Deep Neural Network & Recommendation Engine on TensorFlow

Gary Chen

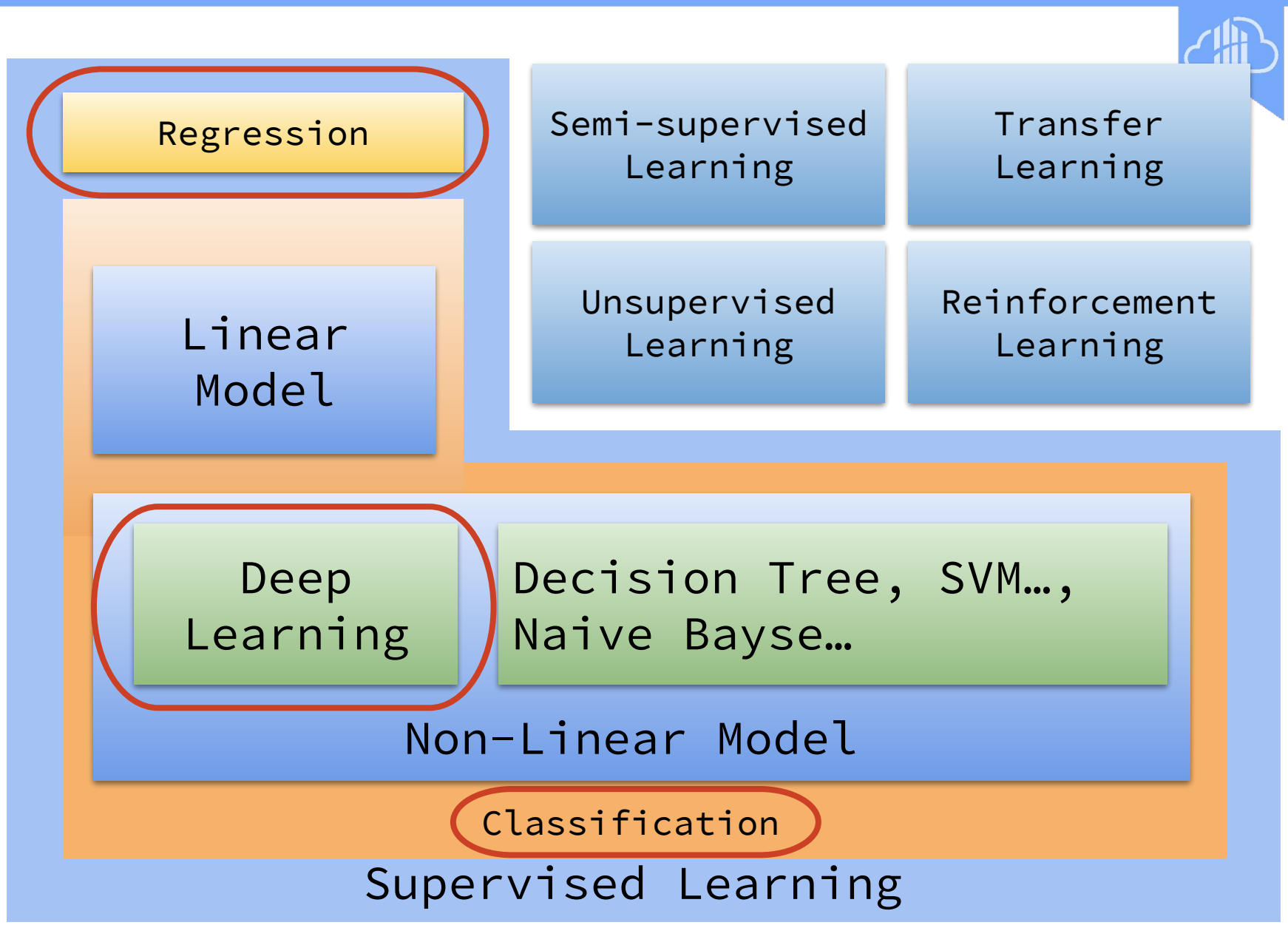
Outline

- Machine Learning Framework
- Deep Neural Network(DNN) Tips
- Recommedation Engine in Matrix Factorization
- Matrix Factorization with DNN

Machine Learning Framework

- Machine Learning Framework
- Deep Neural Network(DNN) Tips
- Recommedation Engine in Matrix Factorization
- Matrix Factorization with DNN

