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

## Physical Principles in Intelligence: The 2024 Nobel Prize in Physics

John Hopfield
Born: 1933, USA

Geoffrey E. Hinton
Born: 1947, UK

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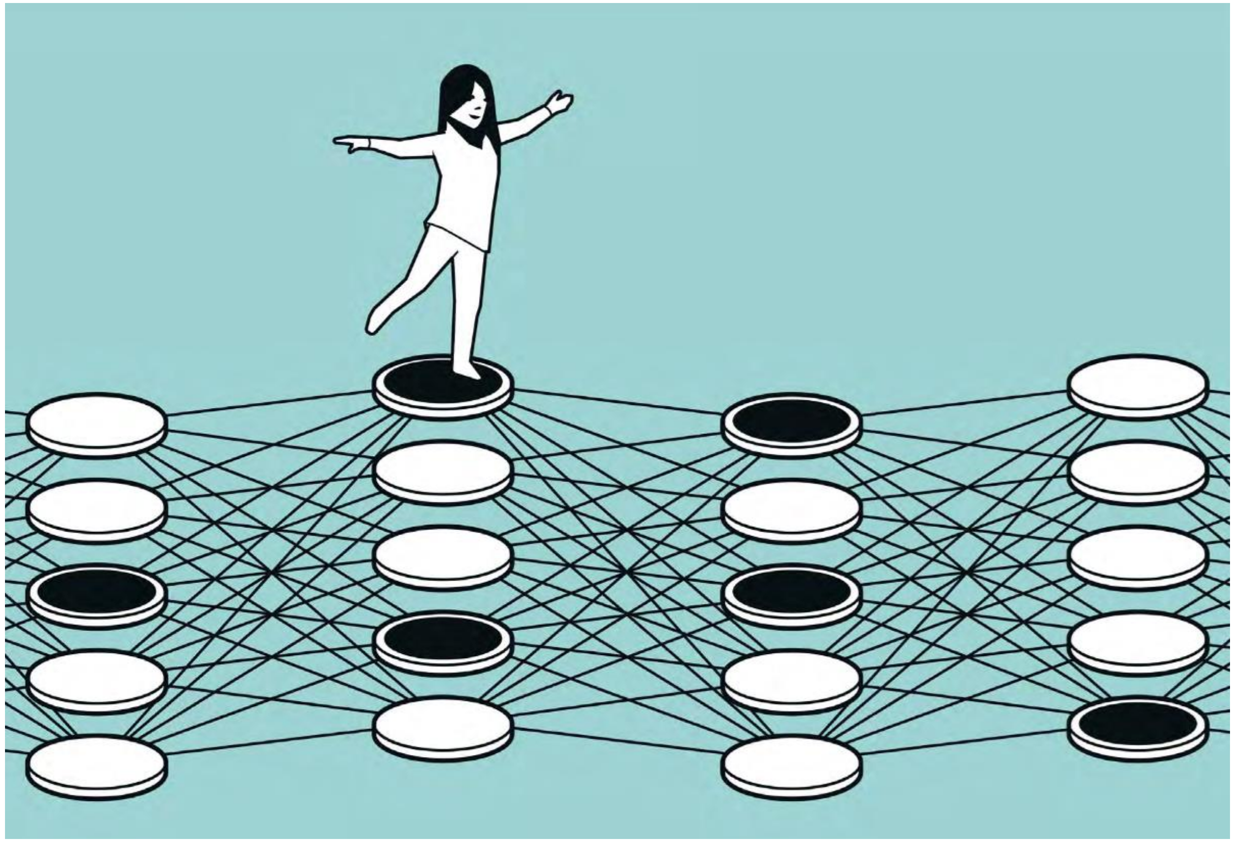
11/20/2024



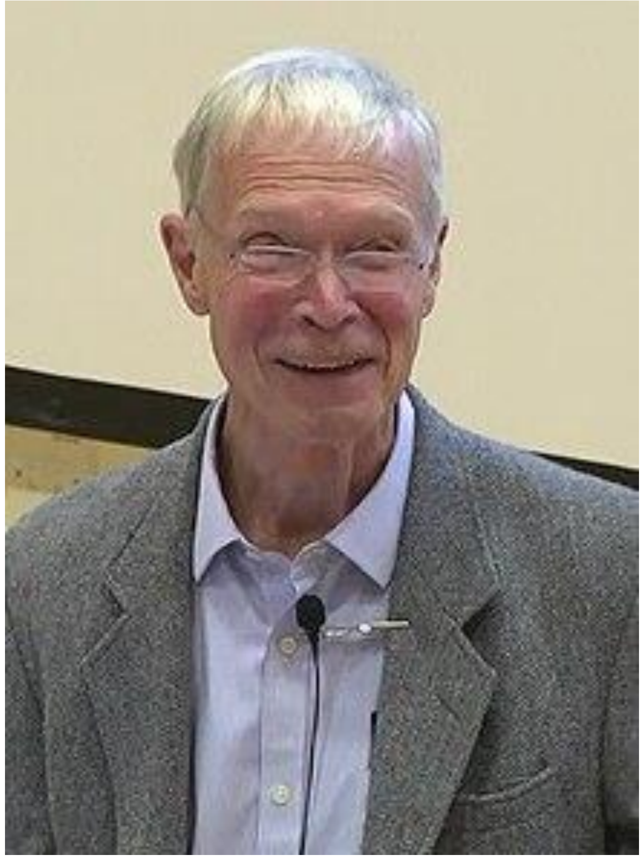
“The Nobel Prize in Physics 2024 recognizes methods that lay the foundation for the development of artificial intelligence.”



Source: nobelprize.org

# John Hopfield

- Condensed matter physics
- Statistical physics
- Biophysics
- Molecular biology
- Complex systems
- Neuroscience



John Hopfield
(born 1933)

Terry Sejnowski
(born 1947)

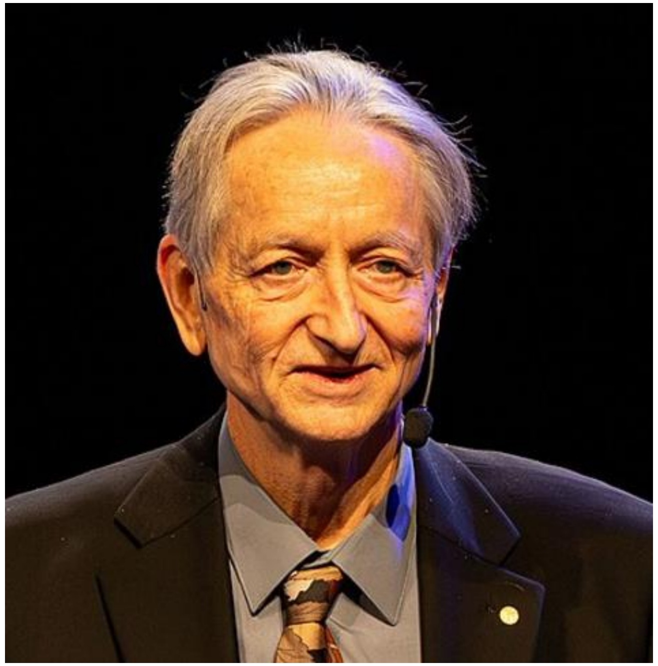
David MacKay
(1967-2016)



Credits: Wikipedia, Zdnet

# Geoffrey Everest Hinton

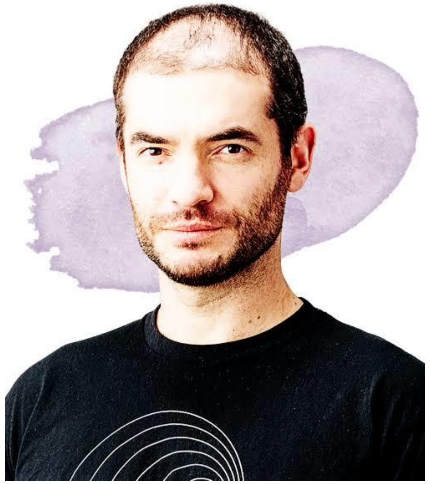
- Psychology
- Cognitive science
- Artificial intelligence
- Ethics



Hinton (born 1933)

Ghahramani (born 1970)

LeCun (born 1960)



Sutskever (born 1986)

Welling (born 1968)

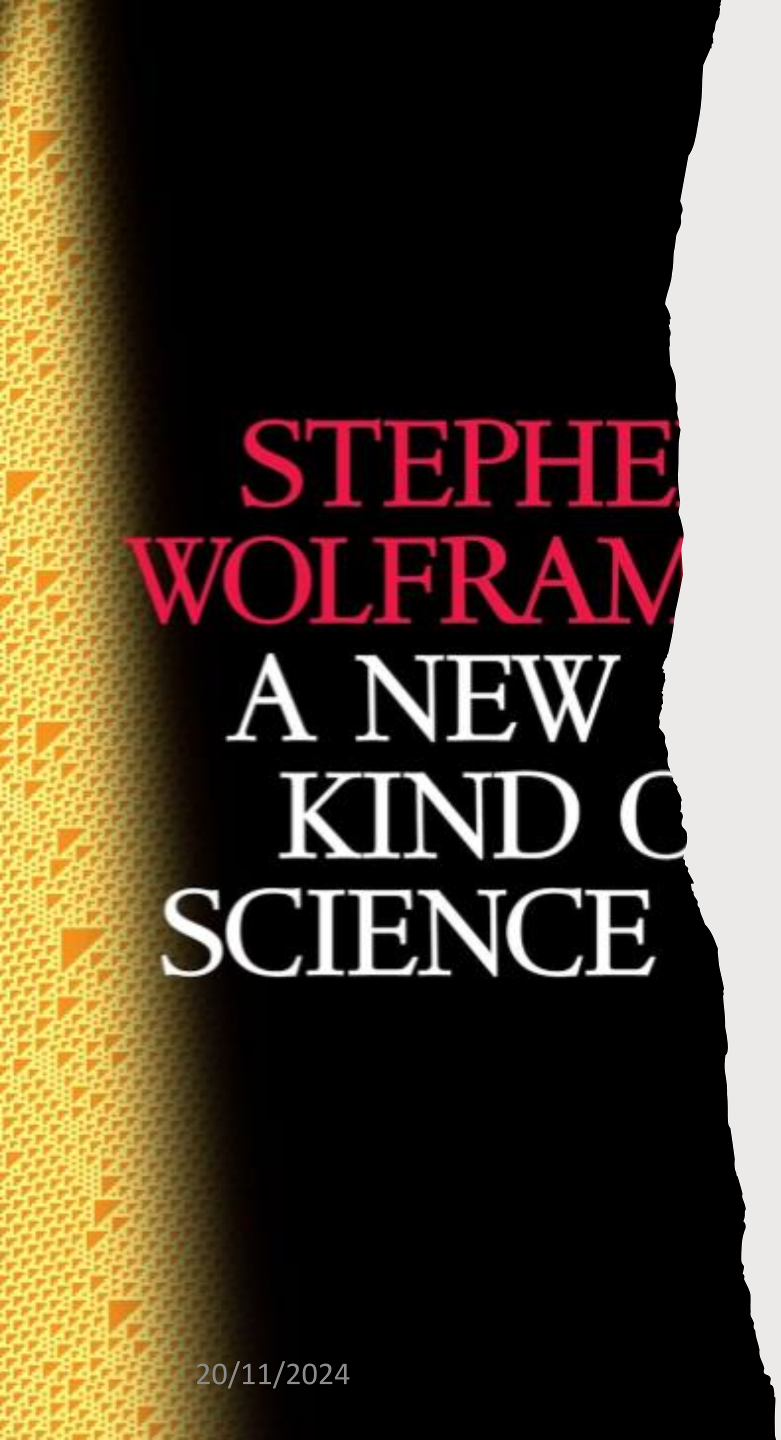


Credits: Wikipedia

# Agenda

- The context
- Hopfield networks
- Boltzmann machines
- Deep learning
- Discussion

*ChatGPT: Generate a picture of the universe and the mind*



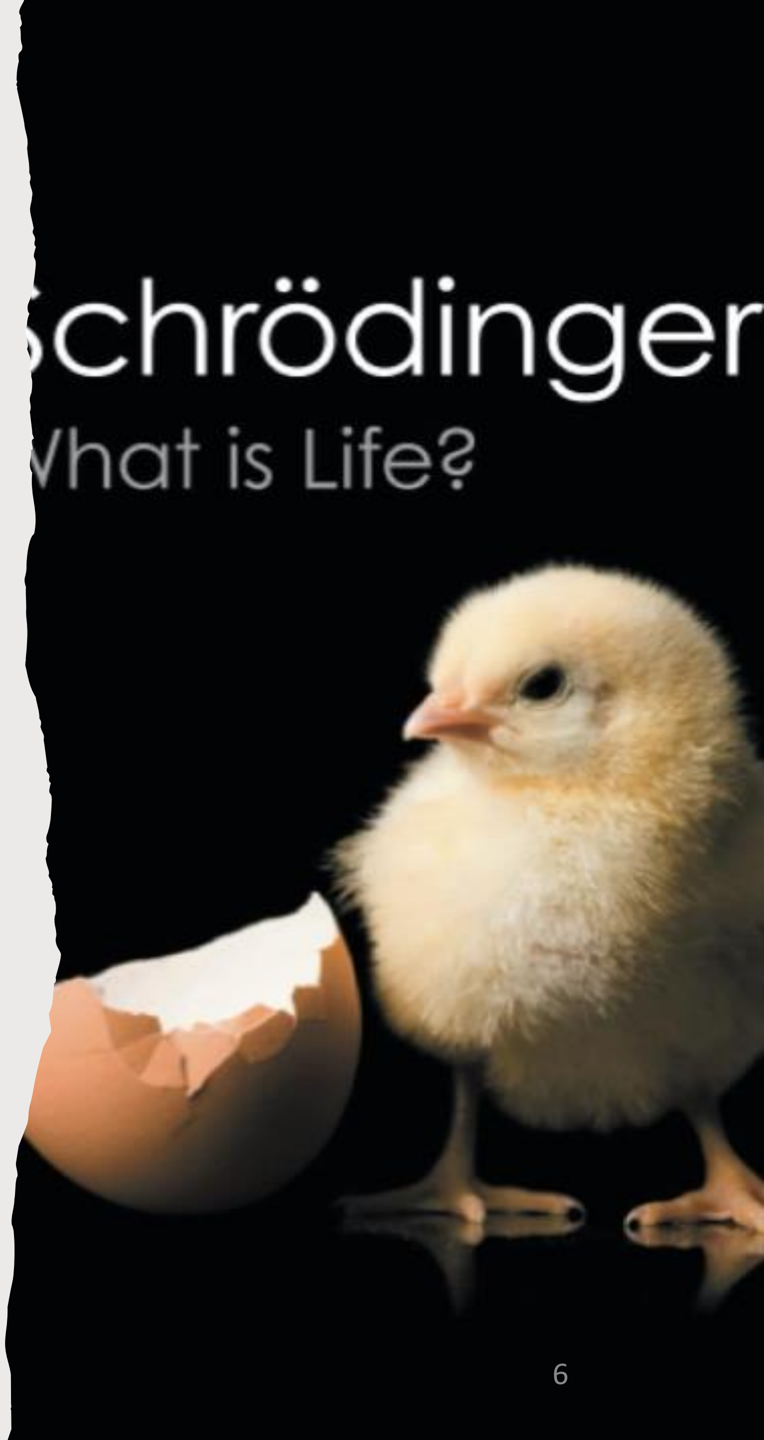

# Physics, life, mind and computation

Great topics studied for thousands of years

- Addressed by many traditions (Taoism, Buddhism, Hinduism, etc)
- Asked by philosophers, physicists, computer scientists, etc.

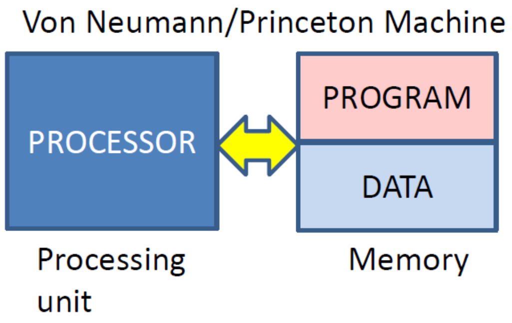
Only recently connections have been made

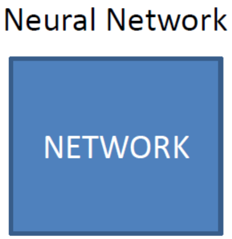
- What is life?
- Is the universe a computer?
- Is mind computation?
- ….

