Neural Networks: Old and New

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Computer Science & Engineering
University of Minnesota, Twin Cities

September 14, 2020

Outline

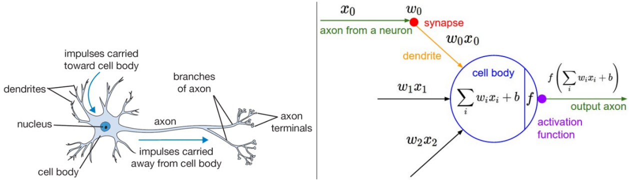
Start from neurons

Shallow to deep neural networks

A brief history of AI

Suggested reading

Model of biological neurons



A cartoon drawing of a biological neuron (left) and its mathematical model (right).

Credit: Stanford CS231N

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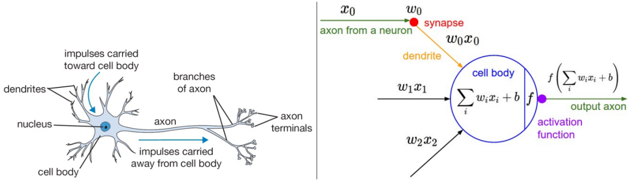

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Biologically ...

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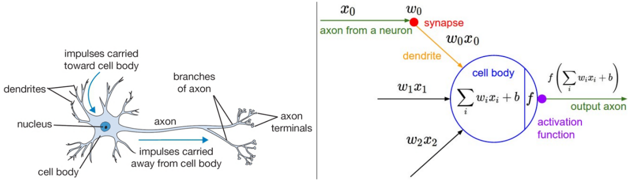

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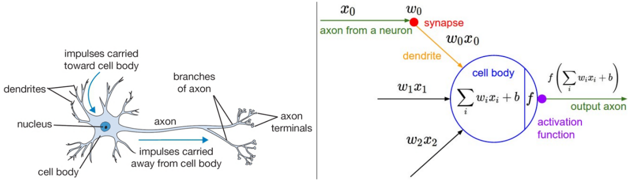

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- The axon branches out and connects via **synapese** to dendrites of other neurons

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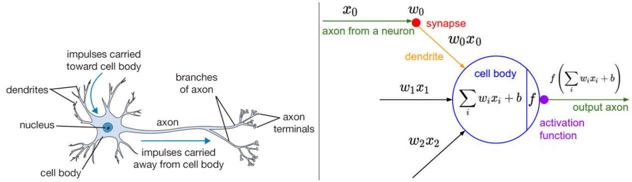

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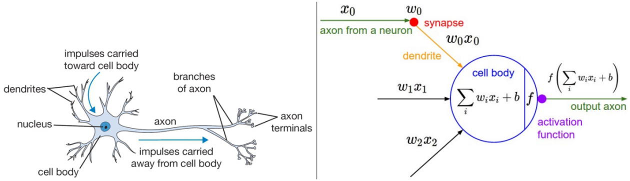

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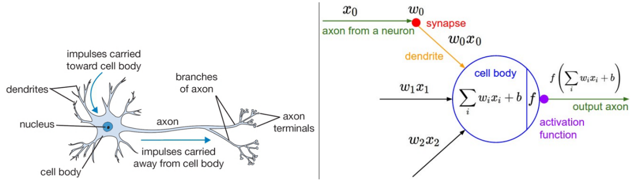

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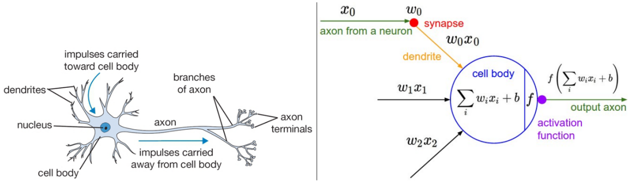

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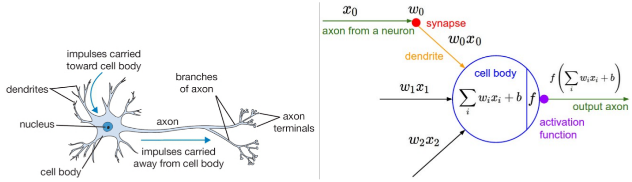

