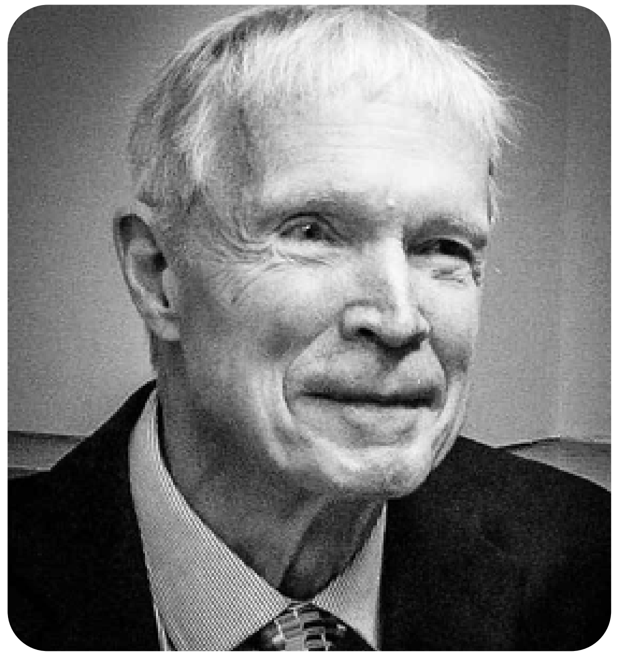
Brains & Machines: How Neural Networks Bridge Neuroscience and AI

Can we build machines that think like the brain?



