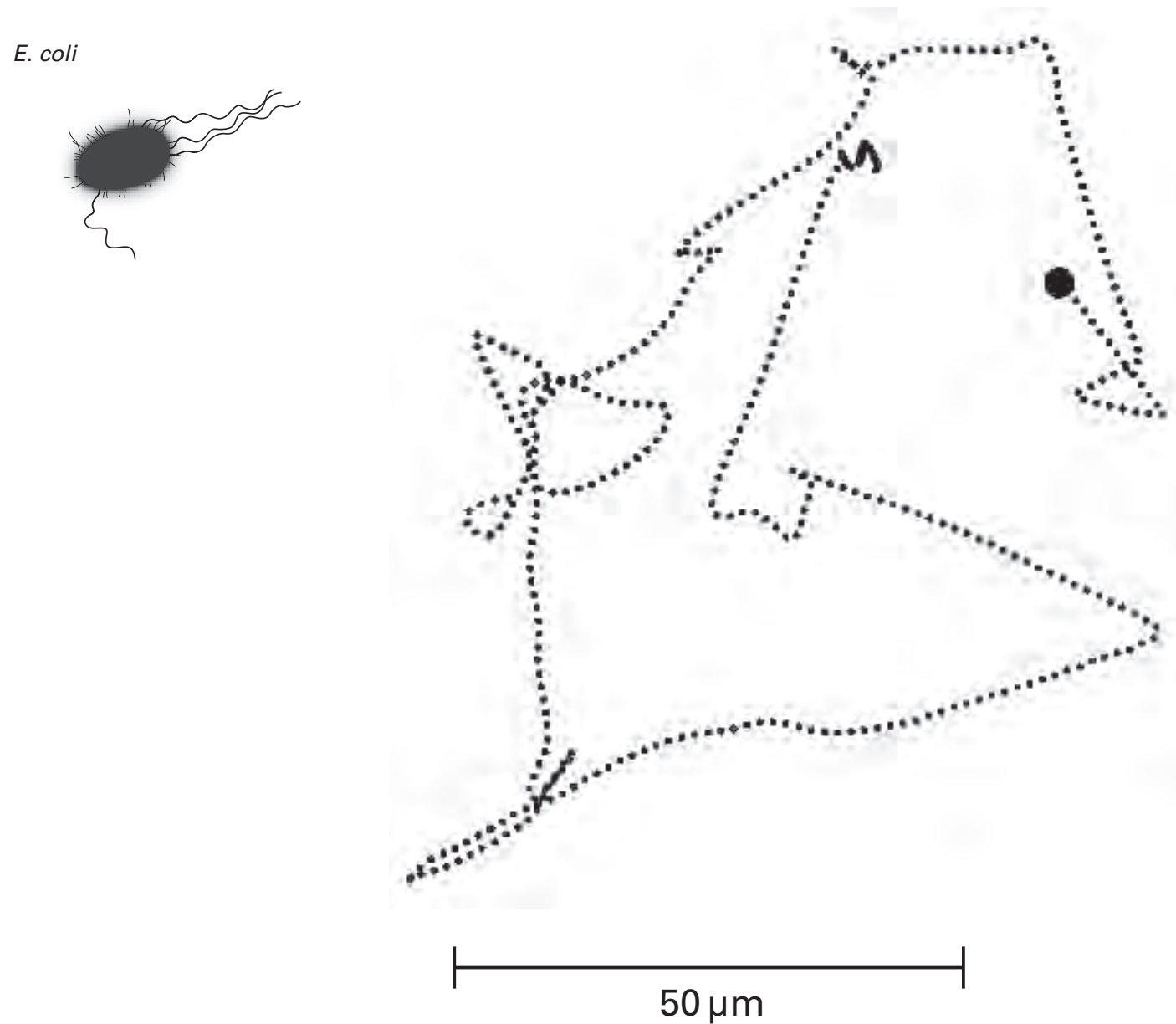


# **Connecting Neurons to Perform Computation**

# *E. coli*'s biased random walk



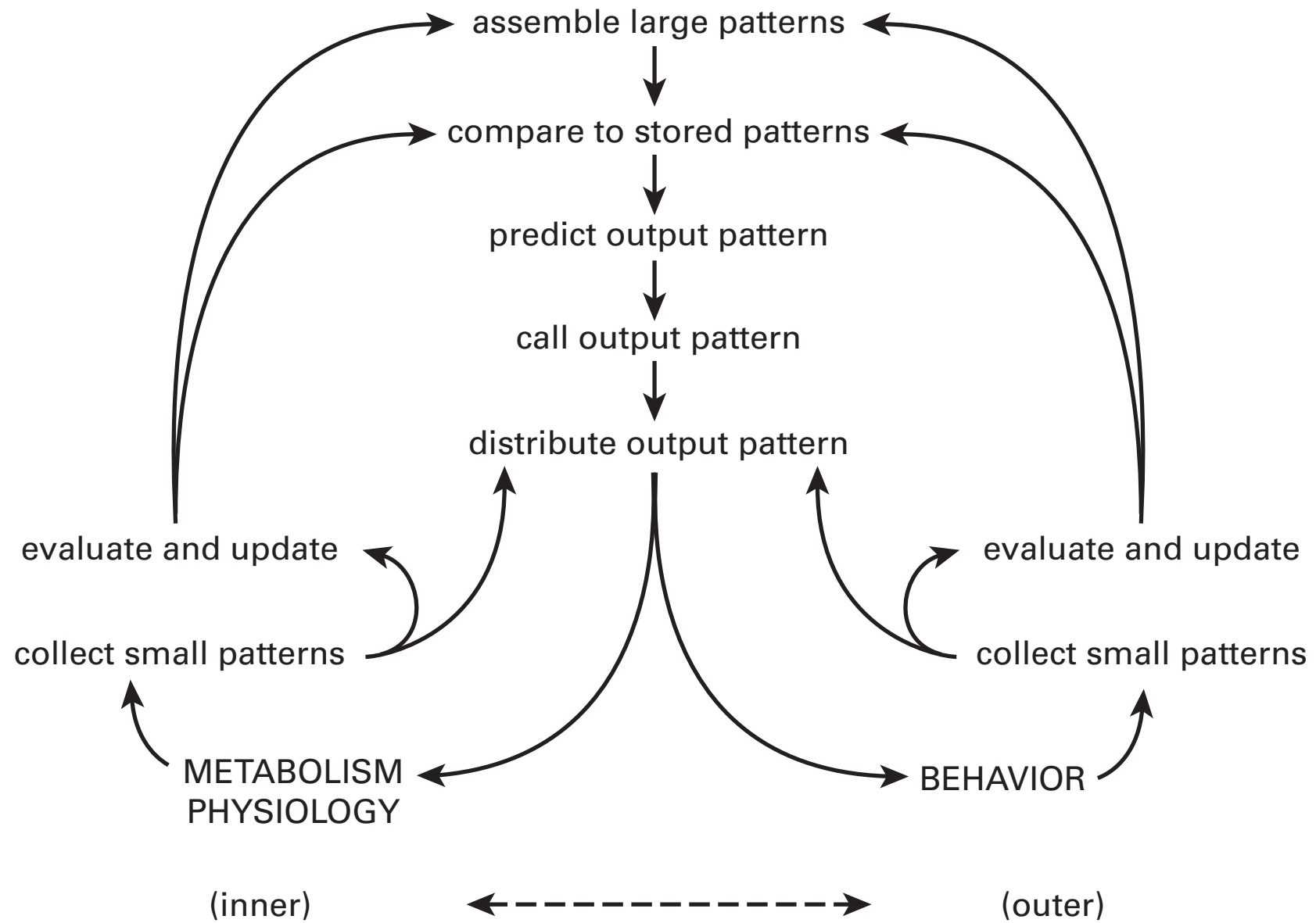
If life is getting better, enjoy more;  
If life is getting worse, don't worry about it.

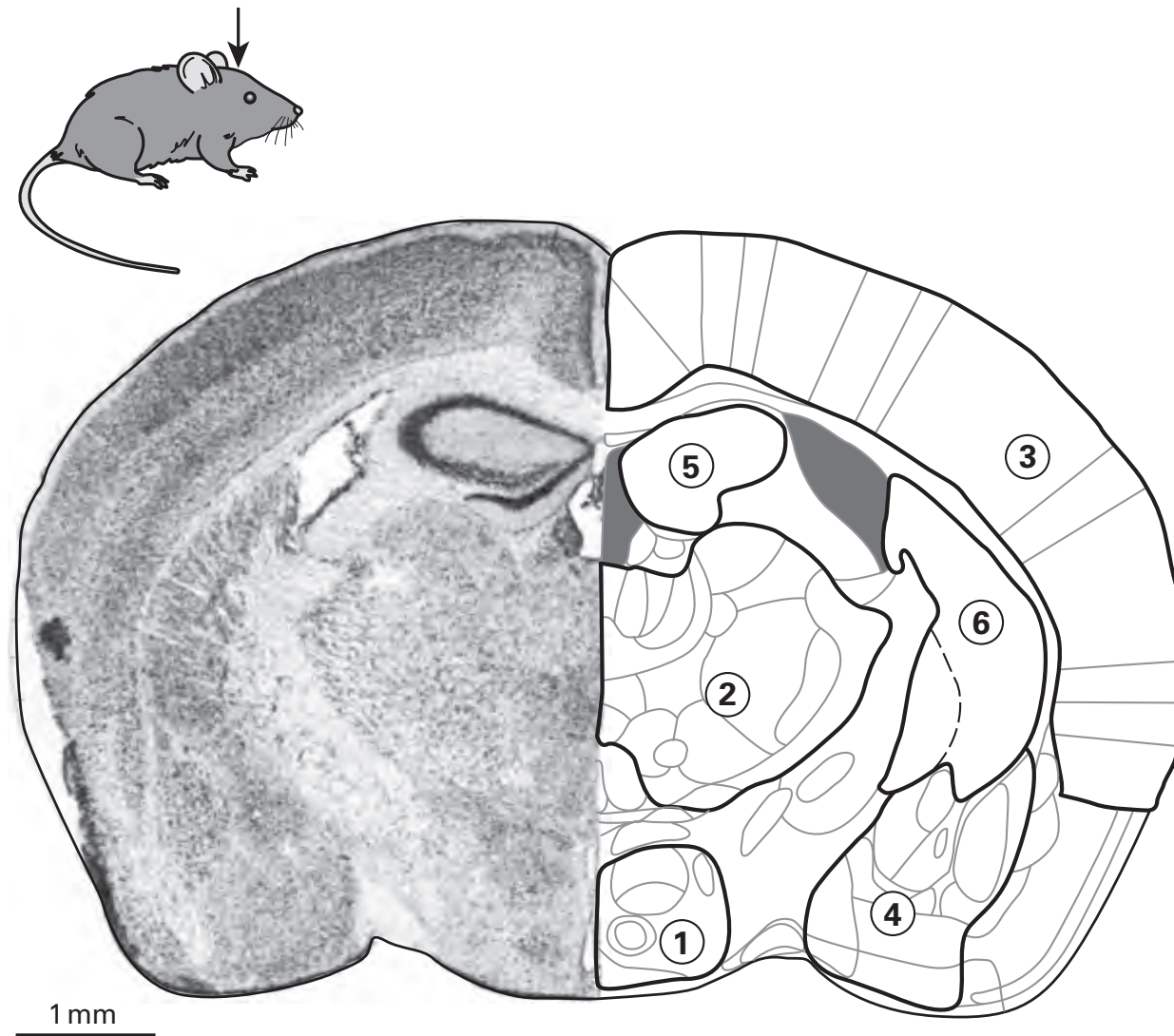
# **Why do we need a brain?**

**My brain is my second favorite organ.**

**Woody Allen**

## BRAIN'S CORE TASKS



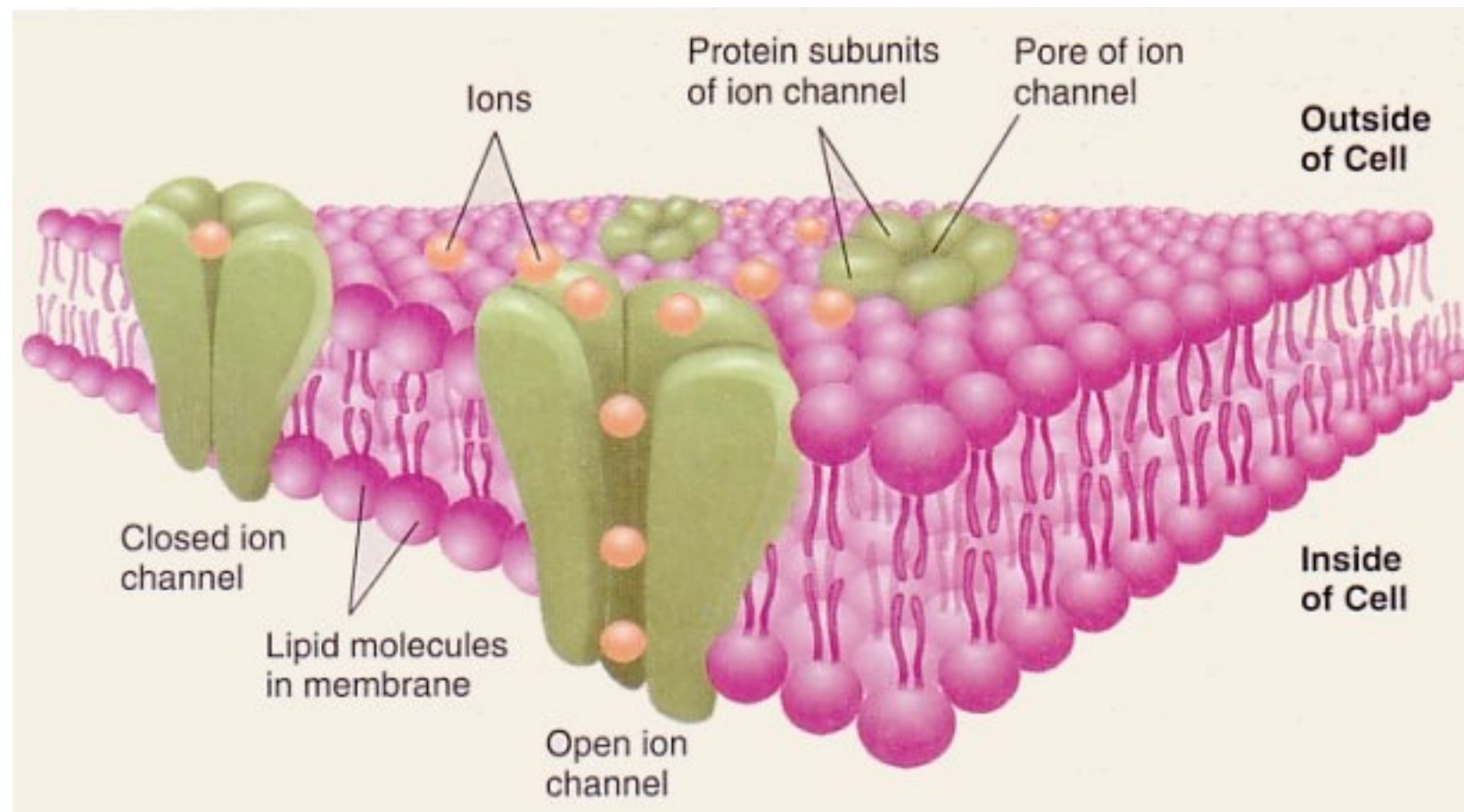


- ① Generate patterns for wireless signaling and appetitive behaviors.
- ② “Preprocessing” to shape signals for higher processing.
- ③ High-level processing: assemble larger patterns, choose behaviors.
- ④ “Tag” high-level patterns for emotional significance.
- ⑤ Store and recall.
- ⑥ Evaluate reward predictions.

## Principles of Neural Design

# **Single neuron dynamics**

**My favorite spherical cow**

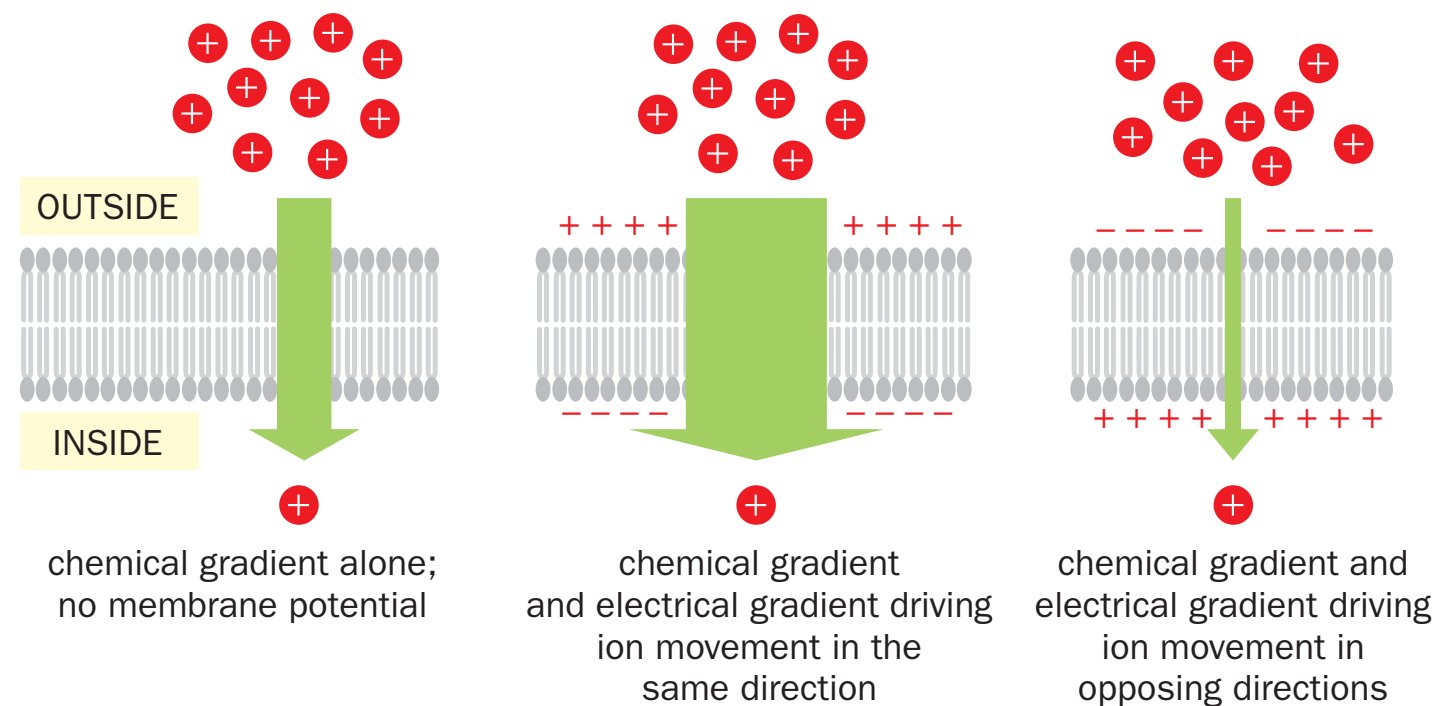


$$qV \sim k_B T$$

$$k_B = 8.6 \times 10^{-5} \text{ eV/K}$$

$$T = 300 \text{ K}$$

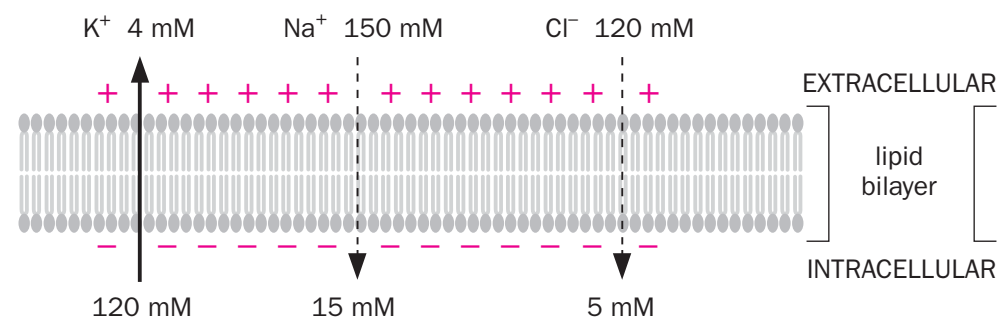
# What determines the resting potential of a neuron?



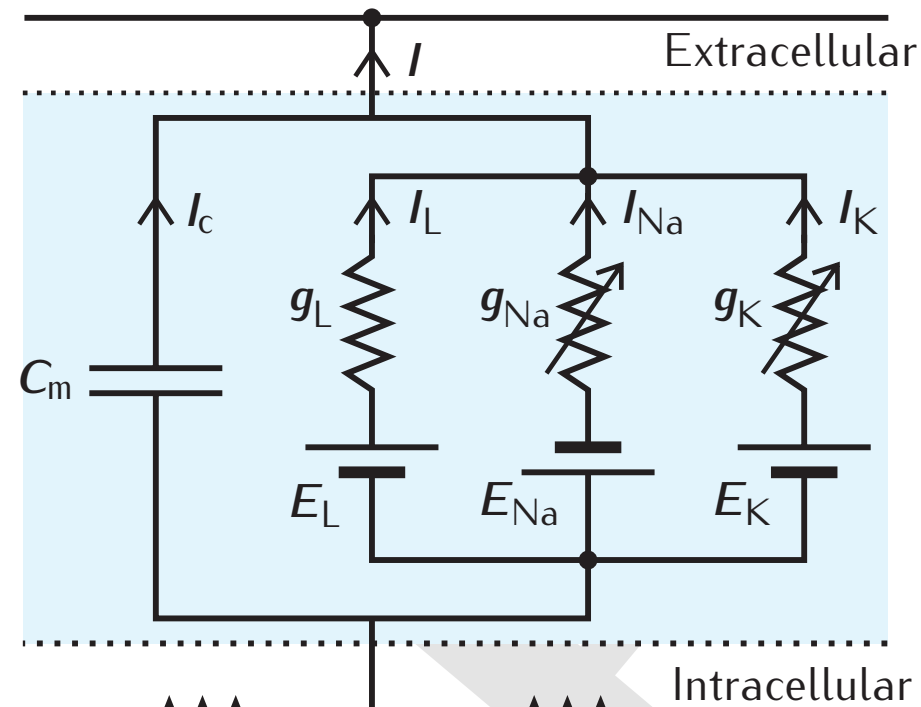
$$E = \frac{k_B T}{ze} \ln \frac{n_{out}}{n_{in}}$$

# Ion pump

(A)



