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AIML231/DATA302 —Techniques in Machine  
Learning

**Week 8 Neural Networks (1)**  
**Introduction to Neural Networks**

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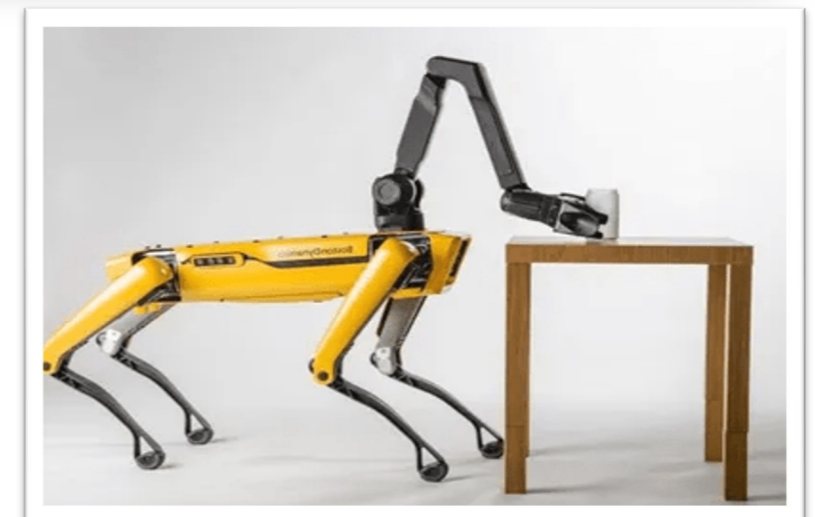
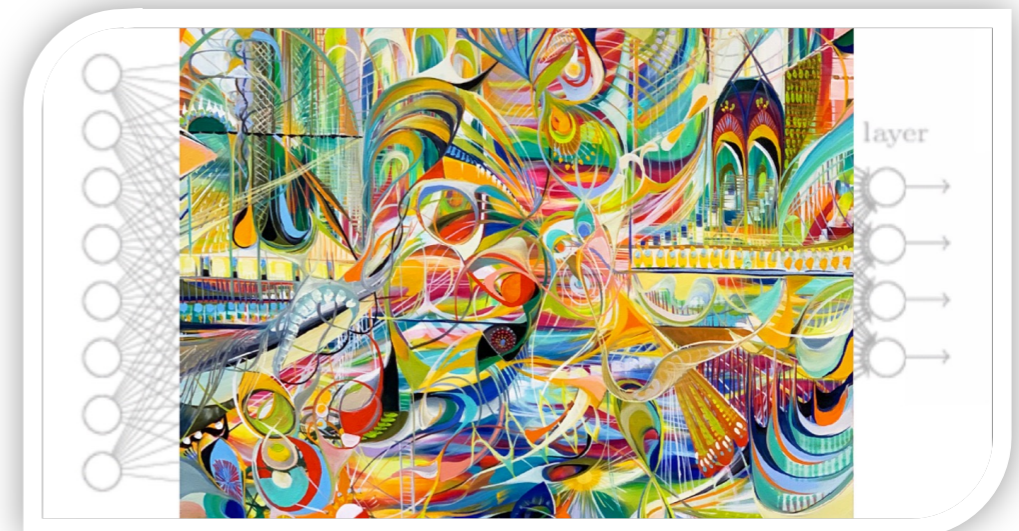
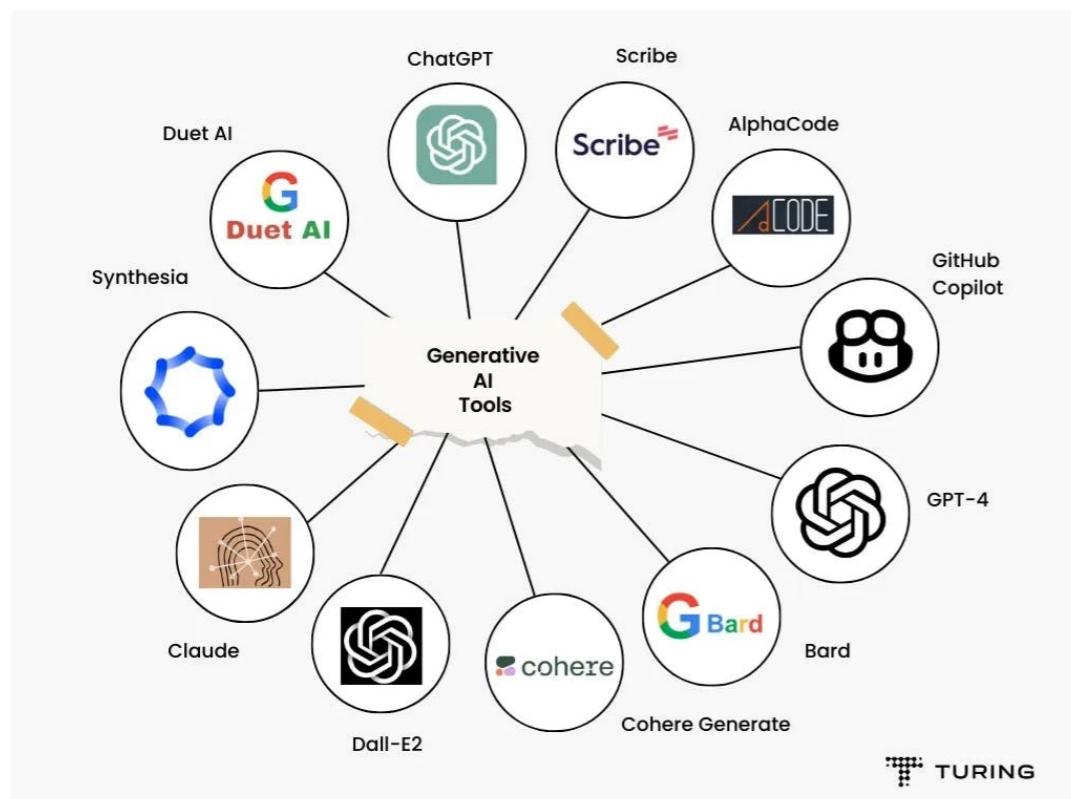
# Outline

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- Neural Network Introduction
- Basic Concepts in NNs
  - Perceptron
  - Neurons, Layers, Weights and Bias
  - NN Architectures
  - Activation functions
- How NNs work – Forward Propagation

