手把手教你深度學習實務

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Lecturers

- 畢業於台大電機系、台大電機所
- 中研院資訊所研究助理
- 研究領域
  - 線上平台定價自動化
  - 線上平台使用者分析
  - 計算社會學

- 台大電機系博士班二年級
- 中研院資訊所研究助理
- 研究領域
  - 多媒體系統效能測量
  - 使用者滿意度分析

Outline

- What is Machine Learning?
- What is Deep Learning?
- Hands-on Tutorial of Deep Learning
- Tips for Training DL Models
- Variants - Convolutional Neural Network

What is Machine Learning?

一句話說明 Machine Learning

Field of study that gives computers the ability to learn without being explicitly programmed.

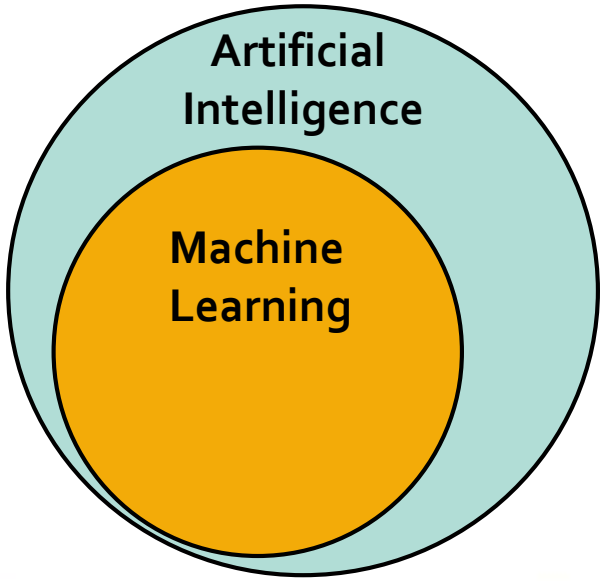
- Arthur Lee Samuel, 1959

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

- Tom Mitchell, 1997

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 的一種方法
  - 從資料當中學習出 rules



Goal of Machine Learning

- For a specific task, find a best function to complete
- Task: 每集寶可夢結束的"猜猜我是誰"

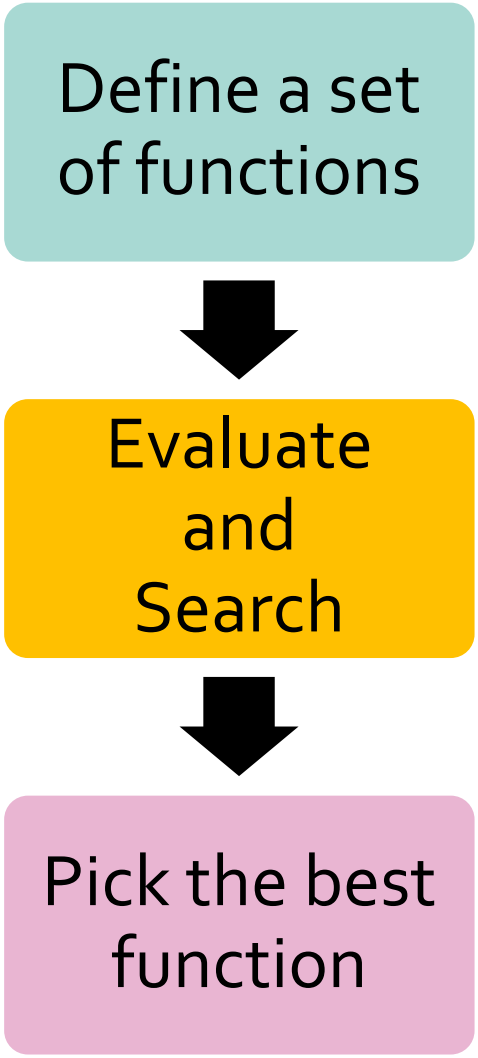
f*() = 

Ans: 妙蛙種子

f*() = 

Ans: 超夢

Framework

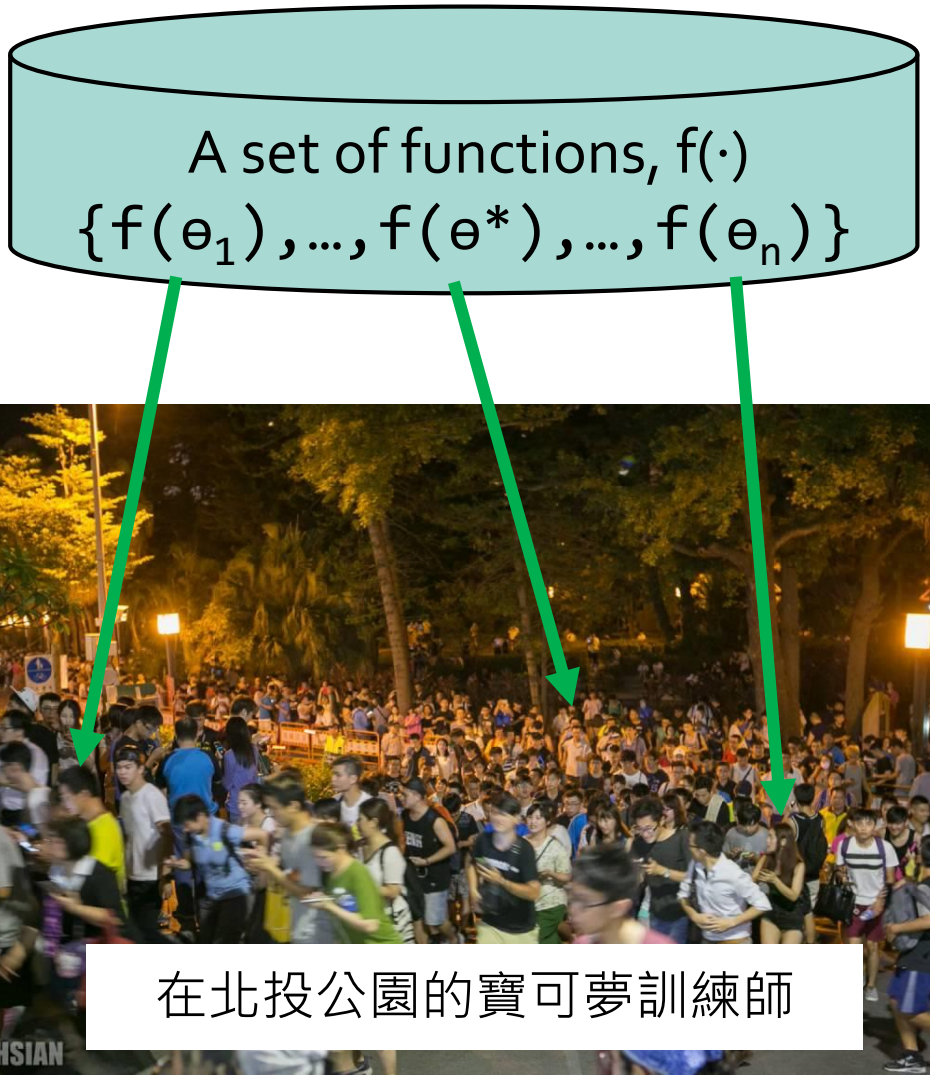

Define a set of functions
Evaluate and Search
Pick the best function

1. Define a Set of Functions

Define a set of functions

Evaluate and Search

Pick the best function



2. Evaluate and Search

Define a set of functions

Evaluate and Search

Pick the best function

$f_1=f(\theta_1)$

f_1() = 

f_1() = 

根據結果，修正 θ ：

避免找身上有皮卡丘的人 (遠離 θ_1)

3. Pick The Best Function

Define a set of functions

Evaluate and Search

Pick the best function

找到寶可夢訓練大師

Machine Learning Framework

Define a set of functions

北投公園的訓練師

Evaluate and Search

評估、修正

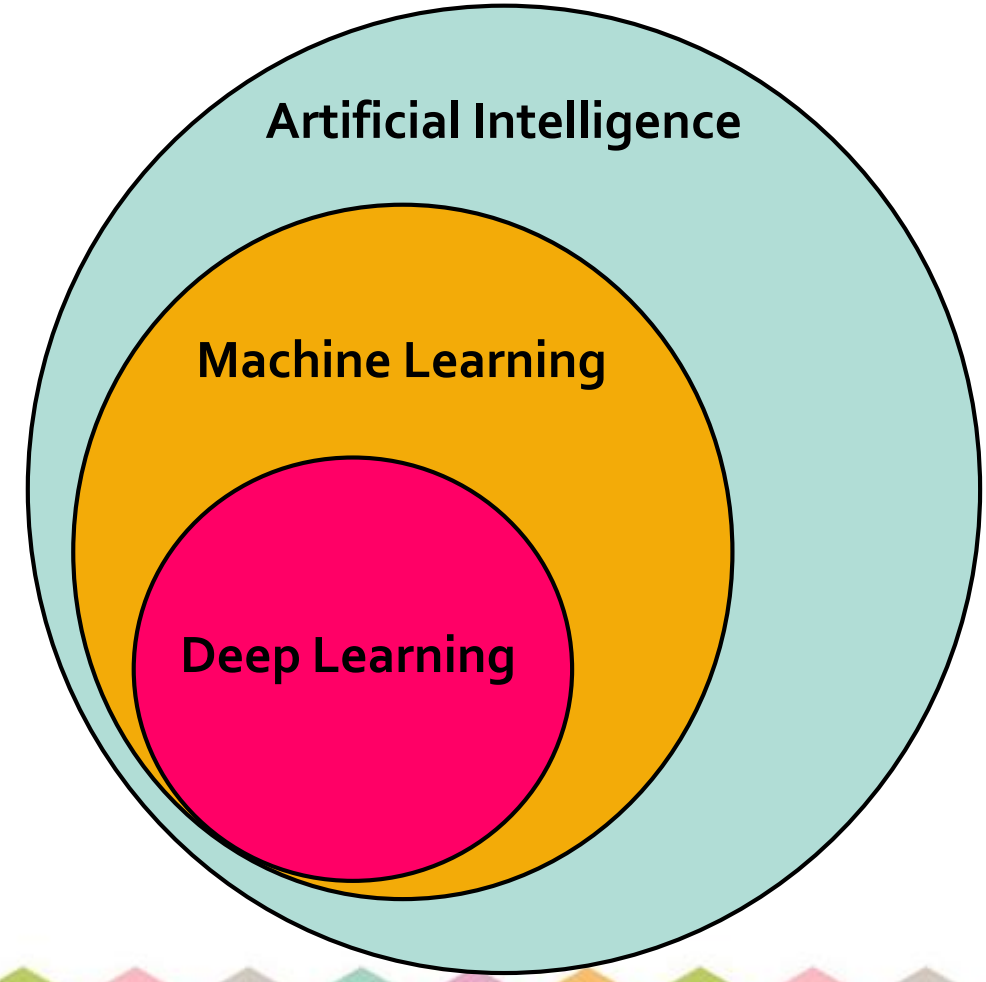
Pick the best function

找到最好的寶可夢專家

What is Deep Learning?

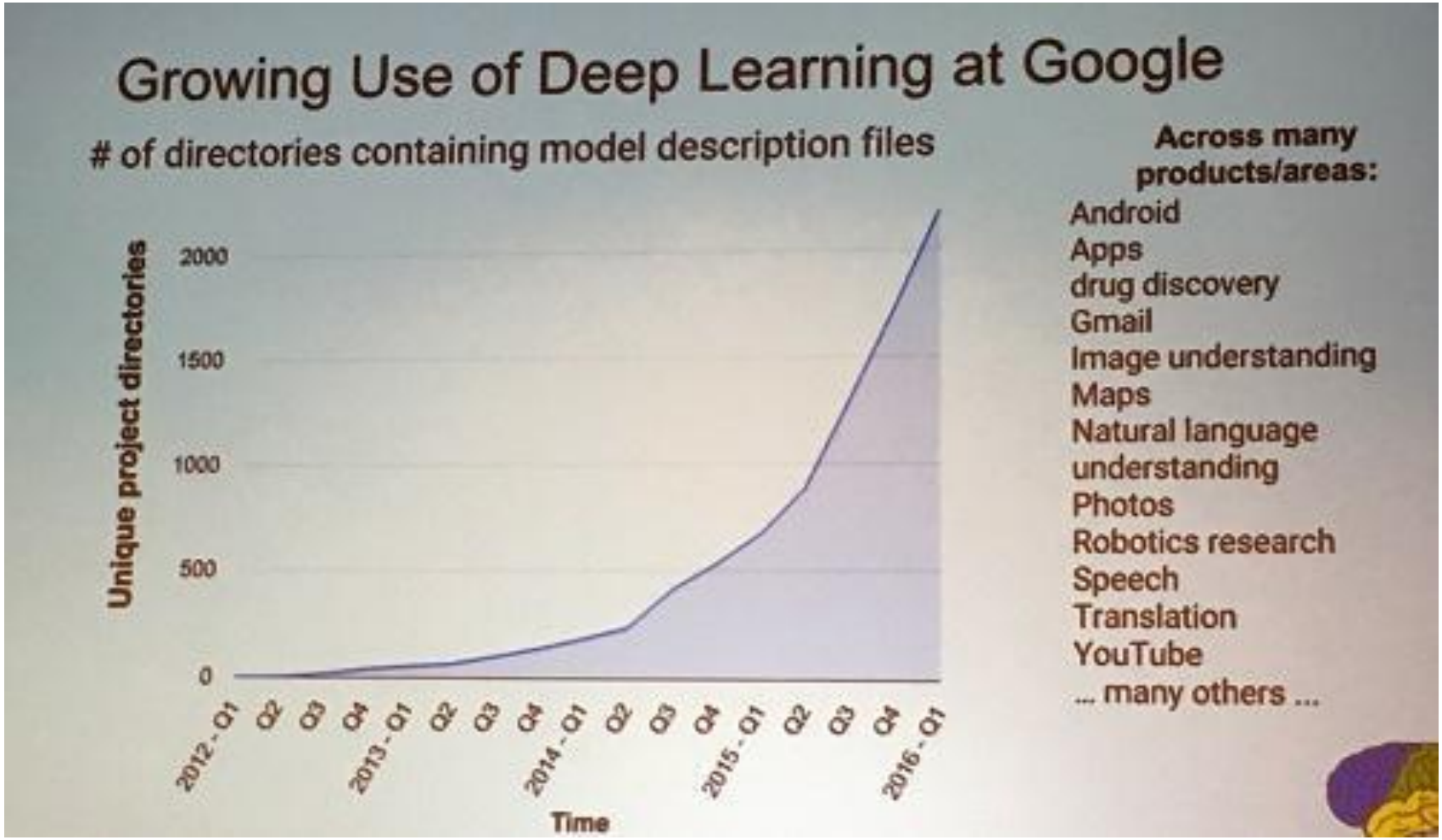
Deep Learning vs Machine Learning

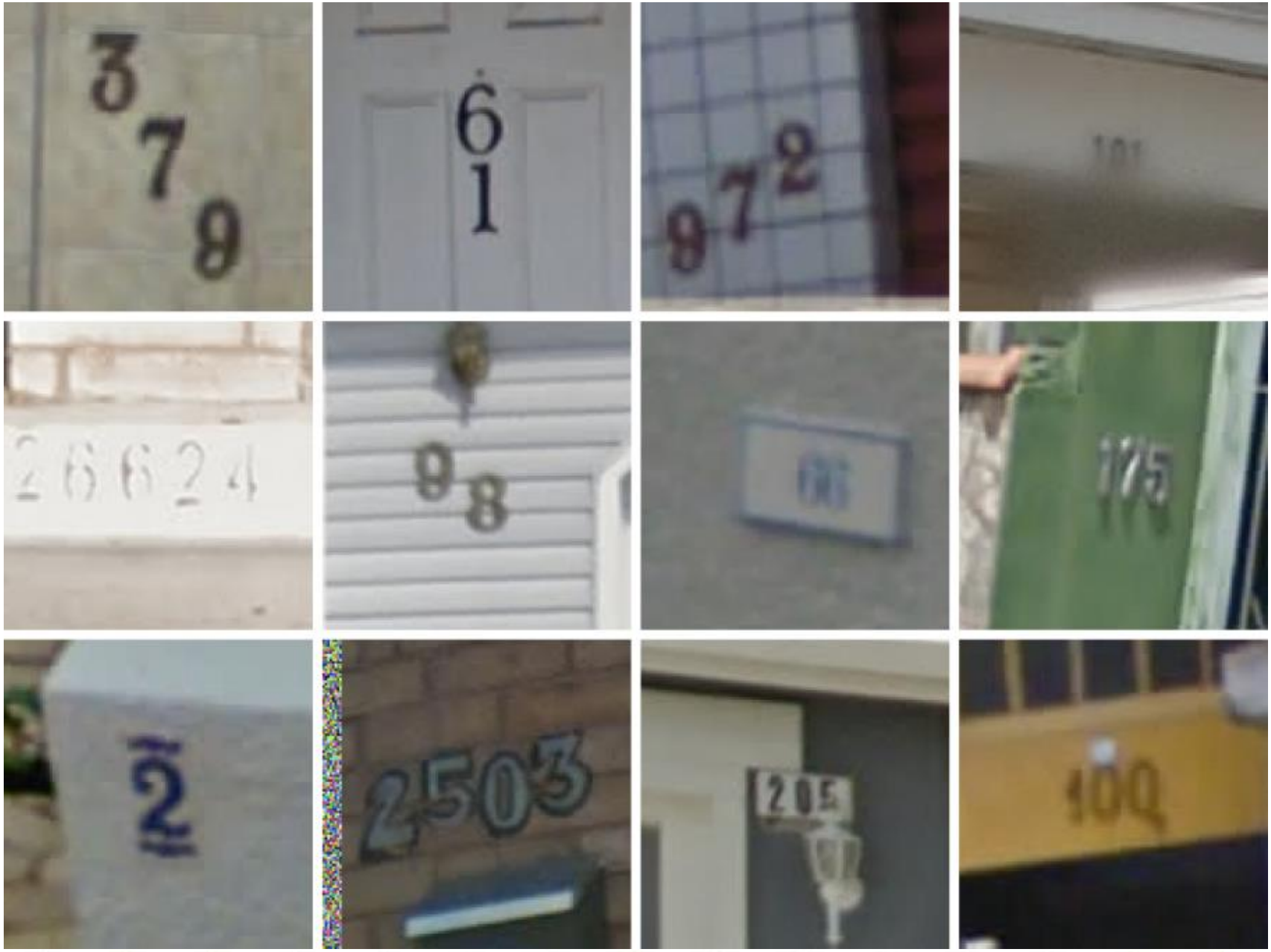
- Deep learning is a subset of machine learning



最近非常夯的技術

(Slide Credit: Hung-Yi Lee)

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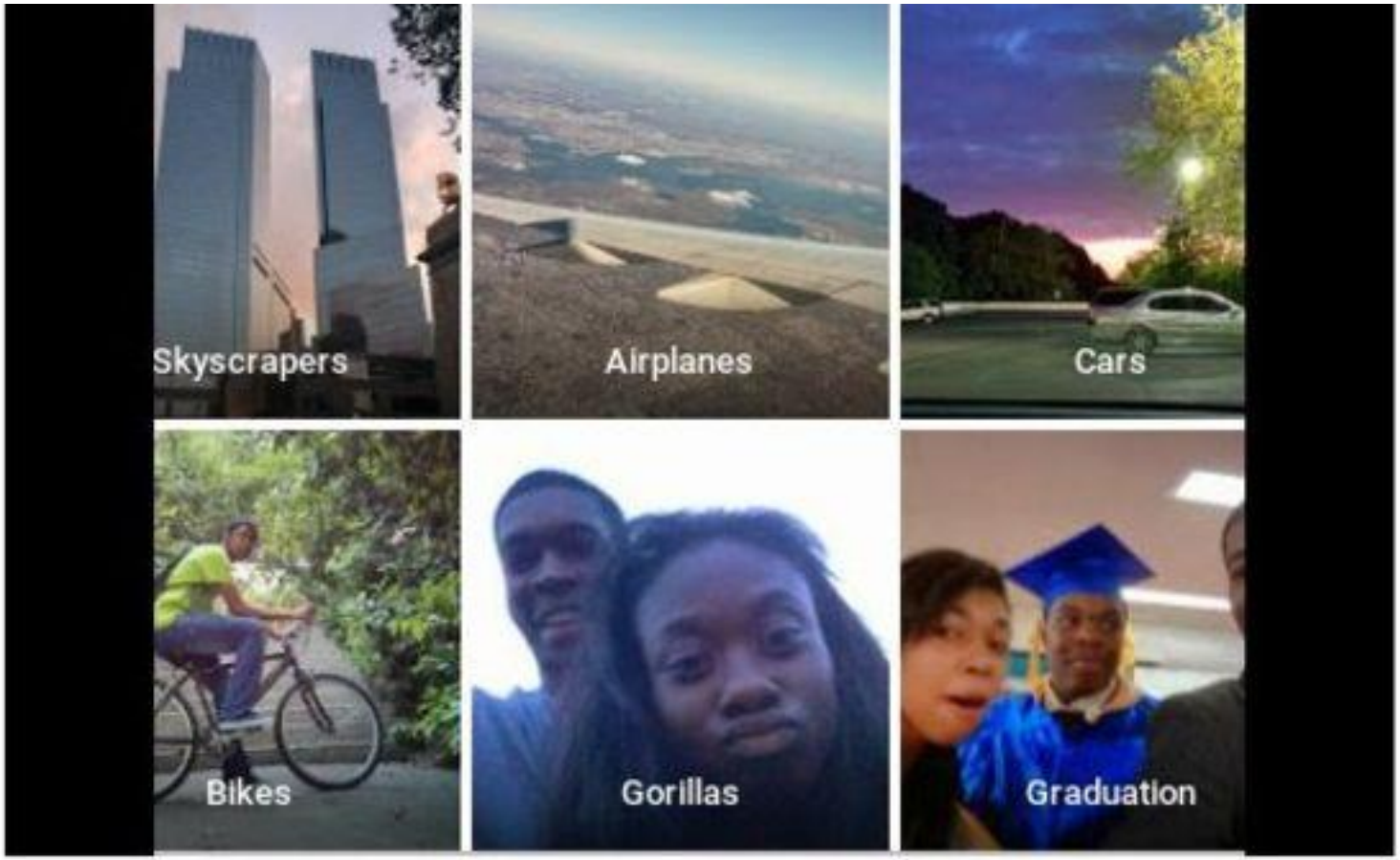


diri noir avec banan @jackyalcine · Jun 29

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

813 394

TWITTER

Image Captioning

Describes without errors	Describes with minor errors	Somewhat related to the image

A person riding a motorcycle on a dirt road.

Two dogs play in the grass.

A skateboarder does a trick on a ramp.

A group of young people playing a game of frisbee.

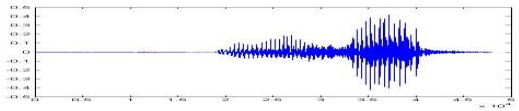
Two hockey players are fighting over the puck.

A little girl in a pink hat is blowing bubbles.

(Slide Credit: Hung-Yi Lee)

Applications of Deep Learning

- Speech Recognition

$f^*($  $) =$ "Morning"

- Handwritten Recognition

$f^*($  $) =$ "2"

- Playing Go

$f^*($  $) =$ "5-5" (step)

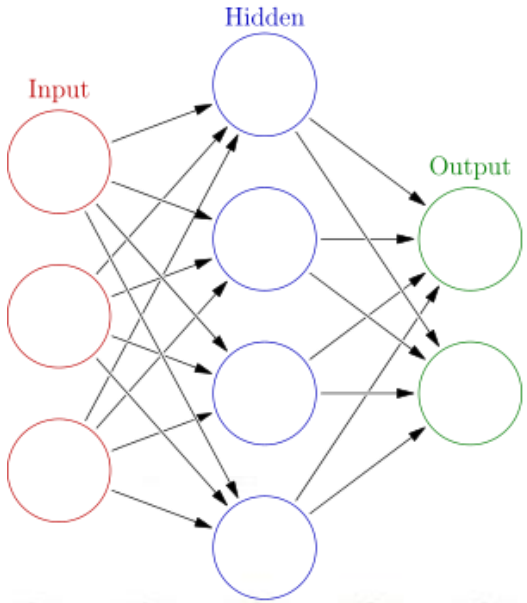
- Dialogue System

$f^*($ "Hi" $) =$ "Hello"

(what the user said) (system response)

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



為什麼叫做 Deep Learning ?

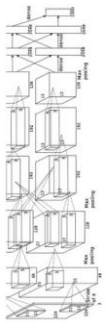
(Slide Credit: Hung-Yi Lee)

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

- 當 hidden layers 層數夠多 (一般而言大於三層) 就稱為 Deep neural network

8 layers

16.4%



AlexNet (2012)

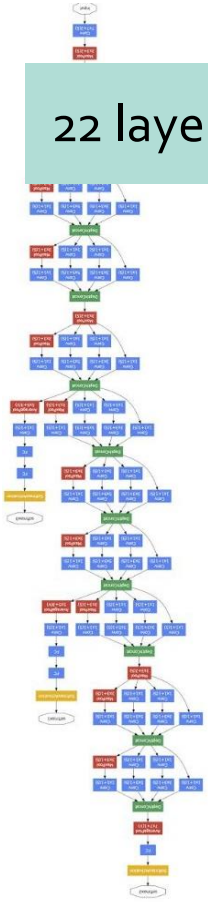
19 layers

7.3%

VGG (2014)

22 layers

6.7%

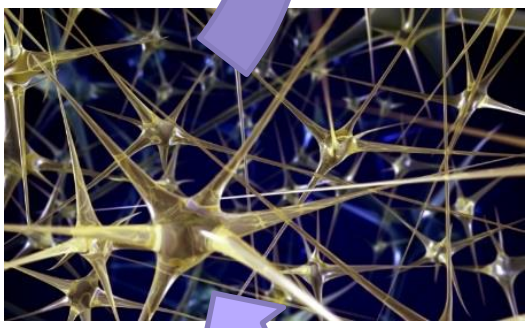


GoogleNet (2014)

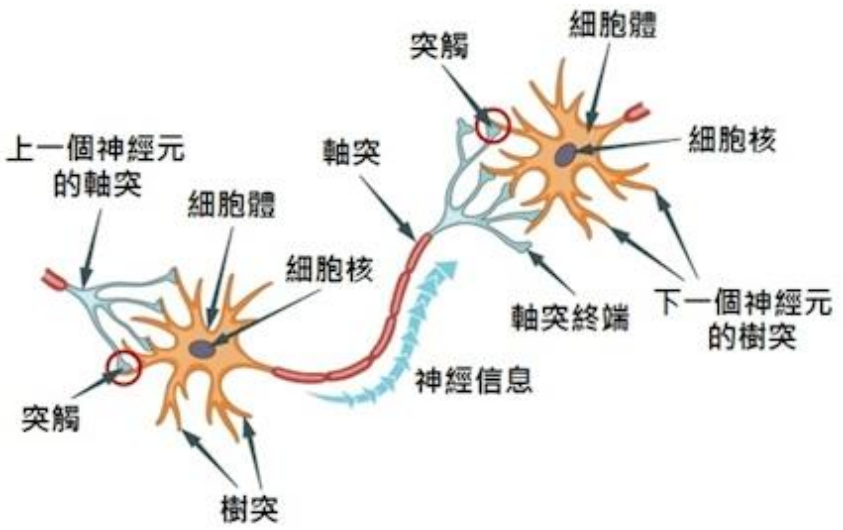
(Slide Credit: Hung-Yi Lee)

