UNIVERSITY OF TECHNOLOGY
IN THE EUROPEAN CAPITAL OF CULTURE
CHEMNITZ

Neurocomputing

Spiking networks

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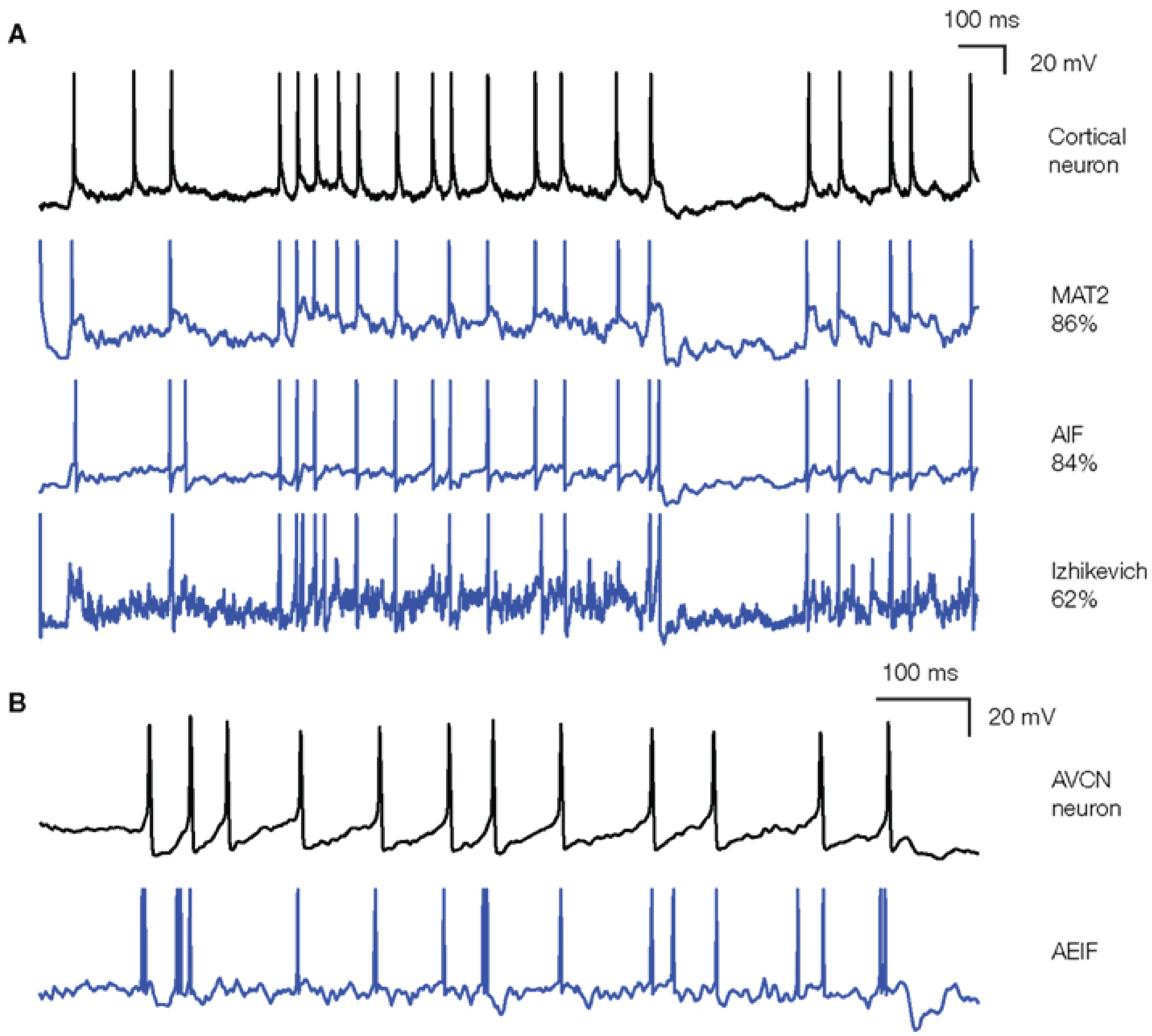
1 - Spiking neurons

Biological neurons communicate through spikes



- The two important dimensions of the information exchanged by neurons are:
  - The instantaneous **frequency** or **firing rate**: number of spikes per second (Hz).
  - The precise **timing** of the spikes.
- The shape of the spike (amplitude, duration) does not matter much.
- Spikes are binary signals (0 or 1) at precise moments of time.
- **Rate-coded neurons** only represent the firing rate of a neuron and ignore spike timing.
- **Spiking neurons** represent explicitly spike timing, but omit the details of action potentials.

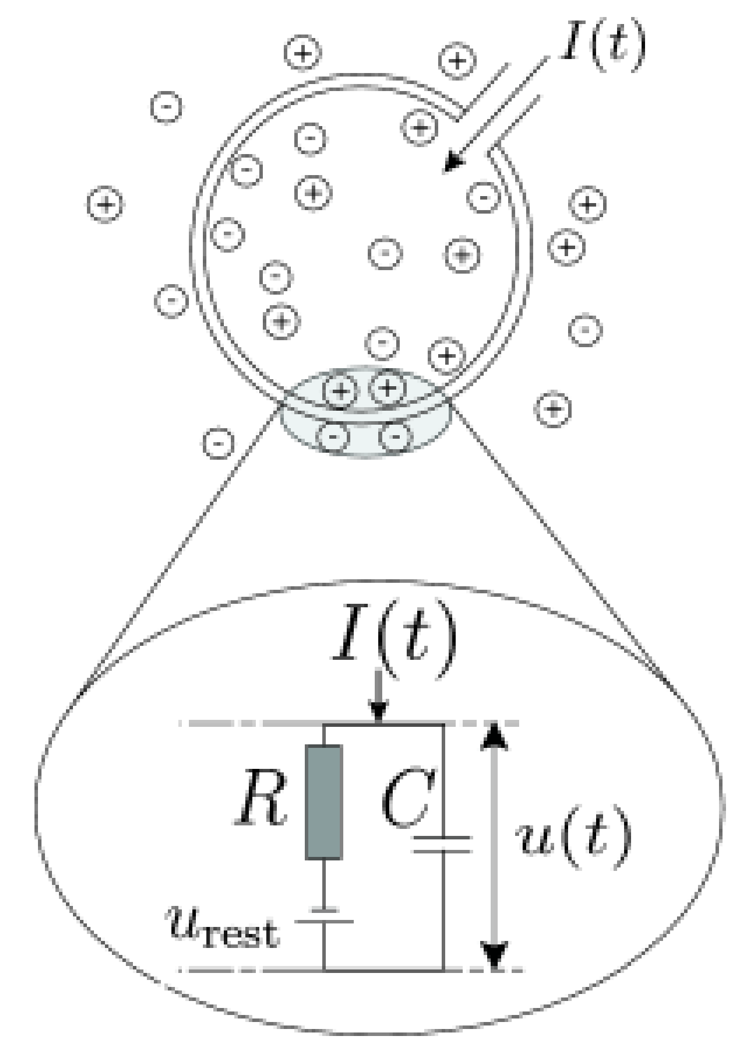
Rossant et al. (2011) Fitting Neuron Models to Spike Trains. Front. Neurosci. 5. doi:10.3389/fnins.2011.00009

The leaky integrate-and-fire neuron (Lapicque, 1907)

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

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

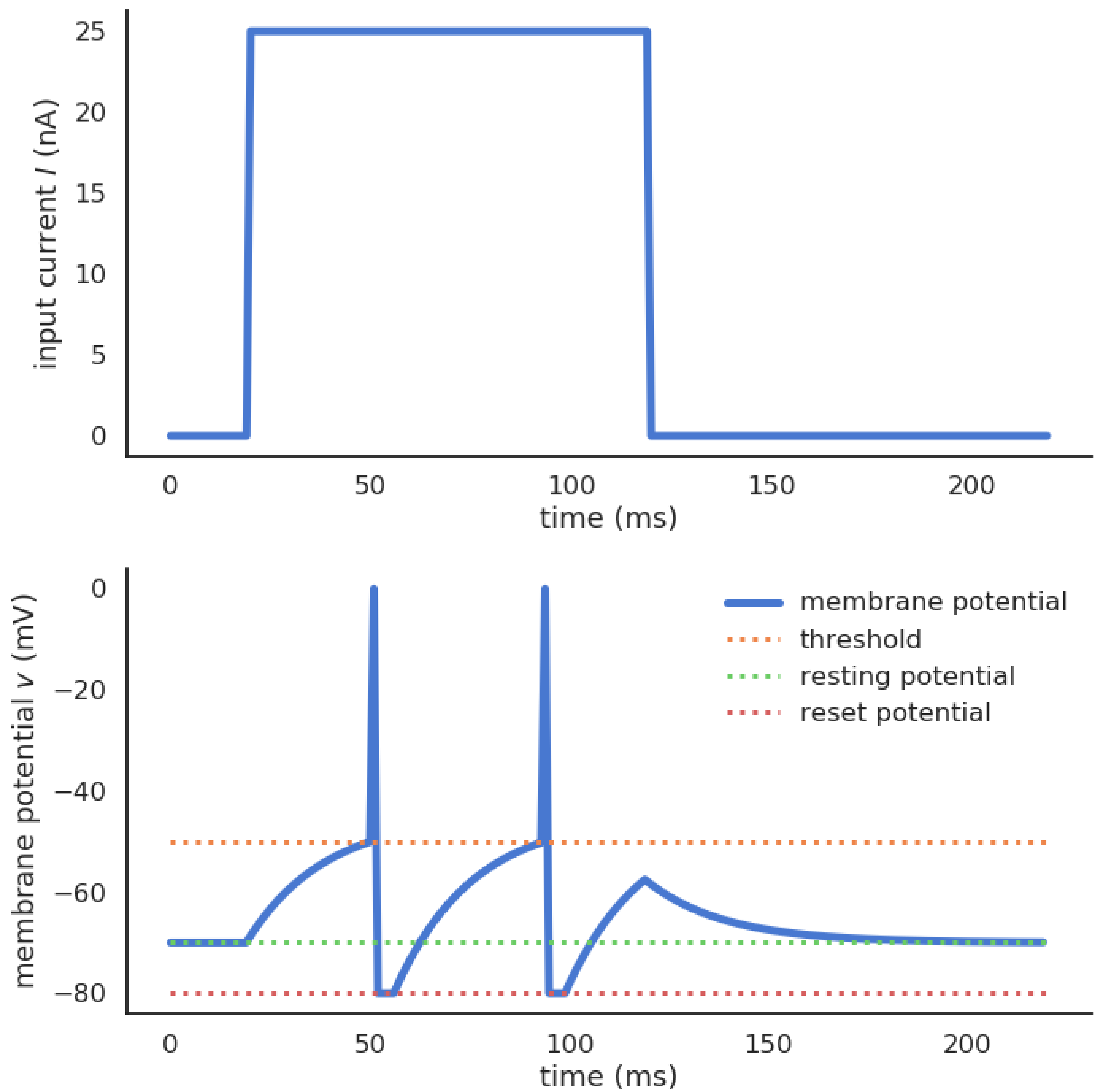
- C is the membrane capacitance, g_L the leak conductance and V_L the resting potential.
- In the absence of input current ($I = 0$), the membrane potential is equal to the resting potential.



Source: https://neuronaldynamics.epfl.ch/online/Ch1.S3.html

- When the membrane potential exceeds a threshold V_T, the neuron emits a spike and the membrane potential is reset to the reset potential V_r for a fixed refractory period t_{ref}.

$$\text{if} \; v(t) > V_T \; \text{: emit a spike and set} \, v(t) = V_r \; \text{for} \, t_{\text{ref}} \, \text{ms.}$$

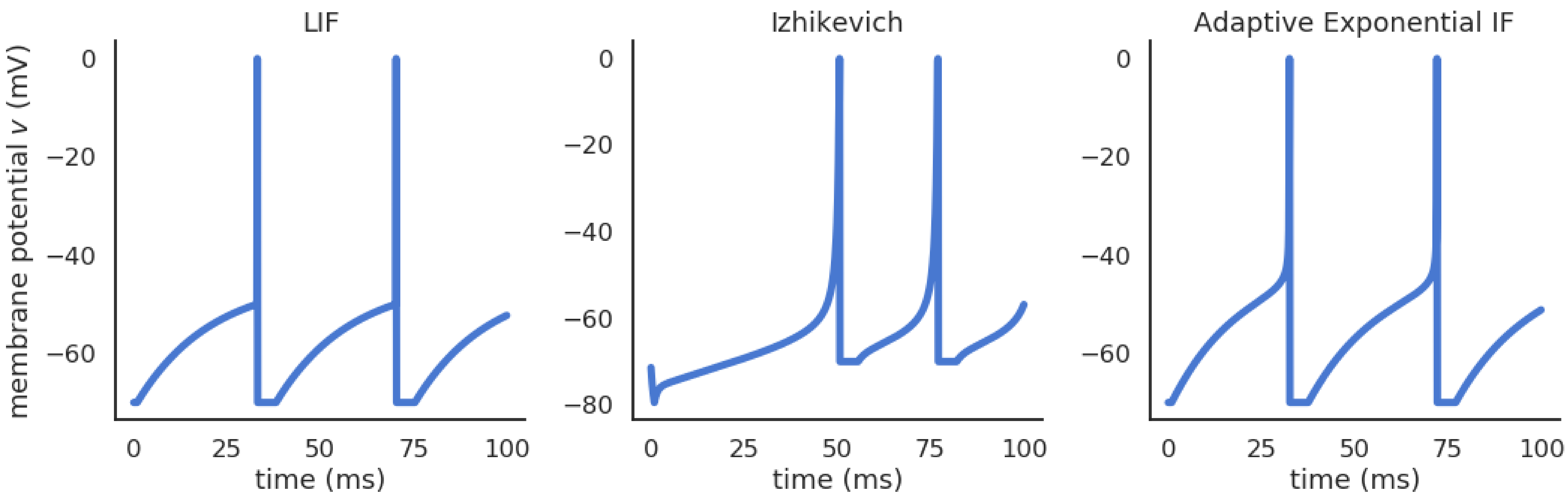

input current I (nA)
25
20
15
10
5
0
0
50
100
150
200
time (ms)
membrane potential v (mV)
0
−20
−40
−60
−80
membrane potential
threshold
resting potential
reset potential
0
50
100
150
200
time (ms)

