手把手教你深度學習實務

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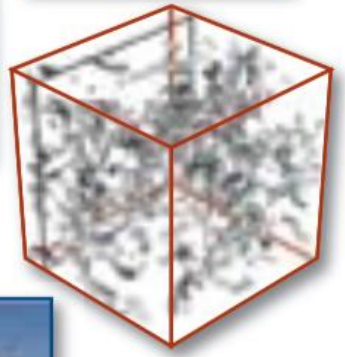
Science Paradigms

- Thousand years ago:
  science was **empirical**
  describing natural phenomena
- Last few hundred years:
  theoretical branch
  using models, generalizations
- Last few decades:
  a **computational** branch
  simulating complex phenomena
- Today: **data exploration** (eScience)
  unify theory, experiment, and simulation
  - Data captured by instruments or generated by simulator
  - Processed by software
  - Information/knowledge stored in computer
  - Scientist analyzes database/files using data management and statistics

$$\left(\frac{\dot{a}}{a}\right)^2 = \frac{4\pi G p}{3} - \mathrm{K}\frac{c^2}{a^2}$$

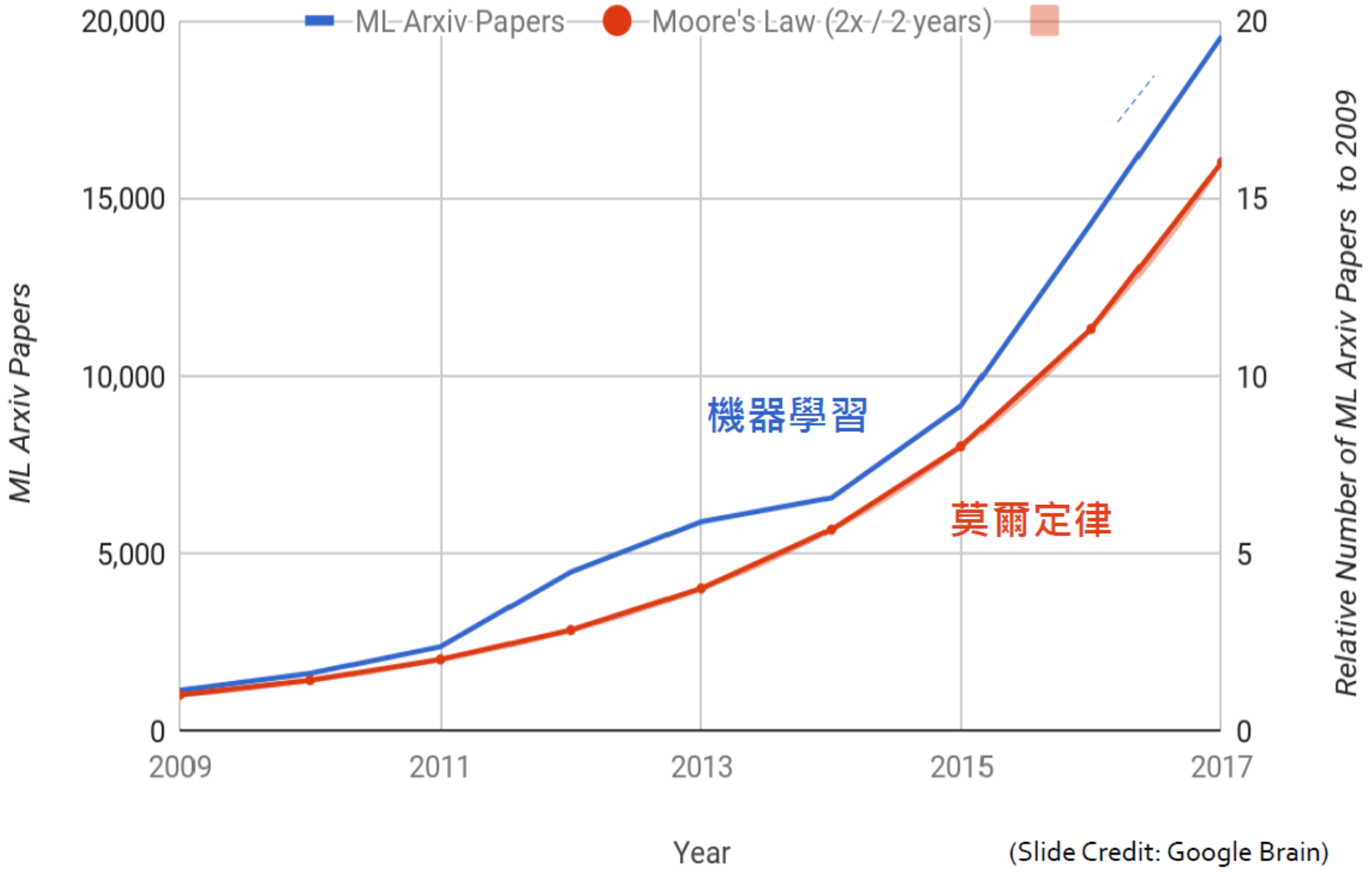


https://www.microsoft.com/en-us/research/publication/fourth-paradigm-data-intensive-scientific-discovery/?from=http%3A%2F%2Fresearch.microsoft.com%2Fen-us%2Fcollaboration%2Ffourthparadigm%2Fdefault.aspx&fbclid=IwAR2KNRcgDlhLgs94EtbCDyOfKa7O-Xg5Lcj39uKPe7Z5FC1Oa4RHhv_hFWM

Outline

- What is Deep Learning?
- Hands-on Tutorial of Deep Learning
- Tips for Training DL Models
- Variants - Convolutional Neural Network
- Transfer Learning and Semi-supervised Learning

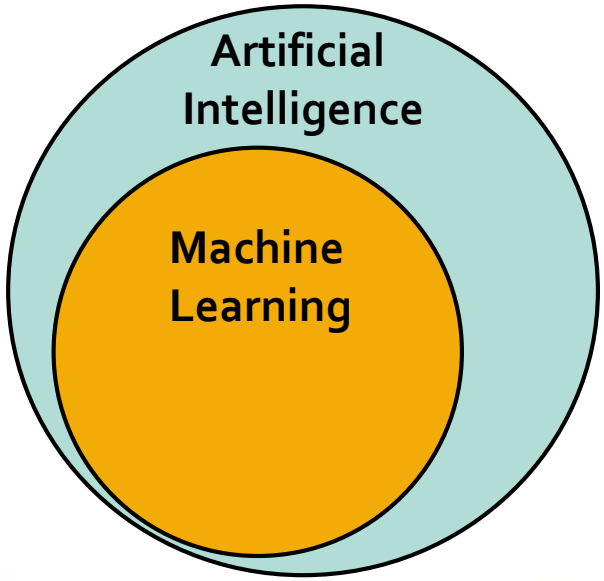
機器學習論文成長曲線



(Slide Credit: Google Brain)

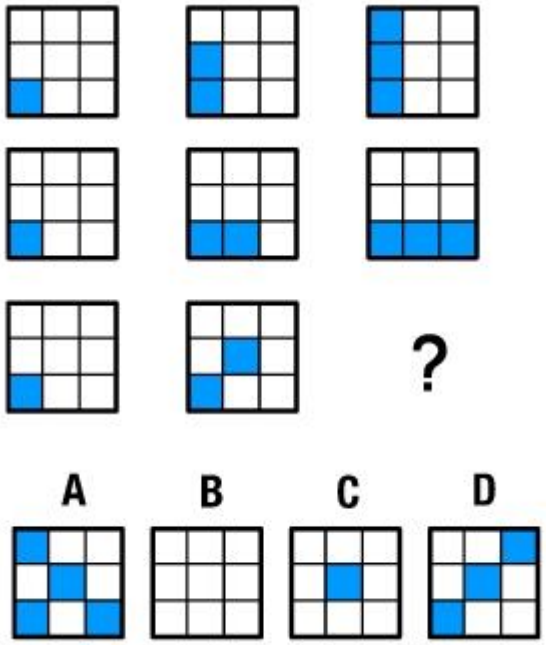
Machine Learning vs Artificial Intelligence

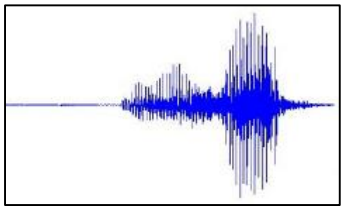
- AI is the simulation of human intelligence processes
  - Outcome-based: 從**結果**來看，是否有 human intelligence
  - 一個擁有非常詳盡的 rule-based 系統也可以是 AI
- Machine learning 是達成 AI 的一種技術
- 從資料當中學習出 rules
  - 找到一個夠好的 function 能解決特定的問題



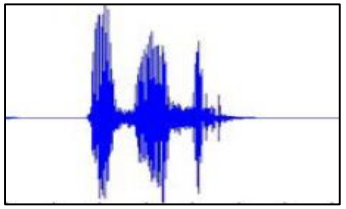
機器學習

讓機器從資料裡萃取出規則的演算法

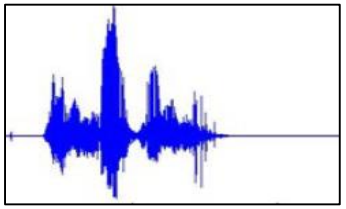




你好



大家好

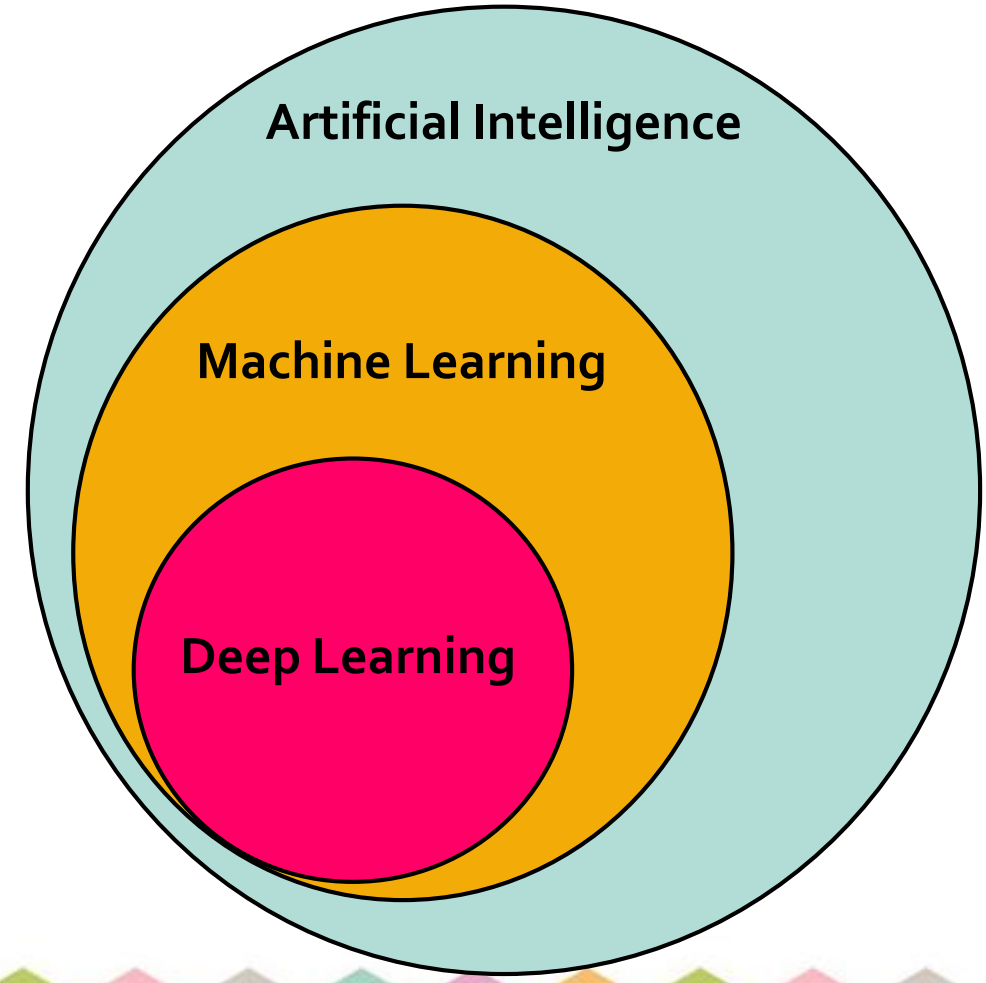


人帥真好

Slide credit: Sheng-Wei Chen

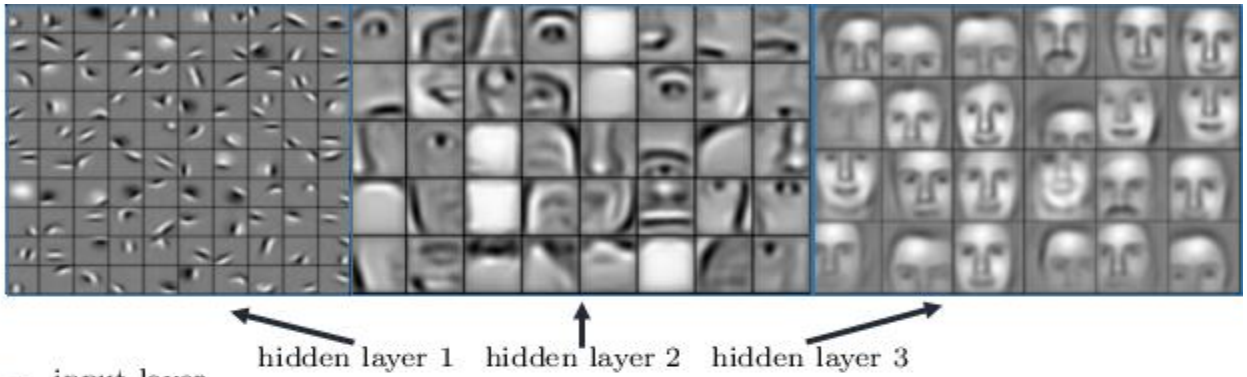
Deep Learning vs Machine Learning

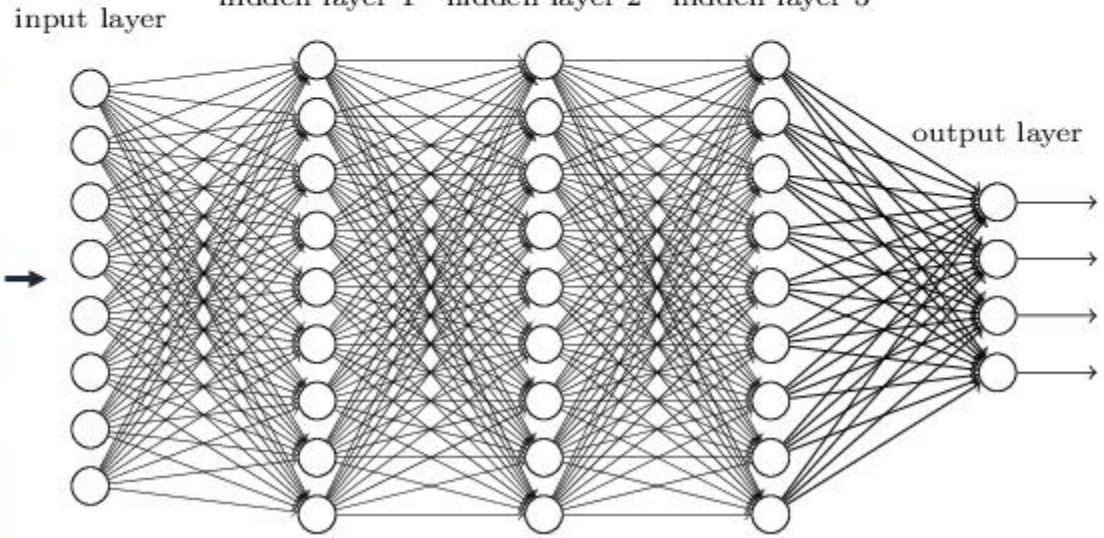
- Deep learning is a subset of machine learning



機器學習算法學習到的複雜規則

Deep neural networks learn hierarchical feature representations





Ref: Deep Learning and Convolutional Neural Networks: RSIP Vision Blogs

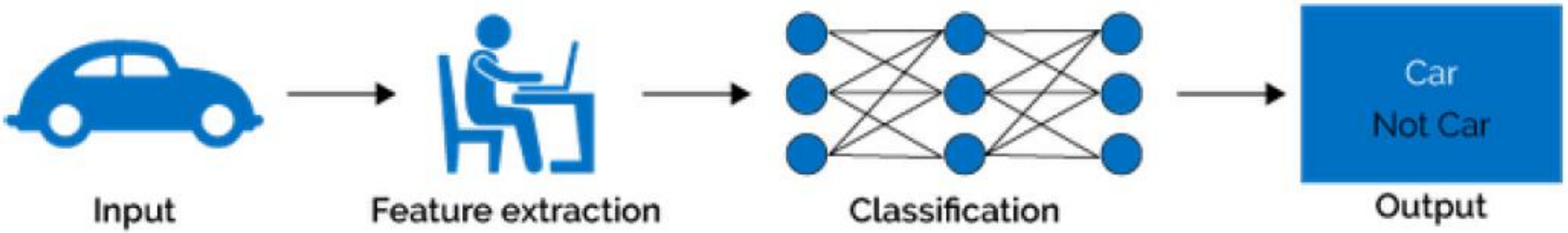
機器學習算法得到的特徵熱點

- Gaydar: detect signs of homosexuality
- Human judges: 61% for men, 54% for women
- AI judges: 91% for men, 83% for women

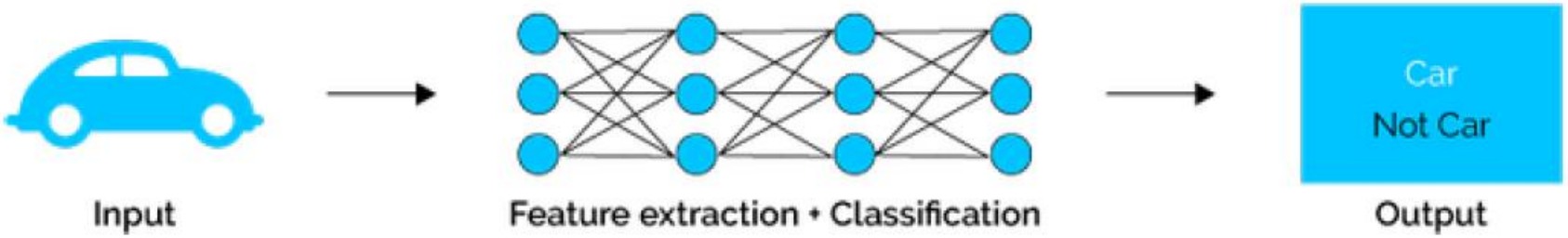
https://osf.io/zn79k/

Rule-based System

Classical Machine Learning



Deep Learning



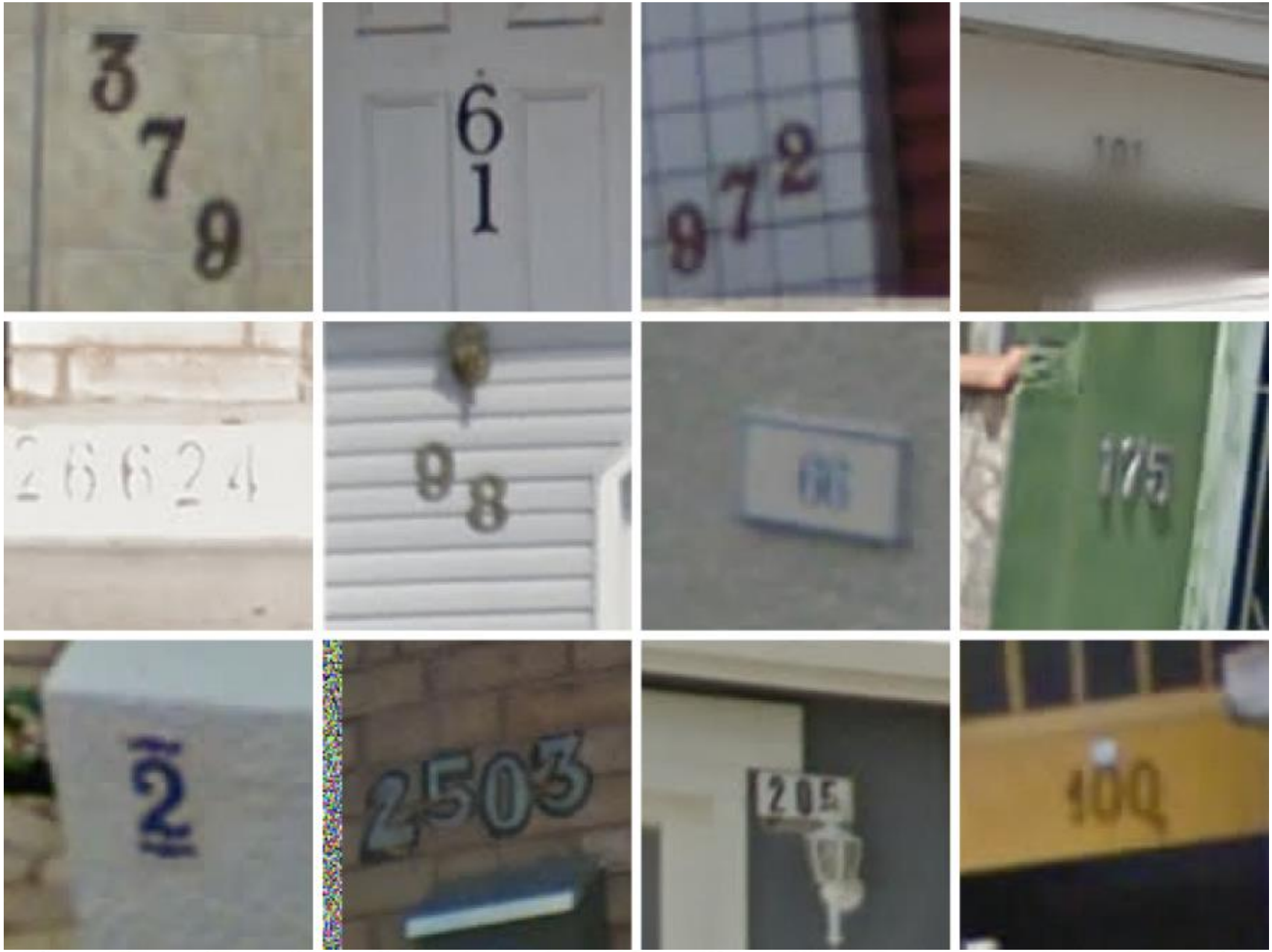
Slide credit: Sheng-Wei Chen

圖像辨識的進步

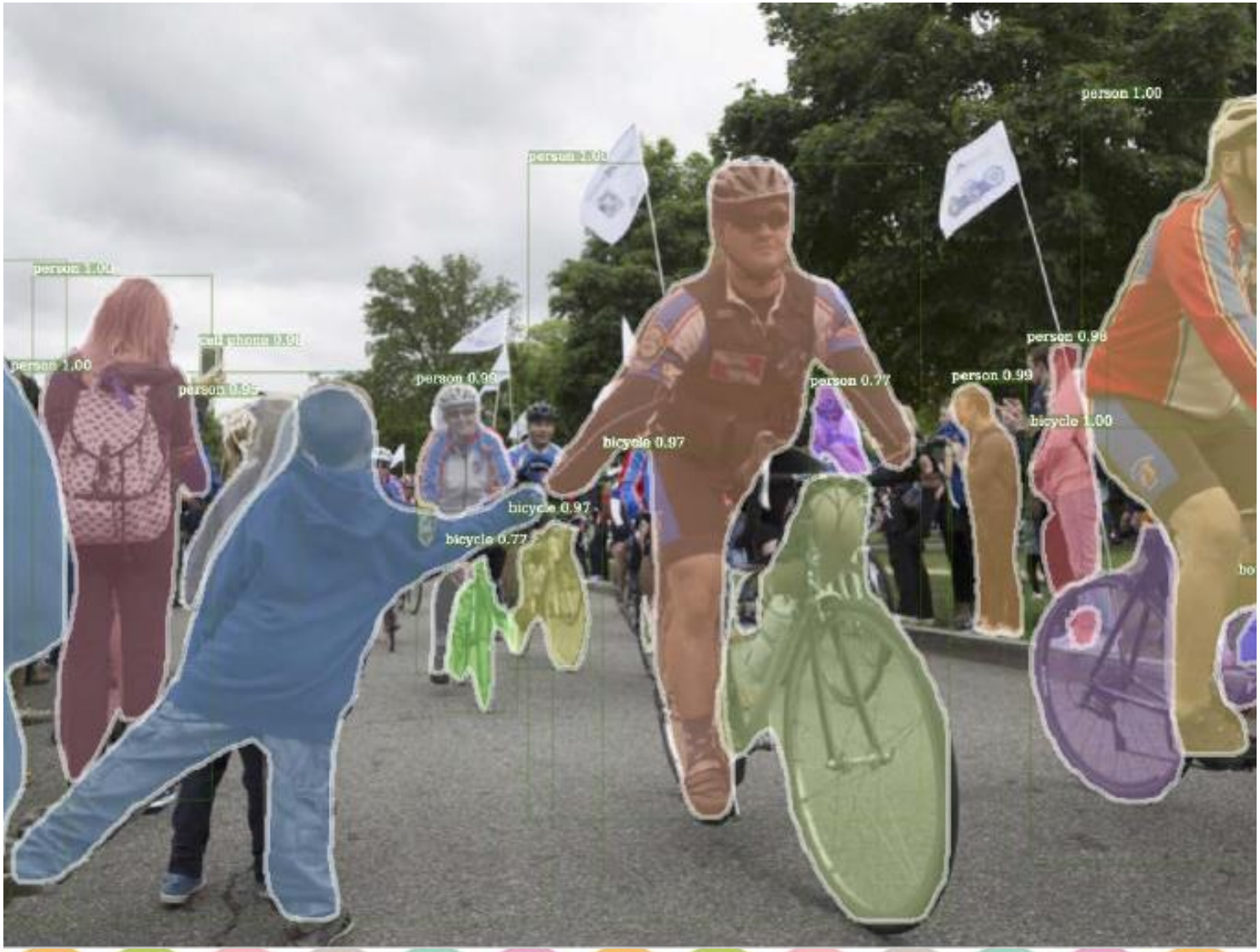
吉娃娃與馬芬

貓頭鷹與蘋果

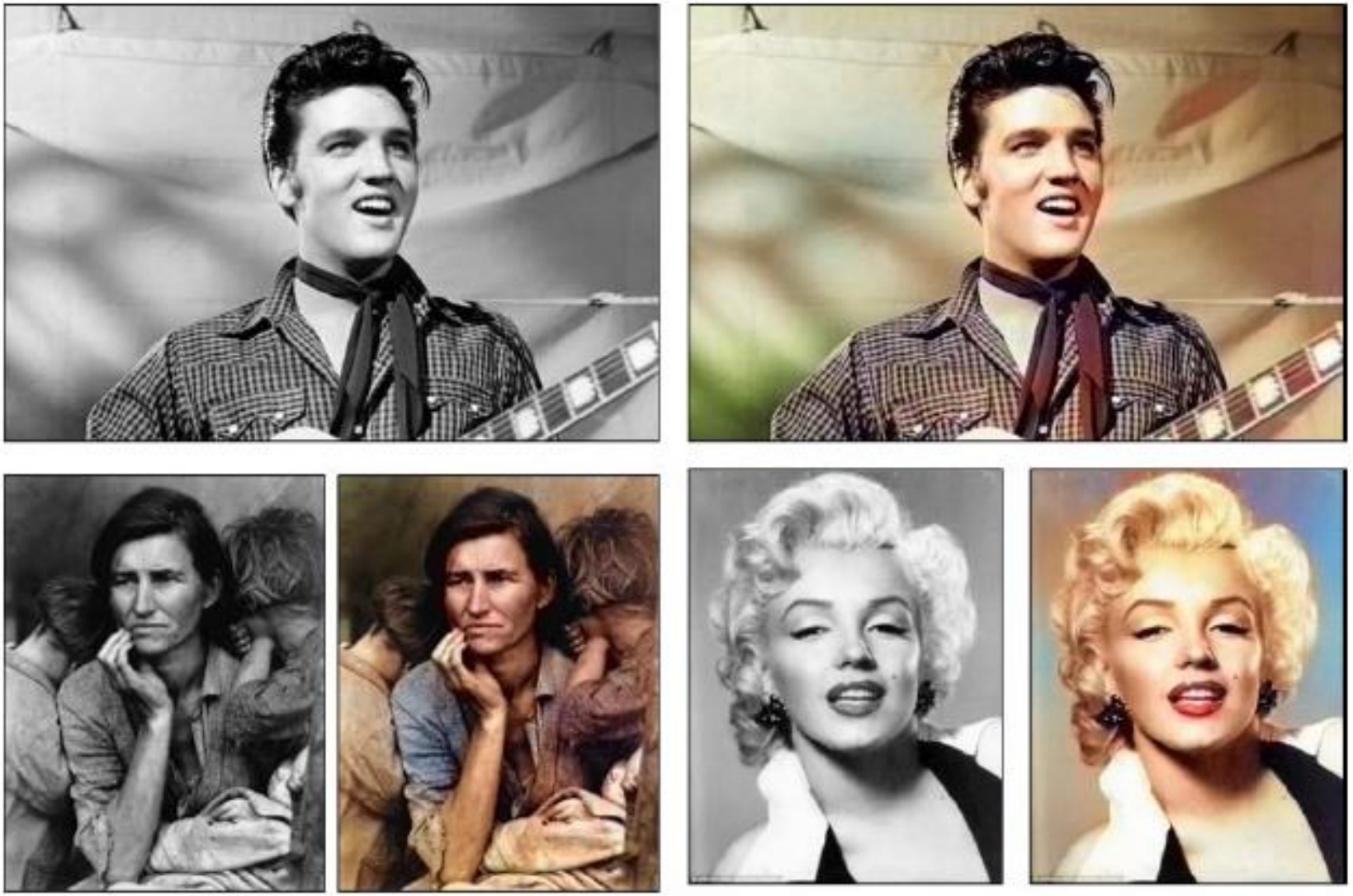
Source: teenybiscuit - twitter


378
61
972
101
26624
98
175
2
2503
205
100

Semantic Segmentation

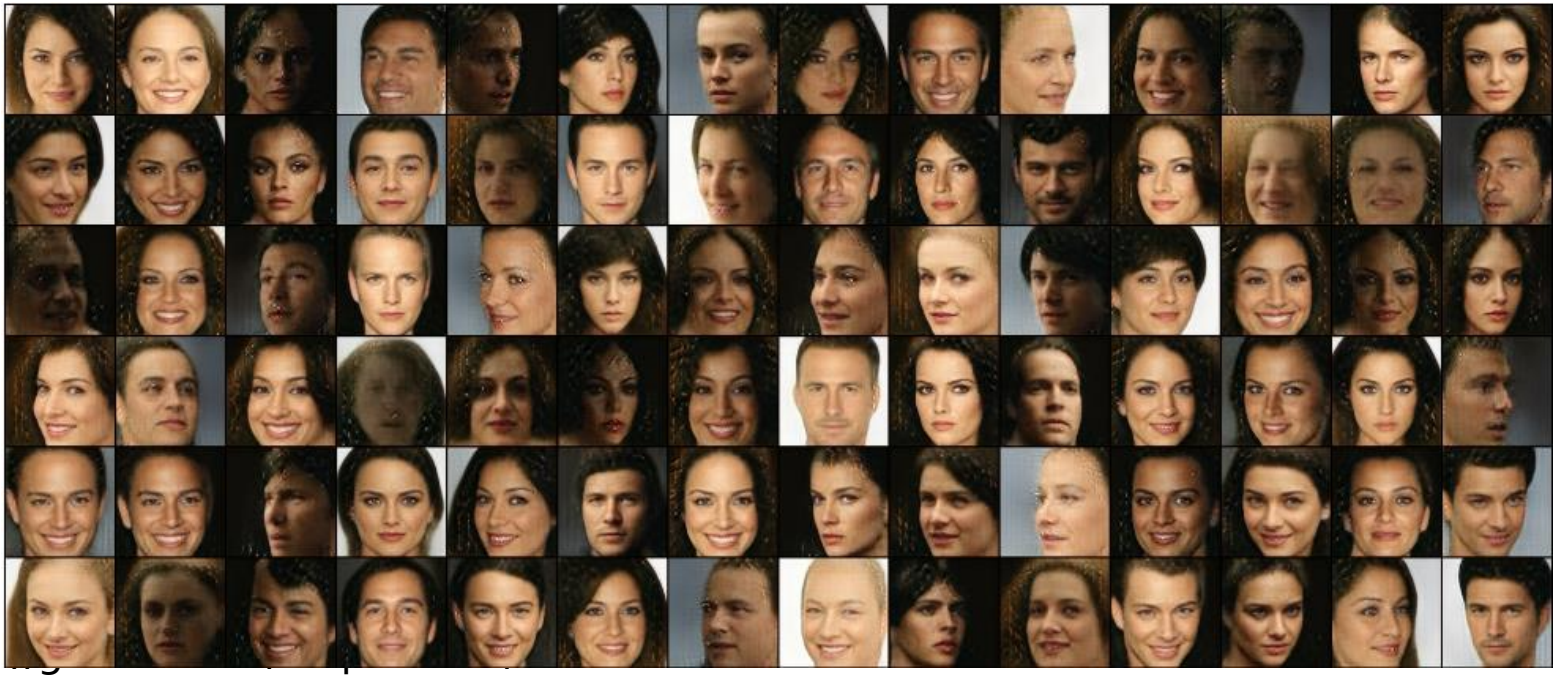


Colorizing Legacy Photos



其他有趣的應用

- Image Generation



https

Video Captioning

Video sequence

Answer: a woman is carefully slicing tofu.

Generated caption: a woman is cutting a block of tofu.

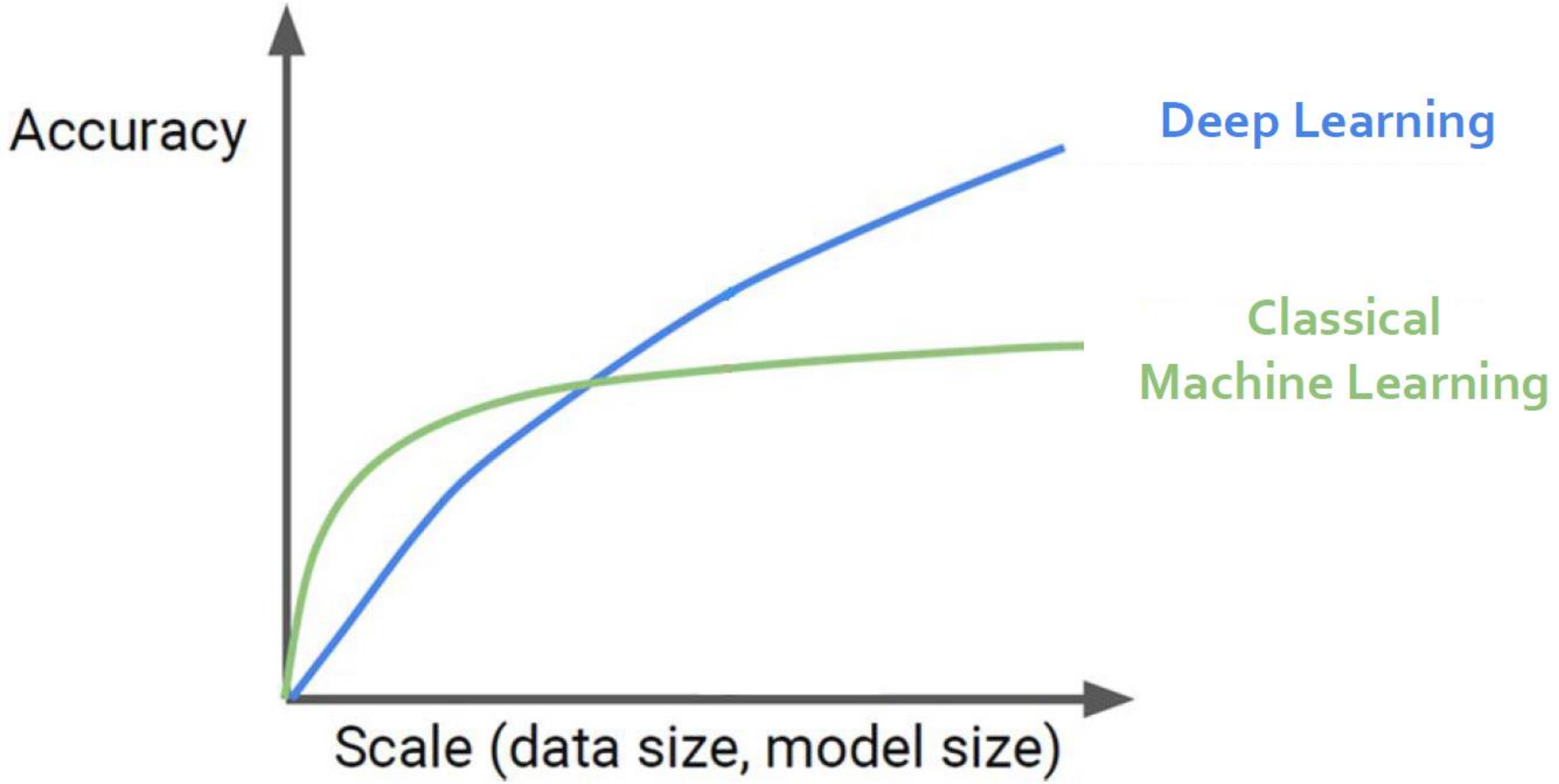
Text-To-Image

the flower has petals that are bright pinkish purple with white stigma

this white and yellow flower have thin white petals and a round yellow stamen

https://arxiv.org/pdf/1701.00160.pdf

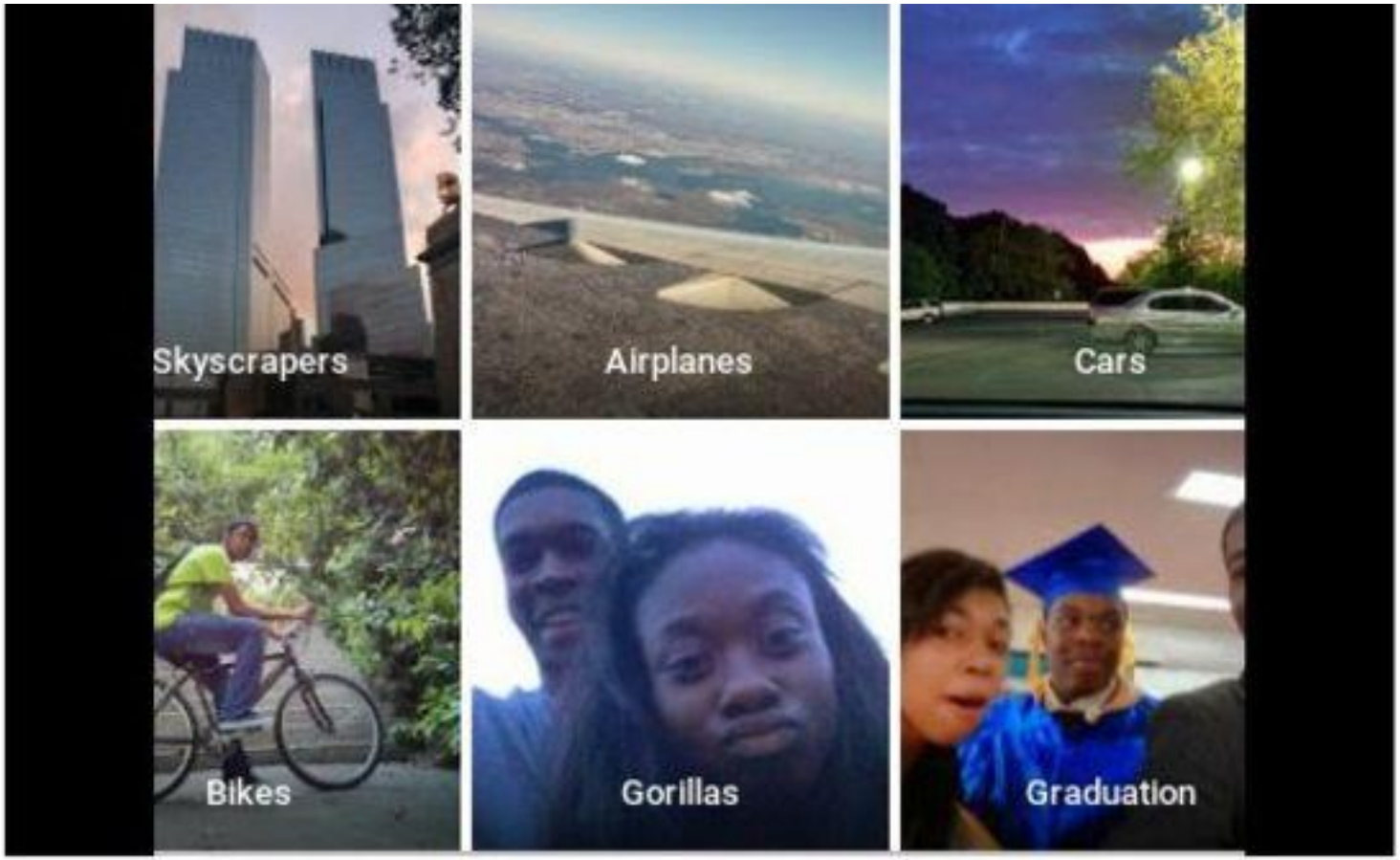
There is no free lunch



Slide credit: Sheng-Wei Chen

Slide credit: Sheng-Wei Chen

Machines may make mistakes as well



diri noir avec banan @jackyalcine · Jun 29

Google Photos, y'all [redacted] My friend's not a gorilla.