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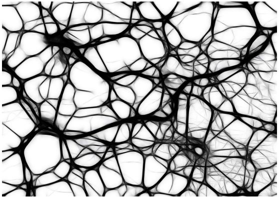
- The neuron fires only when the combined signal is above a certain threshold: $\sum_i w_i x_i + b$
- Fire rate is modeled by an **activation function** f, i.e., outputting $f\left(\sum_i w_i x_i + b\right)$

Artificial neural networks

Brain neural networks



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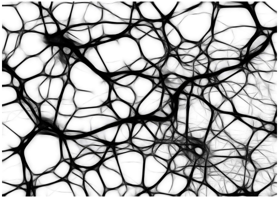

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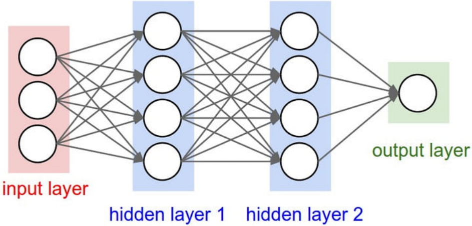

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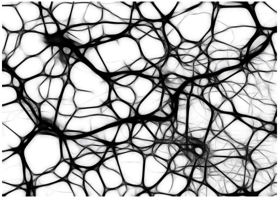

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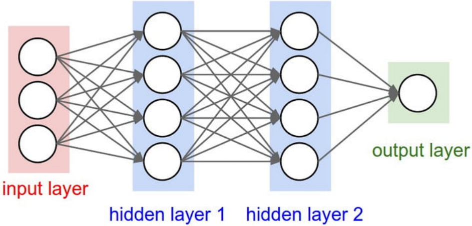

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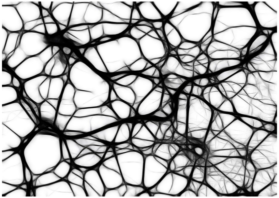

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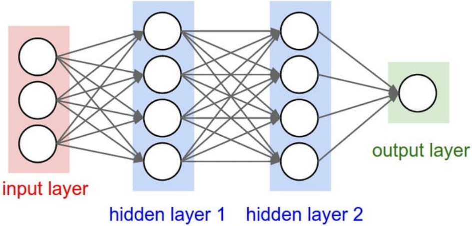

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- (Over-)simplification on connection level

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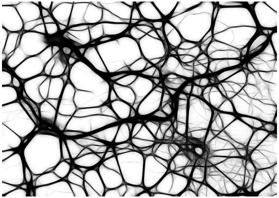

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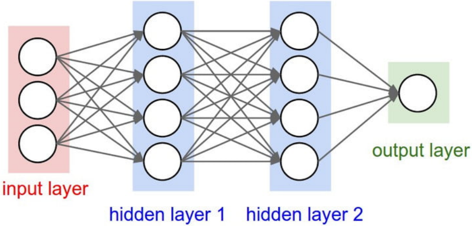

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In this course, neural networks are always artificial.

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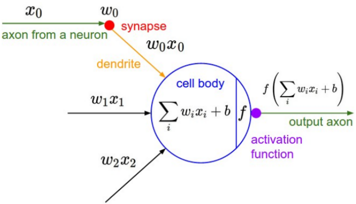

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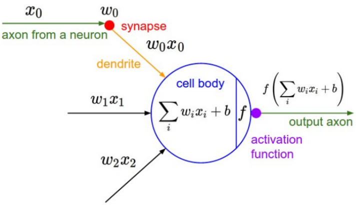

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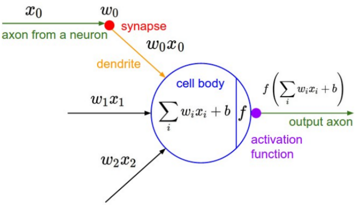

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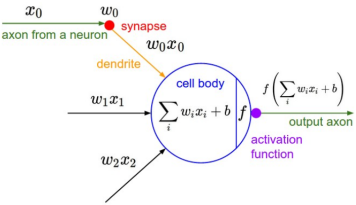

