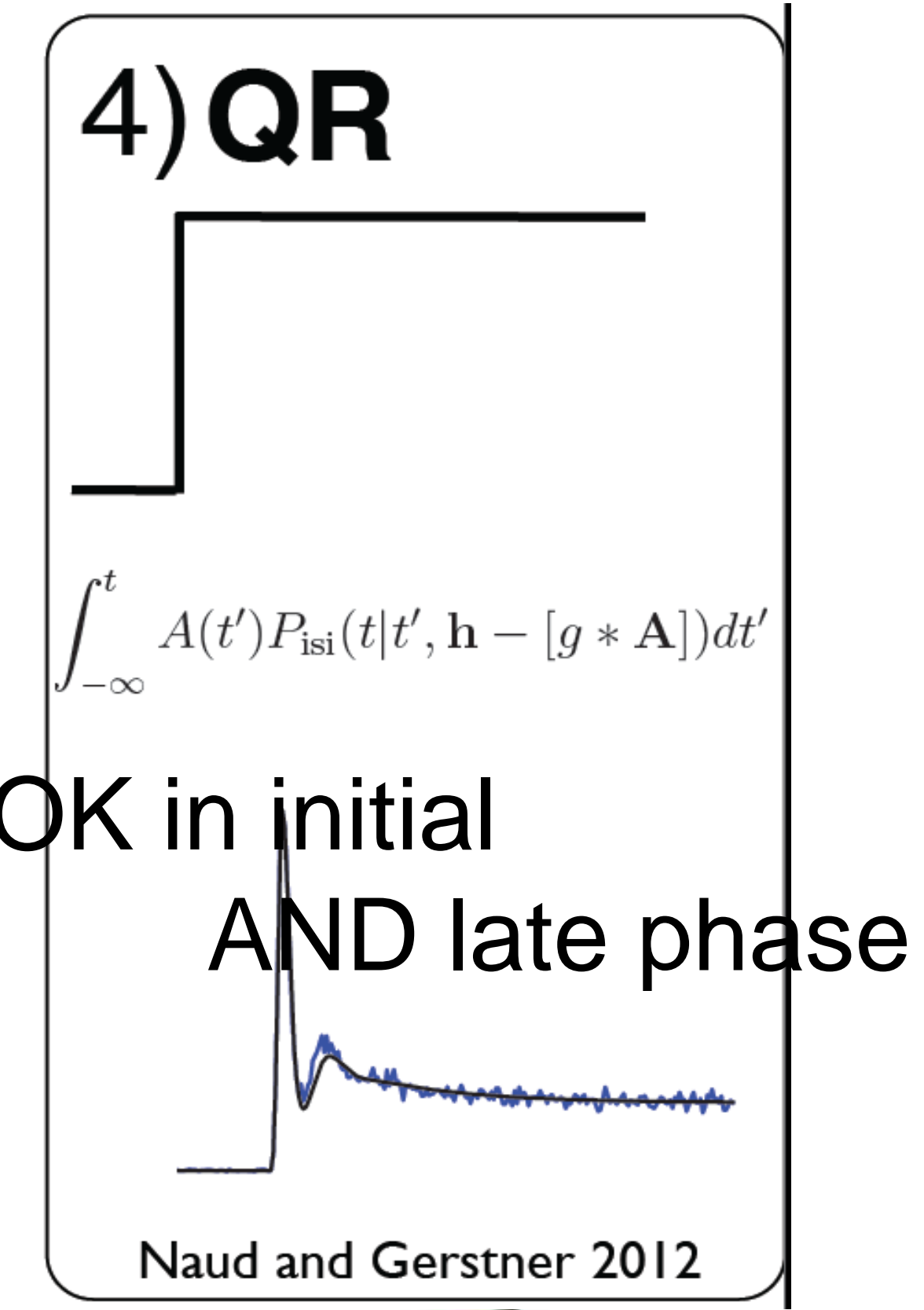
Quasi-Renewal



CAUTION
RESTRICTED
AREA

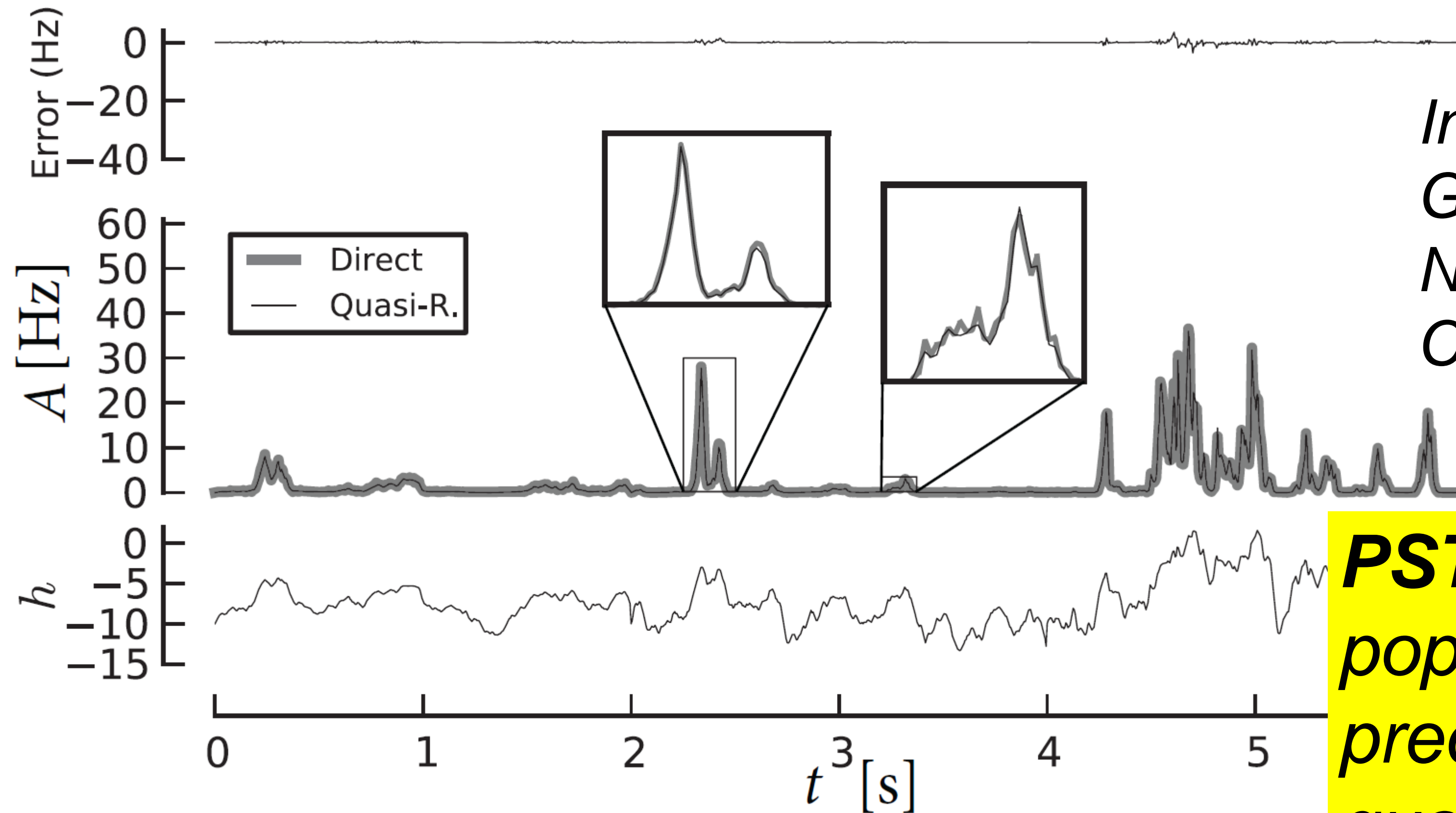


CAUTION
RESTRICTED
AREA



Week 15-part 3: Quasi-renewal theory

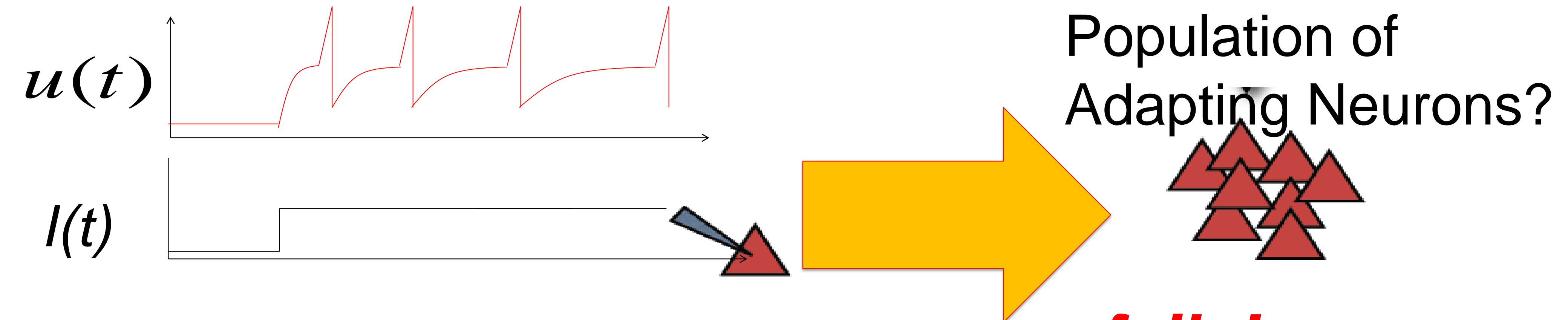
$$\lambda(t \mid h(t), \hat{t}_1, \hat{t}_2, \hat{t}_3, \dots) \approx \lambda(t \mid \hat{t}, A) \longrightarrow A(t) = \int P_{isi}(t \mid \hat{t}, A) A(\hat{t}) d\hat{t}$$



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

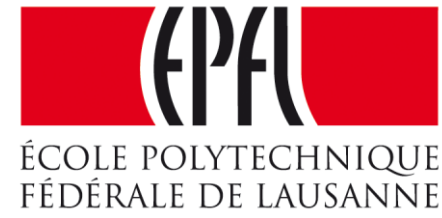
***PSTH or
population activity $A(t)$
predicted by
quasi-renewal theory***

Week 15-part 3: population equation for **adapting** neurons



- 1) Linear-Nonlinear-Poisson (LNP): ***fails!***
- 2) Phenomenological rate adaptation: ***fails!***
- 3) Time-Dependent-Renewal Theory: ***fails!***
- 4) Quasi-Renewal Theory: ***works!!!!***

Week 15 – Integral Equation for population dynamics



Biological Modeling of Neural Networks:

Week 15 – Population Dynamics: The Integral –Equation Approach

Wulfram Gerstner

EPFL, Lausanne, Switzerland

15.1 Populations of Neurons

- review: homogeneous population
- review: parameters of single neurons

15.2 Integral equation

- aim: population activity
- renewal assumption

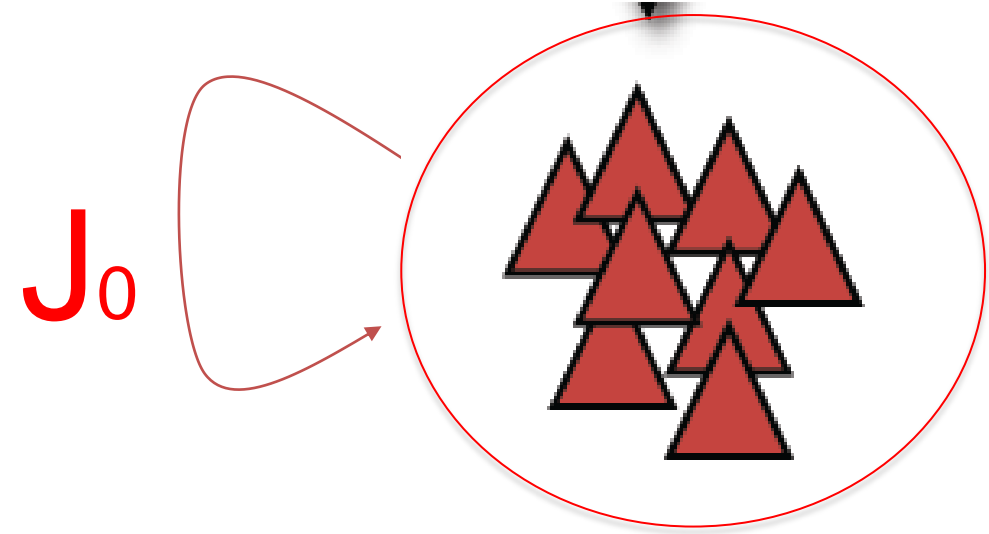
15.3 Populations with Adaptation

- Quasi-renewal theory

15.4. Coupled populations

- self-coupling
- coupling to other populations

Week 15-part 4: population with self-coupling



Same theory works

- Include the self-coupling in $h(t)$

Potential (SRM/GLM) of one neuron

$$u(t) = \sum_{t'} \eta(t - t') + \int_0^\infty \varepsilon(s) I(t - s) ds + \underbrace{J_0 \int_0^\infty \gamma(s) A(t - s) ds}_{h(t)}$$



$h(t)$

$$A(t) = \int P_{isi}(t | \hat{t}, A) A(\hat{t}) d\hat{t}$$

Week 15-part 4: population with self-coupling

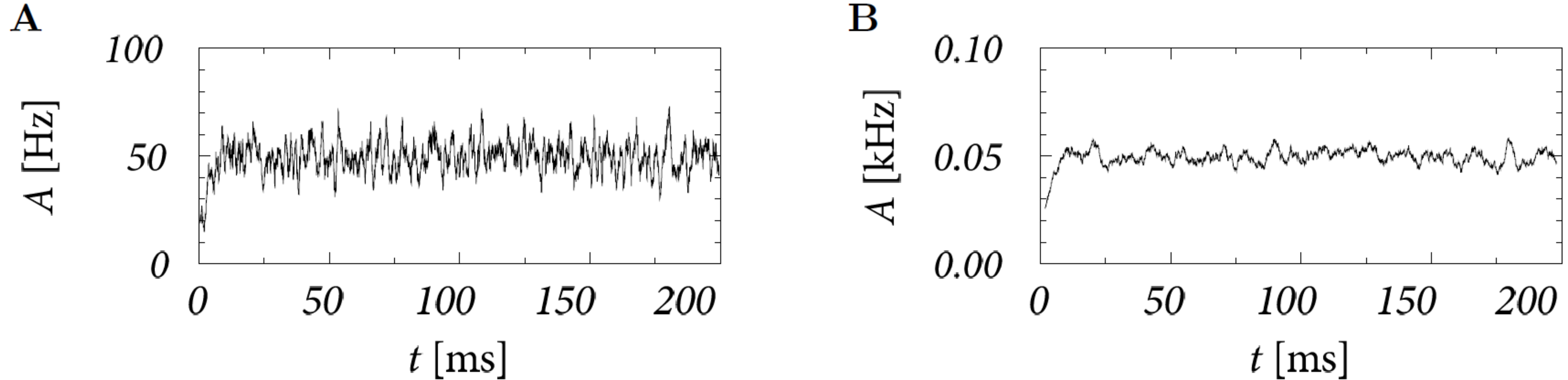


Fig. 14.5: Asynchronous firing. For a sufficient amount of noise, the population activity in a network of coupled spiking neurons with constant external input approaches a stationary value A_0 . **A.** The population activity of 1000 neurons has been filtered with a time window of 1 ms duration. **B.** Same parameters as before, but the size of the population has been increased to $N = 4000$. Fluctuations decrease with N and approach the value of $A_0 = 50$ Hz predicted by theory.

