Lecture 1a

Contents

1 Introduction to Deep Learning

1.1 Definition

Definition 1: Neural Network

Everything in the world is described by functions for e.g. relationships between numbers. And Neural Networks are function building Machines.

Neural Network is a method in AI that teaches computers to process data in a way that is inspired by the human brain.

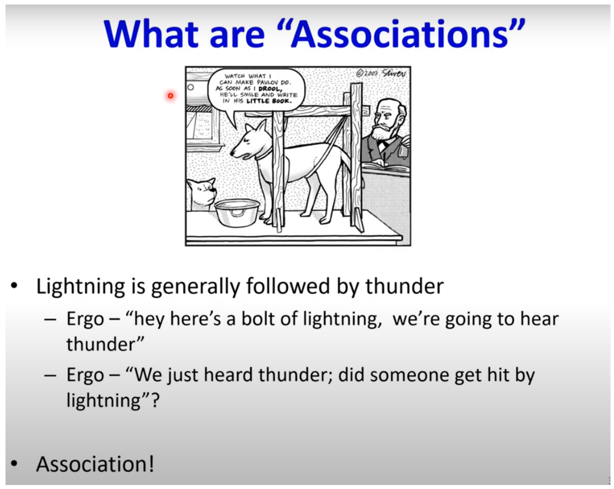
Artificial intelligence can be broken down into a few subfields that include:

1. Deep Learning (DL)
2. Machine Learning (ML)
3. Probabilistic graphical models (PGM)
4. Planning Agents
5. Search Algorithms
6. Knowledge representation (KR)
7. Game Theory

The only subfield that has dramatically improved in performance has been deep learning and machine learning. With advances in GPU computing and the amount of data we have available, training larger neural networks are easier than ever before. With more data, larger neural networks have been shown to out perform all other machine learning algorithms.

1.2 Theory of Associationism

Deep learning (Neural Networks) is heavily inspired by the human brain. The oldest recorded study/theory on how the brain functions was `Theory of Associationism`. But this theory does not explain the brain i.e. how do we do it, where are the percepts stored.



1.3 Theory of Connectionism

Theory of Connectionism was proposed by Alexander Bain in 1873. In his book "Mind and Body", Bain suggested that:

- The brain stores information (referred to as "associationism") through connections between neurons.
- Relationships between stimuli (inputs) and responses (outputs) are encoded in how neurons are connected.

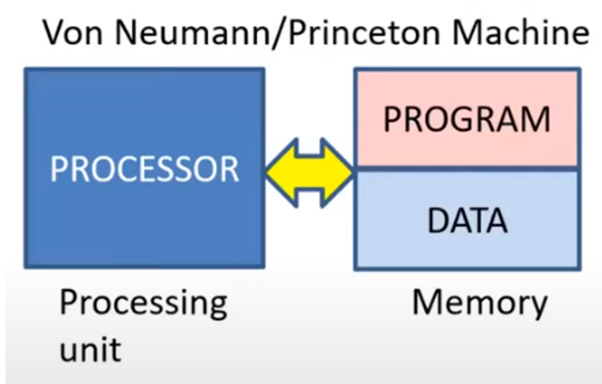
Bain's model showed that different inputs lead to different outputs. The intensity of the inputs (how strong the stimuli is) could also affect the output. He also proposed a mechanism for how connections between neurons could learn or change their strengths over time.
Connectionism is a theory that models cognitive processes as networks of interconnected simple processing units (neurons). Connectionism laid the foundation for artificial neural networks (ANNs), the core idea behind deep learning. Bain initially doubted his theory when he considered the concept of partially formed associations, as it seemed to require an impractical number of neurons. However, The human brain contains around 80 billion neurons and about 100 trillion connections, validating Bain's original ideas about how the brain functions. Watch: This image

Summary 1: Connectionism

- Theory of Connectionism suggests that complex behaviors emerge from the interactions of many simple processing units.
- The brain is a connectionist machine: a network of simple units (neurons) that derive their processing power from the connections between them.
- All world knowledge is stored in these connections, meaning the structure and strength of neural connections define cognitive processing.
- Artificial Neural Networks (ANNs) aim to emulate this structure, modeling how information is processed in the brain.