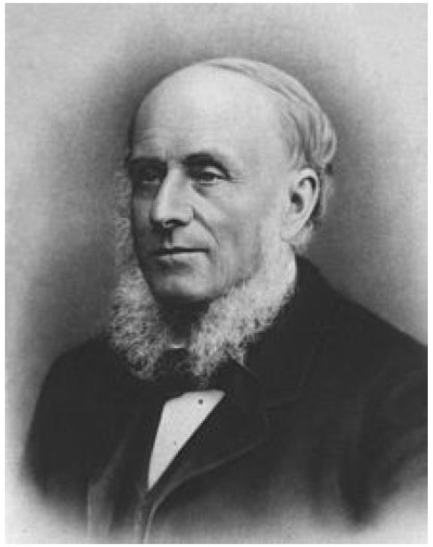


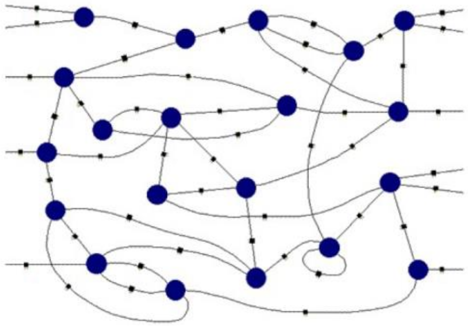
# Early models of human cognition

- **Associationism**: Humans learn through association
- 400BC-1900AD: Plato, John Locke, David Hume, David Hartley, James Mill, John Stuart Mill, Alexander Bain, Ivan Pavlov.



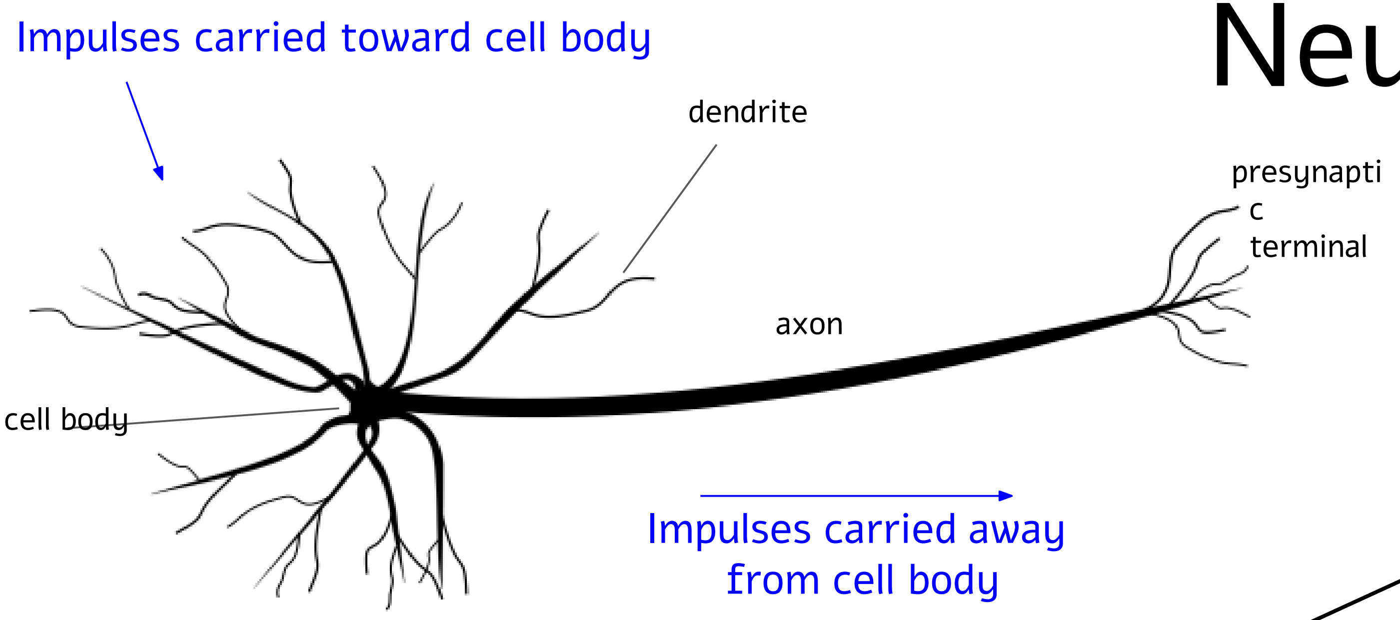





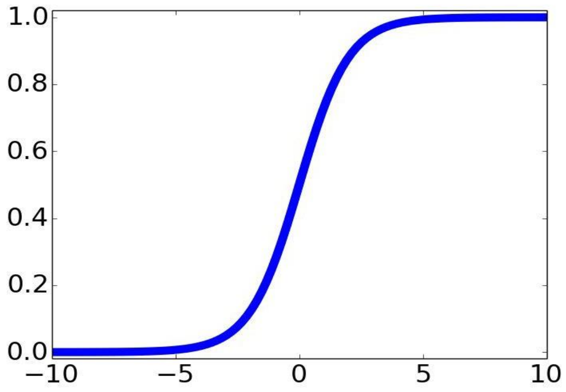
# Connectionism

- Mid 1800s: The brain is a mass of interconnected neurons
- Alexander Bain, philosopher, psychologist, mathematician, logician, linguist, professor
  - 1873: The information is in the connections – *Mind and body.*
- Connectionist machines
  - Network of processing elements
  - All world knowledge is stored in the connections between the elements
- **Neural networks** are connectionist machines
  - As opposed to Von Neumann Machines

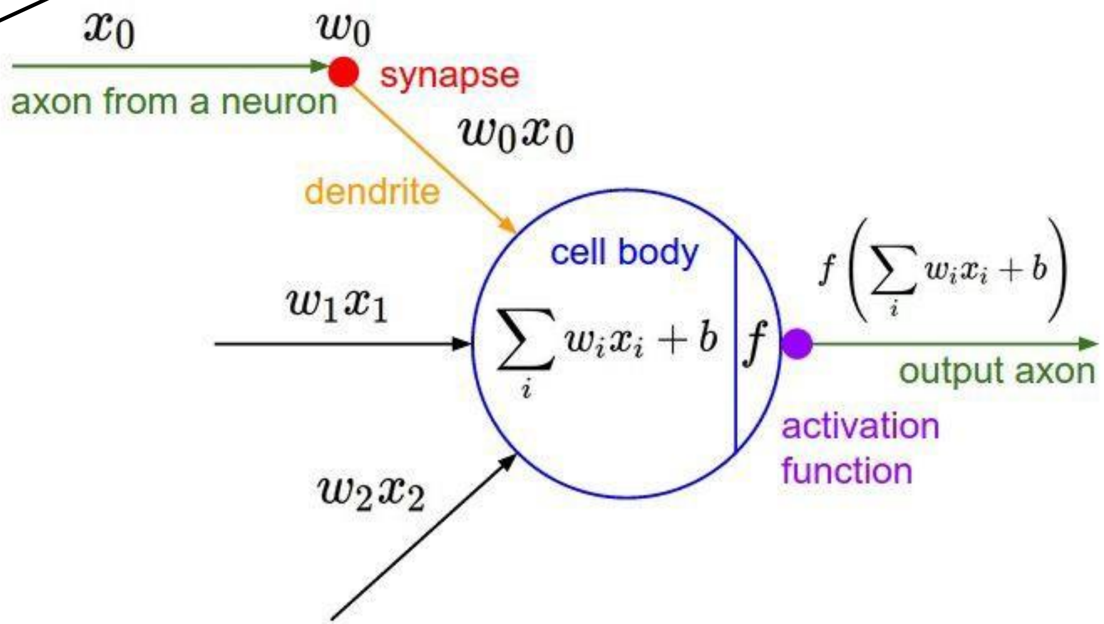
# Neurons *in silico*






sigmoid activation function $\frac{1}{1+e^{-x}}$





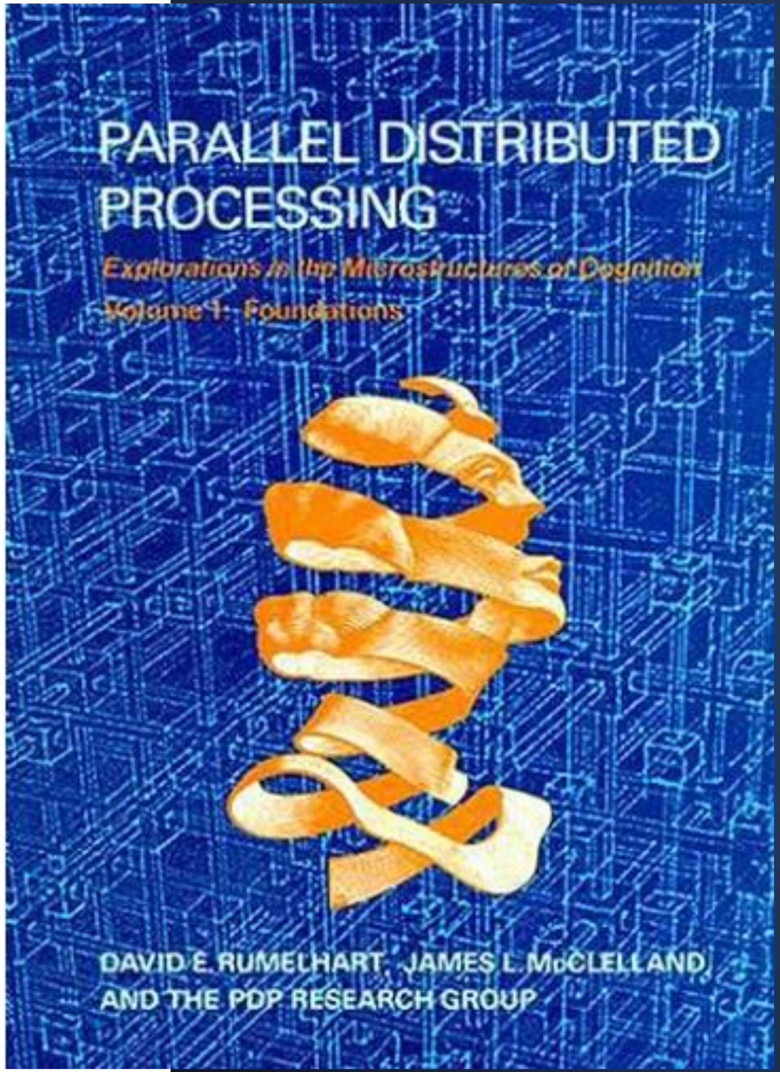

Credits: Fei-Fei Li, Ranjay Krishna, Danfei Xu

# Neural networks as model of mind

- How does the mind work?
  - Perceiving
  - Remembering
  - Learning
  - Reasoning, planning
  - Doing
- Parallel Distributed Processing (1986)
- 1990s: Mind as recurrent neural network

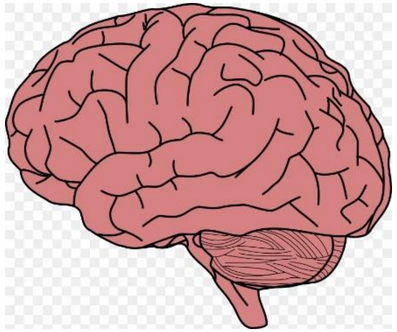
# 1980s: Parallel Distributed Processing

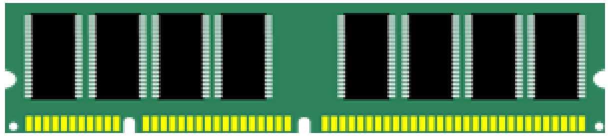
- Information is stored in many places (distributed)
  - Each concept is represented by many neurons
  - Each neuron plays role in many concepts
- Activations are sparse (enabling selectivity and invariance)
- Popular these days: Embedding of everything into the vector space



# Memory is essential to intelligence

- Memory is the ability to store, retain and recall information
- Brain memory stores items, events and high-level structures
- Computer memory stores data and temporary variables





# Associative memory is powerful

| Language | Time | Object | Behaviour |
|---|---|---|---|
| "Green" means "go," but what does "red" mean? | birthday party on 30$^{th}$ Jan | Where is my pen? What is the password? |  |
| Semantic memory | Episodic memory | Working memory | Motor memory |

# ~~Four~~Five things in AI

- Representation
- Inference
- Learning
- Stochasticity
- Scale with compute

# Agenda

- The context
- **Hopfield networks**
- Boltzmann machines
- Deep learning
- Discussion

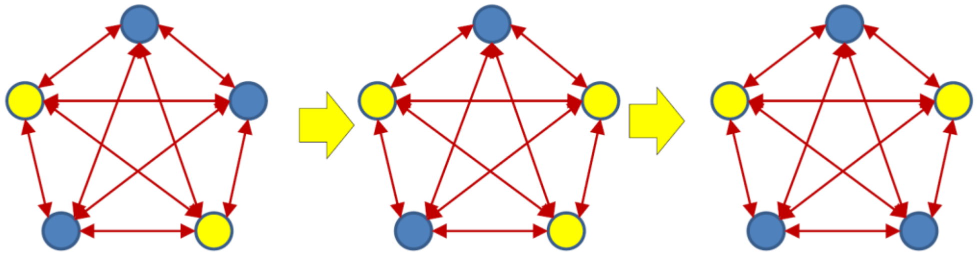
# Questions

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..

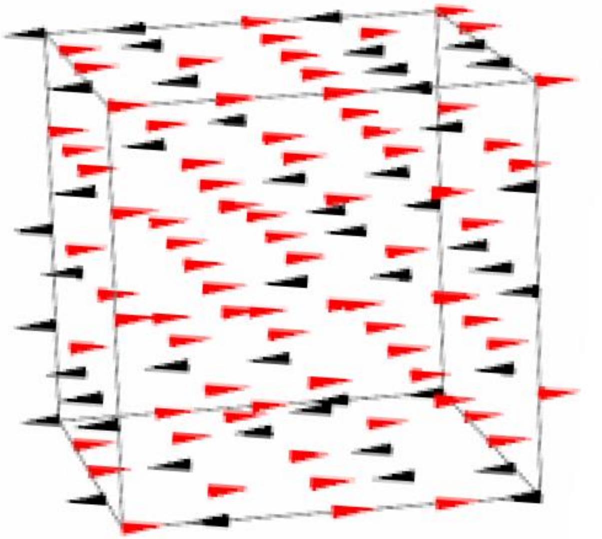
# Hopfield network



- Symmetric weights
- No self-connection
- Update either asynchronous or synchronous
- Neurons attract or repel each other
- The dynamic is deterministic

