Biomathematics / Computational Biology Colloquium

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09/03/2019

Mechanisms of emergence and maintenance of rhythmic and non-rhythmic fluctuations in spiking neuronal networks

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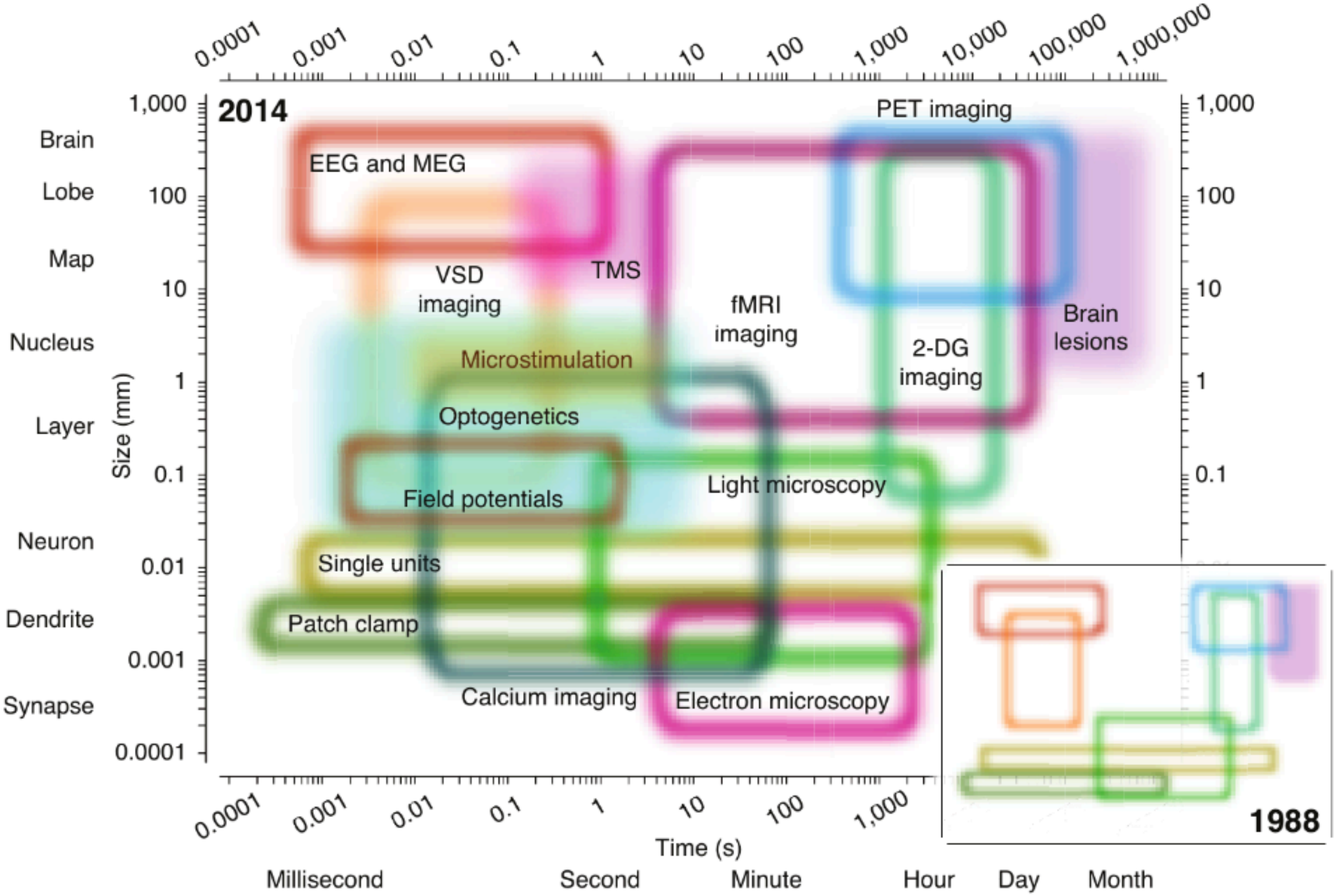
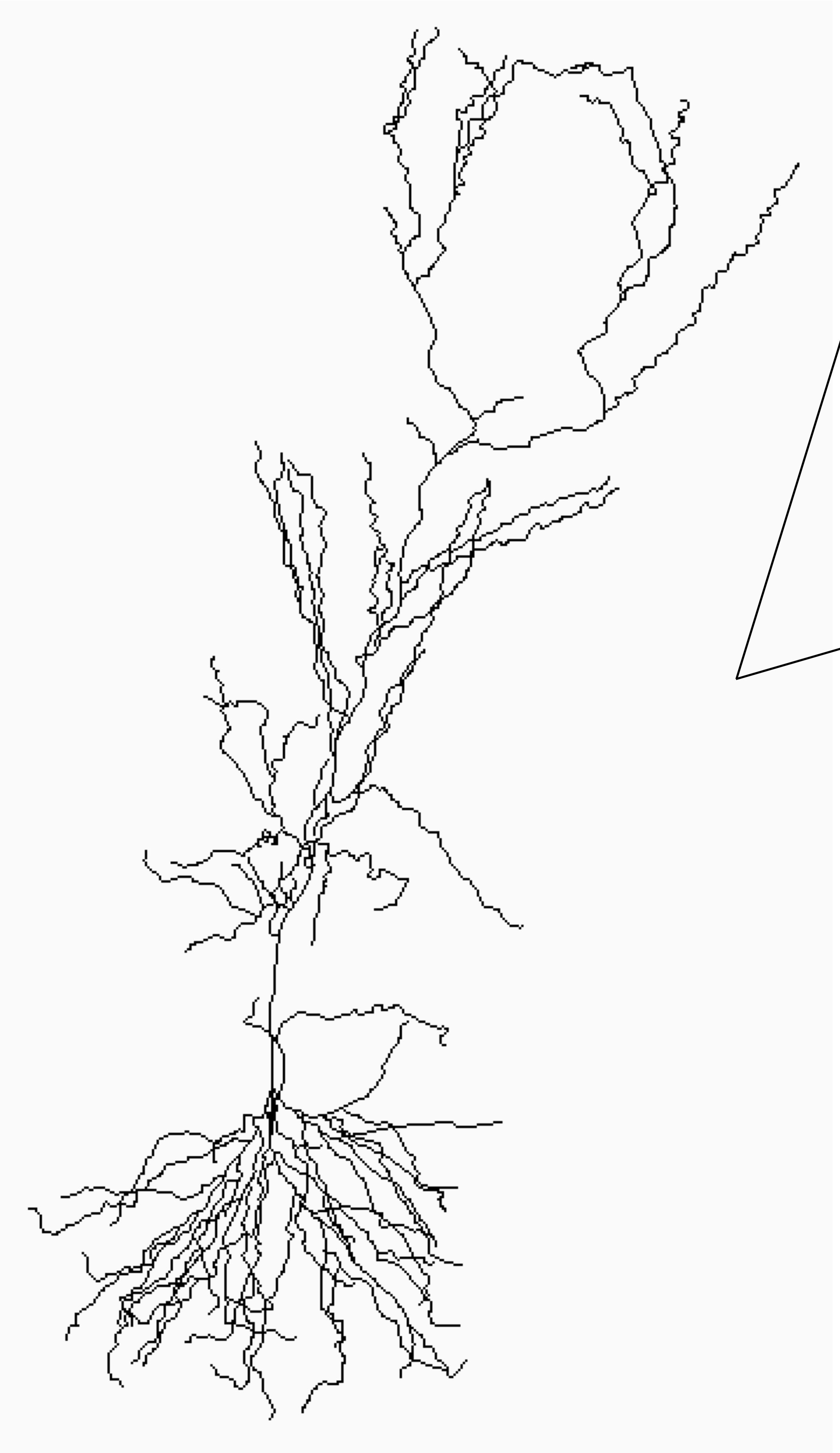
The brain, in its many scales, is subjected to

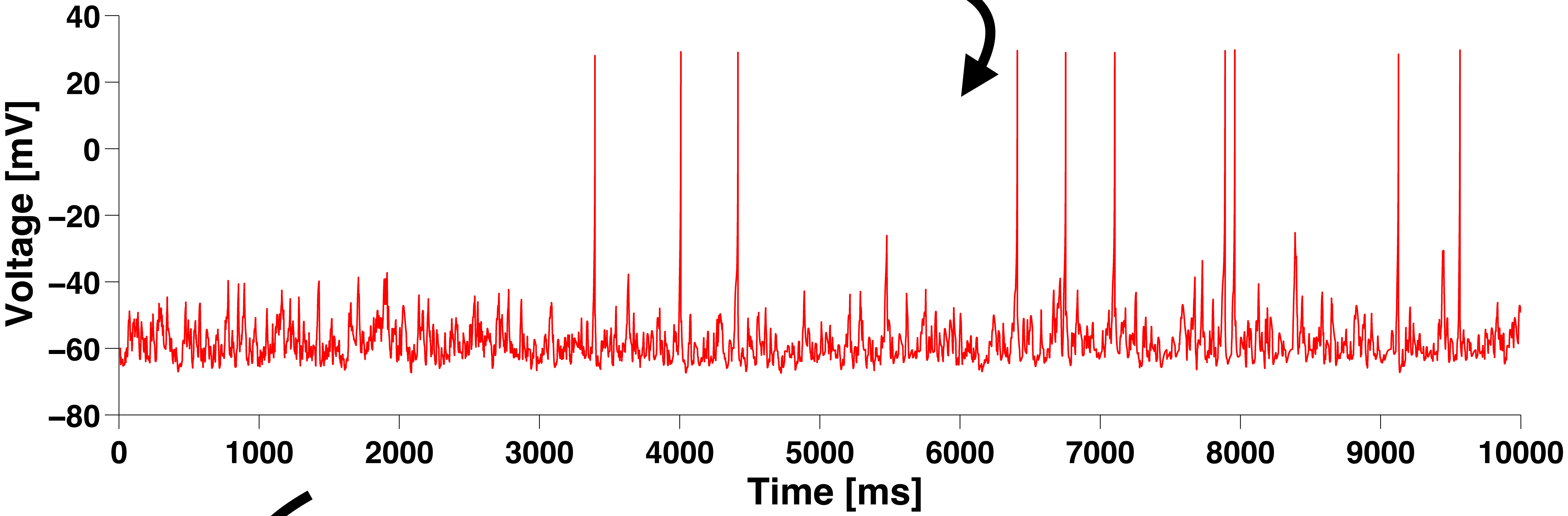
various sources of noise.



Sejnowski et al. (2014) Nature Neuroscience

From membrane voltage

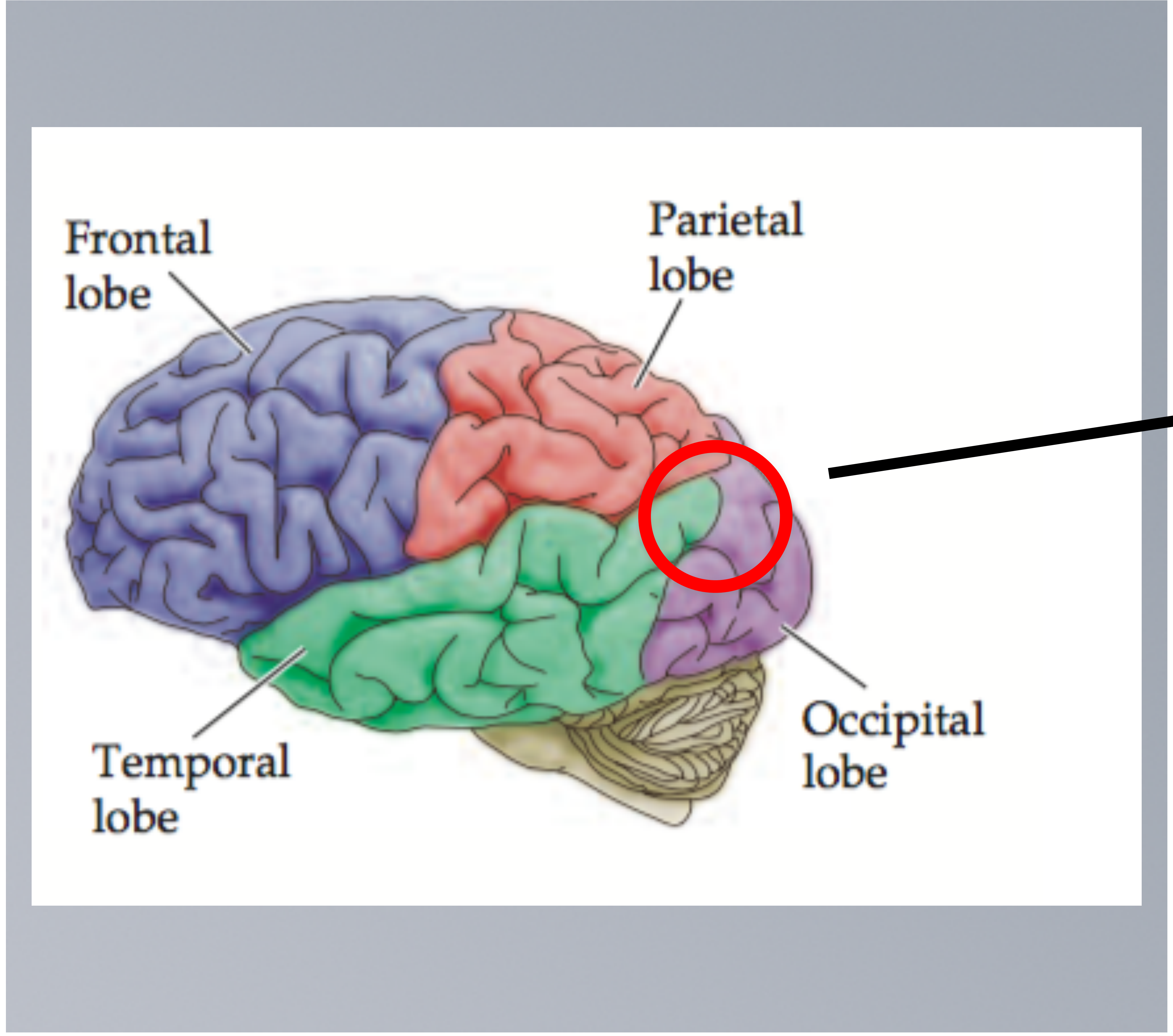


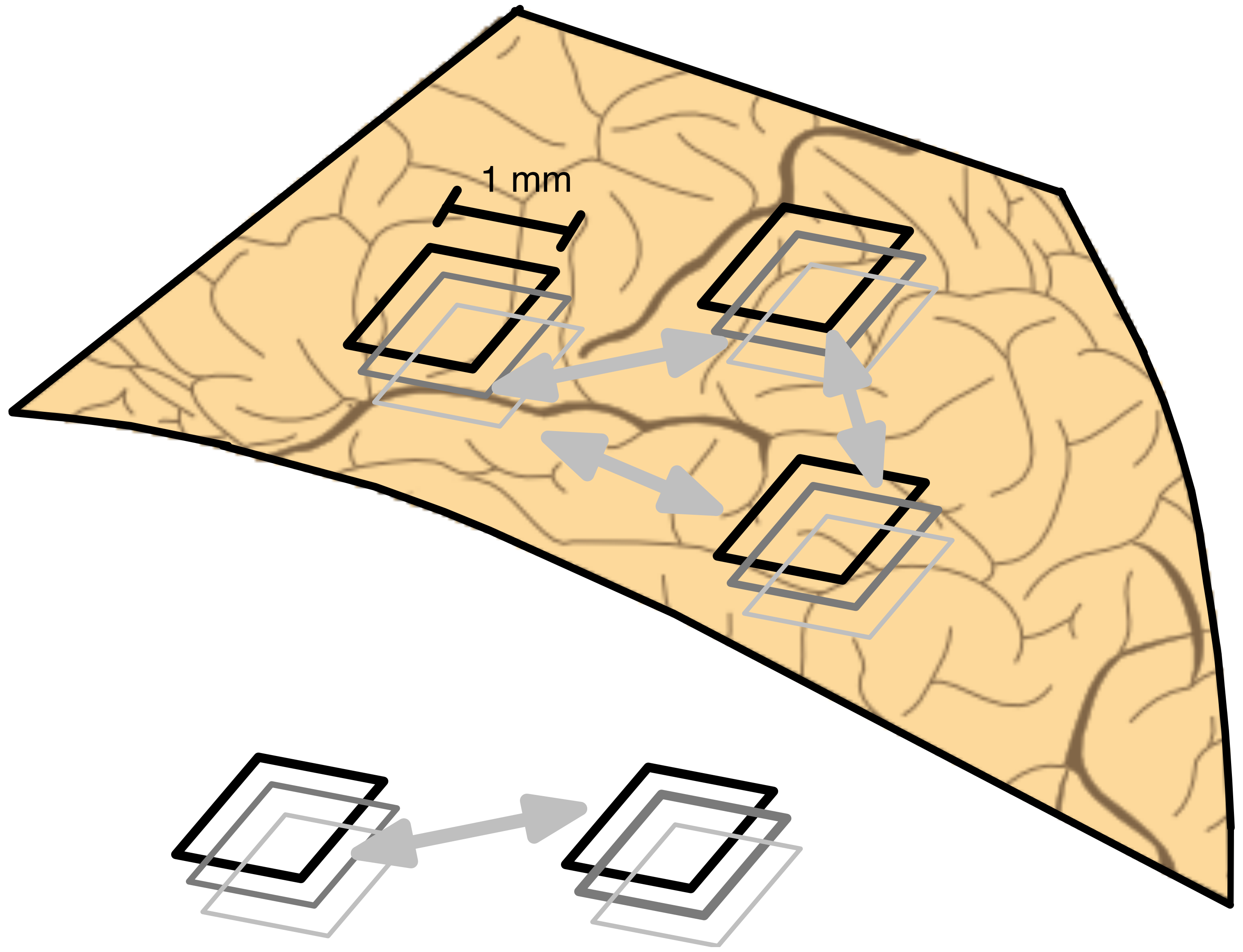


to sensory signals

we have

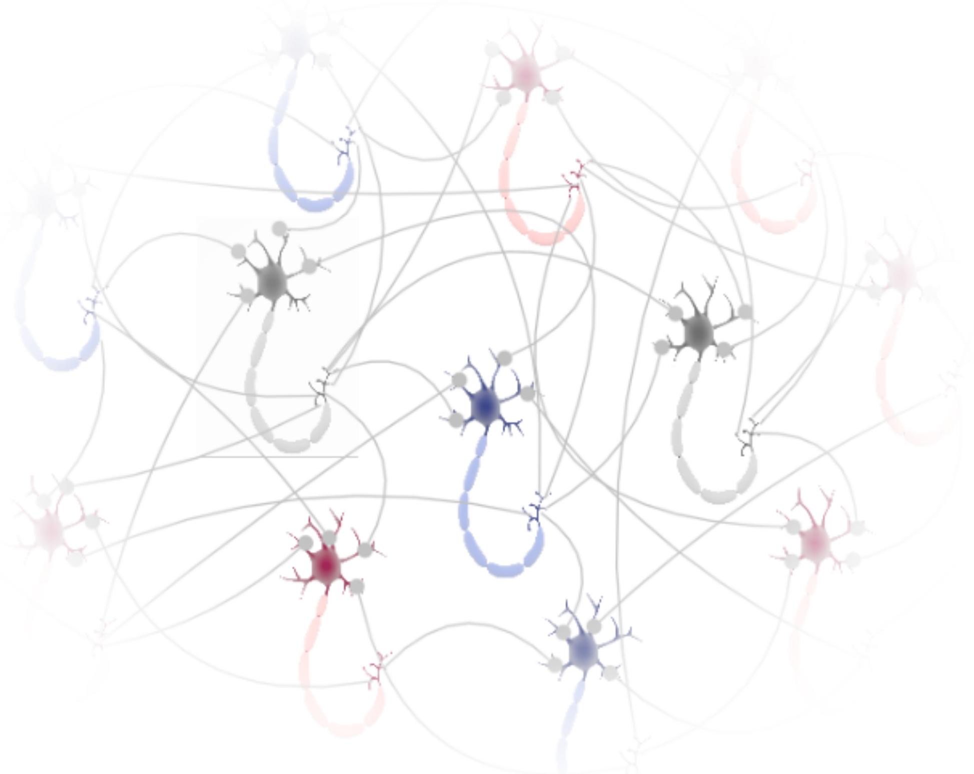
- Rhythmic;
- non-rhythmic fluctuations.



