Deep Learning

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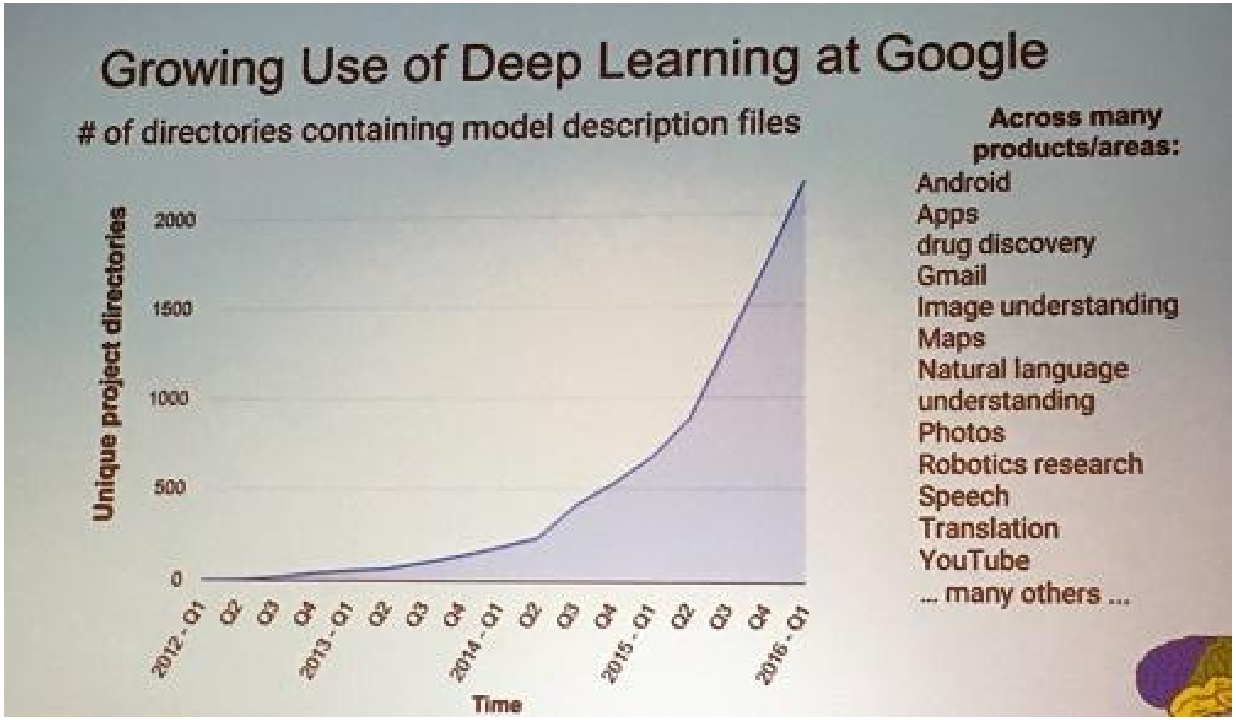
Deep learning attracts lots of attention.

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



Deep learning trends at Google. Source: SIGMOD 2016/Jeff Dean

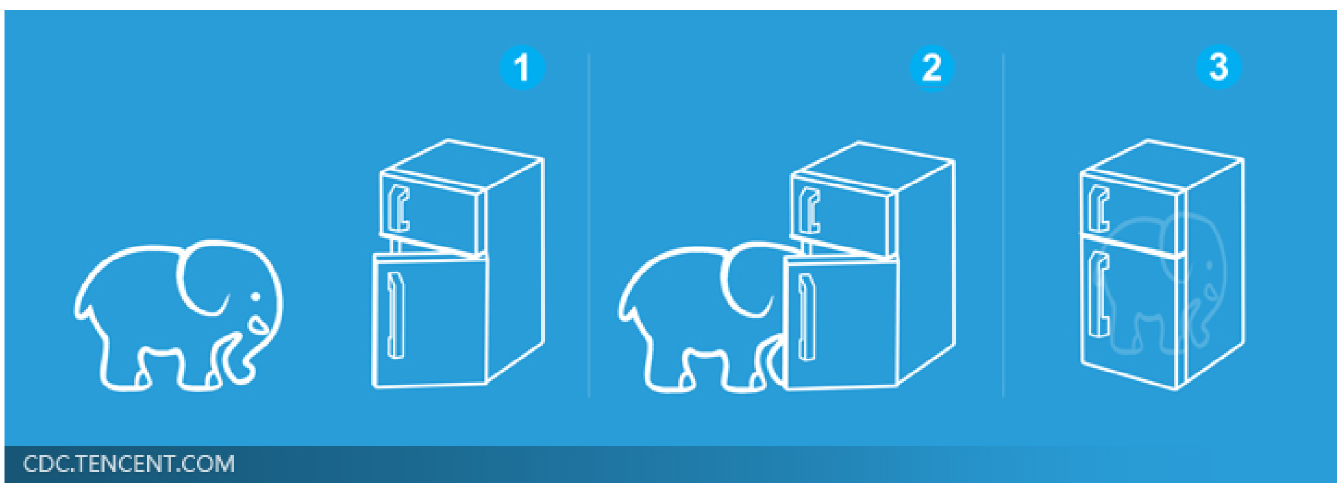
Ups and downs of Deep Learning

- 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
- 2009: GPU
- 2011: Start to be popular in speech recognition
- 2012: win ILSVRC image competition
- 2015.2: Image recognition surpassing human-level performance
- 2016.3: Alpha GO beats Lee Sedol
- 2016.10: Speech recognition system as good as humans

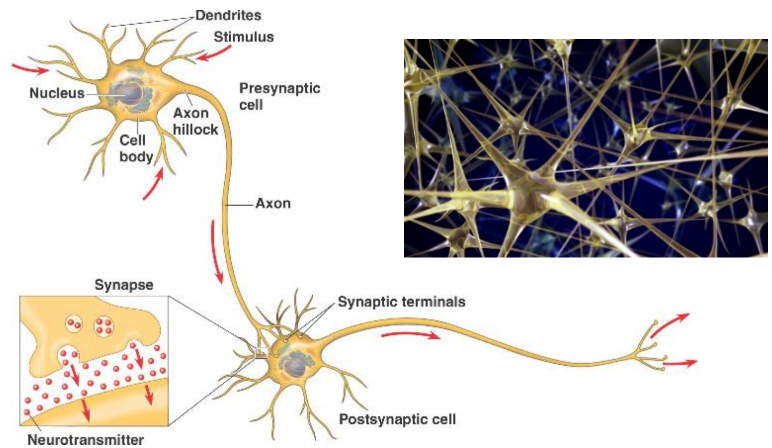
Three Steps for Deep Learning

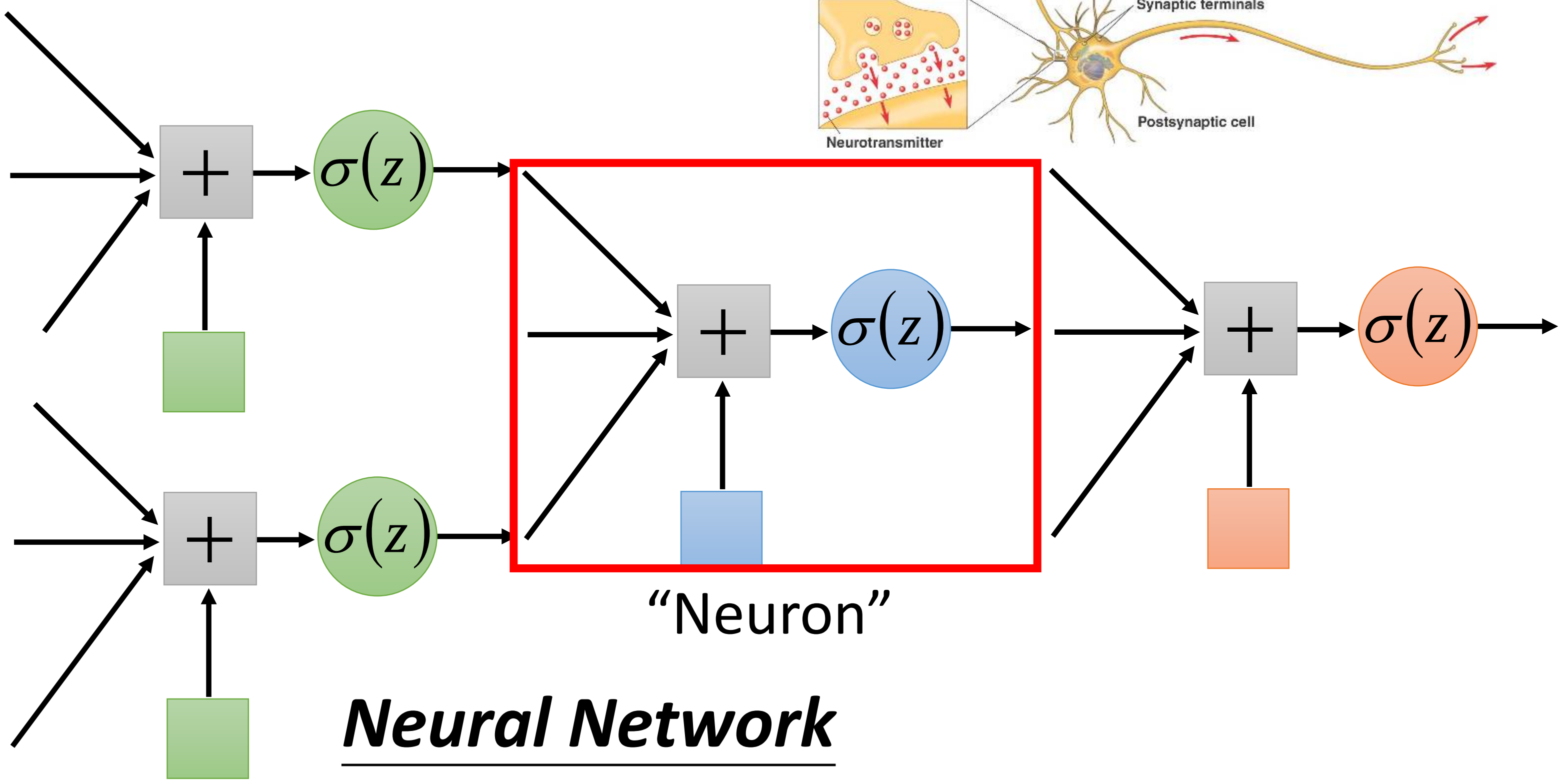
Step 1: Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