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

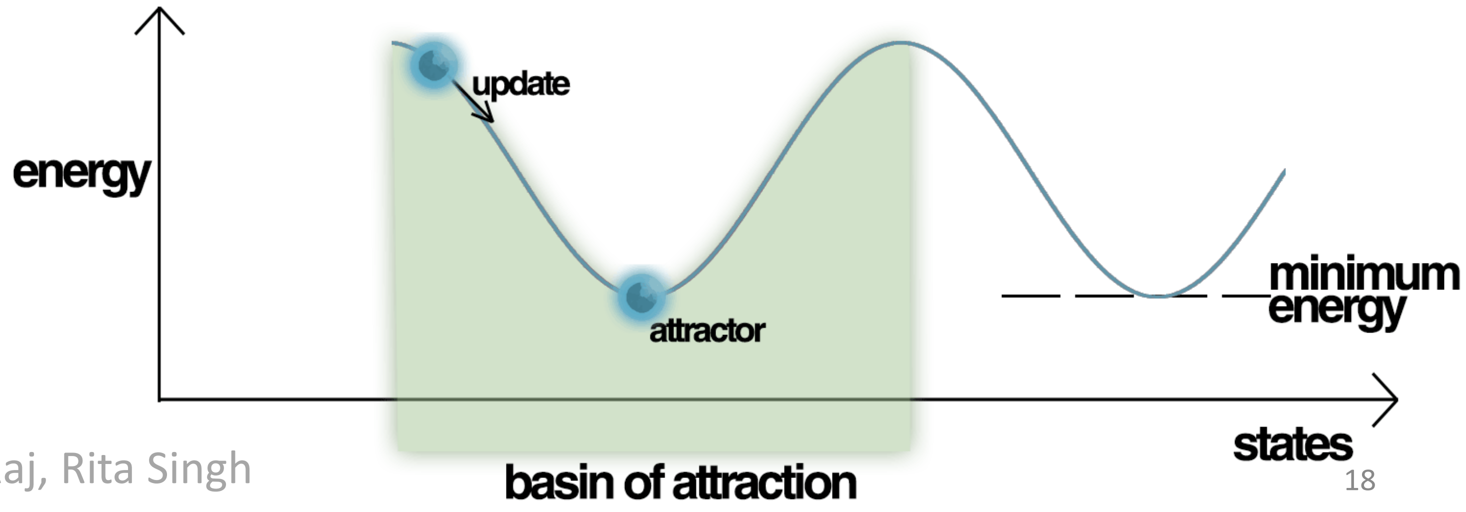
# Update as energy minimization



A spin glass system

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

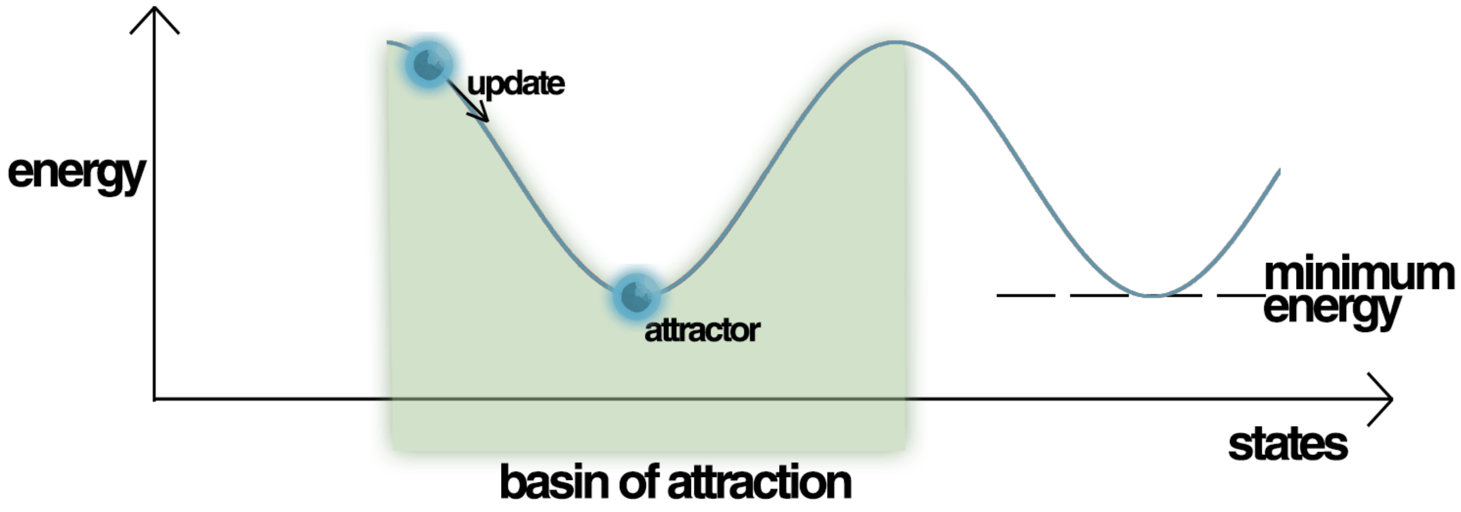
$$E = -\frac{1}{2}\sum_{i,j} w_{ij} s_i s_j - \sum_i \theta_i s_i$$





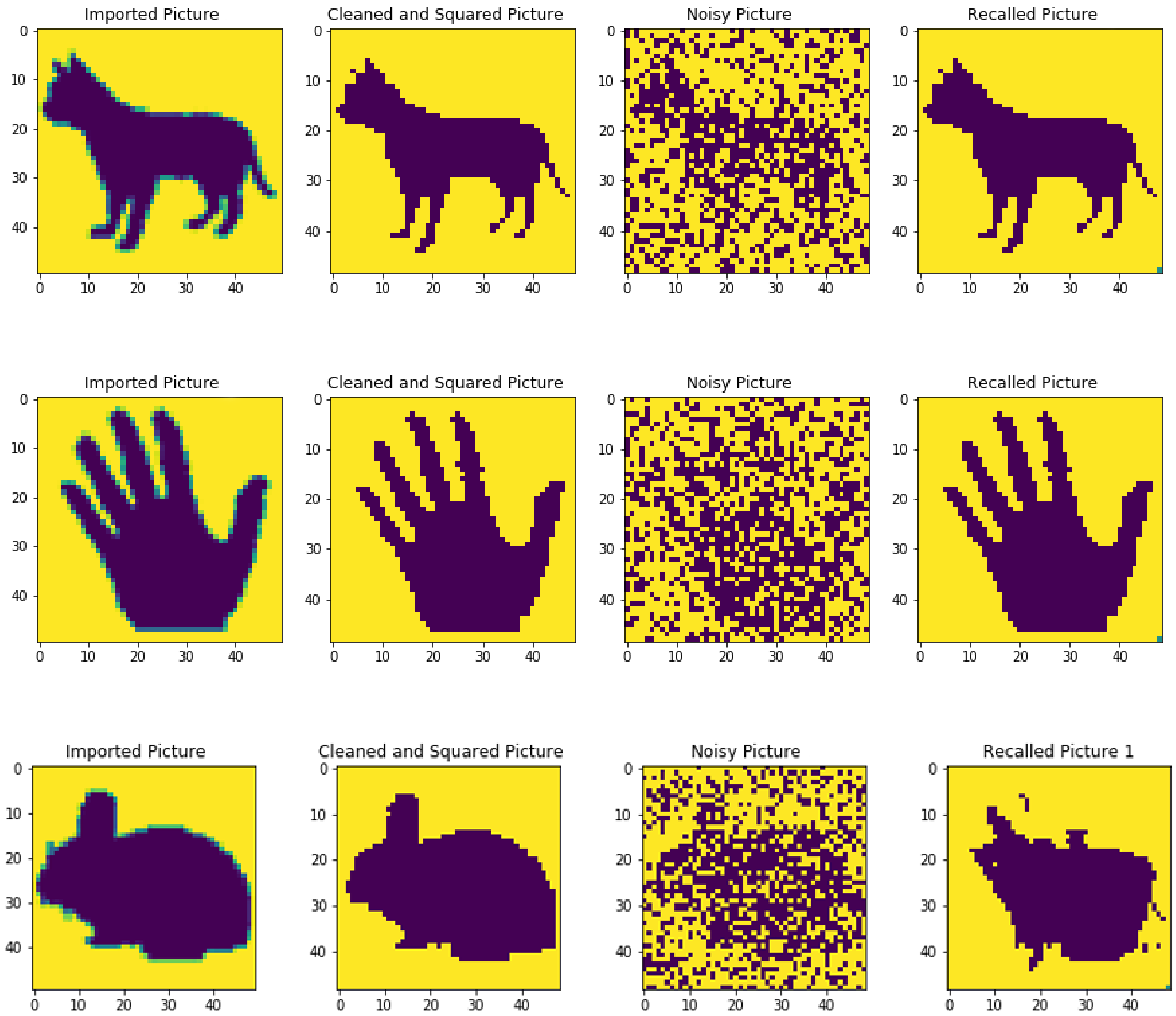

Credits: Wikipedia, Bhiksha Raj, Rita Singh

# Content-addressable memory




- Each of the minima is a "stored" pattern
- => If the network is initialized close to a stored pattern, it will inevitably evolve to the pattern
- **This is a *content addressable memory***
  - Recall memory content from partial or corrupt values
  - Also called ***associative memory***
- ***Indeed, current frontier AI models are!***

# Examples: Image denoising





Credits: Nosrat Mohammadi

# To store one pattern

Hebbian learning rule

$$w_{ji} = y_j y_i$$

"Neurons that fire together, wire together"

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

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

This is the global minimum

$$sign\left(\sum_{j\neq i} w_{ji} y_j\right) = sign\left(\sum_{j\neq i} y_j y_i y_j\right)$$

$$= sign\left(\sum_{j\neq i} y_j^2 y_i\right) = sign(y_i) = y_i$$



Credits: Bhiksha Raj, Rita Singh

# To store multiple patterns

$$w_{ji} = \sum_{\mathbf{y}_p \in \{\mathbf{y}_p\}} y_i^p y_j^p$$

- **Hopfield**: For a network of $N$ neurons can store up to ~0.15$N$ patterns through Hebbian learning
  - Provided they are “far” enough
- **Later**: Guarantees that a network of N bits trained via Hebbian learning can store 0.14N random patterns with less than 0.4% probability that they will be unstable
- A better method: Energy-based methods!
  - Contrastive learning (e.g., CLIP)

# Agenda

THE CONTEXT

HOPFIELD NETWORKS

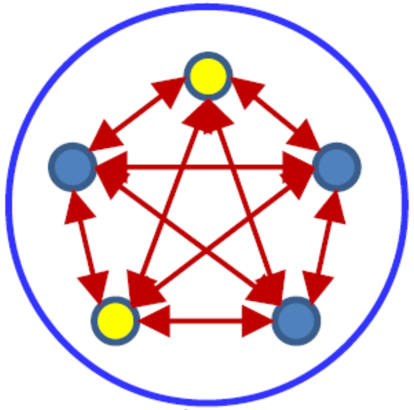
**BOLTZMANN MACHINES**

DEEP LEARNING

DISCUSSION

# 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
- **Observation**: The behavior of the Hopfield net is analogous to annealed dynamics of a spin glass characterized by a Boltzmann distribution
- Linked to MaxEnt principle (Ma Entropy)
    - Everything else equal …



The Helmholtz Free Energy of a System

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

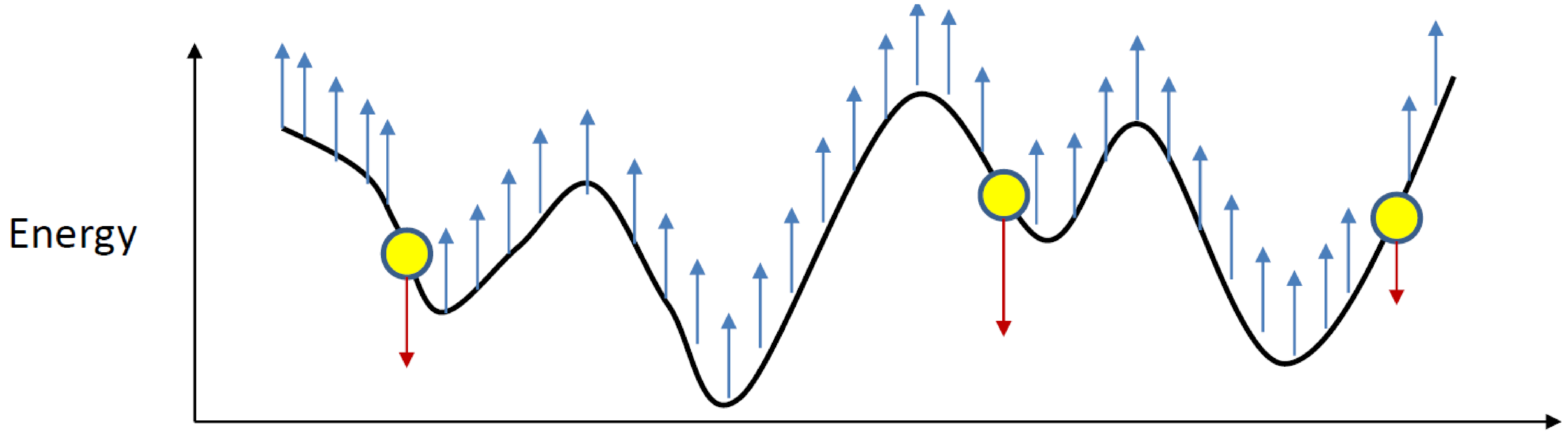
$$P_T(s) = \frac{1}{Z} exp\left(\frac{-E_s}{kT}\right)$$

