



Core Workshop 8: Artificial Neural Network

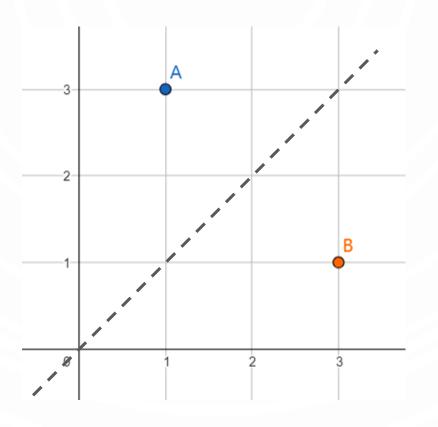
OVERVIEW

- A Simple Linear Classifier
 - One Classifier Is Not Enough
 - Neuron & Activation Function
- Feedforward Signal & Matrix Multiplication
- Backpropagation of Loss
 - Matrix Multiplication Again
 - Update Weights by Gradient Descent
- Input / Output & Initial Weights
- NumPy Code Example on MNIST

A SIMPLE LINEAR CLASSIFIER

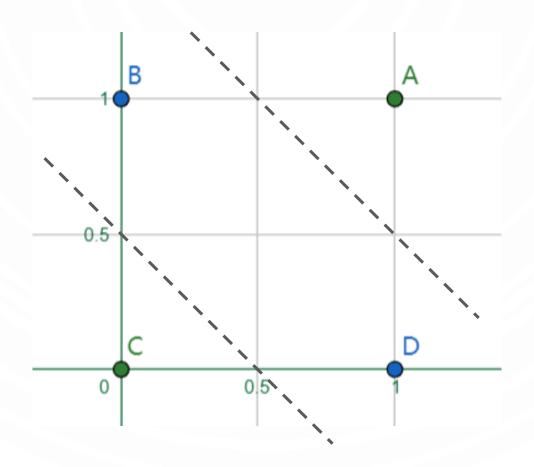