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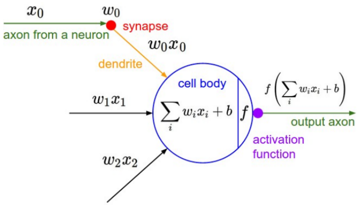

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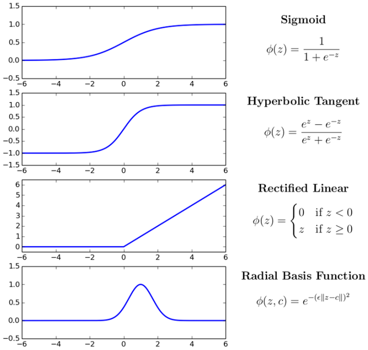

Credit: [Hughes and Correll, 2016]

Neural networks

One neuron: $\sigma\left(\boldsymbol{w}^{\intercal}\boldsymbol{x}+b\right)$

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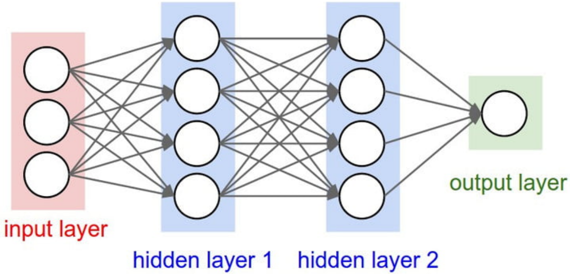
Neural networks (NN): **structured** organization of artificial neurons



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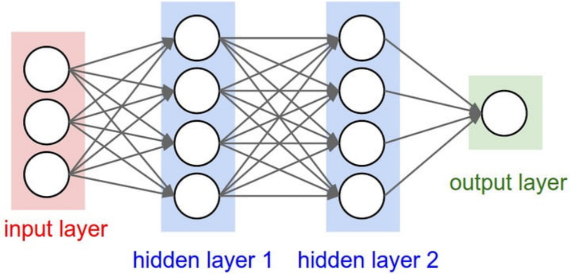

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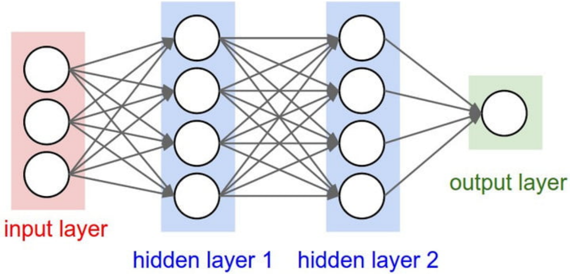

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Many models in machine learning **are** neural networks

A typical setup

Supervised Learning

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... known as **empirical risk minimization** (ERM) framework in learning theory

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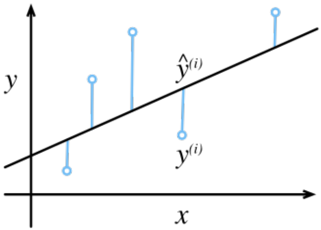
Linear regression



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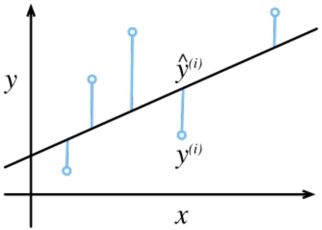

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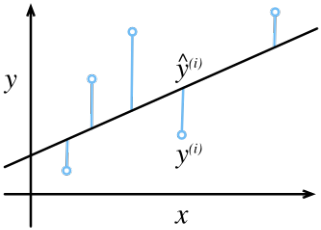

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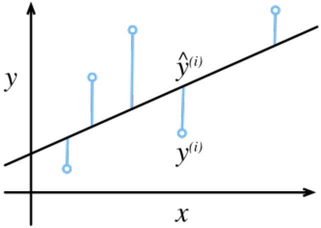

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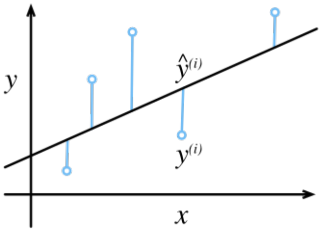

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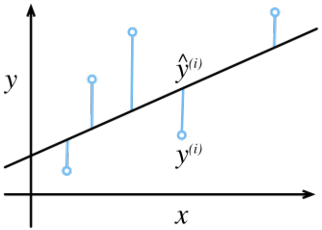

