

Silicon Neurons

NE-I Class

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Zurich, November 2020

Neurons ... in a nutshell

A quick tutorial

Complexity ↑

- Real Neurons
- Conductance based models
- Integrate and fire models
- Rate based models
 - ▶ Sigmoidal units
 - ▶ Linear threshold units

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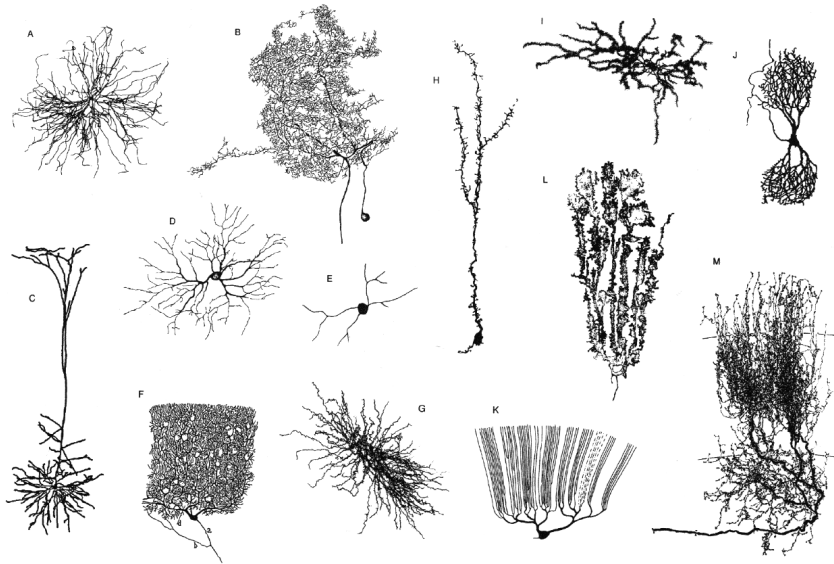
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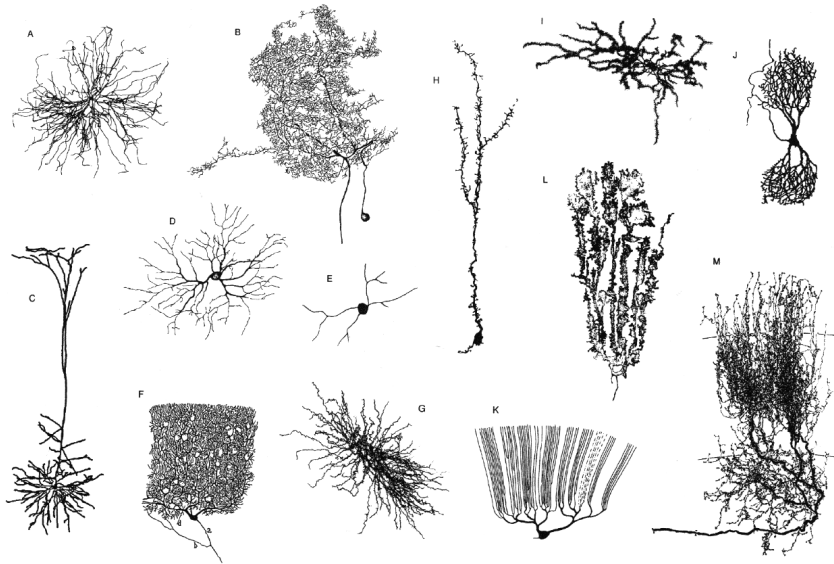
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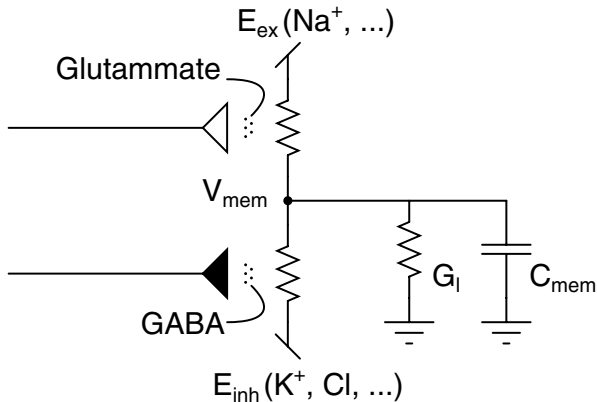
Neurons of the world



Neurons of the world

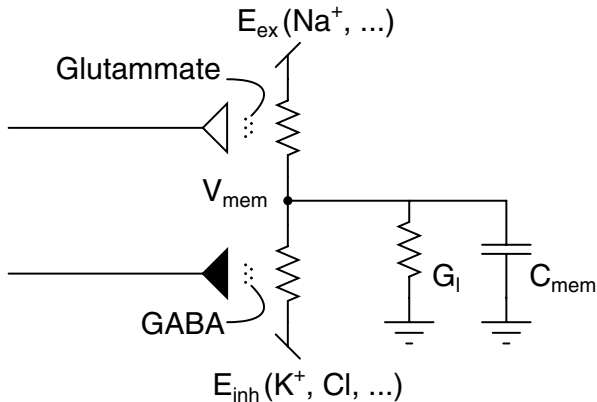


Equivalent Circuit



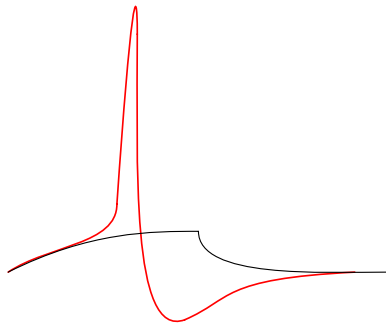
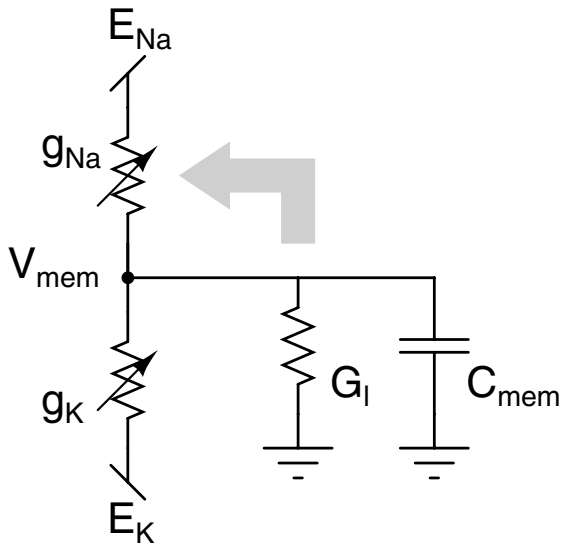
If excitatory input currents are relatively small, the neuron behaves exactly like a first order low-pass filter.

