

AI in Culture and Arts – Tech Crash Course

A Brief History of Artificial Intelligence

Benedikt Zönnchen

9th of April 2025

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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

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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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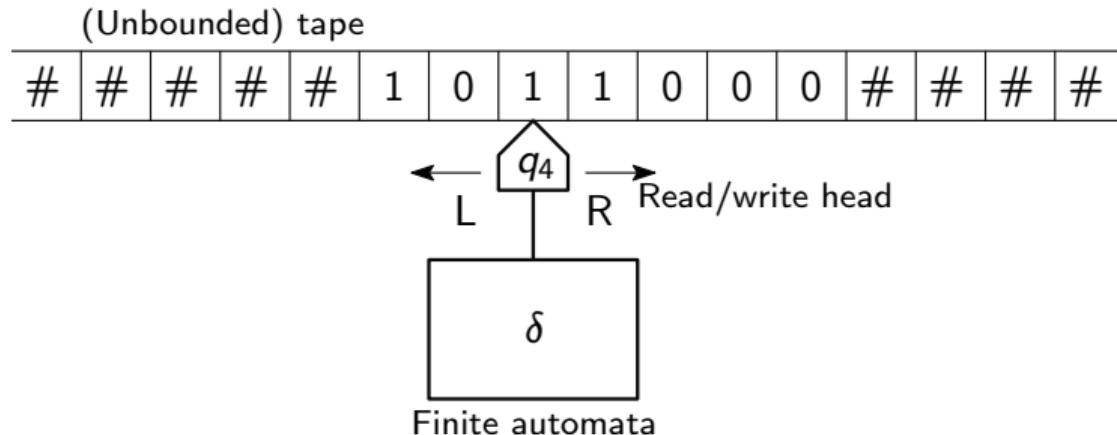
Bool, Frege, Russell



Gödel, Church, Turing

Symbolism I: A Model of Computation

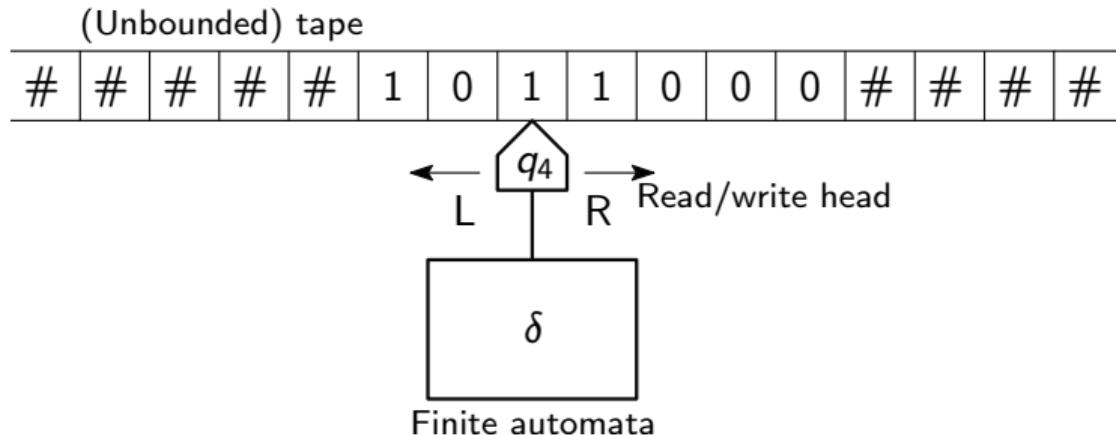
In 1937 Alan Turing presents a general model of computation called the *Turing machine* as a byproduct (? , ?).



