

## 1. Introduction

Artificial Neural Networks (ANNs) are systems of interconnected processing units whose behaviour is governed by two fundamental mechanisms: **activation dynamics** and **synaptic dynamics**.

- **Activation dynamics** describe how neuron states (activations) evolve with time for a fixed input.
- **Synaptic dynamics** describe how connection weights change during learning.

Mathematically, both are represented using **first-order differential equations**, which model the rate of change of activation or weight with respect to time.

## 2. Passive Decay Model

$$\frac{dx_i(t)}{dt} = -A_i x_i(t)$$

### Symbols

- $x_i(t)$ : activation (state) of neuron indexed by  $i$  at time  $t$
- $i$ : index identifying the neuron
- $t$ : time variable
- $\frac{dx_i(t)}{dt}$ : derivative of  $x_i(t)$  with respect to time (rate of change)
- $A_i$ : positive decay (leakage) constant for neuron  $i$
- $-$ : indicates reduction (decay) of activation

## 3. Modified Passive Decay Model

$$\frac{dx_i(t)}{dt} = -\frac{A_i}{C_i} x_i(t)$$

### Symbols

- $x_i(t)$ : activation of neuron  $i$  at time  $t$
- $t$ : time

- $\frac{dx_i(t)}{dt}$ : rate of change of activation
- $A_i$ : decay constant
- $C_i$ : membrane capacitance of neuron  $i$
- $\frac{A_i}{C_i}$ : effective decay rate
- $-$ : decay effect

## **4. Non-Zero Resting Potential Model**

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + P_i$$

### **Symbols**

- $x_i(t)$ : activation of neuron  $i$  at time  $t$
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change of activation
- $A_i$ : decay constant
- $P_i$ : constant input (resting potential or bias)
- $+$ : additive effect

## **5. External Input Activation Model**

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + B_i I_i$$

### **Symbols**

- $x_i(t)$ : activation of neuron  $i$  at time  $t$
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change of activation

- $A_i$ : decay constant
- $B_i$ : input gain (scaling factor)
- $I_i$ : external input signal applied to neuron  $i$
- $+$ : additive contribution

## **6. Additive Autoassociative Model**

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + B_i I_i + \sum_{j=1}^N W_{ij} f_j(x_j(t))$$

### **Symbols**

- $x_i(t)$ : activation of neuron  $i$  at time  $t$
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change of activation
- $A_i$ : decay constant
- $B_i$ : input gain
- $I_i$ : external input to neuron  $i$
- $\sum_{j=1}^N$ : summation over index  $j$  from 1 to  $N$
- $j$ : index of presynaptic neuron
- $N$ : total number of neurons
- $W_{ij}$ : synaptic weight from neuron  $j$  to neuron  $i$
- $f_j(\cdot)$ : output function of neuron  $j$
- $x_j(t)$ : activation of neuron  $j$  at time  $t$

## **7. Inhibitory Feedback Model**

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) - B_i I_i - \sum_{j=1}^N W_{ij} f_j(x_j(t))$$

### Symbols

- $x_i(t)$ : activation of neuron  $i$  at time  $t$
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change
- $A_i$ : decay constant
- $B_i$ : scaling constant
- $I_i$ : external input
- $\sum_{j=1}^N$ : summation over neurons
- $j$ : neuron index
- $N$ : total neurons
- $W_{ij}$ : weight from neuron  $j$  to neuron  $i$
- $f_j(x_j(t))$ : output of neuron  $j$

## 8. Perkel's Model

$$\frac{dx_i(t)}{dt} = \frac{1}{R_i} x_i(t) + \sum_{j=1}^N \frac{1}{R_{ij}} \phi_j(x_j(t))$$

### Symbols

- $x_i(t)$ : activation of neuron  $i$
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change
- $R_i$ : resistance of neuron  $i$

- $\frac{1}{R_i}$ : conductance
- $\sum_{j=1}^N$ : summation over neurons
- $j$ : neuron index
- $N$ : total neurons
- $R_{ij}$ : resistance between neurons  $i$  and  $j$
- $\phi_j(\cdot)$ : output function
- $x_j(t)$ : activation of neuron  $j$

## **9. Hopfield Model**

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + \sum_{j=1}^N W_{ij} f(x_j(t)) + I_i$$

### Symbols

- $x_i(t)$ : activation of neuron  $i$
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change
- $A_i$ : decay constant
- $\sum_{j=1}^N$ : summation
- $j$ : neuron index
- $N$ : total neurons
- $W_{ij}$ : symmetric connection weight
- $f(\cdot)$ : bounded activation function