813 394

TWITTER

Deep Learning 的優勢

- 學習**非結構化**資料
  - 圖片 (2D) ➔ Convolutional neural network (CNN)
    ➔ Residual neural network
  - 序列 ➔ Recurrent neural network (RNN)
    ➔ Long short-term memory (LSTM)
    ➔ Gated recurrent units (GRU)
- 學習**特徵表示** representation learning
  - 取代過去的特徵工程 feature engineering
  - Learning from data (O), learning from human (X)

為什麼叫做 Deep Learning ?

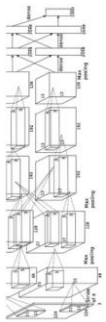
(Slide Credit: Hung-Yi Lee)

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

- 當 hidden layers 層數夠多
  就稱為 Deep neural network

8 layers

16.4%



AlexNet (2012)

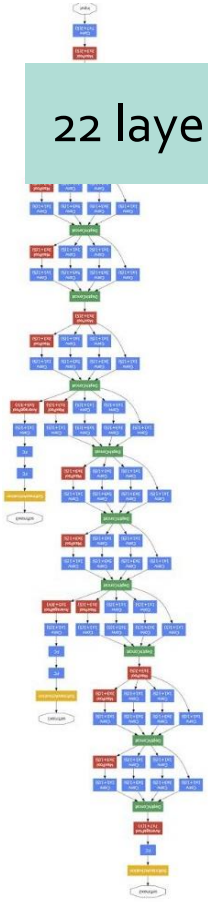
19 layers

7.3%

VGG (2014)

22 layers

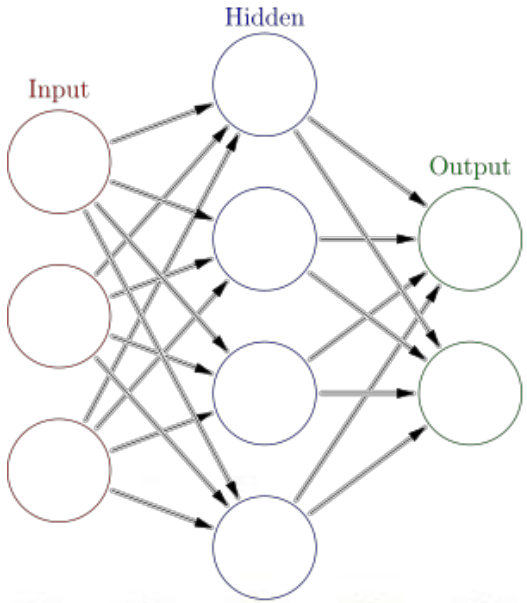
6.7%



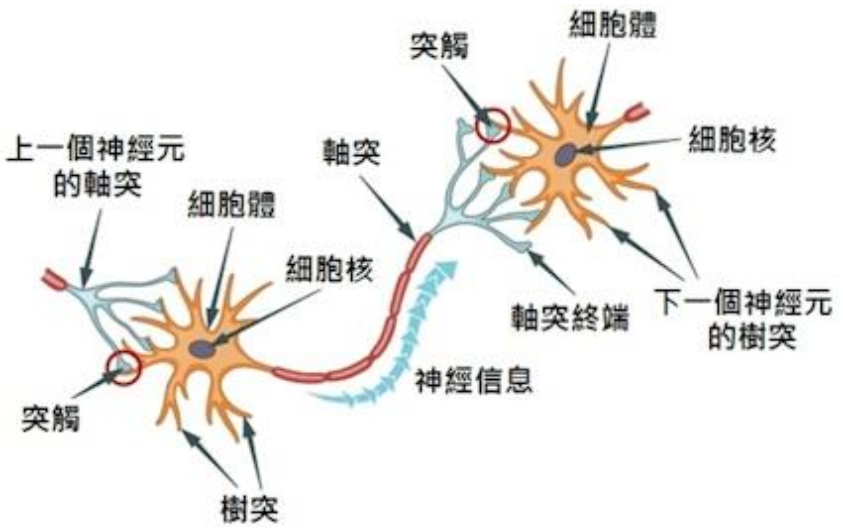
GoogleNet (2014)

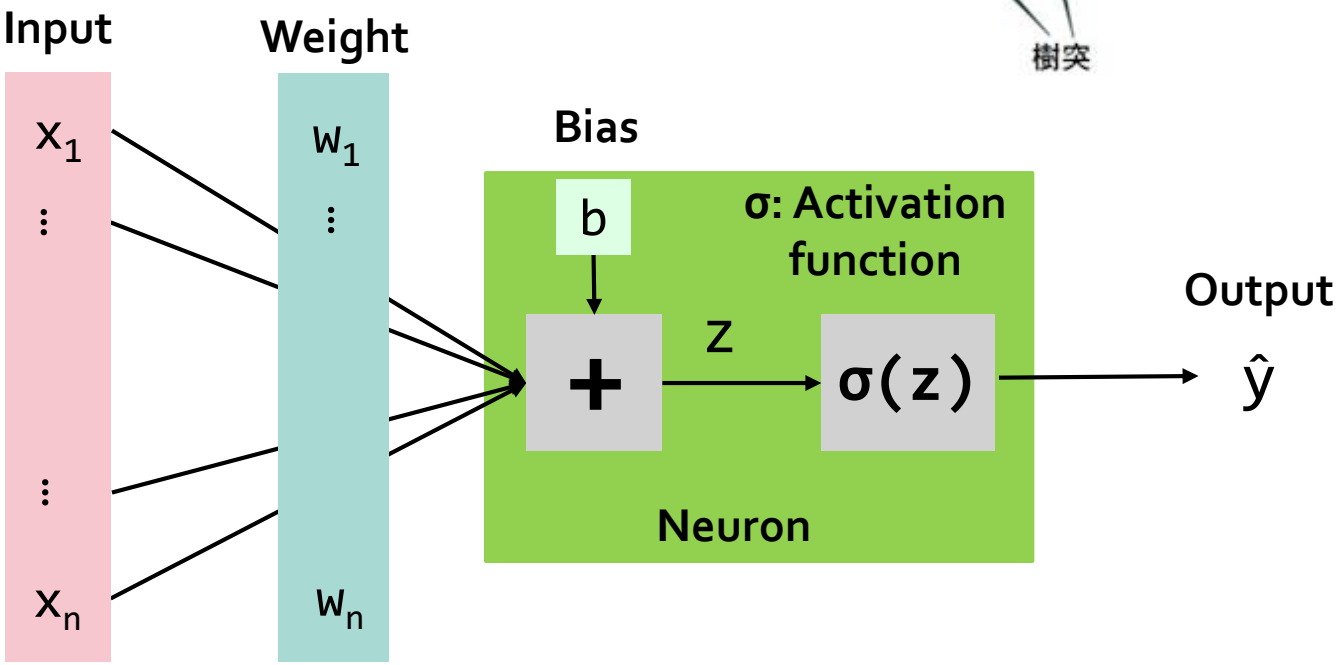
Fundamentals of Deep Learning

- Artificial neural network (ANN, 1943)
  Multi-layer perceptron
- 模擬人類神經傳導機制的設計
  - 由許多層的 neurons 互相連結而形成 neural network



A Neuron



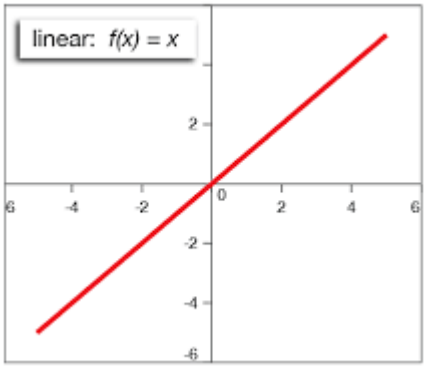


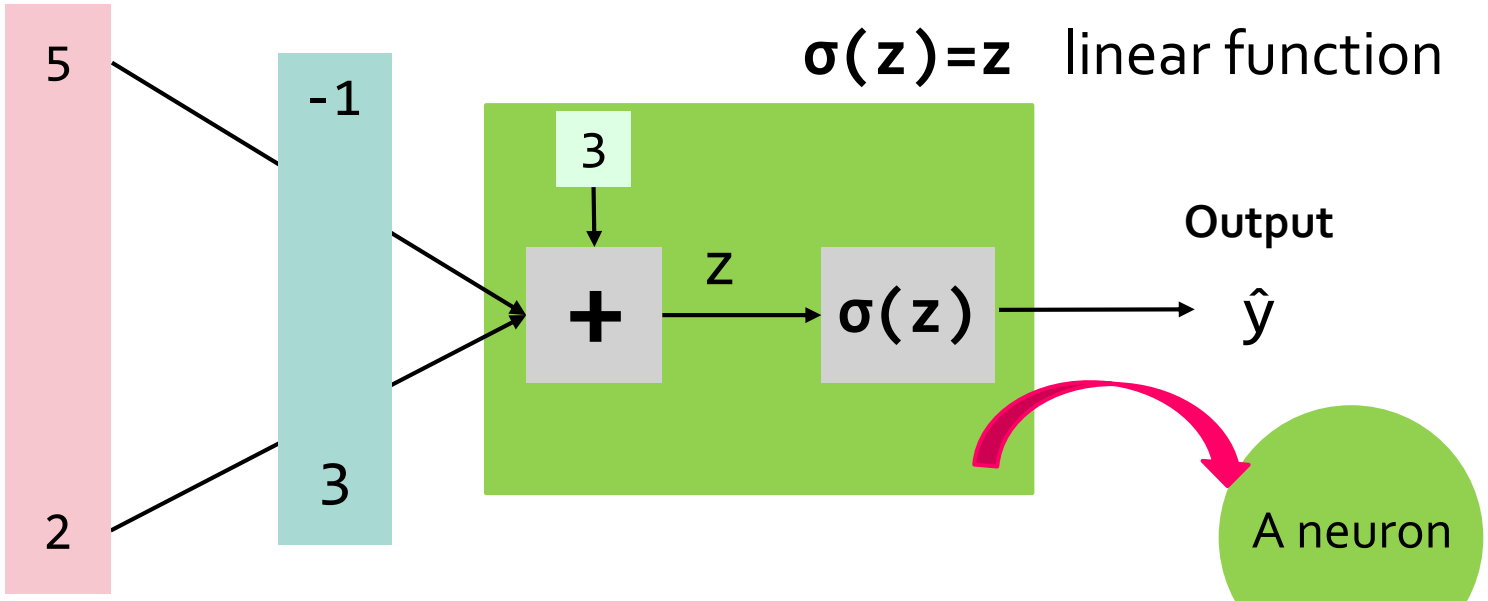
$$z = w_1x_1+w_2x_2+.....+w_nx_n+b$$

$$\hat{y} = \sigma(z)$$

Neuron 的運作

- Example





σ(z)=z linear function

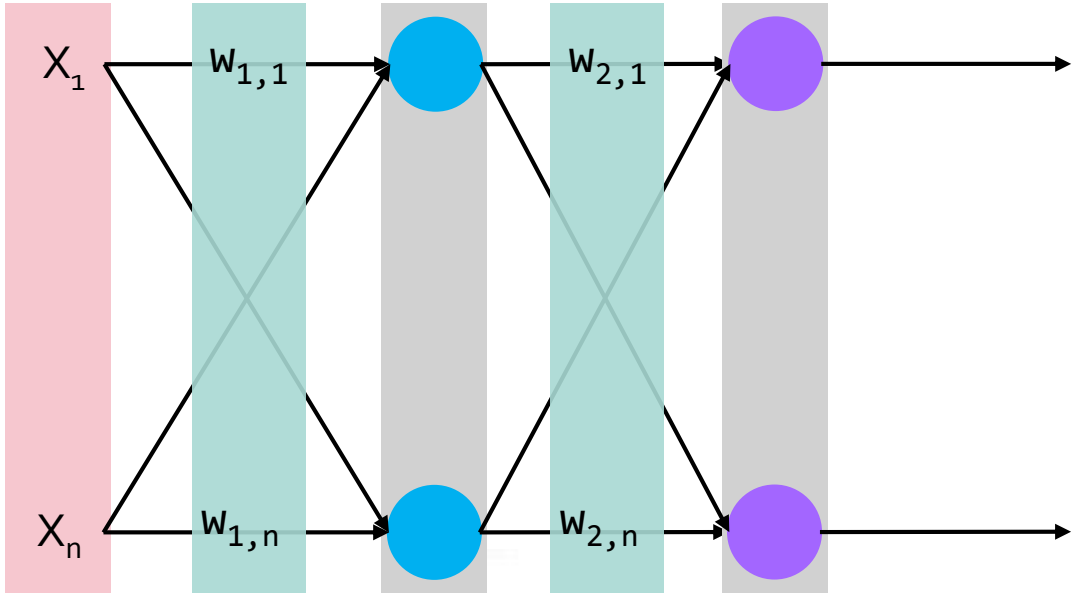
$z = w_1x_1+w_2x_2+\ldots\ldots+w_nx_n+b$

$\hat{y} = z = (-1)*5+3*2+3 = 4$

Θ: weights, bias

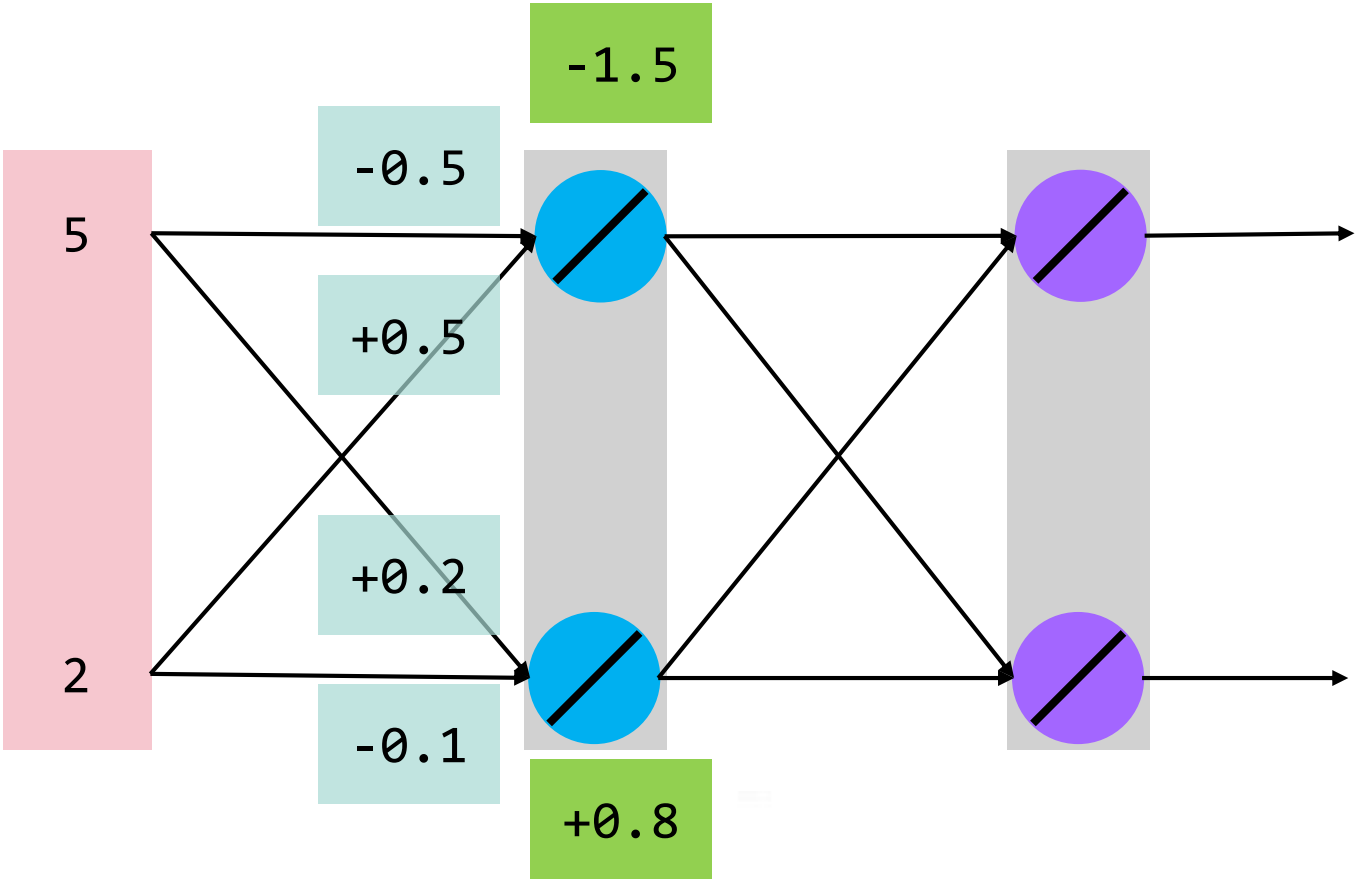
Fully Connected Neural Network

- 很多個 neurons 連接成 network
- Universality theorem: a network with enough number of neurons can present any function



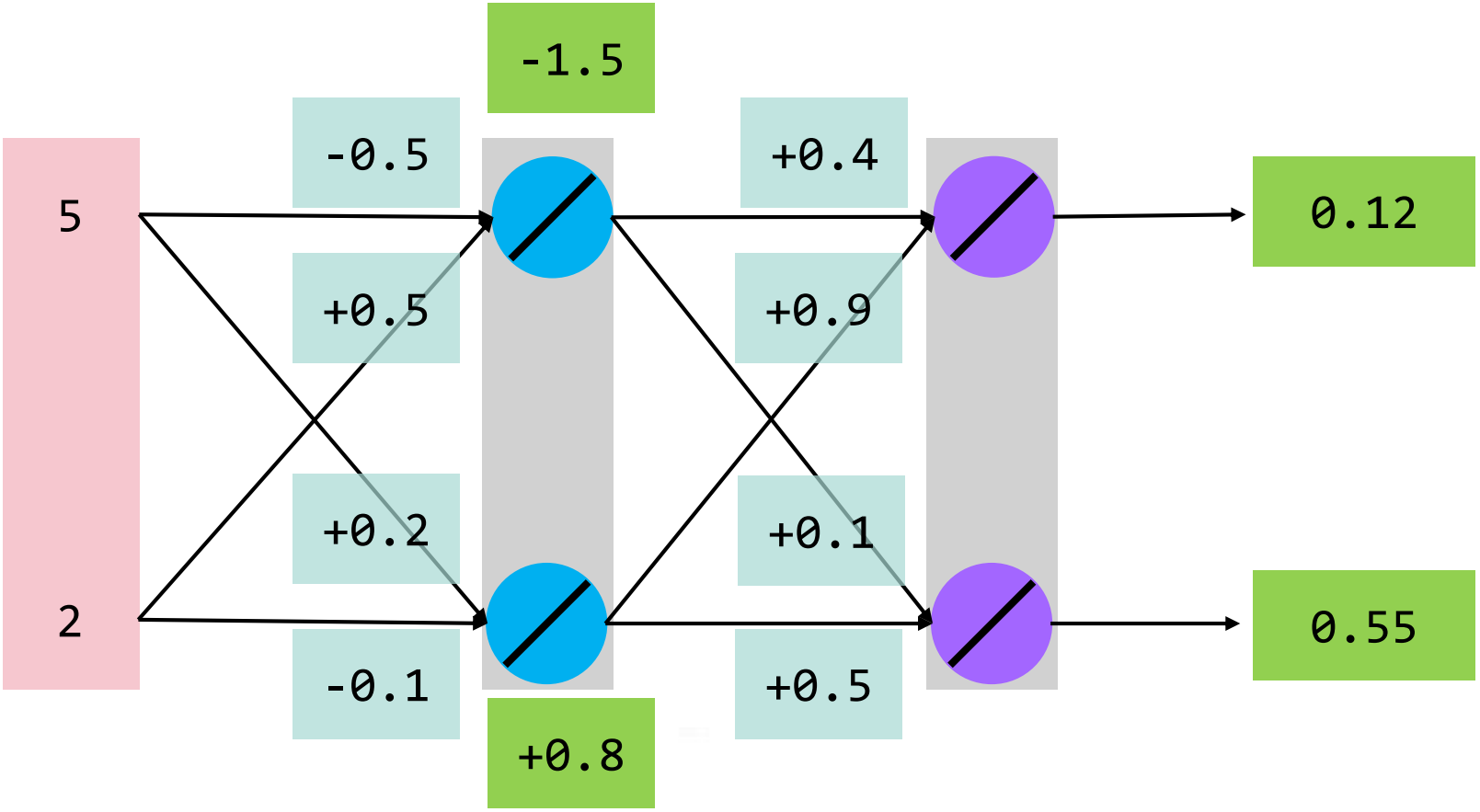
Fully Connected Neural Network

- A simple network with linear activation functions

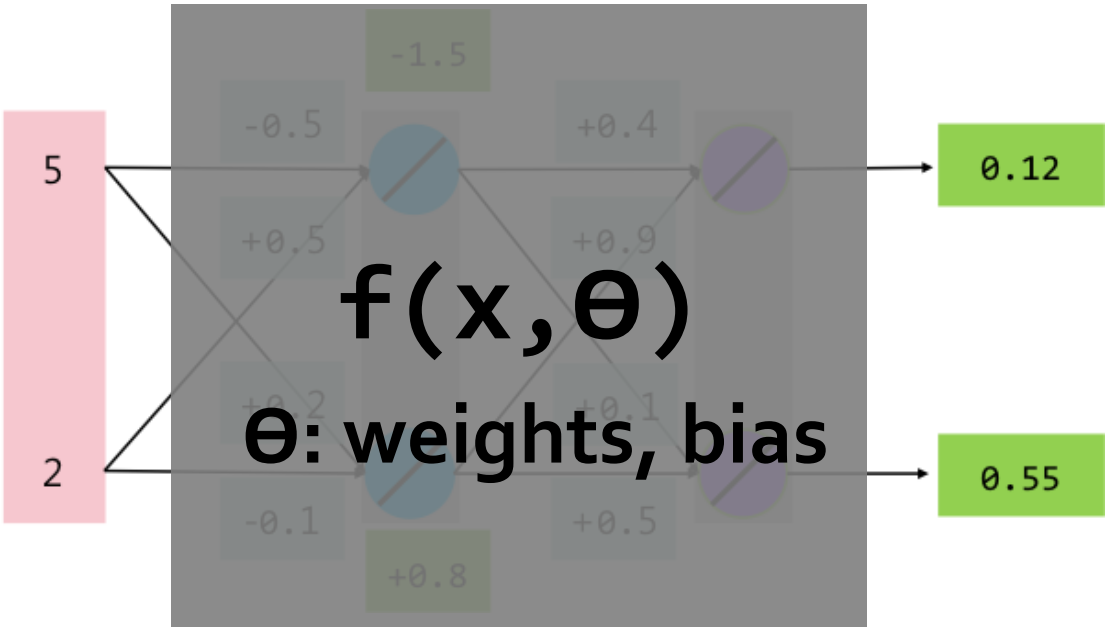


Fully Connected Neural Network

- A simple network with linear activation functions



給定 Network Weights



Given $\begin{bmatrix} -0.5 \\ +0.2 \\ +0.5 \\ -0.1 \end{bmatrix}$ & $\begin{bmatrix} +0.4 \\ +0.9 \\ +0.1 \\ +0.5 \end{bmatrix}$, $f\left(\begin{bmatrix} 5 \\ 2 \end{bmatrix}\right) = \begin{bmatrix} 0.12 \\ 0.55 \end{bmatrix}$

A Neural Network = A Function

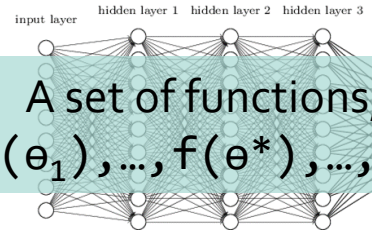
Deep Learning Framework

Define a set of functions

Evaluate and Search

Pick the best function

特定的網絡架構



A set of functions, f(·)

$\{f(\theta_1), \ldots, f(\theta^*), \ldots, f(\theta_n)\}$

不斷修正 f 的參數

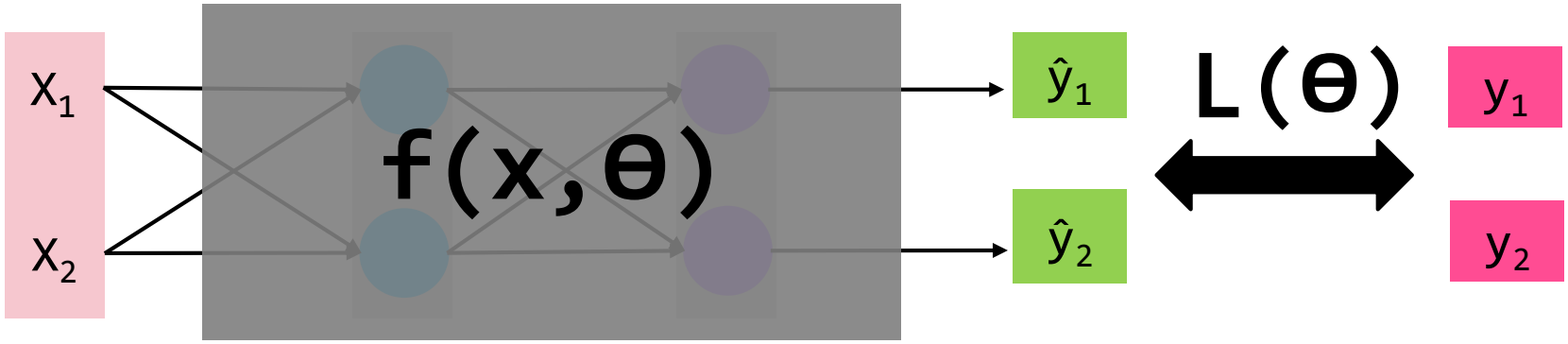
$f(\theta_{94})$ ➔
$f(\theta_{87})$ ➔
$f(\theta_{945})$…

找到最適合的參數

$f(\theta^*)$

如何評估模型好不好？

- output values 跟 actual values 越一致越好



- A loss function is to quantify the gap between network outputs and actual values
- Loss function is a function of **θ**

目標：最佳化 Total Loss

- Find **the best function** that minimize total loss
  - Find the best network weights, θ^*
  - $\theta^* = \underset{\theta}{\operatorname{argmin}} L(\theta)$
- 最重要的問題: 該如何找到 θ^* 呢？
  - 踏破鐵鞋無覓處 (enumerate all possible values)
  - 假設 weights 限制只能 0.0, 0.1, …, 0.9，有 500 個 weights 全部組合就有 10^{500} 組
    - 評估 1 秒可以做 10^6 組，要約 10^{486} 年
    - 宇宙大爆炸到現在才 10^{10} 年
  - Impossible to enumerate

Gradient Descent

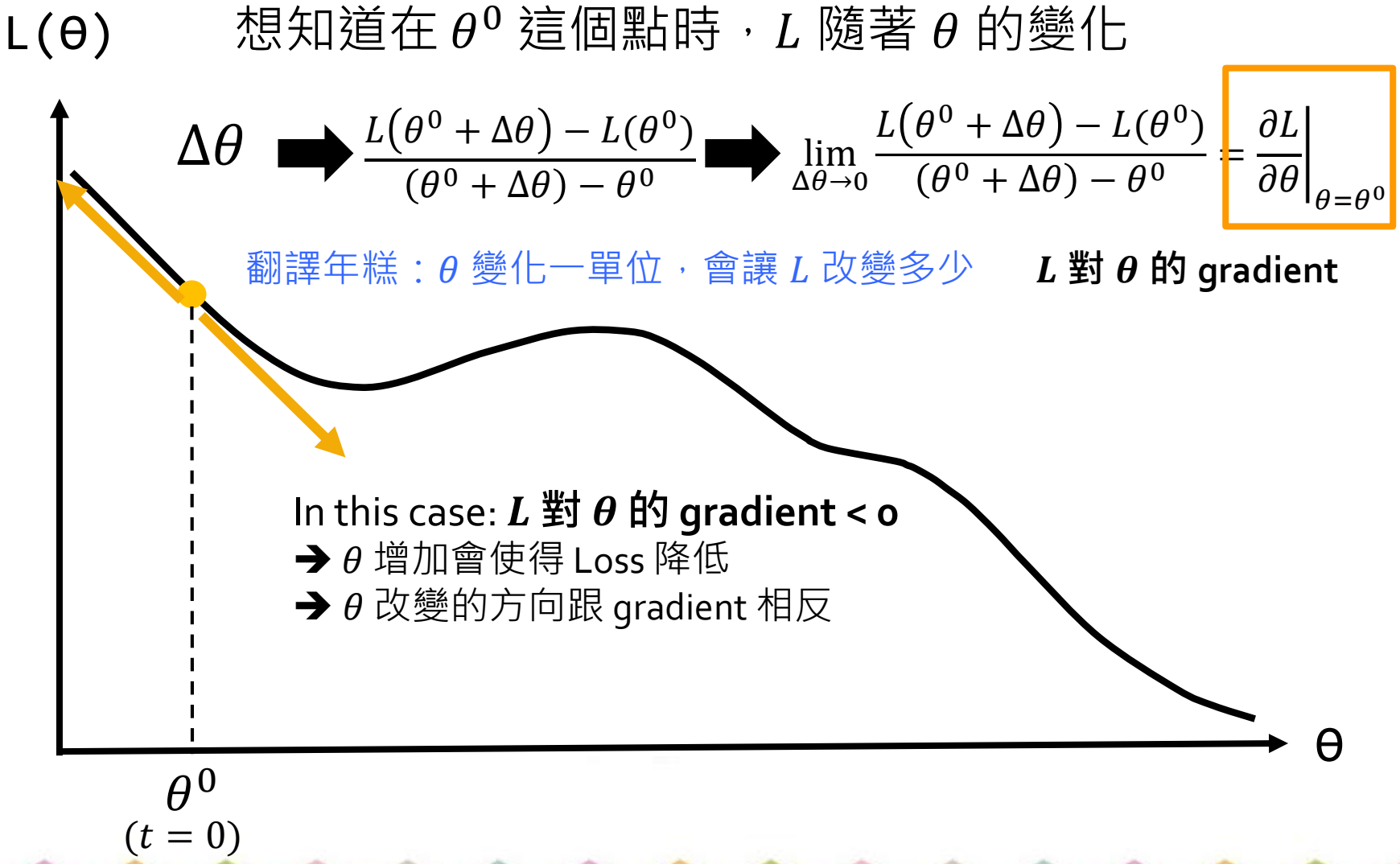
- 一種 heuristic 最佳化方法，適用於連續、**可微**的目標函數
- 核心精神

  每一步都朝著進步的方向，直到沒辦法再進步

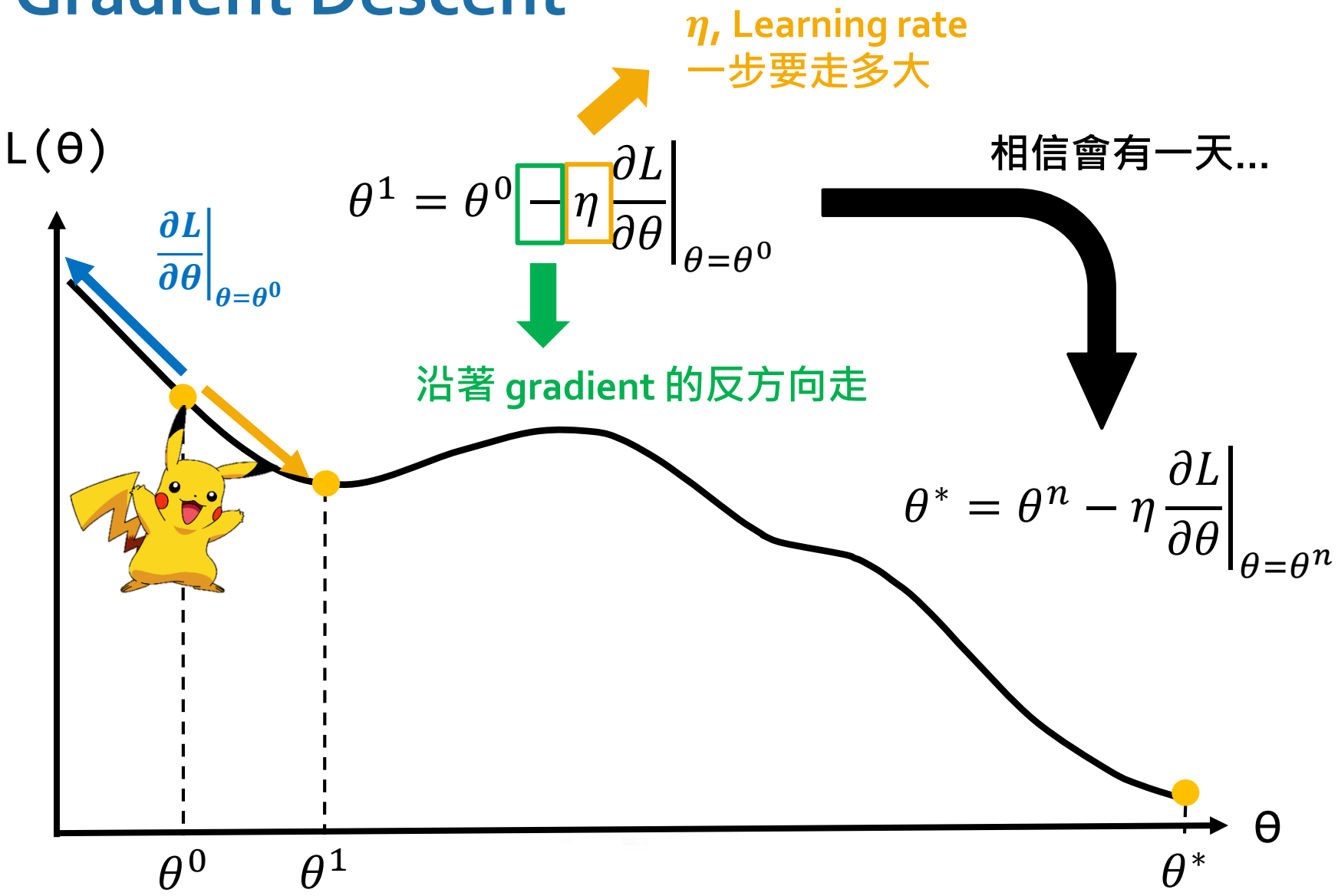
『當有選擇的時候，國家還是要往**進步的方向**前進。』

http://i.imgur.com/xxzpPFN.jpg

Gradient Descent

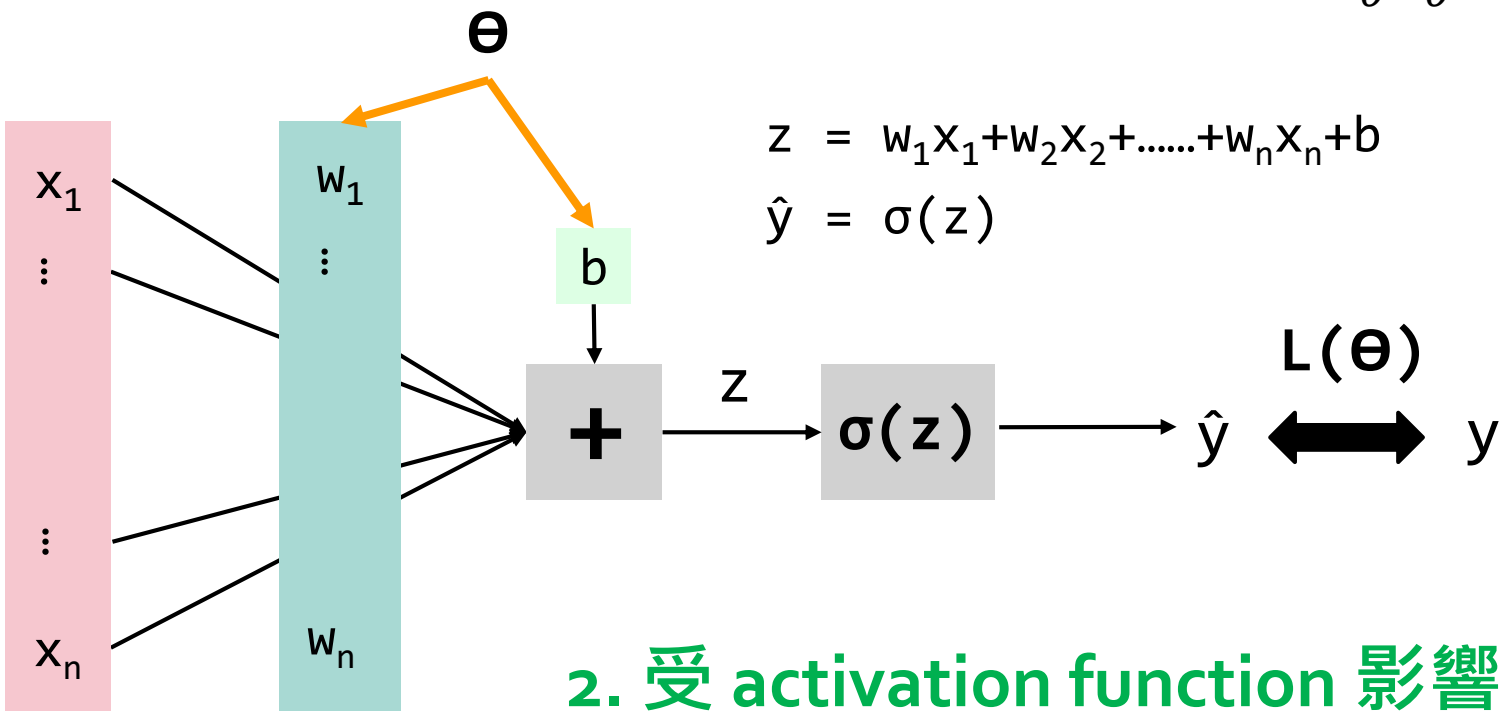


Gradient Descent



影響 Gradient 的因素

$$\theta^1 = \theta^0 - \eta \left.\frac{\partial L}{\partial \theta}\right|_{\theta=\theta^0}$$