# The Equivalent Electronic Circuit of a Neuron



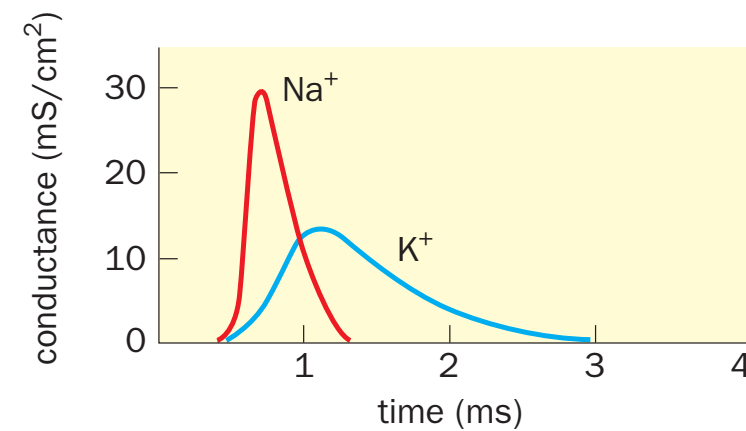
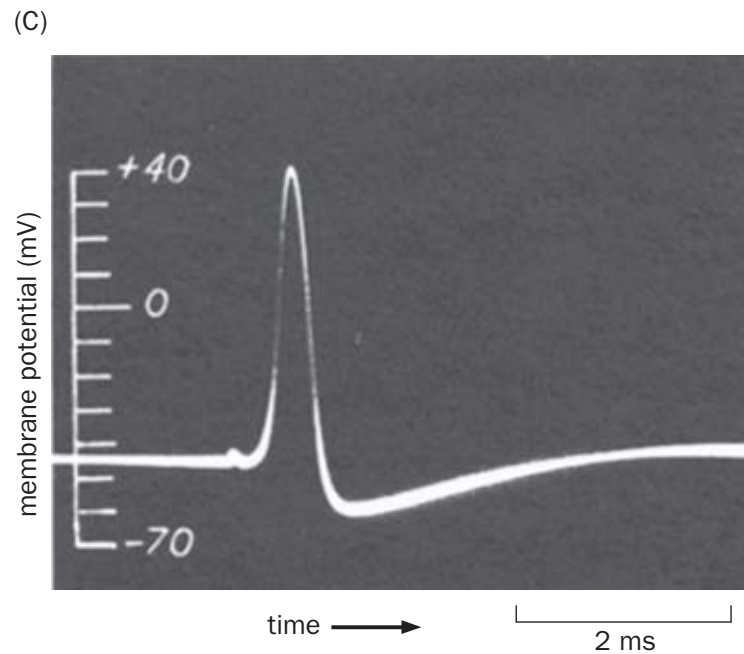
$$C_m \frac{dV}{dt} = - \sum_i g_i(V)(V - E_i) - \bar{g}_L(V - E_L) - I_e$$

$$C_m \approx 0.1 - 1 \text{ nF}$$

$$r_m = 1/g \approx 10 - 100 \text{ M}\Omega$$

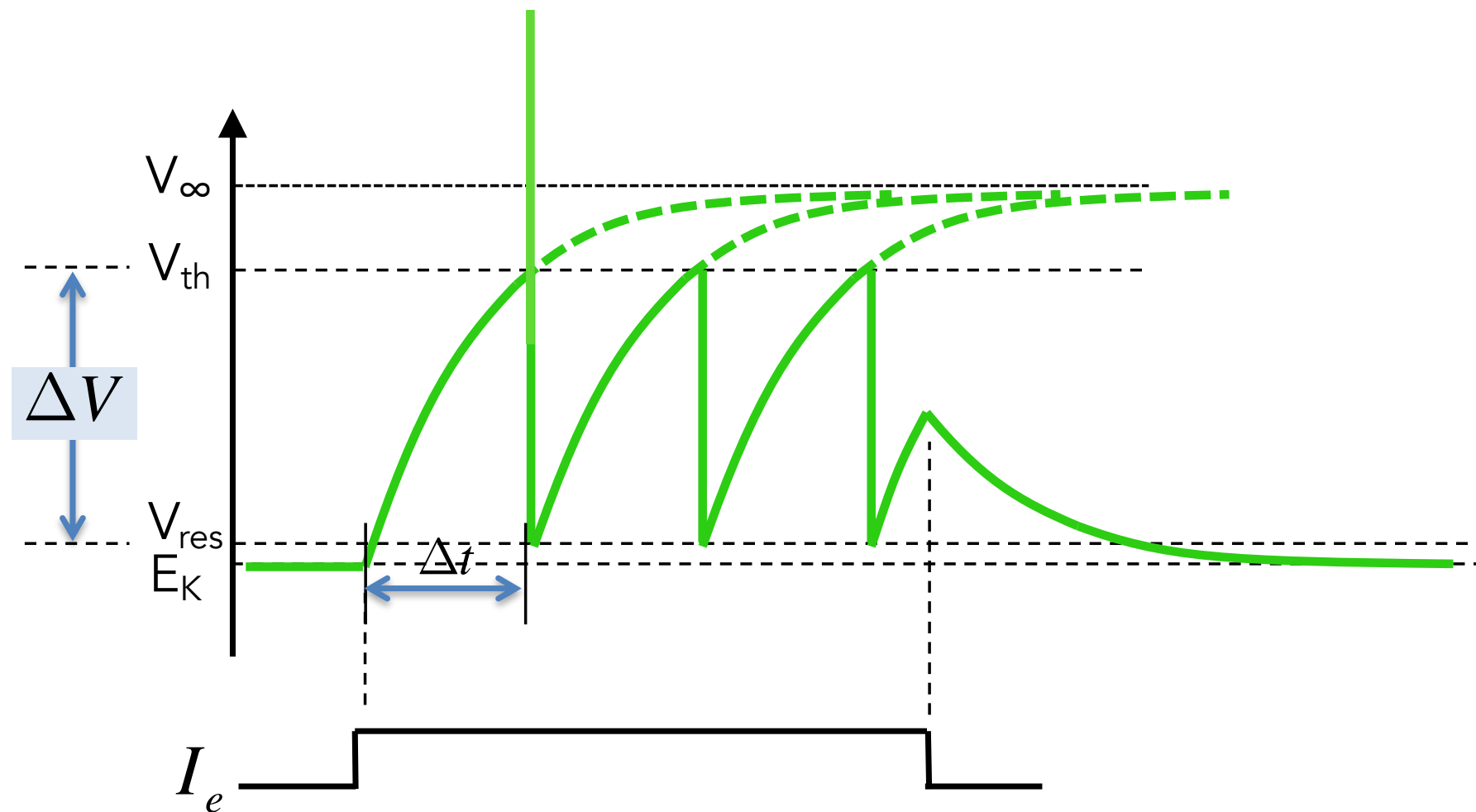
$$\tau_m = C_m r_m \approx 10 - 100 \text{ ms}$$

# The Hodgkin-Huxley model



$$C \frac{dV}{dt} = -g_K n^4 (V - E_K) - g_{Na} m^3 h (V - E_{Na}) - g_L (V - E_L) - I_e$$

# Integrate-and-Fire model



$$C \frac{dV}{dt} = -g(V - E_K) + I_e$$

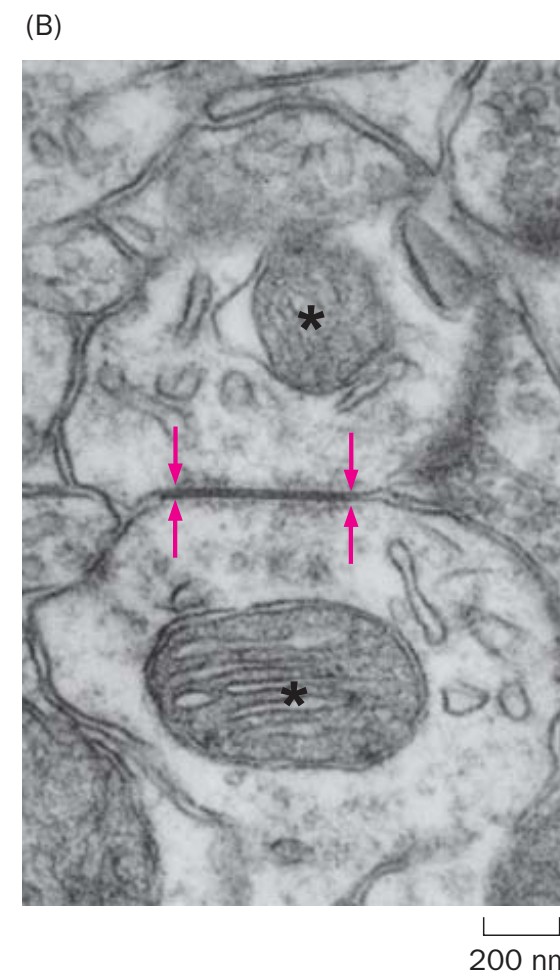
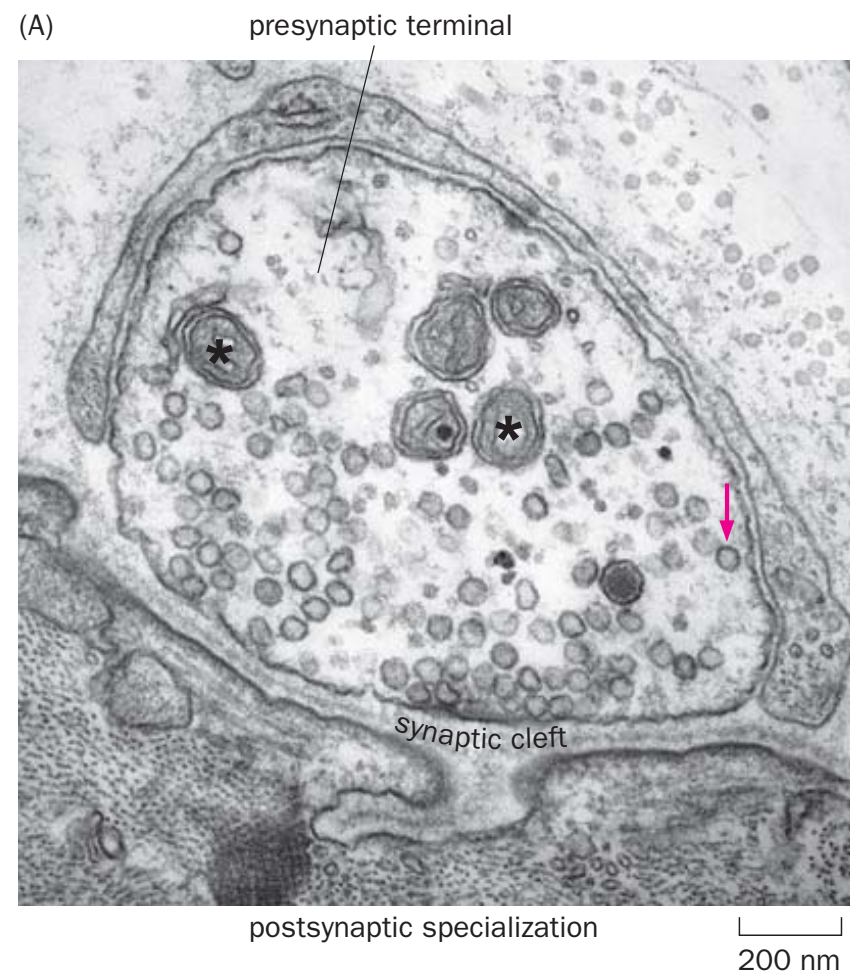
$$V(t_{spike}^-) = V_{th}$$

$$V(t_{spike}^+) = V_{res}$$

# How neurons communicate with each other?

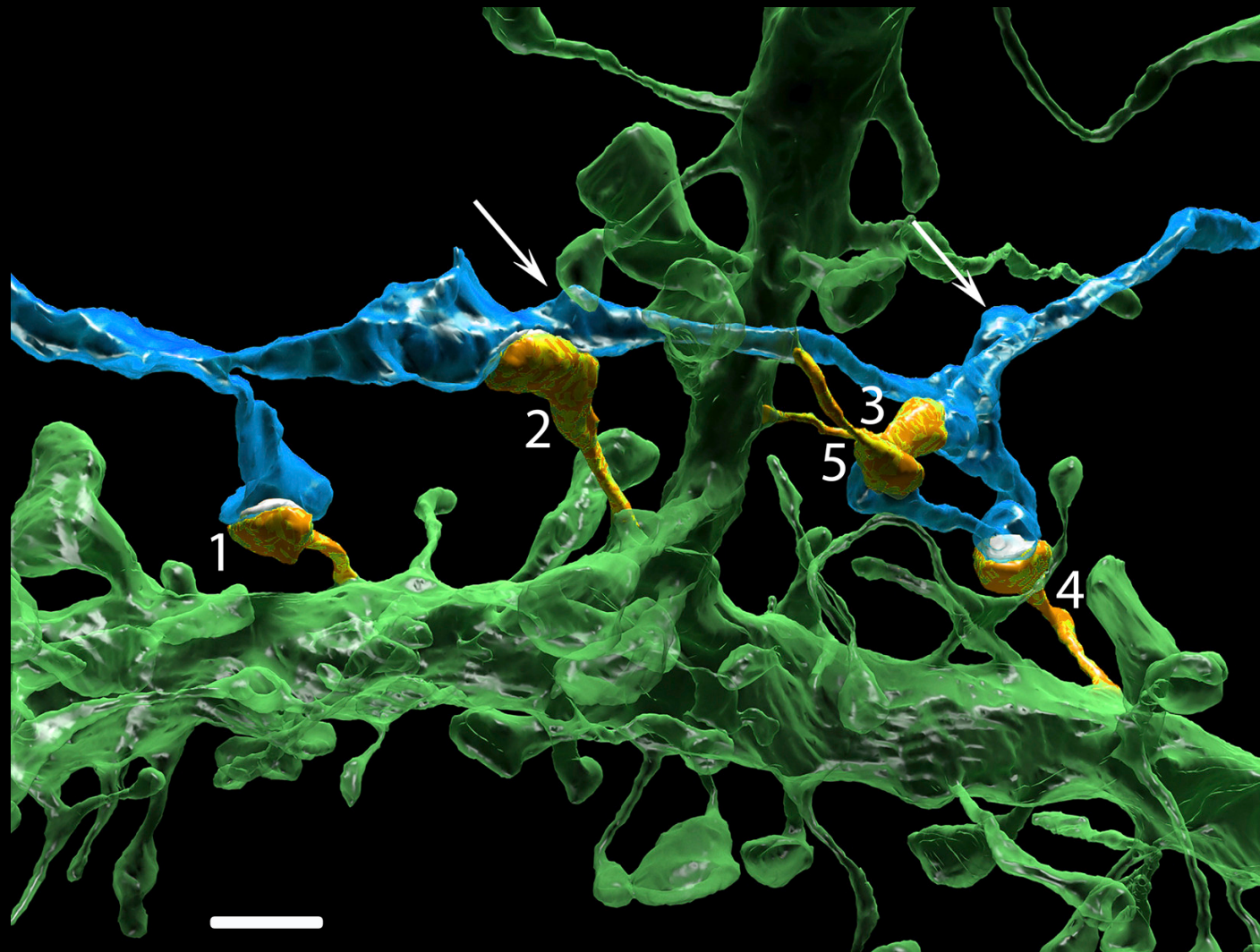
**Nerve cells are related by contiguity rather than continuity**

**Santiago Ramon y Cajal**



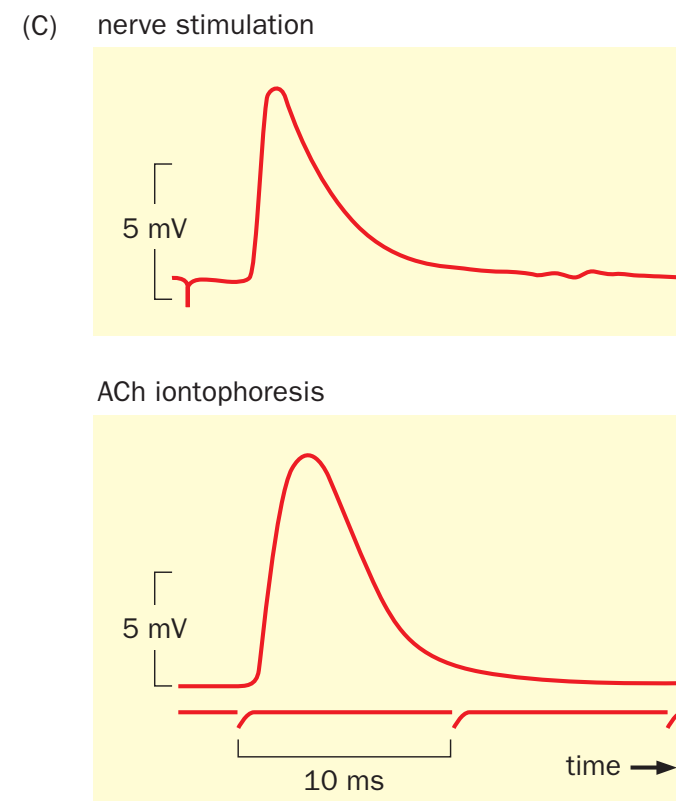
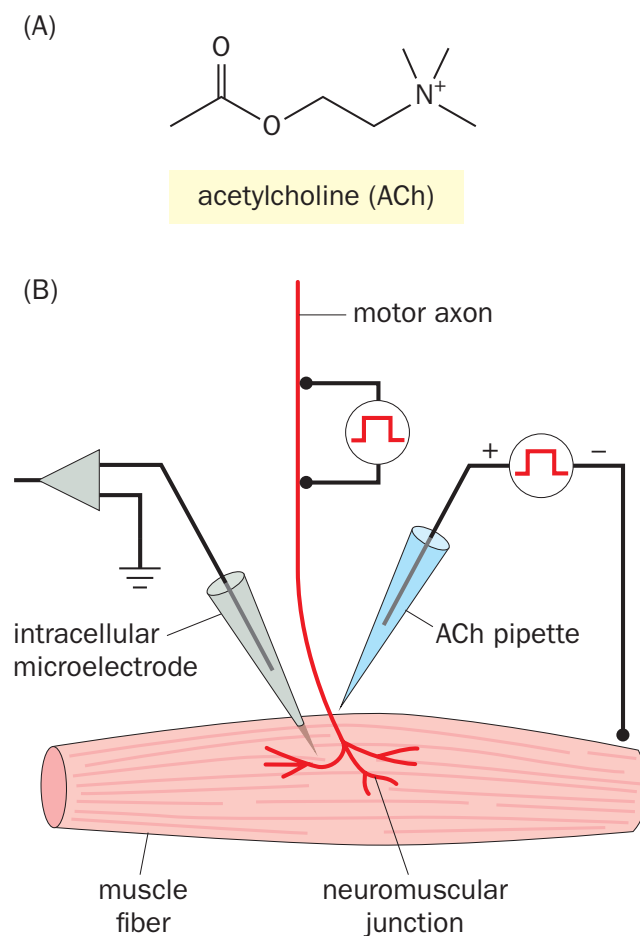
# Chemical and electrical synapses

# Synaptic Connectivity

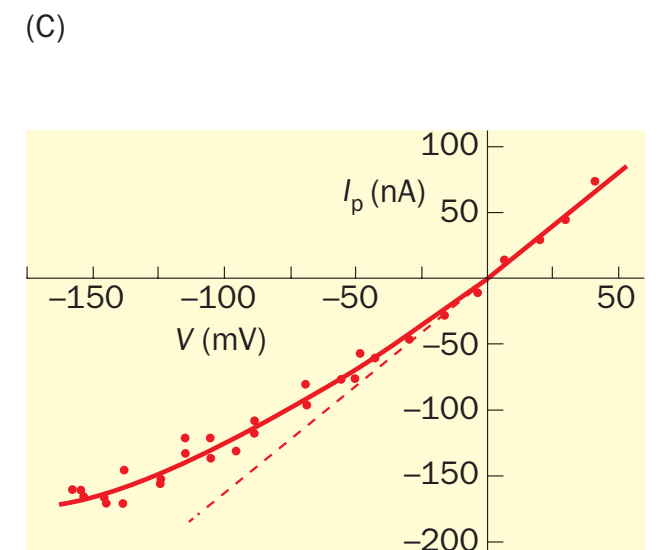
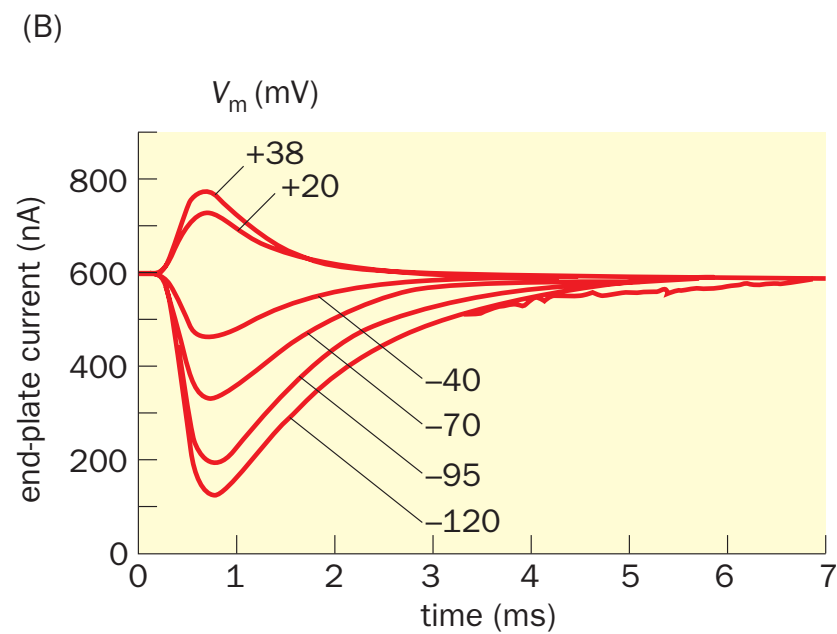
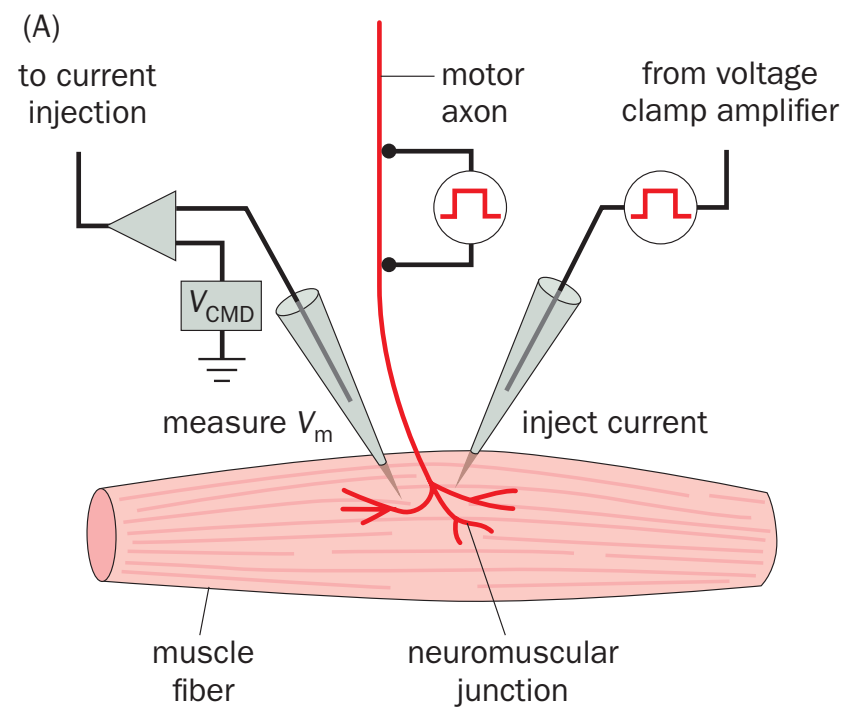


