

# Introduction to Computational Neuroscience

## Lecture 6: Single neuron models

Lesson	Title
1	Introduction
2	Structure and Function of the NS
3	Windows to the Brain
4	Data analysis
5	Data analysis II
6	Single neuron models
7	Network models
8	Artificial neural networks
9	Learning and memory
10	Perception
11	Attention & decision making
12	Brain-Computer interface
13	Neuroscience and society
14	Future and outlook:AI
15	Projects presentations
16	Projects presentations

Basics

Analyses

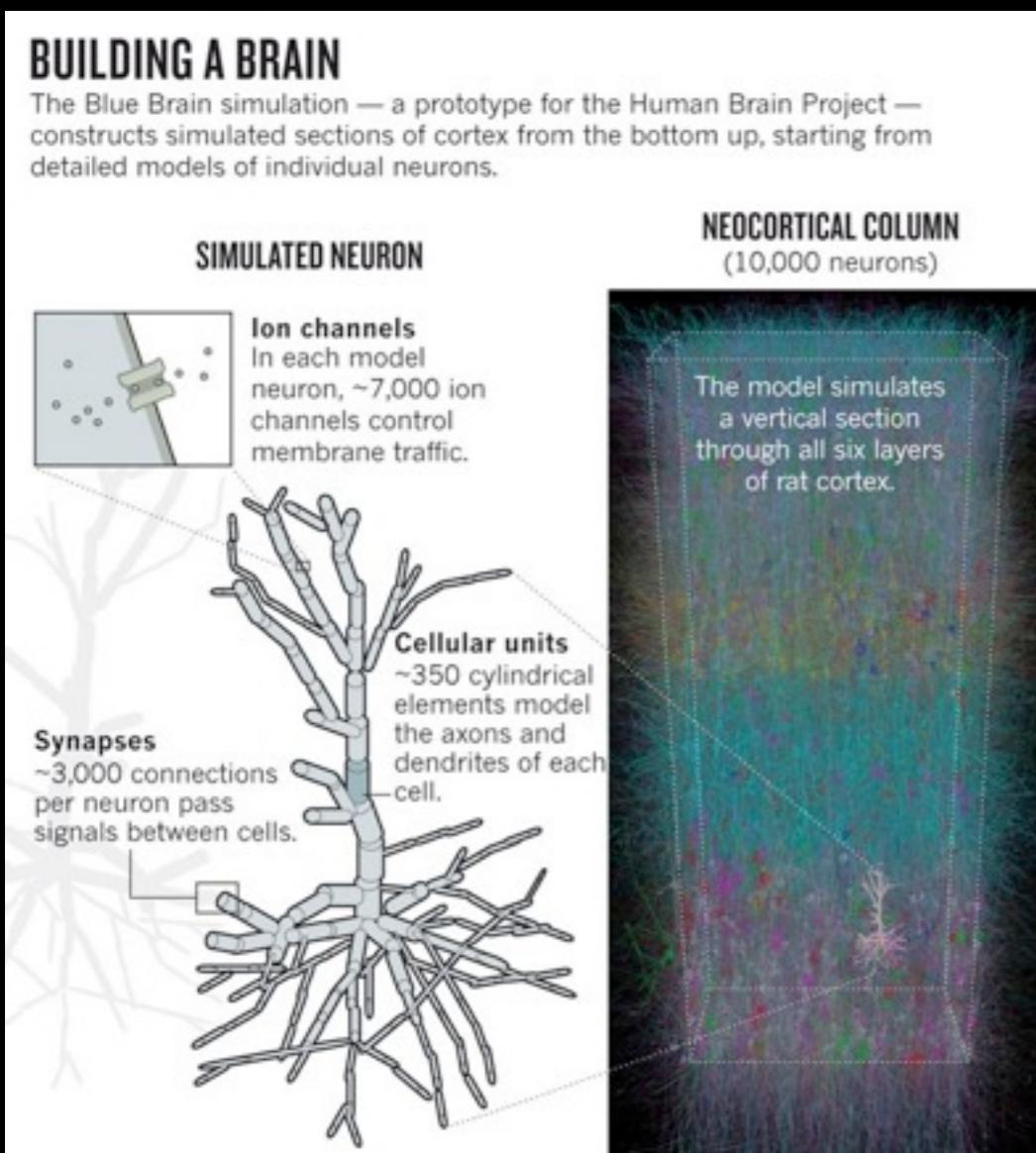
Models

Cognitive

Applications

# Neurons in silico

Artificial neural networks is a major strand in computational neuroscience, machine learning, and artificial intelligence



Let's start easy... how do we simulate the behavior of a single neuron in a computer?

“Make it as simple as possible but not simpler”  
**Einstein**

# Learning objectives

- Understand the different levels of single neuron modeling
- Simulate the most popular single compartment models

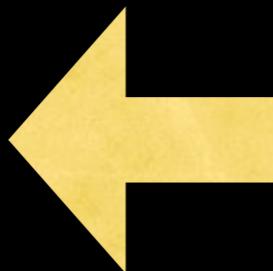
# Appropriate level of models?

Conferences of computational neuroscience...

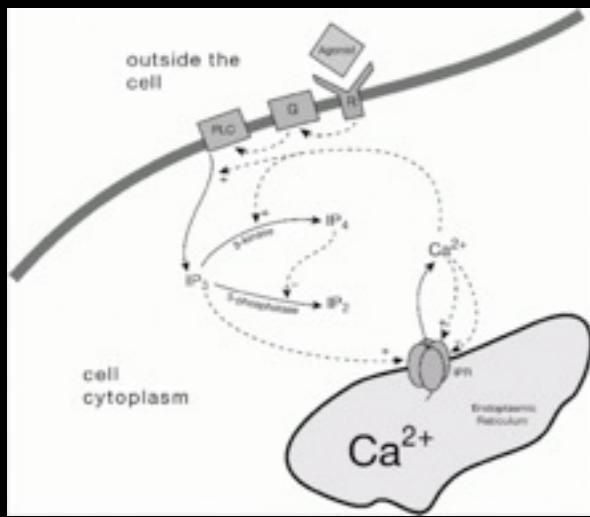
\* **Biologists** (bottom-uppers) believe that a model that deviates from details of known physiology is inadmissibly inaccurate

\* **CS, physicists, and mathematicians** (top-downers) feel that models that fail to simplify do not allow any useful generalization to be made

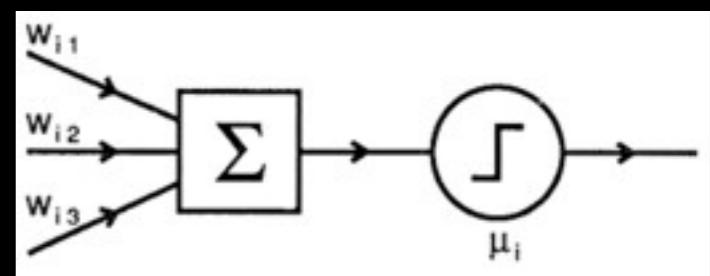
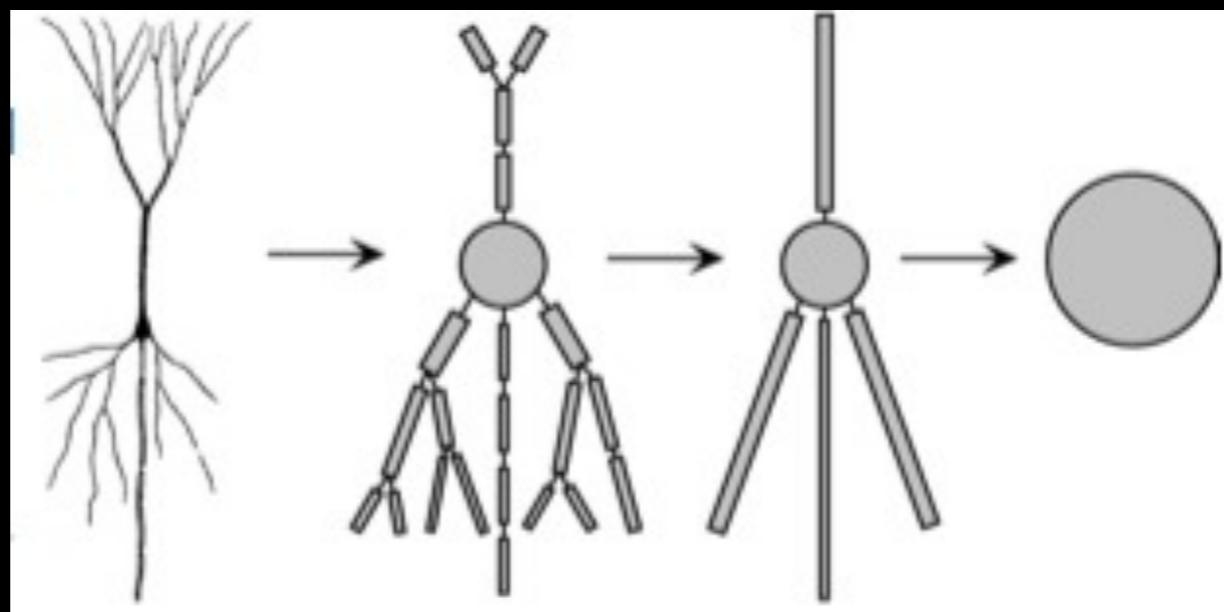
# Appropriate level of models



**Biological detail**



Biological  
processes  
(molecular)



Computational properties (processing)

Electrical properties (average)

# Classification of neuron models

**Point neuron models**

**Spiking neurons**

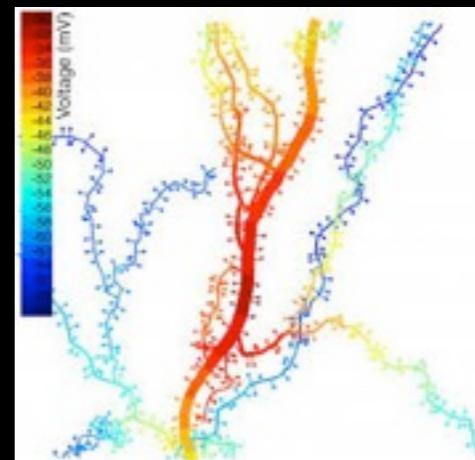
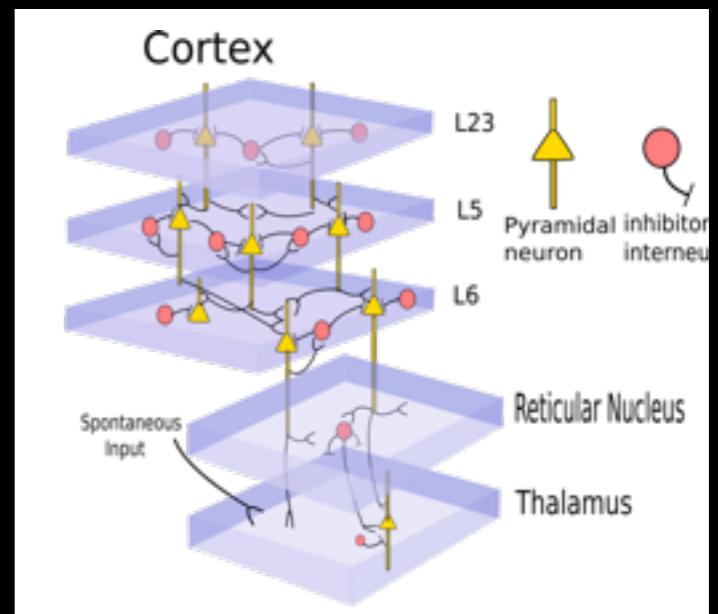
**McCulloch-Pitts**

**Integrate-and-Fire**

**Hodgkin-Huxley**

**Rate neurons**

**Multi-compartment models**



# McCulloch-Pitts

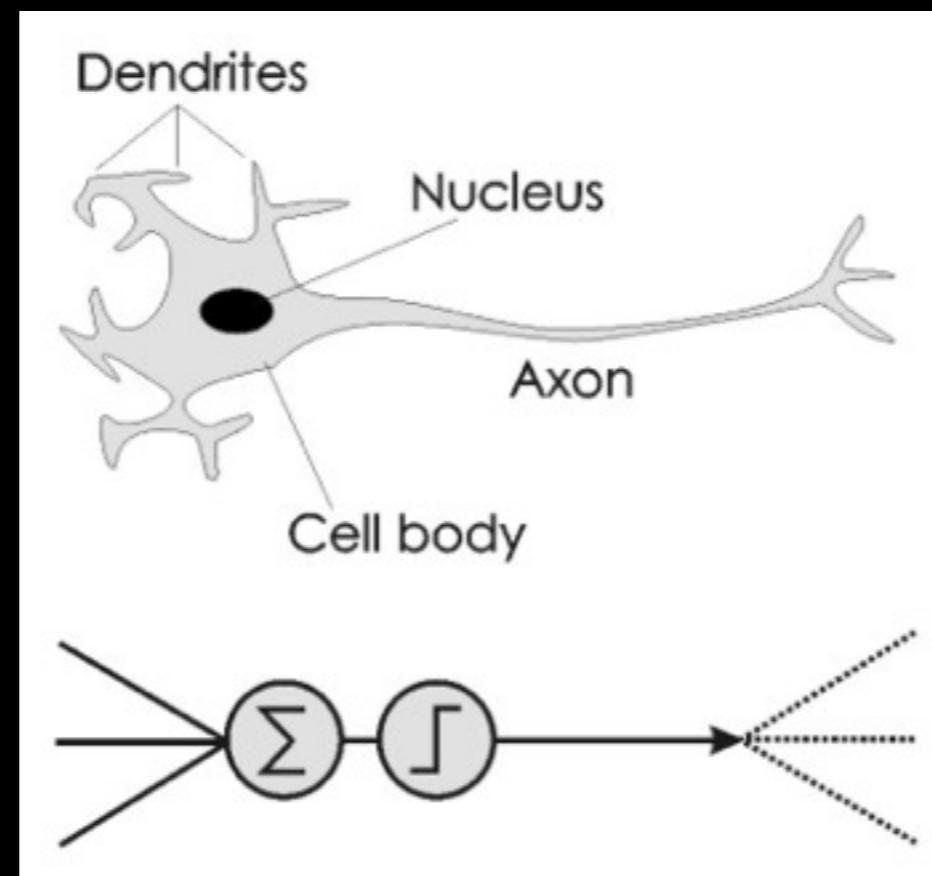
## Integrate-and-Fire

## Hodgkin-Huxley

# McCulloch-Pitts (idea)

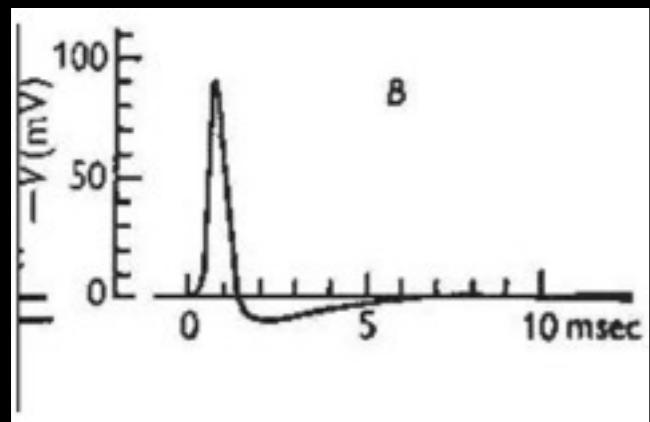
**McCulloch and Pitts (1943):** pioneers to formally define neurons as computational elements

