Experimental Practices course
For Deep Learning

- Theoretical Review of basic concepts of deep learning (~2weeks)
  Neural networks, Deep learning vs. Machine Learning,
  Activation function,
  Learning algorithm : Back Propagation(BP) Algorithm

↓

- Studying how to use MATLAB for performing deep learning tasks (~2 weeks)

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- Experimental practices with some examples (~4 weeks)

↓

- Research Project (~4 weeks)

↓

- Presentation

Goal:

- This class acquires basic knowledge of **artificial intelligence(AI)** and conducts experimental practices to apply it to **imaging processing.**
- After basic training course of deep learning, we will apply AI algorithm to **medical images and perform actual projects.**

Textbook:

MATLAB Deep Learning: With Machine Learning, Neural Networks and Artificial Intelligence, Phil Kim ,2017,APress

Reference:

https://www.mathworks.com/solutions/deep-learning.html

https://kr.mathworks.com/campaigns/products/ppc/google/deep-learning-with-matlab-conf.html?elqsid=1527147885660&potential_use=Education , Mathworks,2017, Online

Grade:

Attendance(10%)

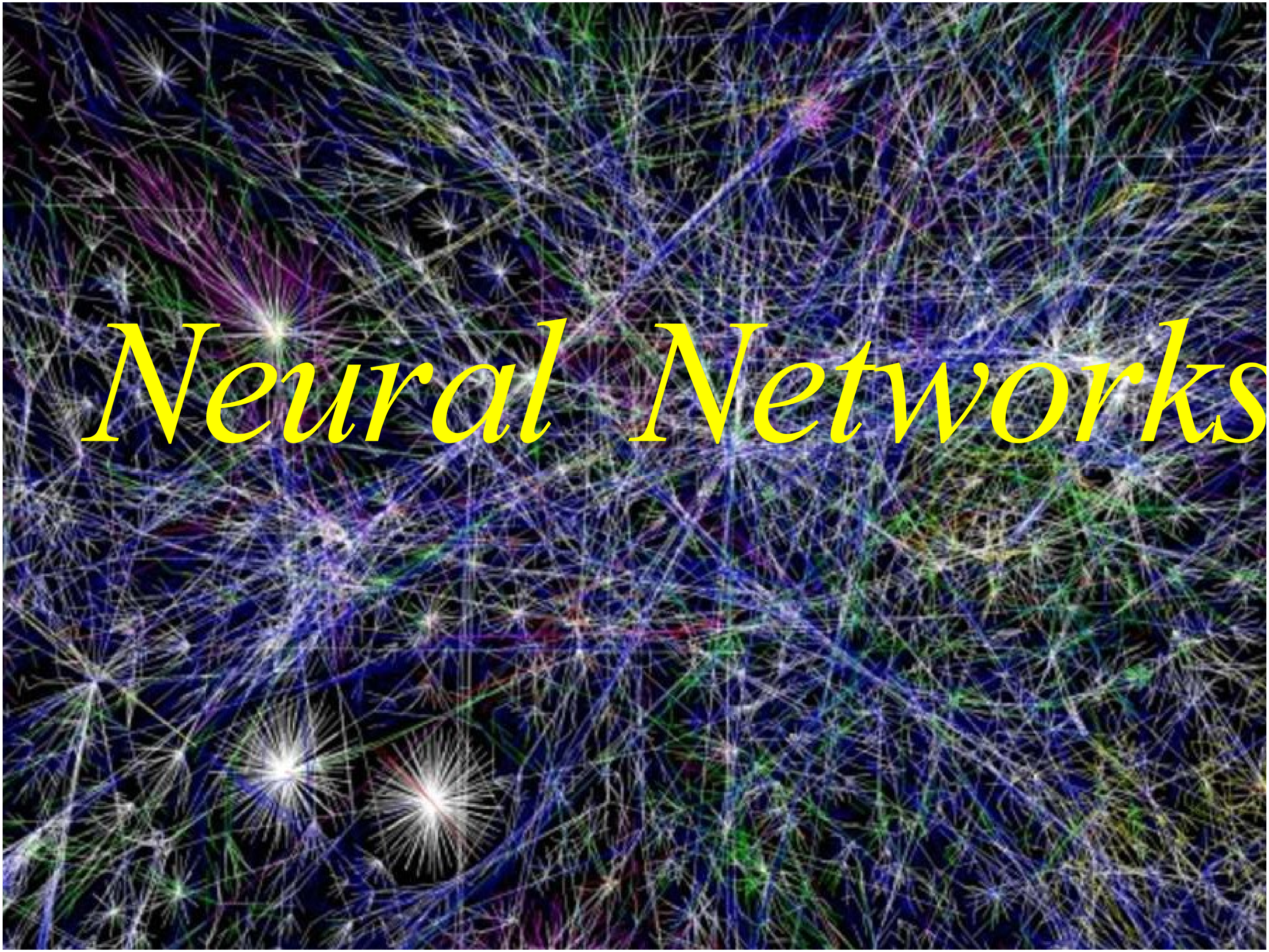
HomeWork (10%)

Research Project(70%)

Presentation(10%)

Project Team 구성

- Team: 4명
- Project leader
- Presenter 는 발표 직전 임의로 선정함.
- 졸업 작품 전시회 참여
  (창의성(40), 실용성(30), 완성도(30))


Neural Networks

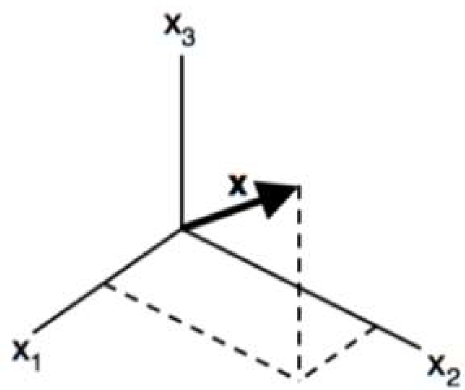
How are they different?

How are they different?

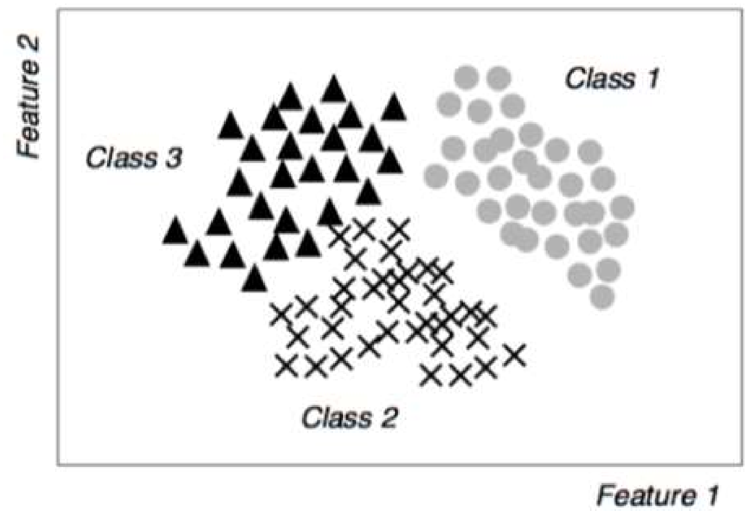
Feature Vector

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \\ x_d \end{bmatrix}$$

Feature vector



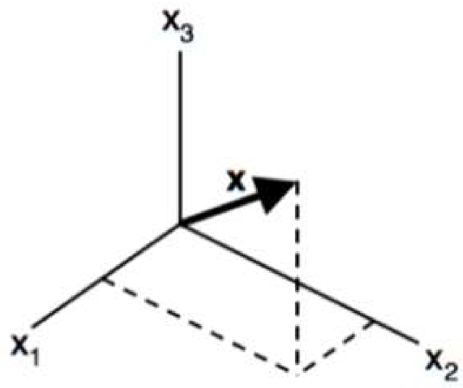
Feature space (3D)



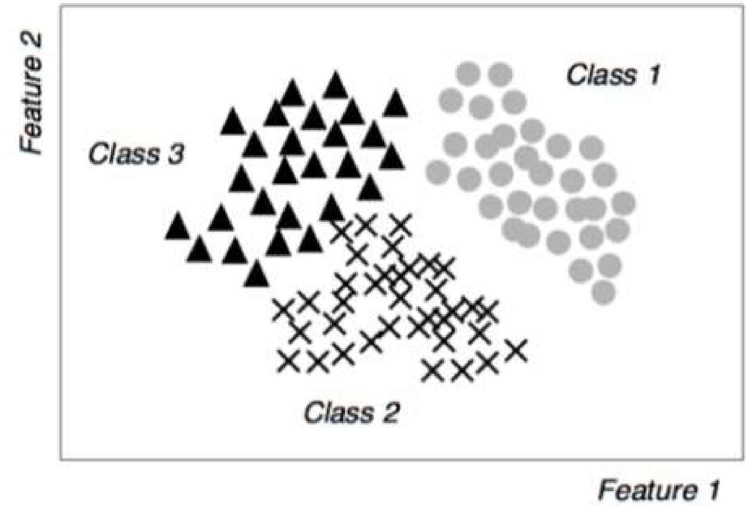
Scatter plot (2D)