A SIMPLE LINEAR CLASSIFIER

A SIMPLE LINEAR CLASSIFIER

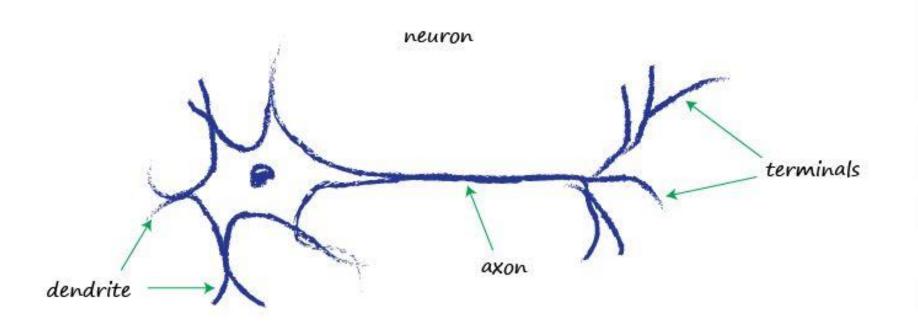


Linear Perceptron

ONE CLASSIFIER IS NOT ENOUGH



NEURONS, NATURAL COMPUTING MACHINE



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Human Brain

100 billion

dendrite terminals

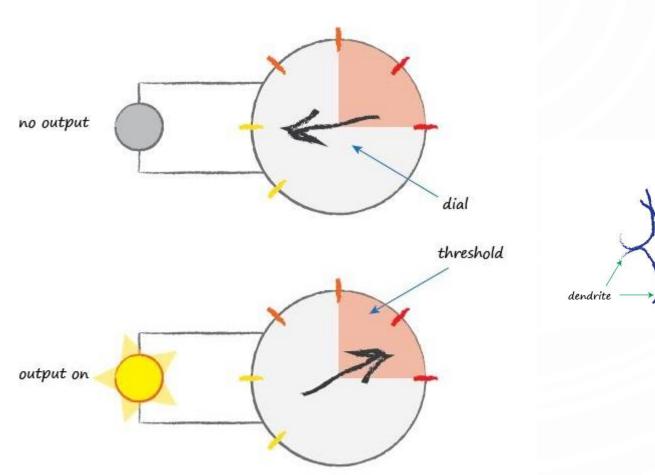
Fruit Fly

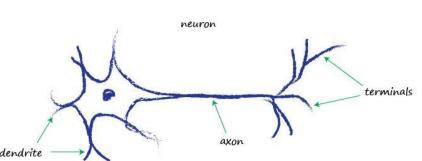
100,000

Nematode Worm

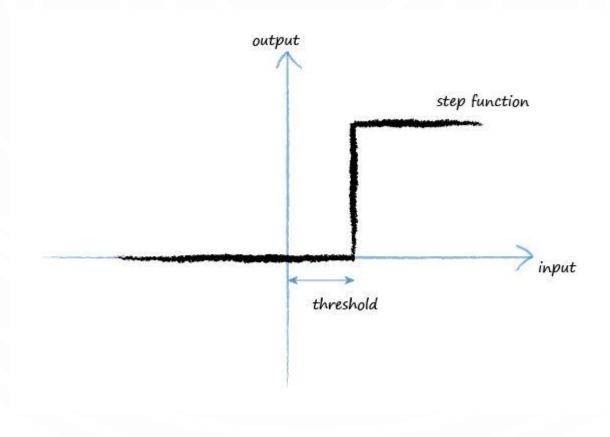
302

NEURONS, NATURAL COMPUTING MACHINE