Kasthuri et. al, Cell 2015

# Neurotransmitter release evokes membrane potential change in the postsynaptic neuron



# Reversal potential of a synapse



# Modelling synaptic transmission

*Release probability ( $u$ )*

$$I = \bar{g}_s u (V - E_s) \approx Au$$

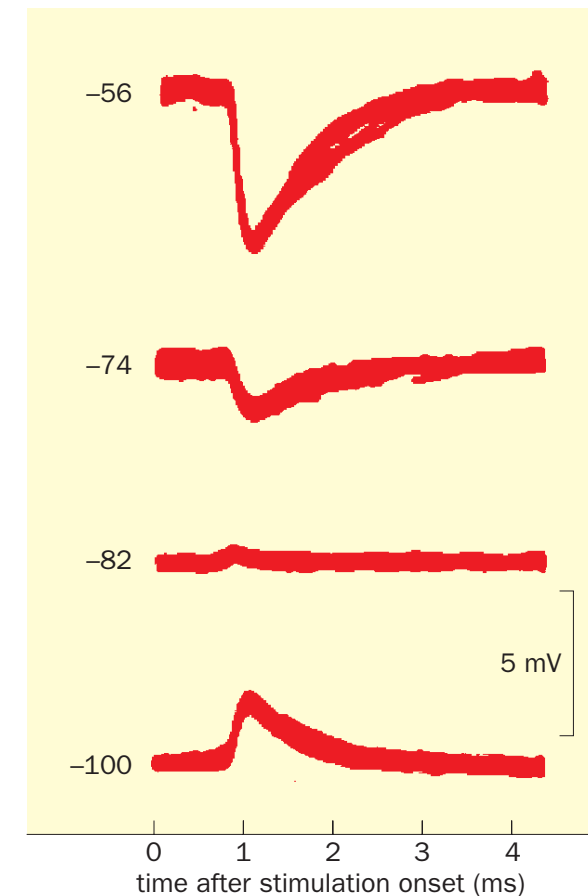
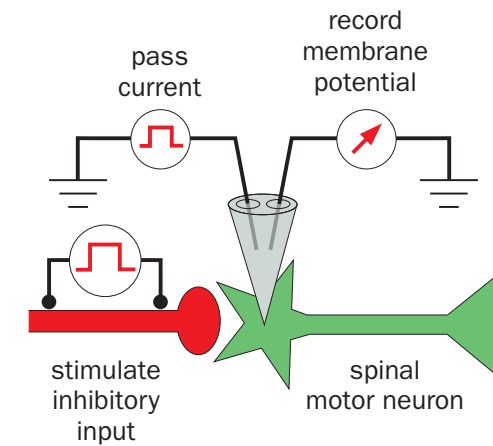
$$u = u_0 e^{-(t-t_{spike})/\tau_s}, \text{ **for** } t > t_{spike}$$

$$\frac{dI}{dt} = -\frac{I}{\tau_s} + Au_0 \delta(t - t_{spike})$$

# Excitatory and Inhibitory Synapses

**Table 3–2: Commonly used neurotransmitters**

| Neurotransmitter | Major uses in the vertebrate nervous system <sup>1</sup>                                          |
|------------------|---------------------------------------------------------------------------------------------------|
| Acetylcholine    | motor neurons that excite muscle; ANS <sup>2</sup> neurons; CNS excitatory and modulatory neurons |
| Glutamate        | most CNS excitatory neurons; most sensory neurons                                                 |
| GABA             | most CNS inhibitory neurons                                                                       |
| Glycine          | some CNS inhibitory neurons (mostly in the brainstem and spinal cord)                             |
| Serotonin (5-HT) | CNS modulatory neurons                                                                            |
| Dopamine         | CNS modulatory neurons                                                                            |
| Norepinephrine   | CNS modulatory neurons; ANS <sup>2</sup> neurons                                                  |
| Histamine        | CNS modulatory neurons                                                                            |
| Neuropeptides    | usually co-released from excitatory, inhibitory, or modulatory neurons; neurosecretory cells      |

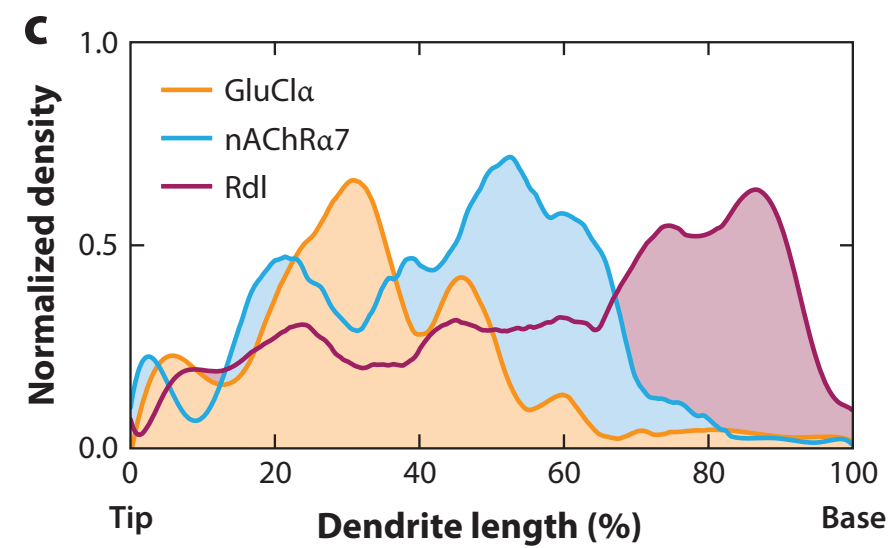
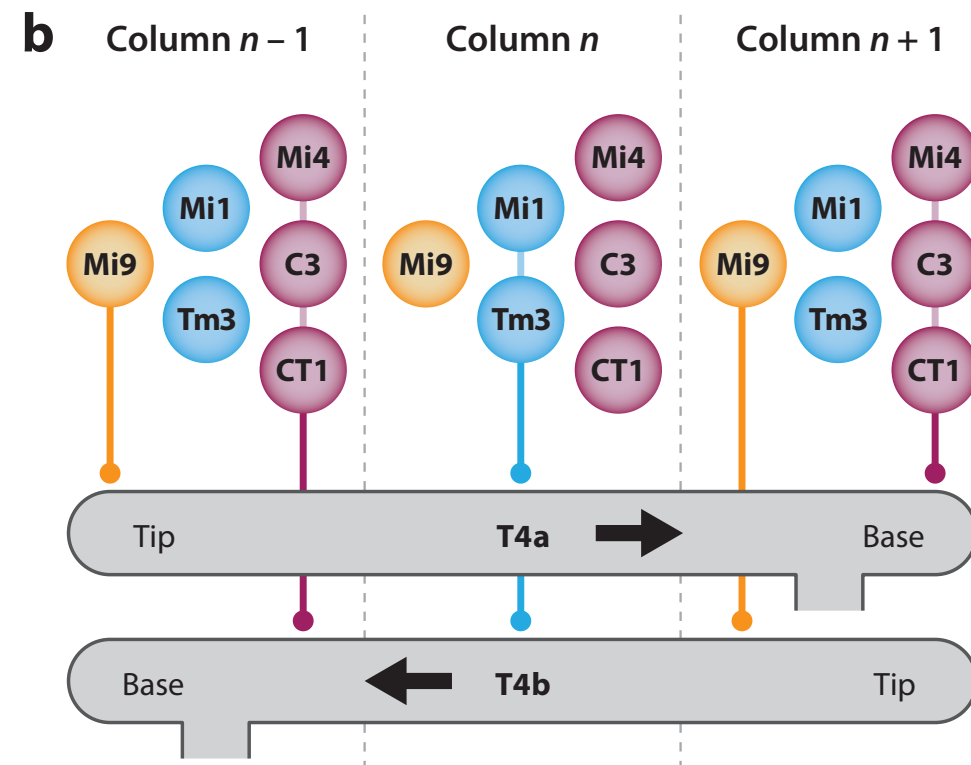
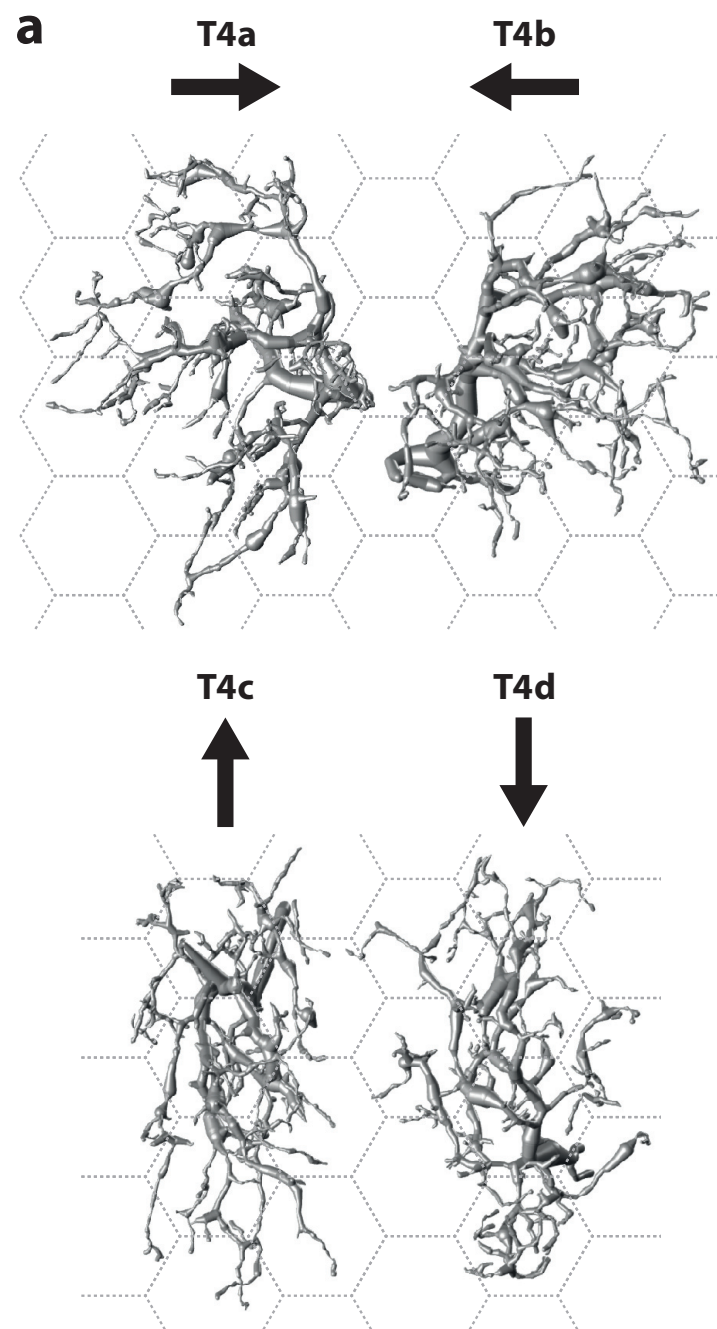


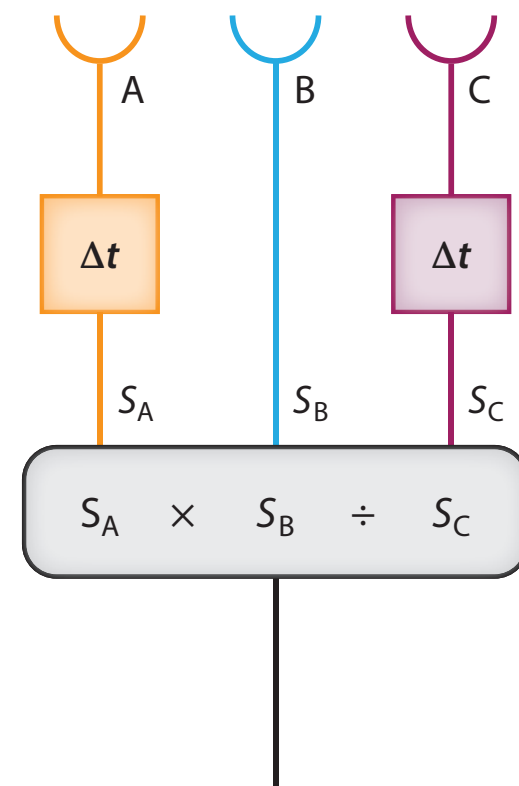
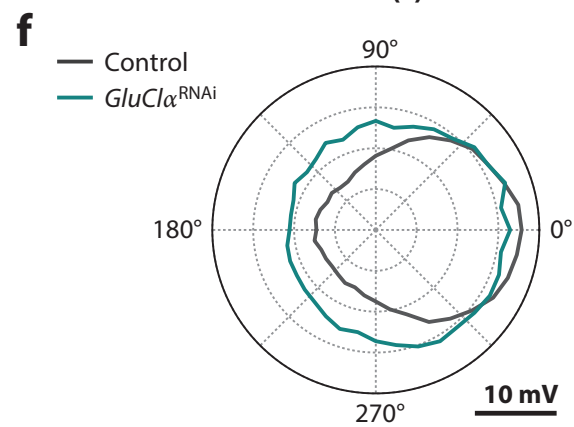
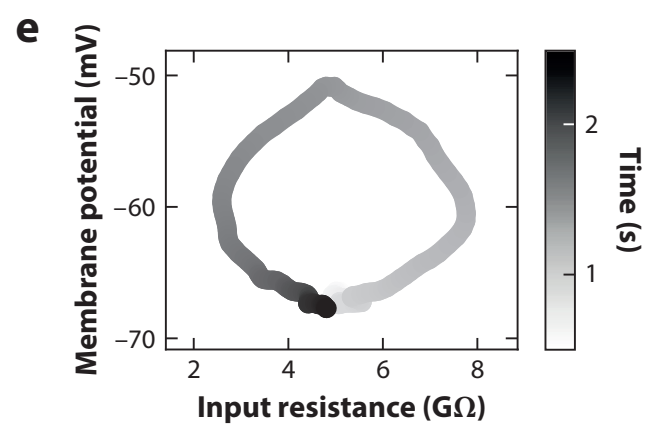
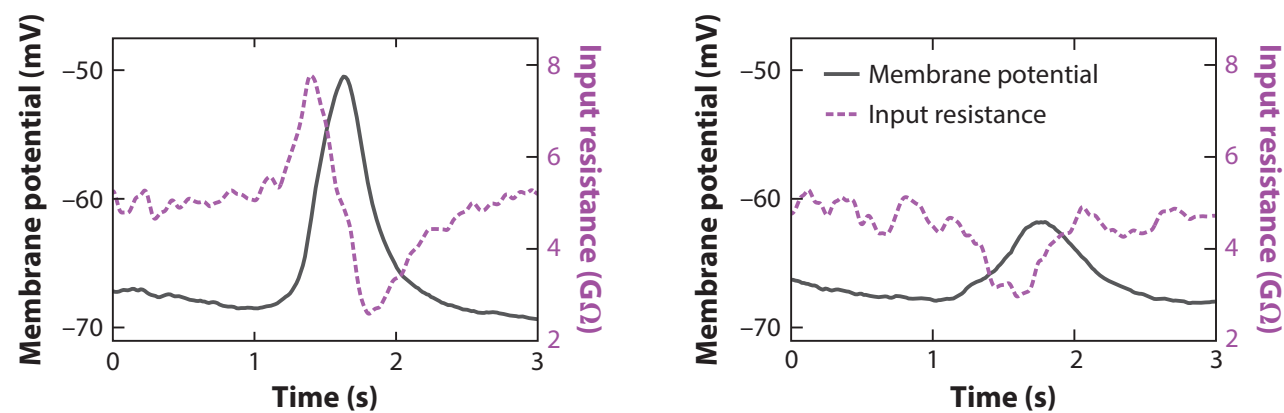
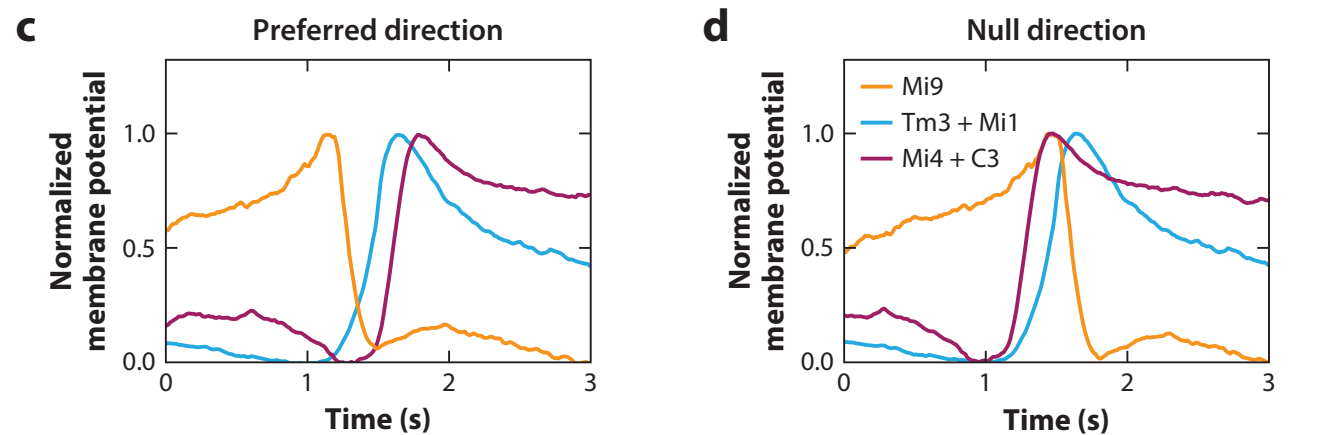
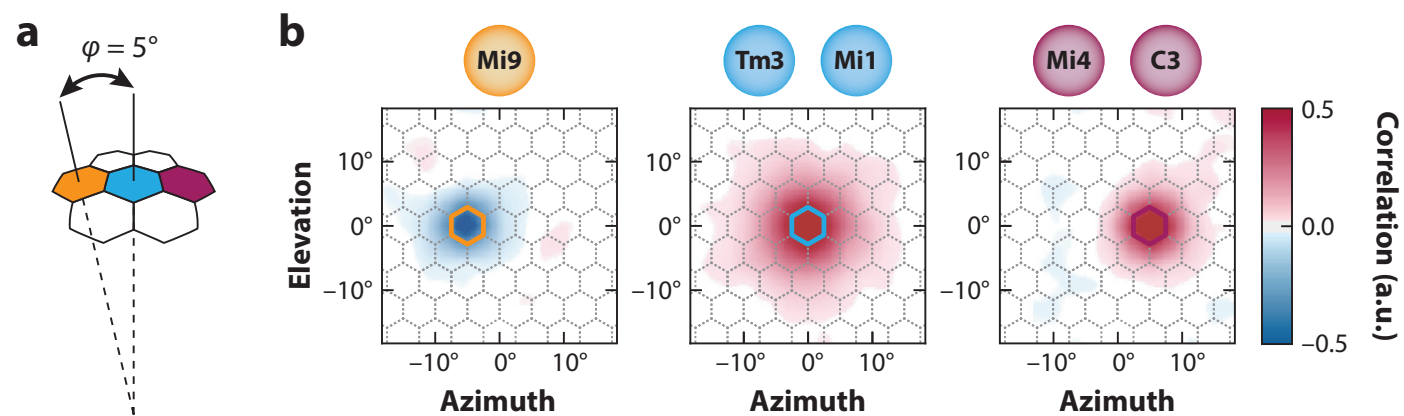
# Shunting inhibition and divisive operation

$$C_m \frac{dV}{dt} = -g_L(V - E_L) - g_{inh}(V - E_L) - g_{exc}(V - E_0)$$

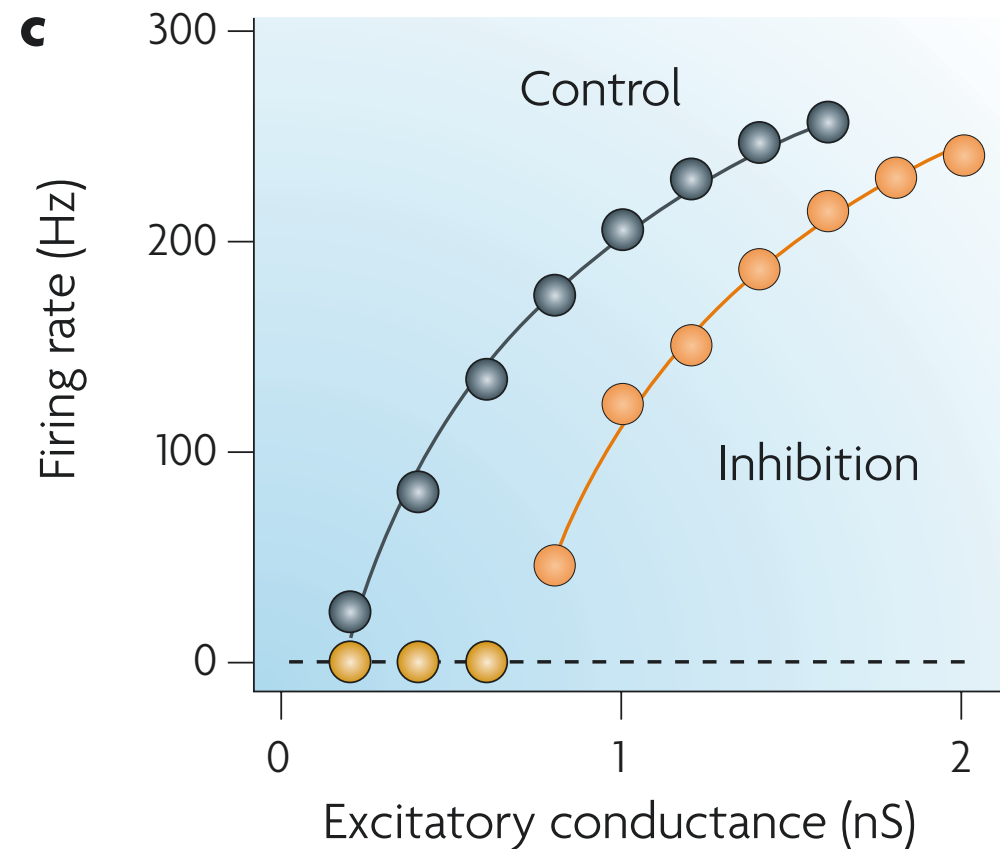
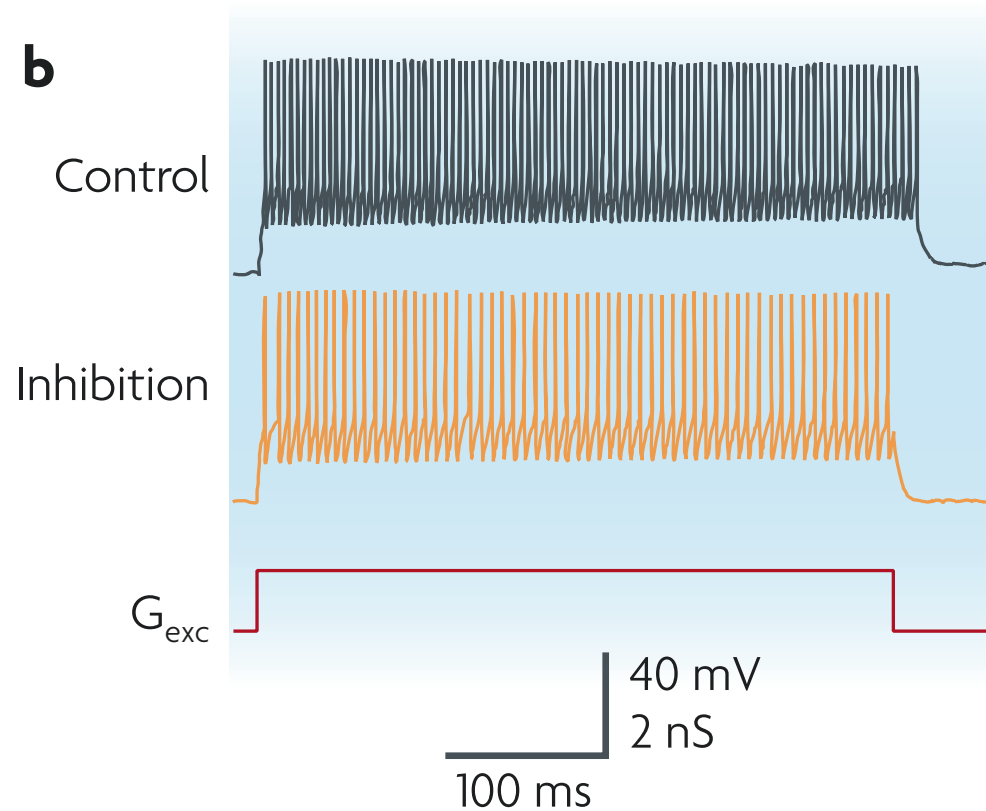
$$V = \frac{(g_L + g_{inh})E_L + g_{exc}E_0}{g_L + g_{inh} + g_{exc}}$$

$$g_{inh} \gg g_L + g_{exc} \qquad V \approx E_L + \frac{g_{exc}}{g_{inh}}E_0$$



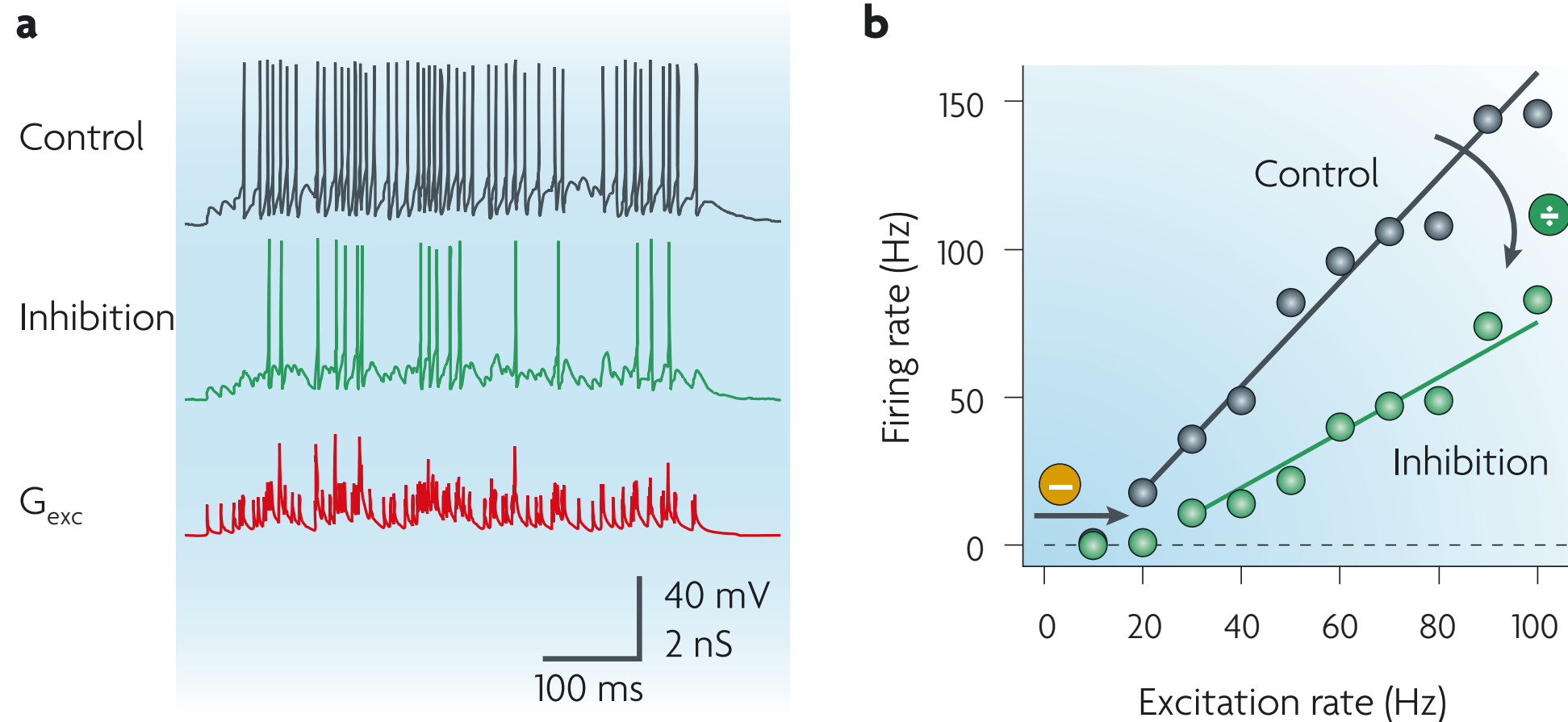


However, shunting inhibition becomes subtractive for firing rate



Why? (Your homework)