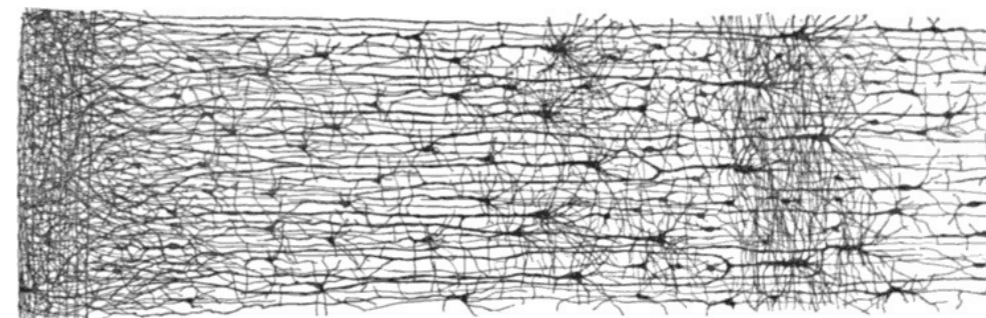
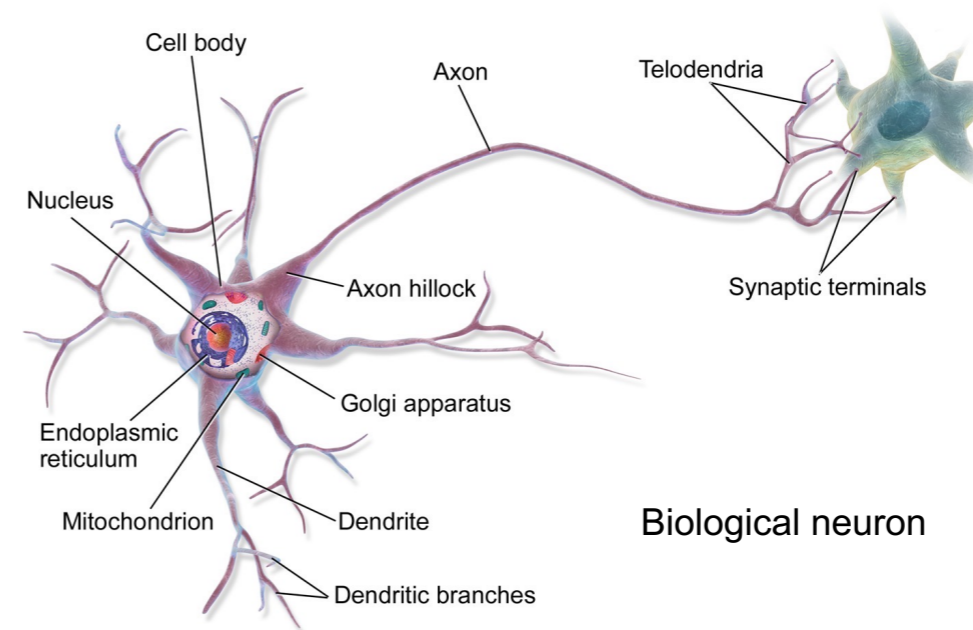
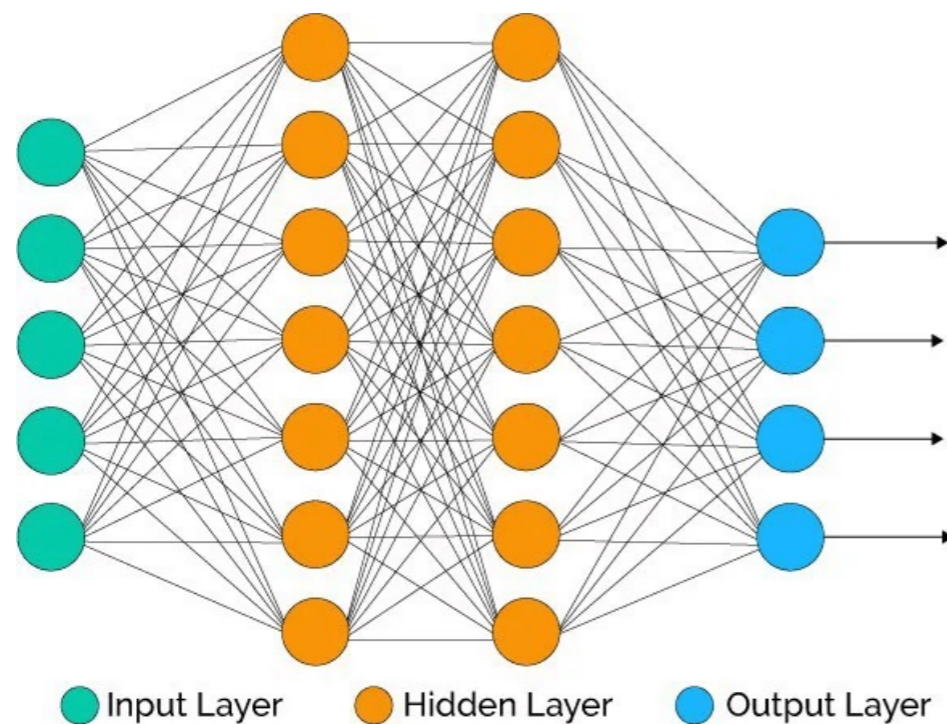
# Why Neural Networks

- Many successful applications
  - Generative models: Large language models, Image/video generation
  - Image processing: medical/game/self-driving vehicles



# Artificial Neural Networks

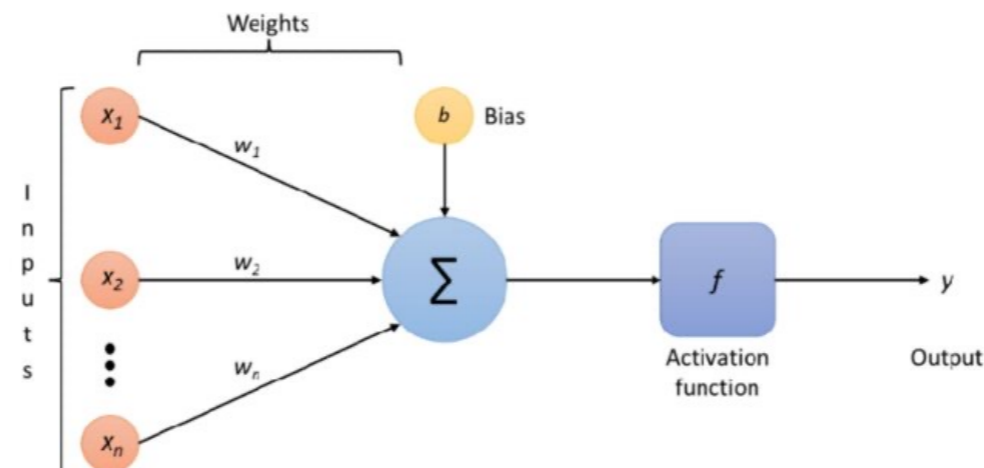
- A **Neural Network** is a **machine learning (ML) model** designed to recognize patterns and solve complex problems in a manner that mimics human thought processes
  - inspired by the structure and function of the human brain
  - consists of layers of interconnected nodes, or "neurons," each of which performs simple computations



Biological neural network

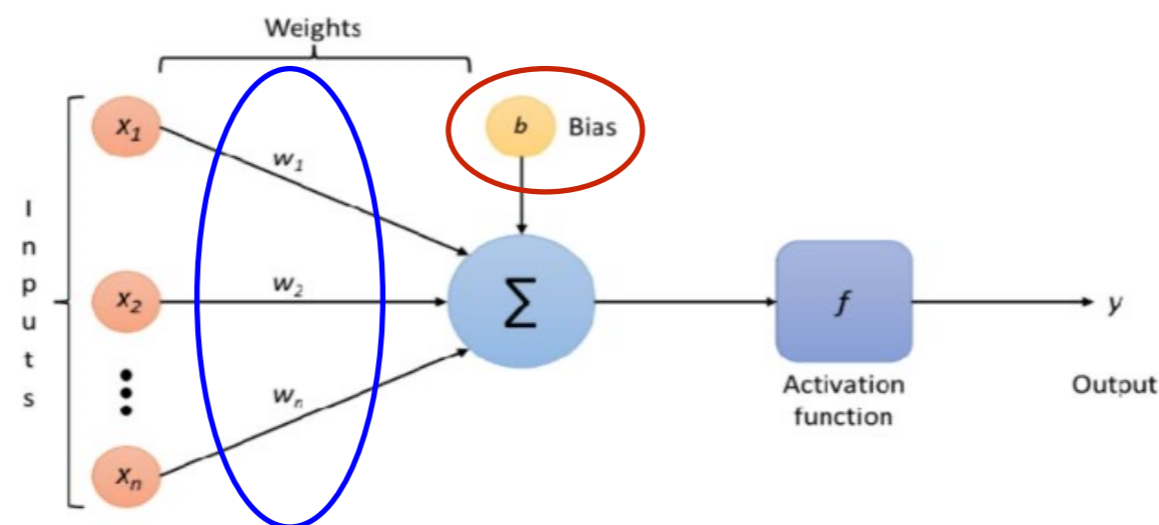
# (Artificial) Neurons

- **Neurons** are the basic units of a neural network
  - also also referred to as a node or a unit,
  - the basic unit of computation, as a processing point for carrying out specific calculations
  - The primary function of a neuron in a neural network is to receive input, processes it, and generates output
  - the input  $x$  is transformed into an output  $y$  using weights  $W$  and a bias  $b$  as:  $y = f(WX + b)$  where  $f$  is the activation function



