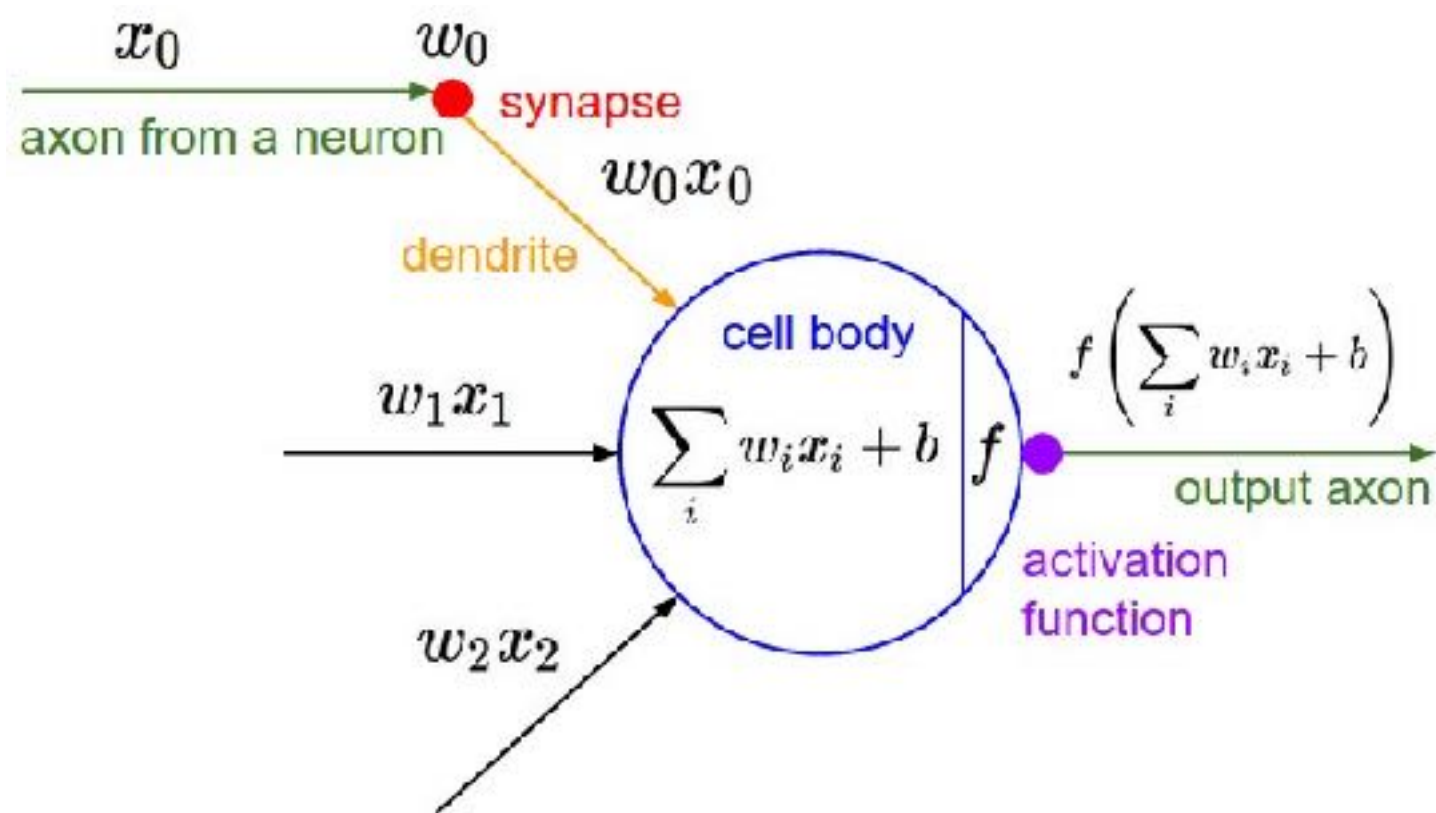
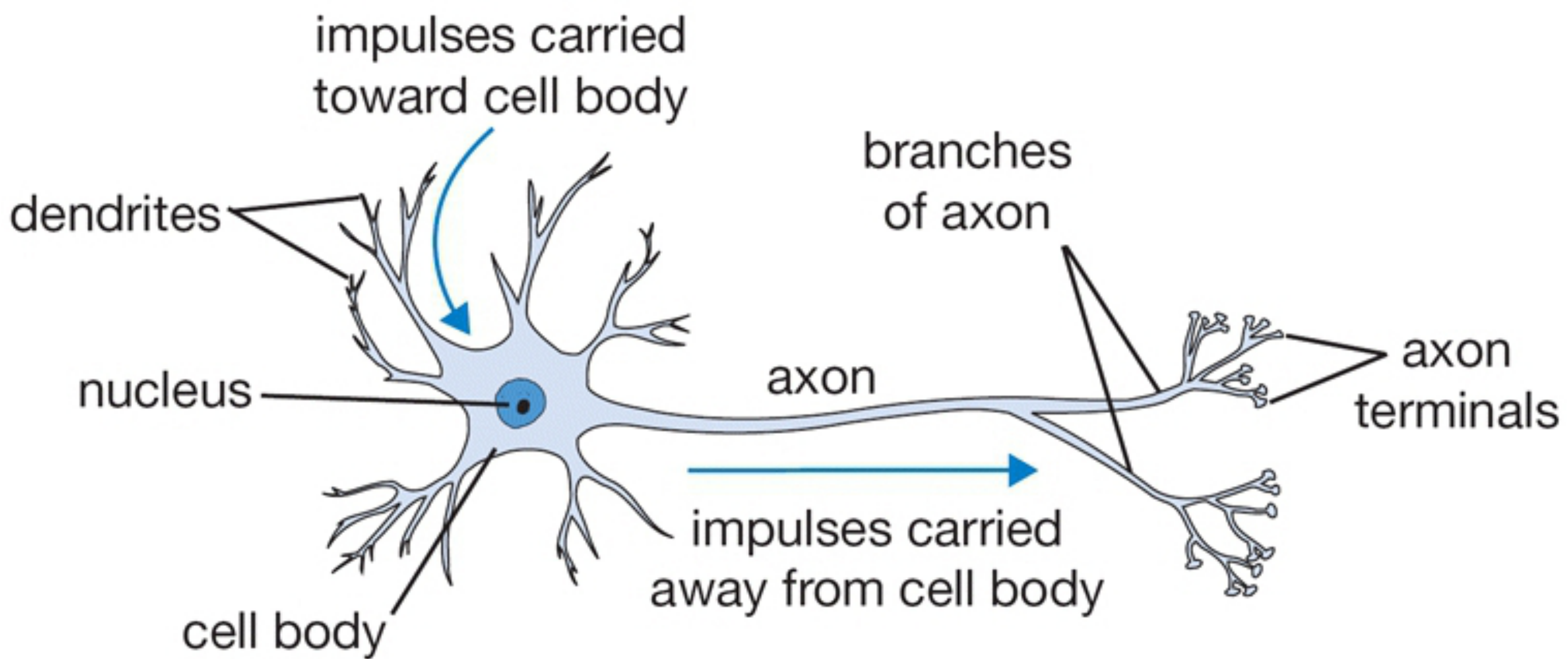