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \\ x_d \end{bmatrix}$$

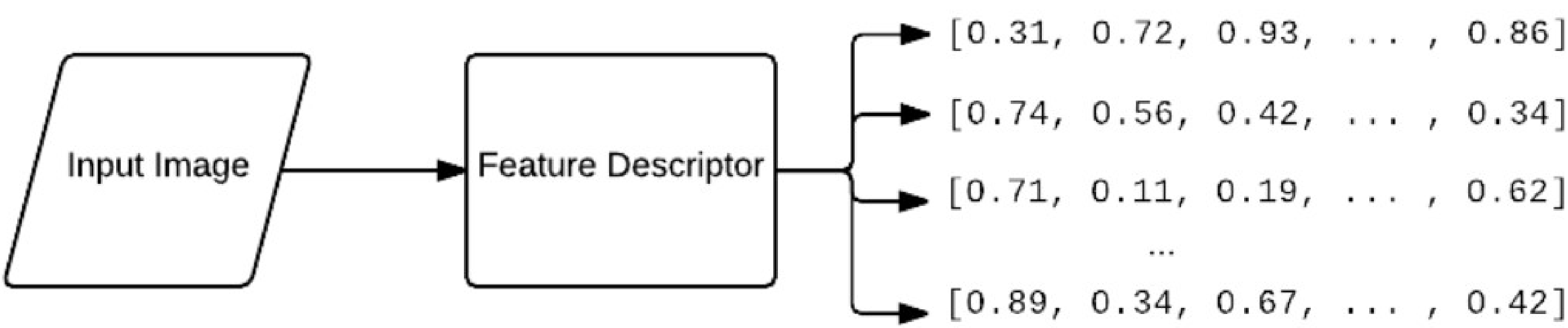
Feature vector



Feature space (3D)



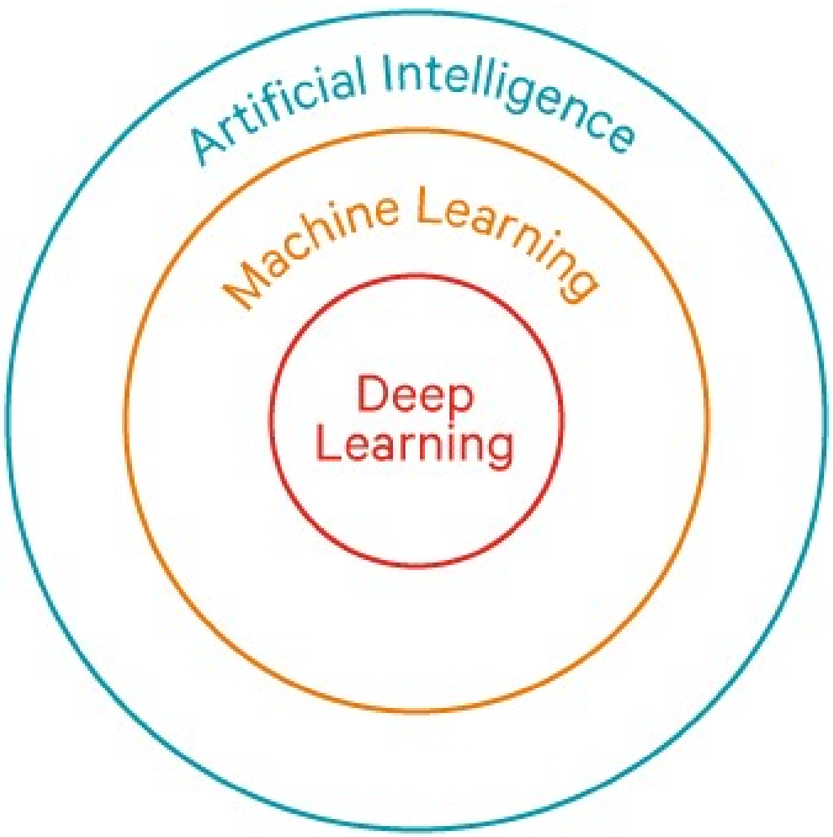
Scatter plot (2D)



Deep Learning vs. Machine Learning

Machine learning is a type of AI that facilitates a computer's ability
to learn and essentially teach itself to evolve
as it becomes exposed to new and ever-changing data.

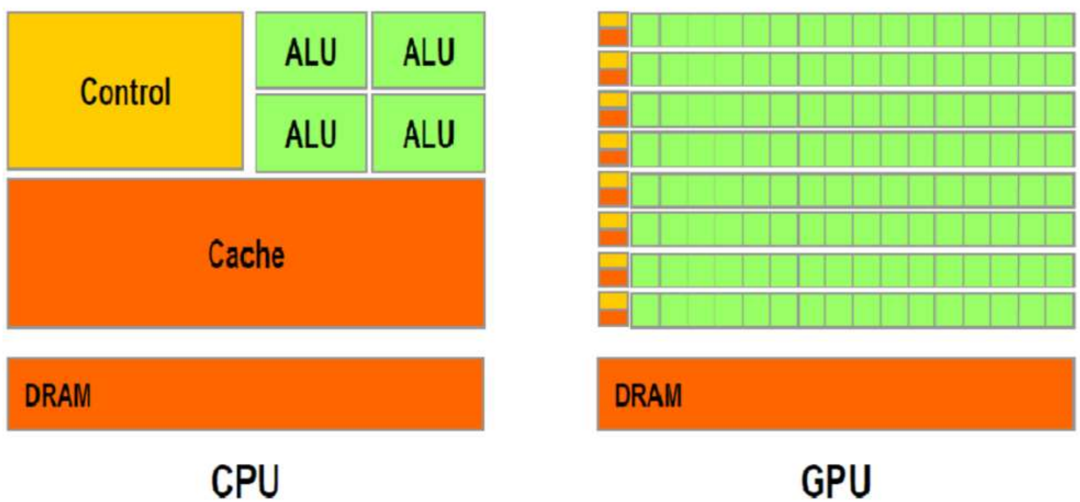
Machine learning refers to any type of computer program that can "learn" by itself without having to be explicitly programmed by a human.

