

AI in Culture and Arts – Tech Crash Course

A Brief History of Artificial Intelligence

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MUC.DAI
Munich Center for
Digital Sciences and AI



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Hochschule
für Musik und Theater
München

“The question of whether a computer can think is no more interesting than the question of whether a submarine can swim.” – Edsger Dijkstra (1930 – 2002)

“If the brain was simple enough for us to understand, we’d be too simple to understand it.” – Ian Stewart

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1. Introduction

2. Symbolism I

3. Connectionism I

4. Symbolism II

5. Connectionism II

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Symbolism

Exploits explicit, rule-based symbolic manipulation, logic, and structured reasoning to represent knowledge and solve problems.

- **Assumption:** Intelligence uses high-level, human-readable symbols to represent problems and logic to solve them.
- **Motivation:** Model the **mind!**

Connectionism

Exploits artificial neural networks & statistics, emphasizing learning from patterns, distributed representations, and emergent behaviors.

- **Assumption:** Intelligence emerges from the interaction of simple and low-level units, i.e. biological neurons.
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Symbolism I: Logos Shall Rule!

- Aristotle's Logic (circa 4th century BCE)

- Origin of formal logic and structured reasoning.
- Introduction of syllogisms as symbolic structures for inference.



Euclid, Eratosthenes, Hypatia

- Symbolic Logic and Mathematics (19th–20th century)

- Formalization of logic (George Boole, Gottlob Frege, Bertrand Russell, David Hilbert).
- Provided a mathematical basis for symbolic reasoning.

- Early Symbolic AI (mid-20th century)

- Models of computation, complexity and information (Kurt Gödel, Alan Turing, Alonzo Church, Claude Shannon)
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Symbolism I: Proofs as Symbolic Manipulations

Idea: Logical inference is mechanical and rule-based. Thus, a computer can do it.

Example: Symbolic Proof (Modus Ponens)

Given the rules:

1. If it rains, the grass is wet. ($\text{Rain} \rightarrow \text{Wet}$)
2. It rains. (Rain)

Conclusion (by applying rules): The grass is wet. (Wet)

Machine “Reasoning” Steps:

1. Represent statements symbolically.
2. Apply inference rules systematically.
3. Derive conclusions automatically.

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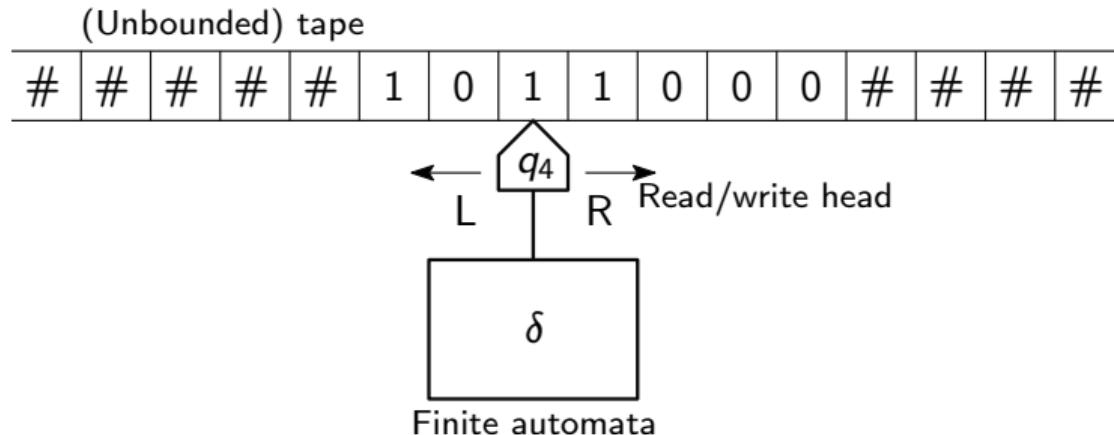
Bool, Frege, Russell



Gödel, Church, Turing

Symbolism I: A Model of Computation

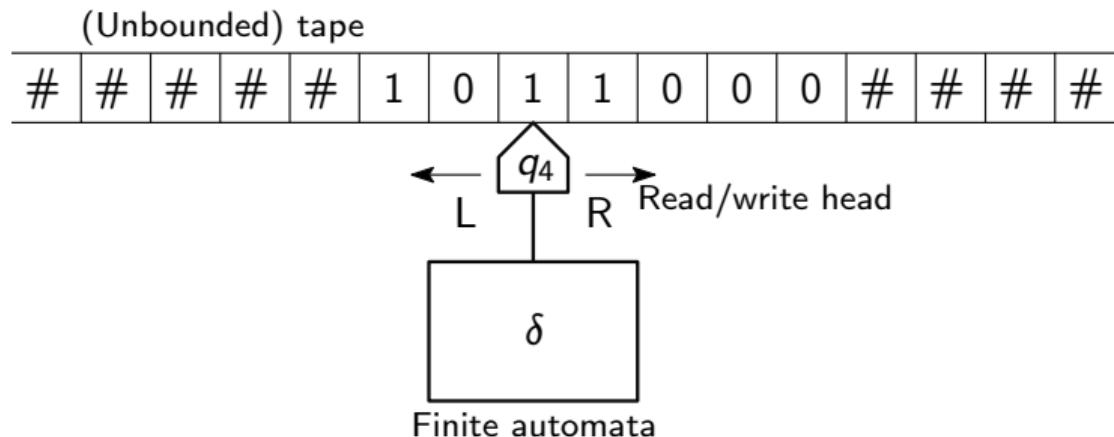
In 1937 Alan Turing presents a general model of computation called the *Turing machine* as a byproduct (Turing, 1937).



To this day, the kind of problems any digital computer can solve, can also be solved by a Turing machine despite its operations being incredibly simple.

