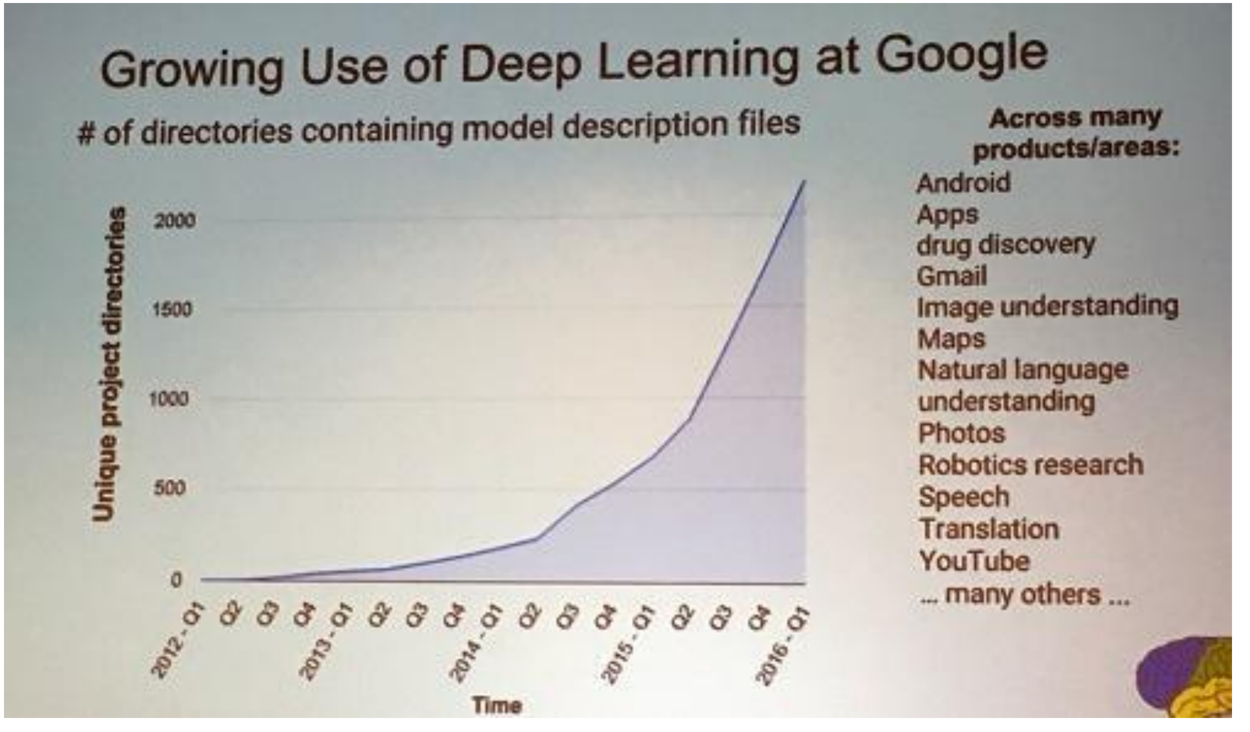
Deep Learning

Deep learning attracts lots of attention.

- I believe you have seen lots of exciting results before.



Deep learning trends at Google. Source: SIGMOD/Jeff Dean

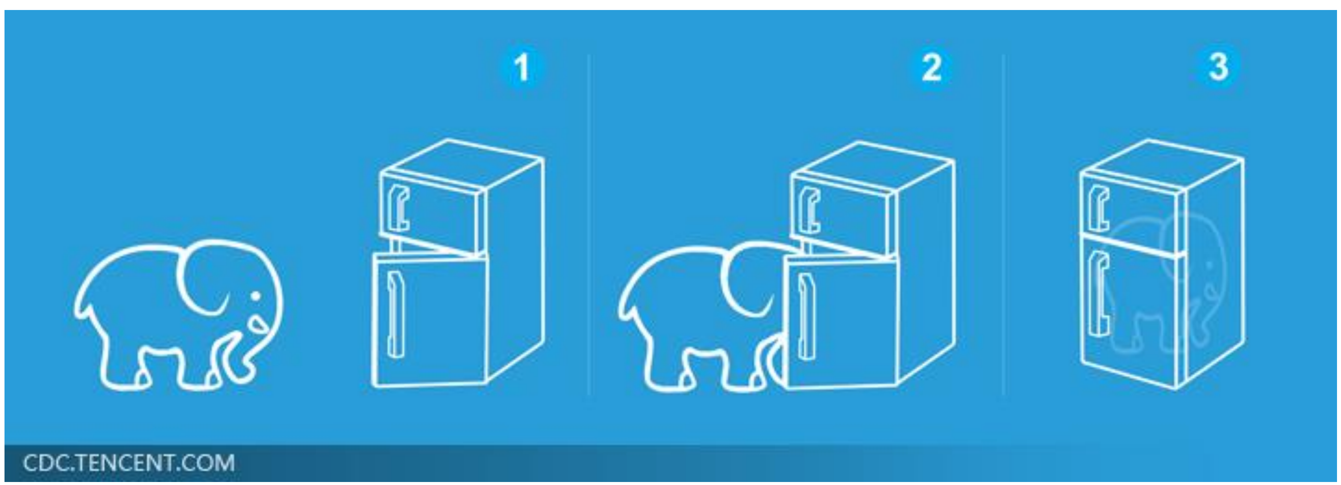
Ups and downs of Deep Learning

- 1958: Perceptron (linear model)
- 1969: Perceptron has limitation
- 1980s: Multi-layer perceptron
  - Do not have significant difference from DNN today
- 1986: Backpropagation
  - Usually more than 3 hidden layers is not helpful
- 1989: 1 hidden layer is “good enough”, why deep?
- 2006: RBM initialization (breakthrough) restricted Boltzmann Machine 弃用
- 2009: GPU
- 2011: Start to be popular in speech recognition
- 2012: win ILSVRC image competition

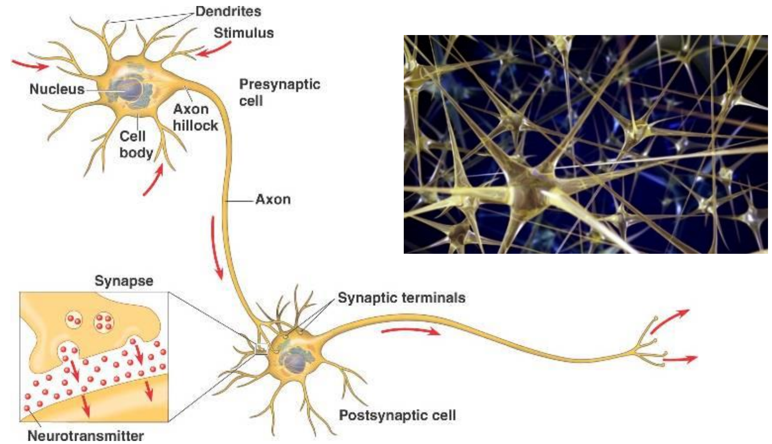
Three Steps for Deep Learning

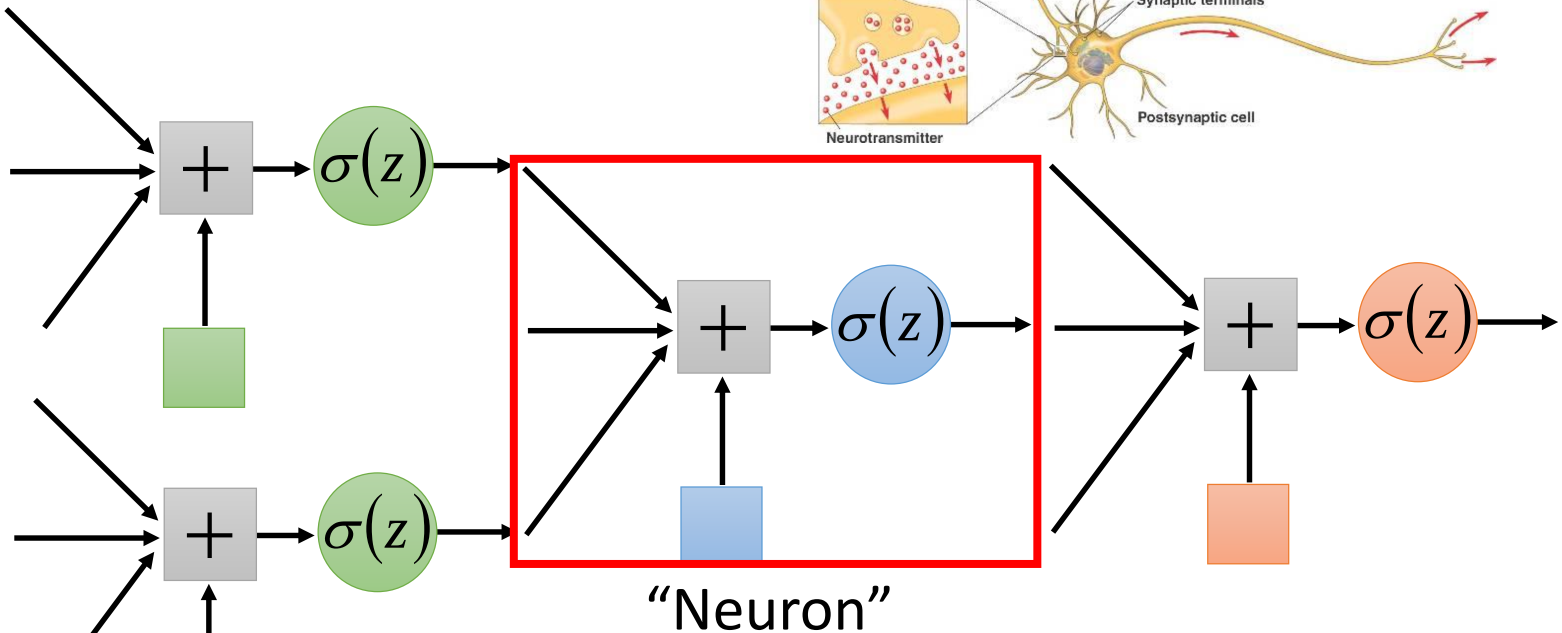
Step 1: Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