Equivalent Circuit

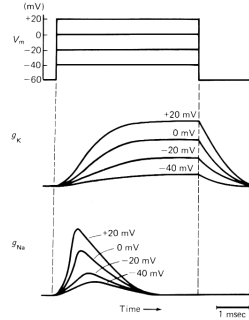
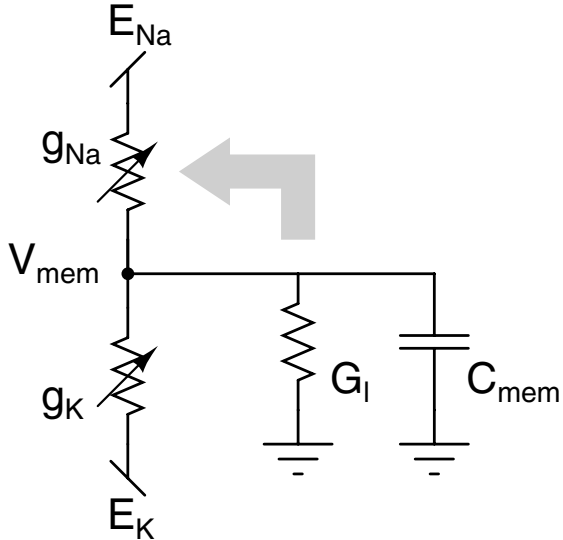


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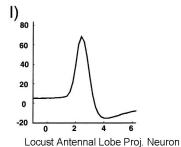
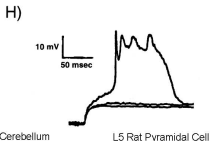
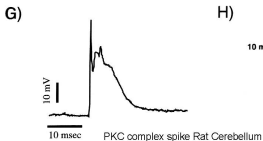
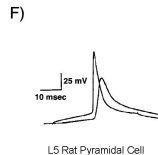
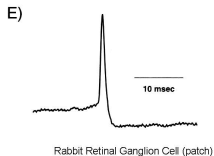
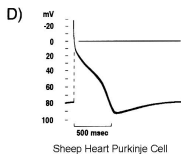
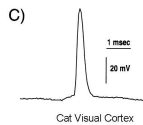
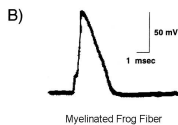
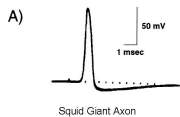
Spike generating mechanism



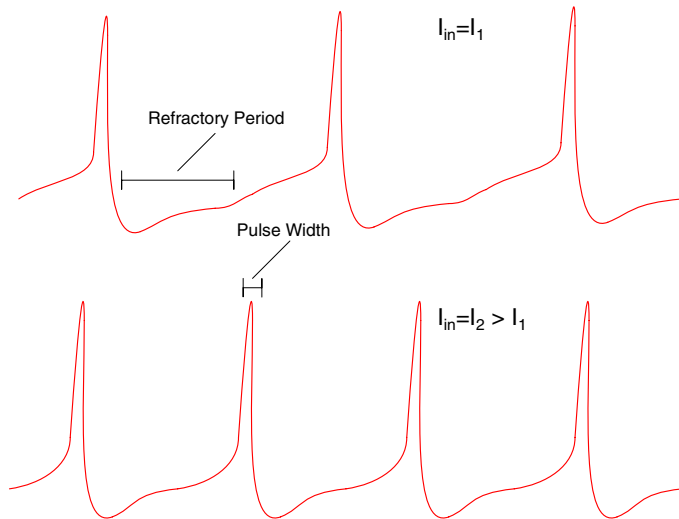
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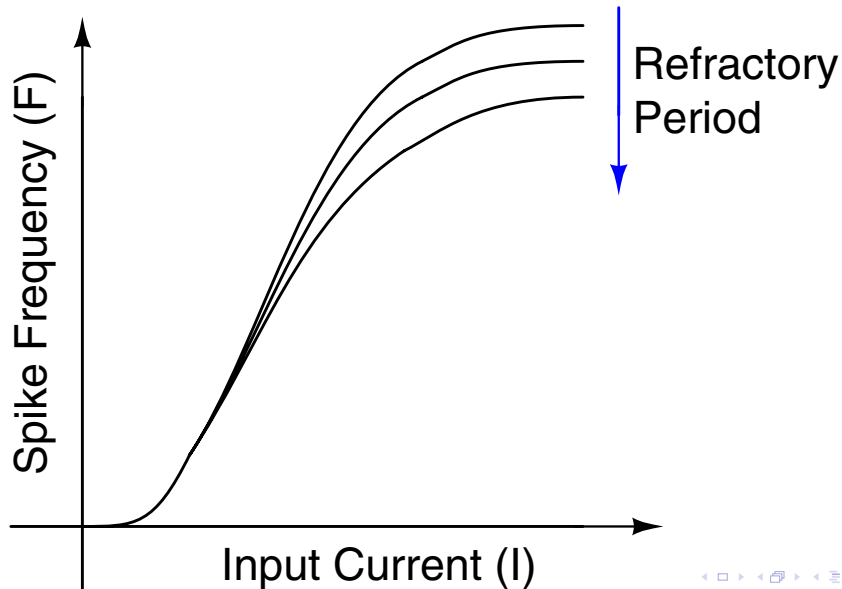
Action potentials of the world



Spike properties



The F-I curve



Hardware implementations of spiking neurons

The first artificial neuron model was proposed in the 1943 by McCulloch and Pitts. Hardware implementations of this model date almost back to the same period.

Hardware implementations of spiking neurons

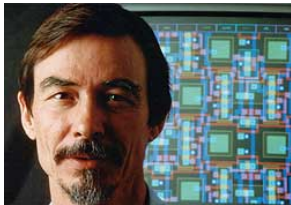
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Hardware implementations of *spiking* neurons are relatively new.

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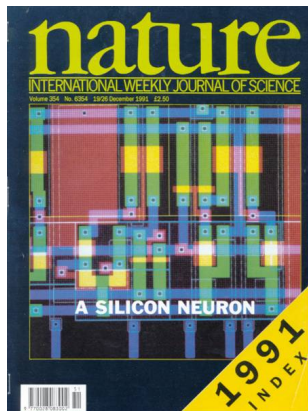
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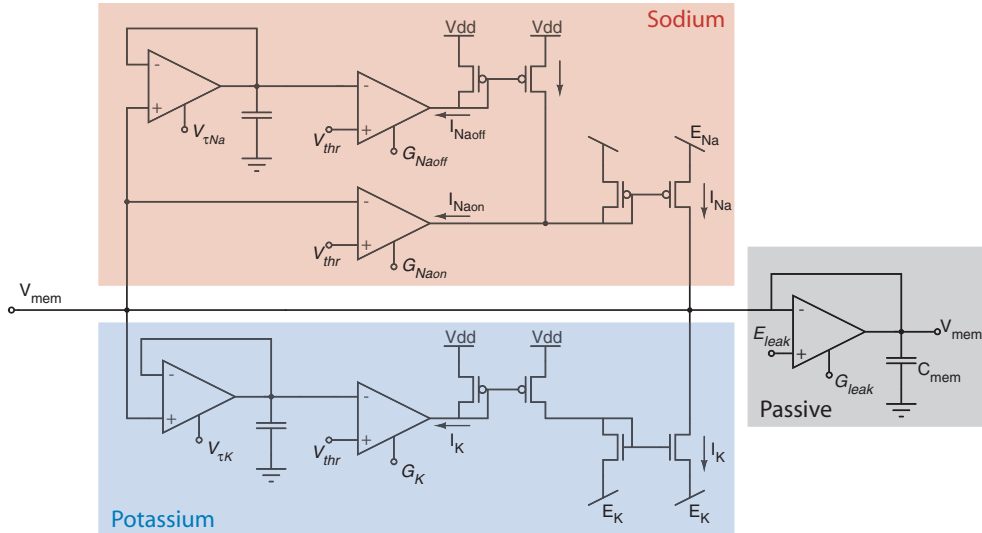
One of the most influential circuits that implements an *integrate and fire* (I&F) model of a neuron was the Axon-Hillock Circuit, proposed by Carver Mead in the late **1980s**.

