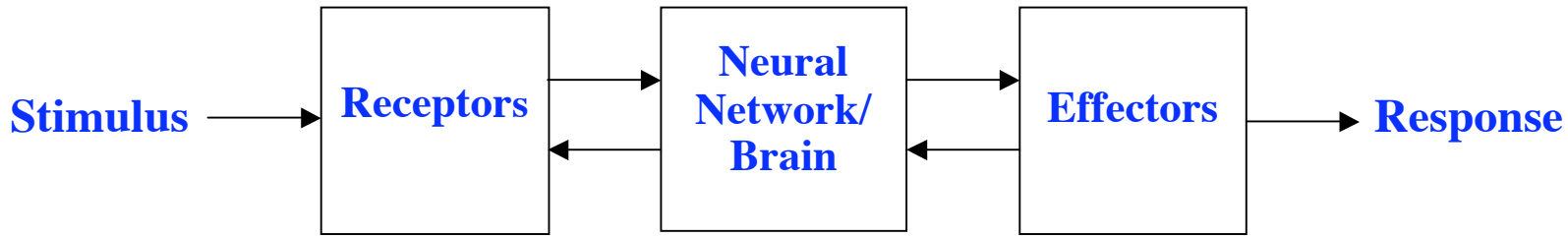
Biological Neurons and Neural Networks, Artificial Neurons

Neural Computation : Lecture 2

1. Organization of the Nervous System and Brain
2. Brains versus Computers: Some Numbers
3. Biological Neurons and Neural Networks
4. Rate Coding versus Spike Time Coding
5. The McCulloch-Pitts Neuron
6. Some Useful Notation: Vectors, Matrices, Functions
7. The McCulloch-Pitts Neuron Equation

The Nervous System

The human nervous system can be broken down into three stages that may be represented in block diagram form as:



The receptors collect information from the environment – e.g. photons on the retina.

The effectors generate interactions with the environment – e.g. activate muscles.

The flow of information/activation is represented by arrows – feedforward and feedback.

Naturally, this module will be primarily concerned with how the neural network in the middle works, but understanding its inputs and outputs is also important.

Levels of Brain Organization

The brain contains both large scale and small scale anatomical structures and different functions take place at the higher and lower levels.

There is a hierarchy of interwoven levels of organization:

1. Molecules and Ions
2. Synapses
3. Neuronal microcircuits
4. Dendritic trees
5. **Neurons**
6. **Local circuits**
7. Inter-regional circuits
8. Central nervous system

The ANNs studied in this module are mostly approximations of levels 5 and 6.

Brains versus Computers : Some numbers

1. There are approximately 10 billion neurons in the human cortex, compared with tens of thousands of processors in the most powerful parallel computers.

