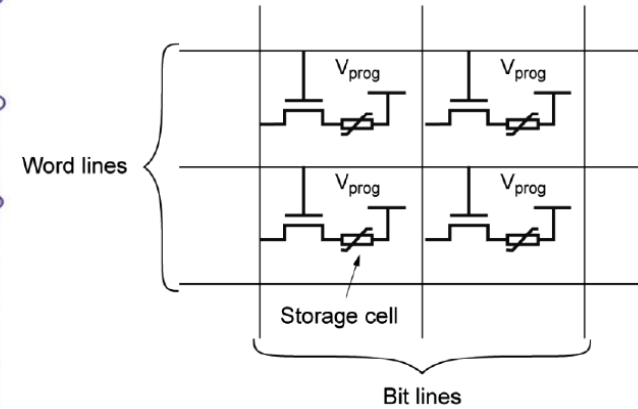
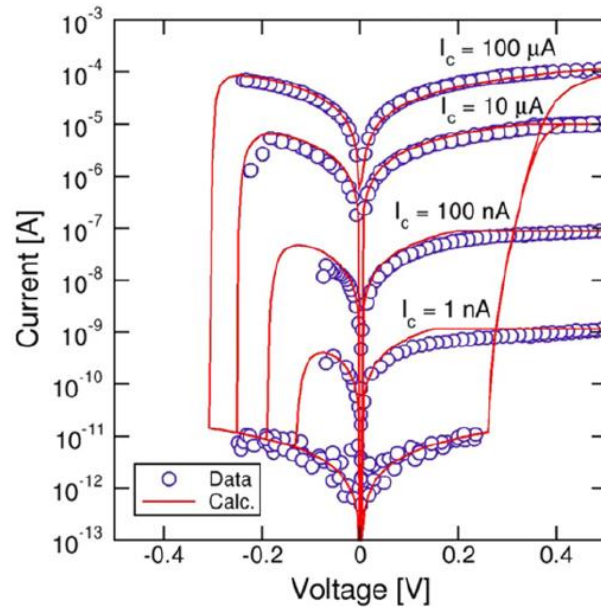
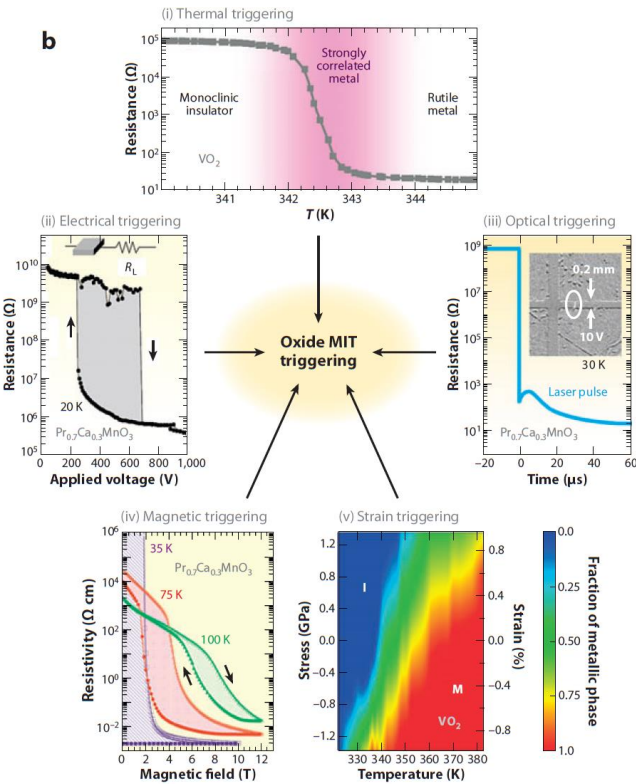


