

UNIVERSITY OF TECHNOLOGY
IN THE EUROPEAN CAPITAL OF CULTURE
CHEMNITZ

Neurocomputing

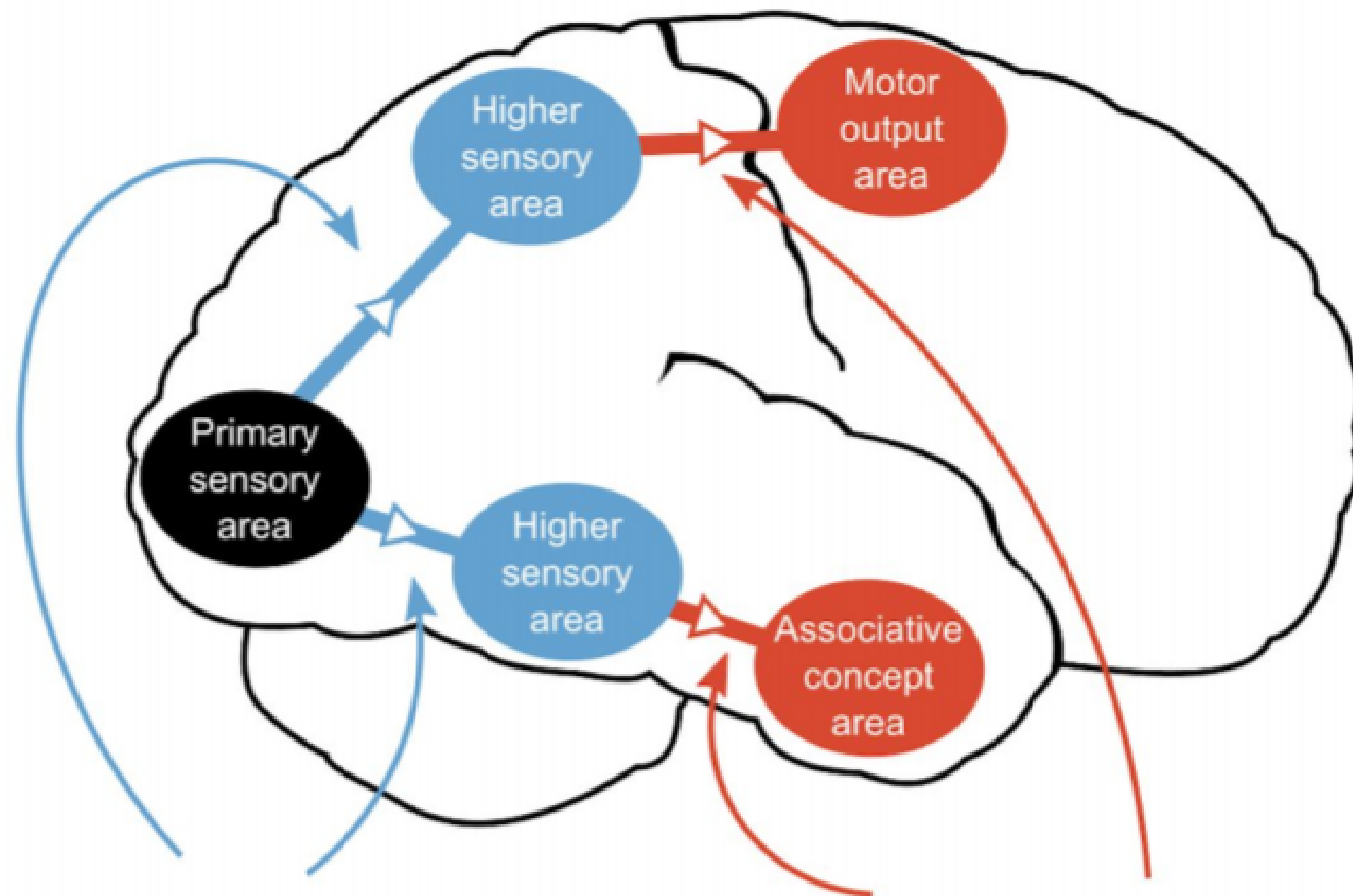
Beyond deep learning

Julien Vitay

Professur für Künstliche Intelligenz - Fakultät für Informatik

1 - Towards biological deep learning?

The credit assignment problem



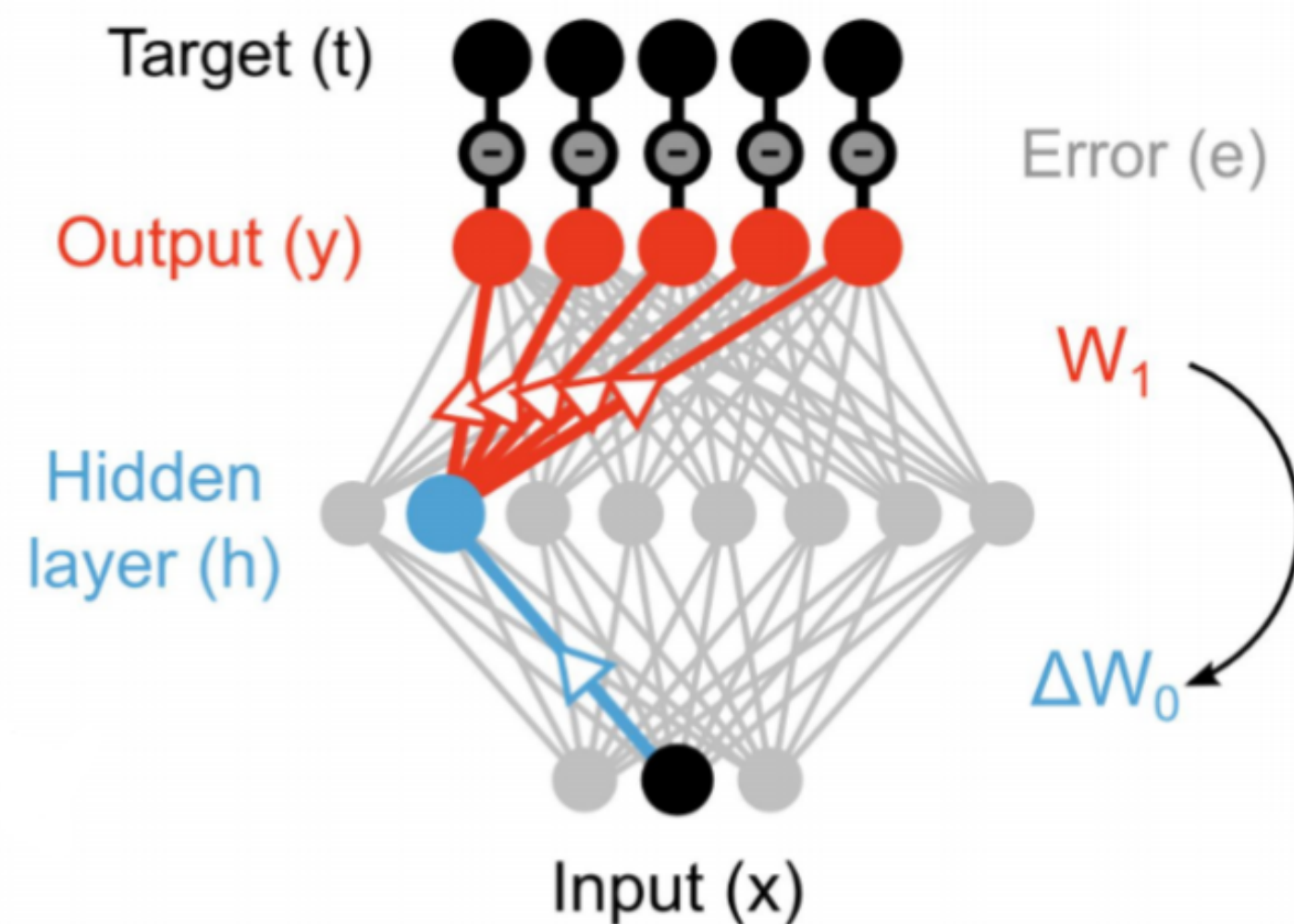
The behavioral effects
of changes to these
synaptic connections...

