Learning to associate

CS786 6th August 2024

What RW could explain







What it couldn't



Pre-exposed



Dog

Latent inhibition

Latent cause modeling of conditioning

Rescorla Wagner model*

Latent cause model*

CS UCS

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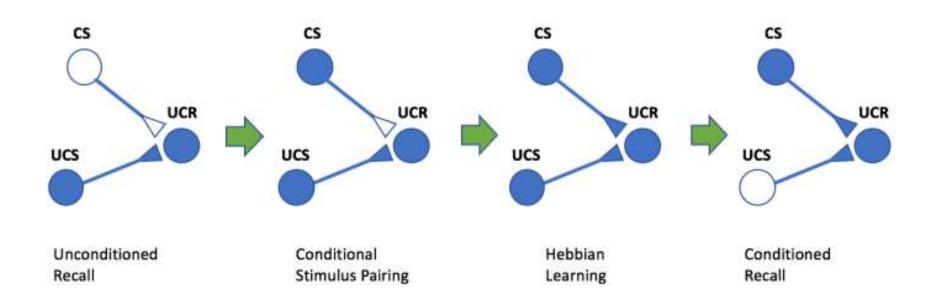
UCS

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^{*} See Courville, Daw & Touretzky (2005) for a formal description

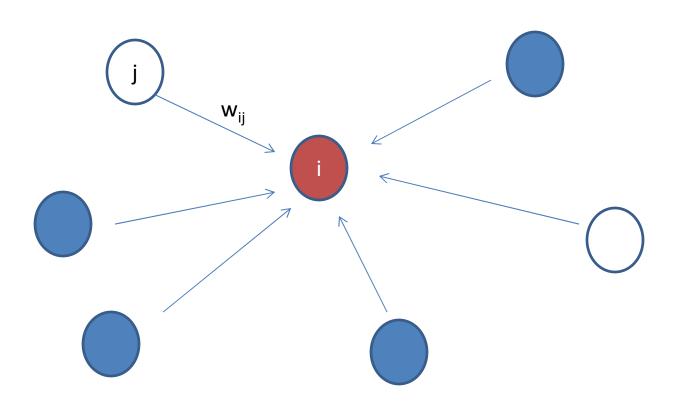
Explaining associativity



Hebbian learning

- If two information processing units are activated simultaneously, their activity will become correlated, such that activity in one will make activity in the other more likely
- We will see
 - How Hebbian learning works in artificial neurons
 - How Hebbian learning works in real neurons

Hebbian learning



$$\Delta w_{ij} = x_i x_j$$

Hebb's rule in action

Common variant

$$\Delta \mathbf{w}_t = \eta \mathbf{x}_t y$$
$$y = \sum_i w_{ij} x_j$$

- Problem
 - No way to weaken weights
 - Weights can climb up without bound
 - Solution: normalization?

Normalizing Hebb's rule

 Oja's rule can be derived as an approximate normalized version of Hebb's rule

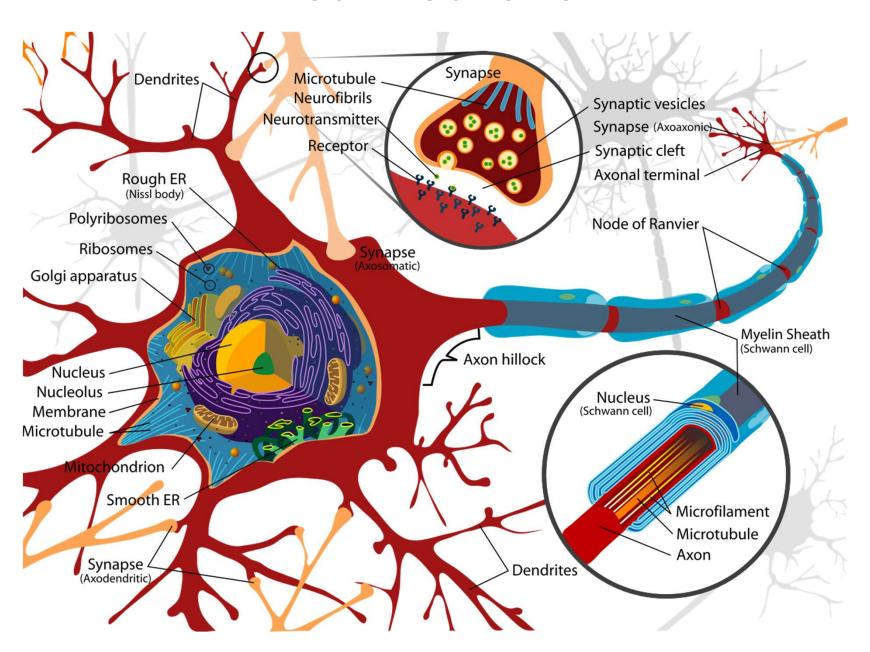
$$\Delta \mathbf{w}_n = \eta y_n (\mathbf{x}_n - y_n \mathbf{w}_n)$$

- Other formulations are also possible, e.g. BCM, generalized Hebb
- Hebbian learning partially explains how neurons can encode new information
 - And explains how this learning is fundamentally associative