Neural Network



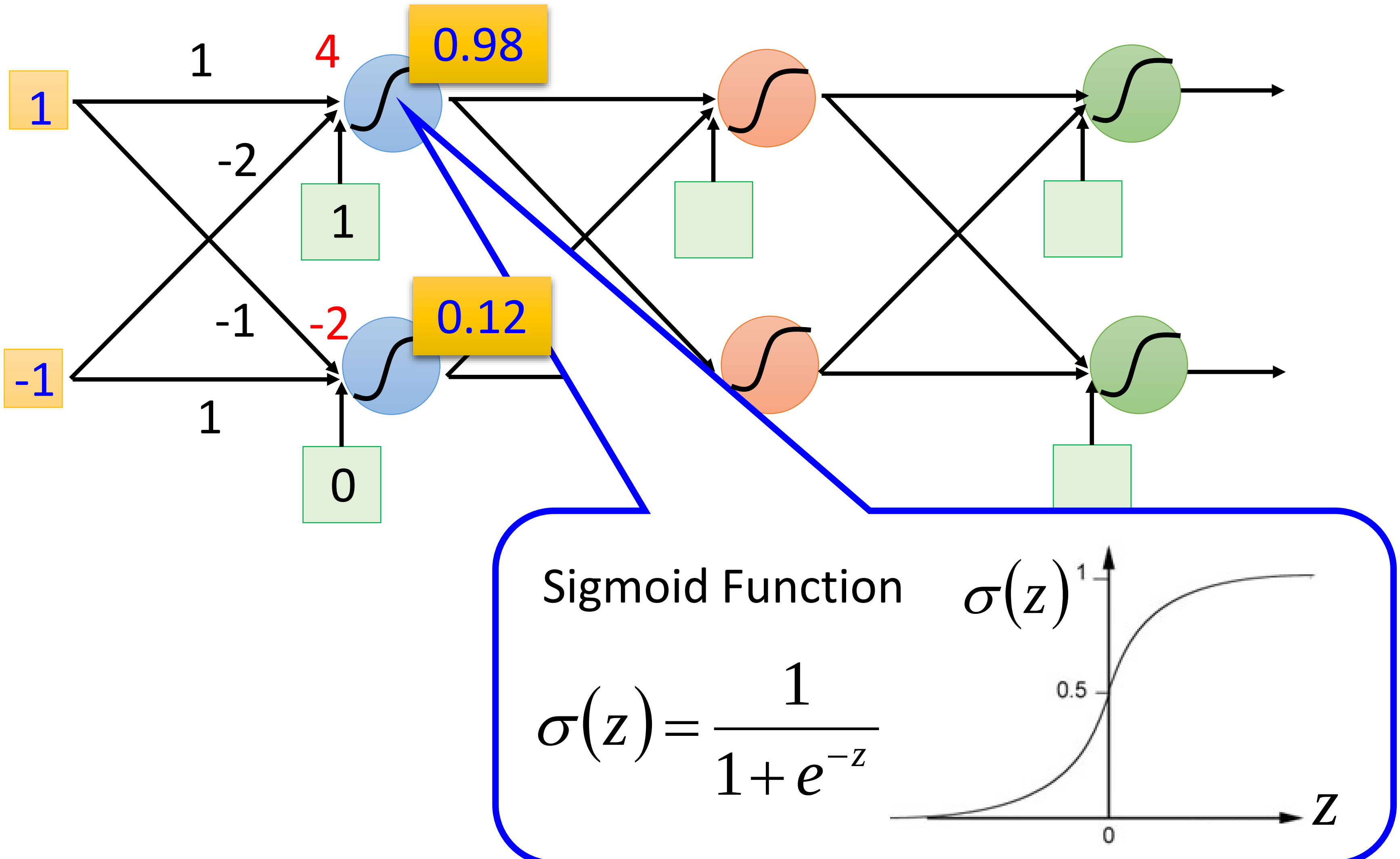


Neural Network

Different connection leads to different network structures

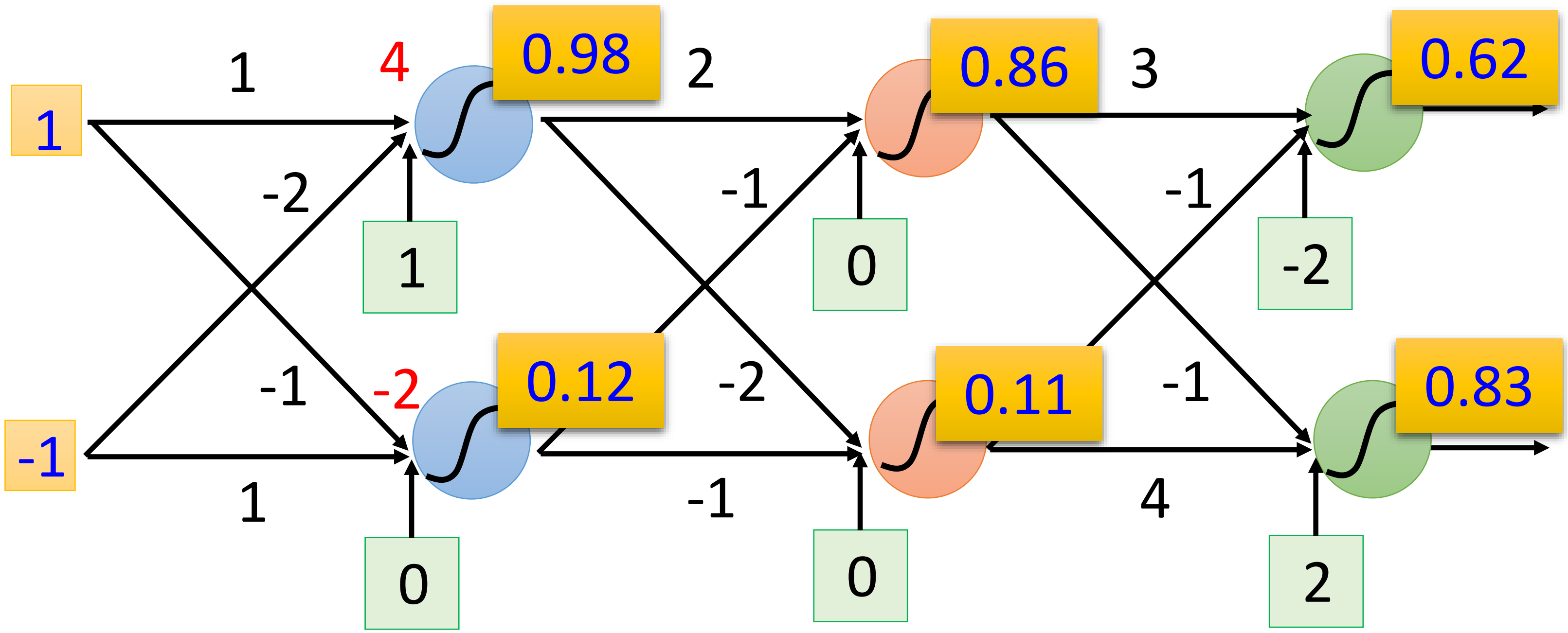
Network parameter θ: all the weights and biases in the "neurons"