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

Week 15-part 4: population with self-coupling

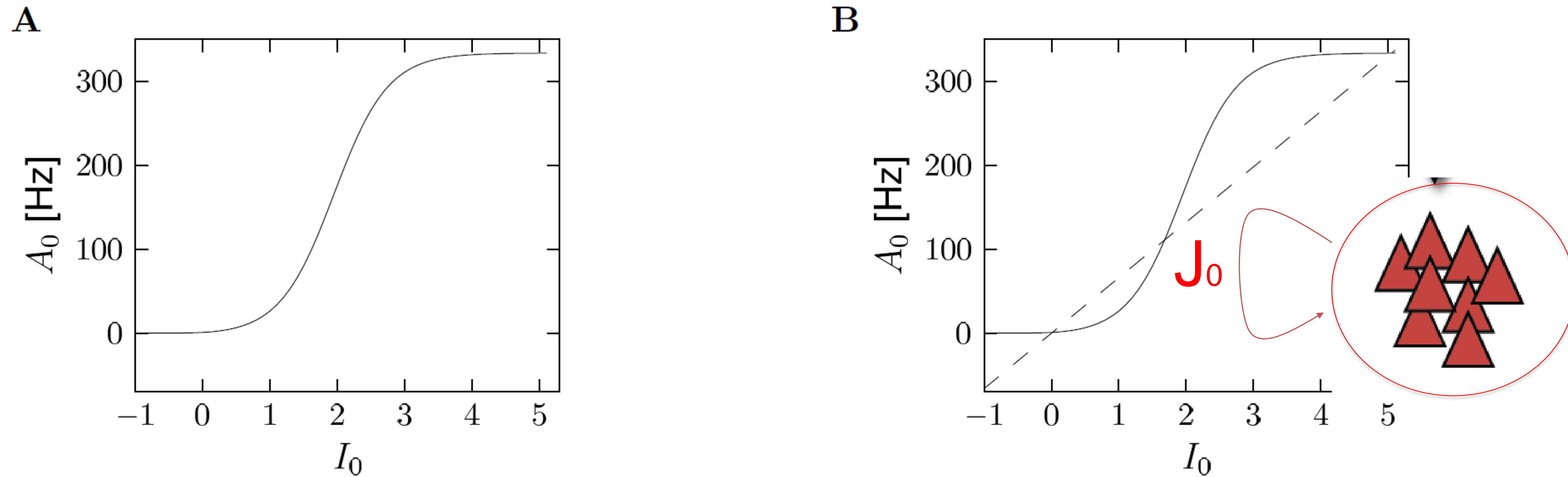


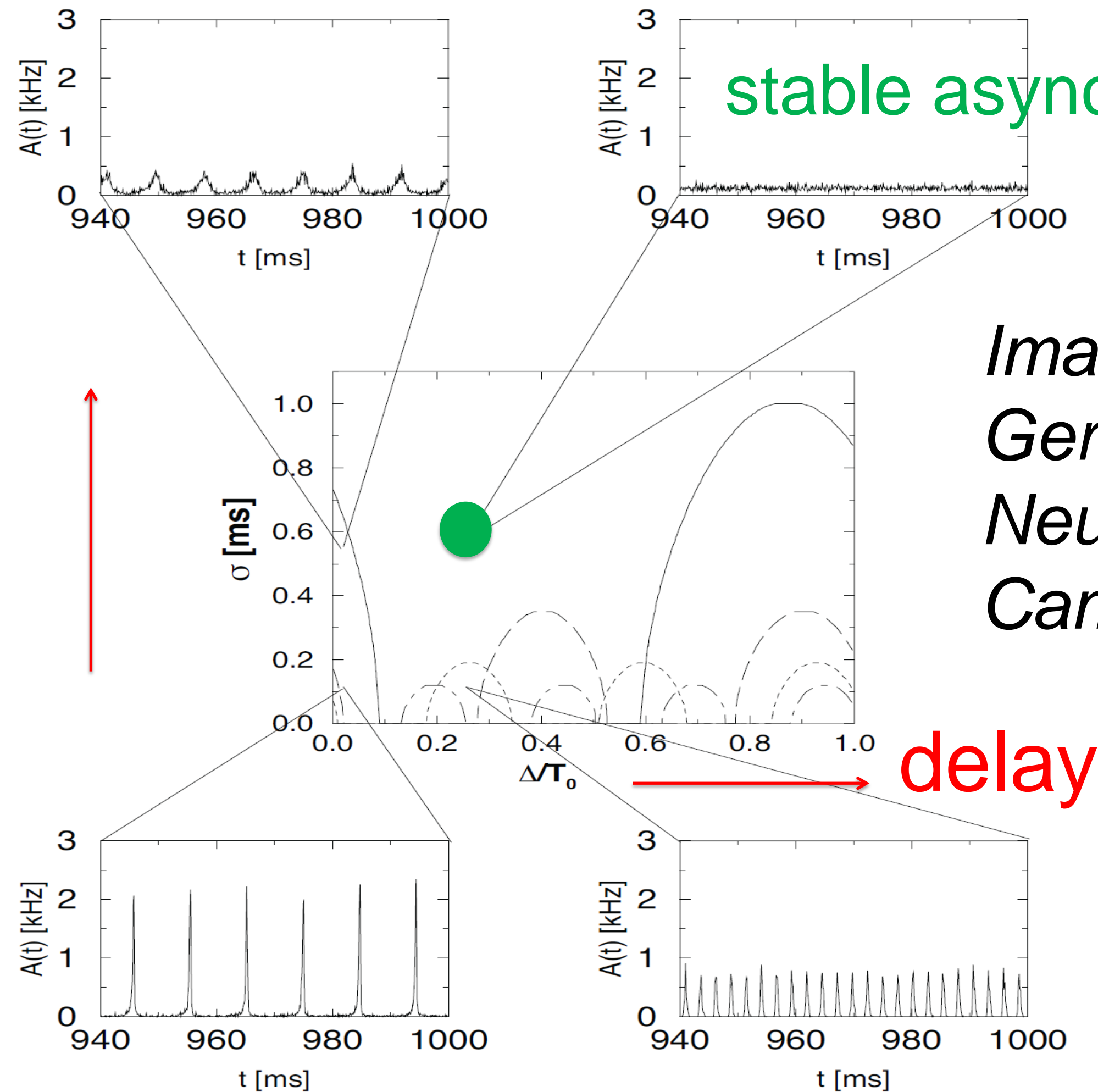
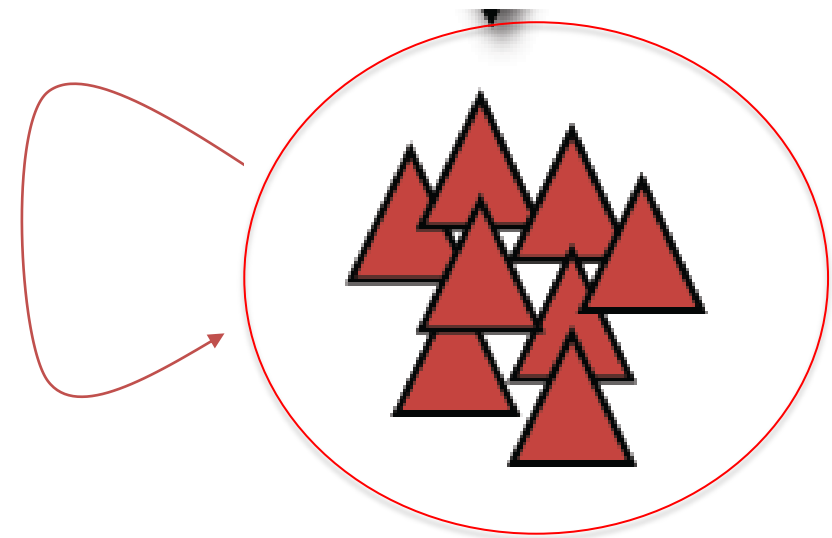
Fig. 14.6: Gain function and stationary activity in a population of SRM neurons with exponential escape noise. **A.** Gain function (single neuron firing frequency ν as a function of constant current I_0) for neurons with refractoriness given by Eq. (14.29). **B.** Self-consistent solution for the population activity $A(t) = A_0$ in a recurrent network of SRM neurons coupled to itself with strength J_0 . Neurons are characterized by the same gain function as in part A of the figure.