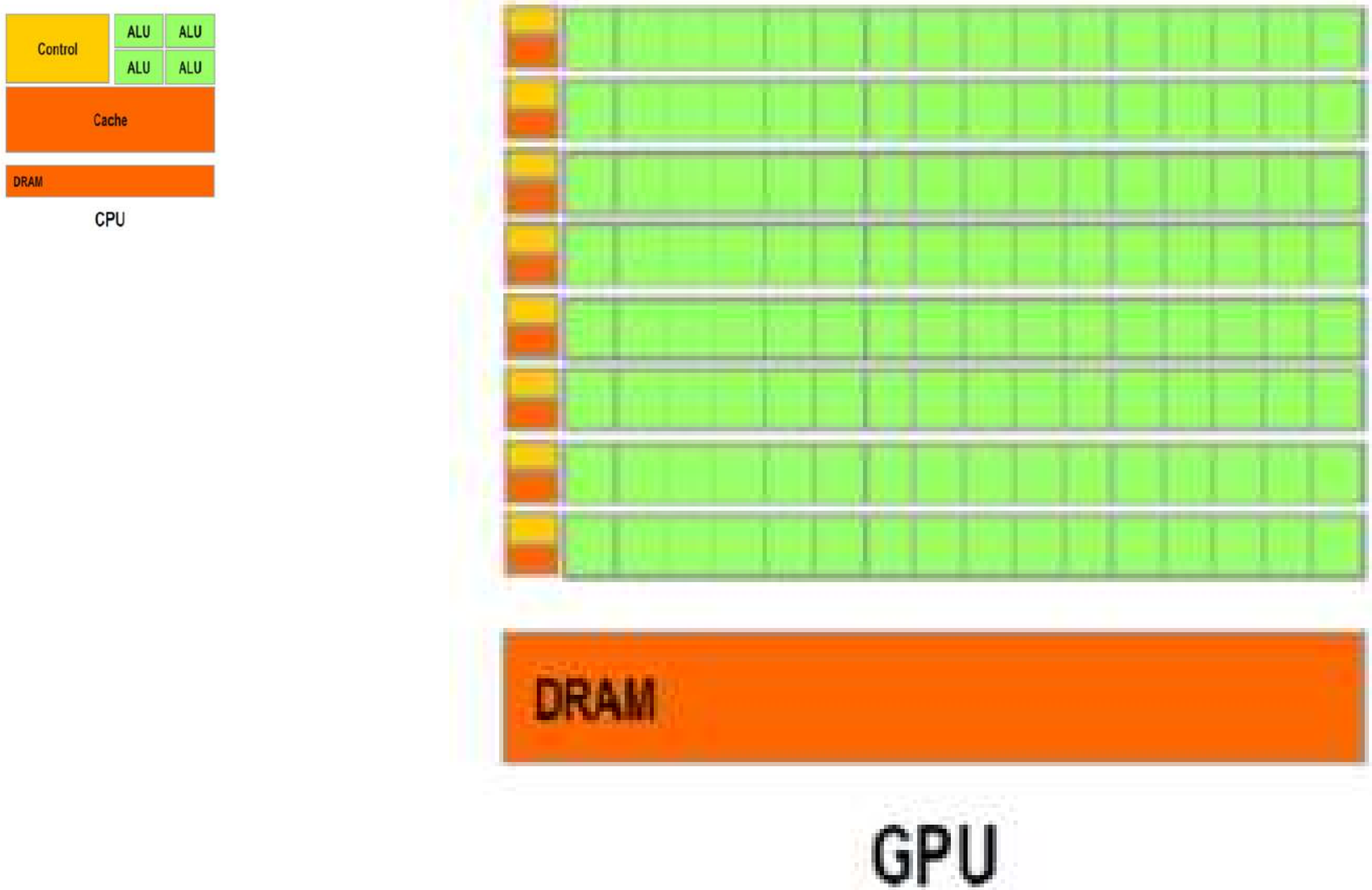


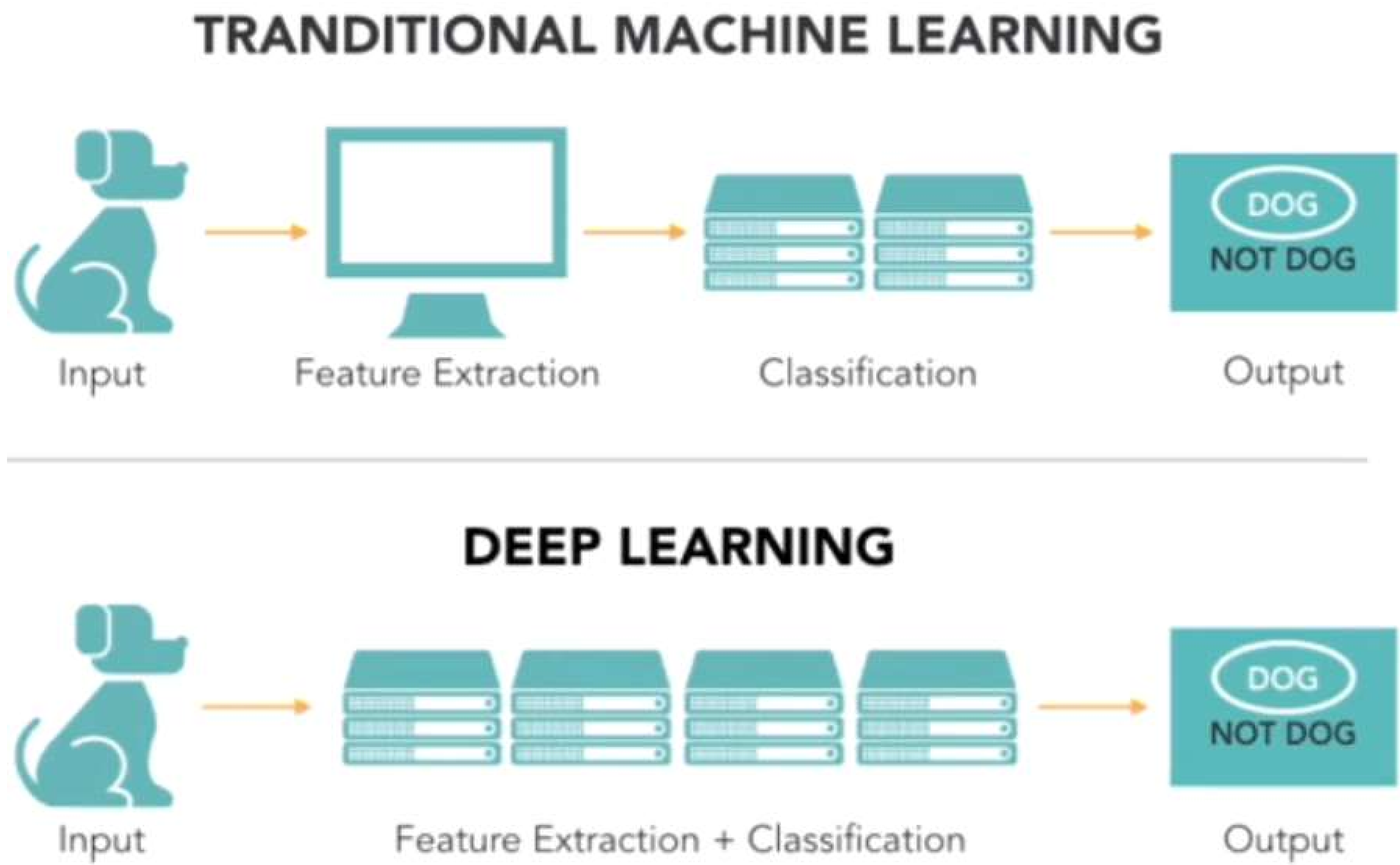
AI> Machine Learning > Deep Learning

GPU
(Graphic Processing Unit)

Deep learning algorithms inherently do a large amount of matrix multiplication operations in parallel.



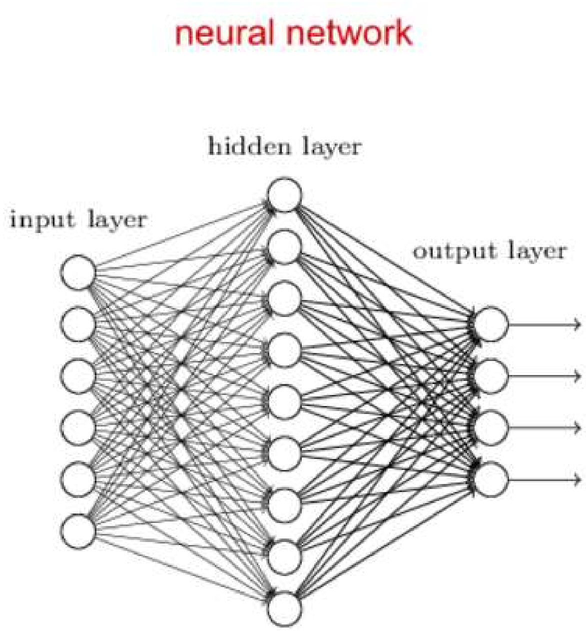

Control
ALU
ALU
ALU
ALU
Cache
DRAM
CPU
DRAM
GPU

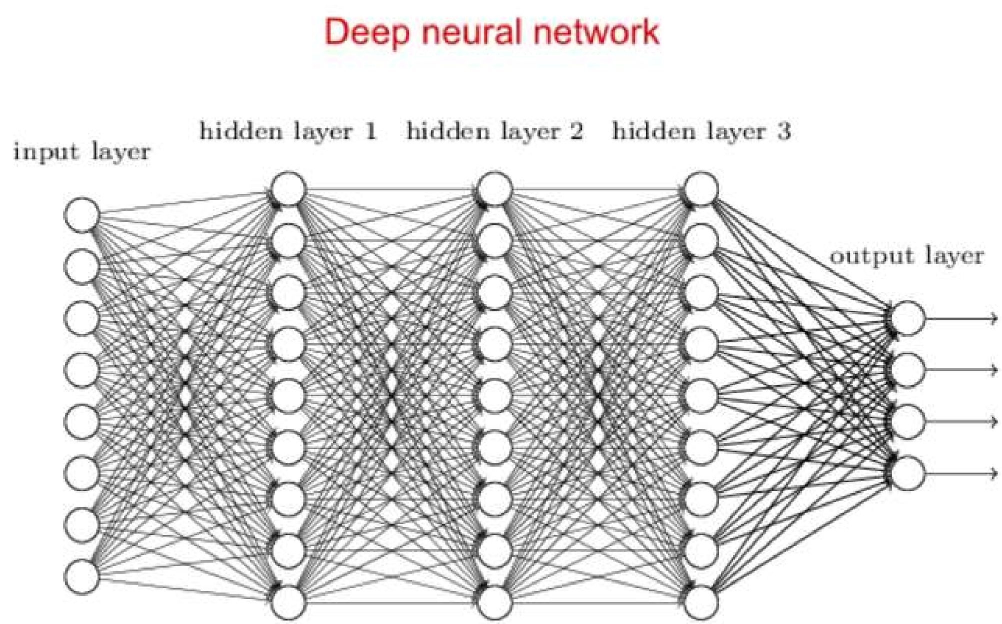

TRANDITIONAL MACHINE LEARNING
Input
Feature Extraction
Classification
DOG
NOT DOG
Output
DEEP LEARNING
Input
Feature Extraction + Classification
DOG
NOT DOG
Output

Machine Learning

N.N without feature extraction → **Deep learning**
(~ hundreds layers)

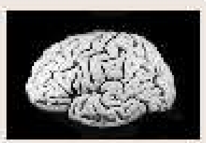
Shallow learning(2~3 layers)



