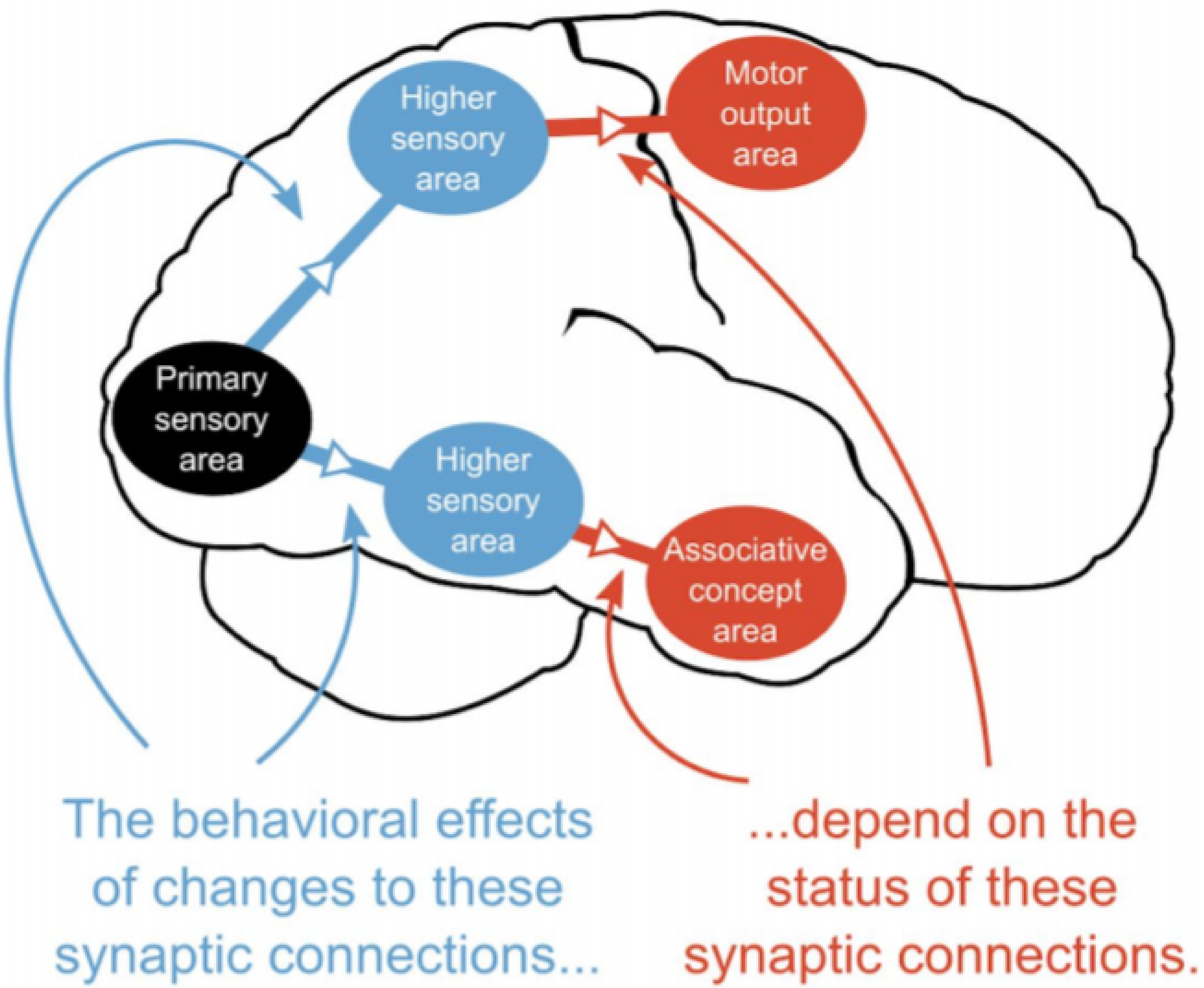
1 - Towards biological deep learning?

