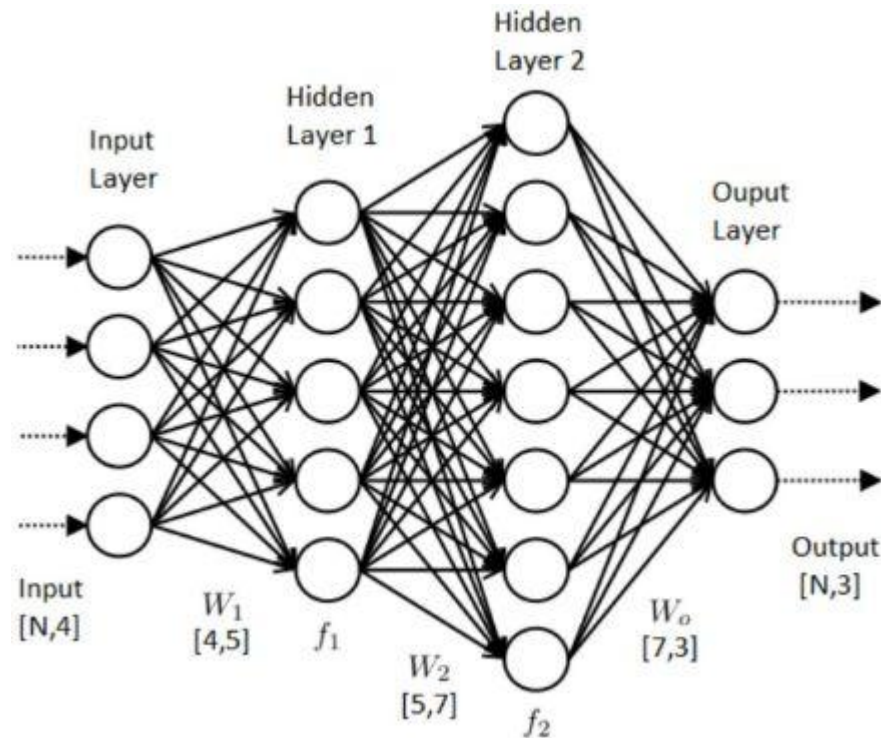


Neuron network

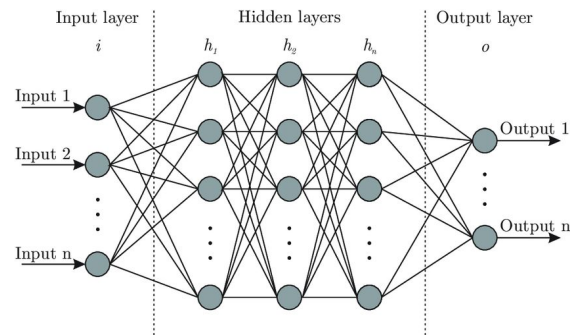
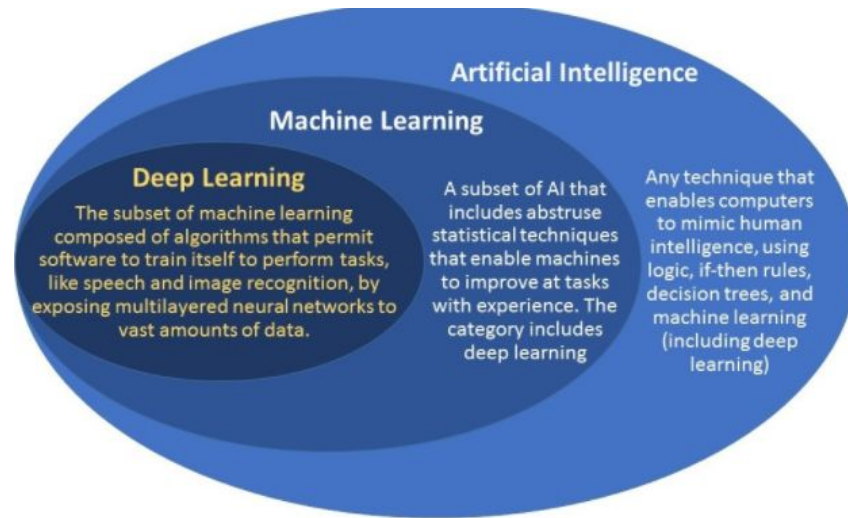
minhtt@vietinbank.vn



1. What is neuron network
2. Application
3. Why we need?
4. Structure
5. Algorithm
 - a. Gradient descent
 - b. Loss function
 - c. Activation function
 - d. Feed forward
 - e. Back propagation
6. Simple neuron network from scratch (lab exercise)
7. Reference

What is neuron network

- Subset of machine learning
- Are comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer



