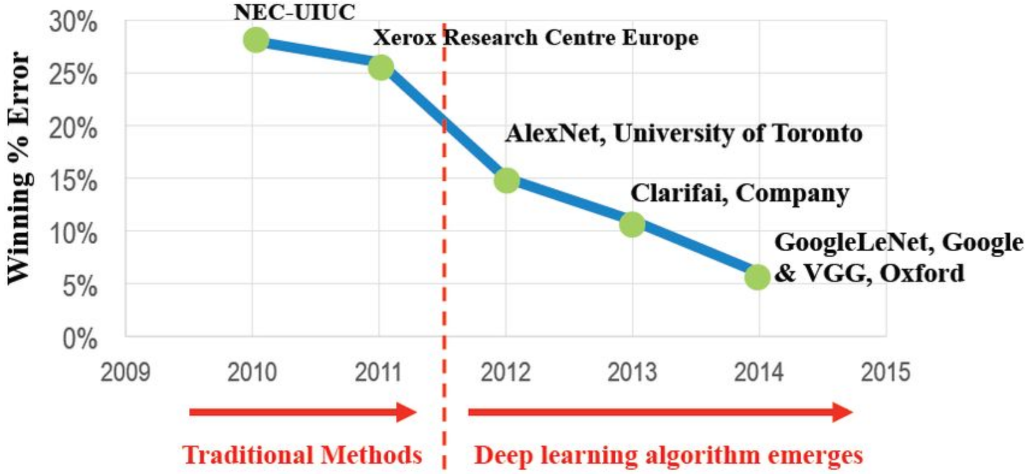
Neuroscience vs AI

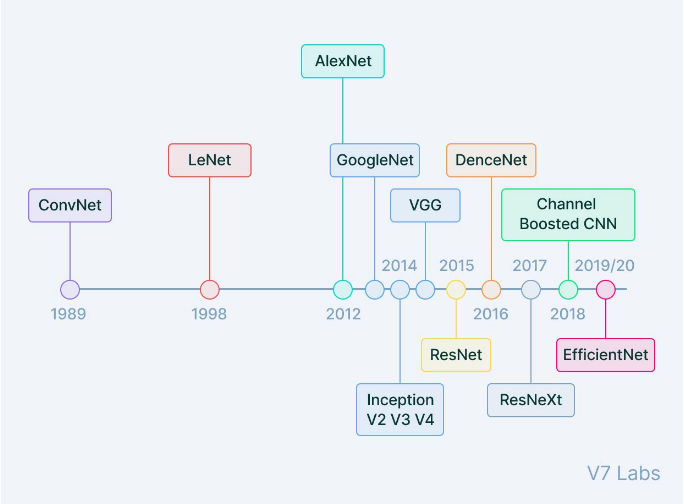
How did neurosciences discoveries formed modern AI techniques?