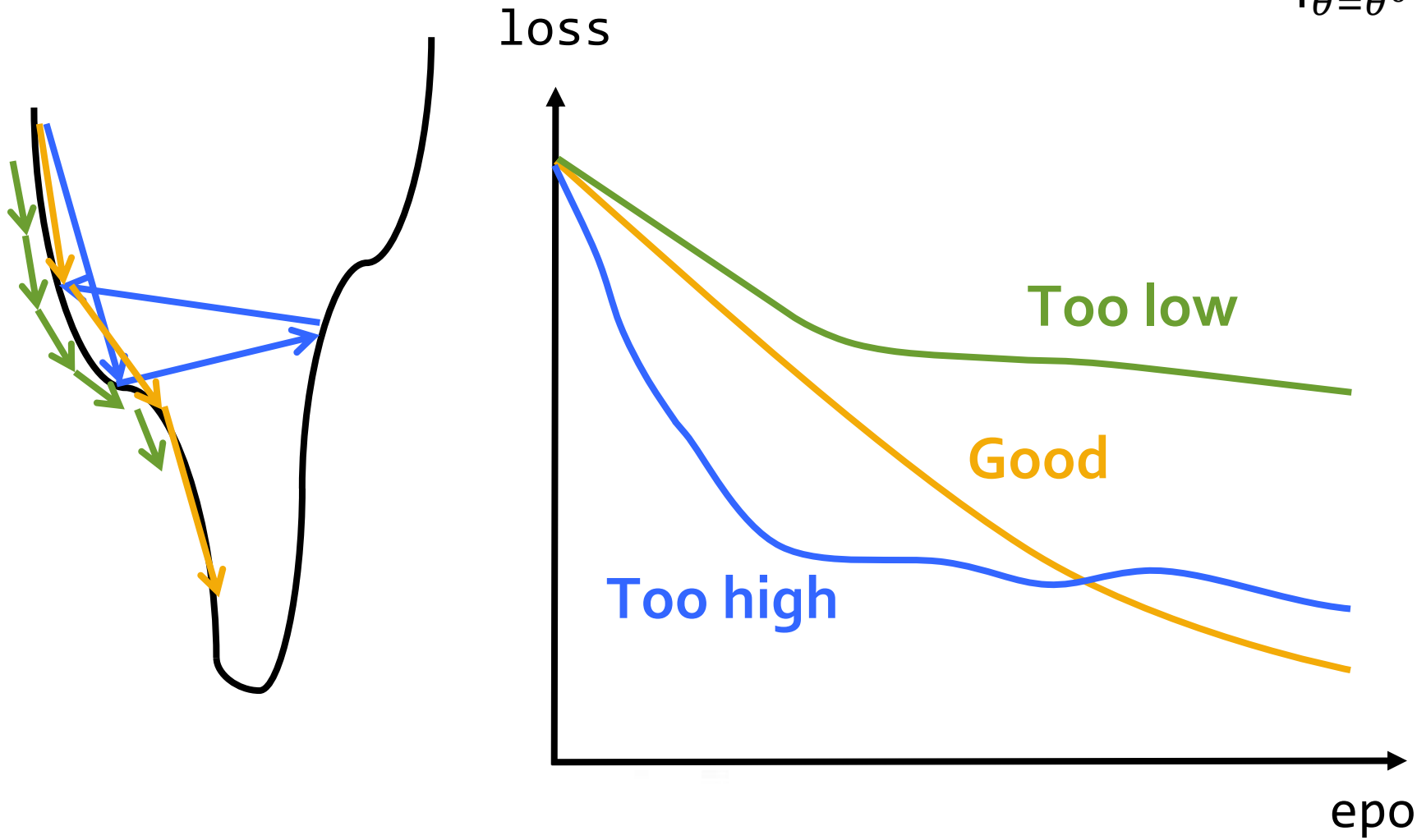
2. 受 activation function 影響

$$\frac{\partial L}{\partial \theta} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \theta} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial \theta}$$

1. 受 loss function 影響

Learning Rate 的影響

$$\theta^1 = \theta^0 - \eta \left.\frac{\partial L}{\partial \theta}\right|_{\theta=\theta^0}$$



Summary – Gradient Descent

- 用來最佳化一個連續的目標函數
- 朝著進步的方向前進
- Gradient descent
  - Gradient 受 loss function 影響
  - Gradient 受 activation function 影響
  - 受 learning rate 影響

Gradient Descent 的缺點

- 一個 epoch 更新一次，收斂速度很慢
  - 一個 epoch 等於看過所有 training data 一次
- Problem 1

  有辦法加速嗎？

  A solution: stochastic gradient descent (SGD)
- Problem 2

  Gradient based method 不能保證找到全域最佳解
  - 可以利用 momentum 降低困在 local minimum 的機率

Gradient Descent 的缺點

- 一個 epoch 更新一次，收斂速度很慢
  - 一個 epoch 等於看過所有 training data 一次
- **Problem 1**

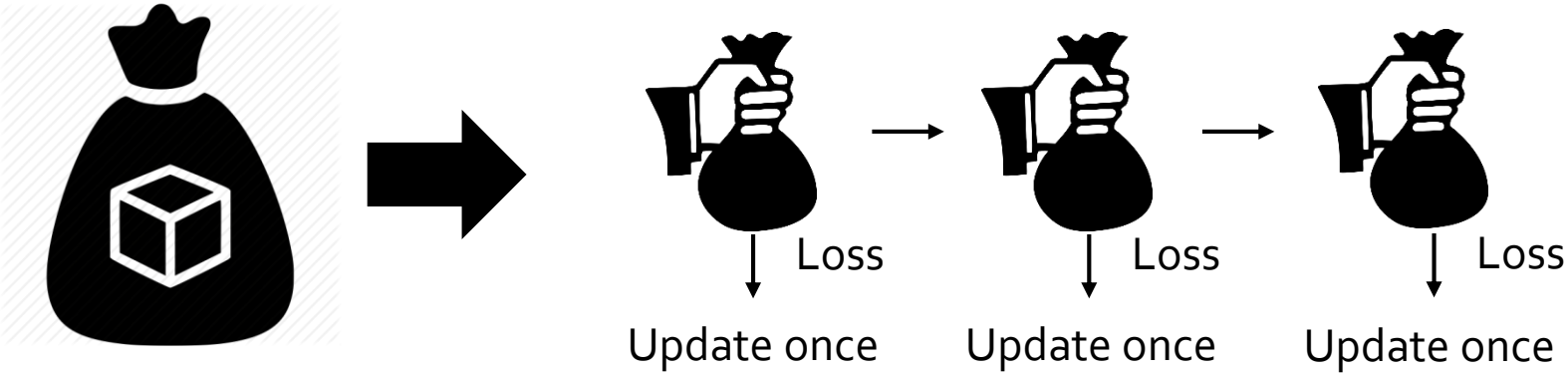
  有辦法加速嗎？

  A solution: stochastic gradient descent (SGD)
- Problem 2

  Gradient based method 不能保證找到全域最佳解
  - 可以利用 momentum 降低困在 local minimum 的機率

Stochastic Gradient Descent

- 隨機抽一筆 training sample，依照其 loss 更新一次
- 另一個問題，一筆一筆更新也很慢
- Mini-batch: **每一個 mini-batch 更新一次**



- Benefits of mini-batch
  - 相較於 SGD: faster to complete one epoch
  - 相較於 GD: faster to converge (to optimum)

Mini-batch vs. Epoch

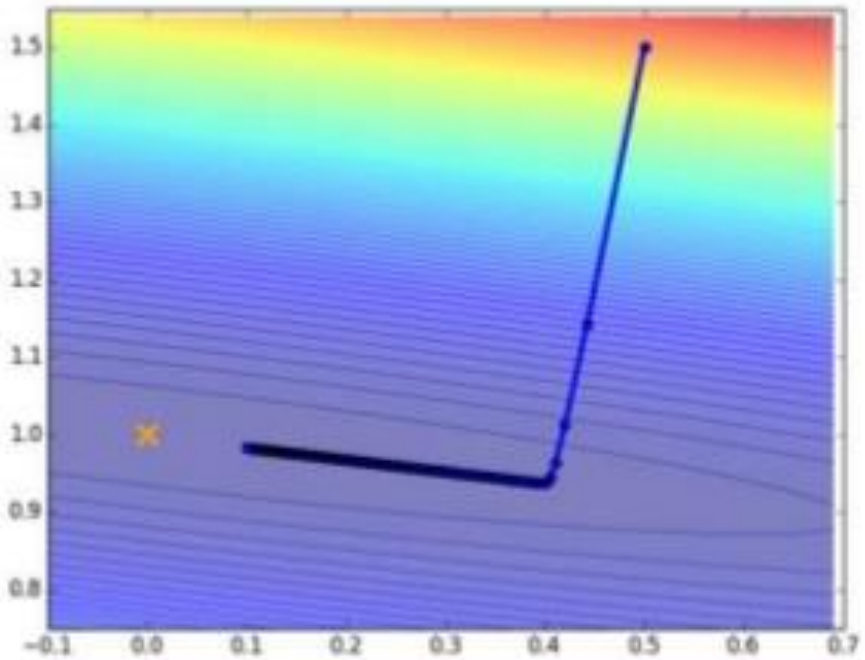
- 一個 epoch = 看完所有 training data 一次
- 依照 mini-batch 把所有 training data 拆成多份
- 假設全部有 1000 筆資料
  - Batch size = 100 可拆成 10 份 ➔ 一個 epoch 內會更新 10 次
  - Batch size = 10 可拆成 100 份 ➔ 一個 epoch 內會更新 100 次
- 如何設定 batch size?
  - 不要設太大，常用 28, 32, 128, 256, …

(Slide Credit: Hung-Yi Lee)

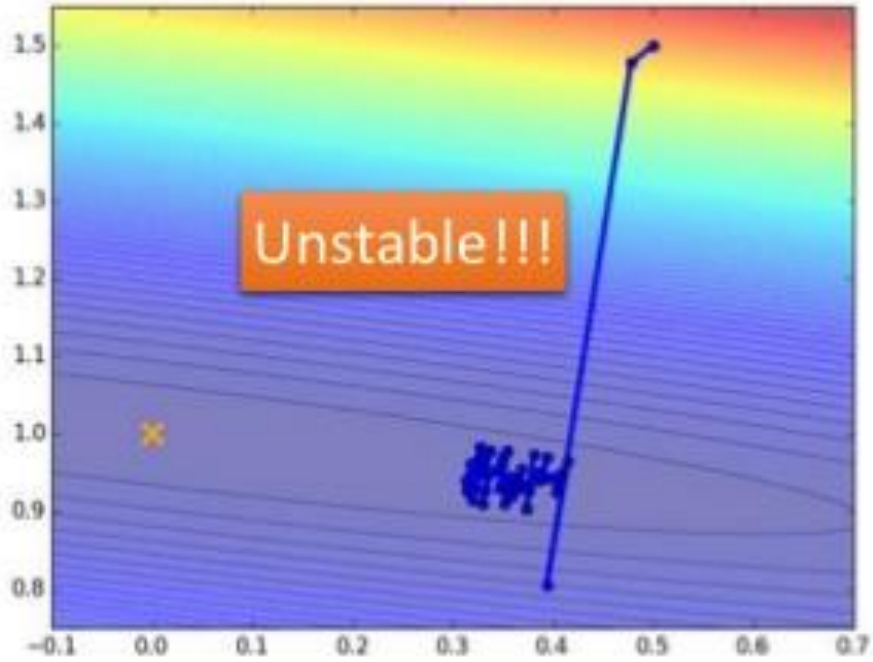
Mini-batch 的影響

- 本質上已經不是最佳化 total loss 而是在最佳化 batch loss

Gradient Descent



Mini-batch



Gradient Descent 的缺點

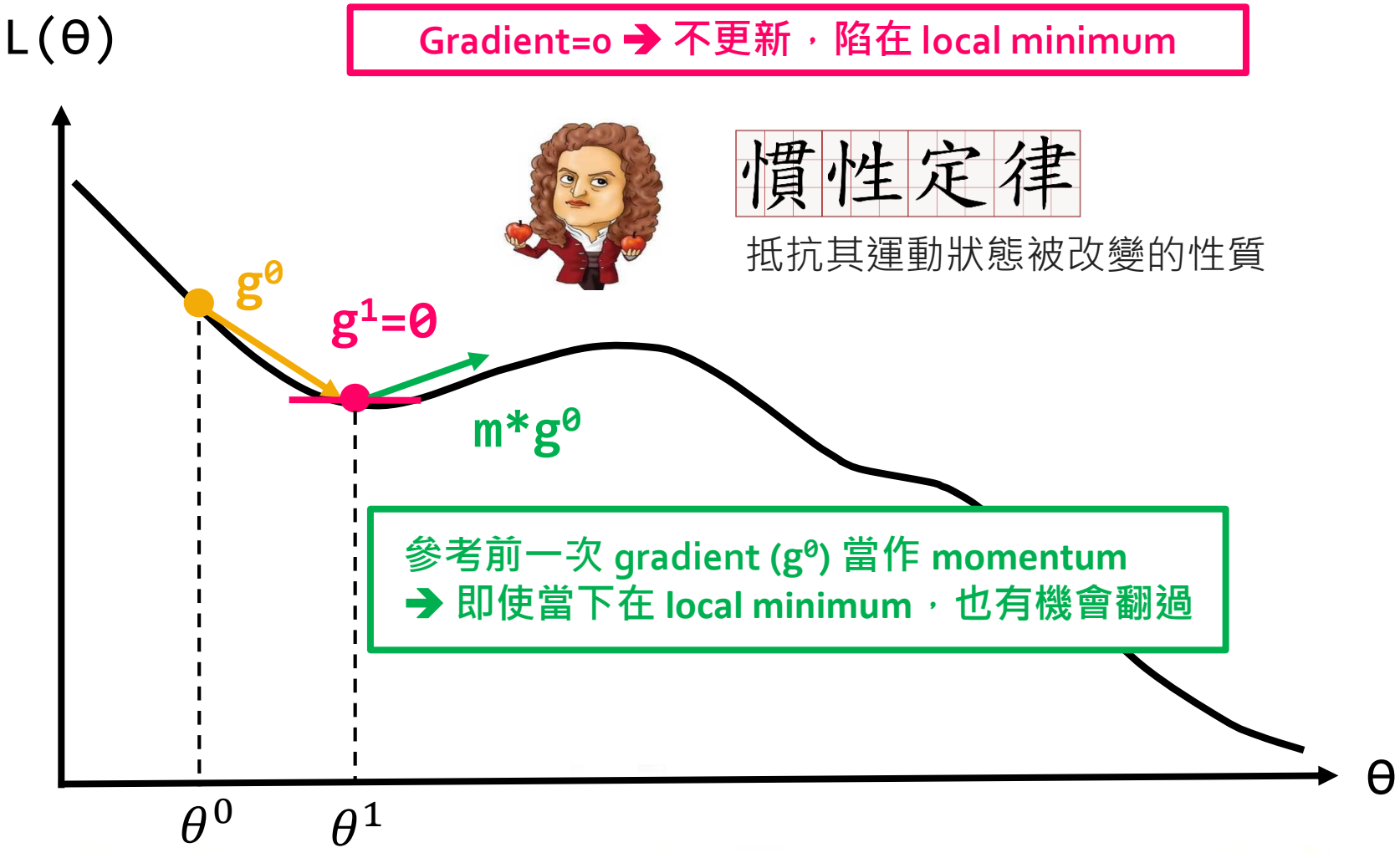
- 一個 epoch 更新一次，收斂速度很慢
  - 一個 epoch 等於看過所有 training data 一次
- Problem 1

  有辦法加速嗎？

  A solution: stochastic gradient descent (SGD)
- **Problem 2**

  Gradient based method 不能保證找到全域最佳解
  - **可以利用 momentum 降低困在 local minimum 的機率**

Momentum

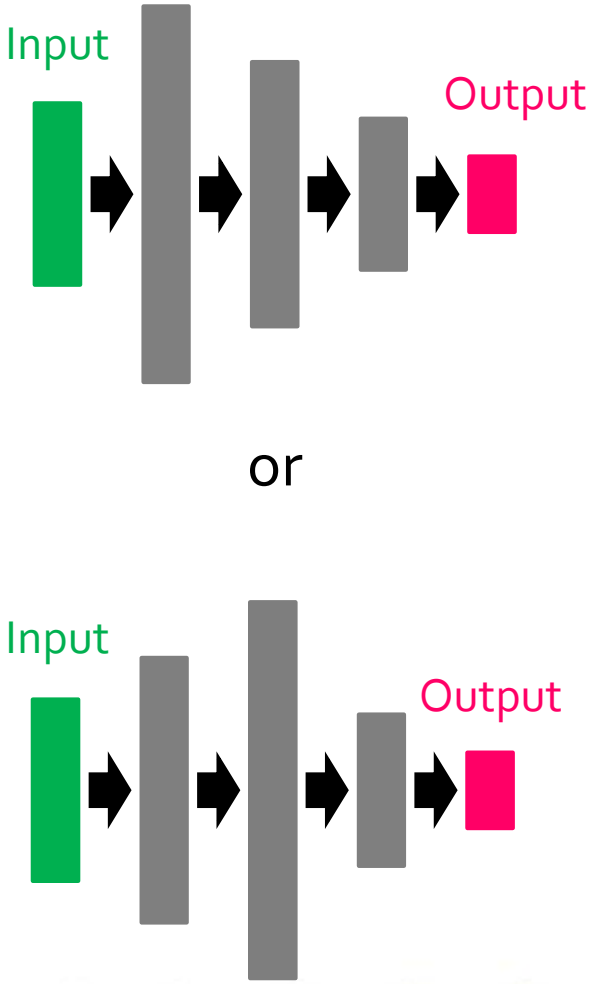

L(θ)
Gradient=o ➔ 不更新，陷在 local minimum
慣性定律
抵抗其運動狀態被改變的性質
g^0
$g^1=0$
$m*g^0$
參考前一次 gradient (g^0) 當作 momentum
➔ 即使當下在 local minimum，也有機會翻過
θ
θ^0
θ^1

Introduction of Deep Learning

- Artificial neural network
- Activation functions
- Loss functions
- Gradient descent
  - Loss function, activation function, learning rate
- Stochastic gradient descent
- Mini-batch
- Momentum

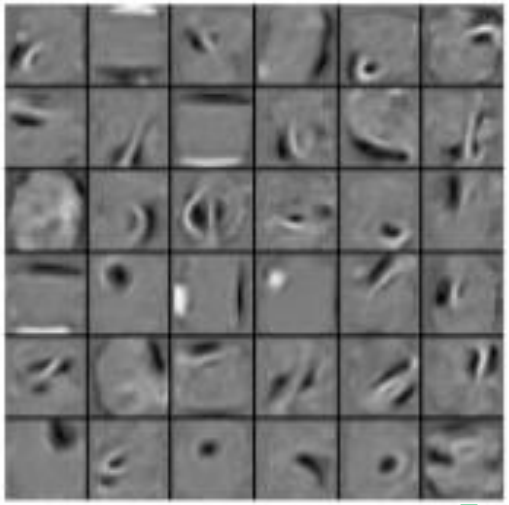
Frequently Asked Questions

- 要有幾層 hidden layers？
- 每層幾個 neurons？
  - Neurons 多寡跟資料多寡有關
  - Intuition + trial and error
- 深會比較好嗎？
  - Deep for modulation

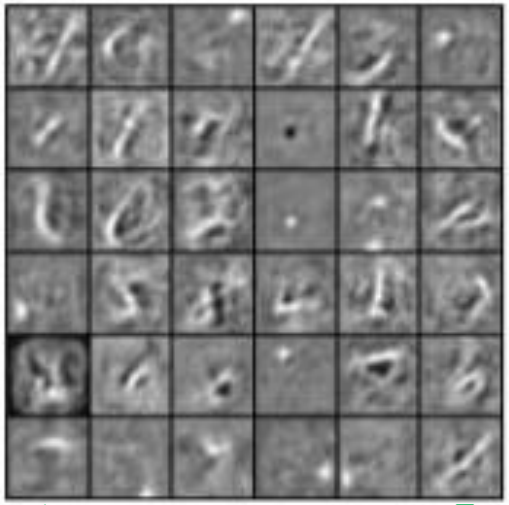


Visualization of Modulation

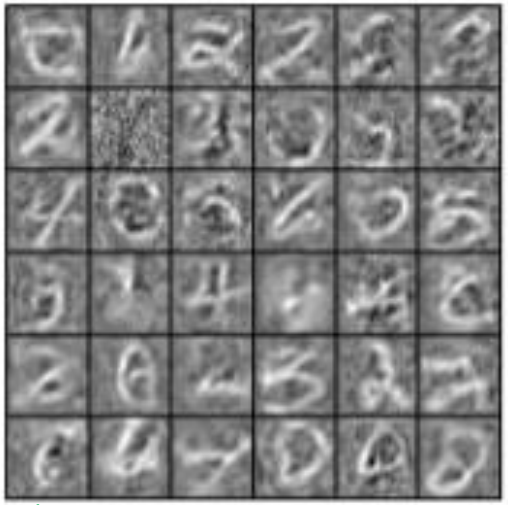
1st hidden layer



2nd hidden layer



3rd hidden layer

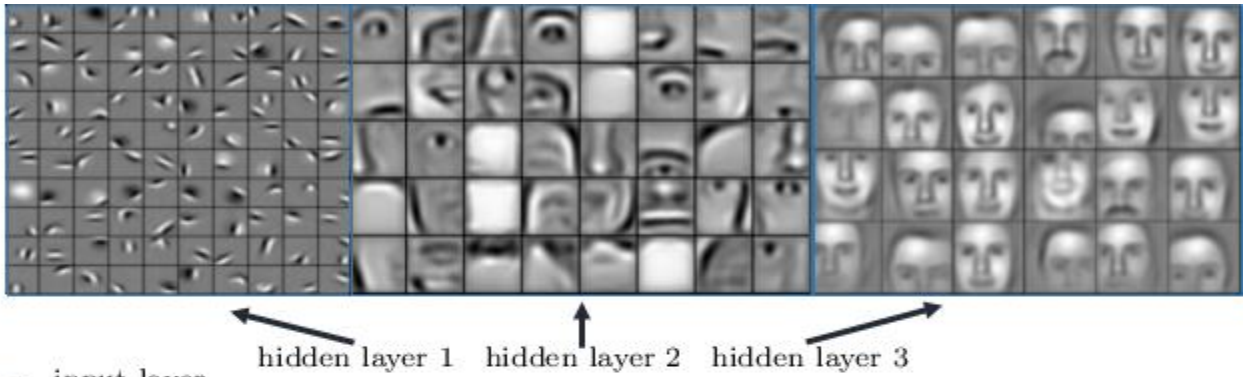


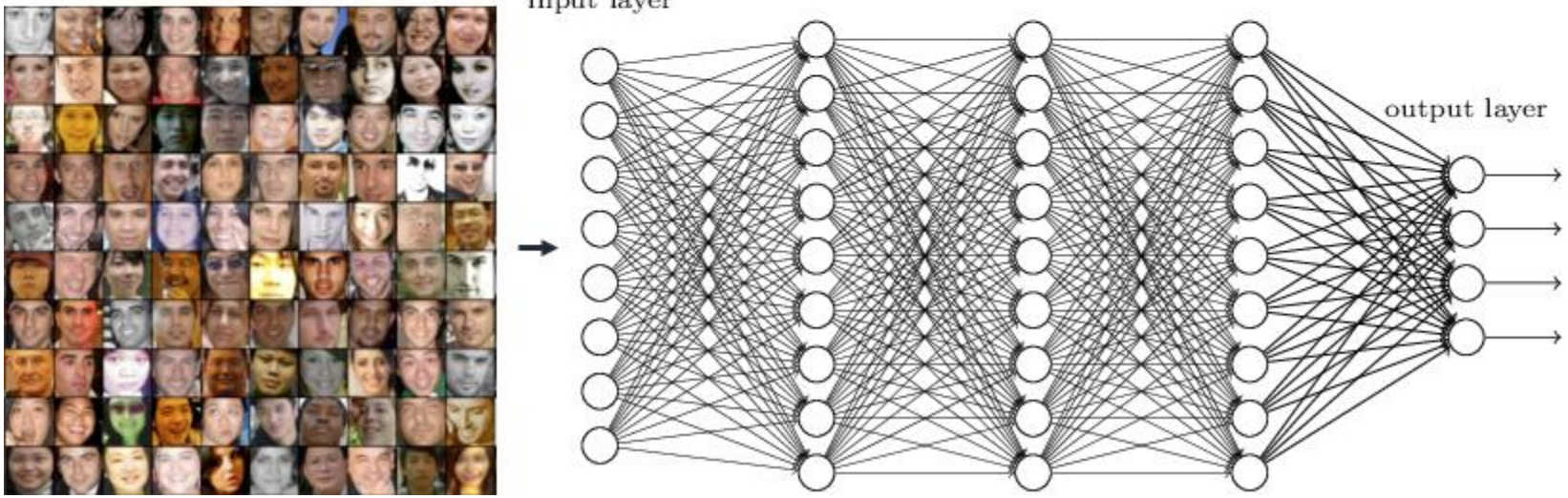
各司其職、由簡馭繁，組織出越來越複雜的 feature extractors

Ref: Visualizing Higher-Layer Features of a Deep Network

Visualization of Modulation

Deep neural networks learn hierarchical feature representations





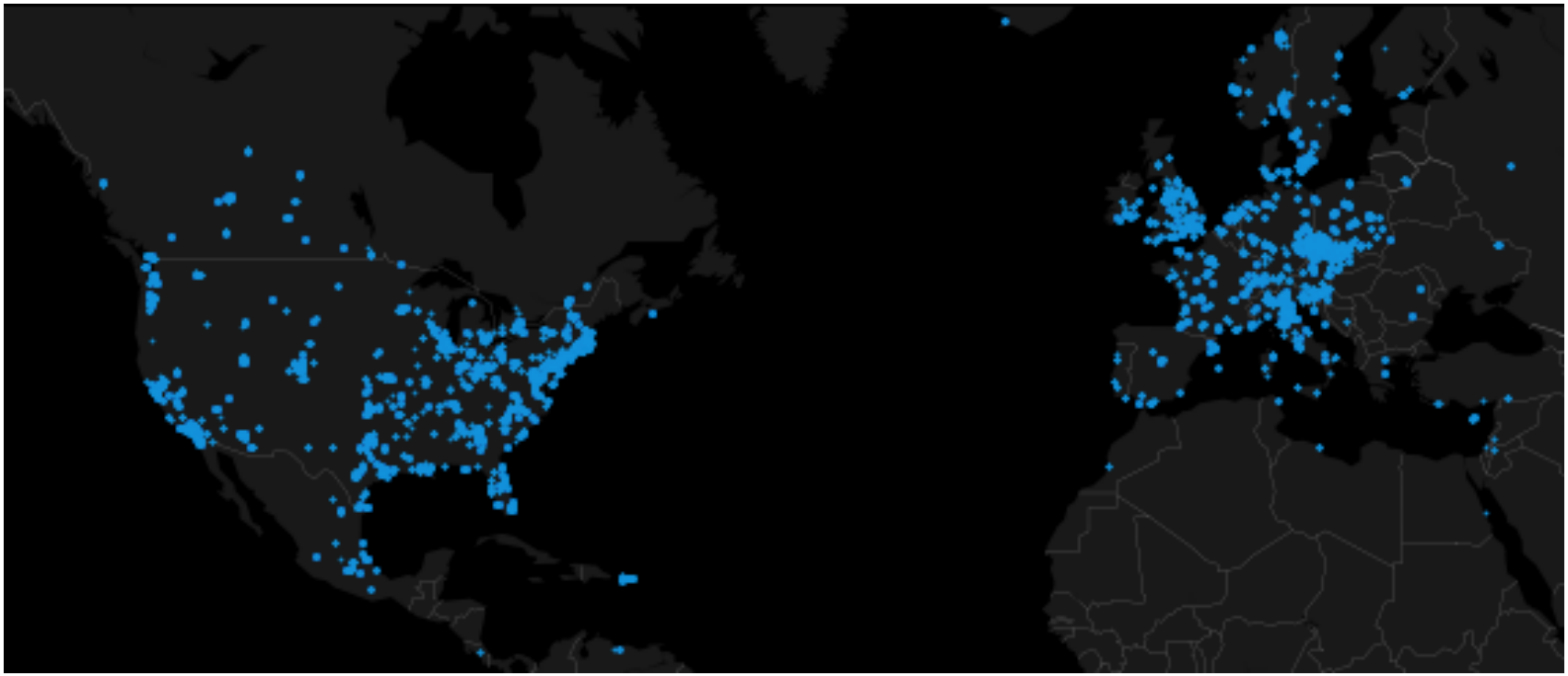
Ref: Deep Learning and Convolutional Neural Networks: RSIP Vision Blogs

Hands-on Tutorial

寶可夢雷達 using Pokemon Go Dataset on Kaggle

範例資料

- 寶可夢過去出現的時間與地點紀錄 (dataset from Kaggle)



Ref: https://www.kaggle.com/kostyabahshetsyan/d/semioniy/predictemall/pokemon-geolocation-visualisations/notebook

Raw Data Overview

latitude	longitude	appearedTimeOfDay	appearedYear	terrainType	closeToWater	city	weather	temperature	windSpeed	·····	cooc_151	class
20.525745	-97.460829	night	2016	14	0	Mexico_City	Foggy	25.5	4.79	·····	0	16
20.523695	-97.461167	night	2016	14	0	Mexico_City	Foggy	25.5	4.79	·····	0	133
38.90359	-77.19978	night	2016	13	0	New_York	Clear	24.2	4.29	·····	0	16
47.665903	-122.312561	night	2016	0	1	Los_Angeles	PartlyClou	15.6	5.84	·····	0	13
47.666454	-122.311628	night	2016	0	1	Los_Angeles	PartlyClou	15.6	5.84	·····	0	133
-31.95498	115.853609	night	2016	13	0	Perth	PartlyClou	16.5	6.39	·····	0	21
-31.954245	115.852038	night	2016	13	0	Perth	PartlyClou	16.5	6.4	·····	0	66
26.235257	-98.197591	night	2016	13	0	Chicago	Clear	28	11.26	·····	0	27
20.525554	-97.4588	night	2016	14	0	Mexico_City	Foggy	25.5	4.79	·····	0	35
32.928558	-84.340278	night	2016	8	0	New_York	Clear	23.7	3.94	·····	0	19
32.930646	-84.339867	night	2016	8	0	New_York	Clear	23.7	3.94	·····	0	116
32.943651	-84.334443	night	2016	8	0	New_York	Clear	23.7	3.94	·····	0	74
26.235552	-98.197249	night	2016	13	0	Chicago	Clear	28	11.26	·····	0	16
20.52577	-97.460237	night	2016	14	0	Mexico_City	Foggy	25.5	4.79	·····	0	19
26.236029	-98.196908	night	2016	13	0	Chicago	Clear	28	11.26	·····	0	19
47.664333	-122.312645	night	2016	0	1	Los_Angeles	PartlyClou	15.6	5.84	·····	0	19
20.526489	-97.460745	night	2016	14	0	Mexico_City	Foggy	25.5	4.79	·····	0	16
53.611417	-113.369528	night	2016	12	0	Edmonton	Clear	8.9	1.47	·····	0	13

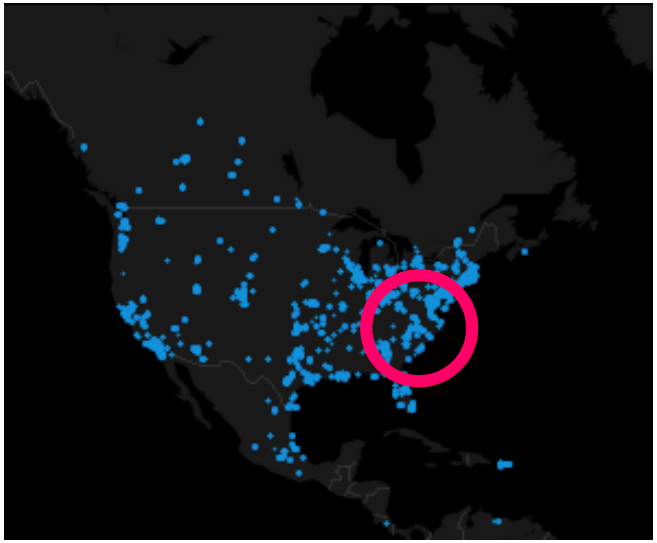
問題: 會出現哪一隻神奇寶貝呢？

寶可夢雷達 Data Field Overview

- 時間: local.hour, local.month, DayofWeek…
- 天氣: temperature, windSpeed, pressure…
- 位置: longitude, latitude, pokestop…
- 環境: closeToWater, terrainType…
- 十分鐘前有無出現其他寶可夢
  - 例如: cooc_1=1 十分鐘前出現過 class=1 之寶可夢
- class 就是我們要預測目標

Sampled Dataset for Fast Training

- 挑選在 New York City 出現的紀錄



- 挑選下列五隻常見的寶可夢

No.4 小火龍

No.43 走路草

No.56 火爆猴

No. 71 喇叭芽

No.98 大鉗蟹

開始動手囉！Keras Go！

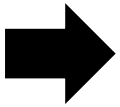
Input 前處理

- 因為必須跟 weights 做運算
  Neural network 的輸入必須為數值 (numeric)
- 如何處理非數值資料？
  - 順序資料
  - 名目資料
- 不同 features 的數值範圍差異會有影響嗎？
  - 溫度: 最低 0 度、最高 40 度
  - 距離: 最近 0 公尺、最遠 10000 公尺

處理順序資料

- Ordinal variables (順序資料)
  - For example: {Low, Medium, High}
  - Encoding in order
    - {Low, Medium, High} ➔ {1,2,3}
- Create a new feature using mean or median

UID	Age
P1	0-17
P2	0-17
P3	55+
P4	26-35



UID	Age
P1	15
P2	15
P3	70
P4	30

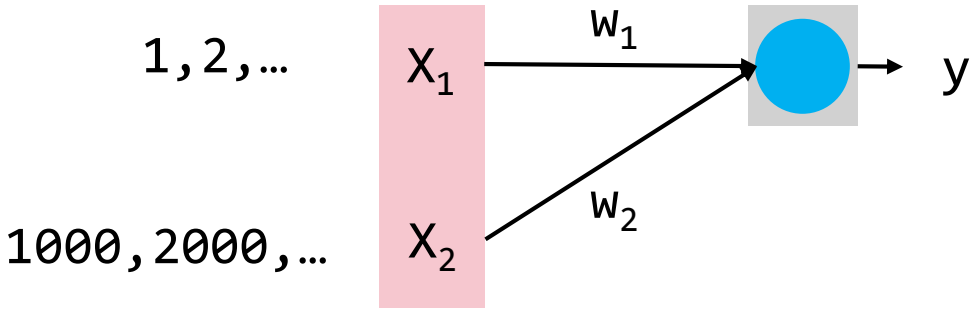
處理名目資料

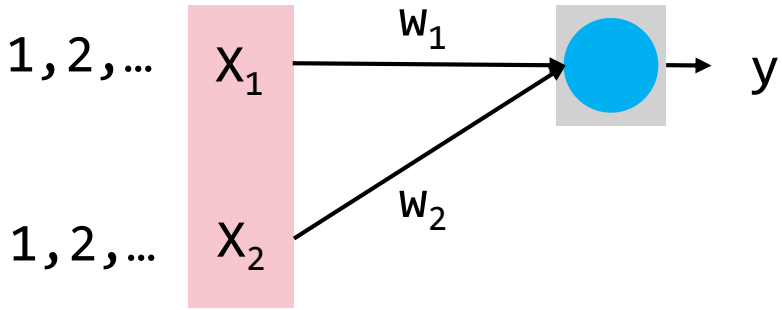
- Nominal variables (名目資料)
  - {"SugarFree","Half","Regular"}
  - One-hot encoding
    - 假設有三個類別
    - Category 1 ➔ [1,0,0]
    - Category 2 ➔ [0,1,0]
  - 給予類別上的解釋 ➔ Ordinal variables
    - {"SugarFree","Half","Regular"} ➔ 1,2,3
  - 特殊的名目資料：地址
    - 台北市南港區研究院路二段128號

    ➔ 轉成經緯度 {25.04,121.61}

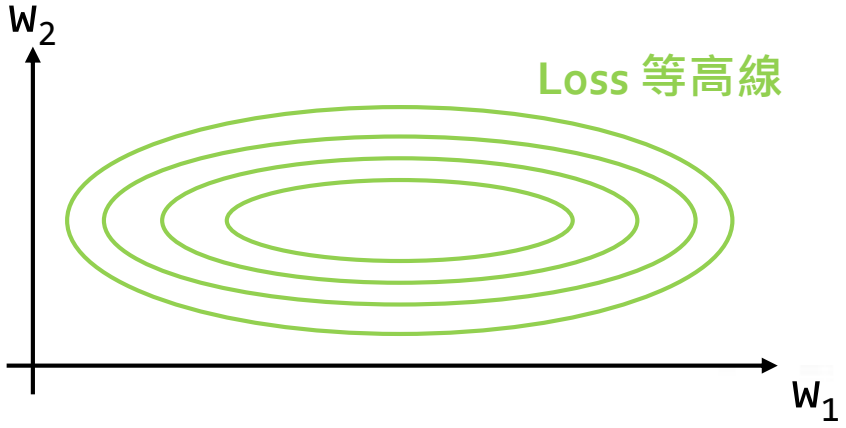
處理不同的數值範圍

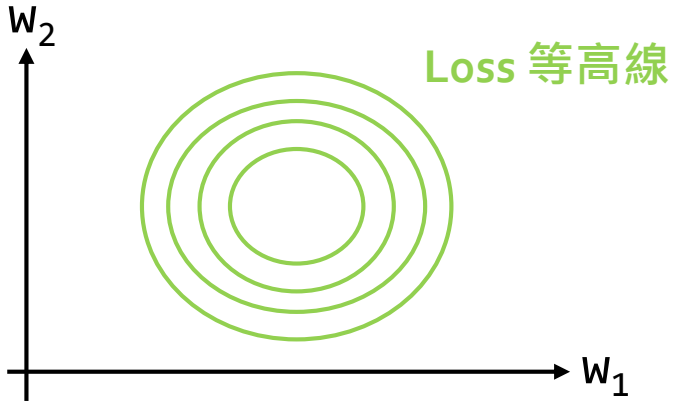
- 先說結論：建議 re-scale！但為什麼？





w_2 的修正(ΔW)對於 loss 的影響比較大

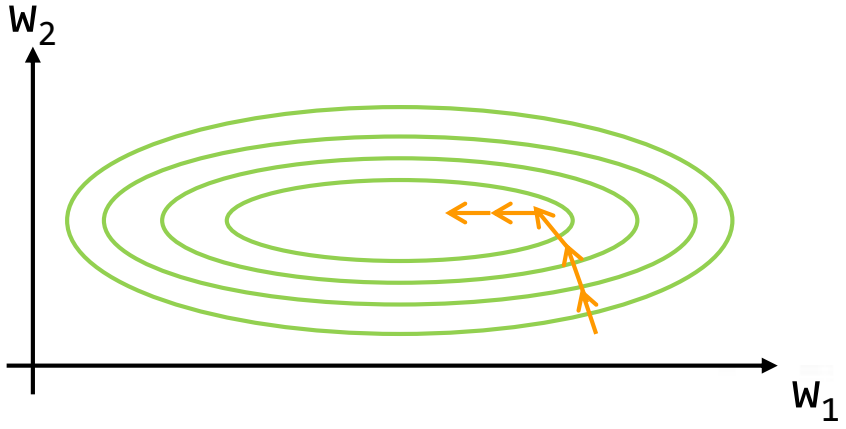


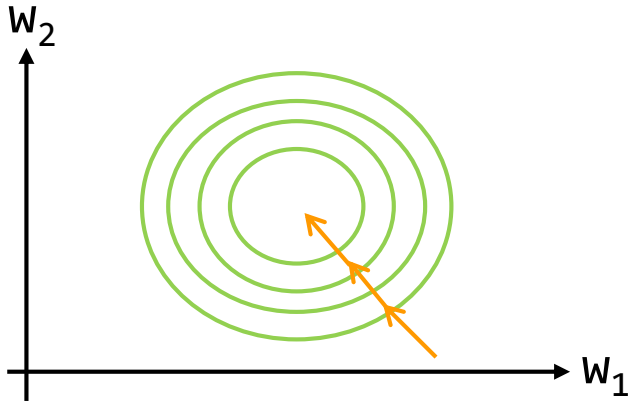


處理不同的數值範圍

- 影響訓練的過程
  - 不同 scale 的 weights 修正時會需要不同的 learning rates
    - 不用 adaptive learning rate 是做不好的
  - 在同個 scale 下，loss 的等高線會較接近圓形

    ➔ gradient 的方向會指向圓心 (最低點)





小提醒

- 輸入 (input) 只能是數值
- 名目資料、順序資料
  - One-hot encoding
  - 順序轉成數值
- 建議 re-scale 到接近的數值範圍

- 今天的資料都已經先幫大家做好了 ☺

Read Input File

```
import numpy as np

# 讀進檔案，以 , (逗號)分隔的 csv 檔，不包含第一行的欄位定義
my_data = np.genfromtext('pkgo_city66_class5_v1.csv',
                         delimiter=',',
                         skip_header=1)

# Input  是有 200 個欄位(index 從 0 – 199)
X_train = my_data[:,0:200]

# Output 是第 201 個欄位(index 為 200)
y_train = my_data[:,200]

# 確保資料型態正確
X_train = X_train.astype('float32')
y_train = y_train.astype('int')
```