**The idea:** explore simplified neural models to get the essence of neural processing by ignoring irrelevant detail and focusing in what is needed to do a computational task



# McCulloch-Pitts (idea)

McCulloch and Pitts knew that spikes (action potential) somehow carry information through the brain:



each spike would represent a binary 1

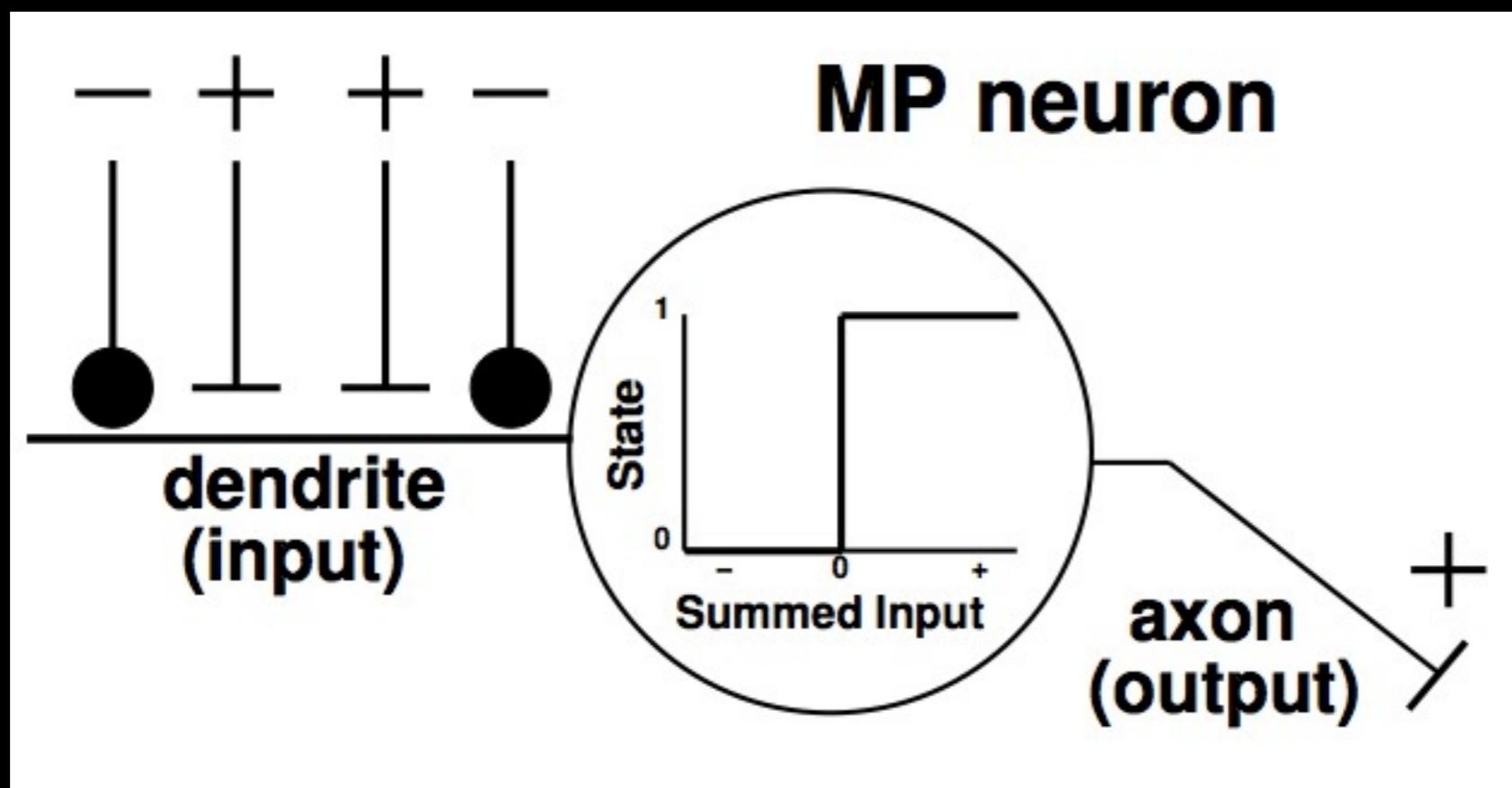
each lack of spike would represent a binary 0

They showed **how spikes could be combined to do logical and arithmetical operations**

From modern perspective there is a design problem for these circuit elements: brevity of a spike (1 ms) compared to the interval between spikes ( $>50$  ms) implies a duty cycle of < 2%

# McCulloch-Pitts (rule)

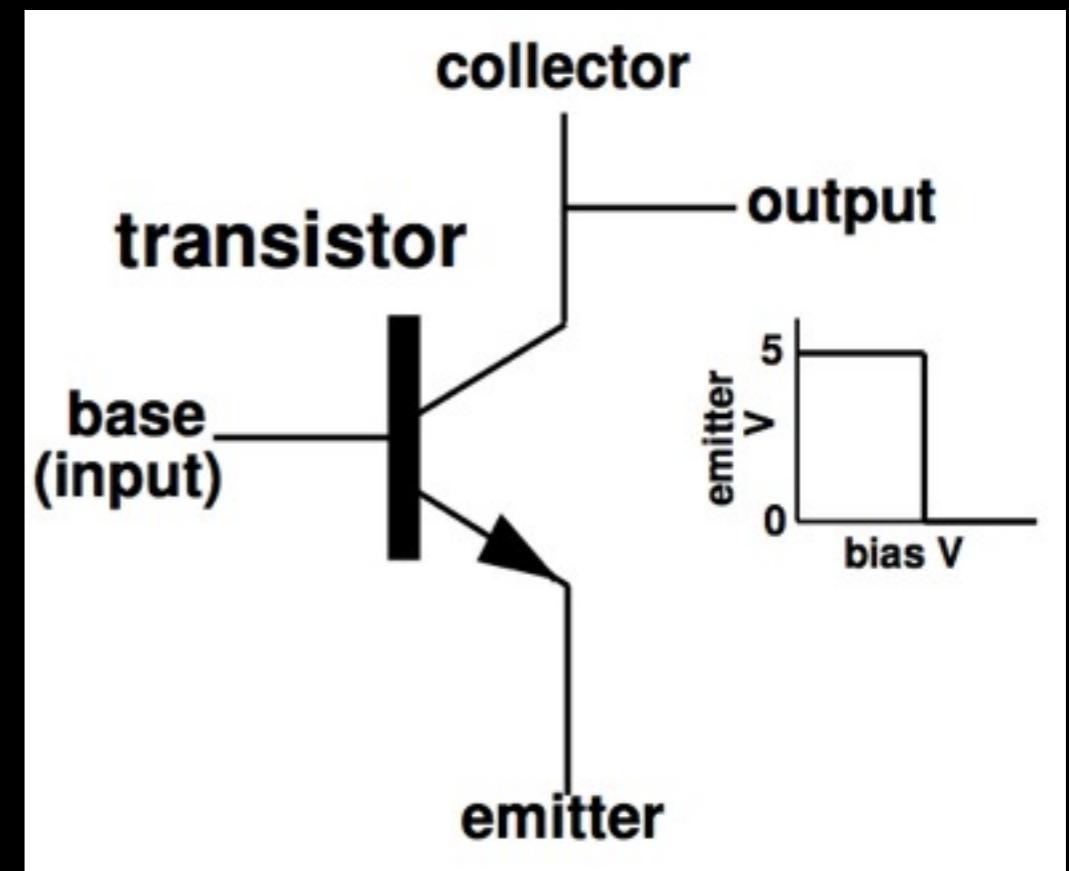
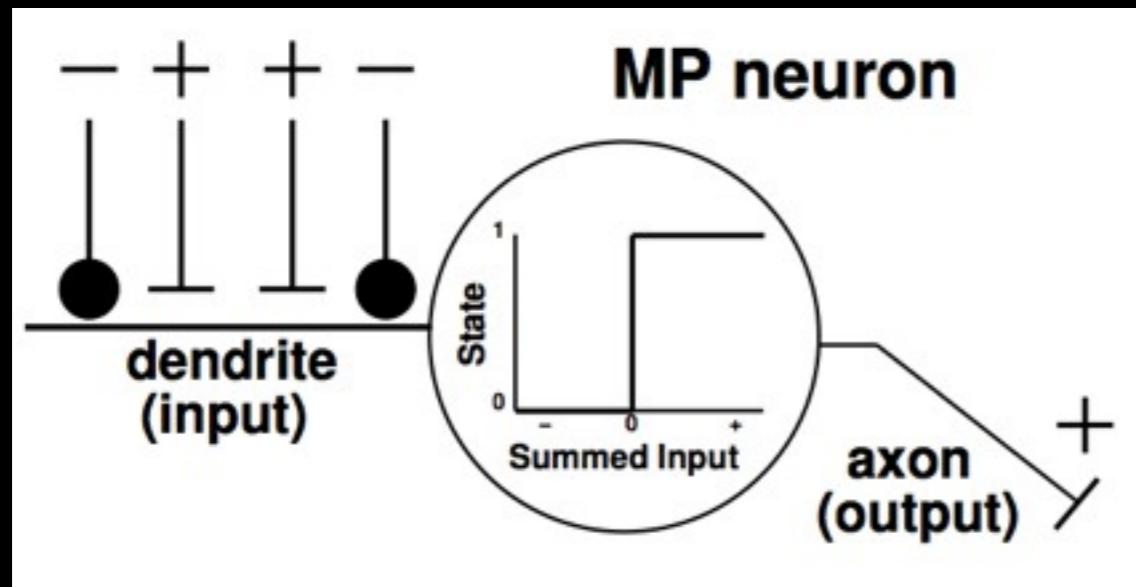
MP neurons are binary: they take as input and produce as output only 0's or 1's



**Rule:** activations from other neurons are summed at the neuron and outputs 1 if threshold is reached and 0 if not

# McCulloch-Pitts (analogy)

MP neurons function much like a transistor:



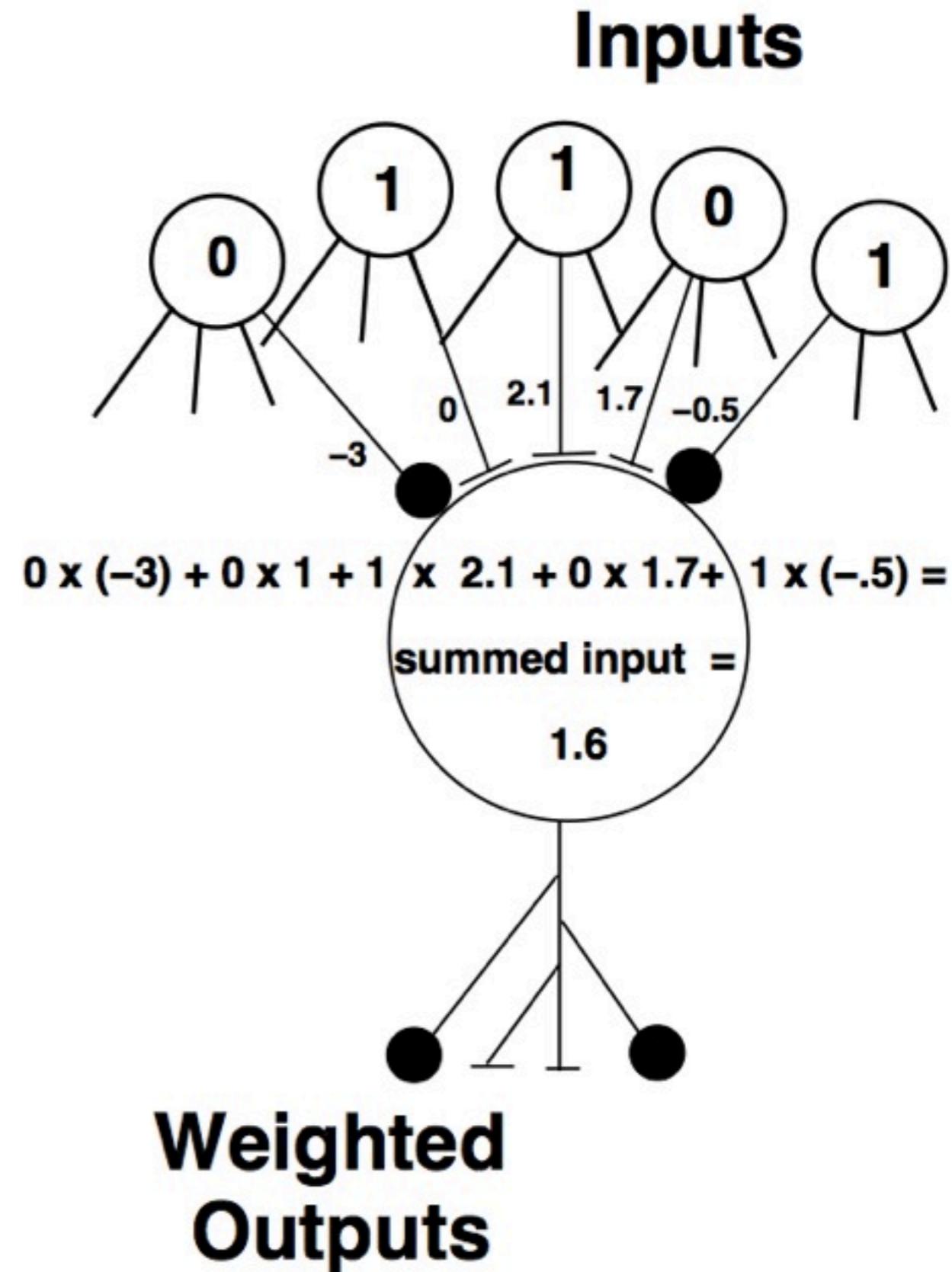
In artificial networks, inputs come from the outputs of other MP neurons (as transistors in a circuit)

