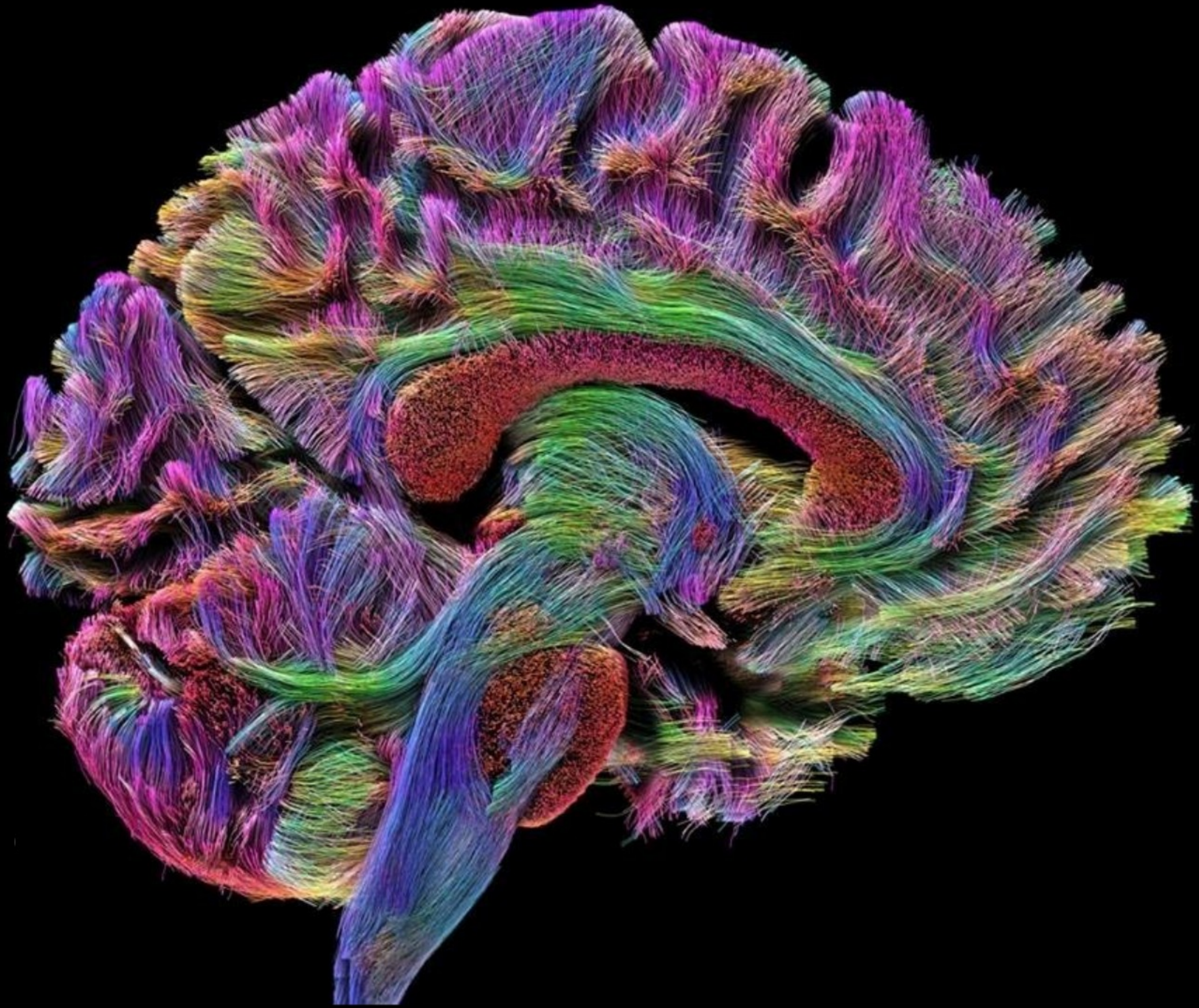
Machine Learning for Neuroimaging and Neuroscience



