

# Could the laws of physics explain not just the universe but also the workings of our minds?

## The 2024 Nobel Prize in Physics

**Prof Truyen Tran**

Applied AI Institute (A2I2), Deakin University

[truyen.tran@deakin.edu.au](mailto:truyen.tran@deakin.edu.au) | [truyentran.github.io](https://truyentran.github.io)



John Hopfield  
Born: 1933, USA



Geoffrey E. Hinton  
Born: 1947, UK



APPLIED ARTIFICIAL  
INTELLIGENCE INSTITUTE



“The Nobel Prize in **Physics** 2024 recognizes methods that lay the foundation for the development of **artificial intelligence.**”



2012

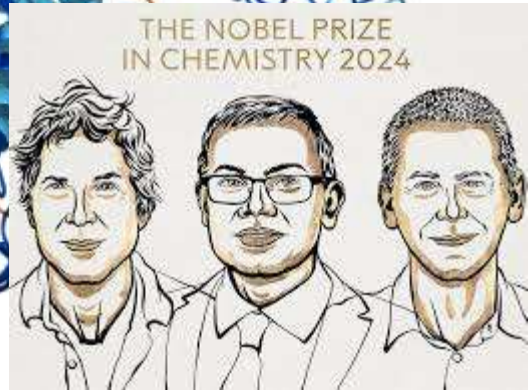
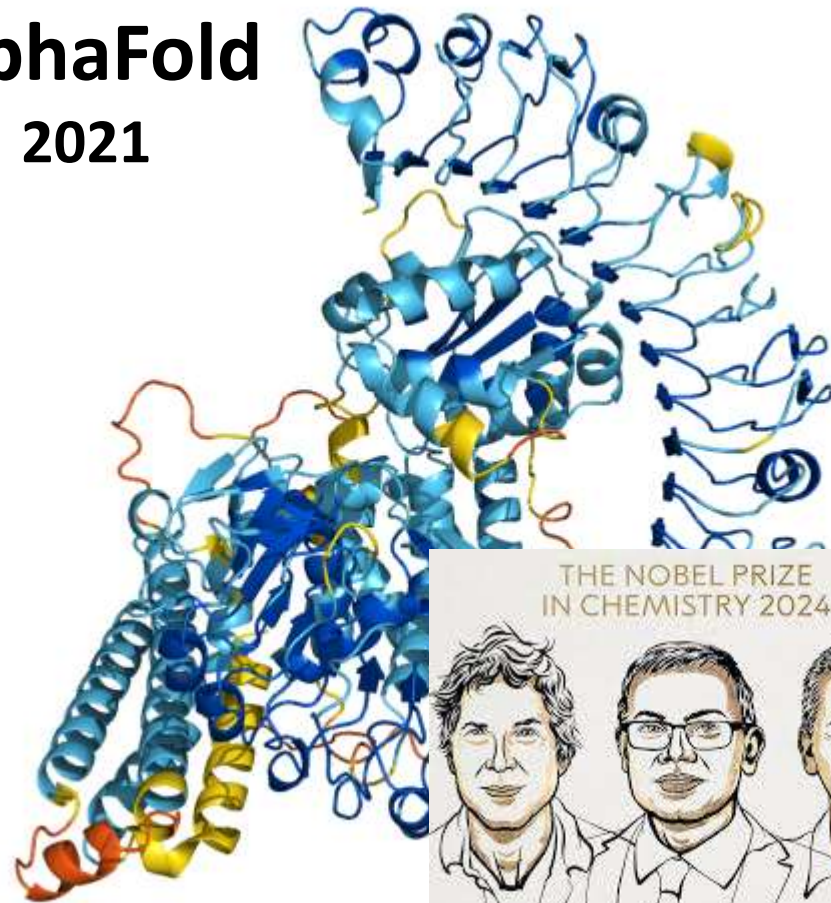
 AlphaGo



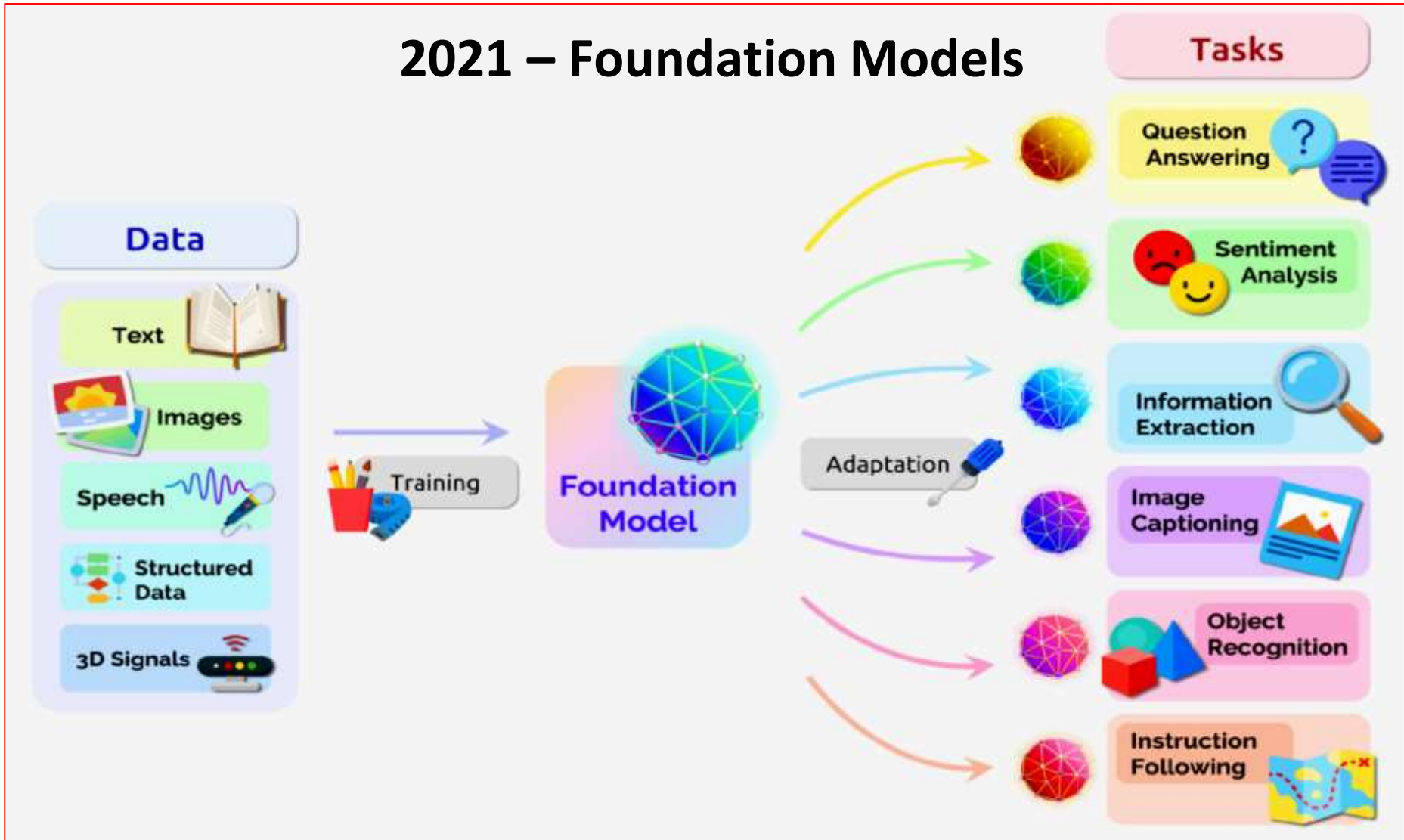
2016

13 years snapshot

AlphaFold  
2021

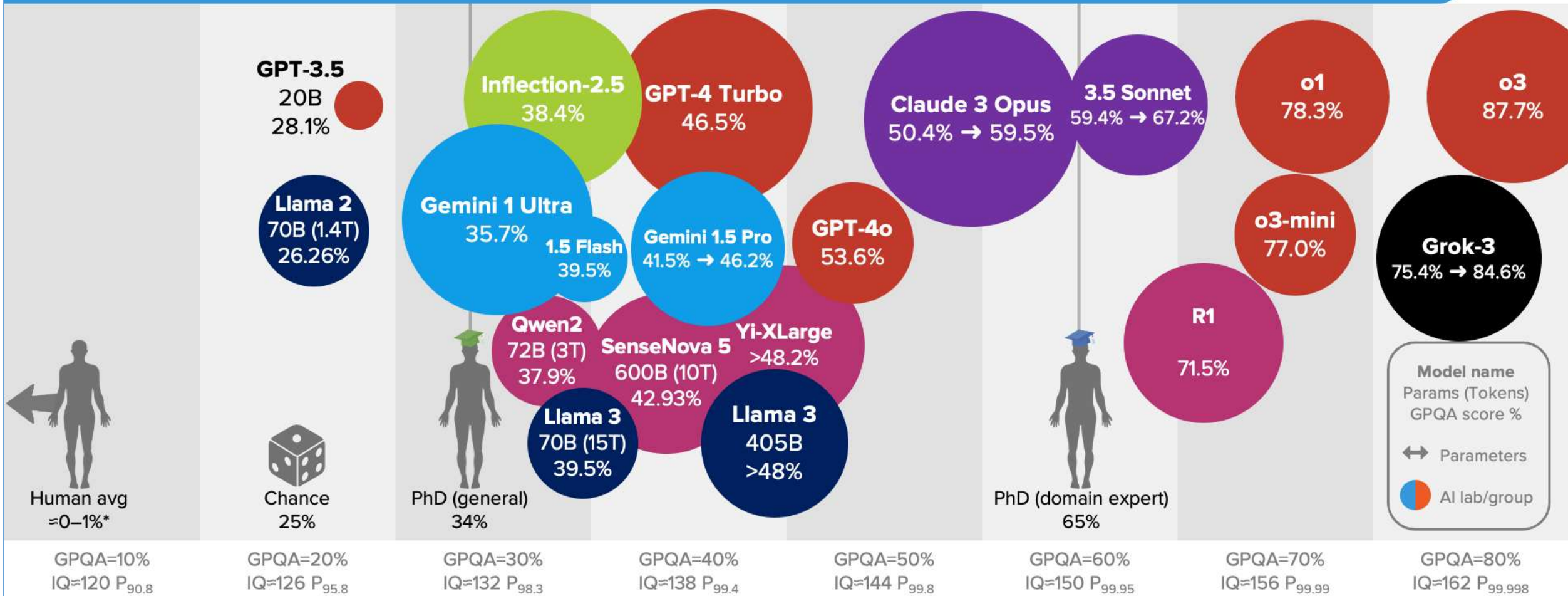


# 2021 – Foundation Models



13 years snapshot

# LARGE LANGUAGE MODELS + GPQA (FEB/2025)



Model sizes near to scale. \* Estimates based on independent analysis. Selected highlights only. IQ correlation estimates only: <http://lifeai.com>

<https://lifeai.com/models-table/> Alan D. Thompson. 2025.