Different spiking neuron models are possible

- Izhikevich quadratic Integrate-and-fire.

$$\frac{dv(t)}{dt} = 0.04\, v(t)^2 + 5\, v(t) + 140 - u(t) + I(t)$$

$$\frac{du(t)}{dt} = a\,(b\, v(t) - u(t))$$



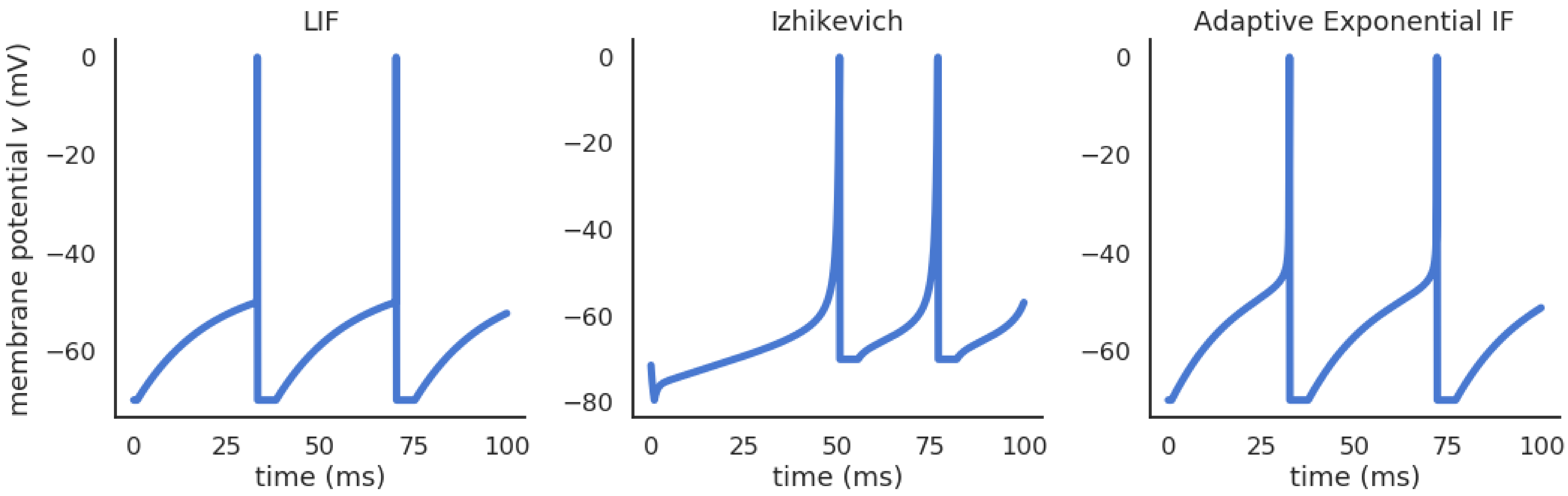
Izhikevich (2003) Simple model of spiking neurons. IEEE transactions on neural networks 14:1569–72. doi:10.1109/TNN.2003.820440

Different spiking neuron models are possible

- Adaptive exponential IF (AdEx).

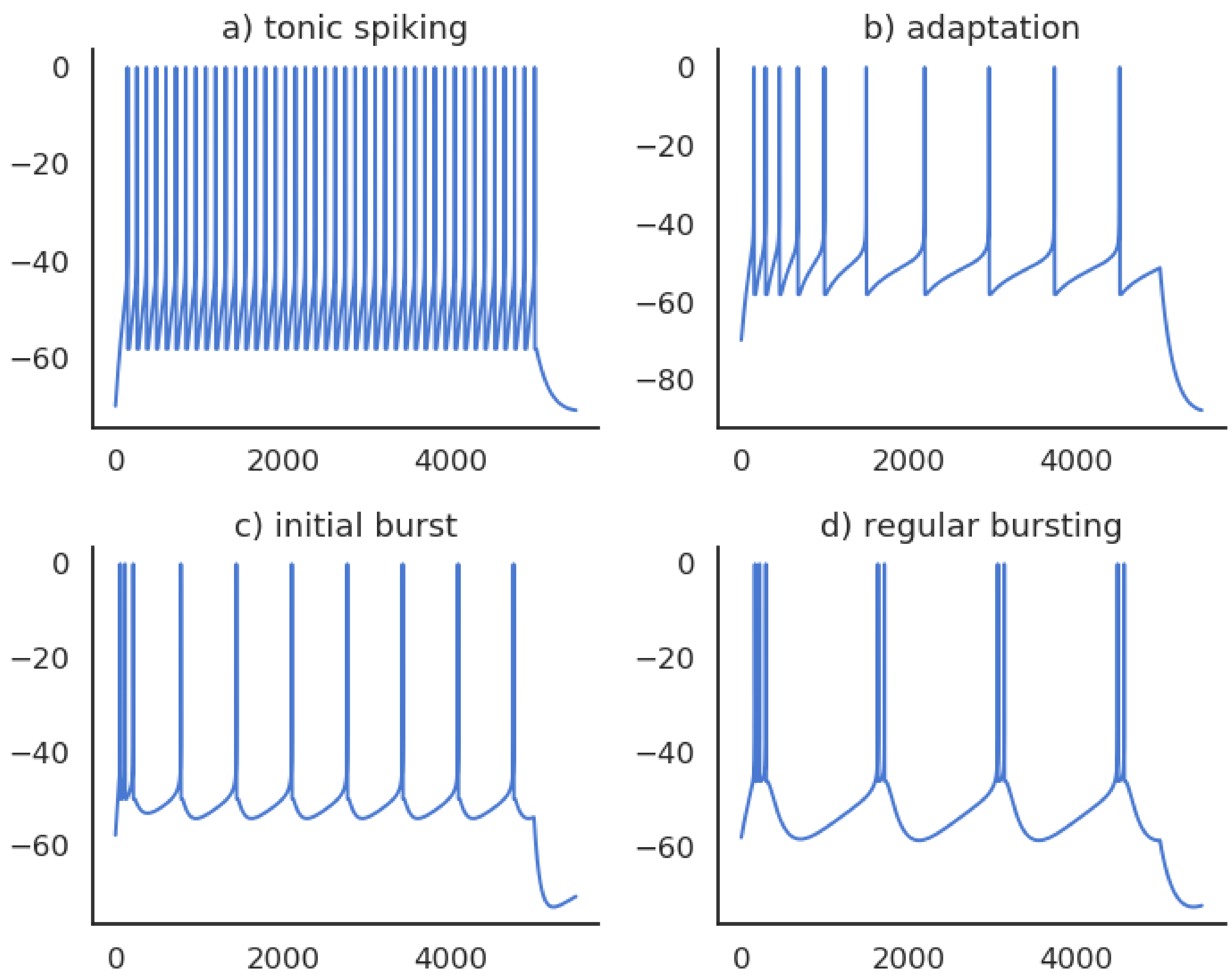
$$C \, \frac{dv(t)}{dt} = -g_L \, (v(t) - E_L) + g_L \, \Delta_T \, \exp(\frac{v(t) - v_T}{\Delta_T}) + I(t) - w$$

$$\tau_w \, \frac{dw}{dt} = a \, (v(t) - E_L) - w$$



Brette and Gerstner (2005) Adaptive Exponential Integrate-and-Fire Model as an Effective Description of Neuronal Activity. Journal of Neurophysiology 94:3637–3642.

Realistic neuron models can reproduce a variety of dynamics

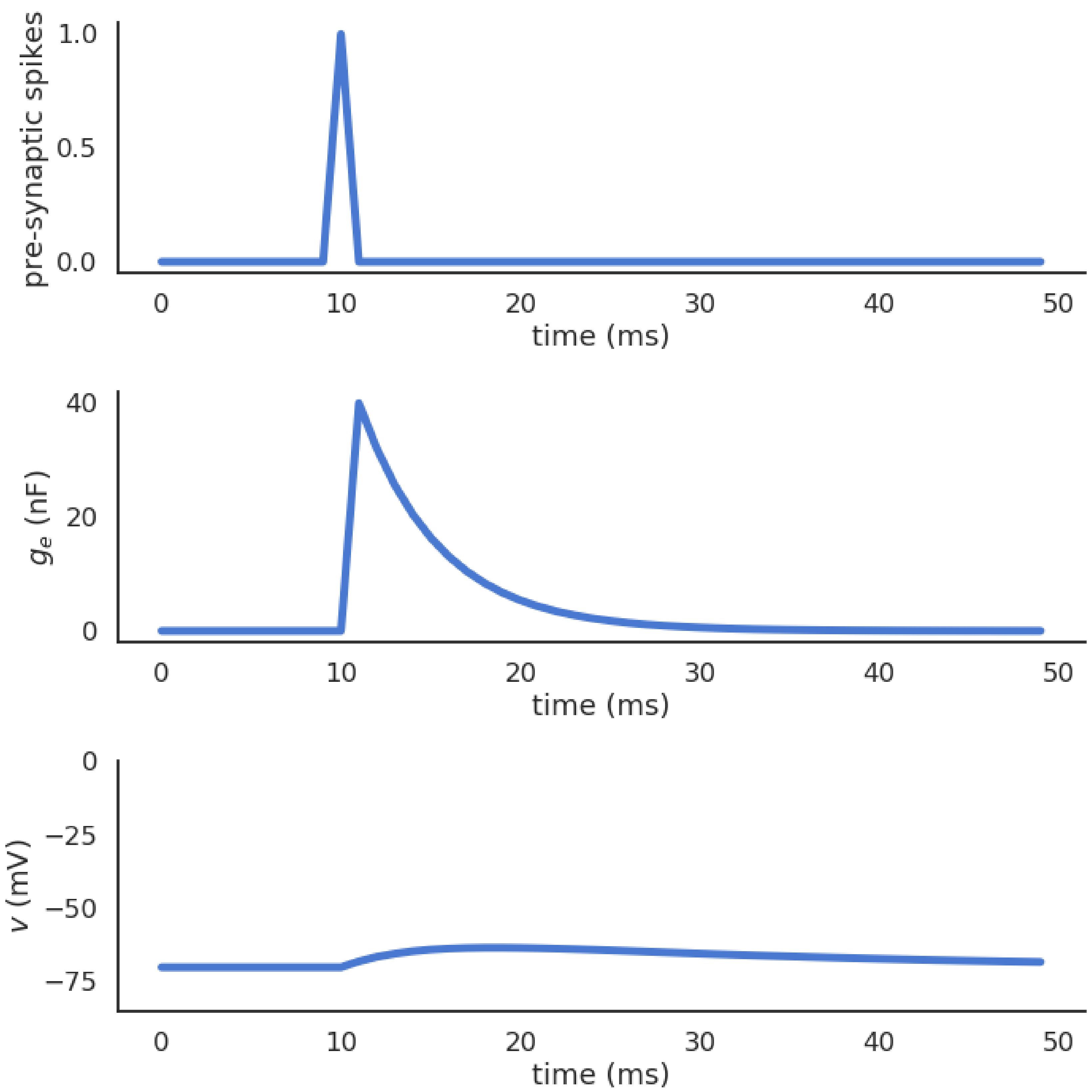


- Biological neurons do not all respond the same to an input current.
  - Some fire regularly.
  - Some slow down with time.
  - Some emit bursts of spikes.
- Modern spiking neuron models allow to recreate these dynamics by changing a few parameters.

Synaptic transmission

- Spiking neurons communicate by **increasing the conductance** g_e of the postsynaptic neuron:

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



- Incoming spikes increase the conductance from a constant w which represents the synaptic efficiency (or weight):