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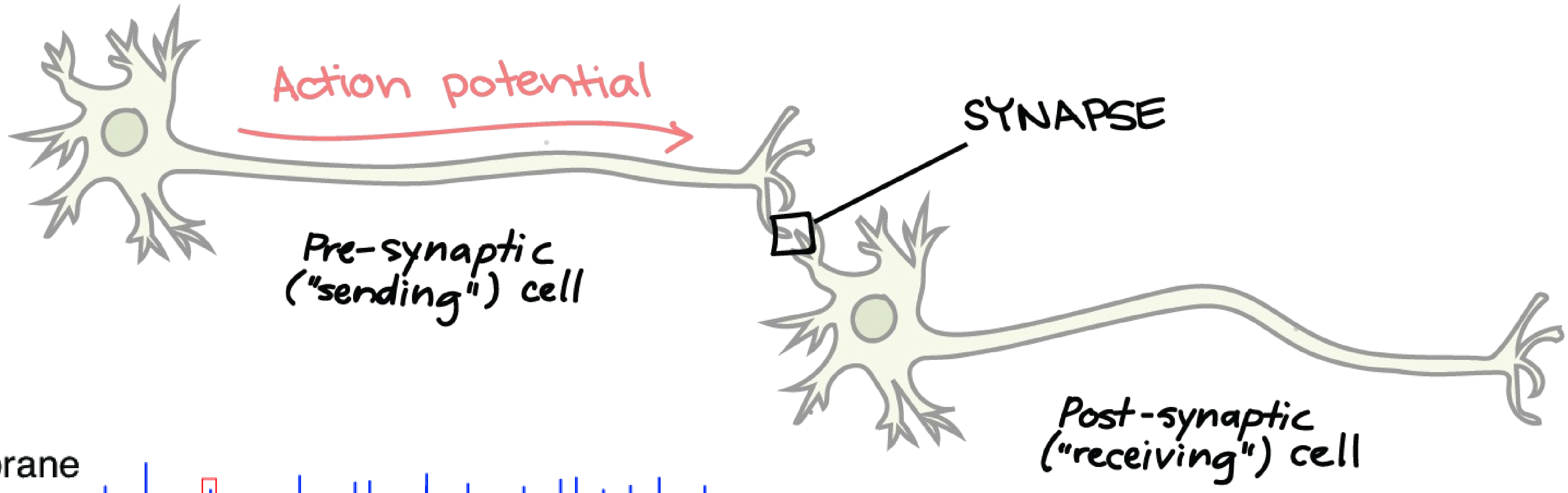
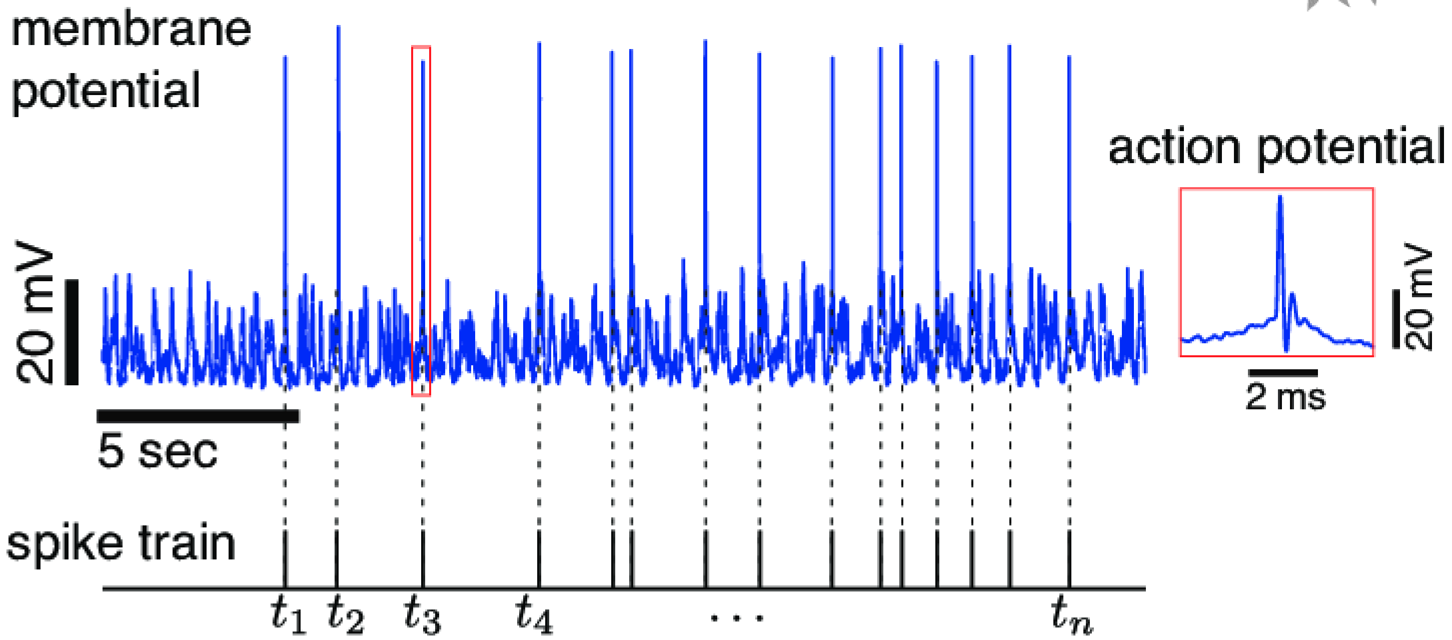
Spiking Neural Networks

What is a spiking neural network?