What neurons do – the ML version

- A neuron collects signals from dendrites
- Sends out spikes of electrical activity through an axon, which splits into thousands of branches.
- At the end of each branch, a synapse converts activity into either exciting or inhibiting activity of a dendrite at another neuron
- Neuron fires when exciting activity surpasses inhibitory activity above some threshold Learning changes the strength of synapses

Real neurons

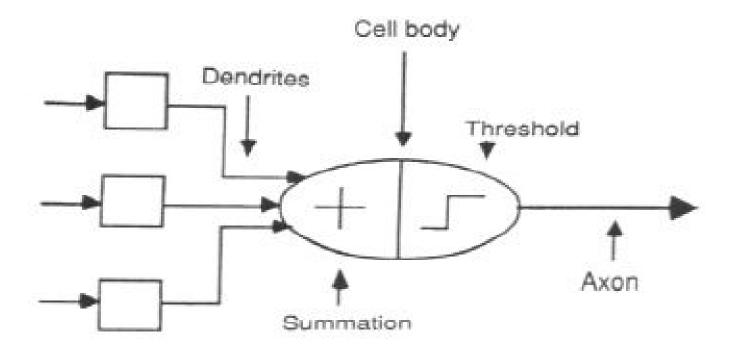


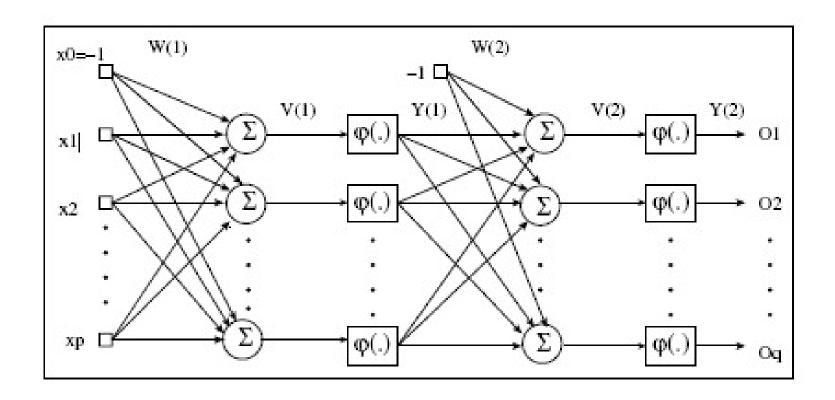
What neurons do – the ML version

- A neuron collects signals from dendrites (not quite)
- Sends out spikes of electrical activity through an axon, which splits into thousands of branches.
- At the end of each branch, a synapse converts activity into either exciting or inhibiting activity of a dendrite at another neuron (more complicated than this)
- Neuron fires when exciting activity surpasses inhibitory activity above some threshold (neurotransmitters govern the threshold and activity rate)
- Learning changes the strength of synapses (but what sort of learning?)

Artificial neurons

 Logical abstraction of natural neurons to perform these functions





- Apply input vector X to layer of neurons.
- Calculate $V_j(n) = \sum_{i=1}^p w_{ij} x_i + w_0$
 - where x_i is the activation of previous layer neuron i
 - w_{ii} is the weight of going from node i to node j
 - p is the number of neurons in the previous layer
- Calculate output activation

$$Y_{j}(n) = \frac{1}{1 + \exp(-V_{j}(n))}$$

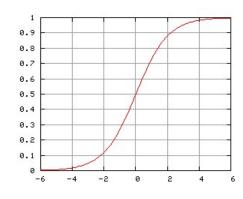
Possible firing rules

- Firing Rules: Sigmoid functions:
 - Hyperbolic tangent function

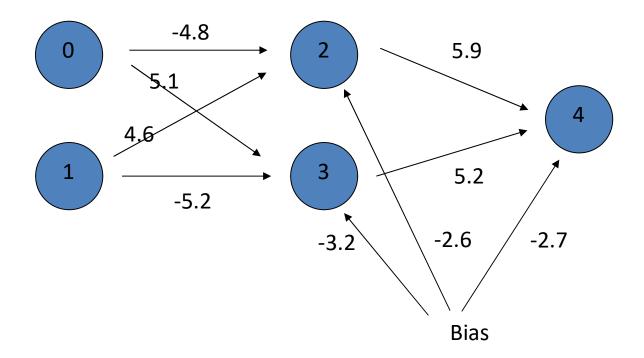
$$\varphi(\nu) = \tanh(\nu/2) = \frac{1 - \exp(-\nu)}{1 + \exp(-\nu)}$$

Logistic activation function

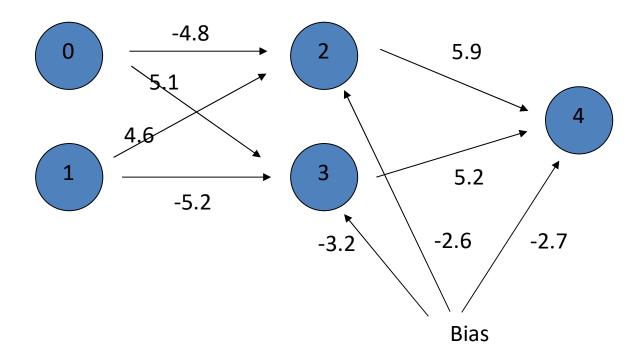
$$\varphi(\nu) = \frac{1}{1 + \exp(-\nu)}$$



