Introduction to Deep Learning: NN, CNN, RNN and beyond

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VSLab

Deep Learning Tutorial

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http://www.slideshare.net/tw_dsconf/ss-62245351

Outline

Lecture I: Introduction of Deep Learning (DL)

Lecture II: ~~Tips for Training Deep Neural Network~~
DL in CV - Convolutional Neural Network

Lecture III: Deep Learning with Memory

Lecture I:
Introduction of Deep Learning

Outline of Lecture 1

Three Steps for Deep Learning

- The three steps can also apply on other machine learning methods

Why Deep Learning?

Three Steps for Deep Learning

Step 1: Network Structure

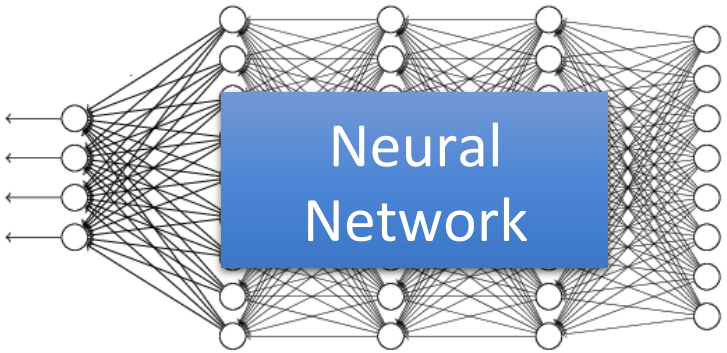
Step 2: Learning Target

Step 3: Learn!

天生的腦

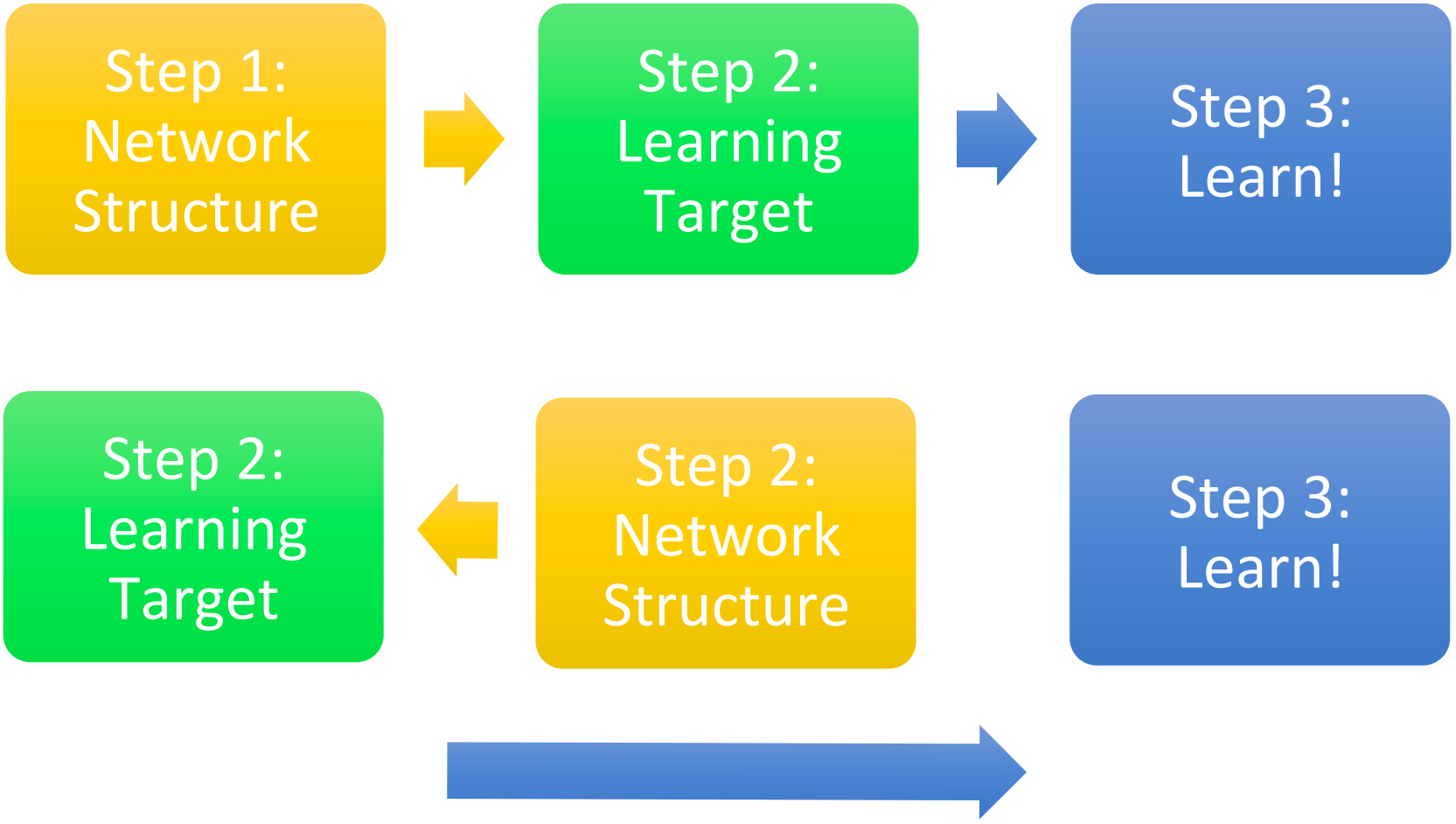
Three Steps for Deep Learning

Step 1: Network Structure → Step 2: Learning Target → Step 3: Learn!



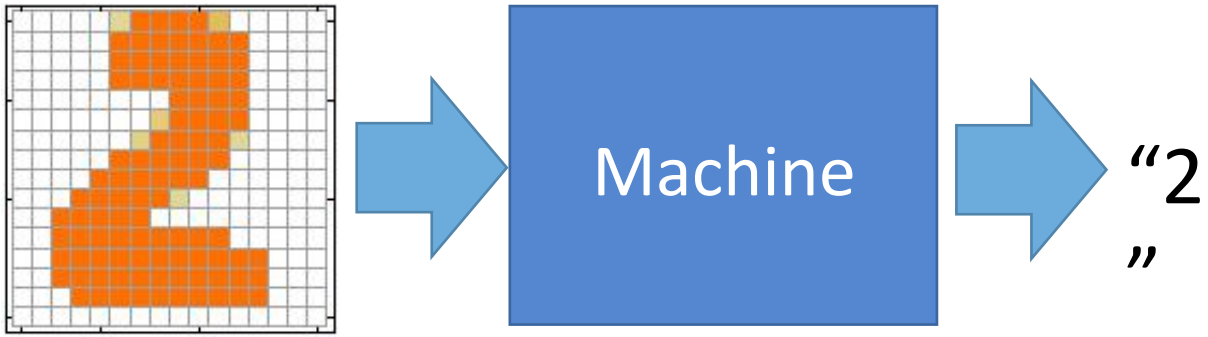
It can do image recognition, speech recognition, playing Go, etc. according to the learning target.

Three Steps for Deep Learning



Example Application

- Handwriting Digit Recognition



“Hello world” for deep learning

Data: http://yann.lecun.com/exdb/mnist/

Three Steps for Deep Learning

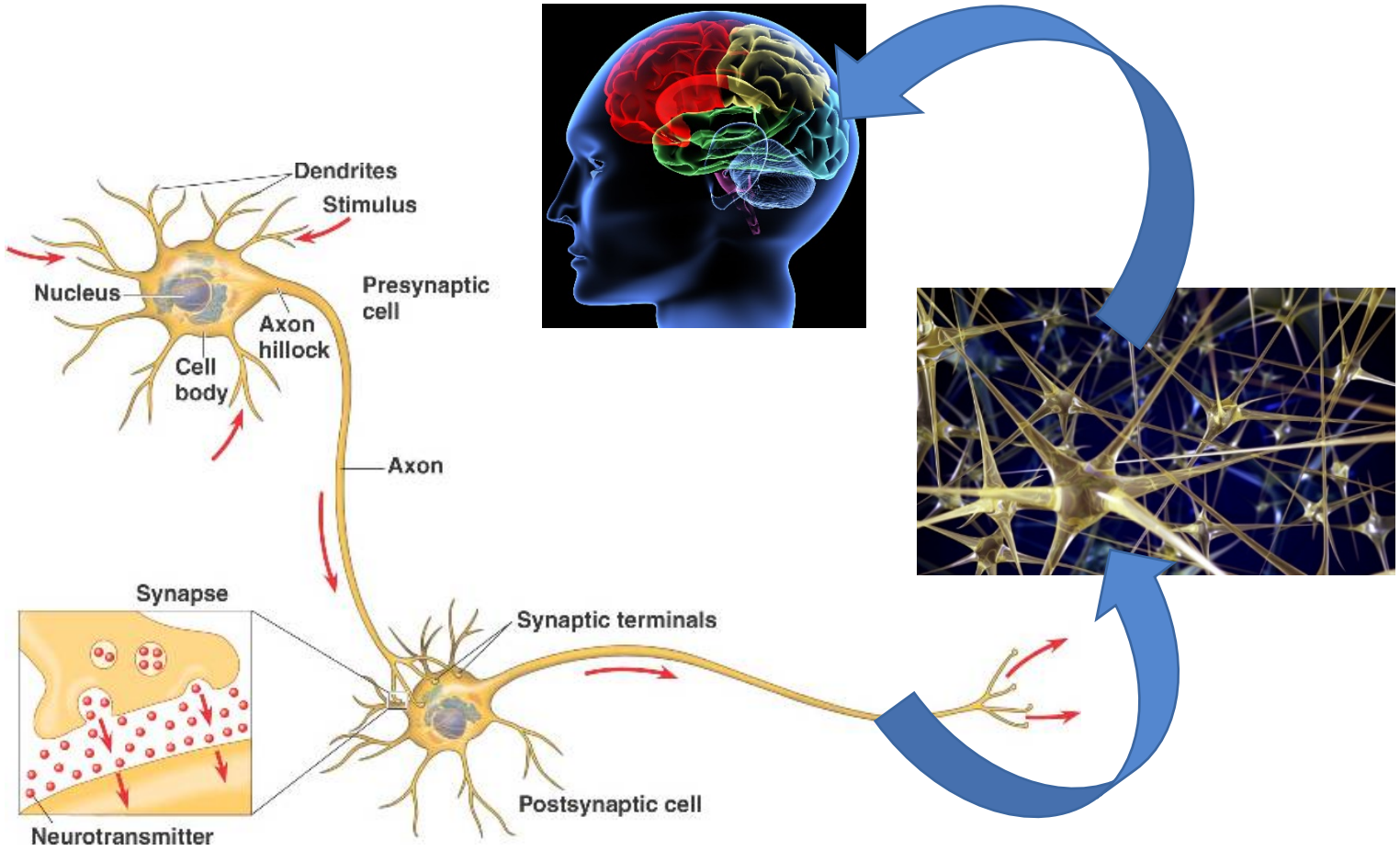
Step 1: Network Structure

Step 2: Learning Target

Step 3: Learn!

天生的腦

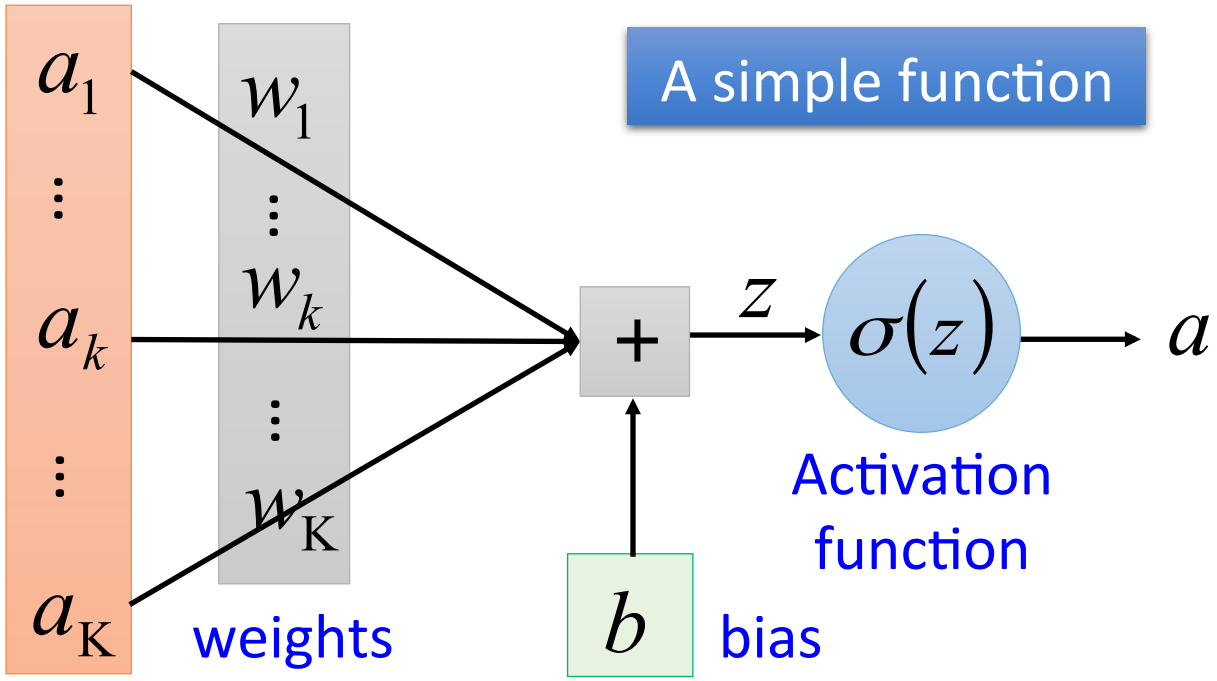
Human Brains



Neural Network

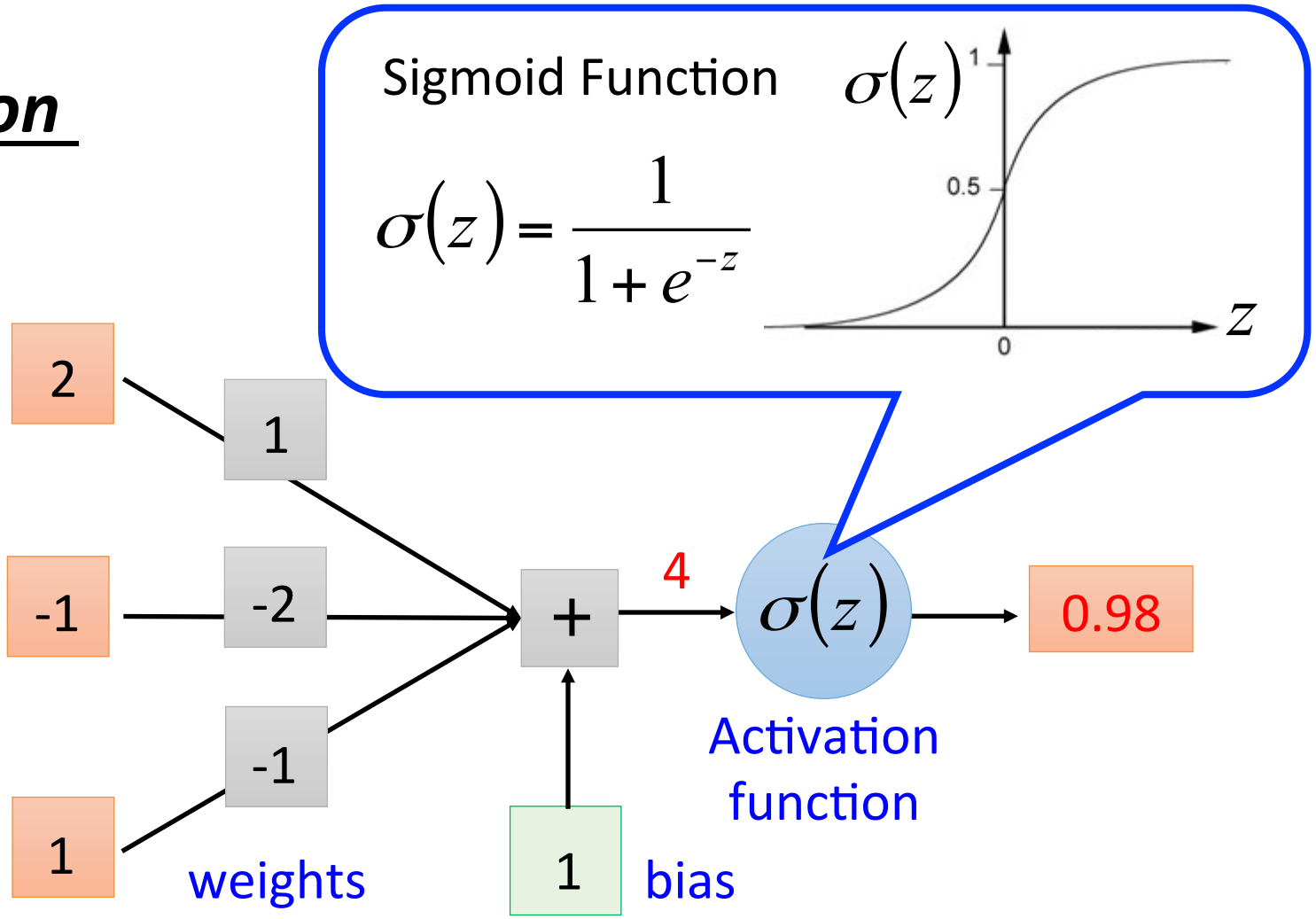
Neuron (a building block)