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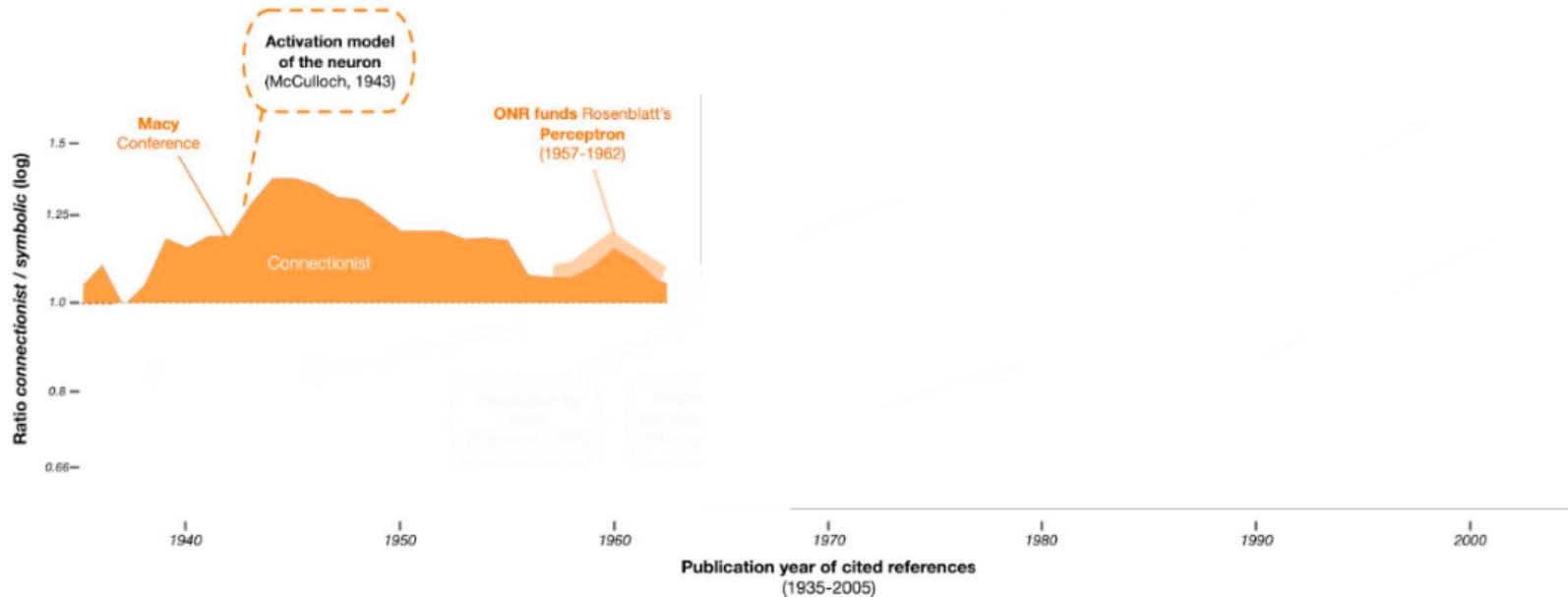
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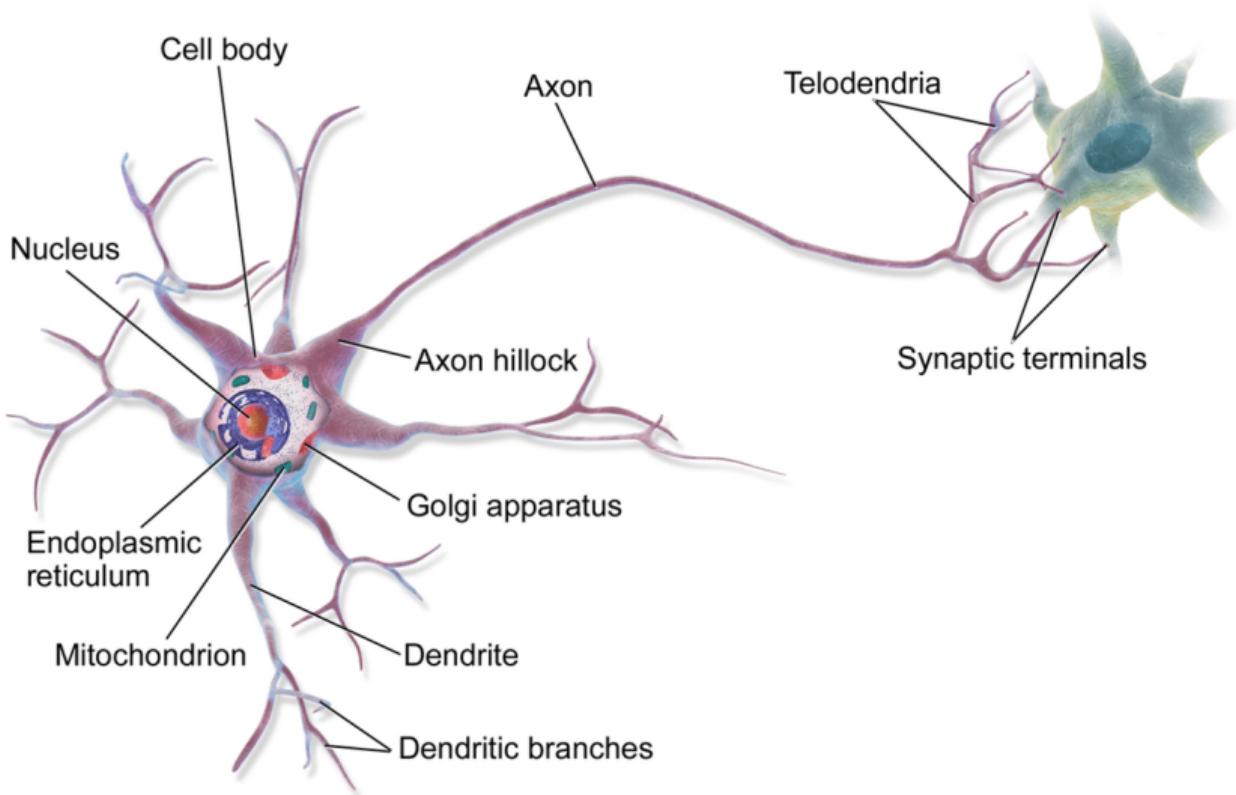
Connectionism I



Source: (Cardon et al., 2018)

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Connectionism I: The Neuron

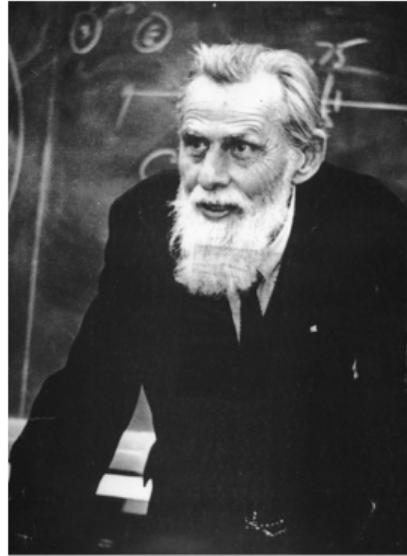


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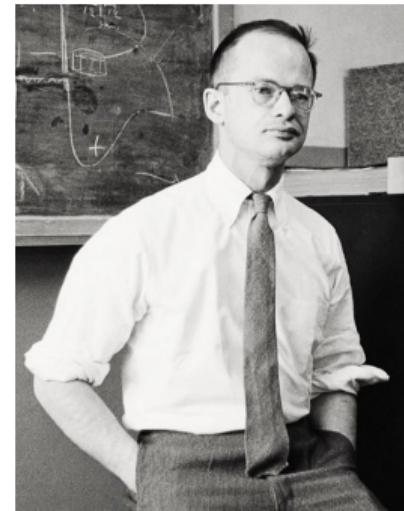
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Connectionism I: The Mathematical Neuron