Input

```
# 觀察一筆 X_train
print(X_train[1,:32])
```

```
print(X_train[1,:32])
```

```
[  7.32567608e-02  -7.03223109e-01   9.00000000e+00   8.00000000e+00
   2.00000000e+00   5.00000000e+01   4.50000000e+01   4.00000000e+00
   4.00000000e+00   5.00000000e+01   1.00000000e+00   8.00000000e+00
   8.00000000e+00   1.30000000e+01   0.00000000e+00   6.60000000e+01
   2.00000000e+00   5.00000000e+00   5.11728227e-01  -1.19994007e-01
   2.61039048e-01   4.33402471e-02   1.20537996e+00   1.83238339e+00
  -1.39905763e+00   1.12362671e+00   6.24226868e-01  -8.81169885e-02
   1.41916251e+00  -1.14249873e+00  -4.79164541e-01   0.00000000e+00]
```

Output 前處理

- Keras 預定的 class 數量與值有關
  - 挑選出的寶可夢中，最大 Pokemon ID = 98
    Keras 會認為『有 99 個 classes 分別為 Class 0, 1, 2, …, 98 class』
  - zero-based indexing (python)
- 把下面的五隻寶可夢轉換成

No.4 小火龍

Class 0

No.43 走路草

Class 1

No.56 火爆猴

Class 2

No. 71 喇叭芽

Class 3

No.98 大鉗蟹

Class 4

Output

```
# 觀察一筆 y_train
print(y_train[0])
```

```
y_train[0]
```

```
1
```

```
# [重要] 將 Output 從特定類別轉換成 one-hot encoding 的形式
from keras.utils import np_utils
Y_train = np_utils.to_categorical(y_train,5)

# 轉換成 one-hot encoding 後的 Y_train
print(Y_train[1,:])
```

```
Y_train[0,:]
```

```
array([ 0.,  1.,  0.,  0.,  0.])
```

接下來的流程

- 先建立一個深度學習模型

就像開始冒險前要先選一隻寶可夢

- 邊移動邊開火

六步完模 – 建立深度學習模型

1. 決定 hidden layers 層數與其中的 neurons 數量
2. 決定該層使用的 activation function
3. 決定模型的 loss function
4. 決定 optimizer
   - Parameters: learning rate, momentum, decay
5. 編譯模型 (Compile model)
6. 開始訓練囉！(Fit model)

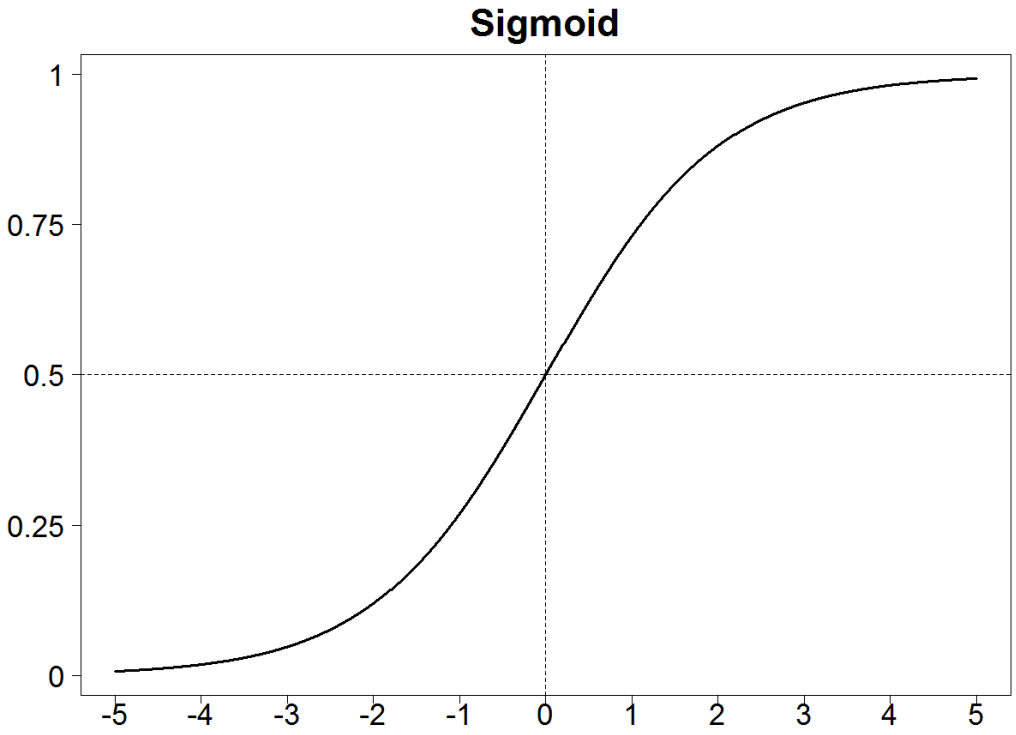
步驟 1+2: 模型架構

```
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.optimizers import SGD

# 宣告這是一個 Sequential 次序性的深度學習模型
model = Sequential()

# 加入第一層 hidden layer (128 neurons)
# [重要] 因為第一層 hidden layer 需連接 input vector
         故需要在此指定 input_dim
model.add(Dense(128, input_dim=200))
```

Model 建構時，是以次序性的疊加 (add) 上去

基本款 activation function

- Sigmoid function

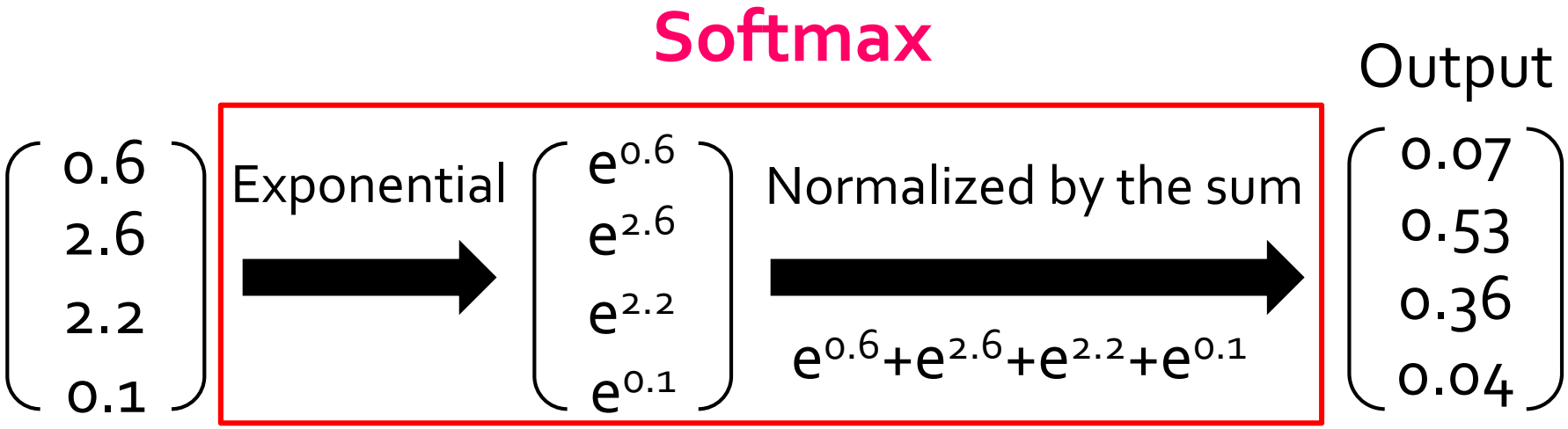


步驟 1+2: 模型架構 (Cont.)

```
# 宣告這是一個 Sequential 次序性的深度學習模型
model = Sequential()

# 加入第一層 hidden layer (128 neurons) 與指定 input 的維度
model.add(Dense(128, input_dim=200))
# 指定 activation function
model.add(Activation('sigmoid'))

# 加入第二層 hidden layer (256 neurons)
model.add(Dense(256))
model.add(Activation('sigmoid'))

# 加入 output layer (5 neurons)
model.add(Dense(5))
model.add(Activation('softmax'))

# 觀察 model summary
model.summary()
```

Softmax

- Classification 常用 softmax 當 output 的 activation function



- Normalization: network output 轉換到[0,1] 之間且 softmax output 相加為 1 ➔ 像 "機率"
- 保留對其他 classes 的 prediction error

Model Summary

Layer (type)	Output Shape	Param #	Connected to
dense_10 (Dense)	(None, 128)	25728	dense_input_4[0][0]
activation_10 (Activation)	(None, 128)	0	dense_10[0][0]
dense_11 (Dense)	(None, 256)	33024	activation_10[0][0]
activation_11 (Activation)	(None, 256)	0	dense_11[0][0]
dense_12 (Dense)	(None, 5)	1285	activation_11[0][0]
activation_12 (Activation)	(None, 5)	0	dense_12[0][0]

Total params: 60037

可以設定 Layer 名稱

```
# 另外一種寫法
model.add(Dense(5,activation='softmax',name='output'))

# 觀察 model summary
model.summary()
```

```
Layer (type)                 Output Shape              Param #   Connected to
=================================================================================
1st hidden layer (Dense)     (None, 128)               25728     dense_input_8[0][0]
_________________________________________________________________________________
2nd hidden layer (Dense)     (None, 256)               33024     1st hidden layer[0][0]
_________________________________________________________________________________
output (Dense)               (None, 5)                 1285      2nd hidden layer[0][0]
=================================================================================
Total params: 60037
```

步驟 3: 選擇 loss function

Prediction	Answer
0.8	0.9
0.2	0.1

- Mean_squared_error

$$\frac{(0.9-0.8)^2+(0.1-0.2)^2}{2}=0.01$$

- Mean_absolute_error

$$\frac{|0.9-0.8|+|0.1-0.2|}{2}=0.1$$

常用於 Regression

- Mean_absolute_percentage_error

$$\frac{|0.9-0.8|/|0.9|+|0.1-0.2|/|0.1|}{2}*100=55$$

- Mean_squared_logarithmic_error

$$\frac{[\log(0.9)-\log(0.8)]^2+[\log(0.1)-\log(0.2)]^2}{2}*100=0.247$$

Loss Function

Prediction	Answer
0.9	0
0.1	1

- binary_crossentropy (logloss)

$$-\frac{1}{N}\sum_{n=1}^{N}[y_n \log(\widehat{y_n}) + (1-y_n)\log(1-\widehat{y_n})]$$

$$-\frac{1}{2}[0\log(0.9) + (1-0)\log(1-0.9) + 1\log(0.1) + 0\log(1-0.1)]$$

$$= -\frac{1}{2}[\log(0.1) + \log(0.1)] = -\log(0.1) = 2.302585$$

- categorical_crossentropy
  - 需要將 class 的表示方法改成 one-hot encoding

    `Category 1` ➔ `[0,1,0,0,0]`

  - 用簡單的函數 keras.np_utils.to_category(input)
- 常用於 classification

步驟 4: 選擇 optimizer

- SGD – Stochastic Gradient Descent
- Adagrad – Adaptive Learning Rate
- RMSprop – Similar with Adagrad
- Adam – Similar with RMSprop + Momentum
- Nadam – Adam + Nesterov Momentum

SGD: 基本款 optimizer

- Stochastic gradient descent
- 設定 learning rate, momentum, learning rate decay, Nesterov momentum

```
# 指定 optimizier
from keras.optimizers import SGD, Adam, RMSprop, Adagrad
sgd = SGD(lr=0.01,momentum=0.0,decay=0.0,nesterov=False)
```

- 設定 Learning rate by experiments (later)

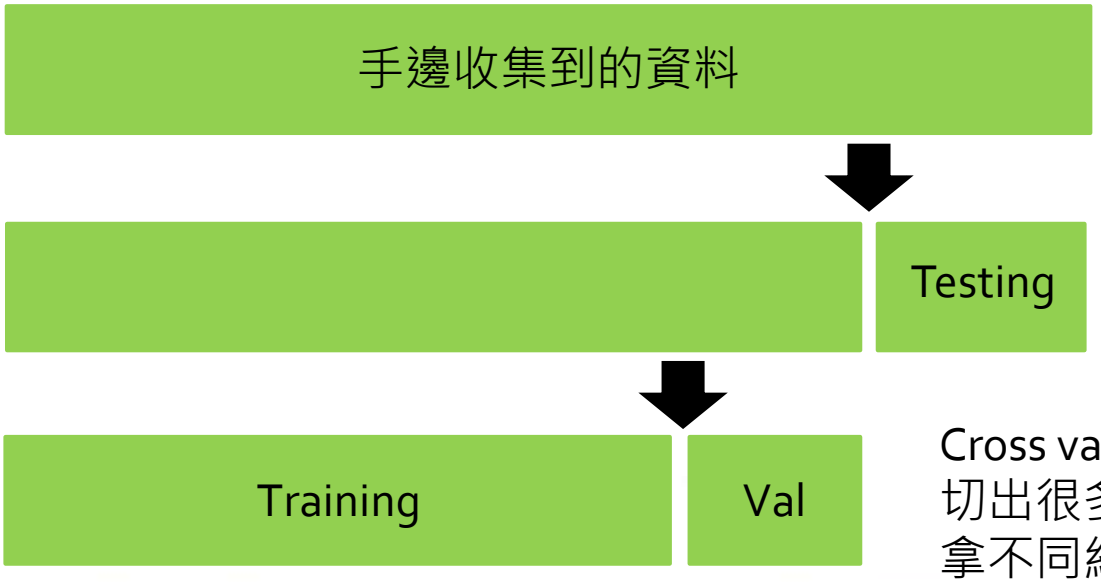
就決定是你了!

```
# 指定 loss function 和 optimizier
model.compile(loss='categorical_crossentropy',
              optimizer=sgd)
```

Validation Dataset

- Validation dataset 用來挑選模型
- Testing dataset 檢驗模型的普遍性 (generalization)
  避免模型過度學習 training dataset

理論上



挑選出最好的模型後，拿 testing 檢驗 generalization

Cross validation:
切出很多組的 (training, validation) 再拿不同組訓練模型，挑選最好的模型

Validation Dataset

- 利用 model.fit 的參數 validation_split
  - 從輸入(X_train,Y_train) 取固定比例的資料作為 validation
  - 不會先 shuffle 再取 validation dataset
  - 固定從資料尾端開始取
  - 每個 epoch 所使用的 validation dataset 都相同

- 手動加入 validation dataset

  validation_data=(X_valid, Y_valid)

Fit Model

```
# 指定 batch_size, nb_epoch, validation 後，開始訓練模型!!!
history = model.fit( X_train,
                     Y_train,
                     batch_size=16,
                     verbose=0,
                     epochs=30,
                     shuffle=True,
                     validation_split=0.1)
```

- batch_size: min-batch 的大小
- nb_epoch: epoch 數量
  - 1 epoch 表示看過全部的 training dataset 一次
- shuffle: 每次 epoch 結束後是否要打亂 training dataset
- verbose: 是否要顯示目前的訓練進度，0 為不顯示

練習 oo_firstModel.py (5 minutes)

Alternative: Functional API

- The way to go for defining a complex model
  - For example: multiple outputs, multiple input source
- Why "Functional API" ?
  - All layers and models are callable (like function call)

```
from keras.layers import Input, Dense

input  = Input(shape=(200,))
output = Dense(10)(input)
```

  - Example

```
#  Sequential (依序的)深度學習模型
model = Sequential()
model.add(Dense(128, input_dim=200))
model.add(Activation('sigmoid'))
model.add(Dense(256))
model.add(Activation('sigmoid'))
model.add(Dense(5))
model.add(Activation('softmax'))
model.summary()
```

```
#  Functional API
from keras.layers import Input, Dense
from keras.models import Model

input = Input(shape=(200,))
x = Dense(128,activation='sigmoid')(input)
x = Dense(256,activation='sigmoid')(x)
output = Dense(5,activation='softmax')(x)

# 定義 Model (function-like)
model = Model(inputs=[input], outputs=[output])
```

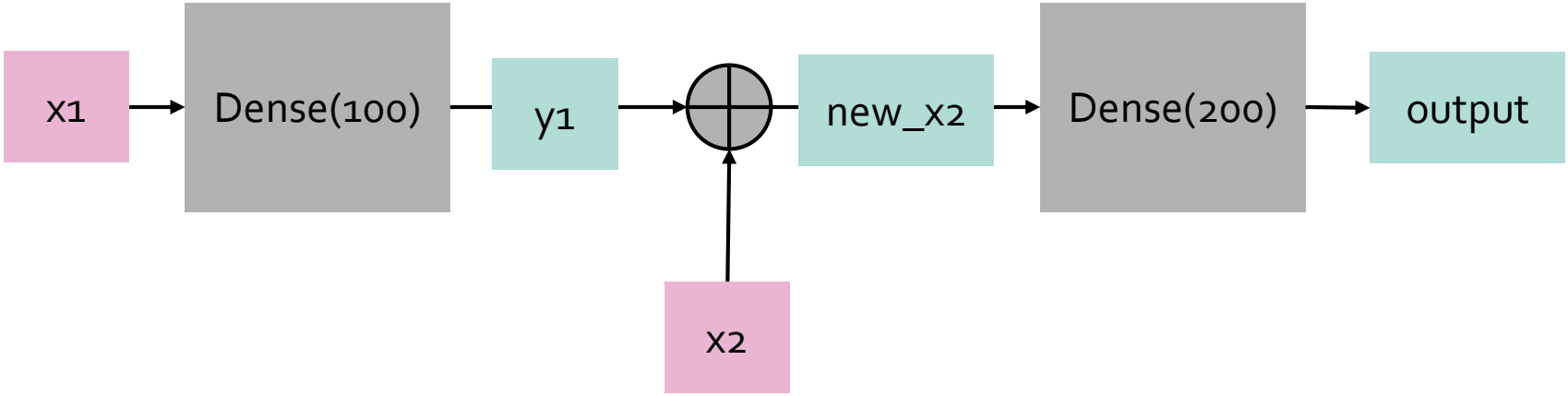
Good Use Case for Functional API (1)

- Model is callable as well, so it is easy to re-use the trained model
  - Re-use the architecture and weights as well

```
# If model and input is defined already
# re-use the same architecture of the above model
y1 = model(input)
```

Good Use Case for Functional API (2)

- Easy to manipulate various input sources

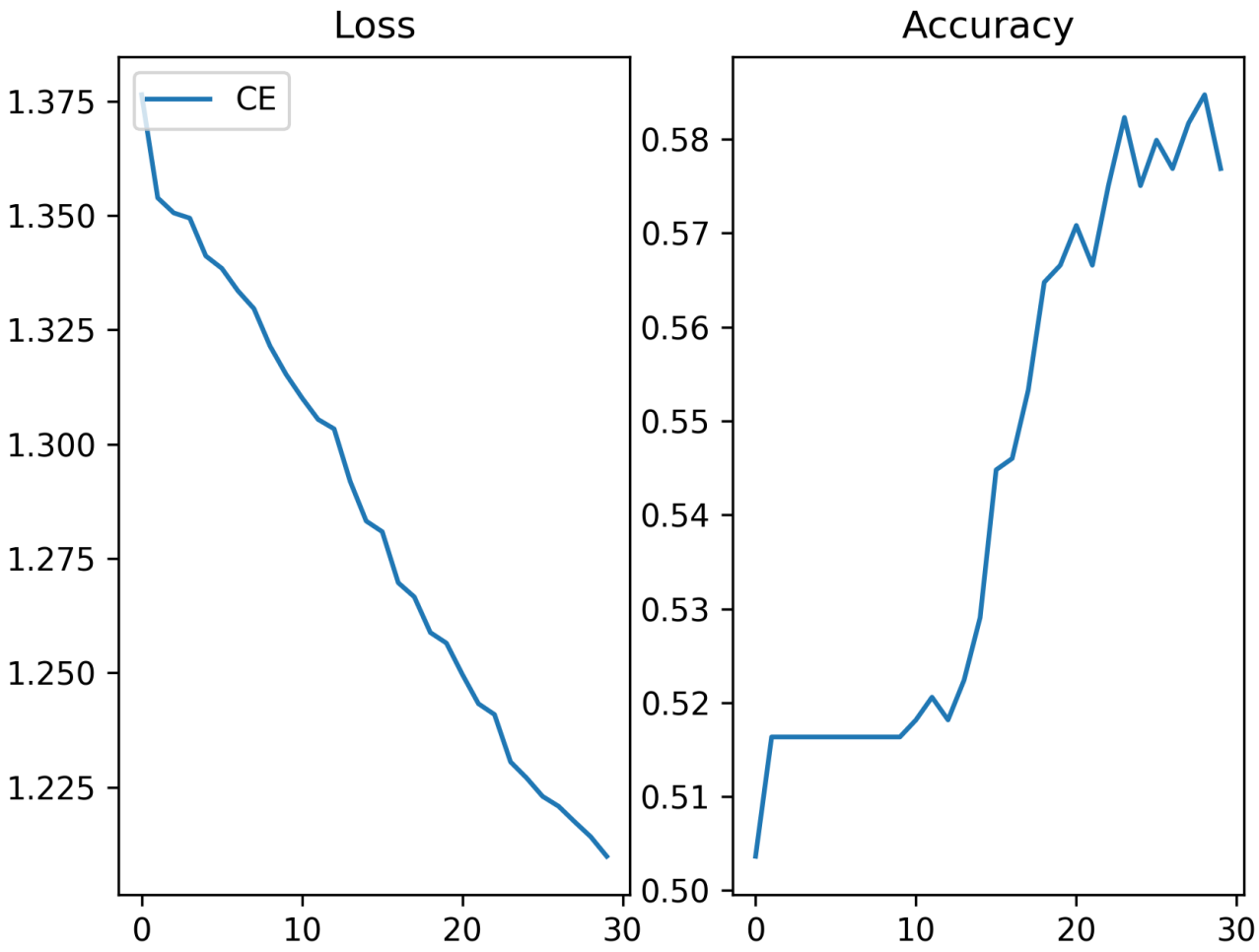



```
x1 = input(shape=(10,))
y1 = Dense(100)(x1)

x2 = input(shape=(20,))
new_x2 = keras.layers.concatenate([y1,x2])
output = Dense(200)(new_x2)

Model = Model(inputs=[x1,x2],outputs=[output])
```

Today

- Our exercise uses “Sequential” model because it is more straight-forward to understand the details of stacking layers

Result


Loss
CE
1.375
1.350
1.325
1.300
1.275
1.250
1.225
0
10
20
30
Accuracy
0.58
0.57
0.56
0.55
0.54
0.53
0.52
0.51
0.50
0
10
20
30

這樣是好是壞？

- 我們選用最常見的

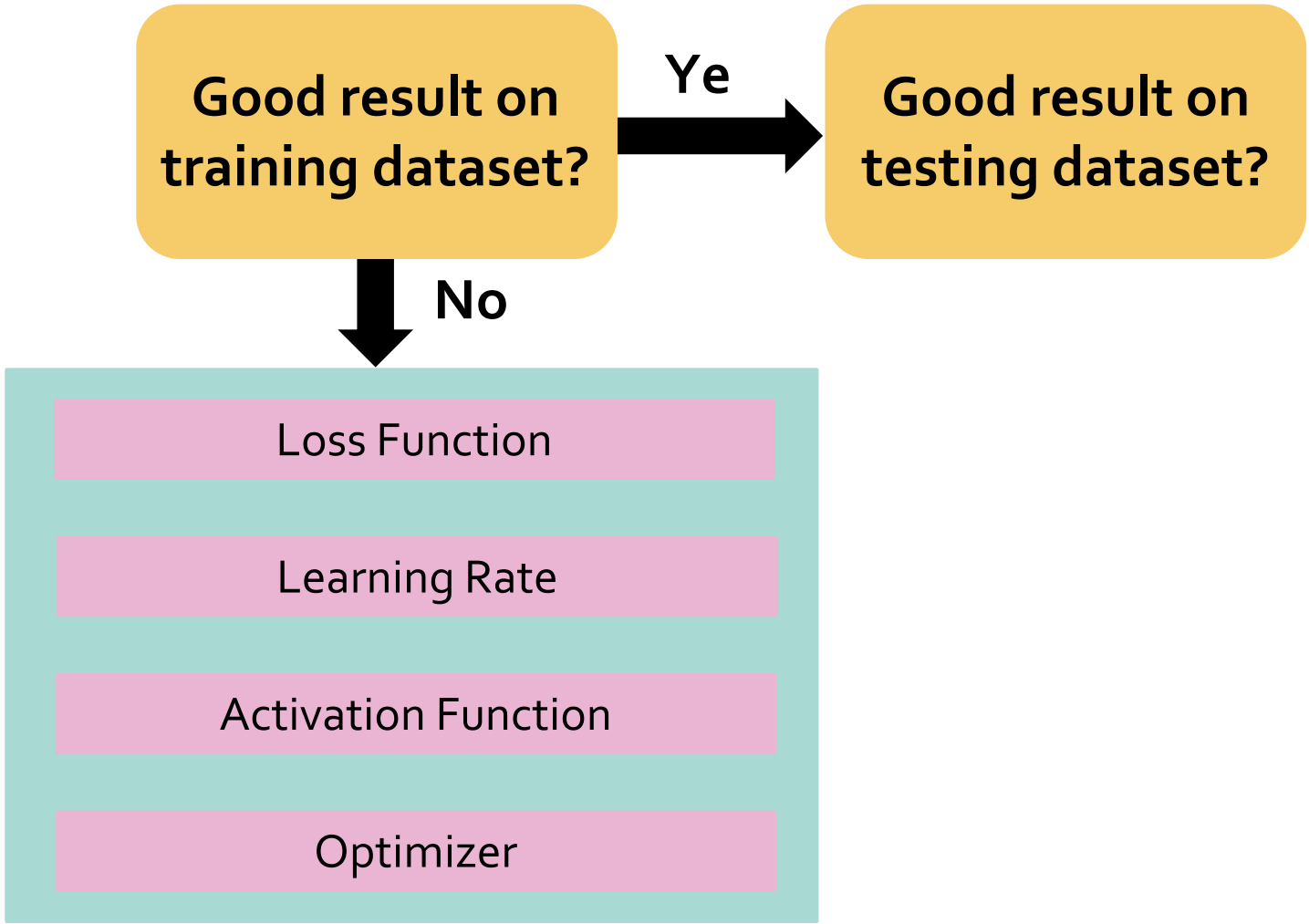
Component	Selection
Loss function	categorical_crossentropy
Activation function	sigmoid + softmax
Optimizer	SGD

用下面的招式讓模型更好吧

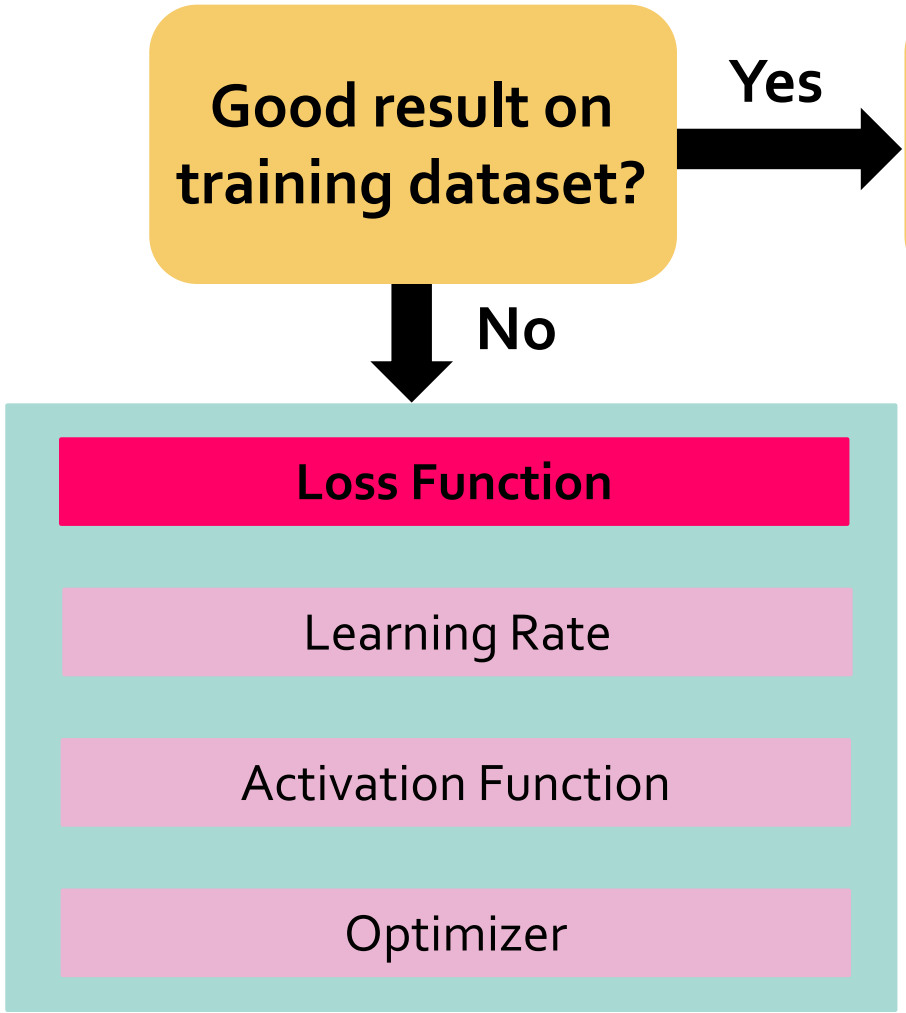
Tips for Training DL Models

不過盲目的使用招式，會讓你的寶可夢失去戰鬥意識

Tips for Deep Learning



Tips for Deep Learning



$$\frac{\partial L}{\partial \theta} = \boxed{\frac{\partial L}{\partial \hat{y}}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial \theta}$$

受 loss function 影響

Using MSE

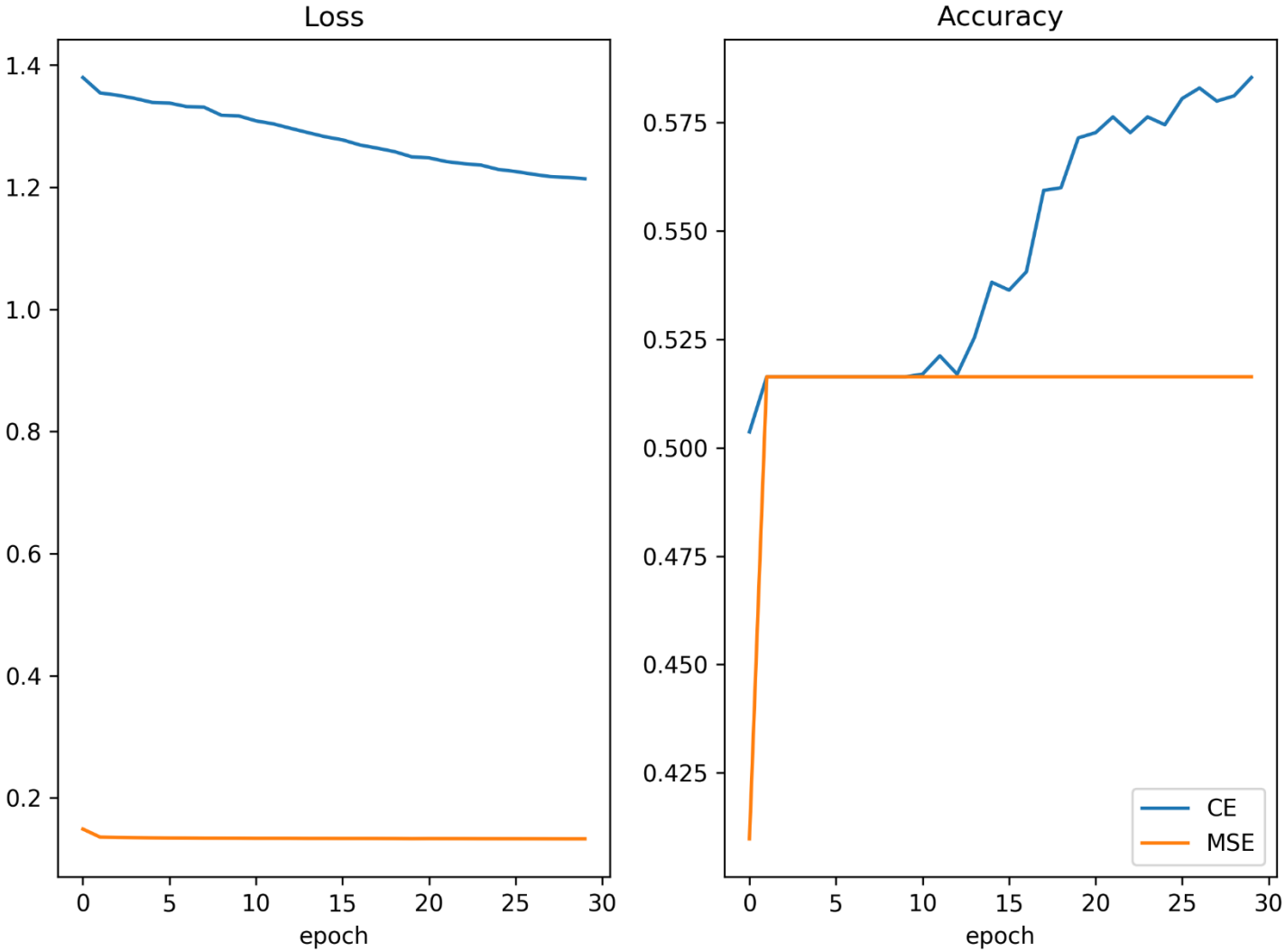
- 在指定 loss function 時

```
# 指定 loss function 和 optimizier
model.compile(loss='categorical_crossentropy',
              optimizer=sgd)
```

```
# 指定 loss function 和 optimizier
model.compile(loss='mean_squared_error',
              optimizer=sgd)
```

練習 01_lossFuncSelection.py (10 minutes)

Result – CE vs MSE



為什麼 Cross-entropy 比較好？

Cross-entropy

Squared error

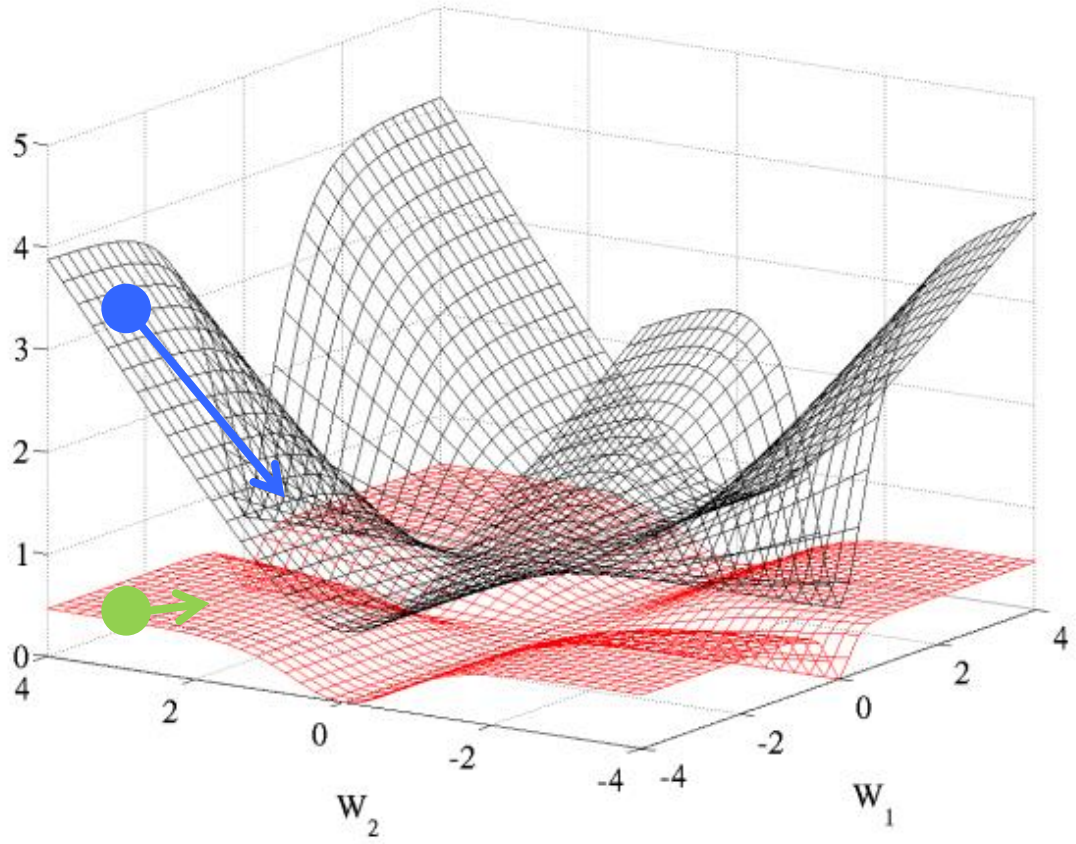


Figure source

The error surface of logarithmic functions is steeper than that of quadratic functions. [ref]

How to Select Loss function

- Classification 常用 cross-entropy
  - 搭配 softmax 當作 output layer 的 activation function
- Regression 常用 mean absolute/squared error
- 對特定問題定義 loss function
  - Unbalanced dataset, class 0 : class 1 = 99 : 1

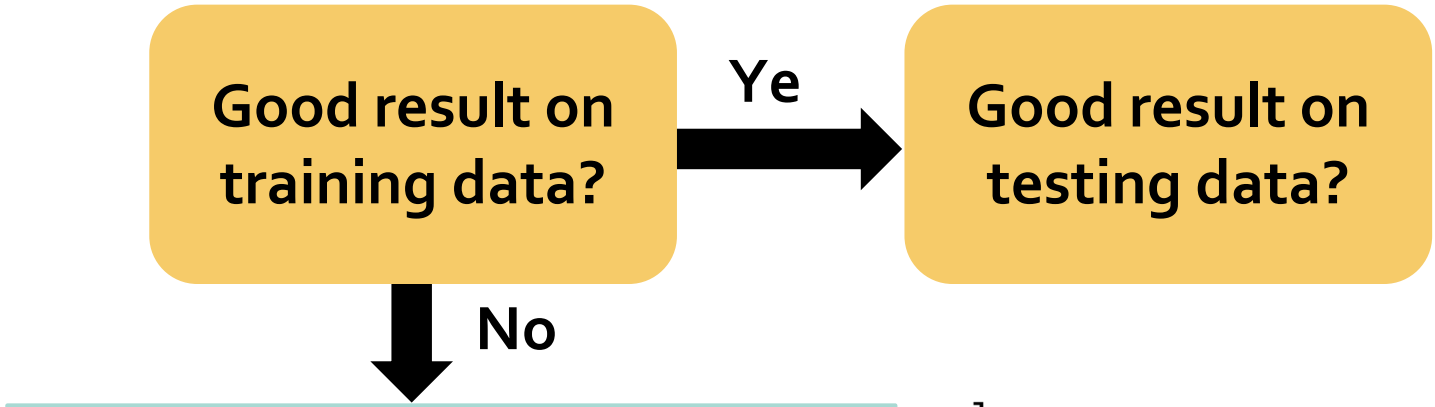
    Self-defined loss function

Loss	Class 0	Class 1
Class 0	0	99
Class 1	1	0

Current Best Model Configuration

Component	Selection
Loss function	categorical_crossentropy
Activation function	sigmoid + softmax
Optimizer	SGD