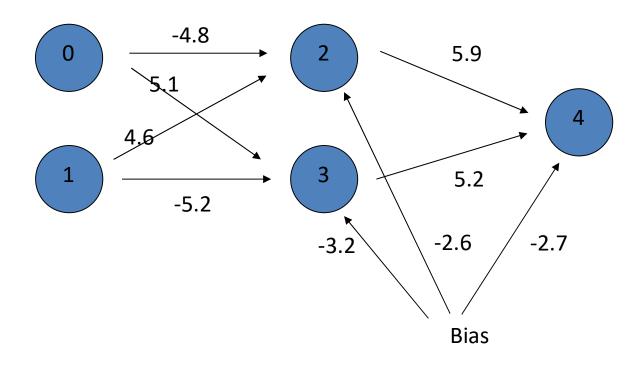
- Example: Three layer network
 - Calculates xor of inputs



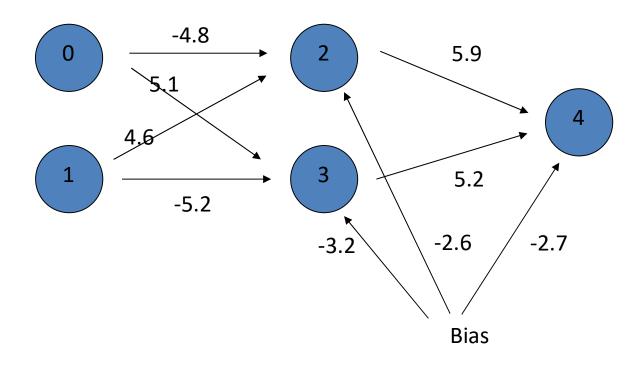
• Input (0,0)



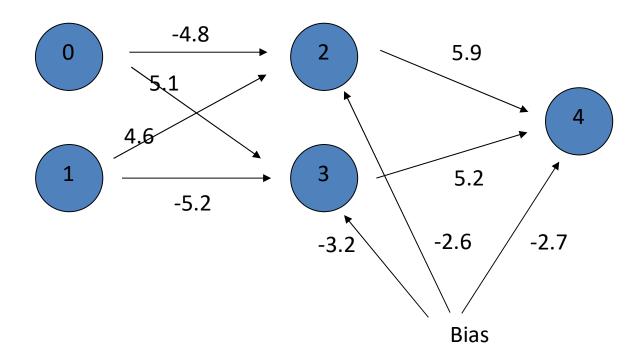
- Input (0,0)
 - Node 2 activation is $\varphi(-4.8 \cdot 0 + 4.6 \cdot 0 2.6) = 0.0691$



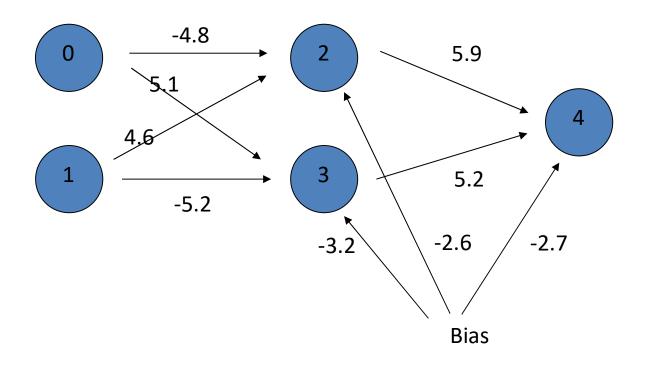
- Input (0,0)
 - Node 3 activation is $\phi(5.1 \cdot 0 5.2 \cdot 0 3.2) = 0.0392$



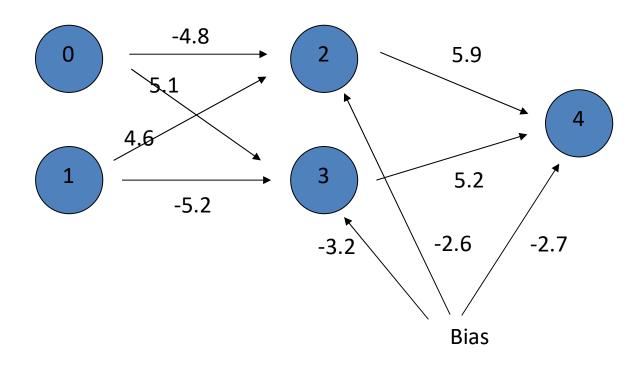
- Input (0,0)
 - Node 4 activation is $\phi(5.9 \cdot 0.069 + 5.2 \cdot 0.04 2.7) = 0.110227$



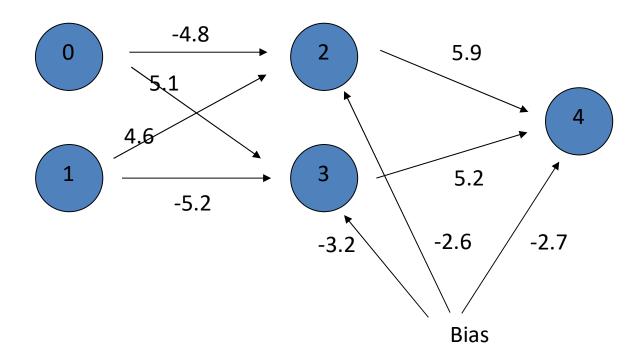
- Input (0,1)
 - Node 2 activation is $\varphi(4.6 2.6) = 0.153269$