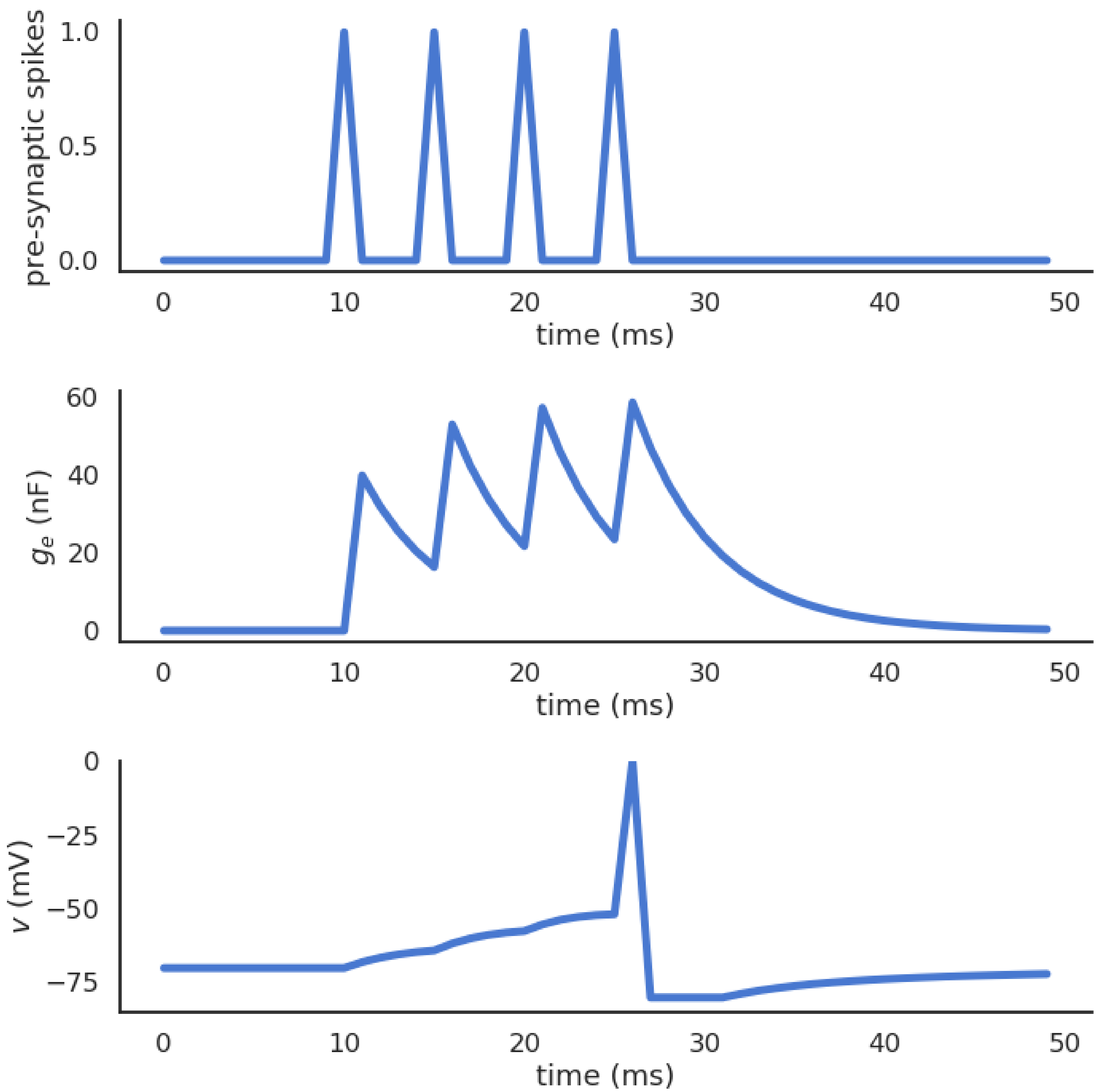
$$g_e(t) \leftarrow g_e(t) + w$$

- If there is no spike, the conductance decays back to zero:

$$\tau_e \, \frac{d g_e(t)}{dt} + g_e(t) = 0$$

- An incoming spike temporarily increases (or decreases if the weight w is negative) the membrane potential of the post-synaptic neuron.

Synaptic transmission



- When enough spikes arrive at the post-synaptic neuron close in time:
  - either one pre-synaptic fires very rapidly,
  - or many different pre-synaptic neurons fire in close proximity,

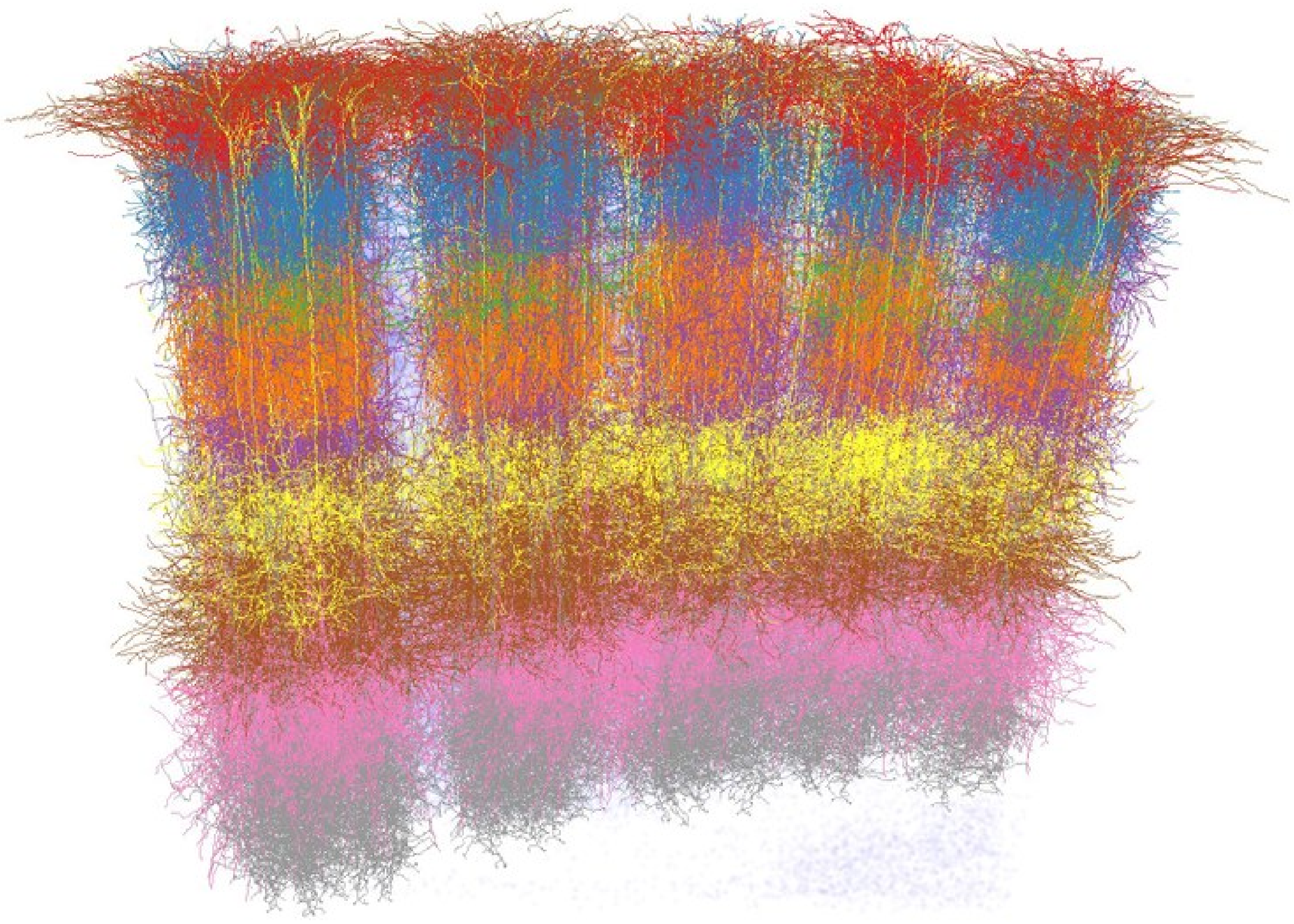
this can be enough to bring the post-synaptic membrane over the threshold, so that it it turns emits a spike.

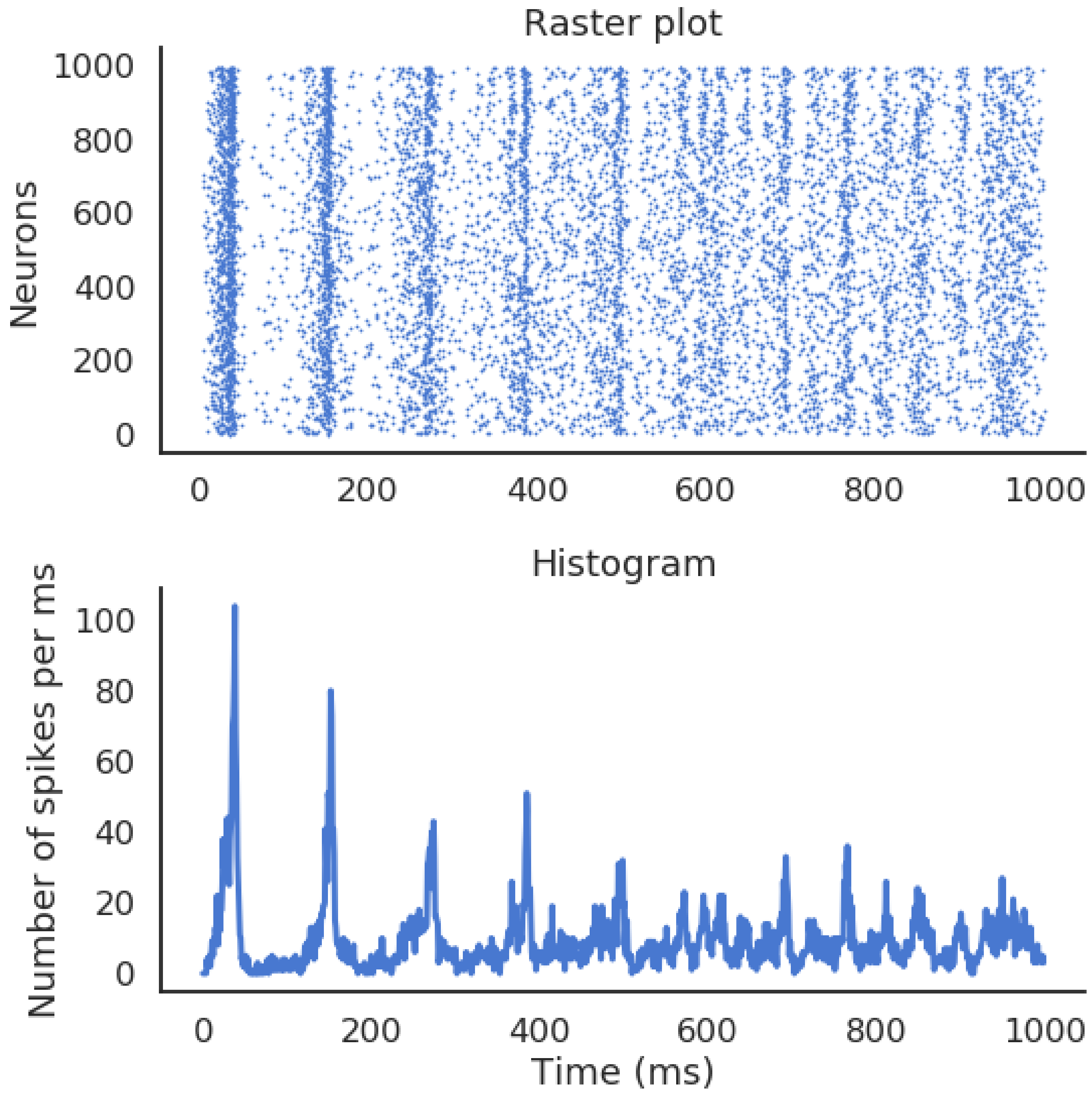
- This is the basic principle of **synaptic transmission** in biological neurons.
  - Neurons emit spikes, which modify the membrane potential of other neurons, which in turn emit spikes, and so on.

Populations of spiking neurons

- **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.



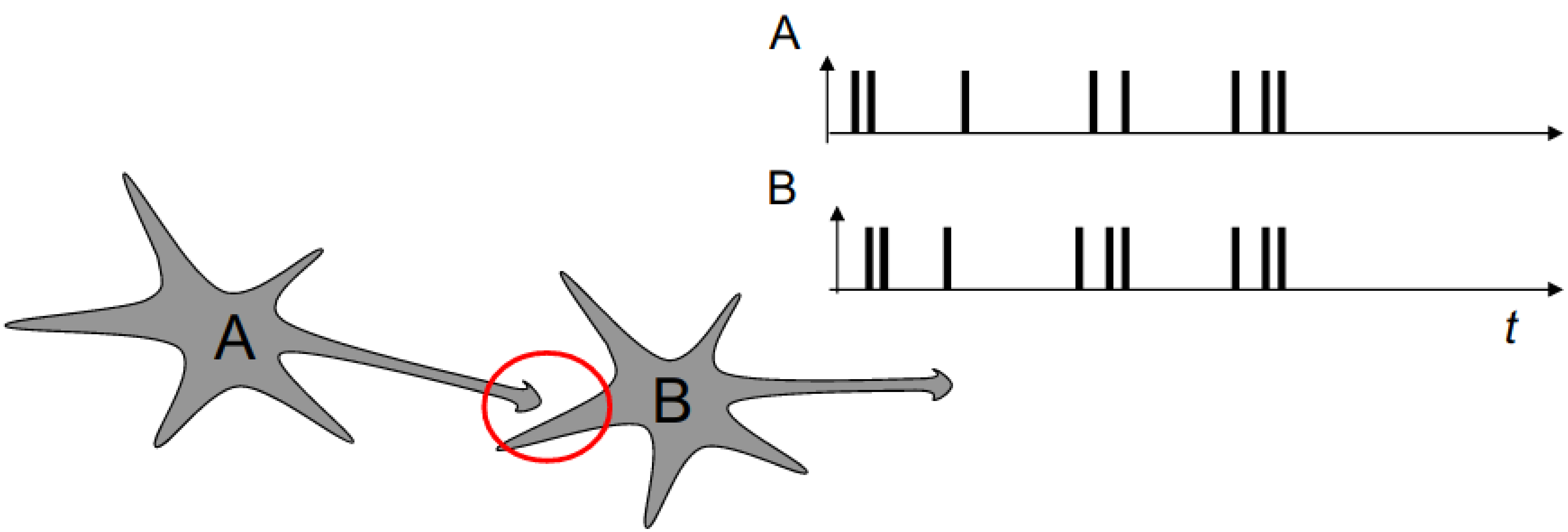


Source: https://www.pnas.org/content/110/47/19113

Hebbian learning

- **Hebbian learning** postulates that synapses strengthen based on the **correlation** between the activity of the pre- and post-synaptic neurons:

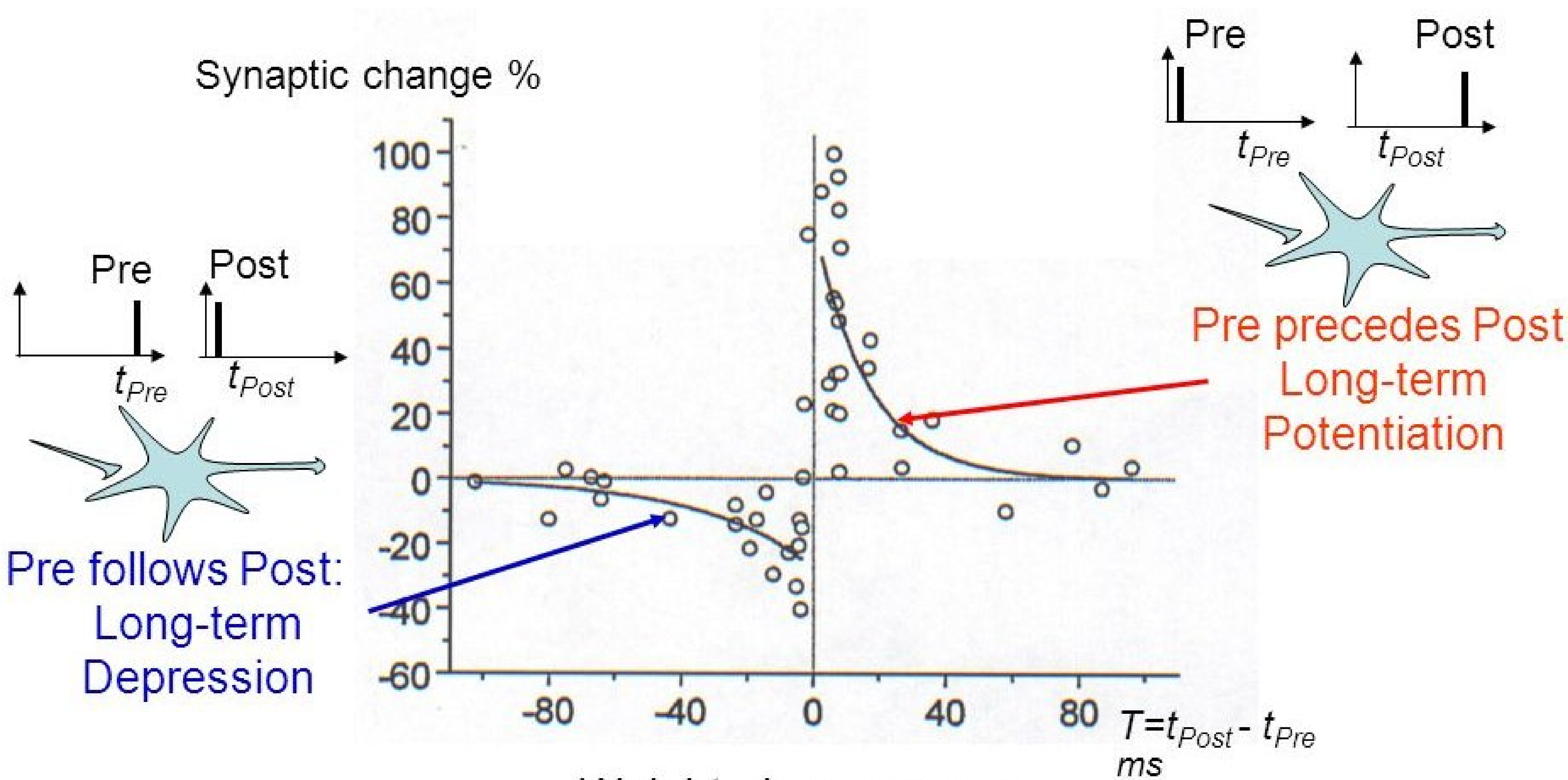
When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased. **Donald Hebb**, 1949



Source: https://slideplayer.com/slide/11511675/

STDP: Spike-timing dependent plasticity

- Synaptic efficiencies actually evolve depending on the the **causation** between the neuron's firing patterns:
  - If the pre-synaptic neuron fires **before** the post-synaptic one, the weight is increased (**long-term potentiation**). Pre causes Post to fire.
  - If it fires **after**, the weight is decreased (**long-term depression**). Pre does not cause Post to fire.



Weight-change curve
(Bi&Poo, 2001)

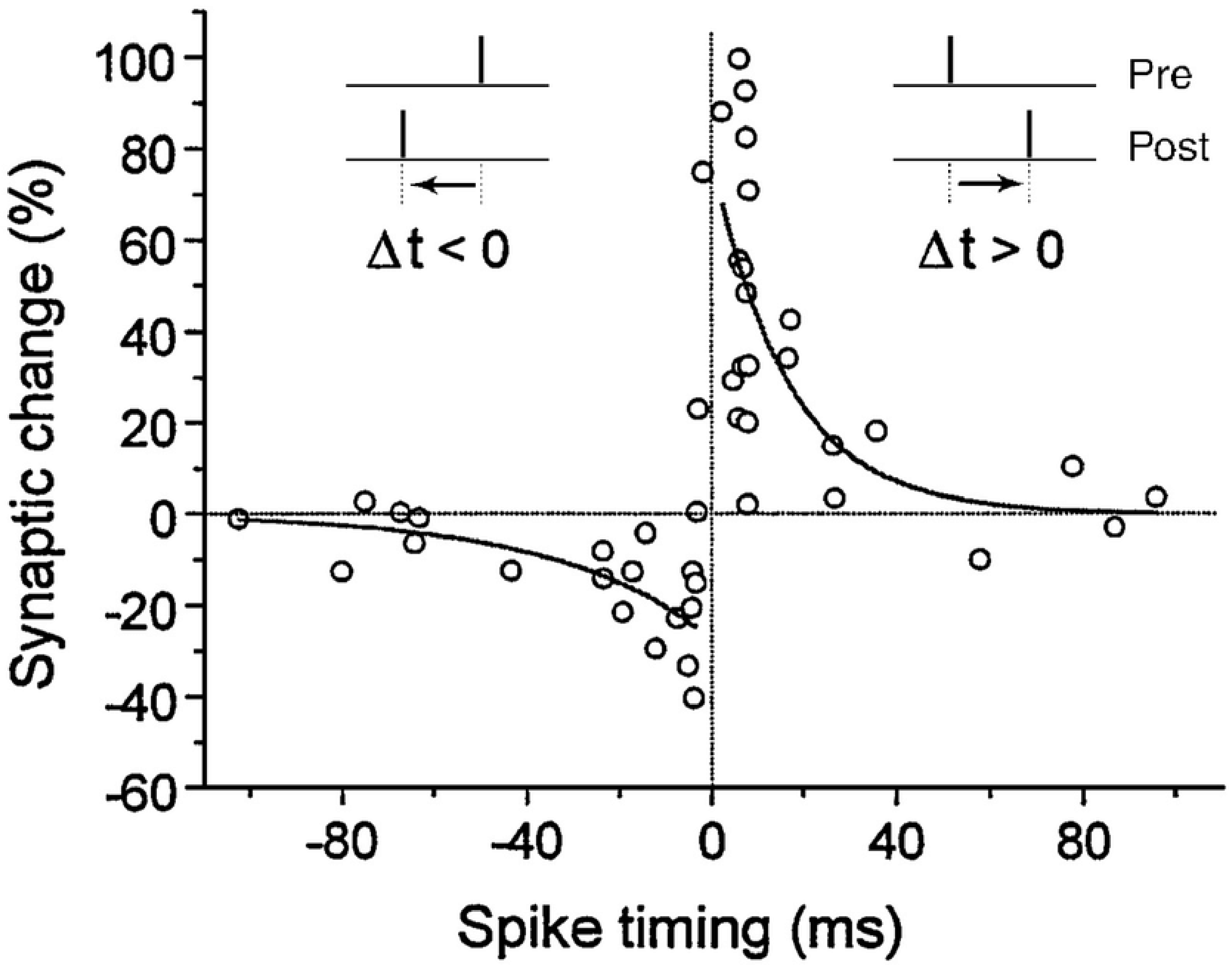
Bi and Poo (2001) Synaptic modification of correlated activity: Hebb's postulate revisited. Ann. Rev. Neurosci., 24:139-166.

STDP: Spike-timing dependent plasticity

- 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.

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

- STDP can be implemented online using traces.
- More complex variants of STDP (triplet STDP) exist, but this is the main model of synaptic plasticity in spiking networks.

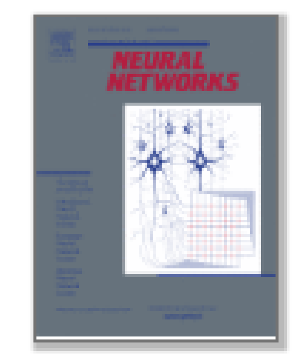


Bi and Poo (2001) Synaptic modification of correlated activity: Hebb's postulate revisited. Ann. Rev. Neurosci., 24:139-166.

2 - Deep convolutional spiking networks

ELSEVIER

Neural Networks
Volume 99, March 2018, Pages 56-67



STDP-based spiking deep convolutional neural networks for object recognition

Saeed Reza Kheradpisheh [a, b], Mohammad Ganjtabesh [a], Simon J. Thorpe [b], Timothée Masquelier [b]

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https://doi.org/10.1016/j.neunet.2017.12.005

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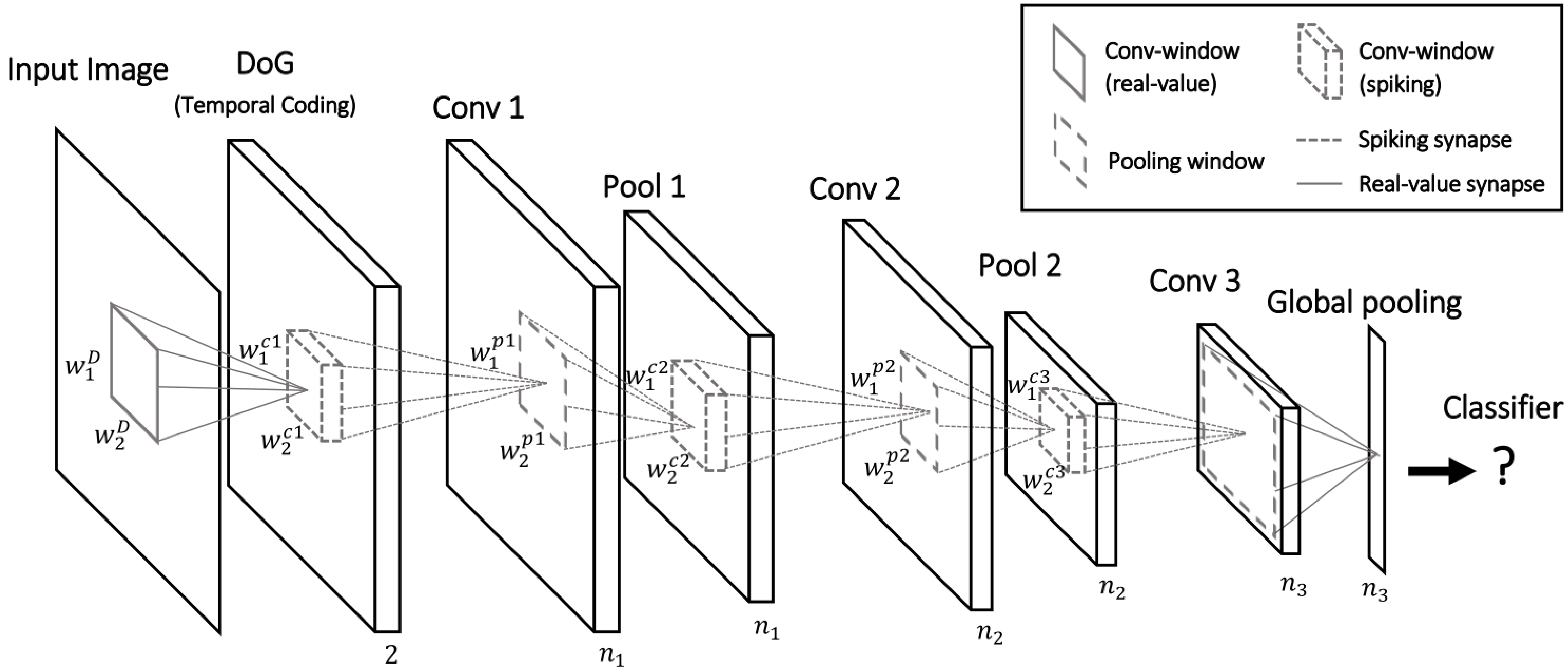
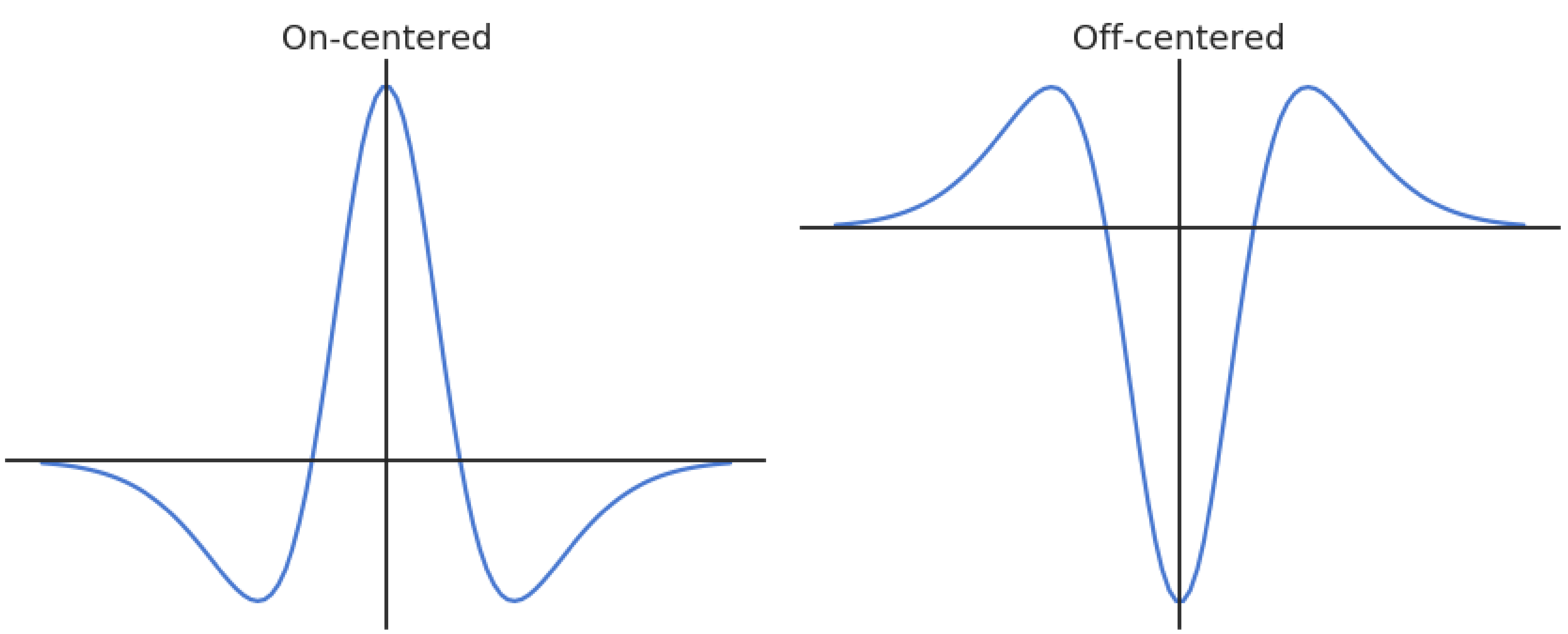
Deep convolutional spiking networks



- A lot of work has lately focused on deep spiking networks, either using a modified version of backpropagation or using STDP.
- The Masquelier lab has proposed a deep spiking convolutional network learning to extract features using STDP (**unsupervised learning**).
- A simple classifier (SVM) then learns to predict classes.