NEURAL NETWORKS

ARTIFICIAL NEURAL NETWORK

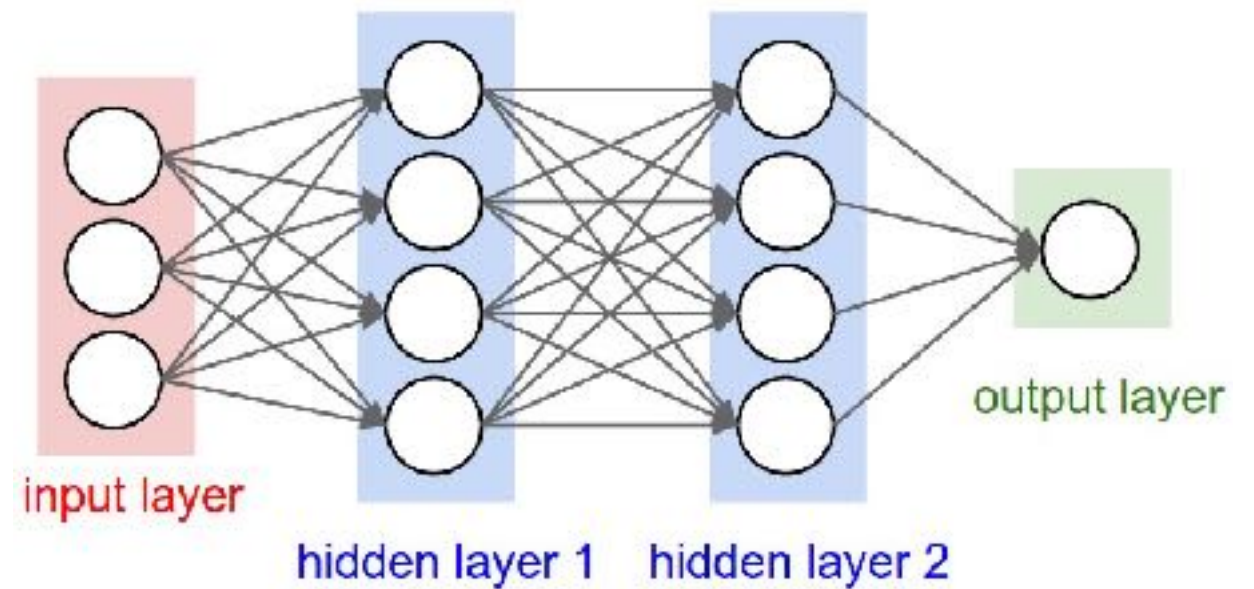
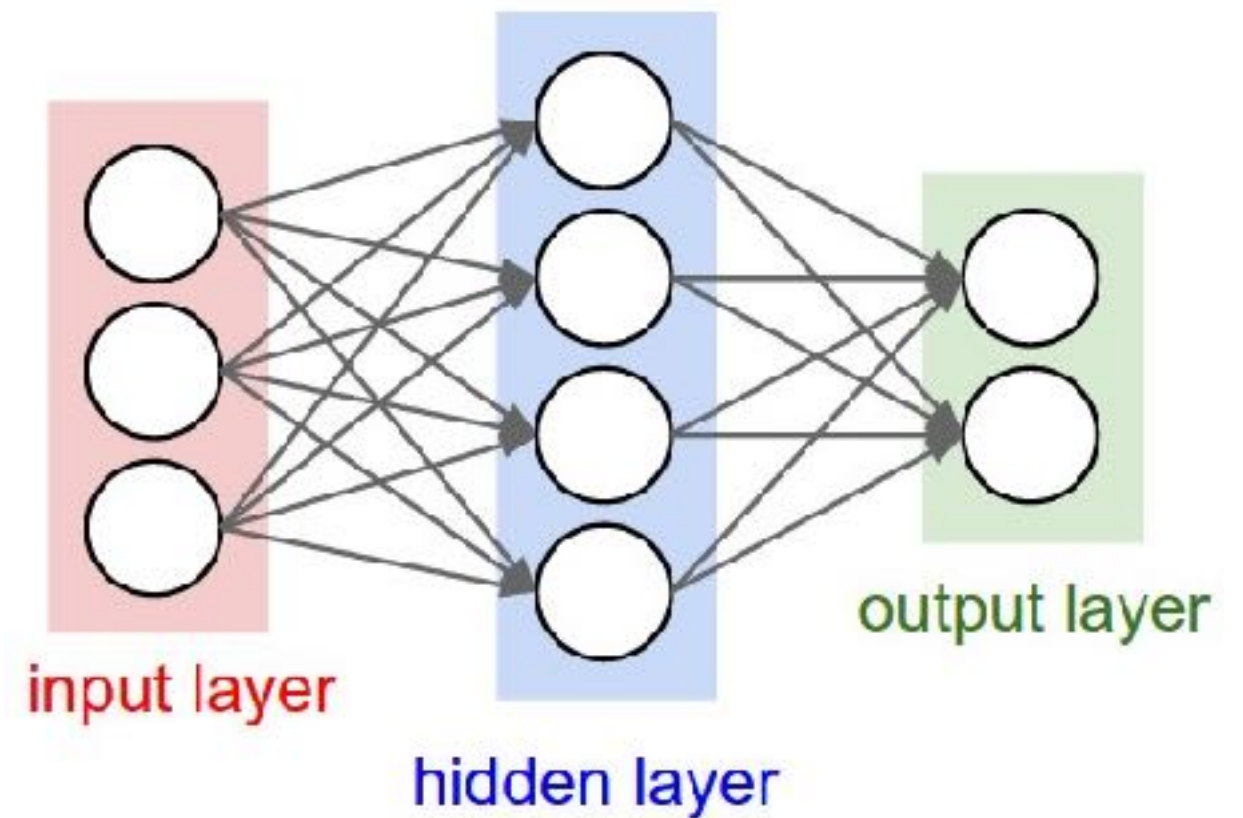
- 인간의 뇌 시스템을 모방
- 뉴런은 연결된 다른 뉴런의 '입력' 들을 받고, 그 결과가 '어느이상'의 자극이 될 시 이를 다른 뉴런에 전달
- 입력 : $XW^T + b$
- '어느이상' 자극의 기준 : Activation function $f()$

