Lecture I: Introduction to Deep Learning

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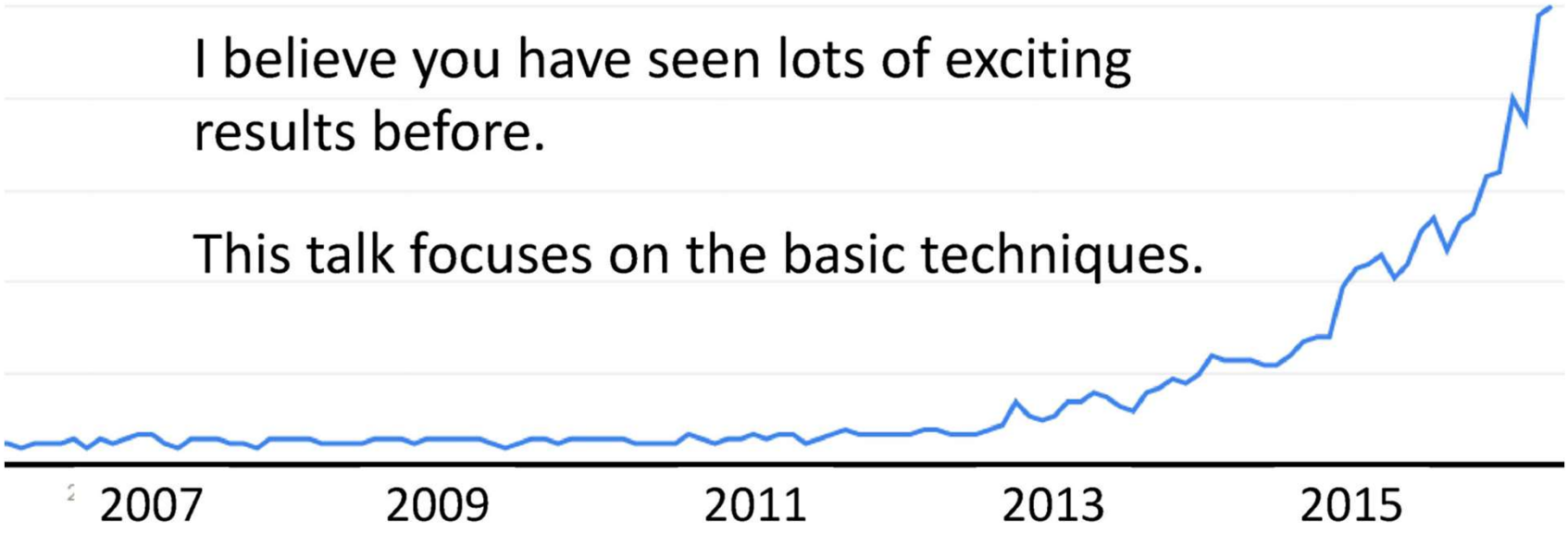
Ref. Deep Learning Tutorial, 李宏毅 （NTU, Hung-Yi Lee）

Deep learning attracts lots of attention.

- Google Trends

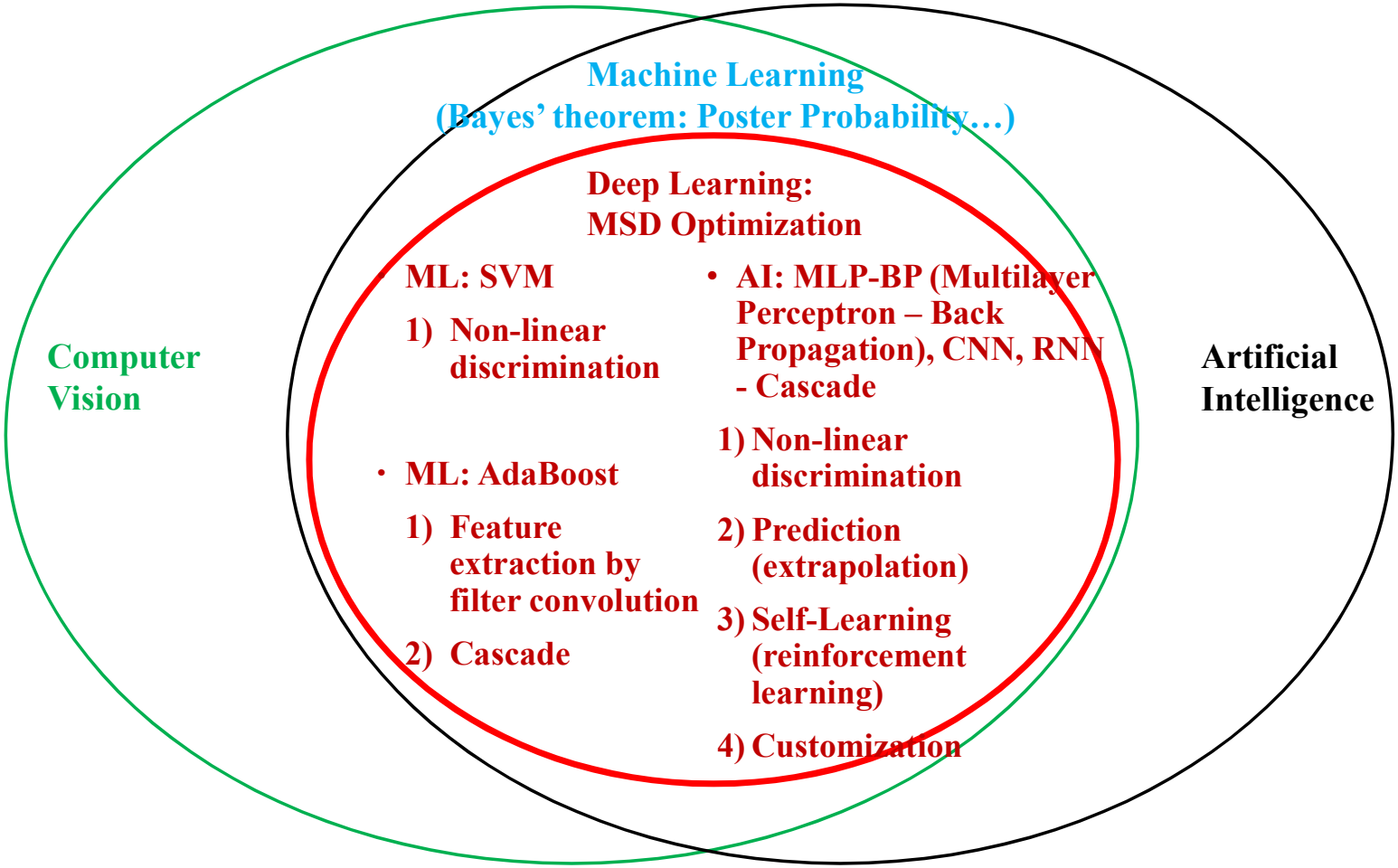


Deep Learning:

Computer Vision Vs. Artificial Intelligence Network

Machine Learning: Need Data + Label

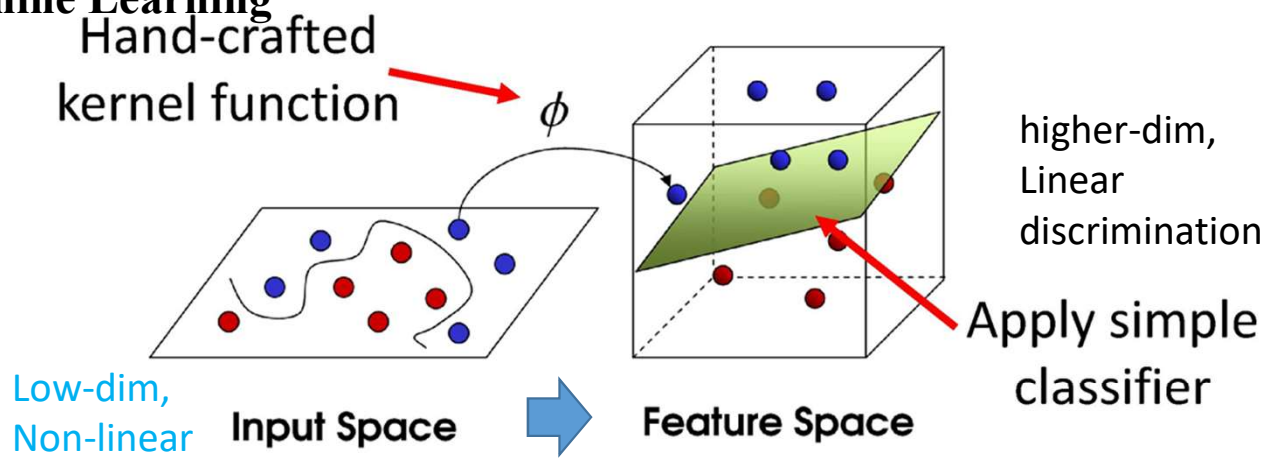
Deep Learning: Need Big Data + Label



Deep Learning with Machine Learning

J: Without cascade concept

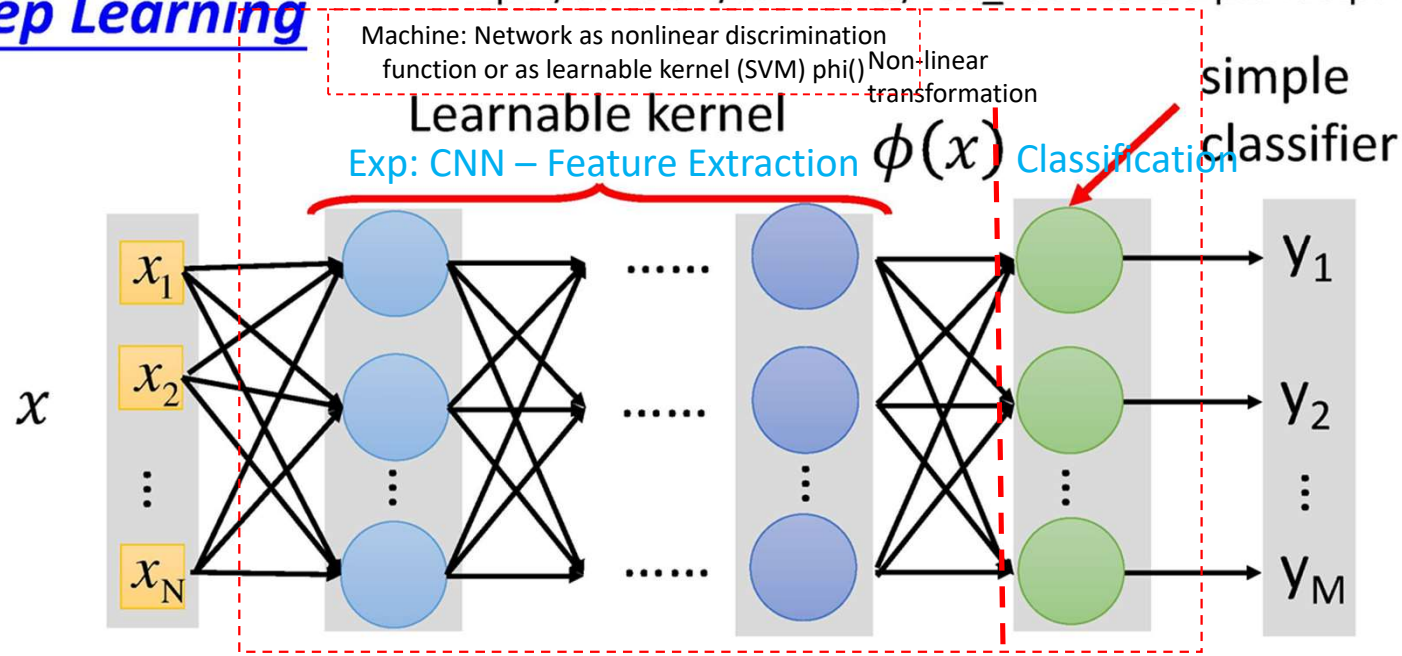
SVM



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

J: With cascade concept

Deep Learning



Deep Learning from ML: Networks as

1) Non-linear discrimination: As learnable kernel (SVM) phi()
2) AdaBoost Cascade: As boosted weak classifier to be strong classifier

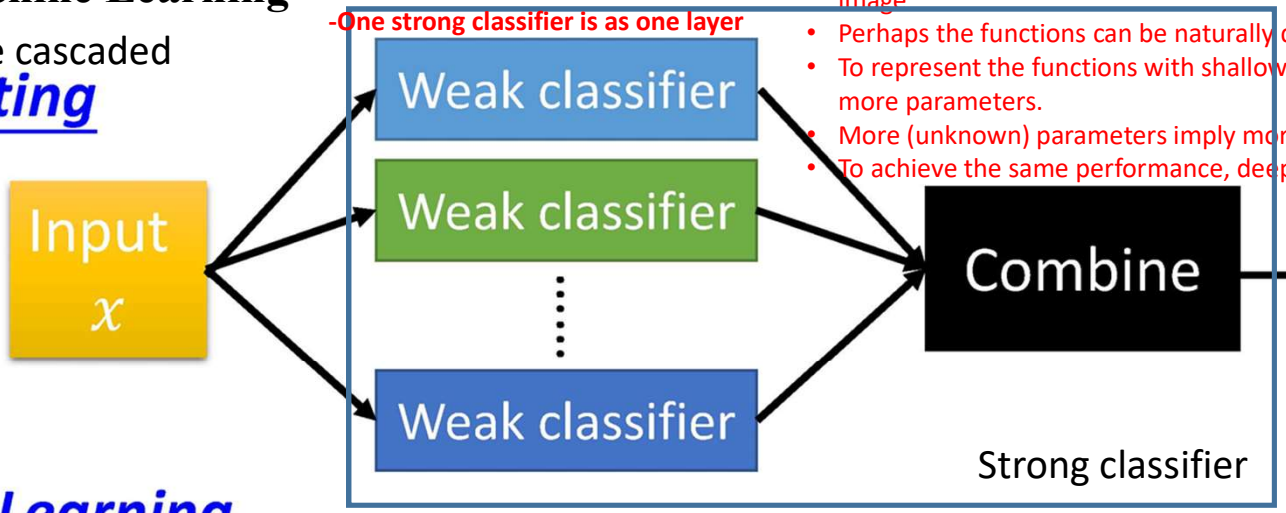
Deep Learning with Machine Learning

Cascade: Strong classifiers are cascaded

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer

- Some functions can be easily represented by deep structure (topology). E.g. image
- Perhaps the functions can be naturally decomposed into several steps.
- To represent the functions with shallow (fat and short) structure needs more parameters.
- More (unknown) parameters imply more training data needed.
- To achieve the same performance, deep learning needs less training data.

Boosting

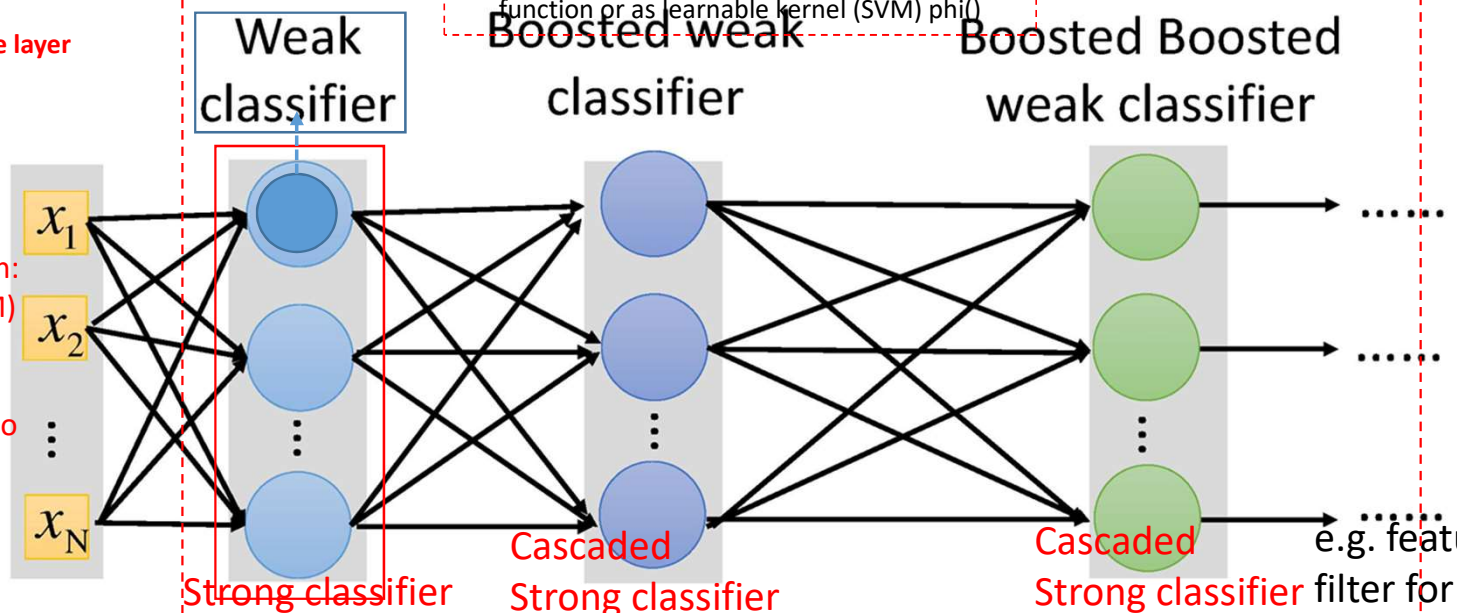


Strong classifier

Deep Learning

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer

Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()



Deep Learning from ML: Networks as
1) Non-linear discrimination: As learnable kernel (SVM) phi()
2) AdaBoost Cascade: As boosted weak classifier to be strong classifier

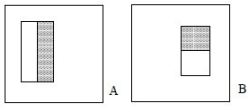
e.g. feature correlation filter for face recognition

ML: AdaBoost - Feature Extraction Using Haar-Like Filter

1) Filter:

- Filter type: Ex. Parameters -1, +1,
- can use II (Integral Image)

Ex: Haar-like filter

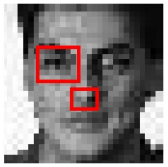


2) Feature:

a. Filter 的座標位置 (position)

b. Filter 的大小 (size)

Ex: Eye , nose



1+2) Feature Value (this is one weak classifier):

-Feature Value = $*$

Filter Feature(Position, Size)

Convolution: Linear combination

Ex:

ML: AdaBoost - Cascade

- Advantage: Reducing testing computation time.
- Method: Cascade stages.

  -Each weak classifier: Consist of one

  Feature Value (this is one weak classifier):

  Feature Value = Filter * Feature(Position,Size) -- convolution

  -Each stage corresponds to one strong classifier: Consists of several weak classifiers

  -The training data is the same for each weak classifier at the same strong classifier.

  -After one strong classifier, the training data is reduced – reduce as many negative data as possible.
- Idea: Reject as many negatives as possible at the earliest stage. More complex classifiers were then used in later stages.
- The detection process is that of a degenerate decision tree, so called "cascade".

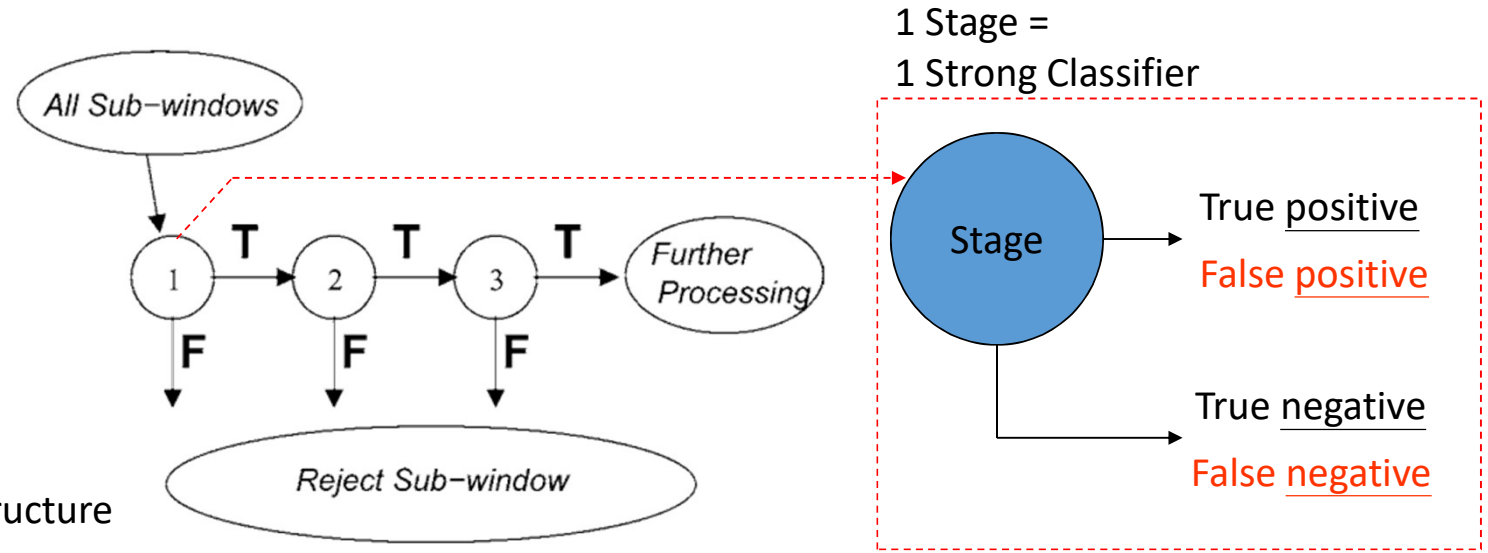
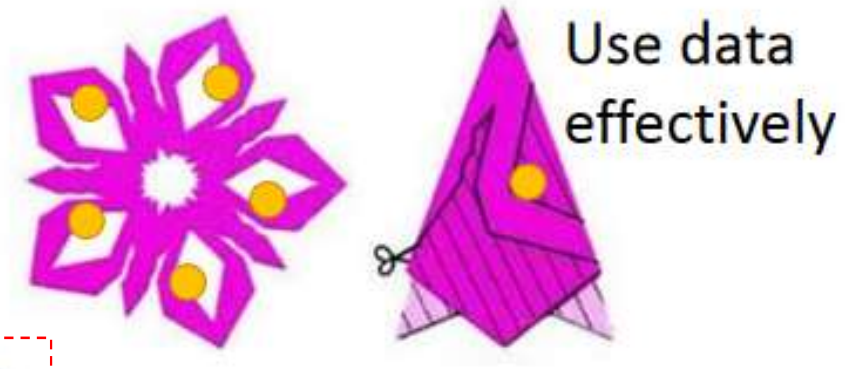


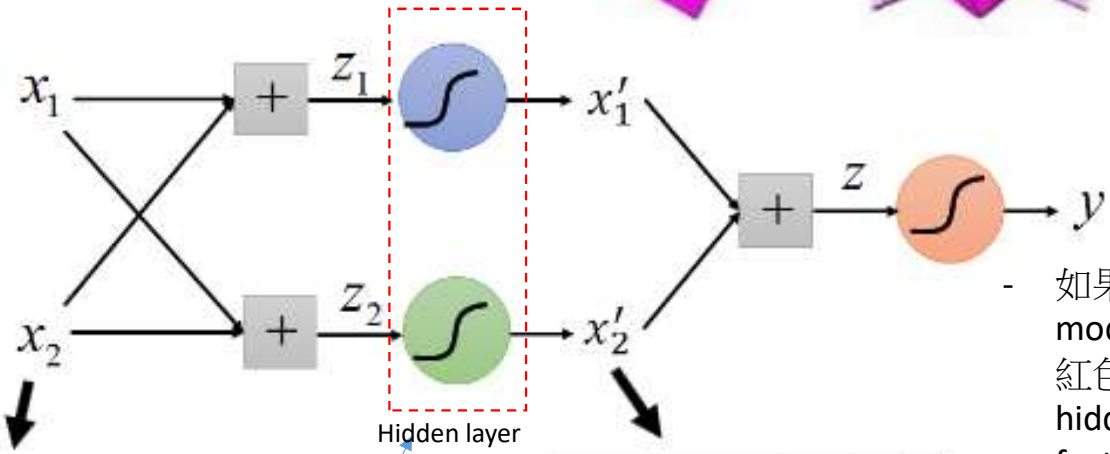
Figure 4: Cascade Structure

❑ Important Concept!!

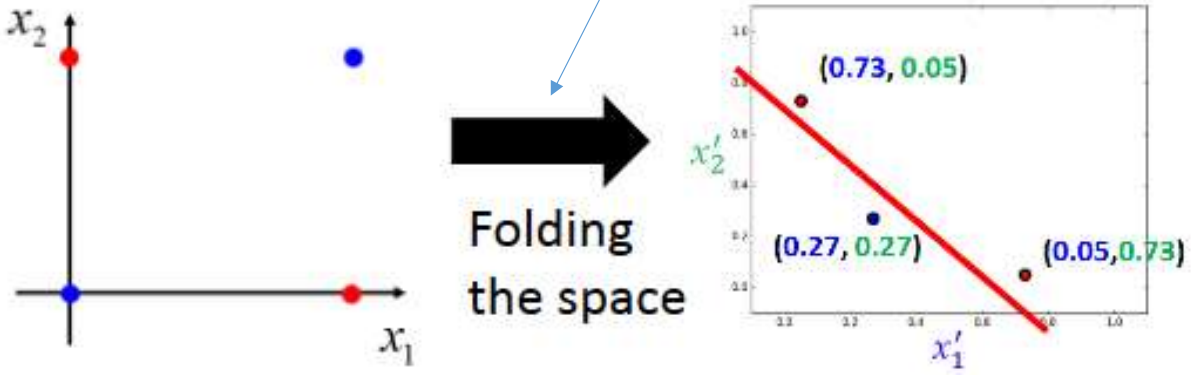
More Analogy



Input: 2d vector (x1,x2)



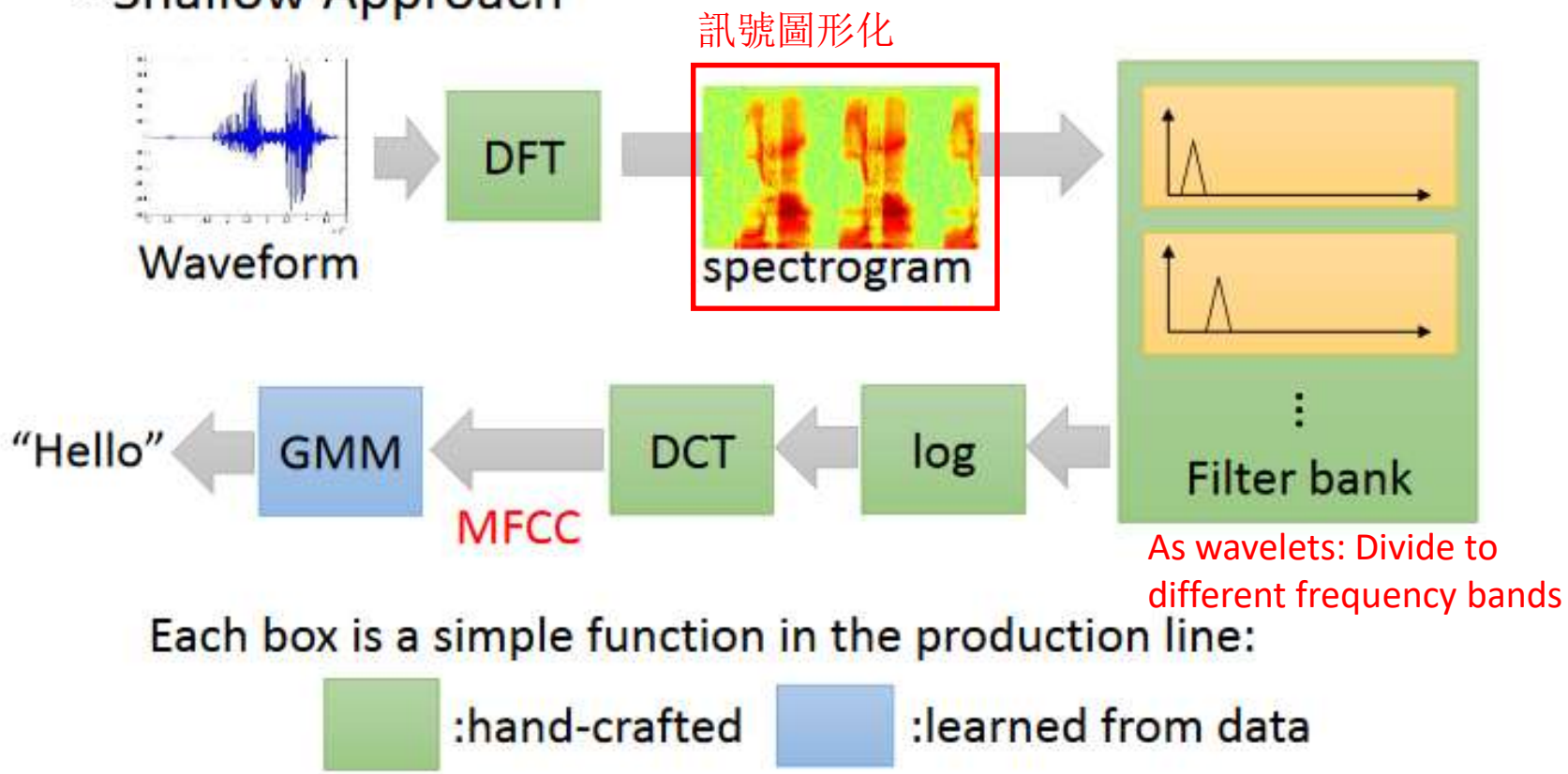
Input: 4 2d data point，the color represent the classification



- 如果沒有hidden layer，linear的model沒有辦法把藍色分在一邊，紅色分在一邊，當加入了hidden layer相當於做了一個feature transformation，將原先的資料project到另一個 (same or a little bit higher) space by using non-linear transformation.
- Many cascaded hidden layers will be as the kernel function of SVM。

End-to-end Learning - Speech Recognition 1/2

- Shallow Approach

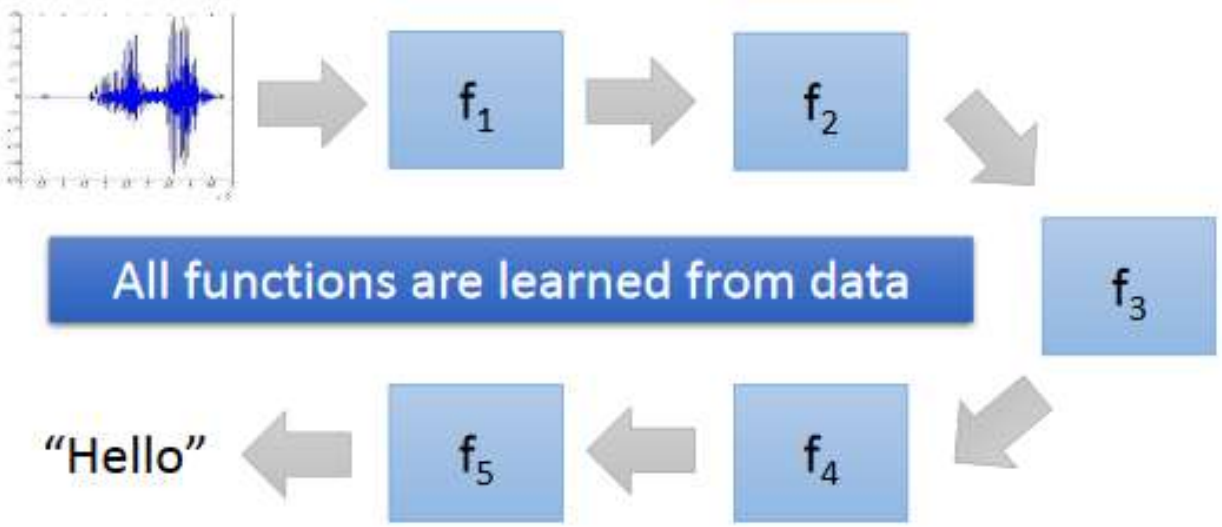


梅爾頻率倒譜系數: Mel-Frequency Cepstral Coefficients

End-to-end Learning - Speech Recognition

- Deep Learning 2/2

Q: 以聲音訊號為例，有學者提出能不能透過deep learning，即只有input(聲音訊號)與output(對應的文字)，完全不對輸入的聲音訊號(time domain)做feature transform(signal processing)，是否能夠不需要signal processing
A: 有學者提出結論，能夠training出一個model與有將input經過 feature transform的結果持平，但沒有更好。

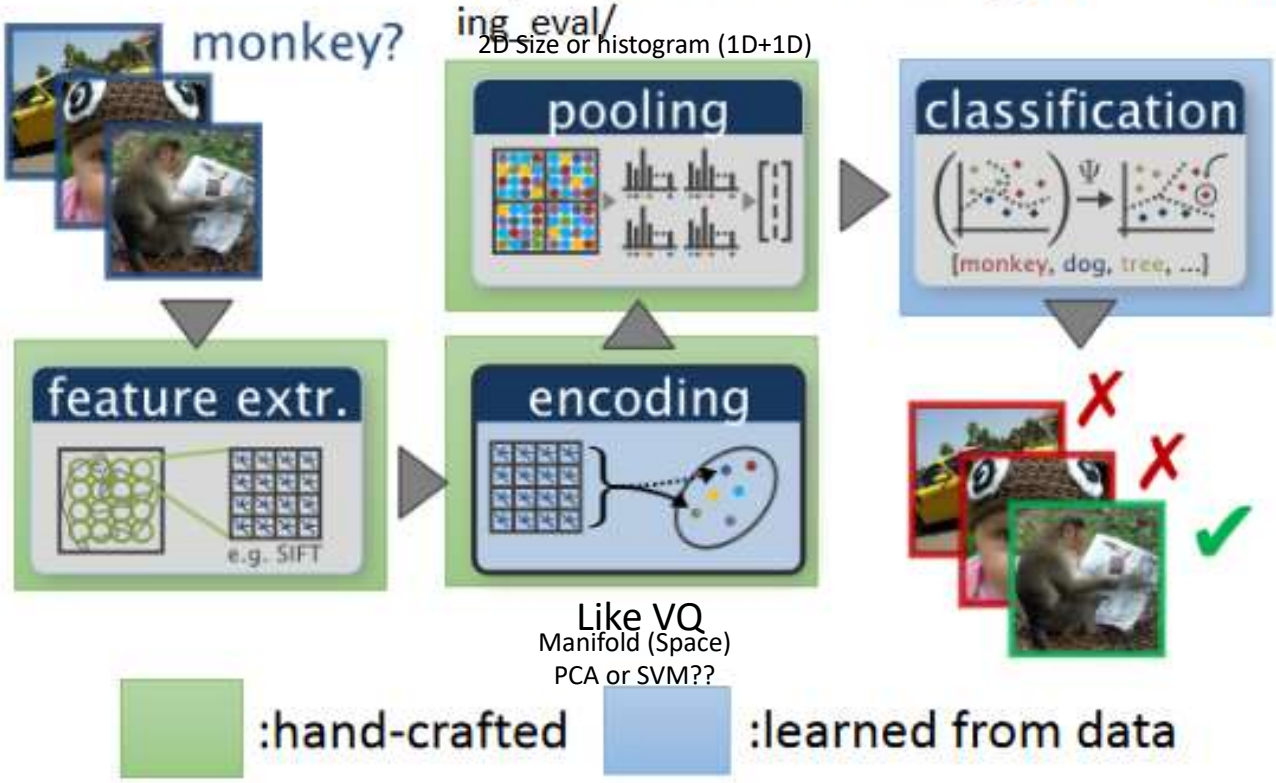


Less engineering labor, but machine learns more

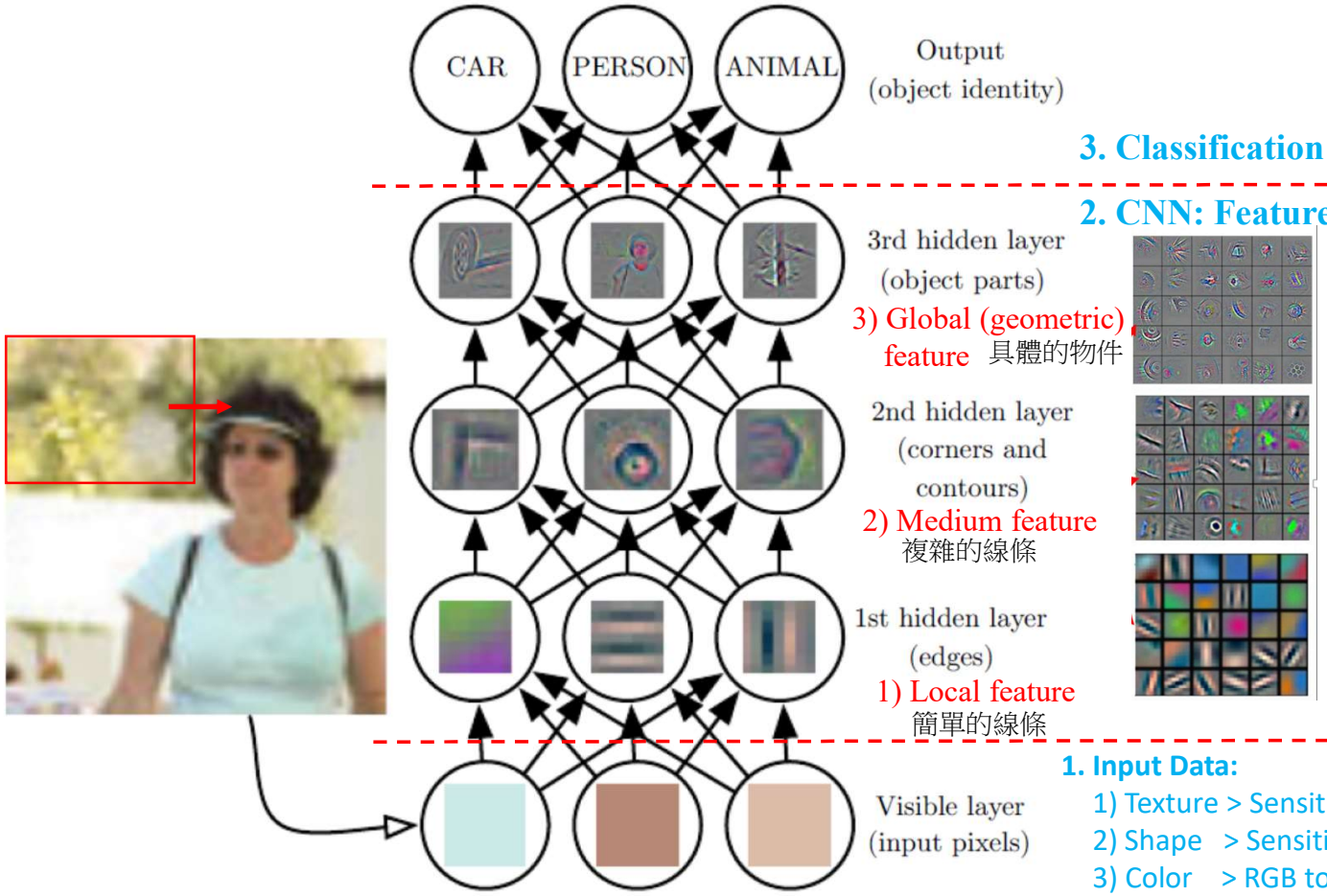
End-to-end Learning - Image Recognition 1/2

- Shallow Approach

http://www.robots.ox.ac.uk/~vgg/research/encoding_eval/



Deep Learning: CNN Classification 2/2



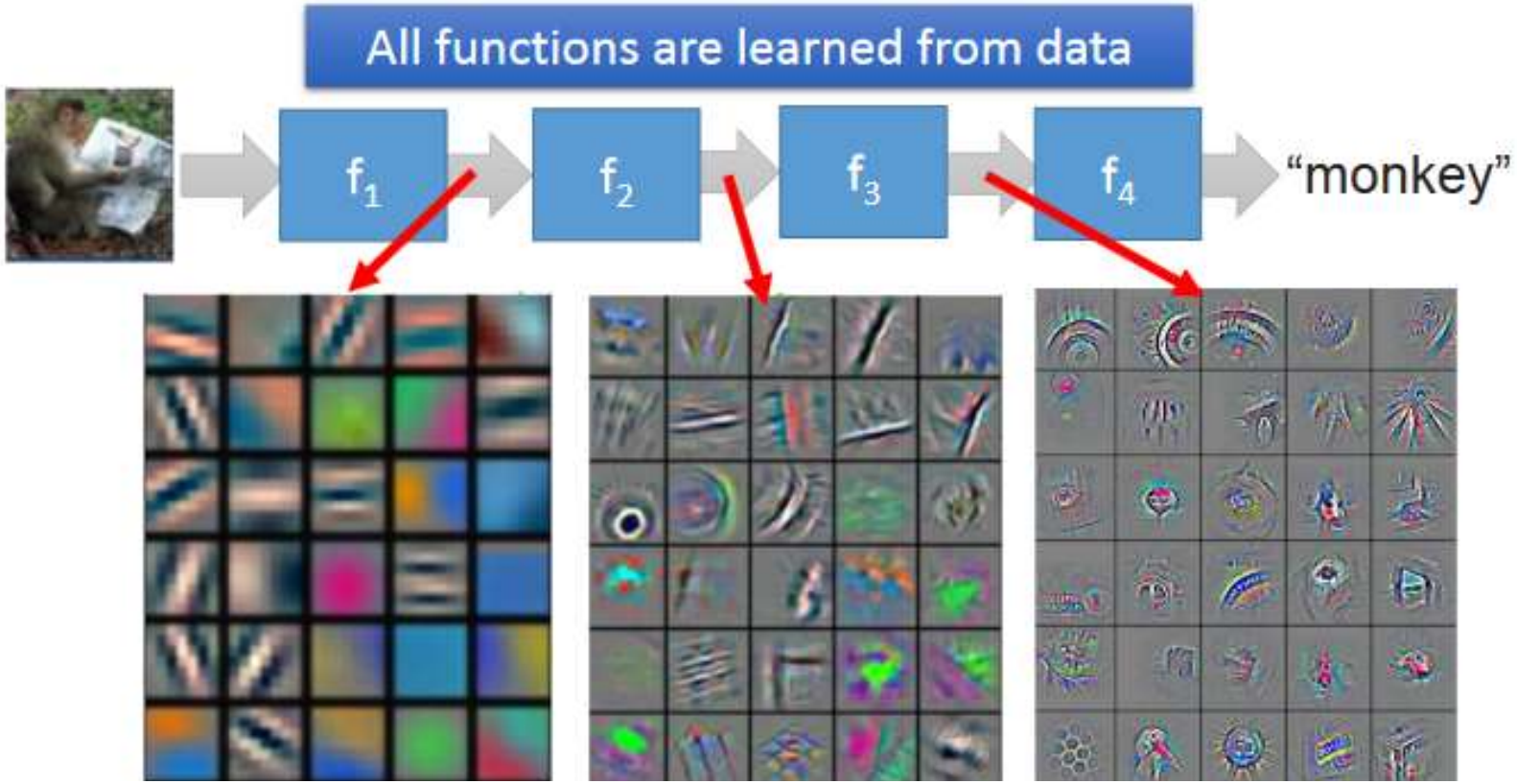
1. Input Data:

1) Texture > Sensitive to light
2) Shape > Sensitive to noise
3) Color > RGB to HSV
> RGB to YUV for compression
4) RGB+Depth

End-to-end Learning - Image Recognition

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

- Deep Learning

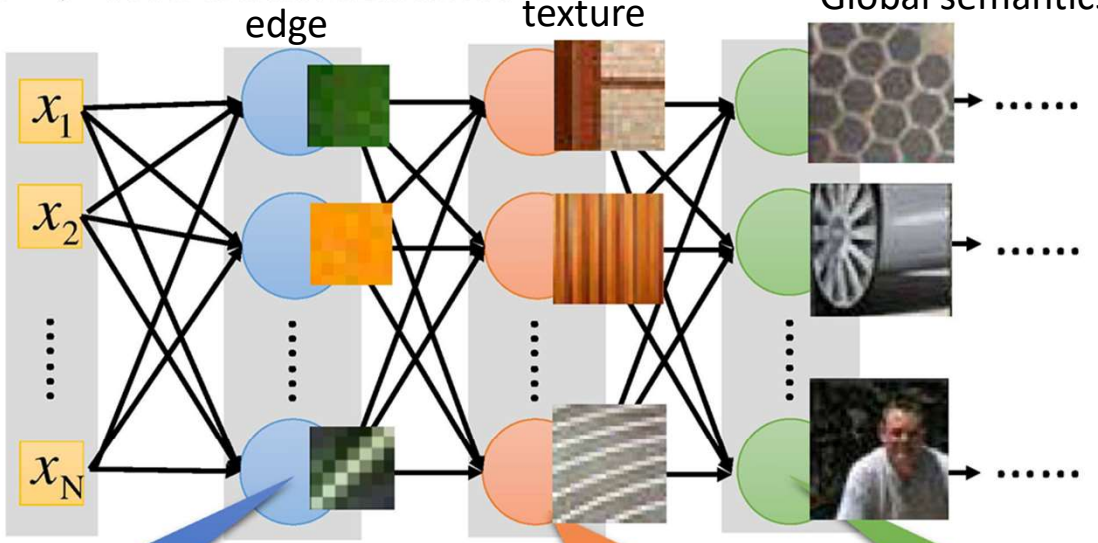


Modularization

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

- Deep → Modularization

Patch: local feature => Global semantics



The most basic classifiers

Use 1st layer as module to build classifiers

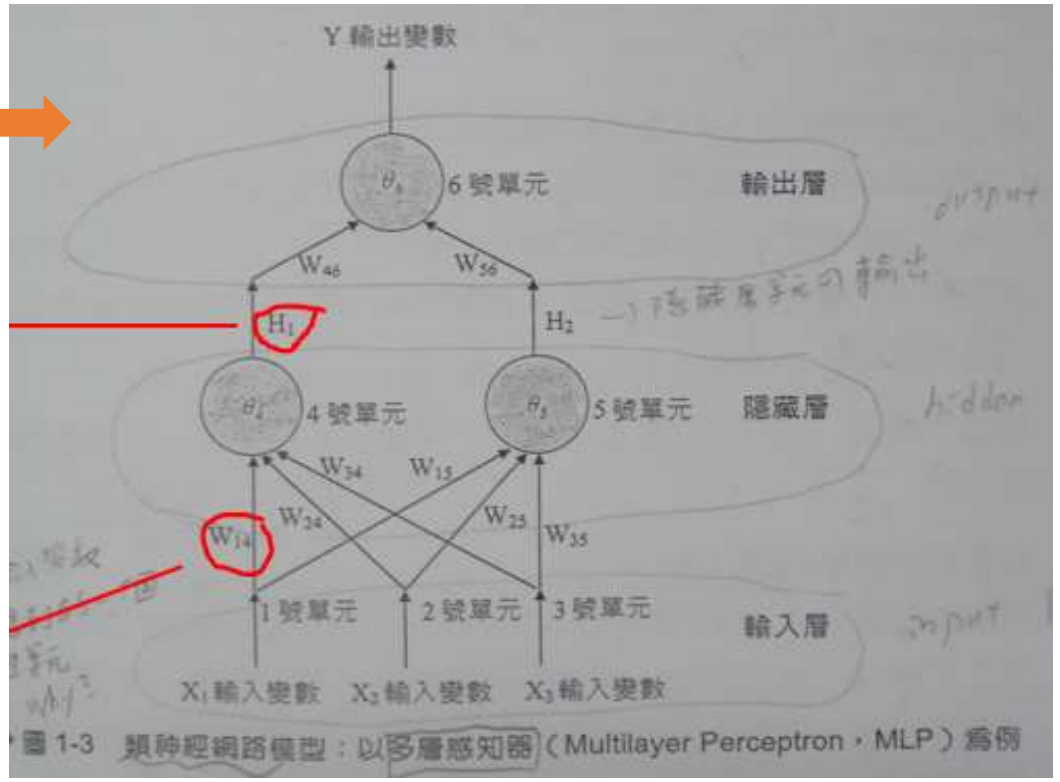
Use 2nd layer as module .....