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

Gibbs distribution


Credits: Wikipedia, Bhiksha Raj, Rita Singh

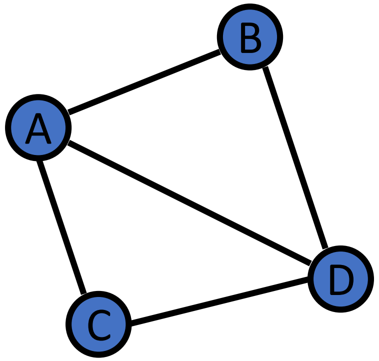
# Training a Boltzmann machine



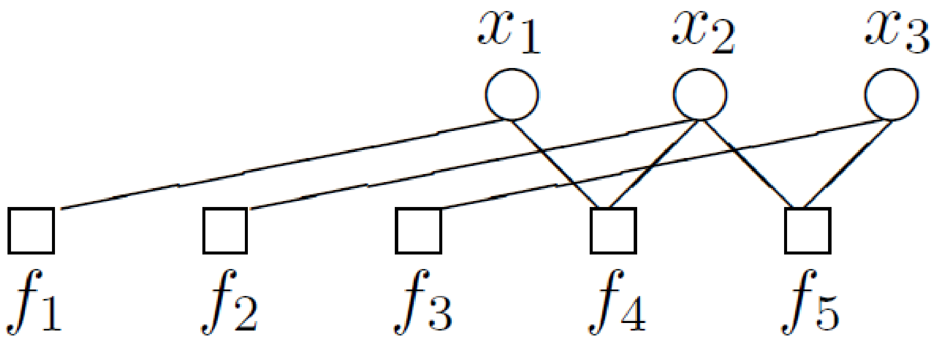

 Credits: Wikipedia, Bhiksha Raj, Rita Singh 

# Generalising Boltzmann machines

Markov network




Factor graph




$$P(x_A, x_B, x_C, x_D) = \frac{1}{Z}\Phi(x_A, x_B, x_D)\Phi(x_A, x_C, x_D)$$

$$Z = \sum_{x_A, x_B, x_C, x_D} \Phi(x_A, x_B, x_D)\Phi(x_A, x_C, x_D)$$

Decoding in Information Theory


Credits: David McKay

# Example: Markov random fields

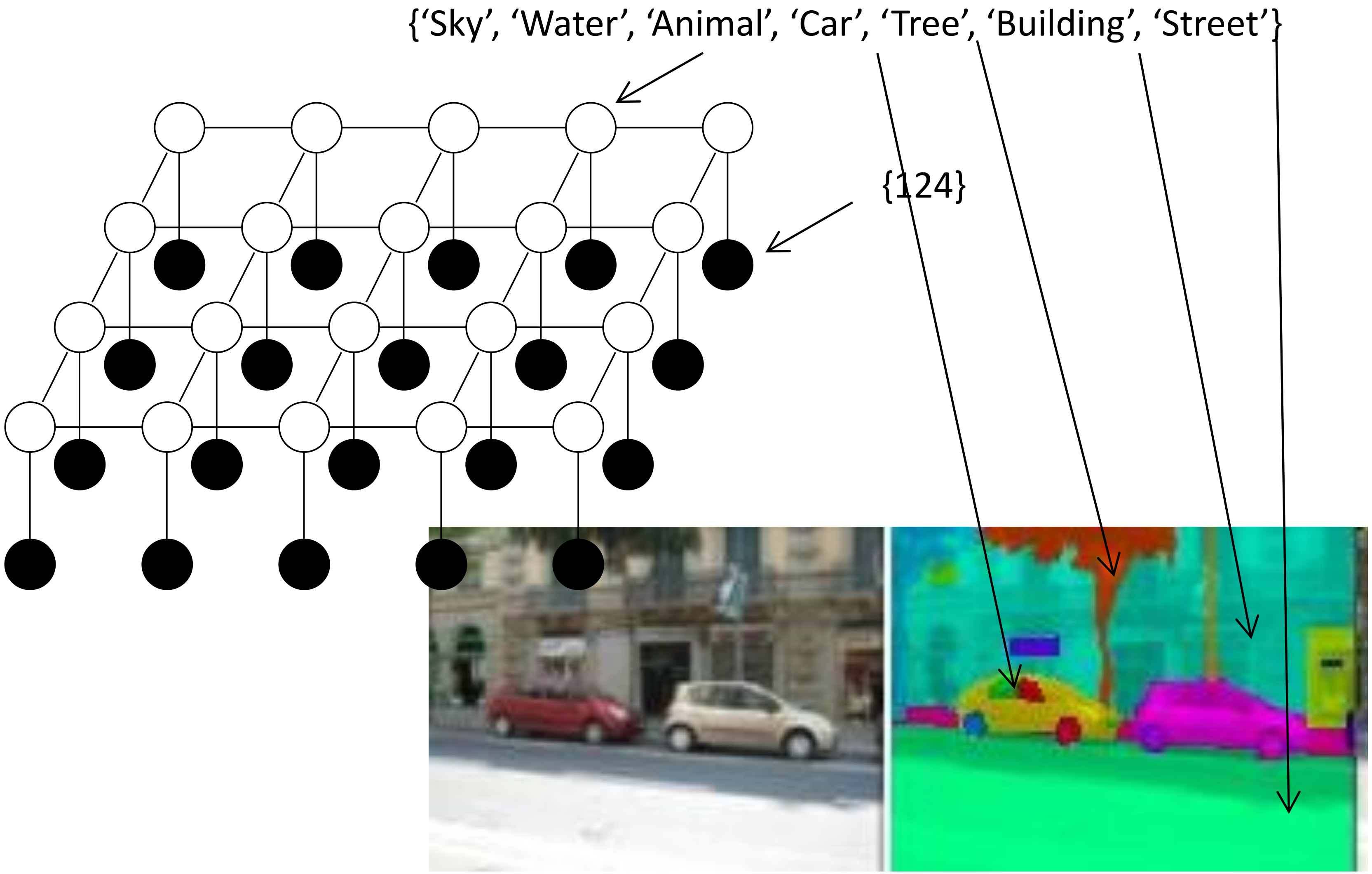



Image from LabelMe

# Inference as Bethe free-energy minimization

- Inference problems
  - →Estimate MAP as energy minimization
  - →Compute marginal probability
  - →Compute expectation & normalisation constant
- Key solution = Belief propagation
  - = Sum-Product algorithm in factor graphs.

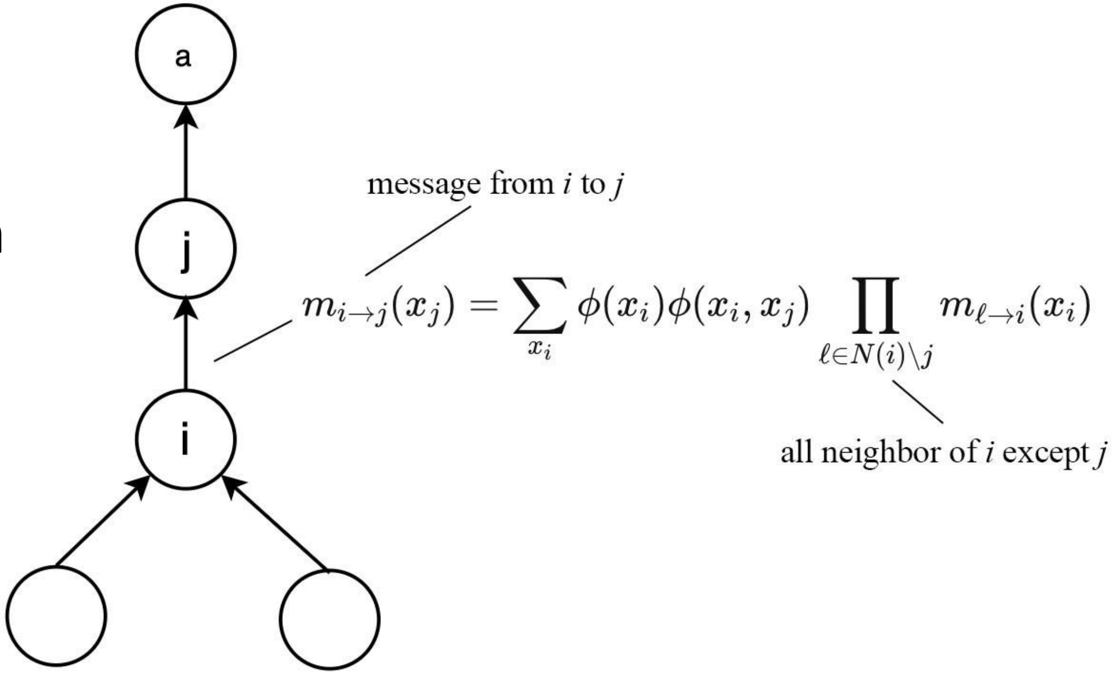
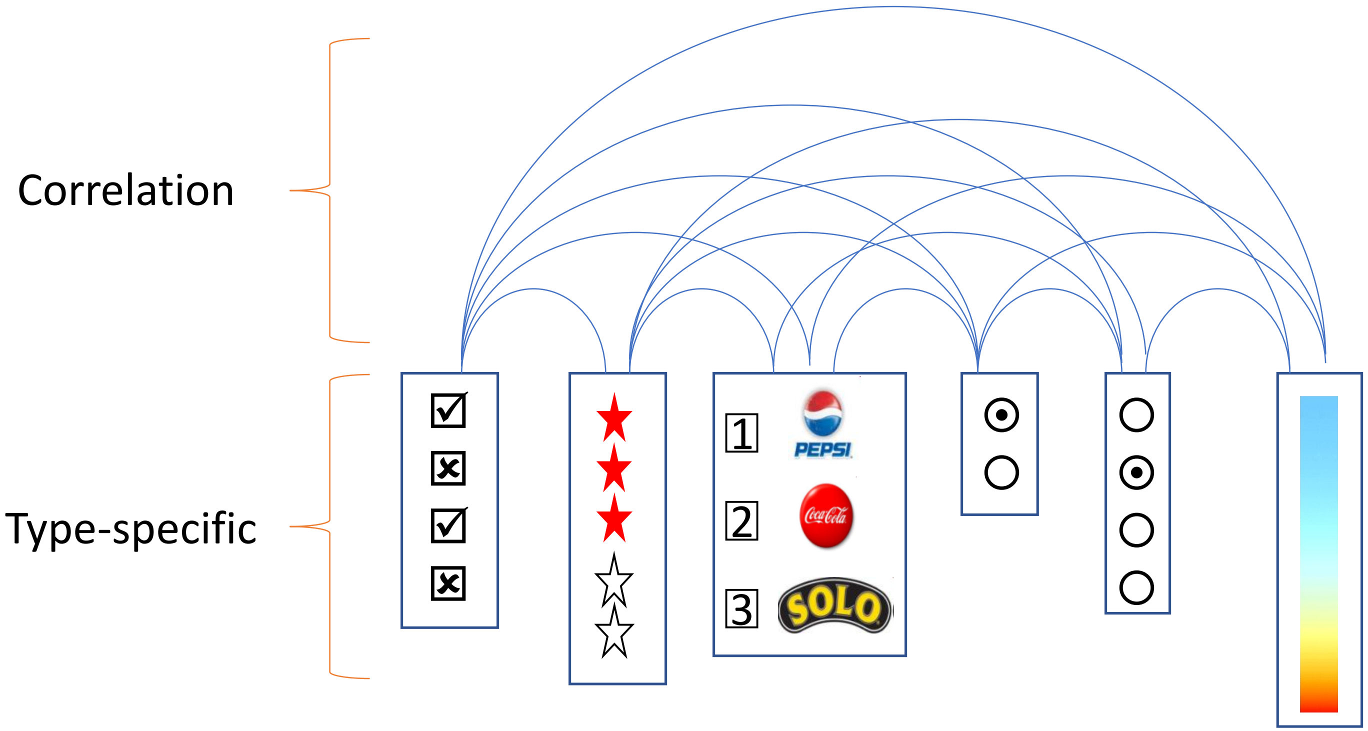



Figure credit: Jonathan Hui

Heskes, Tom. "Stable fixed points of loopy belief propagation are local minima of the bethe free energy." *Advances in neural information processing systems*. 2003.

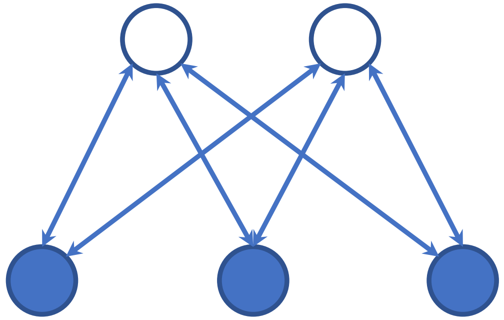
# Generation: Markov networks for mixed data types



# Restricted Boltzmann machines (RBMs)

$$p(\mathbf{v}, \mathbf{h}; \psi) \propto \exp\left[\underbrace{-E(\mathbf{v}, \mathbf{h}; \psi)}_{\textit{energy}}\right]$$

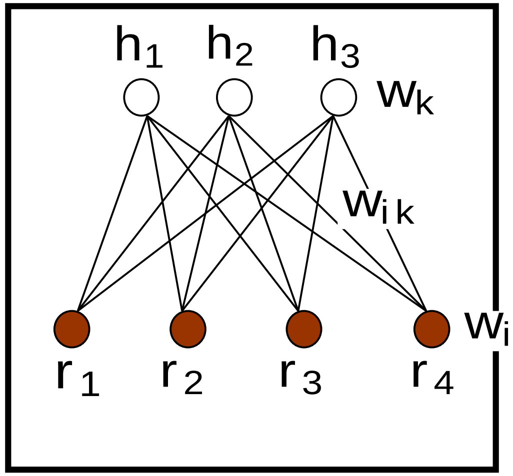
- Hidden variables to denote underlying unobserved processes
- Stack of RBMs is akin to renormalization trick in physics



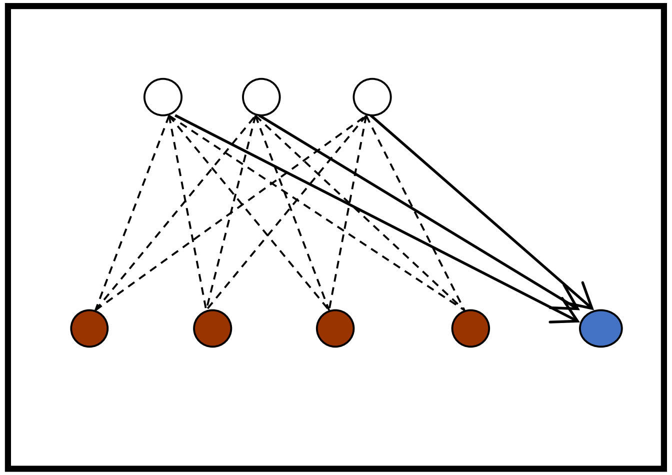
**Restricted Boltzmann Machine (~1994, 2001)**

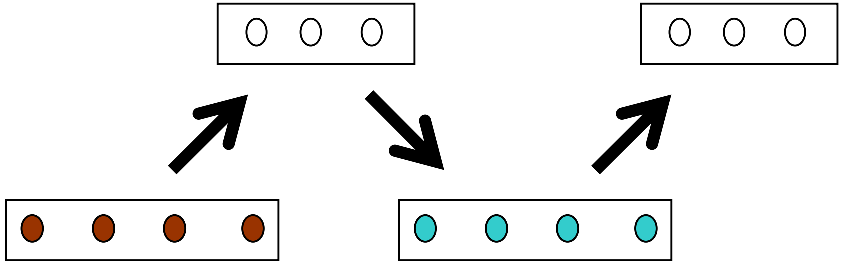
$$p(\mathbf{v},\mathbf{h};\psi) \propto \exp\big[\underbrace{-E(\mathbf{v},\mathbf{h};\psi)}_{\textit{energy}}\big]$$

# Learning and prediction

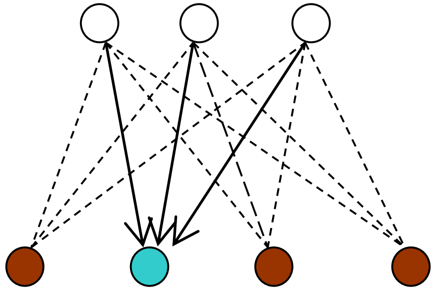



prediction





CD Learning



Pseudo-likelihood Learning

# Agenda

The context

Hopfield networks

Boltzmann machines

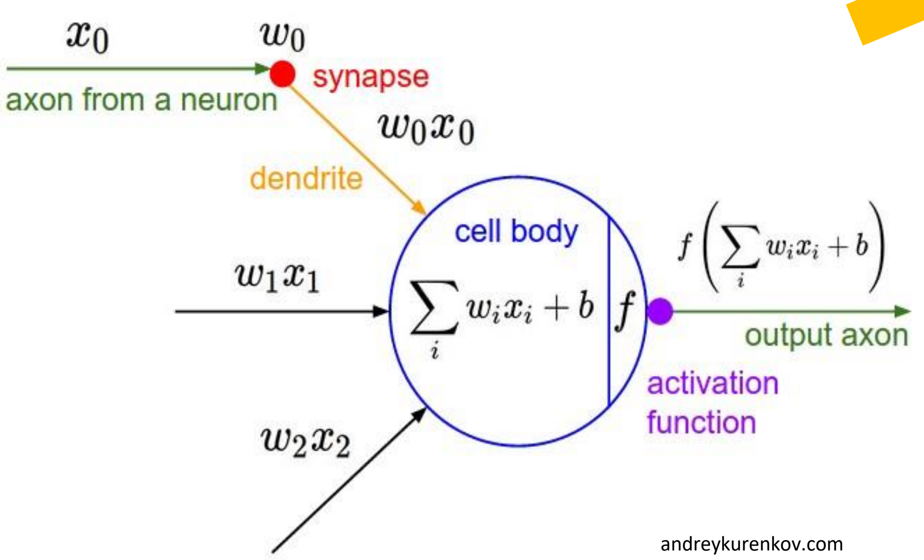
**Deep learning**

Discussion

# Deep models via layer stacking

## Theoretically powerful, but very difficult to train!

**Integrate-and-fire neuron**

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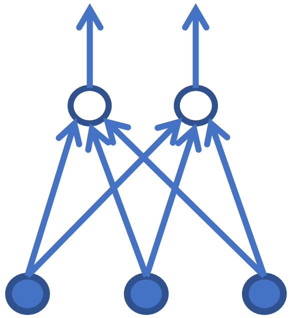
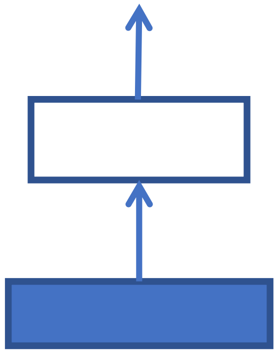
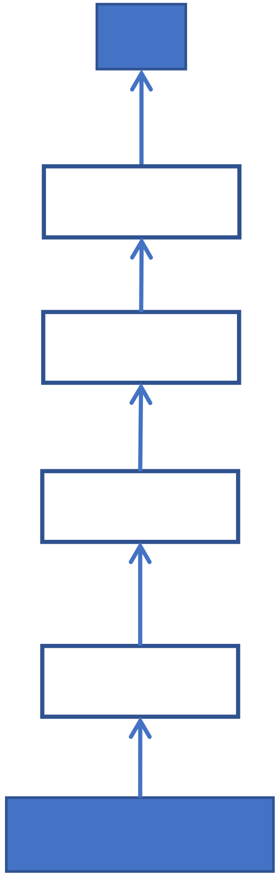