## But Shunting inhibition can become divisive in the presence of large synaptic input noise

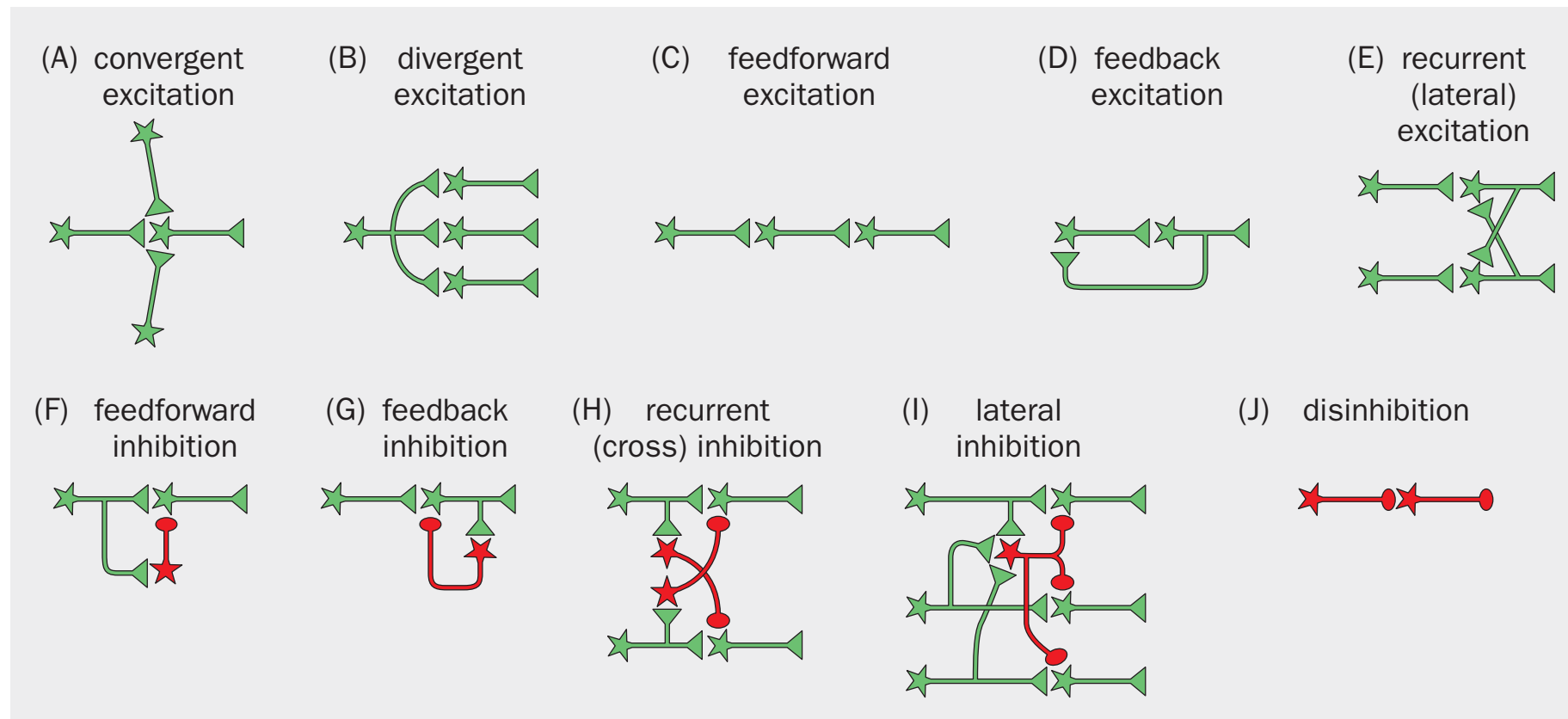


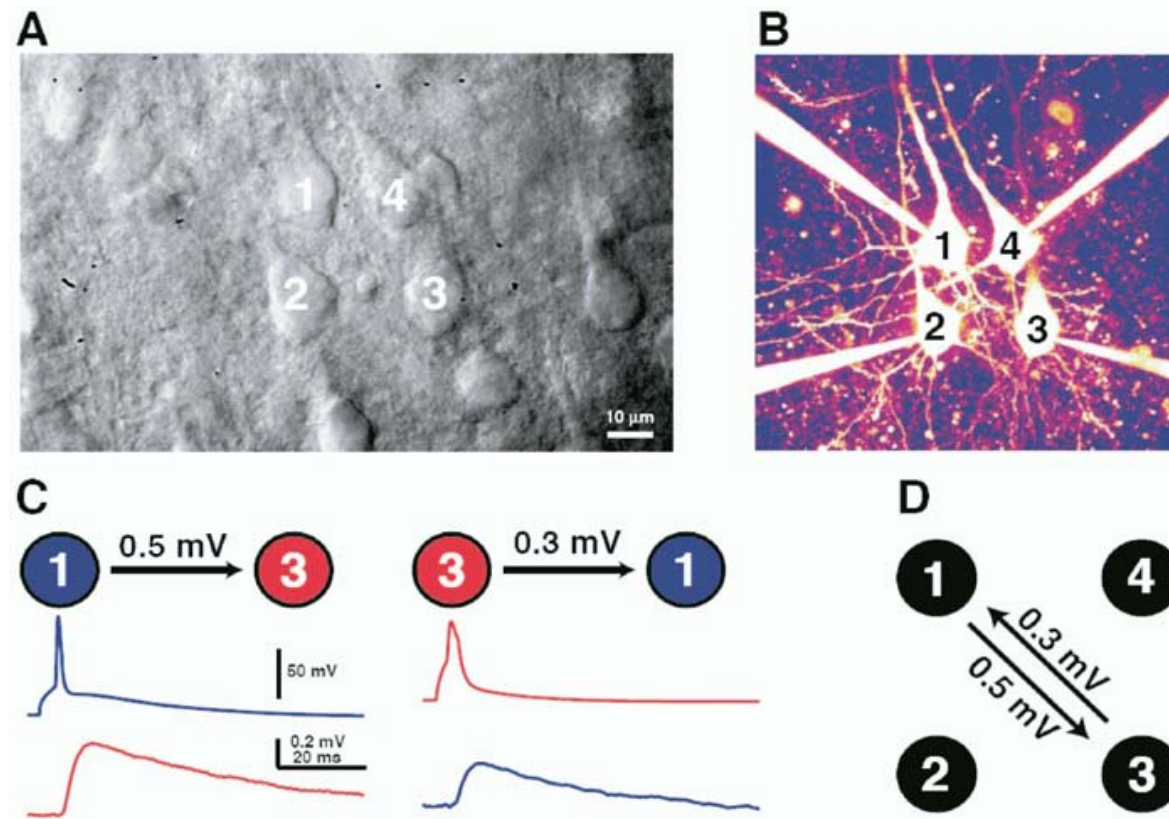
# The organization of neural circuits

Circuit diagrams or connectomes are *absolutely* necessary but *completely* insufficient for understanding nervous system function.

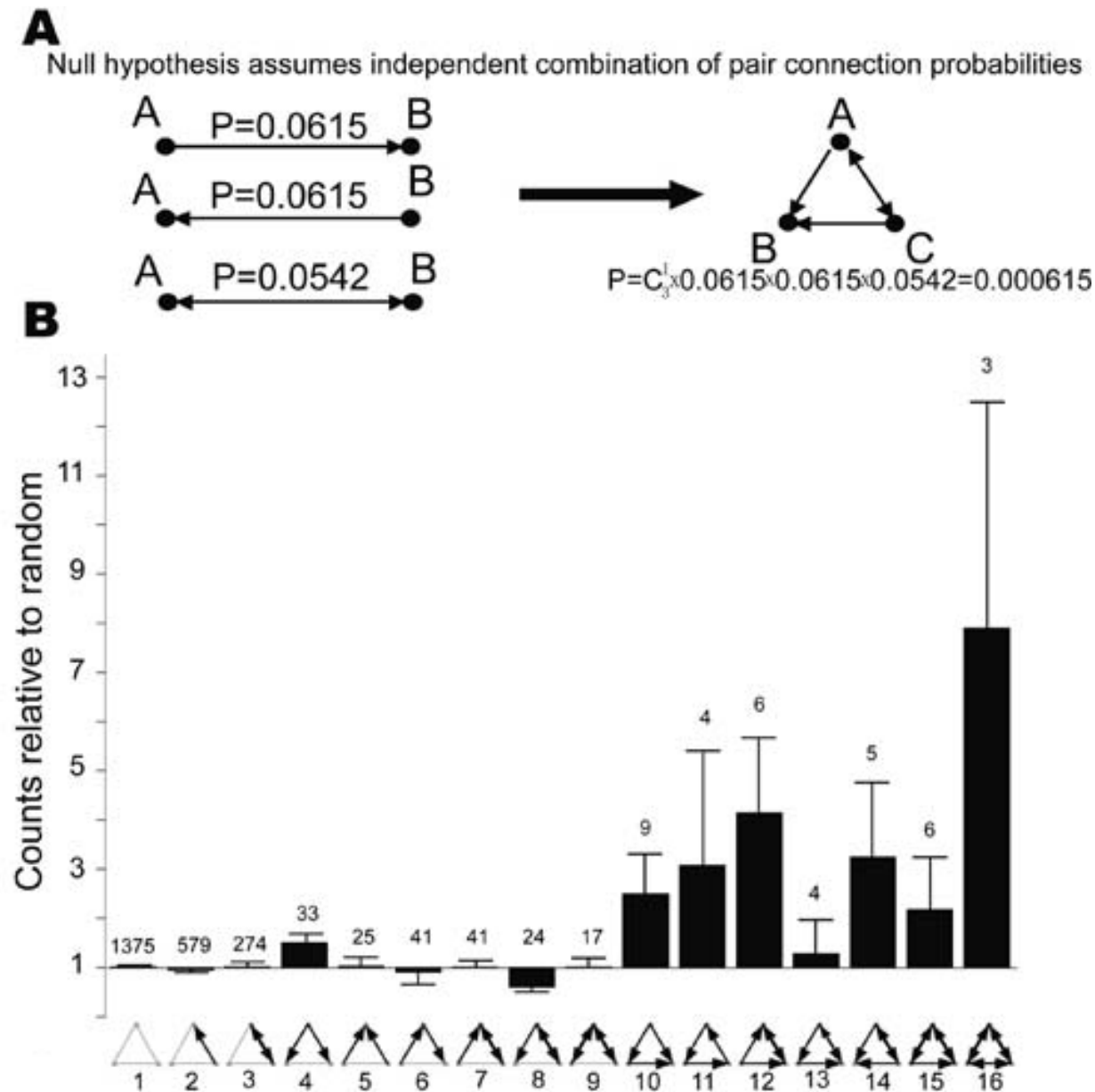
Eve Marder

# Circuit motifs

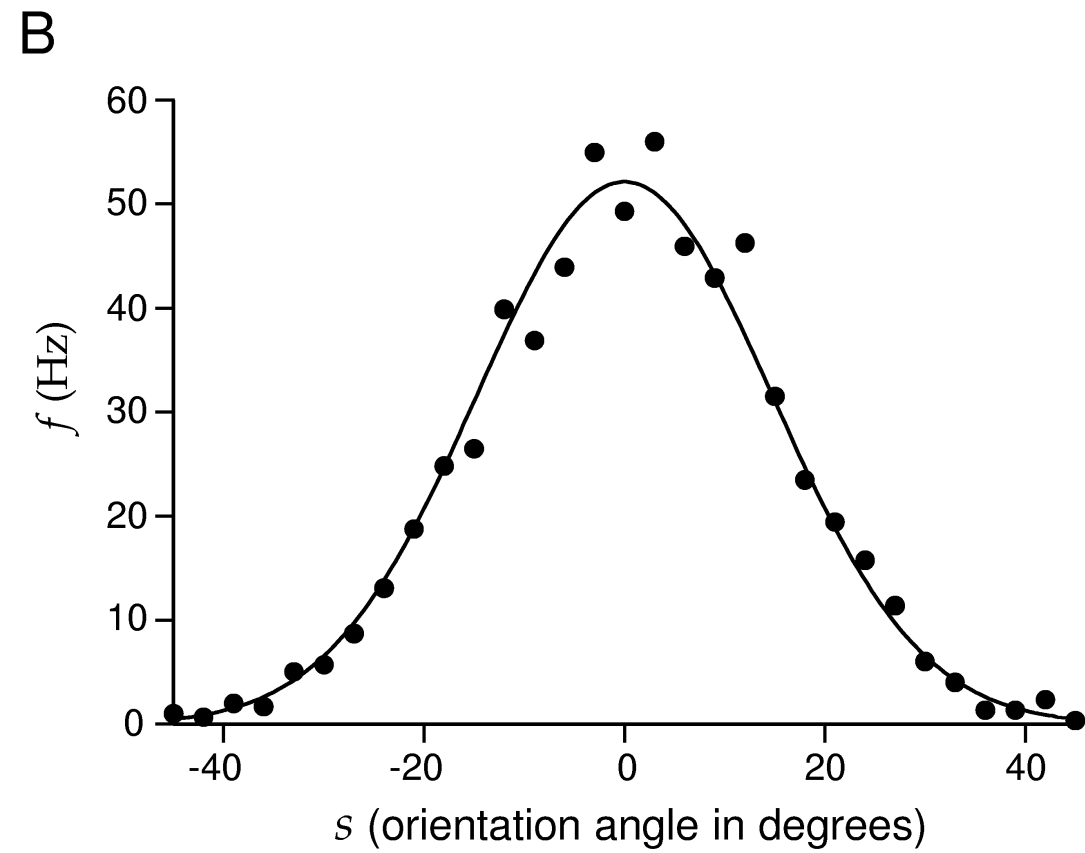
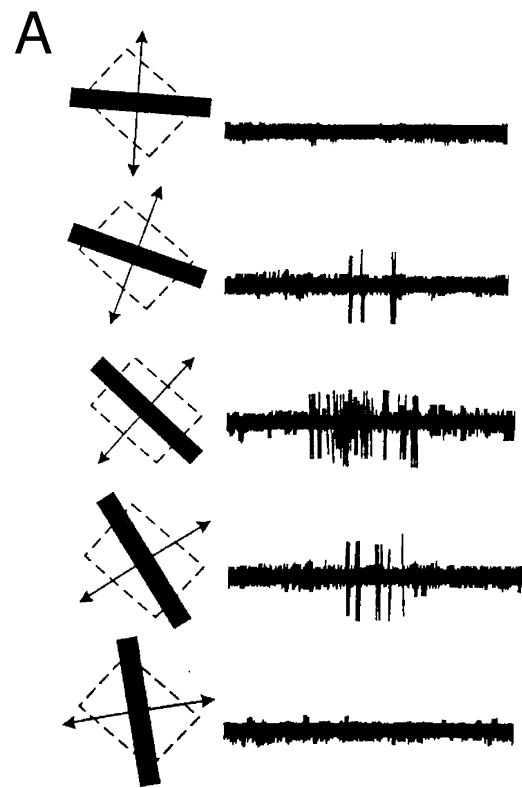




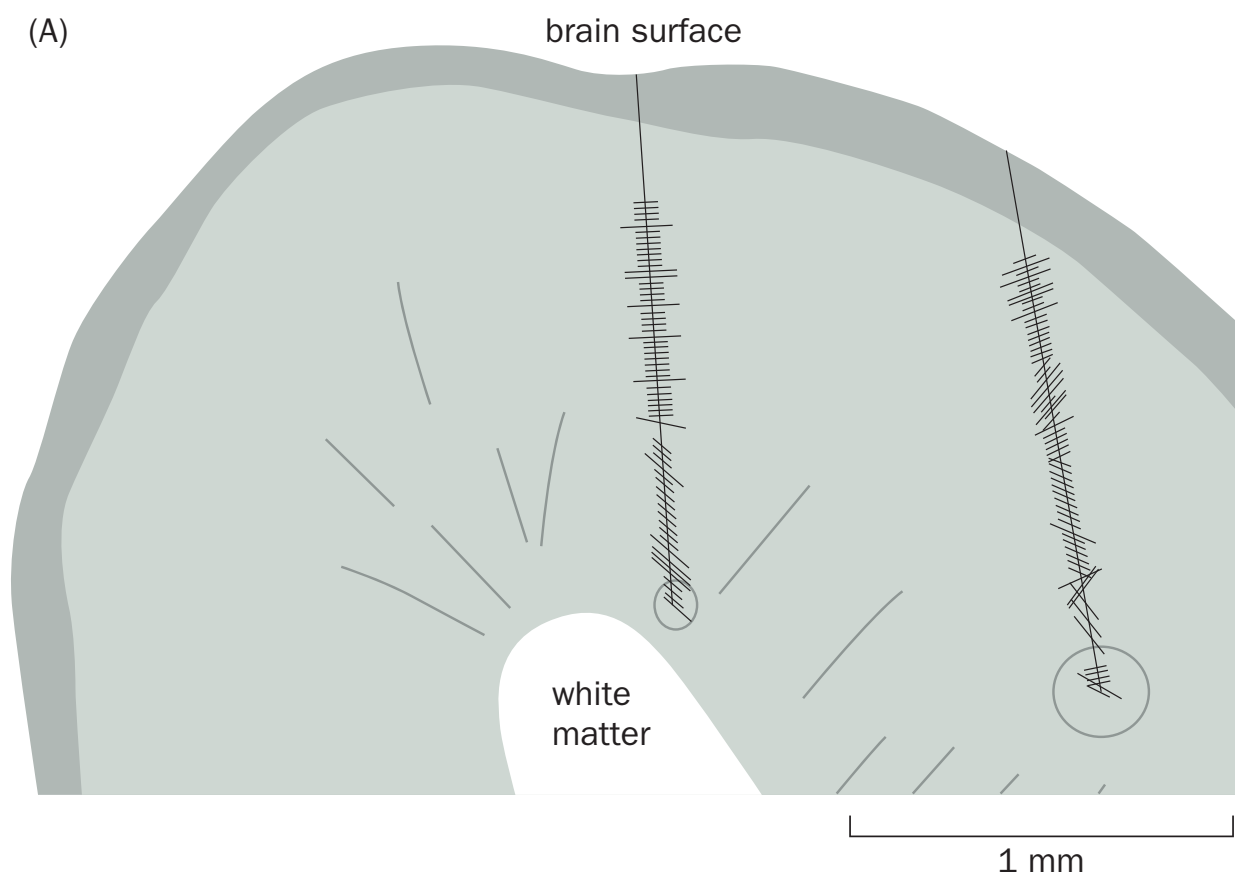
# Some circuit motifs are over-represented