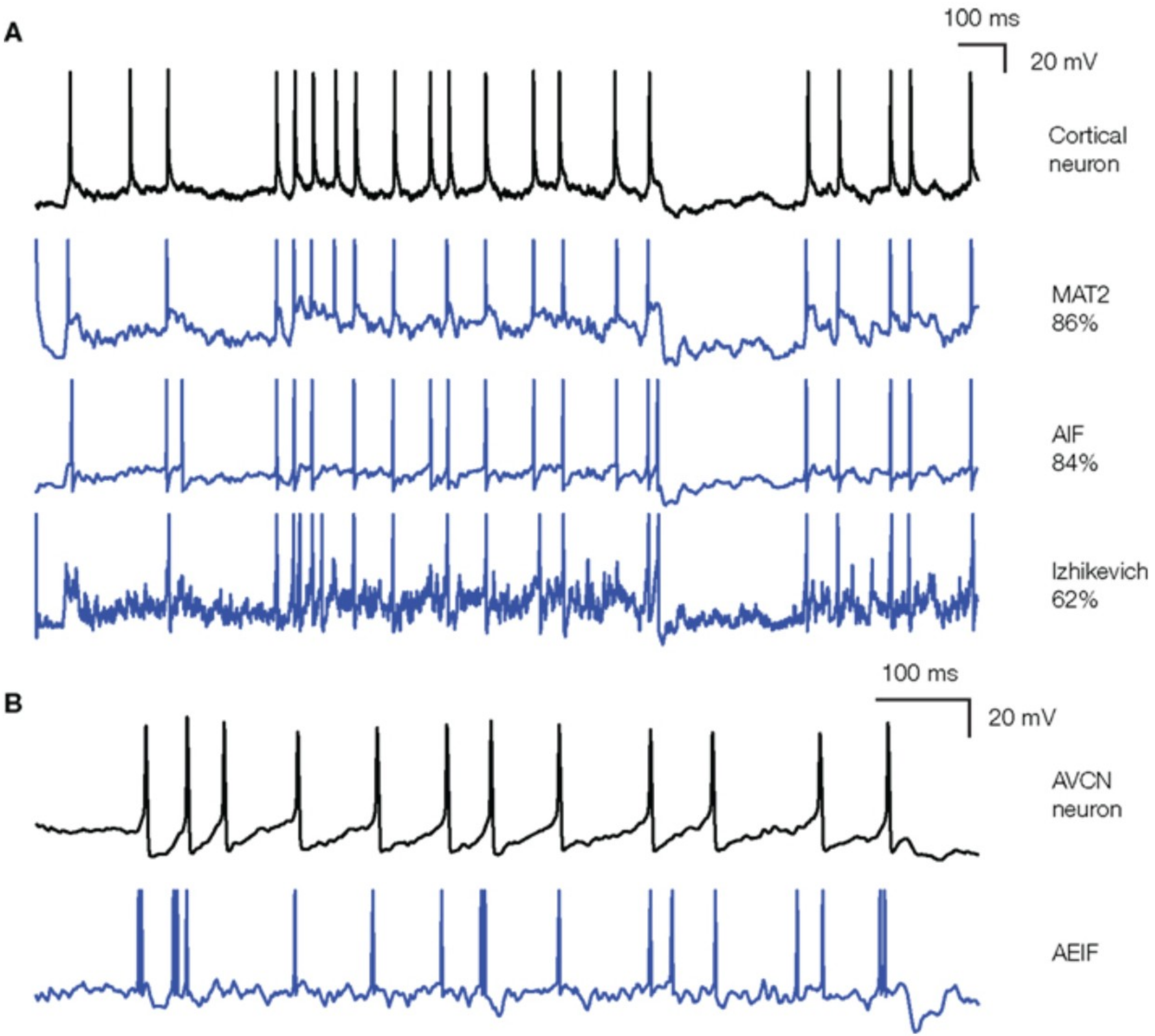


Fig. 5.21 Spike trains. Source: [Rossant et al., 2011].

The **leaky integrate-and-fire** (LIF; Lapicque, 1907) neuron has a **membrane potential** $v(t)$ that integrates its input current $I(t)$:

$$C \frac{dv(t)}{dt} = -g_L \, (v(t) - V_L) + I(t)$$

C is the membrane capacitance, g_L the leak conductance and V_L the resting potential. In the absence of input current ($I = 0$), the membrane potential is equal to the resting potential.

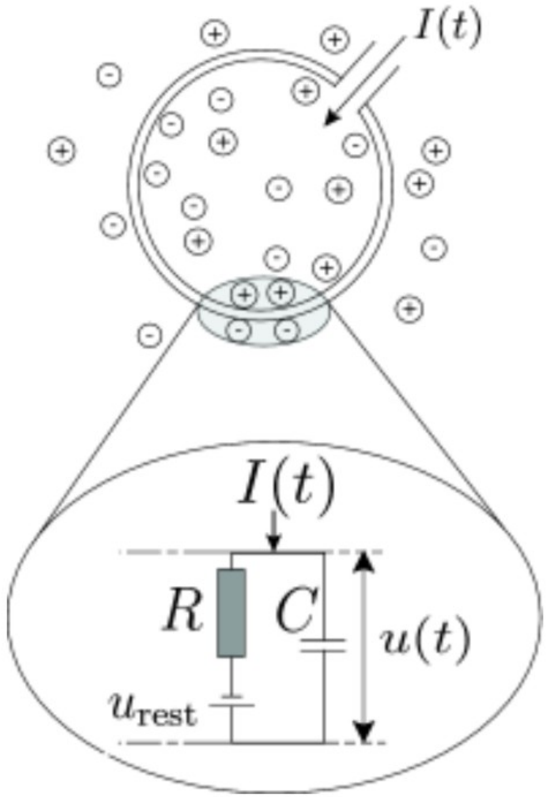


Fig. 5.22 Membrane potential of a leaky integrate-and-fire neuron. Source: https://neuronaldynamics.epfl.ch/online/Ch1.S3.html.