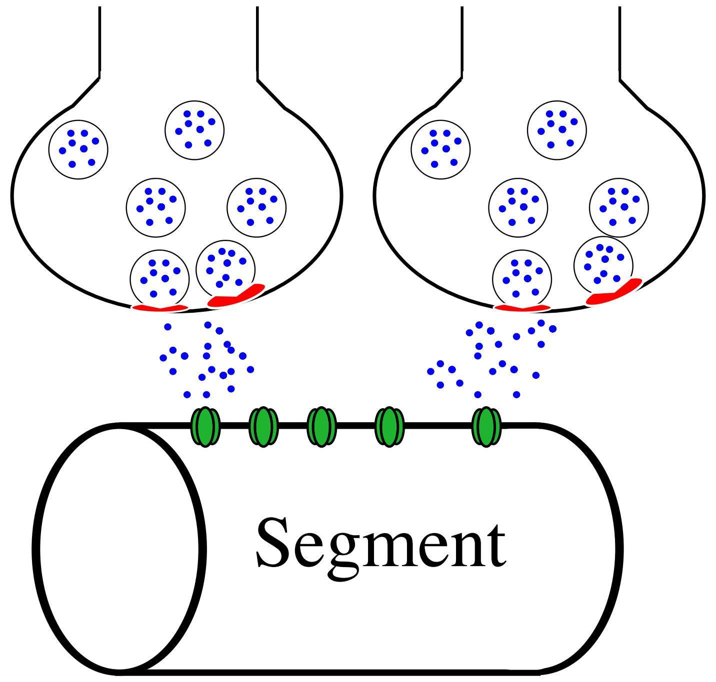


Cortex is a complex system subjected to different sources of fluctuations.

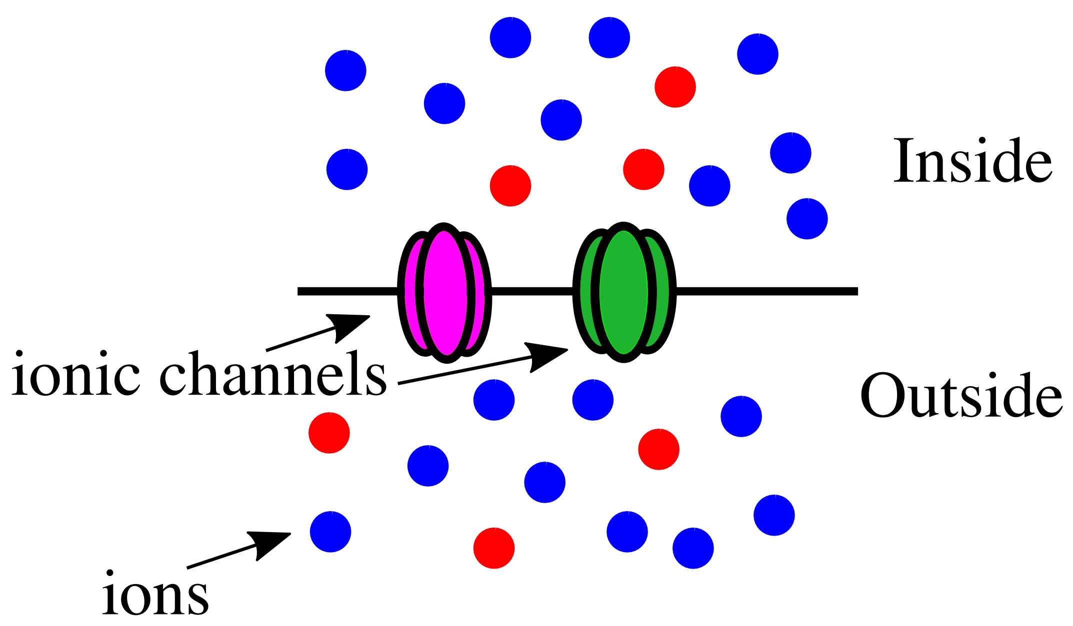
Network noise



Synaptic noise



Channel noise



Outline

01 How fluctuations emerge and sustain spontaneously without noise

02 Synaptic noise

03 Network noise

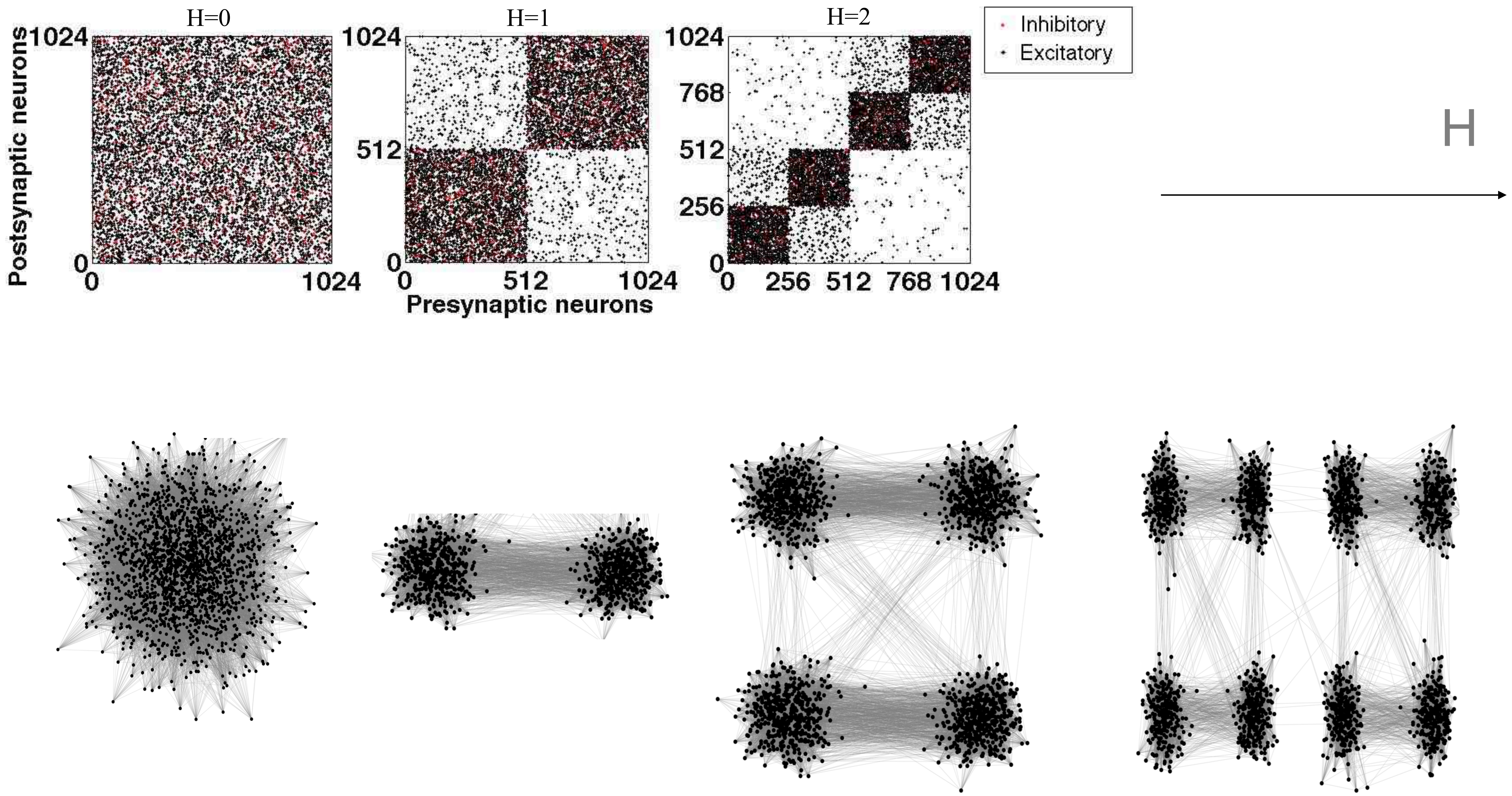
Goal

Analysis of mechanisms of emergence and maintenance of activity fluctuations in these networks.

Cerebral Cortex
(network noise features)

- Evidence for columnar organization;
- Columns with similar functional properties;
- Columns communicate sparsely;
- We employ an algorithm with such evidences to construct networks.

Hierarchical modular networks (HMNs)



Modular hierarchical topology across many scales

Mountcastle (1997), *Brain* 120:701-722
Binzegger et al. (2004), *J Neurosci 24*:8441–8453
} Microcircuits

Hilgetag et al. (2000), *Philos Trans R Soc Lond 355*:91–110.
Kaiser (2007), *Trans R Soc Lond A 365*:3033–3045
} Brain regions

Cerebral Cortex (intrinsic features)

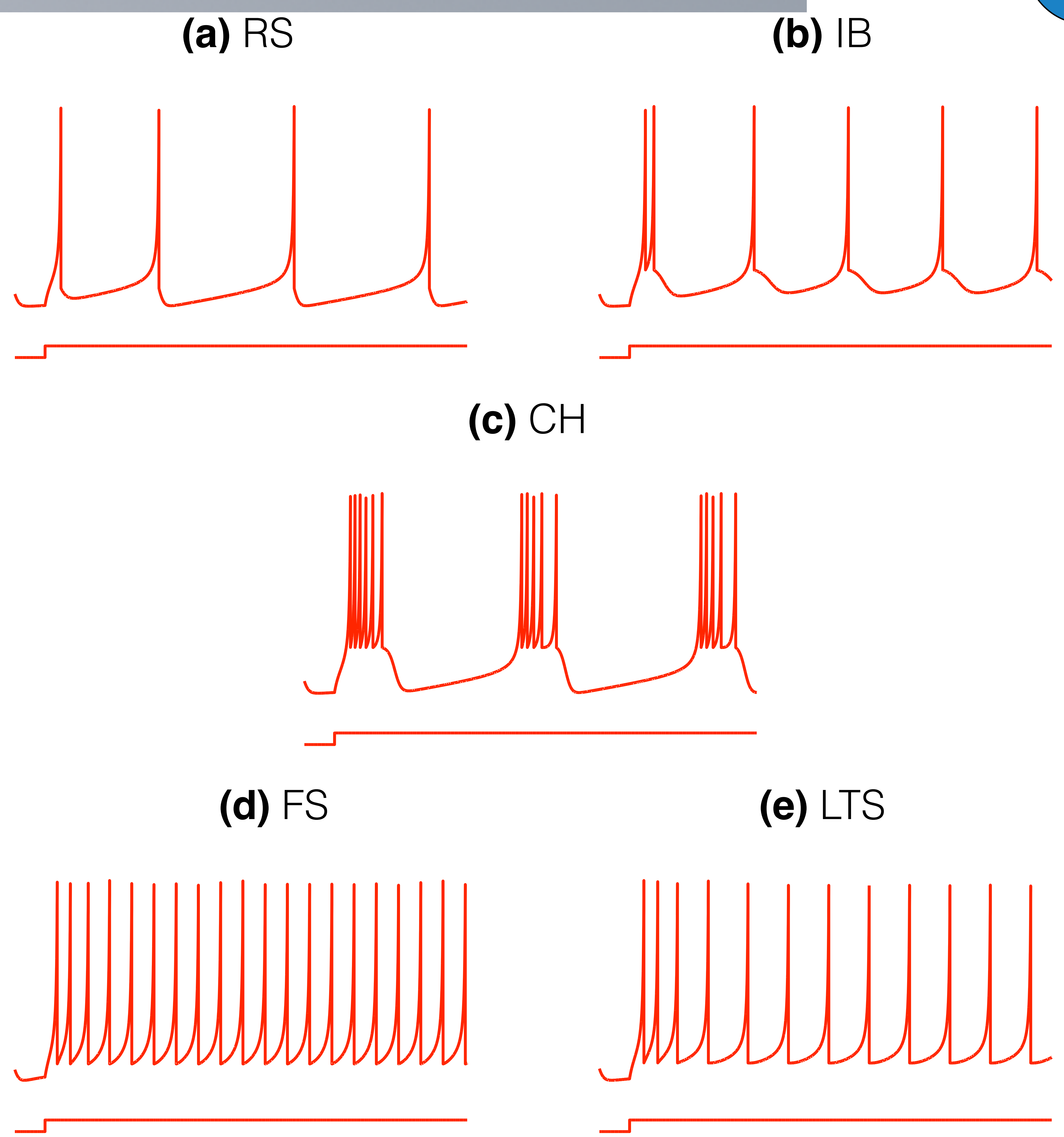
- Mixture of electrophysiological classes;
- All neuron models in this thesis are derived from:

$$\begin{cases} \tau_m \dot{v} & = f(v) - u + \text{input} + \text{update rule} \\ \tau_u \dot{u} & = g(v, u) + \text{update rule}, \end{cases}$$

which can reproduce a rich repertoire;

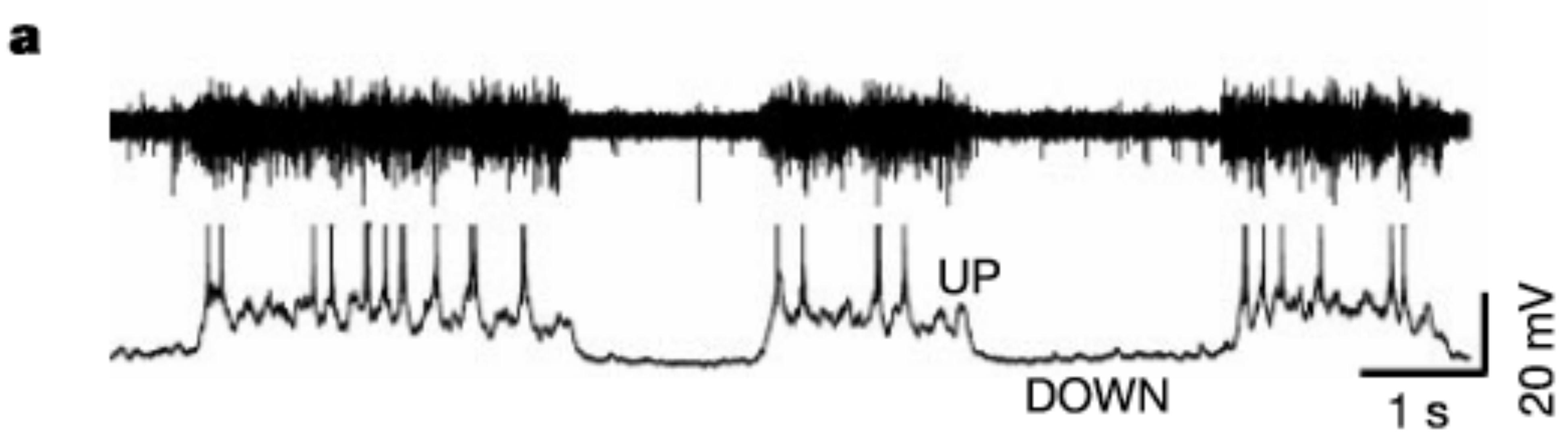
Izhikevich (2003), *IEEE T Neural Network 14*:1569–1572;

Gerstner et al. (2014), Cambridge University Press



Self-sustained activity

- absence of stimuli



Cortical slice *in vitro*

Shu et al., Nature 423:288-293, 2003

Steriade et al., J Neurophysiol 85:1969-1985, 2001.