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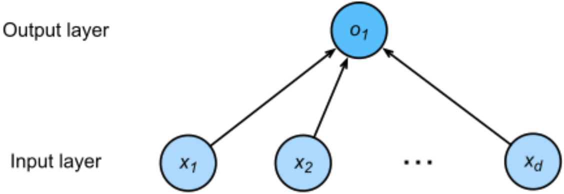

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σ is the identity function

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Frank Rosenblatt

(1928–1971)

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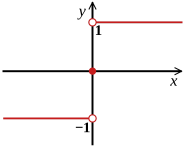

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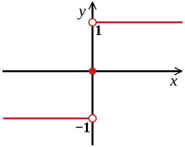

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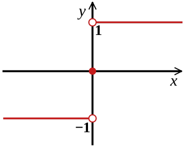

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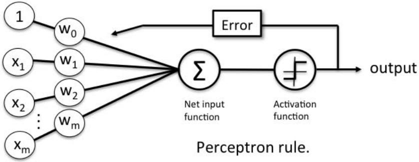

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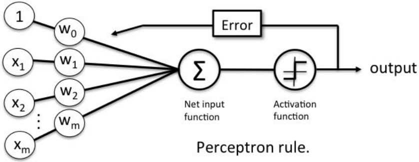

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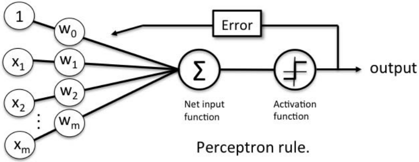
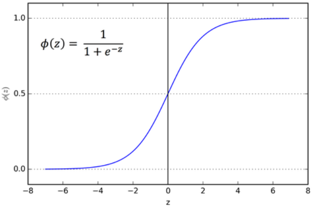


dominated early AI (50's – 70's)

Logistic regression is similar but with **sigmod** activiation



Softmax regression

- Data: $(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_n, y_n)$, $\boldsymbol{x}_i \in \mathbb{R}^d$, $y_i \in \{L_1, \ldots, L_p\}$, i.e., multiclass classification problem

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- Data preprocessing: labels into vectors via one-hot encoding

$$L_k \Longrightarrow [\underbrace{0, \ldots, 0,}_{k-1\,0's}, 1, \underbrace{0, \ldots, 0}_{n-k\,0's}]^\intercal$$

So: $y_i \Longrightarrow \boldsymbol{y}_i$

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- Loss: **cross-entropy loss** $-\sum_j y_j \log \hat{y}_j$

Softmax regression

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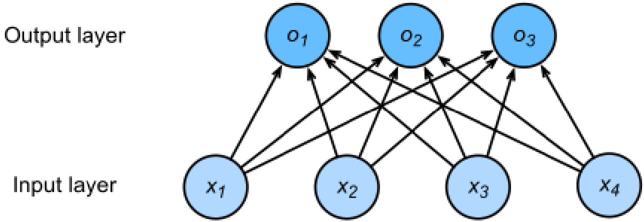
- Loss: **cross-entropy loss** $-\sum_j y_j \log \hat{y}_j$
- Optimization ...

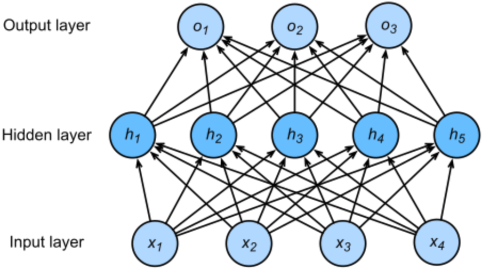
Softmax regression

… for multiclass classification



Credit: D2L

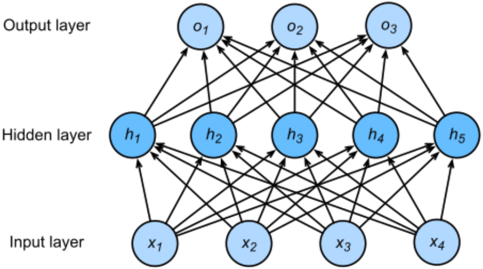
Multilayer perceptrons



Credit: D2L

Model: $\boldsymbol{y}_i \approx \sigma_2\left(\boldsymbol{W}_2^\intercal \sigma_1(\boldsymbol{W}_1^\intercal \boldsymbol{x} + \boldsymbol{b}_1) + \boldsymbol{b}_2\right)$

