手把手教你深度學習實務

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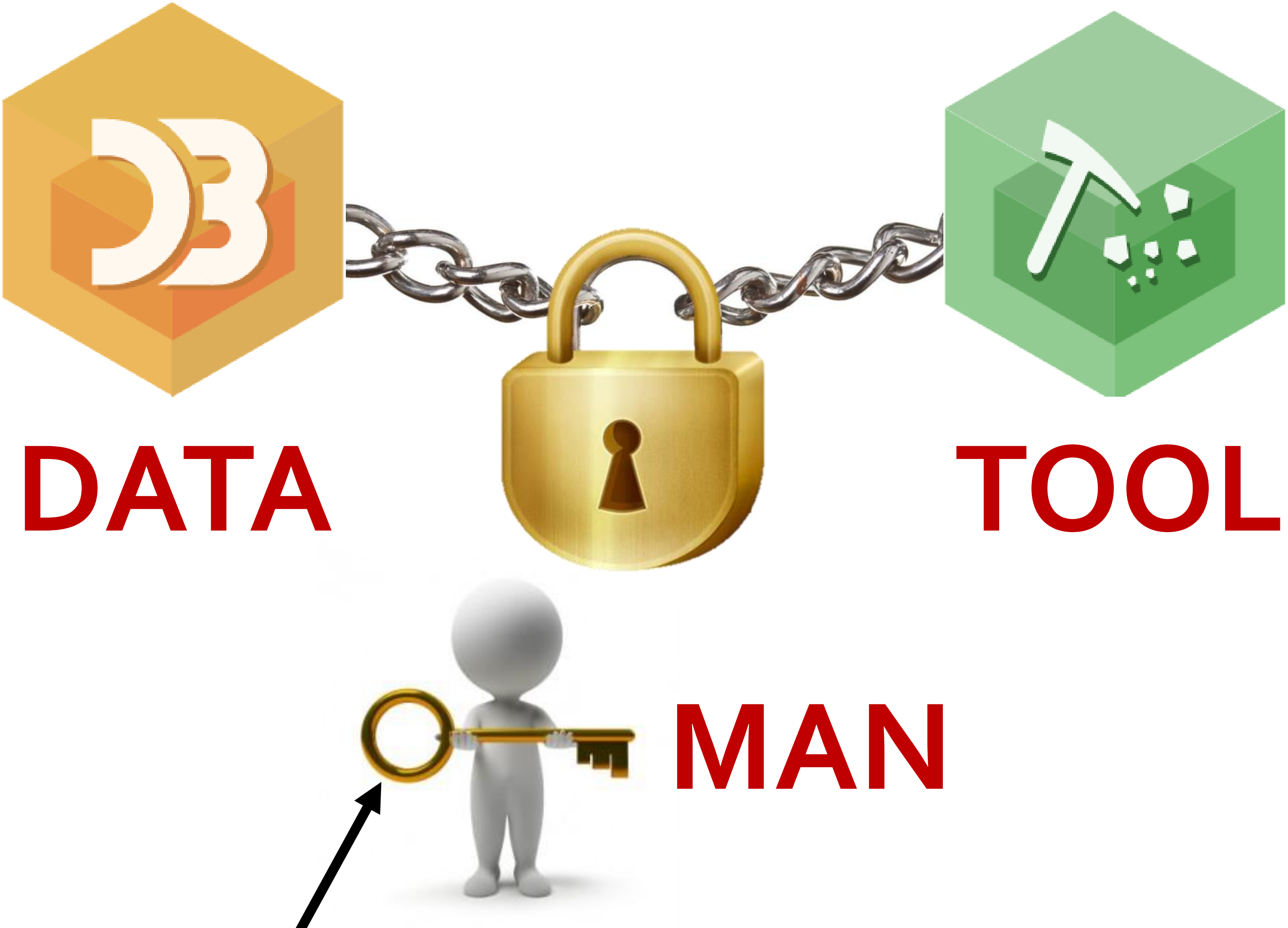
Lecturers

- 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



今天目的：一把 <u>通用</u> 鑰匙 to deep learning

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?

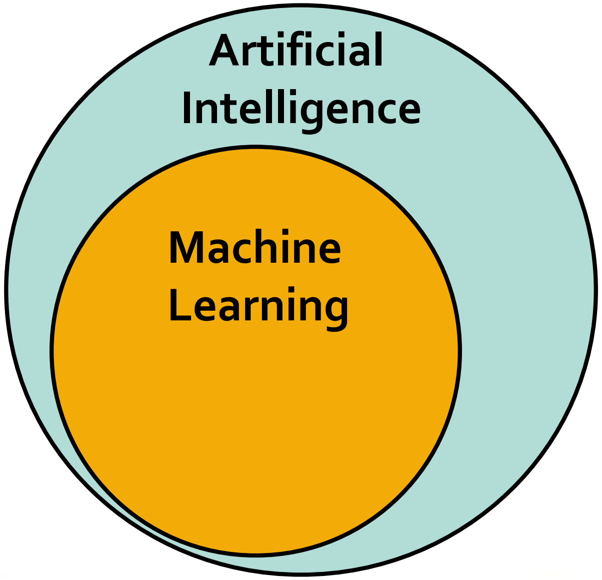
一句話說明 Machine Learning

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

- Arthur Lee Samuel, 1959 』

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
  - 找到一個夠好的 function 能解決特定的問題



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*(

) = 

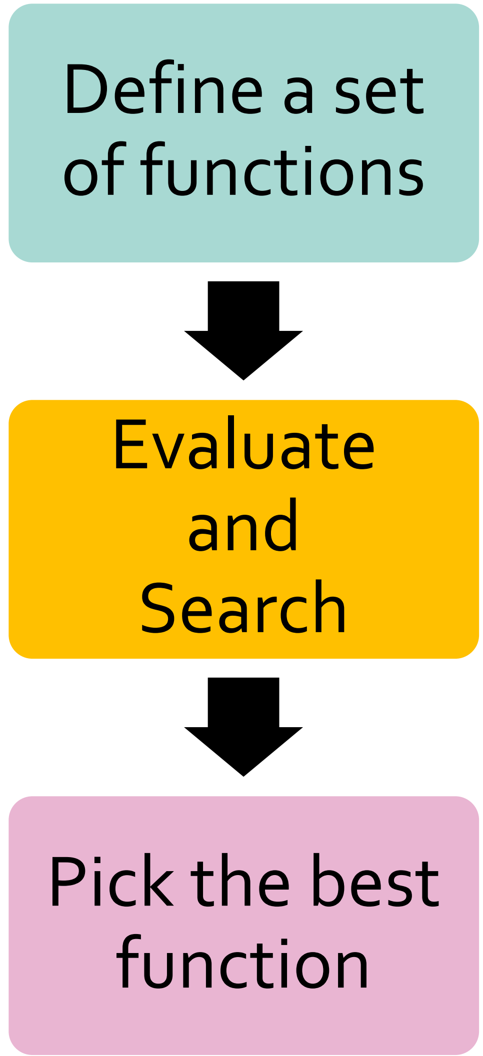
Ans: 妙蛙種子

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

A set of functions, f(·)

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

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

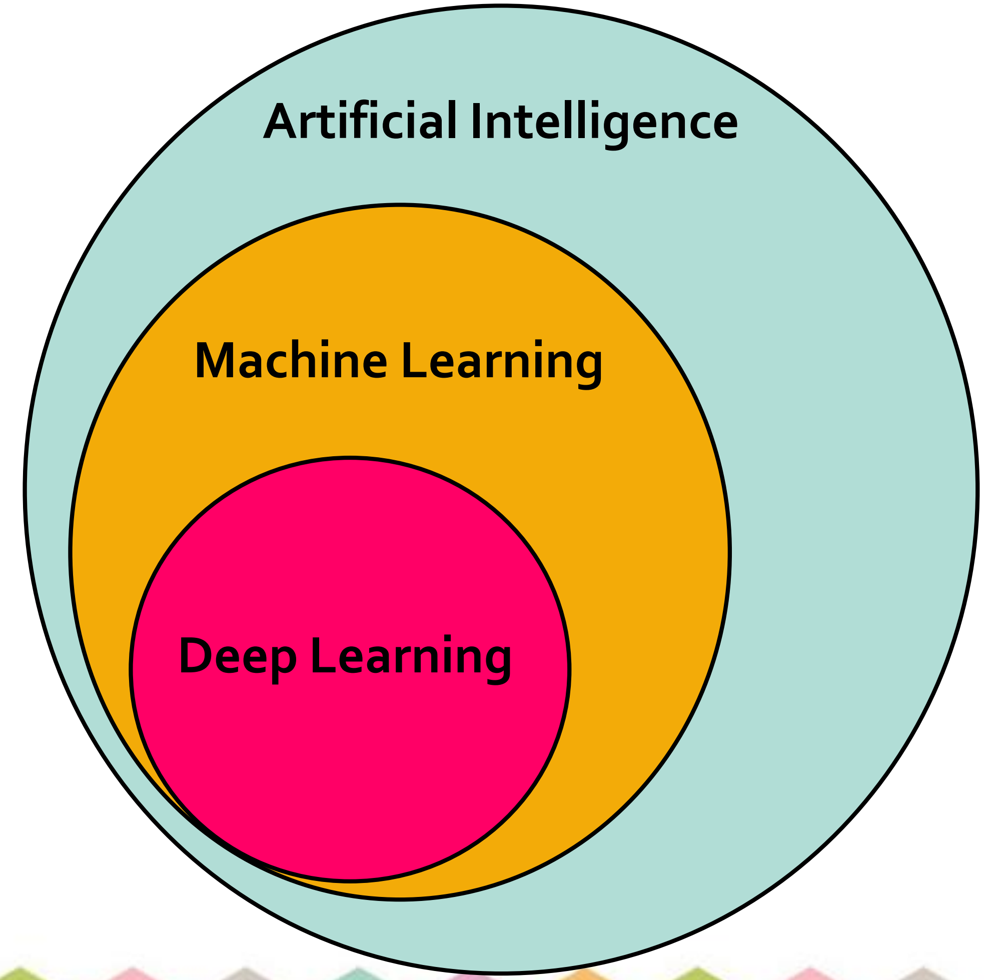
Pick the best function

找到最好的寶可夢專家

What is Deep Learning?

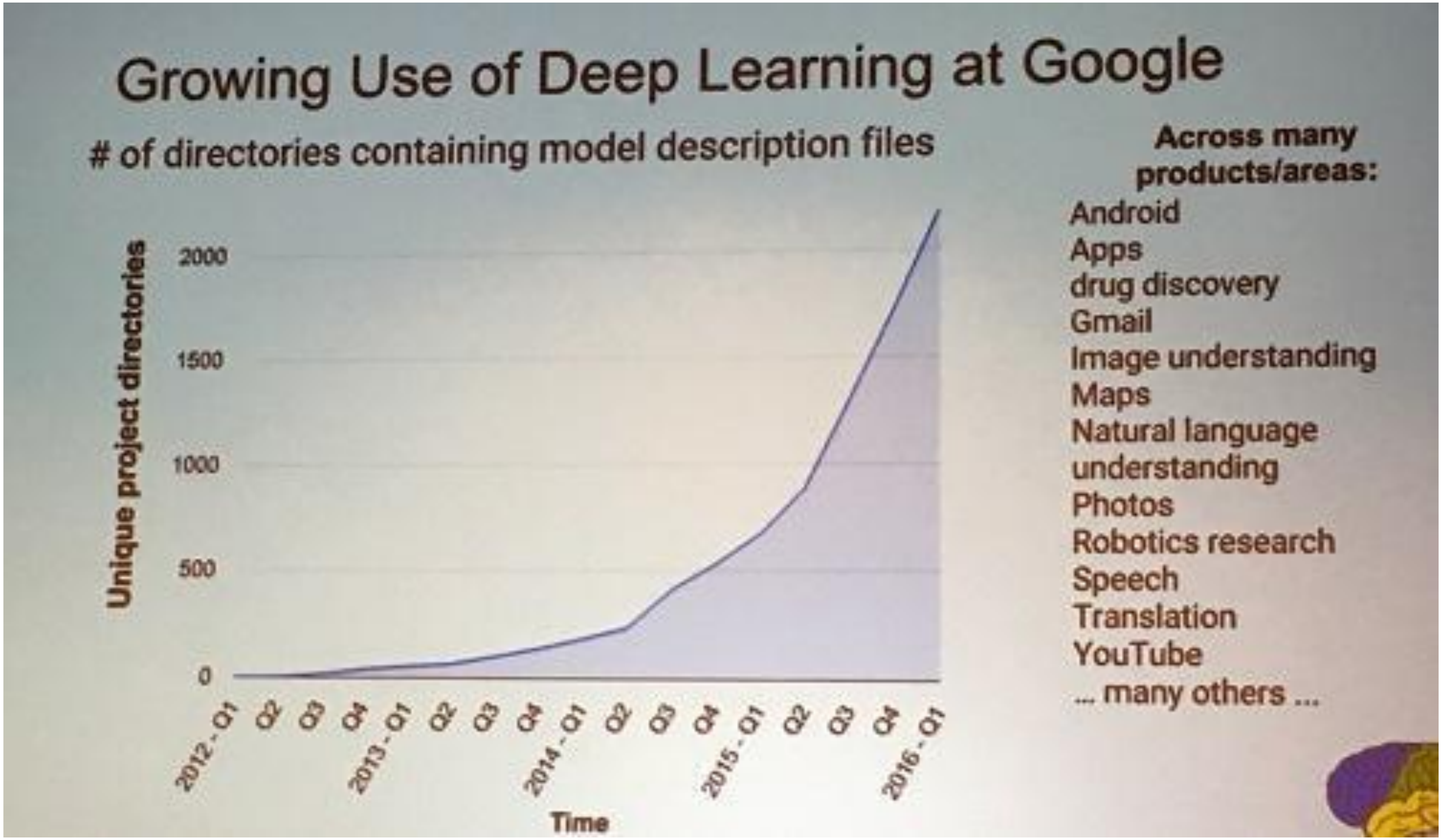
Deep Learning vs Machine Learning

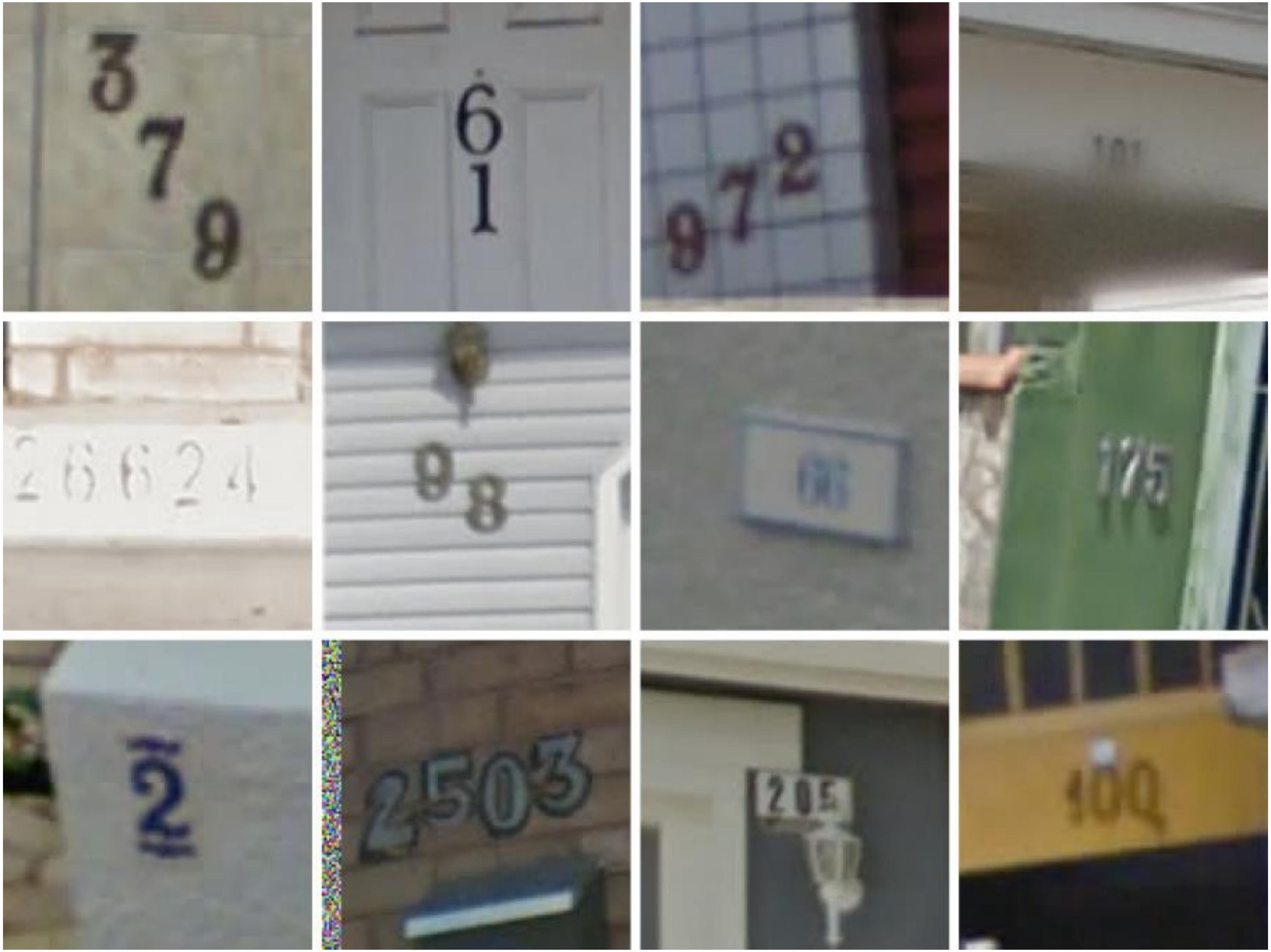
- Deep learning is a subset of machine learning



最近非常夯的技術

(Slide Credit: Hung-Yi Lee)




379
61
972
26624
98
2
2503
205

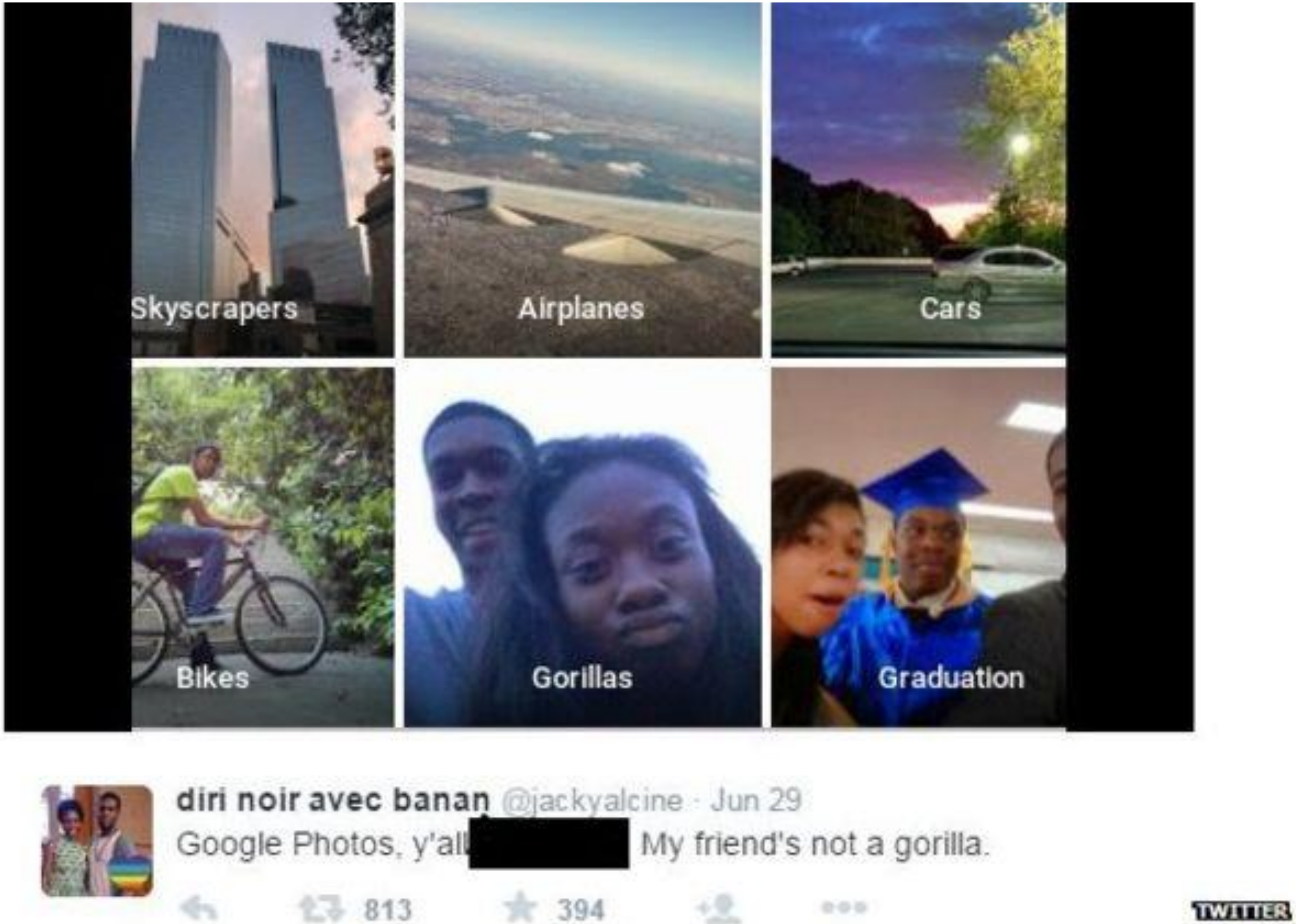

Skyscrapers
Airplanes
Cars
Bikes
Gorillas
Graduation
diri noir avec banan @jackyalcine · Jun 29
Google Photos, y'all [redacted] My friend's not a gorilla.
813
394
TWITTER

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.

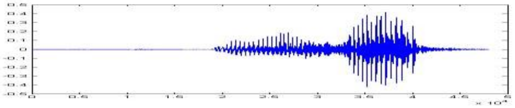

Two hockey players are fighting over the puck.


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

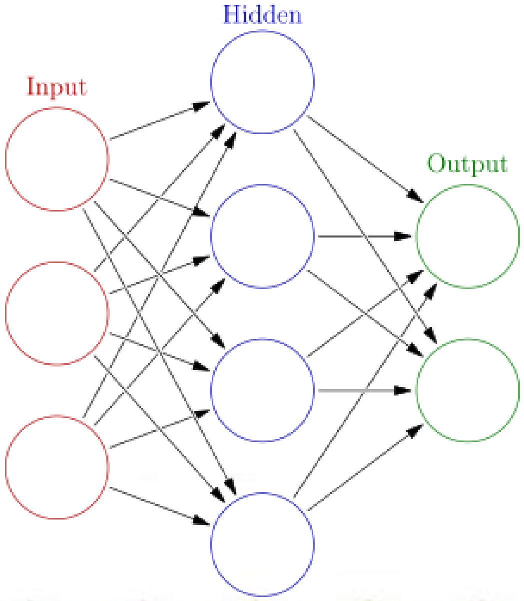
$f*($  $)=$ "5-5"
(step)

- 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？

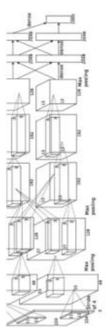
(Slide Credit: Hung-Yi Lee)

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)

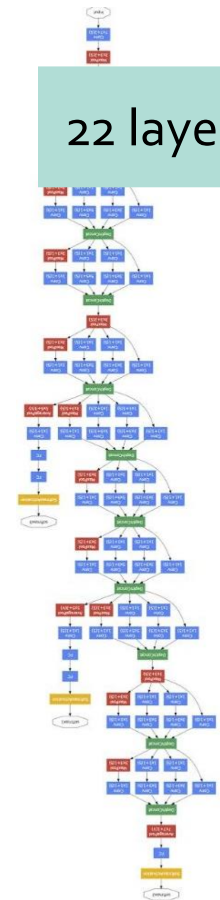
19 layers

7.3%

VGG (2014)

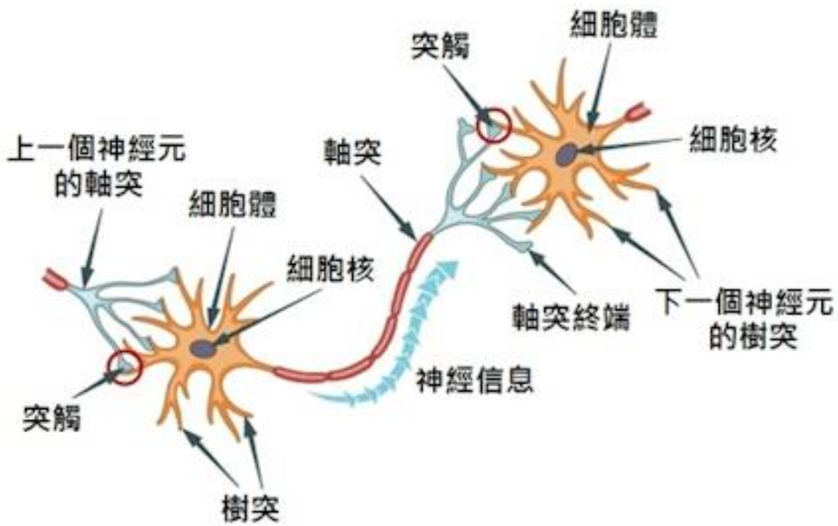
22 layers

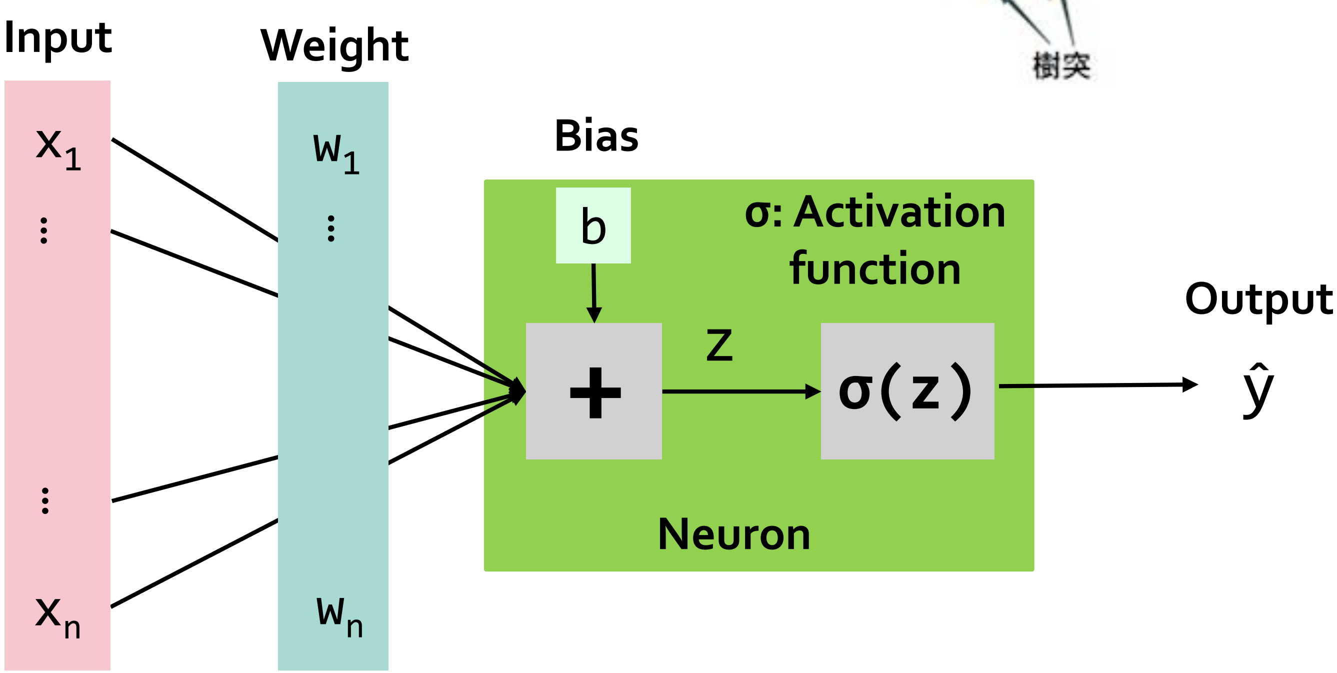
6.7%



GoogleNet (2014)