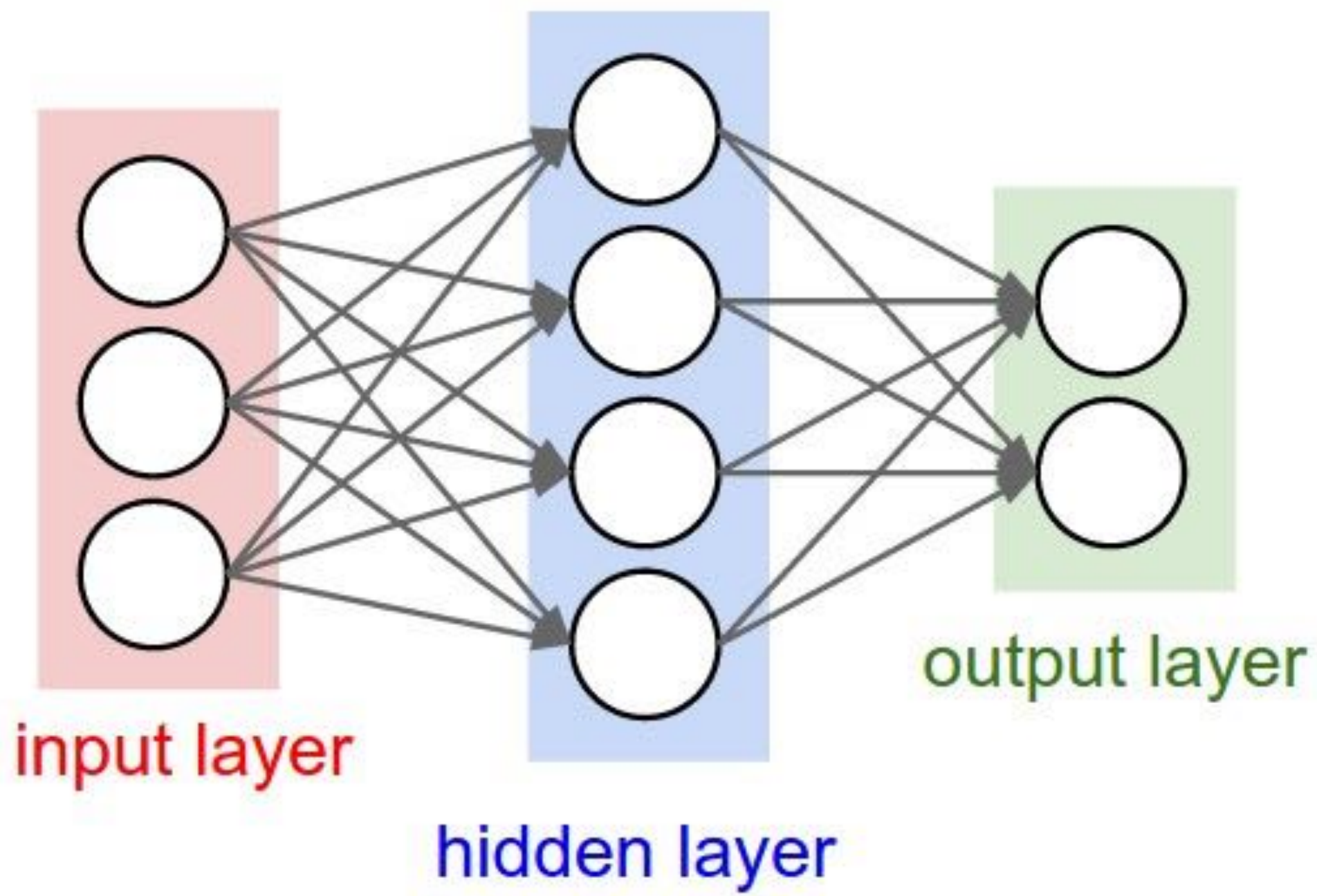


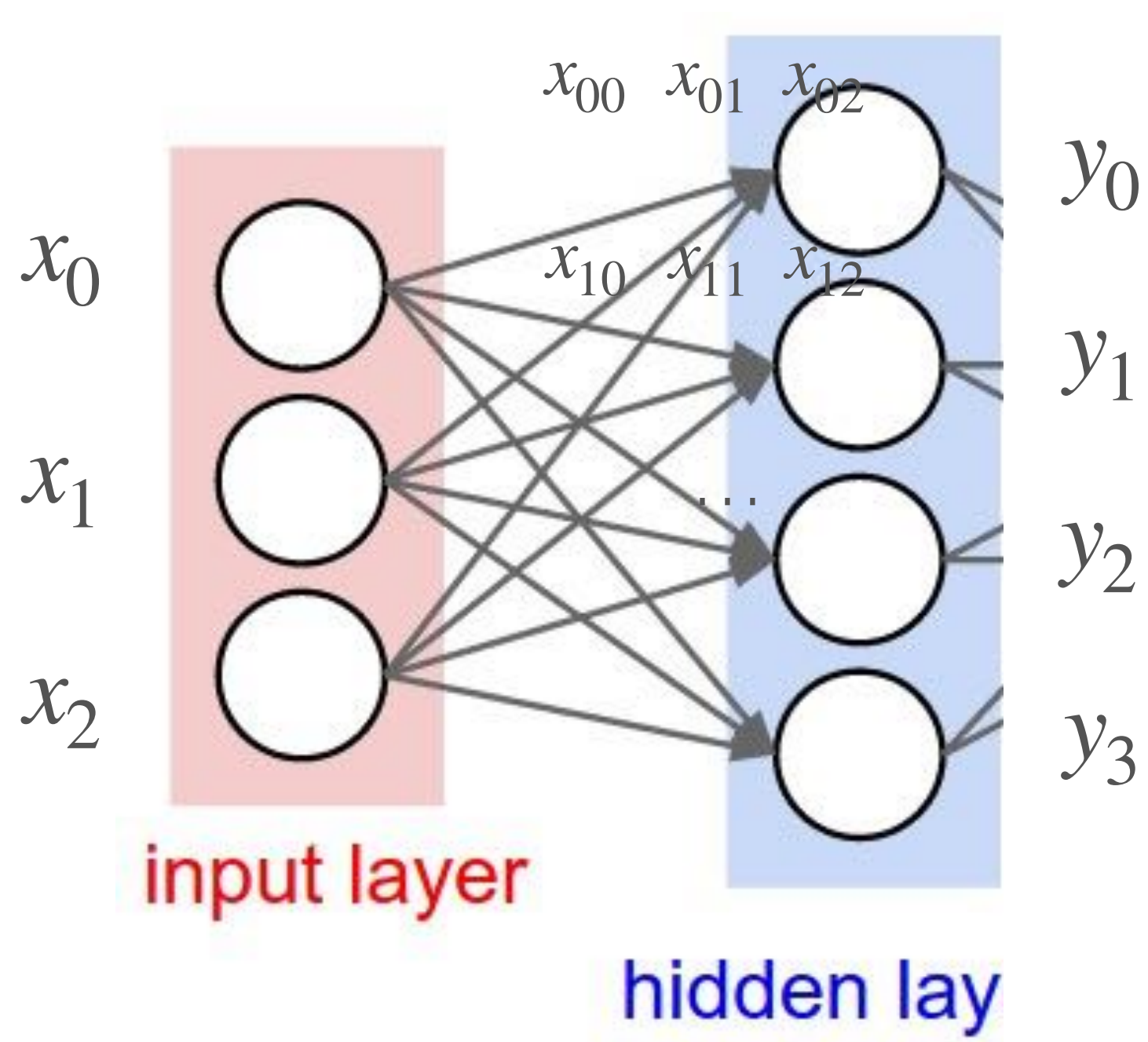
$$y = \phi\left(\sum_i w_i x_i + b\right)$$

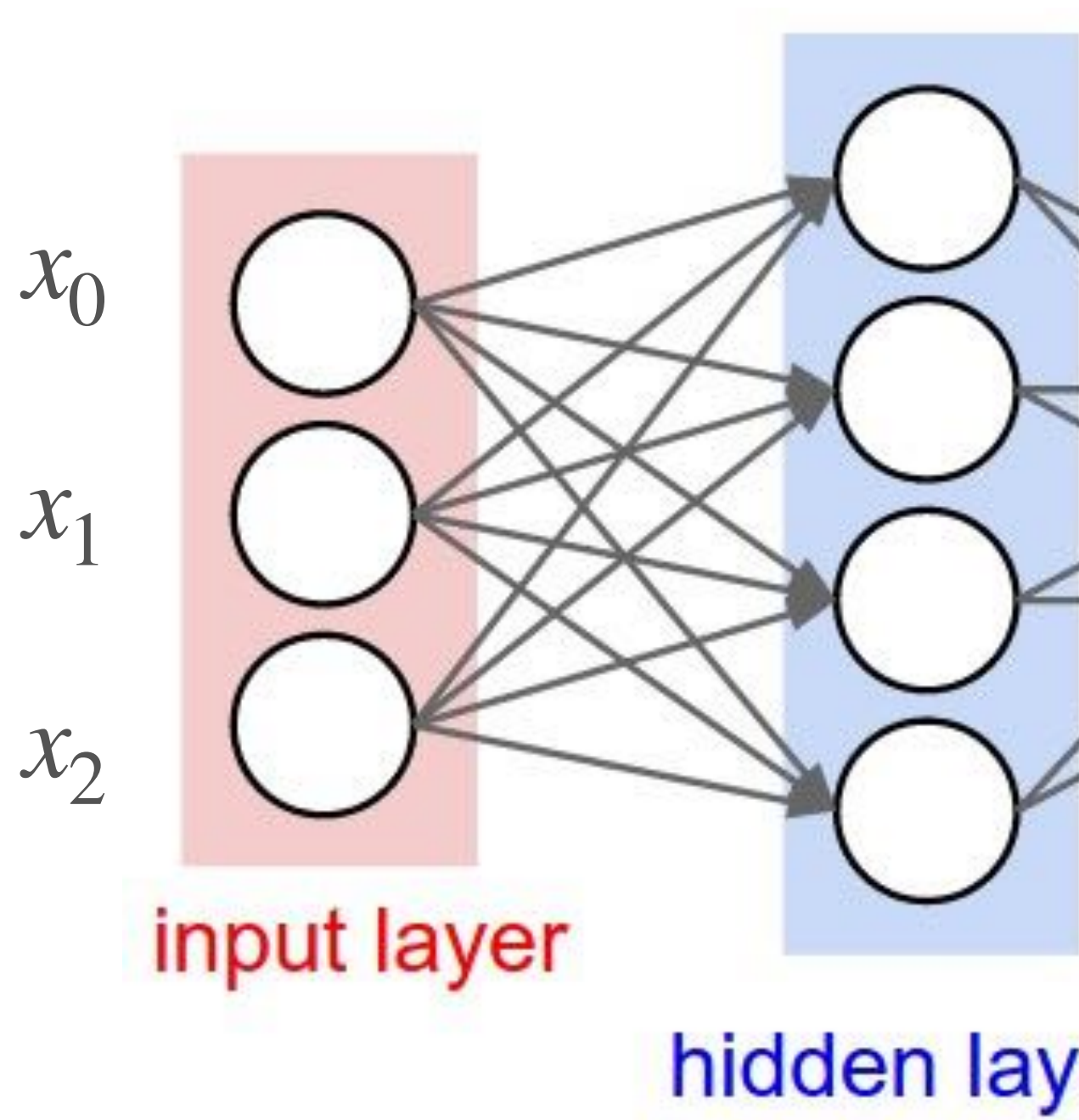
DEEP NEURAL NETWORK

- 2개 이상의 hidden layer 를 가지면 DNN 이라 함
- ^{거의} 실무에 활용되는 모든 NN 모델은 DNN 이라고 보면 됨
- 단순한 Linear 연산의 조합 이 되지 않도록, activation function 단계가 있음