**Feature detector**

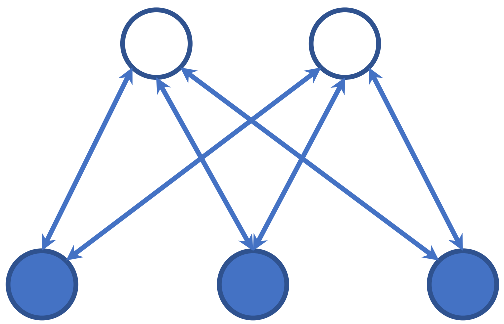




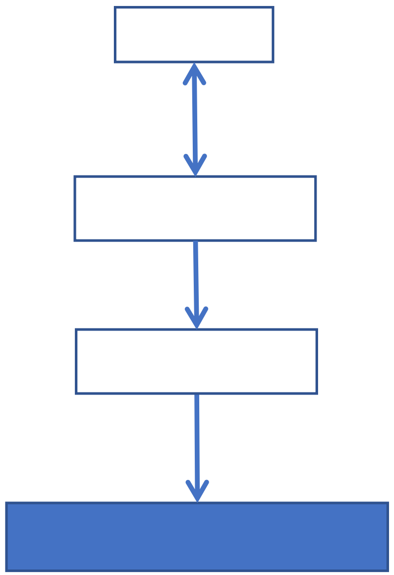
**Block representation**

# Start of deep learning: Layer-wise training

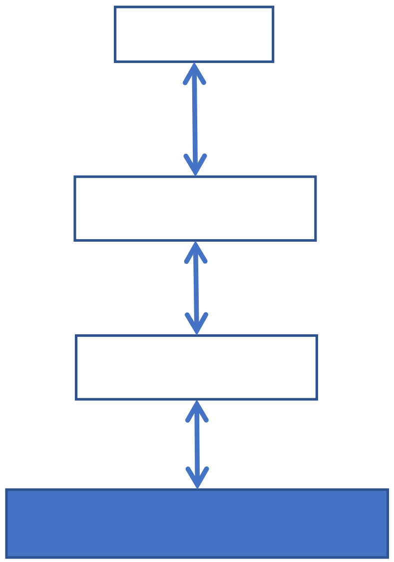
$$p(\mathbf{v},\mathbf{h};\psi) \propto \exp\left[\underbrace{-E(\mathbf{v},\mathbf{h};\psi)}_{energy}\right]$$



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



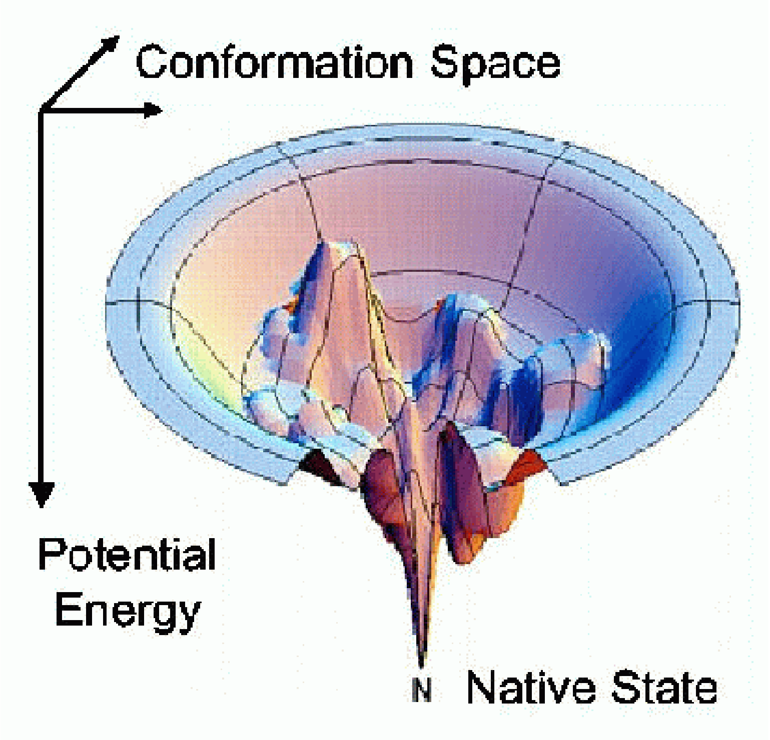
**Deep Belief Net (2006)**



**Deep Boltzmann Machine (2009)**

# Later: Stochastic gradient descent (SGD)

- Using mini-batch to smooth out gradient
- Use large enough learning rate to get over poor local minima
- Periodically reduce the learning rate to land into a good local minima
- It sounds like **Simulated Annealing**, but without proven global minima
- Works well in practice since the **energy landscape** is a **funnel**




Source: https://charlesmartin14.wordpress.com/2015/03/25/why-does-deep-learning-work/

# Modern SGD: Adaptive

**Adagrad** (Duchi et al, 2011)

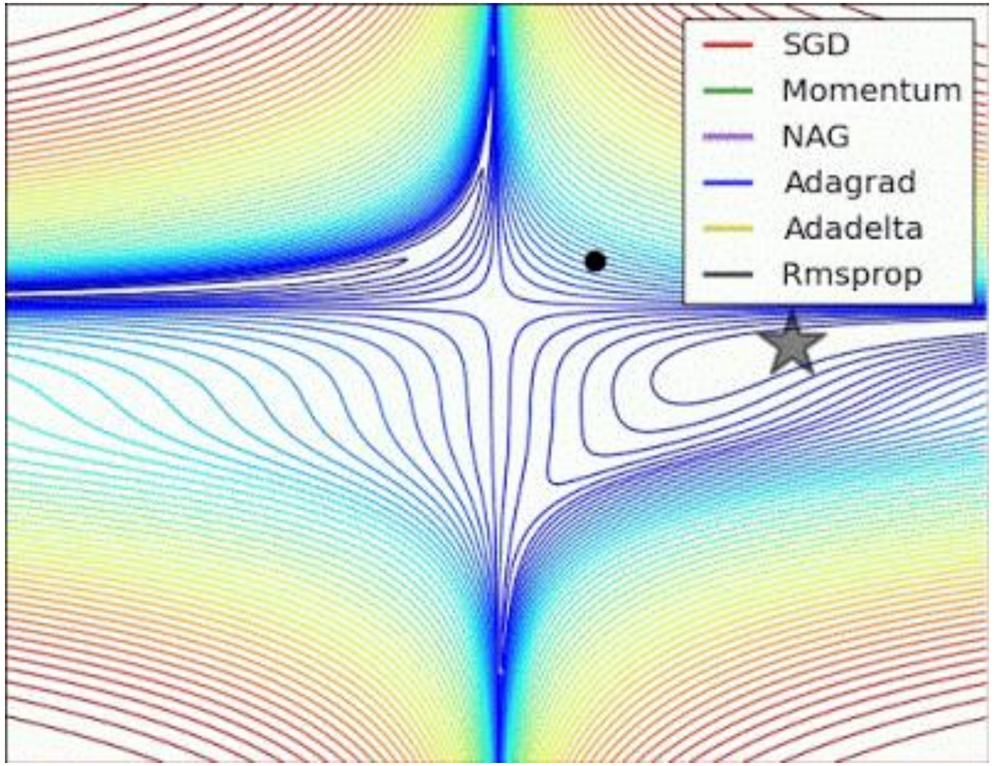
Init learning rate

Gradient

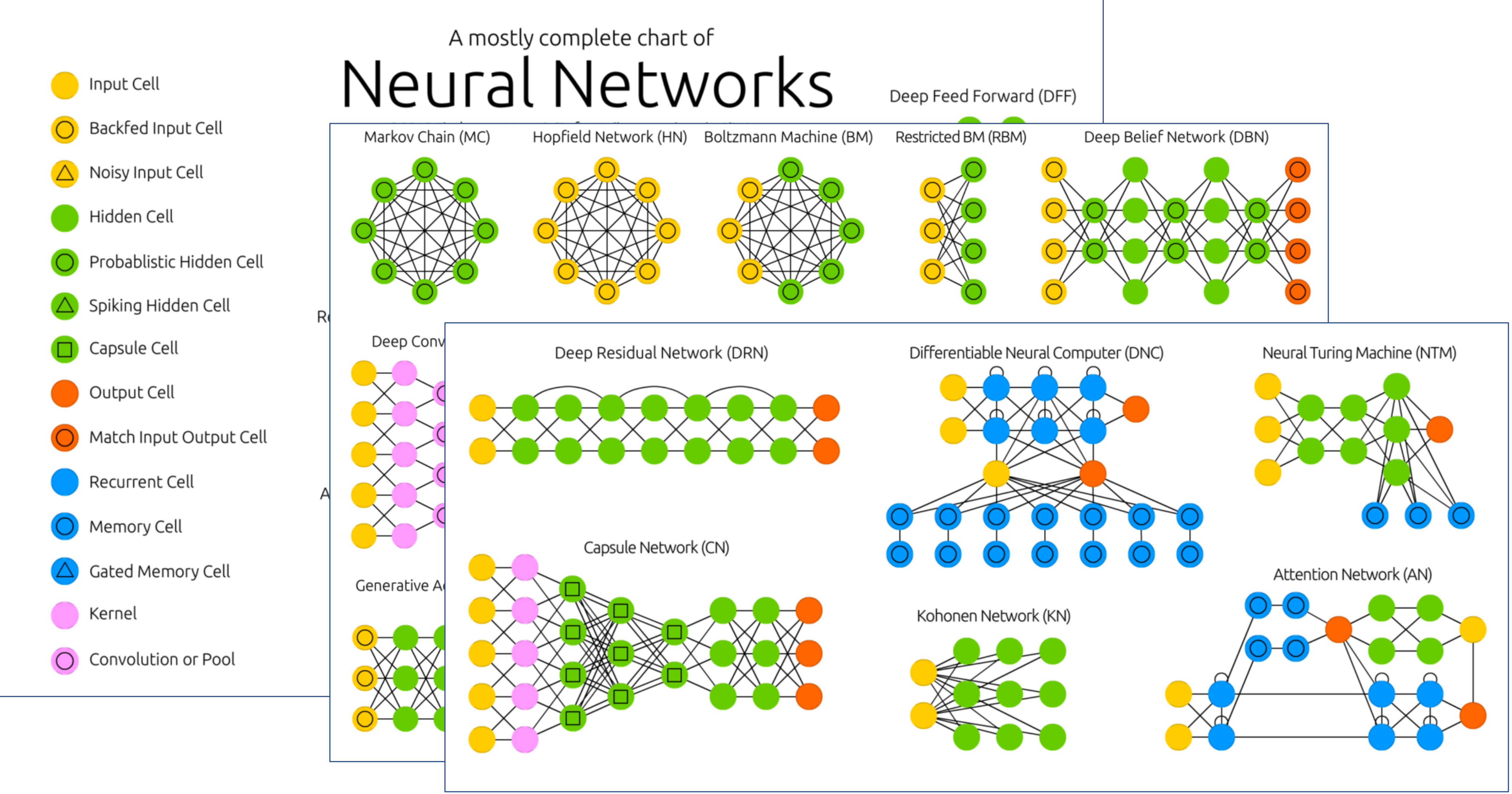
$$w_t \leftarrow w_{t-1} - \eta \frac{g_t}{\sqrt{\epsilon + \sum_{j=1}^{t-1} g_j * g_j}}$$

Smoothing factor

Previous gradients




Credit: Source: Alec Radford



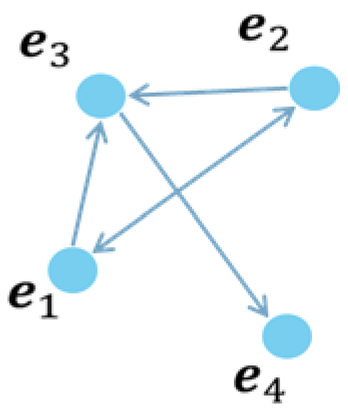


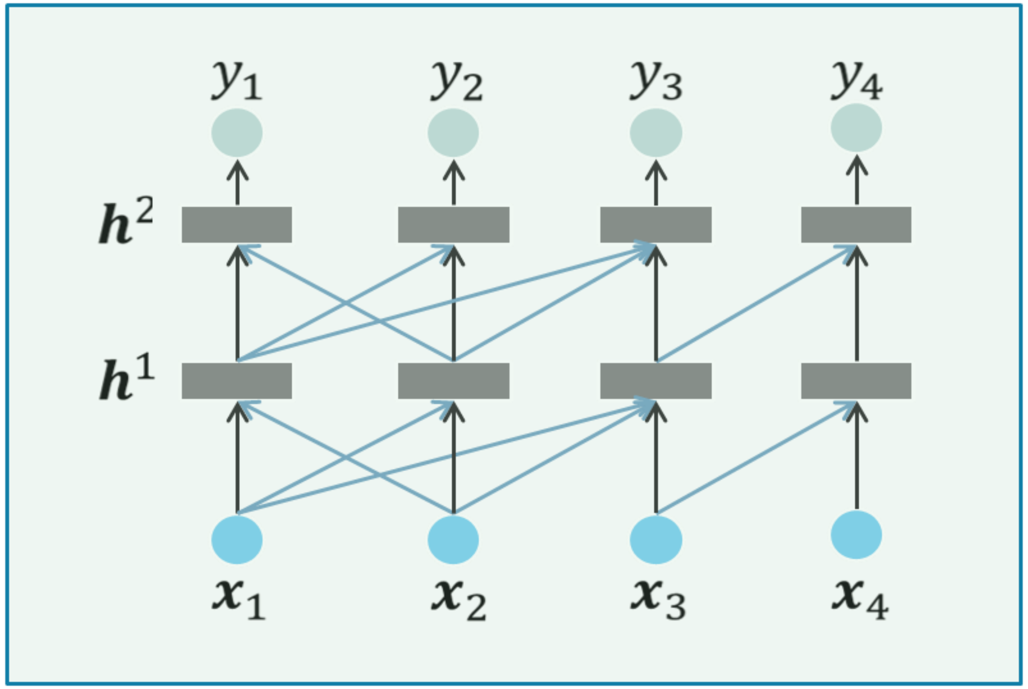

asimovinstitute.org/neural-network-zoo/

# Column Networks inspired from columnar structure of brain

**Generalized message passing**

**Relation graph**

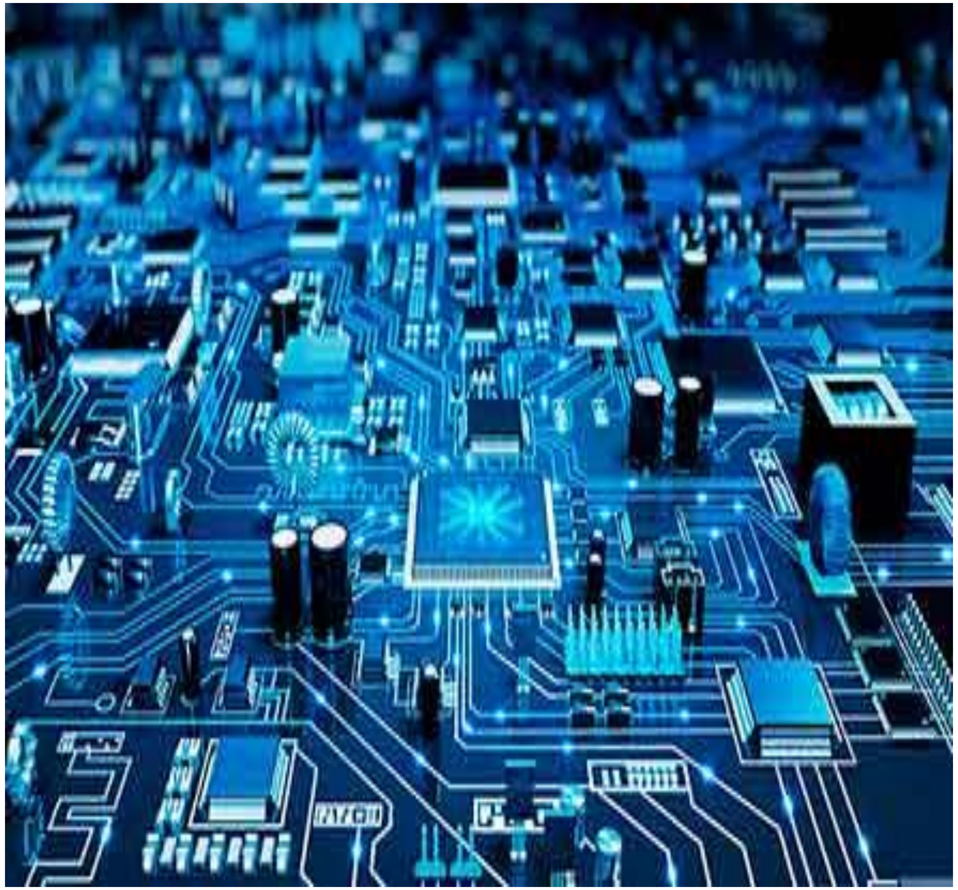



#REF: Pham, Trang, et al. "Column Networks for Collective Classification." *AAAI*. 2017.