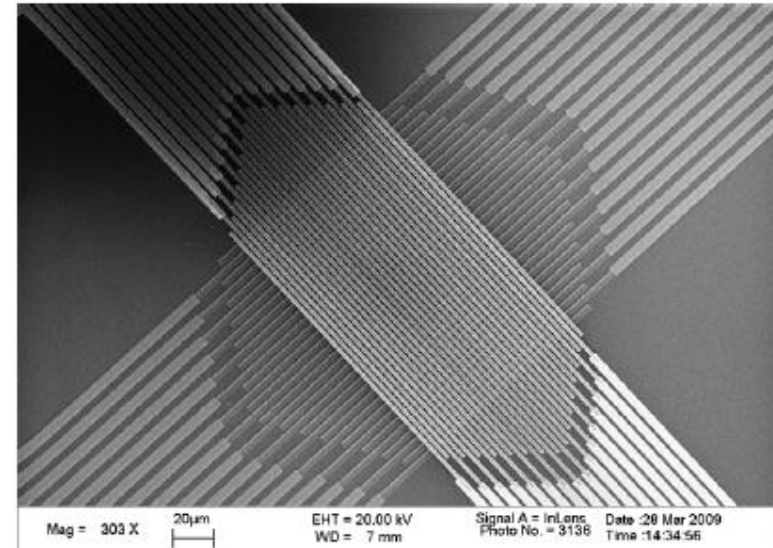
L7: Neuromorphic Computing

Instructor: Prof. Feng Xiong

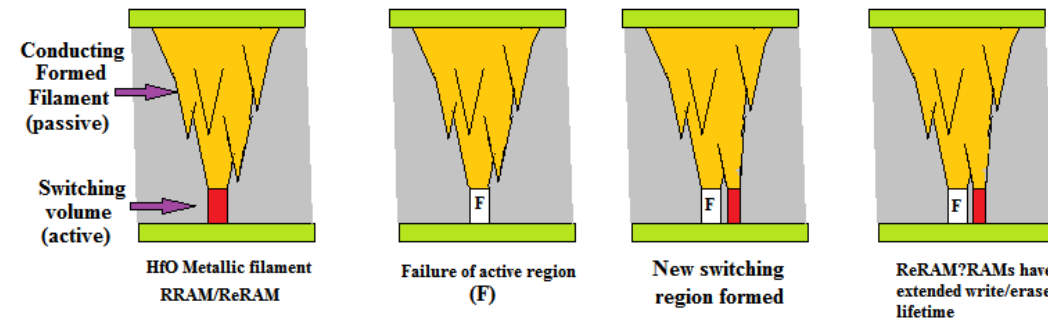
Recap



Crossbar array



Scaling implications: Write/Erase endurance requires the existence of a large filament



Outline

- Introduction to Neuromorphic Computing
- Biological neural network and synapse
- Synaptic plasticity
- Hebbian Learning
- Spike-timing dependent plasticity (STDP)

Computing Challenge

- Computer

- well structured work
- computing
- storage
- high-speed communication

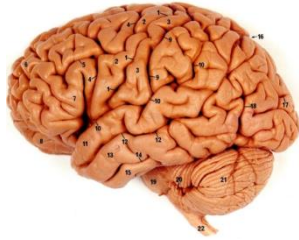
- Human

- fuzzy problems
- image recognition
- creativity: writing a poem
- deep level understanding



Energy Consumption

(IBM Watson, *Jeopardy!* champion)



20 Watts



200 kiloWatts

10,000x

Computer Architecture vs Brain

“von Neumann Bottleneck”

Process
(CPU)



Storage
(RAM)

Human Brain

10^{10} Neurons
 10^4 Connections
↓
 10^{14} Synapses

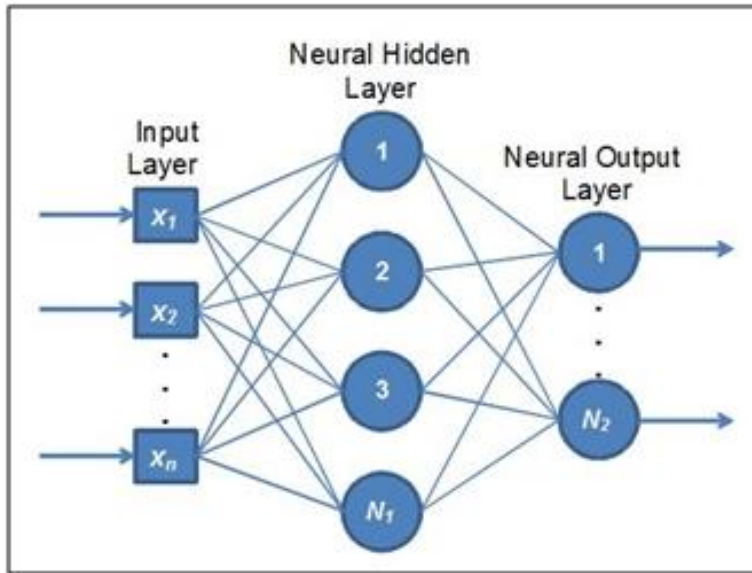
von Neumann Machines
Sequential processing
Only few channels
Fast processing

High degree of complexity
High power consumption



Neuromorphic Machines
Parallel processing
High computing efficiency
Large connectivity