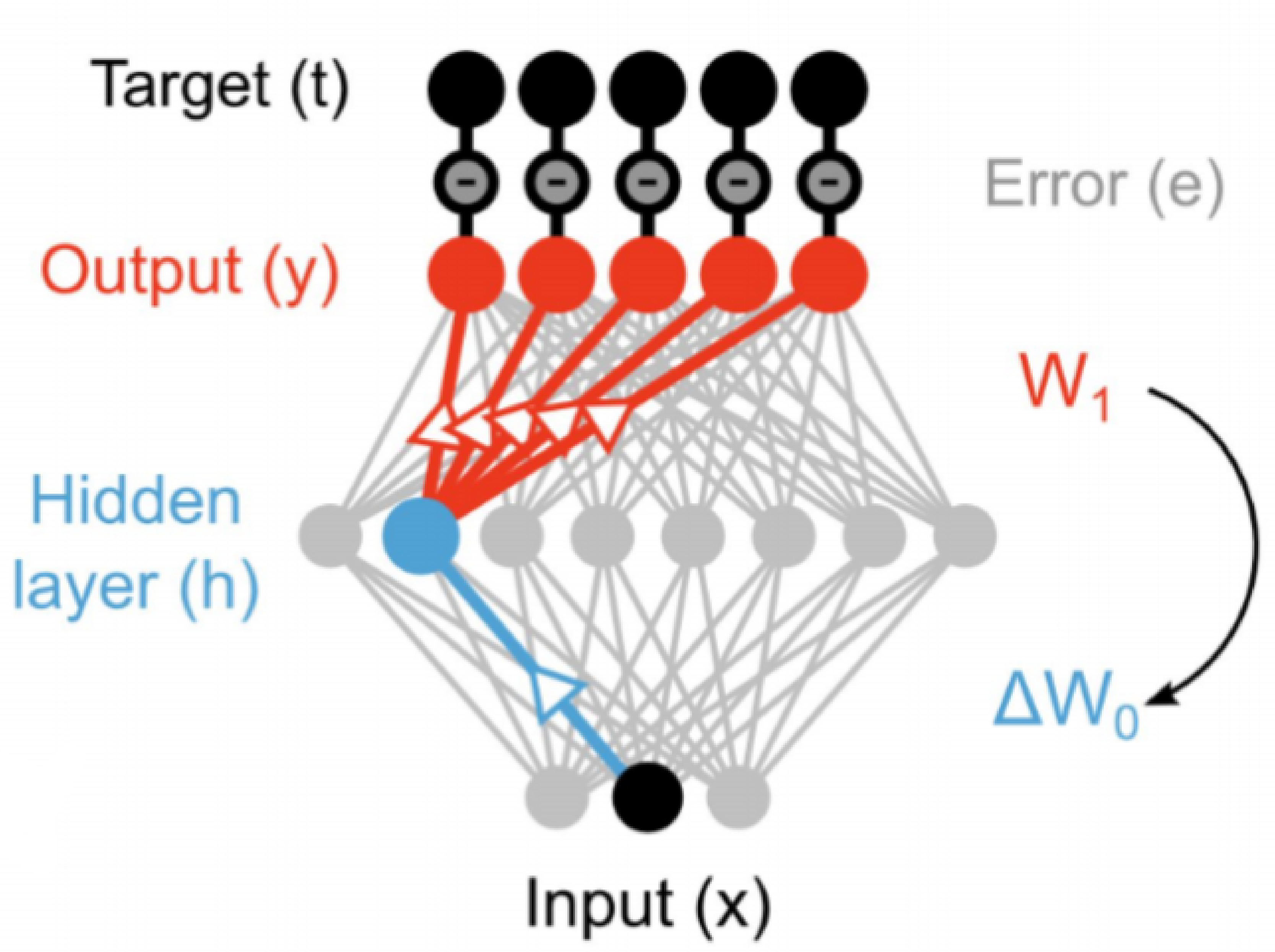
The credit assignment problem



Backpropagation is not biologically plausible

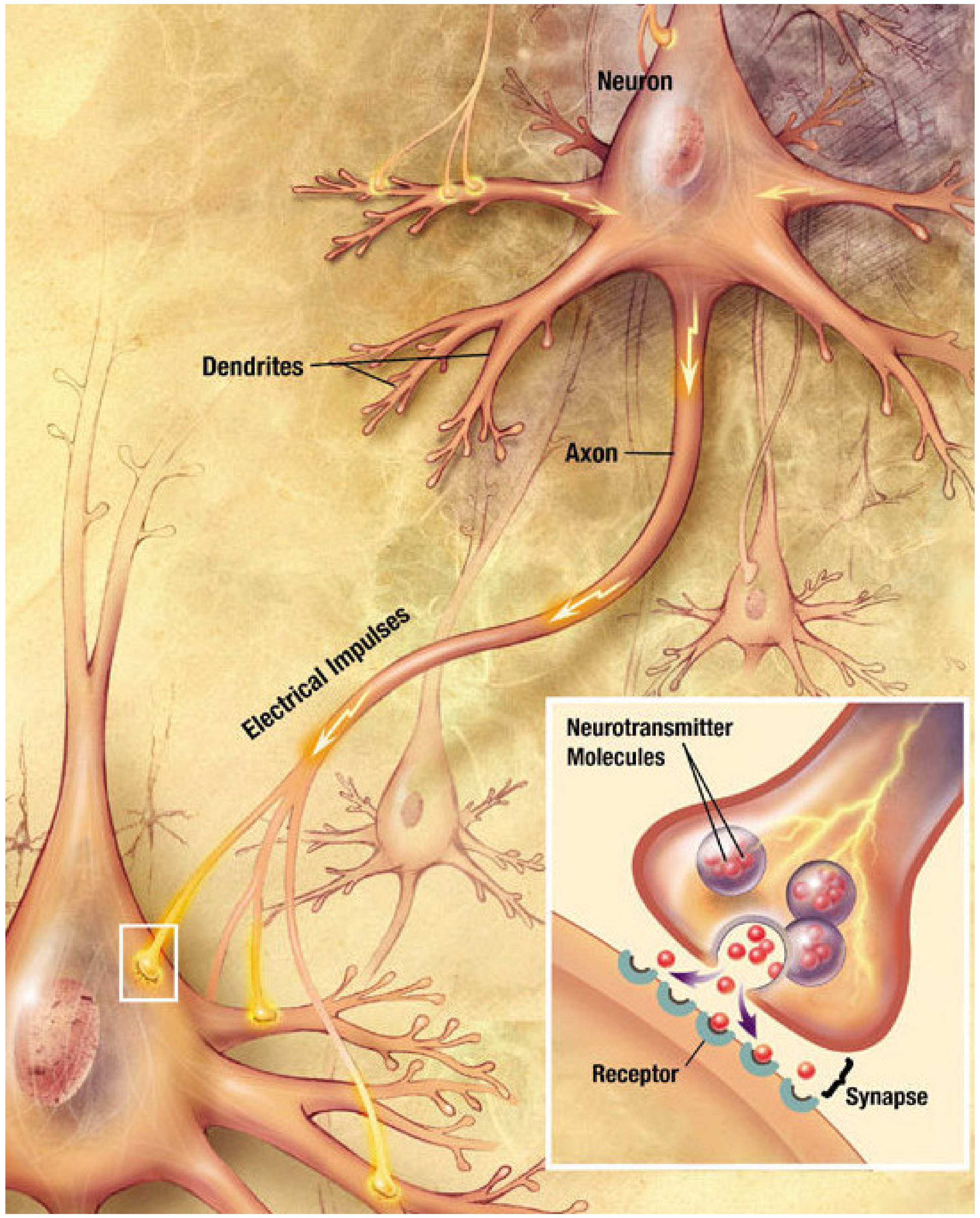
- Backpropagation solves the credit assignment problem by transmitting the error gradient **backwards** through the weights ($\sim$ synapses).