Machine Learning 的種類

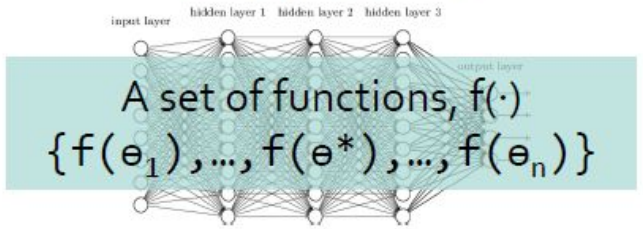


Machine Learning Framework

- Machine Learning 3 Steps

Step1 — **Define a set of functions**

特定的網絡架構



Step2 — **Evaluate and search**

不斷修正 f 的參數

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

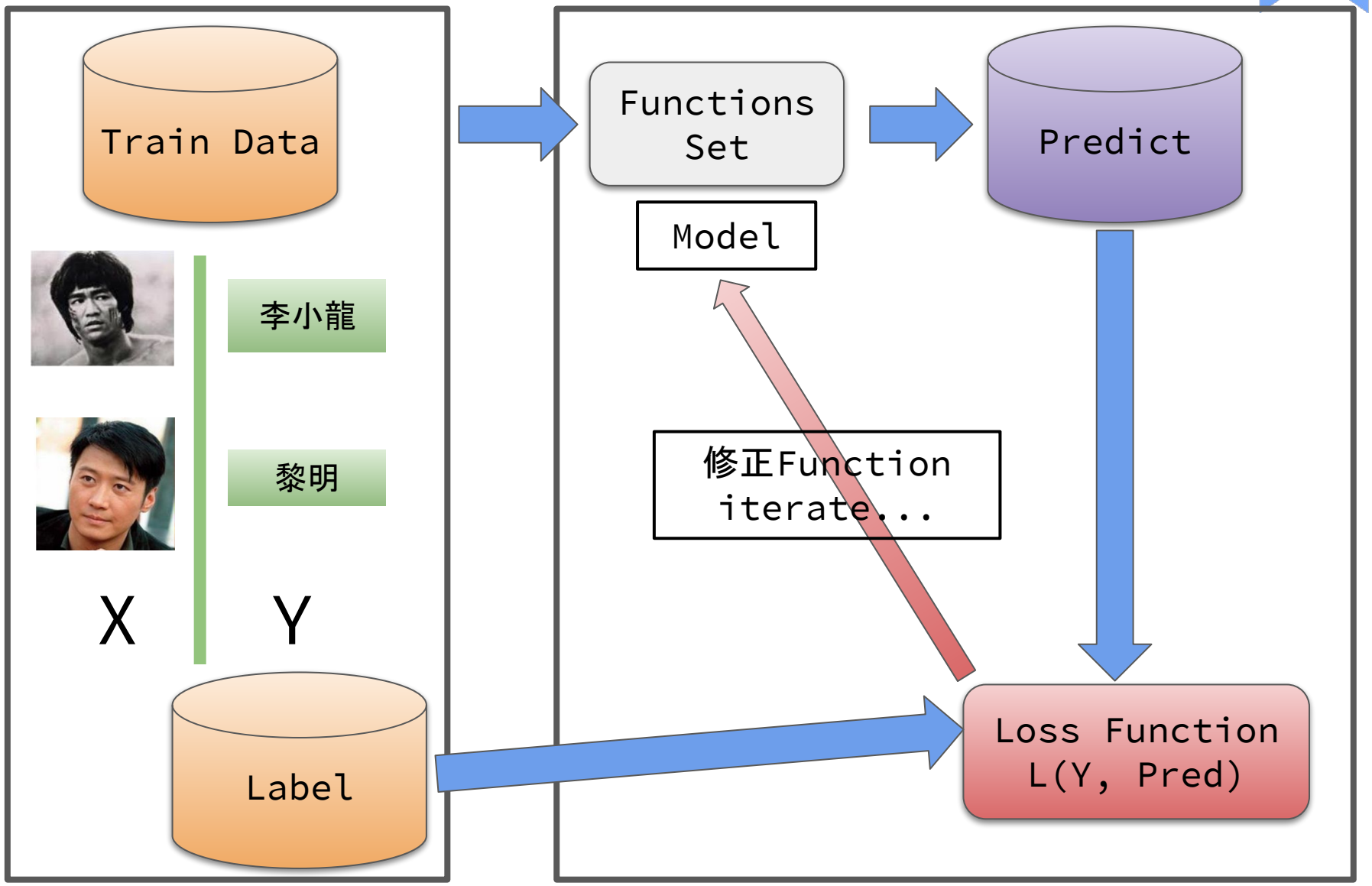
Step3 — **Pick the best function**

找到最適合的參數

$f(\theta^*)$

Machine Learning Framework

❑ Machine Learning 3 Steps in Detail



Machine Learning Framework

快速理解回歸與分類

Case Study On **HunterXHunter**

Subject In Regression and Classification

Regression

西索對十二地支的實力評分?

- **Label: 連續型數值**
- **可比大小**

Classification

如何判斷一個獵人是屬於什麼派系?

- **Label: 離散型類別**
- **沒有大小關係**

Machine Learning Framework

Features

Regression

西索對十二地支的實力評分?

X_1	念能力氣量(基本功)
X_2	屬於什麼派系?
Y	0 ~ 100分

Classification

如何判斷一個獵人是屬於什麼派系?

X_1	念能力氣量(基本功)
X_2	水見式: 水變甜
⋮	⋮
X_7	水見式: 水變多
X_8	西索個性分析: 一味的單純
⋮	⋮
X_{13}	西索個性分析: 反覆無常, 愛騙人
Y	強化系 ... 特質系(6種)

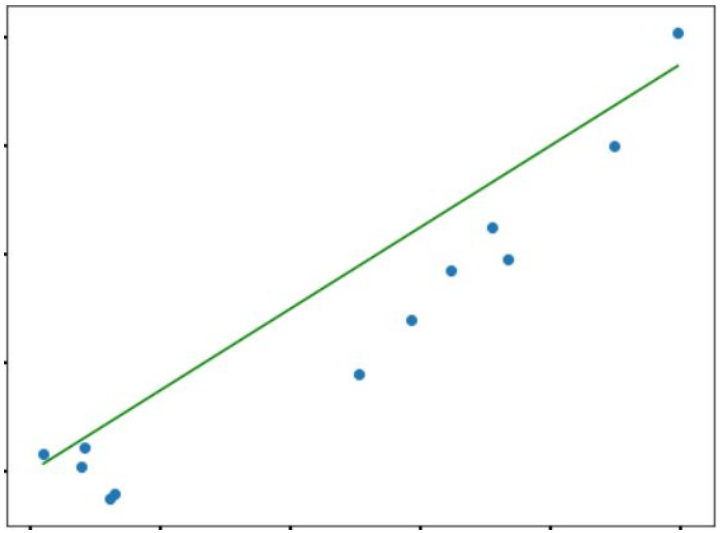
Machine Learning Framework

Step1: Define Function Set(Formulation)

Regression

西索對十二地支的實力評分?

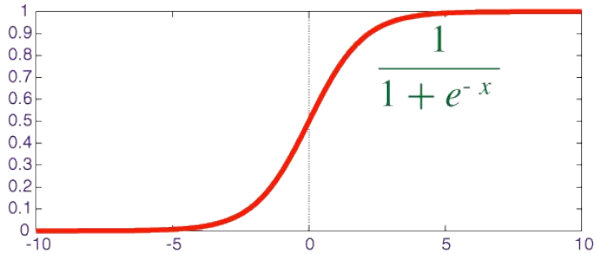
$$y = wx + b$$



Classification

如何判斷一個獵人是屬於什麼派系?

$$y = \sigma(wx + b)$$



sigmoid function
=> 0 ~ 1
=> probability
=> one of activation functions

$$y = softmax(wx + b)$$

a method of normalization
=> 0 ~ 1
=> probability

Step2: Evaluate ⇒ Define The Loss Function!

Regression

-> $z = wx_i + b$

$$\frac{1}{n}\sum_{i}^{n}(\hat{y}_i - z)^2$$ *mean square error*

$$\frac{1}{n}\sum_{i}^{n}|\hat{y}_i - z|$$ *mean absolute error*

- **點對點的誤差平均**
- 值域: real number, 任何值

Classification

-> $z = \sigma(wx + b)$

or

-> $z = softmax(wx + b)$

$$\frac{-1}{n}\sum_{i}^{n}(\hat{y}_i \cdot log(z))$$ *cross entropy*

- **資料分布的誤差**
- 值域: ouput視為機率, 0 ~ 1之間, 處理資料時需要做特殊處理
- cross entropy直觀理解

Step 3: Pick Best Function

Regression

Classification

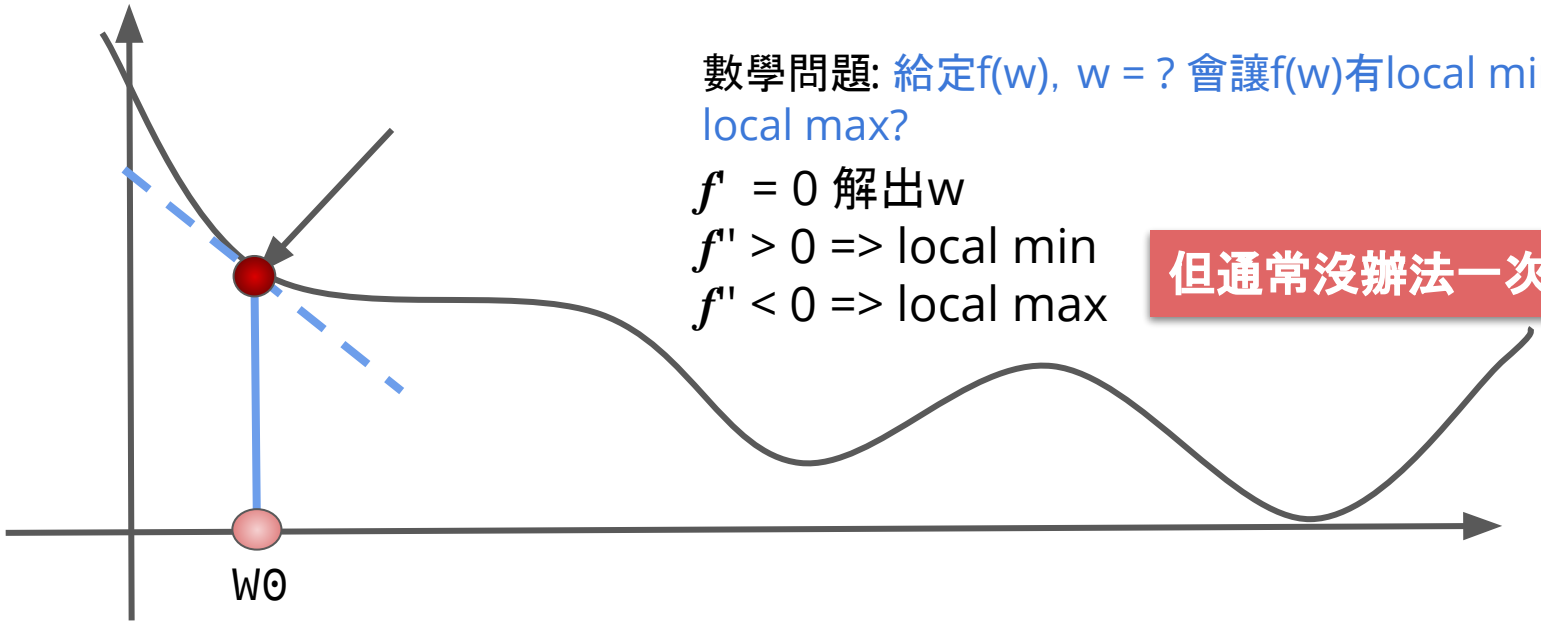
$$\underset{w,b}{\operatorname{argmin}} L(w,b)$$