Fully Connect Feedforward Network

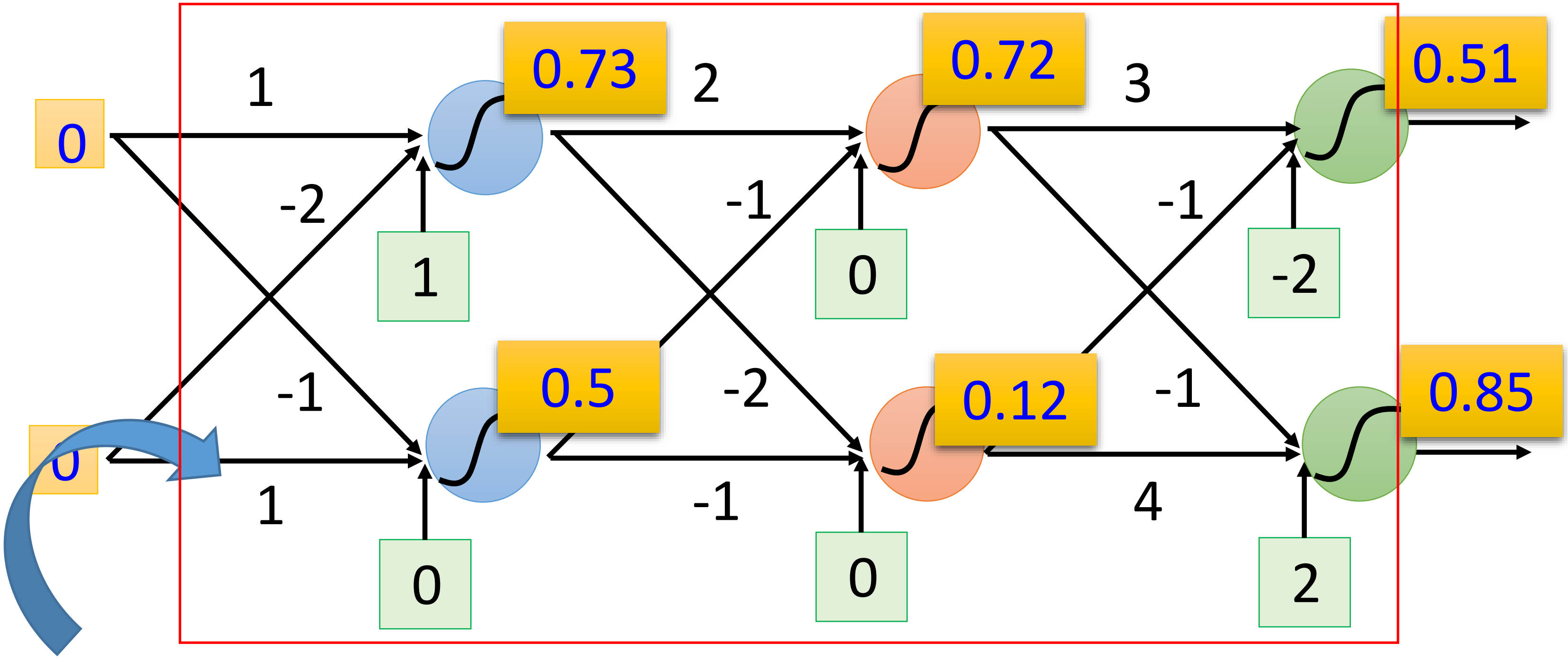


$$\sigma(z) = \frac{1}{1+e^{-z}}$$

Fully Connect Feedforward Network



Fully Connect Feedforward Network



This is a function.

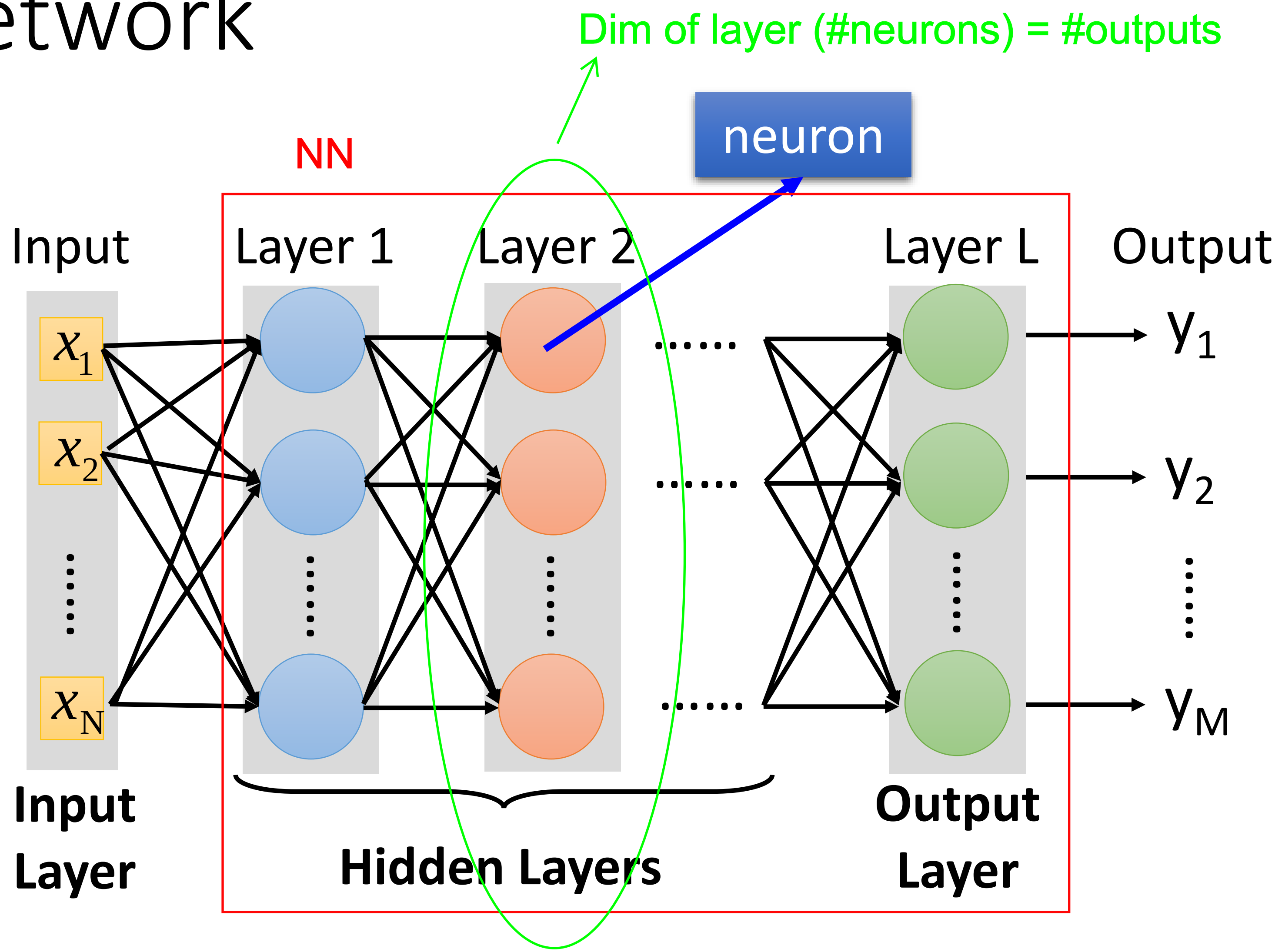
Input vector, output vector

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

Given network structure, define ***a function set***

It means that

Fully Connect Feedforward Network



Deep = Many hidden layers

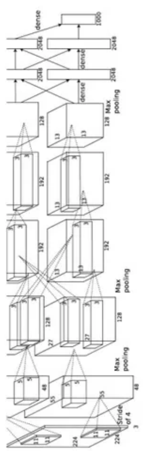
dataset: ImageNet

It's not a NN.

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

8 layers

16.4%



AlexNet (2012)

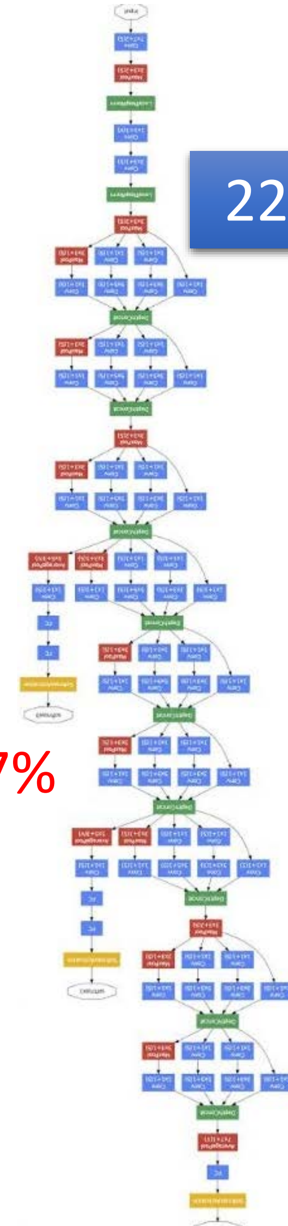
7.3%

19 layers

VGG (2014)