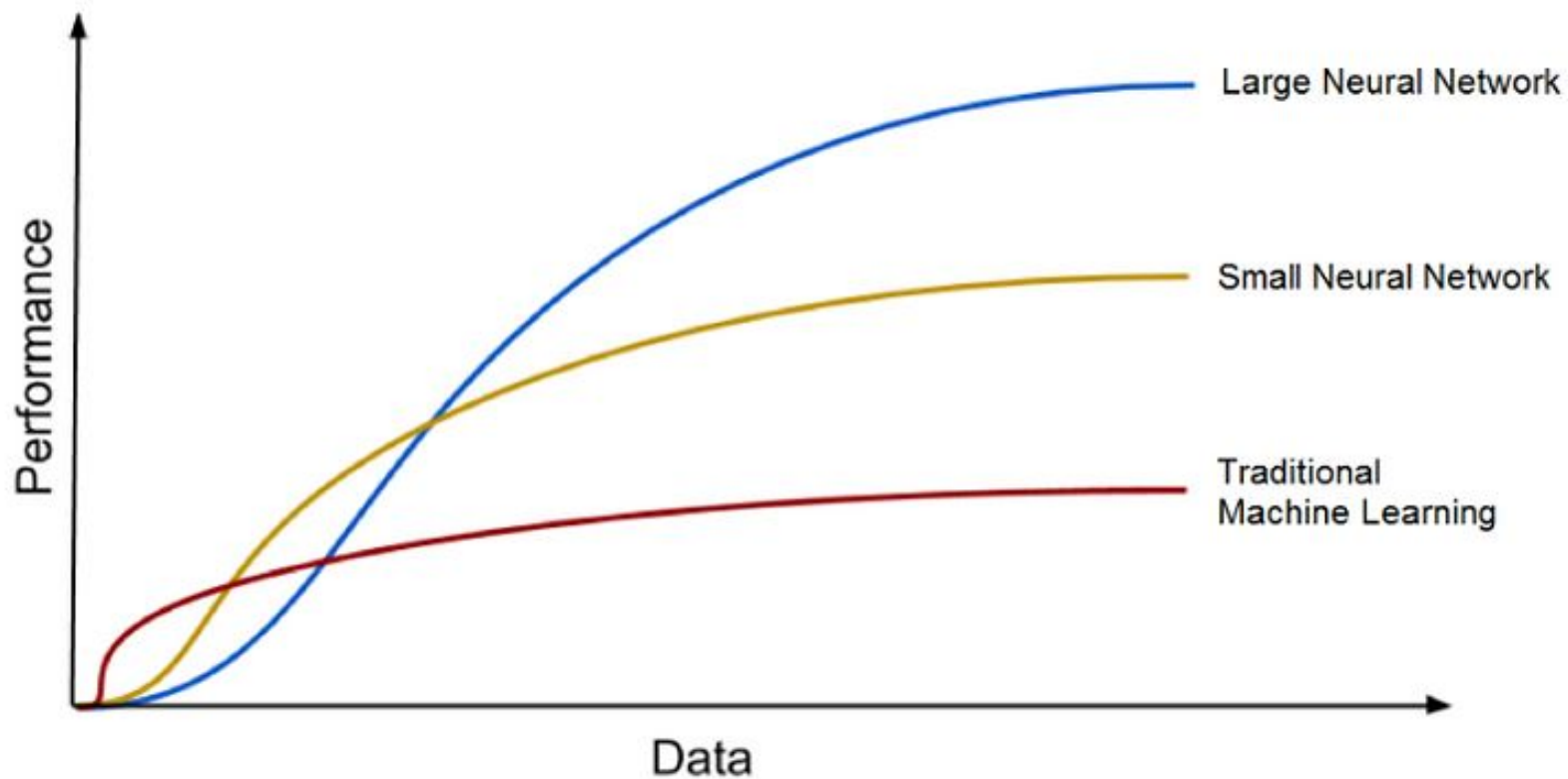
- Facial Recognition
- Stock market prediction
- Machine translation
- OCR
- Fraud detection
- ...

Playground:

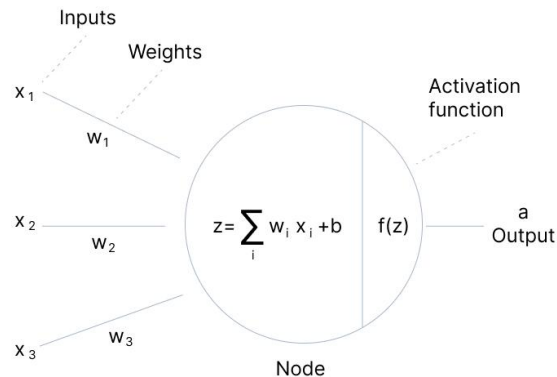
- <https://teachablemachine.withgoogle.com/>
- <https://playground.tensorflow.org/>



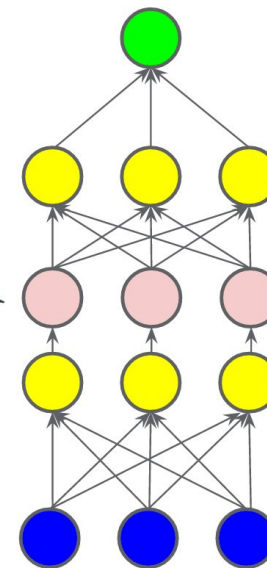
Why we need?