In vivo recordings

Raster plots of multiunit extracellular spiking activity

Down states

El Boustani et al., J Physiol (Paris) 101:99-109, 2007

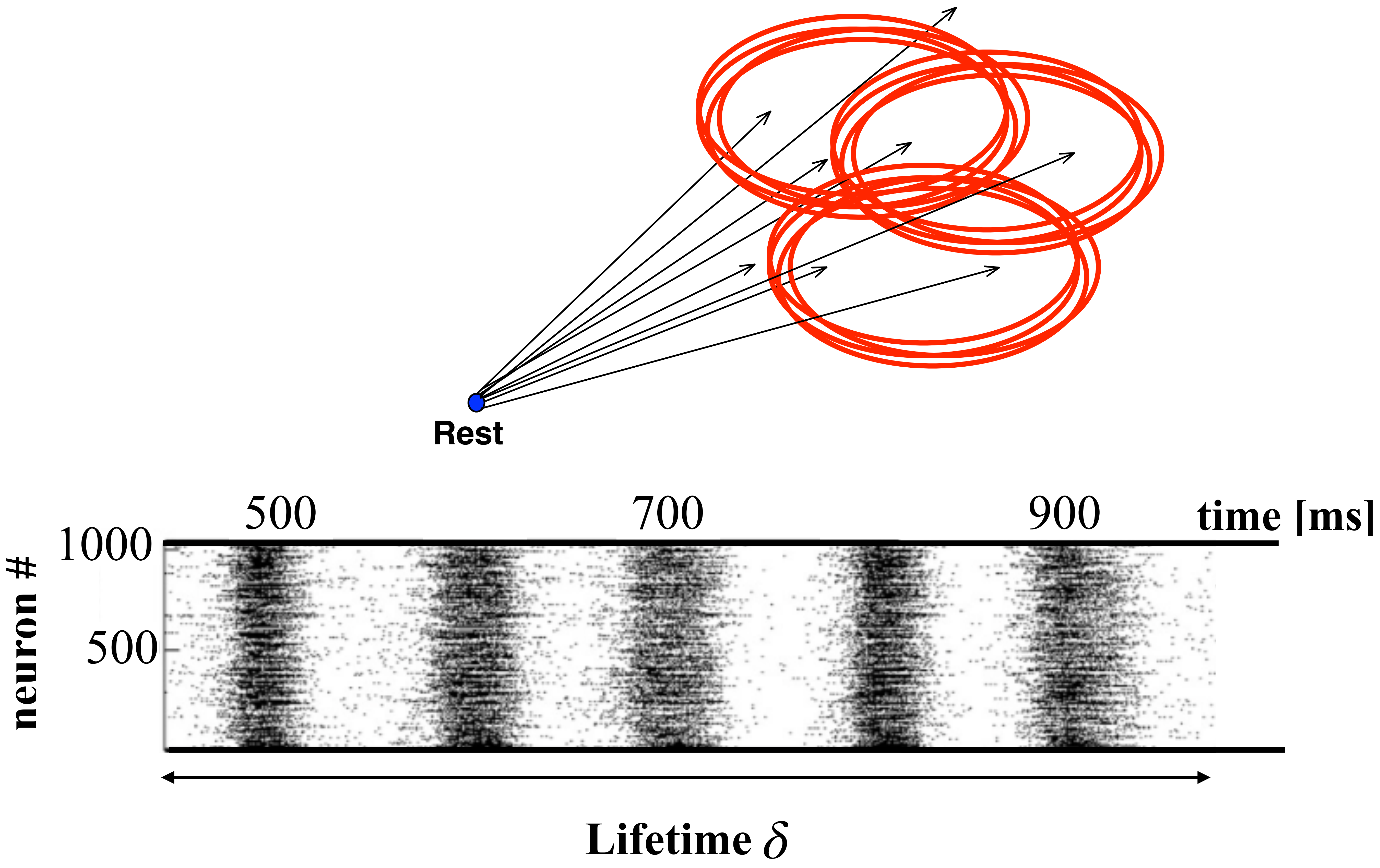
Ensemble of initial conditions

Exploring the system

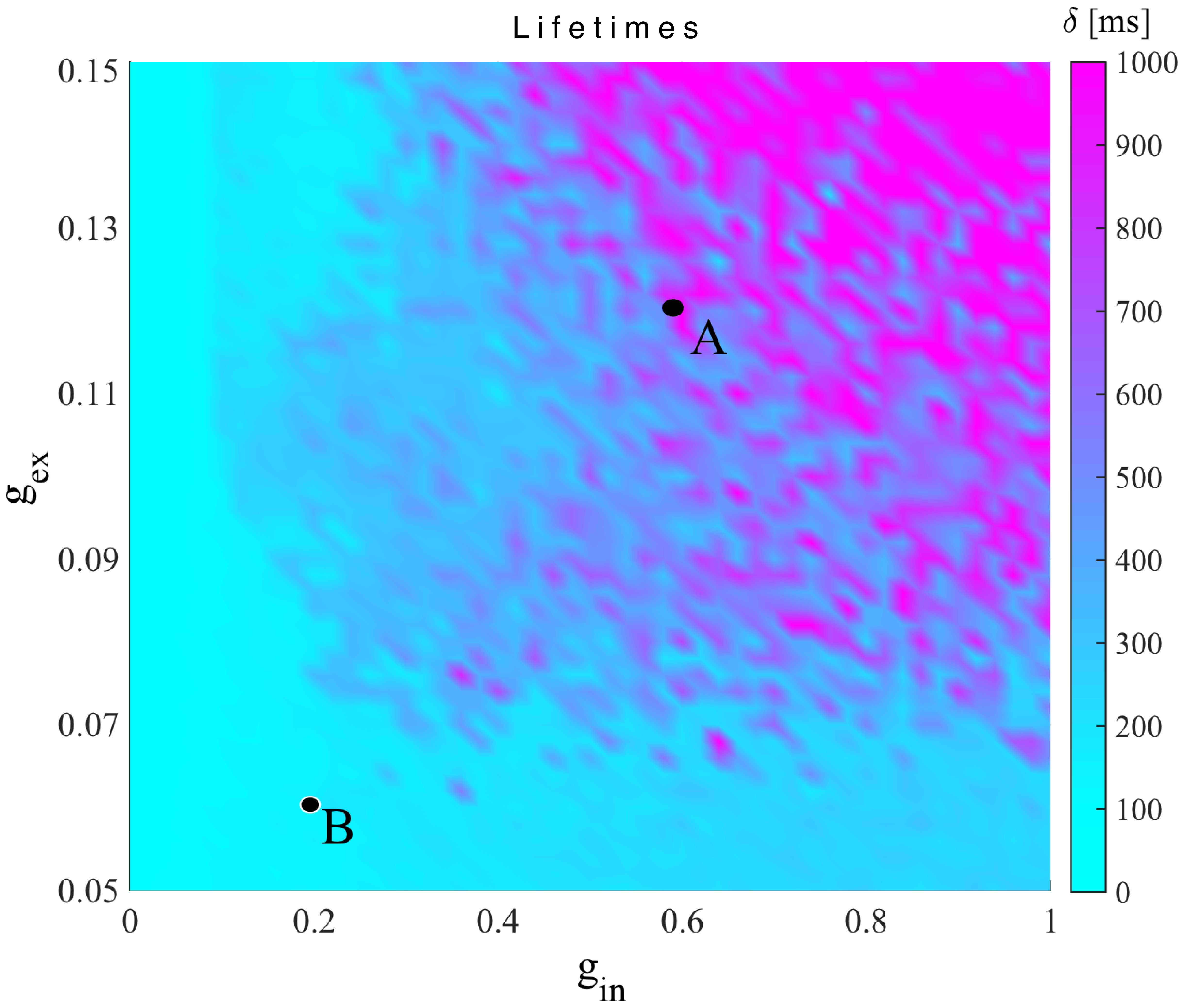
a) the proportion of randomly chosen stimulated neurons: P_{stim} = 1, 1/2, 1/8, 1/16;

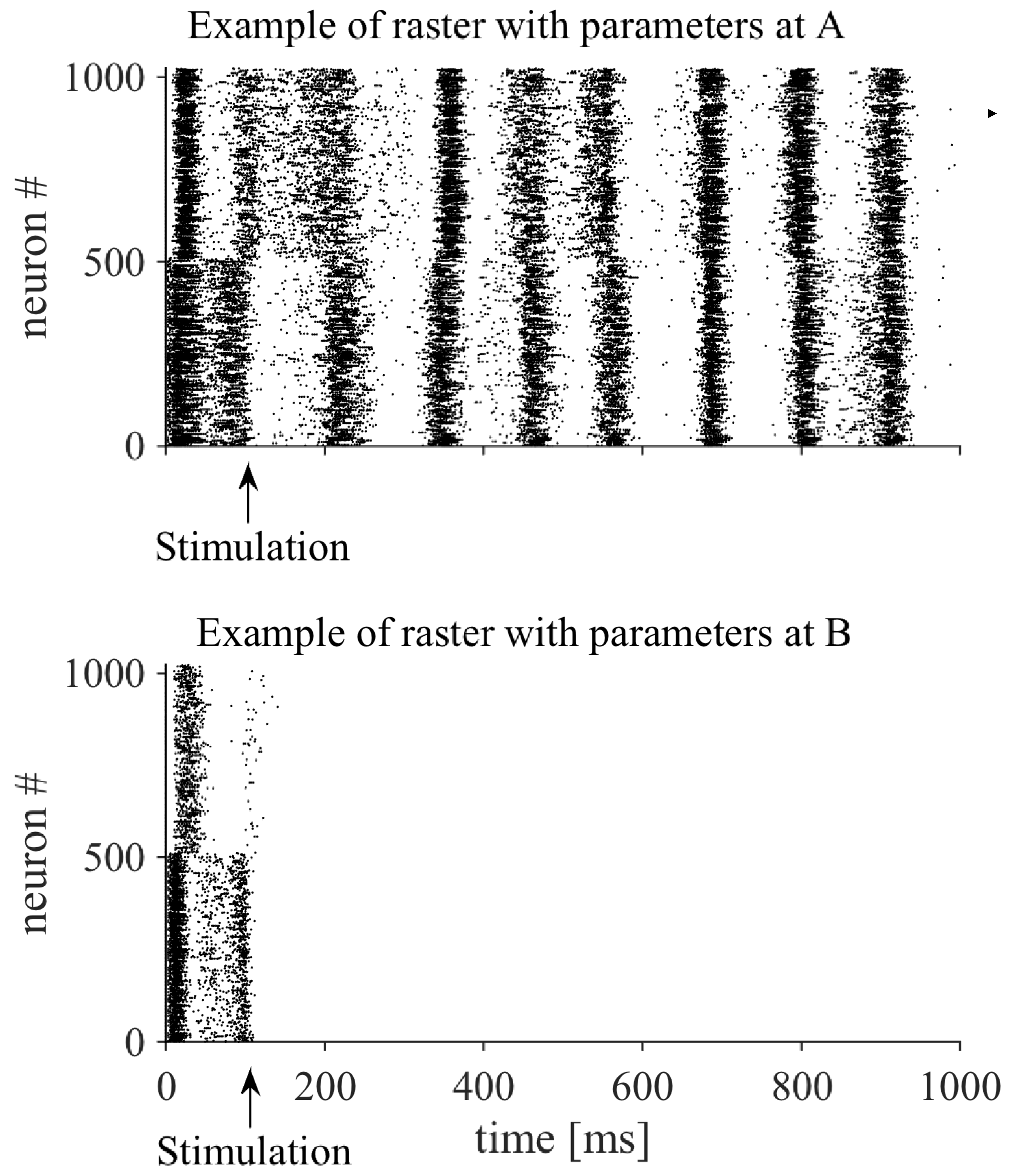
b) the amplitude of the constant external current from I_{stim} = 8 to I_{stim} = 20;

c) the duration of stimulation from t_{stim} = 50 to 300 ms.



Plane of synaptic strengths





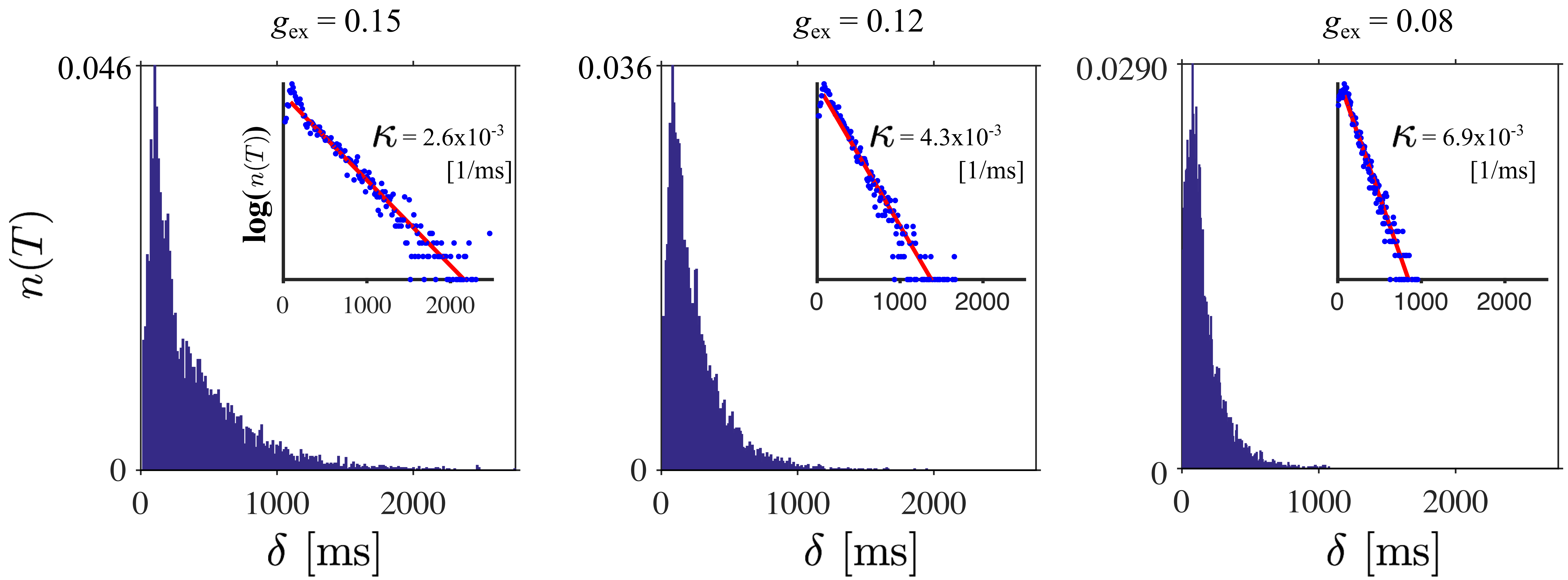
- Network with H=1 and 20% excitatory being CH Inhibitory of LTS type

- Similar behavior for other networks

Exponential decay

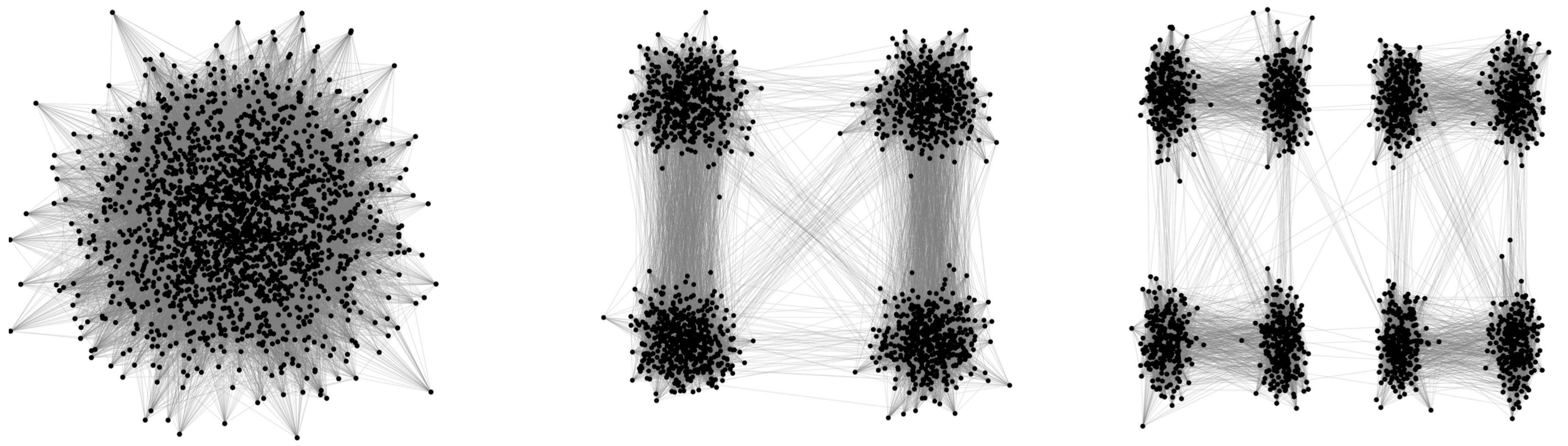
Dependency with excitation

$$n(T) = e^{-\kappa T}$$ (Number of systems with lifetime longer than T)