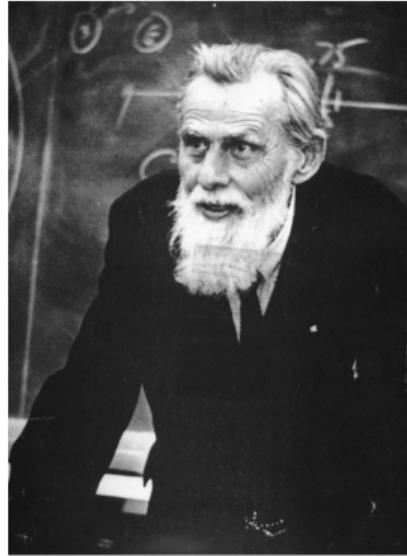
Warren S. McCulloch

- Communication takes place when an electro-chemical signal gets transferred from one neuron to another.
- All the processing then happens in the cell body.
- The processed information then travels to the synaptic terminal which “decides” whether the information should be passed to the next neuron or not.
- The same information passes to millions of neurons.



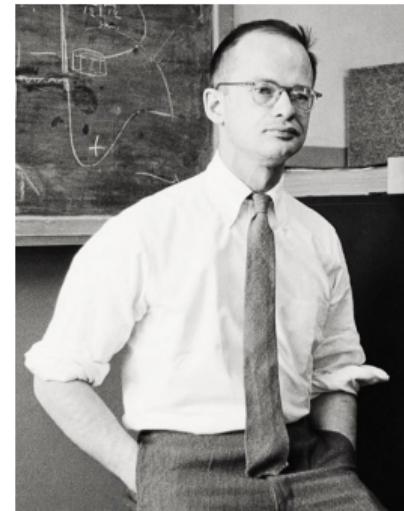
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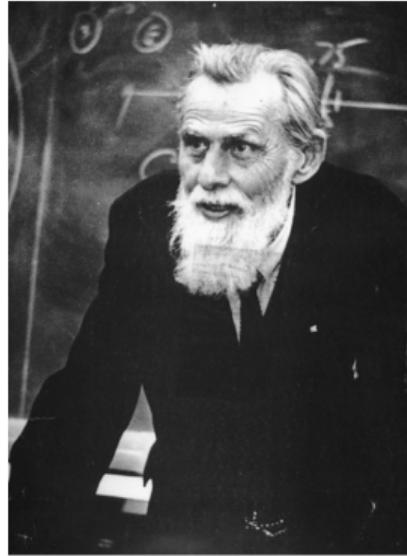
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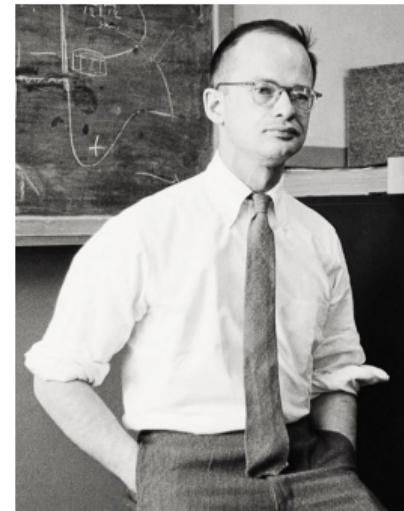
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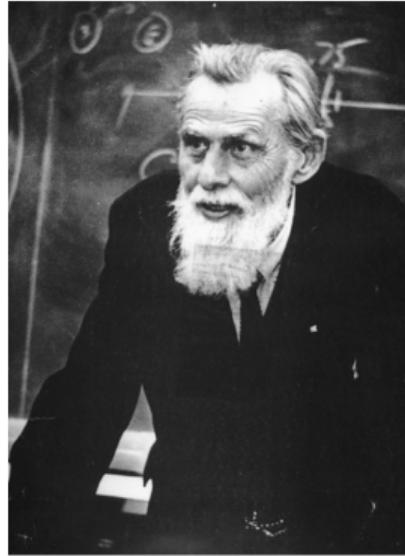
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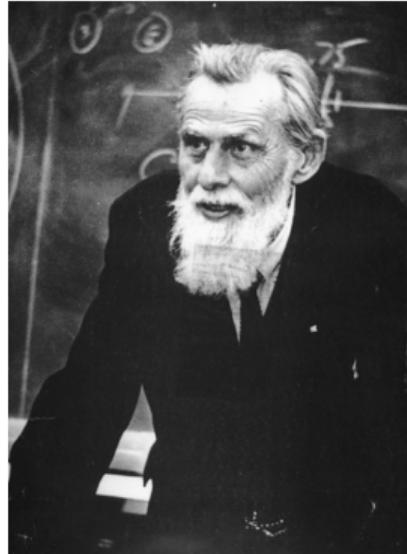
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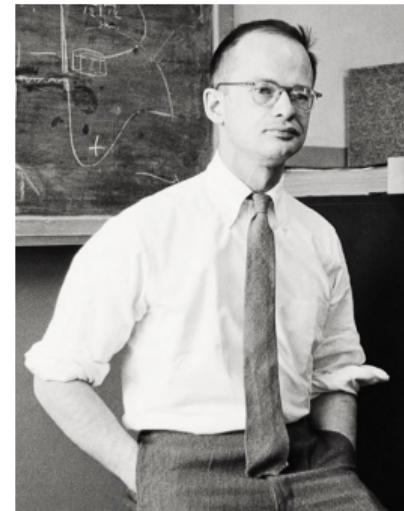
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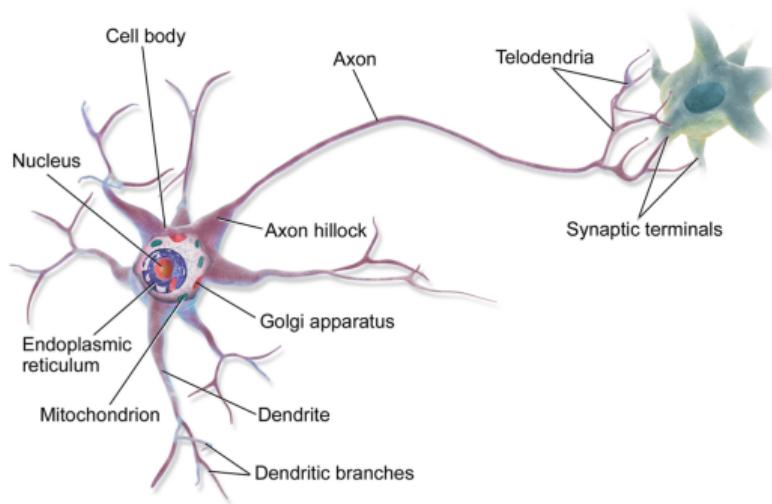
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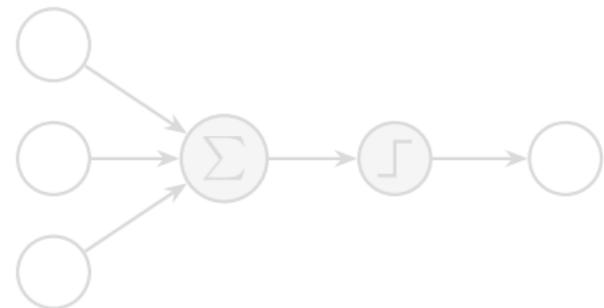
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Neuron