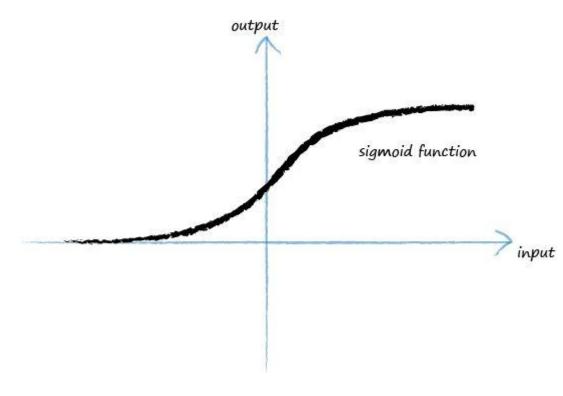




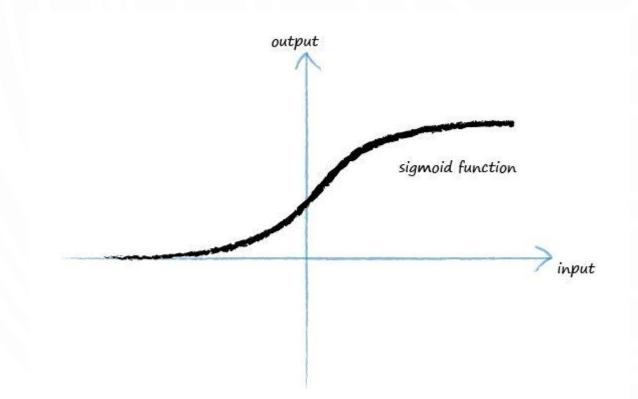
ACTIVATION FUNCTION



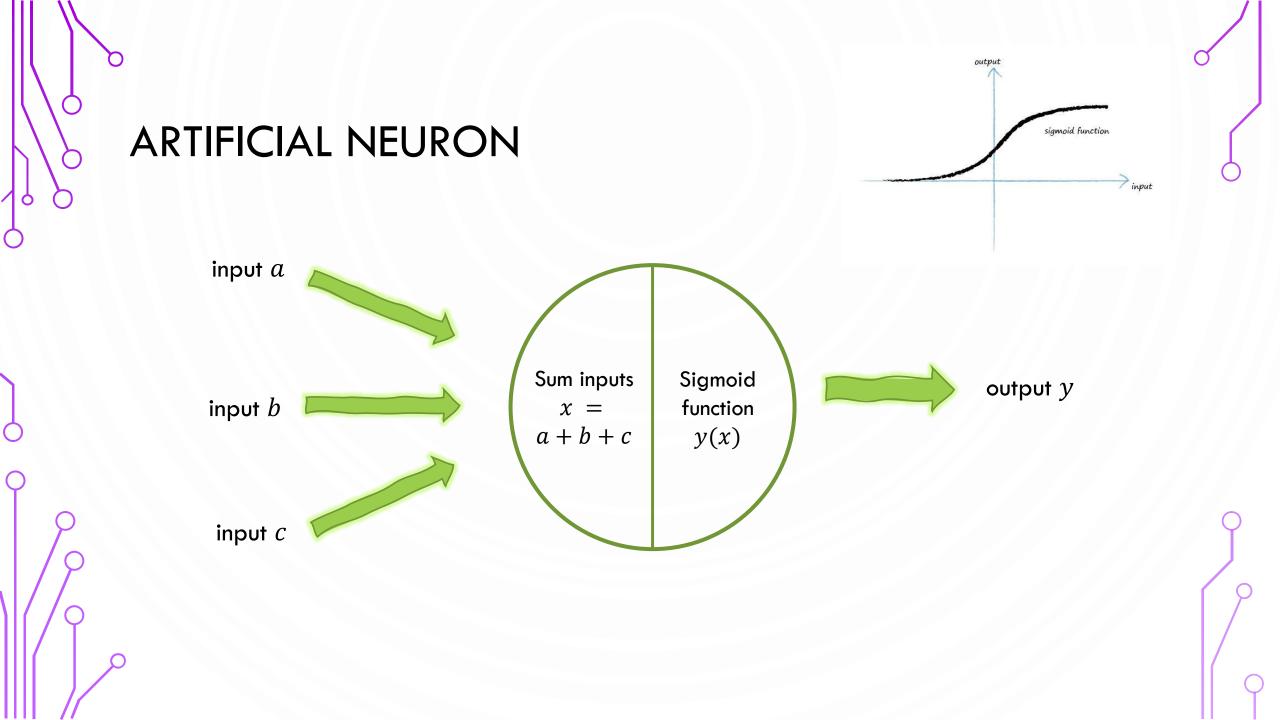
ACTIVATION FUNCTION



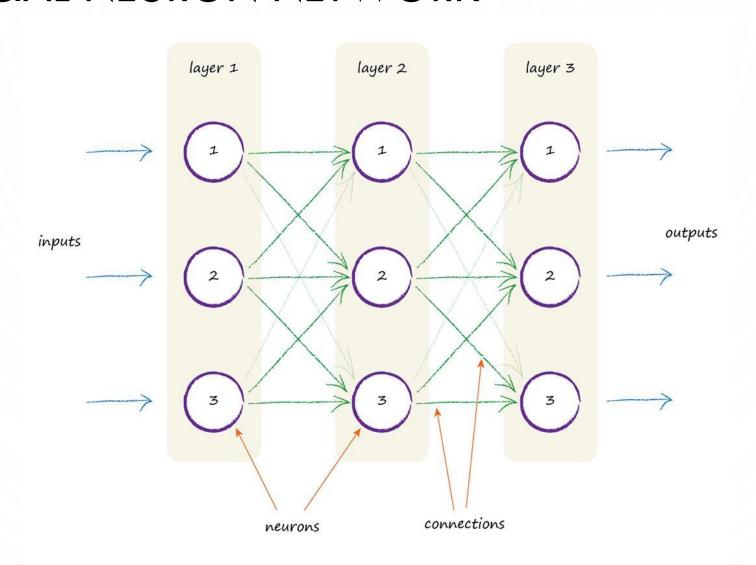
ACTIVATION FUNCTION



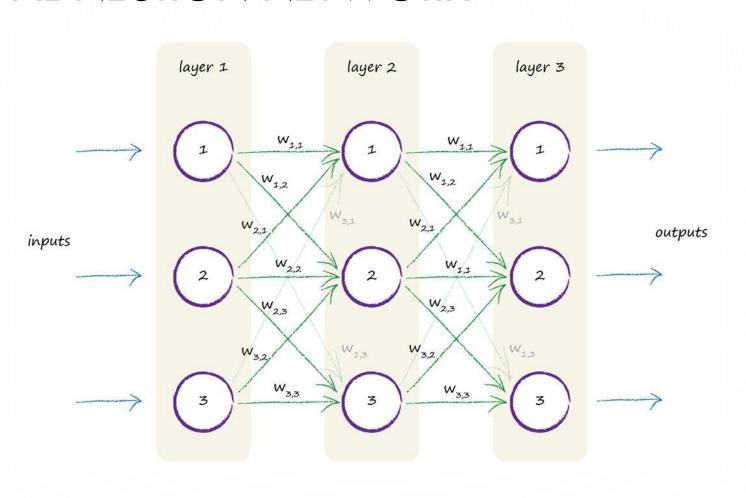
$$y = \frac{1}{1 + e^{-x}}$$



ARTIFICIAL NEURON NETWORK



ARTIFICIAL NEURON NETWORK

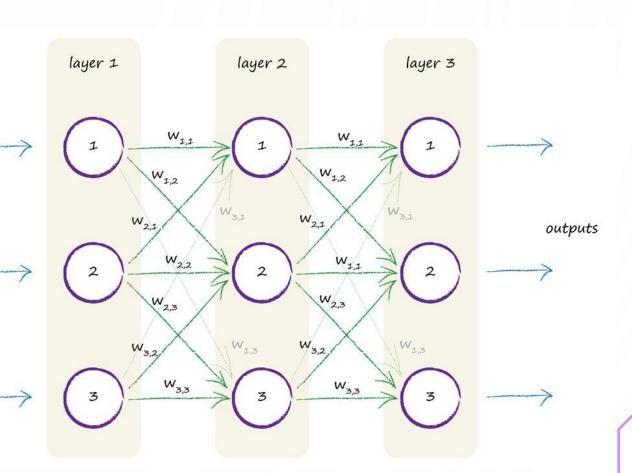


UNIVERSAL APPROXIMATION THEOREM