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

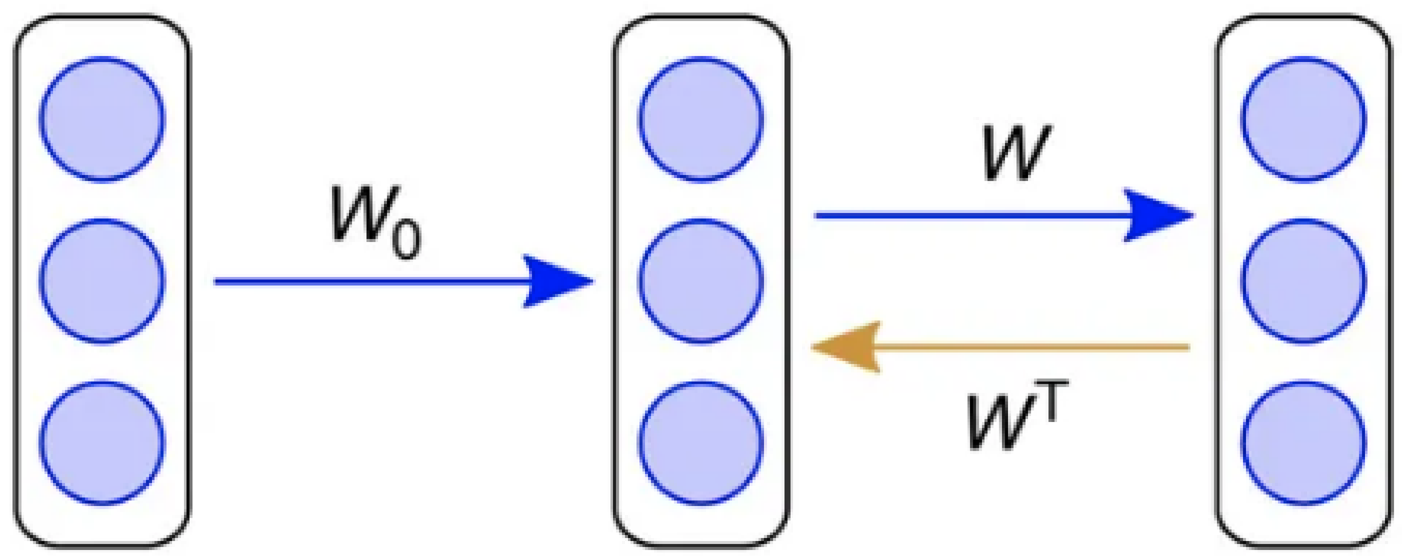


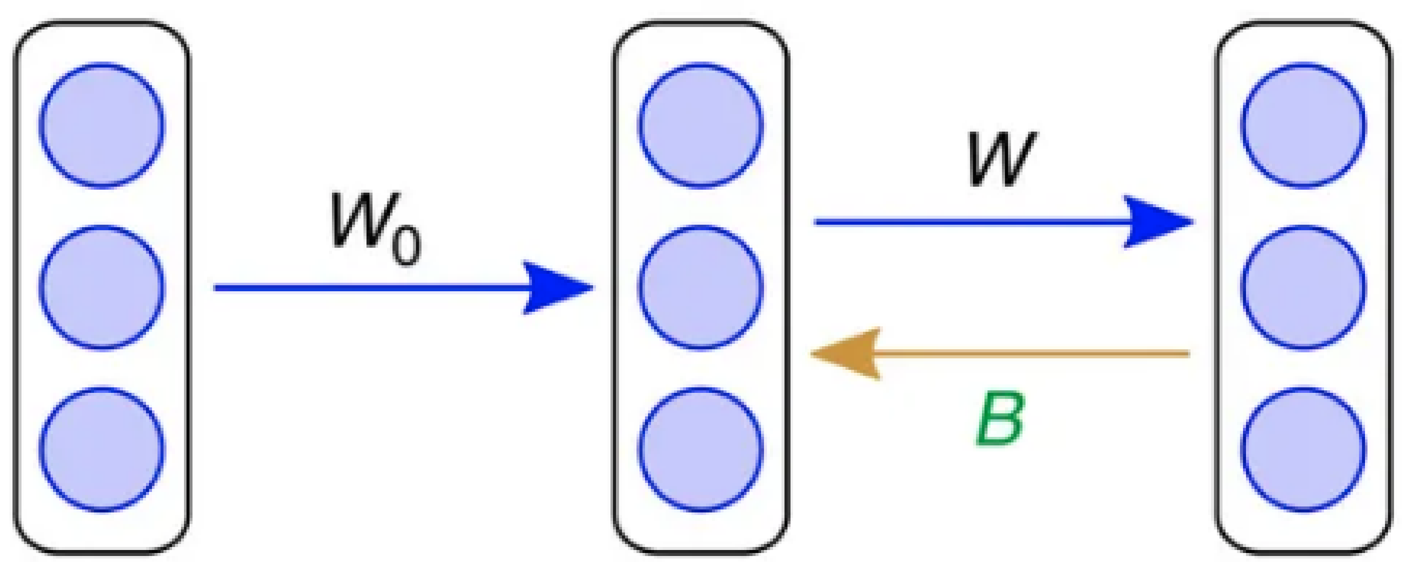
- But information only goes in one direction in the brain: from the presynaptic neuron to the postsynaptic one.

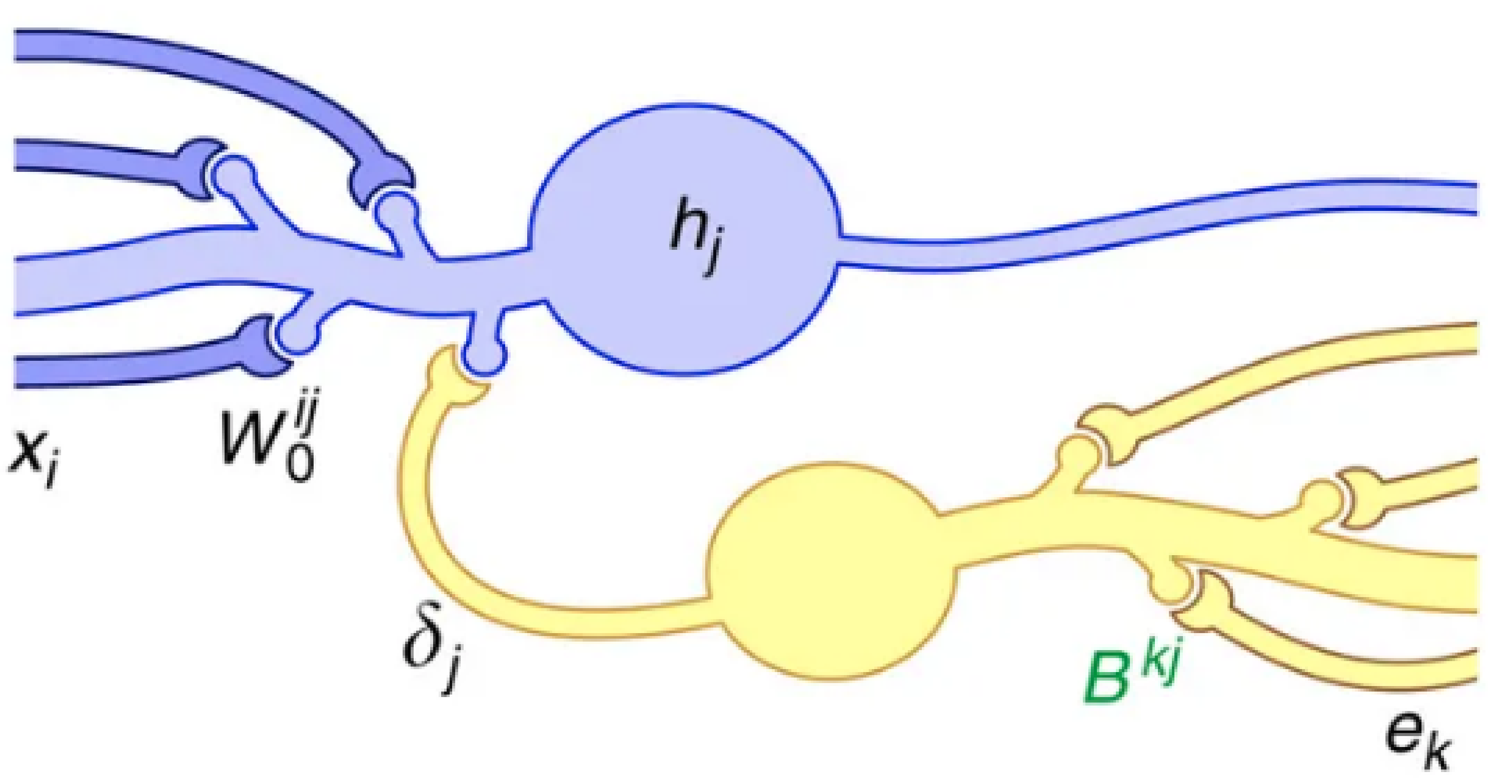
- A synapse does know not the weight of other synapses and cannot transmit anything backwards.