# Five things in modern AI



Representation



Reasoning



Learning

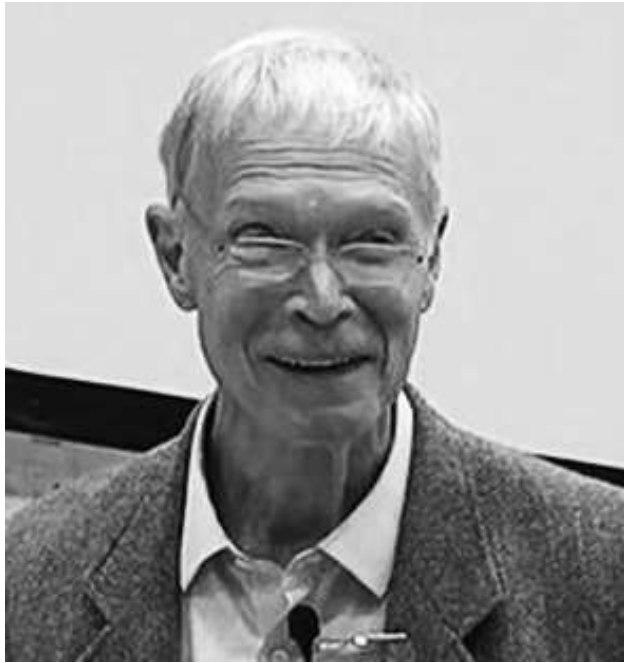


Noise tolerance



Scale with  
compute

# What was the role of physics in shaping modern AI?



John Hopfield (born 1933)

“How mind emerges from brain is to me the deepest question posed by our humanity.”

“Early AI was mainly based on **logic**. You're trying to make computers that **reason like people**.”

The second route is from **biology**: You're trying to make computers that can **perceive and act and adapt like animals**.”

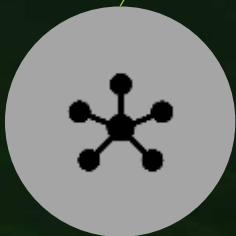


Geoffrey Hinton (born 1947)

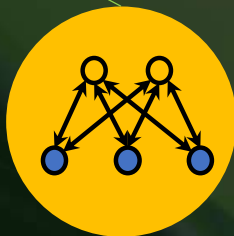




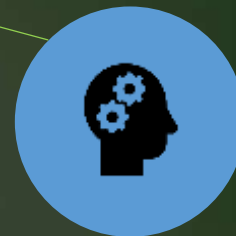
BRAIN, MIND,  
COMPUTATION



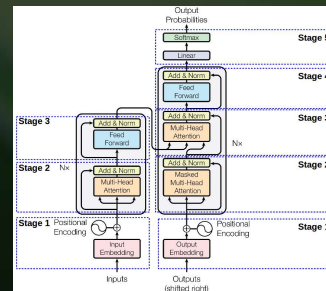
HOPFIELD  
NETWORKS



BOLTZMANN  
MACHINES



AI: DEEP LEARNING  
APPROACH



# Two major concepts



## **Associationism:** Humans learn through association

- 400BC-1900AD: Plato, John Locke, David Hume, David Hartley, James Mill, John Stuart Mill, Ivan Pavlov.

## **Connectionism:** The network that does computation

- Mid 1800s: The brain is a mass of interconnected neurons
- **Alexander Bain (1873):** The information is in the connections.



Alexander Bain  
(1818 –1903)

# The original quest of AI

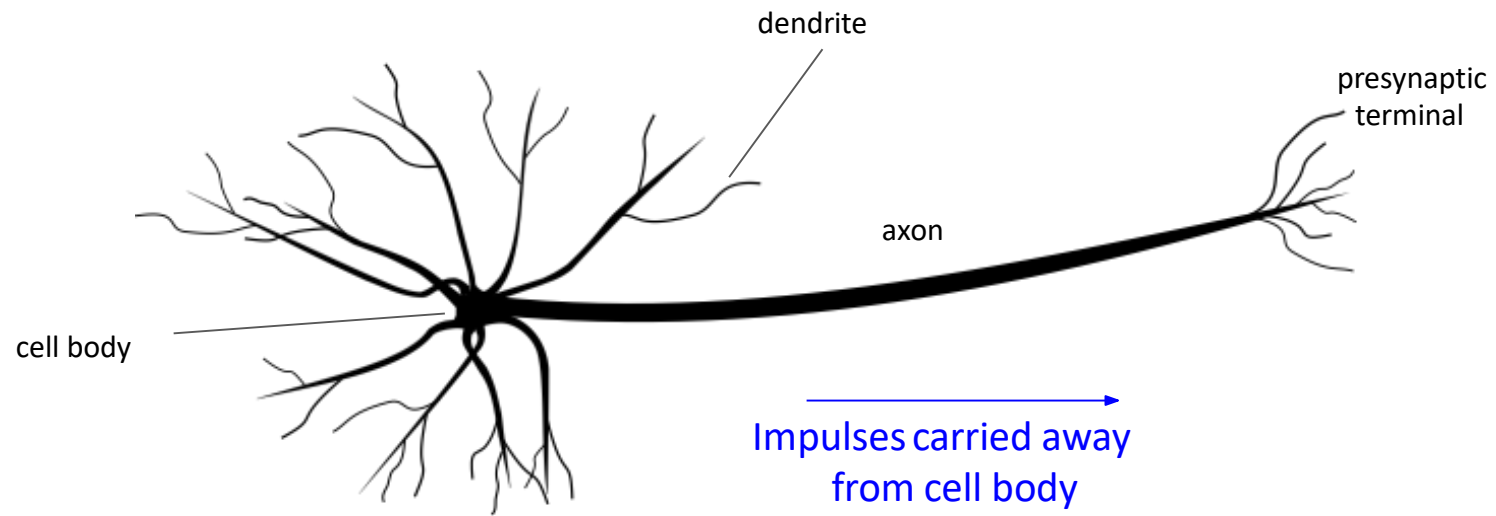


Among the most challenging scientific questions of our time are the corresponding **analytic** and **synthetic** problems:

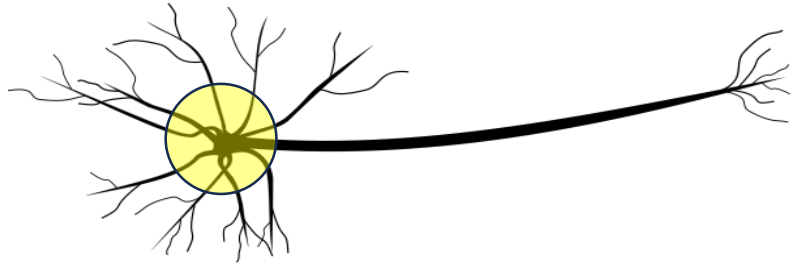
- How does the brain function?
- Can we design a machine which will simulate a brain?

-- *Automata Studies*, 1956.

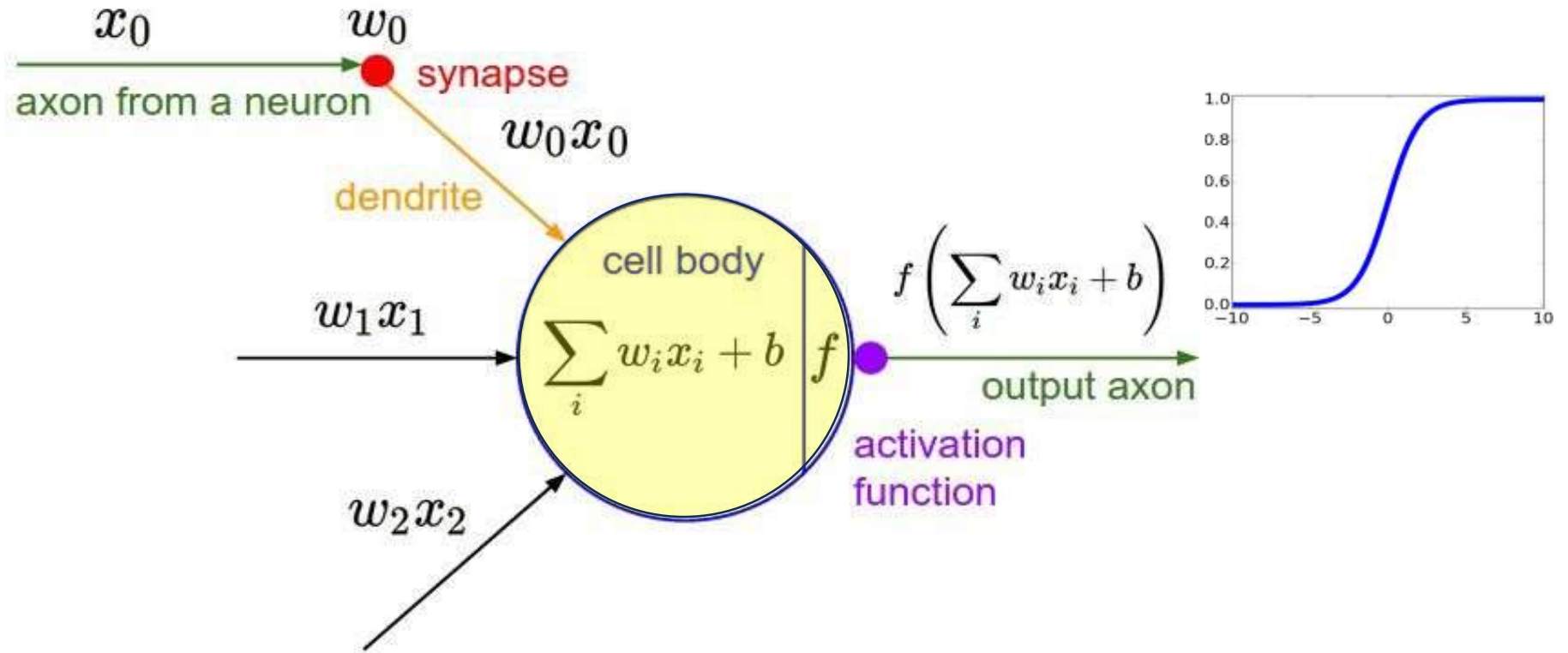
# Neurons

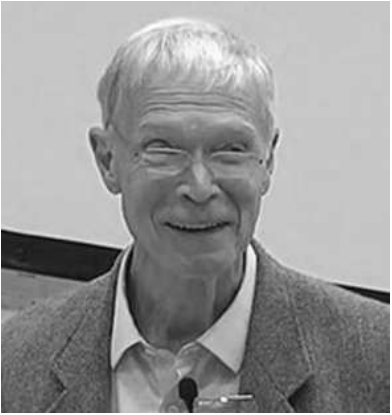


[This image](#) by Felipe Perucho is licensed under [CC-BY 3.0](#)