Conductance-based models of spiking neurons

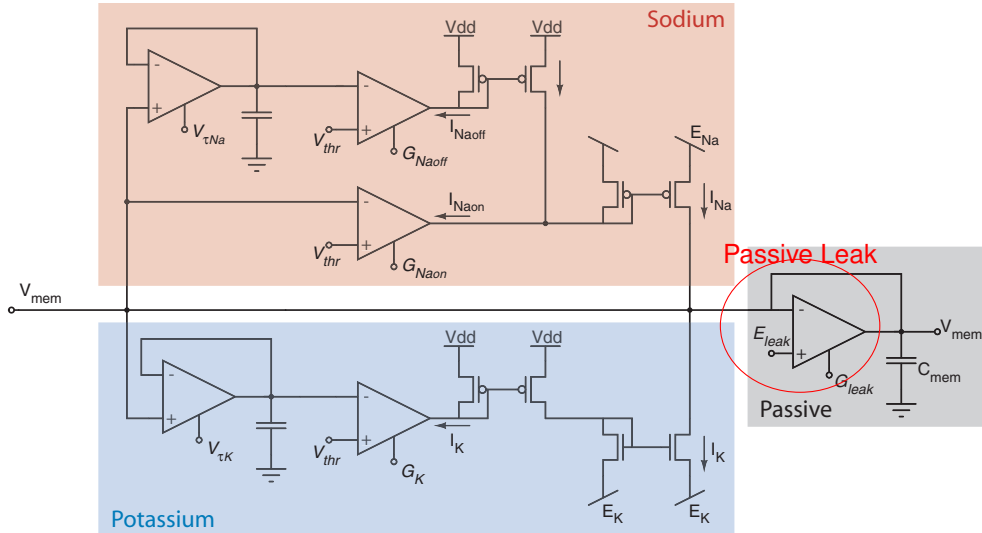


In **1991** Misha Mahowald and Rodney Douglas proposed a conductance-based silicon neuron and showed that it had properties remarkably similar to those of real cortical neurons.

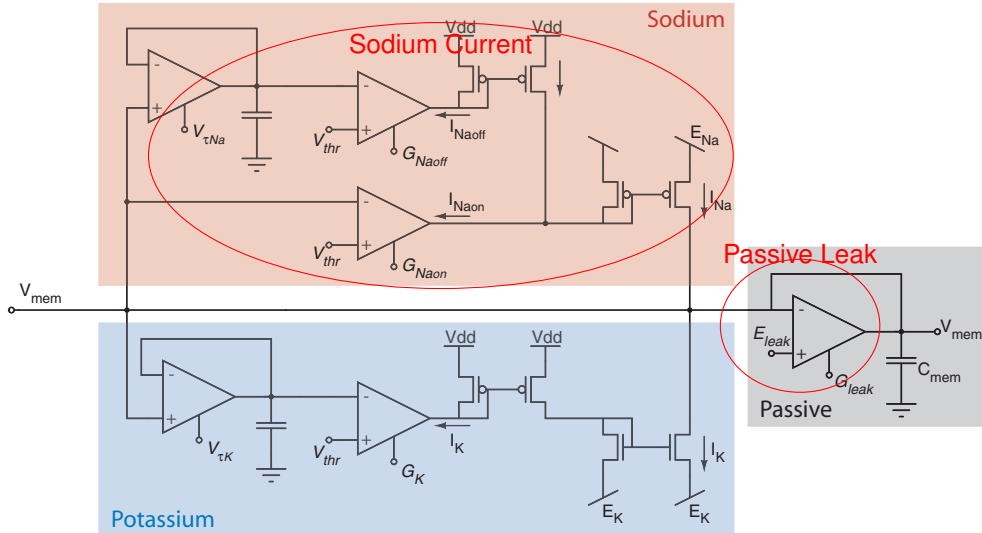
Conductance based Si-Neurons



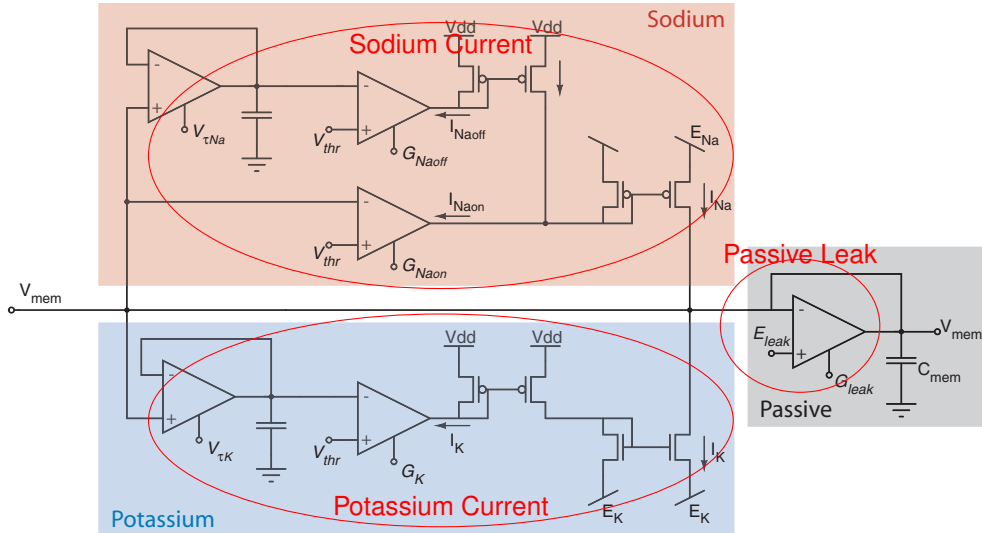
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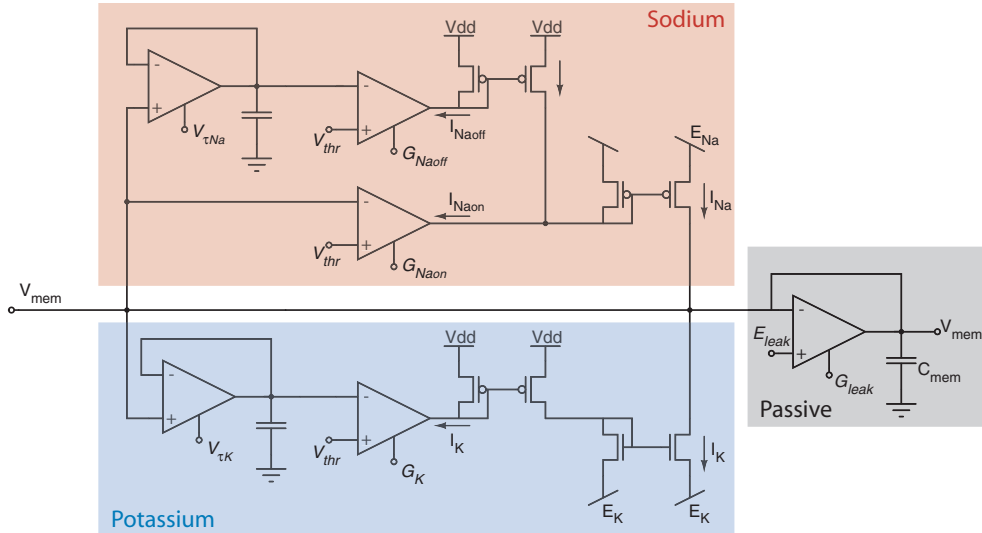
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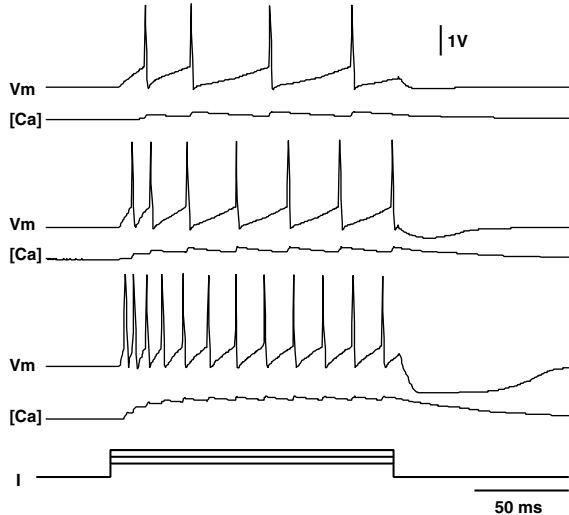