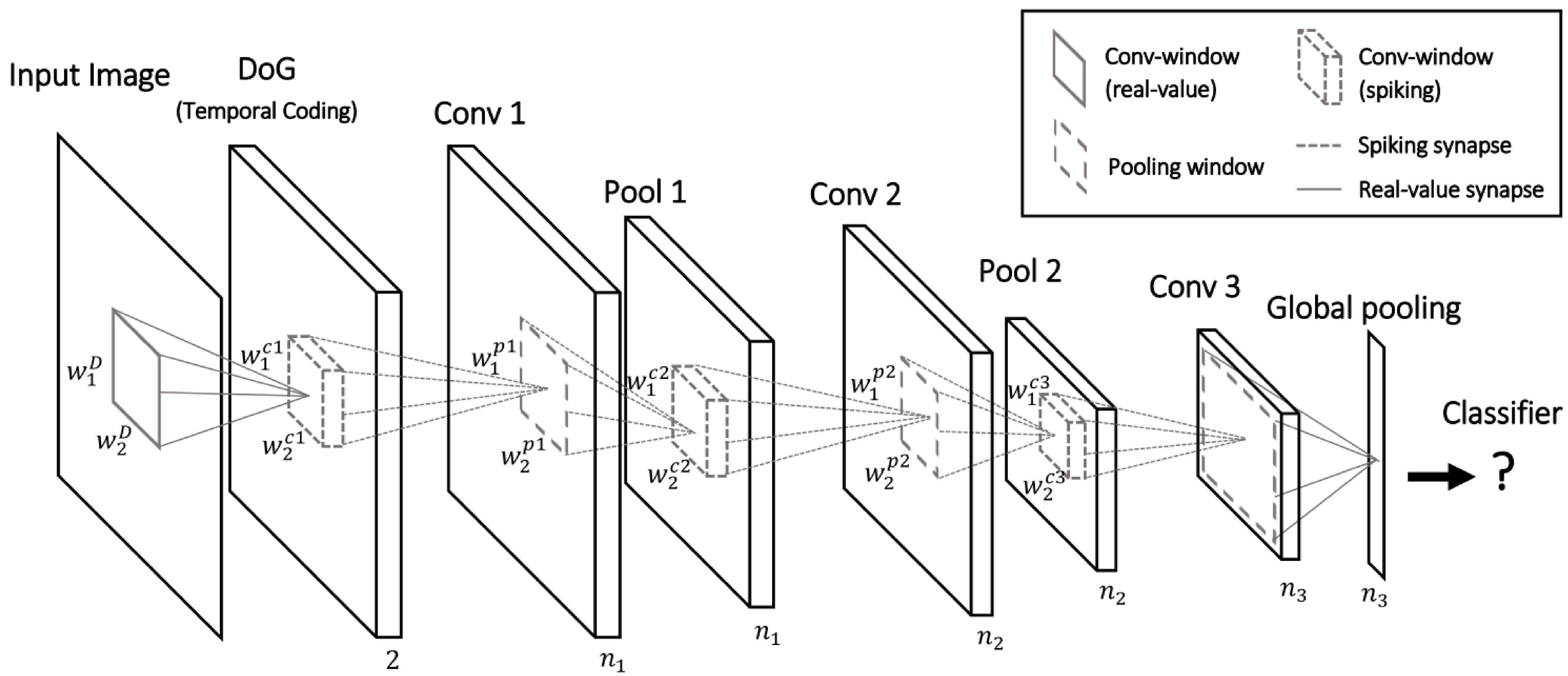
Deep convolutional spiking networks

- 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.



Kheradpisheh et al. (2018) STDP-based spiking deep convolutional neural networks for object recognition. Neural Networks 99, 56–67.

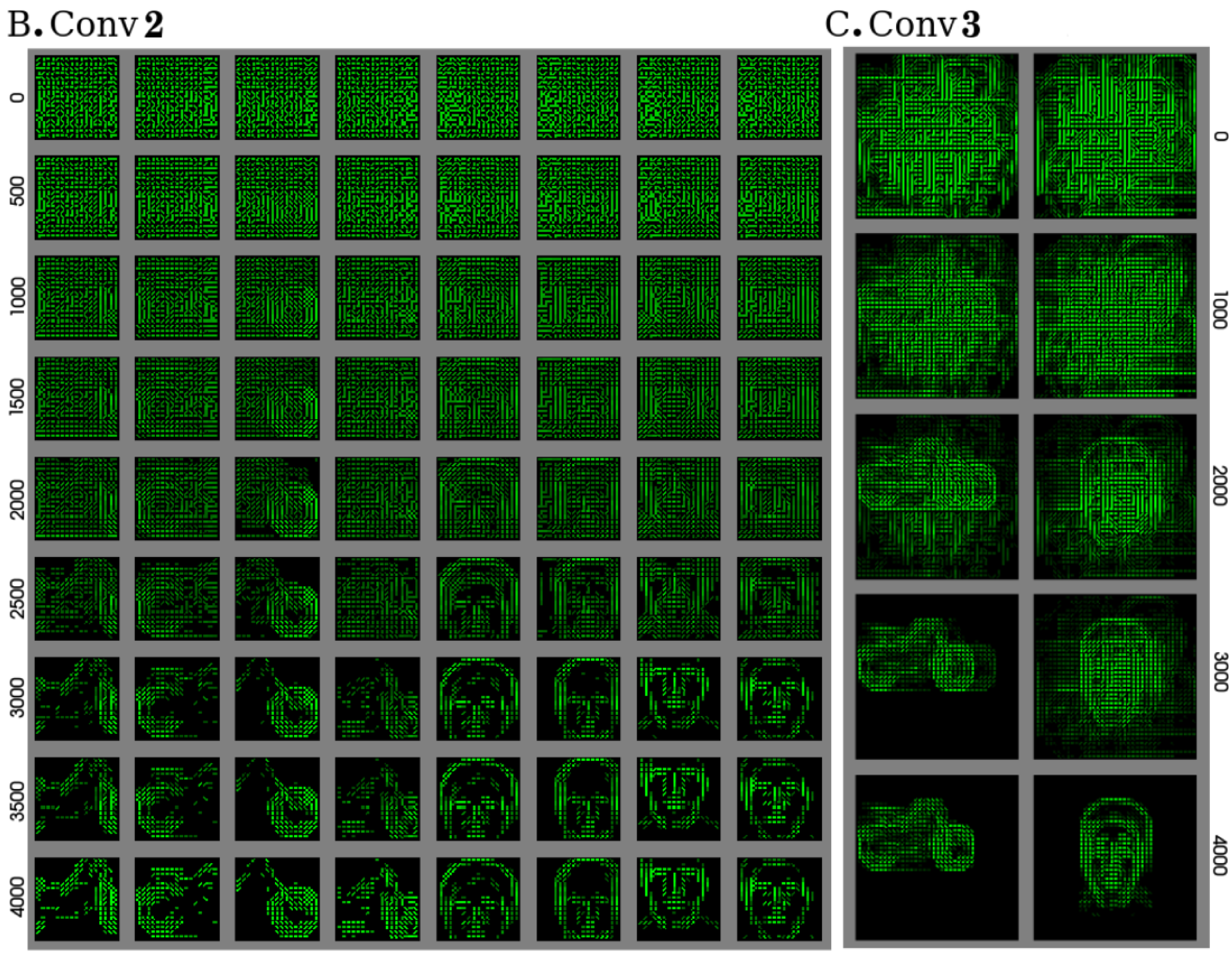
Deep convolutional spiking networks



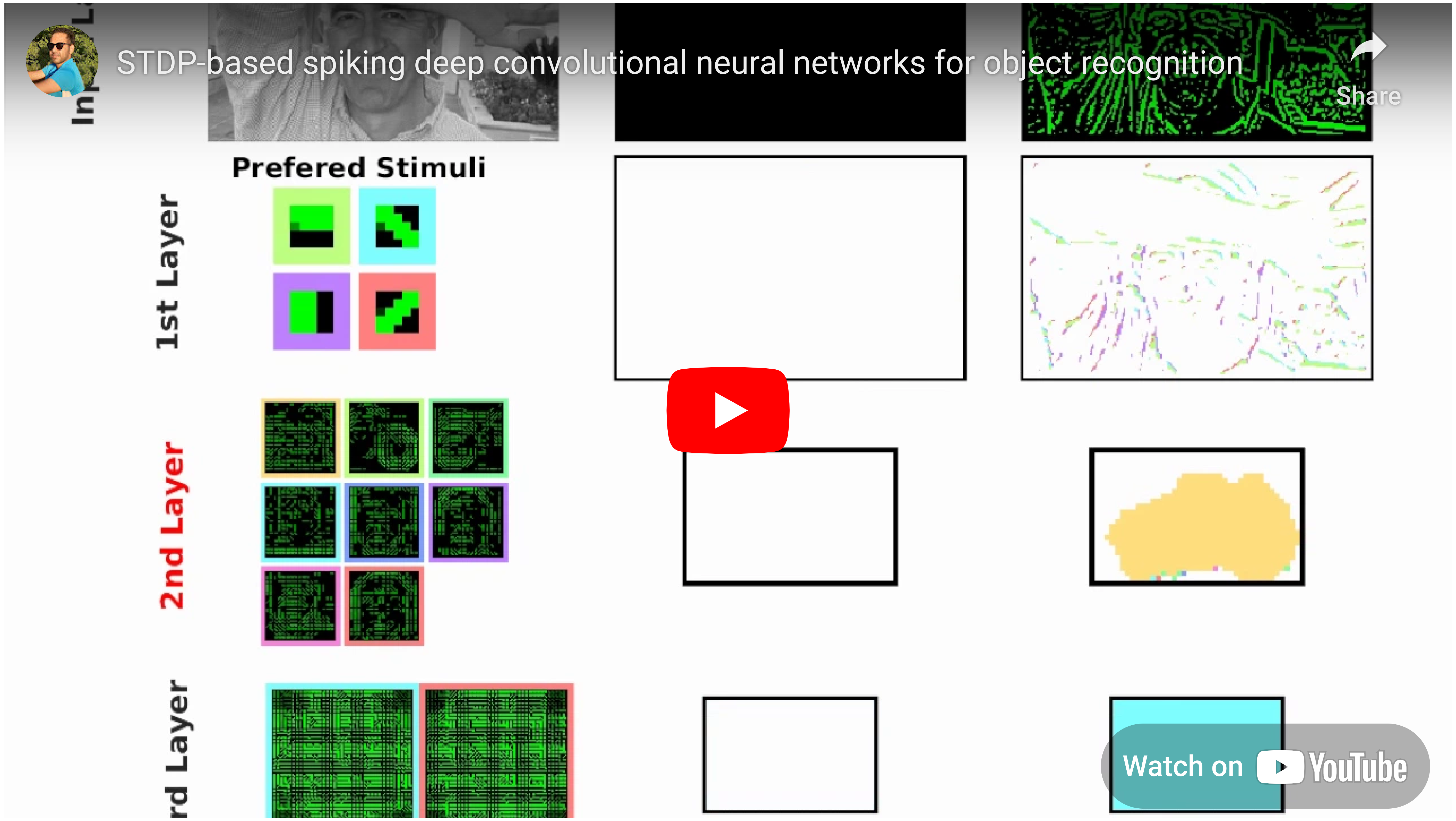
- The convolutional and pooling layers work just as in regular CNNs (shared weights), except the neuron are **integrate-and-fire** (IF).
- There is additionally a **temporal coding scheme**, where the first neuron to emit a spike at a particular location (i.e. over all feature maps) **inhibits** all the others.
- This ensures selectivity of the features through **sparse coding**: only one feature can be detected at a given location.
- STDP allows to learn **causation** between the features and to extract increasingly complex features.

Kheradpisheh et al. (2018) STDP-based spiking deep convolutional neural networks for object recognition. Neural Networks 99, 56–67.

