

Deep Learning

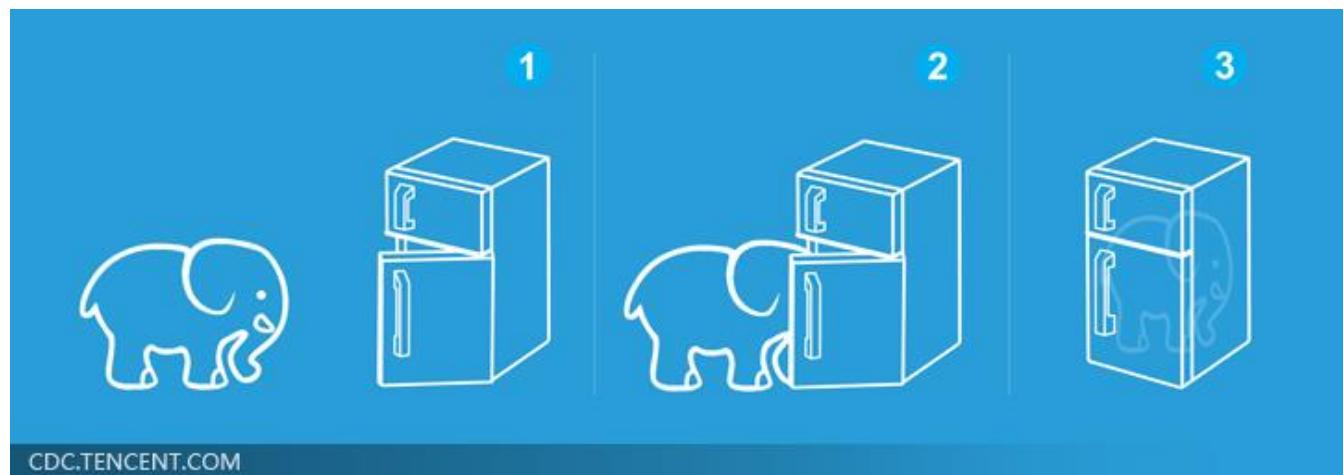
Hung-yi Lee

李宏毅

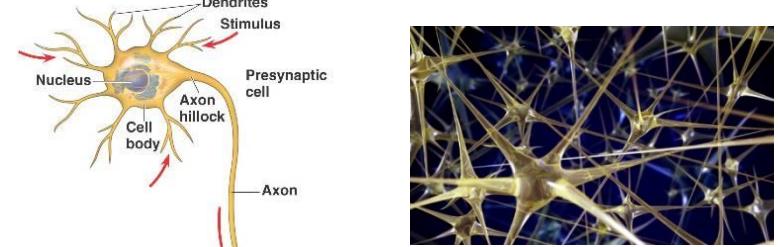
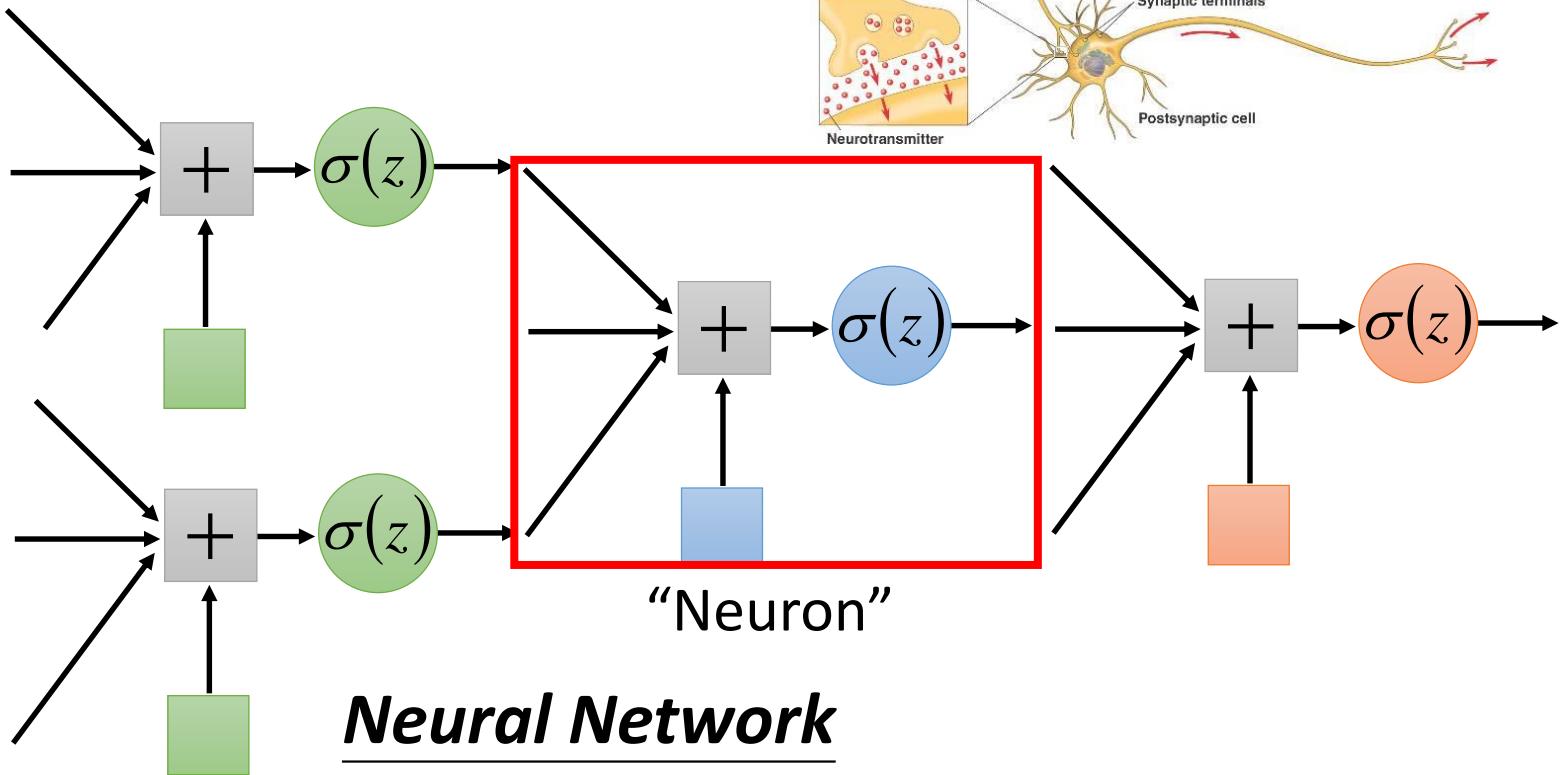
Three Steps for Deep Learning