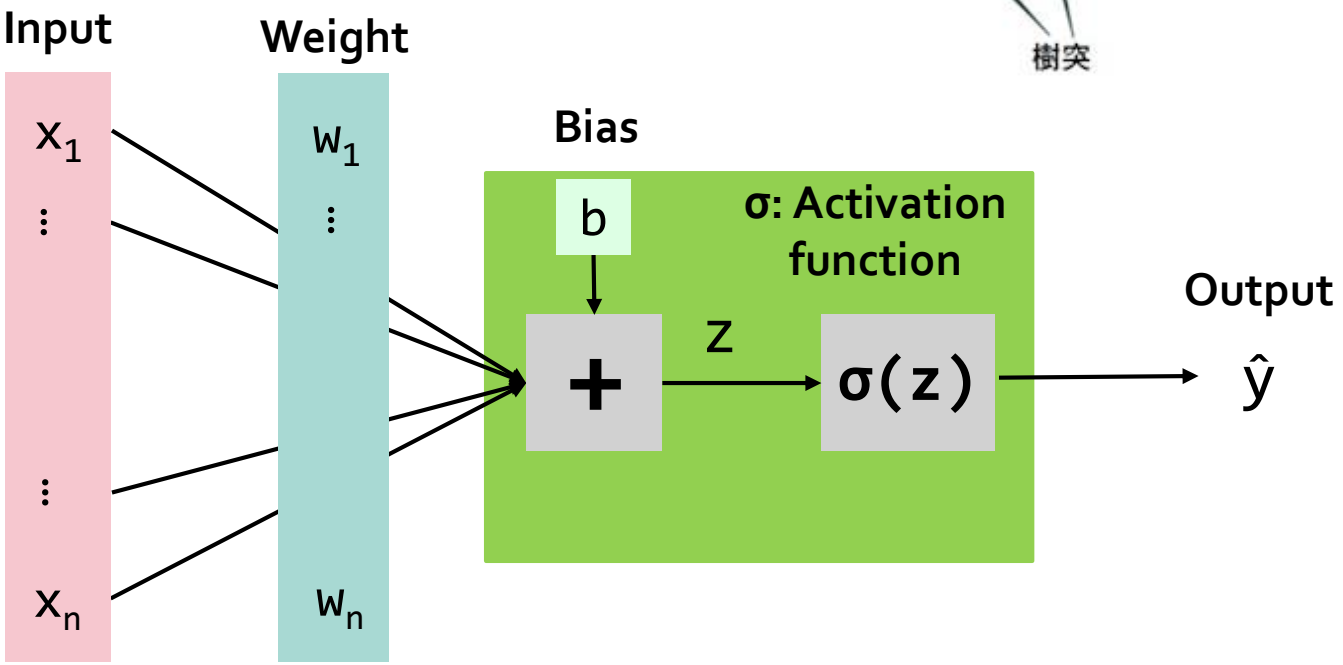
Human Brains

820 億 neurons



A Neuron of ANN



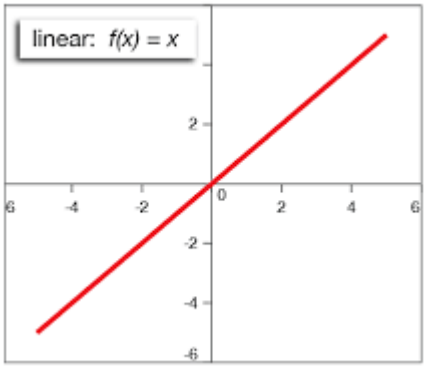


$$z = w_1x_1+w_2x_2+.....+w_nx_n+b$$

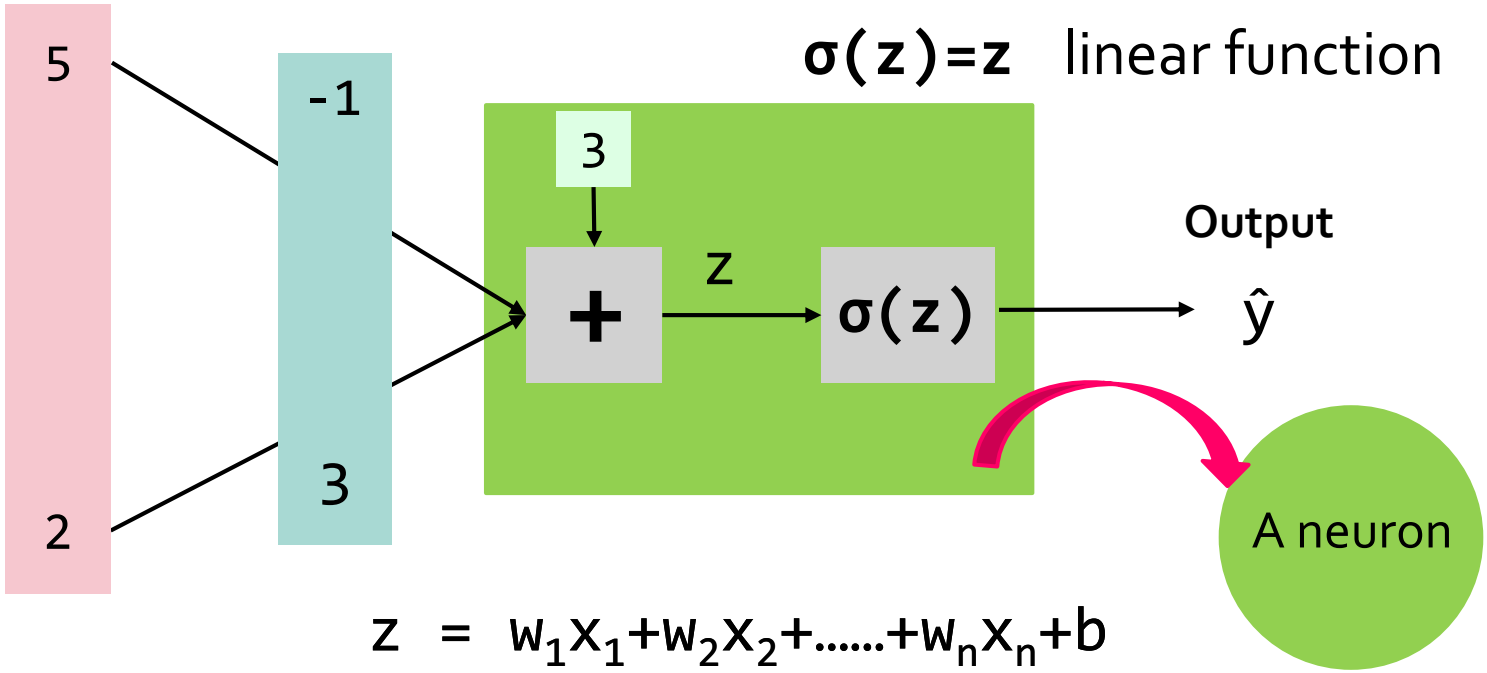
$$\hat{y} = \sigma(z)$$

Neuron 的運作

- Example



$\sigma(z)=z$ linear function

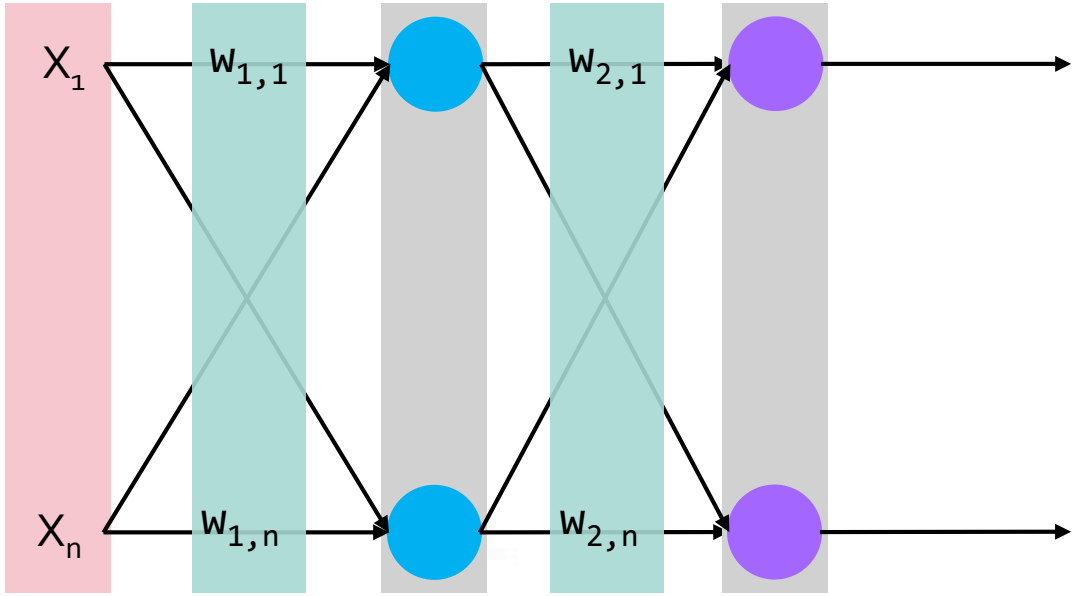


$$z = w_1x_1+w_2x_2+\ldots\ldots+w_nx_n+b$$

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

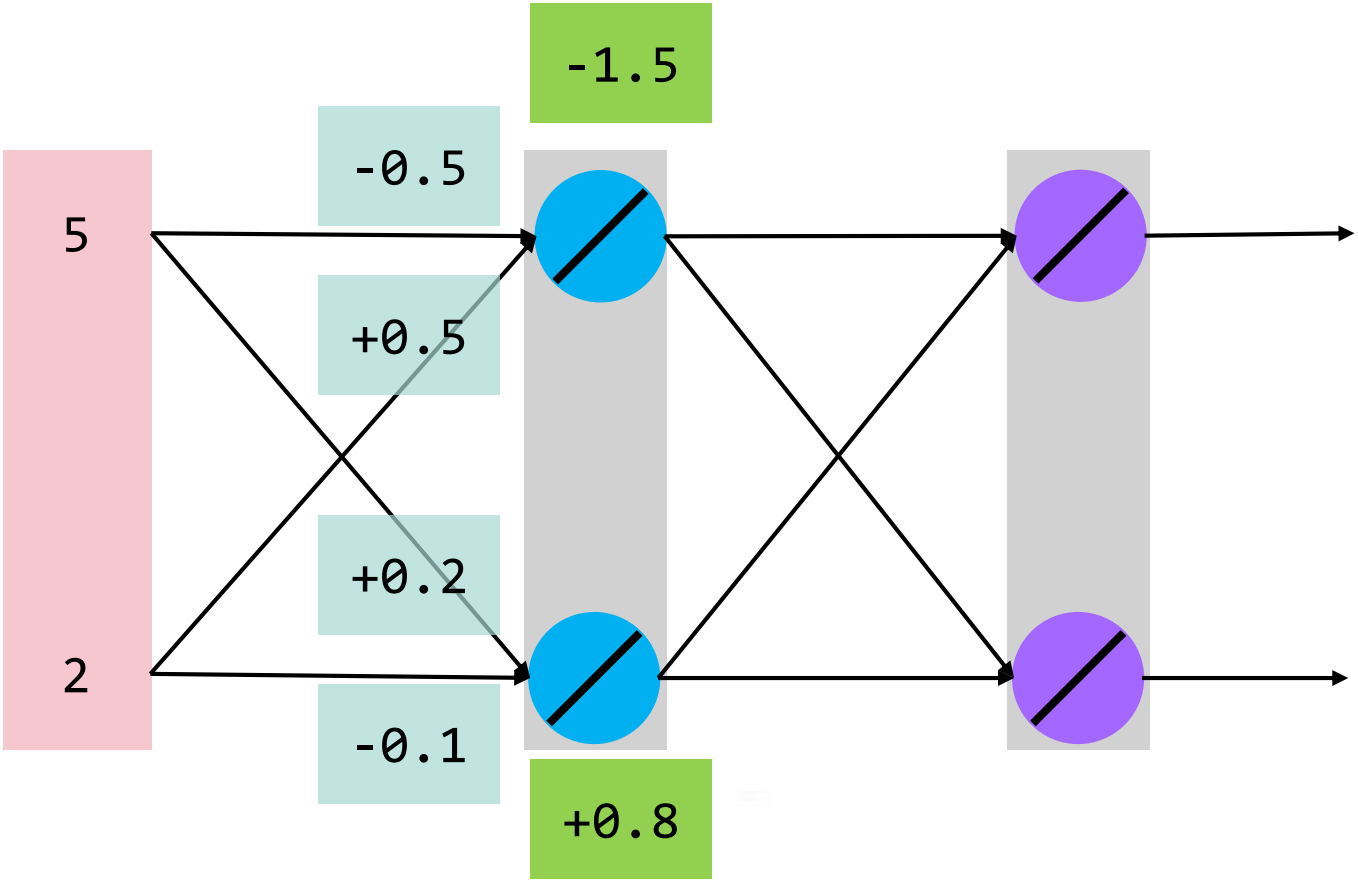
Fully Connected Neural Network

- 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

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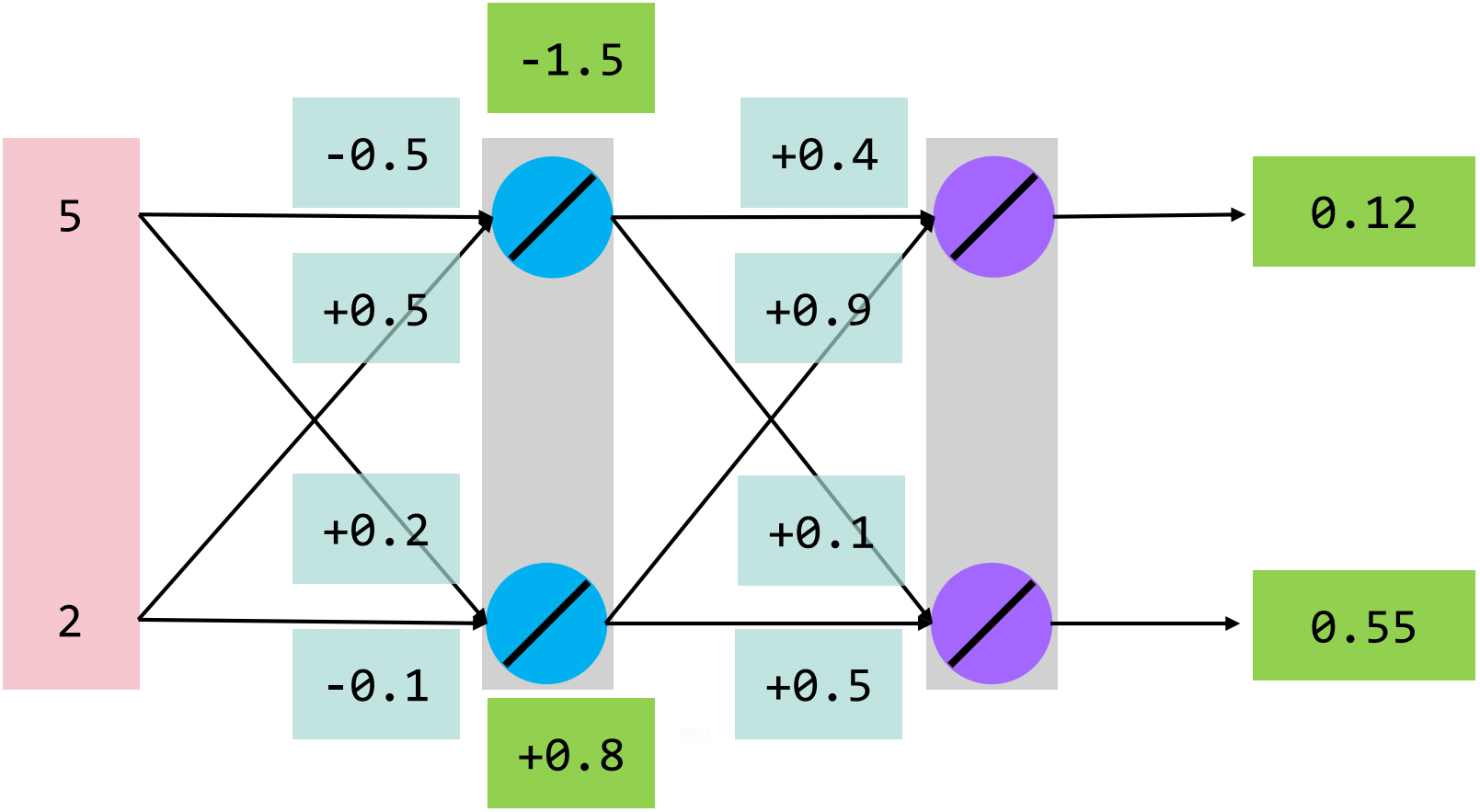
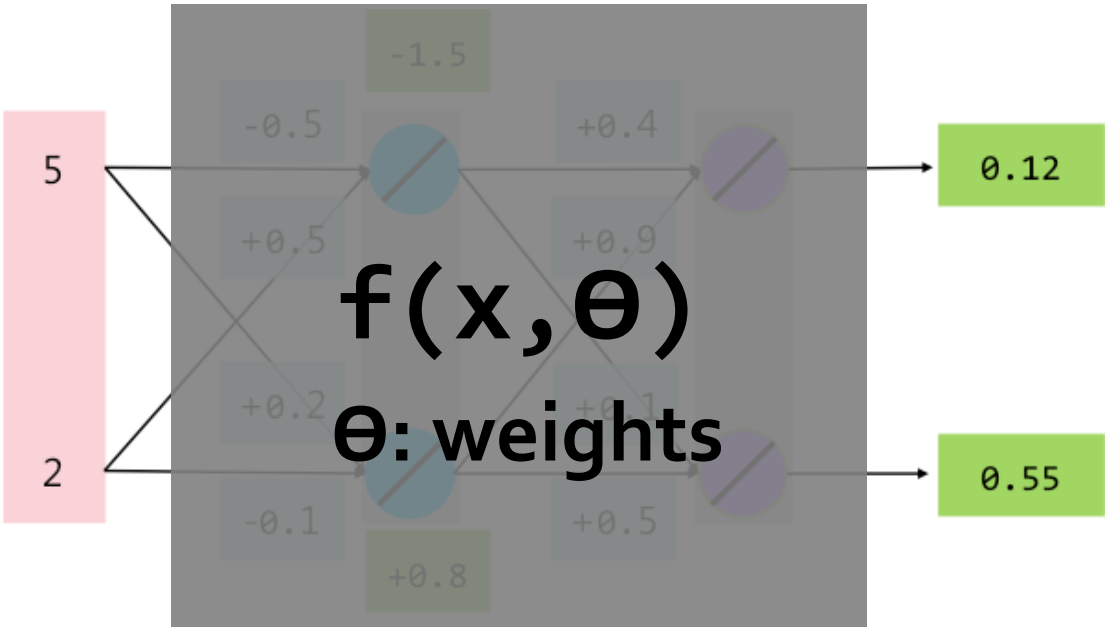


給定 Network Weights



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

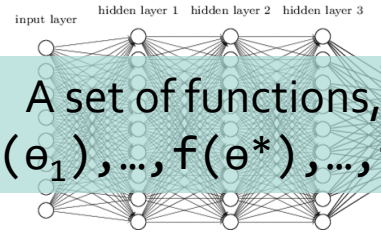
Recall: Deep Learning Framework

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

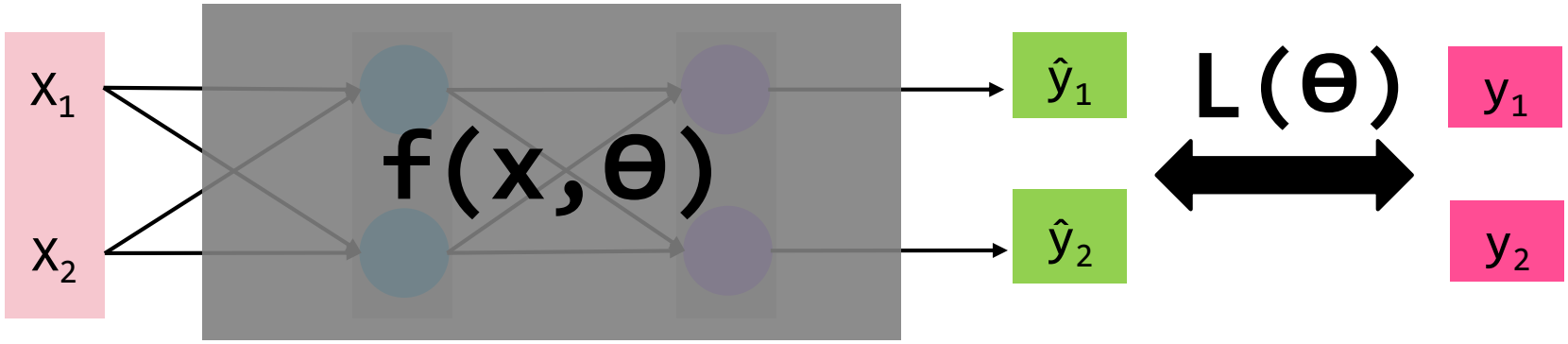
$f(\theta_{94})$ ➔
$f(\theta_{87})$ ➔
$f(\theta_{945})$…

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

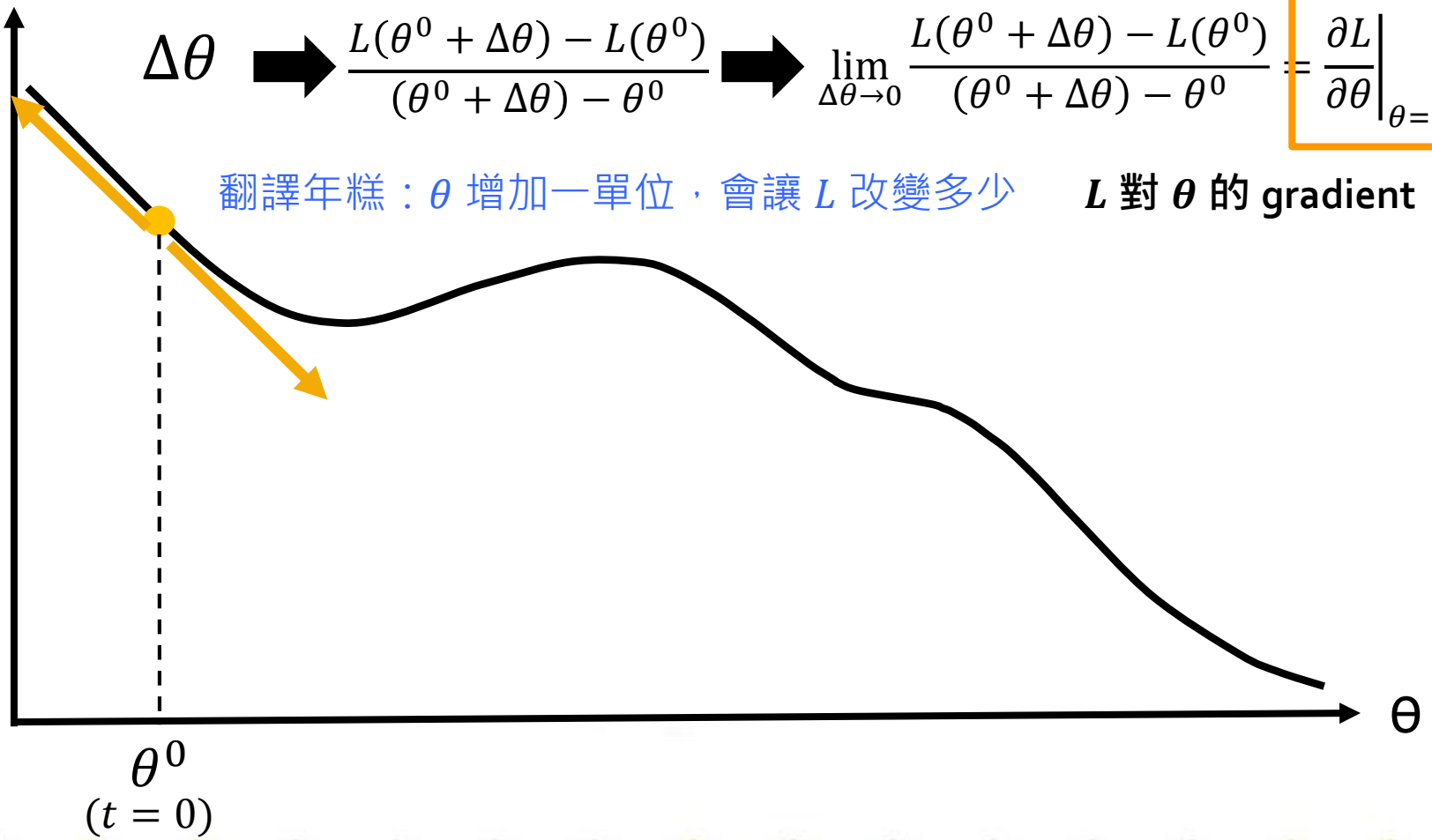
Gradient Descent

L(θ)

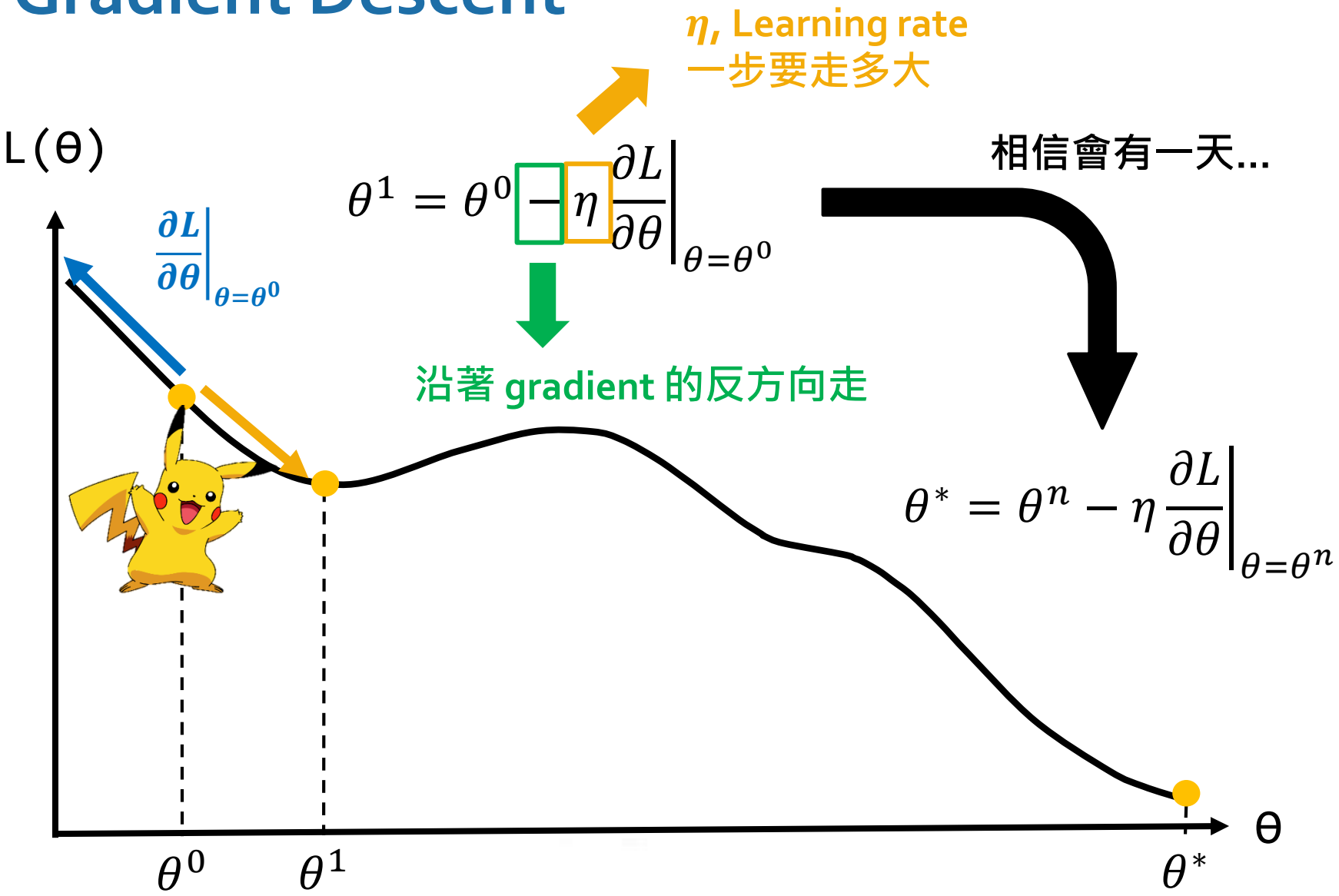
想知道在 θ^0 這個點時，L 隨著 θ 的變化

$$\Delta\theta \rightarrow \frac{L(\theta^0+\Delta\theta)-L(\theta^0)}{(\theta^0+\Delta\theta)-\theta^0} \rightarrow \lim_{\Delta\theta\to 0}\frac{L(\theta^0+\Delta\theta)-L(\theta^0)}{(\theta^0+\Delta\theta)-\theta^0} = \left.\frac{\partial L}{\partial\theta}\right|_{\theta=\theta^0}$$

翻譯年糕：θ 增加一單位，會讓 L 改變多少　　**L 對 θ 的 gradient**

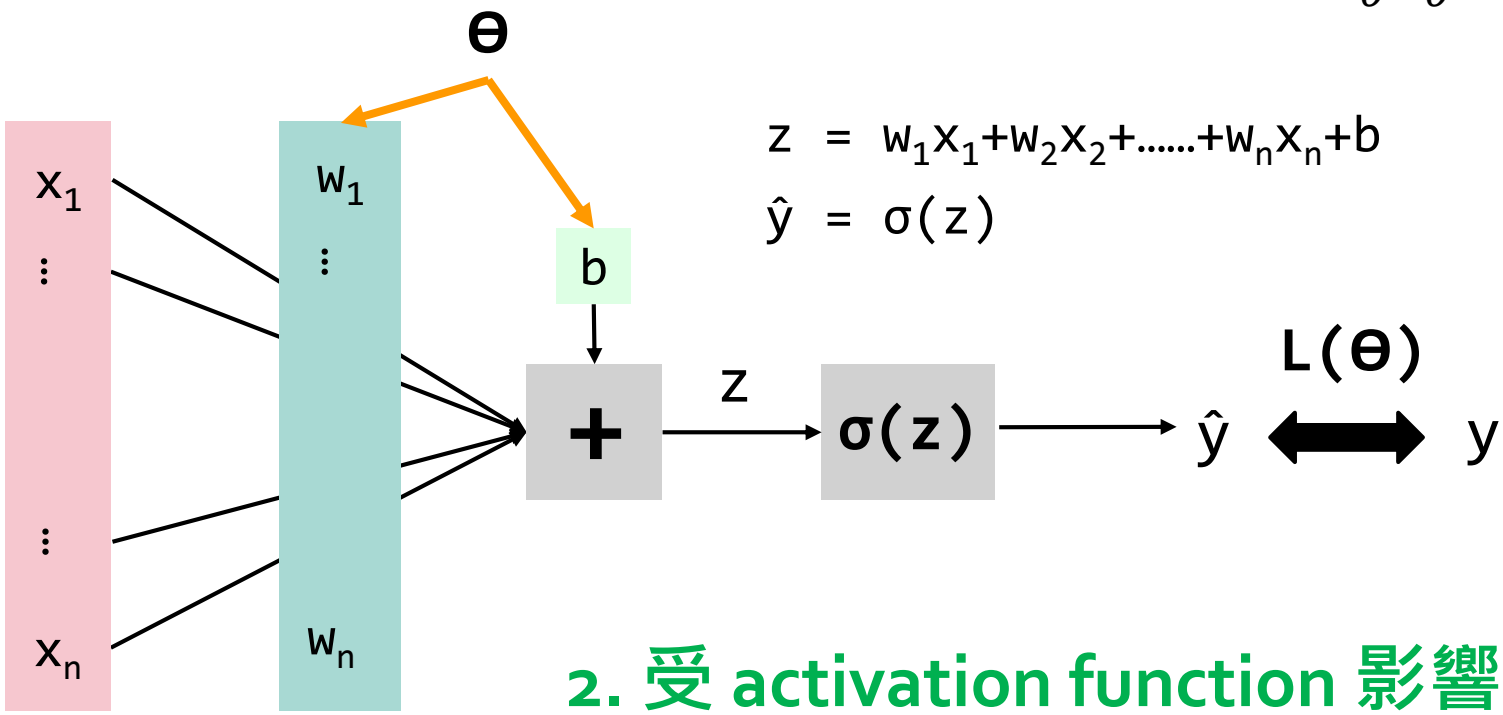


Gradient Descent



影響 Gradient 的因素

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



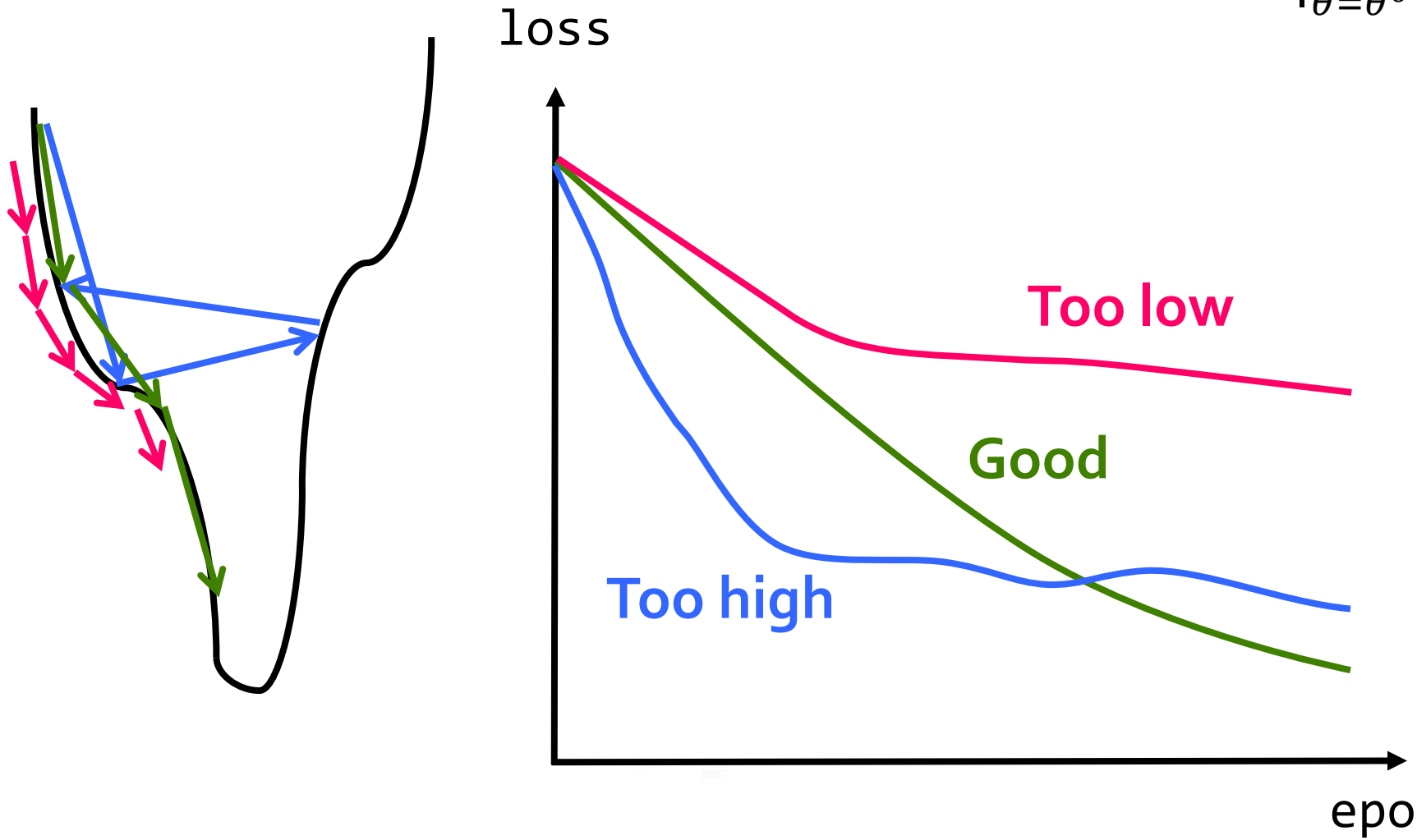
2. 受 activation function 影響

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

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

缺點

- 看完全部 training dataset 更新一次，收斂速度很慢
- 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

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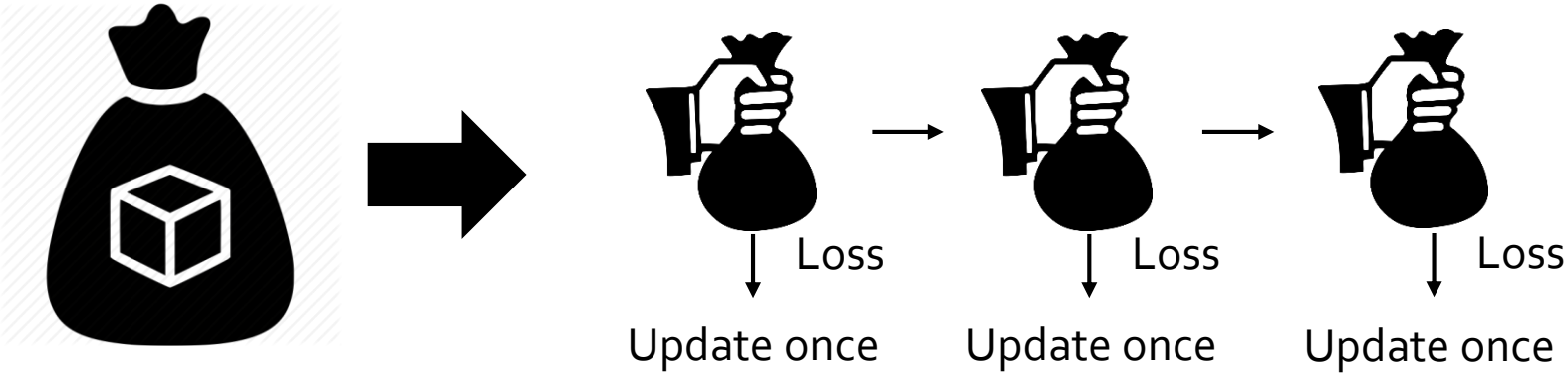
Stochastic Gradient Descent

- 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: 把 training dataset 隨機拆成很多小份



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

Mini-batch 的影響

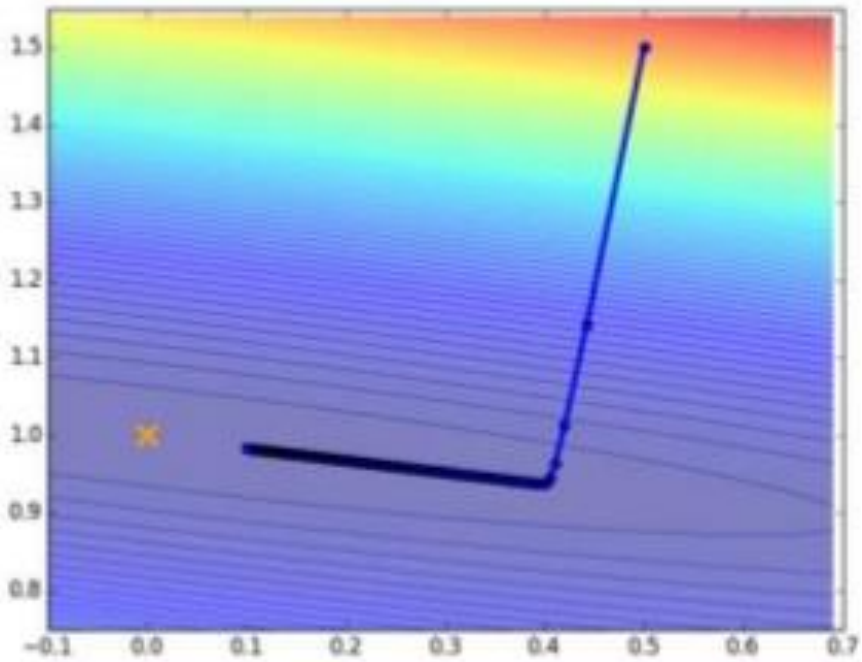
- 相同的時間長度 T 中
  - Batch size 不影響更新次數
  - Batch size 影響 epoch 數，batch size 越大完成越多 epoch
- 假設可以訓練一個小時
  - Batch size = 100 可完成 60 epochs
  - Batch size = 1000 可完成 600 epochs
- 如何設定 batch size?
  - 決定於想要的更新速度: 1% ➔ 100 updates in one epoch
  - 不要設太大，常用 32, 128, 256, 1024, 2048

(Slide Credit: Hung-Yi Lee)

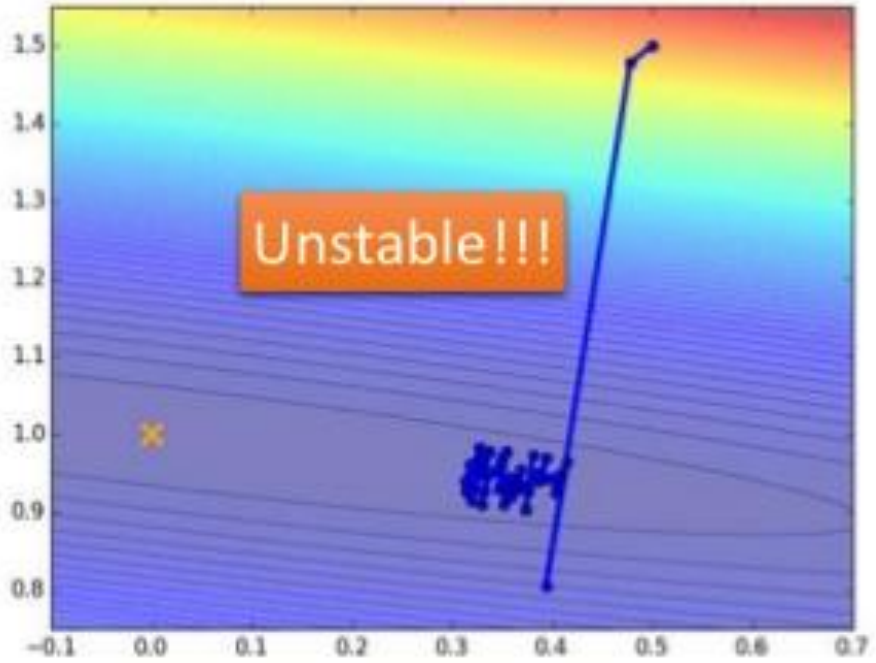
Mini-batch

- 其實已經不是最佳化 total loss

Gradient Descent



Mini-batch



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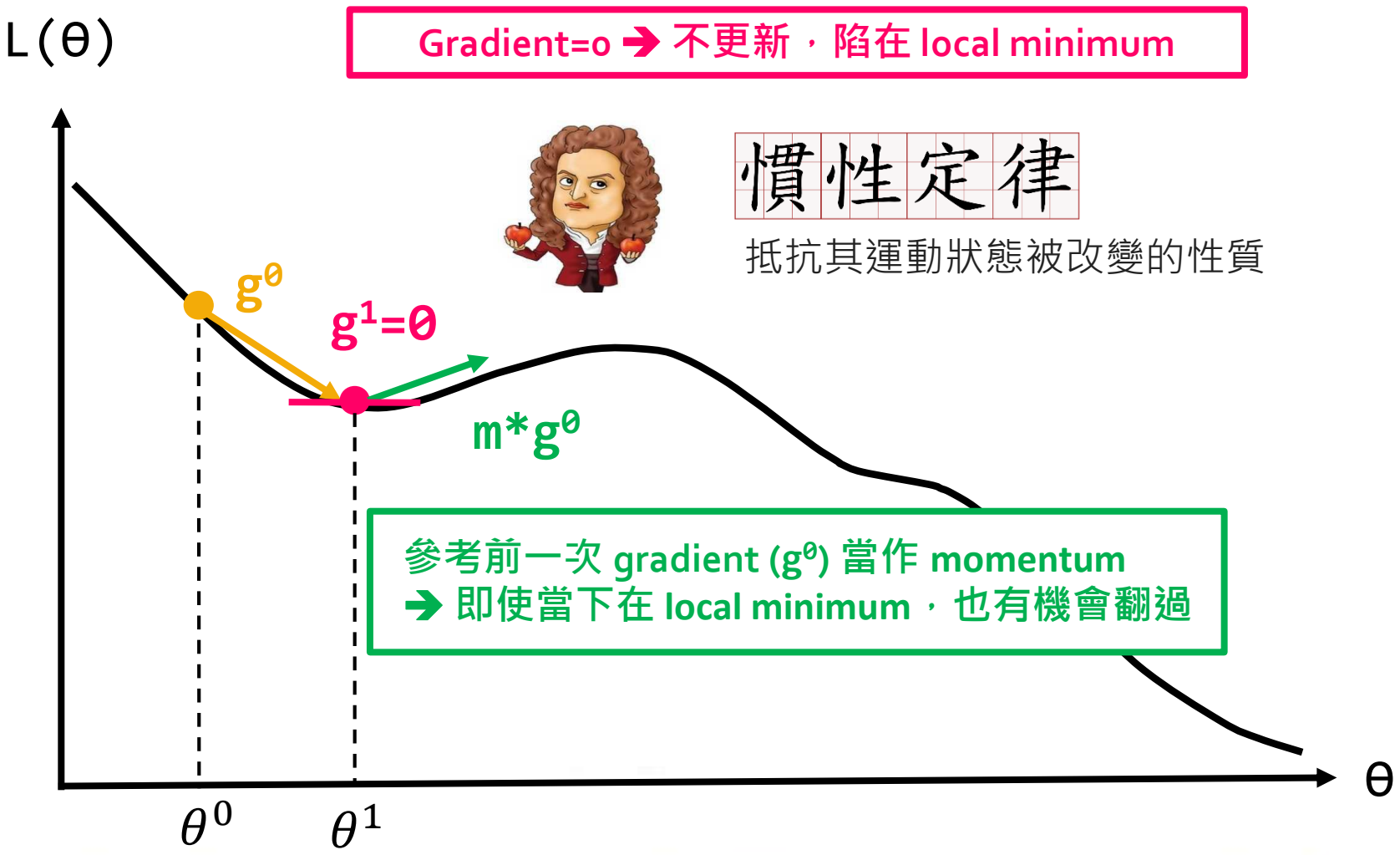
  - **可以利用 momentum 降低困在 local minimum 的機率**

Momentum

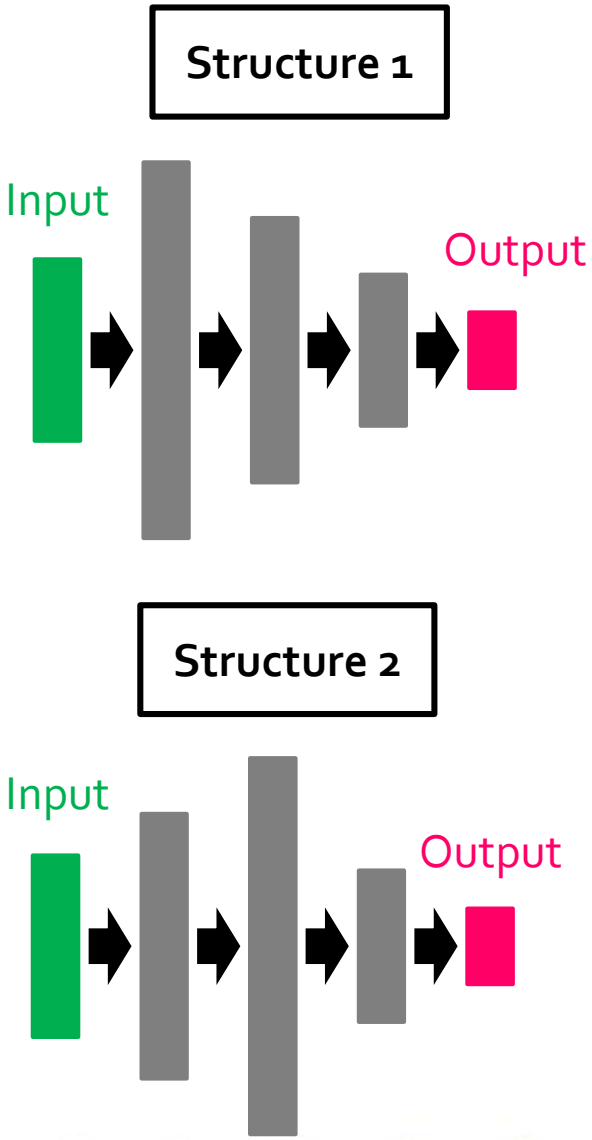

L(θ)
Gradient=o ➔ 不更新，陷在 local minimum
慣性定律
抵抗其運動狀態被改變的性質
g^0
$g^1=0$
$m*g^0$
參考前一次 gradient (g^0) 當作 momentum
➔ 即使當下在 local minimum，也有機會翻過
θ
θ^0
θ^1