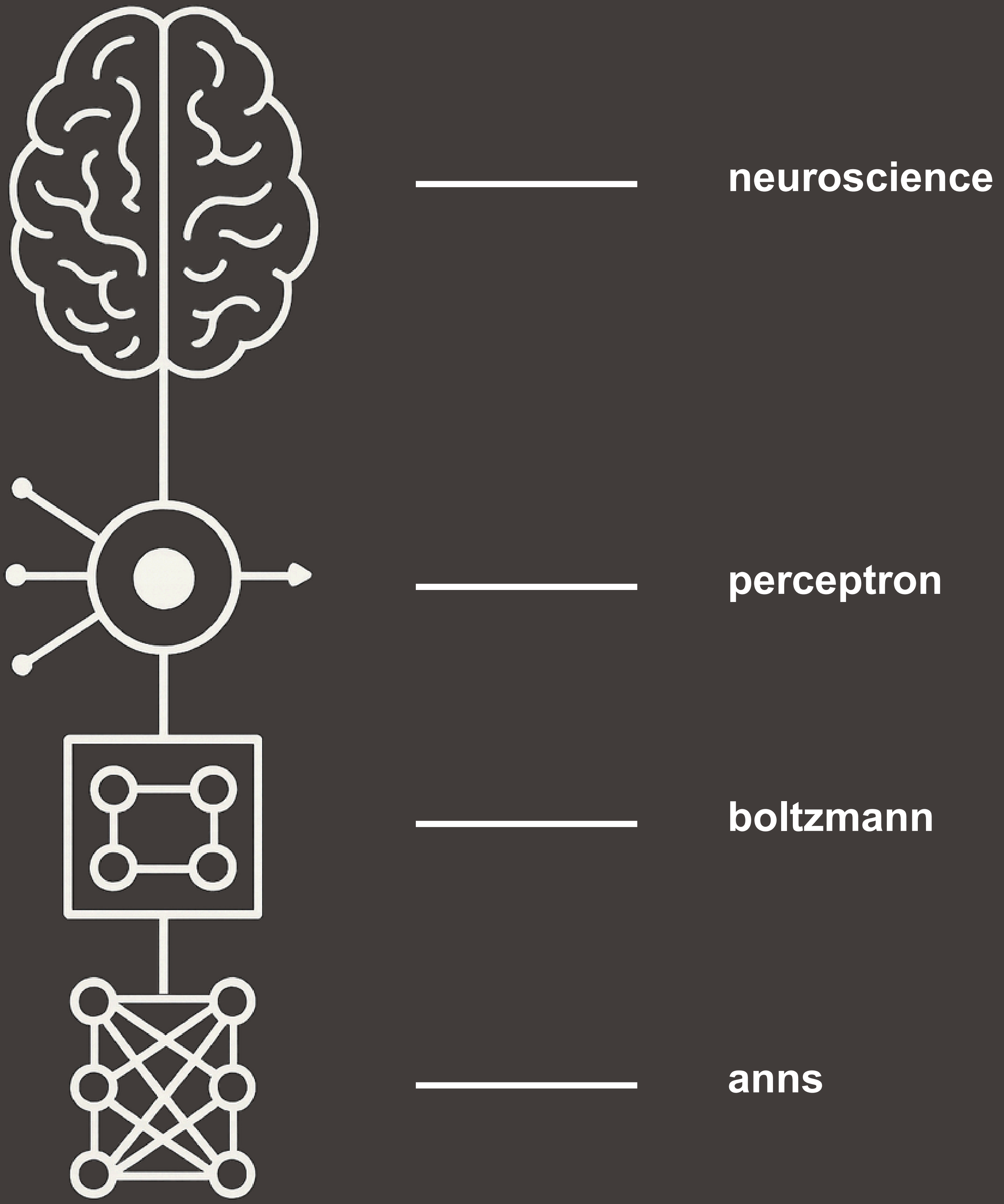
John J. Hopfield

Geoffrey Hinton

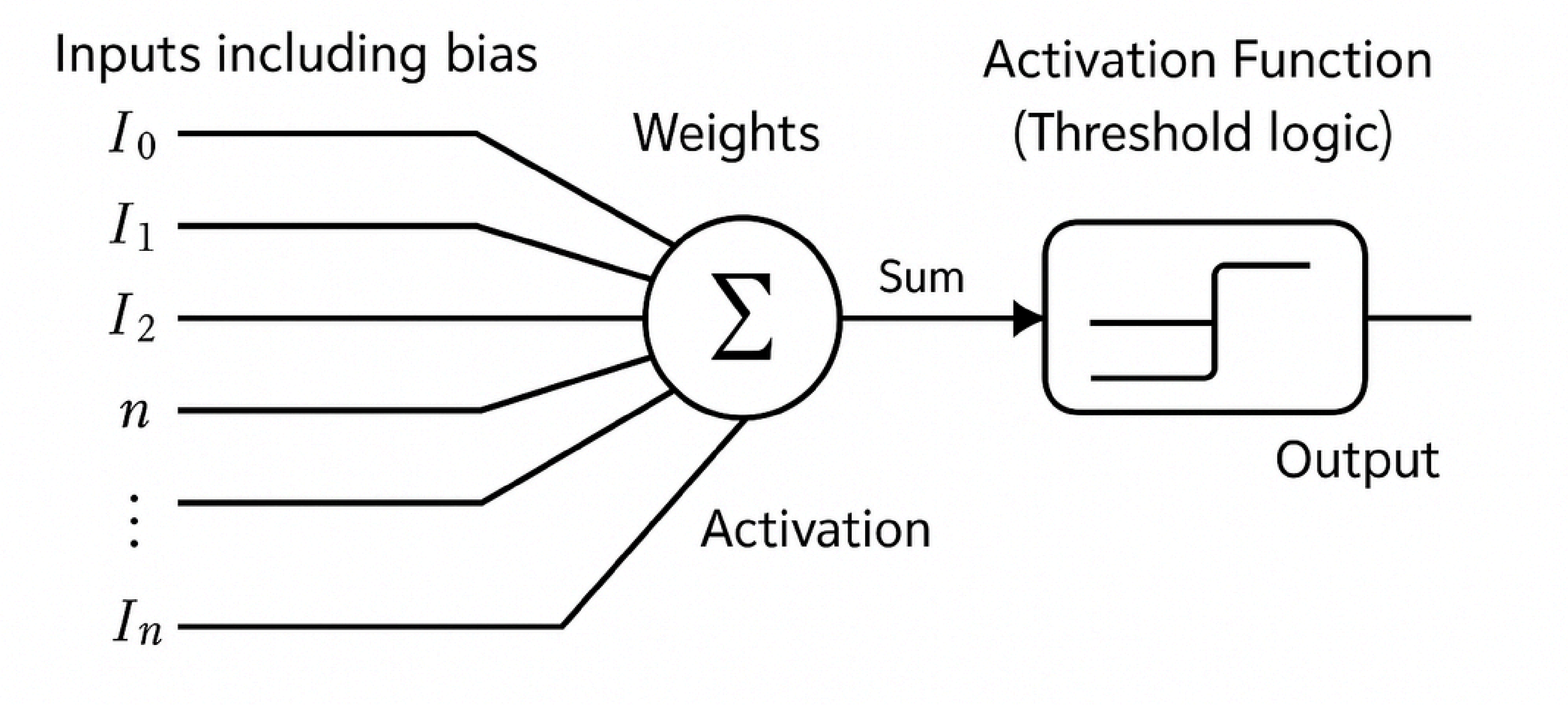
The Royal Swedish Academy of Sciences has decided to award the Nobel Prize in **Physics** 2024 jointly to