$$z = a_1 w_1 + \cdots + a_k w_k + \cdots + a_K w_K + b$$

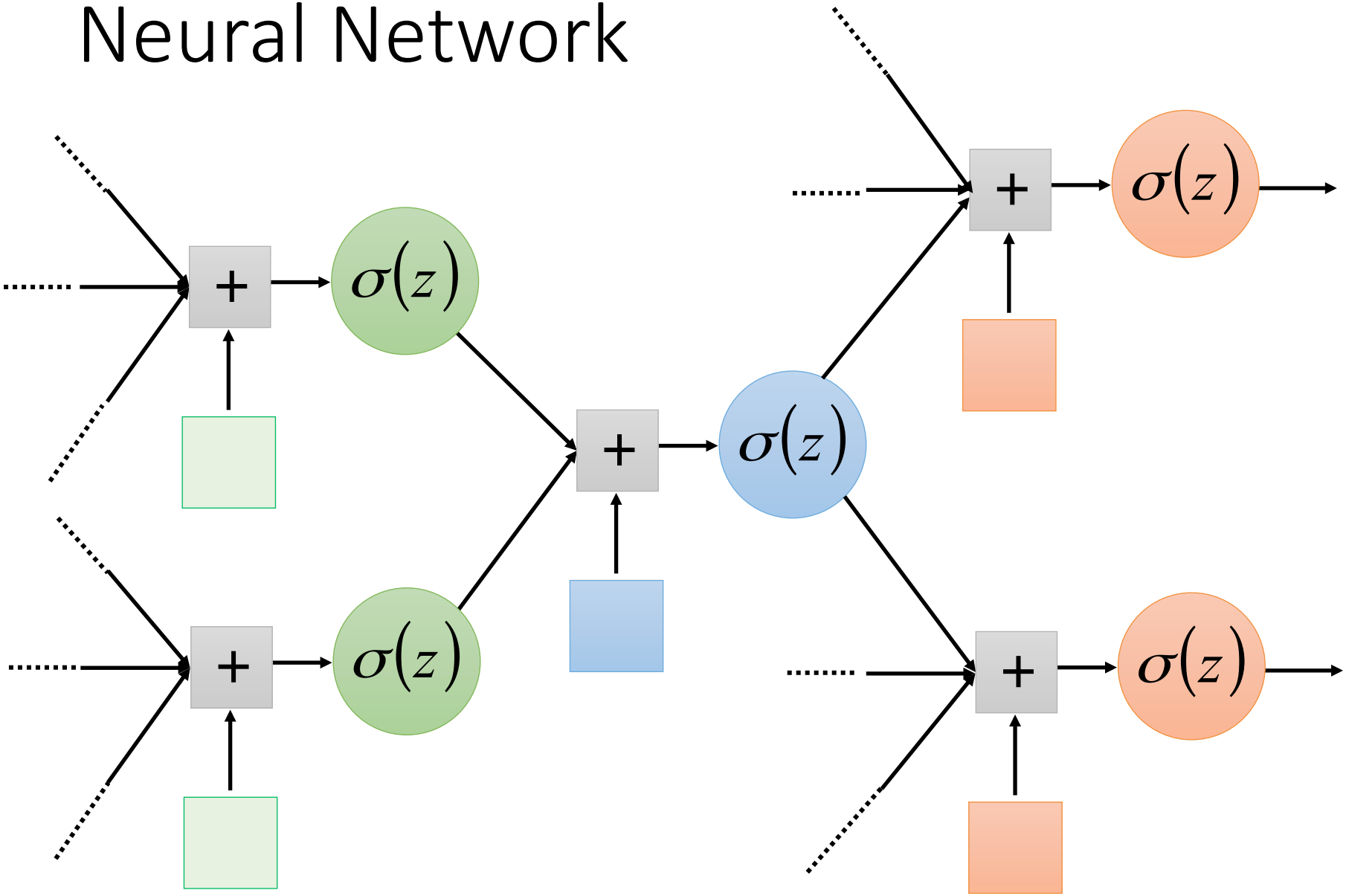


Neural Network

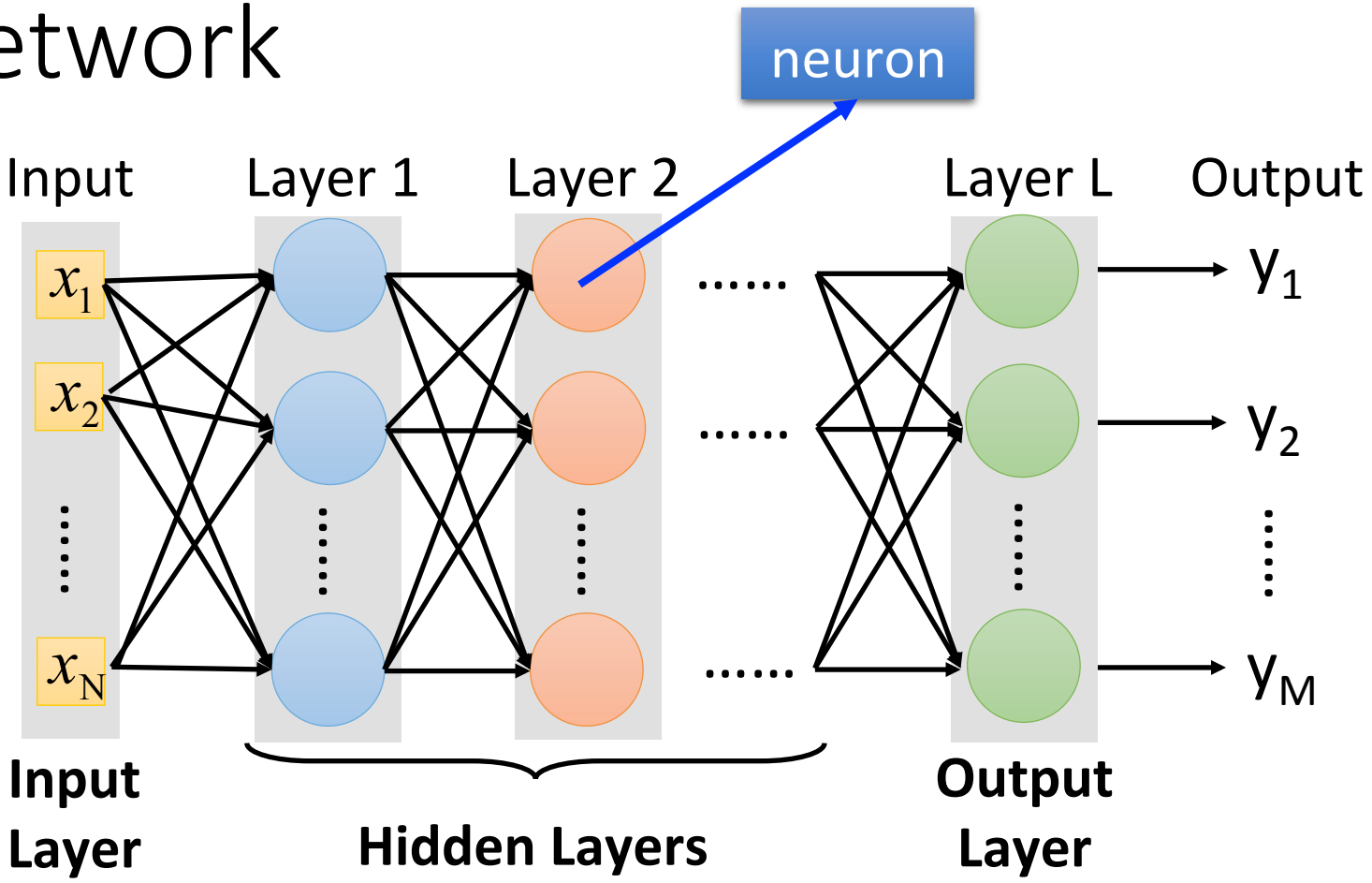
Neuron



Neural Network



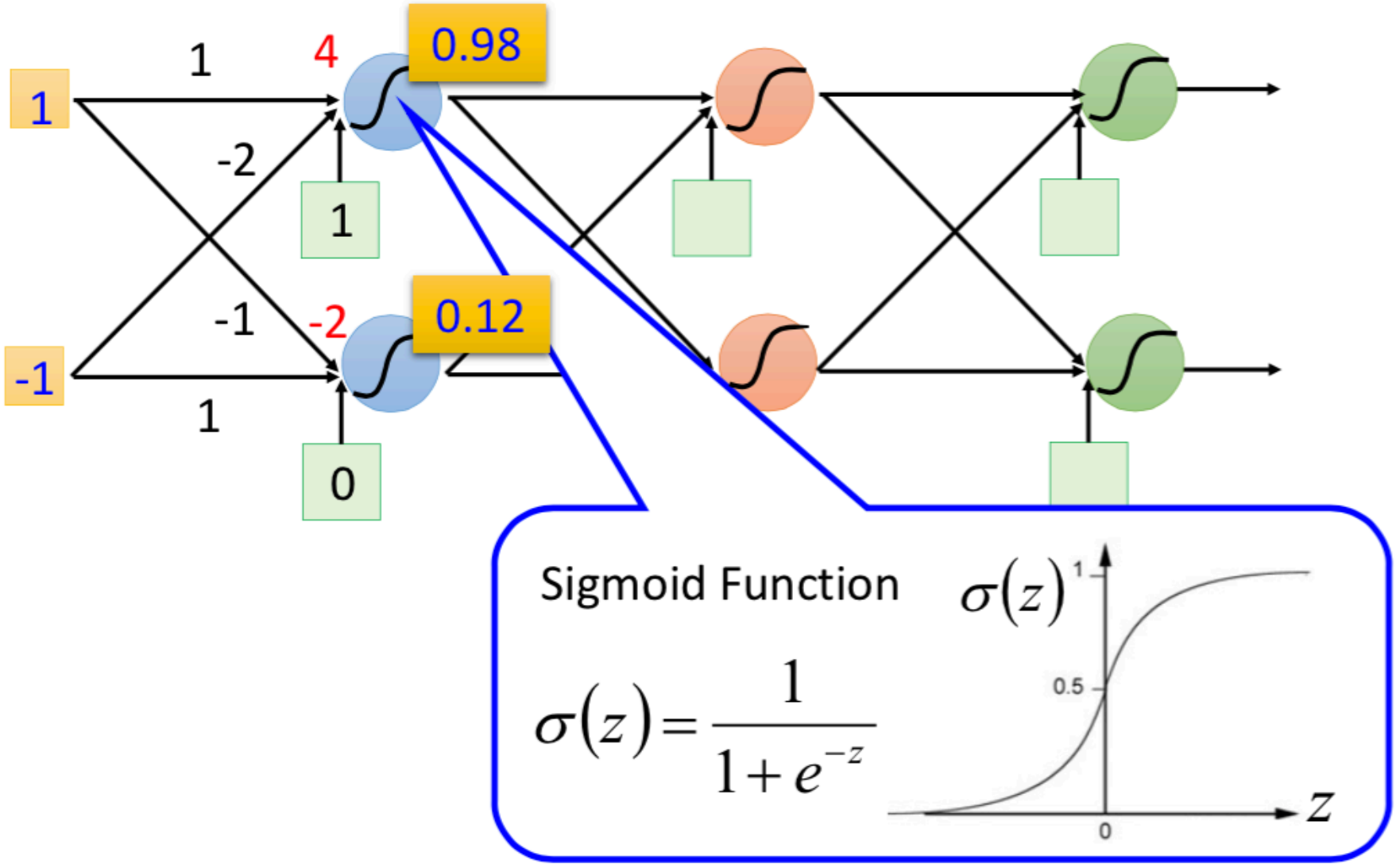
Fully Connect Feedforward Network



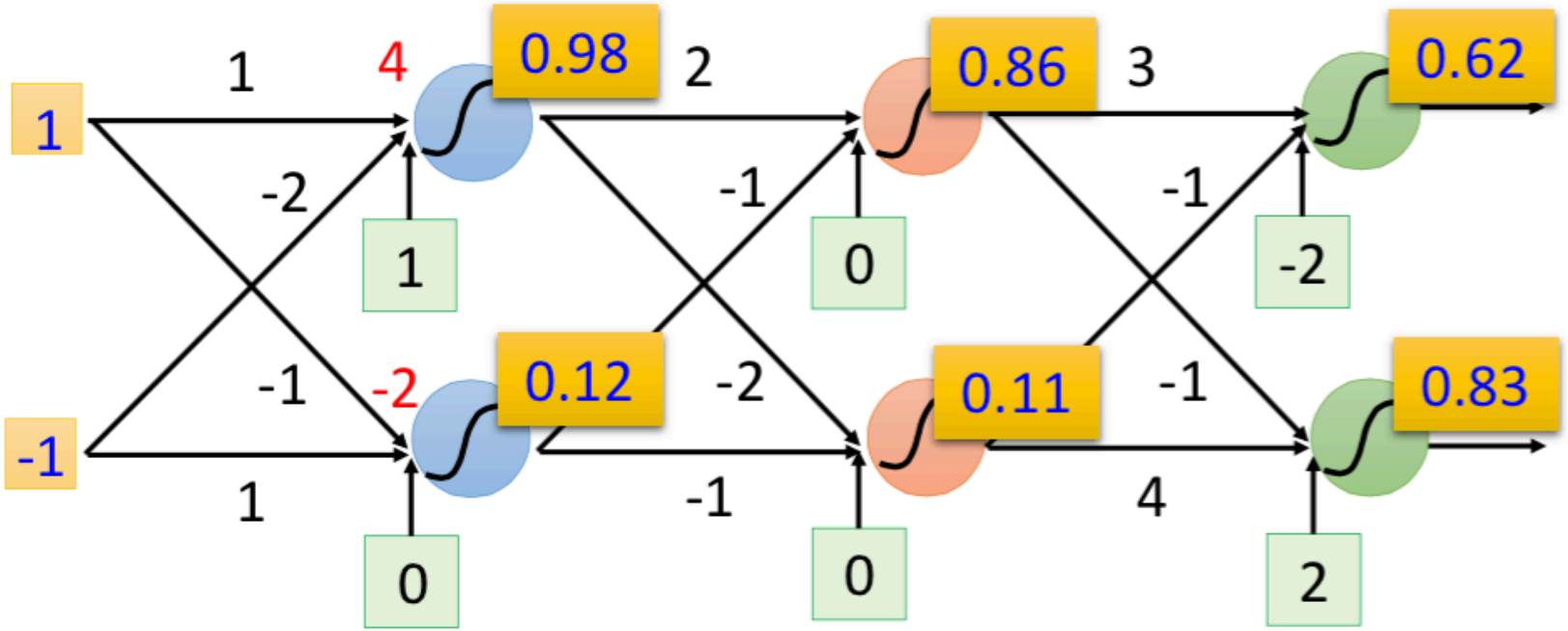
Deep means many hidden layers

You can connect the neurons by other ways you like ☺

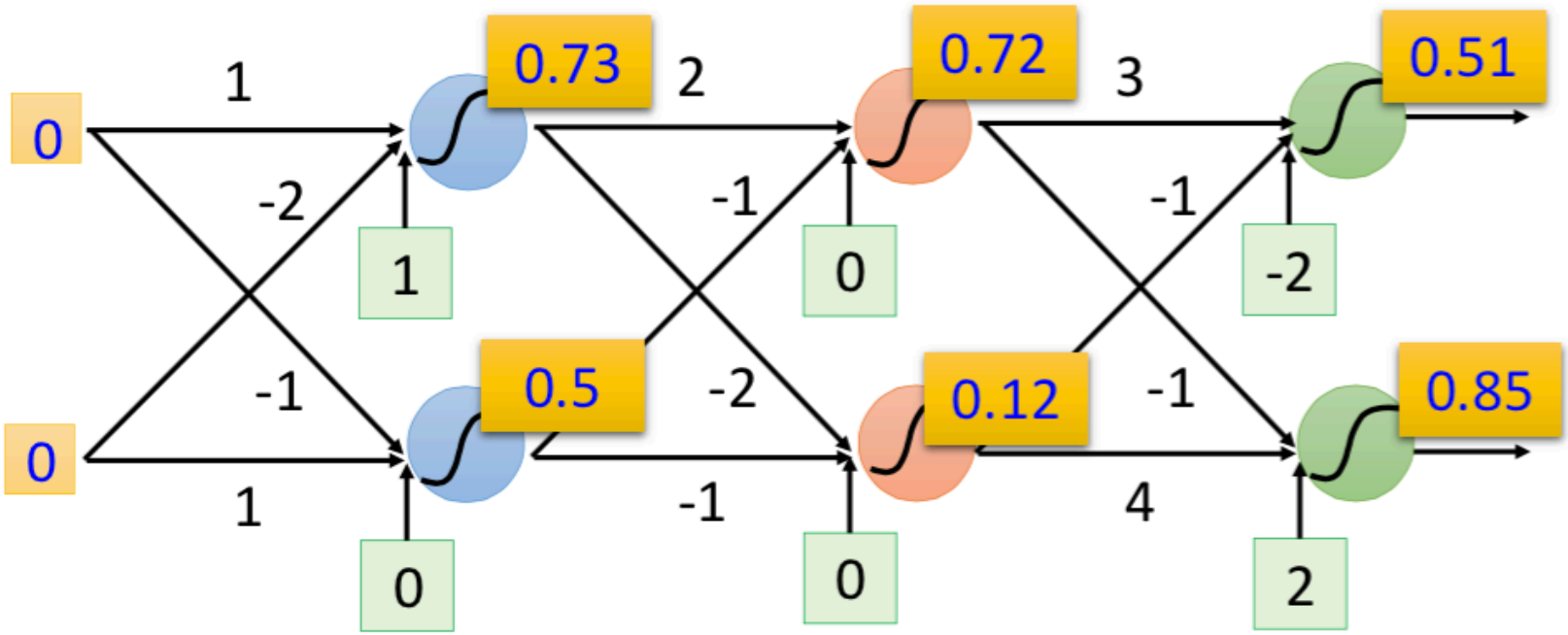
Fully Connect Feedforward Network



Network



Fully Connect Feedforward Network



Network is a function.

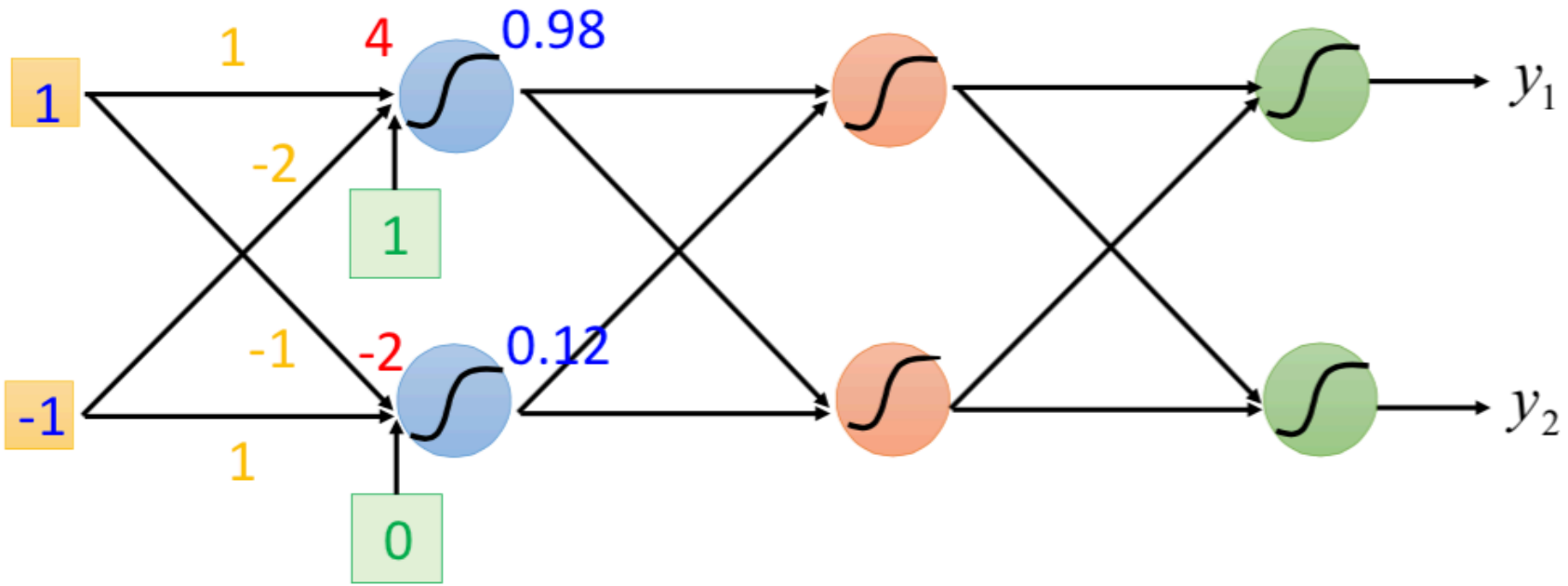
Input vector, output vector

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

Weights and biases are network parameters θ

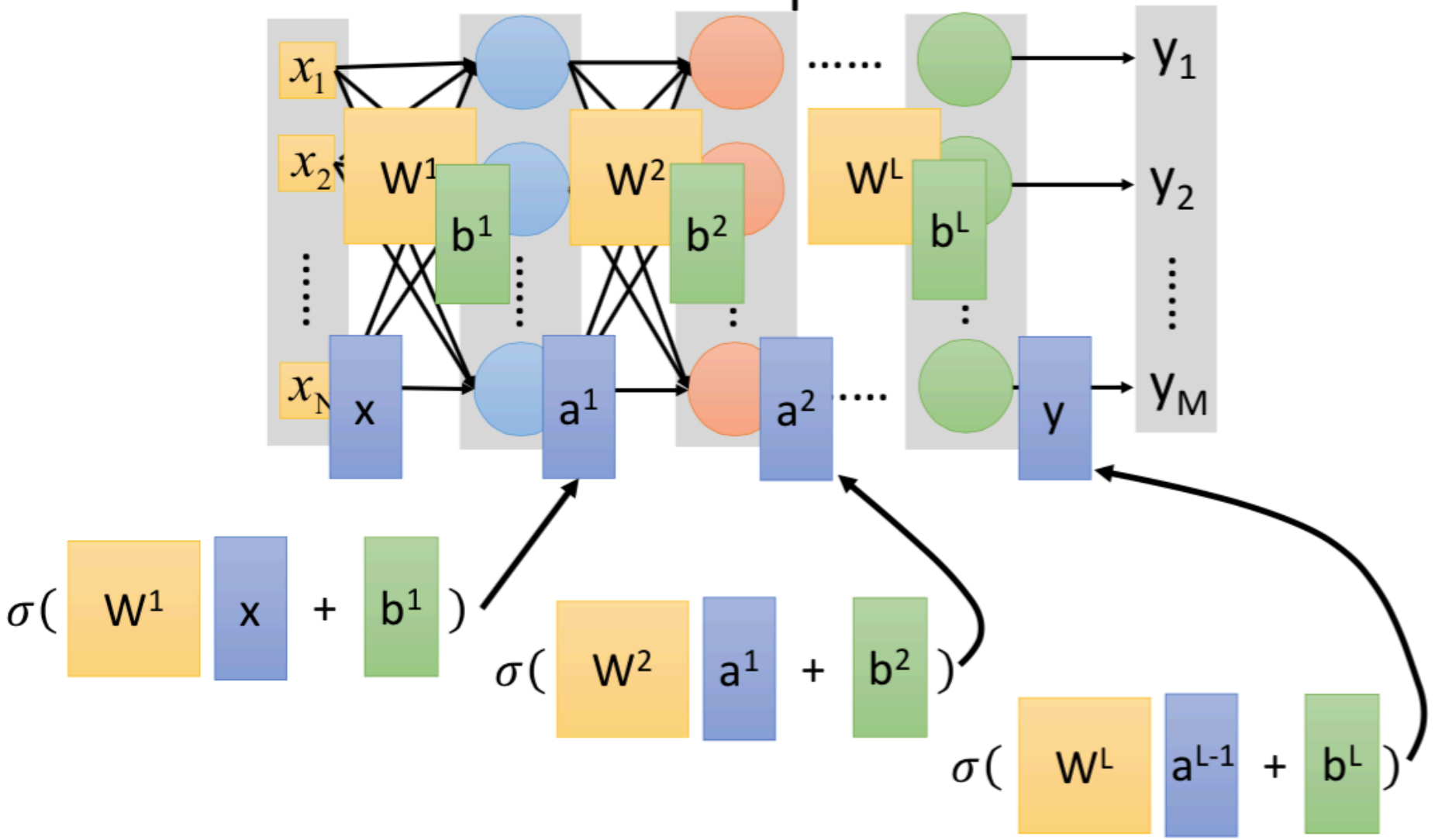
Different parameters θ define different functions