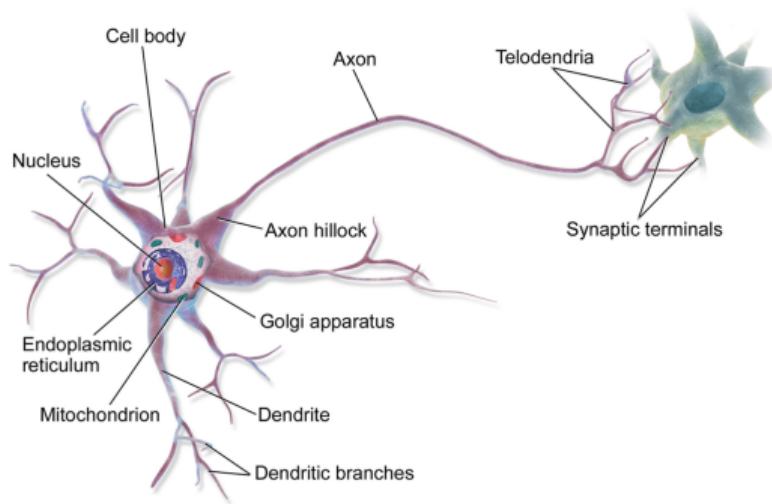


Artificial neuron

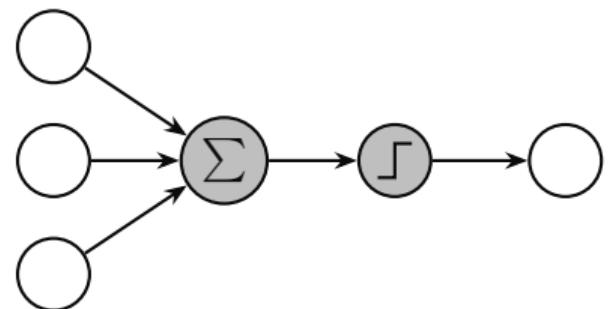


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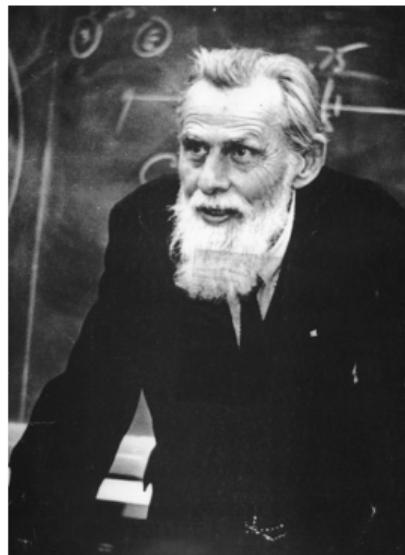
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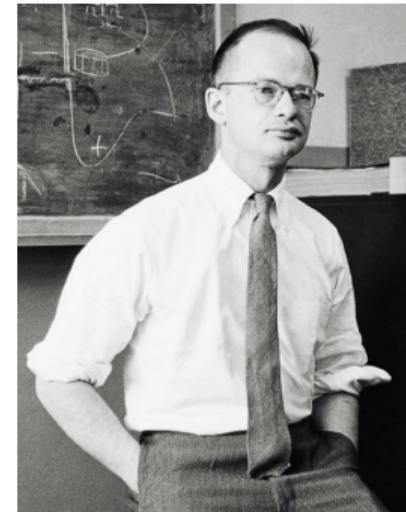
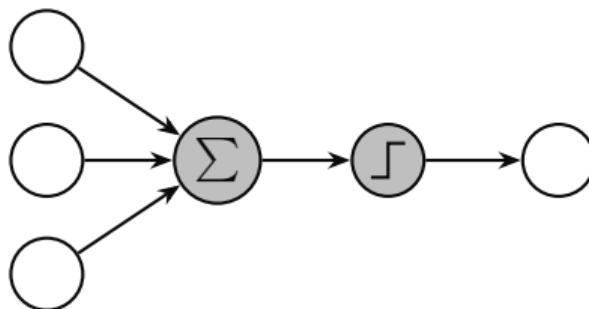


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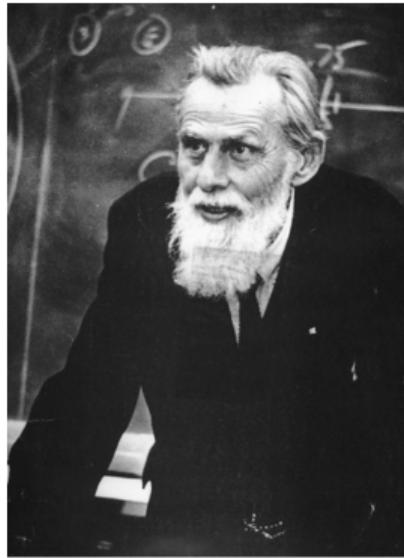
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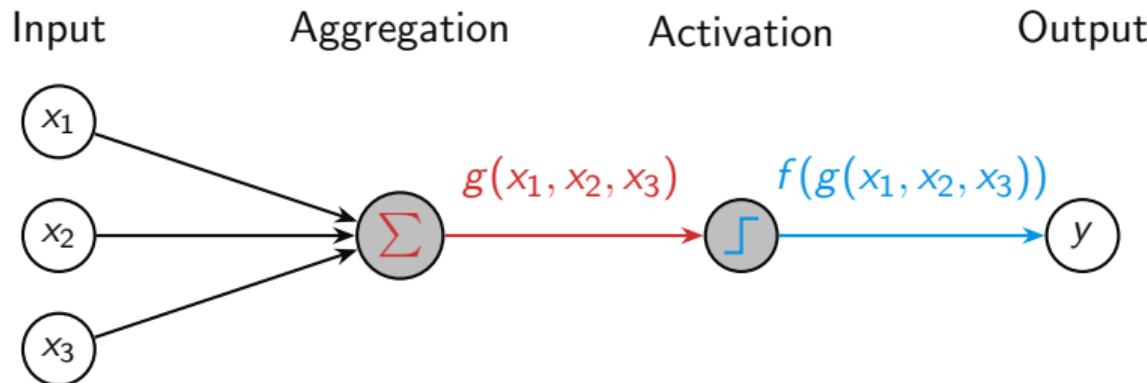
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$$f(x_1, \dots, x_n) = \begin{cases} 1 & \text{if } \sum_{k=1}^n x_k > 1 \\ 0 & \text{otherwise.} \end{cases}$$