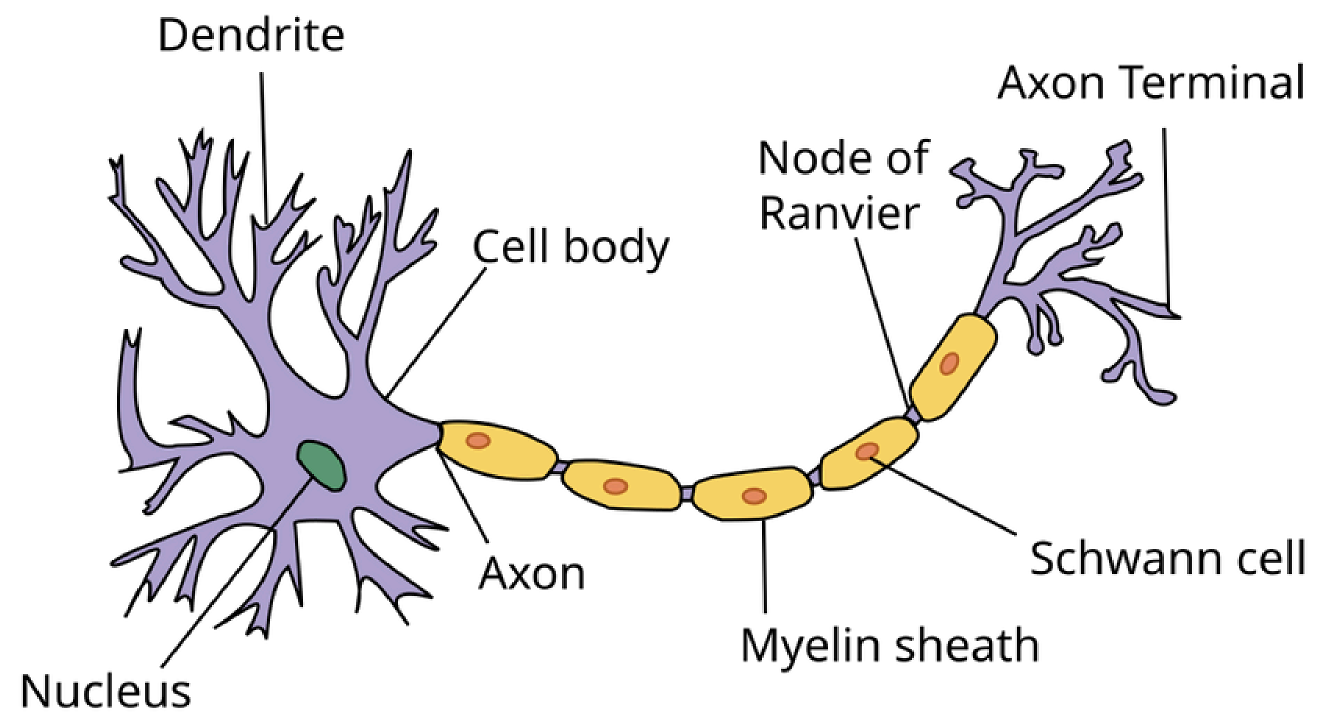
John J. Hopfield and Geoffrey Hinton

“for foundational discoveries and inventions that enable machine learning with artificial neural networks”



From Brain Cells to Logic Gates: The First Artificial Neuron (1943), Warren McCulloch & Walter Pitts