Conductance based Si-Neurons



Conductance based Si-Neurons

Silicon neuron's measurements



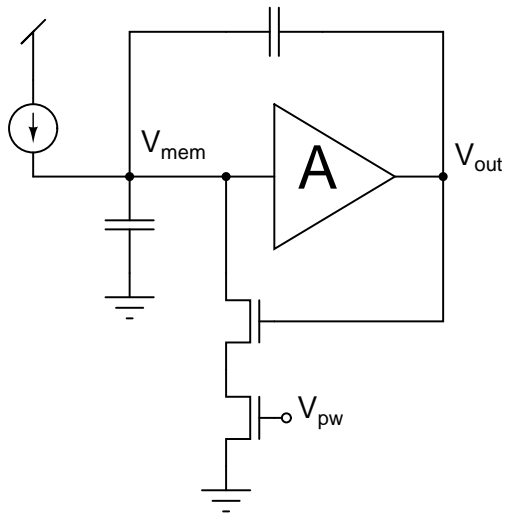
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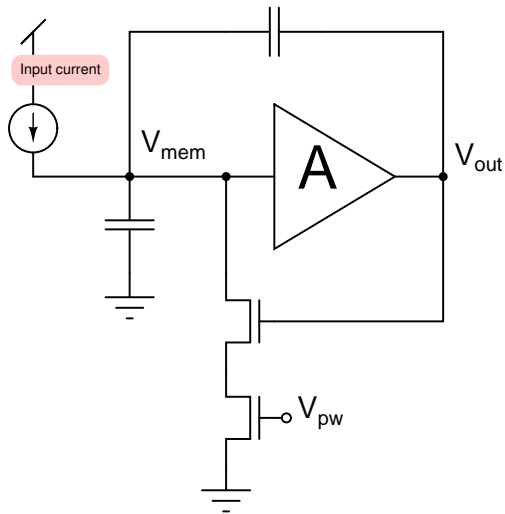
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- **Integrate and fire models**
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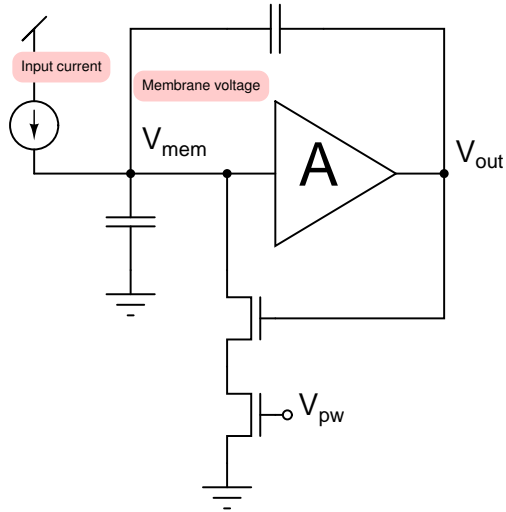
The Axon-Hillock Circuit



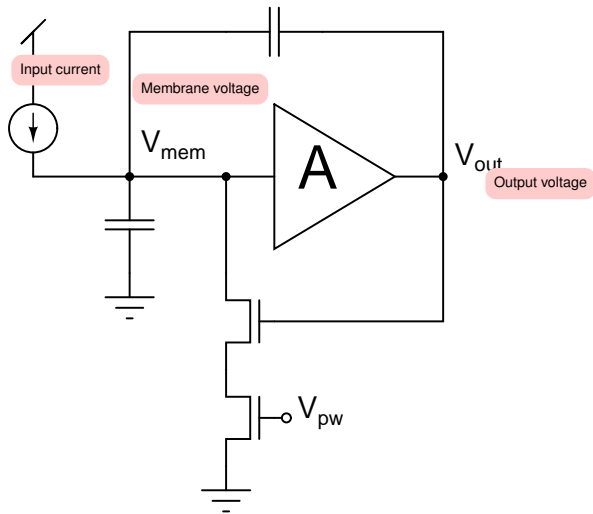
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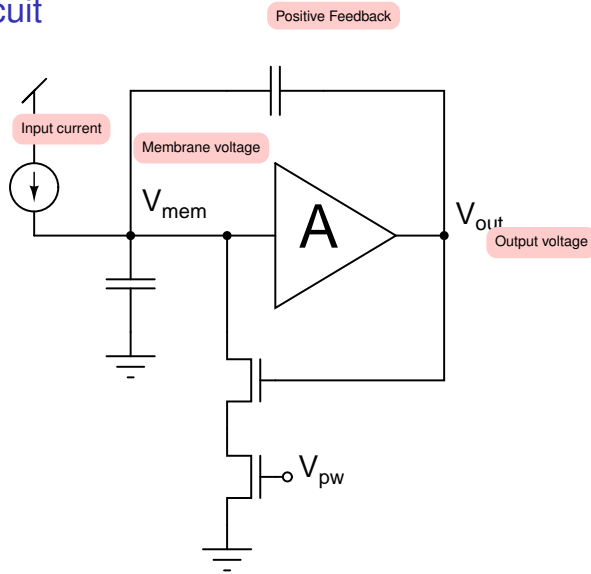
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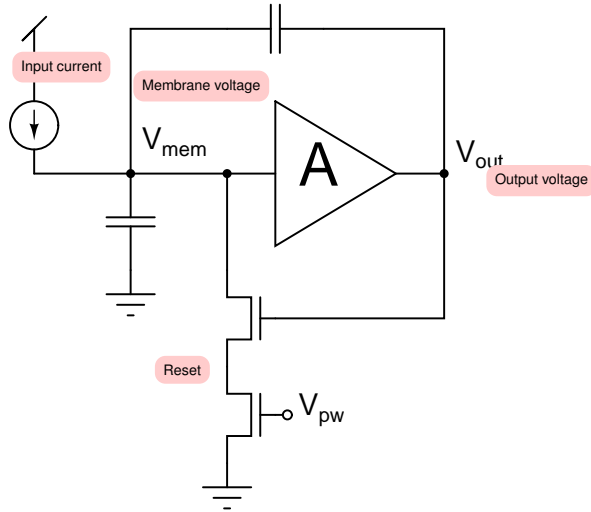
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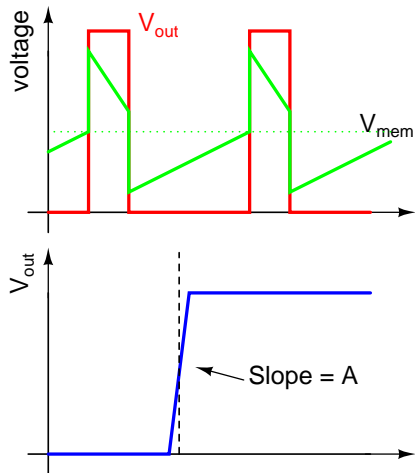
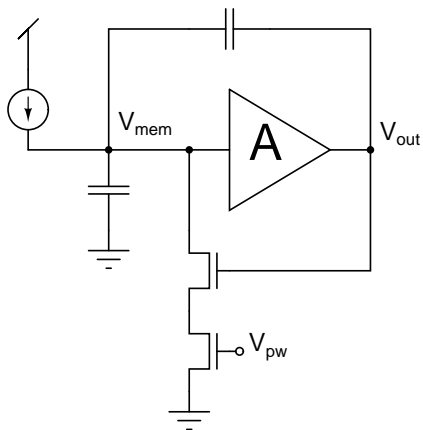
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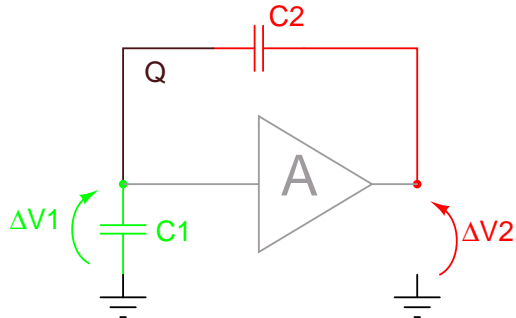
Capacitive Divider