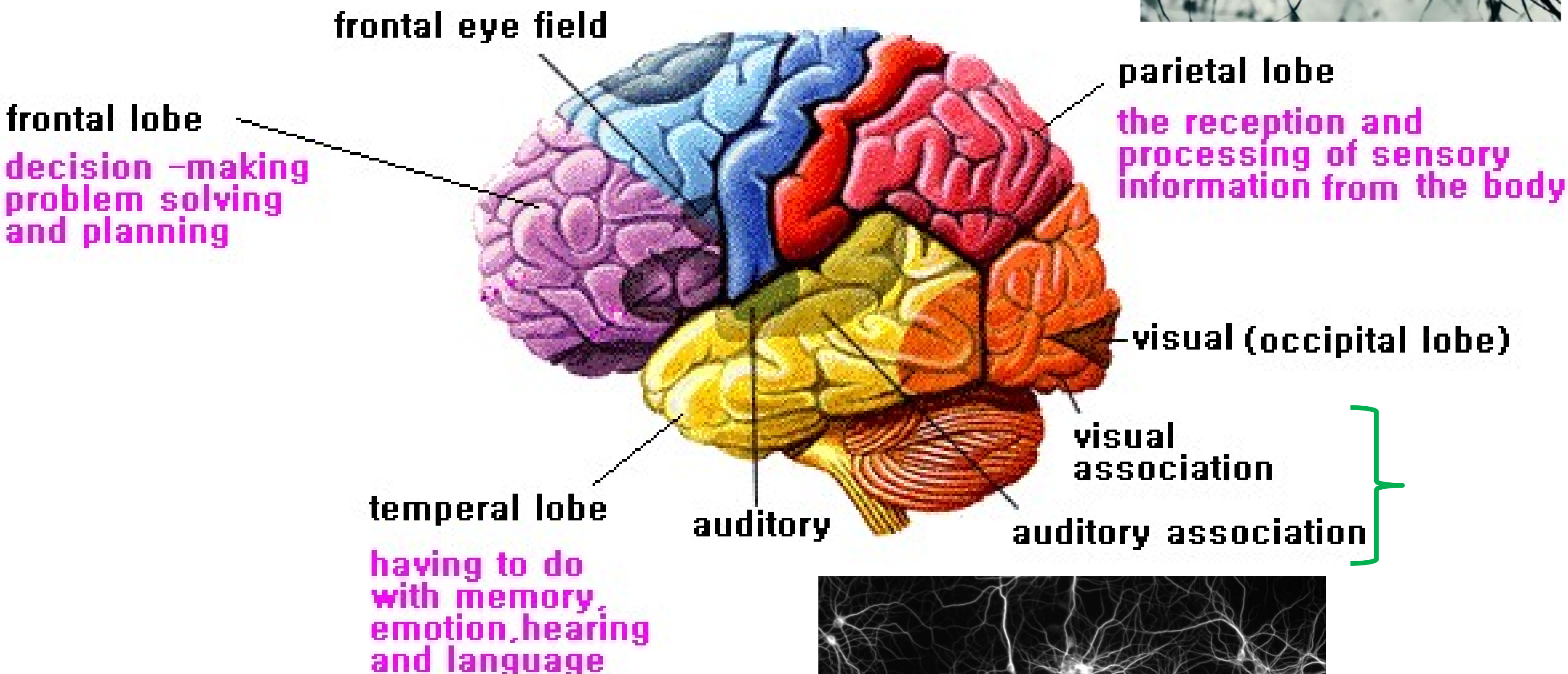


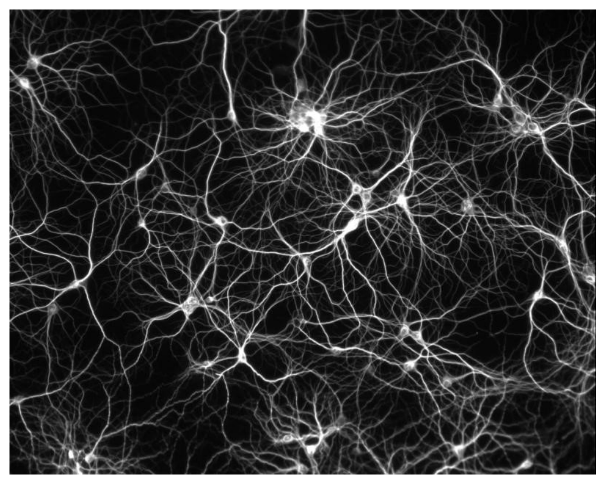
(Artificial) Neural Network ?

- Computational model **inspired from** neurological model of brain
- Human brain computes in different way from digital computer(the von Neumann machine)
  - highly complex, nonlinear, and parallel computing
  - many times faster than digital computer in
    - pattern recognition, perception, motor control
    - continues to develop afterward
      - Language Learning Device before 13 years old
  - has great structure and ability to build up its own rules by experience
    - dramatic development within 2 years after birth
  - Plasticity : ability to adapt to its environment

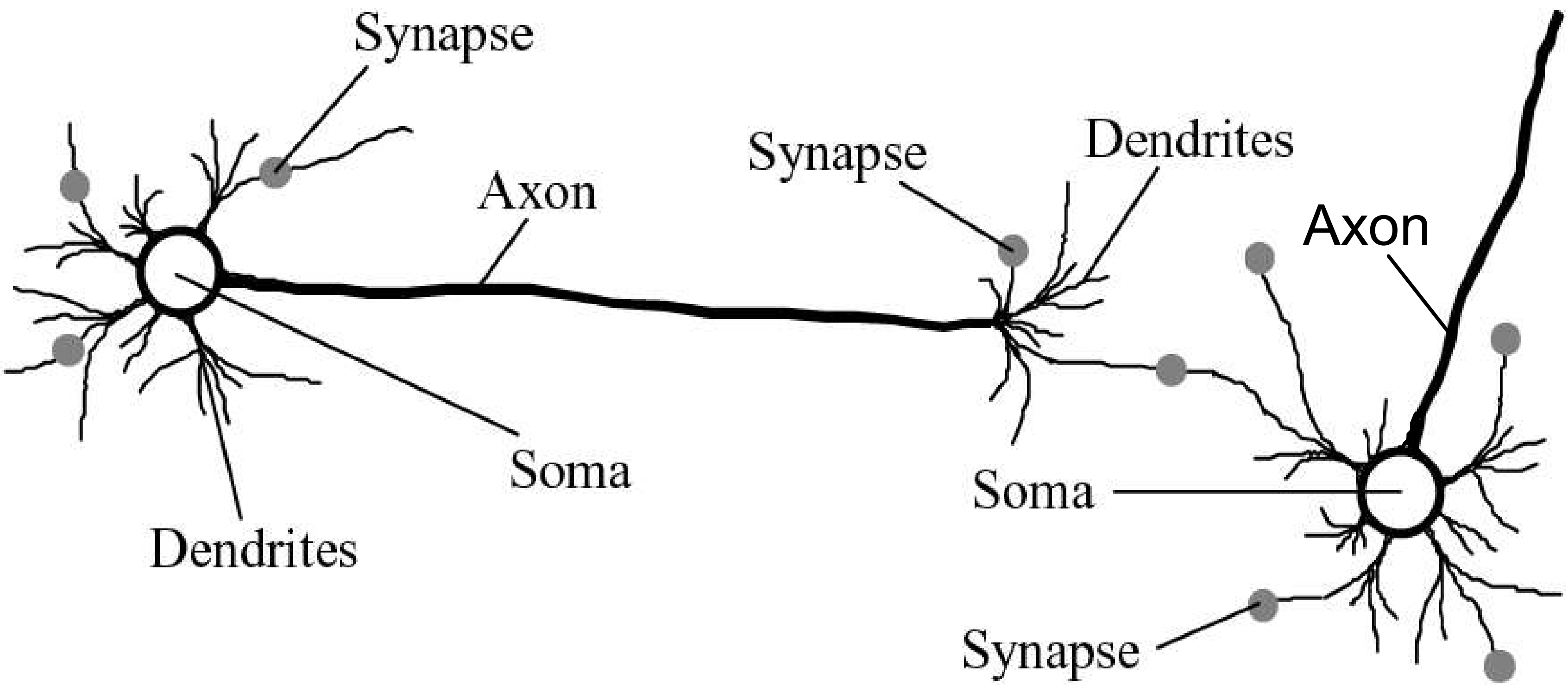
	processing elements	element size	energy use	processing speed	style of computation	fault tolerant	learns	intelligent, conscious
	10^{14} synapses	10^{-6} m	30 W	100 Hz	parallel, distributed	yes	yes	usually
	10^{8} transistors	10^{-6} m	30 W (CPU)	10^{9} Hz	serial, centralized	no	a little	not (yet)

Human Brain


frontal eye field
frontal lobe
decision -making
problem solving
and planning
parietal lobe
the reception and
processing of sensory
information from the body
visual (occipital lobe)
visual
association
auditory association
auditory
temperal lobe
having to do
with memory,
emotion,hearing
and language

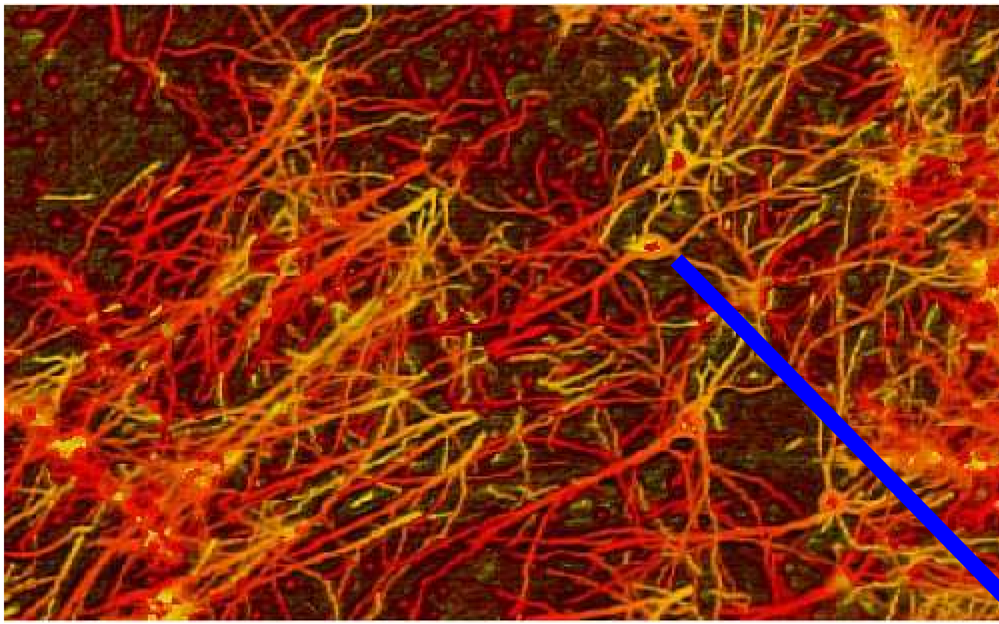


- Neurons respond slowly
  - 10^{-3} s compared to 10^{-9} s for electrical circuits
- The brain uses massively parallel computation
  - $\approx 10^{11}$ neurons in the brain
  - $\approx 10^{4}$ connections per neuron