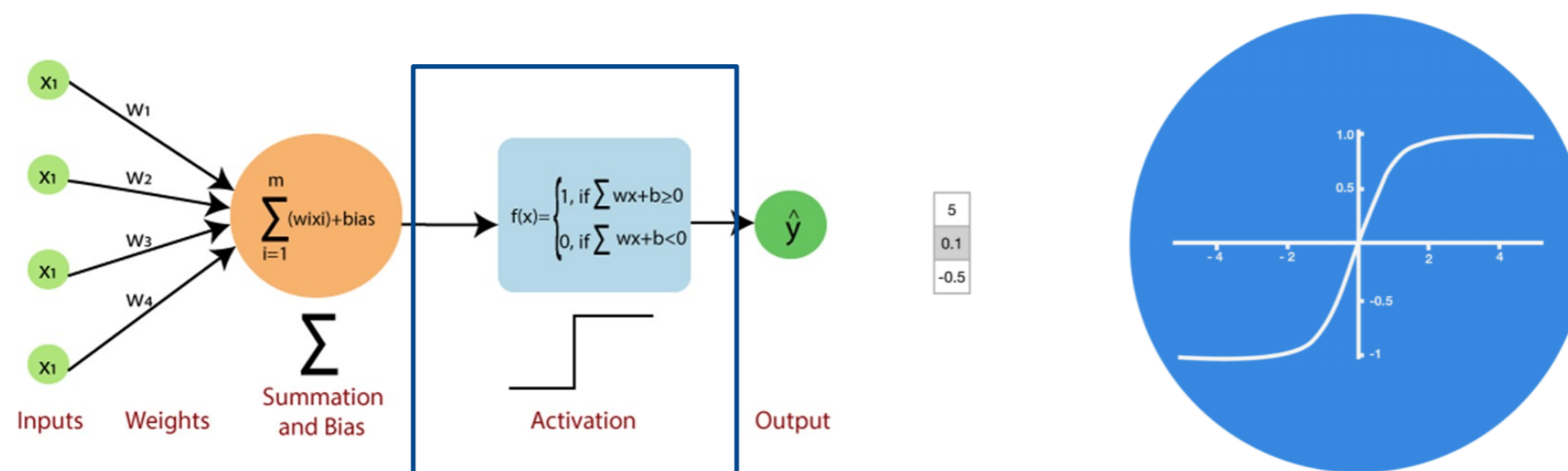
# Weights and Bias

- **Weights** are the numbers assigned to each connection between one neuron in a layer and the neurons from the previous layer
  - each weight is an indication of the strength and influence of the input signals on the neuron's output
- **Bias: an additional parameter** associated with each neuron that allows the model to better fit the data.
  - provides neuron the flexibility to shift the activation function to the left or right
  - the bias tells you how big that weighted sum needs to be before the neuron gets meaningfully active



# Activation Function

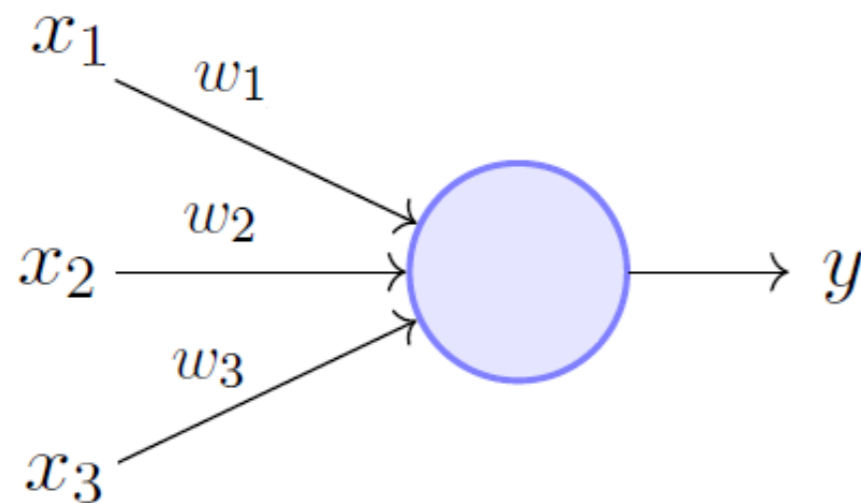
- Activation function is a function that takes the weighted input of a neuron and produces an output, which is used as the input for the next layer of neurons
  - **primary role**: introduce non-linearities into the network and enable complex learning
  - regulate the output and prevent numerical instability
  - affect the speed, accuracy and generalisation performance



# simplest neural network - Perceptron

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- **Perceptron**: the simplest form of a neural network
  - it is a binary linear classifier, based on a linear threshold unit
  - calculate a weighted sum of the input features, apply a **step function**, mathematically represented as  $y = \text{Step}(WX)$   
makes decisions by weighing up evidence

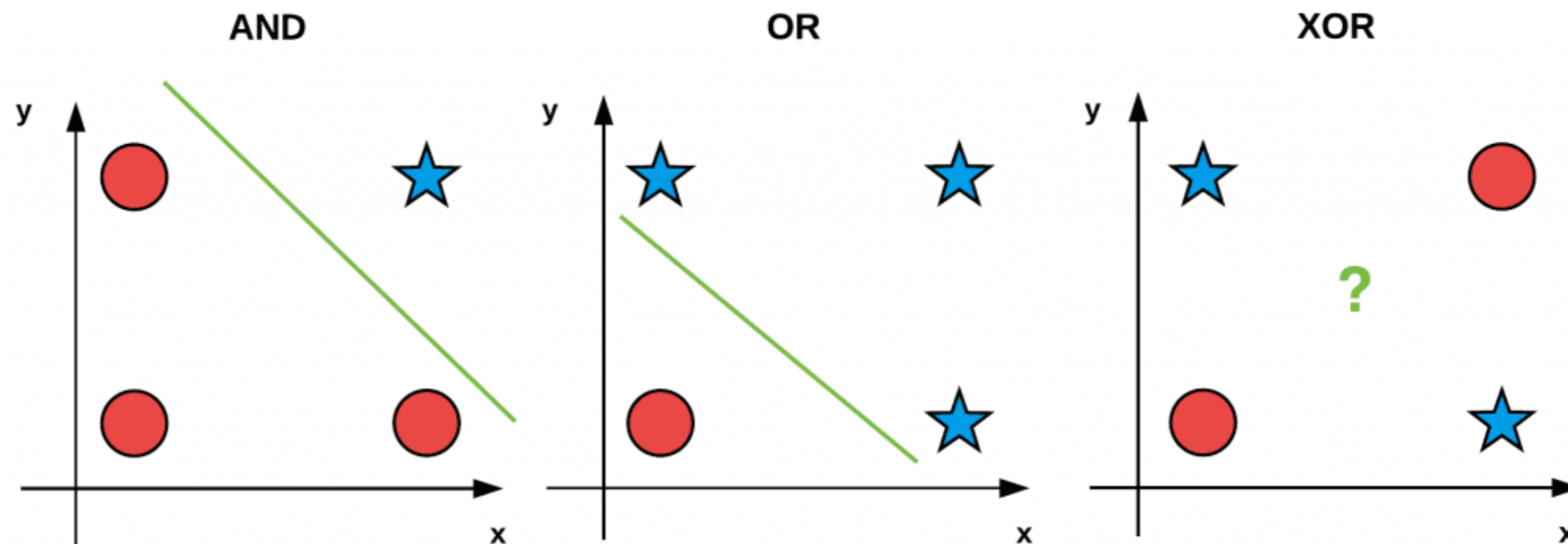


$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{threshold} \end{cases}$$



# Problem with Perceptron

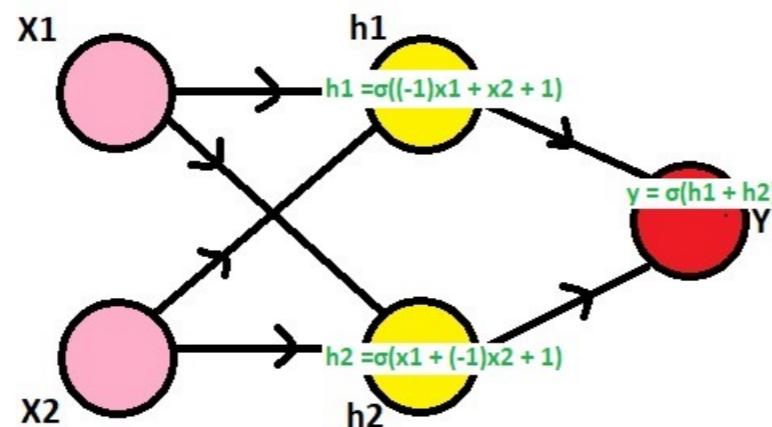
- Famous example of cannot solve the XOR problem (Minsky 1969)



- XOR is not linearly separable, you cannot draw a single straight line that separates the inputs that produce 1 from those that produce 0