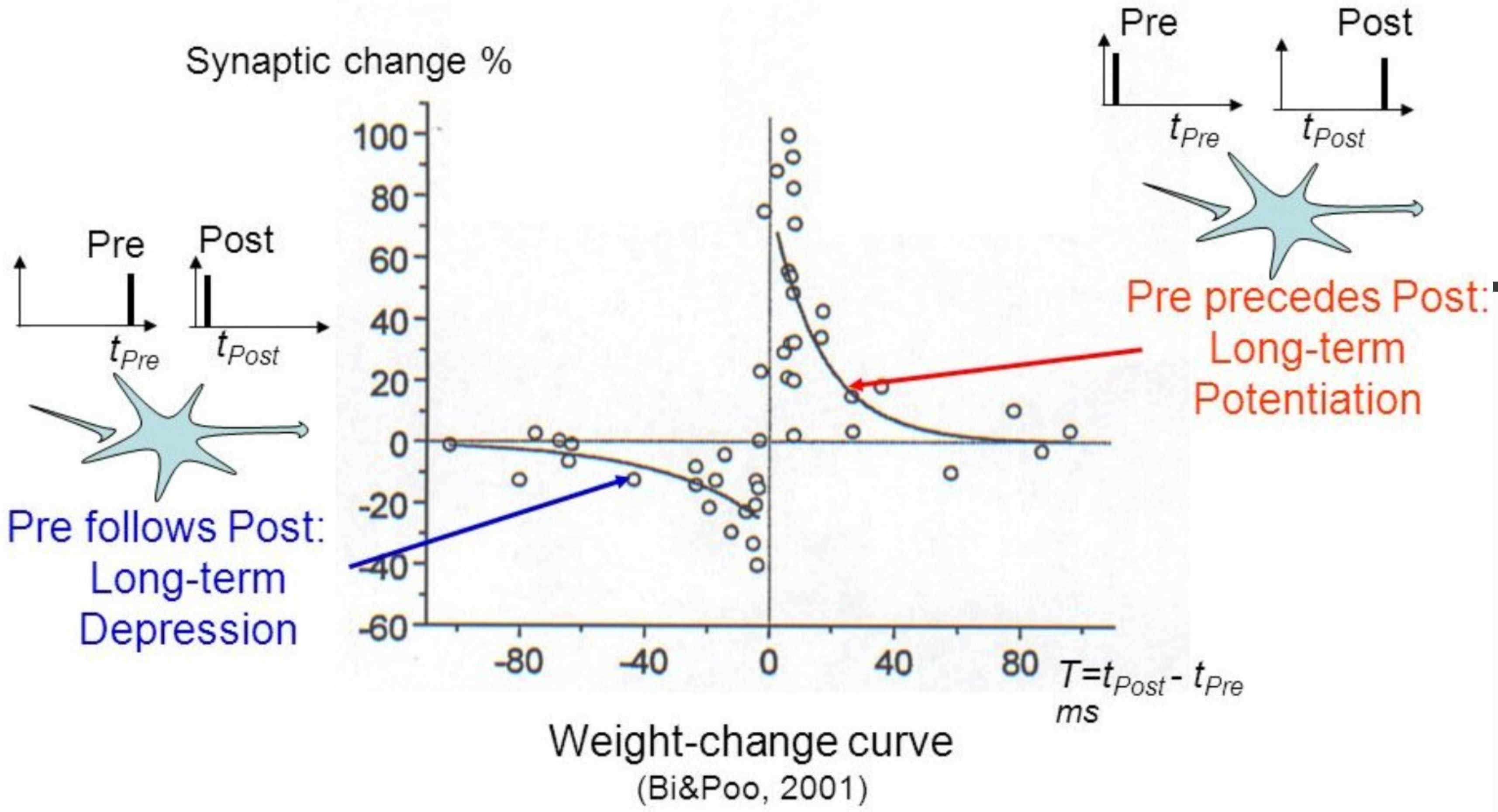


Fig. 5.29 Spike-timing dependent plasticity. Source: [Bi & Poo, 2001].

The STDP (**spike-timing dependent plasticity**) plasticity rule describes how the weight of a synapse evolves when the pre-synaptic neuron fires at t_pre and the post-synaptic one fires at t_post.

$$\Delta w = \begin{cases} A^+ \, \exp - \frac{t_\text{pre} - t_\text{post}}{\tau^+} \; \text{if} \; t_\text{post} > t_\text{pre} \\ A^- \, \exp - \frac{t_\text{pre} - t_\text{post}}{\tau^-} \; \text{if} \; t_\text{pre} > t_\text{post} \end{cases}$$

Recurrent networks of spiking neurons exhibit various dynamics. They can fire randomly, or tend to fire synchronously, depending on their inputs and the strength of the connections. **Liquid State Machines** are the spiking equivalent of echo-state networks.