A Neuron



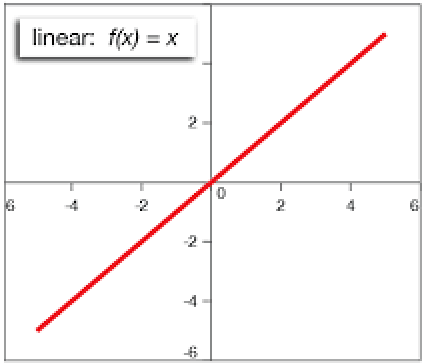


$$z = w_1x_1+w_2x_2+\ldots\ldots+w_nx_n+b$$

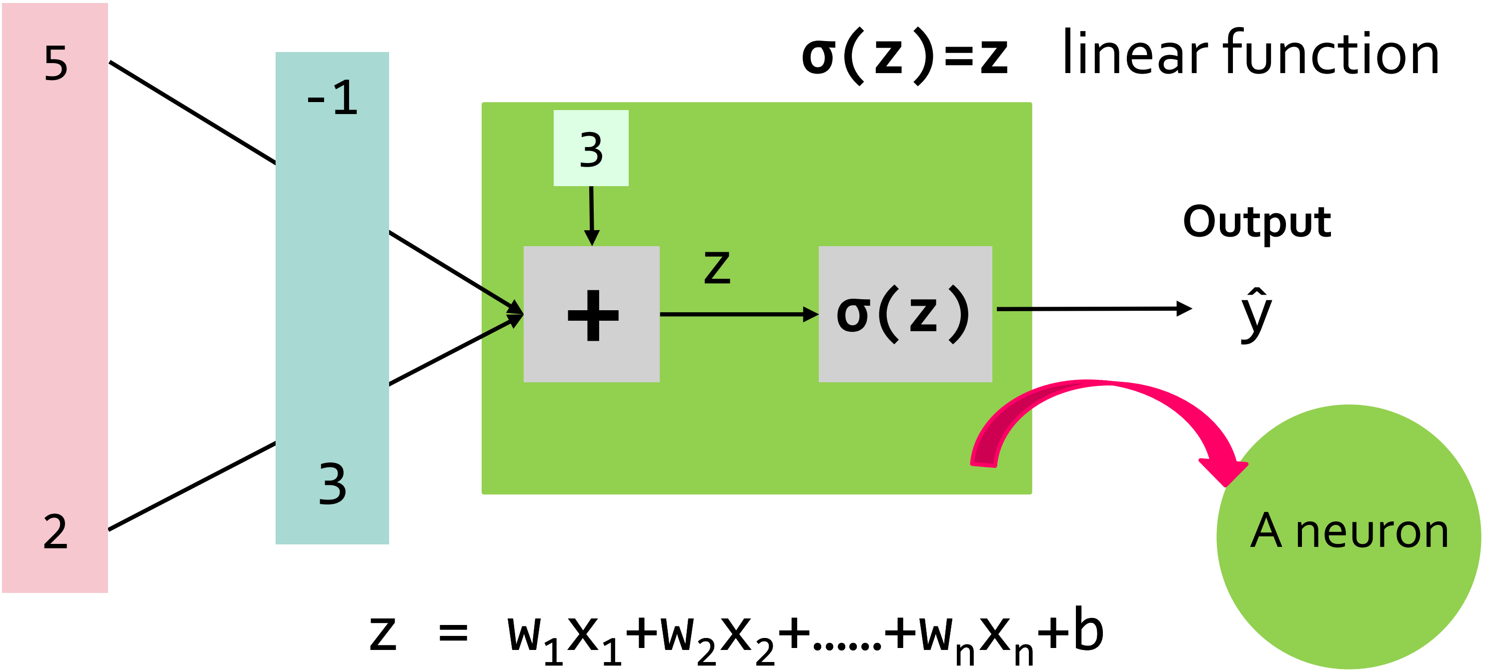
$$\hat{y} = \sigma(z)$$

Neuron 的運作

- Example



$\sigma(z)=z$ linear function



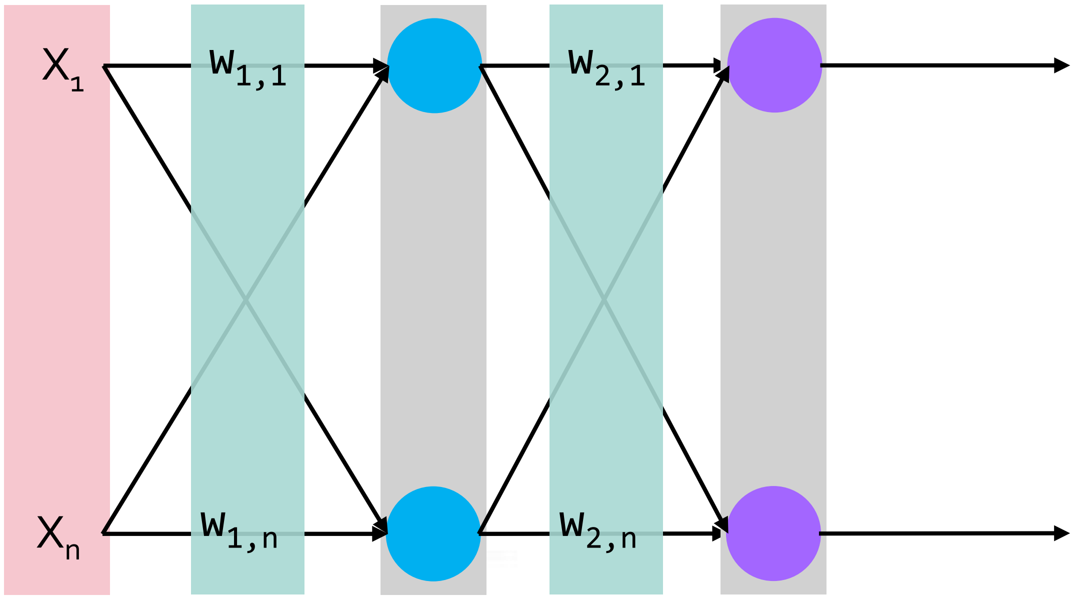
θ: weights, bias

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

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

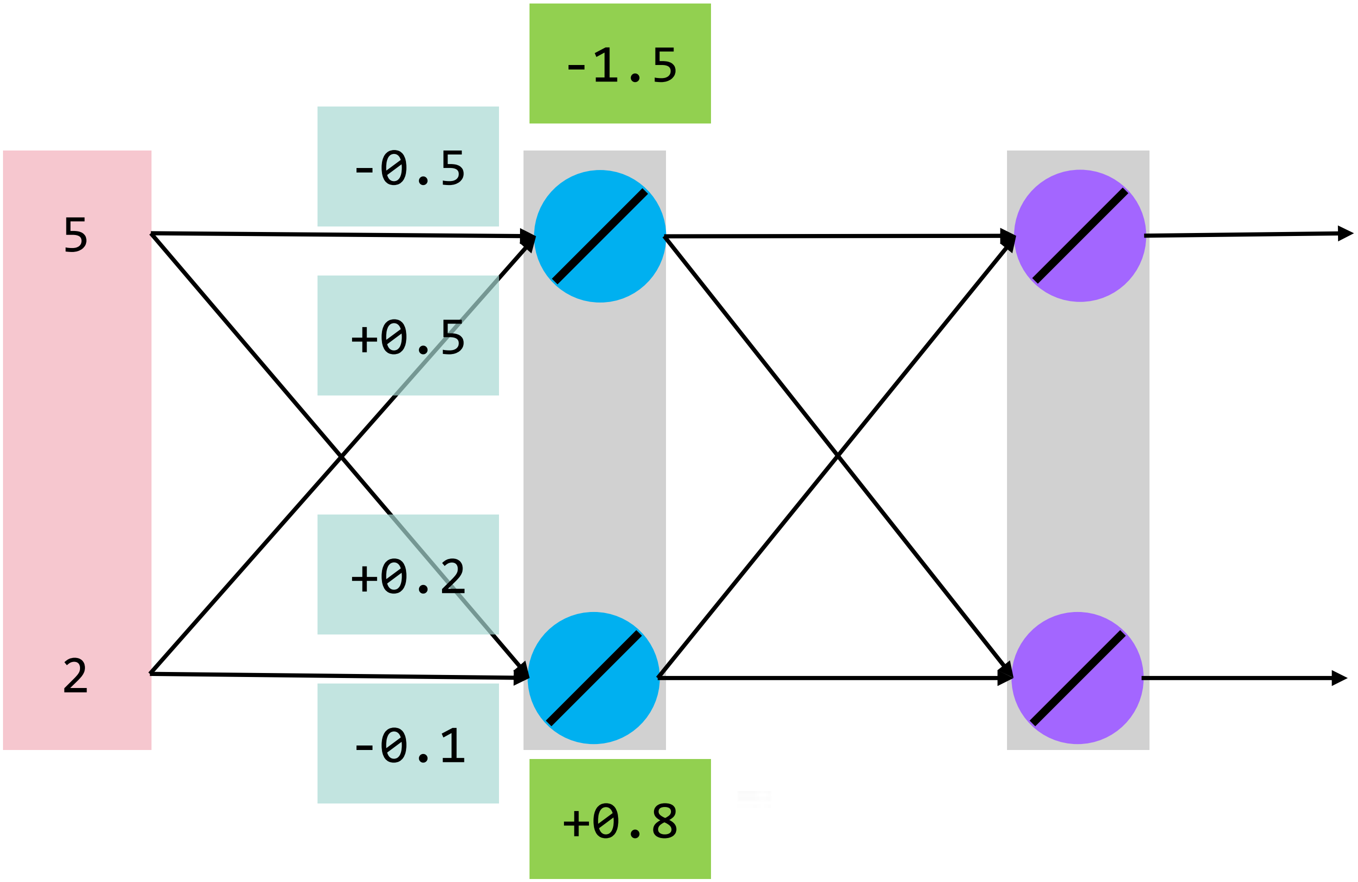
Fully Connected Neural Network

- 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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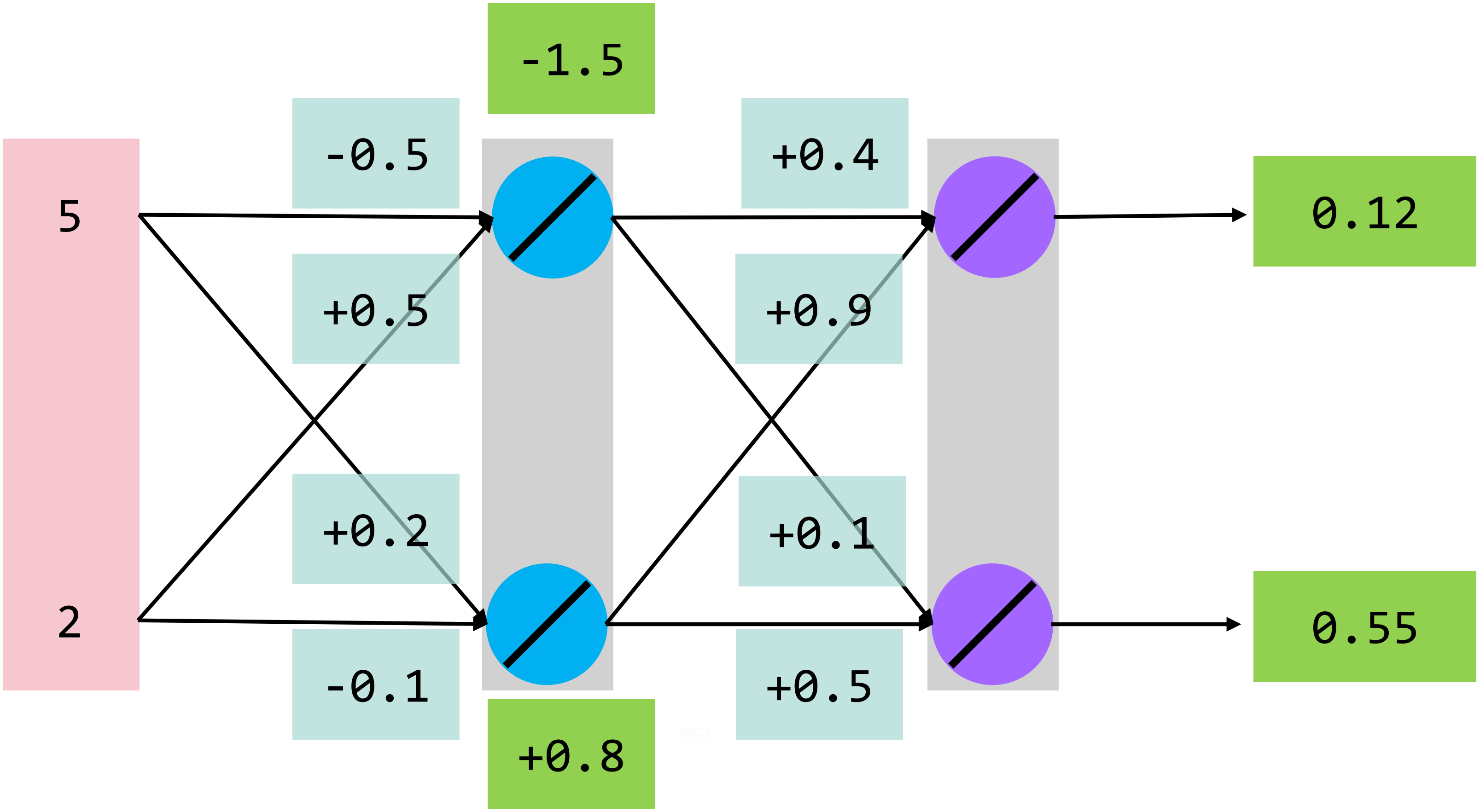
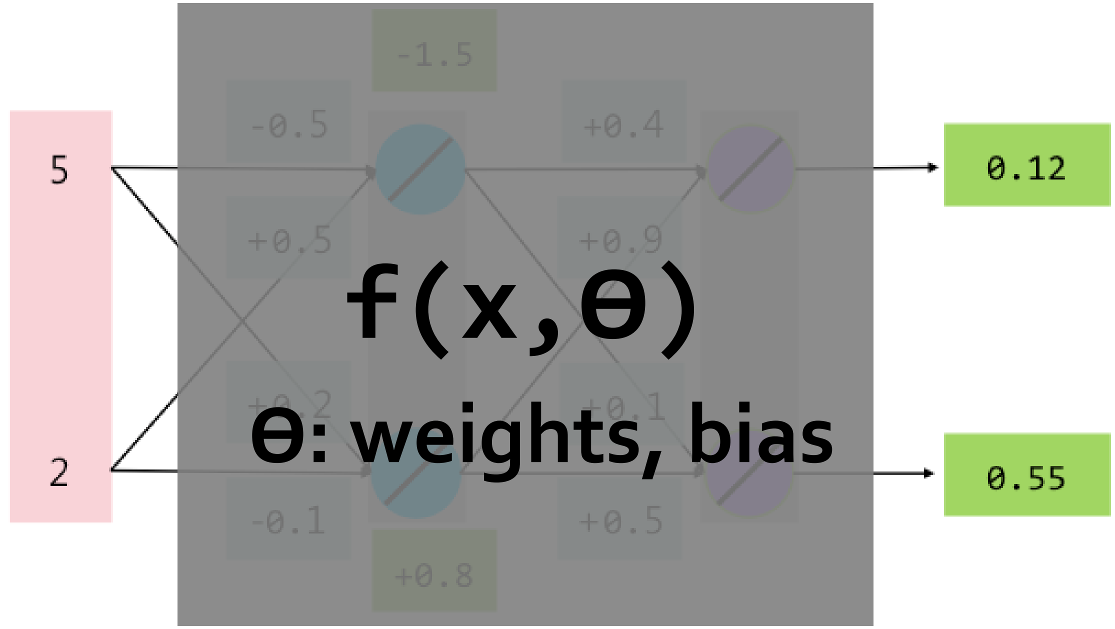


給定 Network Weights



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

A Neural Network = A Function

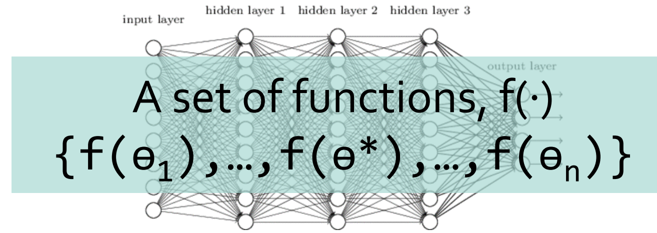
Recall: Deep Learning Framework

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

$f(\theta_{94}) \rightarrow$

$f(\theta_{87}) \rightarrow$

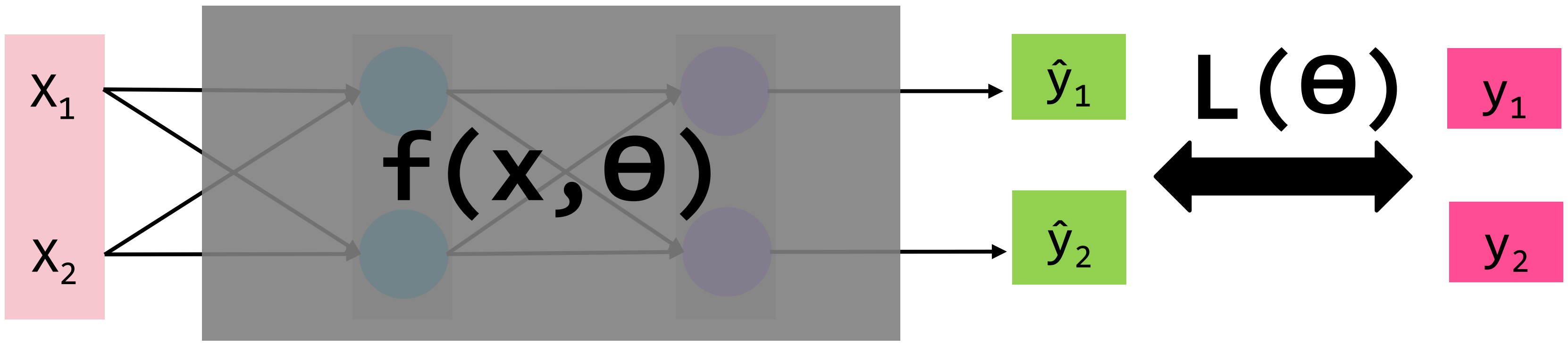
$f(\theta_{945})\ldots$

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*
  - $\theta^* = \arg\min_{\theta} L(\theta)$
- 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。』

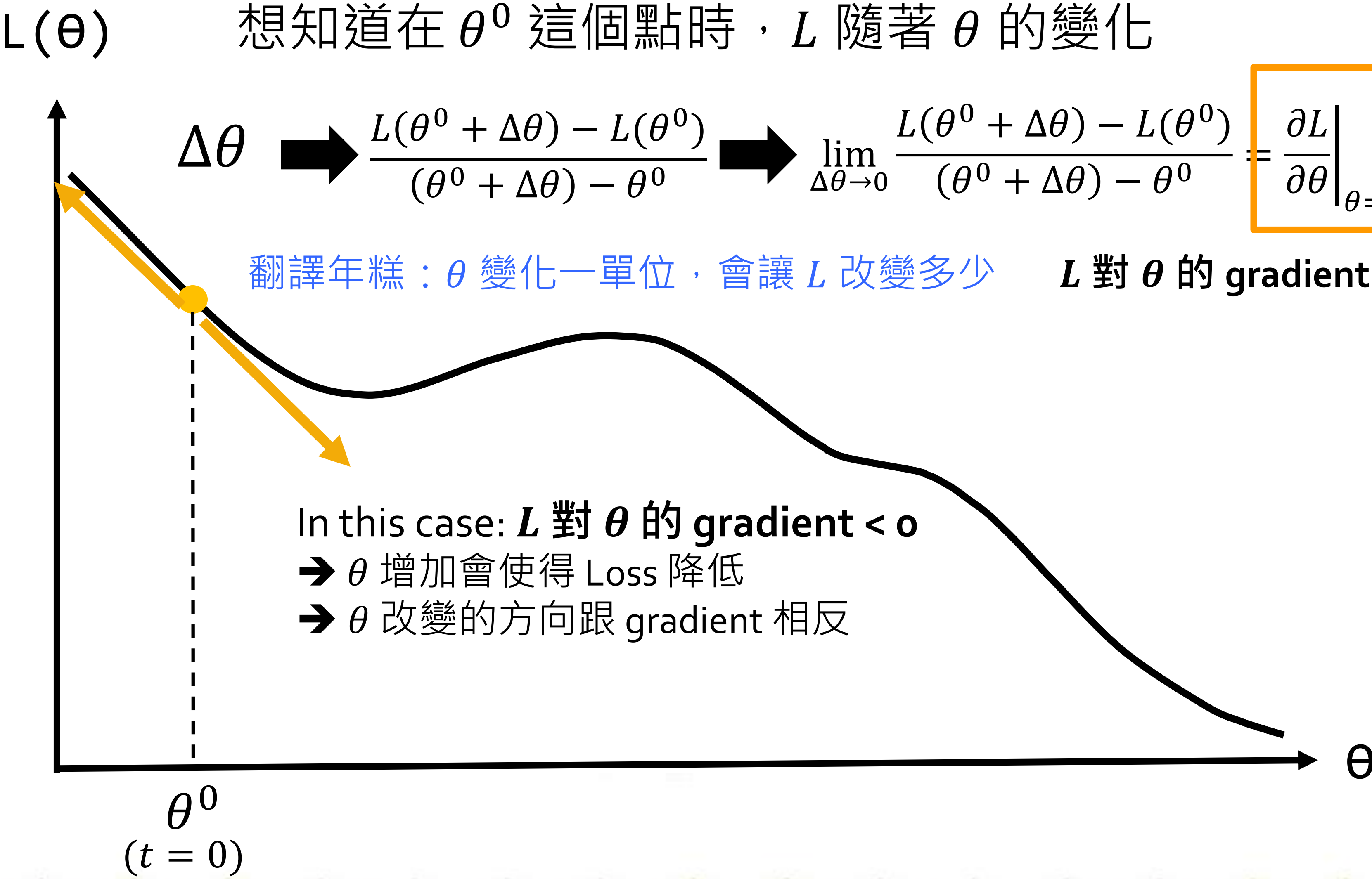
http://i.imgur.com/xxzpPFN.jpg

Gradient Descent

想知道在 θ^0 這個點時，L 隨著 θ 的變化

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

翻譯年糕：θ 變化一單位，會讓 L 改變多少　　　**L 對 θ 的 gradient**



In this case: **L 對 θ 的 gradient < 0**

➔ θ 增加會使得 Loss 降低

➔ θ 改變的方向跟 gradient 相反

Gradient Descent

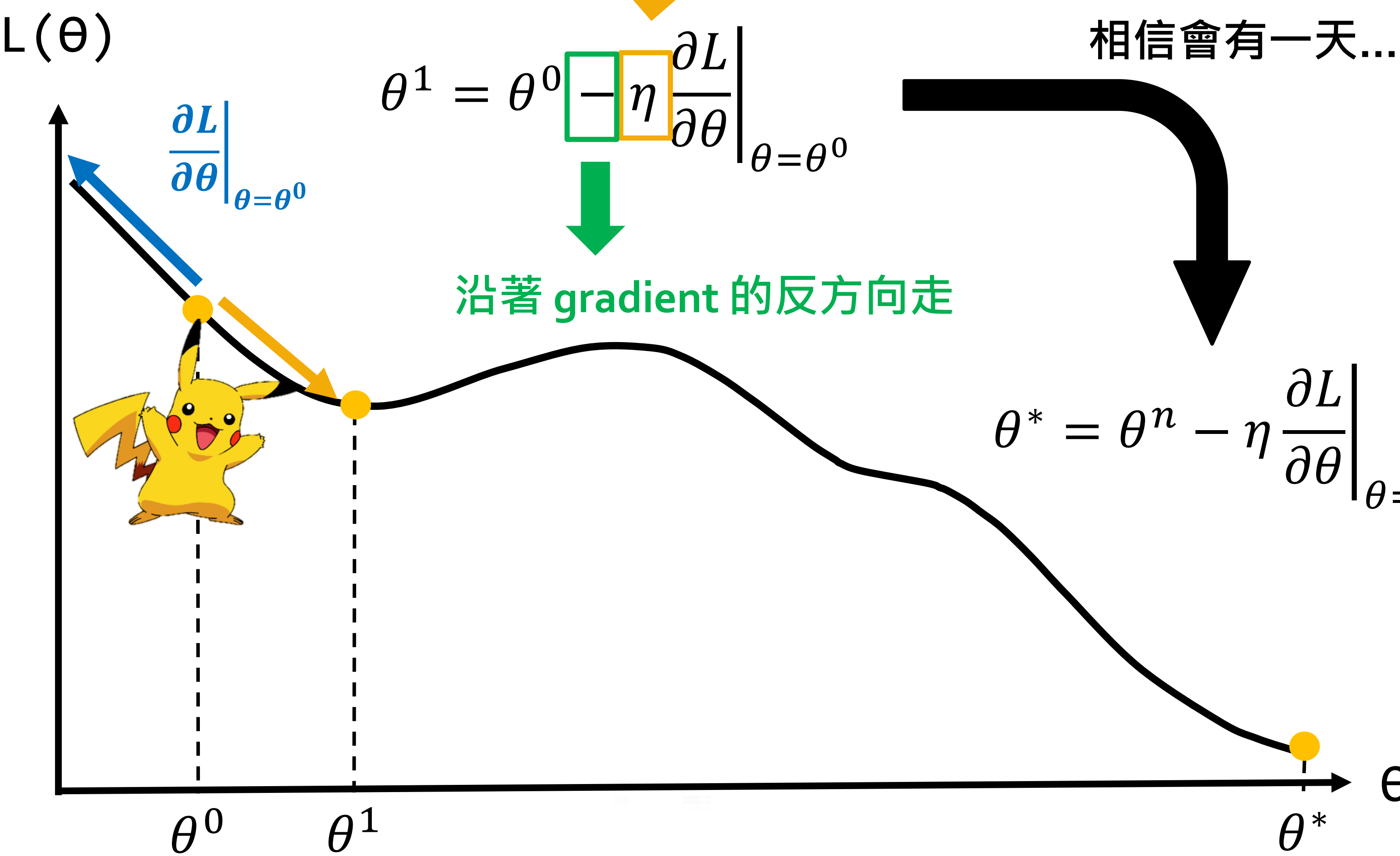
η, Learning rate
一步要走多大

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

沿著 gradient 的反方向走

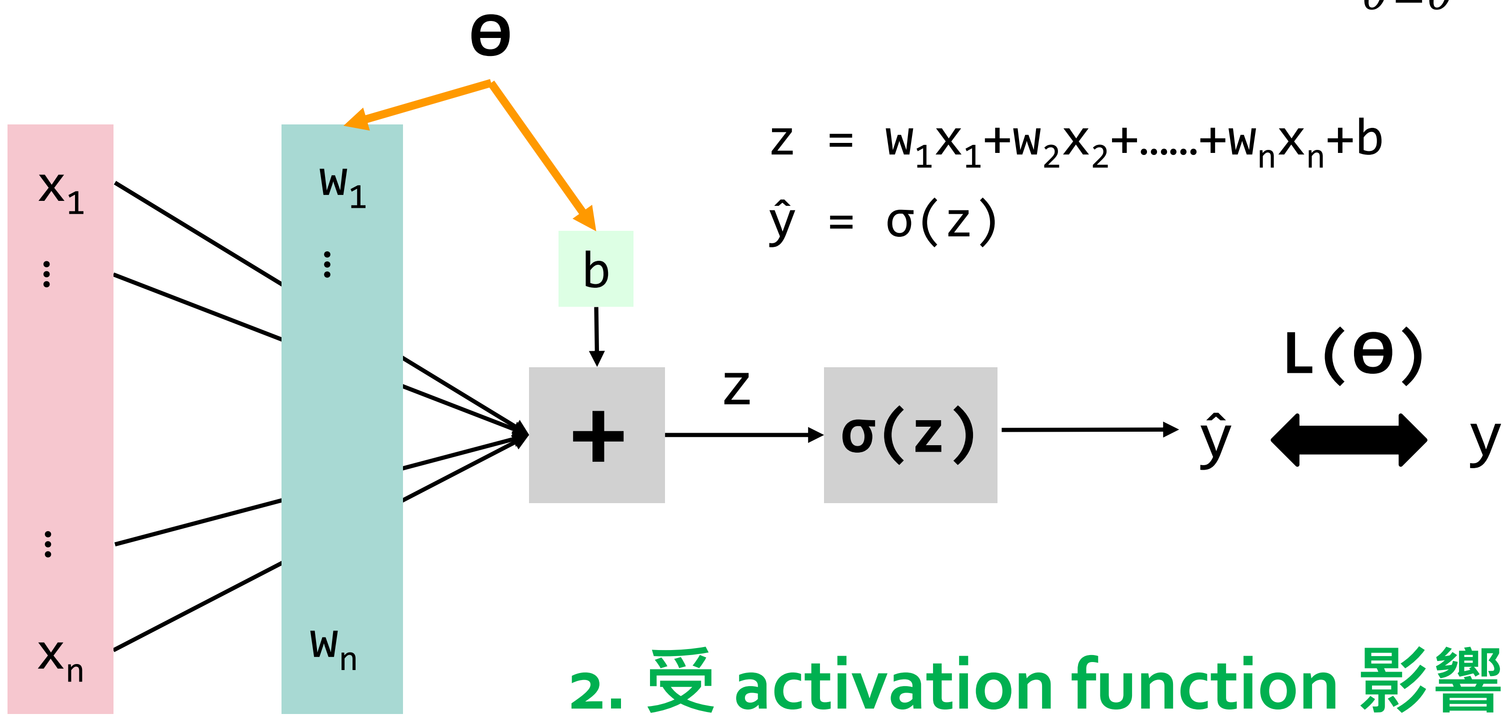
相信會有一天...

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



影響 Gradient 的因素

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



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

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

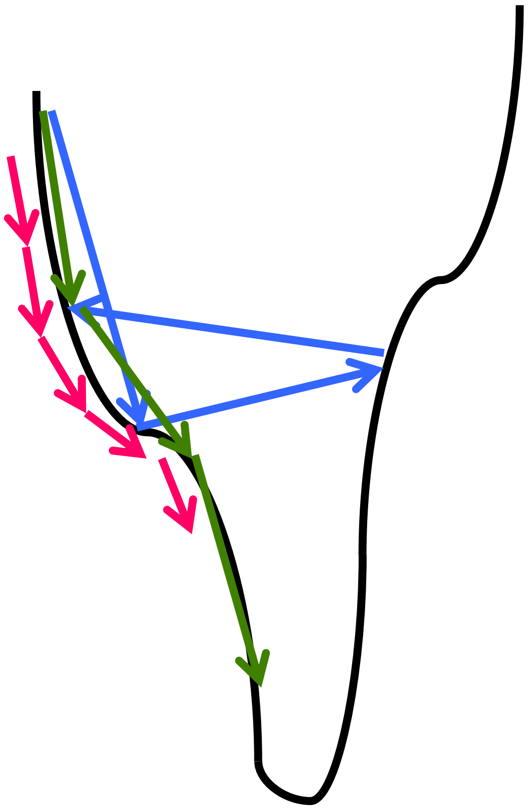
2. 受 activation function 影響

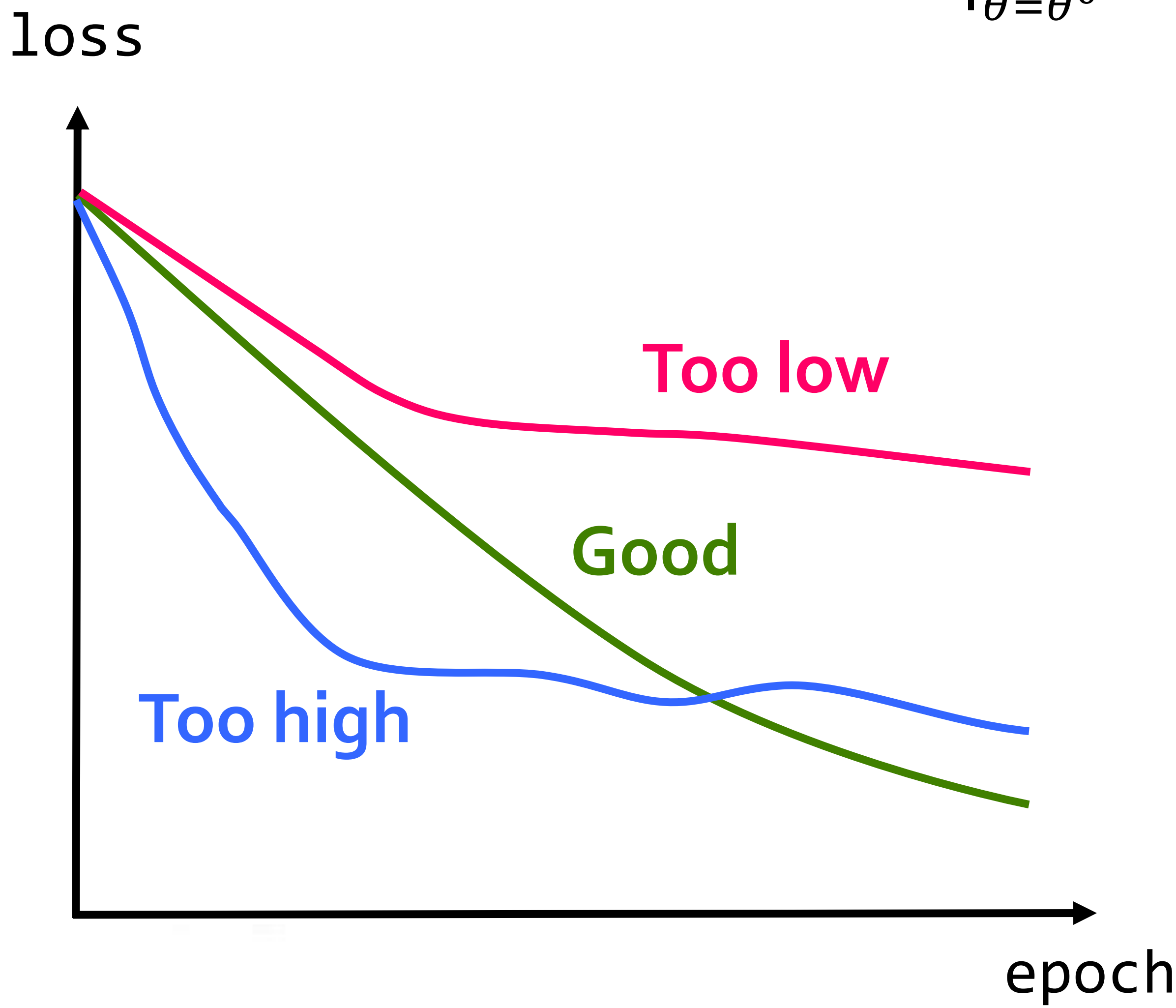
$$\frac{\partial L}{\partial \theta} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \theta} = \boxed{\frac{\partial L}{\partial \hat{y}}} \boxed{\frac{\partial \hat{y}}{\partial z}} \frac{\partial z}{\partial \theta}$$

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

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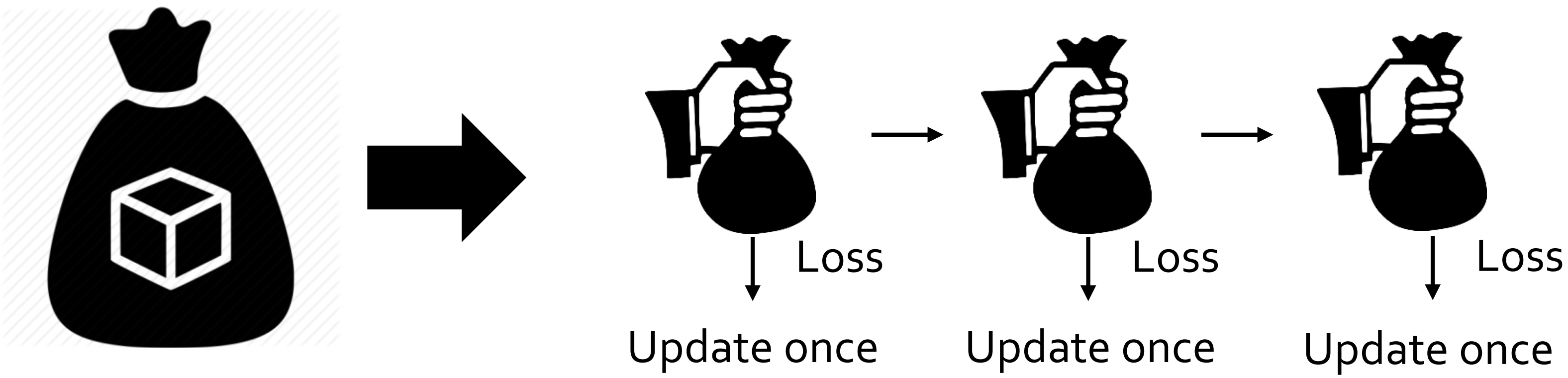
Stochastic Gradient Descent

- 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: **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

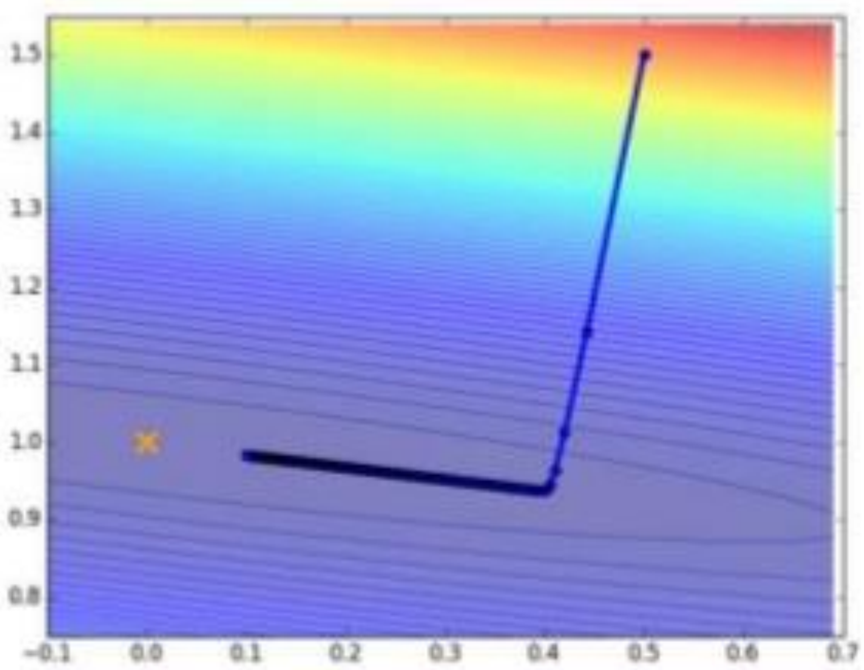
- 一個 epoch = 看完所有 training data 一次
- 依照 mini-batch 把所有 training data 拆成多份
- 假設全部有 1000 筆資料
  - Batch size = 100 可拆成 10 份 ➔ 一個 epoch 內會更新 10 次
  - Batch size = 10 可拆成 100 份 ➔ 一個 epoch 內會更新 100 次
- 如何設定 batch size?
  - 不要設太大，常用 28, 32, 128, 256, …

(Slide Credit: Hung-Yi Lee)

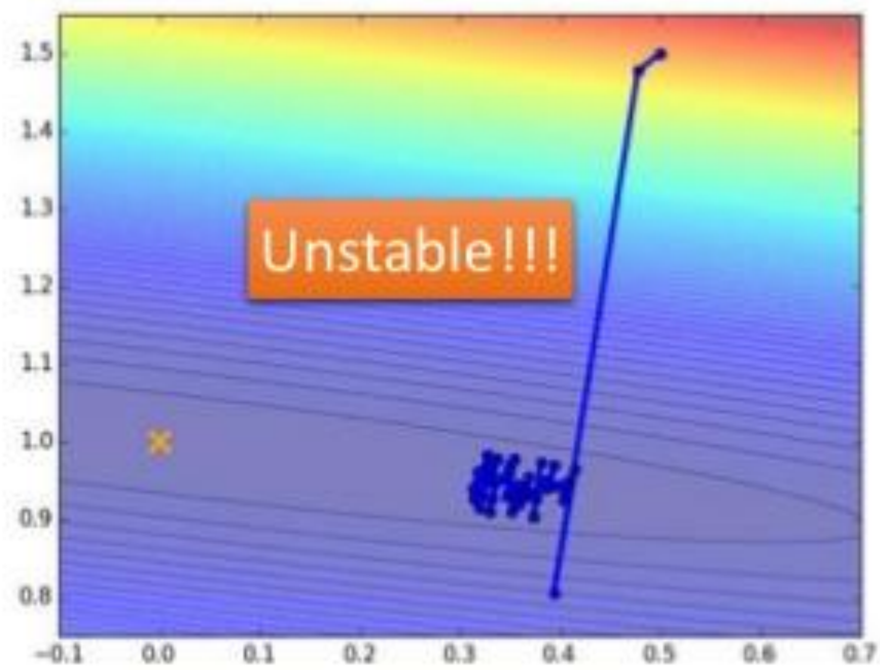
Mini-batch 的影響

- 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

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  - 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**

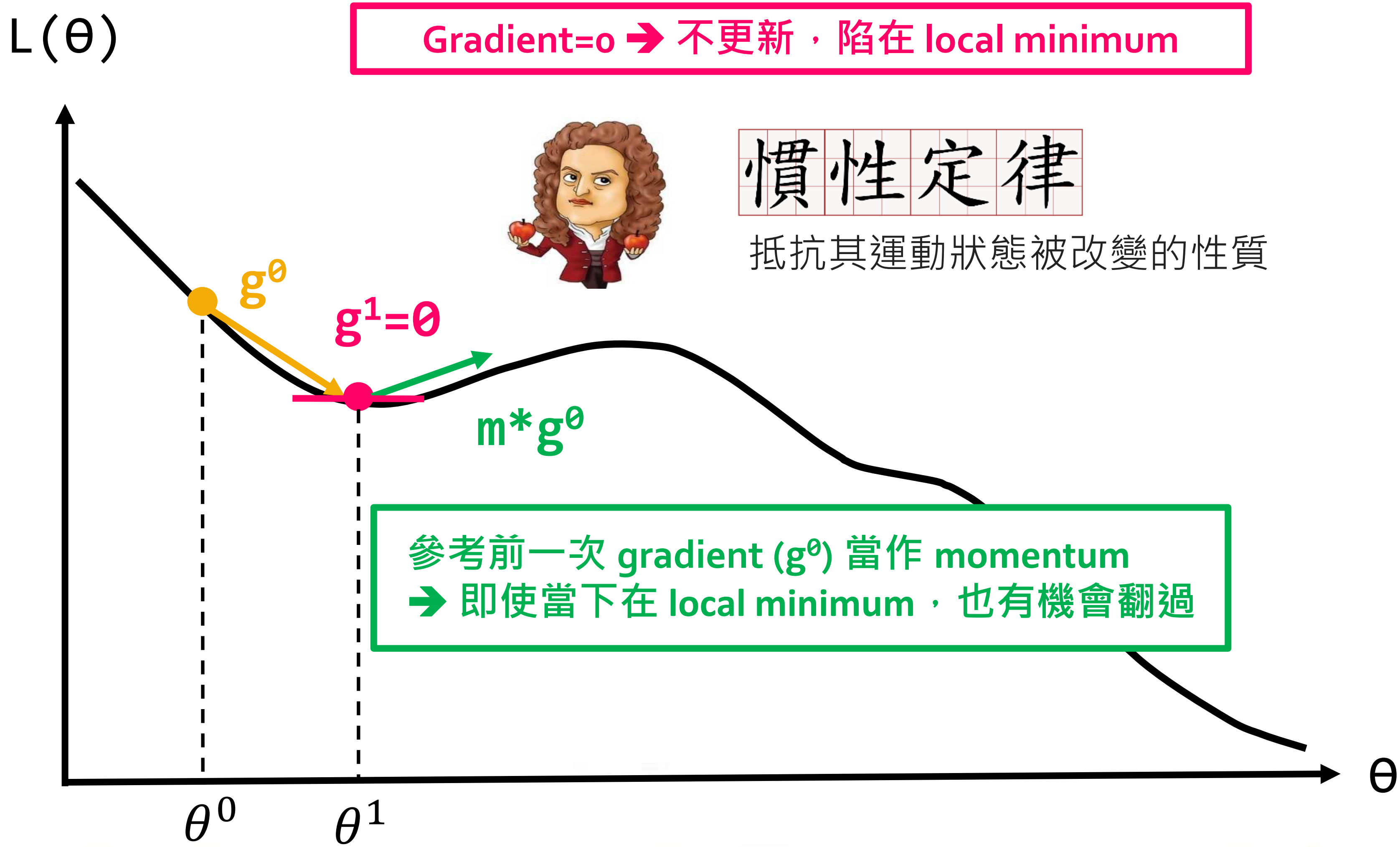
  Gradient based method 不能保證找到全域最佳解
  - **可以利用 momentum 降低困在 local minimum 的機率**