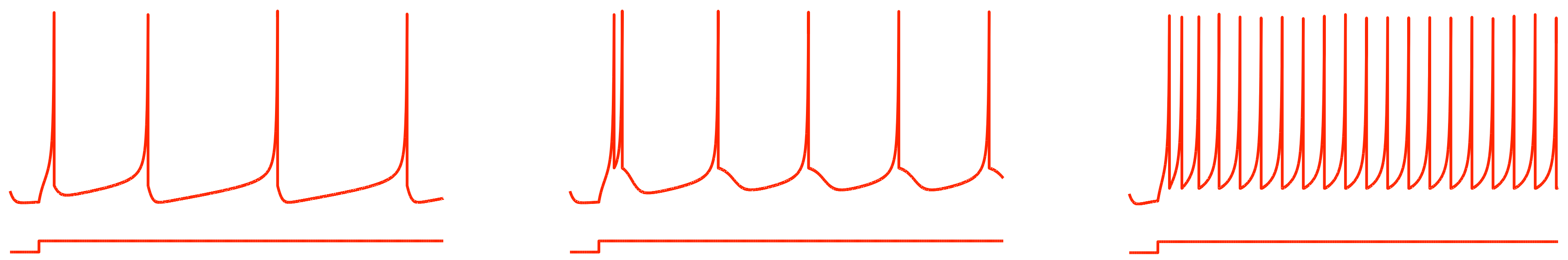
Exponential decay

Other dependencies



- Hierarchical level

The higher *H* the decreases κ



- Mixture of neurons

Inclusion of excitatory CH decreases κ

Substitution of inhibitory to LTS decreases κ

Optimal conditions for long-living SSA

- high *H*
- a portion of CH as excitatory
- LTS as inhibitory

Phenomenological approach

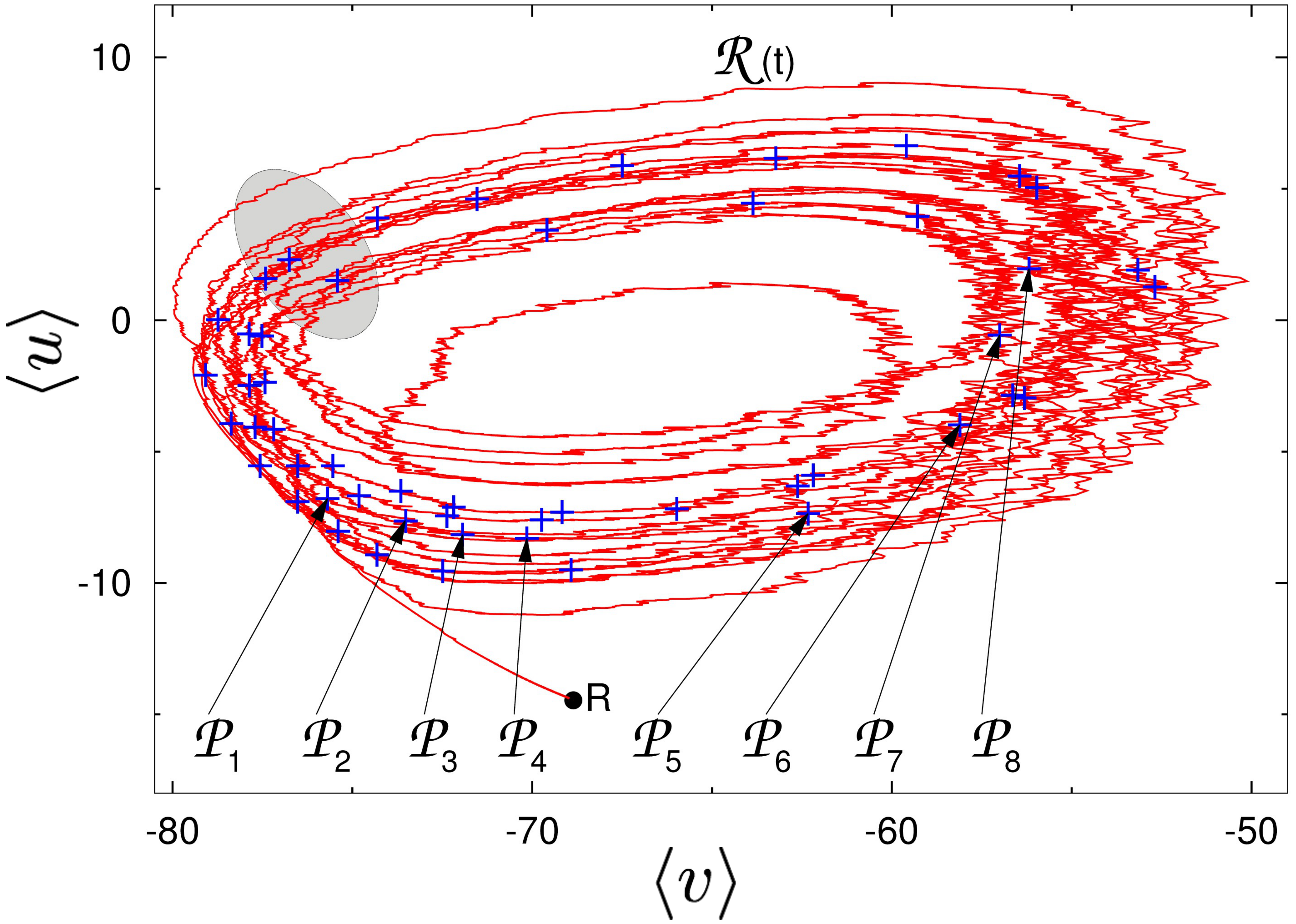
Other dependencies

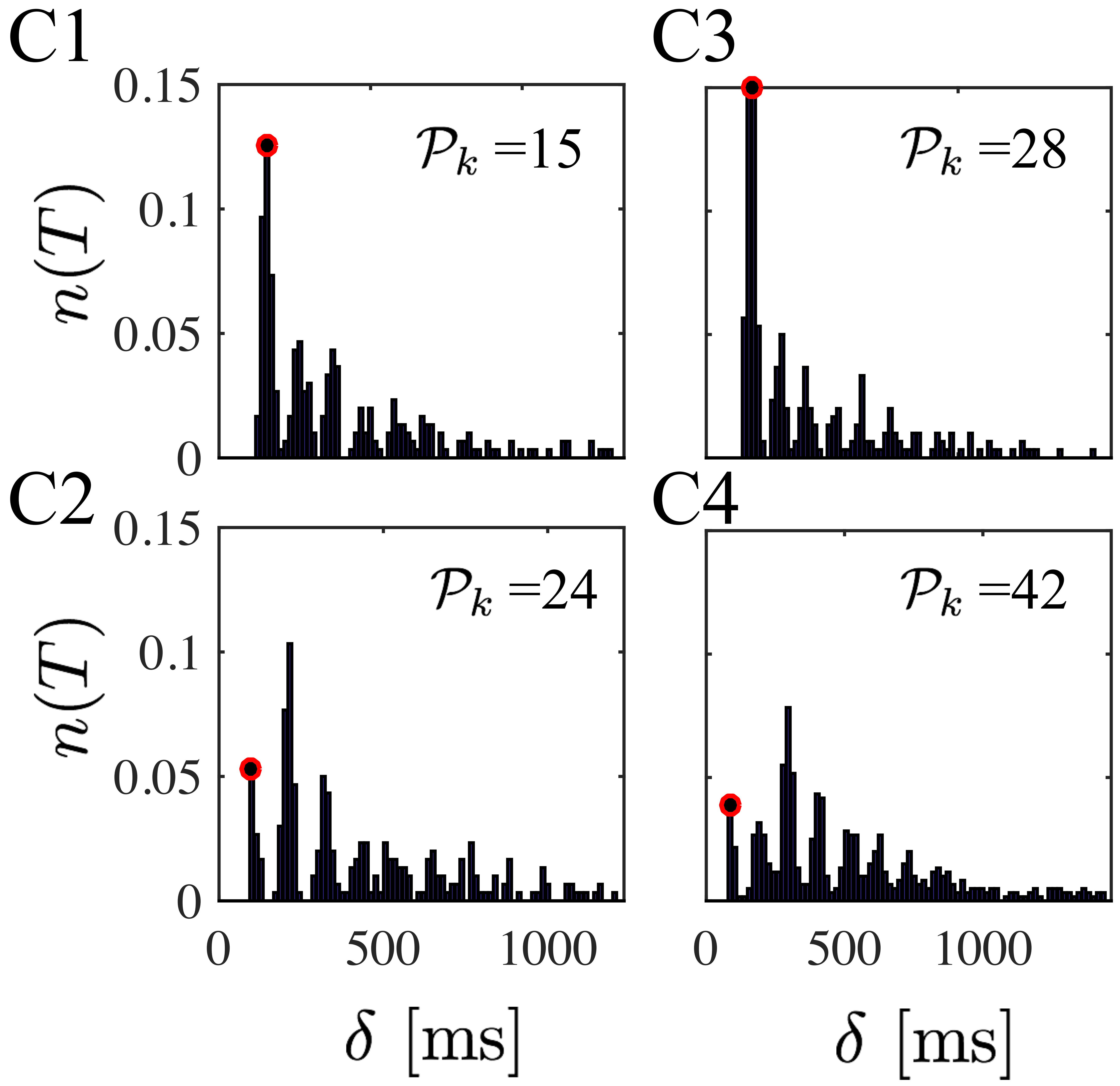
a) Select a reference trajectory $\mathscr{R}(t)$ with long SSA lifetime;

b) On $\mathscr{R}(t)$, we choose fifty equidistant positions $\mathscr{P}_k(t)$.

c) Perturb 600 times, but keep the orbit close to the reference trajectory.

e) Record resulting lifetime δ.

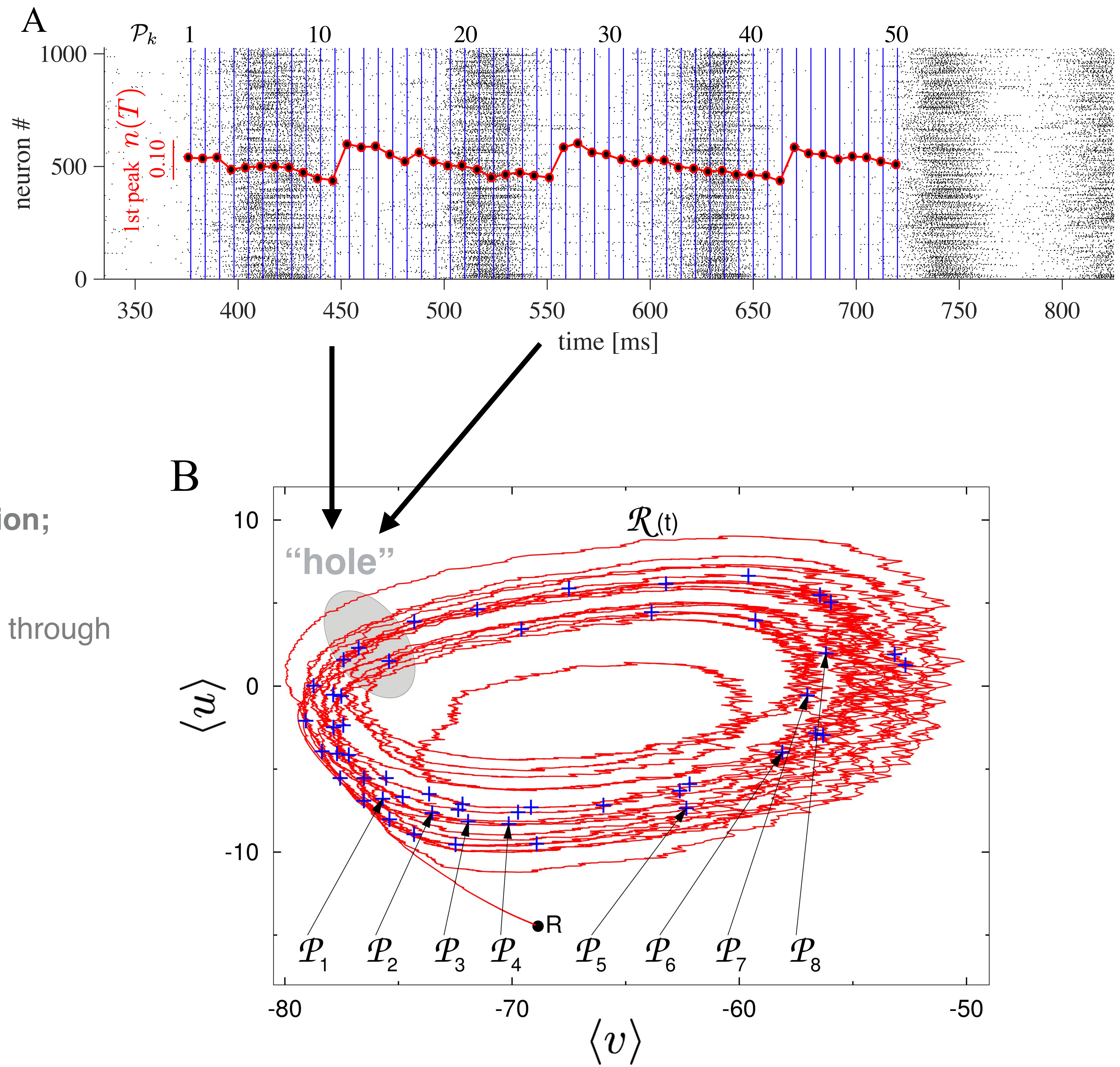




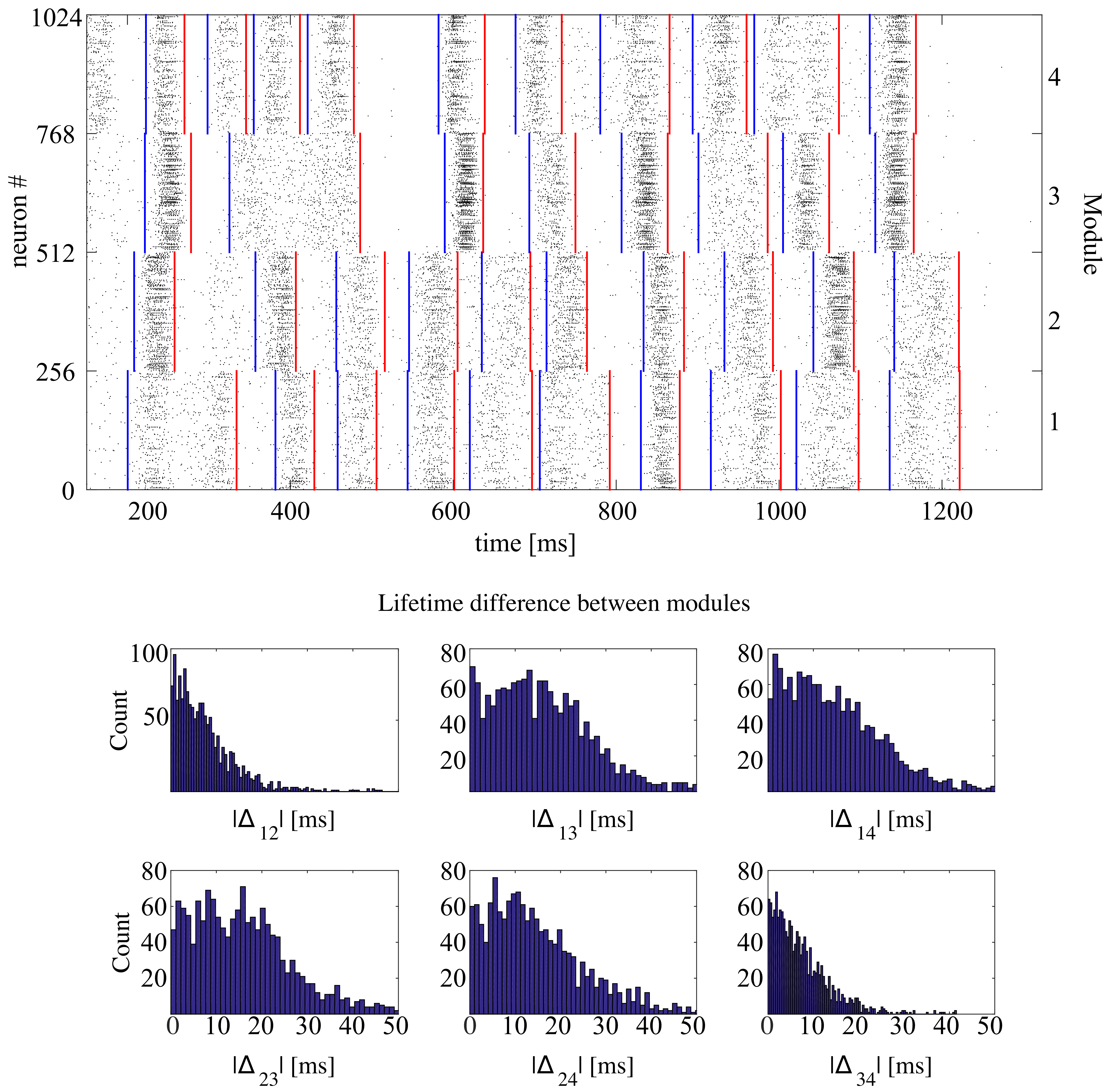
- Distributions of lifetimes are fractured;
- Shorter lifetimes are found in specific positions;

Phenomenological approach shows that

- Escape occurs from a relative small **unstable region;**
- Ensemble of trajectories are lost at every passage through this region;
- This explain the fractured lifetimes distributions;



H=2



Why hierarchy increases SSA?

Every module has its own "hole"

Excitatory intermodular connections

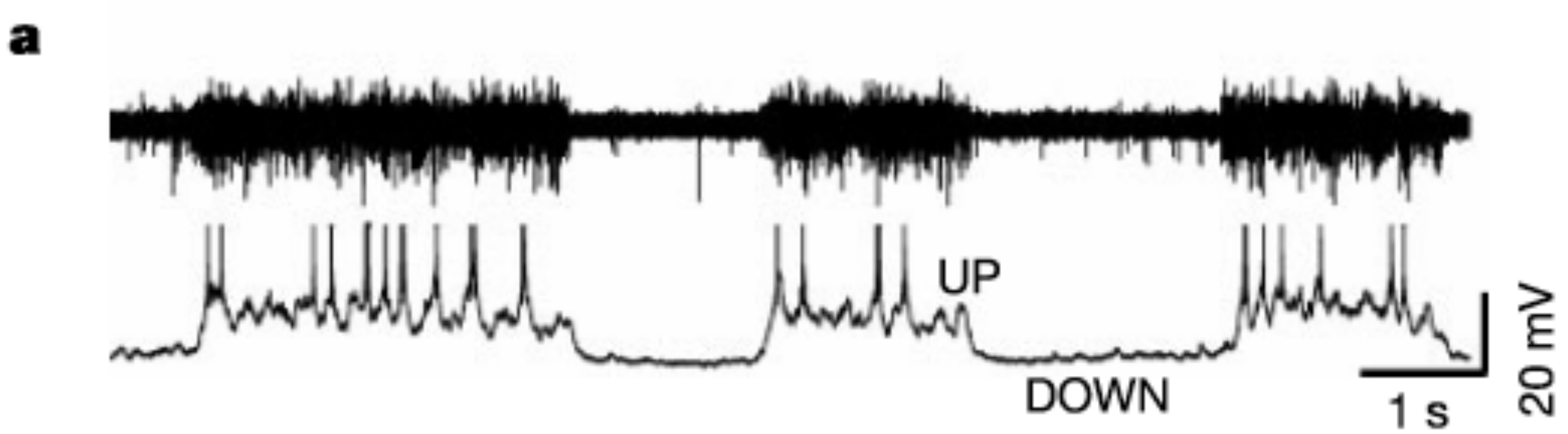
Modules are able to mutually reactivate each other

Sparseness of connections

Weak coupling avoids full synchronization

Self-sustained activity

- absence of stimuli



Cortical slice *in vitro*

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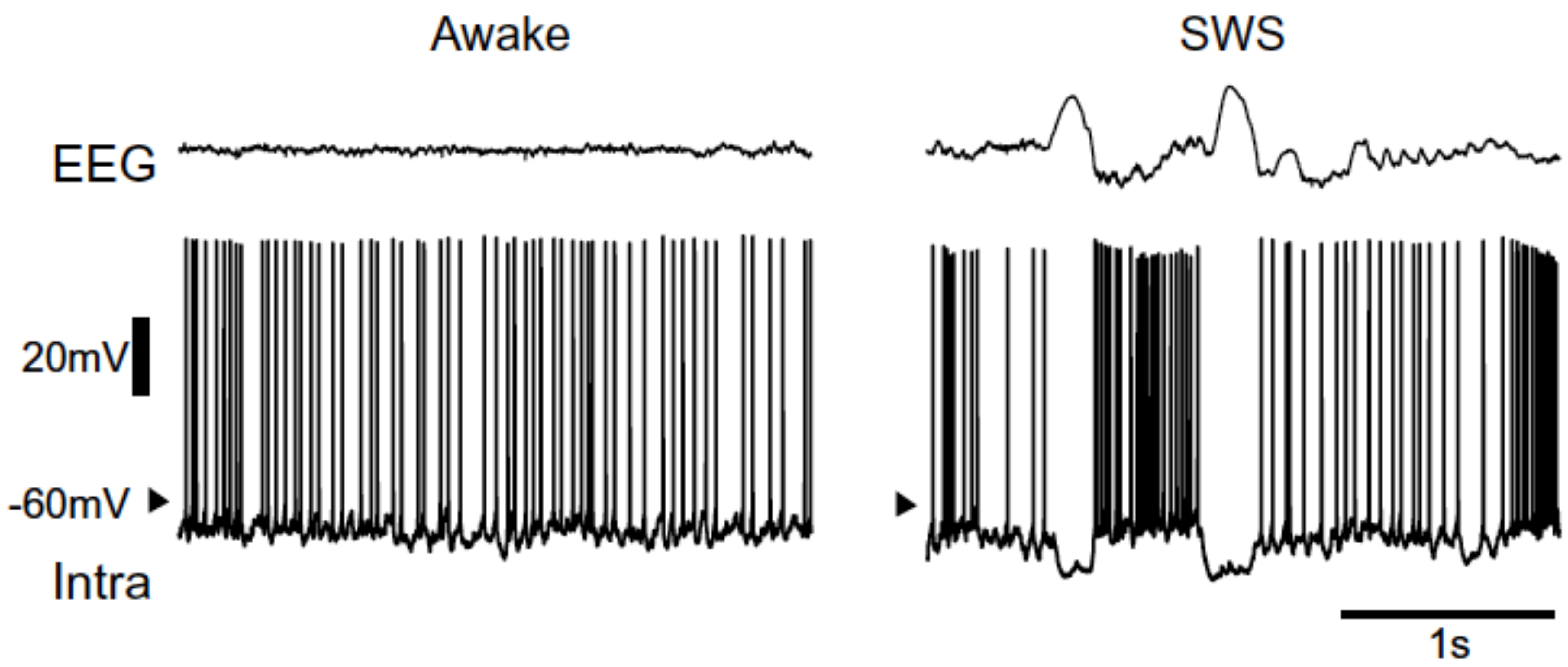
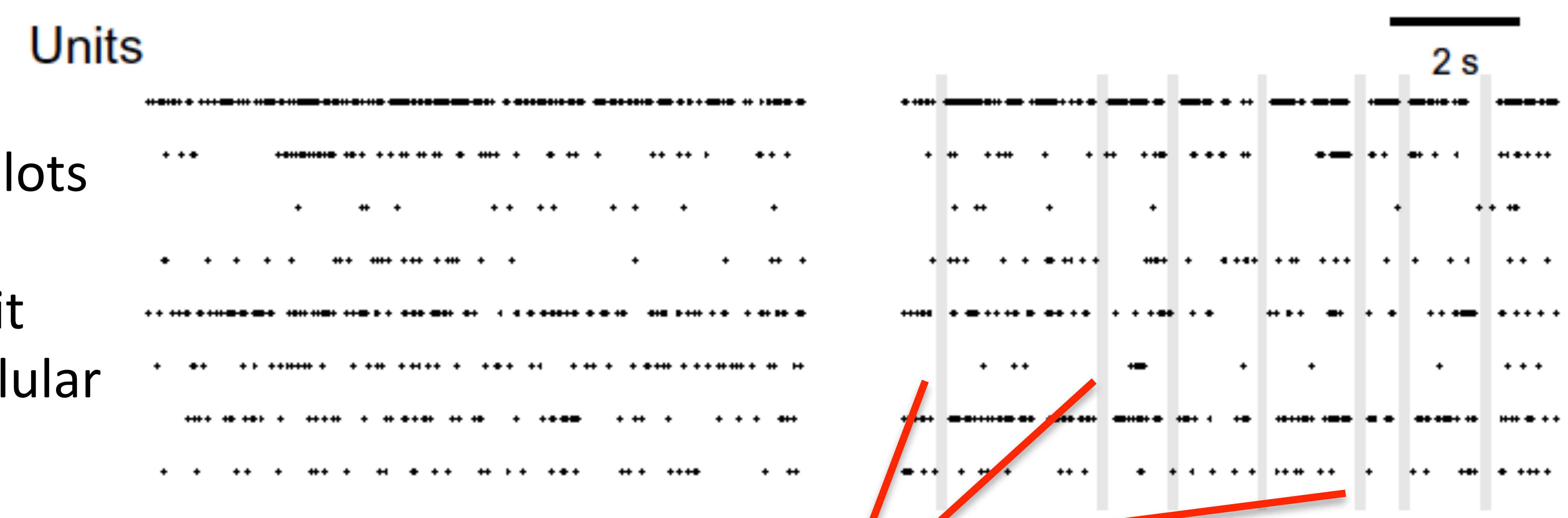