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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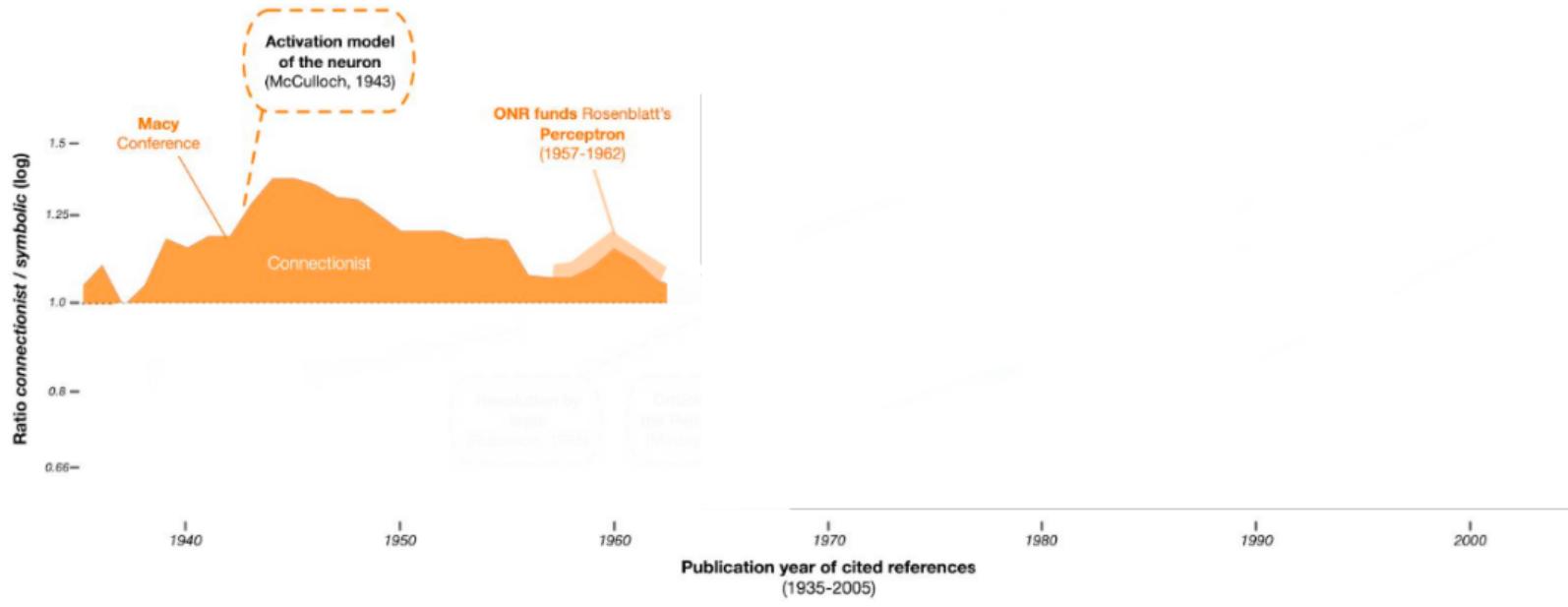
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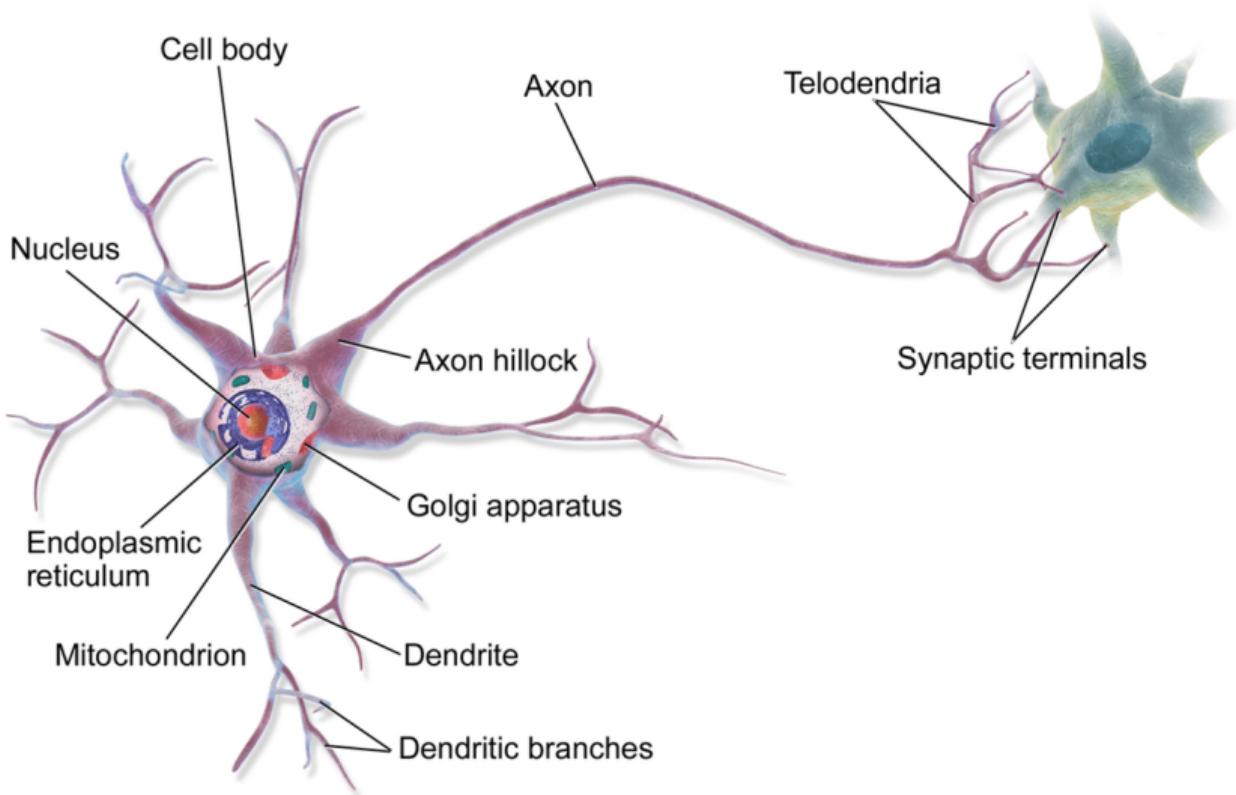
Connectionism I



Source: (?, ?)

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Connectionism I: The Neuron

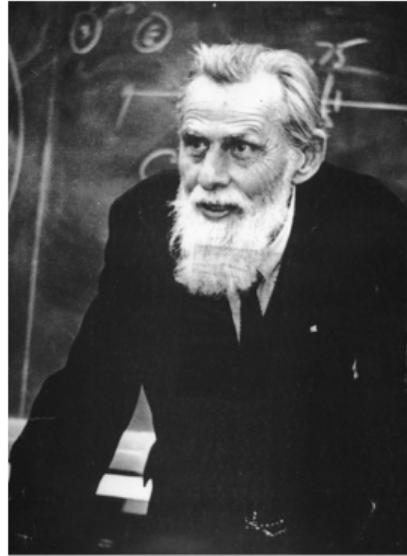


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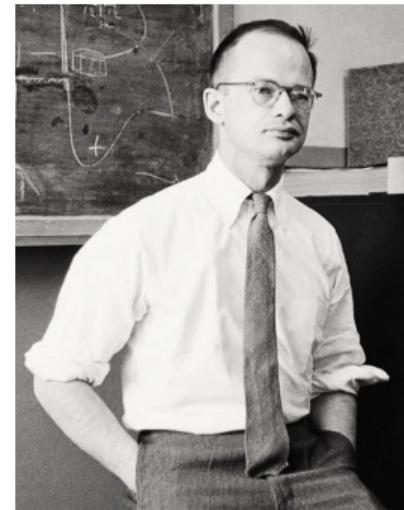
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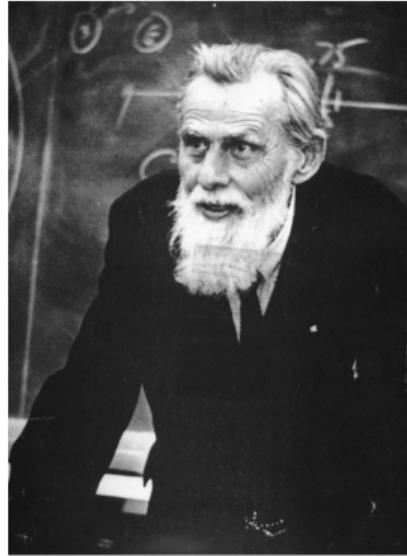
Warren S. McCulloch

- 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.