- Input
- Hidden layer
- Activation function
- Output



We Usually Don't Draw Non-Linear Transforms



Output

Hidden Layer 2

Non-Linear Transformation Layer
(a.k.a. Activation Function)

Hidden Layer 1

Input

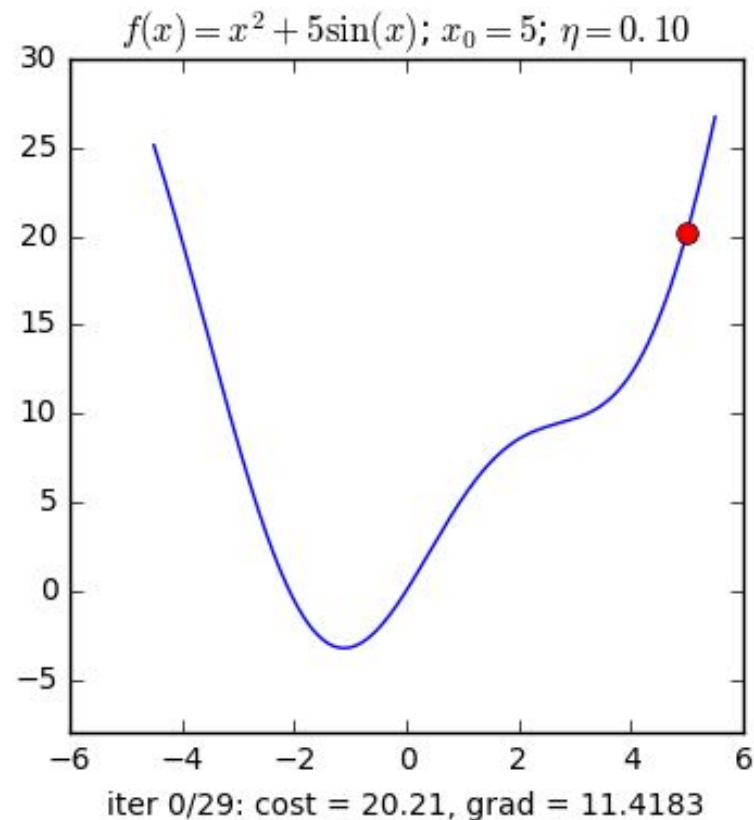
Algorithm

- Gradient descent

$$x_1 = x_0 - \alpha \nabla f(x_0)$$

More generally, we can write a formula for turning x_n into x_{n+1} :

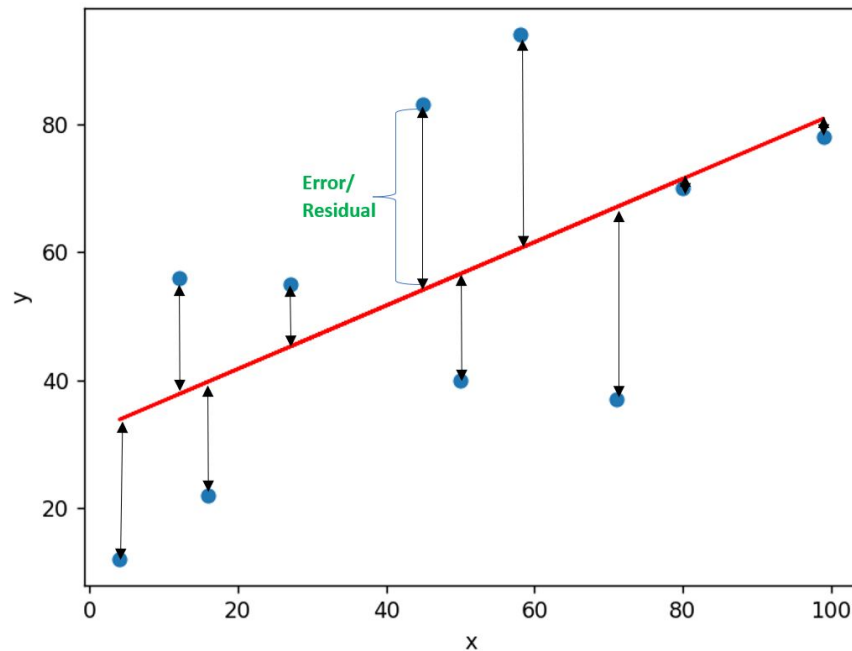
$$x_{n+1} = x_n - \alpha \nabla f(x_n)$$



