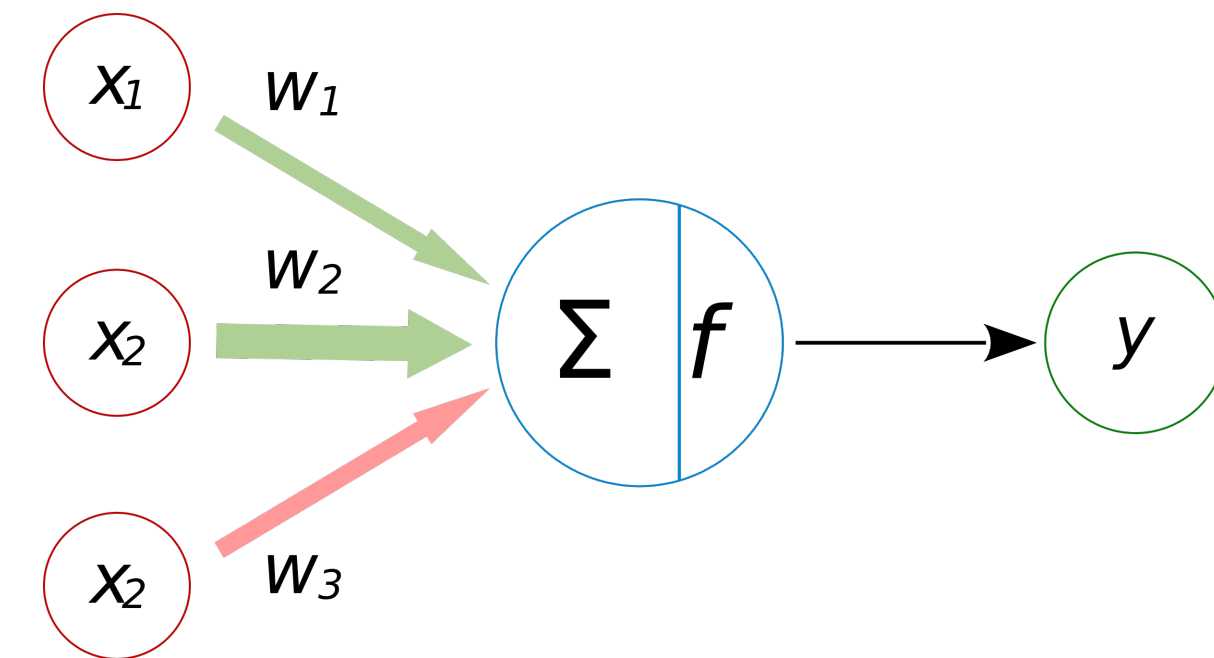
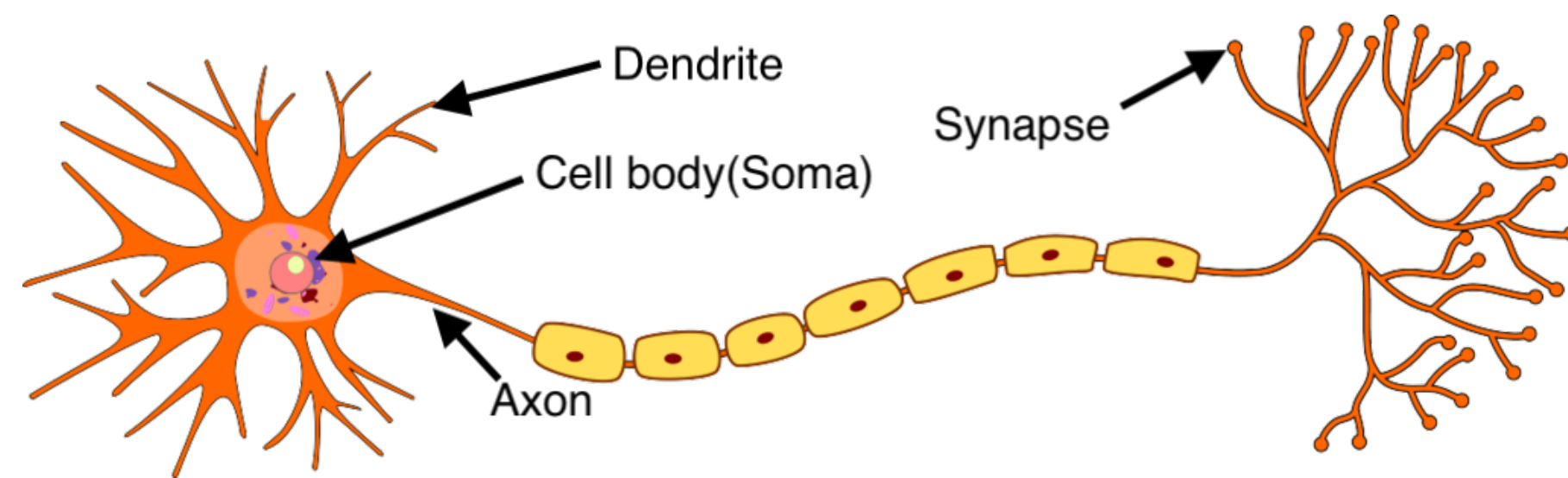


Neuro-inspired Machine Learning And Spiking Neural Networks

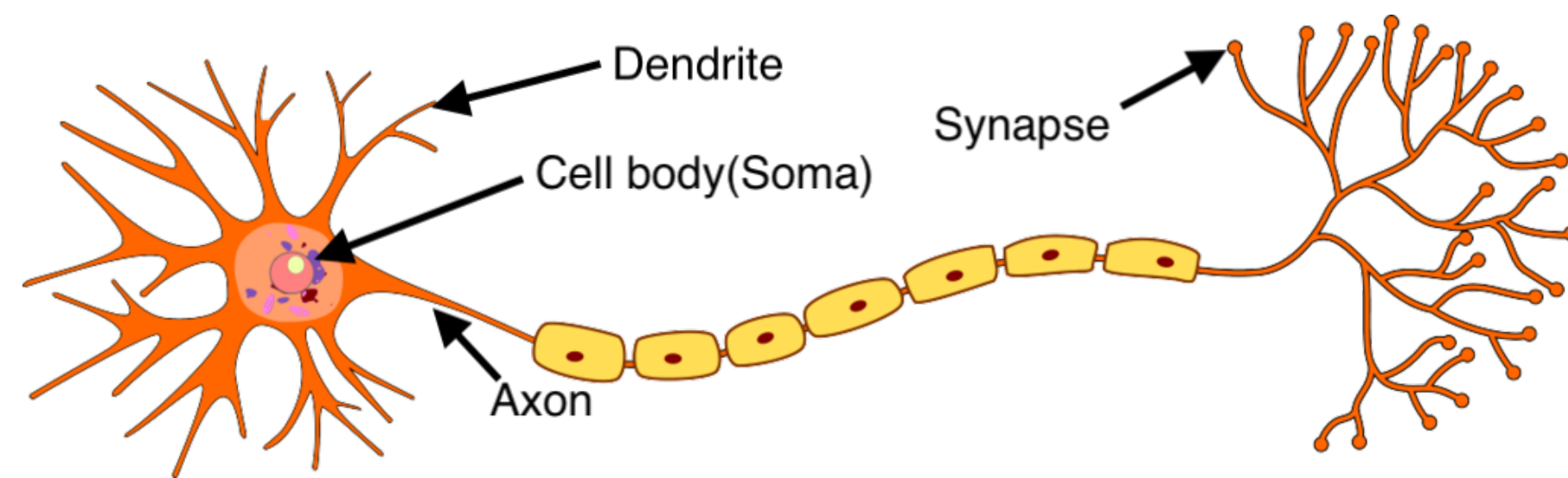
F. De Geeter, D. Ernst & G. Drion



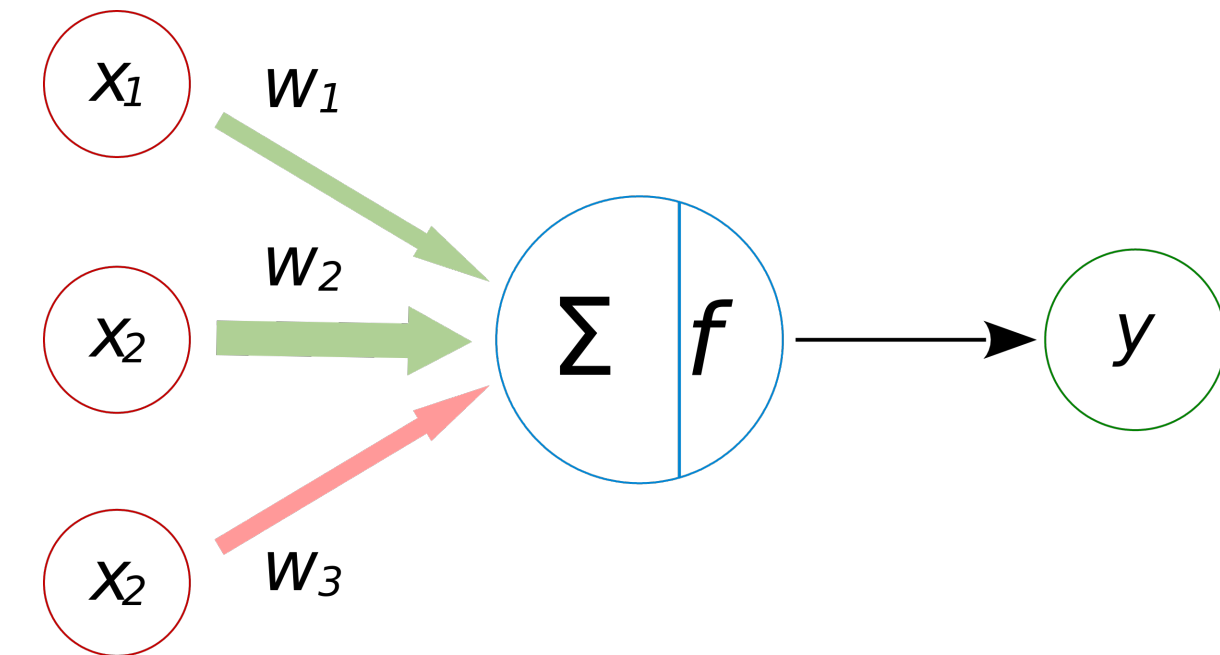
The idea of neural networks comes from the biological brains and neurons



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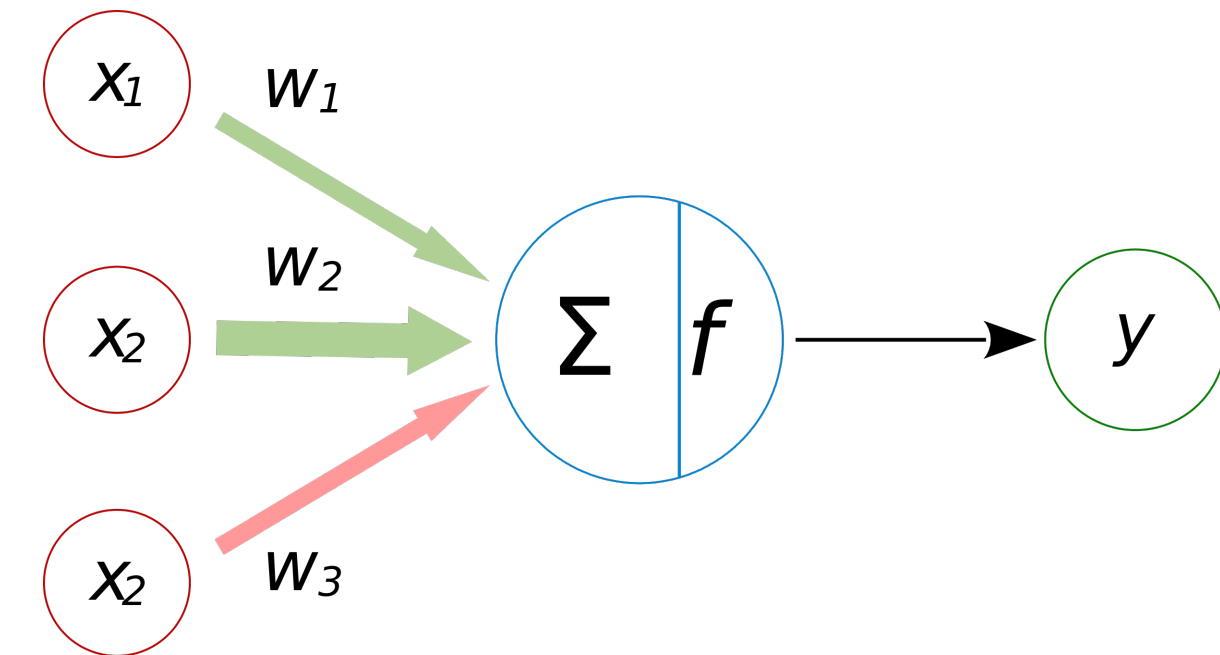
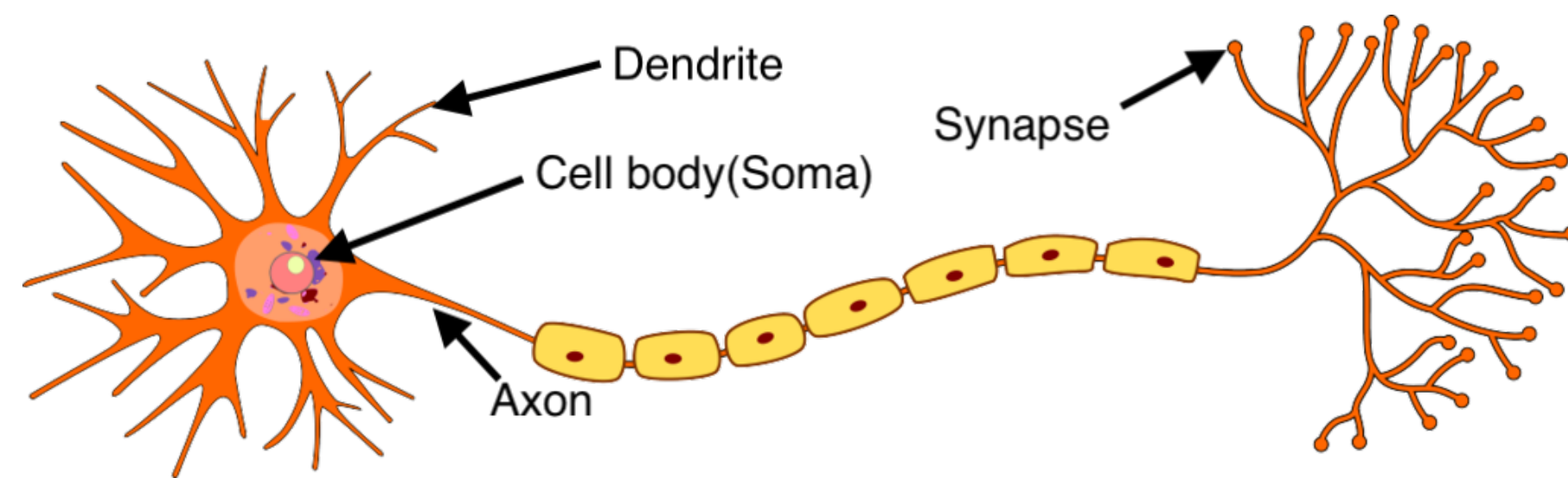
Synapse & Dendrite