# Integrate-and-fire neuron *in silico*





# Hopfield network

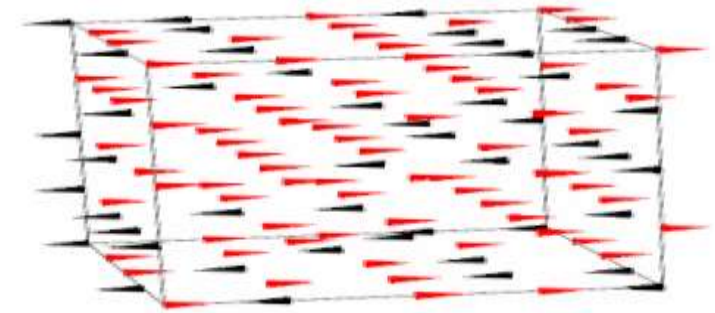
Symmetric weights

No self-connection

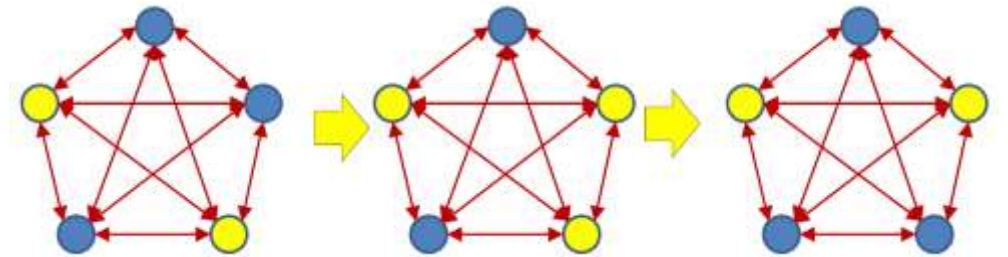
Update either asynchronous or synchronous

Neurons attract or repel each other

The dynamic is deterministic



A spin glass system



$$s_i \leftarrow \begin{cases} +1 & \text{if } \sum_j w_{ij} s_j \geq \theta_i, \\ -1 & \text{otherwise.} \end{cases}$$

# Questions



How do we teach the network to store *a specific* pattern or set of patterns?



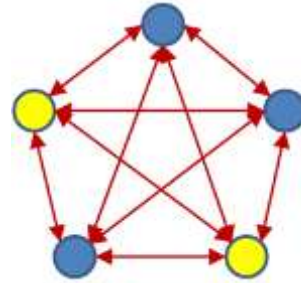
How many patterns can we store?



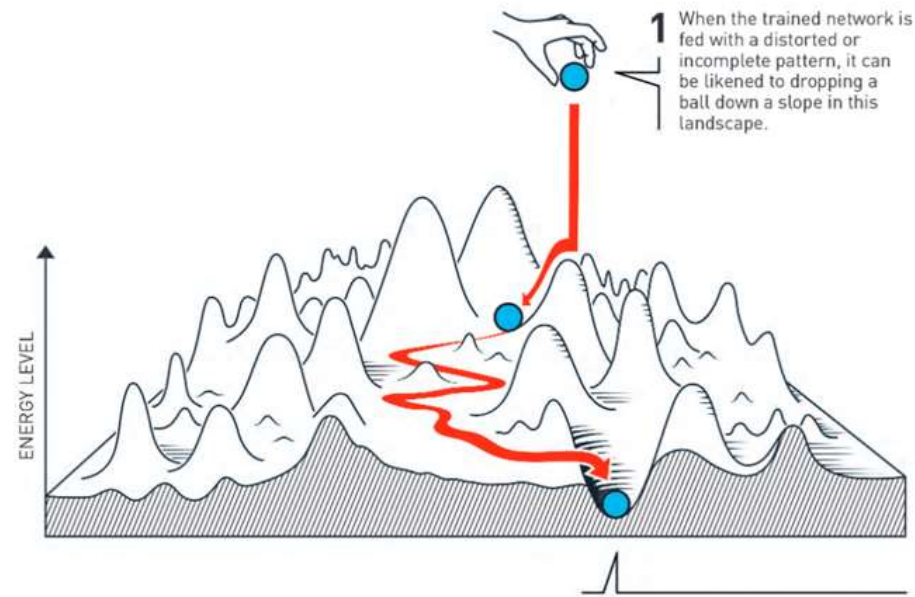
How to “retrieve” patterns better.

# Update as energy minimisation

- Start at some initial pattern (configuration)
- Let the network “runs”
- The convergence is a local attractor (stable)
- The basis for associative memory recall!
- The operation is essentially Iterated Local Mode (ICM) known in spatial statistics, 1975!



$$E = -\frac{1}{2} \sum_{i,j} w_{ij} s_i s_j - \sum_i \theta_i s_i$$



1 When the trained network is fed with a distorted or incomplete pattern, it can be likened to dropping a ball down a slope in this landscape.

2 The ball rolls until it reaches a place where it is surrounded by uphill. In the same way, the network makes its way towards lower energy and finds the closest saved pattern.



# How to store patterns

“Neurons that fire together, wire together”

$$w_{ji} = y_j y_i \quad \text{Hebbian learning rule}$$

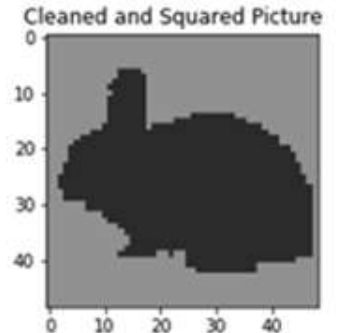
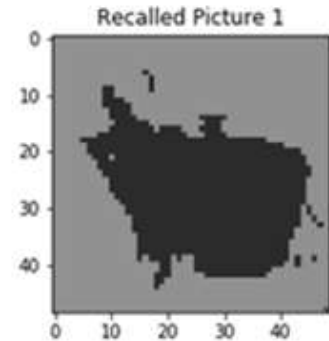
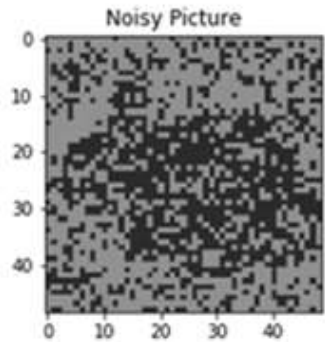
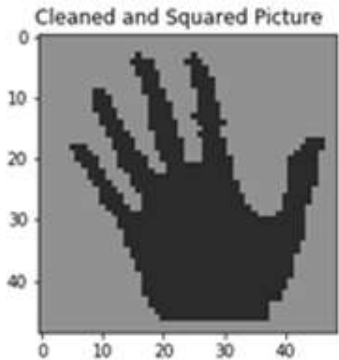
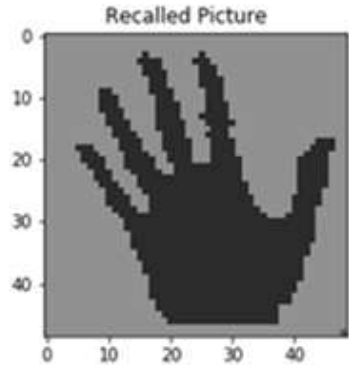
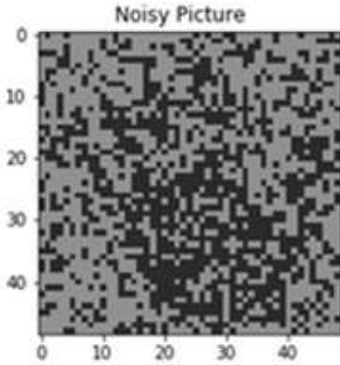
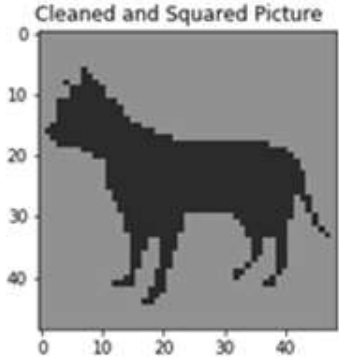
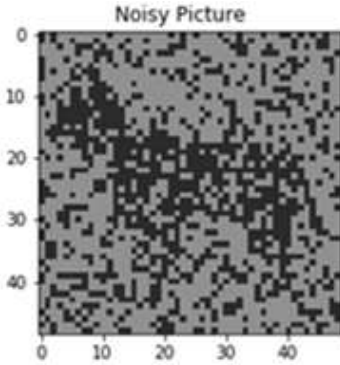
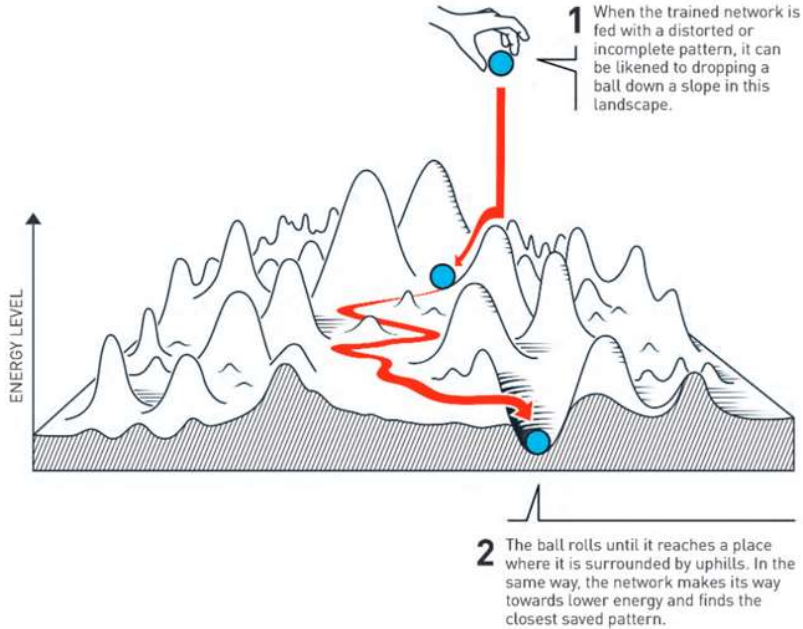
$$E = - \sum_i \sum_{j < i} w_{ji} y_j y_i = - \sum_i \sum_{j < i} y_i^2 y_j^2$$

$$= - \sum_i \sum_{j < i} 1 = -0.5N(N - 1)$$

*This is the global minimum*

For a network of  $N$  neurons can store up to  $\sim 0.15N$  patterns through Hebbian learning

# Examples: Image denoising



# Boltzmann machine

A stochastic Hopfield network with hidden nodes

- Capacity of Hopfield network can be vastly increased by introducing hidden nodes
- Stochasticity gives principled ways to handle uncertainty, randomness and statistical properties
- Hopfield net is a special case when  $T \rightarrow 0$ .