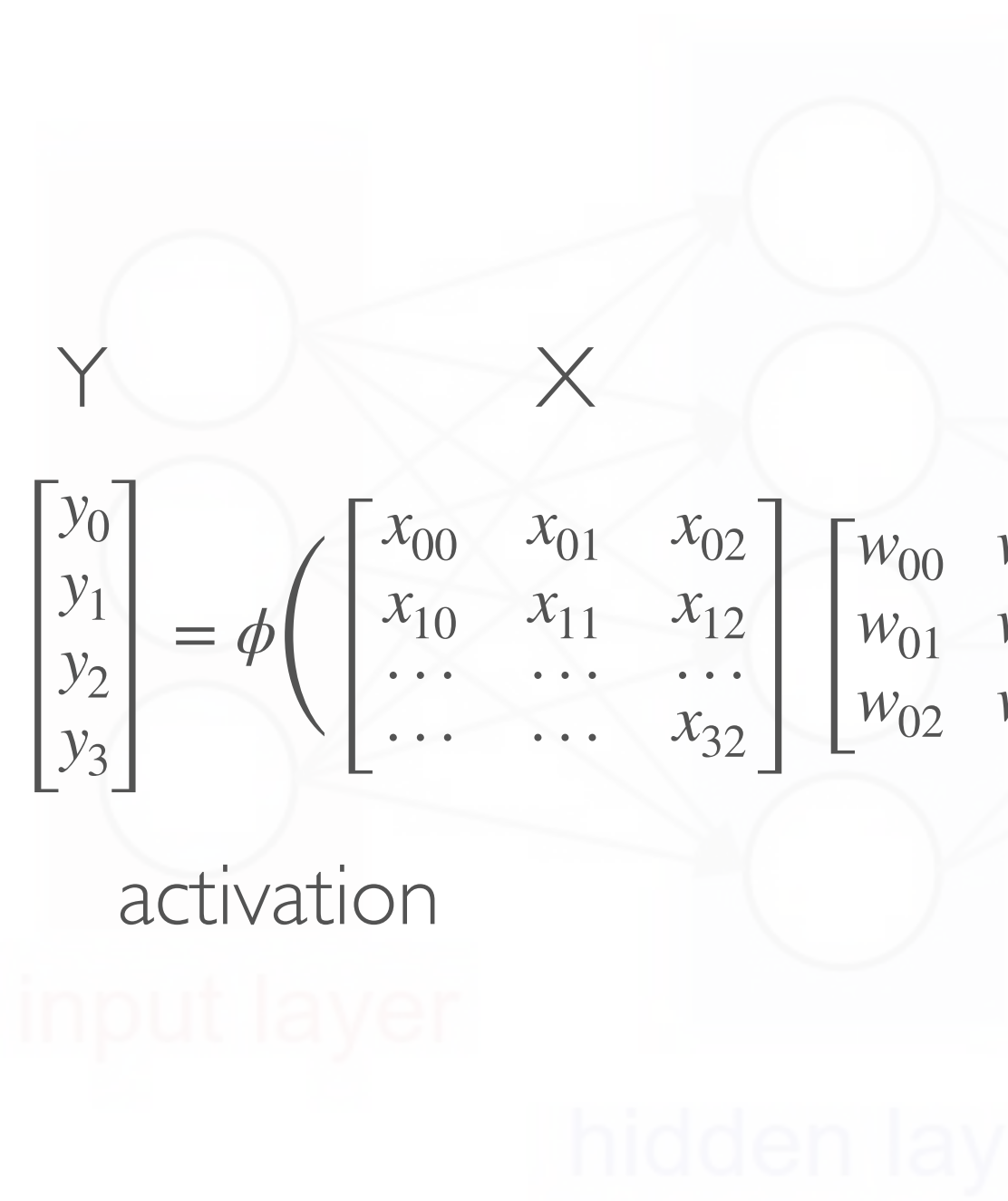




$$y_0 = \phi\left(\sum_{i=0}^2 x_{0i} w_{0i}\right)$$

$$y_1 = \phi\left(\sum_{i=0}^2 x_{1i} w_{1i}\right)$$

...



$$Y = \phi \left(X W^T + b \right)$$

activation


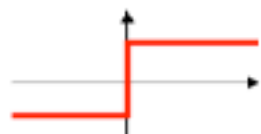
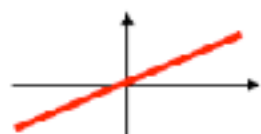

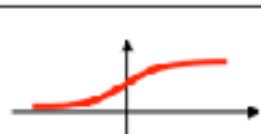
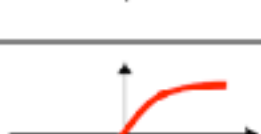