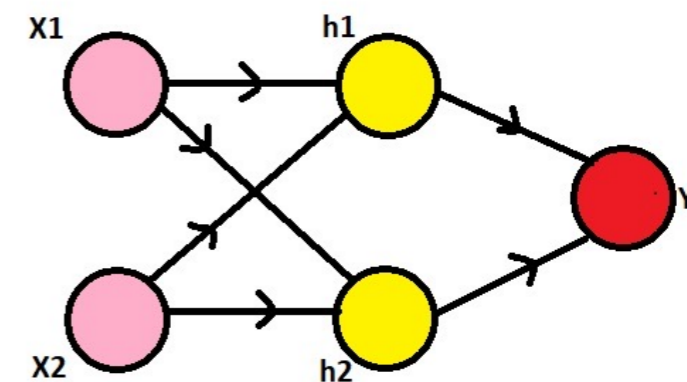
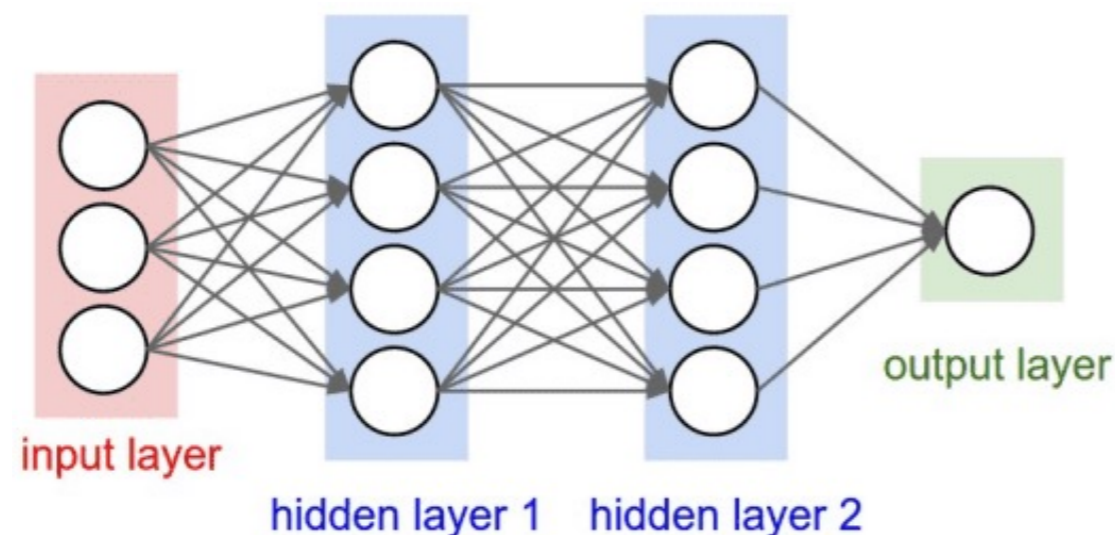
# Multi-layer Perceptron

- MLP: a class of feedforward artificial neural network (ANN) that includes multiple layers of nodes
  - all outputs of previous layer connected to all neurons of a layer or the output of a neuron in one layer is fed as input to neurons in the subsequent layers
  - each node typically using a non-linear activation function
  - solve problems that the single-layer perceptron cannot, such as the XOR problem
  - "universal approximation theorem"- can approximate virtually any continuous function



# Layers of Neural Networks

- **Input Layer:** The first layer that receives the input signal to be processed, neurons simply pass the data on to the subsequent hidden layers without applying any transformation or computation
- **Hidden Layers:** One or more layers that perform computations through neurons and are not exposed to the input or output directly
- **Output Layer:** The final layer that produces the output of the model



$$X1 \text{ XOR } X2 = (X1 \text{ AND NOT } X2) \text{ OR } (X2 \text{ AND NOT } X1)$$

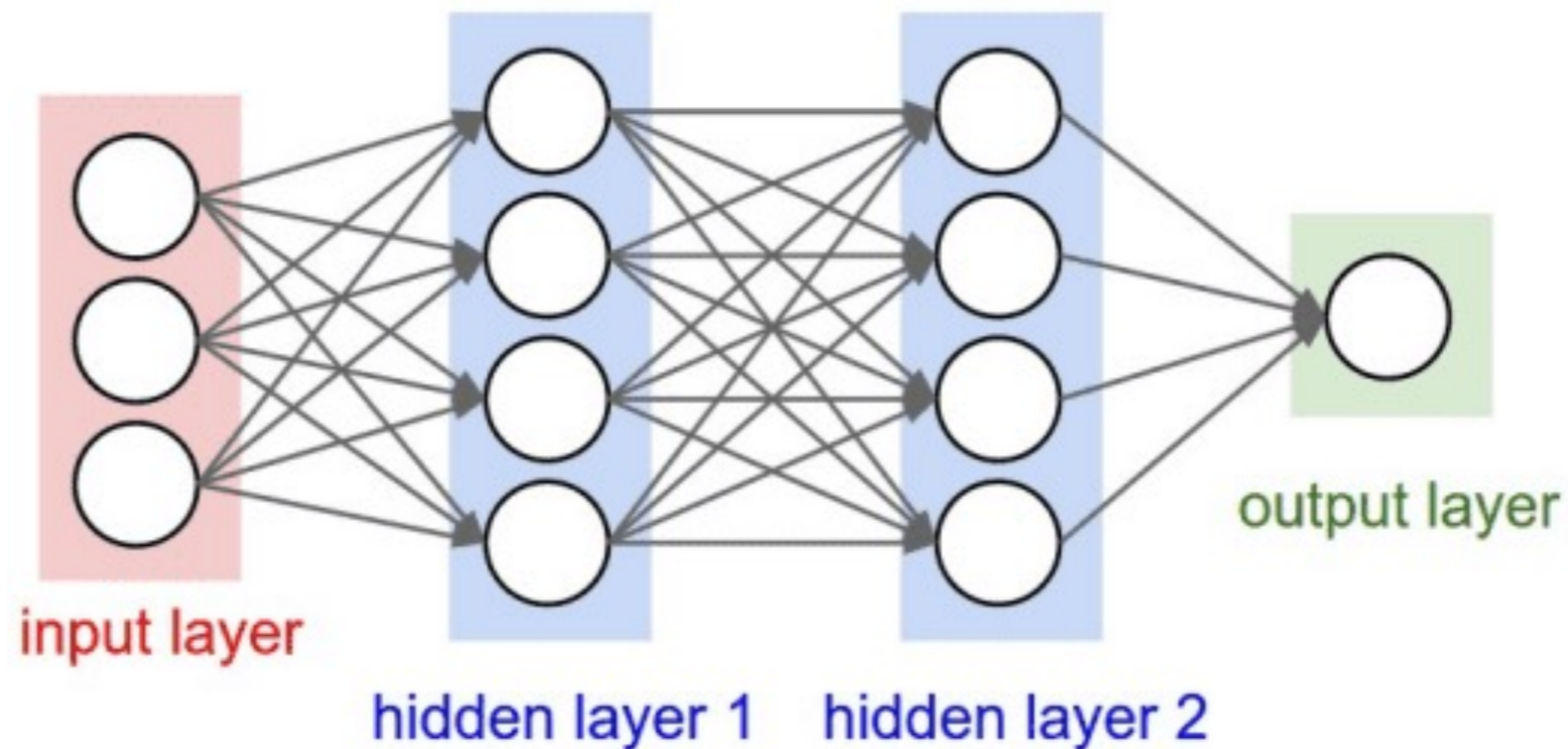
- Why layers: layers break problems into bite-sized pieces

# Designing layers

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- Input layer mirrors the format and structure of input data
  - **number of neurons** in the input layer is typically equal to the number of features in the input data
  - e.g., with images of size 28x28 pixels, need 784 (28x28) neurons, each representing one pixel value.
- the output layer is closely tied to the specific task
  - for **classification** tasks, the **number of neurons** typically corresponds to the **number of classes**, e.g., in a task to identify digits from 0 to 9, the output layer would have 10 neurons,
  - For **regression** tasks, the output layer usually contains **a single neuron**
- it can be quite an art to the design of the hidden layers
  - determining #hidden layers and #neuron in each layer
  - increasing the number of hidden layers can enable the network to learn more complex patterns and features in the data
  - use heuristics-how to trade-off the number of hidden layers against the time required to train the network, trade-off between underfitting and overfitting