Momentum

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



參考前一次 gradient (g^0) 當作 momentum

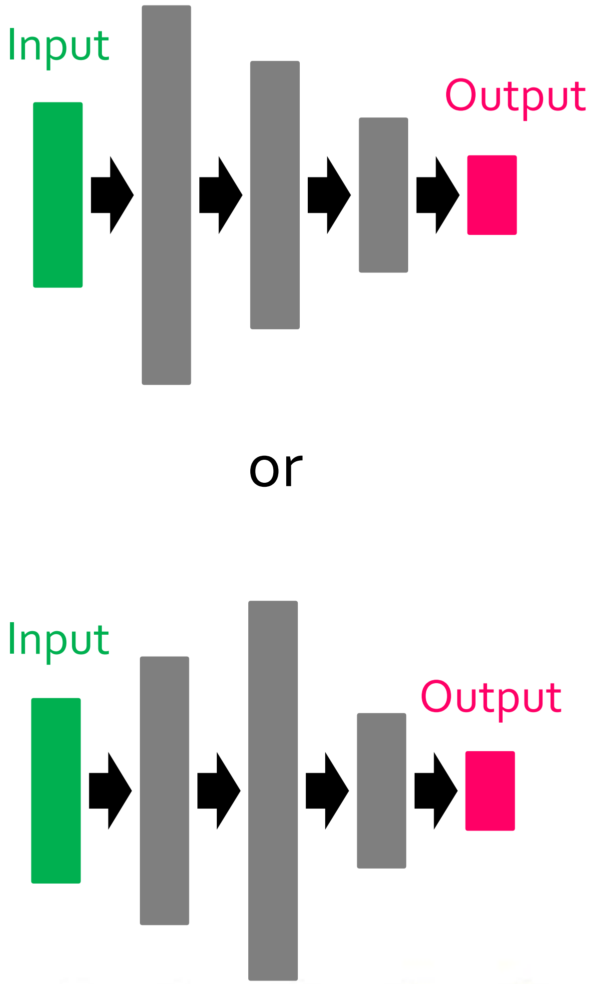
➔ 即使當下在 local minimum，也有機會翻過

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

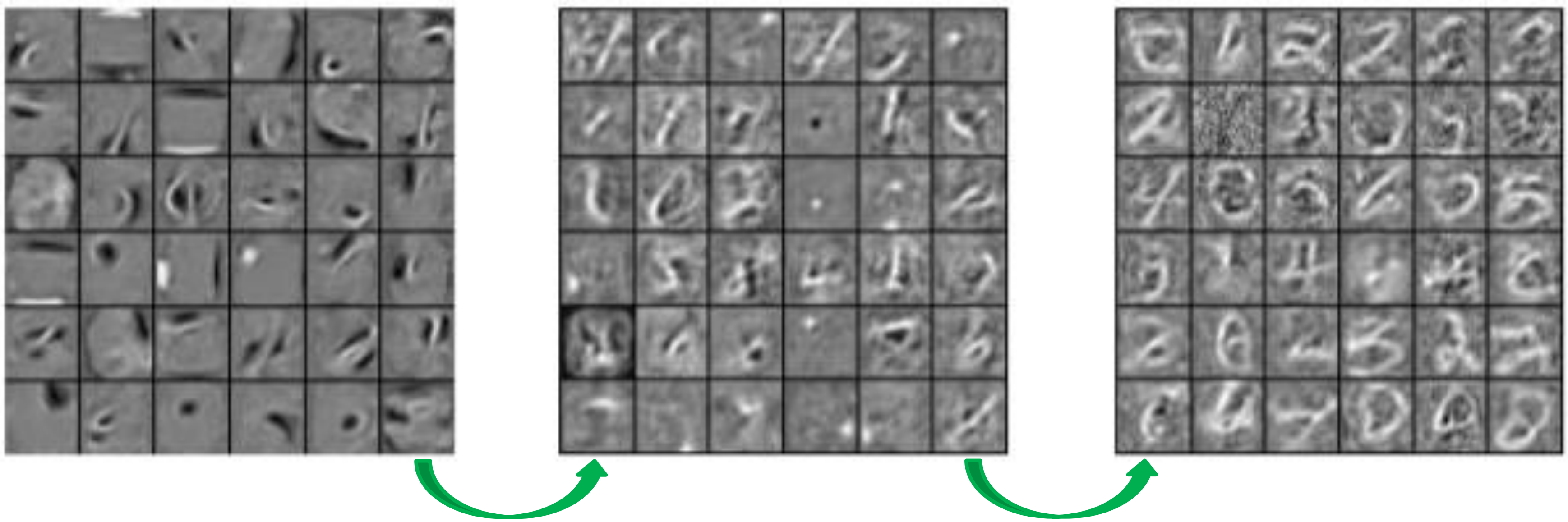
Frequently Asked Questions

- 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

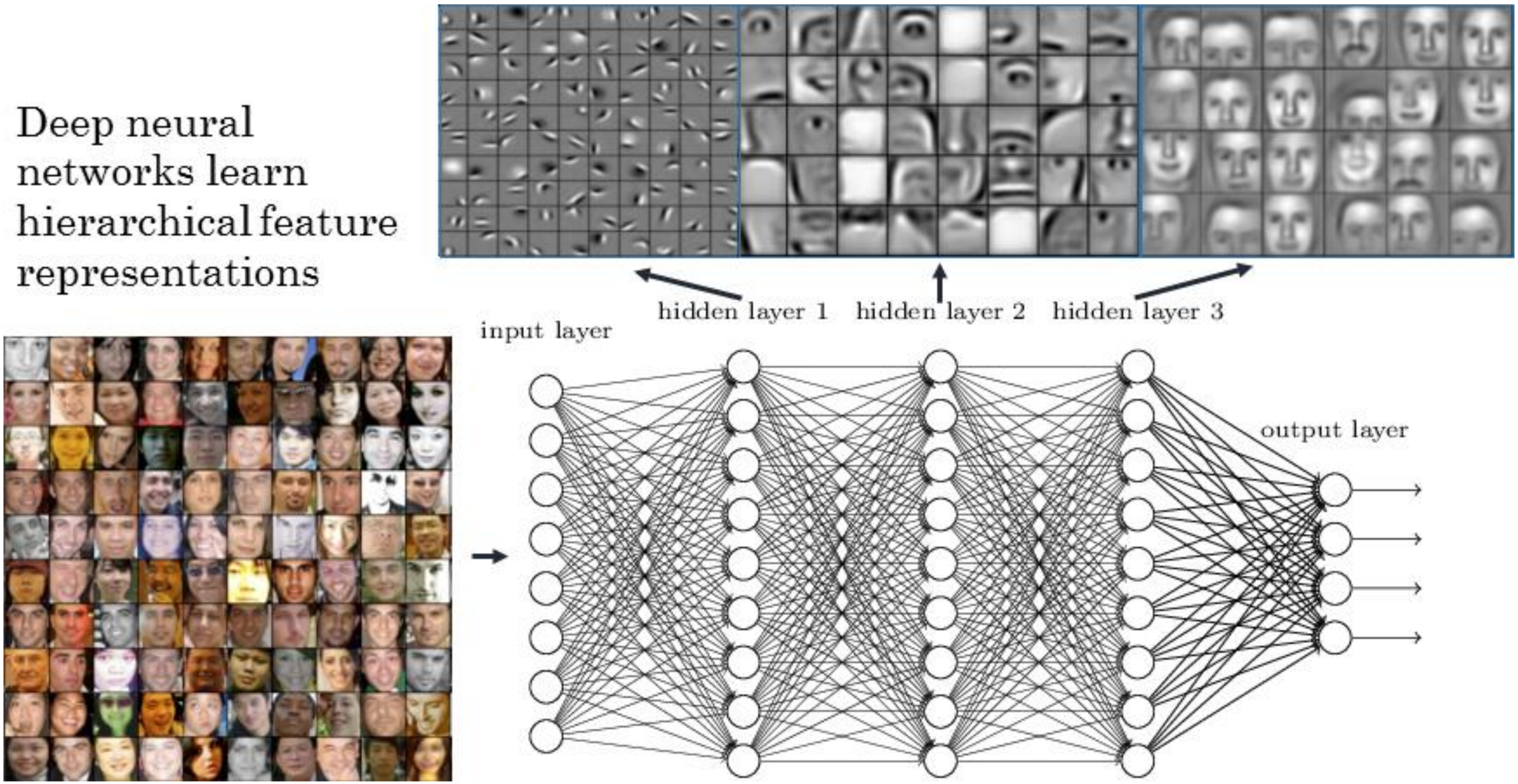
1st hidden layer 2nd hidden layer 3rd hidden layer



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



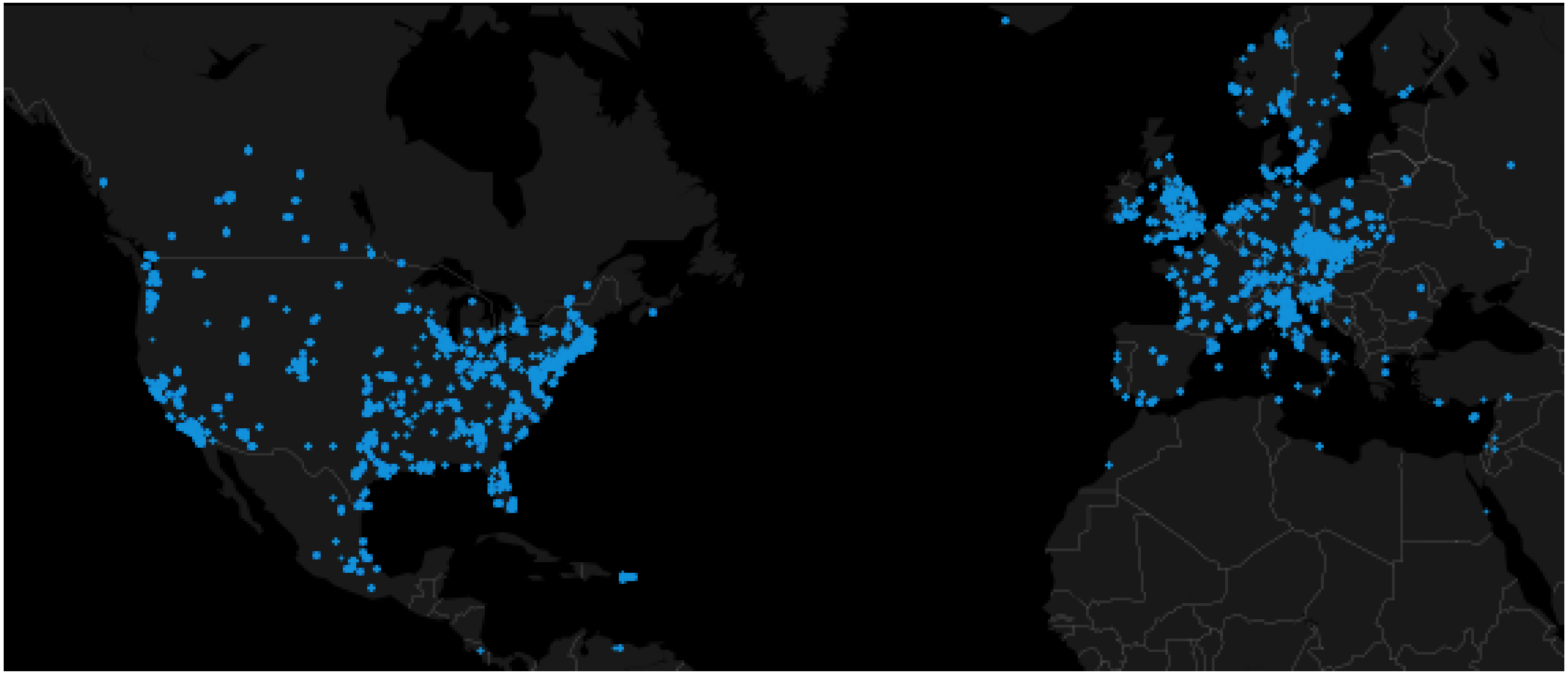
Ref: Deep Learning and Convolutional Neural Networks: RSIP Vision Blogs

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

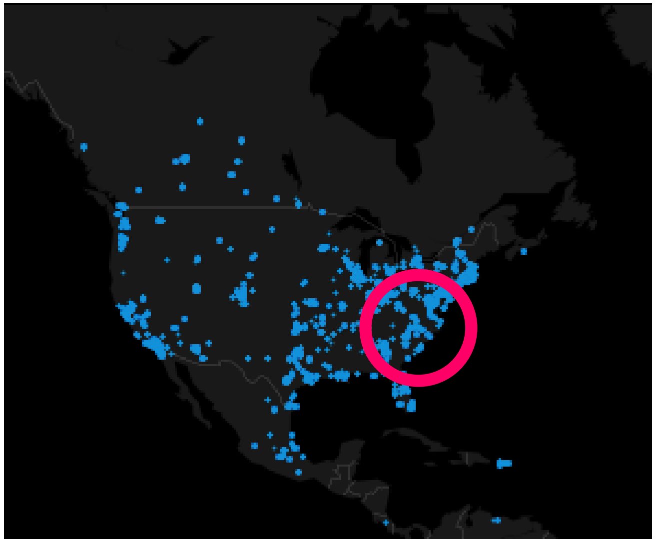
問題: 會出現哪一隻神奇寶貝呢？

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

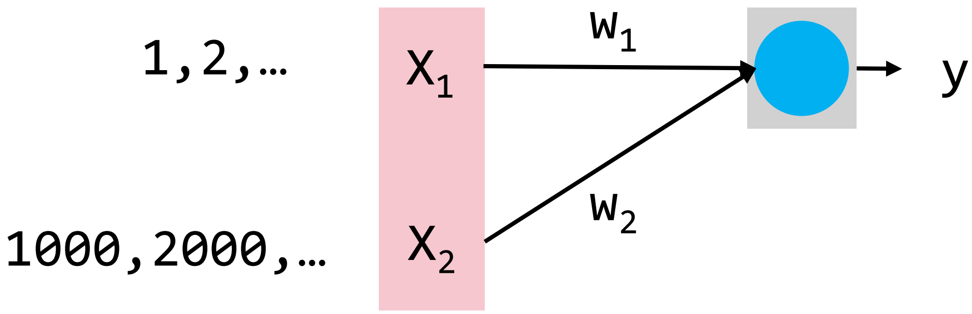
處理名目資料

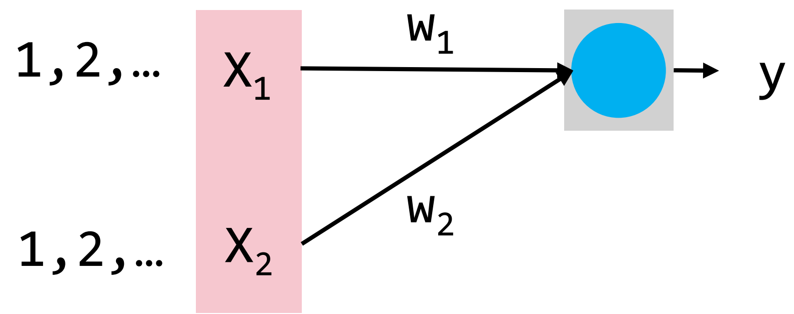
- Nominal variables (名目資料)
  - {"SugarFree","Half","Regular"}
  - One-hot encoding
    - 假設有三個類別
    - Category 1 ➔ [1,0,0]
    - Category 2 ➔ [0,1,0]
  - 給予類別上的解釋 ➔ Ordinal variables
    - {"SugarFree","Half","Regular"} ➔ 1,2,3
  - 特殊的名目資料：地址
    - 台北市南港區研究院路二段128號

    ➔ 轉成經緯度 {25.04,121.61}

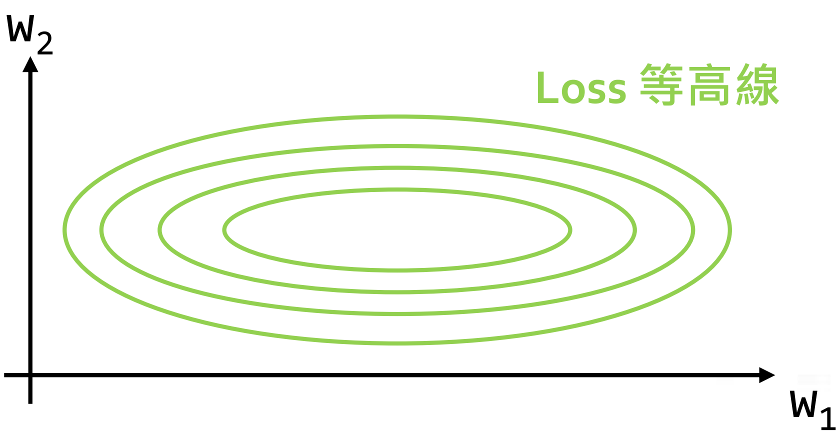
處理不同的數值範圍

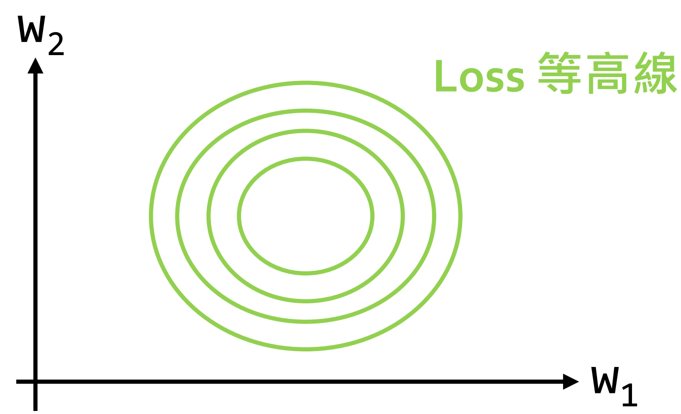
- 先說結論：建議 re-scale！但為什麼？





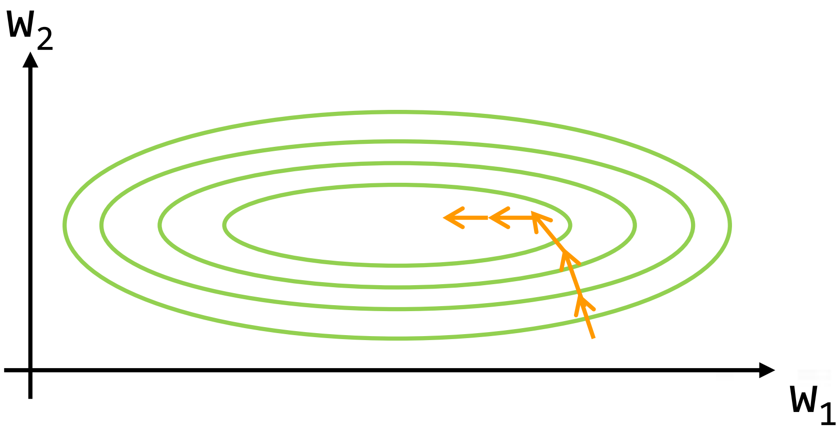
w_2 的修正(ΔW)對於 loss 的影響比較大

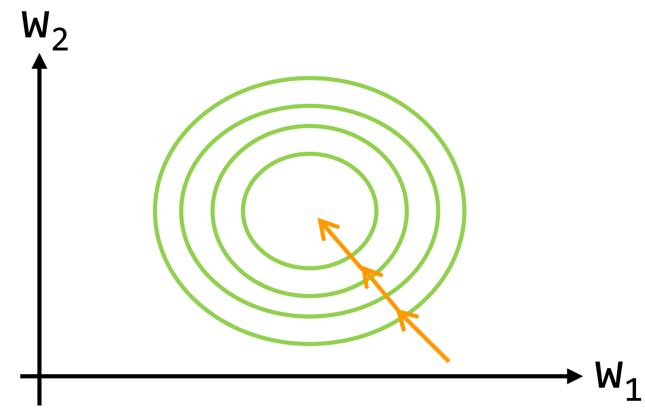




處理不同的數值範圍

- 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)

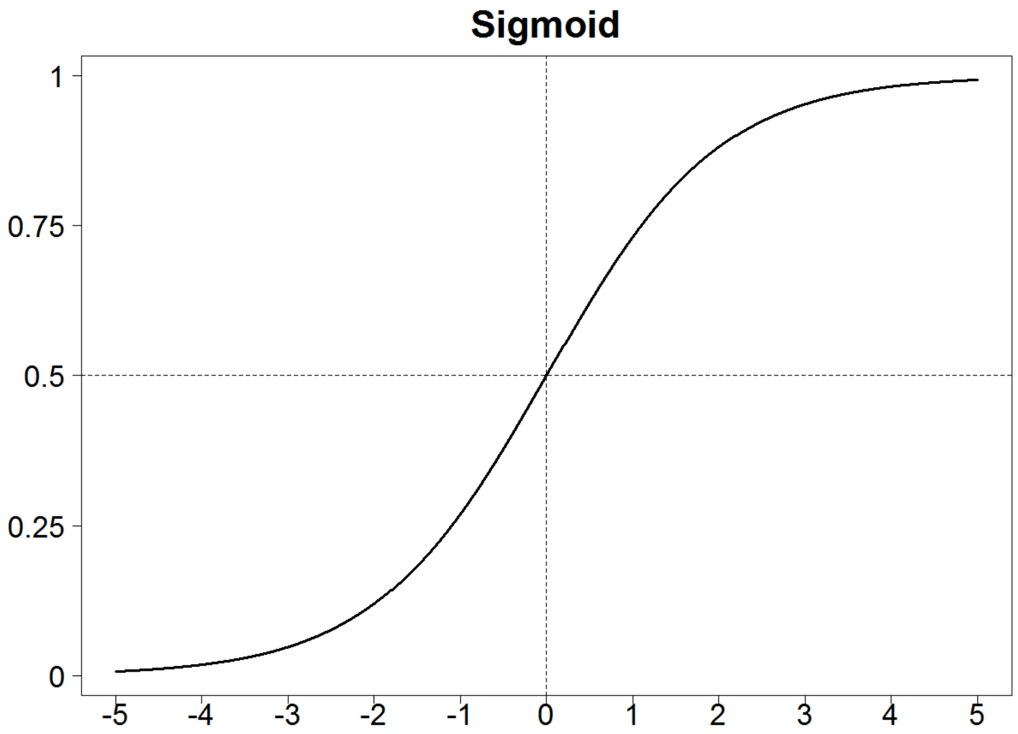
步驟 1+2: 模型架構

```
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

Softmax

$$\begin{pmatrix}0.6\\2.6\\2.2\\0.1\end{pmatrix} \xrightarrow{\text{Exponential}} \begin{pmatrix}e^{0.6}\\e^{2.6}\\e^{2.2}\\e^{0.1}\end{pmatrix} \xrightarrow[e^{0.6}+e^{2.6}+e^{2.2}+e^{0.1}]{\text{Normalized by the sum}} \overset{\text{Output}}{\begin{pmatrix}0.07\\0.53\\0.36\\0.04\end{pmatrix}}$$

- 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

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

- Mean_absolute_percentage_error

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

- Mean_squared_logarithmic_error

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

常用於 Regression

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)

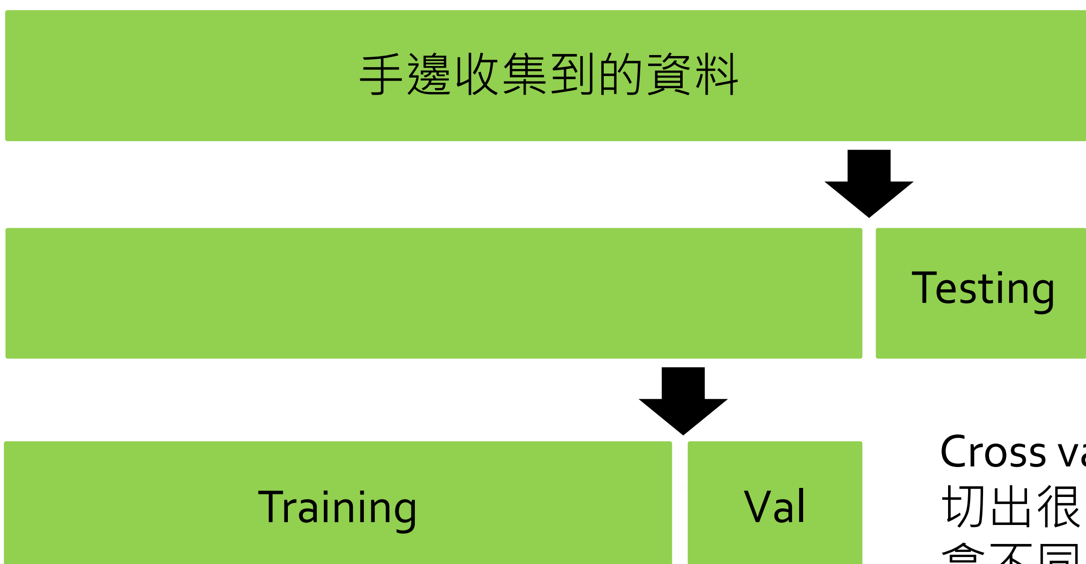
就決定是你了!

```
# 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

```python
#  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()
```

```python
#  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])
```

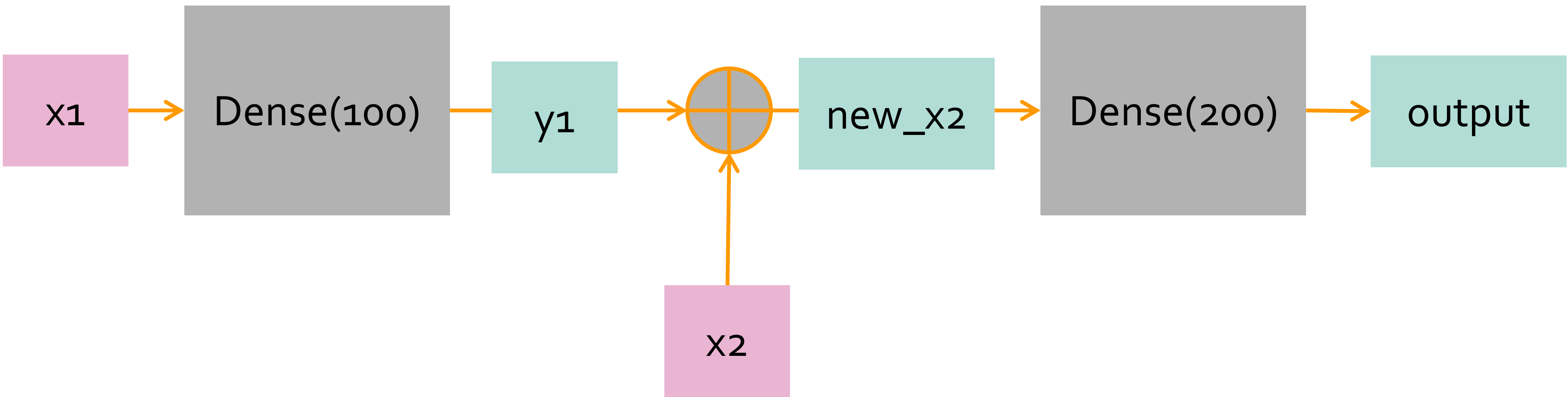
Good Use Case for Functional API (1)

- 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

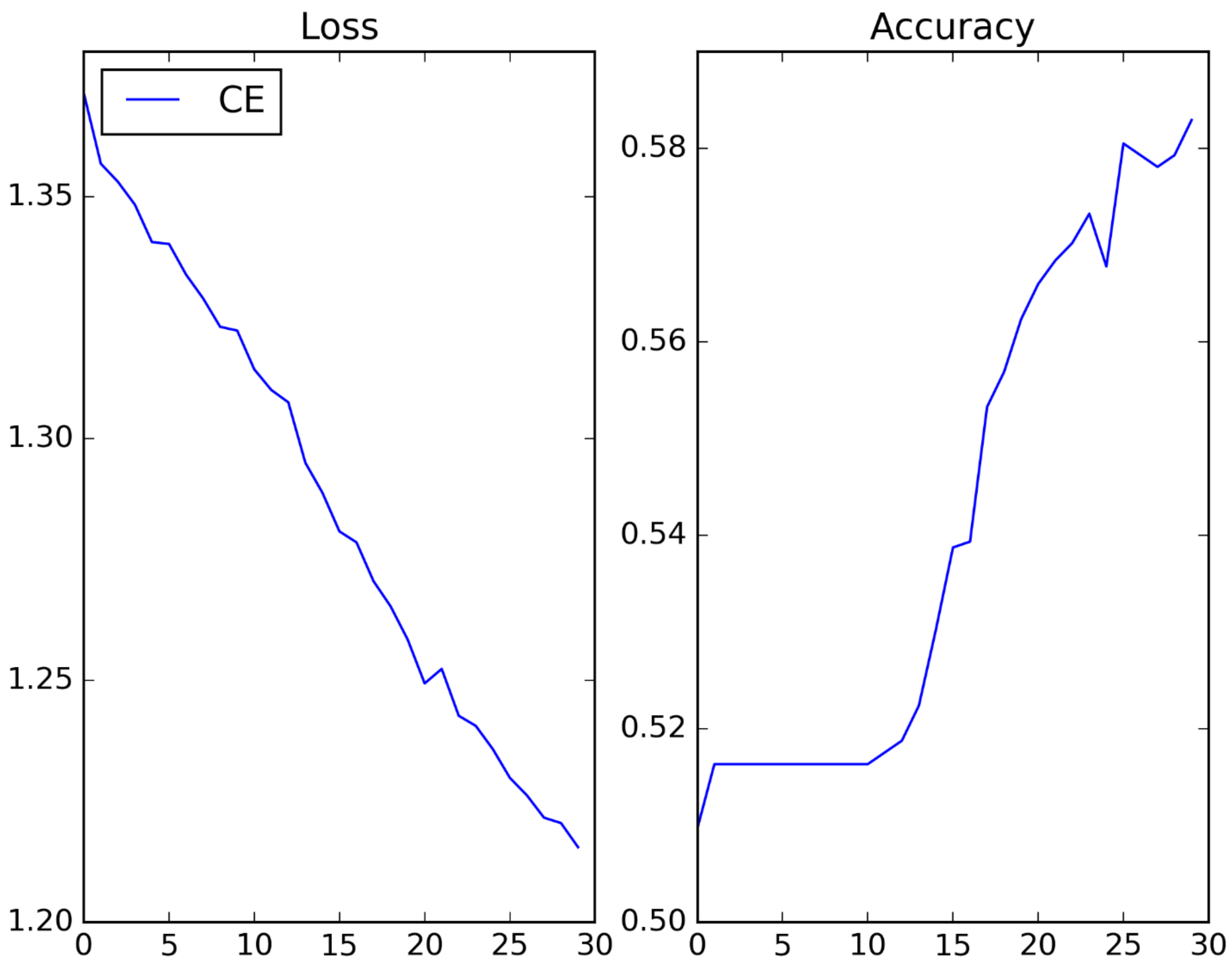



```
x1 = input(shape=(10,))
y1 = Dense(100)(x1)

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
1.35
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

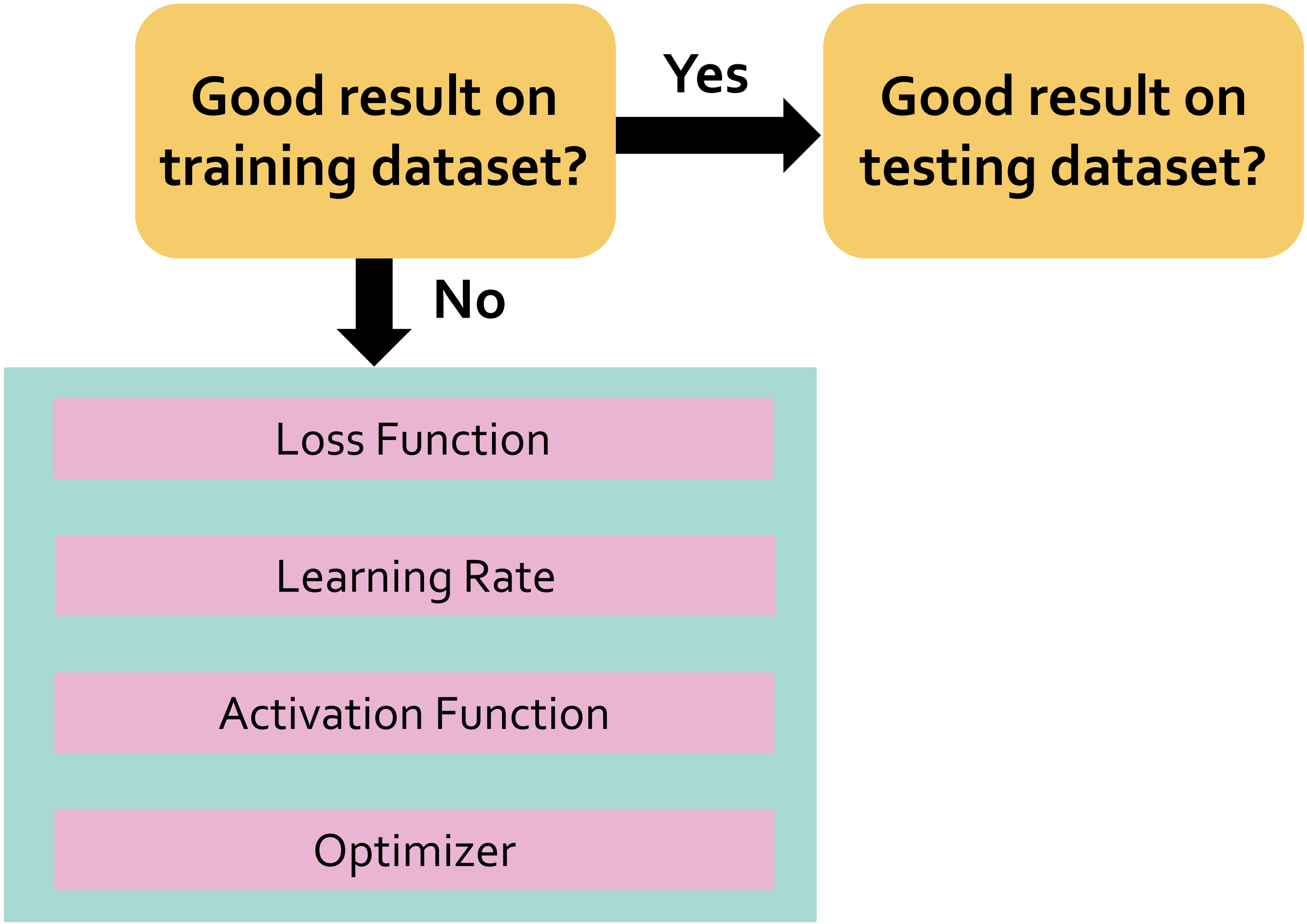
Component	Selection
Loss function	categorical_crossentropy
Activation function	sigmoid + softmax
Optimizer	SGD

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

Good result on training dataset?

Yes → Good result on testing dataset?

No ↓

Loss Function

Learning Rate

Activation Function

Optimizer

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

受 loss function 影響

Using MSE

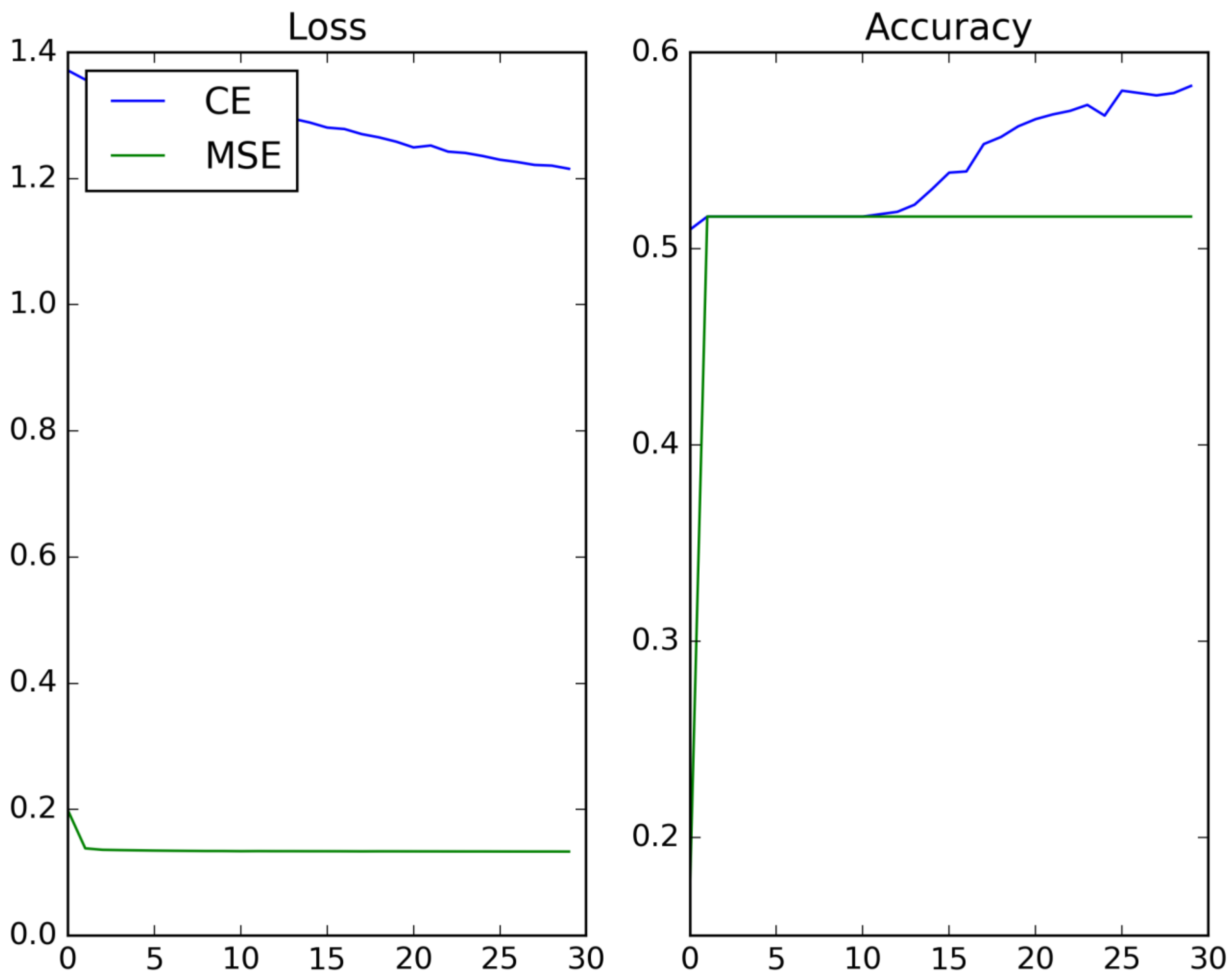
- 在指定 loss function 時

```
# 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？

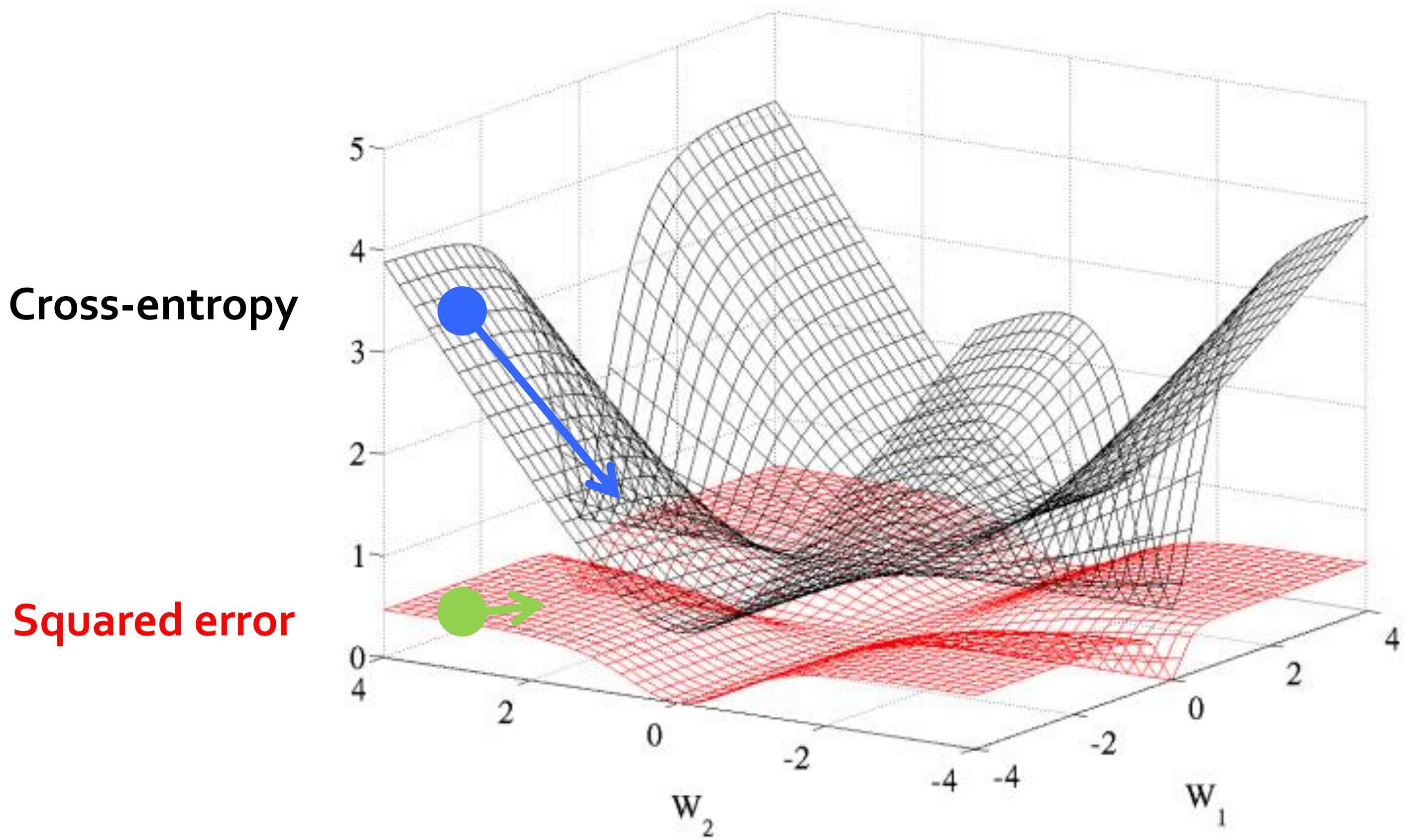


Figure source

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

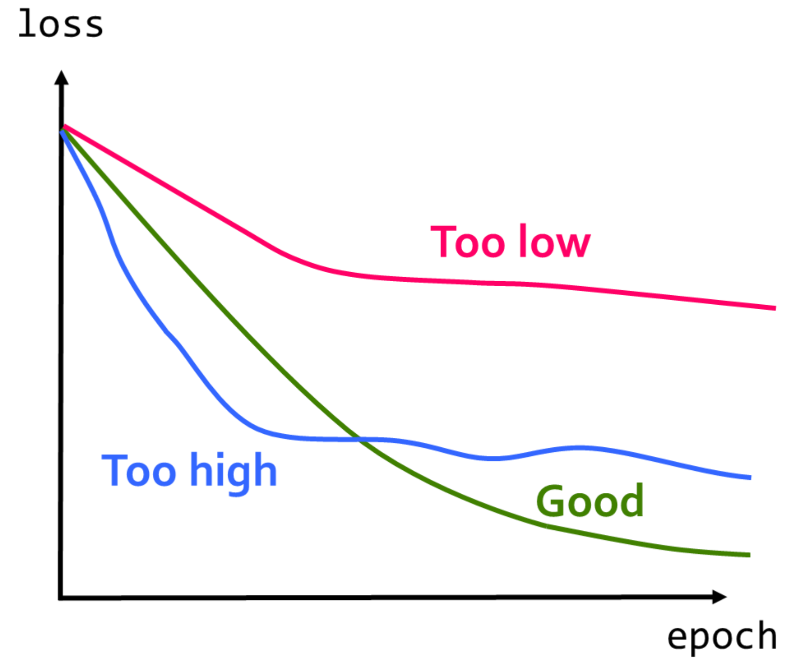
Component	Selection
Loss function	**categorical_crossentropy**
Activation function	sigmoid + softmax
Optimizer	SGD

Tips for Deep Learning

Good result on training data? → **Yes** → Good result on testing data?