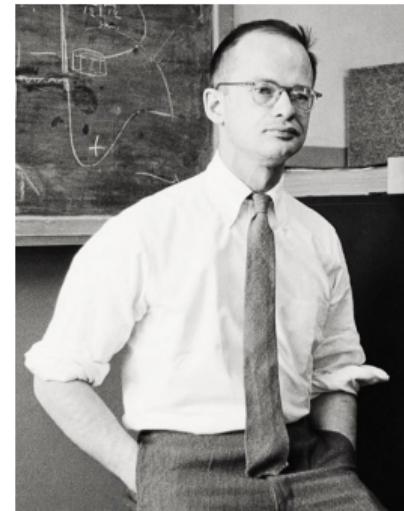
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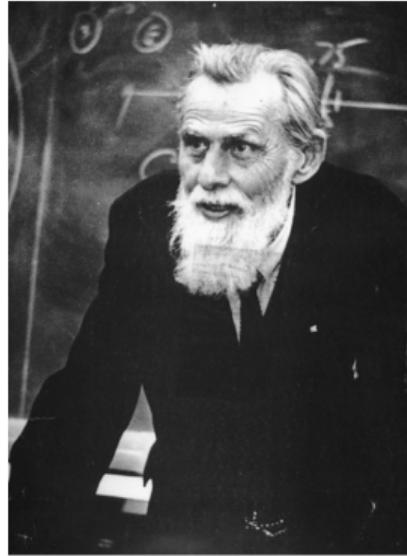
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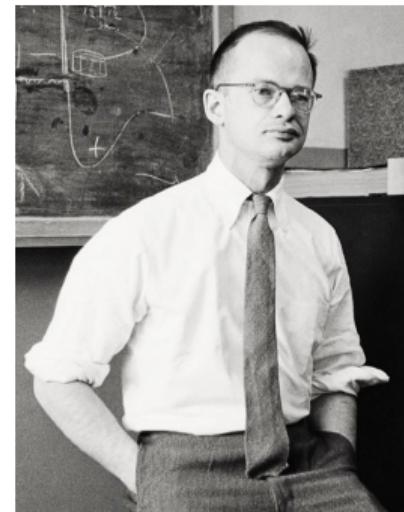
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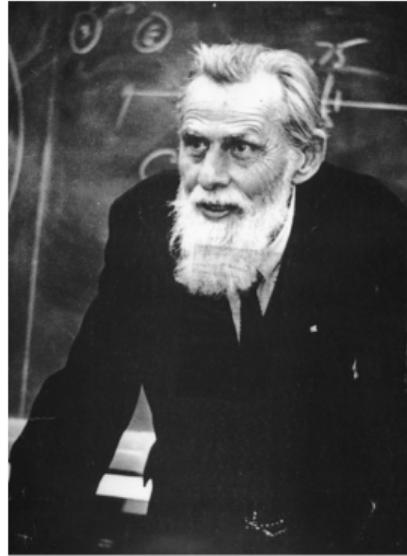
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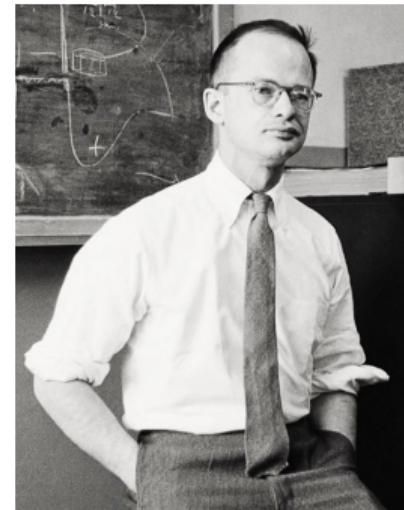
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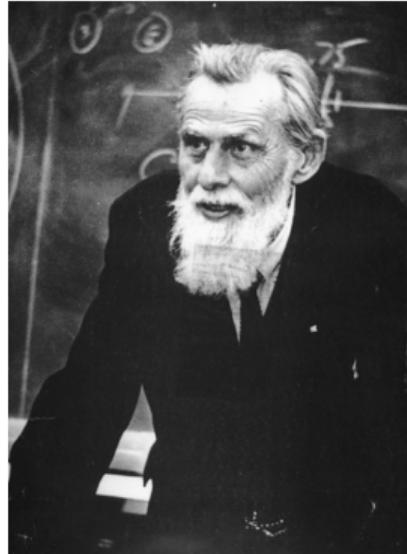
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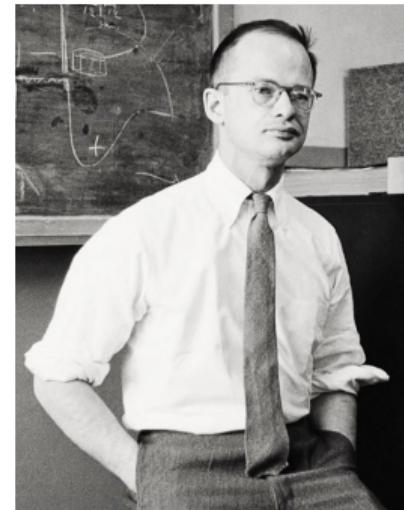
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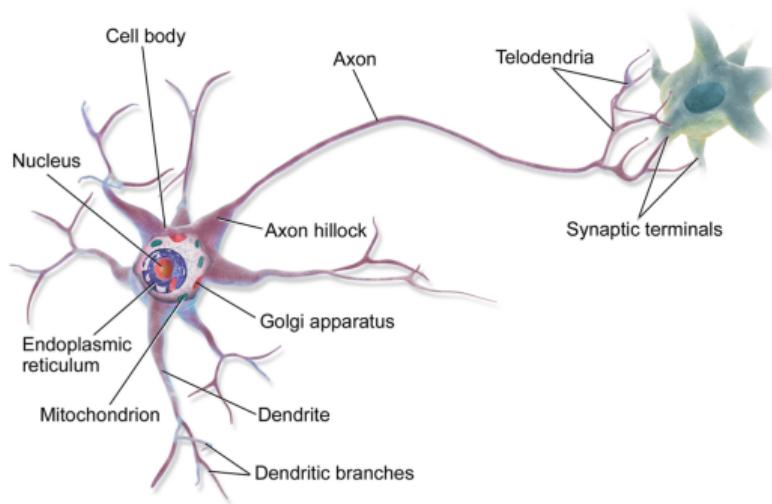
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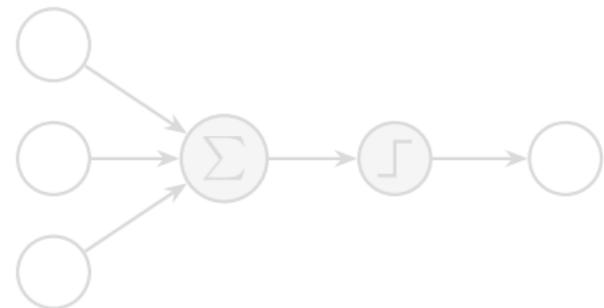
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Neuron