Input integration and weighting

$$\hat{x}_i = w_i x_i$$

The idea of neural networks comes from the biological brains and neurons



Synapse & Dendrite

Soma

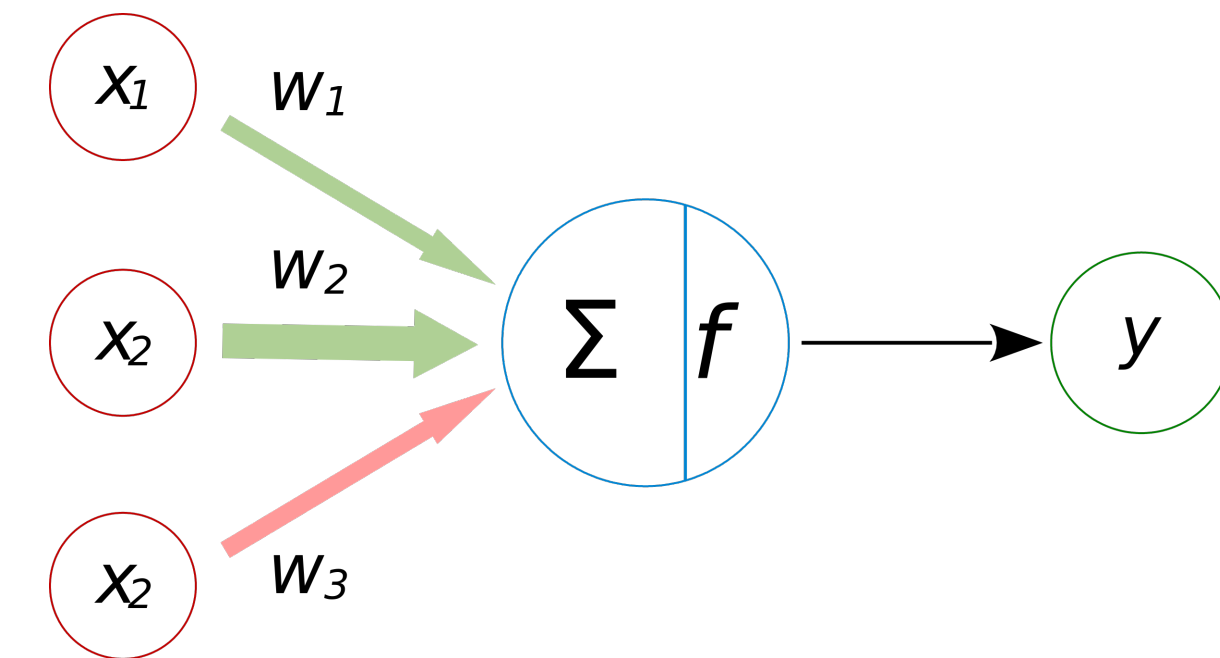
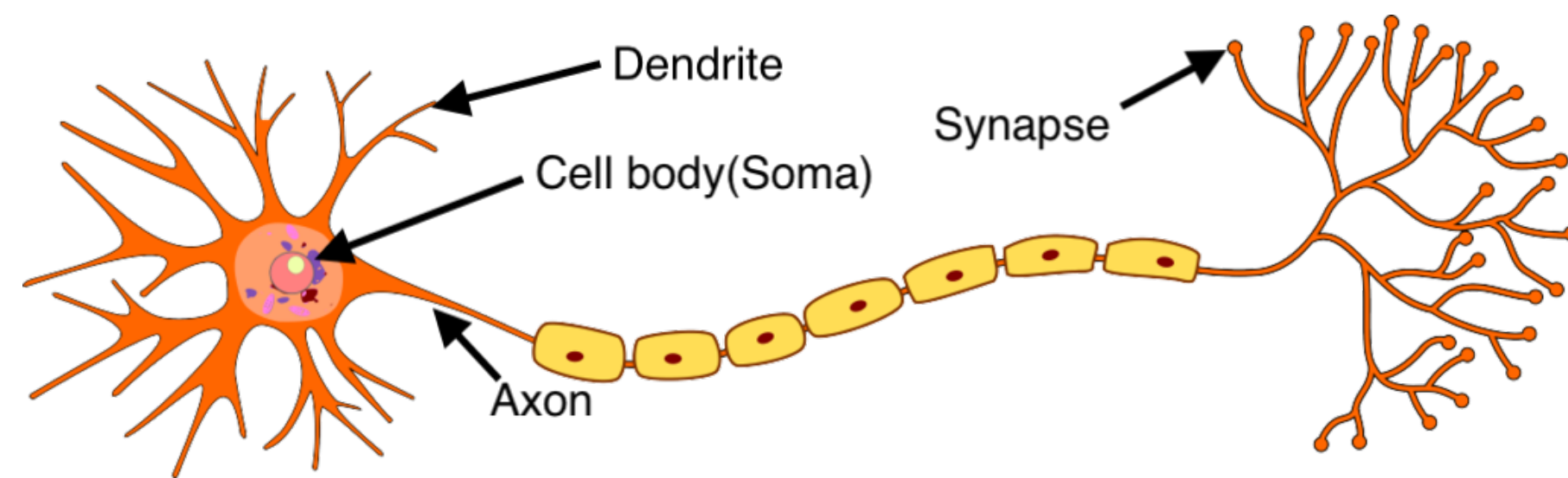
Input integration and weighting

Summation and activation

$$\hat{x}_i = w_i x_i$$

$$y = f\left(\sum_{i=1}^n \hat{x}_i\right)$$

The idea of neural networks comes from the biological brains and neurons



Synapse & Dendrite

Soma

Axon

Input integration and weighting

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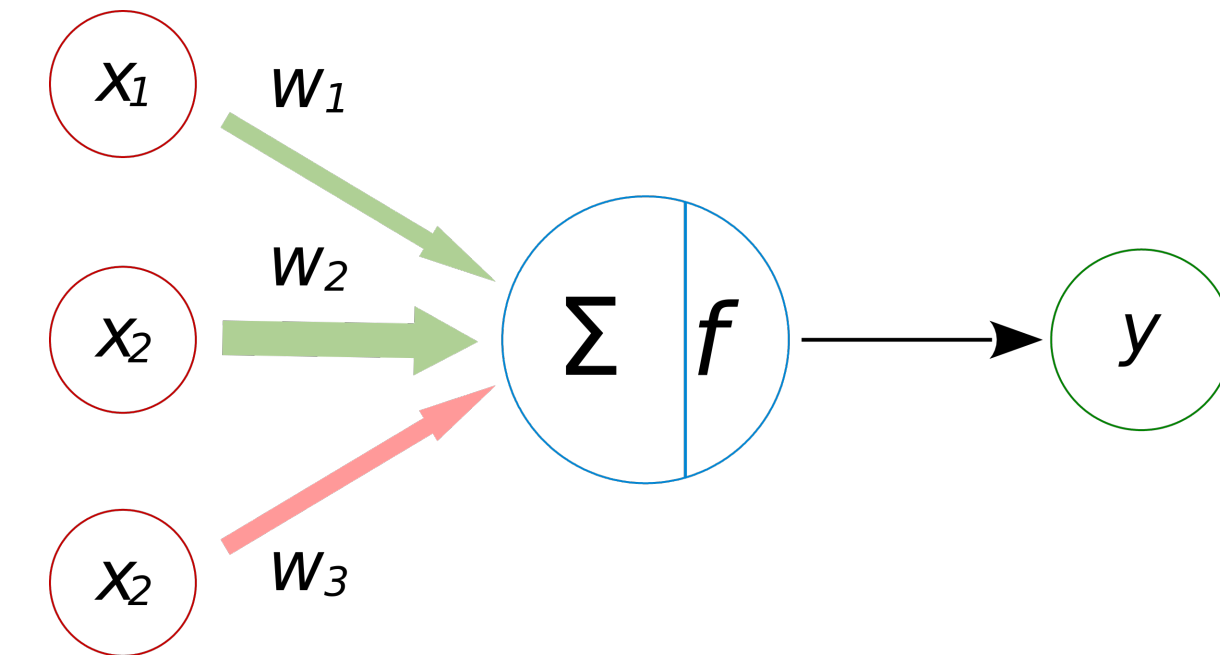
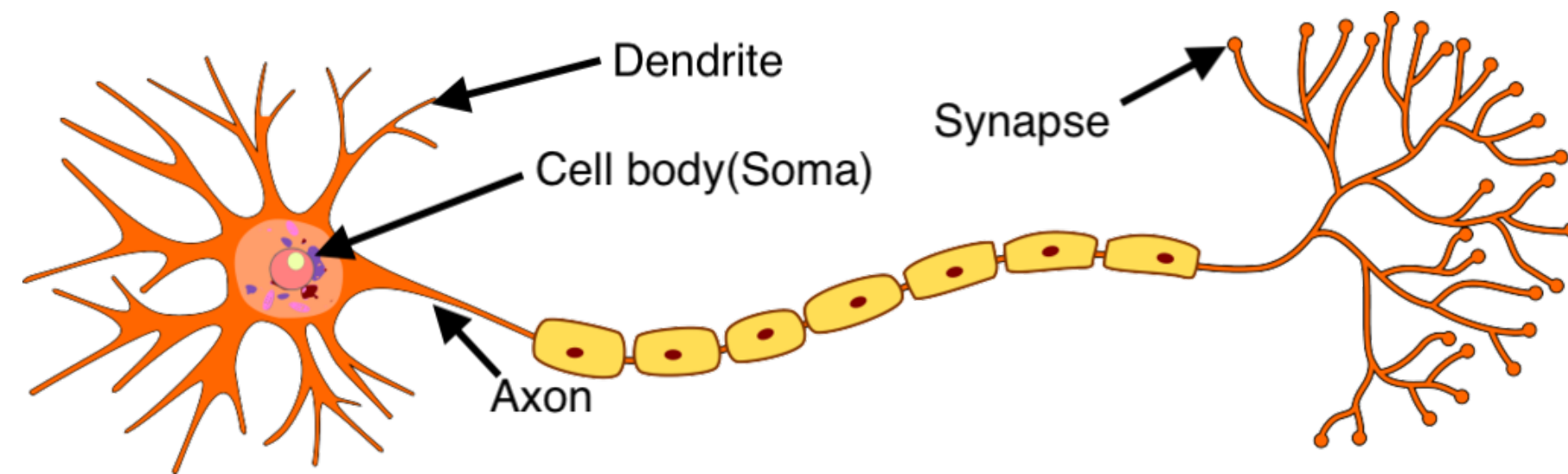
Output transmission

$$\hat{x}_i = w_i x_i$$

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$$x_j^{l+1} = y^l$$

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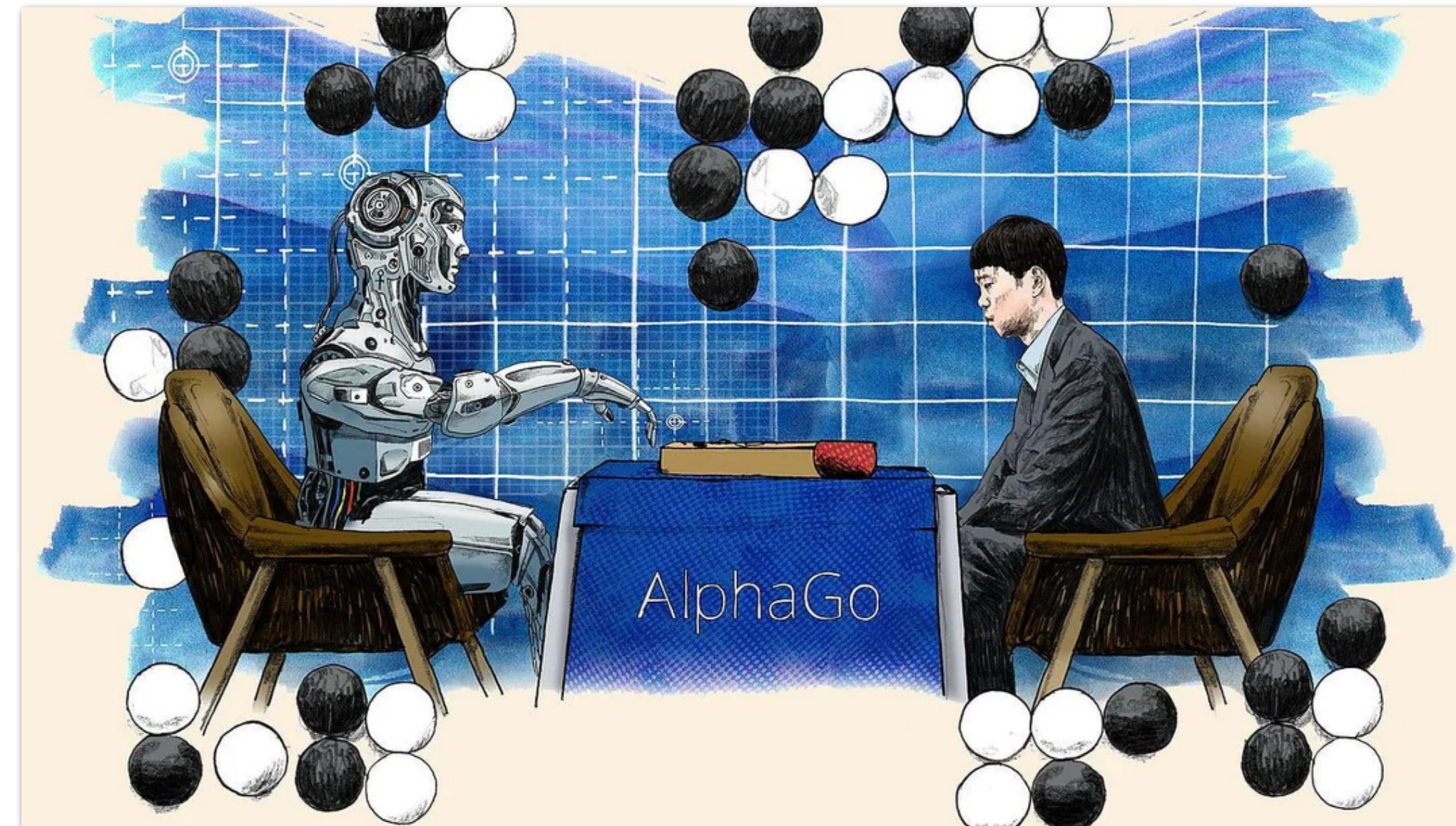
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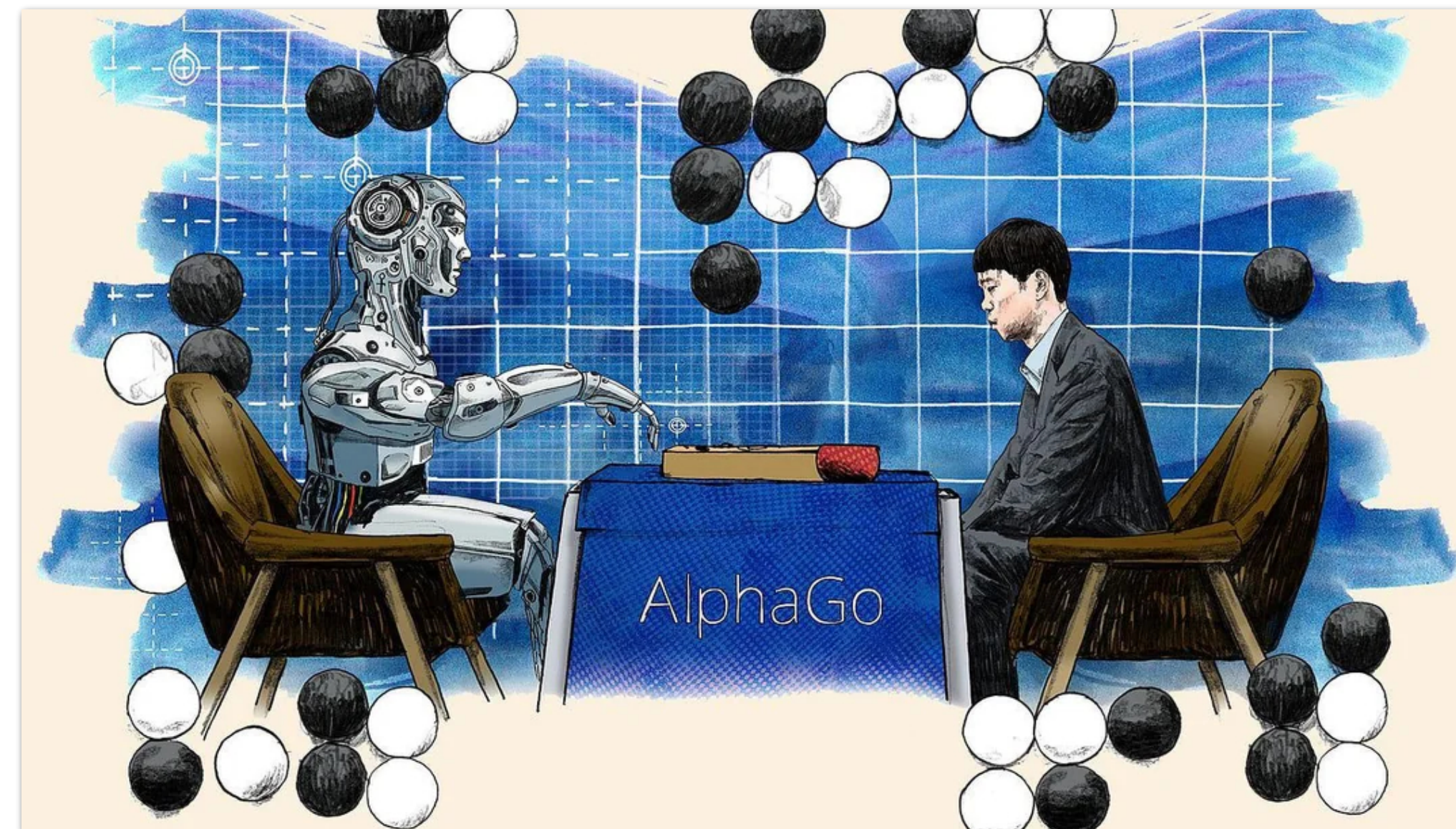
➡ **Simple** units to build **complex** networks