Given the change ΔV_2 , what is ΔV_1 ?

$$Q = C_1 V_1 + C_2 (V_1 - V_2) = \text{constant}$$

$$C_1 \Delta V_1 + C_2 (\Delta V_1 - \Delta V_2) = 0$$

$$\Delta V_1 = \frac{C_2}{C_1 + C_2} \Delta V_2$$



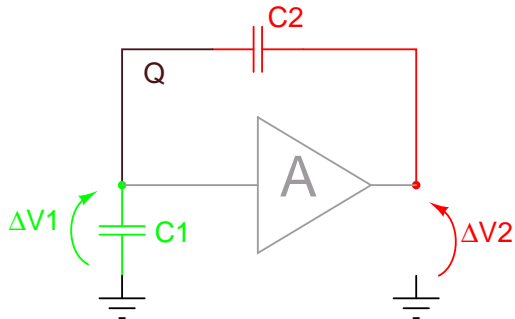
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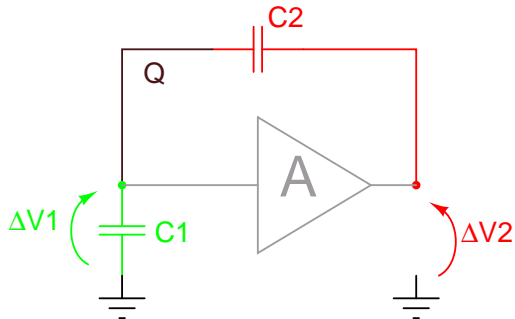
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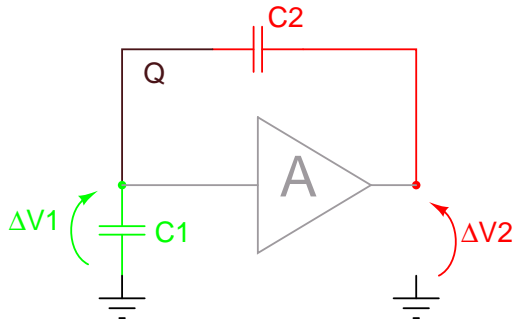
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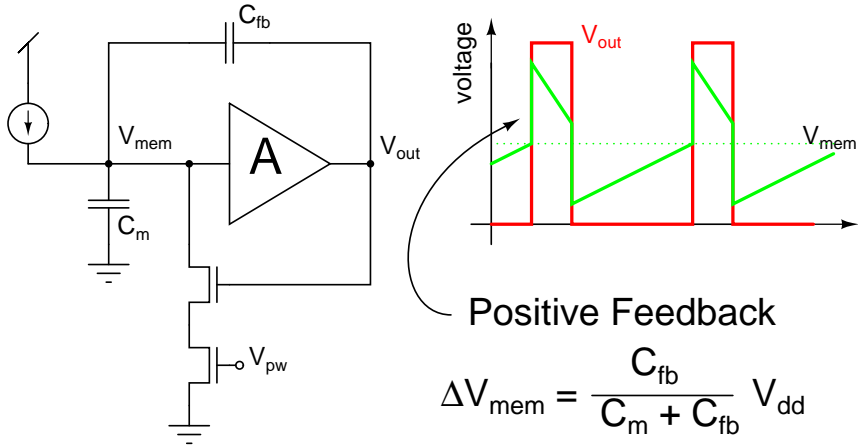
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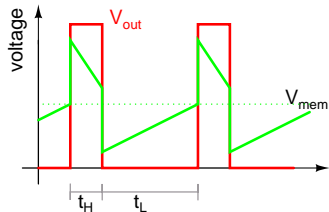
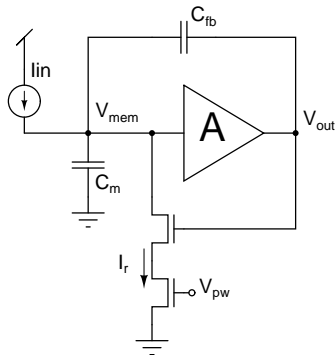
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Positive Feedback



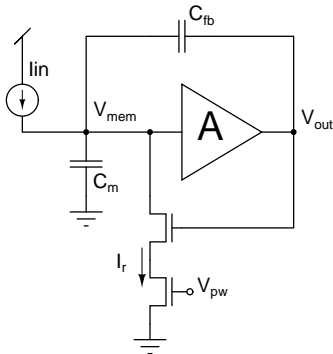
Axon-Hillock Circuit Dynamics



$$t_L = \frac{C_{fb} + C_m}{I_{in}} \Delta V_{mem} = \frac{C_{fb}}{I_{in}} V_{dd}$$