Deep Learning is so simple



Neural Network

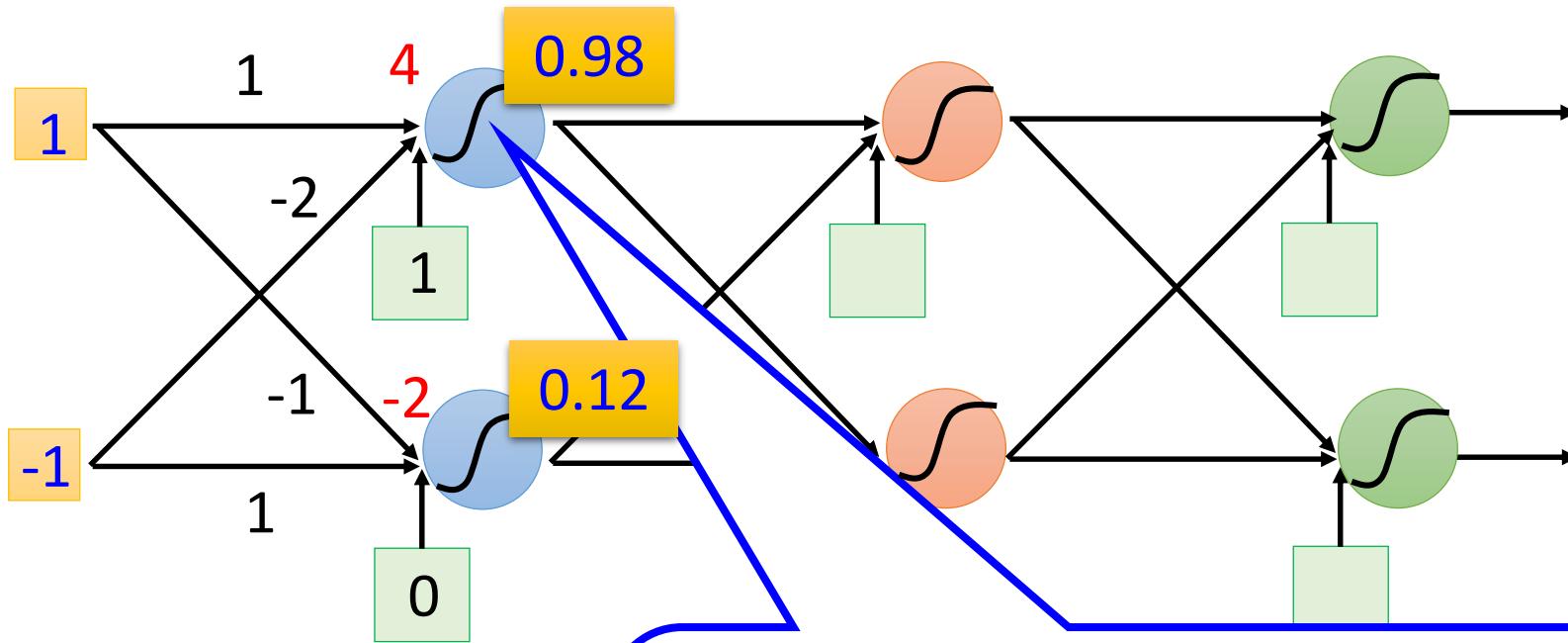


Neural Network

Different connection leads to different network structures

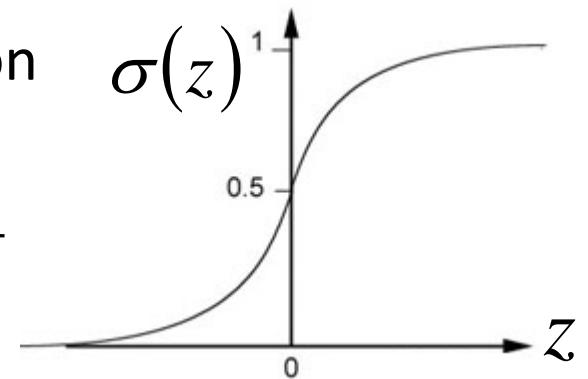
Network parameter θ : all the weights and biases in the “neurons”

Fully Connect Feedforward Network

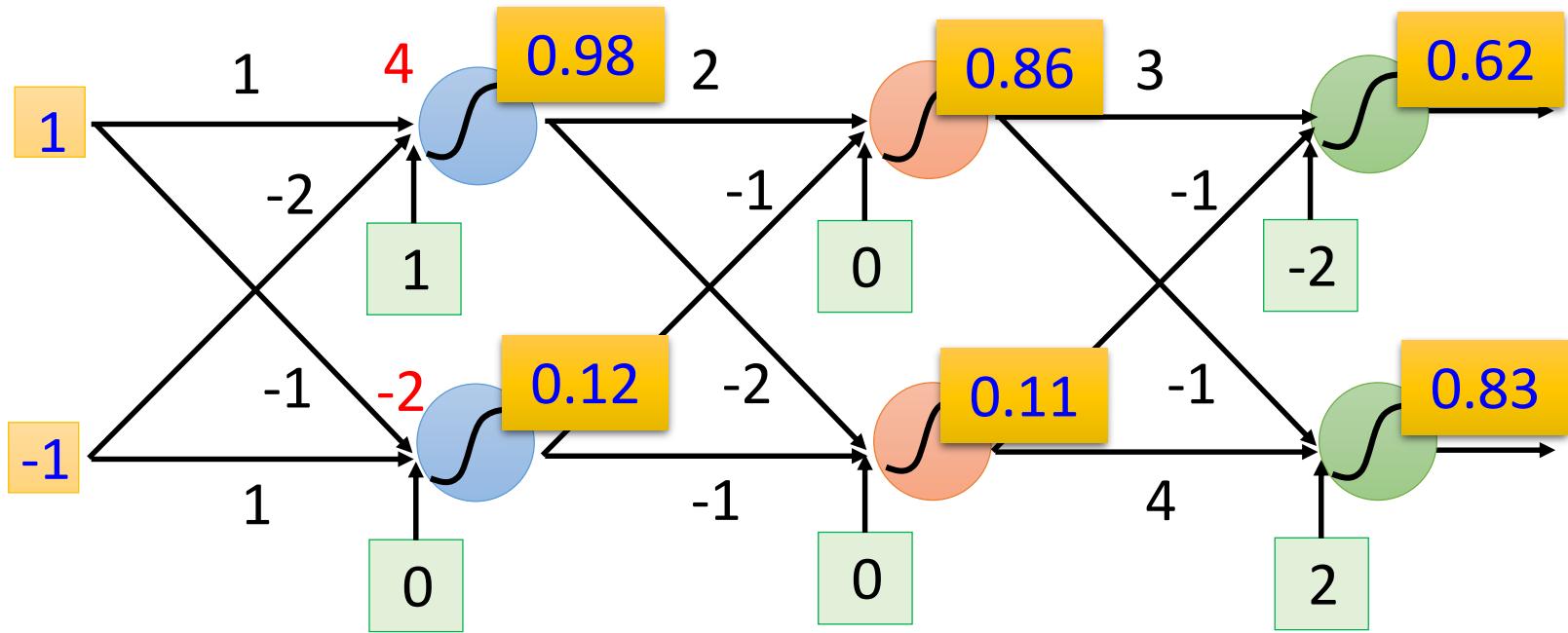


Sigmoid Function

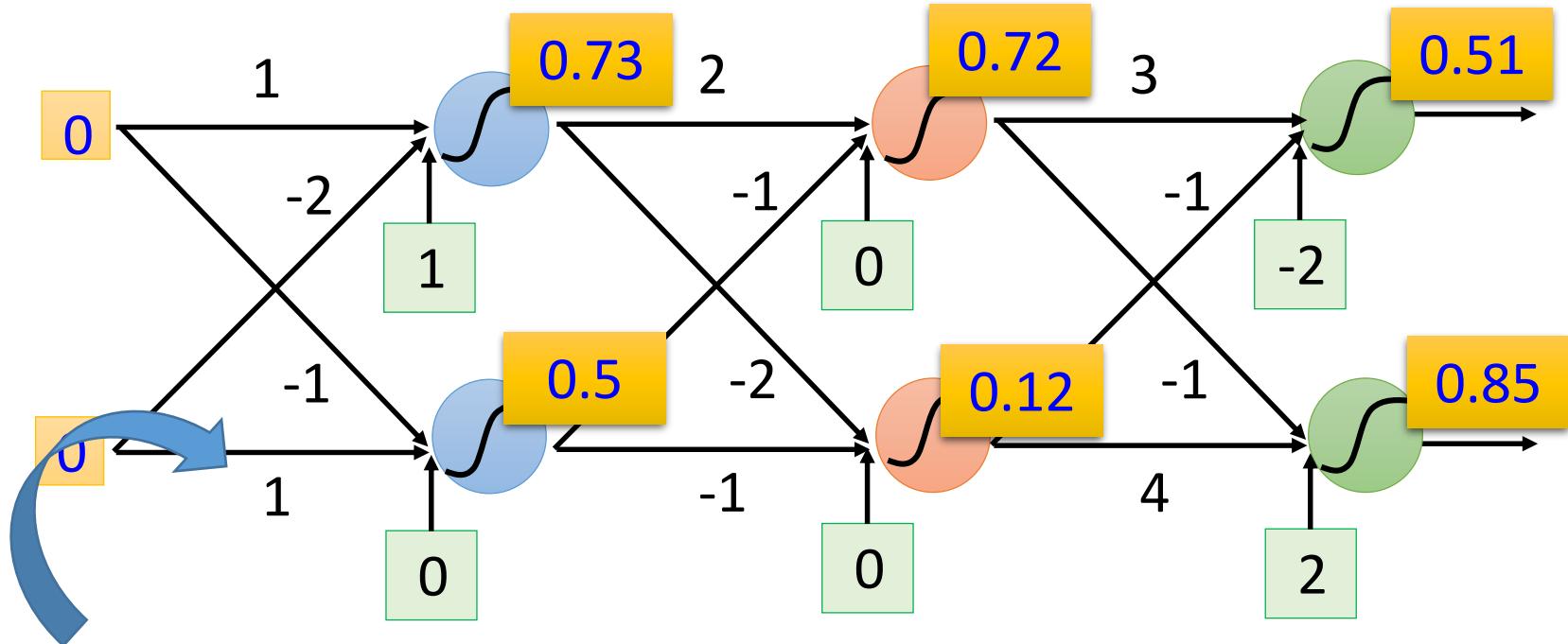
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$