Introduction of Deep Learning

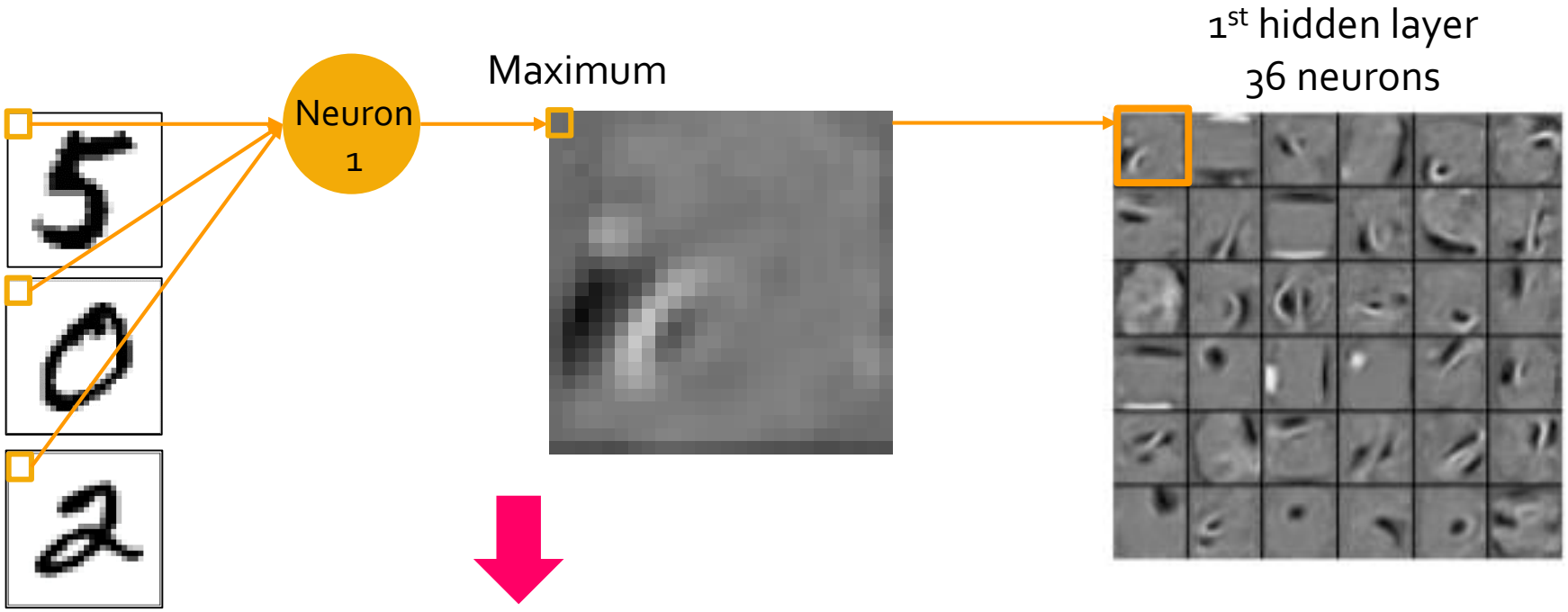
- Artificial neural network
- Activation functions
- Loss functions
- Gradient descent
  - Loss function, activation function, learning rate
- Stochastic gradient descent
- Mini-batch
- Momentum

Frequently Asked Questions

- 要有幾層 hidden layers？
- 每層幾個 neurons？
  - 佛洛伊德－需求金字塔
  - 第一層大一些會比較好
    - Input dimension 數倍
    - For example: input_dim = 12 ➔ 64 or 128
  - Intuition + trial and error
  - Neurons 多寡跟資料多寡有關
- 深會比較好嗎？
  - Deep for modulation



Visualization of A Neuron Output

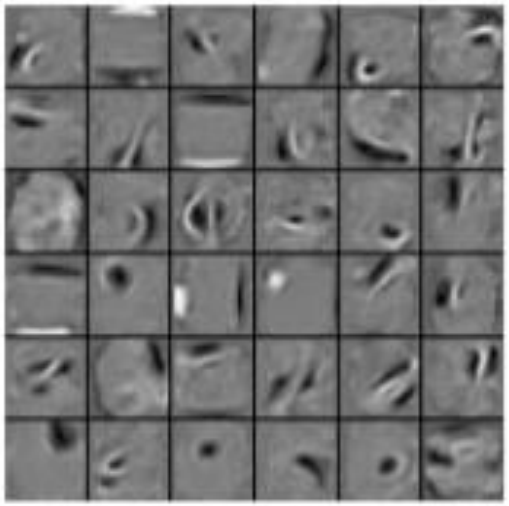


Neuron 1 是用來偵測左下角有沒有一個弧形

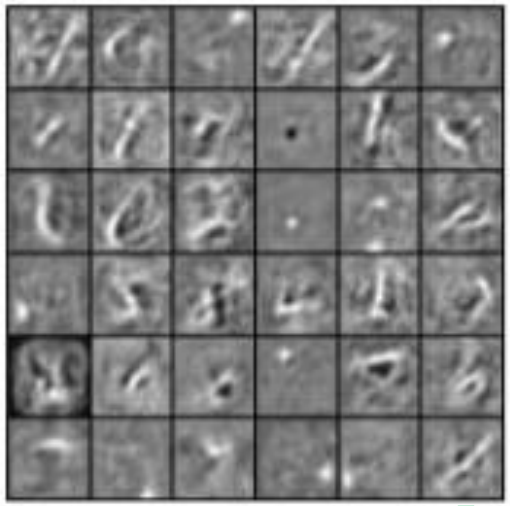
Ref: Visualizing Higher-Layer Features of a Deep Network

Visualization of Modulation

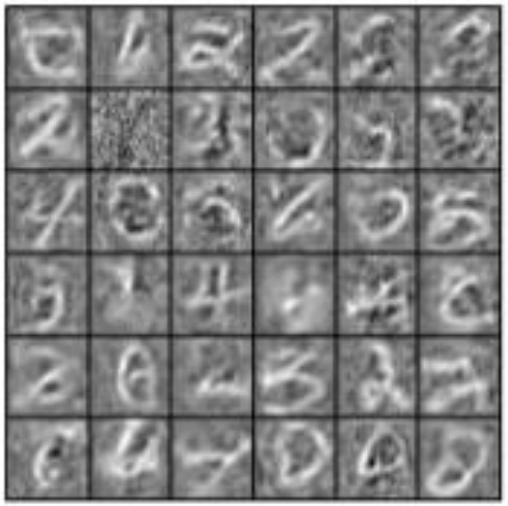
1st hidden layer



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

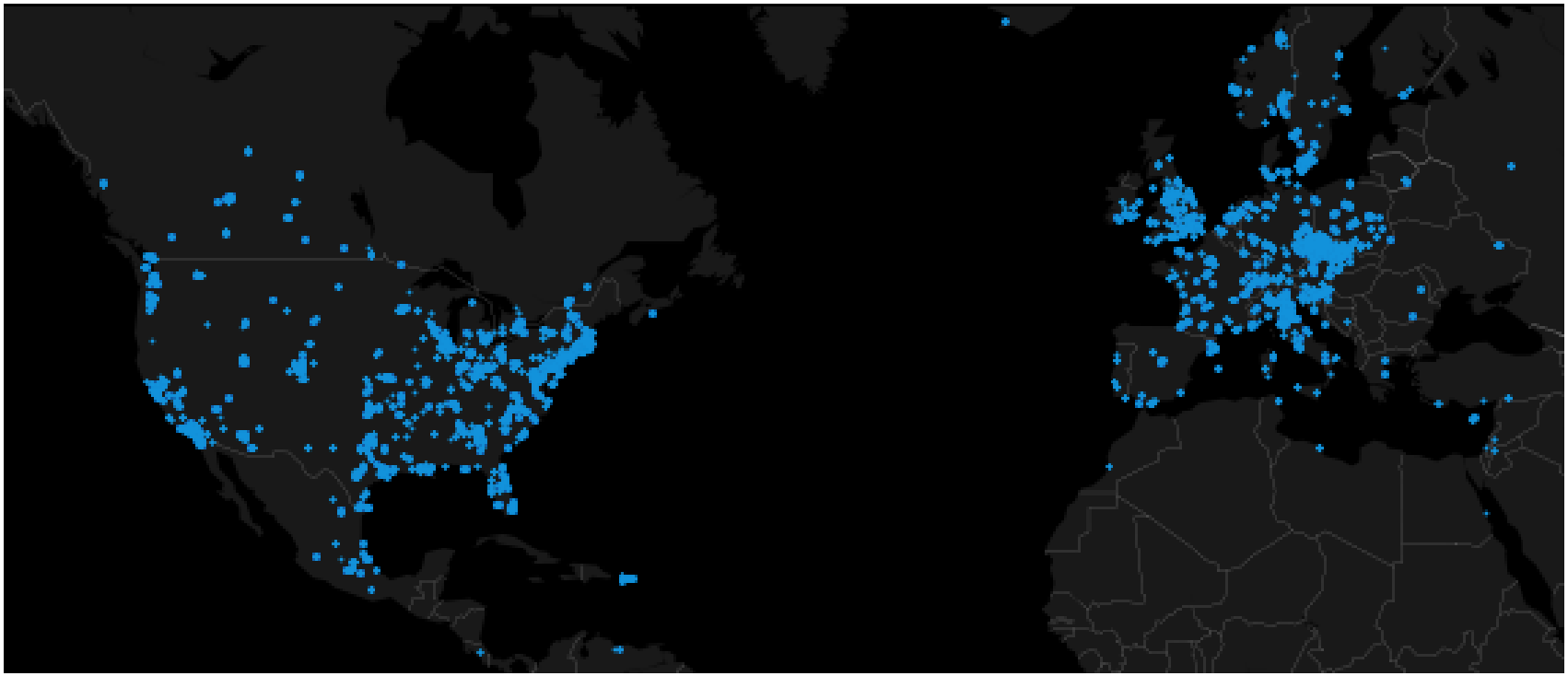
Ref: Visualizing Higher-Layer Features of a Deep Network

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

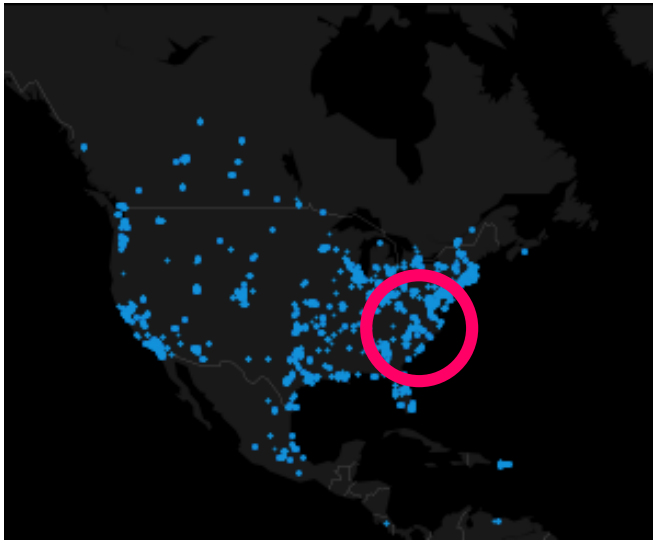
問題: 會出現哪一隻神奇寶貝呢？

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！

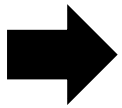
Input 前處理

- 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

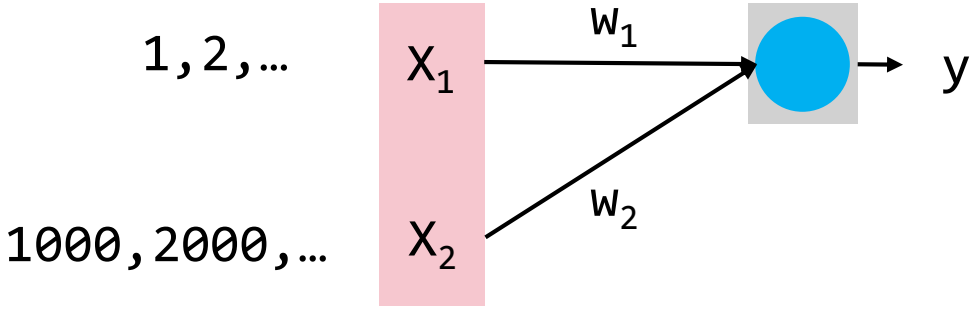
處理名目資料

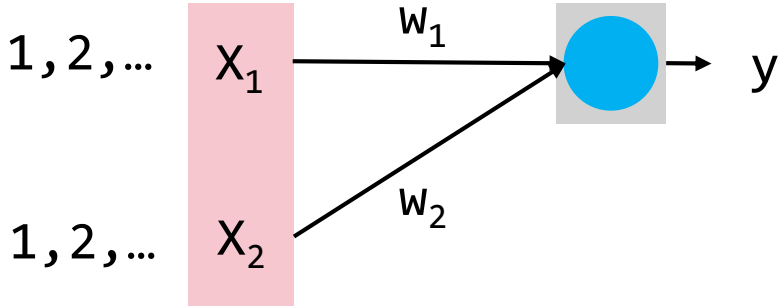
- Nominal variables (名目資料)
  - {"SugarFree","Half","Regular"}
  - One-hot encoding
    - 假設有三個類別
    - Category 1 ➔ [1,0,0]
    - Category 2 ➔ [0,1,0]
  - 給予類別上的解釋 ➔ Ordinal variables
    - {"SugarFree","Half","Regular"} ➔ 1,2,3
  - 特殊的名目資料：地址
    - 台北市南港區研究院路二段128號

    ➔ 轉成經緯度 {25.04,121.61}

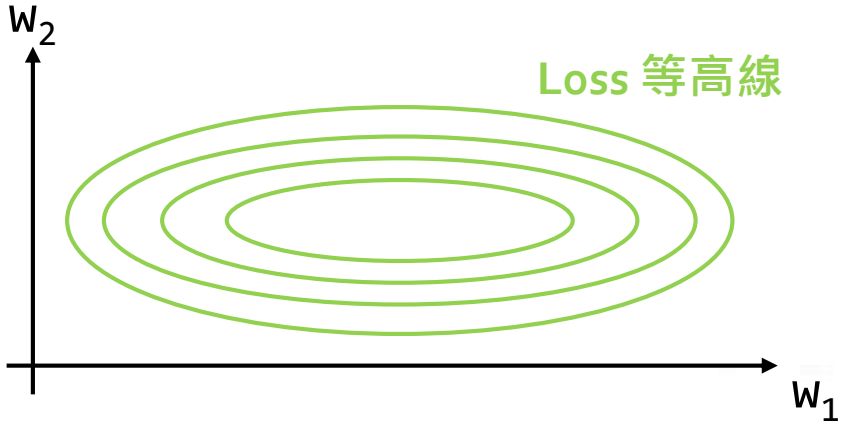
處理不同的數值範圍

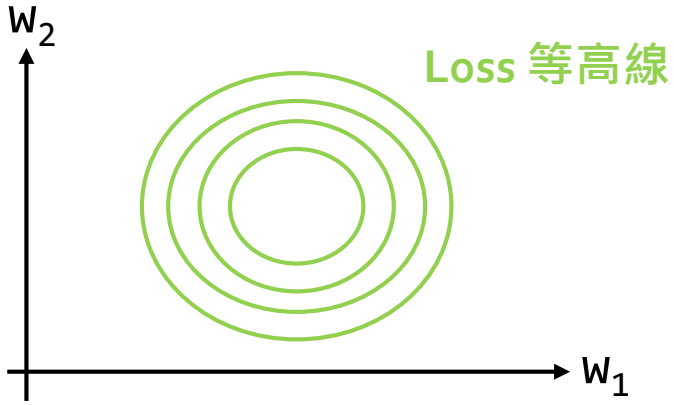
- 先說結論：建議 re-scale！但為什麼？





w_2 的修正(ΔW)對於 loss 的影響比較大

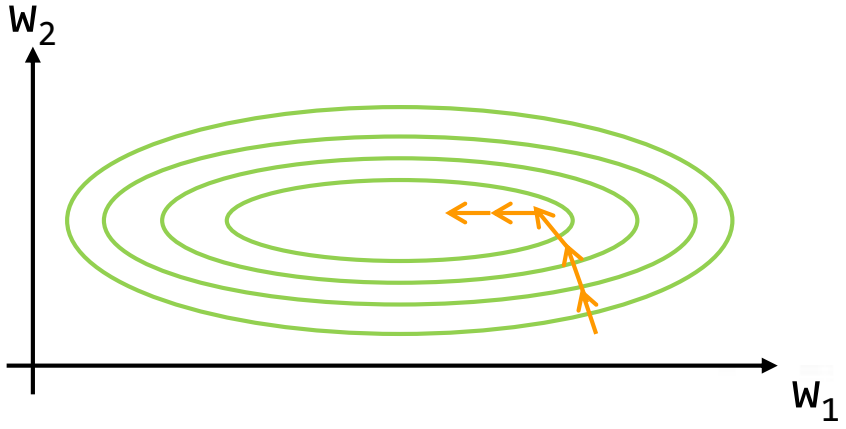


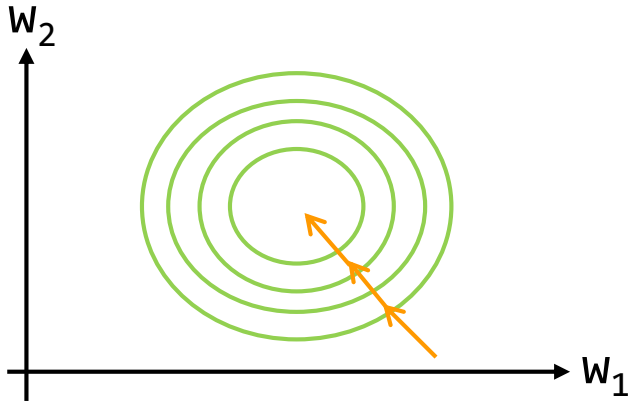


處理不同的數值範圍

- 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)

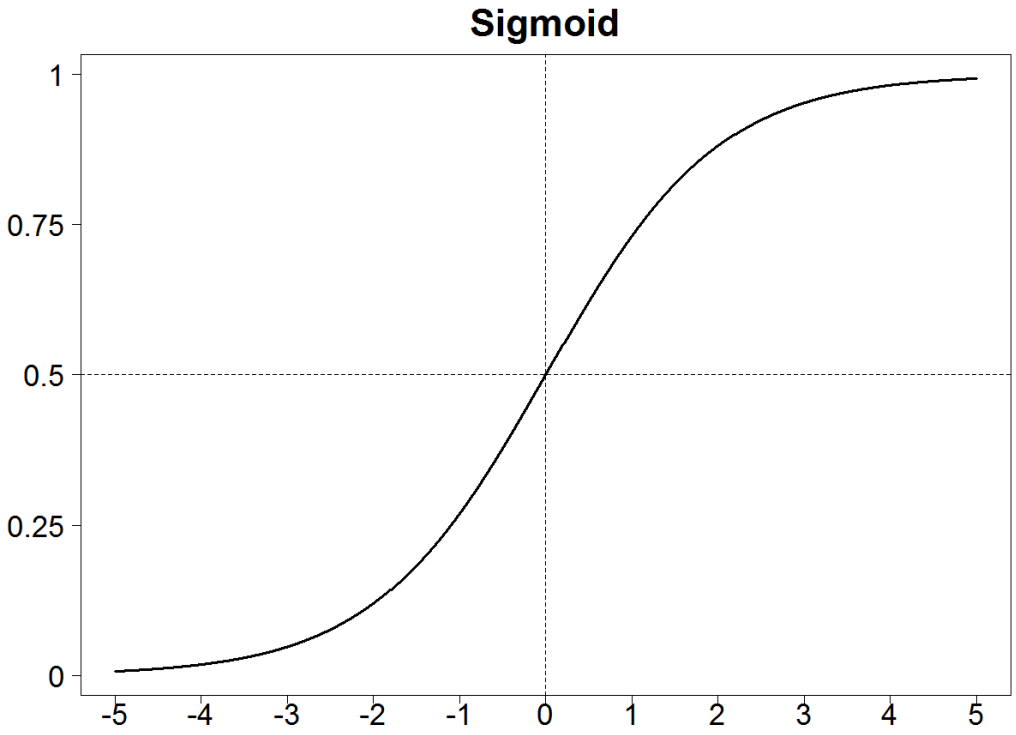
步驟 1+2: 模型架構

```
import theano
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

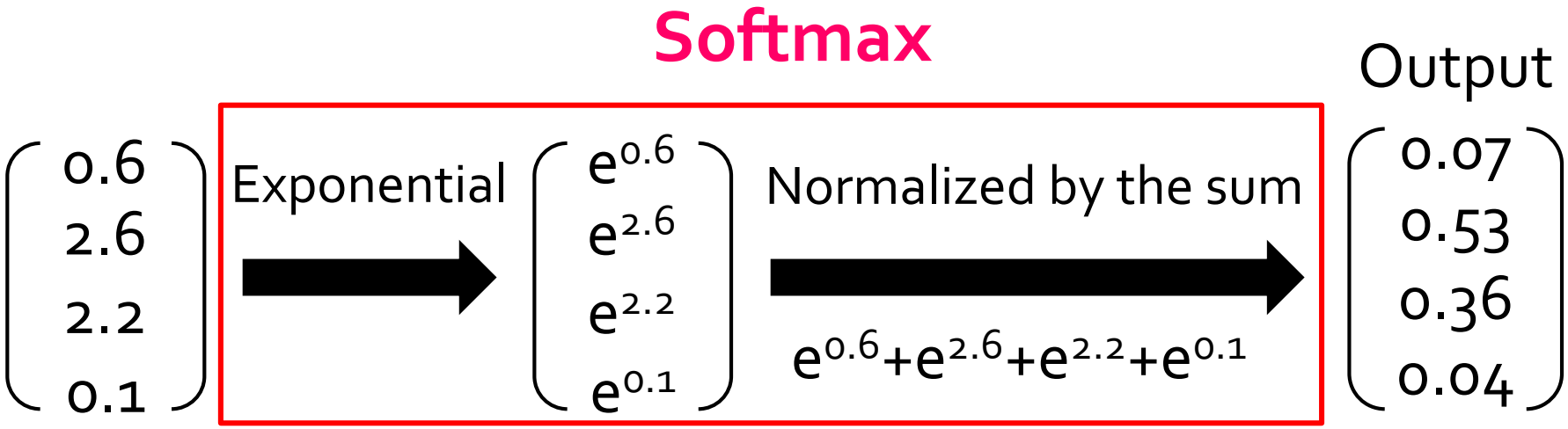


步驟 1+2: 模型架構 (Cont.)

```
# 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 #   
=================================================================
1st hidden layer (Dense)     (None, 128)               25728     
_________________________________________________________________
2nd hidden layer (Dense)     (None, 256)               33024     
_________________________________________________________________
output (Dense)               (None, 5)                 1285      
=================================================================
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)

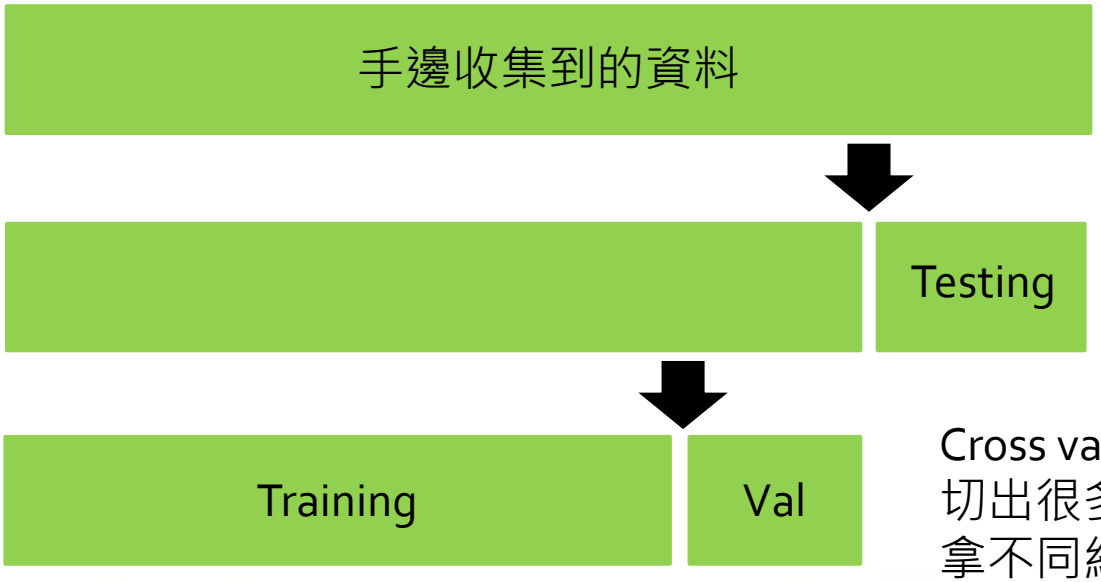
就決定是你了!

```
# 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)

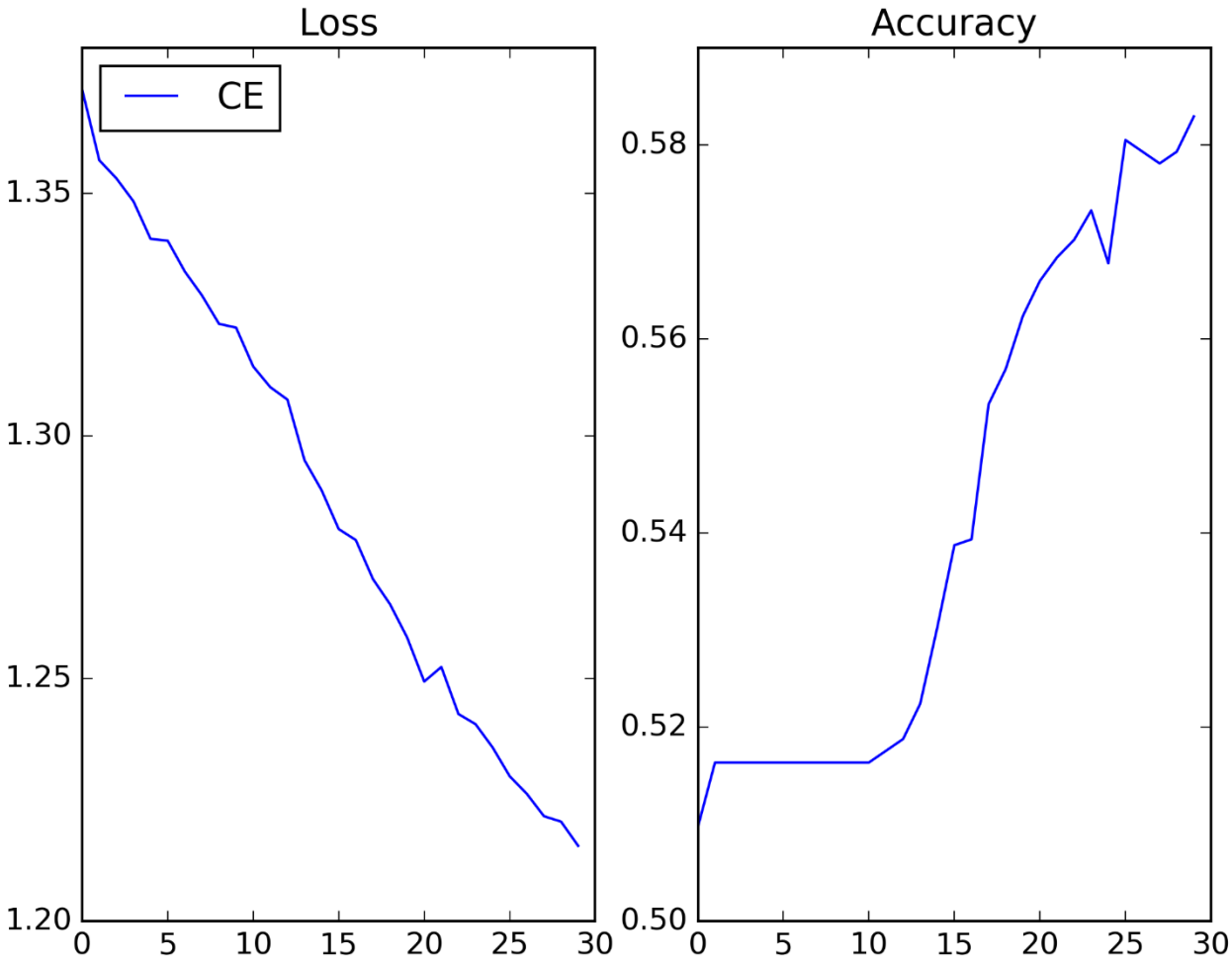
Fit Model

```
# 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,
                     nb_epoch=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)

Result


Loss
CE
1.35
1.30
1.25
1.20
0
5
10
15
20
25
30
Accuracy
0.58
0.56
0.54
0.52
0.50
0
5
10
15
20
25
30

這樣是好是壞？

- 我們選用最常見的

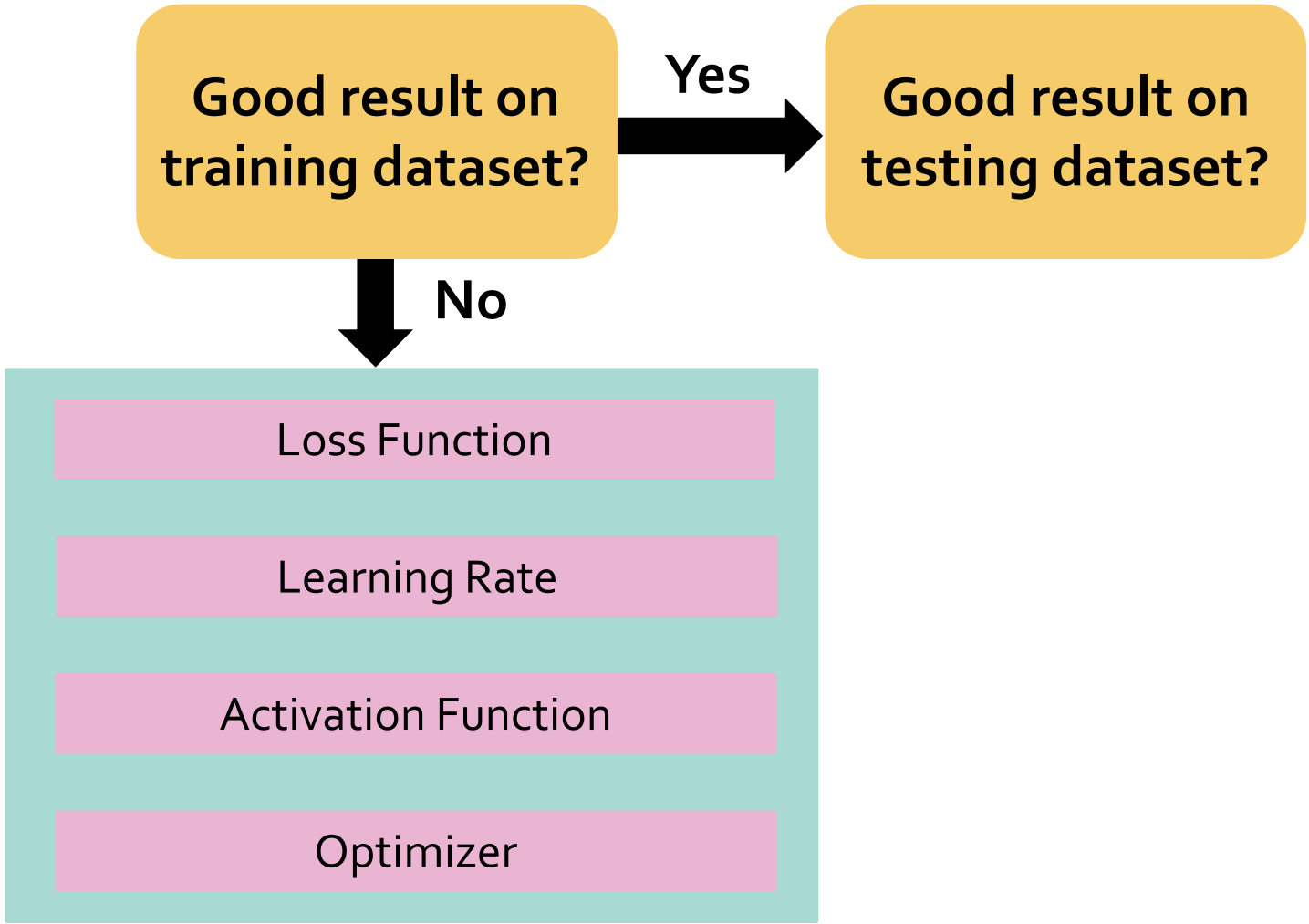
Component	Selection
Loss function	categorical_crossentropy
Activation function	sigmoid + softmax
Optimizer	SGD