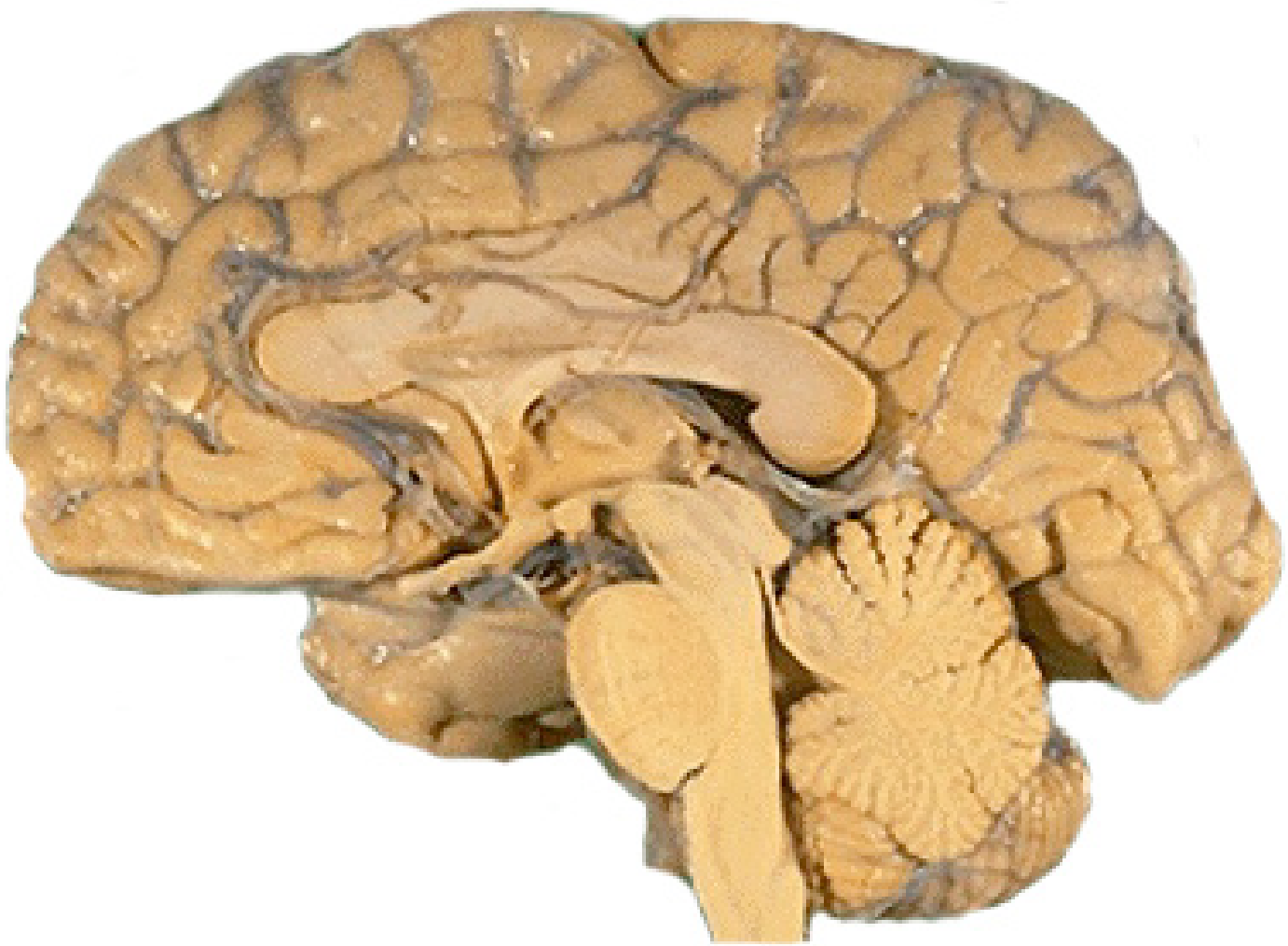
2. Lack of processing units can be compensated by speed. The typical operating speeds of biological neurons is measured in milliseconds (10^{-3} s), while current silicon chips can usually operate in nanoseconds (10^{-9} s).

3. Each biological neuron is connected to several thousands of other neurons, similar to the connectivity in powerful parallel computers.

4. The human brain is extremely energy efficient, using approximately 10^{-16} joules per operation per second, whereas the best computers today use around 10^{-6} joules per operation per second.

