Simulations of cortical network models made of stochastic spiking neurons

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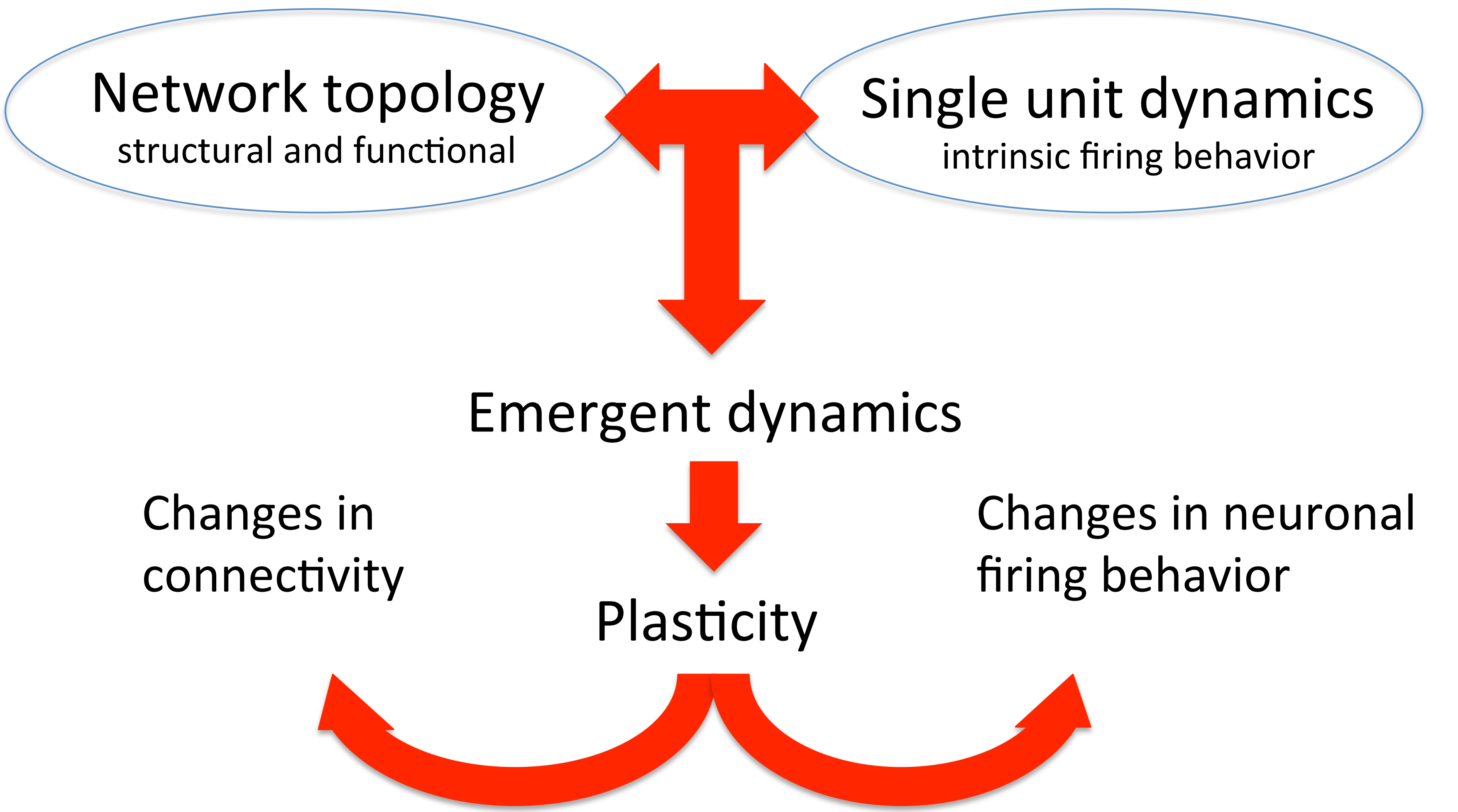
Dynamical phenomena in networks of spiking neurons



Dynamic phenomena: brain activity patterns

- **Spontaneous activity**: brain activity in the absence of an explicit task, such as sensory input or motor output (*resting-state* or *ongoing* brain activity)
- **Evoked activity**: brain activity induced by sensory stimuli or task-related motor response
- **Pathological activity**: brain activity associated to some neurological disorder or disease

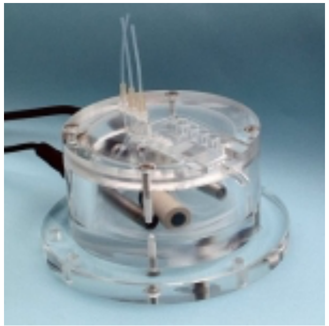
Importance of studying brain activity patterns

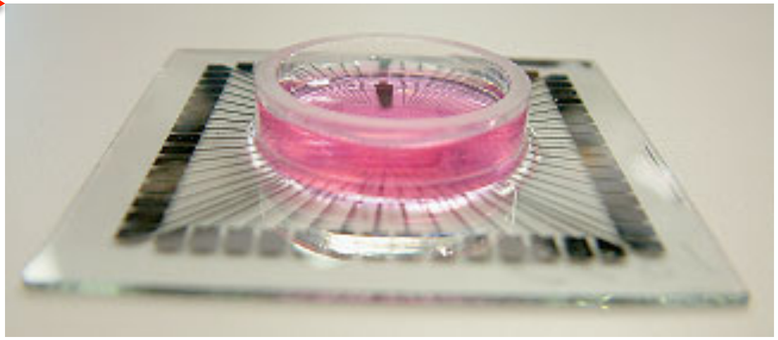
- Cortical activity is not strictly determined by sensory input but reflects an **interaction** of external stimuli with spontaneous patterns that are produced endogenously
- For example: context tree-generated sequence of external inputs applied to a subject at rest

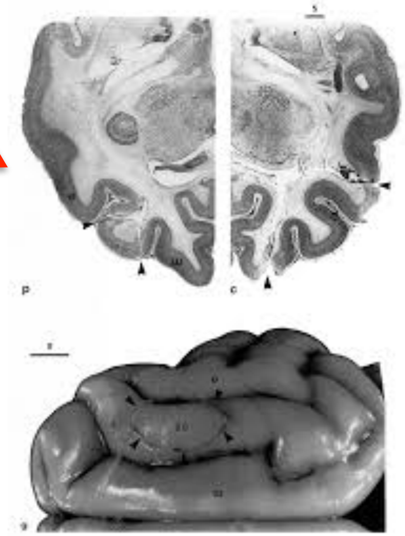
Spontaneous activity (SA) patterns

Spontaneous activity (SA) of cortical neurons 1

- Firing of cortical neurons in the **absence of external input**:
  - *In vitro* preparations of cortical tissue slices;
  - *In vitro* cell culture preparations;
  - *In vivo* cortical slab preparations;







Spontaneous activity (SA) of cortical neurons 2

- Firing of cortical neurons when the brain is **essentially disconnected from external stimuli**:
  - Slow-wave sleep (SWS)
  - Anesthesia

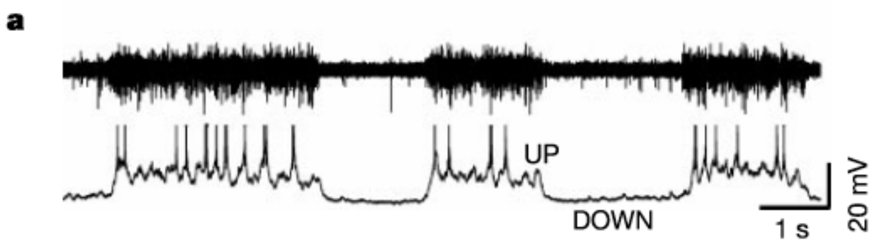
Spontaneous activity (SA) of cortical neurons 3

- Firing of neurons when the subject is awake but **not submitted to sensory or behavioral tasks**: Resting state

Characteristics of cortical SA states
(as revealed by electrophysiological studies)

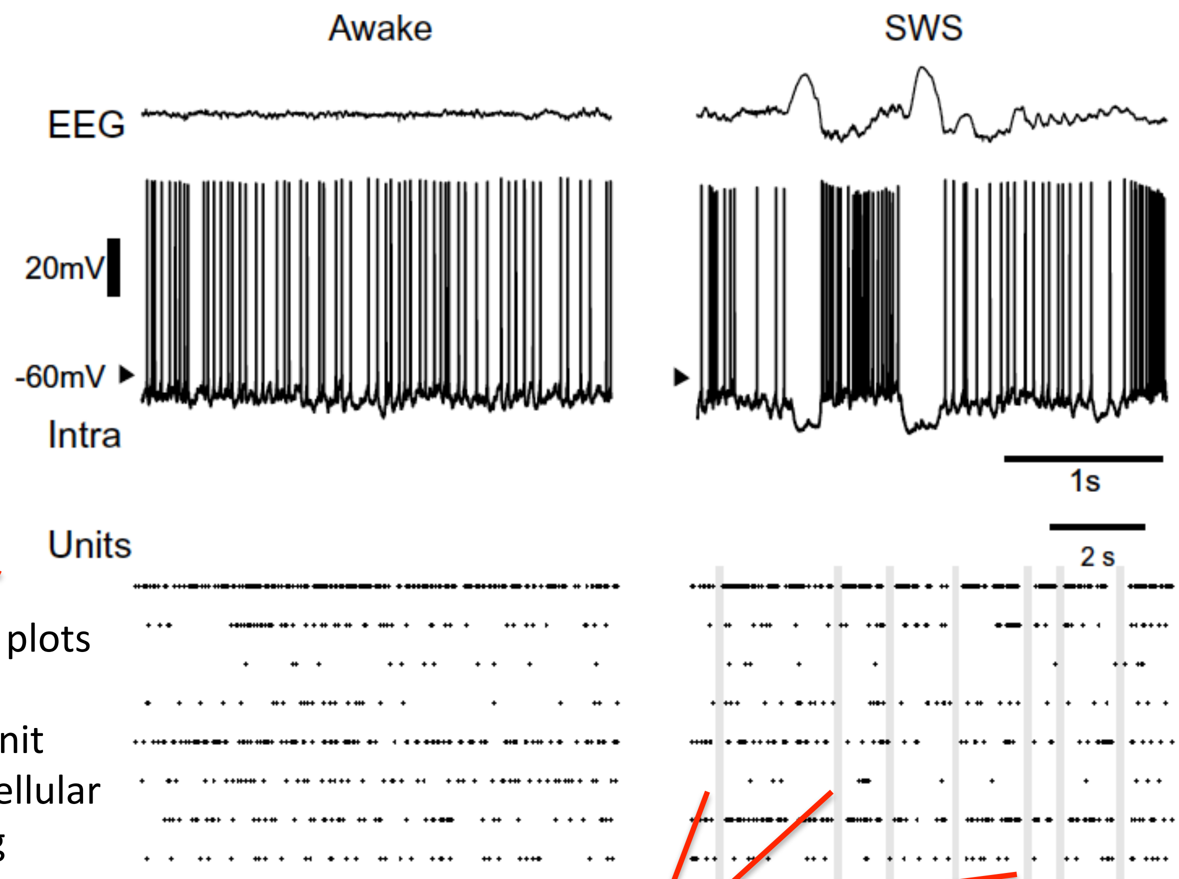
- *In vitro* and *in vivo* preparations, SWS and anesthesia:
  - **Slow** (< 1 Hz) and **high amplitude** network **oscillations**;
  - **Up** and **down** neuronal states.
- Resting state:
  - **Fast** (> 15 Hz) and **low amplitude** network **oscillations**;
  - **Irregular** neuronal **firing**.

