Lecture 1: Introduction to Neural Networks

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What are Neural Networks?

- ***Neural Networks*** are networks of neurons, for example, as found in real (i.e. biological) brains
- ***Artificial neurons*** are crude approximations of the neurons found in real brains. They may be physical devices, or purely mathematical constructs.
- ***Artificial Neural Networks*** (ANNs) are networks of Artificial Neurons and hence constitute crude approximations to parts of real brains. They maybe physical devices, or simulated on conventional computers.
- From a practical point of view, an ANN is just a parallel computational system consisting of many simple processing elements connected together in a specific way in order to perform a particular task
- One should never lose sight of how crude the approximations are, and how over-simplified our ANNs are compared to real brains.

Why are Artificial Neural Networks worth studying?

- They are extremely powerful computational devices
- Massive parallelism makes them very efficient
- They can learn and generalize from training data – so there is no need for enormous feats of programming
- They are particularly fault tolerant
- They are very noise tolerant – so they can cope with situations where normal symbolic systems would have difficulty
- In principle, they can do anything a symbolic/logic system can do, and more

What are Neural Networks used for?

There are two basic goals for neural network research:

Brain modelling: The biological goal of constructing models of how real brains work. This can potentially help us understand the nature of perception, actions, learning and memory, thought and intelligence and/or formulate medical solutions to brain damaged patients

Artificial System Construction: The engineering goal of building efficient systems for real world applications. This may make machines more powerful and intelligent, relieve humans of tedious tasks, and may even improve upon human performance.

Both methodologies **should be** regarded as complementary and not competing. We often use exactly the same network architectures and methodologies for both. Progress is made when the two approaches are allowed to feed one another. There are fundamental differences though, e.g. the need for biological plausibility in brain modelling, and the need for computational efficiency in artificial system construction.

Learning Processes in Neural Networks

Among the many interesting properties of a neural network, is the ability of the network to learn from its environment, and to improve its performance through learning. The improvement in performance takes place over time in accordance with some prescribed measure.

A neural network learns about its environment through an iterative process of adjustments applied to its synaptic weights and thresholds. Ideally, the network becomes more knowledgeable about its environment after each iteration of the learning process.

There are three broad types of learning:

1. Supervised learning (i.e. learning with an external teacher)
2. Unsupervised learning (i.e. learning with no help)
3. Reinforcement learning (i.e. learning with limited feedback)

Historical Notes

1943 McCulloch and Pitts proposed the McCulloch-Pitts neuron model

1949 Hebb published his book *The Organization of Behaviour*, in which the Hebbian learning rule was introduced

1958 Rosenblatt introduced the simple single layer networks called Perceptrons

1969 Minsky and Papert's book Perceptrons demonstrated the limitation of single layer perceptrons

1980 Grossberg introduced his Adaptive Resonance Theory (ART)

1982 Hopfield published a series of papers on Hopfield networks

1982 Kohonen developed the Self-Organizing Feature Maps

1986 Back-propagation learning algorithm for multi-layer perceptrons was re-discovered, and the whole field took off again

1990s ART-variant networks were developed

1990s Radial Basis Functions were developed

2000s Support Vector Machines were developed

Neural Network Applications

Brain modelling

Aid our understanding of how the brain works, how behaviour emerges from the interaction of networks of neurons, what needs to “get fixed” in brain damaged patients

Real world applications

Financial modelling – predicting the stock market

Time series prediction – climate, weather, seizures

Computer games – intelligent agents, chess, backgammon

Robotics – autonomous adaptable robots

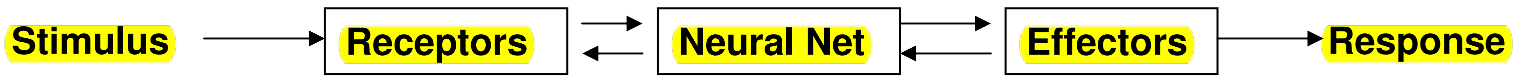
Pattern recognition – speech recognition, seismic activity, sonar signals

Data analysis – data compression, data mining

Bioinformatics – DNA sequencing, alignment

The Nervous System

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



(adapted from Arbib, 1987)

The **receptors** convert stimuli from the external environment into electrical impulses that convey information to the neural net (brain)

The **effectors** convert electrical impulses generated by the neural net into responses as system outputs

The **neural net (brain)** continually receives information, perceives it and makes appropriate decisions.

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

Brains vs. Computers

Processing elements: There are 10^{14} synapses in the brain, compared with 10^{8} transistors in the computer

Processing speed: 100 Hz for the brain compared to 10^{9} Hz for the computer

Style of computation: The brain computes in parallel and distributed mode, whereas the computer mostly serially and centralized.