22 layers

6.7%

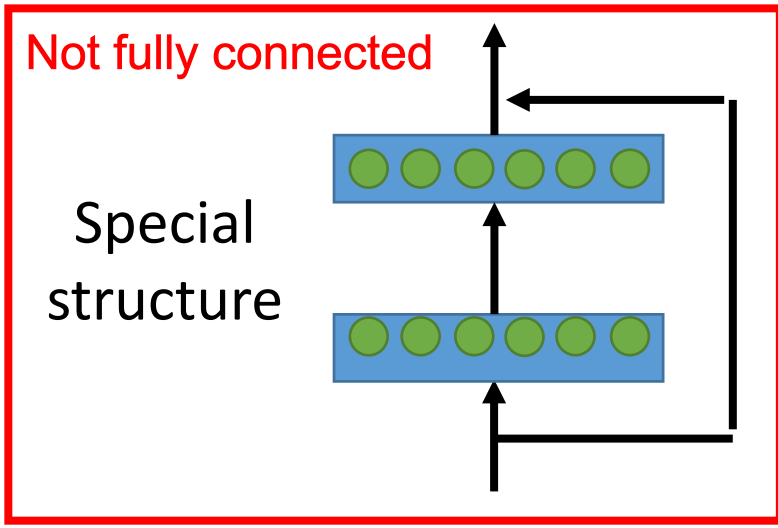


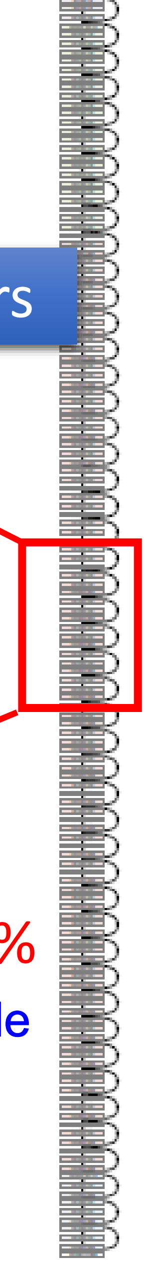
GoogleNet (2014)

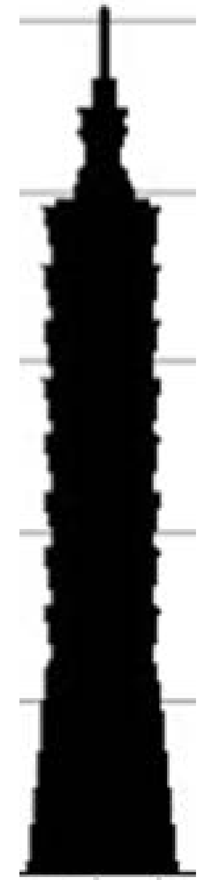
Deep = Many hidden layers

152 layers

101 layers







Ref: https://www.youtube.com/watch?v=dxB6299gpvI

3.57%

Better than people

16.4%

AlexNet (2012)

7.3%

VGG (2014)

6.7%

GoogleNet (2014)

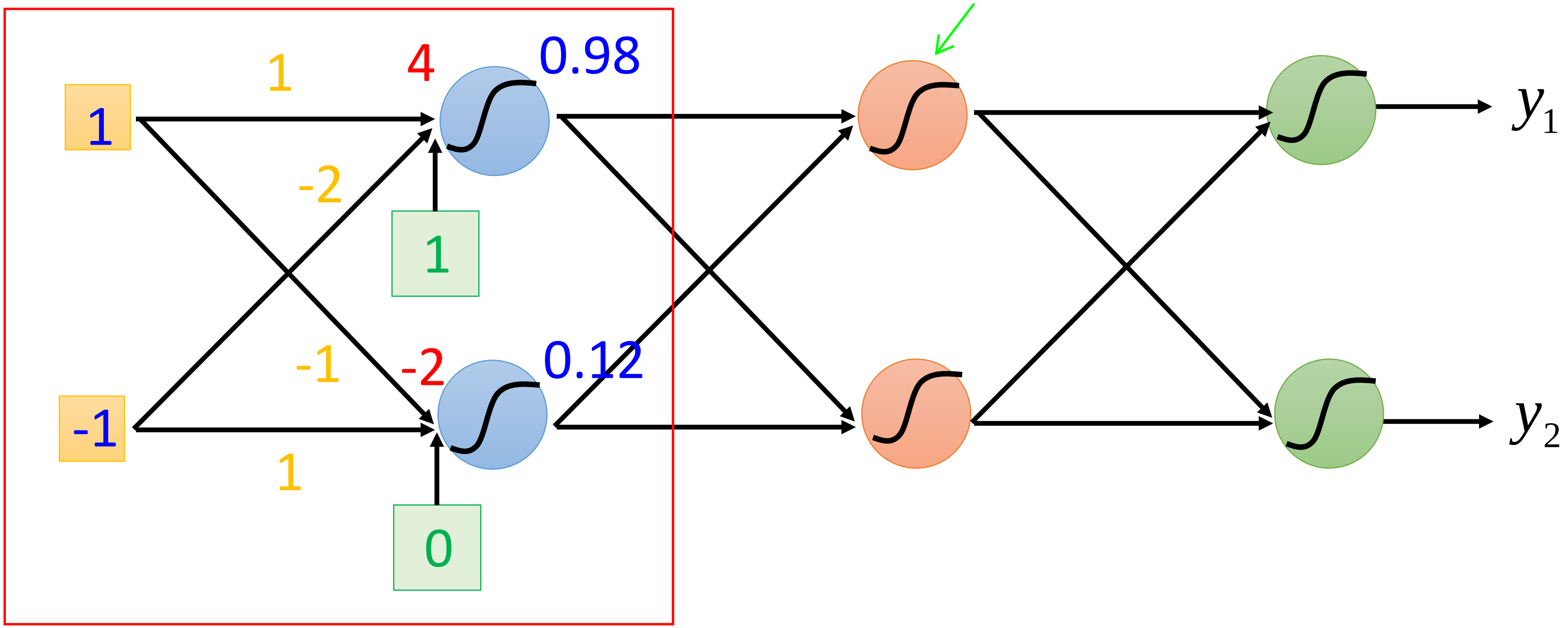
Residual Net (2015)

Taipei 101

For one layer (of all neurons)

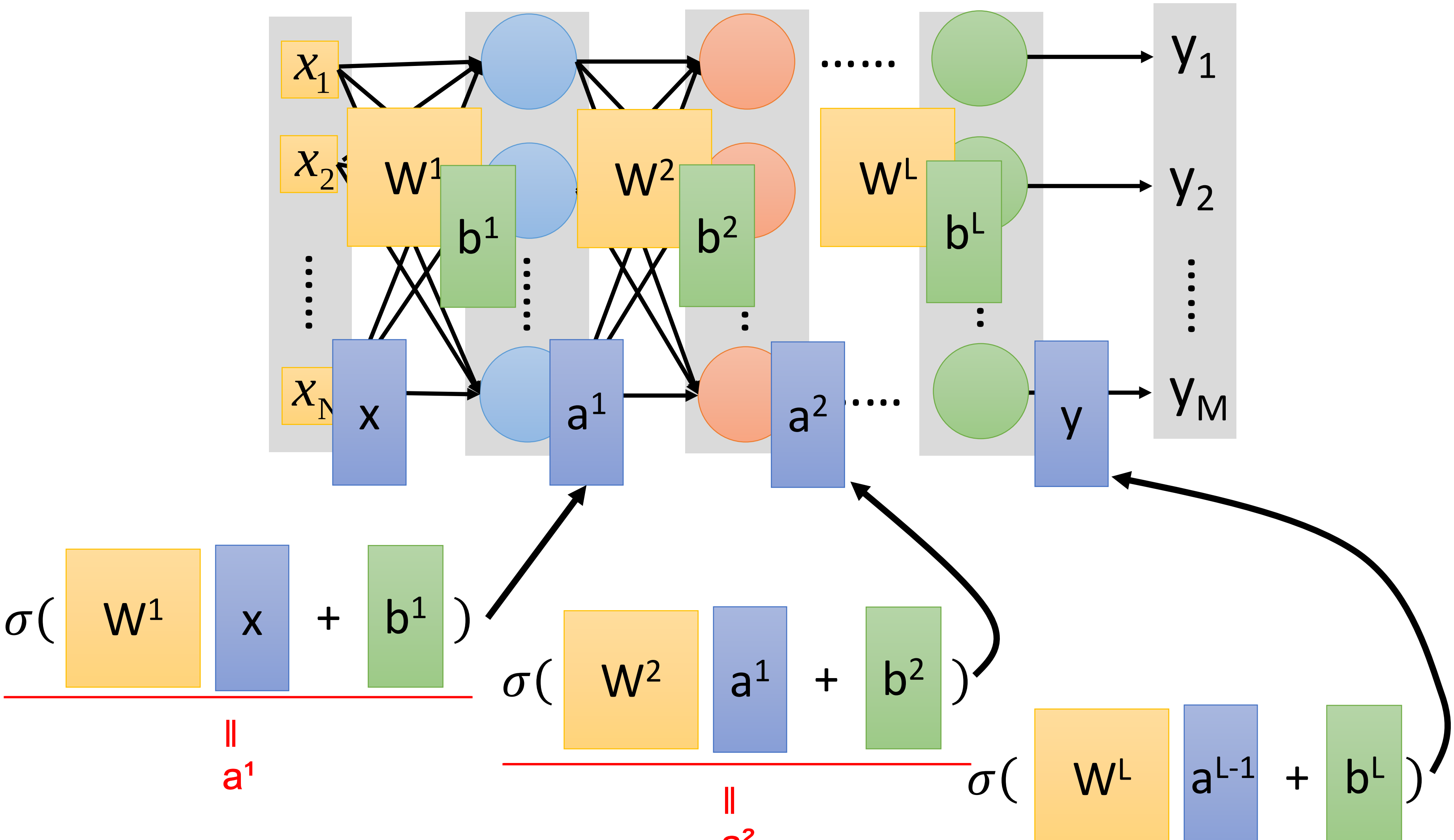
Matrix Operation

We don't usually use "sigmoid" in these days.