Neural Network



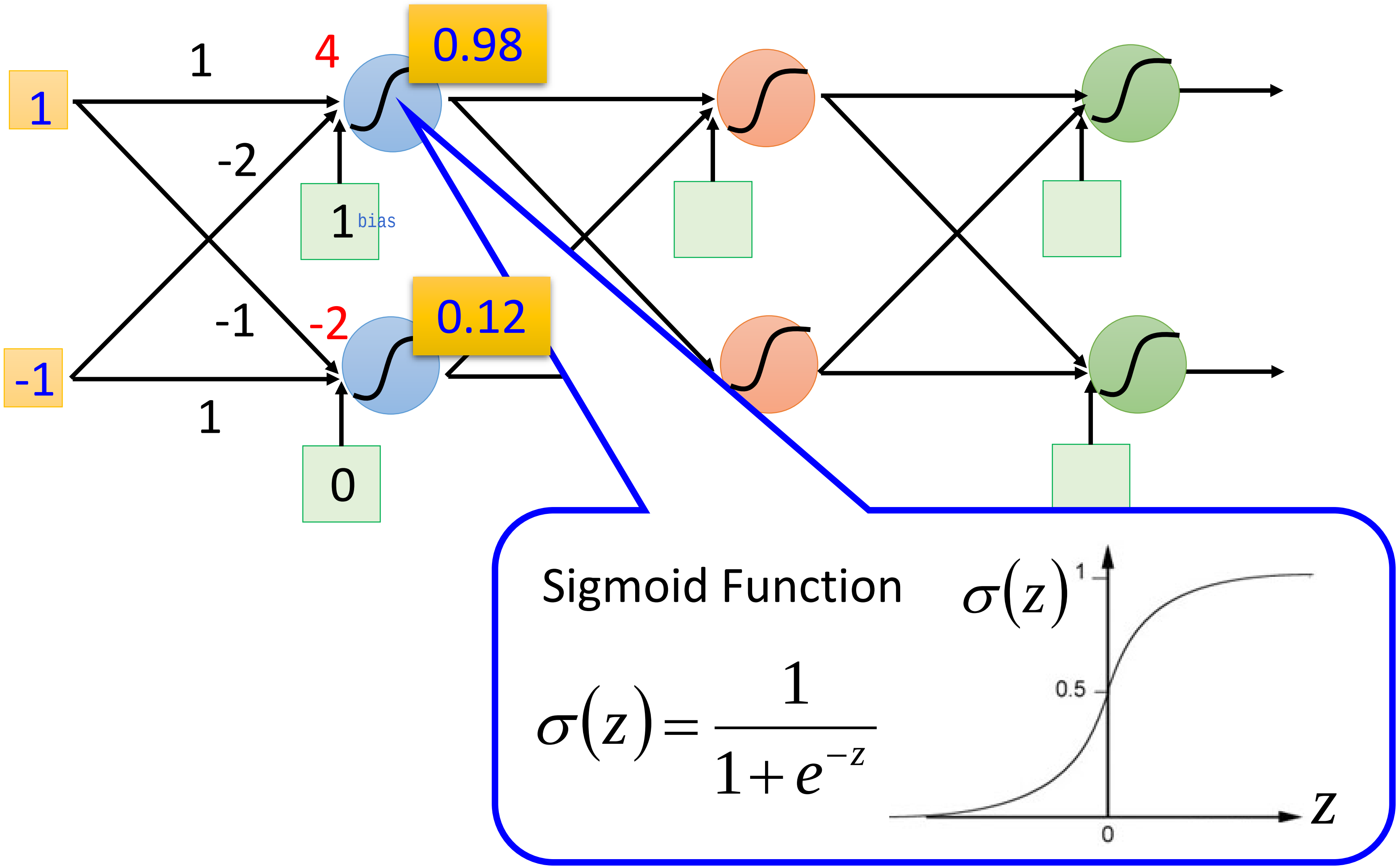


Neural Network

Different connection leads to different network structures

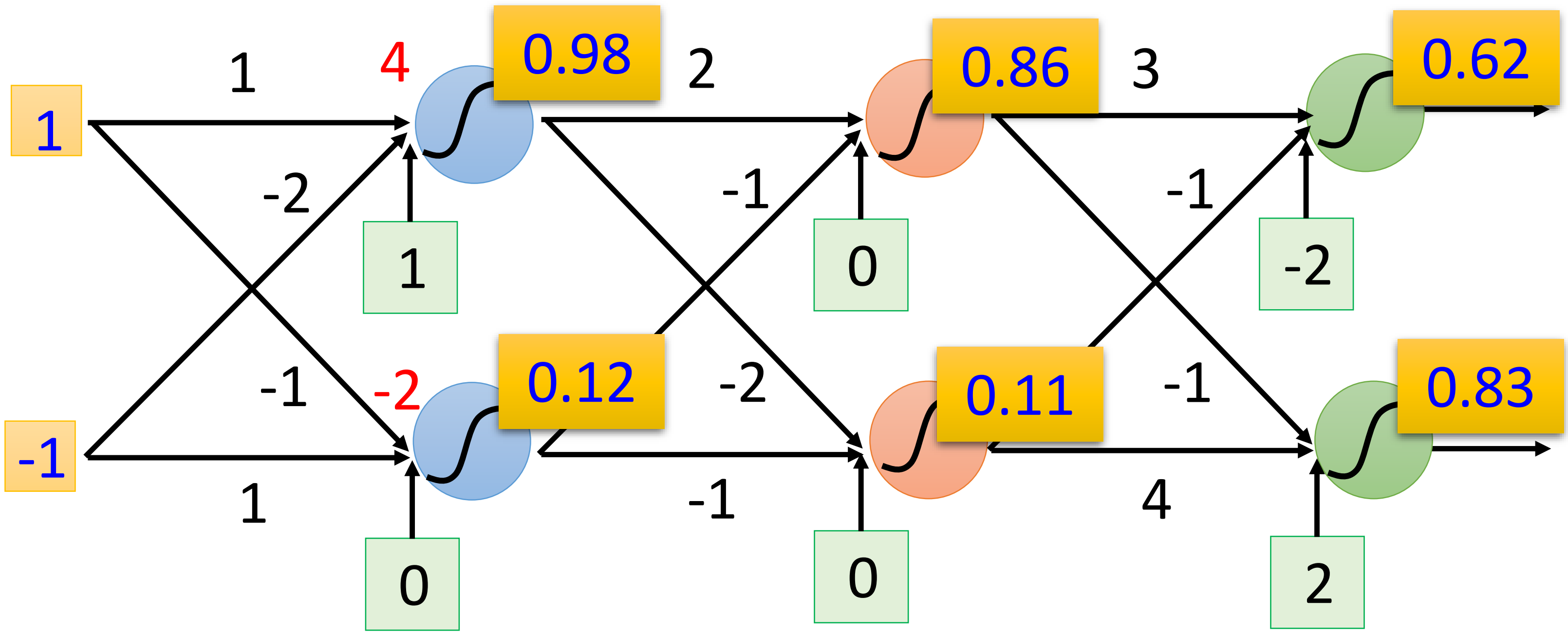
Network parameter θ: all the weights and biases in the “neurons”