# Numbers of Weights and Bias in MLP



In a MLP,

- each neuron in a given layer has as many weights as there are neurons in the preceding layer
- each neuron typically has one bias

How many weights and bias in this feedforward NN?

$$\text{\#Weights} = 3 \times 4 + 4 \times 4 + 4 = 32$$

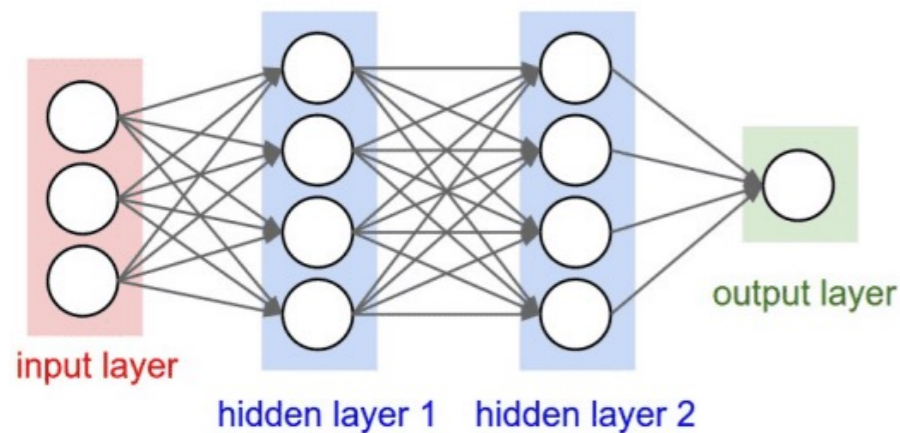
$$\text{\#Bias} = 4 + 4 + 1 = 9$$

$$\text{In total} = 32 + 9 = 41$$

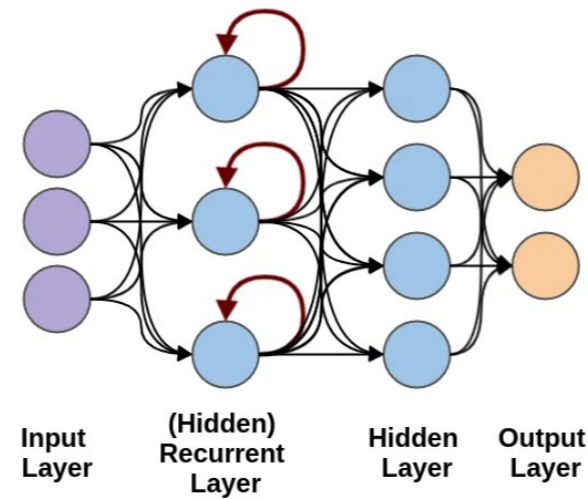
# Neural network architectures

- Various NN architectures designed for specific types of tasks

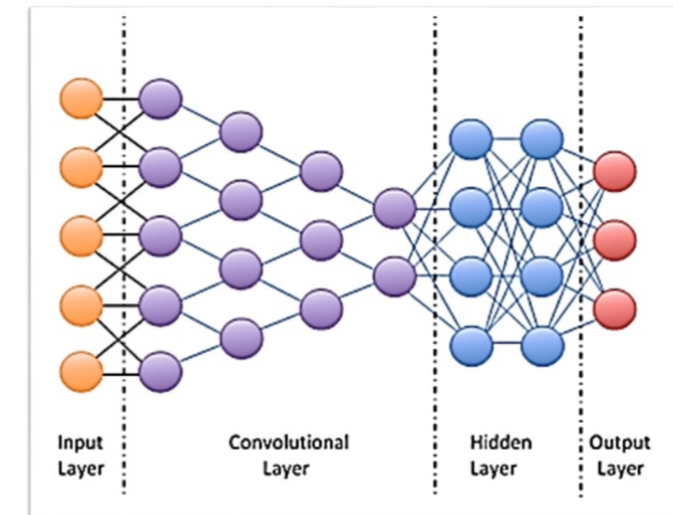
MLP



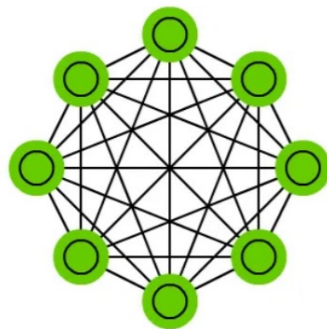
Recurrent NN



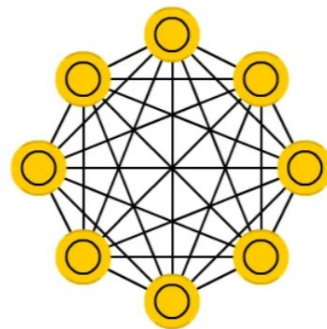
Convolutional NN



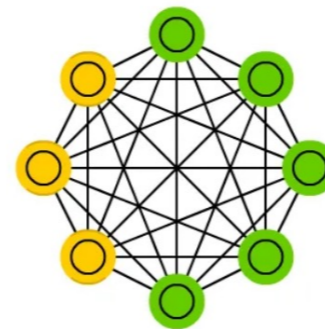
Markov Chain (MC)



Hopfield Network (HN)



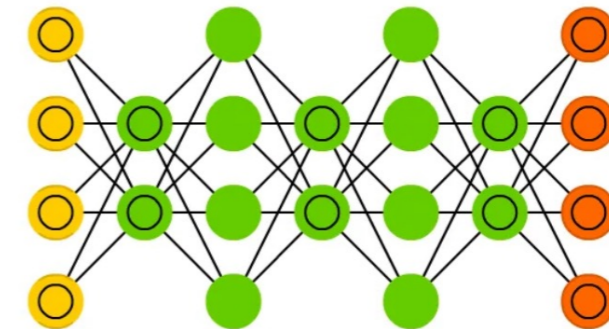
Boltzmann Machine (BM)



Restricted BM (RBM)