Steriade et al., J Neurophysiol 85:1969-1985, 2001.

In vivo recordings



Raster plots of multiunit extracellular spiking activity

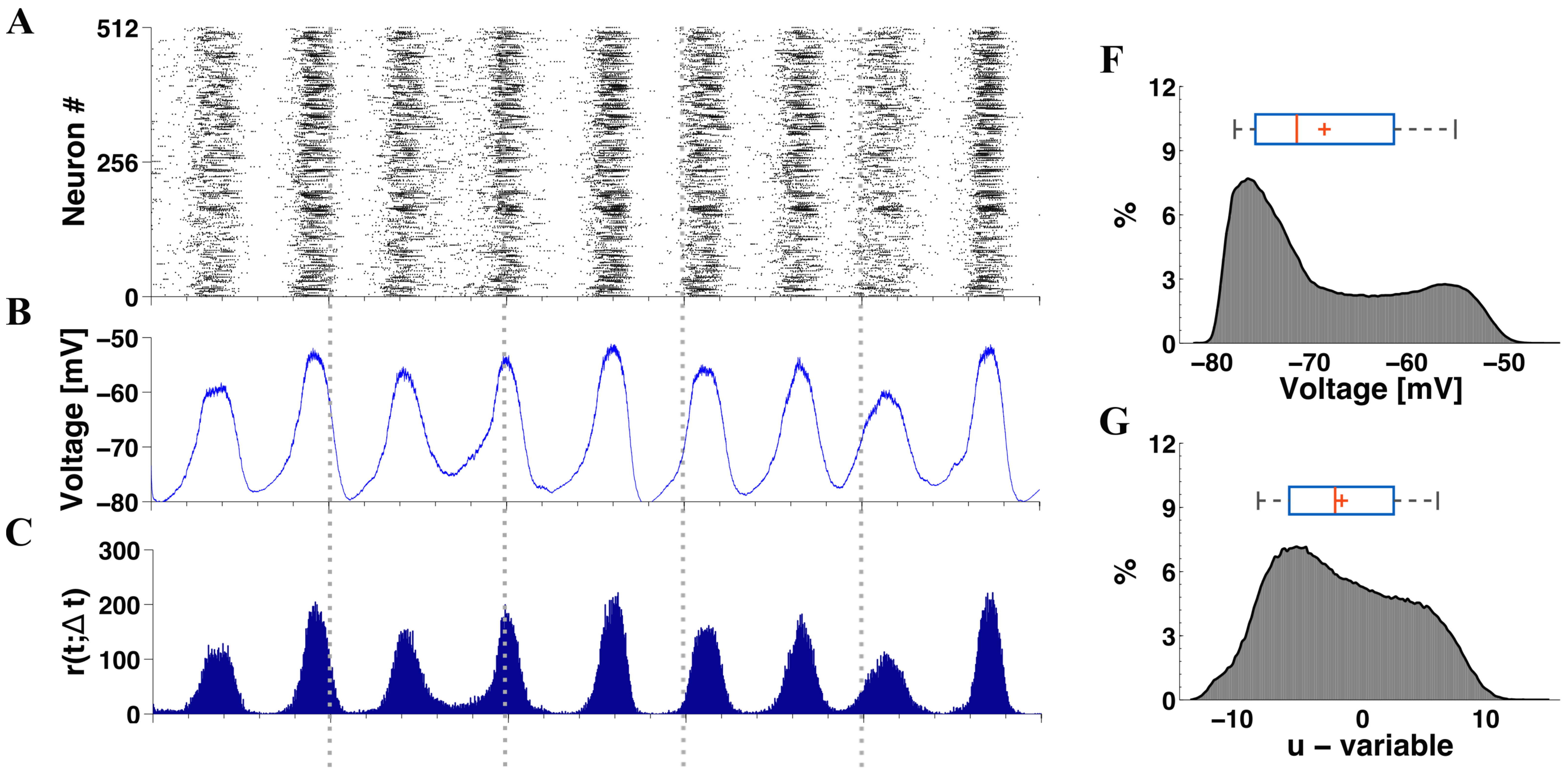
Down states

El Boustani et al., J Physiol (Paris) 101:99-109, 2007

Outline

02

Effect of synaptic noise on spontaneous activity

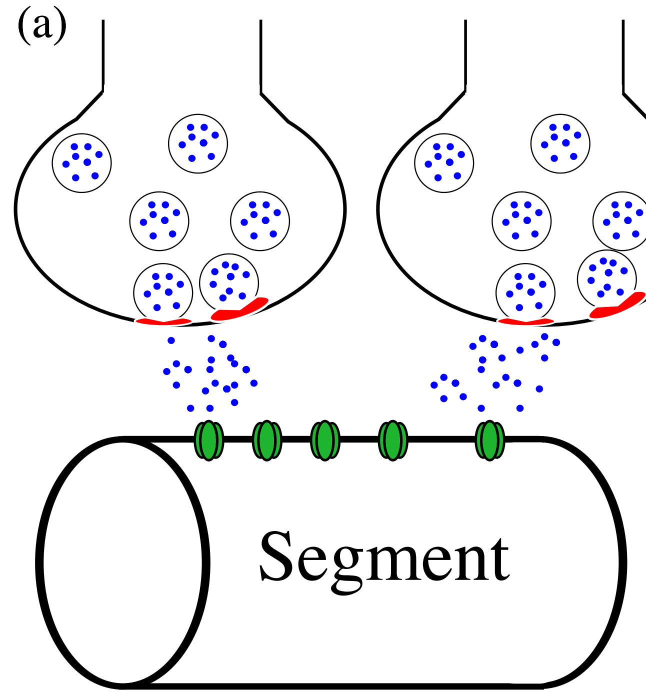


Noiseless activity

Noisy case

Case D=2.5x10^{-6} , $(g_{in}, g_{ex}) = (1, 0.15)$

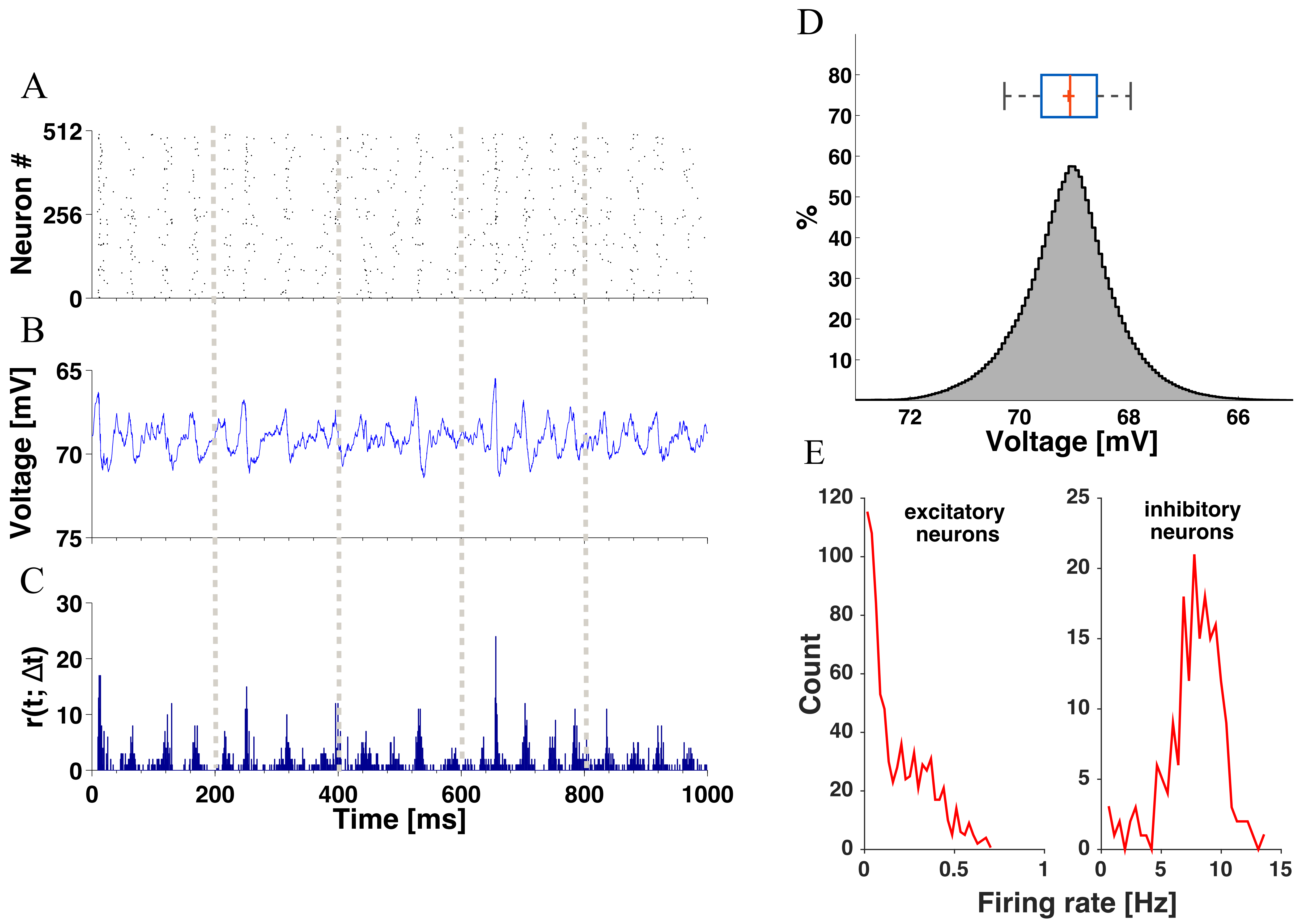
Synaptic noise



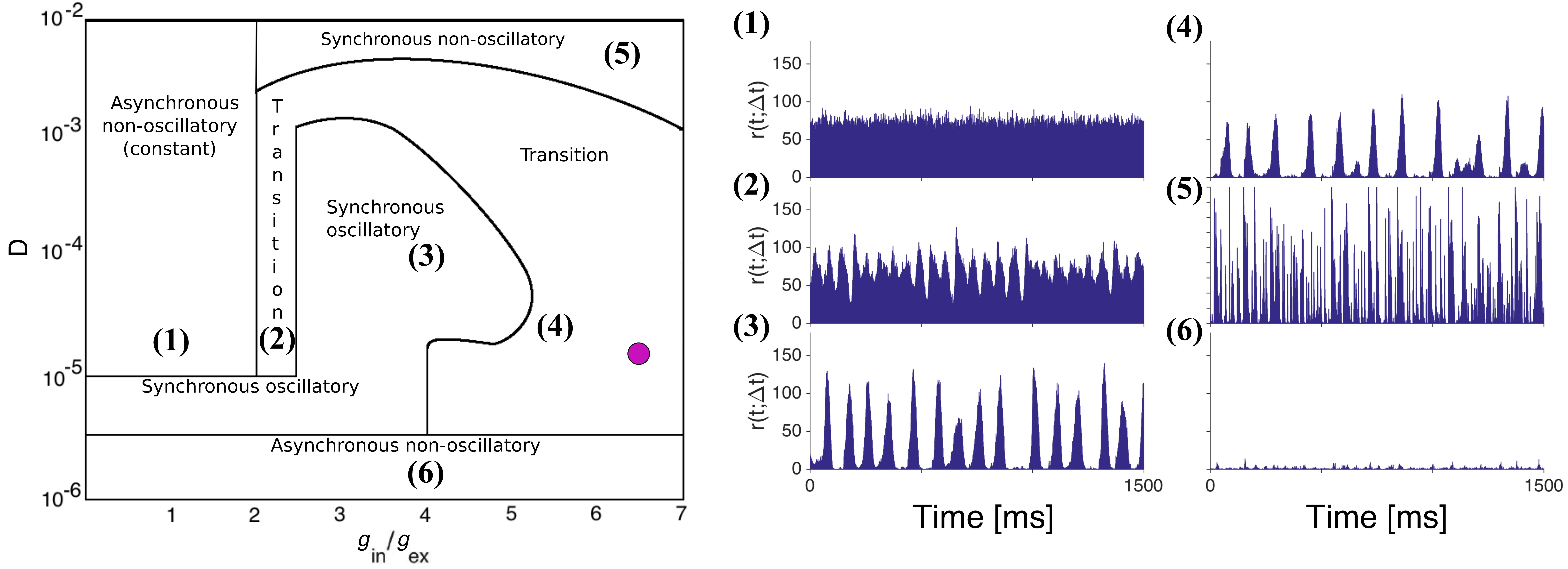
$$\frac{dG_j^{\text{ex/in}}}{dt} = -\frac{G_j^{\text{ex/in}}}{\tau_{\text{ex/in}}} + g_{\text{ex/in}} \sum_i \delta(t - t_i) + \underbrace{\sqrt{2Dn_j}\xi(t)}_{\text{Synaptic Noise}}$$

n_j = No. of synaptic channels

$\langle \xi(t) \rangle = 0$ and $\langle \xi(t)\xi(s) \rangle = \delta(t-s)$



Weak noise delivers asynchronous irregular state



Synaptic noise and g_{in}/g_{ex} define activity patterns.

Switches between active and silent

Intermittent transitions

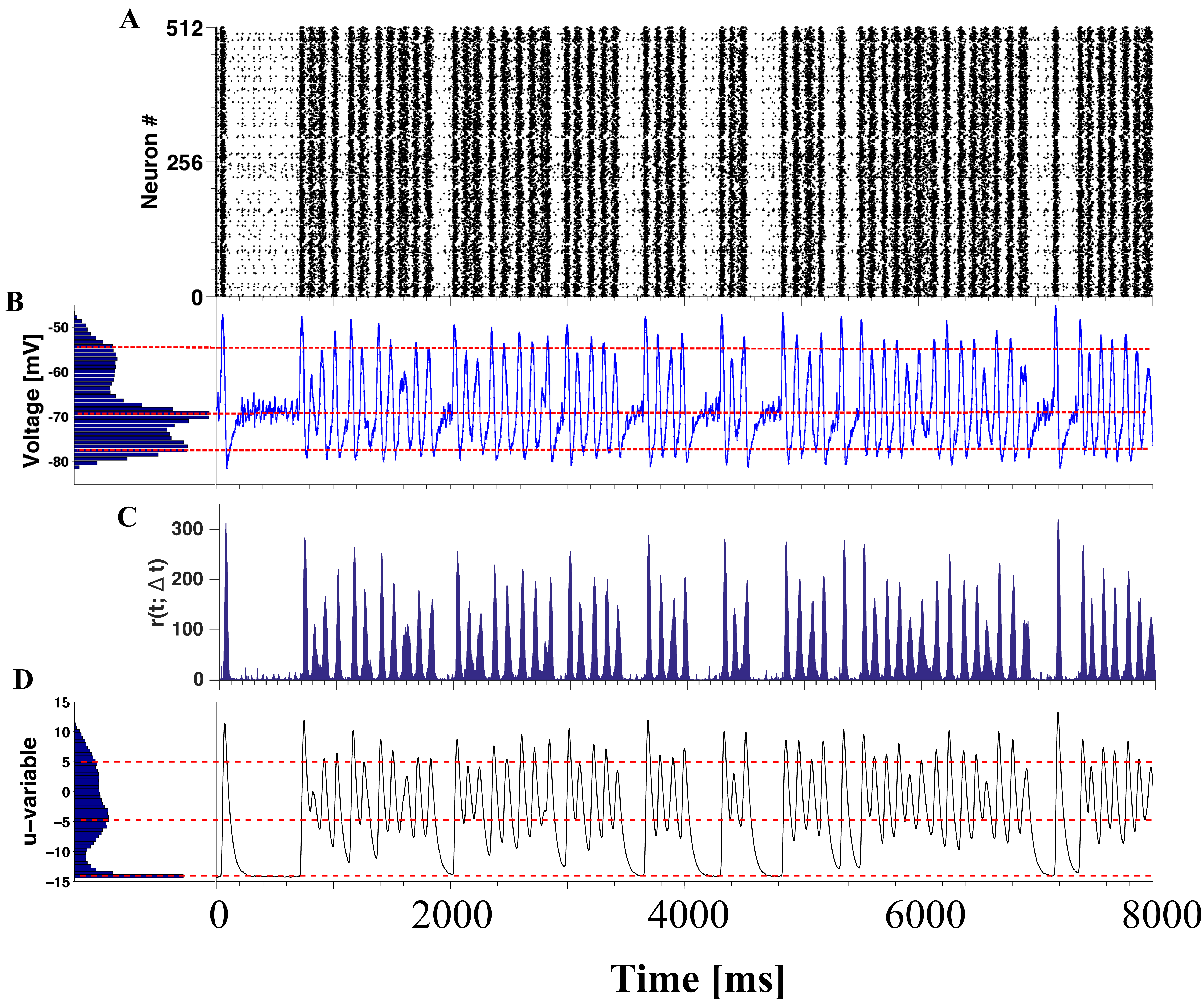
ACTIVE PERIOD

Alternating UP and DOWN states;
Oscillatory activity;