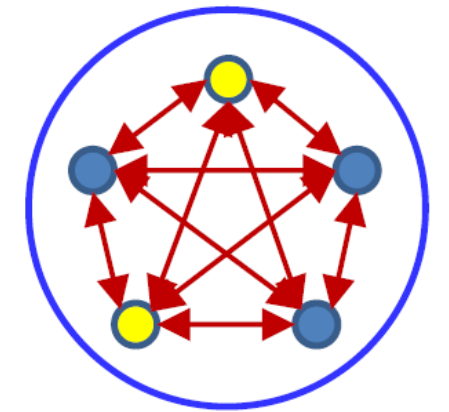
The Helmholtz Free Energy of a System

$$F_T = \sum_s P_T(s) E_s + kT \sum_s P_T(s) \log P_T(s)$$



$$P_T(s) = \frac{1}{Z} \exp\left(\frac{-E_s}{kT}\right)$$

$$E(S) = - \sum_{i < j} w_{ij} s_i s_j$$



Gibbs distribution

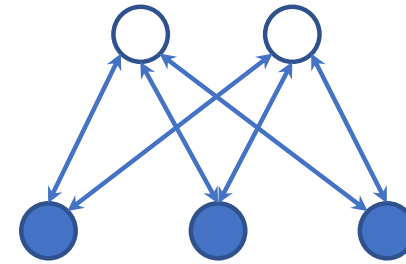
# Restricted Boltzmann machine (RBM)

> **Hidden variables** to denote underlying **unobserved processes**

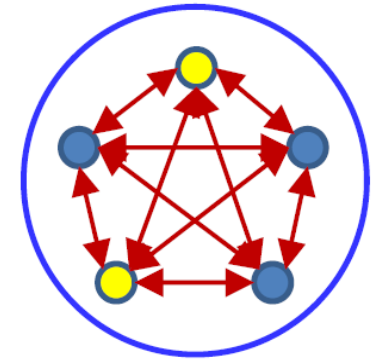
> RBM encourages data representation!

$$p(\mathbf{v}, \mathbf{h}; \psi) \propto \exp[-E(\mathbf{v}, \mathbf{h}; \psi)]$$

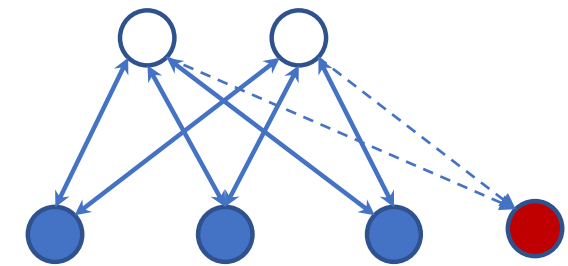
visible
hidden
energy  
y



**Restricted Boltzmann Machine**  
(~1994, 2001)



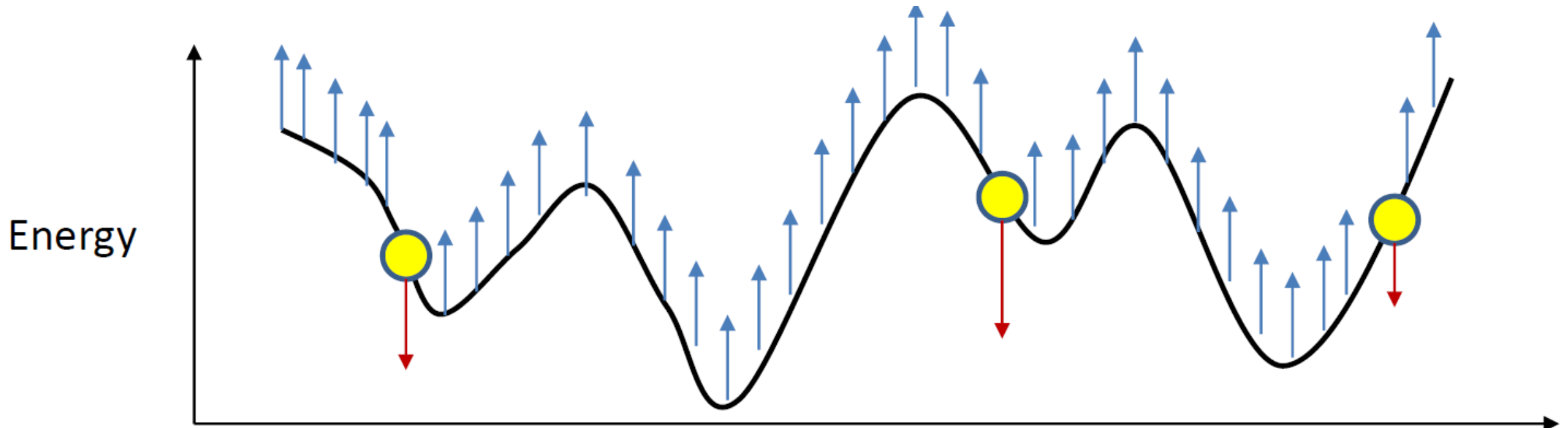
**Boltzmann Machine**  
(1985)



**RBM for prediction**

# Training a Boltzmann machine

By minimising the energy of the observed configurations and raising the energies where else.



Models that can do  
these five things win!