Fully Connect Feedforward Network



Fully Connect Feedforward Network

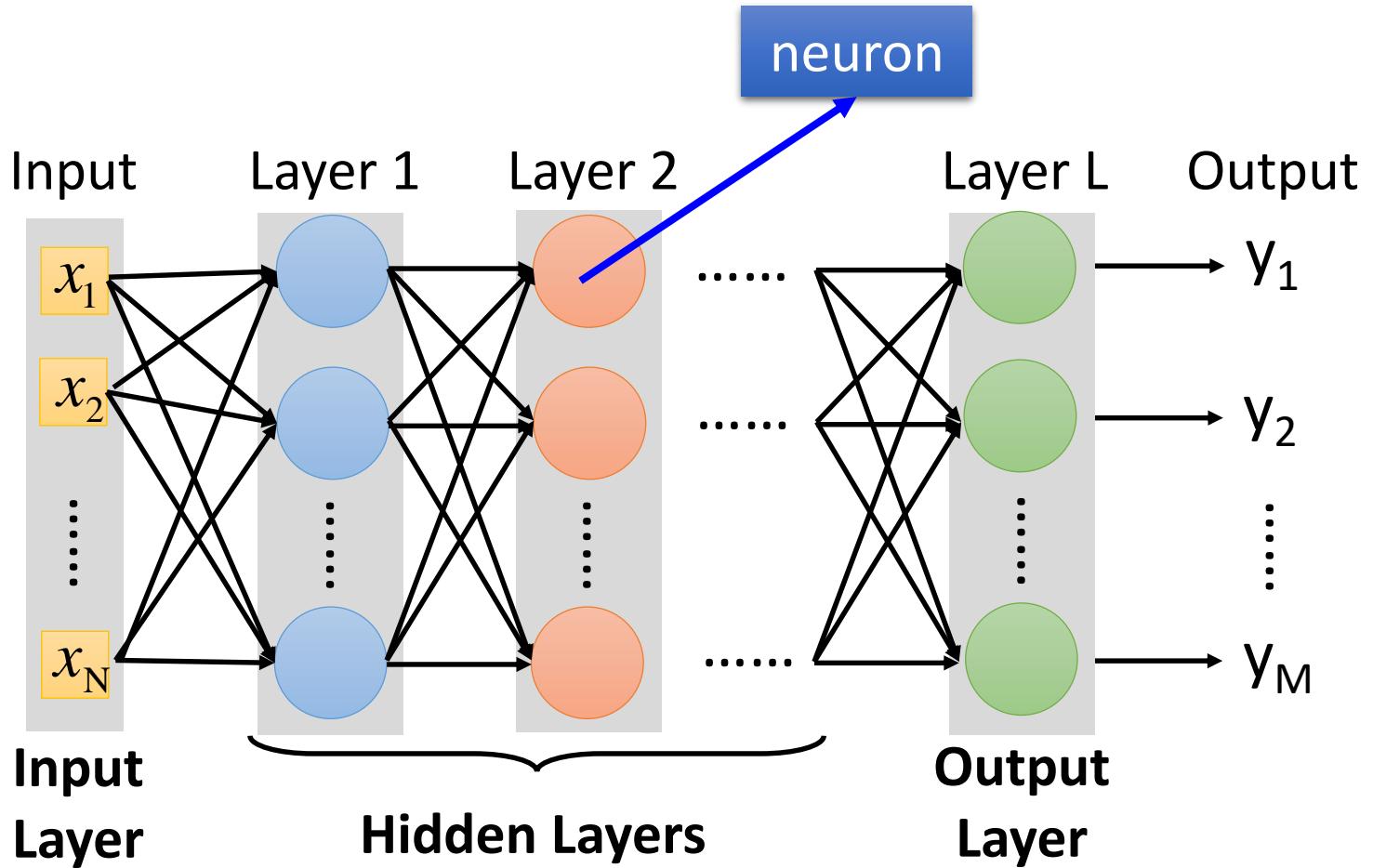


This is a function.
Input vector, output vector

$$f \left(\begin{bmatrix} 1 \\ -1 \end{bmatrix} \right) = \begin{bmatrix} 0.62 \\ 0.83 \end{bmatrix} \quad f \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 0.51 \\ 0.85 \end{bmatrix}$$

Given network structure, define a function set

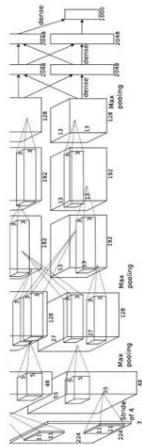
Fully Connect Feedforward Network



Deep = Many hidden layers

http://cs231n.stanford.edu/slides/winter1516_lecuture8.pdf

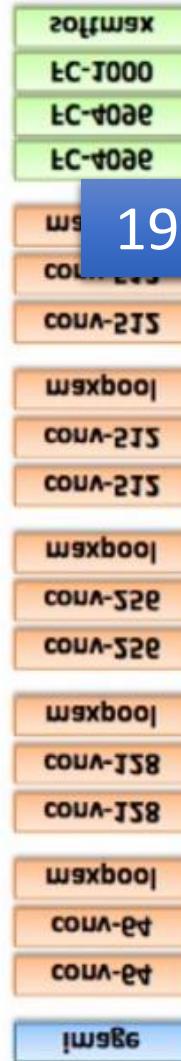
16.4%



AlexNet (2012)

8 layers

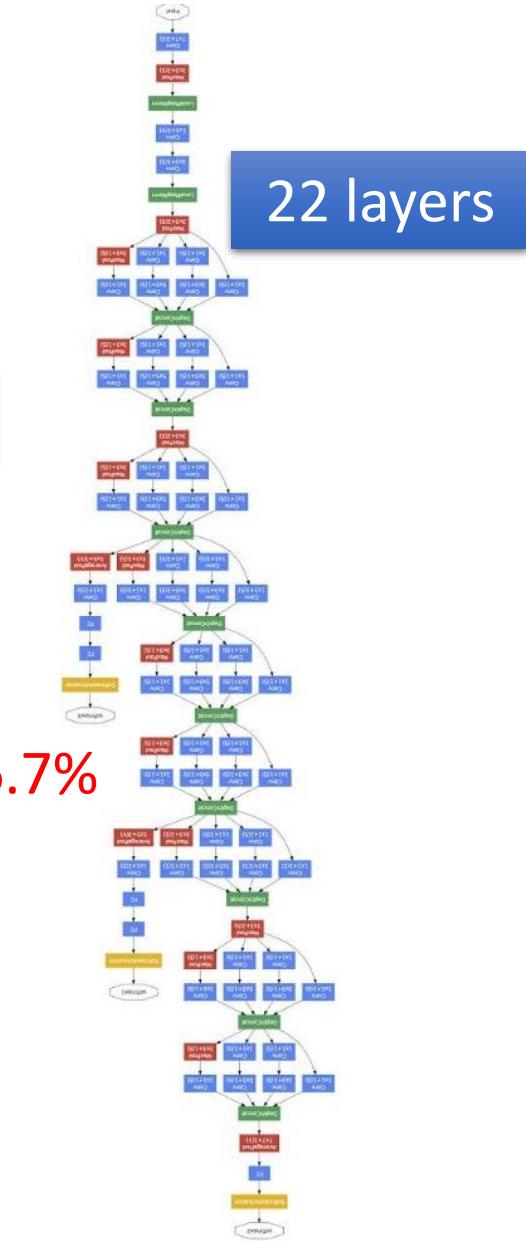
7.3%



VGG (2014)

19 layers

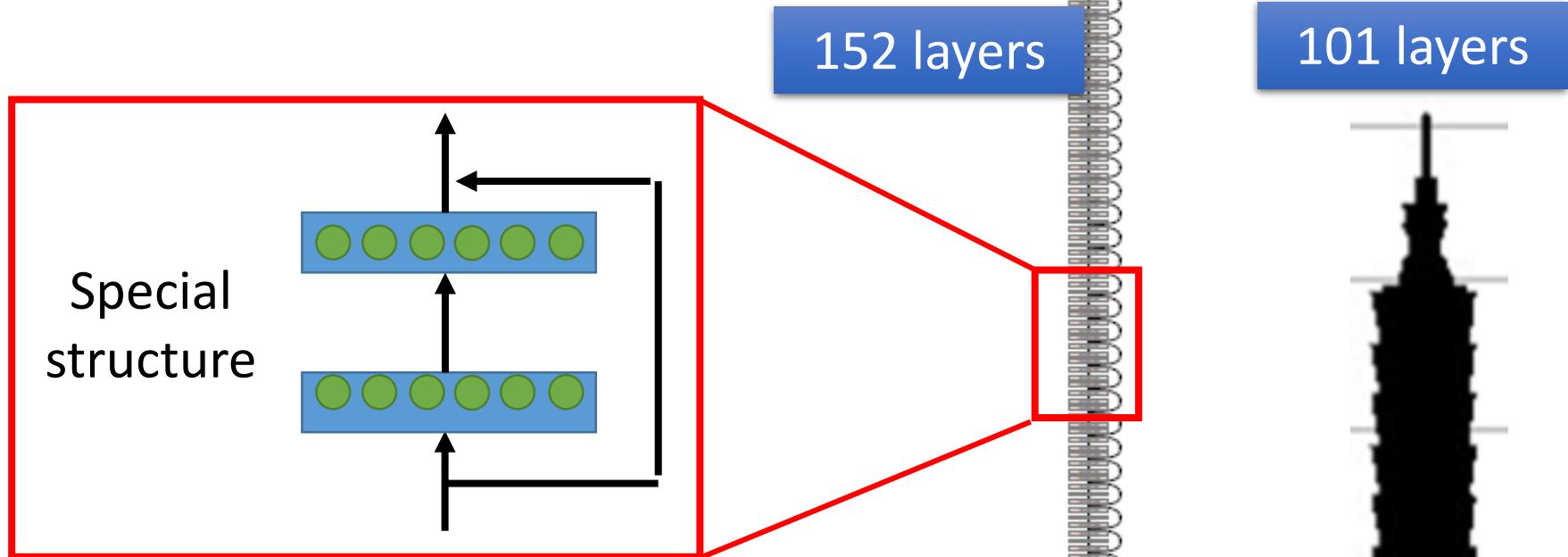
6.7%



GoogleNet (2014)