QUIESCENT PERIOD

Asynchronous irregular activity;
Low firing rate;

Case D=1x10^{-5} , (g_{in}, g_{ex}) = (1, 0.15)



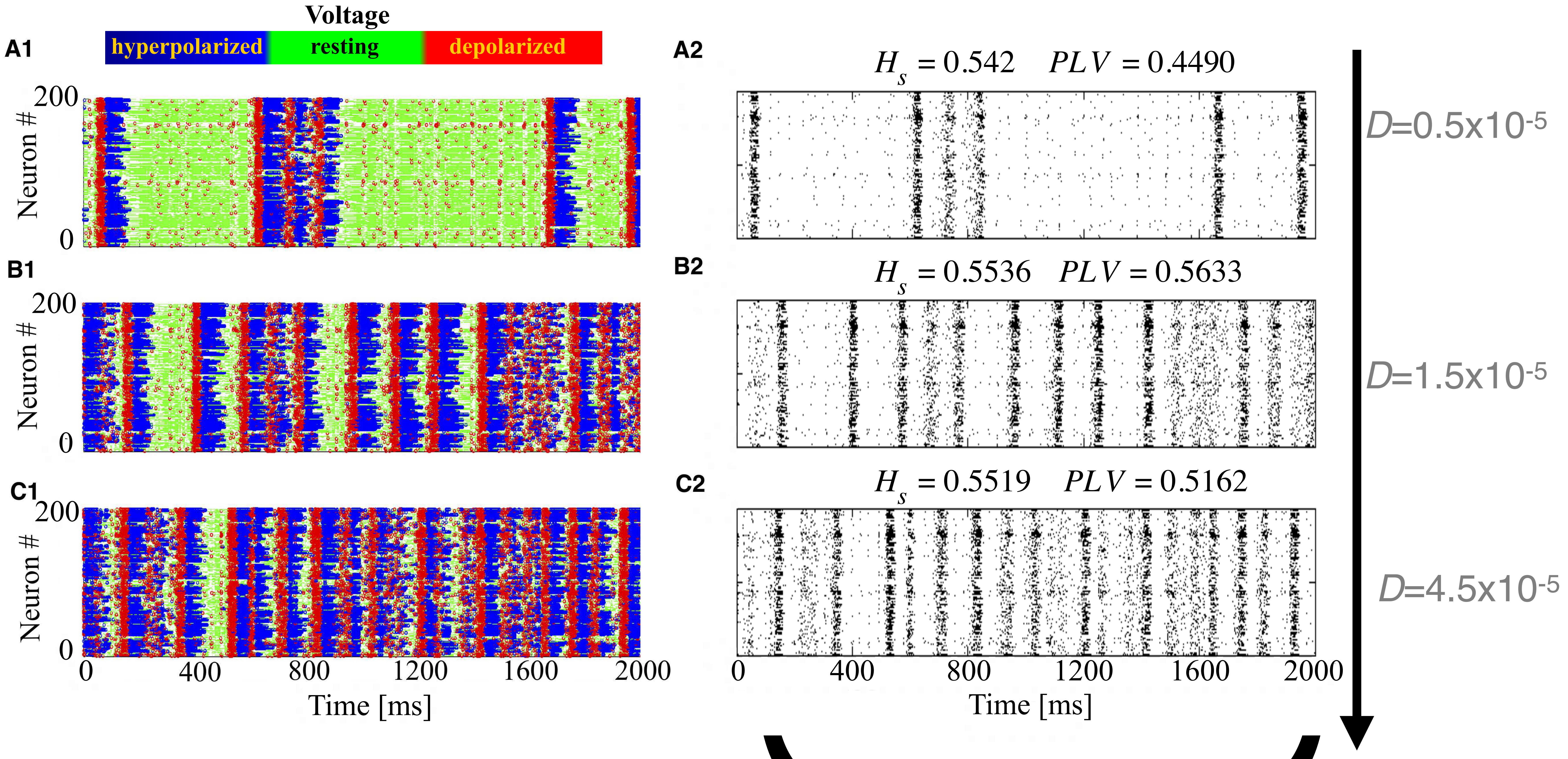
Pena et al. (2018), *J Comput Neurosci 45*:1–28

Noise favors oscillatory activity

Systematically increasing noise

As *D* increases

- Active periods are favored;
- Quiescente periods decrease;



Oscillations start to merge

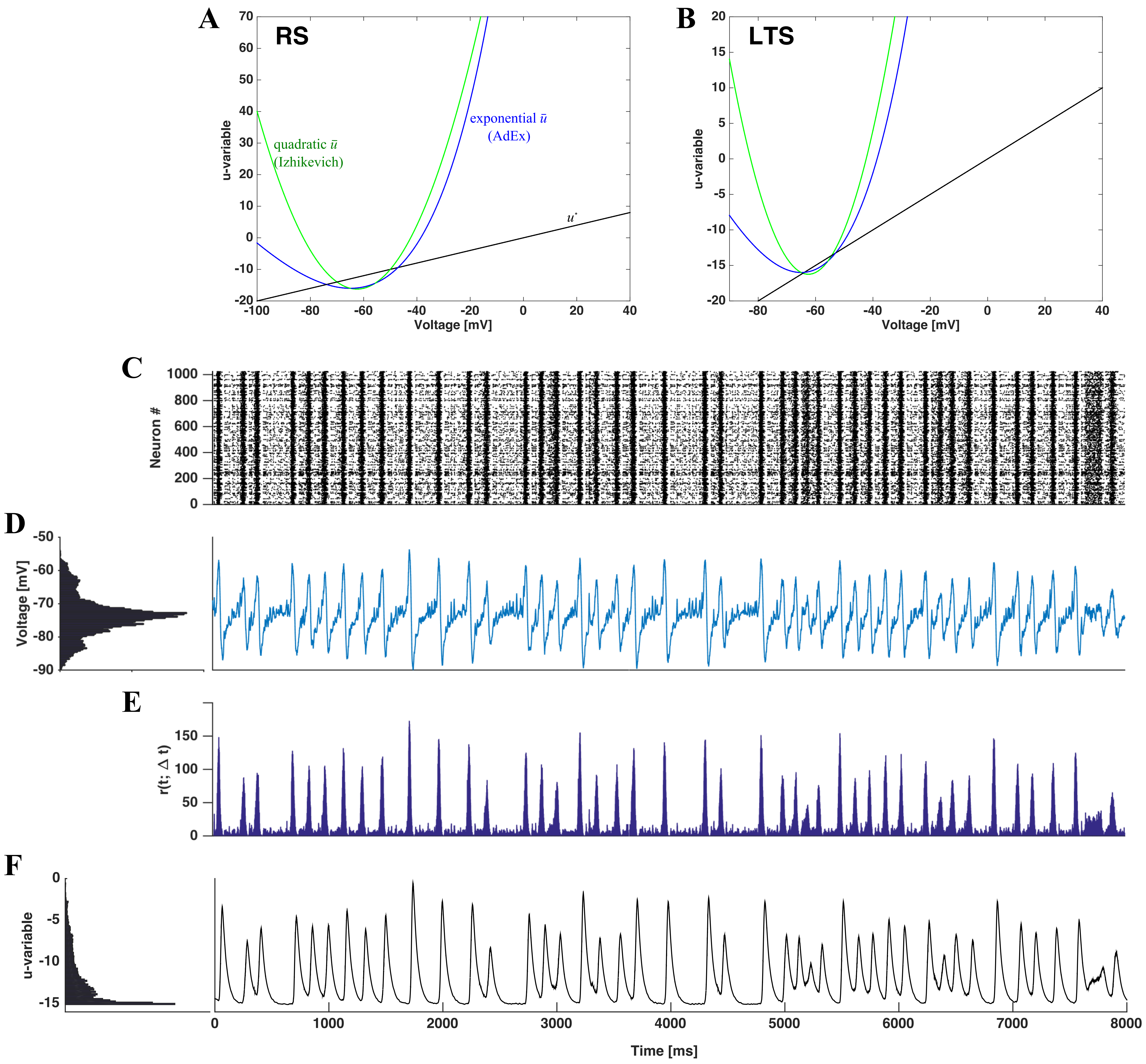
Similarities with other 2D neuron models

AdEx model

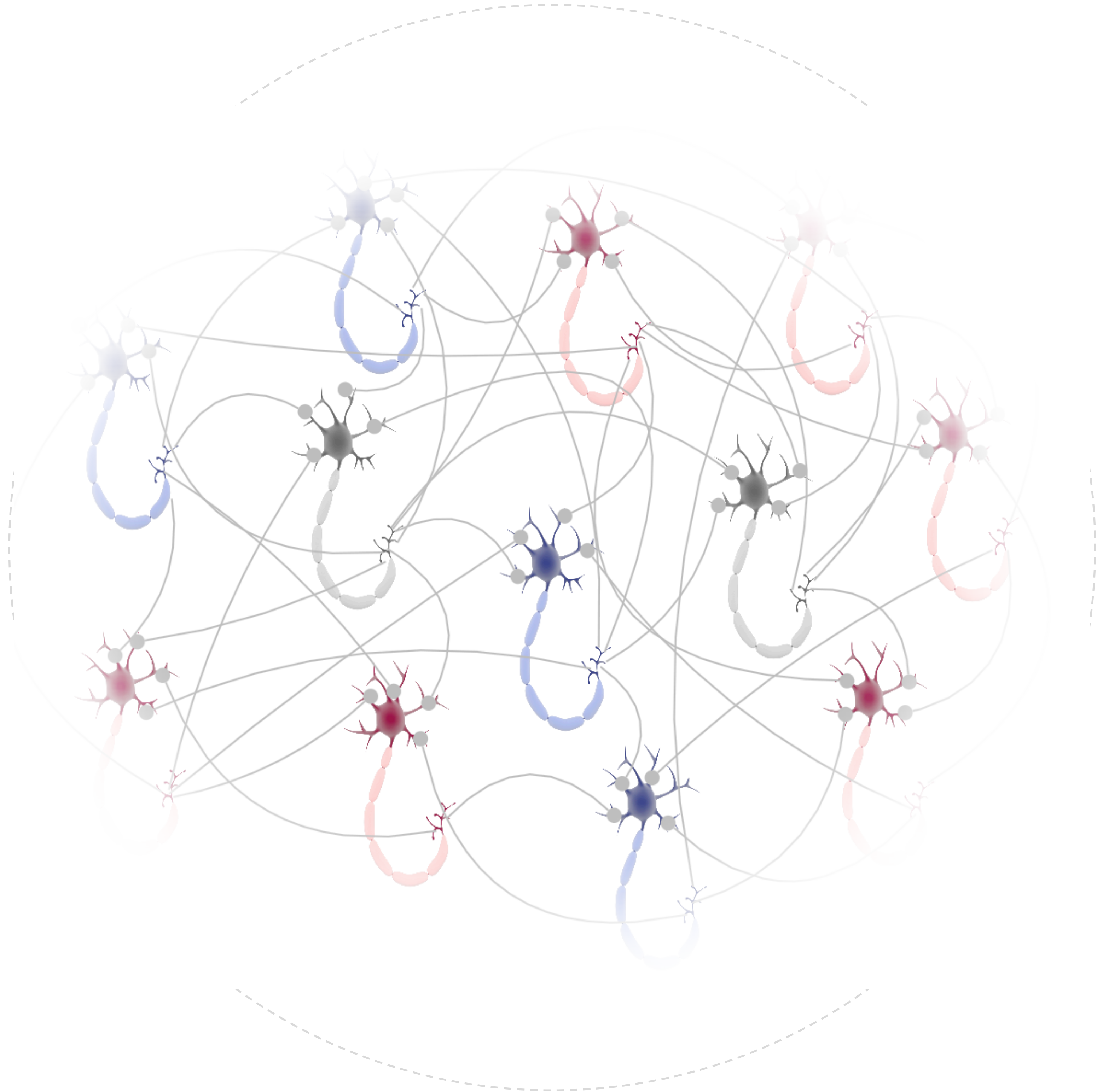
$$\begin{cases} \dot{v} &= -g_L(v - E_L) + g_L \Delta_T \exp(\dfrac{v - v_T}{\Delta_T}) - 46 - u + I(t) \\ \dot{u} &= a(b\,v - u), \end{cases}$$

Izhikevich model

$$\begin{cases} \dot{v} &= 0.04v^2 + 5v + 140 - u + I(t) \\ \dot{u} &= a(b\,v - u), \end{cases}$$



Network



How to describe network noise?

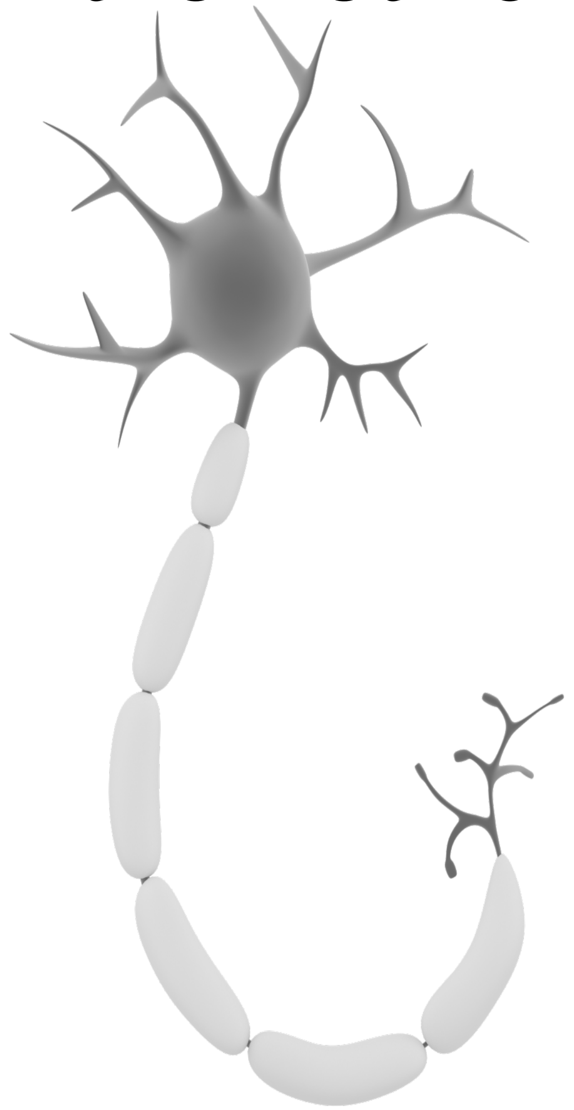
Outline

A reductionist approach

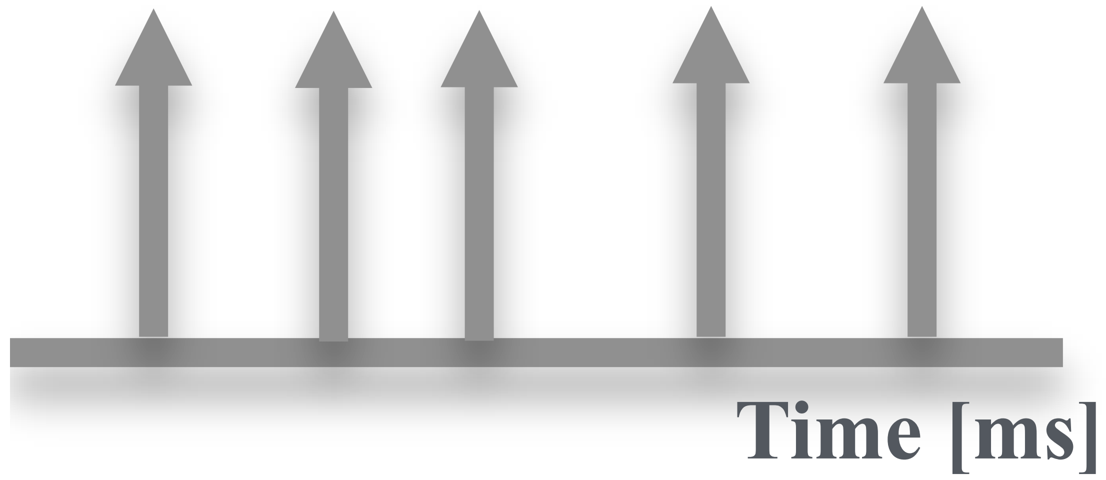
03

A reductionist approach to deal with network noise

Single-neuron in the network



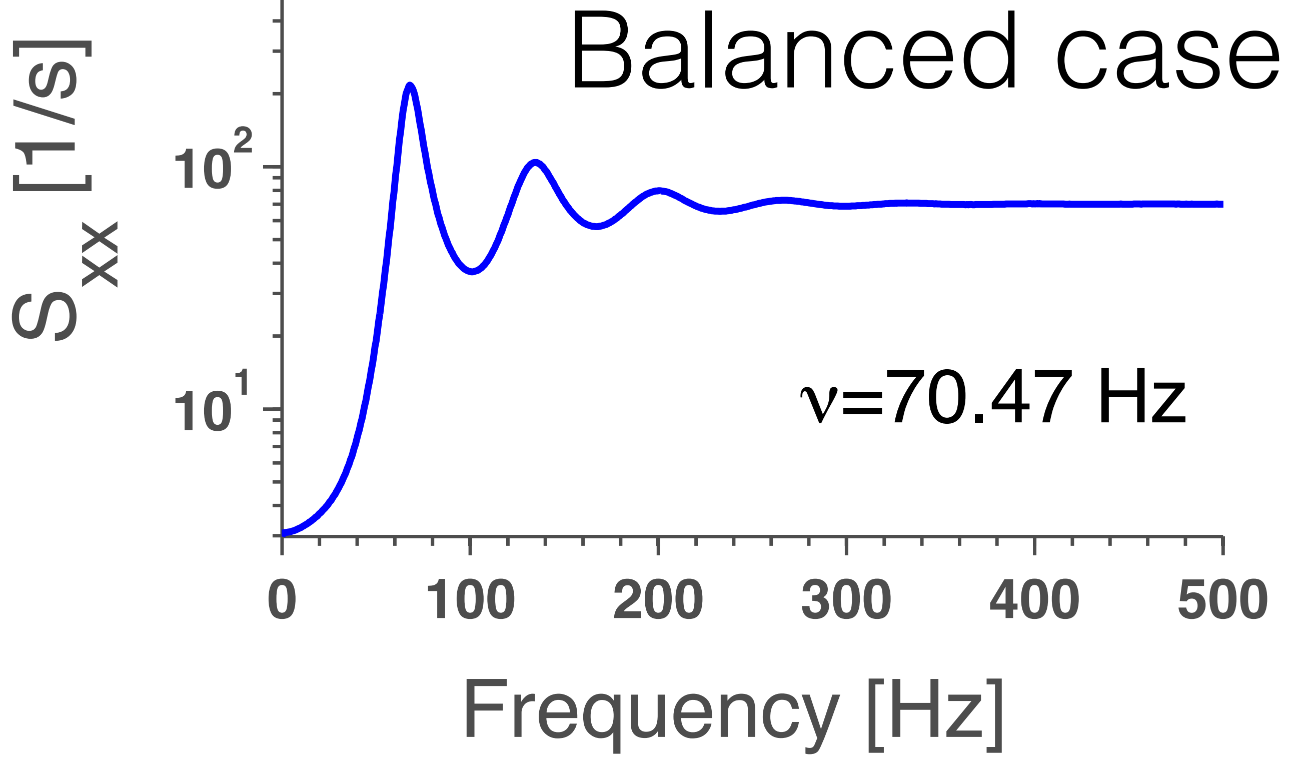
Spike-train: $x(t) = \sum_i \delta(t - t_i)$