Algorithm

- Loss function

The loss function is the function that determines how far the algorithm's current output is from what is desired. This is a technique for assessing how well our algorithm models the input. It can be divided into two categories. Both for regression and for classification



MAE (L1)

Mean Absolute Error, or L1 loss. Excellent overview below [6] and [10].

$$MAE = \frac{1}{m} \sum_{i=1}^m |h(x^{(i)}) - y^{(i)}|$$

MAE - mean absolute error

m - number of samples

$x^{(i)}$ - i-th sample from dataset

$h(x^{(i)})$ - prediction for i-th sample (thesis)

$y^{(i)}$ - ground truth label for i-th sample

- Loss function

MSE (L2)

Mean Squared Error, or L2 loss. Excellent overview below [6] and [10].

$$MSE = \frac{1}{m} \sum_{i=1}^m (y^{(i)} - \hat{y}^{(i)})^2$$

MSE - mean square error

m - number of samples

$y^{(i)}$ - ground truth label for i-th sample

$\hat{y}^{(i)}$ - predicted label for i-th sample

BINARY CROSS-ENTROPY LOSS / LOG LOSS

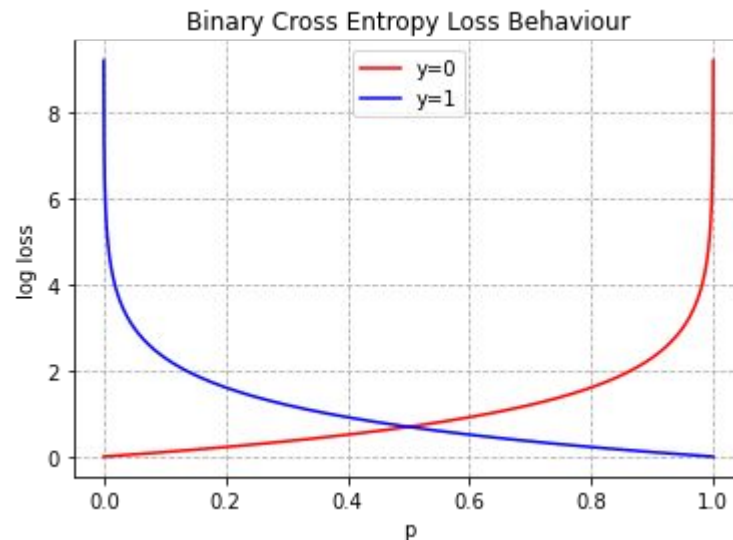
This is the most common loss function used in classification problems. The cross-entropy loss decreases as the predicted probability converges to the actual label. It measures the performance of a classification model whose predicted output is a probability value between 0 and 1.

When the number of classes is 2, it's *binary classification*.

$$L = -\frac{1}{m} \sum_{i=1}^m (y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i))$$

When the number of classes is more than 2, it's *multi-class classification*.

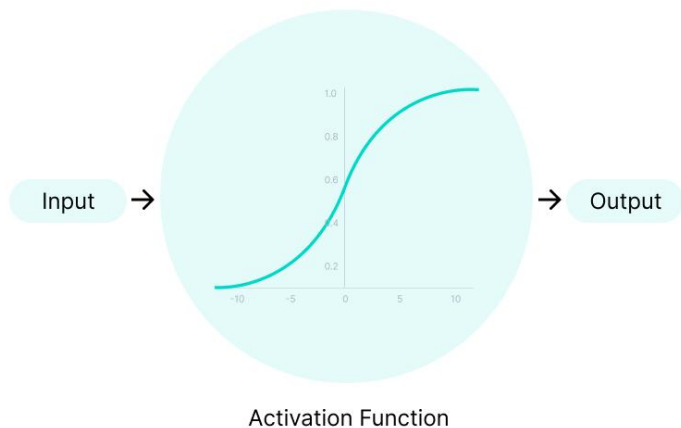
$$L = -\frac{1}{m} \sum_{i=1}^m y_i \cdot \log(\hat{y}_i)$$