Current AI's are performant



Current AI's are performant But not energy-efficient

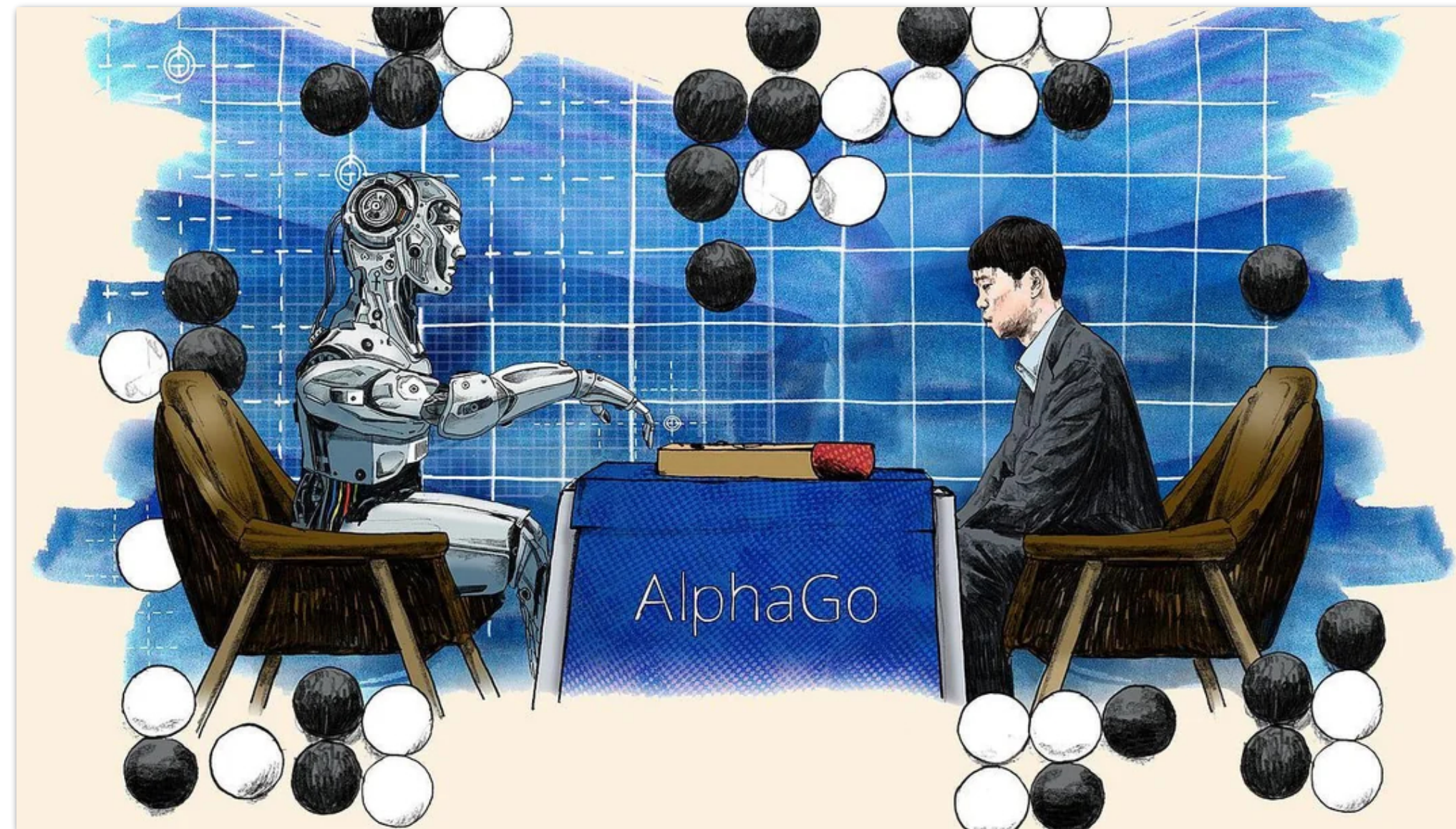
AlphaGo:
 ± 1 MegaWatts



L. Sedol's brain:
 ± 20 Watts

Current AI's are performant But not energy-efficient

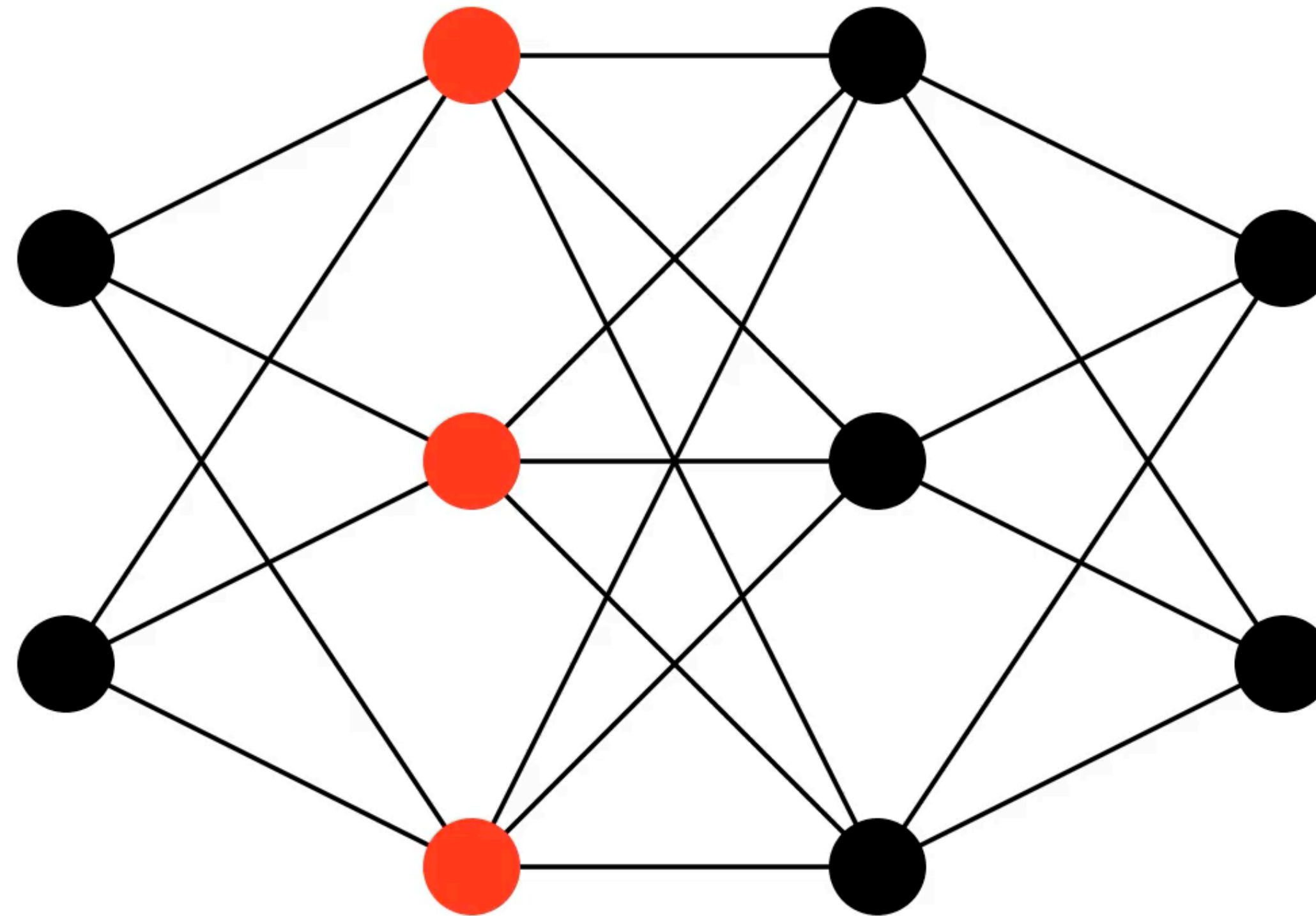
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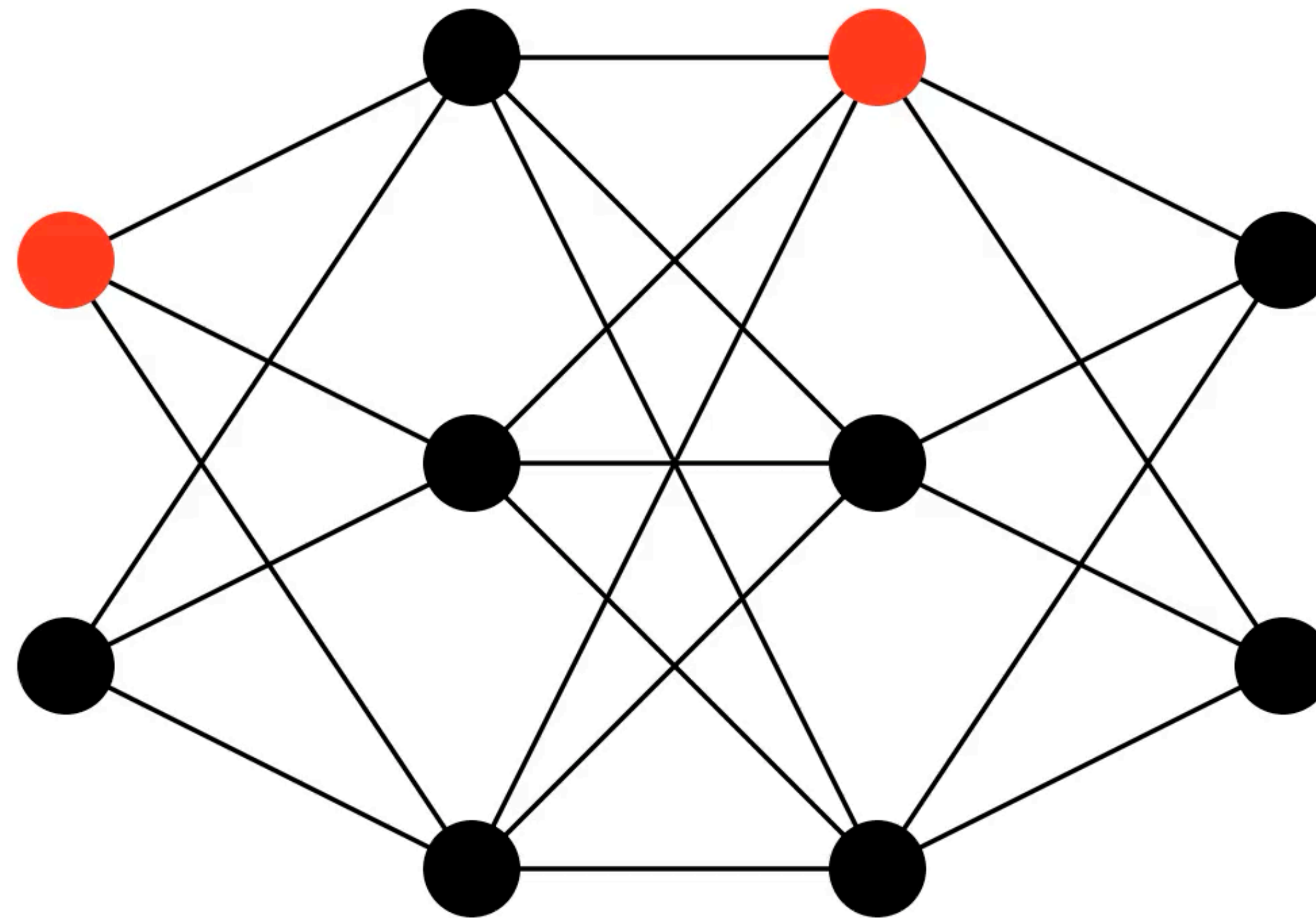
L. Sedol's brain:
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Need more energy-efficiency in some applications (e.g. embedded systems)

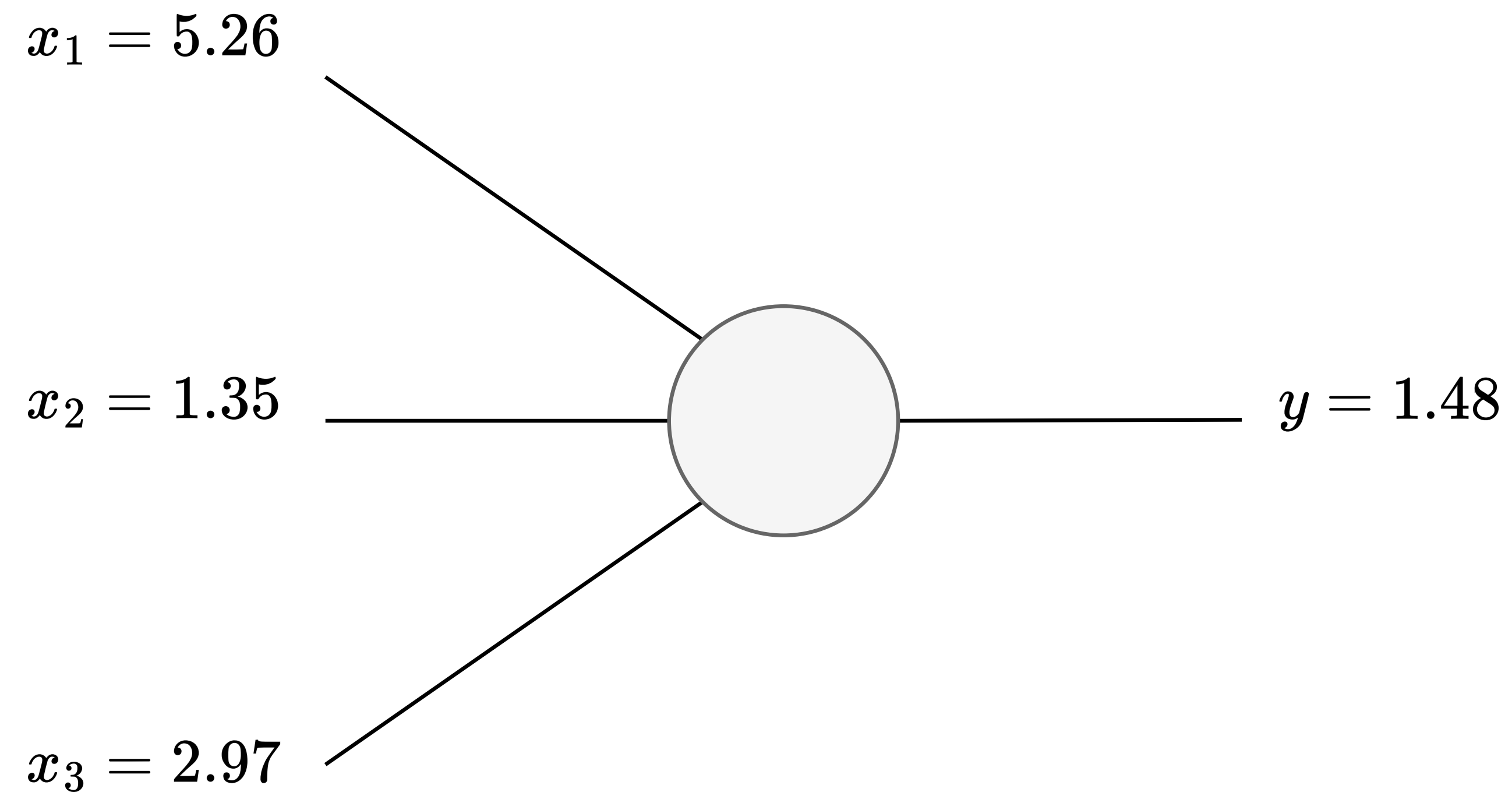
Artificial neurons are clock-driven,



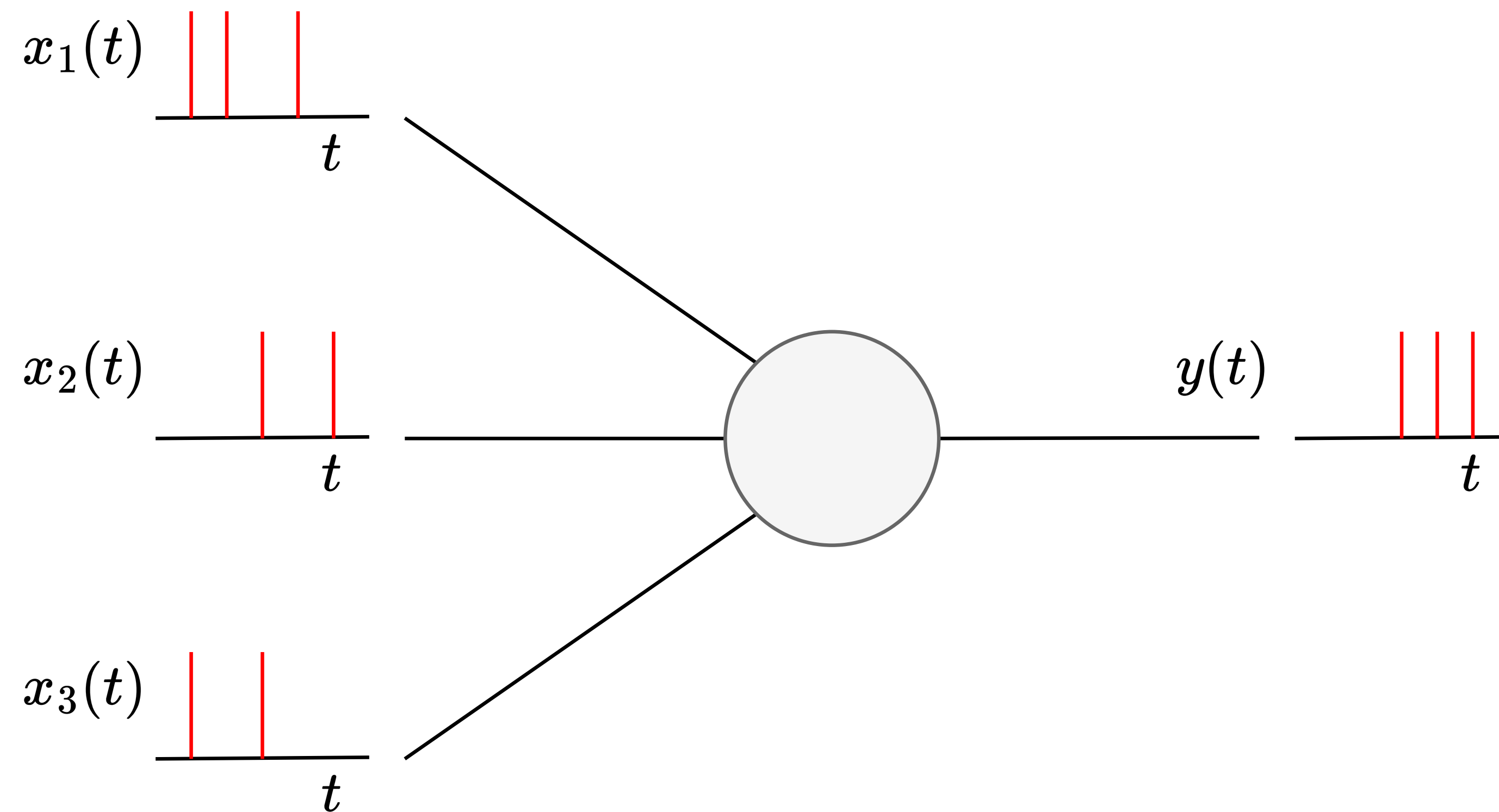
Artificial neurons are clock-driven,
Biological neurons are event-driven