Network - Matrix Operation

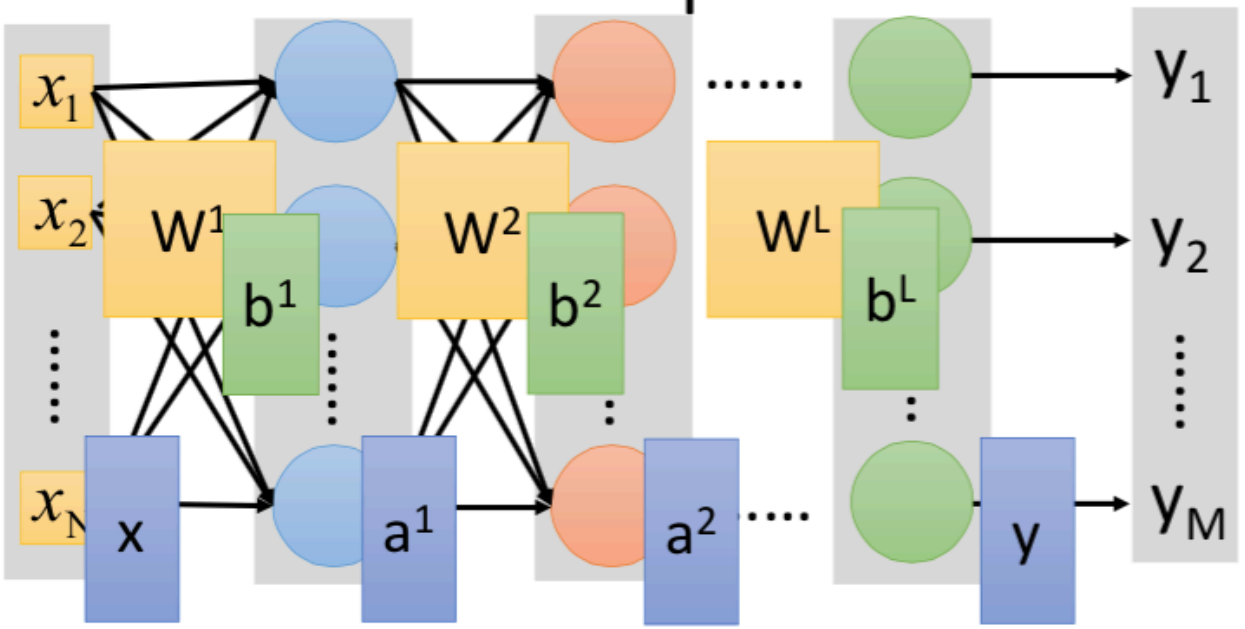


$$\sigma\left(\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Fully Connect Feedforward Network - Matrix Operation



Fully Connect Feedforward Network - Matrix Operation



$$\mathbf{y} = f(\mathbf{x})$$

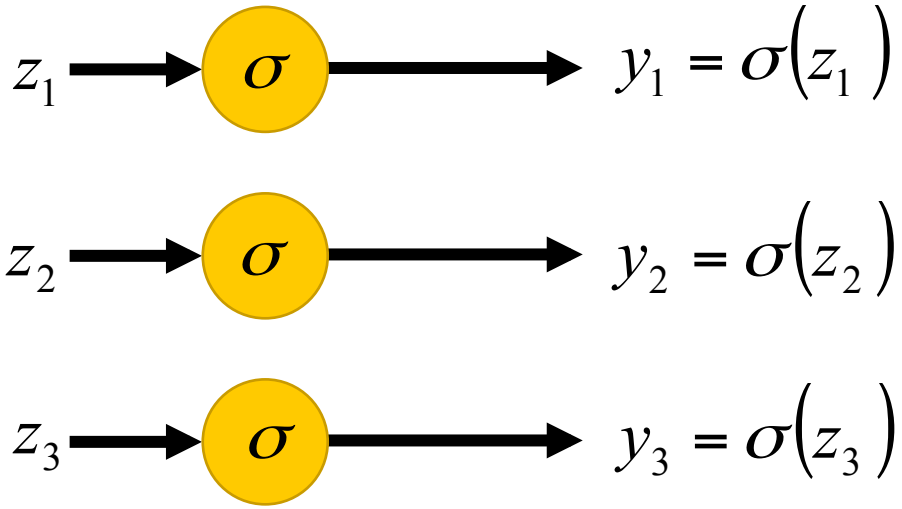
Using parallel computing techniques to speed up matrix operation

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

Output Layer

- Softmax layer as the output layer

Ordinary Layer



In general, the output of network can be any value.

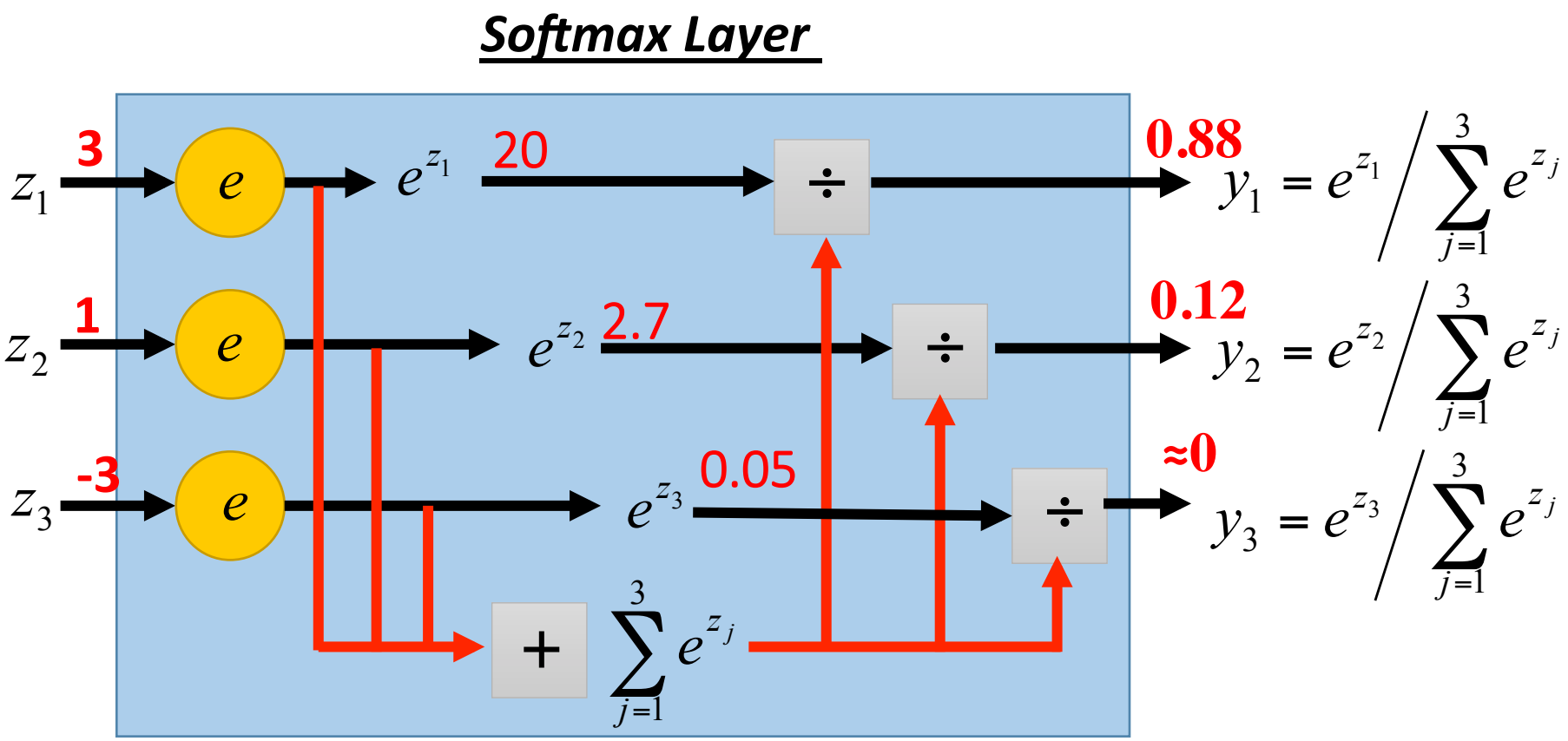
May not be easy to interpret

Output Layer

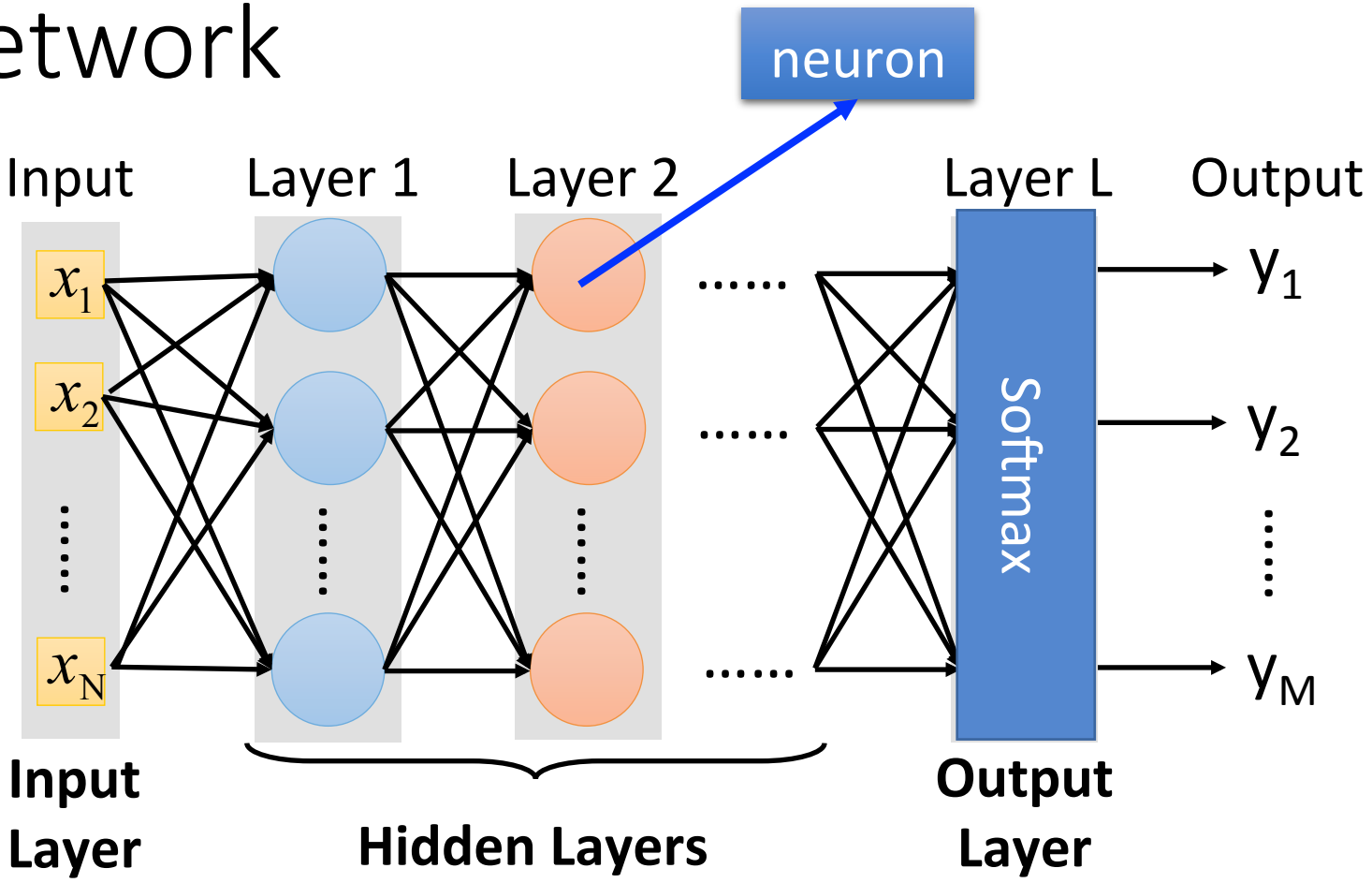
- Softmax layer as the output layer

Probability:

- $0<y_i<1$
- $\text{sum}_i\, y_i = 1$



Fully Connect Feedforward Network



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

Ans: I don't know.

Three Steps for Deep Learning

Step 1: Network Structure

Step 2: Learning Target

Step 3: Learn!

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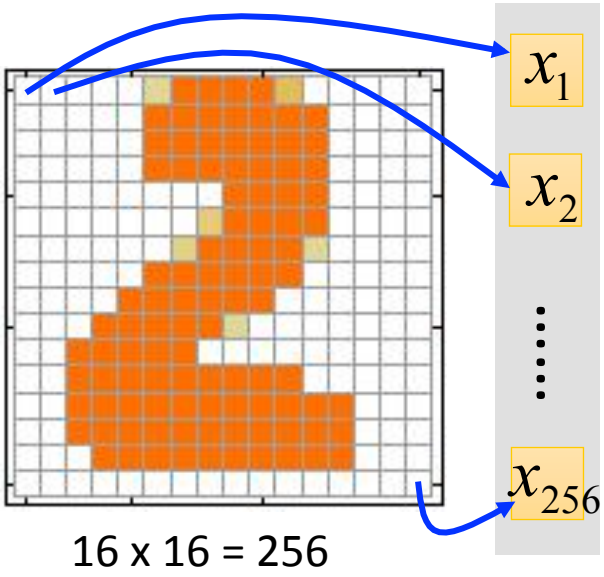
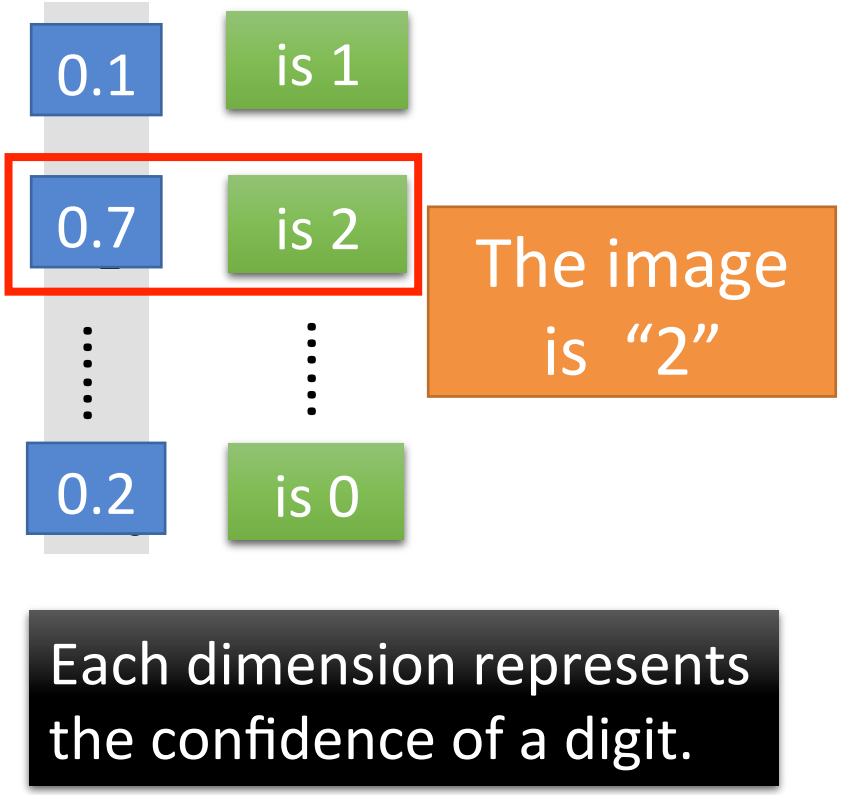
Back to Example Application