# Deep learning vs electronics

- Neuron as feature detector → SENSOR, FILTER
- Multiplicative gates → AND gate, Transistor, Resistor
- Attention mechanism → SWITCH gate
- Memory + forgetting → Capacitor + leakage
- Skip-connection → Short circuit
- Computational graph → Circuit
- Compositionality → Modular design



# 2015 - Attention is a key for efficiency

- Visual attention in human: Focus on specific parts of visual inputs to compute the adequate responses.
- Examples:
  - We focus on objects rather than the background of an image.
  - We skim text by looking at important words.
- In neural computation, we need to select the most relevance piece of information and ignore all other parts

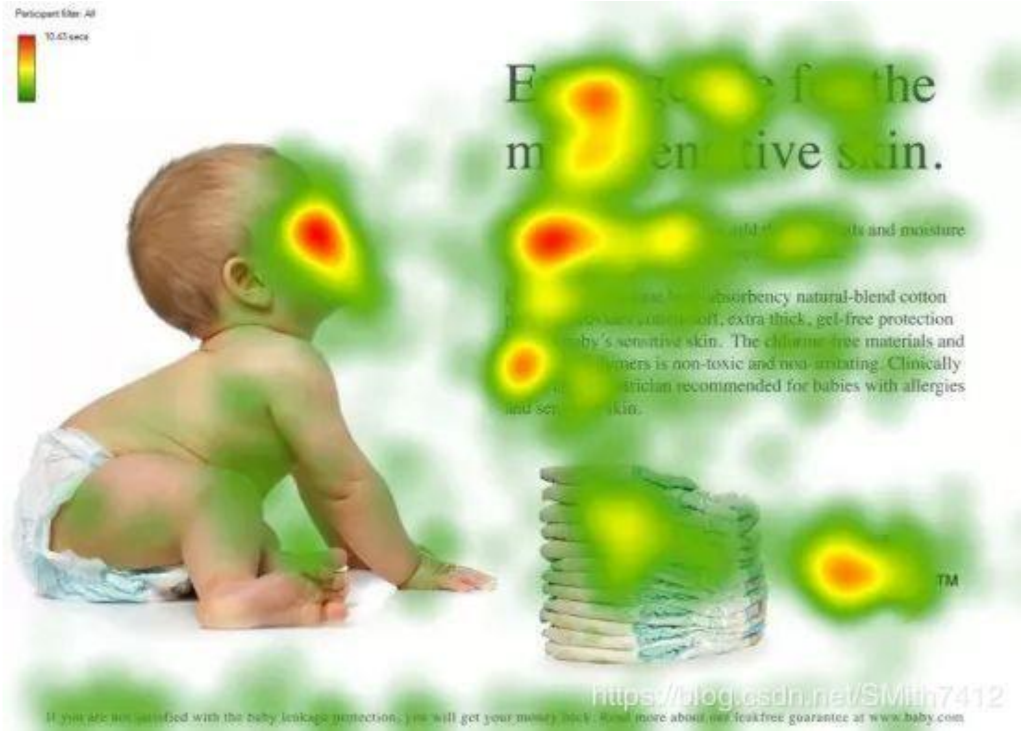
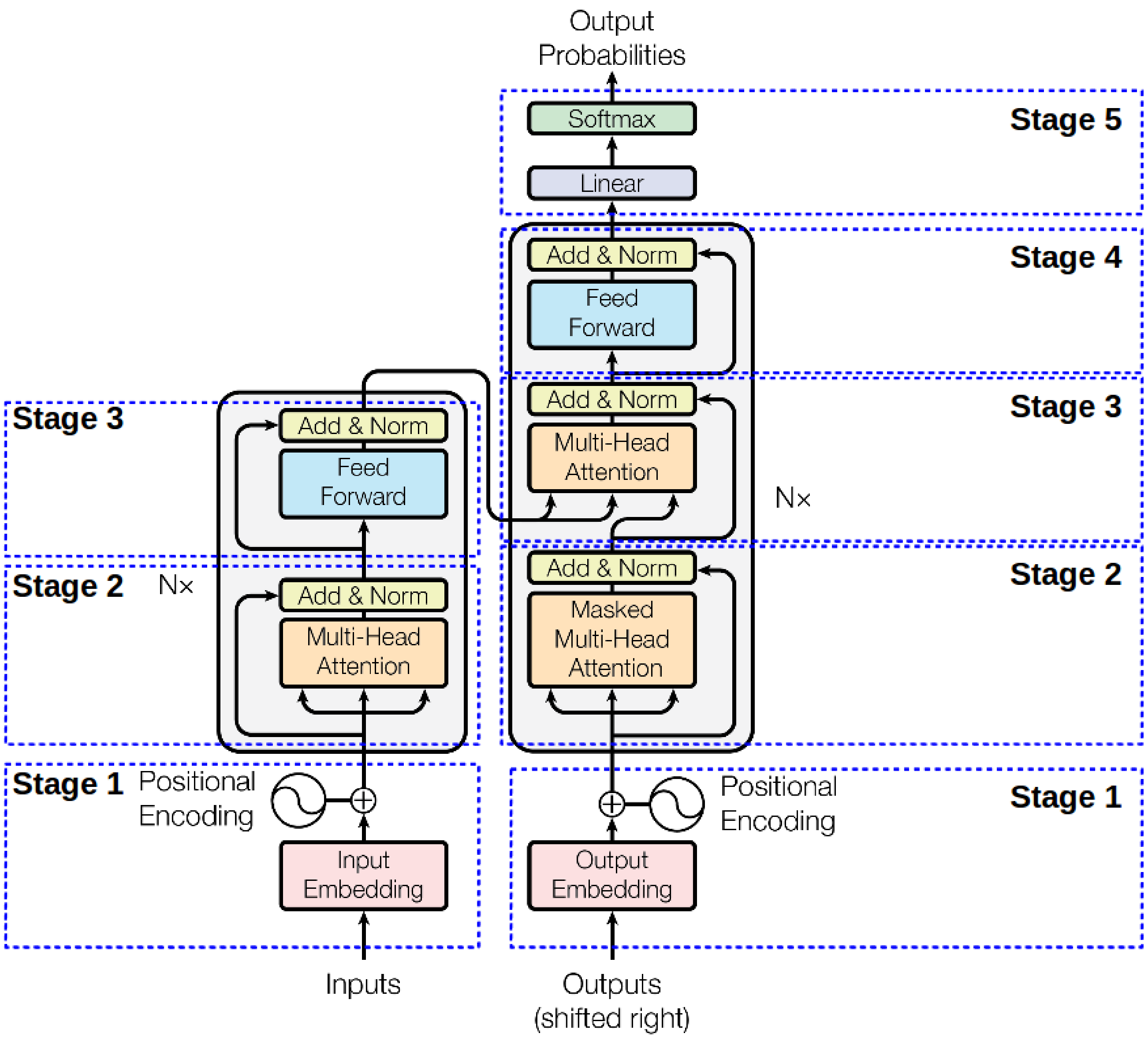


Photo: programmersought

# 2017 - Transformer

- Tokenization
- Token encoding
- Position coding
- Sparsity
- Exploit spatio-temporal structure



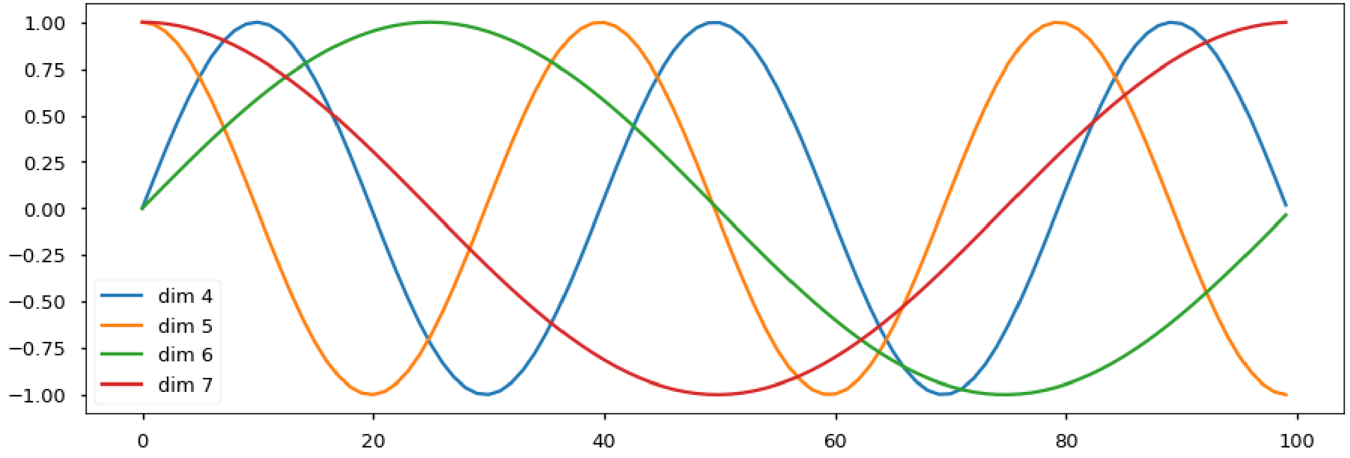
# Transformer: Key ideas

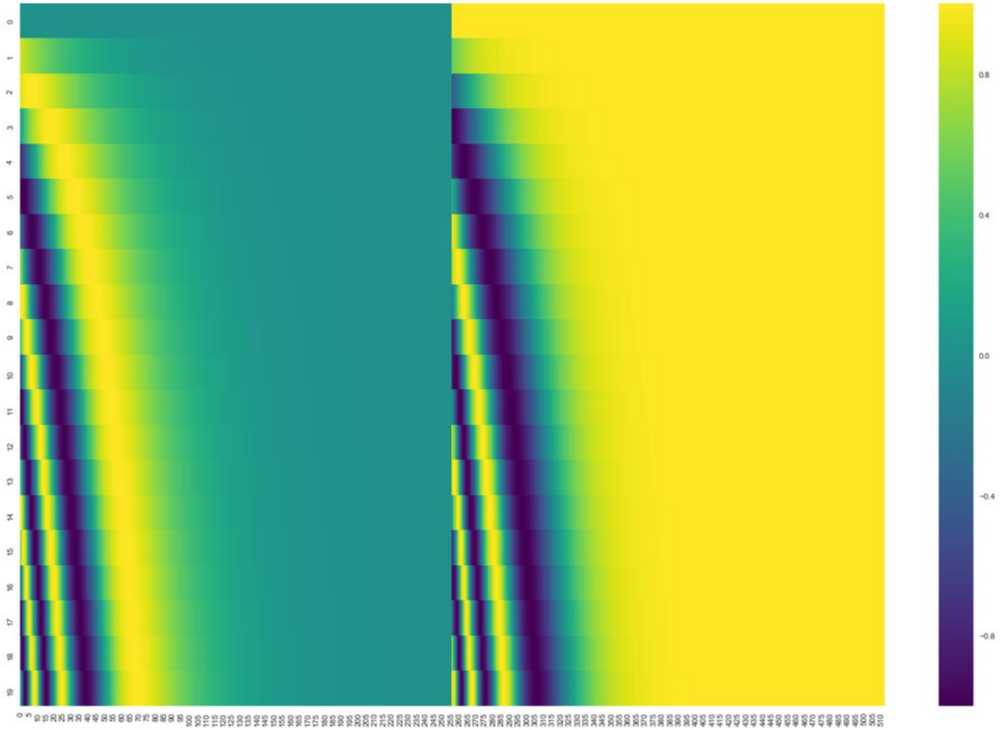
- Use self-similarity to refine token's representation (embedding).
  - "June is happy" -> June is represented as a person's name.
  - Hidden contexts are borrowed from other sentences that share tokens/motifs/patterns, e.g., "She is happy", "Her name is June", etc.
  - Akin to retrieval: matching query to key.
- Context is simply other tokens co-occurring in the same text segment.
  - Related to "co-location".
  - How big is context? → Small window, a sentence, a paragraph, the whole doc.
  - What is about relative position? → Position coding.

# Positional encoding

- The Transformer relaxes the sequentiality of data
  - Positional encoding to embed sequential order in model

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$





Slide credit: Adham Beykikhoshk

# Large Language Models are Transformer trained on the entire Internet!

**Yann LeCun** • 3rd+ + Follow •••

VP & Chief AI Scientist at Meta

11mo •

The weak reasoning abilities of LLMs are partially compensated by their large associative memory capacity.

They are a bit like students who have learned the material by rote but haven't really built deep mental models of the underlying reality.

# Transformers are modern Hopfield net

$$\mathrm{lse}(\beta, \boldsymbol{x}) = \beta^{-1} \log \left( \sum_{i=1}^{N} \exp(\beta x_i) \right)$$

$$\mathrm{E} = -\,\mathrm{lse}(\beta, \boldsymbol{X}^T \boldsymbol{\xi}) + \frac{1}{2} \boldsymbol{\xi}^T \boldsymbol{\xi} + \beta^{-1} \log N + \frac{1}{2} M^2$$

$$\boldsymbol{\xi}^{\mathrm{new}} = f(\boldsymbol{\xi}) = \boldsymbol{X} \boldsymbol{p} = \boldsymbol{X} \mathrm{softmax}(\beta \boldsymbol{X}^T \boldsymbol{\xi})$$

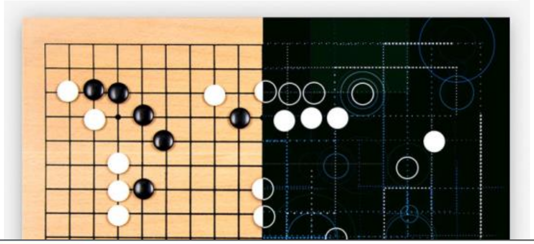
| Hopfield Energy | | New Energy | | Update Rule | | Transformer |
|---|---|---|---|---|---|---|
| $-\exp\left(\mathrm{lse}\left(1, \boldsymbol{\xi}\boldsymbol{X}^T\right)\right)$ | $=$ | $-\mathrm{lse}(\beta, \boldsymbol{\xi}\boldsymbol{X}^T) + \frac{1}{2}\boldsymbol{\xi}^T\boldsymbol{\xi} + c$ | $\Rightarrow$ | $\mathrm{softmax}\left(\beta\, \boldsymbol{\xi}\boldsymbol{X}^T\right) \boldsymbol{X}$ | $=$ | $\mathrm{softmax}\left(\frac{1}{\sqrt{d_k}} \boldsymbol{Q}\boldsymbol{K}^T\right) \boldsymbol{V}$ |

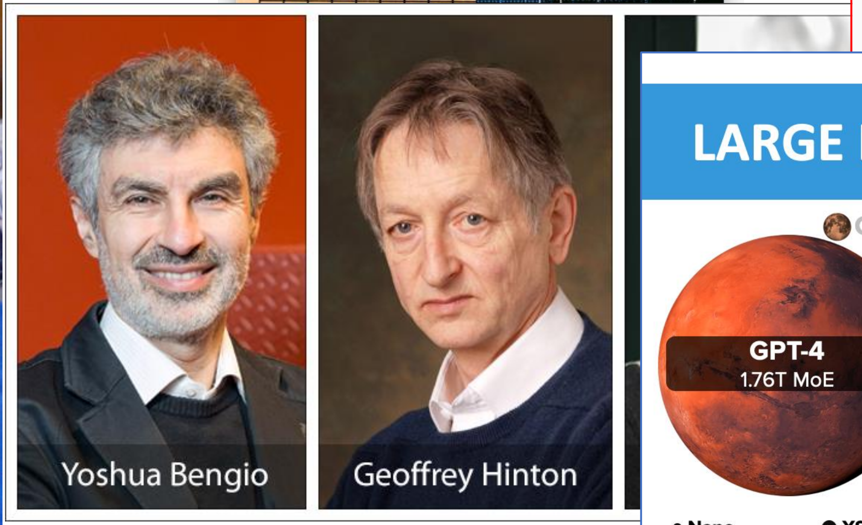


Ramsauer, Hubert, et al. "Hopfield networks is all you need." *arXiv preprint arXiv:2008.02217* (2020).