Neuromorphic Computing

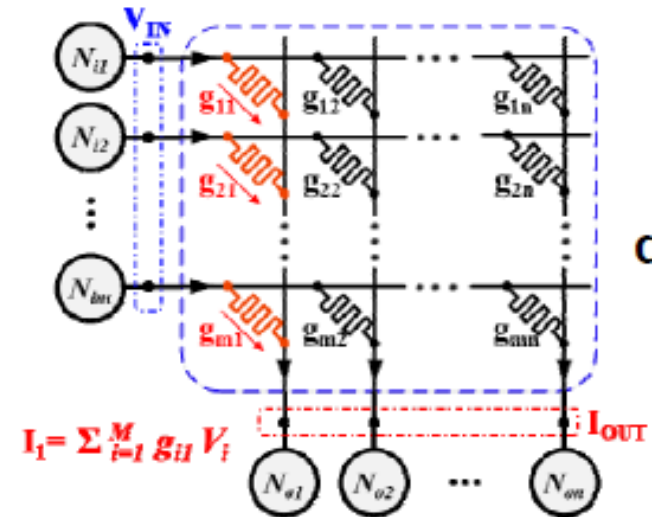


Natural matrix operation

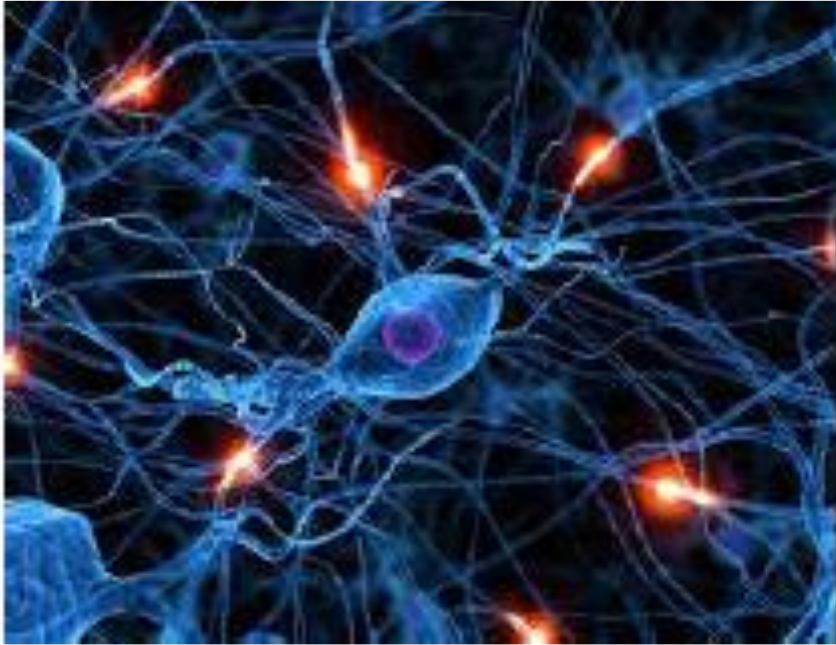
$$[x_1 \ x_2 \ \dots \ x_m] \begin{bmatrix} g_{11} & g_{12} & \dots & g_{1n} \\ g_{21} & g_{22} & \dots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \dots & g_{mn} \end{bmatrix} \parallel \begin{bmatrix} y_1 & y_2 & \dots & y_n \end{bmatrix}$$

$$y_1 = \sum x_i \cdot g_{i1}$$

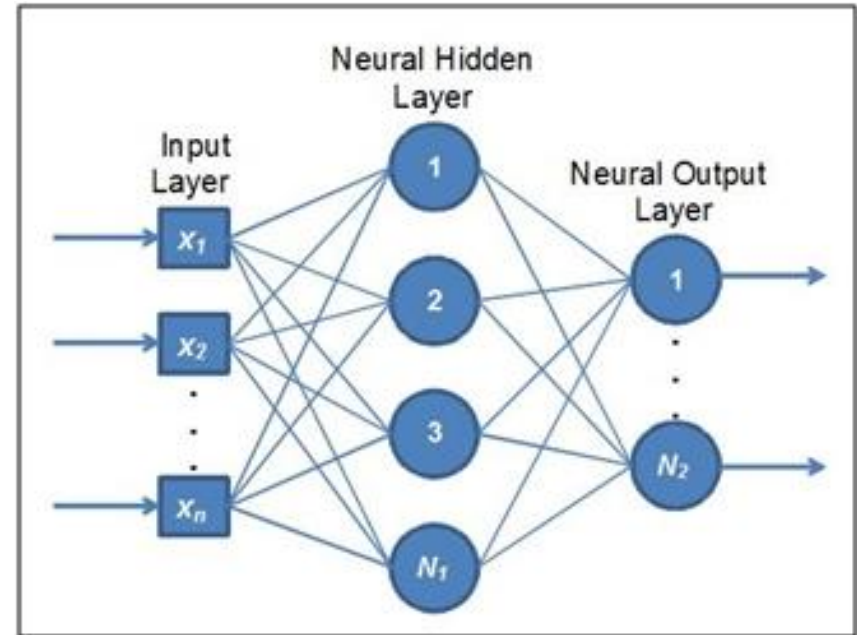
- Mapping a high-dimensional input to a low-dimensional output
- Pioneered by Carver Mead in late 1980s



Neural Network



Artificial Neural Network



- Brain has $\sim 10^{11}$ neurons
- Each neuron has $\sim 10^4$ connections to other neurons
- $\rightarrow 10^{15}$ synapses in our cortex
- Artificial Neural Network (ANN)

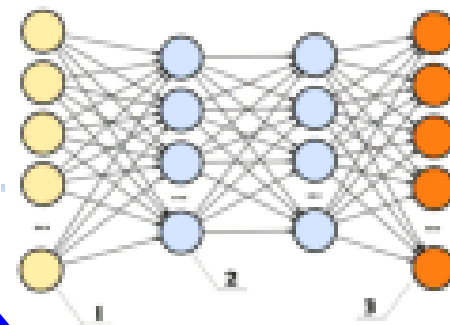
Training and Inference (Supervised)

