**Assignment 2**

**Azhan Saleem**

**11635219**

**PART I: Biological Neural Network & Artificial Neural Network (30 Points)**

* 1. **The human biological neural network**

The human biological neural network, also known as the nervous system, is the most complex structure in the known universe. It is responsible for everything we do, from thinking and feeling to moving and sensing our environment.

Here's a breakdown of its key components and how they work together:

**1. Neurons:**

* The basic building blocks of the nervous system.
* Estimated 86 billion neurons in the human brain alone.
* Each neuron has a cell body, dendrites (which receive signals), and an axon (which sends signals).

A diagram of a nerve cell

Description automatically generated

**2. Synapses:**

* The junctions between neurons where information is transmitted.
* Chemical messengers called neurotransmitters bridge the gap between neurons.
* The strength of these connections can change over time, allowing for learning and memory.

A diagram of a synapse

Description automatically generated

**3. Action potentials:**

* Electrical signals that travel down the axon of a neuron.
* Triggered by the summation of incoming signals at the dendrites.
* All-or-nothing principle: either the signal reaches a threshold and fires, or it doesn't.

**4. Nervous system organization:**

* Central nervous system (CNS): brain and spinal cord.
* Peripheral nervous system (PNS): connects the CNS to the rest of the body.
* Somatic nervous system (controls voluntary movements).
* Autonomic nervous system (controls involuntary functions like heart rate and digestion).

**How it works:**

* Specialized receptors in the PNS detect sensory information.
* These signals are converted into electrical impulses and travel up the spinal cord to the brain.
* In the brain, the signals are processed by different regions depending on the type of information.
* The brain then sends motor commands back down the spinal cord to the muscles, resulting in movement or other actions.
* Learning and memory involve changes in the strength of connections between neurons.

**The human neural network is constantly adapting and evolving, making it an incredibly powerful and versatile system.**

Here are some additional points to consider:

* The brain is not fully developed until around the age of 25.
* The neural network is still not fully understood, and there is much ongoing research in this area.
* Damage to the neural network can lead to a variety of neurological disorders.
  1. **The McCulloch-Pitt neuron model**

The McCulloch-Pitts neuron model, also known as the Threshold Logic Unit (TLU), laid the groundwork for modern artificial neural networks. Though simplistic compared to today's complex models, it served as a crucial first step in understanding how neurons might process information computationally.

Here's a breakdown of its structure and function:

**Structure:**

**Inputs:** Receives multiple binary inputs (0 or 1), representing signals from other neurons.

Weights: Each input has an associated weight, signifying its influence on the final output.

**Summation:** Incoming signals are multiplied by their weights and summed together.

**Threshold**: The summed value is compared to a predetermined threshold.

**Activation Function**: If the summed value exceeds the threshold, the neuron fires, outputting a 1. Otherwise, it remains inactive, outputting a 0.

Diagram of a diagram of a function

Description automatically generated

**Function:**

* Each input signal carries a value (0 or 1) and is multiplied by its corresponding weight.
* These weighted values are summed together.
* If the sum surpasses the set threshold, the neuron "fires," producing an output of 1.
* Conversely, if the sum falls below the threshold, the neuron stays inactive, resulting in an output of 0.

**Think of it as a simple decision-making unit:**

* Imagine inputs representing environmental factors like temperature and humidity.
* Weights reflect the importance of each factor for an insect's survival.
* The threshold might represent the minimum safe combined value.
* When the weighted sum exceeds the threshold (indicating danger), the insect might choose to seek shelter (output of 1).

**Limitations:**

* Binary inputs and outputs restrict the model's complexity.
* Cannot learn or adapt, limiting its real-world applications.

**Importance:**

* Despite its limitations, the McCulloch-Pitts model paved the way for more sophisticated neural network architectures.
* Inspired advancements in artificial intelligence and machine learning by demonstrating the potential of computational models to mimic some aspects of neural processing.

**Key takeaways:**

* The McCulloch-Pitts neuron model, though simple, marked a significant step in understanding how neurons might compute information.
* While limited in its capabilities, it laid the foundation for future neural network developments.
* Its legacy lies in inspiring the exploration of more complex and powerful computational models for artificial intelligence.
  1. **Pioneers in the AI field**

**Early Inspiration:**

**1943: McCulloch & Pitts Neuron**: Inspired by biological neurons, this model laid the groundwork. Imagine simple circles representing interconnected units, each receiving inputs (arrows) and producing an output (another circle). These "artificial neurons" mimicked the basic structure and function of their biological counterparts.

Diagram of a diagram of a function

Description automatically generated

**1949:** **Hebbian Learning:** Donald Hebb proposed that connections between neurons strengthen with use, a principle now known as Hebbian learning. This concept became crucial for designing networks that could learn and adapt from experience.

First Steps:

**1957: Perceptron**: Frank Rosenblatt developed this first true neural network, considered a milestone in AI history. Imagine multiple layers of interconnected McCulloch-Pitts neurons, inspired by the brain's intricate structure. The Perceptron could learn simple patterns by adjusting the weights of its connections, mimicking the brain's learning process.

A diagram of a network

Description automatically generated

**Key Inspirations from the Brain:**

**Interconnected Neurons:** Neural networks mirror the brain's structure, with interconnected processing units (neurons) communicating through weighted connections.

**Learning and Adaptation**: Inspired by Hebbian learning, early networks adjusted connections based on experience, mimicking the brain's learning process.

**Parallel Processing**: Like the brain, neural networks distribute computations across multiple units, making them faster and more efficient.

**Challenges and Advancements:**

**Limitations:** Early models like the Perceptron struggled with complex tasks and lacked the brain's full complexity.

**Training Difficulties**: Training them requires significant resources and specific data formats.

Despite these challenges, pioneers persevered, leading to breakthroughs:

**1974: Backpropagation Algorithm**: Paul Werbos introduced this revolutionary method for training complex networks. Imagine errors flowing back through the network, adjusting weights to improve future performance, just like the brain learns from feedback.