...depend on the
status of these
synaptic connections.

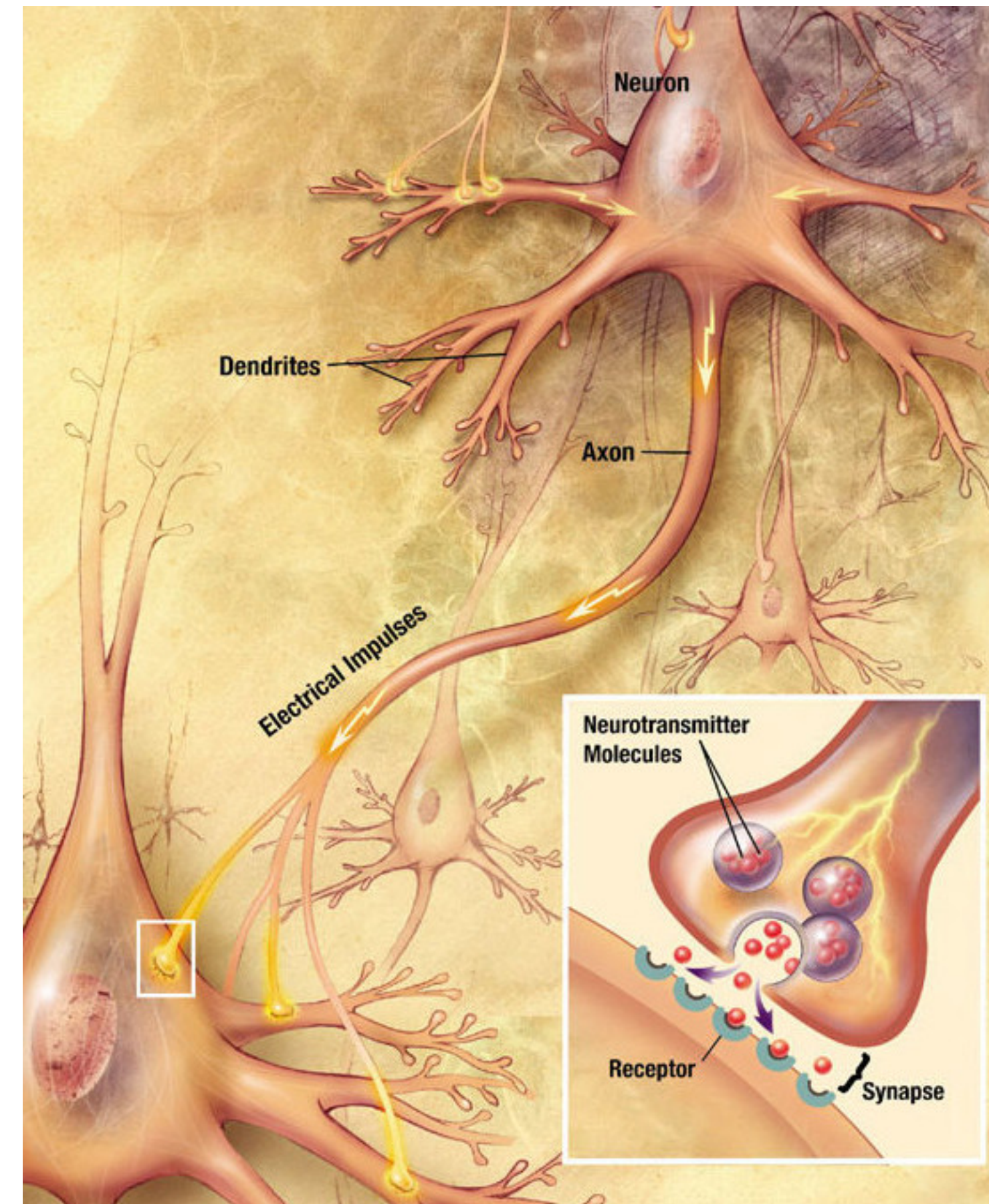
Backpropagation is not biologically plausible

- Backpropagation solves the credit assignment problem by transmitting the error gradient **backwards** through the weights (\sim synapses).
- A synapse does know not the weight of other synapses and cannot transmit anything backwards.