22 layers

Deep = Many hidden layers



Ref:

<https://www.youtube.com/watch?v=dxB6299gpvl>

3.57%

16.4%

7.3%

6.7%

AlexNet
(2012)

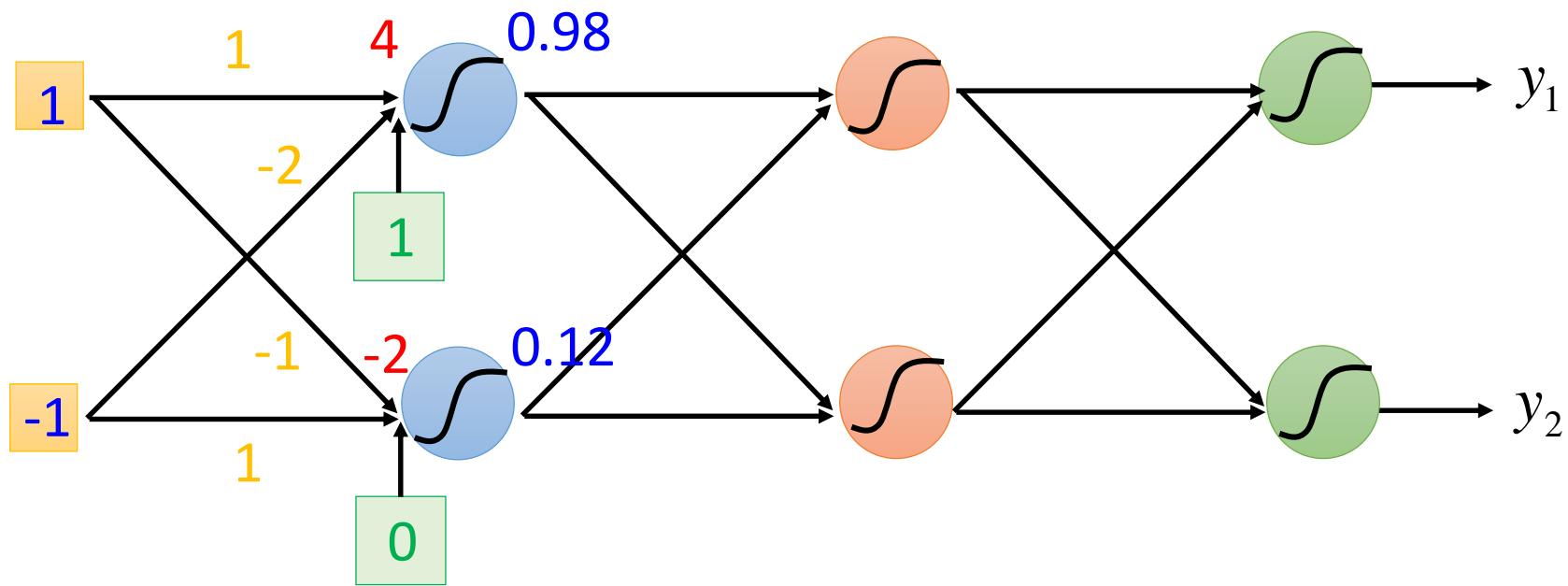
VGG
(2014)

GoogleNet
(2014)

Residual Net
(2015)

Taipei
101

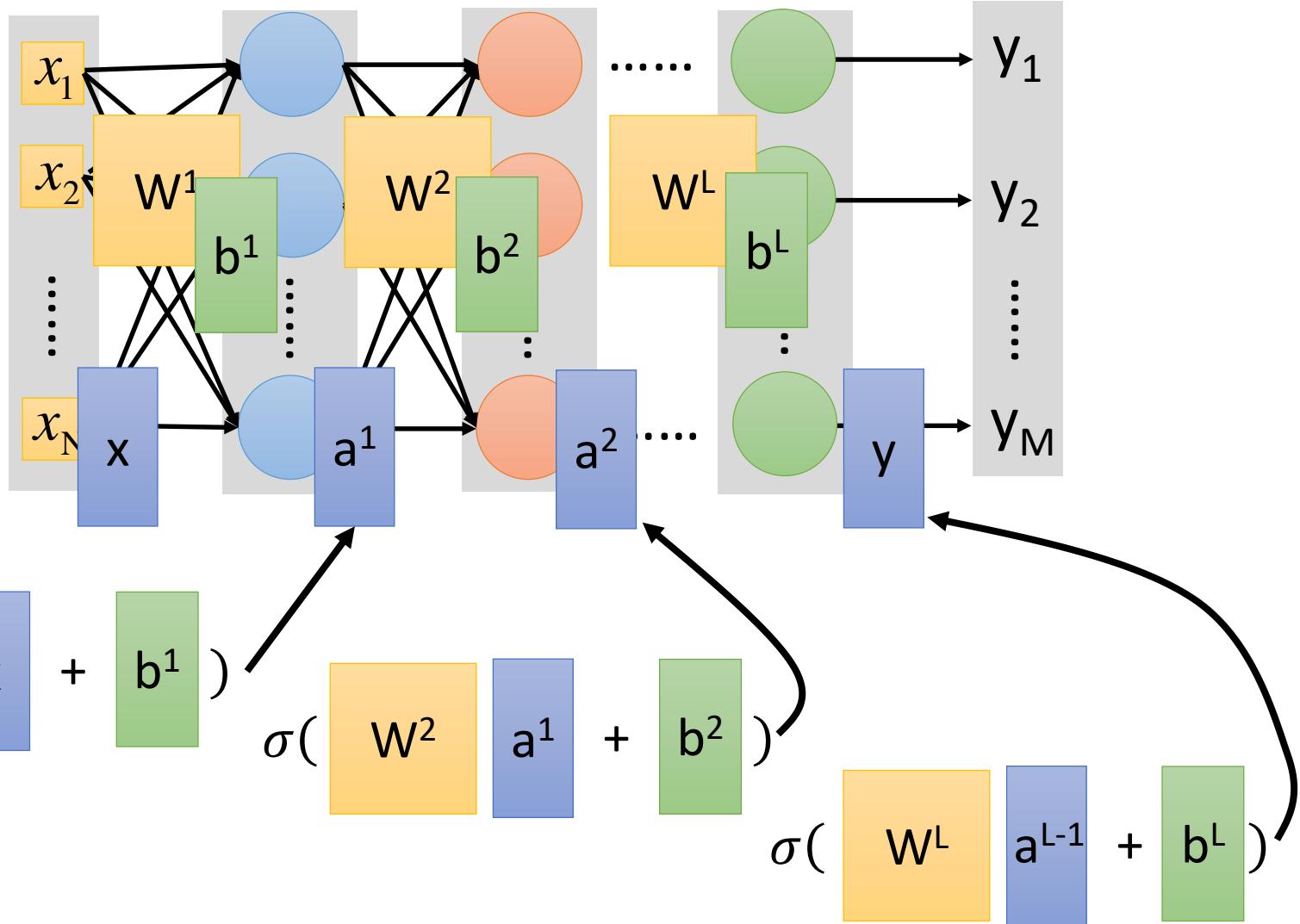
Matrix Operation



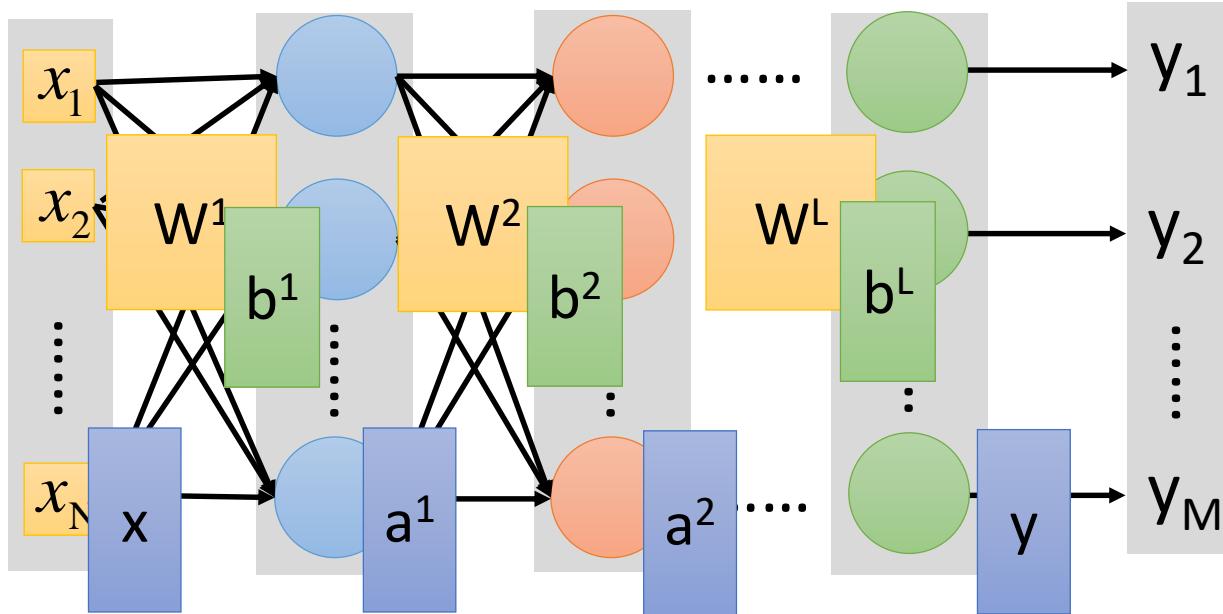
$$\sigma \left(\underbrace{\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}} \right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