**1982:** **Hopfield Network**: John Hopfield created this recurrent neural network, inspired by the brain's associative memory. Imagine the network storing and retrieving patterns, mimicking how we recall memories based on connections.

**Legacy and the Future**:

While not perfect replicas of the human brain, these early models paved the way for the sophisticated deep learning architectures of today, like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These advancements power applications like image recognition, language translation, and self-driving cars.

The journey continues as researchers delve deeper into neuroscience, seeking to develop even more advanced and biologically realistic AI systems. While we may never fully replicate the human brain, the early pioneers' vision of learning from nature's masterpieces continues to inspire the development of ever-more intelligent machines.

**PART II: Linear Algebra for Deep Learning: Matrices (25 Points)**

**Matrix Multiplication Solution**

**Given:**

A = [5, 3, 8

2, -1, 7]

B =?

**To perform matrix multiplication between A and B:**

B must have the same number of rows as A has columns. A has 2 columns, so B must have 2 rows.

Let's define B as the 2x3 matrix:

B = [1, 4, 5]

[2, 2, 1]

The dimensions of matrix C will be the number of rows of A (which is 2) x the number of columns of B (which is 3).

So, the dimensions of C are 2x3.

To calculate the dot product:

Taking the 1st row of A and 1st column of B and multiply element-wise, then sum the result:

(5 \* 1) + (3 \* 2) = 13

Taking the 1st row of A and 2nd column of B and multiply element-wise, then sum the result: (5 \* 4) + (3 \* 2) = 26

Taking the 1st row of A and 3rd column of B and multiply element-wise, then sum the result: (5 \* 5) + (3 \* 1) = 30

Taking the 2nd row of A and 1st column of B and multiply element-wise, then sum the result: (2 \* 1) + (-1 \* 2) = 0

Taking the 2nd row of A and 2nd column of B and multiply element-wise, then sum the result:

(2 \* 4) + (-1 \* 2) = 6

Take the 2nd row of A and 3rd column of B and multiply element-wise, then sum the result: (2 \* 5) + (-1 \* 1) = 9

Thus, the resulting matrix C is:

**C = [13, 26, 30]**

**[0, 6, 9]**

**So in summary:**

B = [1, 4, 5]

[2, 2, 1]

C = A \* B = [13, 26, 30]

[0, 6, 9]

Where C is a 2x3 matrix.

**PART III: Linear Algebra for Deep Learning: Matrices (45 Points)**

**3.1**

Here's how many vector elements the matrix has along Axis 1, and each vector element is listed one by one:

**Number of vector elements:**

The axis along which we're counting the elements determines the number of vectors. In this case, we're considering the matrix as a vector of vectors along Axis 1 (rows). Since the matrix has 4 rows, there are 4 vectors along this axis.

**Listing vector elements:**

Each row of the matrix represents a separate vector. Here's each vector element listed one by one:

**Vector 1: 2, 1, 3, 4, 5**

**Vector 2: 0, 0, 1, 4, 2**

**Vector 3: 4, 2, 6, 8, 10**

**Vector 4: 6, 3, 14, 35, 33**

Therefore, the matrix has 4 vectors along Axis 1, with a total of 20 vector elements (5 elements per vector).

**3.2**

Here is the matrix after adding 3 to the vector element at index 1 along Axis 1:

Original matrix:

\begin{bmatrix}

2 & 1 & 3 & 4 & 5 \\

0 & 0 & 1 & 4 & 2 \\

4 & 2 & 6 & 8 & 10 \\

6 & 3 & 14 & 35 & 33 \\

\end{bmatrix}

**Vector element at index 1:**

1

0

2

3

**After adding 3 to this vector element:**

4

3

5

6

**Updated matrix:**

\begin{bmatrix}

2 & 4 & 3 & 4 & 5 \\

0 & 3 & 1 & 4 & 2 \\

4 & 5 & 6 & 8 & 10 \\

6 & 6 & 14 & 35 & 33 \\

\end{bmatrix}

So, the updated matrix after adding 3 to the vector element at index 1 along Axis 1 is:

\begin{bmatrix}

2 & 4 & 3 & 4 & 5 \\

0 & 3 & 1 & 4 & 2 \\

4 & 5 & 6 & 8 & 10 \\

6 & 6 & 14 & 35 & 33 \\

\end{bmatrix}

**3.3**

To flatten the matrix from Question 3.2, I’m converting the 2D matrix into a 1D vector by appending all the rows into a single row vector.

The matrix after adding 3 to the vector element at index 1 in Question 3.2 is:

\begin{bmatrix}  
2 & 4 & 3 & 4 & 5 \\ 0 & 3 & 1 & 4 & 2 \\ 4 & 5 & 6 & 8 & 10 \\  
6 & 6 & 14 & 35 & 33 \\ \end{bmatrix}

To flatten this matrix:

1. Take the first row and append it to the flattened vector: [2, 4, 3, 4, 5]
2. Add the second row: [2, 4, 3, 4, 5, 0, 3, 1, 4, 2]
3. Add the third row: [2, 4, 3, 4, 5, 0, 3, 1, 4, 2, 4, 5, 6, 8, 10]
4. Finally, add the fourth row: [2, 4, 3, 4, 5, 0, 3, 1, 4, 2, 4, 5, 6, 8, 10, 6, 6, 14, 35, 33]

Therefore, the flattened 1D vector representation of the matrix is:

**[2, 4, 3, 4, 5, 0, 3, 1, 4, 2, 4, 5, 6, 8, 10, 6, 6, 14, 35, 33]**