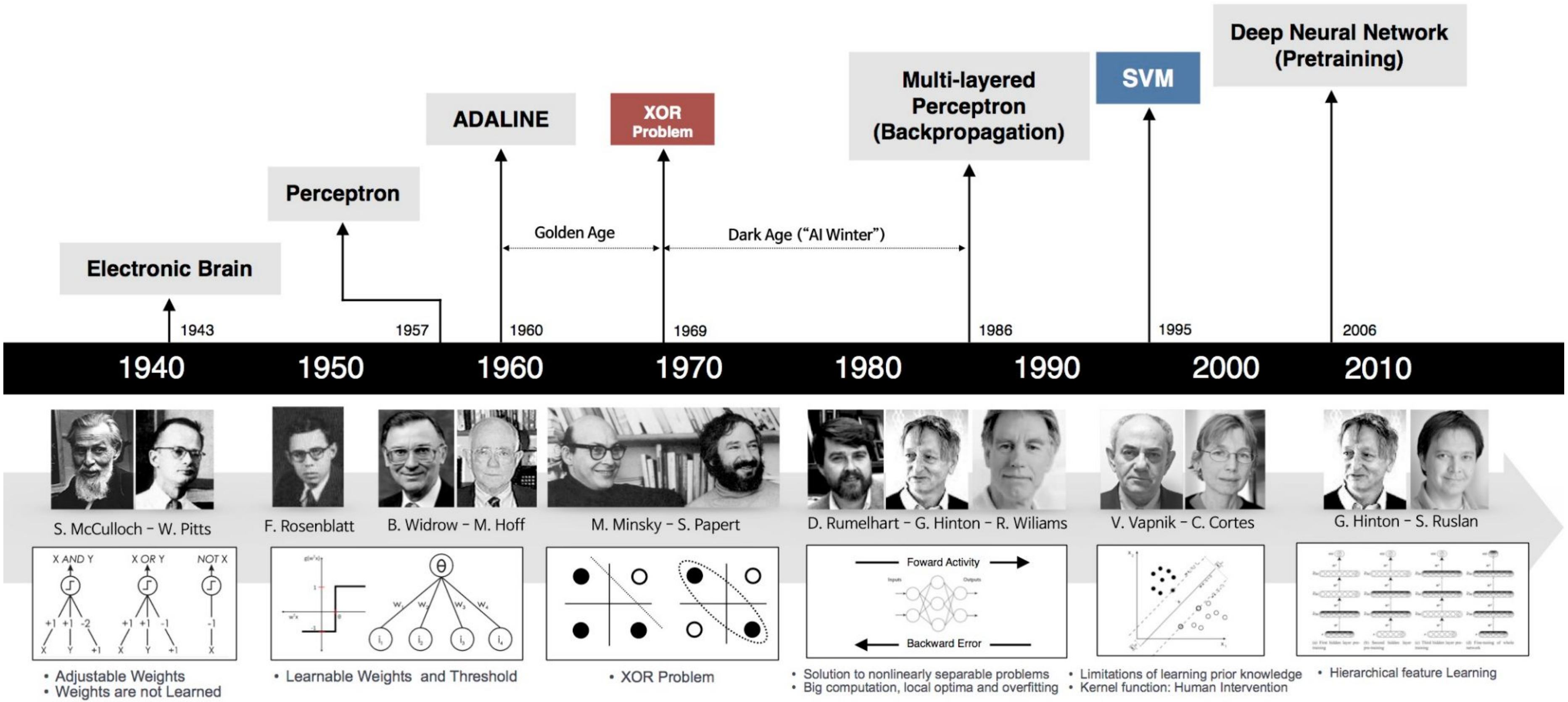
M.Sc. Petr Nejedlý
nejedly@isibrno.cz

Brief recapitulation from yesterday



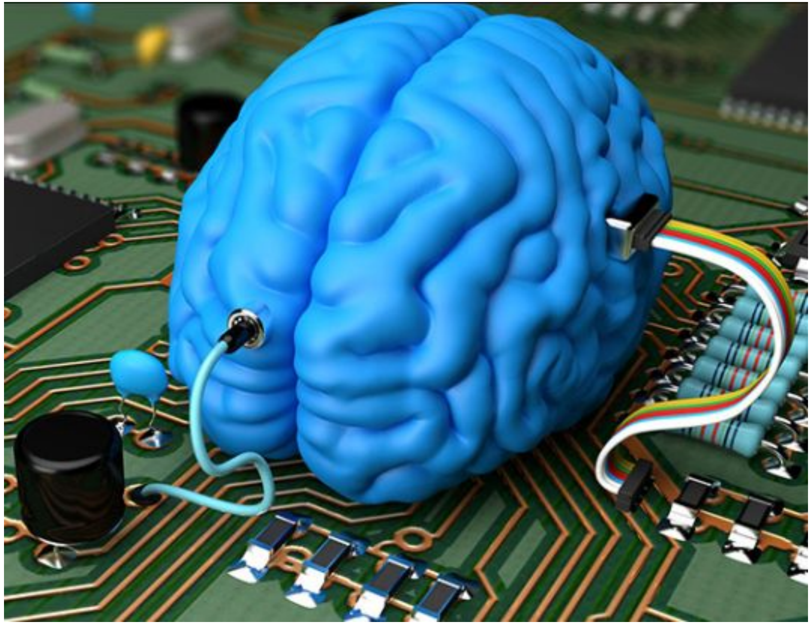
Deep learning hype emerged from Imagenet competition in 2012.




Electronic Brain
Perceptron
ADALINE
XOR Problem
Multi-layered Perceptron (Backpropagation)
SVM
Deep Neural Network (Pretraining)
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
1960
1970
1980
1990
2000
2010
S. McCulloch - W. Pitts
F. Rosenblatt
B. Widrow - M. Hoff
M. Minsky - S. Papert
D. Rumelhart - G. Hinton - R. Wiliams
V. Vapnik - C. Cortes
G. Hinton - S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

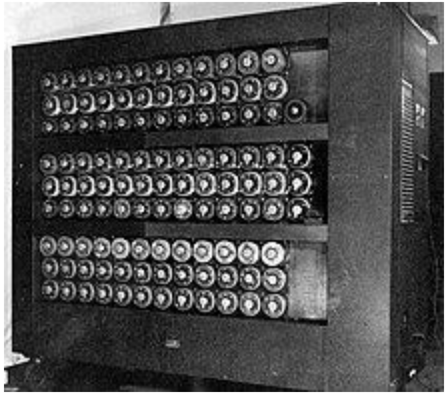
Outline

- Brief Origins of computing
  - Turing Machine
  - Von Neumann architecture
- How did neuroscience experiments in 1950 - 1970 pioneered the idea of neural networks?
- How are CNNs similar to the brain visual cortex?
- Biology inspired computing
  - Spiking Neural Networks
  - Neuromorphic chips
  - Liquid time constant neural networks
- Future directions of AI

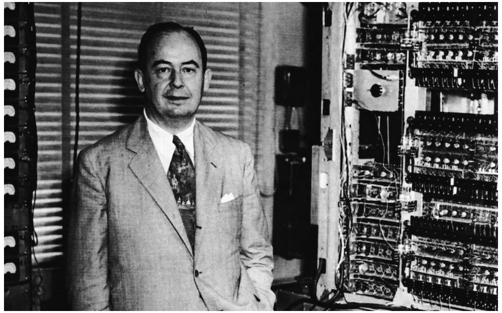


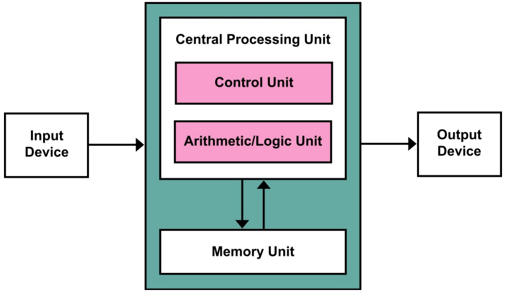
Origins of computing

In 1936, at Cambridge University, **Alan Turing** invented the principle of the modern computer



In 1945, The von Neumann machine was created by its namesake, **John von Neumann**, a physicist and mathematician, building on the work of Alan Turing





How can we further improve the computer architecture?

How can we further improve the computer architecture?

Look deep into nature, and then you will understand everything better.

Albert Einstein

How can we further improve the computer architecture?

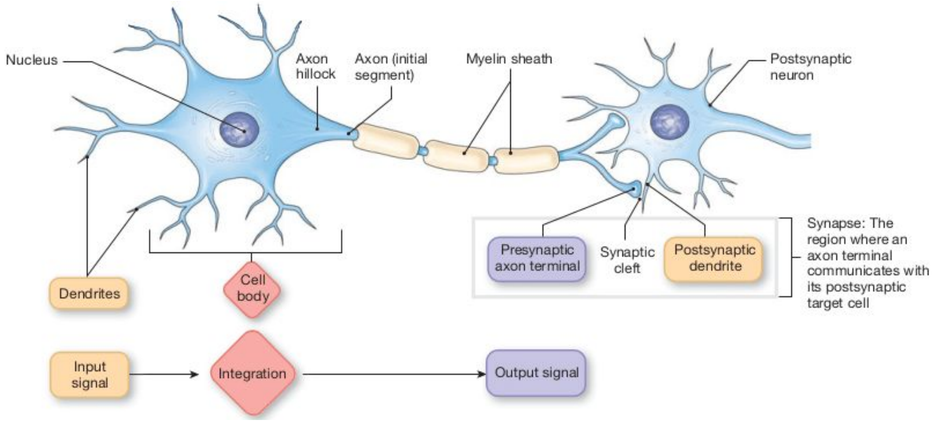
Look deep into nature, and then you will understand everything better.