用下面的招式讓模型更好吧

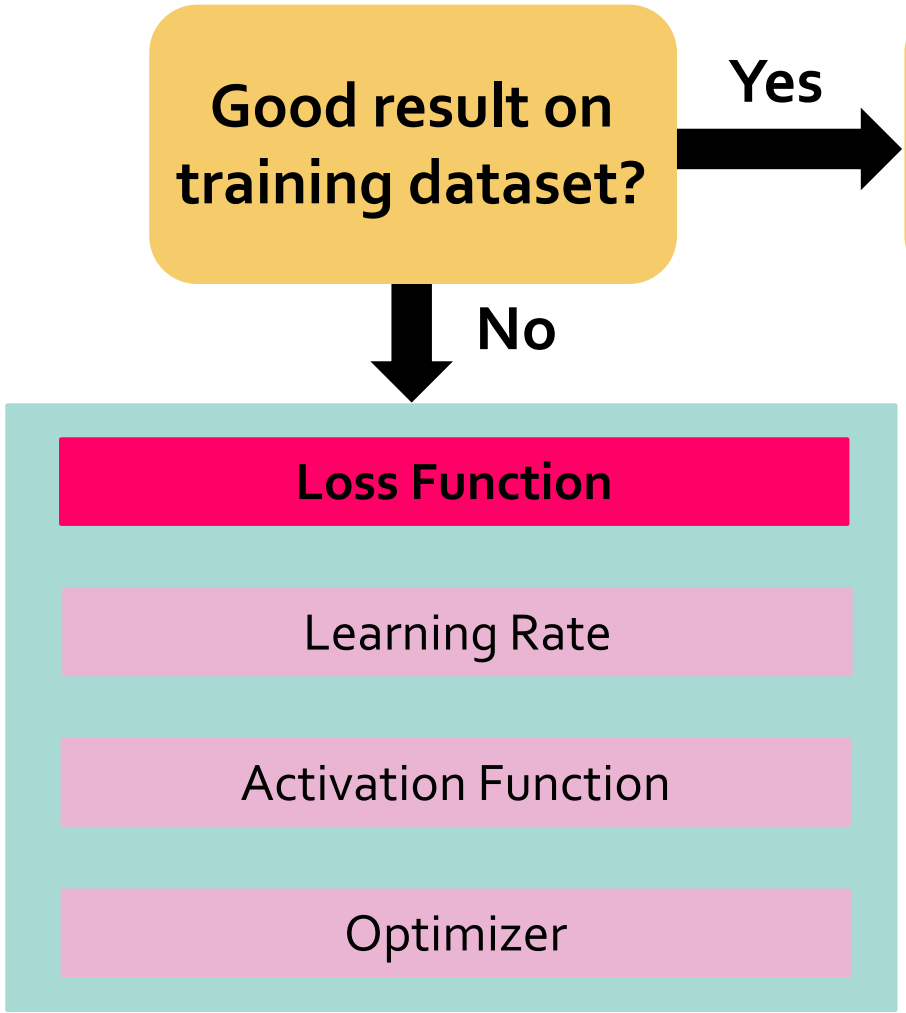
Tips for Training DL Models

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

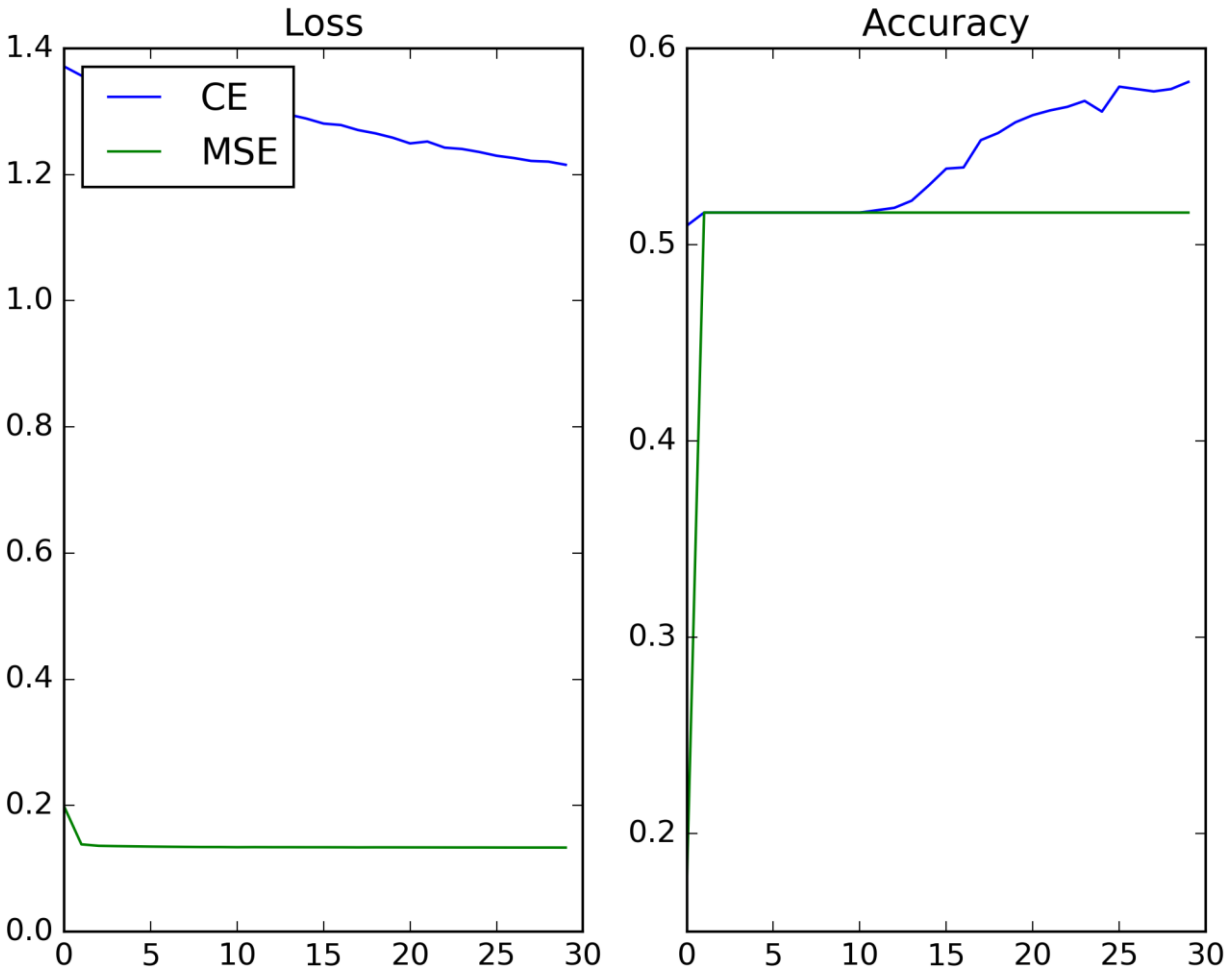
- 在指定 loss function 時

```
# 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

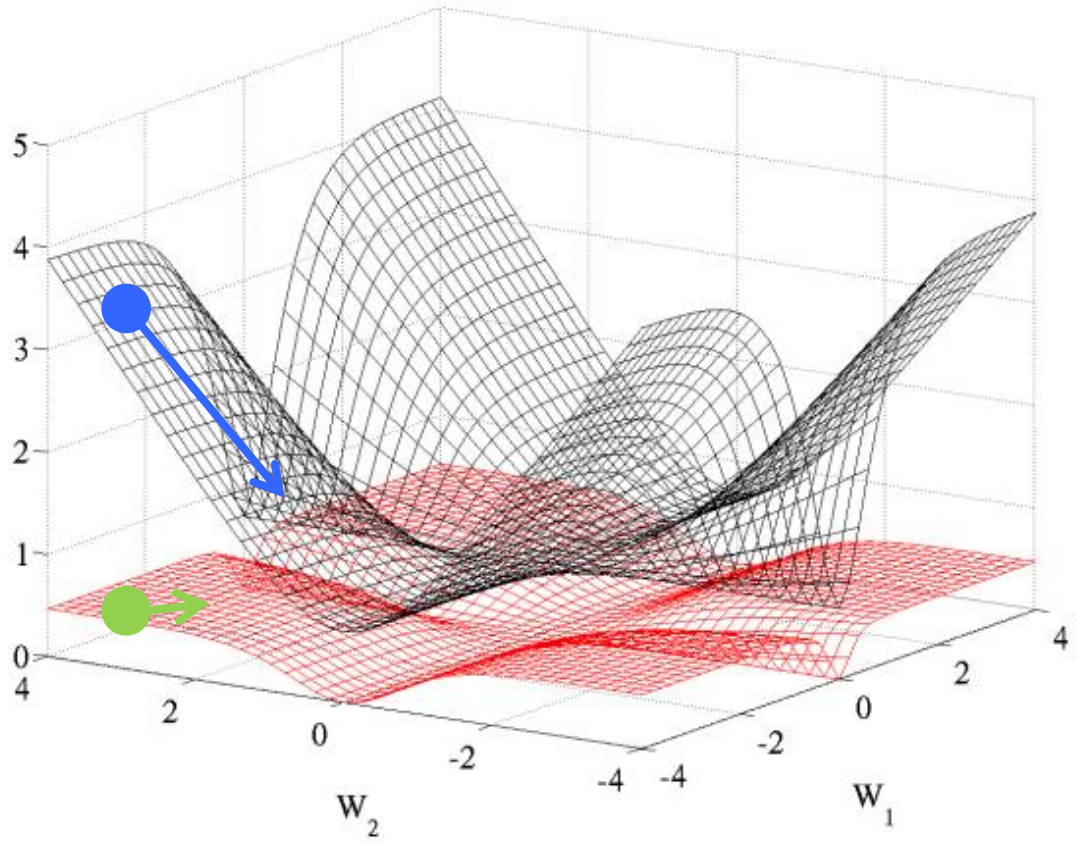


Figure source

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

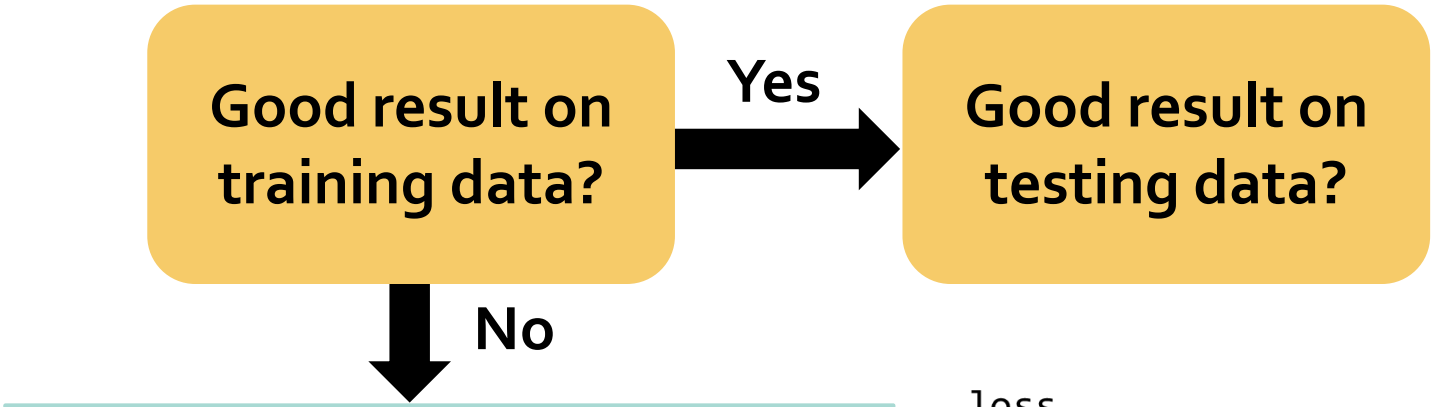
How to Select Loss function

- Classification 常用 cross-entropy 當作 loss function
- 搭配 softmax 當作 output layer 的 activation function
- 對特定問題如何解釋 loss 的意義

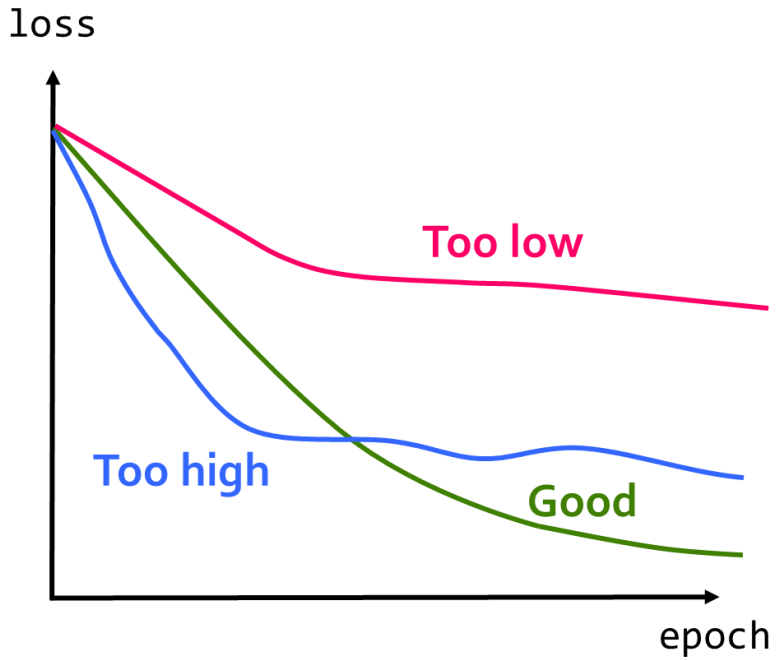
Current Best Model Configuration

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

Tips for Deep Learning



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

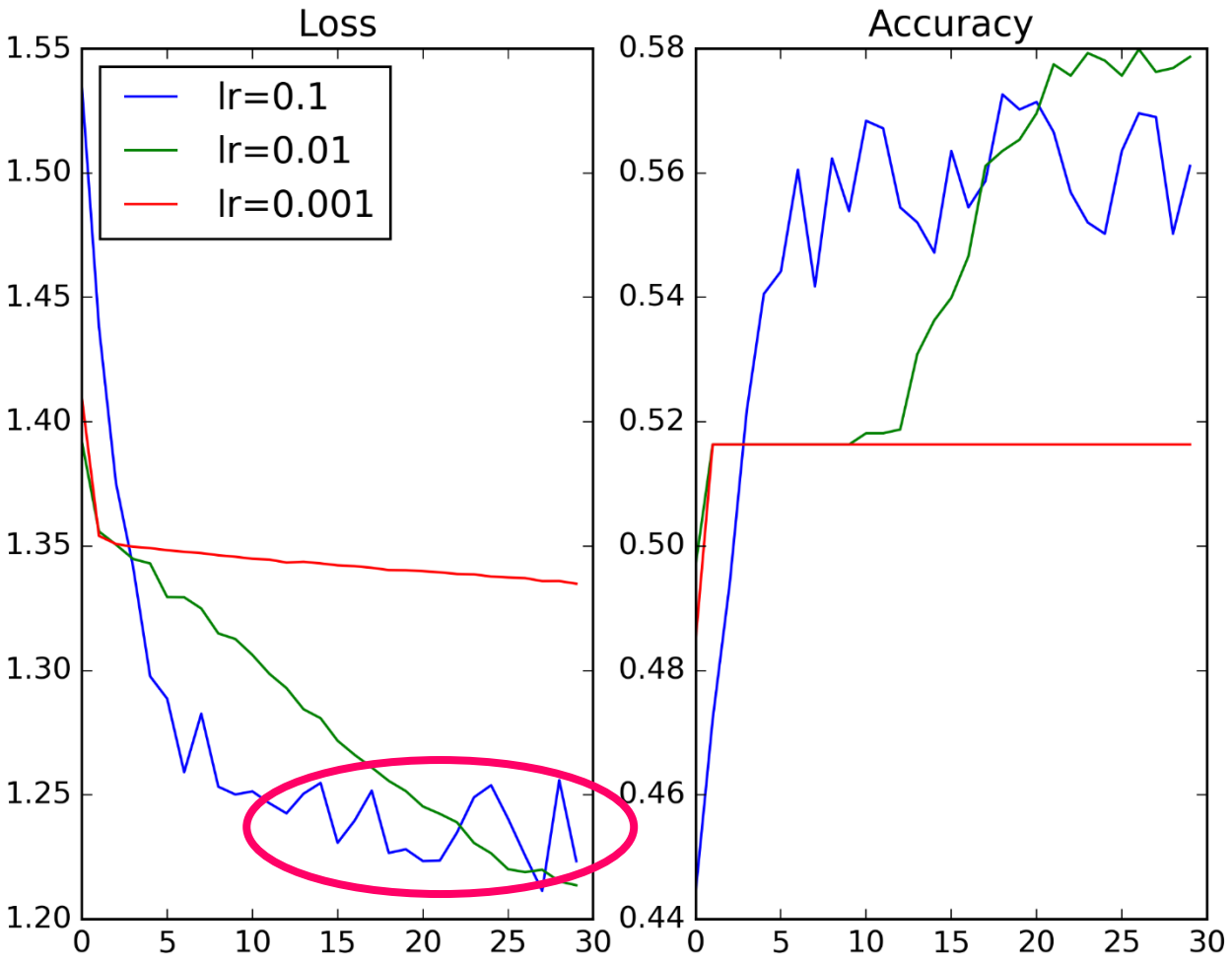


練習 02_learningRateSelection.py (5-8 minutes)

```
# 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

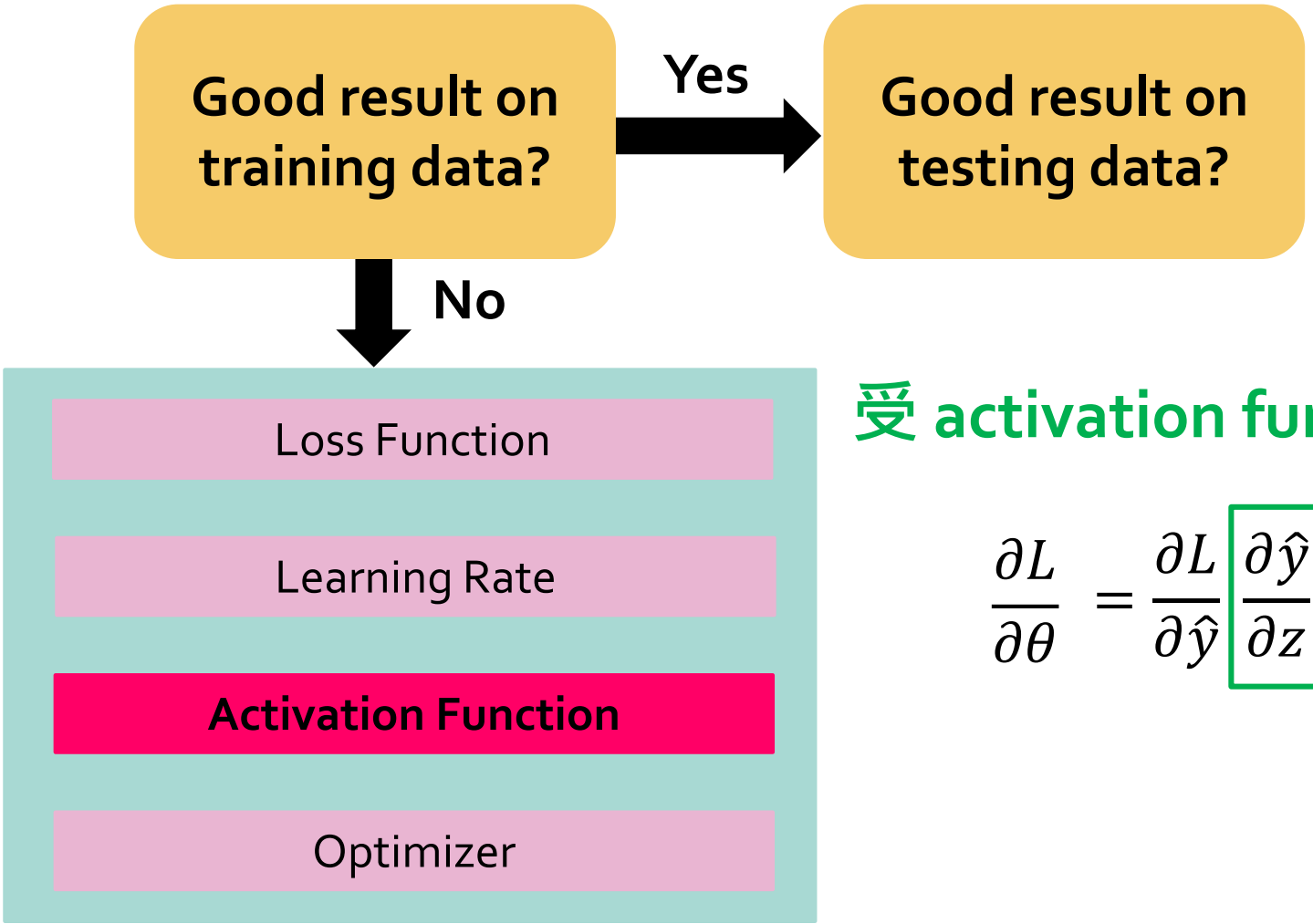


觀察 loss，這樣的震盪表示 learning rate 可能太大

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 …~~
- 我在 2014 年做過一場夢…
  - 在 Coursera 的一堂名為機器學習基石中有提到一個神祕的數字: 0.017, 0.0017,…

Tips for Deep Learning

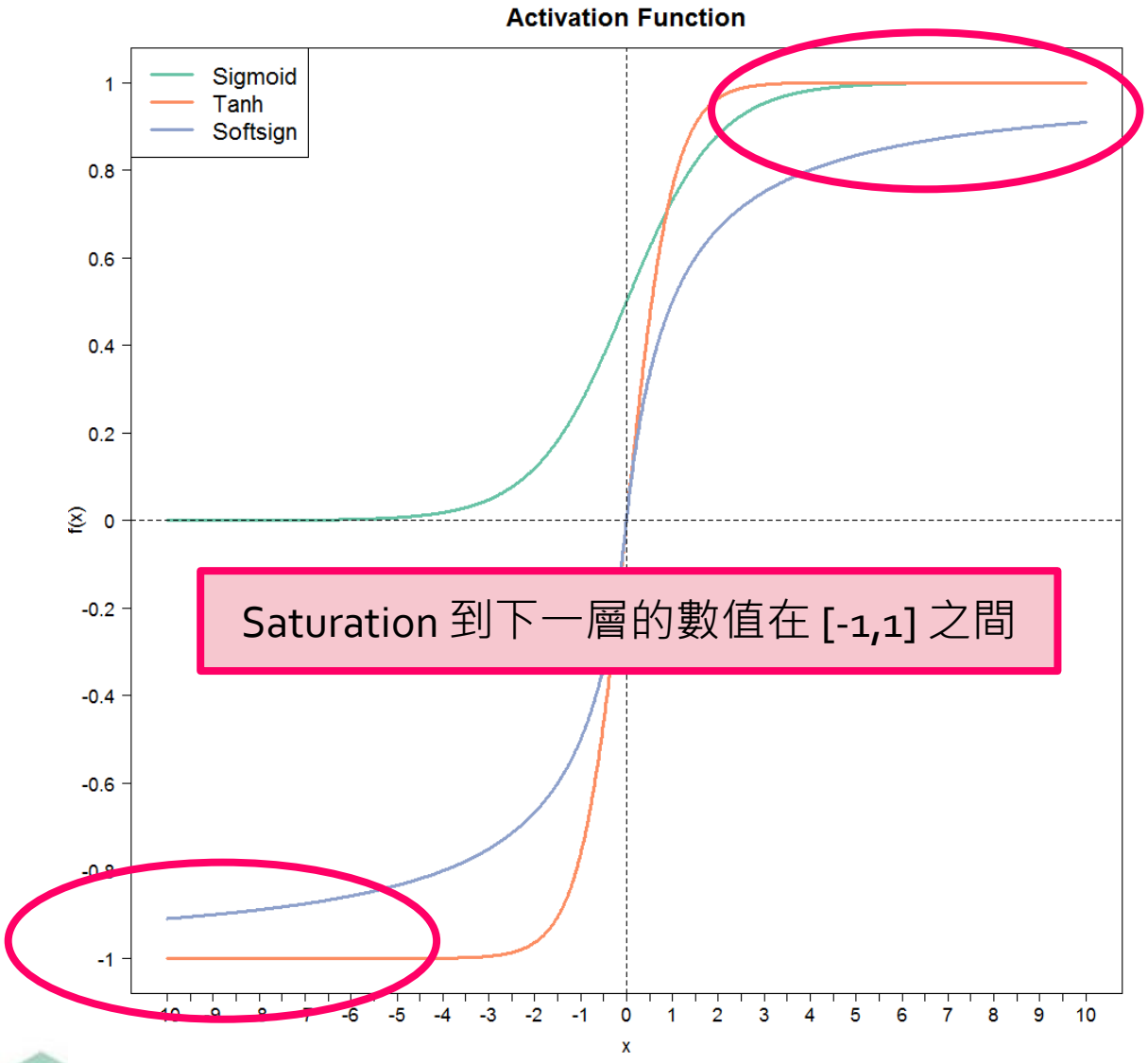


受 activation function 影響

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

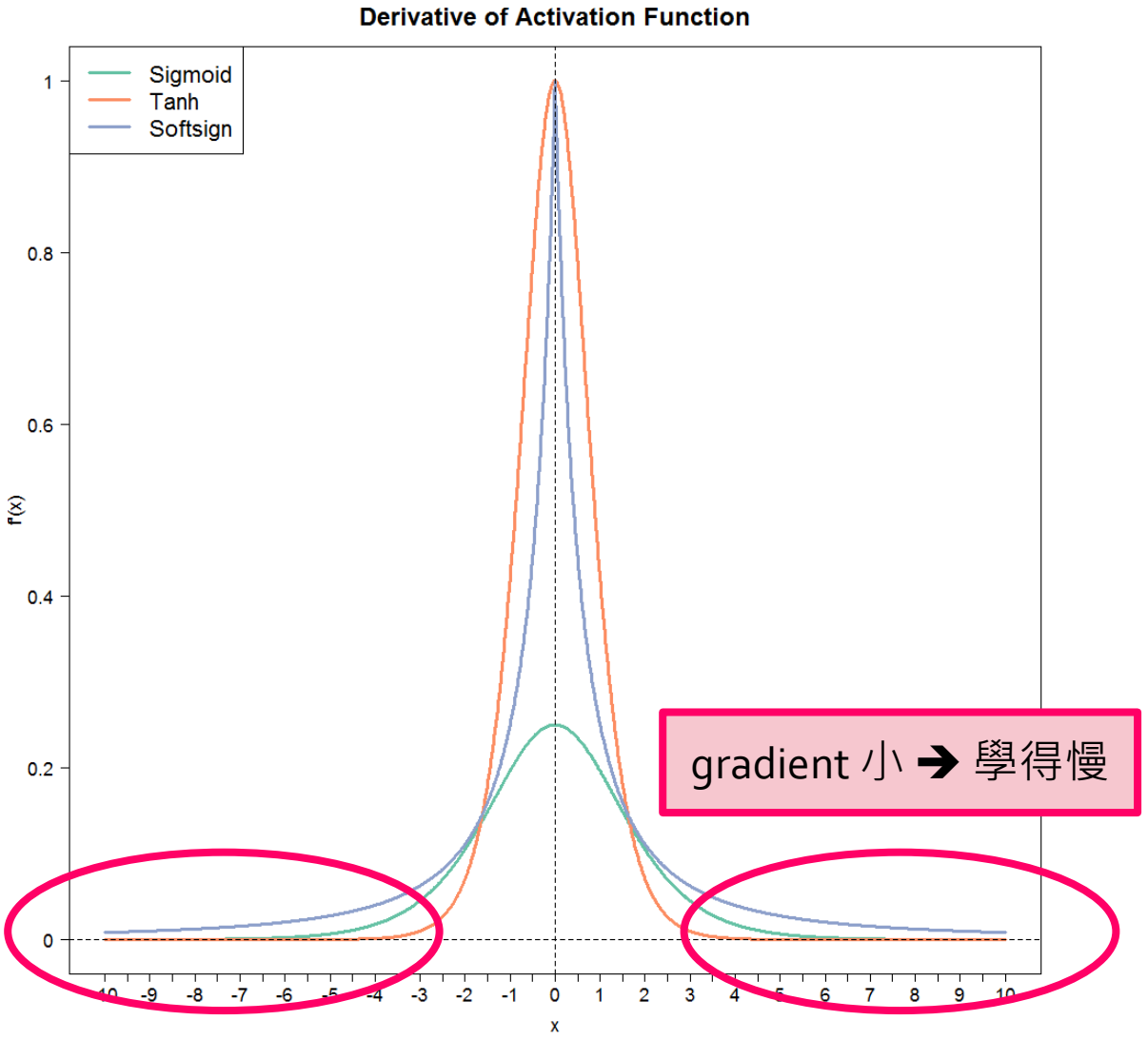
Sigmoid, Tanh, Softsign

- 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
  - $df/dx = \frac{1}{(1+|x|)^2}$



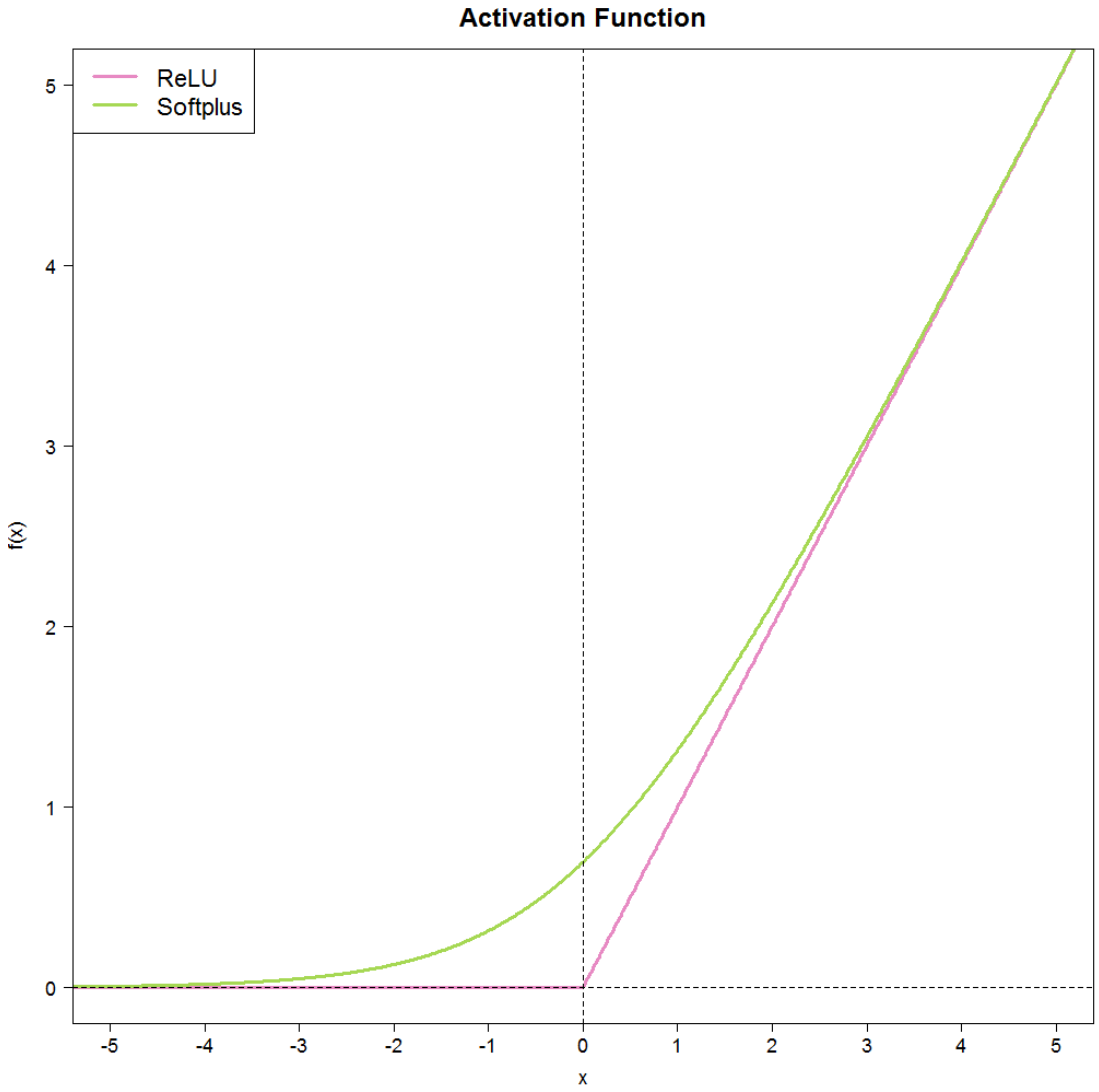
Drawbacks of Sigmoid, Tanh, Softsign

- 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

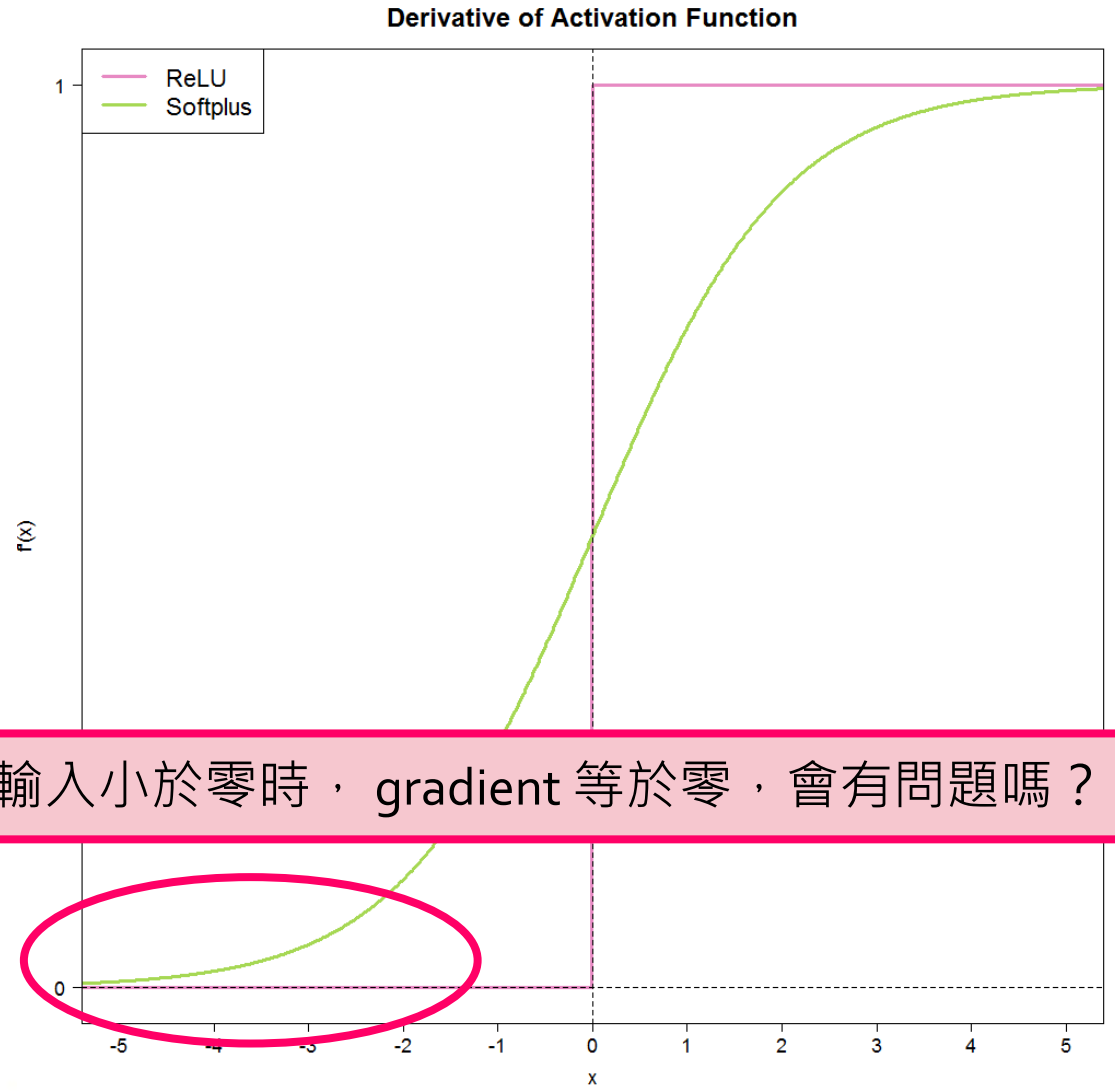
- 特別不適用於深的深度學習模型

ReLU, Softplus

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



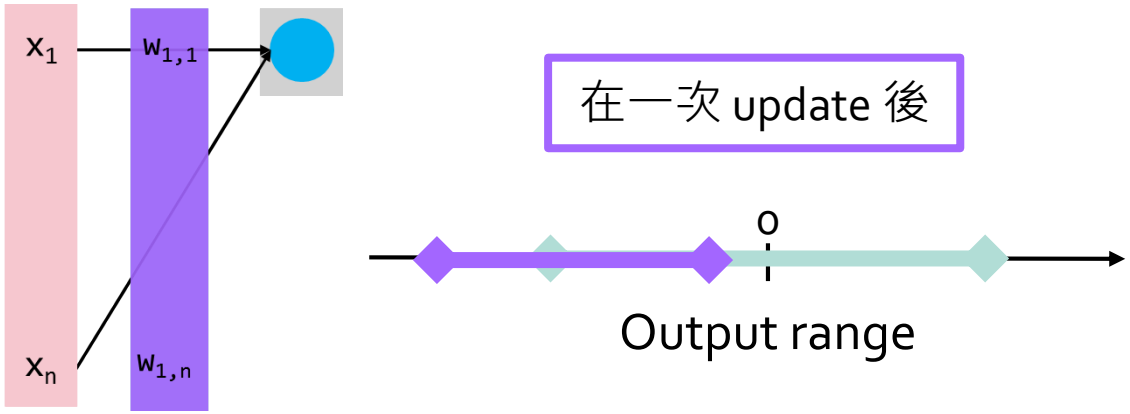
Derivatives of ReLU, Softplus



ReLU 在輸入小於零時， gradient 等於零，會有問題嗎？

Drawback of ReLU

- Dead ReLU problem



- 當輸入 x 都小於 0，ReLU 就不再更新

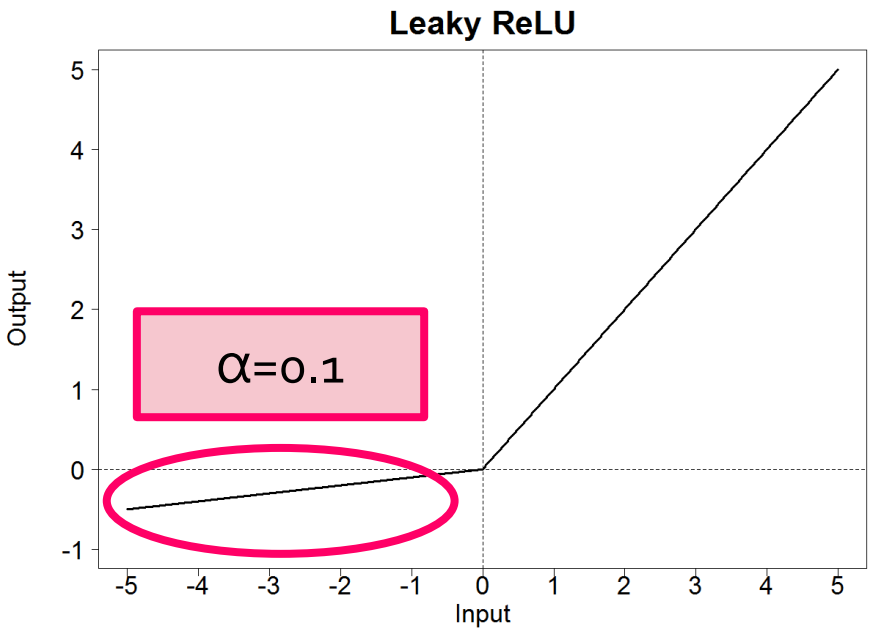
```
df/dx = 0 if x < 0.
```

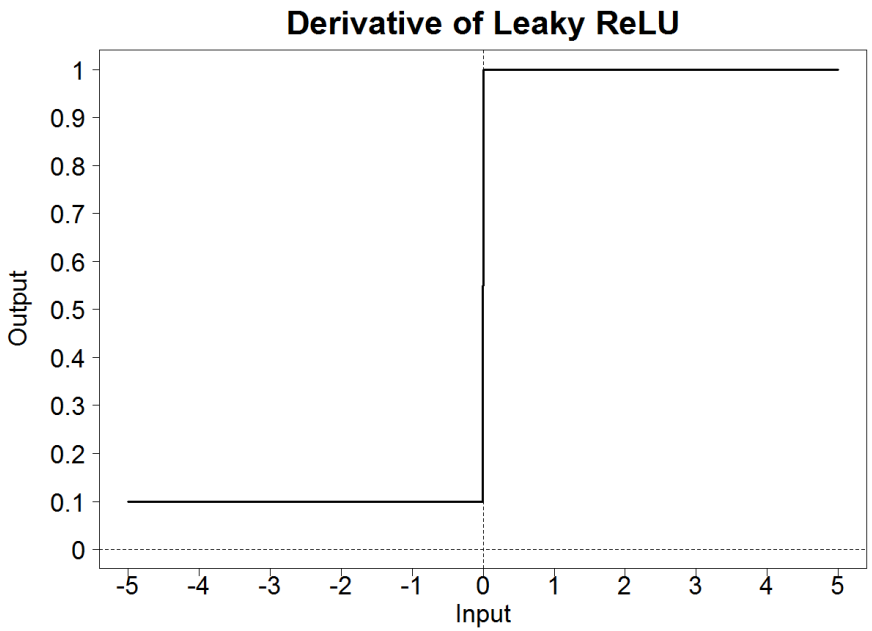
  - 可能因為 Learning rate 大 或是 batch size 小