Algorithm

- Activation function

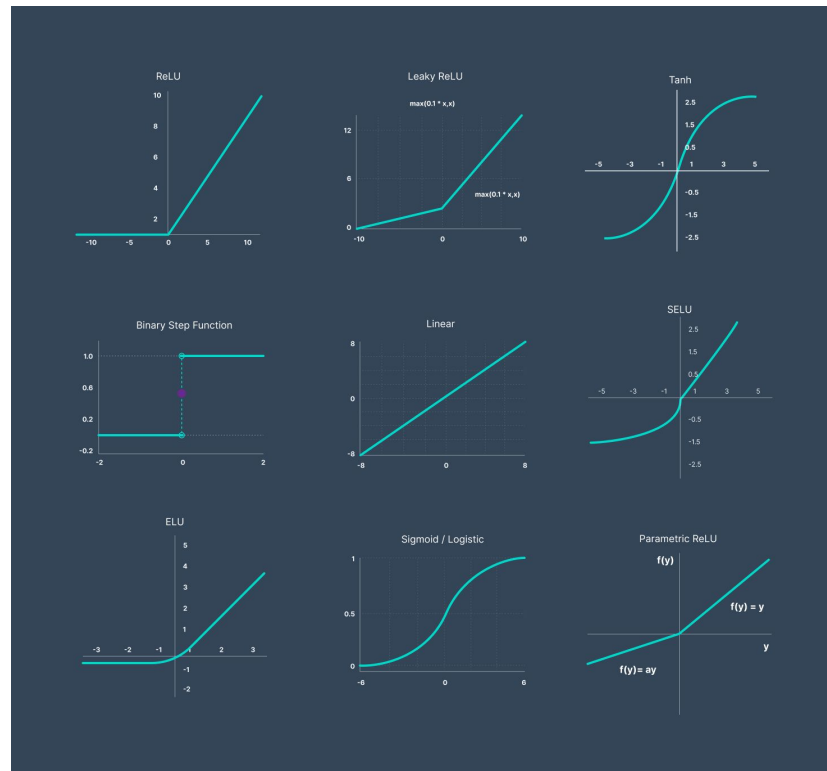
Why do Neural Networks Need an Activation Function



V7 Labs



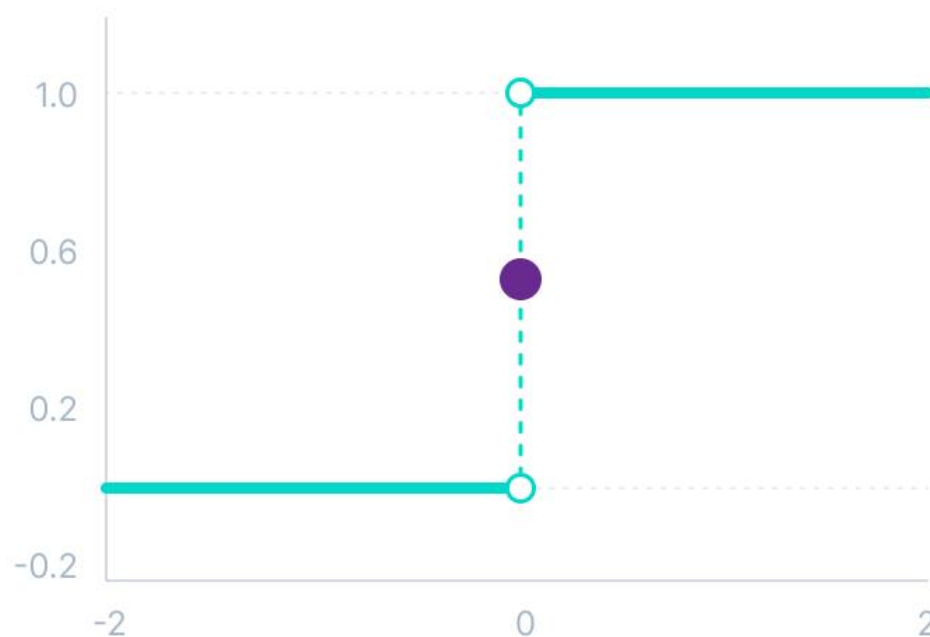
The purpose of an activation function is to add non-linearity to the neural network