No ↓

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

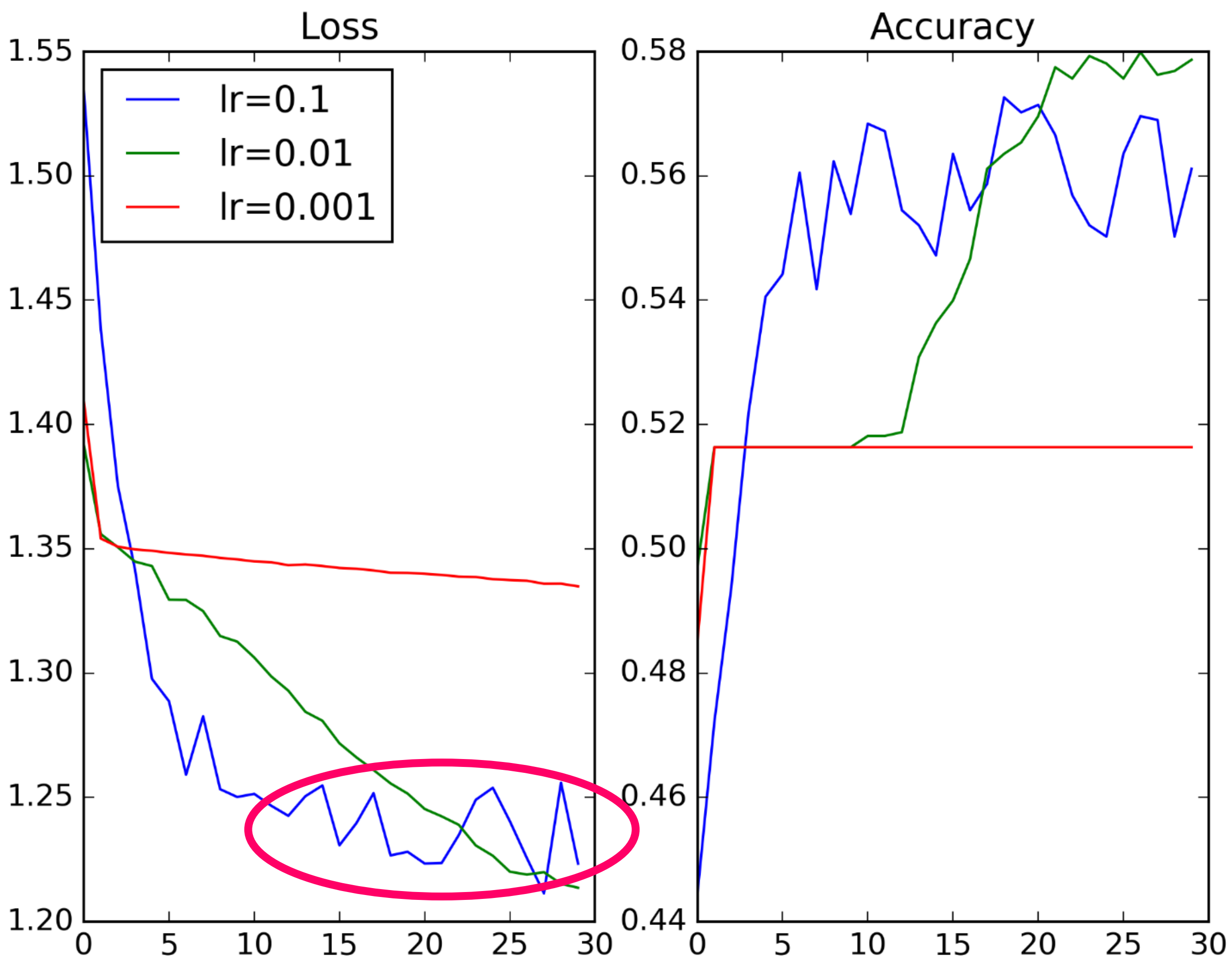


練習 02_learningRateSelection.py (5-8 minutes)

```
# 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

Good result on training data?

Yes

Good result on testing data?

No

Loss Function

Learning Rate

Activation Function

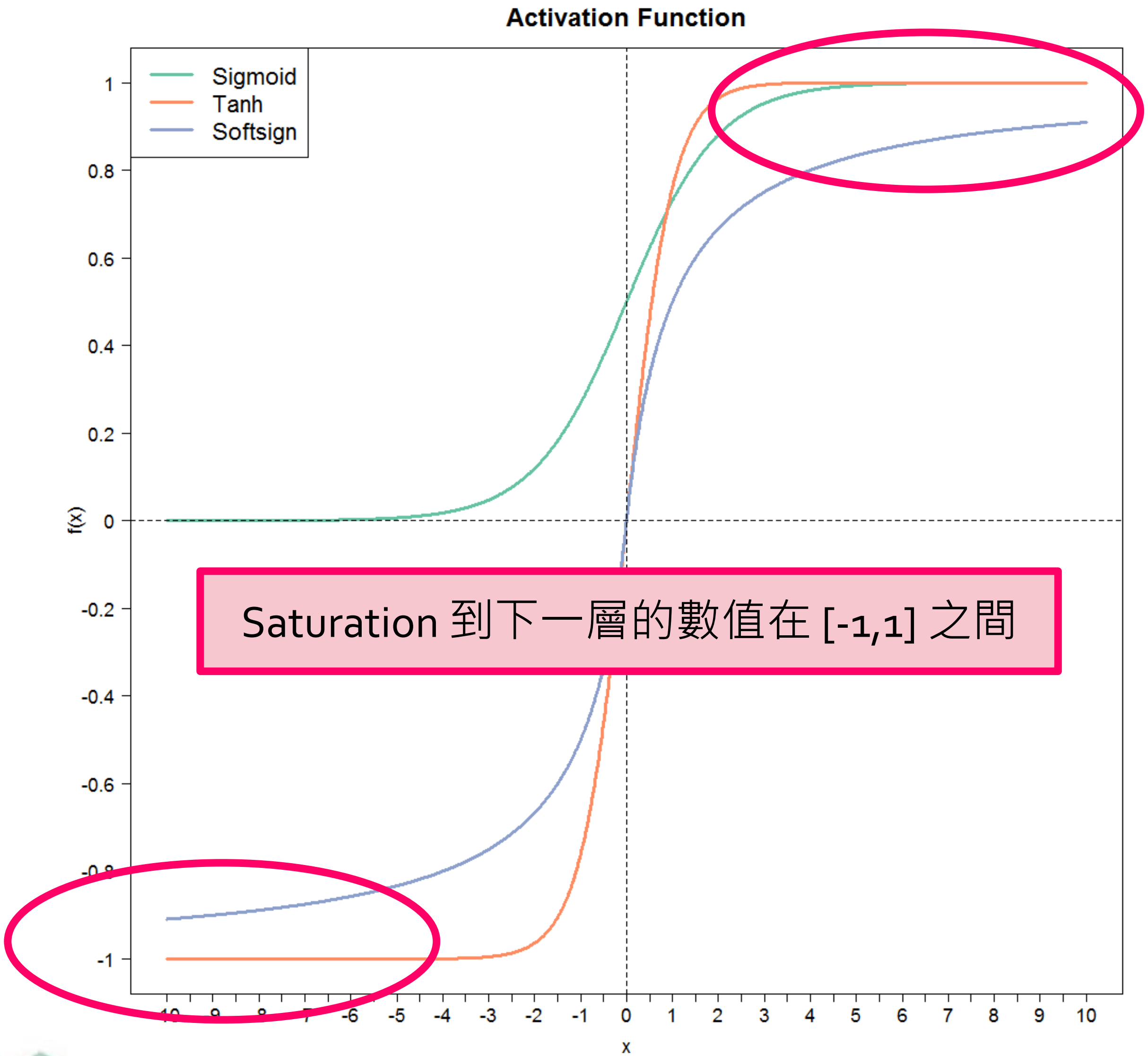
Optimizer

受 activation function 影響

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

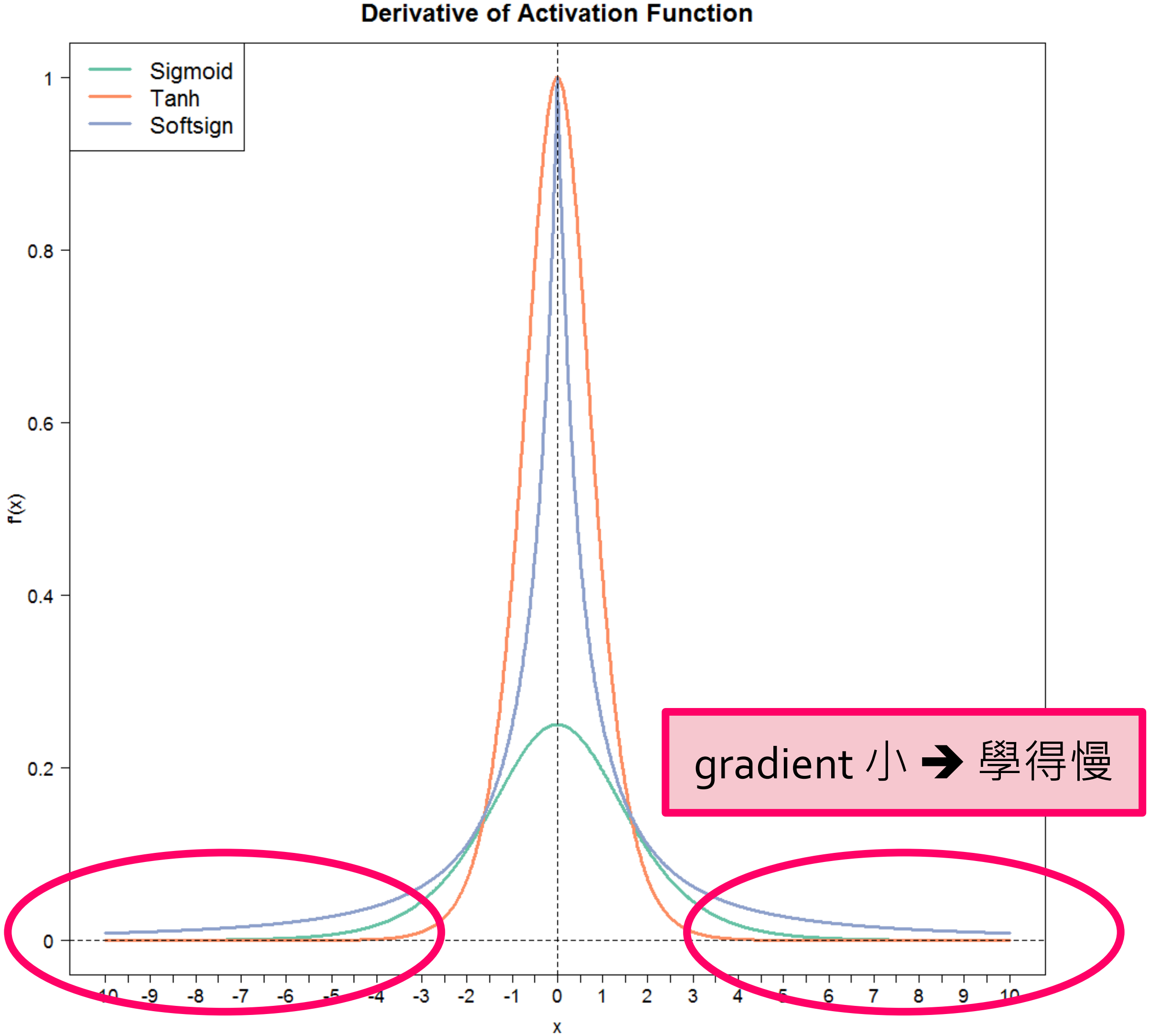
Sigmoid, Tanh, Softsign

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



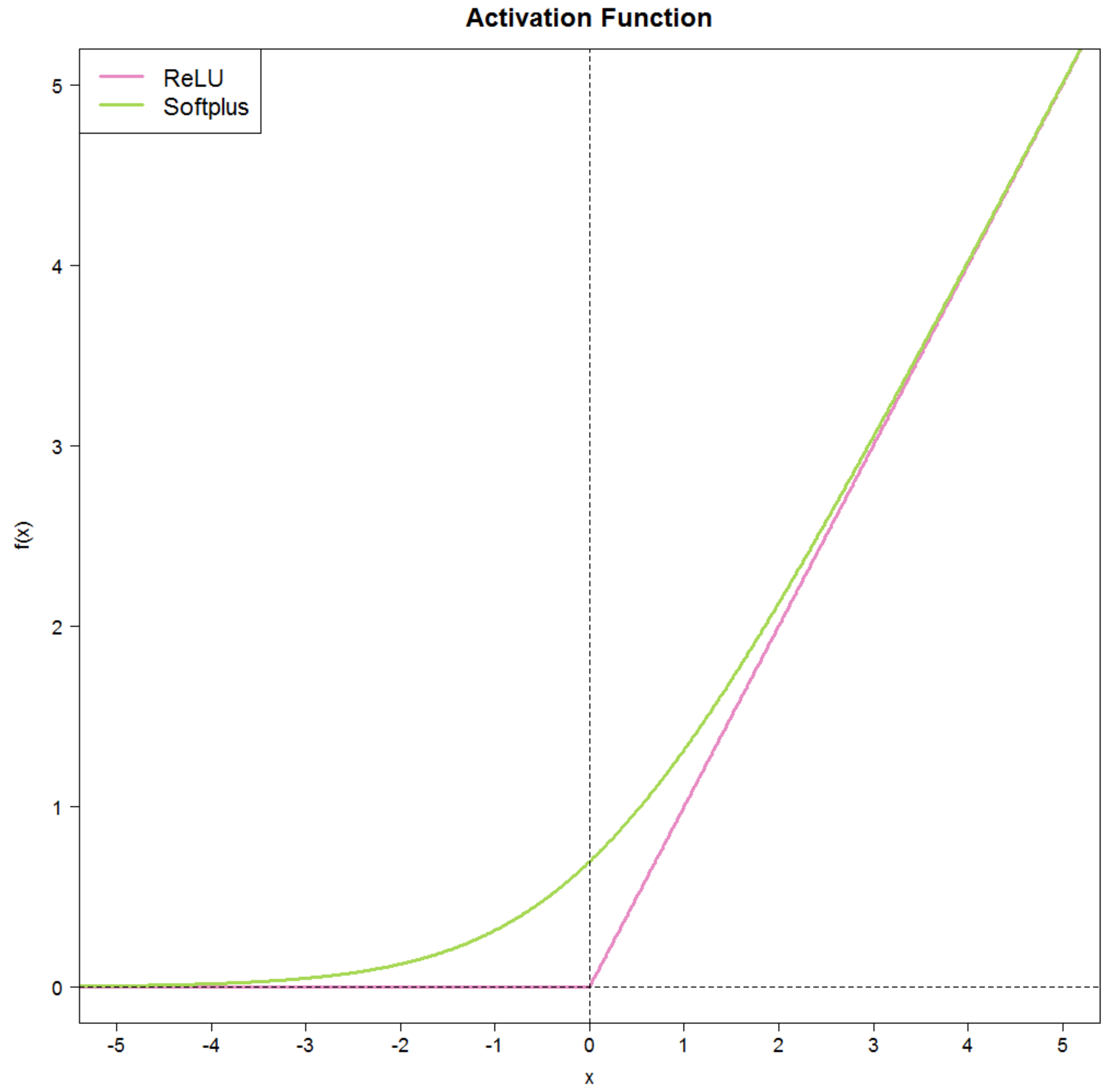
Drawbacks of Sigmoid, Tanh, Softsign

- 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

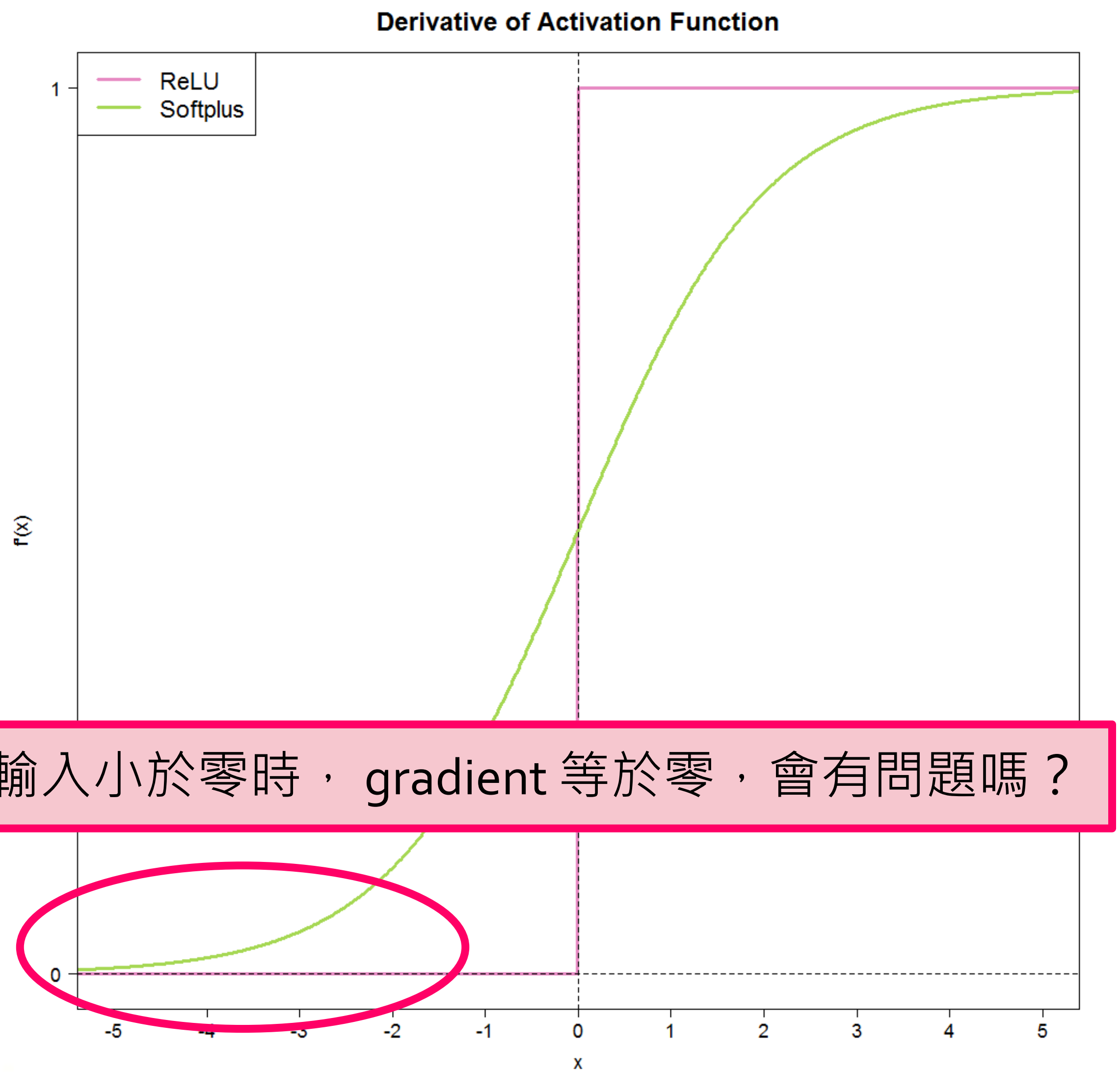
- 特別不適用於深的深度學習模型

ReLU, Softplus

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



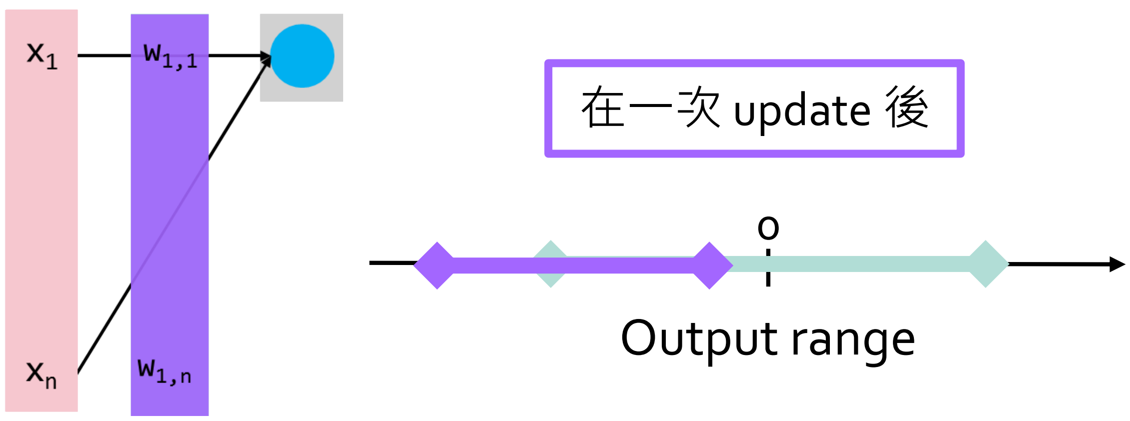
Derivatives of ReLU, Softplus



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.
```

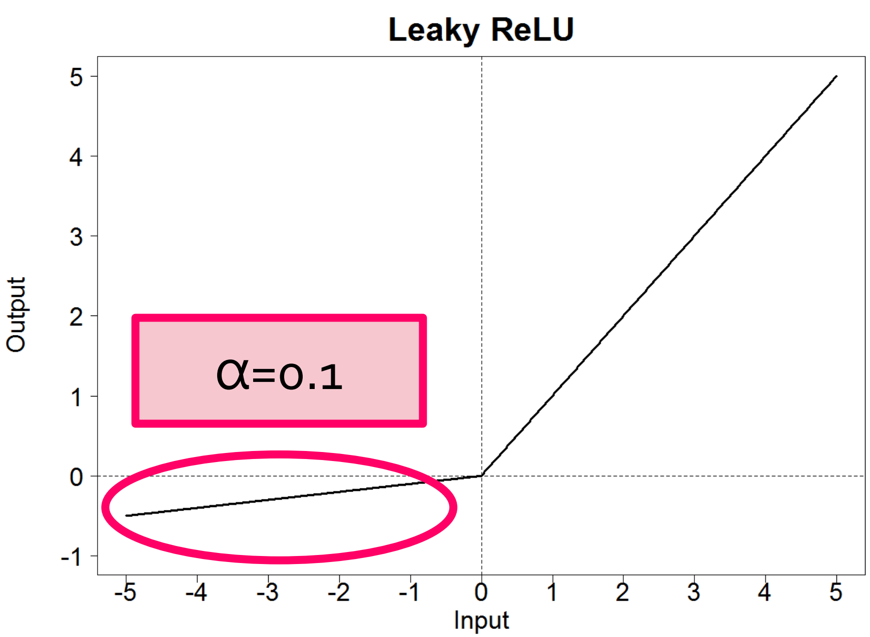
  - 可能因為 Learning rate 大 或是 batch size 小

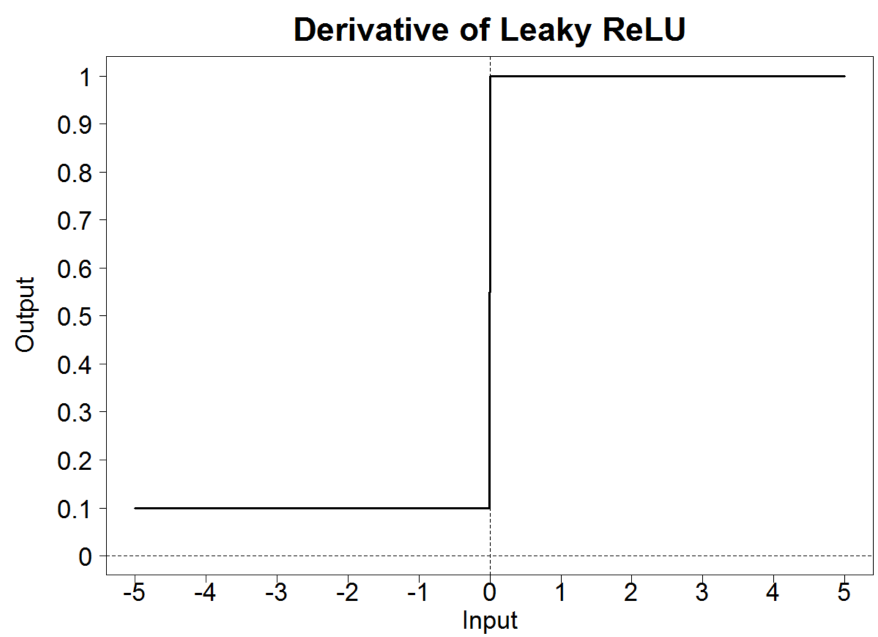
Leaky ReLU

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

```
f(x)=  x if x > 0,
       αx otherwise.
```

```
df/dx=  1 if x > 0,
        α otherwise.
```





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)
```

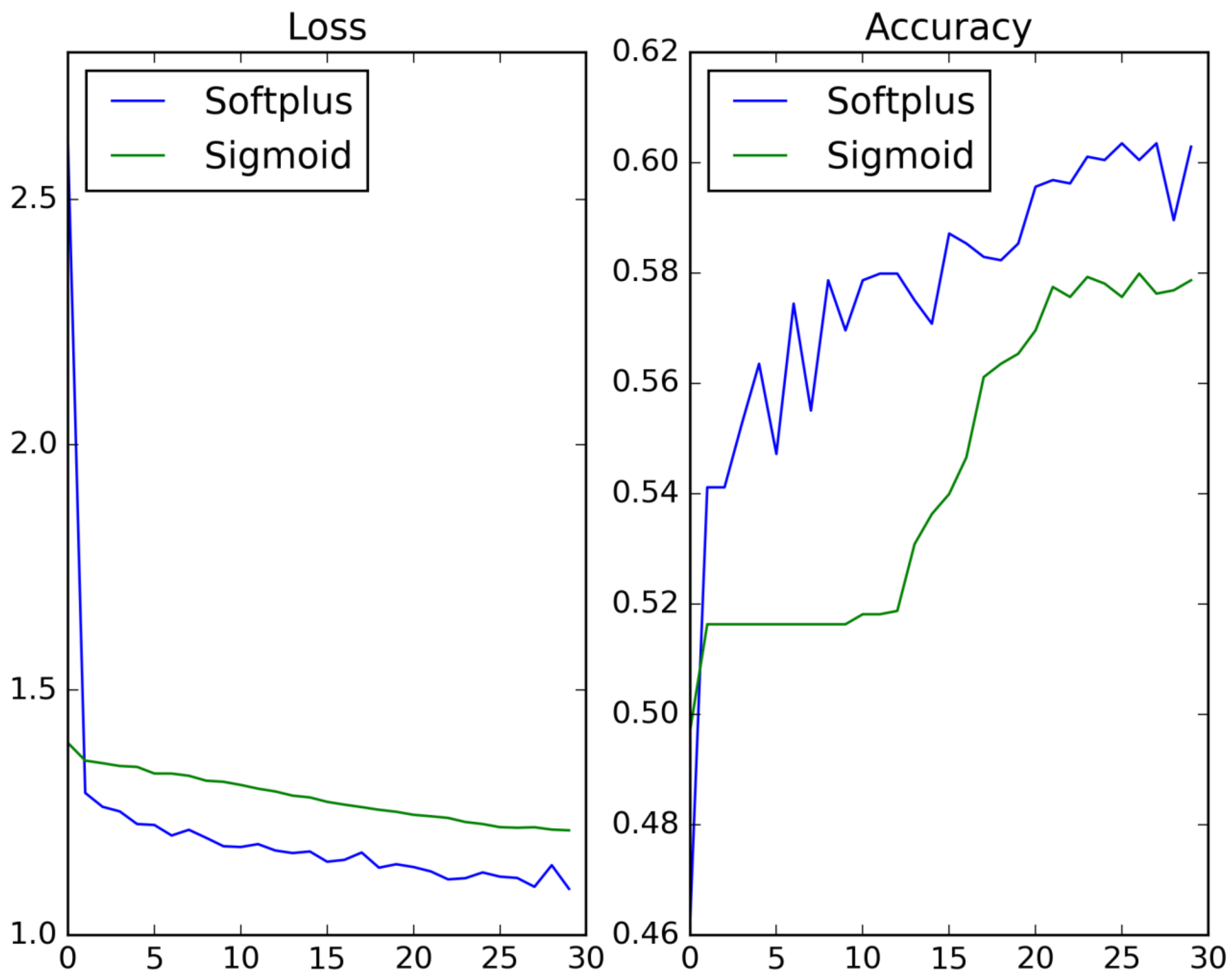
- 更多其他的 activation functions
  https://keras.io/layers/advanced-activations/

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



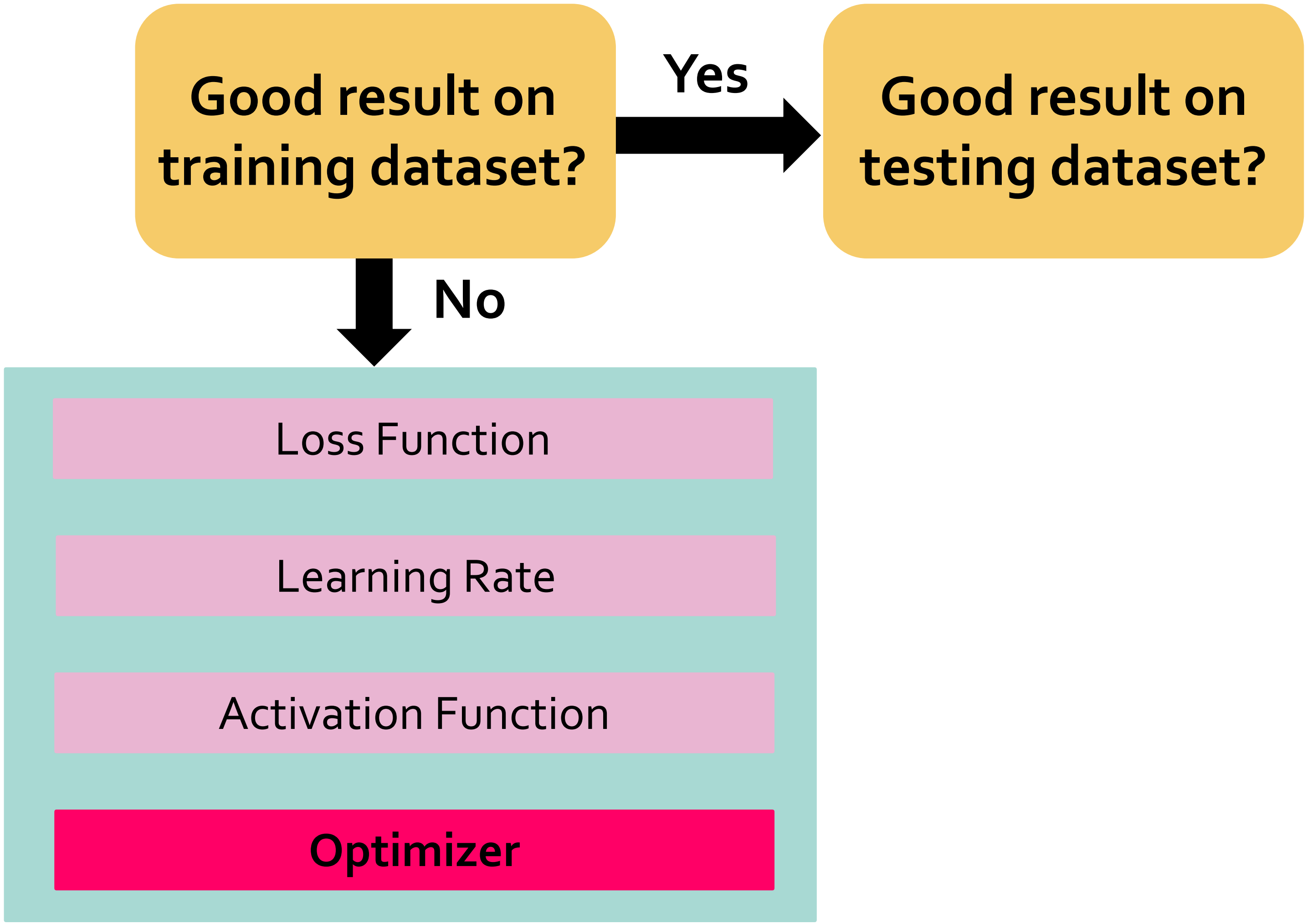
How to Select Activation Functions

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

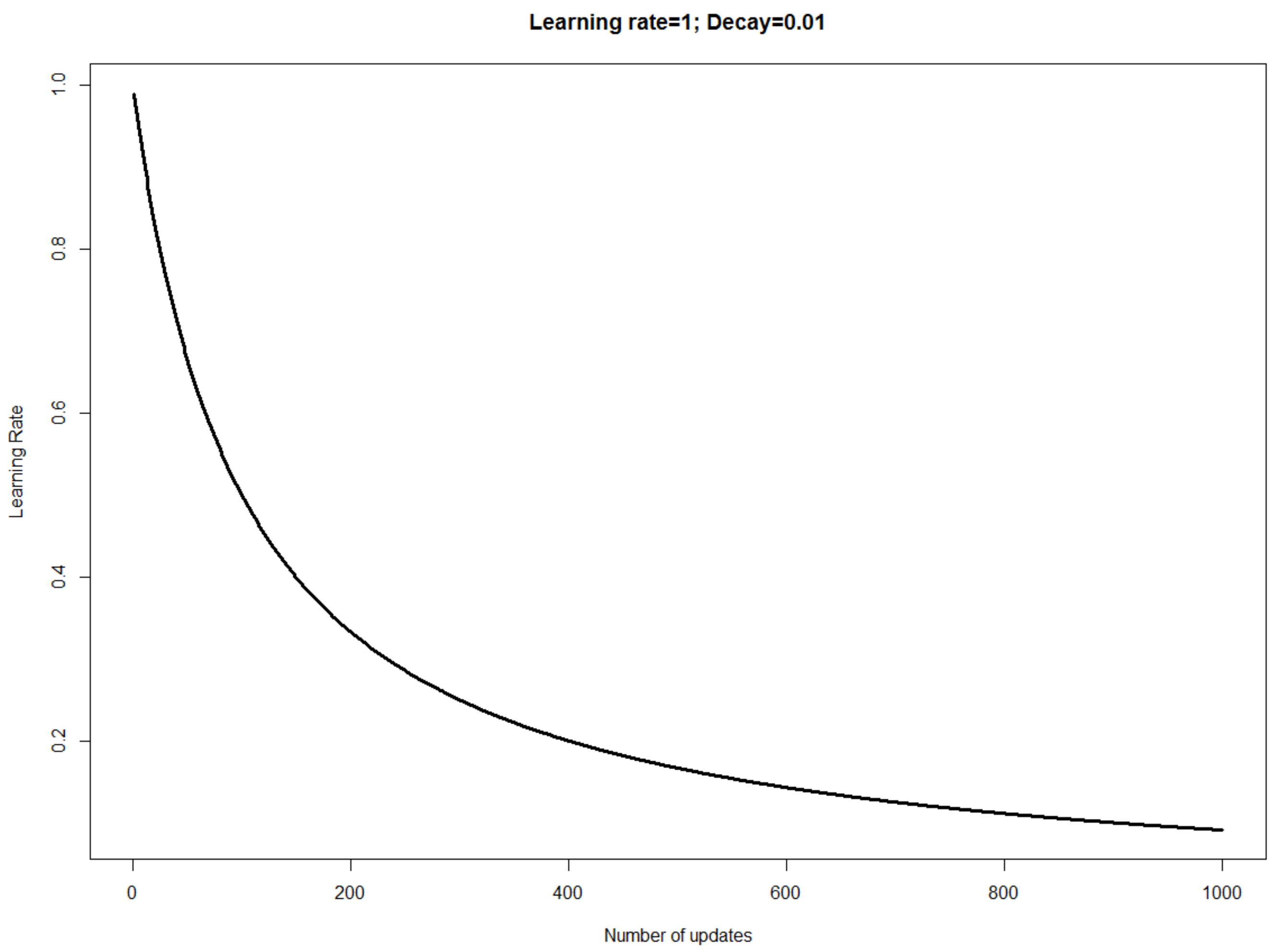
- Stochastic gradient descent
- 支援 momentum, learning rate decay, Nesterov momentum