$$\begin{bmatrix} 4 \\ -2 \end{bmatrix}$$

Neural Network



Neural Network



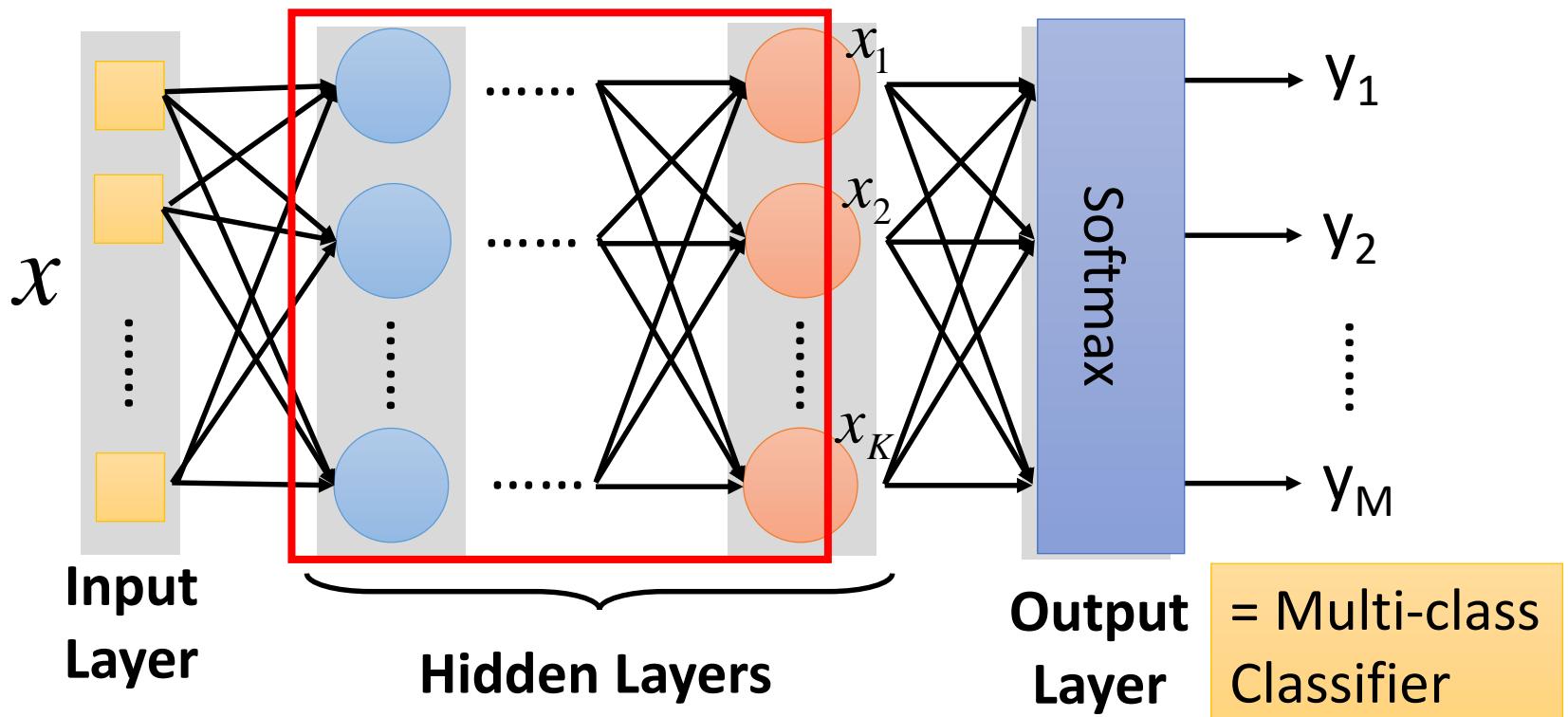
$$y = f(x)$$

Using parallel computing techniques
to speed up matrix operation

$$= \sigma(W^L \cdots \sigma(W^2 \sigma(W^1 x + b^1) + b^2) \cdots + b^L)$$

Output Layer as Multi-Class Classifier

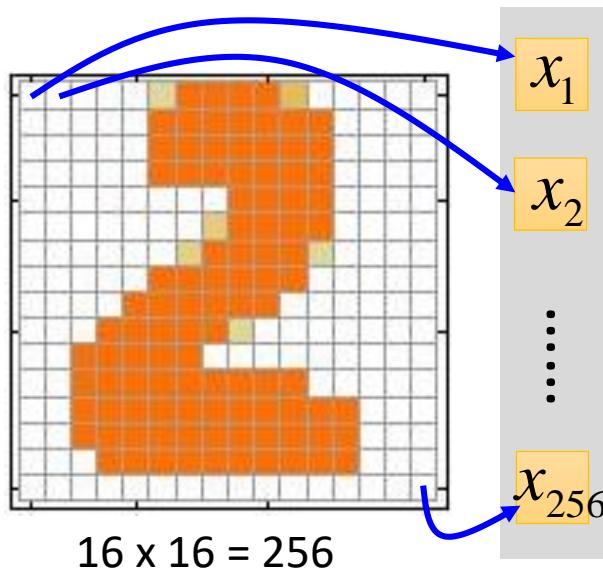
Feature extractor replacing
feature engineering