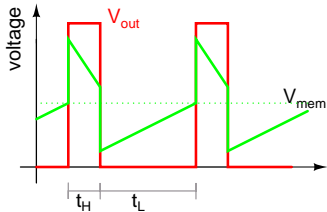
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Axon-Hillock Circuit Dynamics



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Frequency $\propto I_{in}$

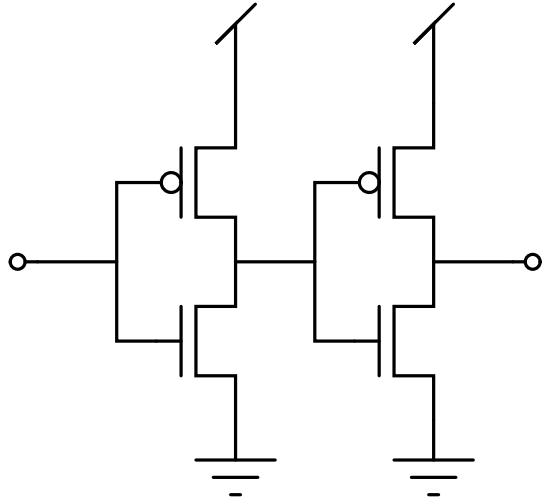
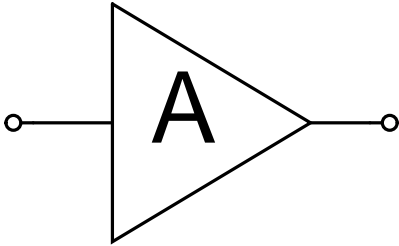


$$t_H = \frac{C_{fb} + C_m}{I_r - I_{in}} \Delta V_{mem} = \frac{C_{fb}}{I_r - I_{in}} V_{dd}$$

Pulse width $\propto 1/I_r$ for $I_r \gg I_{in}$

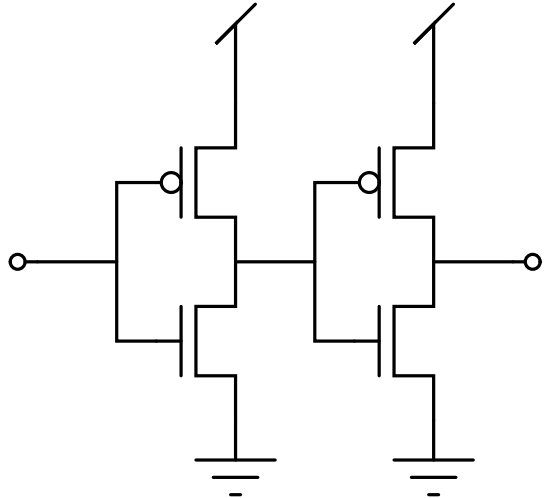
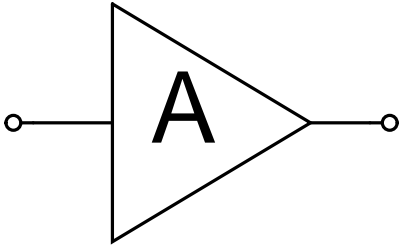
Gain

How to make voltage gain

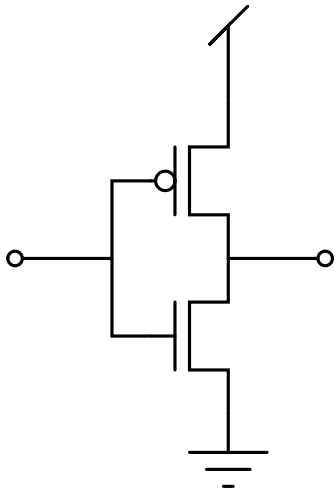


Gain

How to make voltage gain



Power Dissipation

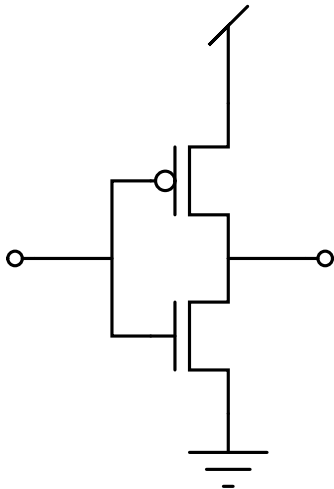


The Axon-Hillock circuit is very compact and allows for implementations of dense arrays of silicon neurons

BUT

it has a major drawback:

Power Dissipation

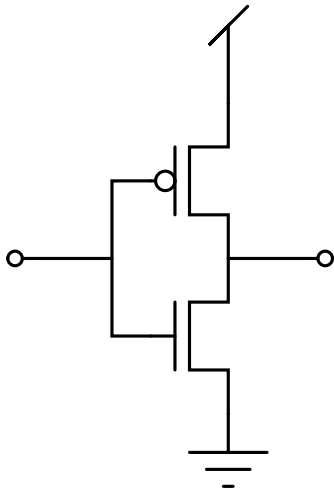


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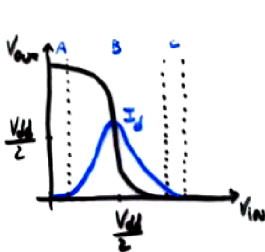


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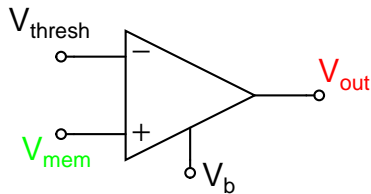
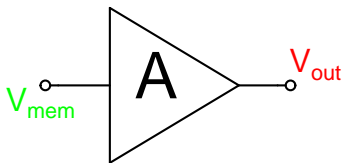
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During the time when an inverter switches, a large amount of current flows from V_{dd} to Gnd .