簡單的線條

複雜的線條

具體的物件 = Global Semantics

MLP-BP



-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer

$$y_j = f\left(\sum_i W_{ij} x_i - \theta_j\right)$$

PROC. OF THE IEEE, NOVEMBER 1998

Deep Learning: CNN

Gradient-Based Learning Applied to Document Recognition

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

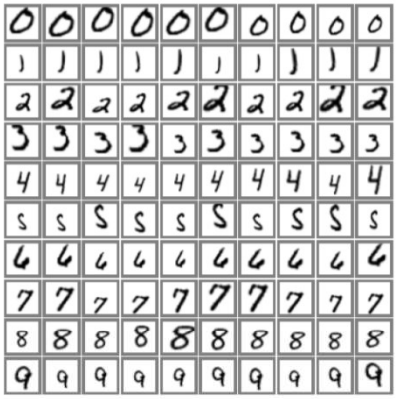


Fig. 7. Examples of distortions of ten training patterns.

Training **Test**

CNN:
Extraction

-2 convolution layers
-2 Pooling Layers

Classification

Fig. 4. Size-normalized examples from the MNIST database.

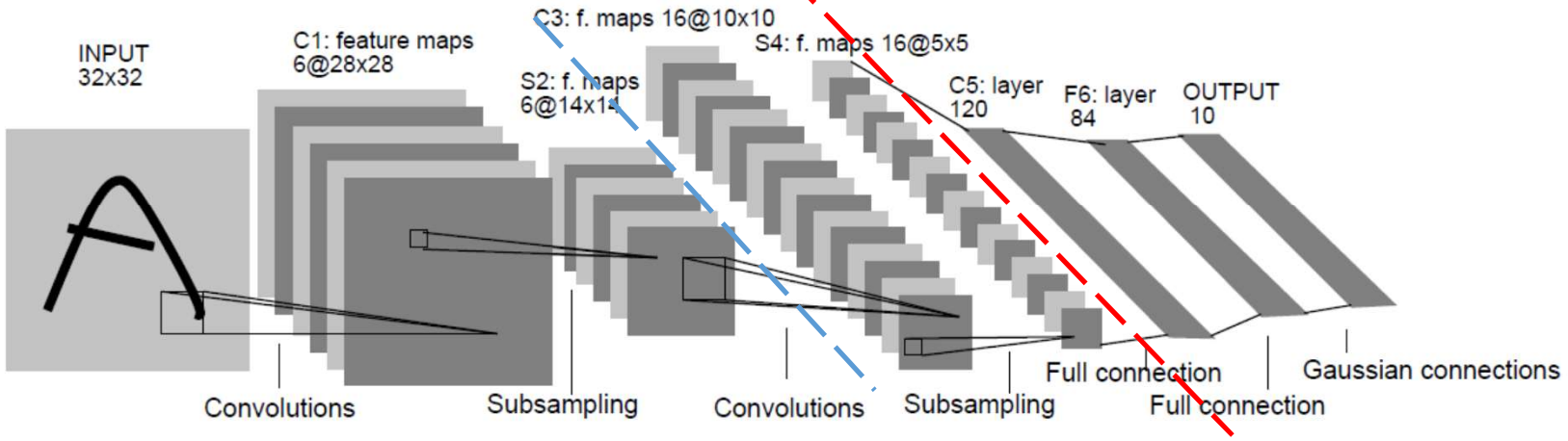


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Outline

I. Lecture I: Introduction to Deep Learning

II. Lecture II: Tips for Training Deep Neural Network

III. Lecture III: Variants of Neural Network

IV. Lecture IV: Next Wave

Lecture I:

Introduction to Deep Learning

Outline of Lecture 1

I.1 Three Steps for Deep Learning

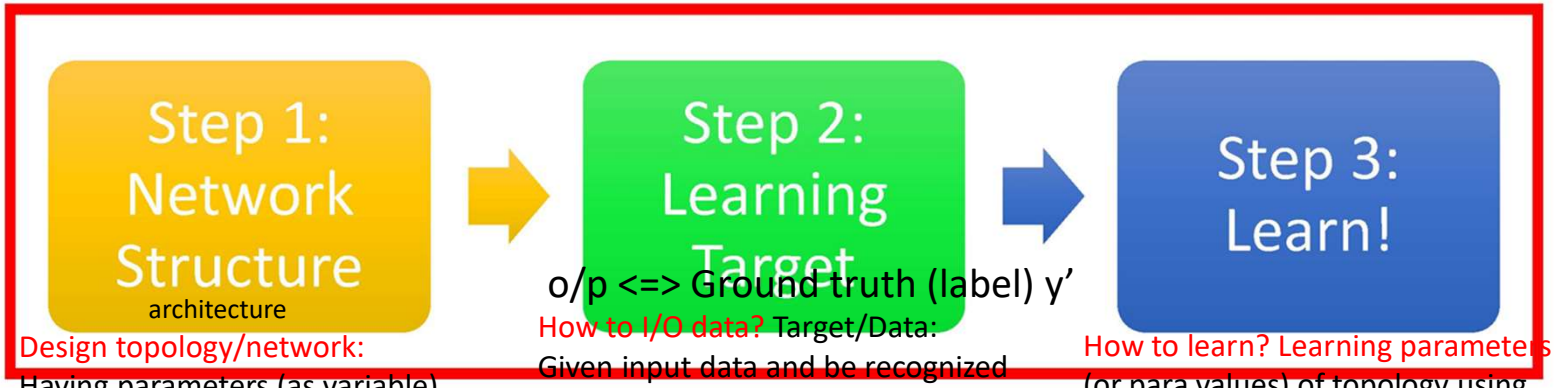
I.2 Why Deep Learning?

1) Fat+Short Vs. Thin+Tall
2) Multi-Task:
   (1) How to reduce para. in order to use less data
   (2) Modularization (logic circuit) – Combine network / Circuit
3) End to End Learning

I.3 "Hello world" for deep learning

Coding Example

Three Steps for Deep Learning



Three Steps for Deep Learning

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

天生的腦

Expected Target: 100

http://onepiece1234567890.blogspot.tw/2013/12/blog-post_8.html

Three Steps for Deep Learning

Design topology/network: Having parameters (as variable) without values

How to I/O data? Target/Data: Given input data and be recognized / classified output data. Exp. Mini batch

How to learn? Learning parameters (or para values) of topology using gradient descent to find global min of MSE

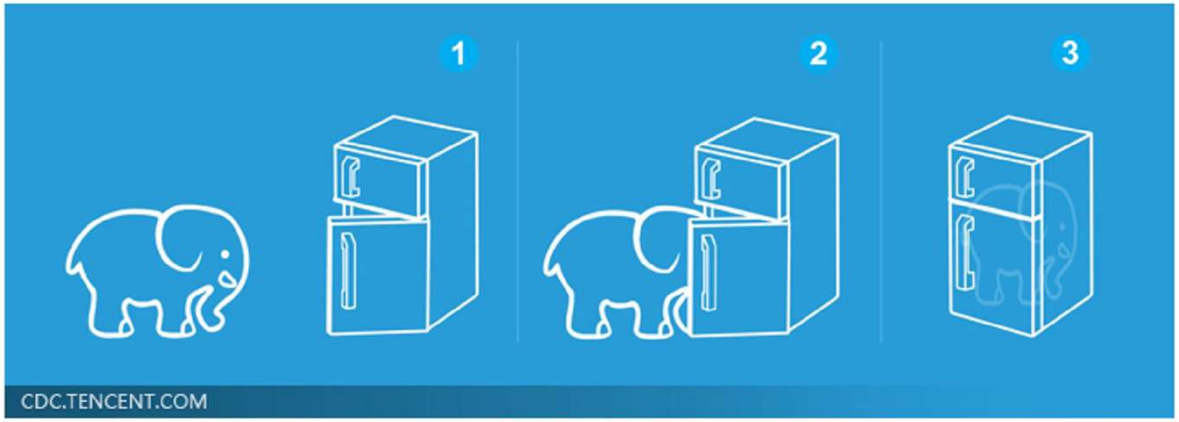
Step 1: Network Structure → Step 2: Learning Target → Step 3: Learn!

Topology: Refrigerator

o/p <=> Ground truth (label) y'

Target/Data: Given elephant to recognize it.

Deep Learning is so simple ……



I.1. Step1

Three Steps for Deep Learning

Design topology/network: Having parameters (as variable) without values

How to I/O data? Target/Data: Given input data and be recognized / classified output data. Exp. Mini batch

How to learn? Learning parameters (or para values) of topology using gradient descent to find global min of MSE

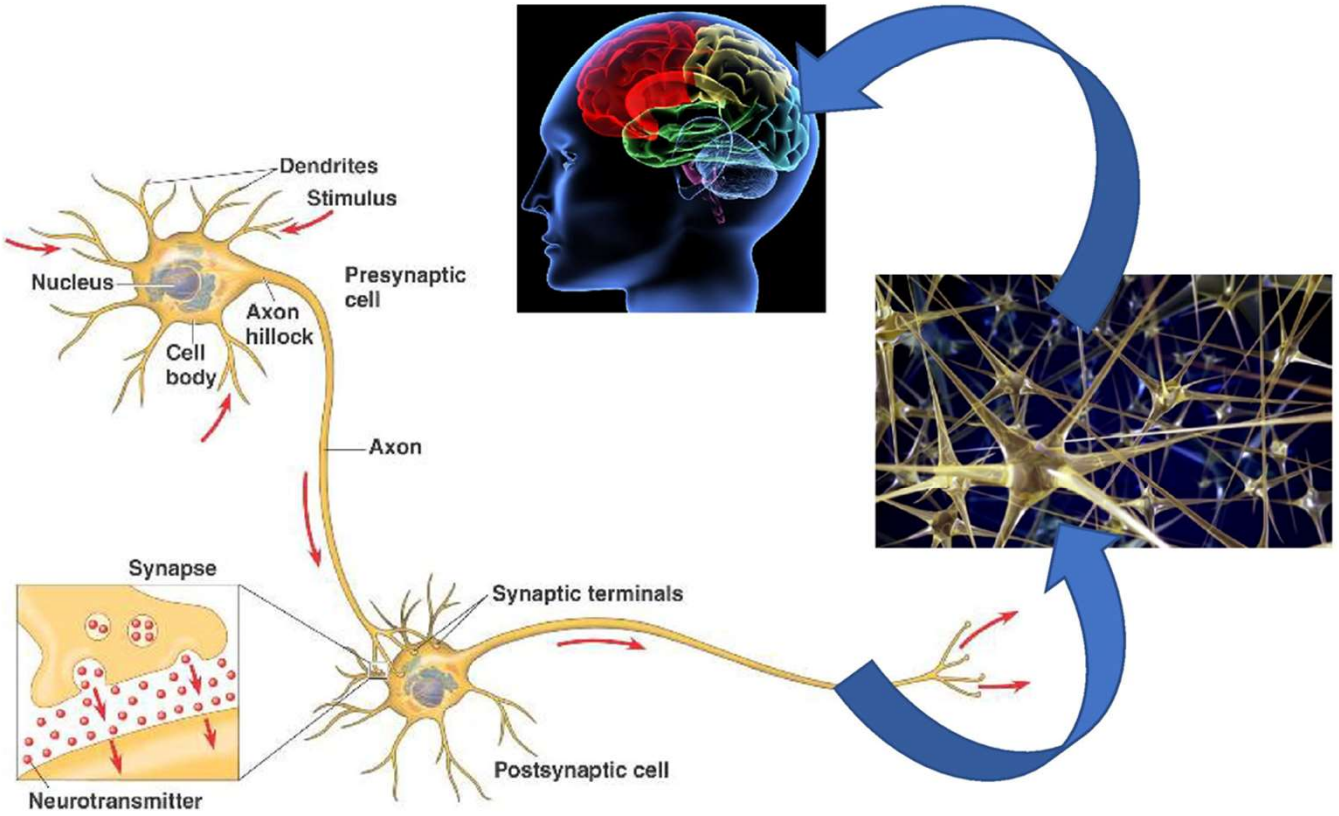
Step 1: Network Structure → **Step 2: Learning Target** → **Step 3: Learn!**

o/p <=> Ground truth (label) y'

天生的腦

http://onepiece1234567890.blogspot.tw/2013/12/blog-post_8.html

Human Brains



EX.人臉 detection

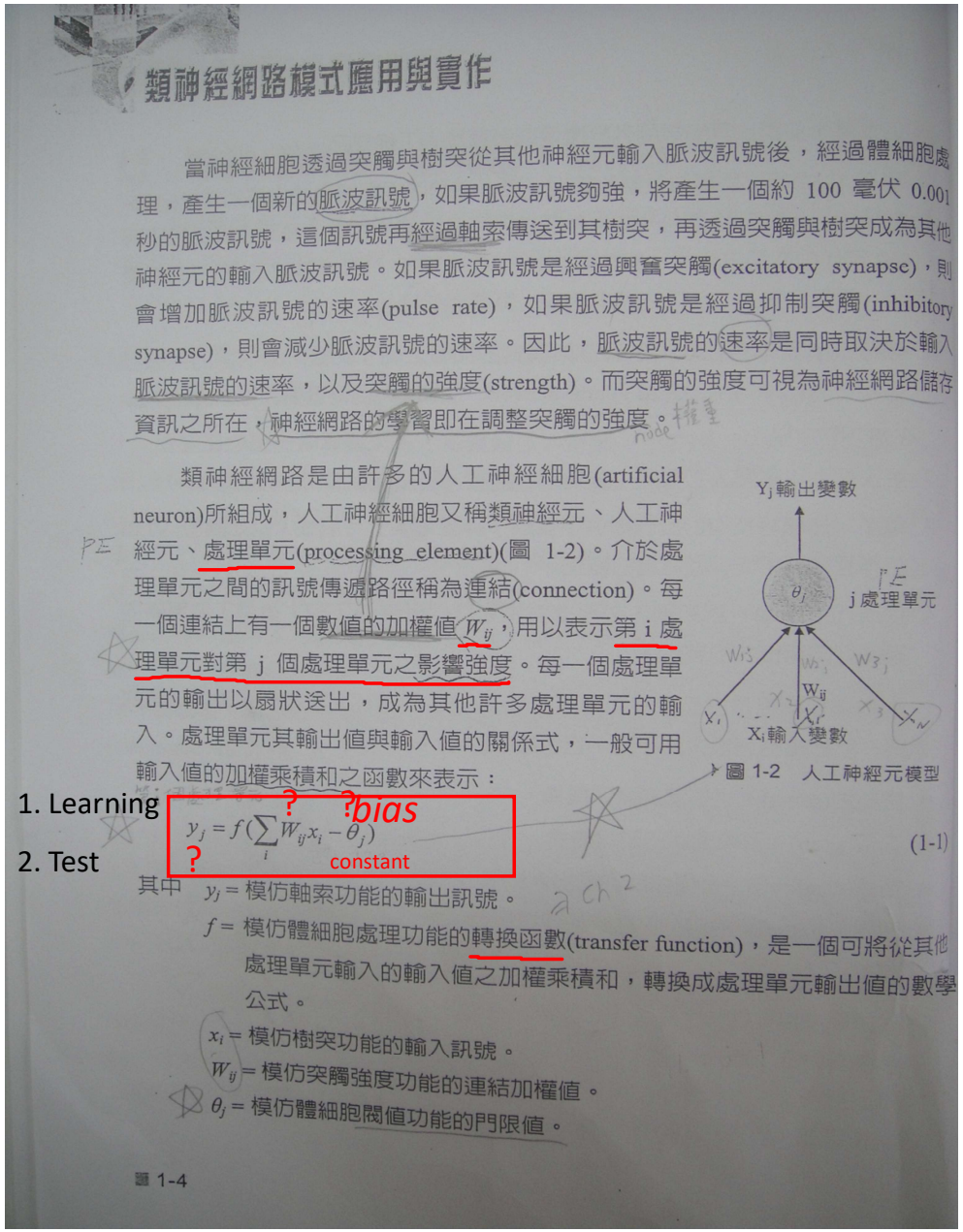
input：
(20X20個pixel的圖)
$x_1, x_2, x_3, \ldots, x_{400}$

output：
(人臉=1 , 非人臉=0)
y_1=1 or y_1=0

Why not as SVM
y_1=1 or y_1=-1

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer

1. Learning
2. Test



類神經網路模式應用與實作

當神經細胞透過突觸與樹突從其他神經元輸入脈波訊號後，經過體細胞處理，產生一個新的脈波訊號，如果脈波訊號夠強，將產生一個約 100 毫伏 0.001 秒的脈波訊號，這個訊號再經過軸索傳送到其樹突，再透過突觸與樹突成為其他神經元的輸入脈波訊號。如果脈波訊號是經過興奮突觸(excitatory synapse)，則會增加脈波訊號的速率(pulse rate)，如果脈波訊號是經過抑制突觸(inhibitory synapse)，則會減少脈波訊號的速率。因此，脈波訊號的速率是同時取決於輸入脈波訊號的速率，以及突觸的強度(strength)。而突觸的強度可視為神經網路儲存資訊之所在，神經網路的學習即在調整突觸的強度。

類神經網路是由許多的人工神經細胞(artificial neuron)所組成，人工神經細胞又稱類神經元、人工神經元、處理單元(processing element)(圖 1-2)。介於處理單元之間的訊號傳遞路徑稱為連結(connection)。每一個連結上有一個數值的加權值 W_{ij}，用以表示第 i 處理單元對第 j 個處理單元之影響強度。每一個處理單元的輸出以扇狀送出，成為其他許多處理單元的輸入。處理單元其輸出值與輸入值的關係式，一般可用輸入值的加權乘積和之函數來表示：

$$y_j = f(\sum_i W_{ij} x_i - \theta_j) \quad (1\text{-}1)$$

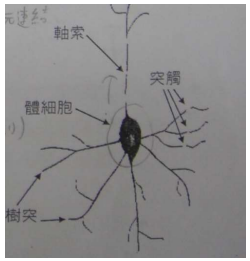
bias
constant

其中 y_j = 模仿軸索功能的輸出訊號。
f = 模仿體細胞處理功能的轉換函數(transfer function)，是一個可將從其他處理單元輸入的輸入值之加權乘積和，轉換成處理單元輸出值的數學公式。
x_i = 模仿樹突功能的輸入訊號。
W_{ij} = 模仿突觸強度功能的連結加權值。
θ_j = 模仿體細胞閥值功能的門限值。

圖 1-2 人工神經元模型

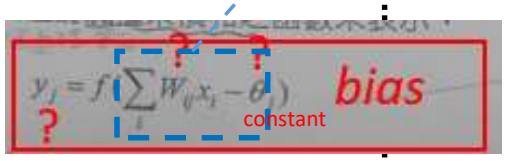
圖 1-4

Review NN (Ch1) :



生物神經元模型

人工神經元模型



A neuron unit

Neural Network

One
Neuron

寫程式不會以equation的方式，會以vector , matrix (Ax = b), homogenous matrix, 的方式撰寫。

Linear Combination: Aw = z

J input data vectors (here J=1)

$$\begin{bmatrix} w_{11}w_{21}\cdots w_{k1}\cdots w_{N1}\ b_1 \\ w_{12}w_{22}\cdots w_{k2}\cdots w_{N2}\ b_2 \\ \vdots \\ w_{1j}w_{2j}\cdots w_{kj}\cdots w_{Nj}\ b_j \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \\ \vdots \\ a_N \\ 1 \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \\ \vdots \\ z_j \end{bmatrix}$$

J x (N+ 1) | (N + 1) x 1 | J x 1

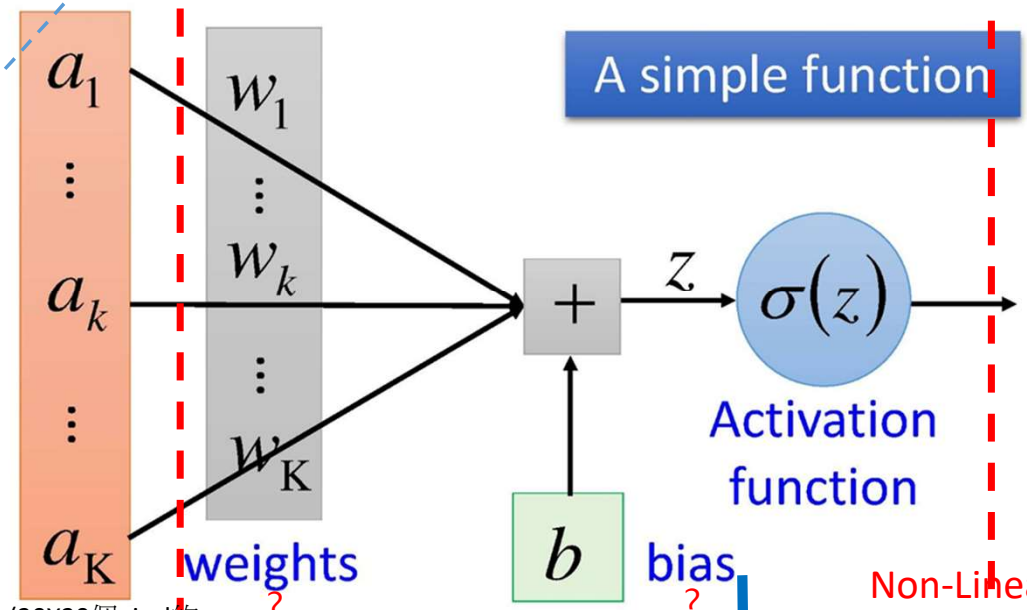
I/P O/P

1 J-dim output result vector, here J=1)

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

Constant, bias

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer



J: Can solve by EM optimization, random (such as Particle filter), … (可見此份投影片 p.38+3)

a=σ(z)

Here, the output is a, which is one input element for next neuron

input：(20X20個pixel的圖) $x_1, x_2, x_3, \ldots, x_{k=400}$

One neuron

Linear Discrimination by Linear Combination

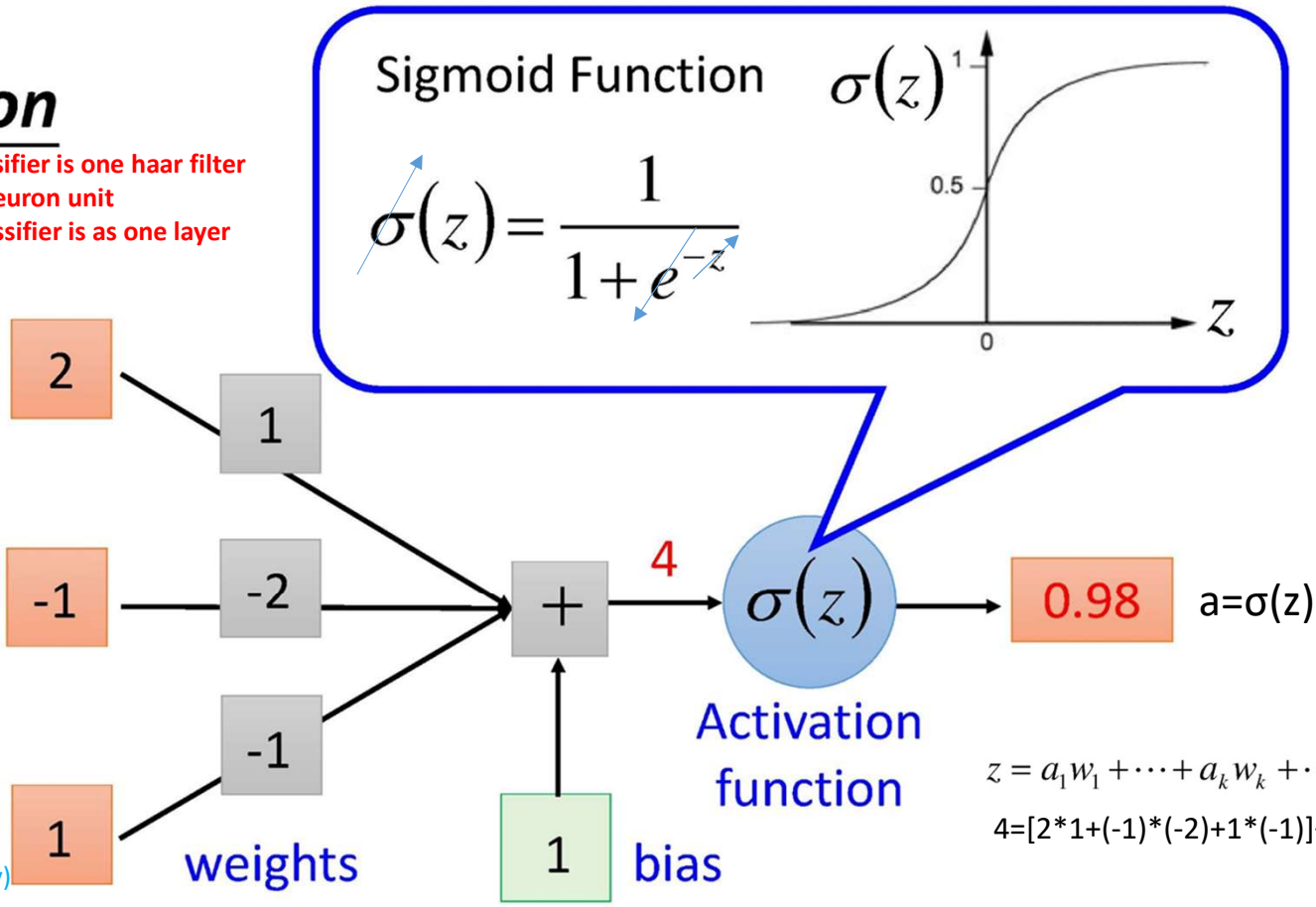
Non-Linear Discrimination by Kernel Function / Activation Function as SVM phi()

Single neuron can only do binary classification, cannot handle multi-class classification

Neural Network

One
Neuron

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer



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

4=[2*1+(-1)*(-2)+1*(-1)]+1

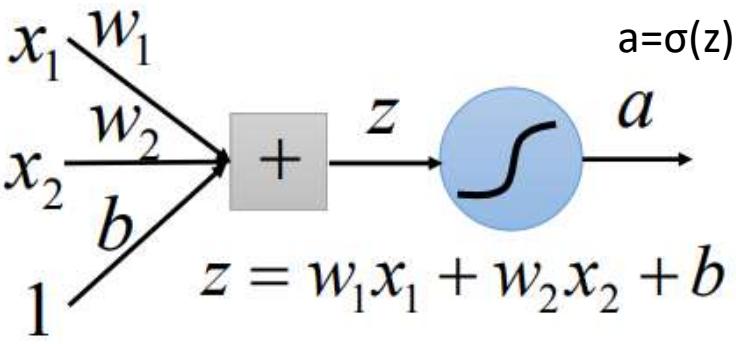
Input pixel of image vector is normalized btw -255 ~ +255 or -1.0~ +1.0 by:

1.1) Ave.(R,G,B) over ImageNet
1.2) Unbiased each pixel(x,y)
2.1) Scaling normalization by divided standard deviation

Pixel_R(x,y) = (Pixel_R(x,y)-Ave_R(x,y)) / Dev_R(x,y)
Pixel_G(x,y) = (Pixel_G(x,y)-Ave_G(x,y)) / Dev_G(x,y)
Pixel_B(x,y) = (Pixel_B(x,y)-Ave_B(x,y)) / Dev_B(x,y)

Reference:
http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf

Limitation of Single Layer



a=σ(z)

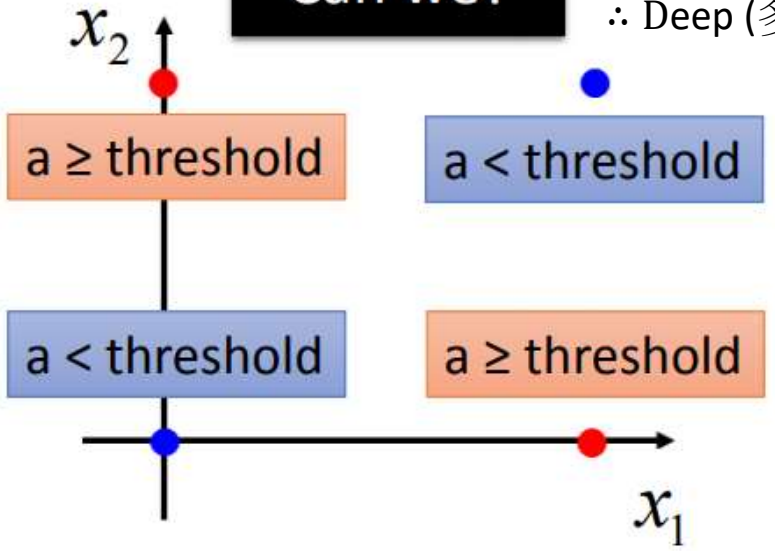
$$\begin{cases} yes & a \geq threshold \\ no & a < threshold \end{cases}$$

XOR問題

Input		Output
x_1	x_2	
0	0	No (0)
0	1	Yes (1)
1	0	Yes (1)
1	1	No (0)

Can we?

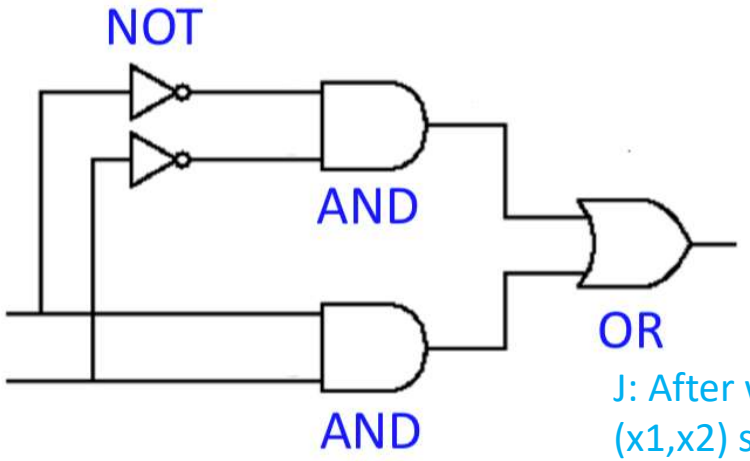
單層無法解決
∴ Deep (多層)



Output: 2 classes 0 or 1, problem: You cannot discrimination to 2 classes
J: You can solve it by using MLP non-linear discrimination. But here it doesn't connect to MLP yet.

??

Neural Network 1/2

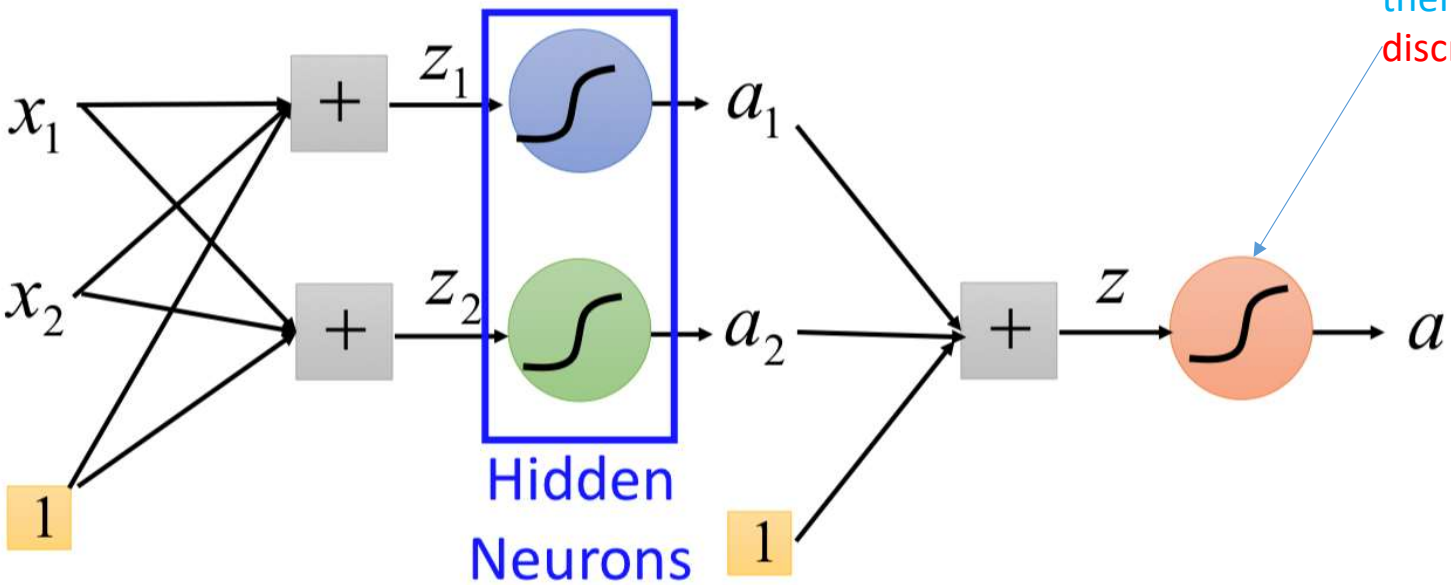


XOR問題

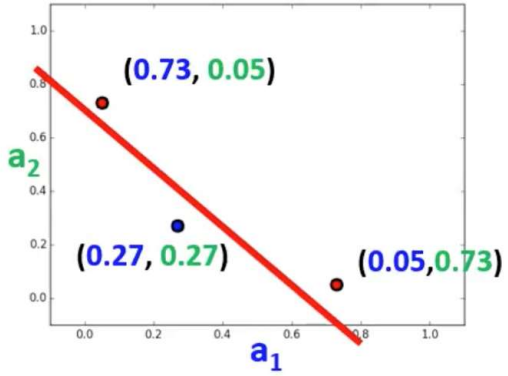
單層無法解決

∴ Deep (多層)

Neural Network



J: After we transform from (x1,x2) space to (a1,a2) space, then we can separate by linear discrimination



Limitation of Single Layer 2/2

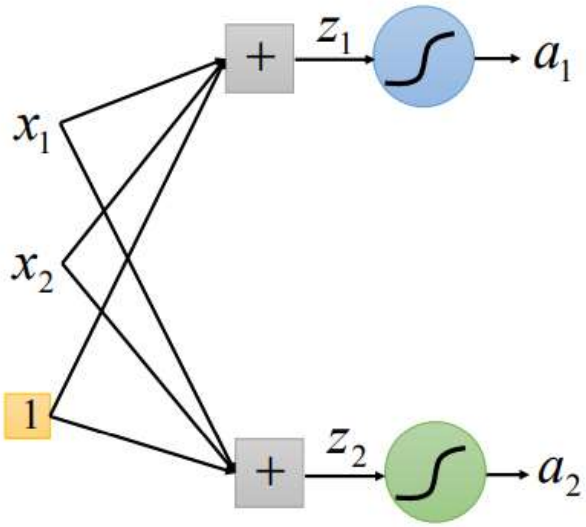
J:

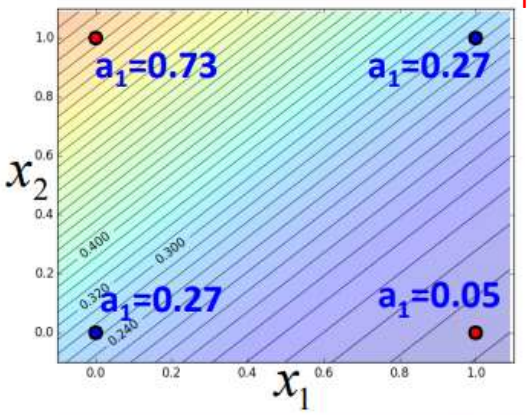
1) After we transform from (x1,x2) space to (a1,a2) space,
2) then we can separate by linear discrimination

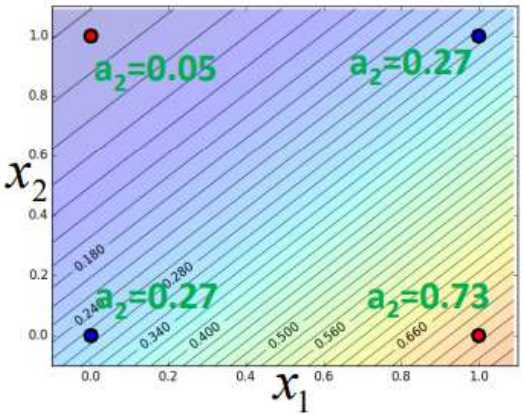
3.1) That is, instead of using SVM directly backproject to very high dimension by using kernel function or high dimensional activation function,

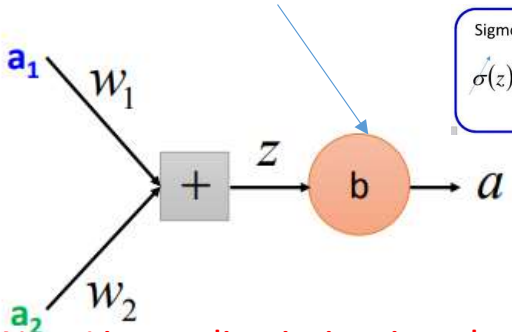
3.2) we can apply more layers (deeper network) to reach the same goal – space transformation layer by layer (step by step) and not so high dimension transform/activation function (nonlinear discrimination but as Fuzzy)

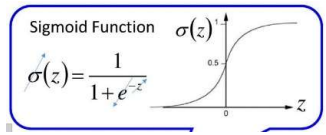
Space domain transform



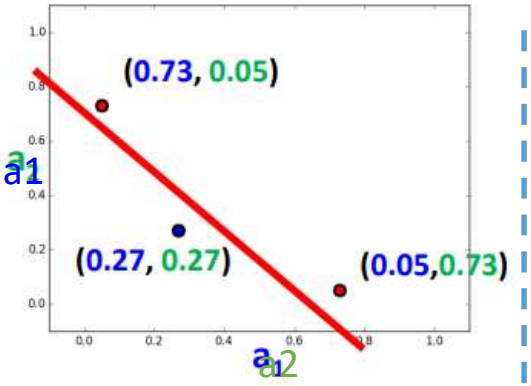




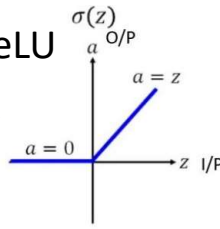




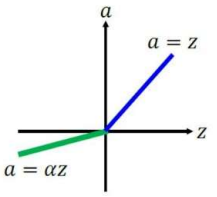
Non-Linear discriminations but here as Fuzzy membership



ReLU



Parametric ReLU



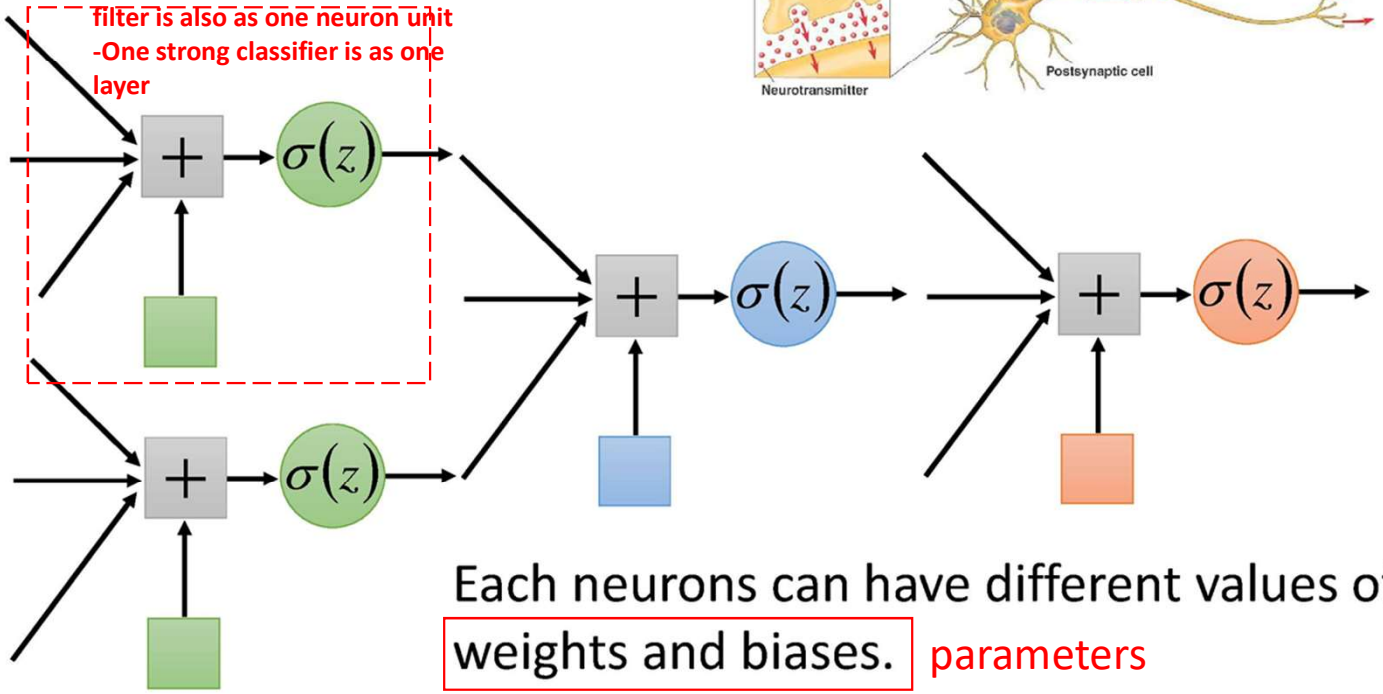
α also learned by gradient descent

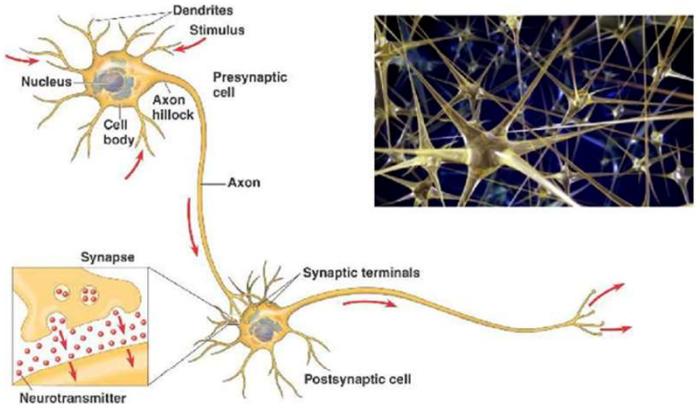
Neural Network

: AdaBoost - Cascade

-One weak classifier is one haar filter is also as one neuron unit

-One strong classifier is as one layer





Each neurons can have different values of weights and biases. parameters

The values of weights and biases will be obtained by learning (step 3).