Fully Connect Feedforward Network

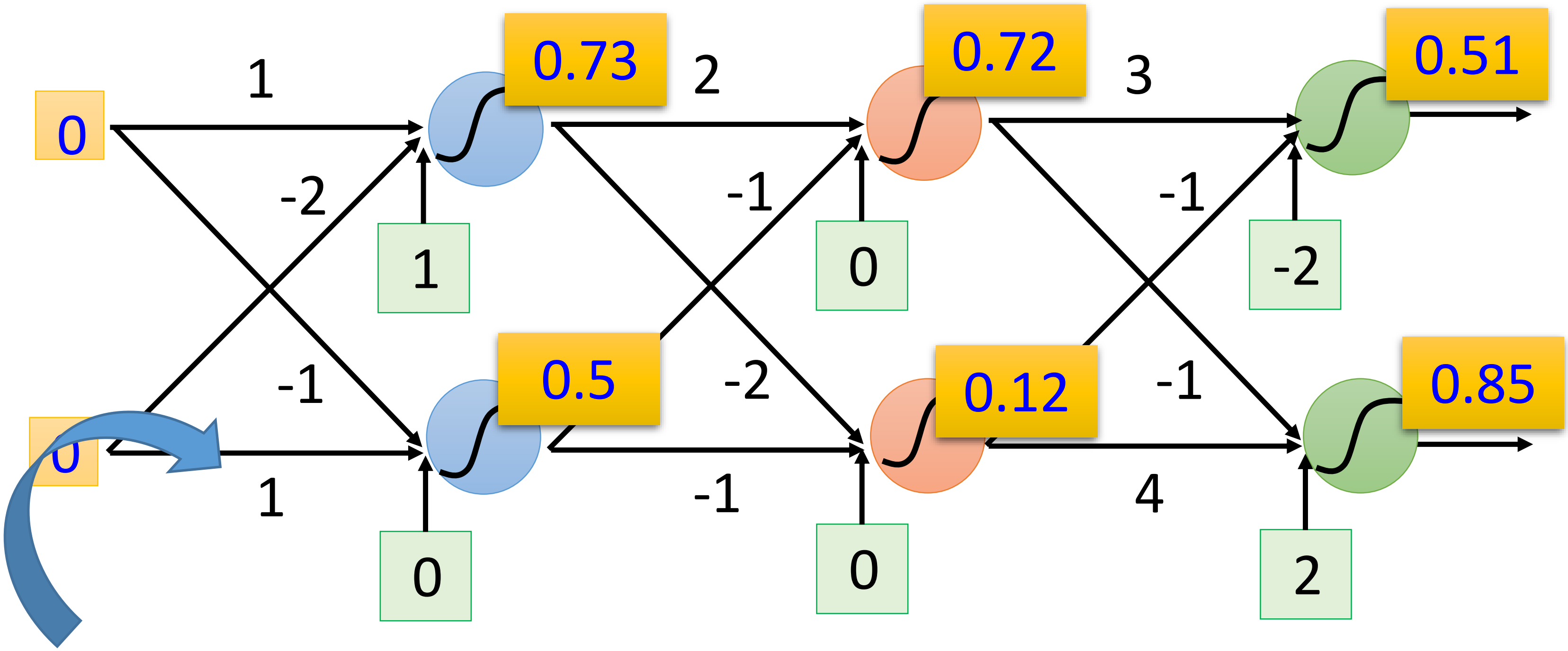


$$\sigma(z) = \frac{1}{1+e^{-z}}$$

Fully Connect Feedforward Network



Fully Connect Feedforward Network



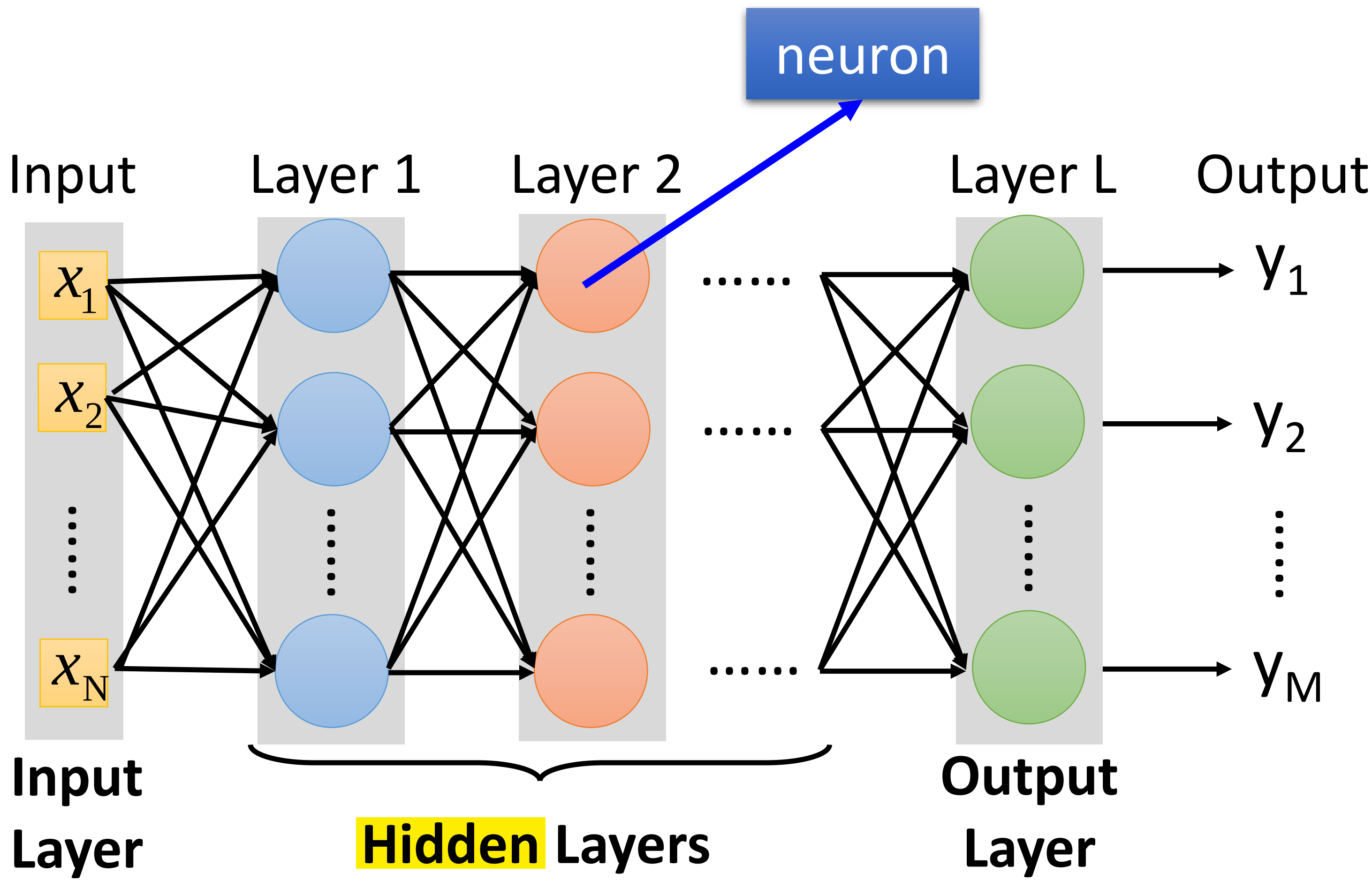
This is a function.

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

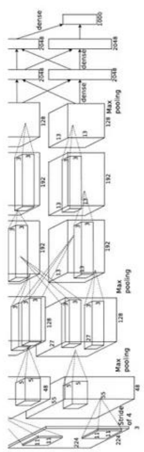


Deep = Many hidden layers

http://cs231n.stanford.edu/slides/winter1516_lecture8.pdf

8 layers

16.4%



AlexNet (2012)

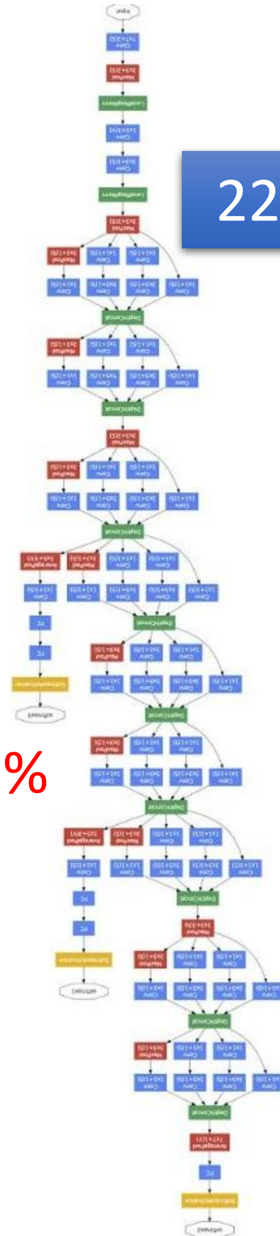
19 layers

7.3%

VGG (2014)