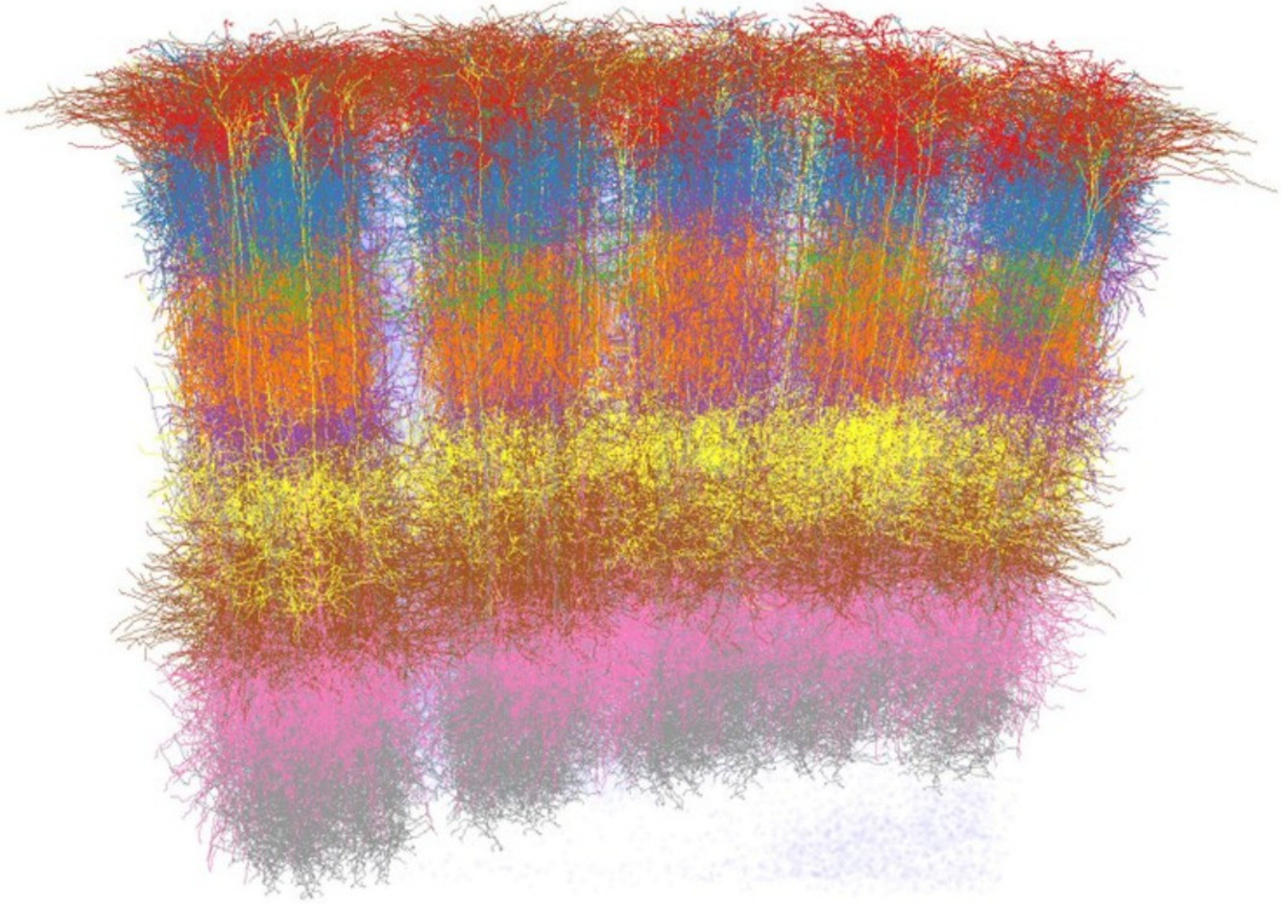


Fig. 5.28 Cortical column of the rat's vibrissal cortex. Source: https://www.pnas.org/content/110/47/19113.