- Input (0,1)
 - Node 3 activation is $\varphi(-5.2 3.2) = 0.000224817$

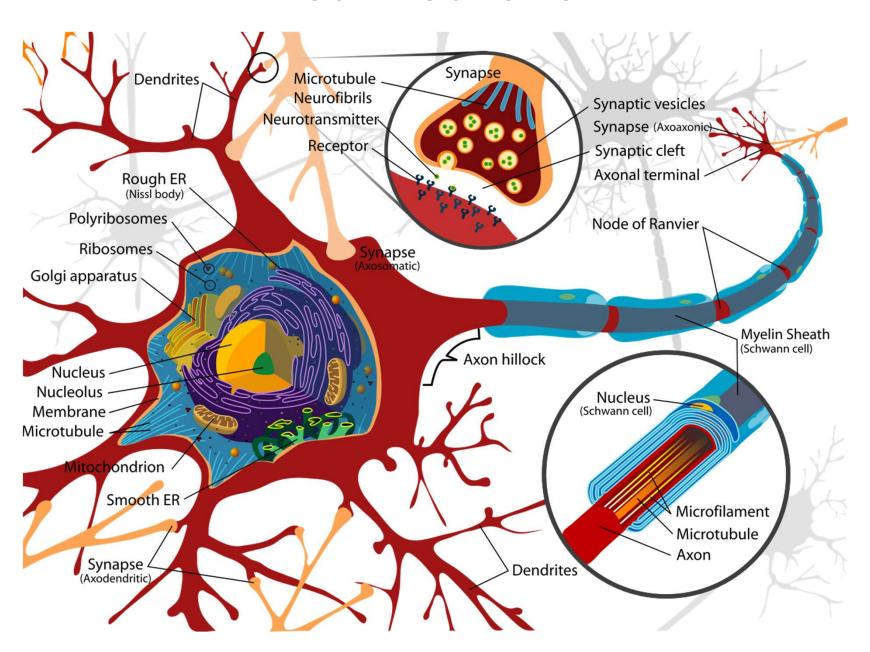


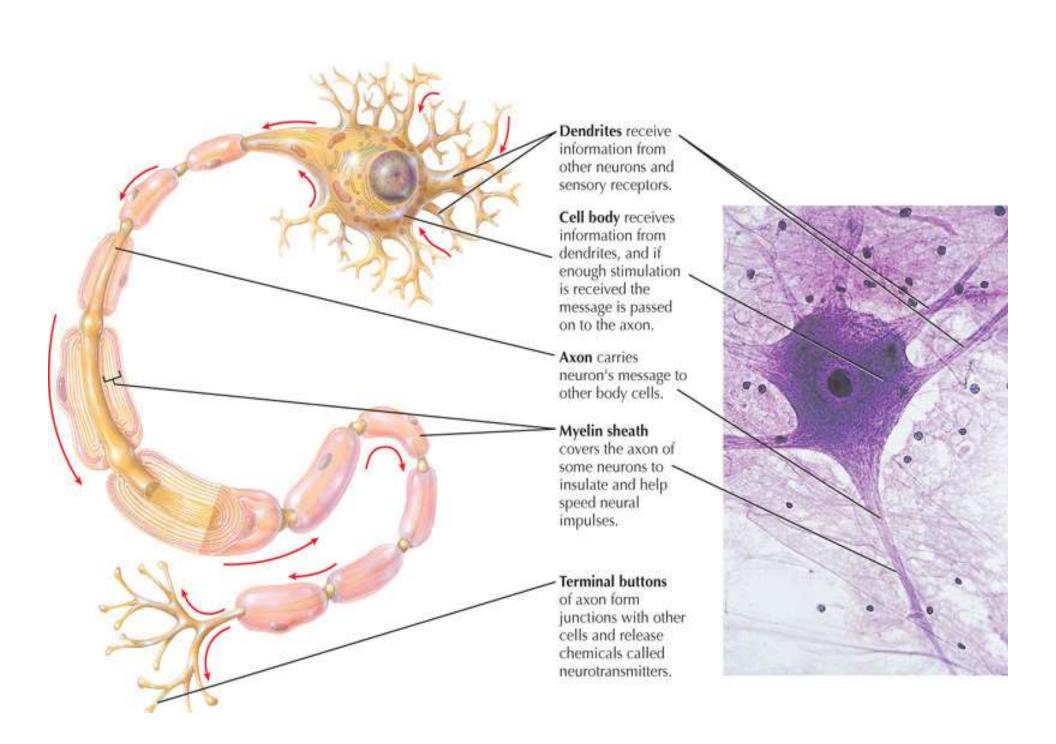
- Input (0,1)
 - Node 4 activation is $φ(5.9 \cdot 0.153269 + 5.2 \cdot 0.000224817 2.7) = 0.923992$



- Network can learn a non-linearly separated set of outputs.
- Need to map output (real value) into binary values.