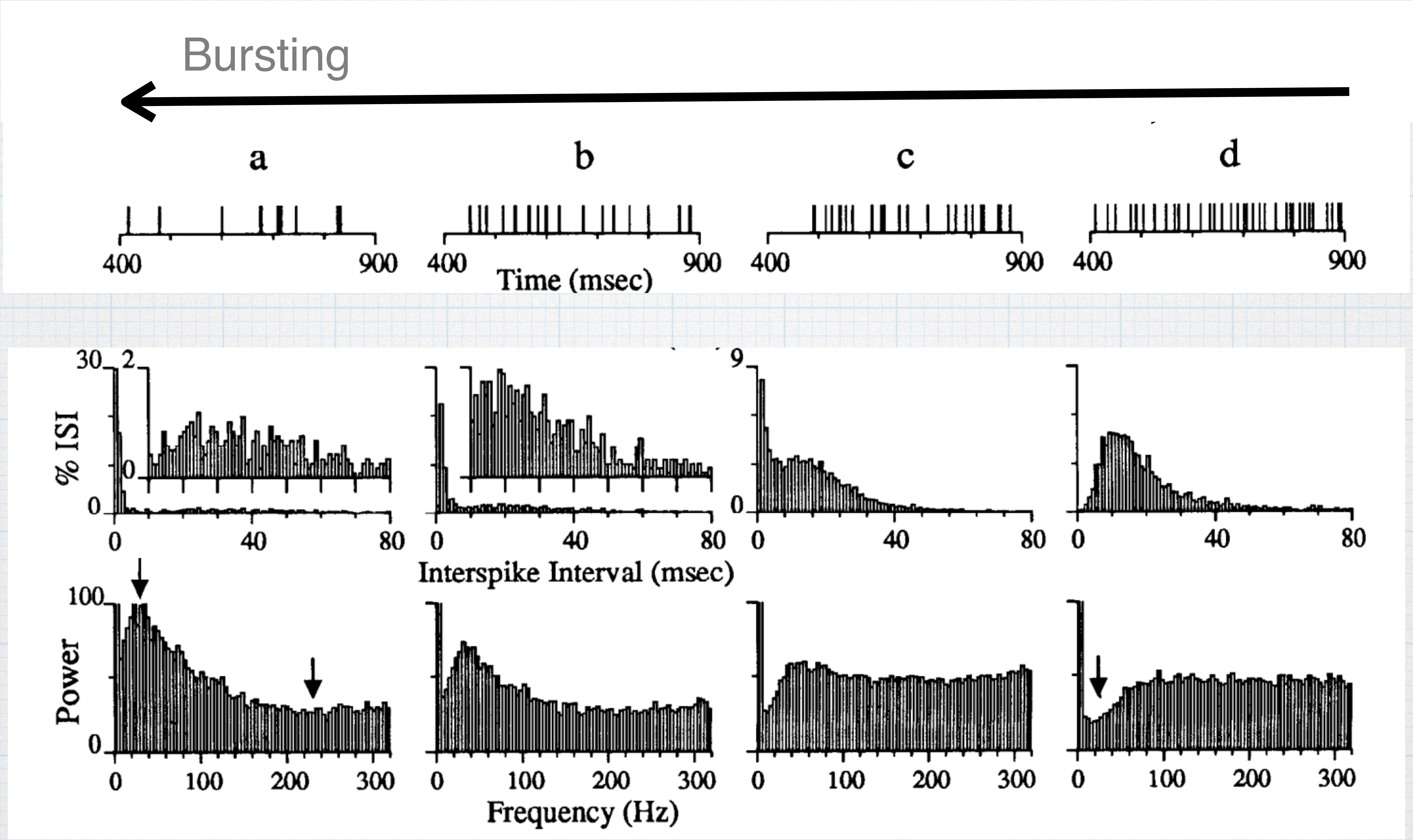
Describing second-order statistics

How fluctuations are built up in a **network** from a **neuron's** point of view

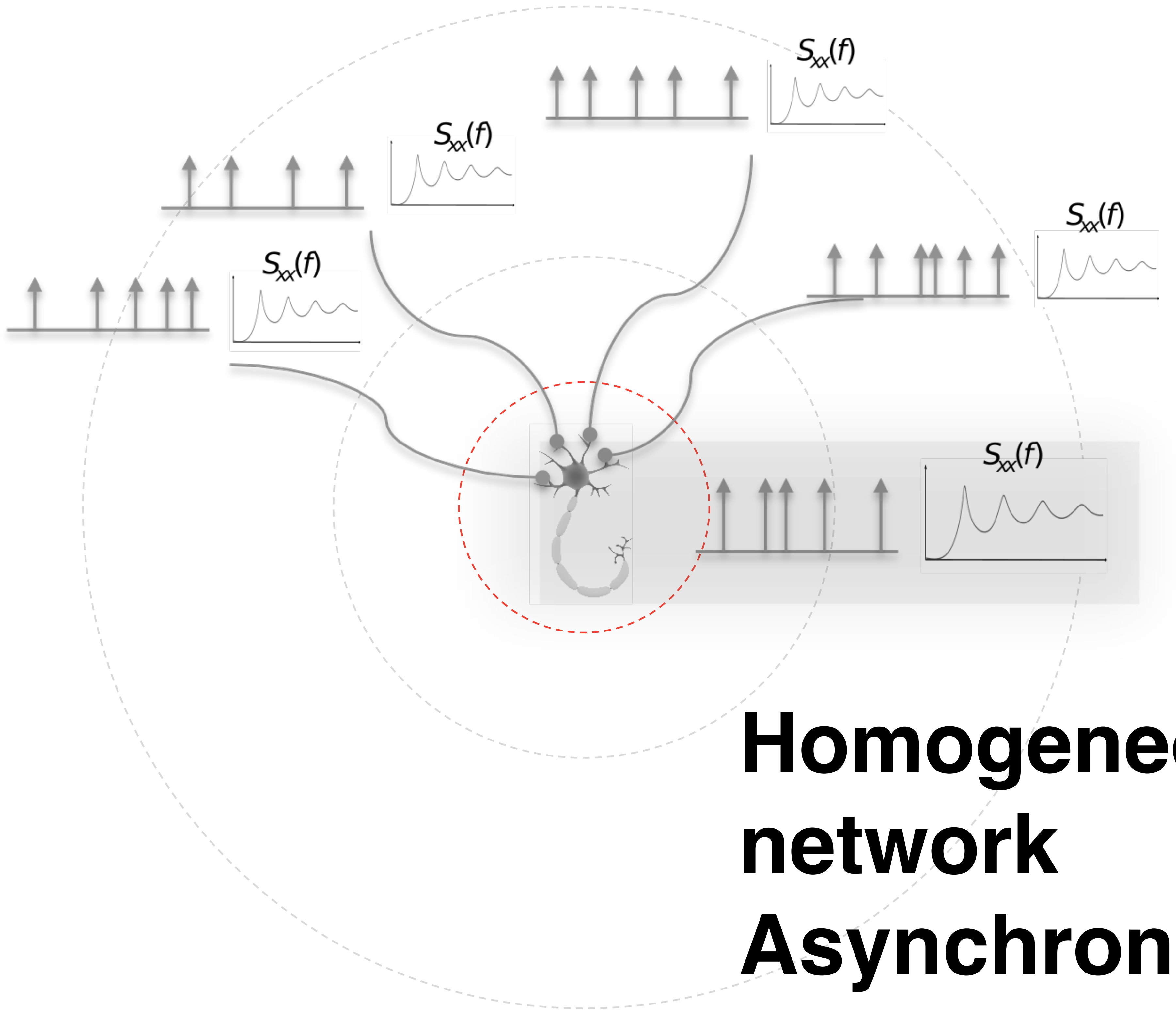
Power spectrum



Neurons recorded in the visual cortex



Bair et al., *J. Neurosci*. (1994), 74:2870-2892



Homogeneous large sparse network

Asynchronous irregular activity

Self-consistency generated

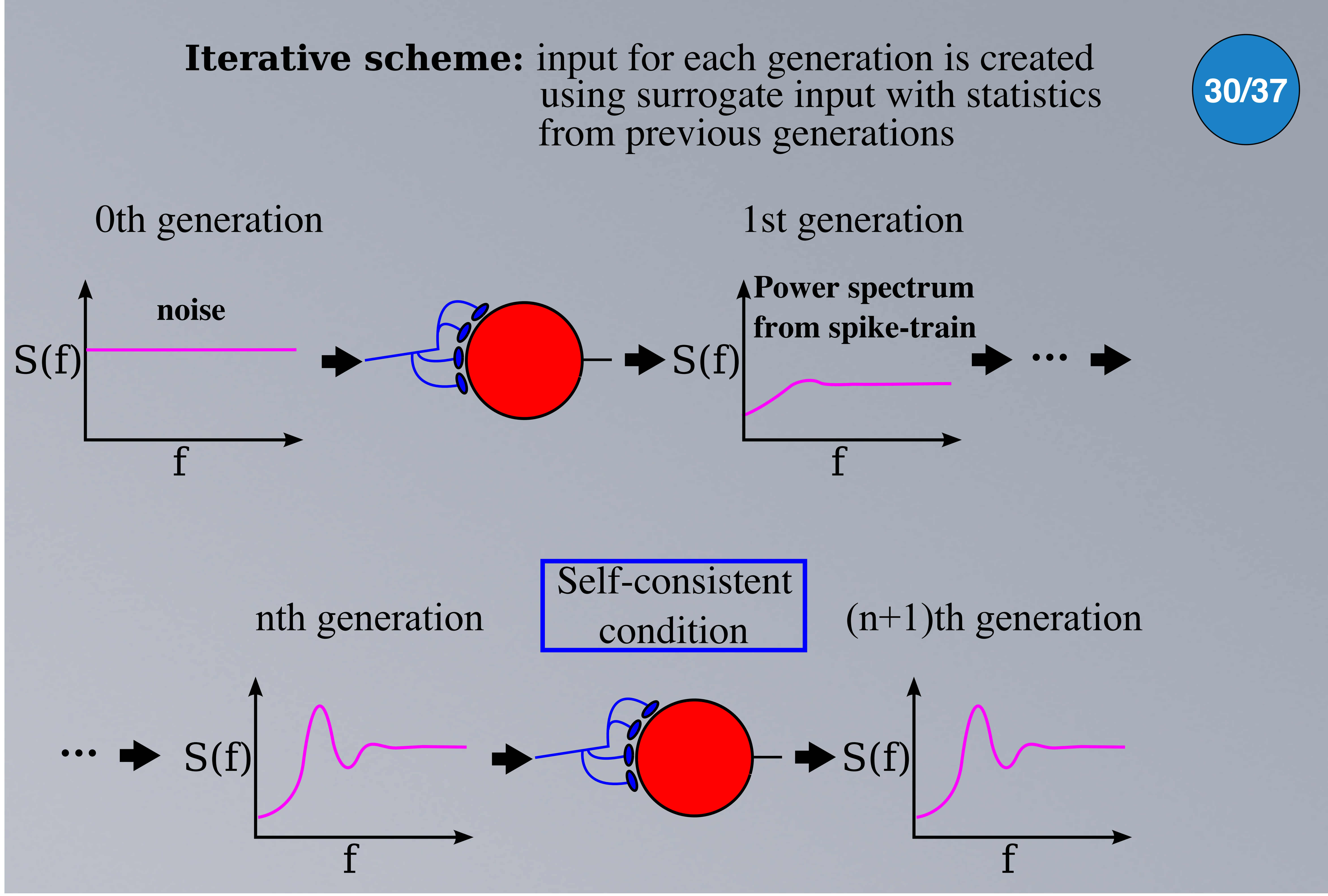
Input should be proportional to output

Iterative scheme

A. Prescribe noise from the **previous** generation;

B. Apply to the **next** generation;

C. Repeat it recursively until self-consistency;



Procedure employed in

Lerchner et al. (2006), *Neural Comput 18*:634-659

Dummer et al. (2014), *Front Comput Neurosci 8*:104

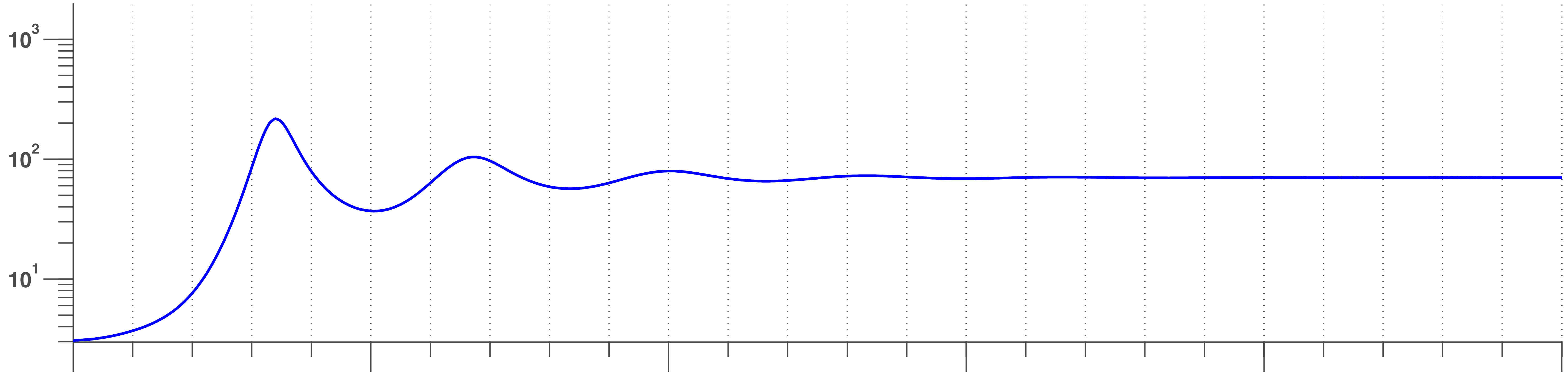
Wieland et al. (2015), *Phys Rev E 92*:040901

Will final statistics be the same as in the network?

How to prescribe an input current with a given power spectrum?

$\bar{S}(f_k)$

$$\bar{S}(f) = \tau^2 J^2 \left(C_E + g^2 C_I\right) S(f)$$



f_k

Draw two Gaussian random numbers at every frequency bin f_k

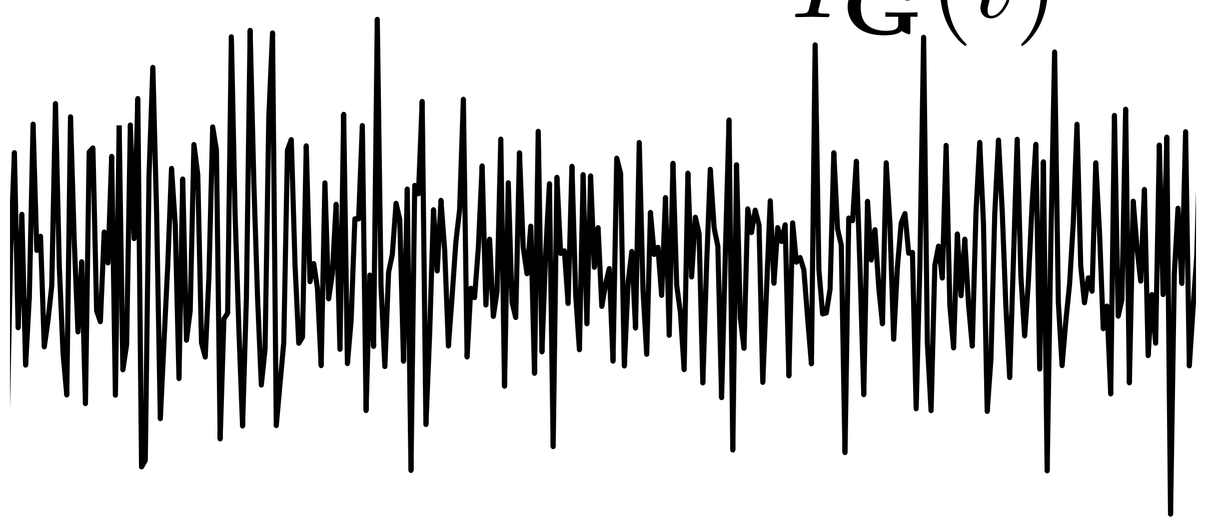
$$\tilde{\eta}_r(f_k), \tilde{\eta}_i(f_k)$$

$$\langle \tilde{\eta}(f_k) \rangle = 0$$

$$R\tilde{I}_G(f_k) = \sqrt{\frac{\bar{S}(f_k)}{2\Delta f}}\left(\tilde{\eta}_r + i\tilde{\eta}_i\right)$$