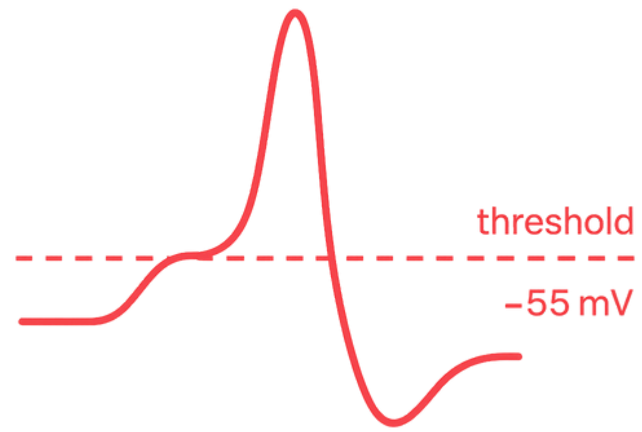




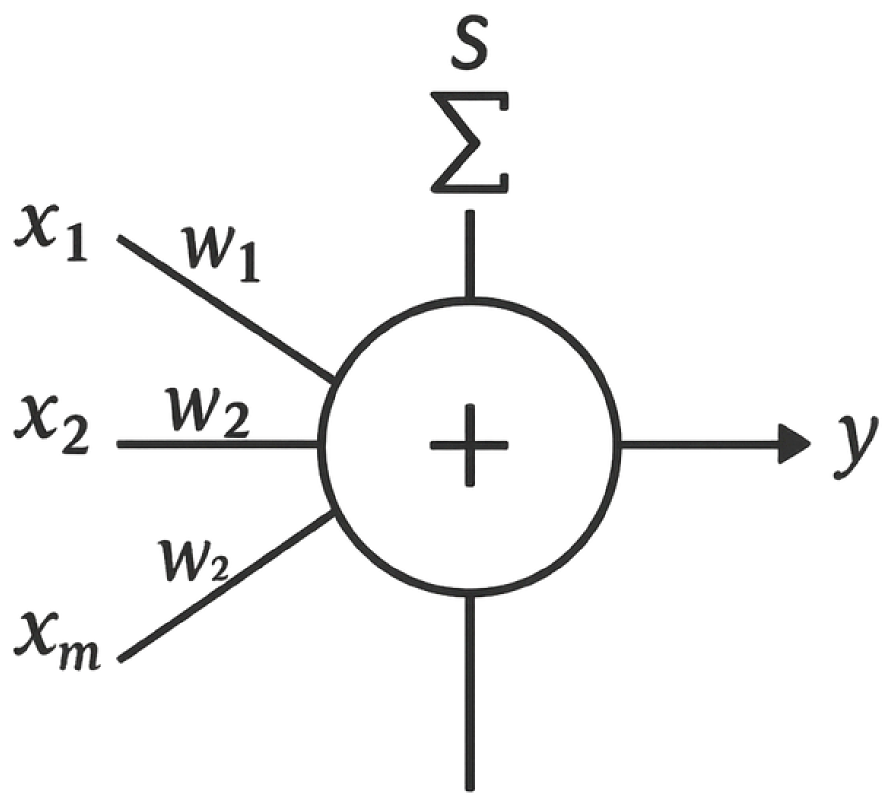
$$S = \sum_{i=1}^{n} w_i I_i$$

$$output = \begin{cases} 1 & if\ S \geq \theta \\ 0 & if\ S < \theta \end{cases}$$

Sum of all postsynaptic potentials at the soma



The Perceptron – Frank Rosenblatt (1957)



Learning Process : Weight update rule

$$w_i \leftarrow w_i + \eta(y - \hat{y})x_i$$

$w_i =$ weight for input x_i

$y =$ true label

$\hat{y} =$ predicted label

$\eta =$ learning rate (small constant)

Perceptron Component	Biological Equivalent
Inputs x_1, x_2, …, x_m	Dendrites receiving signals
Dendrites receiving signals	Synaptic strengths
Summation \sum w_i x_i	Integration in soma (cell body)
Threshold & Output y	Action potential (neuron firing)