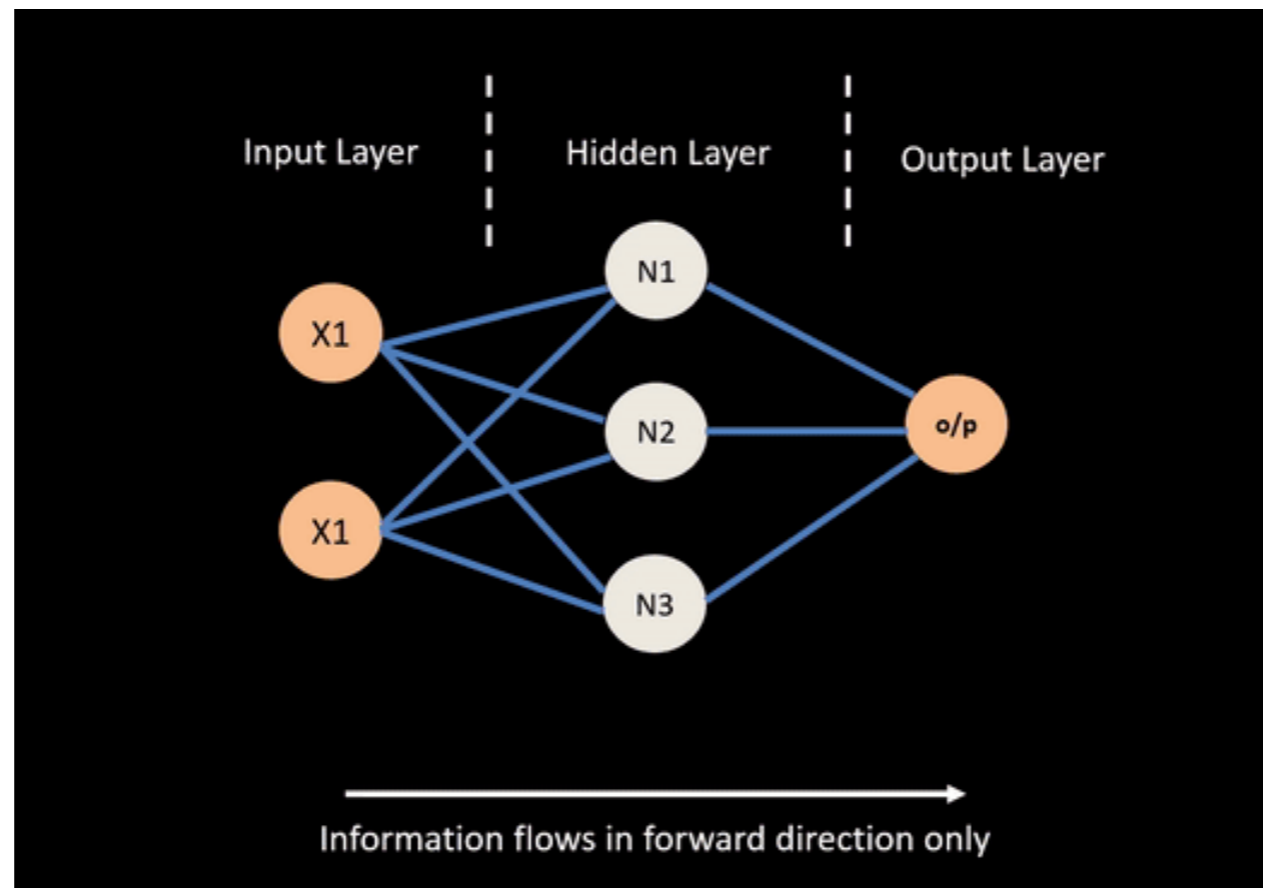


Deep Belief Network (DBN)



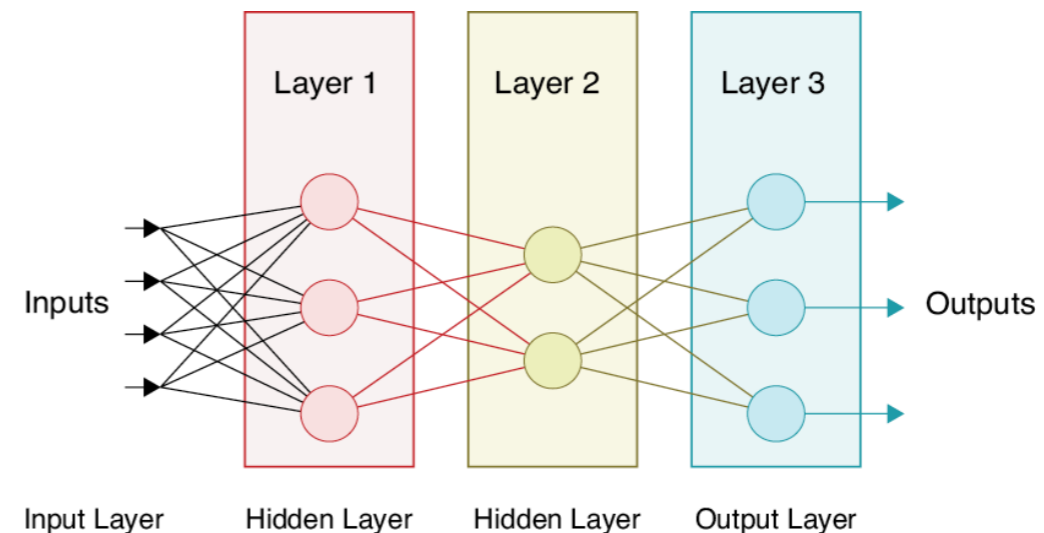
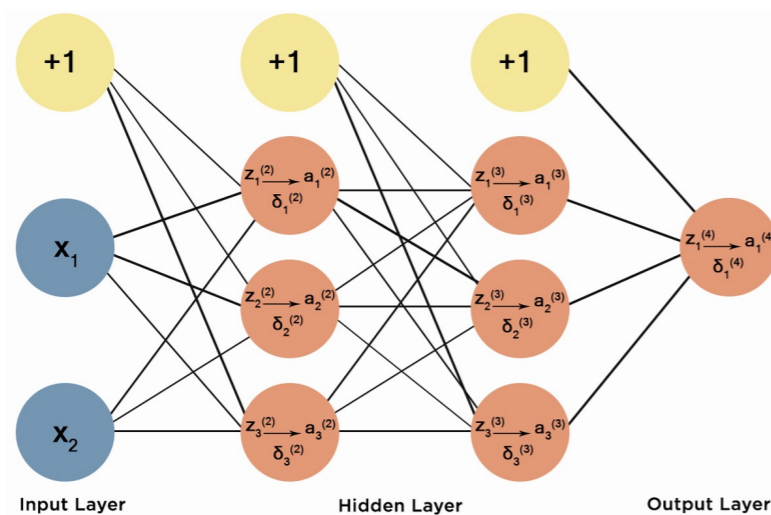
# Forward Propagation

- input data is passed forward through the network to generate an output/prediction
  - This sequence of operations is crucial for both training the network and making predictions/inference



# Tensor

- A tensor is a multidimensional array that represents a collection of numerical values
  - a block of numbers with a given number of dimensions and a size in each dimension
  - the fundamental data structure used to store and operate on data in various machine learning frameworks and libraries, such as TensorFlow, PyTorch, and NumPy.



1	2	3	4	5	6	7	8	9	10	11	12
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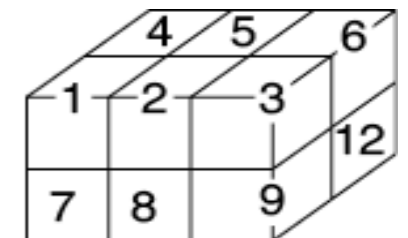
(a)

**Array/list/vector**

1	2	3	4	5	6
7	8	9	10	11	12

(b)

**Grid/Matrix**



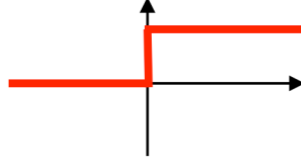
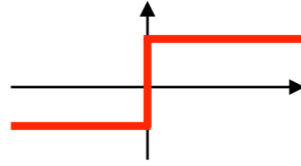
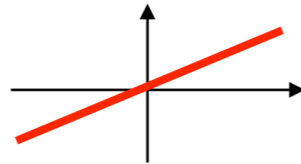
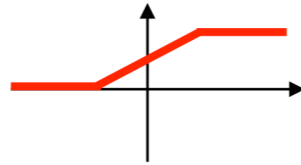
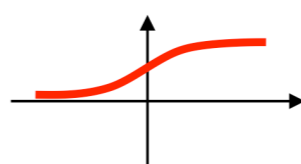
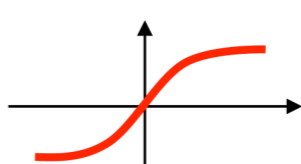
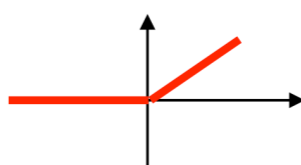
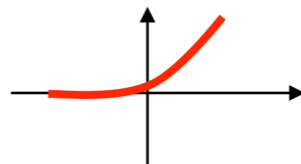
(c)

**Volume/Block**

**Tensors:**



# Activation Functions

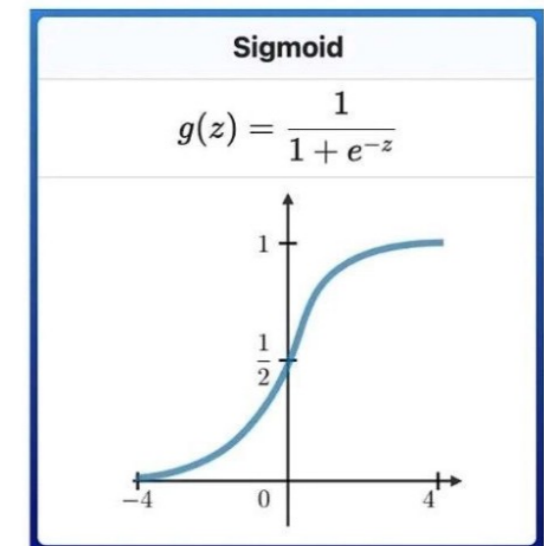
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = \max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^z)$	Multi-layer Neural Networks	

# Activation Functions

- **Sigmoid Function**

*AKA the Logistic function*, maps input values to the range  $(0, 1)$  using a smooth S-shaped curve, making it suitable for binary classification tasks