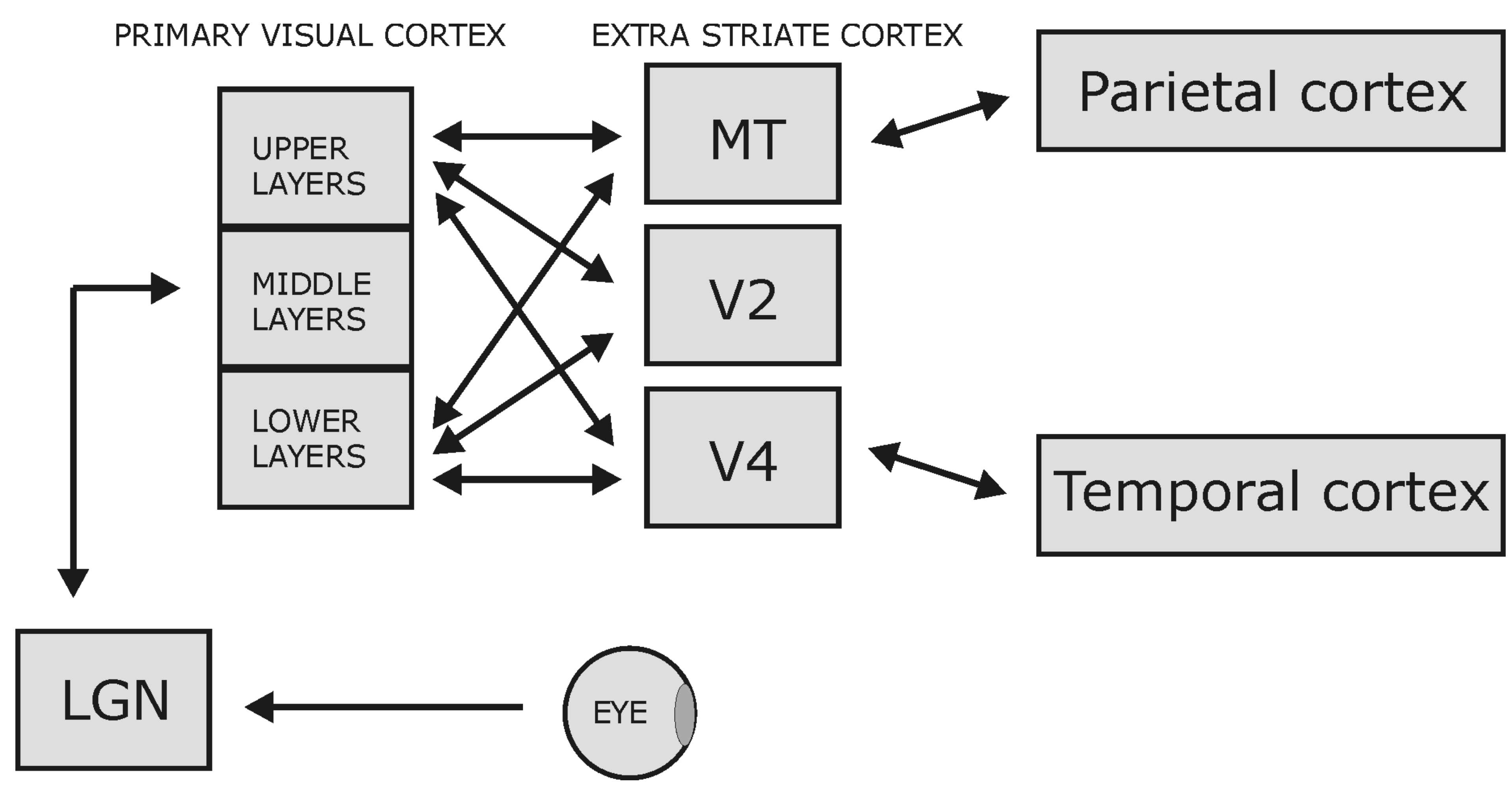
Feedback alignment





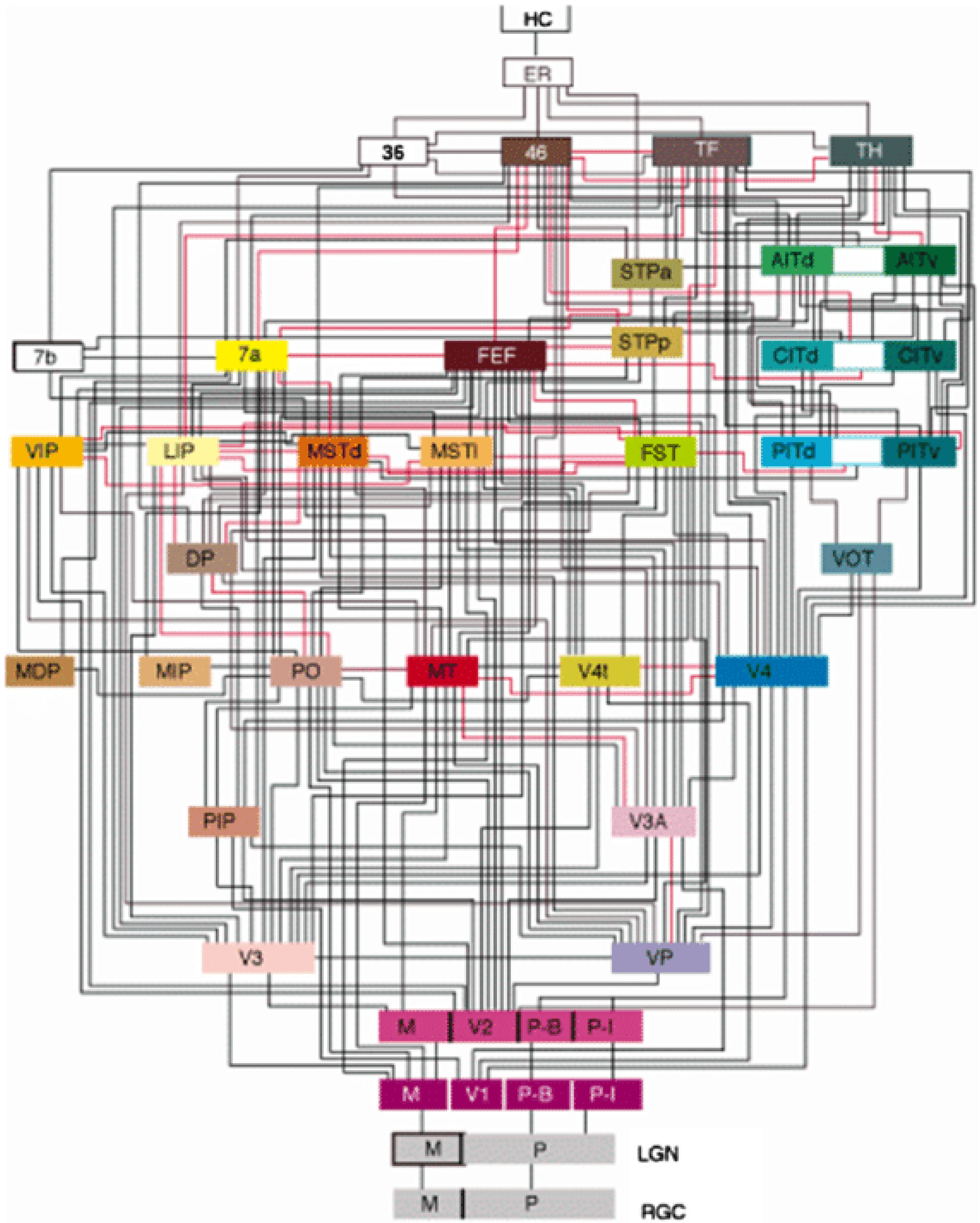


- An alternative mechanism consists of backpropagating the error through another set of **feedback weights**.
- Feedback connections are ubiquitous in the brain, especially in the neocortex.
- The feedback weights do not need to learn: they can stay random.
- The mechanism only works for small networks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