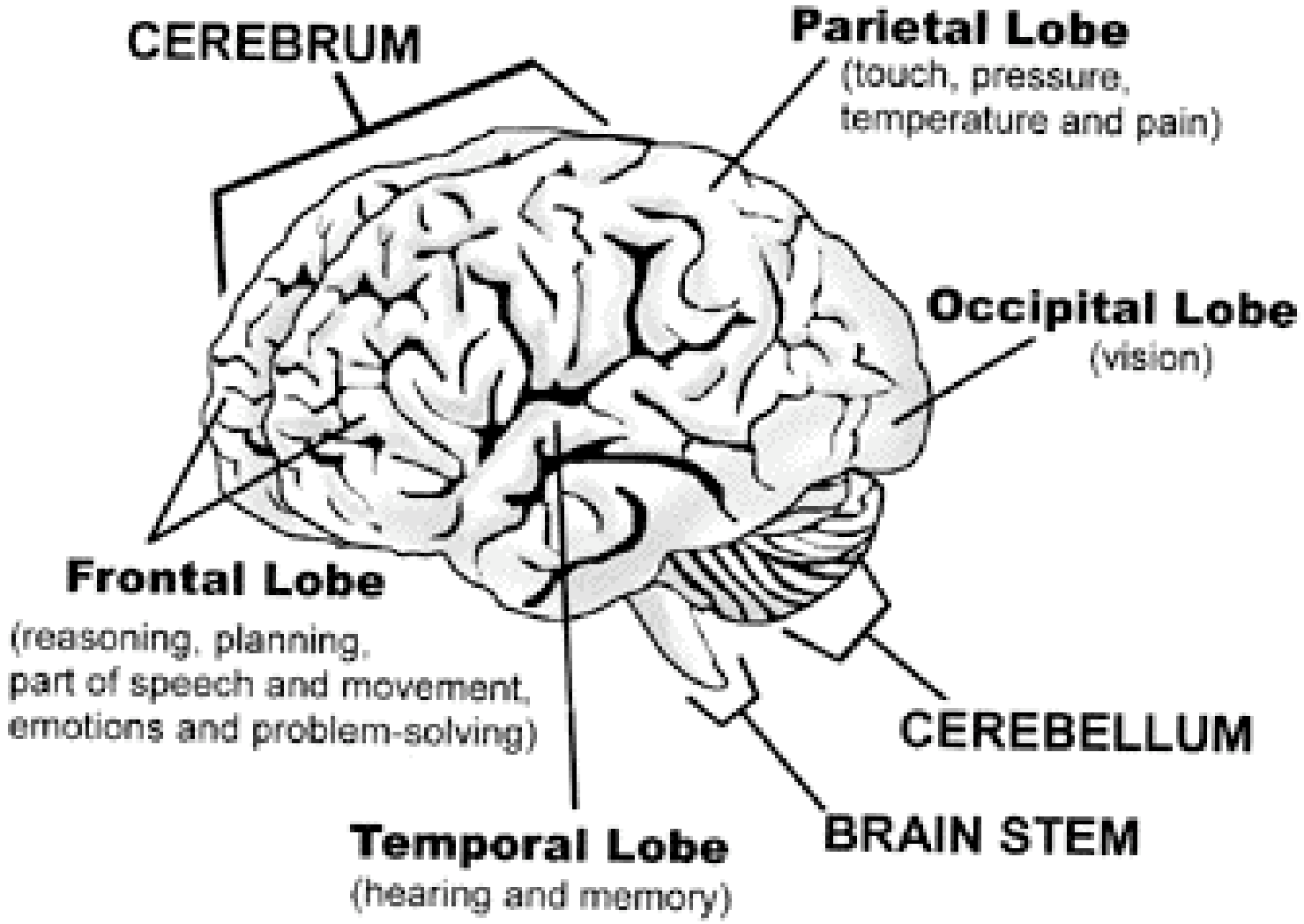
5. Brains have been evolving for tens of millions of years, but computers have only been evolving for tens of decades, though different mechanisms are involved.

Slice Through a Real Brain



http://library.med.utah.edu/WebPath/HISTHTML/NEURANAT/NEURANCA.html

Structure of a Human Brain



Basic Components of Biological Neurons

1. The majority of ***neurons*** encode their activations or outputs as a series of brief electrical pulses (i.e. spikes or action potentials).