Fully Connect Feedforward Network : AdaBoost - Cascade

Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

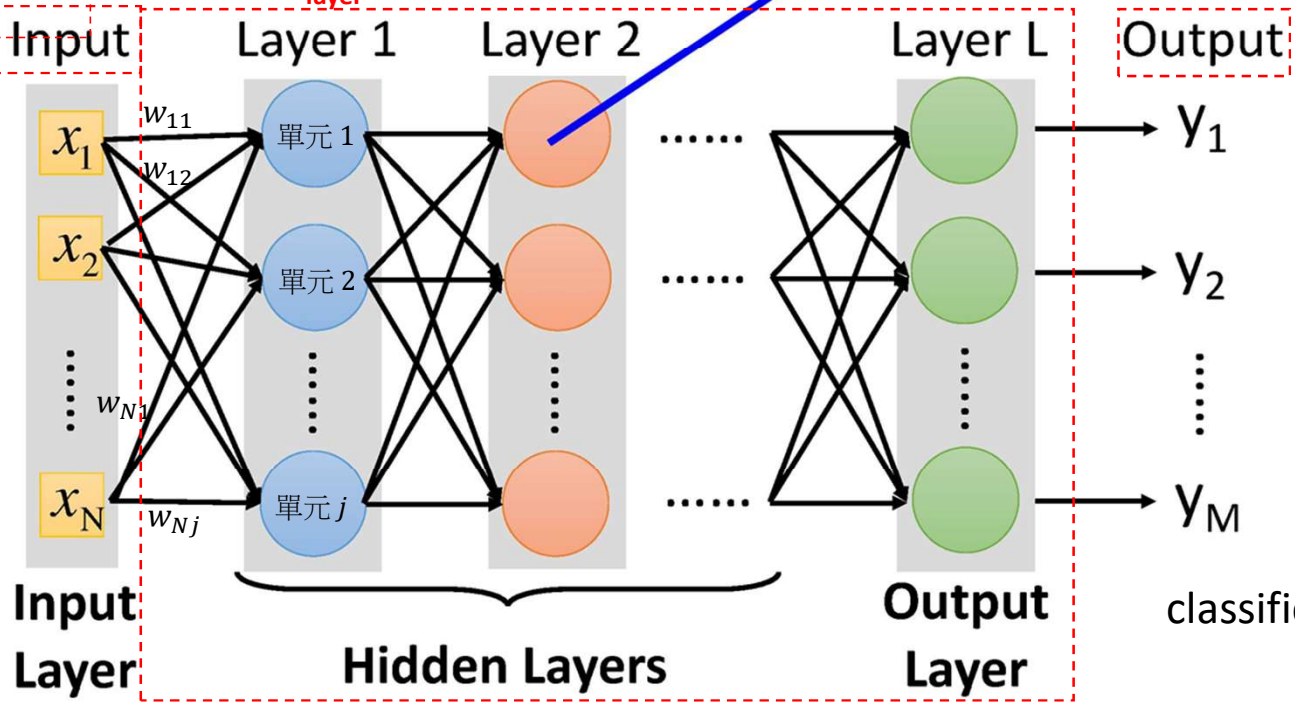
-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer

neuron

Ax =b 型式：

Layer 1 Parameters (known?) I/P O/P

$$\begin{bmatrix} w_{11}w_{21}\cdots w_{k1}\cdots w_{N1}\ b_1 \\ w_{12}w_{22}\cdots w_{k2}\cdots w_{N2}\ b_2 \\ \vdots \\ w_{1j}w_{2j}\cdots w_{kj}\cdots w_{Nj}\ b_j \end{bmatrix}_{j \times (N+1)} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \\ \vdots \\ x_N \\ 1 \end{bmatrix}_{(N+1) \times 1} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \\ \vdots \\ z_j \end{bmatrix}_{j \times 1}$$



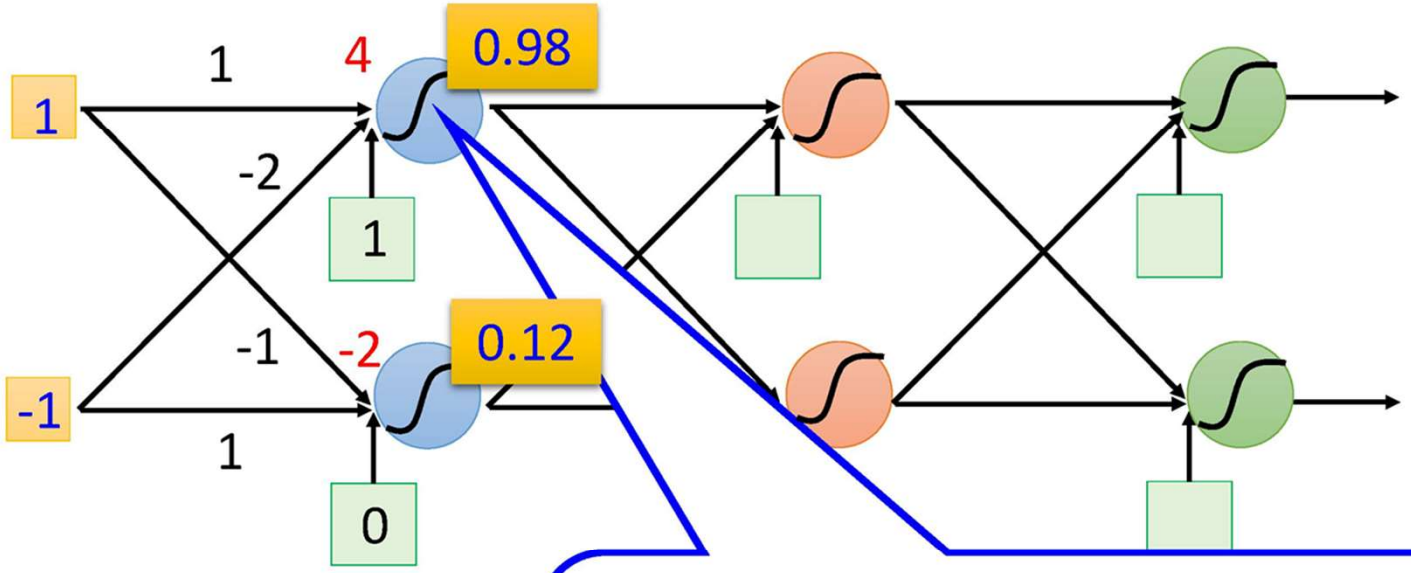
Here, the output is z, a=σ(z) is one input element for next neuron

classifications

AdaBoost Cascade:

Deep means many hidden layers

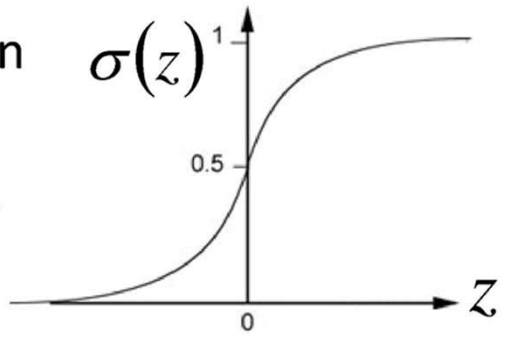
Fully Connect Feedforward Network : AdaBoost - Cascade



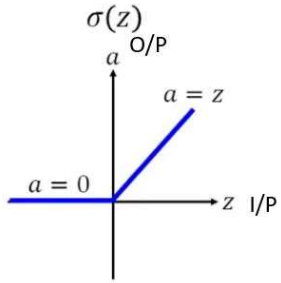
Here assume parameters Theta(w, b) are learned

Sigmoid Function

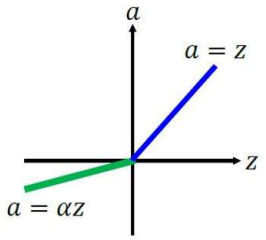
$$\sigma(z) = \frac{1}{1+e^{-z}}$$



ReLU

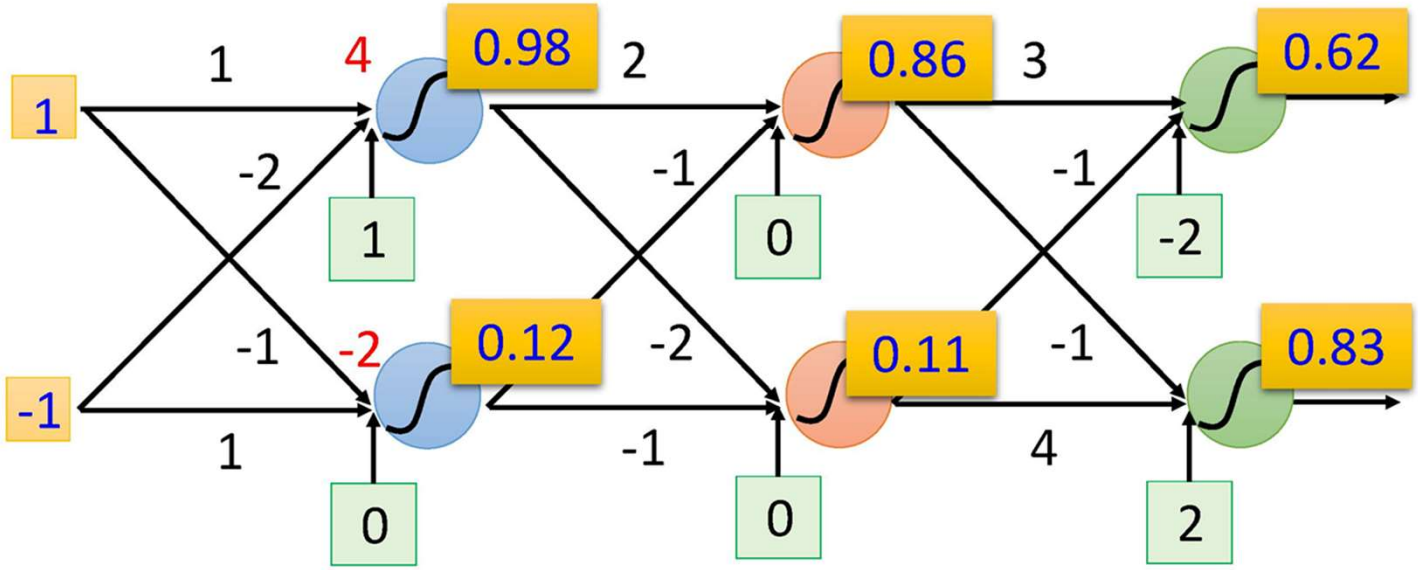


Parametric ReLU



α also learned by gradient descent

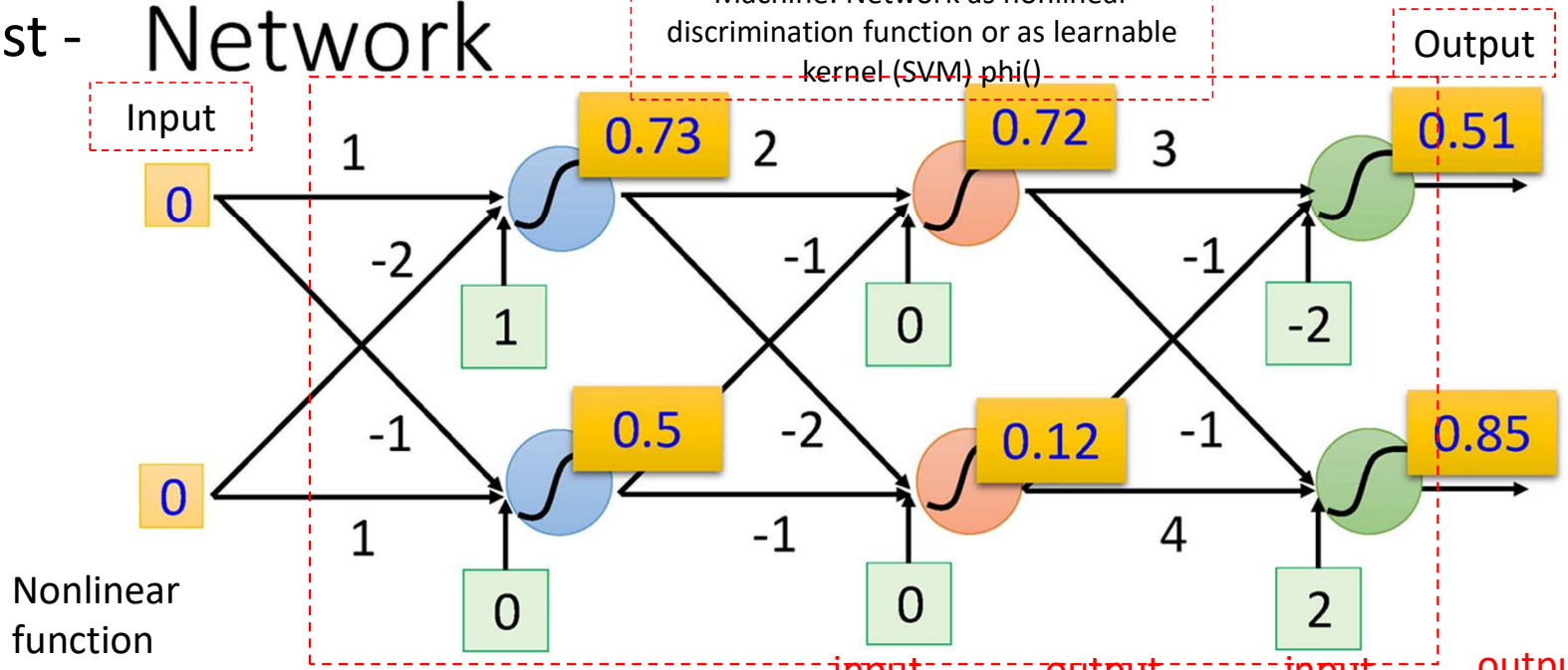
Fully Connect Feedforward Network : AdaBoost - Cascade



Here assume parameters
Theta(w, b) are learned

: AdaBoost - Cascade

Fully Connect Feedforward Network



Network is a function.

Input vector, output vector

input output input output

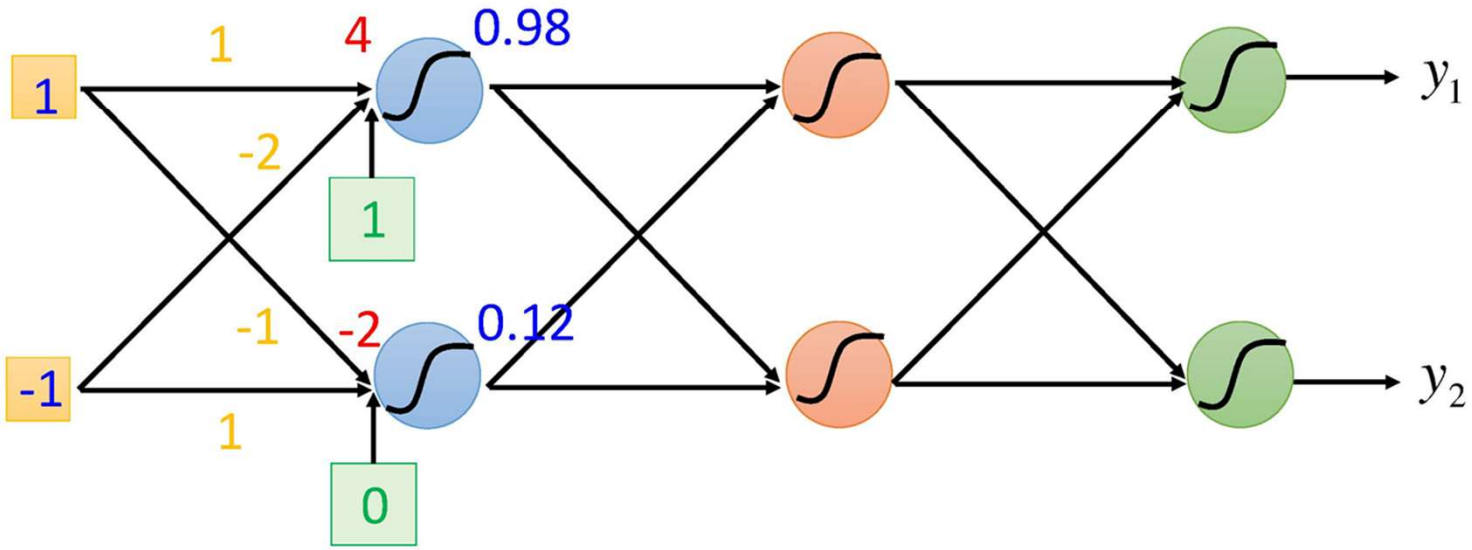
$$f\left(\begin{bmatrix}1\\-1\end{bmatrix}\right)=\begin{bmatrix}0.62\\0.83\end{bmatrix} \quad f\left(\begin{bmatrix}0\\0\end{bmatrix}\right)=\begin{bmatrix}0.51\\0.85\end{bmatrix}$$

Here assume parameters Theta(w, b) are learned

Weights and biases are network parameters θ

Different parameters θ define different functions

Fully Connect Feedforward Network - Matrix Operation



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

w input b output

[a1=σ(z1)
a2=σ(z2)]

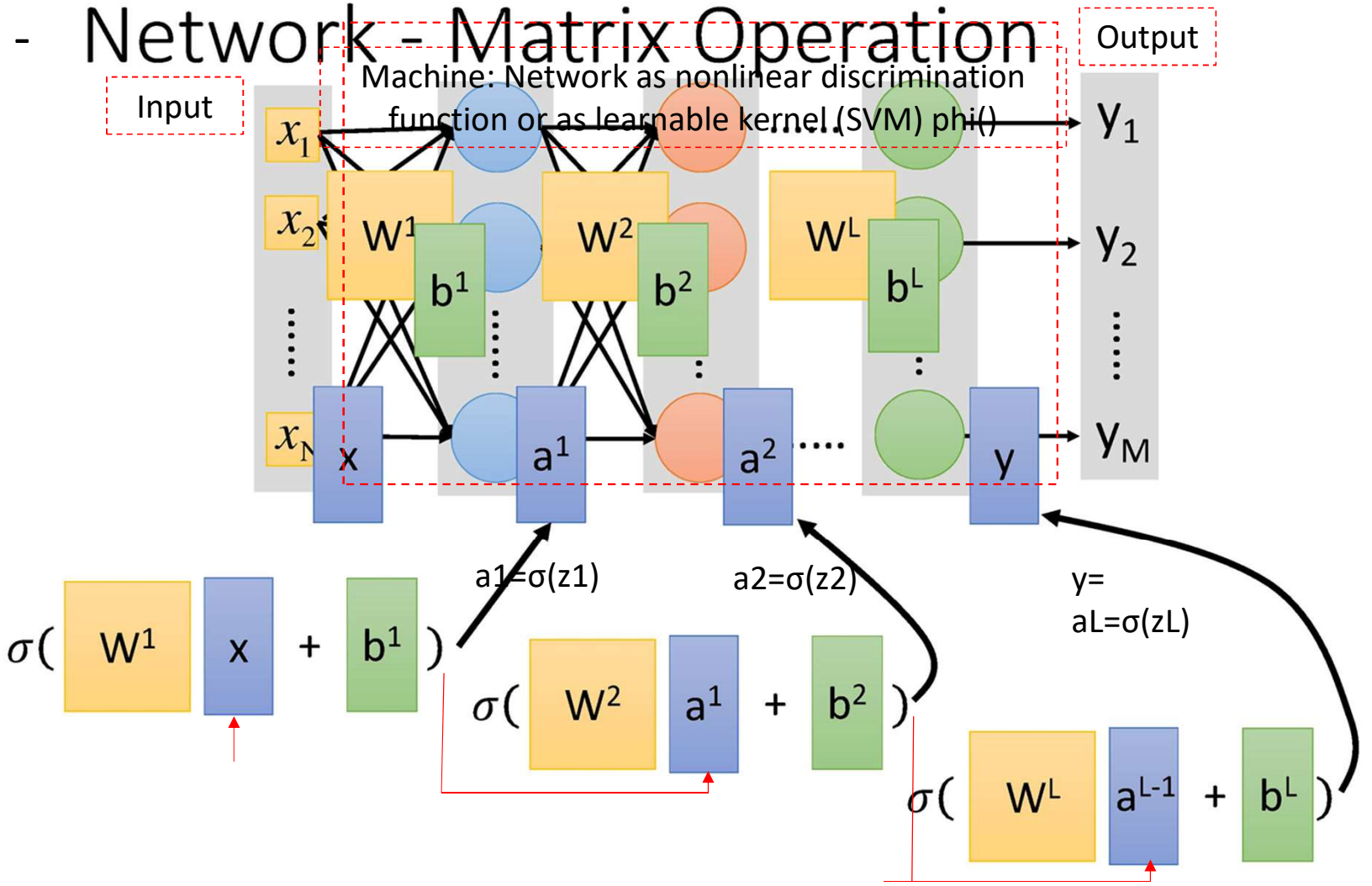
Here assume parameters Theta(w, b) are learned

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

[z1
z2]

: AdaBoost - Cascade

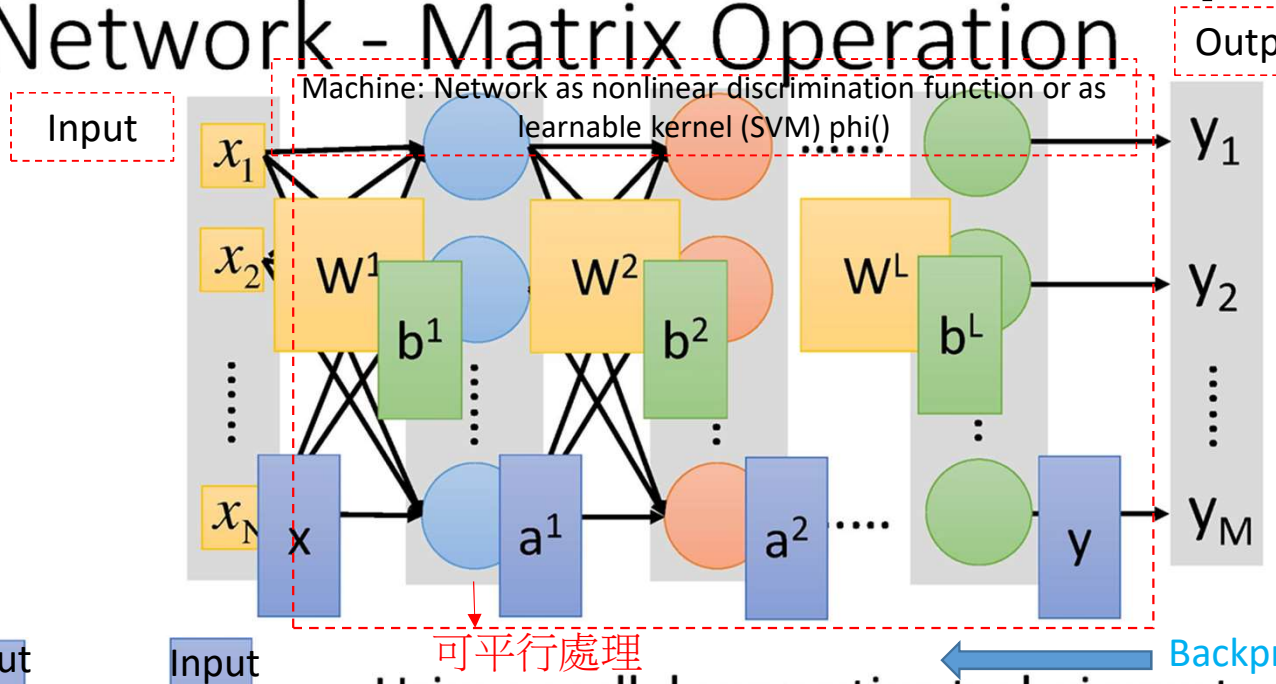
Fully Connect Feedforward Network - Matrix Operation



: AdaBoost - Cascade

Fully Connect Feedforward Network - Matrix Operation

$$\begin{bmatrix} w_{11}w_{21}\cdots w_{k1}\cdots w_{N1}\ b_1 \\ w_{12}w_{22}\cdots w_{k2}\cdots w_{N2}\ b_2 \\ \vdots \\ w_{1j}w_{2j}\cdots w_{kj}\cdots w_{Nj}\ b_j \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \\ \vdots \\ x_N \\ 1 \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \\ \vdots \\ z_j \end{bmatrix}$$



y=a, x=z
a=σ(z)

output y = f(Input x)

Using parallel computing techniques to speed up matrix operation

Replace a(L-1) para.
=> As forward…

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

$W_L\ X_L = Y$
$[W_L * W_{L-1}]\ X_{L-1} = Y$
....
$[W_L * \ldots * W_1]\ X_1 = Y$

W ? I/P & O/P Known

Solve W by gradient decent

Output Layer: Softmax Layer

: AdaBoost - Cascade

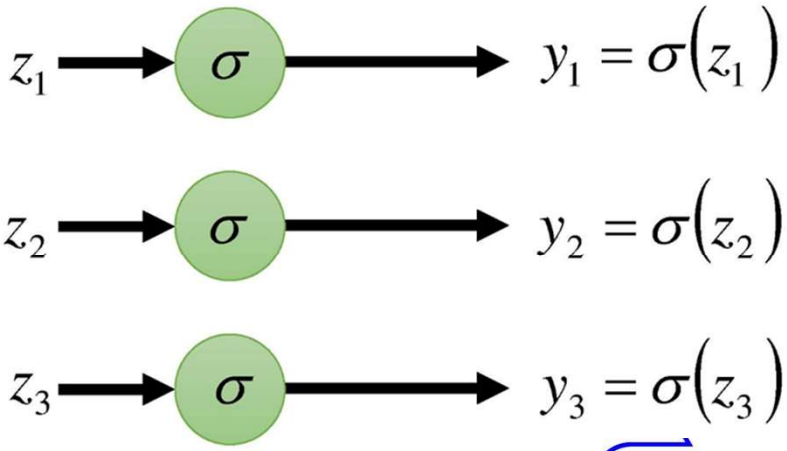
Output Layer (Option)

: Softmax Layer as normalization

- Softmax layer as the output layer

p.26 +4~ p.27+4

Ordinary Layer

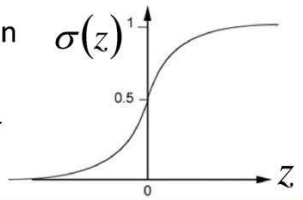


In general, the output of network can be any value.

May not be easy to interpret

Sigmoid Function

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

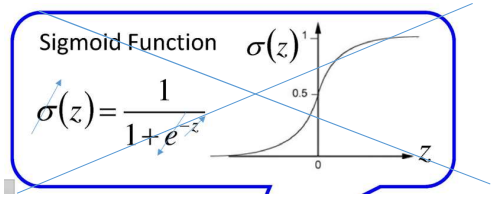


Output Layer: Softmax Layer

Output Layer (Option)

: Softmax Layer as normalization

- Softmax layer as the output layer

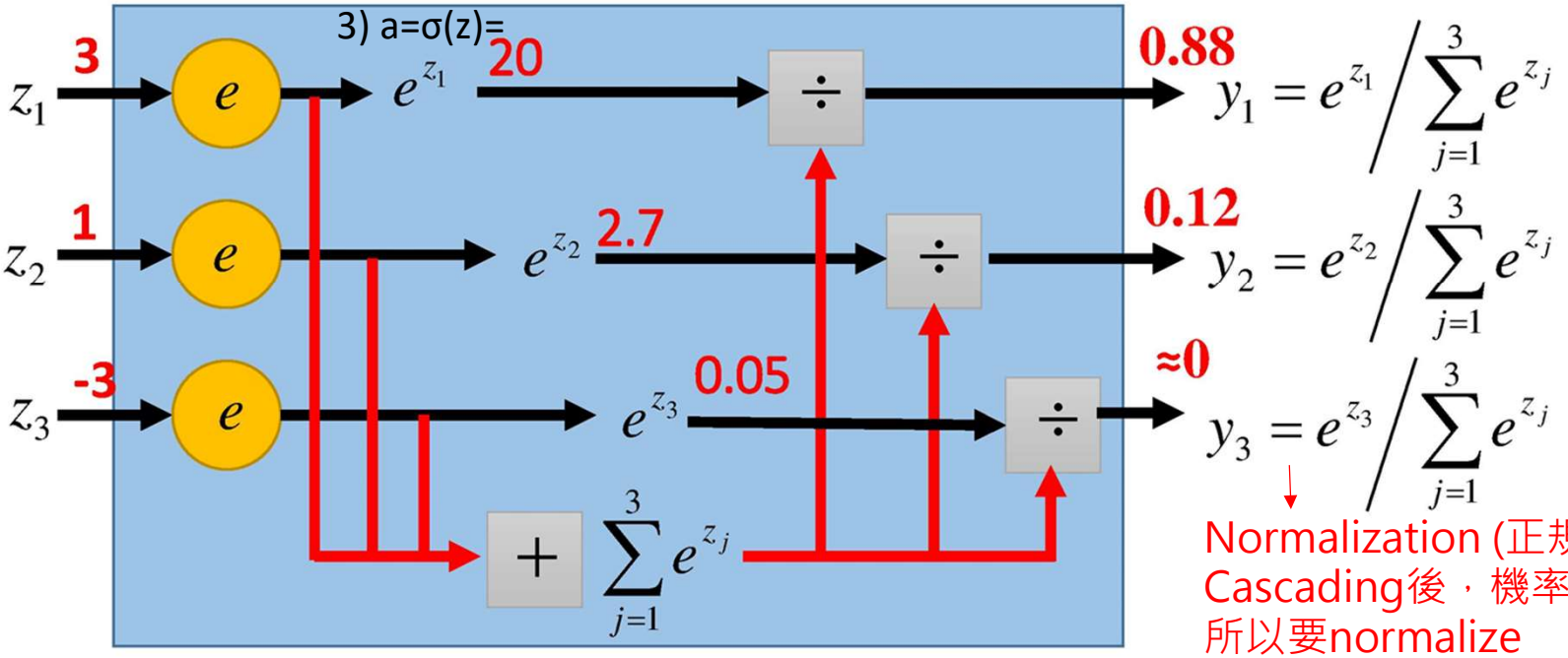
1) 

3) Others

Probability:

- $1 > y_i > 0$
- $\sum_i y_i = 1$

Softmax Layer Confidence value: Probability



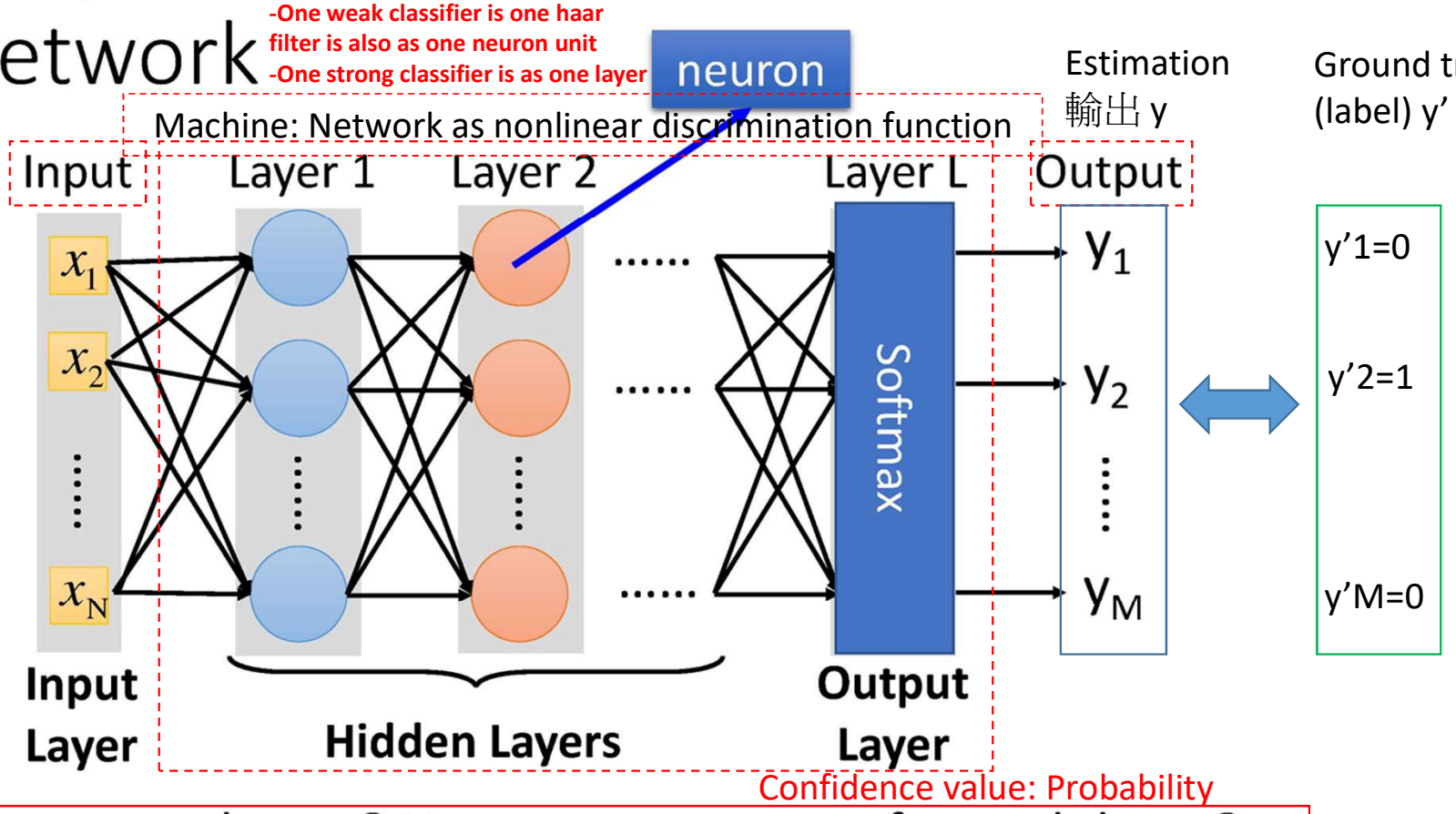
Normalization (正規化 0.0 ~ 1.0)：
Cascading後，機率會越乘越低
所以要normalize

Output Layer: Softmax Layer

: AdaBoost - Cascade

Fully Connect Feedforward Network

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer



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

Q: Can the structure be automatically determined?

Output Layer: Softmax Layer (1/2) ??

Confidence value: Probability

Softmax函數 : Softmax Layer as normalization + enhance or reduce

維基百科，自由的百科全書

在數學，尤其是概率論和相關領域中，**Softmax**函數，或稱歸一化指數函數[1]:198，是邏輯函數的一種推廣。它能將一個含任意實數的K維的向量 $\mathbf{z}$ 的「壓縮」到另一個K維實向量 $\sigma(\mathbf{z})$ 中，使得每一個元素的範圍都在(0, 1)之間，並且所有元素的和為1。該函數的形式通常按下面的式子給出：

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

J: Why exponential? Bigger is getting much bigger, smaller is getting much smaller

Softmax函數實際上是有限項離散概率分布的梯度對數歸一化。因此，Softmax函數在包括 多項邏輯回歸[1]:206–209 ，多項線性判別分析，樸素貝葉斯分類器和人工神經網絡等的多種基於概率的多分類問題方法中都有着廣泛應用。[2] 特別地，在多項邏輯回歸和線性判別分析中，函數的輸入是從K個不同的線性函數得到的結果，而樣本向量 $\mathbf{x}$ 屬於第 $\mathbf{j}$ 個分類的概率為：

Prob. of o/p y classify to j?

$$P(y = j|\mathbf{x}) = \frac{e^{\mathbf{x}^\mathsf{T}\mathbf{w}_j}}{\sum_{k=1}^{K} e^{\mathbf{x}^\mathsf{T}\mathbf{w}_k}}$$

Given x

I/P: x

O/P: y

??

這可以被視作K個線性函數 $\mathbf{x} \mapsto \mathbf{x}^\mathsf{T}\mathbf{w}_1, \ldots, \mathbf{x} \mapsto \mathbf{x}^\mathsf{T}\mathbf{w}_K$ oftmax函數的複合（$\mathbf{x}^\mathsf{T}\mathbf{wxw}$）。

Output Layer: Softmax Layer (2/2)

例子

輸入向量[1,2,3,4,1,2,3]對應的Softmax函數的值為[0.024, 0.064, 0.175, 0.475, 0.024, 0.064, 0.175]。輸出向量中擁有最大權重的項對應着輸入向量中的最大值「4」。這也顯示了這個函數通常的意義：對向量進行歸一化，凸顯其中最大的值並抑制遠低於最大值的其他分量。

參考資料

1. Bishop, Christopher M. (2006).
2. ai-faq What is a softmax activation function? (http://www.faqs.org/faqs/ai-faq/neural-nets/part2/section-12.html)

取自 "https://zh.wikipedia.org/w/index.php?title=Softmax函数&oldid=43648521"

I.1. Step2

Three Steps for Deep Learning

Design topology/network:
Having parameters (as variable) without values

Step 1: Network Structure

How to I/O data? Target/Data:
Given input data and be recognized / classified output data. Exp: Min-batch

Step 2: Learning Target

o/p <=> Ground truth (label) y'

How to learn? Learning parameters (or para values) of topology using gradient descent to find global min of MSE

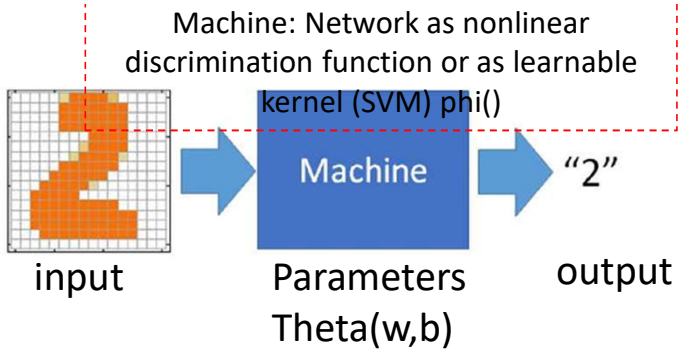
Step 3: Learn!

天生的腦

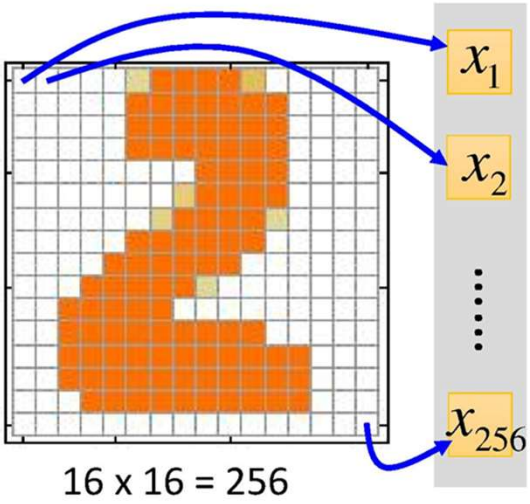
http://onepiece1234567890.blogspot.tw/2013/12/blog-post_8.html

?? So input is binary or gray value??

Example Application



Input



Ink → 1

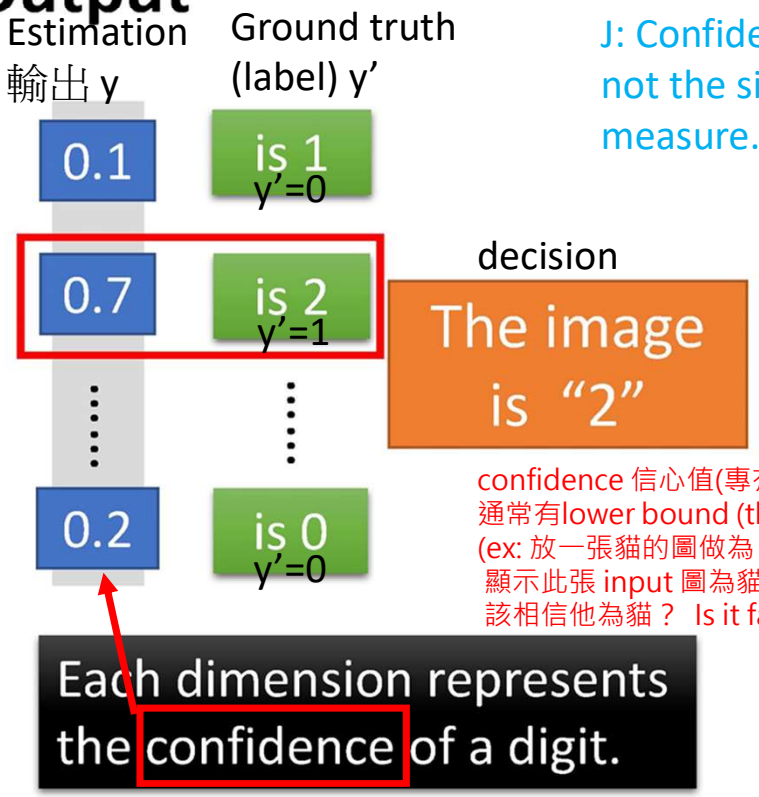
No ink → 0

x: 0~255

?? So input is binary or gray value??

input 二值化
(也可能有非二值化的輸入 like Grayvalue input)

Output



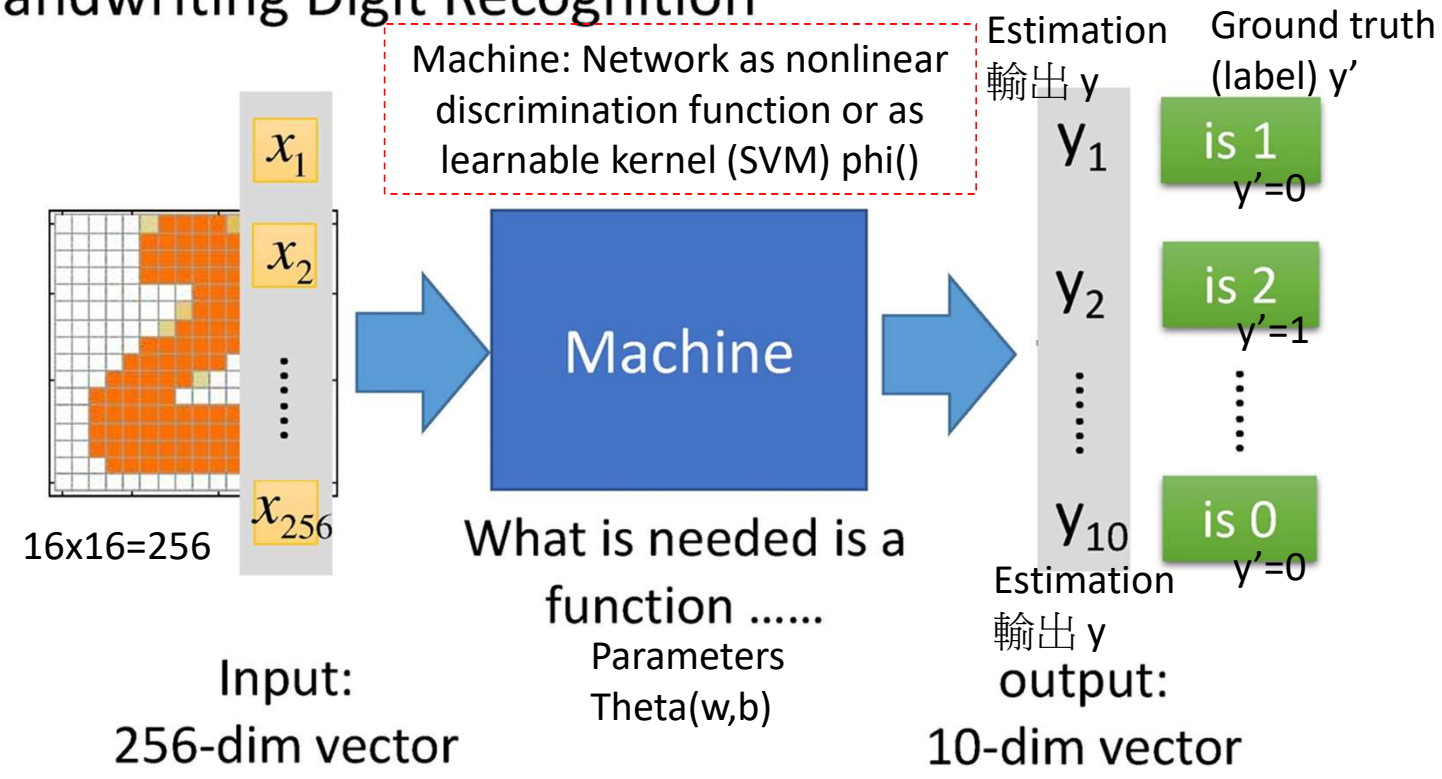
J: Confidence is not the similarity measure.

confidence 信心值(專有名詞)：
通常有lower bound (threshold)
(ex: 放一張貓的圖做為 input
顯示此張 input 圖為貓的confidence 為 0.6
該相信他為貓？ Is it false positive??)