EPFL

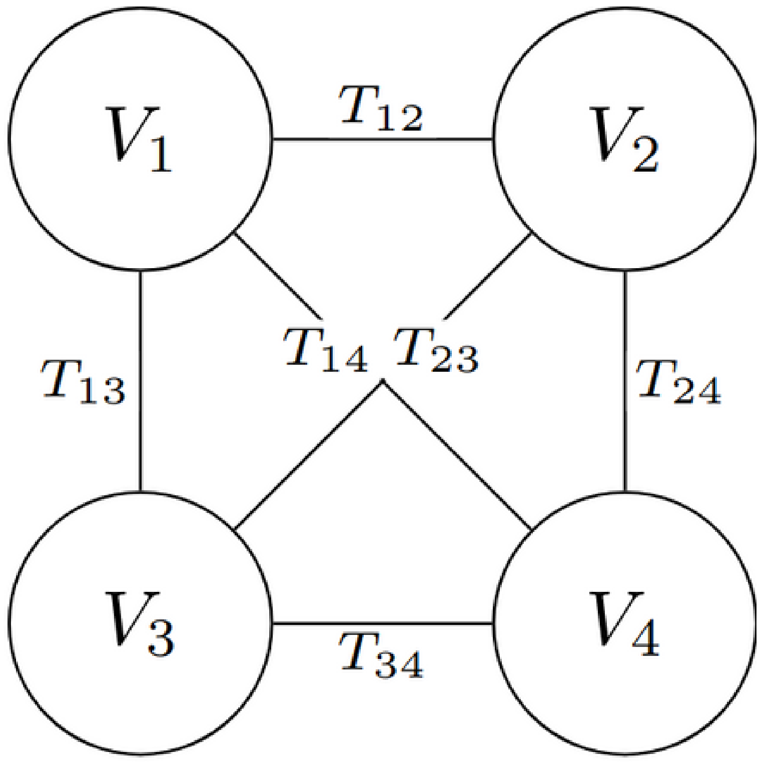
Hopfield's 1982 model : Associative Memory

Let V_i be the state of the neuron, either not firing (0) or firing at maximum rate (1).

Let T_{ij} be the strength of connection between neuron i and neuron j.

$$V_i \rightarrow \begin{cases} 1 & \text{if} \quad \sum_{j \neq i} T_{ij} V_j > U_i \\ 0 & \text{if} \quad \sum_{j \neq i} T_{ij} V_j < U_i \end{cases}$$

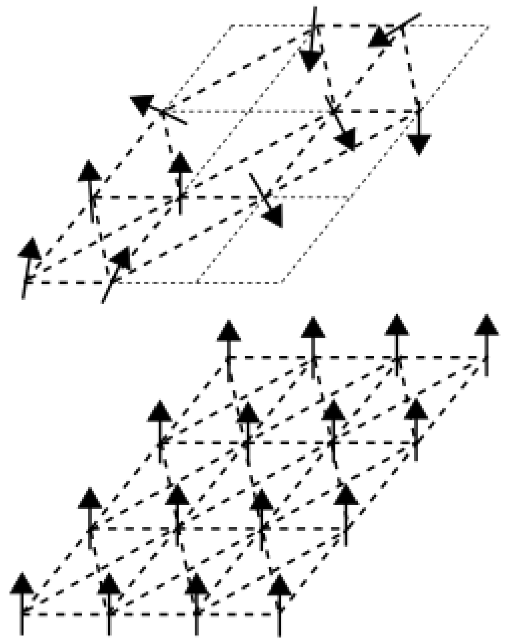
U_i – threshold of neuron i



- aim at retrieving full pattern based on hint or noisy cue
- Store a set of patterns : S = { V^1, V^2, …, V^n }
- Fully connected network

Hopfield JJ. Neural networks and physical systems with emergent collective computational abilities. Proc Natl Acad Sci U S A. 1982 Apr;79(8):2554-8. doi: 10.1073/pnas.79.8.2554. PMID: 6953413; PMCID: PMC346238.

Hopfield's 1982 model : Associative Memory



Spin Glass

Let V_i be the state of the neuron, either not firing (0) or firing at maximum rate (1).

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U_i – threshold of neuron i

$$T_{ij} = \sum_s (2V_i^s - 1)(2V_j^s - 1)$$

Hebbian learning

- Hebbian learning : **training function**
- Minimize Energy function : **loss function**
  - update neurons state one by one till minimal of E
- symmetric weights T_ij = T_ji
  - behave like an Ising model : magnets aligning
    - Spin glass effect
  - Converge
- not symmetric weights
  - May not converge
  - better result with specific values