2. The neuron's ***cell body (soma)*** processes the incoming activations and converts them into output activations.

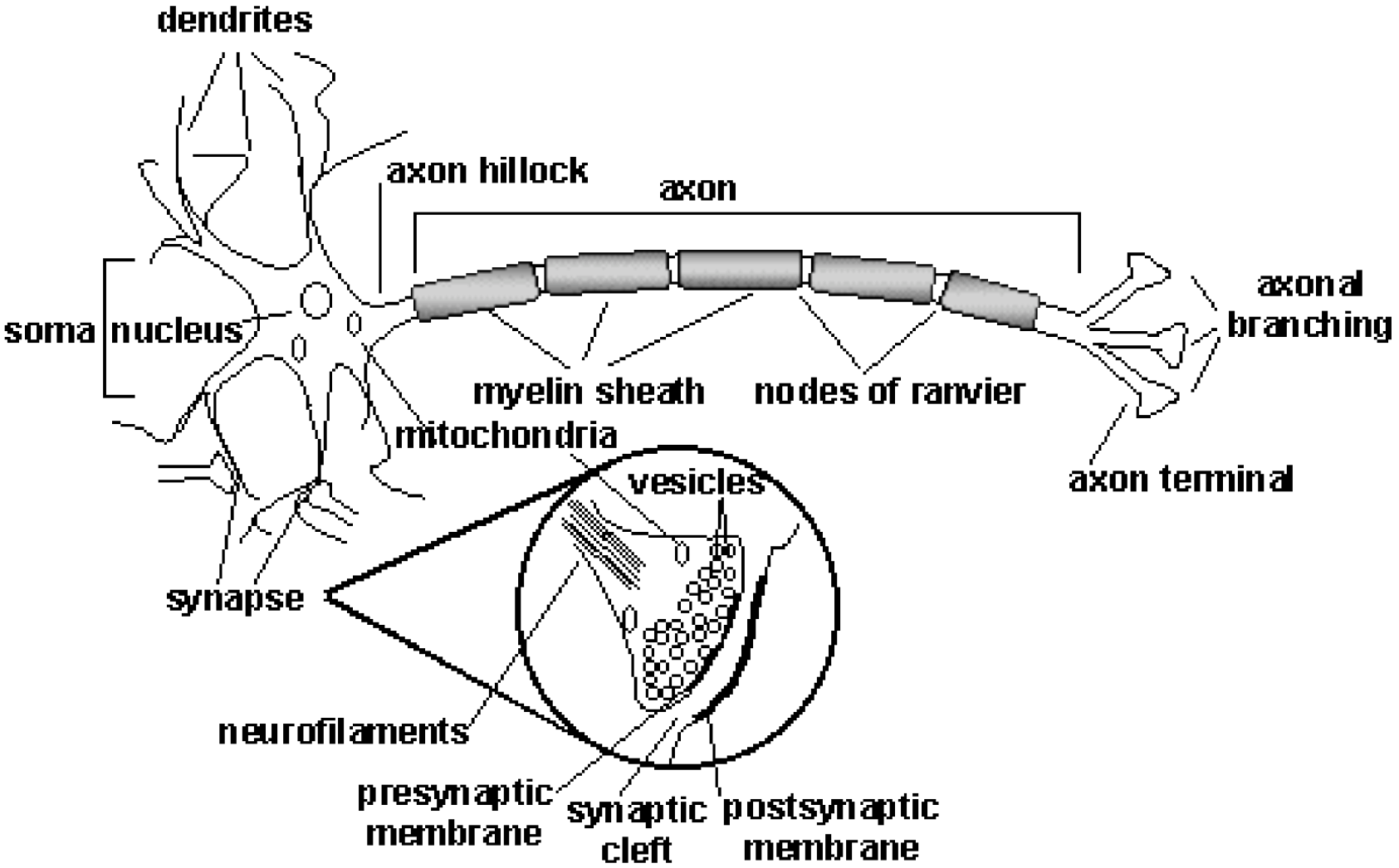
3. The neuron's ***nucleus*** contains the genetic material in the form of DNA. This exists in most types of cells, not just neurons.

4. ***Dendrites*** are fibres which emanate from the cell body and provide the receptive zones that receive activation from other neurons.

5. ***Axons*** are fibres acting as transmission lines that send activation to other neurons.

6. The junctions that allow signal transmission between the axons and dendrites are called ***synapses***. The process of transmission is by diffusion of chemicals called ***neurotransmitters*** across the synaptic cleft.