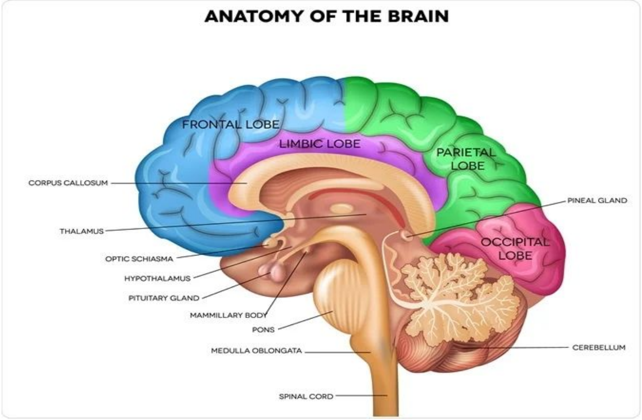
Albert Einstein

Neuroscience is by far the most exciting branch of science because the brain is the most fascinating object in the universe.

Stanley B. Prusiner

How did the evolution form the best “computer” in the universe?





- The average brain weight of the adult is about 1.2 Kg
- Energy consumptions approx. 15 Watts
- maximal firing rate of single neuron max 300-400 Hz

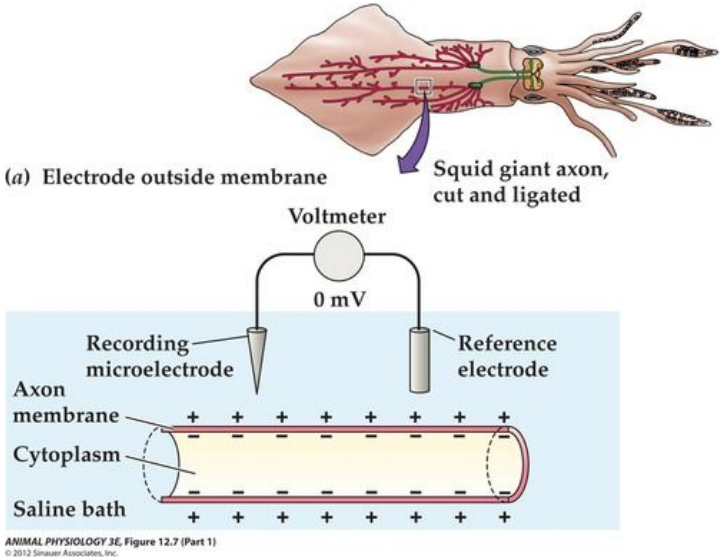
- Modern CPUs use 150 Watts, GPUs 250 Watts
- clock speed is in GHz

Human brain is too complex to study as a whole, let’s start with basic units i.e. Neurons

- the soma of a neuron can vary from 4 to 100 μm in diameter
- axon diameter ~0.1–10 μm

Neurosciences Discoveries that led to modern AI techniques

- Alan Hodgkin and Andrew Huxley described the model in **1952** to explain the ionic mechanisms underlying the initiation and propagation of action potentials in the squid giant axon. They received the **1963** Nobel Prize in Physiology or Medicine for this work.



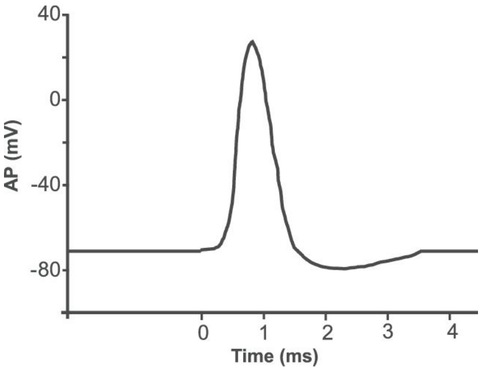
Squid axon might be as large *as **1mm** in diameter (approx. 100x bigger in comparison with humans)*

$$I = C_m \frac{\mathrm{d}V_m}{\mathrm{d}t} + \bar{g}_{\mathrm{K}} n^4 (V_m - V_K) + \bar{g}_{\mathrm{Na}} m^3 h (V_m - V_{Na}) + \bar{g}_l (V_m - V_l),$$

$$\frac{dn}{dt} = \alpha_n(V_m)(1-n) - \beta_n(V_m)n$$

$$\frac{dm}{dt} = \alpha_m(V_m)(1-m) - \beta_m(V_m)m$$

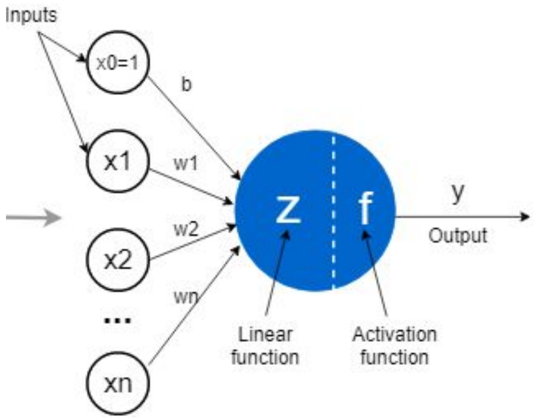
$$\frac{dh}{dt} = \alpha_h(V_m)(1-h) - \beta_h(V_m)h$$



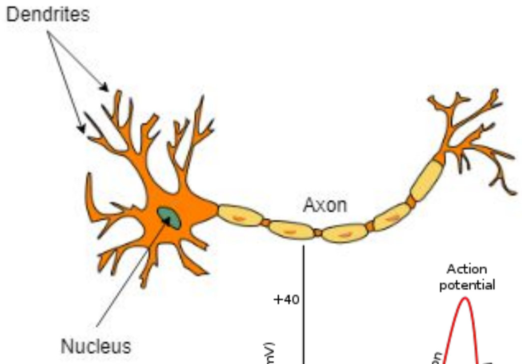
- System of nonlinear differential equations
- Too difficult to solve, complex networks with multiple neurons
- Not very useful in state of the art AI, BUT …..