Lillicrap, T. P., Cownden, D., Tweed, D. B., and Akerman, C. J. (2016). Random synaptic feedback weights support error backpropagation for deep learning. Nat Commun 7, 1–10. doi:10.1038/ncomms13276.

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.

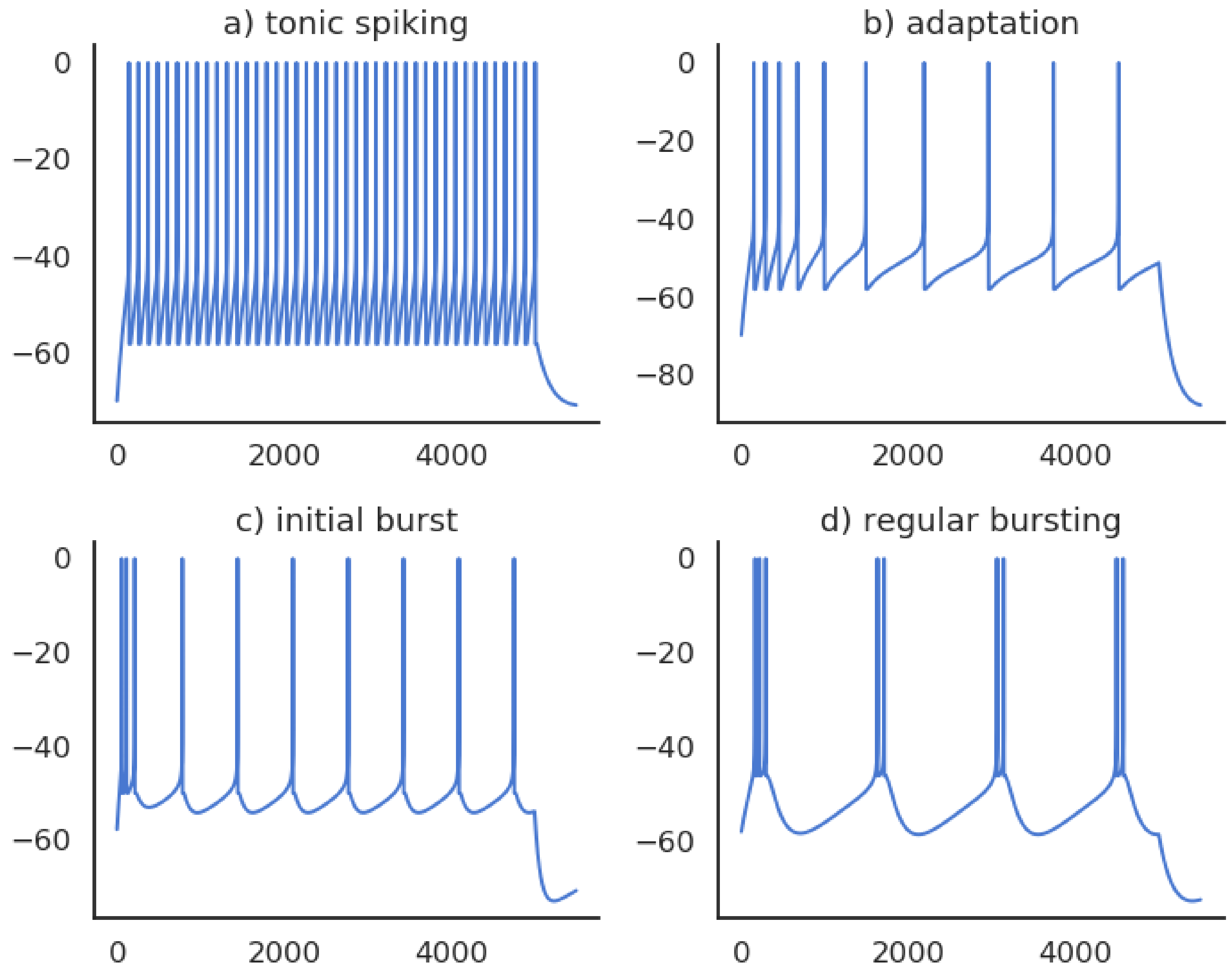
Felleman, D. J., and Van Essen, D. C. (1991). Distributed hierarchical processing in the primate cerebral cortex. Cereb. Cortex 1, 1–47. doi:10.1093/cercor/1.1.1.