Walter H. Pitts Jr

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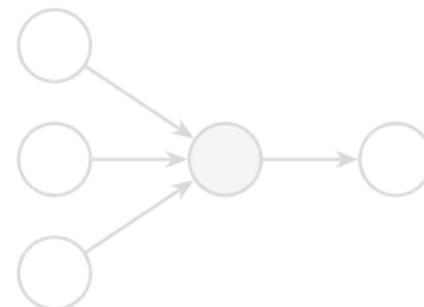
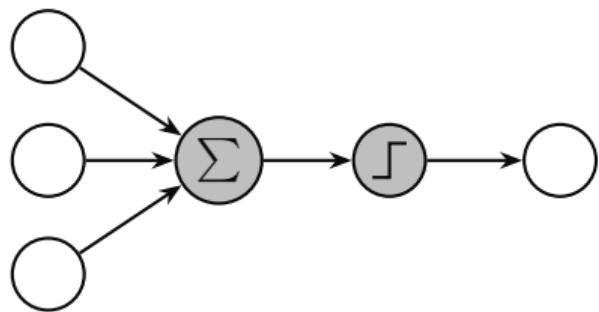


$$g(x_1, x_2, x_3) = x_1 + x_2 + x_3$$

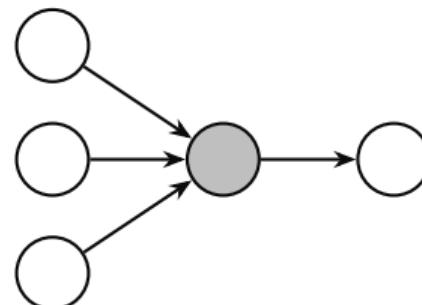
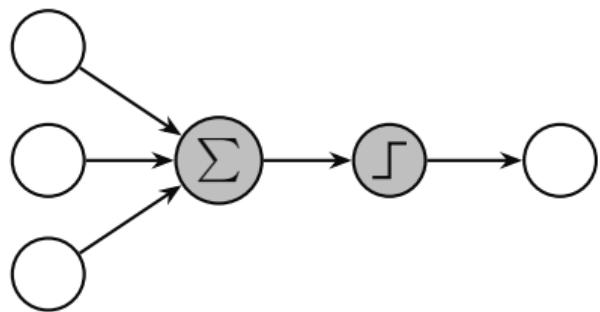
$$f(z) = \begin{cases} 1 & \text{if } z \geq 1 \\ 0 & \text{otherwise.} \end{cases}$$

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Connectionism I: The Mathematical Neuron



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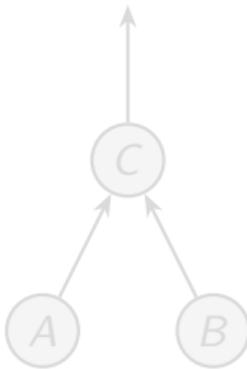


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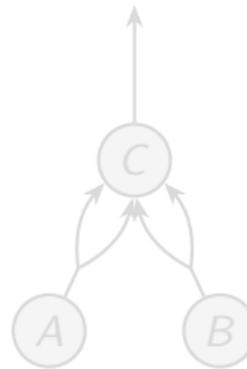
Complex logical operations can be performed using networks of binary neurons.



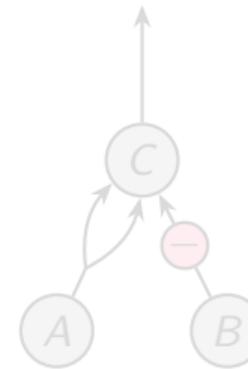
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And: $C = A \wedge B$