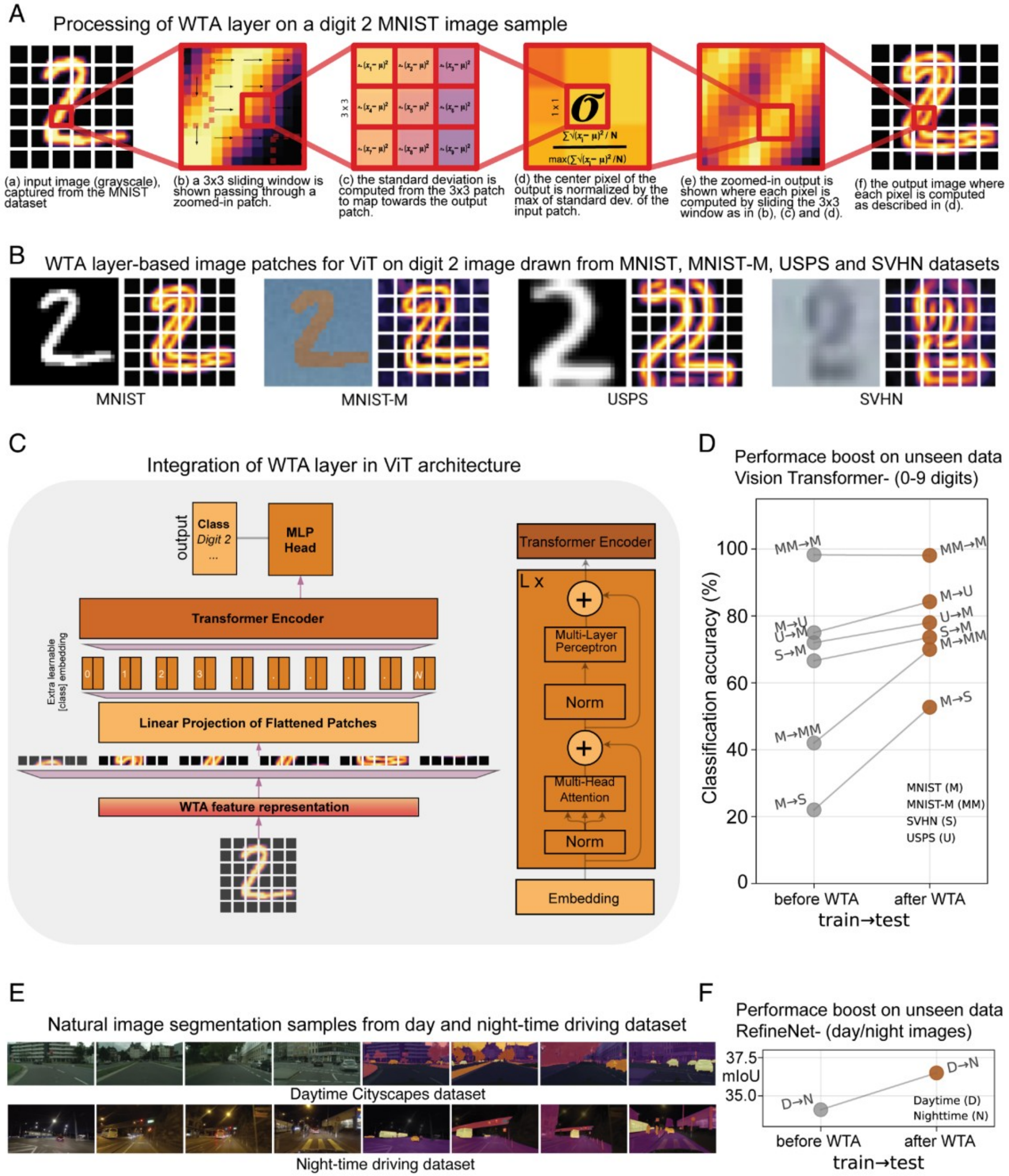


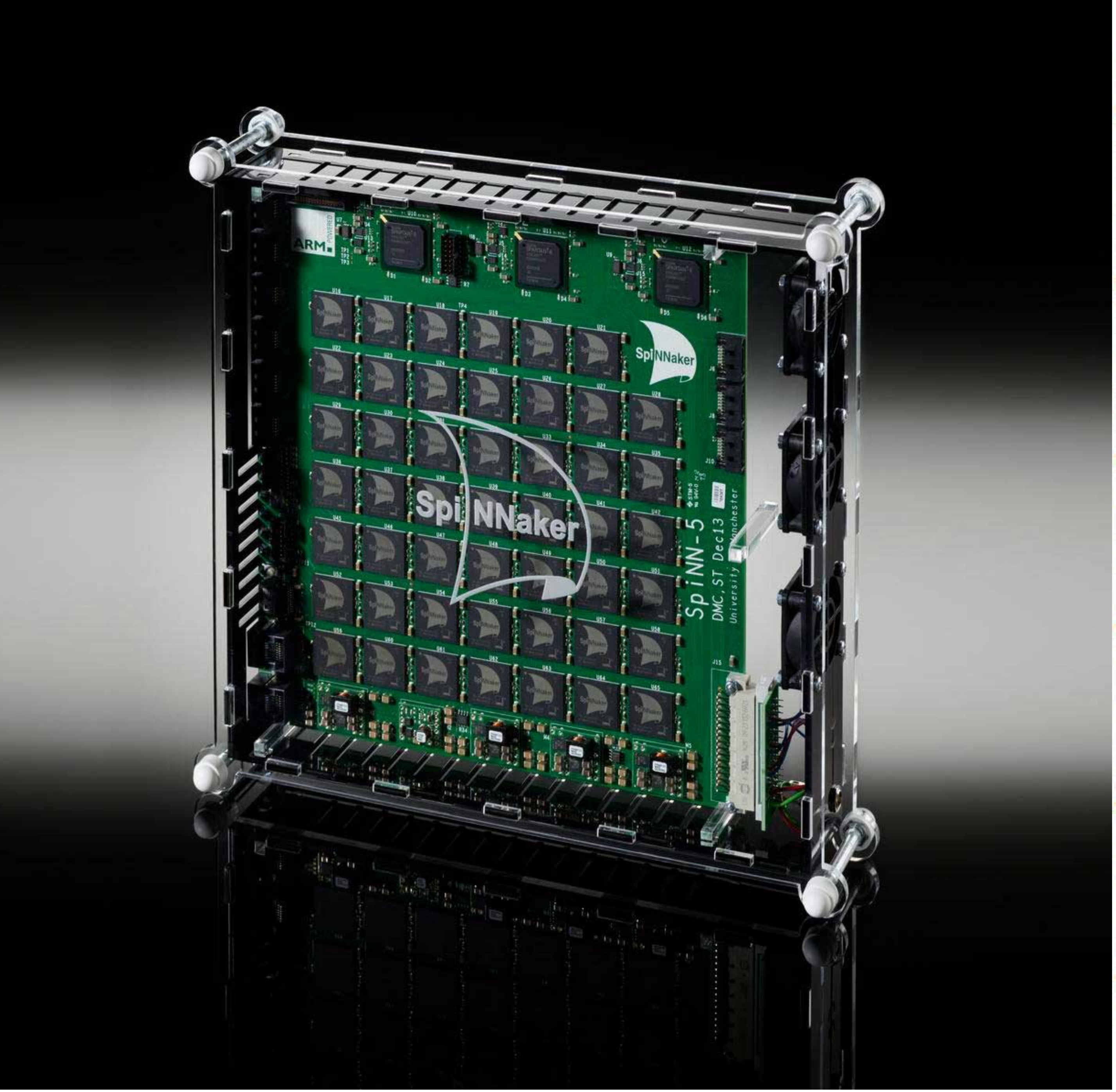
Table 1. Comparison of classification accuracy between WTA-based DNN architectures (Vision Transformer, EfficientNet, CapsuleNet, MobileNet, and ResNet) and source-only models trained on the MNIST (M), MNIST-M (MM), SVHN (S), and USPS (U) datasets