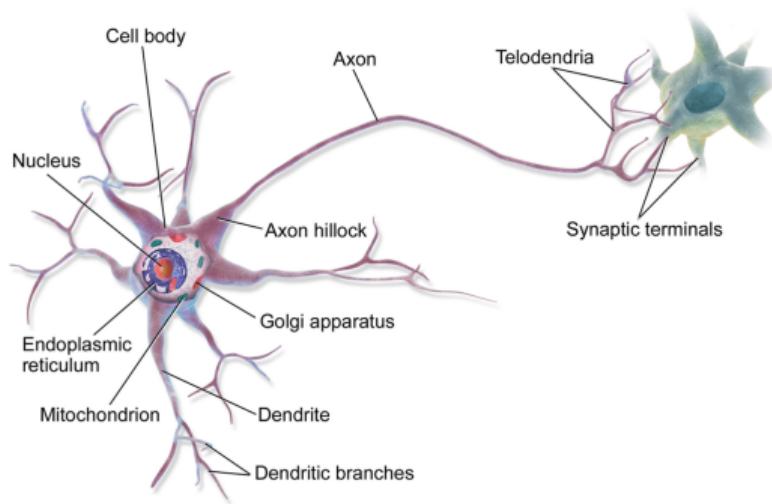


Artificial neuron

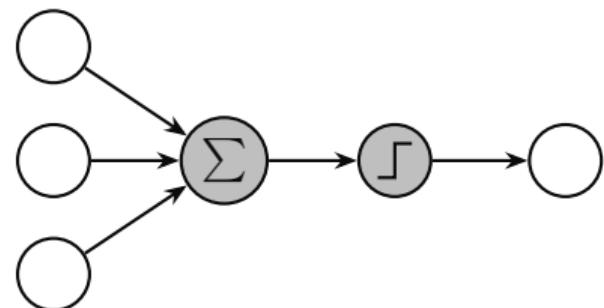


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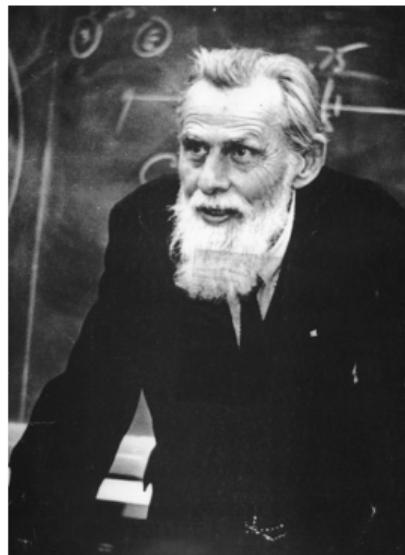
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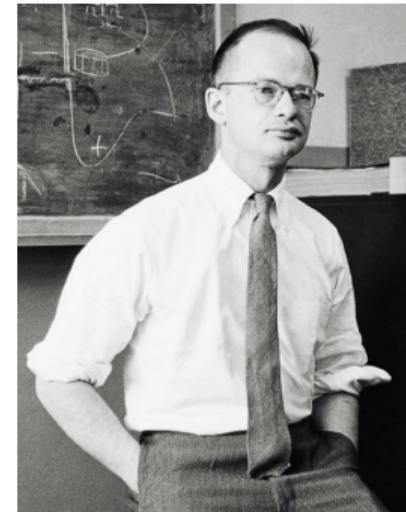
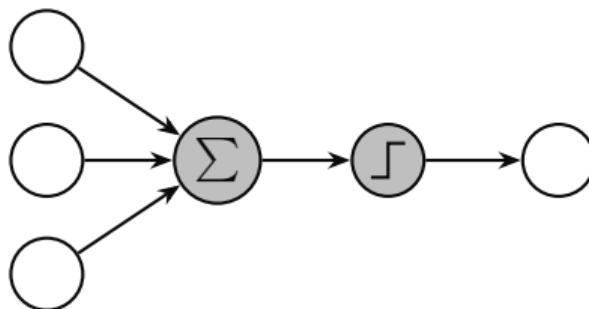