Multilayer perceptrons



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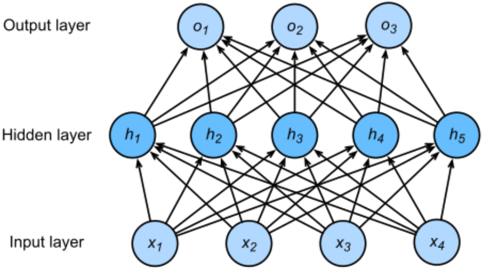
Also called **feedforward networks** or **fully-connected networks**

Multilayer perceptrons



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Also called **feedforward networks** or **fully-connected networks**

Modern NNs: many hidden layers (deep), refined connection structure and/or activations

They're all (shallow) NNs

- Linear regression
- Perception and Logistic regression
- Softmax regression
- Multilayer perceptron (feedforward NNs)

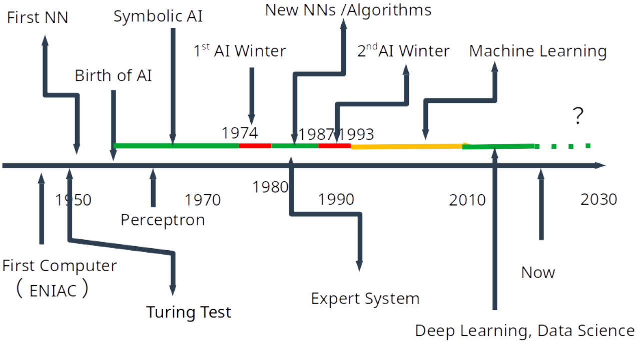
They're all (shallow) NNs

- Linear regression
- Perception and Logistic regression
- Softmax regression
- Multilayer perceptron (feedforward NNs)
- Support vector machines (SVM)
- PCA (autoencoder)
- Matrix factorization

see, e.g., Chapter 2 of [Aggarwal, 2018].

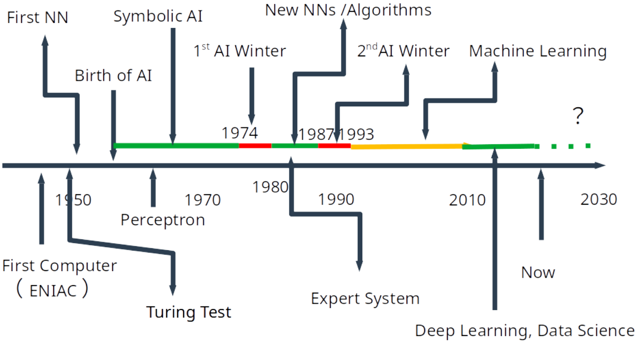
Outline

Birth of AI



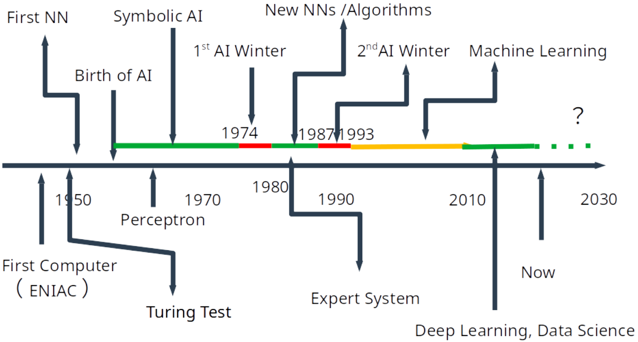
First NN
Symbolic AI
New NNs /Algorithms
1st AI Winter
2nd AI Winter
Machine Learning
Birth of AI
?
1974
1987
1993
1950
1970
1980
1990
2010
2030
Perceptron
First Computer
(ENIAC)
Turing Test
Expert System
Now
Deep Learning, Data Science