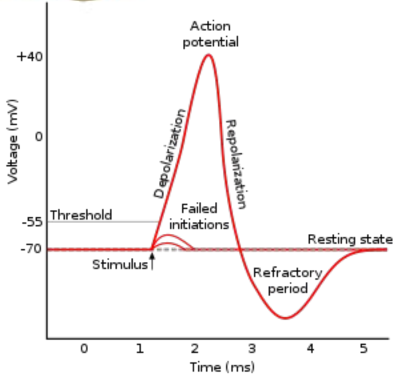
Neurosciences Discoveries that led to modern AI techniques:
PERCEPTRON

- Perceptron, Rosenblatt **1957**
- Can we model neuron behaviour without differential equations? => let's build something simple i.e. **PERCEPTRON**

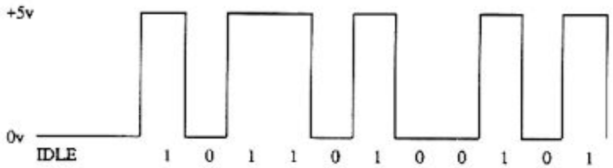


$$f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0, \\ 0 & \text{otherwise} \end{cases}$$



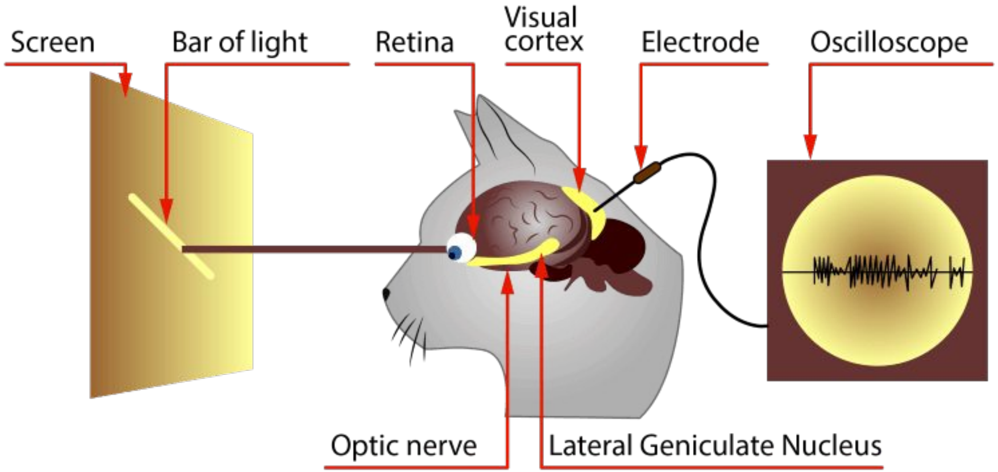


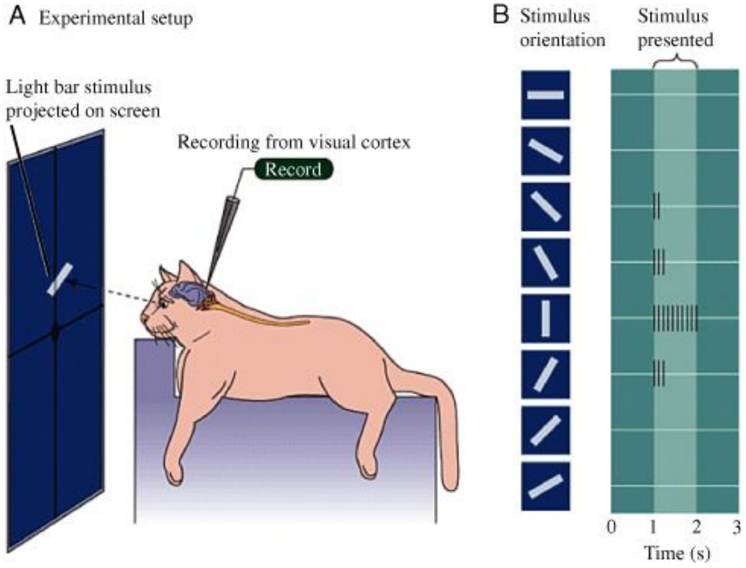
Action potentials in the brain are "basically forming binary code"



Idea of using spatial filters (convolutions) in CNNs

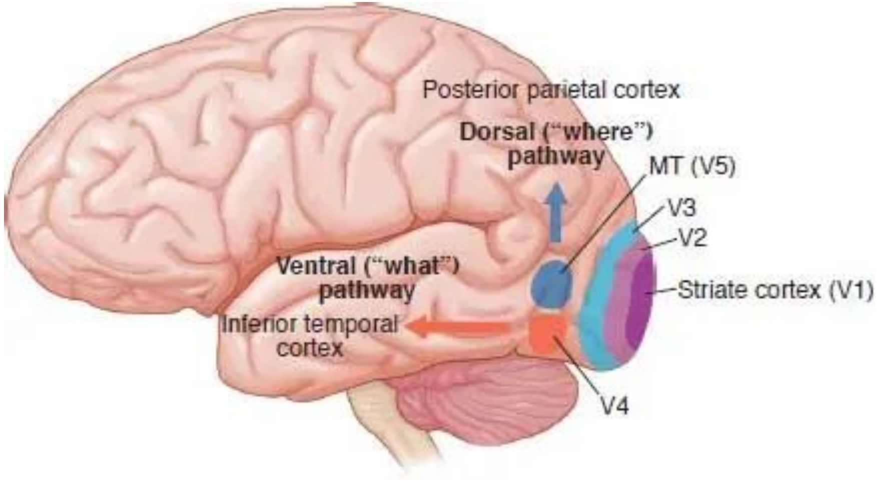
- **1960’s and 1970's** Dr. Hubel and Dr. Wiesel
  Primary visual cortex is responding to basic shapes (e.g. oriented lines). This led to the idea of using spatial filters for detecting specific image features.