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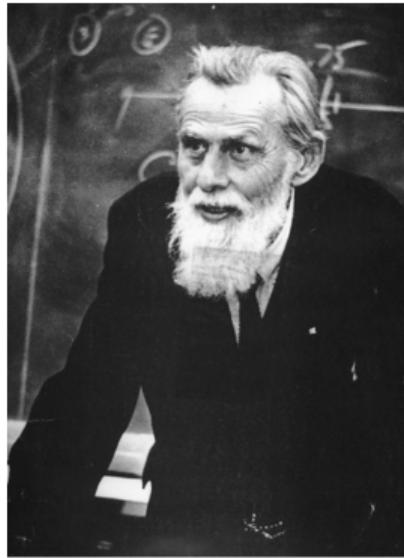
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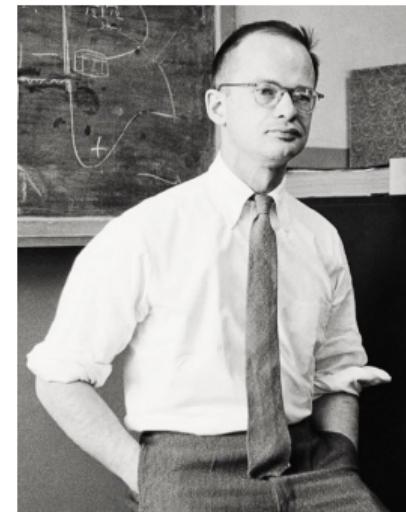
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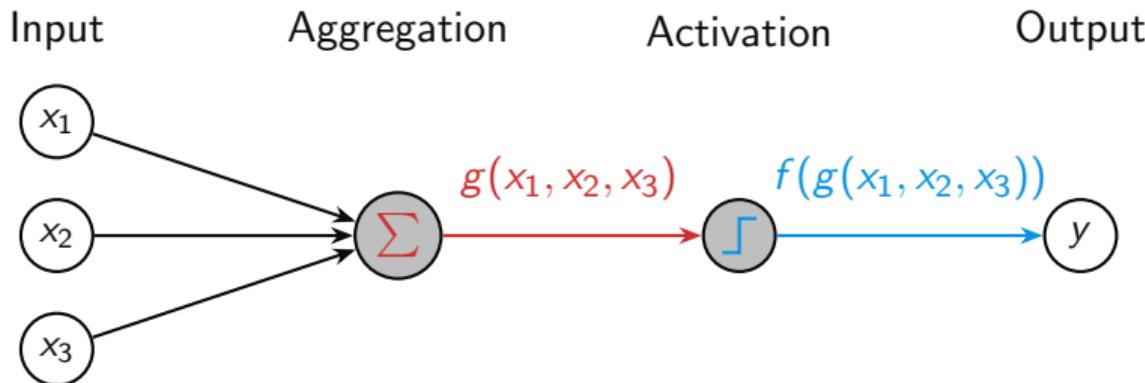
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$$f(x_1, \dots, x_n) = \begin{cases} 1 & \text{if } \sum_{k=1}^n x_k > 1 \\ 0 & \text{otherwise.} \end{cases}$$



Walter H. Pitts Jr

Connectionism I: The Mathematical Neuron

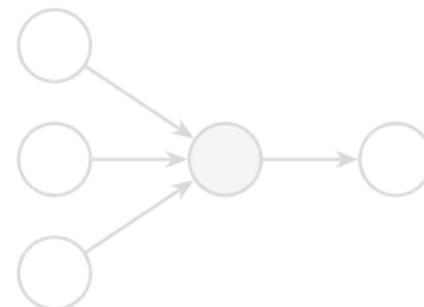
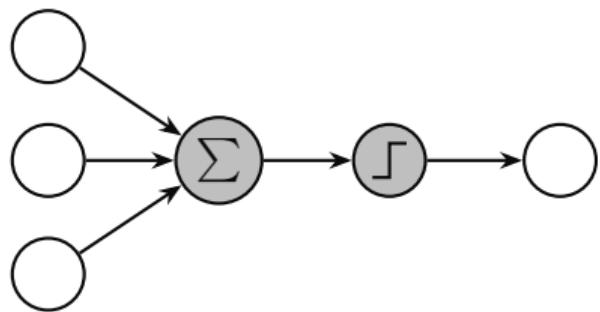


$$g(x_1, x_2, x_3) = x_1 + x_2 + x_3$$

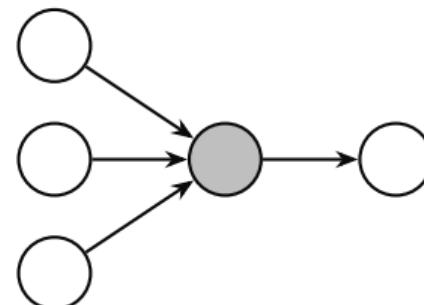
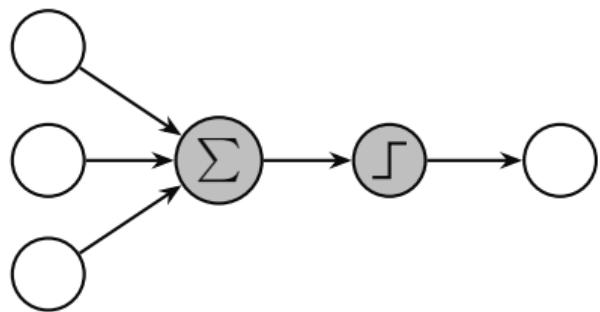
$$f(z) = \begin{cases} 1 & \text{if } z \geq 1 \\ 0 & \text{otherwise.} \end{cases}$$

$$y = \begin{cases} 1 & \text{if } x_1 + x_2 + x_3 \geq 1 \\ 0 & \text{otherwise.} \end{cases}$$

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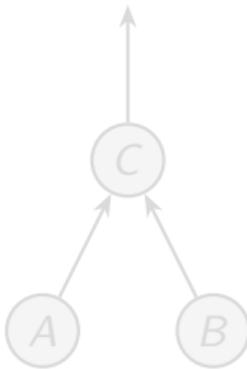


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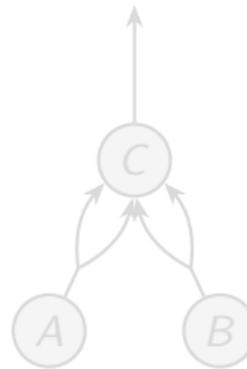
Complex logical operations can be performed using networks of binary neurons.