= Similarity measure value ??

Example Application

- Handwriting Digit Recognition

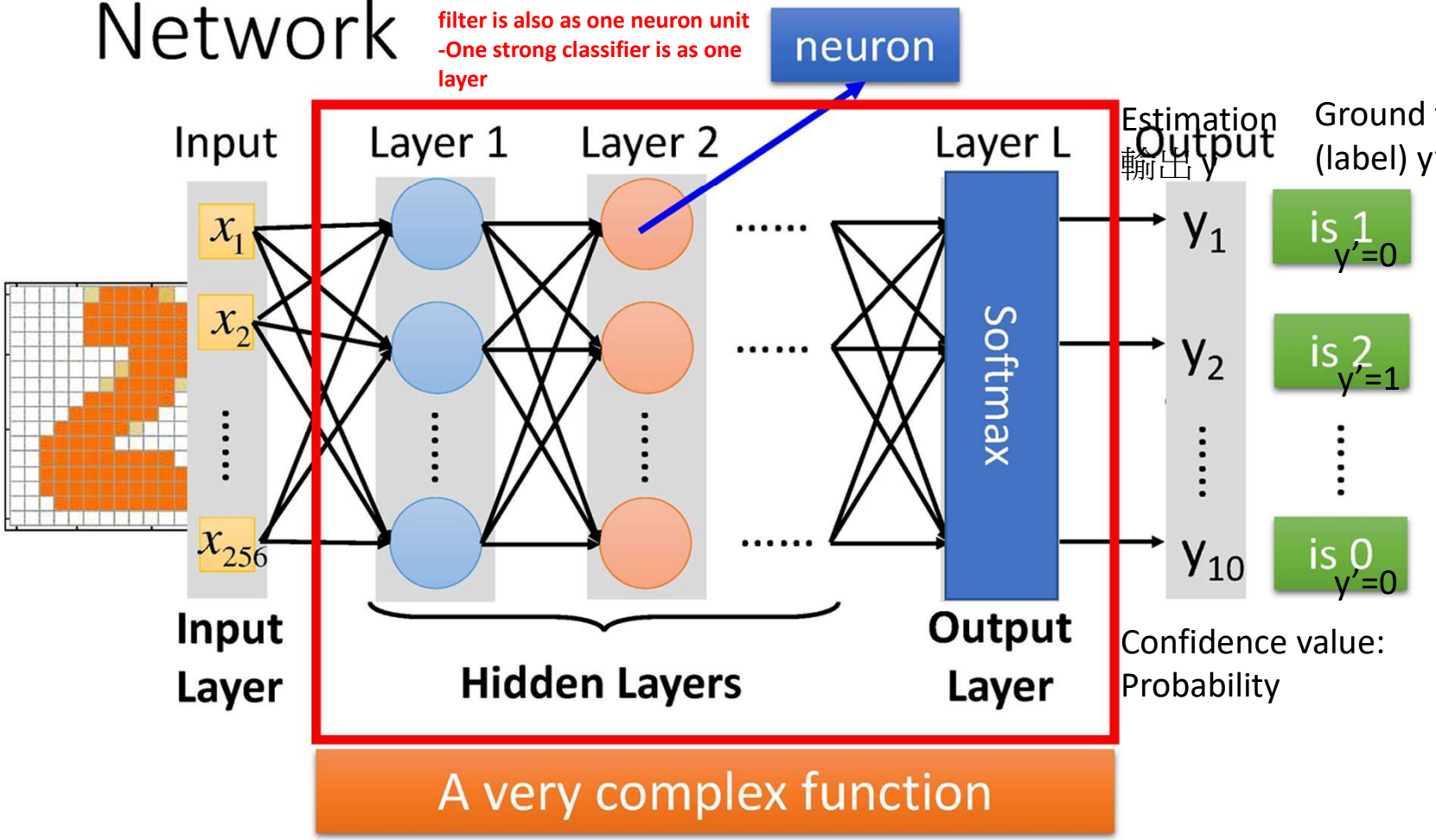


: AdaBoost - Cascade

Fully Connect Feedforward Network

Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer



: AdaBoost - Cascade

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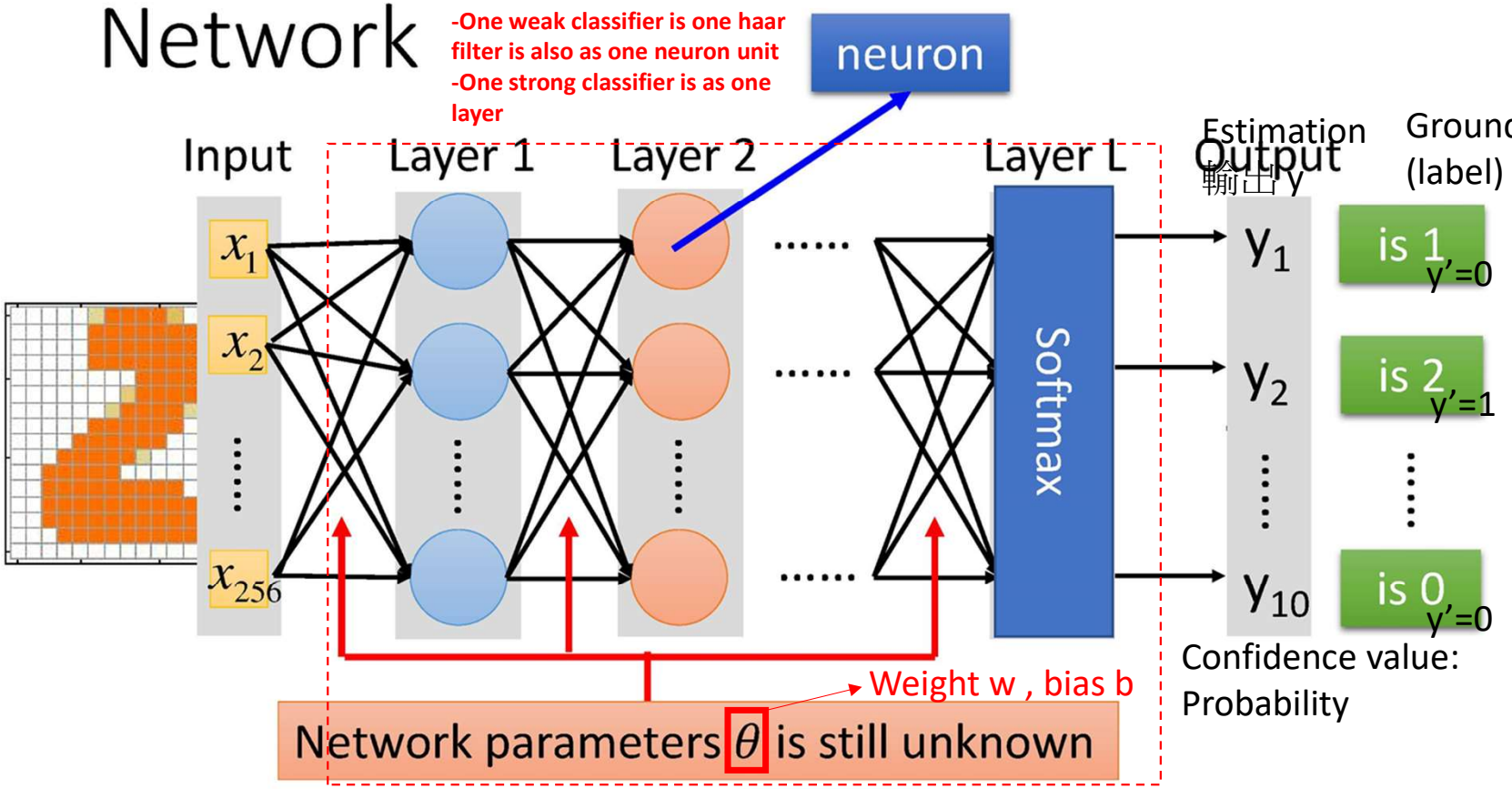


-Given I/P x… and o/p y, **label** y'

-Parameters are learned

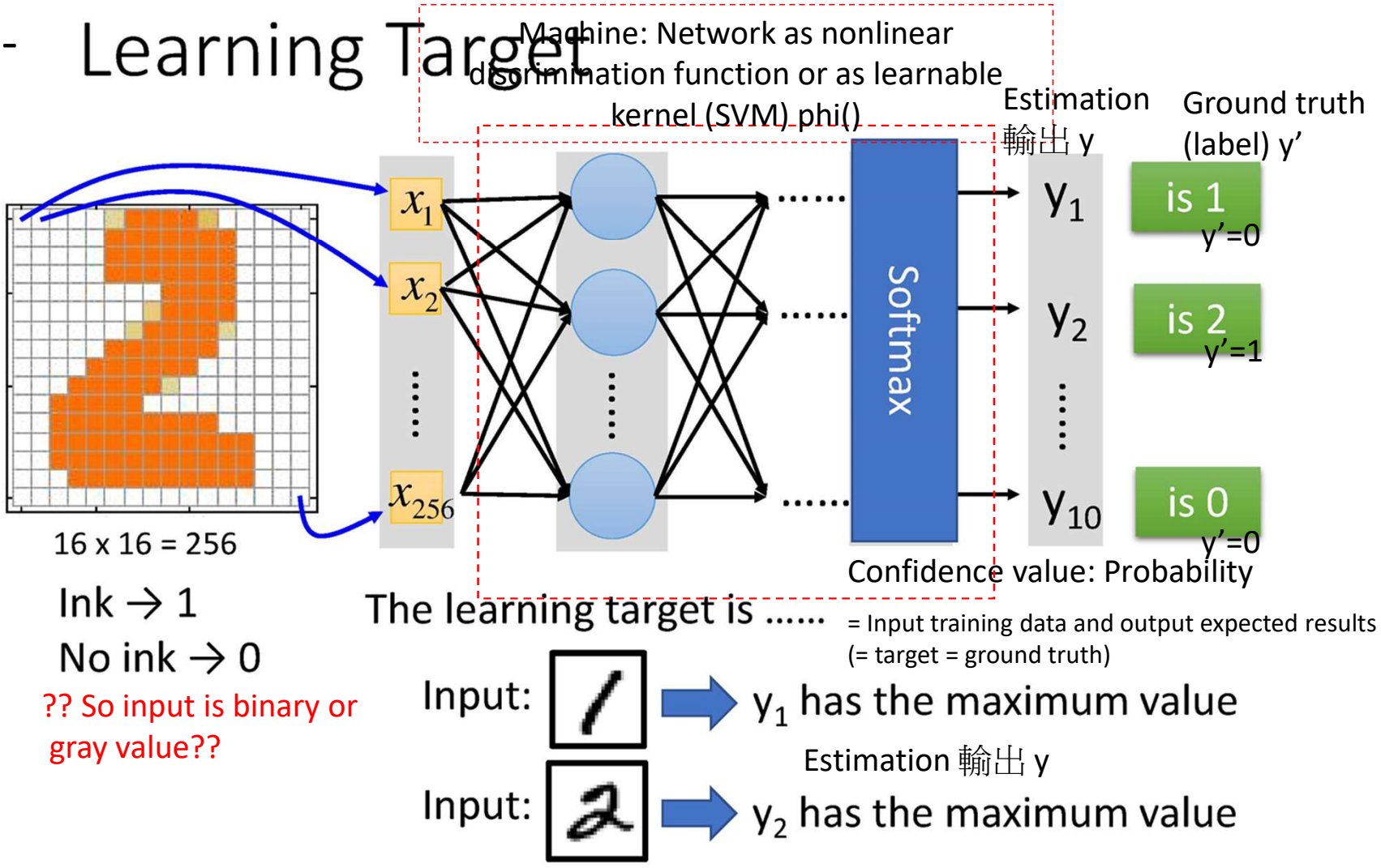
Tell the machine its learning target = Ground truth (label) y' **Step 2** = Input training data and output expected results (= target=ground truth)

Then machine find the parameters θ^* that achieve the target. **Step 3**

: AdaBoost - Cascade

?? So input is binary or gray value??

Learning Target



Interpolation??
Extrapolation??

Training Data

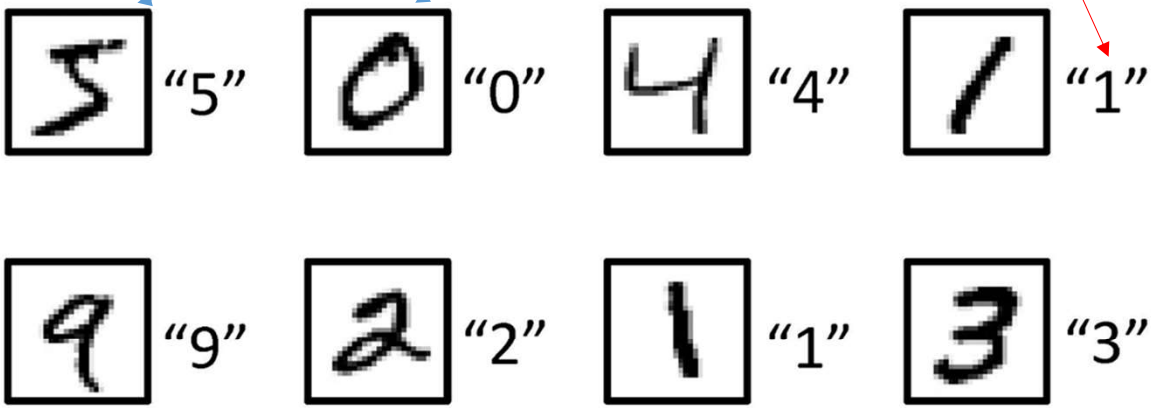
Estimation
輸出 y

I/P

O/P

- Preparing training data: images and their labels

Ground truth (label) y'



Ground truth (label) y'

Label

The learning target is defined on the training data.

Ax = b
? ? ?

最佳化方式：
1. EM (Expectation-maximization)
  (1) 初始值 = mean (expected)
  (2)求max likelihood
  (3)不斷進行(1)~(2)iteration
2. Maximum likelihood estimation
3. 基因演算法
4. Random: Particle filter

Loss : Loss Function

Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

Estimation y

Ground truth y^

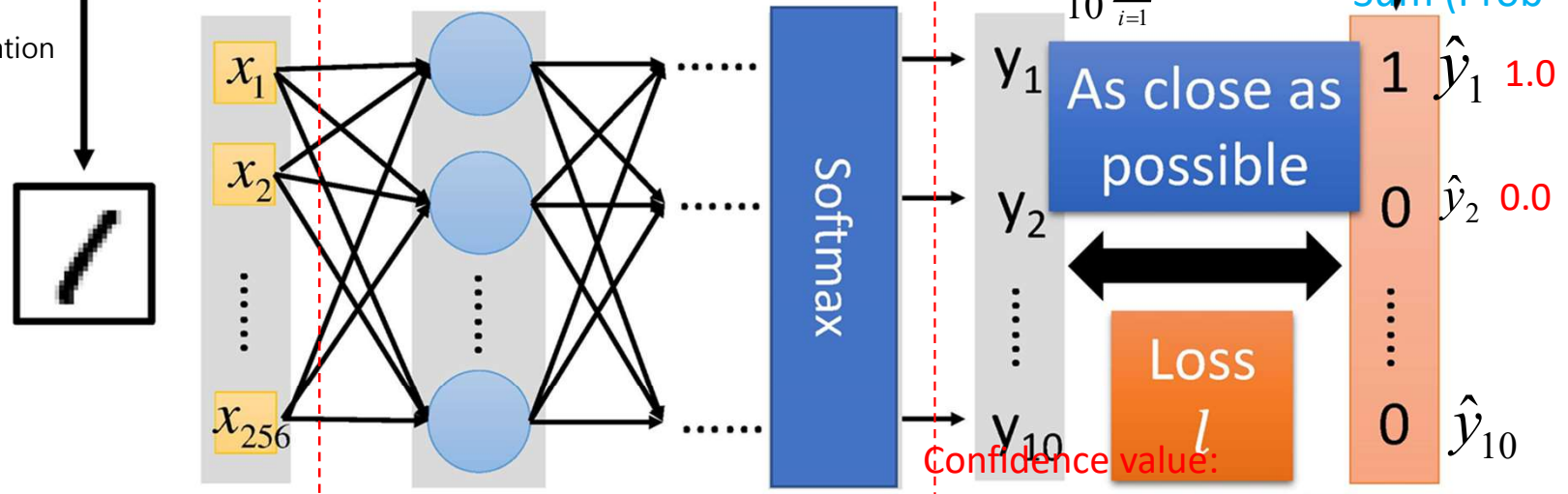
"1"

相似度判斷(similarity measure)：
1) 相減 – MSE, SSD, SAD
2) 相乘 - NCC

1) MSE $\frac{1}{10}\sum_{i=1}^{10}\| y_i - \hat{y}_i \|^2$

=E[ ] ?? // Expected Value

=Sum (Prob * || . ||)



Confidence value: Probability

實際output

target

Label = Ground Truth

J: 相減: SSD, SAD

Loss can be **square error** or **cross entropy** between the network output and target

2) Cross entropy

$0.0 < -\sum_{1}^{10}(\hat{y}_i log y_i)$

= Input training data and output expected results (= target)

-: Because y is prob. 0.0~1.0, so log y will be -, therefore -- = +

Estimation O/P probability y

Ground truth y^

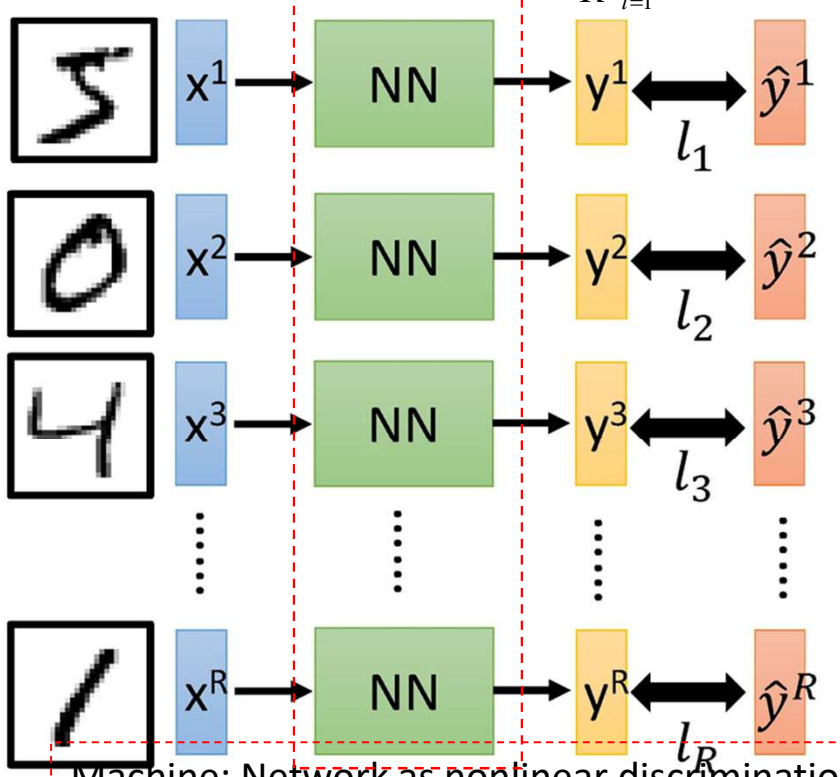
y^=1 Yes, y^=0 No

Loss function
= cost function
= Entropy

Total Loss

1) MSD: 1/R [Sum(y-y')^2]
Where estimation y Ax by computation
y': target value, expected value, ground truth
A(w,b) (=theta): Unknown parameters,

For all training data ... $\frac{1}{R}\sum_{i=1}^{R}\| y_i - \hat{y}_i \|^2$



500 training data

R=10

Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

Total Loss: $L = min \frac{1}{R}\sum_{i=1}^{R}\| y_i - \hat{y}_i \|^2$

$L = \sum_{r=1}^{R} l_r$ R=10

=E[ ] ?? // Expected Value
=Sum (Prob * || . ||)

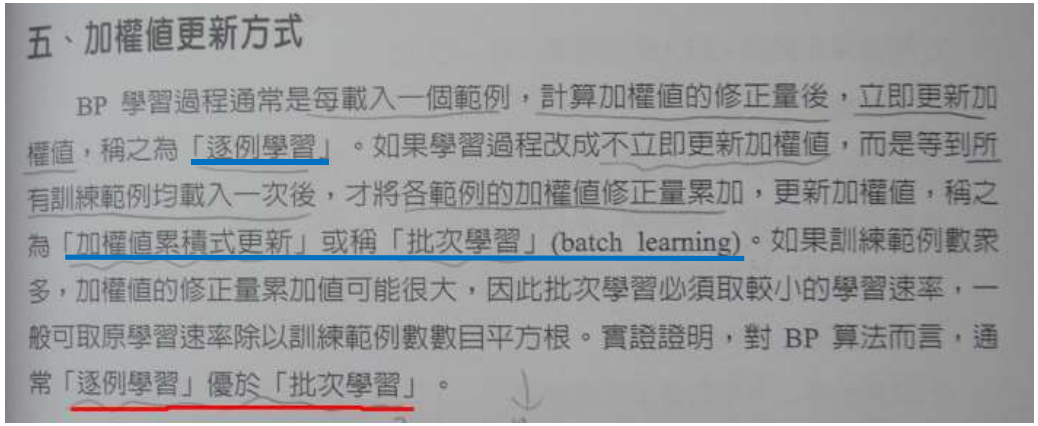
累積所有training data，計算total loss，根據total loss及梯度下降法更新parameters θ^*

Learning Target

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

逐例學習 VS 批次學習(batch learning)

NN book提到的逐例學習和批次學習

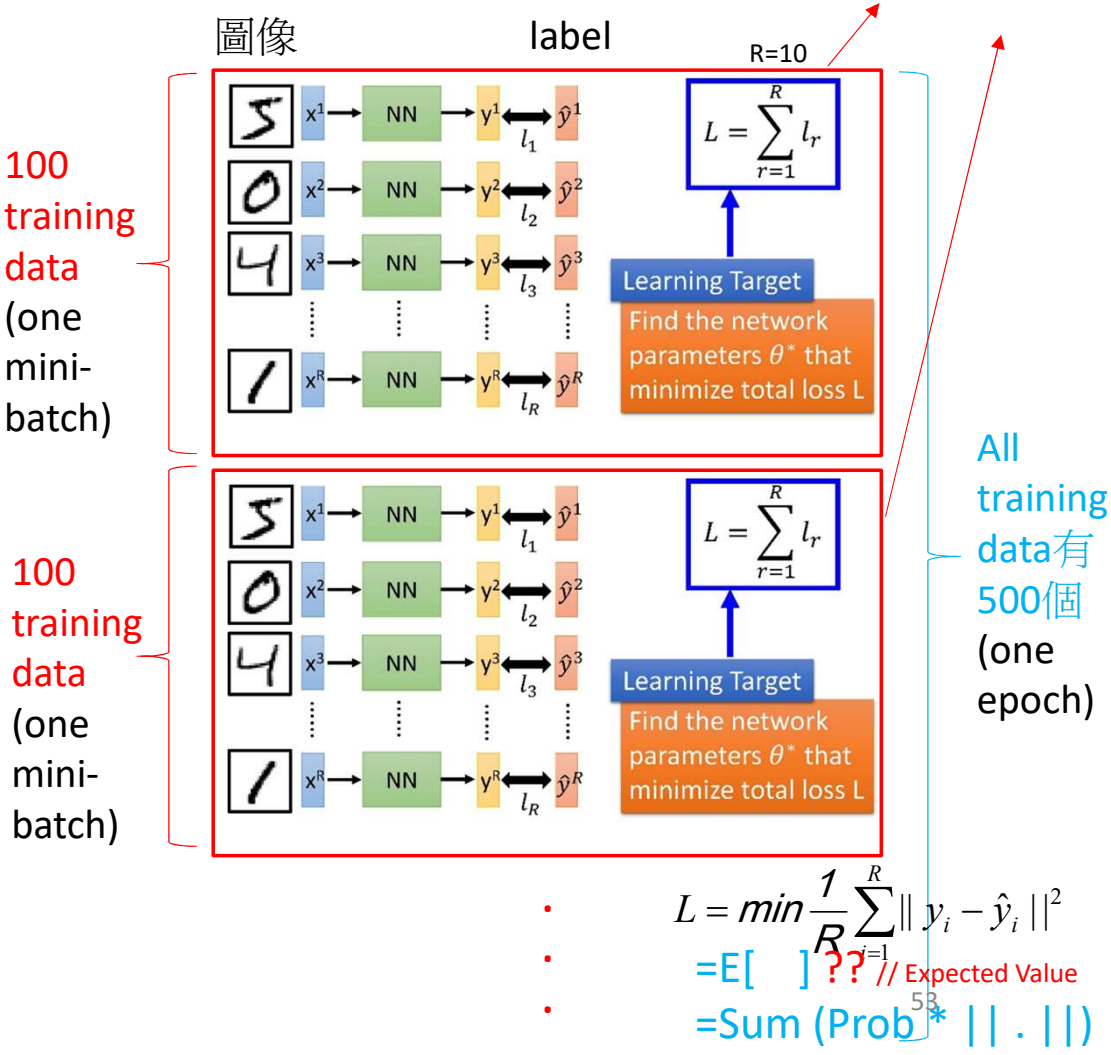


五、加權值更新方式

BP 學習過程通常是每載入一個範例，計算加權值的修正量後，立即更新加權值，稱之為「逐例學習」。如果學習過程改成不立即更新加權值，而是等到所有訓練範例均載入一次後，才將各範例的加權值修正量累加，更新加權值，稱之為「加權值累積式更新」或稱「批次學習」(batch learning)。如果訓練範例數眾多，加權值的修正量累加值可能很大，因此批次學習必須取較小的學習速率，一般可取原學習速率除以訓練範例數數目平方根。實證證明，對 BP 算法而言，通常「逐例學習」優於「批次學習」。

這個講義提到的mini-batch：
一些訓練範例載入網路，根據誤差總和
計算parameters θ^*修正量
(parameters θ^*的修正量不是根據
所有訓練範例(500 training data)計算的total loss，
而是根據每個mini-batch(100 training data)計算的loss總和)

更新一次 parameters θ^*



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

$$L = min \frac{1}{R} \sum_{i=1}^{R} \| y_i - \hat{y}_i \|^2$$

=E[ ] ?? // Expected Value

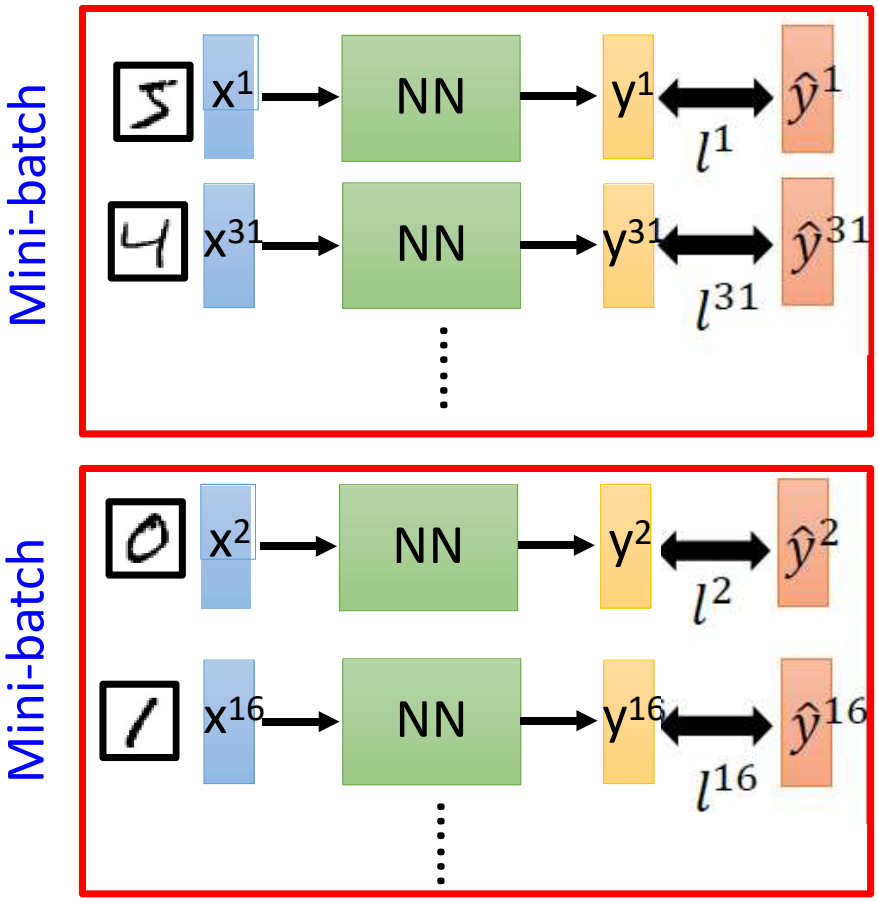
=Sum (Prob * || . ||)

Mini-batch

We do not really minimize total loss!

Originally 500 training samples:

Each mini-batch: uses 100 training samples



(1) Randomly initialize network parameters

(2) one epoch

- Pick the 1st batch
  $L' = l^1 + l^{31} + \cdots$
  Update parameters once
- Pick the 2nd batch
  $L'' = l^2 + l^{16} + \cdots$
  Update parameters once
  ⋮
- Until all mini-batches have been picked

(3)~(x) Repeat the above epoch

I.1. Step3

Three Steps for Deep Learning

Design topology/network: Having parameters (as variable) without values

How to I/O data? Target/Data: Given input data and be recognized / classified output data. Exp. Mini batch

How to learn? Learning parameters (or para values) of topology using gradient descent to find global min of MSE

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

o/p <=> Ground truth (label) y'

天生的腦

http://onepiece1234567890.blogspot.tw/2013/12/blog-post_8.html

$$L = \frac{1}{R} min \sum_{i=1}^{R} \| y_i - \hat{y}_i \|^2$$

Solution for this problem:
1) Gradient decent
2) Random approximation
   Particle filter, andy….

How to Learn?

Step 2: **Learning Target**

Find the network parameters θ^* that minimize total loss

Step 3: **Learning**

Solving the optimization problem

Brute force:
列舉出parameter的所有可能組合
→不可行！

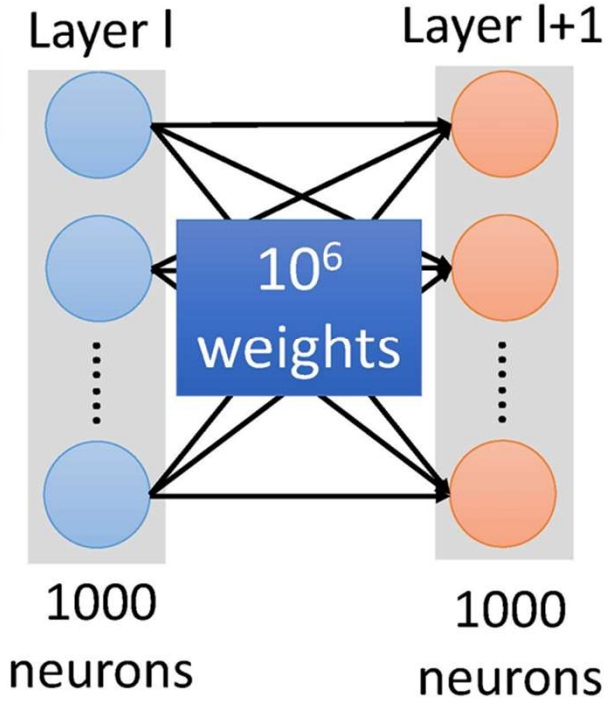
Enumerat[illegible] pos[illegible]e values

Network para[illegible]ers $\theta =$

$\{w_1, w_2, w_3, \cdots, b_1, b_2, b_3, \cdots\}$

Millions of parameters

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



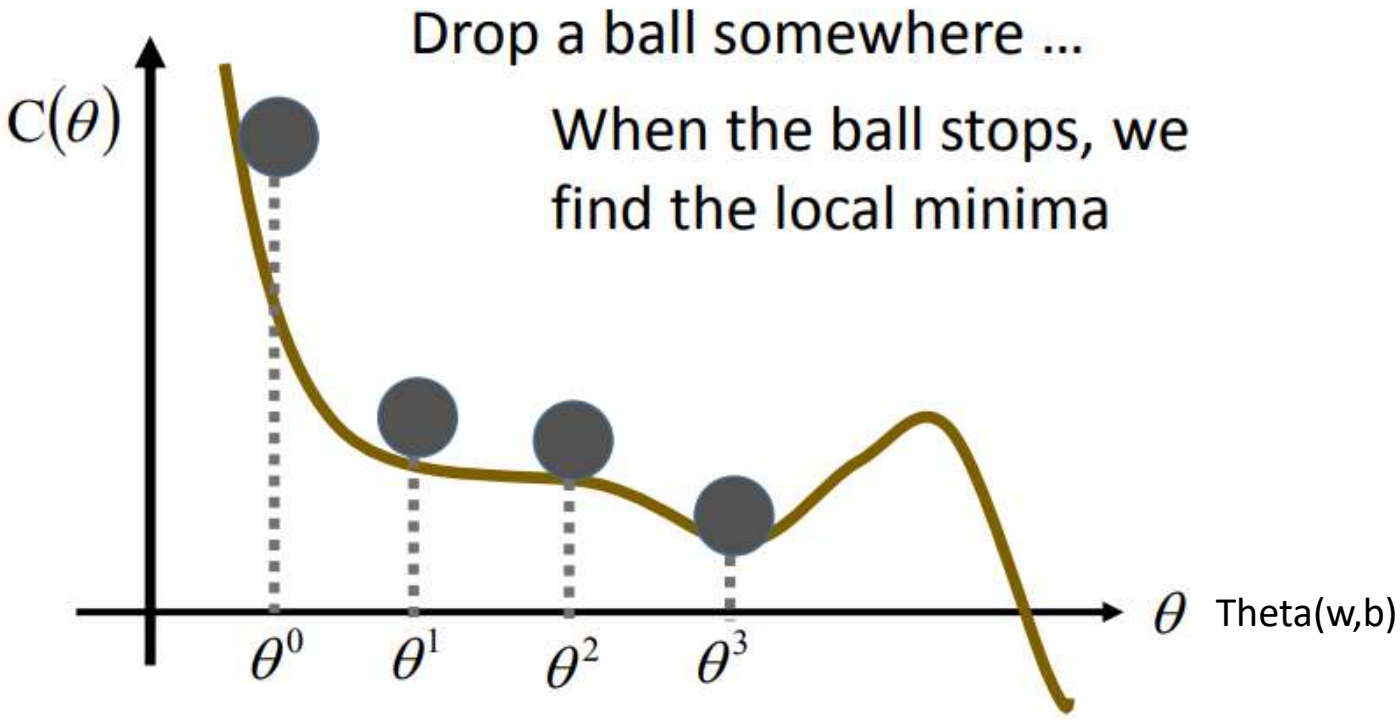
-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer

Reference:
http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf

Gradient Descent – Idea

- For simplification, first consider that θ has only one variable

C(θ): is called cost/loss/error function



Gradient Descent

Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

Step 2: **Learning Target**

Find the network parameters θ^* that minimize total loss

其他方法：
Monte-Carlo(蒙地卡羅法)：是一種隨機模擬方法，以機率和統計理論方法為基礎的一種計算方法。

- Pick an initial value for w

Way 1: random

Usually good enough

Way 2: in Lecture 4

1階微分,找 loss 的 min ，可能問題：只找到 **local min**
→ 有二次微分為佳(gradient + 二階微分; exp. EM)

Image processing:
Physical meaning –
一階微分
二次微分

N-dim Theta
Here we assume 1-dim w for example

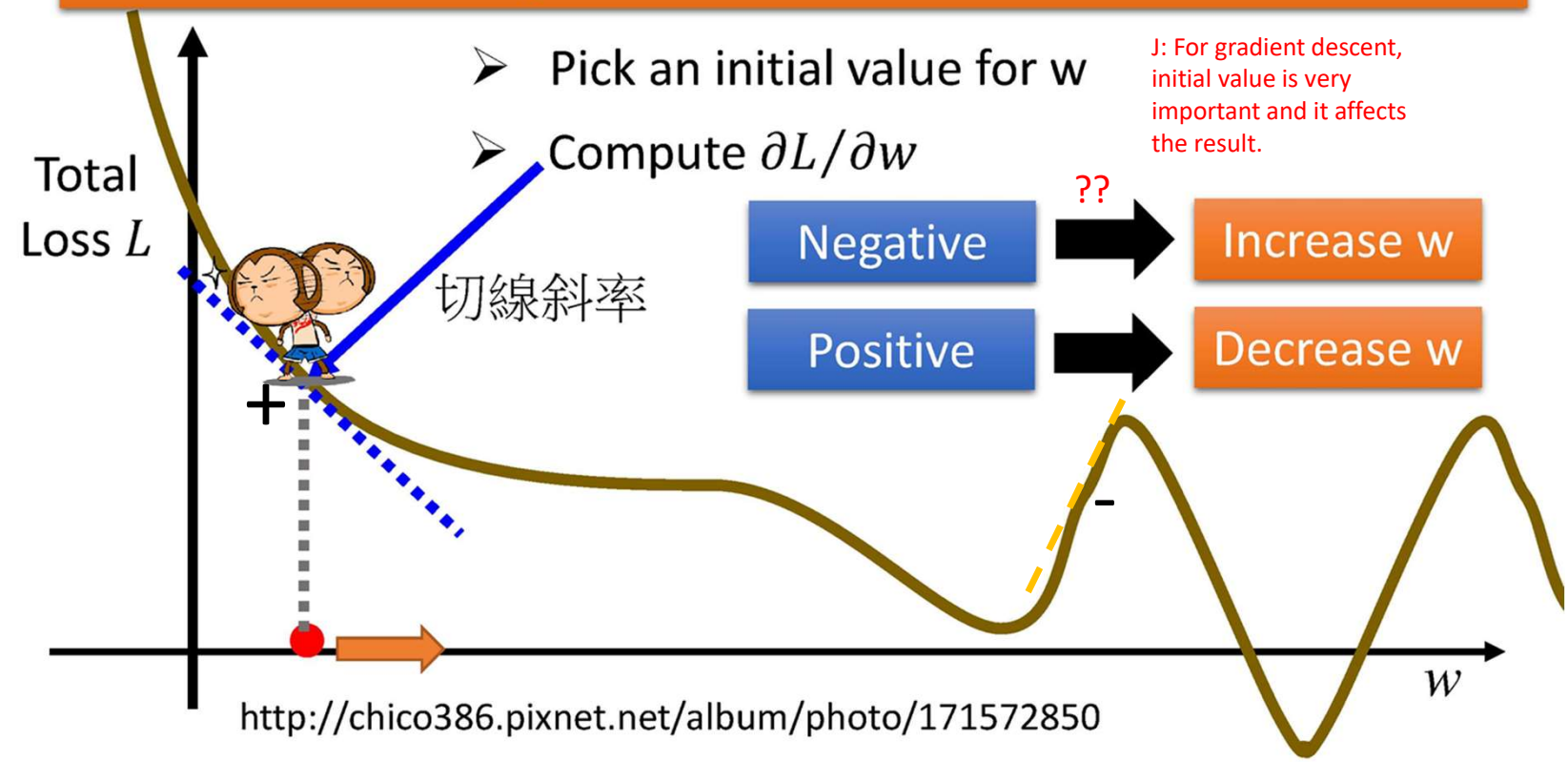
??

Gradient Descent

Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

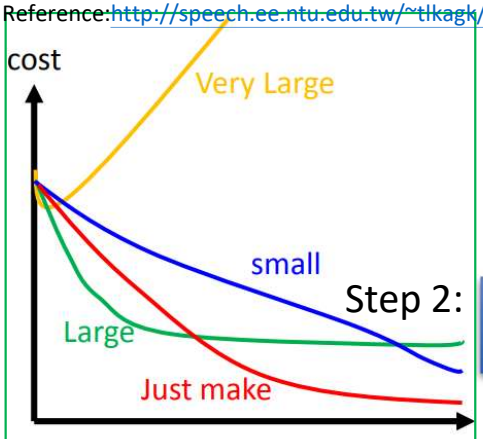
Step 2: Learning Target

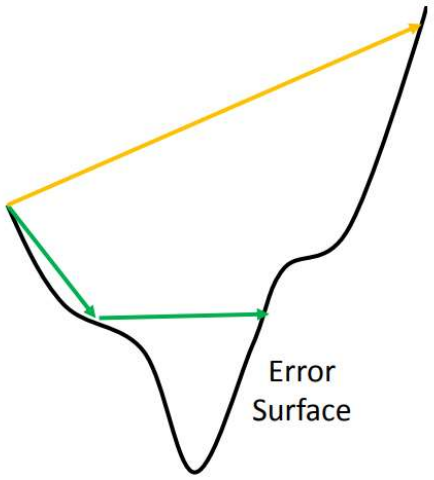
Find the network parameters θ^* that minimize total loss



J: For gradient descent, initial value is very important and it affects the result.