最佳化問題

微分的定義

$$\lim_{\Delta w \to 0} \frac{L(w+\Delta w) - L(w)}{\Delta w}$$

w些微的變化，會讓L改變多少?



數學問題: 給定f(w)，w = ? 會讓f(w)有local min or local max?

$f' = 0$ 解出w

$f' > 0$ => local min

$f' < 0$ => local max

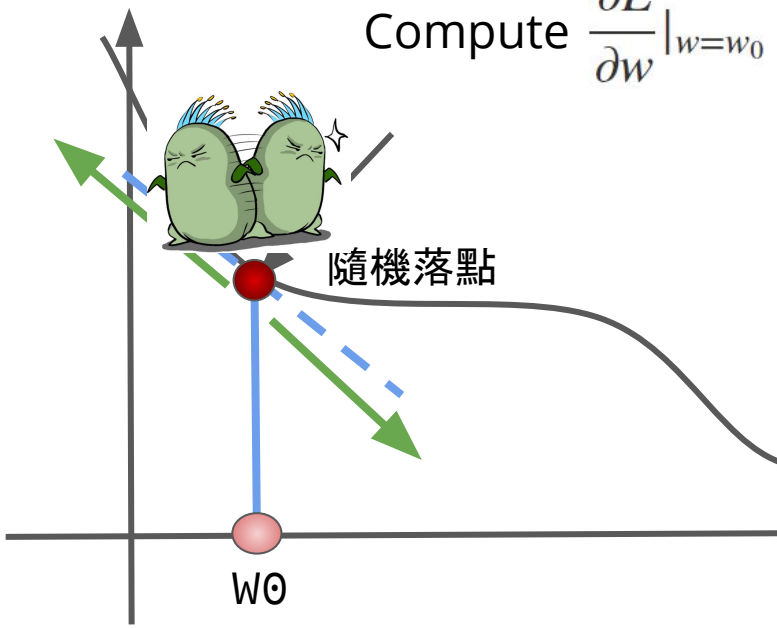
但通常沒辦法一次找出解!

Step 3: Pick Best Function

Regression | Classification

$$\underset{w,b}{\operatorname{argmin}} L(w,b)$$ → 最佳化問題 → **Gradient Descent**

Compute $\frac{\partial L}{\partial w}|_{w=w_0}$



In this case
gradient < 0 ⇒ 增加W0的值
gradient > 0 ⇒ 減少W0的值
⇒ w的變化是跟gradient是反向的

$$w_1 \leftarrow w_0 - \eta \frac{\partial L}{\partial w}|_{w=w_0}$$

η:Learning Rate
每一步走的大小

Step 3: Pick Best Function

Regression

Classification

$$\underset{w,b}{\operatorname{argmin}} L(w,b)$$

最佳化問題

Gradient Descent

$$w_1 \leftarrow w_0 - \eta \frac{\partial L}{\partial w}\Big|_{w=w_0}$$

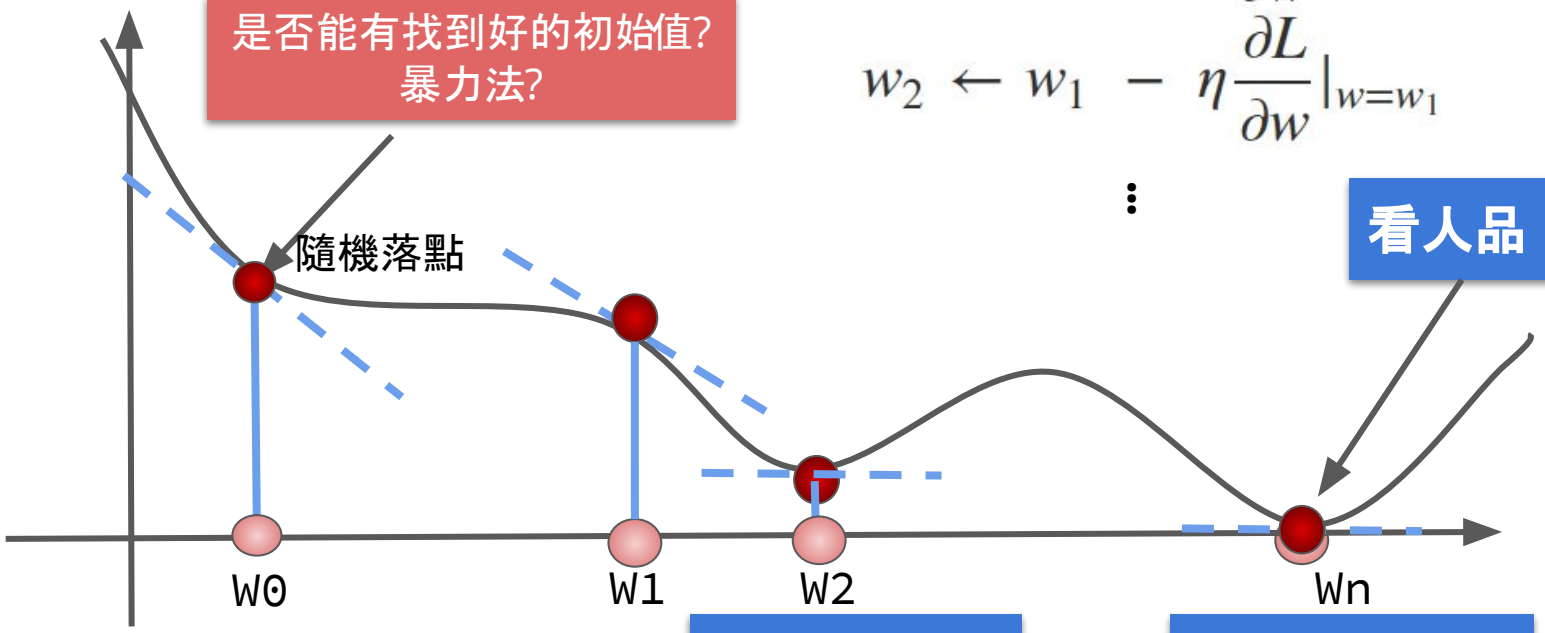
$$w_2 \leftarrow w_1 - \eta \frac{\partial L}{\partial w}\Big|_{w=w_1}$$

$$\vdots$$

是否能有找到好的初始值?
暴力法?