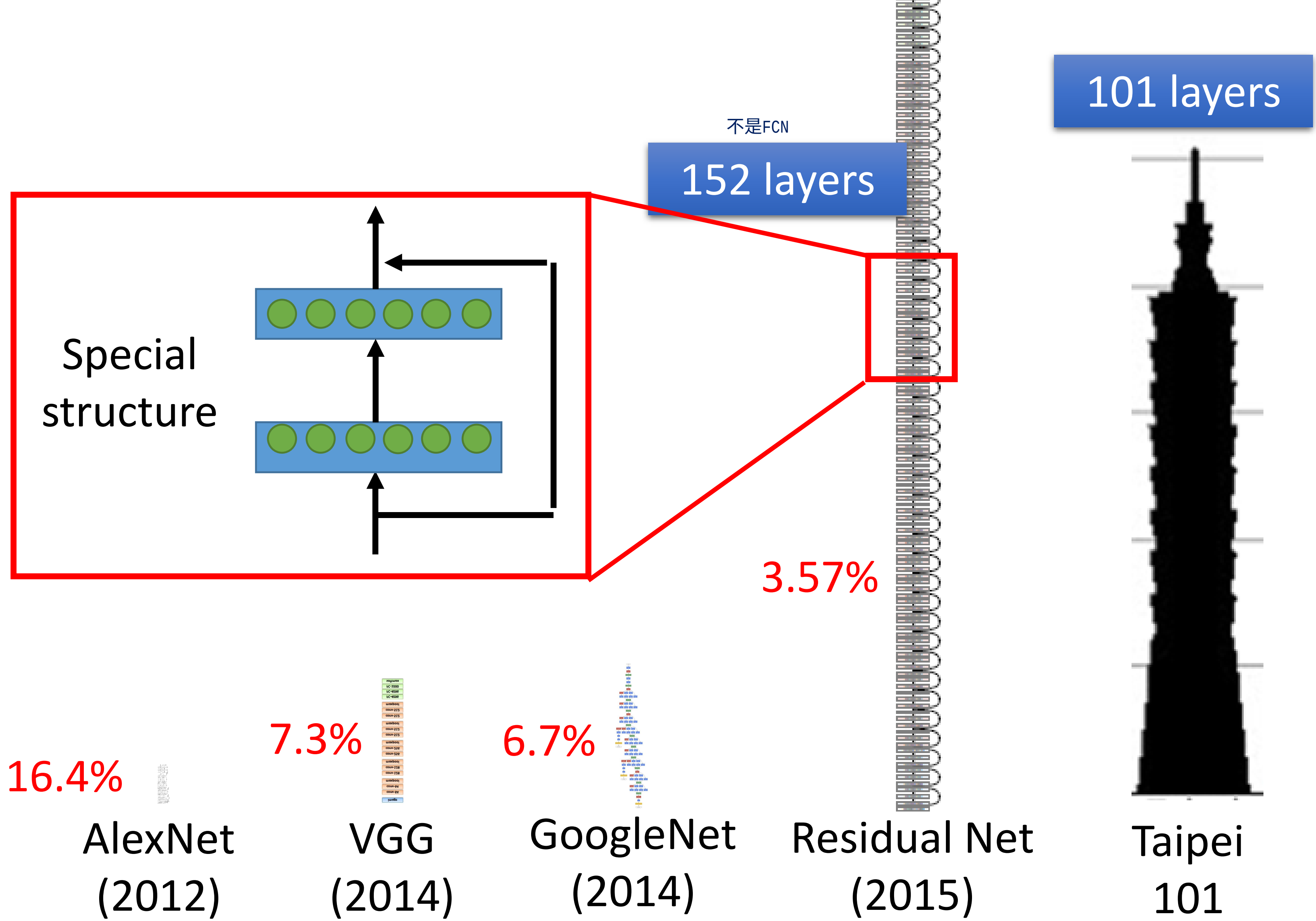
22 layers

6.7%

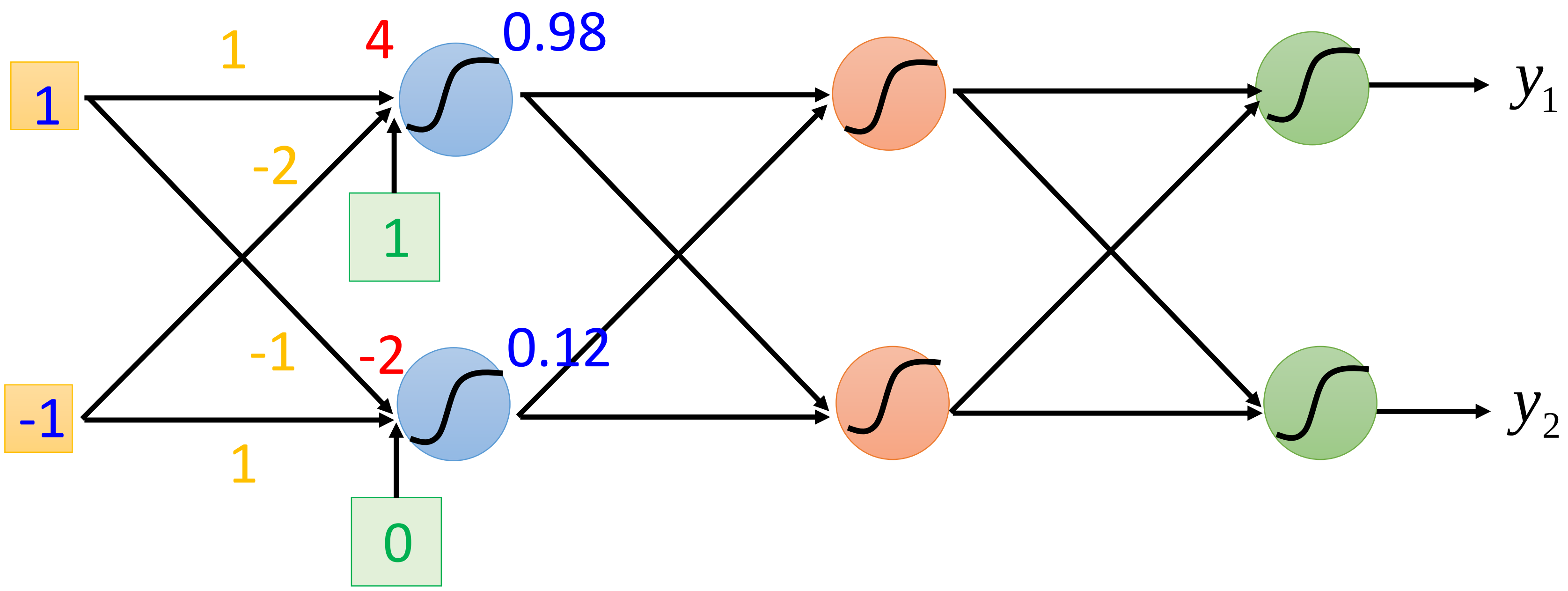


GoogleNet (2014)