Binary step

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$$

Binary Step Function

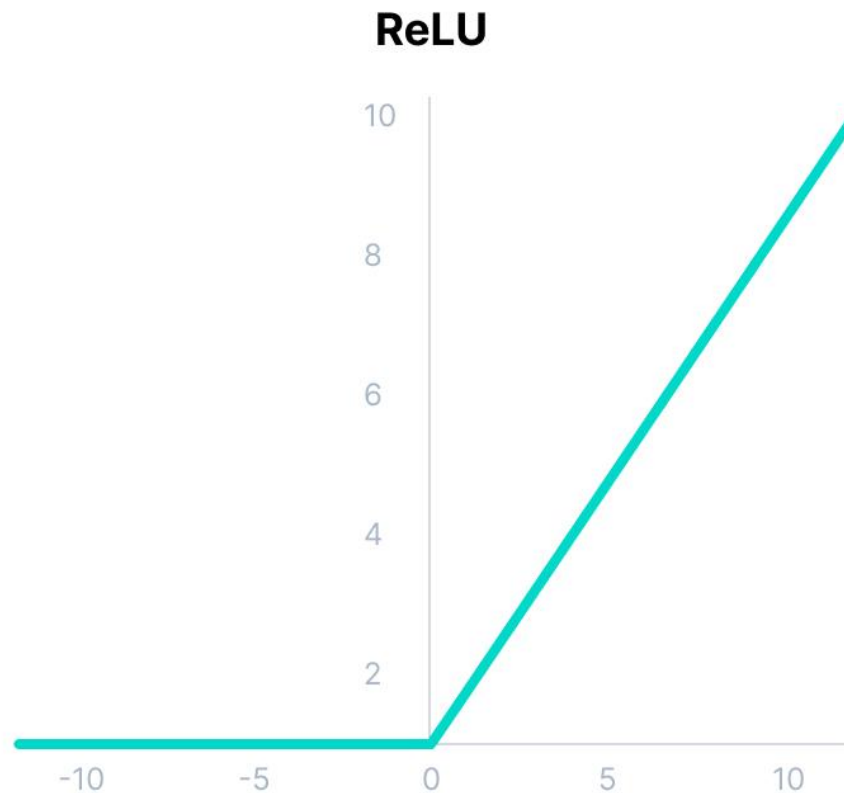


Algorithm

- Activation function

ReLU

$$f(x) = \max(0, x)$$

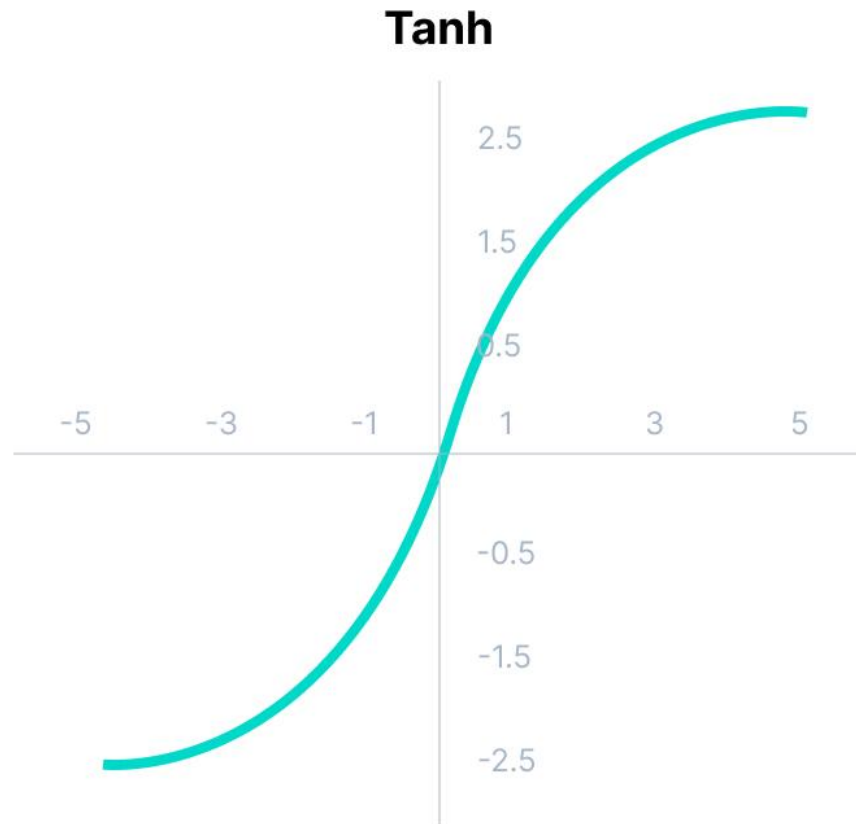


Algorithm

- Activation function

Tanh

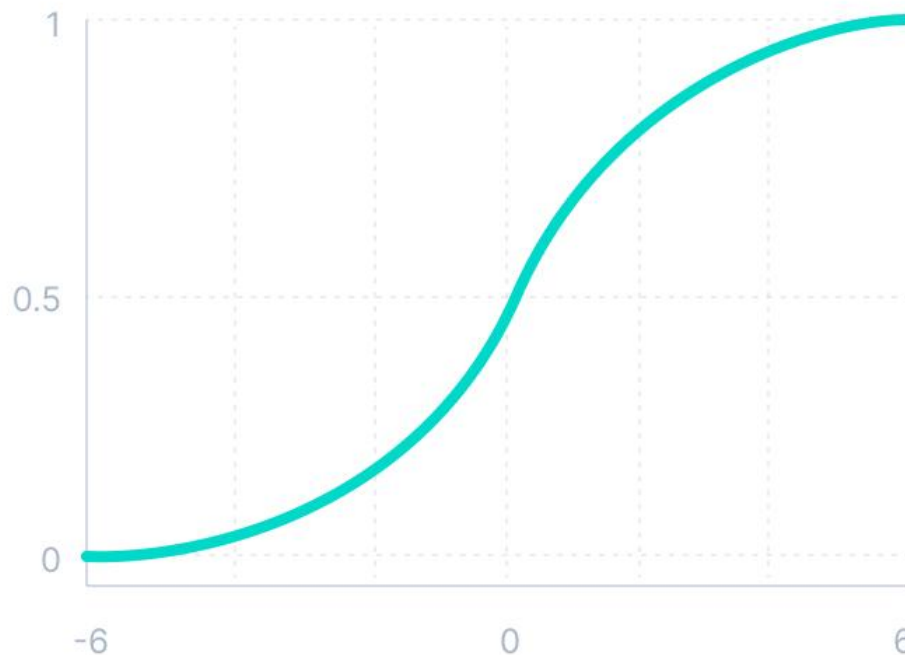
$$f(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$$