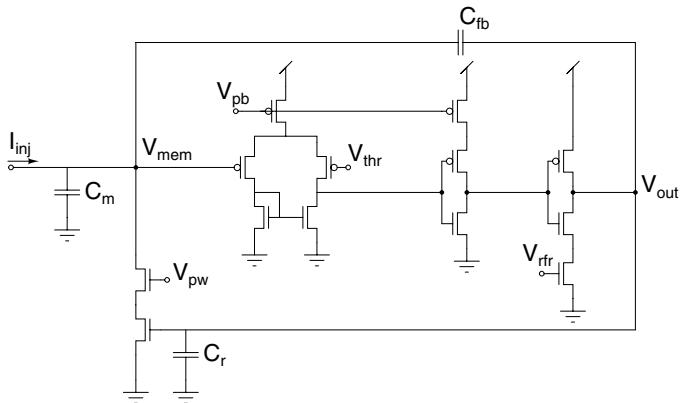


	$\frac{dH}{dt}$	$-\frac{dH}{dt}$
A:	ON	OFF
B:	ON	ON
C:	OFF	ON

Another way to make gain

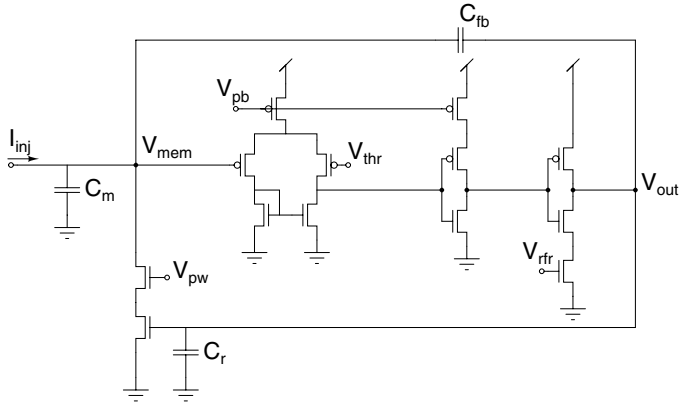


A more elaborate I&F circuit



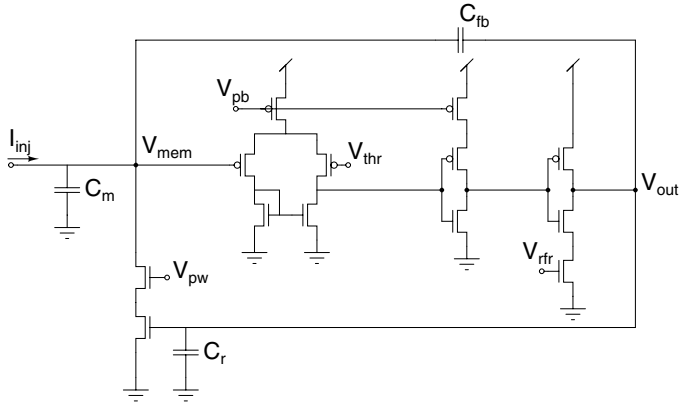
This circuit is low-power, has an explicit voltage threshold, and models the refractory period of real spikes.

A more elaborate I&F circuit



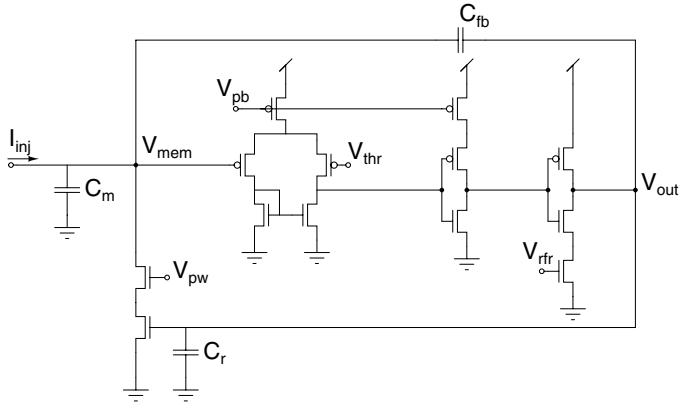
- V_{thr} sets the spiking voltage threshold
- V_{rfr} sets the refractory period length
- V_{pw} sets the pulse width

A more elaborate I&F circuit



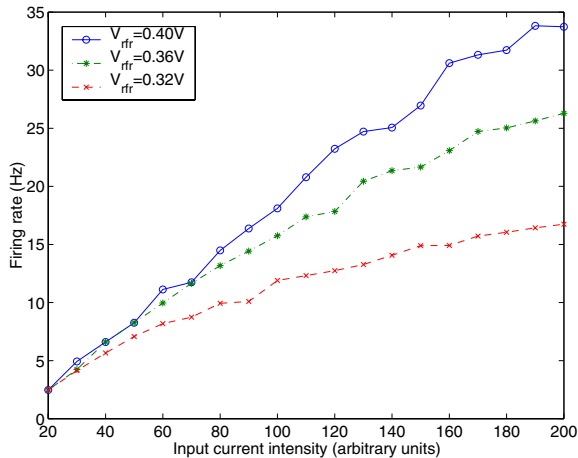
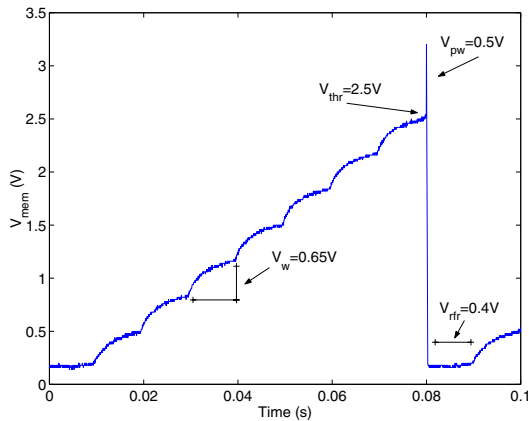
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A more elaborate I&F circuit



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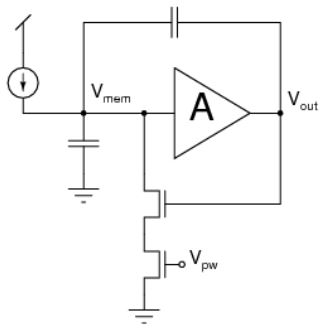
I&F circuit output



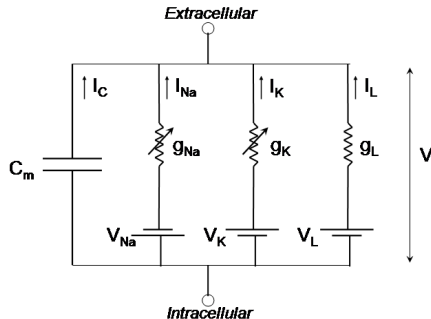
Conductance-based models

Integrate and Fire vs Hodgkin-Huxley

Traditionally there have been two main classes of neuron models:



Integrate and fire (I-C)



Conductance-based (R-C)

Conductance-based models

Integrate and Fire vs Hodgkin-Huxley

But recently proposed models bridge the gap between the two:

Conductance-based models

Integrate and Fire vs Hodgkin-Huxley

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J Neurophysiol 92: 959–976, 2004;
10.1152/jn.00190.2004.

Generalized Integrate-and-Fire Models of Neuronal Activity Approximate
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J Neurophysiol 99: 656–666, 2008.

First published December 5, 2007; doi:10.1152/jn.01107.2007.

Dynamic I - V Curves Are Reliable Predictors of Naturalistic Pyramidal-Neuron Voltage Traces

Laurent Badel,¹ Sandrine Lefort,² Romain Brette,³ Carl C. H. Petersen,² Wulfram Gerstner,¹
and Magnus J. E. Richardson^{1,4}

Biol Cybern (2008) 99:361–370

DOI 10.1007/s00422-008-0259-4

ORIGINAL PAPER

Biological
Cybernetics

Extracting non-linear integrate-and-fire models from experimental data using dynamic I - V curves

Conductance-based models

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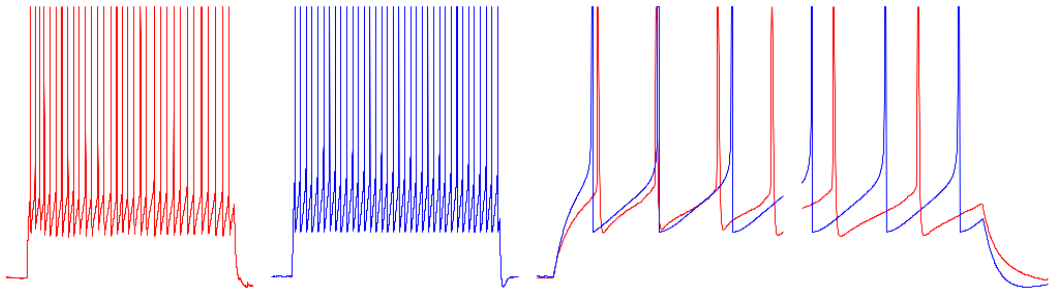
Generalized Integrate and Fire models can account for a very large set of behaviors captured by far more complicated Hodgkin-Huxley models.

$$\frac{d}{dt}u_{mem} = \frac{i_{in}}{C_{mem}} + F(u_{mem})$$

where $F(u_{mem})$ is a non-linear function of $u_{mem}(t)$.