# McCulloch-Pitts (nomenclature)

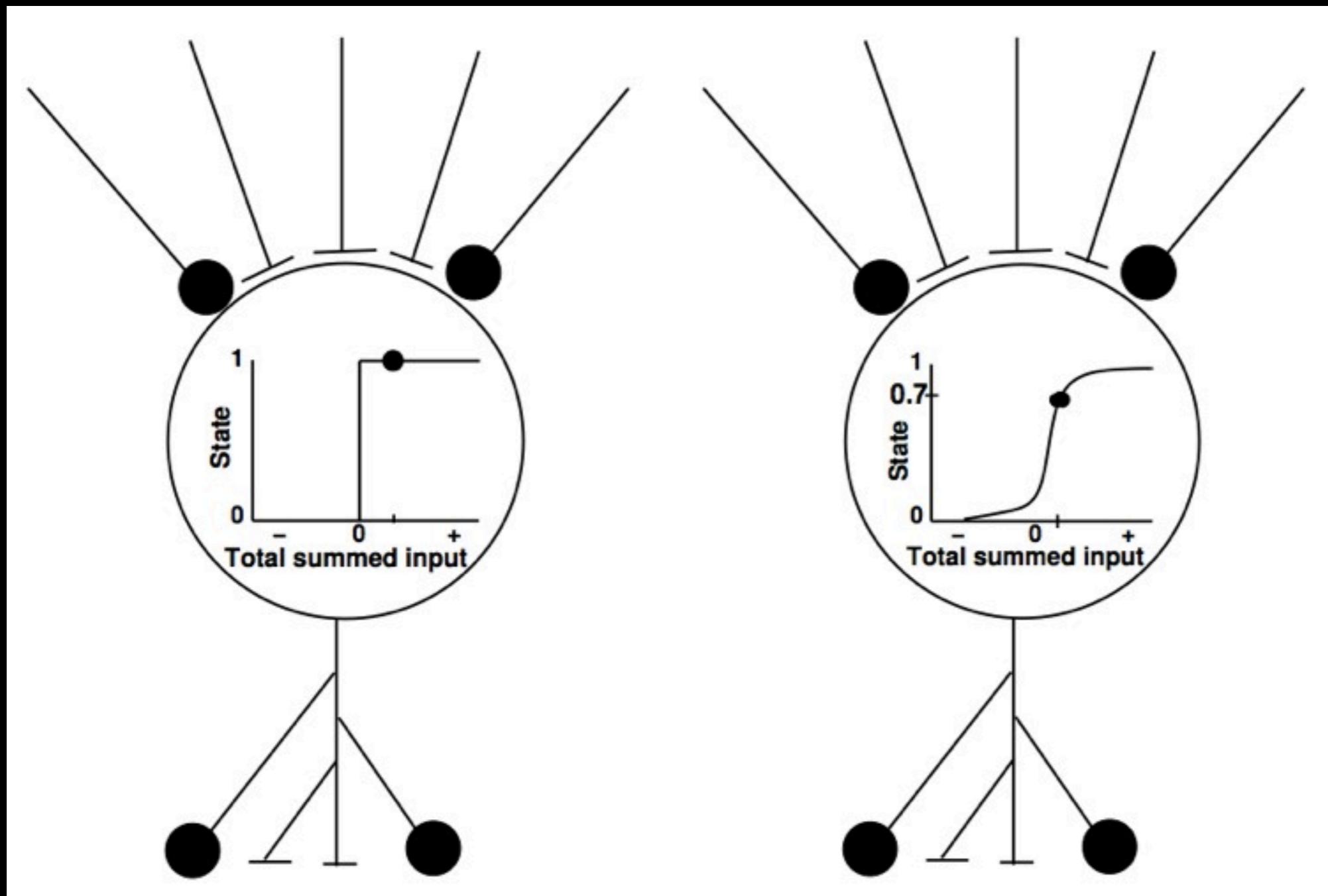
**State:** is the degree of activation of a single neuron

**Weight:** is the strength of the connection between two neurons

**Update rule:** determines how input to a neuron is translated into the state of that neuron



# McCulloch-Pitts (states)



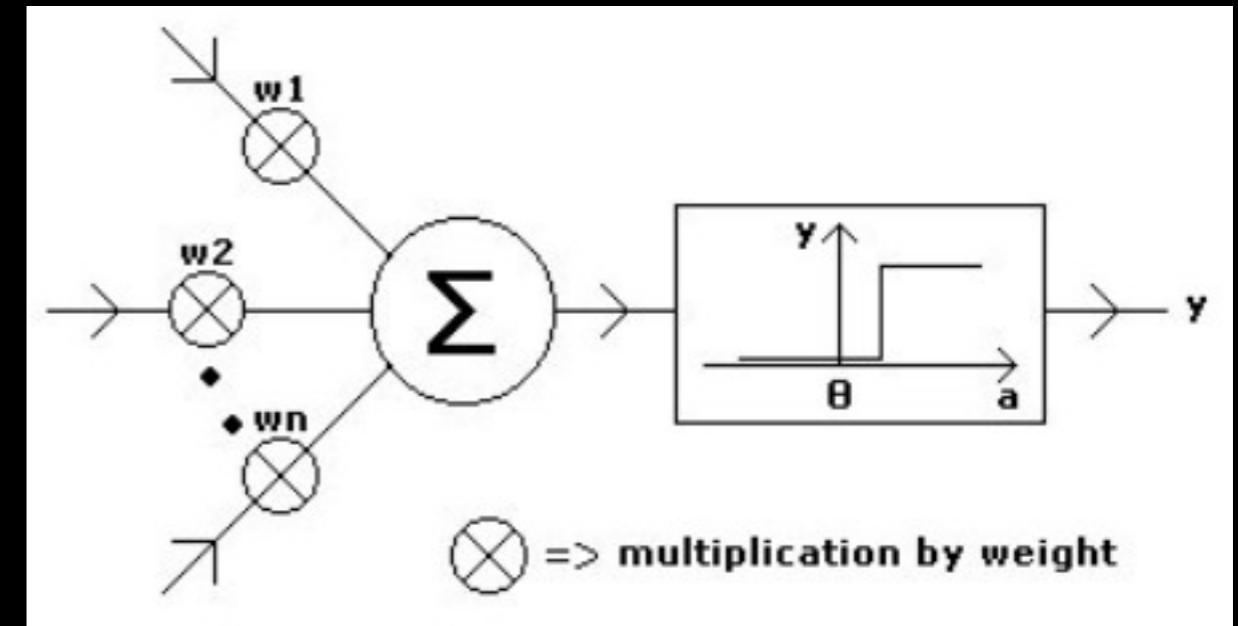
**Sharp threshold  
(digital)**

**Sigmoid function  
(analog)**

# McCulloch-Pitts (states)

In mathematical terms:

$$y = \phi \left( \sum_{i=1}^n \omega_i \cdot x_i \right)$$

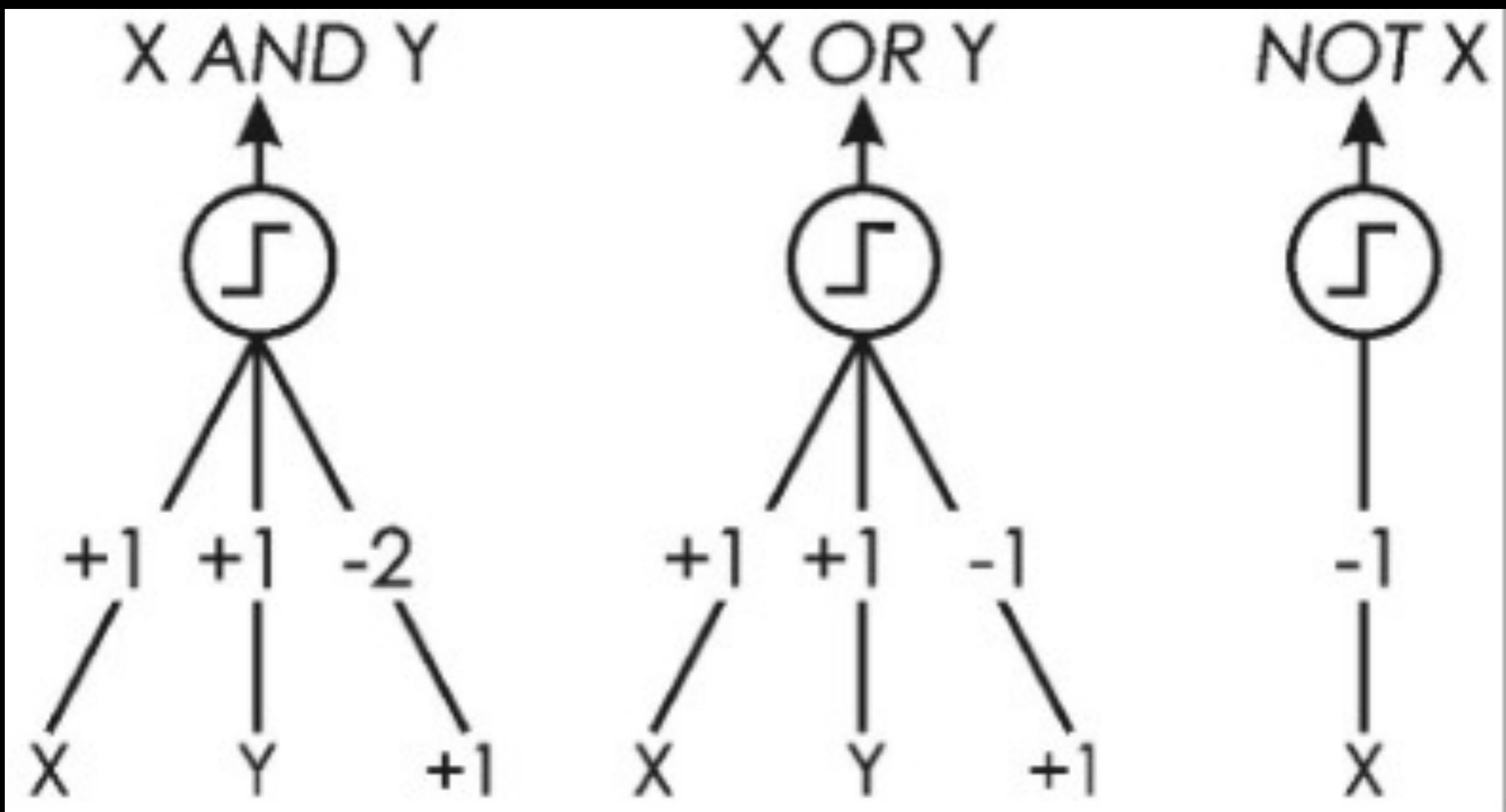


where  $\phi$  represents a threshold or a sigmoid function

```
total_input = sum(w.*x);  
if total_input >= 0  
    y = 1;  
else  
    y = 0;  
end
```

# McCulloch-Pitts (logic)

MP neurons are capable of logic functions



McCulloch-Pitts

Integrate-and-Fire

Hodgkin-Huxley

# Prerequisites

**Differential equations (1 slide)**

**Neurons as electronic circuits (4 slides)**

# Differential equations

The most common and simplest types of dynamic models come in the form of differential equations

They describe the rate of change of some variable, say  $u$ , as a function  $u$  and other variables

$\frac{du}{dt}$  = change per unit time = sum of production rates – sum of removal rates.

$$c_m \frac{dV}{dt} = -i_m + \frac{I_e}{A} .$$

# Generation of electric potential in neuron's membrane

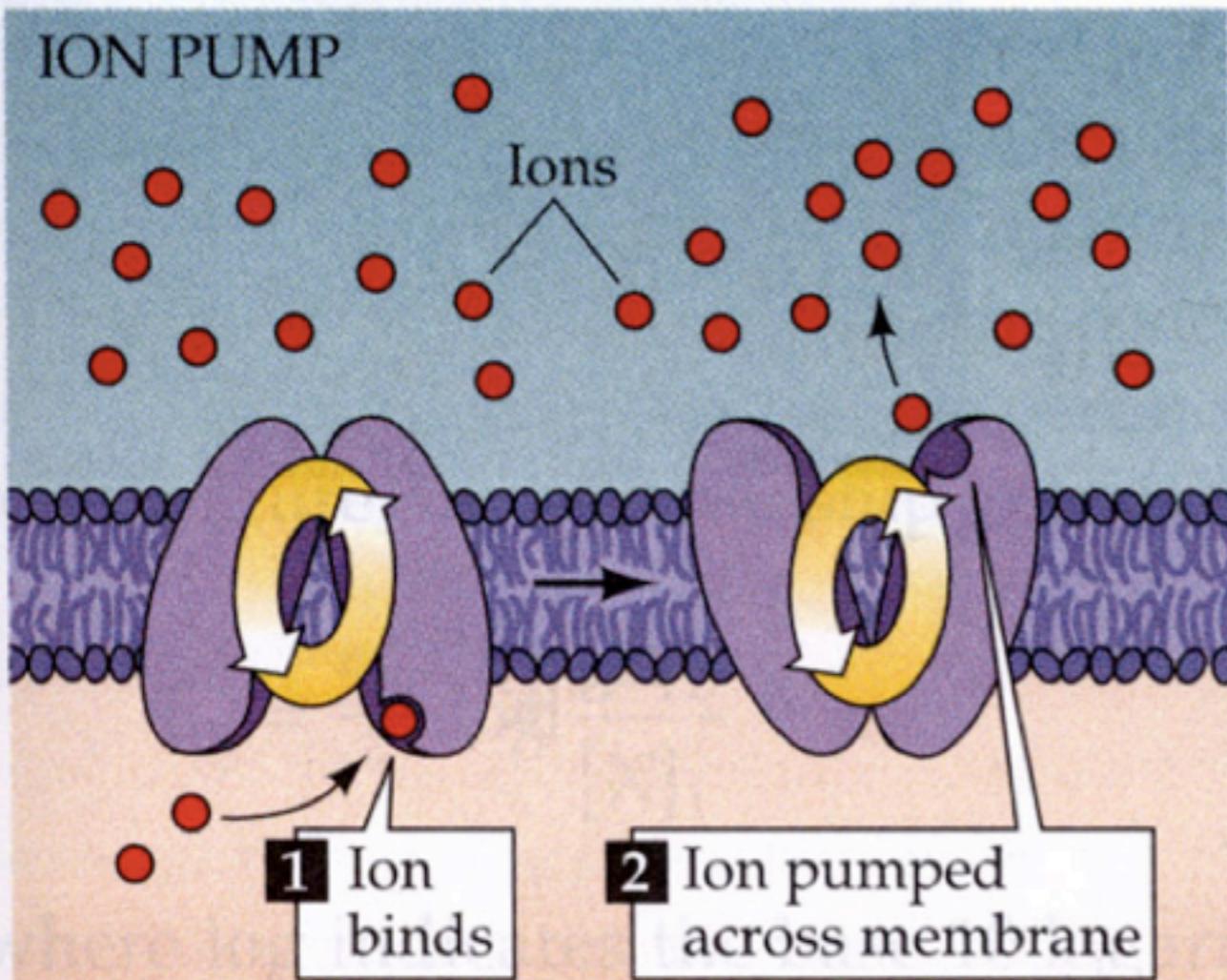
Chief factors that determine the **membrane potential**:

1. The permeability of the membrane to different ions
2. Difference in ionic concentrations

**Ion pumps:** maintain the concentration difference by actively moving ions against the gradient using metabolic resources