[Building blocks of the human brain]

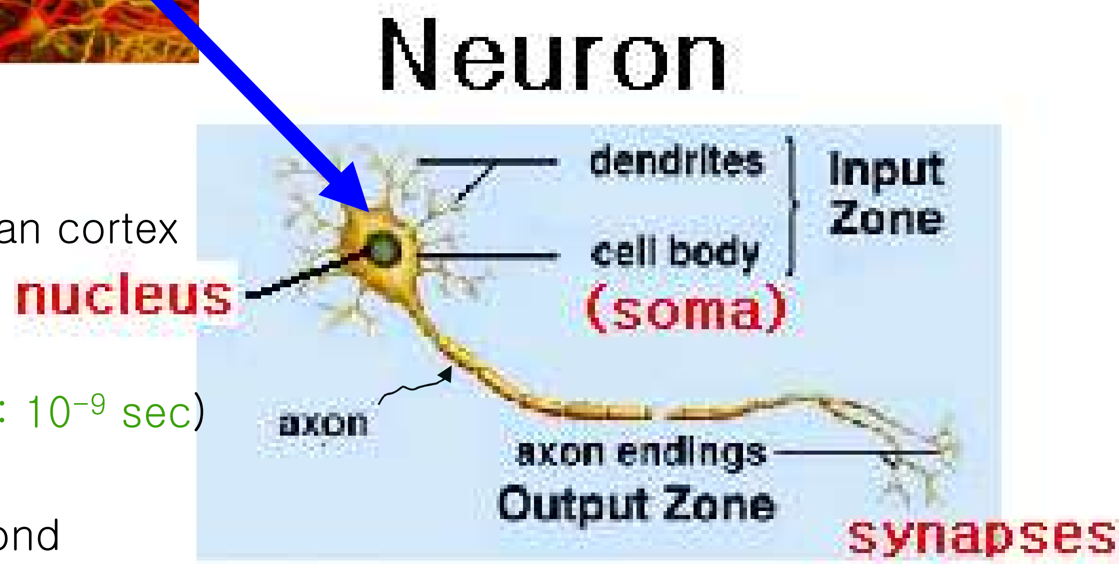
Neurons link up with many thousands of their neighbours. In this way they form very dense, complex local networks:



- Human nervous system
  - 10^{11} (10 billion)neurons in human cortex
  - 60×10^{12} synaptic connections
  - 10^4 synapses per neuron
  - 10^{-3} sec cycle time (computer : 10^{-9} sec)
  - energetic efficiency :

    10^{-16} joules operation per second

    (computer : 10^{-6} joules)



Synaptic Learning:

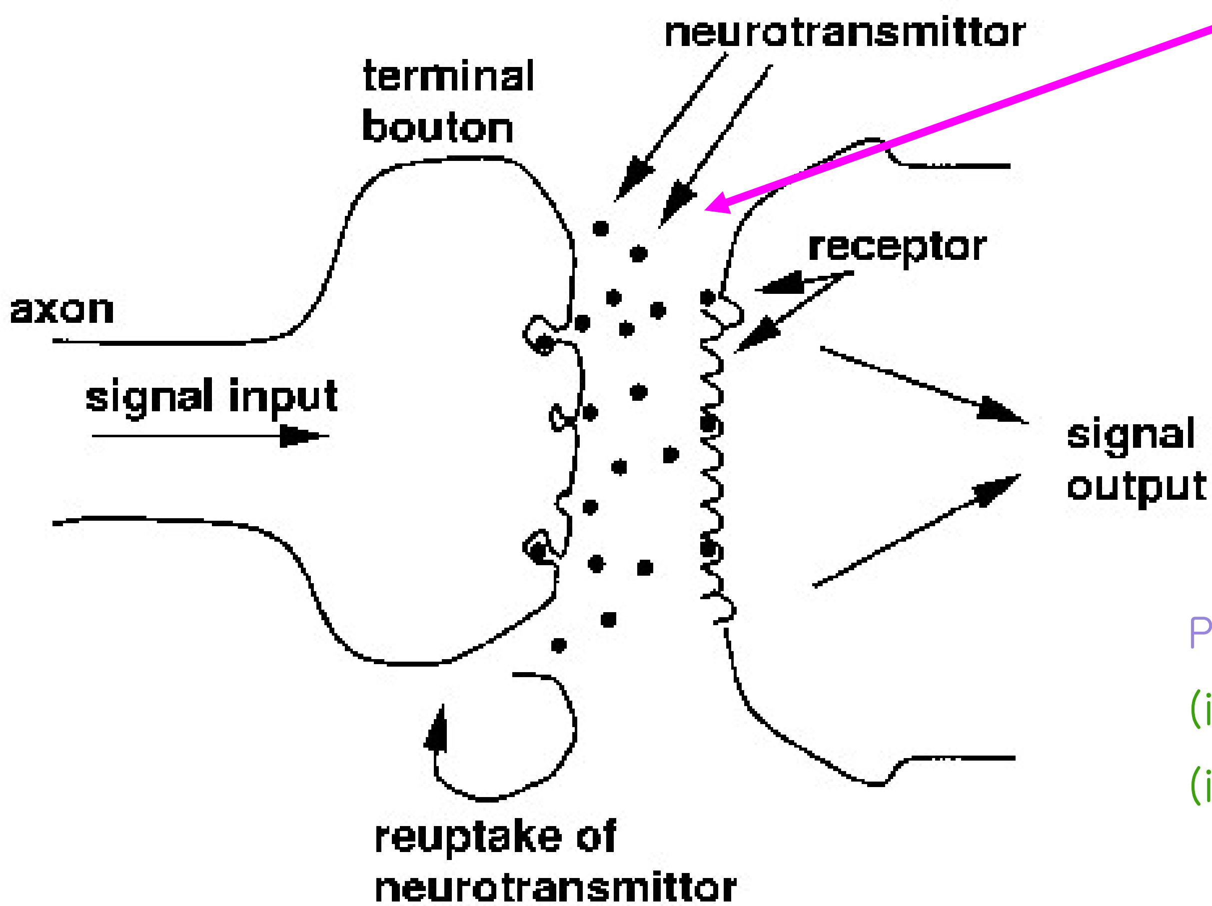
Brains learn. From what we know of neuronal structures, one way brains learn is by **altering the strengths** of connections between neurons, and by adding or deleting connections between neurons. Furthermore, they learn "on-line", based on experience, and typically without the benefit of a benevolent teacher.

Synapses

Presynaptic

Postsynaptic

Synaptic junction



PSP(PostSynaptic Potential)

(i)EPSPs(Excitatory PSPs)

(ii)IPSPs(Inhibitory PSPs)

Neurotransmission

- Neuron's output is encoded as a series of voltage pulses
  - called action potentials or spikes
- excitatory or inhibitory