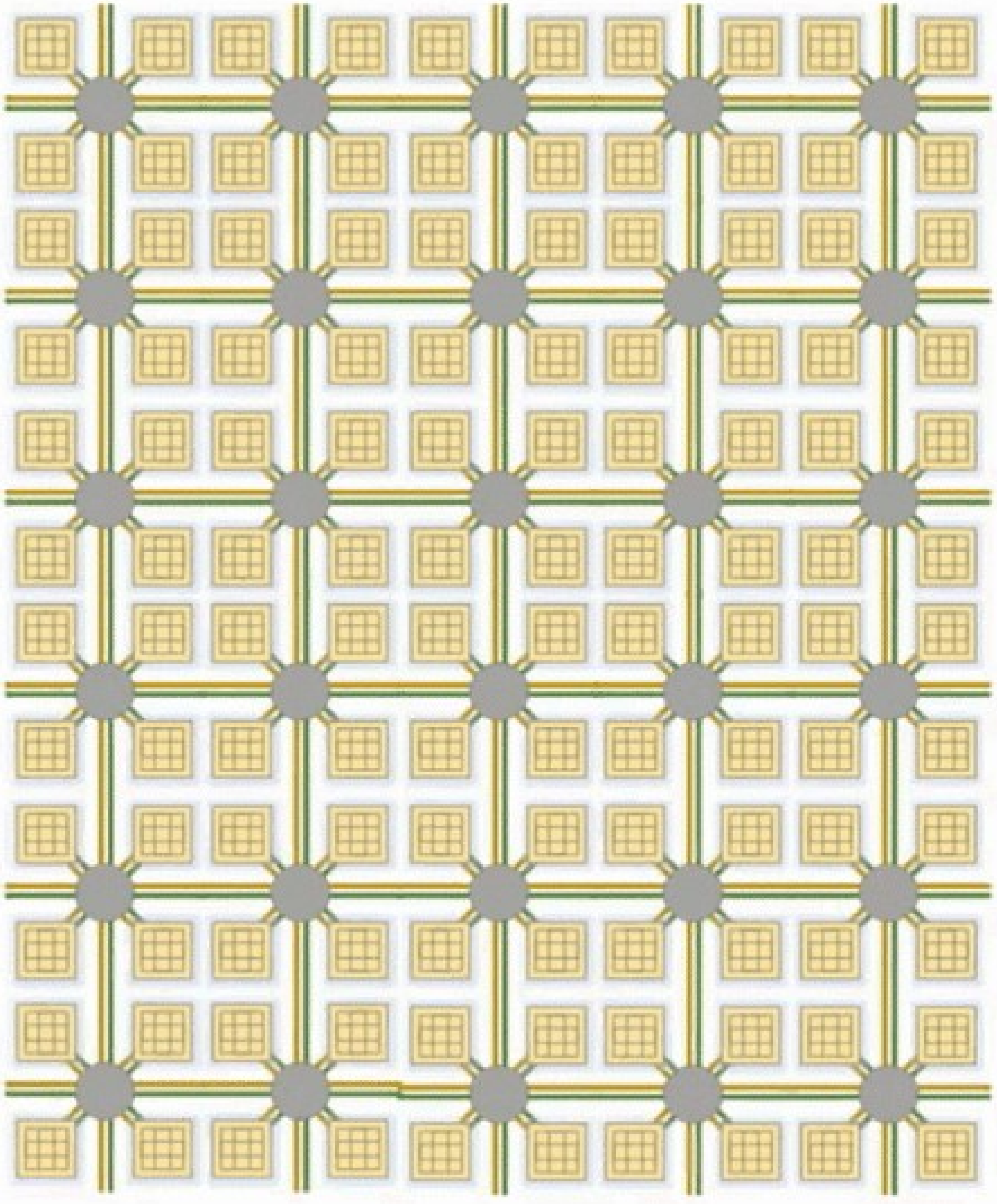
Source-only Models	M→U	U→M	S→M	M→S	M→MM	MM→M
ViT	75.0	72.0	66.6	22.0	42.0	98.3
EfficientNet	77.9	50.7	61.4	18.6	18.8	95.0
CapsuleNet	**96.4**	**87.2**	58.1	11.8	22.5	**98.4**
MobileNet	84.4	60.0	72.2	22.4	33.9	97.3
ResNet	82.5	58.5	63.4	27.2	38.2	97.4
ViT+WTA	84.26	78.0	**73.6**	**52.7**	**70.0**	98.1
EfficientNet+WTA	83.5	74.2	69.1	19.6	48.8	96.3
CapsuleNet+WTA	**94.1**	**87.8**	**75.9**	32.1	57.2	**98.6**
MobileNet+WTA	82.5	70.9	73.5	**40.5**	**73.4**	97.8
ResNet+WTA	82.8	66.0	71.2	27.7	**70.2**	97.8

The top panel shows performance without the WTA layer, and the bottom panel shows performance with the WTA layer. The best value in each column is shown in bold red, and the second-best value in bold black.

Biologically grounded neocortex computational primitives implemented on neuromorphic hardware improve vision transformer performance