$$E = -\sum_{i \neq j} T_{ij} V_i V_j$$

$$\Delta E = -\Delta V_i \sum_{j \neq i} T_{ij} V_j$$

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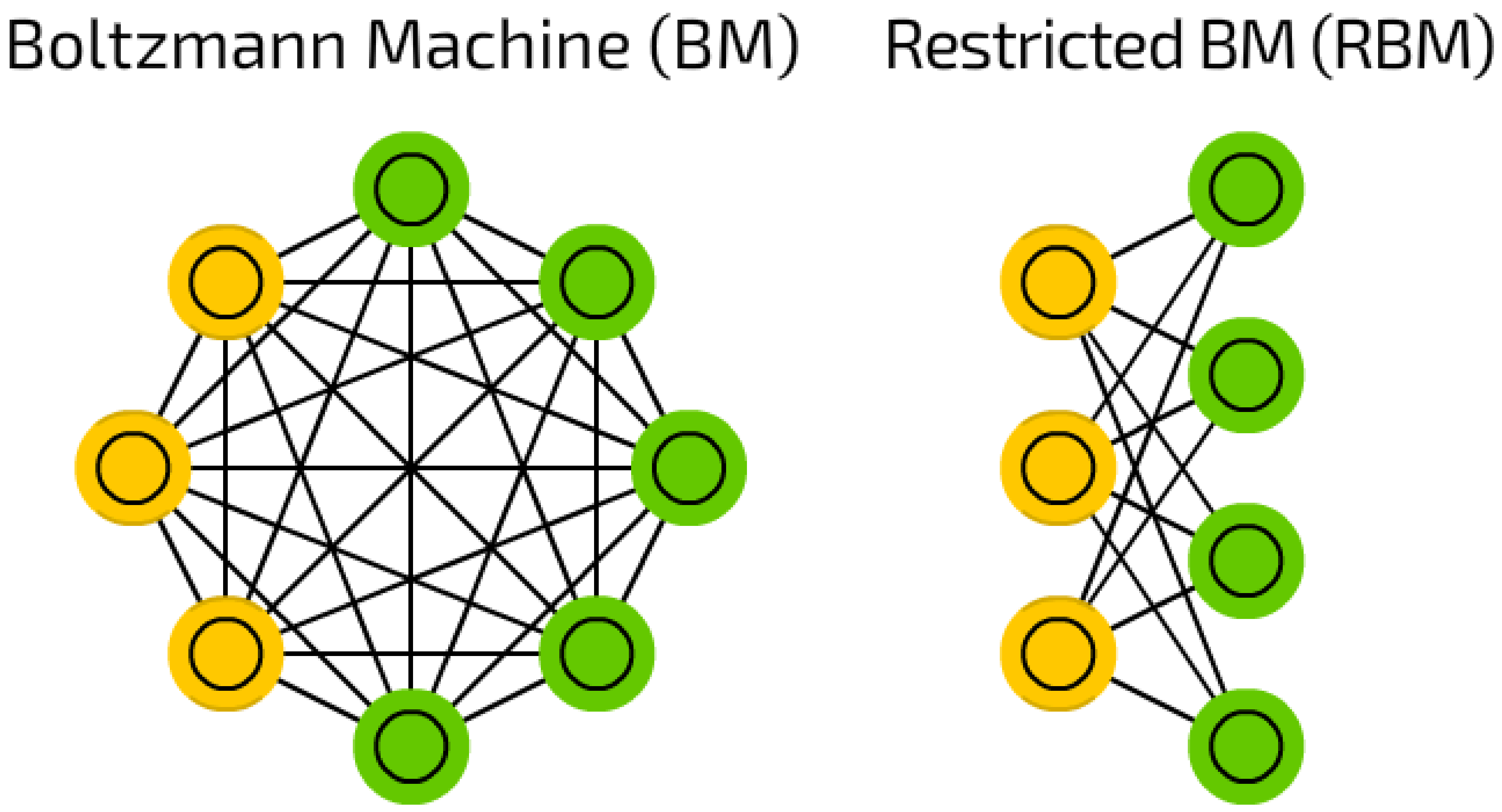
Hinton and Boltzmann Machines (1985)