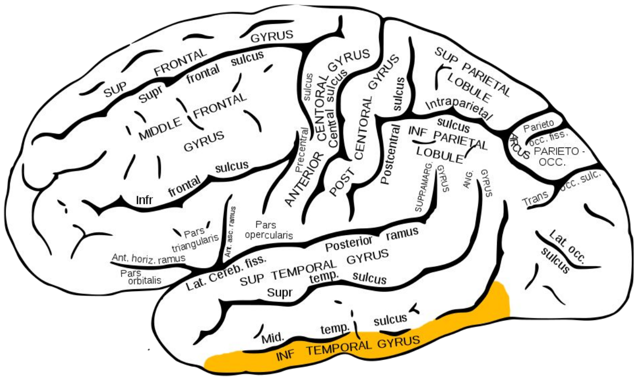




Visual pathway inspired architecture of CNNs

- V1 Neurons detect basic shapes i.e. oriented lines
- Visual neurons in the inferior temporal cortex fire selectively to hands and faces and other complex shapes





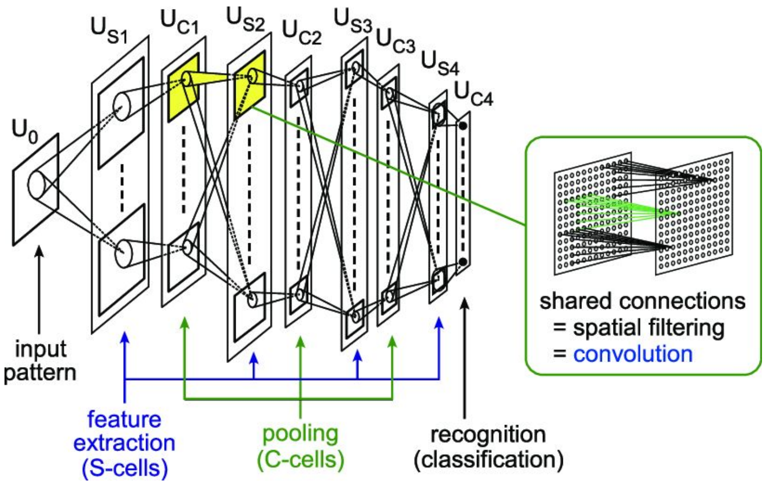
Origins of CNNs

1980

Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

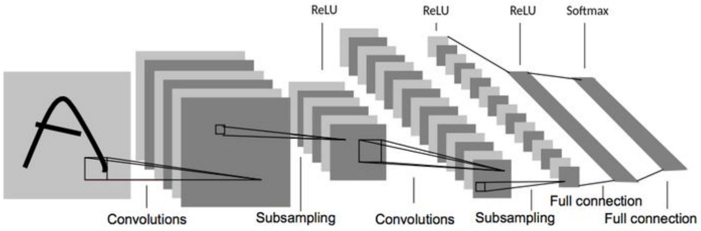
Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

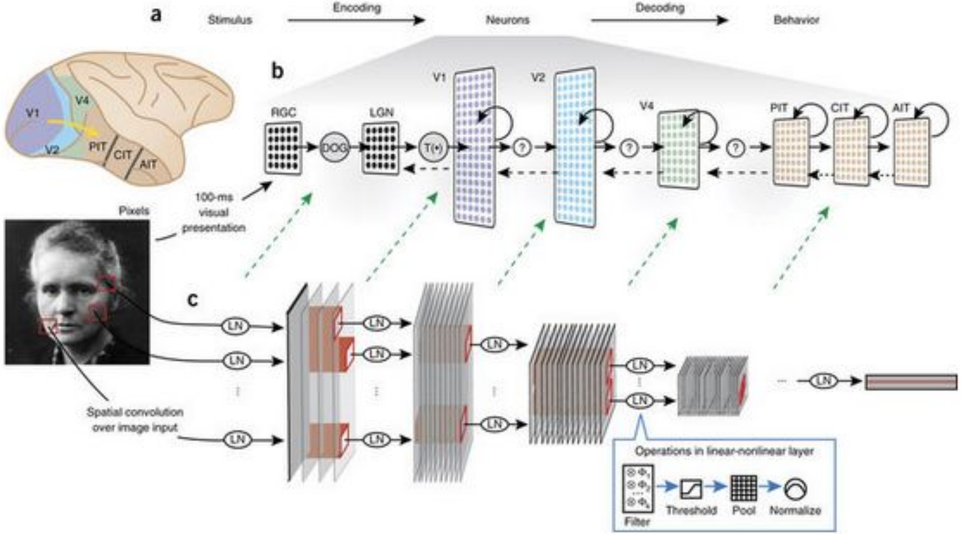


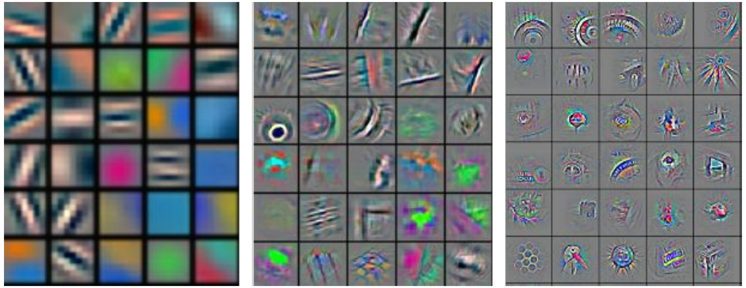
1998

LeNet is a convolutional neural network structure proposed by Yann LeCun et al.