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)
```

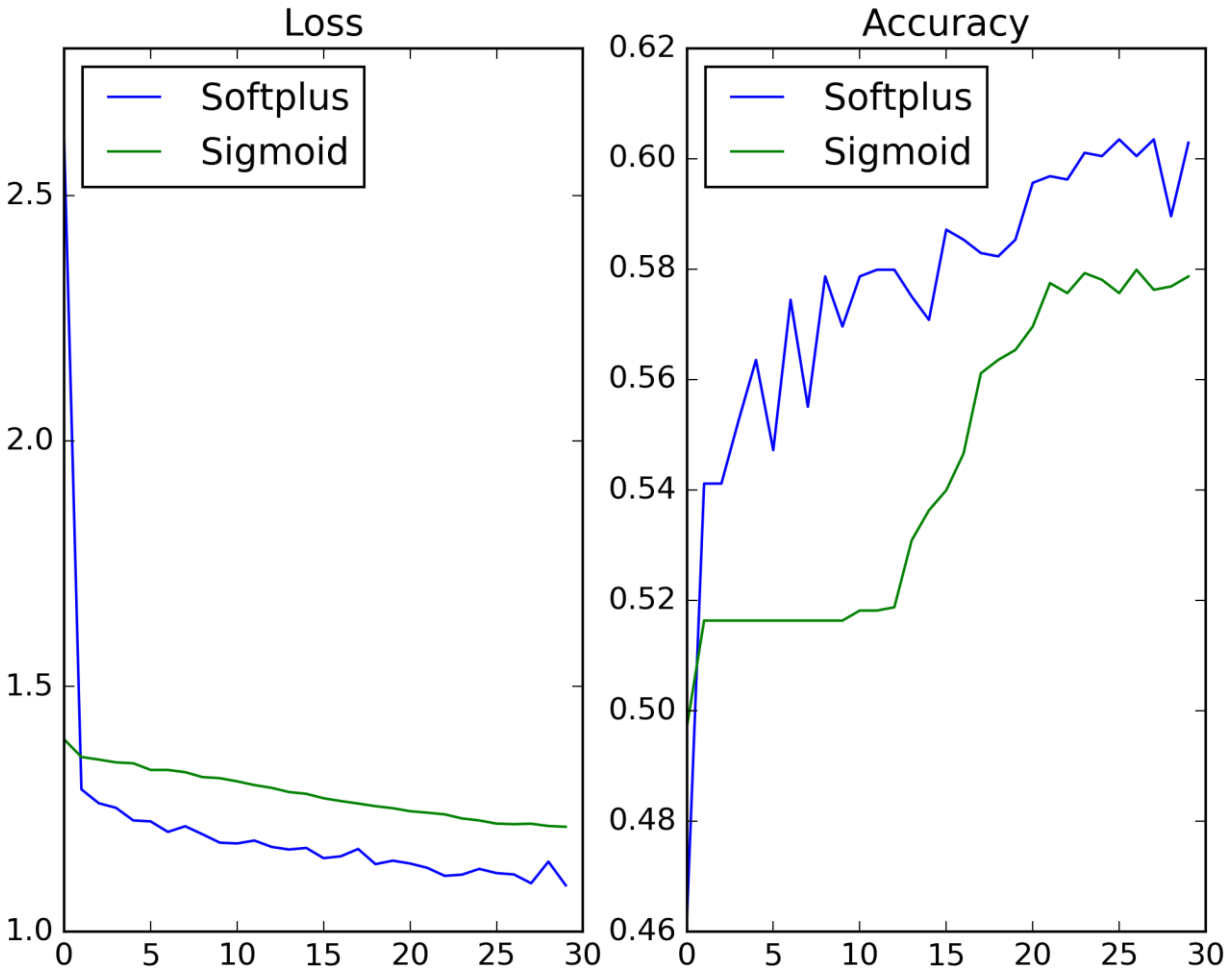
- 更多其他的 activation functions
  https://keras.io/layers/advanced-activations/

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('softplus'))

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

# 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 – Softplus versus Sigmoid



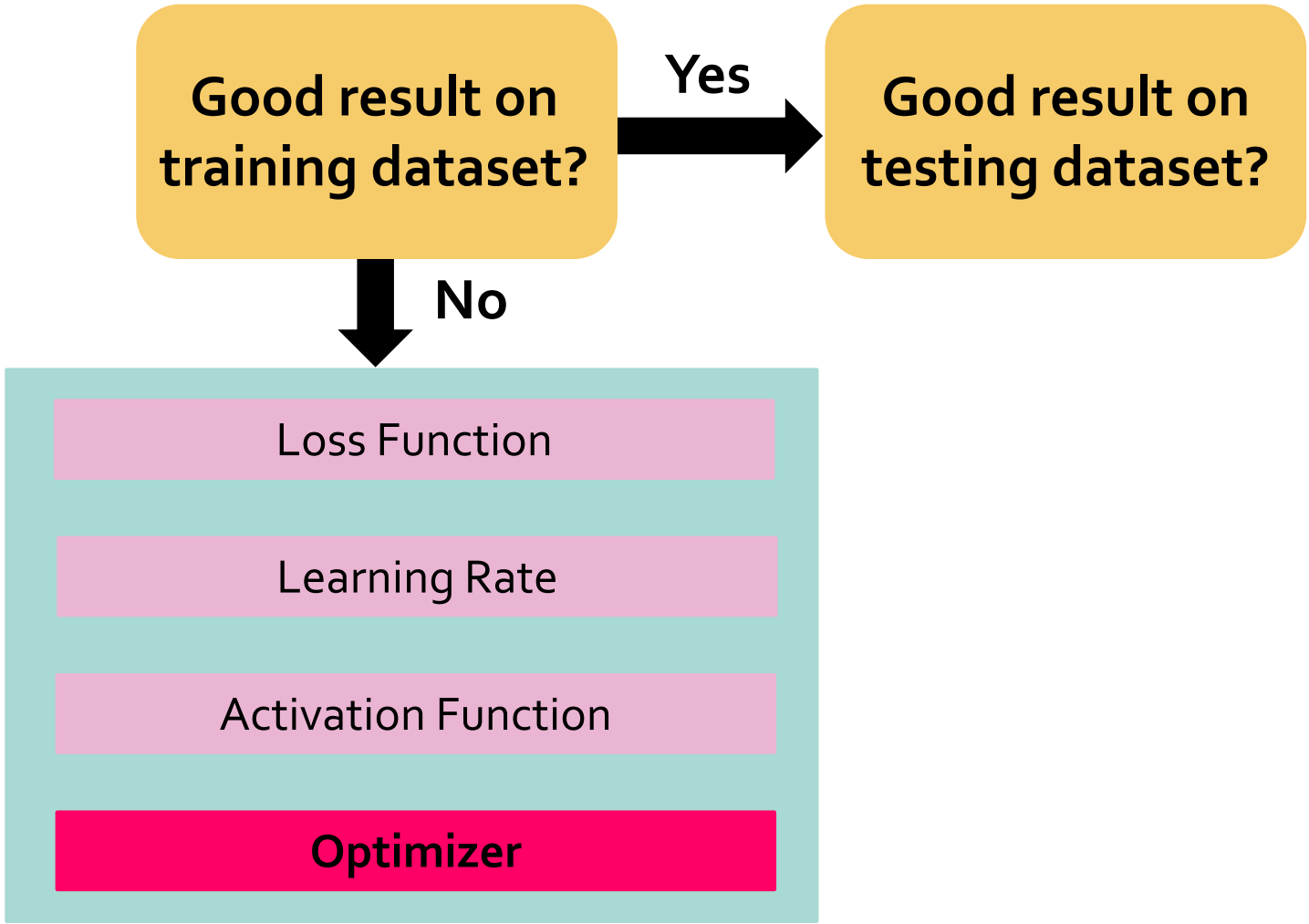
How to Select Activation Functions

- Hidden layers
  - 通常會用 ReLU
  - Sigmoid 有 vanishing gradient 的問題較不推薦
- Output layer
  - Regression
    - 常用 linear
    - 若 output 一定大於零, 可以用 ReLU
  - Classification
    - Output layer 常用 softmax

Current Best Model Configuration

Component	Selection
Loss function	categorical_crossentropy
Activation function	softplus + 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

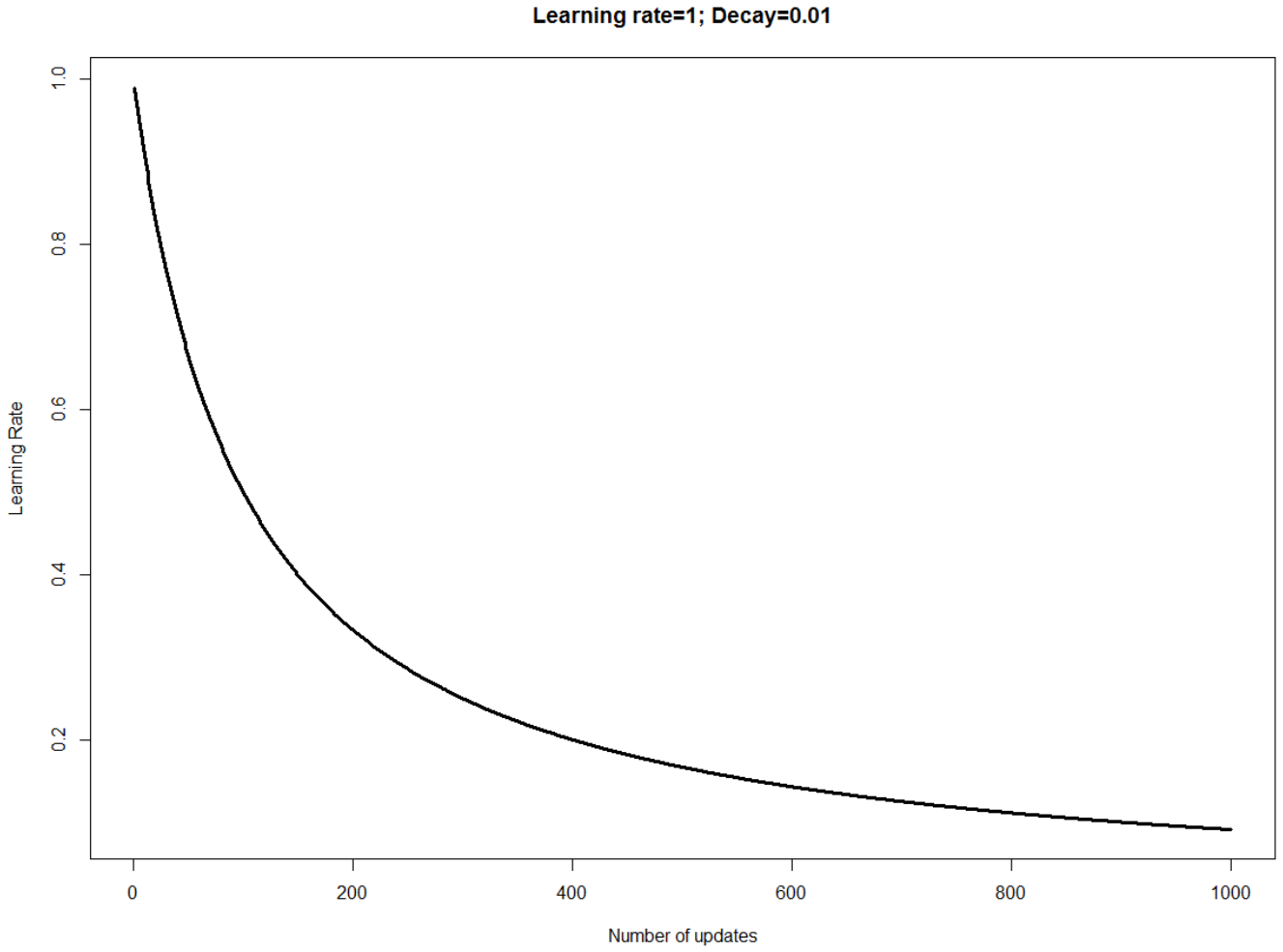
- Stochastic gradient descent
- 支援 momentum, learning rate decay, Nesterov momentum

```
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)
```



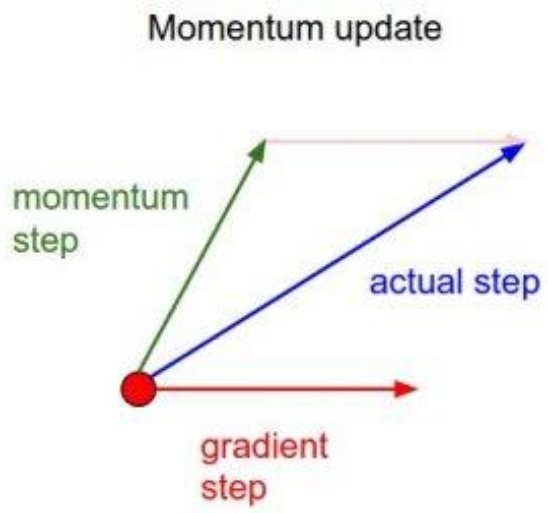
Nesterov Momentum

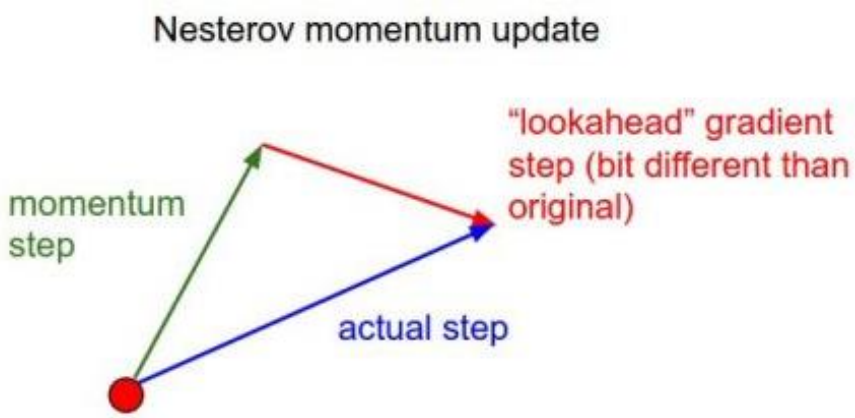
Momentum

- 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

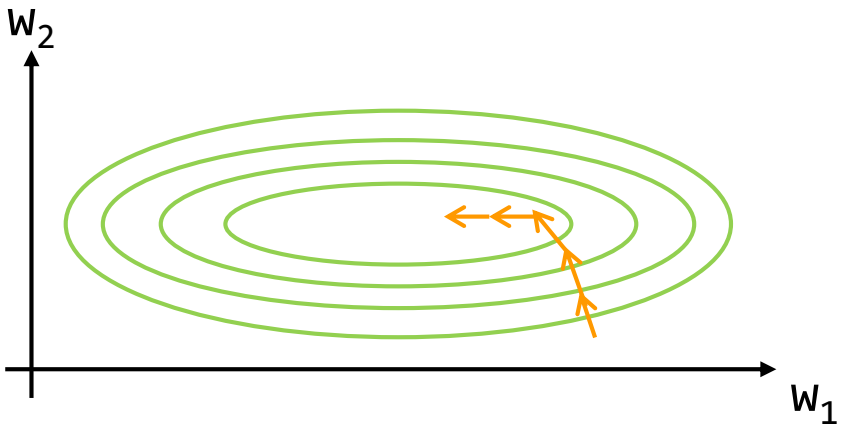
$$\theta^{t+1} = \theta^t - \frac{\eta}{\sigma^t} g^t$$

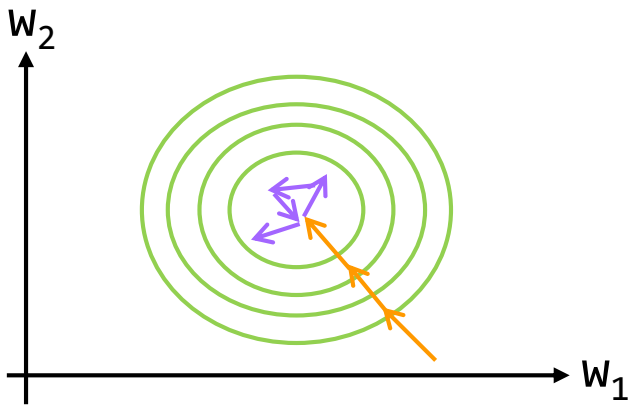
所有 gradient 的 root mean square

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

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

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

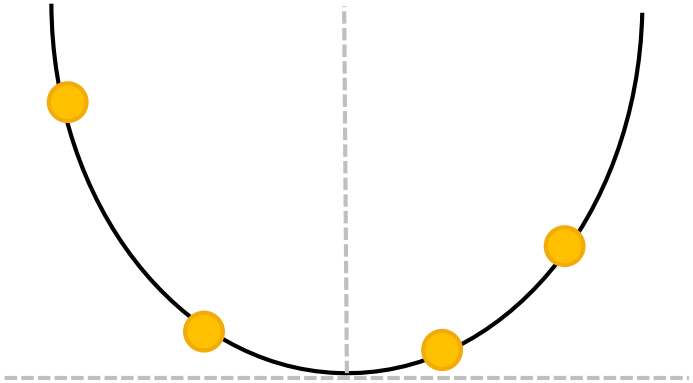
$$\theta^2 = \theta^1 - \frac{\eta}{\sigma^1} g^1 \qquad \sigma^1 = \sqrt{\frac{(g^0)^2+(g^1)^2}{2}}$$

$$\vdots$$

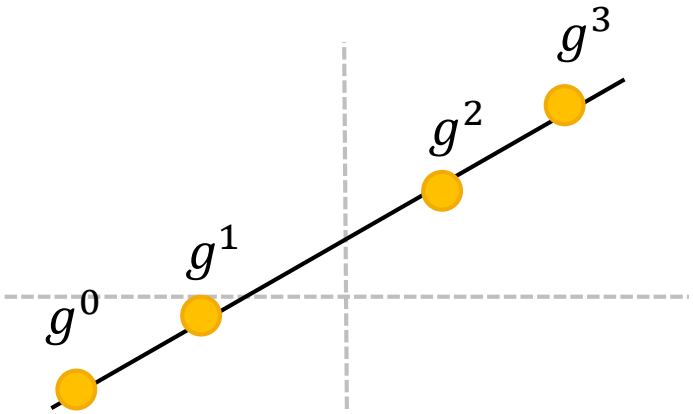
$$\theta^t = \theta^{t-1} - \frac{\eta}{\sigma^{t-1}} g^{t-1} \qquad \sigma^t = \sqrt{\frac{(g^0)^2+(g^1)^2+\ldots+(g^t)^2}{t+1}}$$

- g^t 是一階微分，那 σ^t 隱含什麼資訊？

σ^t 的意義

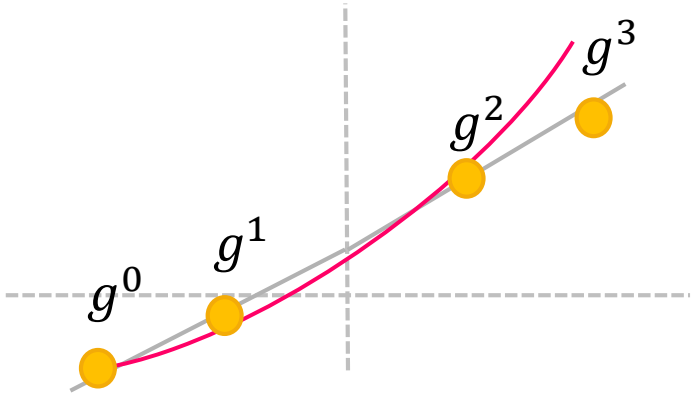


$$y = ax^2 + bx + c$$



$$\frac{dy}{dx} = 2ax + b$$

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



- 實際上算一階微分曲率
- σ^t 可視為二階微分

An Example of Adagrad

gradient				
W_1	0.001	0.003	0.002	0.1
W_2	1.8	2.1	1.5	0.1

W_1	0.001	0.002	0.002	0.05
W_2	1.8	1.956	1.817	1.57

Lr	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

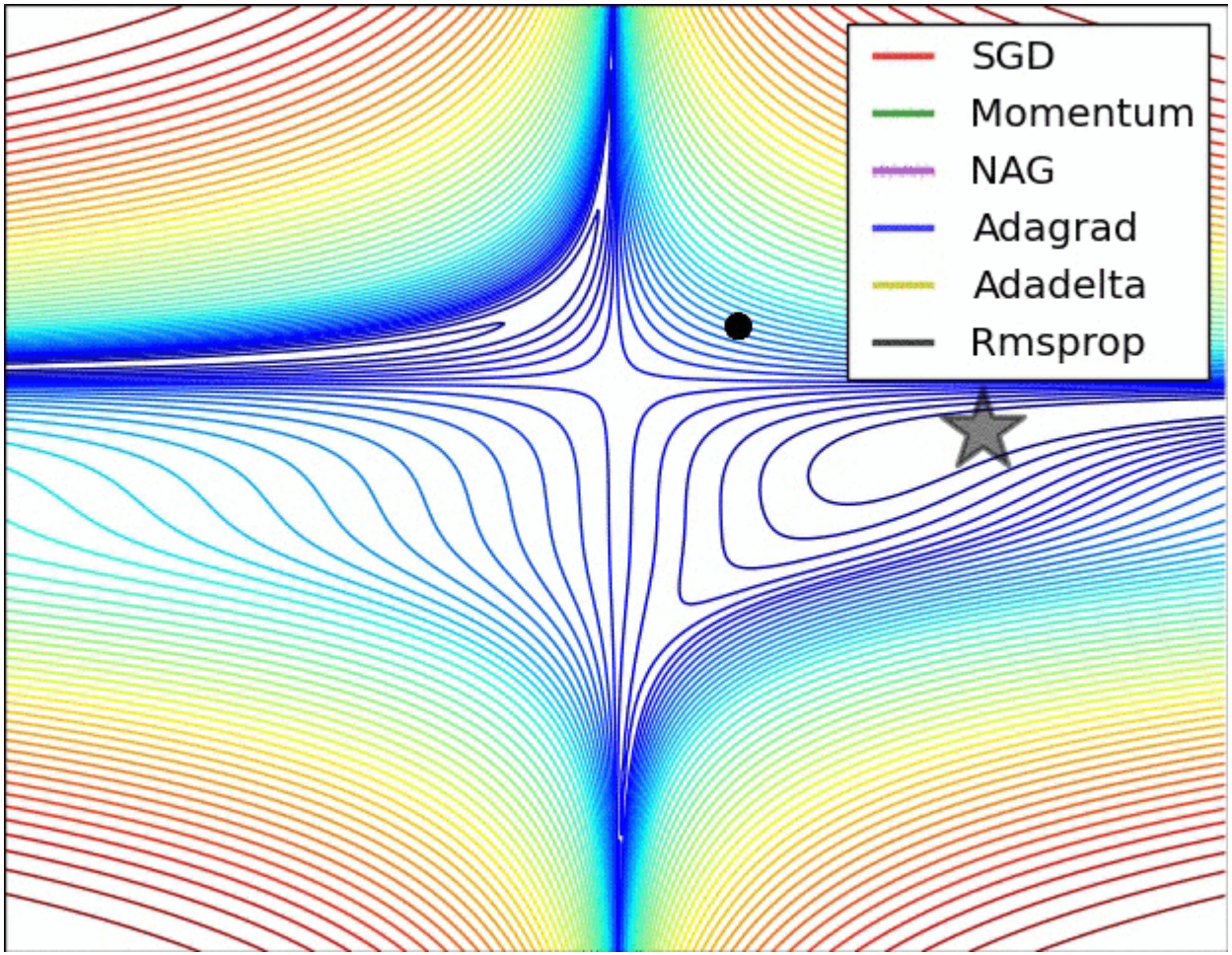
```
keras.optimizers.RMSprop(lr=0.001, rho=0.9, epsilon=1e-08, decay=0.0)
```

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)

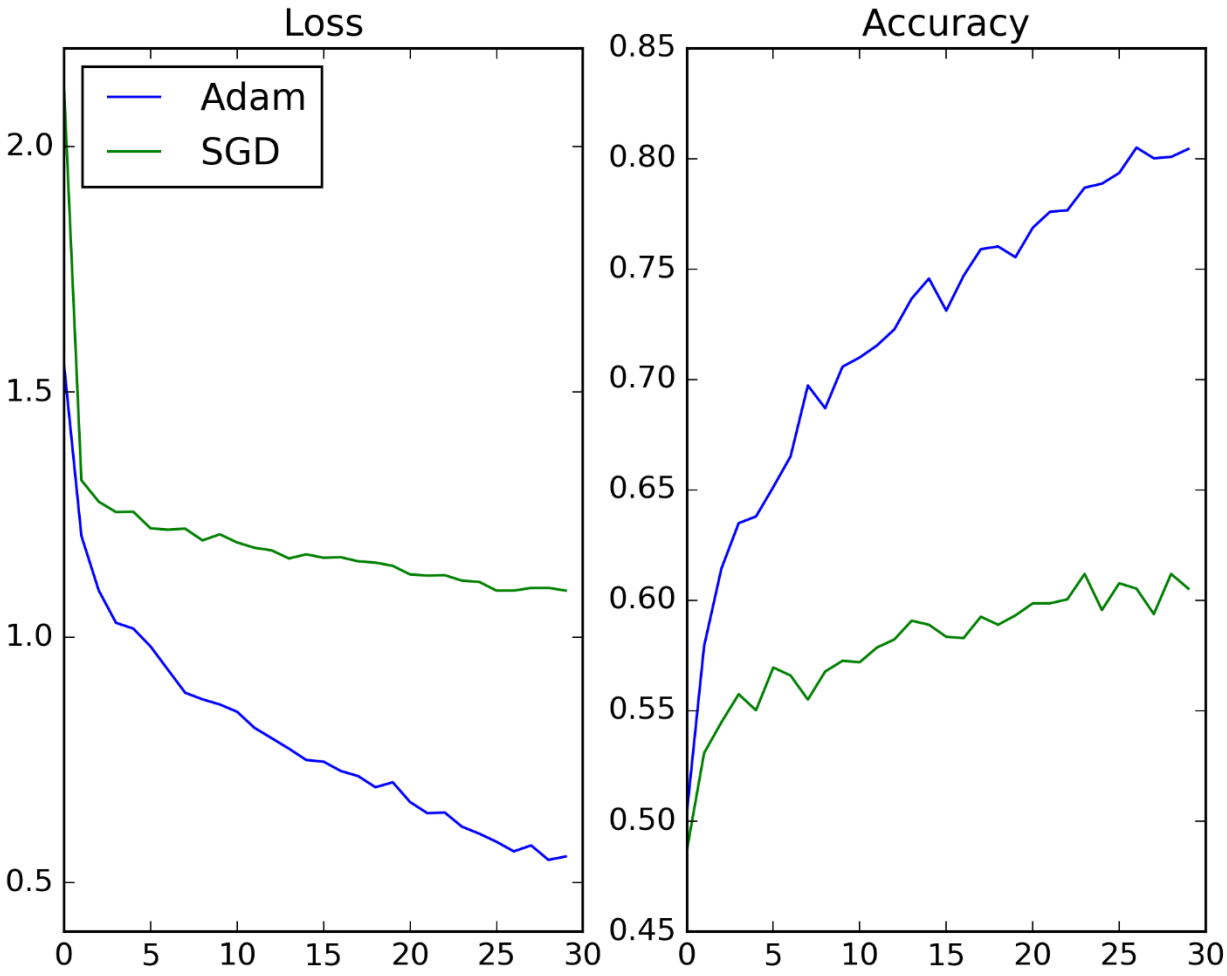
1. 設定選用的 optimizer

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

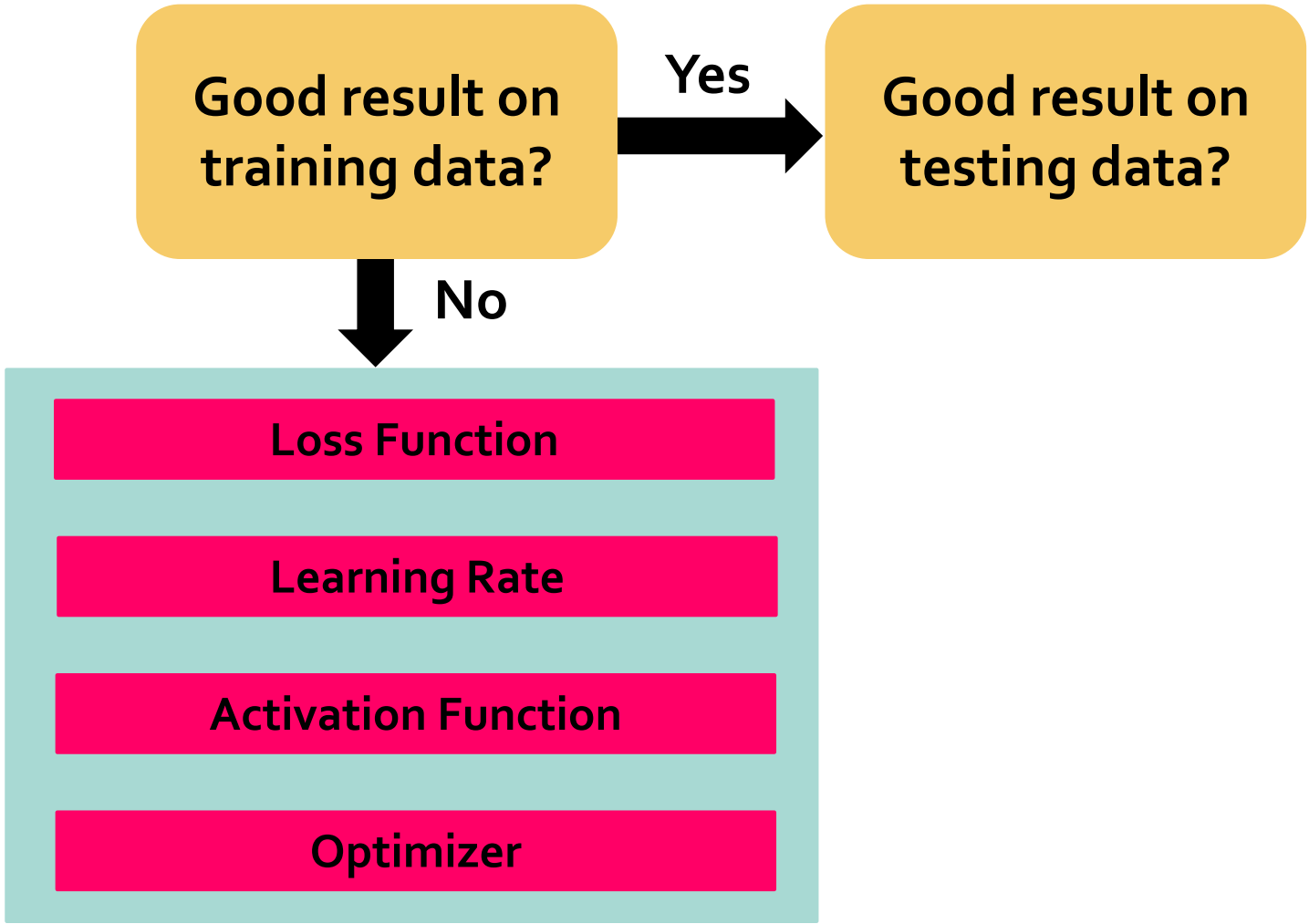
2. 修改 model compilation

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

Result – Adam versus SGD



Tips for Deep Learning

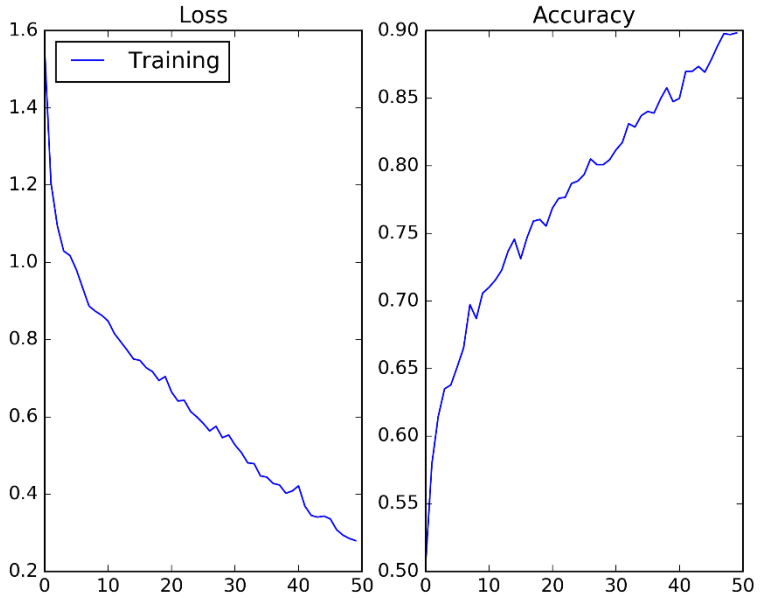


Current Best Model Configuration

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

50 epochs 後

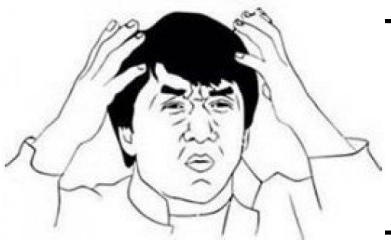
90% 準確率！



進度報告

我們有90%準確率了！

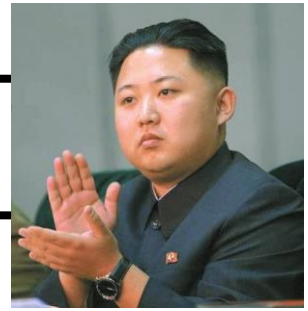
但是在 training dataset 上的表現

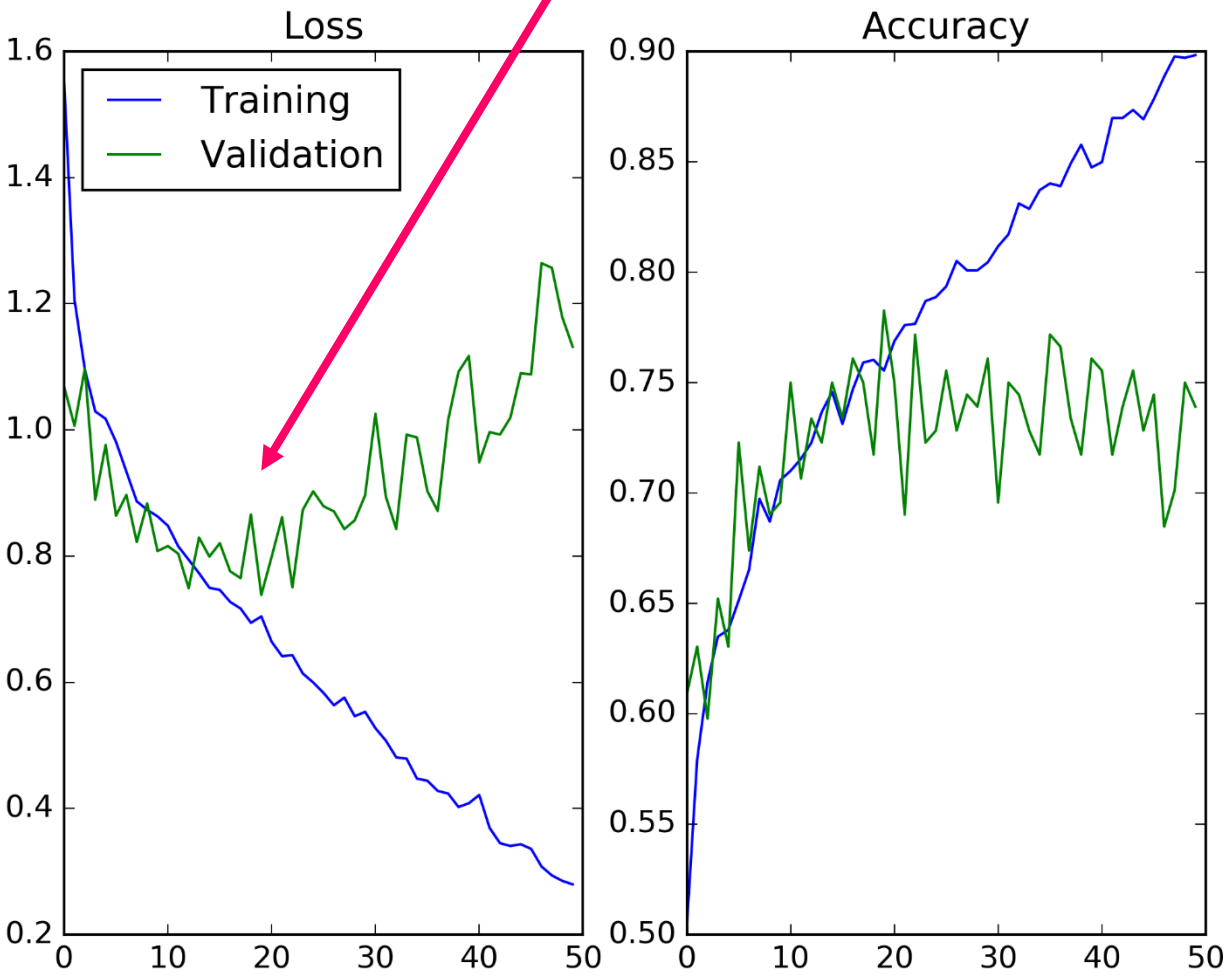


這會不會只是一場美夢？

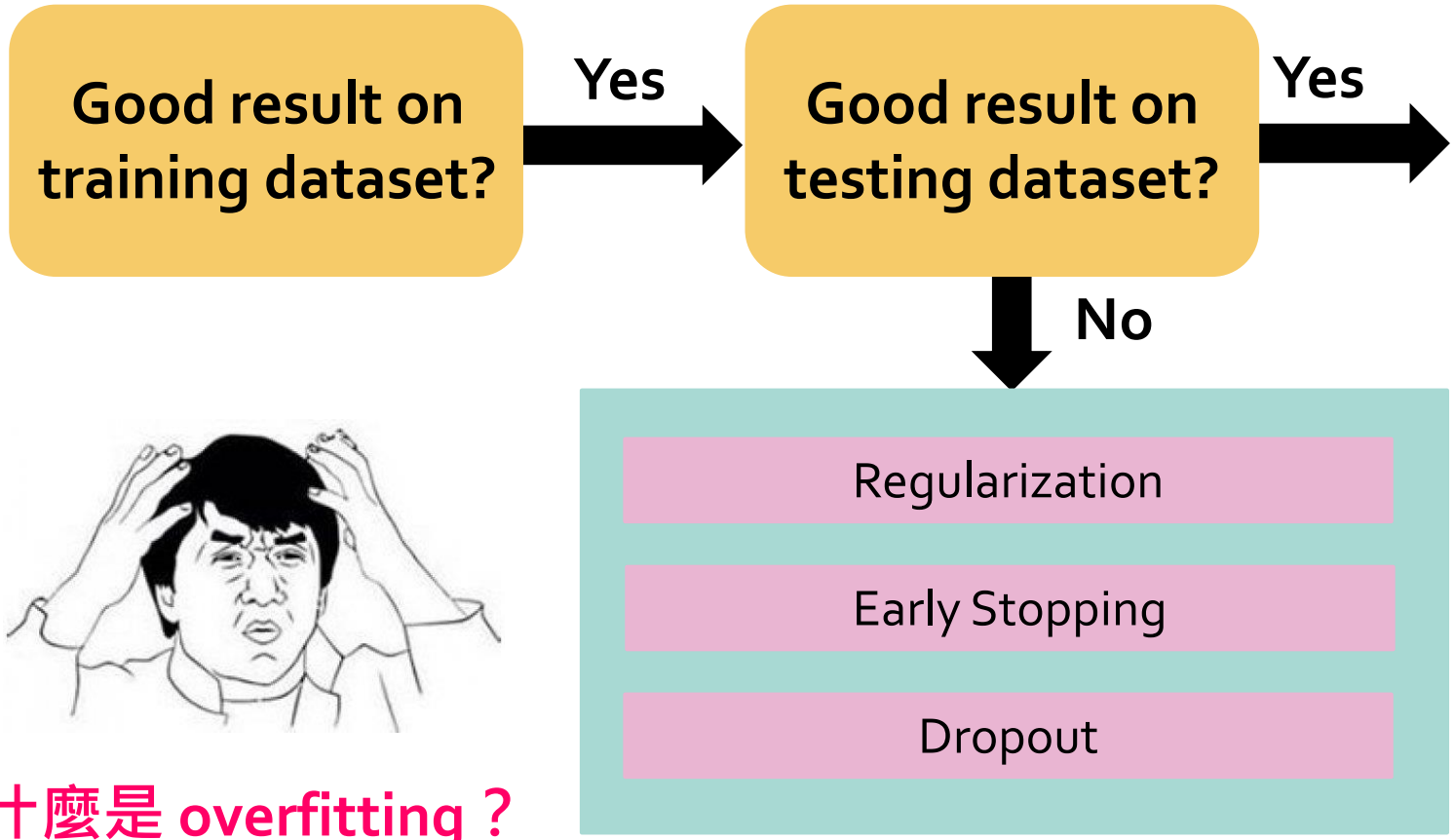
見真章

Overfitting 啦!





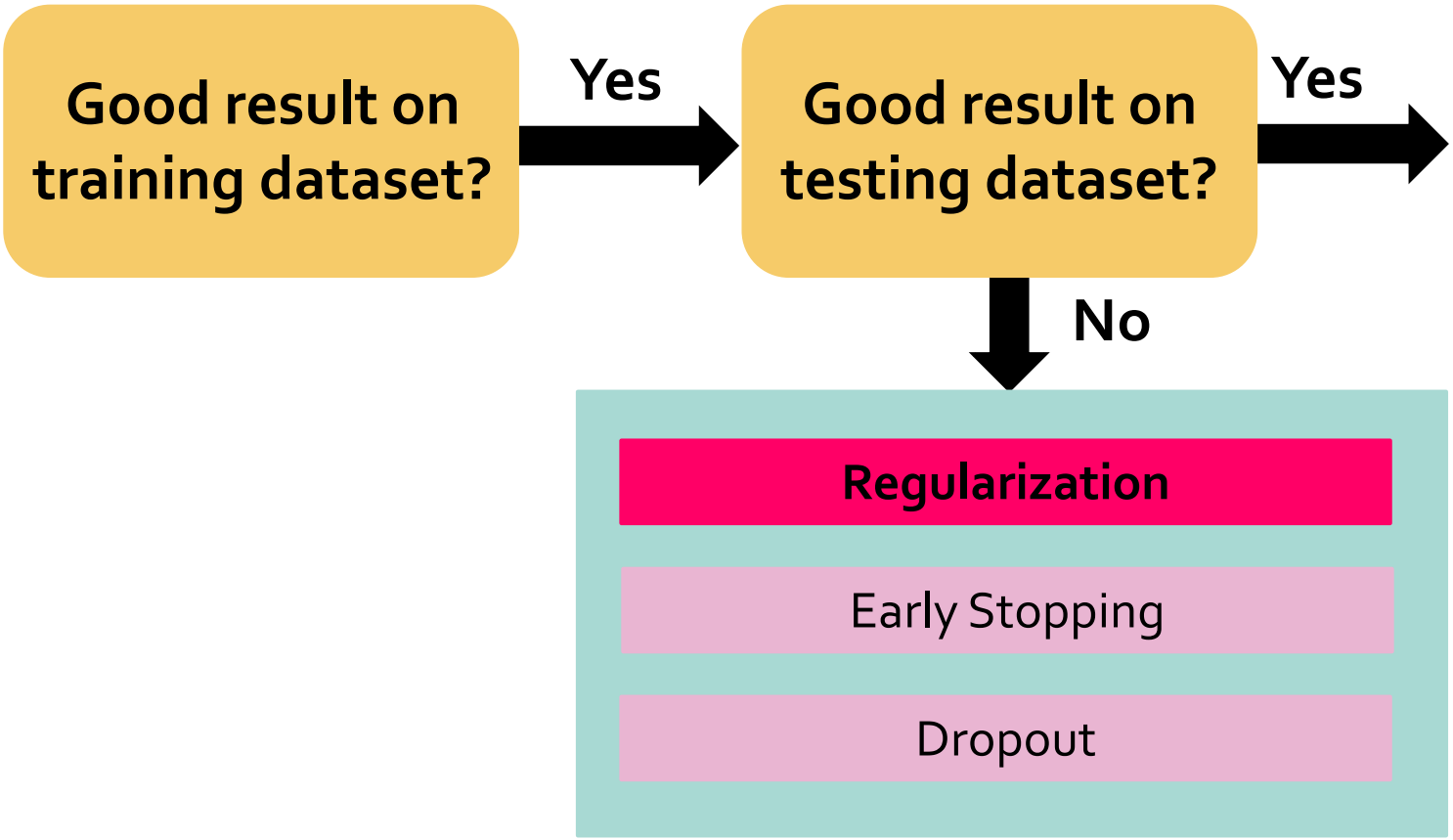
Tips for Deep Learning



什麼是 overfitting？

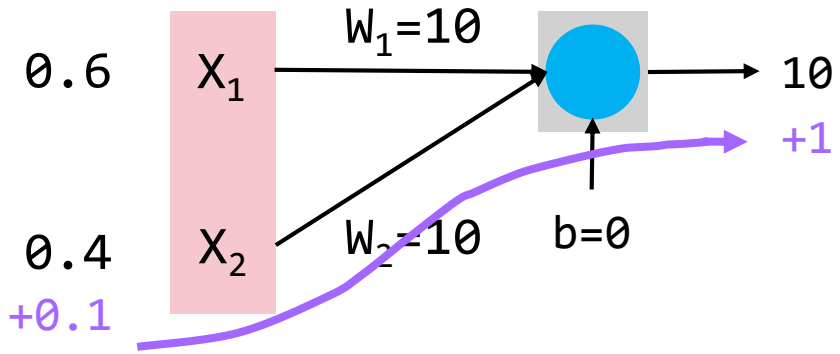
training result 進步，但 testing result 反而變差

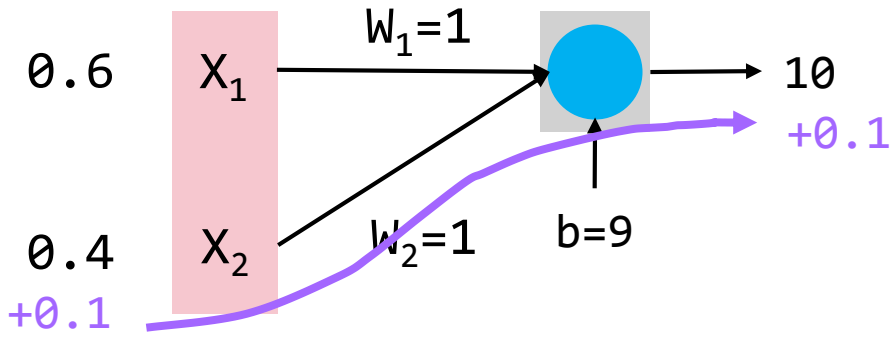
Tips for Deep Learning



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

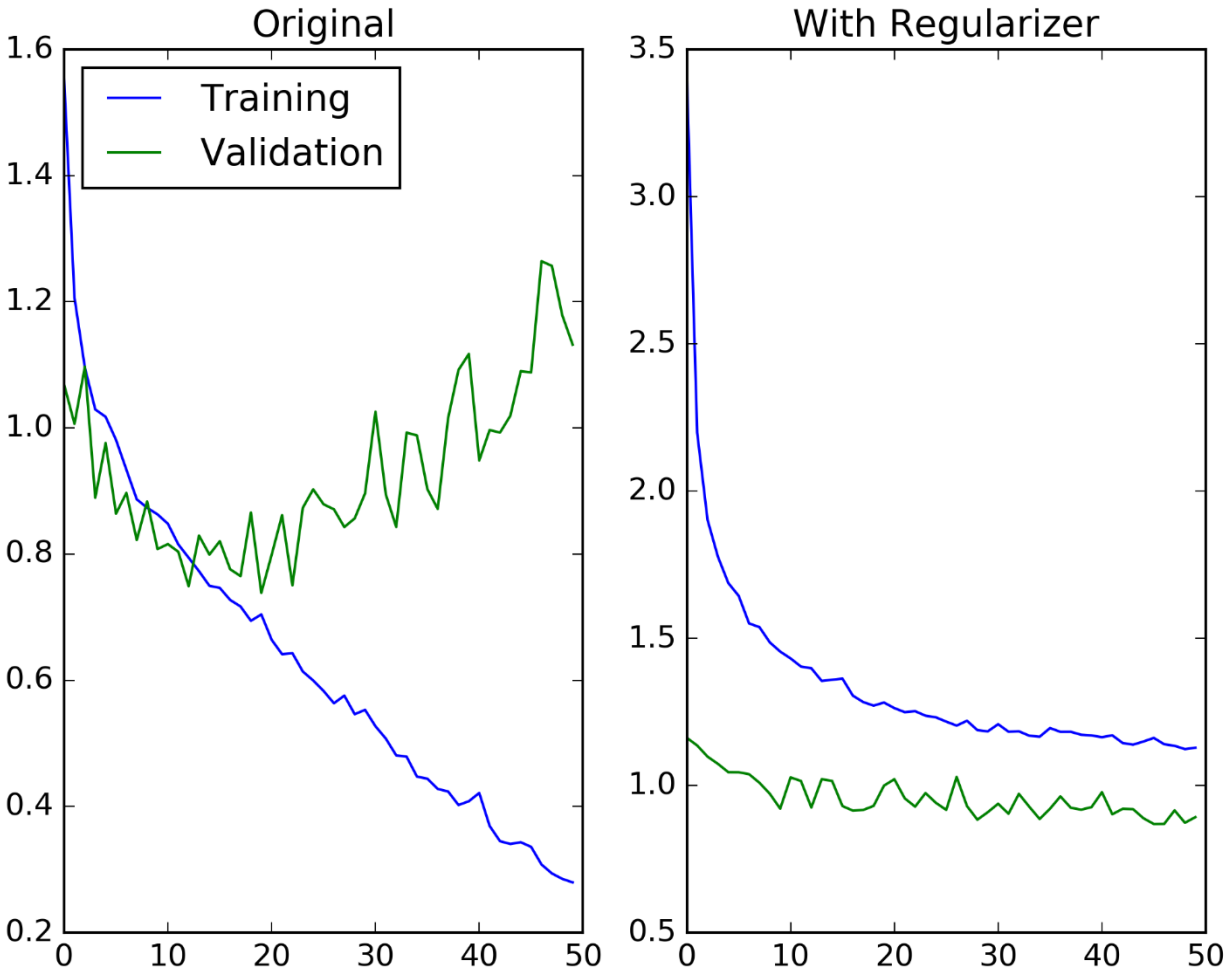
```
''' Import l1,l2 (regularizer) '''
from keras.regularizers import l1,l2