# The cortex uses maps to organize information

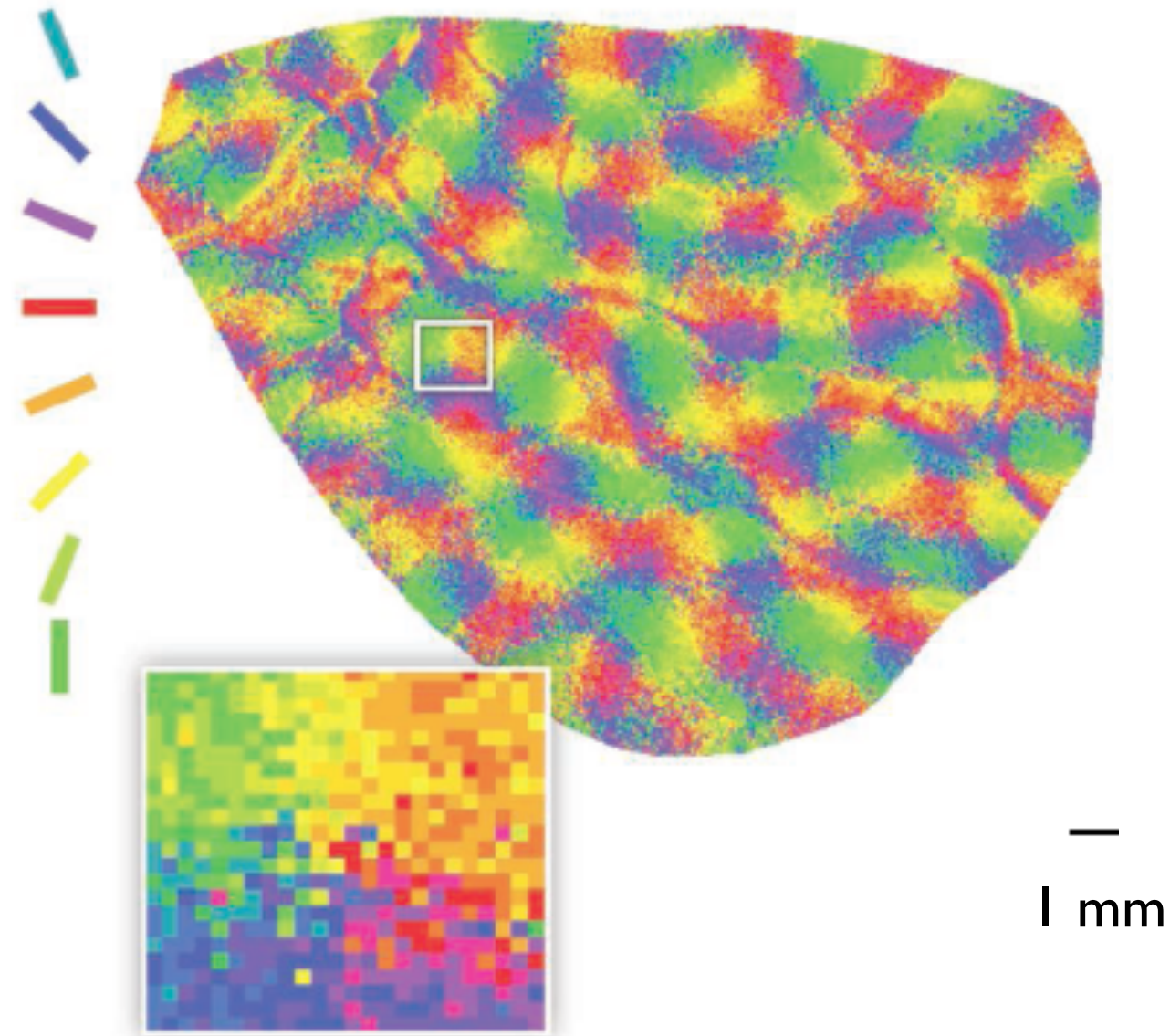


# The Cortical Column

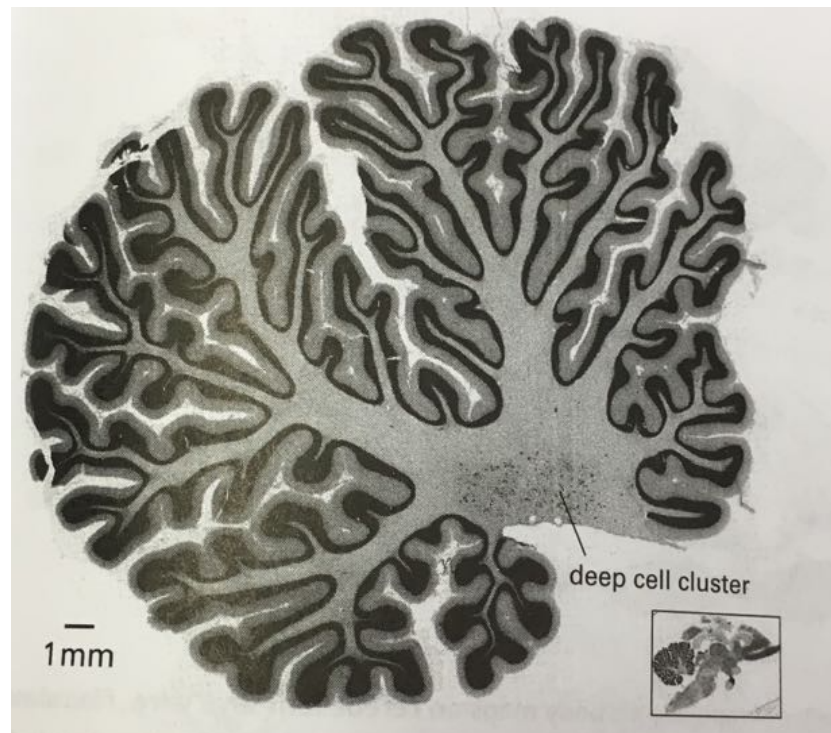


Hubel DH & Wiesel TN (1962) J Physiology 160: 106-154

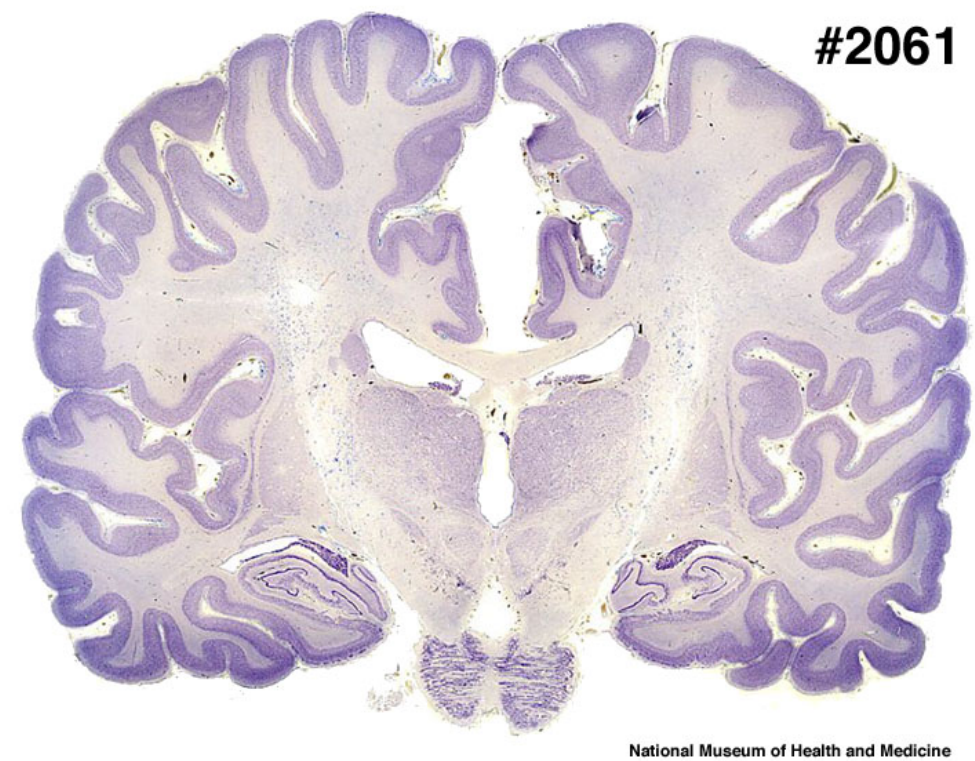
# The cortex uses maps to organize information



**cerebral cortex vs. cerebellar cortex**



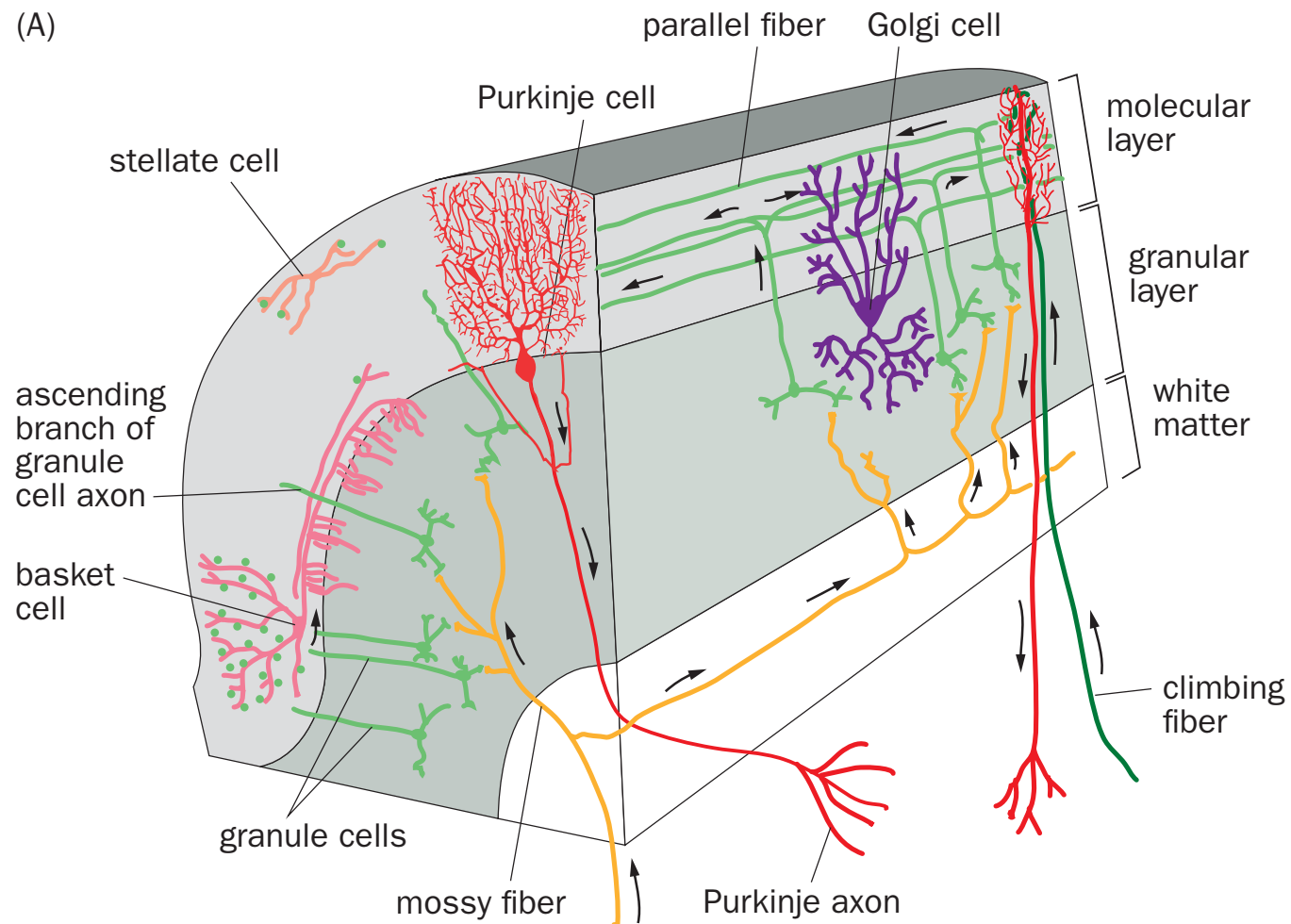
**cerebellum**



**cerebral cortex**

Connecting dense array to sparse array with  
extreme convergence and divergence

# The organization of cerebellar cortex



$$N_g D = N_p C$$

$$N_g \gg N_p$$

$$C \gg D$$

Connecting many dense arrays to many other dense arrays with moderate convergence and divergence

# The organization of the cortical column

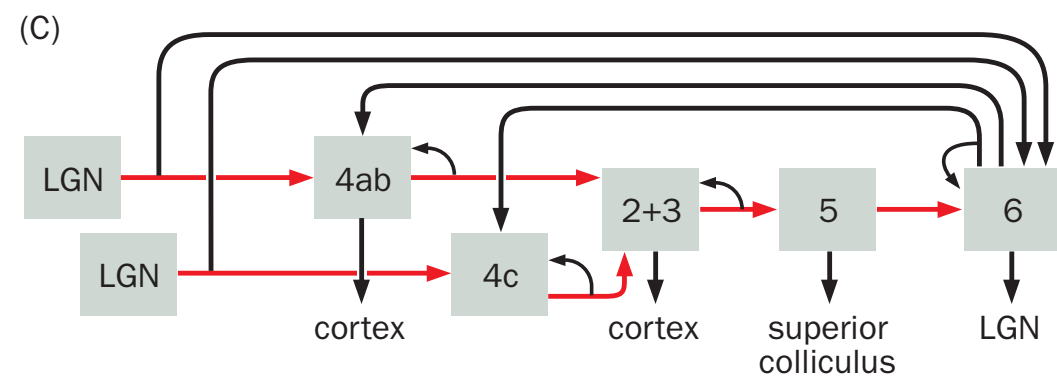
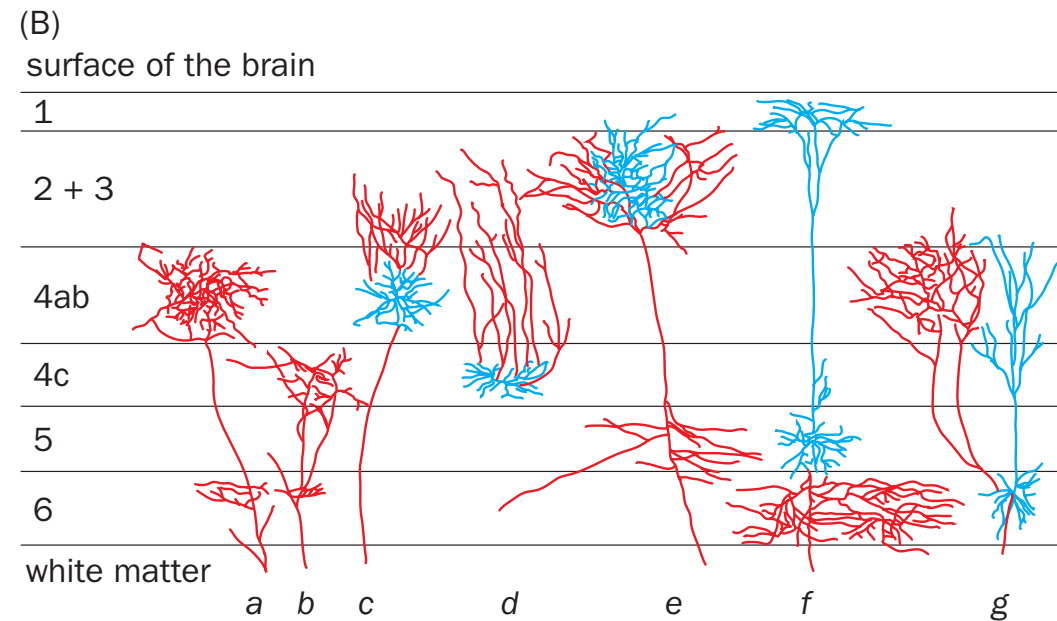
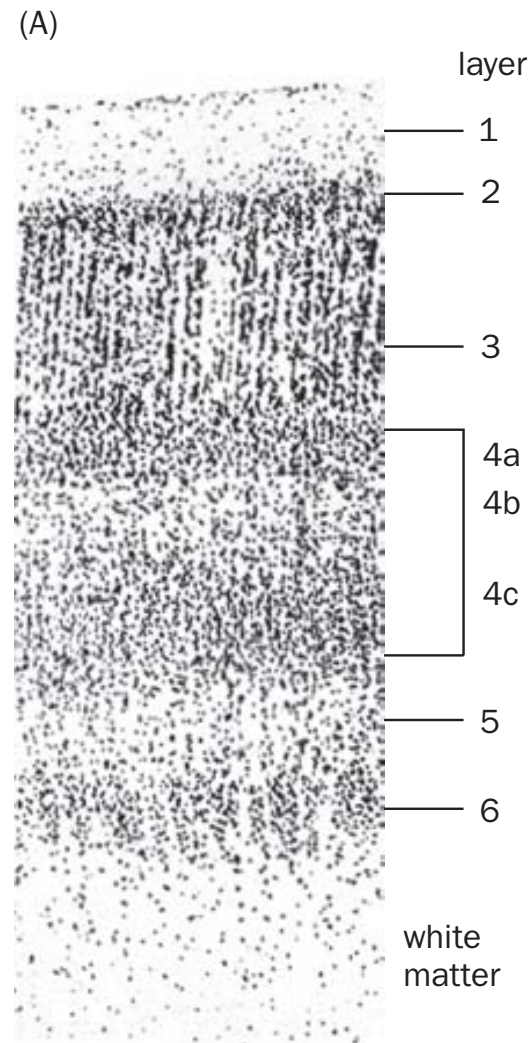
85% excitatory cells