Biological neurons have dynamics

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

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

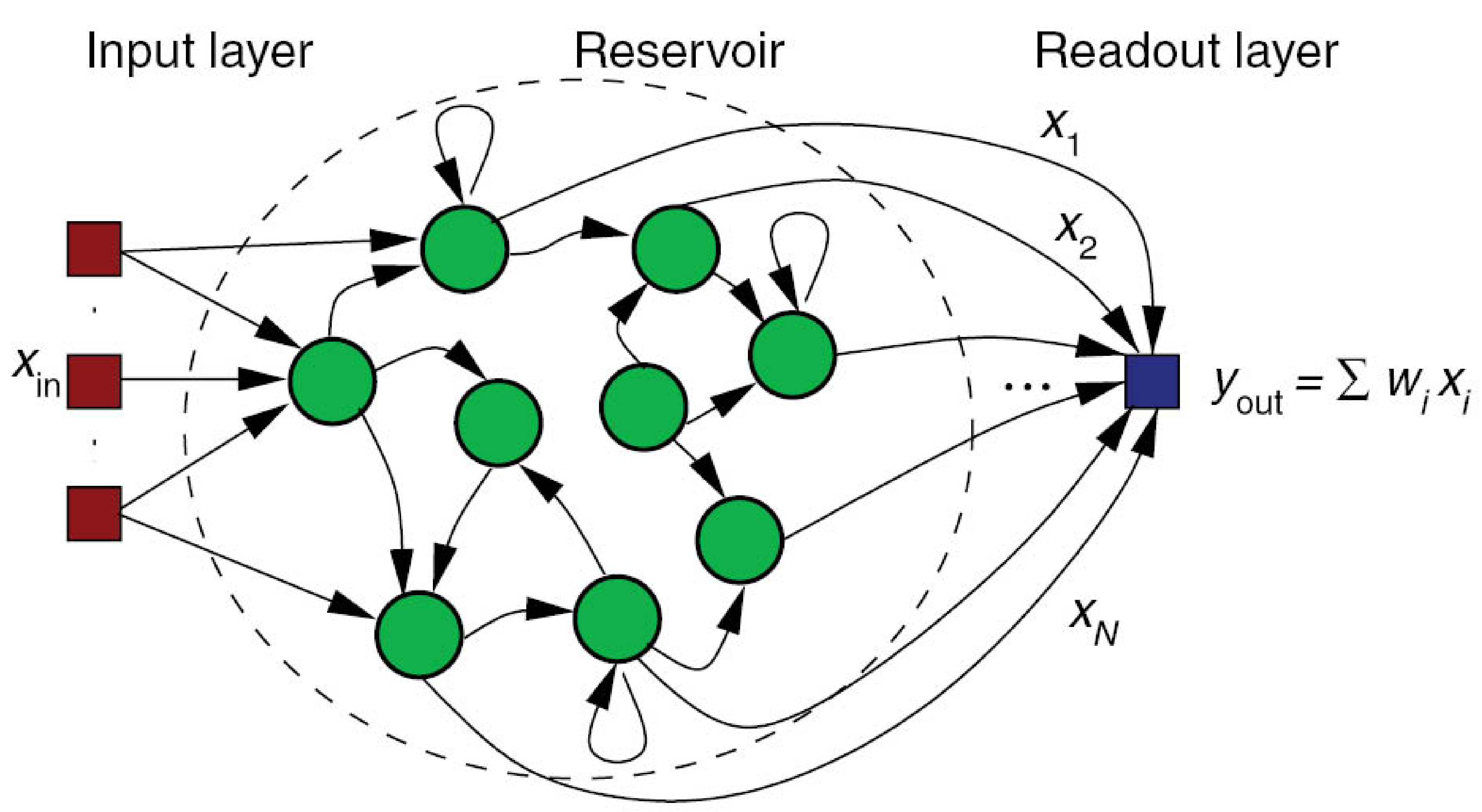
- If you do not change the inputs to an artificial neuron, its output won't change.
- Time does not exist, even in a LSTM: the only temporal variable is the frequency at which inputs are set.