Or: $C = A \vee B$



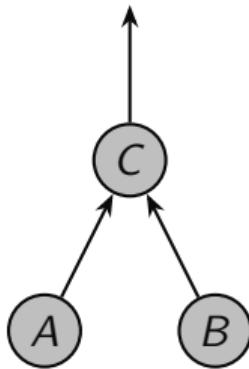
Negation: $C = A \vee \neg B$

Connectionism I: The Mathematical Neuron

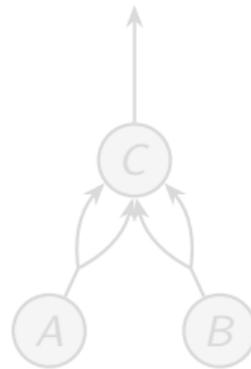
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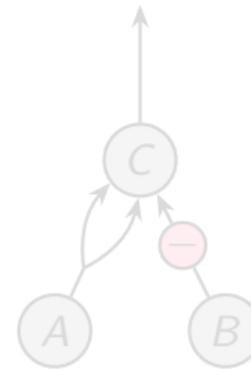
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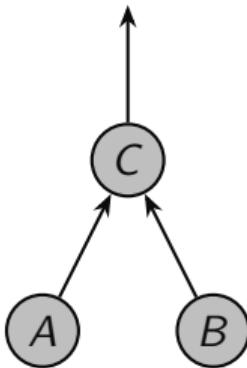
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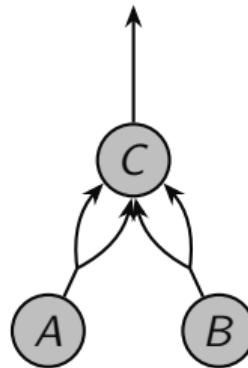
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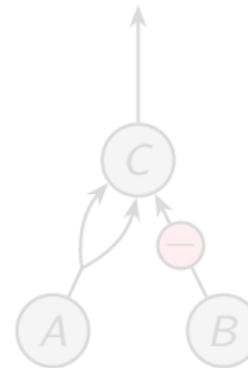
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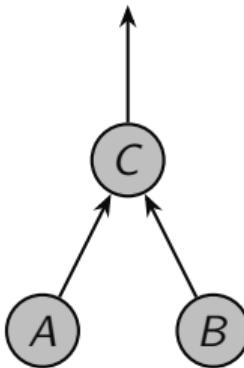
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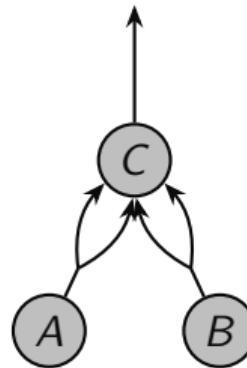
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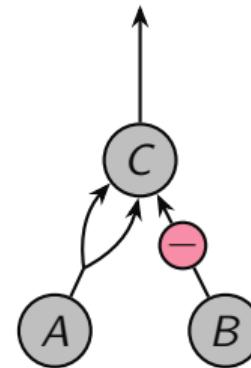
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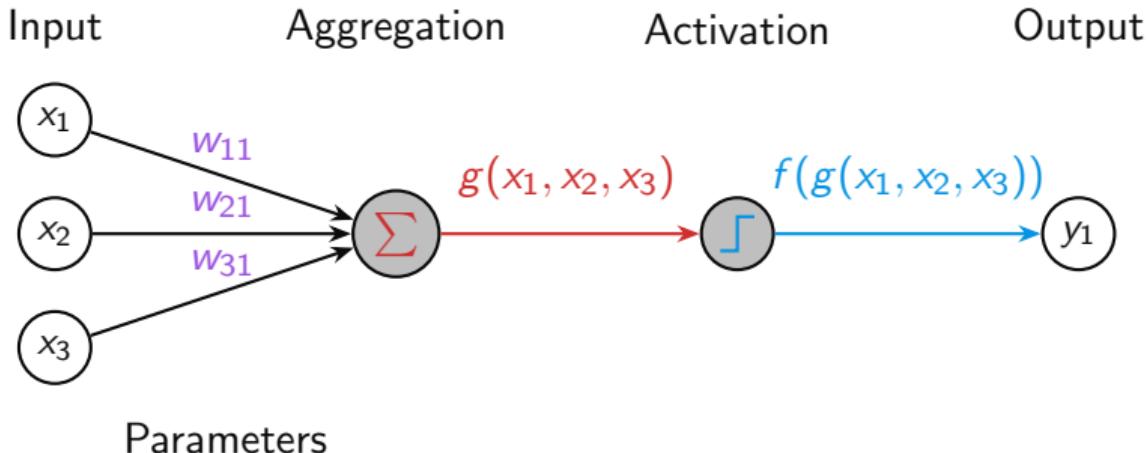
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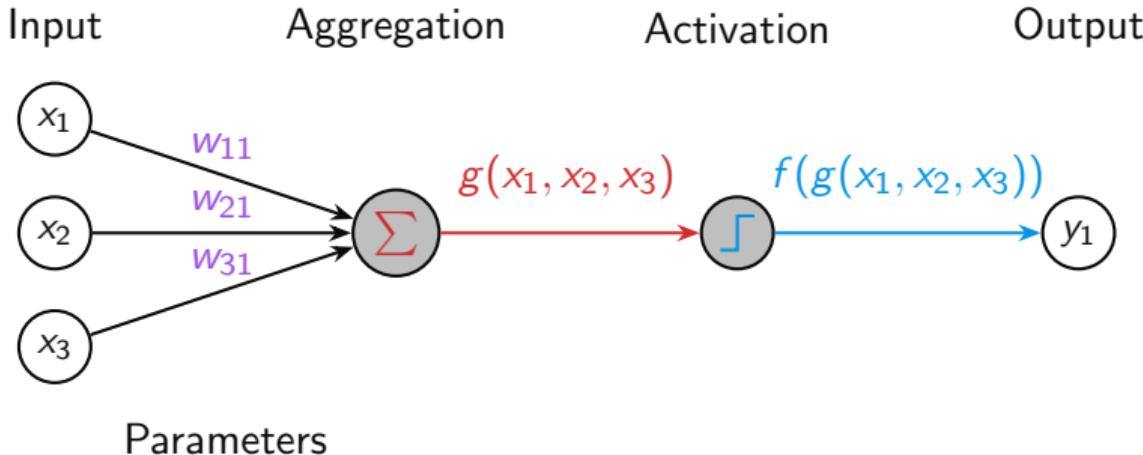
Connectionism I: Synaptic Plasticity



Parameters determine how strong neurons are wired together:

$$g(x_1, x_2, x_3) = x_1 \cdot w_{11} + x_2 \cdot w_{21} + x_3 \cdot w_{31}$$

Connectionism I: Synaptic Plasticity



“Neurons that fire together, wire together.”

$$w_{ij} = w_{ij} - \eta \cdot x_i \cdot y_j$$

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Connectionism I: Mark I Perceptron

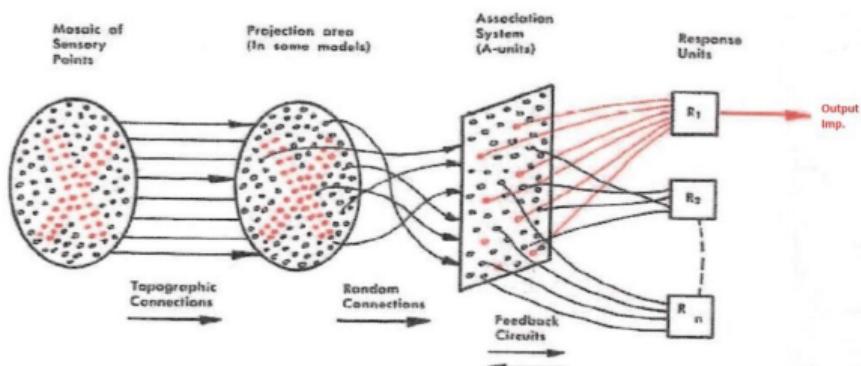
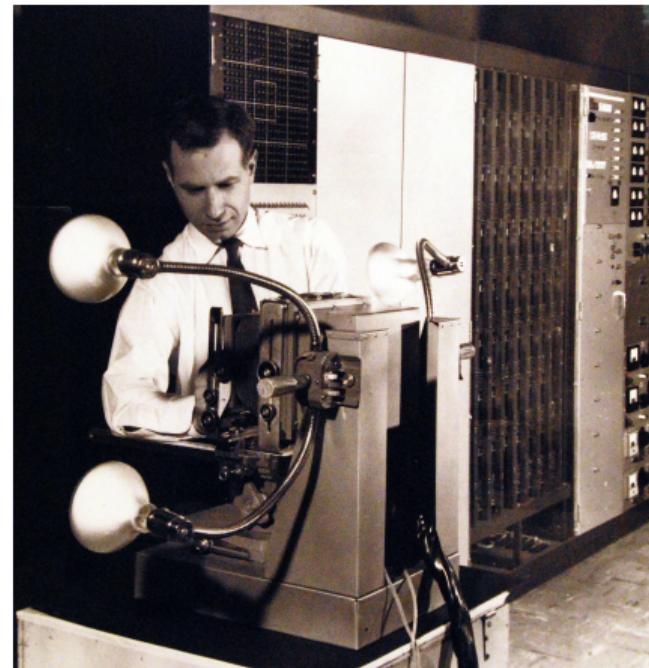


FIG. 2 — Organization of a perceptron.