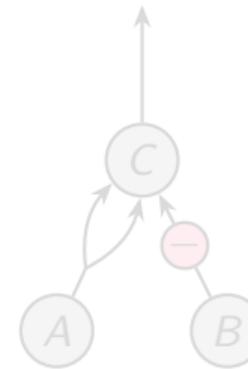
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And: $C = A \wedge B$



Or: $C = A \vee B$



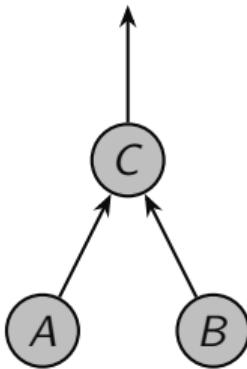
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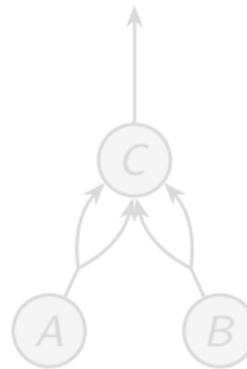
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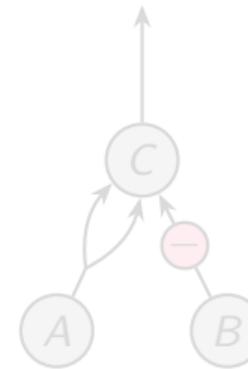
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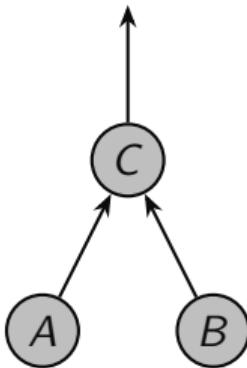
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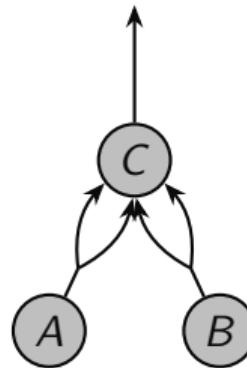
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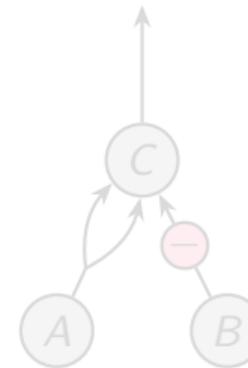
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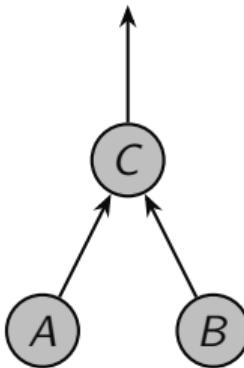
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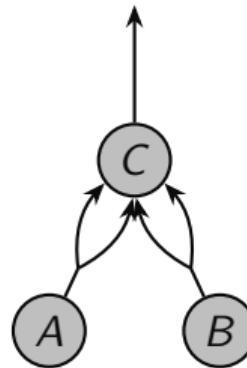
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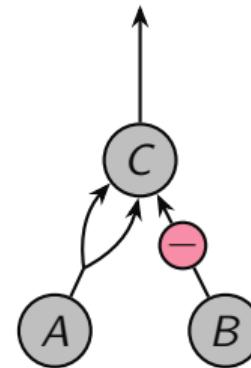
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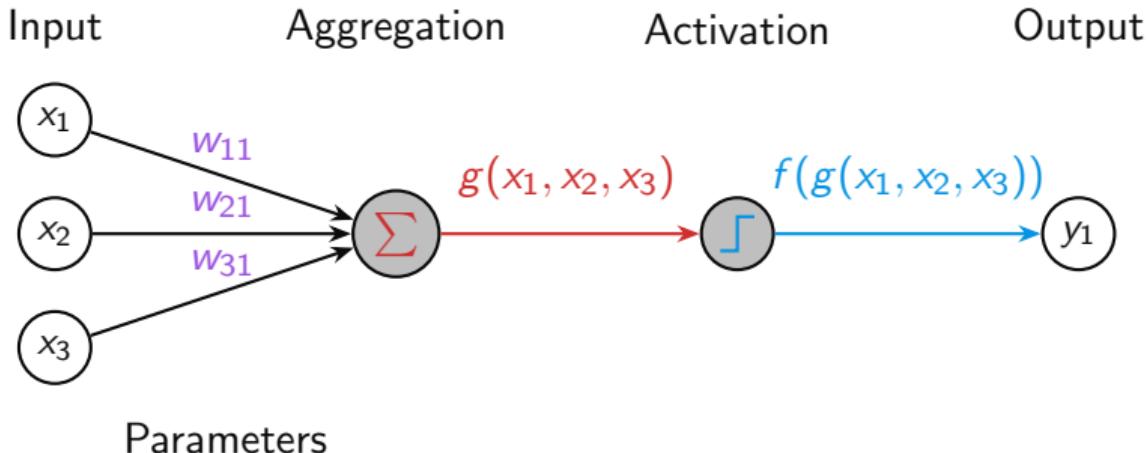
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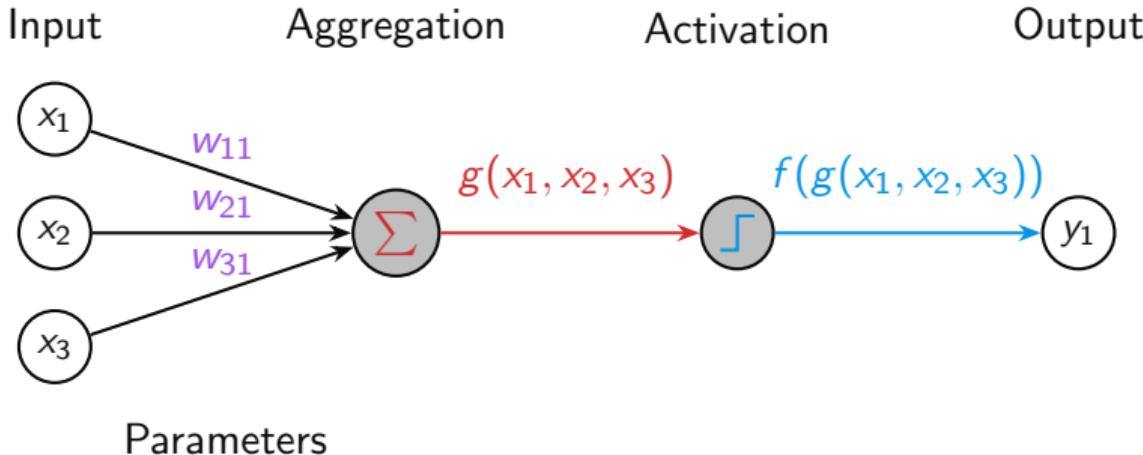
Connectionism I: Synaptic Plasticity