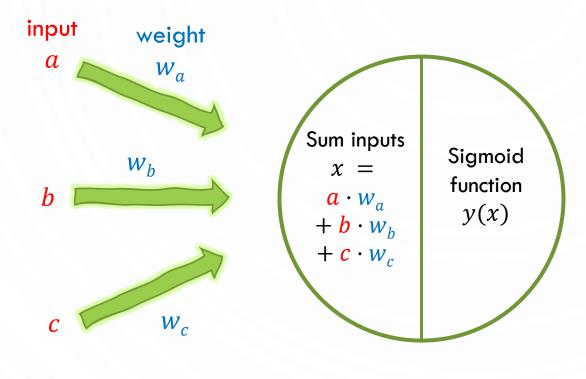
inputs

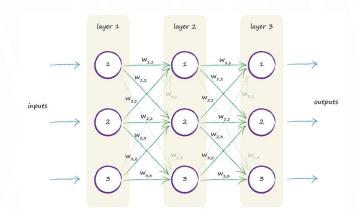
Neural networks can represent a wide variety of interesting functions when given appropriate weights.

It is capable of approximating any continuous functions between two Euclidean spaces, as long as having enough depths and nodes.



ARTIFICIAL NEURON



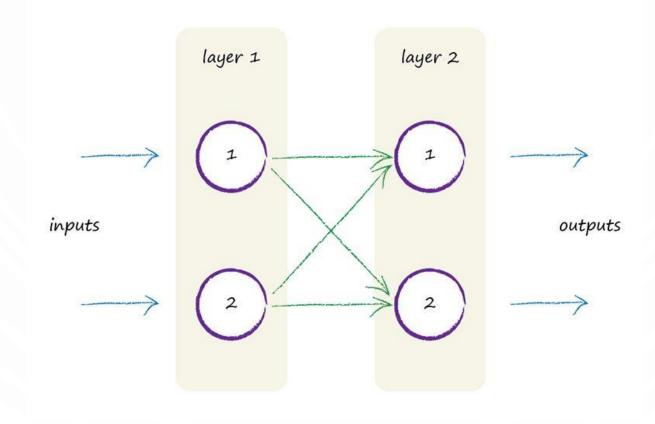




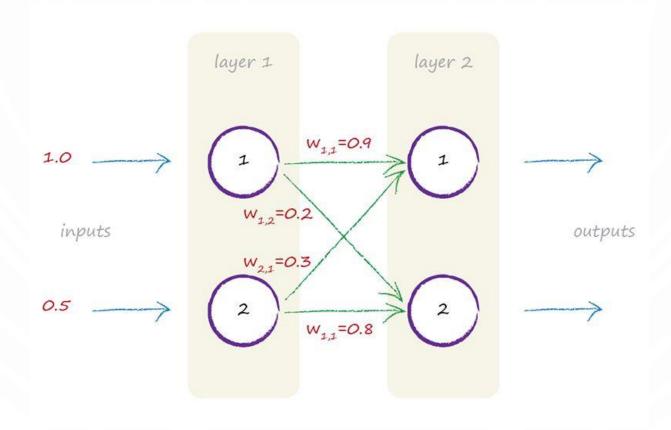
$$y = sigmoid(a \cdot w_a + b \cdot w_b + c \cdot w_c)$$