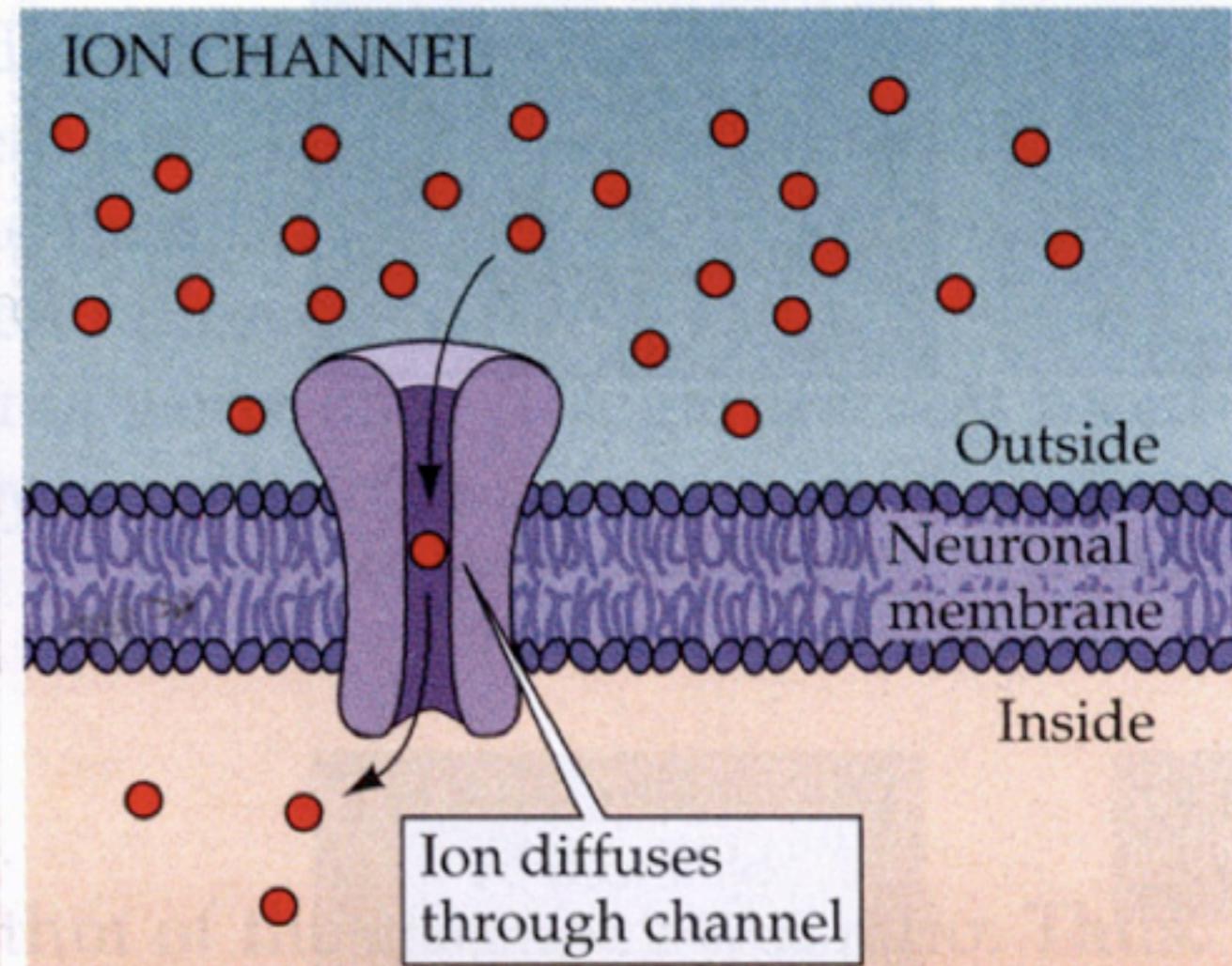
**Ion channels:** “holes” that allow the passage of ions in the direction of the concentration gradient. Some channels are selective for specific ions and some are not selective

# Neuron as an electric circuit



## Ion pumps

- Actively move ions against concentration gradient
- Create ion concentration gradients



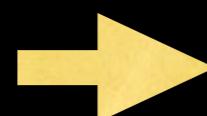
## Ion channels

- Allow ions to diffuse down concentration gradient
- Cause selective permeability to certain ions

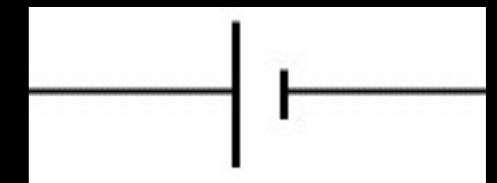
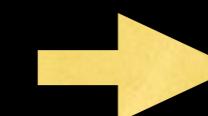
# Neuron as an electric circuit

Can we describe an equivalent circuit to calculate the change in membrane potential  $V$ ?

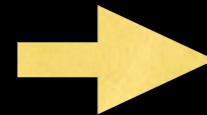
**Differences in  
ion concentration**



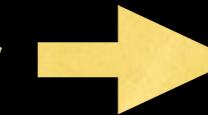
**Batteries**



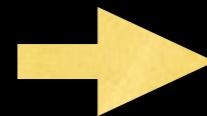
**Cell membrane**



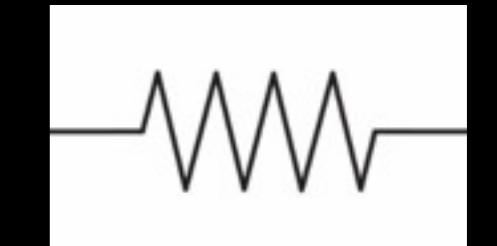
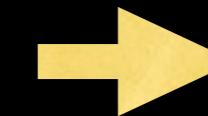
**Capacitor**



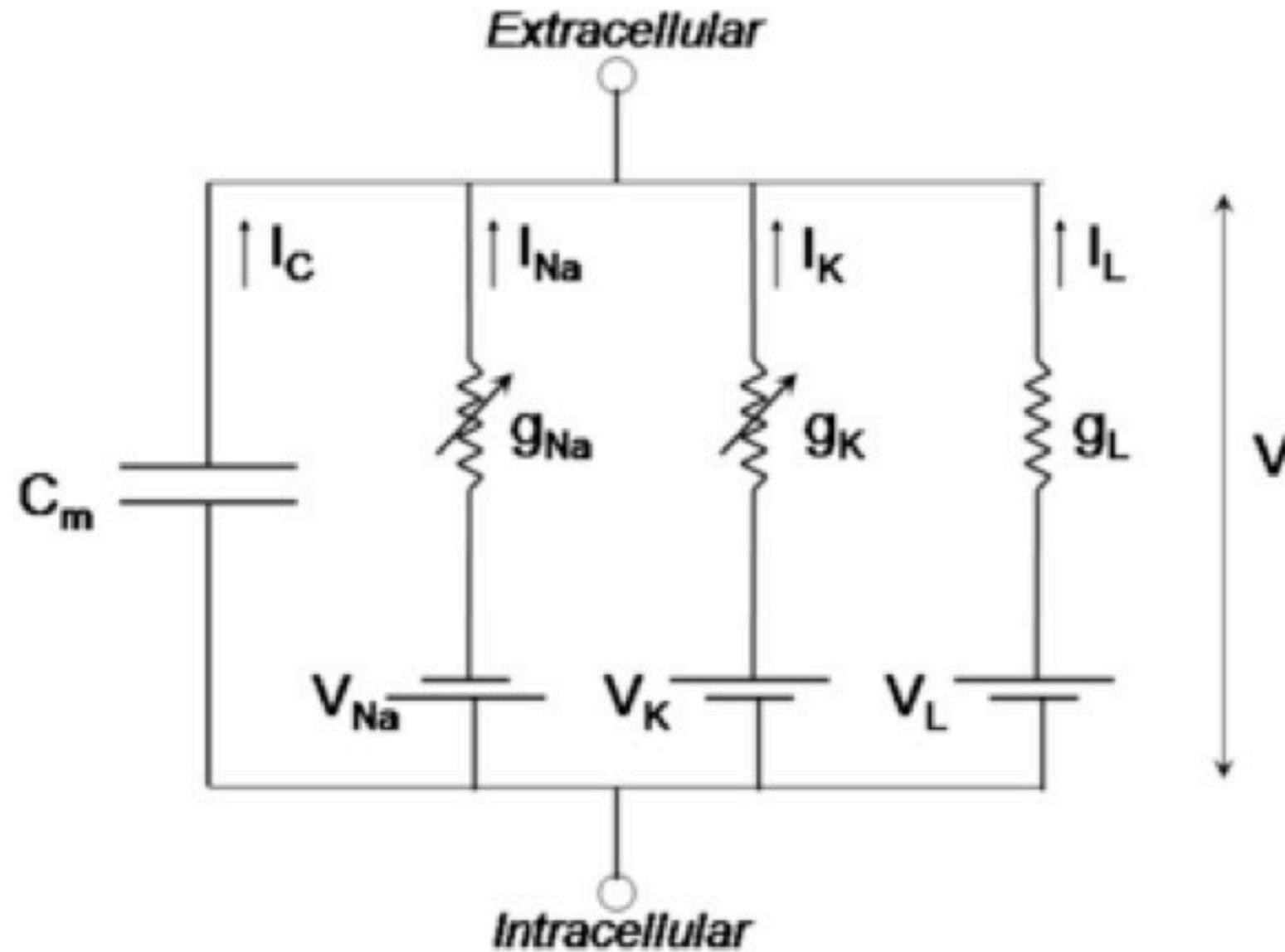
**Ionic channels**



**Resistors**



# Neuron as an electric circuit



$$\text{Ohm law: } I = \frac{V}{R} = gV$$

$$I_{\text{cap}} = C \frac{dV}{dt}$$

$$I_{\text{app}} = C \frac{dV}{dt} + I_{\text{ion}}$$

**Kirchoff's law:** the total current flowing across the cell membrane is the sum of the capacitive current and the ionic currents

# Integrate-and-fire (idea)

One of the most popular neuronal models (simple but capture important neuronal properties)

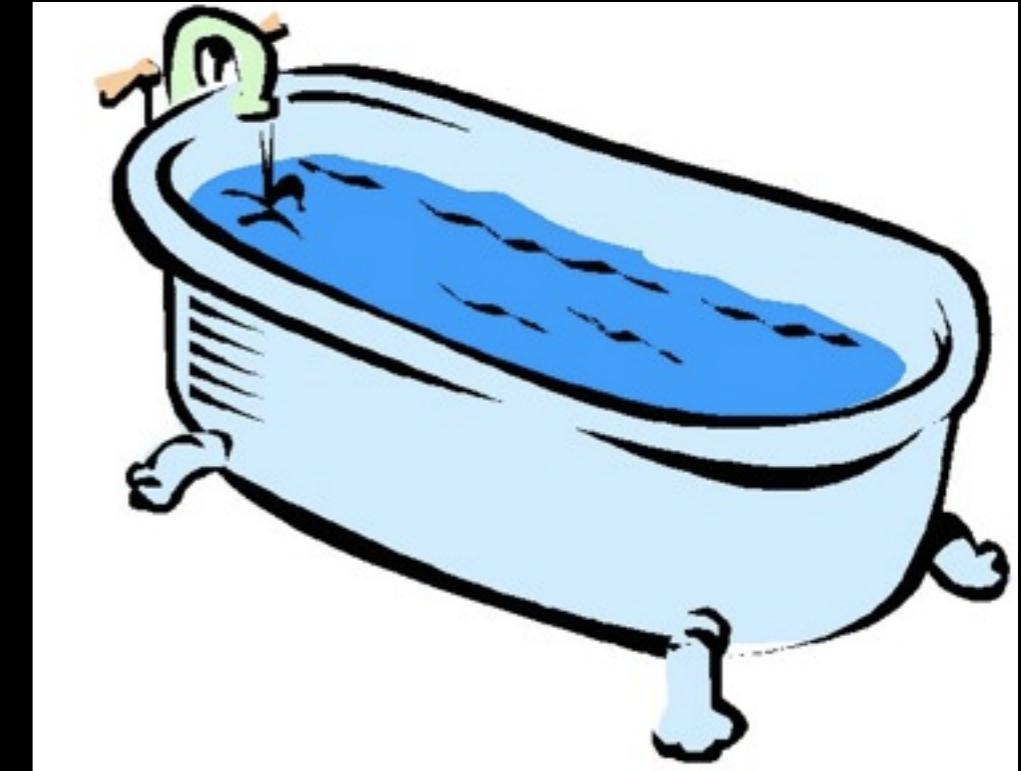
One of the oldest... proposed by Lapicque (1907) way before the mechanisms that generate action potential we understood

Neurons **integrate** inputs (synaptic currents) from other neurons, and when “enough” are received they **fire** an action potential and reset their membrane voltage

# Integrate-and-fire (bath tube)

**Analogy:** imagine a bath tube with a hole in the bottom, and thus leaking water

Incoming action potentials are like buckets of water that are poured in time into the bath tube

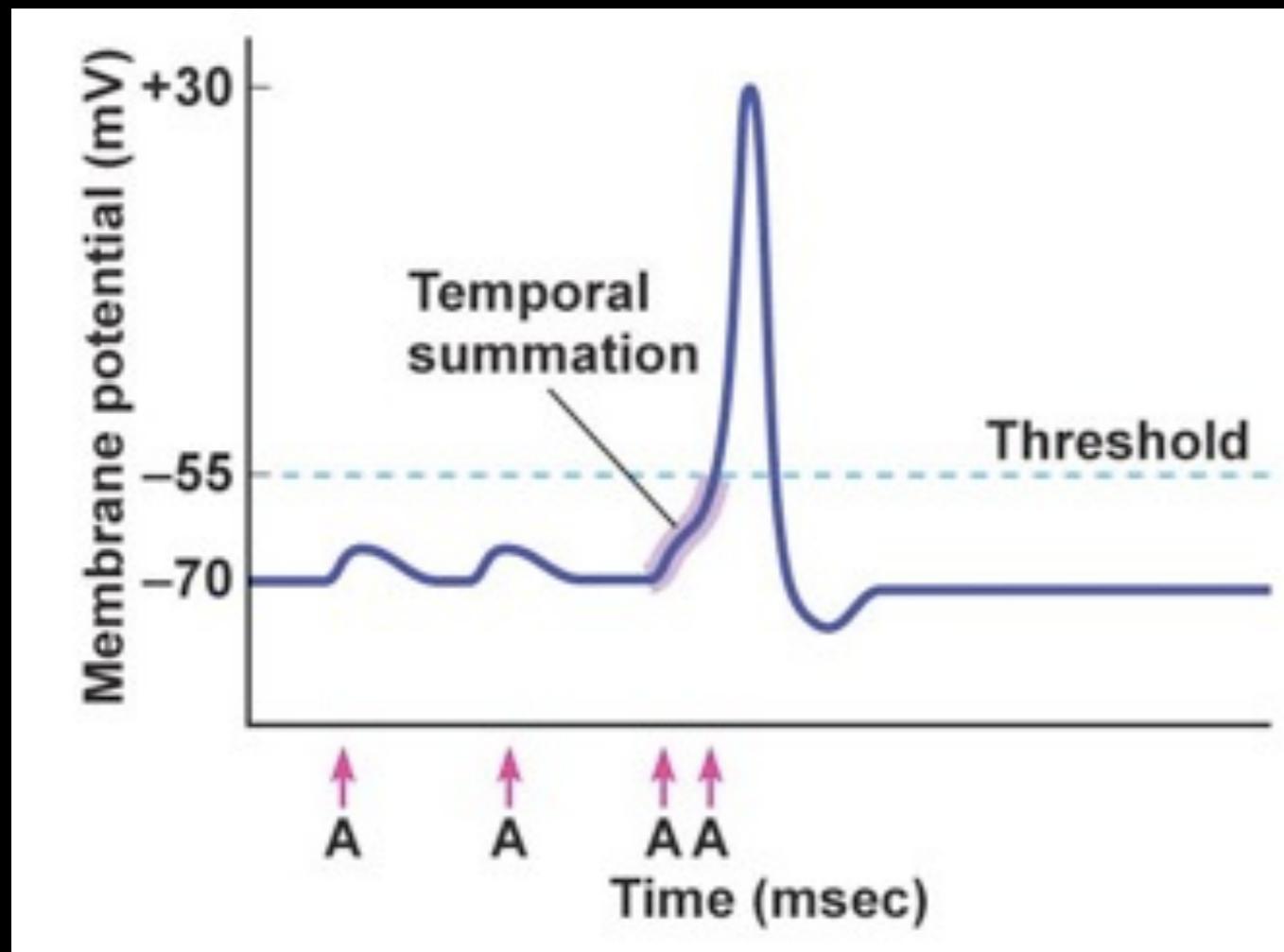


If enough are coming during a short time, and thus compensating for the leak, water will overflow