  (i) Exitatory: make the cell more likely to fire

  (ii) Inhibitory: make the cell less likely to fire

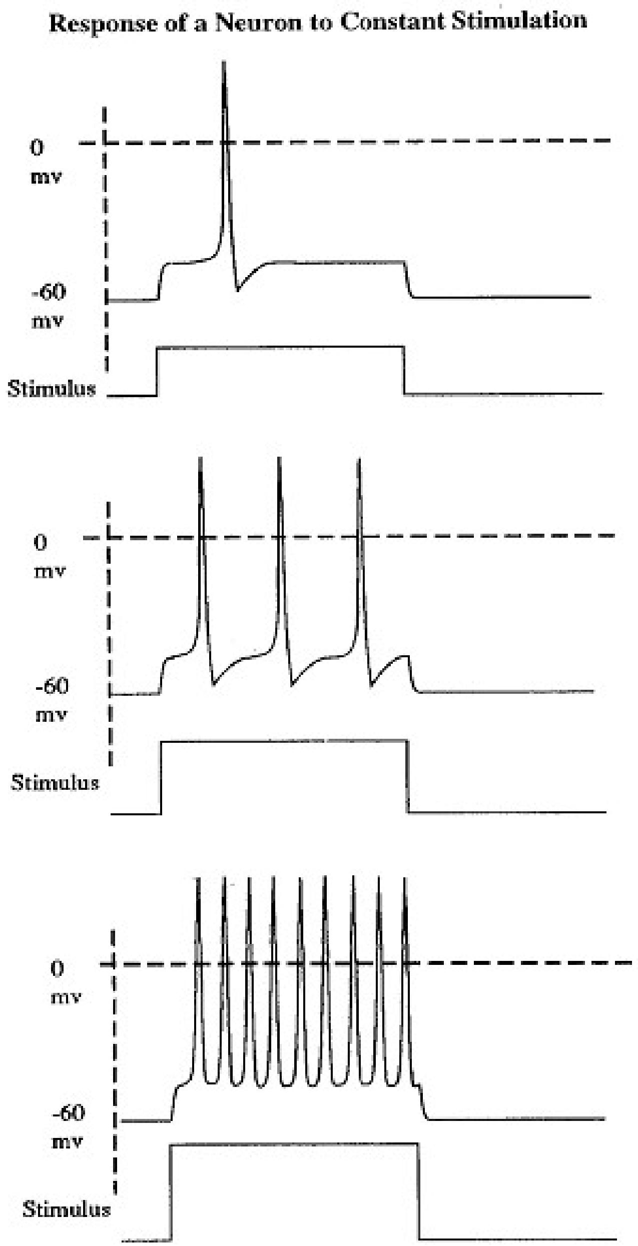
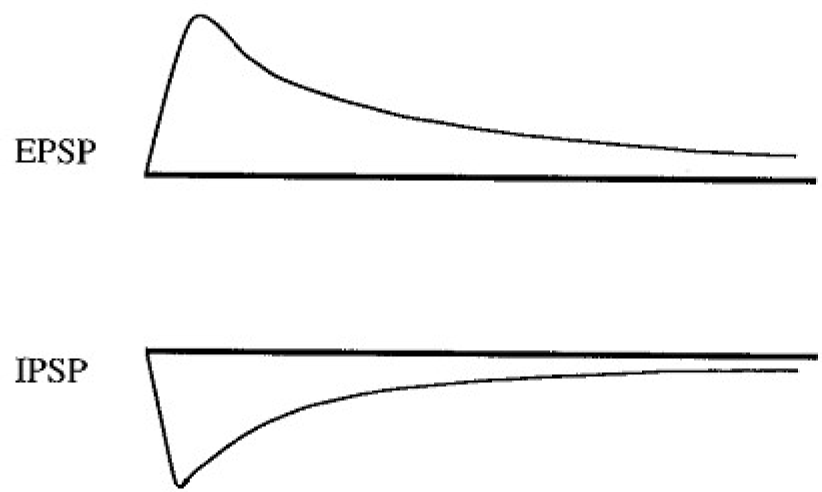
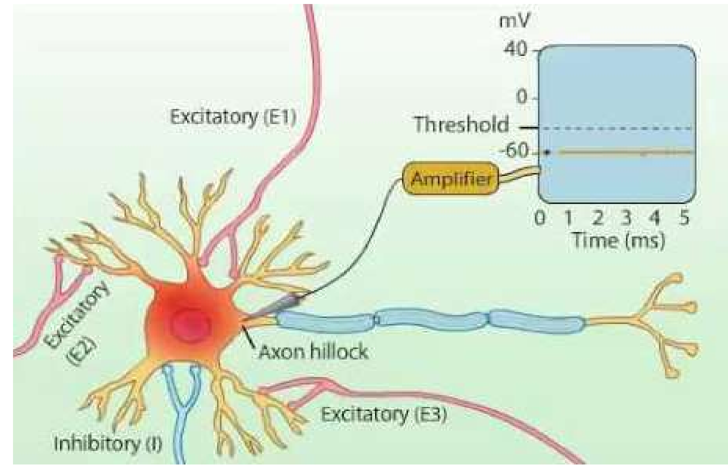


Figure 1.13 Frequency coding in the neuron. When a steady stimulus is applied the frequency of firing of the neuron is a function of the magnitude of the stimulus This suggests that what is important in neural activity is not the presence or absence of action potentials, but the frequency of action potentials.





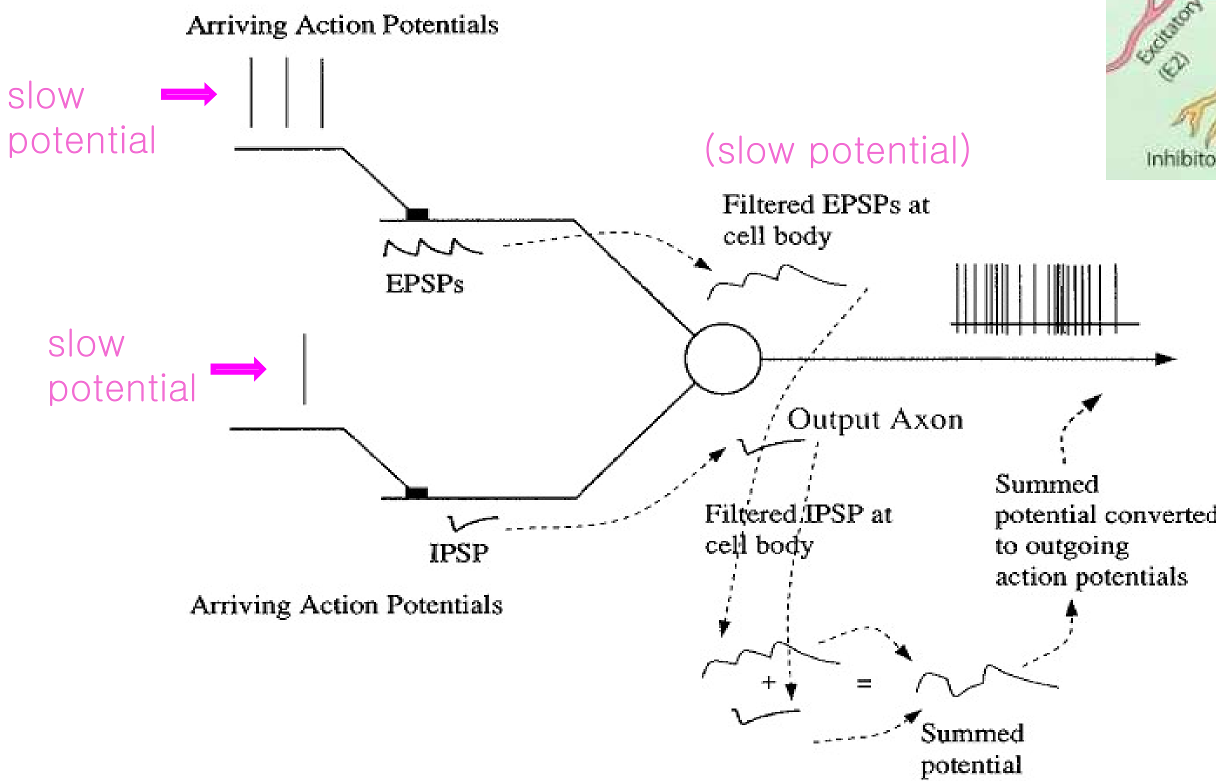


Figure 2.8 A slow-potential neuron. The input to a neuron generates a slow potential that is turned into a train of action potentials, which are transmitted to a distant synaptic terminal. The integrative action of the distant synapse and the membrane of the postsynaptic cell give rise to a reconstructed slow potential. By various combinations of excitation, inhibition, and time and space constants, very complex analog computations are possible with neurons.