Deep convolutional spiking networks



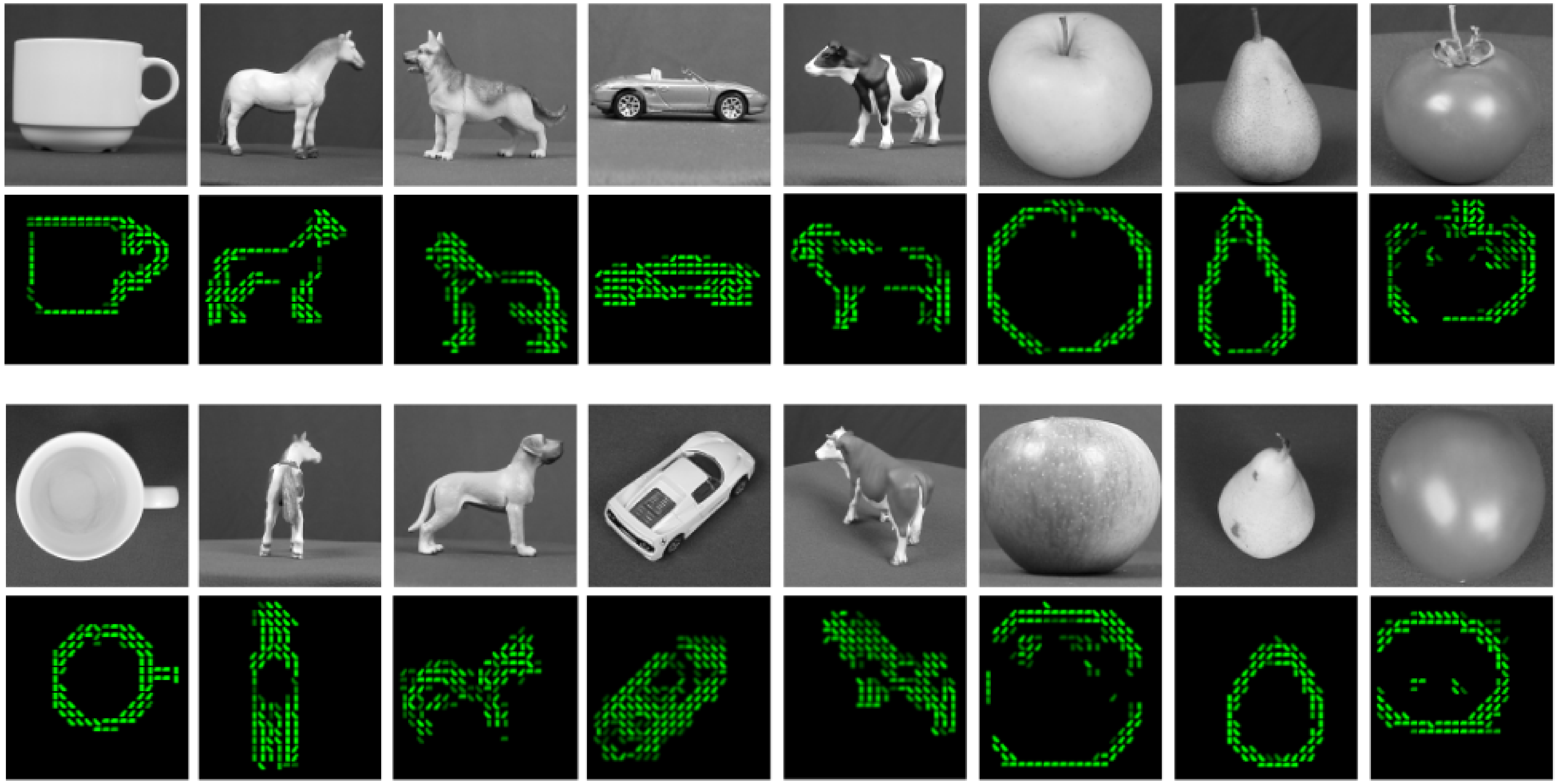
Deep convolutional spiking networks



https://www.youtube.com/watch?v=u32Xnz2hDkE

Deep convolutional spiking networks

- The network is trained **unsupervisedly** on various datasets and obtains accuracies close to the state of the art:
    - Caltech face/motorbike dataset.
    - ETH-80
    - MNIST



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Deep convolutional spiking networks

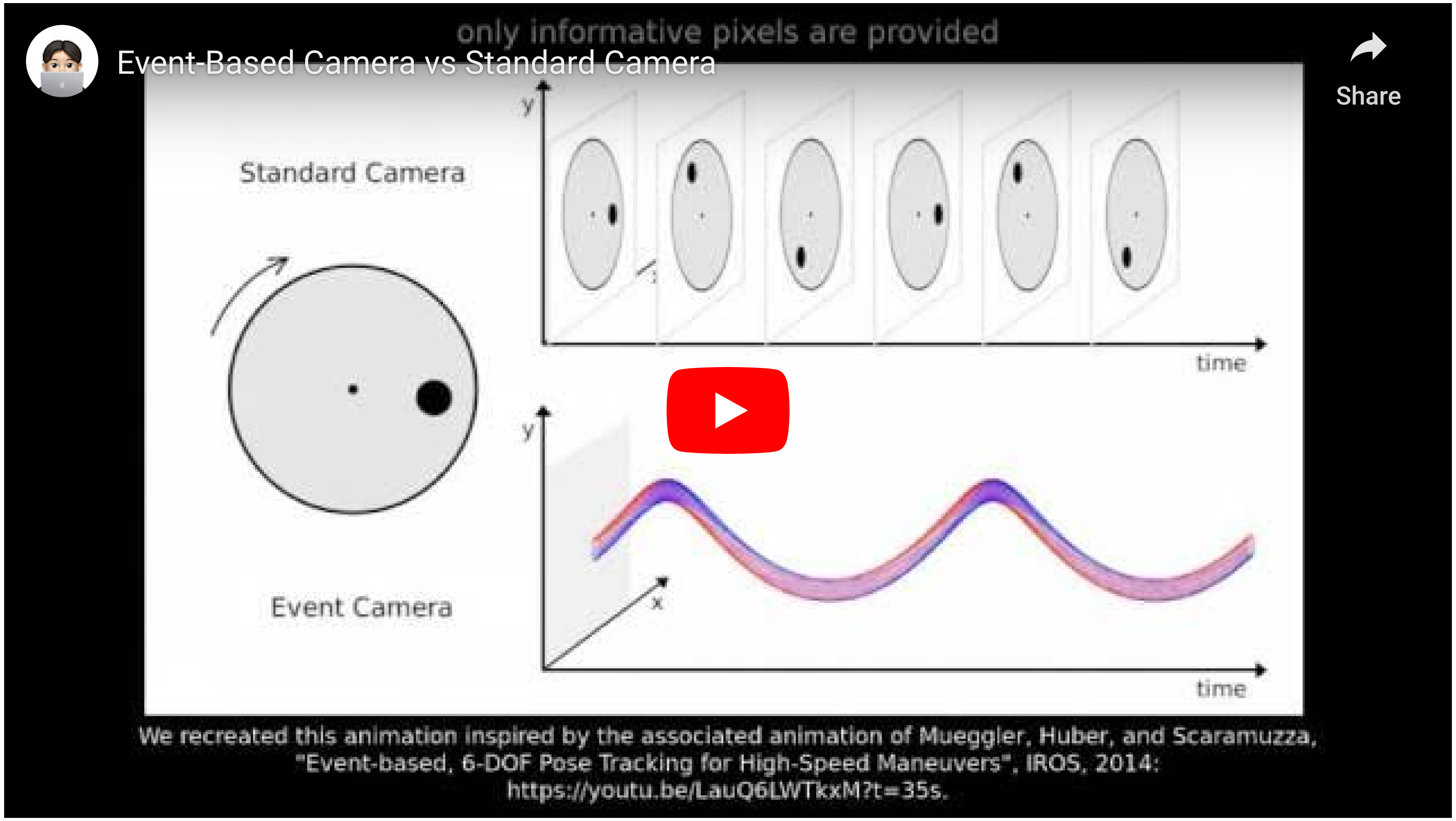
- The performance on MNIST is in line with classical 3-layered CNNs, but without backpropagation!

Architecture	Neural coding	Learning-type	Learning-rule	Accuracy (%)
Dendritic neurons [21]	Rate-based	Supervised	Morphology learning	90.3
Convolutional SNN [59]	Spike-based	Supervised	Tempotron rule	91.3
Two layer network [44]	Spike-based	Unsupervised	STDP	93.5
Spiking RBM [39]	Rate-based	Supervised	Contrastive divergence	94.1
Two layer network [11]	Spike-based	Unsupervised	STDP	95.0
Convolutional SNN [12]	Rate-based	Supervised	Back-propagation	**99.1**
Proposed SDNN	Spike-based	Unsupervised	STDP	98.4

Kheradpisheh et al. (2018) STDP-based spiking deep convolutional neural networks for object recognition. Neural Networks 99, 56–67.

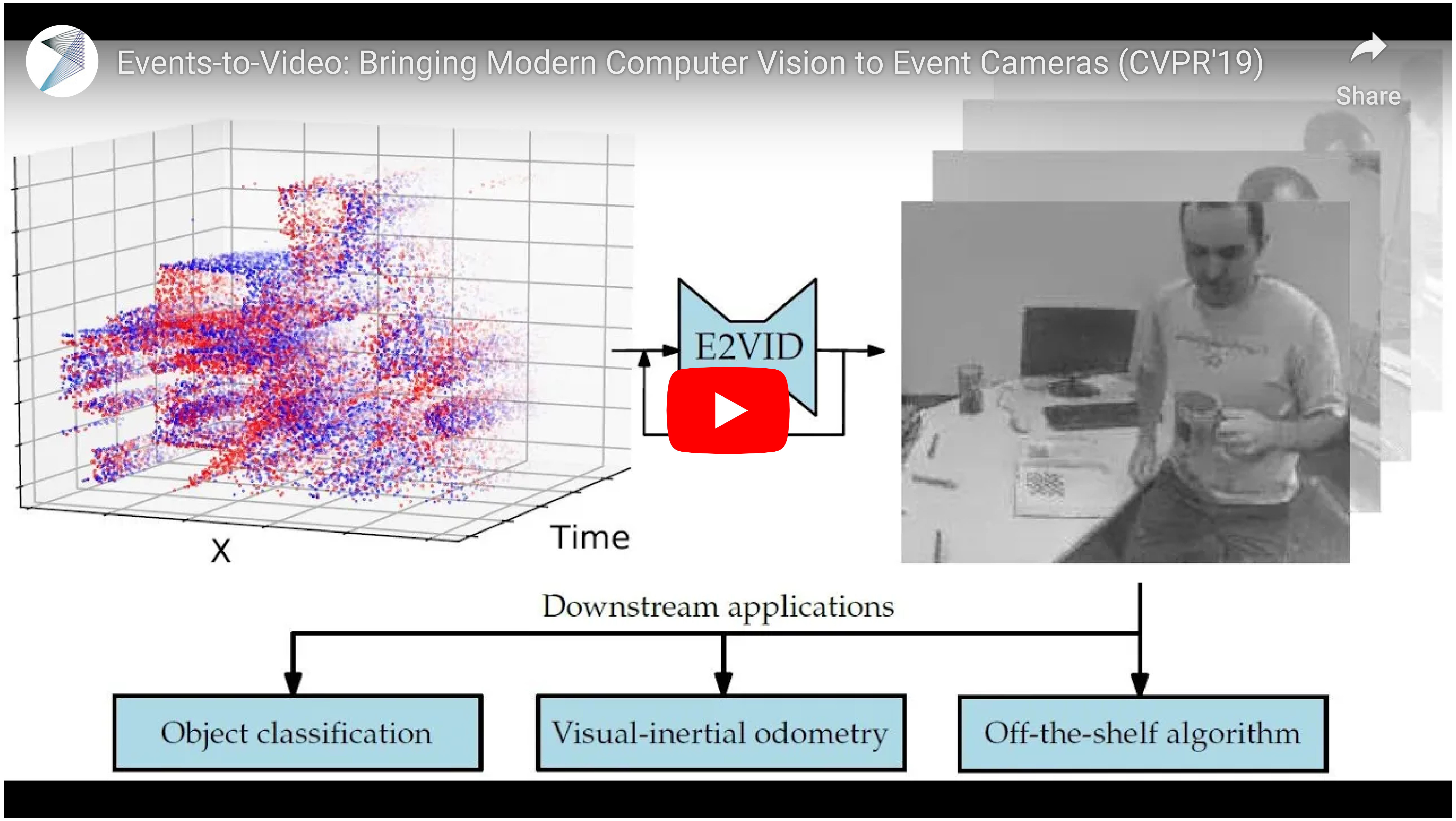
3 - Neuromorphic computing

Event-based cameras



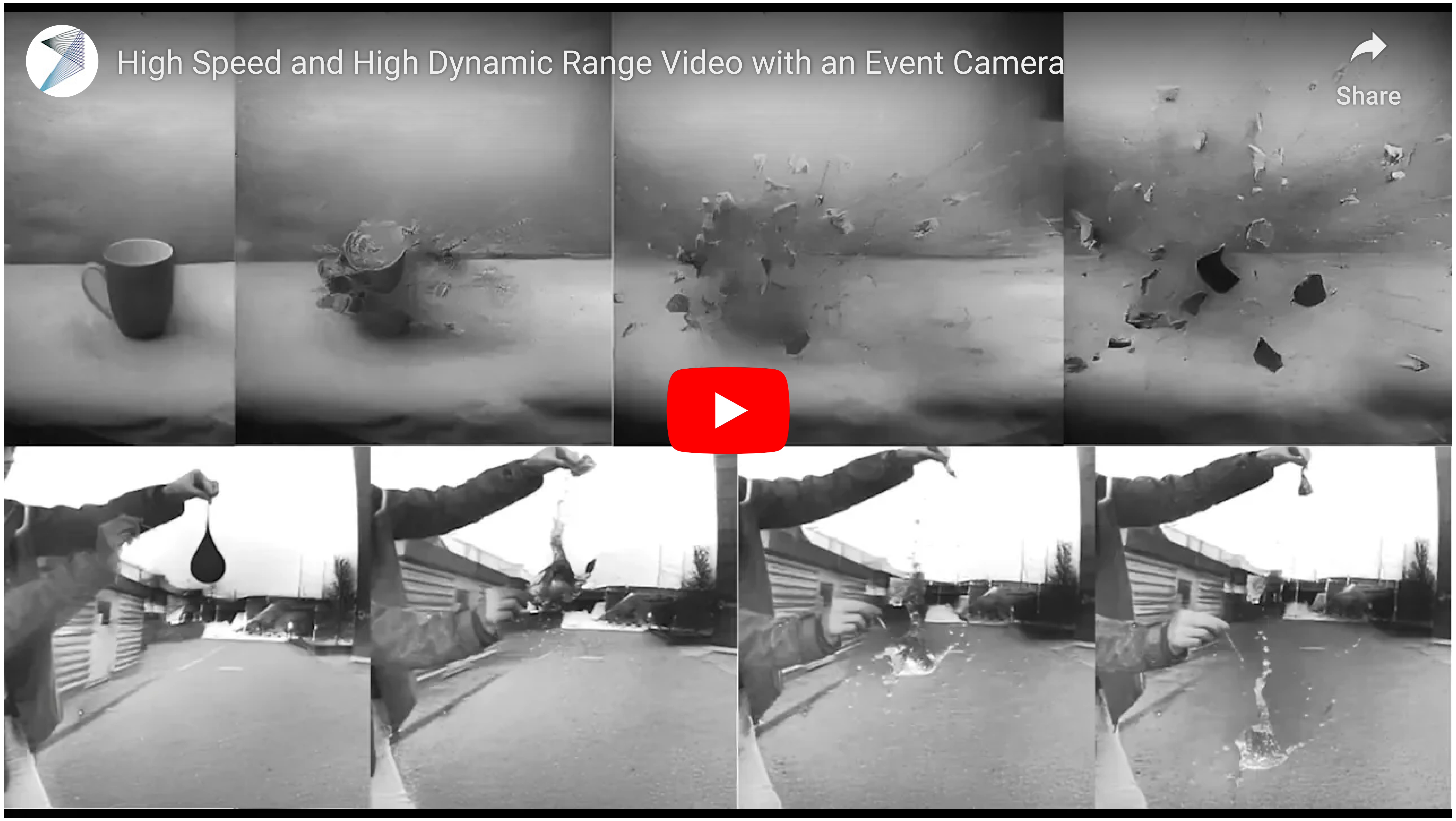
https://www.youtube.com/watch?v=kPCZESVfHoQ