At threshold the neuron emits an action potential and its voltage (equivalent to the water level) will be reset to a default value

# Integrate-and-fire (threshold)

## Threshold mechanism



For  $V = V_{Th}$  neuron fires a spike and resets

For  $V < V_{Th}$  neuron obeys a passive dynamics

The shape of the action potentials are more or less the same

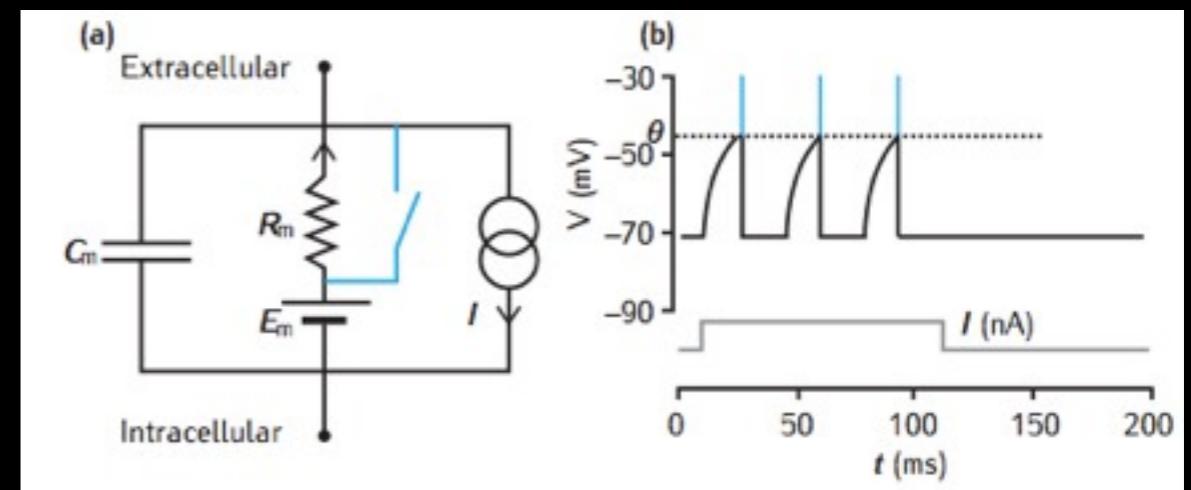
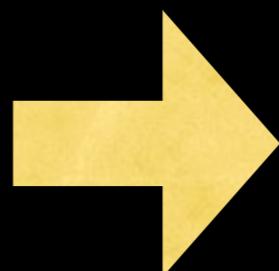
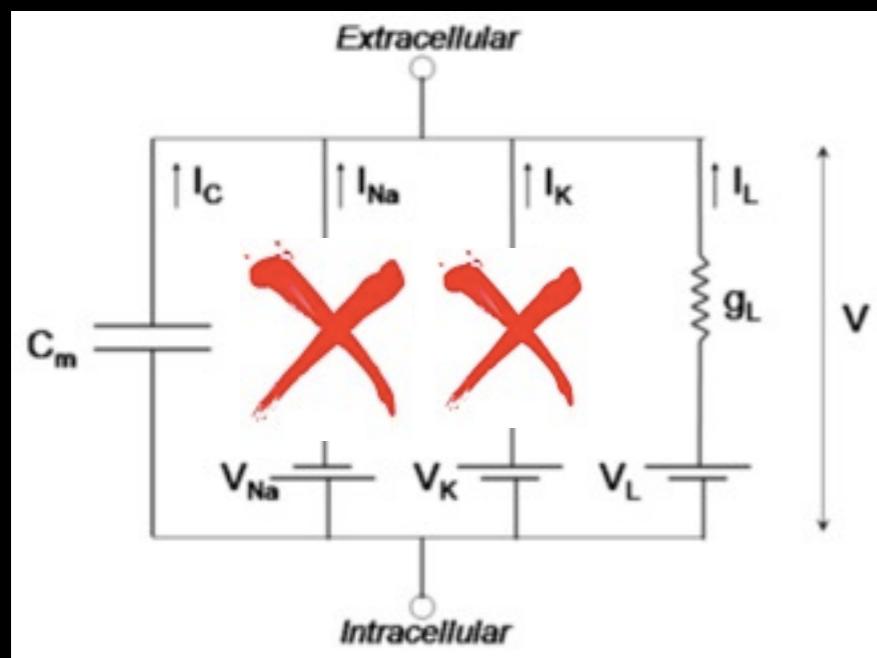
As far as neural communications is concerned, the exact shape of the spike is not important, rather its time of occurrence

# Integrate-and-fire (equation)

Let's divide the behavior of a neuron in two regimes

**Supra-threshold** (if  $V = V_{\text{Th}}$  then spike and reset)

**Sub-threshold** (voltage according to equivalent circuit):

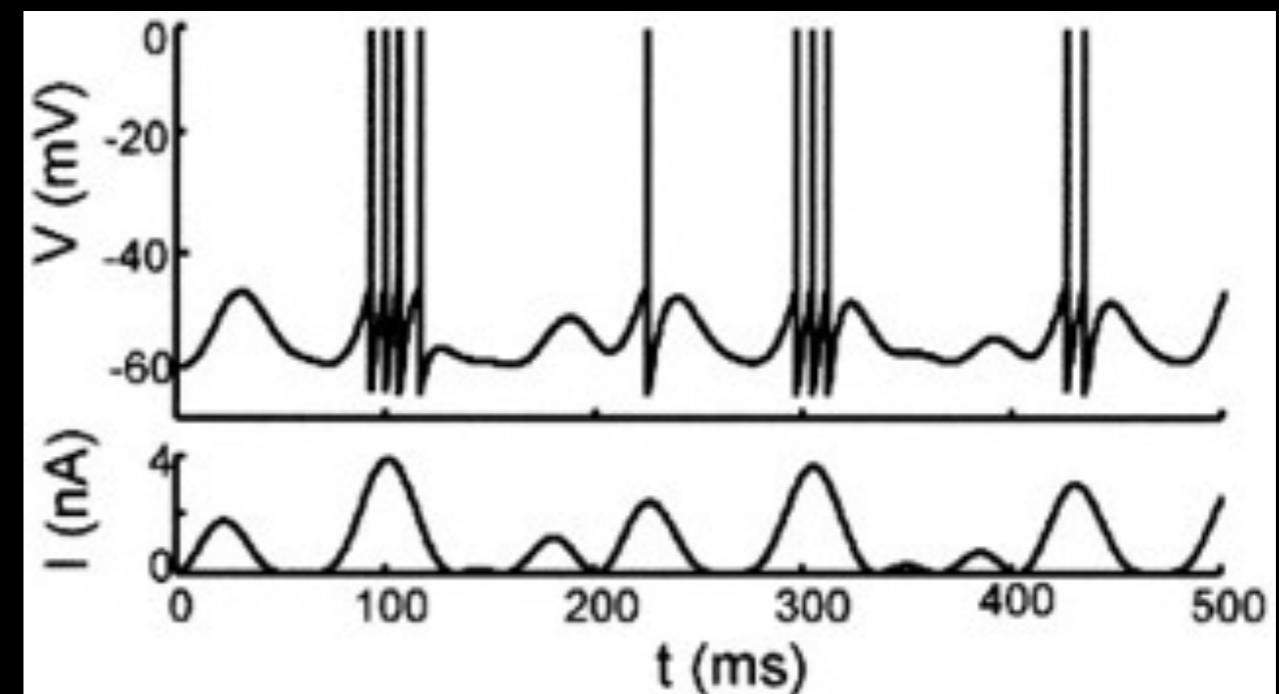
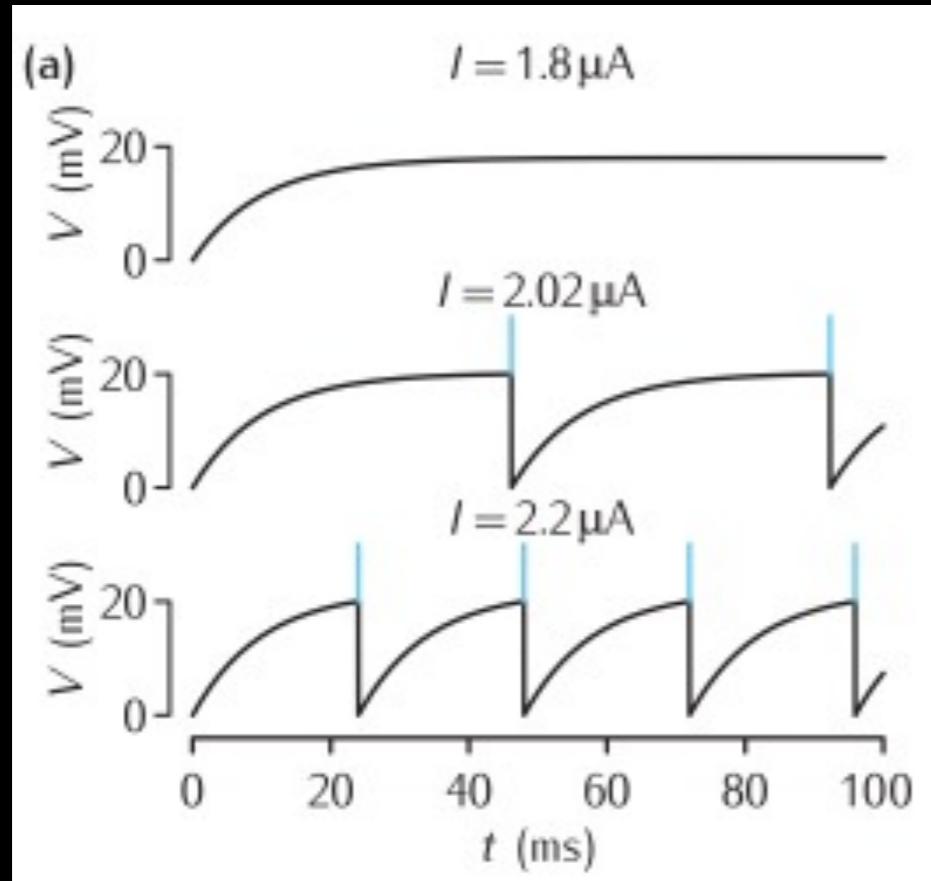


$$C_m \frac{dV}{dt} = -\frac{V - E_m}{R_m} + I$$

# Integrate-and-fire (simulation)

Now we are ready to simulate an I&F neuron...

$$C_m \frac{dV}{dt} = -\frac{V - E_m}{R_m} + I$$



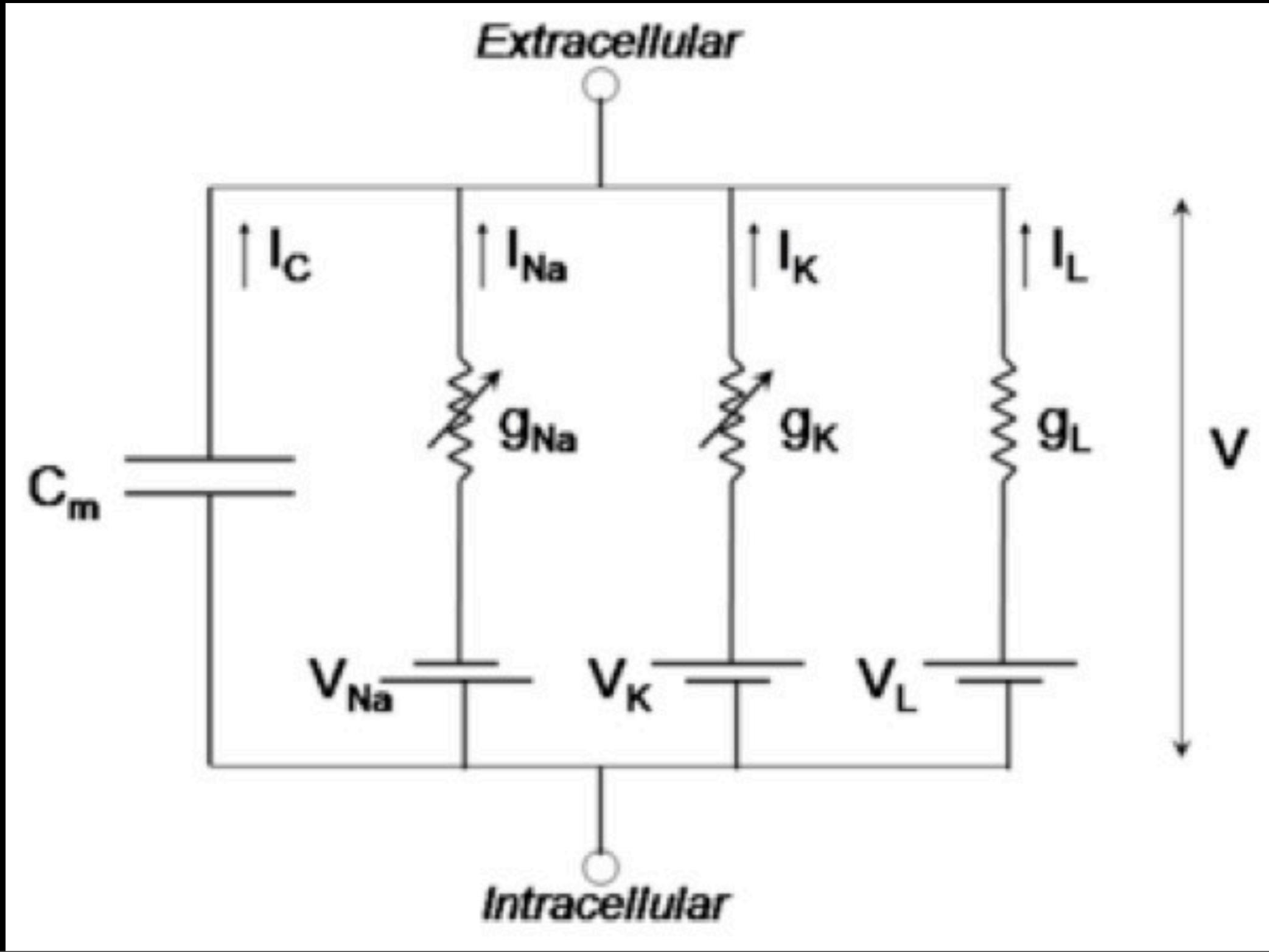
We still lack synaptic currents from other neurons... (later)