Sigmoid / Logistic

$$f(x) = \frac{1}{1 + e^{-x}}$$

Sigmoid / Logistic



Algorithm

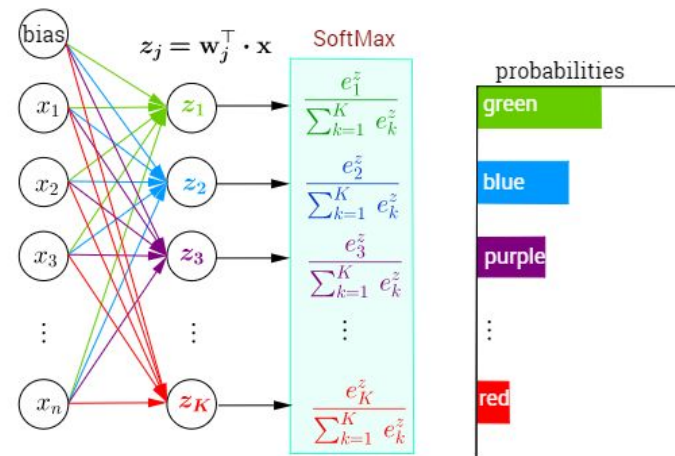
- Activation function

Softmax

$$\text{softmax}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

$$\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ \vdots \\ z_K \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1^\top \\ \mathbf{w}_2^\top \\ \mathbf{w}_3^\top \\ \vdots \\ \mathbf{w}_K^\top \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$

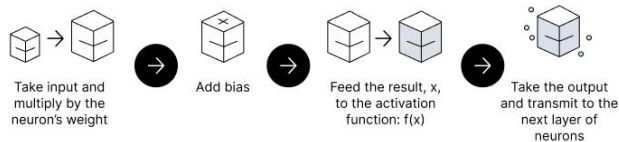
Multi-Class Classification with NN and SoftMax Function



Algorithm

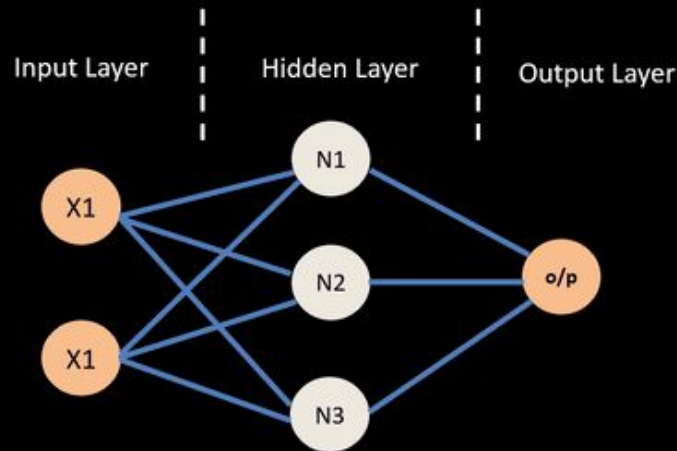
- Feed forward

The flow of information occurs in the forward direction. The input is used to calculate some intermediate function in the hidden layer, which is then used to calculate an output.