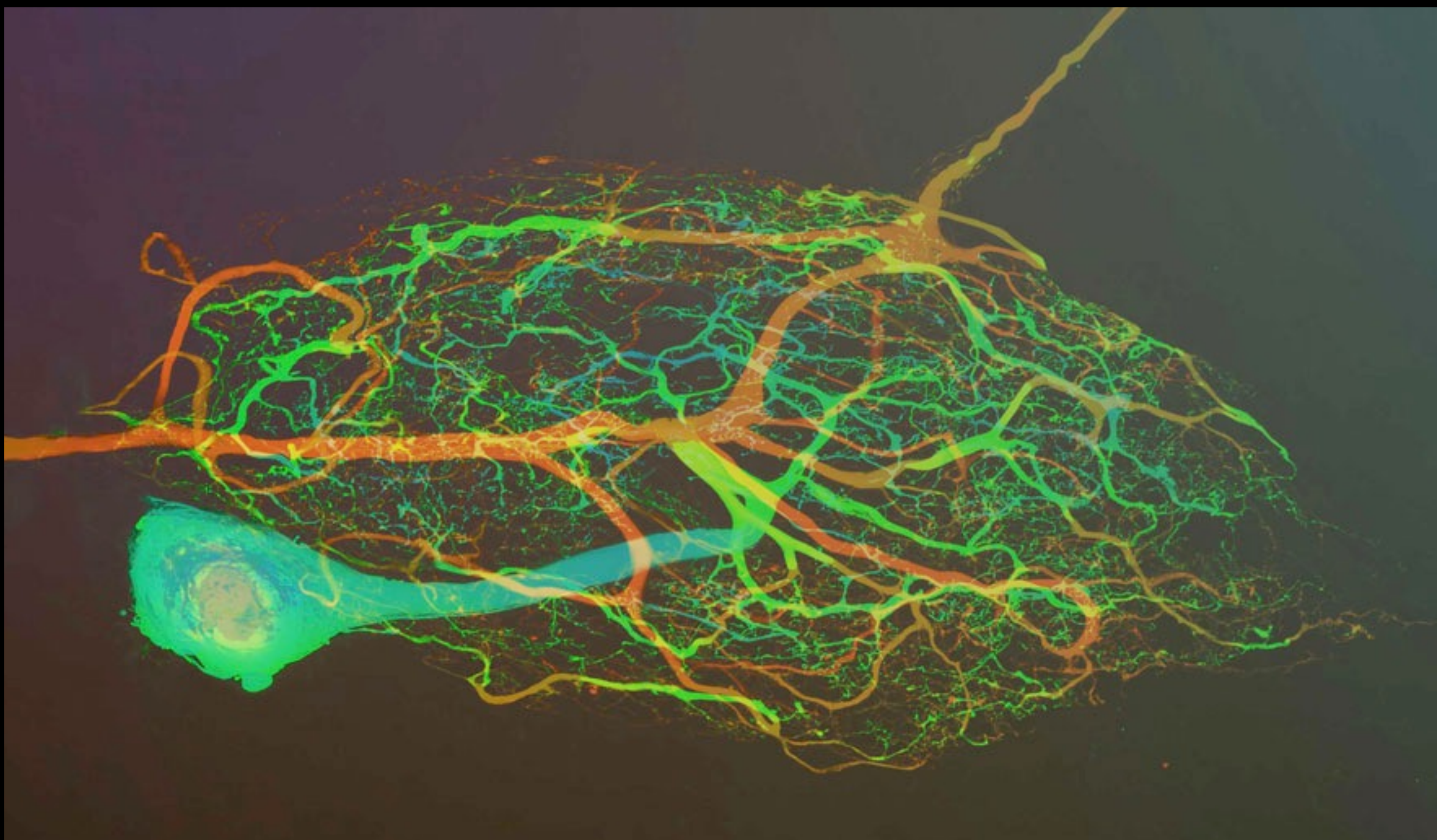
15% inhibitory cells

$10^5$  neurons

$10^9$  synapses

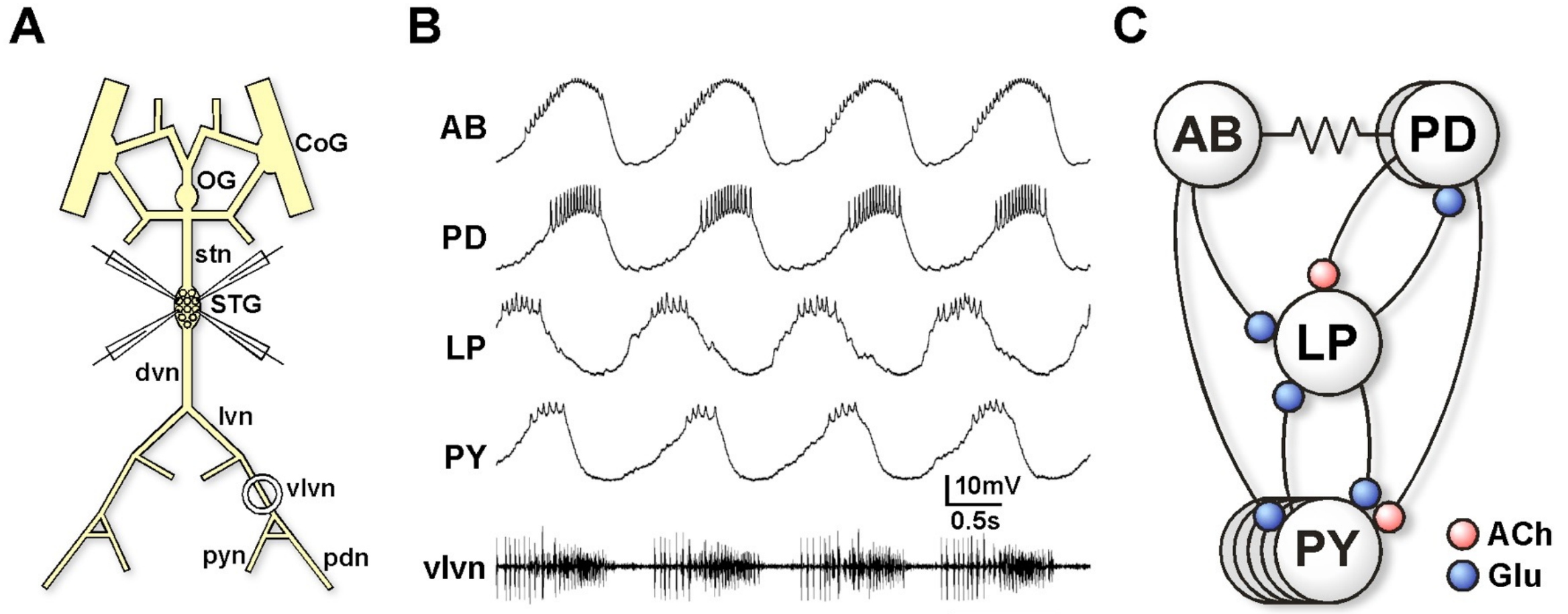
5000 m wires



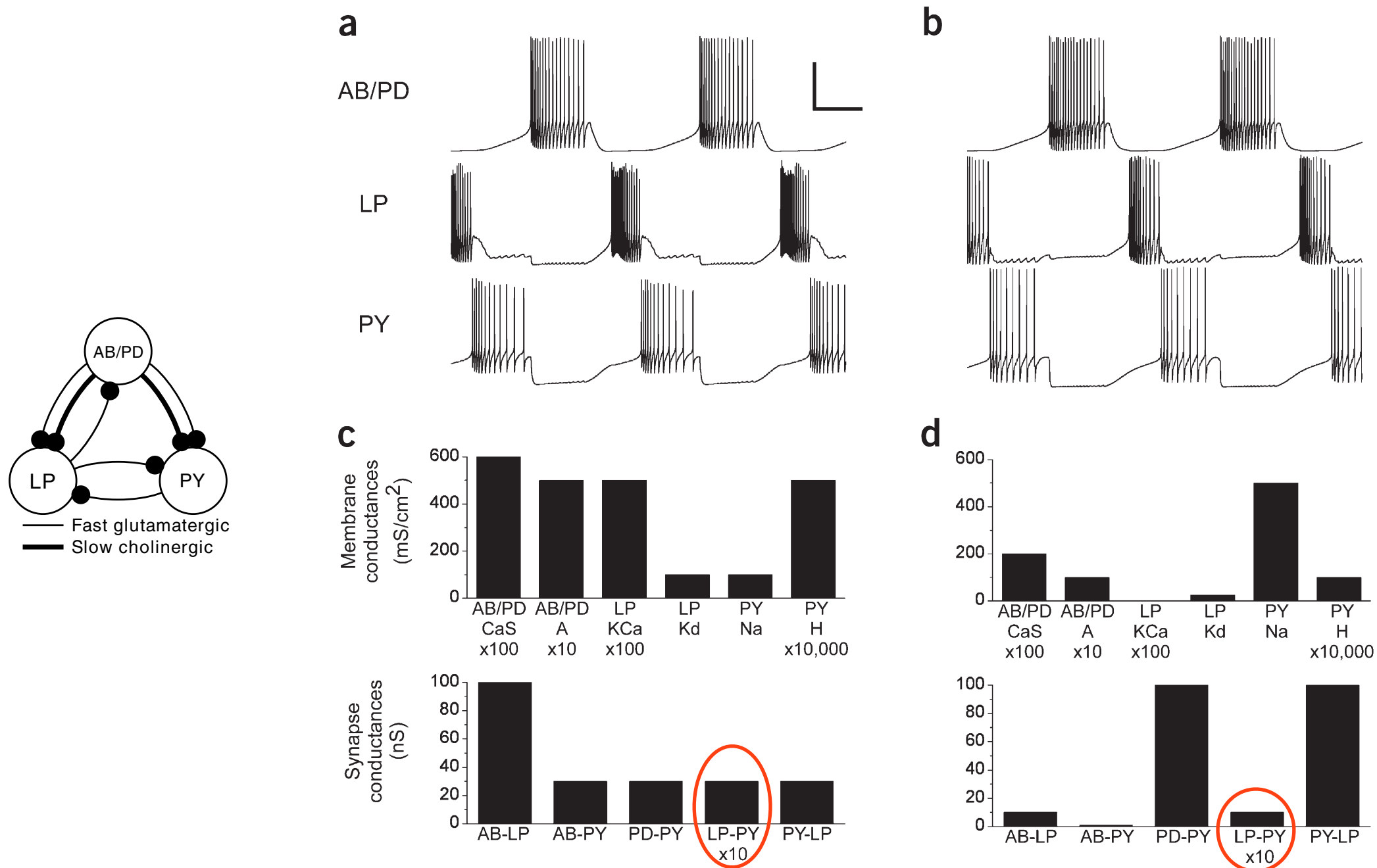


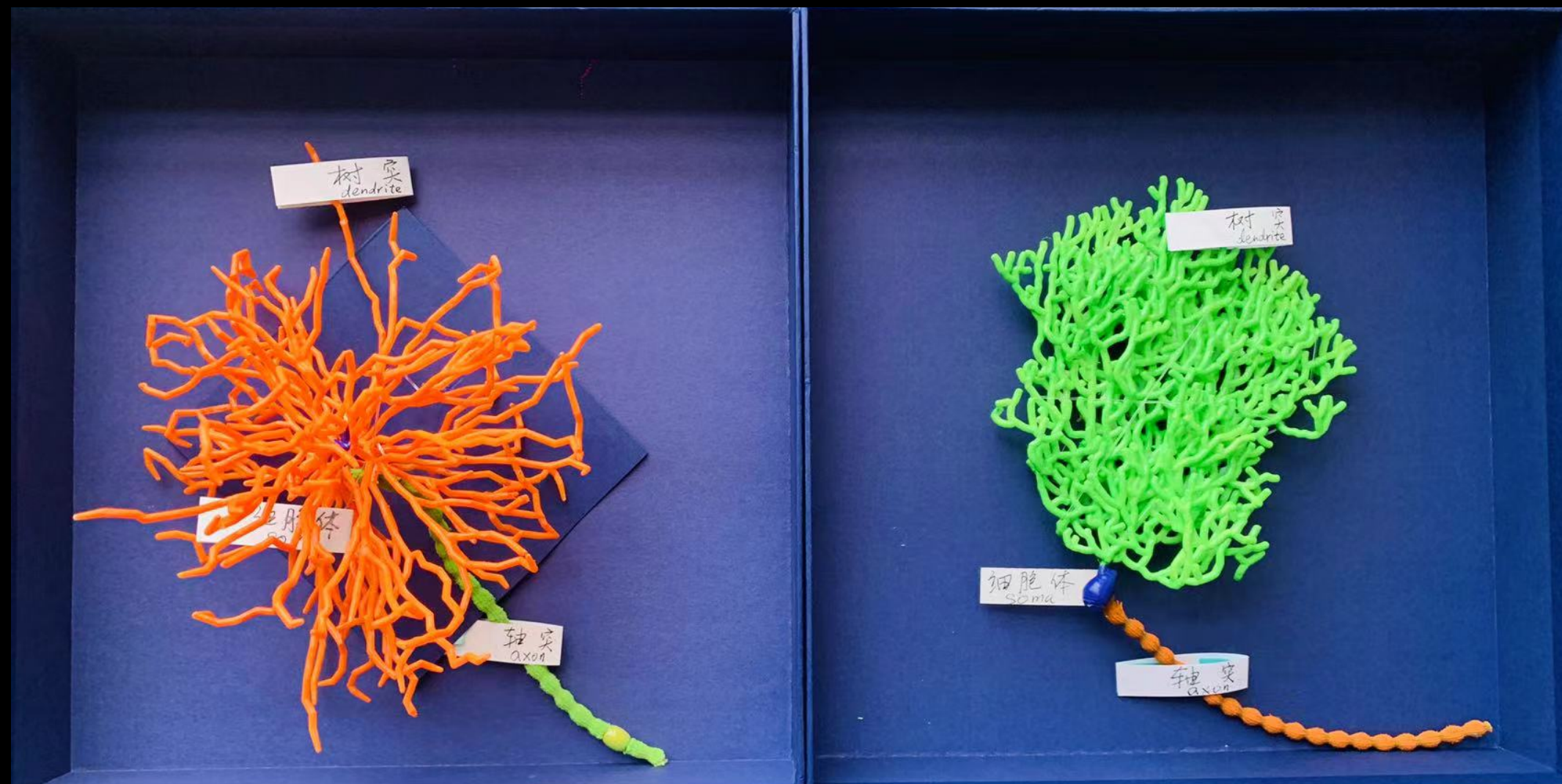
*Eve Marder*

# STG has identified neurons with stereotypical activity patterns



# Similar neural activities with widely different model-network properties





**Why do we need axons and dendrites?**

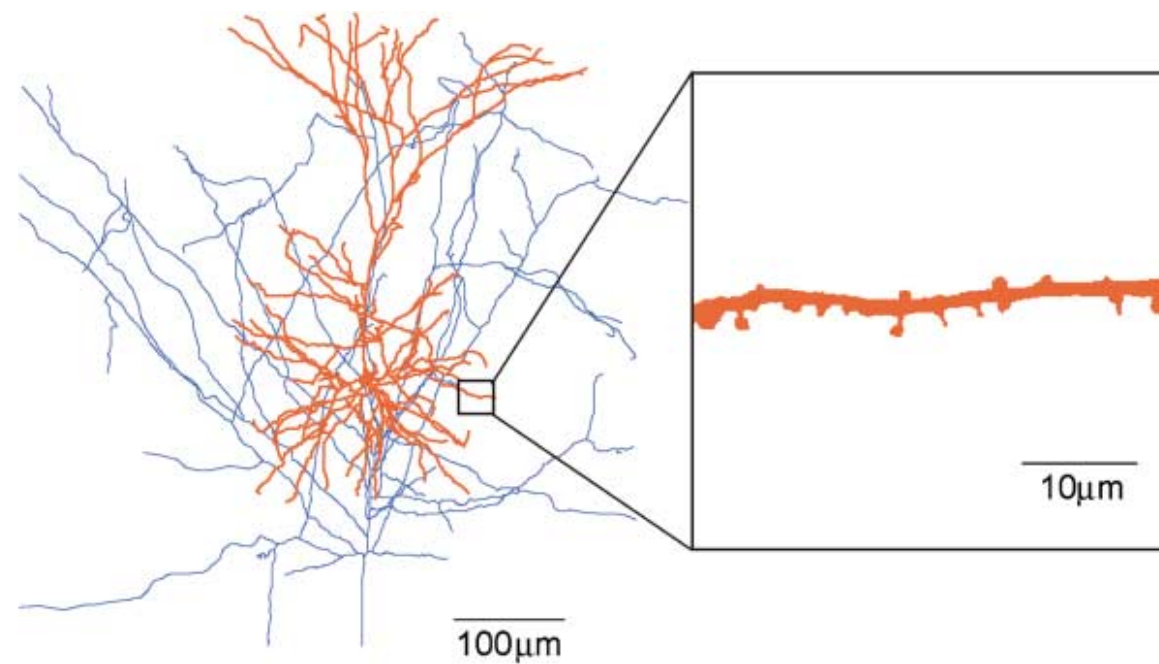


# **Wiring Optimization of Neural Circuit**

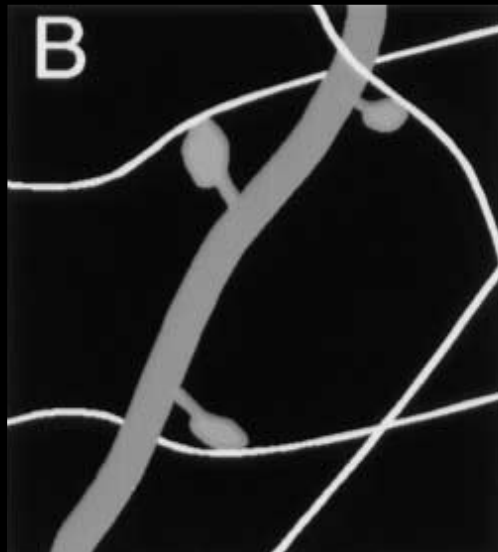
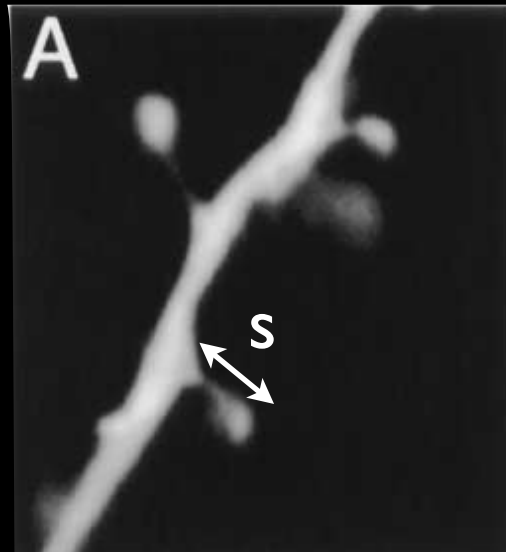
**“After the many shapes assumed by neurons, we are now in a position to ask whether this diversity ... has been left to chance and is insignificant, or whether it is tightly regulated and provides an advantage to the organism. ... we realized that all of the various conformations of the neuron and its various components are simply morphological adaptations governed by laws of conservation for time, space, and material.”**

**Ramon y Cajal**

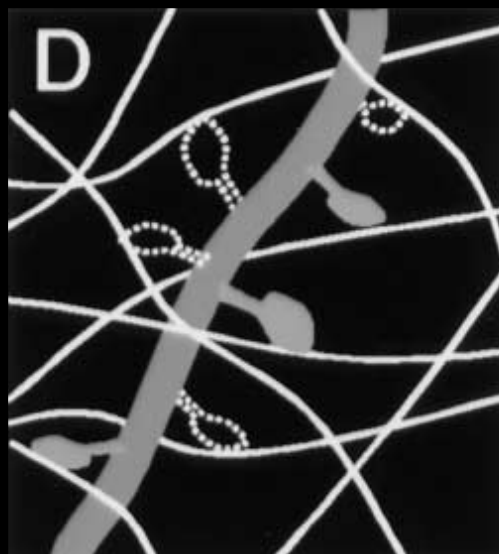
A toy problem: why do we need axons, dendrites and spines?



# Structural Plasticity of Synaptic Connectivity



$$f = \frac{2}{\pi s L_d b n}$$



$s$ : spine length

$L_d$ : total dendritic length per neuron

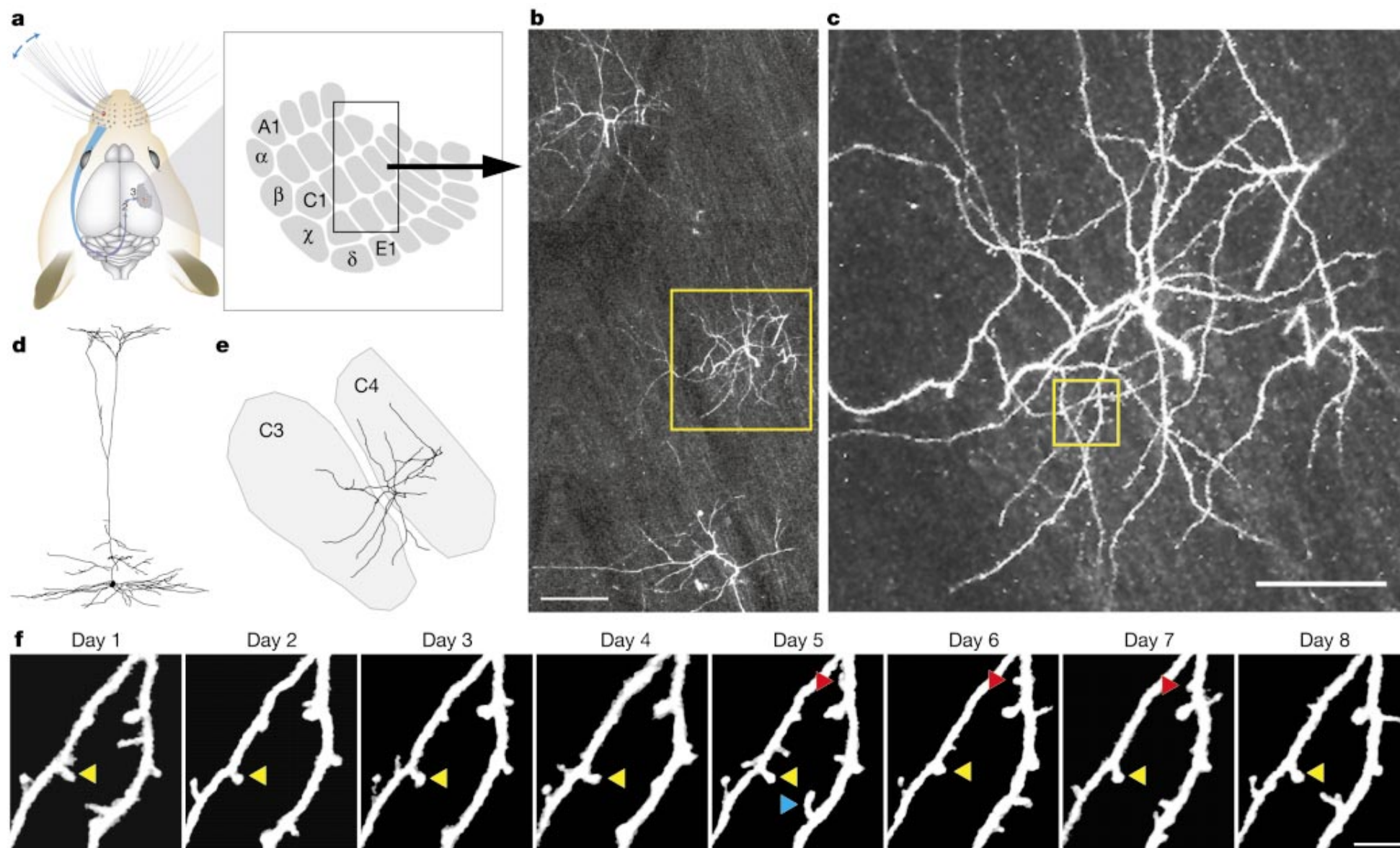
$b$ : inter-bouton distance

$n$ : neuronal density

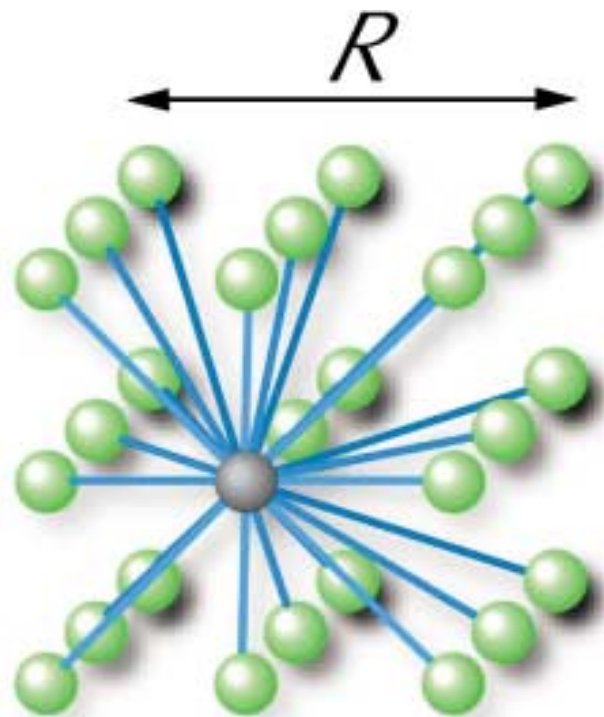
filling fraction =  $3/7$

Stepanyants et. al., *Neuron* 2001

# Structural Plasticity of Synaptic Connectivity

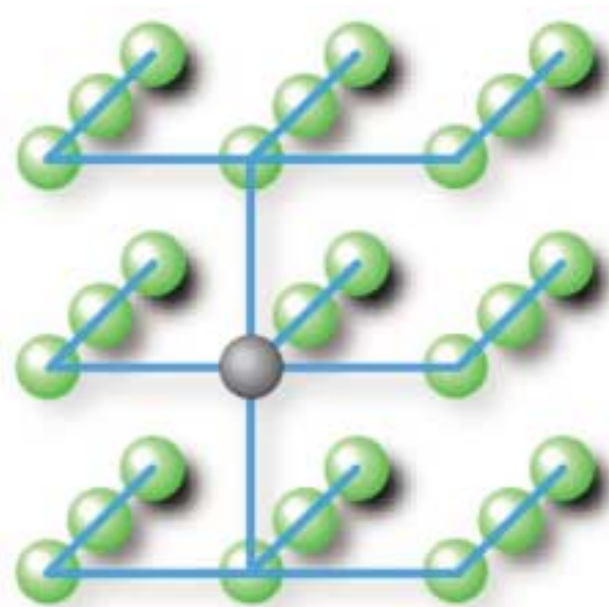


A toy problem: why do we need axons and dendrites?



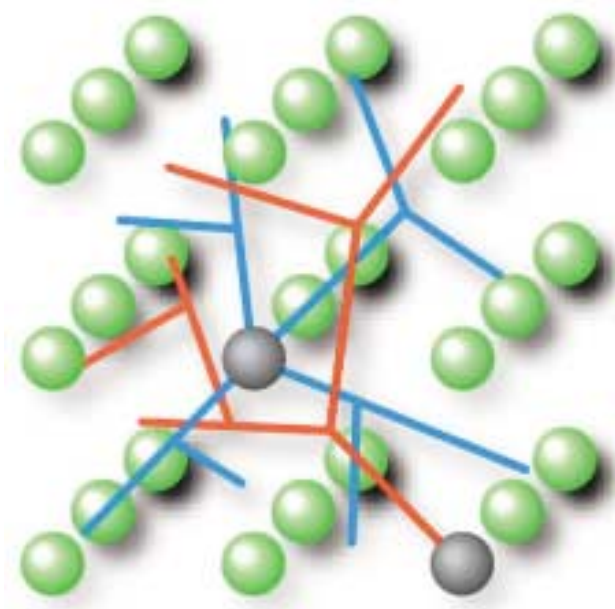
Design I

A toy problem: why do we need axons and dendrites?



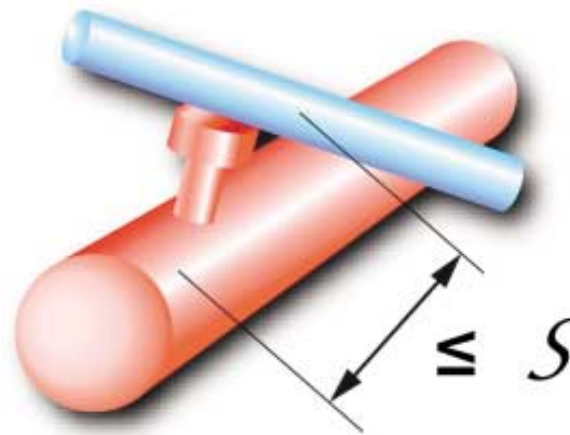
Design II

A toy problem: why do we need axons and dendrites?



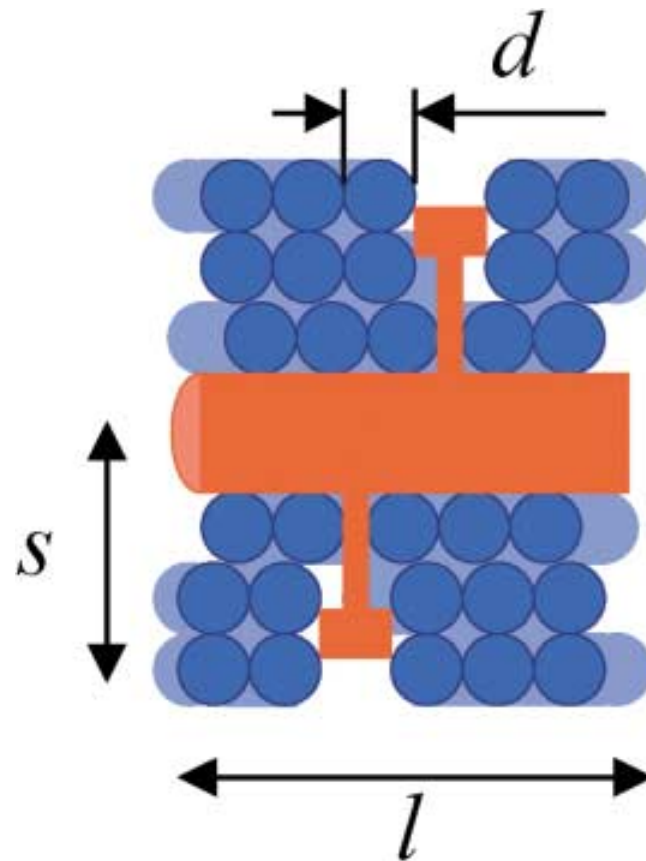
Design III

A toy problem: why do we need axons and dendrites?