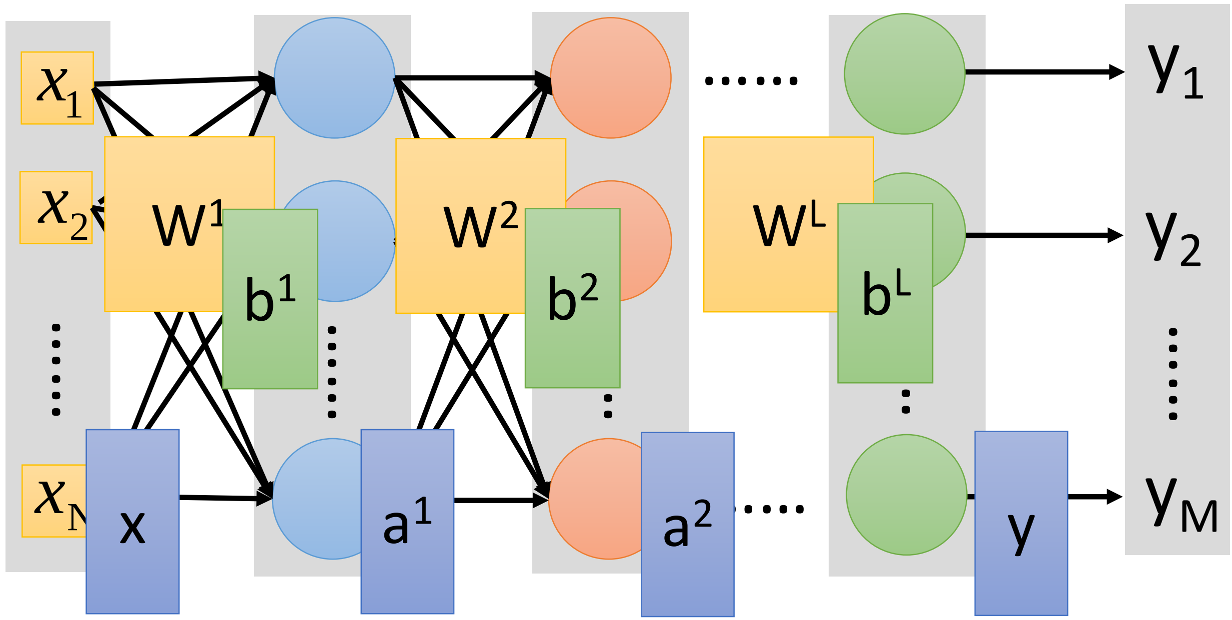


$$\sigma\Bigg(\underbrace{\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix}\begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}}\Bigg) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Neural Network



Neural Network



$$y = f(x)$$

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

GPU

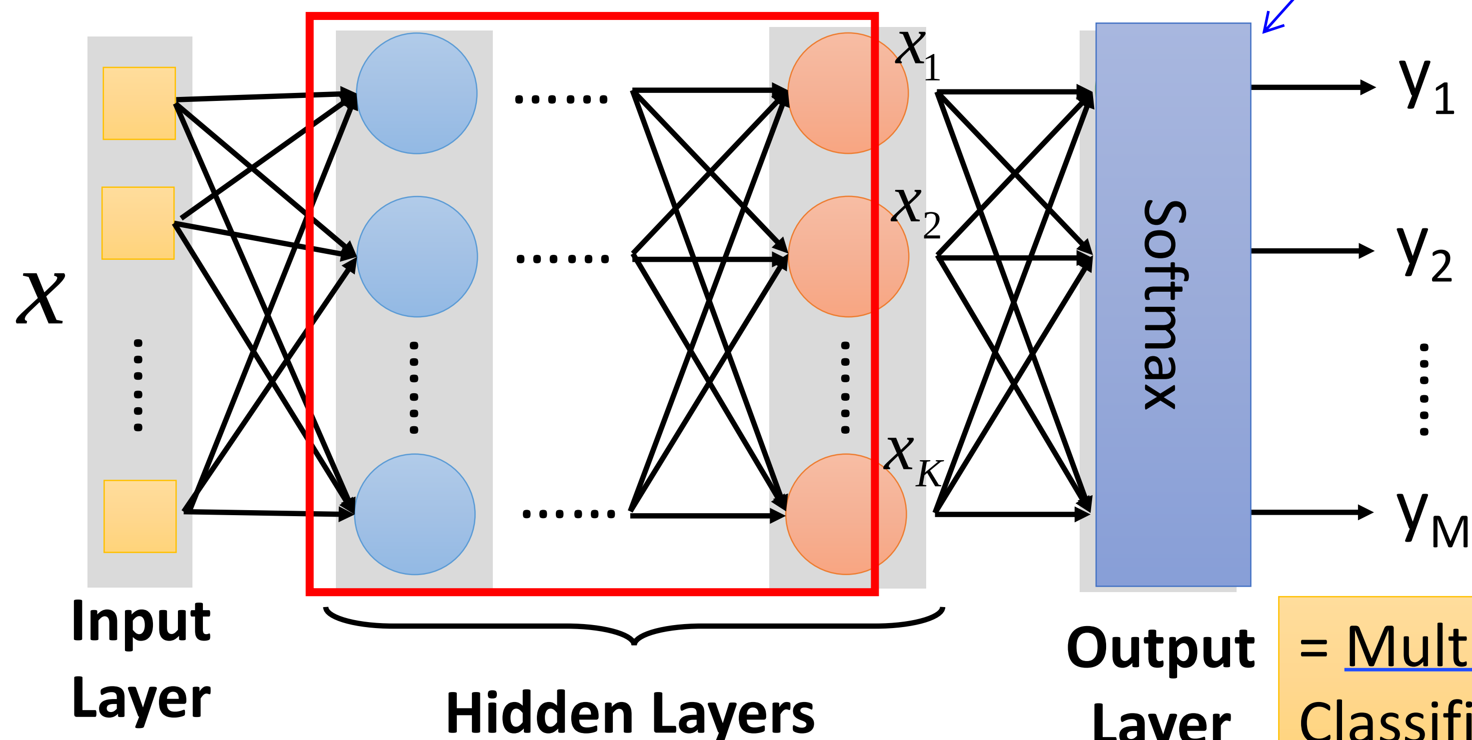
Using parallel computing techniques to speed up matrix operation

Output Layer as Multi-Class Classifier

The output will be linearly separable features.

Feature extractor replacing feature engineering

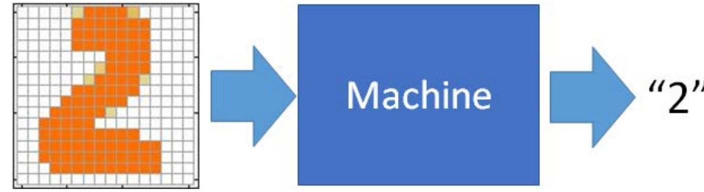
Normally, the last layer's activation function is "softmax."



= Multi-class Classifier

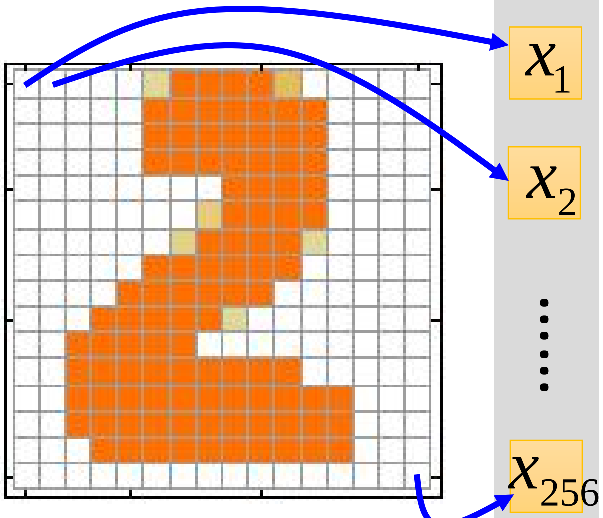
"categorical cross entropy": one-hot representation
"sparse categorical cross entropy": integers
These two loss functions are exactly the same.
The only difference is the format of y.

Example Application



We can use one-hot encoding on y. (We can also don't use it of course.)