Schematic Diagram of a Biological Neuron

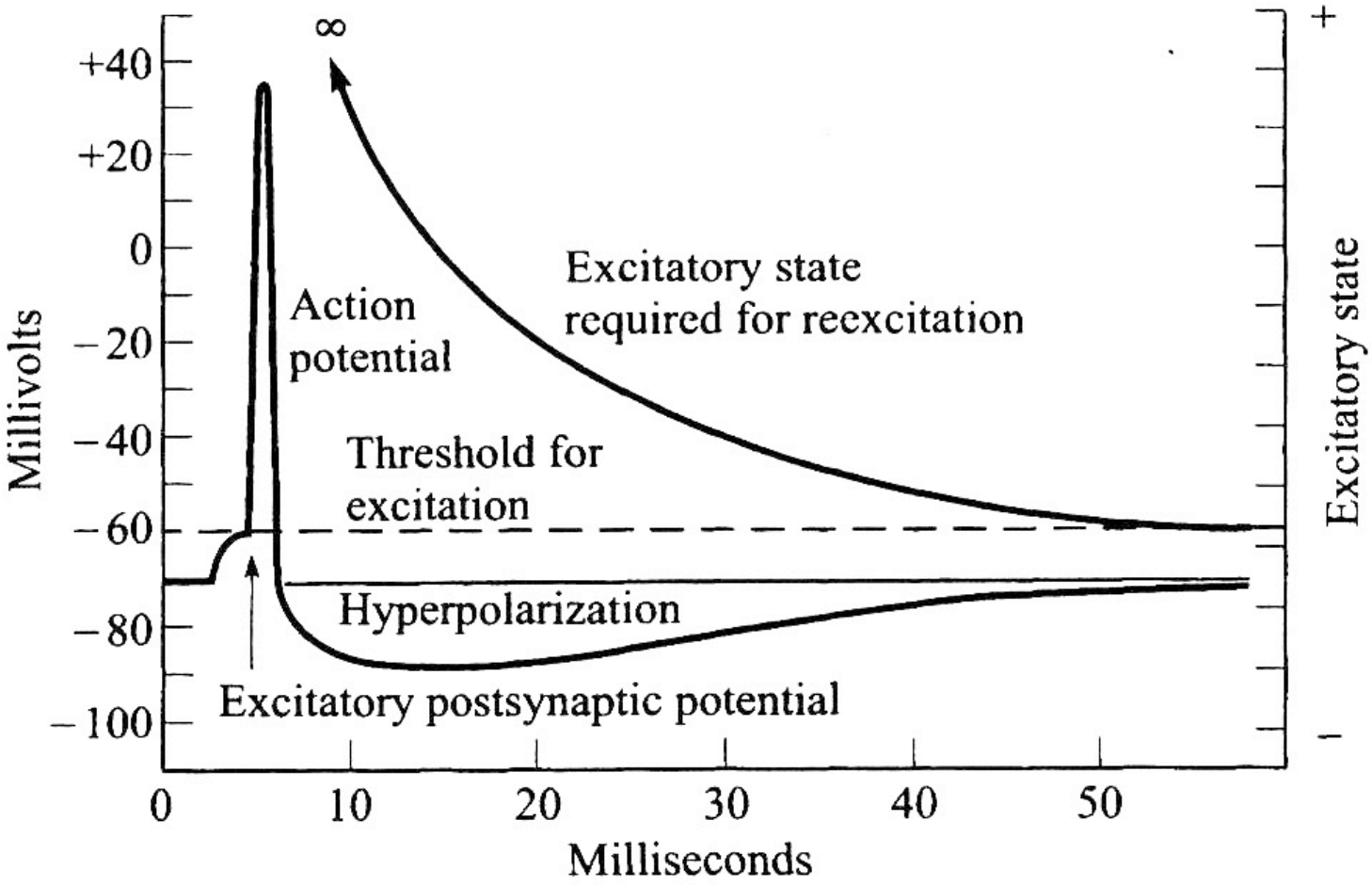


Neural Signal Processing

The key components of neural signal processing are:

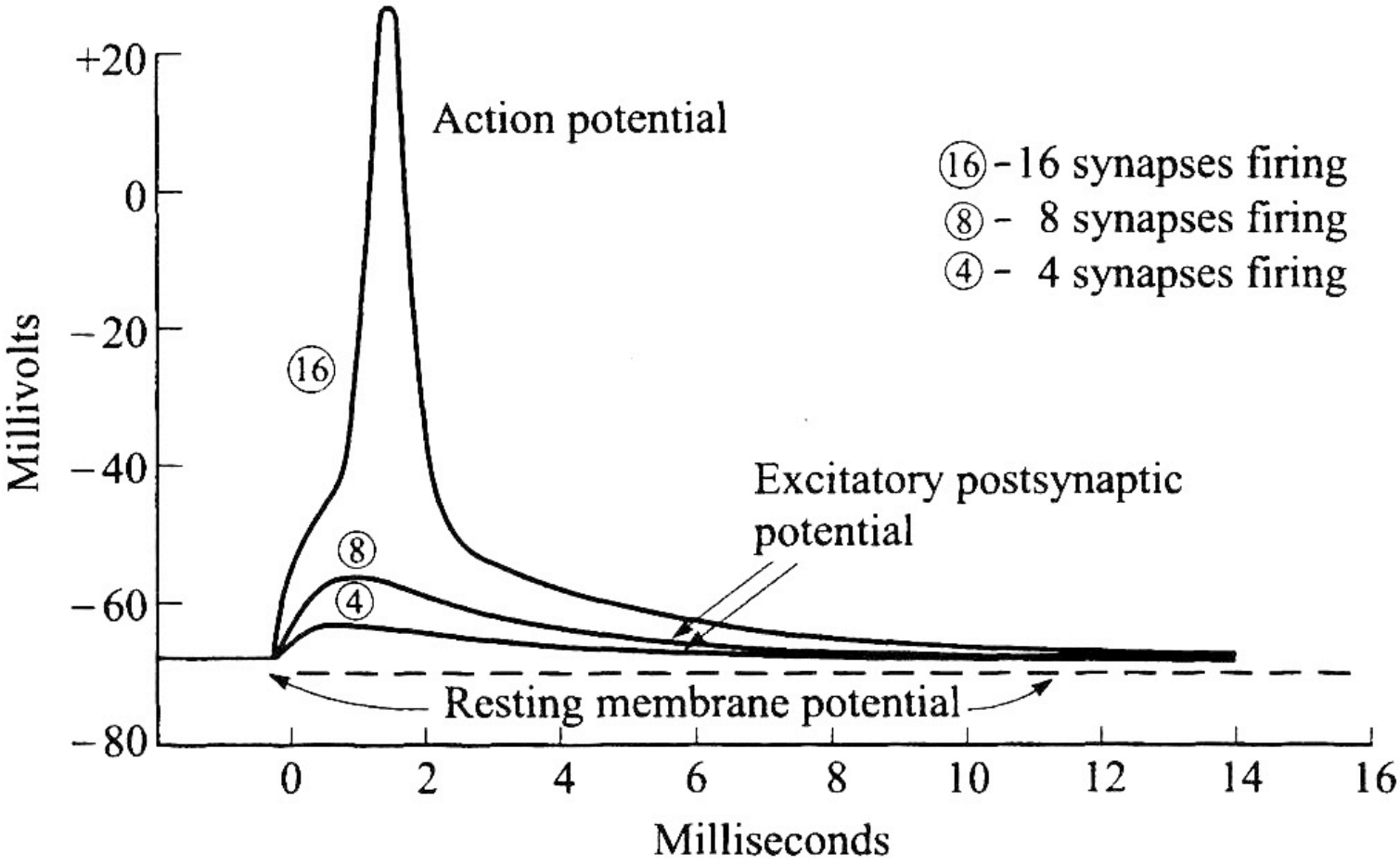
1. Signals from connected neurons are collected by the dendrites.
2. The cells body (soma) sums the incoming signals (spatially and temporally).
3. When sufficient input is received (i.e., a threshold is exceeded), the neuron generates an action potential or 'spike' (i.e., it 'fires').
4. That action potential is transmitted along the axon to other neurons, or to structures outside the nervous systems (e.g., muscles).
5. If sufficient input is not received (i.e. the threshold is not exceeded), the inputs quickly decay and no action potential is generated.
6. Timing is clearly important – input signals must arrive together, strong inputs will generate more action potentials per unit time.