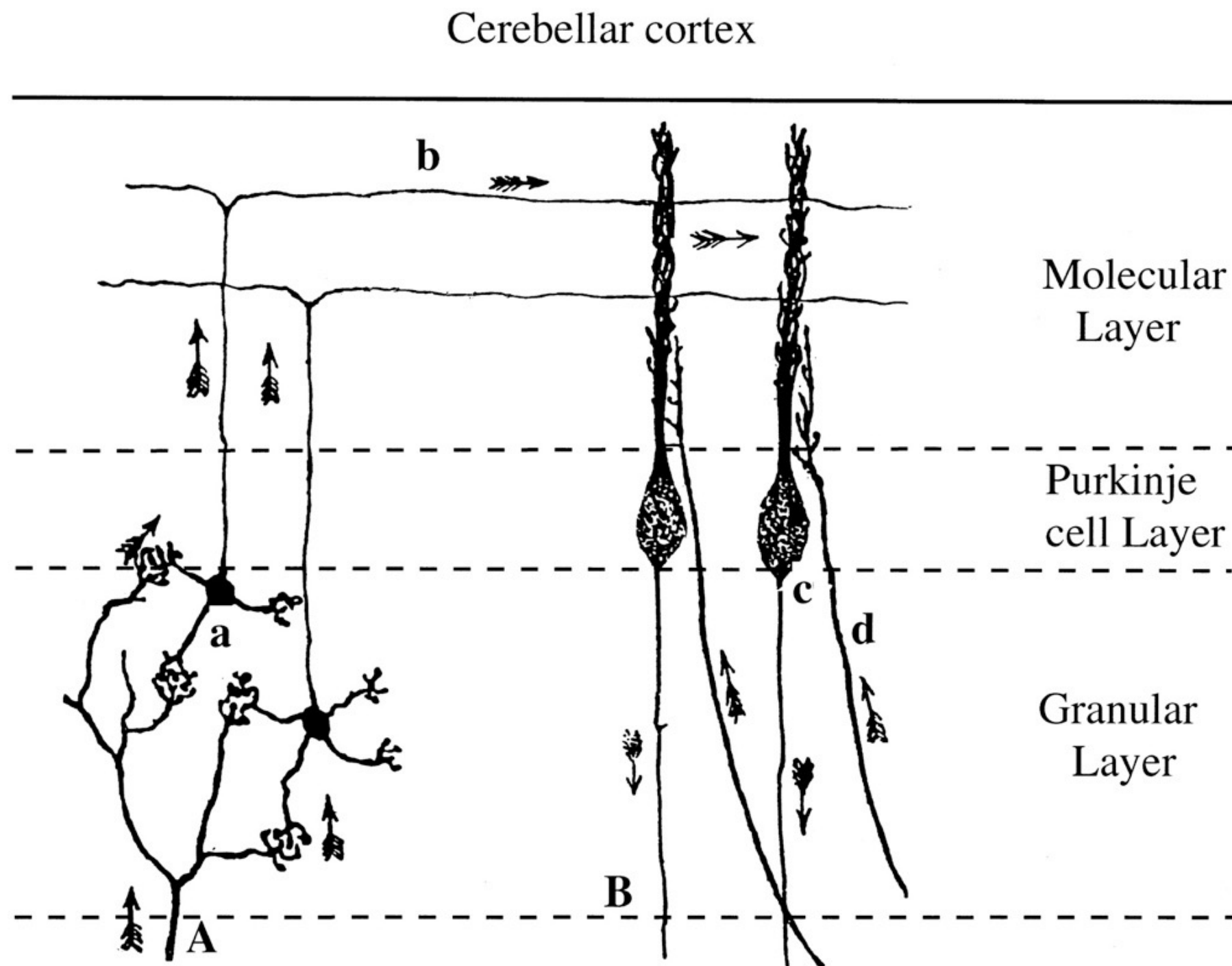


Design IV

Why do we need axons and dendrites?

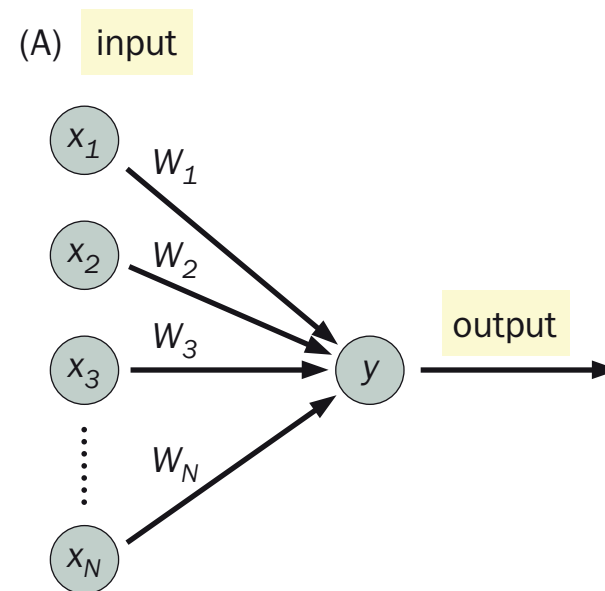


The Optimality of the design



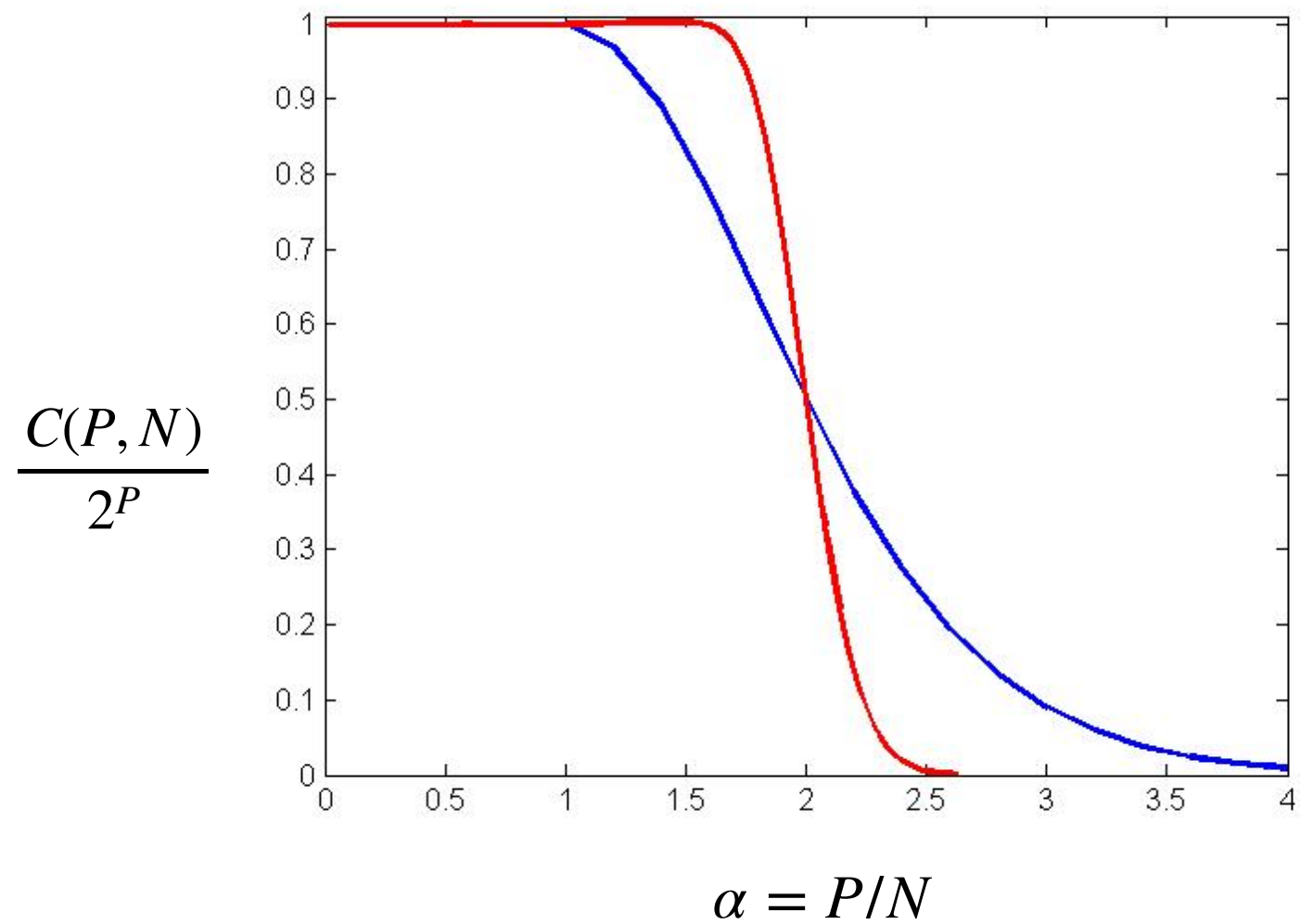
Cajal's drawing of the cerebellar cortex

# Mcculloch-Pitts neuron and the Perceptron model



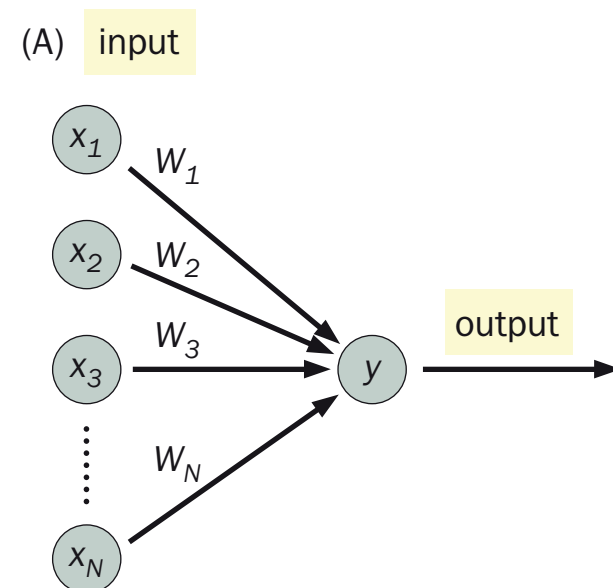
$$y = \text{sign} \left( \sum_{i=1}^N W_i x_i - \theta \right)$$

# Critical Capacity



$$C(P, N) = 2 \sum_{k=0}^{N-1} \binom{P-1}{k}$$

# The Perceptron learning algorithm

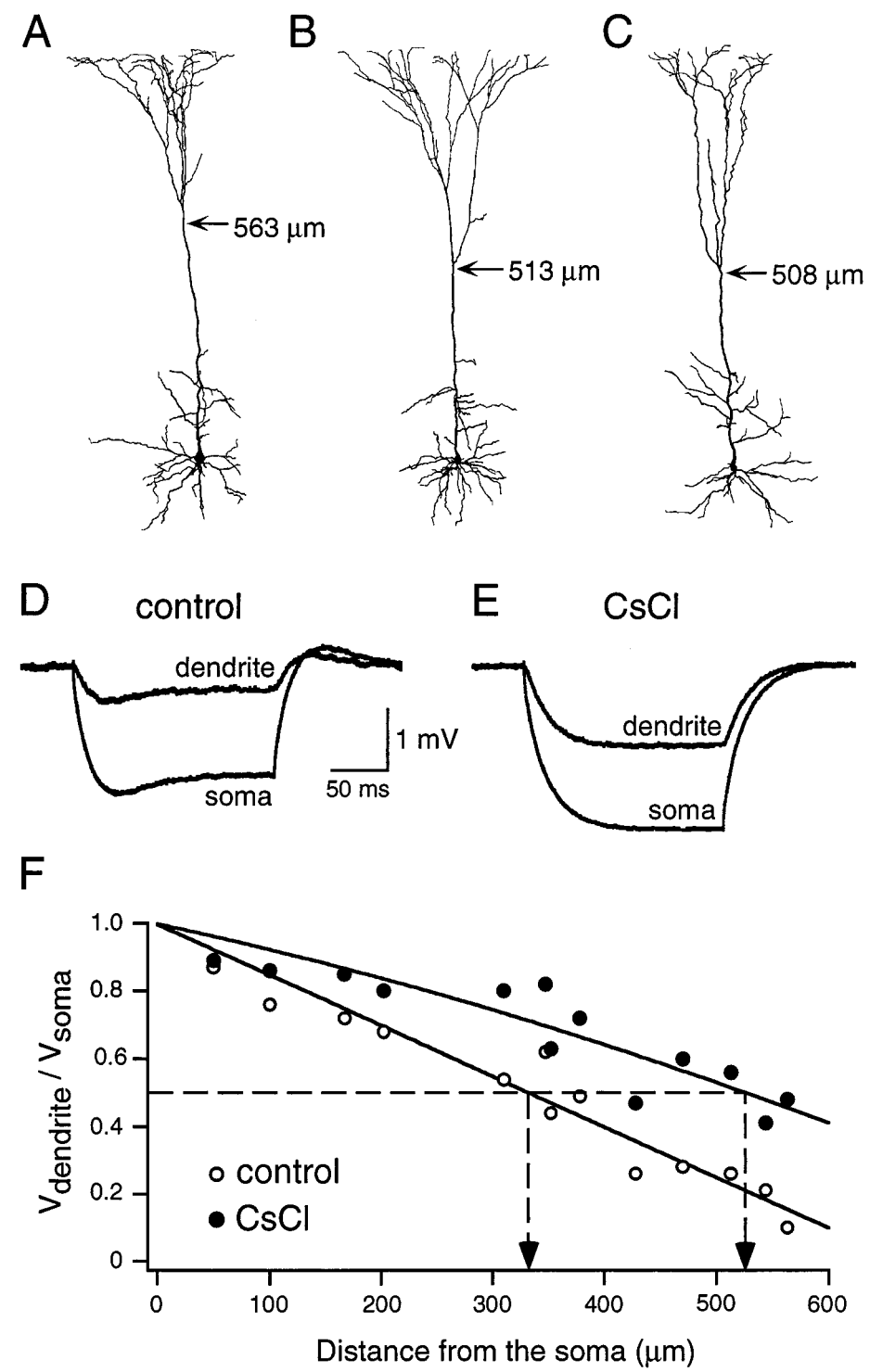


$$y = \text{sign} \left( \sum_{i=1}^N w_i x_i - \theta \right)$$

$$\mathbf{W} \leftarrow \mathbf{W} + \eta(y_0^n - y)\mathbf{X}^n$$

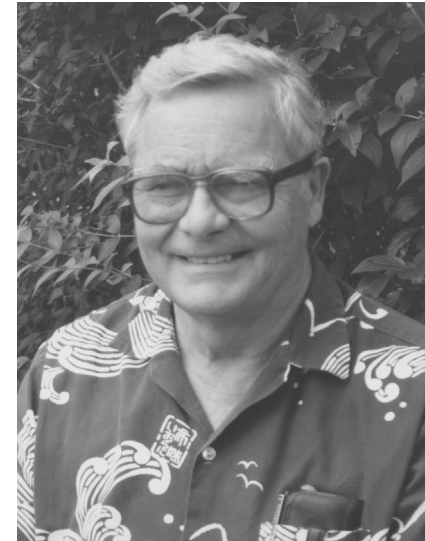
# **The roles of dendrites beyond connectivity**

**One of the hidden features that you cannot see in the wiring diagram**



Stuart & Spruston J Neuroscience 1998

# Wilfred Rall and the cable equation



Wilfrid Rall

## FUNDAMENTAL EQUATIONS

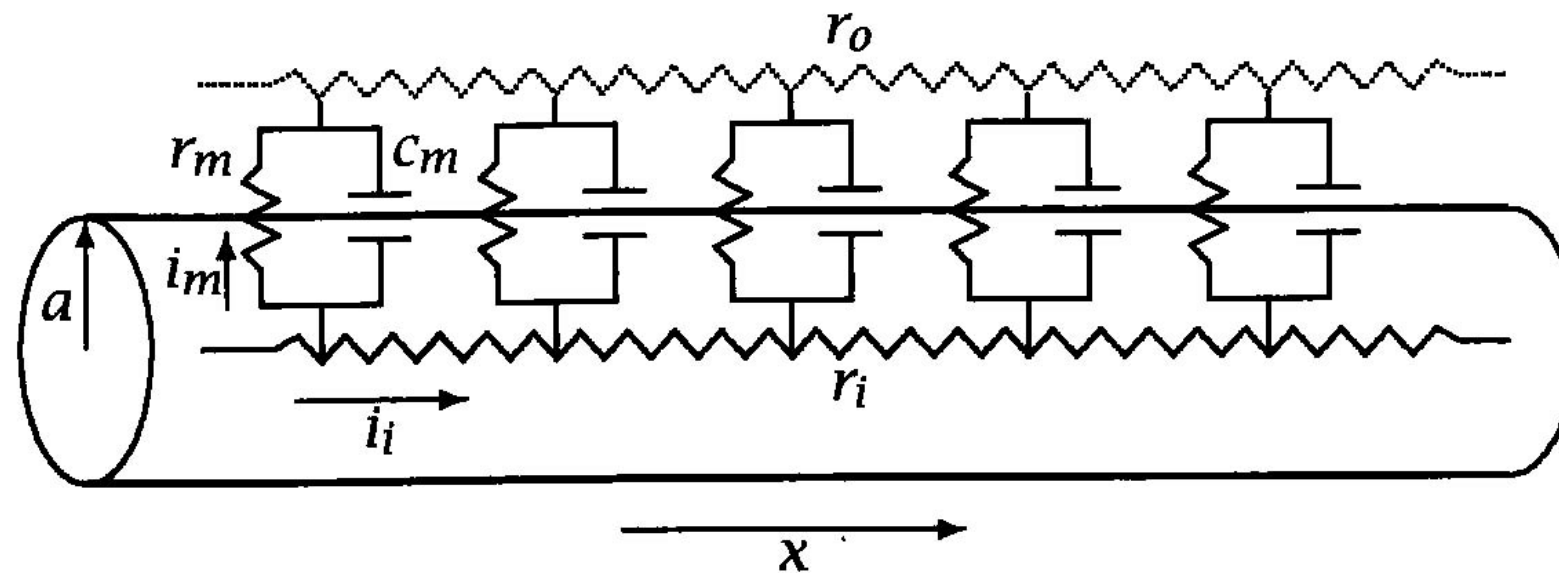
The derivation of the differential equation for distributions of passive electrotonic potential in uniform cylinders is well established in the theory developed for axons (5, 9, 20). In regions containing no sources or sinks of externally applied current, this differential equation can be expressed

$$\lambda^2 \frac{\partial^2 V}{\partial x^2} = V + \tau \frac{\partial V}{\partial t}, \quad [1]$$

where  $V = V_m - E$  is the electrotonic potential,  $x$  represents distance along the axis of the cylinder,  $\tau = R_m C_m$  is the membrane time constant, and  $\lambda = [(d/4)(R_m/R_i)]^{1/2}$  is the characteristic length constant.<sup>3</sup>

Experimental Neurology 1959

The basic assumption of cable theory: dendrites are cylinders!



$r_i$  = axial resistance ( $\Omega/\text{cm}$ )

$r_m$  = membrane resistance ( $\Omega\text{-cm}$ )

$C_m$  = membrane capacitance ( $\text{F}/\text{cm}$ )

### Simplifying assumptions:

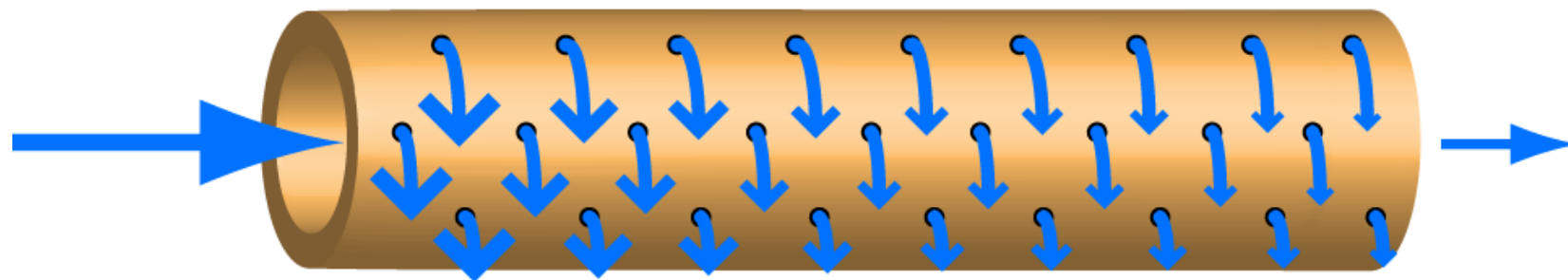
1. Extracellular resistance  $r_o=0$
2. Membrane properties are uniform throughout, for all parts of the cylinder and are independent of membrane potential – no voltage gated channels.
3. Current flow is along a single dimension,  $x$ . So, there's no radial current

# Cable equation: a garden hose analogy

Non-leaky hose



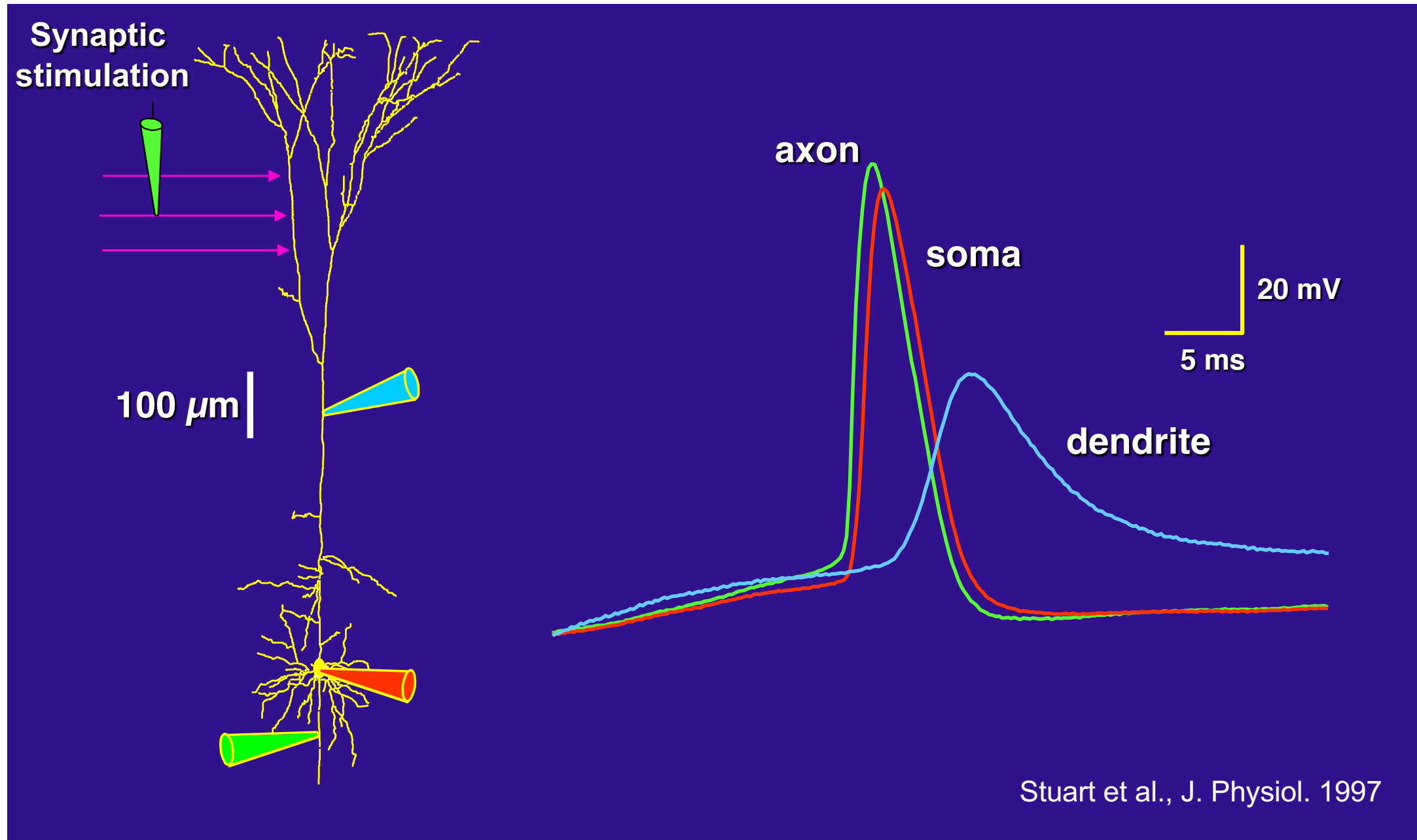
Leaky hose



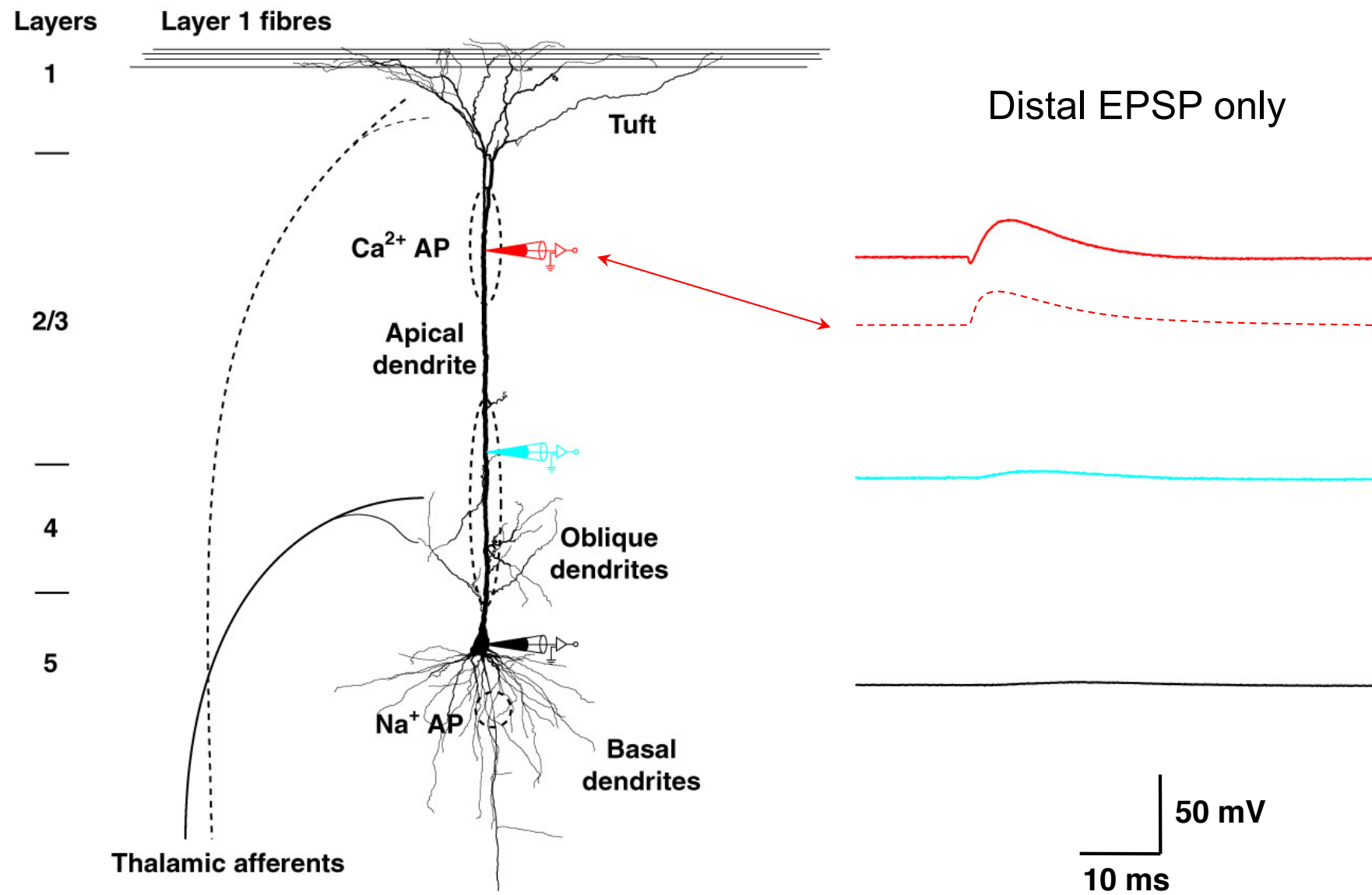
Propagation through neuronal dendrites is similar to water flow through a leaky hose!