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

Week 15-part 4: population with self-coupling

instabilities and oscillations

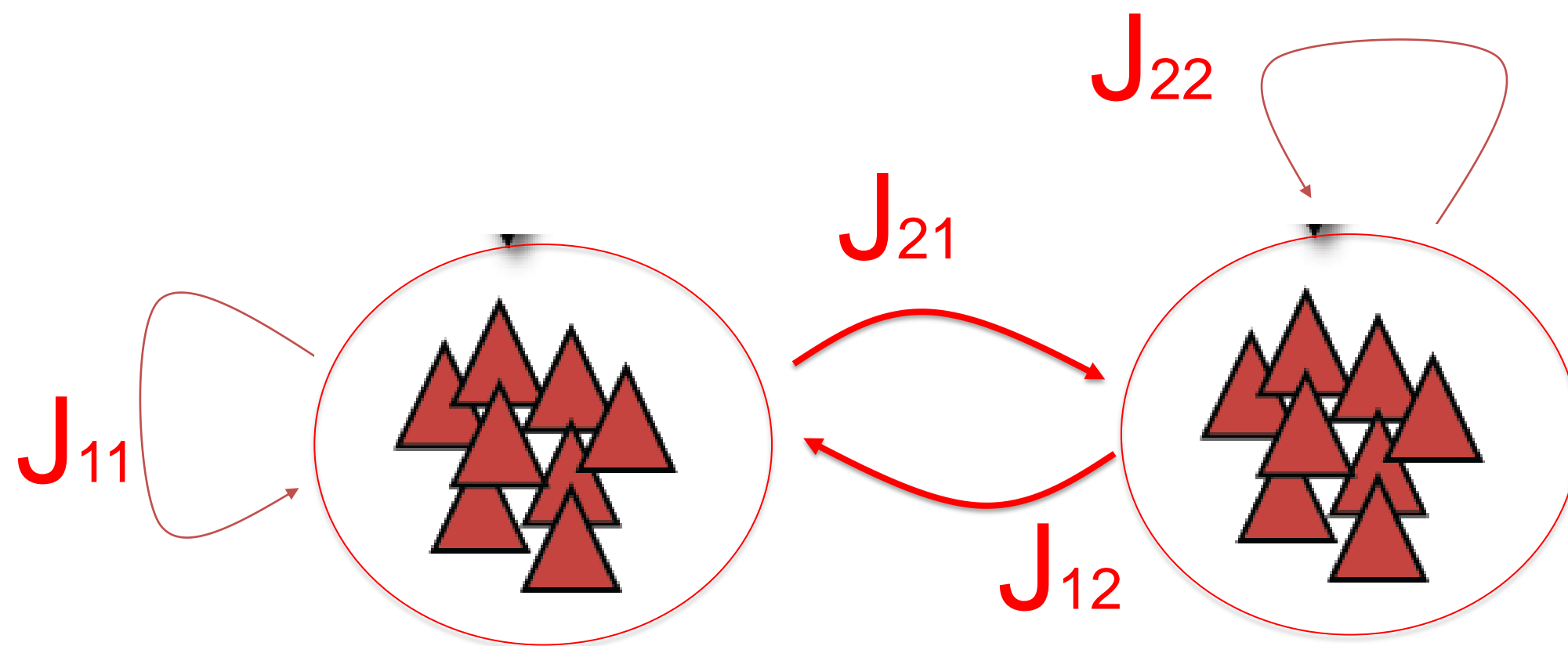
noise level



stable asynchronous state

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

Week 15-part 4: multiple coupled populations



Same theory works

- Include the cross-coupling in $h(t)$

Potential (SRM/GLM) of one neuron in population n

$$u_n(t) = \sum_{t'} \eta(t - t') + \underbrace{\int_0^\infty \varepsilon_n(s) I_n(t - s) ds + \sum_k J_{nk} \int_0^\infty \gamma_k(s) A_k(t - s) ds}_{h_n(t)}$$