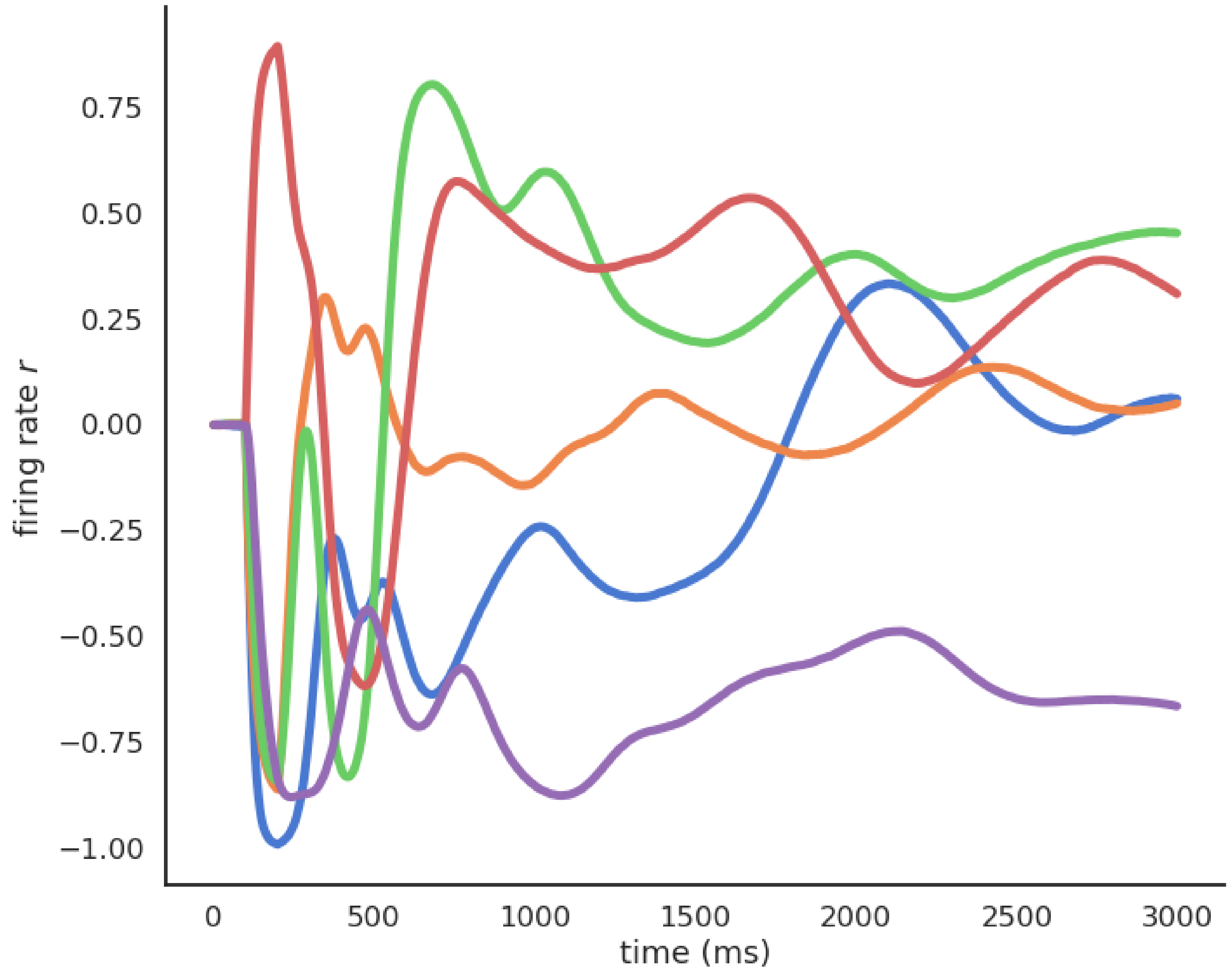


- Biological neurons have **dynamics**:
  - They adapt their firing rate to constant inputs.
  - they continue firing after an input disappears.
  - they fire even in the absence of inputs (tonic).
- These dynamics are essential to information processing in the brain.

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.