Representation

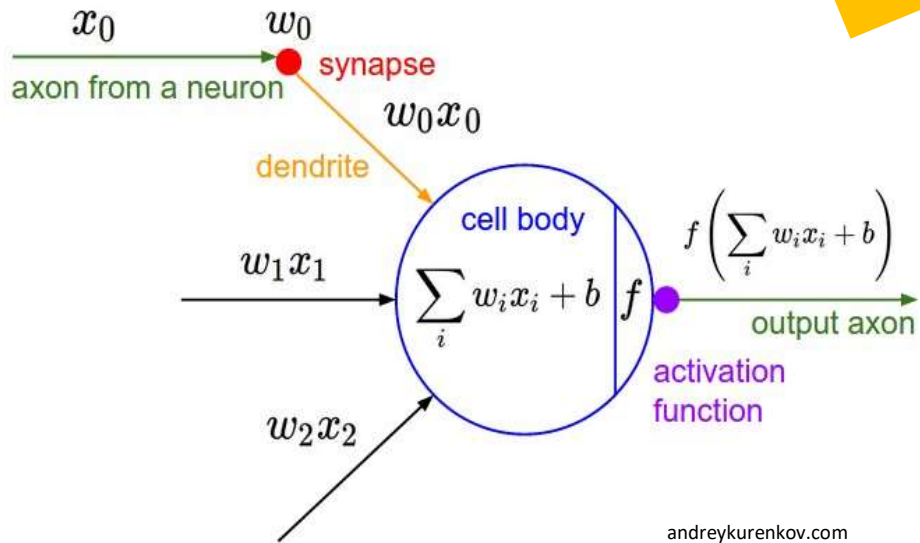
Reasoning

Learning

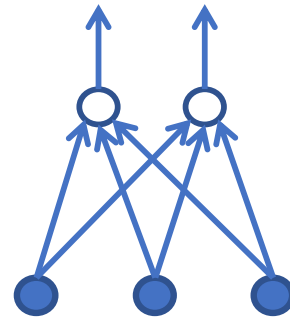
Noise tolerance

Scale with compute

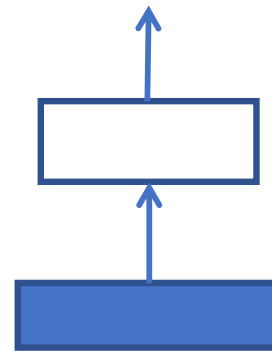
# Deep neural networks



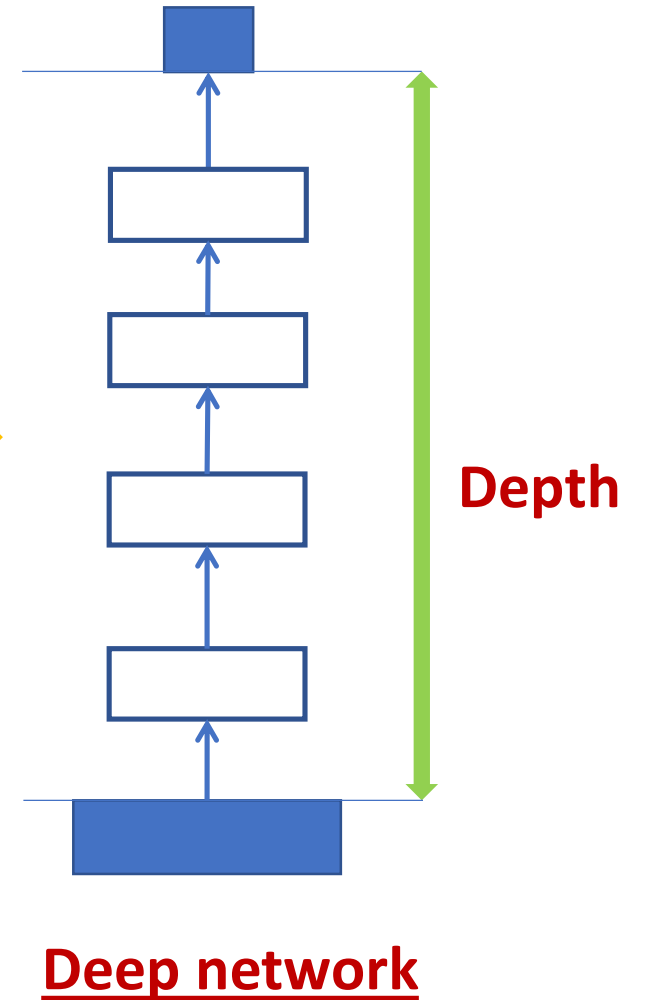
Integrate-and-fire neuron



Feature detector

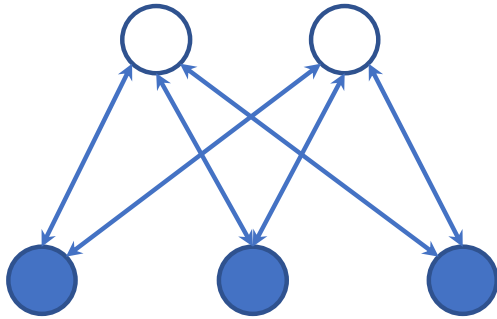


Block representation

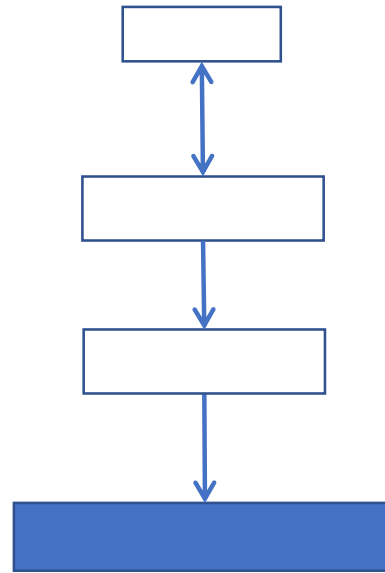


Deep network

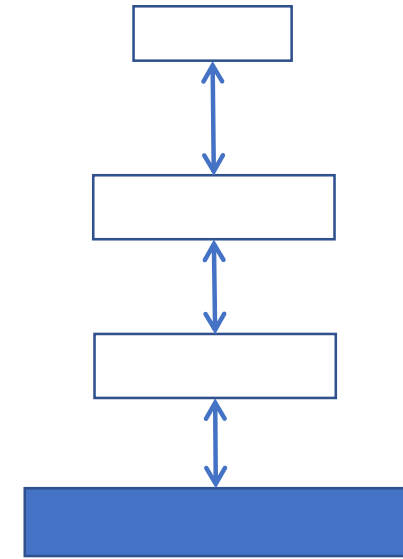
# Layer-wise training



**Restricted Boltzmann Machine**  
(~1994, 2001)



**Deep Belief Net**  
(2006)



**Deep Boltzmann Machine**  
(2009)

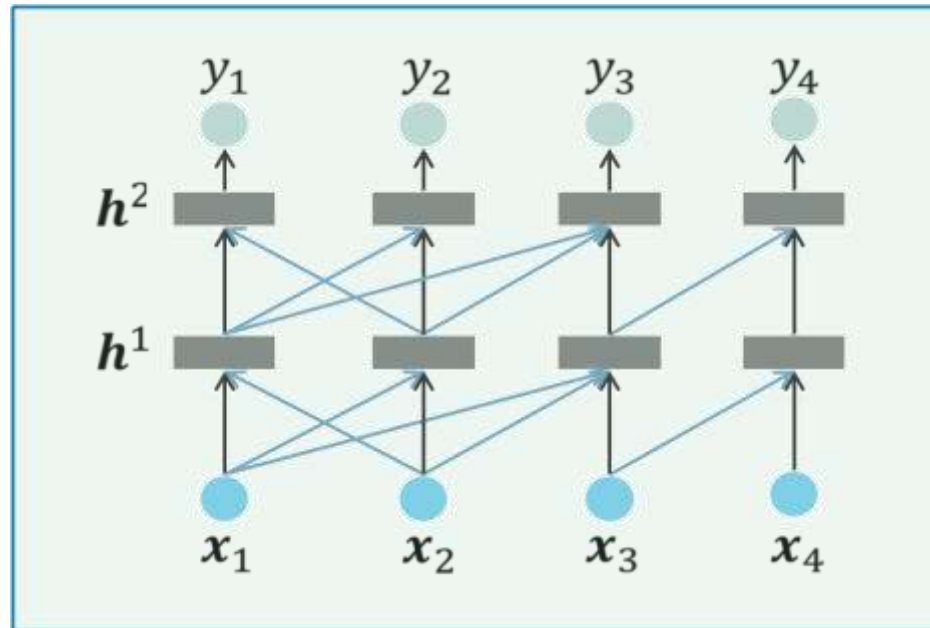
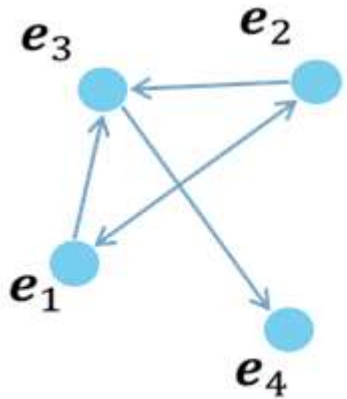
**Spoil alert:** Stack of RBMs is akin to **renormalization** trick in physics



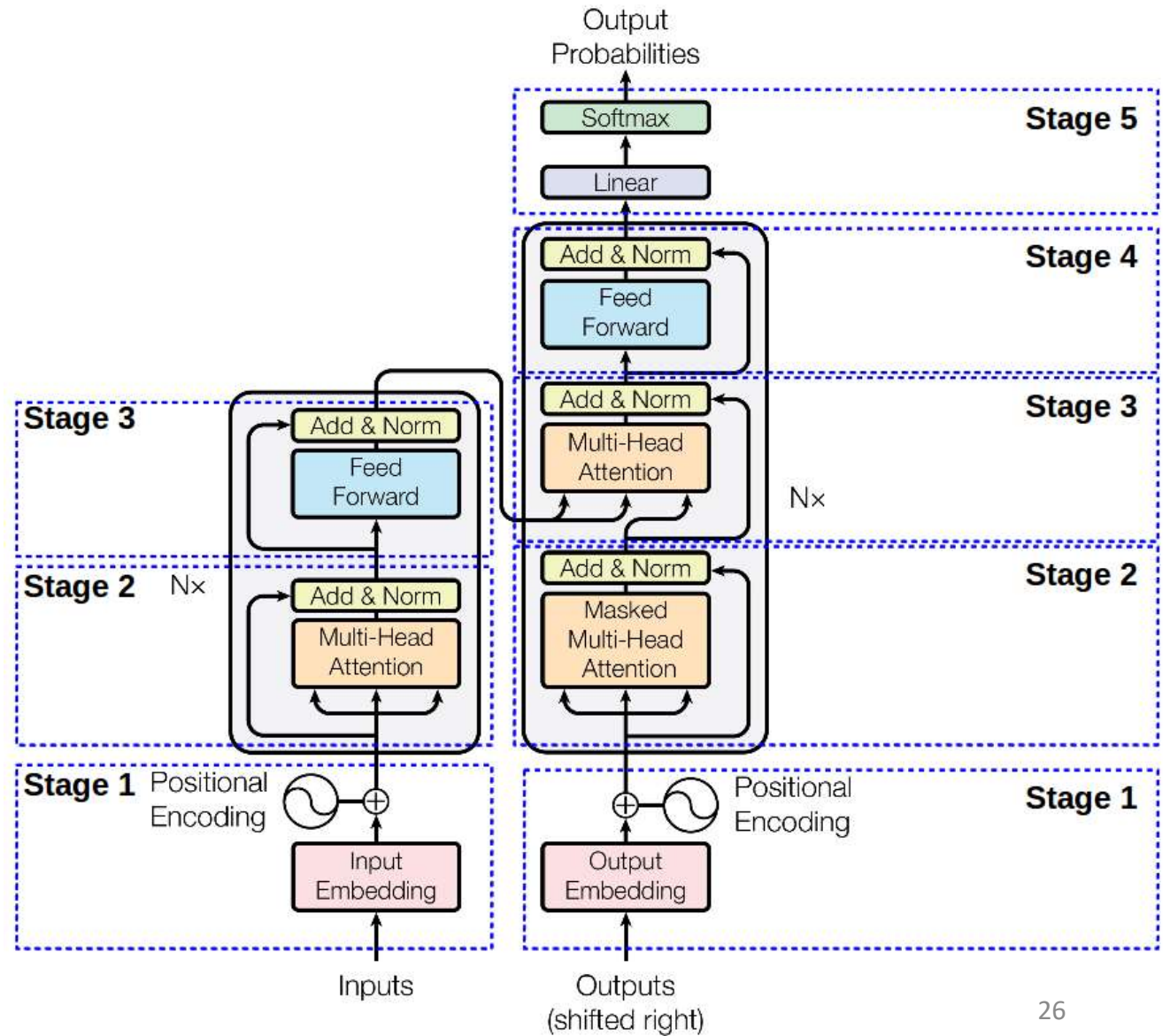
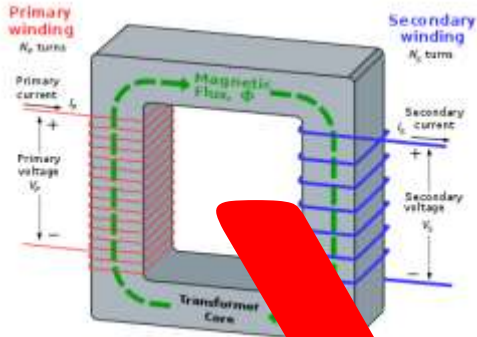
# Modelling the world with neural networks