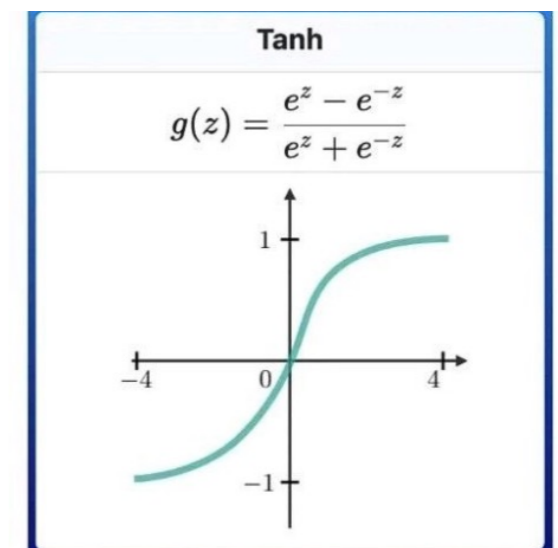
- output can be interpreted as a probability
- nonlinear activation function



- **Tanh (Hyperbolic Tangent) Function**

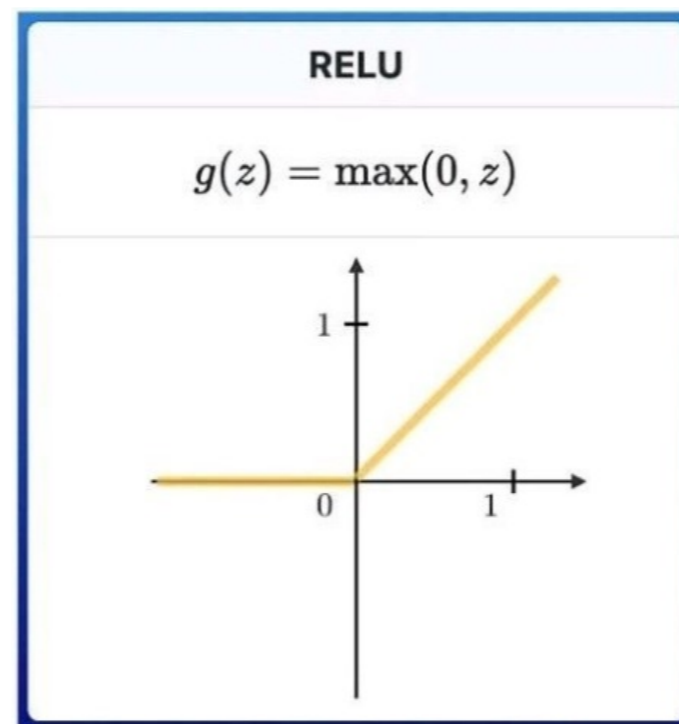
similar to the sigmoid but maps input values to  $(-1, 1)$

- providing a better symmetry around zero



# Activation Functions

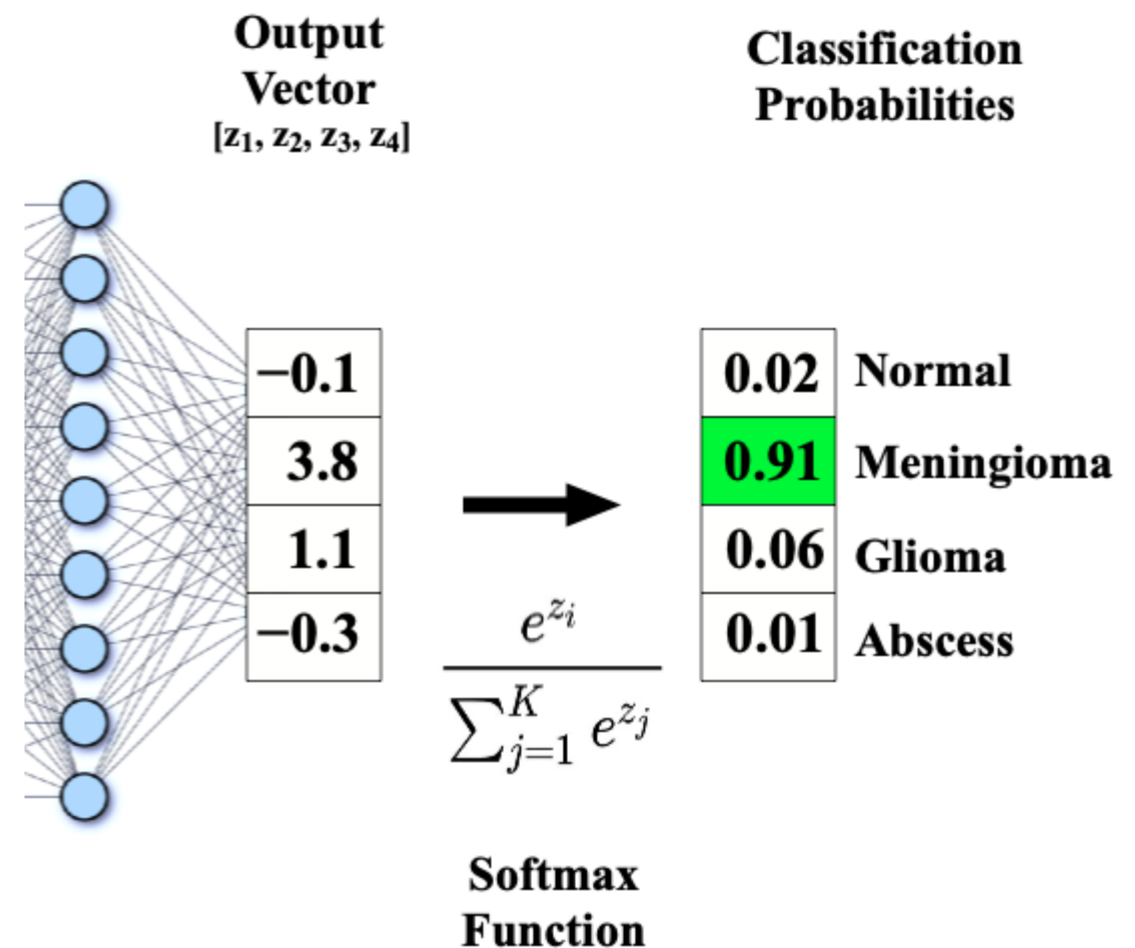
- **ReLU (Rectified Linear Unit) Function:** a nonlinear function that returns the input if it is positive, and zero otherwise,  $\max(0, z)$ 
  - one of the most widely used activation functions due to simplicity and effectiveness
  - encourages sparse representations by activating only a subset of neurons for any given input



# Activation Functions

- **Softmax Function:** maps the input to a probability distribution over a set of possible outcomes, using an exponential function
  - convert a vector of numbers into a new vector that reflects the probability distribution of the original vector's values
  - commonly used in the output layer of a neural network for multi-class classification tasks
  - computationally expensive