Birth of AI



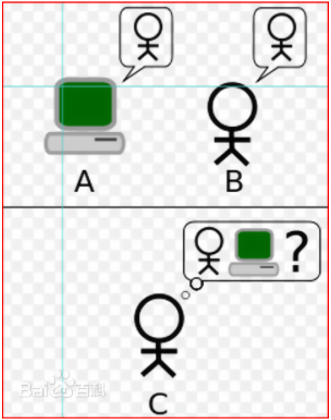
– Crucial precursors: first computer, Turing test

Birth of AI

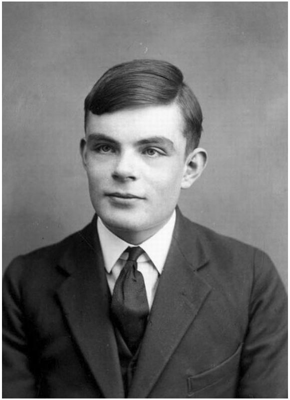


- Crucial precursors: first computer, Turing test
- 1956: Dartmouth Artificial Intelligence Summer Research Project — Birth of AI

Turing test

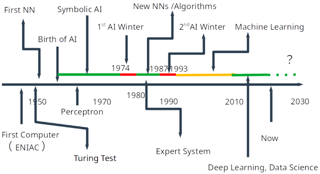


Turing Test

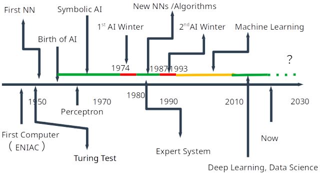


Alan Turing (1912–1954)

First golden age

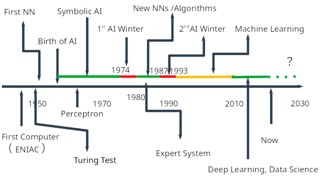


First golden age

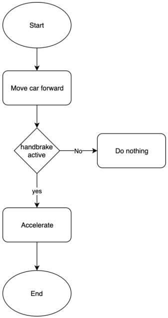


Symbolic AI: based on rules and logic

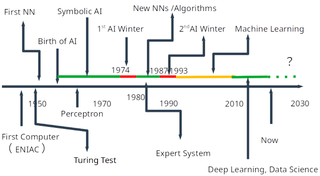
First golden age



Symbolic AI: based on rules and logic



First golden age



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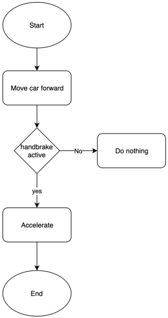
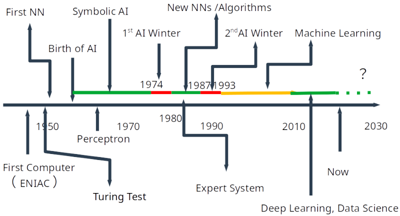
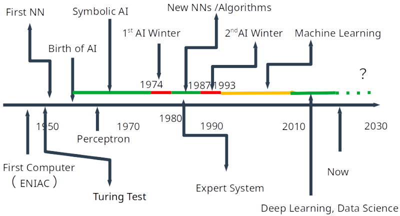


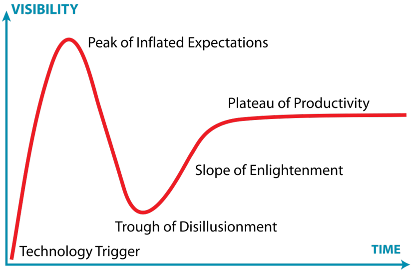
rules for recognizing dogs?

First AI winter



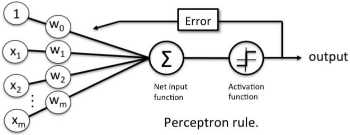
First AI winter





Gartner hype cycle

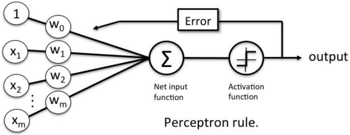
Perceptron



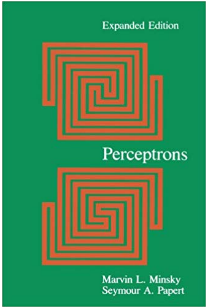
Perceptron rule.