```
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)
```



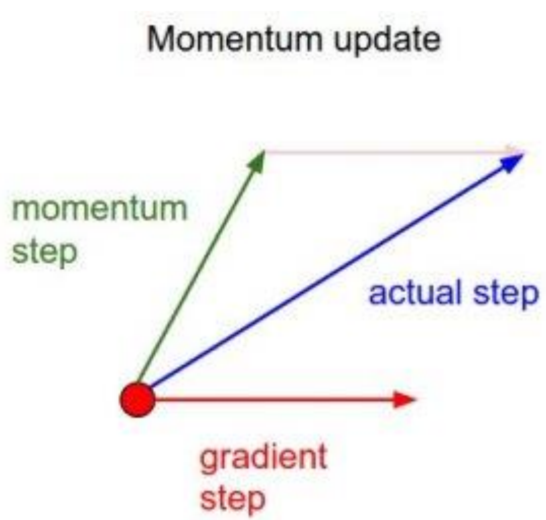
Nesterov Momentum

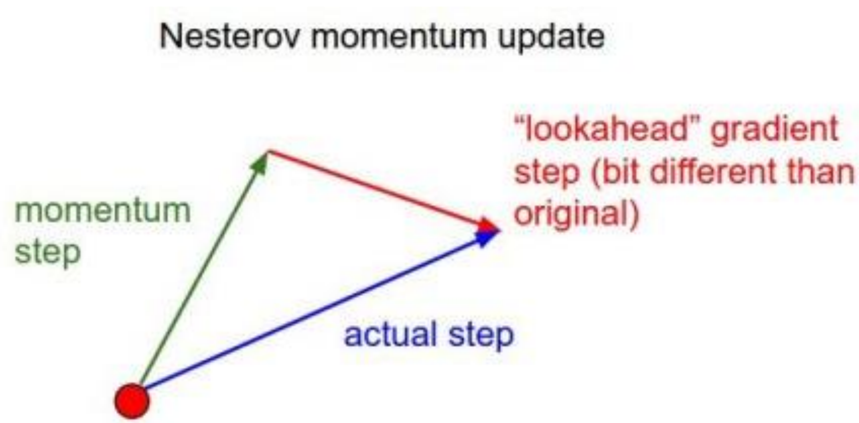
Momentum

- 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

$$g^t = \frac{\partial L}{\partial \theta}\bigg|_{\theta=\theta^t}$$

Gradient descent

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

Adagrad

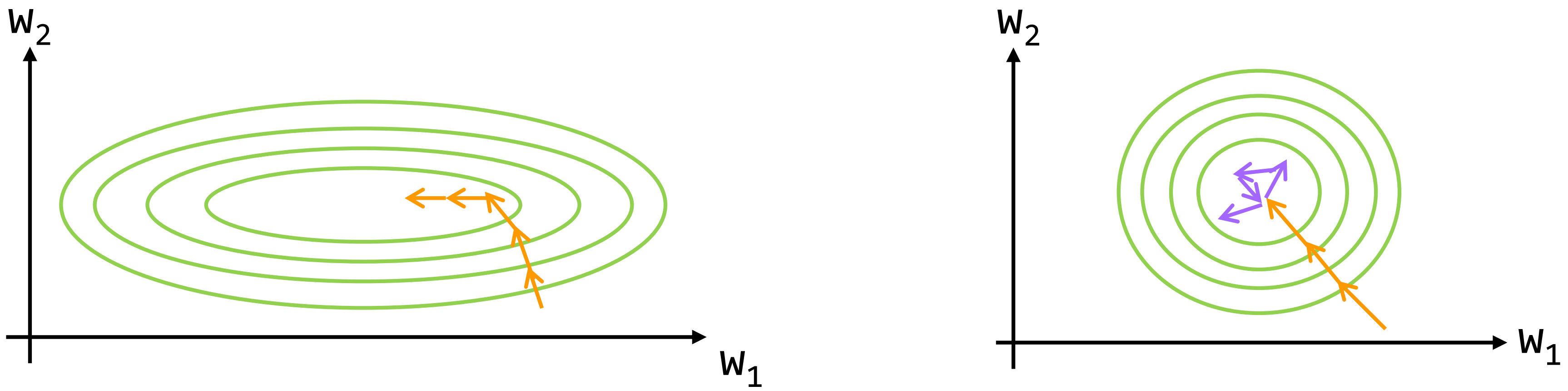
$$\theta^{t+1} = \theta^t - \frac{\eta}{\boxed{\sigma^t}} g^t$$

所有 gradient 的 root mean square

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

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

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

所有 gradient 的 root mean square

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

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

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

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

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

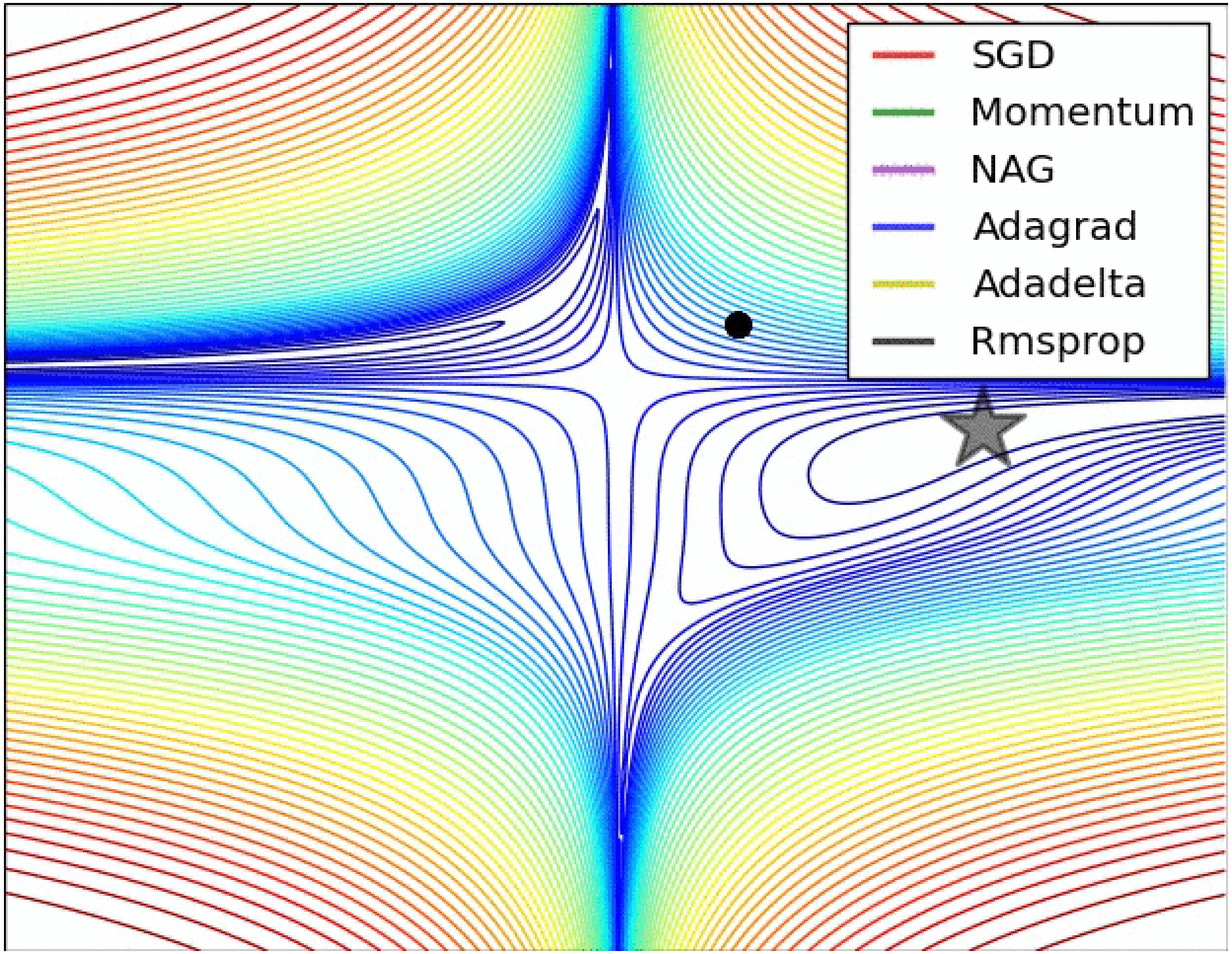
```
keras.optimizers.RMSprop(lr=0.001, rho=0.9, epsilon=1e-08, decay=0.0)
```

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)

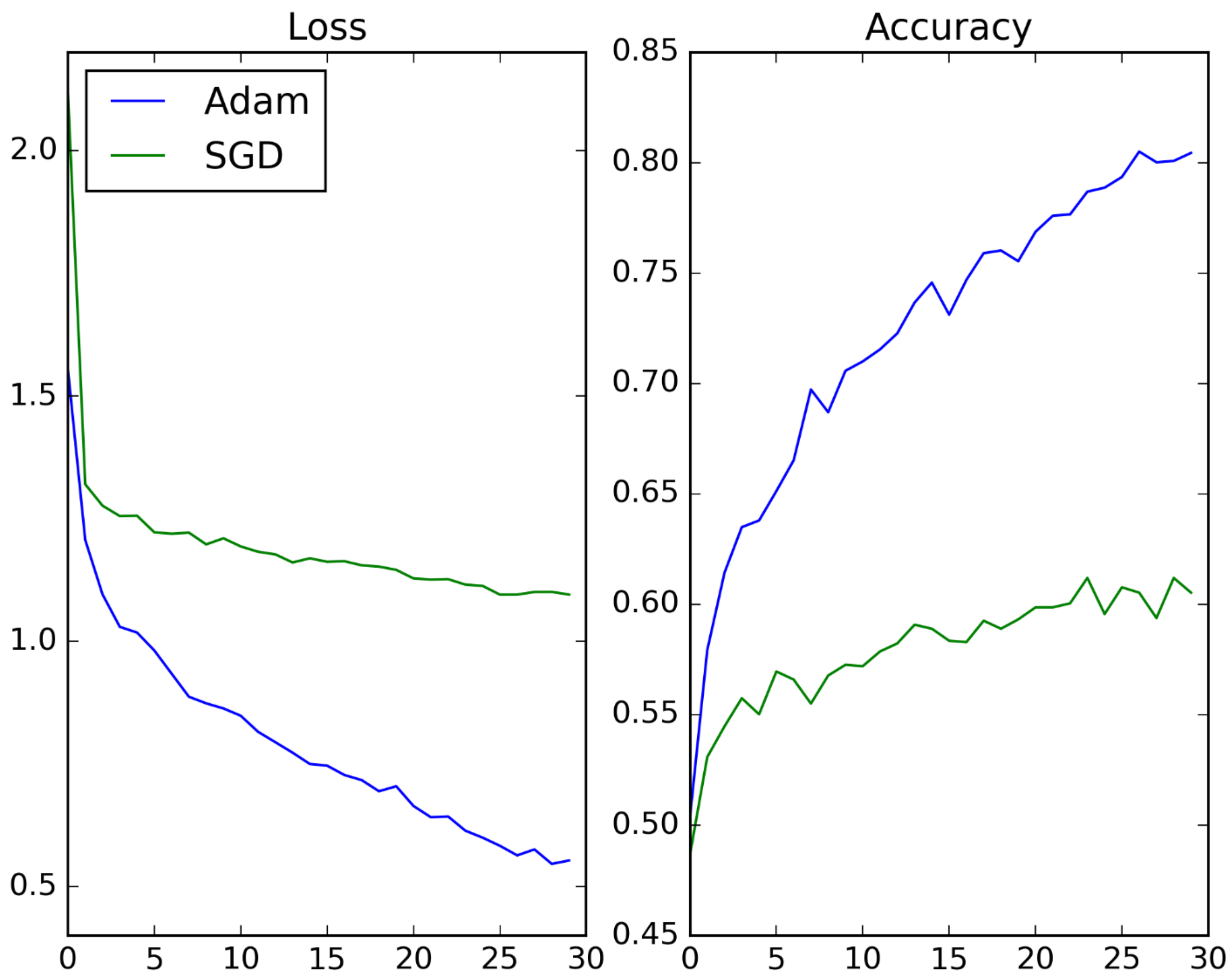
1. 設定選用的 optimizer

```
# 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

Good result on training data?

Yes

Good result on testing data?

No

Loss Function

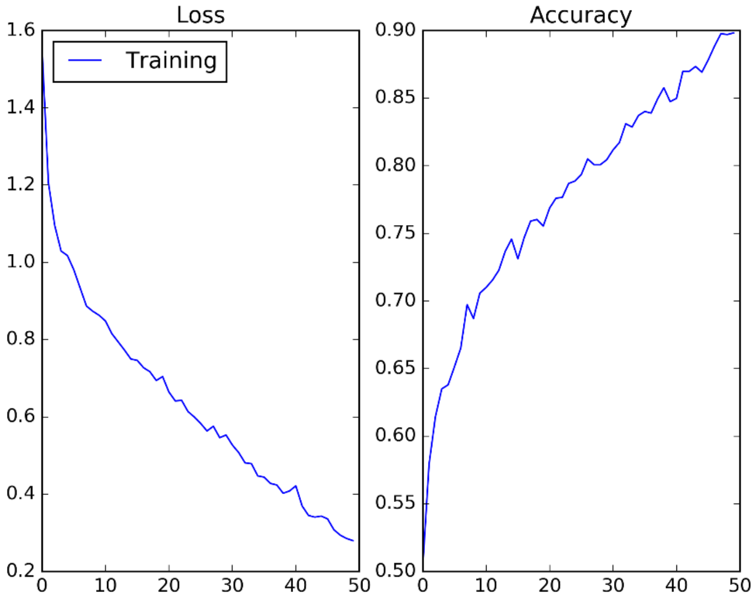
Learning Rate

Activation Function

Optimizer

Current Best Model Configuration

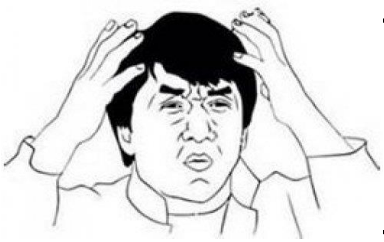
Component	Selection
Loss function	categorical_crossentropy
Activation function	softplus + softmax
Optimizer	Adam



進度報告

我們有90%準確率了！

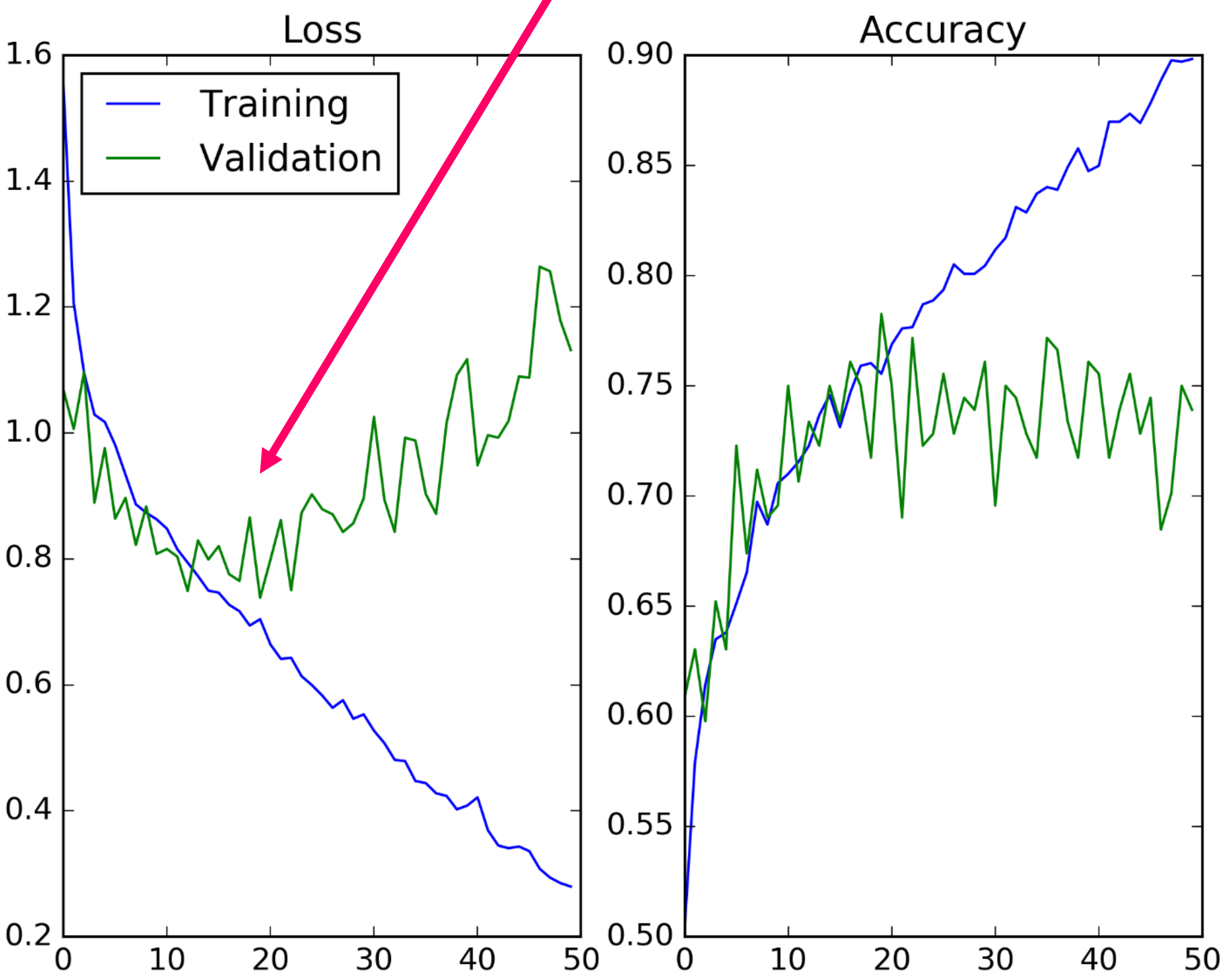
但是在 training dataset 上的表現



這會不會只是一場美夢？

見真章

Overfitting 啦!

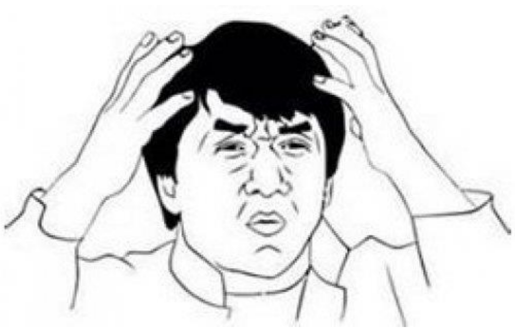


Tips for Deep Learning

Good result on training dataset? → Yes → Good result on testing dataset? → Yes →

Good result on testing dataset? → No ↓

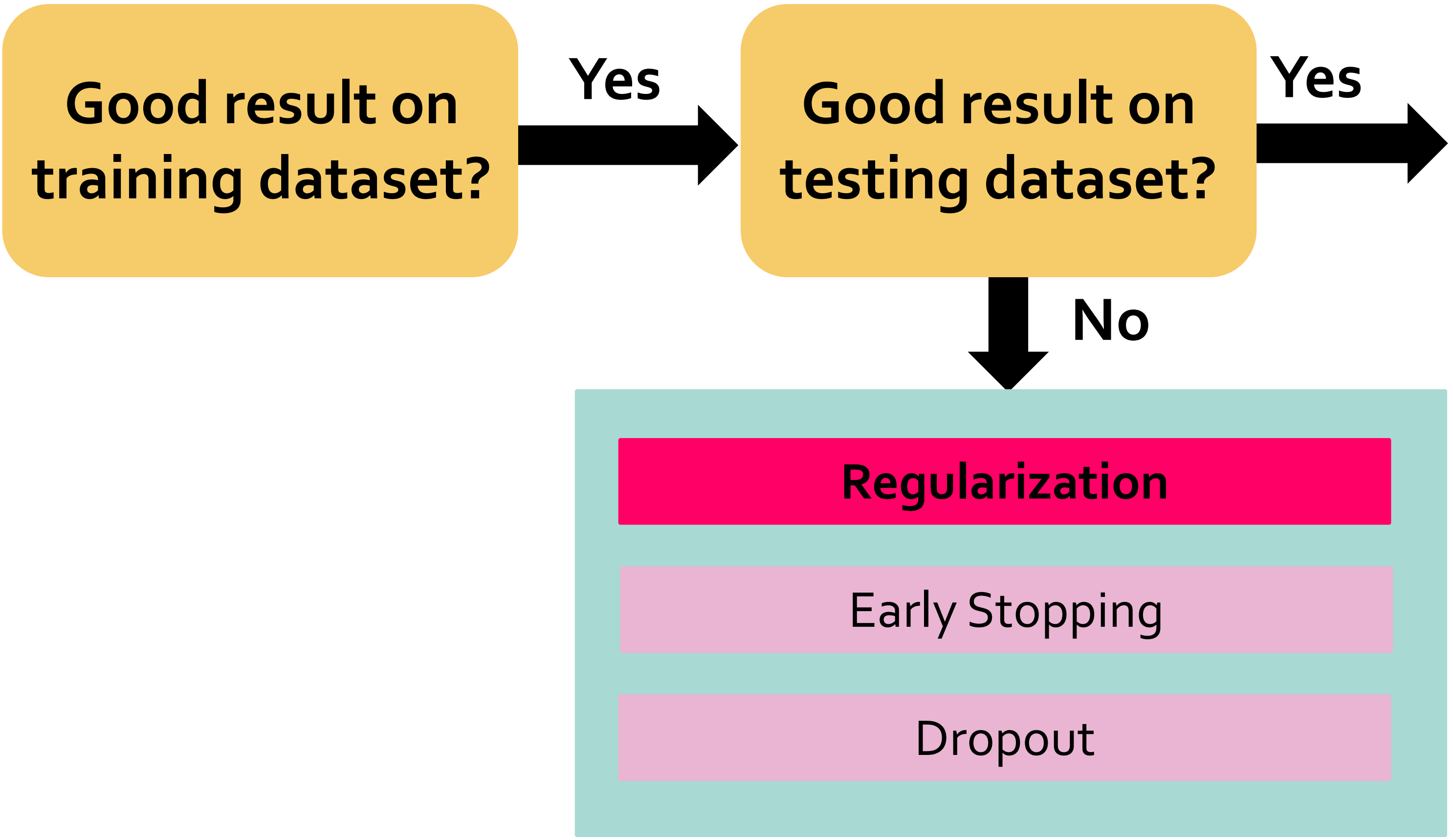
- Regularization
- Early Stopping
- Dropout



什麼是 overfitting？

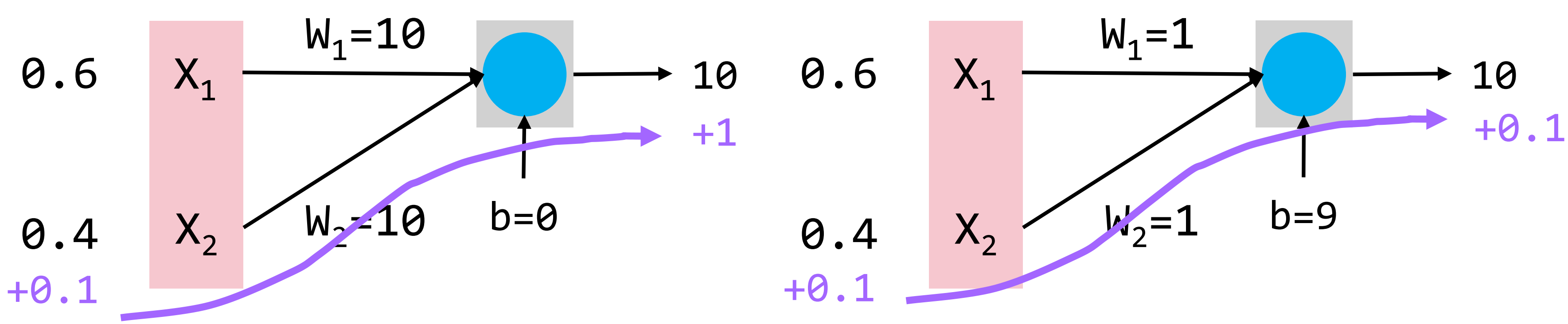
training result 進步，但 testing result 反而變差

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

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

- 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

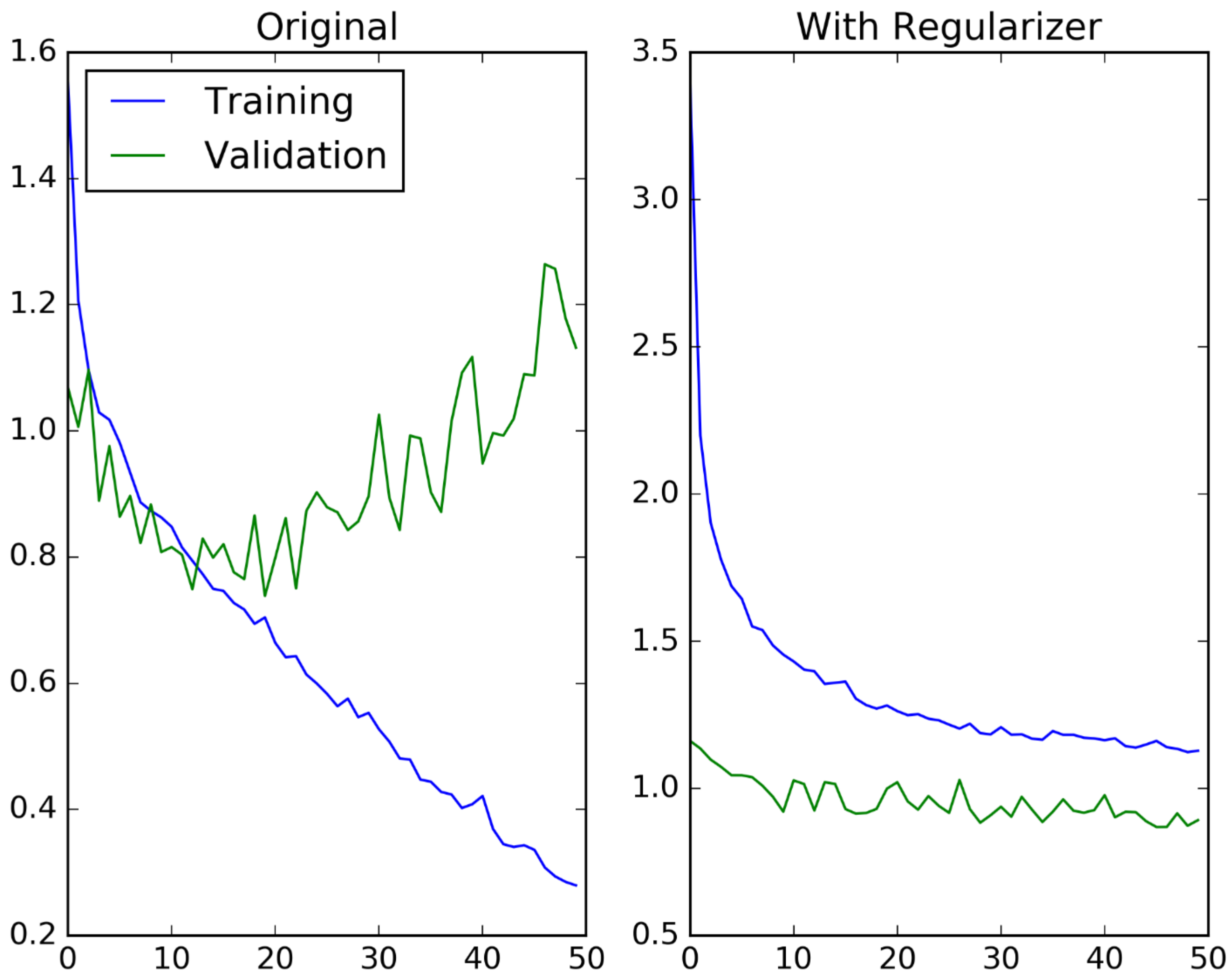
```
''' Import l1,l2 (regularizer) '''
from keras.regularizers import l1,l2

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('softplus'))

# 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('softplus'))

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

練習 06_regularizer.py (5-8 minutes)

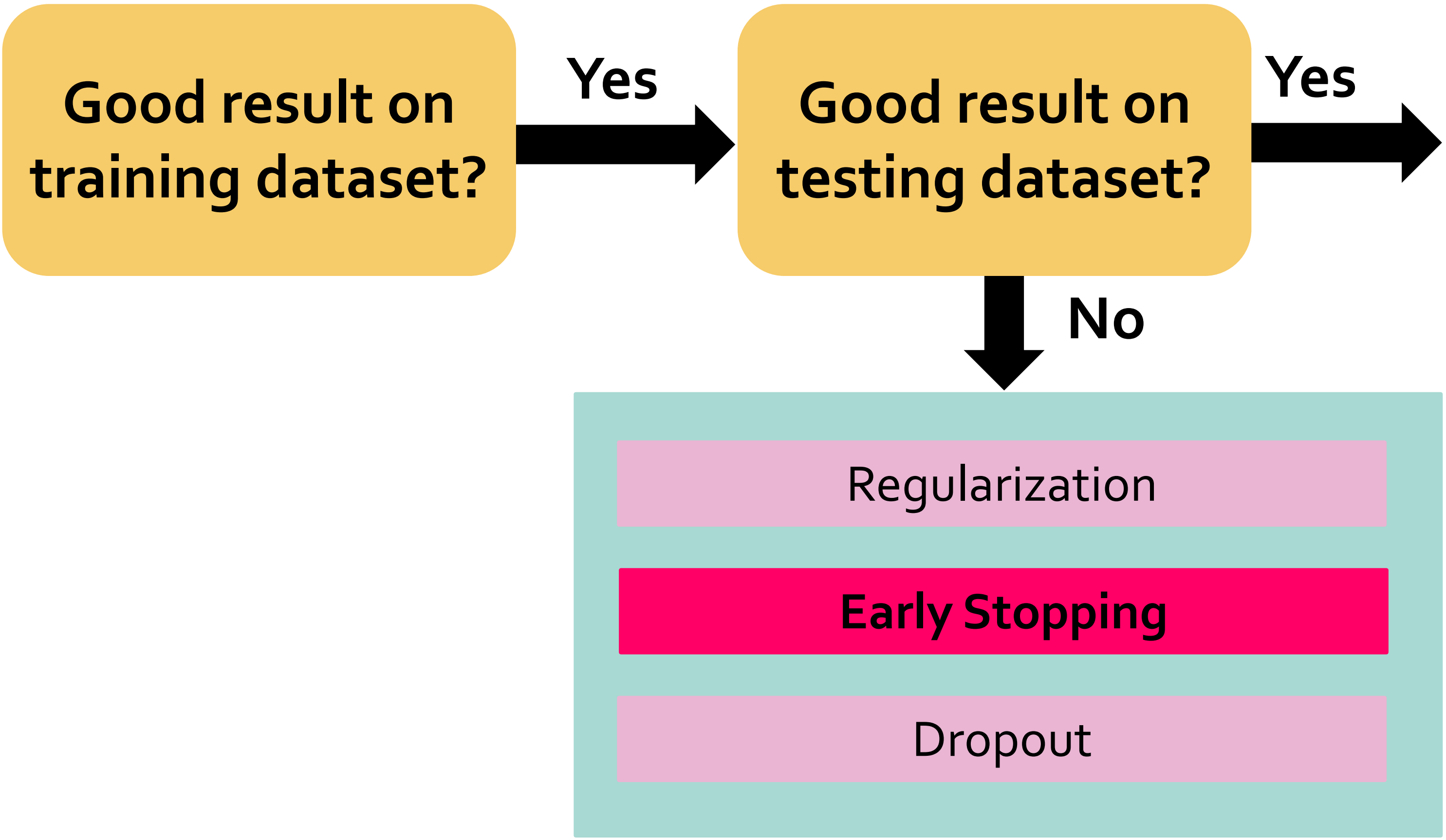
```
''' Import l1,l2 (regularizer) '''
from keras.regularizers import l1,l2
# 加入第一層 hidden layer 並加入 regularizer (alpha=0.01)
Model_l2.add(Dense(128,input_dim=200,kernel_regularizer=l2(0.01)))
Model_l2.add(Activation('softplus'))
```

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=0.01)

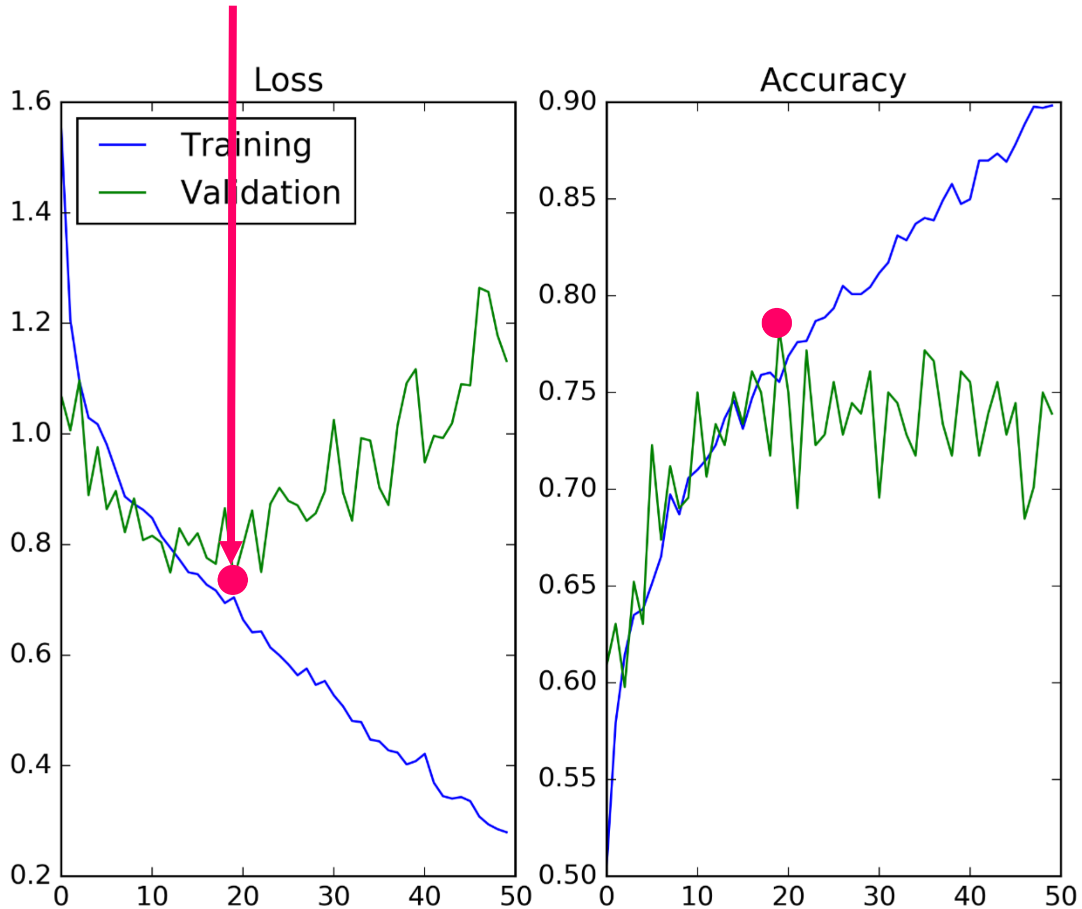


Tips for Deep Learning



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

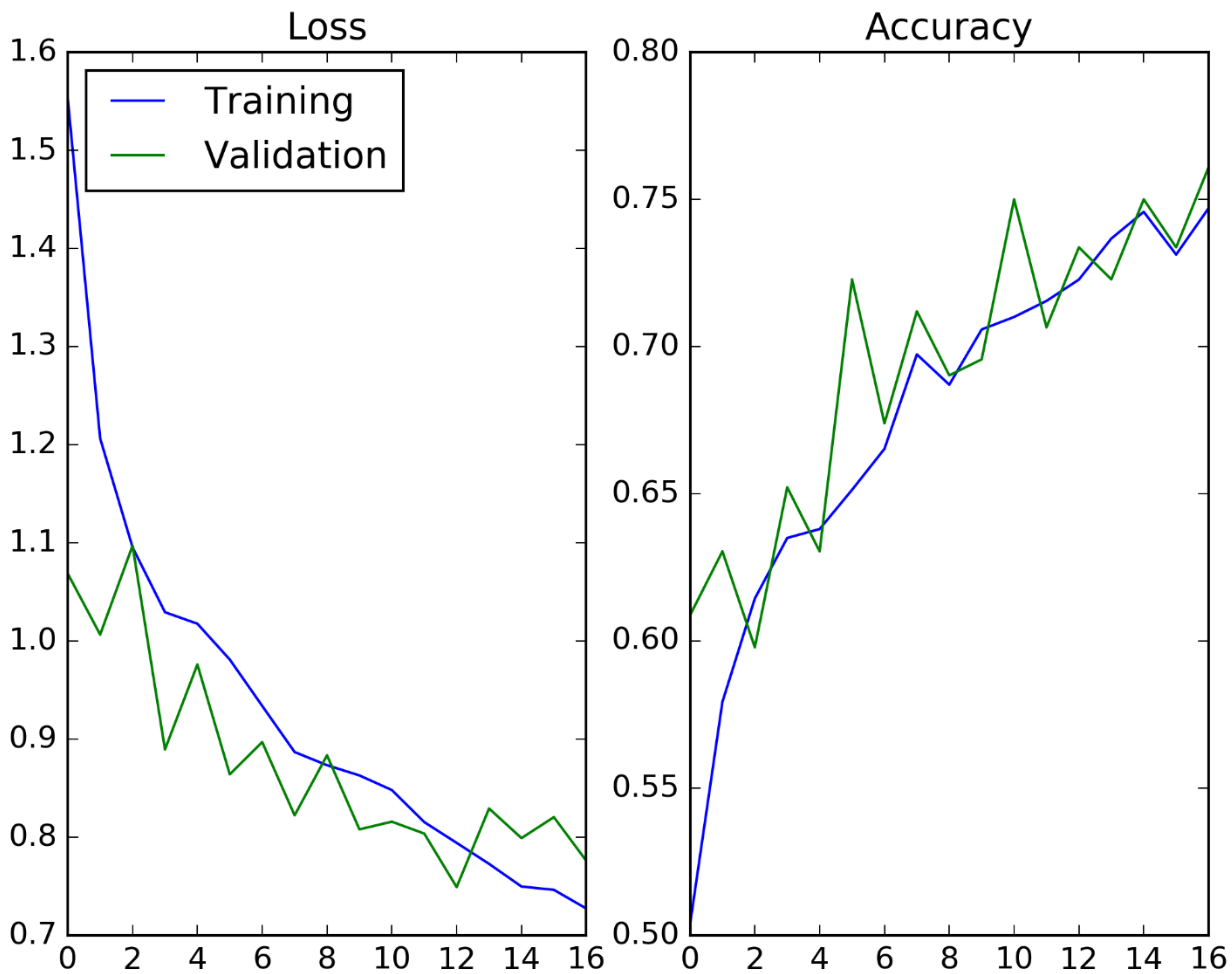
加入 Early Stopping

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

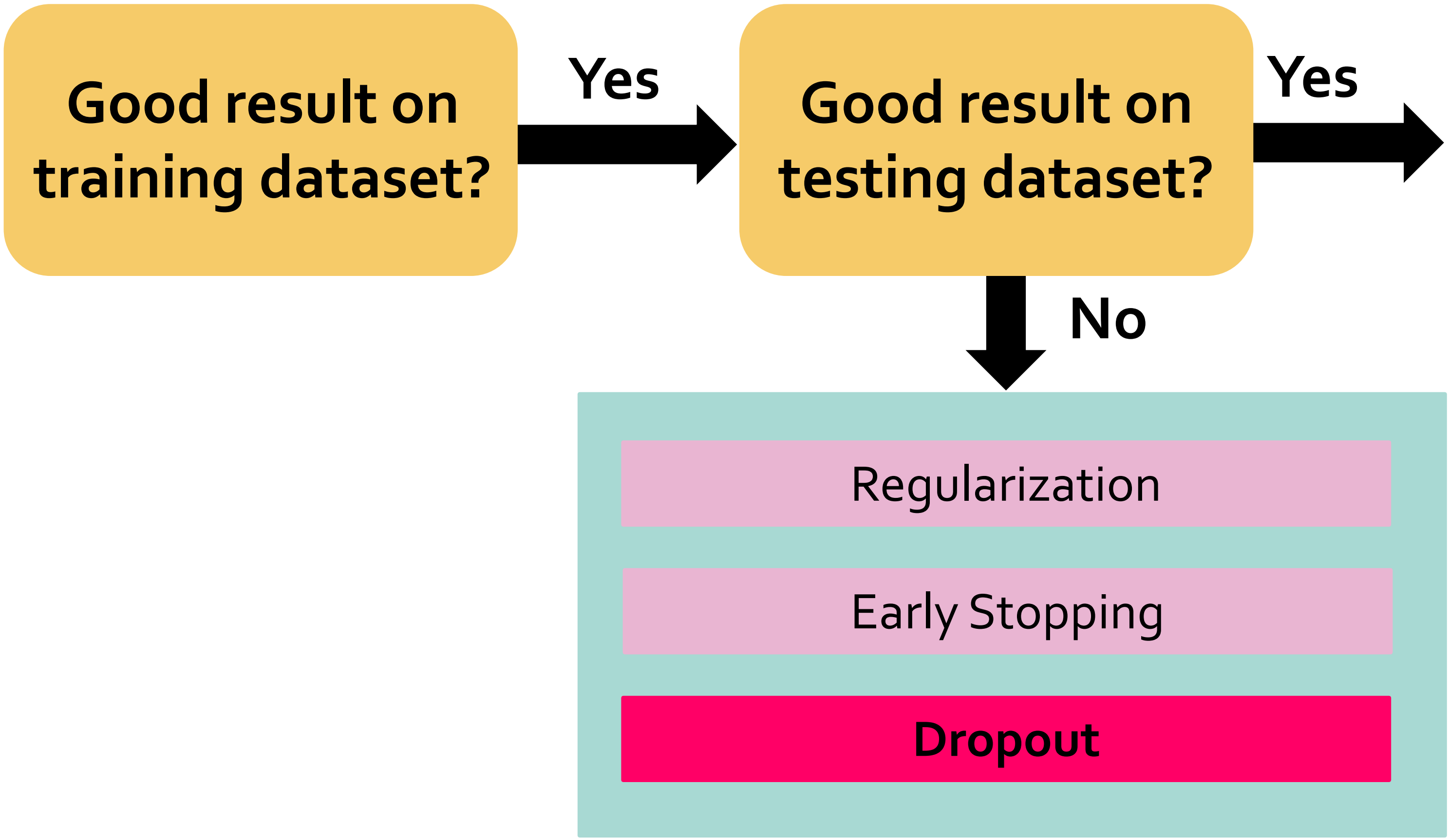
```
# 指定 batch_size, nb_epoch, validation 後，開始訓練模型!!!
history = model.fit( X_train,
                     Y_train,
                     batch_size=16,
                     verbose=0,
                     epochs=30,
                     shuffle=True,
                     validation_split=0.1,
        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