Input

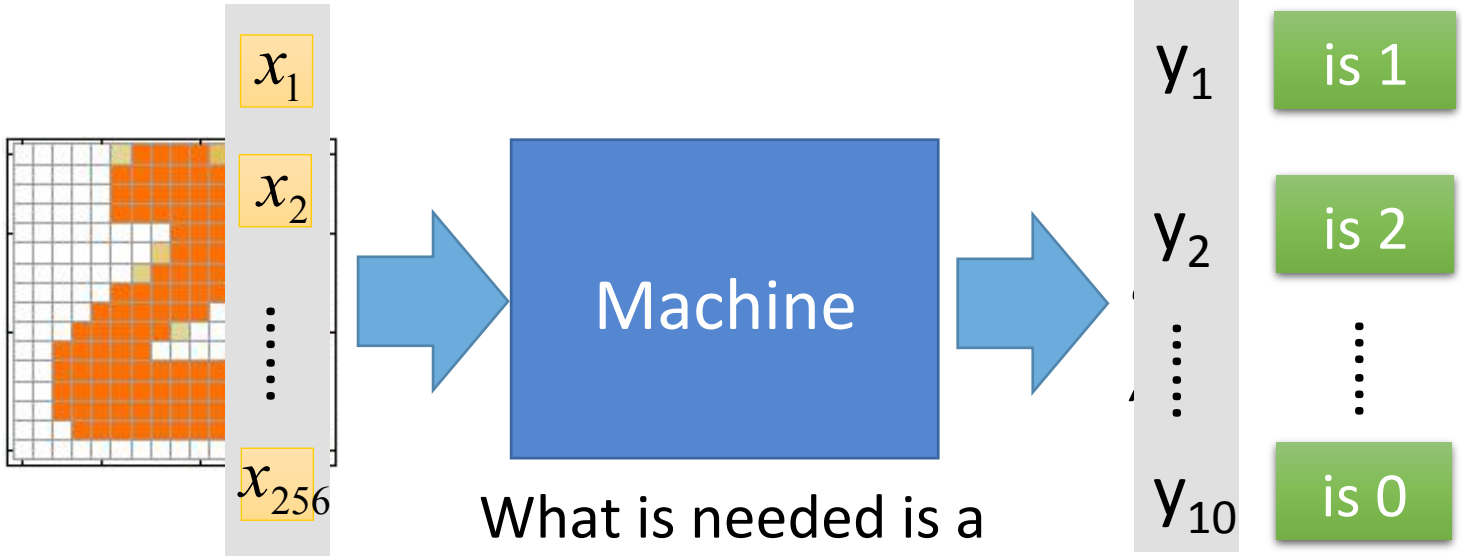


Output



Back to Example Application

- Handwriting Digit Recognition

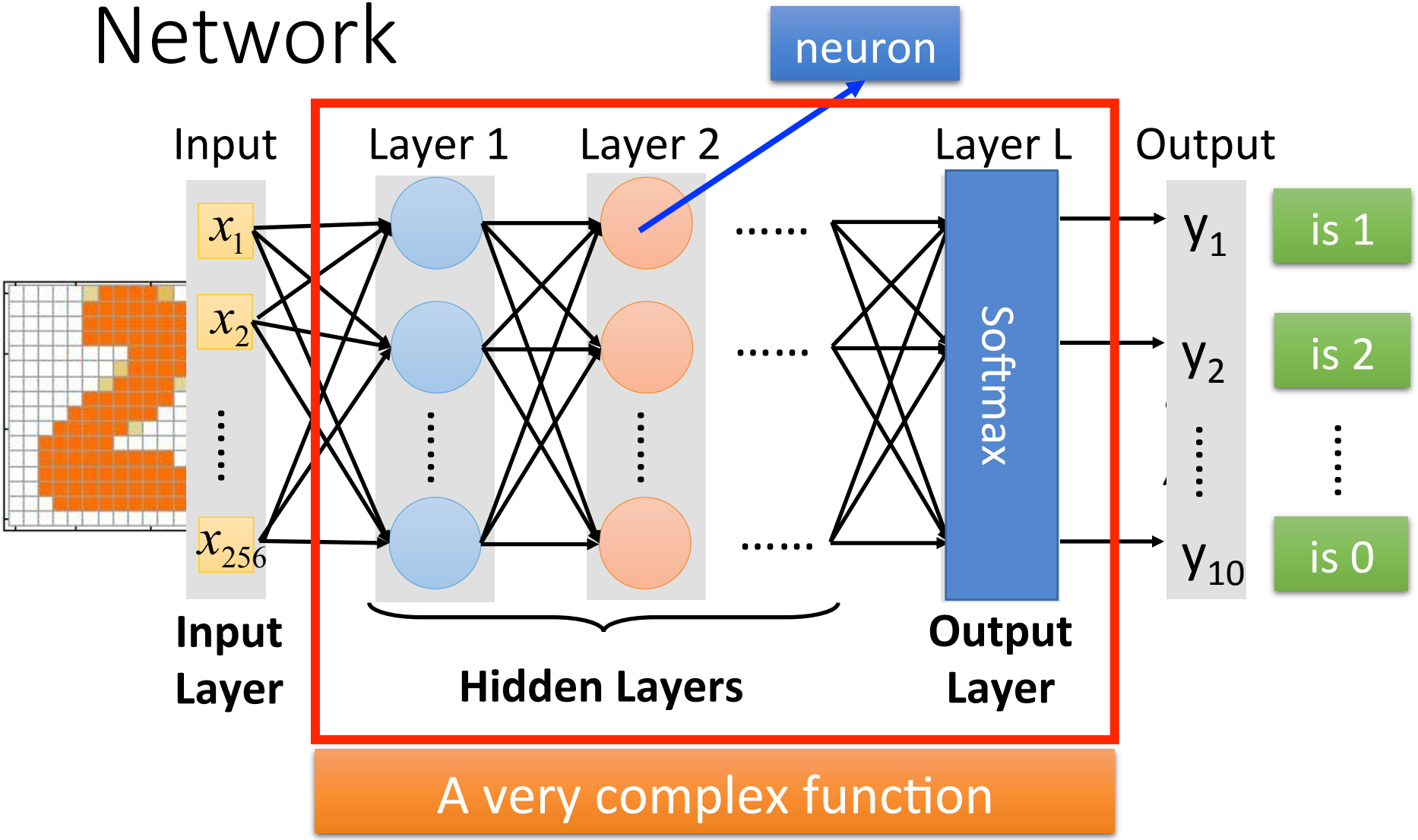


What is needed is a function ……

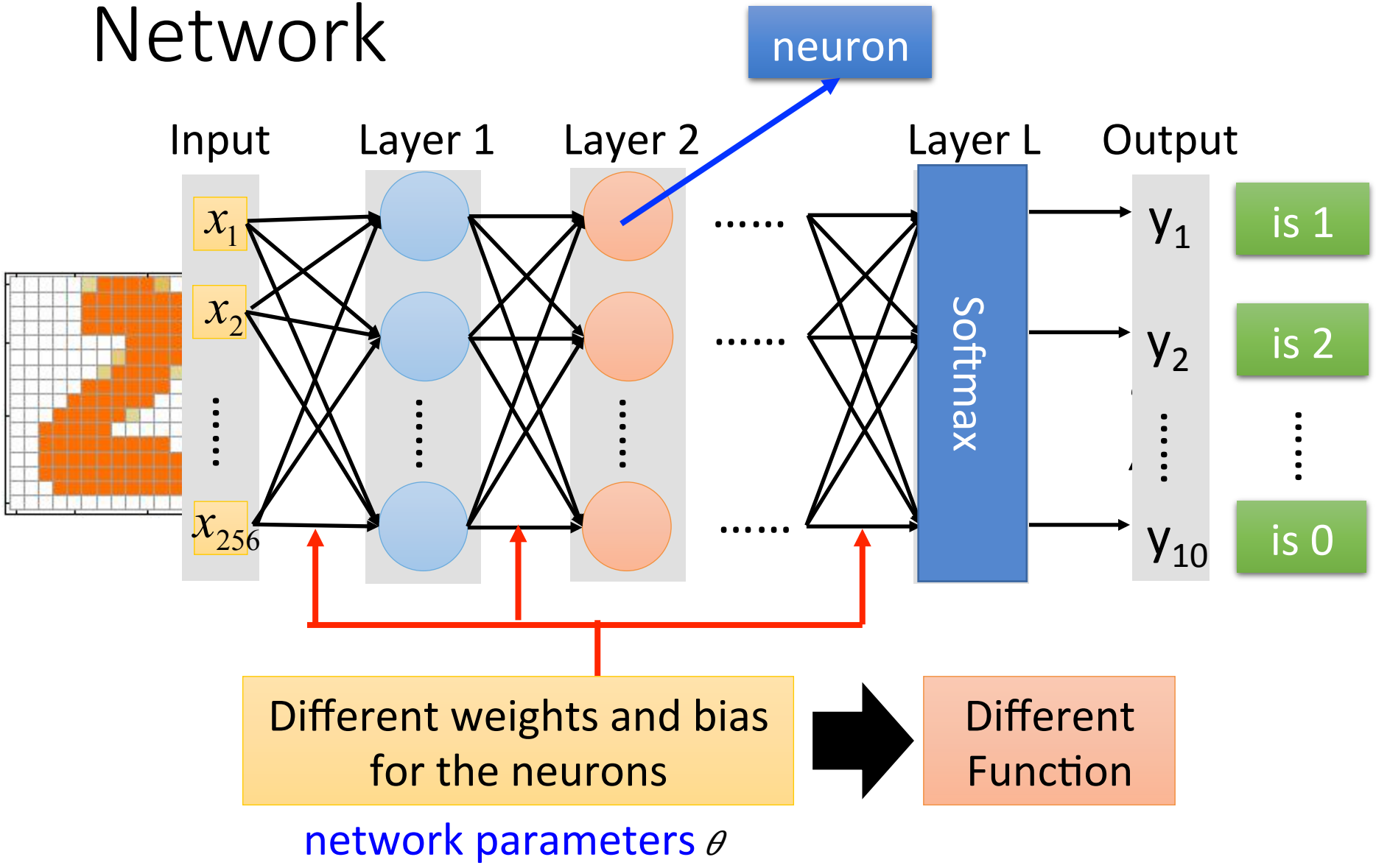
Input:
256-dim vector

output:
10-dim vector

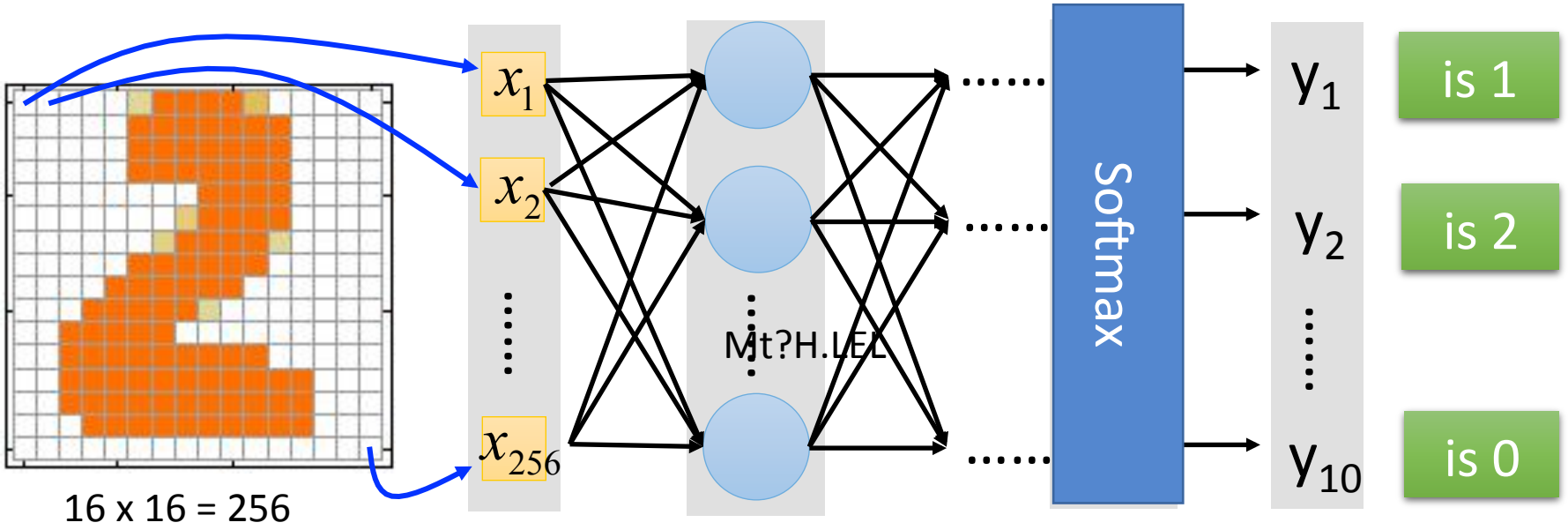
Fully Connect Feedforward Network



Fully Connect Feedforward Network



Learning Target



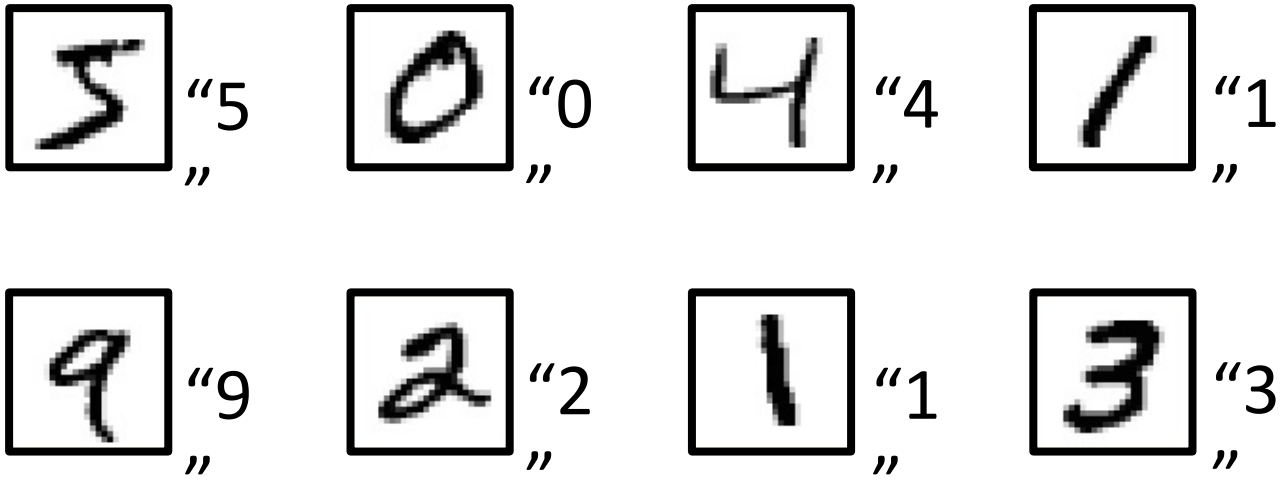
The learning target is ……

Input:  y_1 has the maximum value

Input:  y_2 has the maximum value

Training Data (Supervised Training)

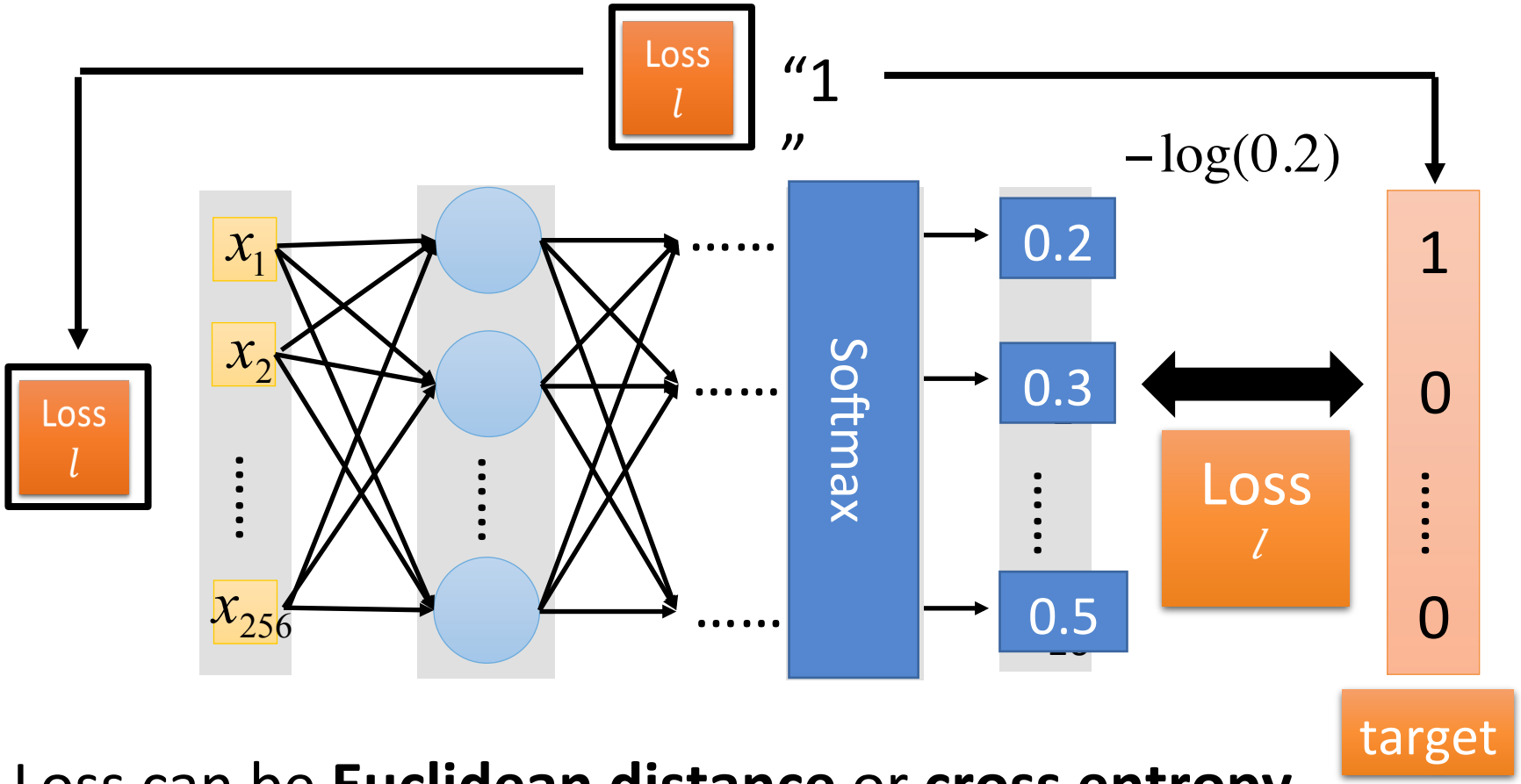
- Preparing training data: images and their labels



The learning target is defined on the training data.

Loss

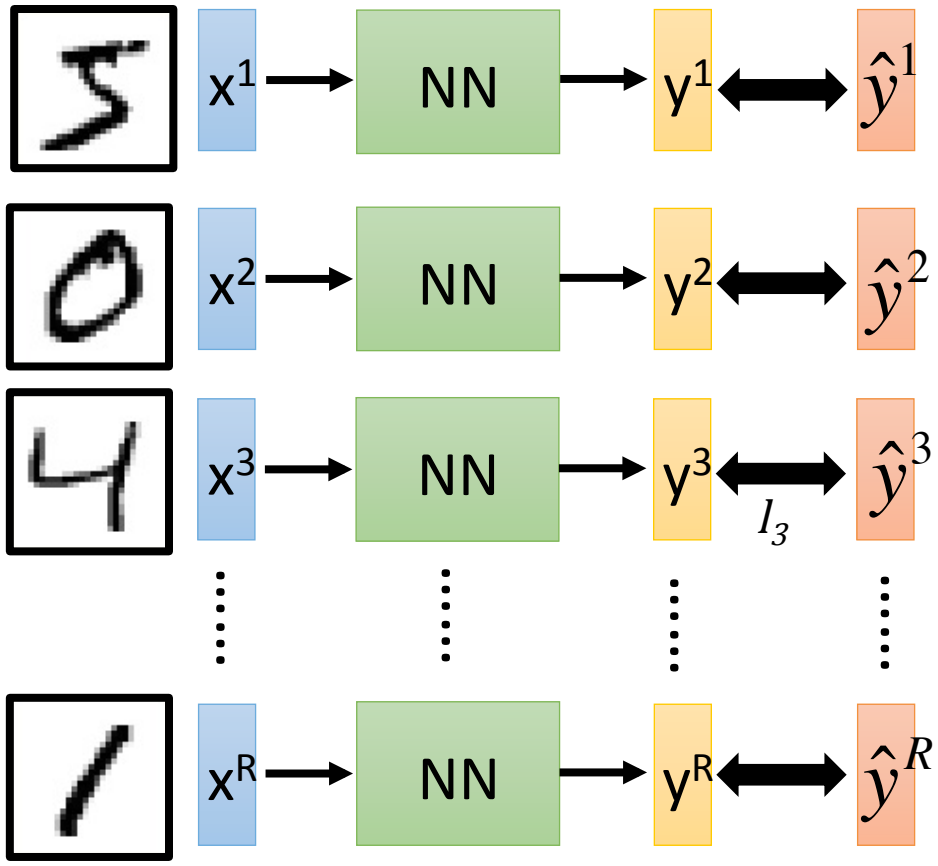
Given a set of network parameters θ, each example has a loss value.



Loss can be **Euclidean distance** or **cross entropy** between the network output and target

Total Loss

For all training data …



Total Loss:

$$L = \sum_{r=1}^{R} l_r$$

Find the network parameters θ* that minimize total loss

Next Step

Three Steps for Deep Learning

Step 1: Network Structure

Step 2: Learning Target

Step 3: Learn!

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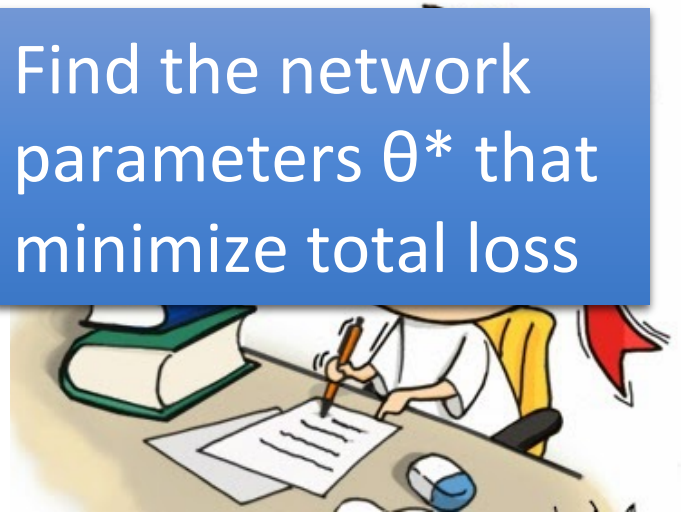
Find the network parameters θ* that minimize total loss



How to Learn?

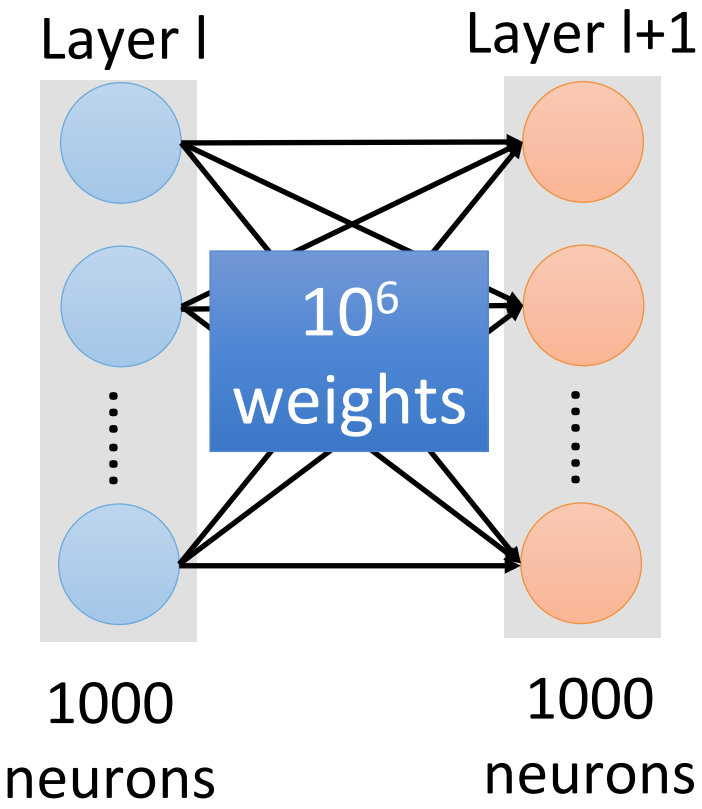
Find the network parameters θ* that minimize total loss

Enumerate all possible values

Network parameters

Millions of parameters

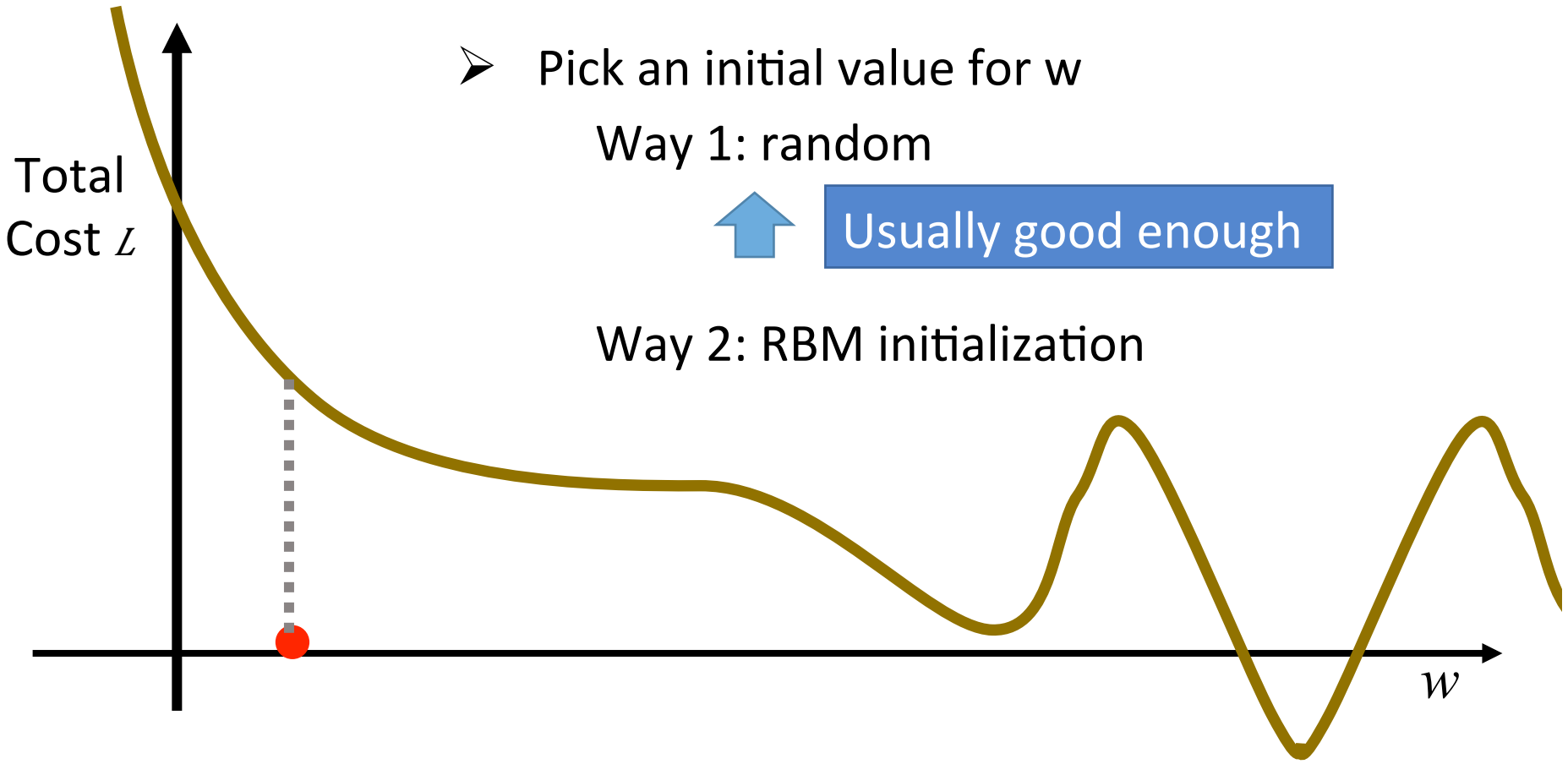
E.g. speech recognition: 8 layers and 1000 neurons each layer