McCulloch-Pitts

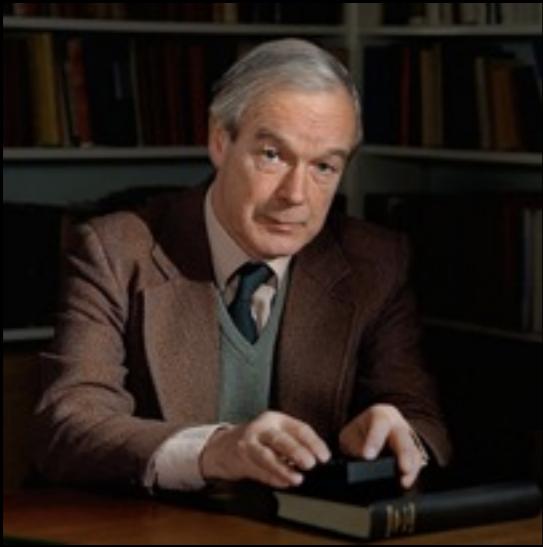
Integrate-and-Fire

Hodgkin-Huxley

# Hodgkin-Huxley



# Hodgkin-Huxley (heroic)



Empirical model that describes the ionic conductance and  
**generation of nerve action potential**

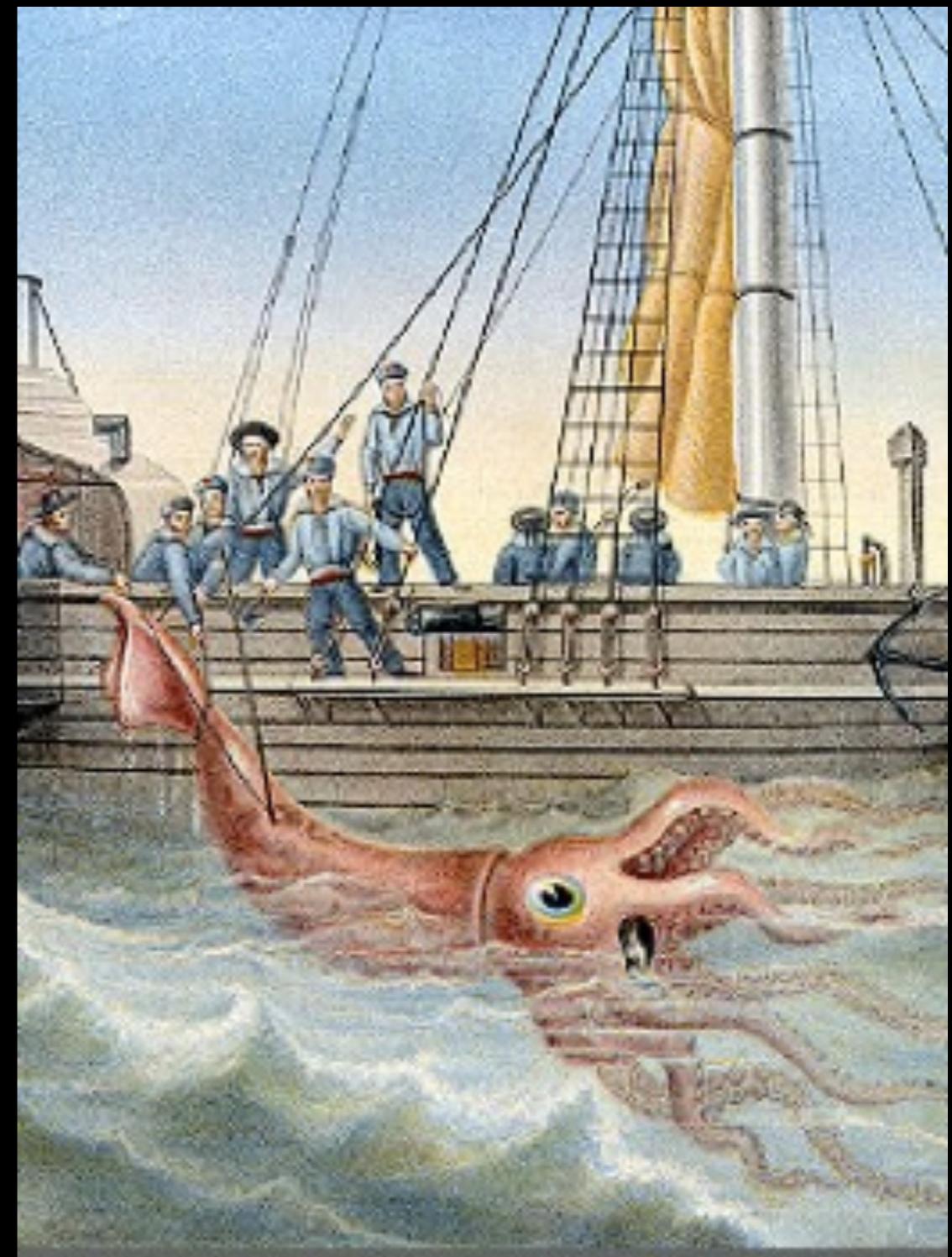
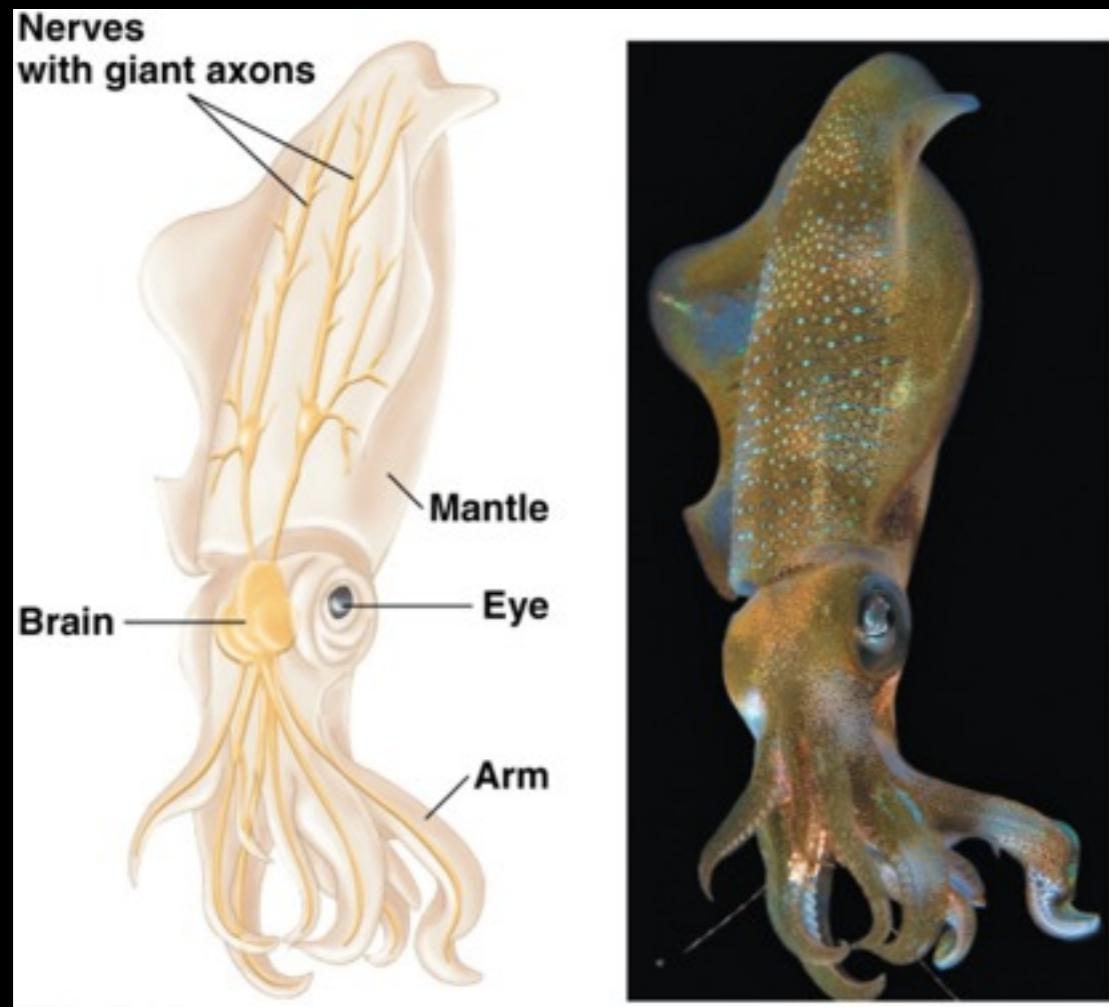
Published in 1952

Nobel Prize in Medicine or Physiology in 1963

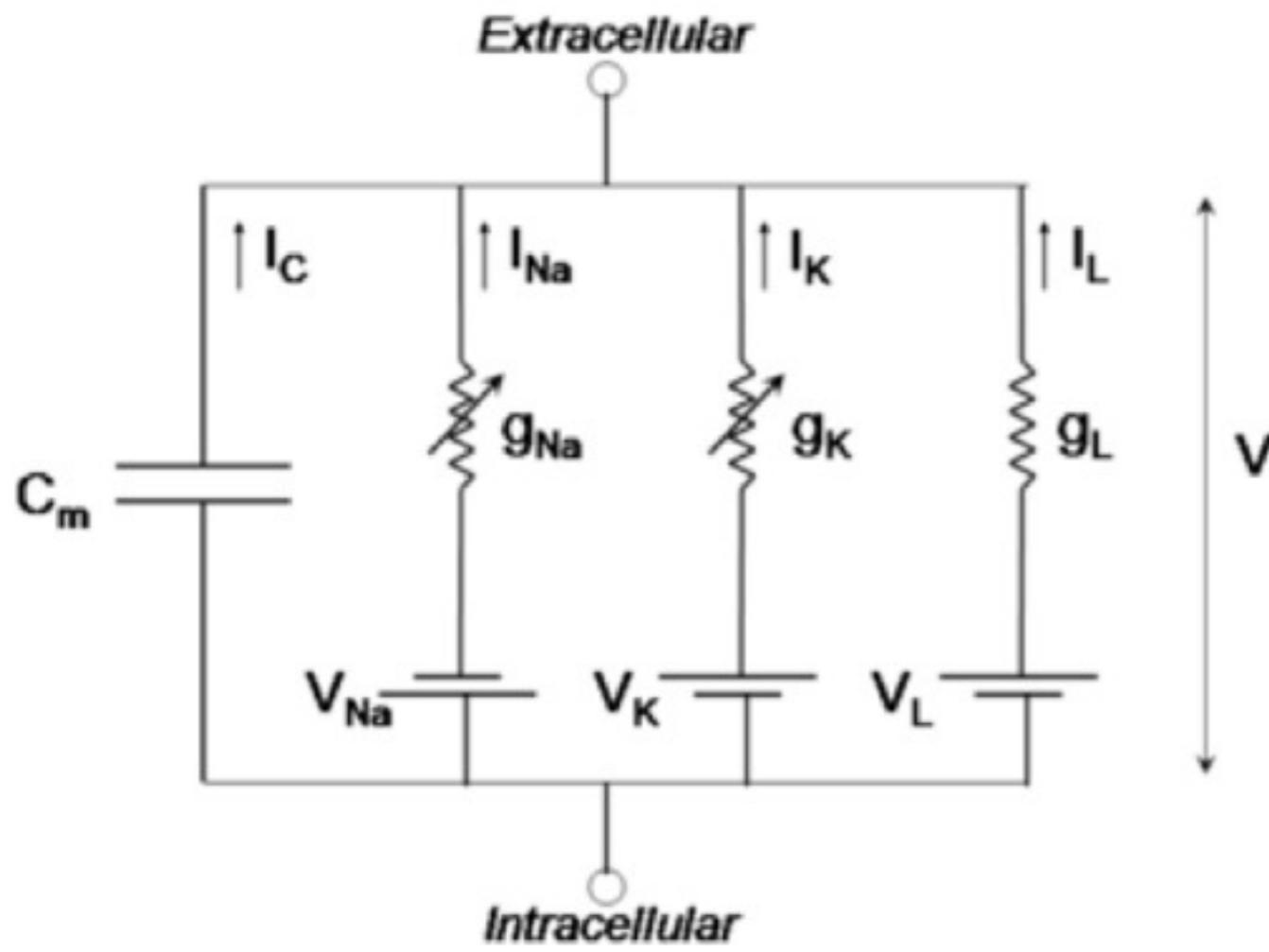
Work reflects a combination of experimental work, theoretical hypothesis, computational data fitting, and model prediction

# Hodgkin-Huxley (big is good)

Made their experiments on the squid giant axon, not the giant squid axon!



# Hodgkin-Huxley (as a circuit)



$$I = I_c + I_i = C_m \frac{dV}{dt} + I_i$$

$$I_i = I_{Na} + I_K + I_L$$

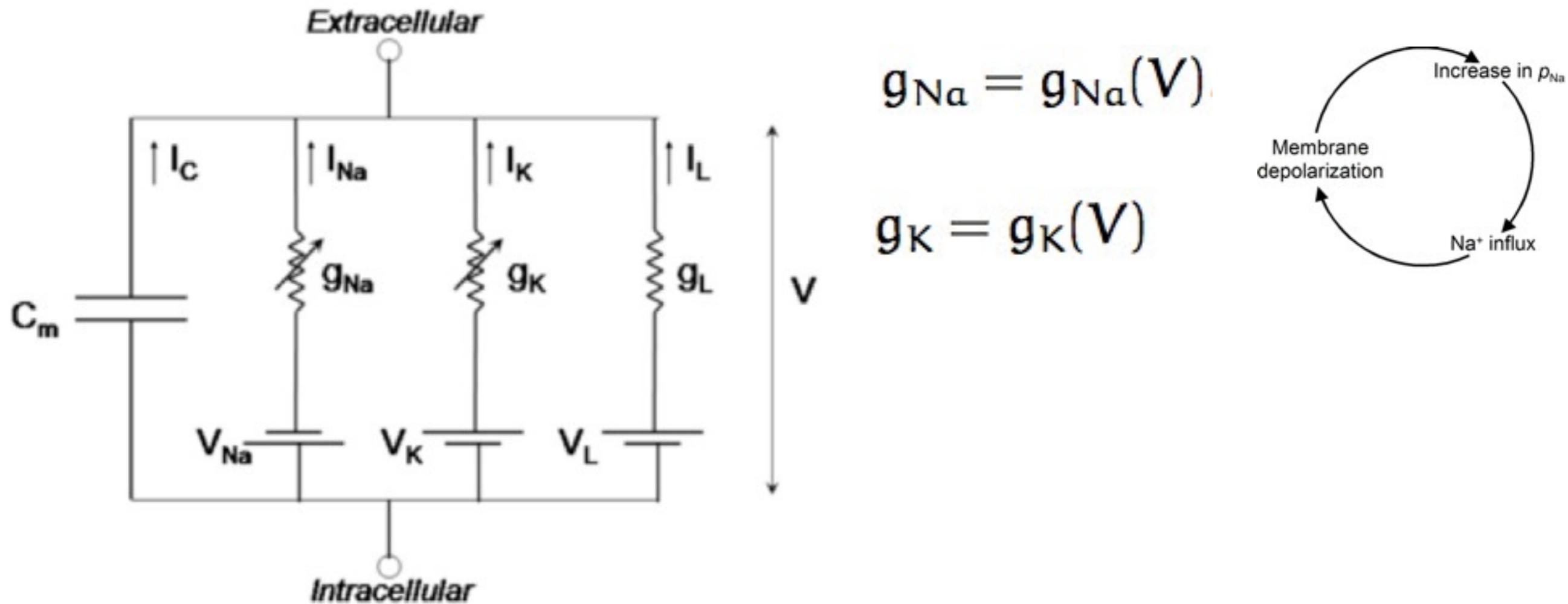
$$I_{Na} = g_{Na}(V - E_{Na}),$$

$$I_K = g_K(V - E_K),$$

$$I_L = \bar{g}_L(V - E_L),$$

# Hodgkin-Huxley (Na and K)

The data of HH indicated that Na and K ion channels conductance (open) depended on voltage



But how exactly?