IFFT

$I_{\mathbf{G}}(t)$



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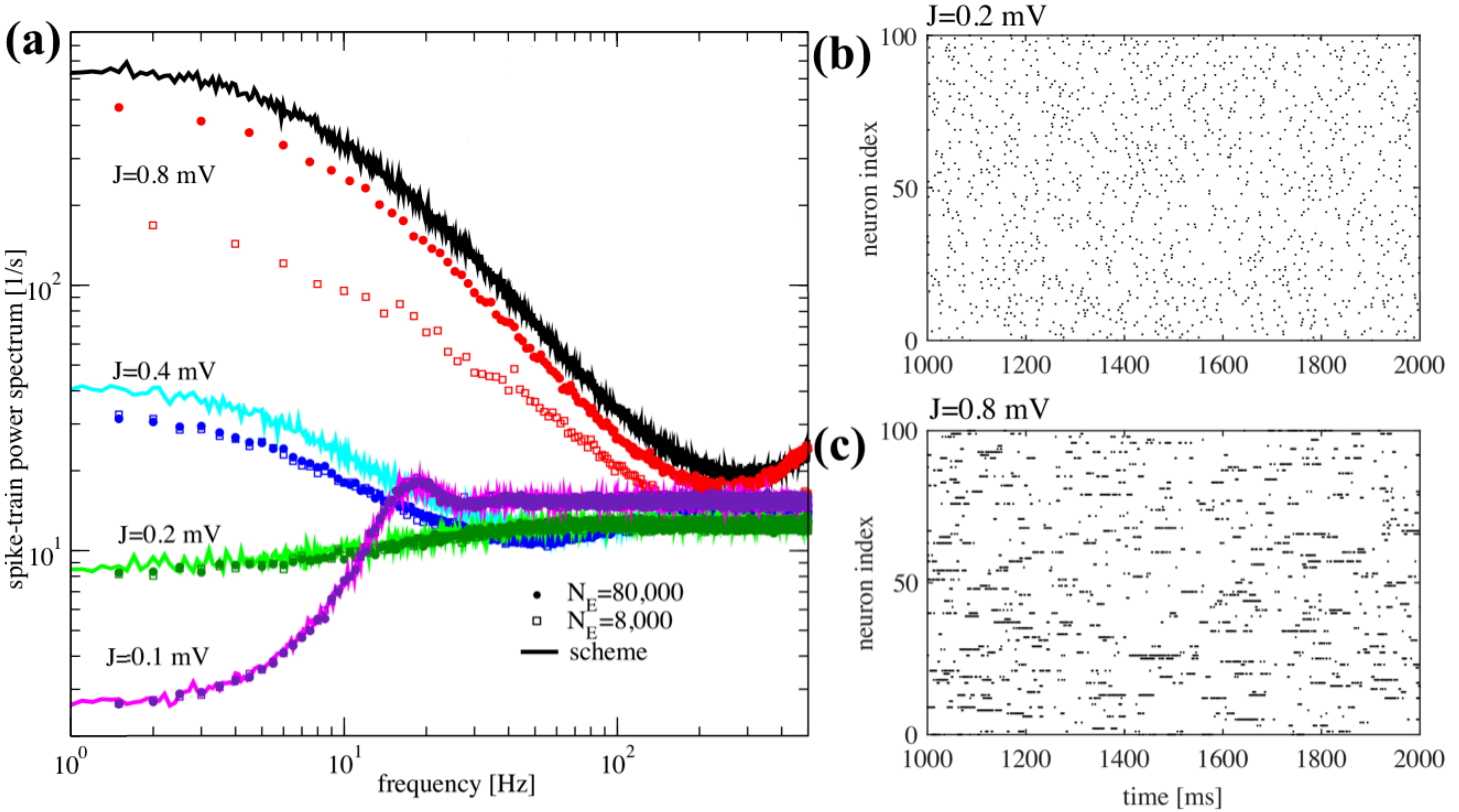
Homogeneous case with strong recurrent inhibition (non-balanced case)

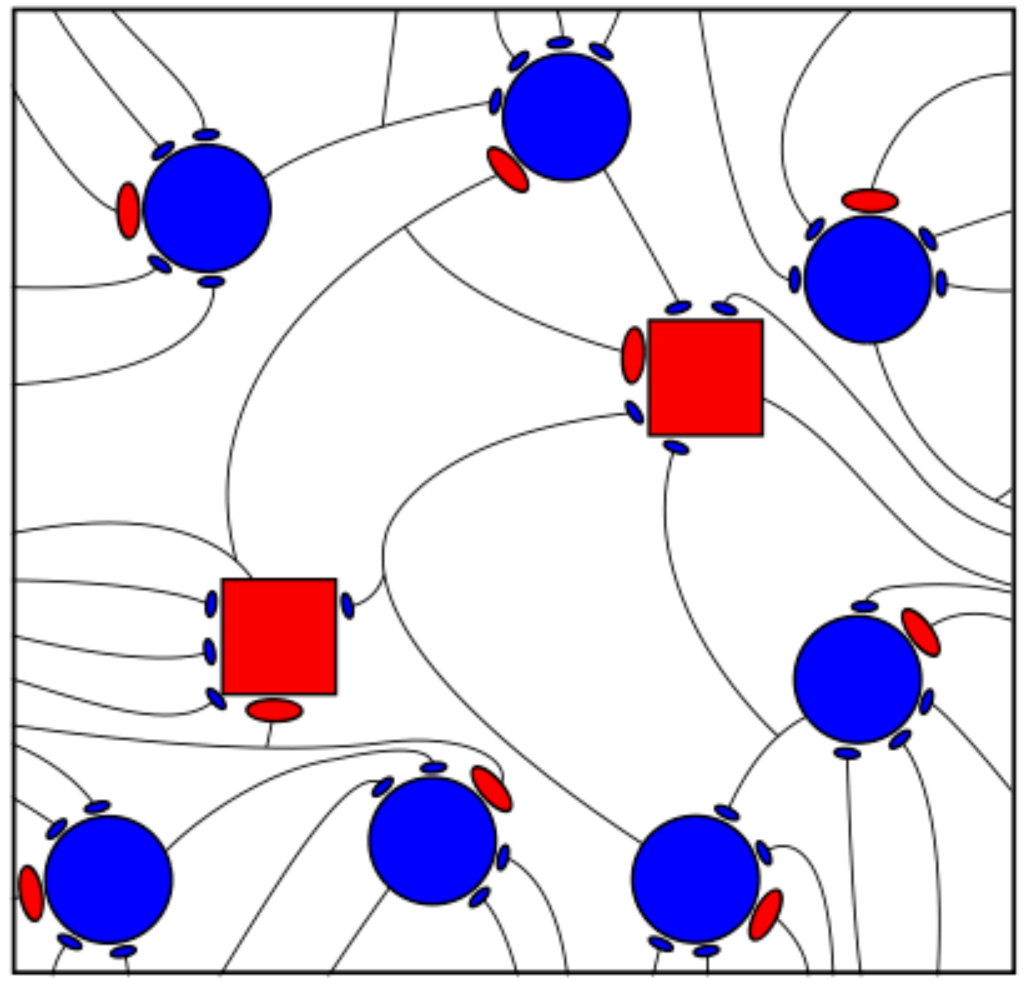


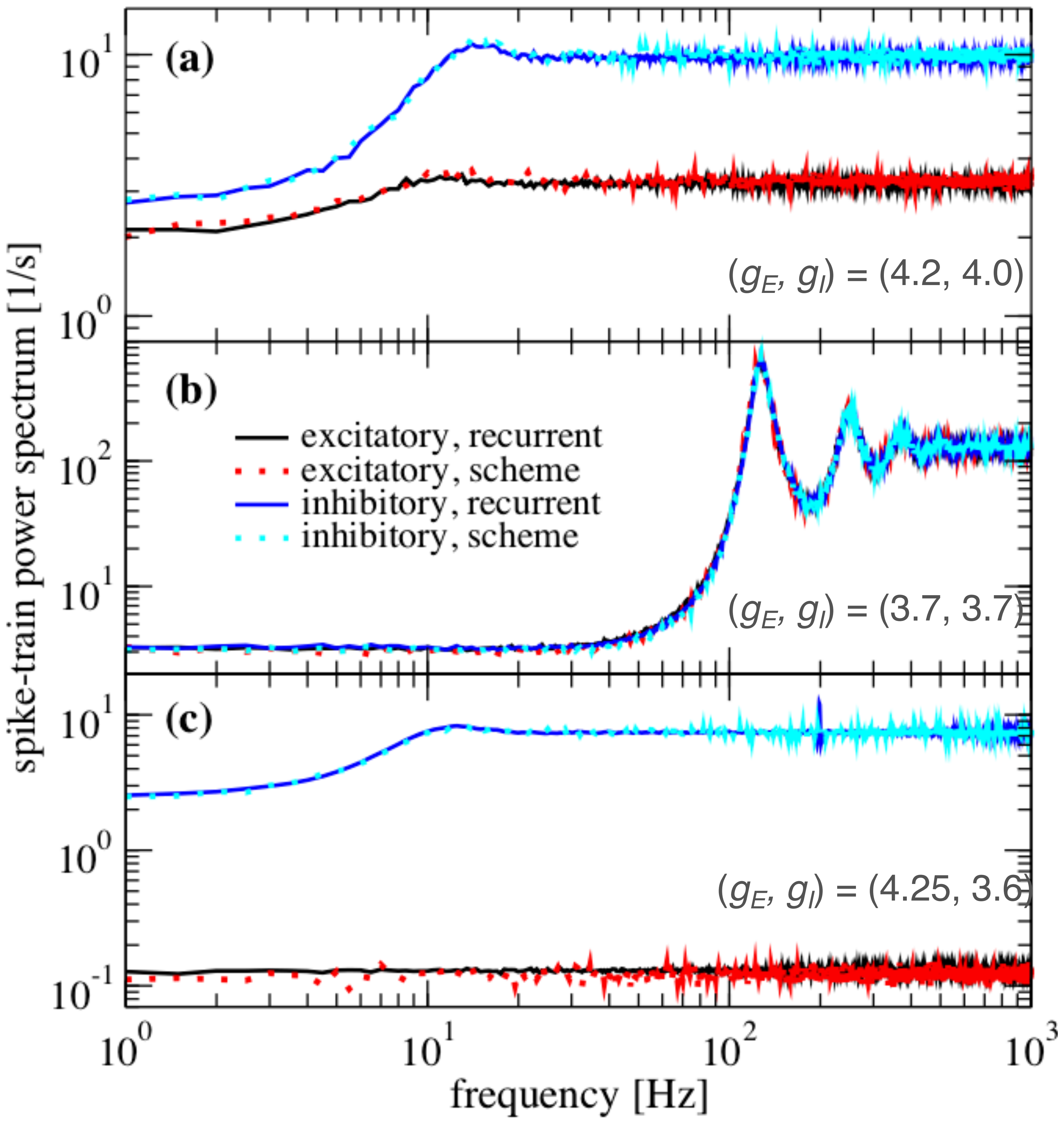
Homogeneous AI

Heterogeneous AI

- **Integrate and fire neurons, fixed in-degree, Exc:Inh 4:1 (setup from Brunel 2000; Ostojic 2014);**
- **Large amplification of slow fluctuations explain heterogeneous AI;**

Different **excitatory** and **inhibitory** cells

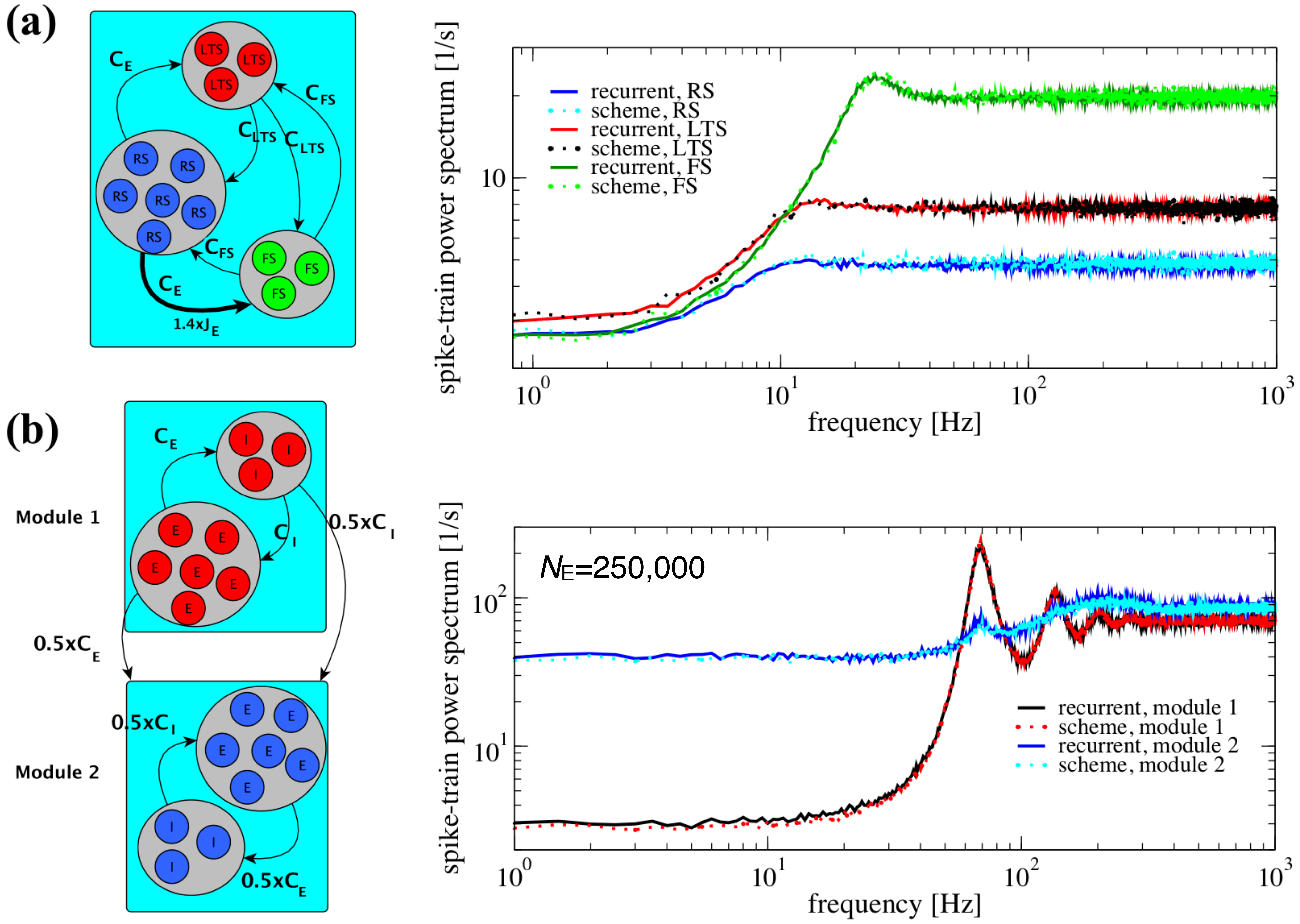




- Second-order statistics are well captured by iterative scheme;
- Configurations with ν_E as low as 0.1Hz;

More than two populations

- Heterogeneity with respect to classes (RS, FS, LTS);
- Heterogeneity with respect to modularity;



Pena et al. (2018), *Front Comput Neurosci 12*:9

More than two populations

- **Heterogeneity with**
to classes (RS, FS,

- **Heterogeneity with**
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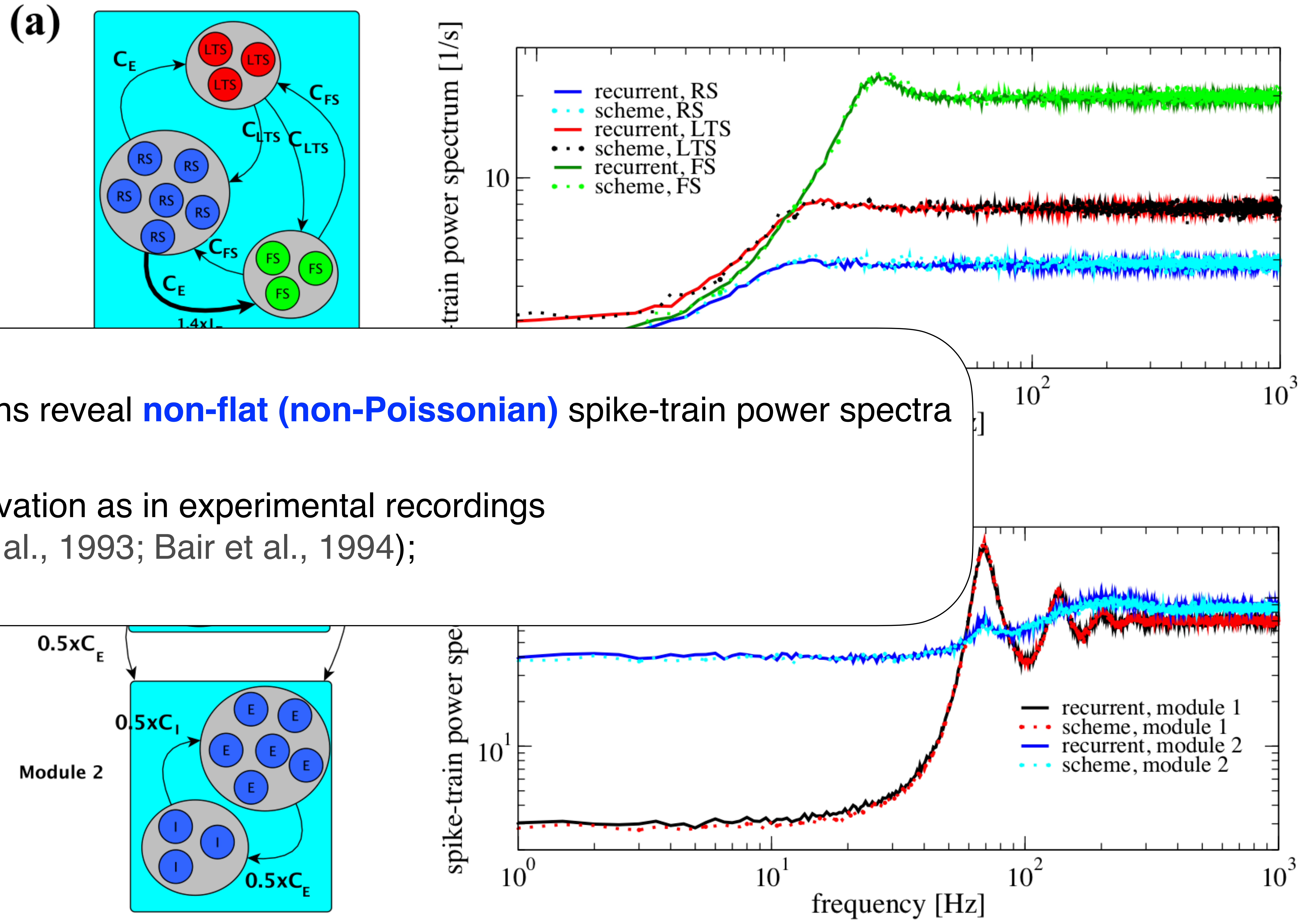

- All simulations reveal **non-flat (non-Poissonian)** spike-train power spectra

- Same observation as in experimental recordings
(Edwards et al., 1993; Bair et al., 1994);

Pena et al. (2018), *Front Comput Neurosci 12*:9

Many thanks to

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Humboldt Universität Berlin

Lab SisNe Members
NeuroMat SimLab

IRTG 1740

IRTG 1740

NeuroMat

CEPID NeuroMat

FAPESP

Processo 2013/25667-8

And many others…

LASCON

Latin American School on Computational Neuroscience

NeuroMat

- One month intensive course
- International team of world-renowned researchers
- Applications are open!

Lab SisNe
http://sisne.org/

sisne.org/lascon-viii

References

Front Comput Neurosci (2016) *10*:23

J Comput Neurosci (2018) *45*:1–28

Front Comput Neurosci (2018) *12*:9

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Thank you very much!