Real neurons

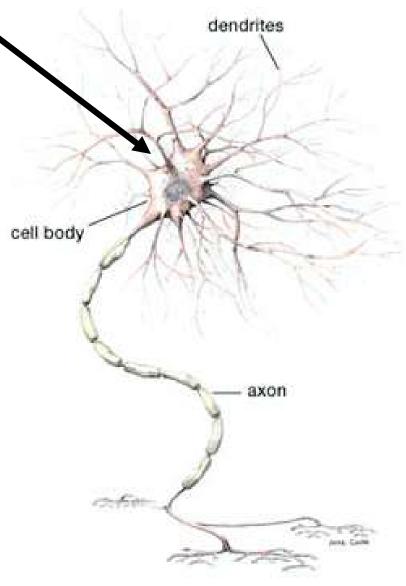




The Neuron

2. The Cell body contains the c€ nucleus

 The cell body relays the information down to the axon

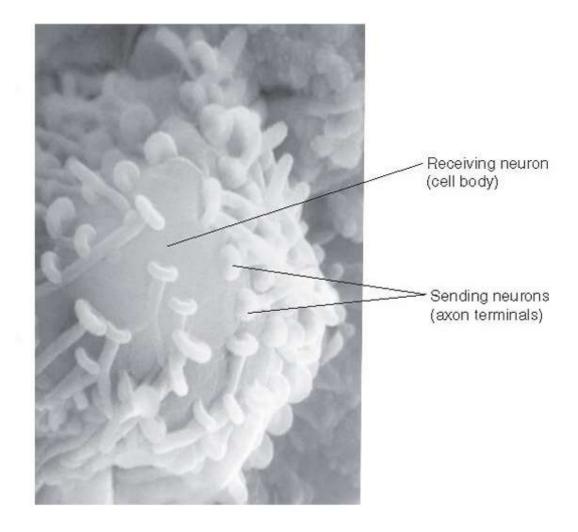




A Cell Body Virtually Covered With Axon Terminals.

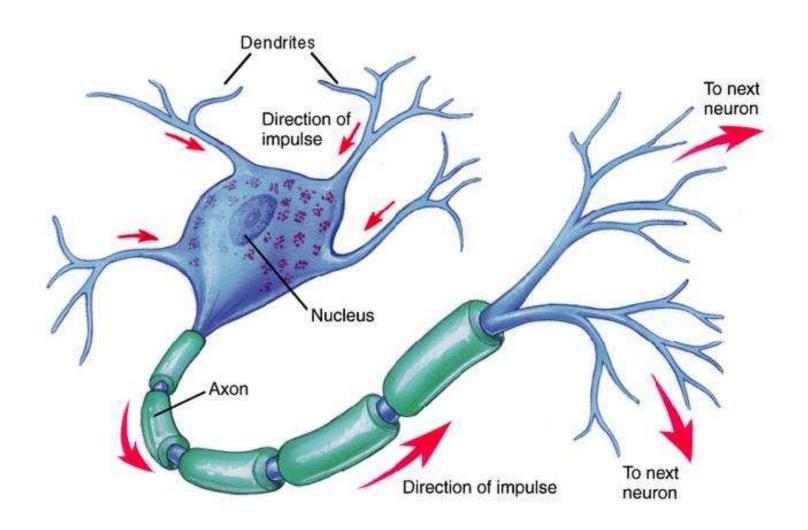
Source: © Science VU/Lewis-Everhart-Zeevi / Visuals Unlimited

The cell body is covered with Axon Terminals



How do Neurons Communicate?

- -Electrical Communication
- -Chemical Communication

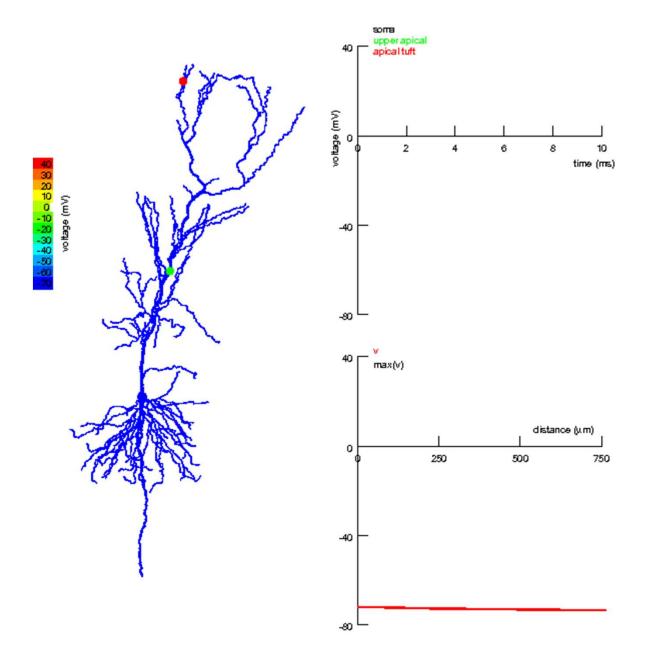


The Electrical Part

• Action potential is an electrical current sent down the axon.