練習 07_earlyStopping.py
(5-8 minutes)

Result – EarlyStopping (patience=3)

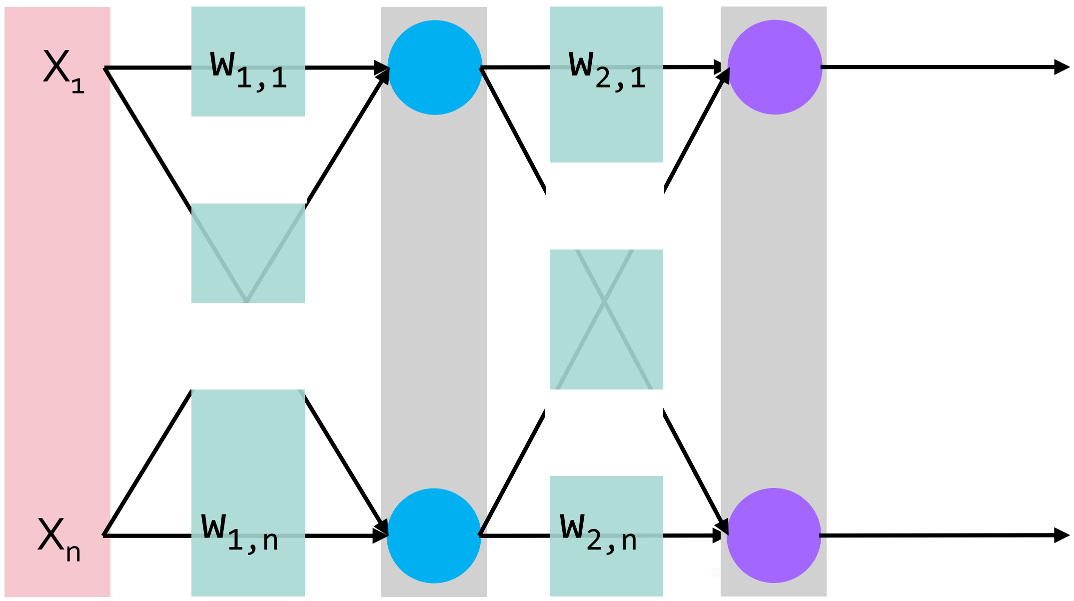


Tips for Deep Learning



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)



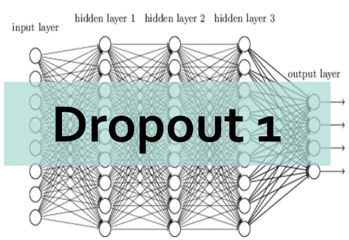
Dropout 的結果

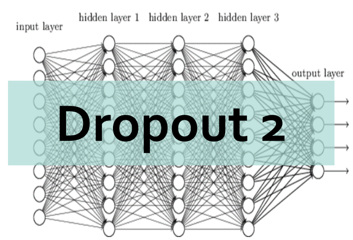
- 會造成 training performance 變差
  - 用全部的 neurons 原本可以做到 $(\hat{y} - y) < \epsilon$
  - 只用某部分的 neurons 只能做到 $(\hat{y}' - y) < \epsilon + \Delta\epsilon$
  - Error 變大 ➔ 每個 neuron 修正得越多 ➔ 做得越好

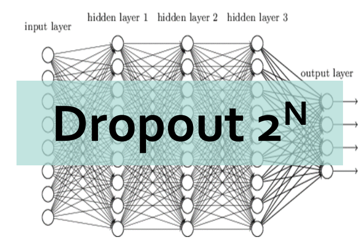
Implications

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





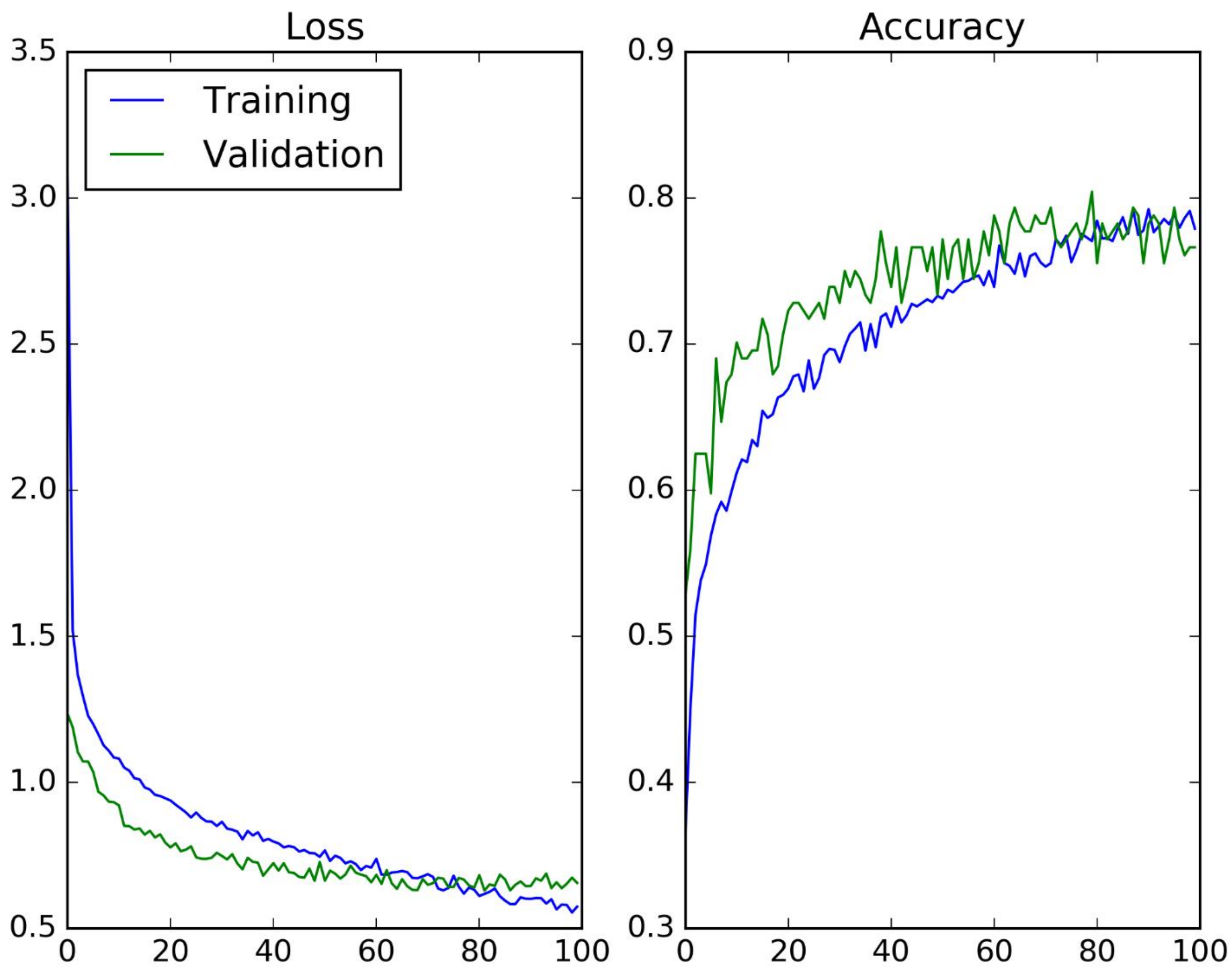


Dropout in Keras

```
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



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

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

LearningRateScheduler

```
from keras.callbacks import LearningRateSchedler

def step_decay(epoch):
      initial_lrate = 0.1
      lrate = initial_lrate * (0.999^epoch)
      return lrate

Lrate = LearningRateScheduler(step_decay)
```

感謝同學指正！

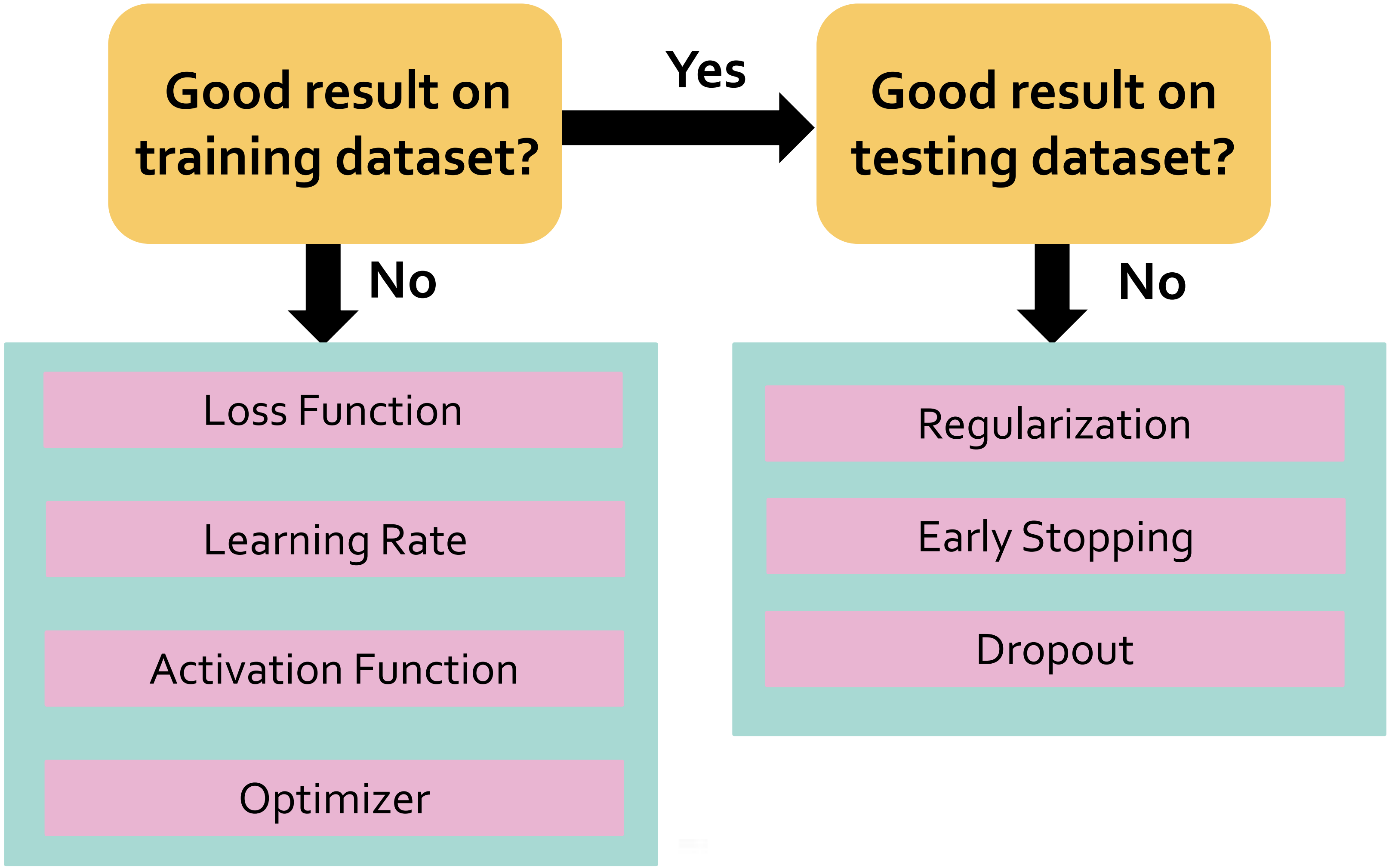
ModelCheckpoint