Gradient Descent

Network parameters

Find the network parameters θ* that minimize total loss



- Pick an initial value for w

  Way 1: random

  Usually good enough

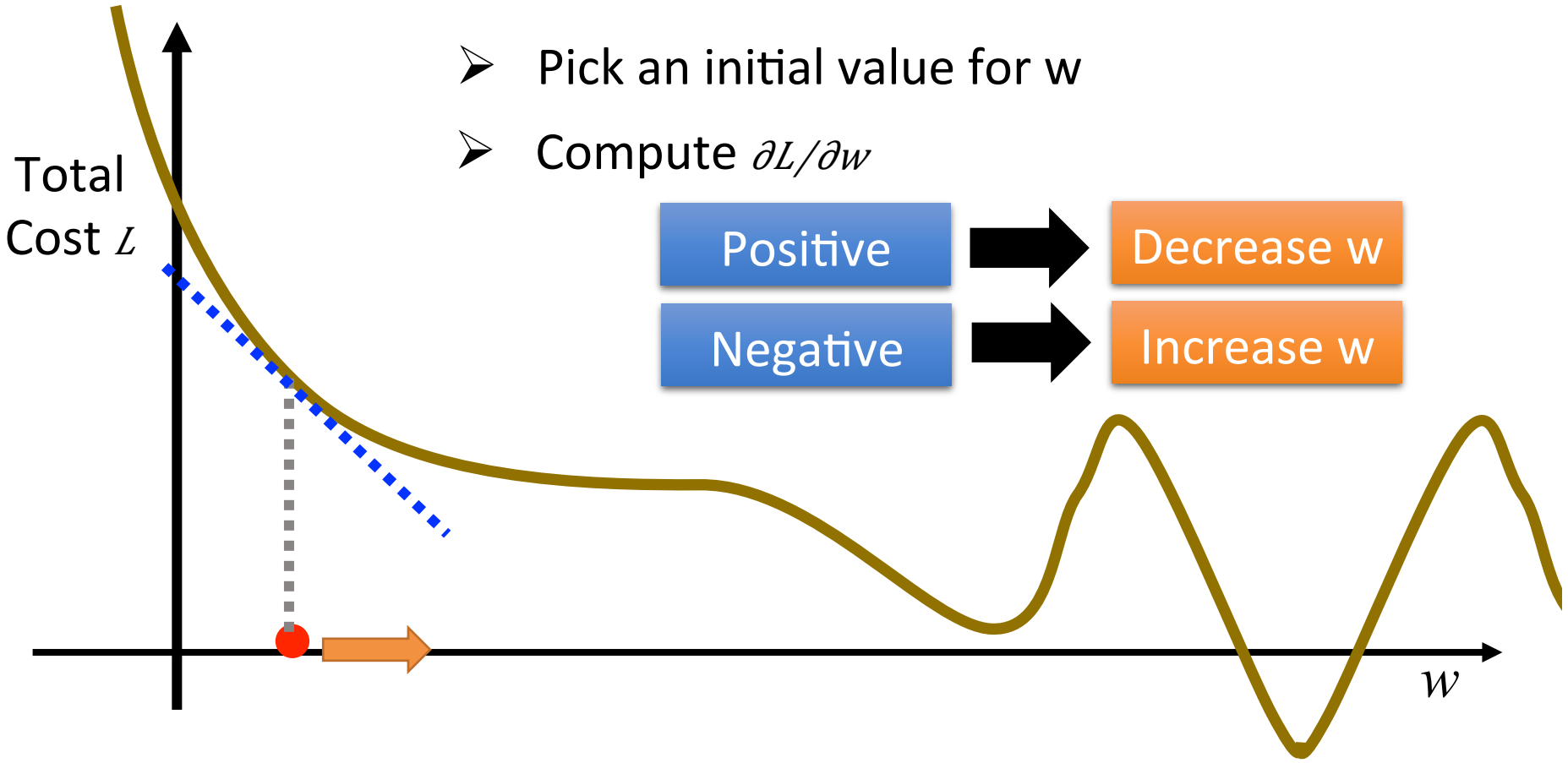
  Way 2: RBM initialization

Gradient Descent

Network parameters

Find the network parameters θ* that minimize total loss

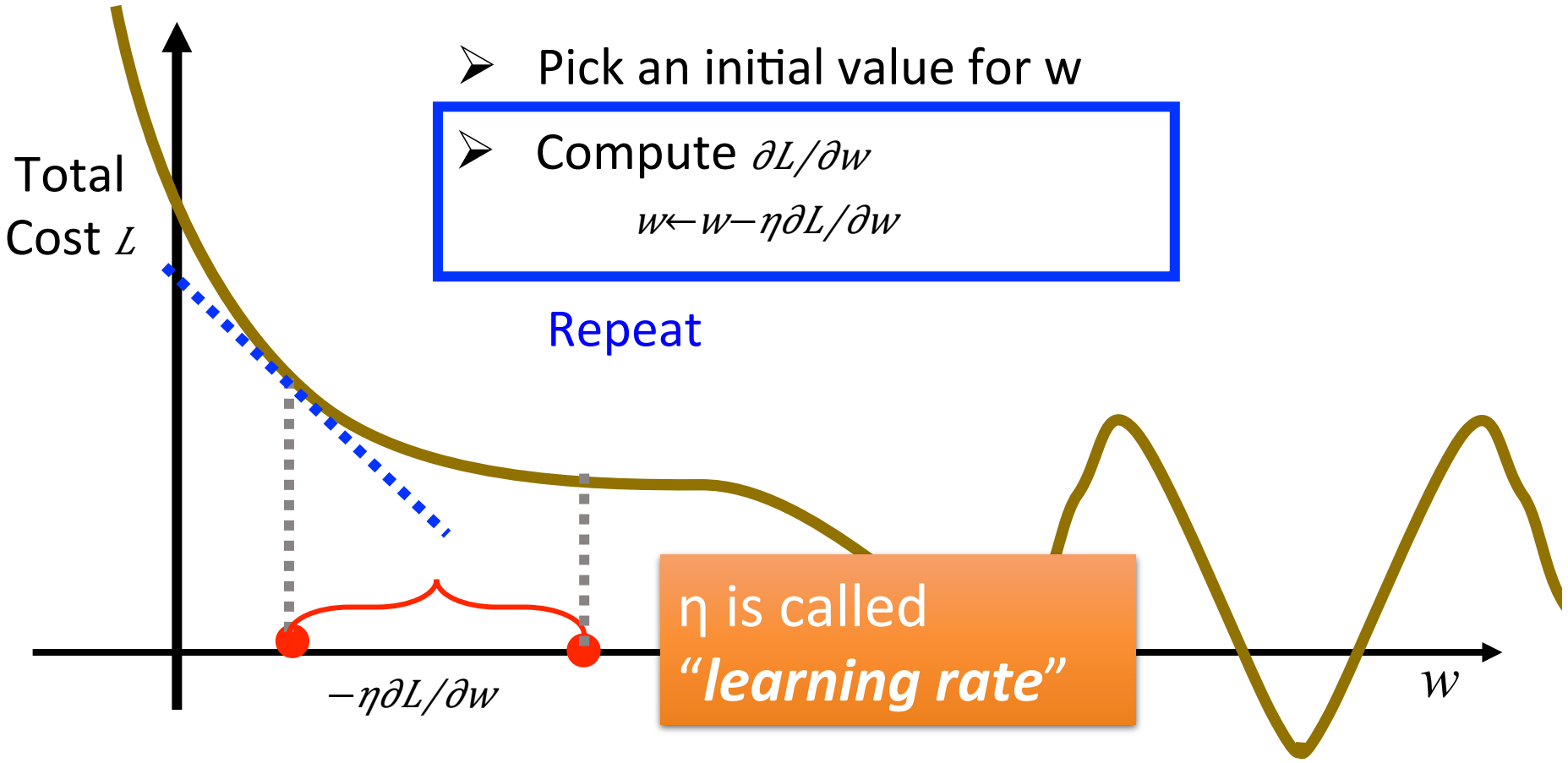
- Pick an initial value for w
- Compute $\partial L/\partial w$



Gradient Descent

Network parameters

Find the network parameters θ* that minimize total loss



Gradient Descent

Network parameters

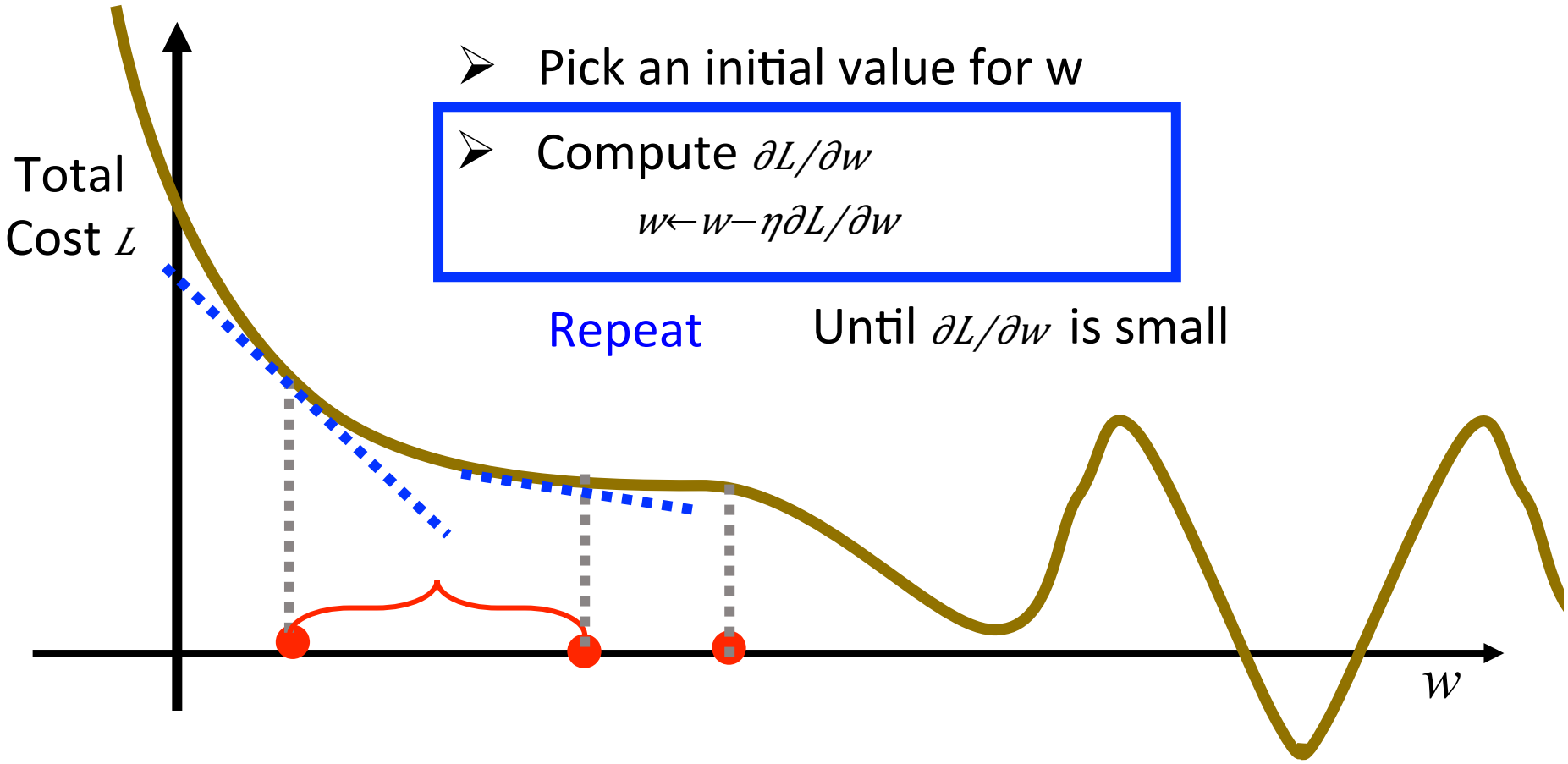
Find the network parameters θ* that minimize total loss

- Pick an initial value for w
- Compute $\partial L/\partial w$

$$w \leftarrow w - \eta \partial L/\partial w$$

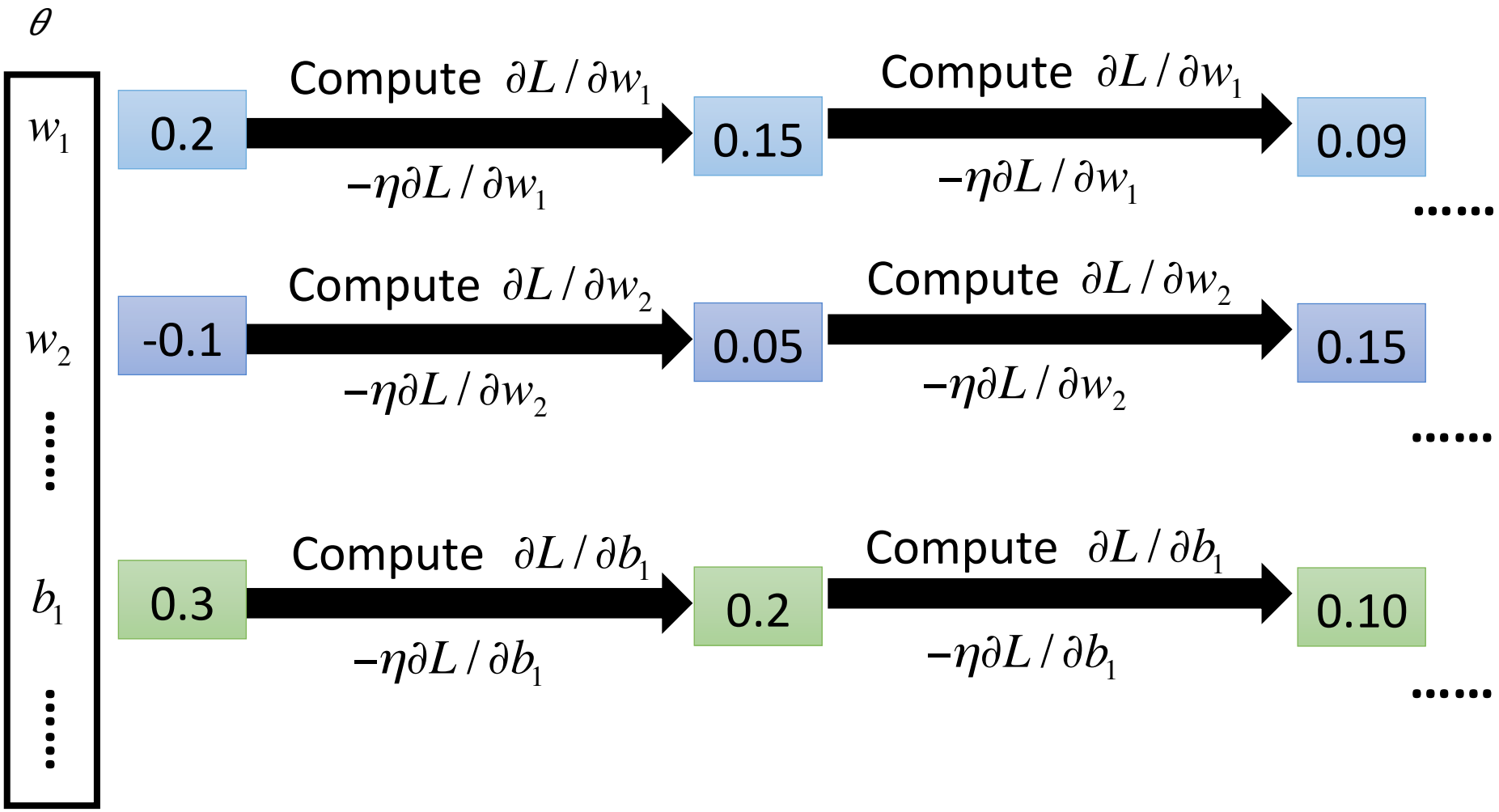
Repeat

Until $\partial L/\partial w$ is small



Gradient Descent

- Compute




2/0
Imperial Age
想像你在玩世紀帝國.....
$(-\eta\,\partial L/\partial w_1, -\eta\,\partial L/\partial w_2)$
Compute $\partial L/\partial w_1, \partial L/\partial w_2$
w_2
w_1
AGE OF EMPIRES II
HD EDITION

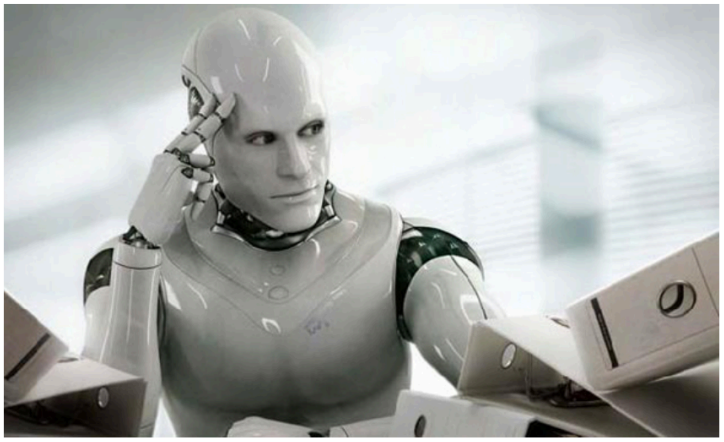
Gradient Descent

This is the “learning” of machines ……

Speech recognition, image recognition and alpha go, etc. use this learning approach.

➡ Even alpha go using this approach.

大家以為 Learning 是 ……



其實 Learning 只是 ……

I hope you are not too disappointed :p

Backpropagation

- Backpropagation: an efficient way to compute $\partial L/\partial w$
  - Ref: http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Theano%20DNN.ecm.mp4/index.html

theano

libdnn
台大周伯威
同學開發

Caffe

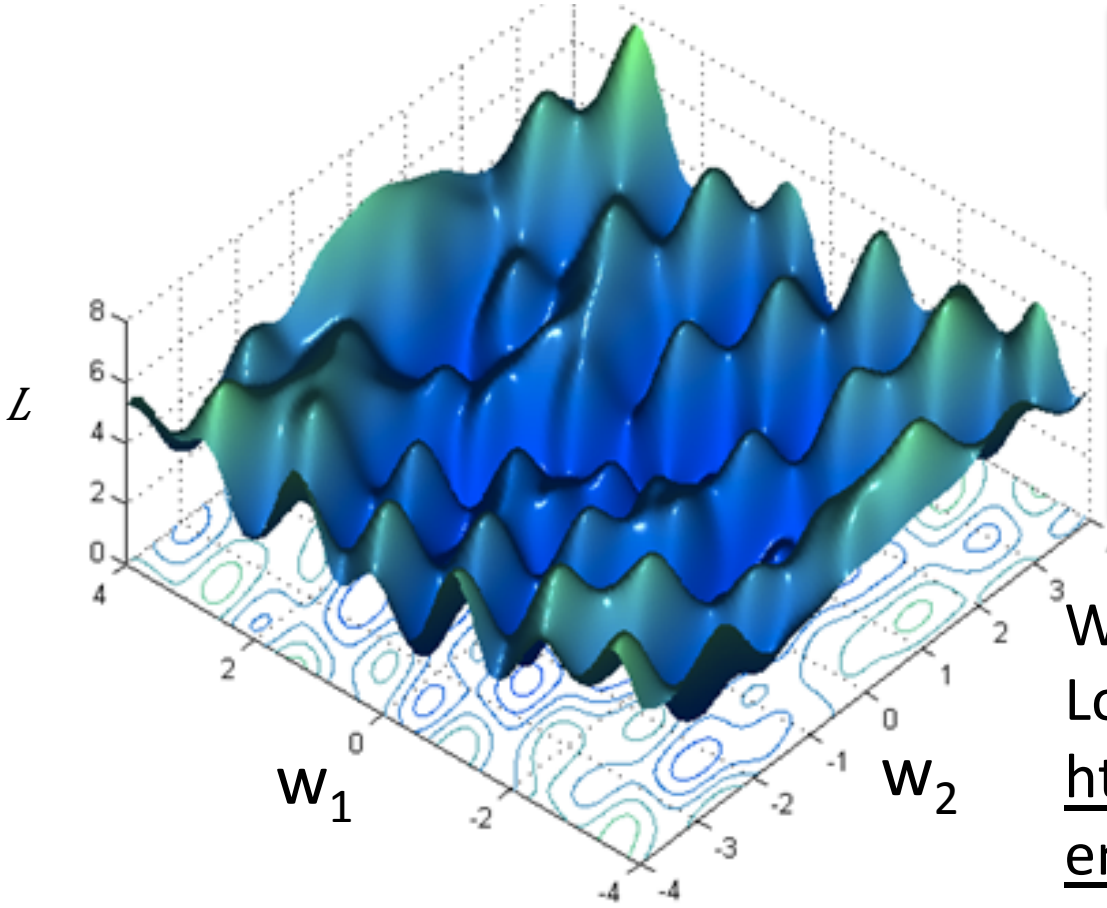
keras

Don't worry about $\partial L/\partial w$, the toolkits will handle it.