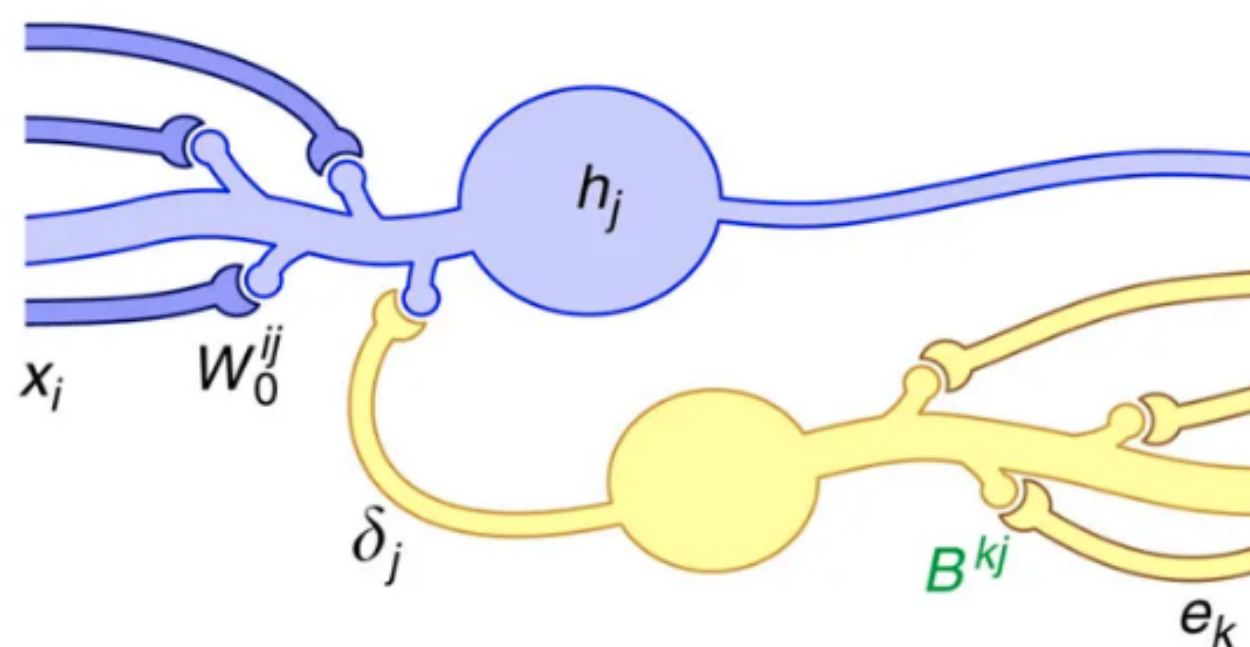
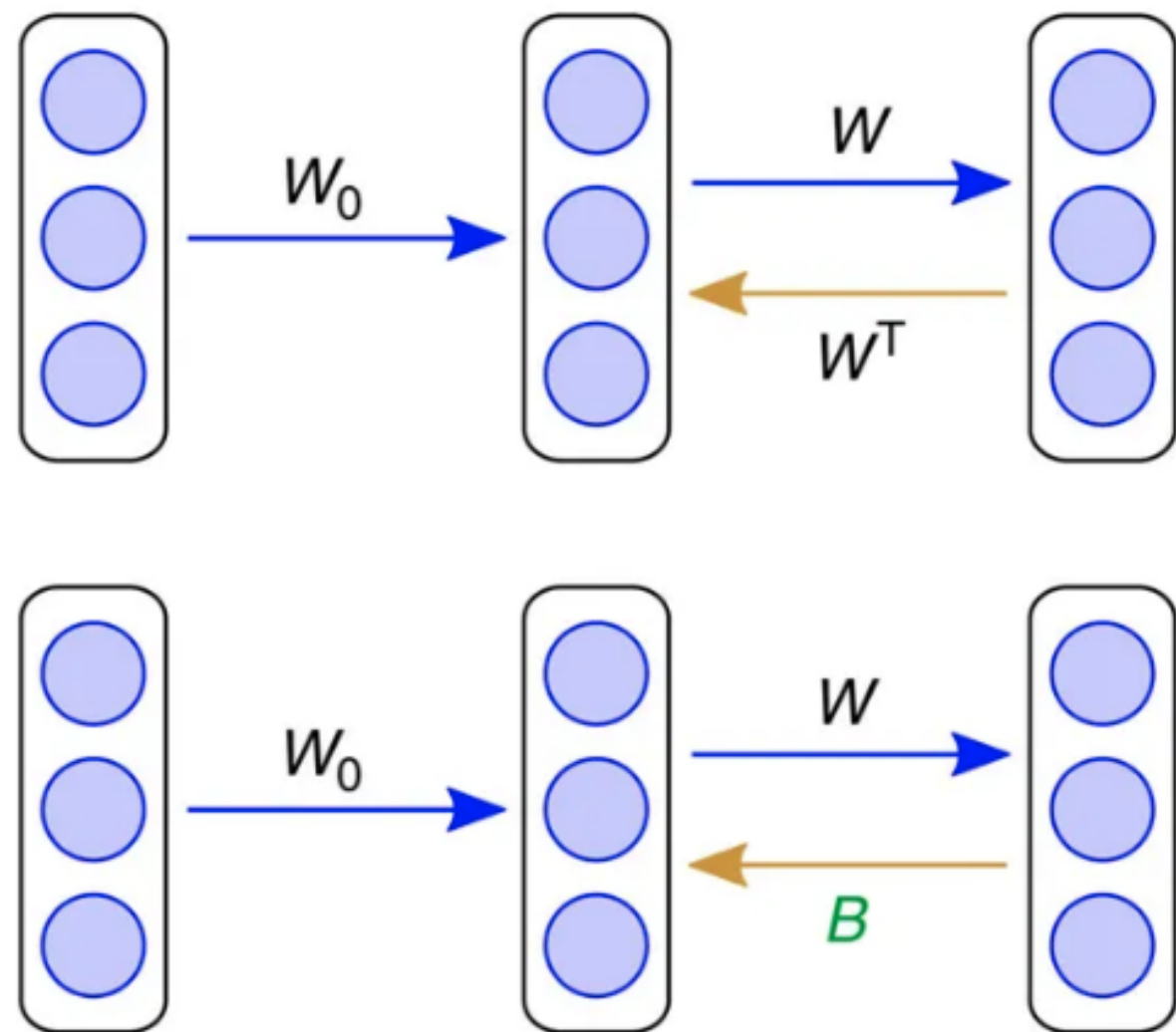
$$\Delta W_0 = \eta (\mathbf{t} - \mathbf{y}) \times W_1 \times \mathbf{x}^T$$