SA: *in vitro* and *in vivo*



Cortical slice *in vitro*

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

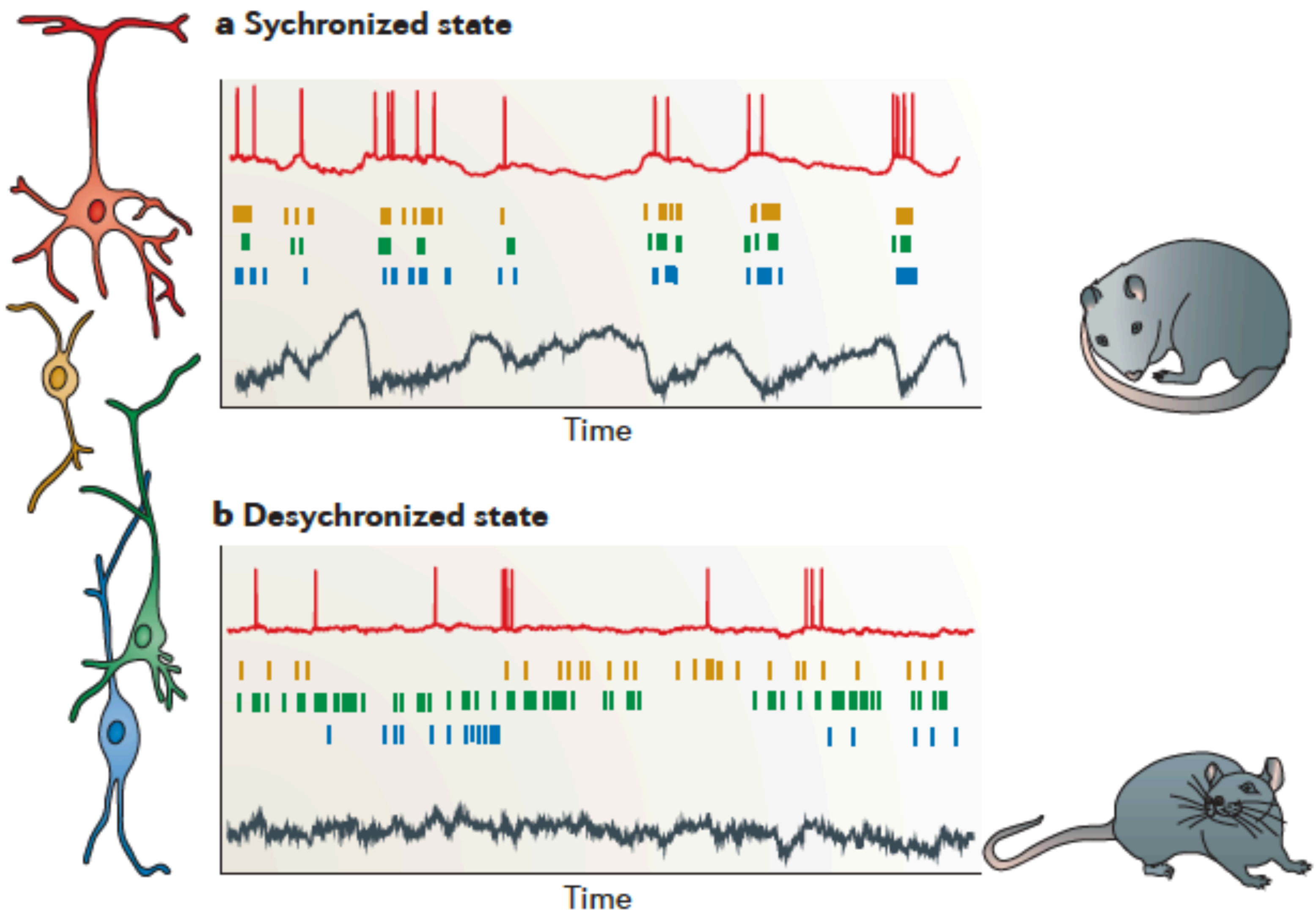


In vivo recordings

Raster plots of multiunit extracellular spiking activity

Down states

Steriade et al., J Neurophysiol 85:1969-1985, 2001.
El Boustani et al., J Physiol (Paris) 101:99-109, 2007

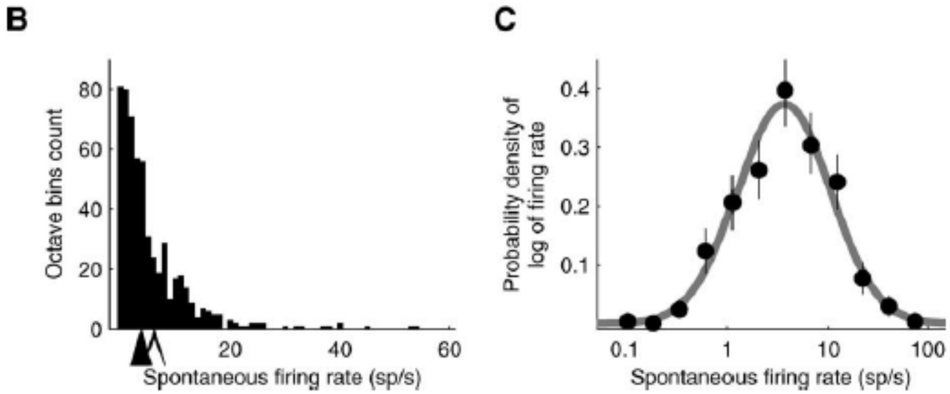


Harris & Thiele, Nat Rev Neurosci 12:509-523, 2011

Typical signatures of SA neuronal firing

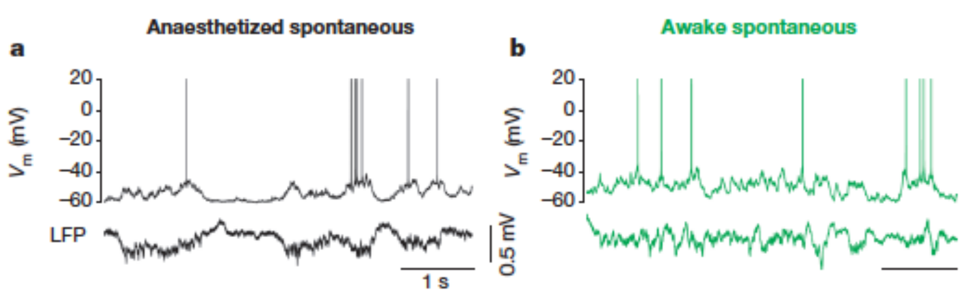
- Neurons with **low firing rates**
- **Non-Gaussian** firing rate distribution

Data from rat auditory cortex

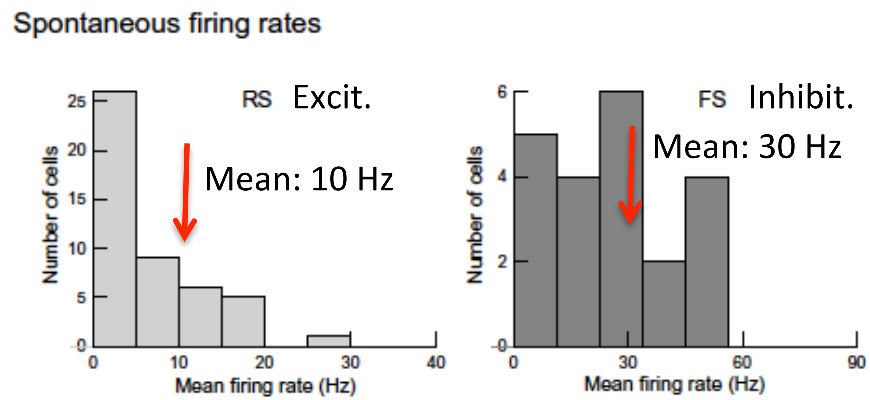


(B and C) Firing rates of most neurons were low and followed a lognormal distribution.

Hromádka et al., PLoS Biology 6:e16, 2008



Data from cat association cortex



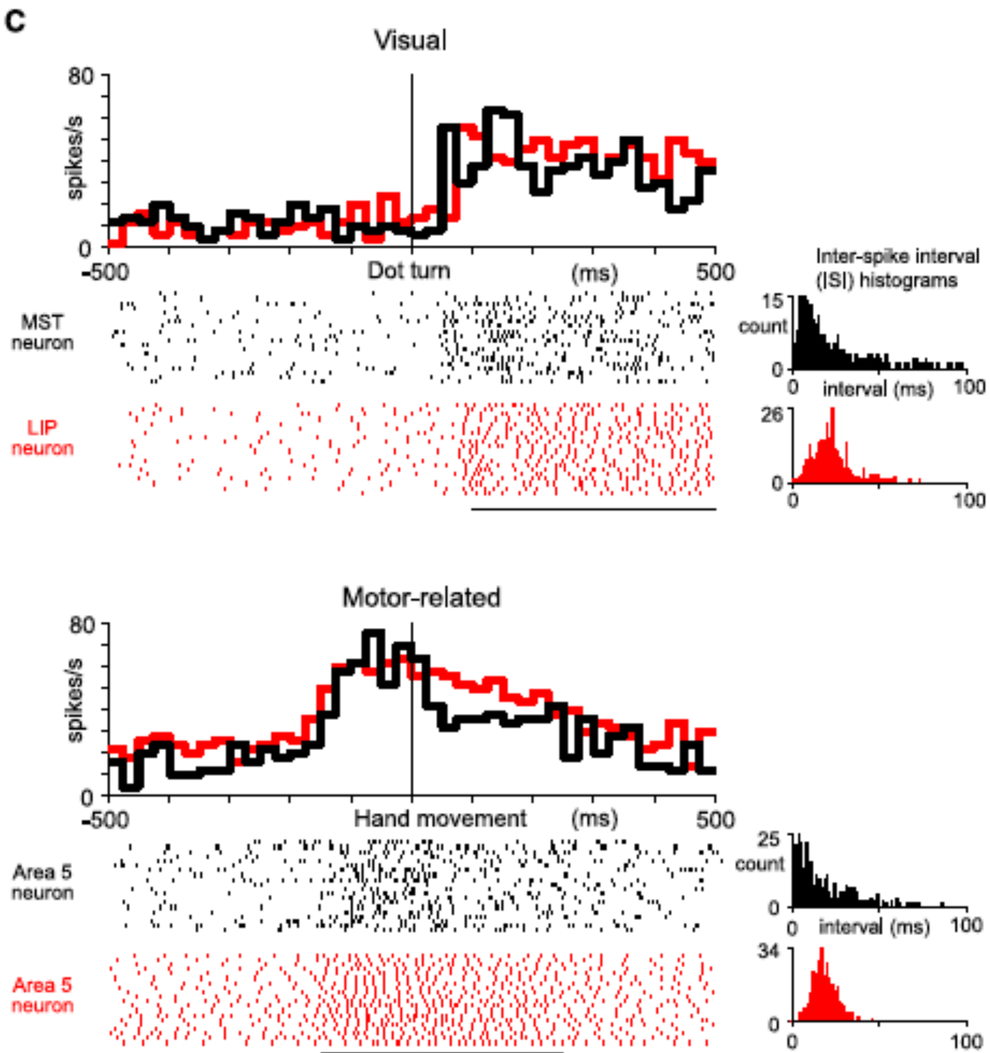
Inhibitory neurons have larger firing rates than excitatory neurons

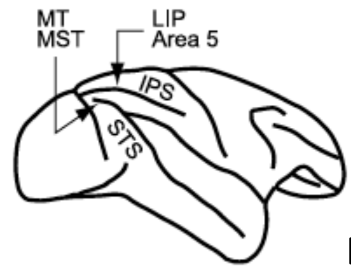
Rudolph et al., J. Neurosci 27:5280-5290, 2007

Data from mouse visual cortex

Haider et al., Nature 493:97-102, 2013

• **Irregular** neuronal firing (ISI distribution)





Data from the macaque monkey

"Some cortical neurons fire with Poisson-like irregularity, but others fire in a more regular fashion than Poisson".

Maimon & Assad, Neuron 62:426-440, 2009

Questions

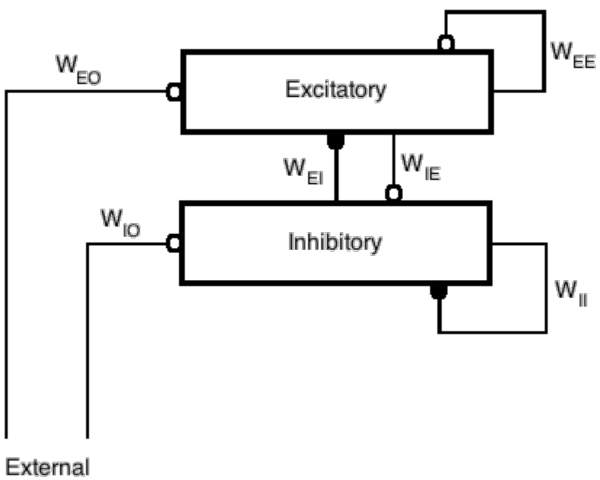
- What are the **mechanisms** responsible for the existence of neuronal spiking activity in the cortex **without external input**?
- Do these mechanisms depend on the **structural organization** of cortical **connections**?
- Do these mechanisms depend on **intrinsic characteristics** of cortical **neurons**?
- What mechanisms make neuronal SA **irregular**?