Tips for Deep Learning



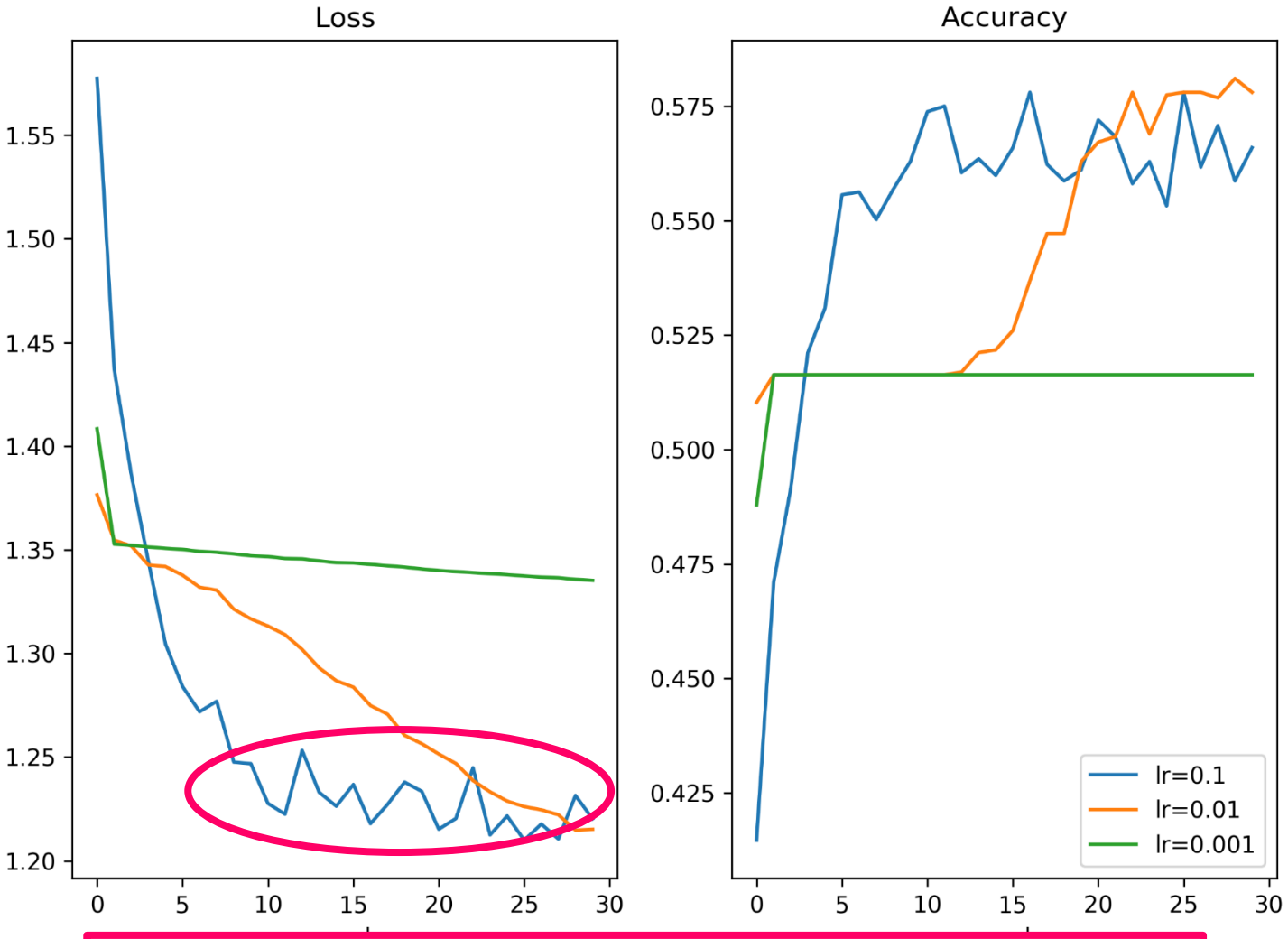
- Loss Function
- **Learning Rate**
- Activation Function
- Optimizer

練習 02_learningRateSelection.py (5-8 minutes)

```
# 指定 optimizier
from keras.optimizers import SGD, Adam, RMSprop, Adagrad
sgd = SGD(lr=0.01, momentum=0.0,decay=0.0,nesterov=False)
```


試試看改變 learning rate，挑選出最好的 learning rate。
建議一次降一個數量級，如: `0.1 vs 0.01 vs 0.001`

Result – Learning Rate Selection

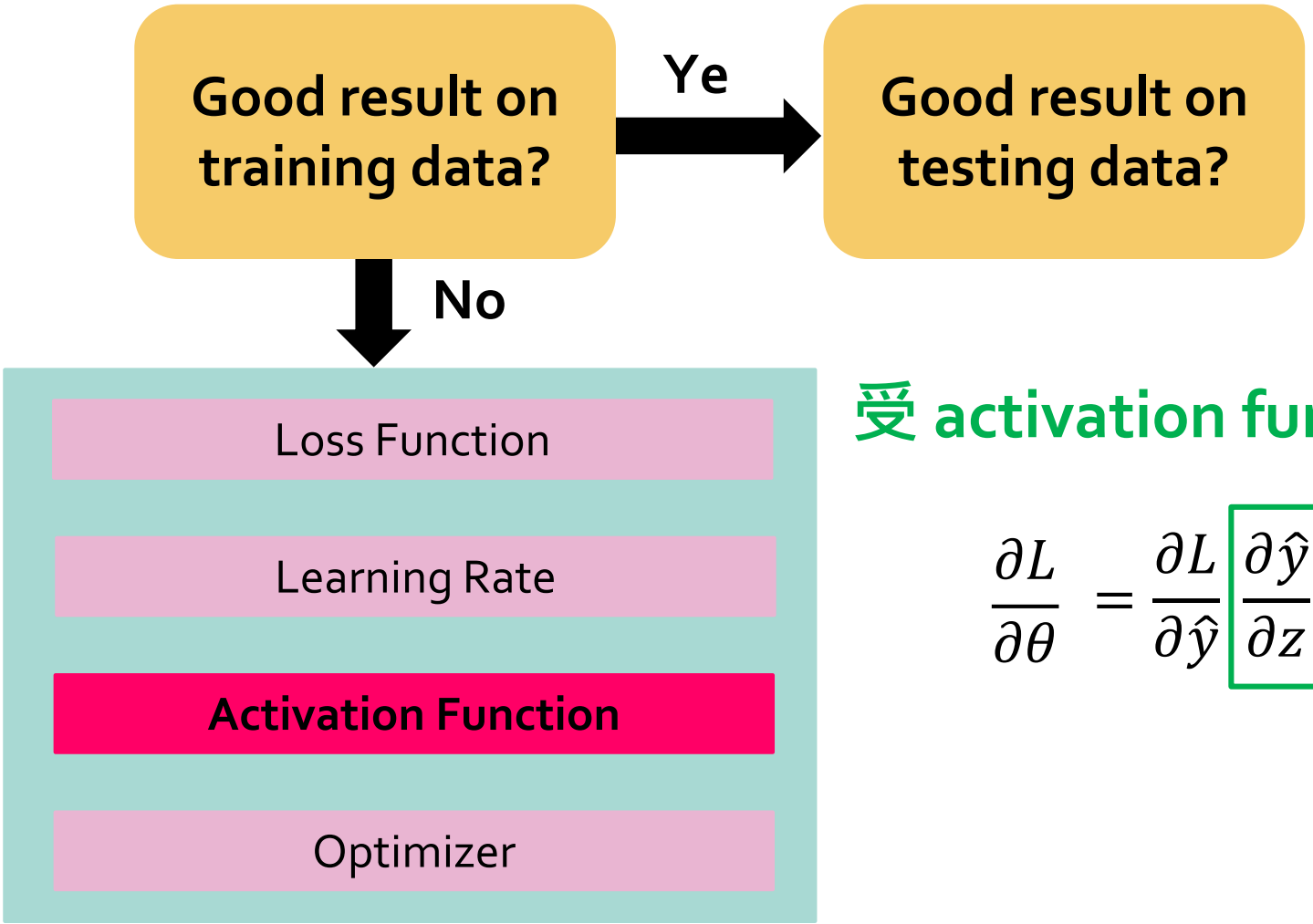


觀察 loss，這樣的震盪表示 learning rate 可能太大

How to Set Learning Rate

- 大多要試試看才知道，通常不會大於 0.1
- 一次調一個數量級
  - 0.1 → 0.01 → 0.001
  - ~~0.01 → 0.012 → 0.015 → 0.018 …~~
- 幸運數字！

Tips for Deep Learning

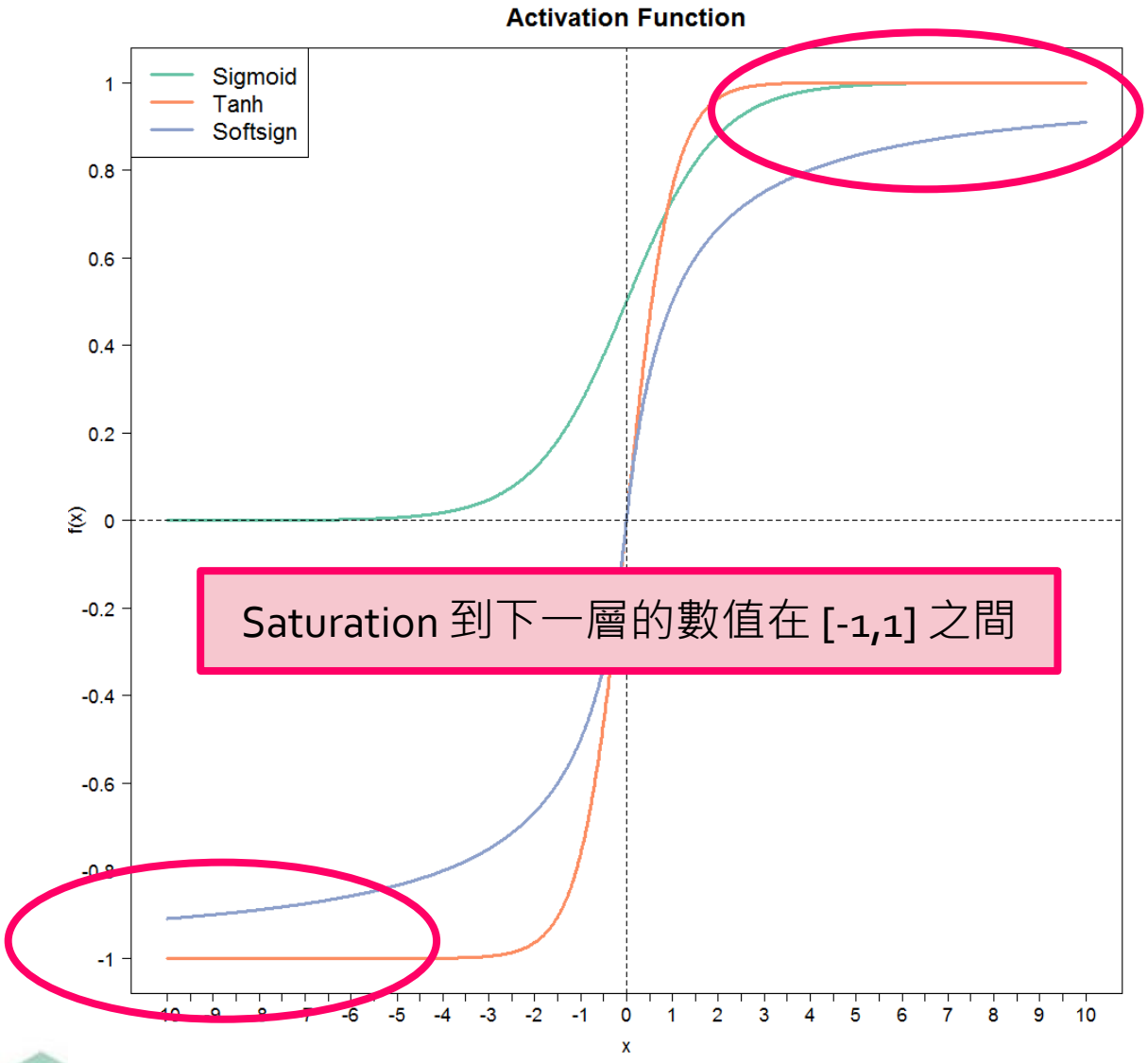


受 activation function 影響

$$\frac{\partial L}{\partial \theta} = \frac{\partial L}{\partial \hat{y}} \boxed{\frac{\partial \hat{y}}{\partial z}} \frac{\partial z}{\partial \theta}$$

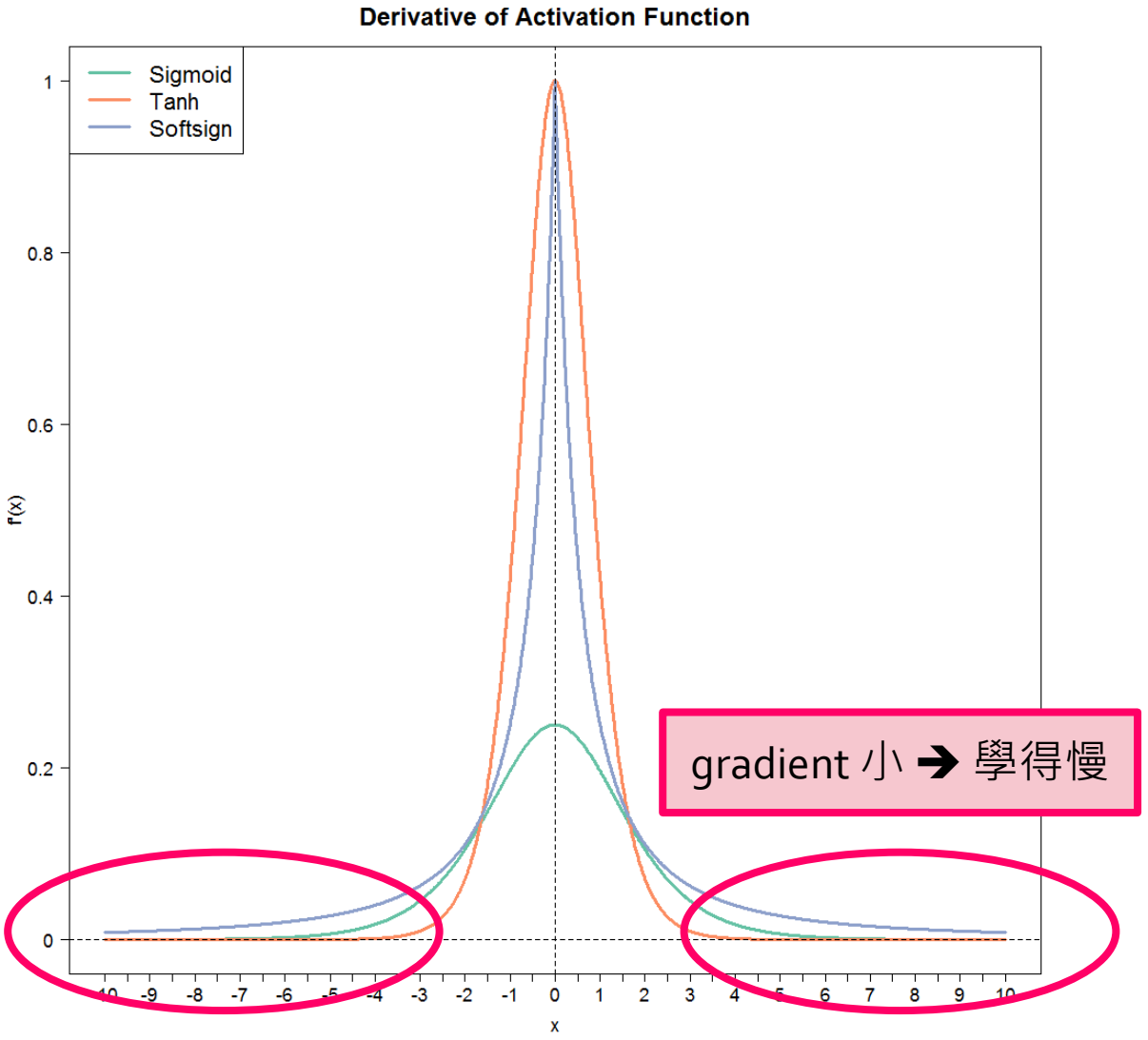
Sigmoid, Tanh, Softsign

- Sigmoid
  - $f(x) = \frac{1}{(1+e^{-x})}$
- Tanh
  - $f(x) = \frac{(1-e^{-2x})}{(1+e^{-2x})}$
- Softsign
  - $f(x) = \frac{x}{(1+|x|)}$



Derivatives of Sigmoid, Tanh, Softsign

- Sigmoid
  - $df/dx = \frac{e^{-x}}{(1+e^{-x})^2}$
- Tanh
  - $df/dx = 1-f(x)^2$
- Softsign
  - $df/dx = \frac{1}{(1+|x|)^2}$



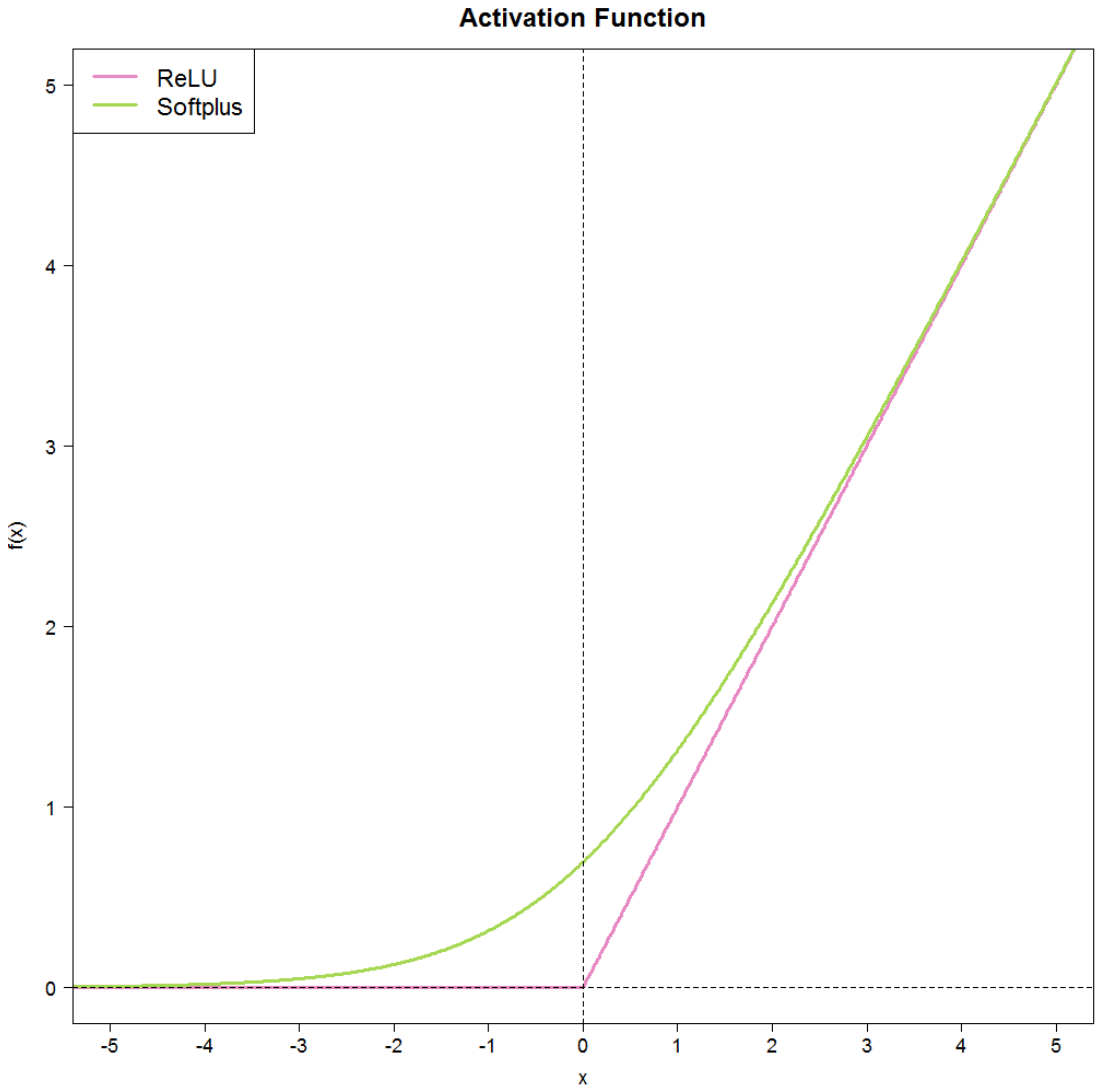
Drawbacks of Sigmoid, Tanh, Softsign

- Vanishing gradient problem
  - 原因: input 被壓縮到一個相對很小的output range
  - 結果: 很大的 input 變化只能產生很小的 output 變化
    ➔ Gradient 小 ➔ 無法有效地學習
  - Sigmoid, Tanh, Softsign 都有這樣的特性

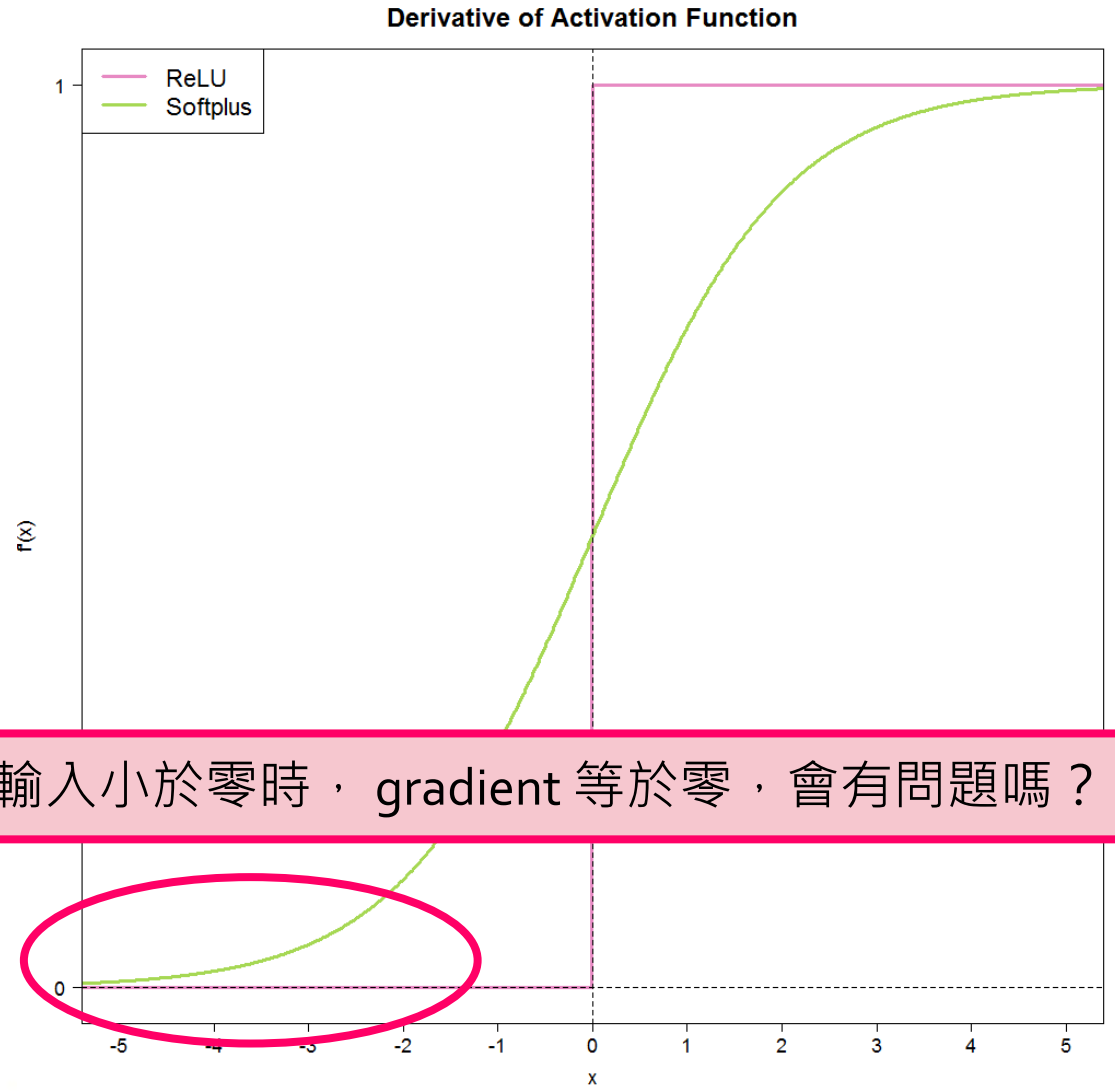
- 特別不適用於深的深度學習模型

ReLU, Softplus

- ReLU
  - f(x)=max(0,x)
  - df/dx=1 if x > 0,
    0 otherwise.
- Softplus
  - $f(x) = \ln(1+e^x)$
  - $df/dx = e^x/(1+e^x)$



Derivatives of ReLU, Softplus

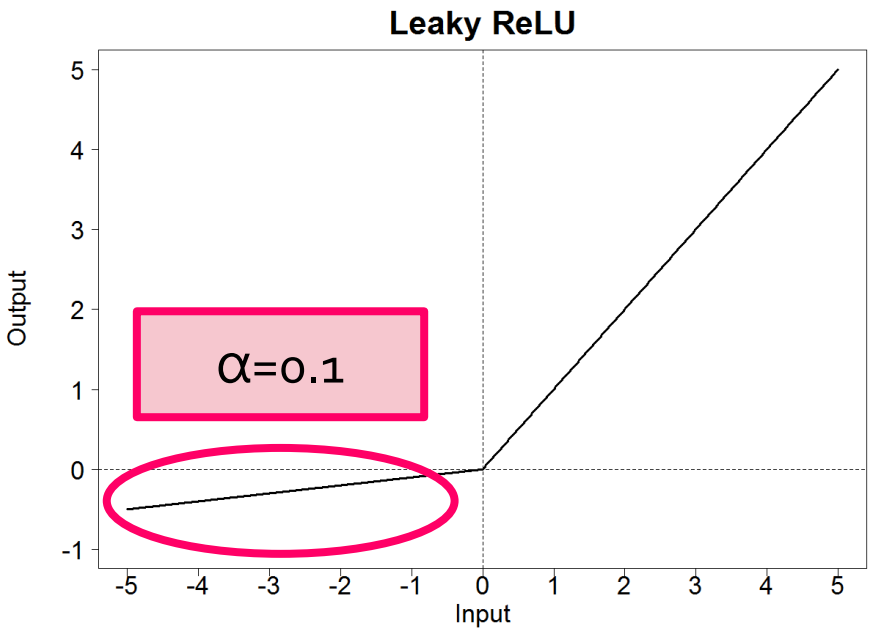


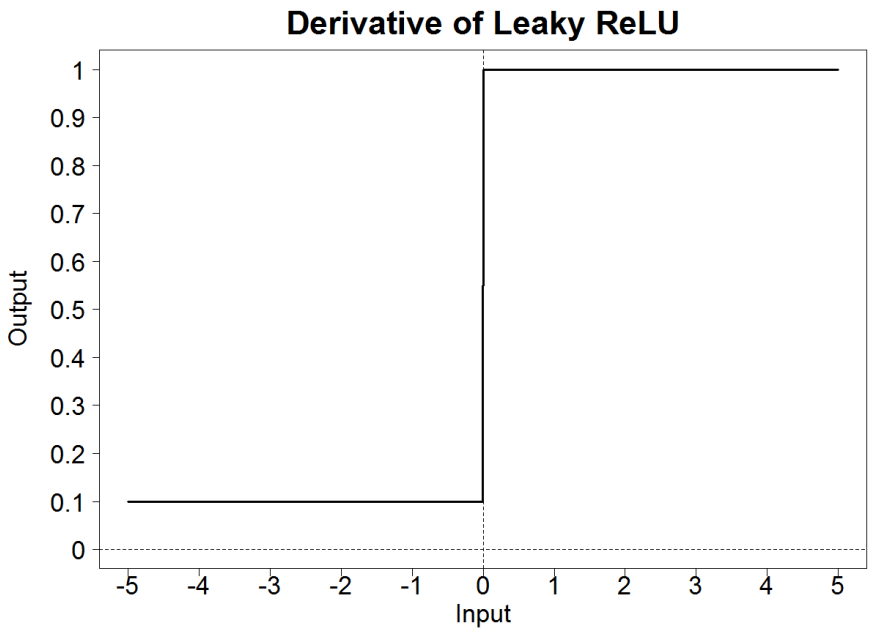
ReLU 在輸入小於零時， gradient 等於零，會有問題嗎？

Leaky ReLU

- Allow a small gradient while the input to activation function smaller than 0

$$f(x) = \begin{cases} x & \text{if } x > 0, \\ \alpha x & \text{otherwise.} \end{cases} \qquad df/dx = \begin{cases} 1 & \text{if } x > 0, \\ \alpha & \text{otherwise.} \end{cases}$$





Leaky ReLU in Keras

```
# For example
From keras.layer.advanced_activation import LeakyReLU
lrelu = LeakyReLU(alpha = 0.02)
model.add(Dense(128, input_dim = 200))
# 指定 activation function
model.add(lrelu)
```

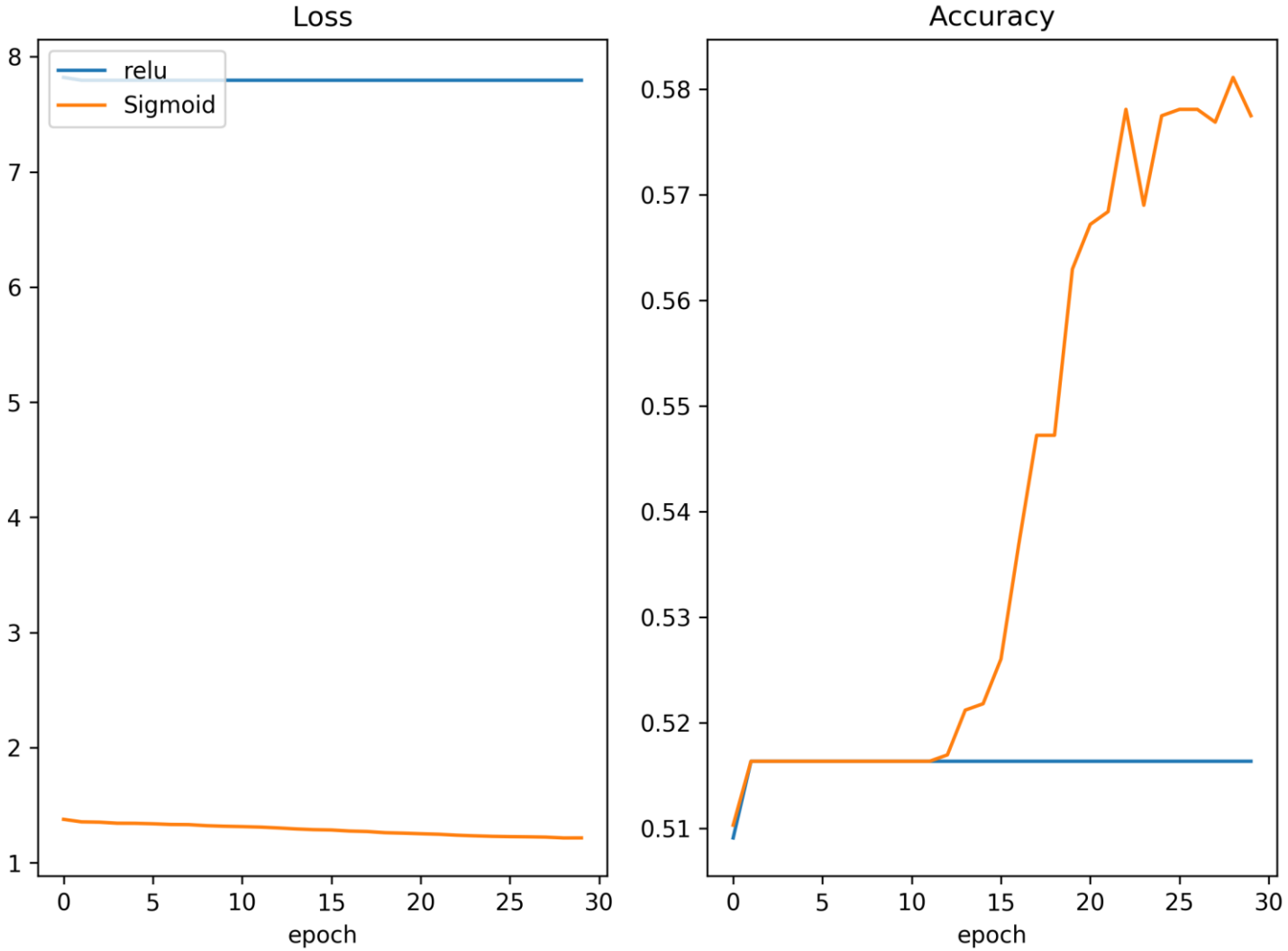
- 更多其他的 activation functions
  https://keras.io/layers/advanced-activations/

嘗試其他的 activation functions

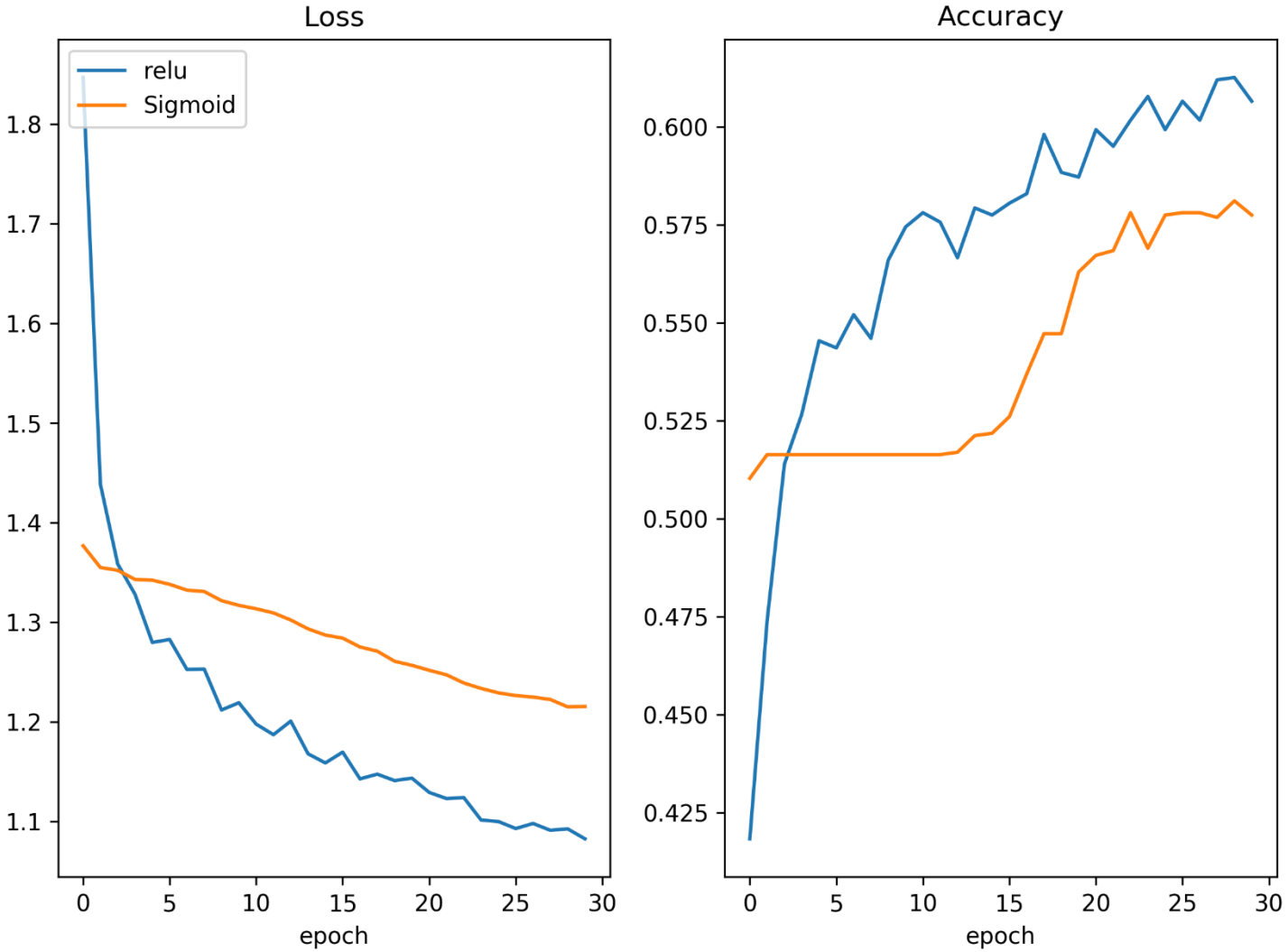
```
# 宣告這是一個 Sequential 次序性的深度學習模型
model = Sequential()

# 加入第一層 hidden layer (128 neurons) 與指定 input 的維度
model.add(Dense(128, input_dim=200))
# 指定 activation function
model.add(Activation('relu'))

# 加入第二層 hidden layer (256 neurons)
model.add(Dense(256))
model.add(Activation('relu'))

# 加入 output layer (5 neurons)
model.add(Dense(5))
model.add(Activation('softmax'))

# 觀察 model summary
model.summary()
```

練習 03_activationFuncSelection.py (5-8 minutes)

Result – ReLU versus Sigmoid



Result – ReLU versus Sigmoid



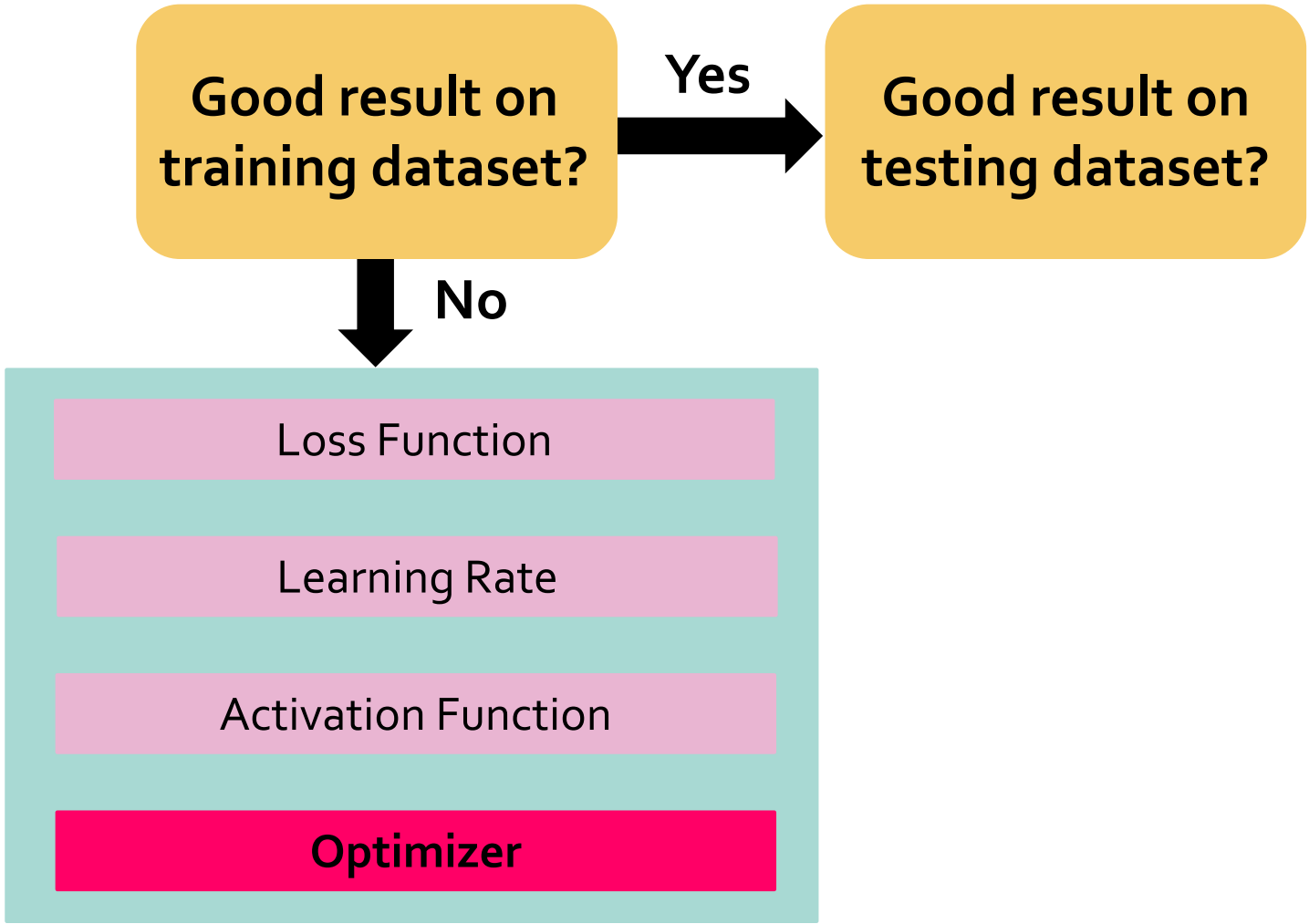
How to Select Activation Functions

- Hidden layers
  - 通常會用 ReLU
  - Sigmoid 有 vanishing gradient 的問題較不推薦
- Output layer
  - Regression: linear
  - Classification: softmax

Current Best Model Configuration

Component	Selection
Loss function	categorical_crossentropy
Activation function	relu + softmax
Optimizer	SGD

Tips for Deep Learning



Optimizers in Keras

- SGD – Stochastic Gradient Descent
- Adagrad – Adaptive Learning Rate
- RMSprop – Similar with Adagrad
- Adam – Similar with RMSprop + Momentum
- Nadam – Adam + Nesterov Momentum