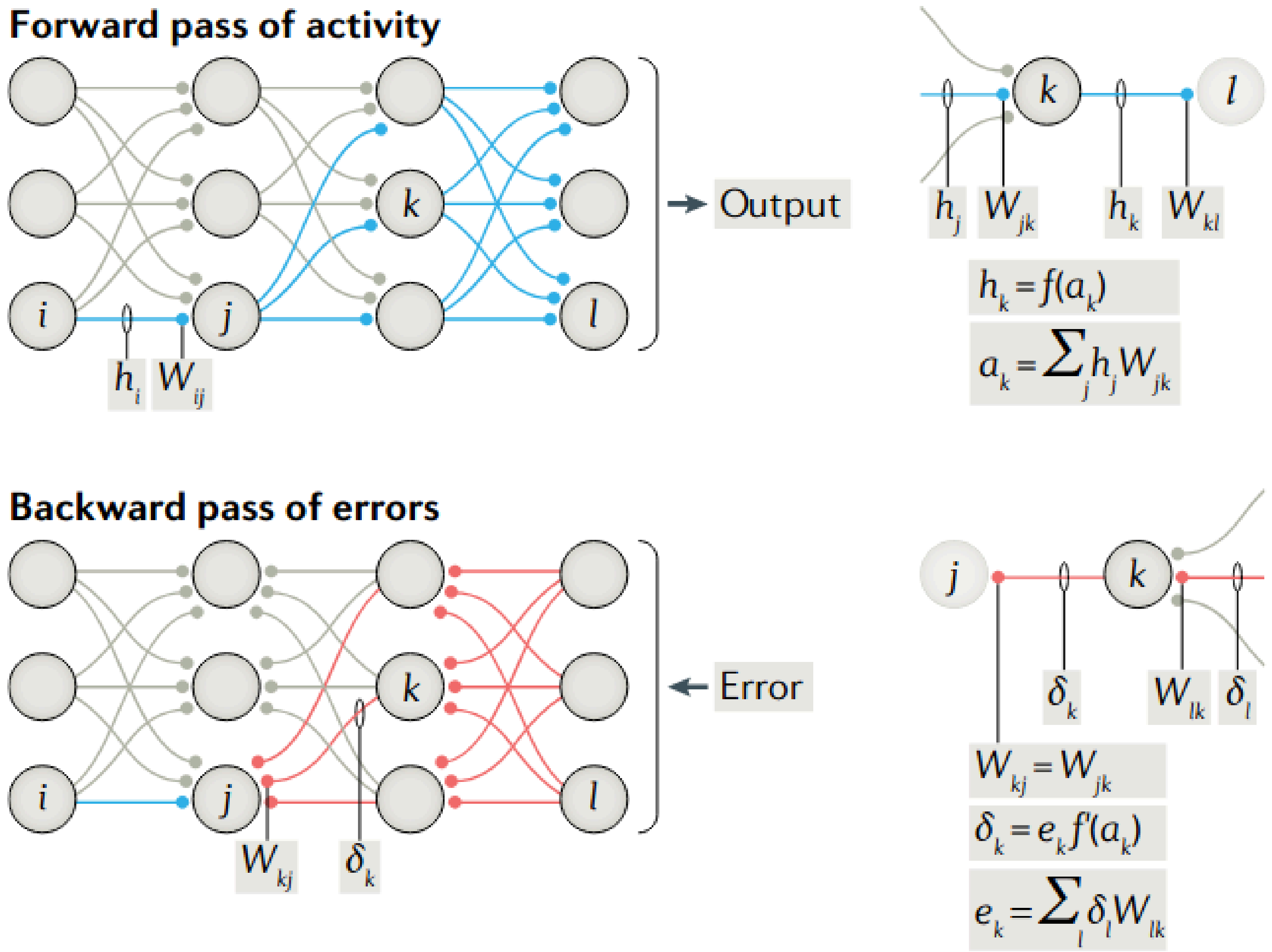
Boltzmann Machine (BM)
Fully connected network
Models brain-like collective activity
Hard to train due to recurrent loops

Restricted Boltzmann Machine (RBM)
Only visible-to-hidden connections
Inspired by layered brain structures (like retina to visual cortex)
Efficient learning → foundation of deep learning