1.4 Computer & the Von Neumann Architecture

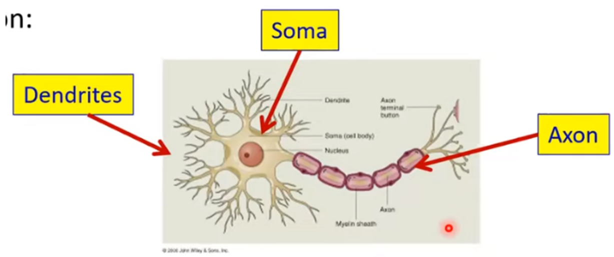
The Von Neumann architecture is the standard model for how computers are structured. In this model, the processor is separate from the memory, which holds both data and programs. Data and programs are stored in memory. The processor reads the data from memory to perform tasks. The processor is independent of the program and the data. You can load different programs into memory, and the processor will then execute the new program.



In a connectionist machine (like an artificial neural network), this separation of the processor and memory is impossible.
In a neural network, the workings of the program are encoded in the connections between the units (neurons). If you need to change the program, you would have to change the entire structure of the network itself. This is fundamentally different from the Von Neumann architecture, where changing the program is as simple as loading new instructions into memory.
Traditional processors (computers) aren't built as connectionist machines because It would require rebuilding the entire machine to change the program.

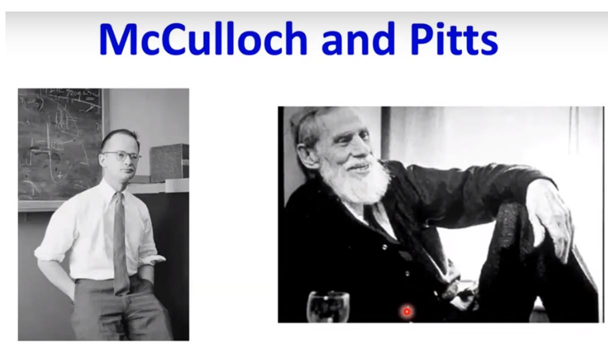
1.5 Inside the Brain

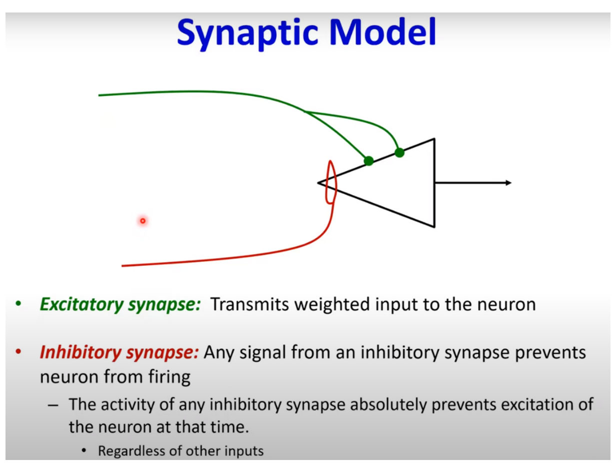
The axon is protected by a `myelin sheath`, a fatty layer produced by glial cells. This sheath is critical for fast and efficient signal transmission. When the total signal from all connected neurons exceeds a certain threshold, the neuron generates an electrical spike. The strength of the spike is proportional to the total incoming signal. This signal is transmitted out through the axon. Neurons are unique because they do not split or regenerate. All neurons are formed at birth.



1.6 The Synaptic Model

Watch: Warren Sturgis McCulloch On Artificial Intelligence
The Synaptic Model (computational theory of the neuron) describes how neurons can be modeled mathematically to understand their behavior in processing signals. This model illustrates how neurons and their synaptic connections work to process signals.





- Neuron (Triangle): Represents a neuron in the model.
- Outgoing Line: The line where the signal, produced by the neuron, exits.

- Incoming Colored Lines: Represent the signals coming into the neuron from other neurons.