**training data
(labeled)**

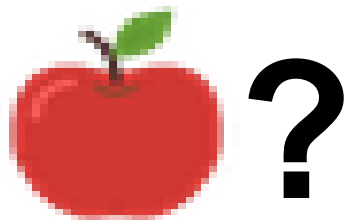


**Training
(Learning)**

trained model



input



**Inference
(Prediction)**

output

95% apple
3% orange
1% cat

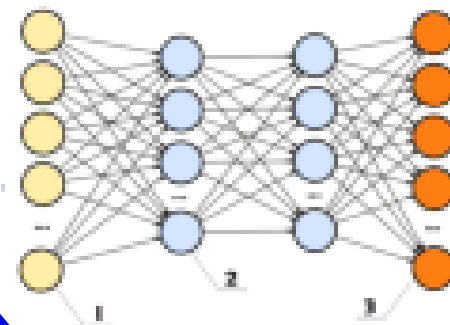
Training and Inference (Un-supervised)

training data
(not labeled)

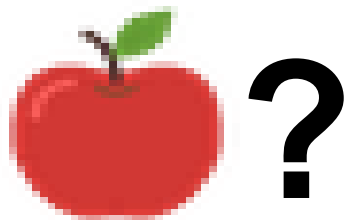


**Training
(Learning)**

trained model






input



**Inference
(Prediction)**

output

95%	
3%	
1%	

Training Process

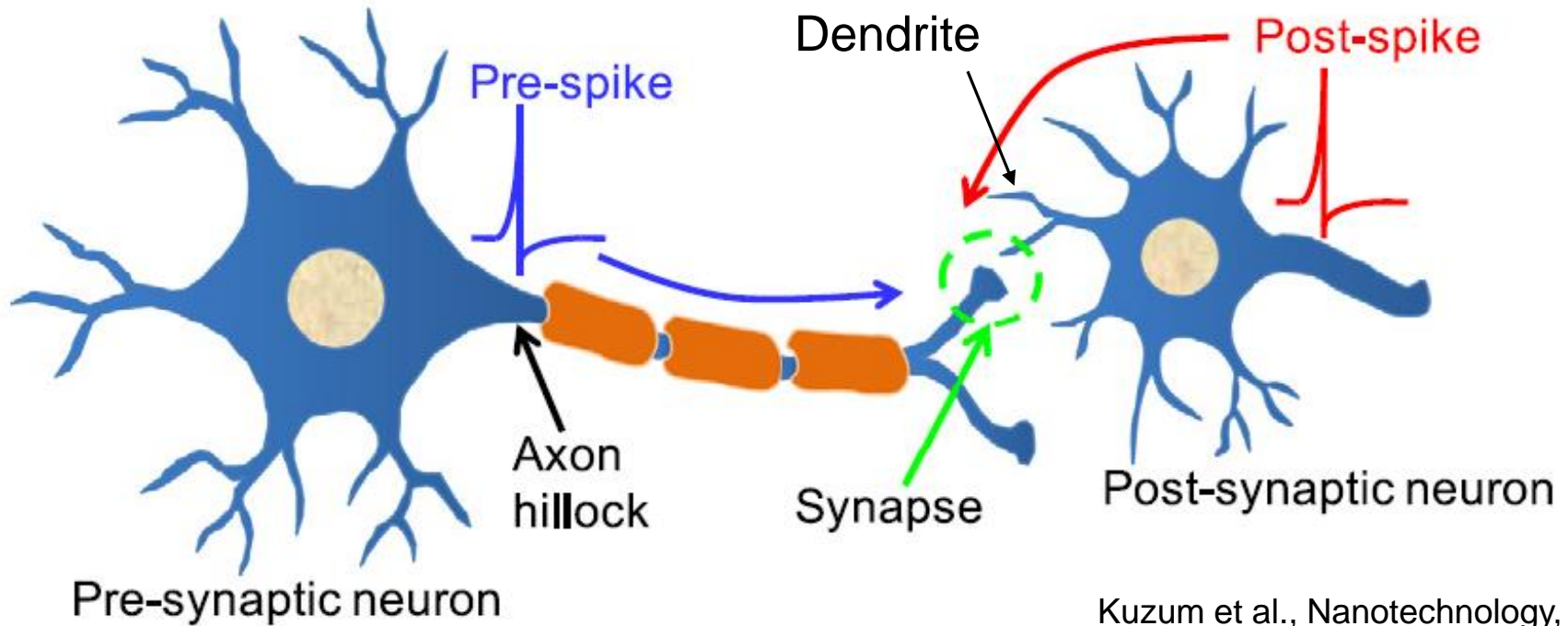


DeepDream



- Training and labeling can be energy and cost expensive
- Excels when the labelling/training cost is low (e.g. GO)
- Applications: self-driving, facial recognition, industrial 4.0