$$sigmoid = \frac{1}{1 + e^{-x}}$$

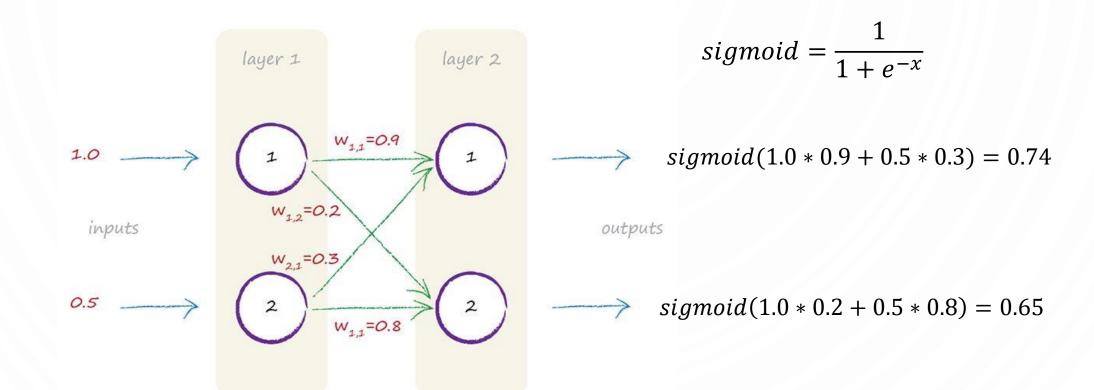
EXAMPLE - FEEDFORWARD SIGNAL



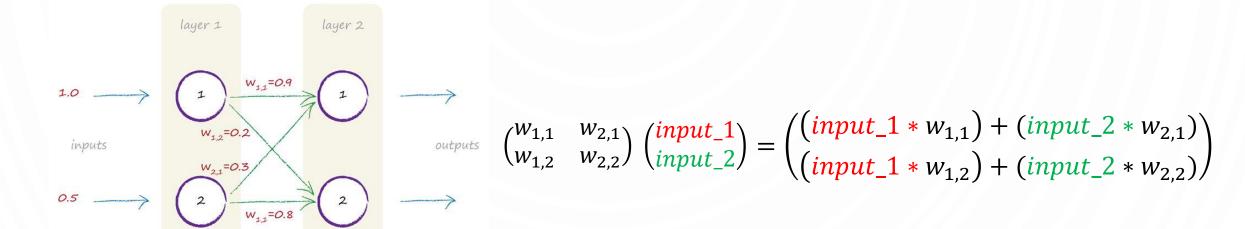
EXAMPLE - FEEDFORWARD SIGNAL



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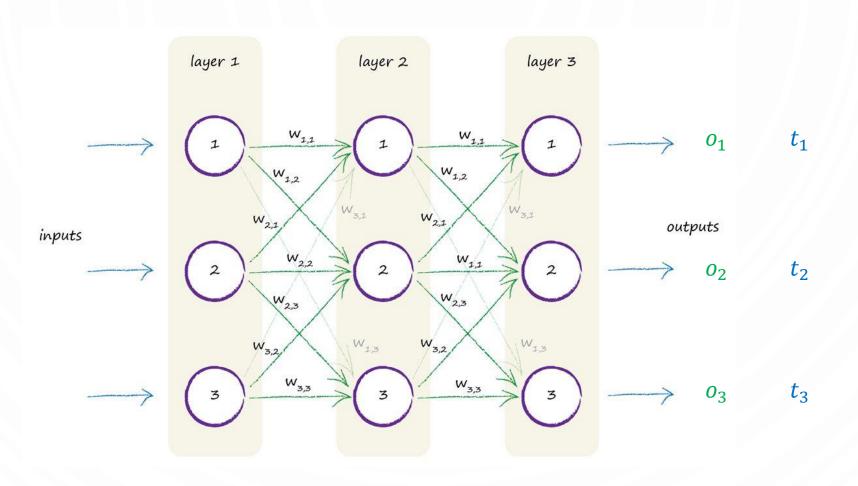
USING MATRIX MULTIPLICATION