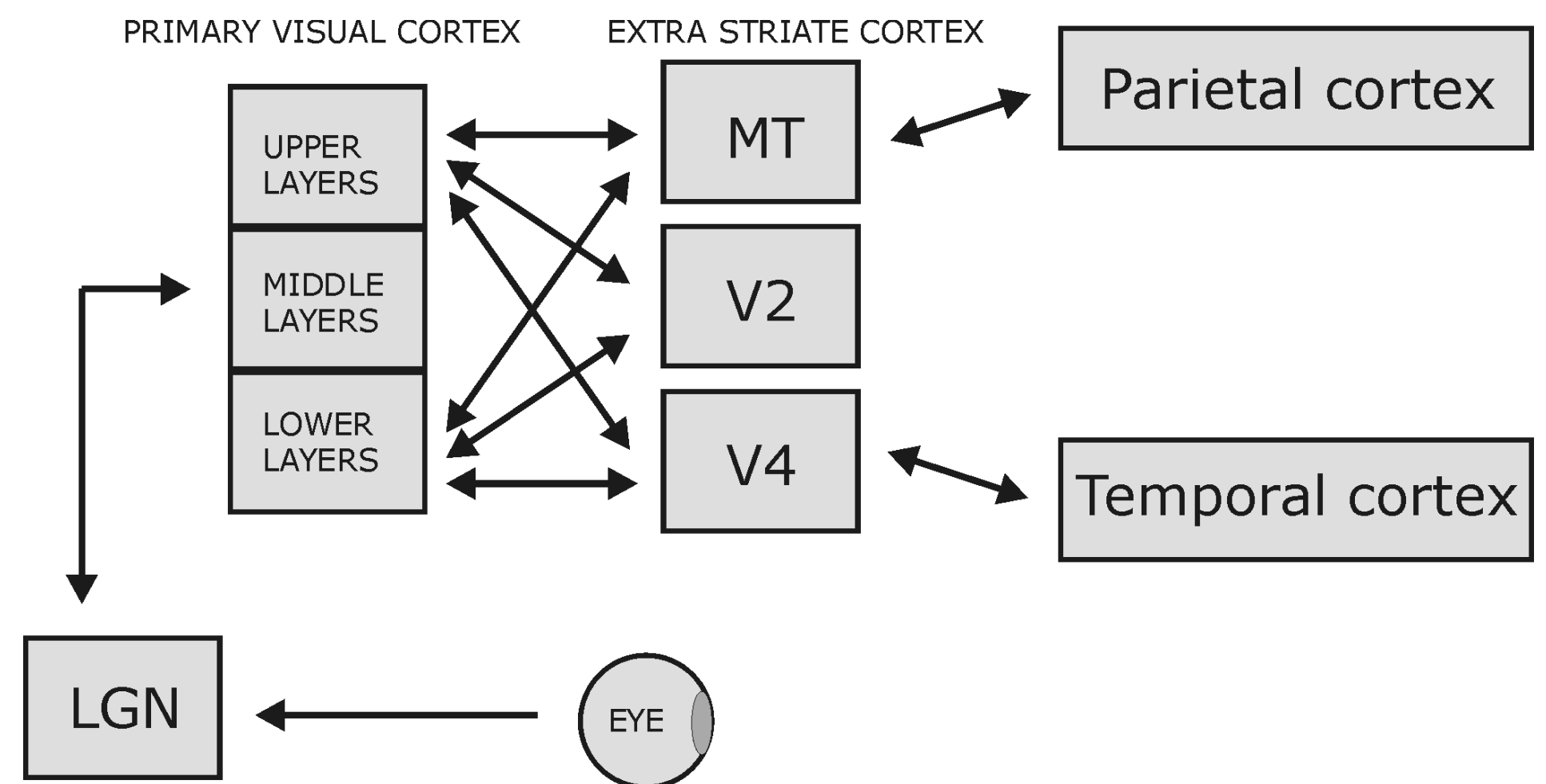
- But information only goes in one direction in the brain: from the presynaptic neuron to the postsynaptic one.