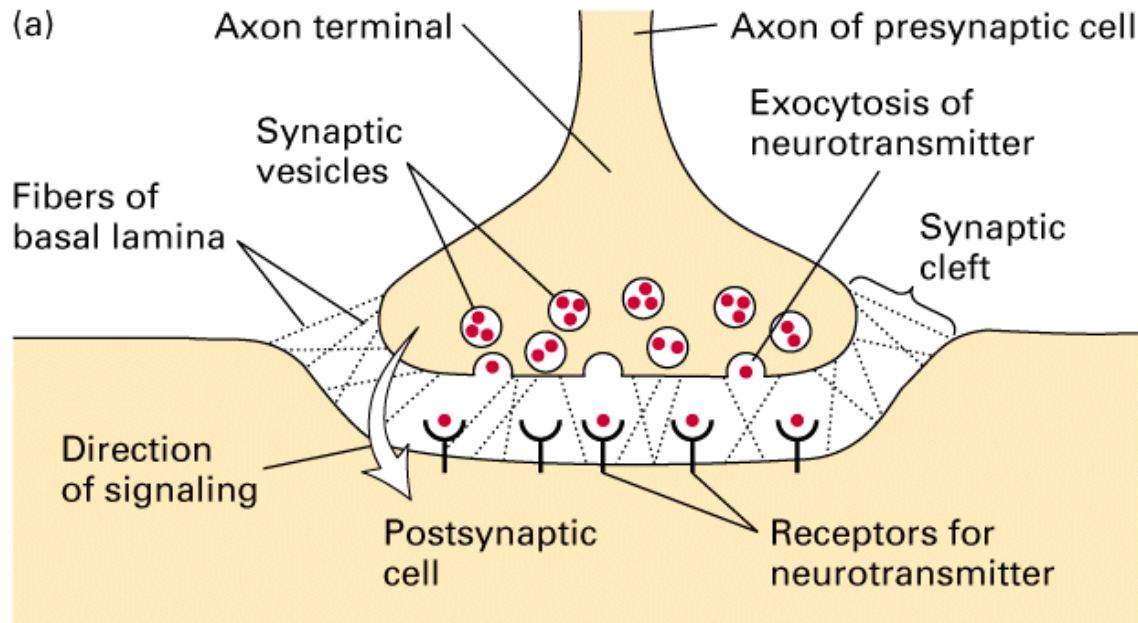
Neurons and Synapses



Kuzum et al., Nanotechnology, 2013

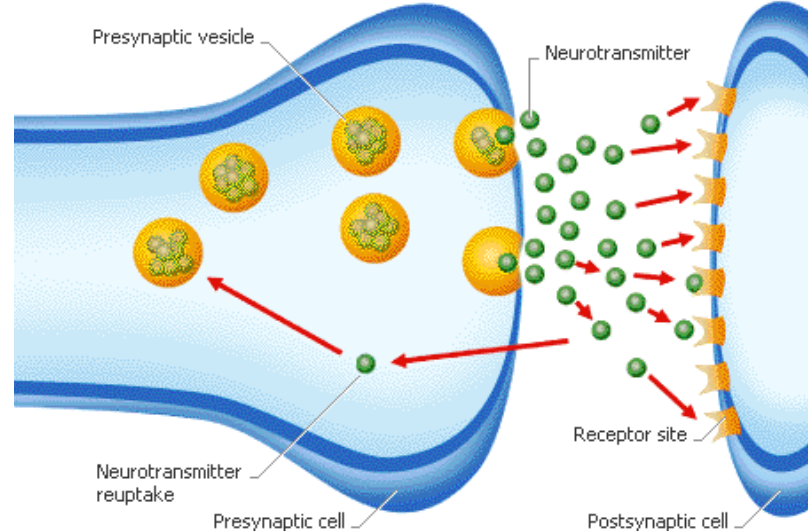
- Neuron: cell body, nucleus, axon, dendrite
- Synapse: connection between neurons
- Axon (pre-) → Synapse → Dendrite (post-)

Synaptic Transmission



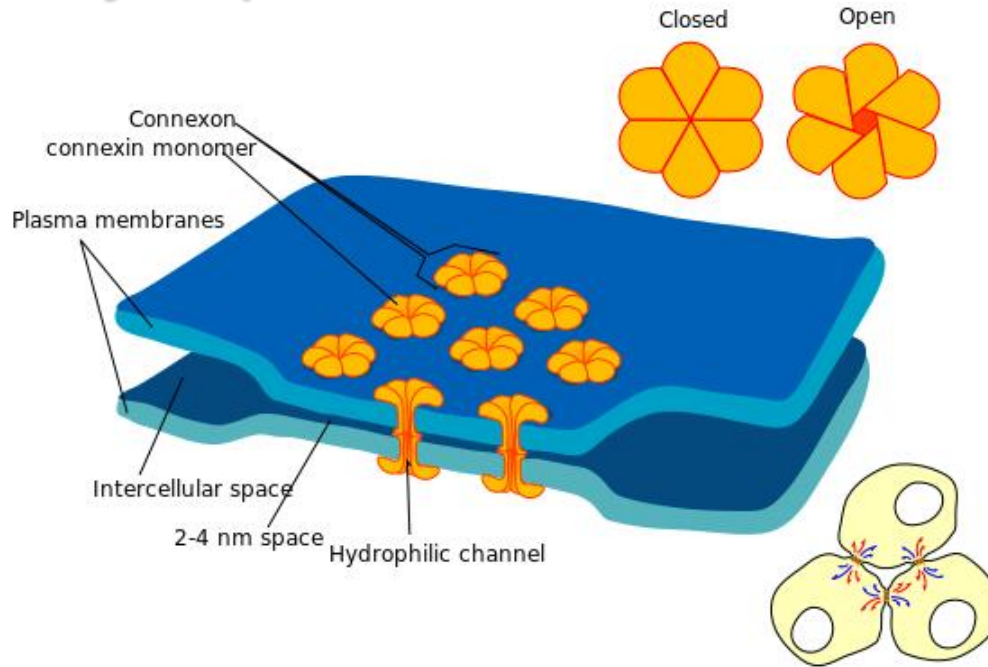
- Neurons are electrically polarized – maintaining a voltage difference across the cell's membrane → membrane potential
- Resting potential and threshold potential
- Synaptic transmission
 1. Pre-synaptic neuron receives a threshold action potential
 2. Release neurotransmitter across synapse and captured by the receptor
 3. Resulting in short term or long term change in post-synaptic potential