invented 1962

Perceptron



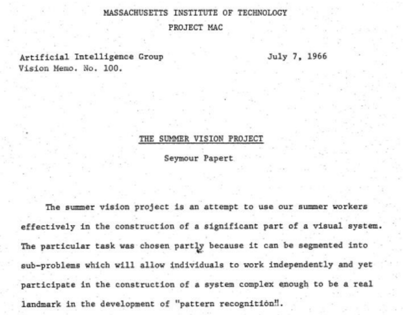
invented 1962



written in 1969, end of Perceptron era

Marvin Minsky (1927–2016)

Birth of computer vision


MASSACHUSETTS INSTITUTE OF TECHNOLOGY
PROJECT MAC

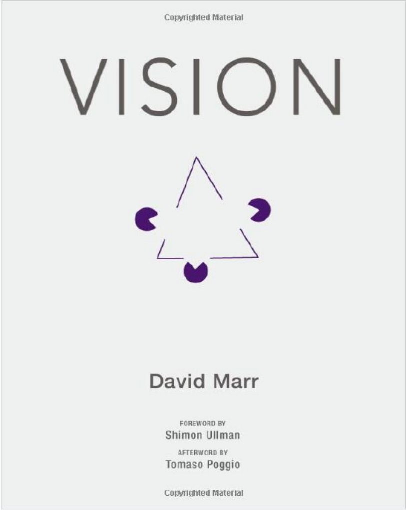
Artificial Intelligence Group July 7, 1966
Vision Memo. No. 100.

THE SUMMER VISION PROJECT

Seymour Papert

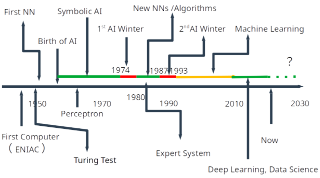
The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".

1966

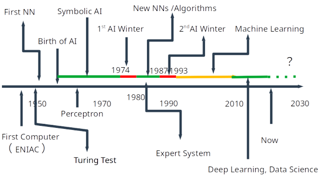


around 1980

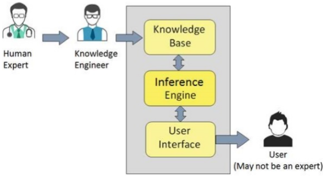
Second golden age



Second golden age



expert system



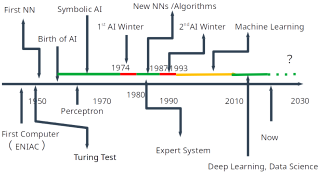
Can we build comprehensive knowledge bases and know all rules?

Big bang in DNNs

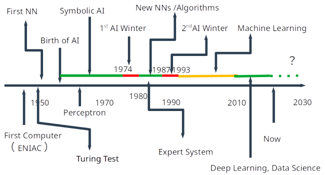
Key ingredients of DL have been in place for 25-30 years:

Landmark	Emblem	Epoch
Neocognitron	Fukushima	1980
CNN	Le Cun	mid 1980s'
Backprop	Hinton	mid 1980's
SGD	Le Cun, Bengio etc	mid 1990's
Various	Schmidhuber	mid 1980's
CTF	*DARPA etc*	*mid 1980's*

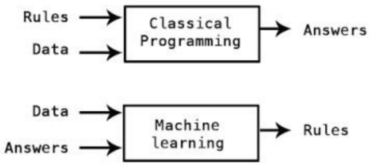
After 2nd AI winter



After 2nd AI winter



Machine learning takes over ...



Golden age of Machine learning

Starting 1990's

- Support vector machines (SVM)
- Adaboost
- Decision trees and random forests
- Deep learning
- ...

Outline

Suggested reading

- Chap 2, Neural Networks and Deep Learning.
- Chap 3–4, Dive into Deep Learning.
- Chap 1, Deep Learning with Python.

References i

[Aggarwal, 2018] Aggarwal, C. C. (2018). **Neural Networks and Deep Learning.** Springer International Publishing.

[Hughes and Correll, 2016] Hughes, D. and Correll, N. (2016). **Distributed machine learning in materials that couple sensing, actuation, computation and communication.** *arXiv:1606.03508*.