Iqbal et al. PNAS 2025


SpiNNaker
SpiNNaker
SpiNN-5
DMC,ST Dec13

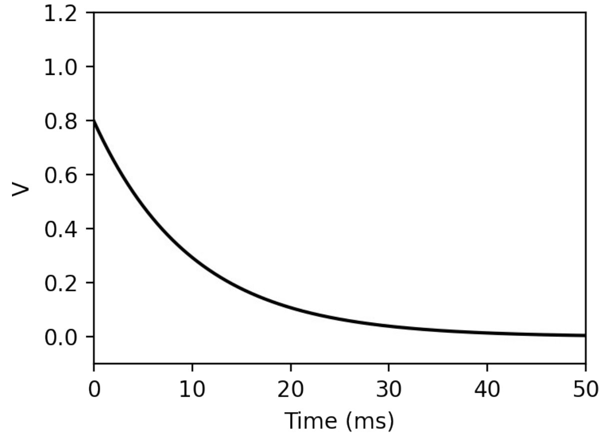


A simple model: the leaky integrate-and-fire (LIF) neuron

Membrane potential V evolves according to a differential equation

$$\tau \frac{\mathrm{d}V}{\mathrm{d}t} = -V$$

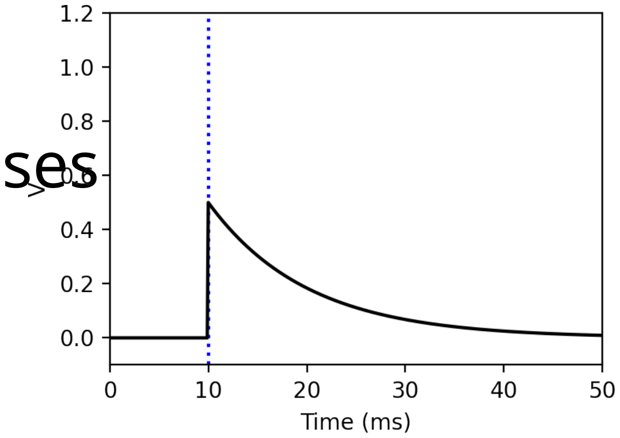
Leak



When a neuron receives a spike, V increases synaptic weight w:

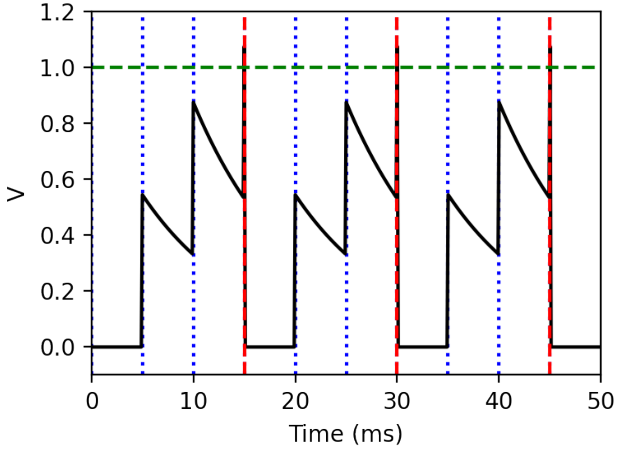
$$V \leftarrow V + w$$

Integrate



When $V > V_t$ the neuron "fires a spike" and Resets: $V \leftarrow 0$

Nonlinear, discontinuous dynamics!



Spiking NN deep learning

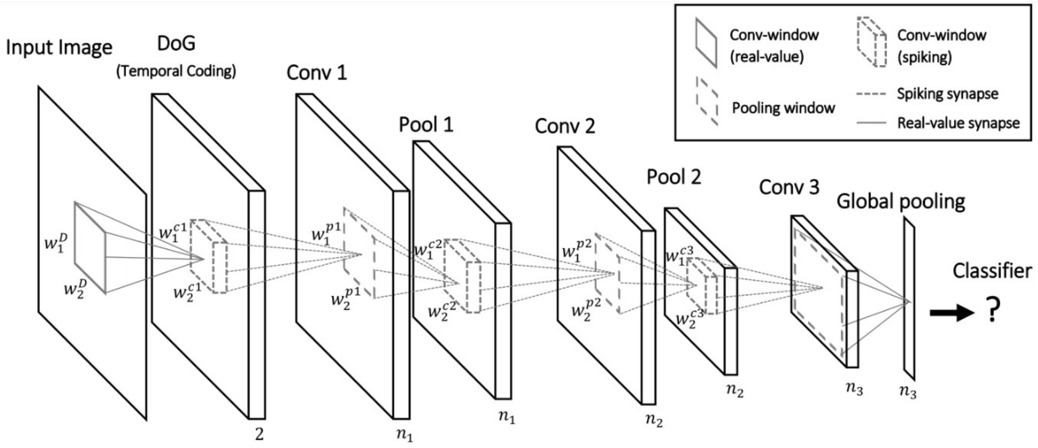
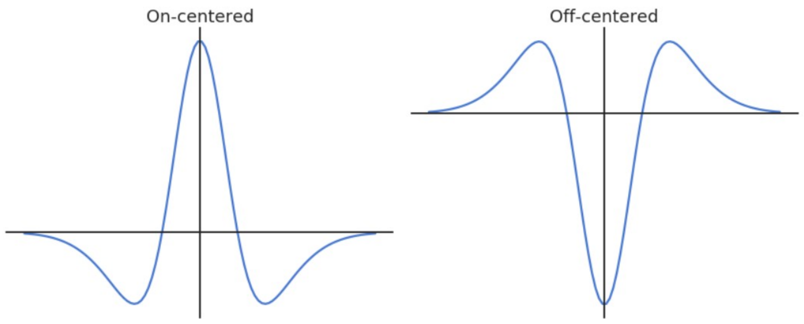


Fig. 5.30 Deep convolutional spiking network of [Kheradpisheh et al., 2018].

The image is first transformed into a spiking population using **difference-of-Gaussian** (DoG) filters.

- **On-center** neurons fire when a bright area at the corresponding location is surrounded by a darker area.
- **Off-center** cells do the opposite.



Snn-Torch
SpikeJelly
Etc

Neuron
Nest
PyNN

Questions?