Neuron Action Potential



From: Principles of Neurocomputing for Science & Engineering, Ham & Kostanic, McGraw-Hill, 2001.

Excitatory Postsynaptic Potential



From: Principles of Neurocomputing for Science & Engineering, Ham & Kostanic, McGraw-Hill, 2001.

Rate Coding versus Spike Time Coding

In biological neural networks, the individual spike timings are often important. So "***spike time coding***" is the most realistic representation for artificial neural networks.

However, averages of spike rates across time or populations of neurons carry a lot of the useful information, and so "***rate coding***" is a useful approximation.

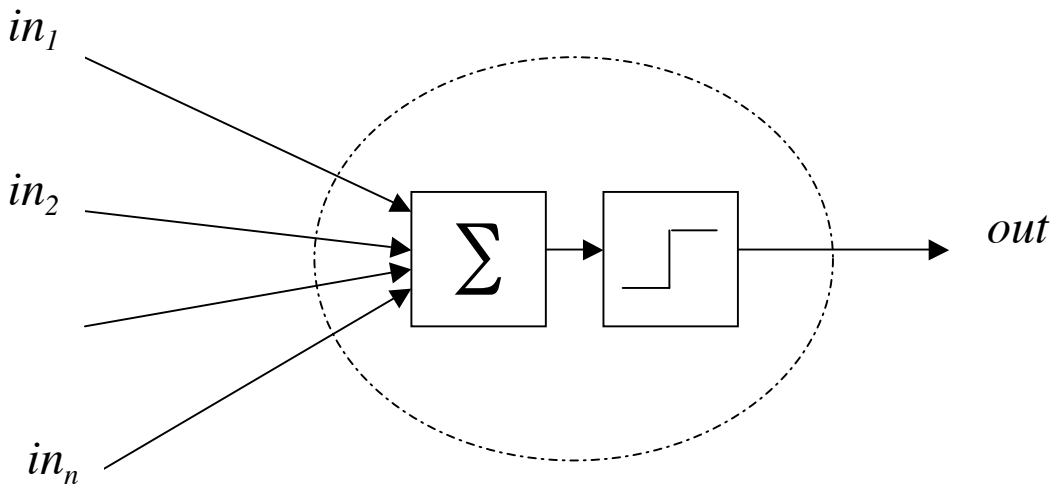
Spike coding is more powerful, but the computer models are much more complicated and more difficult to train.

Rate coding blurs the information coded in individual neurons, but usually leads to simpler models with differentiable outputs, which we will see later is important for generating efficient learning algorithms.

Sigmoid shaped activation functions in the rate coding approach follow from the cumulative effect of Gaussian distributed spikes.

The McCulloch-Pitts Neuron

A simple rate coding model of real neurons is also known as a ***Threshold Logic Unit*** :



1. A set of synapses (i.e. connections) brings in activations from other neurons.
2. A processing unit sums the inputs, and then applies a non-linear activation function (which is also often called a threshold or transfer or squashing function).
3. An output line transmits the result to other neurons.

Some Useful Notation

We often need to deal with ordered sets of numbers, which we write as ***vectors***, e.g.

$$\boldsymbol{x} = (x_1, x_2, x_3, \ldots, x_n) \quad , \quad \boldsymbol{y} = (y_1, y_2, y_3, \ldots, y_m)$$

The components x_i can be added up to give a ***scalar*** (number), e.g.

$$s = x_1 + x_2 + x_3 + \ldots + x_n = \sum_{i=1}^{n} x_i$$

Two vectors of the same length may be ***added*** to give another vector, e.g.

$$\boldsymbol{z} = \boldsymbol{x} + \boldsymbol{y} = (x_1 + y_1, x_2 + y_2, \ldots, x_n + y_n)$$

Two vectors of the same length may be ***multiplied*** to give a scalar, e.g.

$$p = \boldsymbol{x}.\boldsymbol{y} = x_1 y_1 + x_2 y_2 + \ldots + x_n y_n = \sum_{i=1}^{n} x_i y_i$$

To avoid any ambiguity or confusion, we will mostly be using the component notation (i.e. explicit indices and summation signs) throughout this module.