```
from keras.callbacks import ModelCheckpoint

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

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])
```

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
STOP
OUTPUT HELLO <NAME>
COMPUTER
SOFTWARE
CHAT
WWW
LOADING..
S
O
E

Variants of Deep Neural Network

Convolutional Neural Network (CNN)

2-dimensional Inputs

- DNN 的輸入是一維的向量，那二維的矩陣呢? 例如圖形資料

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

Ordinary Feedforward DNN with Image

- 將圖形轉換成一維向量
  - Weight 數過多，造成 training 所需時間太長
  - 左上的圖形跟右下的圖形真的有關係嗎?

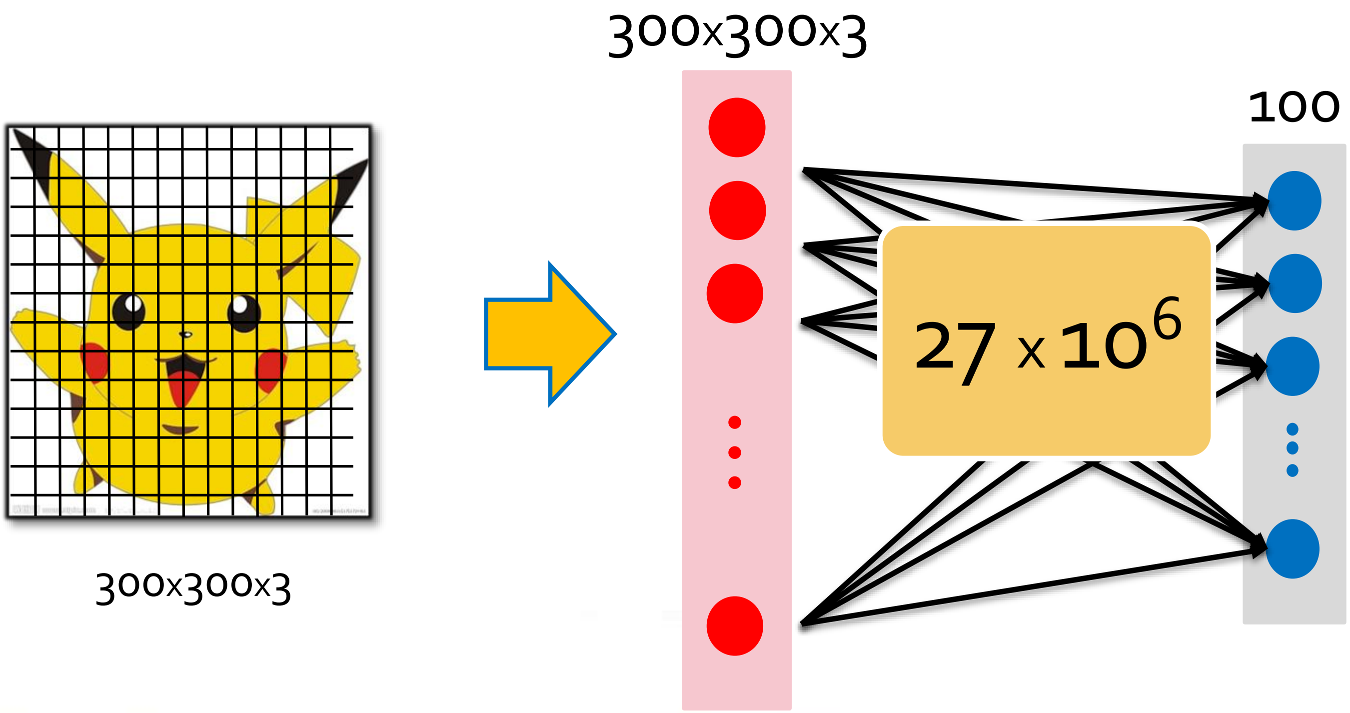


Figure reference
http://www.ettoday.net/dalemon/post/12934

Characteristics of Image

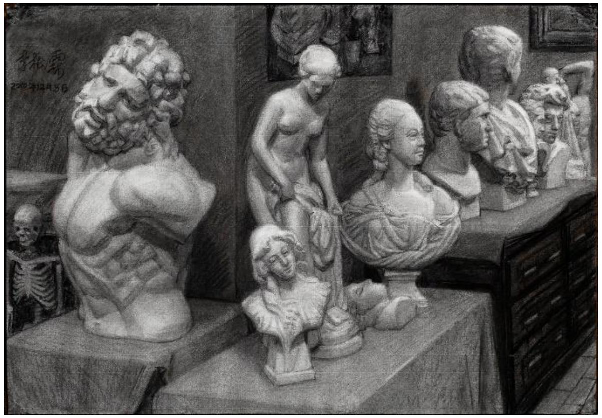
- 圖的構成：線條 → 圖案 (pattern)→物件 →場景

Line Segment

Pattern

Object

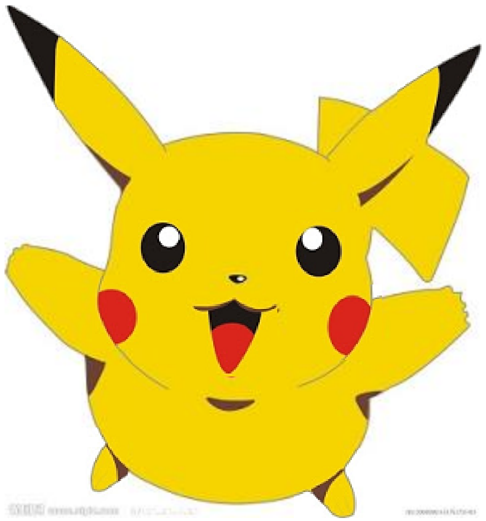
Scene



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

Patterns

- 猜猜看我是誰
- 辨識一個物件只需要用幾個特定圖案



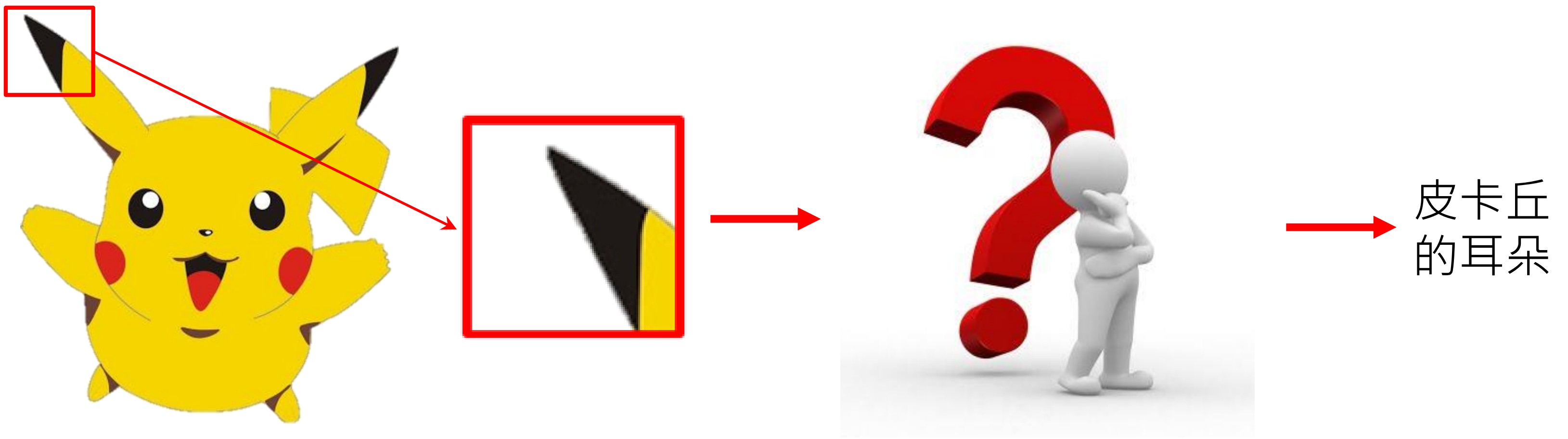
皮卡丘

小火龍

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

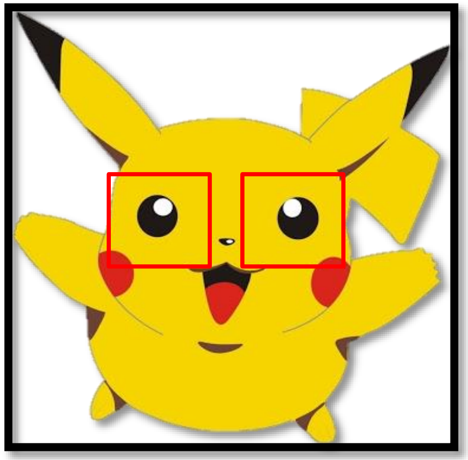
Property 1: What

- 圖案的類型



Property 2: Where

- 重複的圖案可能出現在很多不同的地方



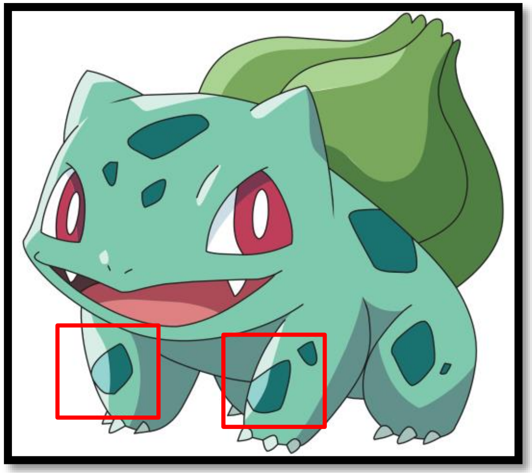
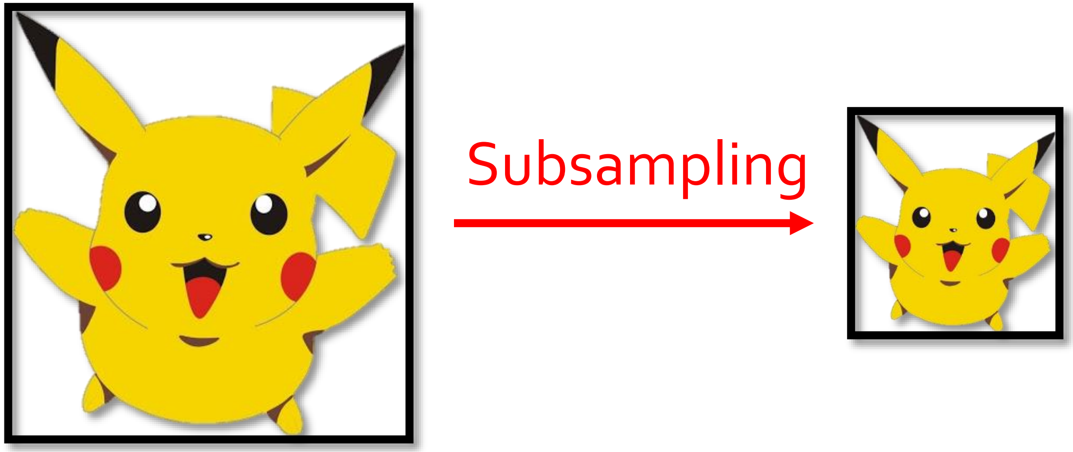


Figure reference
https://www.youtube.com/watch?v=NN9LaU2NlLM

Property 3: Size

- 大小的變化並沒有太多影響



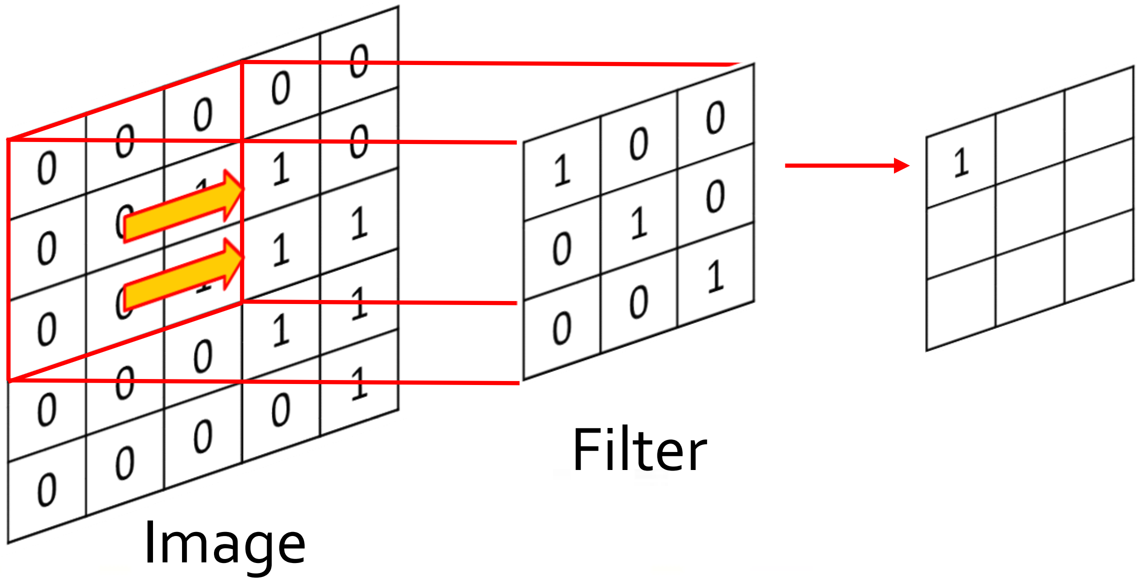
Convolution in Computer Vision (CV)

- Common applications
  - 模糊化, 銳利化, 浮雕
  - http://setosa.io/ev/image-kernels/

Convolution in Computer Vision (CV)

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

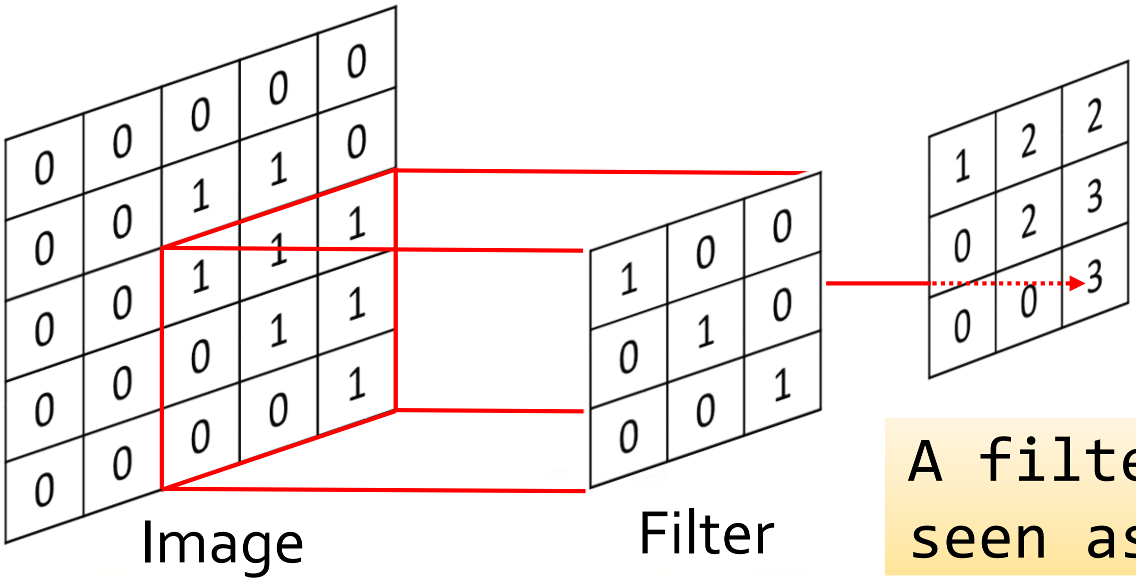
- Perform this convolution process to every pixels



Convolution in Computer Vision (CV)

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

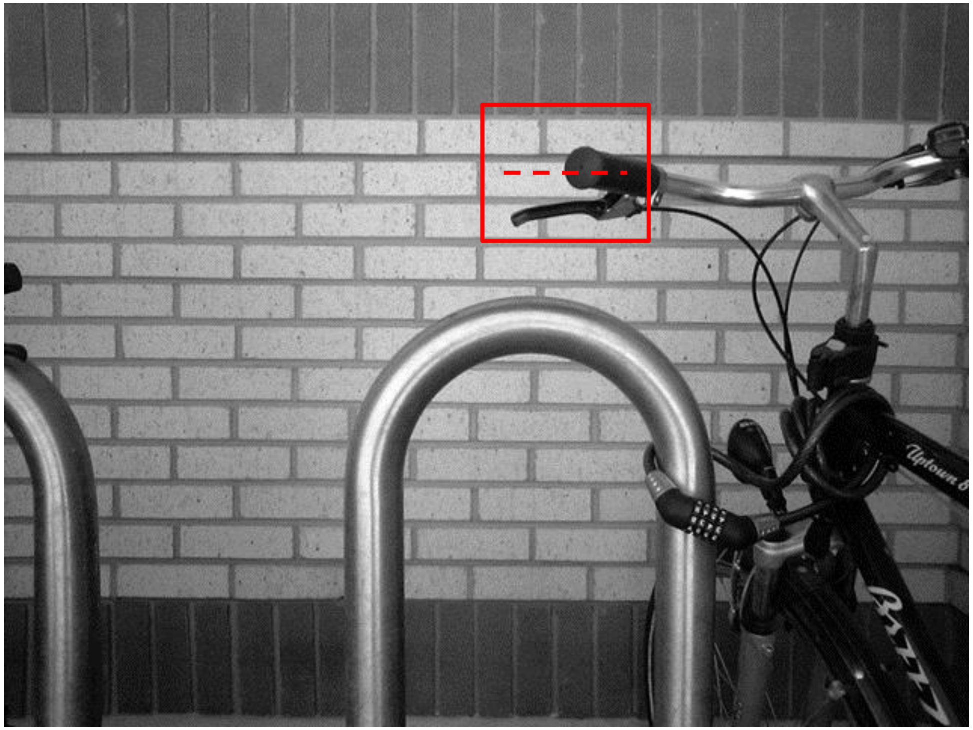
- Perform this convolution process to every pixels

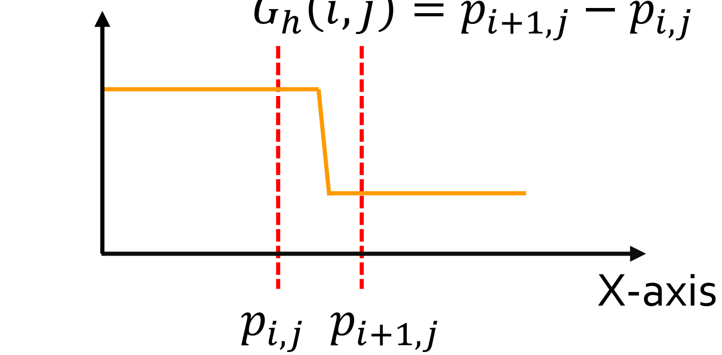


A filter could be seen as a pattern

Real Example: Sobel Edge Detection

- edge = 亮度變化大的地方





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

Multiply by a constant c

$c * G_h(i,j)$

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

凸顯兩像素之間的差異

Real Example: Sobel Edge Detection

- 相鄰兩像素值差異越大，convolution 後新像素絕對值越大

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

=

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

Original Image

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

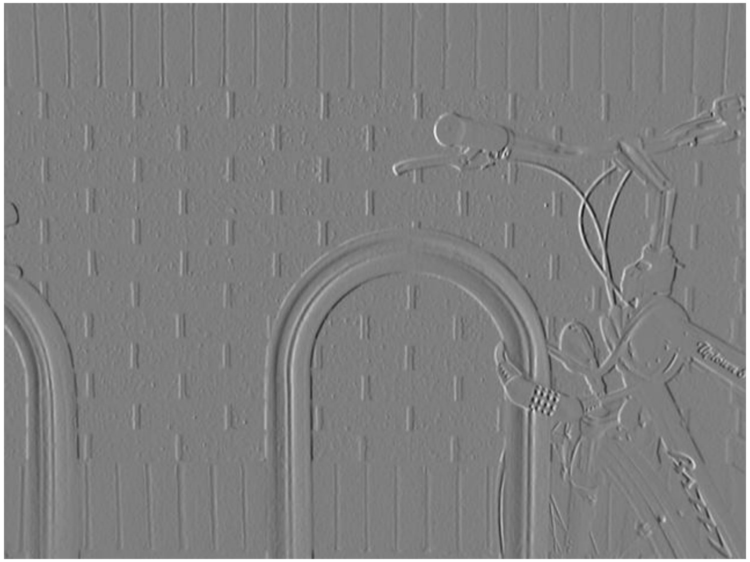
Real Example: Sobel Edge Detection

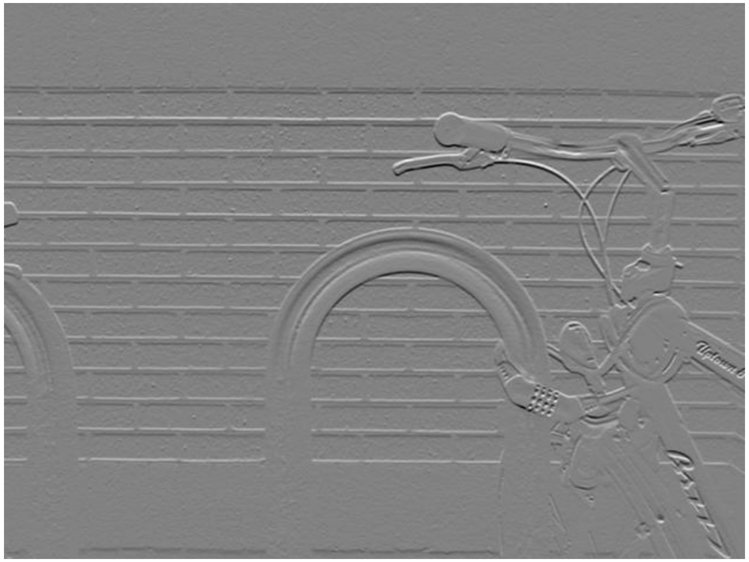
x-gradient

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

y-gradient

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

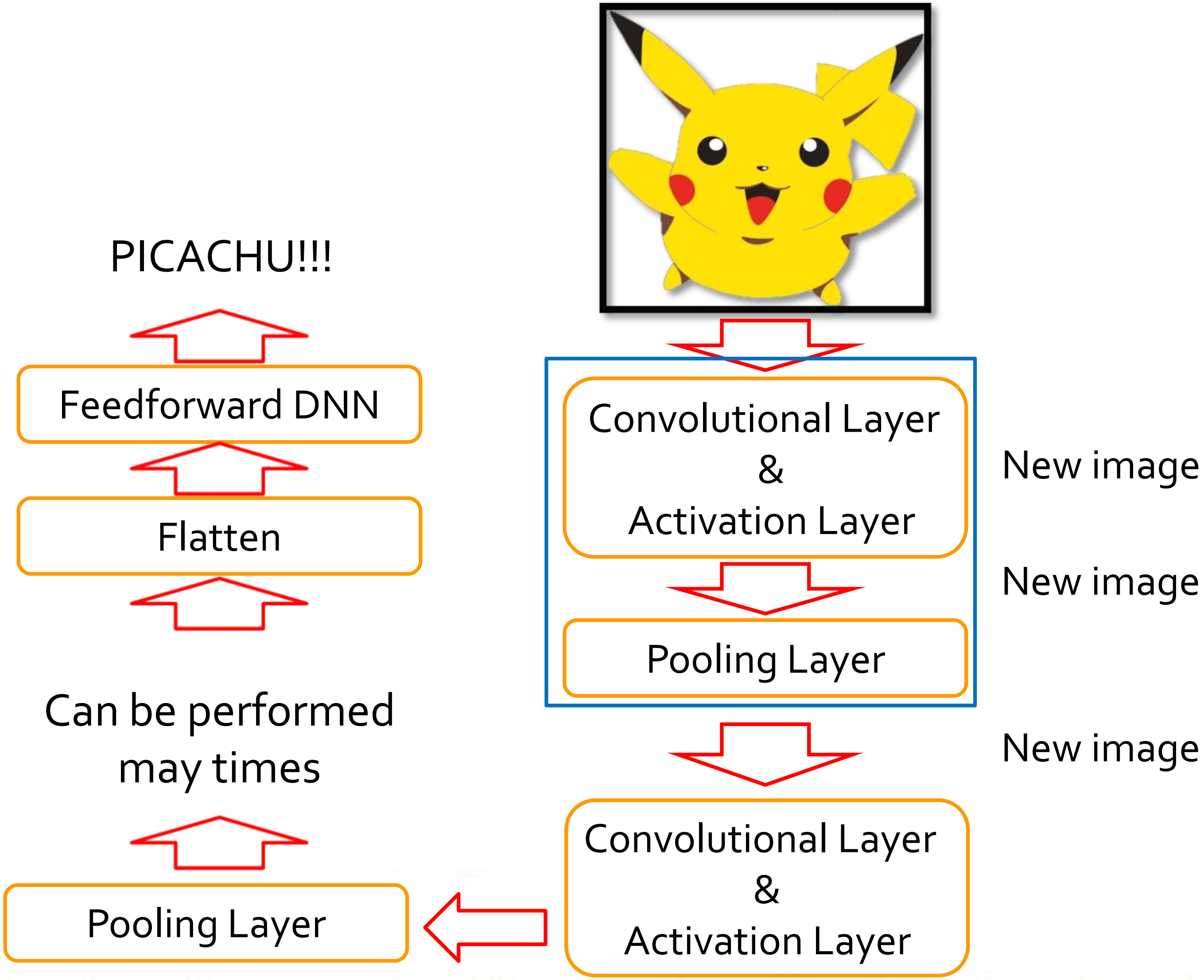




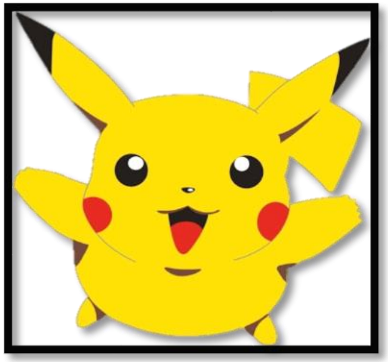
Real Example: Sobel Edge Detection

- Edge image

CNN Structure



Convolution Layer vs. Convolution in CV



Convolutional Layer
&
Activation Layer

New image

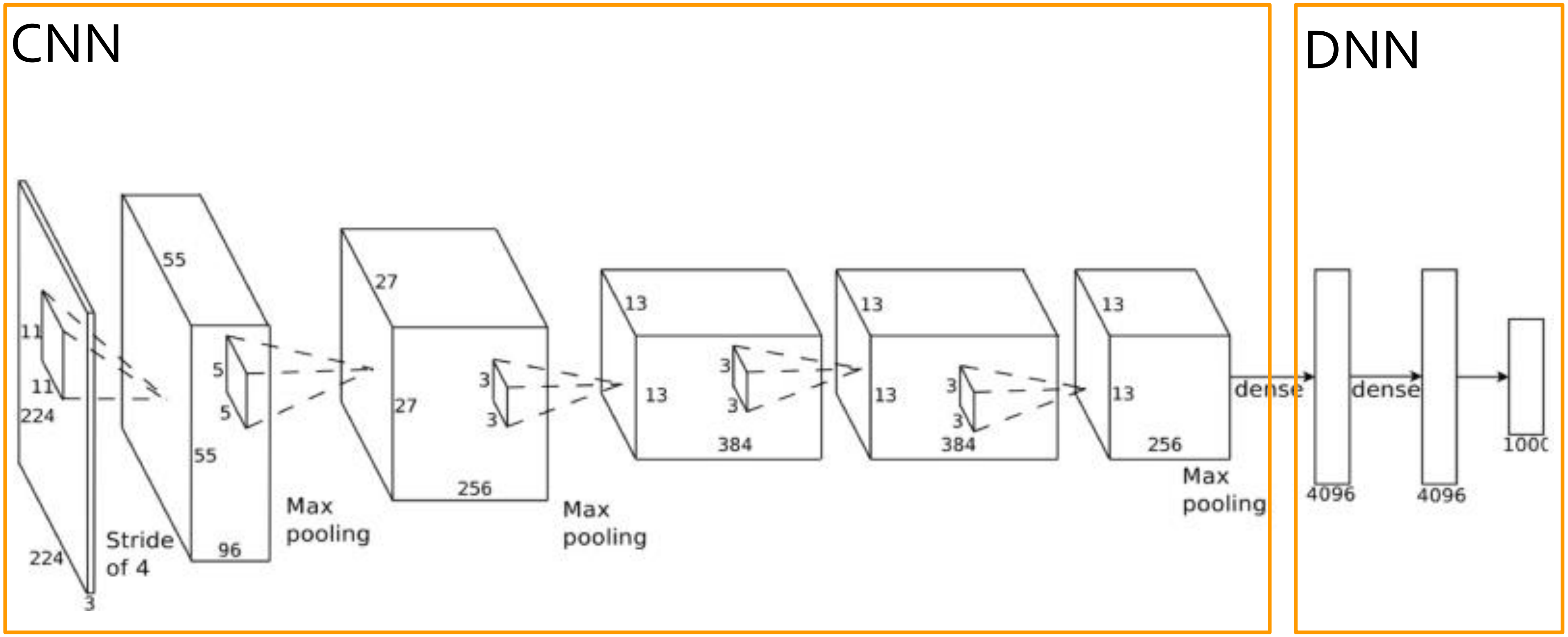
x-gradient

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

y-gradient

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

An Example of CNN Model



Flatten

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

這個步驟有那些地方是可以變化的呢?

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

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

Filter Size

- 5x5 filter

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

=

New image

3

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

Zero-padding 不會影響 convolution 的性質

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

1	2
3	3

Convolution on RGB Image

Filters, RGB image, Conv. image

$$\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix} * \begin{bmatrix}0&0&1&1\\1&1&1&1\\0&1&0&1\\0&0&1&0\end{bmatrix} = \begin{bmatrix}1&1&2&1\\2&1&2&2\\0&3&1&2\\0&0&2&0\end{bmatrix}$$

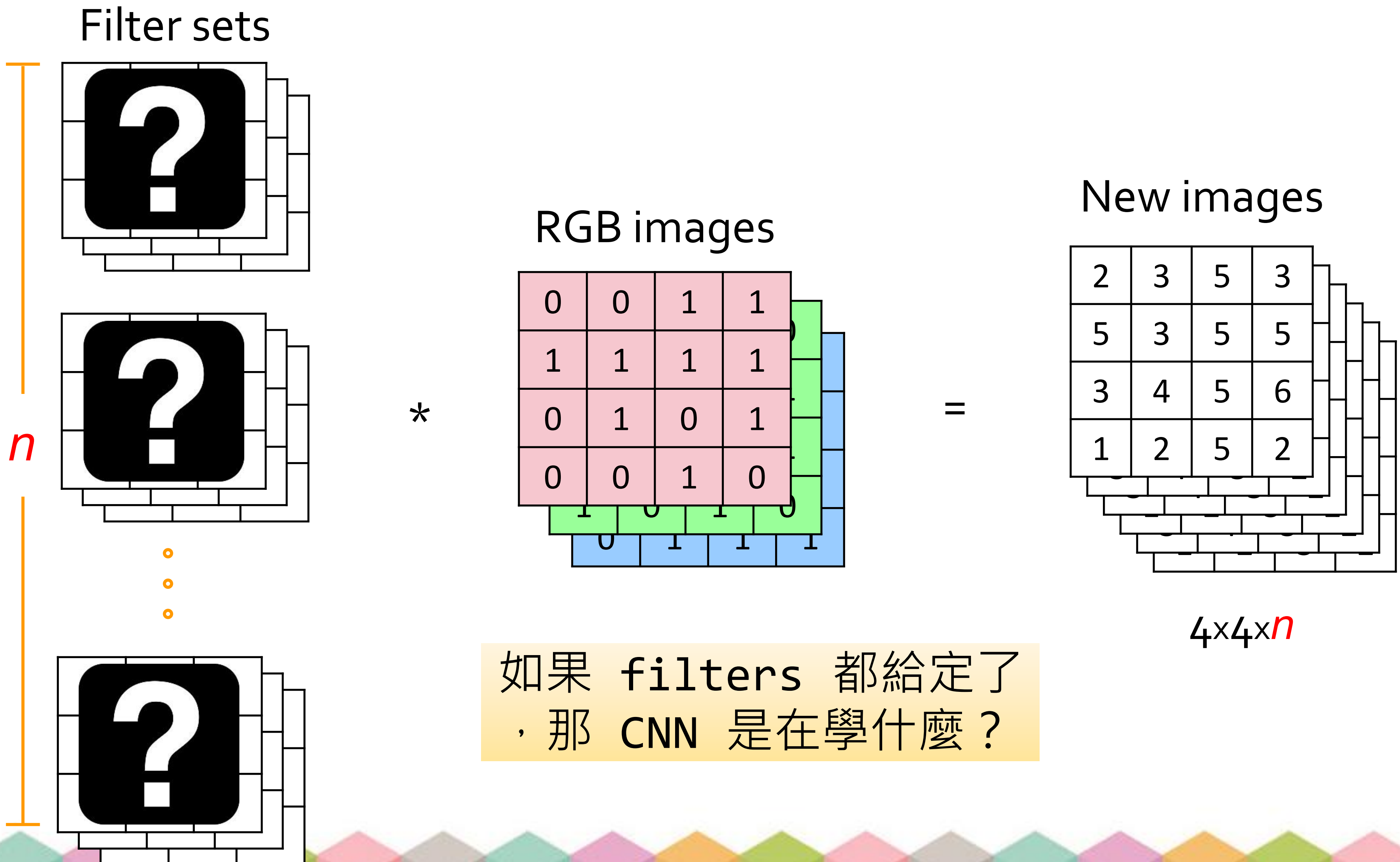
$$\begin{bmatrix}0&1&0\\0&1&0\\0&1&0\end{bmatrix} * \begin{bmatrix}0&0&1&0\\1&0&1&1\\0&1&0&1\\1&0&1&0\end{bmatrix} = \begin{bmatrix}1&0&2&1\\1&1&2&2\\2&1&2&2\\1&1&1&1\end{bmatrix}$$

$$\begin{bmatrix}0&0&1\\0&1&0\\1&0&0\end{bmatrix} * \begin{bmatrix}0&1&0&1\\1&1&0&1\\0&0&0&1\\0&1&1&1\end{bmatrix} = \begin{bmatrix}0&2&1&1\\2&1&1&1\\1&0&2&2\\0&1&2&1\end{bmatrix}$$

$+ \rightarrow$ New image

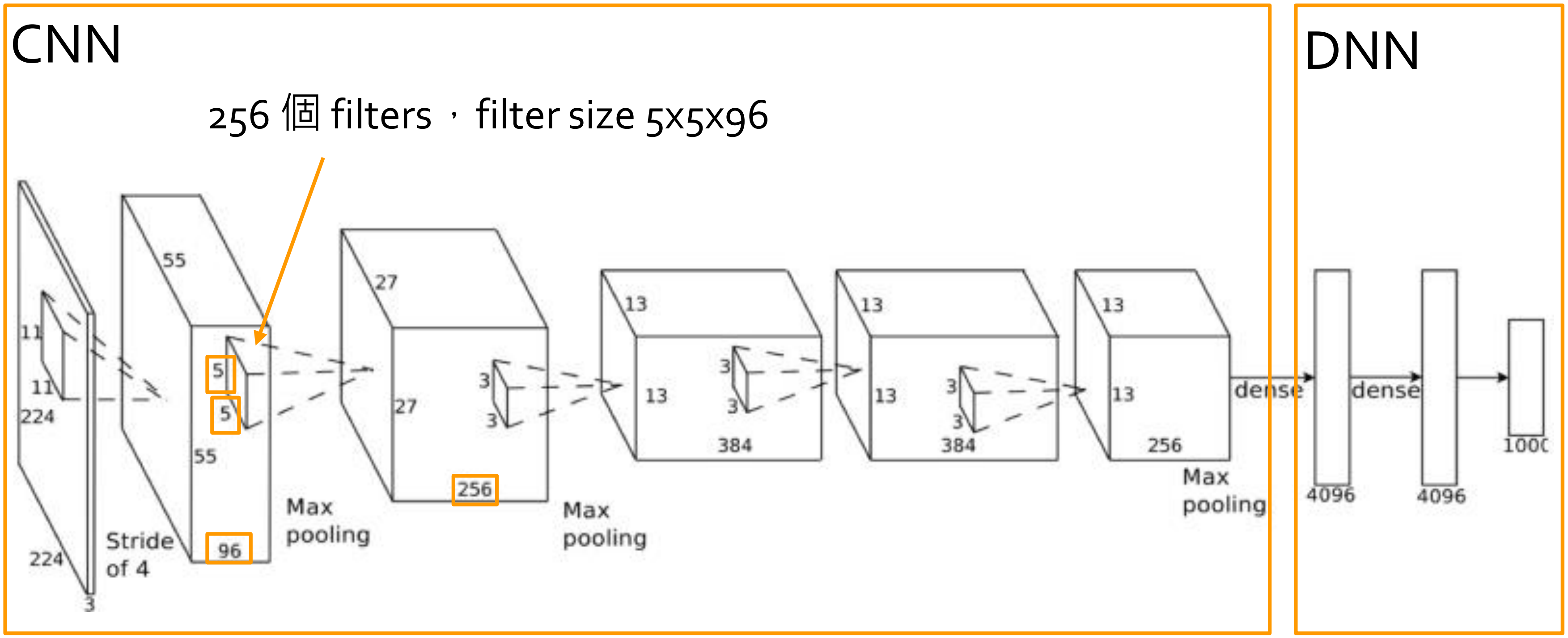
$$\begin{bmatrix}2&3&5&3\\5&3&5&5\\3&4&5&6\\1&2&5&2\end{bmatrix}$$

Depth *n*



如果 filters 都給定了，那 CNN 是在學什麼？

An Example of CNN Model

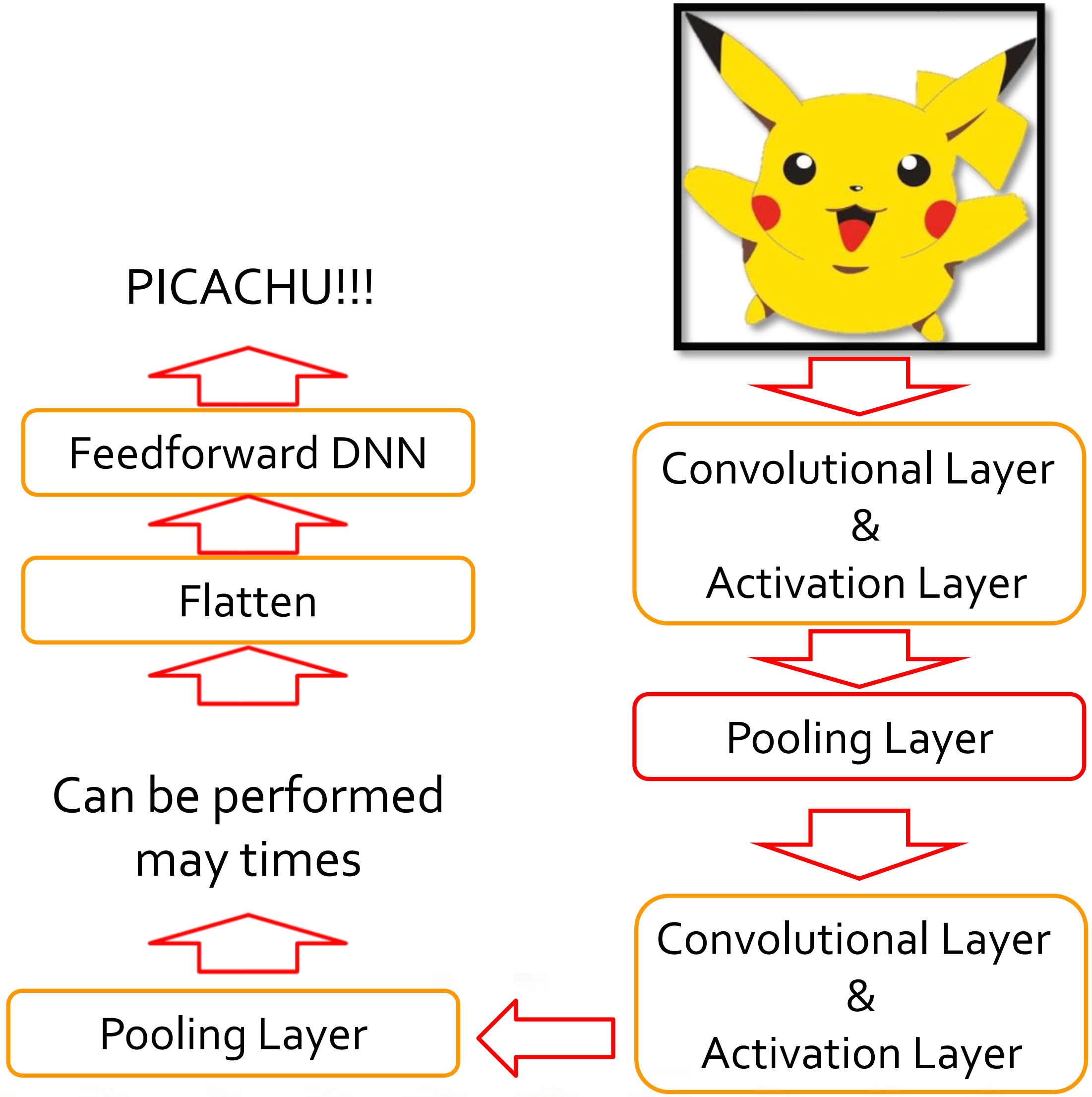


Flatten

Total Number of Weights

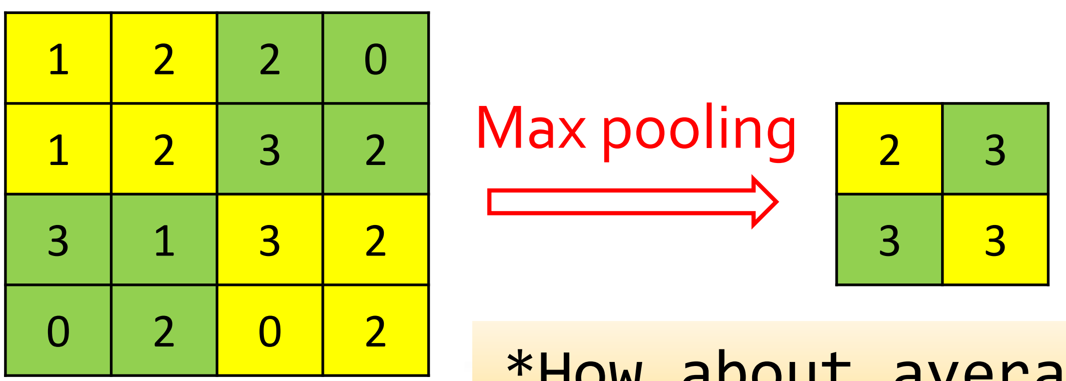
- Zero-padding
  - With $:(W_{n+1}, H_{n+1}, \times) = (W_n, H_n, \times)$
  - Without: $(W_{n+1}, H_{n+1}, \times) = (W_n - \frac{W_f - 1}{2}, H_n - \frac{H_f - 1}{2}, \times)$
- Stride = s
  - $(W_{n+1}, H_{n+1}, \times) = \left(\frac{W_n}{s}, \frac{H_n}{s}, \times\right)$
- k filters
  - $(W_{n+1}, H_{n+1}, k) = (W_n, H_n, D_n)$
- 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



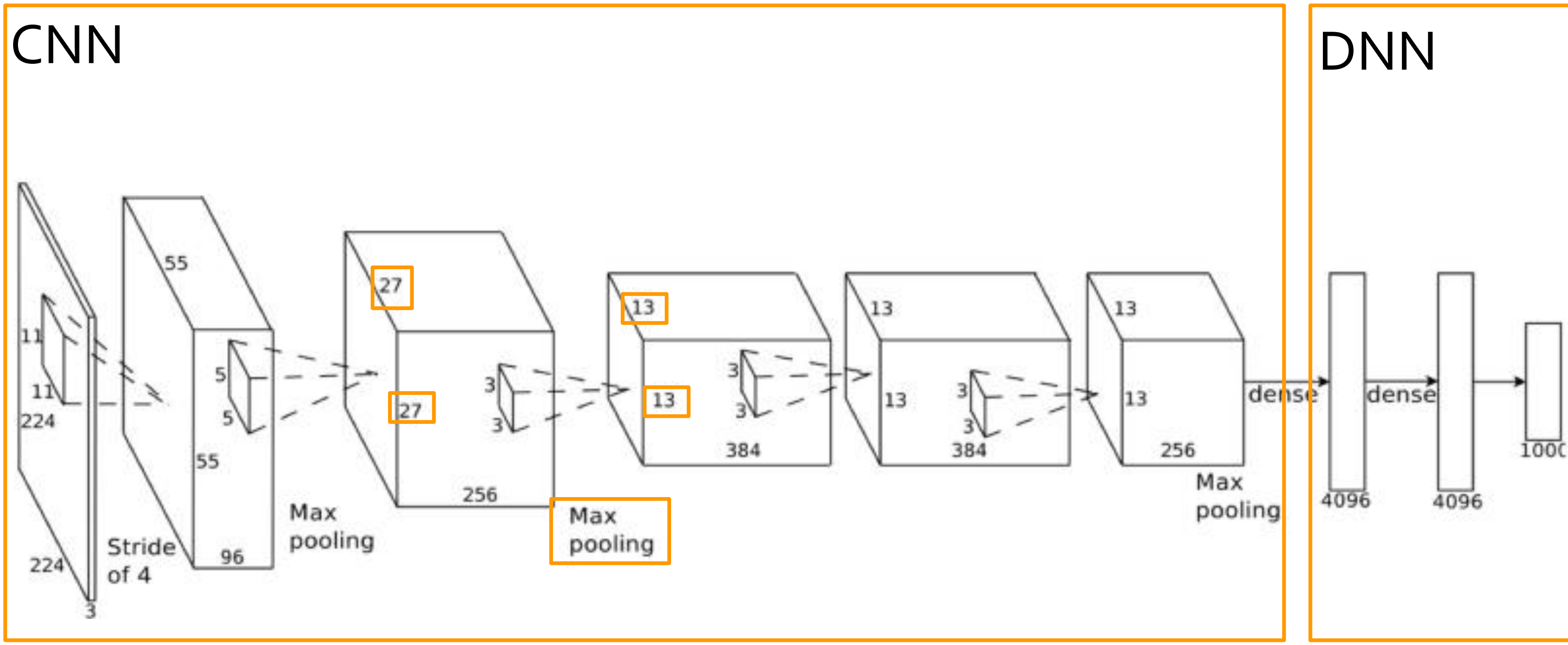
Pooling Layer

- Why do we need pooling layers?
  - Reduce the number of weights
  - Prevent overfitting
- Max pooling
  - Consider the existence of patterns in each region



*How about average pooling?

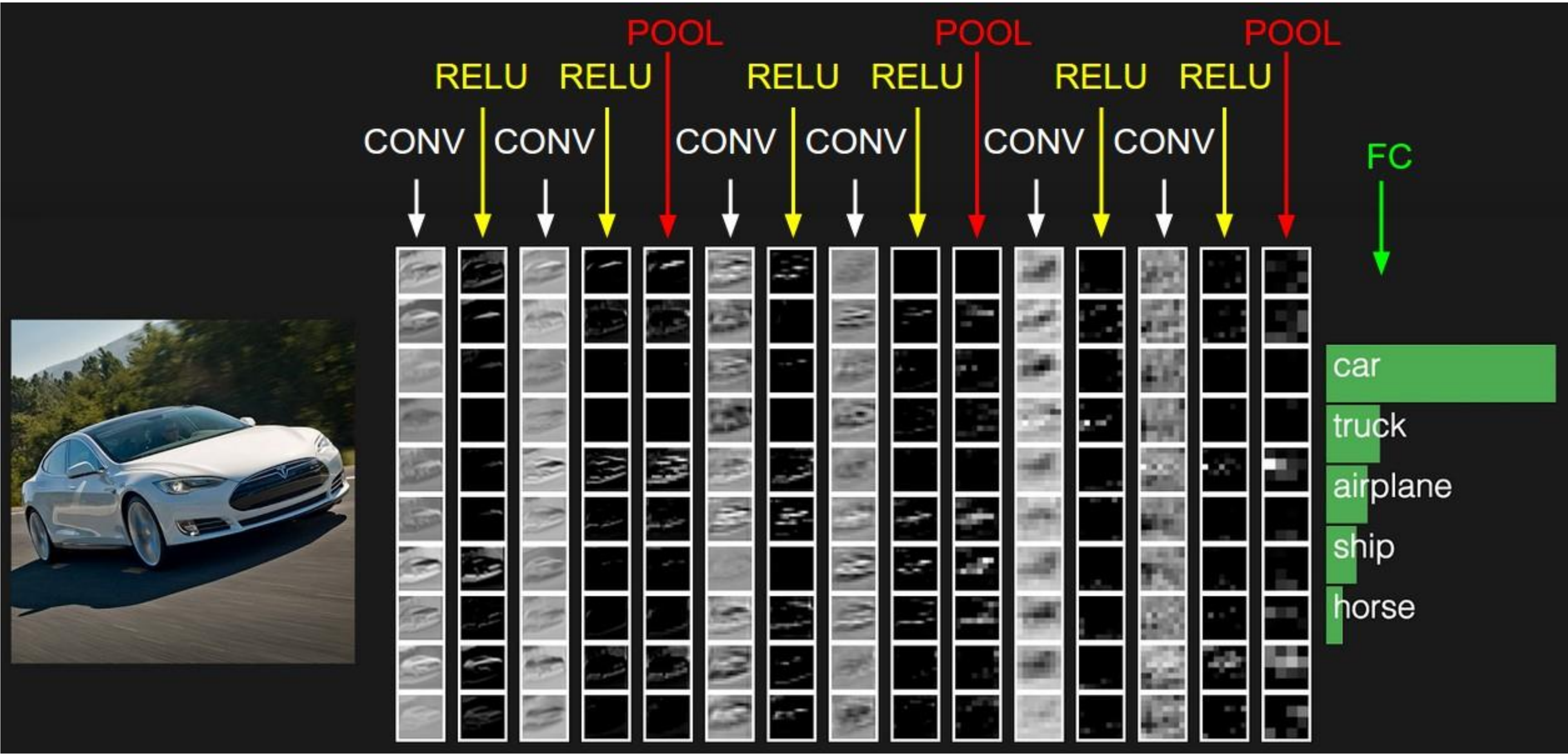
An Example of CNN Model



Flatten

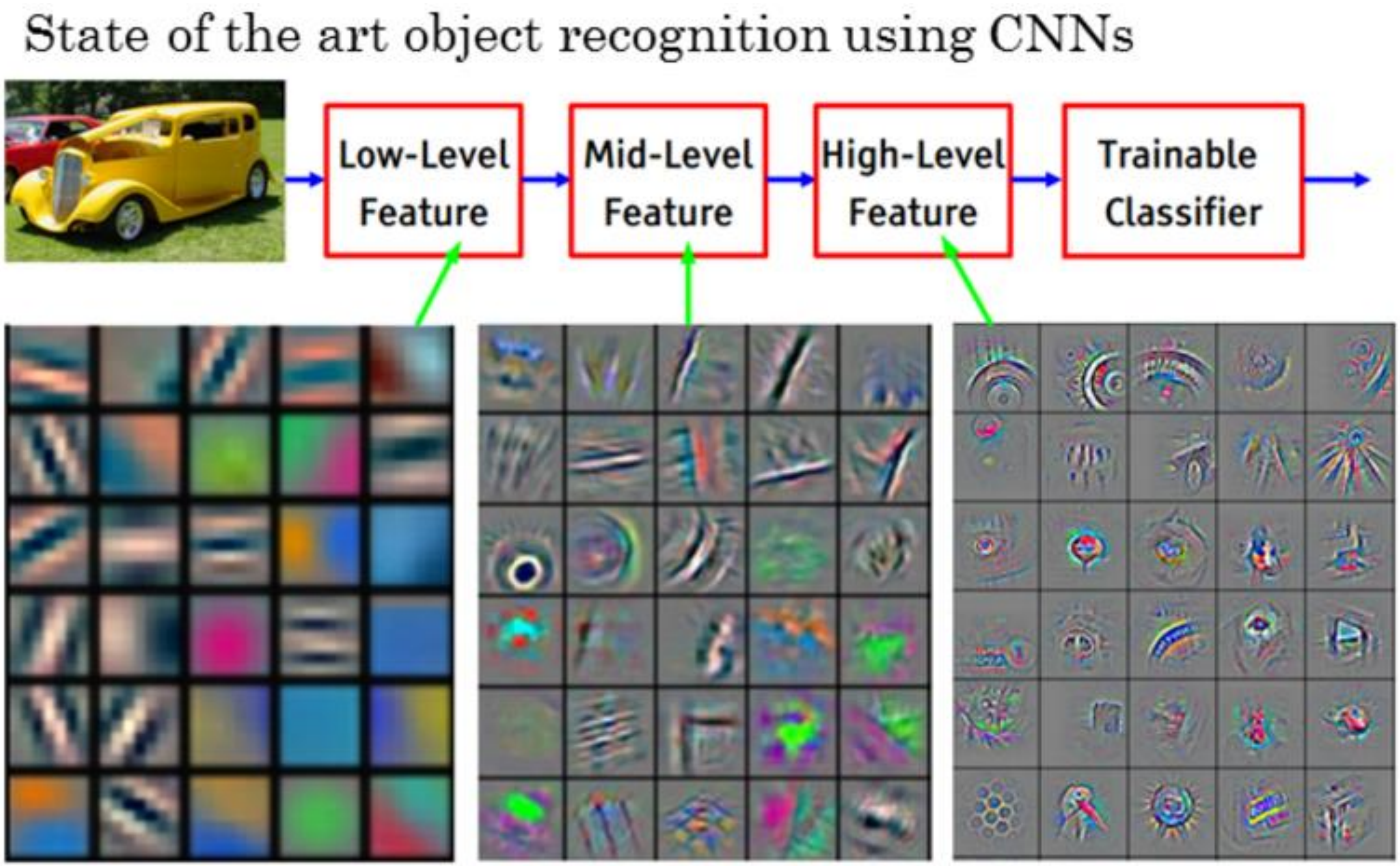
A CNN Example (Object Recognition)

- CS231n, Stanford [Ref]



Filters Visualization

- RSIP VISION [Ref]

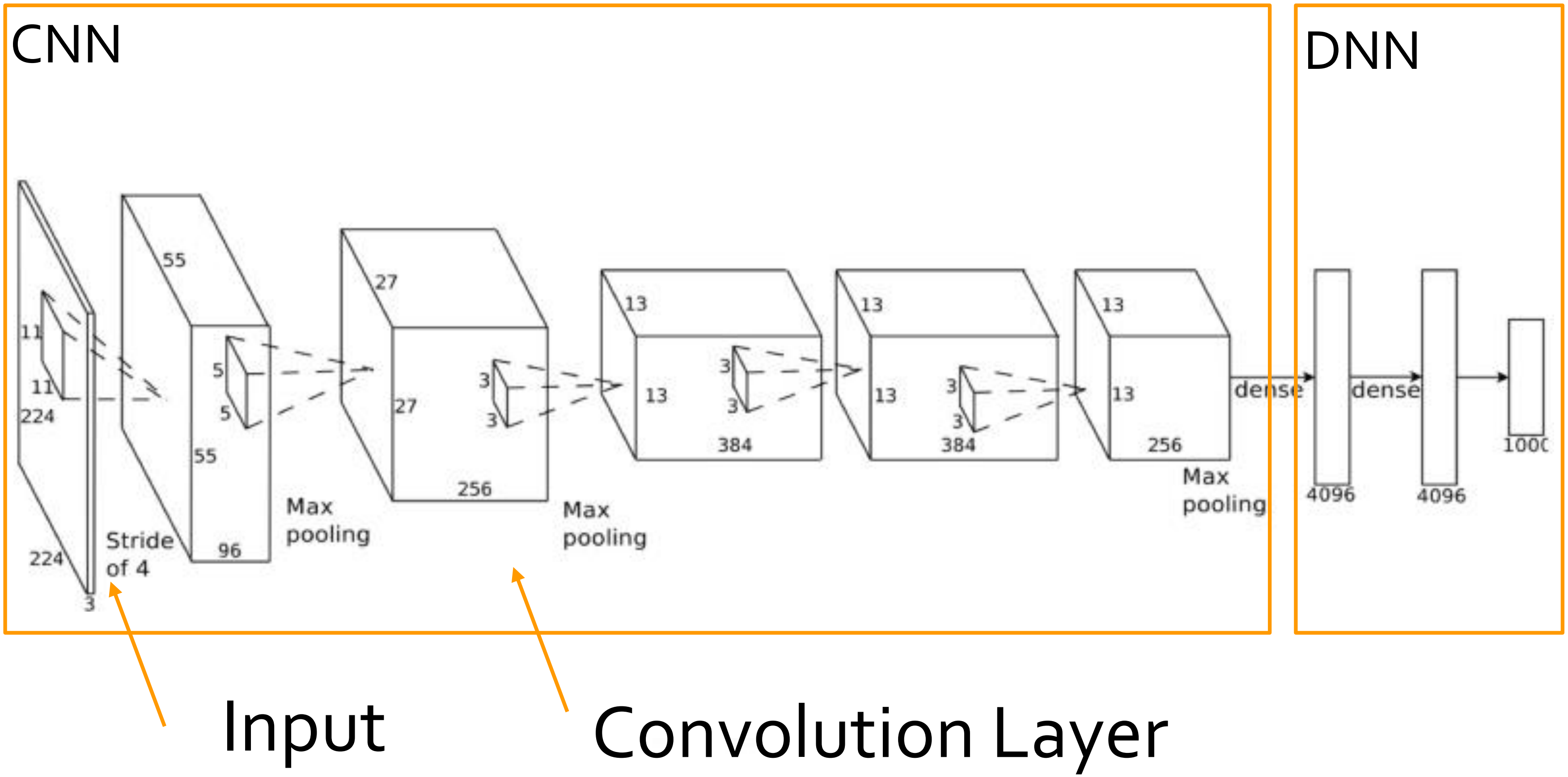


CNN in Keras

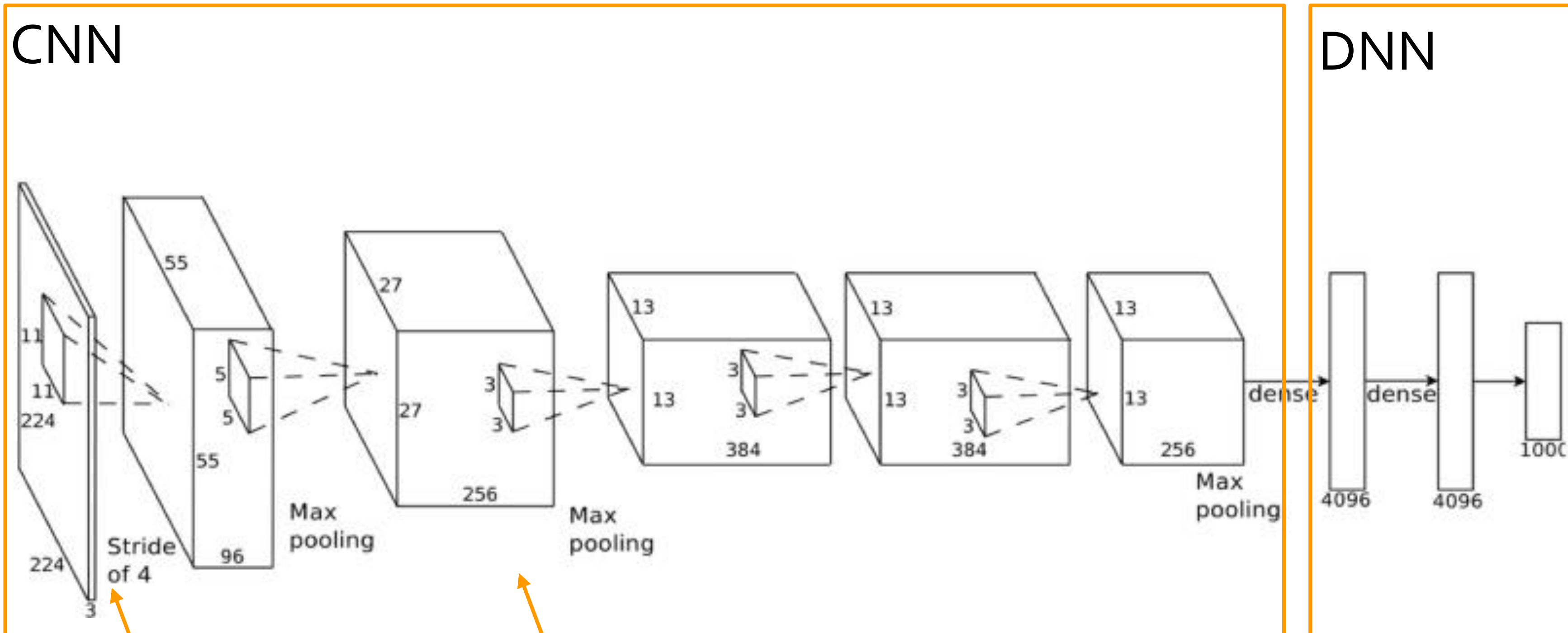
Object Recognition

Dataset: CIFAR-10

Differences between CNN and DNN



Differences between CNN and DNN

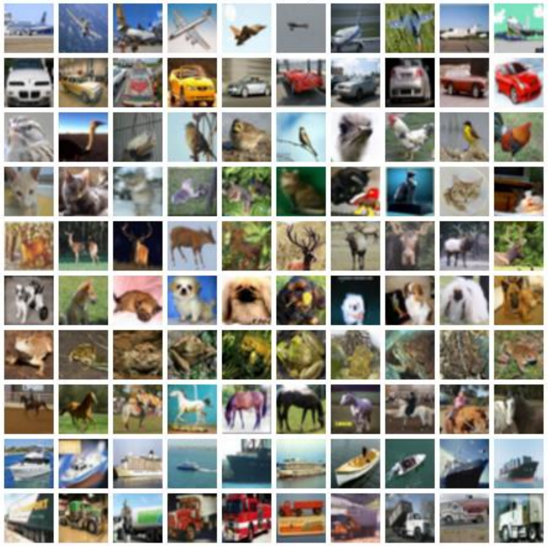


Input

Convolutional Layer

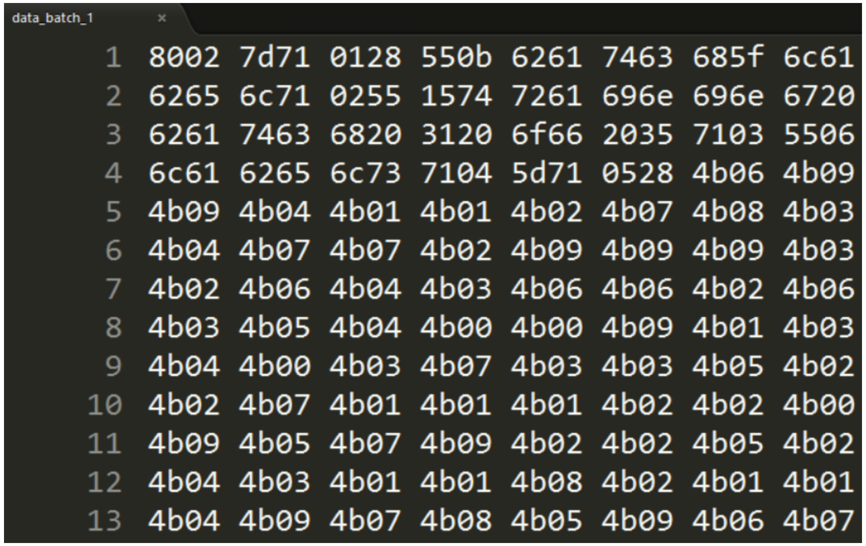
CIFAR-10 Dataset

- 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



data_batch_1