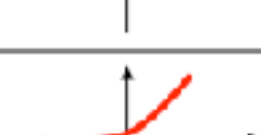

$$Y = \phi(XW^T + b)$$

input layer

hidden lay

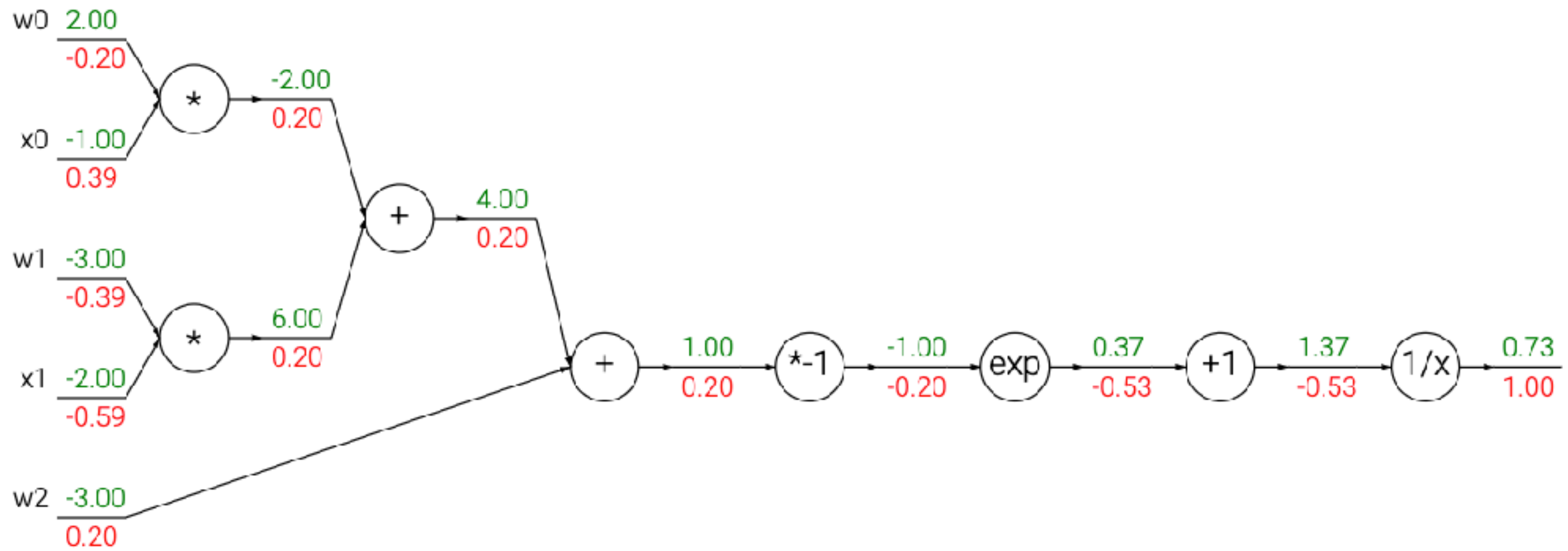
$$Y = \phi(XW^T + b)$$

MATRIX REPRESENTATION
OF **SINGLE LAYER FORWARDING**

Activation function	Equation	Example	1D Graph
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	

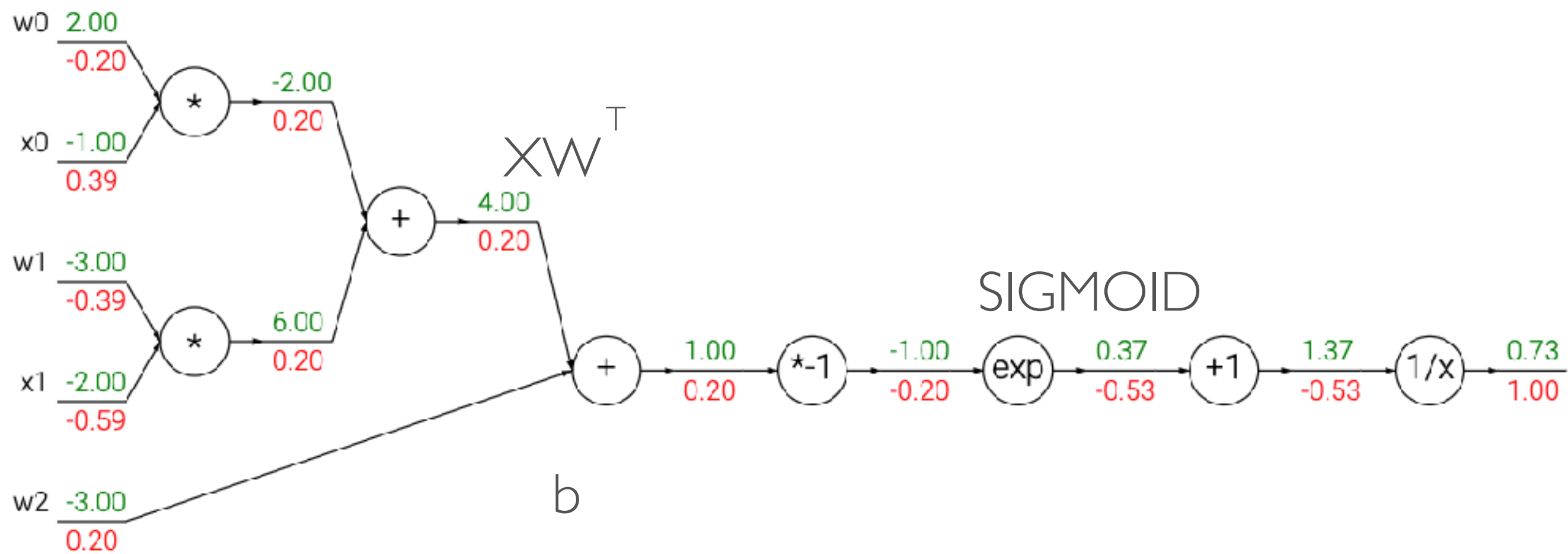
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[<http://sebastianraschka.com>]