Human brain vs CNN architecture

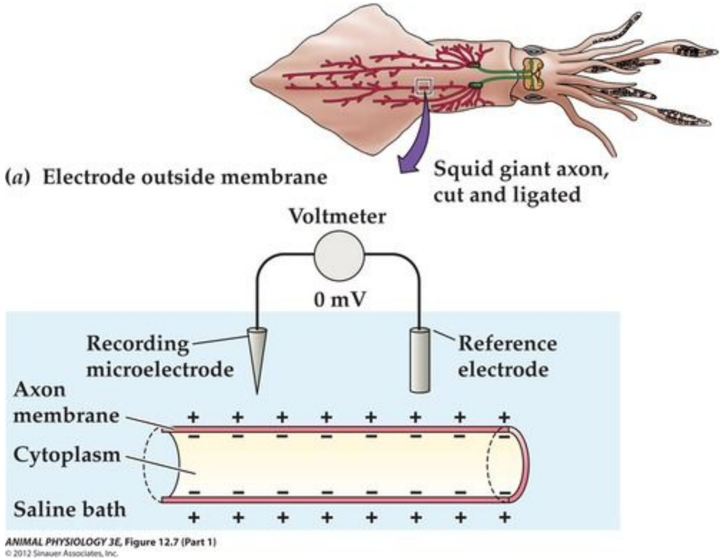




Kuzovkin, I., Vicente, R., Petton, M. *et al.* Activations of deep convolutional neural networks are aligned with gamma band activity of human visual cortex. *Commun Biol* **1**, 107 (2018). https://doi.org/10.1038/s42003-018-0110-y

Neurosciences Discoveries that led to modern AI techniques

- Alan Hodgkin and Andrew Huxley described the model in **1952** to explain the ionic mechanisms underlying the initiation and propagation of action potentials in the squid giant axon. They received the **1963** Nobel Prize in Physiology or Medicine for this work.



$$I = C_m \frac{\mathrm{d}V_m}{\mathrm{d}t} + \bar{g}_{\mathrm{K}} n^4 (V_m - V_K) + \bar{g}_{\mathrm{Na}} m^3 h (V_m - V_{Na}) + \bar{g}_l (V_m - V_l),$$

$$\frac{dn}{dt} = \alpha_n(V_m)(1-n) - \beta_n(V_m)n$$

$$\frac{dm}{dt} = \alpha_m(V_m)(1-m) - \beta_m(V_m)m$$

$$\frac{dh}{dt} = \alpha_h(V_m)(1-h) - \beta_h(V_m)h$$

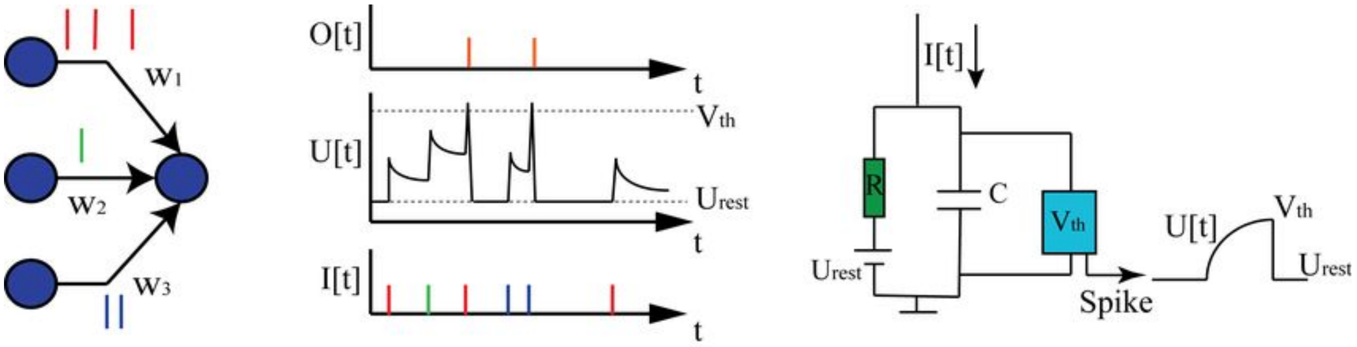
- System of nonlinear differential equations
- Too difficult to solve, complex networks with multiple neurons
- Currently not very useful in AI, BUT CAN BE FURTHER SIMPLIFIED

Squid axon might be as large *as **1mm** in diameter (approx. 100x in comparison with humans)*

Leaky Integrate and Fire Neuron model

- Simplification of Hodgkin-Huxley model
- Only one simple differential equation
- Can be created by analog circuit => Neuromorphic computing

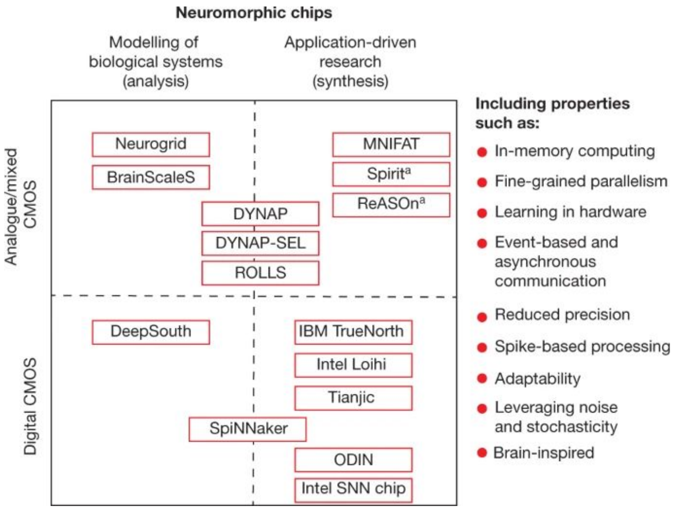
$$C_m \frac{dV_m(t)}{dt} = I(t) - \frac{V_m(t)}{R_m}$$



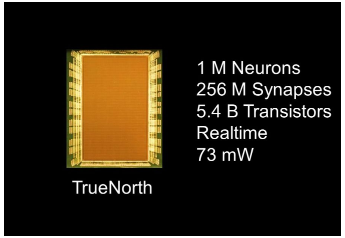
(a) (b) (c)

Neuromorphic computing

- Neuromorphic engineering aims to create computing hardware that mimics biological nervous systems, and it is expected to play a key role in the next era of hardware development.