# Hodgkin-Huxley (gating)

HH proposed that **channels** behaved as a system of gates or doors

**Example** for K channels:

$g_K = \text{maximal conductance} \times \text{probability all gates are open}$

For 1 gate

$$g_K = \bar{g}_K n$$
 *n being the probability gate is open*

For 4 gates

$$g_K = \bar{g}_K n^4$$

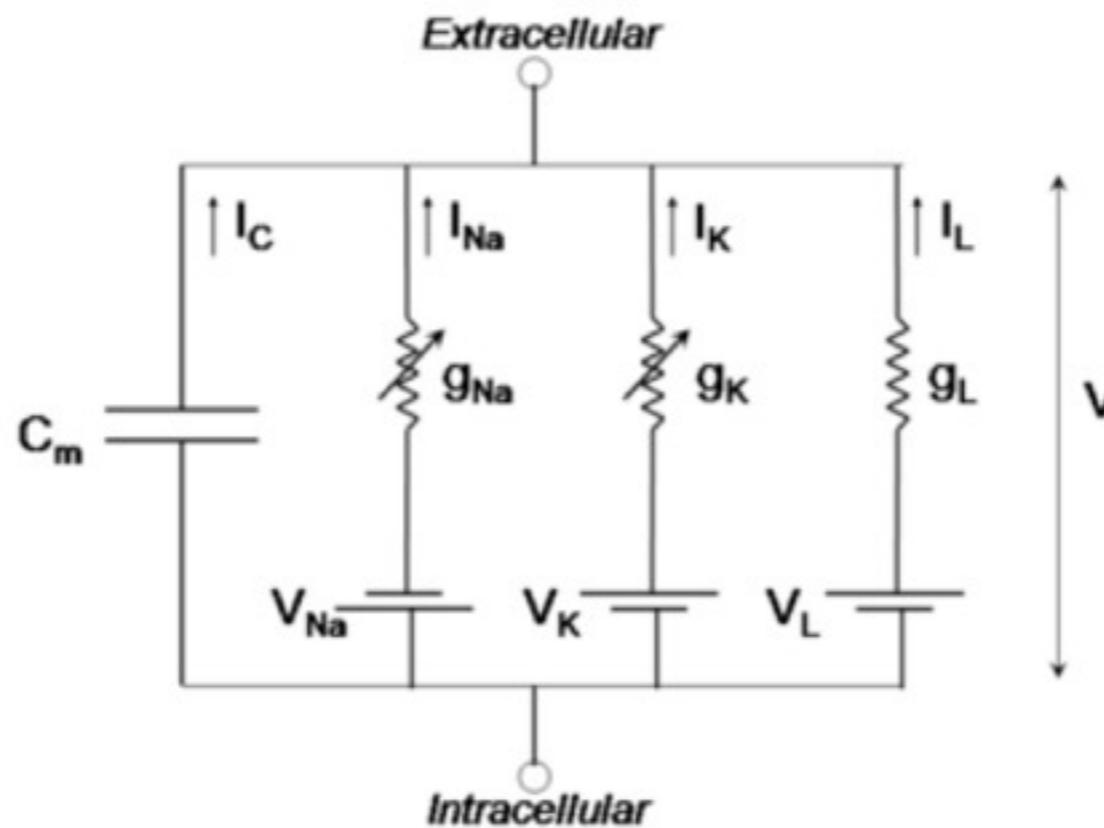
$n$  changes over time:

$$\frac{dn}{dt} = \alpha_n(1-n) - \beta_n n.$$

# Hodgkin-Huxley (full model)

Full model: Inserting gating mechanisms of Na and K conductances into current equations...

$$C_m \frac{dV}{dt} = -\bar{g}_L(V - E_L) - \bar{g}_{Na}m^3h(V - E_{Na}) - \bar{g}_Kn^4(V - E_K) + I_i$$



# Hodgkin-Huxley (full model)

$$C_m \frac{dV}{dt} = -\bar{g}_L(V - E_L) - \bar{g}_{Na}m^3h(V - E_{Na}) - \bar{g}_K n^4(V - E_K).$$

Sodium activation and inactivation gating variables:

$$\frac{dm}{dt} = \alpha_m(1 - m) - \beta_m m,$$

$$\frac{dh}{dt} = \alpha_h(1 - h) - \beta_h h,$$

$$\alpha_m = 0.1 \frac{V + 40}{1 - \exp(-(V + 40)/10)},$$

$$\alpha_h = 0.07 \exp(-(V + 65)/20),$$

$$\beta_m = 4 \exp(-(V + 65)/18),$$

$$\beta_h = \frac{1}{\exp(-(V + 35)/10) + 1}.$$

Potassium activation gating variable:

$$\frac{dn}{dt} = \alpha_n(1 - n) - \beta_n n,$$

$$\alpha_n = 0.01 \frac{V + 55}{1 - \exp(-(V + 55)/10)},$$

$$\beta_n = 0.125 \exp(-(V + 65)/80).$$

Parameter values (from Hodgkin and Huxley, 1952d):

$$C_m = 1.0 \text{ } \mu\text{F cm}^{-2}$$

$$E_{Na} = 50 \text{ mV}$$

$$\bar{g}_{Na} = 120 \text{ mS cm}^{-2}$$

$$E_K = -77 \text{ mV}$$

$$\bar{g}_K = 36 \text{ mS cm}^{-2}$$

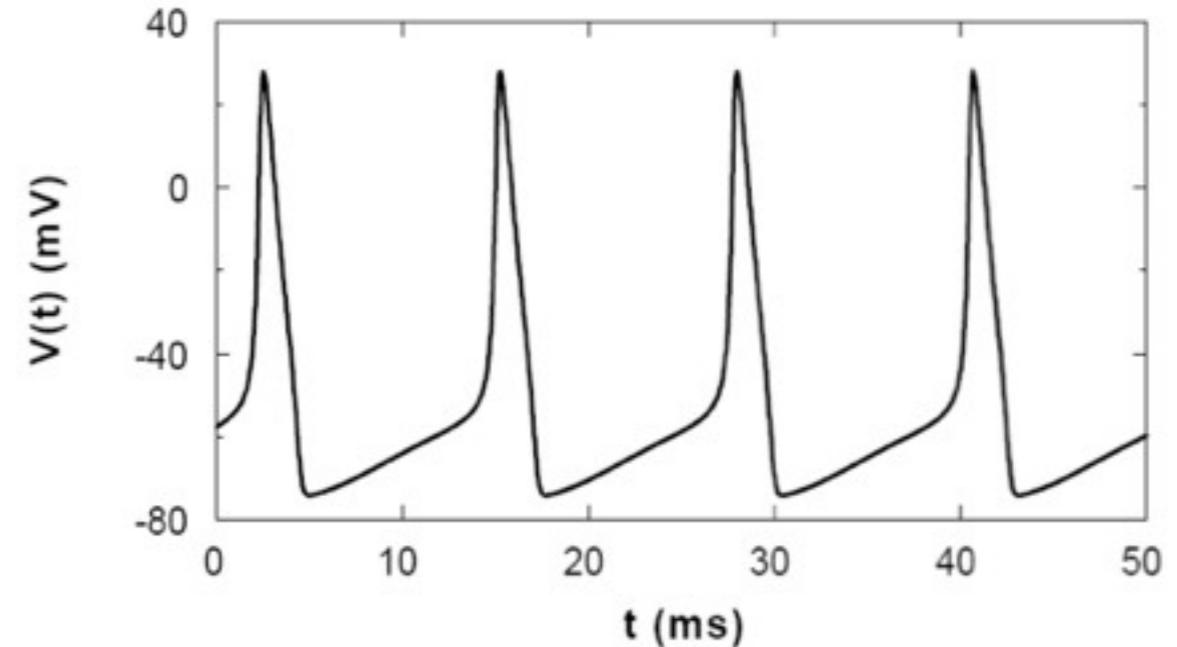
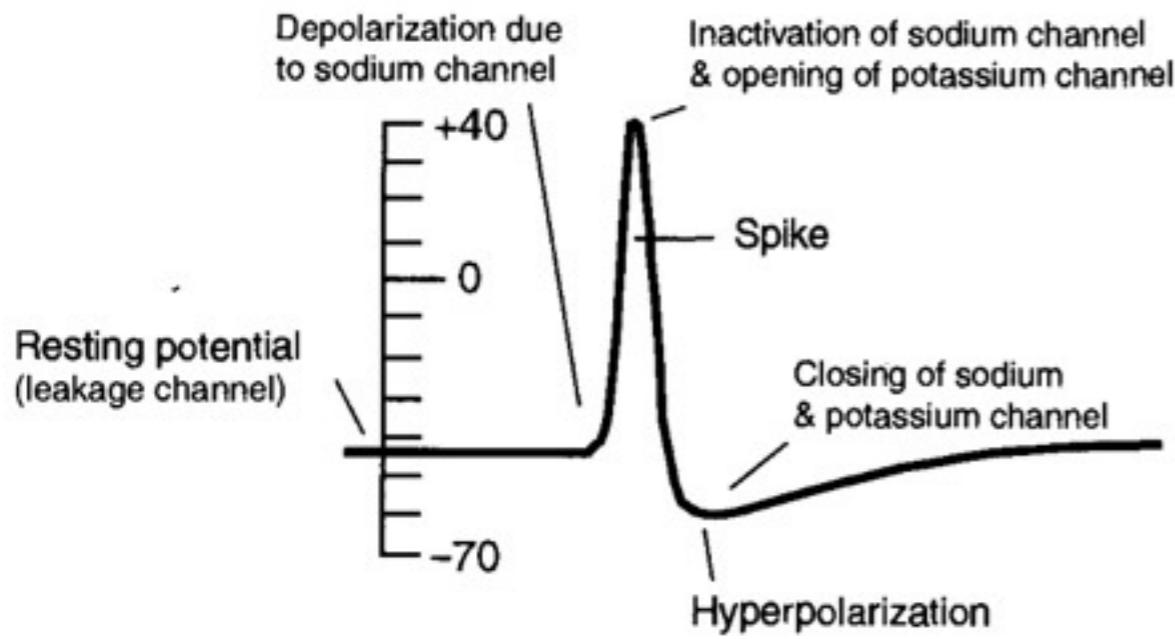
$$E_L = -54.4 \text{ mV}$$

$$\bar{g}_L = 0.3 \text{ mS cm}^{-2}$$

HHsim

# Hodgkin-Huxley (full model)

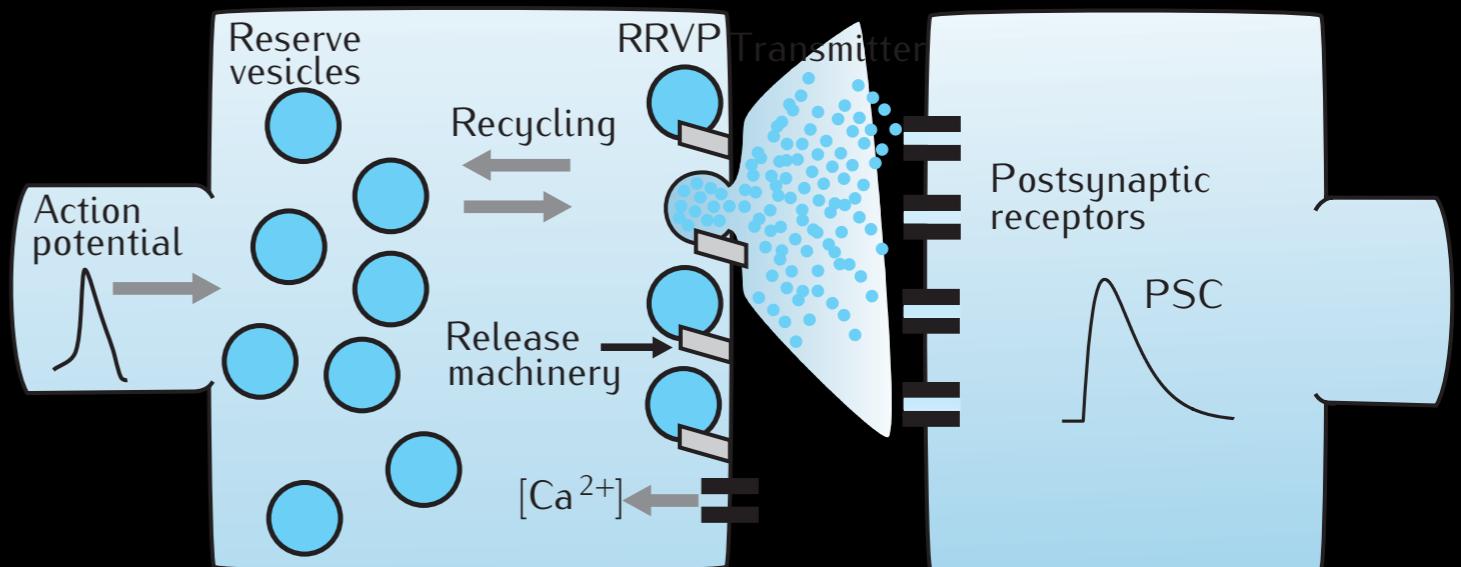
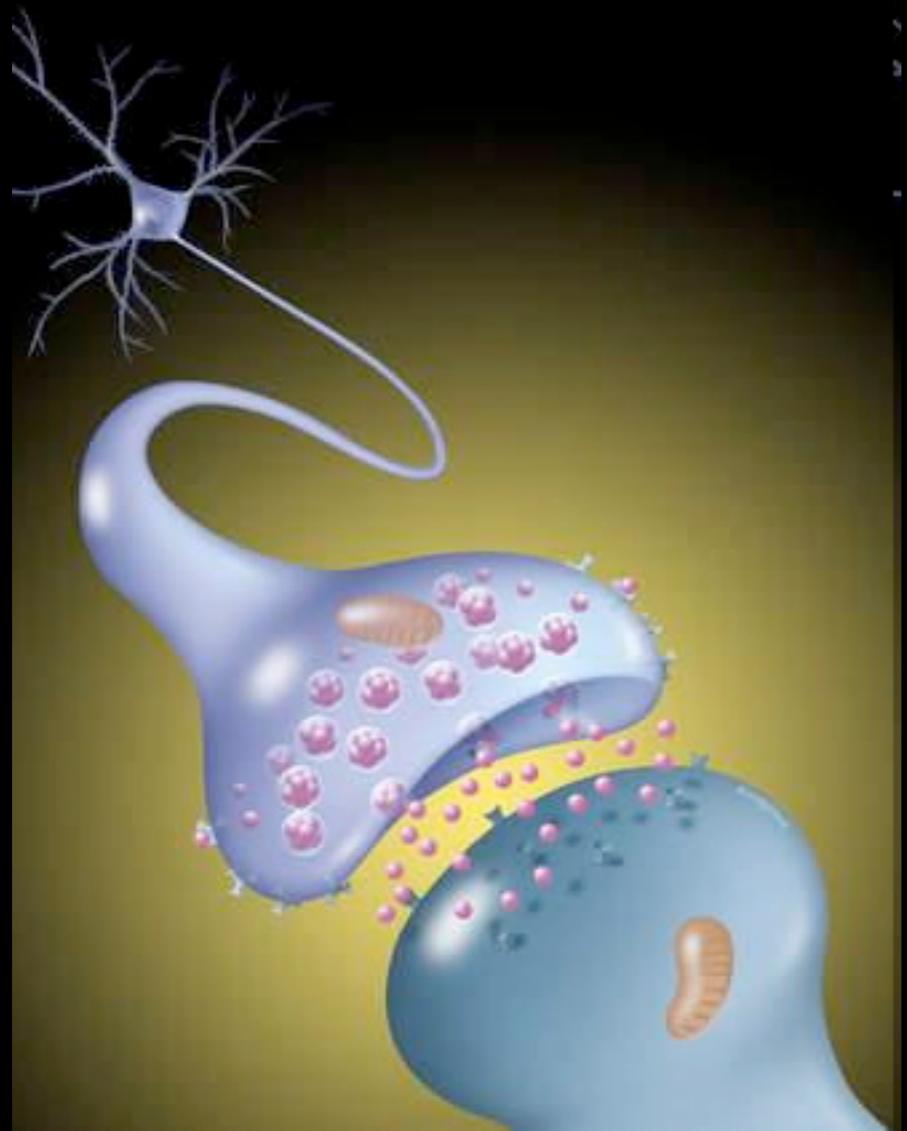
$$C \frac{dV}{dt} = - \sum_i g_i (V - V_i) + I_{app}$$