Reference:http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf





Set the learning rate η carefully

Learning rate: (movement)
取的小，跳很慢
取的大，可能跳過global min

Learning rate is given by experience

Gradient Descent

Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

Step 2:

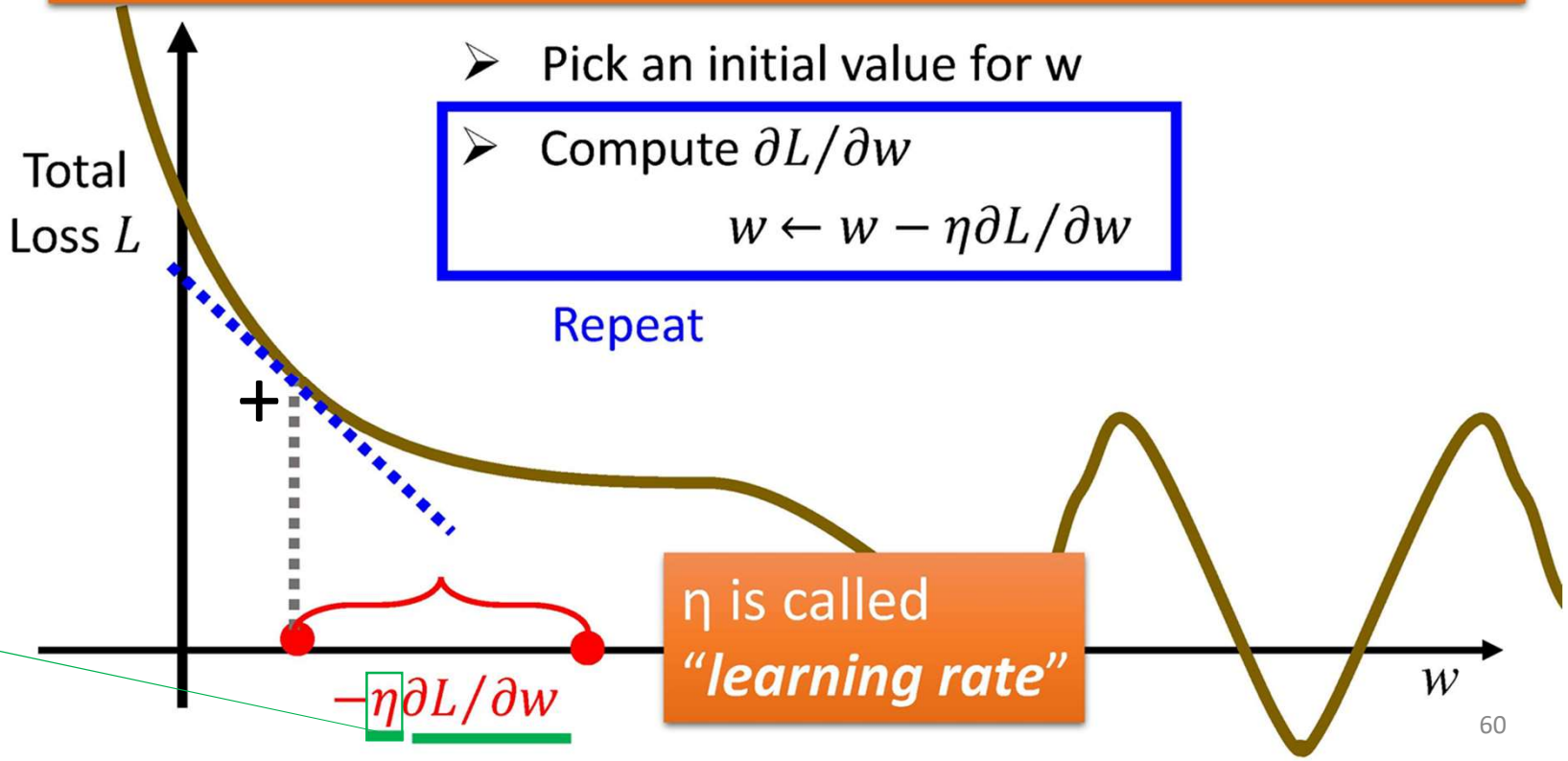
Learning Target

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

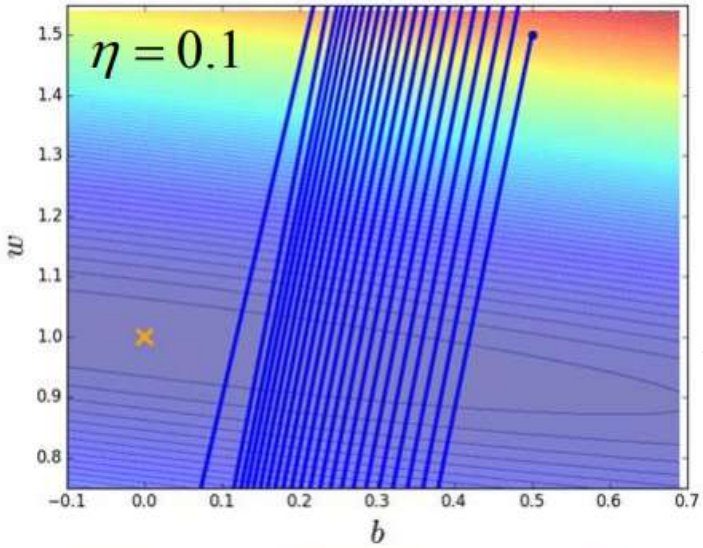


Reference:http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf

?? Learning Rate

- ***Toy Example***

  Different learning rate η

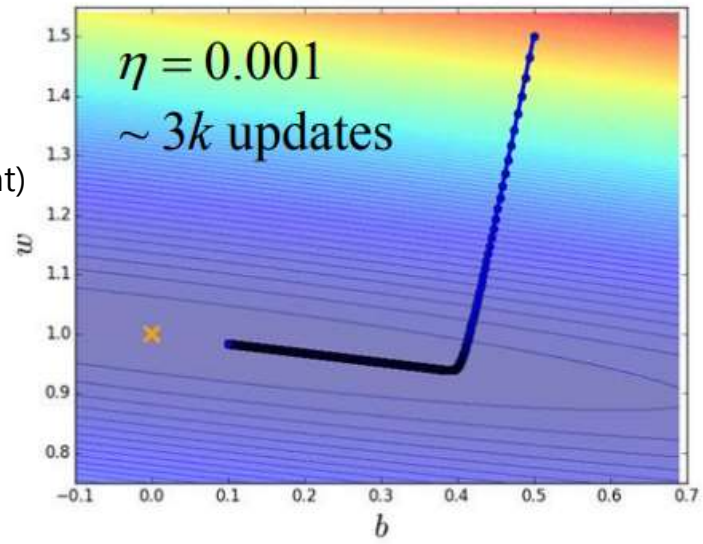


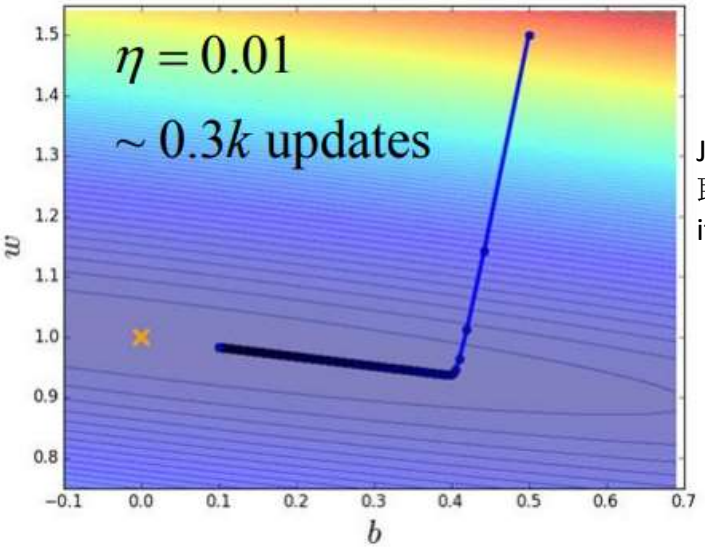
震盪，到不了min

J: Learning rate: (movement)
取的大，可能跳過global min

??
~~收斂速度快~~

J: Learning rate: (movement)
取的很小，跳的很慢
收斂速度很慢，
iteration many times





??
收斂速度較快

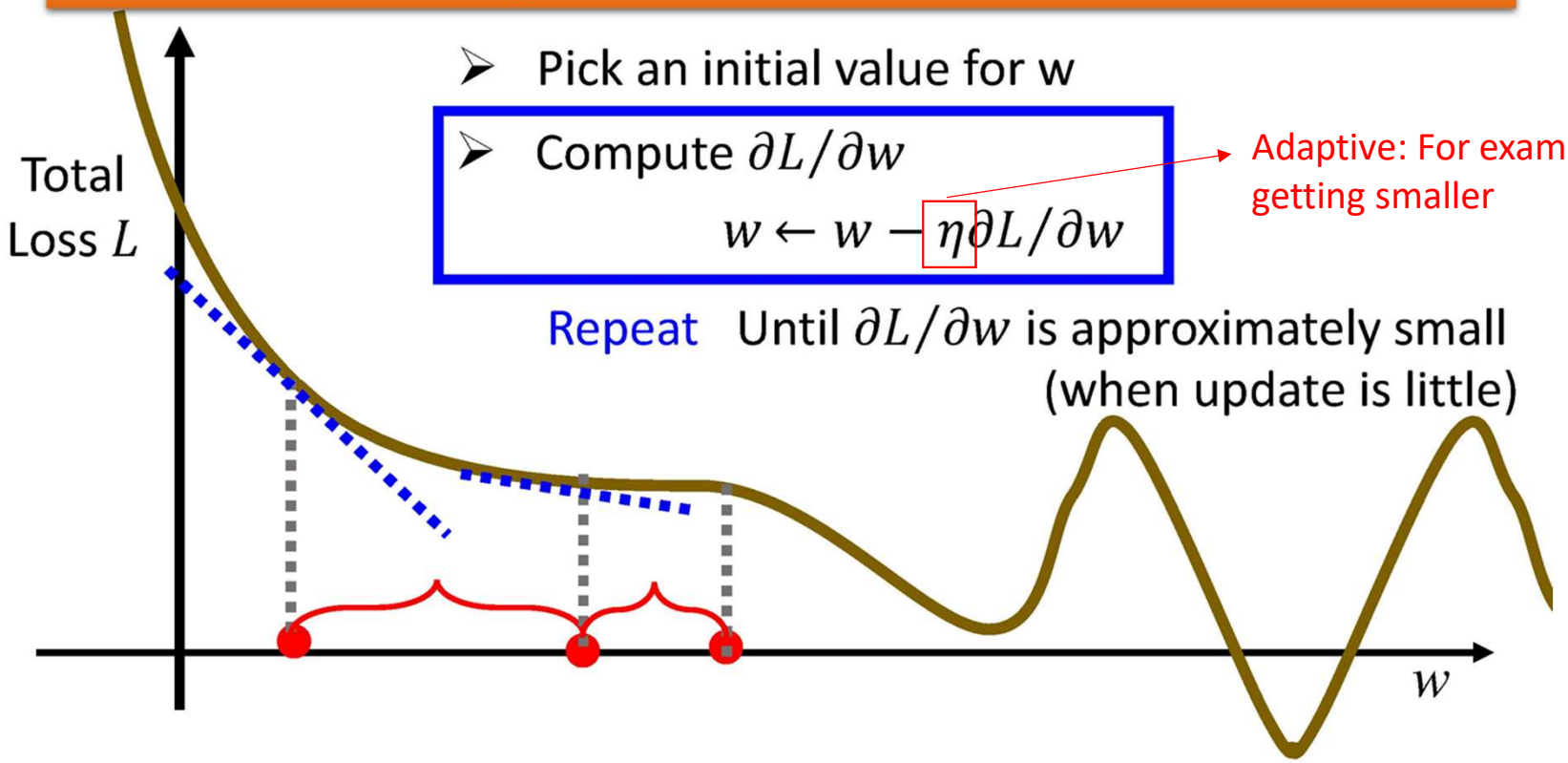
J: Learning rate: (movement)
取的適中，收斂速度ok，
iteration ok times

Gradient Descent

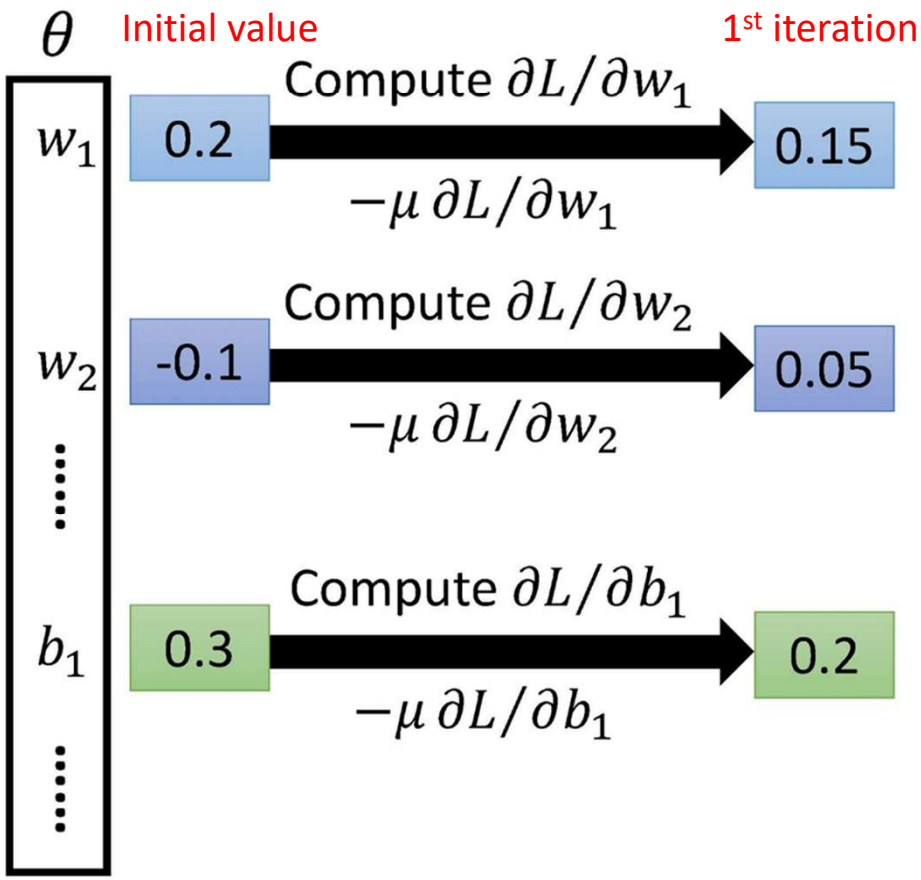
Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

Step 2: **Learning Target**

Find the network parameters θ^* that minimize total loss



Gradient Descent



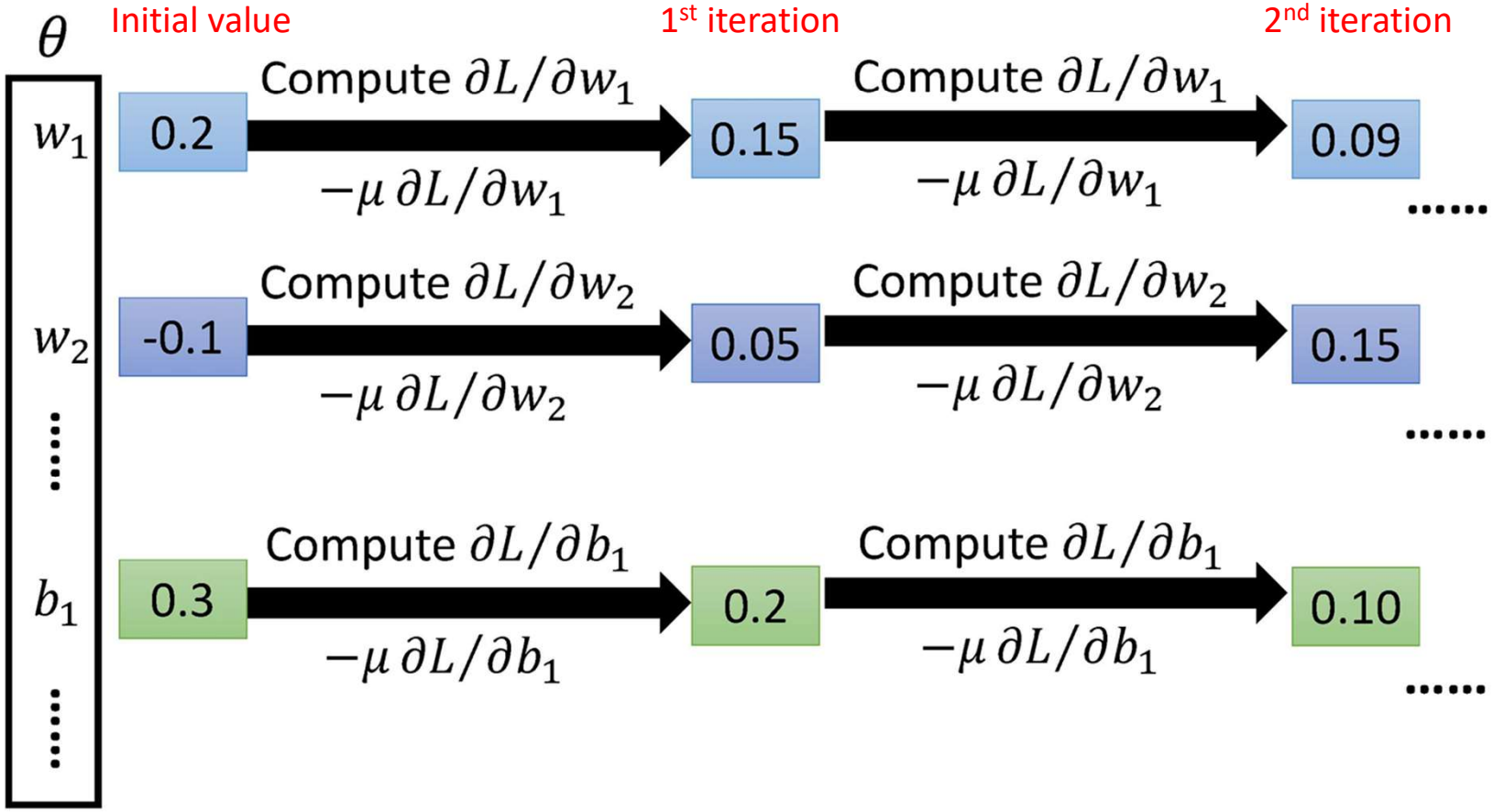
Ax=b

$$[w_1 w_2 w_3 \cdots w_K \; 1]_{\text{J(=1) X (k + 1)}} \begin{bmatrix} b \\ b \\ b_3 \\ \vdots \\ b_K \\ 1 \end{bmatrix}_{\text{(k + 1) X 1}} = z$$

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

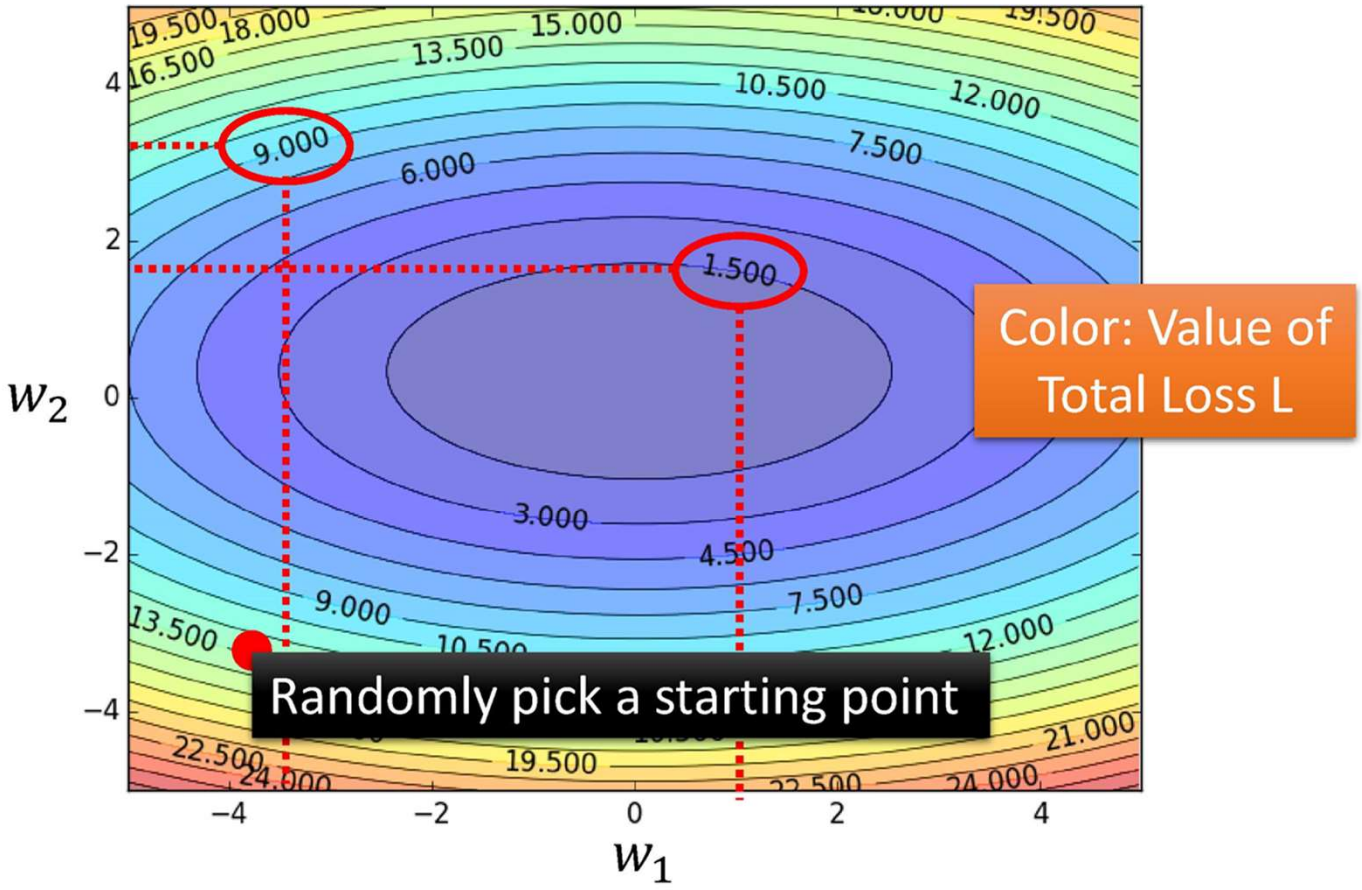
gradient

Gradient Descent



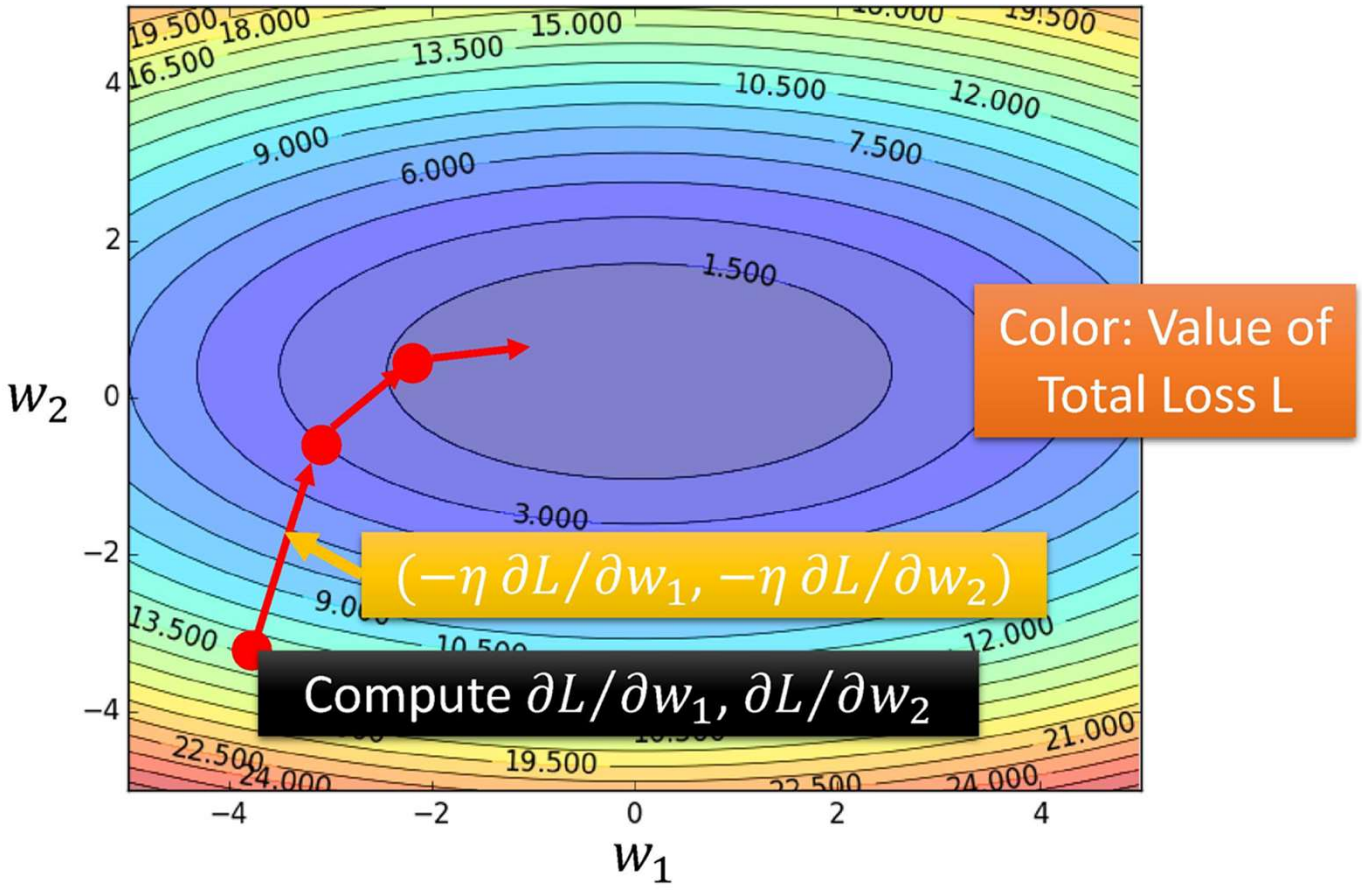
Gradient Descent

Suppose that θ has two variables $\{w_1, w_2\}$



Gradient Descent

Hopfully, we would reach a minima .....



??

Reference: http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf
https://www.quora.com/Whats-the-difference-between-gradient-descent-and-stochastic-gradient-descent

Trained neural network to get the estimation result y=f( ) for each epoch

Stochastic Gradient Descent and Mini-batch

$$C(\theta)=\frac{1}{R}\sum_{r}\left\|f\left(x^r;\theta\right)-\hat{y}^r\right\|$$

=E[ ] ?? // Expected Value
=Sum (Prob * || . ||)

◆ ***Gradient Descent***

$$=\frac{1}{R}\sum_{r}C^r\left(\theta\right)$$

$$\theta^i=\theta^{i-1}-\eta\nabla C\left(\theta^{i-1}\right) \qquad \nabla C\left(\theta^{i-1}\right)=\frac{1}{R}\sum_{r}\nabla C^r\left(\theta^{i-1}\right)$$

run through **ALL** the samples in your training set to do a single update

◆ ***Stochastic Gradient Descent*** Faster! Better!

Pick an example x^r

$$\theta^i=\theta^{i-1}-\eta\nabla C^r\left(\theta^{i-1}\right)$$

use **ONLY ONE** of training sample from your training set to do the update

If all example x^r have equal probabilities to be picked

$$E\left[\nabla C^r\left(\theta^{i-1}\right)\right]=\frac{1}{R}\sum_{r}\nabla C^r\left(\theta^{i-1}\right)$$

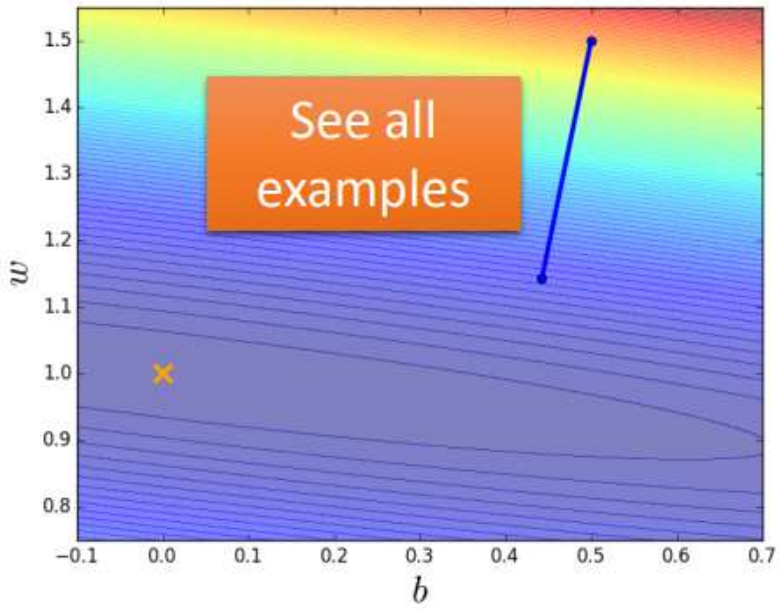
Reference:http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf

Stochastic Gradient Descent and Mini-batch

- ***Toy Example***

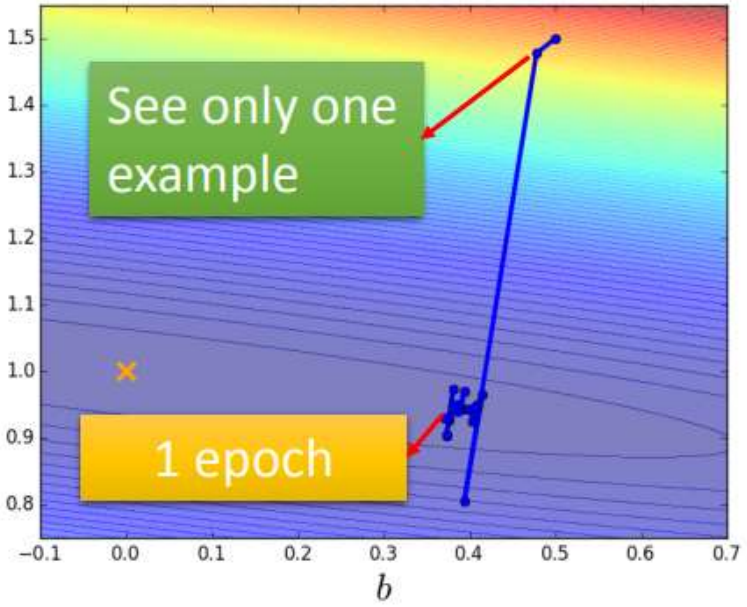
Gradient Descent

Update after seeing all examples



Stochastic Gradient Descent

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



Reference:http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf

Stochastic Gradient Descent and Mini-batch

What is epoch?

Training Data: $\left\{\left(x^1,\hat{y}^1\right),\left(x^2,\hat{y}^2\right),\cdots\left(x^r,\hat{y}^r\right),\cdots\left(x^R,\hat{y}^R\right)\right\}$

When using stochastic gradient descent

Starting at θ_0

pick x^1 $\quad\theta^1=\theta^0-\eta\nabla C^1\left(\theta^0\right)$

pick x^2 $\quad\theta^2=\theta^1-\eta\nabla C^2\left(\theta^1\right)$

$\vdots$ $\qquad\vdots$

pick x^r $\quad\theta^r=\theta^{r-1}-\eta\nabla C^r\left(\theta^{r-1}\right)$

$\vdots$ $\qquad\vdots$

pick x^R $\quad\theta^R=\theta^{R-1}-\eta\nabla C^R\left(\theta^{R-1}\right)$

Seen all the examples once

One epoch

---

pick x^1 $\quad\theta^{R+1}=\theta^R-\eta\nabla C^1\left(\theta^R\right)$

??

Reference: http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf

Stochastic Gradient Descent and Mini-batch

=E[ ] ?? // Expected Value

=Sum (Prob * || . ||)

◆ ***Gradient Descent*** (Batch Gradient Descent)

$$\theta^i = \theta^{i-1} - \eta \nabla C(\theta^{i-1}) \qquad \nabla C(\theta^{i-1}) = \frac{1}{R} \sum_r \nabla C^r(\theta^{i-1})$$

◆ ***Stochastic Gradient Descent***

Pick an example x_r $\theta^i = \theta^{i-1} - \eta \nabla C^r(\theta^{i-1})$

◆ ***Mini Batch Gradient Descent***

Pick B examples as a batch b

B is batch size

Shuffle your data

$$\theta^i = \theta^{i-1} - \eta \frac{1}{B} \sum_{x_r \in b} \nabla C^r(\theta^{i-1})$$

Average the gradient of the examples in the batch b

1. Performance order: ???
1) Stochastic Gradient Descent
2) Mini Batch Gradient
3) Gradient Descent

➢ Why??

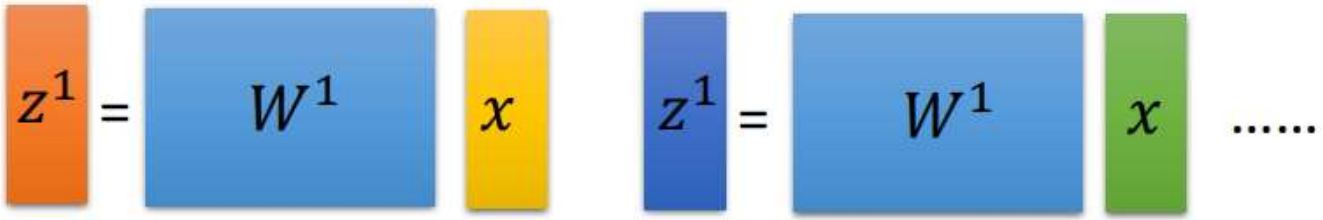
1. Speed order: ???
1) Mini Batch Gradient
2) Stochastic Gradient Descent
3) Gradient Descent

➢ Why??

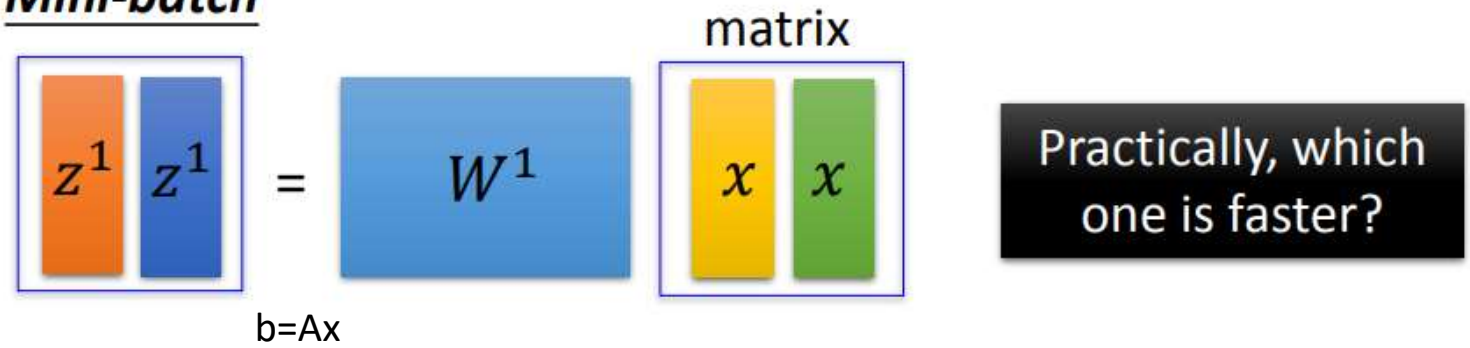
Stochastic Gradient Descent and Mini-batch

- Why mini-batch is faster than stochastic gradient descent?

Stochastic Gradient Descent



Mini-batch



Practically, which one is faster?

Gradient Descent

- When considering multiple parameters together, do you see any problem?


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

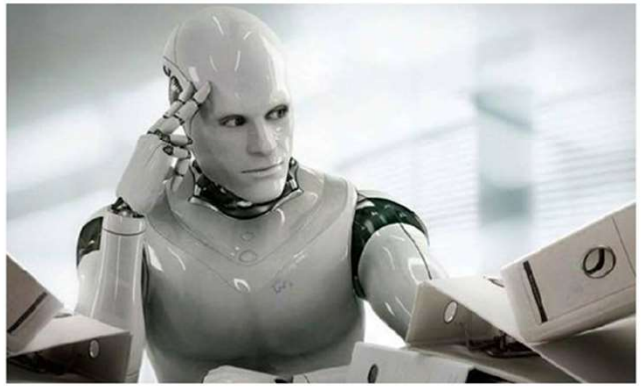
Gradient Descent

This is the “learning” of machines in deep learning ……

Keep finding min value??

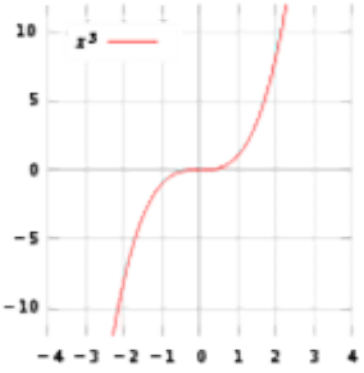
➡ Even alpha go using this approach.

大家以為 Learning 是 ……



其實 Learning 只是 ……

I hope you are not too disappointed :p



??

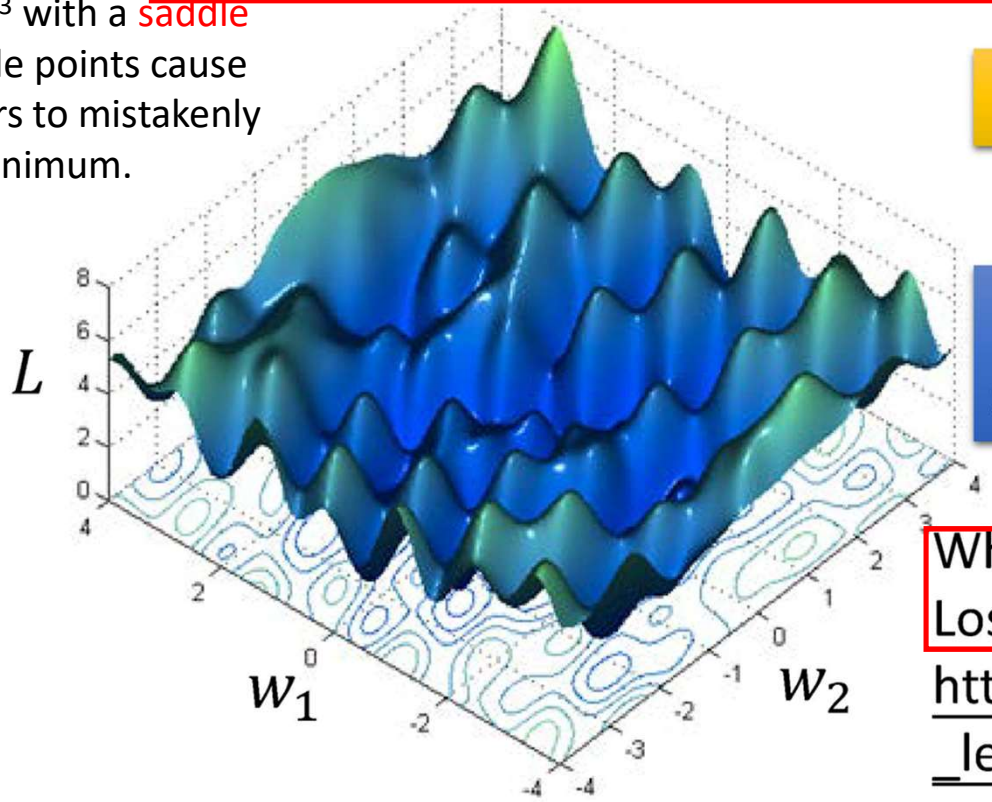
Local Minima

1) Saddle Point Problem
2) Non-Convex Problem

-Still find saddle point, which is worse than local minimum.
-Solution is trying to use different initial points.
-So solution….

- Gradient descent never guarantee global minima

The plot of $y = x^3$ with a saddle point at 0. Saddle points cause the programmers to mistakenly find the local minimum.



Different initial point

↓

Reach different minima, so different results

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

?? Why call BP??
How ??

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

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

Backpropagation: Background

If we want to train a neural network, we need to define a cost function first.

- Cost Function $C(\theta)$
  - Given training examples: $\{(x^1, \hat{y}^1), \cdots, (x^r, \hat{y}^r), \cdots, (x^R, \hat{y}^R)\}$
  - Find a set of parameters θ^* minimizing C(θ)
    - $C(\theta) = \frac{1}{R}\sum_r C^r(\theta), C^r(\theta) = \| f(x^r;\theta) - \hat{y}^r \|$

Trained neural network to get the estimation result y=f( ) for each epoch

=E[ ] ?? // Expected Value

=Sum (Prob * || . ||)

Calculated value

Expected value = target

- Gradient Descent
  - $\nabla C(\theta) = \frac{1}{R}\sum_r \nabla C^r(\theta)$
  - Given w_{ij}^l and b_i^l, we have to compute $\partial C^r / \partial w_{ij}^l$ and $\partial C^r / \partial b_i^l$

If we want to find a set of parameter θ^*, we use the gradient descent to solve it.

Network parameters

- There is an efficient way to compute the gradients of the network parameters – ***backpropagation***.

因為今天我們要訓練一個neural network而network parameter非常非常的多，一個一個去計算cost function的偏微分是不切實際的。

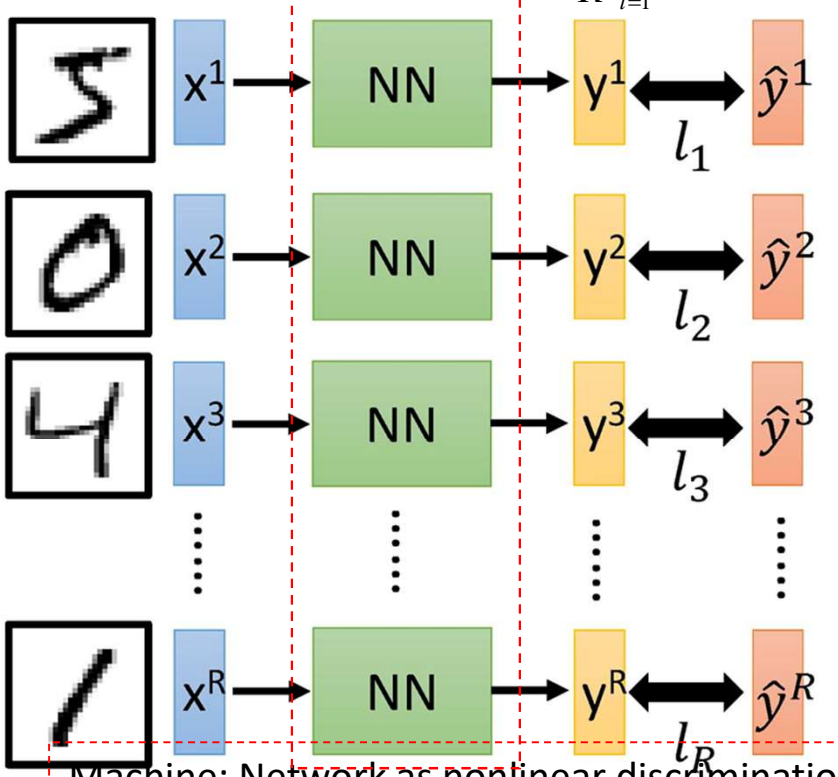
Review 1

MSD: 1/R [Sum(y-y')^2]
where y⇐Ax by computation
y': target value, expected value
A(w,b) (=theta): Unknown parameters,

Loss function
= cost function
= Entropy

Total Loss

For all training data ... $\frac{1}{R}\sum_{i=1}^{R}\| y_i - \hat{y}_i \|^2$



500 training data

Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

Total Loss: $L = min \frac{1}{R}\sum_{i=1}^{R}\| y_i - \hat{y}_i \|^2$

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

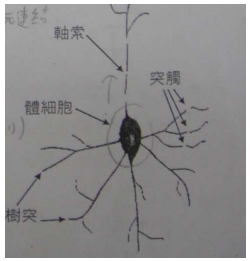
=E[ ] ?? // Expected Value
=Sum (Prob * || . ||)

累積所有training data，計算total loss，根據total loss及梯度下降法更新parameters θ^*

Learning Target

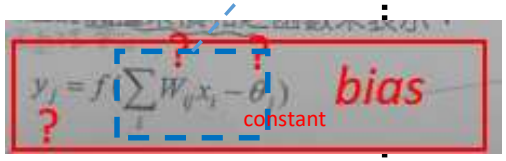
Find the network parameters θ^* that minimize total loss L

Review NN (Ch1) :



生物神經元模型

人工神經元模型



A neuron unit

Review 2

寫程式不會以equation的方式，會以vector , matrix (Ax = b), homogenous matrix, 的方式撰寫。

Neural Network ? ?