Column Networks inspired from columnar structure of brain

Relation graph

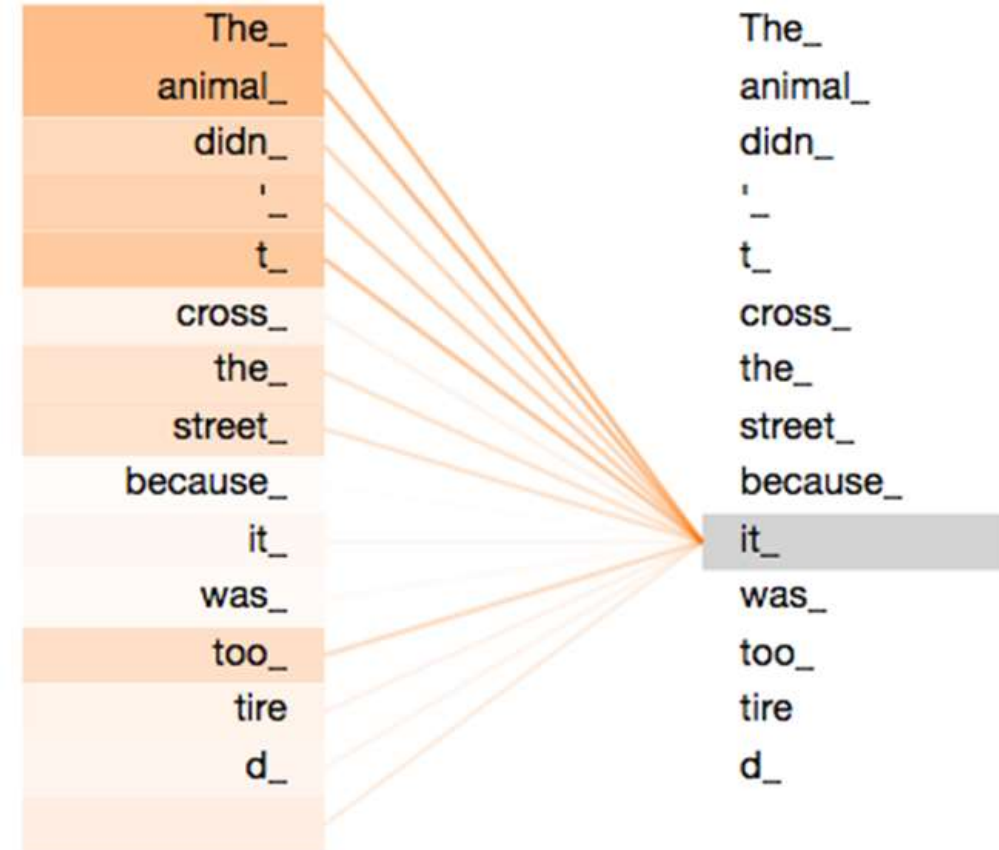


# Workhorse of modern AI: Transformer

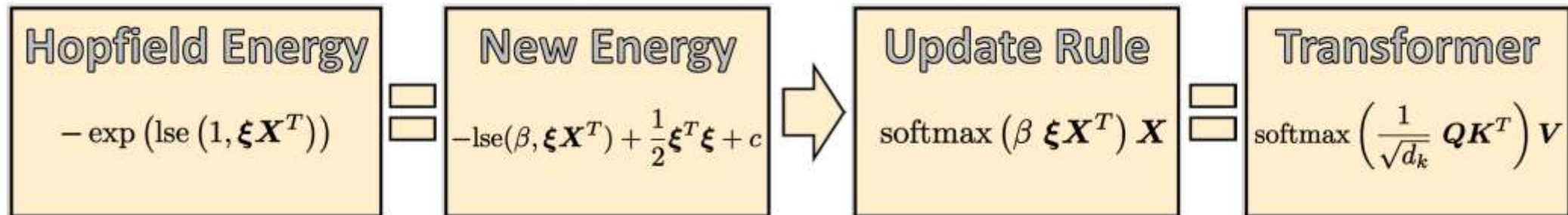
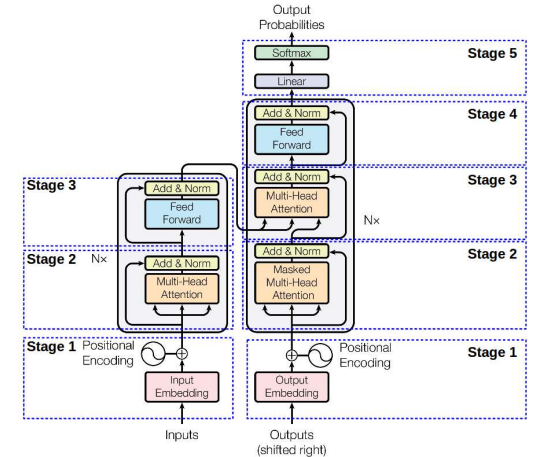
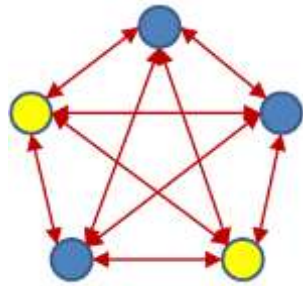


# Transformer: Key ideas

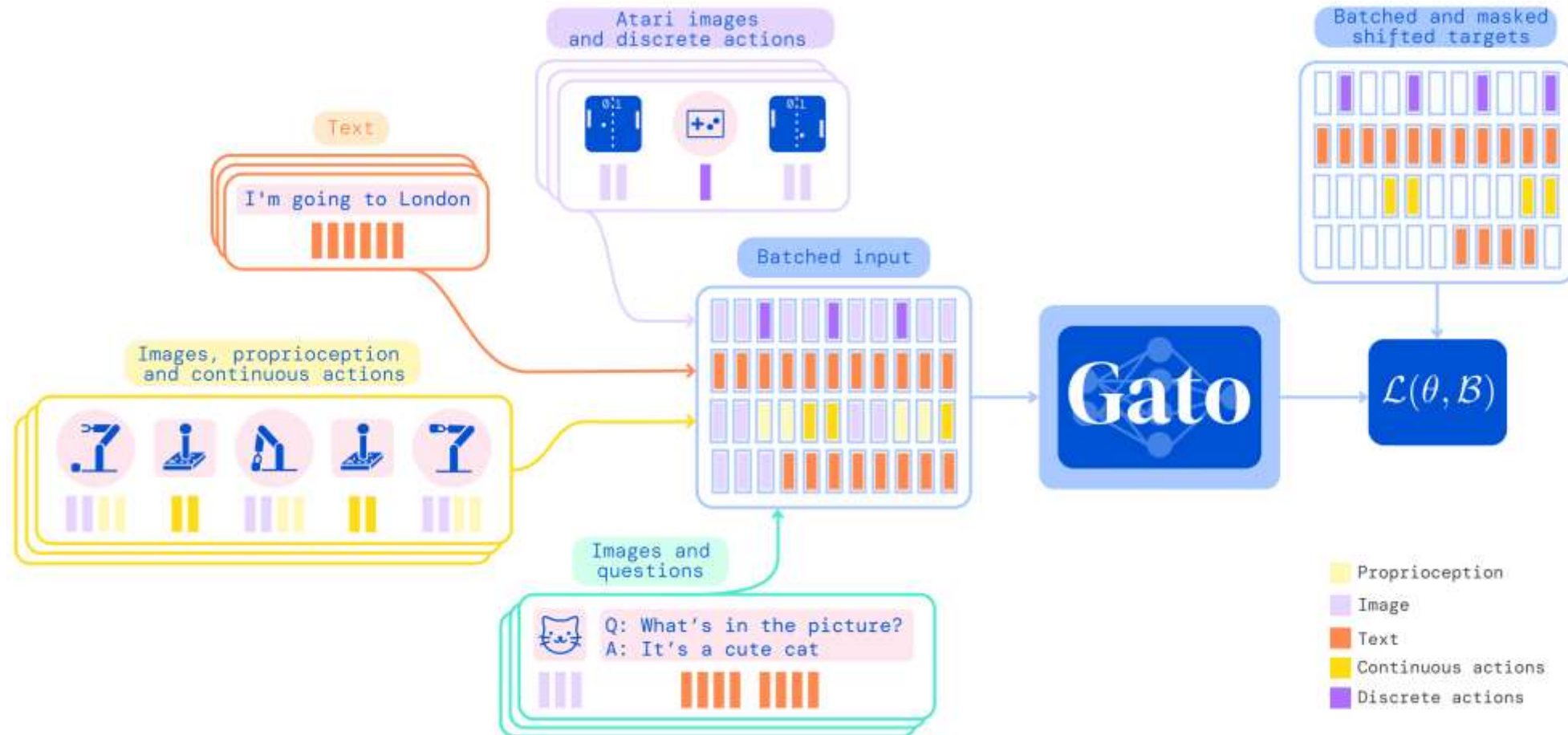
- >A special case of Graph Neural Networks
- >Everything is a set of tokens (e.g., words)
- >Tokens are “embedded” into a high-dim vector (a set of neurons)
- >Tokens in the same context are jointly considered
- >Token embedding is “shaped” by their relationship with other tokens.



# Transformers are Hopfield nets!



# Convergence: One-model-for-all – the case of Gato (2022)



# Why **one-model-for-all** possible?

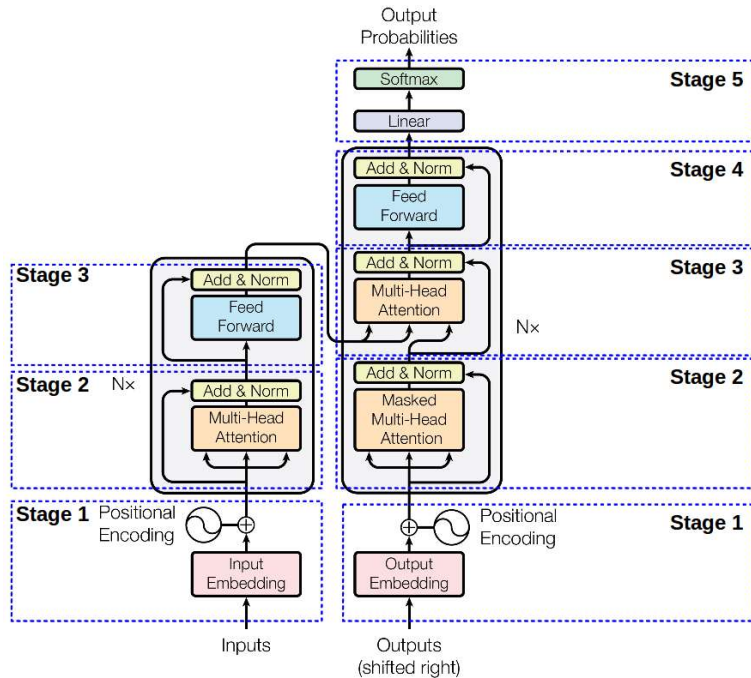
The world is regular: Rules, patterns, motifs, grammars, recurrence

- World models are learnable from data!

Human brain gives an example

- One brain processes all modalities, doing plenty of tasks, and learning from different kind of training signals.
- Thinking at high level is independent of input modalities and task-specific skills.

# Deep neural networks | Electronics



Neuron → **SENSOR, FILTER**

Gate → **AND gate, Transistor, Resistor**

Attention mechanism → **SWITCH gate**

Memory + forgetting → **Capacitor + leakage**

Skip-connection → **Short circuit**

Computational graph → **Circuit**

Compositionality → **Modular design**



The current  
wave:

# Generative AI

(e.g., ChatGPT, Midjourney,  
Sora, Veo)



Gen AIs are  
compression  
engine

Prompting is conditioning  
for the (preference-  
guided) decompression.



Gen AIs are  
approximate  
program database

Prompting is retrieving an  
approximate program that  
takes input and delivers  
output.