 The activity <u>within</u> the neurons is <u>electrical</u>. This current causes the neuron to "fire"

This is an "all-or-none" process



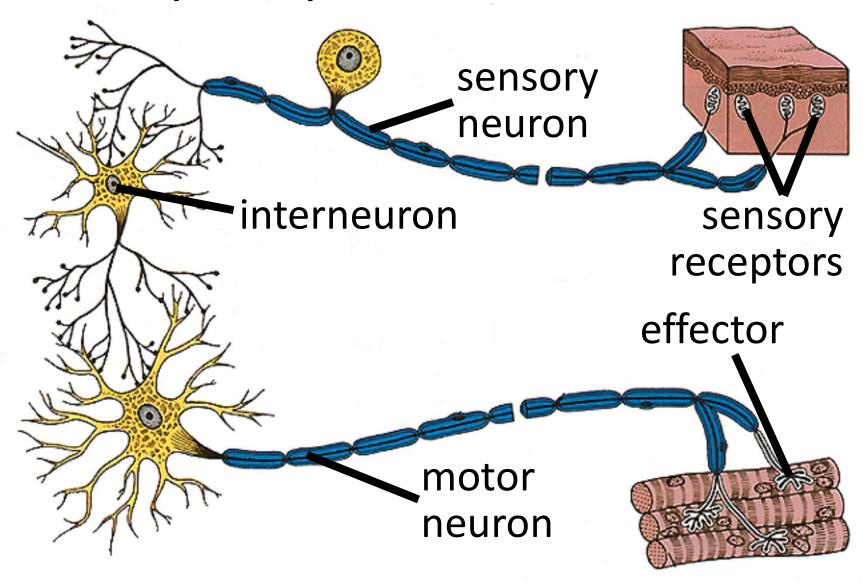
Synaptic transmission

- The <u>Synapse</u> is the space between neurons
 - The synaptic gap or cleft

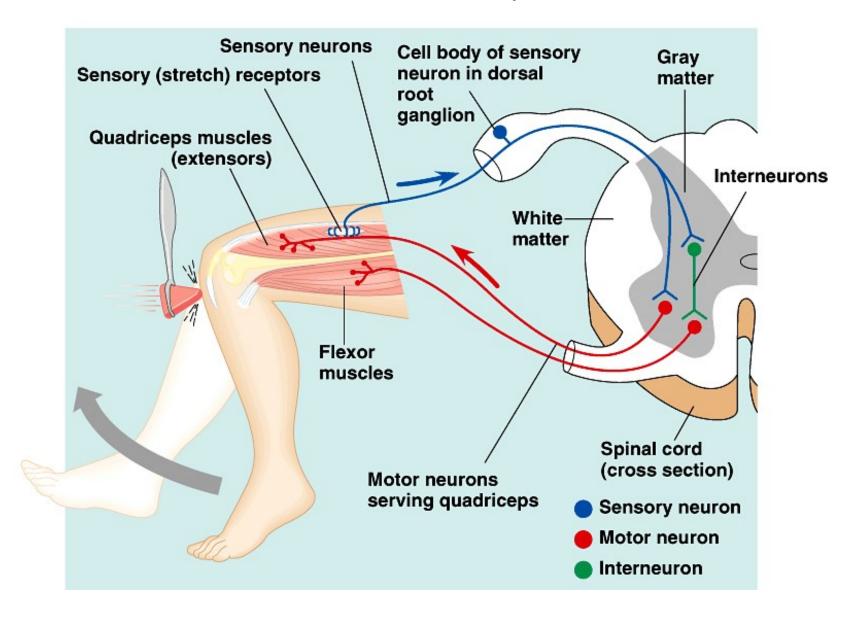
 Information must be transmitted across the synapse to other neurons via the neurotransmitters.

This is an <u>electrochemical process</u>

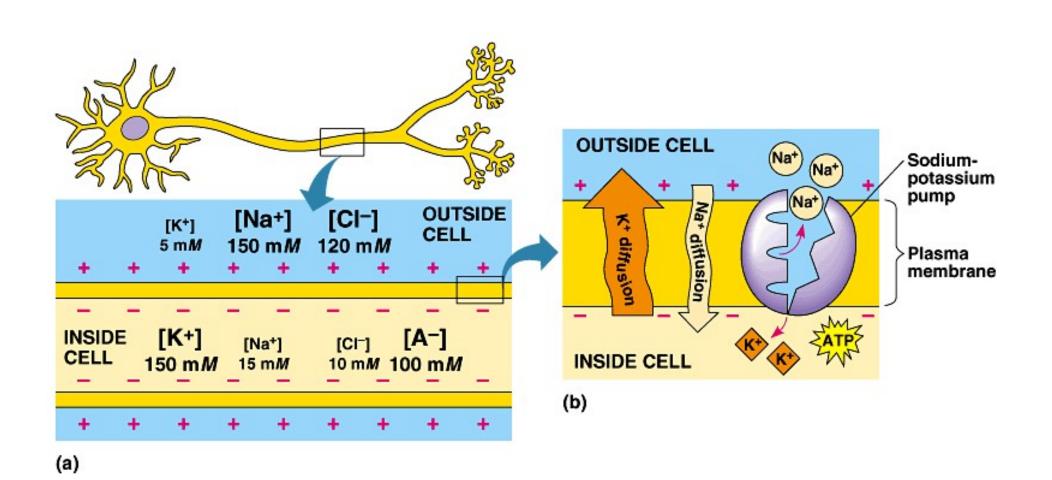
The perception-action circuit



- A Simple Nerve Circuit the Reflex Arc.
 - A reflex is an autonomic response.