**A derivation**

# Action potential generation and back propagation in dendrites

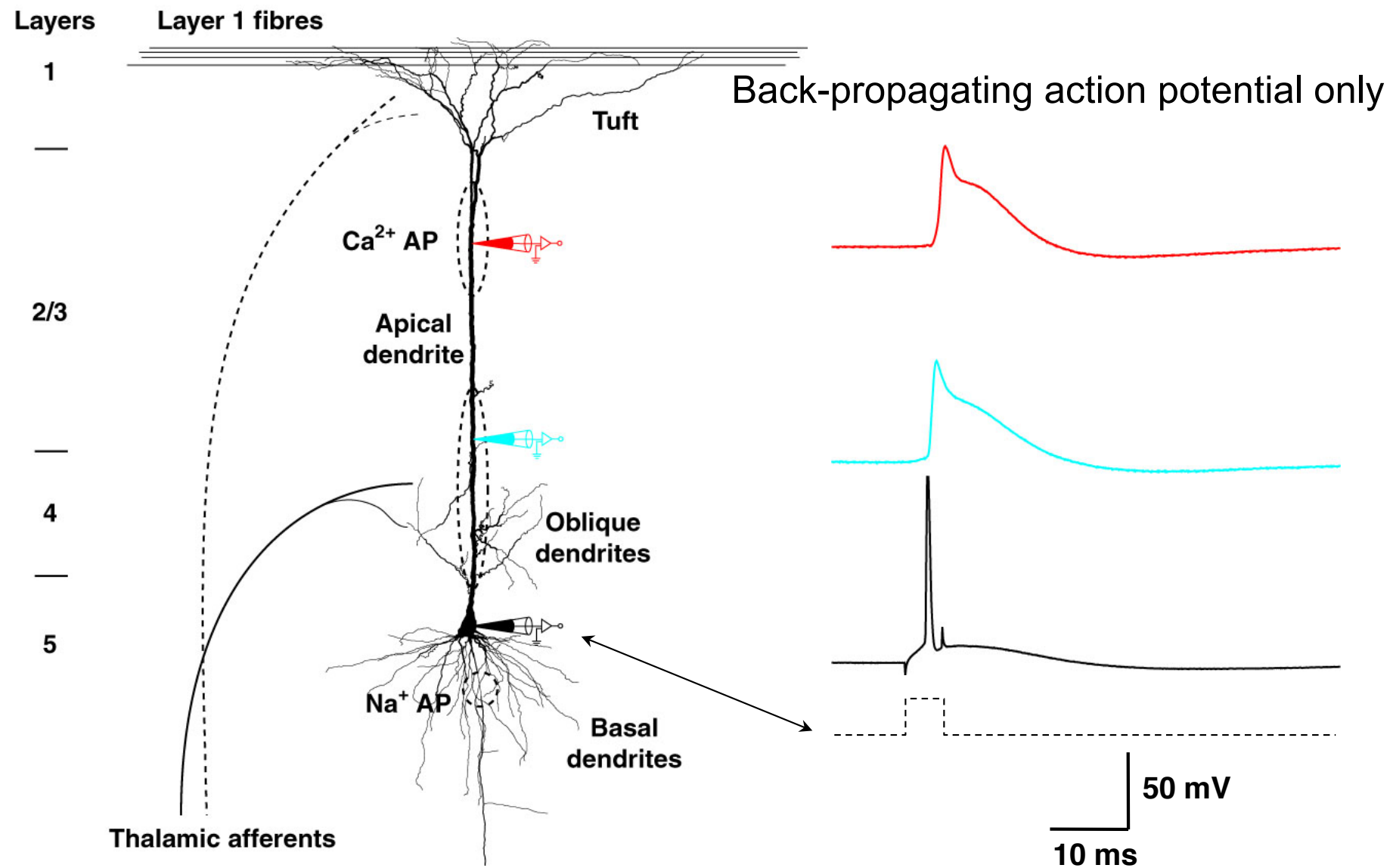


# Interaction between back-propagation of action potentials and $\text{Ca}^{2+}$ spike



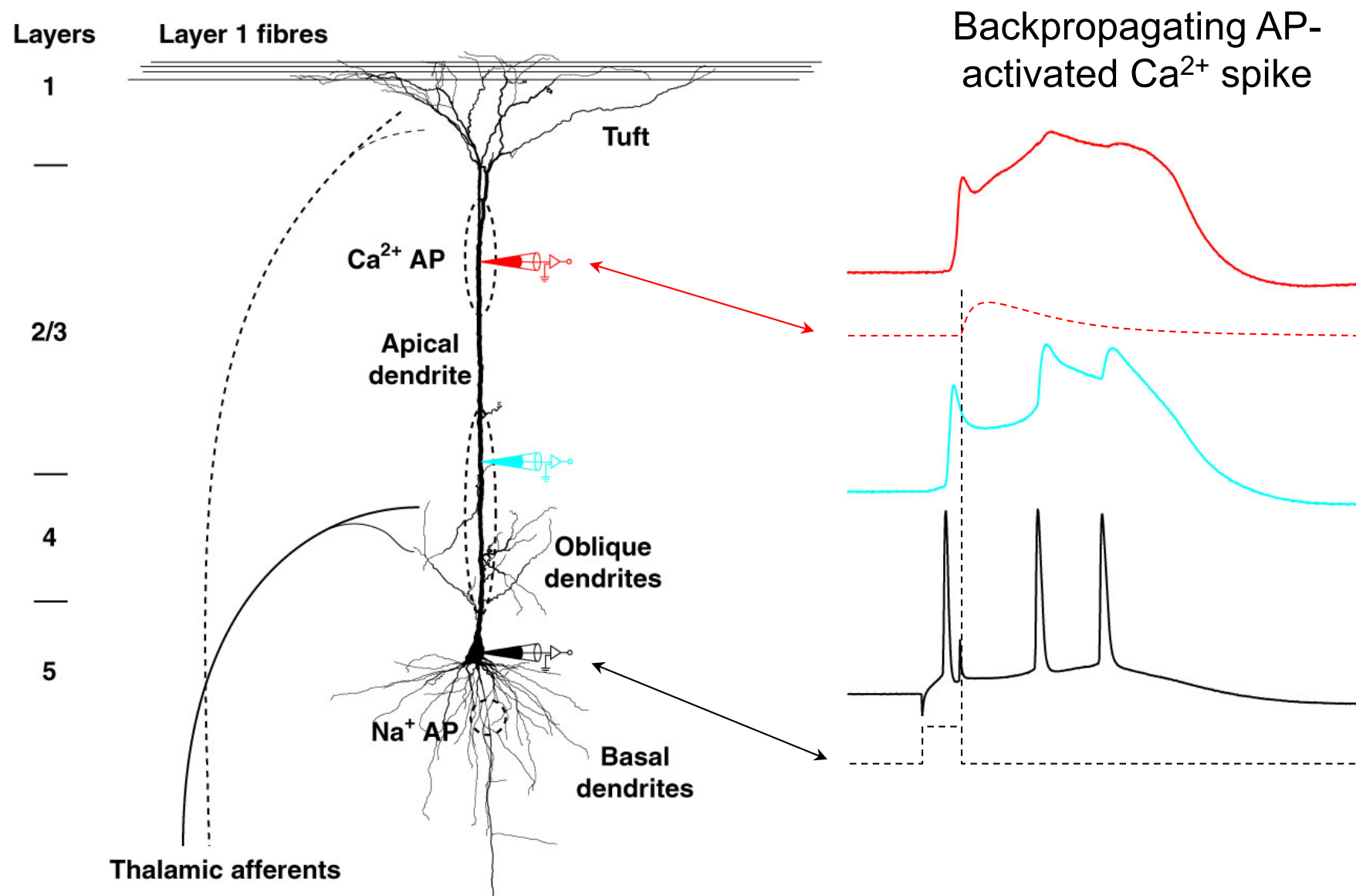
Larkum, Zhu & Sakmann - Nature, 1999

# Interaction between back-propagation of action potentials and $\text{Ca}^{2+}$ spike



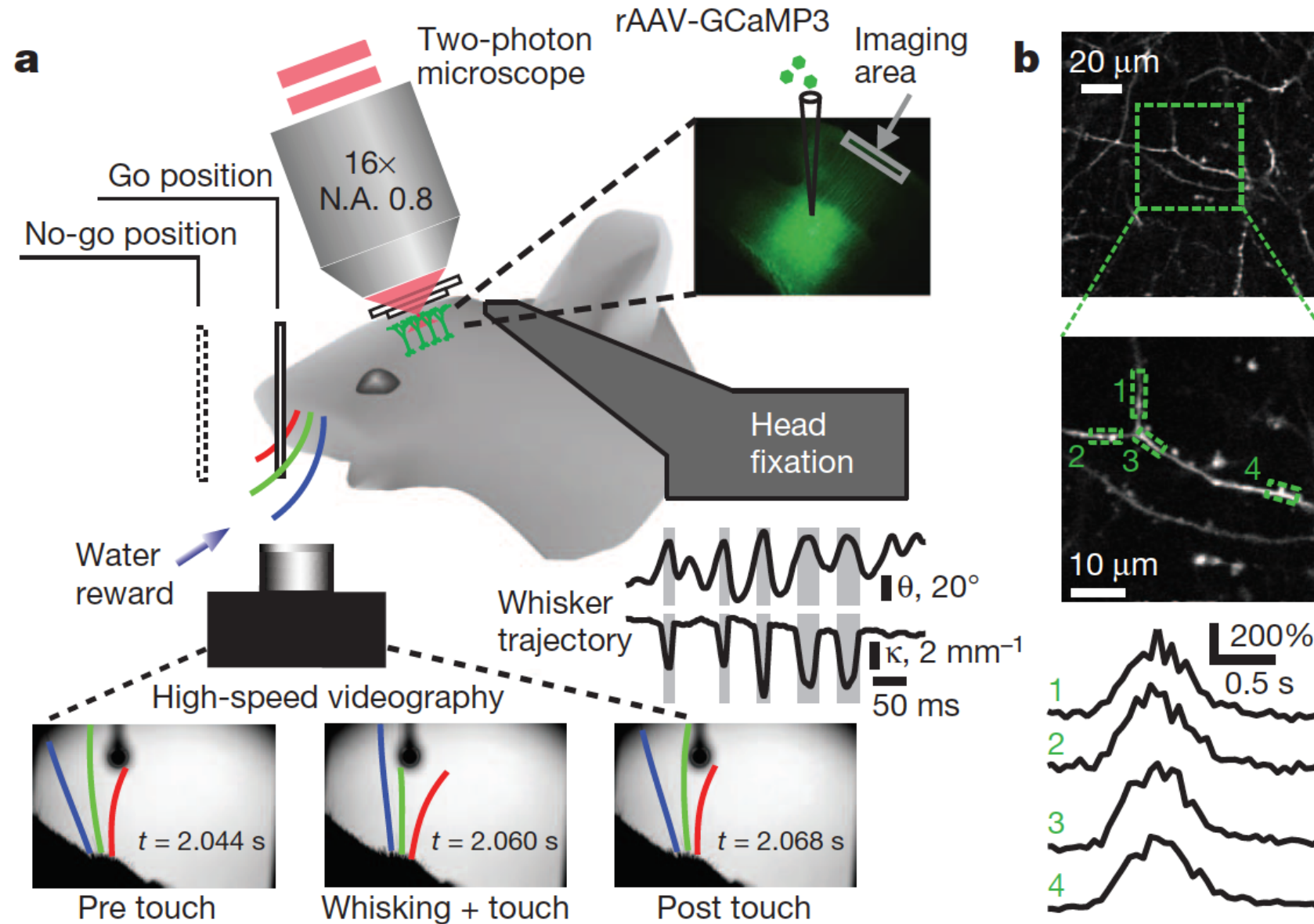
Larkum, Zhu & Sakmann - Nature, 1999

# Interaction between back-propagation of action potentials and $\text{Ca}^{2+}$ spike



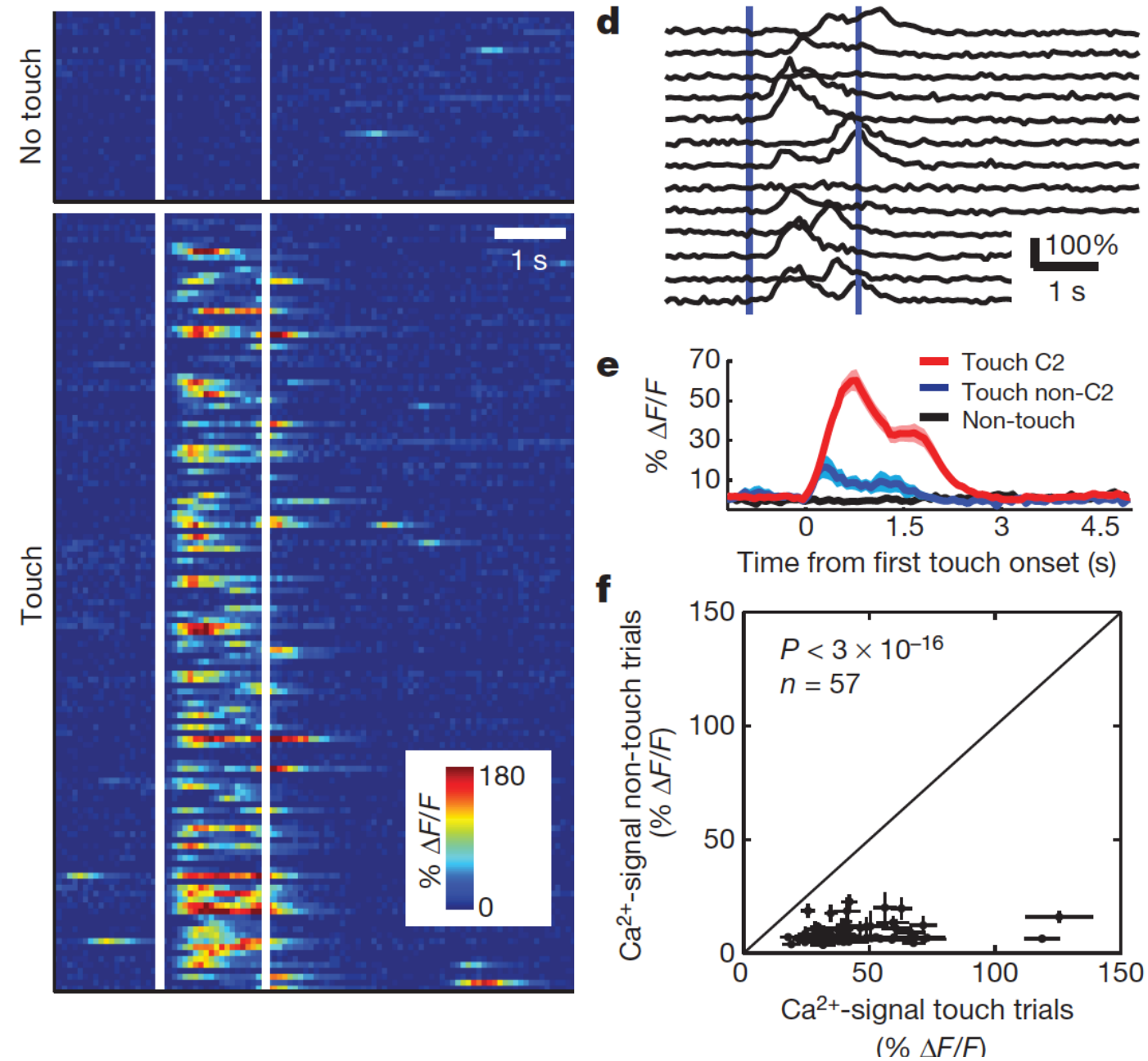
Larkum, Zhu & Sakmann - Nature, 1999

# Specific dendritic $\text{Ca}^{2+}$ signal during active sensing

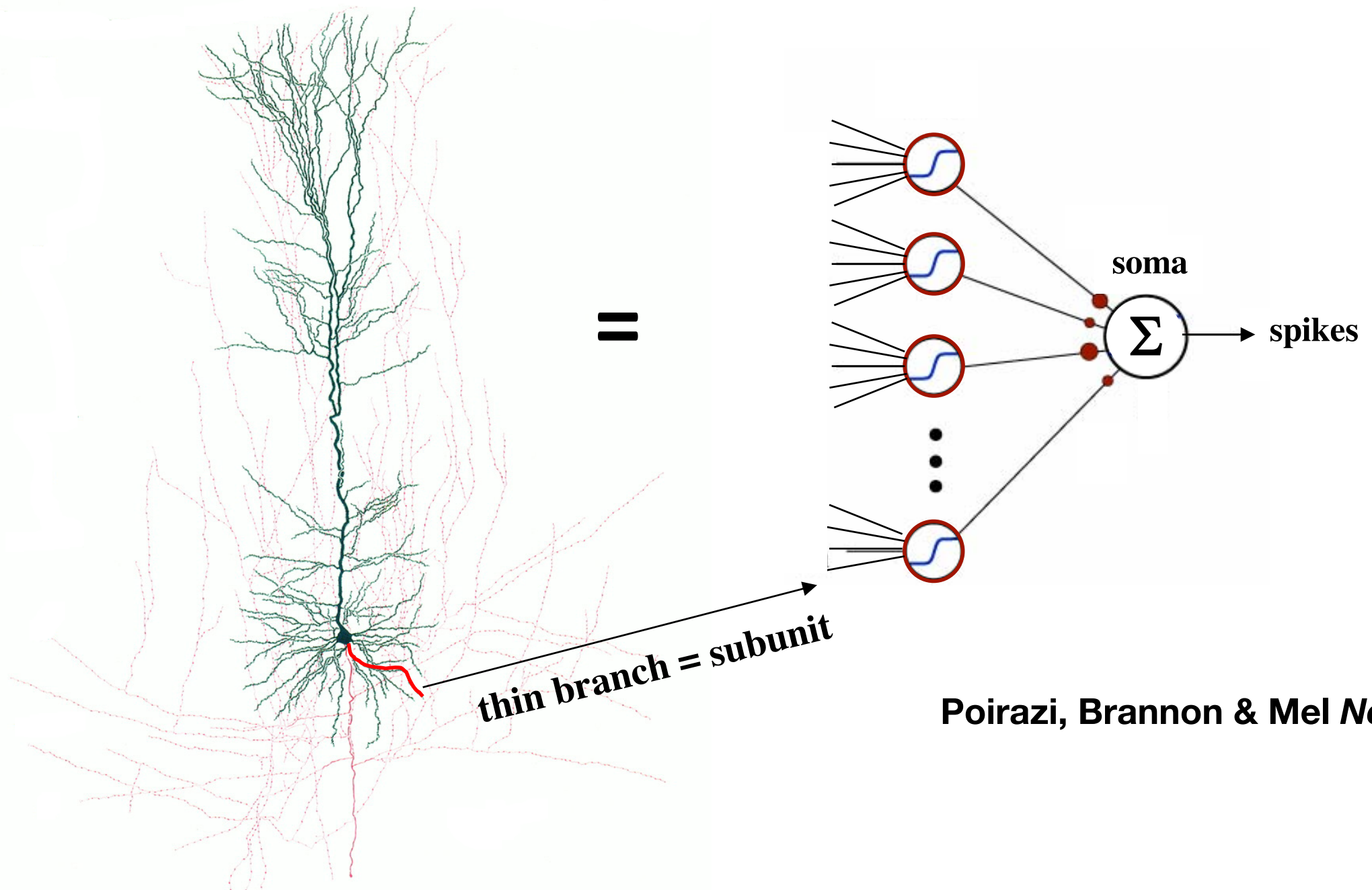


Xu et al *Nature* 2012

# Specific dendritic $\text{Ca}^{2+}$ signal during active sensing



# Dendritic compartment and nonlinear integration



Poirazi, Brannon & Mel *Neuron* 2003

# Single Cortical Neurons as Deep Artificial Neural Networks

<sup>1</sup>David Beniaguev, <sup>1,2</sup>Idan Segev and <sup>1,2</sup>Michael London

<sup>1</sup>The Edmond and Lily Safra Center for Brain Sciences and <sup>2</sup>Department of Neurobiology, The Hebrew University of Jerusalem, Jerusalem, Israel.

Communication: David Beniaguev - david.beniaguev@gmail.com

## Can Single Neurons Solve MNIST? The Computational Power of Biological Dendritic Trees

Ilenna Simone Jones<sup>1</sup> and Konrad Kording<sup>2</sup>

<sup>1</sup>Department of Neuroscience, University of Pennsylvania

<sup>2</sup>Departments of Neuroscience and Bioengineering, University of Pennsylvania

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