Fault tolerant: The brain is fault tolerant, whereas the computer is not

Adaptive: The brain learns fast, whereas the computer doesn't even compare with an infant's learning capabilities

Intelligence and consciousness: The brain is highly intelligent and conscious, whereas the computer shows lack of intelligence

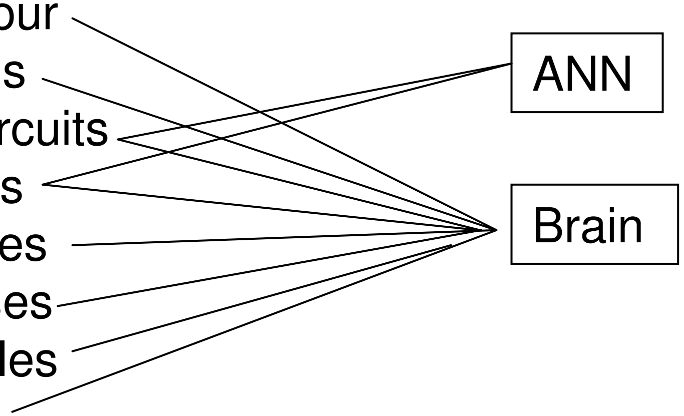
Evolution: The brains have been evolving for tens of millions of years, computers have been evolving for decades.

Levels of Organization in the Brain

In the brain there are both small-scale and large-scale anatomical organizations, and different functions take place at lower and higher levels.

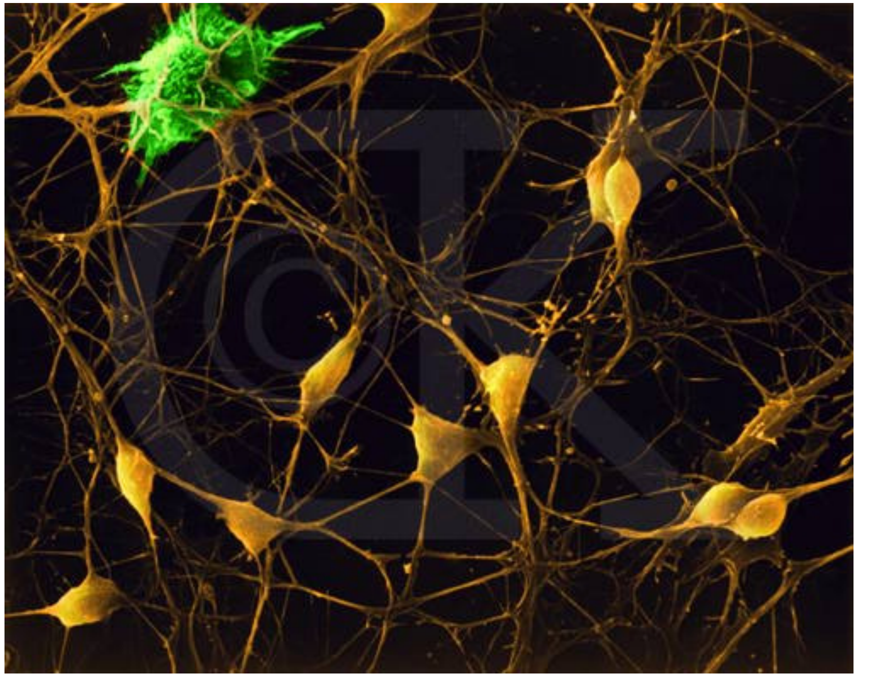
There is a hierarchy of interwoven levels of organization:

1. Behaviour
2. Systems
3. Microcircuits
4. Neurons
5. Dendrites
6. Synapses
7. Molecules
8. Genes

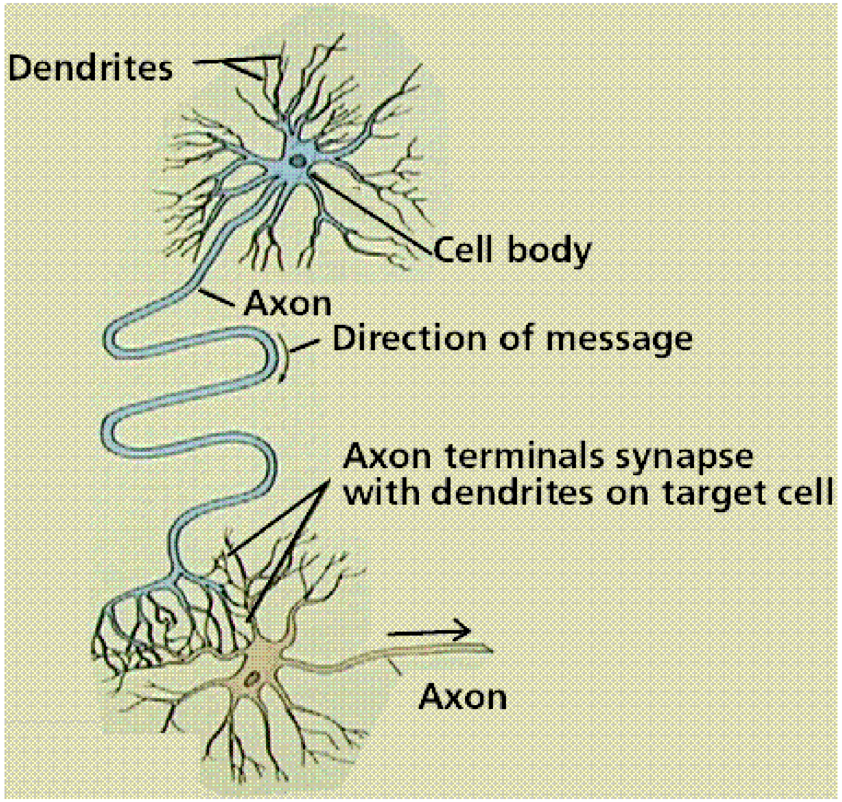


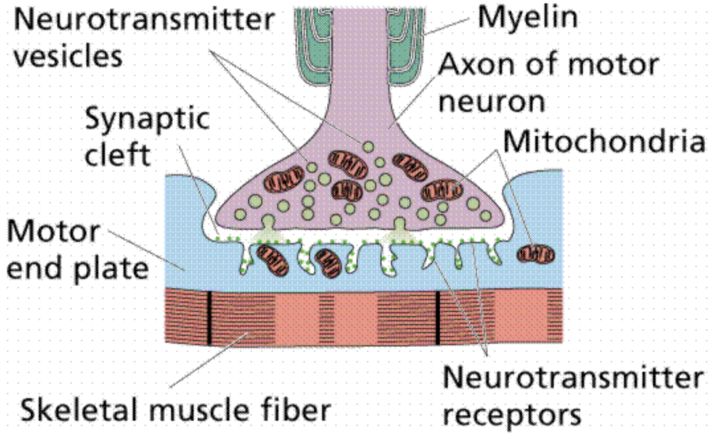
Microscopic View of the Nervous System

- Nervous system is made up of cells
- A cell has a fatty membrane, which is filled with liquid and proteins known as cytoplasm as well as smaller functional parts called organelles
- There are two major types of brain cells: (1) neurons, and (2) glia
- Neurons are the principal elements involved in information processing in the brain
- Glia provide support and homeostasis to neurons.



Schematic Diagram of a Biological Neuron



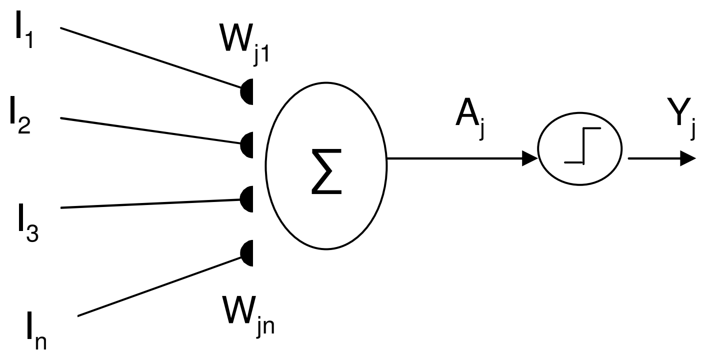


Basic Components of Biological Neurons

- The majority of neurons encode their activation or outputs as a series of brief electrical pulses (i.e. **spikes** or **action potentials**)
- The neuron's **cell body** (**soma**) processes the incoming activations and converts them into output activations
- The neuron's **nucleus** contains the genetic material (DNA)
- **Dendrites** are fibres which emanate from the cell body and provide the receptive zone that receive activation from other neurons
- **Axons** are fibres acting as transmission lines that send action potentials to other neurons
- The junctions that allow signal transmission between the axons and the dendrites are called **synapses**. The process of transmission is by diffusion of chemicals called **neurotransmitters** across the synaptic cleft.

The McCulloch-Pitts Neuron

- This vastly simplified 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
3. An output line transmits the result to other neurons

How the Model Neuron Works

- Each input I_i is multiplied by a weight w_{ji} (synaptic strength)
- These weighted inputs are summed to give the activation level, A_j
- The activation level is then transformed by an activation function to produce the neuron's output, Y_i
- W_{ji} is known as the weight from unit i to unit j
  - $W_{ji} > 0$, synapse is excitatory
  - $W_{ji} < 0$, synapse is inhibitory
- Note that I_i may be
  - External input
  - The output of some other neuron

The McCulloch-Pitts Neuron Equation

We can now write down the equation for the output Y_j of a McCulloch-Pitts neuron as a function of its inputs I_i:

$$Y_j = \mathrm{sgn}\left(\sum_{i=1}^{n} I_i - \theta\right)$$

where θ is the neuron's **activation threshold**. When

$$Y_j = 1, \quad if \sum_{k=1}^{n} I_k \geq \theta \qquad\qquad Y_j = 0, \quad if \sum_{k=1}^{n} I_k < \theta$$

Note that the McCulloch-Pitts neuron is an extremely simplified model of real biological neurons. Nevertheless, they are computationally very powerful. One can show that assemblies of such neurons are capable of universal computation.