隨機落點

看人品



Step 3: Pick Best Function

蟻王用**暴力法**找出尼特羅百式觀音掌法當中的規律，突破防守！

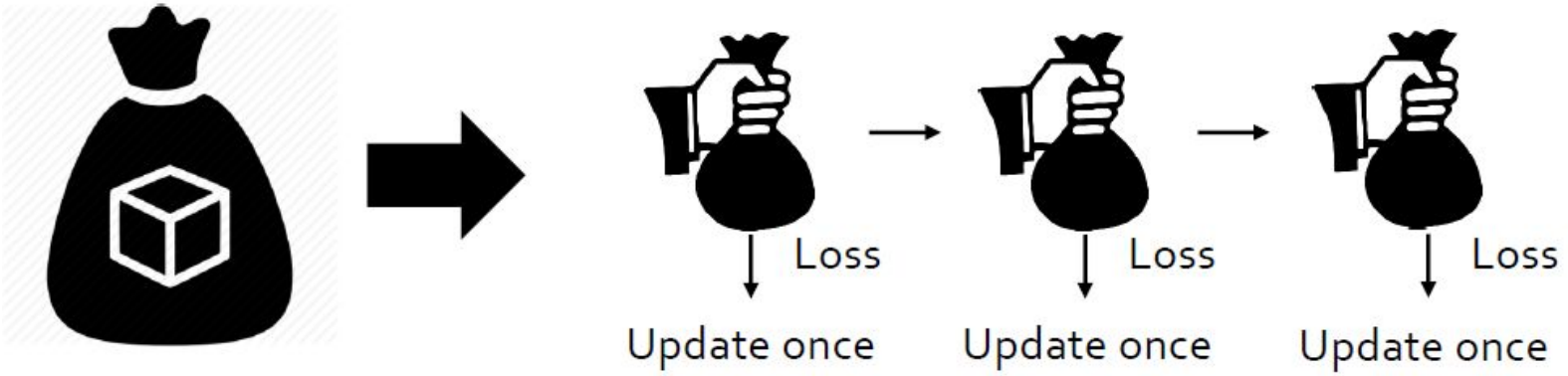

```
initFn = tf.glorot_uniform_initializer()
initFn = tf.glorot_normal_initializer()
init_var = tf.Variable(initFn(shape=[100, 80]))
```

Ref: Xavier uniform initializer

Step 3: Pick Best Function (Stochastic Gradient Descent)

Regression | Classification

- Shuffle training data
- Mini-batch update



- 假設有10000筆資料, batch = 100
  - Train一輪(one epoch)就更新了100次weights
  - 一次丟所有data下去**只更新了一次**, 沒有效率
- Batch size advice: 32, 64, 128, 256, 512, ...

回頭看看資料~

Regression

西索對十二地支的實力評分?

Data	Label	
$x_1 \dots x_2$	y	
…	78.5	
…	87.8	
…	35.0	
…	64.0	
…	33.64	
…	90.2	

Classification

如何判斷一個獵人是屬於什麼派系?

Data	Label	
$x_1 \dots x_{13}$	y	
…	1	強化系
…	2	變化系
…	3	放出系
…	4	具現化系
…	5	操作系
…	6	特質系

離散的類別想辦法轉換成數字

分類資料如何處理

Classification 如何判斷一個獵人是屬於什麼派系?

Data	Label	
$x_1 \dots x_{13}$	y	
…	1	強化系
…	2	變化系
…	3	放出系
…	4	具現化系
…	5	操作系
…	6	特質系

這樣有點問題，**各類別間產生了原本資料中沒有的距離的關係...**

Distance(強化系, 變化系) = 2 - 1 = 1
Distance(強化系, 放出系) = 3 - 1 = 2

解決方式?

分類資料如何處理

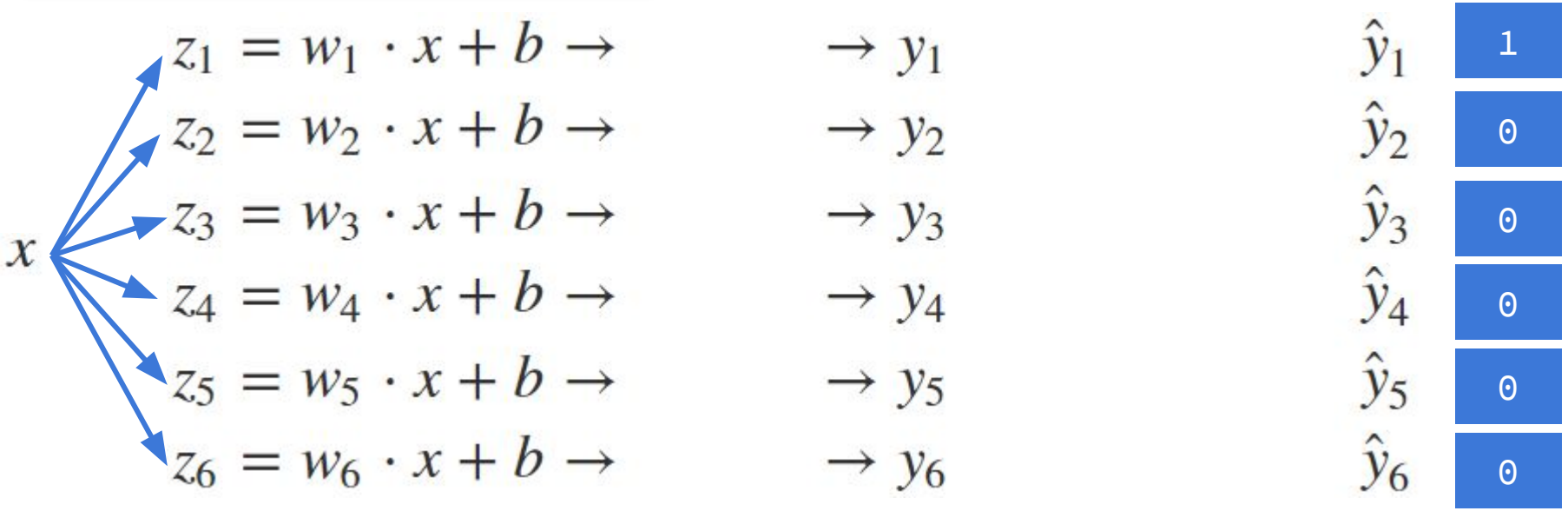
Classification 如何判斷一個獵人是屬於什麼派系?

Data	Label (One Hot Encoding)						
$x_1 \ldots x_{13}$	y_1	y_2	y_3	y_4	y_5	y_6	
...	1	0	0	0	0	0	強化系
...	0	1	0	0	0	0	變化系
				. . .			. . .
...	0	0	0	0	0	1	特質系

Label的形式是Vector，怎麼處理?

如何判斷一個獵人是屬於什麼派系?