Local Minima

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

- Gradient descent never guarantee global minima

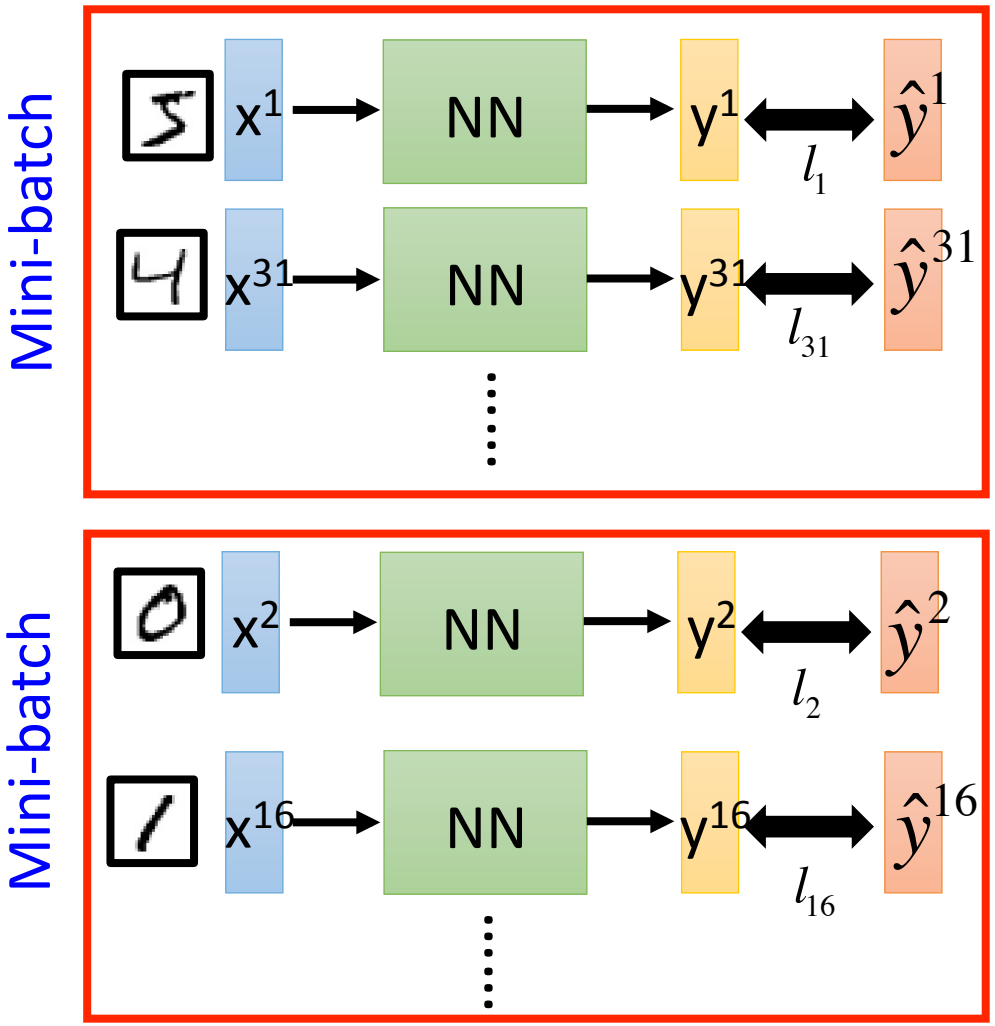


Different initial point

Reach different minima, so different results

Who is Afraid of Non-Convex Loss Functions?
http://videolectures.net/eml07_lecun_wia/

Mini-batch



- Randomly initialize network parameters
- (Randomly) Pick the 1st batch $L = l_1 + l_{31} + \ldots$

  Update parameters once
- Pick the 2nd batch

  $L = l_2 + l_{16} + \ldots$

  Update parameters once

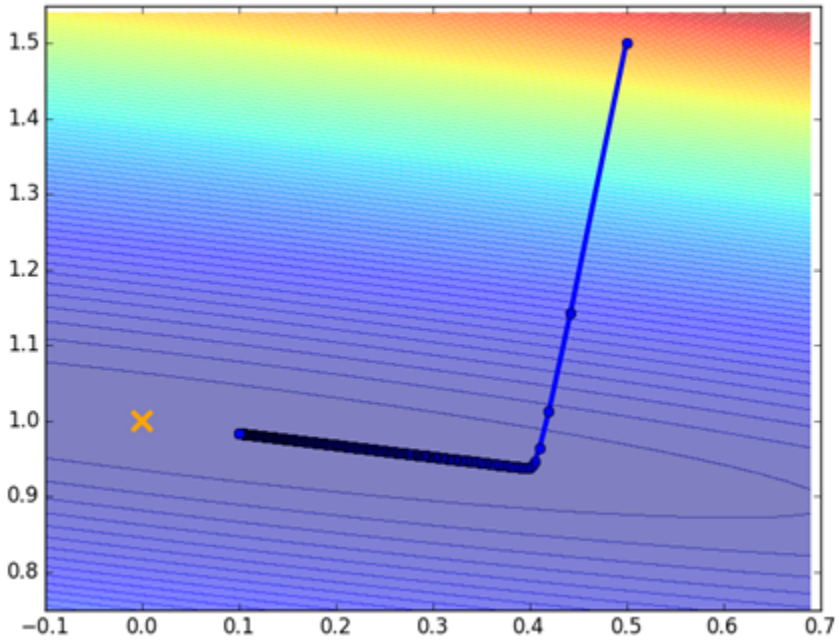
⋮

L is different each time when we update parameters!

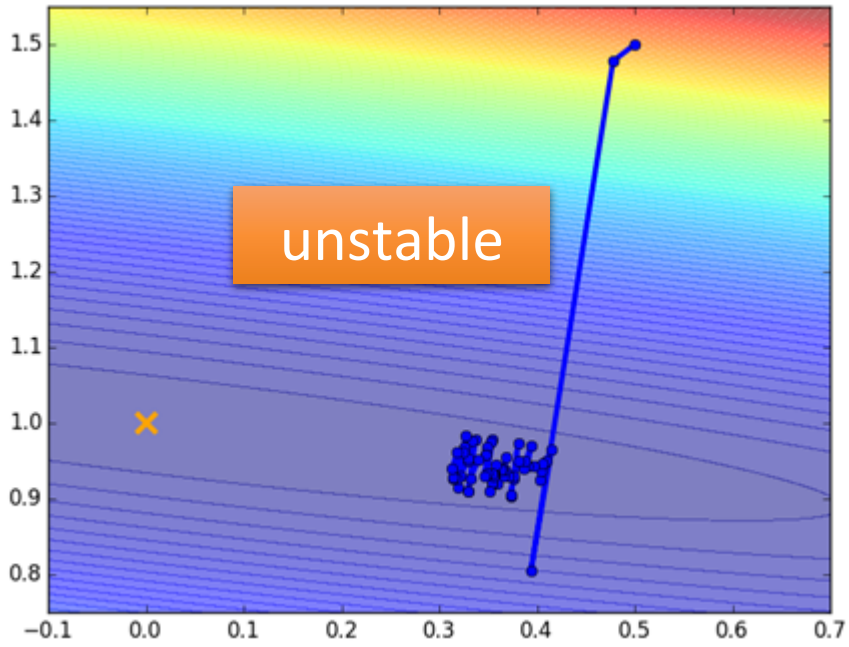
目標換來換去?!

Mini-batch

Batch Gradient Descent

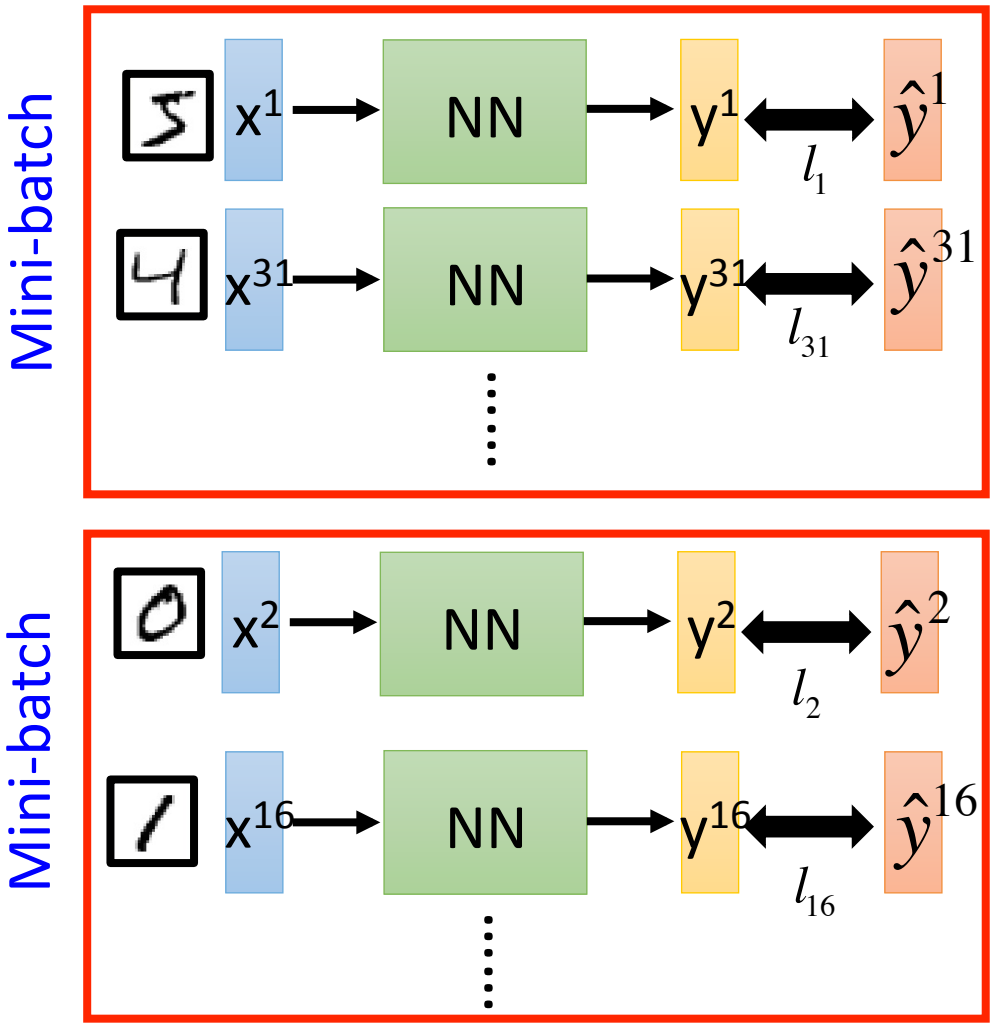


With Mini-batch



The colors represent the total loss on all training data.

Mini-batch



- Randomly initialize network parameters

- Pick the 1st batch

  $L = l_1 + l_{31} + \ldots$

  Update parameters once

- Pick the 2nd batch

  $L = l_2 + l_{16} + \ldots$

  Update parameters once

  ⋮

- Until all mini-batches have been picked

one epoch

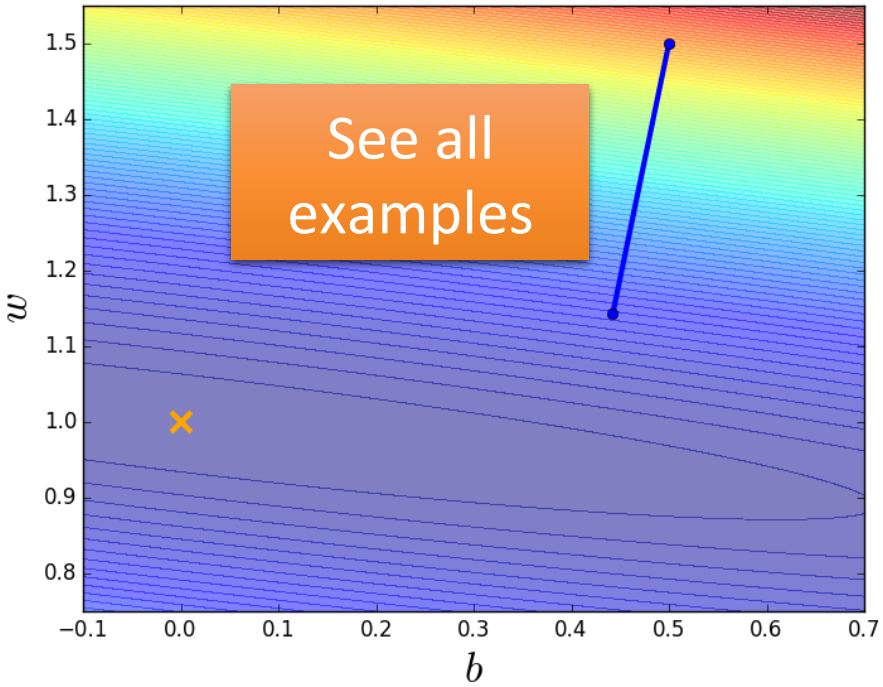
Repeat the above process

Mini-batch is Faster

勝!

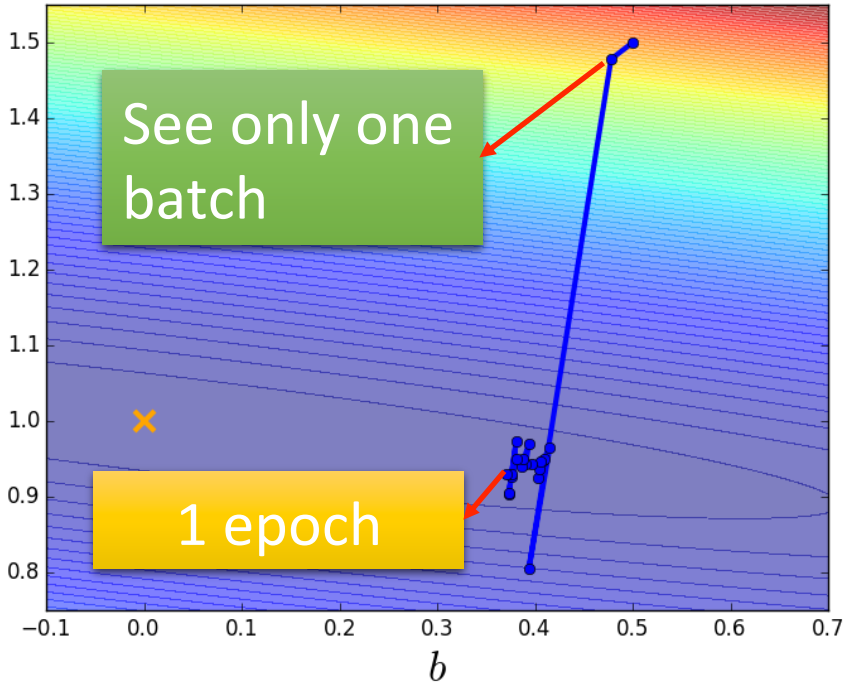
Batch Gradient Descent

Update after seeing all examples



With Mini-batch

If there are 20 batches, update 20 times in one epoch.

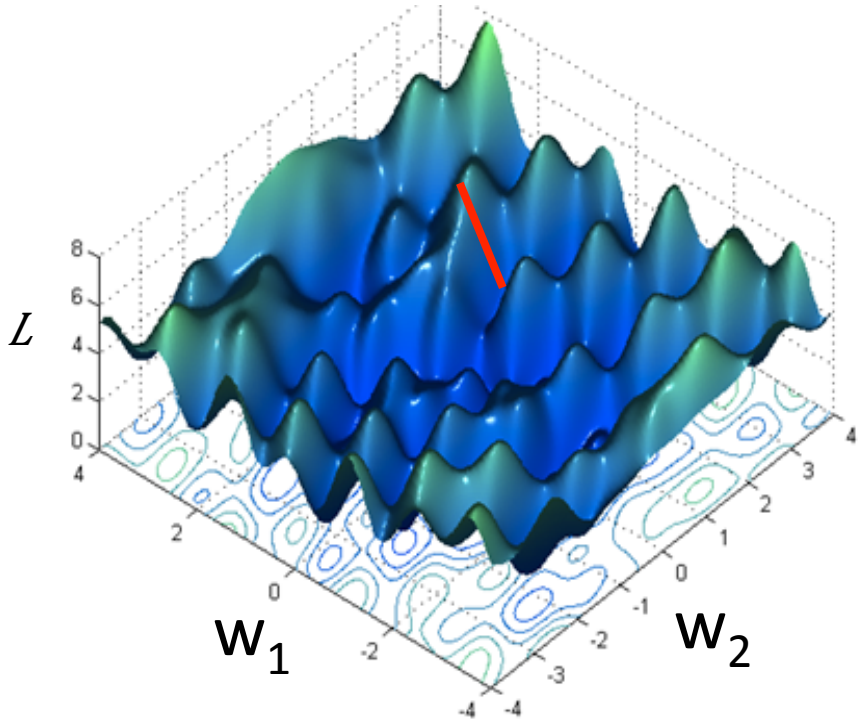


Mini-batch is typically **better**

勝!

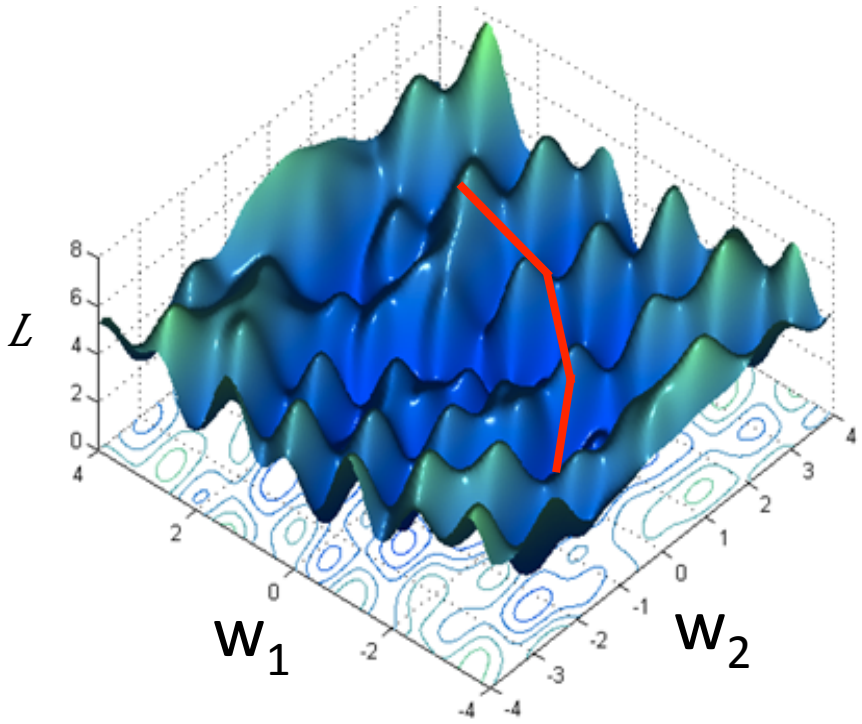
Batch Gradient Descent

Given the same initial parameters and hyper-parameters->
Same local minimal



With Mini-batch

Explore more in space of non-convex loss function



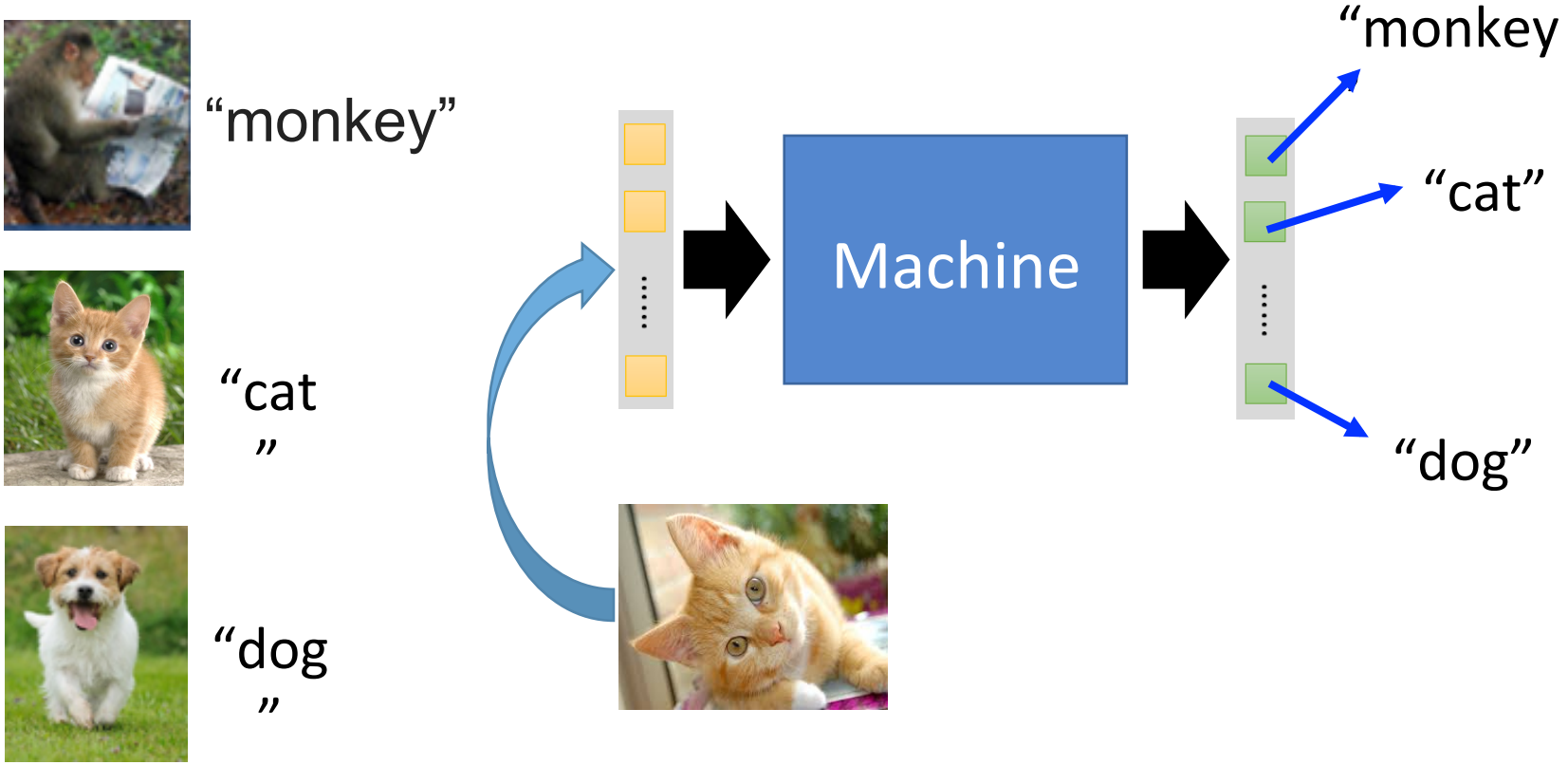
Three Steps for Deep Learning

That's it!