Input



16 x 16 = 256

Ink → 1

No ink → 0

Output

$\Sigma\ y_i = 1$

0.1	y_1	is 1
0.7	y_2	is 2
⋮	⋮	⋮
0.2	y_{10}	is 0

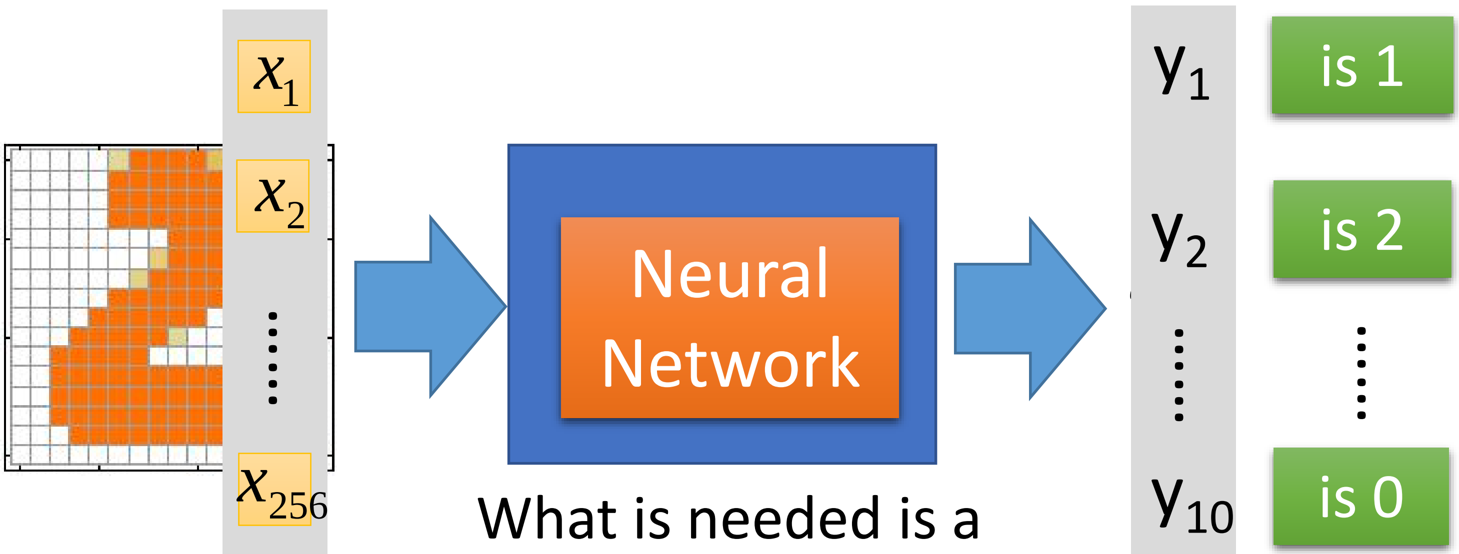
Biggest

The image is "2"

Each dimension represents the confidence of a digit.

Example Application

- Handwriting Digit Recognition

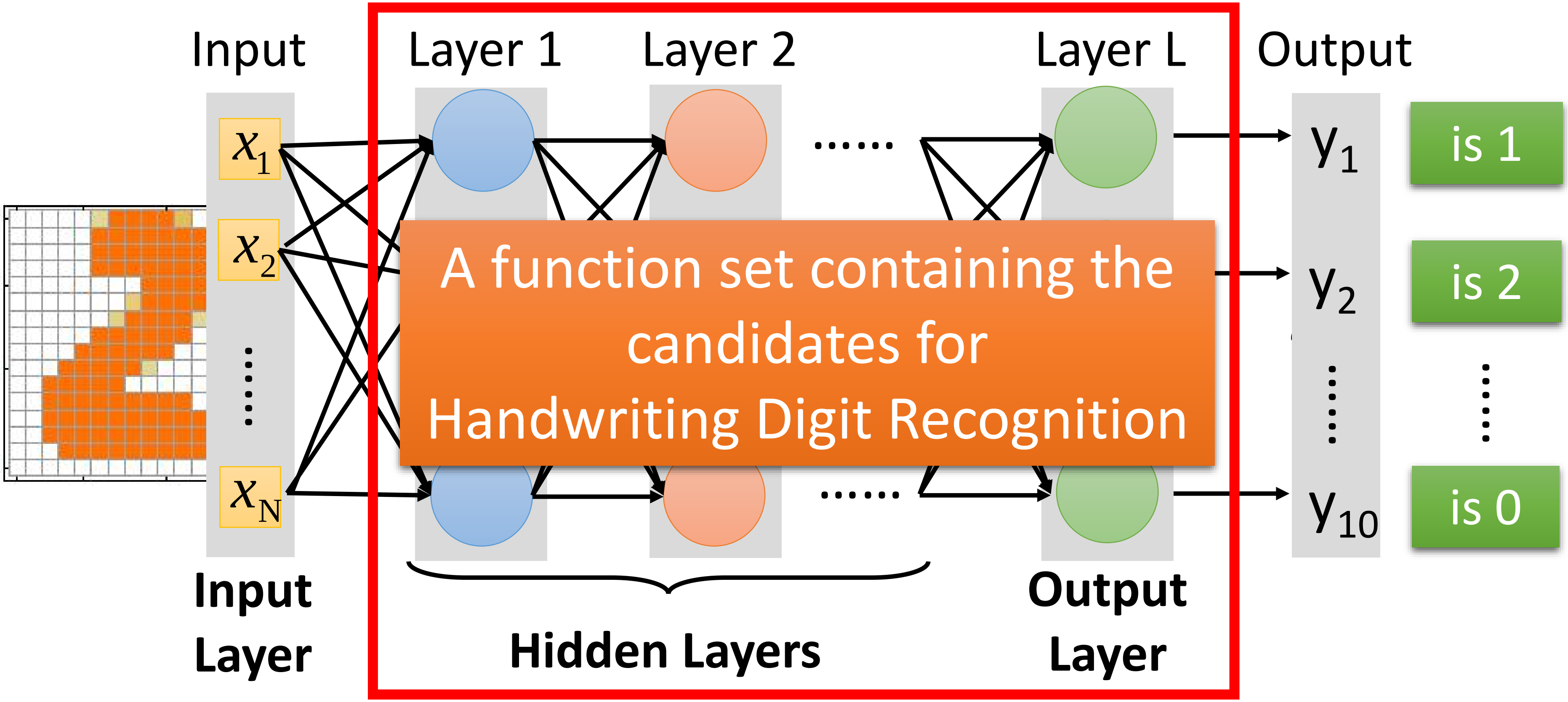


What is needed is a function ......

Input:
256-dim vector

output:
10-dim vector

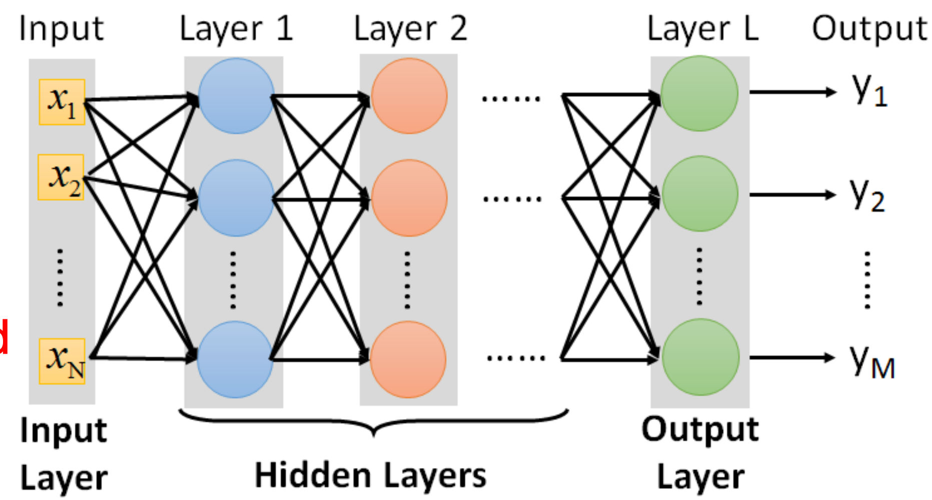
Example Application



You need to <u>decide the network structure</u> to let a good function in your function set.

FAQ

When do we need DL?
When the feature extraction is very hard
(harder than the network design)
ex: Speech recognition



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

Trial and Error + Intuition

- Q: Can the structure be automatically determined? Yes (ex: genetic algorithm)
  - E.g. Evolutionary Artificial Neural Networks
- Q: Can we design the network structure? Sure
  ex:

Convolutional Neural Network (CNN)