Optimizer – SGD

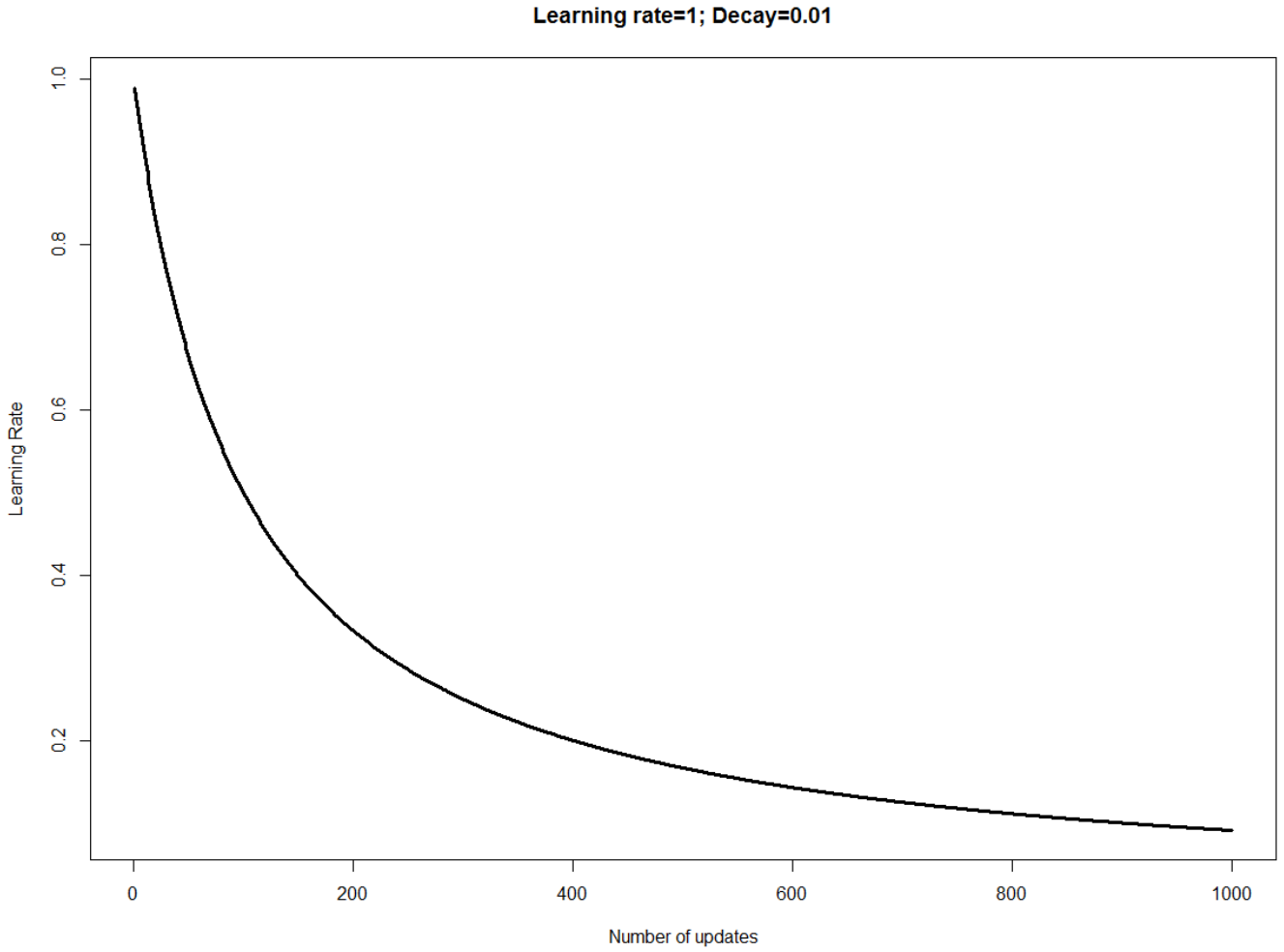
- Stochastic gradient descent
- 支援 momentum, learning rate decay, Nesterov momentum

```
keras.optimizers.SGD(lr=0.01, momentum=0.0, decay=0.0, nesterov=False)
```

- Momentum 的影響
  - 無 momentum: **update = -lr*gradient**
  - 有 momentum: **update = -lr*gradient + m*last_update**
- Learning rate decay after update once
  - 屬於 1/t decay ➔ **lr = lr / (1 + decay*t)**
  - t: number of done updates

Learning Rate with 1/t Decay

```
lr = lr / (1 + decay*t)
```



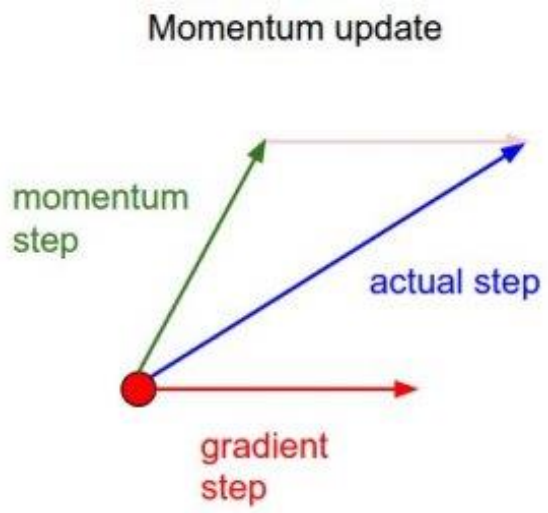
Nesterov Momentum

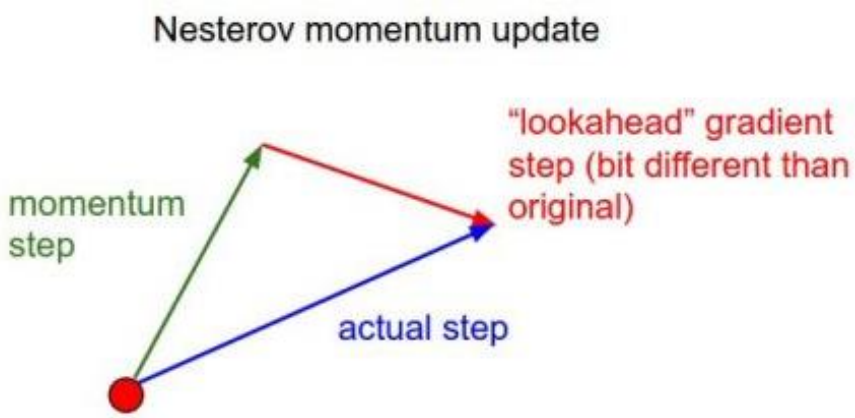
Momentum

- 先算 gradient
- 加上 momentum
- 更新

Nesterov momentum

- 加上 momentum
- 再算 gradient
- 更新





Optimizer – Adagrad

- 因材施教：每個參數都有不同的 learning rate
- 根據之前所有 gradient 的 root mean square 修改

第 t 次更新

$$g^t = \left.\frac{\partial L}{\partial \theta}\right|_{\theta=\theta^t}$$

Gradient descent

$$\theta^{t+1} = \theta^t - \eta g^t$$

Adagrad

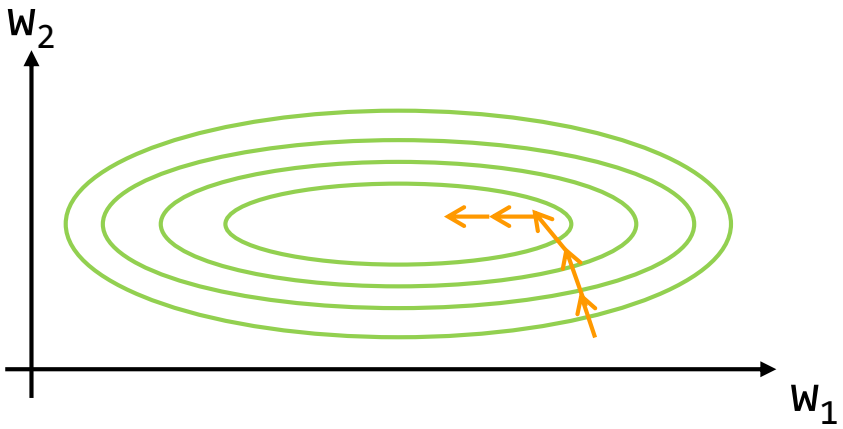
$$\theta^{t+1} = \theta^t - \frac{\eta}{\sigma^t} g^t$$

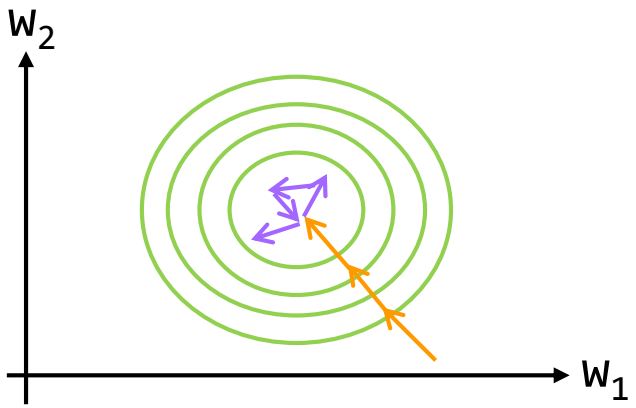
所有 gradient 的 root mean square

$$\sigma^t = \sqrt{\frac{(g^0)^2 + \ldots + (g^t)^2}{t+1}}$$

Adaptive Learning Rate

- Feature scales 不同，需要不同的 learning rates





- 每個 weight 收斂的速度不一致
  - 但 learning rate 沒有隨著減少的話 ➔ **bumpy**
- 因材施教：每個參數都有不同的 learning rate

Optimizer – Adagrad

- 根據之前所有 gradient 的 root mean square 修改

第 t 次更新

$$g^t = \left.\frac{\partial L}{\partial \theta}\right|_{\theta=\theta^t}$$

Gradient descent

$$\theta^{t+1} = \theta^t - \eta g^t$$

Adagrad

$$\theta^{t+1} = \theta^t - \frac{\eta}{\sigma^t} g^t$$

所有 gradient 的 root mean square

$$\sigma^t = \sqrt{\frac{(g^0)^2 + \ldots + (g^t)^2}{t+1}}$$

Step by Step – Adagrad

$$\theta^1 = \theta^0 - \frac{\eta}{\sigma^0} g^0 \qquad \sigma^0 = \sqrt{(g^0)^2}$$

$$\theta^2 = \theta^1 - \frac{\eta}{\sigma^1} g^1 \qquad \sigma^1 = \sqrt{\frac{(g^0)^2+(g^1)^2}{2}}$$

$$\vdots$$

$$\theta^t = \theta^{t-1} - \frac{\eta}{\sigma^{t-1}} g^{t-1} \qquad \sigma^t = \sqrt{\frac{(g^0)^2+(g^1)^2+\ldots+(g^t)^2}{t+1}}$$

- g^t 是一階微分，那 σ^t 隱含什麼資訊？

An Example of Adagrad

g^t	g^0	g^1	g^2	g^3
W_1	0.001	0.003	0.002	0.1
W_2	1.8	2.1	1.5	0.1

σ^t	σ^0	σ^1	σ^2	σ^3
W_1	0.001	0.002	0.002	0.05
W_2	1.8	1.956	1.817	1.57

g^t/σ^t	t=0	t=1	t=2	t=3
W_1	1	1.364	0.952	2
W_2	1	1.073	0.826	0.064

- 老馬識途，參考之前的經驗修正現在的步伐
- 不完全相信當下的 gradient

Optimizer – RMSprop

Adagrad

$$\theta^{t+1} = \theta^t - \frac{\eta}{\sigma^t} g^t$$

$$\sigma^t = \sqrt{\frac{(g^0)^2 + \ldots + (g^t)^2}{t+1}}$$

RMSprop

$$\theta^{t+1} = \theta^t - \frac{\eta}{\sqrt{r^t}} g^t$$

$$r^t = (1-\rho)(g^t)^2 + \rho r^{t-1}$$

- 另一種參考過去 gradient 的方式

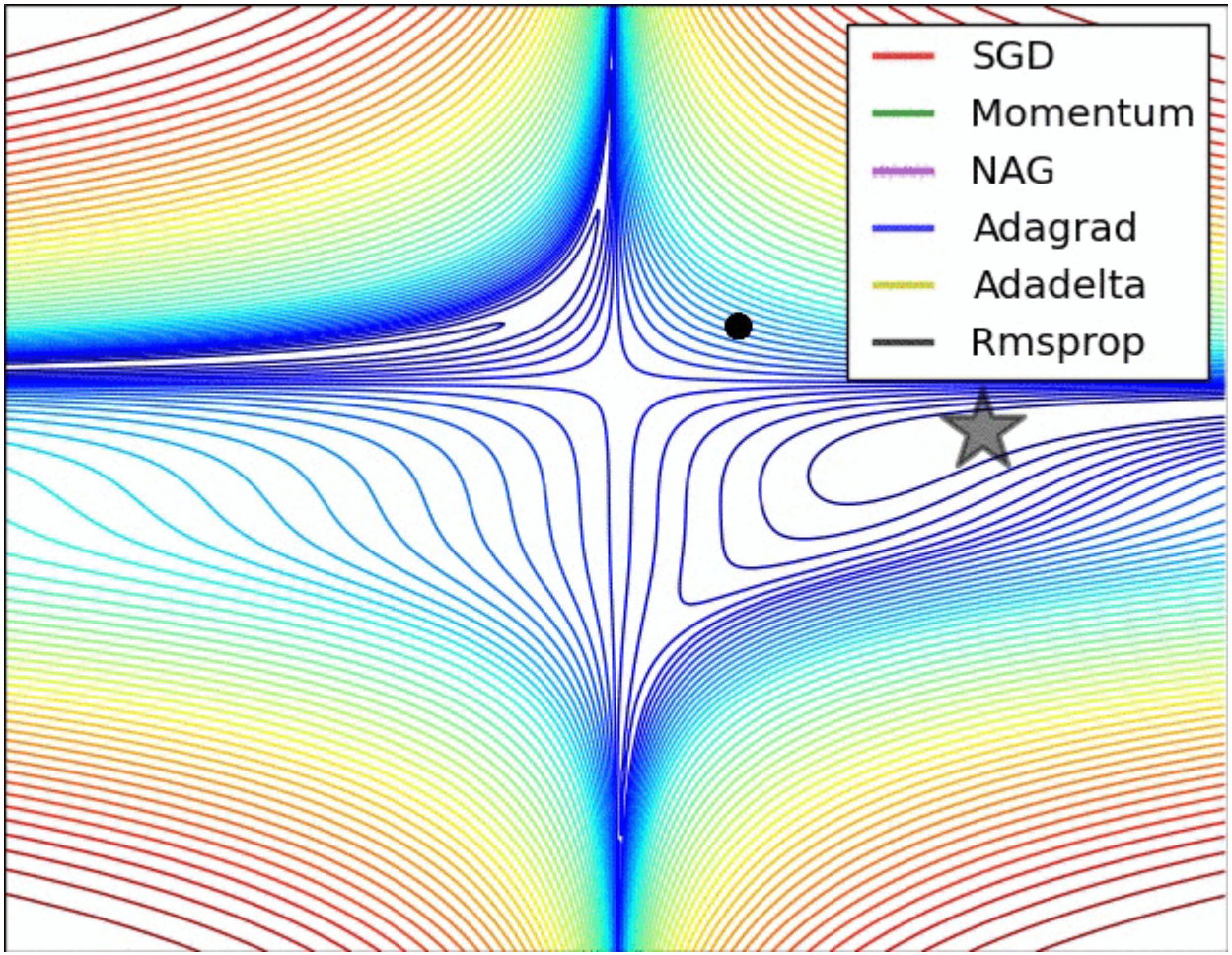
```
keras.optimizers.RMSprop(lr=0.001, rho=0.9, epsilon=1e-08, decay=0.0)
```

Optimizer – Adam

- Close to RMSprop + Momentum
- ADAM: A Method For Stochastic Optimization
- In practice, 不改參數也會做得很好

```
keras.optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.0)
```

比較 Optimizers



來源

練習 04_optimizerSelection.py (5-8 minutes)

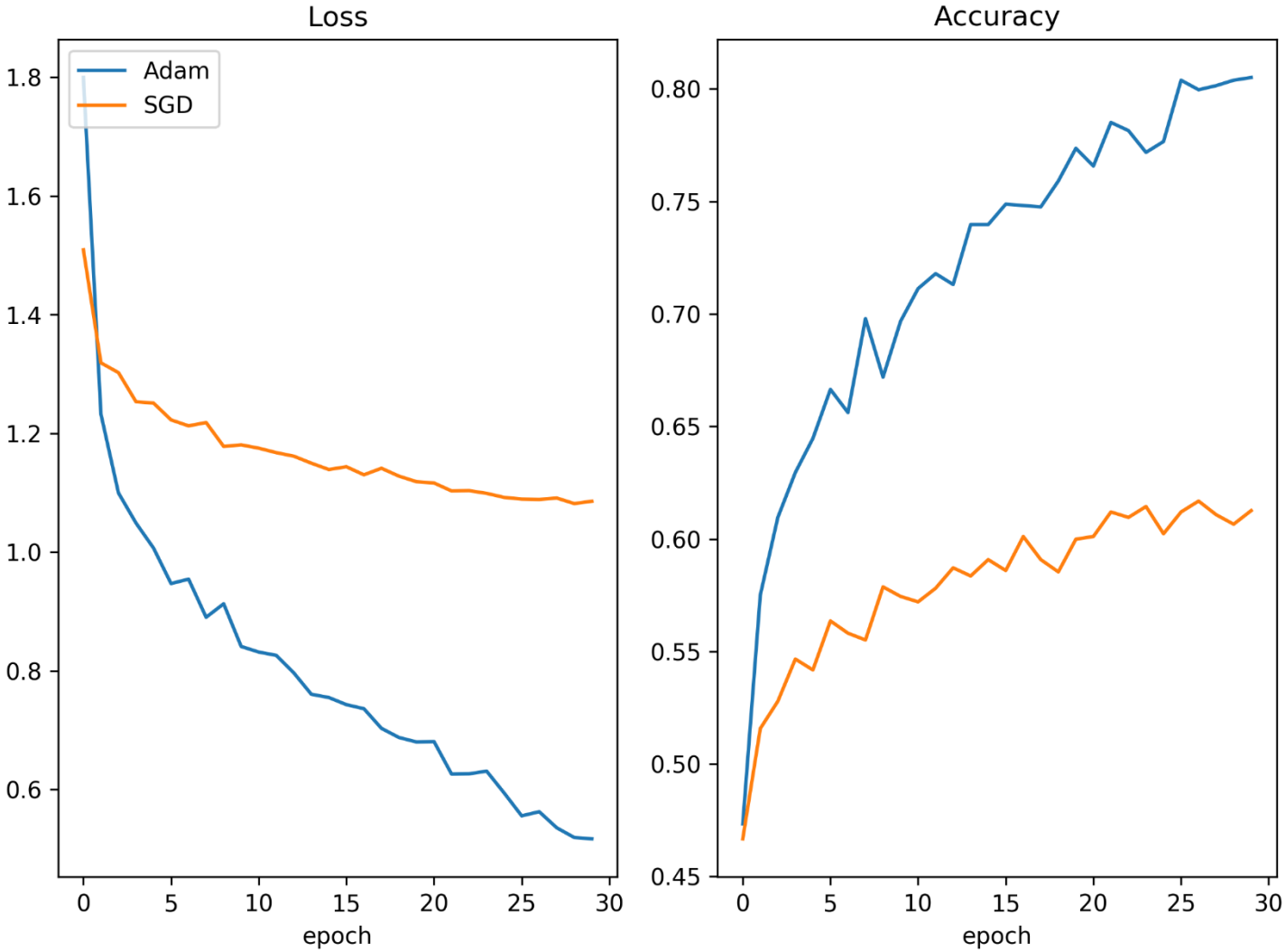
1. 設定選用的 optimizer

```
# 指定 optimizier
from keras.optimizers import SGD, Adam, RMSprop, Adagrad
sgd = SGD(lr=0.01,momentum=0.0,decay=0.0,nesterov=False)
```

2. 修改 model compilation

```
# 指定 loss function 和 optimizier
model.compile(loss='categorical_crossentropy',
              optimizer=sgd)
```

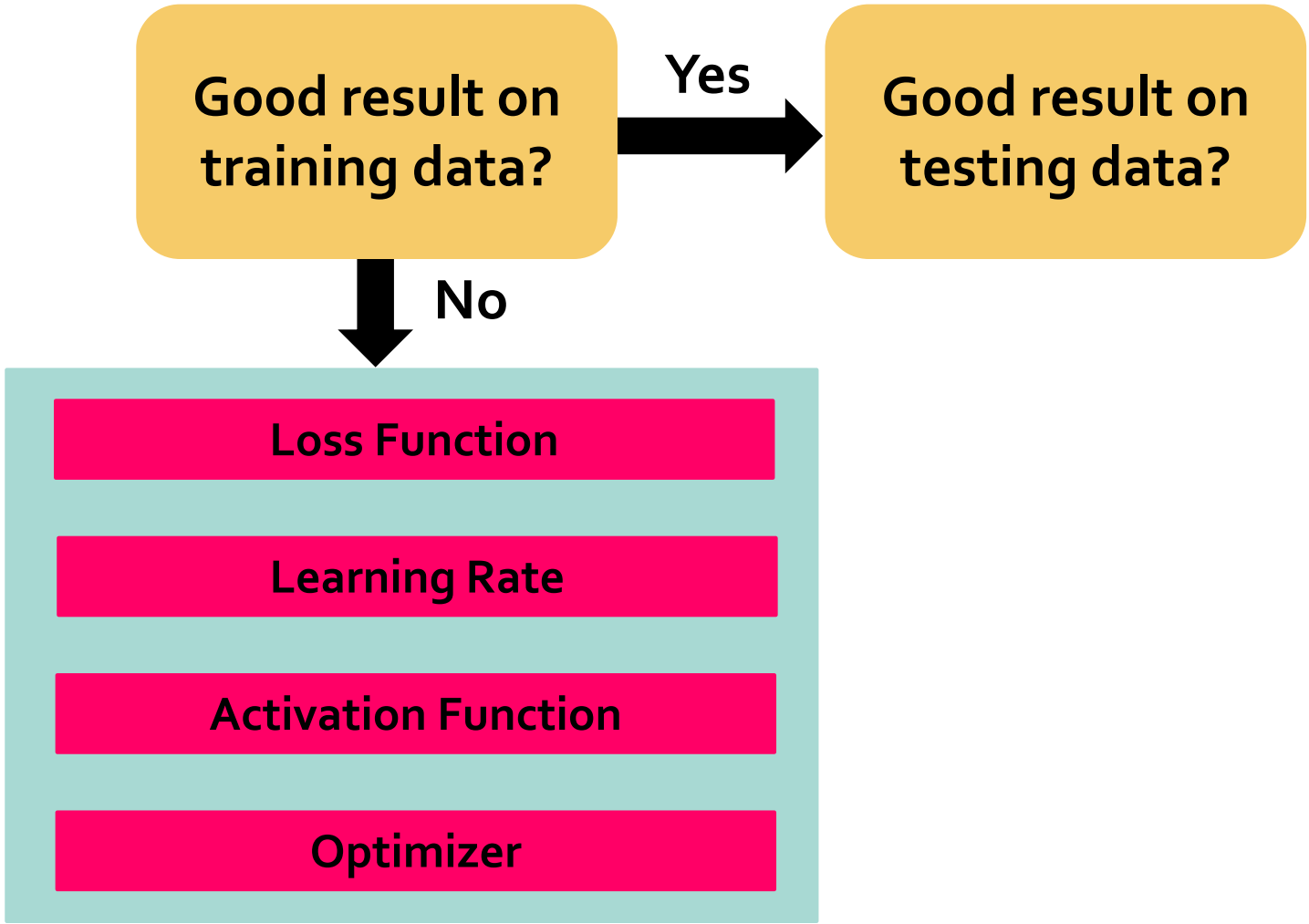
Result – Adam versus SGD



How to Select Optimizers

- 一般的起手式： Adam
  - Adaptive learning rate for every weights
  - Momentum included
- Keras 推薦 RNN 使用 RMSProp
  - 在訓練 RNN 需要注意 explosive gradient 的問題
    ➔ clip gradient 的暴力美學
- RMSProp 與 Adam 的戰爭仍在延燒

Tips for Deep Learning

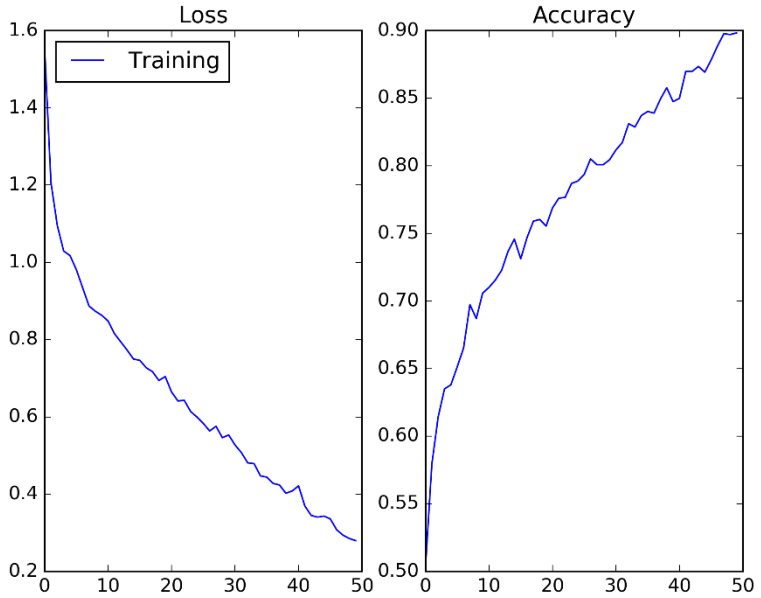


Current Best Model Configuration

Component	Selection
Loss function	categorical_crossentropy
Activation function	relu + softmax
Optimizer	Adam

50 epochs 後

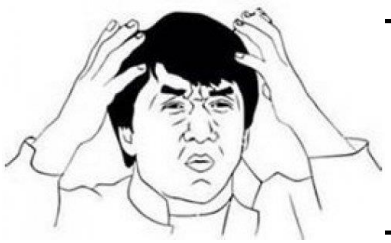
90% 準確率！



進度報告

我們有90%準確率了！

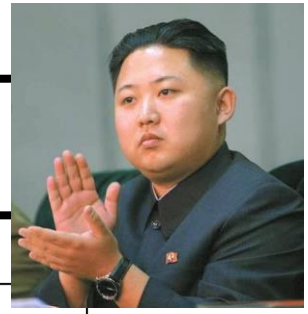
但是在 training dataset 上的表現

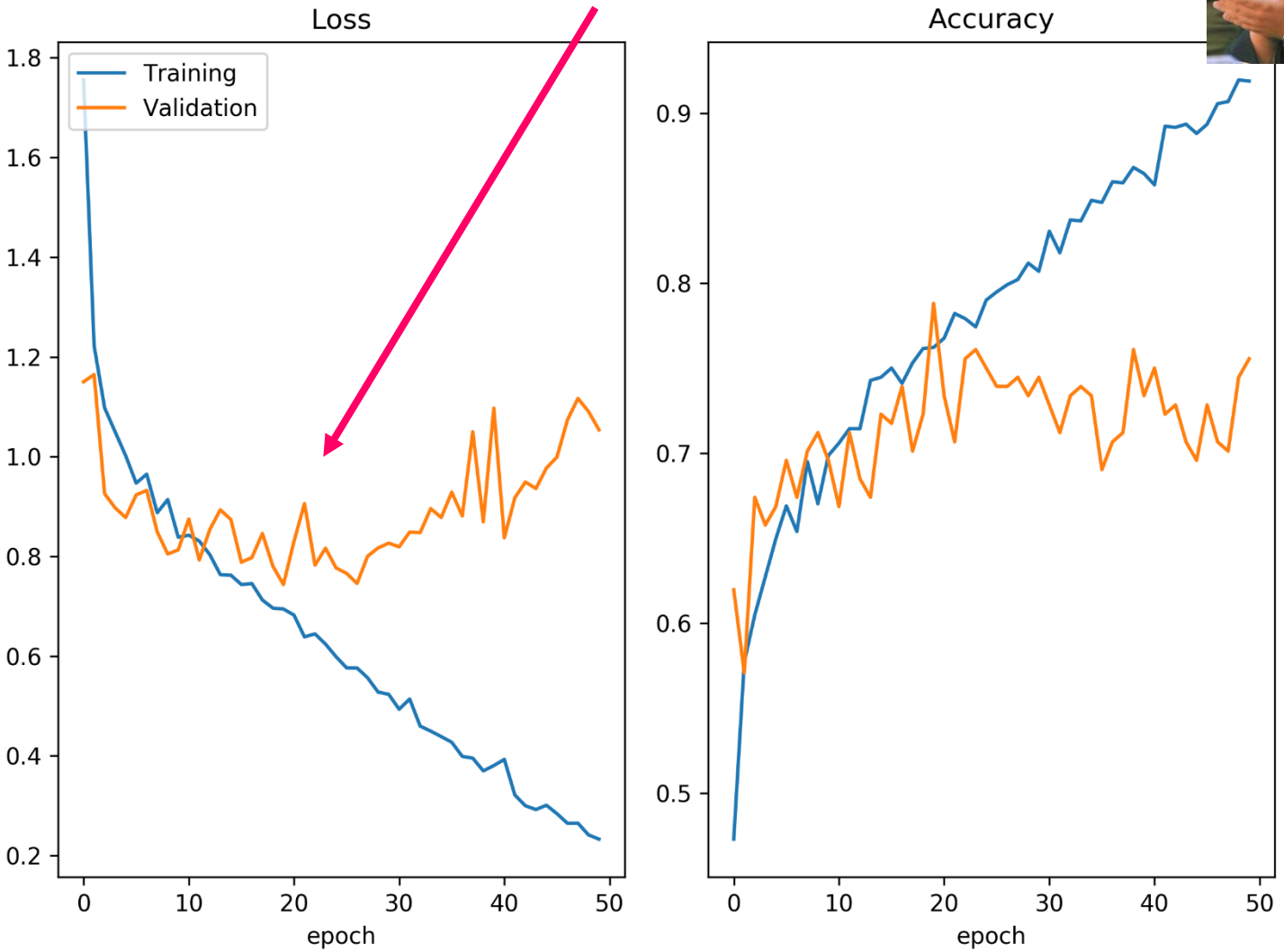


這會不會只是一場美夢？

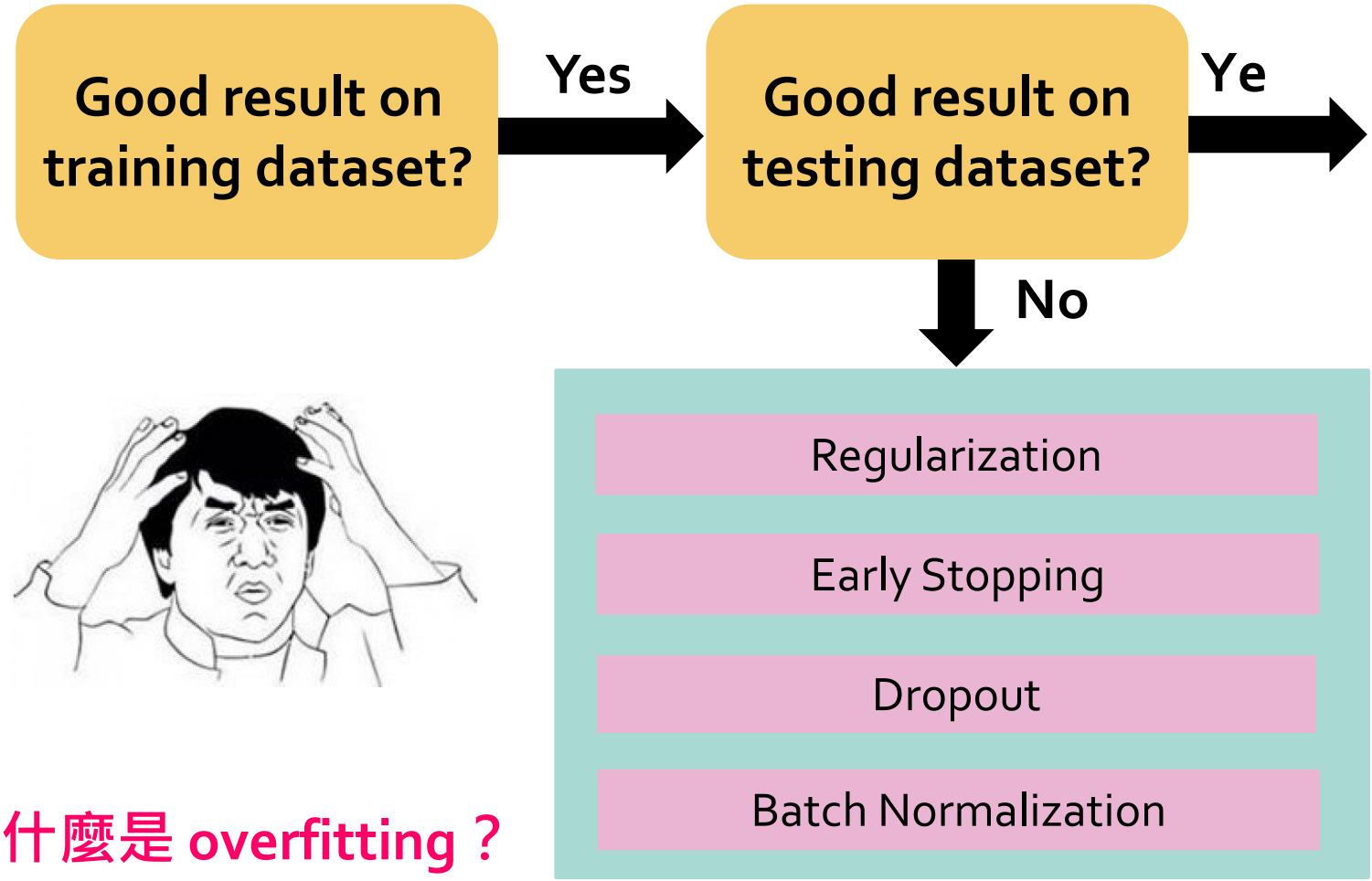
見真章

Overfitting 啦!





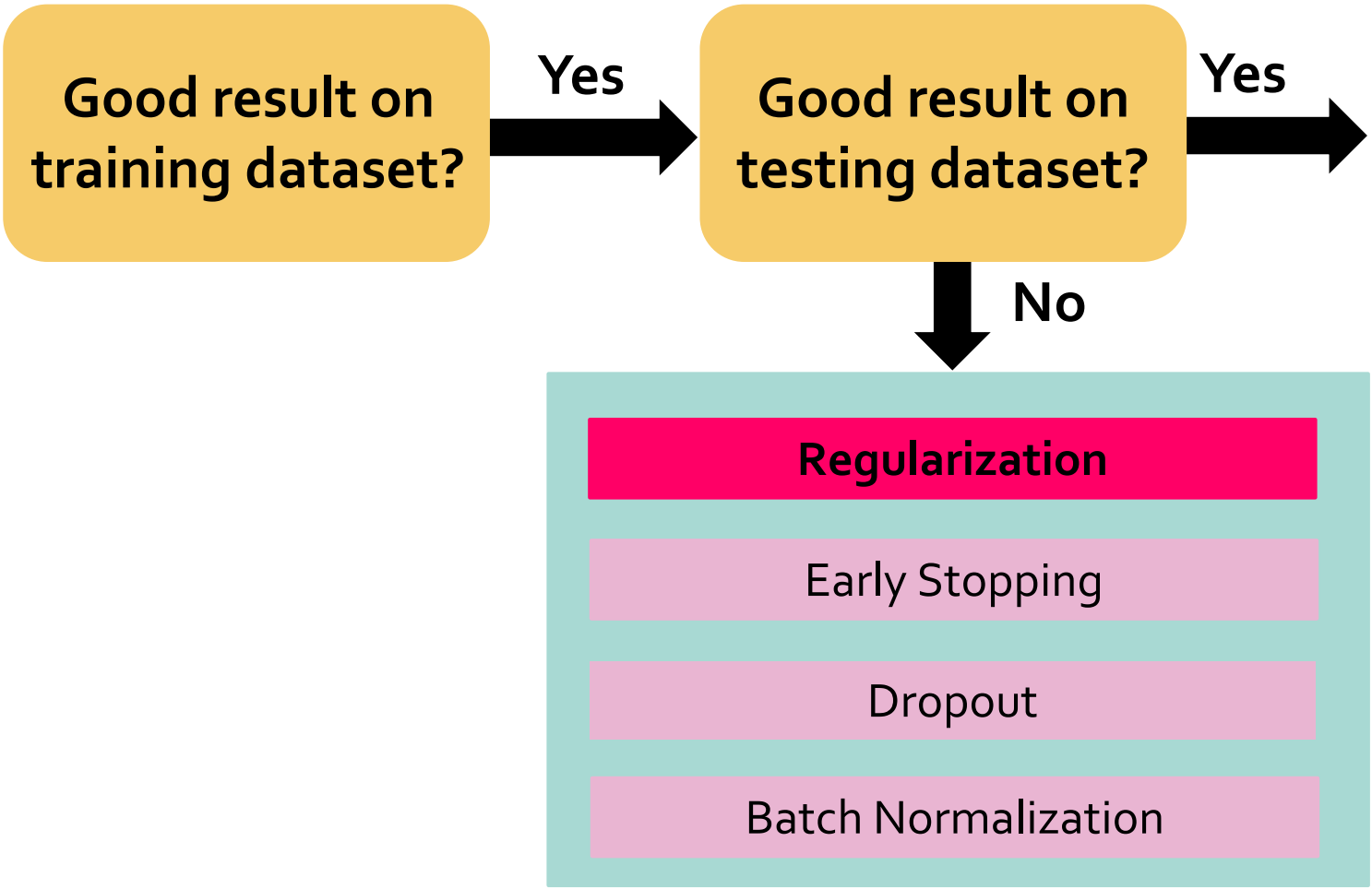
Tips for Deep Learning



什麼是 overfitting？

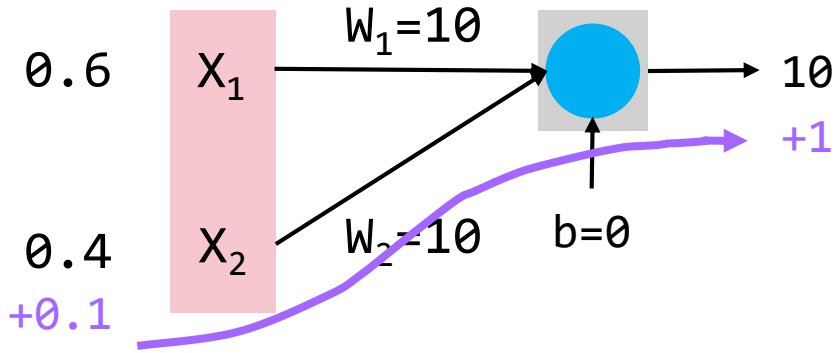
training result 進步，但 testing result 反而變差

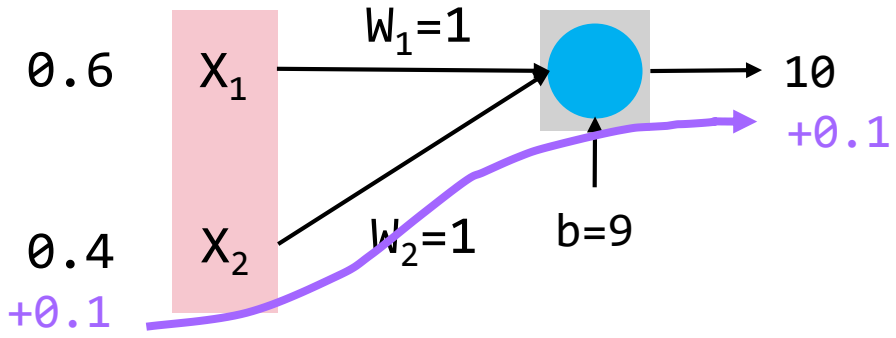
Tips for Deep Learning



Regularization

- 限制 weights 的大小讓 output 曲線比較平滑
- 為什麼要限制呢？





w_i 較小 ➔ Δx_i 對 $\hat{y}$ 造成的影響($\Delta\hat{y}$)較小
➔ 對 input 變化比較不敏感 ➔ generalization 好

Regularization

- 怎麼限制 weights 的大小呢？
  加入目標函數中，一起優化

$$Loss_{reg}=\sum(y-(b+\sum w_i x_i))+\alpha(regularizer)$$

$\hat{y}$

- α 是用來調整 regularization 的比重
  - 避免顧此失彼 (降低 weights 的大小而犧牲模型準確性)