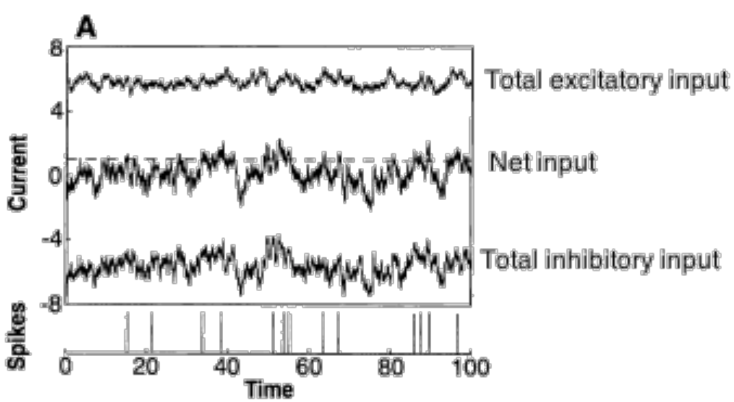
“Classical” hypothesis

Chaos in Neuronal Networks with Balanced Excitatory and Inhibitory Activity

C. van Vreeswijk and H. Sompolinsky

SCIENCE • VOL. 274 • 6 DECEMBER 1996





- The cortex operates at a **balanced state** in which average excitatory and inhibitory input currents to a neuron mutually cancel.
- Neuronal spikes are caused by **fluctuations** around average net input.
- This explains the irregular spiking of neurons.

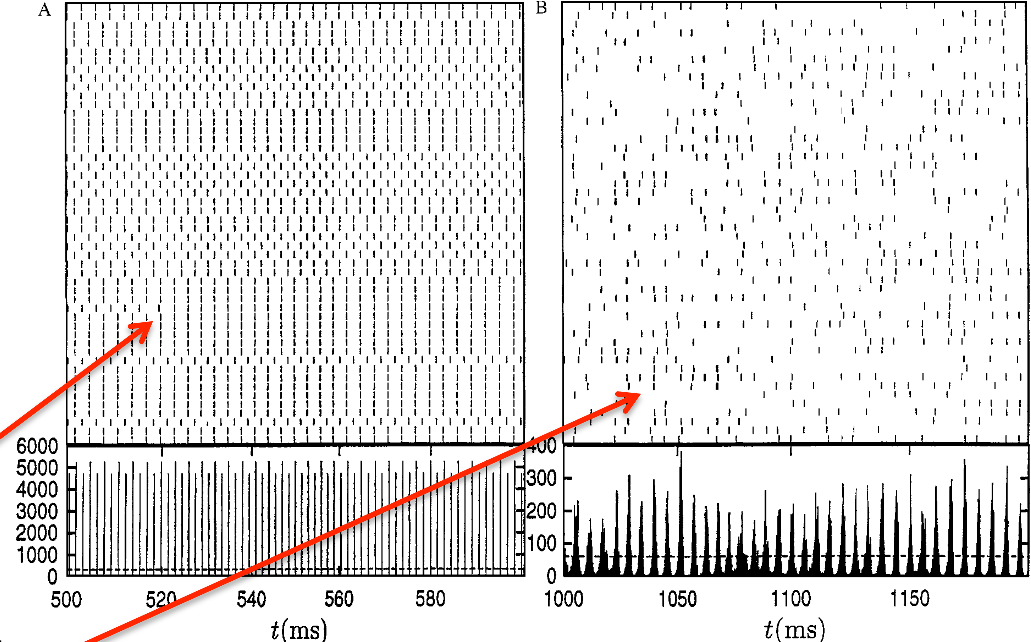
“Classical” model

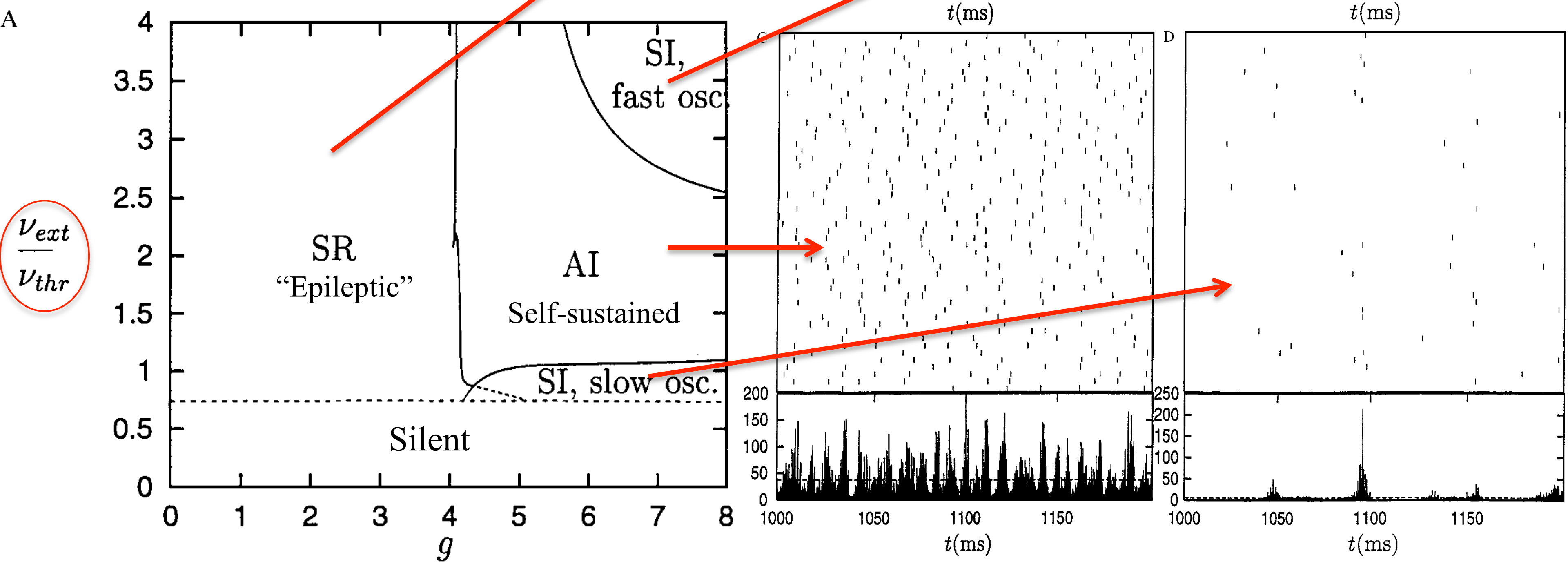
- Network: **Erdős–Rényi** graph (80% excitatory neurons, 20% inhibitory neurons);
- **Sparse** connectivity (# connections k << # neurons N);
- **Integrate-and-fire** (I&F) neurons;
- Conditions for SSA:
  - Inhibitory synapses **stronger** than excitatory synapses;
  - **External stimulus** applied to all neurons.

Journal of Computational Neuroscience 8, 183–208 (2000)

Dynamics of Sparsely Connected Networks of Excitatory and Inhibitory Spiking Neurons

NICOLAS BRUNEL
LPS, Ecole Normale Supérieure, 24 rue Lhomond, 75231 Paris Cedex 05, France





g = inhibition/excitation

Neural Network Dynamics

Tim P. Vogels, Kanaka Rajan, and L.F. Abbott

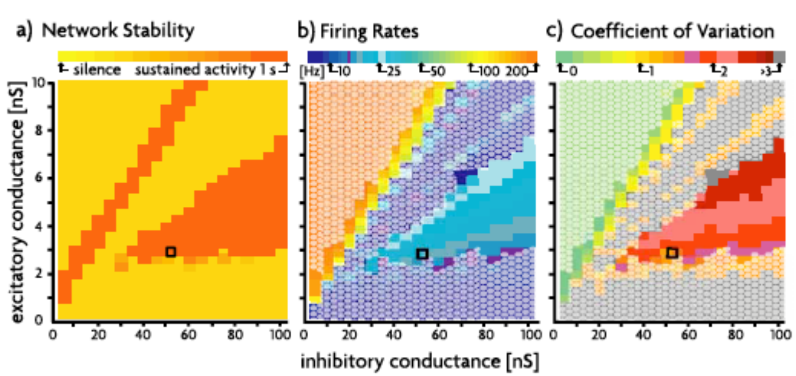
Volen Center for Complex Systems and Department of Biology, Brandeis University, Waltham, Massachusetts 02454-9110; email: vogels@brandeis.edu

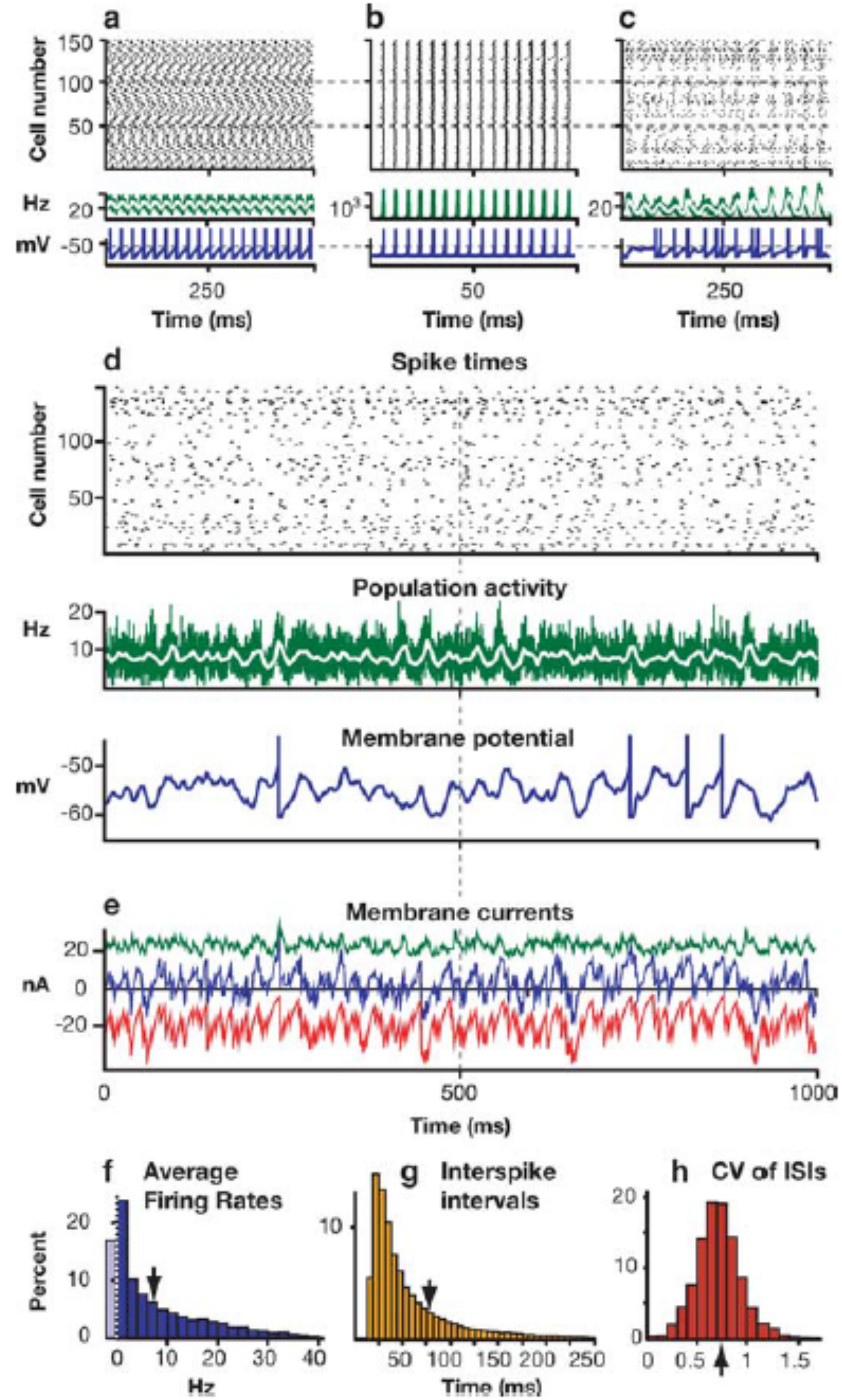
(a) Asynchronous regular activity: individual neurons fire regularly and the population rate is roughly constant;

(b) Synchronous regular activity: Both the individual neurons and the population rate oscillate;

(c) Synchronous irregular activity: individual neurons fire irregularly and the population rate oscillates;

(d) Asynchronous irregular activity: Individual neurons fire irregularly and the population rate is roughly constant.