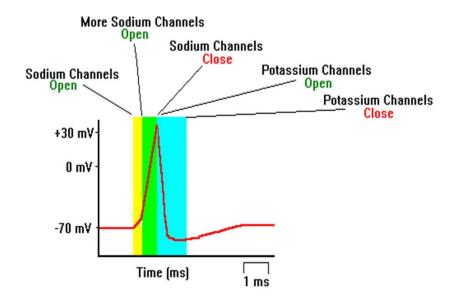


Neuron electrochemistry

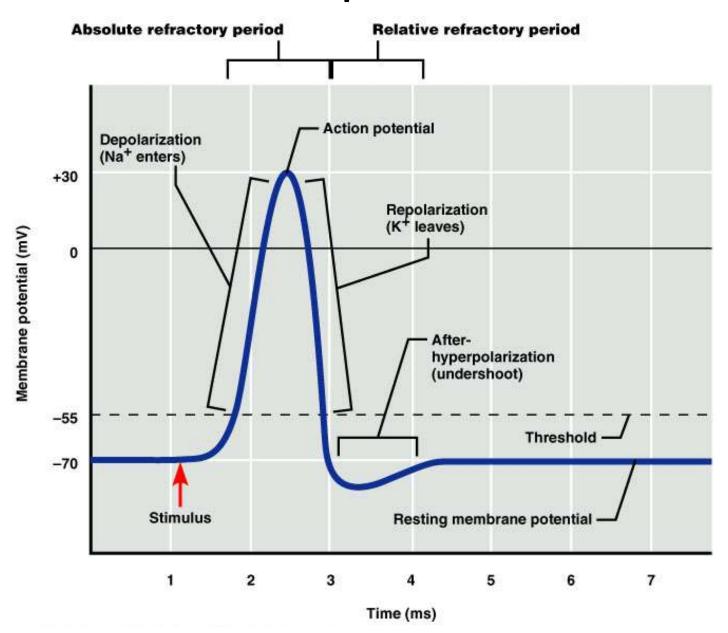


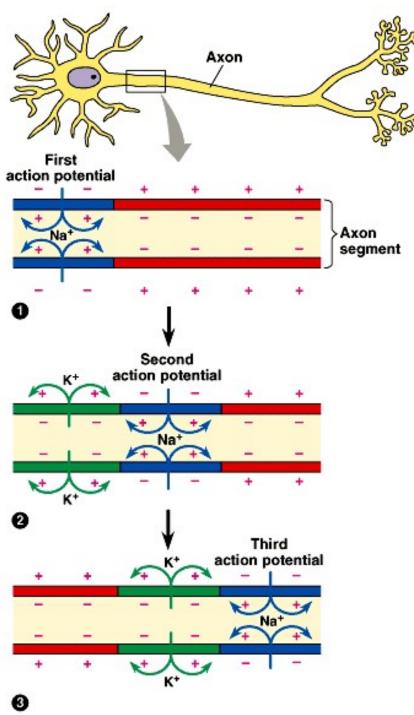
Neuron electrochemistry

- At rest, the neuron has a higher concentration of K than Na
- Channels
 - Na channels are quickresponding
 - K channels are slow-responding
- Impulse from neurotransmitters opens ion channels locally in neuron
- Na rushes into neuron cell body quickly
- K takes time, because channels are slower



Action potential





Three Steps for firing

- Resting potential: voltage is about -70mV
 - Dendrites receive incoming signals
 - If sufficient, cell goes into firing mode
- Action potential
 - Voltage changes from -70mV to +40mV
 - Ions exchange places
 - Repeats itself rapidly down axon
 - Only in places where myelin sheath doesn't cover: Nodes of Ranvier
- Refractory Period:
 - below resting or lower than -70mV
 - Cell recovers from firing
 - Absolute refractor period: Brief time period when cannot fire again
 - Relative refractory period: Brief time period when difficult for it to fire again.