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,W_regularizer=l2(0.01))
Model_l2.add(Activation('softplus'))

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

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

練習 06_regularizer.py (5-8 minutes)

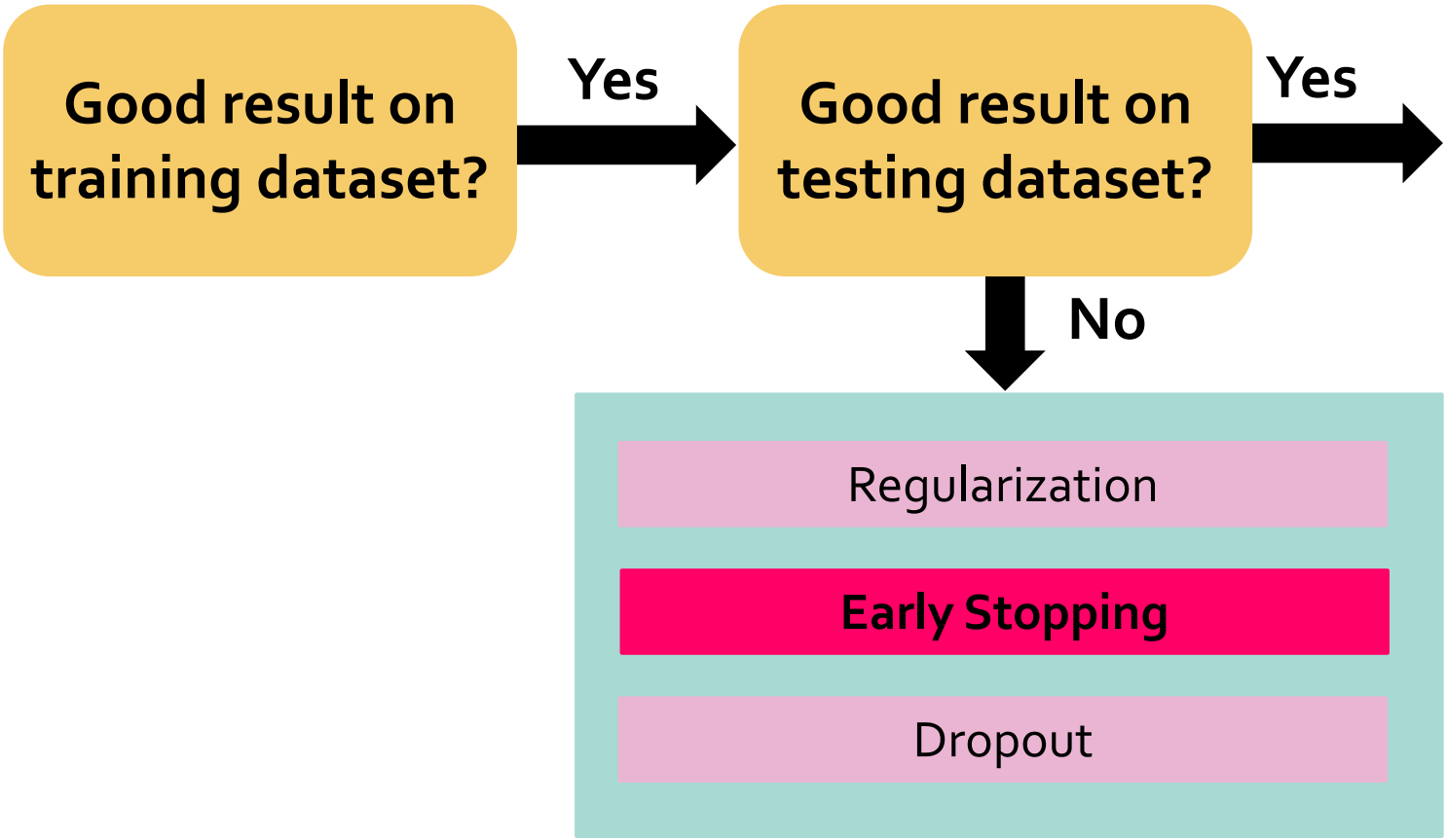
```
''' Import l1,l2 (regularizer) '''
from keras.regularizers import l1,l2
# 加入第一層 hidden layer 並加入 regularizer (alpha=0.01)
Model_l2.add(Dense(128,input_dim=200,W_regularizer=l2(0.01)))
Model_l2.add(Activation('softplus'))
```

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=0.01)

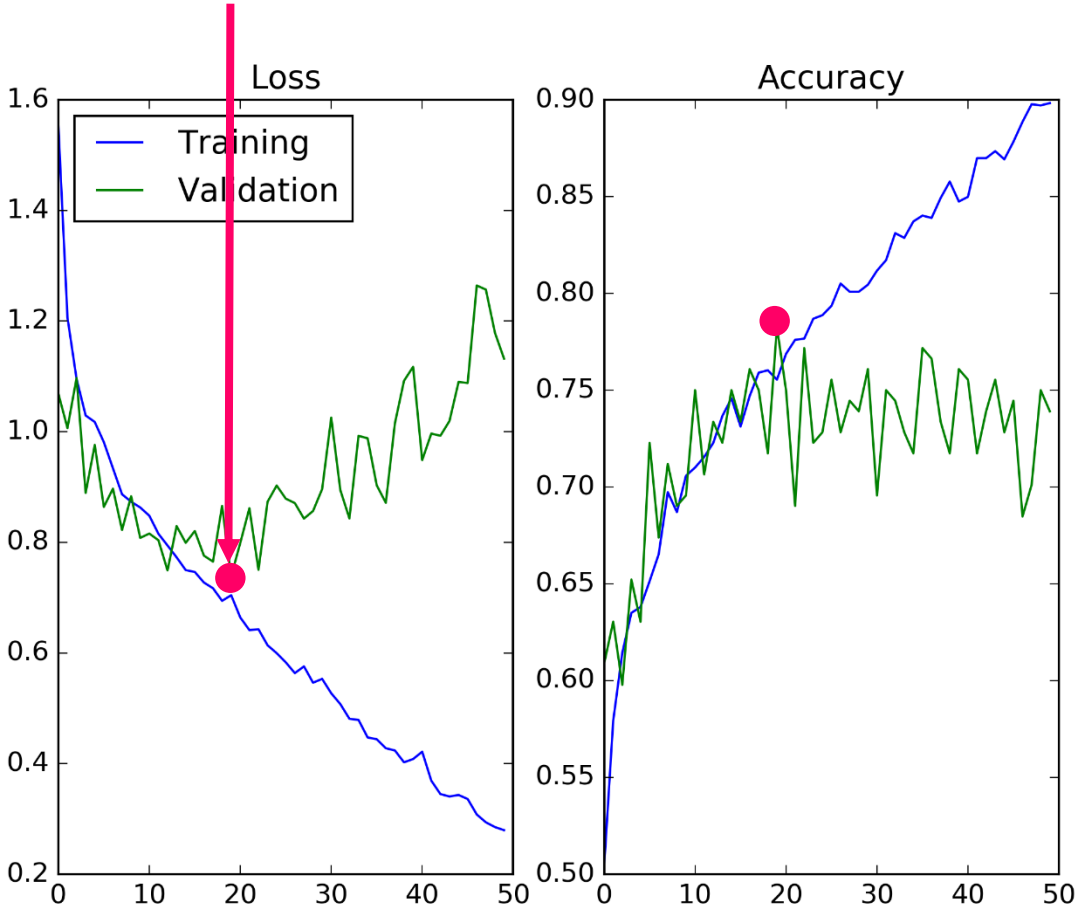


Tips for Deep Learning



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',
                            patience = 3)
```

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

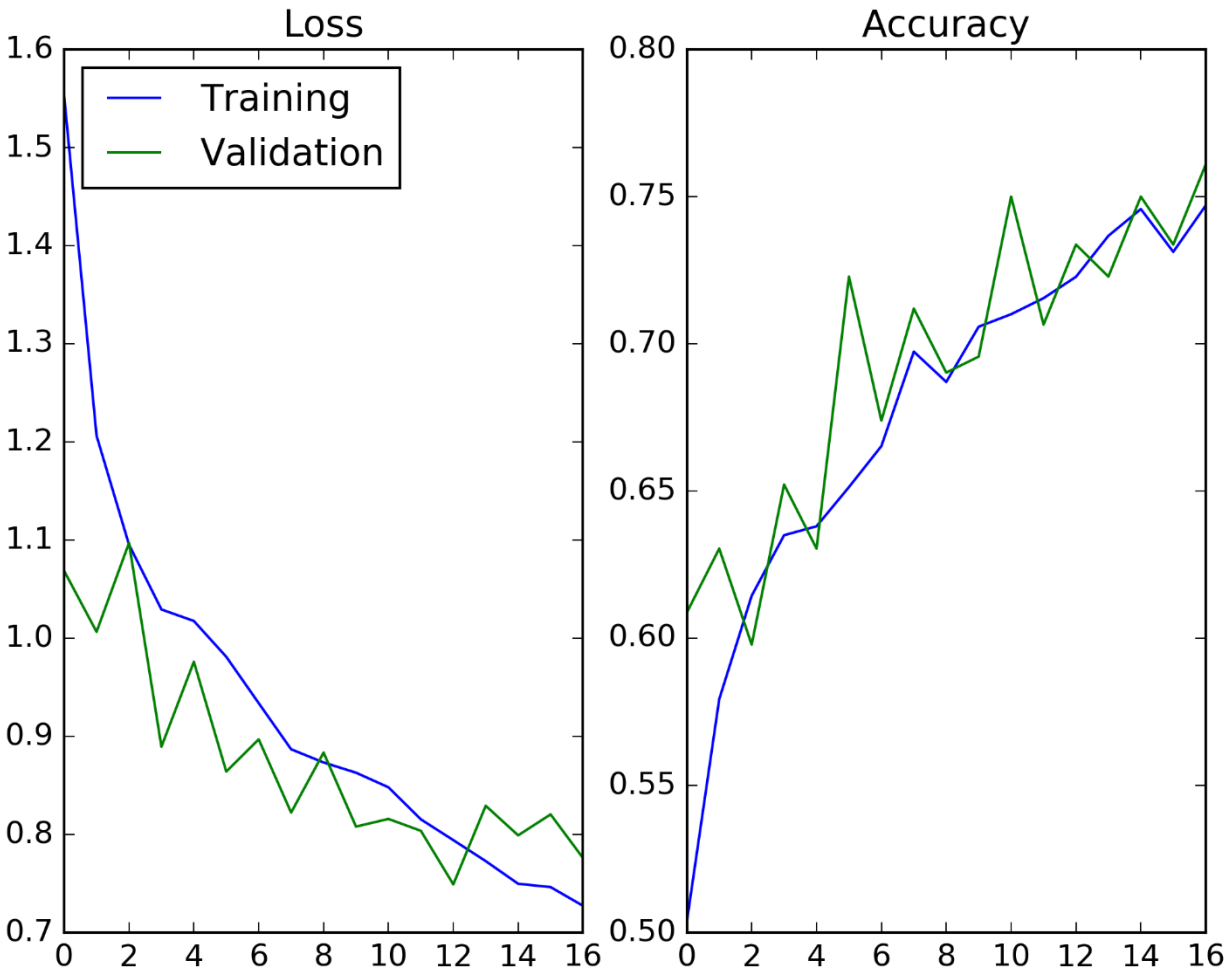
加入 Early Stopping

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

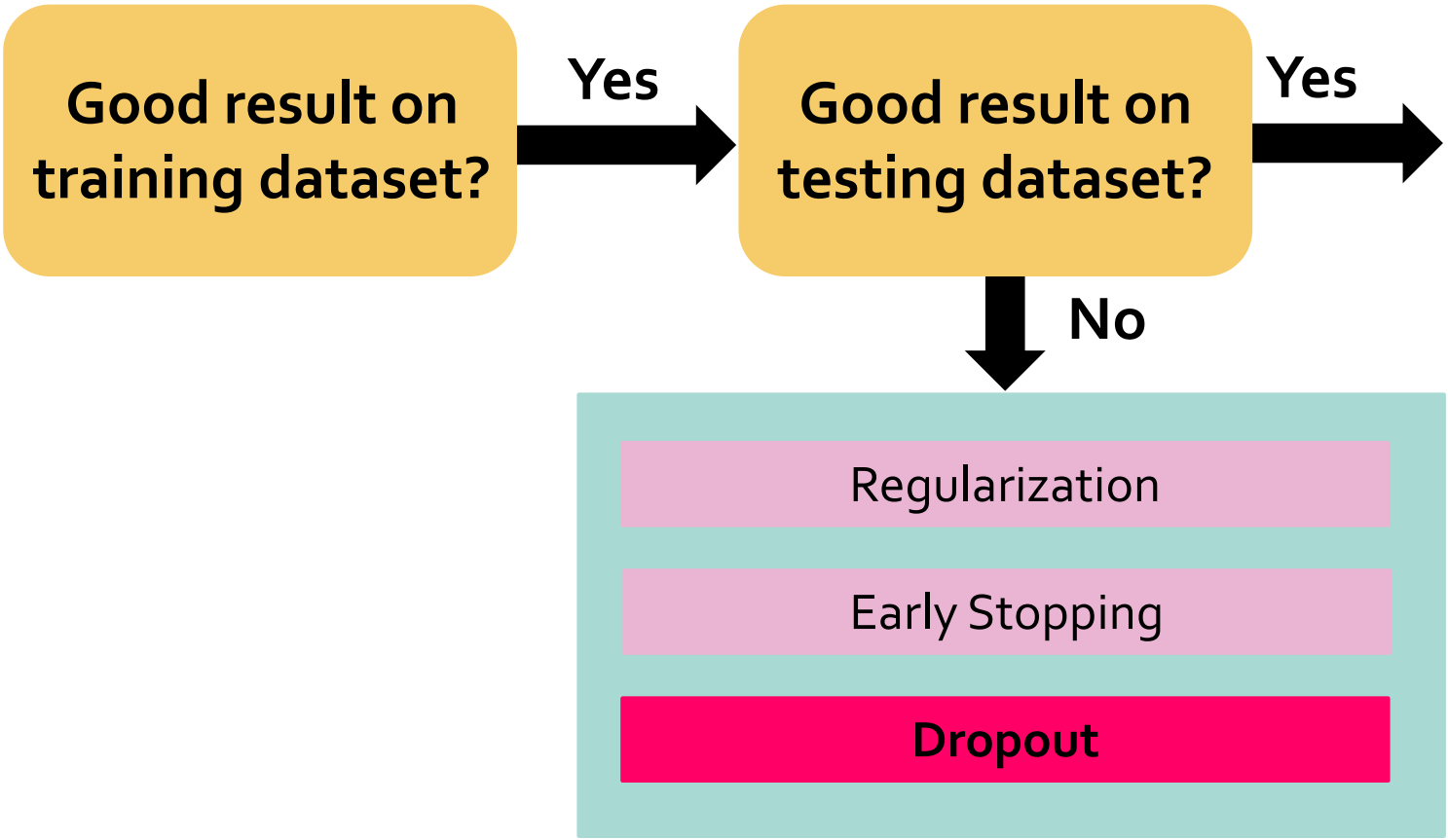
```
# 指定 batch_size, nb_epoch, validation 後，開始訓練模型!!!
history = model.fit( X_train,
                     Y_train,
                     batch_size=16,
                     verbose=0,
                     nb_epoch=30,
                     shuffle=True,
                     validation_split=0.1,
      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

練習 07_earlyStopping.py (5-8 minutes)

Result – EarlyStopping (patience=3)

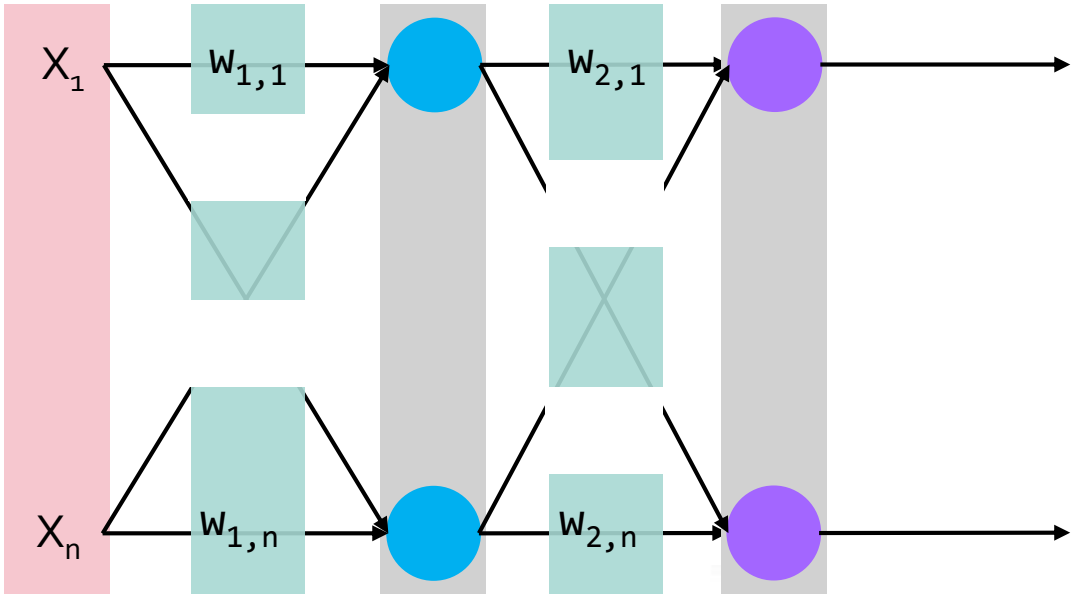


Tips for Deep Learning



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)

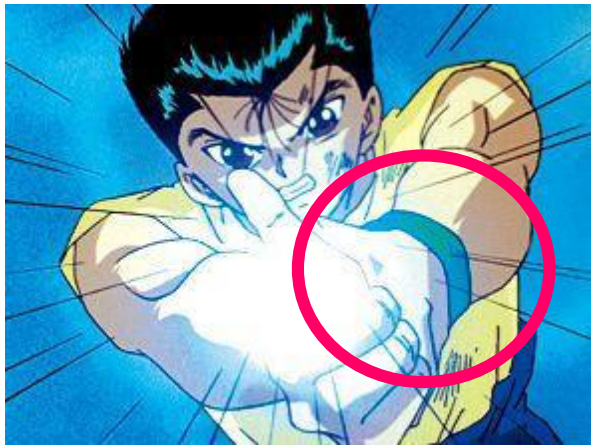


Dropout 的結果

- 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 $(\hat{y}' - y) < \epsilon + \Delta\epsilon$
  - Error 變大 ➔ 每個 neuron 修正得越多 ➔ 做得越好