L1 and L2 Regularizers

- L1 norm

$$L_1 = \sum_{i=1}^{N} |W_i|$$

Sum of absolute values

- L2 norm

$$L_2 = \sqrt{\sum_{i=1}^{N} |W_i|^2}$$

Root mean square of absolute values

Regularization in Keras

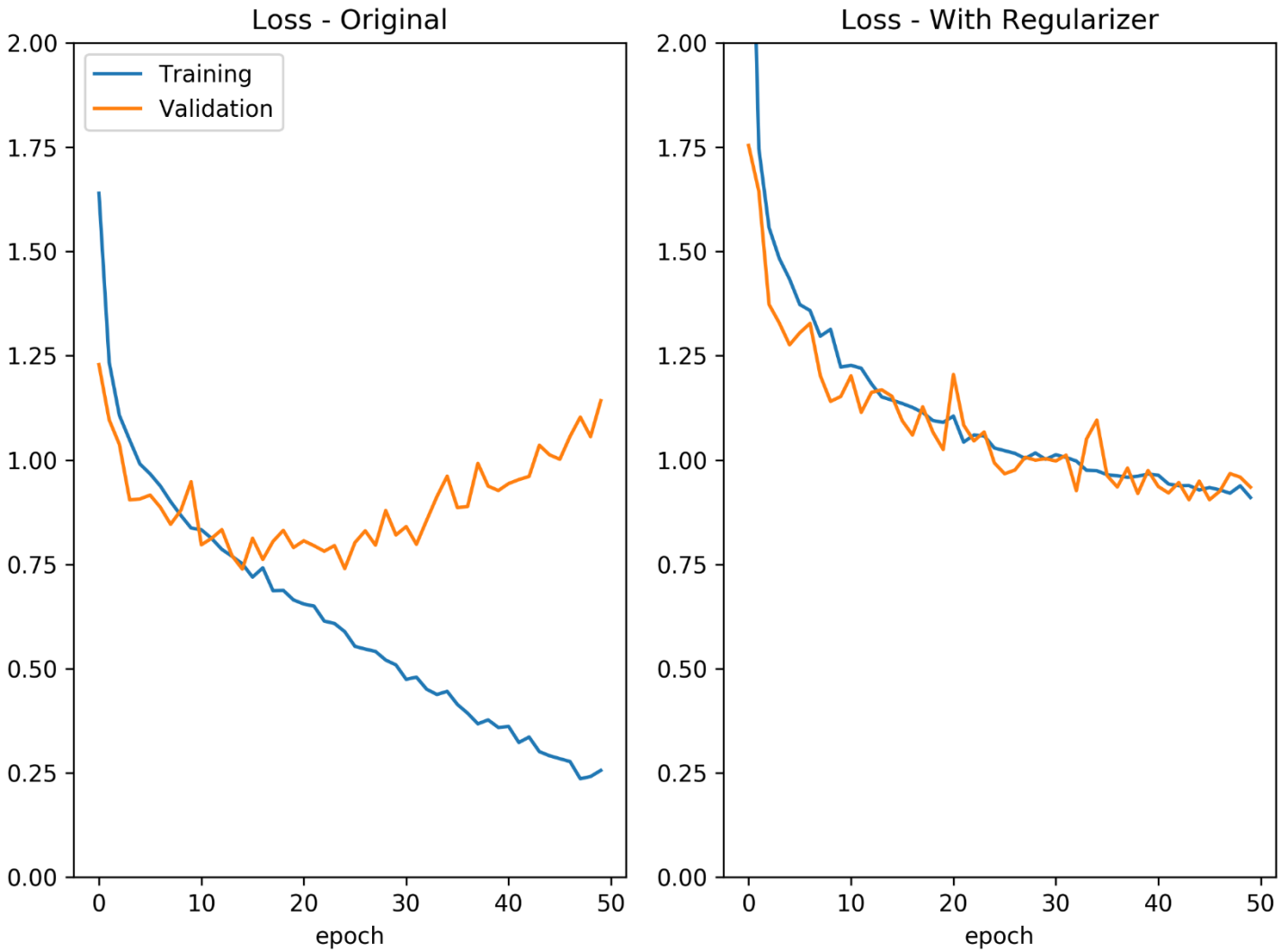
```
''' Import l1,l2 (regularizer) '''
from keras.regularizers import l1,l2

model_l2 = Sequential()

# 加入第一層 hidden layer 並加入 regularizer (alpha=0.01)
Model_l2.add(Dense(128,input_dim=200,kernel_regularizer=l2(0.01))
Model_l2.add(Activation('relu'))

# 加入第二層 hidden layer 並加入 regularizer
model_l2.add(Dense(256, kernel_regularizer=l2(0.01)))
model_l2.add(Activation('relu'))

# 加入 Output layer
model_l2.add(Dense(5, kernel_regularizer=l2(0.01)))
model_l2.add(Activation('relu'))
```

練習 06_regularizer.py (5-8 minutes)

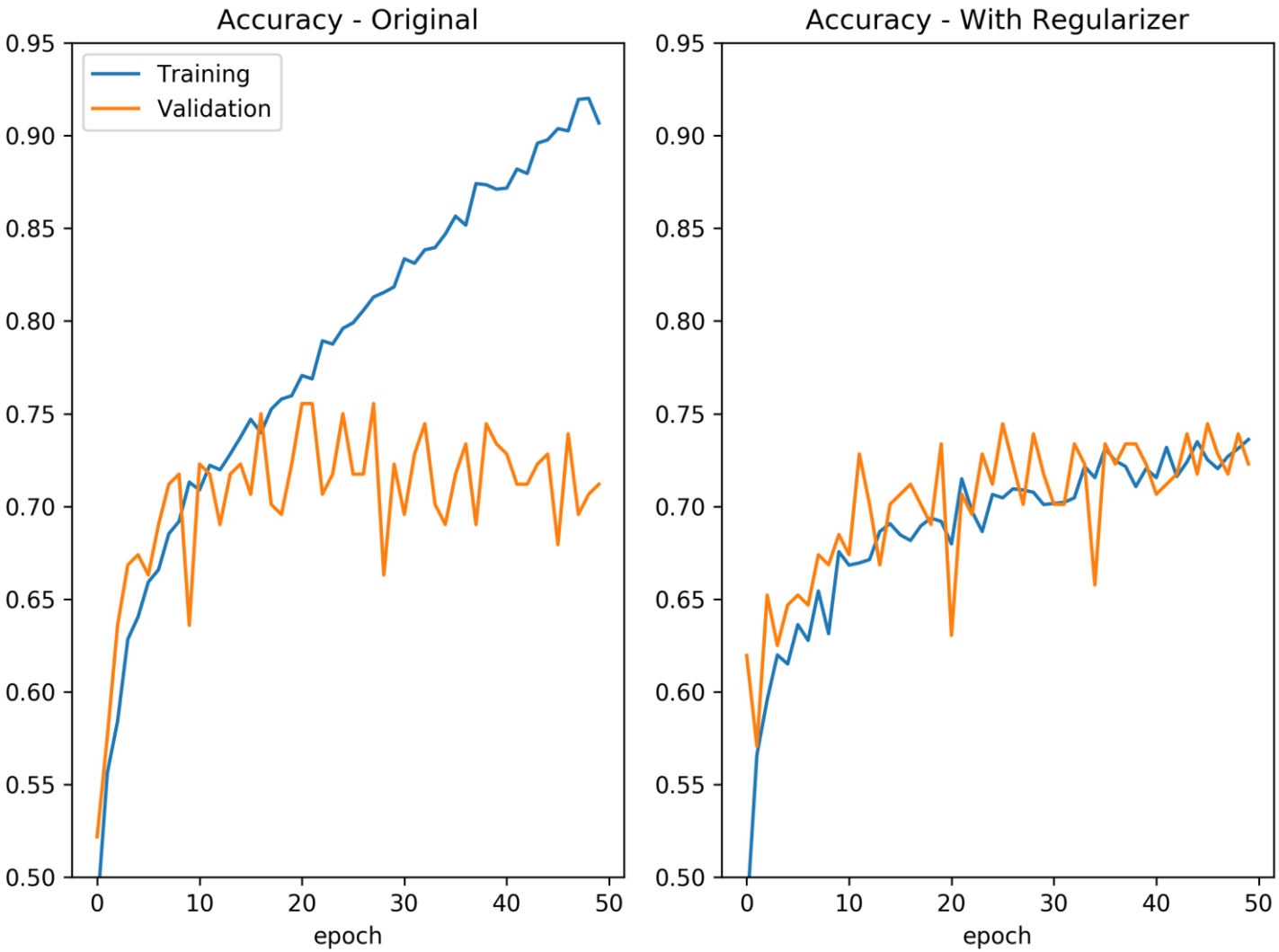
```
''' Import l1,l2 (regularizer) '''
from keras.regularizers import l1,l2,l1l2
# 加入第一層 hidden layer 並加入 regularizer (alpha=0.01)
Model_l2.add(Dense(128,input_dim=200,kernel_regularizer=l2(0.01)))
Model_l2.add(Activation('softplus'))
```

1. alpha = 0.01 會太大嗎？該怎麼觀察呢？
2. alpha = 0.001 再試試看

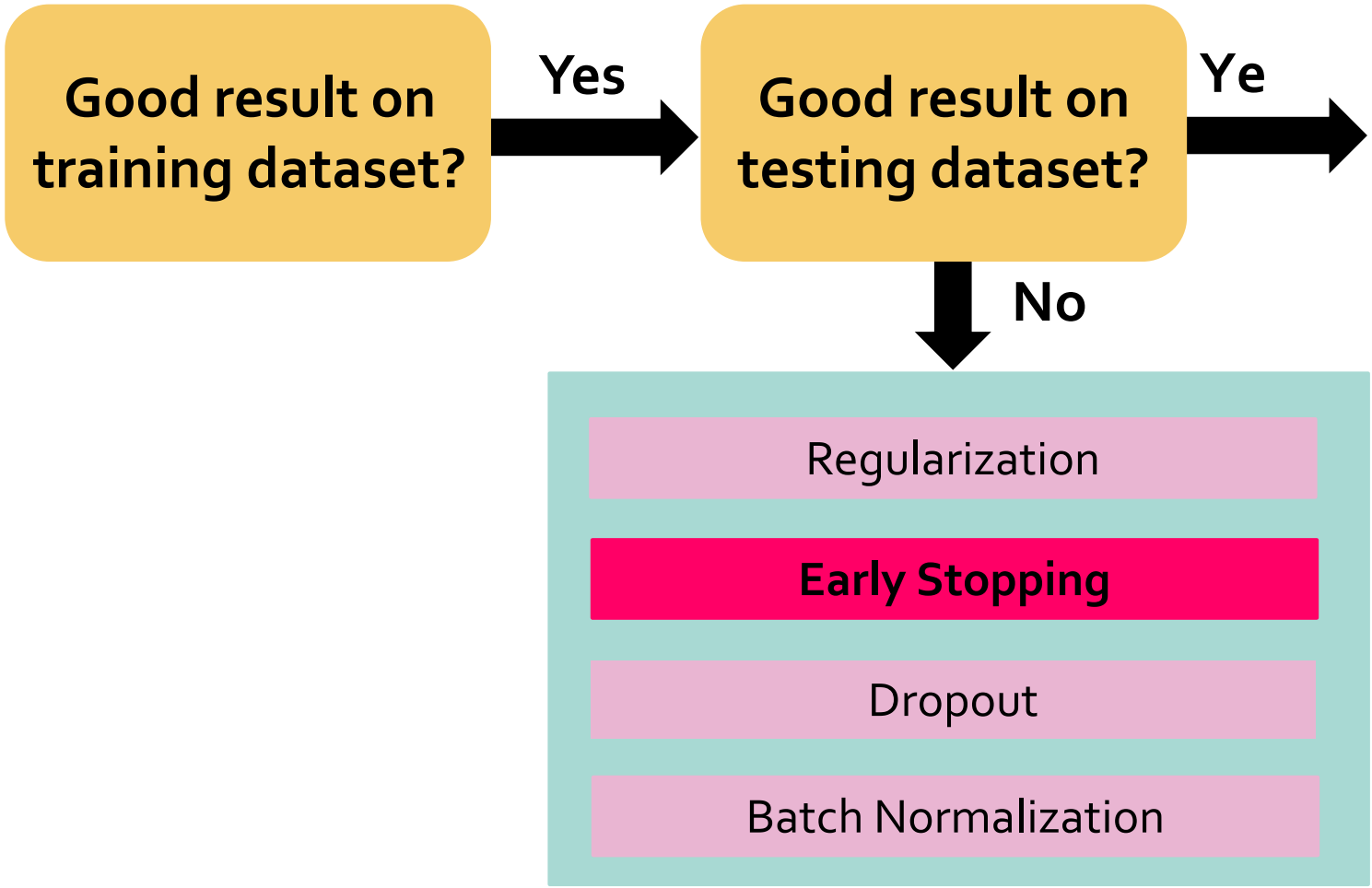
Result – L2 Regularizer (alpha=0.001)



Result – L2 Regularizer (alpha=0.001)

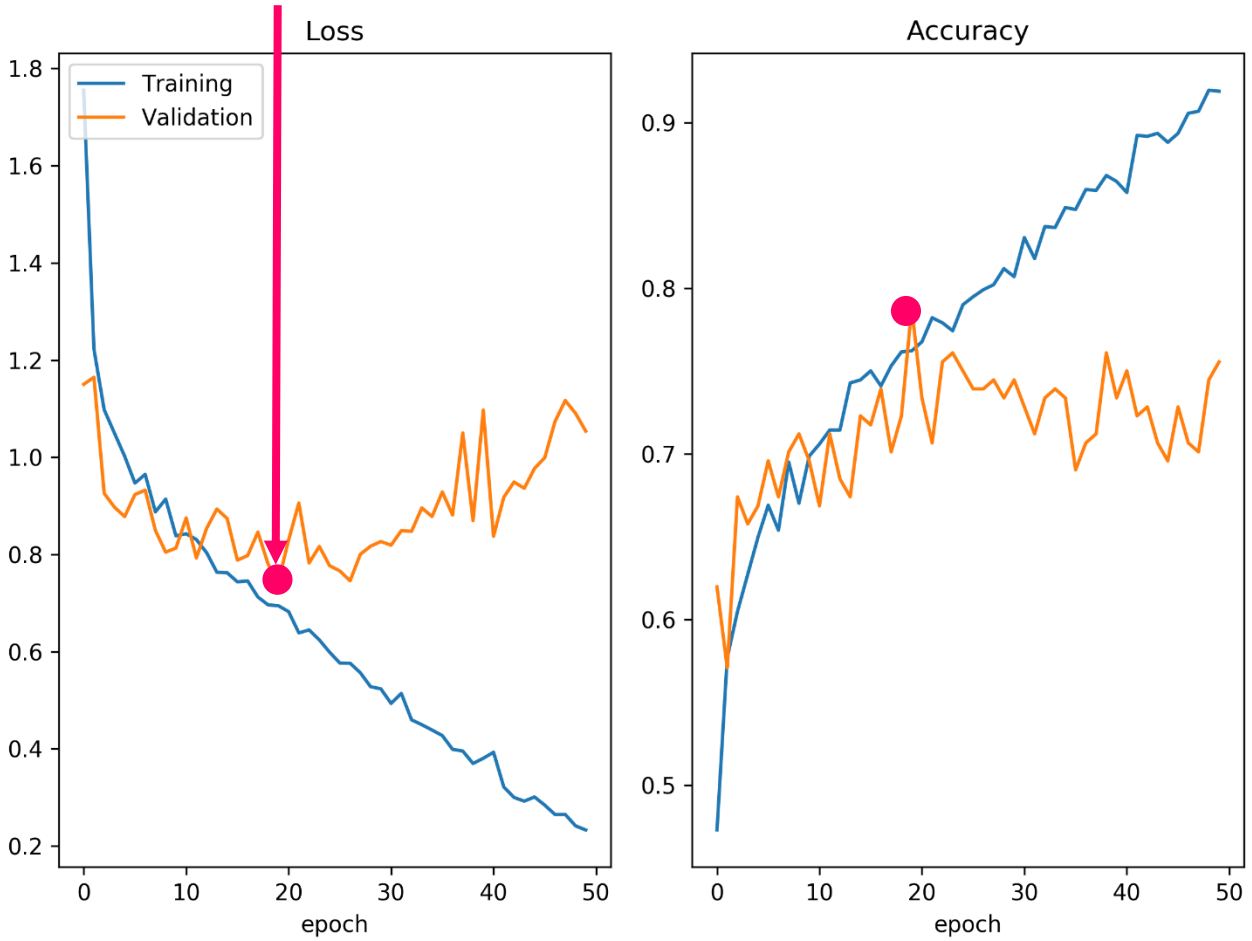


Tips for Deep Learning



Early Stopping

- 假如能早點停下來就好了...



Early Stopping in Keras

- Early Stopping

```
''' EarlyStopping '''
from keras.callbacks import EarlyStopping
earlyStopping=EarlyStopping( monitor = 'val_loss',
                             min_delta = 0.0001,
                              patience = 3)
```

- monitor: 要監控的 performance index
- patience: 可以容忍連續幾次的不思長進

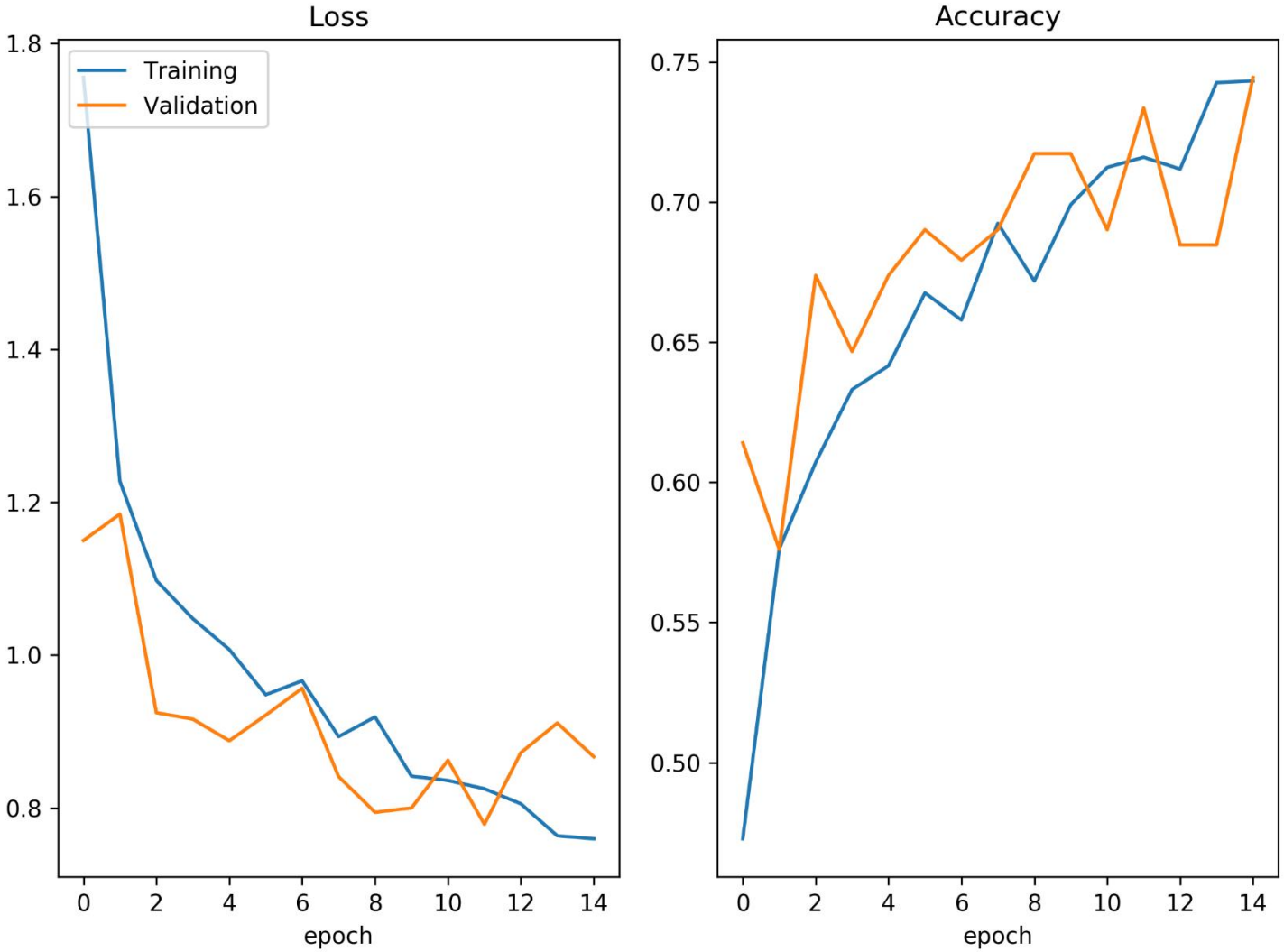
加入 Early Stopping

```
''' EarlyStopping '''
from keras.callbacks import EarlyStopping
earlyStopping=EarlyStopping( monitor = 'val_loss',
                             min_delta = 0.0001,
                              patience = 3)
```

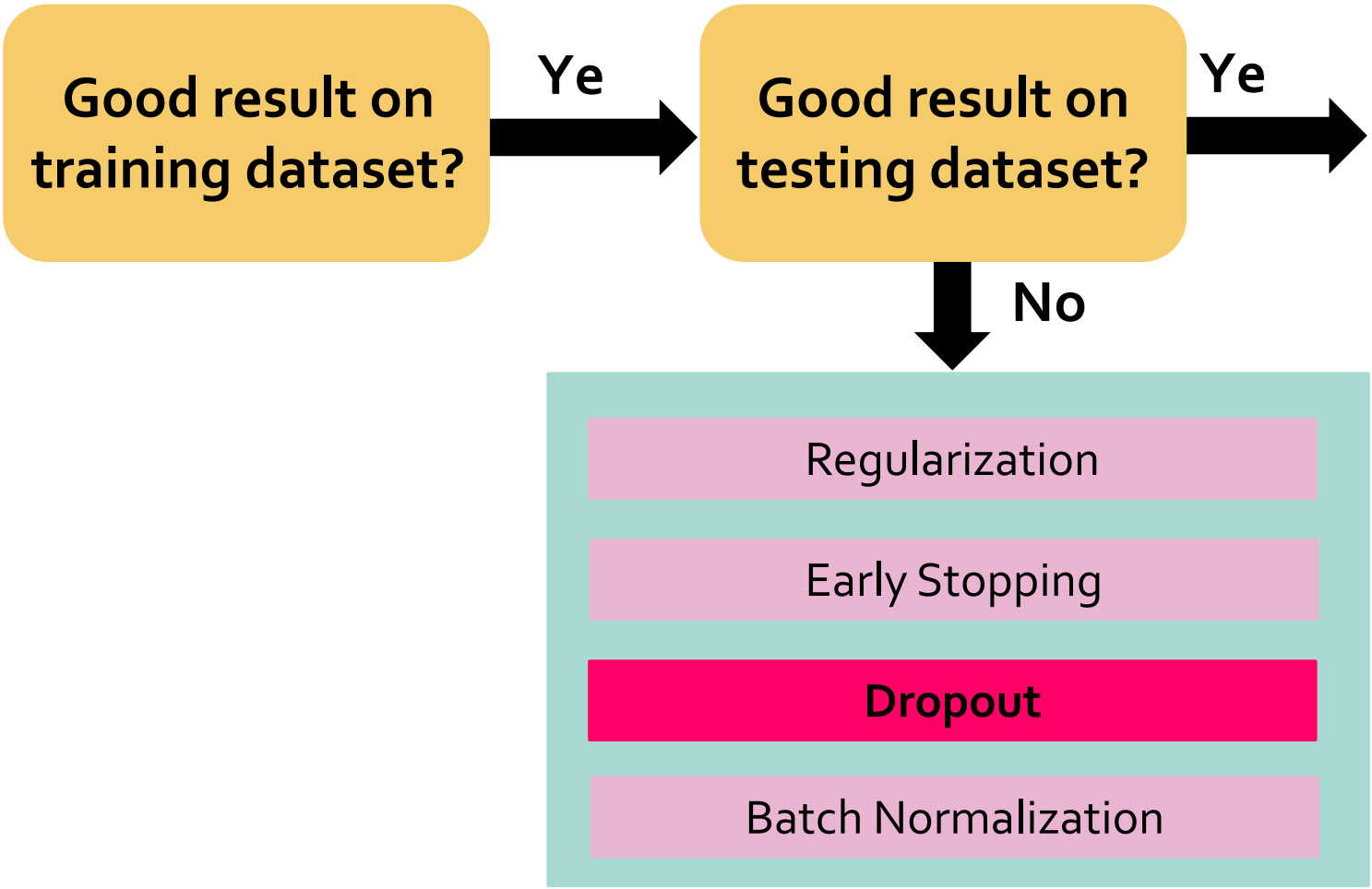
```
# 指定 batch_size, nb_epoch, validation 後，開始訓練模型!!!
history = model.fit( X_train,
                     Y_train,
                     batch_size=16,
                     verbose=0,
                     epochs=30,
                     shuffle=True,
                     validation_split=0.1,
                     callbacks=[earlyStopping])
```

練習 07_earlyStopping.py (5-8 minutes)

Result – EarlyStopping (patience=3)

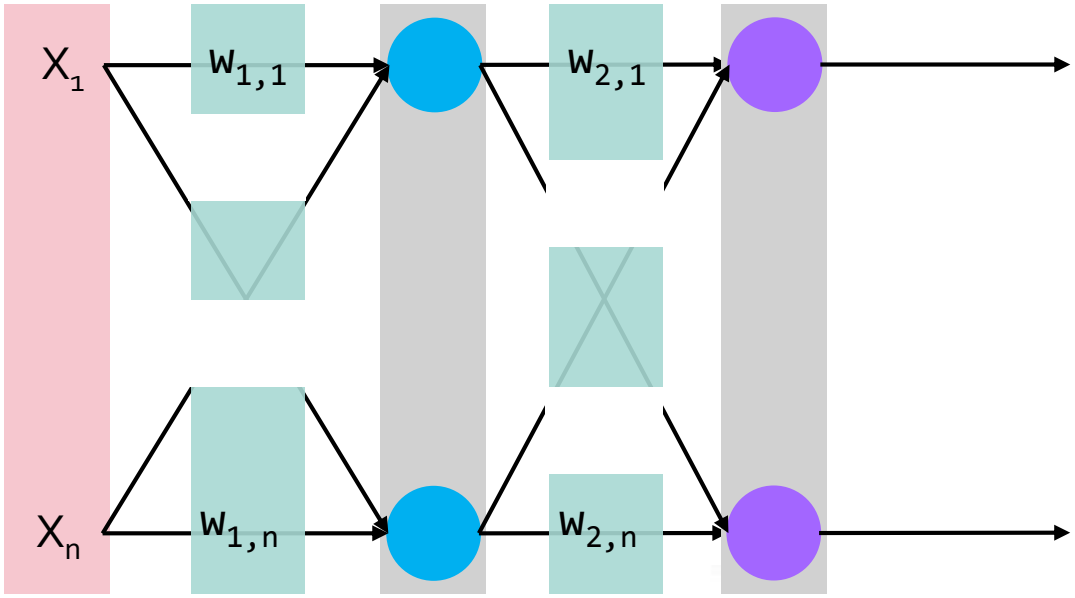


Tips for Deep Learning



Dropout

- What is Dropout?
  - 原本為 neurons 跟 neurons 之間為 fully connected
  - 在訓練過程中，隨機拿掉一些連結 (weight 設為0)

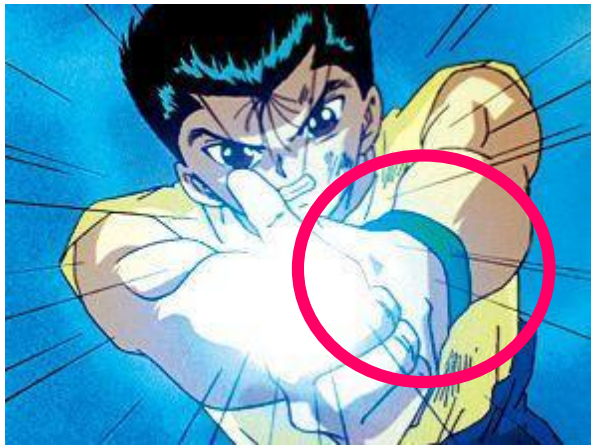


Dropout 的結果

- 會造成 training performance 變差
  - 用全部的 neurons 原本可以做到 $(\hat{y} - y) < \epsilon$
  - 只用某部分的 neurons 只能做到 $(\hat{y}' - y) < \epsilon + \Delta\epsilon$

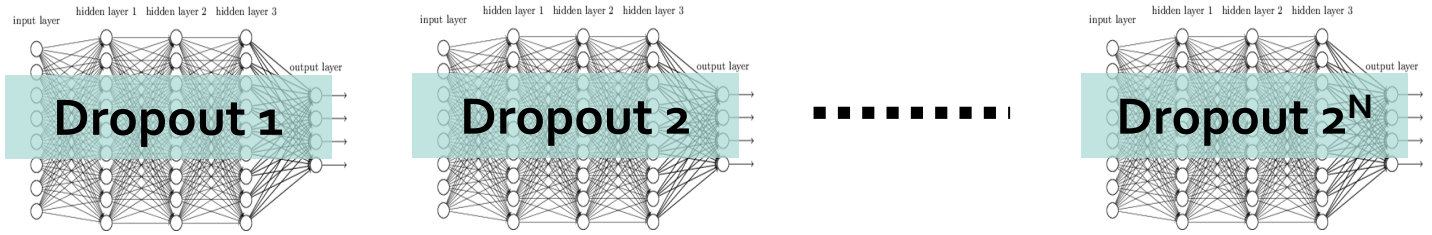
Implications

1. 增加訓練的難度



在真正的考驗時爆發

2. Dropout 可視為一種終極的 ensemble 方法
N 個 weights 會有 2^N 種 network structures

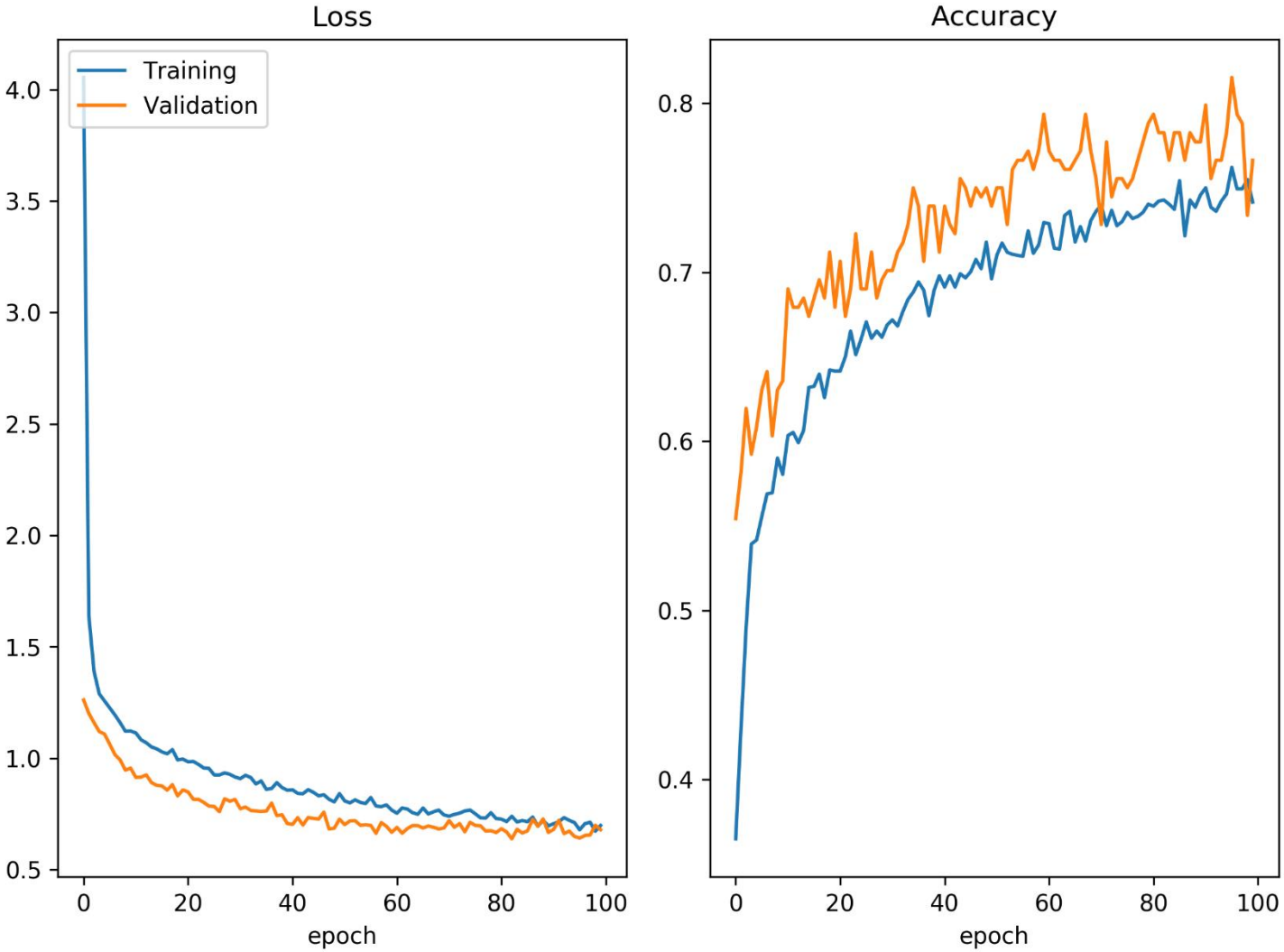


Dropout in Keras

```
from keras.layers.core import Dropout
model = Sequential()

# 加入第一層 hidden layer 與 dropout=0.4
model.add(Dense(128, input_dim=200))
model.add(Activation('relu'))
model.add(Dropout(0.4))

# 加入第二層 hidden layer 與 dropout=0.4
model.add(Dense(256))
model.add(Activation('relu'))
model.add(Dropout(0.4))

# 加入 output layer (5 neurons)
model.add(Dense(5))
model.add(Activation('softmax'))
```

練習 08_dropout.py (5-8 minutes)

Result – Dropout or not

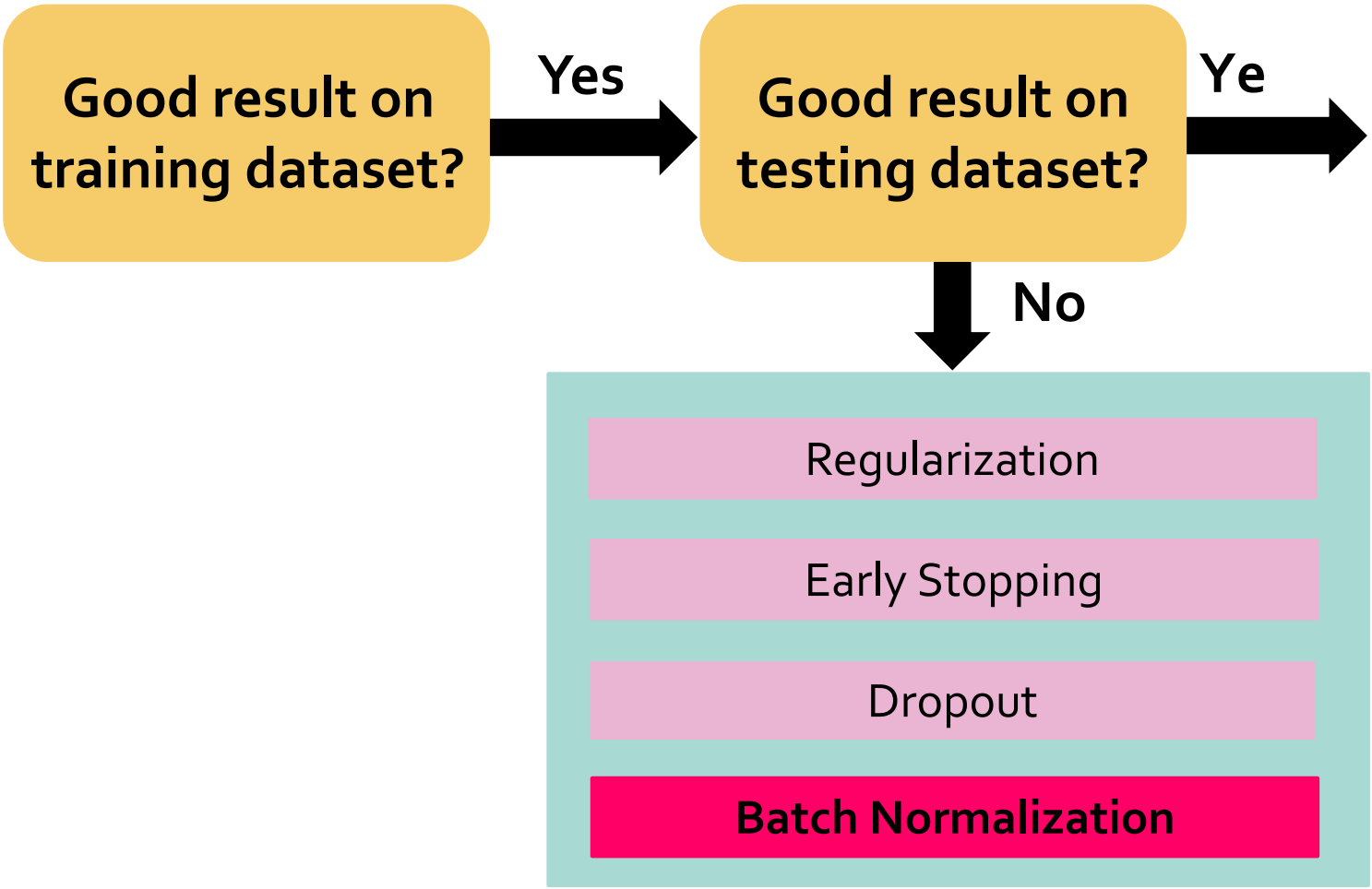


How to Set Dropout

- 不要一開始就加入 Dropout
- 不要一開始就加入 Dropout
- 不要一開始就加入 Dropout

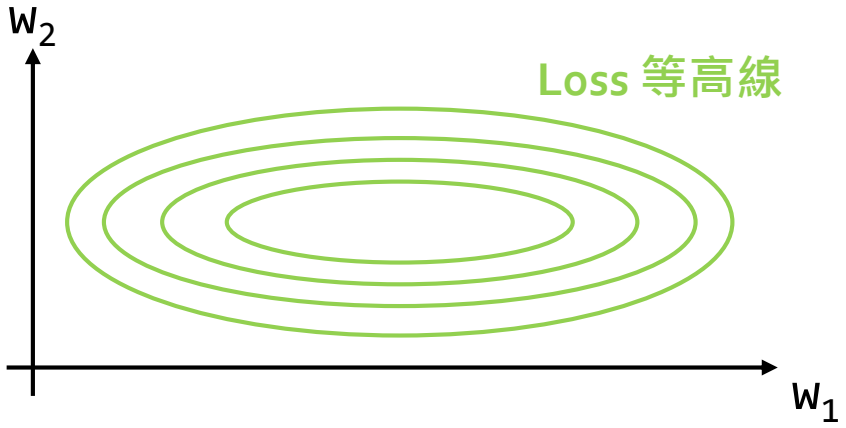
a) Dropout 會讓 training performance 變差
b) Dropout 是在避免 overfitting，不是萬靈丹
c) 參數少時，regularization

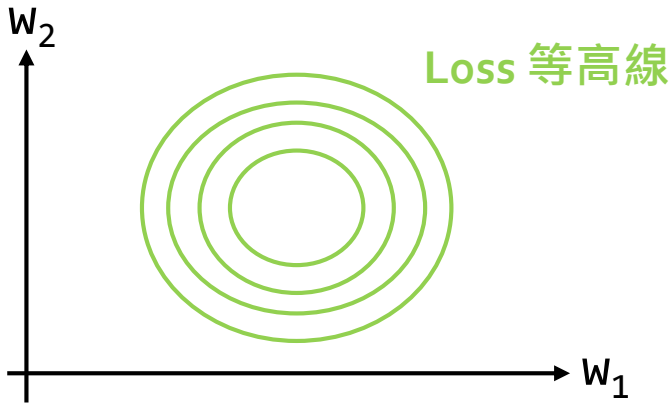
Tips for Deep Learning



回顧一下

- 對於 Input 的數值，前面提到建議要 re-scale
  - Weights 修正的路徑比較會在同心圓山谷中往下滑

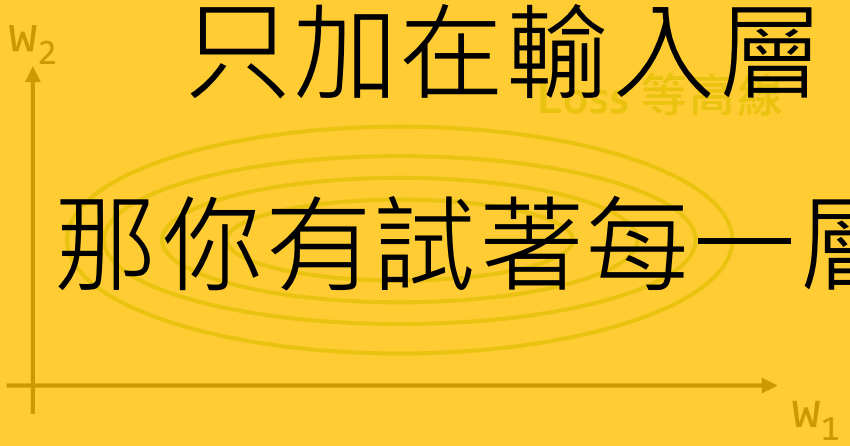




- But ..., 這是只有在 inputs 啊? 如果神經網路很深, 中間每一層的輸出會變得無法控制 (due to nonlinear functions inside networks)

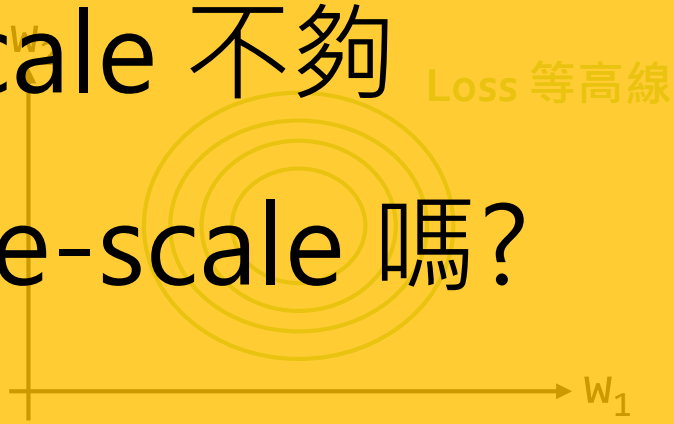
回顧一下

- 對於 Input 的數值，前面提到建議要 re-scale
  - Weights 修正的路徑比較會在同心圓山谷中往下滑



只加在輸入層 re-scale 不夠

那你有試著每一層都 re-scale 嗎?