V7 Labs

Feed Forward Neural Network

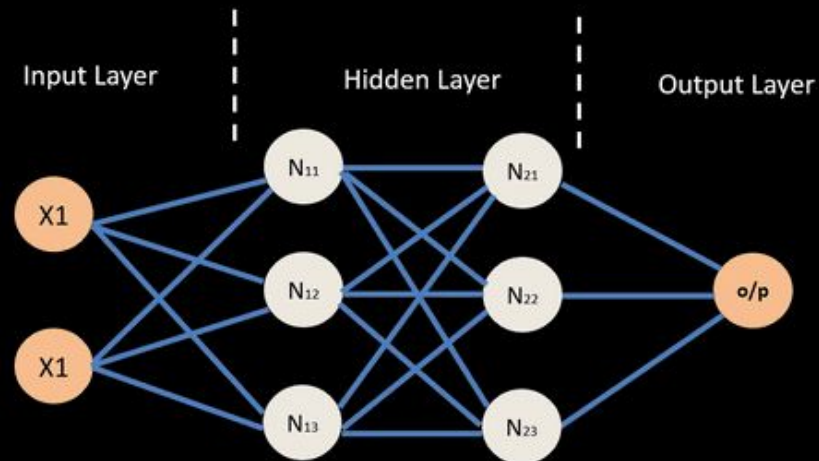


Information flows in forward direction only

Algorithm

- Back propagation

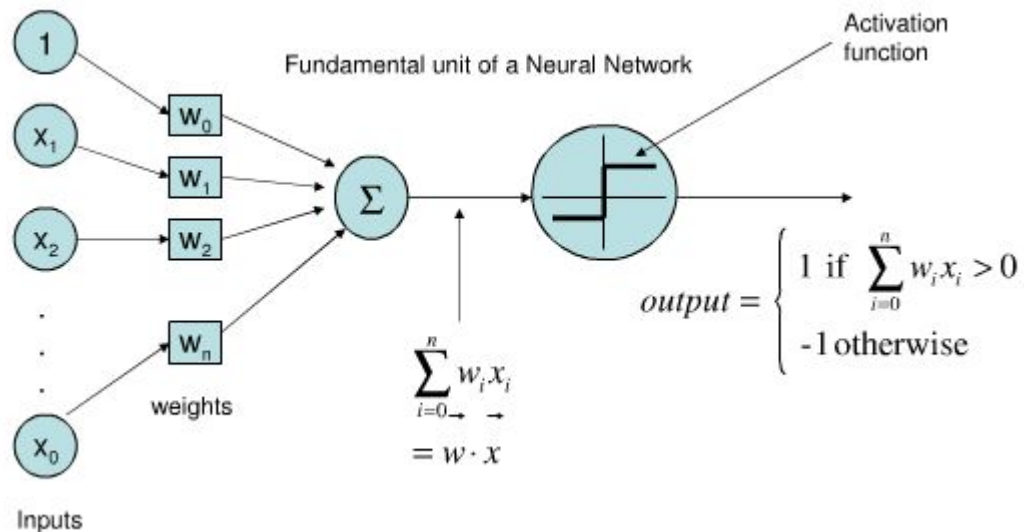
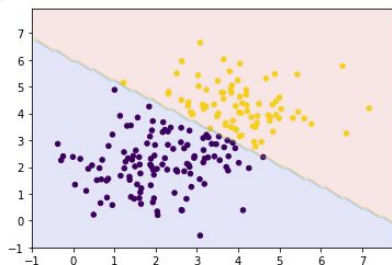
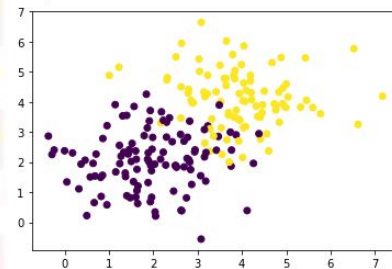
Neural Network – Backpropagation



Simple neuron network from scratch

	x1	x2	y
0	0.575939	1.506680	-1
1	4.687881	4.049857	1
2	3.817095	4.896248	1
3	4.239867	4.158959	1
4	1.352819	2.472247	-1
...
995	3.230291	3.202380	-1
996	0.981958	1.922145	-1
997	4.844996	3.324406	1
998	3.831786	4.377910	1
999	4.623454	4.890672	1

1000 rows × 3 columns



- Predict: $\hat{y}_i = \text{sign}(\dot{\mathbf{w}}^\top \dot{\mathbf{x}}_i)$
- Update rule: $\dot{\mathbf{w}} = \dot{\mathbf{w}} - \eta \dot{\mathbf{x}}_i y_i$ for all missclassified $\dot{\mathbf{x}}_i$

- <https://playground.tensorflow.org>
- <https://teachablemachine.withgoogle.com>
- <https://www.v7labs.com/blog/neural-networks-activation-functions>
- <https://builtin.com/machine-learning/common-loss-functions>
- https://rpubs.com/harshaash/ANN_1
- https://ml-cheatsheet.readthedocs.io/en/latest/loss_functions.html
- <https://machinelearningknowledge.ai/animated-explanation-of-feed-forward-neural-network-architecture/>

The image features a teal background with a bokeh effect of colorful confetti in shades of pink, orange, yellow, and blue. The text "Thank You!" is written in a dark blue, elegant script font, centered horizontally and slightly tilted upwards to the right.

Thank You!