Charles Wightman

Connectionism I: Mark I Perceptron

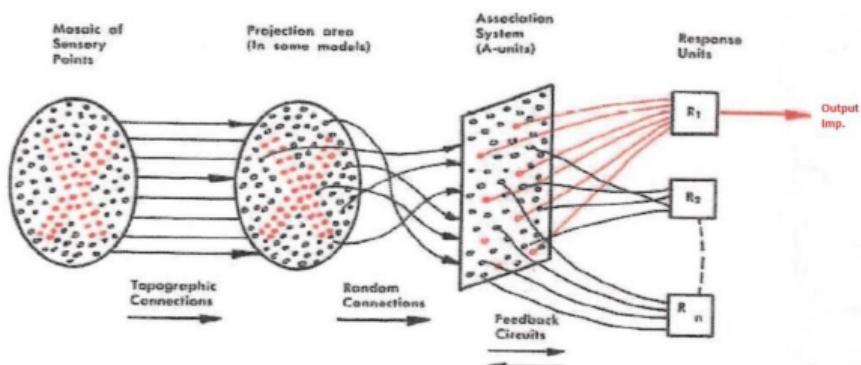
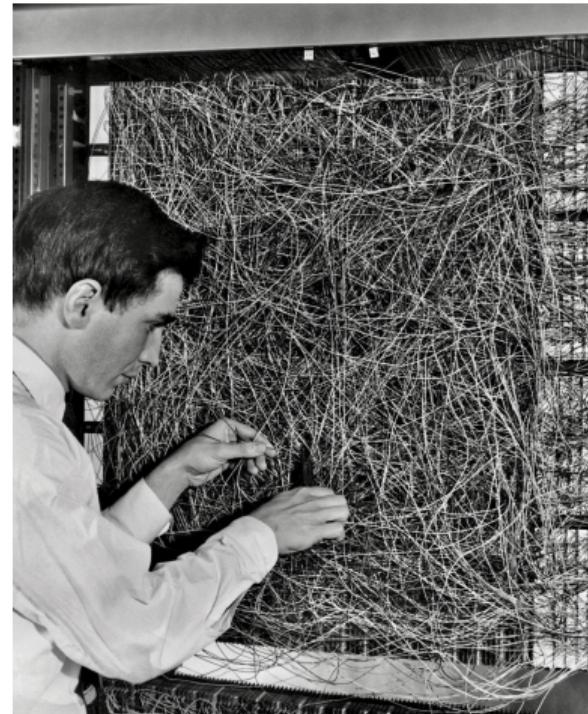


FIG. 2 — Organization of a perceptron.



Frank Rosenblatt

Connectionism I: Mark I Perceptron

Video

1. Introduction

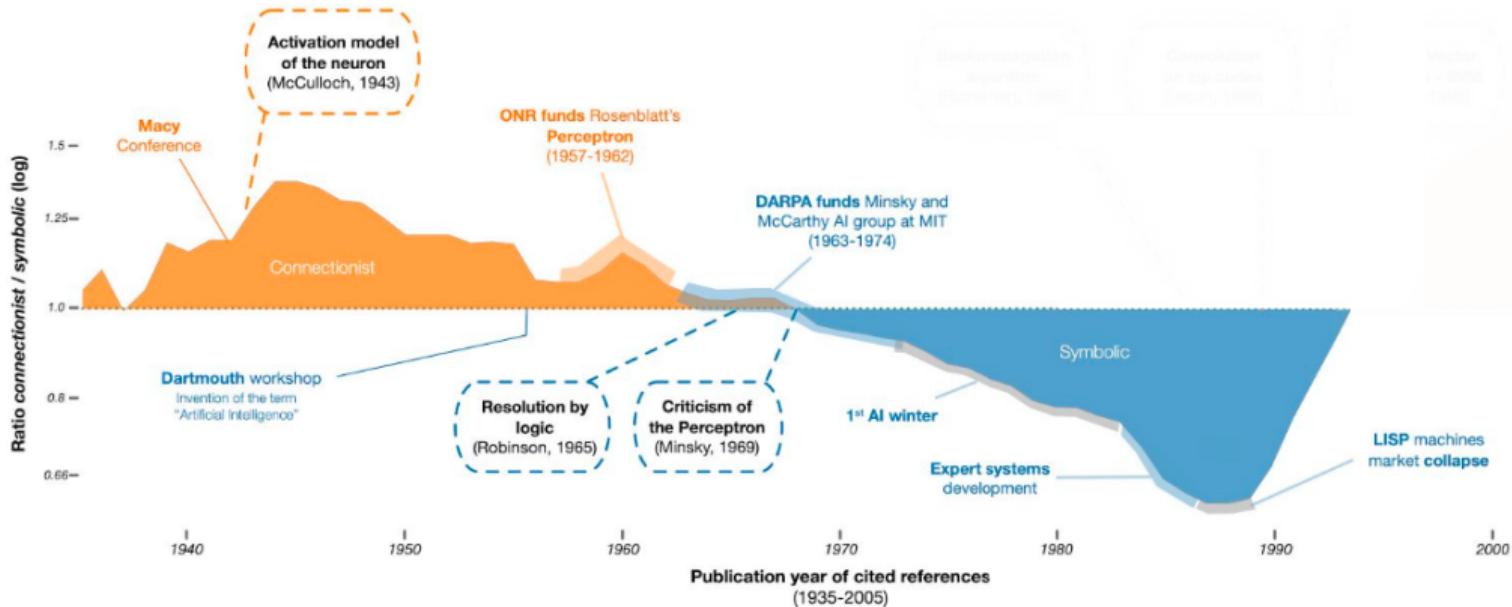
2. Symbolism I

3. Connectionism I

4. Symbolism II

5. Connectionism II

Symbolism II



Source: (Cardon et al., 2018)

Symbolism II: The Dartmouth Workshop



John McCarthy, Marvin Minsky, Claude Shannon, Tranchard More, Ray Solomonoff, Olivier Selfridge, Nathaniel Rochester

Symbolism II: Logos Meets Computation

- Origins of Symbolic AI (1950-1960s)
 - Logic Theorist (1956, Newell & Simon)
 - LISP, logic-based reasoning (McCarthy, 1958)
 - General Problem Solver (1959)
 - Early focus on explicit rule-based reasoning
- Expert systems (1970s–1980s)
 - DENDRAL (chemistry)
 - MYCIN (medical diagnosis)
 - Creation of the Prolog programming language (France, 1972)
- AI Winter (Late 1970s–1980s)
 - Unrealistic expectations unmet by symbolic methods
 - Funding cuts, skepticism
 - Critiques, e.g., Hubert Dreyfus *What Computers Can't Do*

Symbolism II: Toy Problems



Christopher Strachey developed AI program in 1951.