Deep = Many hidden layers

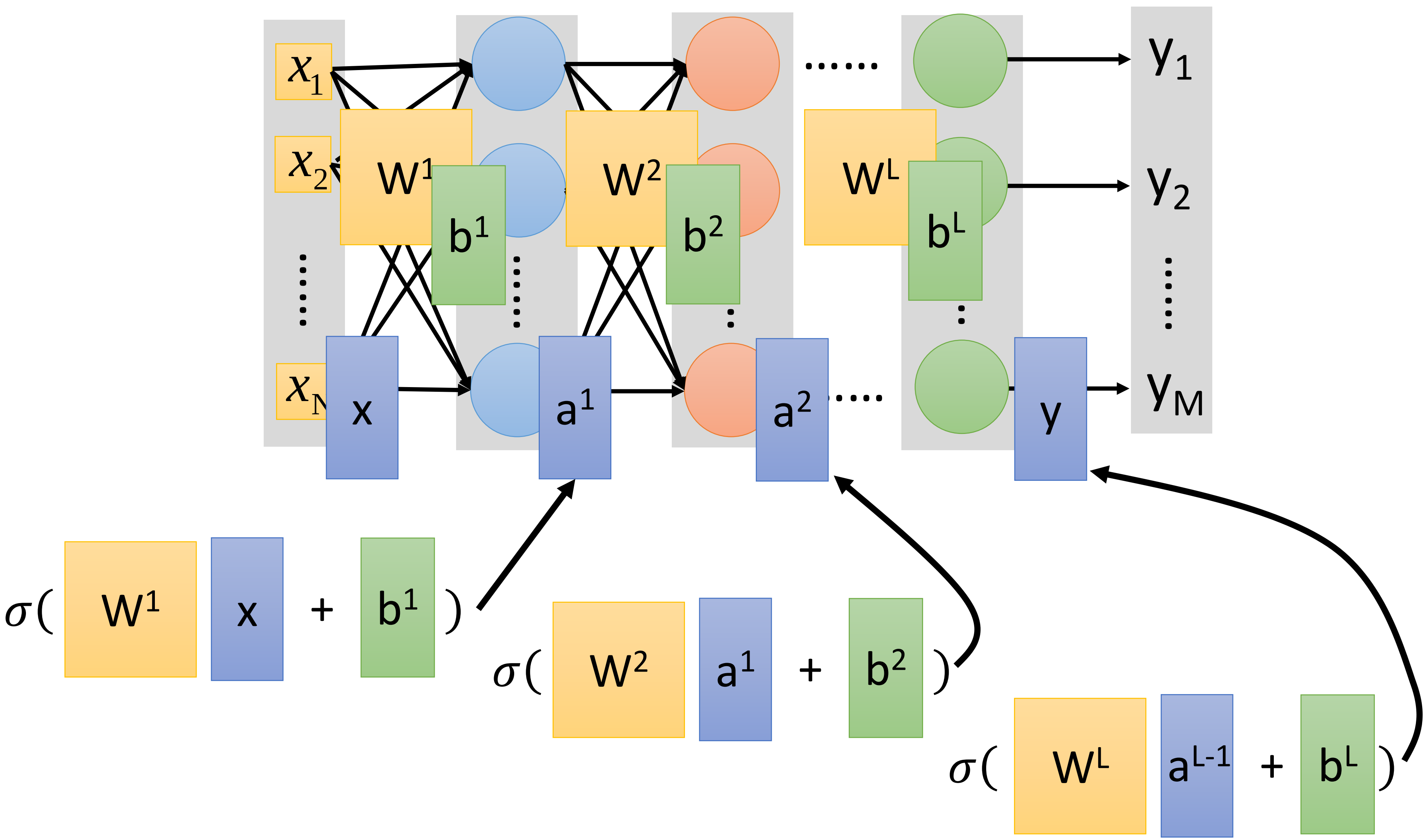


Matrix Operation

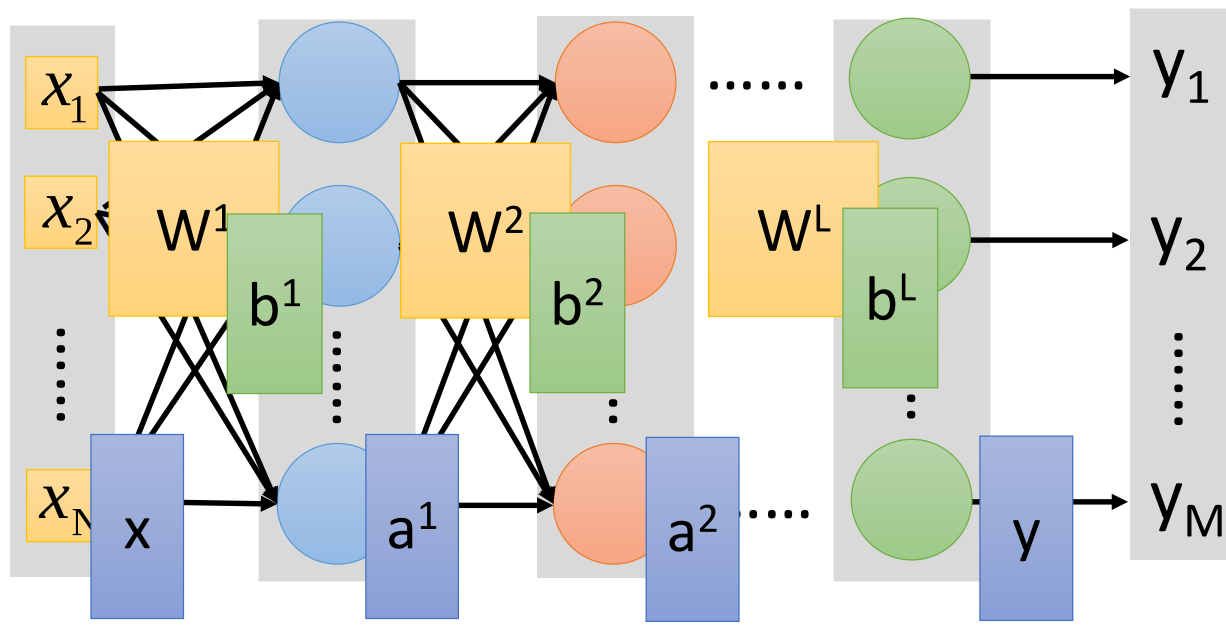


$$\sigma\left(\underbrace{\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix}\begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}}\right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Neural Network



Neural Network

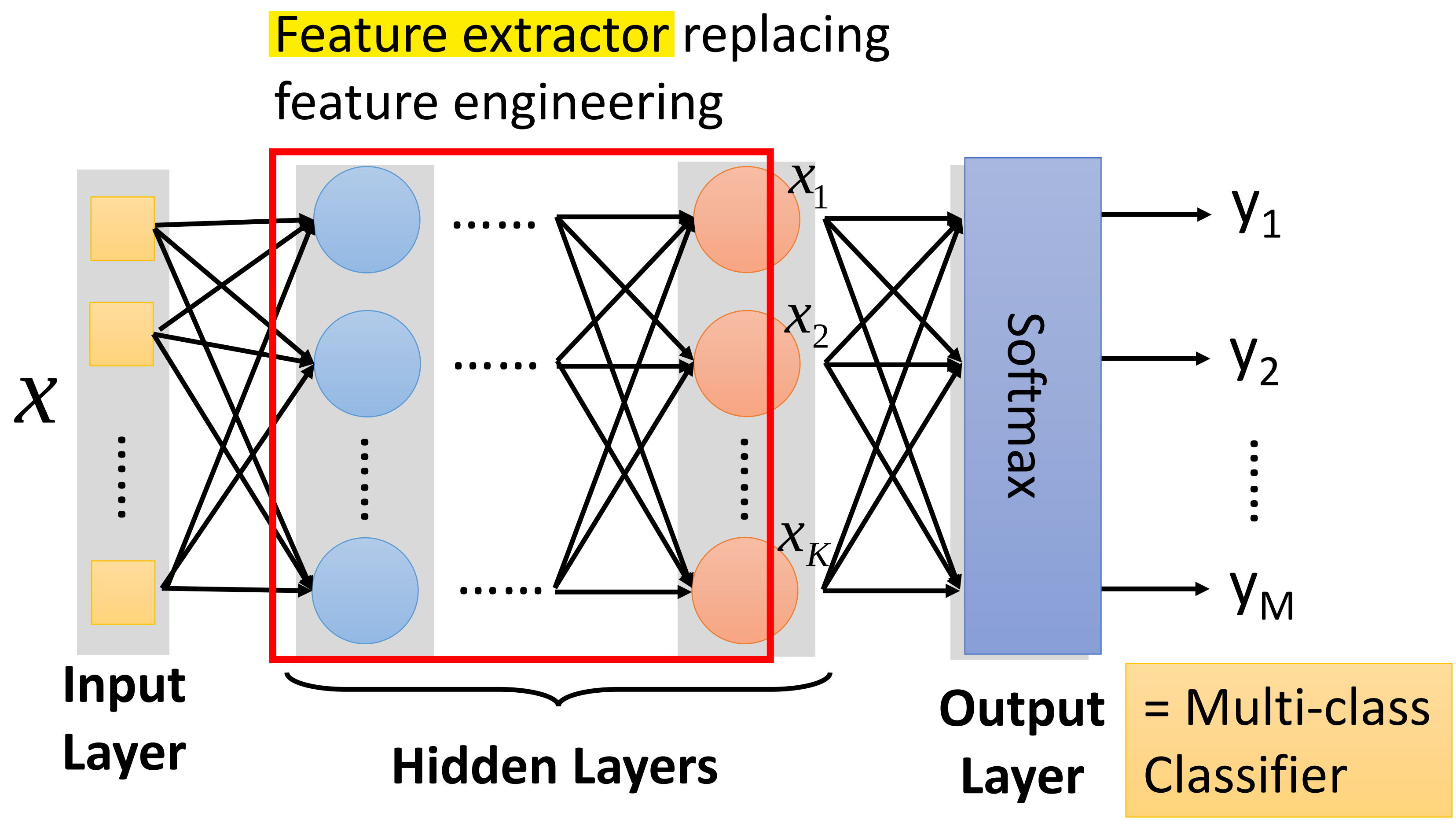


$$\mathrm{y} = f(\mathrm{x})$$

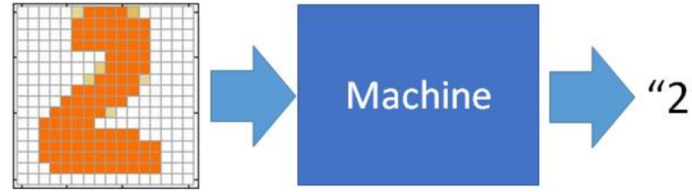
Using parallel computing techniques to speed up matrix operation