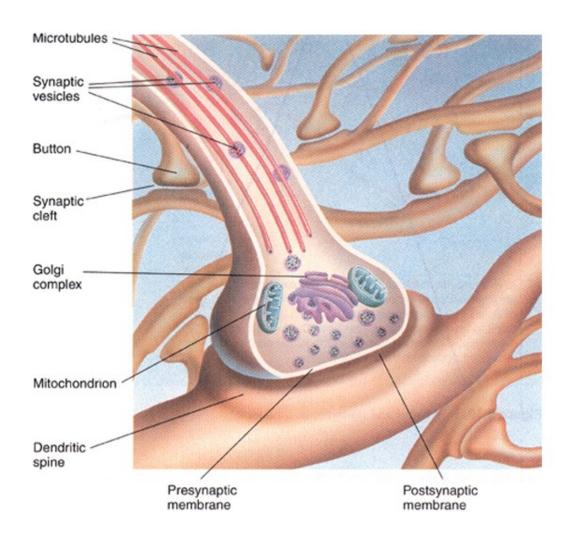
The Neuron Fires

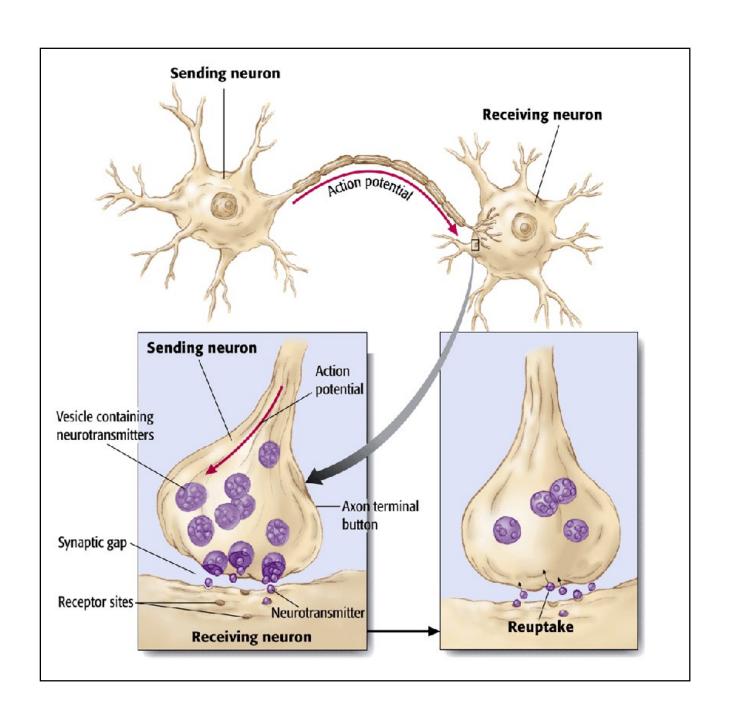
- Action potential causes nearby Na+ channels to open, so another action potential is triggered right next to first one, and this continues all the way down the axon
 - Chain reaction
 - Like a bunch of dominoes
- Action potential ≠ local potential in several important ways:
 - Local potential = graded potential- it varies in magnitude depending on strength of stimulus that produced it; action potential is ungraded
 - Action potential obeys all or none law: occurs at full strength or not at all
 - Action potential is nondecremental: does NOT lose strength at each successive point (local potentials do degrade)

The Neurotransmitter

- Neurotransmitter is chemical
 - Several specific kinds- each act on certain neurons
 - Most neurons respond to and release one kind of neurotransmitter
- Neurotransmitter stored in synaptic vesicles
- The synaptic vesicles move to and fuse to end of membrane
 - Action potential opens channels that allow Ca+ ions to enter terminals from extracellular fluid
 - Ca+ ions cause vesicles nearest the membrane to fuse with membrane
 - Membrane then opens and transmitter is dumped into synapse
 - Diffuses across synapse to postsynaptic neuron and attaches to chemical receptor

► Anatomy of a Typical Synapse





Action in the Synapse

- Neurotransmitter is released into the synapse
 - diffuses across synapse to next neuron's dendrite
 - This "next dendrite" is post-synaptic
- Neurotransmitter is attracted to the POST-synaptic side:
 - receptor sites on the next neurons dendrites
 - neurotransmitter must match molecular shape of receptor site
 - Activation of receptor causes ion channels in membrane to open

Two kinds of Receptor Action

- Ionotropic receptors open channels directly to produce immediate reactions required for motor and sensory processing
- Metabotropic receptors open channels indirectly
 - slower: but produce longer-lasting effects
 - Sets off graded potentials for next action potential
- Movement across the synapse is relatively slow: several milliseconds

Excitation and Inhibition

- The NT opens ion channels on dendrites and soma
- Two effects on local membrane potential:
 - shifts in positive direction (towards 0), partially depolarizing
 - Shifts in negative direction (away from 0): hyperpolarization
- Thus two effects:
 - Excitatory: depolarization (moves toward and past 0)
 - Inhibitory: hyperpolarization (moves away from 0)

Two kinds of postsynaptic potentials:

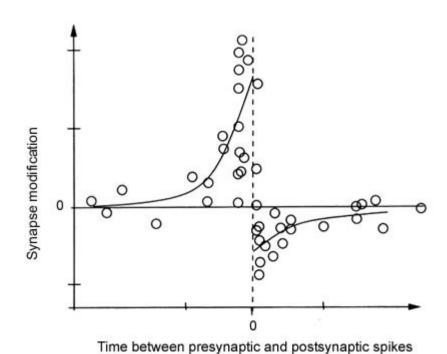
- EPSPs: excitatory postsynaptic potentials
 - Excitatory effect: increases likelihood of action potential
 - Opens Na+ channels
- IPSPs: inhibitory postsynaptic potentials
 - Inhibitory effect: decreases likelihood of action potential
 - Opens K+ channels
- Thus: bidirectional effects
 - Summative effects
 - Overall change must be sufficient to produce action potential

Postsynaptic integration

- Summation across all the IPSPs and EPSPs
 - Summates algebraically
 - Adds both positive and negatives together
- Two kinds:
 - Spatial summation:
 - Sum of all IPSPs and EPSPs occurring simultaneously at different locations along dendrites and cell body
 - Must be sufficient number of "hits"
 - Temporal summation
 - Sum of all IPSPs and EPSPs occurring within a short time
 - Must occur within a few milliseconds
 - Must get sufficient number of "hits" within certain time
- Neuron is an information integrator!
 - A decision maker
 - Small microprocessor

Temporal dynamics of synaptic response

Spike-timing dependent plasticity has been experimentally documented



Neurotransmitters