Action potentials come naturally

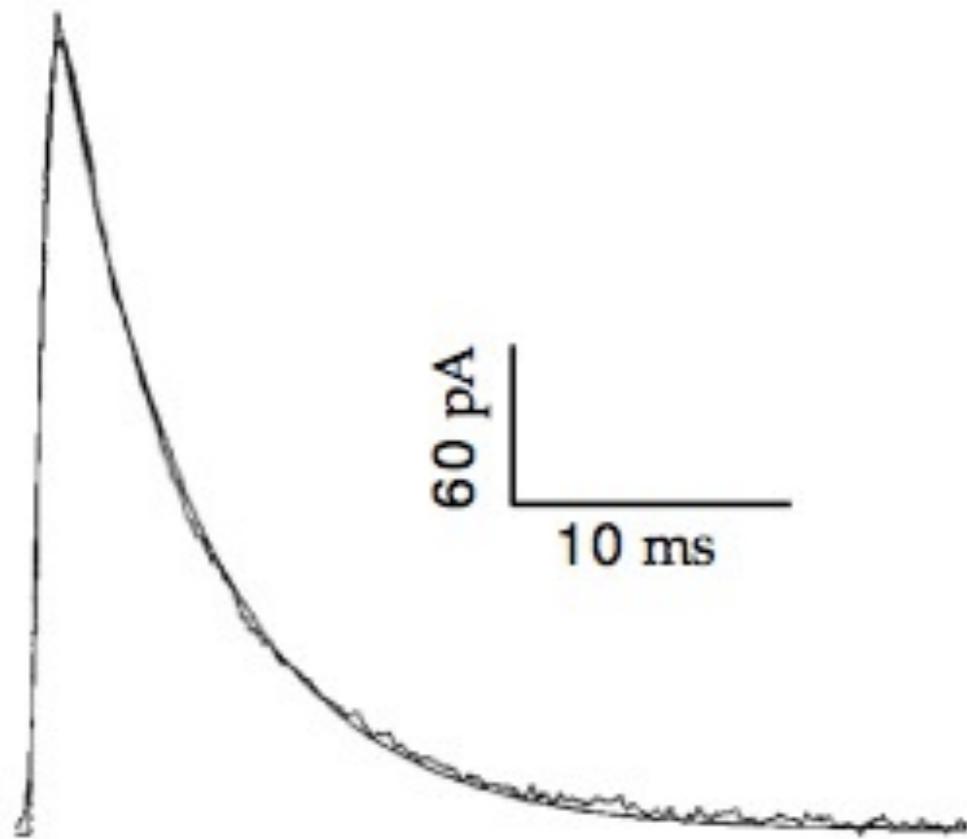
# What about the synapses?

To simulate circuits of neurons we also need to include the synaptic currents ( $I_{syn}$ )



# What about the synapses?

To simulate circuits of neurons we also need to include the synaptic currents ( $I_{syn}$ )



How do we model  
synaptic currents?

PSC (excitatory)

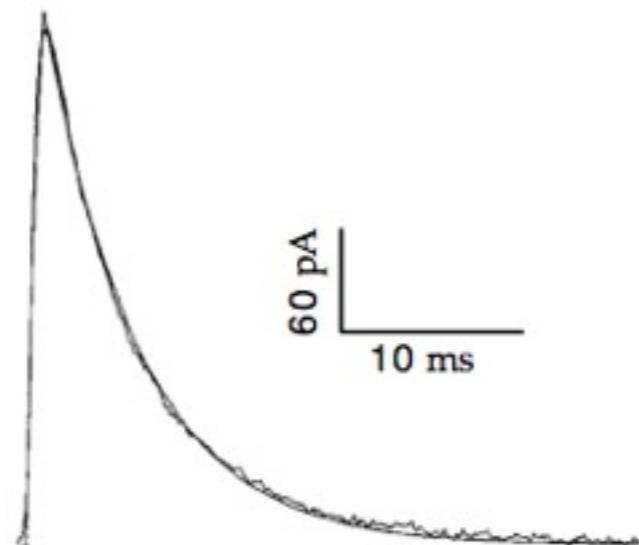
# What about the synapses?

Synaptic currents also occur due to the opening and closing of ion channels:

$$I_{syn} = g_{syn}(V - E_R)$$

as with Hodgkin-Huxley the difficulty is to find how  $g$  changes with time

Solution I:



PSC (excitatory)

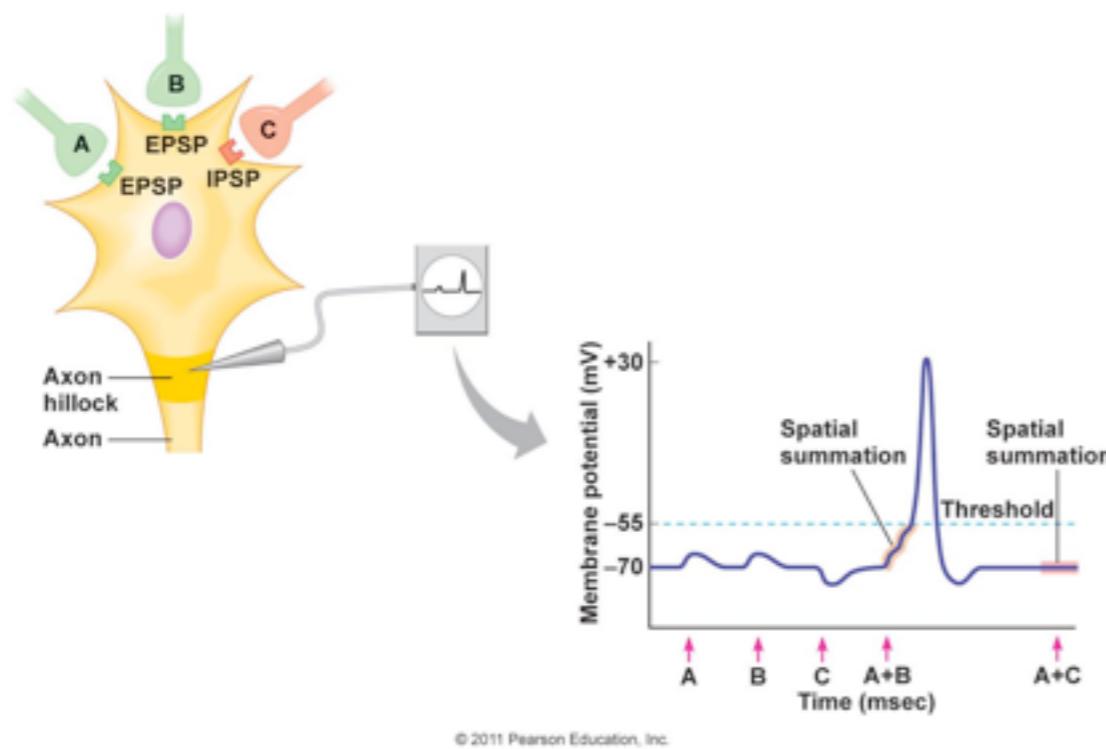
Arrival of incoming spike from other neuron:

- 1)  $g_{syn} \rightarrow g_{syn} + dg$
- 2) exponential decay

# What about the synapses?

Two important remarks:

- \* There are excitatory and inhibitory synapses



$$I_{syn} = I_{exc} + I_{inh}$$

- \* There MANY synapses

# What about the synapses?

Now, we can couple a synaptic model with I&F or HH

I&F

$$\tau_m \frac{dV_m(t)}{dt} = -V_m(t) + RI(t)$$

+

synaptic  
currents

$$g_{\text{exc}}(t)(E_{\text{exc}} - V_m(t)) + g_{\text{inh}}(t)(E_{\text{inh}} - V_m(t))$$

=

Full  
model

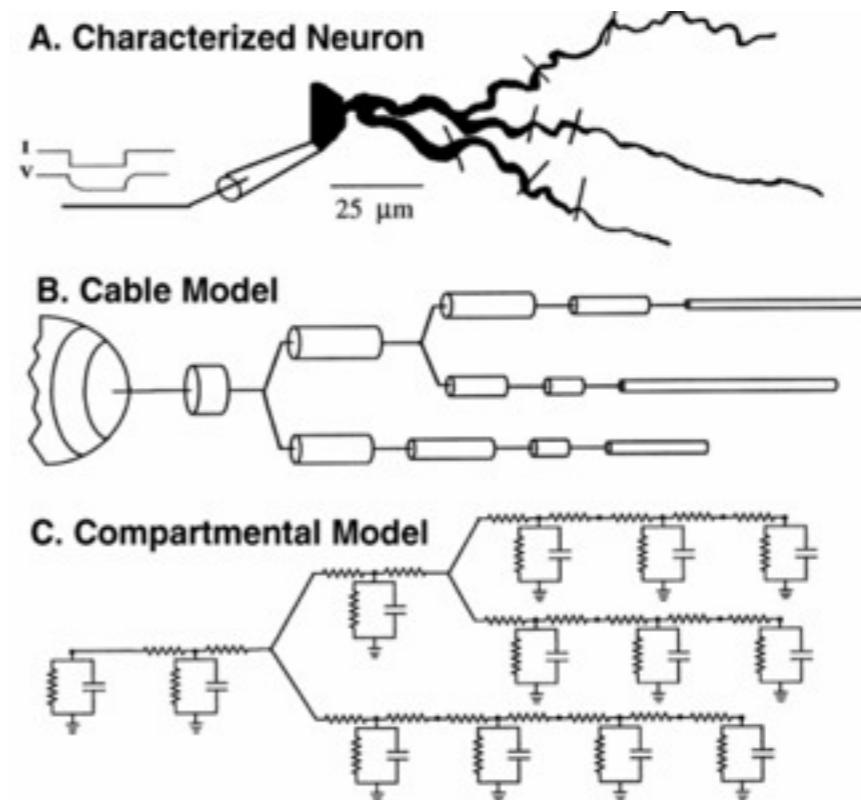
$$\tau_m \frac{dV_m(t)}{dt} = (V_{\text{rest}} - V_m(t)) + g_{\text{exc}}(t)(E_{\text{exc}} - V_m(t)) + g_{\text{inh}}(t)(E_{\text{inh}} - V_m(t))$$

Ready to simulate any neuronal circuit!

# Multicompartment models

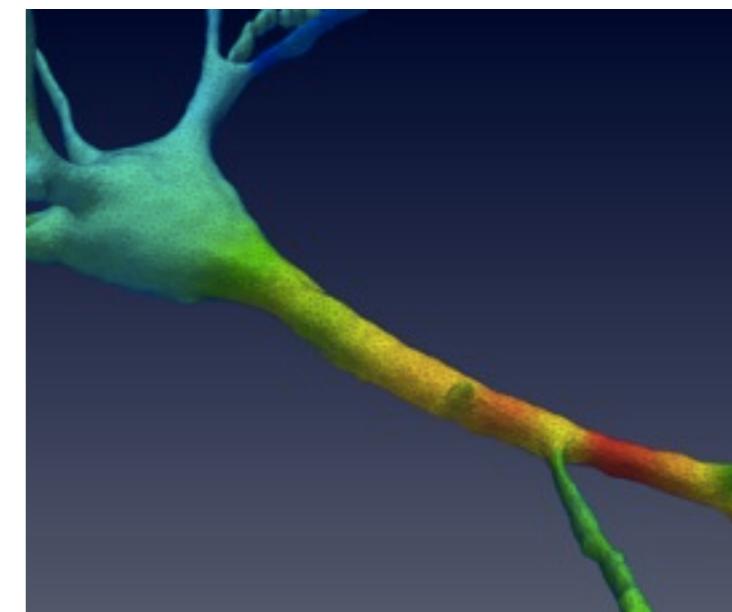
Used for very detailed simulations of one or few neurons

**Idea:** divide a neuron in compartments (with distinct electrical properties) & connect the equivalent circuits



Allows fine study of morphological, pharmacological, or electrical effects

Simulated using NEURON or GENESIS



# Summary

- Single compartment models include McCulloch-Pitts, Integrate-and-Fire, and Hodgkin-Huxley
- MP is good for exploring computational properties
- I&F and HH capture important details of neuronal activity and are the basis for simulating realistic neuronal circuits

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