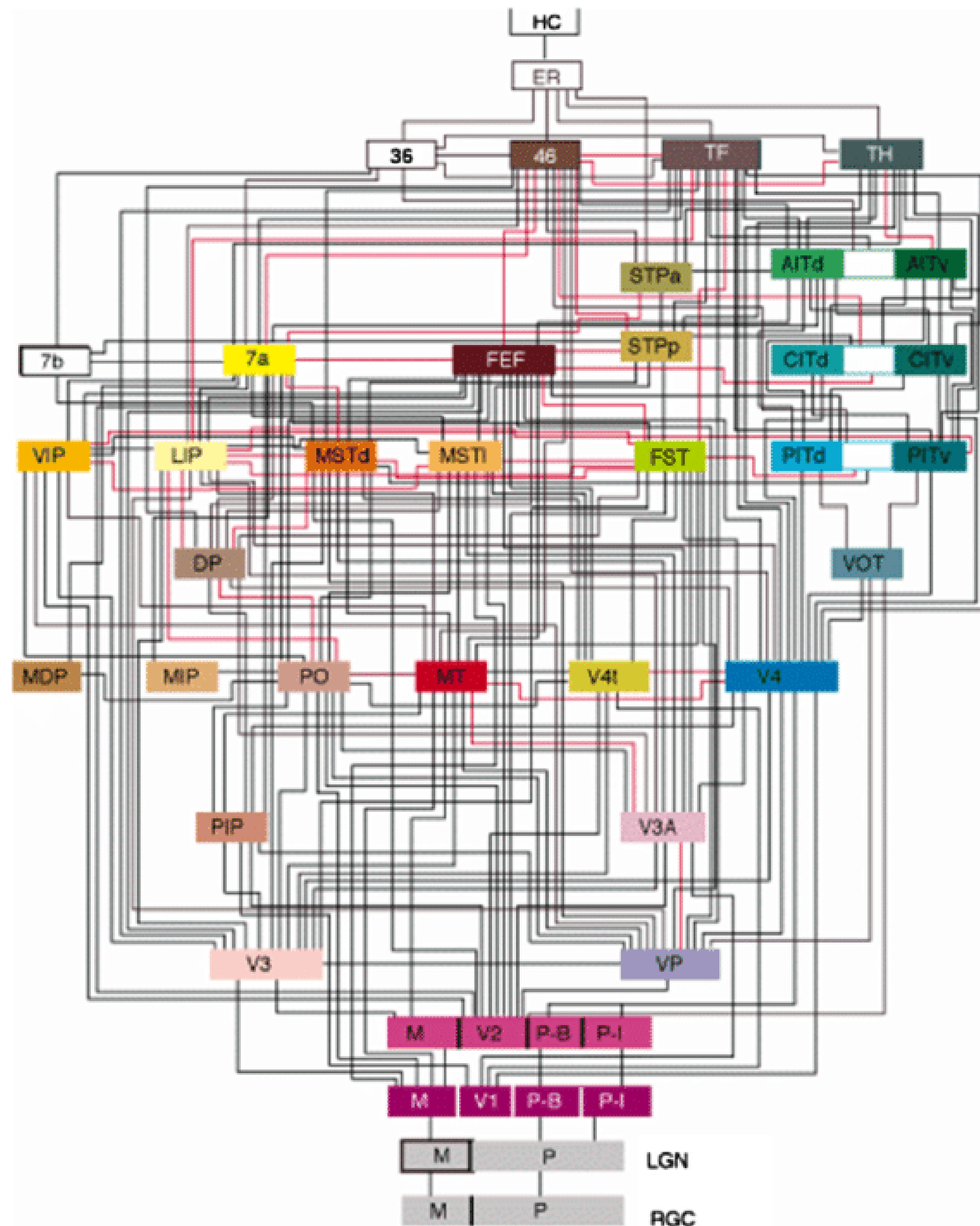
Feedback alignment



- An alternative mechanism consists of backpropagating the error through another set of **feedback weights**.
- Feedback connections are ubiquitous in the brain, especially in the neocortex.
- The feedback weights do not need to learn: they can stay random.
- The mechanism only works for small networks on MNIST until now.



Deep learning architectures are way too simple and unidirectional



- Deep learning architectures are mostly unidirectional, from the input to the output, without feedback connections.
- The brain is totally differently organized: a big “mess” of interconnected areas processing everything in parallel.
- The figure on the left is only for vision, and only for the cerebral cortex: the thalamus, basal ganglia, hippocampus, cerebellum, etc, create additional shortcuts.
- Is the complex structure of the brain just a side effect of evolution, or is it the only possible solution?
- **Inductive bias:** the choice of the architecture constrains the functions it can perform / learn.

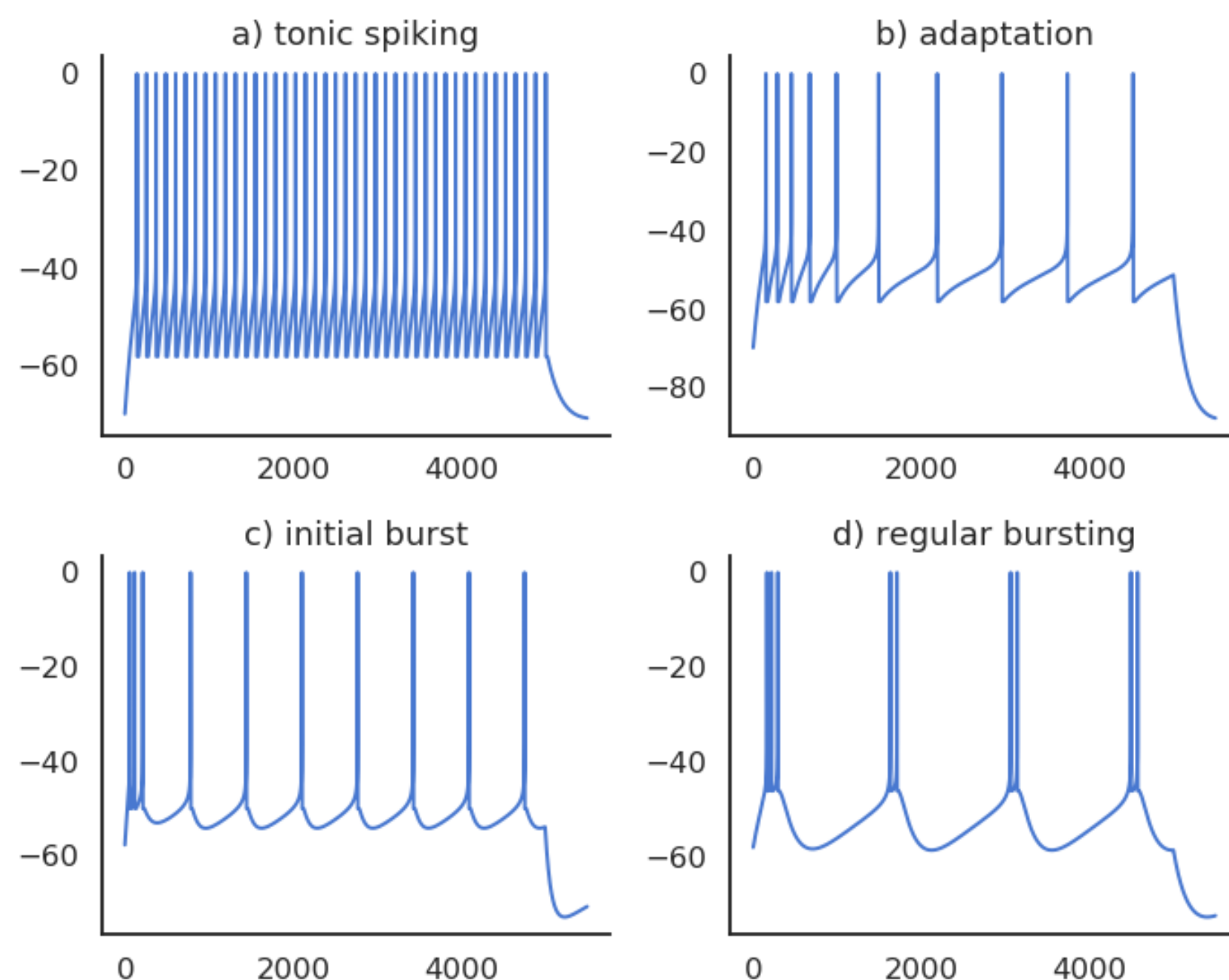
2 - Neural dynamics

Biological neurons have dynamics

- The **artificial neuron** has no dynamics, it is a simple mathematical function:

$$y = f\left(\sum_{i=1}^d w_i x_i + b\right)$$

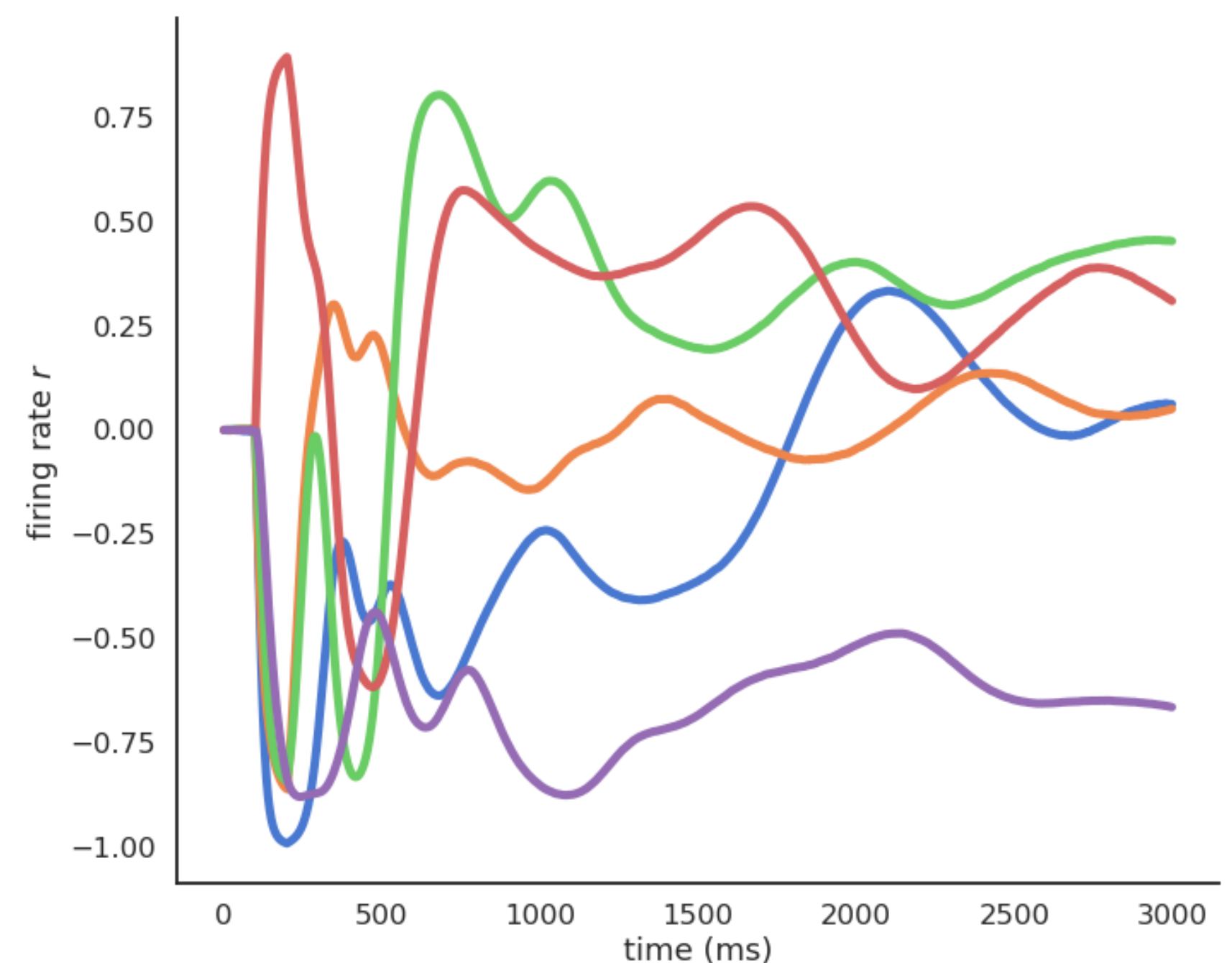
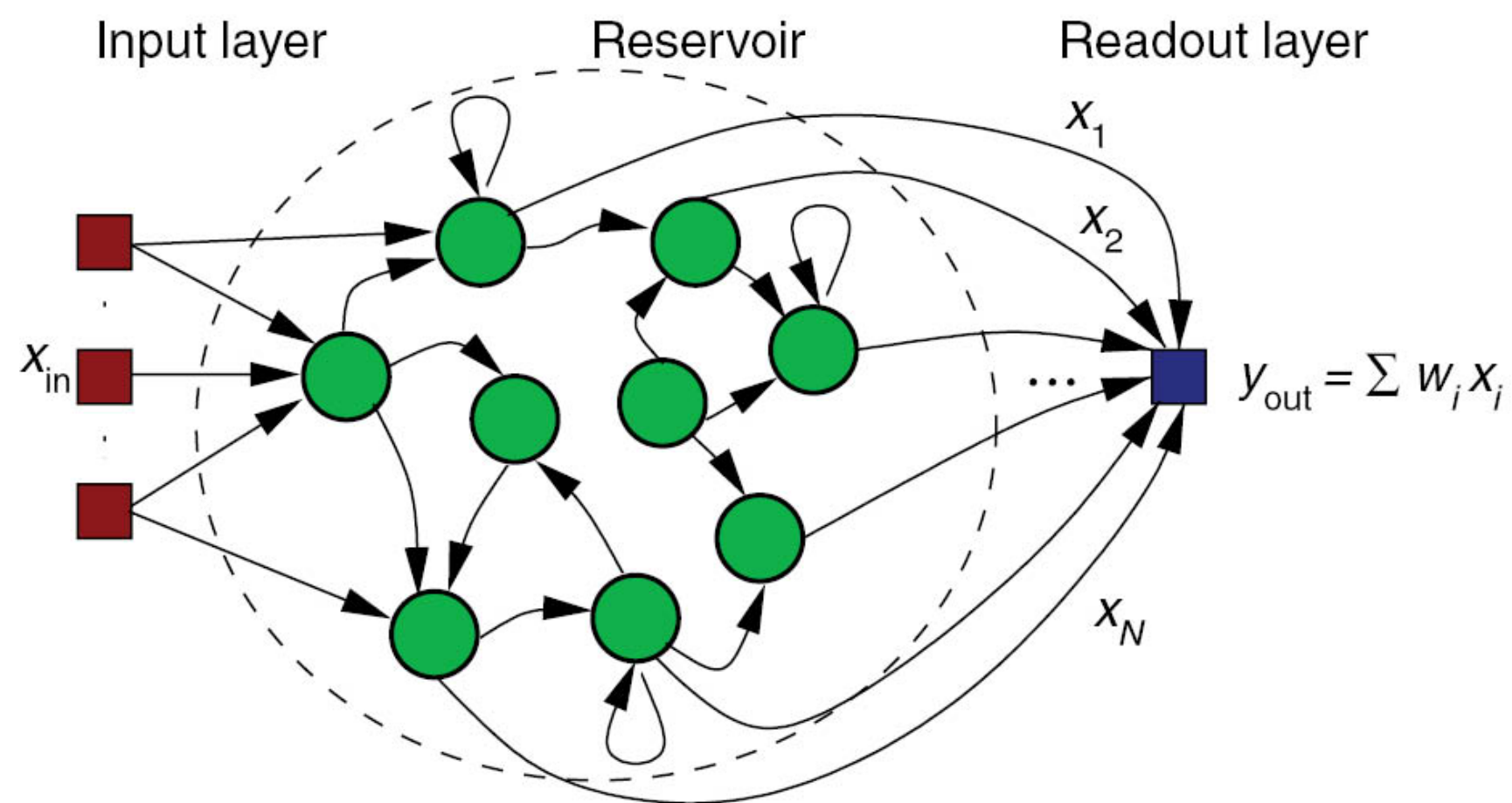
- If you do not change the inputs to an artificial neuron, its output won't change.
- Time does not exist, even in a LSTM: the only temporal variable is the frequency at which inputs are set.