Synaptic Connections are of 2 types:

1. Excitatory Connections:
   - These connections strengthen the signal.
   - The strength of each connection (known as the weight) is proportional to the number of times it connects to the neuron.
   - In this example, the connection has a weight of 2.
2. Inhibitory Connections:
   - These suppress the neuron's activity.
   - If an inhibitory neuron sends a signal, the neuron will not produce any output (it will always output 0).

1.6.1 Boolean Gates in the Synaptic Model

McCulloch and Pitts showed that using this model we can perform all kinds of boolean logics. Below, top left image: Neuron 1 generates signals and neuron 2 will fire if the total input is greater than or equal to 2. Top right, the second neuron will fire if the toal input is greater than or equal to 3 - which is an `AND` gate.

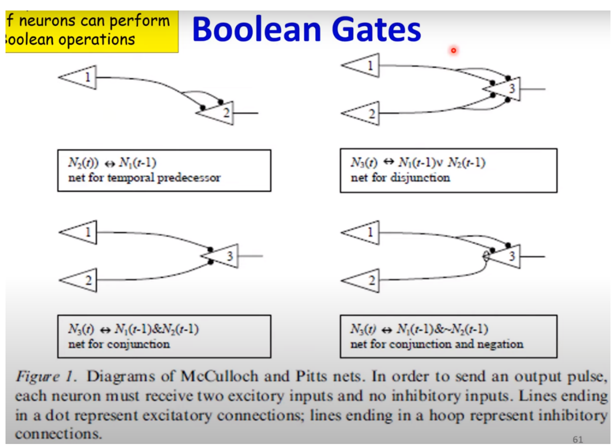
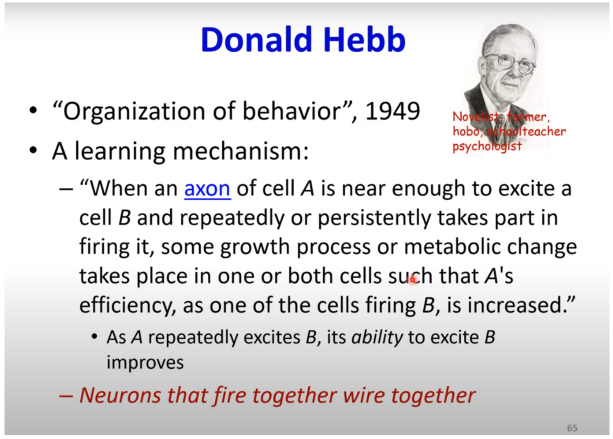
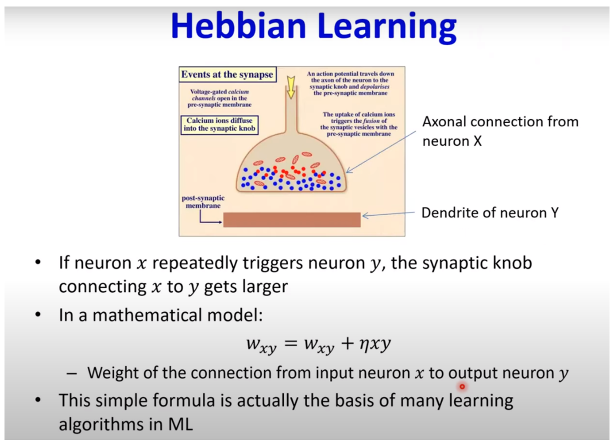


Figure 1. Diagrams of McCulloch and Pitts nets. In order to send an output pulse, each neuron must receive two excitory inputs and no inhibitory inputs. Lines ending in a dot represent excitatory connections; lines ending in a hoop represent inhibitory connections.

The Synaptic model didn't prove the learning of connections i.e. how many connections needed? Enter Hebbian Learning `Which are the Bottom 2 Gates?`

1.7 Hebbian Learning





Donald Hebb proposed a mechanism to explain how neurons can learn the weights of their synaptic connections. Hebb's Rule: If there are two neurons, A and B, and the firing of A causes the firing of B, then the connection between them becomes stronger. But this theory had some flaws:

1. Unbounded Growth: The weights always increase, and over time, every neuron could be connected to every other neuron.
2. No Weight Reduction: Hebbian learning lacks a mechanism to reduce the weights, which makes the system unstable.