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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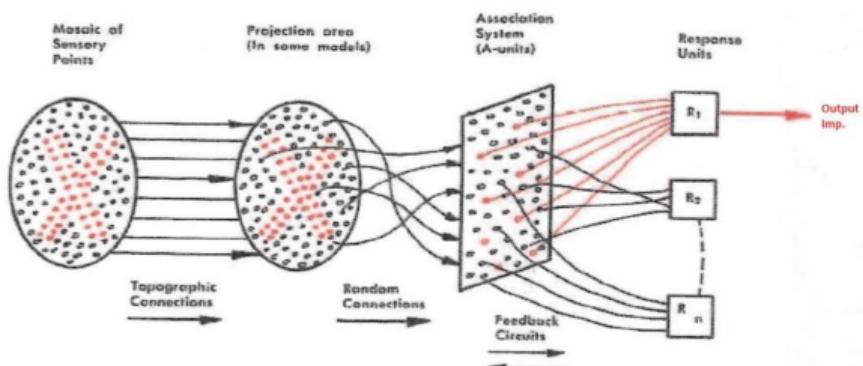
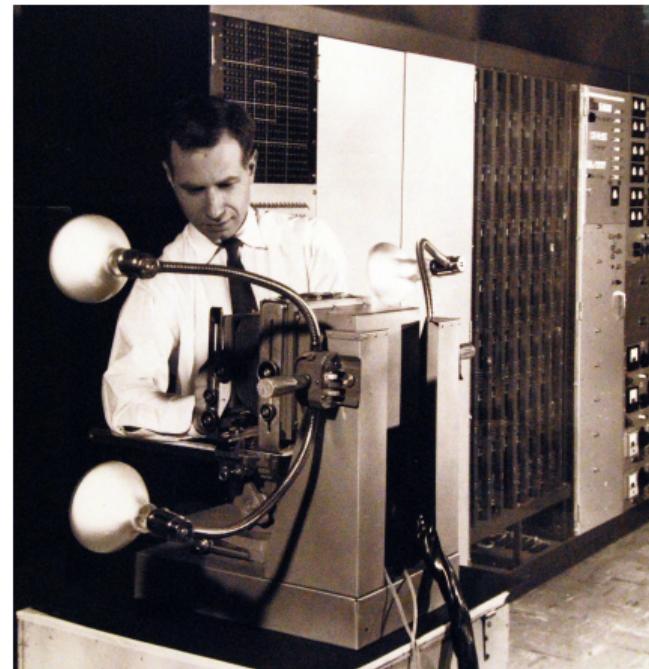


FIG. 2 — Organization of a perceptron.



Charles Wightman

Connectionism I: Mark I Perceptron

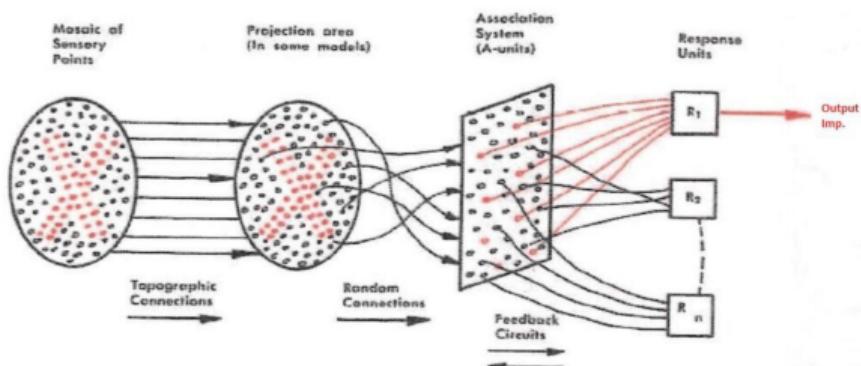
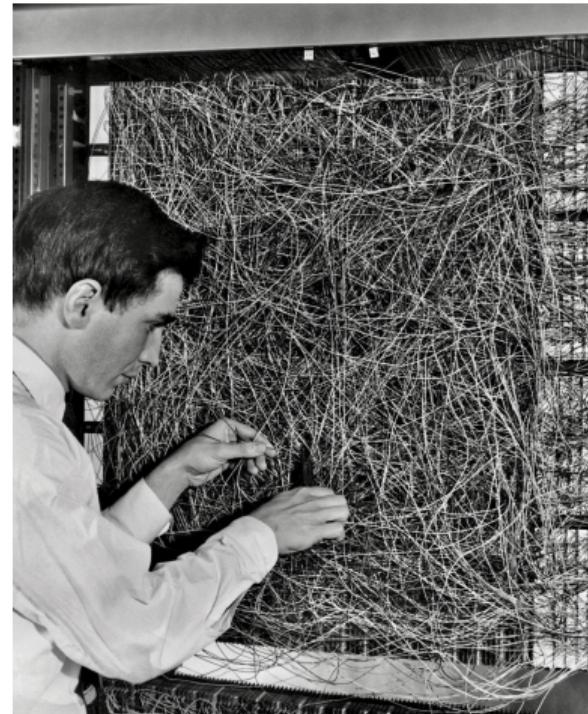


FIG. 2 — Organization of a perceptron.