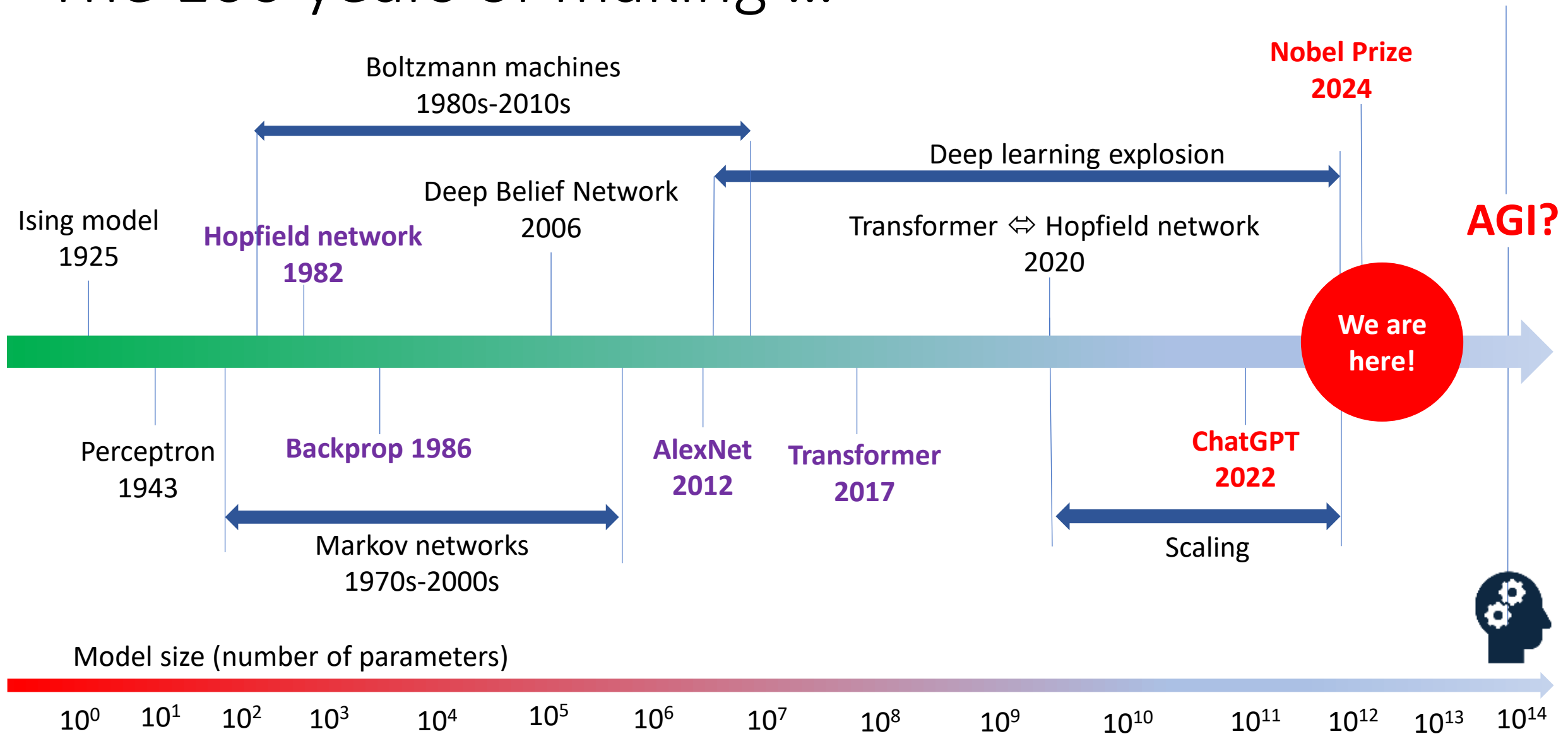
Gen AIs are  
World Model

We can live entirely in  
simulation!



# The 100 years of making ...

AGI = Artificial General Intelligence





# Recognition of the 2024 Nobel Prize in Physics

4/03/2025

The interdisciplinary nature of modern physics, crossing with:

- Computation & information theory
- Cognition.

Concepts foundational to AI stem from physics

- Reshaping the discipline's boundaries.
- Foundational work => practical AI systems.

Innovation: AI has pervasive societal impact.

# Looking into the future



Giorgio Parisi, 2021 Nobel in Physics for complex systems

**AI as a discovery tool:** e.g., quantum mechanics, materials science, and complex systems.

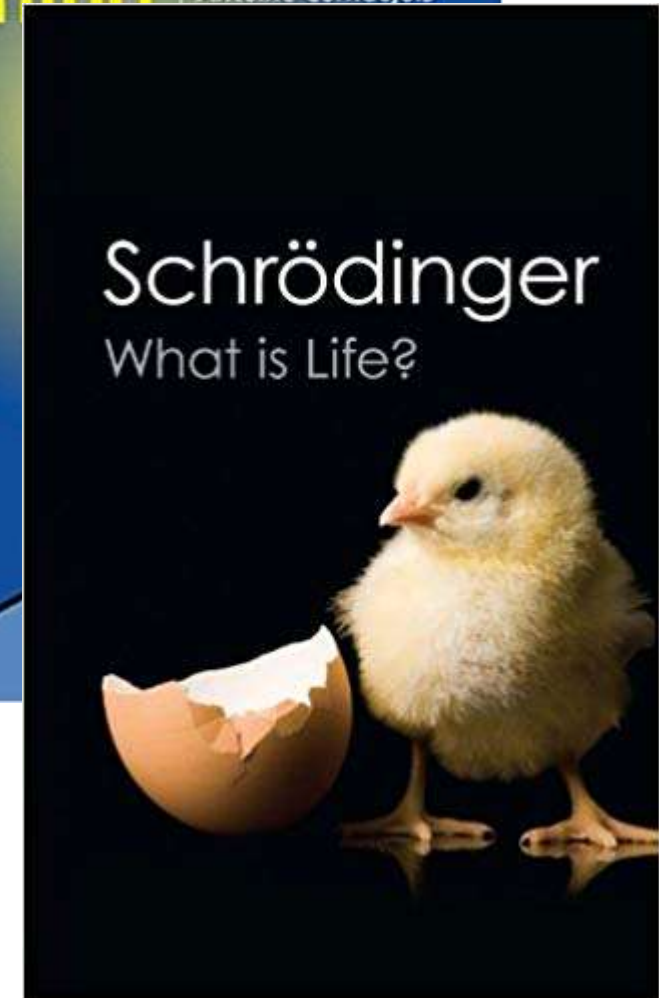
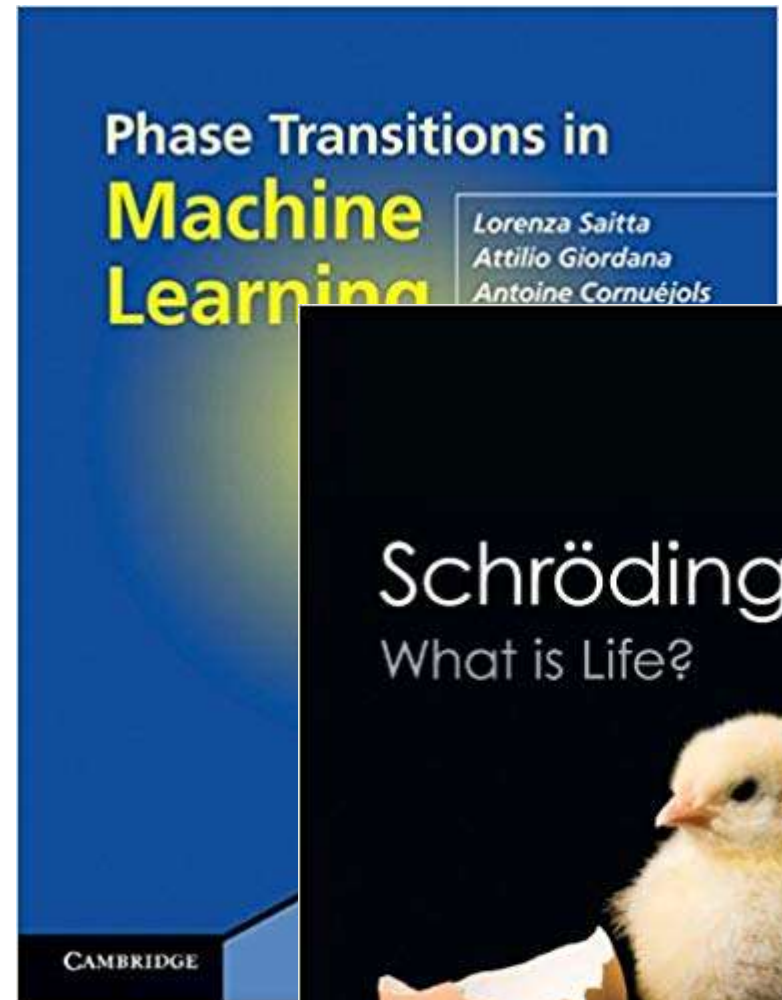
**Interdisciplinary:** Physics + AI + cognitive sciences for study of universe and human cognition.

**Philosophical implications:** Informational fabric => the nature of consciousness, intelligence, and the universe's computational structure.