Three Steps for Deep Learning

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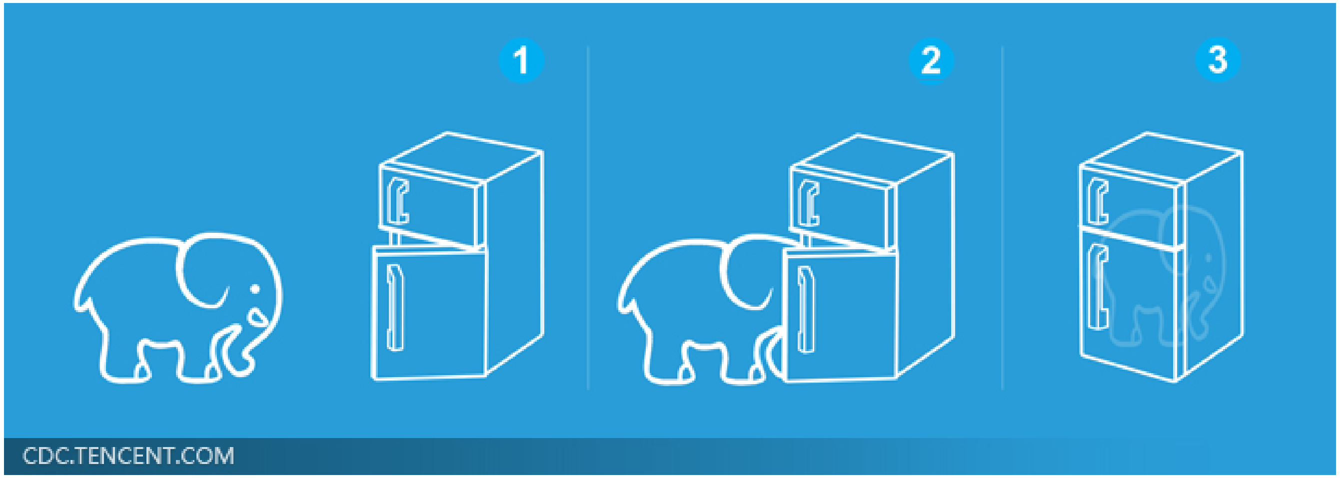
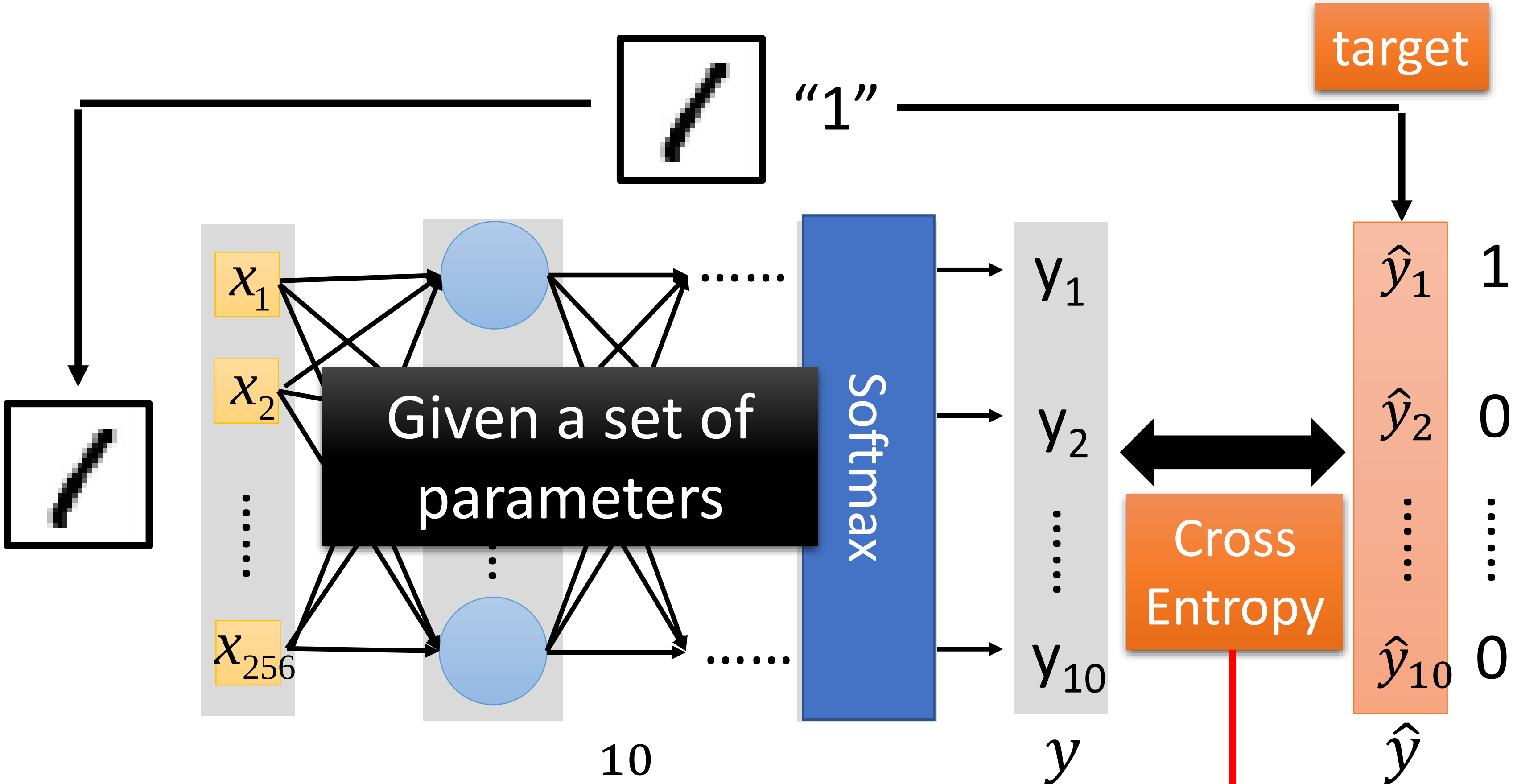
Deep Learning is so simple ……



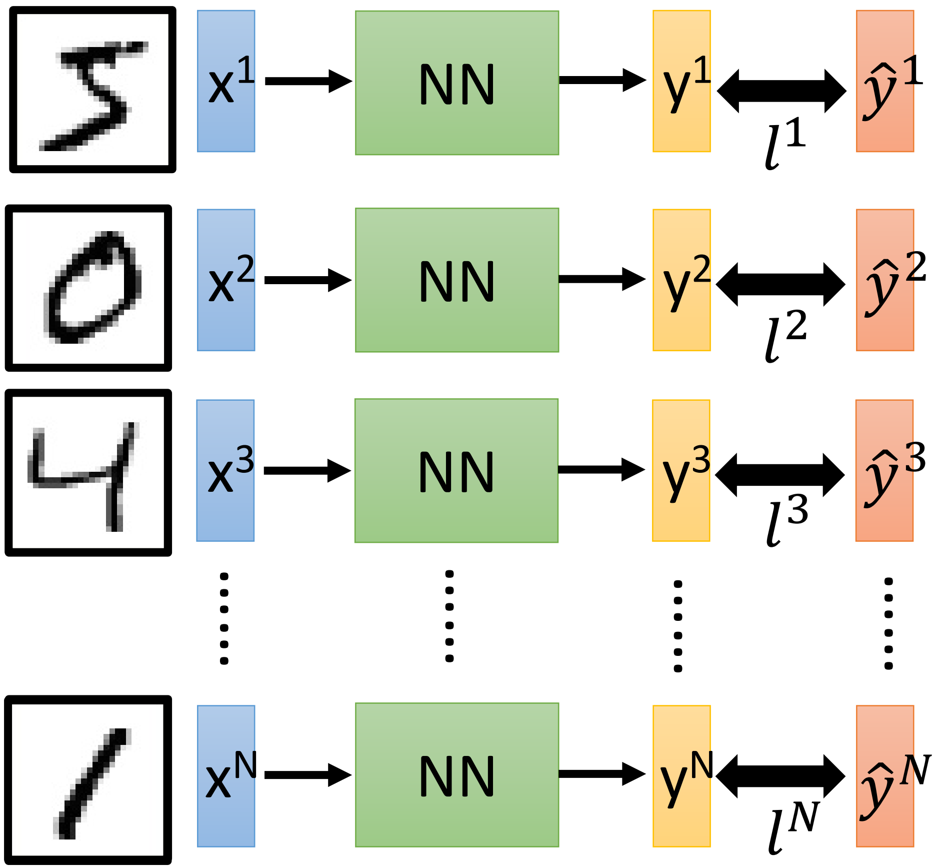
Loss for an Example



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

Total Loss

For all training data …



Total Loss:

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

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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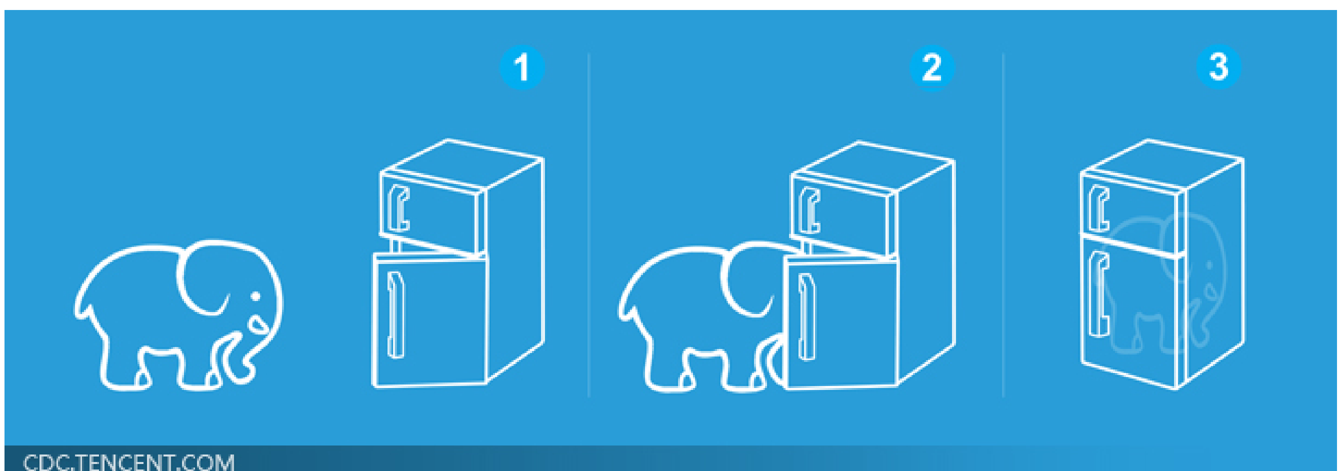