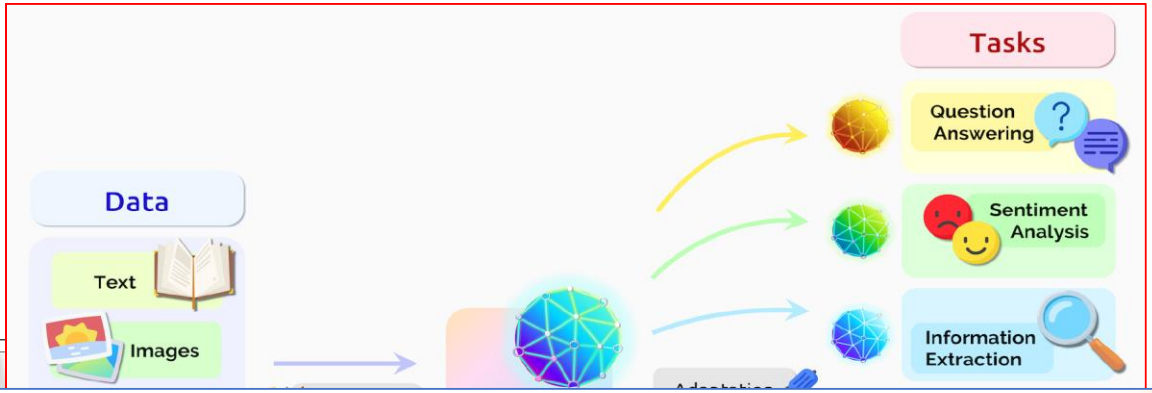

2012

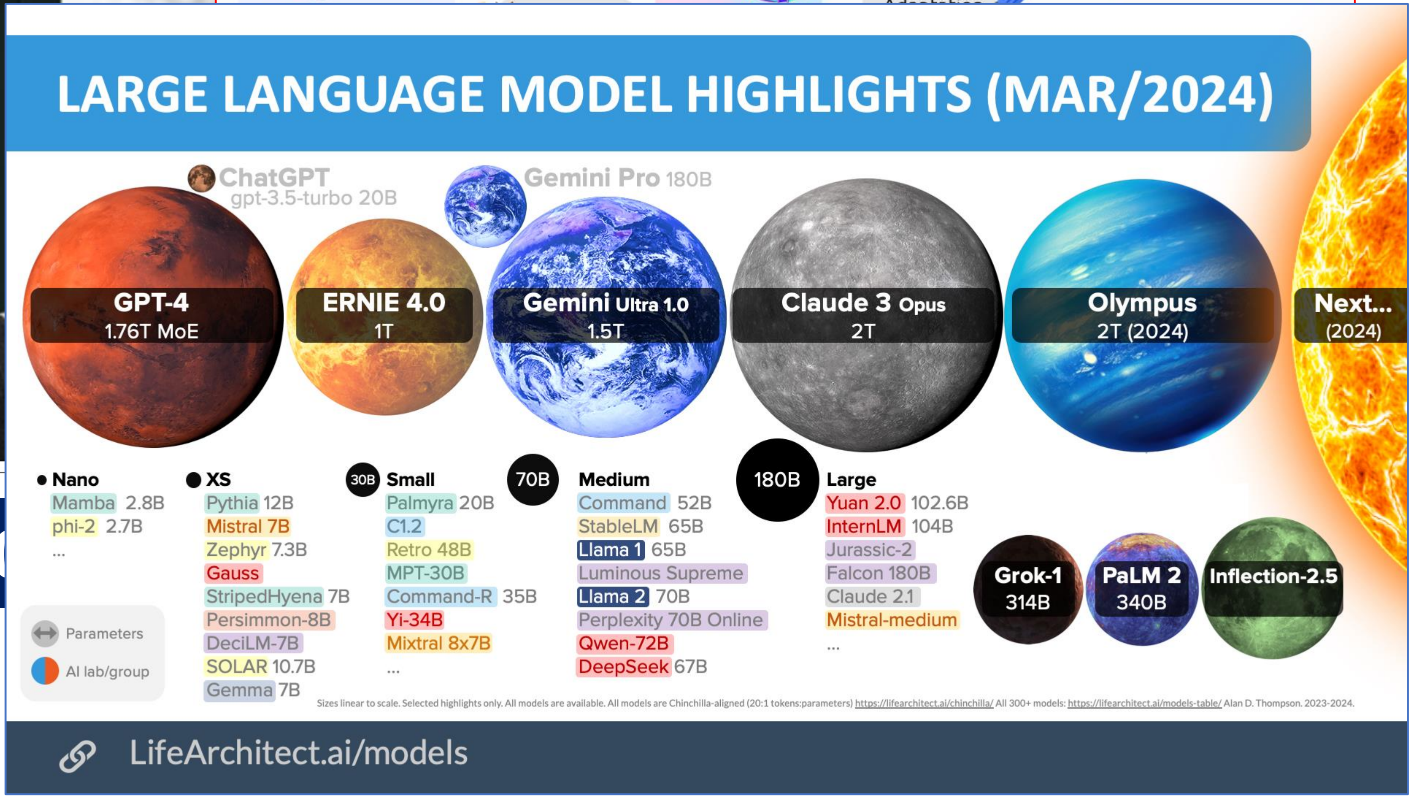
AlphaGo






Turing Awards 20

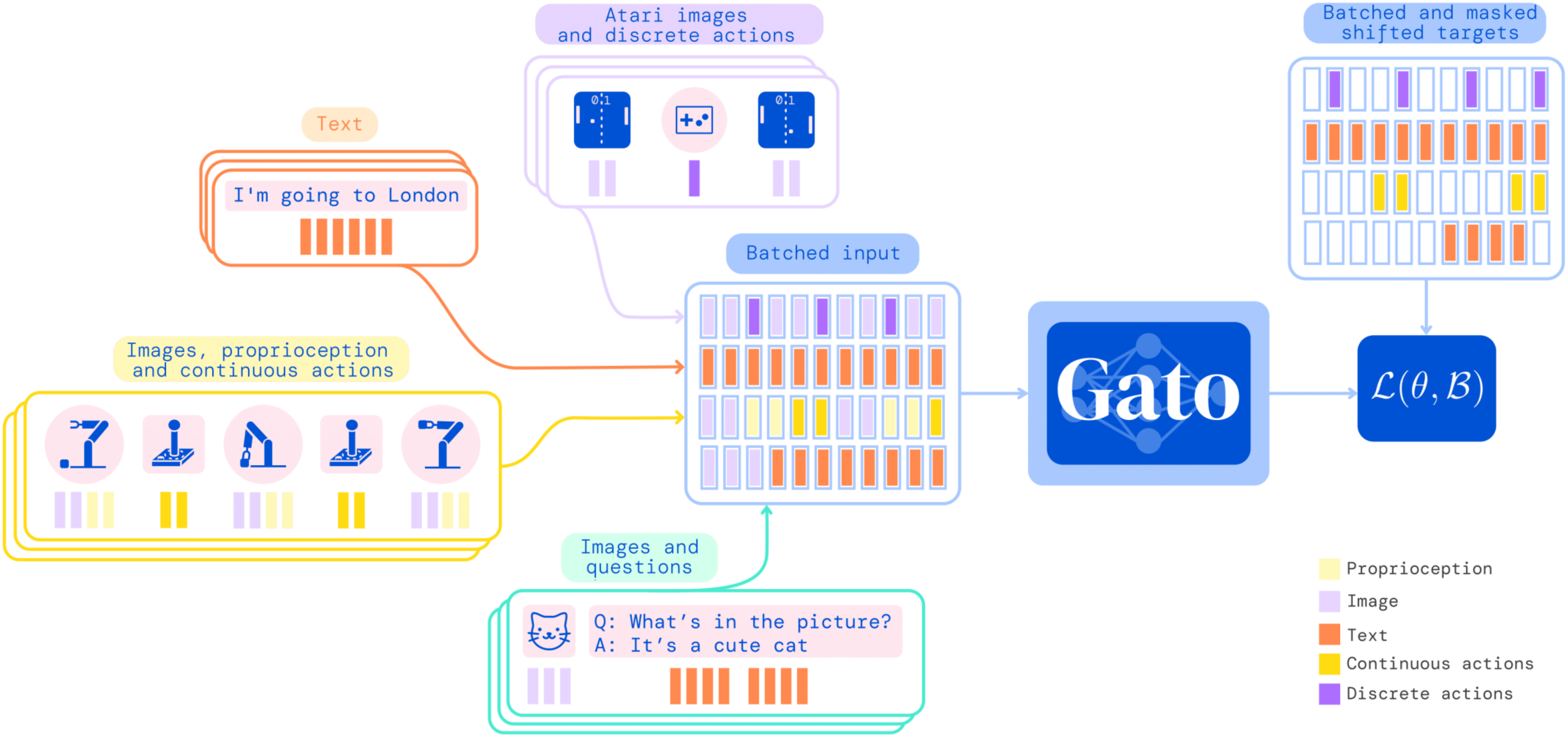



# 12 years snapshot

2024

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




Reed, Scott, Konrad Zolna, Emilio Parisotto, Sergio Gomez Colmenarejo, Alexander Novikov, Gabriel Barth-Maron, Mai Gimenez et al. "A generalist agent." *arXiv preprint arXiv:2205.06175* (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, but capable of processing 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.
- Advances in modern AI:
  - Model flexibility
  - Powerful training and inference machines
  - Smart tricks

# Current Generative AI

| | |
|---|---|
| GenAIs are compression engine | Prompting is conditioning for the (preference-guided) decompression. |
| GenAIs are approximate program database | Prompting is retrieving an approximate program that takes input and delivers output. |
| GenAIs are World Model | We can live entirely in simulation! |

# Agenda

The context

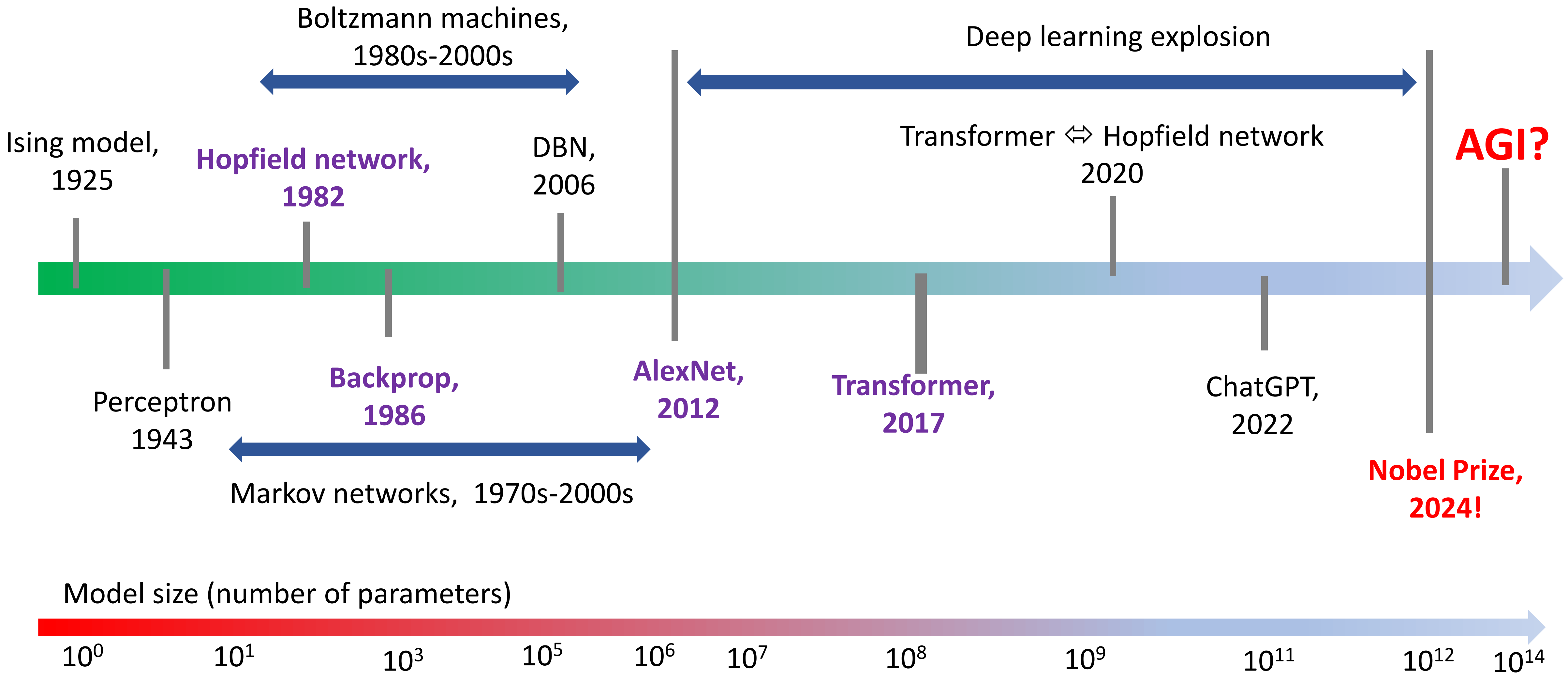
Hopfield networks

Boltzmann machines

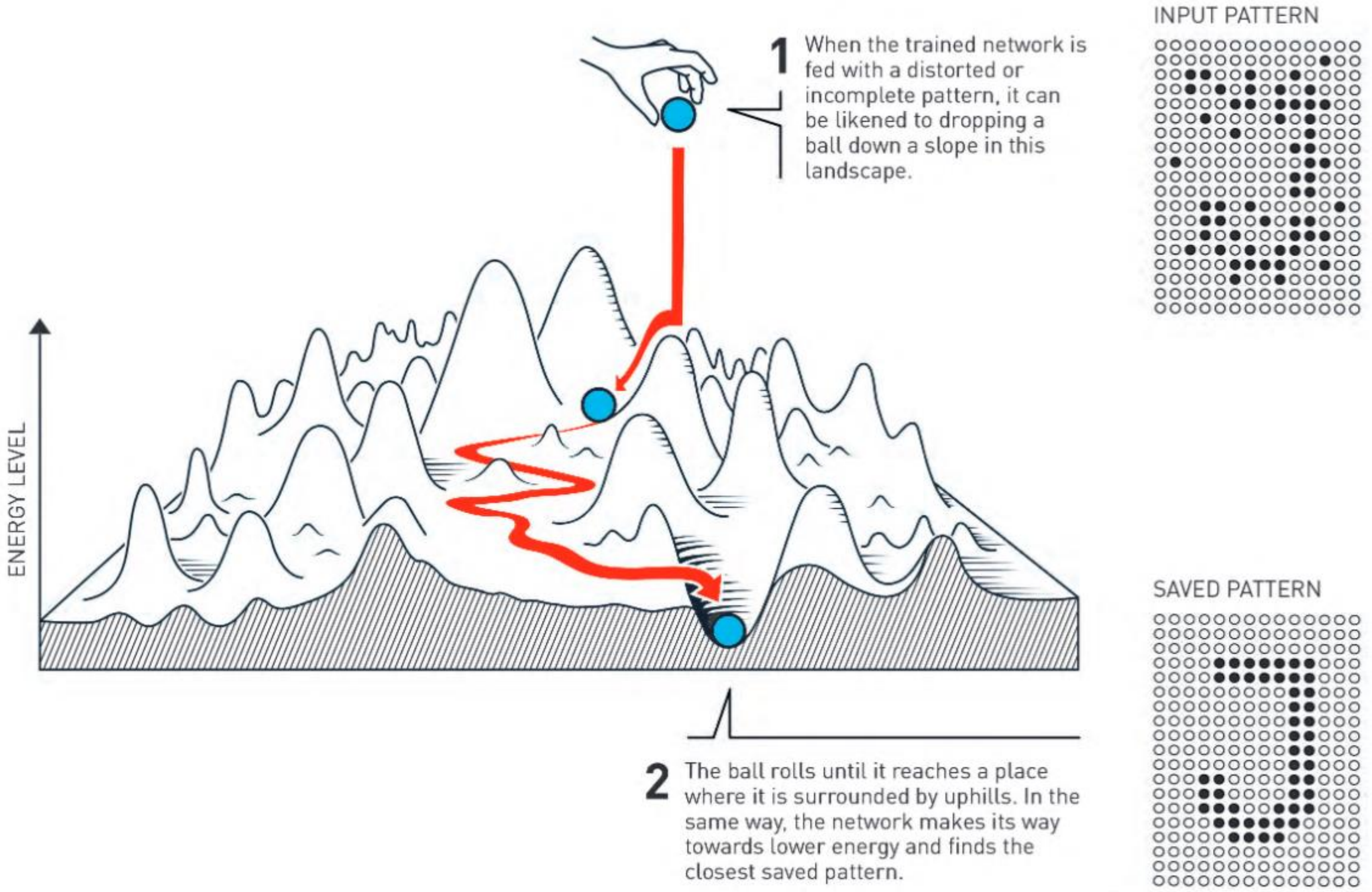
Deep learning

**Discussion**

# A very brief timeline of 100 years



# Memories are stored at attractors in a landscape




Credit: nobelprize.org

# Recognition of the 2024 Nobel Prize in Physics

**The interdisciplinary nature of modern physics, crossing with:**

- Computation
- Information theory
- Cognition.