**Future-ready scientists:** Technology + science.

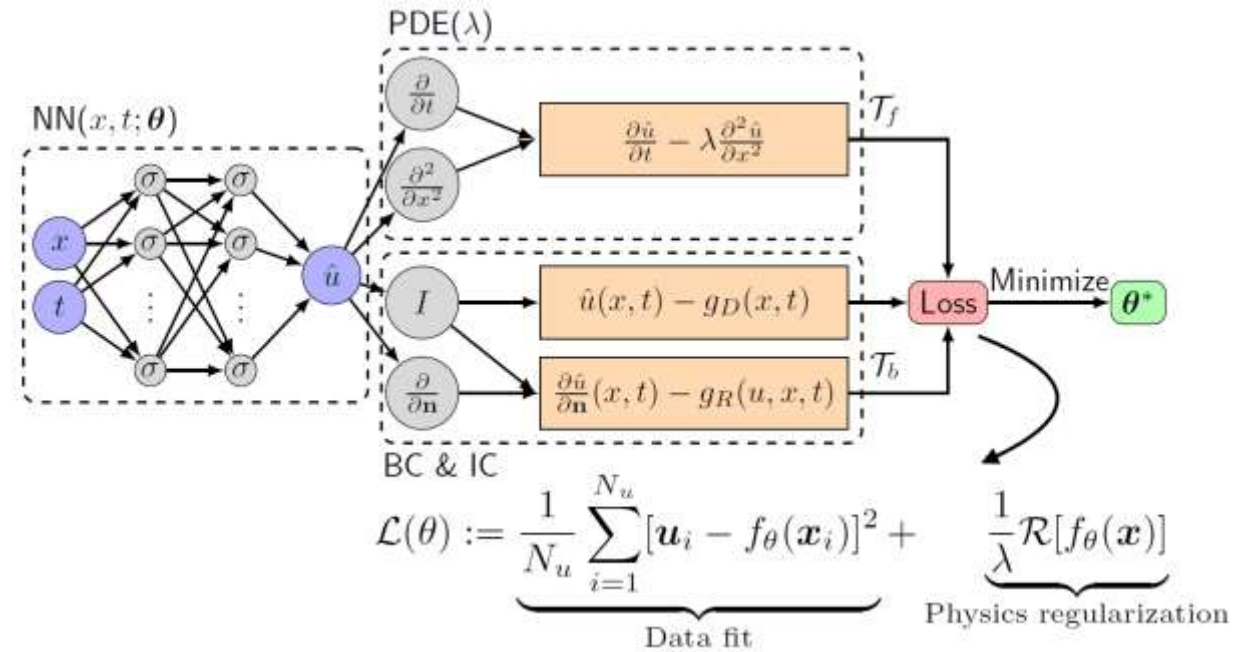
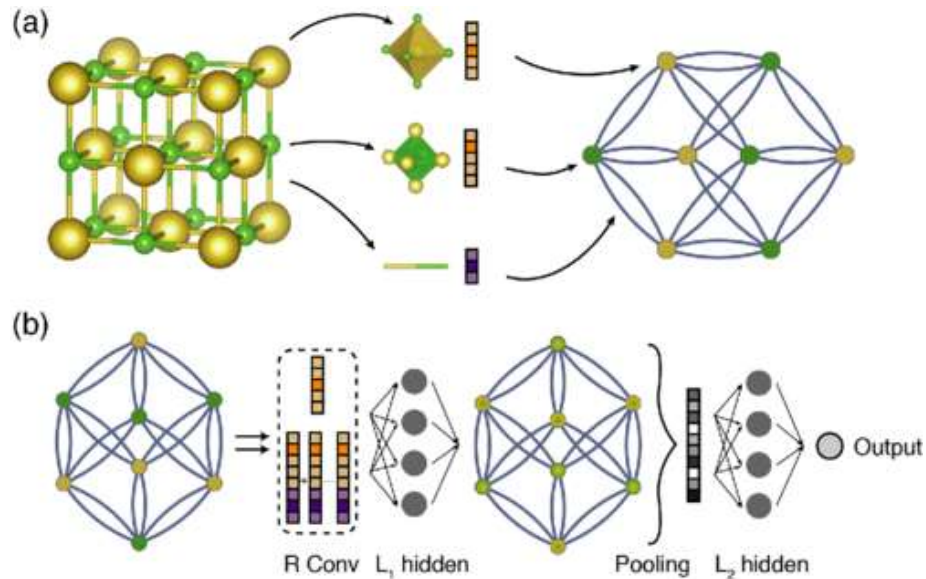
# AI as physics

- > Intelligence as self-organizing phenomena: reducing ignorance/entropy
- > Neural networks as a statistical mechanical system
- > Learning as variational optimization
- > Reasoning free-energy minimization
- > Phase transition may occur in AI systems
- > Ultimate AI must solve the **consciousness problem**, which may require new physics.



# AI for Physics

## Physics-informed AI



Xie, Tian, and Jeffrey C. Grossman. "Crystal Graph Convolutional Neural Networks for an Accurate and Interpretable Prediction of Material Properties." *Physical review letters* 120.14 (2018): 145301.

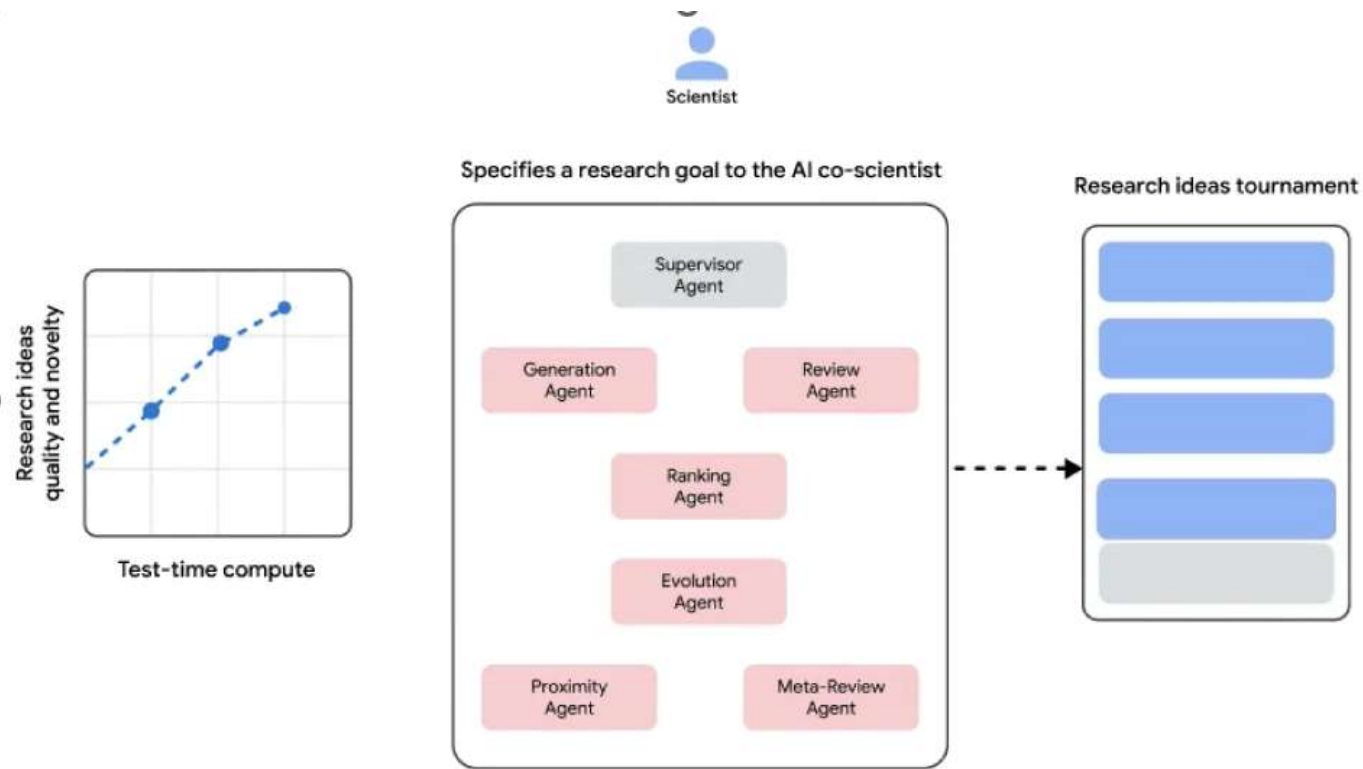


AI for automating **chemistry**



AI to accelerate **medicinal discovery**

# AI Co-Scientist, Google DeepMind







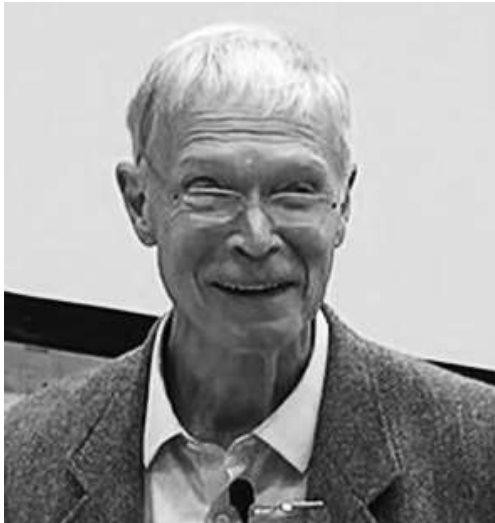
# Why is AI scientist possible?

The world is regular: Rules, patterns, motifs, grammars, recurrence

> World models are learnable from data (real or simulated)!

> "Any pattern that can be generated or found in nature can be efficiently discovered or modelled by a classical learning algorithm".

*(Demis Hassabis, World Chess Championship, CEO of Google DeepMind, Nobel Laureate in Chemistry, 2024)*



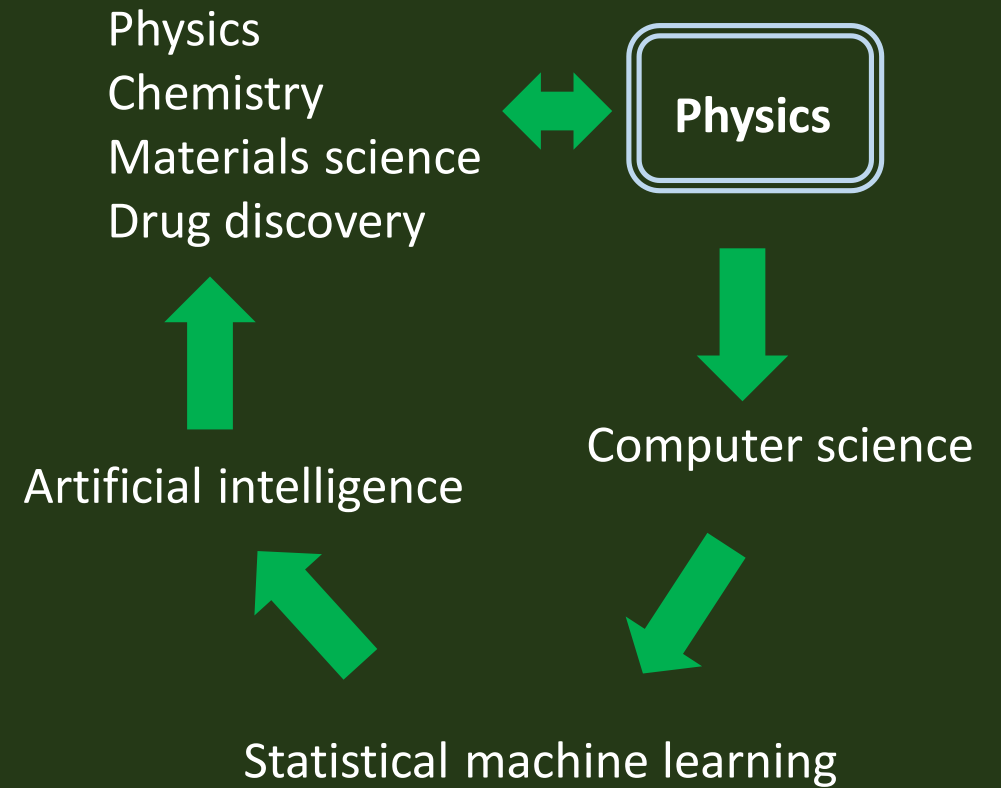
“Physics is a point of view that the world around us is, with effort, ingenuity, and adequate resources, understandable in a predictive and reasonably quantitative fashion.”

(John Hopfield)

# My full-loop journey from physics to AI and back



*Me and my teammates representing Vietnam at the International Physics Olympiad 1997, Canada.*





Crossing the boundaries can take us really far.



*A church in my home village in Vietnam in style of Buddhist temple*

Fusing traditions can be very beautiful