一個類別一個Function對付他！



Probability:

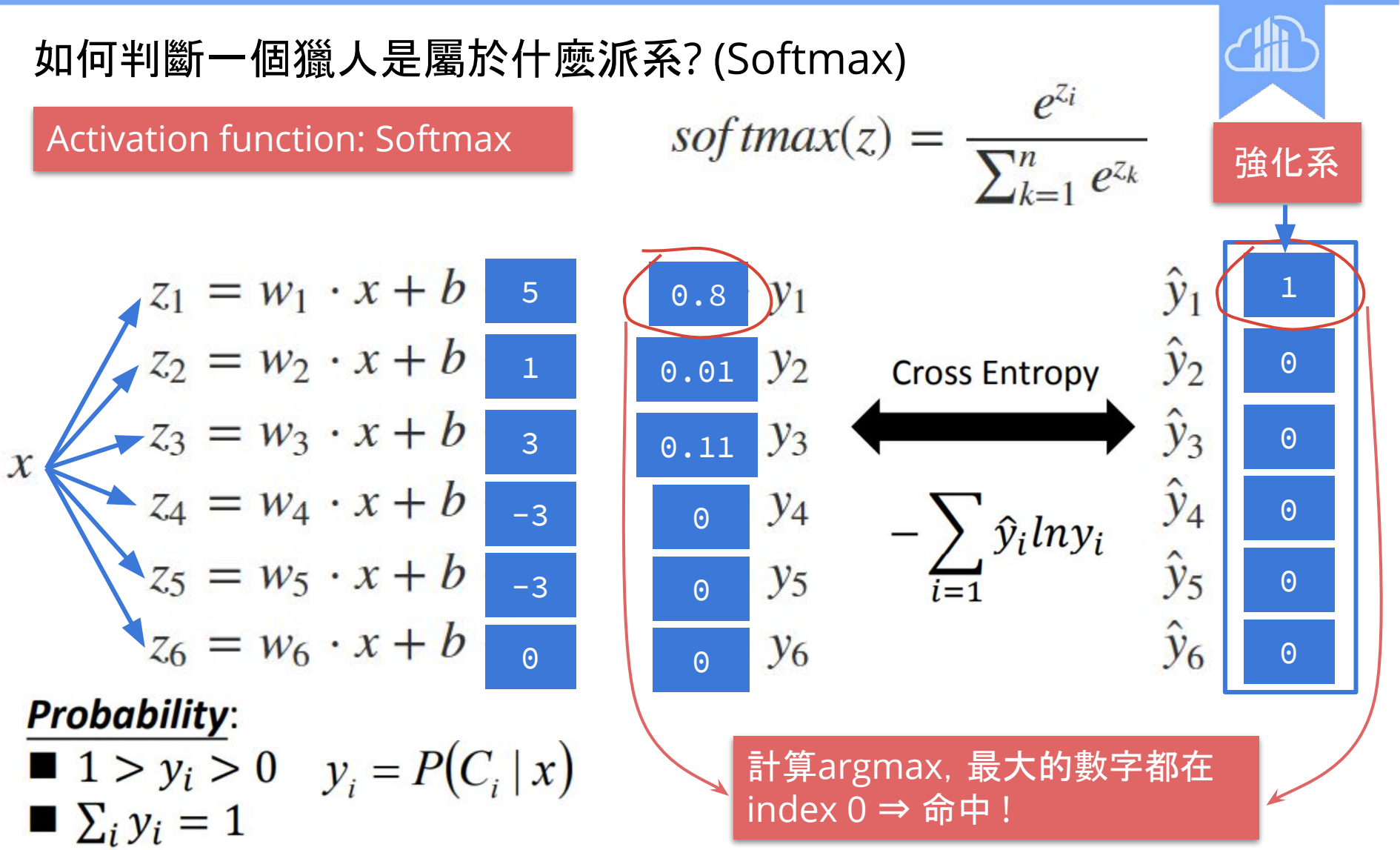
- $1 > y_i > 0 \quad y_i = P(C_i \mid x)$
- $\sum_i y_i = 1$

Sigmoid不滿足這個需求!

如何判斷一個獵人是屬於什麼派系? (Softmax)

Activation function: Softmax

$$softmax(z) = \frac{e^{z_i}}{\sum_{k=1}^{n} e^{z_k}}$$



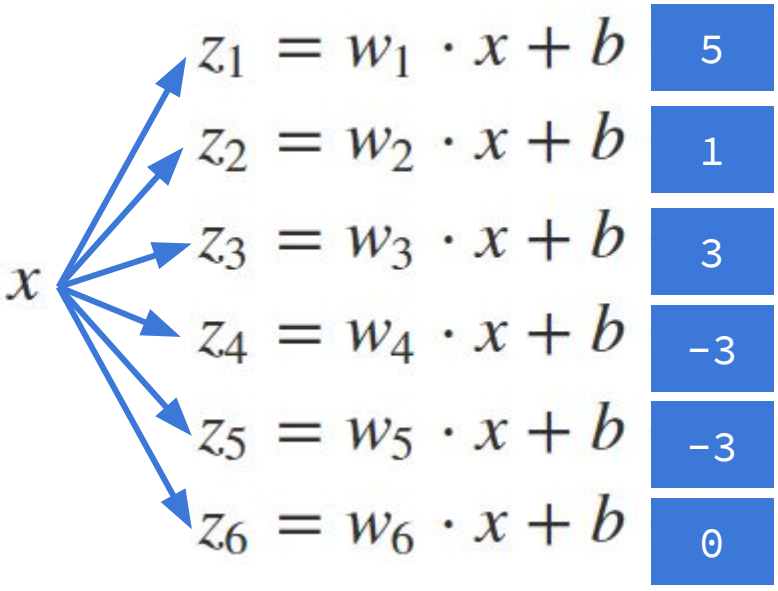
Probability:

- $1 > y_i > 0$ $\quad y_i = P(C_i \mid x)$
- $\sum_i y_i = 1$

如何判斷一個獵人是屬於什麼派系? (Sigmoid)

Activation function: Sigmoid

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



強化系

算argmax是沒有意義的! 要考慮的是每個class的分數

Softmax與Sigmoid的差別

$$softmax(z) = \frac{e^{z_i}}{\sum_{k=1}^{n} e^{z_k}}$$

- ❏ 所有類別視為一個母體
- ❏ Single-label for one record

一個獵人只能屬於一個系別!