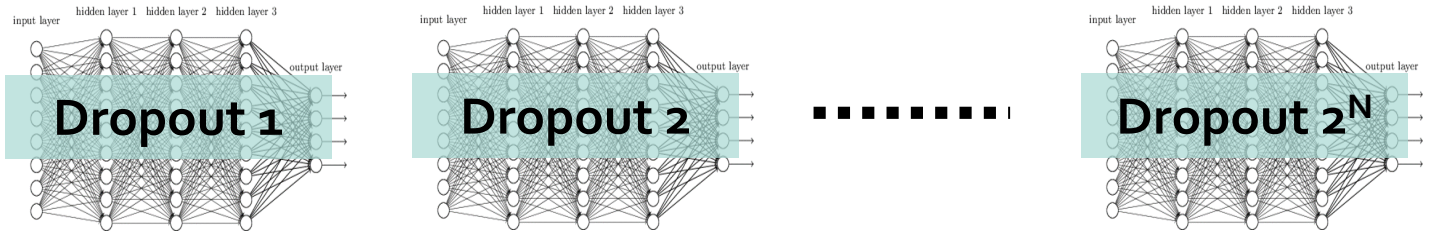
Implications

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

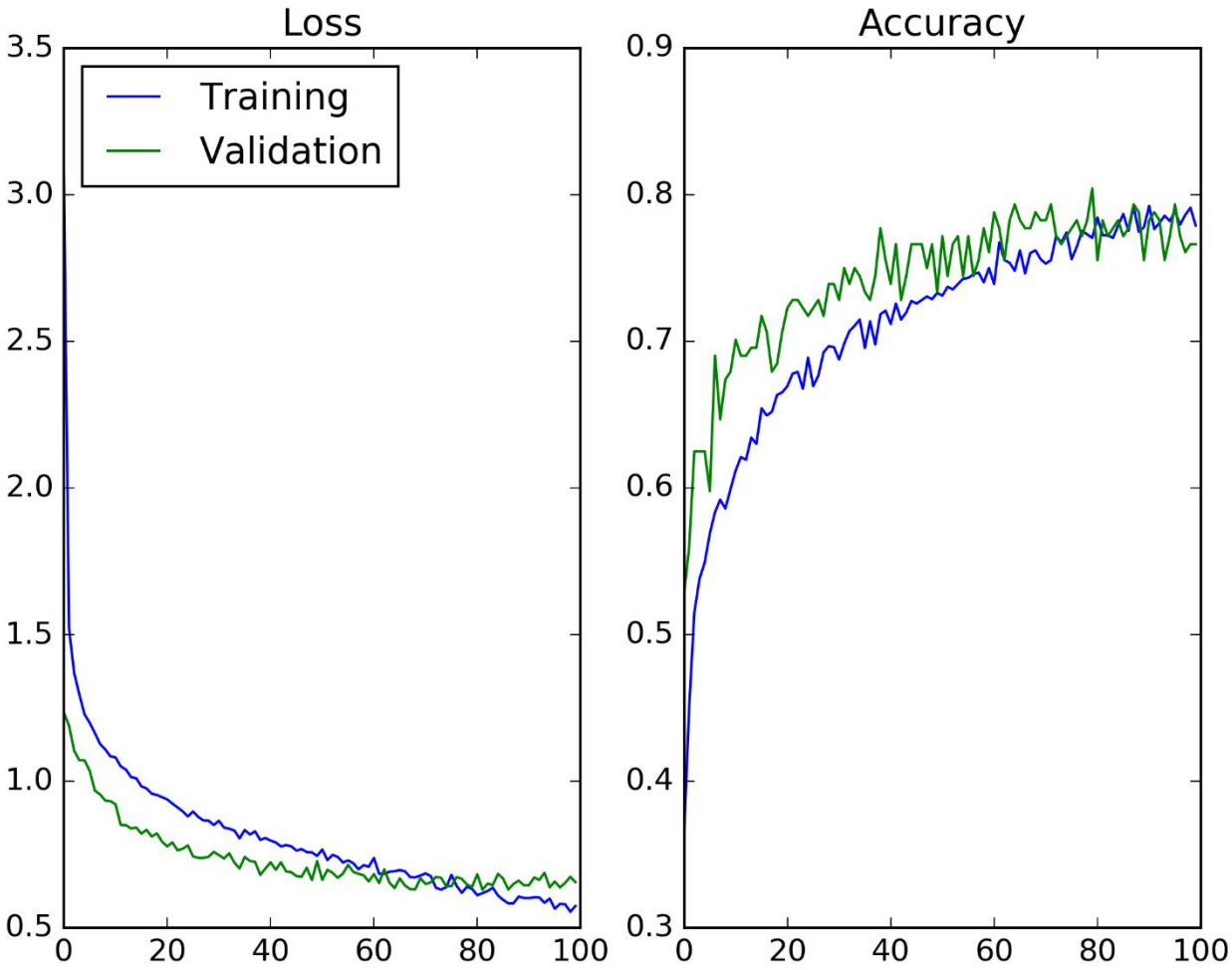


Dropout in Keras

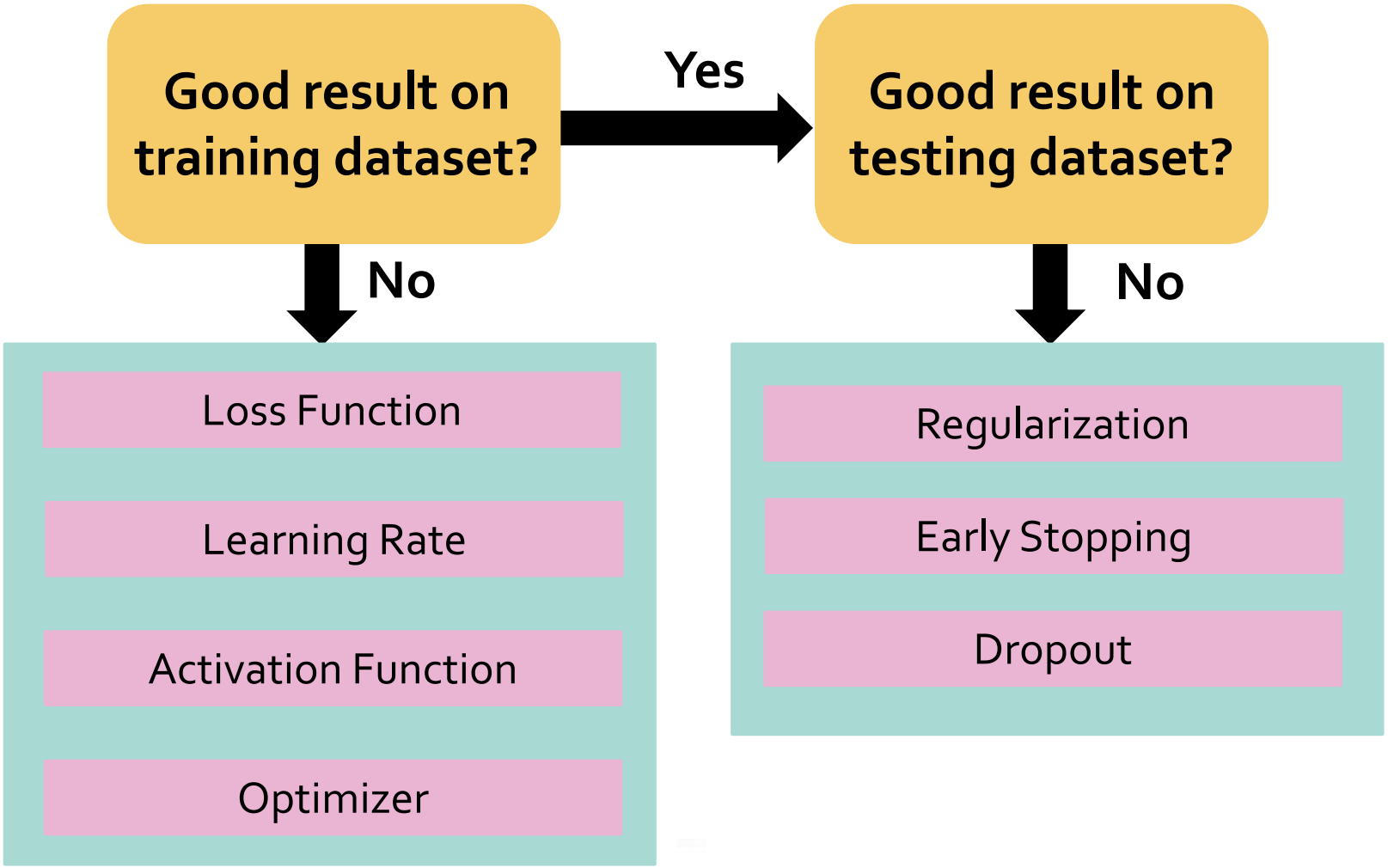
```
from keras.layers.core import Dropout
model = Sequential()

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

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



Tips for Training Your Own DL Model



Yeah, Win


LAMP DOESN'T WORK
LAMP PLUGGED IN?
PLUG IN LAMP
BULB BURNED OUT?
REPLACE BULB
REPAIR LAMP
START
READ X
X>0
READ Y
X:=2*X
X:=X*Y
HALT
INPUT NAME
HAS LOOP RUN 3 TIMES
OUTPUT,HELLO <NAME>
STOP
COMPUTER
SOFTWARE
CHAT
WWW
LOADING..

Variants of Deep Neural Network

Convolutional Neural Network (CNN)

2-dimensional Inputs

- Ordinary feedforward DNN focuses on 1-d input data
- How about 2-d or 3-d data, such as images

Figures reference
https://twitter.com/gonainlive/status/507563446612013057

Ordinary Feedforward DNN with Image

- The number of weights between input layer and first hidden layer will become very large

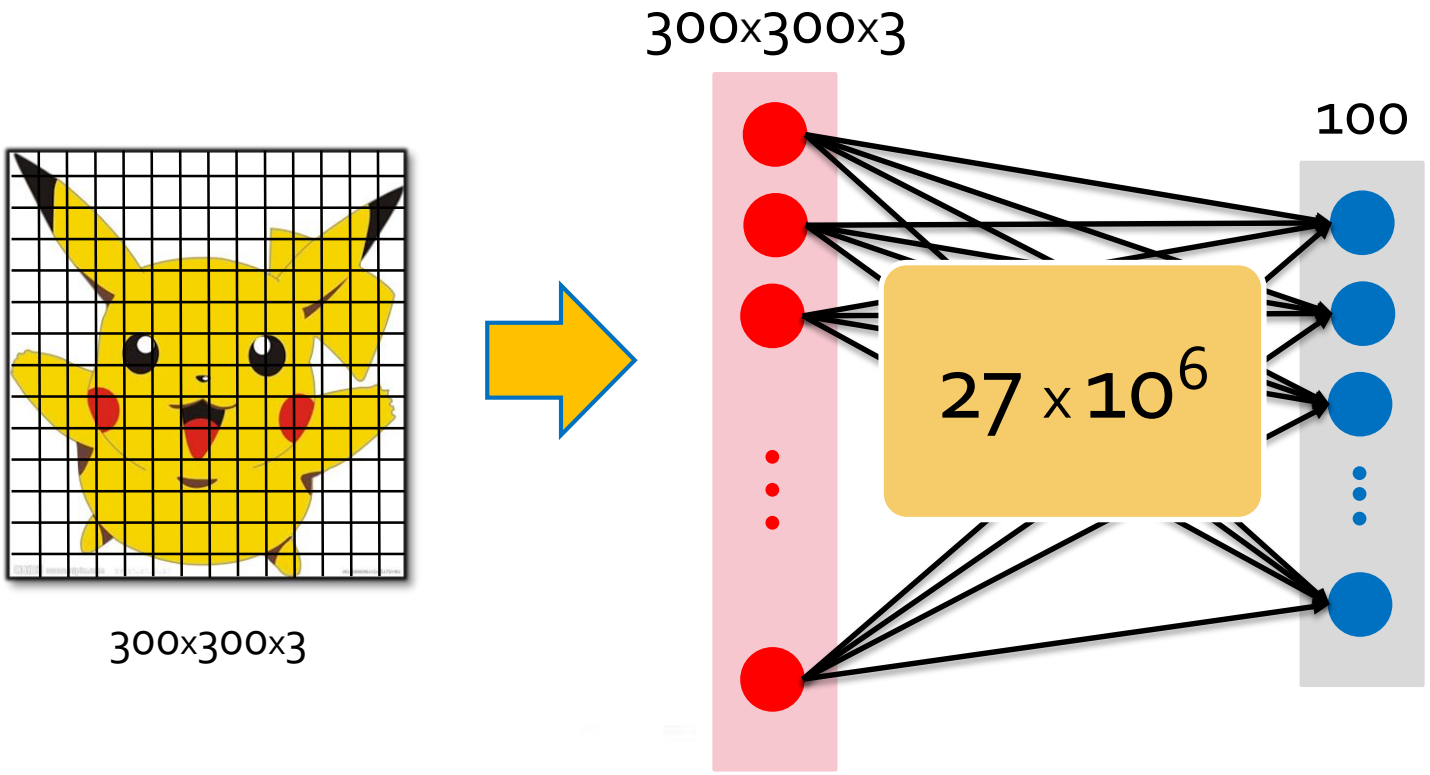


Figure reference
http://www.ettoday.net/dalemon/post/12934

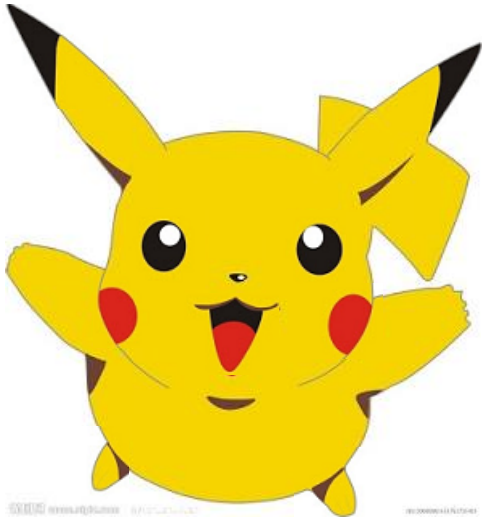
Characteristics of Image

- From line segments, patterns, objects, to a scene

Figures reference
http://www.sumiaozhijia.com/touxiang/471.html
http://122311.com/tag/su-miao/2.html

Patterns

- Guessing game



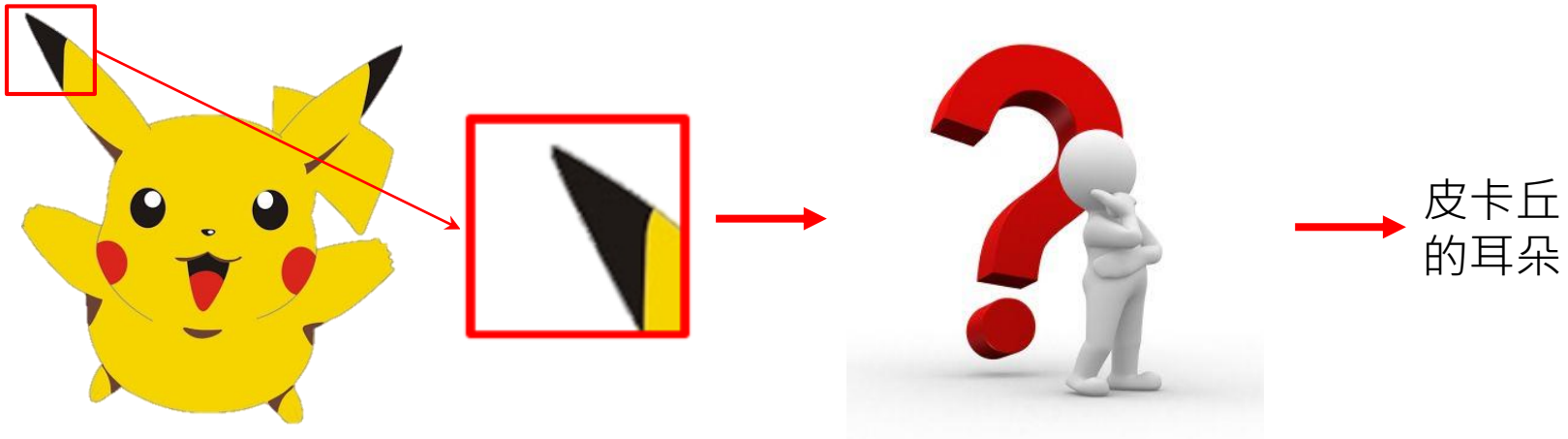
皮卡丘

小火龍

Figures reference
http://arcadesushi.com/charmander-drunken-pokemon-tattoo/#photogallery-1=1

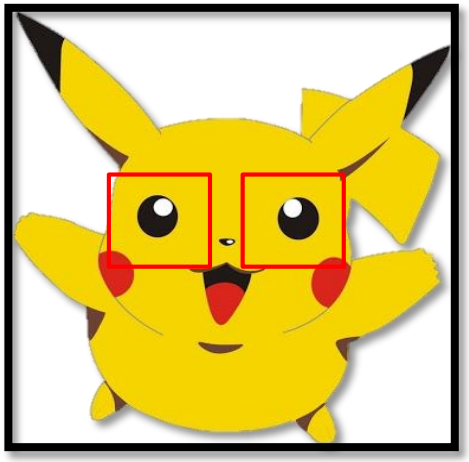
Property 1 of Image

- We don't need to scan the whole image to define patterns



Property 2 of Image

- The same pattern may appear in many locations



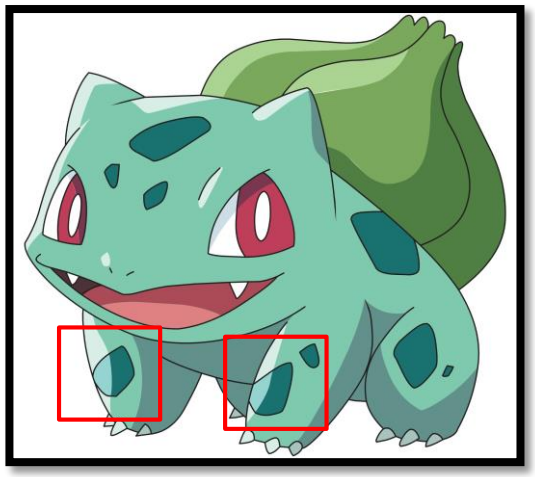
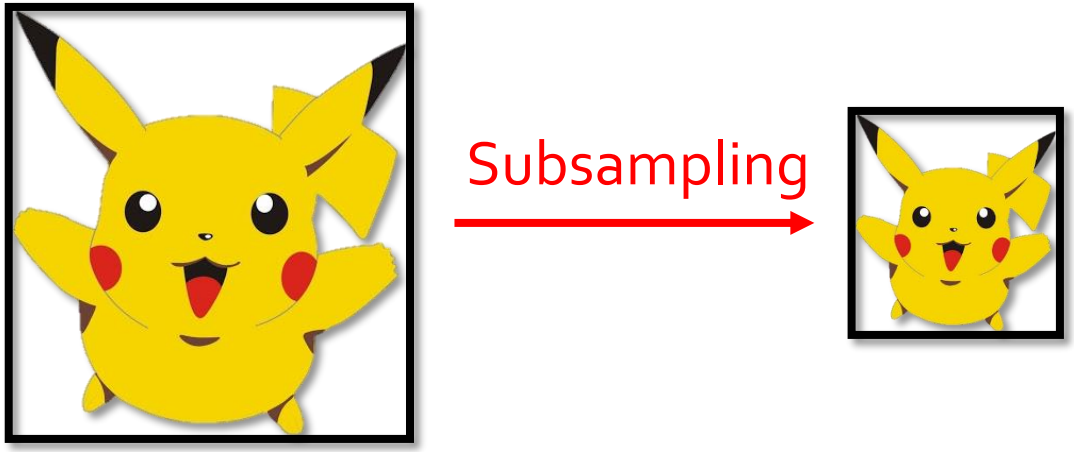


Figure reference
https://www.youtube.com/watch?v=NN9LaU2NlLM

Property 3 of Image

- Patterns are not changed after subsampling



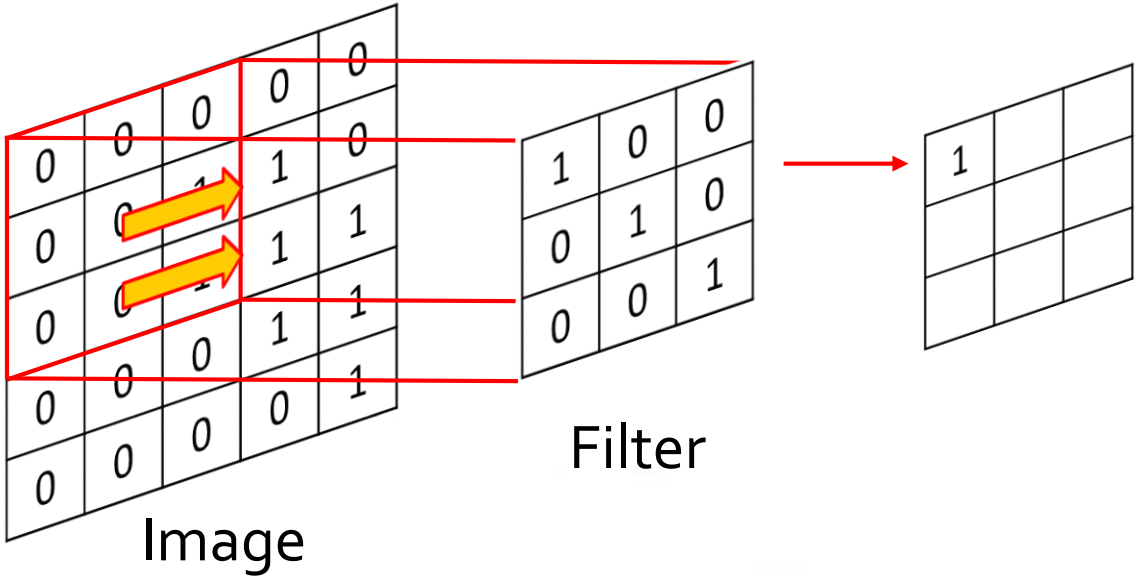
Convolution in Computer Vision

- Common applications
  - Blurring, sharpening, embossing, and edge detection

Convolution in Computer Vision

- Adding each pixel and its local neighbors which are weighted by a filter (kernel)

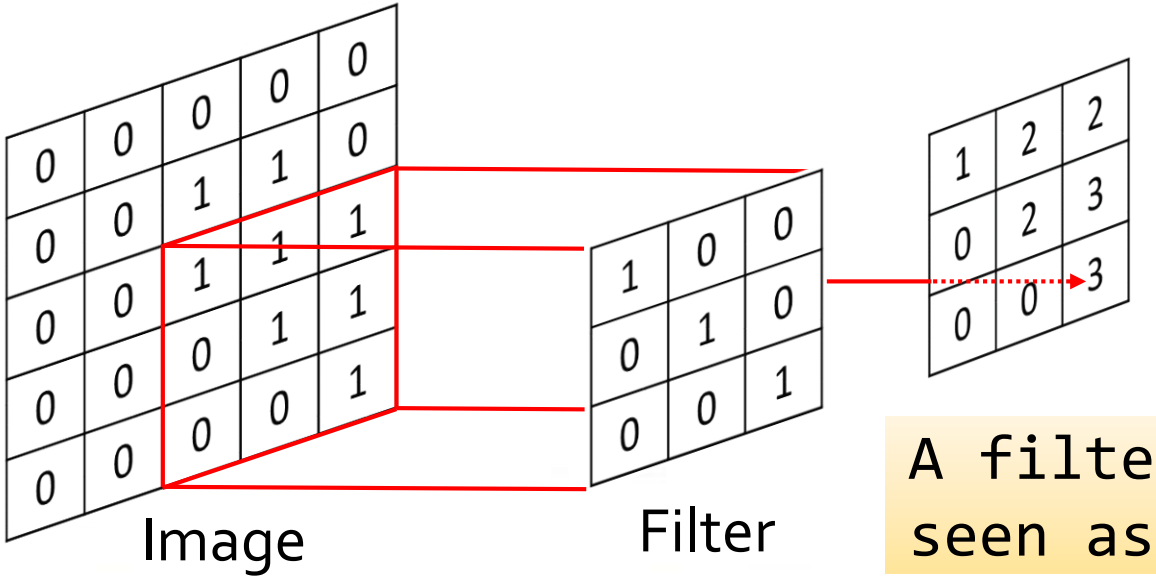
- Perform this convolution process to every pixels



Convolution in Computer Vision

- Adding each pixel and its local neighbors which are weighted by a filter (kernel)

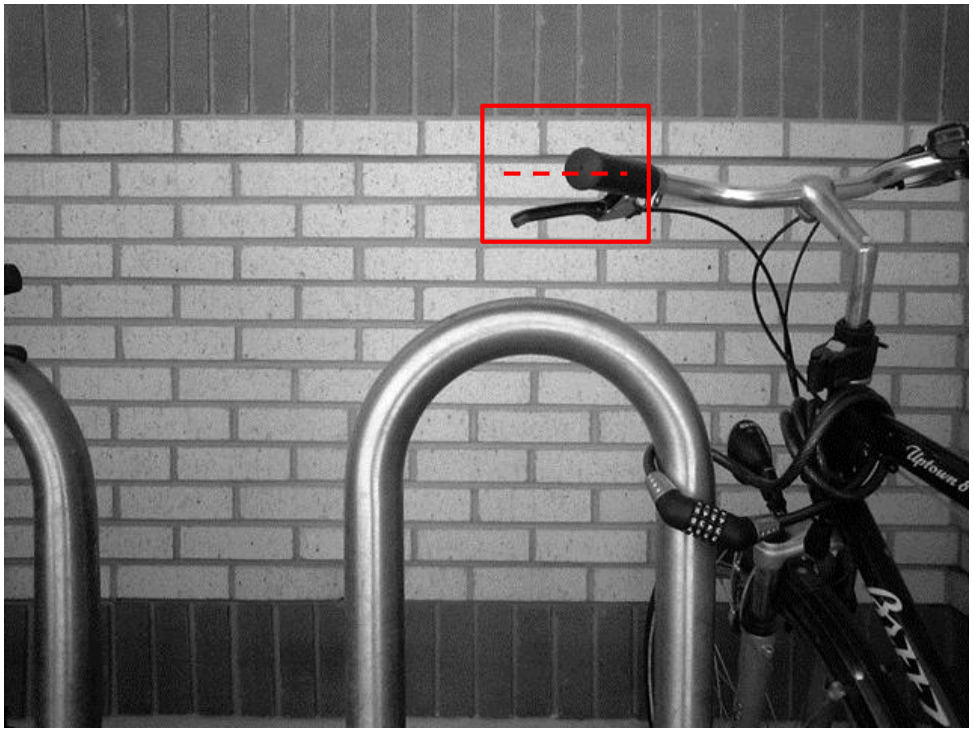
- Perform this convolution process to every pixels

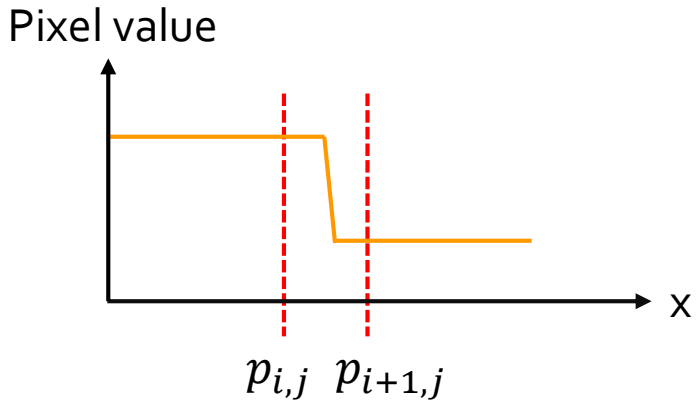


A filter could be seen as a pattern

Real Example: Sobel Edge Detection

- Detect the changing of image gradient G





$$G_h(i,j) = p_{i+1,j} - p_{i,j}$$

Multiply by a constant c

$$c * p_{i+1,j} - c * p_{i,j}$$

凸顯兩像素之間的差異

Figure reference
https://en.wikipedia.org/wiki/Sobel_operator#/media/File:Bikesgraygh.jpg

Real Example: Sobel Edge Detection

- 相鄰兩像素值差異越小，convolution 後新像素值越小

x-gradient

-1	0	1
-2	0	2
-1	0	1

*

3	3	0	0	0
3	3	0	0	0
3	3	0	0	0
3	3	0	0	0
3	3	0	0	0

Original Image

=

-12	-12	0
-12	-12	0
-12	-12	0

New Image

y-gradient

-1	-2	-1
0	0	0
1	2	1

*

3	3	3	3	3
3	3	3	3	3
3	3	3	3	3
0	0	0	0	0
0	0	0	0	0

=

0	0	0
-12	-12	-12
-12	-12	-12

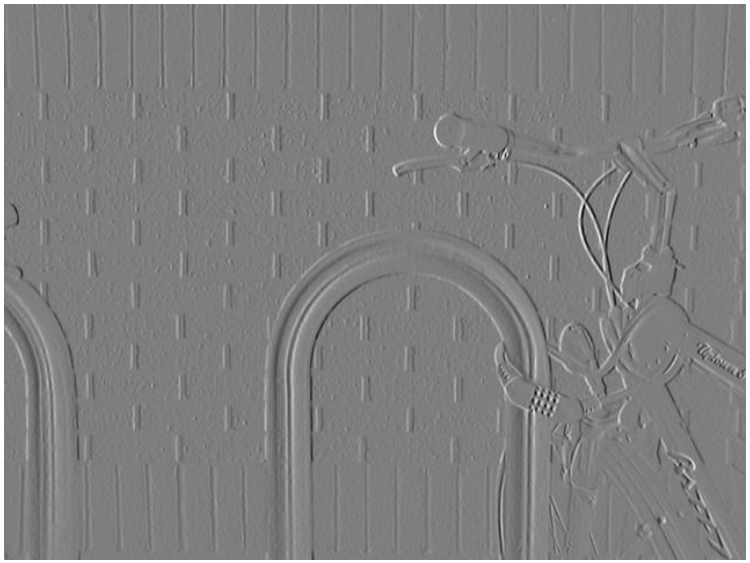
Real Example: Sobel Edge Detection

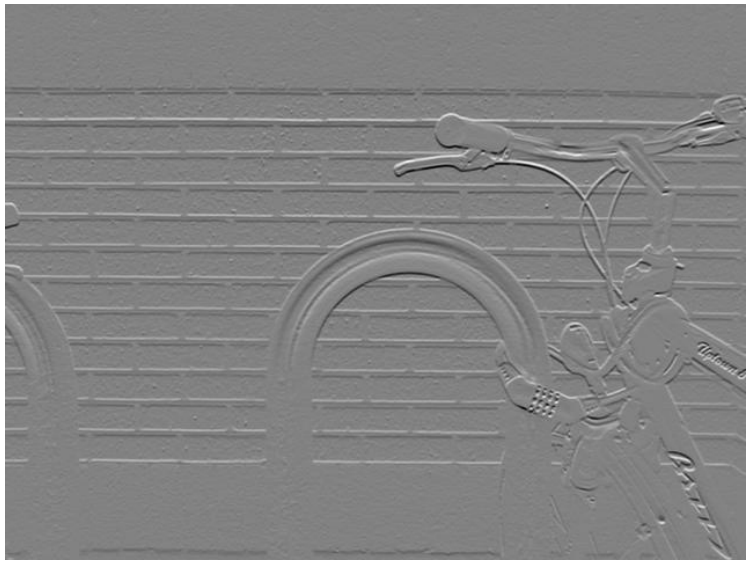
x-gradient

-1	0	1
-2	0	2
-1	0	1

y-gradient

-1	-2	-1
0	0	0
1	2	1

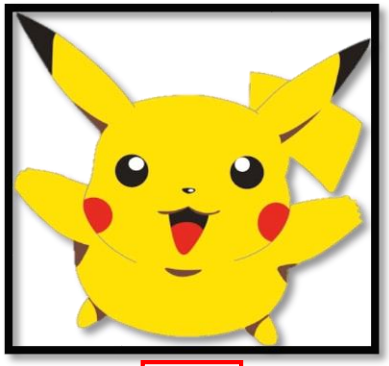




Real Example: Sobel Edge Detection

- Edge image

CNN Structure



Convolutional Layer & Activation Layer

Pooling Layer

New image

Convolutional Layer & Activation Layer

Pooling Layer

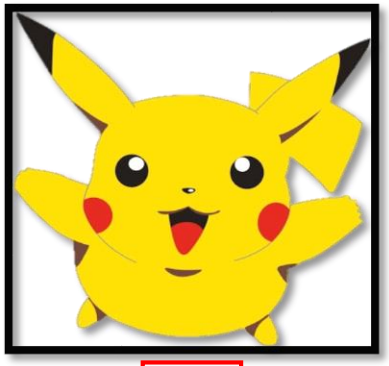
Can be performed may times

Flatten

Feedforward DNN

PICACHU!!!

CNN Structure



Convolutional Layer & Activation Layer

Pooling Layer

Convolutional Layer & Activation Layer

Pooling Layer

Can be performed may times

Flatten

Feedforward DNN

PICACHU!!!

Convolutional Layer

- Convolution 執行越多次影像越小

Layer 1

Image

0	0	0	0	0
0	0	1	1	0
1	1	1	1	1
0	1	0	1	1
0	0	1	0	1

Filter

1	0	0
0	1	0
0	0	1

New image

1	2	2
1	2	3
3	1	3

Layer 2

1	2	2
1	2	3
3	1	3

1	0	0
0	1	0
0	0	1

6

Hyper-parameters of Convolutional Layer

- Zero-padding
- Stride
- Depth (total number of filters)

Zero-padding

- Add additional zeros at the border of image

Image

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	1	0	0
0	1	1	1	1	1	0
0	0	1	0	1	1	0
0	0	0	1	0	1	0
0	0	0	0	0	0	0

Filter

1	0	0
0	1	0
0	0	1

New image

0	1	1	0	0
1	1	2	2	0
2	1	2	3	2
0	3	1	3	2
0	0	2	0	2

Stride

- Shrink the output of the convolutional layer
- Set stride as 2

Image

0	0	0	0	0
0	0	1	1	0
1	1	1	1	1
0	1	0	1	1
0	0	1	0	1

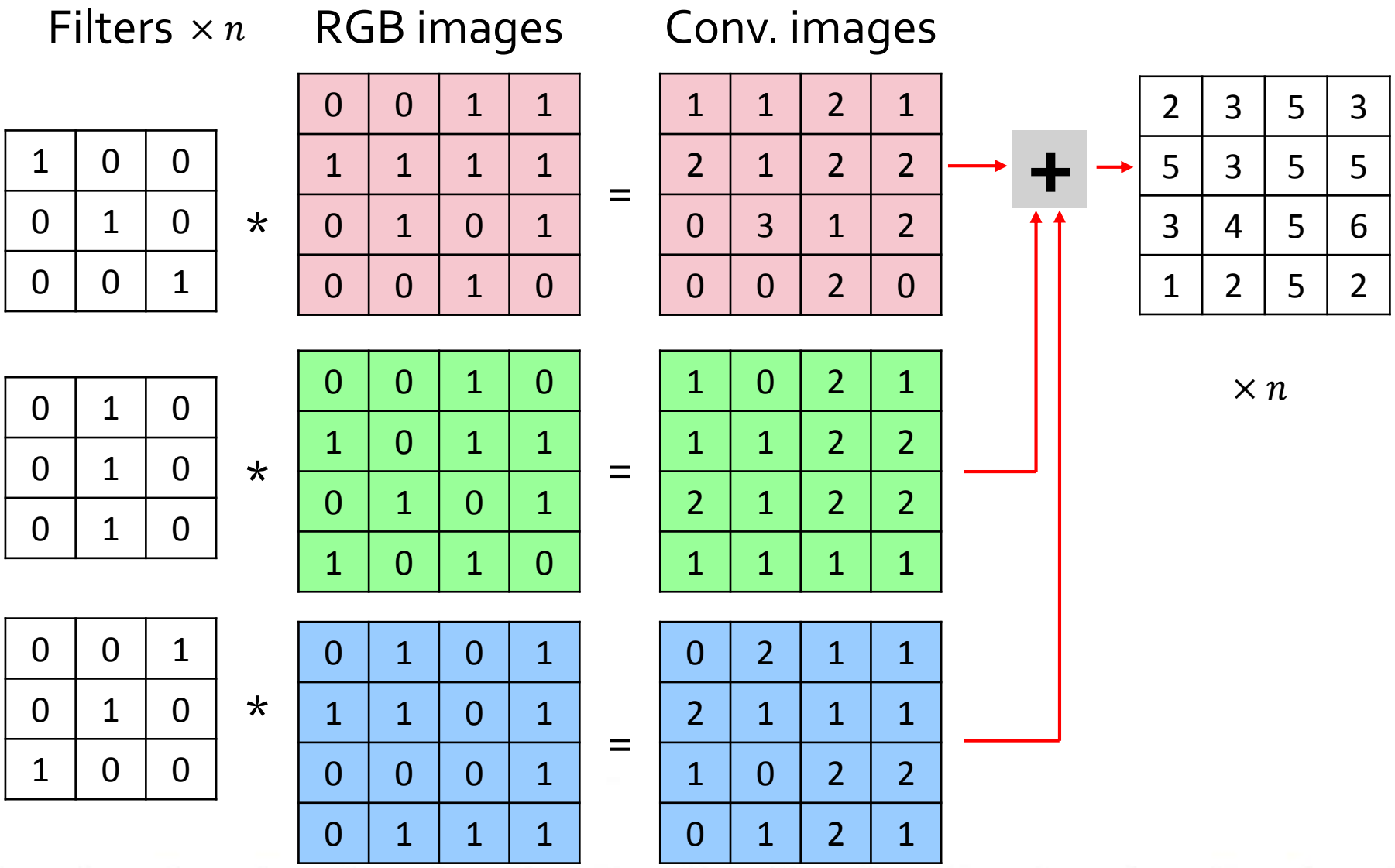
Filter

1	0	0
0	1	0
0	0	1

New image

2	2
1	3

Depth


Filters $\times n$
RGB images
Conv. images
1 0 0
0 1 0
0 0 1
*
0 0 1 1
1 1 1 1
0 1 0 1
0 0 1 0
=
1 1 2 1
2 1 2 2
0 3 1 2
0 0 2 0
+
2 3 5 3
5 3 5 5
3 4 5 6
1 2 5 2
$\times n$
0 1 0
0 1 0
0 1 0
*
0 0 1 0
1 0 1 1
0 1 0 1
1 0 1 0
=
1 0 2 1
1 1 2 2
2 1 2 2
1 1 1 1
0 0 1
0 1 0
1 0 0
*
0 1 0 1
1 1 0 1
0 0 0 1
0 1 1 1
=
0 2 1 1
2 1 1 1
1 0 2 2
0 1 2 1

Total Number of Weights

- Zero-padding
  - Without: $(W_{n+1}, H_{n+1}, \times) = (W_n - \frac{W_f - 1}{2}, H_n - \frac{H_f - 1}{2}, \times)$
  - With : $(W_{n+1}, H_{n+1}, \times) = (W_n, H_n, \times)$
- Stride = s
  - $(W_{n+1}, H_{n+1}, \times) = \left(\frac{W_n}{s}, \frac{H_n}{s}, \times\right)$
- k filters
  - $(W_{n+1}, H_{n+1}, k) = (W_n, H_n, D_n)$
- Total number of weights is needed from L_n to L_{n+1}
  - $W_f \times H_f \times D_n \times k + k$

CNN Structure

Convolutional Layer & Activation Layer

Pooling Layer

Convolutional Layer & Activation Layer

Pooling Layer

Can be performed may times

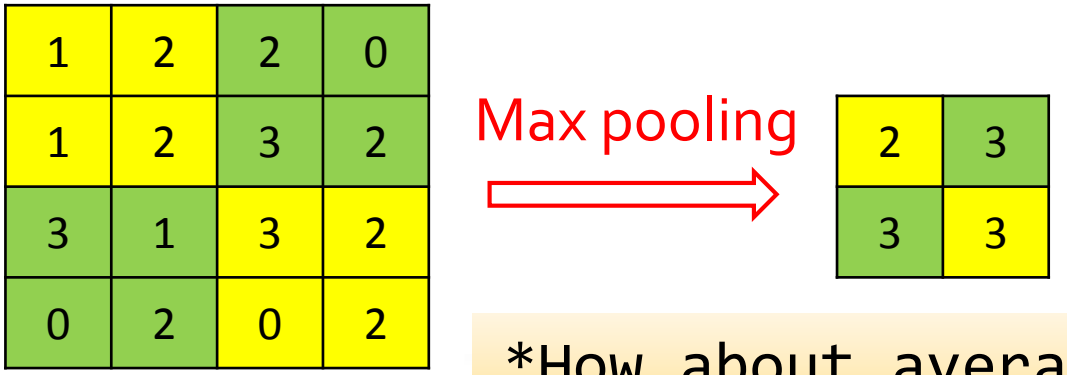
Flatten

Feedforward DNN

PICACHU!!!

Pooling Layer

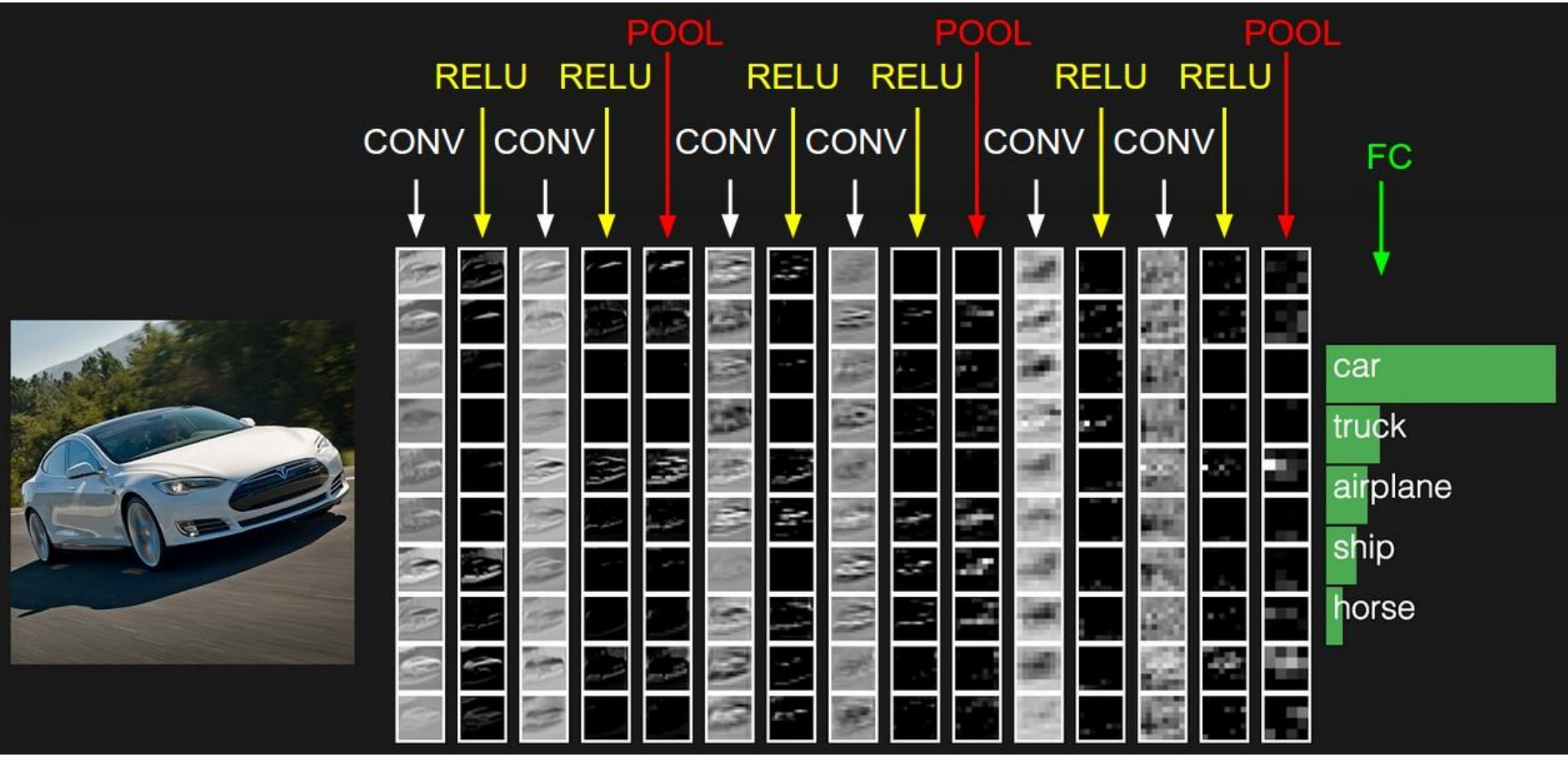
- Advantages of pooling layers
  - Reduce the number of weights
  - Prevent overfitting
- Max pooling
  - Consider the existence of patterns in each region



*How about average pooling?

A CNN Example (Object Recognition)

- CS231n, Stanford [Ref]



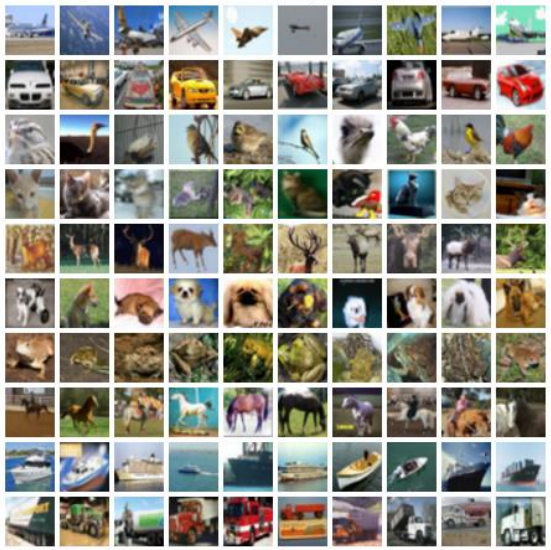
CNN in Keras

Object Recognition

Dataset: CIFAR-10

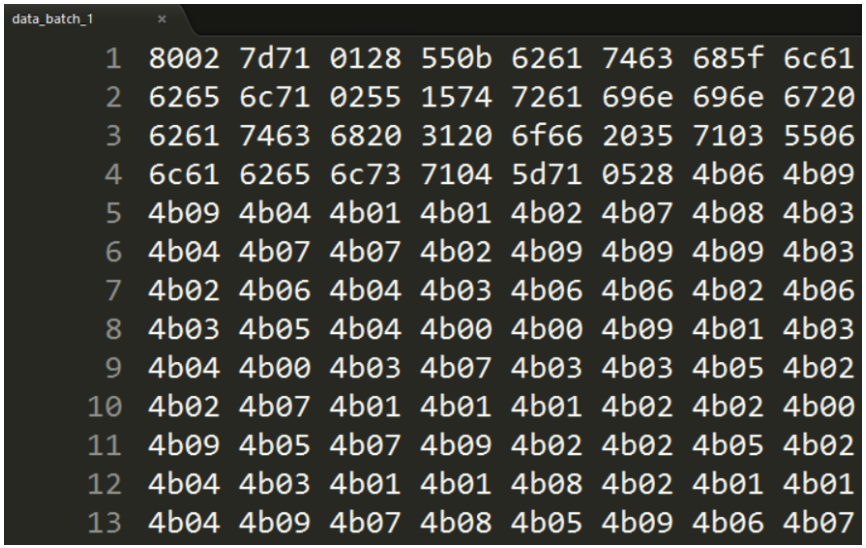
CIFAR-10 Dataset

- 60,000 (50,000 training + 10,000 testing) samples, 32x32 color images in 10 classes
- 10 classes
  - airplane, automobile, ship, truck, bird, cat, deer, dog, frog, horse
- Official website
  - https://www.cs.toronto.edu/~kriz/cifar.html



Overview of CIFAR-10 Dataset

- Files of CIFAR-10 dataset
  - data_batch_1, …, data_batch_5
  - test_batch
- 4 elements in the input dataset
  - ✓ data
  - ✓ labels
  - batch_label
  - filenames



How to Load Samples form a File

- This reading function is provided from the official site