Neurotransmitter in Chemical Synapse



- Neurotransmitters are chemical messengers such as amino acids; over 100 have been identified
- Generated from voltage-gated ion channels in neuron
 - Channels are closed near resting potential;
 - Open if over threshold potential
- Synaptic activities result in Na^+ and Ca^{2+} ion movement in a neuron → changing its membrane potential

Electrical Synapses



- **Electrical synapses**

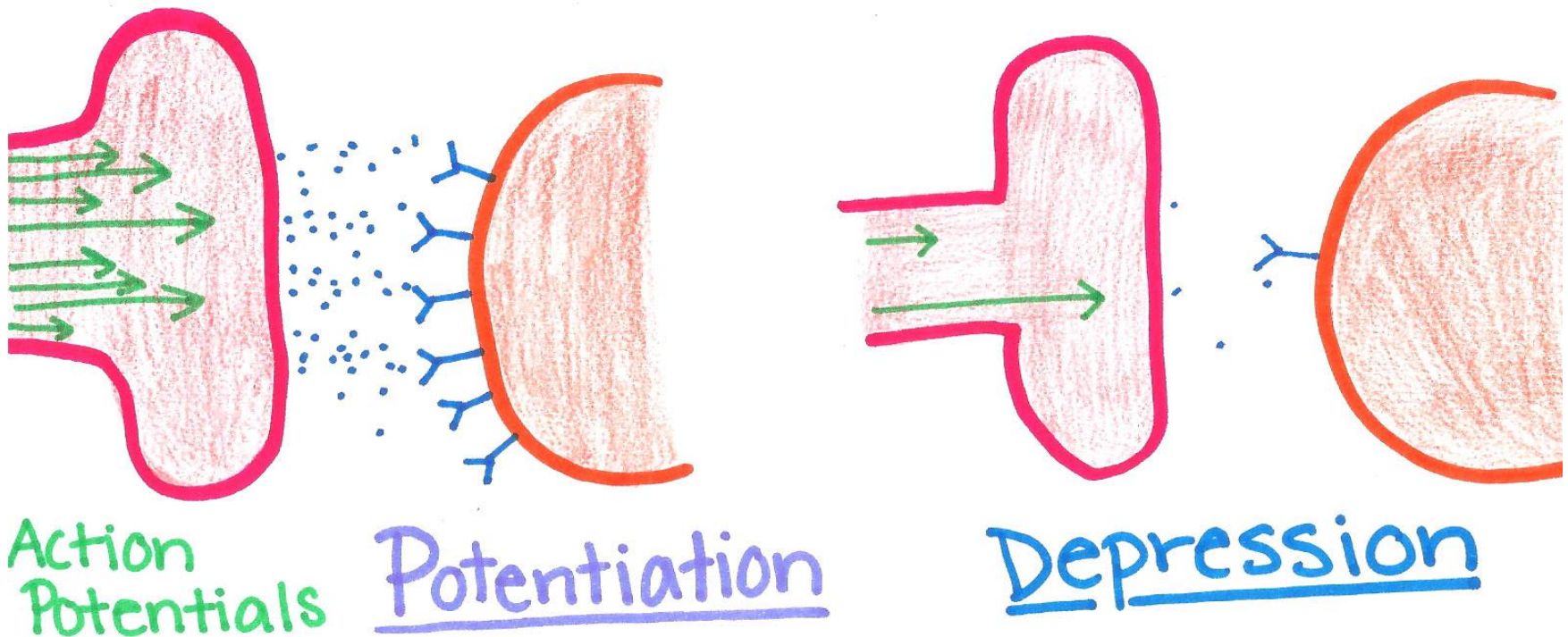
- Mechanical and electrically conductive link
- minority in the nervous systems
- direct connection between neurons through gap junctions
- action potential can be transmitted directly via free flow of ions in a non-chemical mediated transmission
- faster but lacking gain