Beyond classical models

- Networks with more realistic architectures;
- Stochastic neuron models.

Large-scale models

- Anatomical estimates:
  - Probability of synaptic contact between two cortical neurons within 1 mm: $p \approx 0.1$
  - Mean number of synapses per cortical neuron: $\langle k \rangle \approx 10^4$
- Then, minimum number of neurons in a realistic network: $N \approx 10^5$ $(=\langle k \rangle/p)$
- This implies a total number of synapses of:

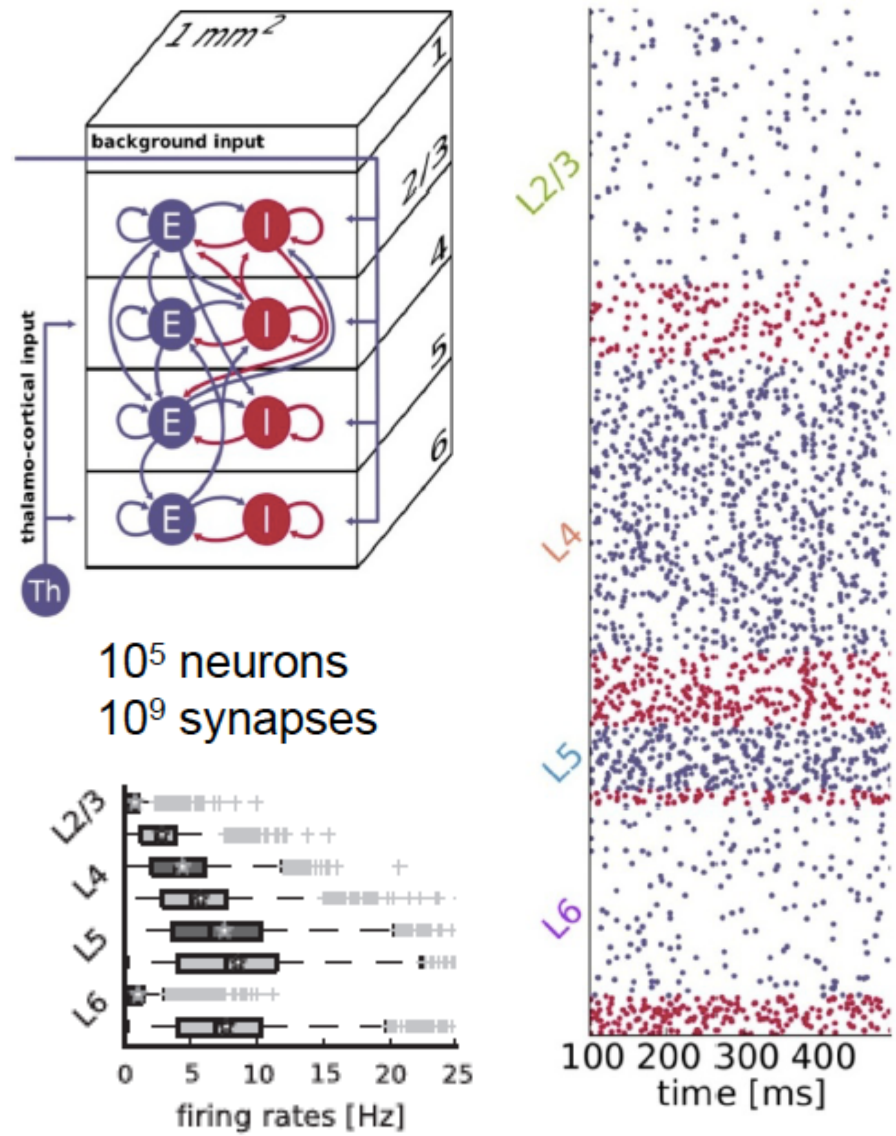
  $N_{syn} \approx 10^9$
- These figures determine the **minimum size** of a large-scale cortical model (local cortical network)

Multiscale Models

- A hierarchy of large-scale network models:
  - Local cortical network models;
  - Mesoscopic cortical network models (cortical areas);
  - Macroscopic cortical network model (brain size)
- Models will be built based on available connectivity data at micro-, meso- and macroscopic scales from various experimental techniques

Local cortical microcircuit model

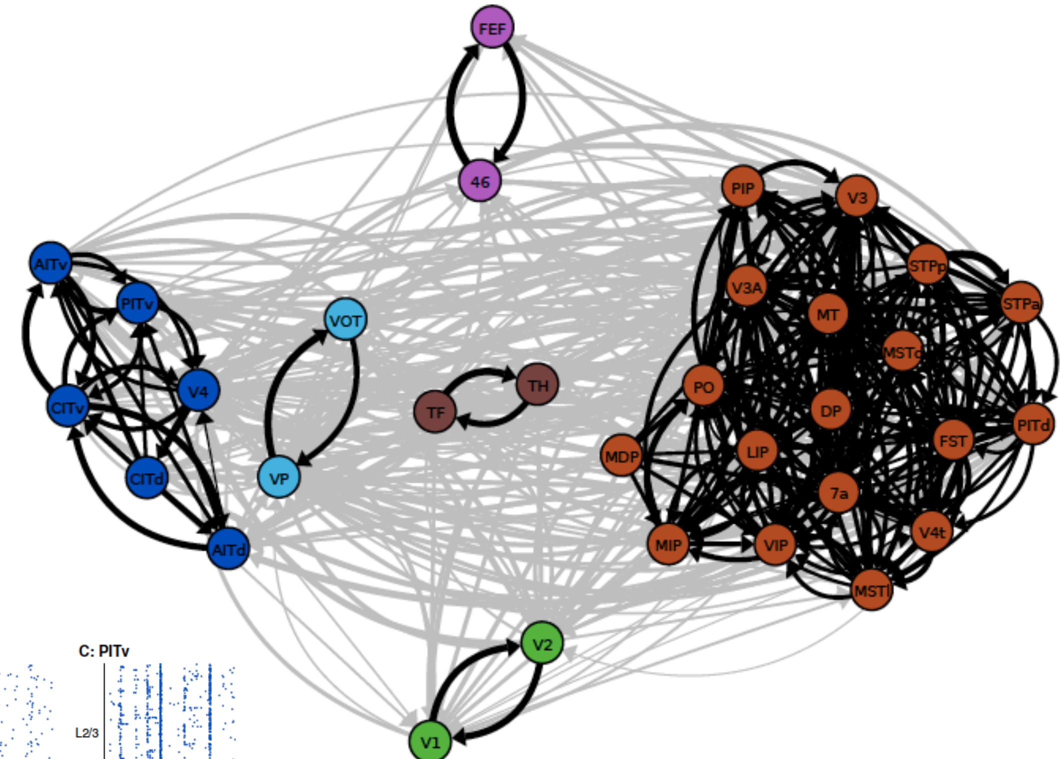
- Takes into account layer and neuron-type specific connectivity (integrates knowledge of many experimental papers)
- Asynchronous-irregular activity
- Higher firing rate of inhibitory neurons
- Replicates well the distribution of spike rates across layers
- Still misses about 50% of synapses

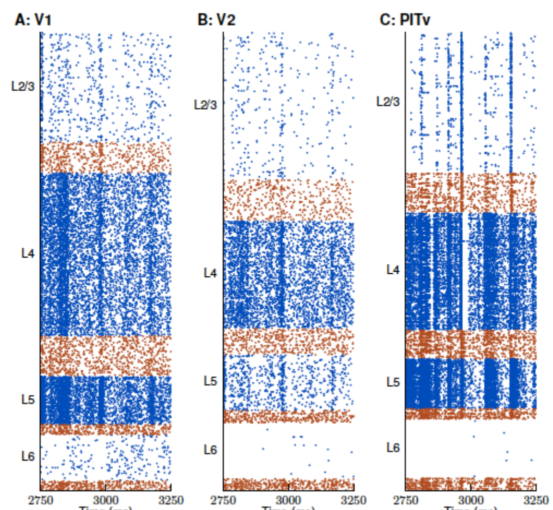


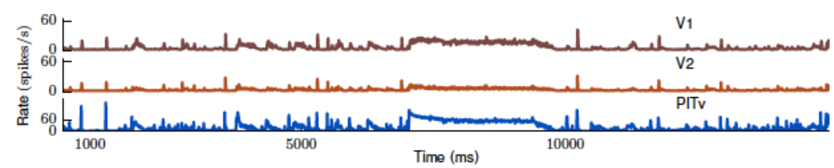
Potjans and Diesmann, 2014
Available at www.opensourcebrain.org

Large-scale cortical model

- 32 areas of macaque cortex involved in visual processing
- Each area is represented by a local microcircuit model (previous slide)







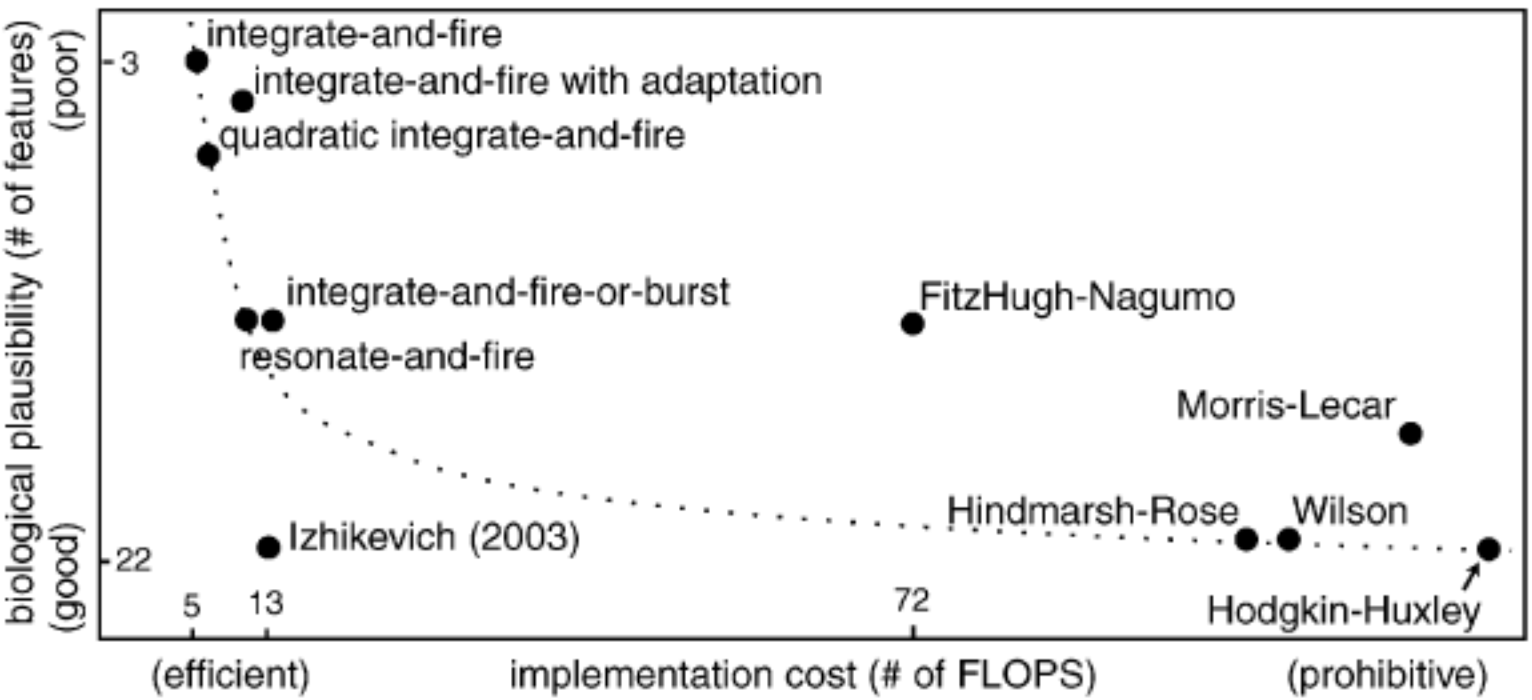
Schmidt et al., 2016
arXiv:1511.09364

Neuron models

IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL. 15, NO. 5, SEPTEMBER 2004 1063

Which Model to Use for Cortical Spiking Neurons?