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

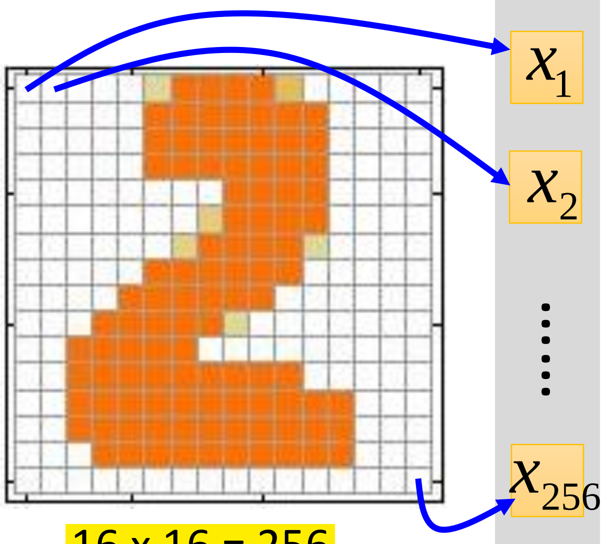
Output Layer



Example Application



Input

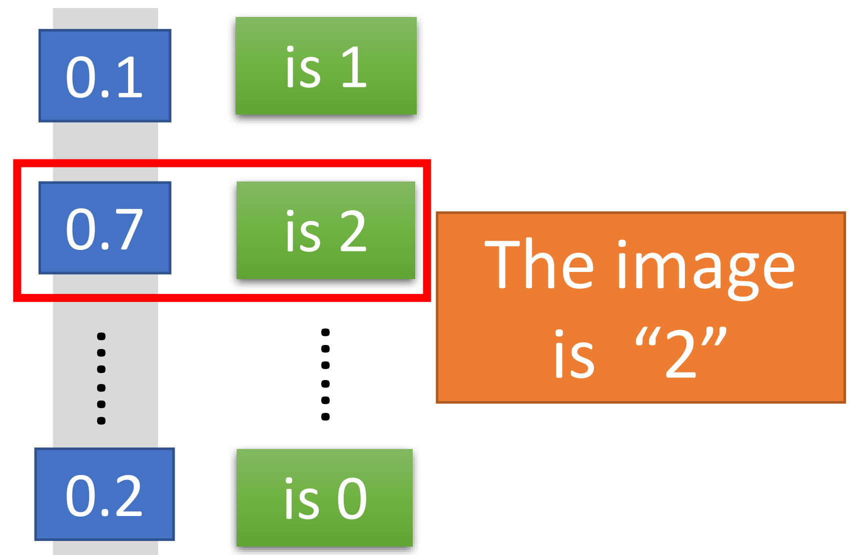


16 x 16 = 256

Ink → 1

No ink → 0

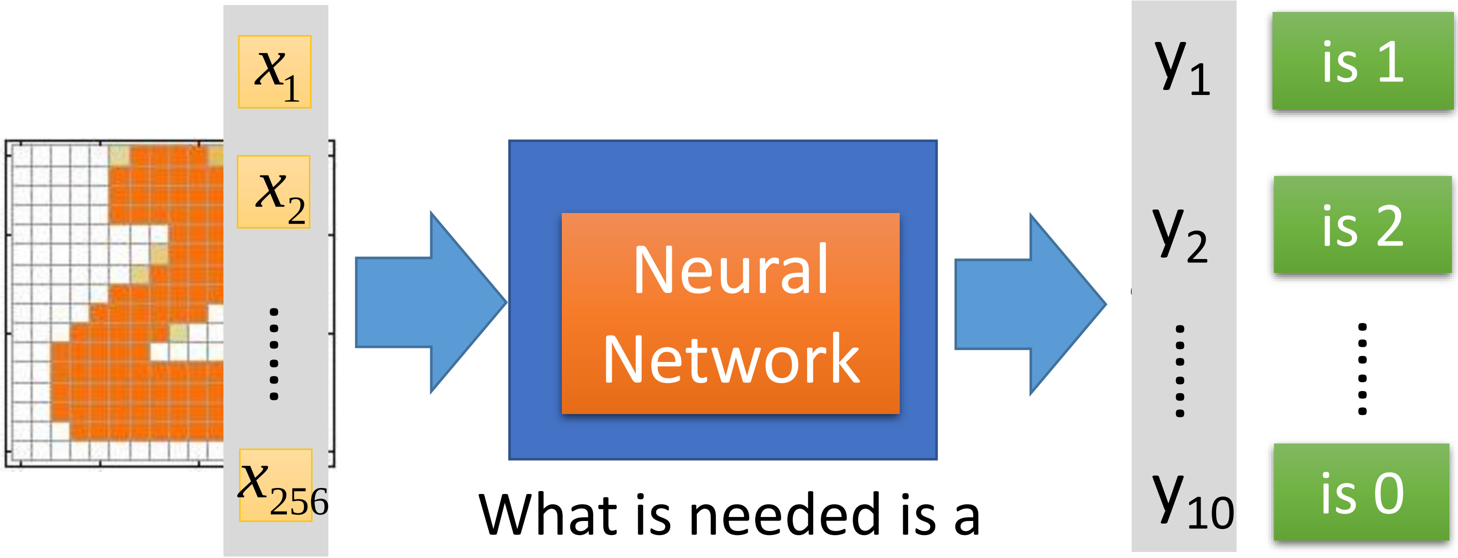
Output



Each dimension represents the confidence of a digit.

Example Application

- Handwriting Digit Recognition

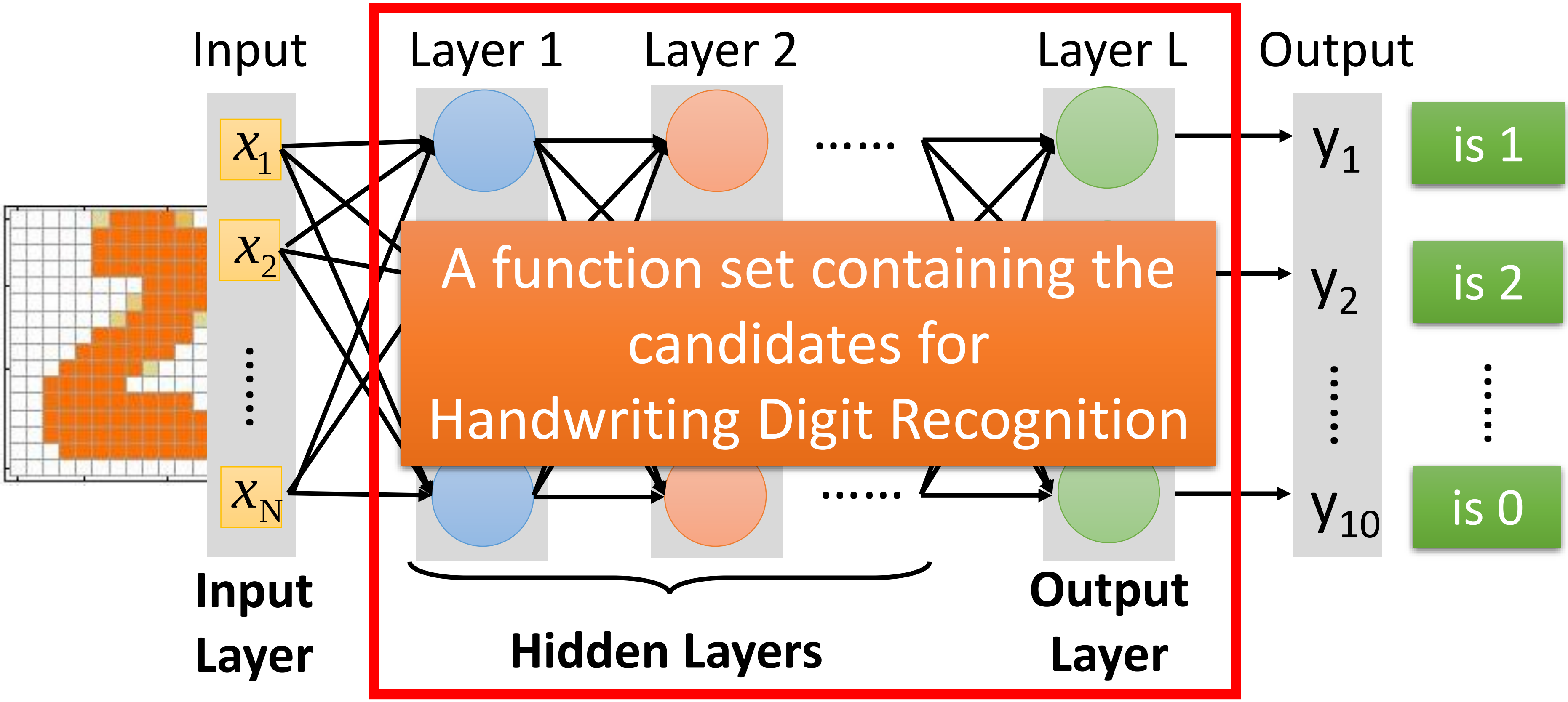


What is needed is a function ……

Input:
256-dim vector

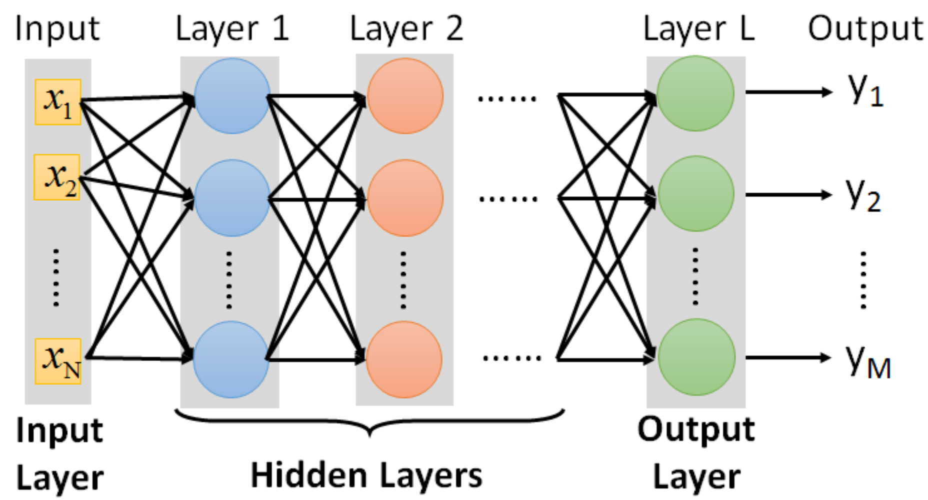
output:
10-dim vector

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

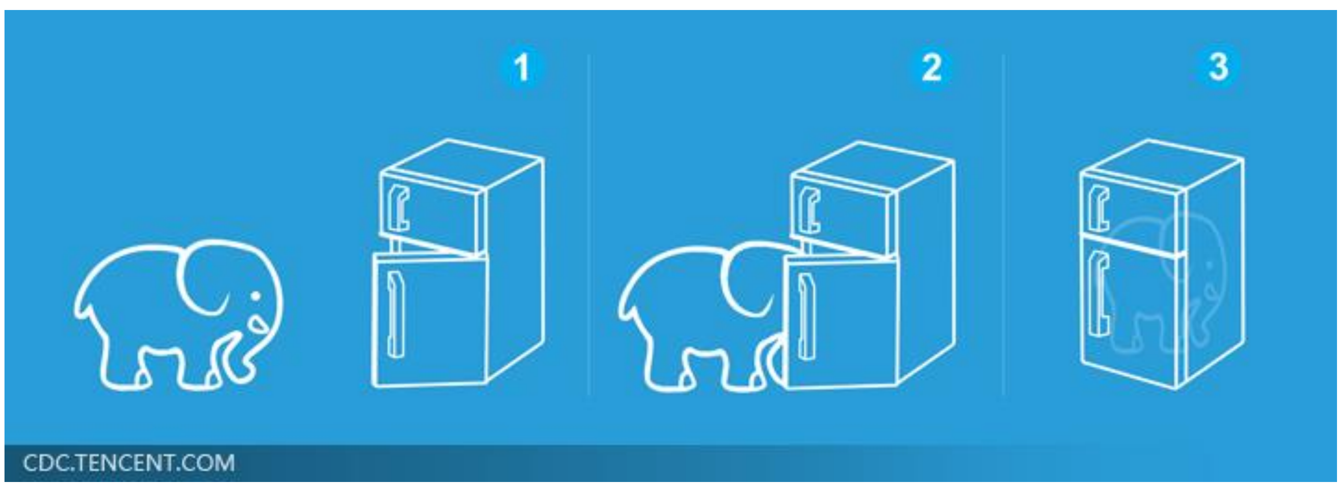
- Q: Can the structure be automatically determined?
  - E.g. Evolutionary Artificial Neural Networks
- Q: Can we design the network structure?