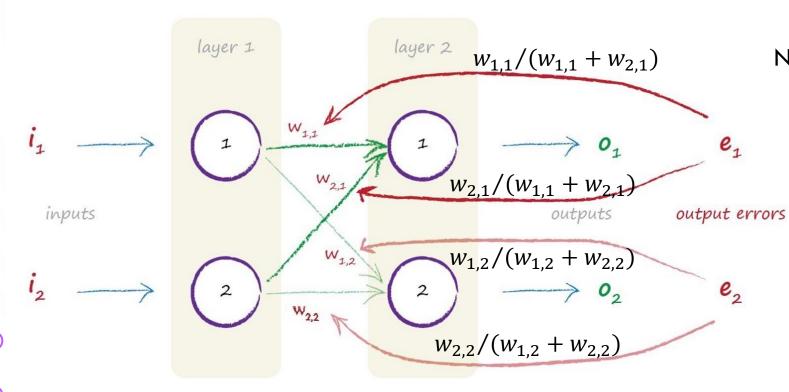
$$X = W \cdot I$$
$$O = sigmoid(X)$$

$o_{k} = \frac{1}{1 - \sum_{j=1}^{3} (w_{j,k} \cdot \frac{1}{1 + e^{-\sum_{i=1}^{3} (w_{i,j} \cdot x_{i})}})}$

BACKPROPAGATION OF LOSS



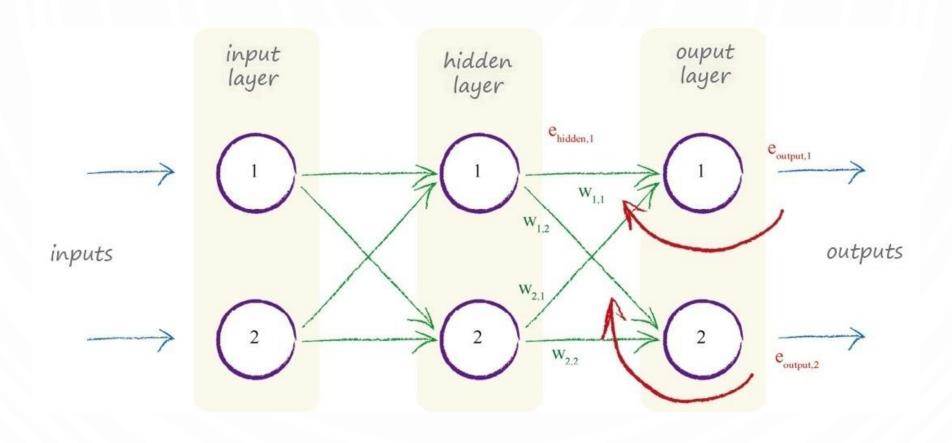
BACKPROPAGATION OF LOSS



Node Loss = (actual - real)²
$$e_{2,k} = (t_k - o_k)^2$$

$$e_{1,1} = e_{2,1} * \frac{w_{1,1}}{w_{1,1} + w_{2,1}} + e_{2,2} * \frac{w_{1,2}}{w_{1,2}}$$