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What are Expert Systems?

Expert systems are rule-based programs designed to emulate the decision-making abilities of human experts in specialized fields.

Key Examples:

- **DENDRAL** (1965–1983)
 - Identified molecular structures from mass spectra data.
 - First practical expert system in chemistry.
- **MYCIN** (1972–1980)
 - Diagnosed infectious blood diseases.
 - Provided explanations for its reasoning.



A Symbolics 3640 Lisp machine: an early (1984) platform for expert systems

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Strengths:

- Explicit representation of knowledge.
- Transparent reasoning (explainability).

Limitations:

- Lack of flexibility (brittle under unexpected scenarios).
- Difficulty handling uncertain or ambiguous situations.



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Assumptions of AI Research of the Time

- **The biological assumption:** The brain processes information in discrete operations by way of some biological equivalent of on/off switches.
- **The psychological assumption:** The mind can be viewed as a device operating on bits of information according to formal rules.
- **The epistemological assumption:** All knowledge can be formalized.
- **The ontological assumption:** The world consists of independent facts that can be represented by independent symbols.

Dreyfus attacks all of these assumptions in (Dreyfus & Dreyfus, 1986; Dreyfus, 1965) using the (European) tradition of phenomenology (Husserl, Heidegger, Merleau-Ponty).

Symbolism II: Dreyfus Critique

“What does [Dreyfus] offer us? Phenomenology! That ball of fluff. That cotton candy!” – Edward Feigenbaum

Dreyfus was right (and successfully ignored):

- Neurons are not essentially digital, rather the action of analog neurons can be simulated by digital machines to a reasonable level of accuracy.
- Human reasoning does not consist primarily of high-level symbol manipulation.
- Humans also solve problems by a fast, intuitive and unconscious System (Kahneman, 2011).
- Common knowledge is difficult to model logically
- Economic collapse of LISP machines.

Symbolism II: Dreyfus Critique

[Dreyfus'] derisiveness has been so provoking that he has estranged anyone he might have enlightened. And that's a pity. – Pamela McCorduck

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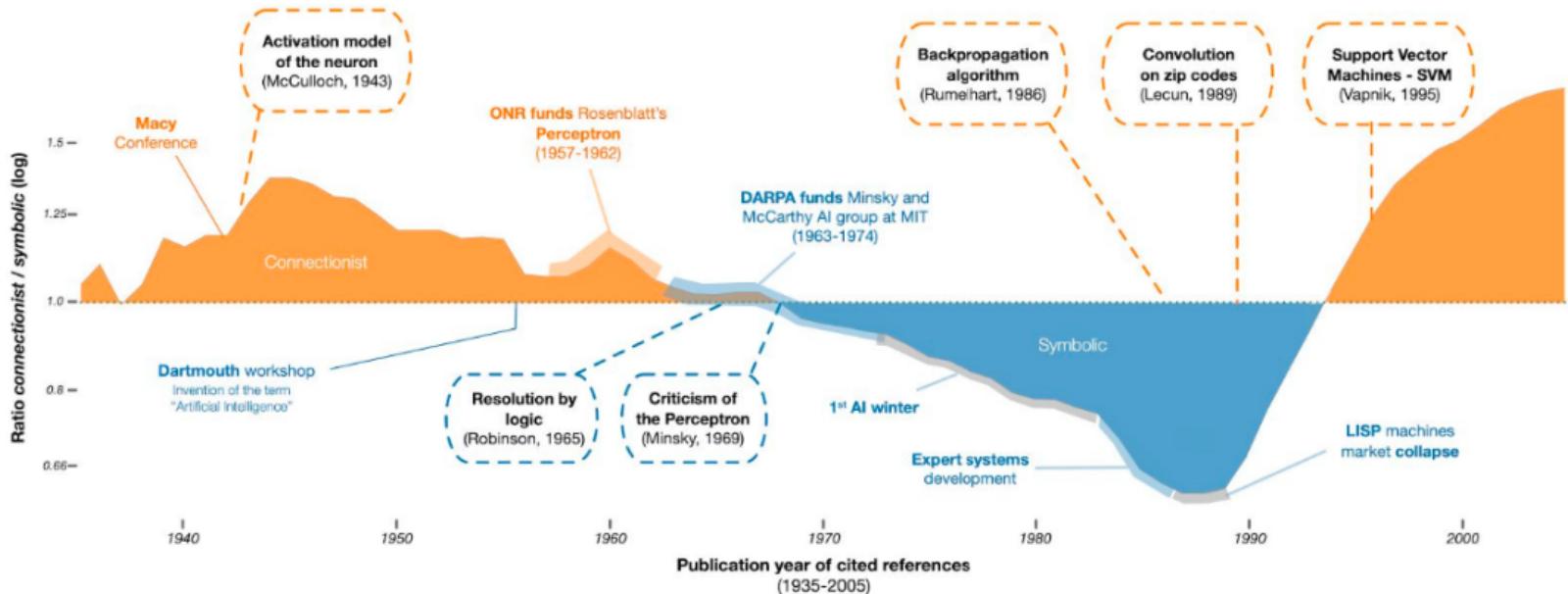
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Connectionism II: Revenge of the Neuron



Source: (Cardon et al., 2018)

Connectionism II: Revenge of the Neuron

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Connectionism II: AI Renaissance (2000–Present)

- **2006–2012: Early Breakthroughs**
 - Revival of deep neural networks
 - Major success: ImageNet competition (AlexNet, 2012)
- **2013–2017: Rapid Expansion of Deep Learning**
 - CNN dominance in image recognition
 - Reinforcement Learning breakthroughs (AlphaGo, 2016)
- **2018–Present: Transformers and Large Language Models**
 - Natural Language Processing revolution (BERT, GPT)
 - Generative AI models (GPT-3, ChatGPT, Stable Diffusion)
- **Modern Symbolic Revival and Hybrid AI (Ongoing)**
 - Neurosymbolic AI: Combining deep learning and symbolic reasoning
 - Explainable AI (XAI): Interpretable, trustworthy systems
 - Importance for ethics, transparency, and safety

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1. Computational Power

- Massive increase in GPU computing capacity.
- Parallelization of neural network training.

2. Big Data

- Availability of huge, labeled datasets.
- Online data collection (ImageNet, web scraping).

3. Algorithmic Advances

- Improved training algorithms (e.g., backpropagation, Adam optimizer).
- New network architectures (CNNs, RNNs, Transformers).

4. Open-source Ecosystem

- Accessible tools: TensorFlow, PyTorch.
- Community-driven knowledge sharing.

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**Any
questions?**

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