ACTIVATION FUNCTIONS



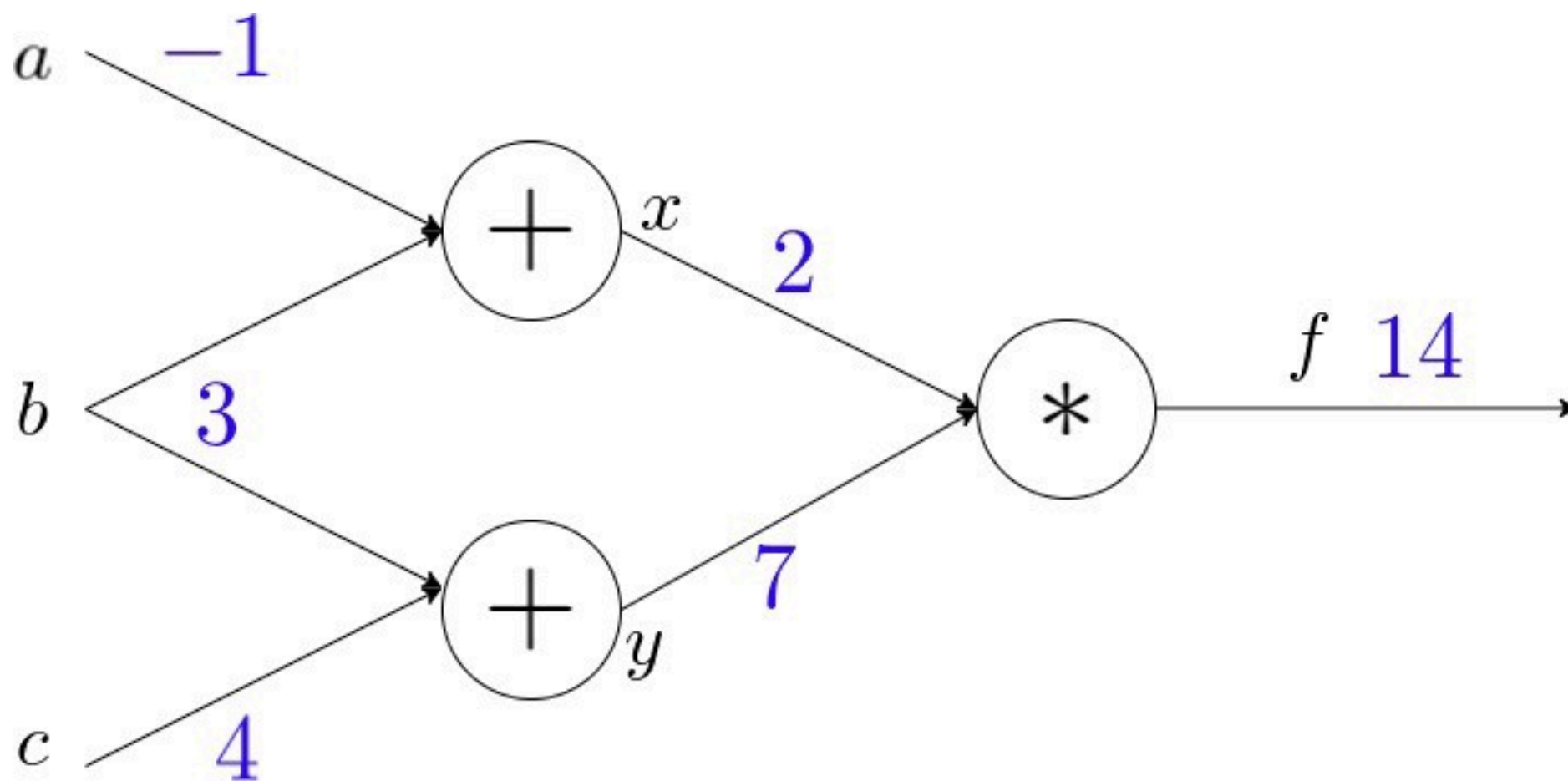
PROPAGATIONS

Forwards / Backwards

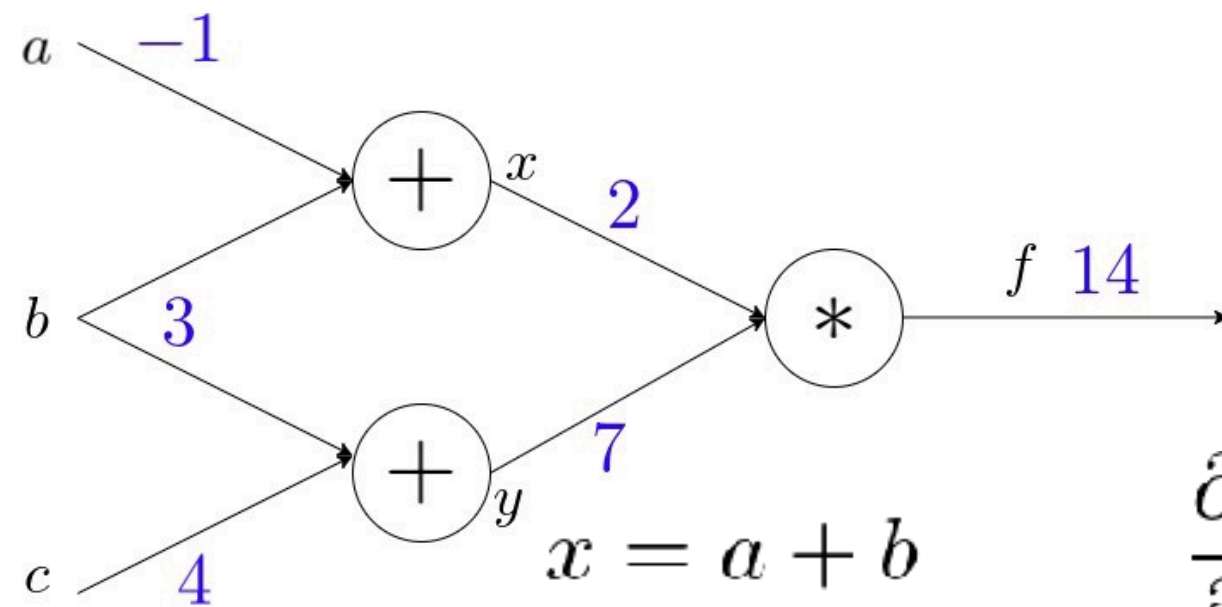


$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g} \frac{\partial g}{\partial x}$$