If the input/output of the machine in your task are both vectors, you know how to deal with it.

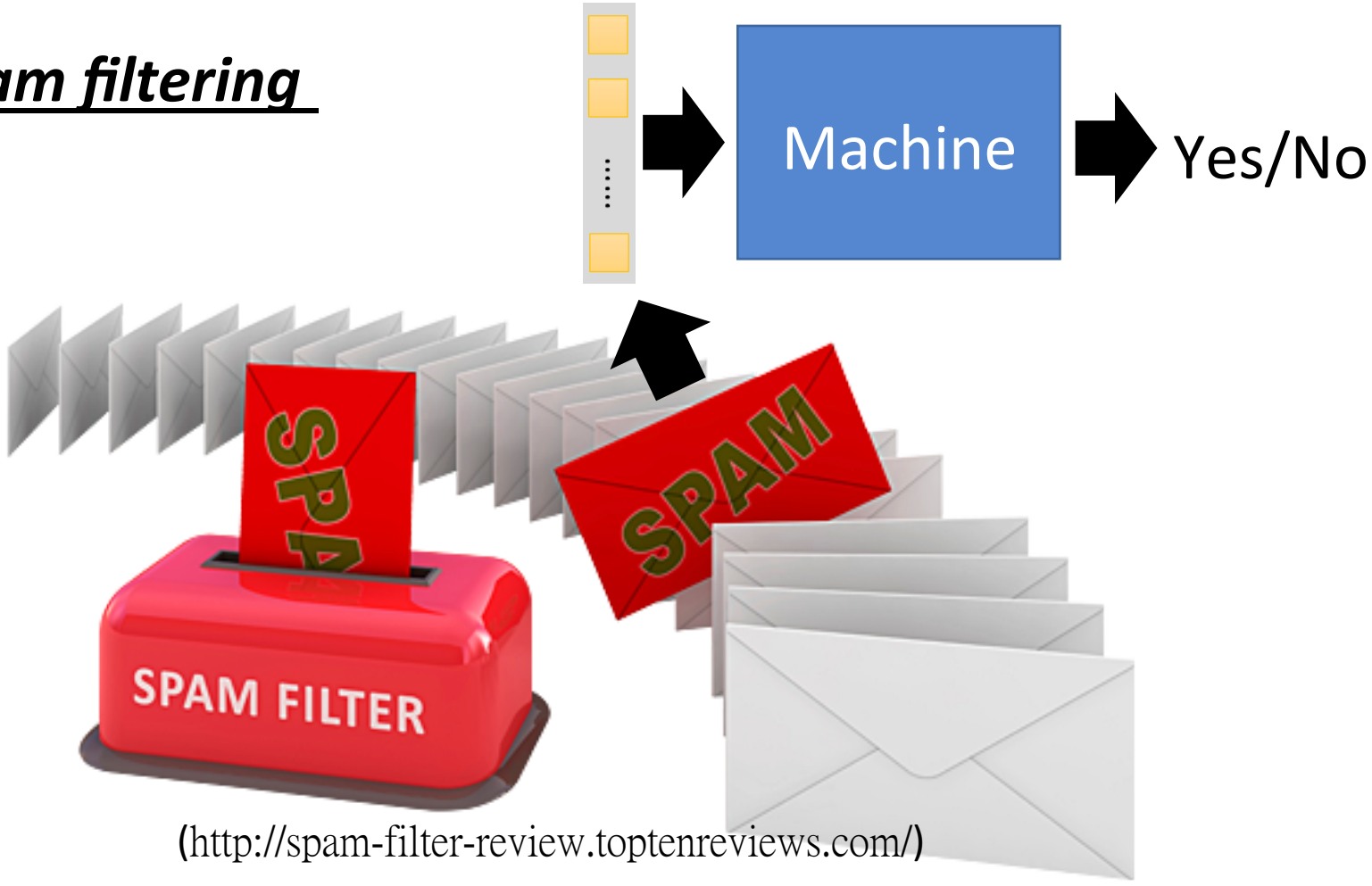
For example, you can do …….

- Image Recognition



For example, you can do …….

Spam filtering



(http://spam-filter-review.toptenreviews.com/)

Outline of Lecture 1

Three Steps for Deep Learning

- The three steps can also apply on other machine learning methods

Why Deep Learning?

Deeper is Better?

Layer X Size	Word Error Rate (%)
1 X 2k	24.2
2 X 2k	20.4
3 X 2k	18.4
4 X 2k	17.8
5 X 2k	17.2
7 X 2k	17.1

Not surprised, more parameters, better performance

Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

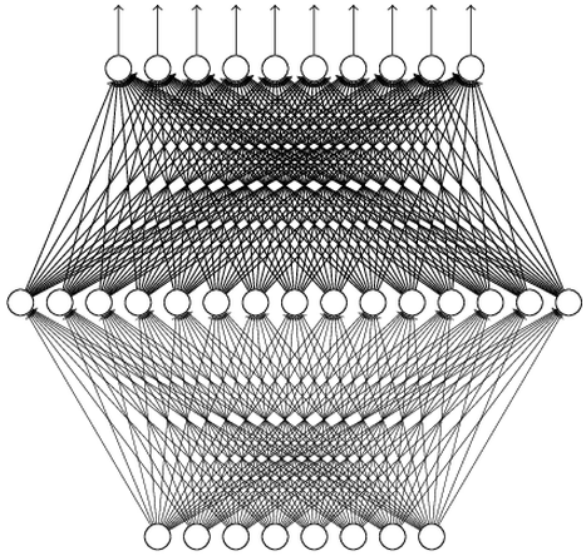
Universality Theorem

Any continuous function f

$$f : R^N \rightarrow R^M$$

Can be realized by a network with one hidden layer

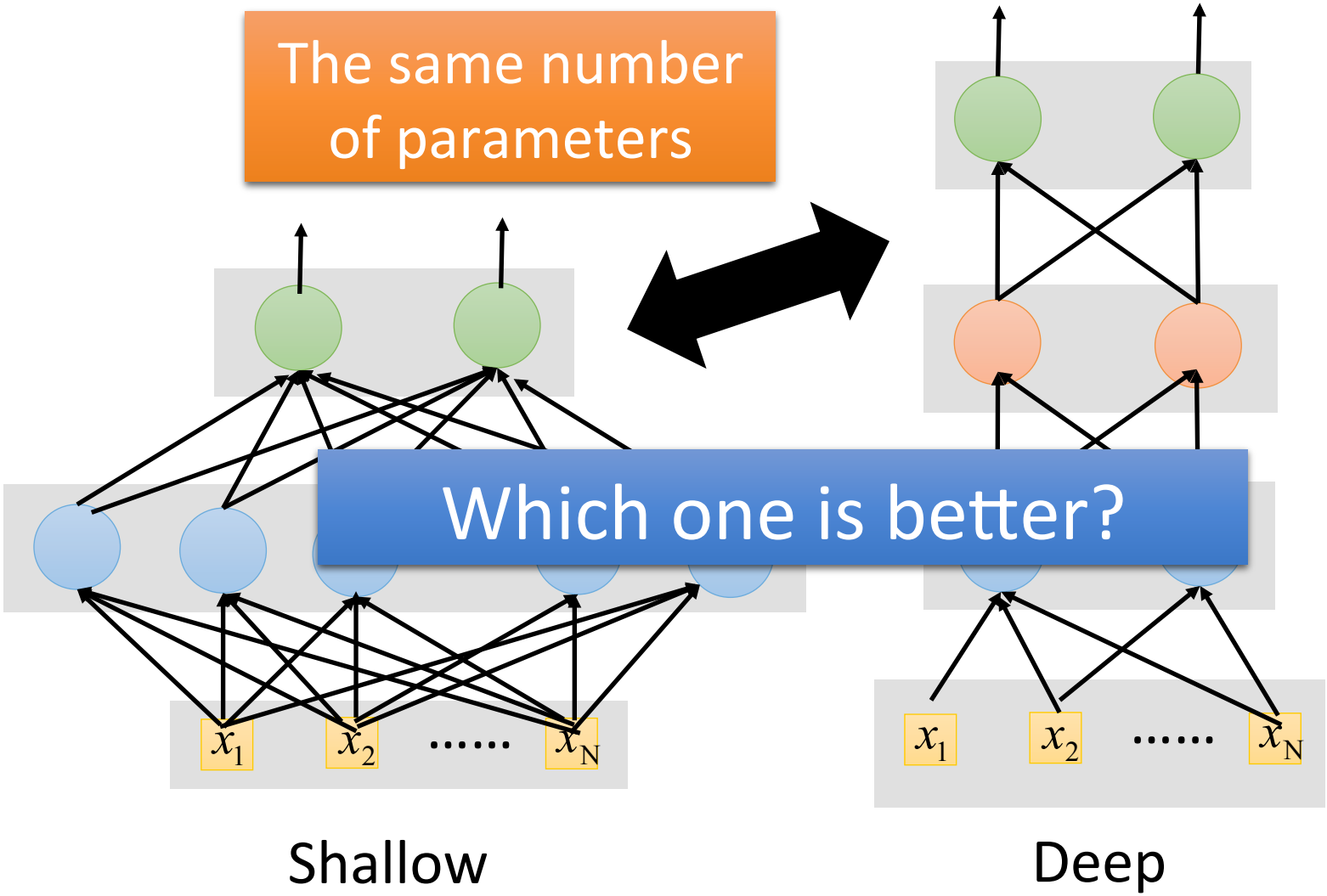
(given **enough** hidden neurons)



Reference for the reason: http://neuralnetworksanddeeplearning.com/chap4.html

Why “Deep” neural network not “Fat” neural network?

Fat + Short v.s. Thin + Tall



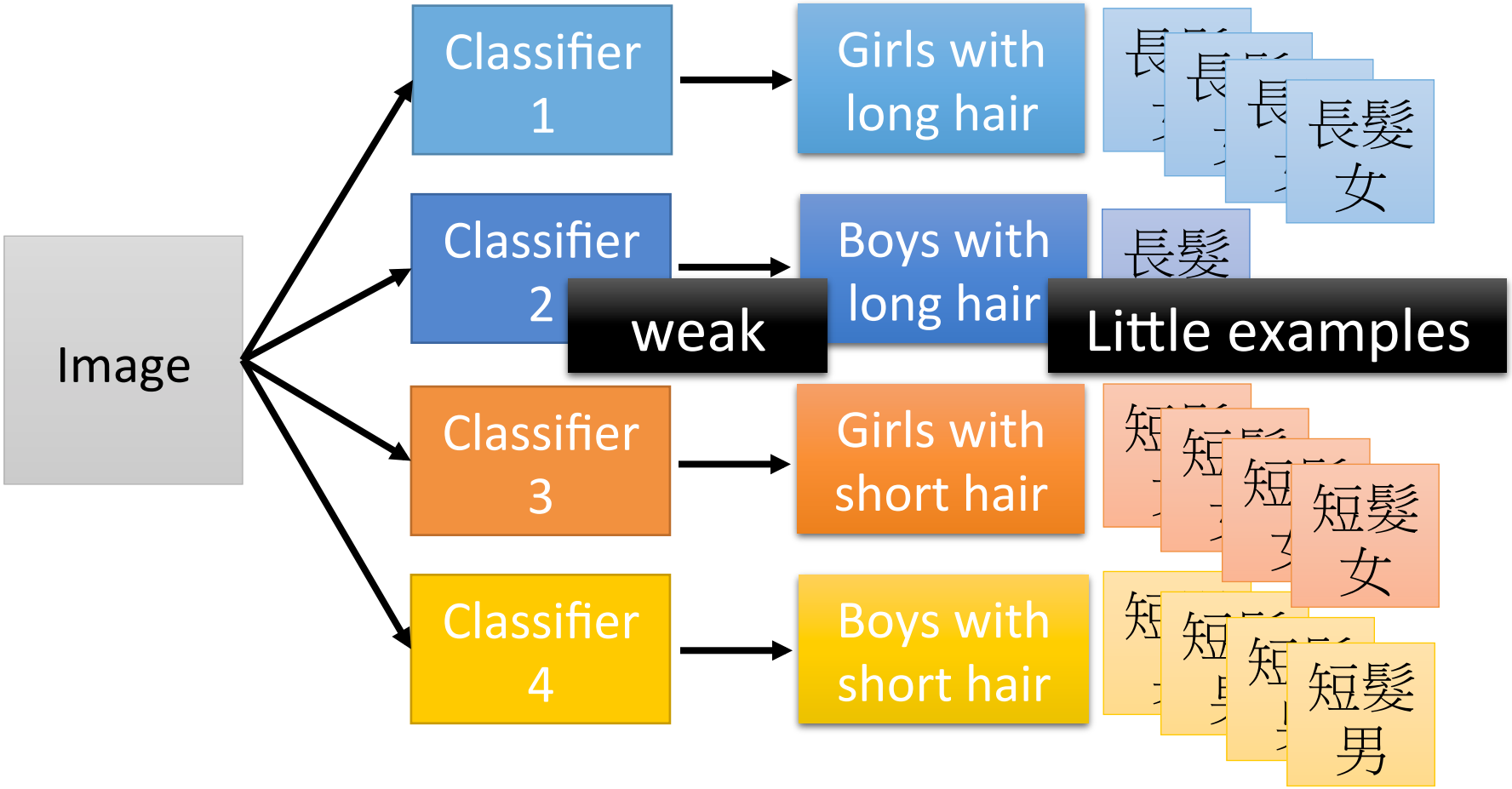
Fat + Short v.s. Thin + Tall

Layer X Size	Word Error Rate (%)	Layer X Size	Word Error Rate (%)
1 X 2k	24.2		
2 X 2k	20.4		
3 X 2k	18.4		
4 X 2k	17.8		
5 X 2k	17.2	1 X 3772	22.5
7 X 2k	17.1	1 X 4634	22.6
		1 X 16k	22.1

Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

Why Deep?

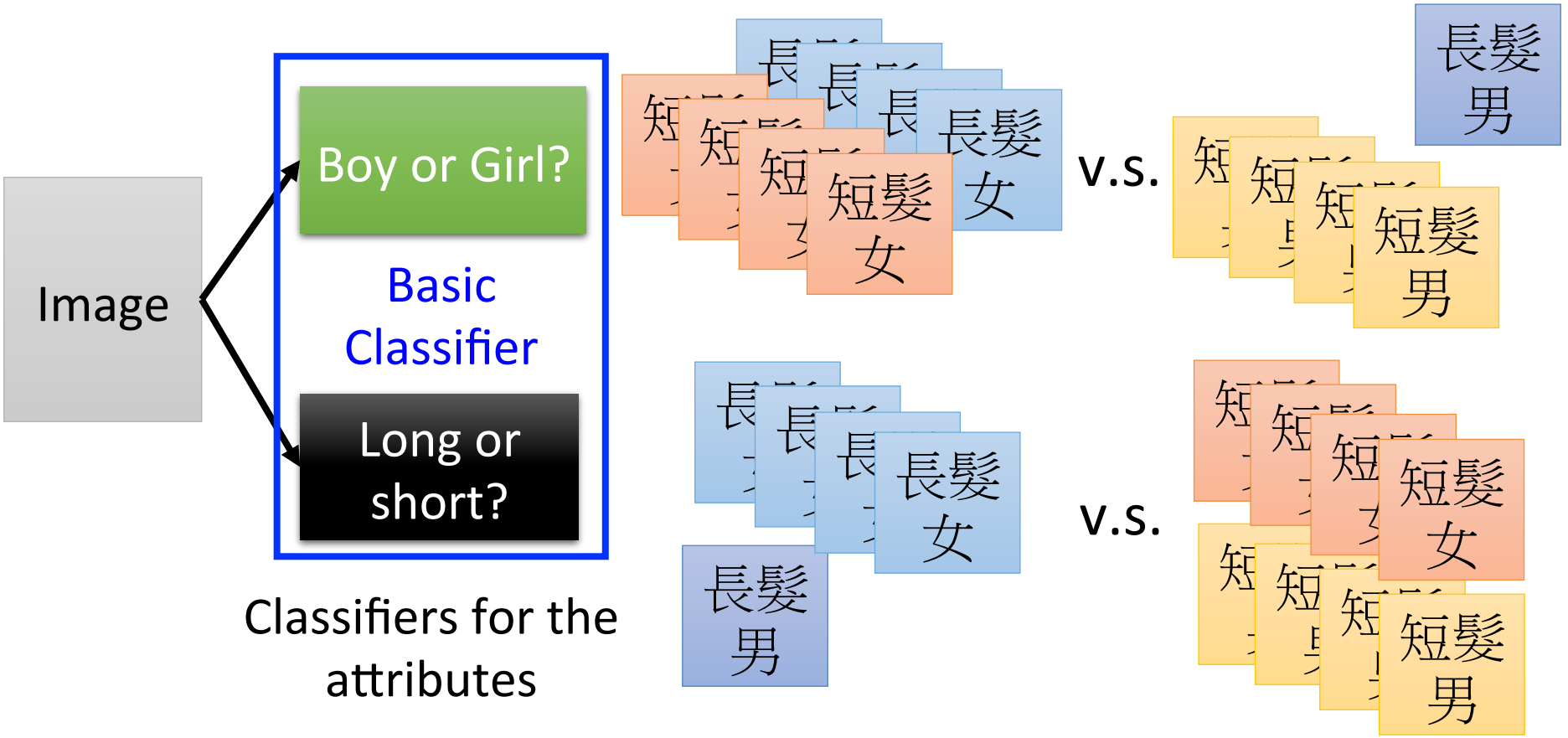
- Deep → Modularization



Why Deep?