Artificial neurons output numbers,



Artificial neurons output numbers, Biological neurons output events



Good results have been obtained
with spiking neural networks

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- Training
 - Hard to train
 - But more and more progress

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- Performance
 - Comparable to ANNs on simple benchmarks
 - Less performant for more complex ones
- Energy-efficiency
 - Less than 1 Watt for Loihi 2
 - For ± 1 million neurons and ± 120 million synapses

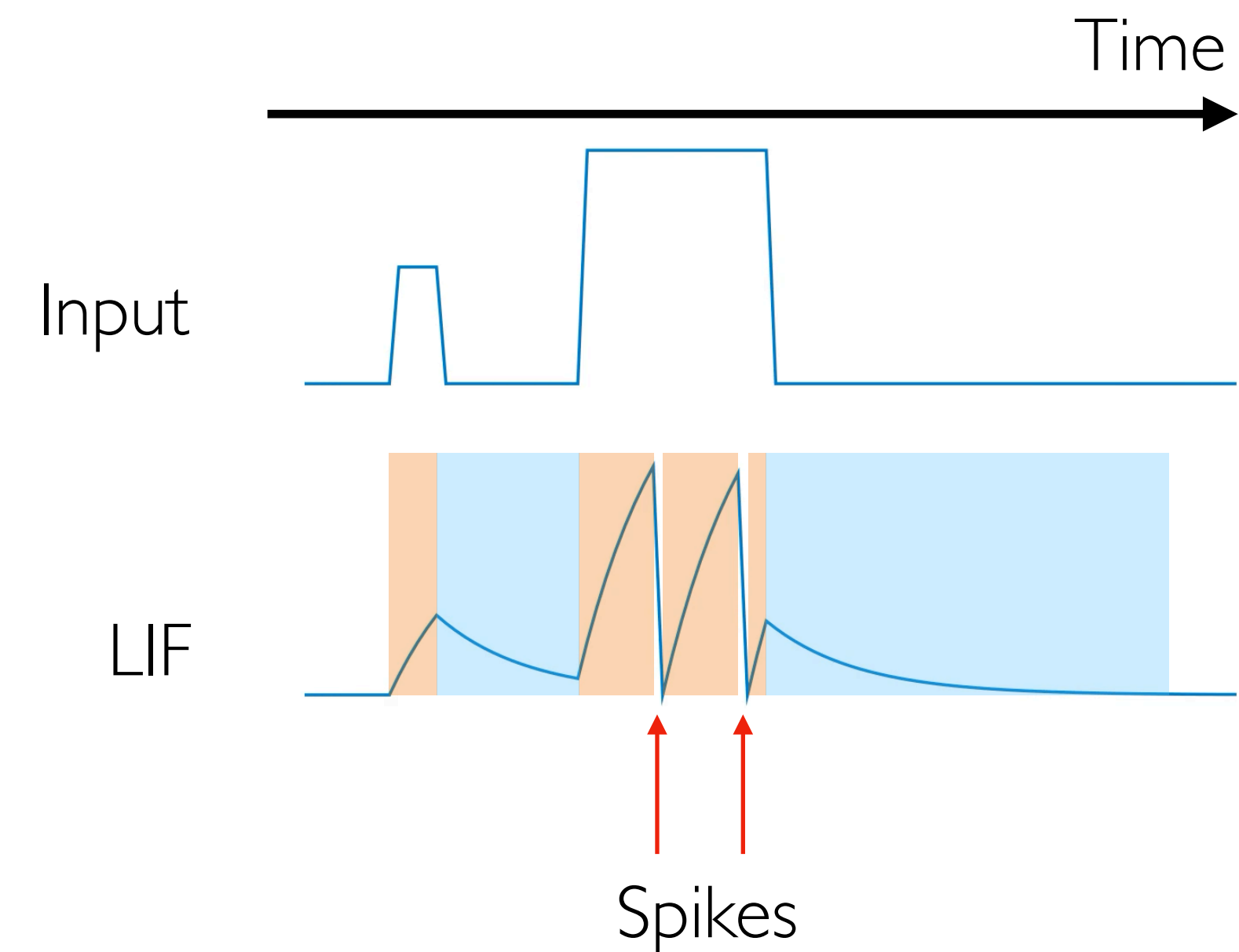


LIF neurons are used in SNNs

- Leaky Integrate-and-Fire
 - Simple leaky integrator with a reset
 - Spikes manually generated
 - Sub-threshold dynamic is purely linear

LIF neurons are used in SNNs

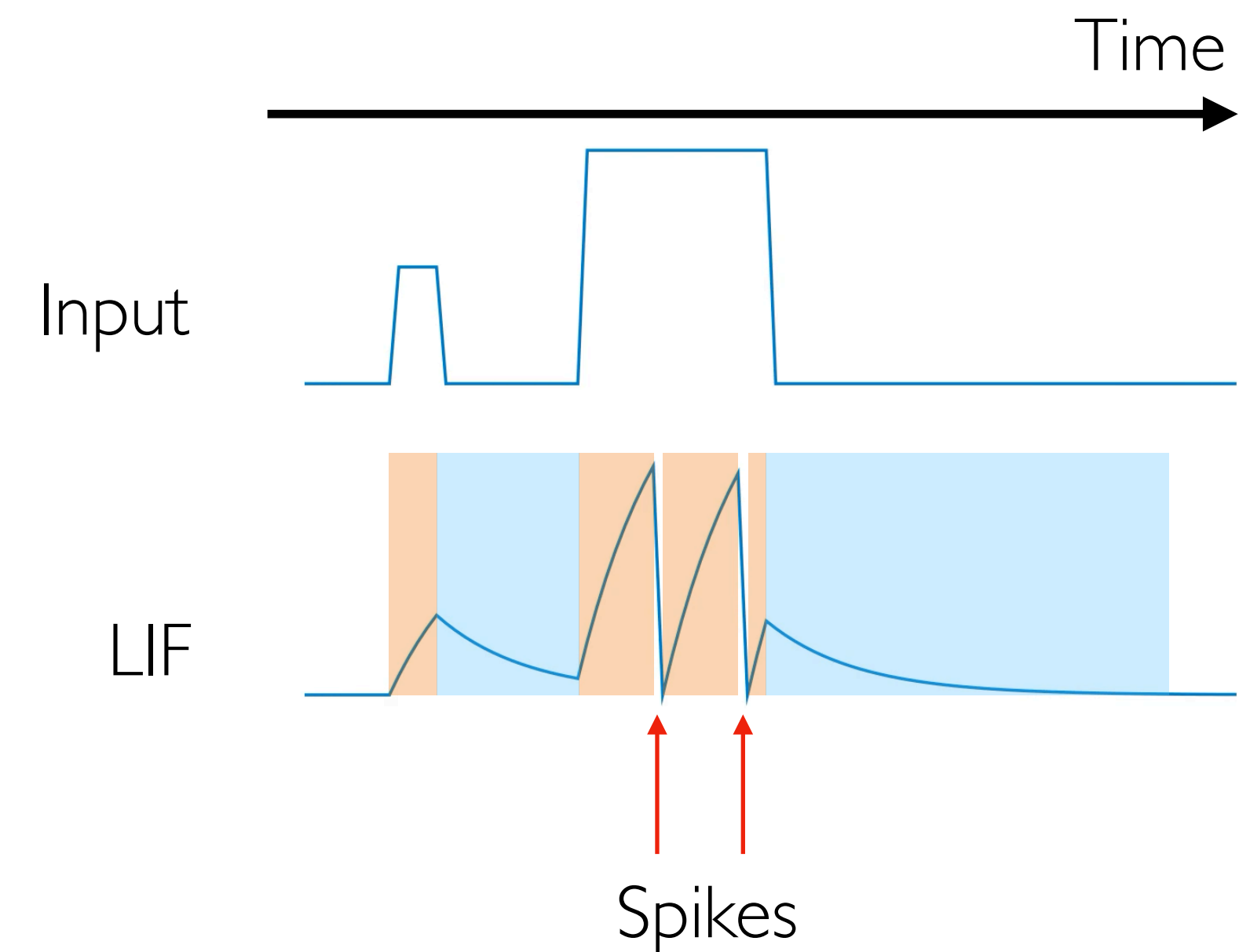
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LIF neurons are used in SNNs

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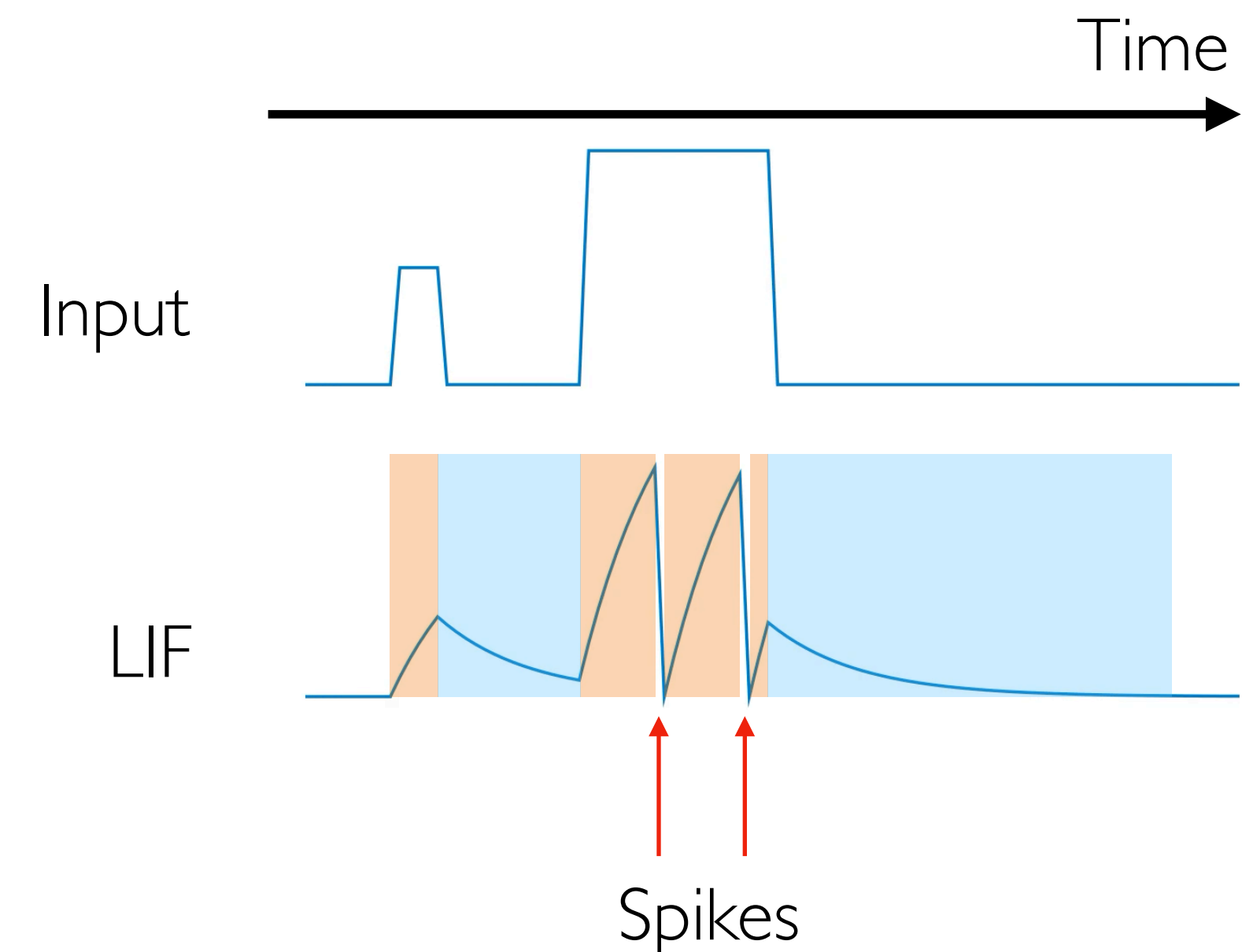
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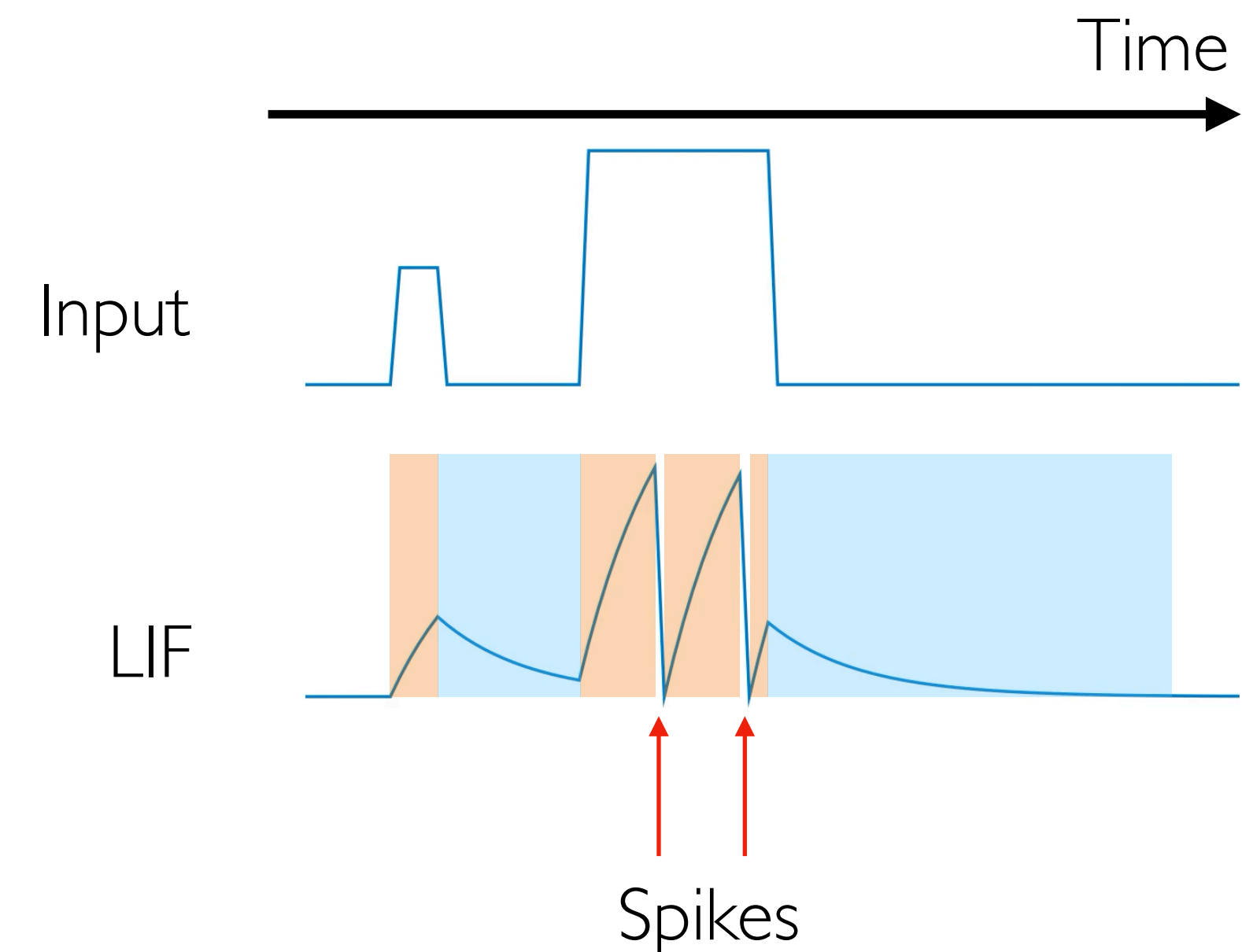
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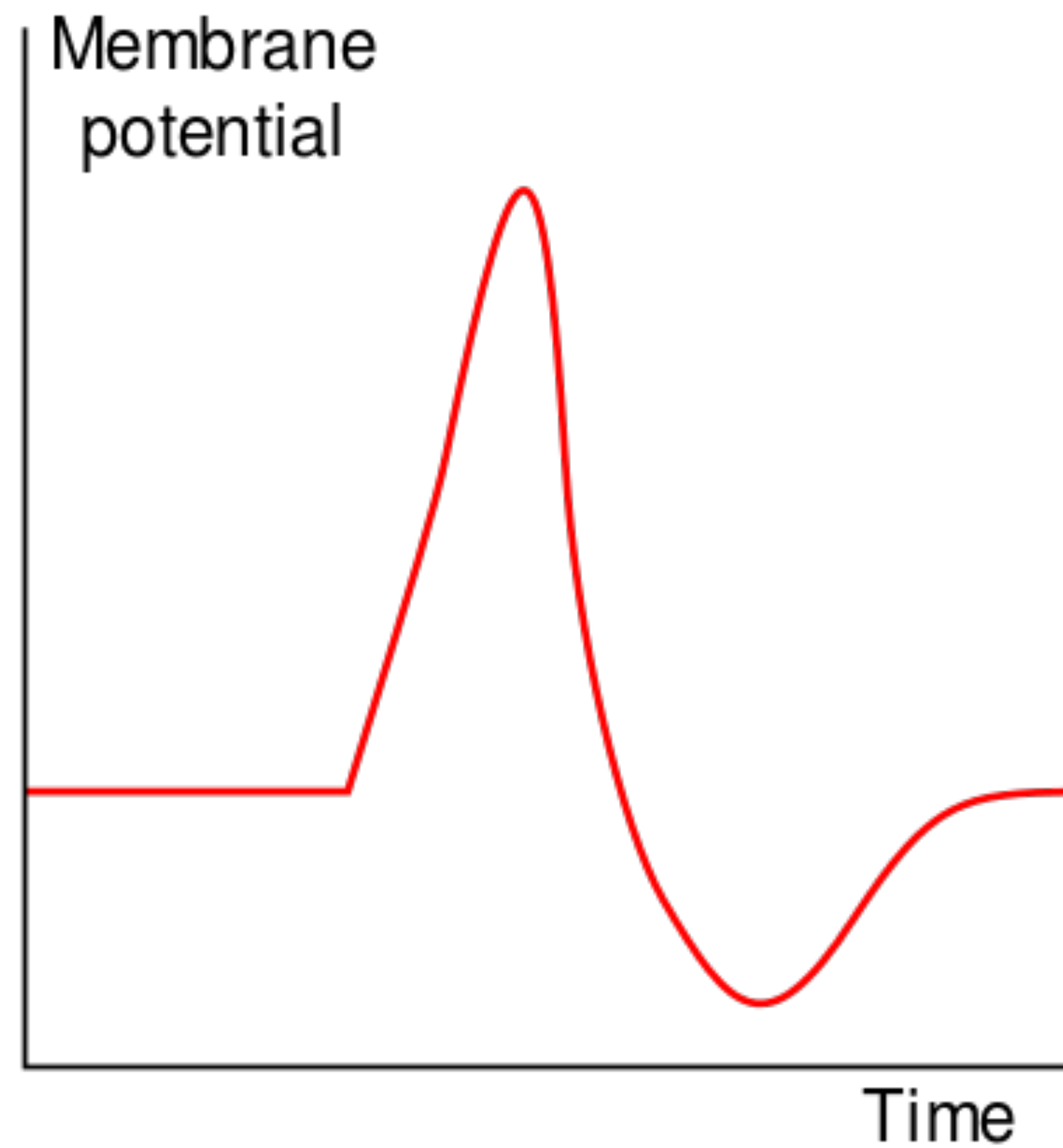
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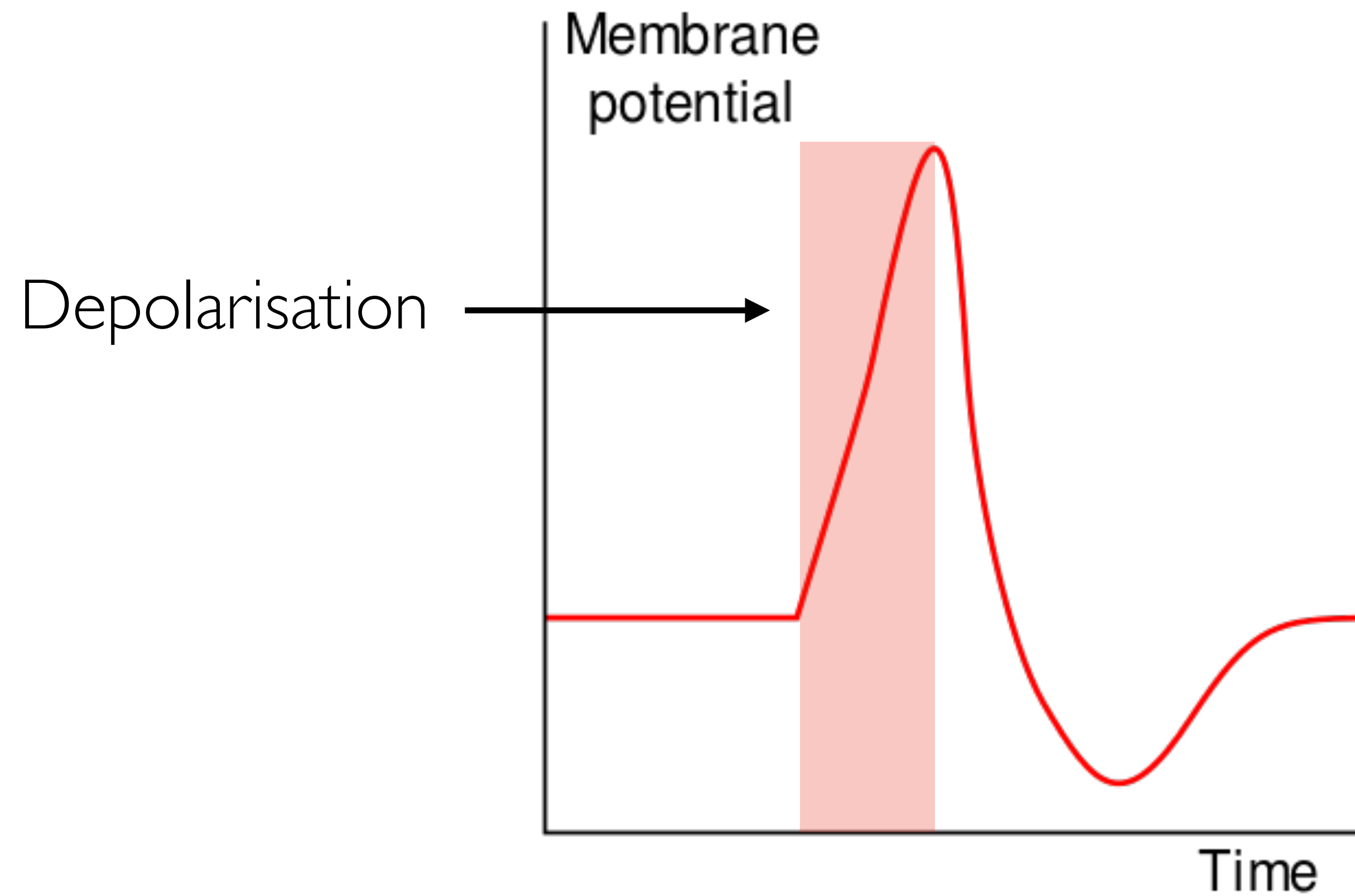