Eugene M. Izhikevich

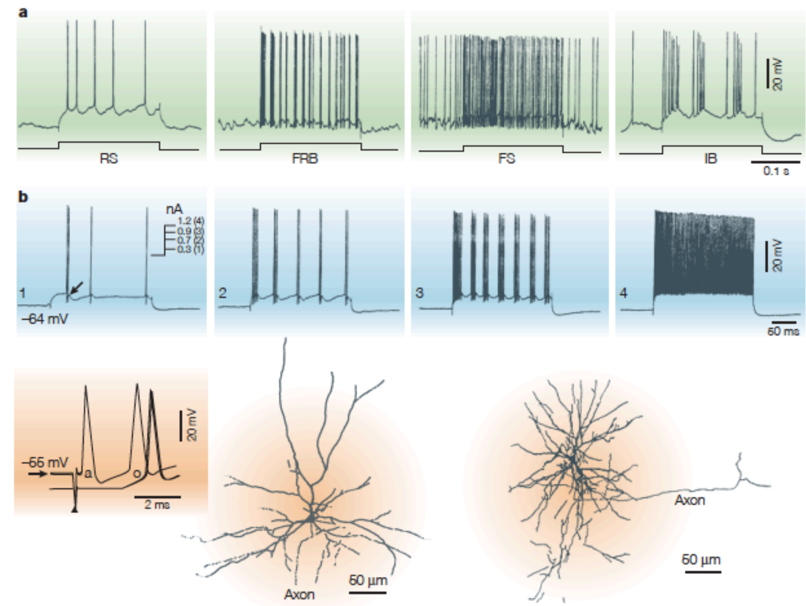


Simple spiking neuron models

- 1D or 2D, non-HH type models (not explicit)
- Emphasis on neuronal response (spike trains)
- Spikes generated by hand
- Examples:
  - Leaky integrate-and-fire (LIF) model (Lapicque 1907)
  - Non-linear LIF models (quadratic, exponential)
  - Izhikevich model
  - Adaptive exponential integrate-and-fire (AdEx) model

Cortical neurons

- Different “personalities”



Steriade, 2004

Electrophysiological classes of neocortical neurons

Diego Contreras*

Neural Networks 17 (2004) 633–646

Cortical neurons are classified into five main electrophysiological categories according to their firing patterns in response to intracellular current injection: regular spiking (RS), intrinsically bursting (IB), fast spiking (FS), fast repetitive bursting (FRB, also called chattering) and cells producing low threshold spikes (LTS). These differences are determined by the expression of different sets of ionic conductances that also determine the integrative properties of the neuron.

But: NEOCORTICAL CELL CLASSES ARE FLEXIBLE ENTITIES

Mircea Steriade

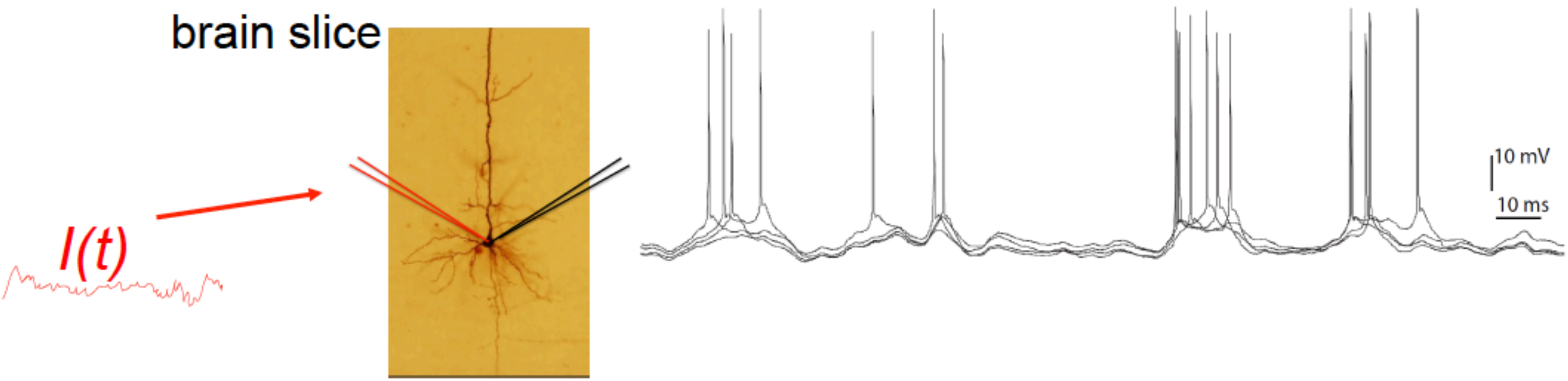
NATURE REVIEWS | NEUROSCIENCE VOLUME 5 | FEBRUARY 2004 | 121

Neurons display stochastic behavior

- *In vivo* and *in vitro* recordings of single neuron spike trains are characterized by a high degree of variability

Trial to trial variability *in vitro*

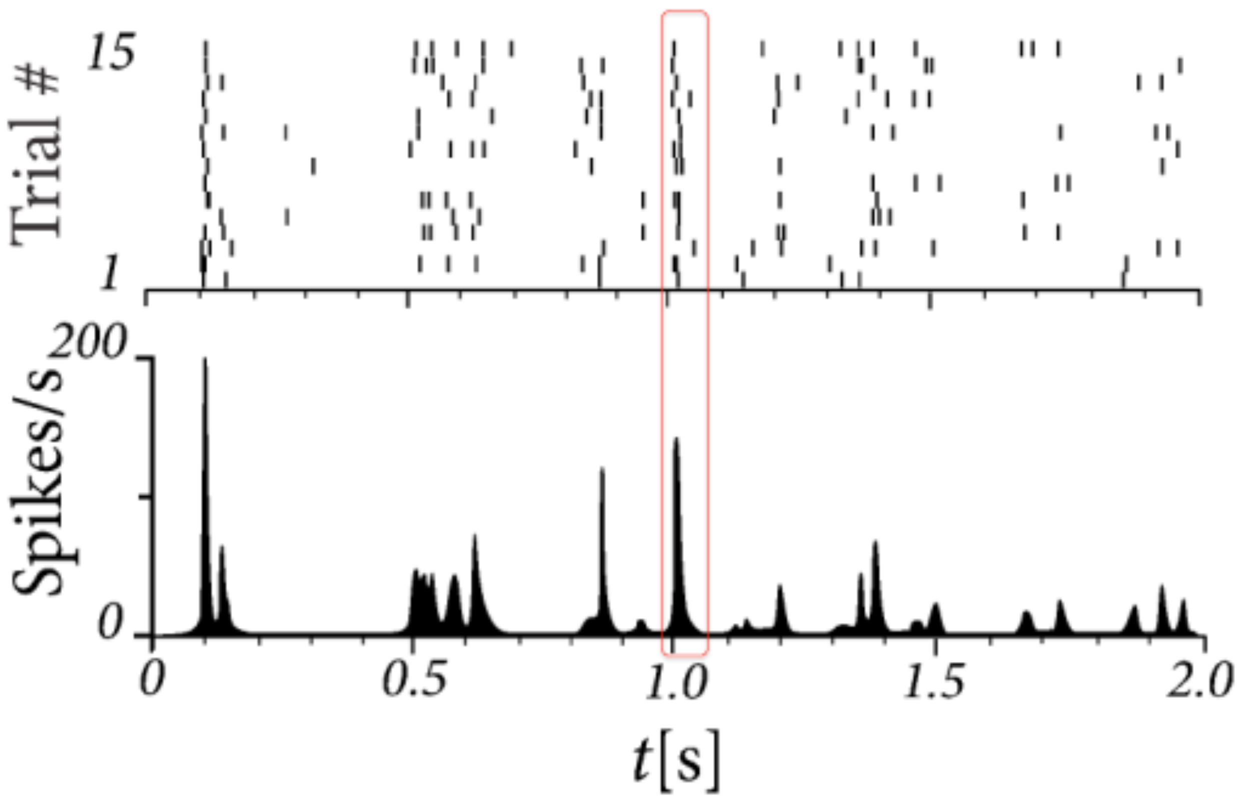
4 repetitions of the same time-dependent stimulus

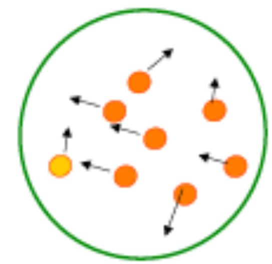


Modified from Naud and Gerstner, 2012

Trial to trial variability *in vivo*

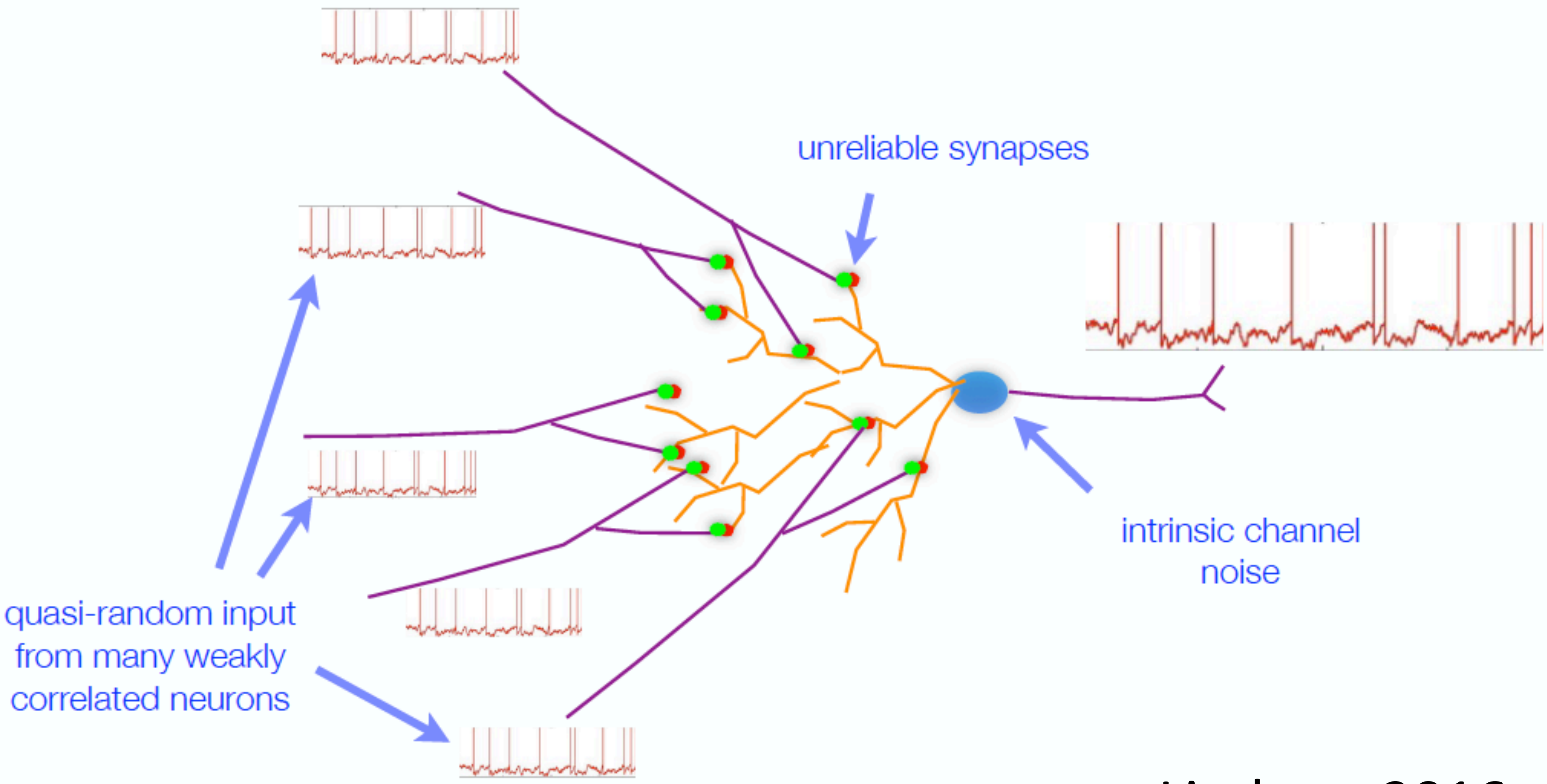
15 repetitions of the same random dot motion pattern