Frank Rosenblatt

Connectionism I: Mark I Perceptron

Video

1. Introduction

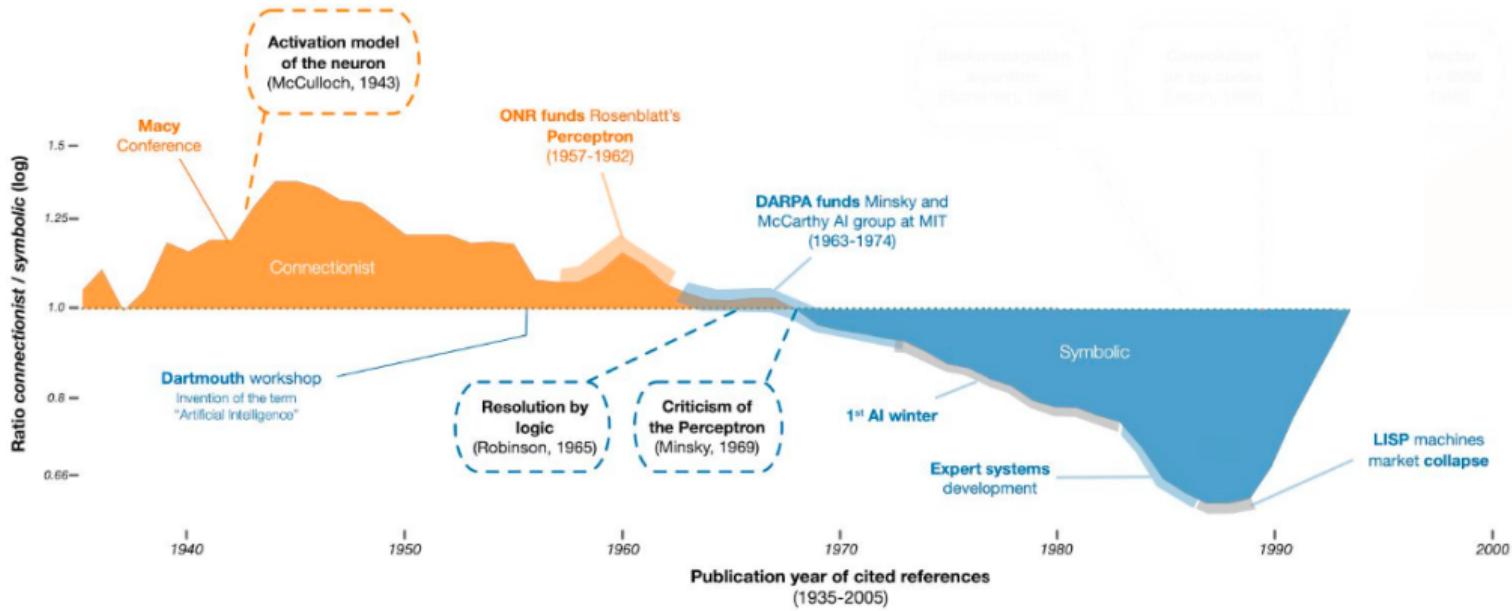
2. Symbolism I

3. Connectionism I

4. Symbolism II

5. Connectionism II

Symbolism II



Source: (? , ?)

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.



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

Symbolism II

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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 (?, ?, ?) 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 (? , ?).
- 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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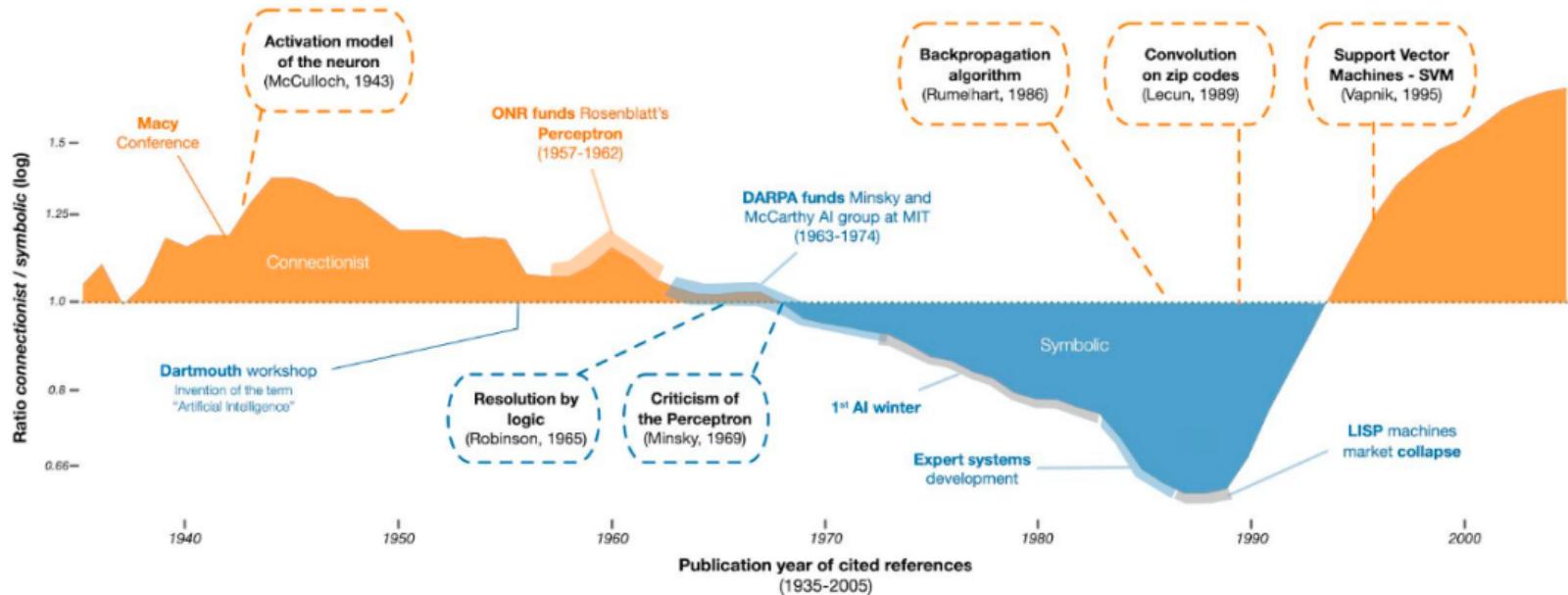
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Connectionism II: Revenge of the Neuron



Source: (? , ?)

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?**

References I

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