One **Neuron**

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer

Linear Combination: Aw = z ?

$$\begin{bmatrix} w_{11}w_{21}\cdots w_{k1}\cdots w_{N1}\ b_1 \\ w_{12}w_{22}\cdots w_{k2}\cdots w_{N2}\ b_2 \\ \vdots \\ w_{1j}w_{2j}\cdots w_{kj}\cdots w_{Nj}\ b_j \end{bmatrix}$$

J x (N+ 1)

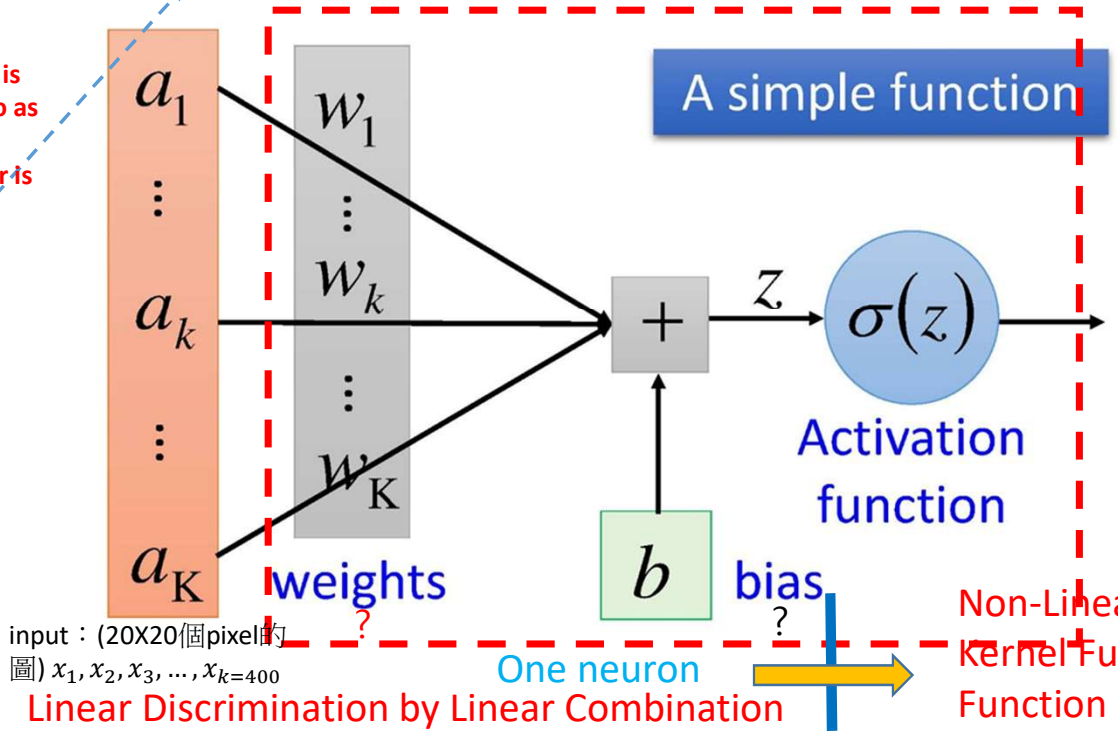
J input data vectors (here J=1)

I/P $\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \\ \vdots \\ a_N \\ 1 \end{bmatrix}$ (N + 1) x 1 = O/P $\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \\ \vdots \\ z_j \end{bmatrix}$ J x 1

1 J-dim output result vector, here J=1)

Linear Combination: $z = a_1 w_1 + \cdots + a_k w_k + \cdots + a_K w_K + b$ Constant, bias

-One weak classifier is one haar filter is also as one neuron unit
-One strong classifier is as one layer



J: Can solve by EM optimization, random (such as Particle filter), … (可見此份投影片 p.38+2??)

a=lo(z)

Here, the output is a, which is one input element for next neuron

input：(20X20個pixel的圖) $x_1, x_2, x_3, \ldots, x_{k=400}$

One neuron

Linear Discrimination by Linear Combination

Non-Linear Discrimination by Kernel Function / Activation Function as SVM phi()

Review 3-1

Reference: http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf
https://www.quora.com/Whats-the-difference-between-gradient-descent-and-stochastic-gradient-descent

Stochastic Gradient Descent and Mini-batch

$$C(\theta)=\frac{1}{R}\sum_r \left\| f\left(x^r;\theta\right)-\hat{y}^r \right\|$$

$$=\frac{1}{R}\sum_r C^r(\theta)$$

=E[ ] ?? // Expected Value
=Sum (Prob * || . ||)

◆ ***Gradient Descent***

run through **ALL** the samples in your training set to do a single update

$$\theta^i=\theta^{i-1}-\eta\nabla C\left(\theta^{i-1}\right) \qquad \nabla C\left(\theta^{i-1}\right)=\frac{1}{R}\sum_r \nabla C^r\left(\theta^{i-1}\right)$$

◆ ***Stochastic Gradient Descent*** Faster! Better!

use **ONLY ONE** of training sample from your training set to do the update

Pick an example x^r

$$\theta^i=\theta^{i-1}-\eta\nabla C^r\left(\theta^{i-1}\right)$$

If all example x^r have equal probabilities to be picked

$$E\left[\nabla C^r\left(\theta^{i-1}\right)\right]=\frac{1}{R}\sum_r \nabla C^r\left(\theta^{i-1}\right)$$

Review 3-2

Reference: http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20(v4).pdf

Stochastic Gradient Descent and Mini-batch

=E[ ] ?? // Expected Value

=Sum (Prob * || . ||)

◆ ***Gradient Descent*** (Batch Gradient Descent)

$$\theta^i = \theta^{i-1} - \eta \nabla C\left(\theta^{i-1}\right) \qquad \nabla C\left(\theta^{i-1}\right) = \frac{1}{R}\sum_r \nabla C^r\left(\theta^{i-1}\right)$$

◆ ***Stochastic Gradient Descent***

Pick an example x_r

$$\theta^i = \theta^{i-1} - \eta \nabla C^r\left(\theta^{i-1}\right)$$

◆ ***Mini Batch Gradient Descent***

Pick B examples as a batch b

B is batch size

Shuffle your data

$$\theta^i = \theta^{i-1} - \eta \frac{1}{B}\sum_{x_r \in b} \nabla C^r\left(\theta^{i-1}\right)$$

Average the gradient of the examples in the batch b

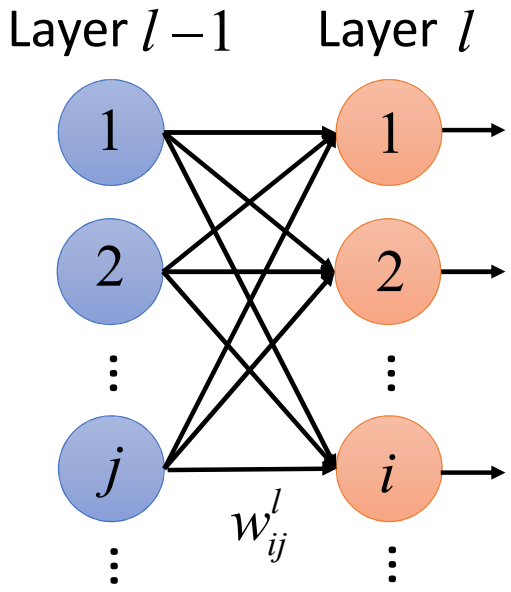
Review 4

Concluding Remarks

Forward pass

Backward pass

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l}$$



$$\begin{cases} a_j^{l-1} & l > 1 \\ x_j^r & l = 1 \end{cases}$$

δ_i^l

Forward Pass

$$z^1 = W^1 x^r + b^1$$

$$a^1 = \sigma(z^1)$$

$$\cdots\cdots$$

$$z^{l-1} = W^{l-1} a^{l-2} + b^{l-1}$$

$$a^{l-1} = \sigma(z^{l-1})$$

Backward Pass

$$\delta^L = \sigma'(z^L) \bullet \nabla C^r(y^r)$$

$$\delta^{L-1} = \sigma'(z^{L-1}) \bullet (W^L)^T \delta^L$$

$$\cdots\cdots$$

$$\delta^l = \sigma'(z^l) \bullet (W^{l+1})^T \delta^{l+1}$$

$$\cdots\cdots$$

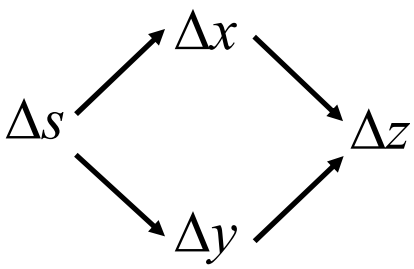
Review: Chain Rule

Case 1 $y = g(x) \quad z = h(y)$

$$\Delta x \to \Delta y \to \Delta z \qquad \frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}$$

Case 2

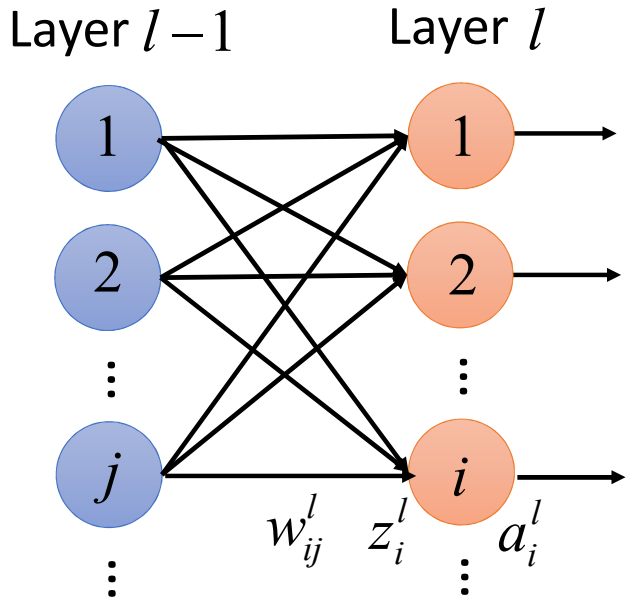
$$x = g(s) \qquad y = h(s) \qquad z = k(x, y)$$



$$\frac{\partial z}{\partial s} = \frac{\partial z}{\partial x}\frac{\partial x}{\partial s} + \frac{\partial z}{\partial y}\frac{\partial y}{\partial s}$$

舉例: 以neural network中的一個network parameter (weighting)
對cost function做partial derivative

$$\partial C^r / \partial w_{ij}^l$$



$$\Delta w_{ij}^l \rightarrow \Delta z_i^l \cdots\cdots \rightarrow \Delta C^r$$

According to the chain rule, we can get the following equation:

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l}$$

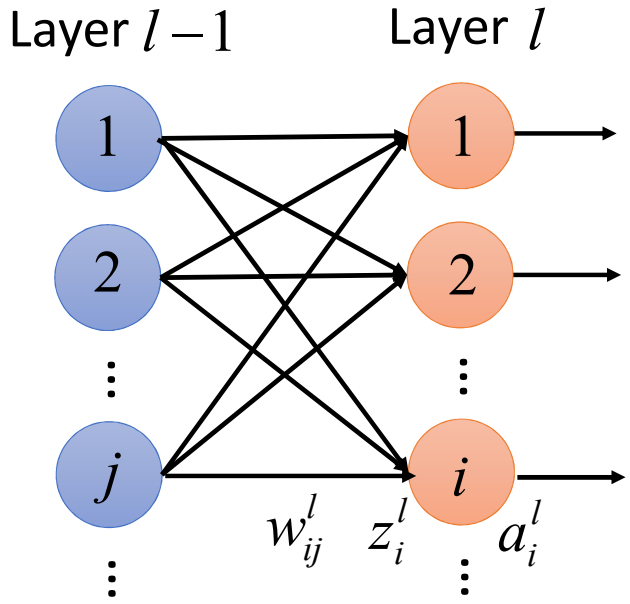
Forward pass

Backward pass

- $\frac{\partial C^r}{\partial w_{ij}^l}$ is the multiplication of two terms

We will talk about how to calculate this two terms in the following lecture

$\partial C^r / \partial w_{ij}^l$ - First Term



$$\Delta w_{ij}^l \rightarrow \Delta z_i^l \cdots\cdots \rightarrow \Delta C^r$$

The calculation of the first term will be easier than the second terms.

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l}$$

Forward pass

Backward pass

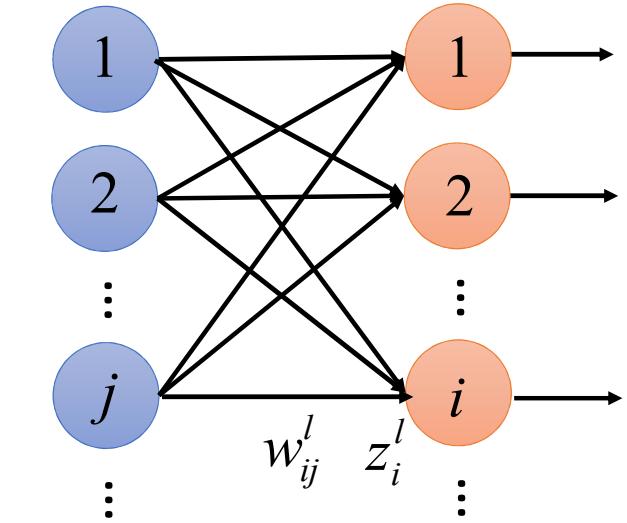
- $\frac{\partial C^r}{\partial w_{ij}^l}$ is the multiplication of two terms

$\partial C^r / \partial w_{ij}^l$ - First Term

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l}$$

Forward pass

Backward pass



If l > 1

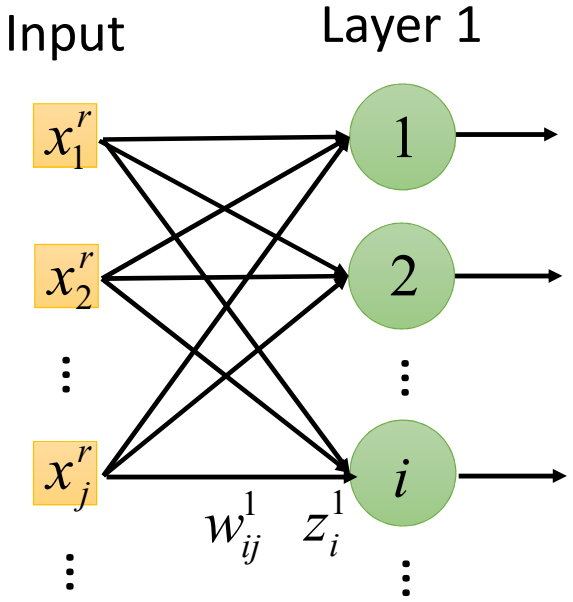
$$z_i^l = \sum_j w_{ij}^l a_j^{l-1} + b_i^l \qquad \frac{\partial z_i^l}{\partial w_{ij}^l} = a_j^{l-1}$$

$\partial C^r / \partial w_{ij}^l$ - First Term

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l}$$

Forward pass

Backward pass



If l > 1

$$z_i^l = \sum_j w_{ij}^l a_j^{l-1} + b_i^l$$

$$\frac{\partial z_i^l}{\partial w_{ij}^l} = a_j^{l-1}$$

The output of the previous layer

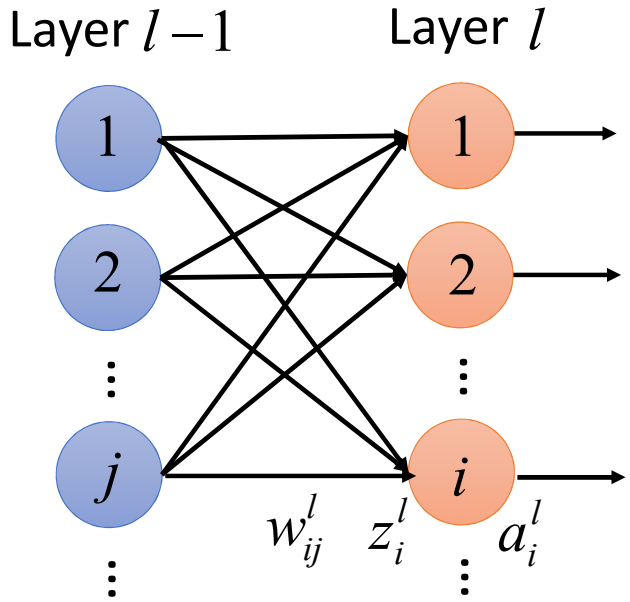
If l = 1

$$z_i^1 = \sum_j w_{ij}^1 x_j^r + b_i^1$$

$$\frac{\partial z_i^1}{\partial w_{ij}^1} = x_j^r$$

The input layer

$\partial C^r / \partial w_{ij}^l$ - Second Term



$$\Delta w_{ij}^l \rightarrow \Delta z_i^l \cdots\cdots \rightarrow \Delta C^r$$

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l} \rightarrow \delta_i^l$$

Forward pass

Backward pass

- $\frac{\partial C^r}{\partial w_{ij}^l}$ is the multiplication of two terms

$\partial C^r / \partial w_{ij}^l$ - Second Term

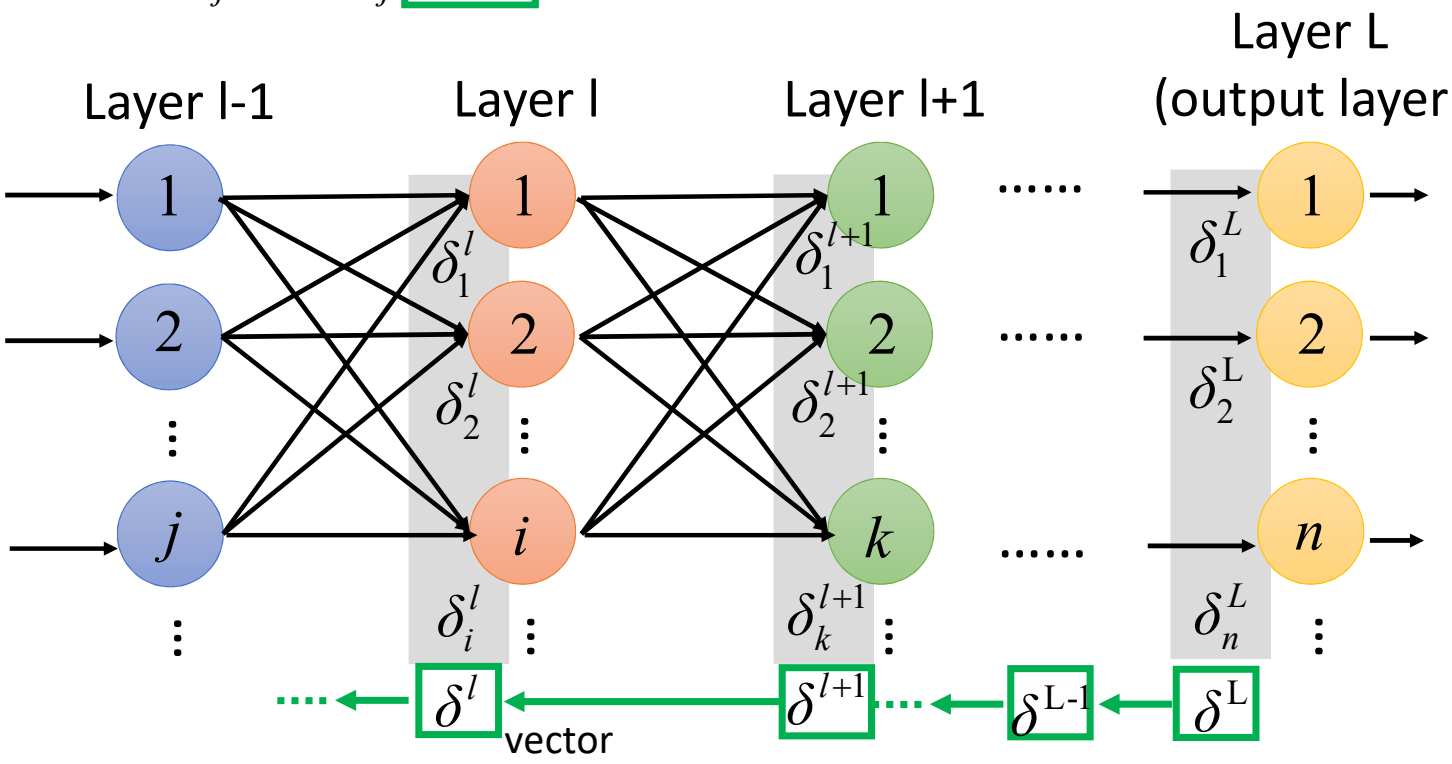
Forward pass

Backward pass

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l} \rightarrow \delta_i^l$$

To fulfill this process (backpropagation), we need to solve the following problem:

1. How to compute δ^L
2. The relation of δ^l and δ^{l+1}



$\partial C^r / \partial w_{ij}^l$ - Second Term

Forward pass Backward pass

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l} \rightarrow \delta_i^l$$

1. How to compute δ^L

2. The relation of δ^l and δ^{l+1}

Before calculate the δ^L, we first demonstrate how to calculate one of element δ_n^L of the δ^L

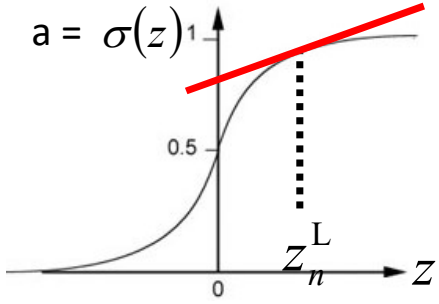
$$\delta_n^{\mathrm{L}} = \frac{\partial C^r}{\partial z_n^{\mathrm{L}}}$$

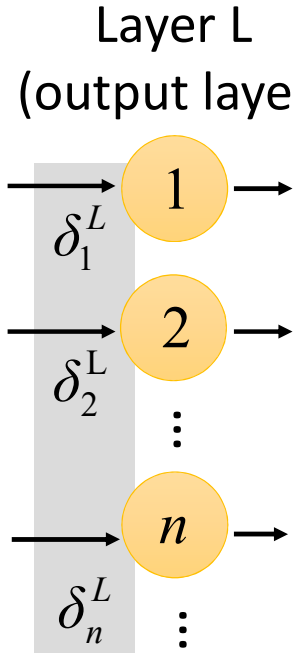
$$= \frac{\partial y_n^{\mathrm{r}}}{\partial z_n^{\mathrm{L}}} \frac{\partial C^r}{\partial y_n^{\mathrm{r}}}$$

$$\sigma'\left(z_n^{\mathrm{L}}\right)$$

$$\Delta z_n^{\mathrm{L}} \rightarrow \Delta a_n^{\mathrm{L}} = \Delta y_n^{\mathrm{r}} \rightarrow \Delta C^{\mathrm{r}}$$

Depending on the definition of cost function





$$z_k^{l+1} = \sum_i w_{ki}^{l+1} a_i^l + b_k^{l+1}$$

$\partial C^r / \partial w_{ij}^l$ - Second Term

Forward pass Backward pass

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l} \rightarrow \delta_i^l$$

1. How to compute δ^L

2. The relation of δ^l and δ^{l+1}

$$\delta_n^{\mathrm{L}} = \frac{\partial C^r}{\partial z_n^{\mathrm{L}}}$$

$$= \frac{\partial y_n^{\mathrm{r}}}{\partial z_n^{\mathrm{L}}} \frac{\partial C^r}{\partial y_n^{\mathrm{r}}}$$

$$= \sigma'\left(z_n^L\right) \frac{\partial C^r}{\partial y_n^{\mathrm{r}}}$$

δ^{L}?

$$\sigma'\left(z^L\right) = \begin{bmatrix} \sigma'\left(z_1^L\right) \\ \sigma'\left(z_2^L\right) \\ \vdots \\ \sigma'\left(z_n^L\right) \\ \vdots \end{bmatrix} \quad \nabla C^r\left(y^r\right) = \begin{bmatrix} \partial C^r / \partial y_1^r \\ \partial C^r / \partial y_2^r \\ \vdots \\ \partial C^r / \partial y_n^r \\ \vdots \end{bmatrix}$$

$$\delta^{\mathrm{L}} = \sigma'\left(z^l\right) \bullet \nabla C^r\left(y^r\right)$$

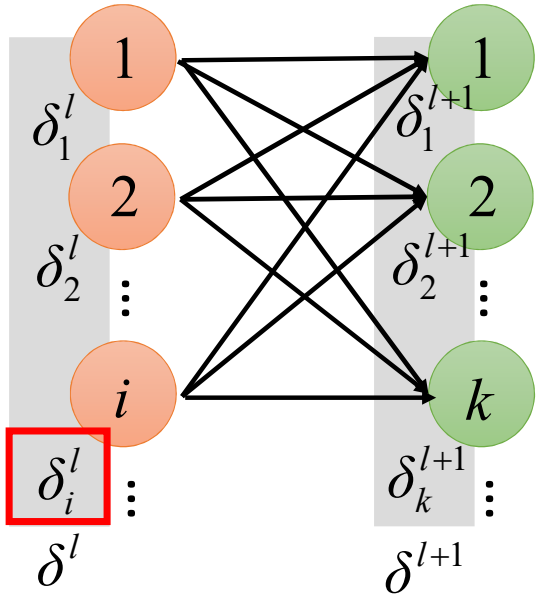
element-wise multiplication

$\partial C^r / \partial w_{ij}^l$ - Second Term

Forward pass

Backward pass

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l} \rightarrow \delta_i^l$$

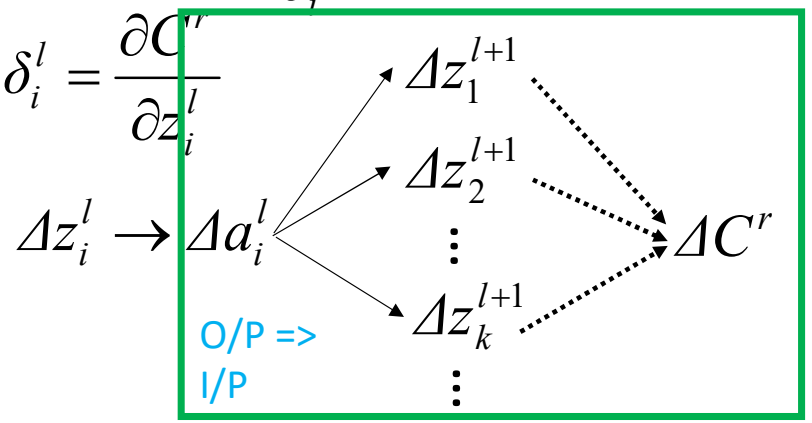


1. How to compute δ^L

2. The relation of δ^l and δ^{l+1}

The definition of δ_i^l

$$\delta_i^l = \frac{\partial C^r}{\partial z_i^l}$$



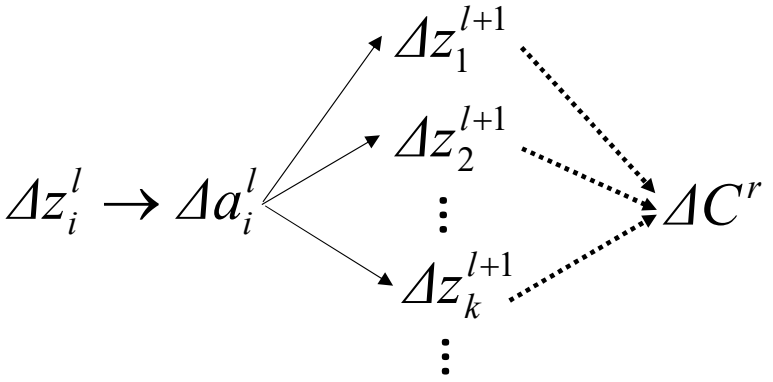
$$\delta_i^l = \frac{\partial C^r}{\partial z_i^l} = \frac{\partial a_i^l}{\partial z_i^l} \sum_k \frac{\partial z_k^{l+1}}{\partial a_i^l} \frac{\partial C^r}{\partial z_k^{l+1}} \rightarrow \delta_k^{l+1}$$

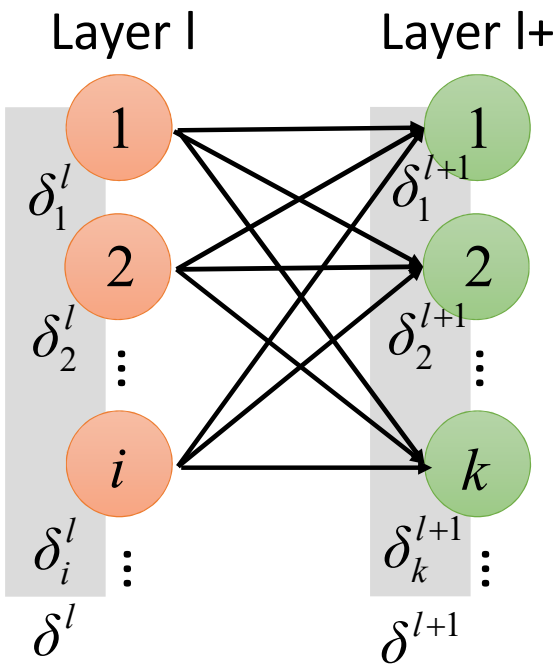
$\partial C^r / \partial w_{ij}^l$ - Second Term

Forward pass

Backward pass

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l} \rightarrow \delta_i^l$$





$$\delta_i^l = \frac{\partial a_i^l}{\partial z_i^l} \sum_k \frac{\partial z_k^{l+1}}{\partial a_i^l} \delta_k^{l+1}$$

$$\sigma'(z_i^l) \qquad z_k^{l+1} = \sum_i w_{ki}^{l+1} a_i^l + b_k^{l+1}$$

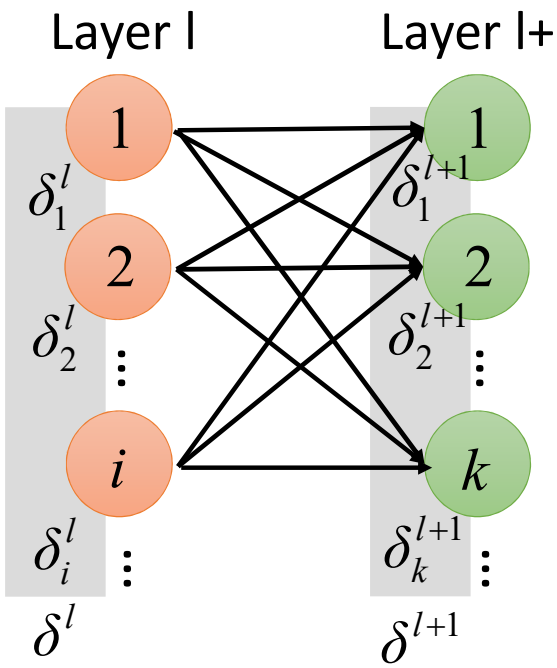
$$\delta_i^l = \sigma'(z_i^l) \sum_k w_{ki}^{l+1} \delta_k^{l+1}$$

$\partial C^r / \partial w_{ij}^l$ - Second Term

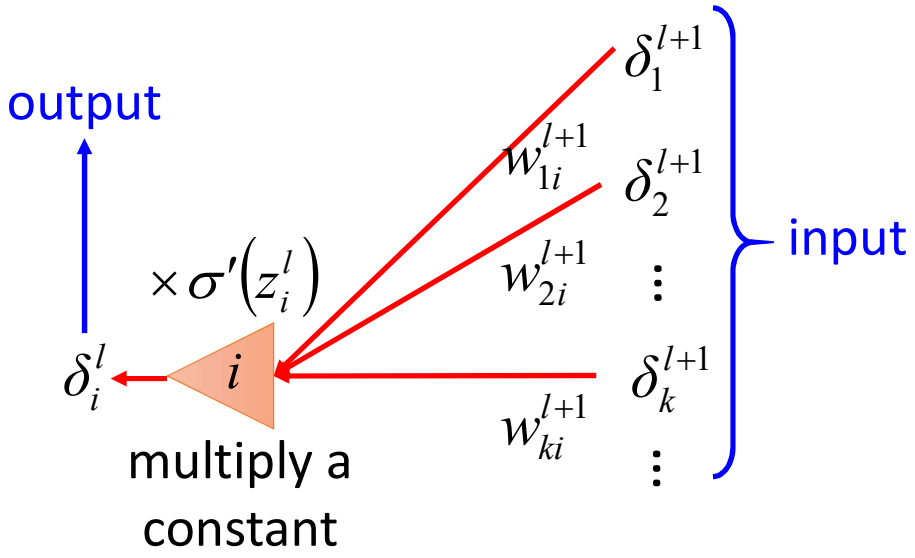
Forward pass

Backward pass

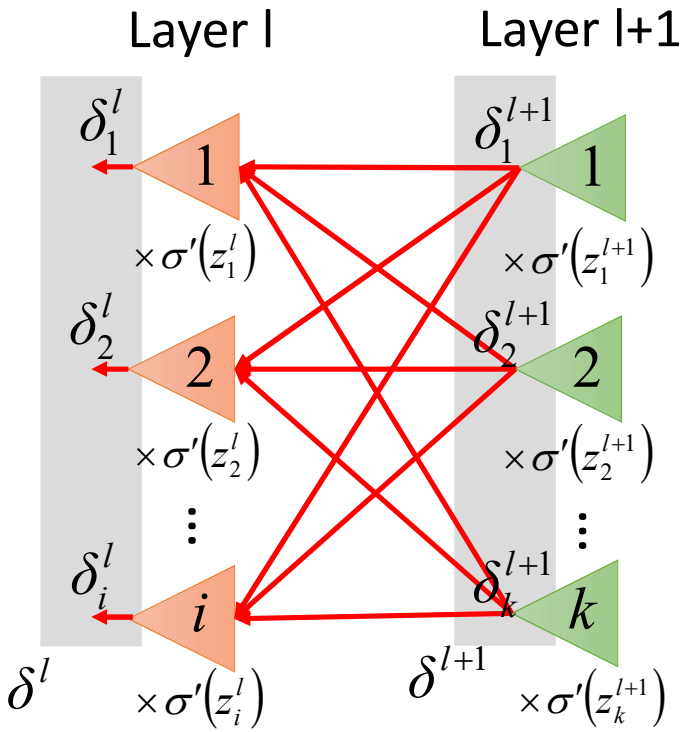
$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l} \rightarrow \delta_i^l \qquad \delta_i^l = \sigma'\left(z_i^l\right) \sum_k w_{ki}^{l+1} \delta_k^{l+1}$$



new type of neuron



$\partial C^r / \partial w_{ij}^l$ - Second Term



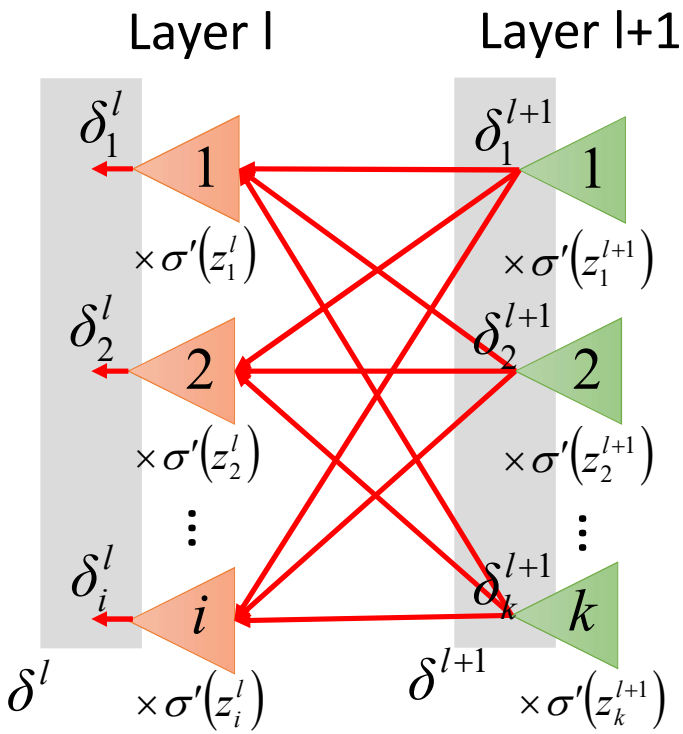
$$\delta_i^l = \sigma'(z_i^l)\sum_k w_{ki}^{l+1}\delta_k^{l+1}$$

$$\sigma'(z^l) = \begin{bmatrix} \sigma'(z_1^l) \\ \sigma'(z_2^l) \\ \vdots \\ \sigma'(z_i^l) \\ \vdots \end{bmatrix}$$

$$\delta^l = \sigma'(z^l) \bullet (W^{l+1})^T \delta^{l+1}$$

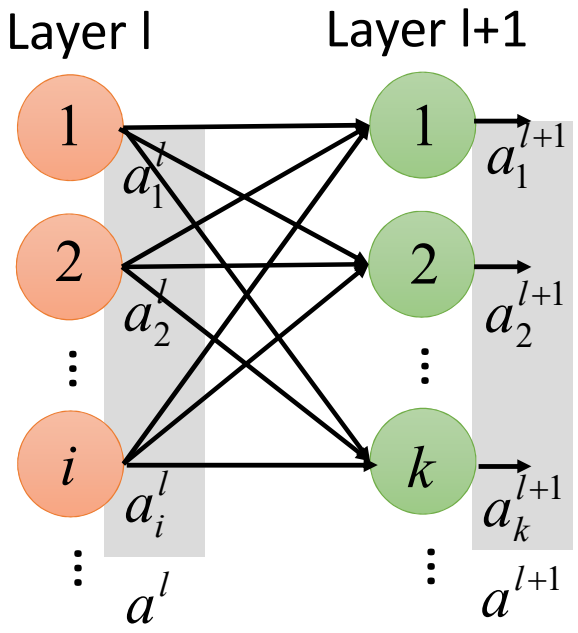
Weight matrix

$\partial C^r / \partial w_{ij}^l$ - Second Term



$$\delta^l = \sigma'(z^l) \bullet (W^{l+1})^T \delta^{l+1}$$

Compare



$$a^{l+1} = \sigma(W^{l+1} a^l + b^{l+1})$$

Forward pass Backward pass

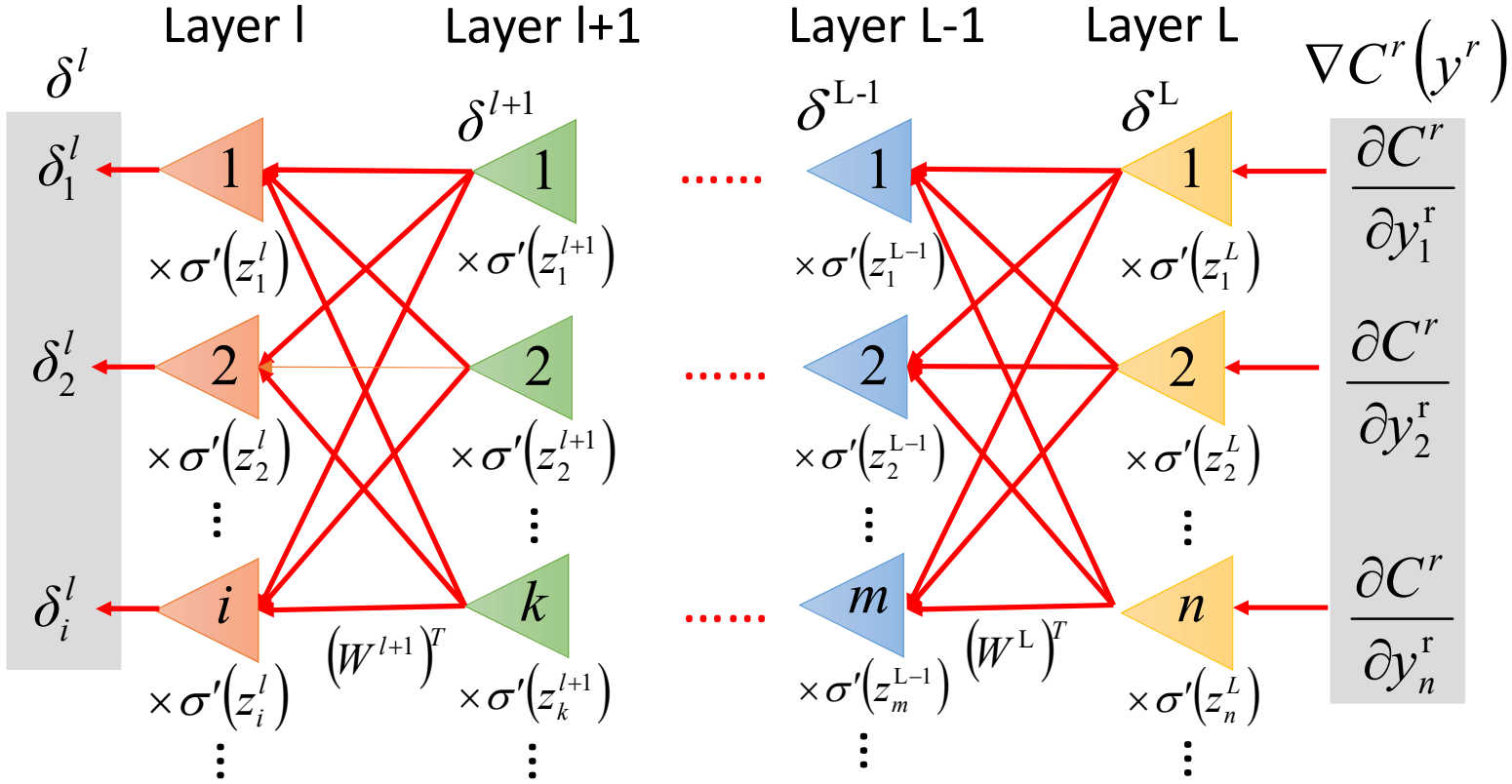
$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l}, \quad \frac{\partial C^r}{\partial z_i^l} = \delta_i^l$$

1. How to compute δ^L

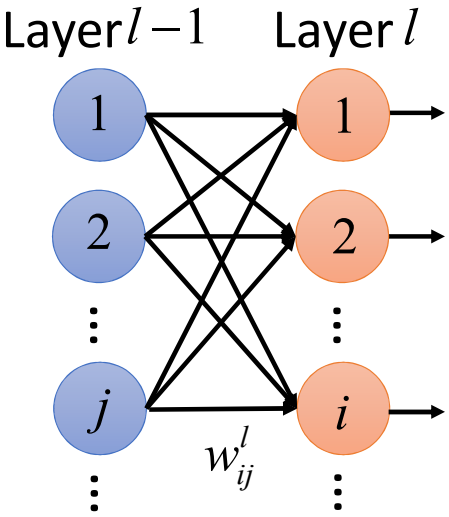
$$\delta^{\mathrm{L}} = \sigma'\left(z^{\mathrm{L}}\right) \bullet \nabla C^r\left(y^r\right)$$

2. The relation of δ^l and δ^{l+1}

$$\delta^l = \sigma'\left(z^l\right) \bullet \left(W^{l+1}\right)^T \delta^{l+1}$$



Concluding Remarks



Forward pass

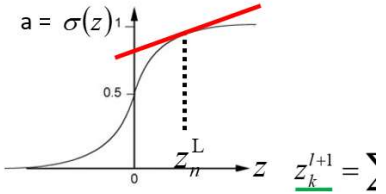
Backward pass

$$\frac{\partial C^r}{\partial w_{ij}^l} = \frac{\partial z_i^l}{\partial w_{ij}^l} \frac{\partial C^r}{\partial z_i^l}$$

$$\delta_n^{\mathrm{L}} = \frac{\partial C^r}{\partial z_n^{\mathrm{L}}} = \frac{\partial y_n^{\mathrm{r}}}{\partial z_n^{\mathrm{L}}} \frac{\partial C^r}{\partial y_n^{\mathrm{r}}} \rightarrow \sigma'\left(z_n^{\mathrm{L}}\right)$$

$$\Delta z_n^{\mathrm{L}} \rightarrow \Delta a_n^{\mathrm{L}} = \Delta y_n^{\mathrm{r}} \rightarrow \Delta C^{\mathrm{r}}$$

Depending on the definition of cost function



$$z_k^{l+1} = \sum_i w_{ki}^{l+1} a_i^l + b_k^{l+1}$$

$$\begin{cases} a_j^{l-1} & l > 1 \\ x_j^r & l = 1 \end{cases}$$

$$\delta_i^l$$

$$\delta_i^l = \frac{\partial C^r}{\partial z_i^l} = \frac{\partial a_i^l}{\partial z_i^l} \sum_k \frac{\partial z_k^{l+1}}{\partial a_i^l} \frac{\partial C^r}{\partial z_k^{l+1}} \rightarrow \delta_k^{l+1}$$

Forward Pass

$$z^1 = W^1 x^r + b^1$$

$$a^1 = \sigma\left(z^1\right)$$

$$\cdots\cdots$$

$$z^{l-1} = W^{l-1} a^{l-2} + b^{l-1}$$

$$a^{l-1} = \sigma\left(z^{l-1}\right)$$

Backward Pass

$$\delta^{\mathrm{L}} = \sigma'\left(z^L\right) \bullet \nabla C^r\left(y^r\right)$$

$$\delta^{L-1} = \sigma'\left(z^{L-1}\right) \bullet \left(W^L\right)^T \delta^L$$

$$\cdots\cdots$$

$$\delta^l = \sigma'\left(z^l\right) \bullet \left(W^{l+1}\right)^T \delta^{l+1}$$

$$\cdots\cdots$$

$$\delta_i^l = \frac{\partial a_i^l}{\partial z_i^l} \sum_k \frac{\partial z_k^{l+1}}{\partial a_i^l} \delta_k^{l+1}$$

$$\sigma'\left(z_i^l\right)$$

$$z_k^{l+1} = \sum_i w_{ki}^{l+1} a_i^l + b_k^{l+1}$$

$$\delta_i^l = \sigma'\left(z_i^l\right) \sum_k w_{ki}^{l+1} \delta_k^{l+1}$$

Define a function set: f(x; θ)
x: input
θ: network parameter

Define the total loss function L

That's it!