Can we find a trade-off ?
I.e., a simple model capable of simulating spikes

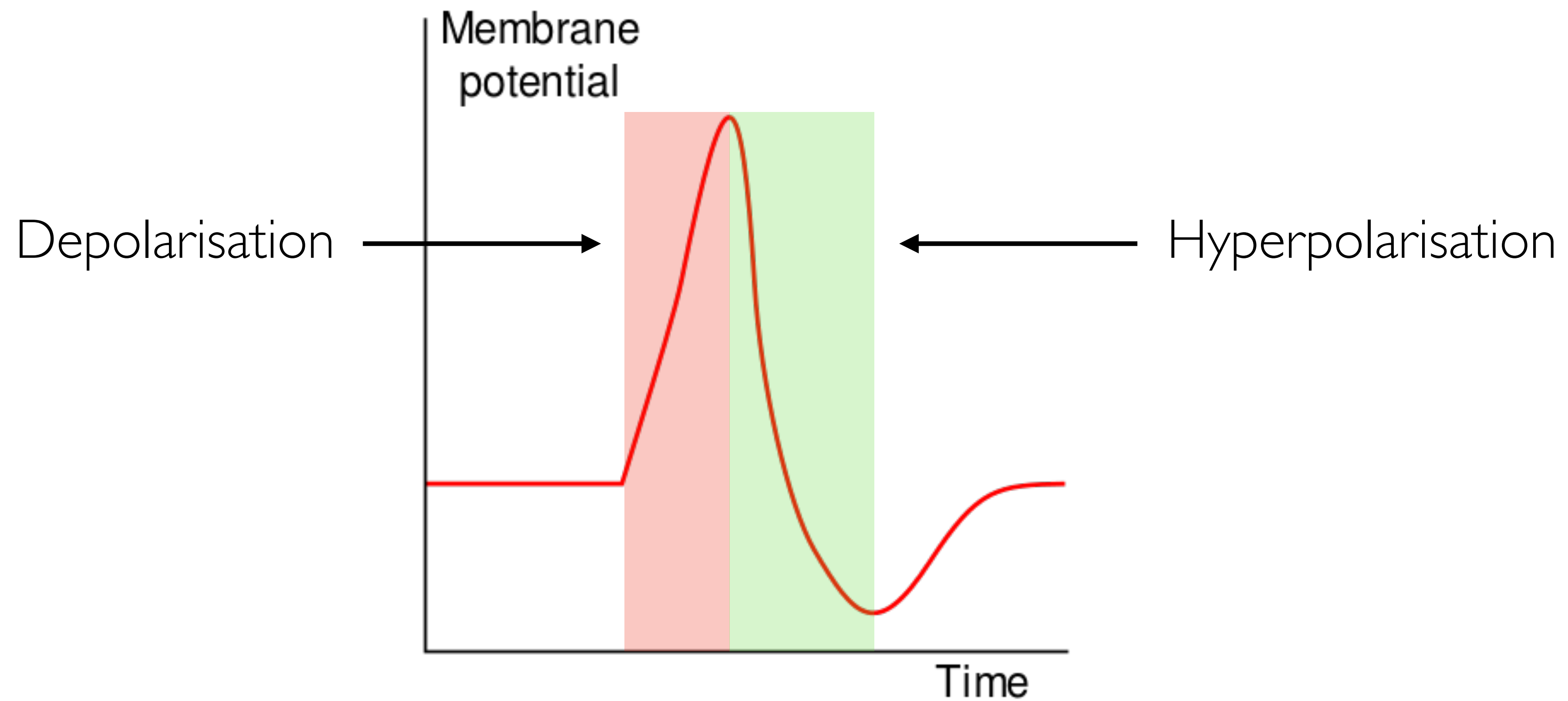
Spikes can be generated by a mixed-feedback system



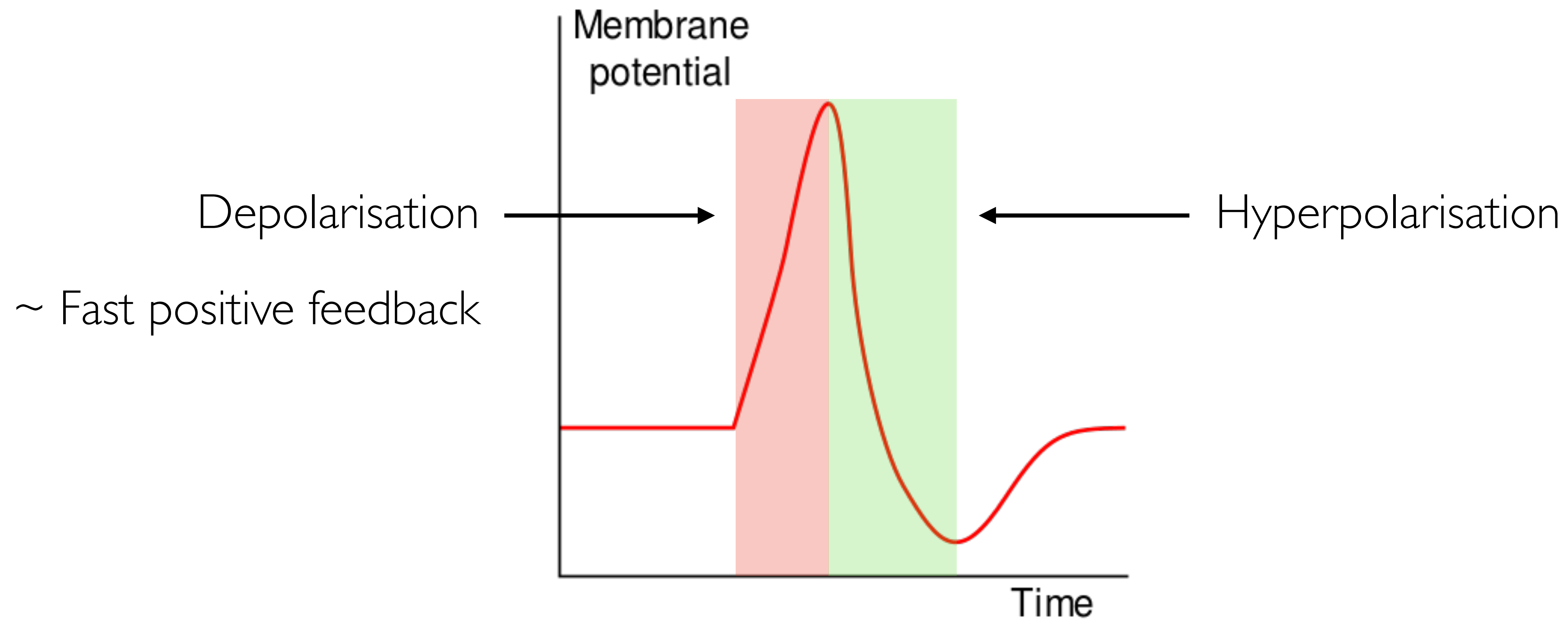
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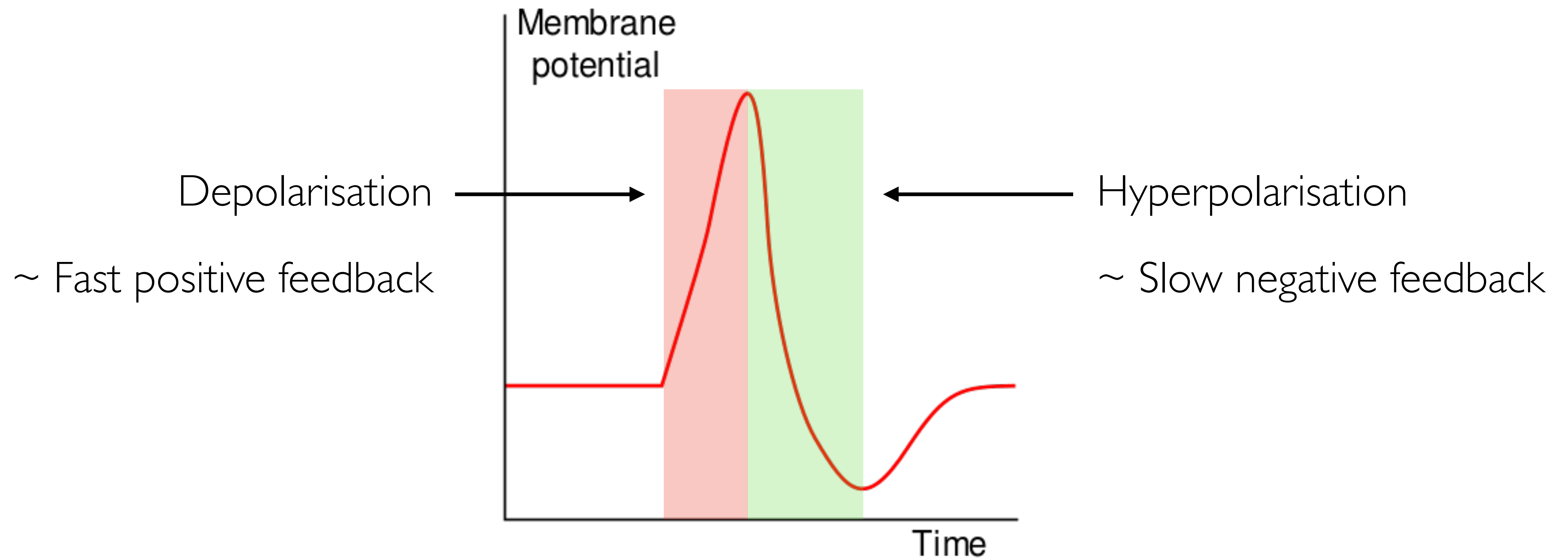
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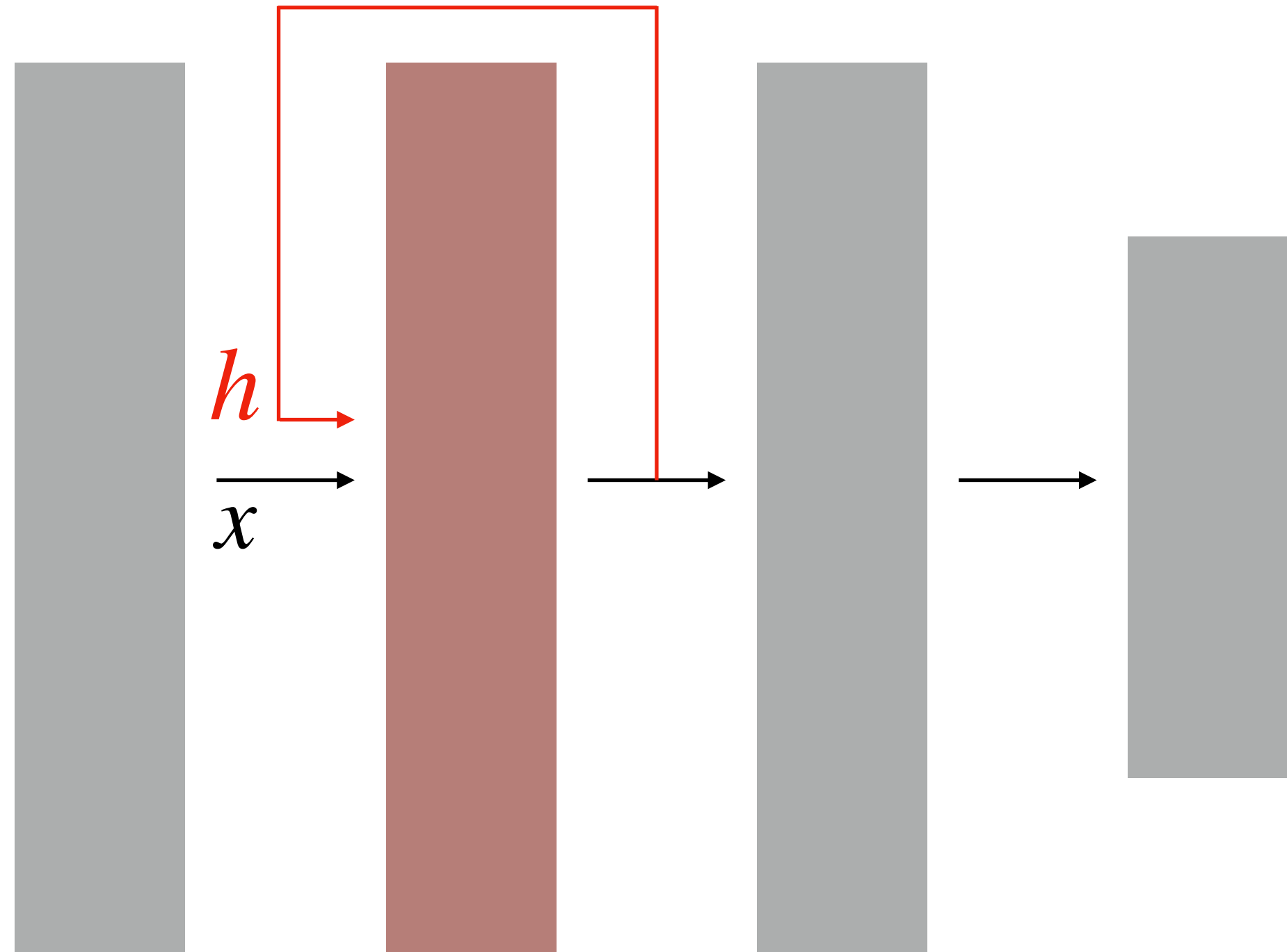
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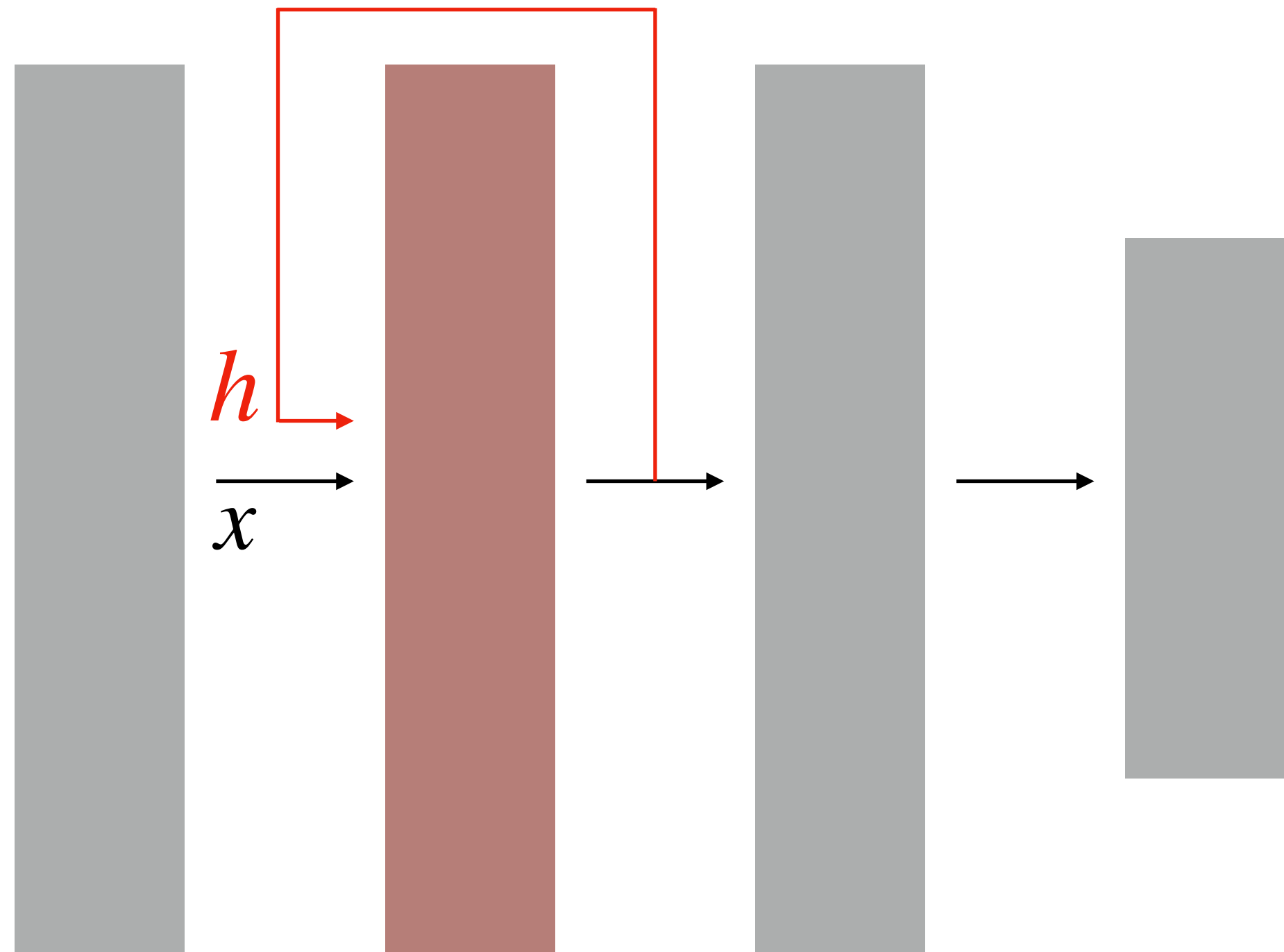