THE CHAIN RULE



FORWARDS



$$x = a + b$$

$$y = b + c$$

$$f = x * y$$

$$\frac{\partial x}{\partial a} = 1$$

$$\frac{\partial y}{\partial b} = 1$$

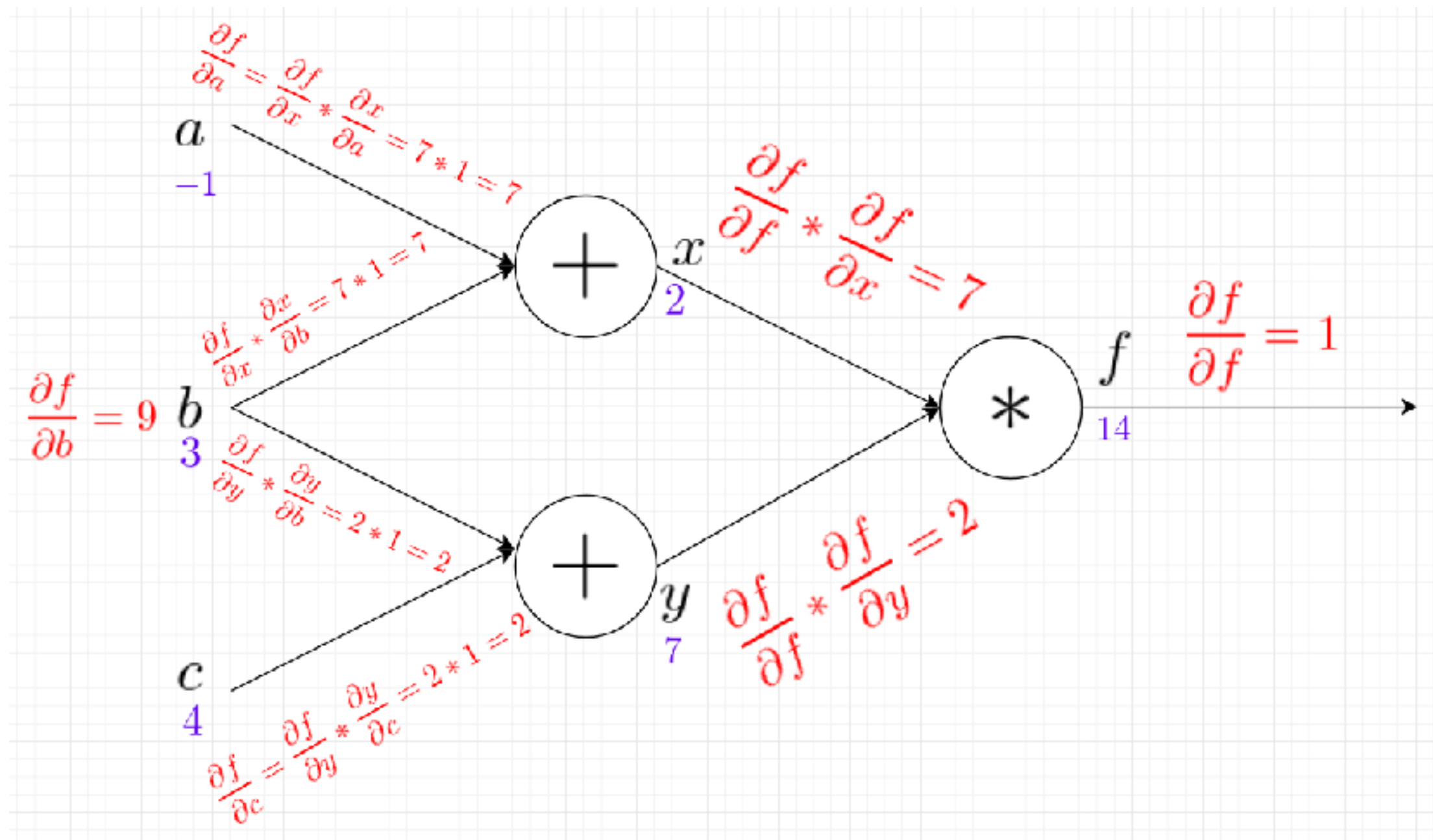
$$\frac{\partial f}{\partial x} = y$$

$$\frac{\partial x}{\partial b} = 1$$

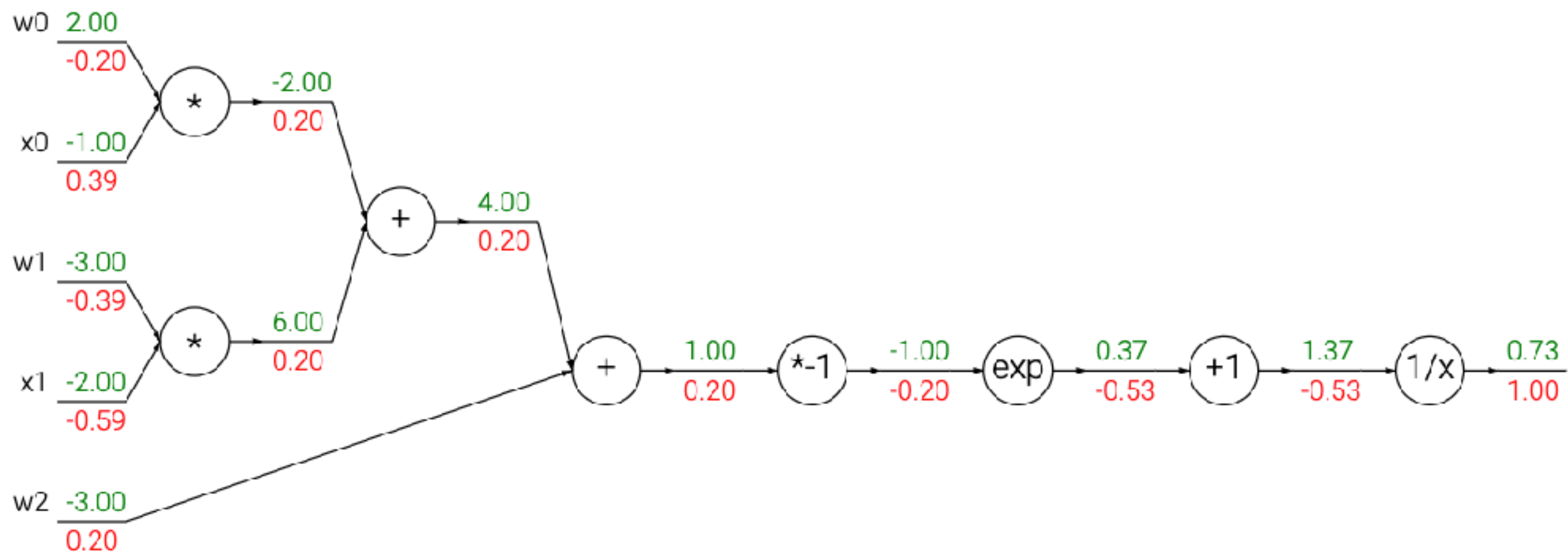
$$\frac{\partial y}{\partial c} = 1$$

$$\frac{\partial f}{\partial y} = x$$

GET LOCAL GRADIENTS



BACKWARDS



NOW, DO IT URSELF :)

APPENDIX

VISUALIZED PLAYGROUND

- <https://developers.google.com/machine-learning/crash-course/introduction-to-neural-networks/playground-exercises?hl=ko>

WHY MATRIX REPRESENTATION?

- TC of matmul : $\sim O(N^{2.3xx})$
 - https://en.wikipedia.org/wiki/Coppersmith%E2%80%93Winograd_algorithm
- **Massive** parallel executions on GPU
 - CPU : # of cores (~hundreds)
 - NVIDIA GPU : # of CUDA cores (>thousands)

REFERENCES

- <http://cs231n.github.io/neural-networks-1/>
- http://rasbt.github.io/mlxtend/user_guide/general_concepts/activation-functions/
- <https://medium.com/spidernitt/breaking-down-neural-networks-an-intuitive-approach-to-backpropagation-3b2ff958794c>
- <https://deeplearningzerotoall.github.io/season2/>