Synaptic Plasticity

- Electrical synapse are stable
- Chemical synapses possess plasticity
- Plastic → reshaping or the art of modeling
- Plasticity: synapse' ability to strengthen or weaken their connection, in response to increase or decrease neural activities
- Physically: change in the number of neurotransmitter receptors in a synapse; as well as how much neuron responds to neurotransmitters
- Important to memory and learning

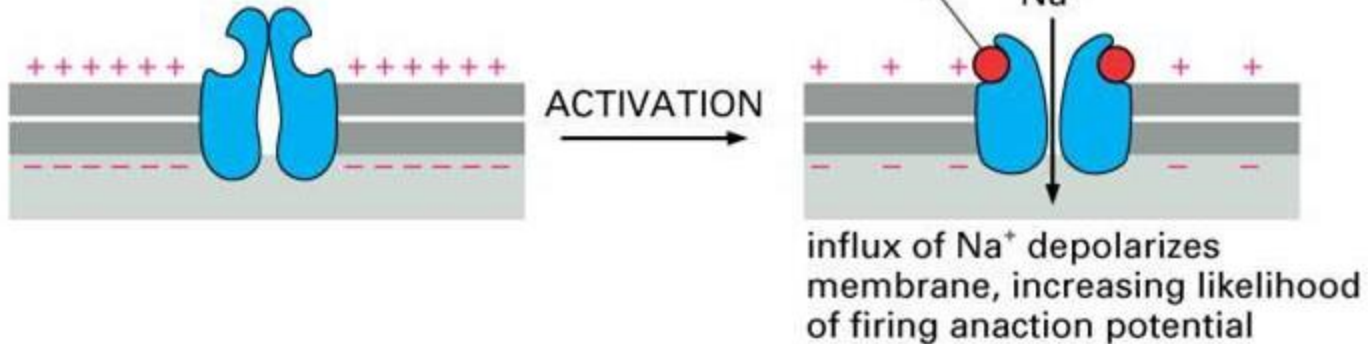
Potential and Depression

- Potentiation: synapse connection increases in weight or conductance
- Depression: synapse connection decreases in weight or conductance