Adapted from Bair and Koch, 1996;
Data from Newsome, 1989

Sources of noise: extrinsic and intrinsic to neurons



Lindner, 2016

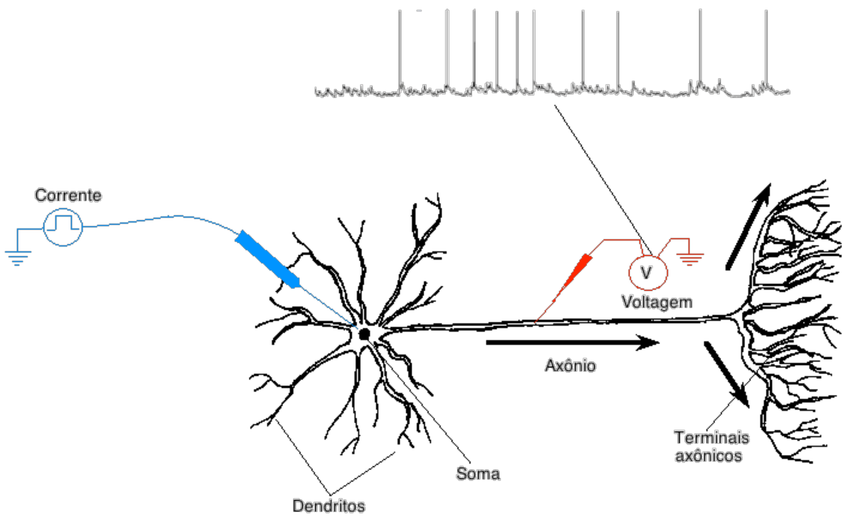
Two types of noise model for a neuron

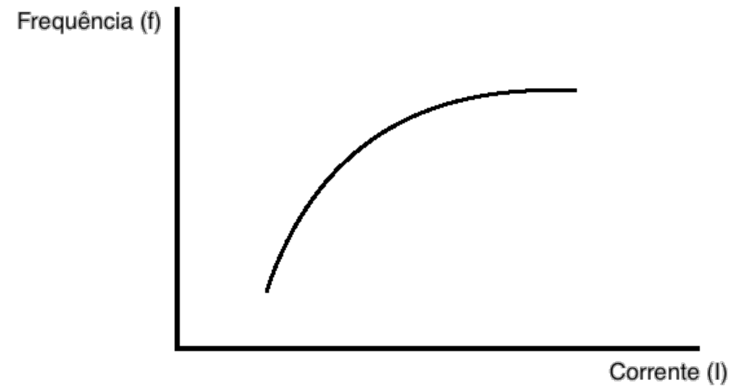
- Spike generation is directly modeled as a stochastic process
- Spike generation is modeled deterministically and noise enters the dynamics via additional stochastic terms

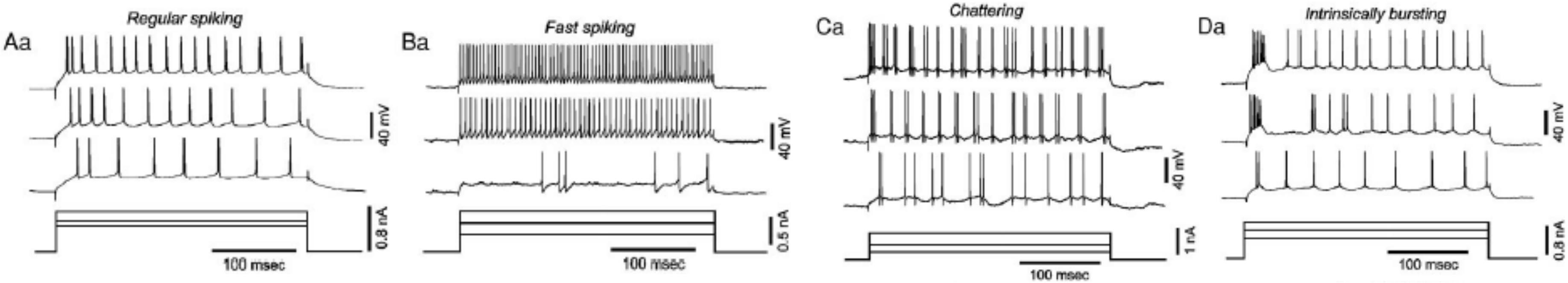
Interval: FI curves

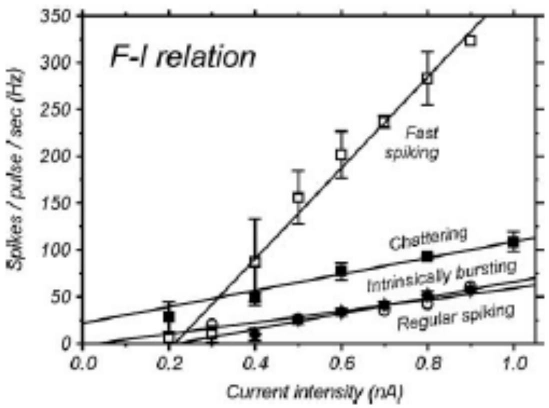
F-I Curve

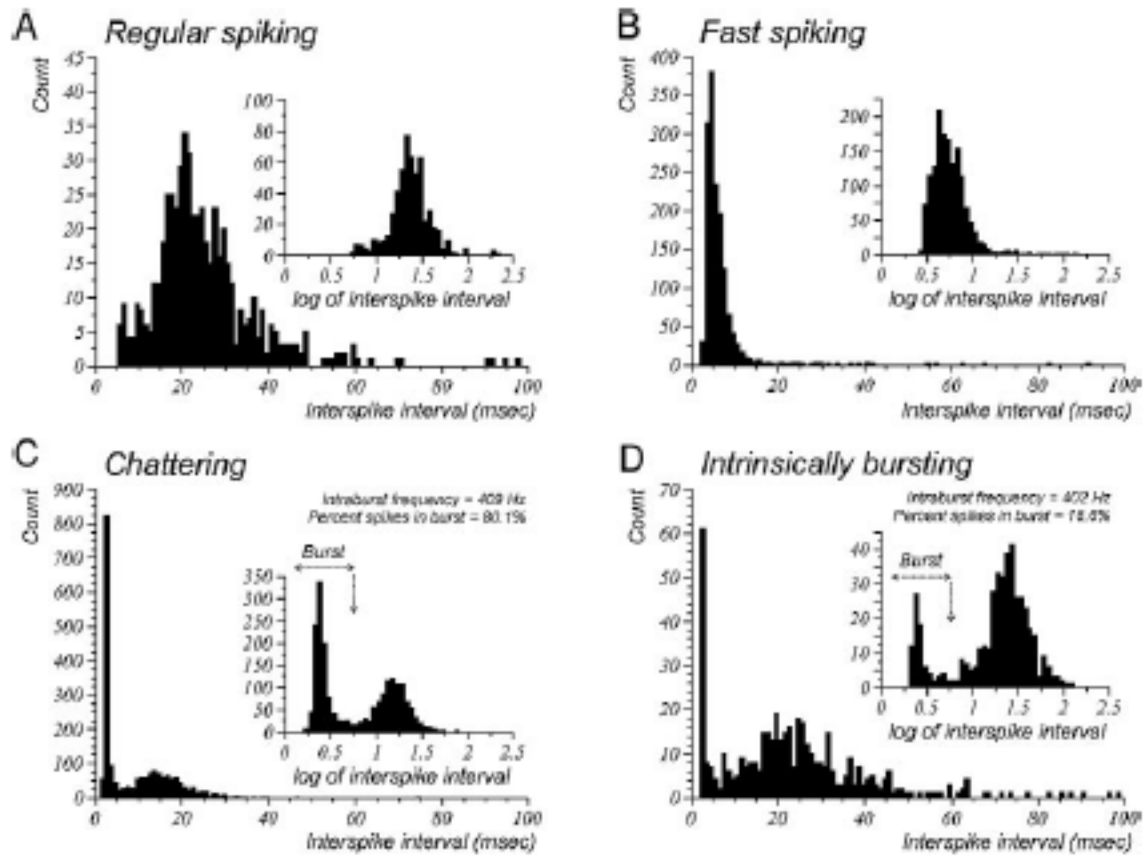
- Firing rate (F) of a neuron as a function of its input current (I)
- Each I value corresponds to a constant step current applied for a given time
- Describes the input-output transfer function of the neuron
- In general, F-I curves are nonlinear with saturation for high input values







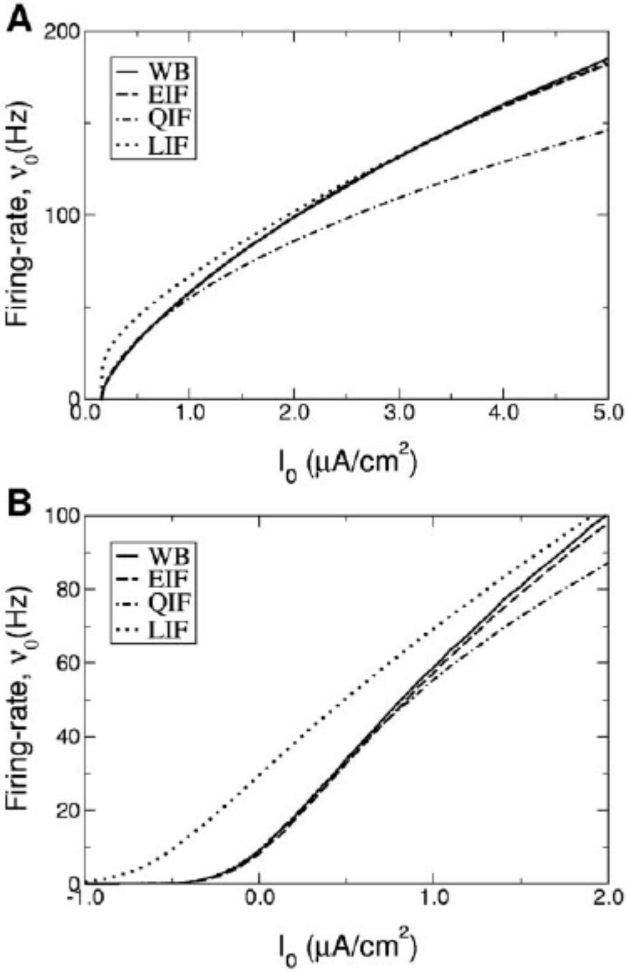


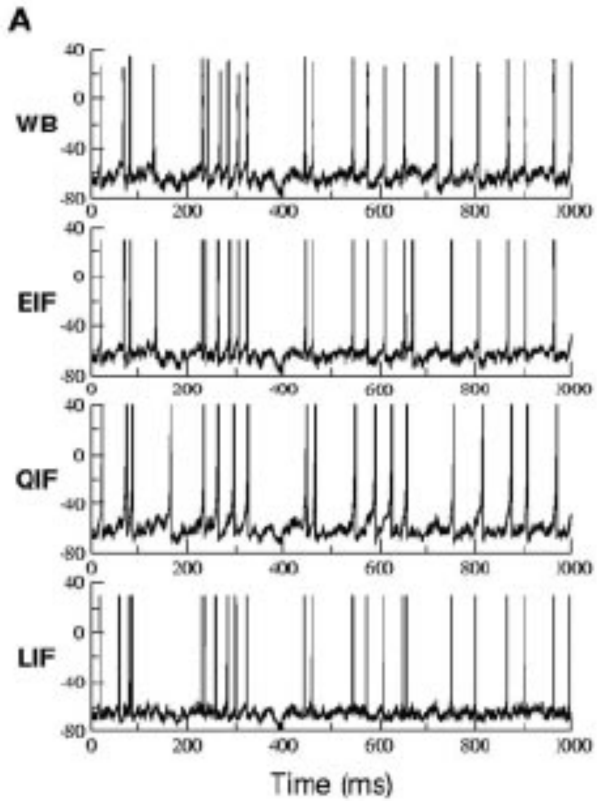


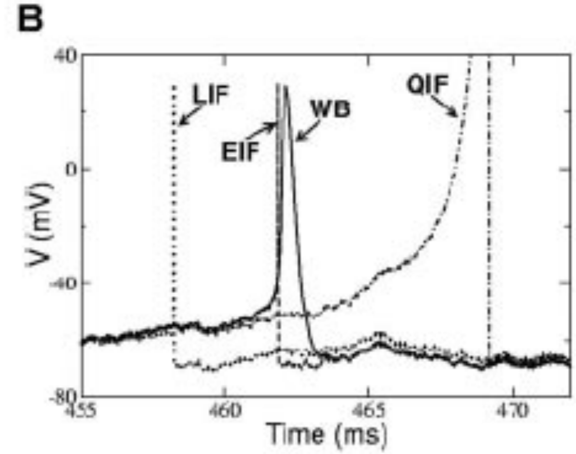
FI curves and ISI histograms of cortical neurons from four different cell classes