- $x_j(t)$ : activation of neuron  $j$
- $I_i$ : external input

## 10. Heteroassociative Network

### Layer-1

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + \sum_{j=1}^M f_j(y_j(t))V_{ji} + I_i$$

#### Symbols

- $x_i(t)$ : activation of neuron  $i$  in layer-1
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change
- $A_i$ : decay constant
- $\sum_{j=1}^M$ : summation over layer-2 neurons
- $j$ : index of neuron in layer-2
- $M$ : number of neurons in layer-2
- $f_j(\cdot)$ : output function of neuron  $j$
- $y_j(t)$ : activation of neuron  $j$  in layer-2
- $V_{ji}$ : weight from neuron  $j$  to neuron  $i$
- $I_i$ : external input

### Layer-2

$$\frac{dy_j(t)}{dt} = -B_j y_j(t) + \sum_{i=1}^N g_i(x_i(t))W_{ij} + J_j$$

#### Symbols

- $y_j(t)$ : activation of neuron  $j$  in layer-2
- $t$ : time

- $\frac{dy_j(t)}{dt}$ : rate of change
- $B_j$ : decay constant
- $\sum_{i=1}^N$ : summation over layer-1 neurons
- $i$ : neuron index in layer-1
- $N$ : number of neurons in layer-1
- $g_i(\cdot)$ : output function of neuron  $i$
- $x_i(t)$ : activation of neuron  $i$
- $W_{ij}$ : weight from neuron  $i$  to neuron  $j$
- $J_j$ : external input

## 11. Bidirectional Associative Memory (BAM)

Same equations as heteroassociative network with

- $V = W^T$ : weight matrix  $V$  equals transpose of weight matrix  $W$

## 12. Basic Shunting Model

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + (B_i - x_i(t))I_i$$

### Symbols

- $x_i(t)$ : activation
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change
- $A_i$ : decay constant
- $B_i$ : upper saturation limit

- $I_i$ : external input
- $(B_i - x_i(t))$ : remaining activation capacity

## 13. On-Center Off-Surround Model

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + (B_i - x_i(t))I_i - x_i(t) \sum_{j \neq i} I_j$$

### Symbols

- $x_i(t)$ : activation
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change
- $A_i$ : decay constant
- $B_i$ : upper bound
- $I_i$ : excitatory input
- $\sum_{j \neq i}$ : summation over all neurons except  $i$
- $j \neq i$ : index condition
- $I_j$ : inhibitory inputs

## 14. Modified Shunting Model

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + (B_i - x_i(t))I_i - (E_i + x_i(t)) \sum_{j \neq i} I_j$$

### Symbols

- $x_i(t)$ : activation
- $t$ : time

- $\frac{dx_i(t)}{dt}$ : rate of change
- $A_i$ : decay constant
- $B_i$ : upper bound
- $E_i$ : lower bound parameter
- $I_i$ : excitatory input
- $\sum_{j \neq i}$ : summation excluding neuron  $i$
- $I_j$ : inhibitory inputs

## 15. Shunting Model with Feedback

$$\frac{dx_i(t)}{dt} = -A_i x_i + (B_i - C_i x_i)[I_i + f_i(x_i)] - (E_i + D_i x_i)J_i + \sum_{j \neq i} f_j(x_j)$$

### Symbols

- $x_i$ : activation of neuron  $i$
- $t$ : time
- $\frac{dx_i(t)}{dt}$ : rate of change
- $A_i$ : decay constant
- $B_i$ : upper bound
- $C_i$ : scaling constant for excitatory term
- $I_i$ : external excitatory input
- $f_i(x_i)$ : feedback function of neuron  $i$
- $E_i$ : lower bound parameter
- $D_i$ : scaling constant for inhibitory term
- $J_i$ : external inhibitory input

- $\sum_{j \neq i}$ : summation over neurons except  $i$
- $f_j(x_j)$ : output of neuron  $j$
- $w_{ji}$ : feedback weight from neuron  $j$  to neuron  $i$

## **16. Synaptic Dynamics Model**

$$\frac{dw_{ij}(t)}{dt} = -w_{ij}(t) + f_i(x_i(t))f_j(x_j(t))$$

### **Symbols**

- $w_{ij}(t)$ : synaptic weight from neuron  $j$  to neuron  $i$  at time  $t$
- $\frac{dw_{ij}(t)}{dt}$ : rate of change of weight
- $t$ : time
- $f_i(x_i(t))$ : output of neuron  $i$
- $x_i(t)$ : activation of neuron  $i$
- $f_j(x_j(t))$ : output of neuron  $j$
- $x_j(t)$ : activation of neuron  $j$