```
# this function is provided from the official site
def unpickle(file):
    import cPickle
    fo = open(file, 'rb')
    dict = cPickle.load(fo)
    fo.close()
    return dict

# reading a batch file
raw_data = unpickle(dataset_path + fn)
```

Checking the Data Structure

- Useful functions and attributes

```
# [1] the type of input dataset
type(raw_data)
# <type 'dict'>

# [2] check keys in the dictionary
raw_data_keys = raw_data.keys()
# ['data', 'labels', 'batch_label', 'filenames']

# [3] check dimensions of pixel values
print "dim(data)", numpy.array(raw_data['data']).shape
# dim(data) (10000, 3072)
```

Pixel values and Labels

- Pixel values (data) x 5

0	32 x 32 = 1,024	1,024	1,024
1	1,024	1,024	1,024
…	…	…	…
9,999	1,024	1,024	1,024

- Labels x 5

0	**1**	**2**	**3**	**…**	**9,999**
6	9	9	4	…	5

Datasets Concatenation

- Pixel values

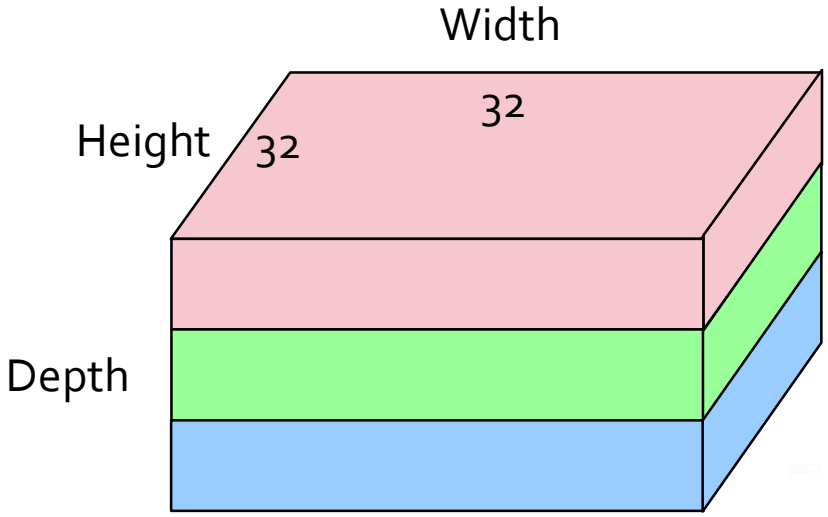
0	1,024	1,024	1,024
1	1,024	1,024	1,024
…	…	…	…
9,999	1,024	1,024	1,024
10,000	1,024	1,024	1,024
…	…	…	…

- Labels

0	**1**	**…**	**9,999**	**10,000**	**…**
6	9	…	5	7	…

Input Structures in Keras

- Depends on the configuration parameter of Keras
  - "image_dim_ordering": "tf " → (Height, Width, Depth)
  - "image_dim_ordering": "th" → (Depth, Height, Width)




```
{
    "image_dim_ordering": "tf",
    "epsilon": 1e-07,
    "floatx": "float32",
    "backend": "theano"
}
```

Concatenate Datasets by Numpy Functions

A	B
[1,2,3]	[4,5,6]

- hstack, dim(6,)

[1, 2, 3, 4, 5, 6]

Labels

- vstack , dim(2,3)

[[1, 2, 3],
[4, 5, 6]]

Pixel values

- dstack, dim(1, 3, 2)

[[[1, 4],
[2, 5],
[3, 6]]]

Dimensions

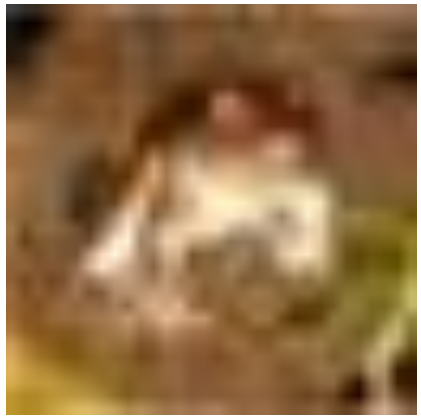
Saving Each Data as Image

- SciPy library

```
''' saving ndarray to image'''
from scipy.misc import imsave
def ndarray2image(arr_data, image_fn):
    imsave(image_fn, arr_data)
```

- Dimension of "arr_data" should be (height, width, 3)

- Supported image format
  - .bmp, .png



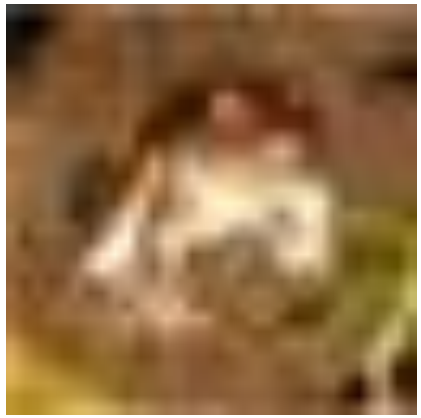
Saving Each Data as Image

- PIL library (Linux OS)

```
''' saving ndarray to image'''
from PIL import Image
def ndarray2image(arr_data, image_fn):
    img = Image.fromarray(arr_data, 'RGB')
    img.save(image_fn)
```

- Dimension of "arr_data" should be (height, width, 3)

- Supported image format
  - .bmp, .jpeg, .png, etc.



Building Your Own CNN Model

32 個 3x3 filters

'valid' : without padding
'same': perform padding
default value is zero

```
'''CNN model'''
model = Sequential()
model.add(Convolution2D(32, 3, 3, border_mode='same',
                        input_shape=X_train[0].shape))
model.add(Activation('relu'))
model.add(Convolution2D(32, 3, 3))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.2))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(10))
model.add(Activation('softmax'))
```

Model Compilation

```
'''setting optimizer'''
# define the learning rate
learning_rate = 0.01
learning_decay = 0.01 / 32

# define the optimizer
sgd = SGD(lr=learning_rate, decay=learning_dacay, momentum=0.9,
          nesterov=True)

# Let's compile
model.compile(loss='categorical_crossentropy', optimizer=sgd,
              metrics=['accuracy'])
```

Number of Parameters of Each Layers

- Only one function

```
# cl
mod
```

Layer (type)	Output Shape	Param #
convolution2d_1 (Convolution2D)	(32*3*3*3 + 32=896	896
activation_1 (Activation)	(None, 32, 32, 32)	0
convolution2d_2 (Convolution2D)	32*3*3*32 + 32=9,248	9248
activation_2 (Activation)	(None, 30, 30, 32)	0
maxpooling2d_1 (MaxPooling2D)	(None, 15, 15, 32)	0
dropout_1 (Dropout)	(None, 15, 15, 32)	0
flatten_1 (Flatten)	(None, 7200)	0
dense_1 (Dense)	7200*512 + 512=3,686,912	3686912
activation_3 (Activation)	(None, 512)	0
dropout_2 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 10)	5130
activation_4 (Activation)	(None, 10)	0

Total params: 3702186

- To

Let's Start Training

- Two validation methods
  - Validate with splitting training samples
  - Validate with testing samples

```
''' training'''
# define batch size and # of epoch
batch_size = 128
epoch = 32

# [1] validation data comes from training data
fit_log = model.fit(X_train, Y_train, batch_size=batch_size,
                    nb_epoch=epoch, validation_split=0.1,
                    shuffle=True)
# [2] validation data comes from testing data
fit_log = model.fit(X_train, Y_train, batch_size=batch_size,
                    nb_epoch=epoch, shuffle=True,
                    validation_data=(X_test, Y_test))
```

Saving Training History

- Save training history to .csv file

```
'''saving training history'''
import csv
# define the output file name
history_fn = 'ccmd.csv'

# create the output file
with open(history_fn, 'wb') as csv_file:
        w = csv.writer(csv_file)
        # convert the data structure from dictionary to ndarray
        temp = numpy.array(fit_log.history.values())
        # write headers
        w.writerow(fit_log.history.keys())
        # write values
        for i in range(temp.shape[1]):
                w.writerow(temp[:,i])
```

Model Saving and Prediction

- Saving/loading the whole CNN model

```
'''saving model'''
from keras.models import load_model
model.save('cifar10.h5')
del model

'''loading model'''
model = load_model('cifar10.h5')
```

- Predicting the classes with new image samples

```
'''prediction'''
pred = model.predict_classes(X_test, batch_size, verbose=0)
```

Let's Try CNN

- Hints
  - Check the format of training dataset / validation dataset
  - Design your own CNN model
  - Don't forget saving the model

Figure reference
https://unsplash.com/collections/186797/coding

Tips for Setting Hyper-parameters (1)

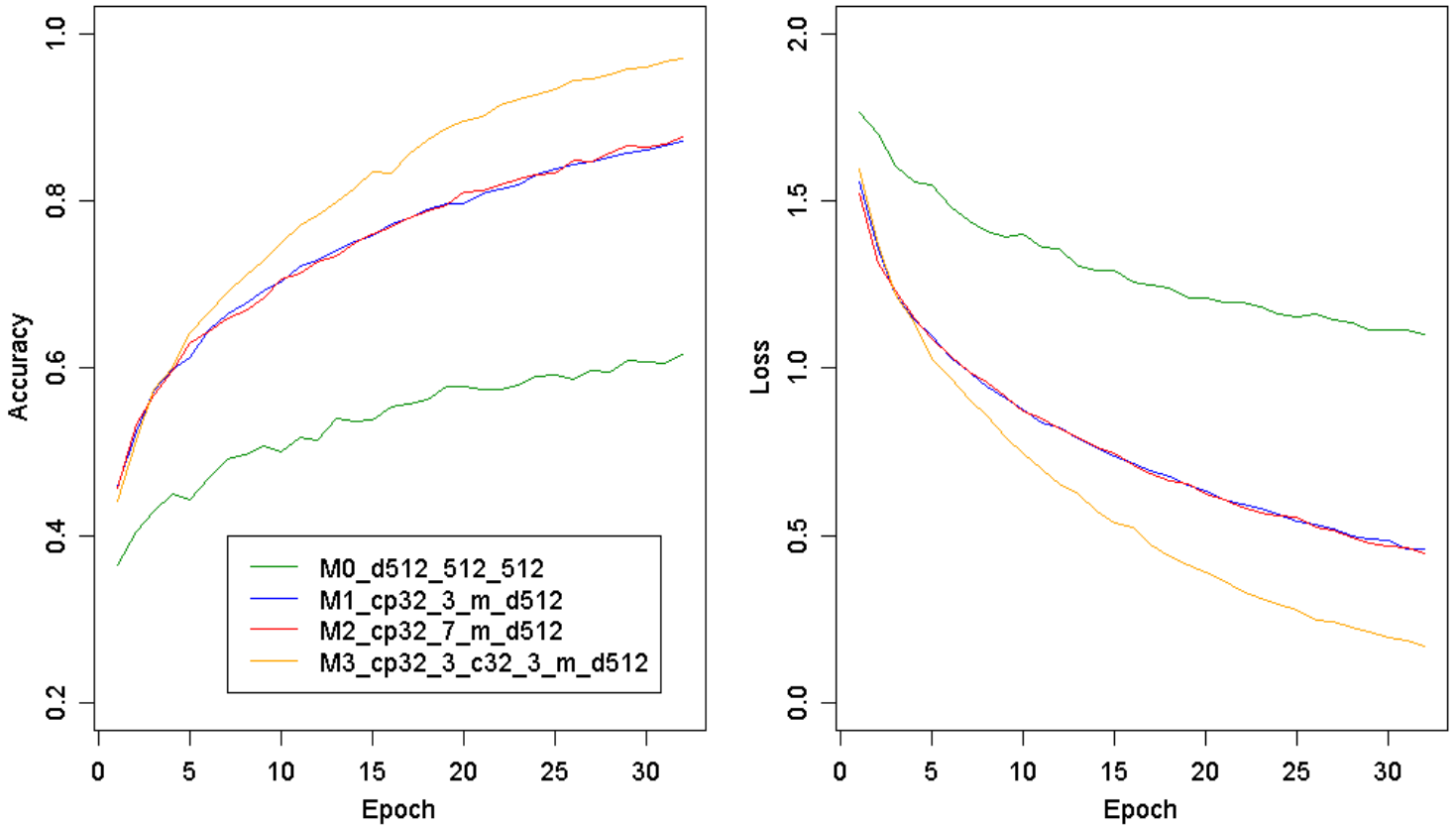
- 影像的大小須要能夠被 2 整除數次
  - 常見的影像 size 32, 64, 96, 224, 384, 512
- Convolutional Layer
  - 比起使用一個 size 較大的 filter (7x7)，可以先嘗試連續使用數個 size 小的 filter (3x3)
  - Stride 的值與 filter size 相關，通常 $stride \leq \frac{W_f - 1}{2}$
- Very deep CNN model (16+ Layers) 多使用 3x3 filter 與 stride 1

Tips for Setting Hyper-parameters (2)

- Zero-padding 與 pooling layer 是選擇性的結構
- Zero-padding 的使用取決於是否要保留邊界的資訊
- Pooling layer 旨在避免 overfitting 與降低 weights 的數量，但也減少影像所包含資訊，一般不會大於 3x3
- 嘗試修改有不錯效能的 model，會比建立一個全新的模型容易收斂，且 model weights 越多越難 tune 出好的參數

Training History of Different Models

- cp32_3 → convolution layer with zero-padding, 32 3x3 filters
- d → fully connected NN layers



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

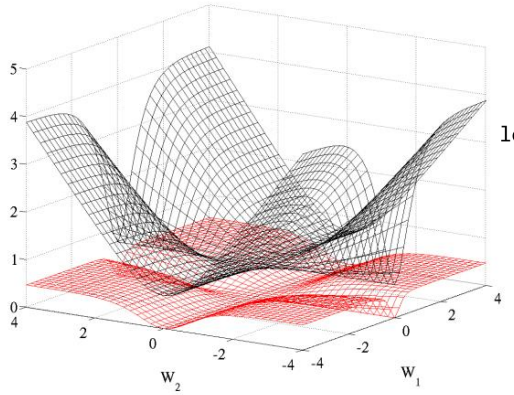
- How to improve performance on training dataset

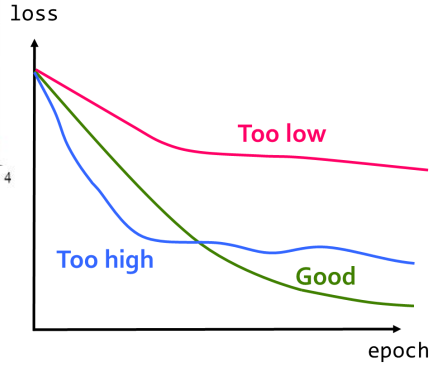
Loss Function

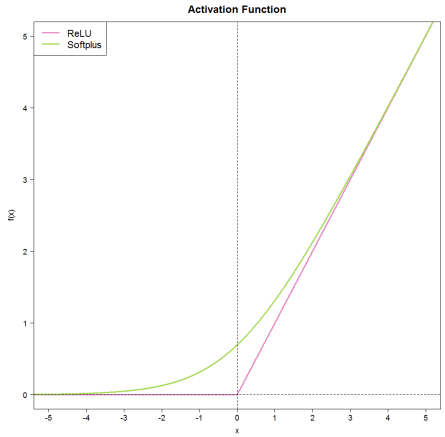
Learning Rate

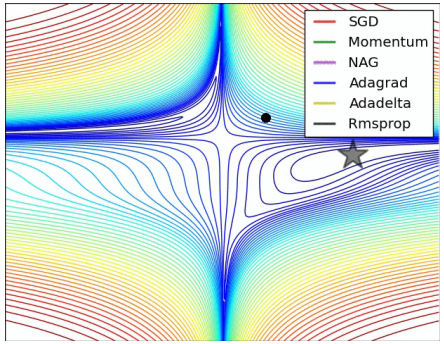
Activation Function

Optimizer









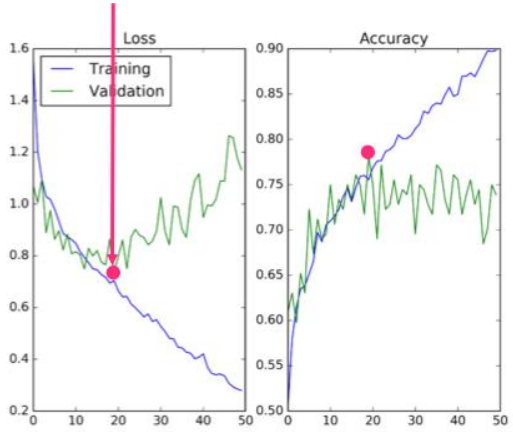
Recap – Improvement on Testing Set

- How to improve performance on training dataset

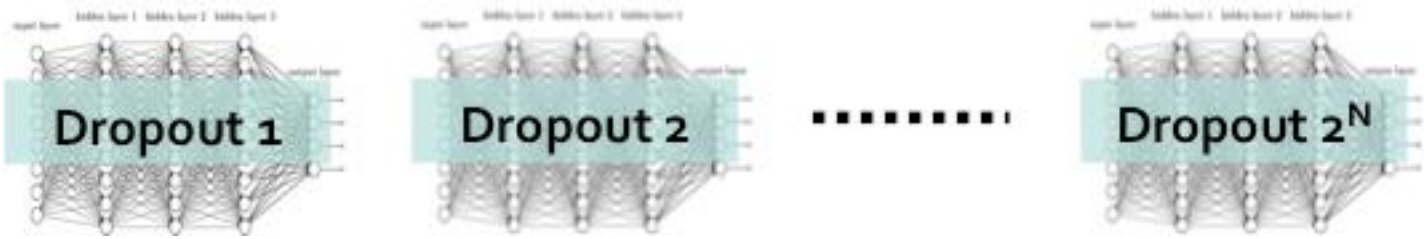
Regularization

Early Stopping

Dropout



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



Recap – CNN

- Fundamentals of CNN
  - Concept of filters
  - Hyper-parameters
    - Zero-padding
    - Stride
    - Depth (total number of filters)
  - Pooling layers
- How to train a CNN in Keras
  - CIFAR-10 dataset

Image

0	0	0	0	0
0	0	1	1	0
1	1	1	1	1
0	1	0	1	1
0	0	1	0	1

Filter

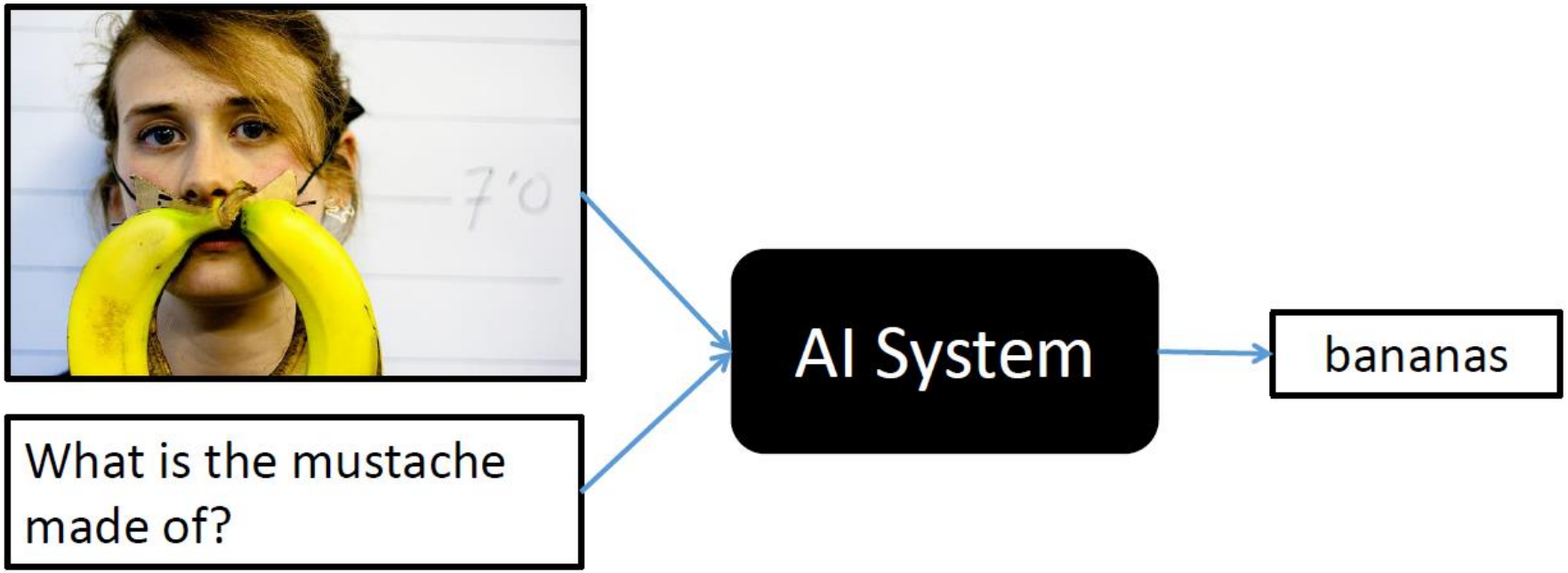
1	0	0
0	1	0
0	0	1

New image

2	2
1	3

Deep Learning Applications

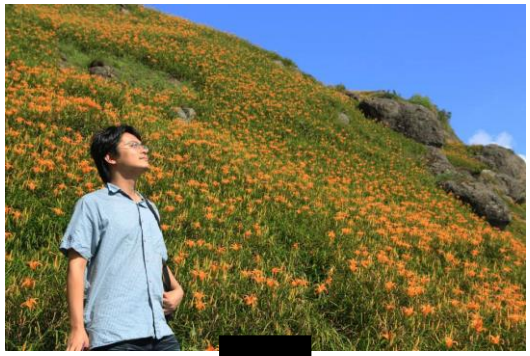
Visual Question Answering

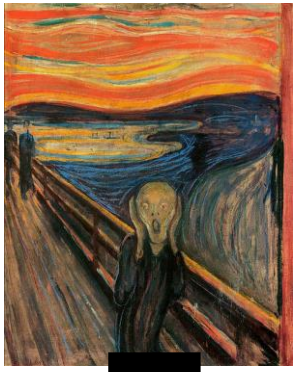


source: http://visualqa.org/

(Slide Credit: Hung-Yi Lee)

Deep Style





CNN

CNN

content

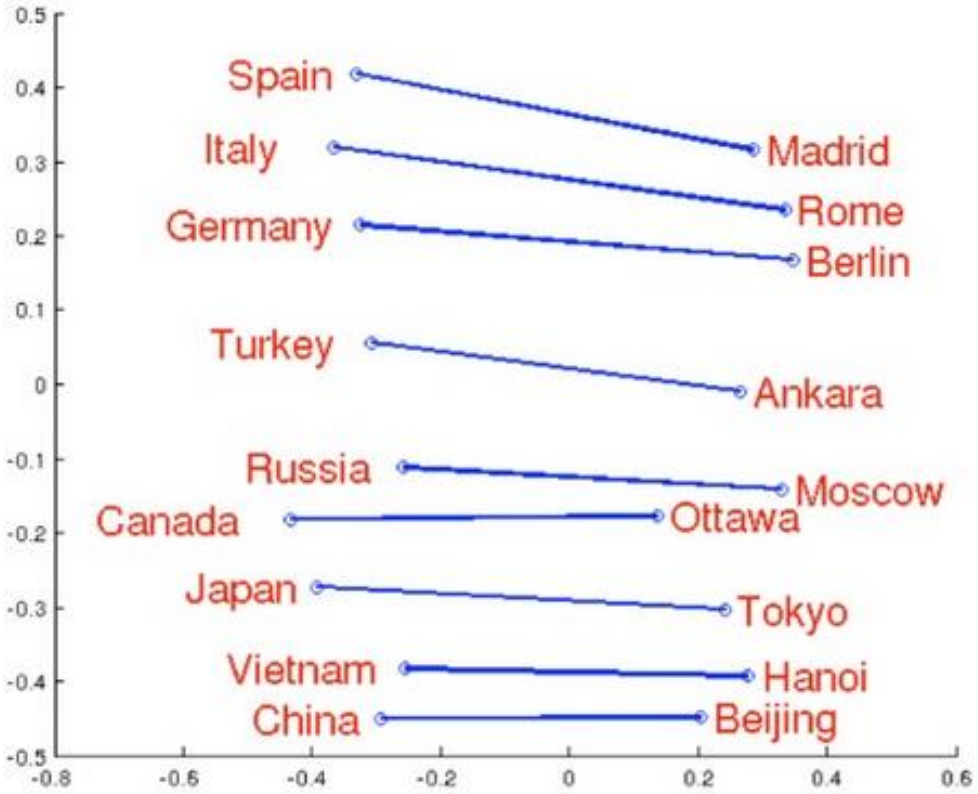
style

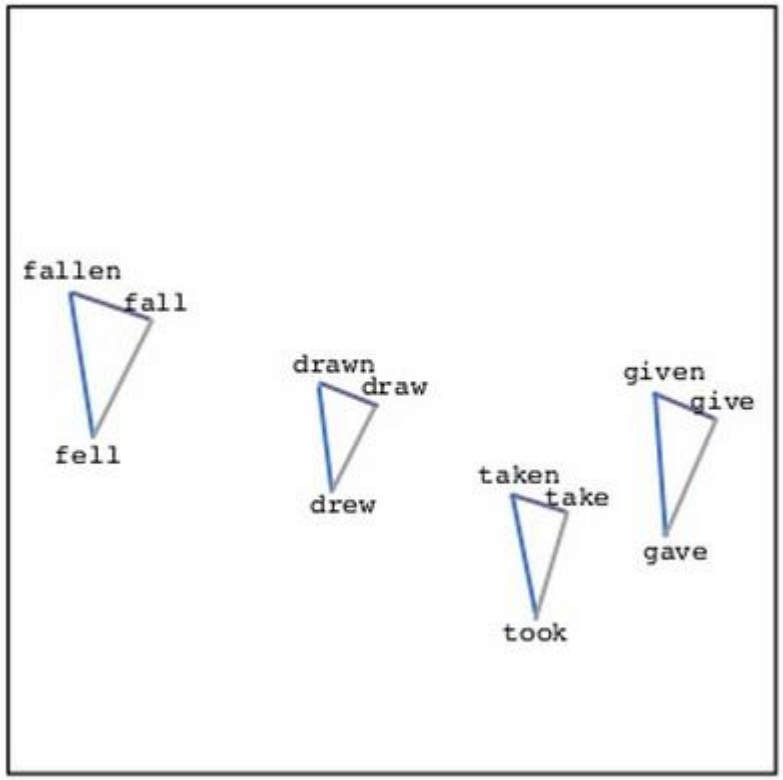
CNN

?

(Slide Credit: Hung-Yi Lee)

Word Vector



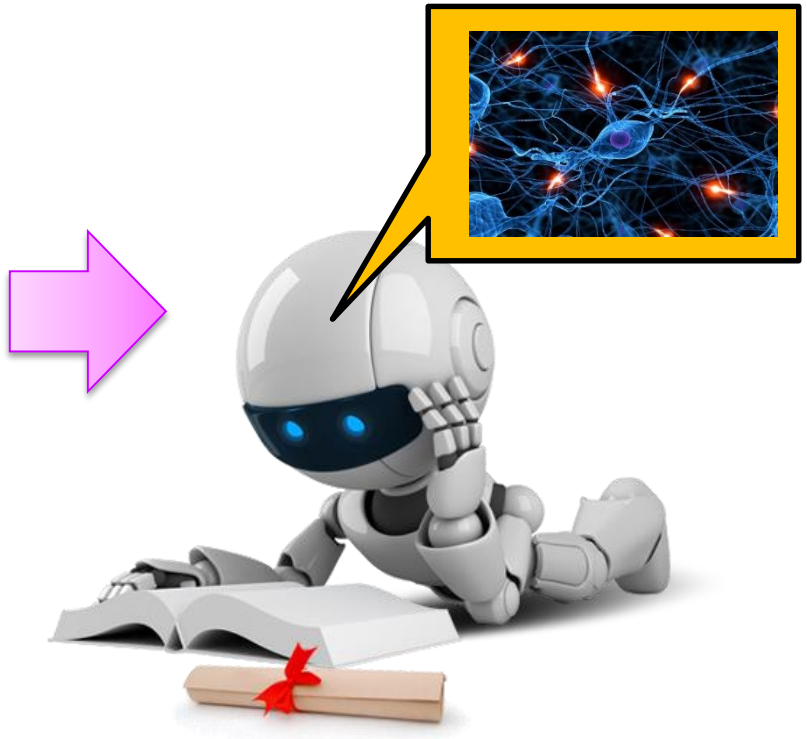


Source: http://www.slideshare.net/hustwj/cikm-keynotenov2014

(Slide Credit: Hung-Yi Lee)

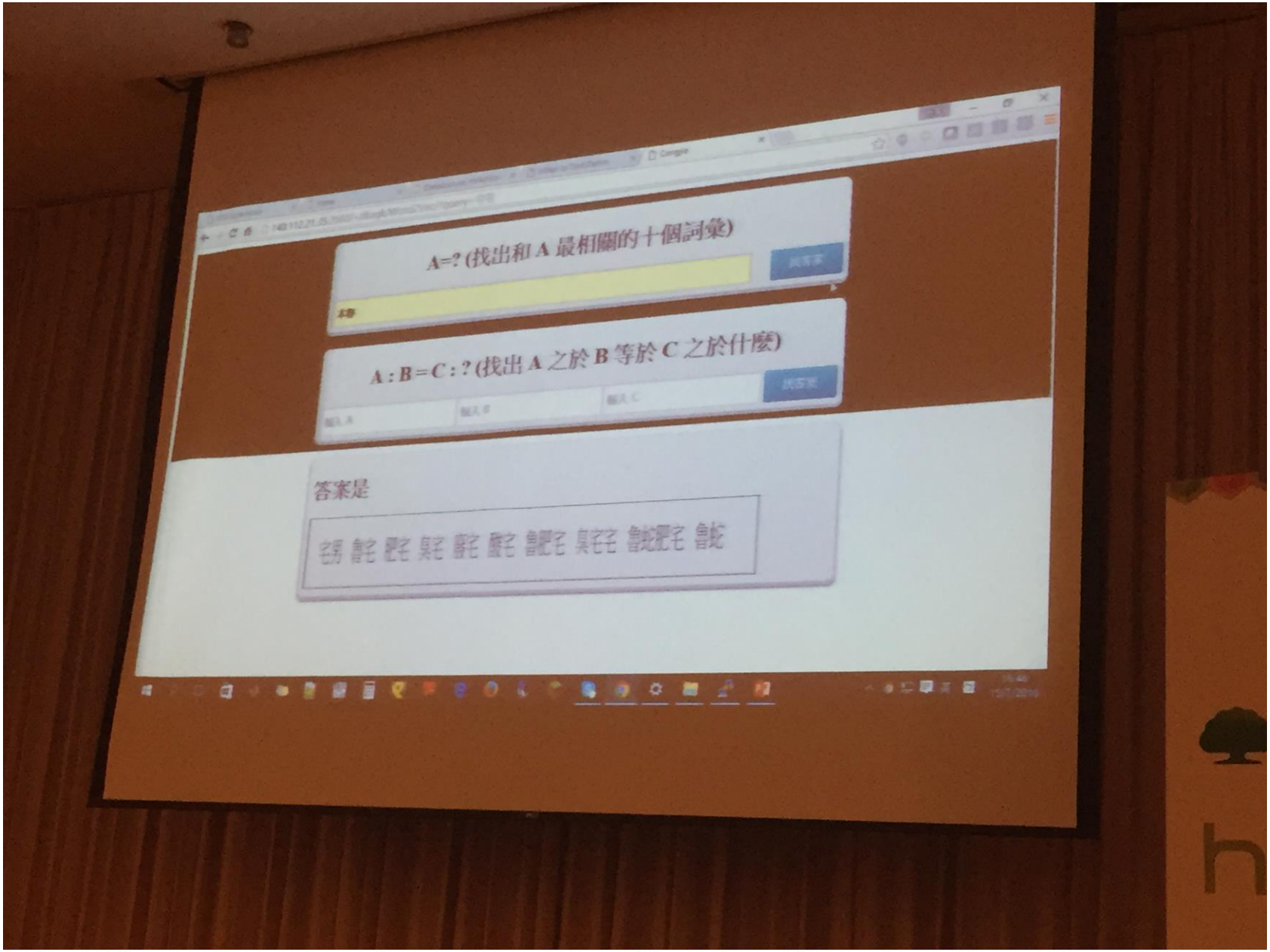
Machine Reading

- Machine learn the meaning of words from reading a lot of documents without supervision



Machine learns to understand netizens via reading the posts on PTT

(Slide Credit: Hung-Yi Lee)


A=? (找出和 A 最相關的十個詞彙)
A : B = C : ? (找出 A 之於 B 等於 C 之於什麼)
答案是

Reference

- Keras documentation Keras 官方網站，非常詳細
- Keras Github 可以從 example/ 中找到適合自己應用的範例
- 一天搞懂深度學習 – 台大電機李宏毅教授
- Youtube 頻道 – 台大電機李宏毅教授
- Convolutional Neural Networks for Visual Recognition

- 若有課程上的建議，歡迎來信
  cmchang@iis.sinica.edu.tw or chihfan@iis.sinica.edu.tw

Go Deeper in Deep Learning

- "Neural Networks and Deep Learning"
  - written by Michael Nielsen
  - http://neuralnetworksanddeeplearning.com/
- "Deep Learning"
  - Written by Yoshua Bengio, Ian J. Goodfellow and Aaron Courville
  - http://www.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

(Slide Credit: Hung-Yi Lee)