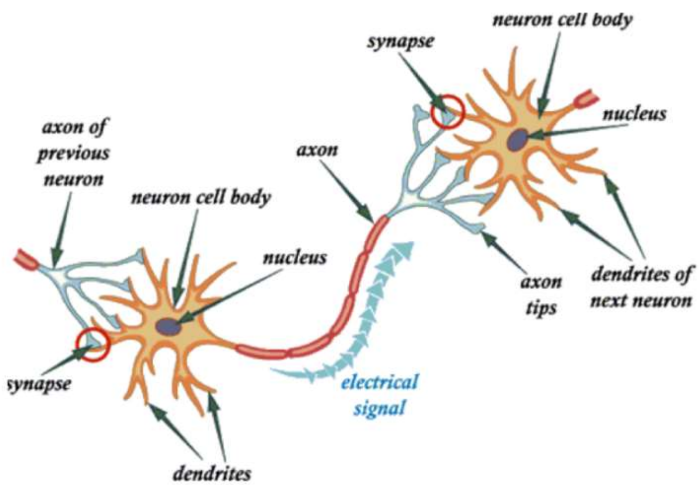
Human Nervous system

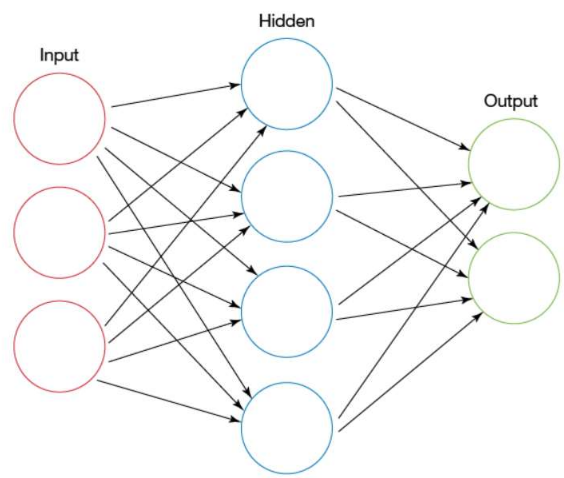
Convert stimuli into electrical impuses

Convert electrical impuses into discernible response as system outputs

stimulus → Receptors ⇄ Neural Net (brain) ⇄ Effectors → response

From human body



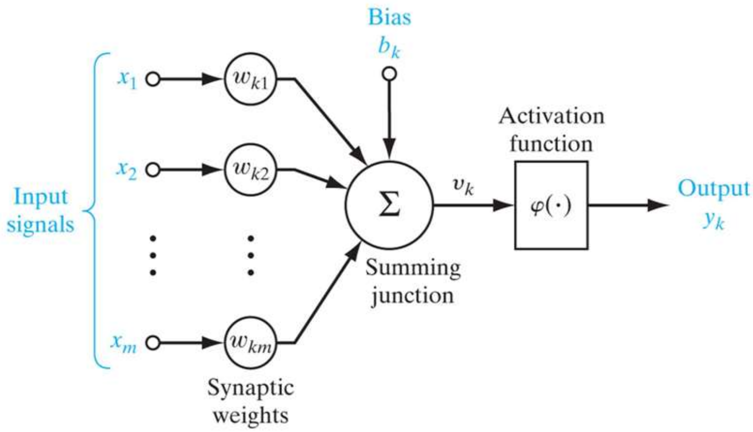


Models of Neuron

- Neuron is information processing unit

Three basic elements of the neuronal model

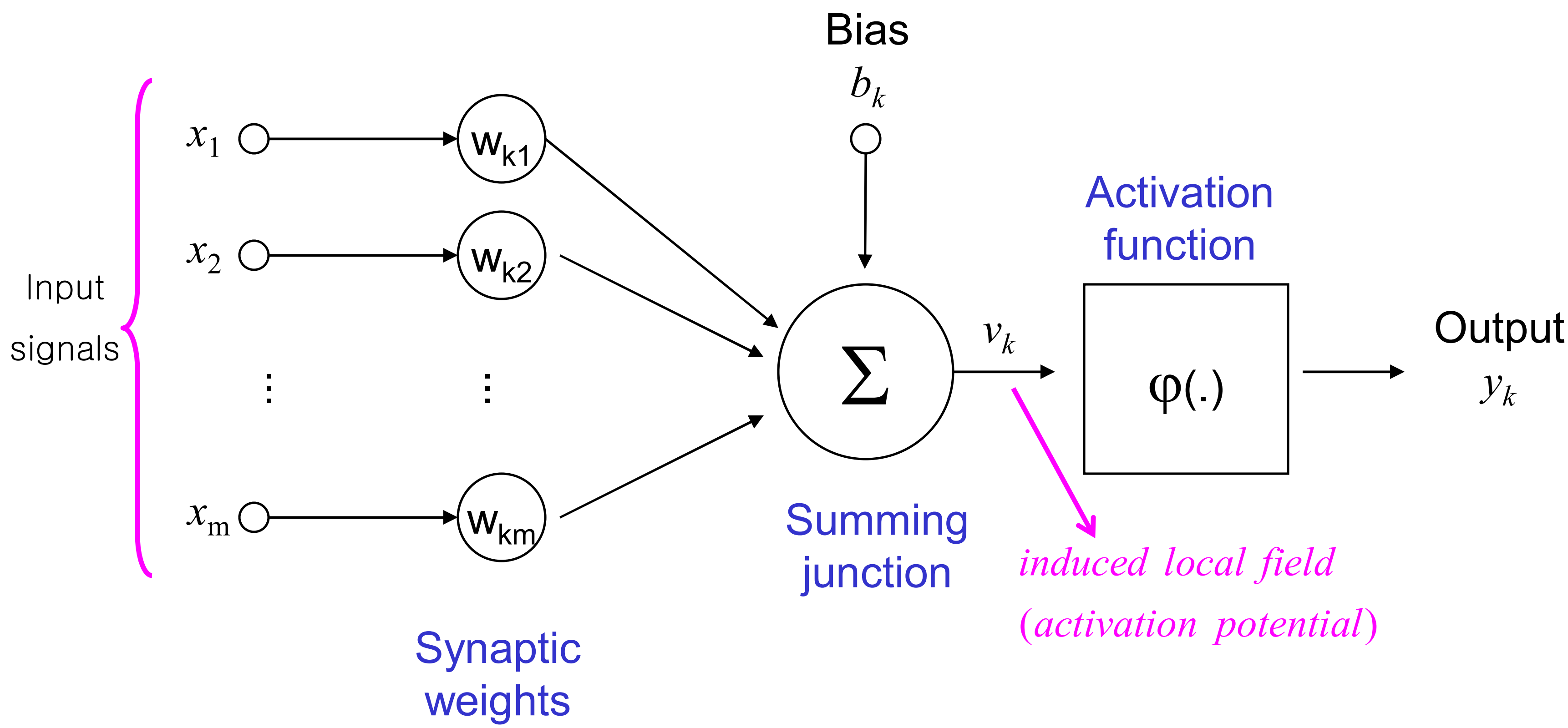
(i) **A set of synapses or connecting links**
- Each of which is characterized by weight or strength of its own



(ii) **An adder (a linear combiner)**
- For summing the input signals weighted by the respective synaptic weight of the neuron

(iii) **An activation function**
- For limiting the amplitude of the output of a neuron, and it is also referred to as squashing function, i.e., squash (limits) the output to some finite values

Nonlinear model of a neuron



The output of the summing function is the linear combiner output:

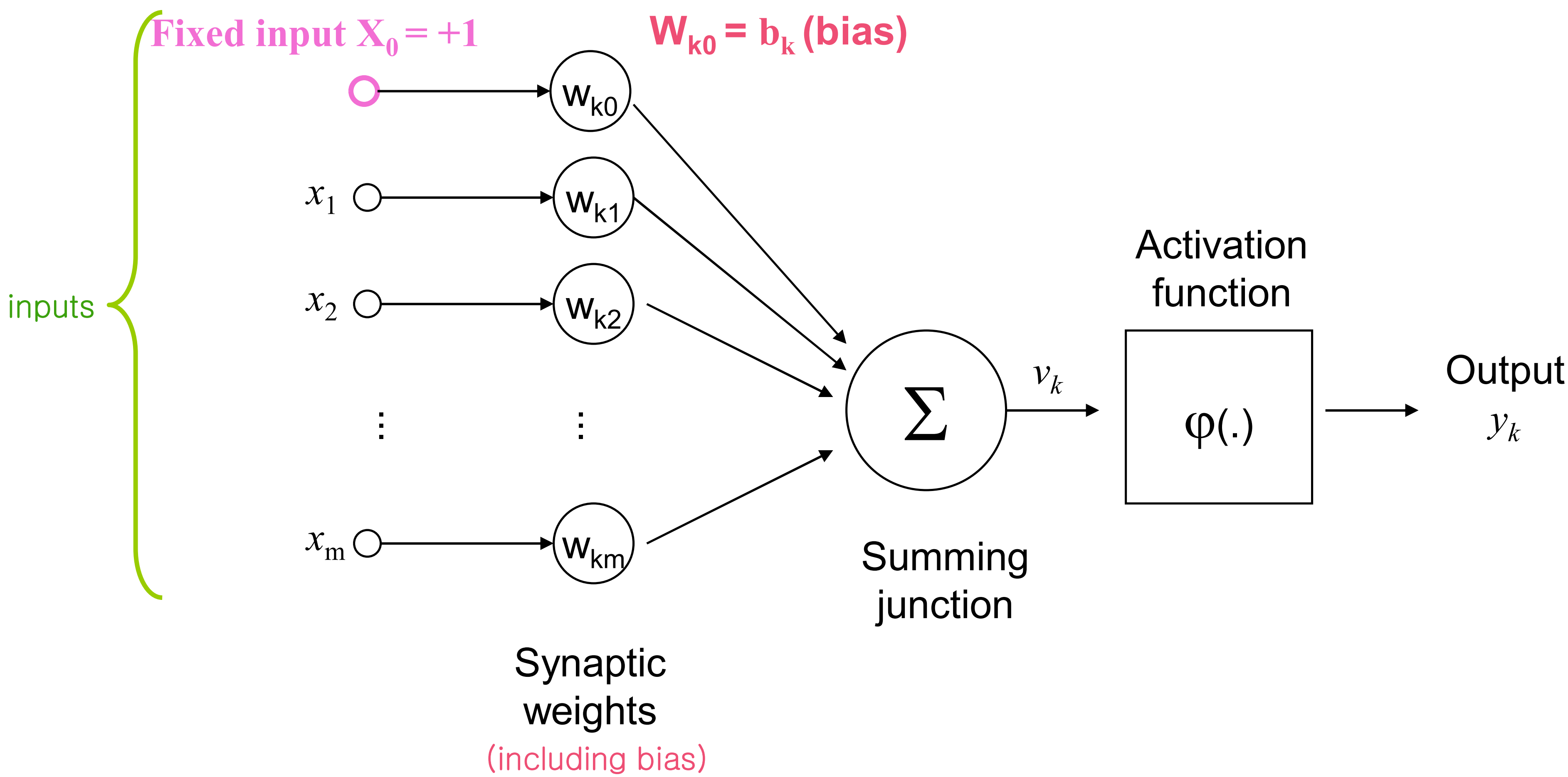
linear combiner

$$v_k = \underbrace{\sum_{j=1}^{m} w_{kj} x_j}_{u_k} + b_k$$

and the final output signal of the neuron:

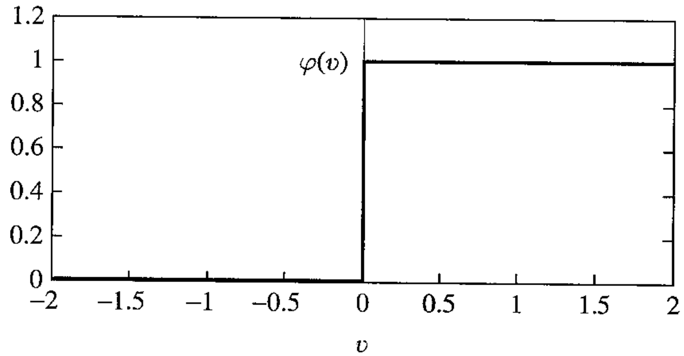
$$y_k = \varphi(v_k)$$

φ(.) is the activation function.



$$v_k = \sum_{j=0}^{m} w_{kj} x_j \qquad y_k = \varphi(v_k)$$

Types of Activation Function range from 0 to 1



(a)

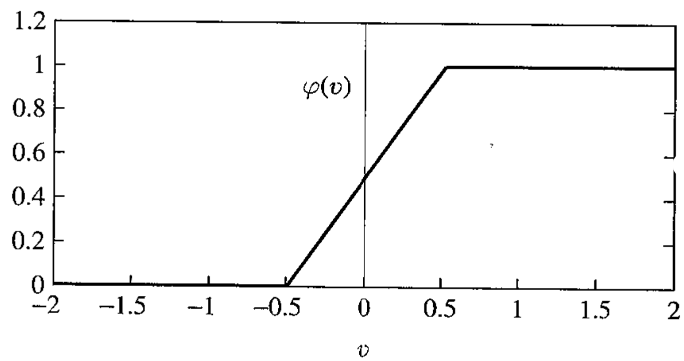
Heaviside function

$$y_k = \varphi(v_k) = \begin{cases} 1 & if \quad v_k \geq 0 \\ 0 & if \quad v_k < 0 \end{cases}$$

$$\text{where} \quad v_k = \sum_{j=1}^{m} w_{kj} x_j + b_k$$

McClloch-pitts neuron model

That is, the neuron will has output signal only if its activation potential is *non-negative*, a property known as *all-or-none*.