- Biological neurons have **dynamics**:
 - They adapt their firing rate to constant inputs.
 - they continue firing after an input disappears.
 - they fire even in the absence of inputs (tonic).
- These dynamics are essential to information processing in the brain.

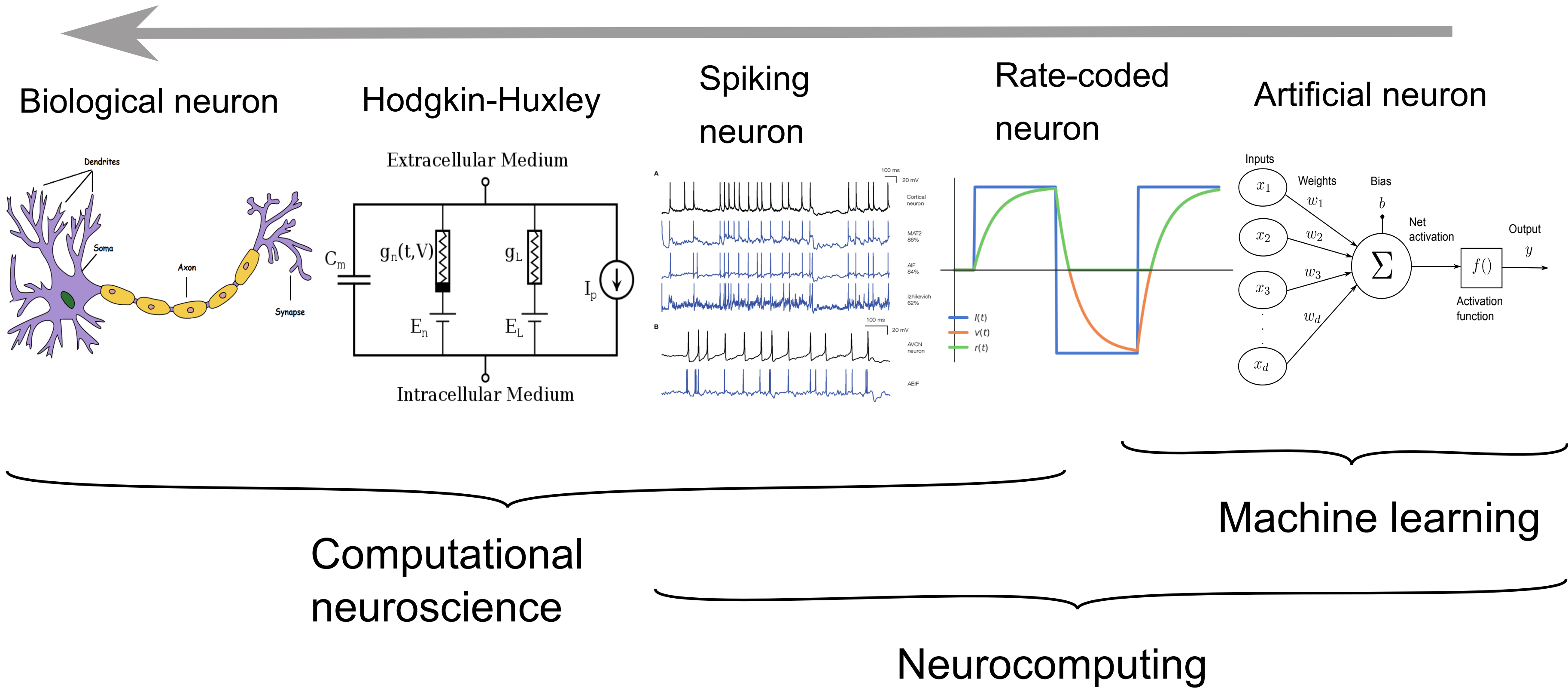
Recurrent dynamics and emergence of functions

- Recurrent networks of dynamical neurons can exhibit very complex dynamics.
- Biological neural networks evolve at the **edge of chaos**, i.e. in a highly non-linear regime while still being deterministic.
- This allows the **emergence** of complex functions:
 - the whole is more than the sum of its parts.