~~Gradient Descent~~

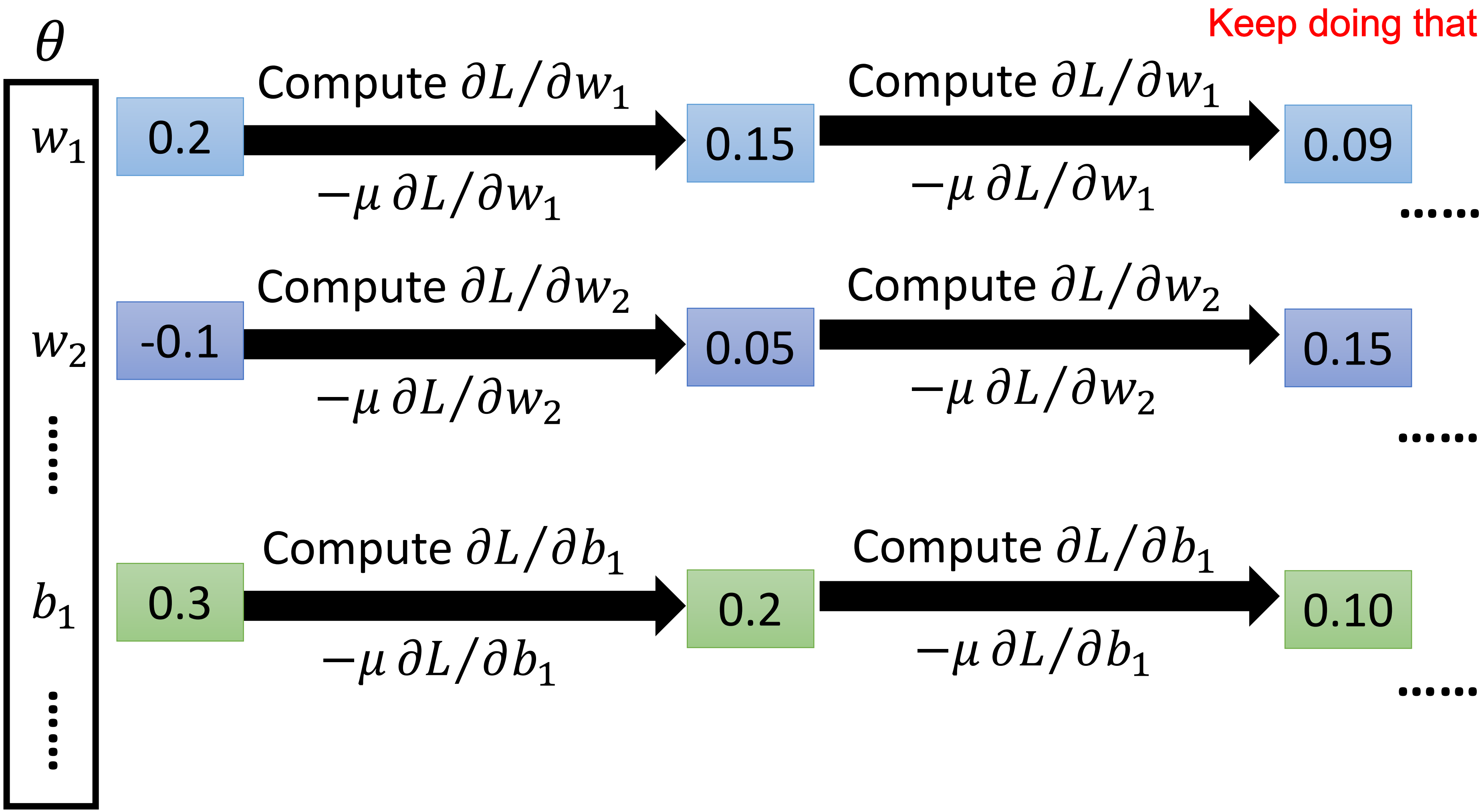
θ

θ			
w_1	0.2	Compute $\partial L/\partial w_1$ $-\mu\, \partial L/\partial w_1$	0.15
w_2	-0.1	Compute $\partial L/\partial w_2$ $-\mu\, \partial L/\partial w_2$	0.05
$\vdots$			
b_1	0.3	Compute $\partial L/\partial b_1$ $-\mu\, \partial L/\partial b_1$	0.2
$\vdots$			

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

gradient

Gradient Descent

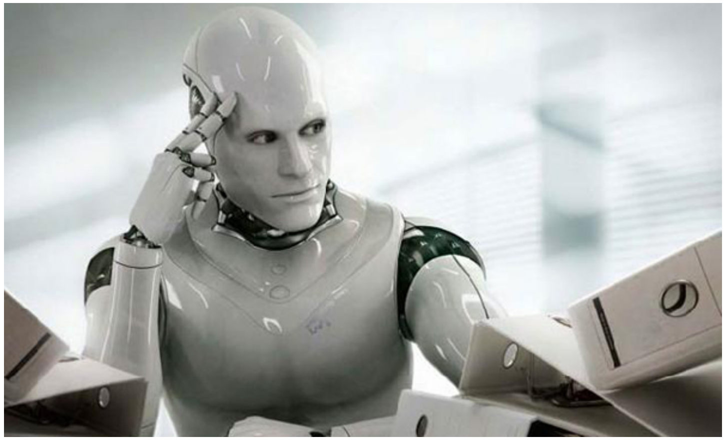


Gradient Descent

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 Ch.8

- 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

Three Steps for Deep Learning

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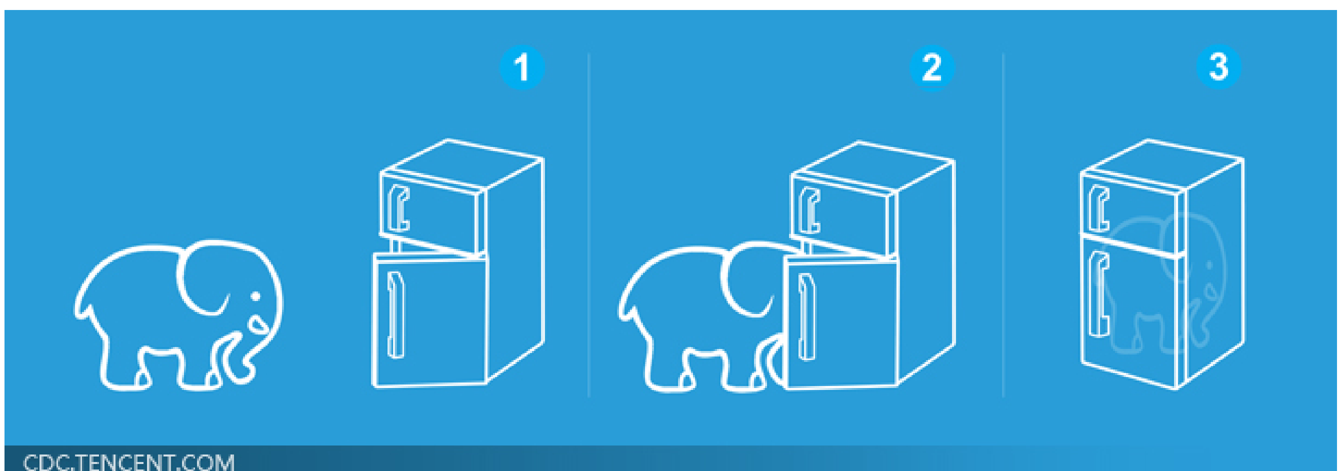


Concluding Remarks

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

Overfitting

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

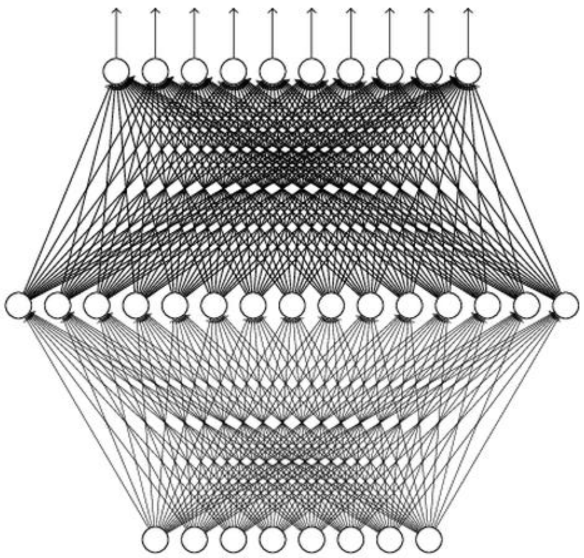
Universality Theorem

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?

Ch.12

“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