Convolutional Neural Network (CNN)

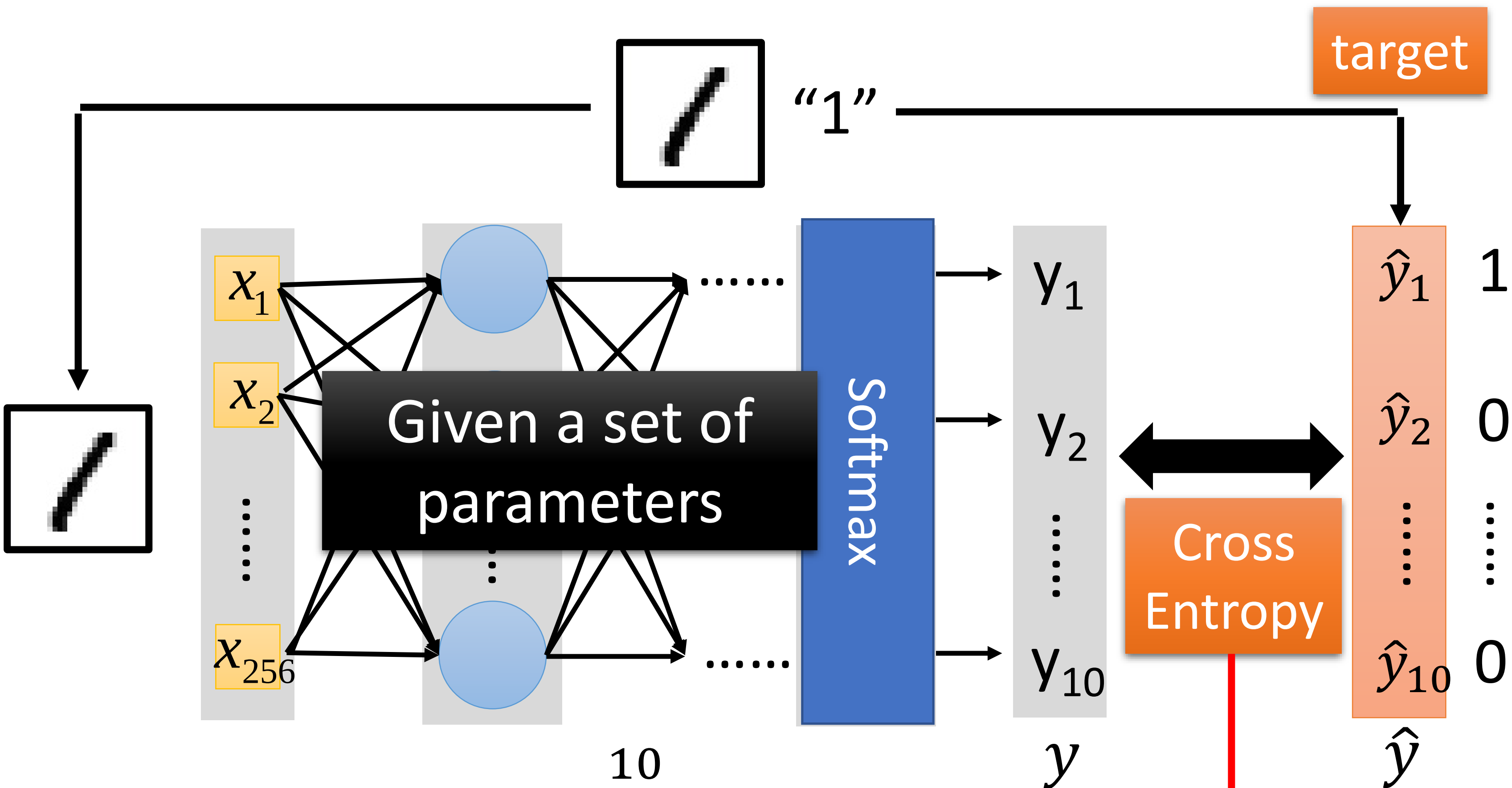
Three Steps for Deep Learning

Step 1: Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



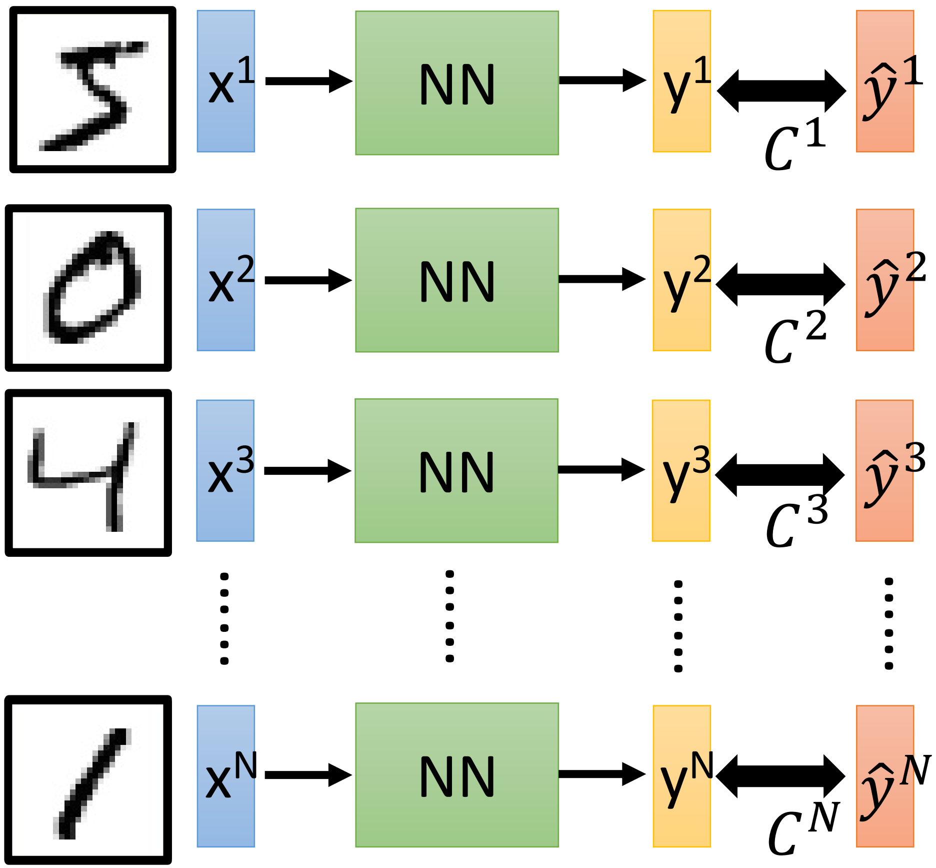
Loss for an Example



$$C(y, \hat{y}) = -\sum_{i=1}^{10} \hat{y}_i \ln y_i$$

Total Loss

For all training data …



Total Loss:

$$\boxed{L = \sum_{n=1}^{N} C^n}$$

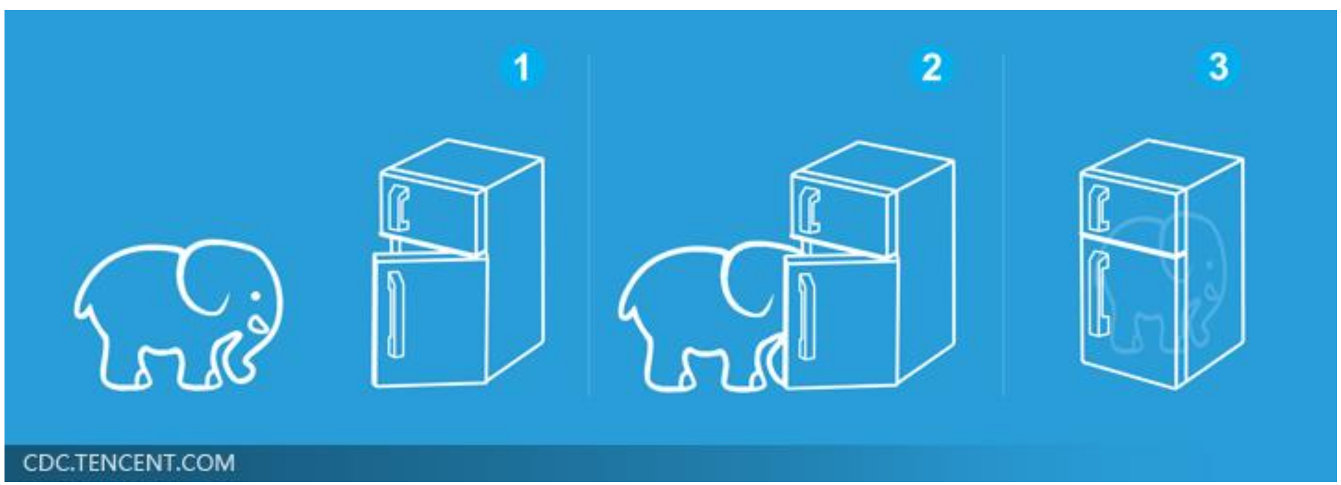
Find ***a function in function set*** that minimizes total loss L