Example Application

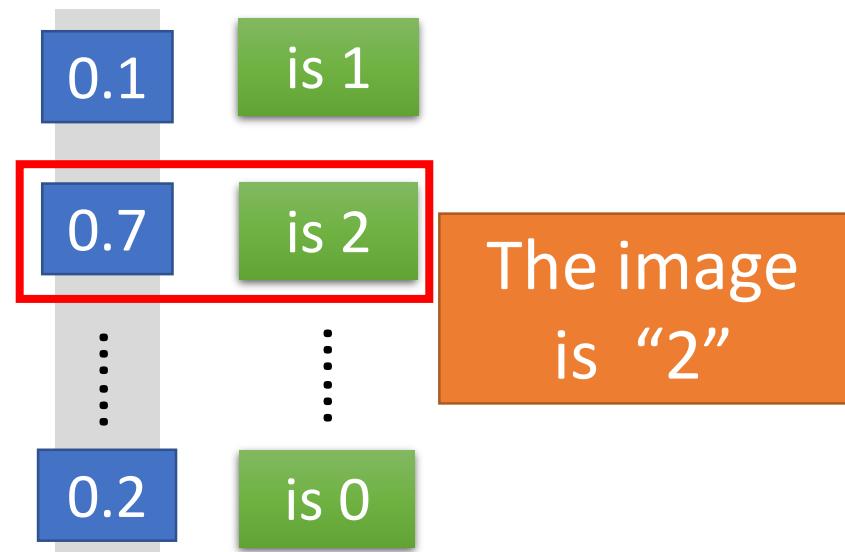


Input



Ink → 1
No ink → 0

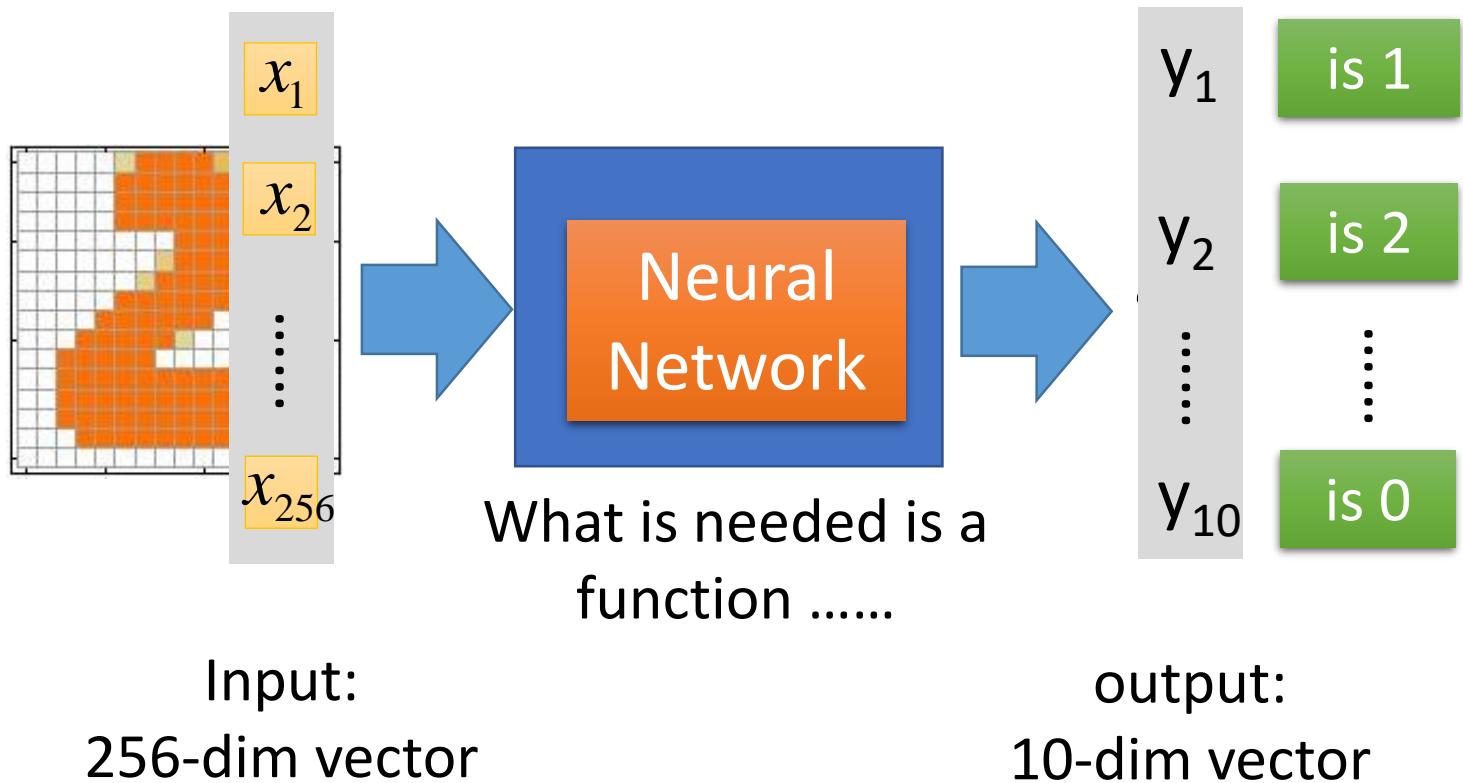
Output



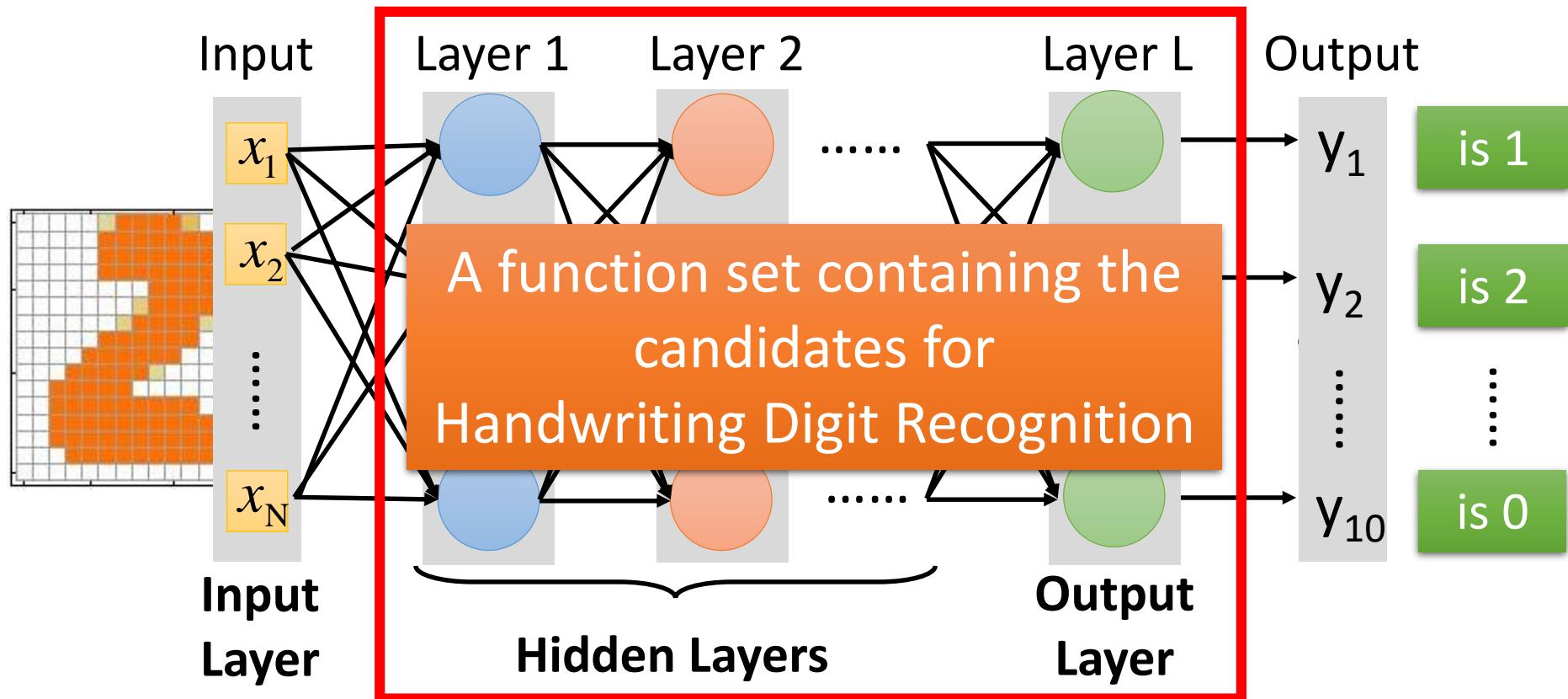
Each dimension represents the confidence of a digit.

Example Application

- Handwriting Digit Recognition

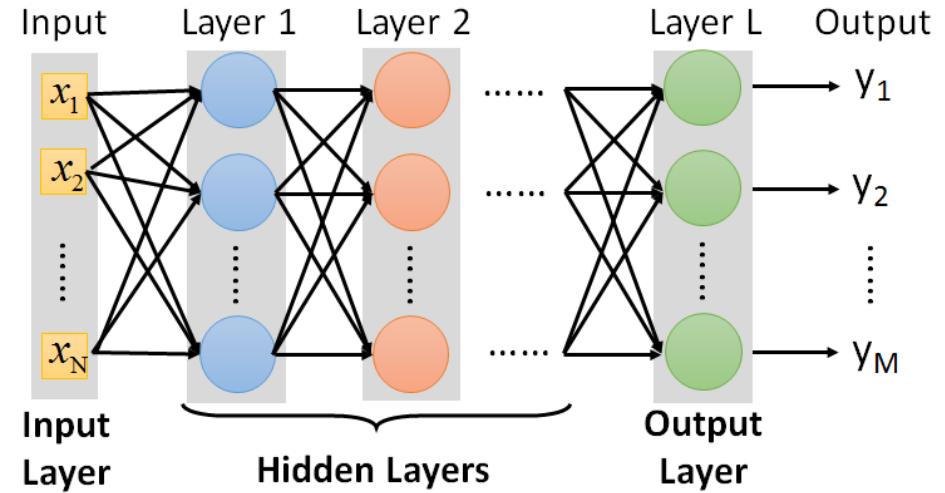


Example Application



You need to decide the network structure to let a good function in your function set.

FAQ



- Q: How many layers? How many neurons for each layer?

Trial and Error

+

Intuition

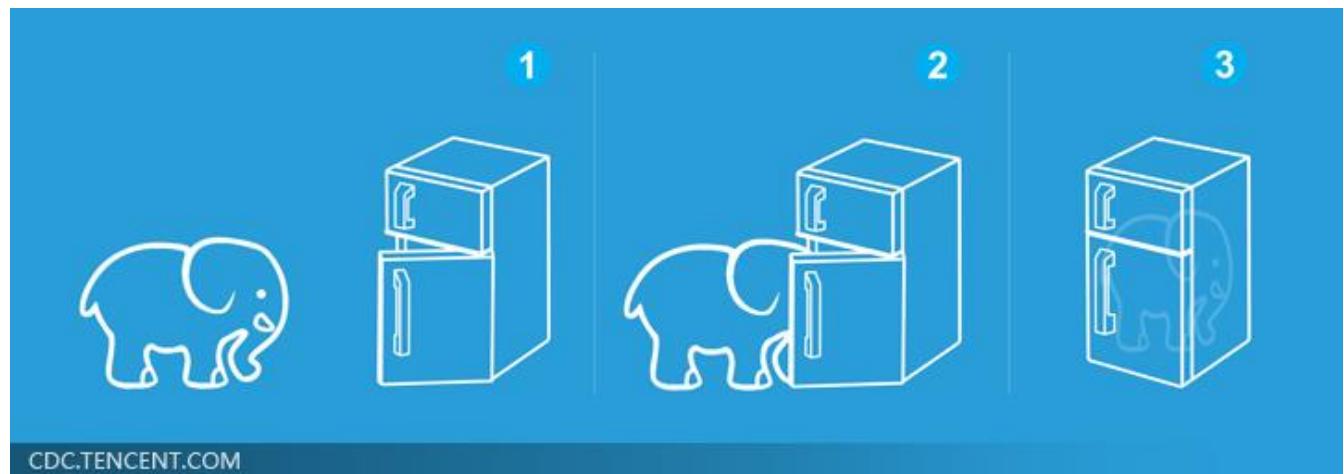
- Q: Can the structure be automatically determined?
 - E.g. Evolutionary Artificial Neural Networks
- Q: Can we design the network structure?