Model neurons

The adaptive exponential I&F neuron model



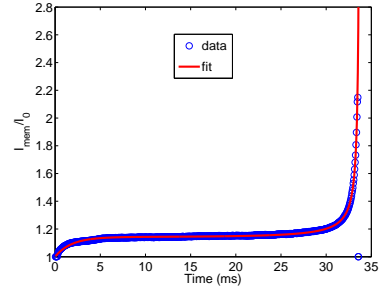
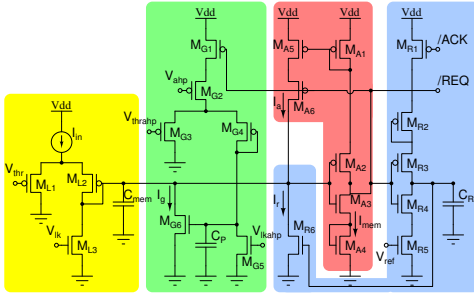
$$C \frac{d}{dt} V + g_L (V - E_L) = I - w + f(V)$$

$$\tau_w \frac{d}{dt} w + w = a(V - E_L)$$

[Brette and Gerstner, 2005]

Silicon neurons

The low power I&F neuron



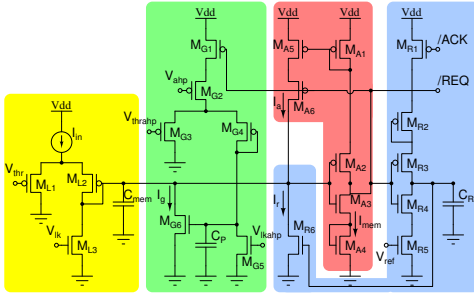
$$\tau \frac{d}{dt} I_{mem} + I_{mem} \approx \frac{I_{thr} I_{in}}{I_{\tau}} - I_g + f(I_{mem})$$

$$\tau_{ahp} \frac{d}{dt} I_g + I_g = \frac{I_{thr} I_{ahp}}{I_{\tau_{ahp}}}$$

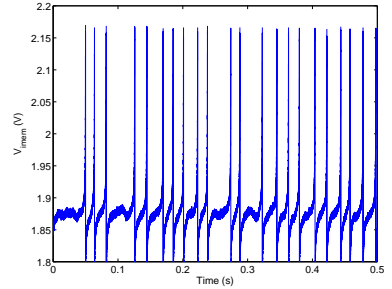
[Indiveri et al., 2010] [Brette and Gerstner, 2005]

Silicon neurons

The low power I&F neuron



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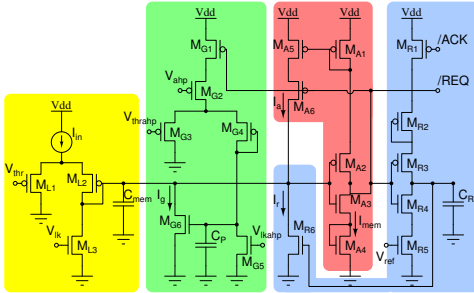


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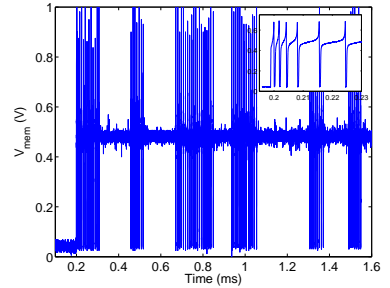
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Silicon neurons

The low power I&F neuron



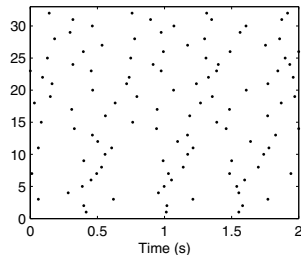
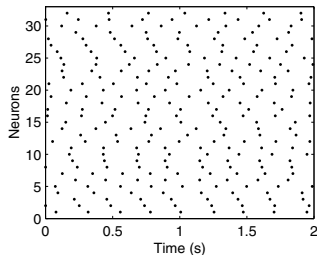
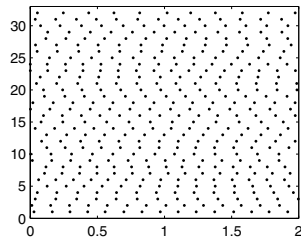
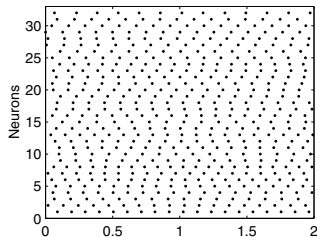
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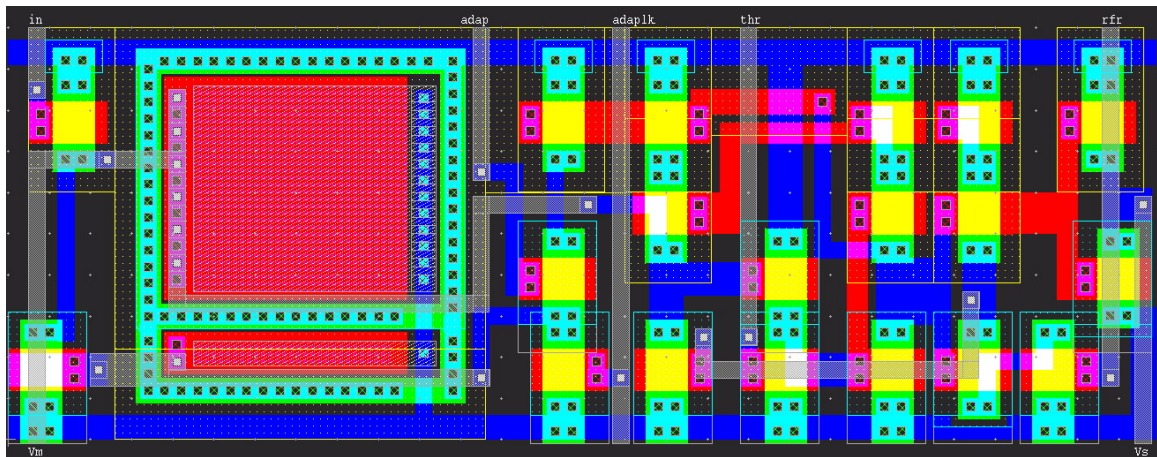
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[Indiveri et al., 2010] [Brette and Gerstner, 2005]

An ultra low-power array of I&F circuits



Silicon neuron layout



Applications

- Basic research
- Neuromorphic Sensors
- Multi-chip sensor-actuator systems
- Computation ?

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