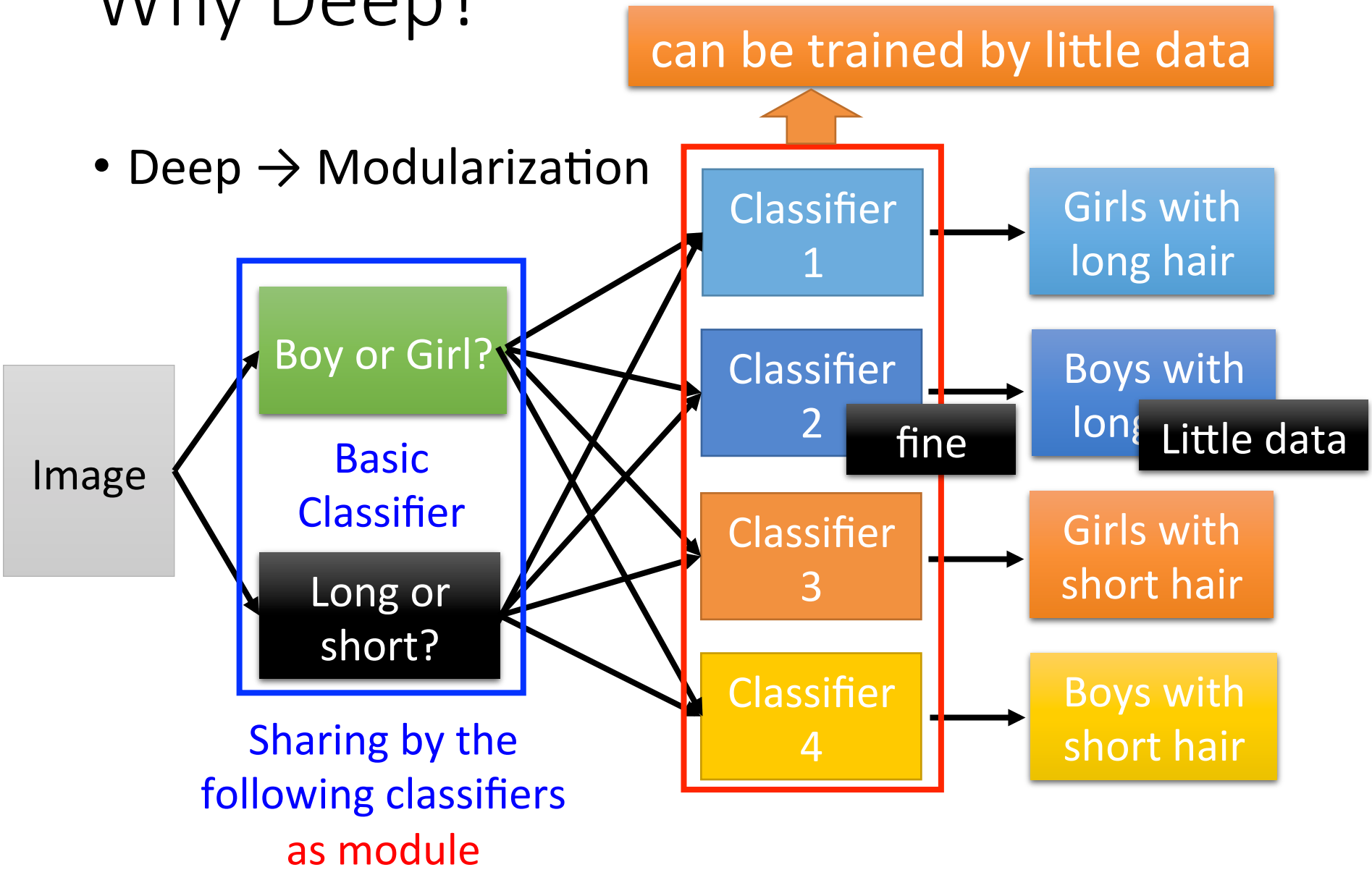
Each basic classifier can have sufficient training examples.

- Deep → Modularization



Why Deep?

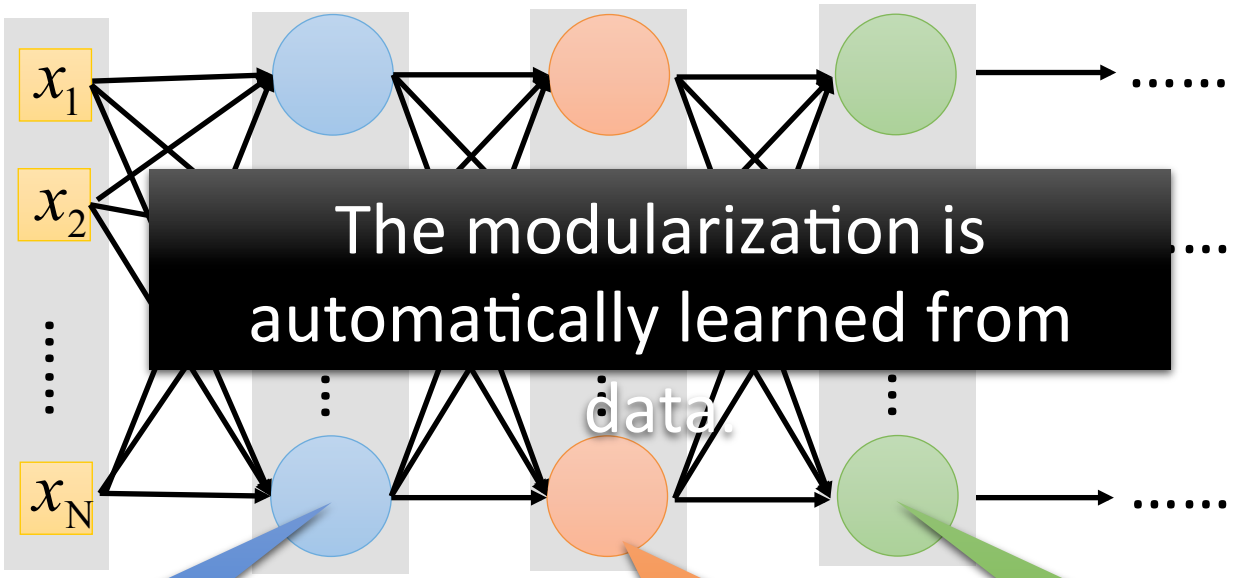
- Deep → Modularization



Why Deep?

Deep Learning also works on small data set.

- Deep → Modularization → Less training data?



The most basic classifiers

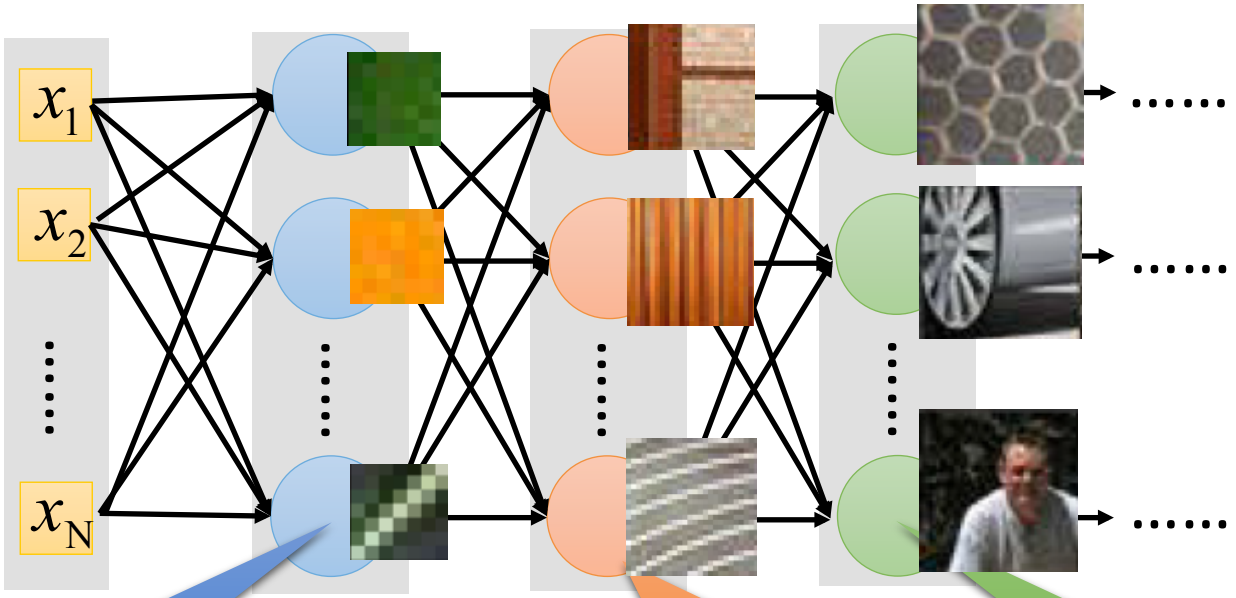
Use 1st layer as module to build classifiers

Use 2nd layer as module .....

Why Deep?

Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818-833)

- Deep → Modularization

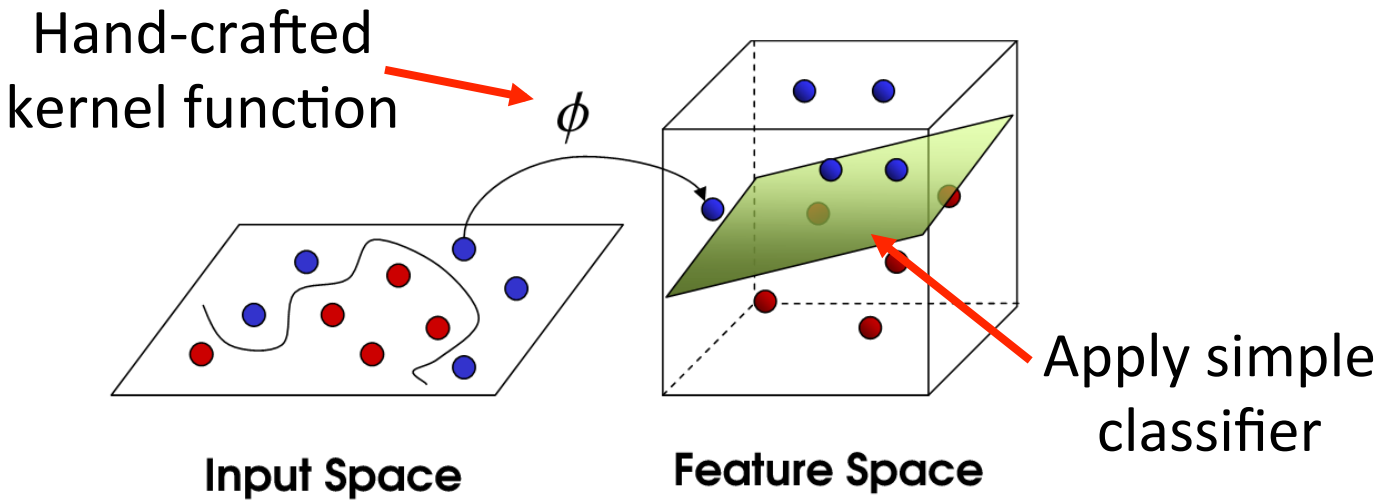


The most basic classifiers

Use 1st layer as module to build classifiers

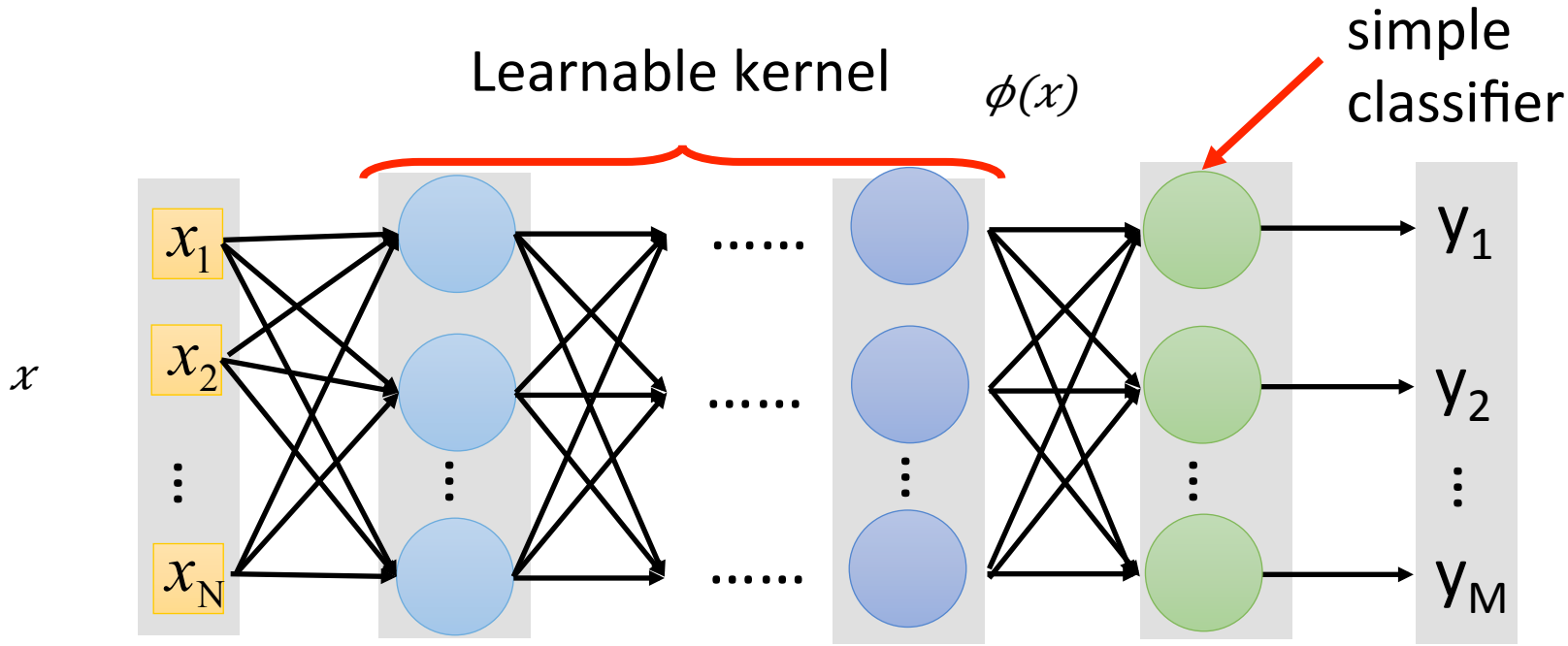
Use 2nd layer as module .....

SVM

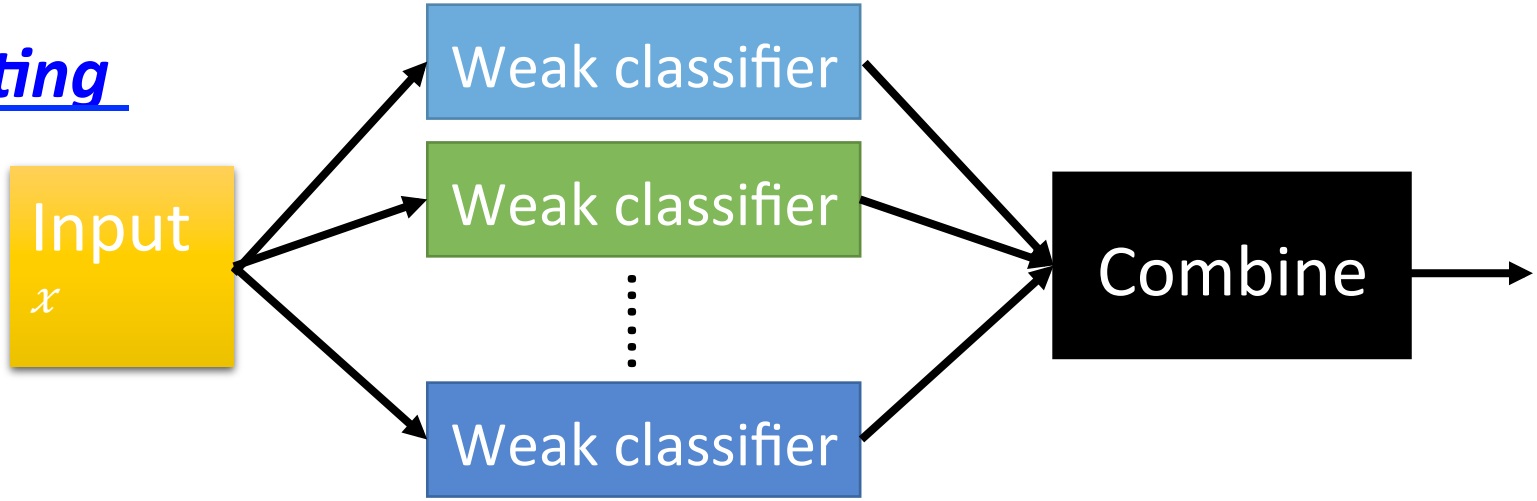


Source of image: http://www.gipsa-lab.grenoble-inp.fr/transfert/seminaire/455_Kadri2013Gipsa-lab.pdf

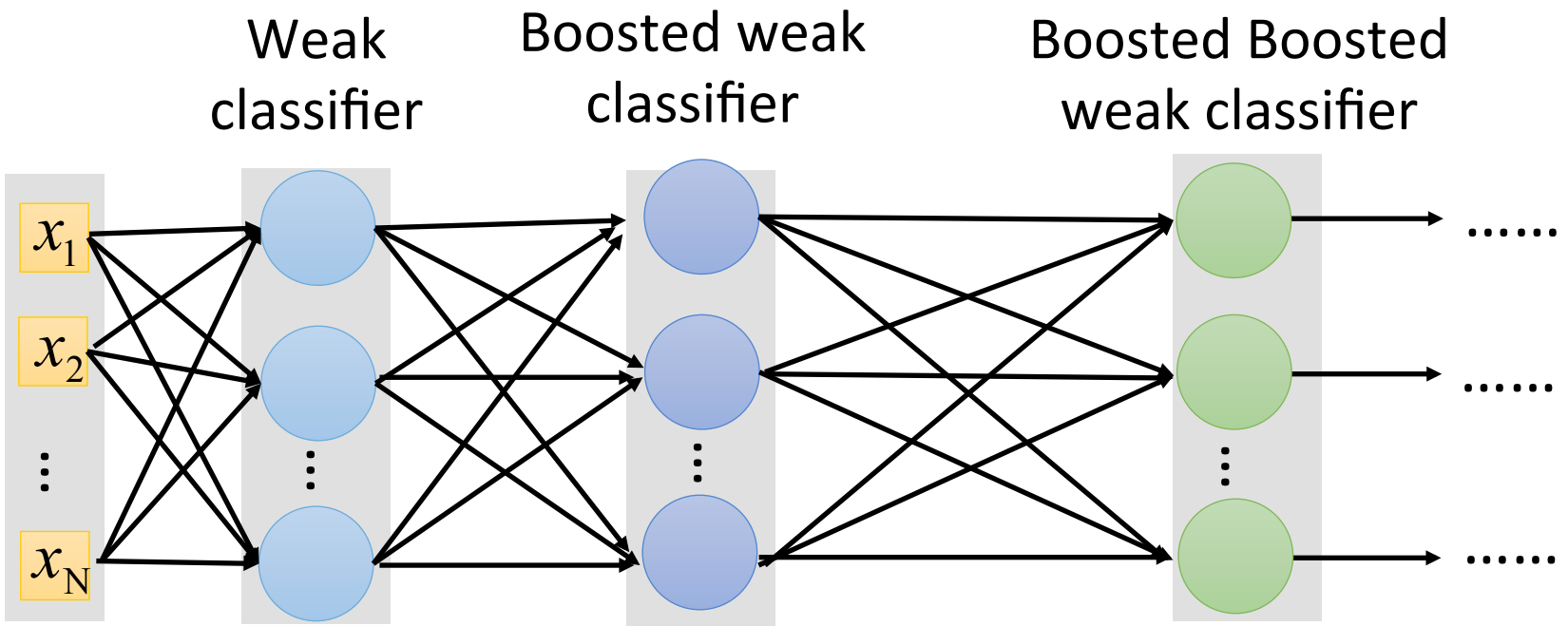
Deep Learning



Boosting



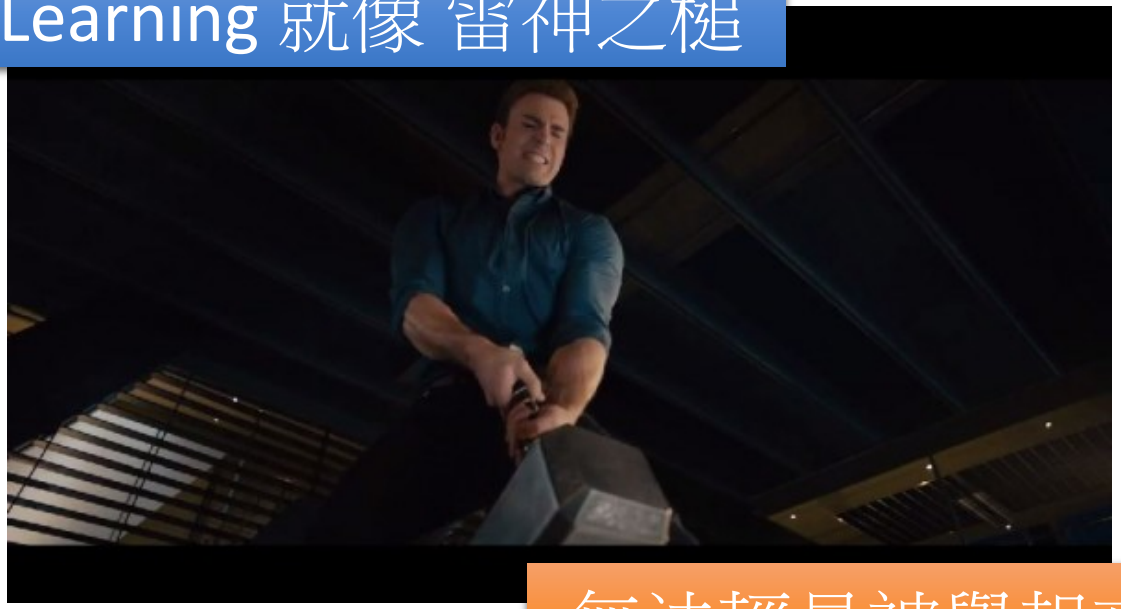
Deep Learning



Concluding Remarks of Lecture I

- Deep Learning is simple!
- Deep Learning is powerful!

Deep Learning 就像 雷神之槌



無法輕易被舉起來 .....

http://ent.ltn.com.tw/news/breakingnews/1144545