Convolutional Neural Network (CNN)

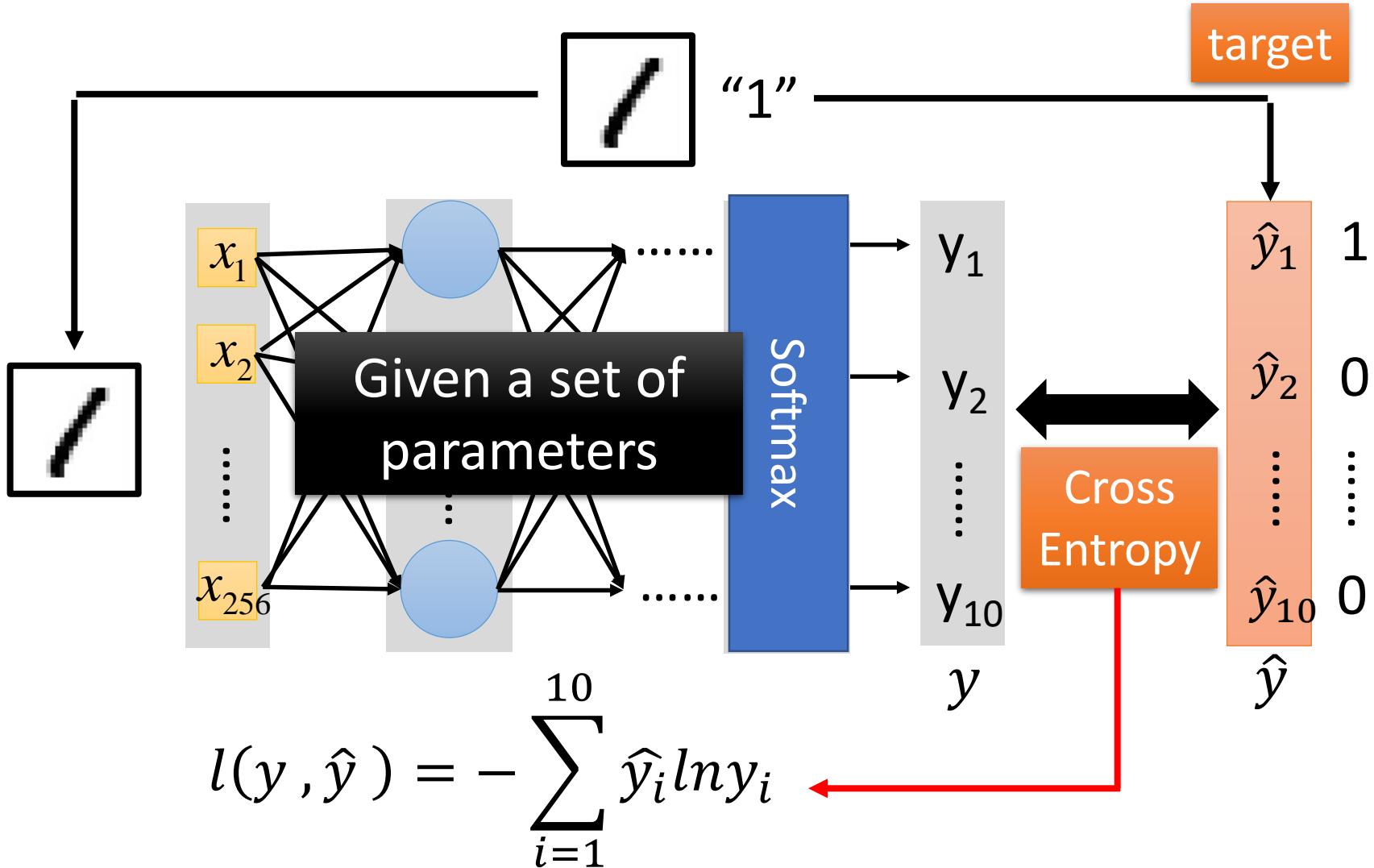
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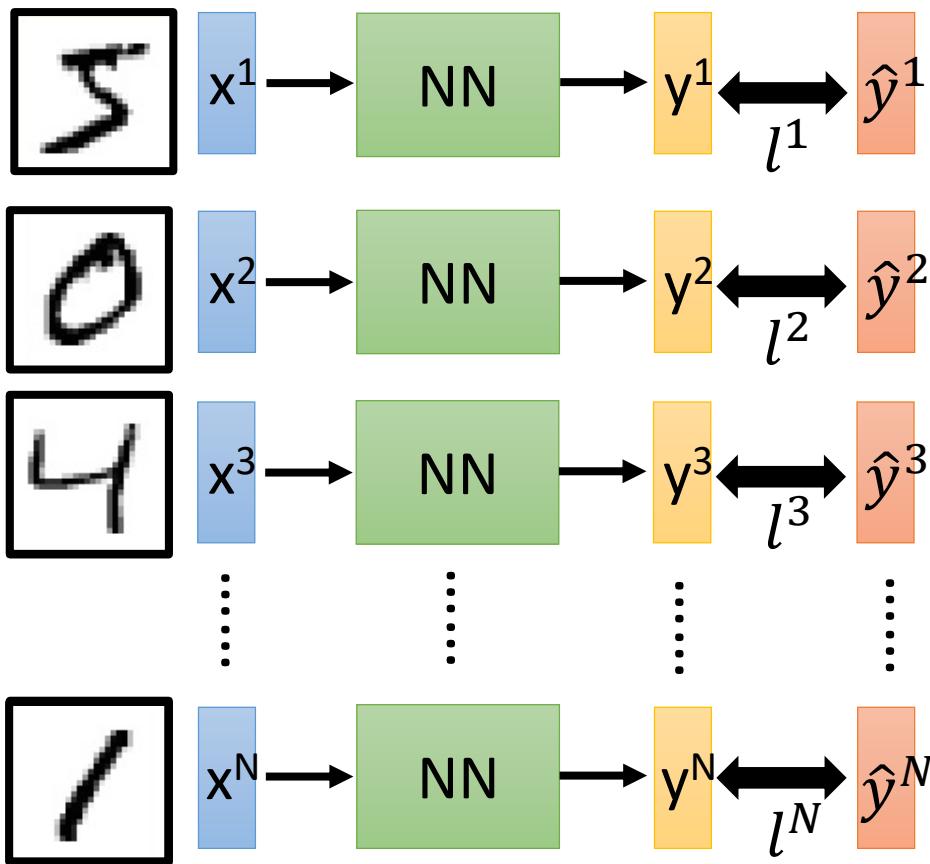


Loss for an Example



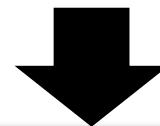
Total Loss

For all training data ...



Total Loss:

$$L = \sum_{n=1}^N l^n$$



Find a function in function set that minimizes total loss L

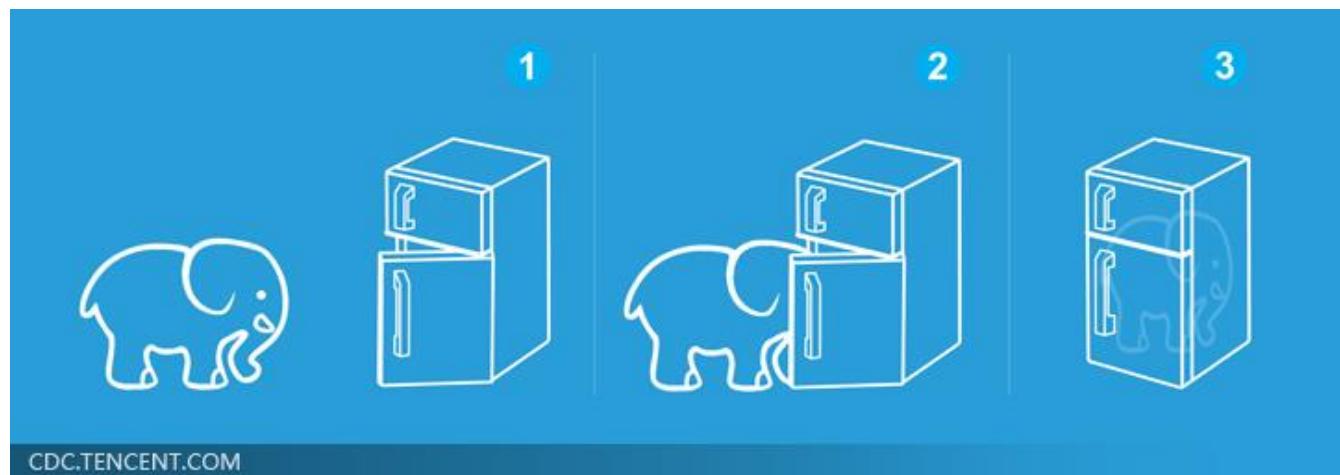


Find the network parameters θ^* that minimize total loss L

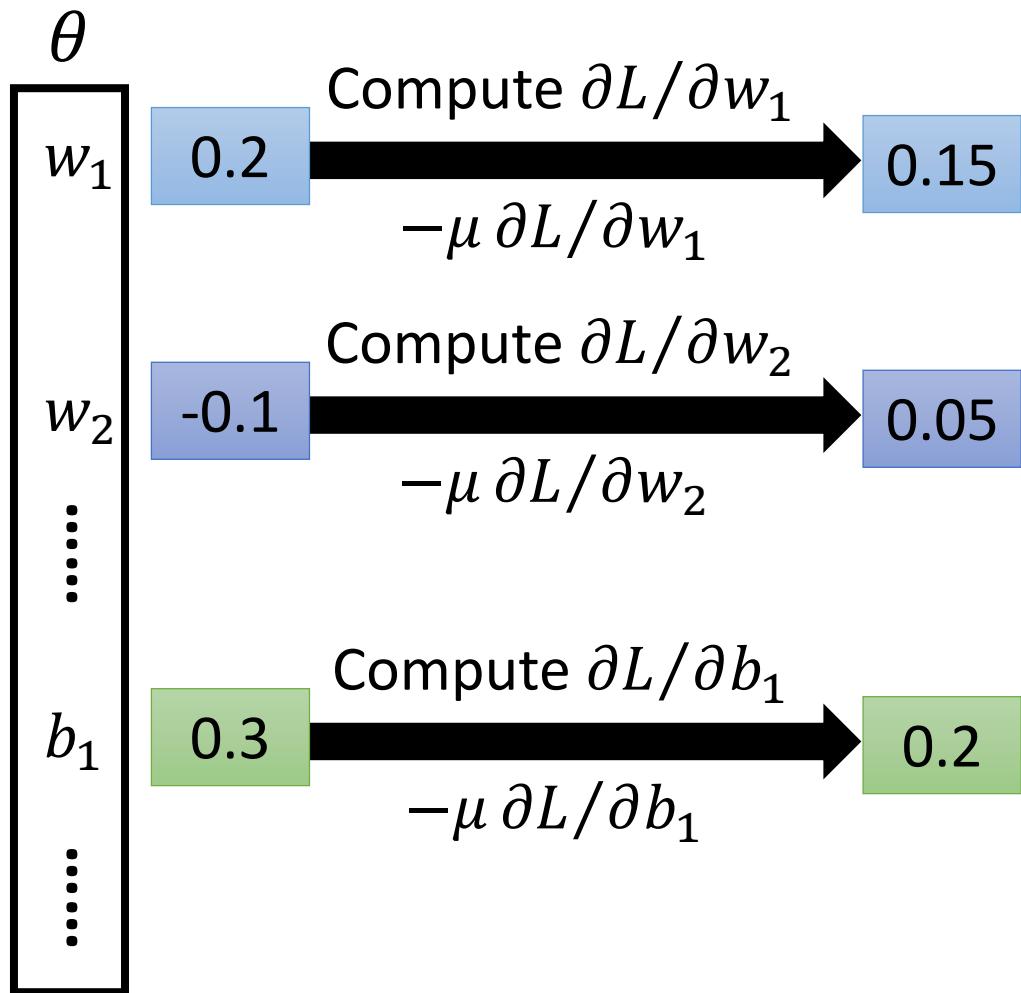
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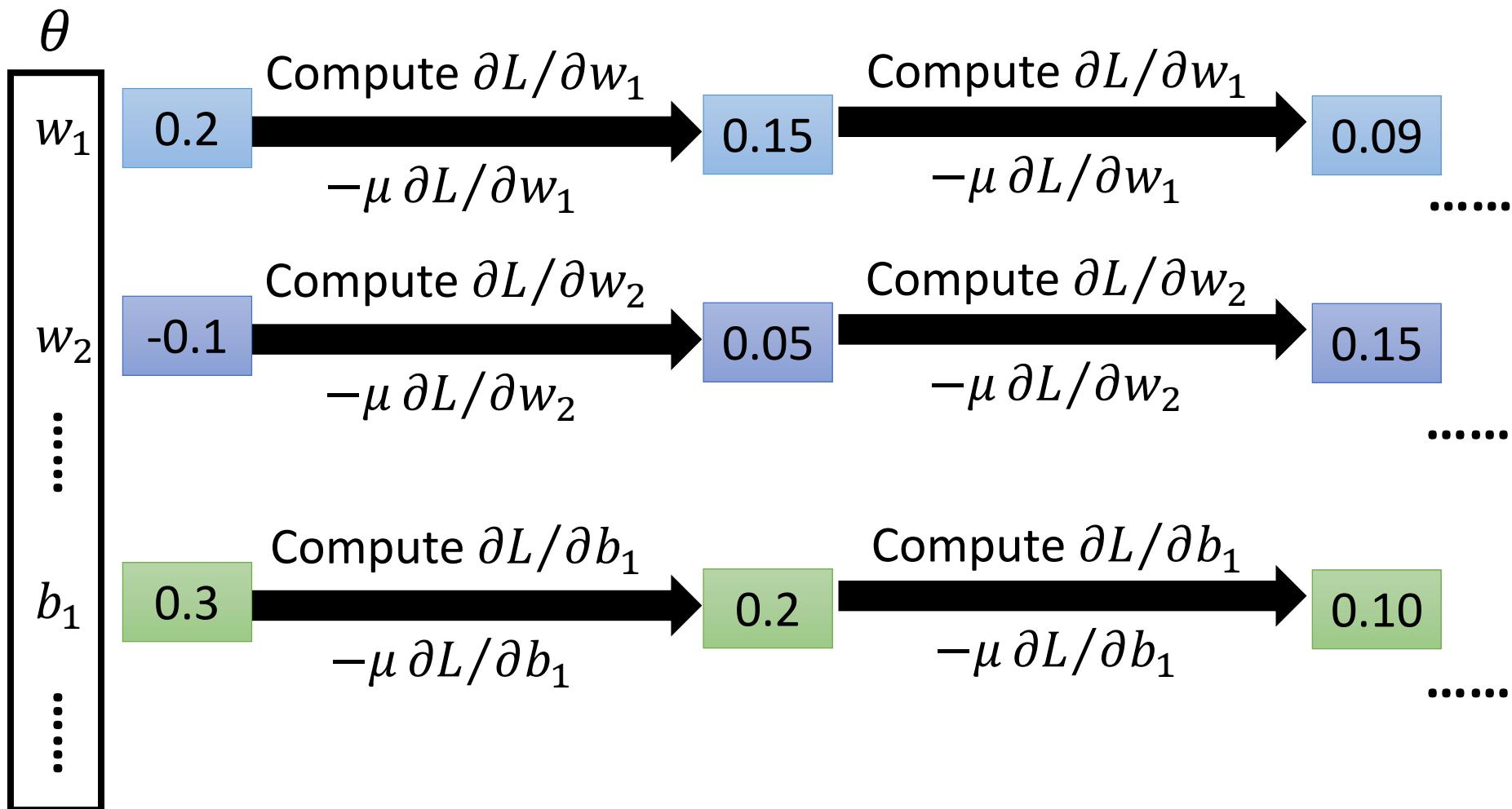
Gradient Descent



$$\nabla L = \begin{bmatrix} \frac{\partial L}{\partial w_1} \\ \frac{\partial L}{\partial w_2} \\ \vdots \\ \frac{\partial L}{\partial b_1} \\ \vdots \end{bmatrix}$$

gradient

Gradient Descent

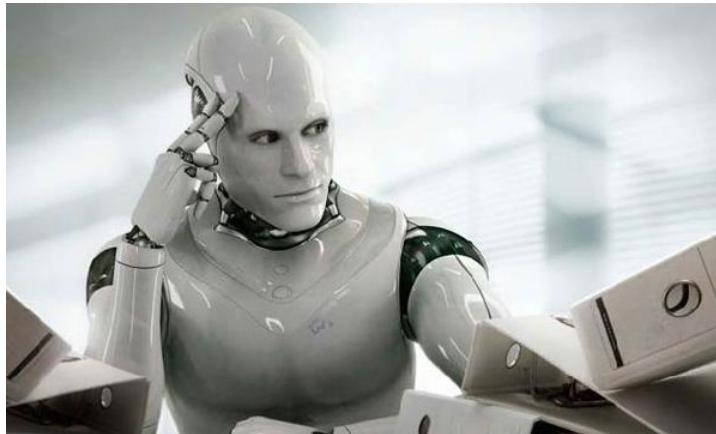


Gradient Descent

This is the “learning” of machines in deep learning

→ Even alpha go using this approach.

People image



Actually



I hope you are not too disappointed :p

Backpropagation

- Backpropagation: an efficient way to compute $\partial L / \partial w$ in neural network



Caffe



theano



libdnn
台大周伯威
同學開發

Ref:

http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20backprop.ecm.mp4/index.html

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