Nowak et al., J. Neurophysiol (2003)

Firing behavior of IF models







F-I curves of IF models for a constant input current (**A**) and a noisy input current (**B**)

Voltage traces of IF models for the same noisy input current. **B** shows a higher resolution for a short time interval in which a spike has been generated in all models

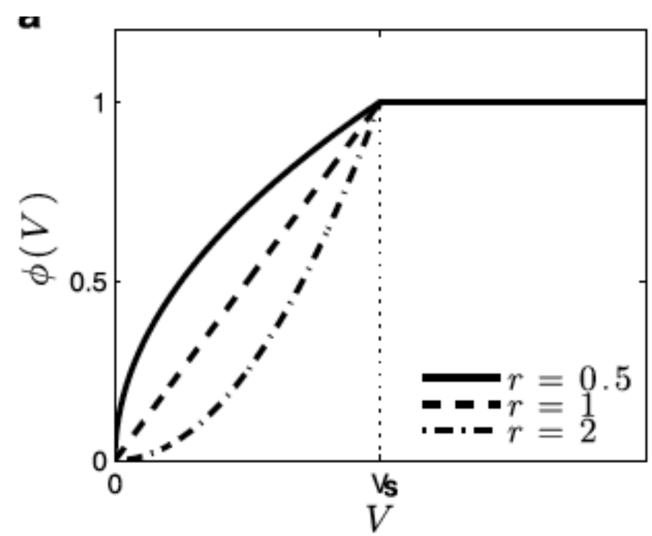
Fourcaud-Trocmé et al. (2003)

Galves-Löcherbach (GL) model

(Version of Brochini *et al*. 2016)

$$V_i[t+1] = \begin{cases} V_R & \text{if } X_i[t] = 1, \\ \mu(V_i[t] - V_B) + V_B + I_i[t] + \sum_{j=1}^{N} w_{ij} X_j[t] & \text{if } X_i[t] = 0. \end{cases}$$

$$\Phi(V) = (\Gamma(V - V_T))^r$$

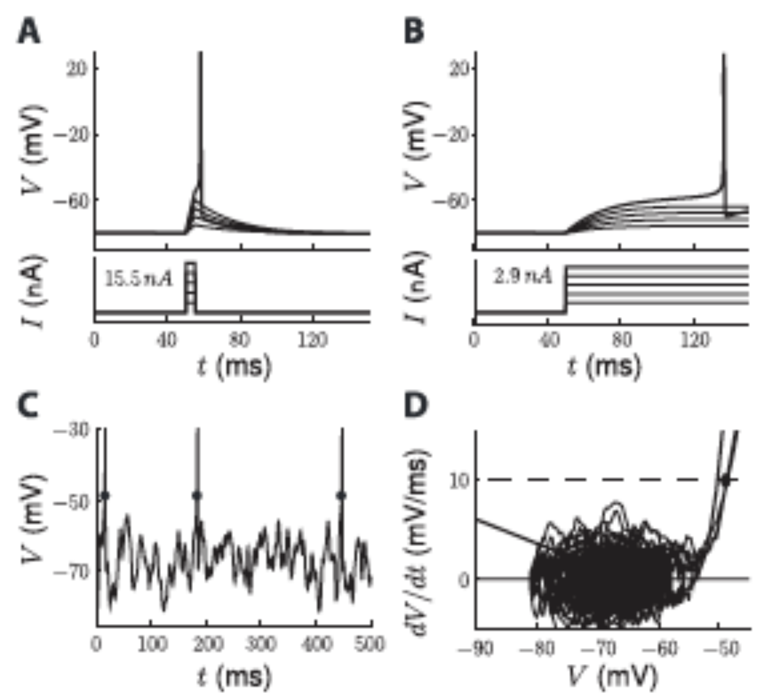


How to determine $\Phi(V)$?

- First, one has to choose a criterion to determine the exact value of V at which a spike occurs
- Second, one has to estimate $\Phi(V)$ by some empirical probability measure

V of a spike

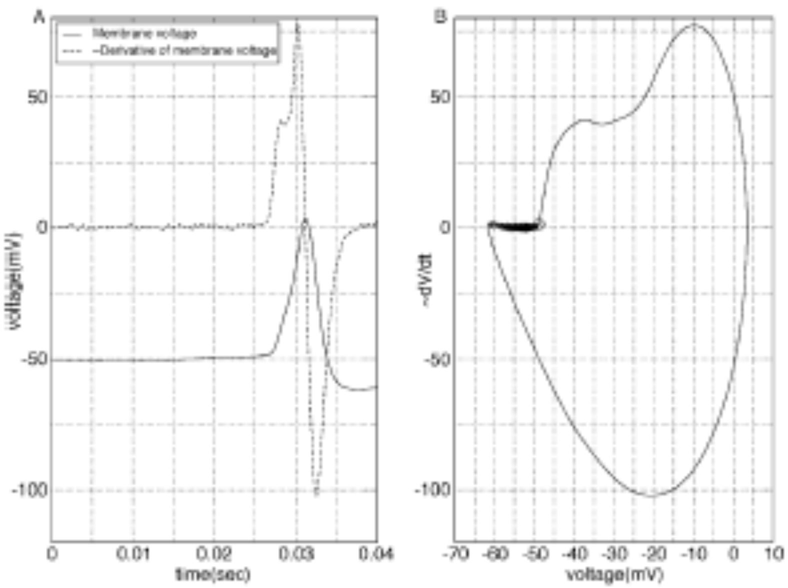
- In vitro: use the **minimum stimulus value**, e.g. rheobase current, for which a spike occurs. In this case, the corresponding voltage value is the desired *V*
- In vivo: use the **onset voltage** for a spike. The problem is that there are many possible definitions of the onset voltage.



Platkiewicz and Brette, 2010

Estimating Action Potential Thresholds From Neuronal Time-Series: New Metrics and Evaluation of Methodologies

Murat Sekerli, *Student Member, IEEE*, Christopher A. Del Negro, Robert H. Lee, and Robert J. Butera*, *Senior Member, IEEE*

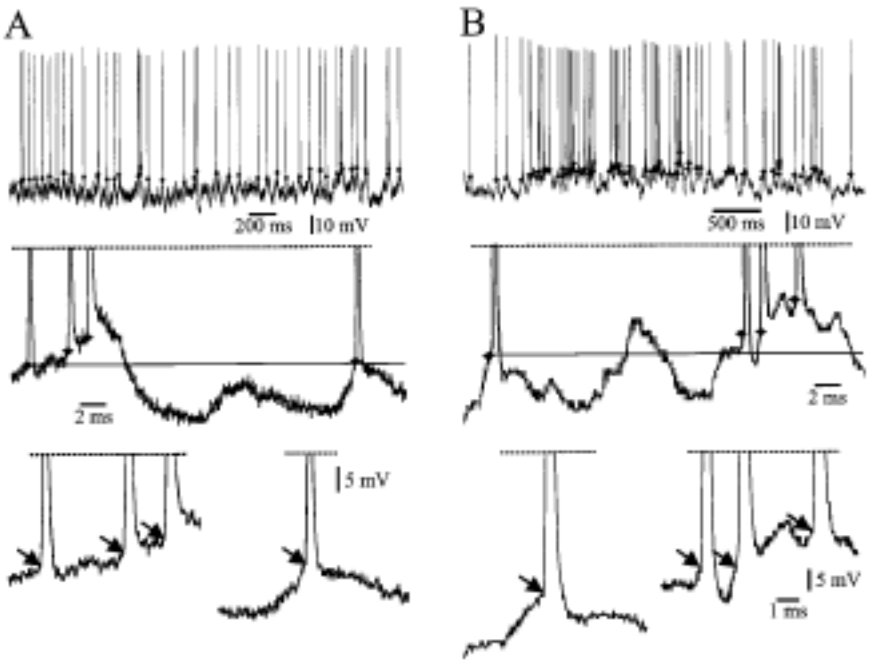


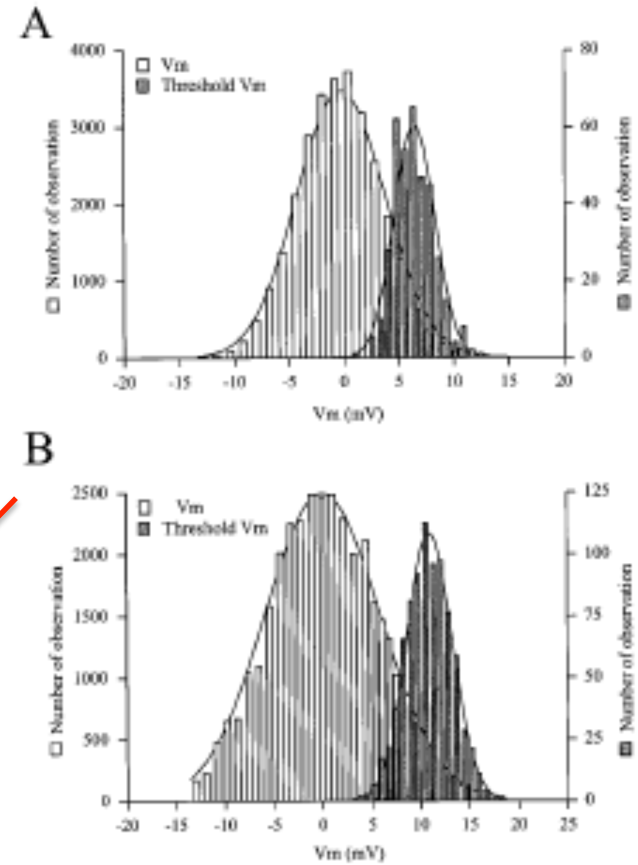
$$f = \frac{\mathrm{d}V}{\mathrm{d}t} = V'$$

$$g(t) = \frac{\mathrm{d}f}{\mathrm{d}V} = \frac{\mathrm{d}f}{\mathrm{d}t}\frac{\mathrm{d}t}{\mathrm{d}V} = \frac{\frac{\mathrm{d}f}{\mathrm{d}t}}{\frac{\mathrm{d}V}{\mathrm{d}t}} = \frac{\frac{\mathrm{d}^2V}{\mathrm{d}t^2}}{\frac{\mathrm{d}V}{\mathrm{d}t}} = \frac{V''}{V'}$$

where V_{th} is the membrane potential where the maximum positive value of $g(t)$ occurs, within the region where $V' > 0$ for each action potential. Thus, the maximum value of $g(t)$ is the maximum slope of the V' versus V graph in Fig. 2(b).