Recurrent neural networks

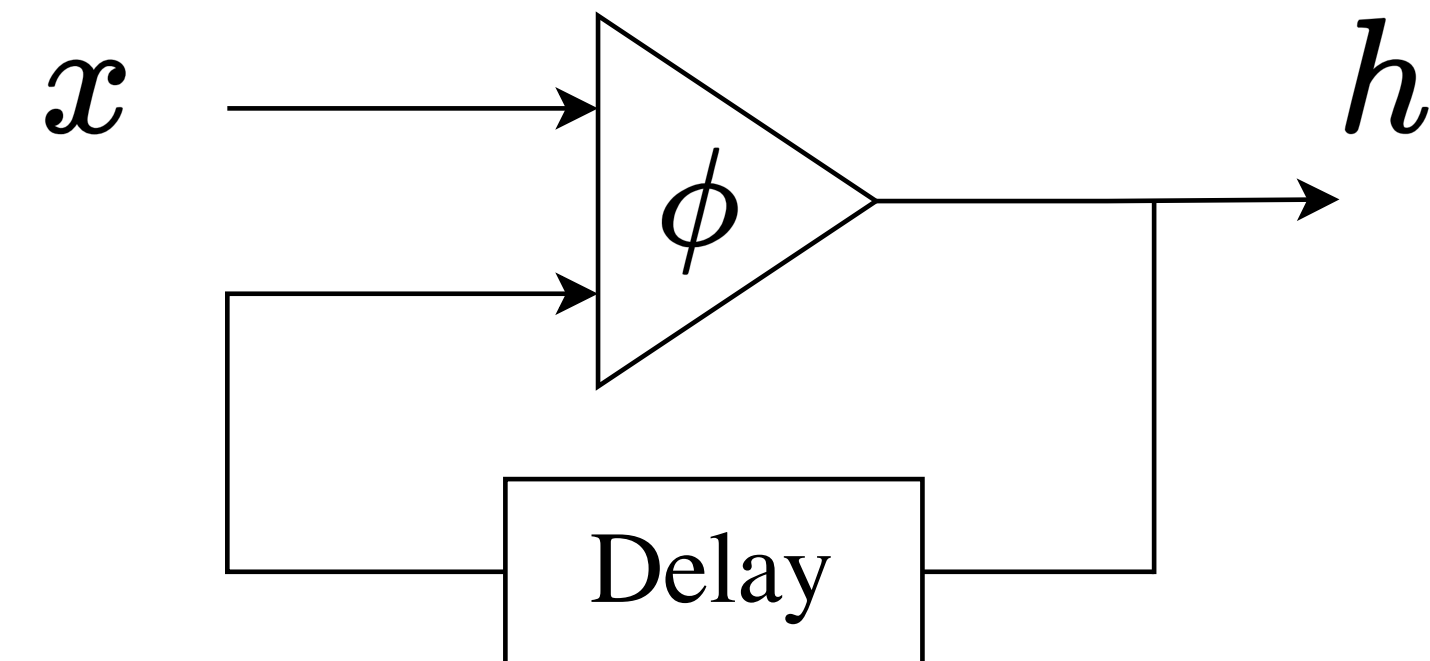


$$h[t] = \phi(x[t], h[t - 1])$$

Recurrent neural networks can be seen as dynamical systems



$$h[t] = \phi(x[t], h[t - 1])$$



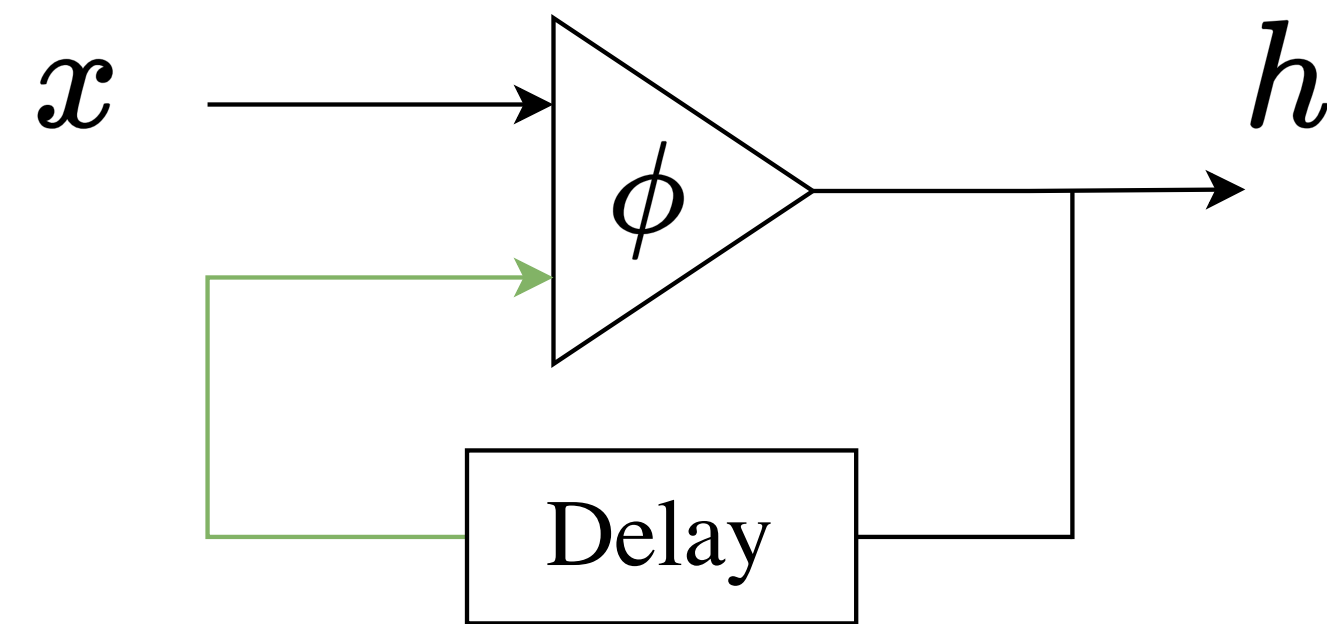
Small feedback loop

Controlling feedbacks leads to a spiking RNN

Controlling feedbacks leads to a spiking RNN

GRU

$$r \in [0,1]$$



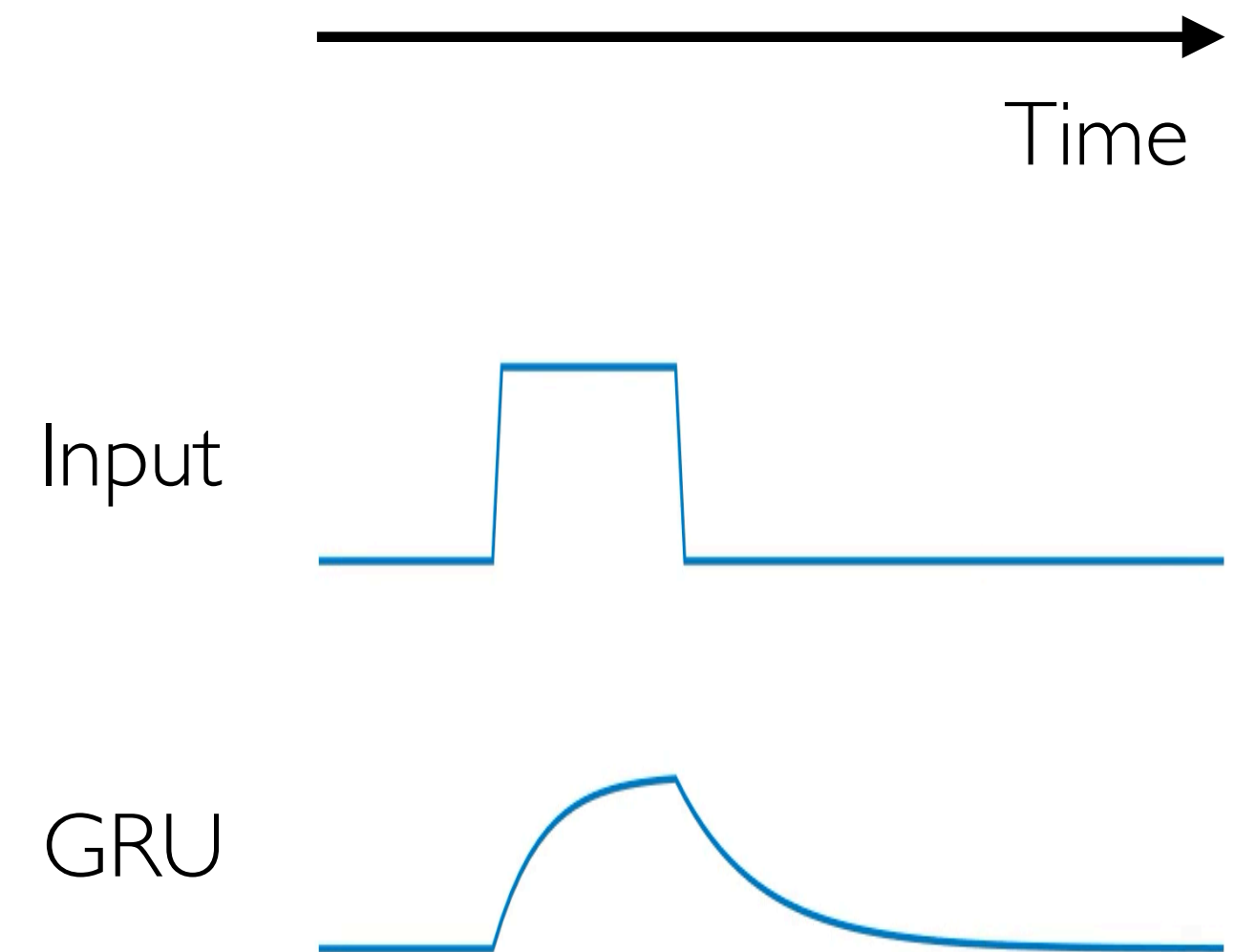
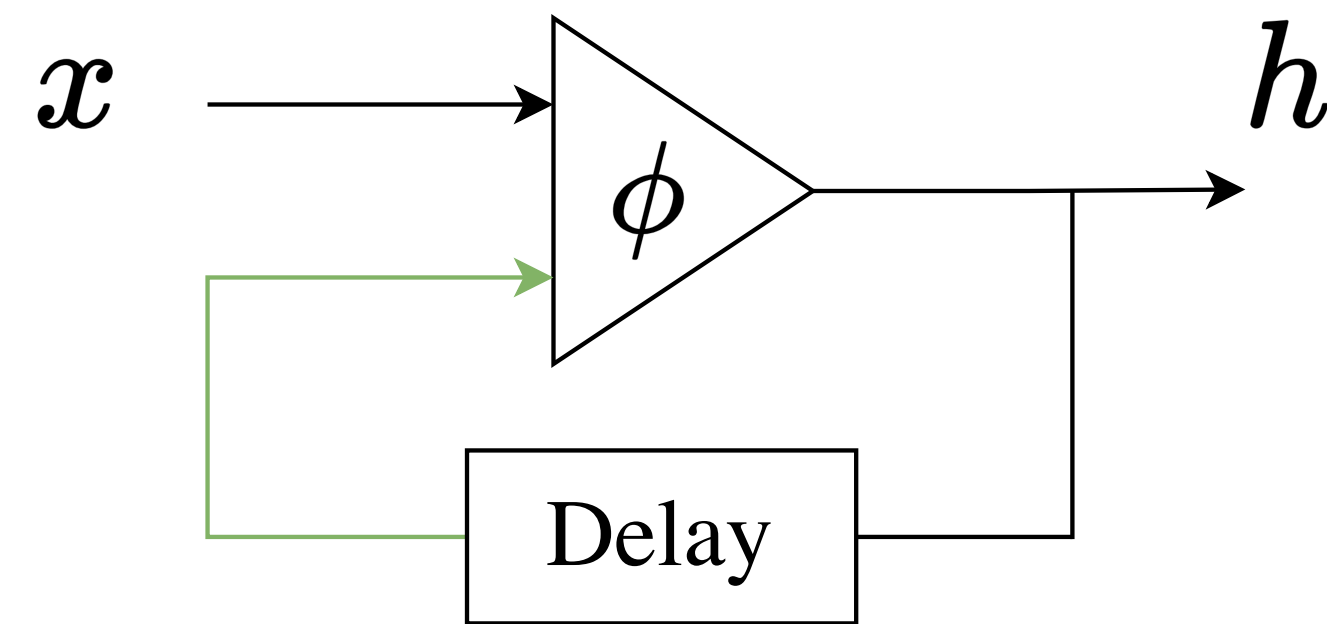
$$\hat{h}[t] = \tanh (x + r \cdot h[t - 1])$$