BACKPROPAGATION OF LOSS

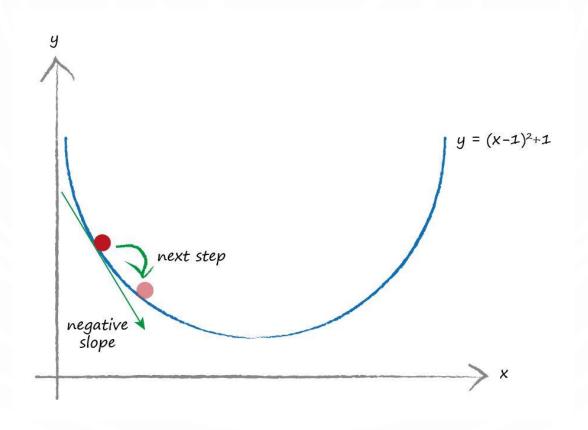


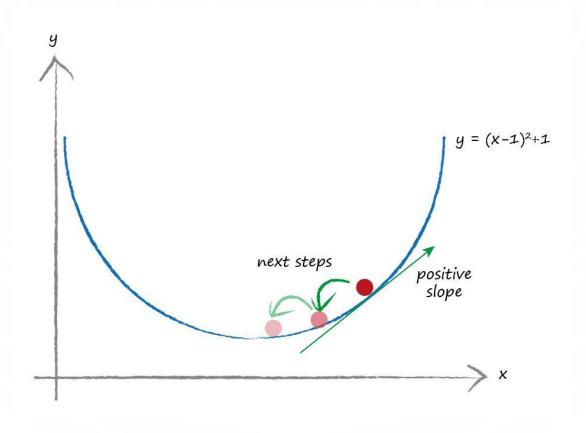
MATRIX MULTIPLICATION AGAIN

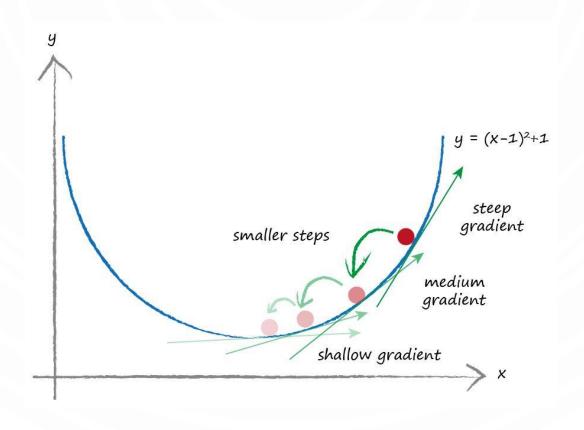
$$e_h = \begin{pmatrix} \frac{w_{1,1}}{w_{1,1} + w_{2,1}} & \frac{w_{1,2}}{w_{1,2} + w_{2,2}} \\ \frac{w_{2,1}}{w_{1,1} + w_{2,1}} & \frac{w_{2,2}}{w_{1,2} + w_{2,2}} \end{pmatrix} \cdot \begin{pmatrix} e_{o,1} \\ e_{o,2} \end{pmatrix}$$



$$e_h = \begin{pmatrix} w_{1,1} & w_{1,2} \\ w_{2,1} & w_{2,2} \end{pmatrix} \cdot \begin{pmatrix} e_{o,1} \\ e_{o,2} \end{pmatrix} = w^T \cdot e_o$$







$$\begin{split} &\frac{\partial E}{\partial w_{j,k}} = \frac{\partial (t_k - o_k)^2}{\partial w_{j,k}} = \frac{\partial (t_k - o_k)^2}{\partial o_k} \cdot \frac{\partial o_k}{\partial w_{j,k}} = -2(t_k - o_k) \cdot \frac{\partial o_k}{\partial w_{j,k}} \\ &= -2(t_k - o_k) \cdot \frac{\partial sigmoid(\sum_j w_{j,k} \cdot o_j)}{\partial w_{j,k}} \\ &= -2(t_k - o_k) \cdot sigmoid(\sum_j w_{j,k} \cdot o_j) \left(1 - sigmoid(\sum_j w_{j,k} \cdot o_j)\right) \cdot \frac{\partial (\sum_j w_{j,k} \cdot o_j)}{\partial w_{j,k}} \\ &= -2(t_k - o_k) \cdot sigmoid(\sum_j w_{j,k} \cdot o_j) \left(1 - sigmoid(\sum_j w_{j,k} \cdot o_j)\right) \cdot o_j \end{split}$$

$$\Delta w_{j,k} = -\alpha \cdot \frac{\partial E}{\partial w_{j,k}} = -\alpha \cdot (-E_k \cdot o_k (1 - o_k) \cdot o_j^T)$$

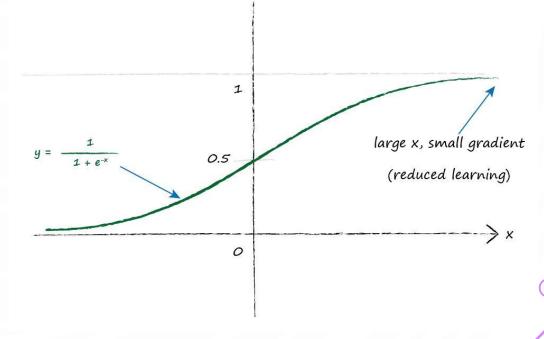
INPUT / OUTPUT & INITIAL WEIGHTS

$$-2(t_k - o_k) \cdot sigmoid(\sum_j w_{j,k} \cdot o_j) (1 - sigmoid(\sum_j w_{j,k} \cdot o_j)) \cdot o_j$$

Input/Output 0.01~0.99

Initial Weights $\frac{-1}{\sqrt{n}} \sim \frac{1}{\sqrt{n}}$

n = number of nodes in target layer



* Break Symmetry: never set initial weights to the same constant value, especially no zero.

CODE EXAMPLE - NUMPY





THANK YOU!

References:

Rashid, Tariq. *Make your own neural network*. CreateSpace Independent Publishing Platform, 2016.