Loihi is Intel’s version of what neuromorphic hardware, designed for brain-inspired spiking neural networks (SNNs)



IBM TrueNorth chip
TrueNorth was **a neuromorphic CMOS integrated** circuit produced by IBM in 2014. It is a manycore processor network on a chip design, with 4096 cores, each one having 256 **programmable simulated neurons** for a total of just over a **million neurons**.

Opportunities for neuromorphic computing algorithms and applications

Catherine D. Schuman et al

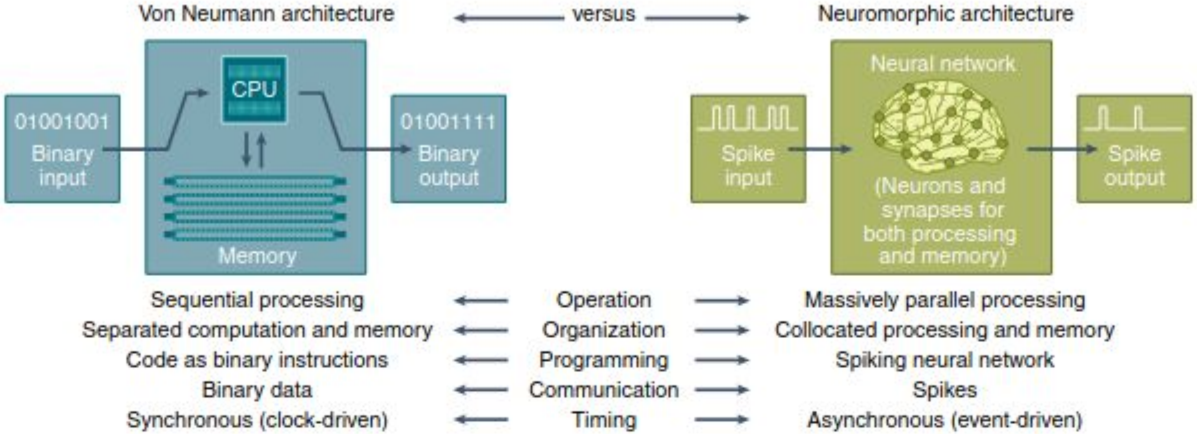
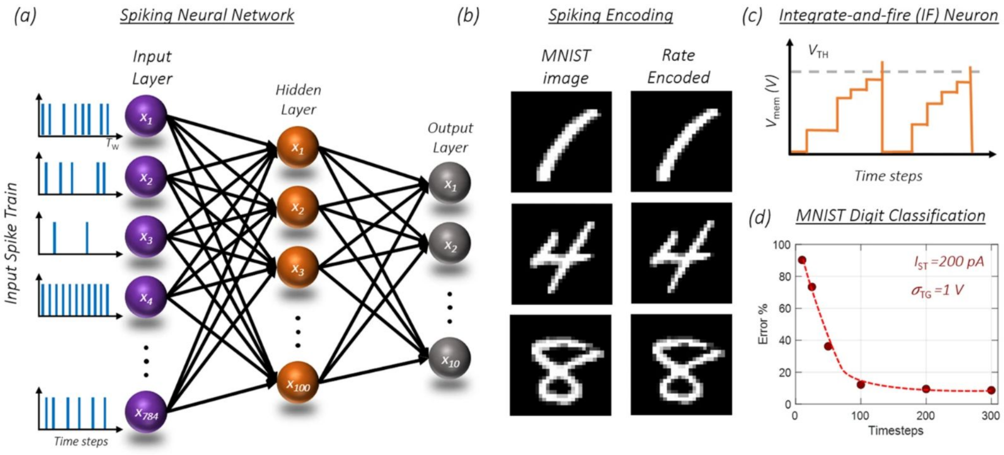


Fig. 1 | Comparison of the von Neumann architecture with the neuromorphic architecture. These two architectures have some fundamental differences when it comes to operation, organization, programming, communication, and timing, as depicted here.

Spiking Neural Networks

- using LIF neurons instead of standard neurons
- New learning algorithms for **unsupervised learning**.
- **implementation of bio-inspired local learning rules** such as Hebbian learning and **Spike-Time-Dependant-Plasticity** (STDP), Lateral Inhibition

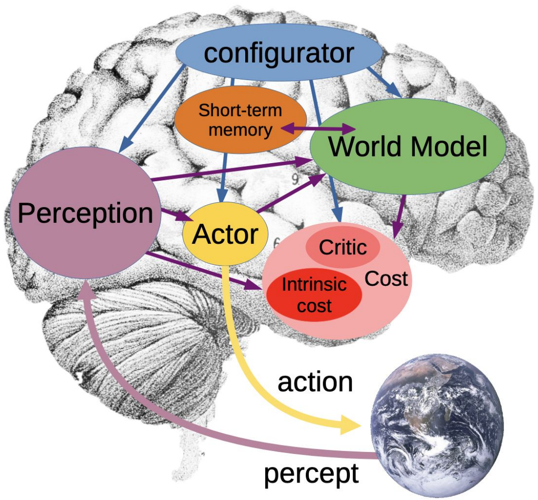


Subbulakshmi Radhakrishnan, S., Sebastian, A., Oberoi, A. *et al.* A biomimetic neural encoder for spiking neural network. *Nat Commun* **12**, 2143 (2021). https://doi.org/10.1038/s41467-021-22332-8

Diehl, P. U., & Cook, M. (2015). Unsupervised learning of digit recognition using spike-timing-dependent plasticity. *Frontiers in Computational Neuroscience*, *0*. https://doi.org/10.3389/fncom.2015.00099