Event-based cameras



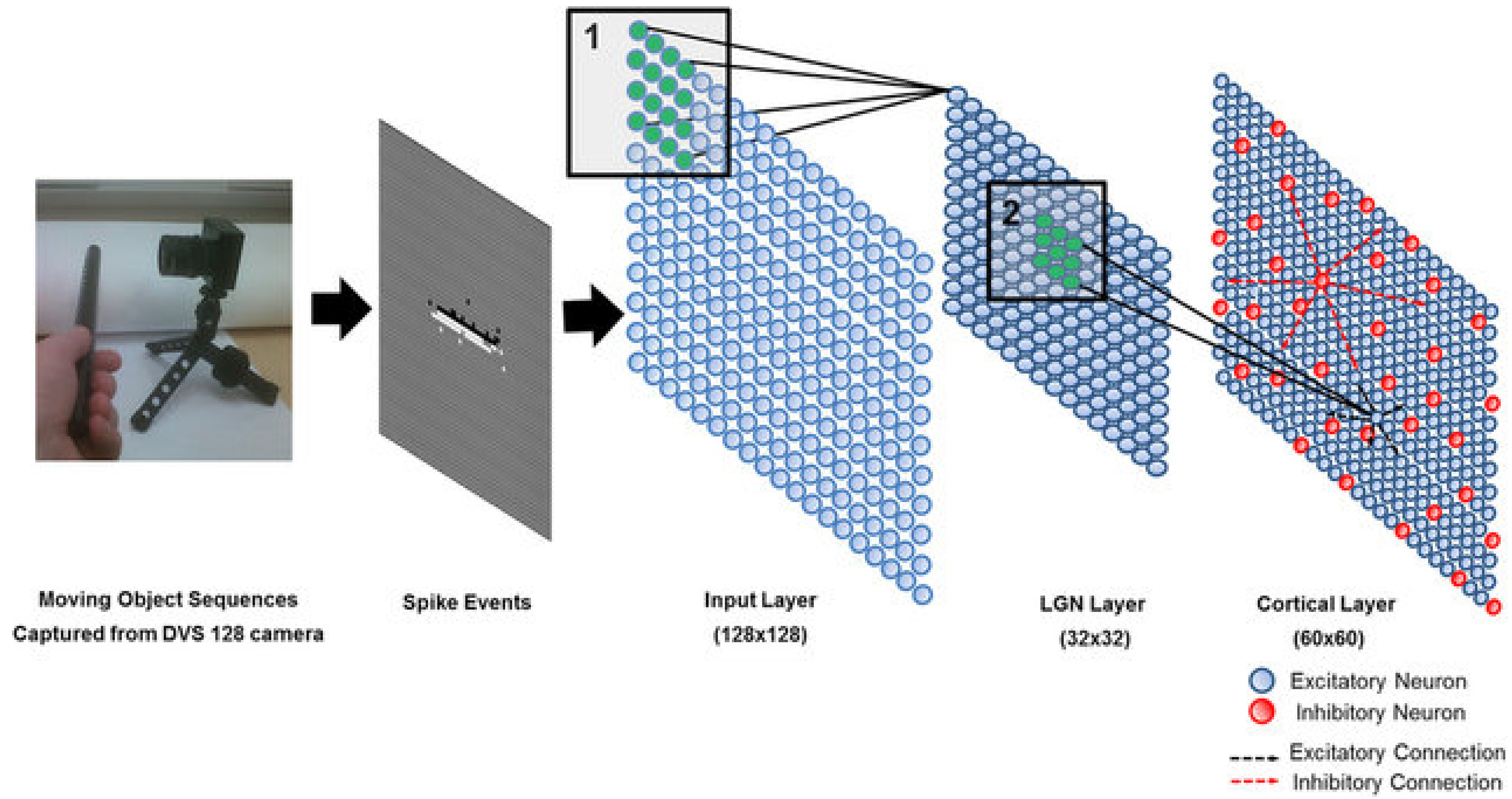
https://www.youtube.com/watch?v=IdYrC4cUO0I

Event-based cameras



https://www.youtube.com/watch?v=eomALySSGVU

Neuromorphic computing



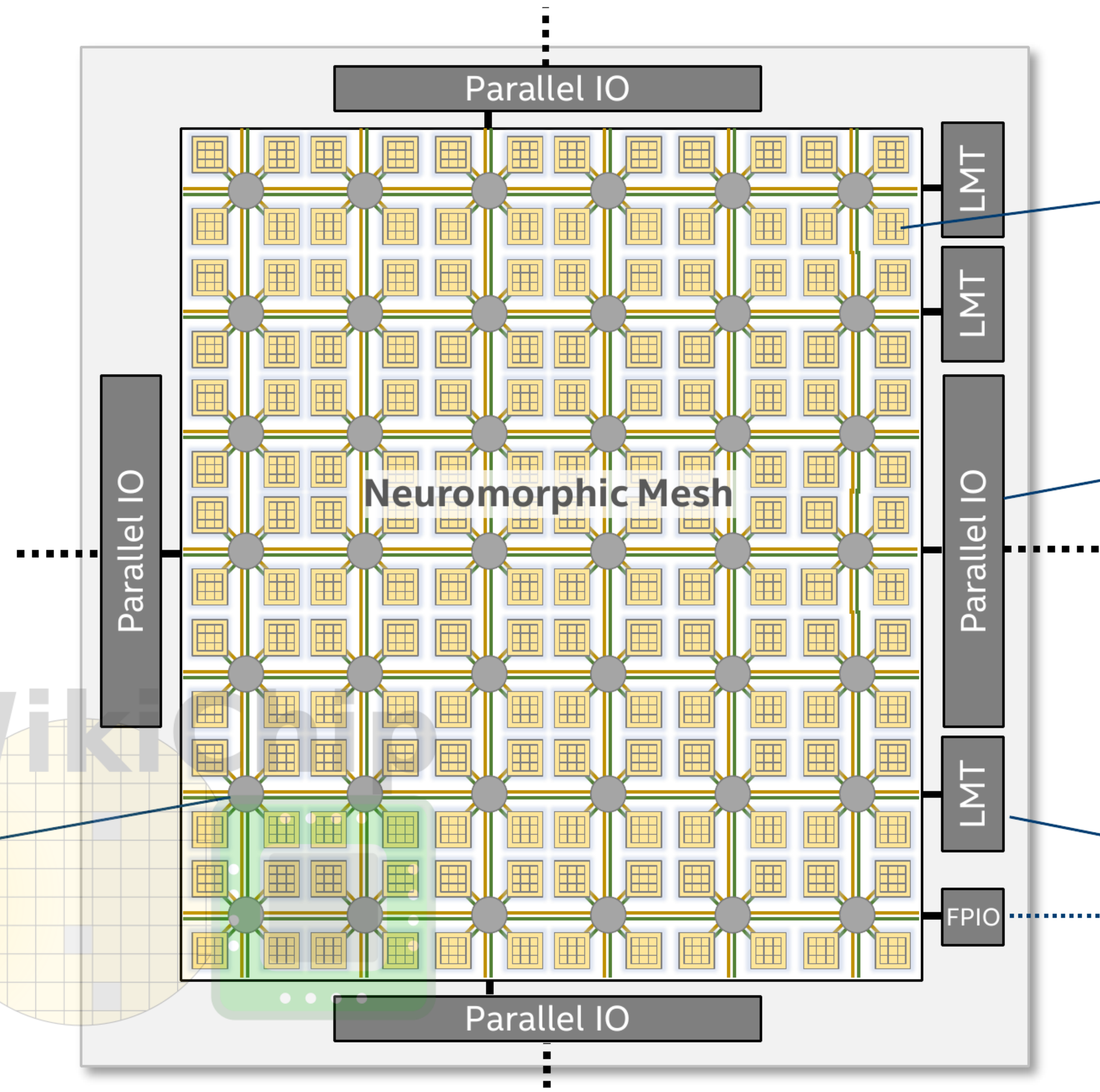
Source: https://www.researchgate.net/publication/280600732_A_Computational_Model_of_Innate_Directional_Selectivity_Refined_by_Visual_Experience

- Event-based cameras are inspired from the retina (**neuromorphic**) and emit spikes corresponding to luminosity changes.
- Classical computers cannot cope with the high fps of event-based cameras.
- Spiking neural networks can be used to process the events (classification, control, etc). But do we have the hardware for that?

Intel Loihi

Chip Architecture

Technology:	14nm
Die Area:	60 mm²
Core area:	0.41 mm²
NmC cores:	128 cores
x86 cores:	3 LMT cores
Max # neurons:	128K neurons
Max # synapses:	128M synapses
Transistors:	2.07 billion



Neuromorphic core
- LIF neuron model
- Programmable learning
- 128 KB synaptic memory
- Up to 1,024 neurons
- Asynchronous design

Parallel off-chip interfaces
- Two-phase asynchronous
- Single-ended signaling
- 100-200 MB/s BW

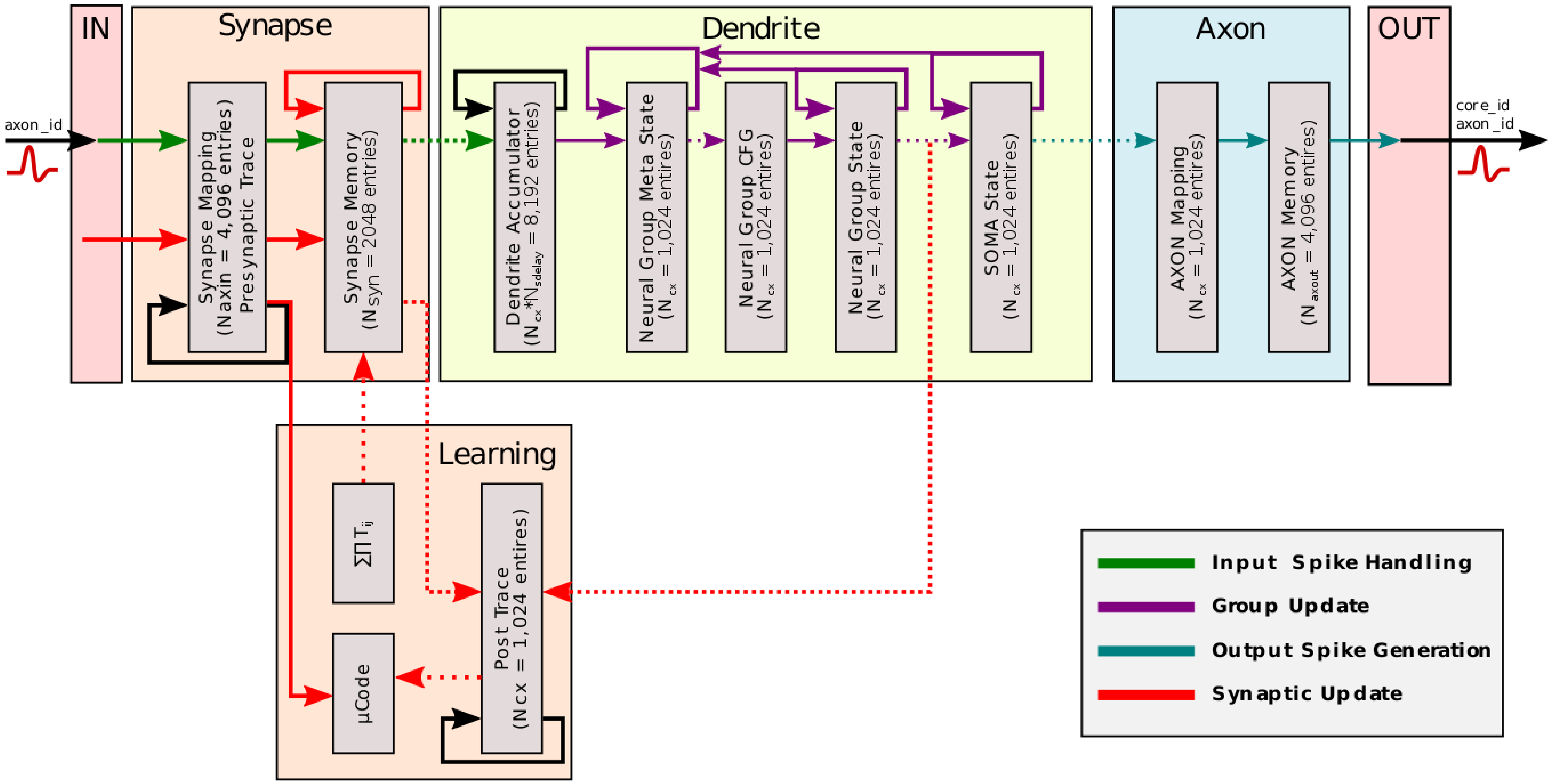
Embedded x86 processors
- Efficient spike-based communication with neuromorphic cores
- Data encoding/decoding
- Network configuration
- Synchronous design

Low-overhead NoC fabric
- 8x16-core 2D mesh
- Scalable to 1000's cores
- Dimension order routed
- Two physical fabrics
- 8 GB/s per hop

https://en.wikichip.org/wiki/intel/loihi

Intel Loihi

- Loihi implements 128 neuromorphic cores, each containing 1,024 primitive spiking neural units grouped into tree-like structures in order to simplify the implementation.