$$h[t] = z \cdot h[t - 1] + (1 - z) \cdot \hat{h}[t - 1]$$

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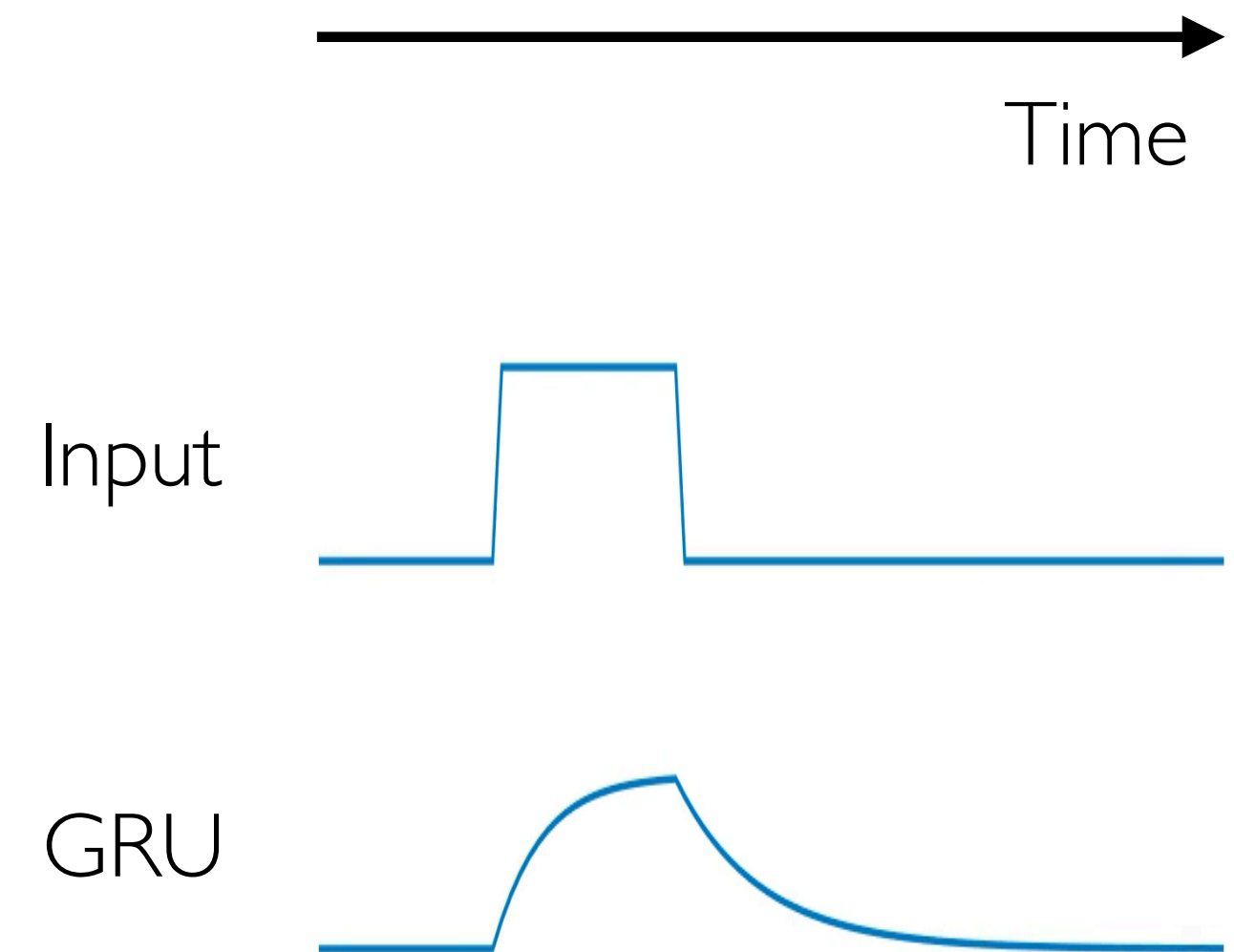
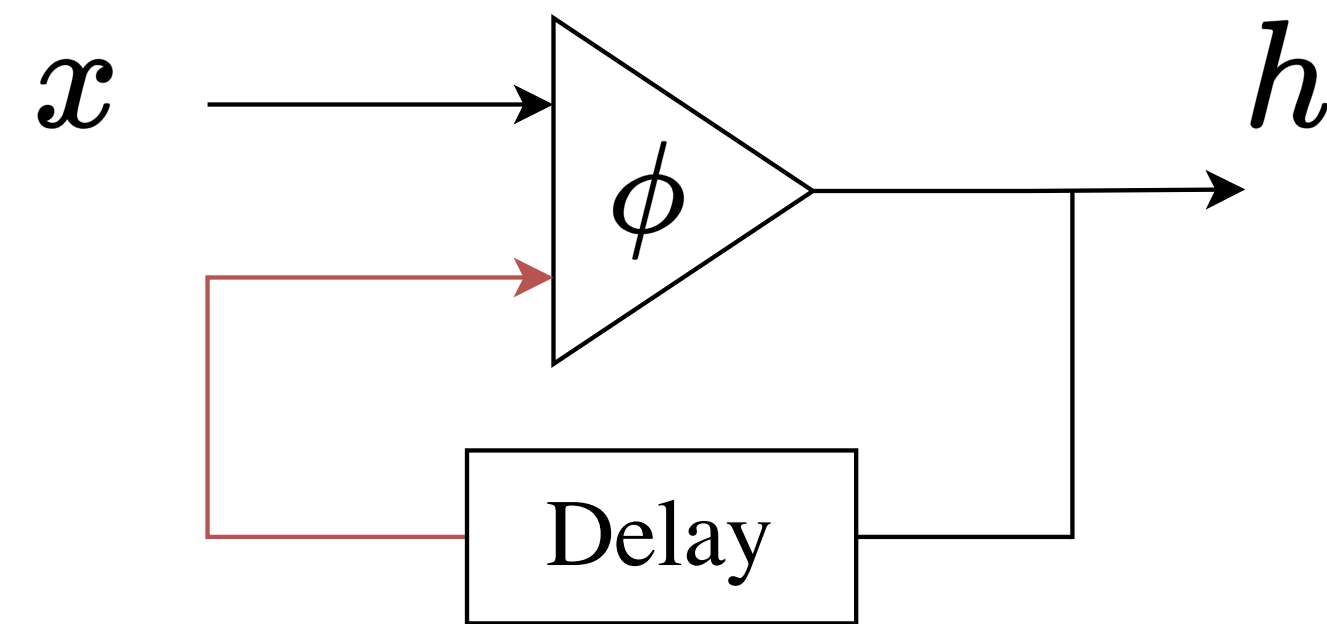
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BRC

$$r > 1$$



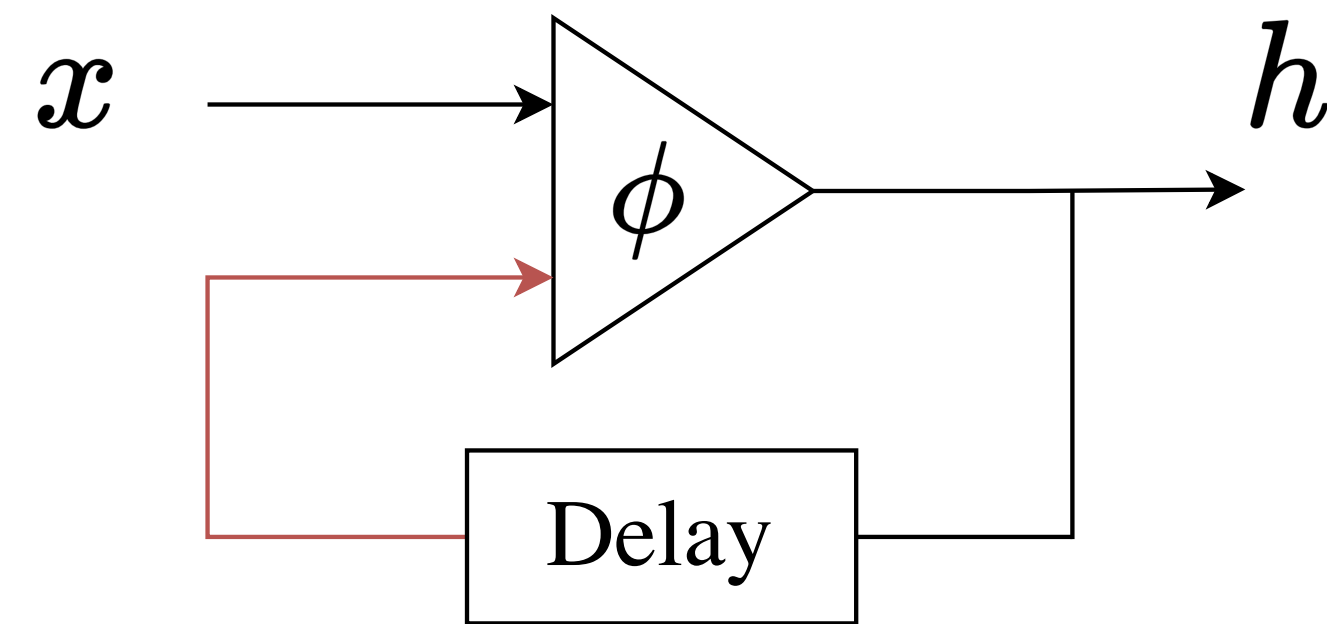
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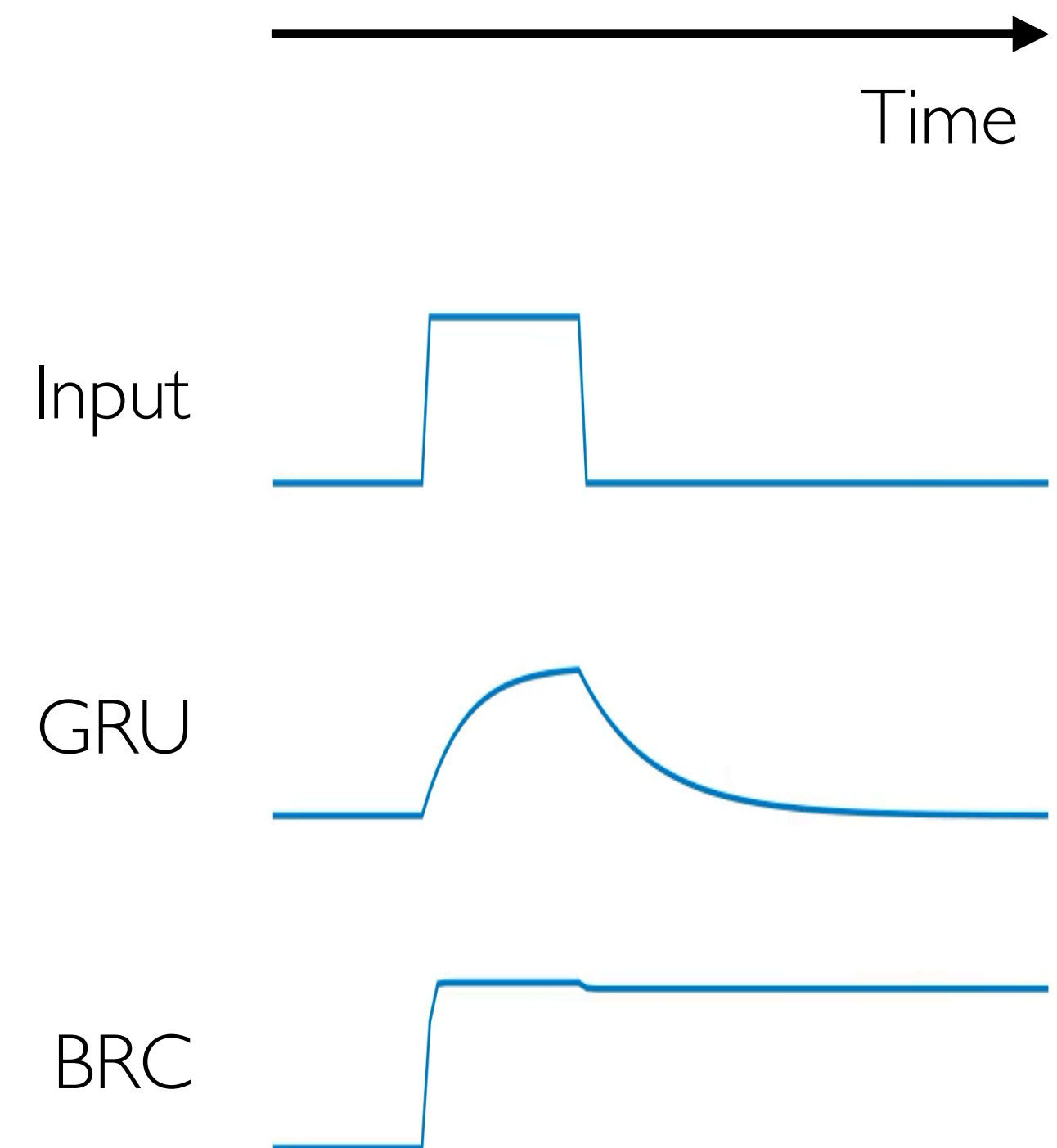
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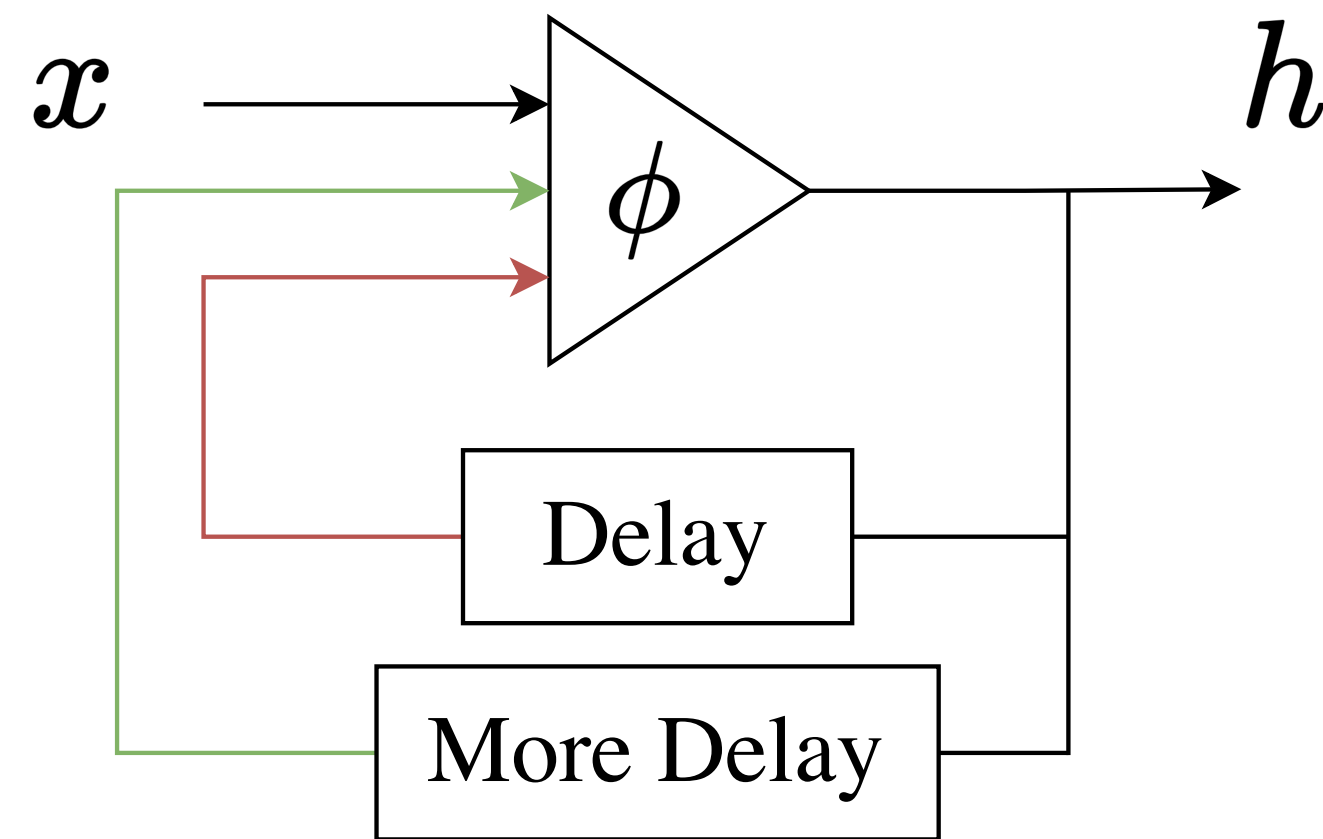