Design topology/network: Having parameters (as variable) without values

How to I/O data? Target/Data: Given input data and be recognized / classified output data. Exp. Mini batch

How to learn? Learning parameters (or para values) of topology using gradient descent to find global min of MSE

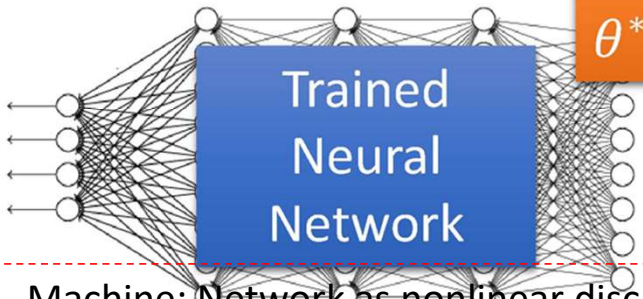
Step 1: Network Structure

Step 2: Learning Target

Step 3: Learn!

o/p <=> Ground truth (label) y'

The network parameters θ^* minimizing total loss



Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

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

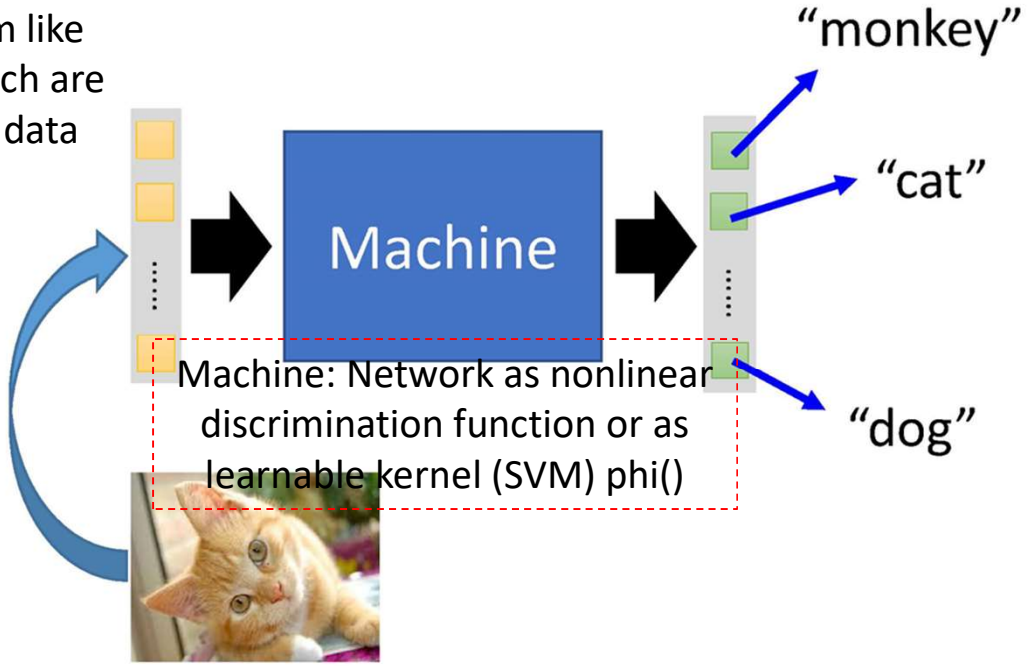
Only change the learning target

JJ: Learning, NN is one by one input image, but the parameter can estimate either 1) one time by one image input 2) one time by one batch, or 3) wait until input all then estimate once.

This is different form like PCA, LDA, SVM, which are input by all training data

For example, you can do .....

- Image Recognition



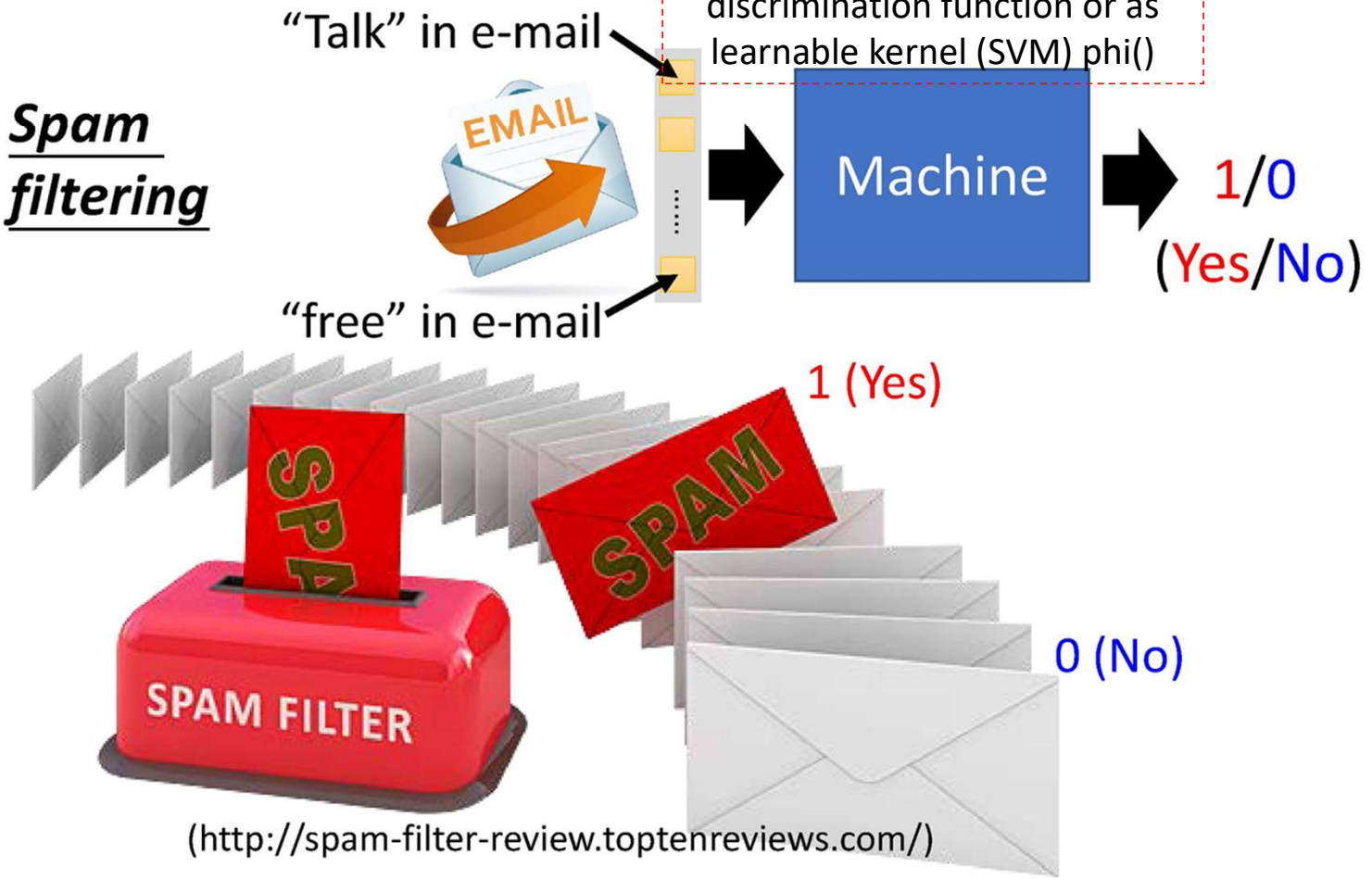
Application:

1. Image Recognition
2. Spam Filtering
3. Documentation Classification

For example, you can do ……

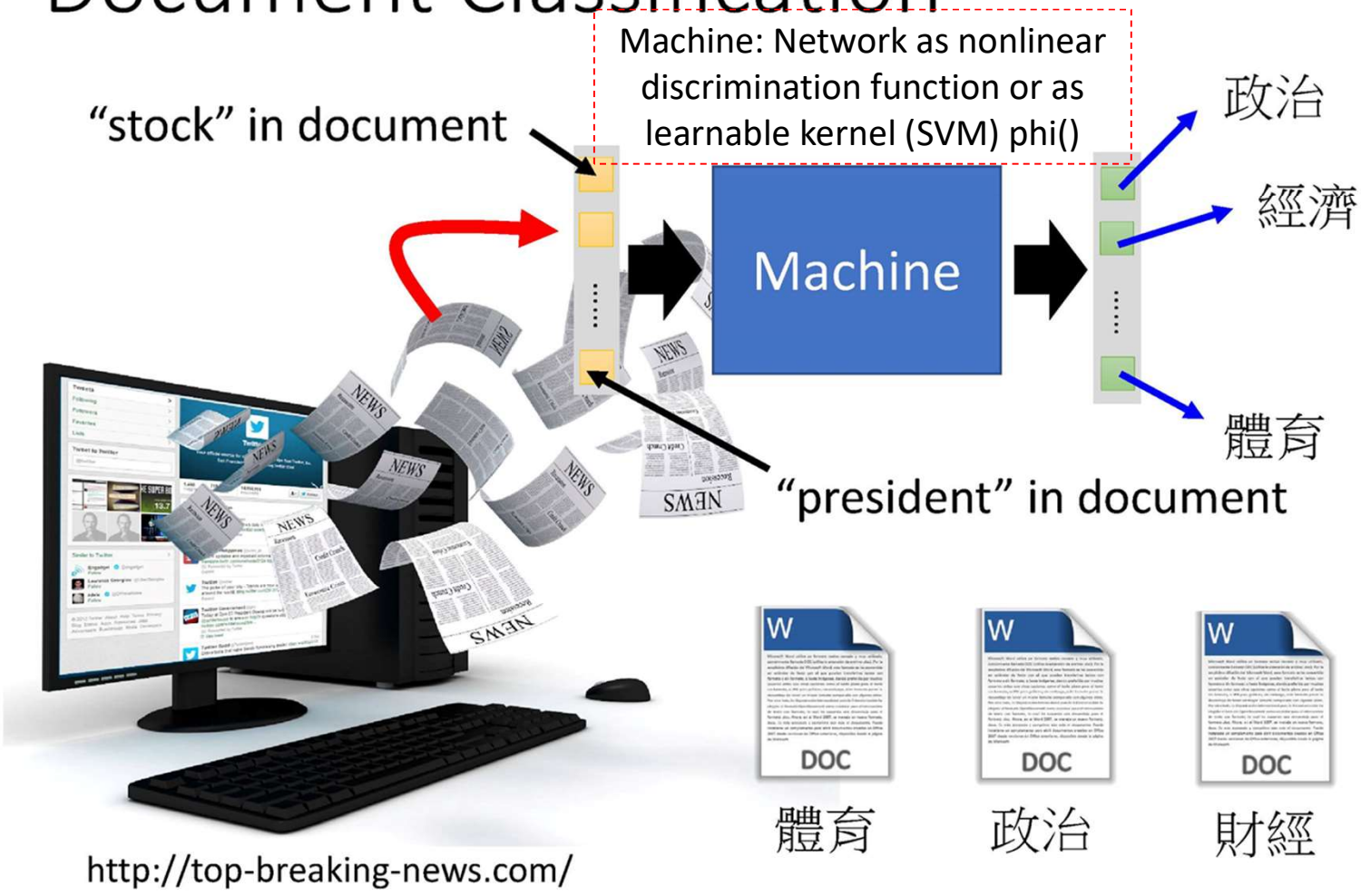
Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

Spam filtering



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

Document Classification



Outline of Lecture 1

I.1 Three Steps for Deep Learning

I.2 Why Deep Learning?

1) Fat+Short Vs. Thin+Tall
2) Multi-Task:
   (1) How to reduce para. in order to use less data
   (2) Modularization (logic circuit) – Combine network / Circuit
3) End to End Learning

I.3 "Hello world" for deep learning — Coding Example

1) NN Vs. Deep NN:
In the beginning of deep learning, compare regular NN with Deep, deep works better simply because it uses more parameter.

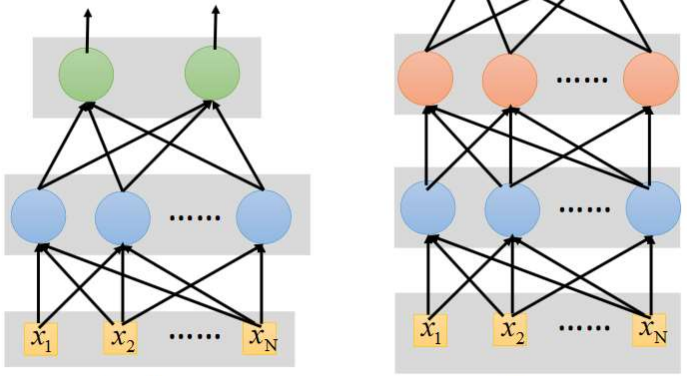
2) Deep NN Vs. Deeper NN:
Later, deeper NN using 3x3 filter has less para. than deep NN using 7x7 filter.
Exp. For para numbers:
AlexNet (5+3) >
VGG16 (13+3) >
ResNet50 or 101 >
DenseNet

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
layer neuron	

Deep works better simply because it uses more parameters.

Shallow neural network has only one hidden layer



Not surprised, more parameters, better performance

Deep neural network (DNN) has multiple hidden layers. It has more network parameter than shallow neural network. Suppose we have enough training data, the result of DNN will get better performance.

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

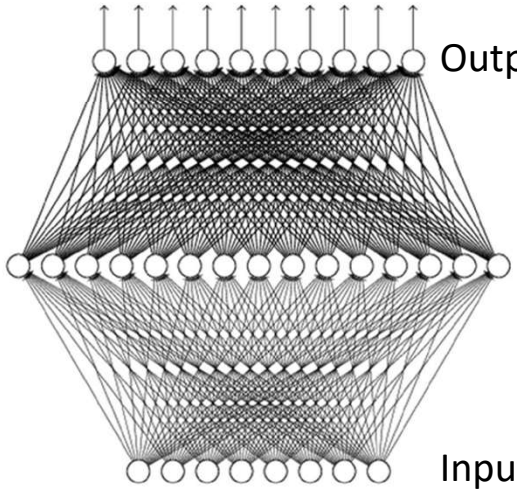
Universality Theorem

Any continuous function f

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

Can be realized by a network with one hidden layer

(given **enough** hidden neurons)



Output: M dimensional vector

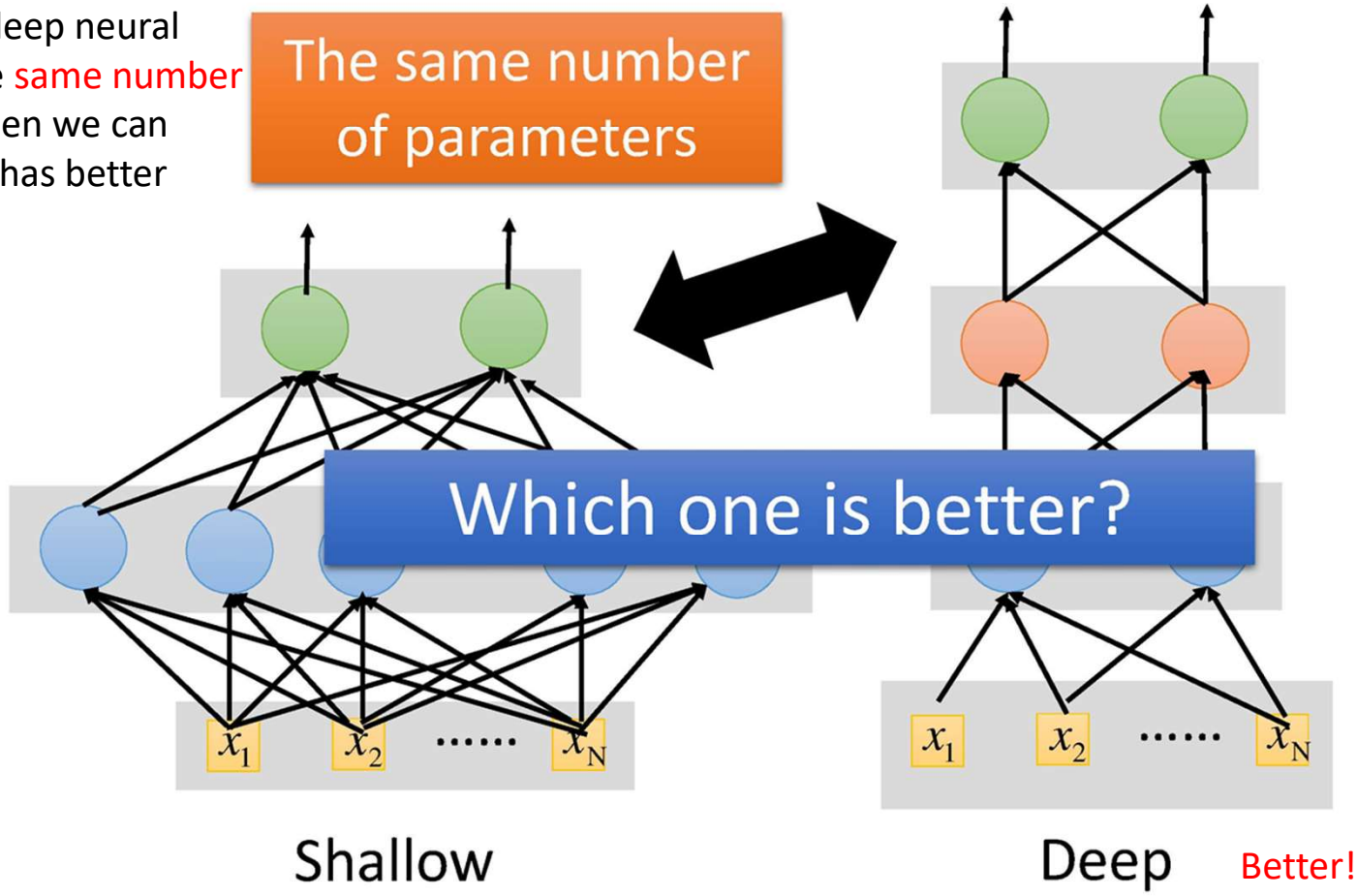
Input: N dimensional vector

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

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

Fat + Short v.s. Thin + Tall

Let shallow and deep neural network have the same number of parameters, then we can check which one has better performance



Fat + Short v.s. Thin + Tall

AdaBoost: Cascade

Multiple Layer

1 Hidden Layer

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

Why?

Multiple layer and 1 hidden layer in the same row has the same number of the parameters.

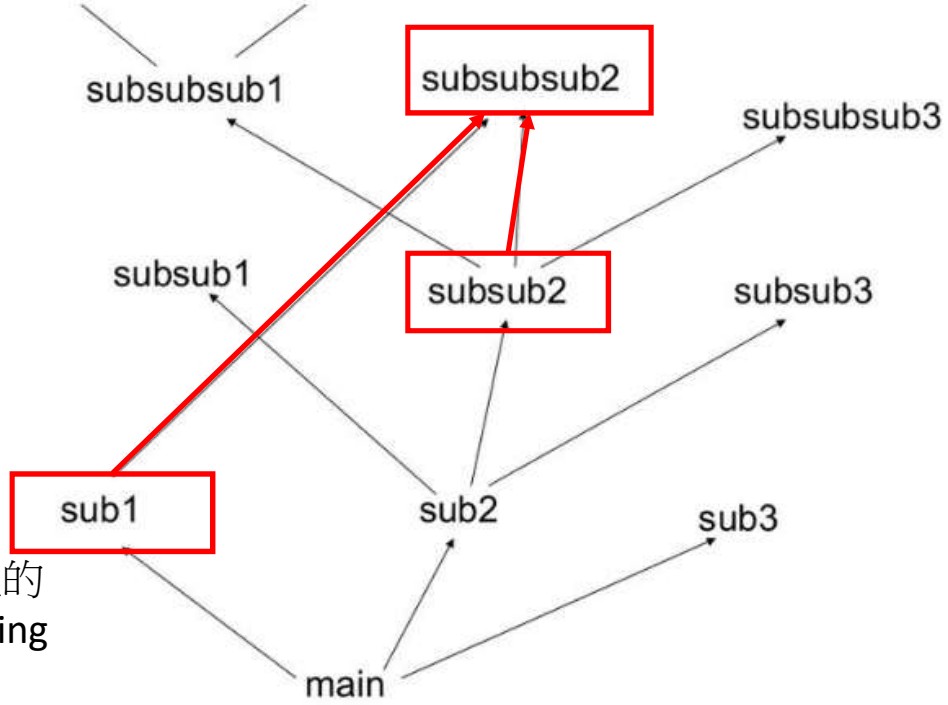
1 X 16k is better than 1 X 2k, but not better than 2 X 2k.

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

Modularization

- Deep → Modularization

Don't put everything in your main function.



Advantage of modularization in programming:

1. 有一些函式是可以共用的
2. 減少程式的複雜度

舉例: 當subsubsub2函數是sorting，只要在其他的函式(sub1, subsub2)使用到，就不用在需要sorting的時候在自己的函式中重新implement一個。

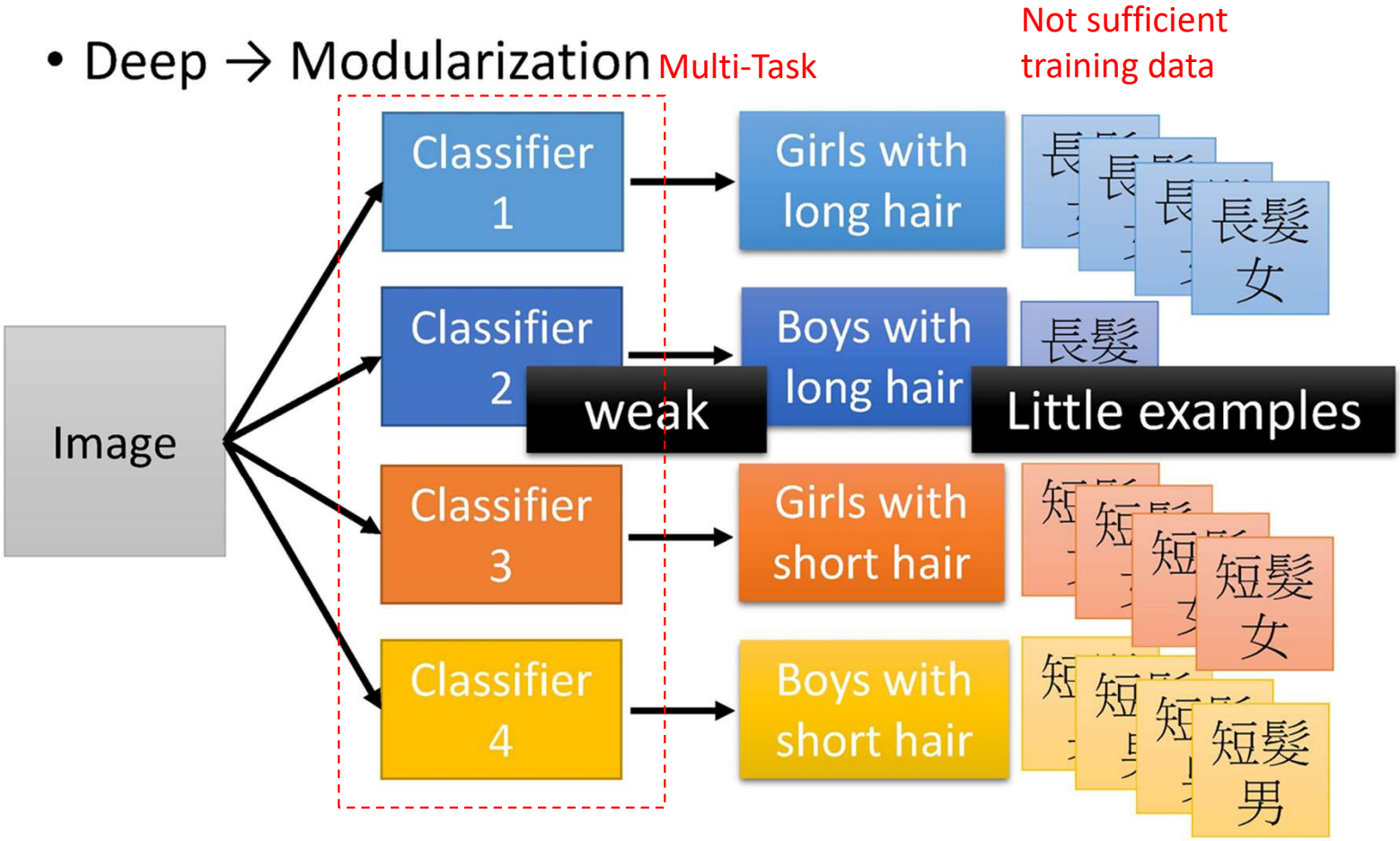
http://rinuboney.github.io/2015/10/18/theoretical-motivations-deep-learning.html

Modularization

Example = sample

Similar work as Faster R-CNN for multi-task: ROI + classification

- Deep → Modularization

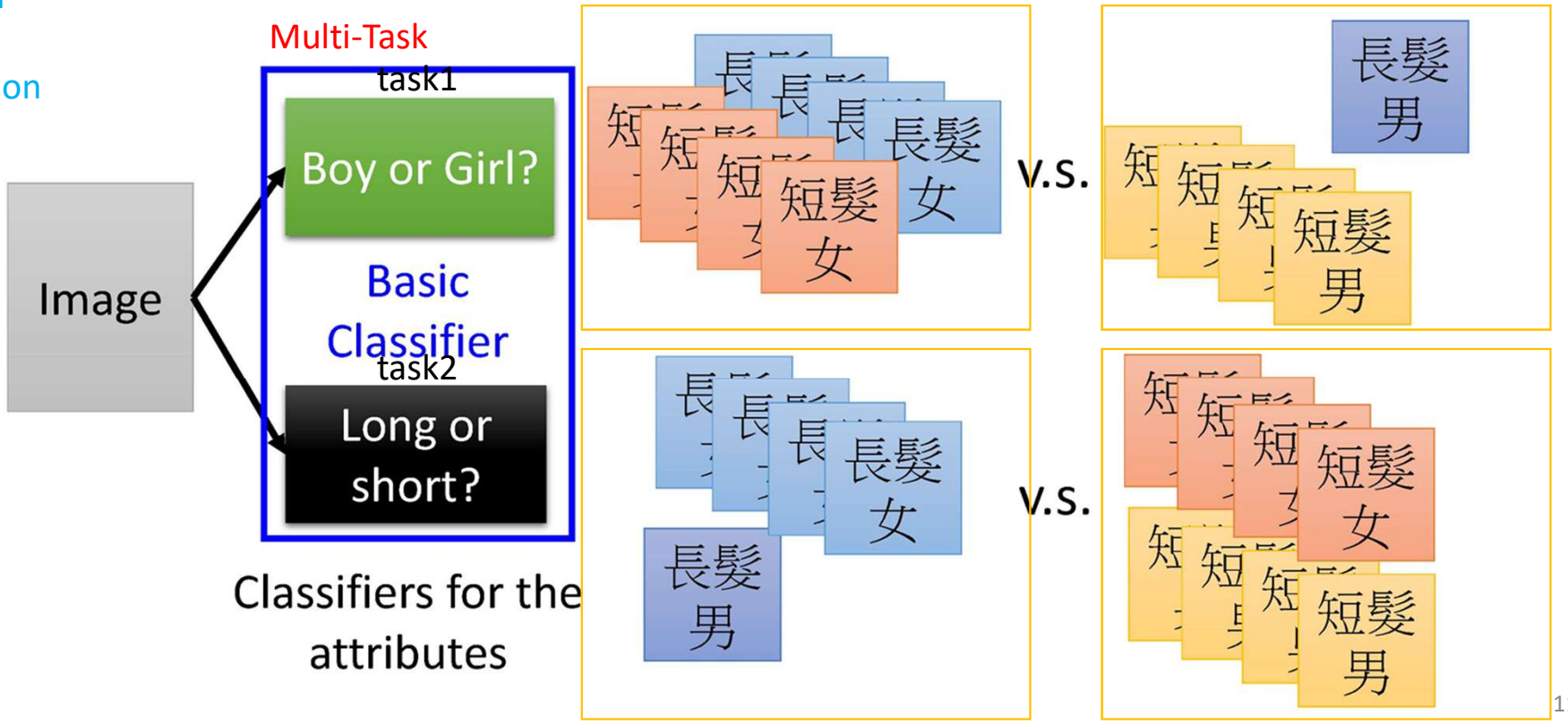


Modularization

Each basic classifier can have sufficient training examples.

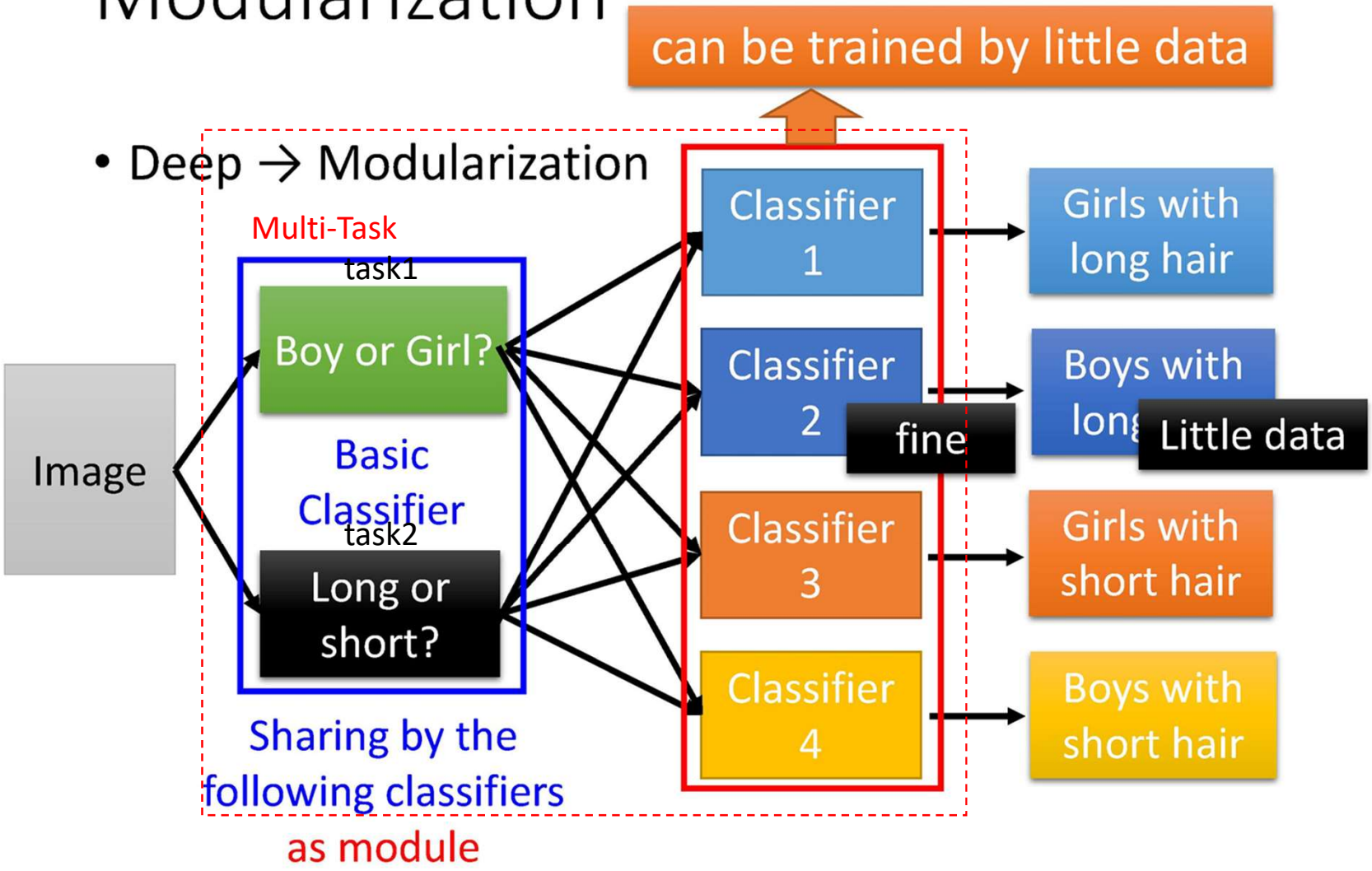
Similar work as Faster R-CNN for multi-task: ROI + classification

- Deep → Modularization



Modularization

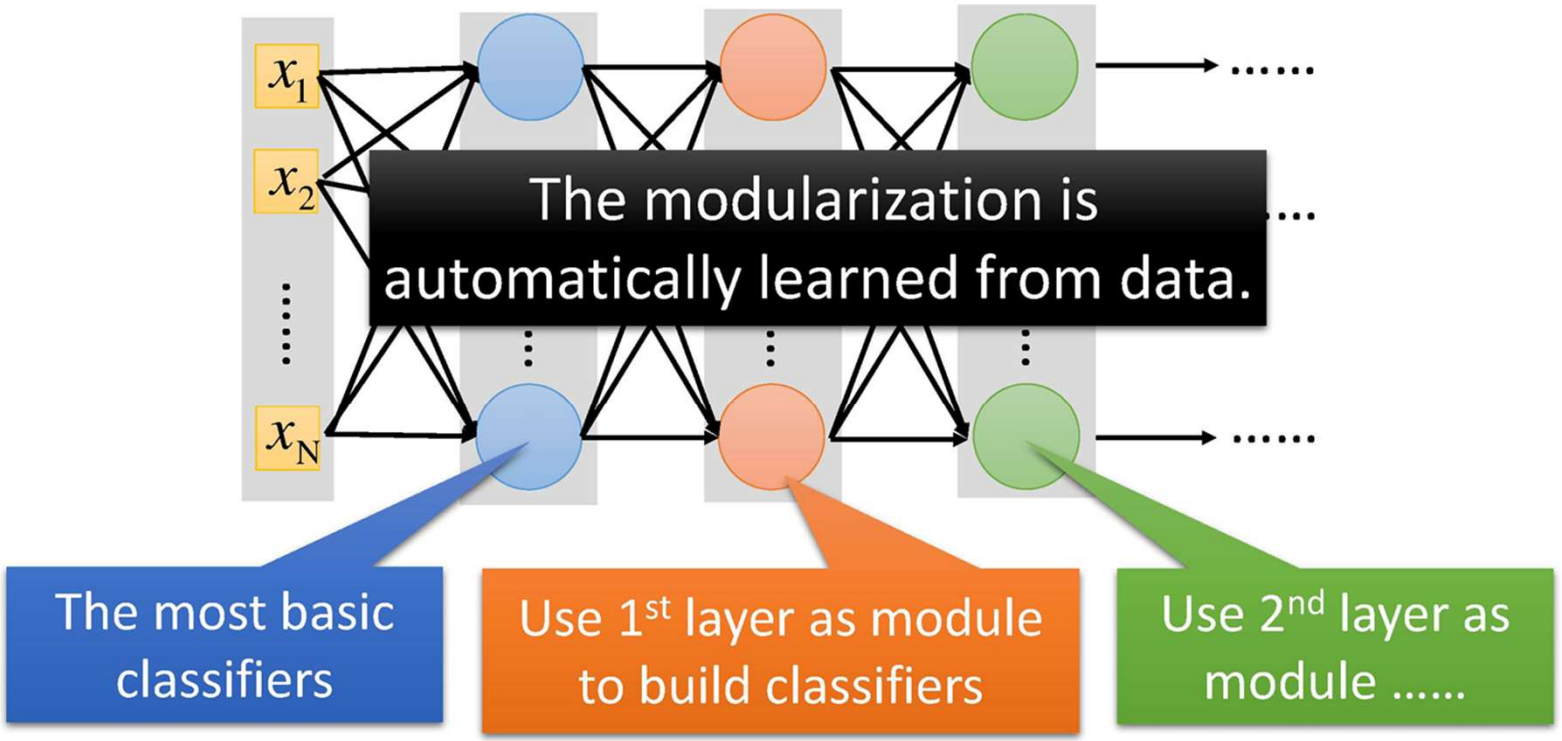
J: Less parameters need less data



Modularization

Coarse to Fine

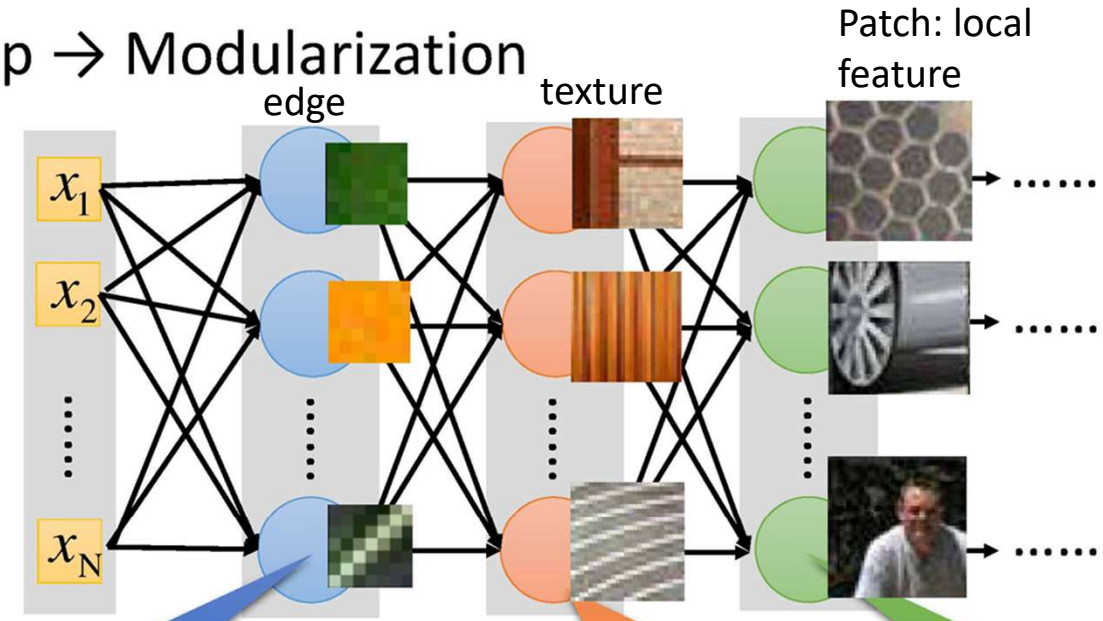
- Deep → Modularization → Less training data?



Modularization

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

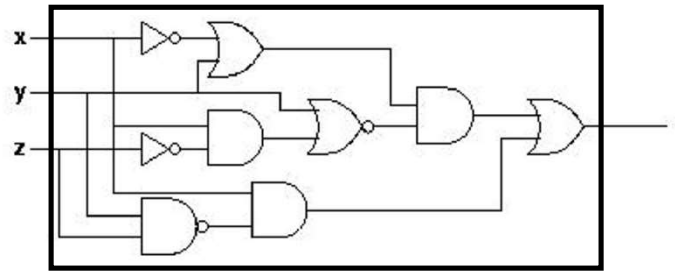
Use 2nd layer as module .....

簡單的線條

複雜的線條

具體的物件

More Reasons



modularization

Logic circuits

- Logic circuits consists of **gates**
- **A two layers of logic gates** can represent **any Boolean function.**
- Using multiple layers of logic gates to build some functions are much simpler

→ less gates needed

Neural network

- Neural network consists of **neurons**
- **A hidden layer network** can represent **any continuous function.**
- Using multiple layers of neurons to represent some functions are much simpler

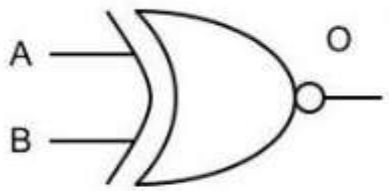
→ less parameters → less data?

Fat Vs. Thin and Tall

Shallow Vs. Deep

This page is for EE background.

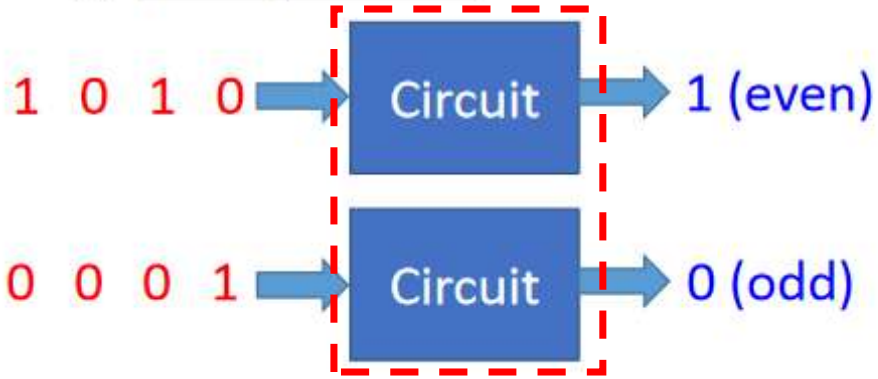
Analogy



A	B	O
0	0	1
0	1	0
1	0	0
1	1	1

- E.g. ***parity check***

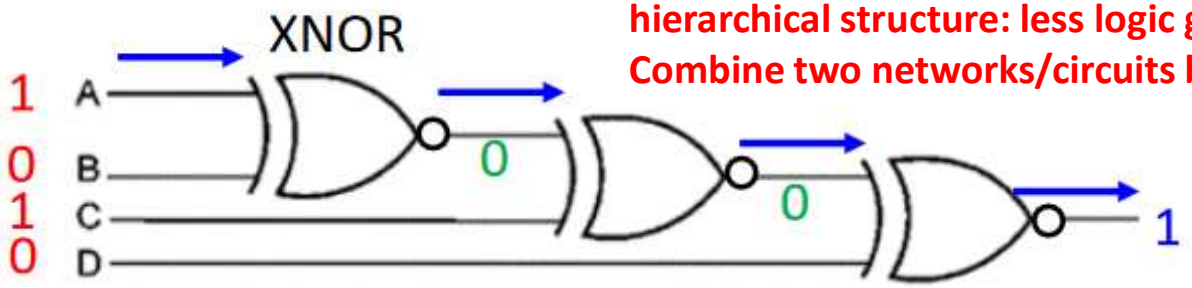
目的:設計一個電路，使輸入出現1的數目是偶數的話，output是1，出現1的數目是奇數的話，output是0



For input sequence with d bits,

Two-layer circuit need $O(2^d)$ gates.