$h_n(t)$

$$A_n(t) = \int P_{isi}(t | \hat{t}, A_n) A_n(\hat{t}) d\hat{t}$$

Week 15-part 1: Summary and aims

- We can extract parameters for SINGLE neuron

(see NEURONAL DYNAMICS, Chs. 8-11)

- Different neuron types have different parameters

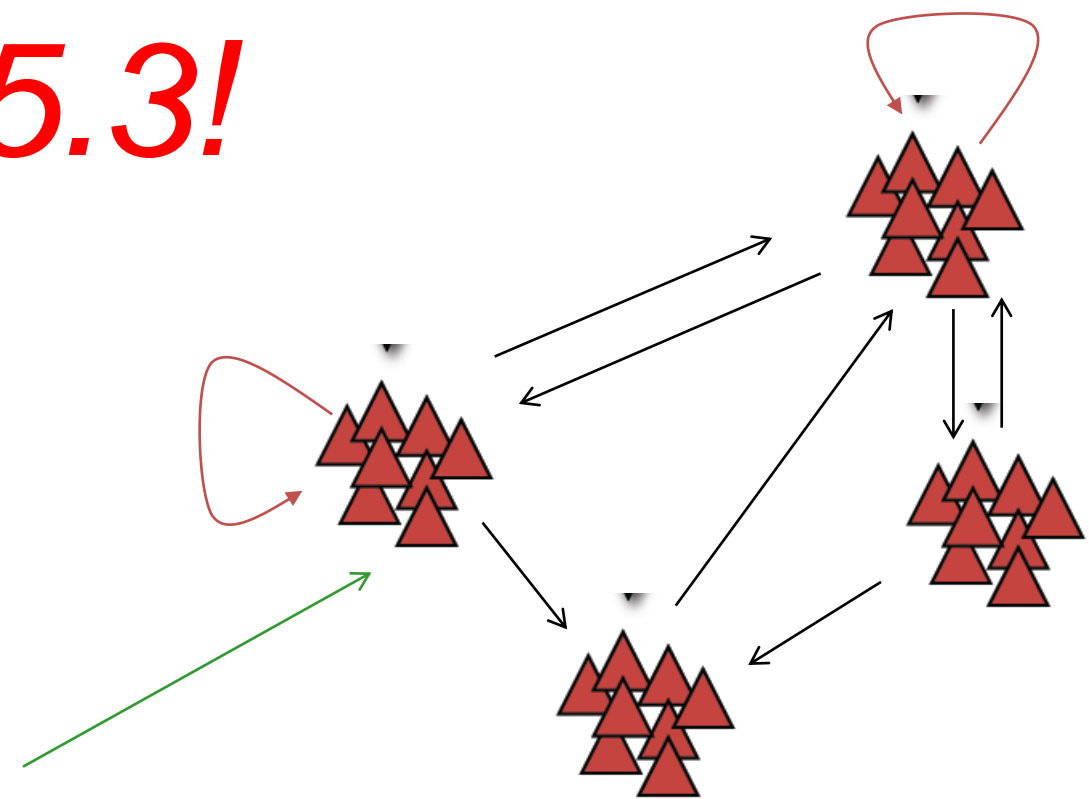
- Model Dynamics in one (homogeneous) population

Today, parts 15.2 and 15.3!

- Couple different populations

Today, parts 15.4!

Sensory input



Eventually: Understand Coding and Brain dynamics

The end

*Reading: Chapter 14 of
NEURONAL DYNAMICS,
Gerstner et al., Cambridge Univ. Press (2014)*