```
8002 7d71 0128 550b 6261 7463 685f 6c61
6265 6c71 0255 1574 7261 696e 696e 6720
6261 7463 6820 3120 6f66 2035 7103 5506
6c61 6265 6c73 7104 5d71 0528 4b06 4b09
4b09 4b04 4b01 4b01 4b02 4b07 4b08 4b03
4b04 4b07 4b07 4b02 4b09 4b09 4b09 4b03
4b02 4b06 4b04 4b03 4b06 4b06 4b02 4b06
4b03 4b05 4b04 4b00 4b00 4b09 4b01 4b03
4b04 4b00 4b03 4b07 4b03 4b03 4b05 4b02
4b02 4b07 4b01 4b01 4b01 4b02 4b02 4b00
4b09 4b05 4b07 4b09 4b02 4b02 4b05 4b02
4b04 4b03 4b01 4b01 4b08 4b02 4b01 4b01
4b04 4b09 4b07 4b08 4b05 4b09 4b06 4b07
```

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)
```

How to Load Samples form a File

- Fixed function for Python3

```
# this function is provided from the official site
def unpickle(file):
    import pickle
    fo = open(file, 'rb')
    dict = pickle.load(fo, encoding='latin1')
    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

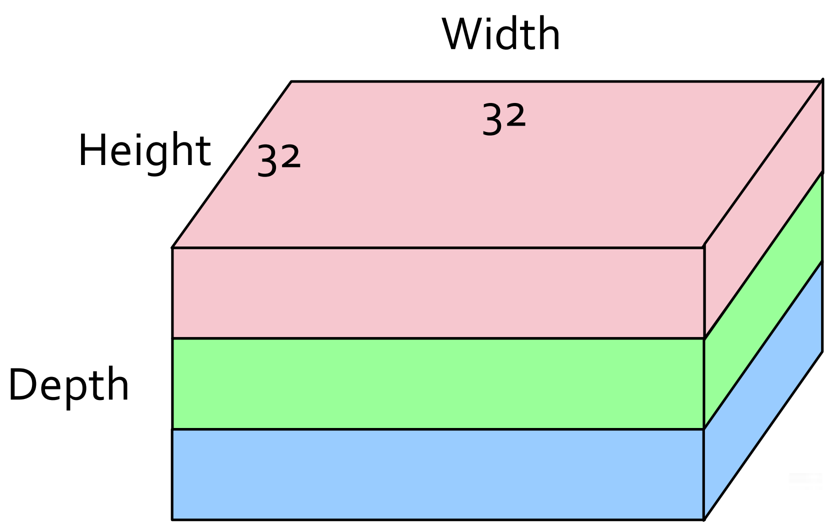
0	1,024	1,024	1,024
1	1,024	1,024	1,024
...	...	...	...
9,999	1,024	1,024	1,024
10,000	1,024	1,024	1,024
...	...	...	...

- 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],	Pixel values
[4, 5, 6]]	

- dstack, dim(1, 3, 2)

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

Concatenating Input Datasets

- 利用 vstack 連接 pixel values；用 hstack 連接 labels

```
img_px_values = 0
img_lab = 0
for fn in train_fns:
        raw_data = unpickle(dataset_path + fn)
        if fn == train_fns[0]:
                img_px_values = raw_data['data']
                img_lab = raw_data['labels']
        else:
                img_px_values = numpy.vstack((img_px_values,
                                        raw_data['data']))
                img_lab = numpy.hstack((img_lab,
                                raw_data['labels']))
```

Reshape the Training/Testing Inputs

- 利用影像的長寬資訊先將 RGB 影像分開，再利用 reshape 函式將一維向量轉換為二維矩陣，最後用 dstack 將 RGB image 連接成三維陣列

```
X_train = numpy.asarray(
    [numpy.dstack(
    (
        r[0:(width*height)].reshape(height,width),
        r[(width*height):(2*width*height)].reshape(height,width),
        r[(2*width*height):(3*width*height)].reshape(height,width))
    ) for r in img_px_values]
)

Y_train = np_utils.to_categorical(numpy.array(img_lab), classes)
```

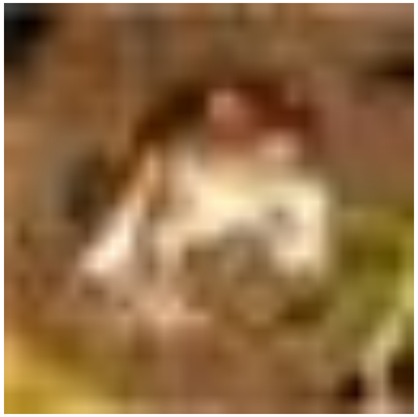
Saving Each Data as Image

- 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

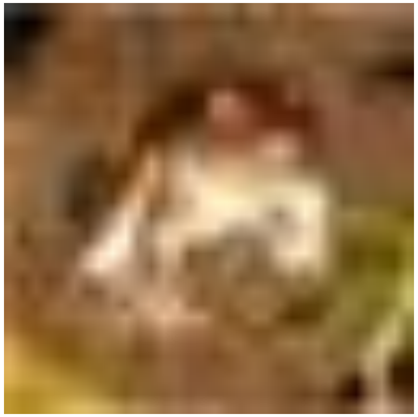


Saving Each Data as Image

- PIL library (Linux OS)

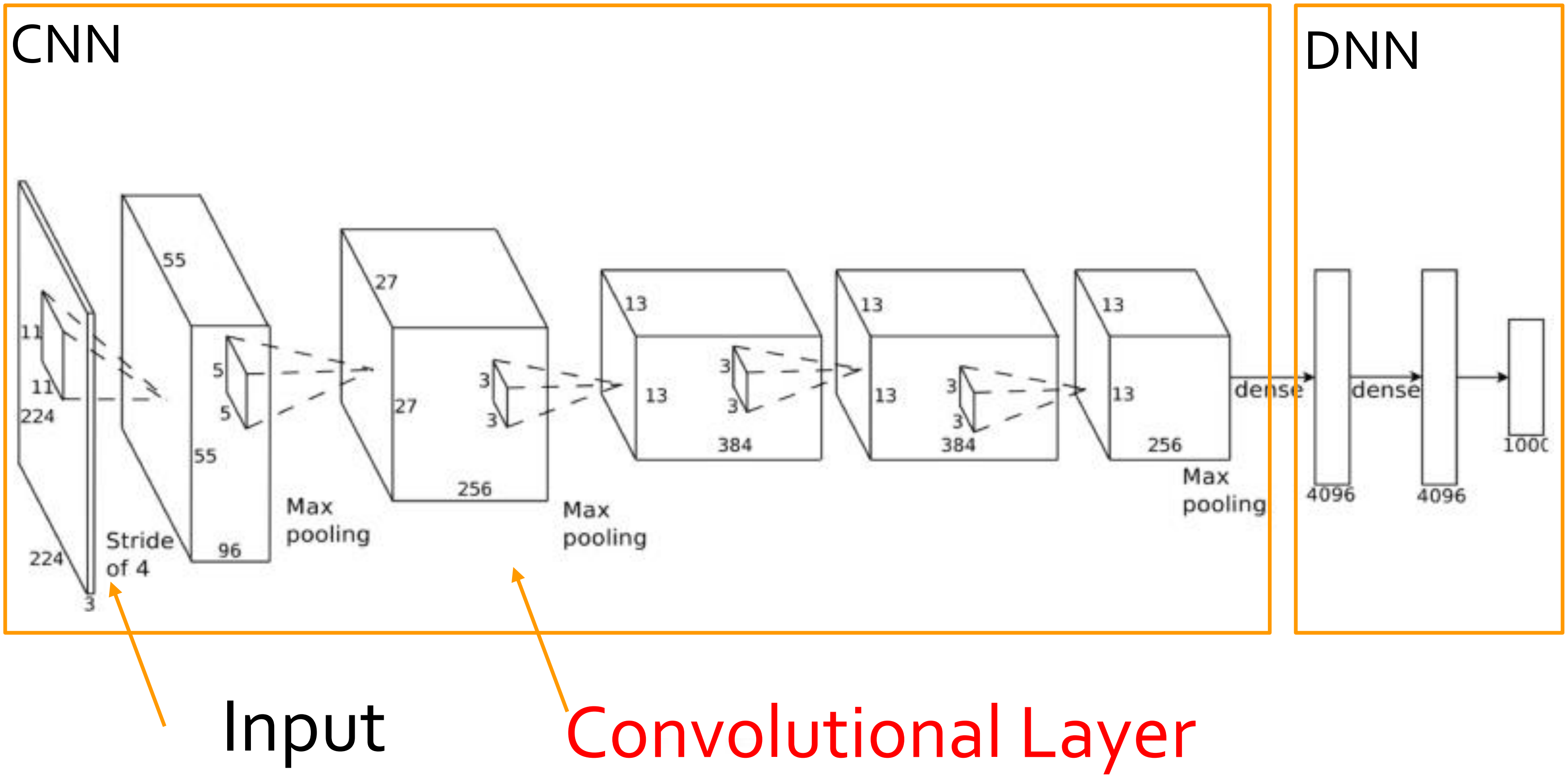
```
''' saving ndarray to image'''
from PIL import Image
def ndarray2image(arr_data, image_fn):
    img = Image.fromarray(arr_data, 'RGB')
    img.save(image_fn)
```

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



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

Differences between CNN and DNN



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'))
```

CNN

DNN

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
```

- To

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

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

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

Practice 1 – Dimensions of Inputs

- Find the dimensions of image and class of labels in read_dataset2vec.py and read_dataset2img.py

```
# define the information of images which can be obtained from
official website
height, width, dim = 32, 32, 3
classes = 10
```

- Following the dimension transformation from raw inputs to training inputs (Line 50-110)

Practice 2 – Design a CNN Model

- 設計一個 CNN model，並讓他可以順利執行 (Line 16-25)

```
# set dataset path
dataset_path = './cifar_10/'
exec(open("read_dataset2img.py").read())

'''CNN model'''
model = Sequential()
# 請建立一個 CNN model
# CNN

model.add(Flatten())
# DNN
```

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)

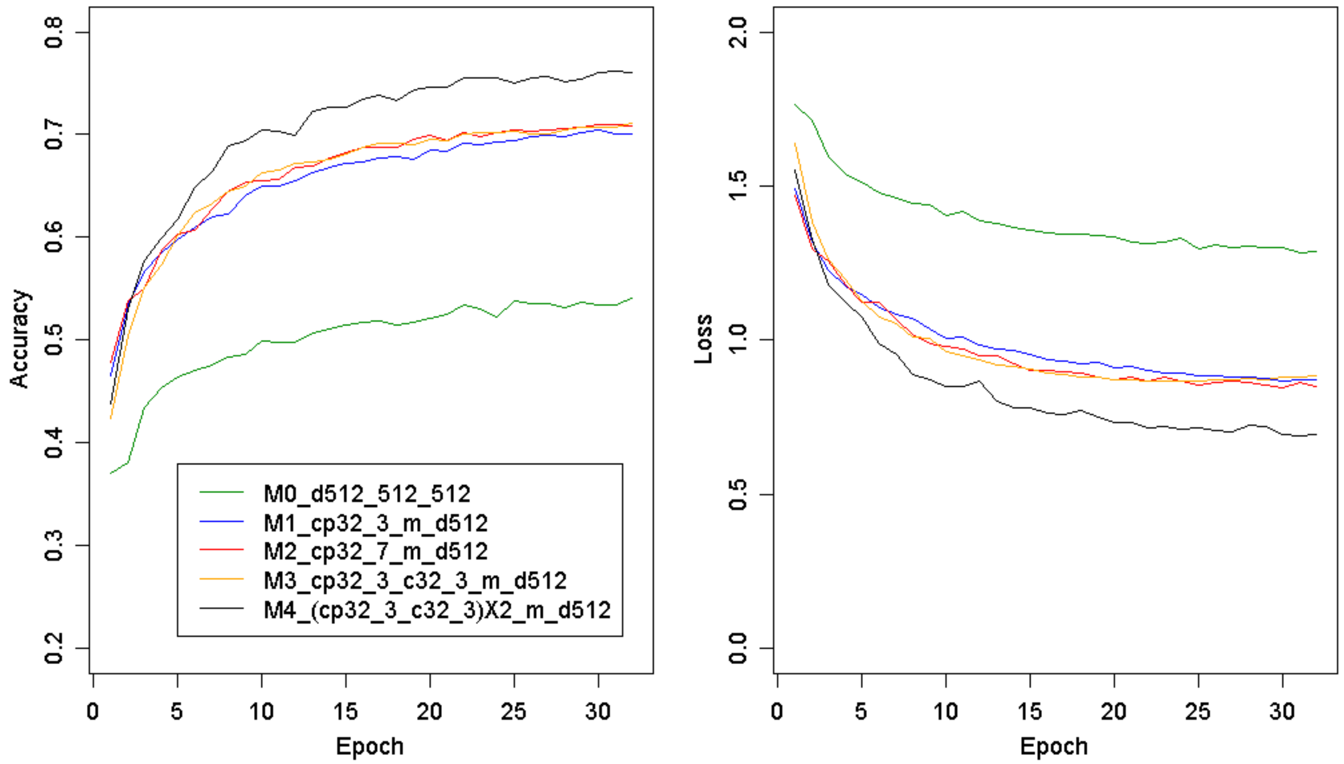
- 影像的大小須要能夠被 2 整除數次
  - 常見的影像 size 32, 64, 96, 224, 384, 512
- Convolutional Layer
  - 比起使用一個 size 較大的 filter (7x7)，可以先嘗試連續使用數個 size 小的 filter (3x3)
  - Stride 的值與 filter size 相關，通常 $stride \leq \frac{W_f - 1}{2}$
- Very deep CNN model (16+ Layers) 多使用 3x3 filter 與 stride 1

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



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)

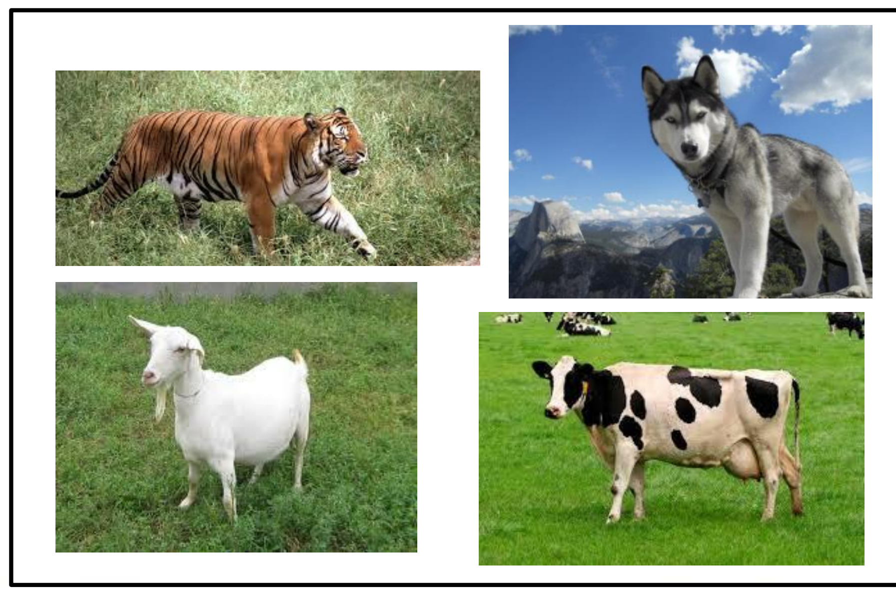
Introduction

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

綿羊

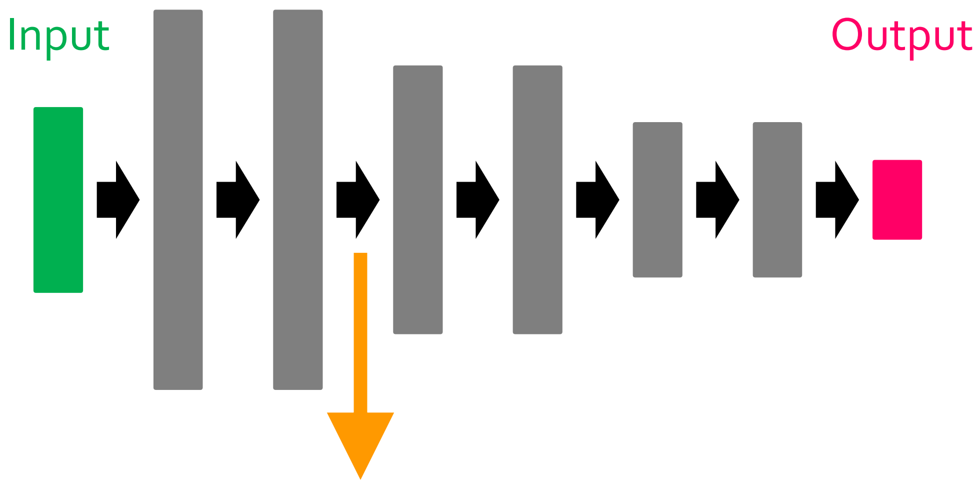
羊駝

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

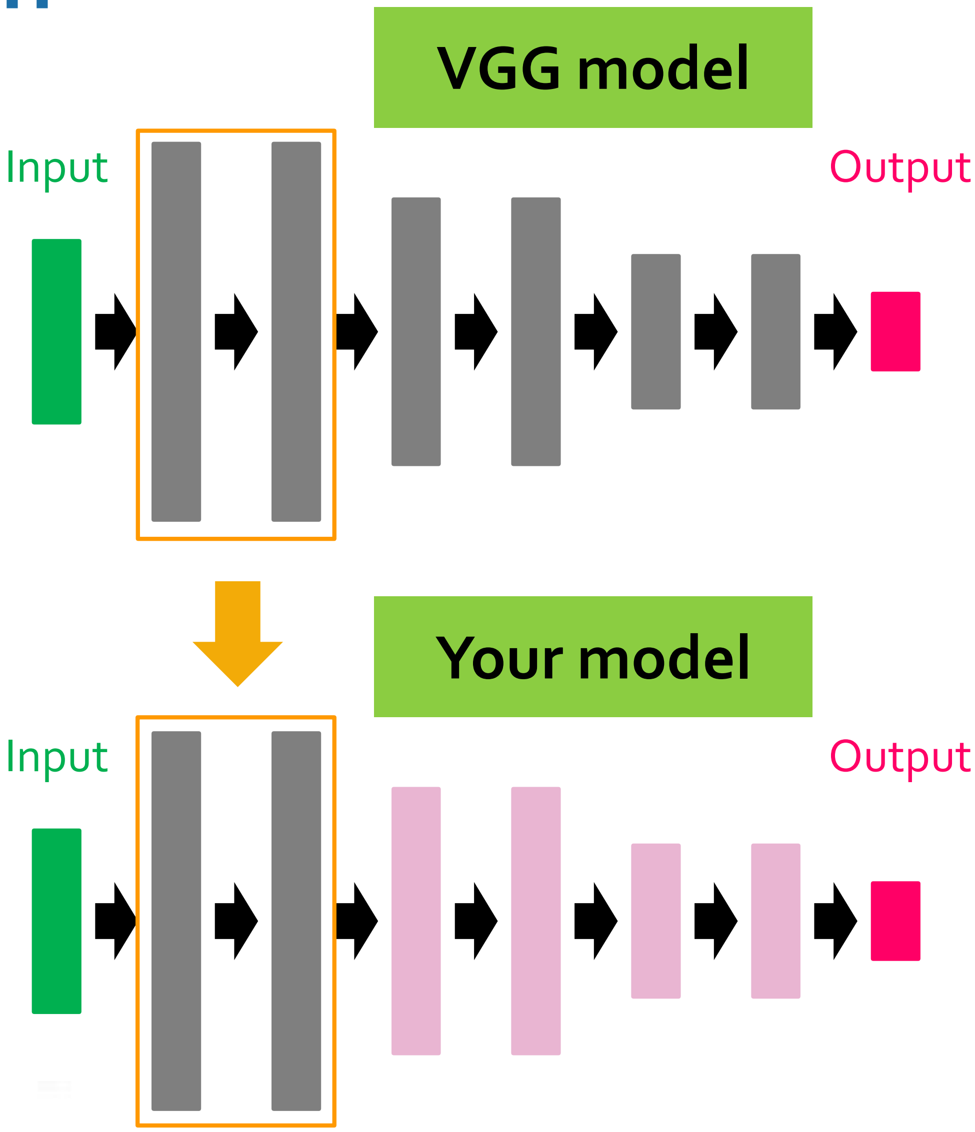


取某一個 layer output
當作 **feature vectors**

Train a classifier based on the features extracted by a known model

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

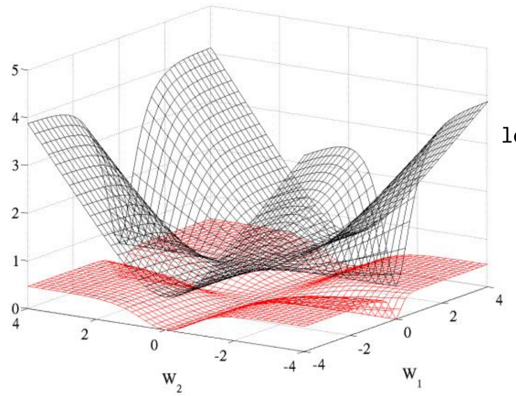
- How to improve performance on training dataset

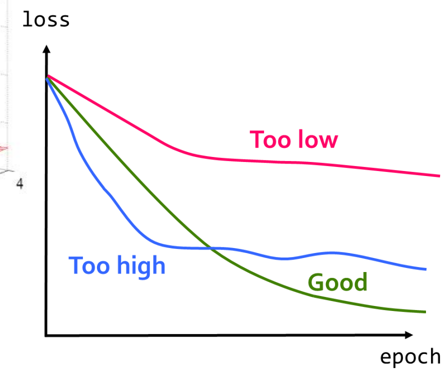
Loss Function

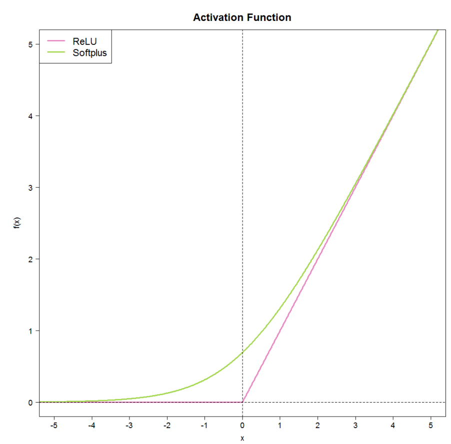
Learning Rate

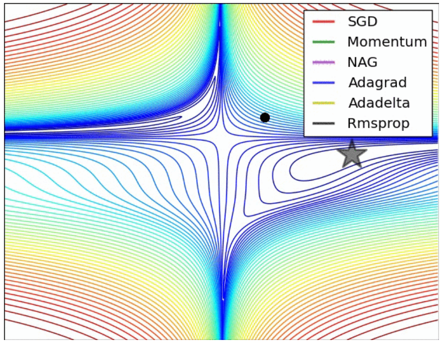
Activation Function

Optimizer









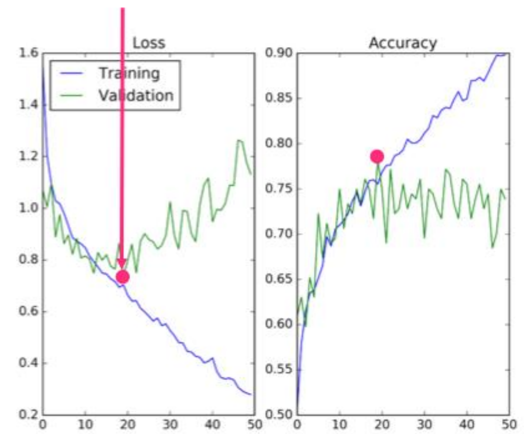
Recap – Improvement on Testing Set

- How to improve performance on testing dataset

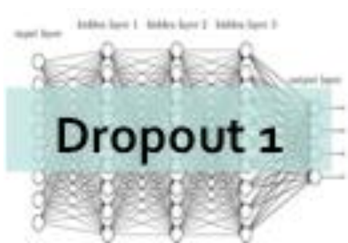
Regularization

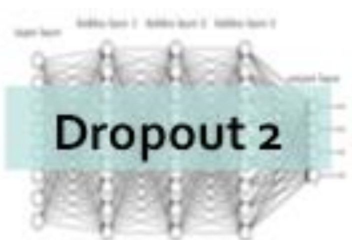
Early Stopping

Dropout



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





....

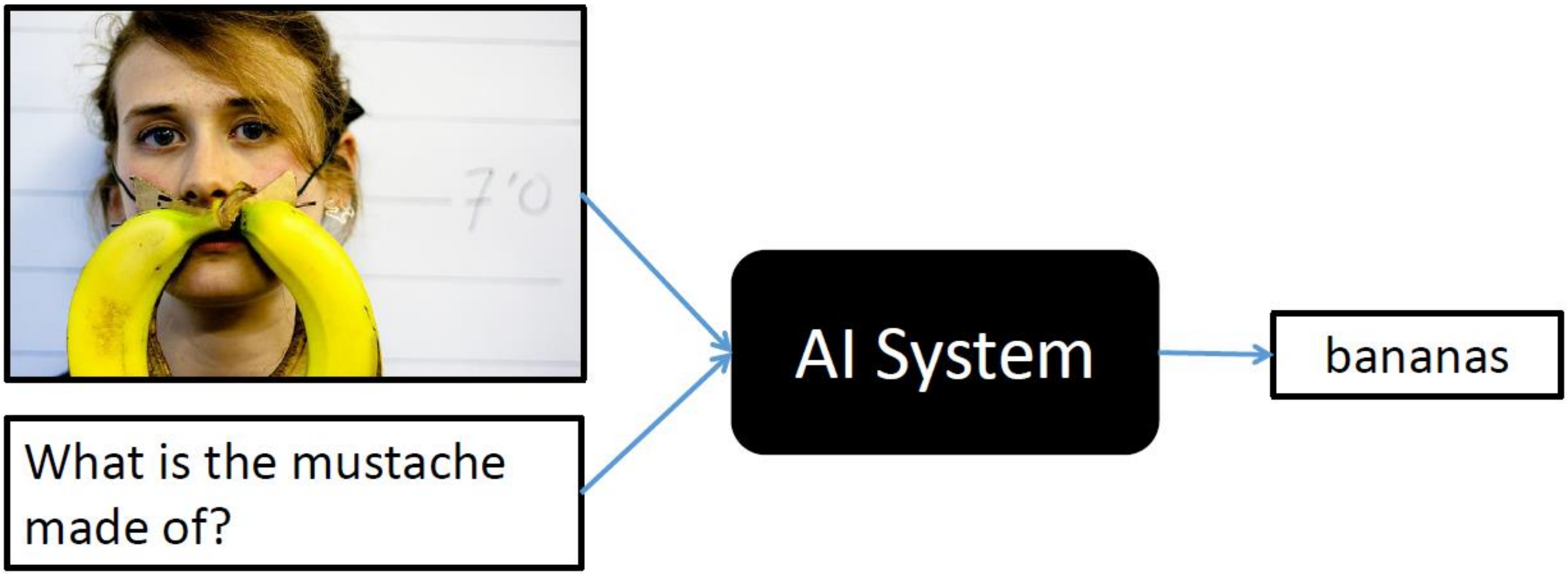
Recap – CNN

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

$$\underset{\text{Image}}{\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \end{bmatrix}} * \underset{\text{Filter}}{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}} = \underset{\text{New image}}{\begin{bmatrix} 1 & 2 \\ 3 & 3 \end{bmatrix}}$$

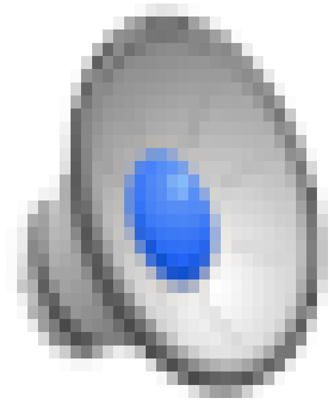
Deep Learning Applications

Visual Question Answering



source: http://visualqa.org/

Video Captioning



Answer: a woman is carefully slicing tofu.

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

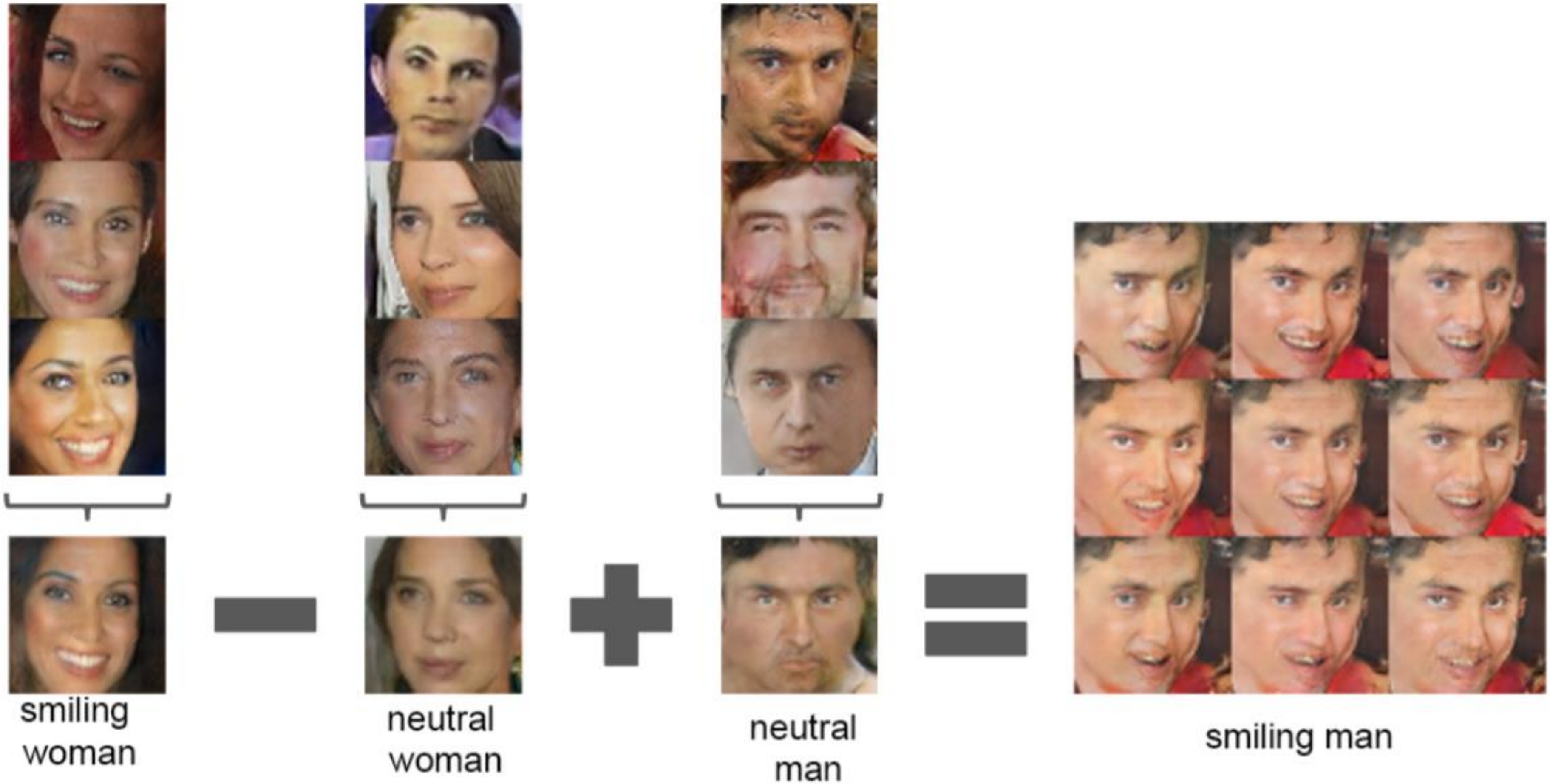
Text-To-Image

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

Vector Arithmetic for Visual Concepts



https://arxiv.org/pdf/1511.06434.pdf

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)

References

- 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
- Youtube 頻道 – 台大電機李宏毅教授
- Convolutional Neural Networks for Visual Recognition cs231n

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

一起往訓練大師的路邁進吧！
謝謝大家！