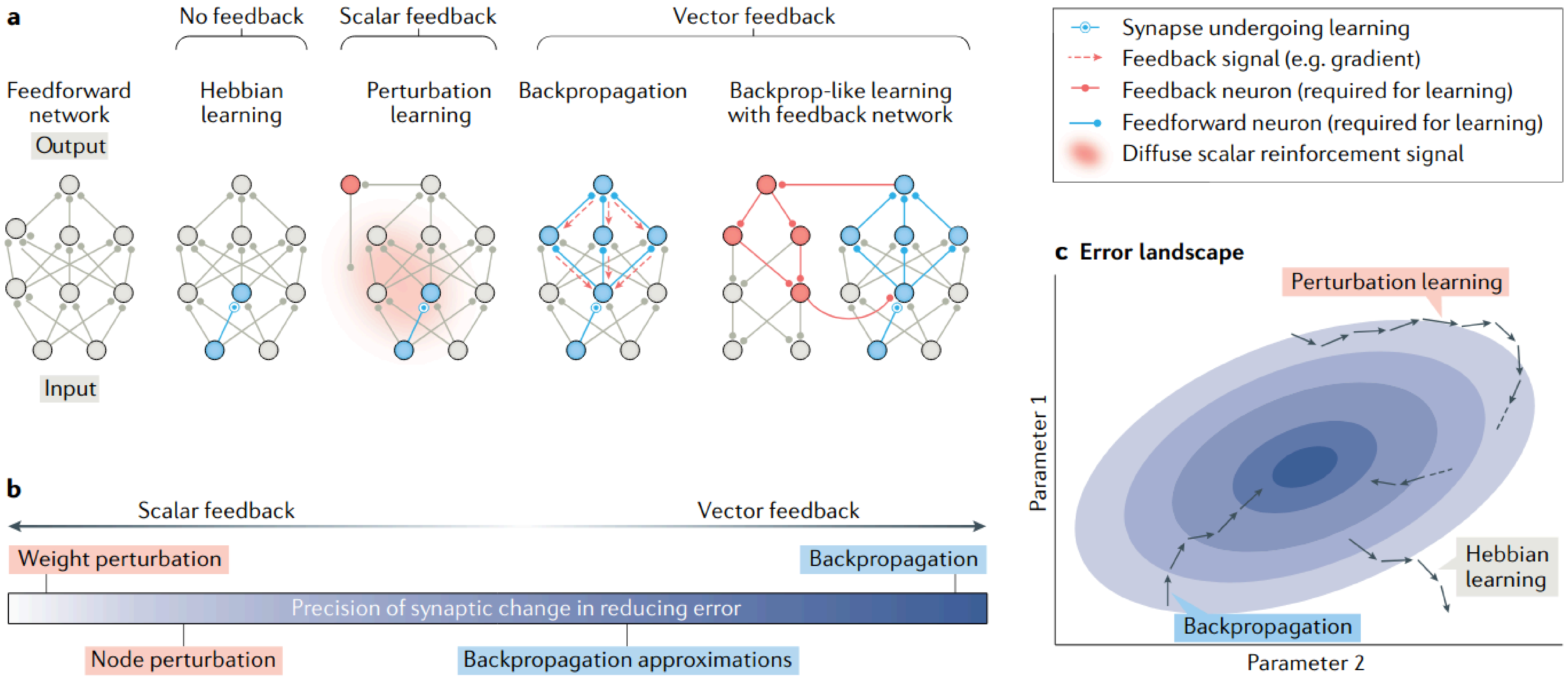
- compare input with output to calculate error
- Apply local correction to each weight using chain rule
- vector feedback

1. Forward pass and freeze
2. Calculate local output errros : chain rule
3. Backprop pass using 2.
4. Update the weights using 1 and 3
5. Repeat

Backpropagation and Deep Learning



Lillicrap, T.P., Santoro, A., Marris, L. et al. Backpropagation and the brain. Nat Rev Neurosci 21, 335–346 (2020). https://doi.org/10.1038/s41583-020-0277-3



Learning in Neural Network

- Backprob is hardly implementable in biology
  - only local feedback instead of global
- Still possible to run PCA, ICA and more
  - Taylor expansion of Hebbian Rule
- Neurons are starting to be used a chip
  - more efficients
  - active research

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EPFL

Sources :

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Hopfield JJ. Neural networks and physical systems with emergent collective computational abilities. Proc Natl Acad Sci U S A. 1982 Apr;79(8):2554-8. doi: 10.1073/pnas.79.8.2554. PMID: 6953413; PMCID: PMC346238.

Gerstner Wulfram CS-479 : Learning in neural networks

https://www.reuters.com/video/watch/idRW684906032025RP1/?chan=technology

Lillicrap, T.P., Santoro, A., Marris, L. et al. Backpropagation and the brain. Nat Rev Neurosci 21, 335–346 (2020). https://doi.org/10.1038/s41583-020-0277-3

CHATGPT - OpenAI 4o & o3

https://en.wikipedia.org/wiki/Spin_glass