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

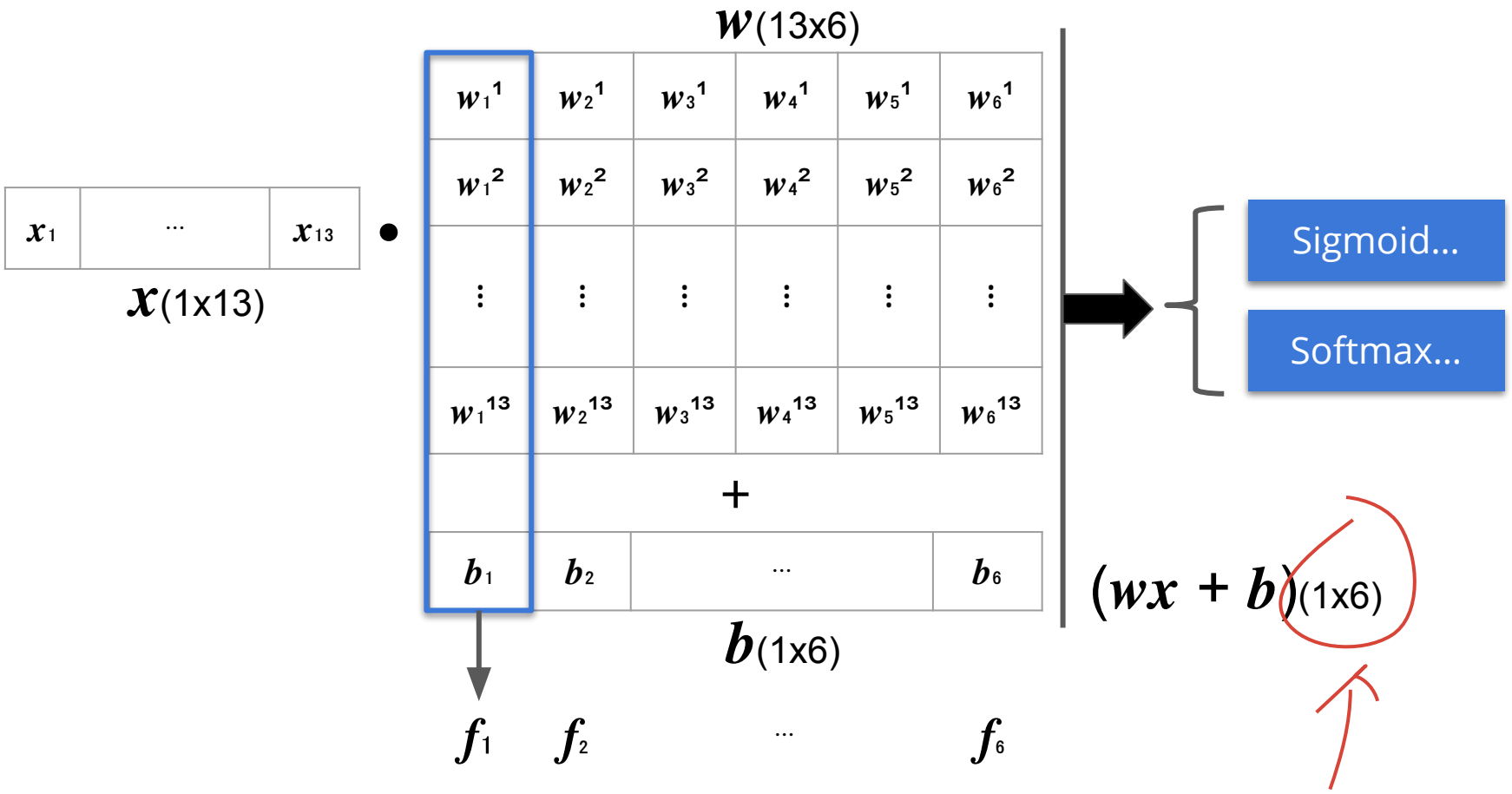
- ❏ 不考慮類別間的關係
- ❏ Multi-label for one record

一個獵人可以有多個系別
ex: 同時是強化系與特質系!

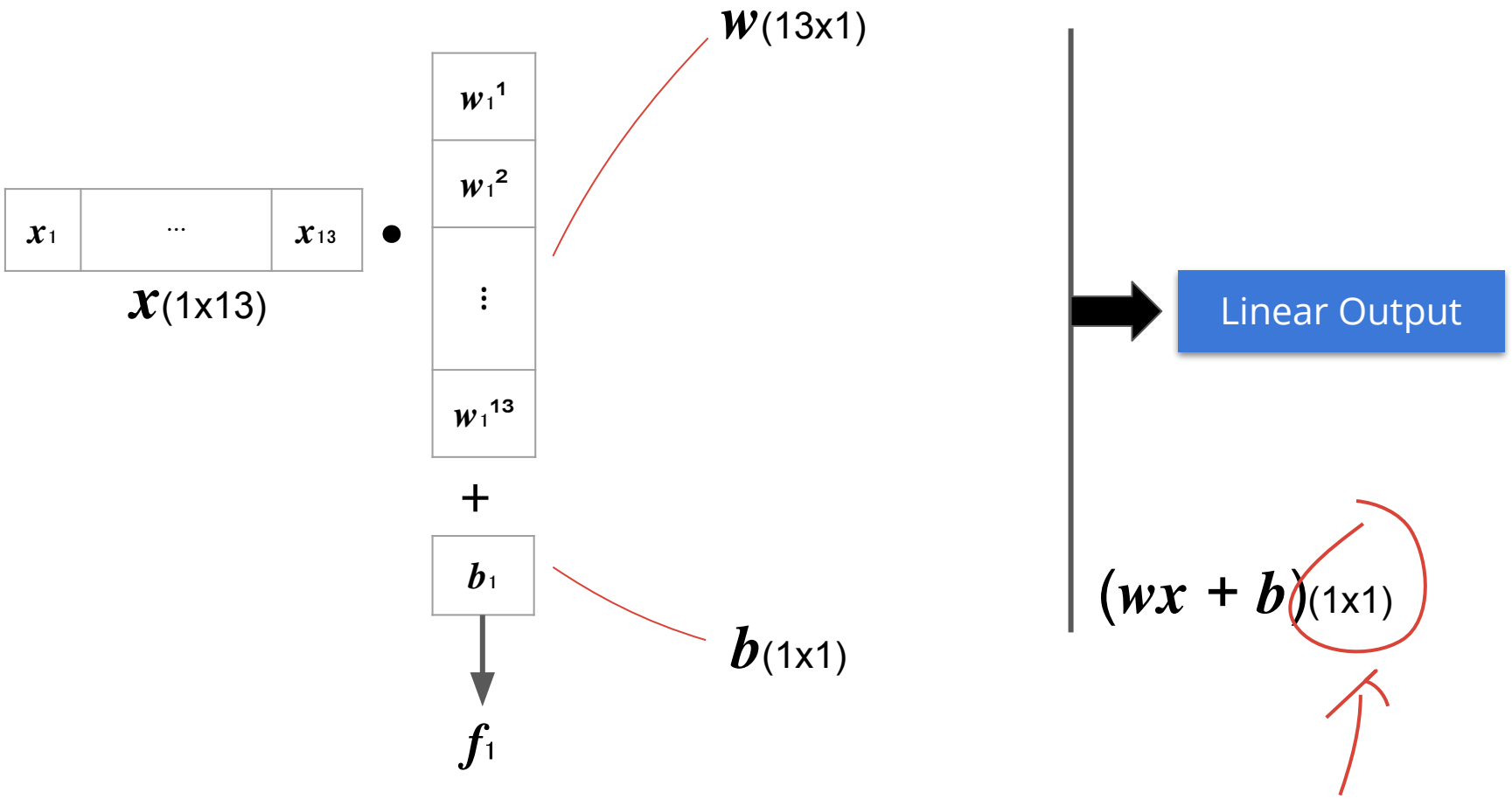
Computes sigmoid cross entropy given `logits`.

Measures the probability error in discrete classification tasks in which each class is independent and not mutually exclusive. For instance, one could perform multilabel classification where a picture can contain both an elephant and a dog at the same time.