Overview of neuron models

Biological plausibility



3 - Self-organization

Self-organization



- There are two complementary approaches to unsupervised learning:
 - the **statistical approach**, which tries to extract the most relevant information from the distribution of unlabeled data (autoencoders, etc).
 - **self-organization**, which tries to understand the principles of organization of natural systems and use them to create efficient algorithms.
- Self-organization is a generic process relying on four basic principles: locality of computations, learning, competition and cooperation.

Self-organization

- **Self-organization** is observed in a wide range of natural processes:
 - Physics: formation of crystals, star formation, chemical reactions...
 - Biology: folding of proteins, social insects, flocking behavior, brain functioning, Gaia hypothesis...
 - Social science: critical mass, group thinking, herd behavior...



Self-organization : locality of computations and learning

Not self-organized:



Self-organized:



- A self-organizing system is composed of elementary units (particles, cells, neurons, organs, individuals...) which all perform similar deterministic functions (rule of behavior) on a small part of the available information.
- There is **no central supervisor** or coordinator that knows everything and tells each unit what to do:
 - they have their own rule of behavior and apply it to the information they receive.
- The units are able to adapt their behavior to the available information: principle of **localized learning**.
- There is no **explicit loss function** specifying what the system should do: **emergence**.

Example: Conway's game of life.



Source: <https://www.jakubkonka.com/2015/03/15/game-of-life.html>

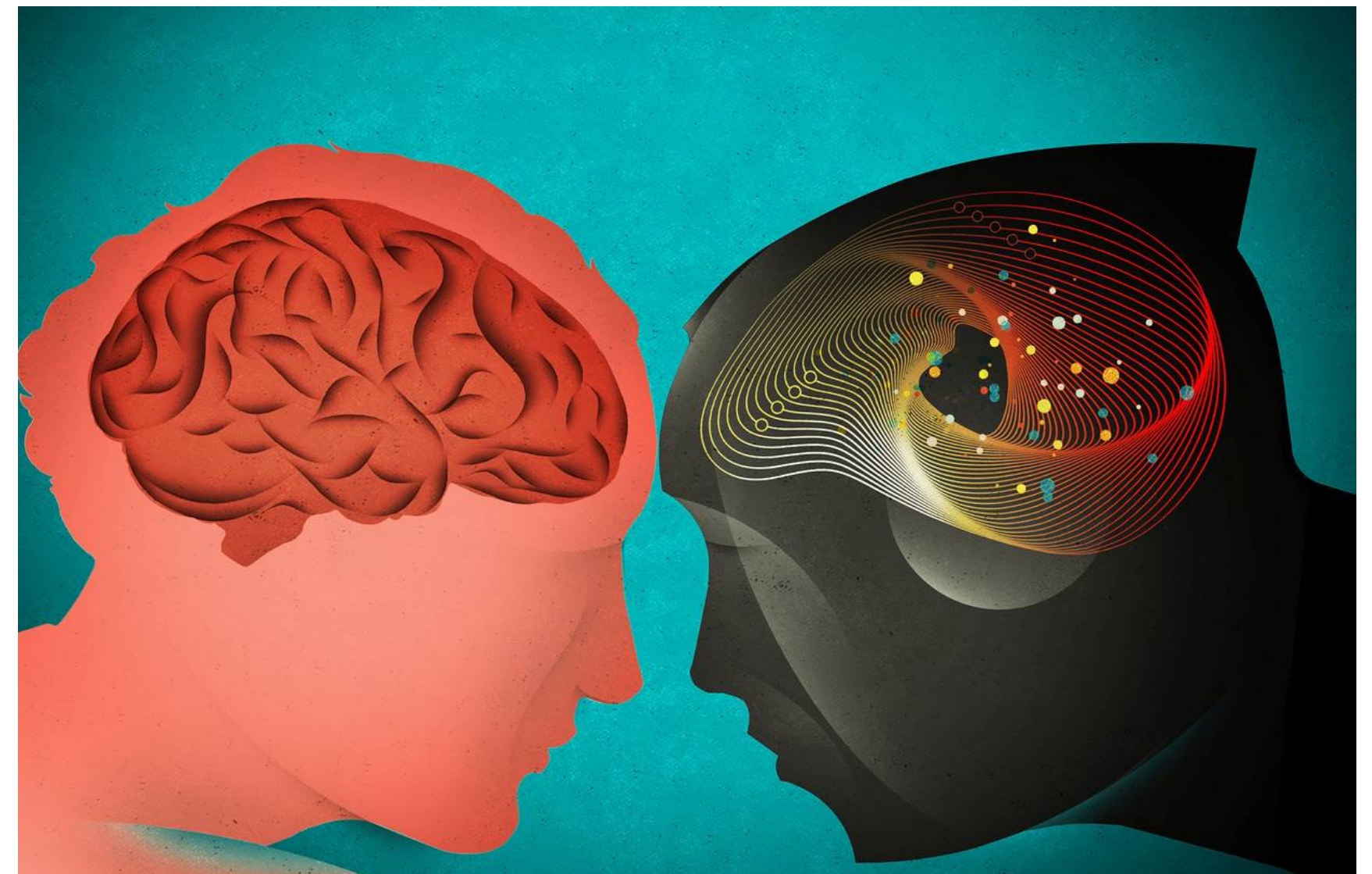
- The rules of Conway's **Game of Life** (1970) are extremely simple:
 - A cell is either **dead** or **alive**.
 - A living cell with less than 1 neighbor dies.
 - A living cell with more than 4 neighbors dies.
 - A dead cell with 3 neighbors relives.

- Despite this simplicity, GoL can exhibit very complex patterns (fractals, spaceships, pulsars).
- The GoL is an example of self-organizing **cellular automata**.

Key differences between deep networks and the brain

Bio-inspired AI has to tackle many challenges.

- **No backpropagation** in the brain, at least in its current form.
- Information processing is **local** to each neuron and synapse.
- Complex **recurrent** architecture (feedback connections).
- Neurons have **non-linear dynamics**, especially as populations (edge of chaos).
- **Emergence** of functions: the whole is more than the sum of its parts
- **Self-organization**. There is no explicit loss function to minimize: the only task of the brain is to ensure survival of the organism (homeostasis).
- **Embodiment**: the brain is part of a body.



Source: <https://www.wsj.com/articles/should-artificial-intelligence-copy-the-human-brain-1533355265>