- But ..., 這是只有在 inputs 啊? 如果神經網路很深, 中間每一層的輸出會變得無法控制 (due to nonlinear functions inside networks)

Batch Normalization

- 每個 input feature 獨立做 normalization
- 利用 batch statistics 做 normalization 而非整份資料
  - 同一筆資料在不同的 batch 中會有些微不同 (a kind of data augmentation)

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

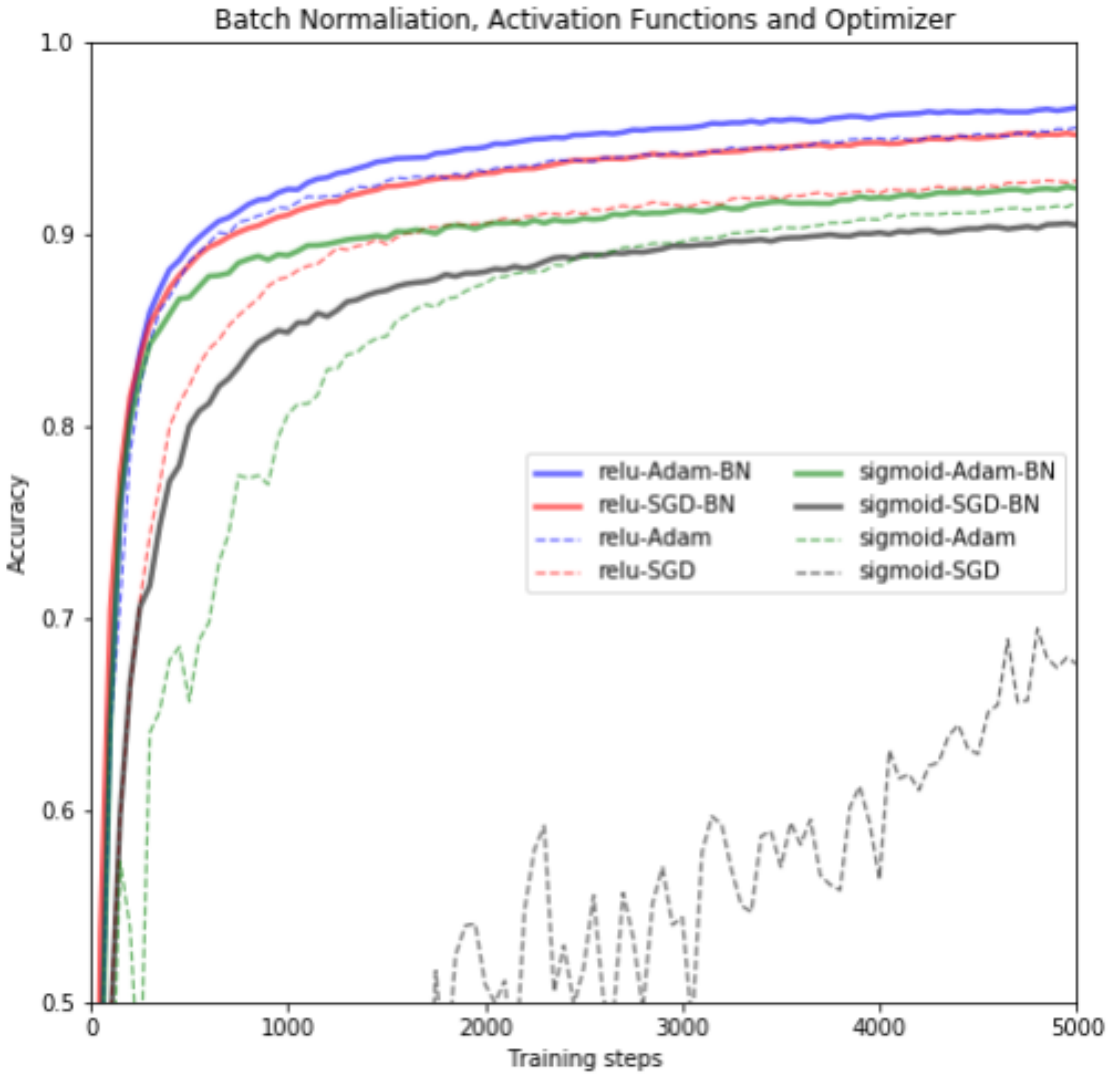
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch Normalization 好處多多

- 可以解決 Gradient vanishing 的問題
- 可以用比較大的 learning rate
- 加速訓練
- 取代 dropout & regularizes
- 目前大多數的 Deep neural network 都會加

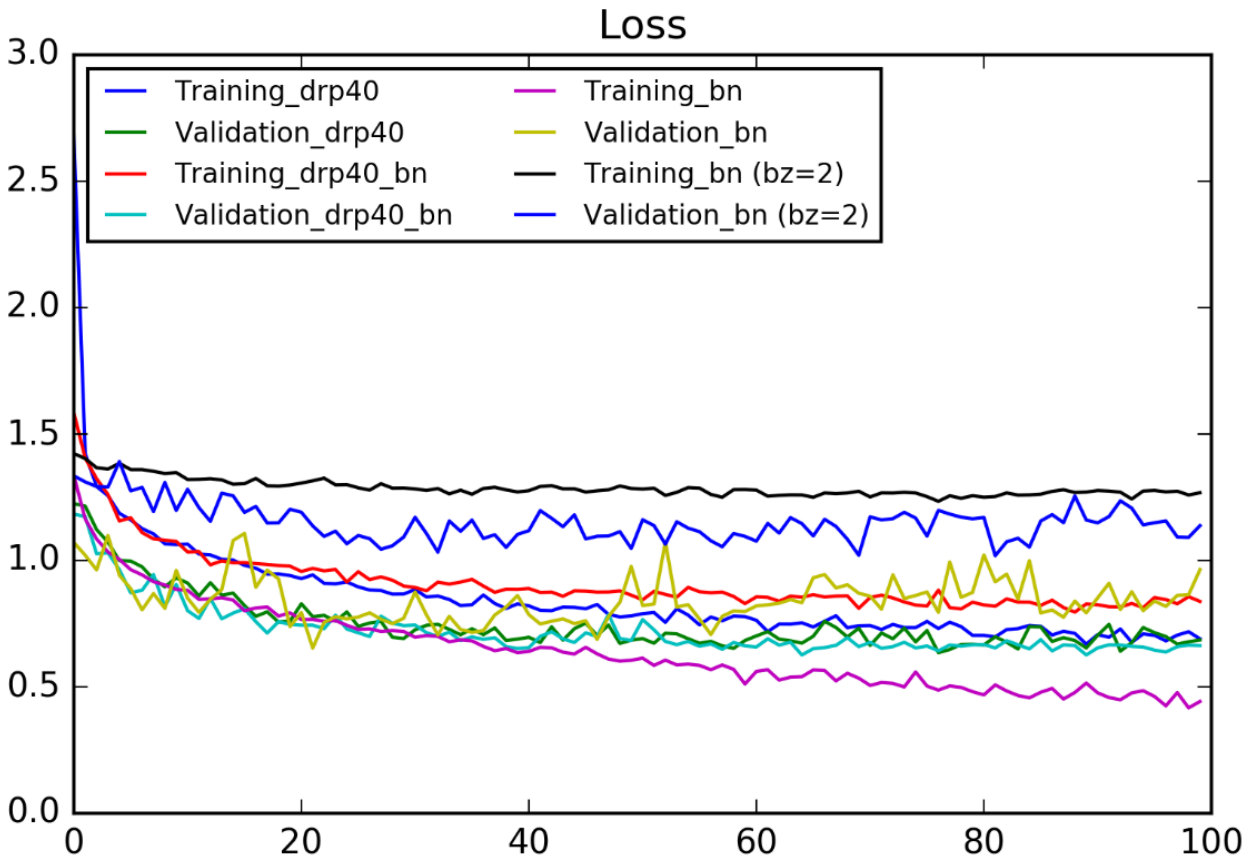
- 大多加在 activation function 前 (Pre-activation!)

Comparisons

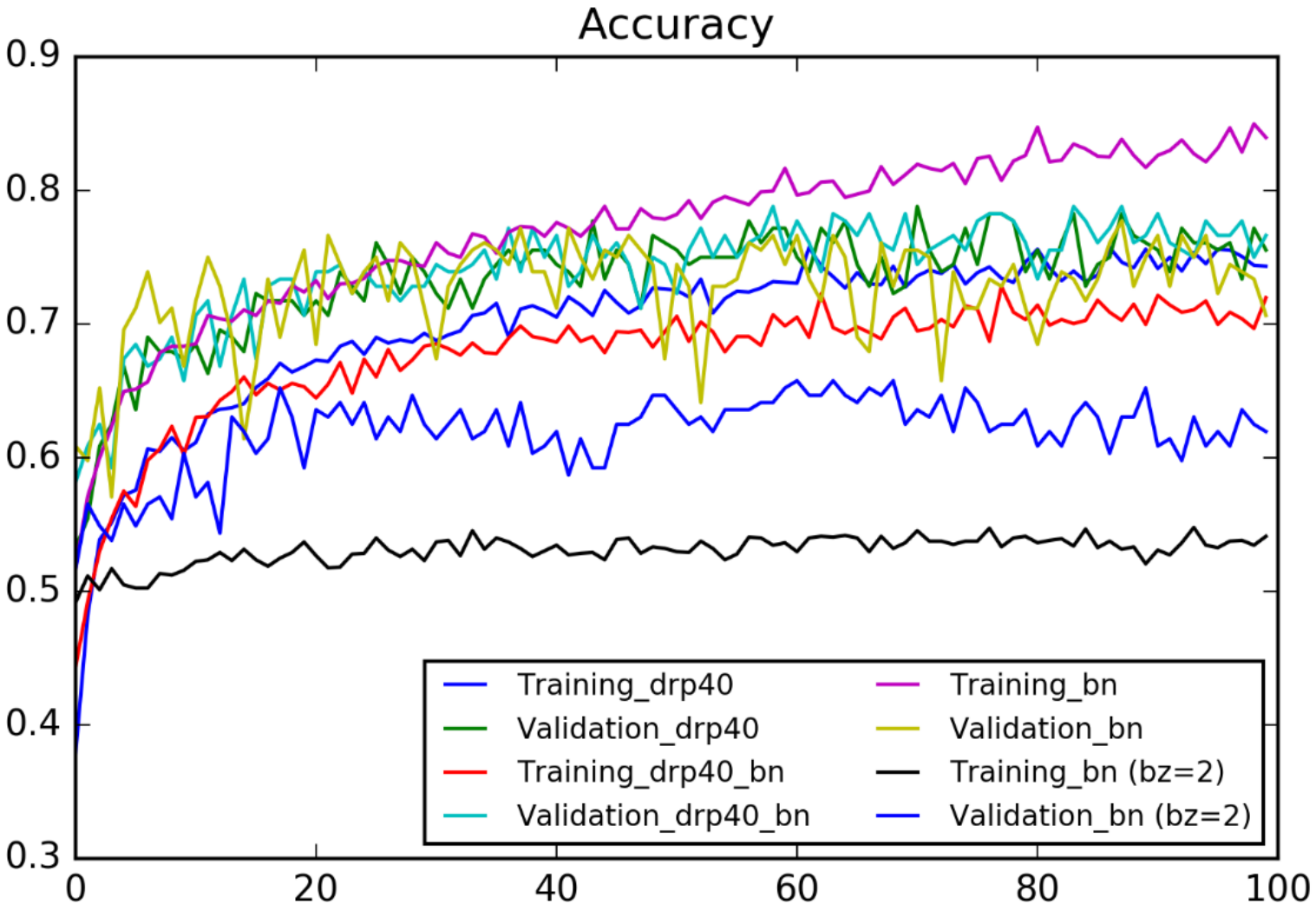


Shortcomings of BN

- 當 batch size 設定很小時不要用! 會爆炸 (general speaking, batch size should at least > 16 / 32)



Result of BN


Accuracy
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
20
40
60
80
100
Training_drp40
Validation_drp40
Training_drp40_bn
Validation_drp40_bn
Training_bn
Validation_bn
Training_bn (bz=2)
Validation_bn (bz=2)

BN in Keras

```
from keras.layers import BatchNormalization
model = Sequential()

model.add(Dense(128, input_dim=200))
model.add(BatchNormalization())
model.add(Activation('relu'))

model.add(Dense(256))
model.add(BatchNormalization())
model.add(Activation('relu'))

# 加入 output layer (5 neurons)
model.add(Dense(5))
model.add(Activation('softmax'))

# 觀察 model summary
model.summary()
```

(Answer) 09_batchnorm.py (5-8 minutes)

大家的好朋友 Callbacks

善用 Callbacks 幫助你躺著 train models

Callbacks Class

```
from keras.callbacks import Callbacks
Class LossHistory(Callbacks):
      def on_train_begin(self, logs={}):
            self.loss = []
            self.acc = []
            self.val_loss = []
            self.val_acc = []
      def on_batch_end(self, batch, logs={}):
            self.loss.append(logs.get('loss'))
            self.acc.append(logs.get('acc'))
            self.val_loss.append(logs.get('val_loss'))
            self.val_acc.append(logs.get('val_acc'))

loss_history = LossHistory()
```

Callback 的時機

- on_train_begin
- on_train_end
- on_batch_begin
- on_batch_end
- on_epoch_begin
- on_epoch_end

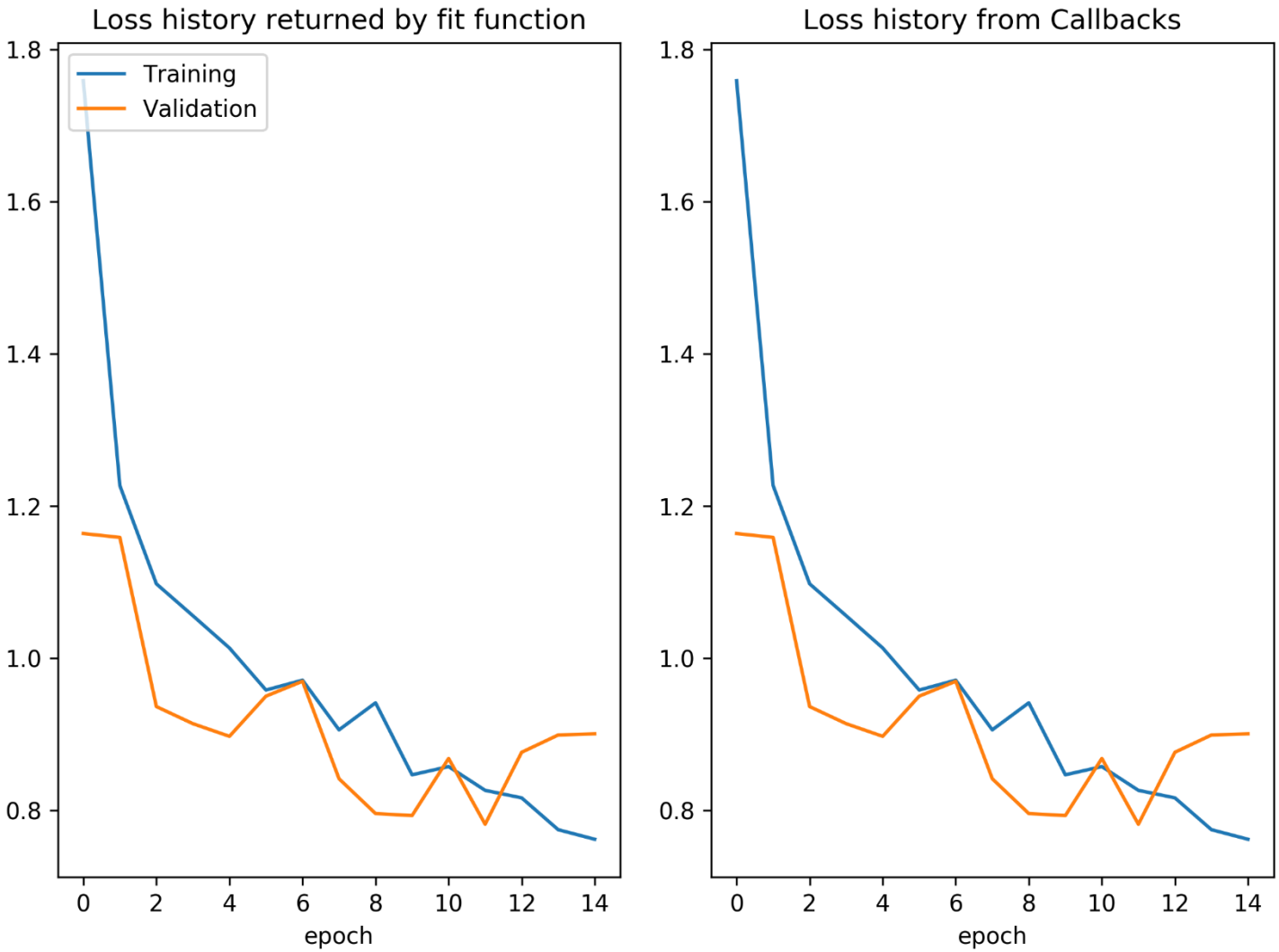
ModelCheckpoint

```
from keras.callbacks import ModelCheckpoint

checkpoint = ModelCheckpoint('model.h5',
                             monitor = 'val_loss',
                             verbose = 1,
                             save_best_only = True,
                             mode = ‘min’)
```

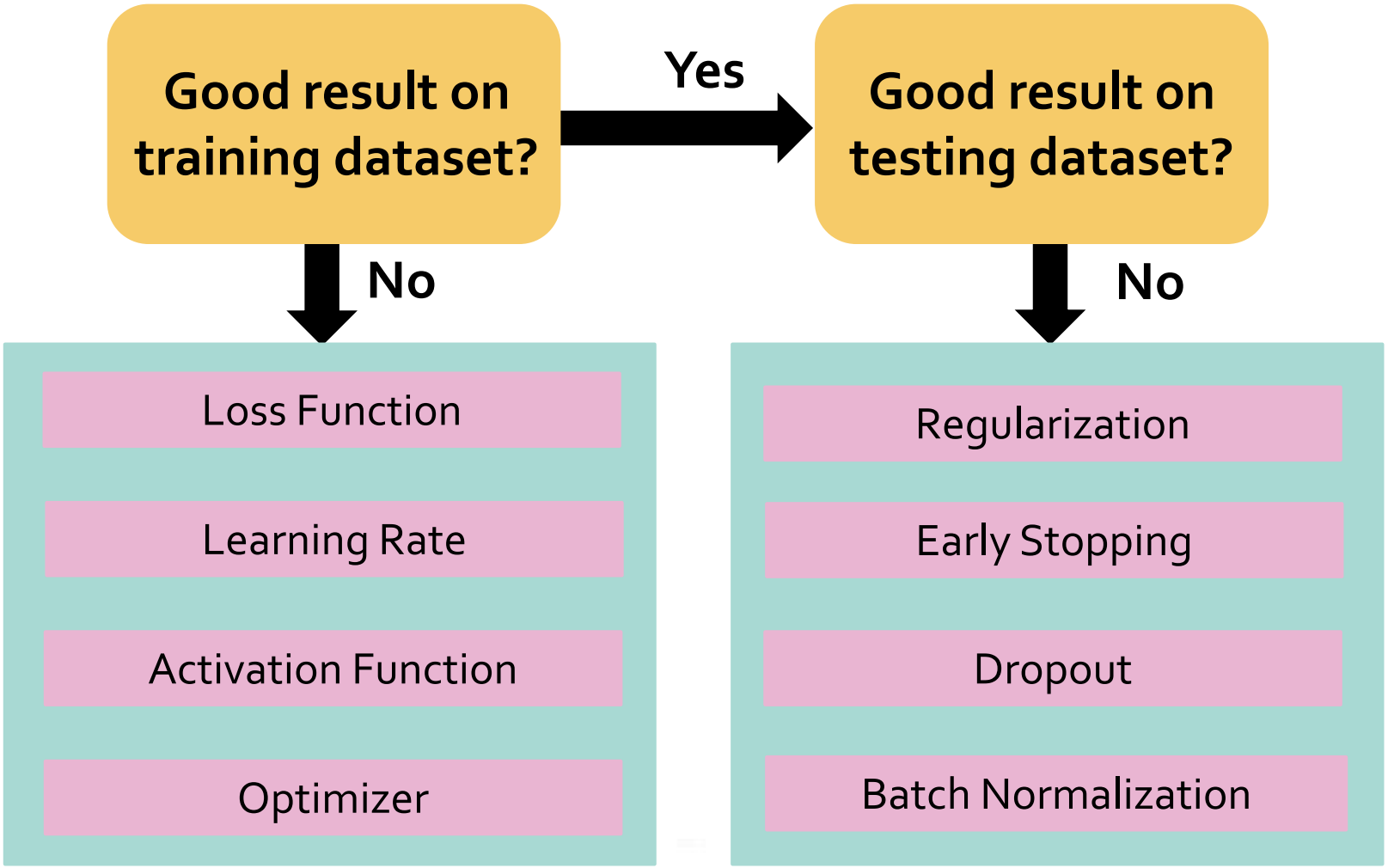
在 model.fit 時加入 Callbacks

```
history = model.fit(X_train, Y_train,
                    batch_size=16,
                    verbose=0,
                    epochs=30,
                    shuffle=True,
                    validation_split=0.1,
                    callbacks=[early_stopping,
                               loss_history,
                               lrate,
                               checkpoint])
```

Example (10_Callback.py)



Tips for Training Your Own DL Model



Semi-supervised Learning

妥善運用有限的標籤資料 (optional)

常面對到的問題

- 收集到的標籤遠少於實際擁有的資料量
- 有 60,000 張照片，只有 5,000 張知道照片的標籤
- 該如何增加 label 呢？
  - Crowd-sourcing
  - Semi-supervised learning

Semi-supervised Learning

- 假設只有 5000 個圖有 label
- 先用 labeled dataset to train model
  - 至少 train 到一定的程度 (良心事業)
- 拿 unlabeled dataset 來測試，挑出預測**好**的 unlabeled dataset
  - Example: softmax output > 0.9 ➔ self-define
- 假設預測的都是對的 (unlabeled ➔ labeled)

  ➔ 有更多 labeled dataset 了！

  ➔ Repeat the above steps

七傷拳

- 加入品質不佳的 labels 反而會讓 model 變差
  - 例如：加入的圖全部都是 “馬”，在訓練過程中，模型很容易變成 “馬” 的分類器
- 慎選要加入的 samples
  - Depends on your criteria ☺

Transfer Learning

Utilize well-trained model on YOUR dataset (optional)

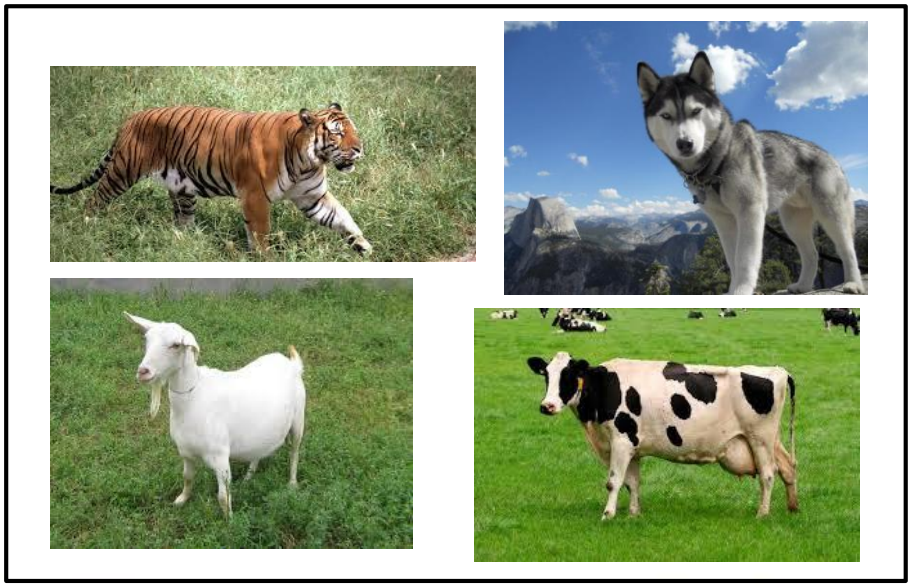
Introduction

- "transfer": use the knowledge learned from task A to tackle another task B
- Example: 綿羊/羊駝 classifier

綿羊

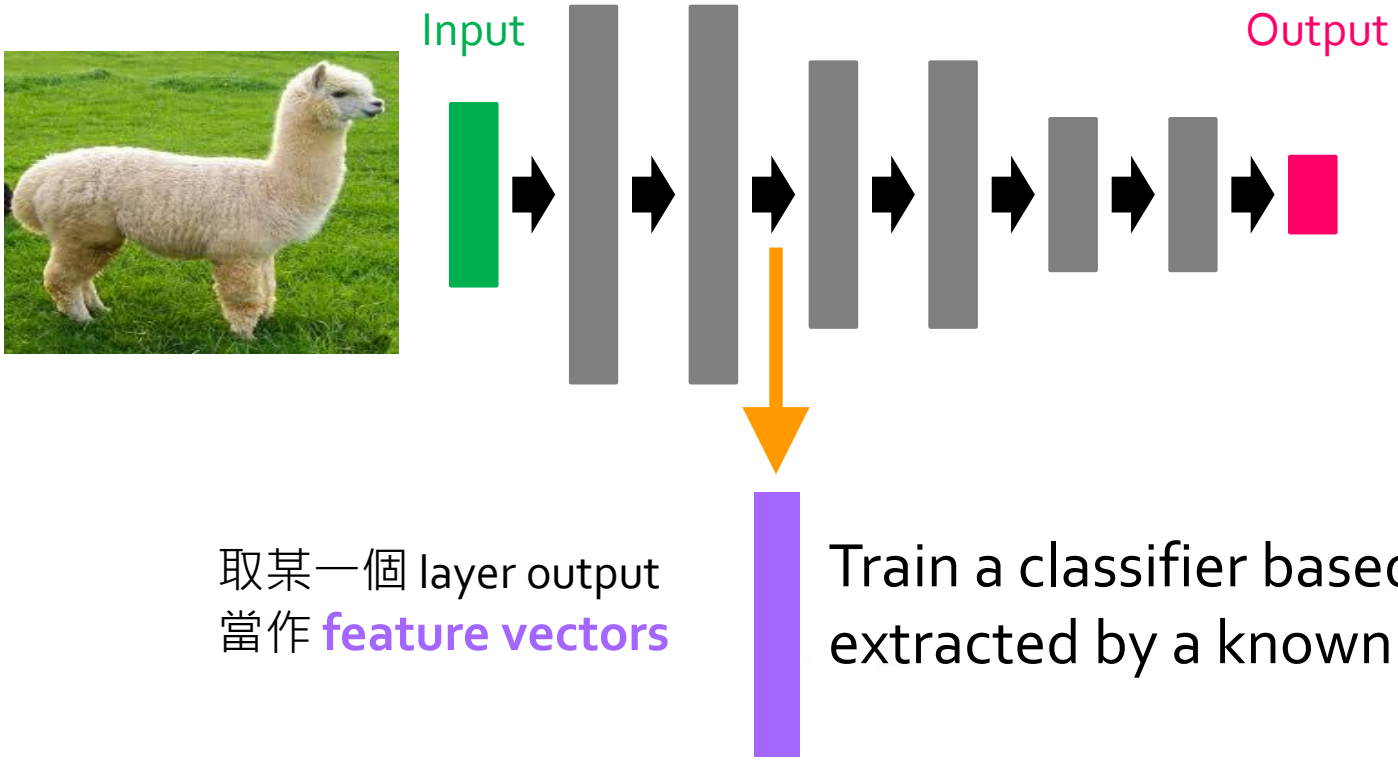
羊駝

其他動物的圖



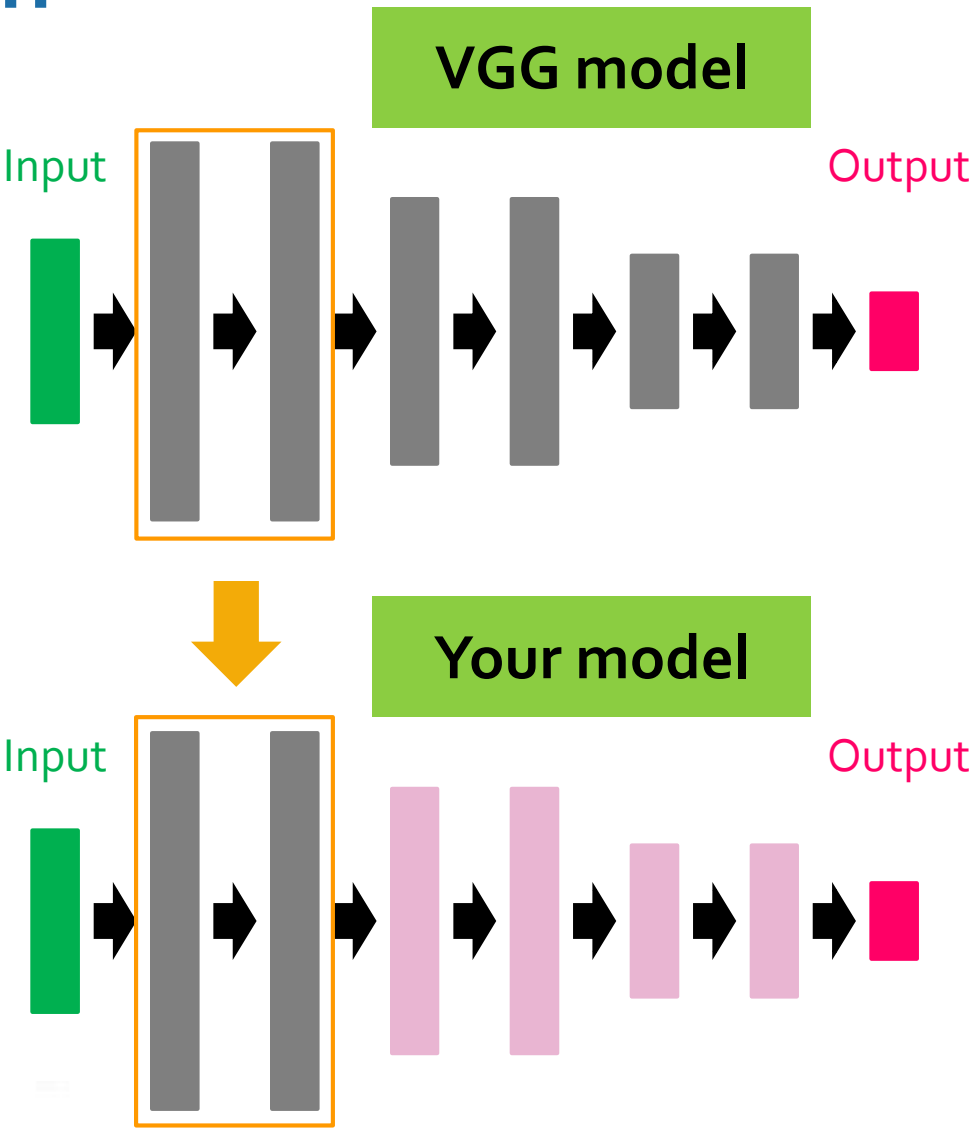
Use as Fixed Feature Extractor

- A known model, like VGG, trained on ImageNet
  - ImageNet: 10 millions images with labels



Use as Initialization

- Initialize your net by the weights of a known model
- Use your dataset to further train your model
- Fine-tuning the known model



Short Summary

- Unlabeled data (lack of y)

  ➔ Semi-supervised learning

- Insufficient data (lack of both x and y)

  ➔ Transfer learning (focus on layer transfer)

  - Use as fixed feature extractor
  - Use as initialization
  - Resources: https://keras.io/applications/

Jason Yosinski, Jeff Clune, Yoshua Bengio, Hod Lipson, "How transferable are features in deep neural networks?", https://arxiv.org/abs/1411.1792, 2014

Summarization

What We Have Learned Today

Recap – Fundamentals

- Fundamentals of deep learning
  - A neural network = a function
  - Gradient descent
  - Stochastic gradient descent
  - Mini-batch
  - Guidelines to determine a network structure

Recap – Improvement on Training Set

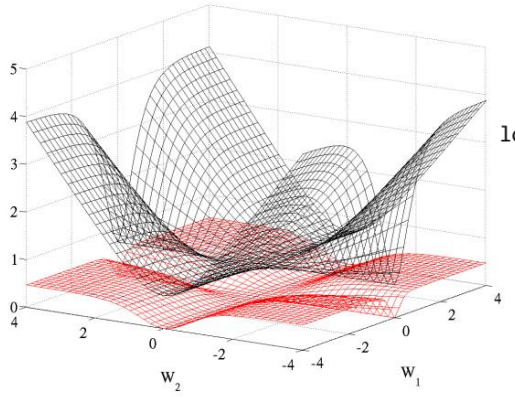
- How to improve performance on training dataset

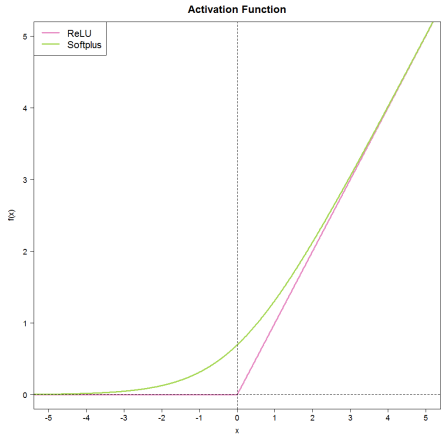
Loss Function

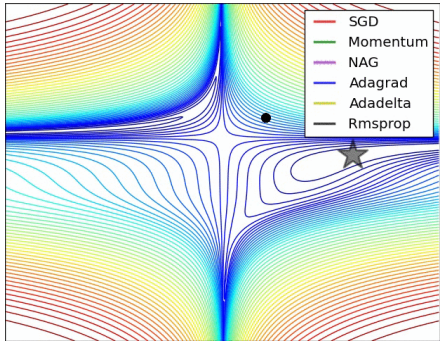
Learning Rate

Activation Function

Optimizer







Recap – Improvement on Testing Set

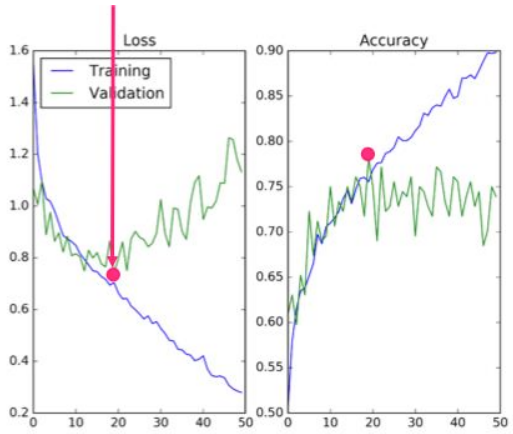
- How to improve performance on testing dataset

Regularization

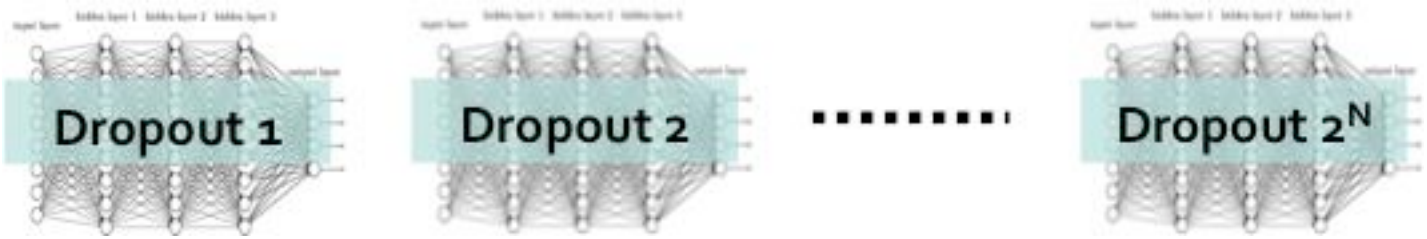
Early Stopping

Dropout

Batch Normalization



$$Loss_{reg} = \sum(y - (b + \sum w_i x_i)) + \alpha(\text{regularizer})$$



補充資料

Model 儲存與讀取

```
# save model
model.save(“filename.h5”)

# load model
from keras.model import load_model
model_test = load_model(“filename.h5”)

# BTW, use model.summary() to check your layers
Model_test.summary()
```

How to Get Trained Weights

- weights = model.get_weights()
- model.layers[1].set_weights(weights[0:2])

```
# get weights
myweight = model_test.get_weights()

# set weights
model_test.layers[1].set_weights(myweights[0:2])

# BTW, use model.summary() to check your layers
model_test.summary()
```

How to Get Layer Output

```
# get weights
model_layer1 = Sequential()
model_layer1.add(Dense(128,input_dim=200,
       weights=model_test.layers[0].get_weights()))

model_layer1.add(Activation('relu'))

# predict
model_layer1.predict(X_train[0:1])
```

Fit_Generator

- 當資料太大無法一次讀進時 (memory limitation)

```
# get weights
def train_generator(batch_size):
    while 1:
        data = np.genfromtext('pkgo_city66_class5_v1.csv',
                              delimiter=',',
                              skip_header=1)
        for i in range(0,np.floor(batch_size/len(data)))
            x = data[i*batch_size:(i+1)*batch_size,:200]
            y = data[i*batch_size:(i+1)*batch_size,200]
            yield x,y

Model.fit_generator(train_generator(28),
                    epochs=30,
                    steps_per_epoch=100,
                    validation_steps=100) # or validation_data
```

Go Deeper in Deep Learning

- "Neural Networks and Deep Learning"
  - http://neuralnetworksanddeeplearning.com/
- "Deep Learning"
  - http://www.iro.umontreal.ca/~bengioy/dlbook/
- Course: Machine learning and having it deep and structured
  - http://speech.ee.ntu.edu.tw/~tlkagk/courses_MLSD15_2.html
- Keras 官方網站，非常詳細
  - Keras documentation and Keras Github 從 example/ 中找適合範例
- 台大電機李宏毅教授 Youtube 頻道
- Stanford cs231n Convolutional Neural Networks for Visual Recognition

- 若有任何問題，歡迎來信 twcmchang@gmail.com

(Slide Credit: Hung-Yi Lee)

一起往訓練大師的路邁進吧
謝謝大家！