$$s(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}}$$

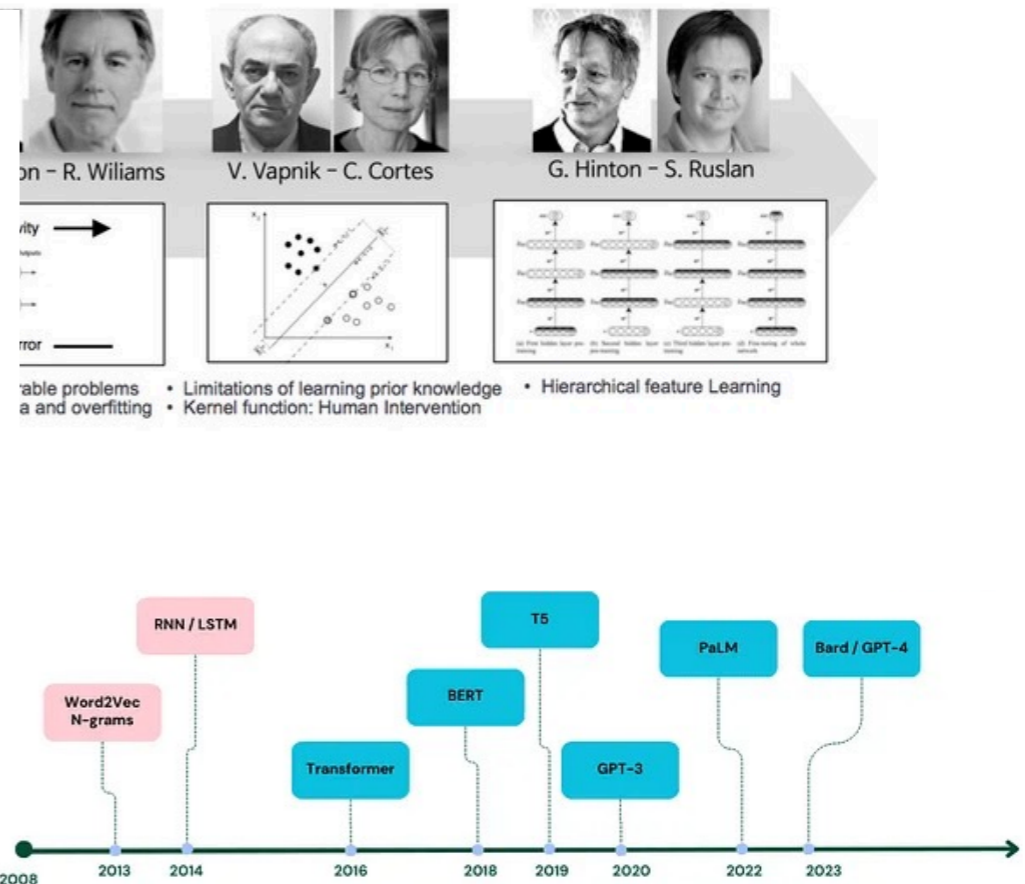
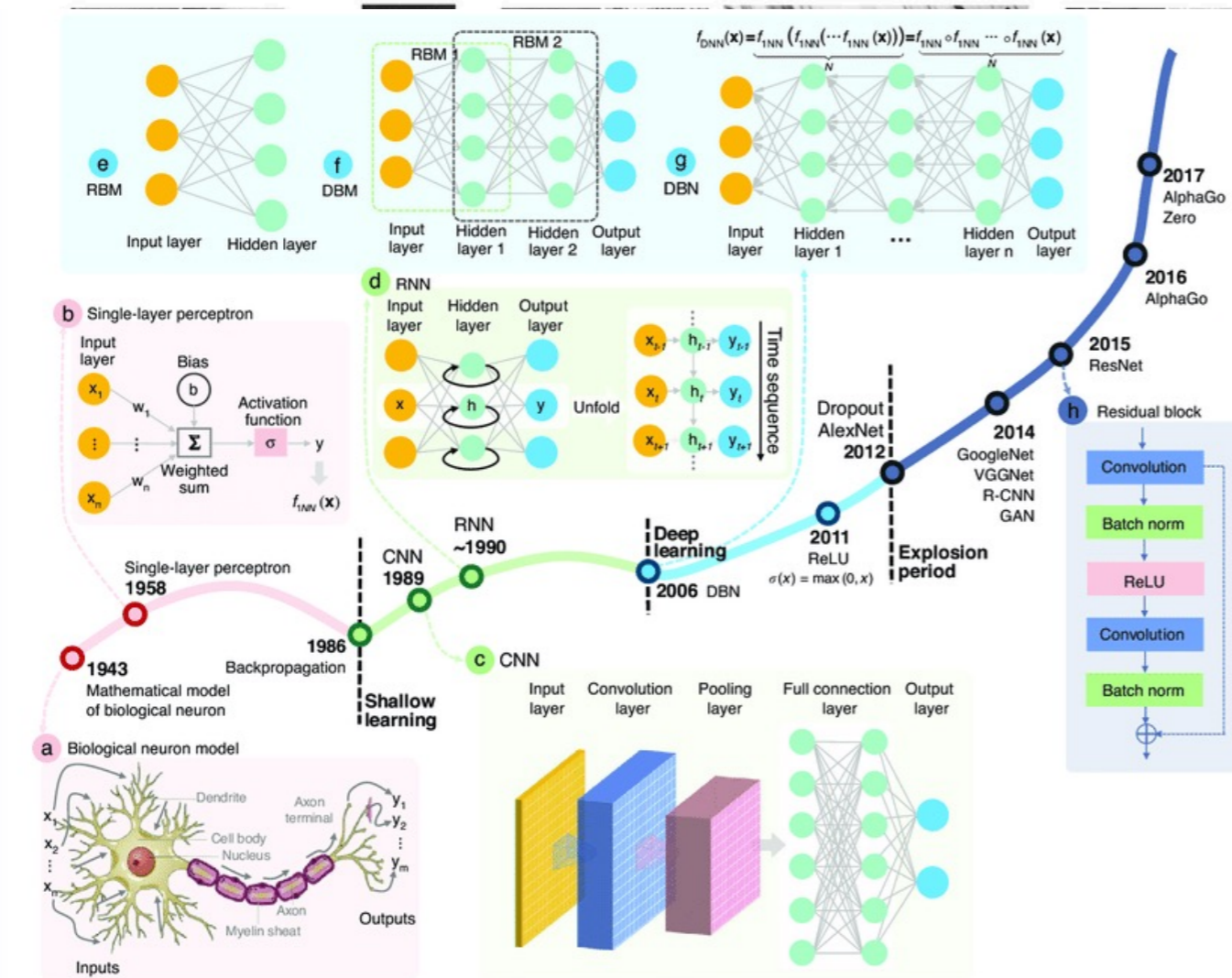
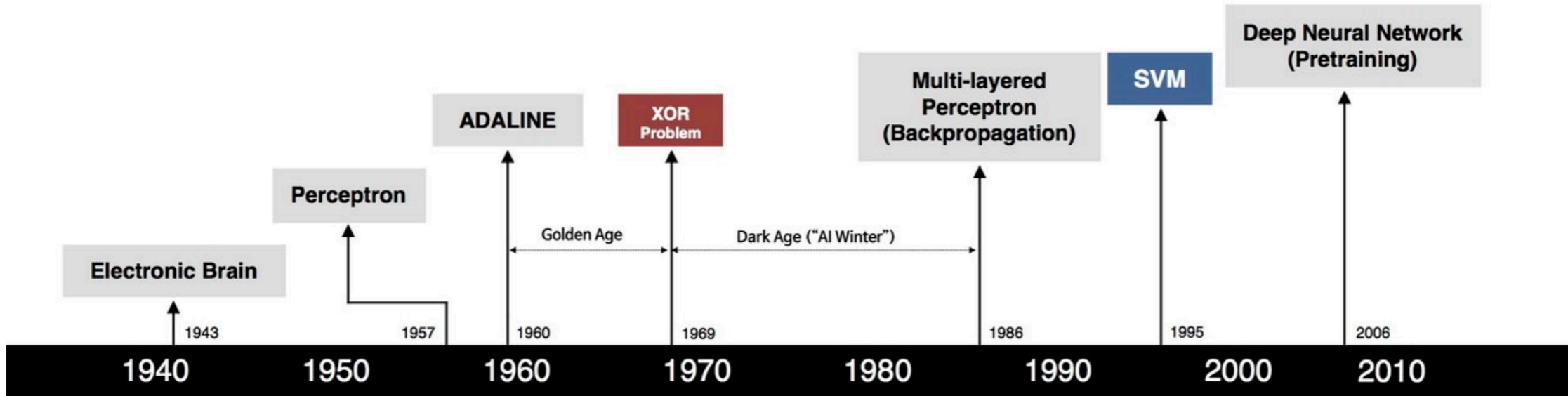


# Which Activation function to use

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- different activation functions may work better or worse for different problems, architectures, and datasets
- no definitive answer or rule for selecting an activation function
- **some general guidelines**
  - **type of problem:** binary classification uses a sigmoid activation function, multi-class classification softmax activation function
  - **architecture of the neural network:** may need a different activation function for the hidden layers of your neural network, deep neural network-> a ReLU activation function, while a recurrent neural network-> a tanh activation function
  - **properties of the activation function:** depending on the properties of the activation function, such as the range, the slope, the smoothness, the sparsity, etc.

# History of Neural Networks



# Summary

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- What is Neural Networks
- Why Neural Networks
- Neural network basic components
  - Neurons, Weights and bias, Activation Function
- Types of Neural Networks
- Neural Network Working Mechanisms
  - Various Activation functions
  - Forward Propagation