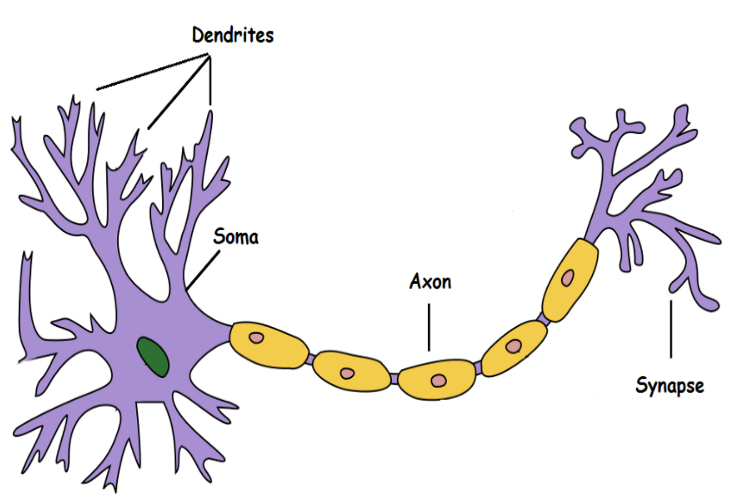




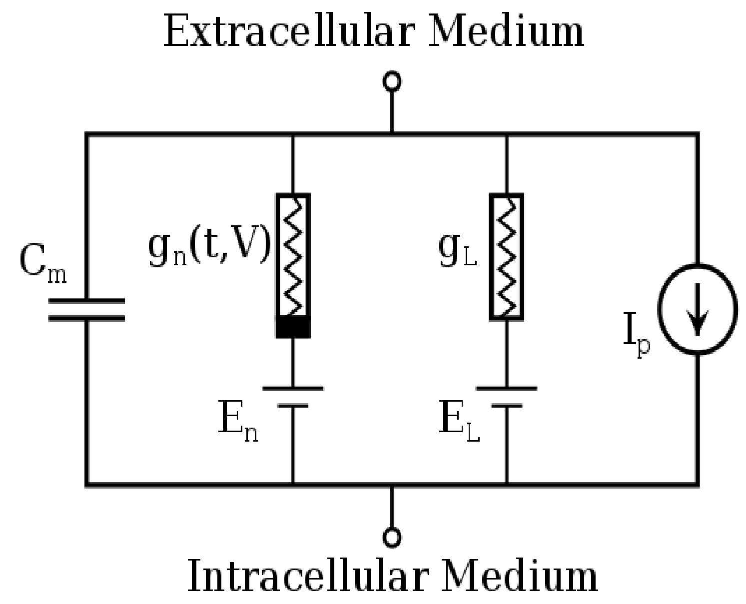
Overview of neuron models

Biological plausibility

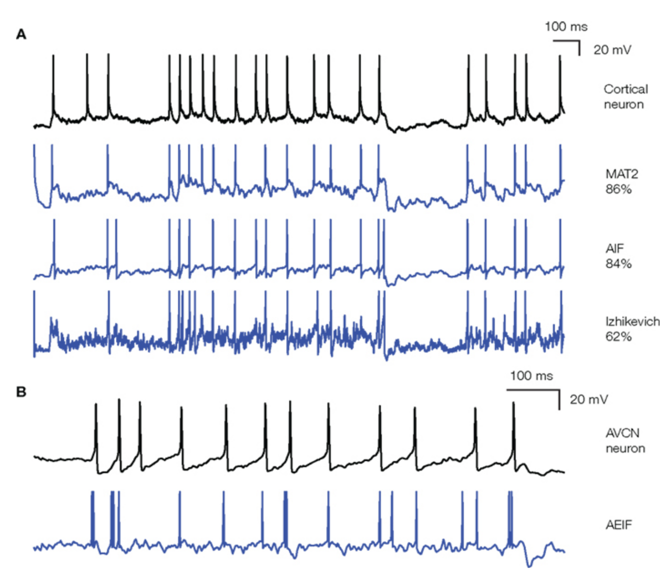
Biological neuron



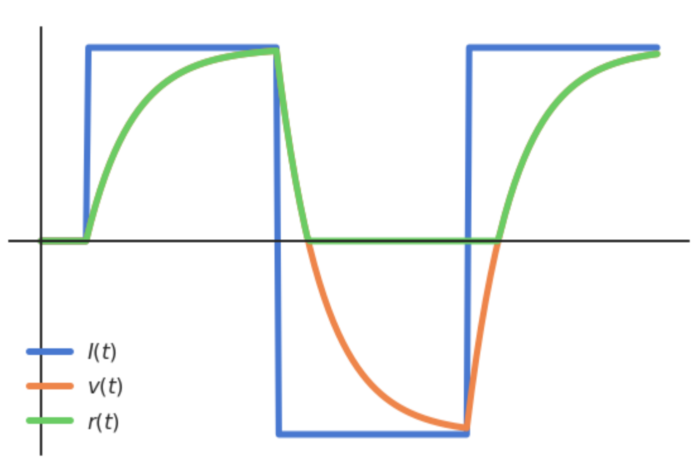
Hodgkin-Huxley



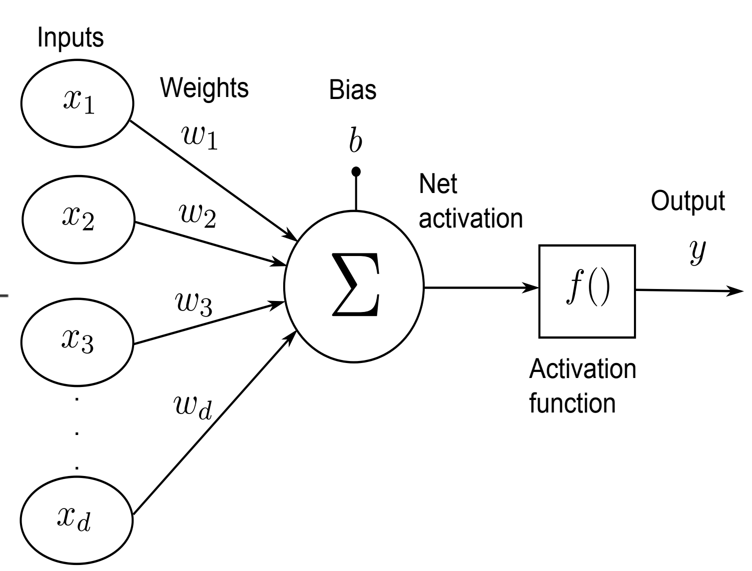
Spiking neuron



Rate-coded neuron



Artificial neuron



Machine learning

Computational neuroscience

Neurocomputing

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**.

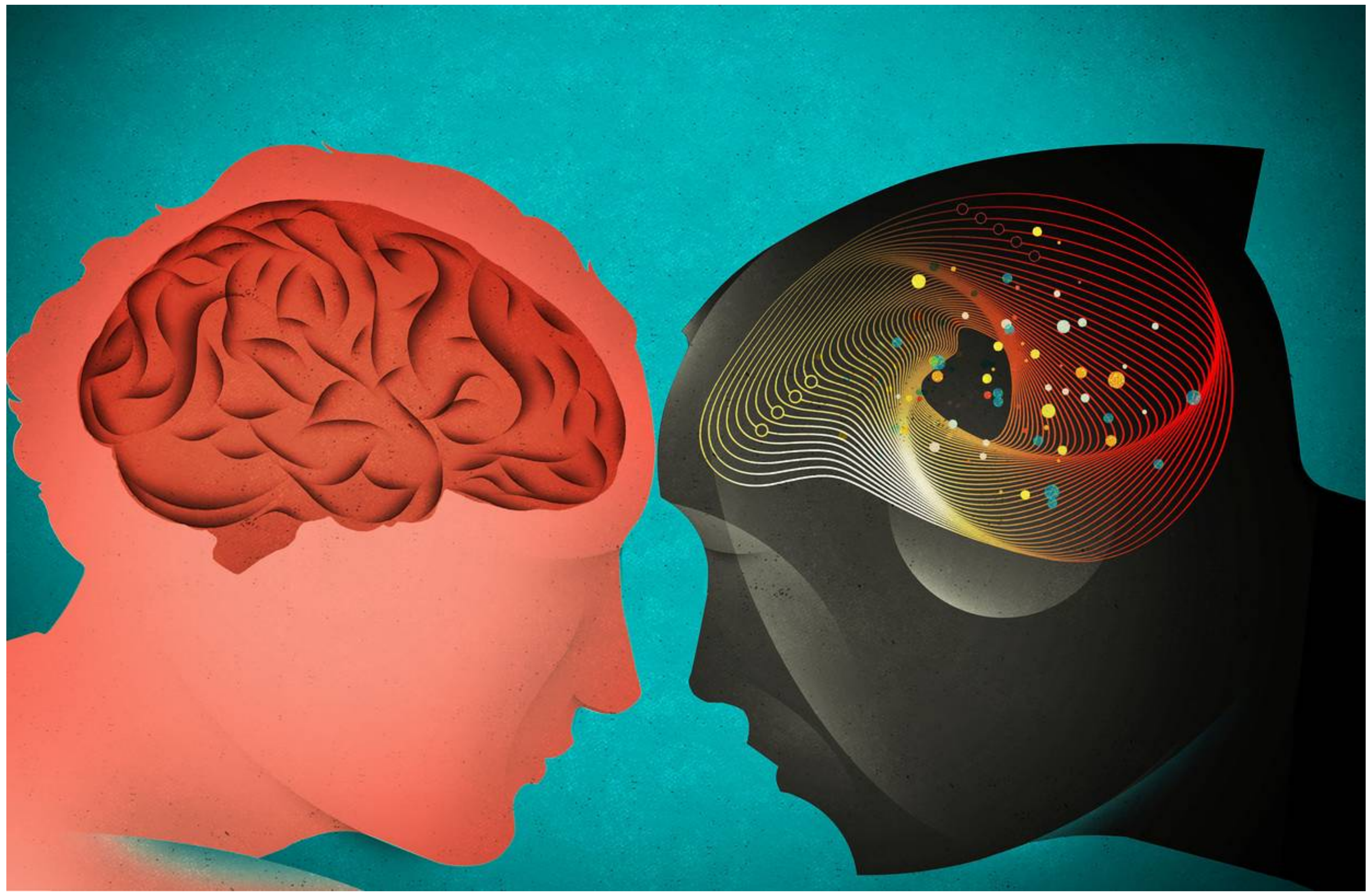
Example: Conway’s game of life.

- 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**.

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

Key differences between deep networks and the brain



- **No backpropagation** in the brain, at least in its current form.
- Information processing is **local** to each neuron and synapse.
- Highly **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).

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