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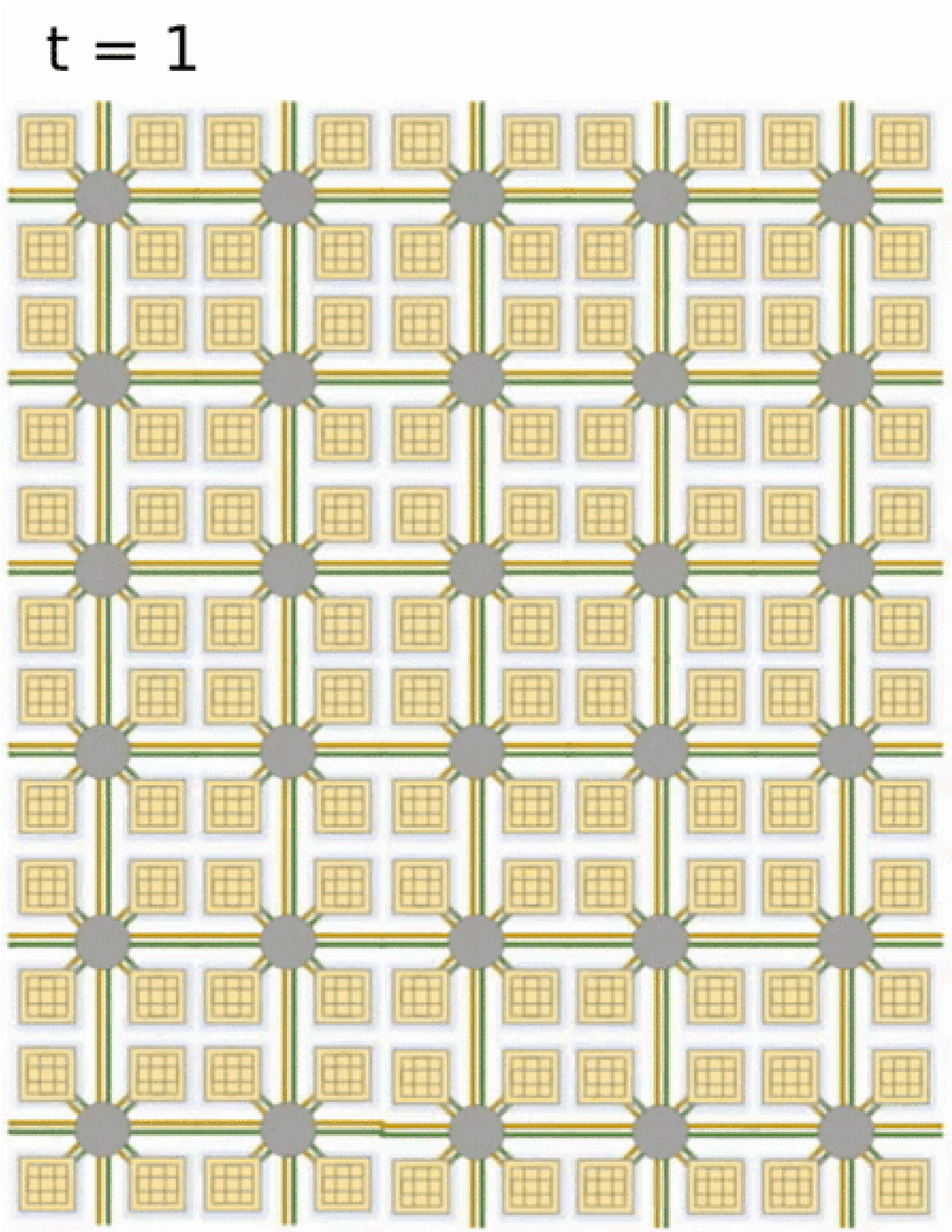
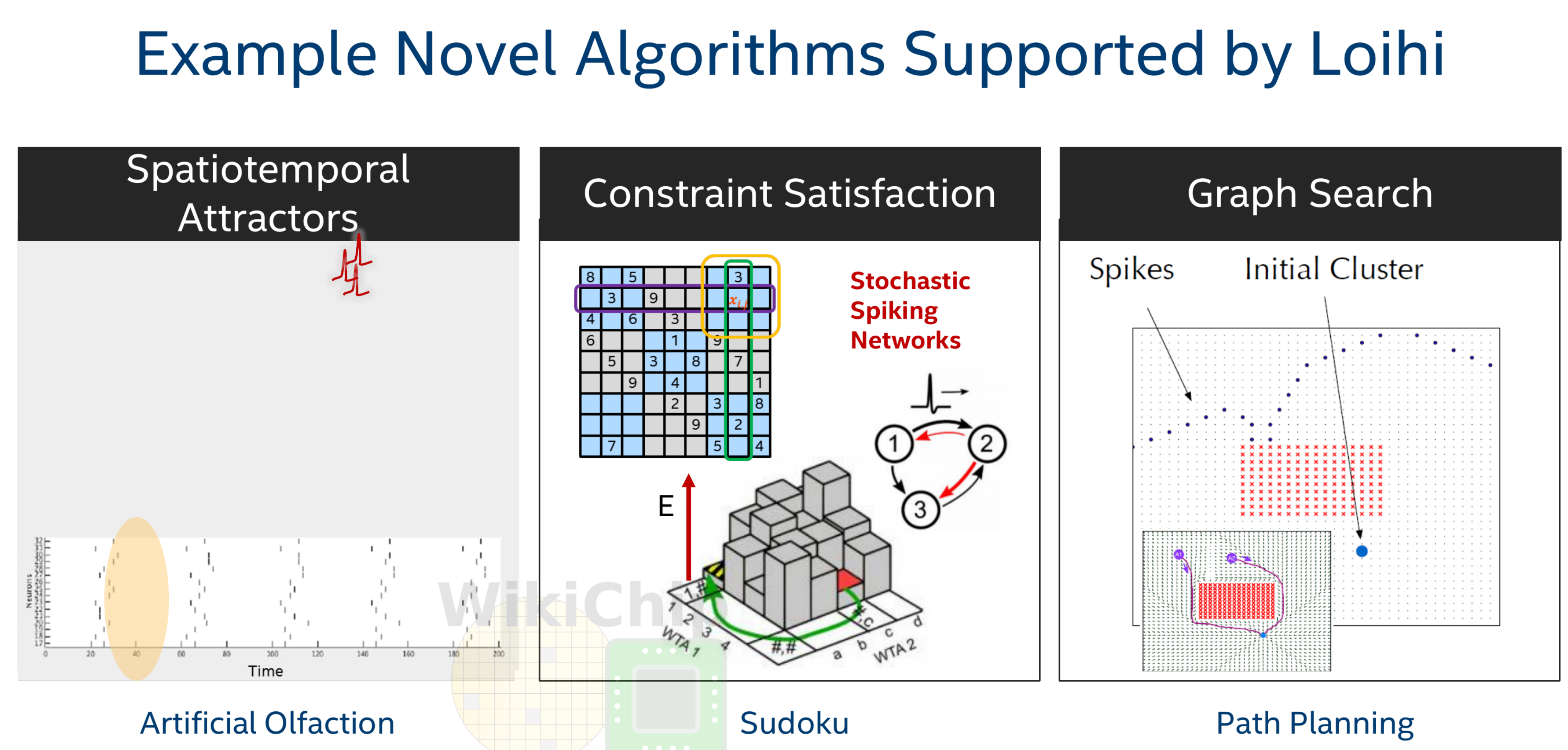
Intel Loihi



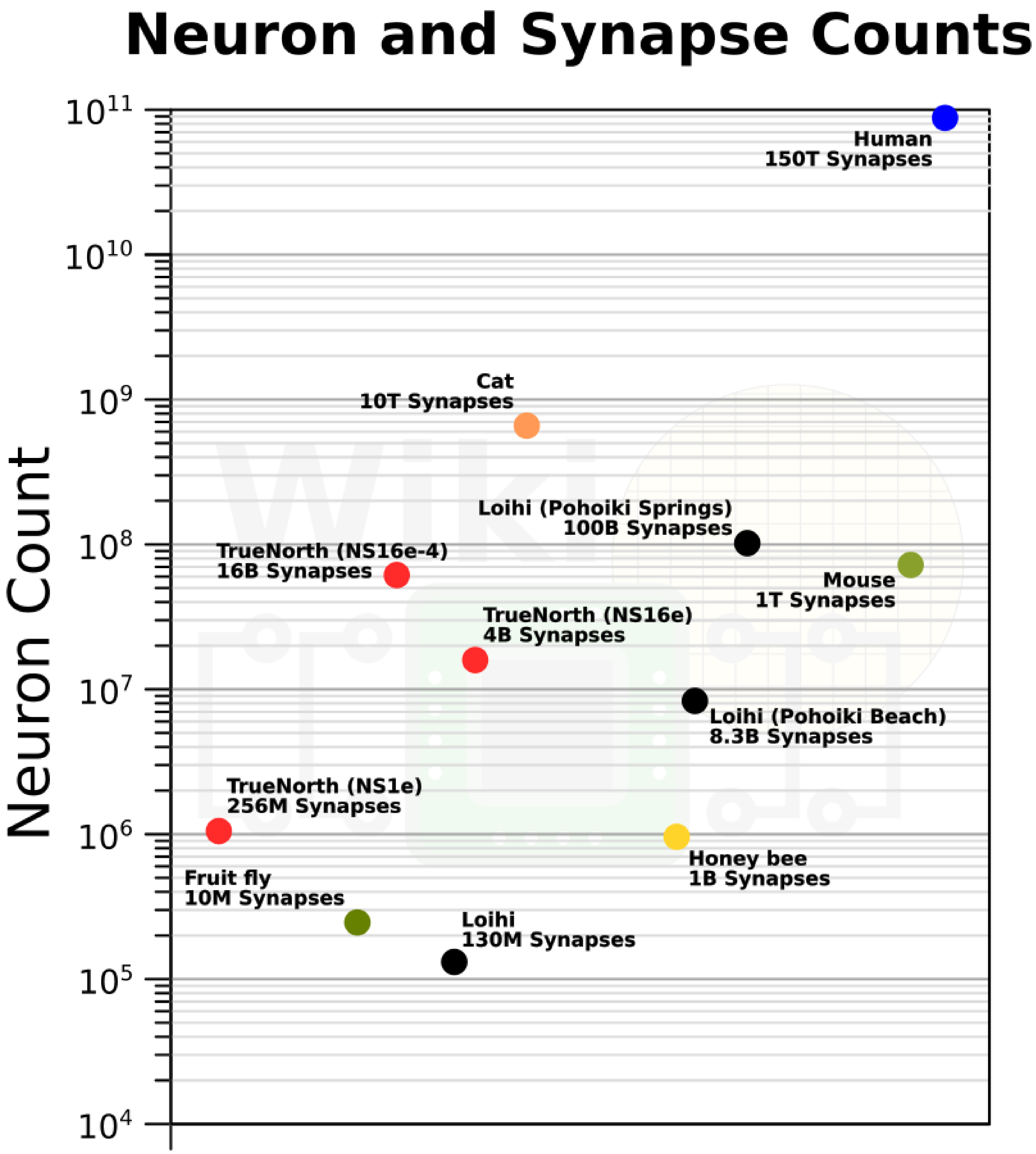
- Each neuromorphic core transits spikes to the other cores.
- Fortunately, the firing rates are usually low (10 Hz), what limits the communication costs inside the chip.
- Synapses are **learnable** with STDP mechanisms (memristors), although offline.



https://en.wikichip.org/wiki/intel/loihi

Neuromorphic computing

- Intel Loihi consumes 1/1000th of the energy needed by a modern GPU.
- Alternatives to Intel Loihi are:
  - IBM TrueNorth
  - Spinnaker (University of Manchester).
  - Brainchip
- The number of simulated neurons and synapses is still very far away from the human brain, but getting closer!



https://fuse.wikichip.org/news/2519/intel-labs-builds-a-neuromorphic-system-with-64-to-768-loihi-chips-8-million-to-100-million-neurons/

References

Bi, G., and Poo, M. (2001). Synaptic Modification by Correlated Activity: Hebb's Postulate Revisited. *Annual Review of Neuroscience* 24, 139–166. doi:10.1146/annurev.neuro.24.1.139.

Brette, R., and Gerstner, W. (2005). Adaptive Exponential Integrate-and-Fire Model as an Effective Description of Neuronal Activity. *Journal of Neurophysiology* 94, 3637–3642. doi:10.1152/jn.00686.2005.

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Rossant, C., Goodman, D. F. M., Fontaine, B., Platkiewicz, J., Magnusson, A. K., and Brette, R. (2011). Fitting Neuron Models to Spike Trains. *Front. Neurosci.* 5. doi:10.3389/fnins.2011.00009.