Controlling feedbacks leads to a spiking RNN

SRC

$$r > 1$$

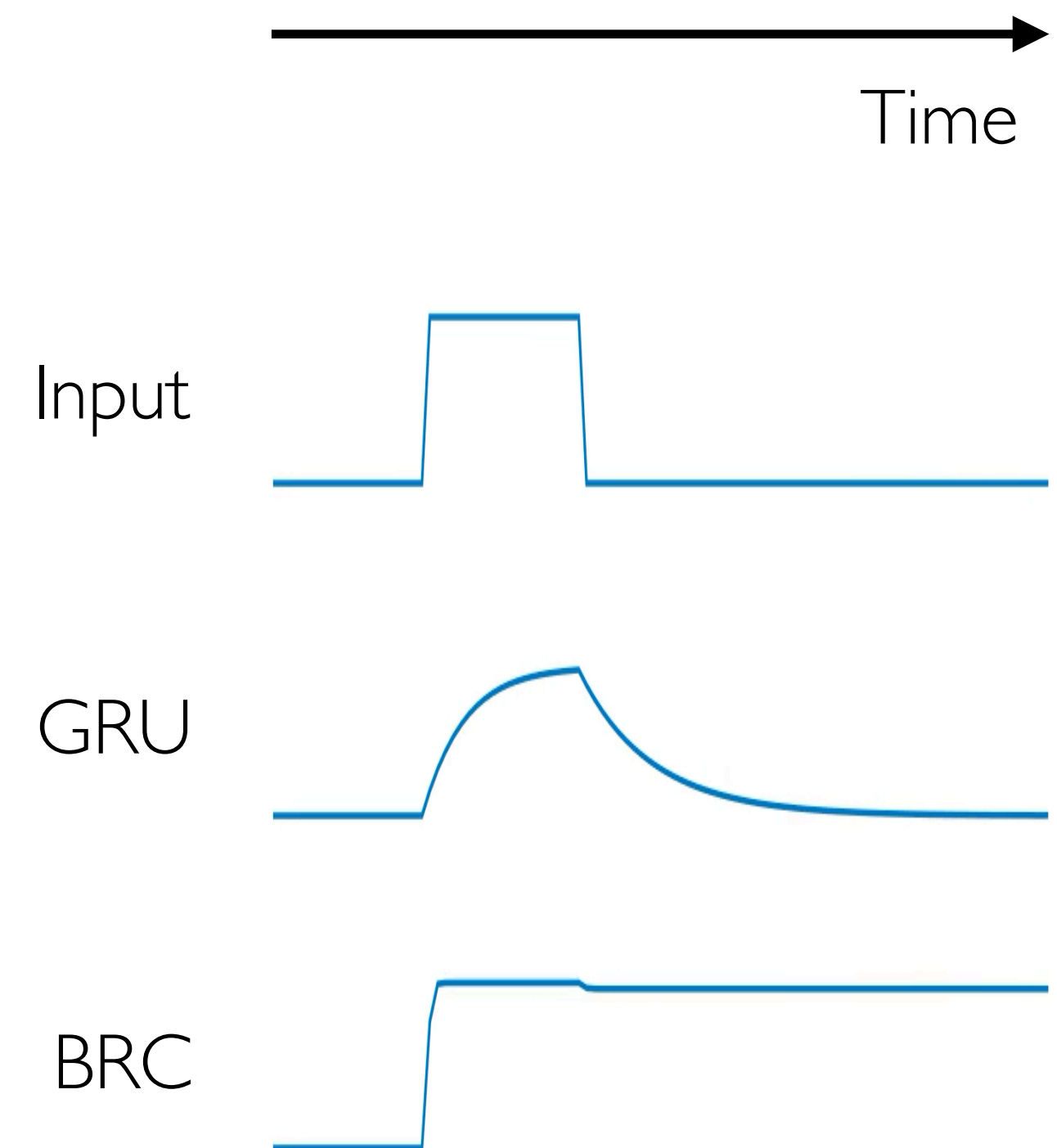
$$r_s = -5$$



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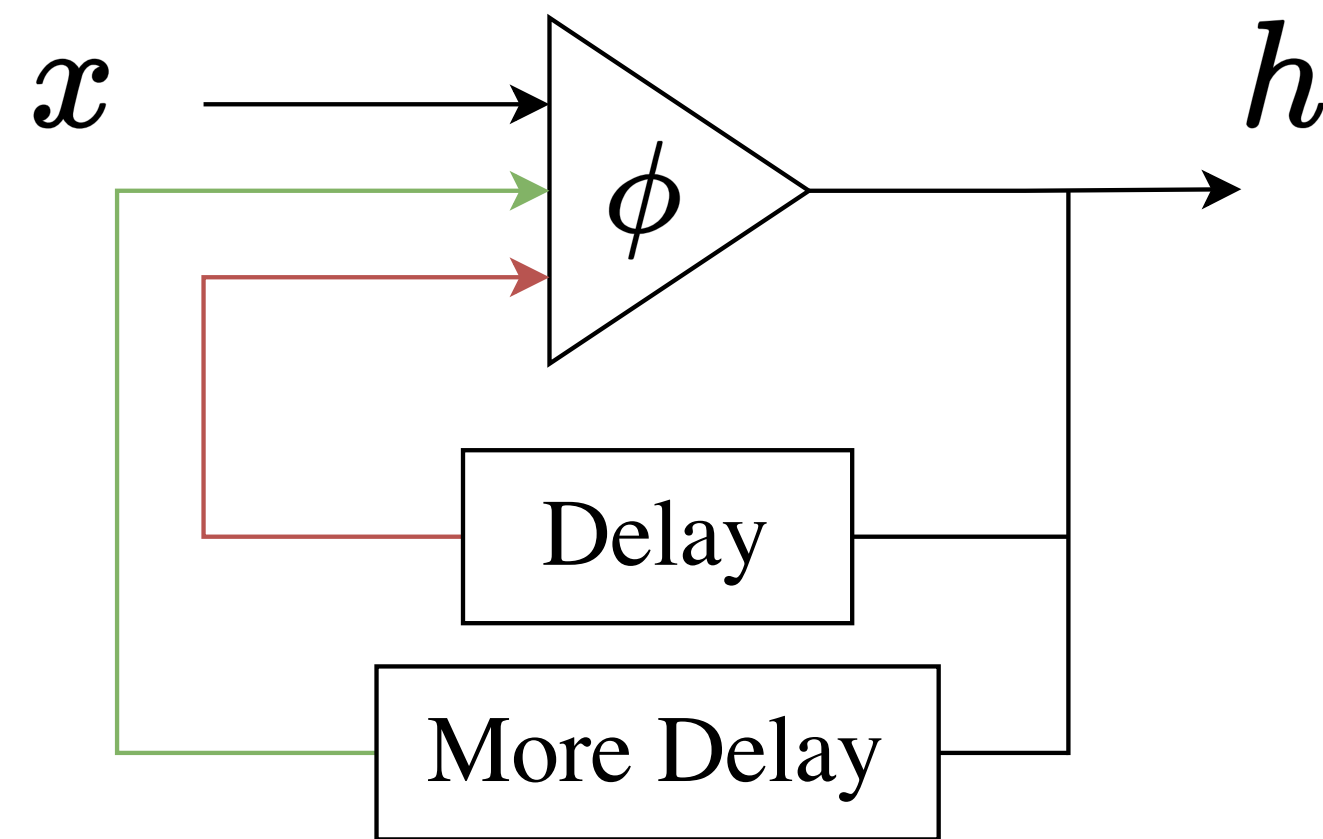


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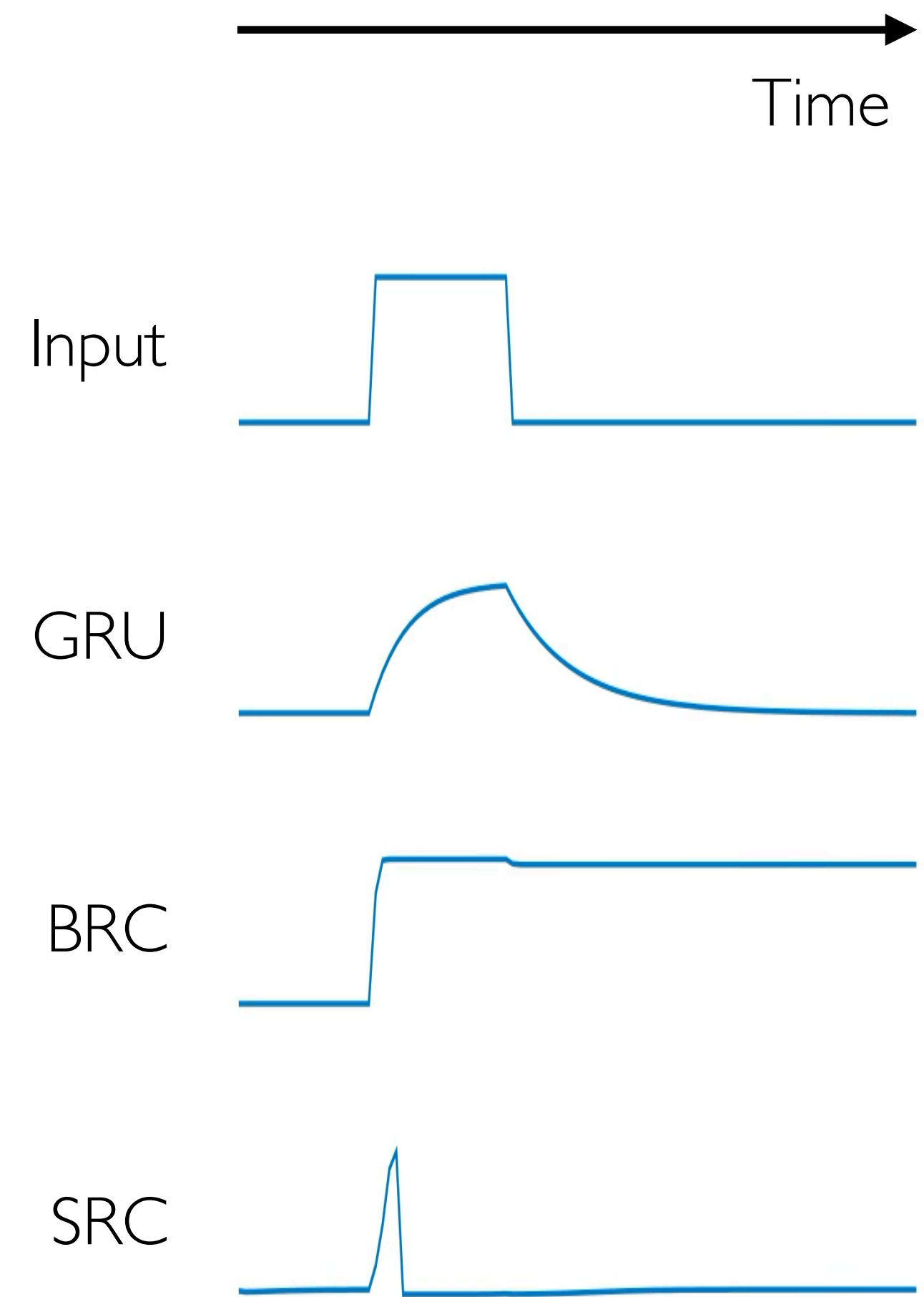
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SRC networks can be trained like usual recurrent networks

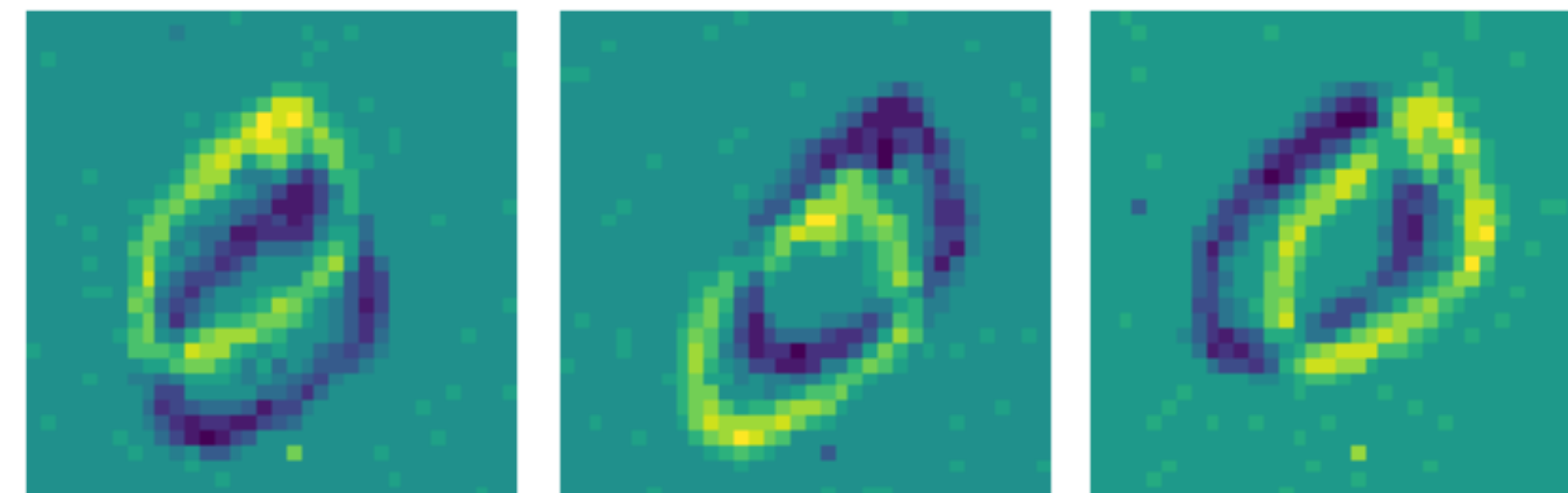
- Tested on simple benchmarks (MNIST and variants)
 - Same performance than LIFs
- Training seems to be more stable
 - Especially with deeper networks
- Resilient to noise in dynamics



MNIST



Fashion-MNIST



Neuromorphic MNIST

What we have and what's next

We derived SRC, a artificial spiking neuron that is:

What we have and what's next

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Simple like LIF neurons

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3 main directions are considered for future works:

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Machine Learning

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Neuro-inspired

- Modify SRC equations to add new firing patterns
- See if model learns to use them

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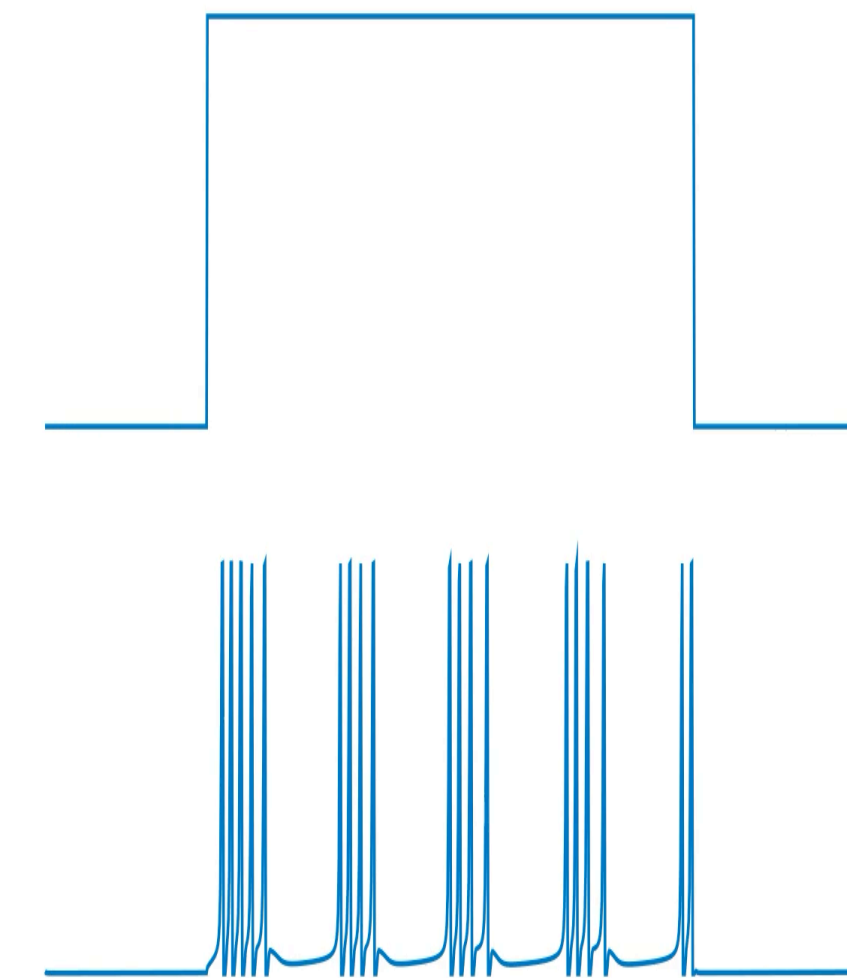
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Input

Output



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Electronics

- Try SRC on hardware
 - FPGA
 - Analog circuit

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Thank you !

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References

- Recurrent neural networks
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Xiao, H., et al. “Fashion-MNIST: A Novel Image Dataset for Benchmarking Machine Learning Algorithms.” arXiv, September 15, 2017.
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