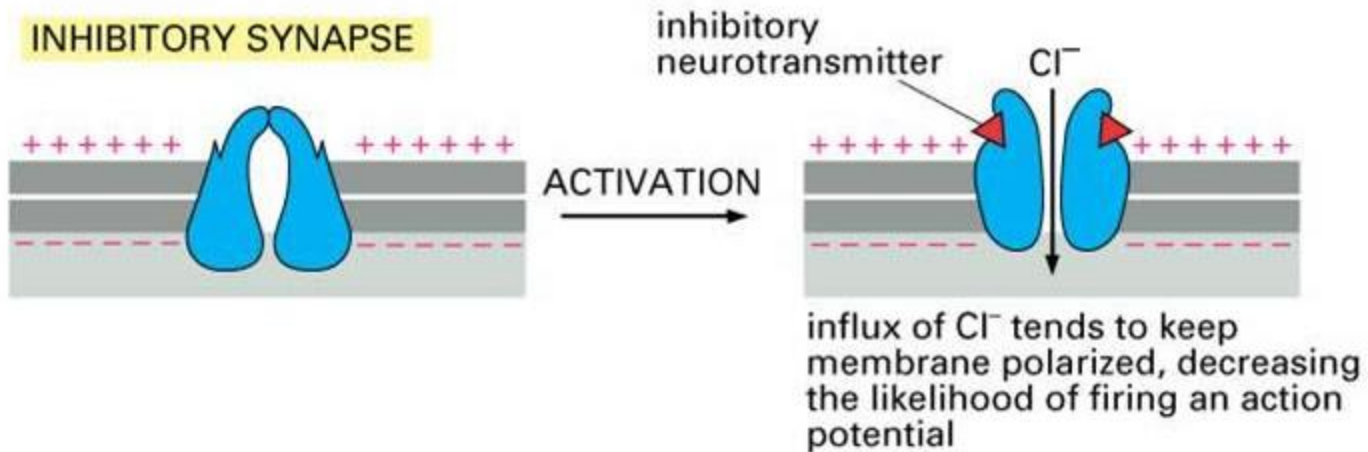


Excitatory and Inhibitory Synapse

EXCITATORY SYNAPSE



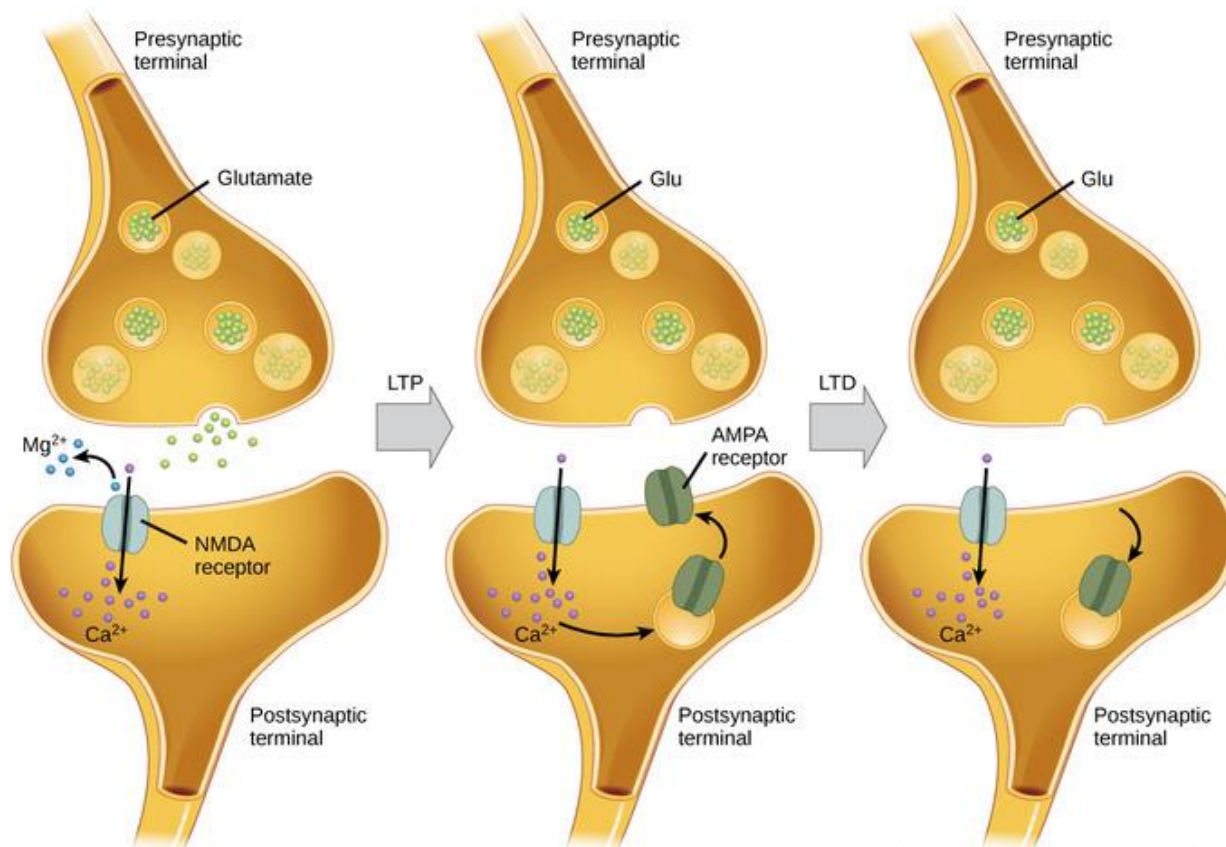
INHIBITORY SYNAPSE



- Excitatory synapse: potentiates upon pre-synaptic signal
- Inhibitory synapse: depresses upon pre-synaptic signal

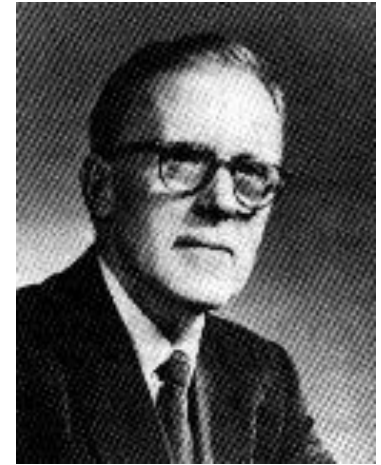
Long Term Potentiation and Depression

- Long term plasticity: durable and persistent
- LTP: long term potentiation
- LTD: long term depression

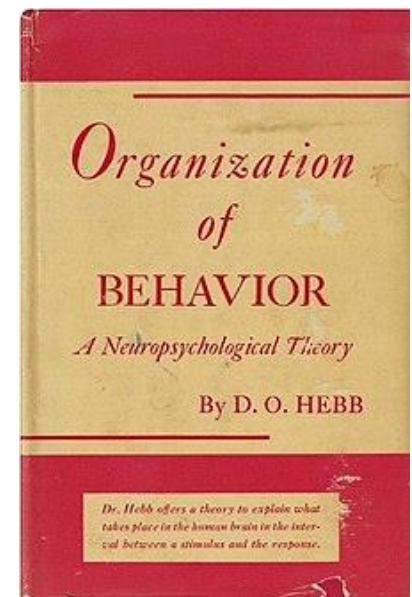


Hebbian Learning

- Neurons that fire together, wire together!
- First introduced by Donald Hebb in 1949 in his book “The Organization of Behavior”
- Principle: any two cells or systems of cells that are repeatedly active around the same time tend to become associated, so that activity in one facilitates activity in the other



Donald Hebb
Canadian Psychologist



Spike Timing Dependent Plasticity (STDP)

- Hebbian learning: connection strength between neurons are modified based on neural activities during learning
- STDP
 - spike timing dependent plasticity
 - focus on **temporal order** of spikes in cellular learning
 - plasticity depends on relative timing of pre- and post-synaptic spikes