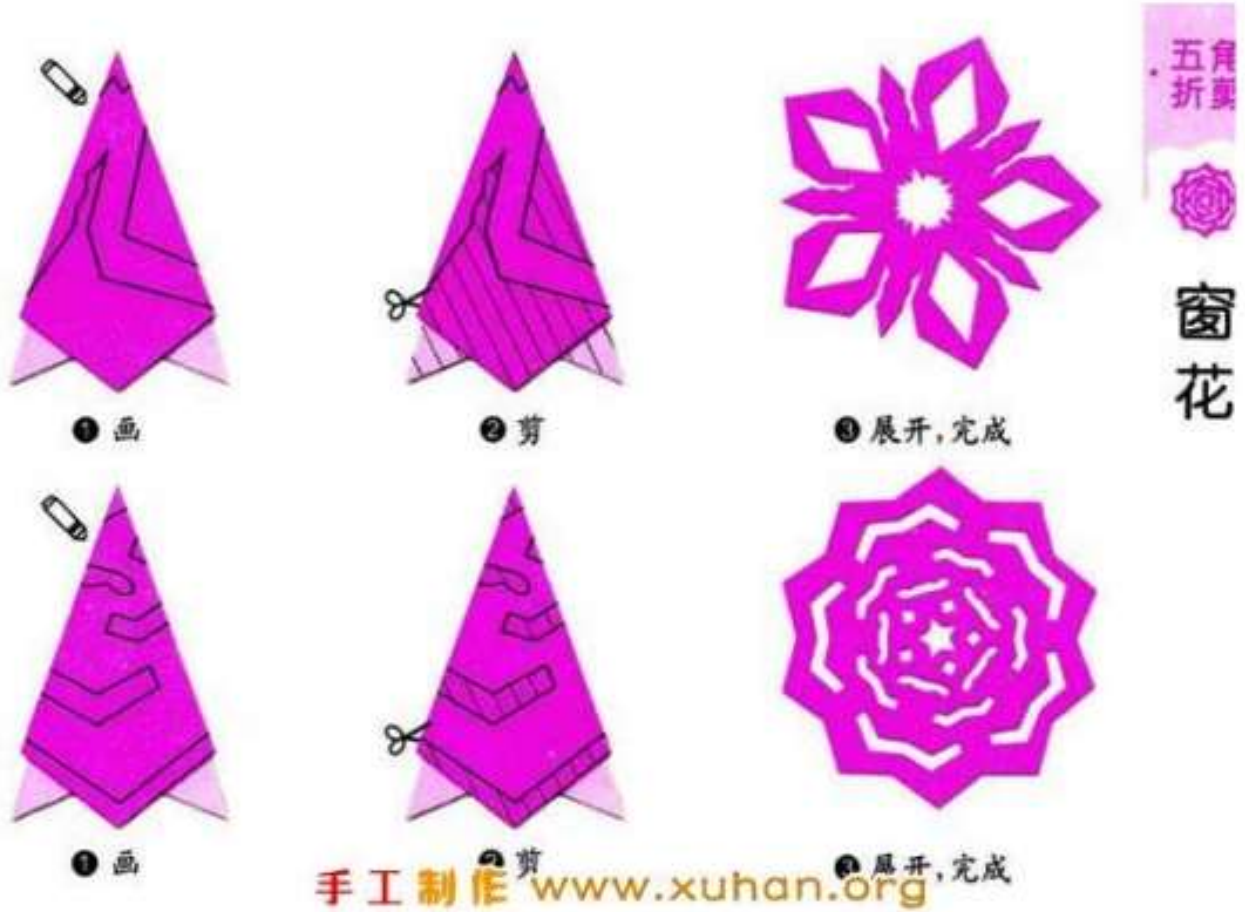
more logic gates



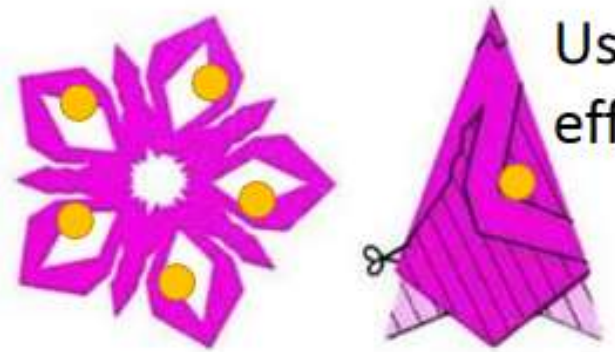
hierarchical structure: less logic gates
Combine two networks/circuits by sharing network

With multiple layers, we need only O(d) gates.

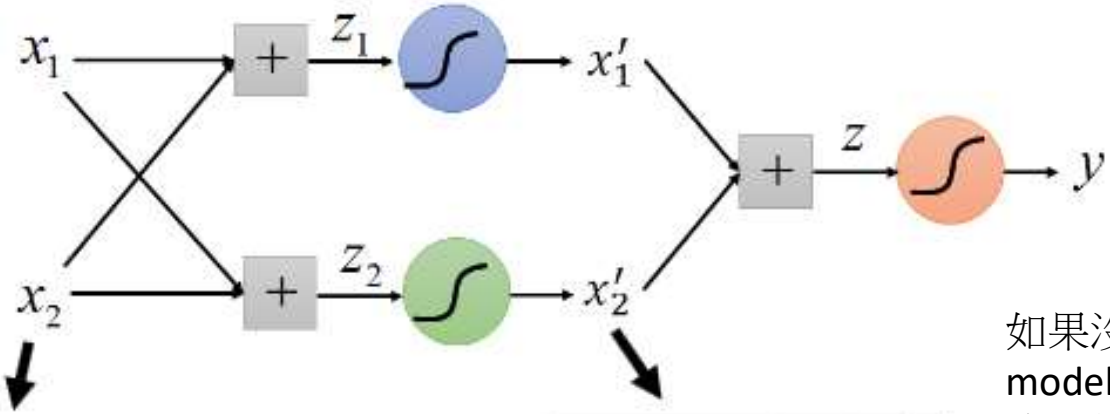
More Analogy

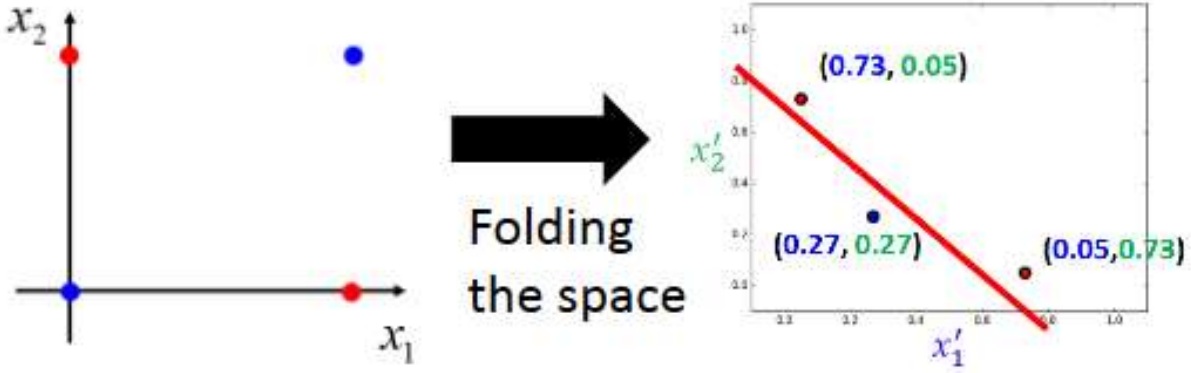


More Analogy



Use data effectively





Input: 4 data point，the color represent the classification

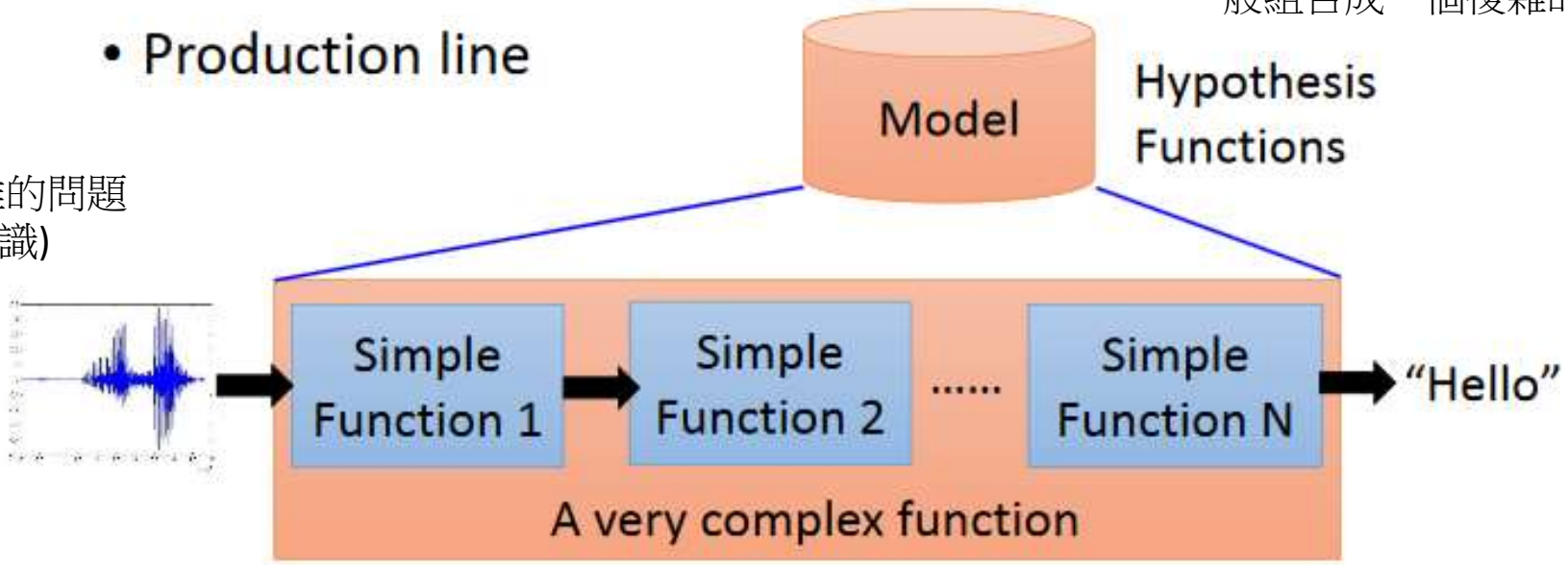
如果沒有hidden layer，linear的model沒有辦法把藍色分在一邊，紅色分在一邊，當加入了hidden layer相當於做了一個feature transformation，將原先的資料project到另一個space by using non-linear transformation as kernel function of SVM。

Another reason to use deep learning

End-to-end Learning

1. 與解決一個ML的問題時需要先找到一個Hypothesis function set
2. 將比較簡單的function如生產線一般組合成一個複雜的function

- Production line



欲解決複雜的問題
(例: 語音辨識)

End-to-end training:
What each function should do is learned automatically

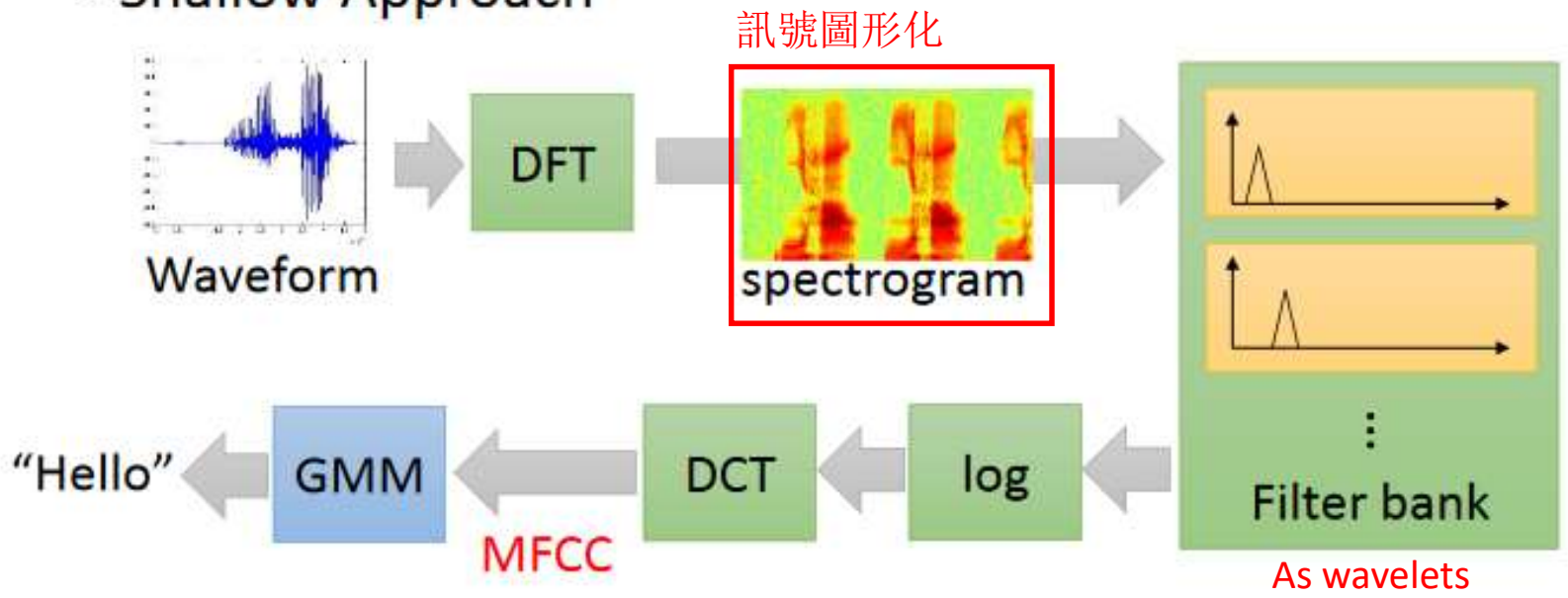
只給input與output，不決定中間的function如何分工

➢ End-to-End for visual-guided robot arm control

End-to-end Learning - Speech Recognition

J: End-to-End, users just care of input and output, deep learning will take care of all processing for you.
J: My experience is we still need to design the number of output for each layers, especially for the last few layers.

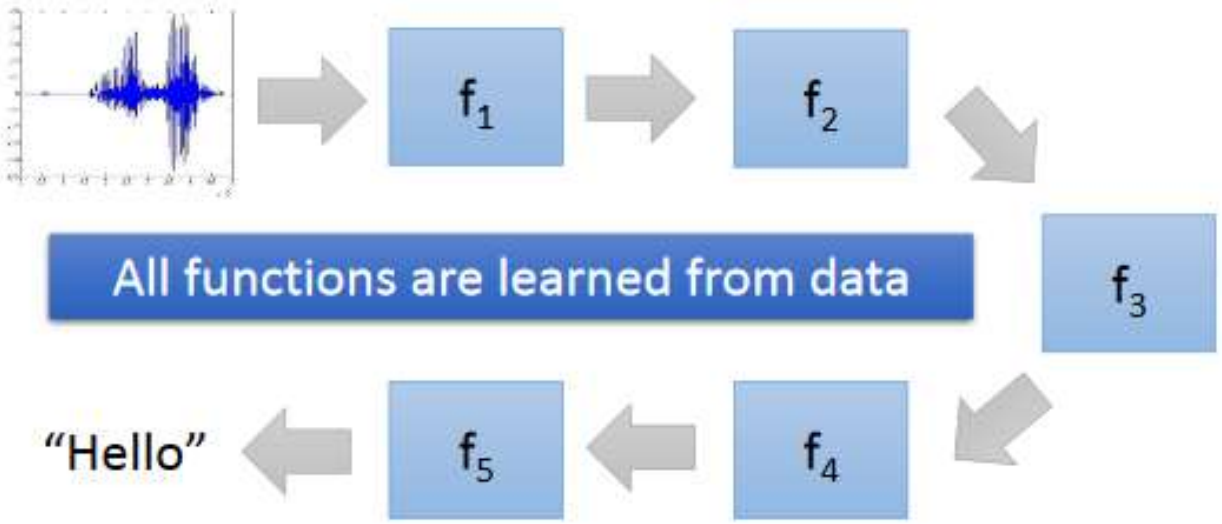
- Shallow Approach



梅爾頻率倒譜系數: Mel-Frequency Cepstral Coefficients

End-to-end Learning - Speech Recognition

- Deep Learning



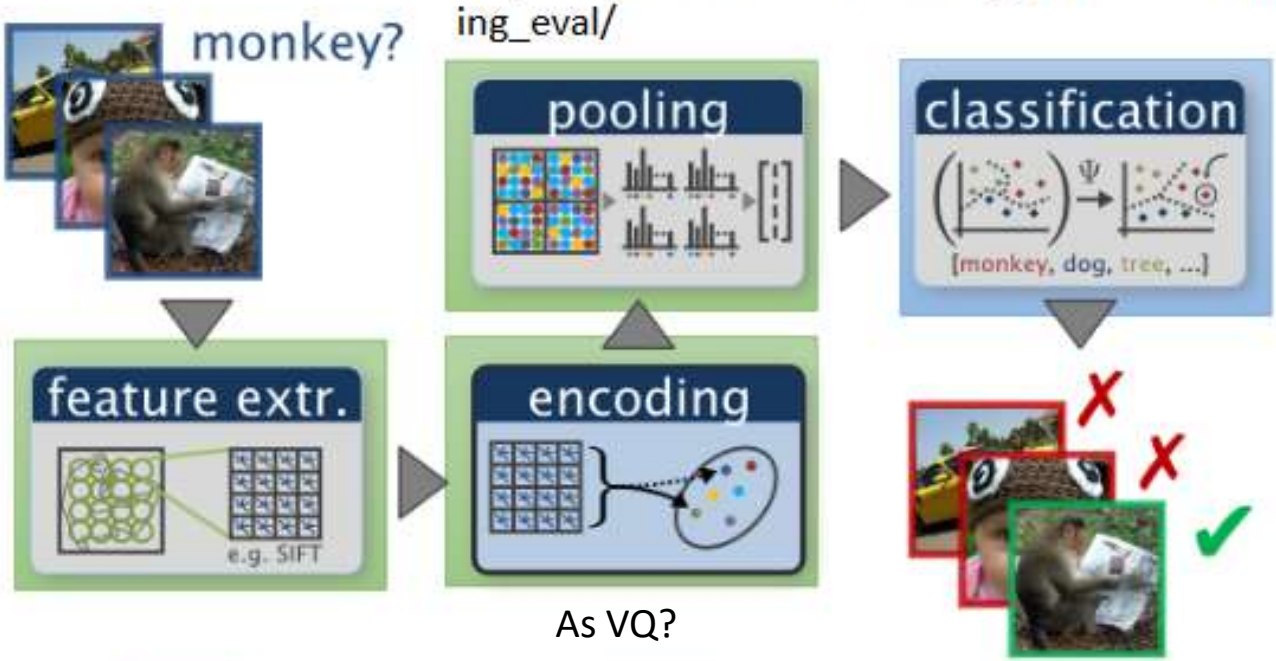
Less engineering labor, but machine learns more

Q: 以聲音訊號為例，有學者提出能不能透過deep learning，即只有input(聲音訊號)與output(對應的文字)，完全不對輸入的聲音訊號(time domain)做feature transform (signal processing)，是否能夠不需要signal processing
A: 有學者提出結論，能夠training出一個model與有將input經過 feature transform的結果持平，但沒有更好。

End-to-end Learning - Image Recognition

- Shallow Approach

http://www.robots.ox.ac.uk/~vgg/research/encoding_eval/



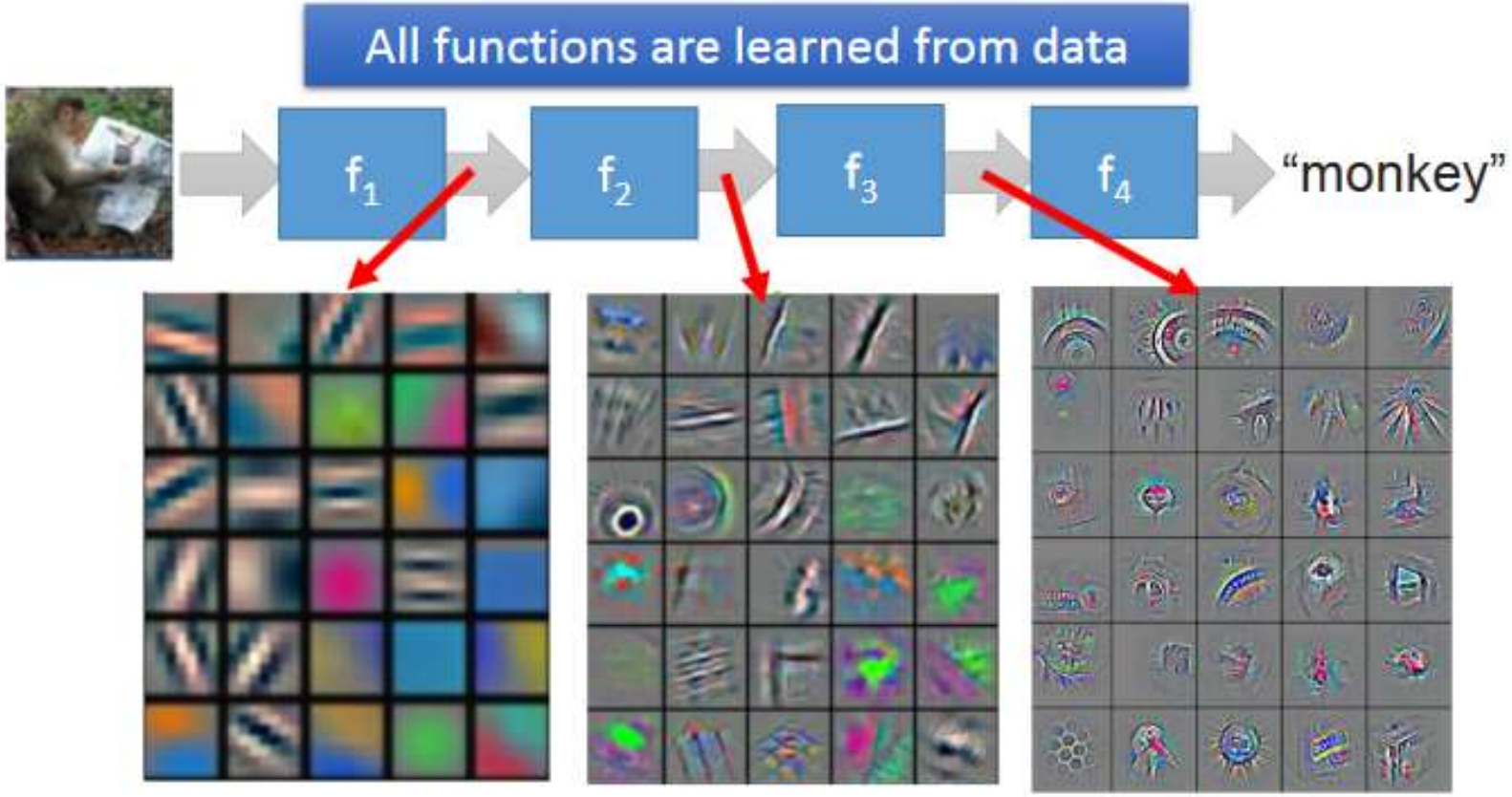
As VQ?

:hand-crafted :learned from data

End-to-end Learning - Image Recognition

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

- Deep Learning



More Reasons

- Do Deep Nets Really Need To Be Deep? (by Rich Caruana)
- http://research.microsoft.com/apps/video/default.aspx?id=232373&r=1

keynote of Rich Caruana at ASRU 2015

Outline of Lecture 1

I.1 Three Steps for Deep Learning

I.2 Why Deep Learning?

1) Fat+Short Vs. Thin+Tall
2) Multi-Task:
   (1) How to reduce para. in order to use less data
   (2) Modularization (logic circuit) – Combine network / Circuit
3) End to End Learning

I.3 "Hello world" for deep learning — Coding Example

Keras

If you want to learn theano:

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

http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/RNN%20training%20(v6).ecm.mp4/index.html

or theano

微分器:

Very flexible

Taking some time to learn

Interface of TensorFlow or Theano

keras

Easy to use

(still have some flexibility)

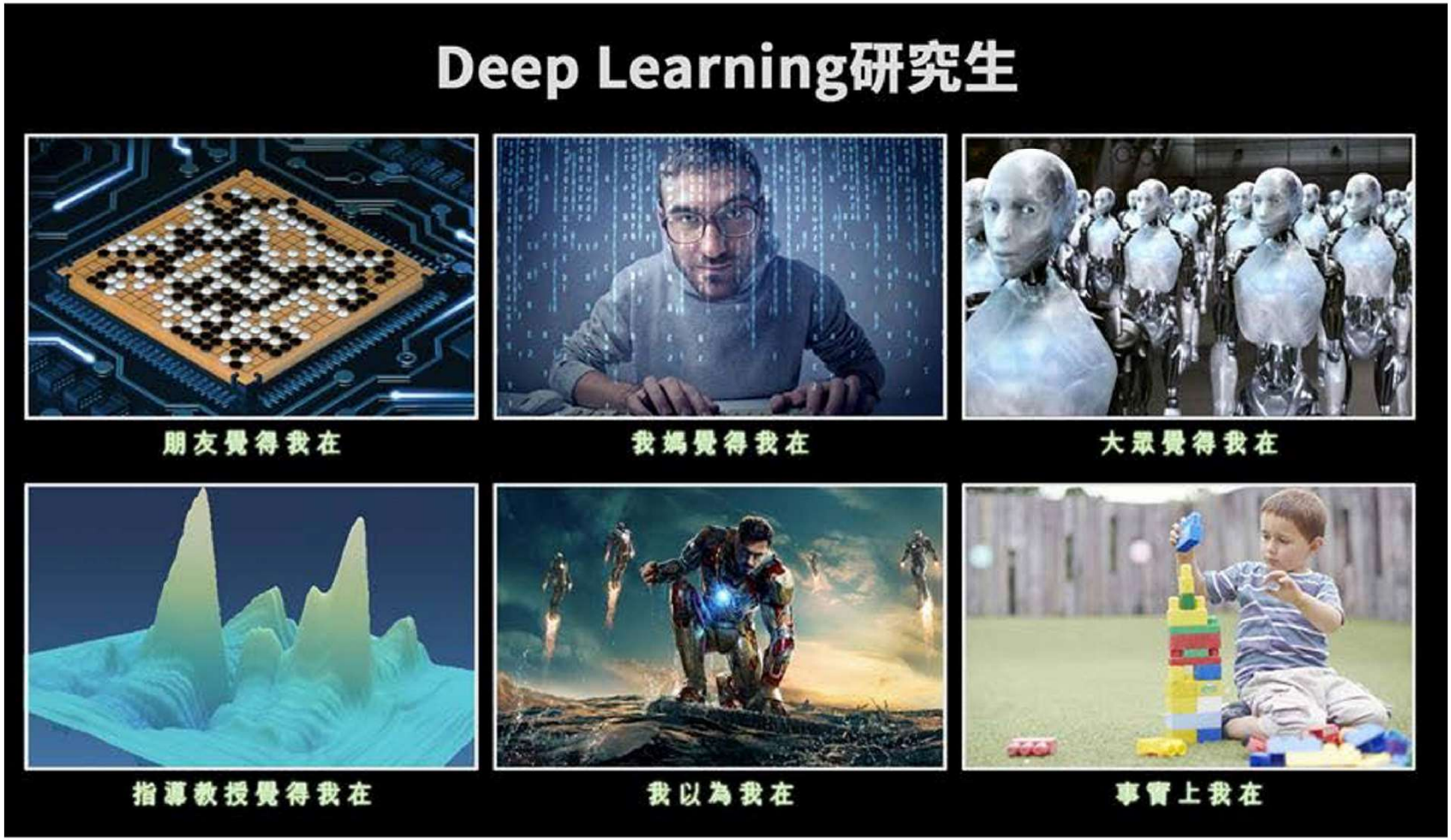
You can modify it if you can write TensorFlow or Theano

Keras

- François Chollet is the author of Keras.
  - He currently works for Google as a deep learning engineer and researcher.
- Keras means *horn* in Greek
- Documentation: http://keras.io/
- Example: https://github.com/fchollet/keras/tree/master/examples

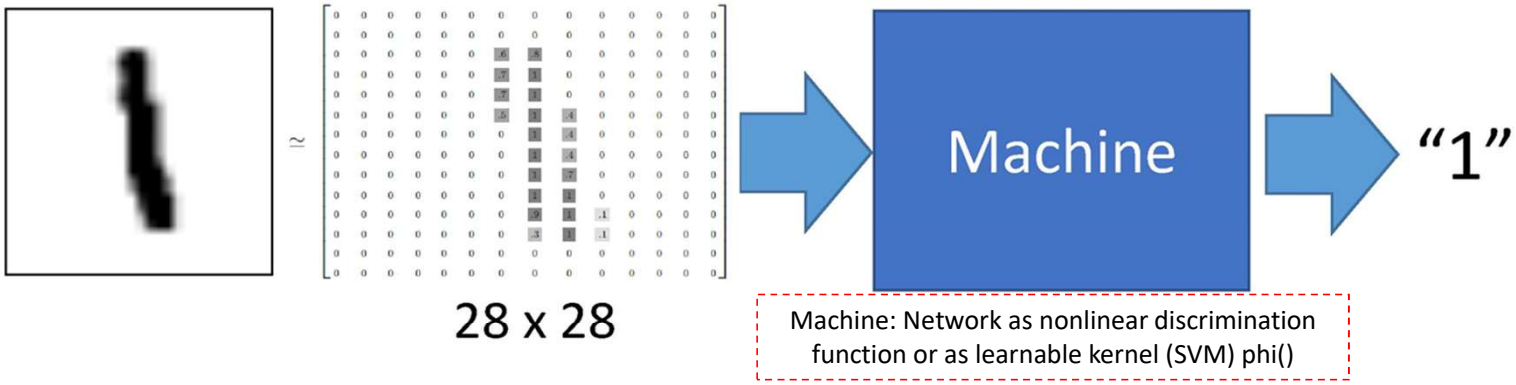
感謝 沈昇勳 同學提供圖檔

使用 Keras 心得



Example Application

- Handwriting Digit Recognition



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

“Hello world” for deep learning

Keras provides data sets loading function: http://keras.io/datasets/

Training Process:

Keras

Design topology/network: Having parameters (as variable) without values

Step 1: Network Structure

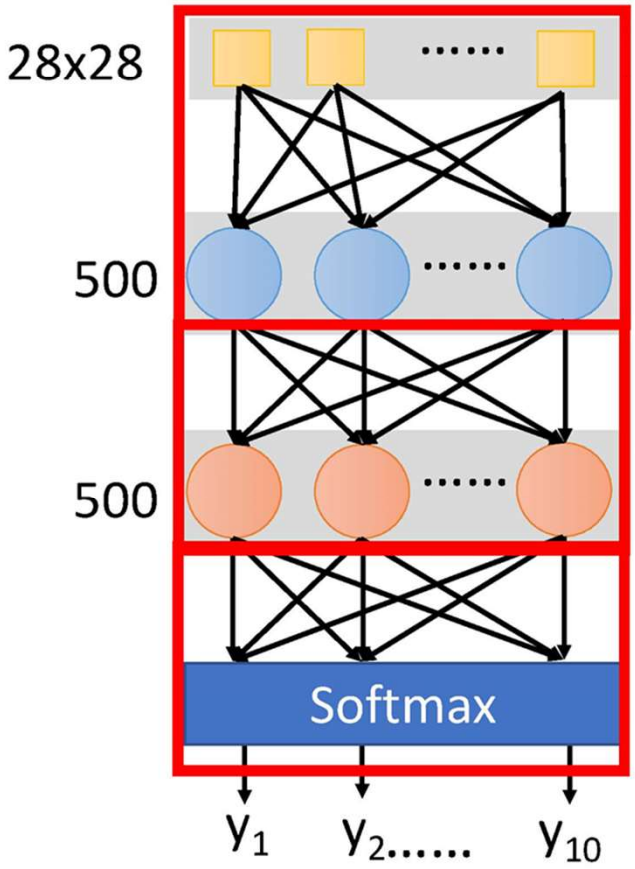
How to I/O data? Target/Data: Given input data and be recognized / classified output data. Exp. Mini batch

Step 2: Learning Target

o/p <=> Ground truth (label) y'

How to learn? Learning parameters (or para values) of topology using gradient descent to find global min of MSE

Step 3: Learn!




```
model = Sequential()
```

"Dense" represents a fully connected layer

```
model.add( Dense( input_dim=28*28,
                  output_dim=500 ))
model.add( Activation('sigmoid') )
```

28x28 vector，represent an input image

Vs. ReLU

500 neurons

Activation function can also be chose as softplus, softsign, relu, tanh, hard_sigmoid, linear

```
model.add( Dense( output_dim=500 ) )
model.add( Activation('sigmoid') )
```

No need to define the number of the input neuron, hence current input will be the output of previous layer

Ten digits

```
model.add( Dense(output_dim=10 ) )
model.add( Activation('softmax') )
```

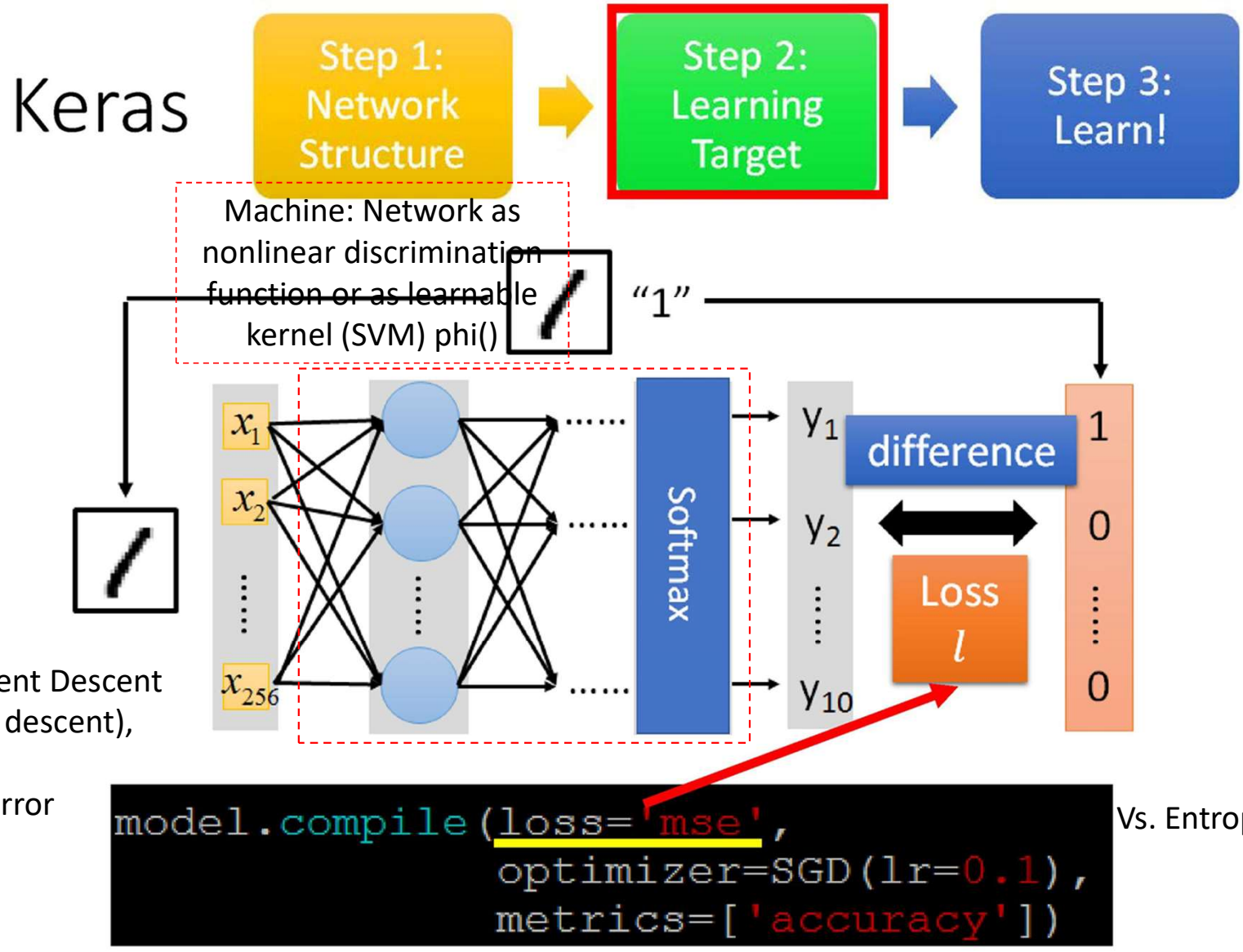
Output layer can be seem as a multi-class classifier, so we choose softmax as our activation

Training Process:

1) Batch = input all, update once
2) Mini – batch =

3) SGD belongs to stochastic = 隨機 = input 1 data, update once

10000 training data, based on stochastic, probably you just need 1000 data to train, then parameter reaches convergence.



SGD: Stochastic Gradient Descent (incremental gradient descent),
Loss: Loss function
MSE: Mean squared error
lr: Learning rate

$$\frac{1}{10}\sum_{i=1}^{10}\| y_i - \hat{y}_i \|^2$$

Vs. Entropy

$$-\sum_{1}^{10}(\hat{y}_i log y_i)$$

y^=1 Yes, y^=0 No

Training Process:

1) Batch = input all, update once
2) Mini – batch =

3) SGD belongs to stochastic = 隨機 = input 1 data, update once

10000 training data, based on stochastic, probably you just need 1000 data to train, then parameter reaches convergence.

1. Introduction - 2) Gradient-Based Learning

As gradient decent:
Learning rate = Epsonlon,
K = kth iteration

Elpslon: weight for current k situation

K-1 previous situation

$$W_k = W_{k-1} - \epsilon \frac{\partial E(W)}{\partial W}.$$

ϵ is a scalar constant. More sophisticated procedures use variable ϵ, or substitute it for a diagonal matrix, or substitute it for an estimate of the inverse Hessian matrix as in Newton or Quasi-Newton methods.

Gradient-Based Learning algorithms can use one of two classes of methods to update the parameters. The first method, dubbed "Batch Gradient", is the classical one: the gradients are accumulated over the entire training set, and the parameters are updated after the exact gradient has been so computed. In the second method, called "Stochastic Gradient", a partial, or noisy, gradient is evaluated on the basis of one single training sample (or a small number of samples), and the parameters are updated using this approximate gradient. The training samples can be selected randomly or according to a properly randomized sequence. In the stochastic version, the gradient estimates are noisy, but the parameters are updated much more often than with the batch version. An empirical result of considerable practical importance is that on tasks with large, redundant data sets, the stochastic version is considerably faster than the batch version, sometimes by orders of magnitude [117]. Although the reasons for this are not totally understood theoretically, an intuitive explanation can be found in the following extreme example. Let us take an example where the training database is composed of two copies of the same subset. Then accumulating the gradient over the whole set would cause redundant computations to be performed. On the other hand, running Stochastic Gradient once on this training set would amount to performing two complete

Batch gradient or stochastic gradient

Stochastic gradient algorithm (on-line update):

$$W_k = W_{k-1} - \epsilon \frac{\partial E^{P_k}(W)}{\partial W}$$

??

It consists in updating the parameter vector using a noisy, or approximated, version of the average gradient. In the most common instance of it, W is updated on the basis of a single sample:

J: Pk for example, each pk=1000 samples for ith iteration, total P=10000 samples

Training Process:

??

Step 3.1: Configuration

```
model.compile(loss='mse',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

??

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

0.1

$$\frac{1}{10}\sum_{i=1}^{10} \| y_i - \hat{y}_i \|^2$$

$$-\sum_{1}^{10} (\hat{y}_i log y_i)$$

y^=1 Yes, y^=0 No

Step 3.2: Find the optimal network parameters

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```

Training data (Images)

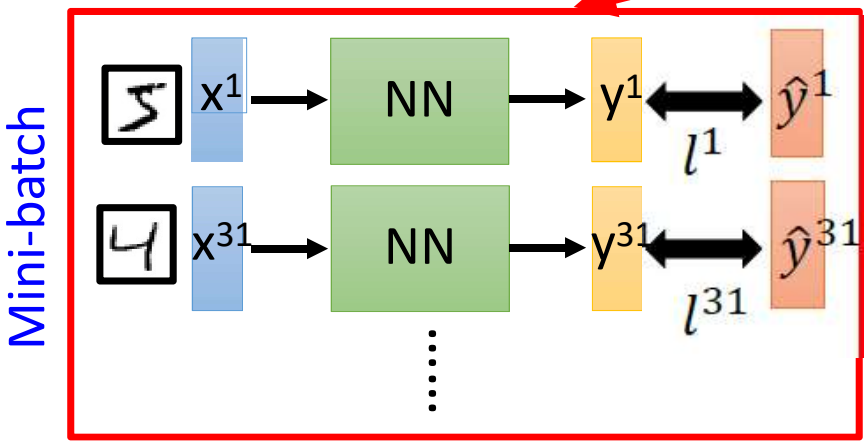
Labels (digits)

等一下再講 ??

Stochastic gradient descent : Batch size = 1
Full batch gradient descent: Batch size = number of training data
Mini batch gradient descent: Batch size between stochastic and full batch

Mini-batch

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```



100 examples in a mini-batch

Ex.All 500 examples→5 mini-batch

- Pick the 1st batch
  $L' = l^1 + l^{31} + \cdots$
  Update parameters once
- Pick the 2nd batch
  $L'' = l^2 + l^{16} + \cdots$
  Update parameters once
  ⋮
- Until all mini-batches have been picked

one epoch

Repeat 20 times

Repeat 20 times = repeat 20 epochs
For each epoch, entire samples are randomly shuffled to have new 5 mini-batches (Shuffle: a method to select the training examples for each epoch, detail will be talked in lecture 2)

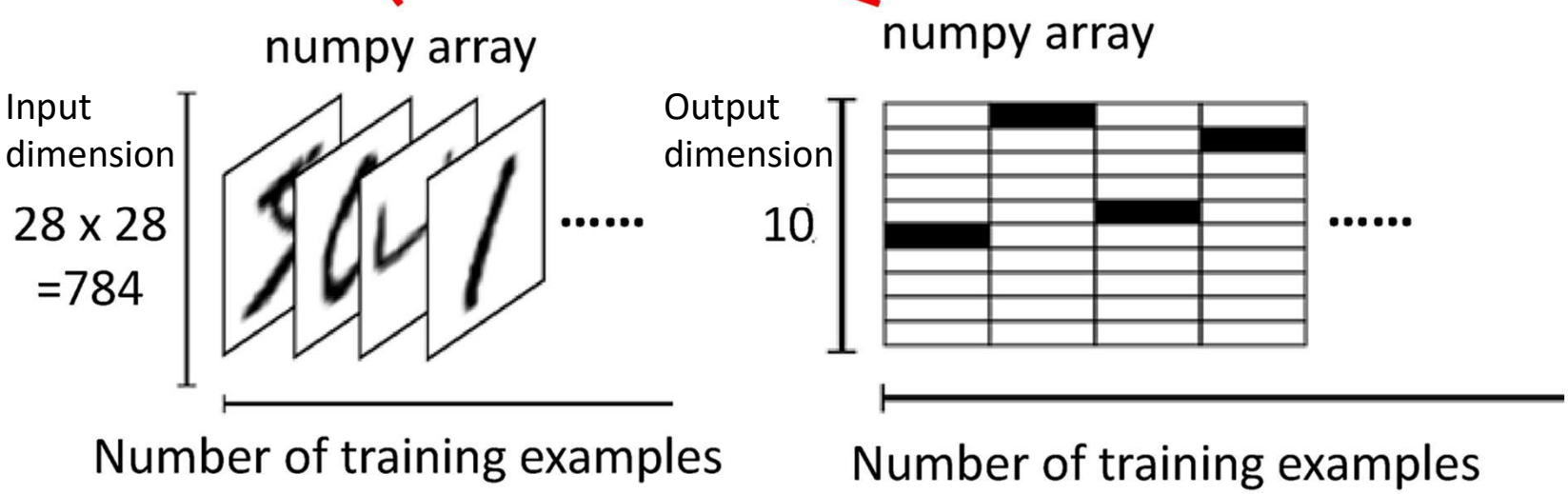
Training Process:

Step 3.2: Find the optimal network parameters

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```

Input Image

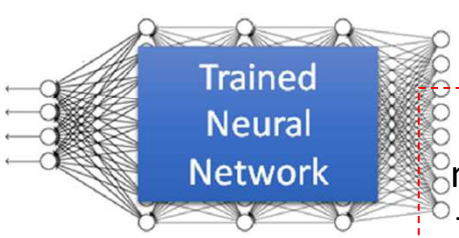
Output Label



https://www.tensorflow.org/versions/r0.8/tutorials/mnist/beginners/index.html

Test Process: ??

Keras



Machine: Network as nonlinear discrimination function or as learnable kernel (SVM) phi()

Save and load models

http://keras.io/getting-started/faq/#how-can-i-save-a-keras-model

How to use the neural network (testing):

case 1:

```
score = model.evaluate(x_test,y_test)
print('Total loss on Testing Set:', score[0])
print('Accuracy of Testing Set:', score[1])
```

case 2:

```
result = model.predict(x_test)
```

Get your hand dirty

- Using GPU
  - THEANO_FLAGS=device=gpu0 python YourCode.py

Concluding Remarks of Lecture I

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

但 Deep Learning 就像 雷神之槌

無法輕易被舉起來 .....

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

Reference ??

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