以向量運算表示(分類)~

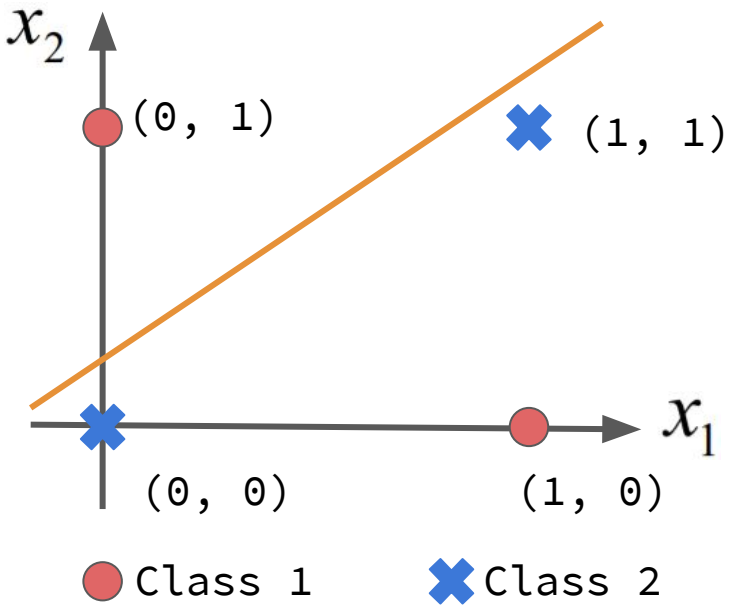

x_1 ... x_{13}
x(1x13)
W(13x6)
w_1^1 w_2^1 w_3^1 w_4^1 w_5^1 w_6^1
w_1^2 w_2^2 w_3^2 w_4^2 w_5^2 w_6^2
w_1^{13} w_2^{13} w_3^{13} w_4^{13} w_5^{13} w_6^{13}
b_1 b_2 ... b_6
b(1x6)
f_1 f_2 ... f_6
Sigmoid...
Softmax...
$(wx + b)$(1x6)

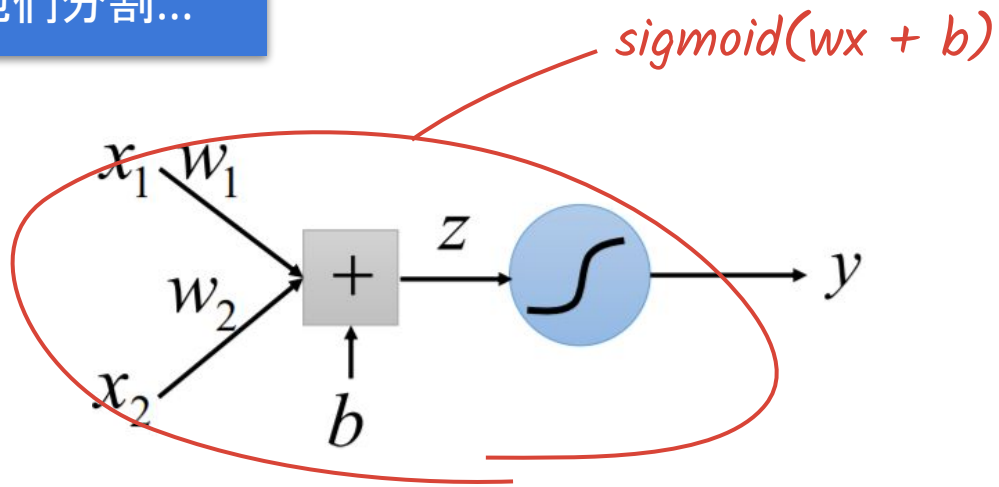
以向量運算表示(回歸)~


w(13x1)
x_1 ... x_{13}
x(1x13)
w_1^1
w_1^2
w_1^{13}
+
b_1
b(1x1)
f_1
Linear Output
$(wx + b)$(1x1)

以分類來說, 常碰到的瓶頸(Limitation)

以下狀況似乎不能用一條線將他們分割...





$$\begin{cases} Class1 & y \geq 0.5 \\ Class2 & y < 0.5 \end{cases}$$

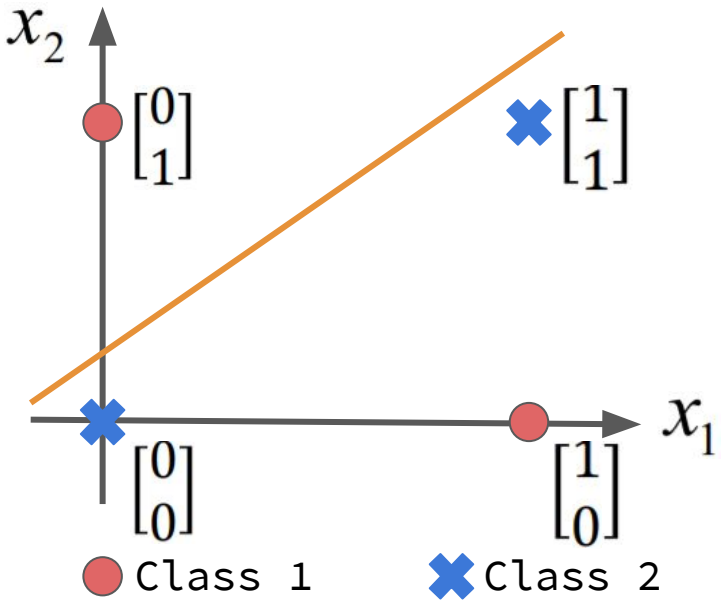
以分類來說, 常碰到的瓶頸(Limitation)

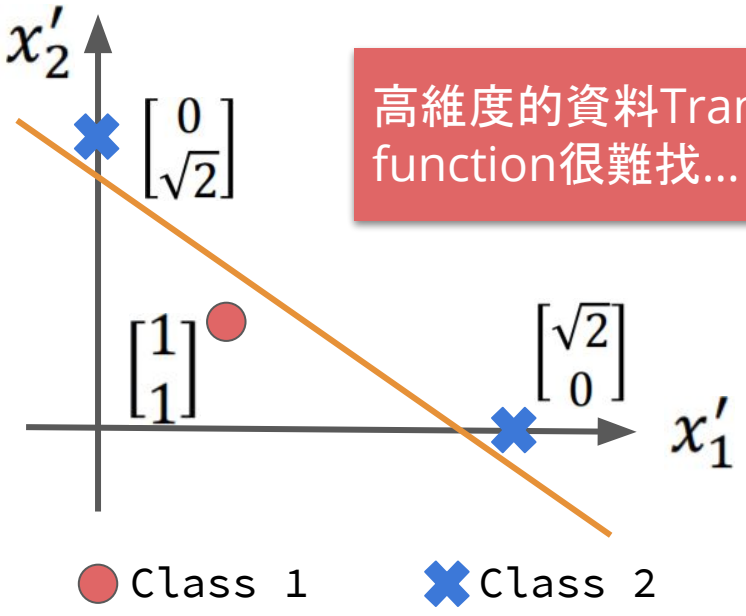
Feature Transformation!