The Power of the Notation : Matrices

We can use the same vector component notation to represent more complex things with many dimensions/indices. For two indices we have matrices, e.g. an $m \times n$ ***matrix***

$$\mathbf{w} = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{1n} \\ \vdots & \vdots & & \vdots \\ w_{m1} & w_{m1} & \cdots & w_{mn} \end{pmatrix}$$

Matrices of the same size can be ***added*** or ***subtracted*** component by component.

An $m \times n$ matrix **a** can be ***multiplied*** with an $n \times p$ matrix **b** to give an $m \times p$ matrix **c**. This becomes straightforward if we write it in terms of components:

$$c_{ik} = \sum_{j=1}^{n} a_{ij} b_{jk}$$

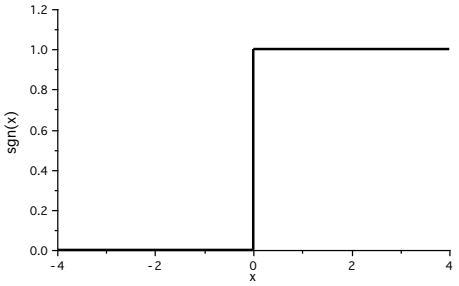
An n component vector can be regarded as a $1 \times n$ or $n \times 1$ matrix.

Some Useful Functions

A function $y = f(x)$ describes a relationship (input-output mapping) from x to y.

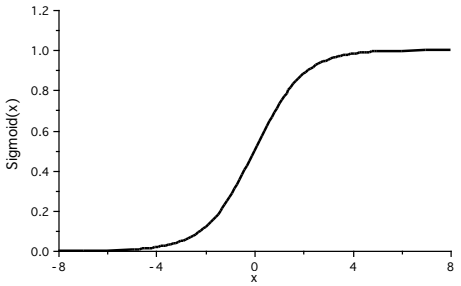
Example 1 The threshold or step function step(x) is defined as

$$step(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$



Example 2 The logistic sigmoid function Sigmoid(x) is defined as

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}}$$



This is a smoothed (differentiable) form of the threshold function.

The McCulloch-Pitts Neuron Equation

Using the above notation, it is possible to write down a simple equation for the ***output*** *out* of a McCulloch-Pitts neuron as a function of its *n* ***inputs*** in_i :

$$out = step(\sum_{i=1}^{n} in_i - \theta)$$

where θ is the neuron's activation ***threshold***. We can easily see that:

$$out = 1 \quad \text{if} \quad \sum_{k=1}^{n} in_k \geq \theta \qquad\qquad out = 0 \quad \text{if} \quad \sum_{k=1}^{n} in_k < \theta$$

Note that the McCulloch-Pitts neuron is an extremely simplified model of real biological neurons. Some of its missing features include: non-binary inputs and outputs, non-linear summation, smooth thresholding, stochasticity, and temporal information processing.

Nevertheless, McCulloch-Pitts neurons are computationally very powerful. One can show that networks of such neurons are capable of universal computation.

Overview and Reading

1. Biological neurons, consisting of a cell body, axons, dendrites and synapses, are able to process and transmit neural activation.
2. The McCulloch-Pitts neuron model (Threshold Logic Unit) is a crude rate-coding approximation to real neurons, that performs a simple summation and thresholding function on activation levels.
3. Appropriate mathematical notation facilitates the specification and programming of artificial neurons and networks of artificial neurons.

Reading

1. Haykin-1999: Sections 1.1, 1.2, 1.3
2. Ham & Kostanic: Sections 1.2, 1.3
3. Beale & Jackson: Sections 1.2, 3.1, 3.2
4. Gurney: Sections 2.1, 2.2.