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

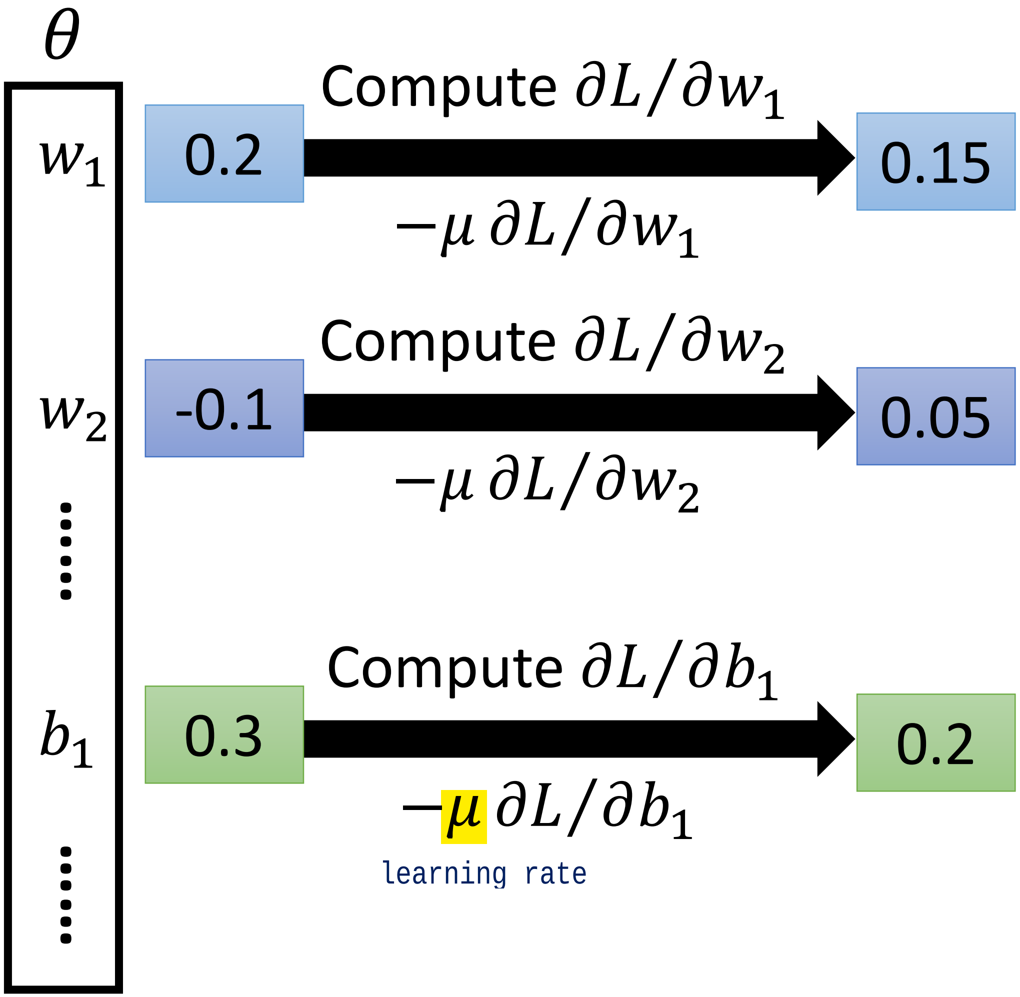
Three Steps for Deep Learning

Step 1: Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



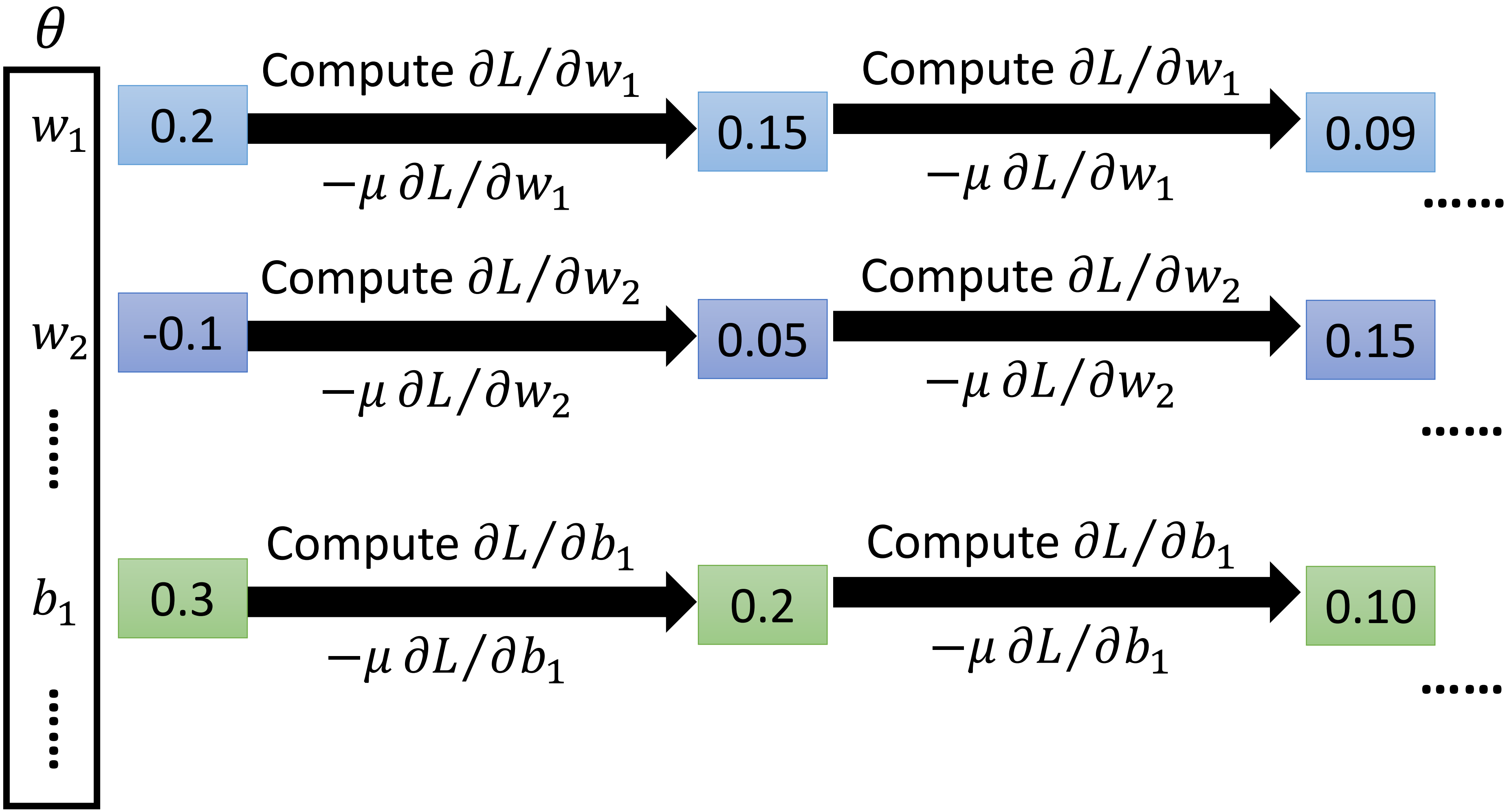
Gradient Descent



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

gradient

Gradient Descent

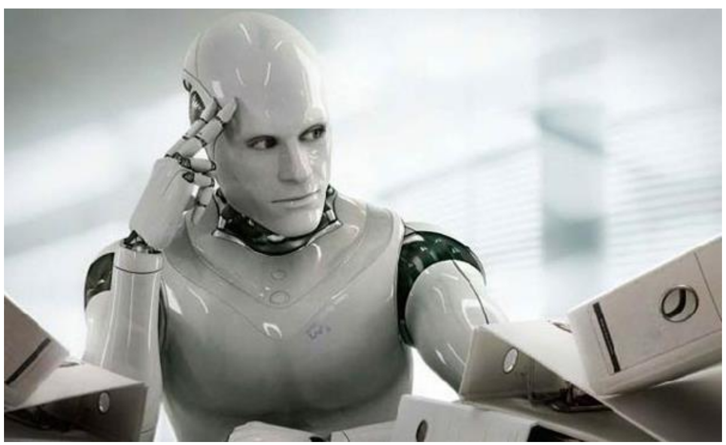


Gradient Descent

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

TensorFlow
torch
theano

Caffe
Microsoft CNTK
Chainer

Deep Learning library produced by Amazon
DSSTNE
mxnet
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

Concluding Remarks

What are the benefits of deep architecture?

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.

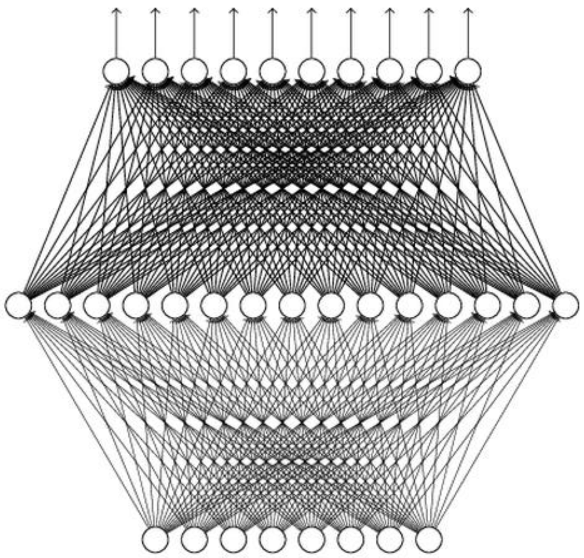
Universality Theorem

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?

(next lecture)

"深度學習深度學習"

- My Course: Machine learning and having it deep and structured
  - http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD15_2.html
  - 6 hour version: http://www.slideshare.net/tw_dsconf/ss-62245351
- "Neural Networks and Deep Learning"
  - written by Michael Nielsen
  - http://neuralnetworksanddeeplearning.com/
- "Deep Learning"
  - written by Yoshua Bengio, Ian J. Goodfellow and Aaron Courville
  - http://www.deeplearningbook.org

Acknowledgment

- 感謝 Victor Chen 發現投影片上的打字錯誤