A Path Towards Autonomous Machine Intelligence

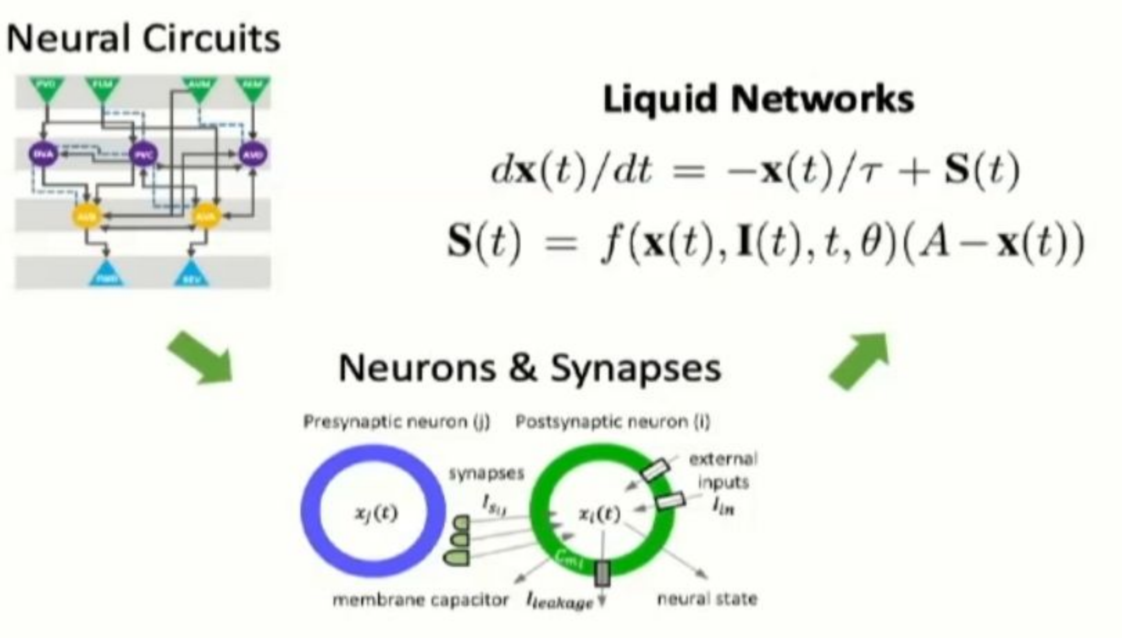
Yann LeCun



- How could machines learn as efficiently as humans and animals?
- How could machines learn representations of percepts and action plans at multiple levels of abstraction, enabling them to reason, predict, and plan at multiple time horizons?

Liquid Time-Constant Network

Ramin Hasani et al
CSAIL, Massachusetts Institute of Technology, USA

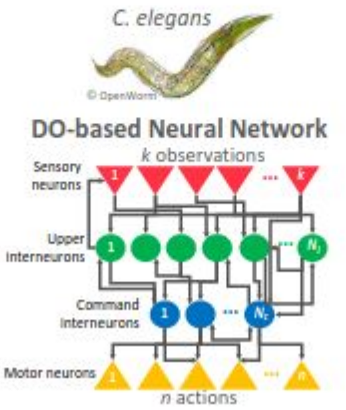


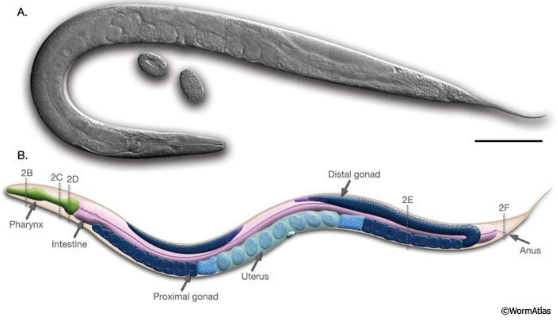
Designing Worm-inspired Neural Networks for Interpretable Robotic Control

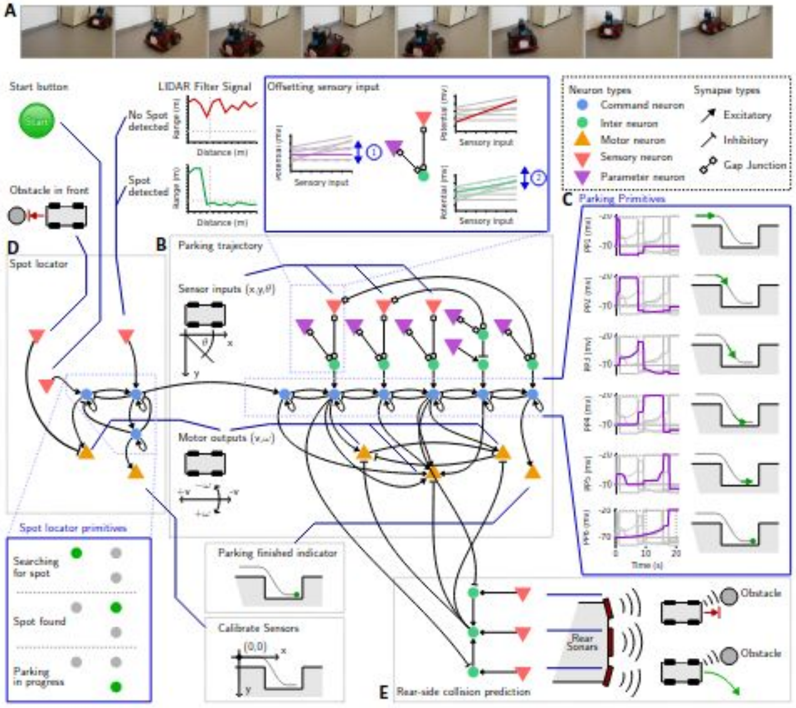
Mathias Lechner et al

C. elegans

- 302 neurons and 8000 synapses
- sensing complex chemical input
- sleeping
- adaptive behavior
- mechano-sensation
- controlling 96 muscles.
- How does C. elegans perform so much with so little?








THANK YOU FOR WATCHING OUR PRESENTATION
WE HOPE YOU LIKED IT :D