$\Phi(V)$



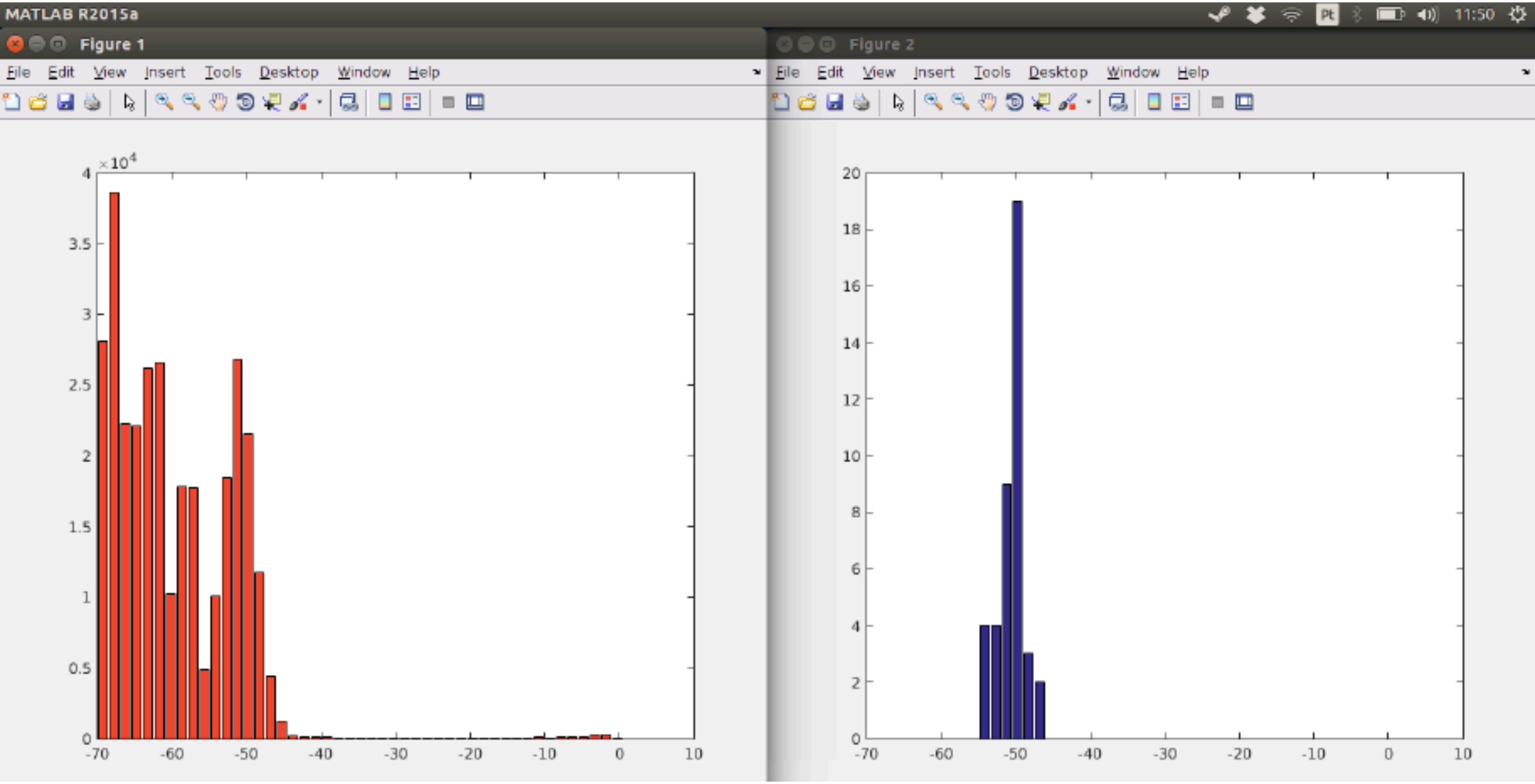


Azouz and Gray, 1999

For each discretization bin, $\Phi(V)$ is estimated by

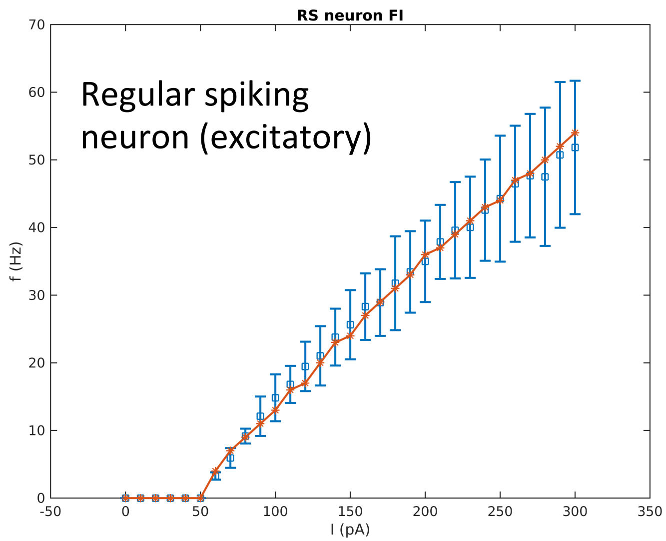
$$\frac{\#\ \text{Threshold Vm}}{\#\ \text{Vm} + \#\ \text{Threshold Vm}}$$

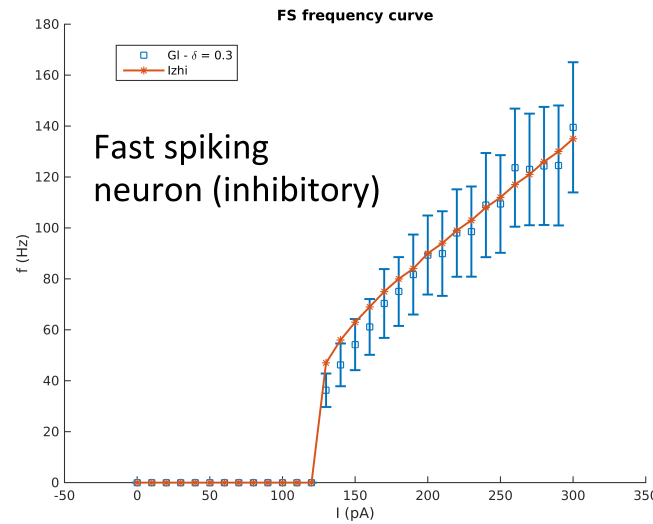
Preliminary results
Experimental data provided by César C. Ceballos

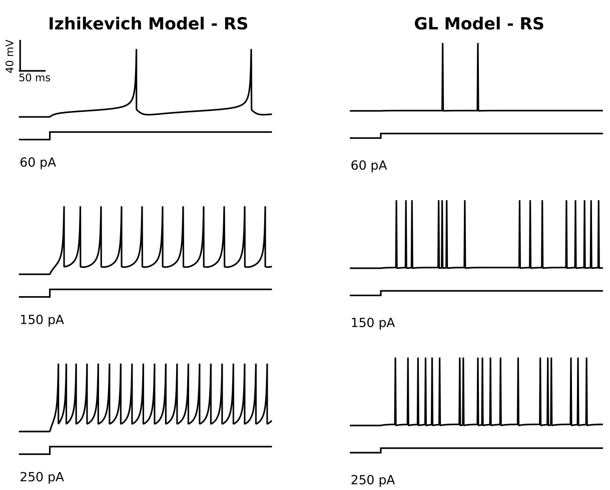


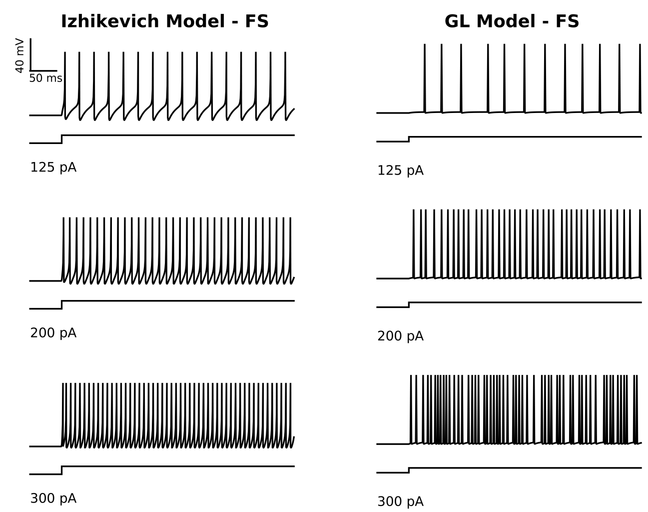
Alternative procedure:
use the FI curves

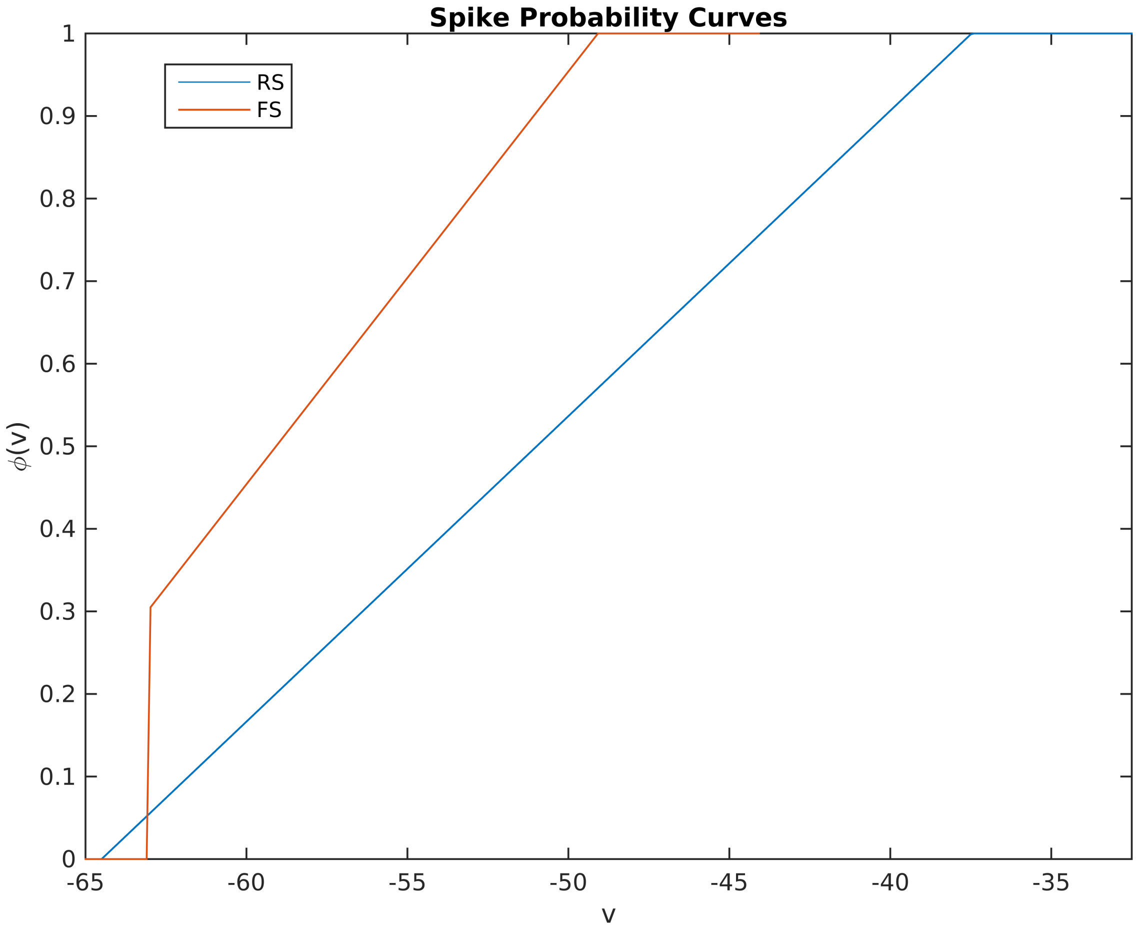
Fit of average behavior of GL model to FI curves of Izhikevich model neurons











Parameter values

	RS	FS
V_R	−65 mV	−65 mV
V_T	−64 mV	−63 mV
μ	0.9	0.9
r	1	1
Γ	0.037	0.05
δ	0	0.3

$$V(t+1) = \mu V(t) + RI$$

$$\Phi(V) = \begin{cases} 0 & \text{if } V \leq V_T, \\ [\Gamma(V - V_T)]^r + \delta & \text{if } V_T < V < V_S, \\ 1 & \text{if } V \geq V_S = V_T + (1-\delta)^{1/r}/\gamma. \end{cases}$$

Work in progress

Suggestions welcome

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Thanks!

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