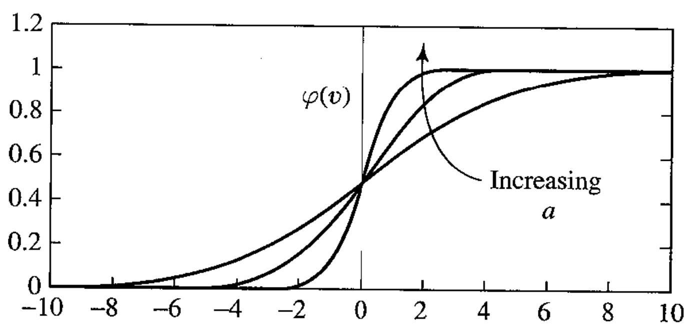
(b)

; Piecewise-linear Function

- the most commonly used function. It is a strictly increasing function that exhibit a graceful balance between linear and nonlinear behavior.
  - This function is differentiable, which is an important feature for the neural network theory.

$$\varphi(v) = \frac{1}{1 + \exp(-av)}$$

a: slope parameter



logistic function is also called binary sigmoid function.

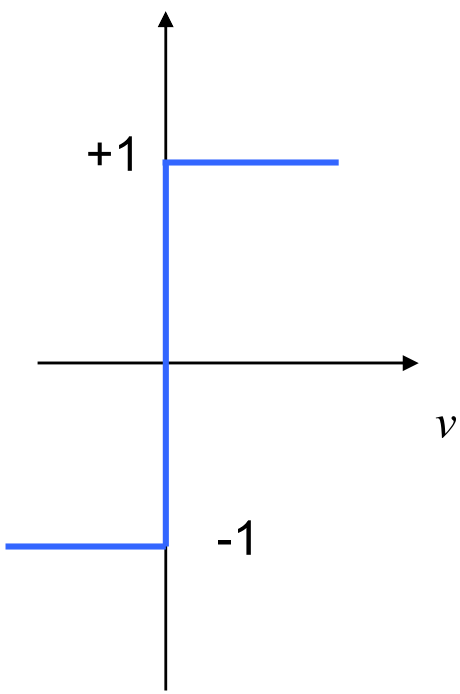
(c)

FIGURE 1.8 (a) Threshold function. (b) Piecewise-linear function. (c) Sigmoid function for varying slope parameter *a*.

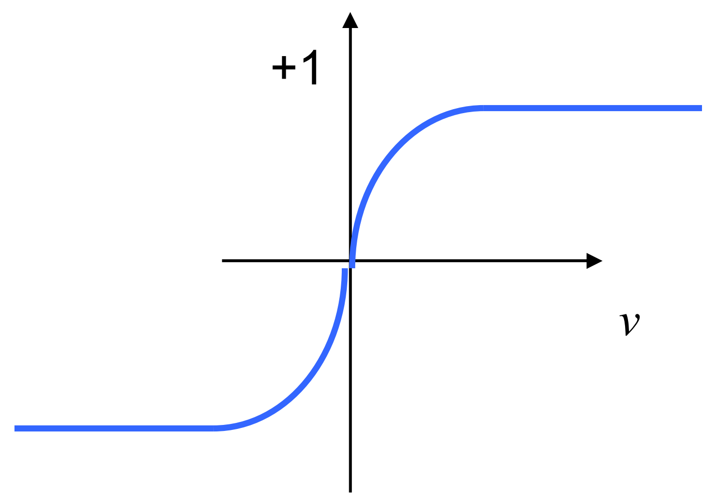
As "a" increases ,
it is close to the threshold func

Activation Function range from 1 to -1

- the *signum function*, which is an *odd* function of its activation potential *v*.
- The *hyperbolic tangent function*, which allows for an *odd* sigmoid-type function.



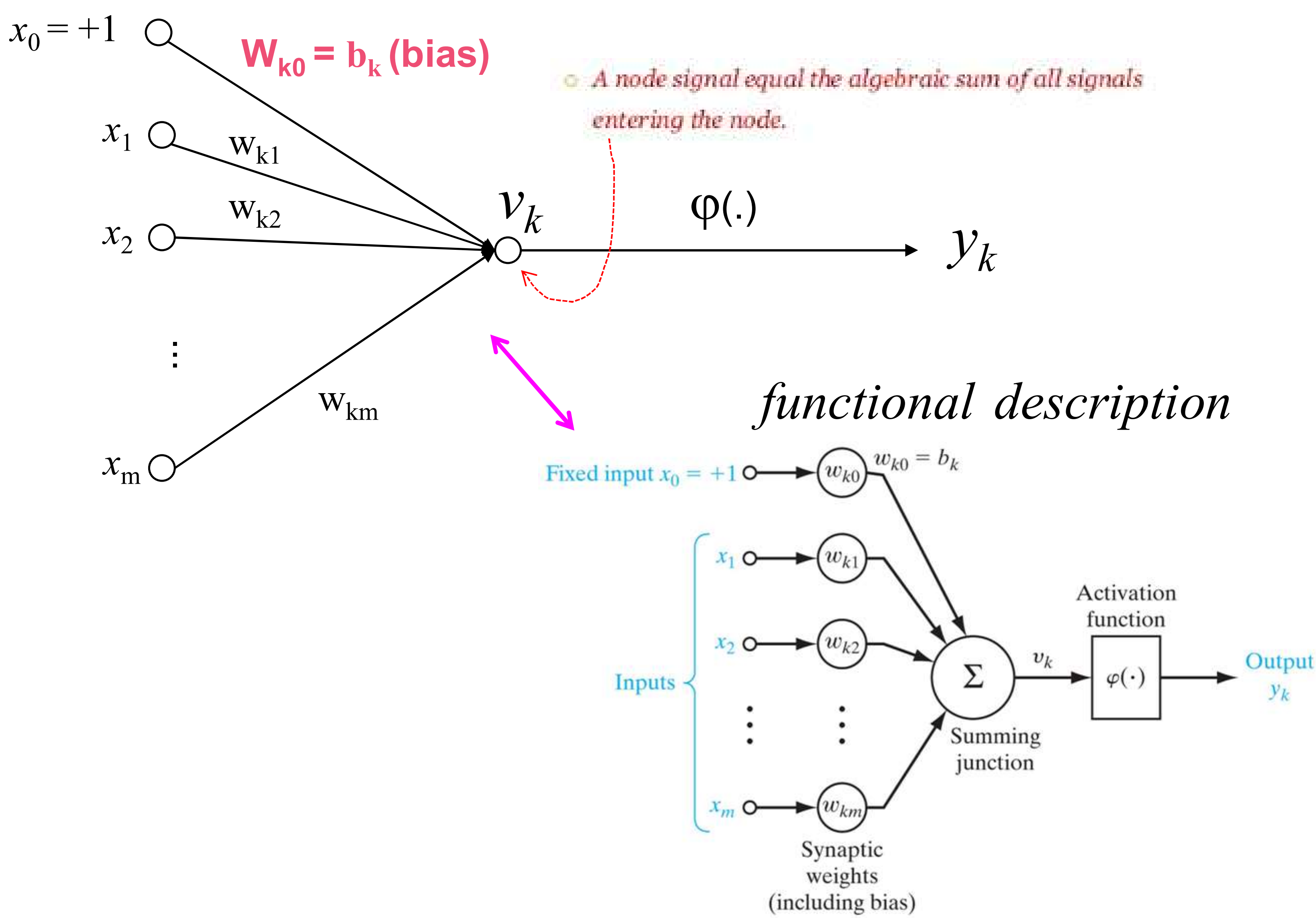
Signum Function



Hyperbolic tangent Function

$$\varphi(v) = \tanh(v)$$

Signal Flow Graph of a Neuron



Matlab Tutorial 1

https://www.youtube.com/watch?v=w1cnxqBaljA&list=PLnVYEpTNGNtX6FcQm90I0WXdvhoEJPp3p&index=1

https://www.youtube.com/watch?v=No7T3mB5otg&list=PLnVYEpTNGNtX6FcQm90I0WXdvhoEJPp3p&index=2

https://www.youtube.com/watch?v=vAH81yZ8nWk&list=PLnVYEpTNGNtX6FcQm90I0WXdvhoEJPp3p&index=3

https://www.youtube.com/watch?v=D7R999SogAM&list=PLnVYEpTNGNtX6FcQm90I0WXdvhoEJPp3p&index=4

https://www.youtube.com/watch?v=ygGF3RR1NyM&list=PLnVYEpTNGNtX6FcQm90I0WXdvhoEJPp3p&index=5