**Concepts foundational to AI stem from physics (energy landscapes and statistical mechanics).**

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

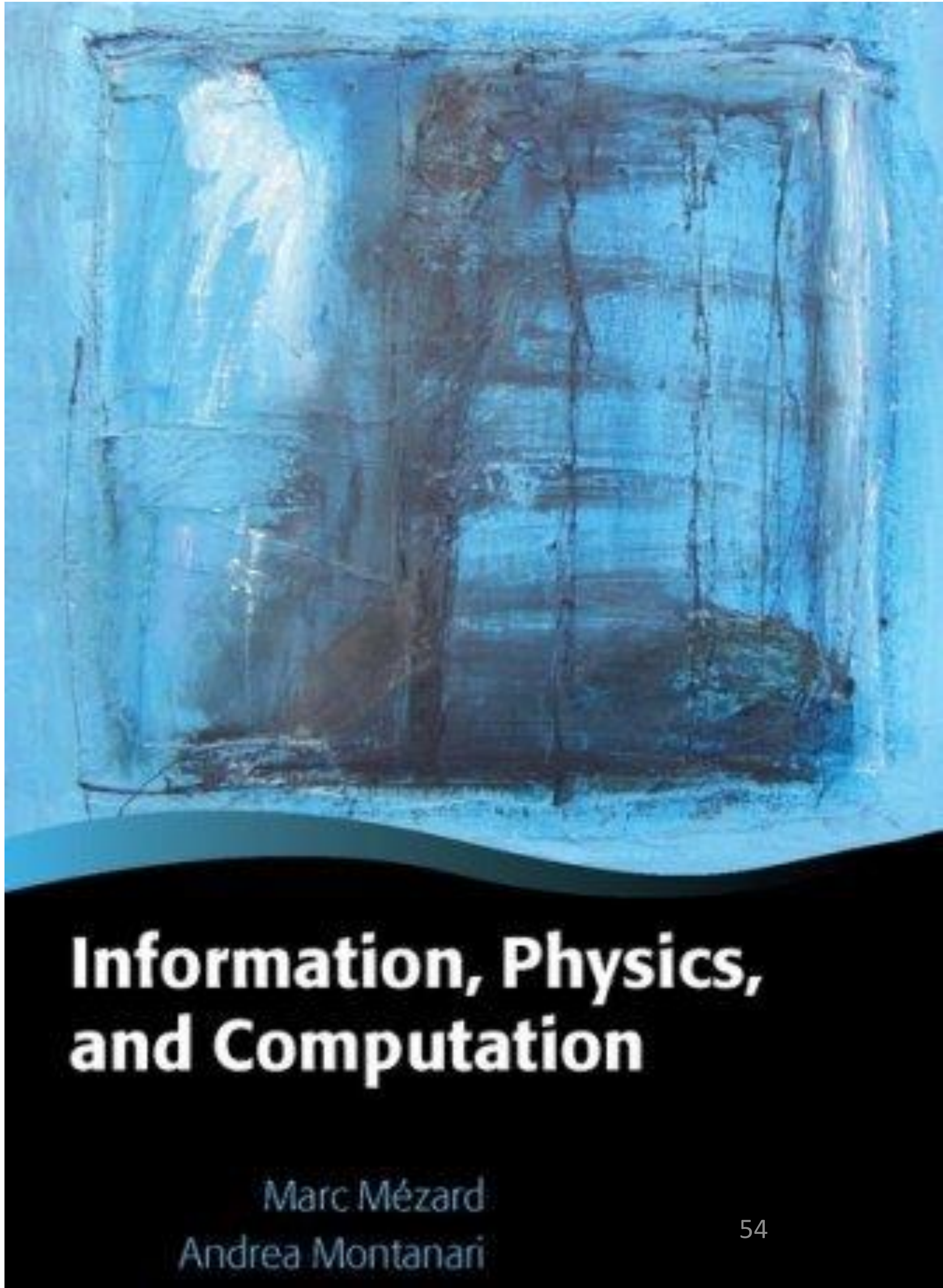
**Timeliness & innovation: AI has pervasive societal impact.**

# The bridges between physics, mind, and computer science

Physical principles can model cognitive processes

- Memory as energy states
- Learning as optimization.

Modern physics and AI treat information processing as intrinsic to the fabric of nature, akin to matter and energy.



# Criticisms

- AI belongs to computer science or technology, not physics.
- Prioritizing applied technologies over fundamental discoveries.
- Inadequate recognition of prior works
  - Prior to Hopfield network (1982): Lenz-Ising recurrent architecture (1925); Amari (1972), Nakano (1972).
  - Prior to Boltzmann machine (1985): Glauber (1963); Ivakhnenko & Lapa (1965); Edwards-Anderson (1975); Sherrington & Kirkpatrick (1975)
  - Prior to layer-wise training of DBN (2006): Ivakhnenko & Lapa (1965); Schmidhuber (1990, 1991)
  - Prior to backprop (1986): Amari & Saito (1967), Linnainmaa, 1970; Werbos (1982)
  - Prior to modern deep networks: Ivakhnenko's 1971

# Looking into the future

Giorgio Parisi, 2021 Nobel in Physics for complex systems
Solved Sherrington-Kirkpatrick model (1979)

**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.

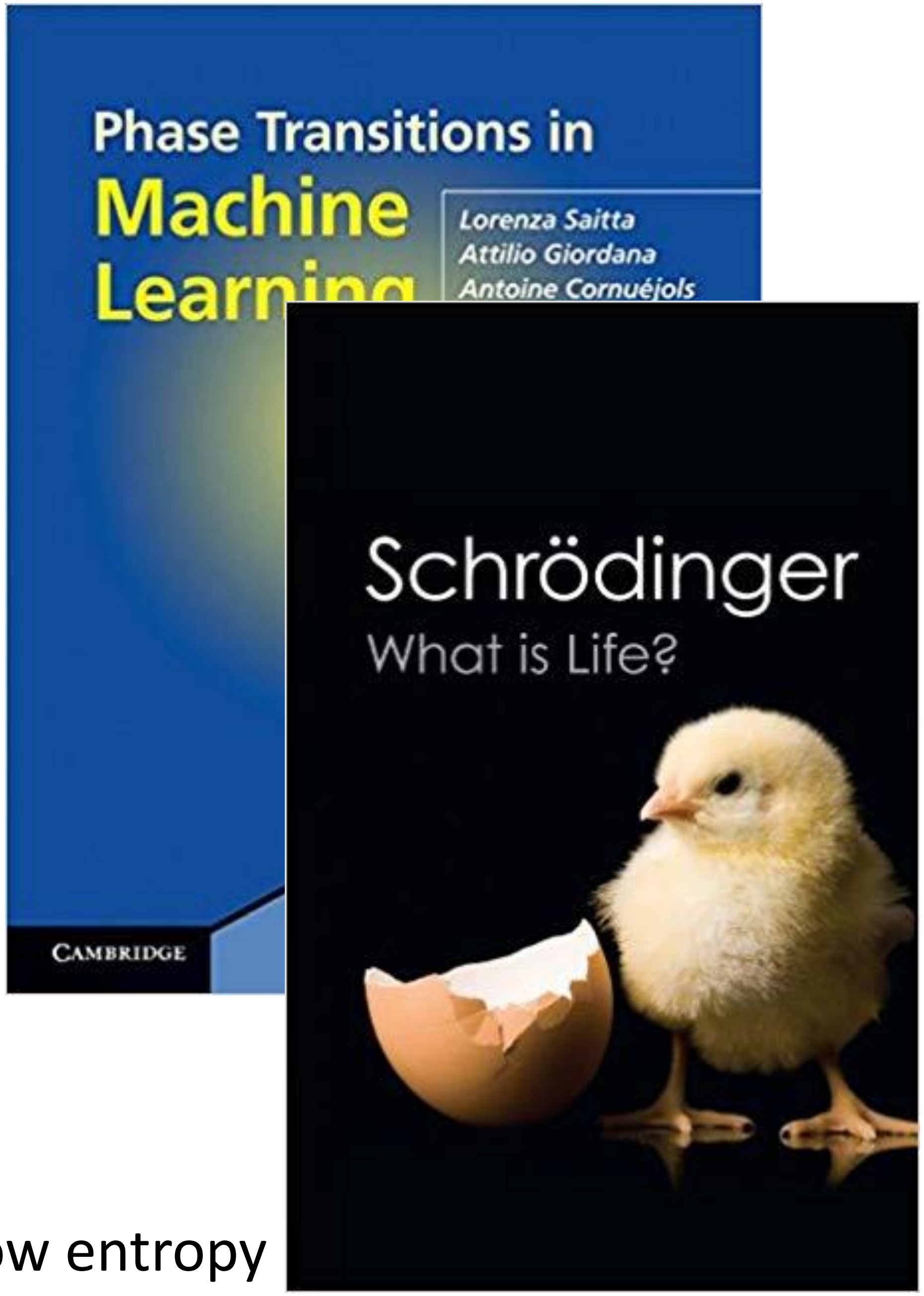
**Future-ready scientists**: Technology + science.



Credit: nobelprize.org

# AI as physics

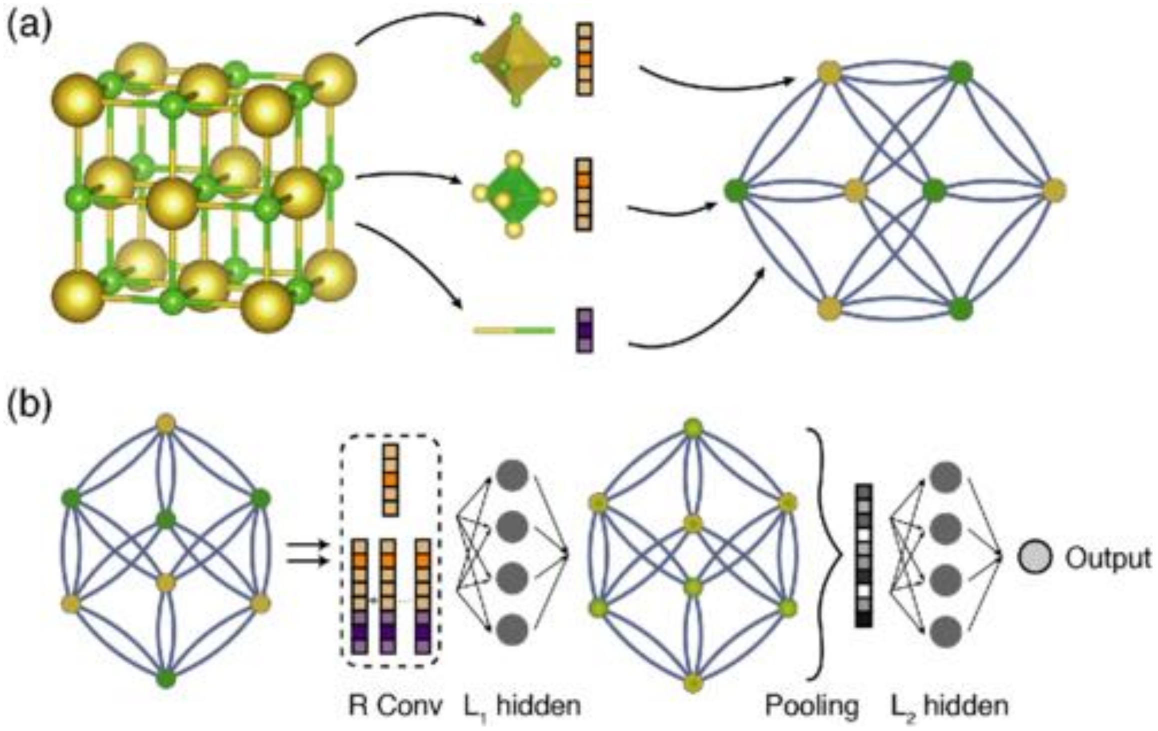
- Intelligence as self-organizing phenomena: reducing ignorance/entropy
- Neural networks as a statistical mechanical system
- Learning as variational optimization
- Inference free-energy minimization
- Phase transition may occur in AI systems
- Ultimate AI must solve the **consciousness problem**, which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

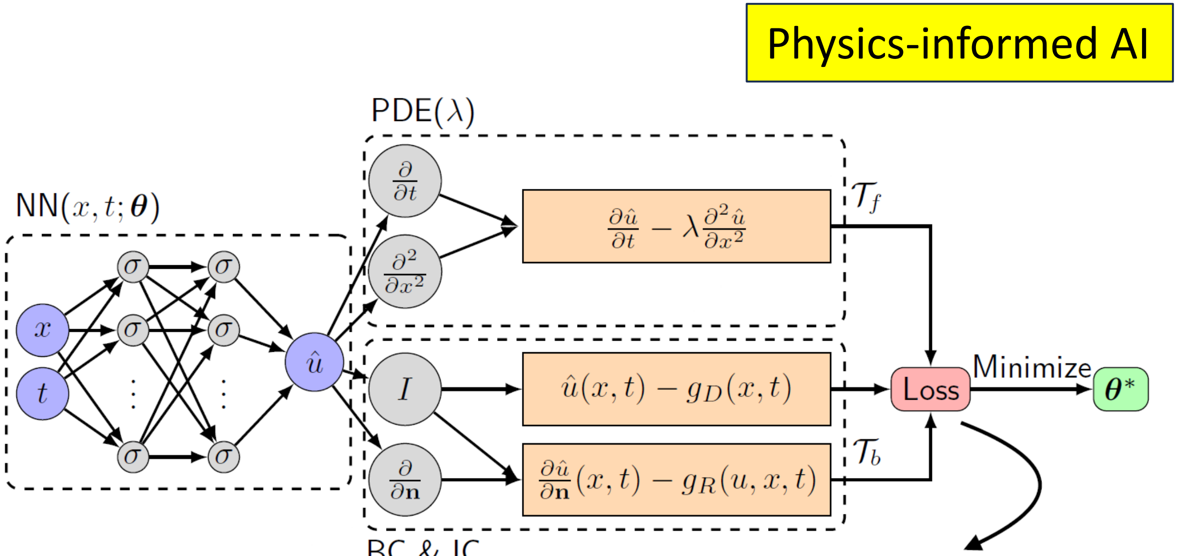



Life has low entropy

# AI for Physics

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.




$$\mathcal{L}(\theta) := \underbrace{\frac{1}{N_u}\sum_{i=1}^{N_u}[\boldsymbol{u}_i - f_\theta(\boldsymbol{x}_i)]^2}_{\text{Data fit}} + \underbrace{\frac{1}{\lambda}\mathcal{R}[f_\theta(\boldsymbol{x})]}_{\text{Physics regularization}}$$

# Thank you!