$$trans(x) = \begin{bmatrix} x到(0,\ 0)的距離 \\ x到(1,\ 1)的距離 \end{bmatrix}$$

x_1': distance to $\begin{bmatrix}0\\0\end{bmatrix}$

x_2': distance to $\begin{bmatrix}1\\1\end{bmatrix}$

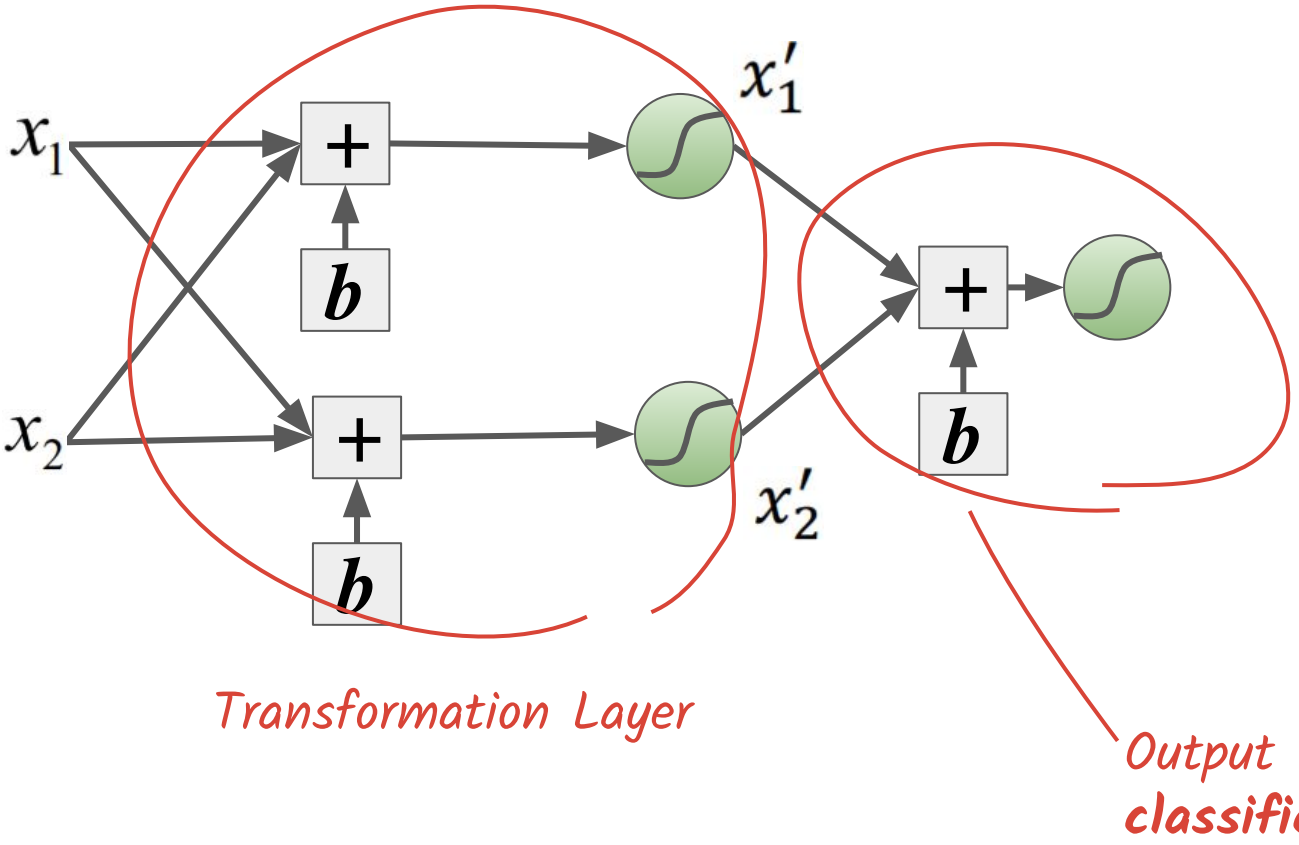




高維度的資料Transform function很難找...

Cascading Functions

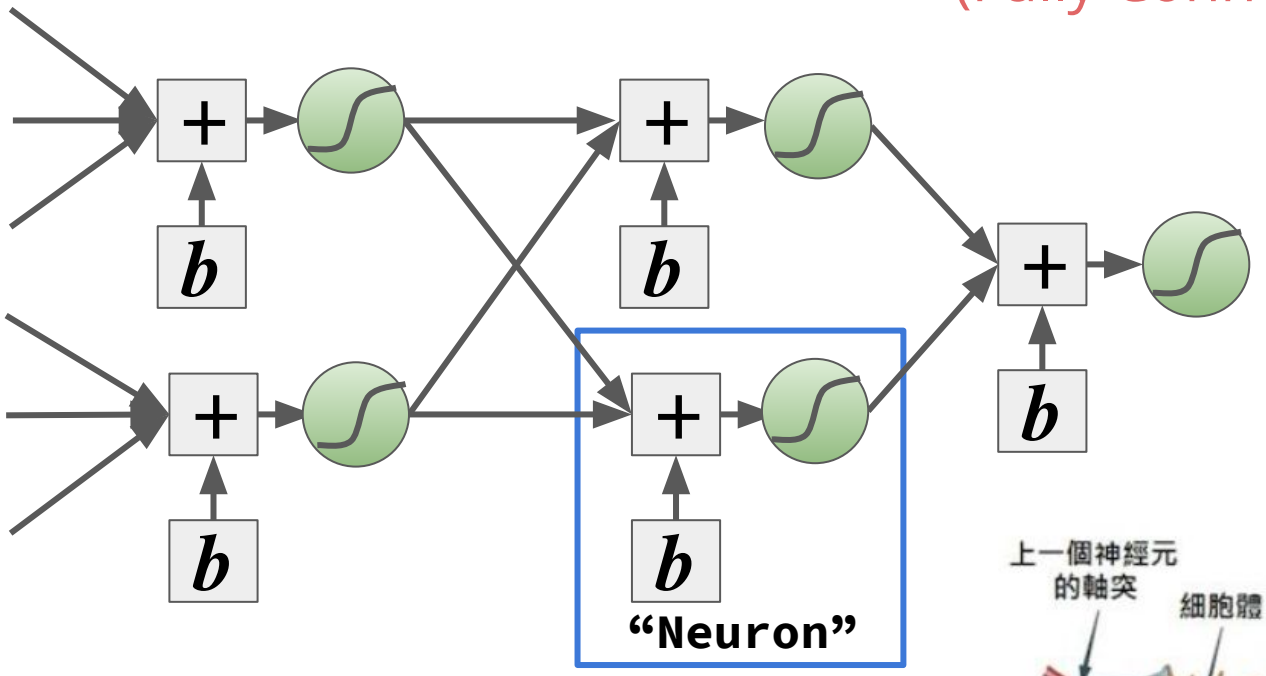
也許Machine可以自己learn feature transformation...

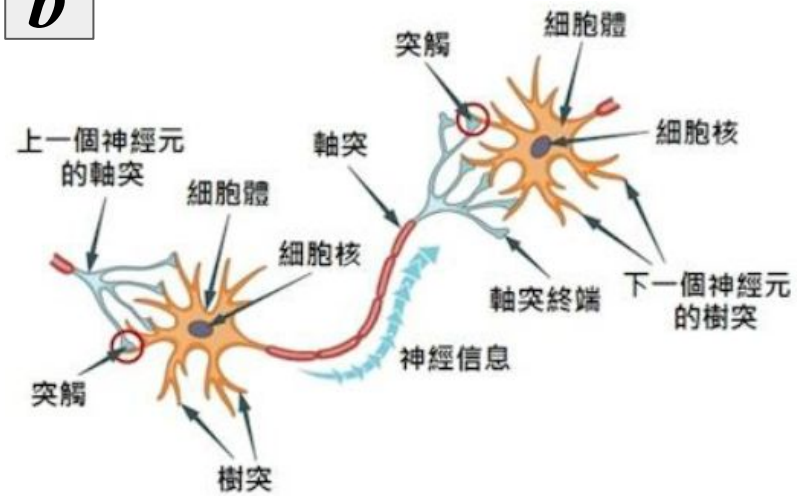


Cascading Functions

串聯 + 並聯

Deep Learning!
(Fully Connected Structure)

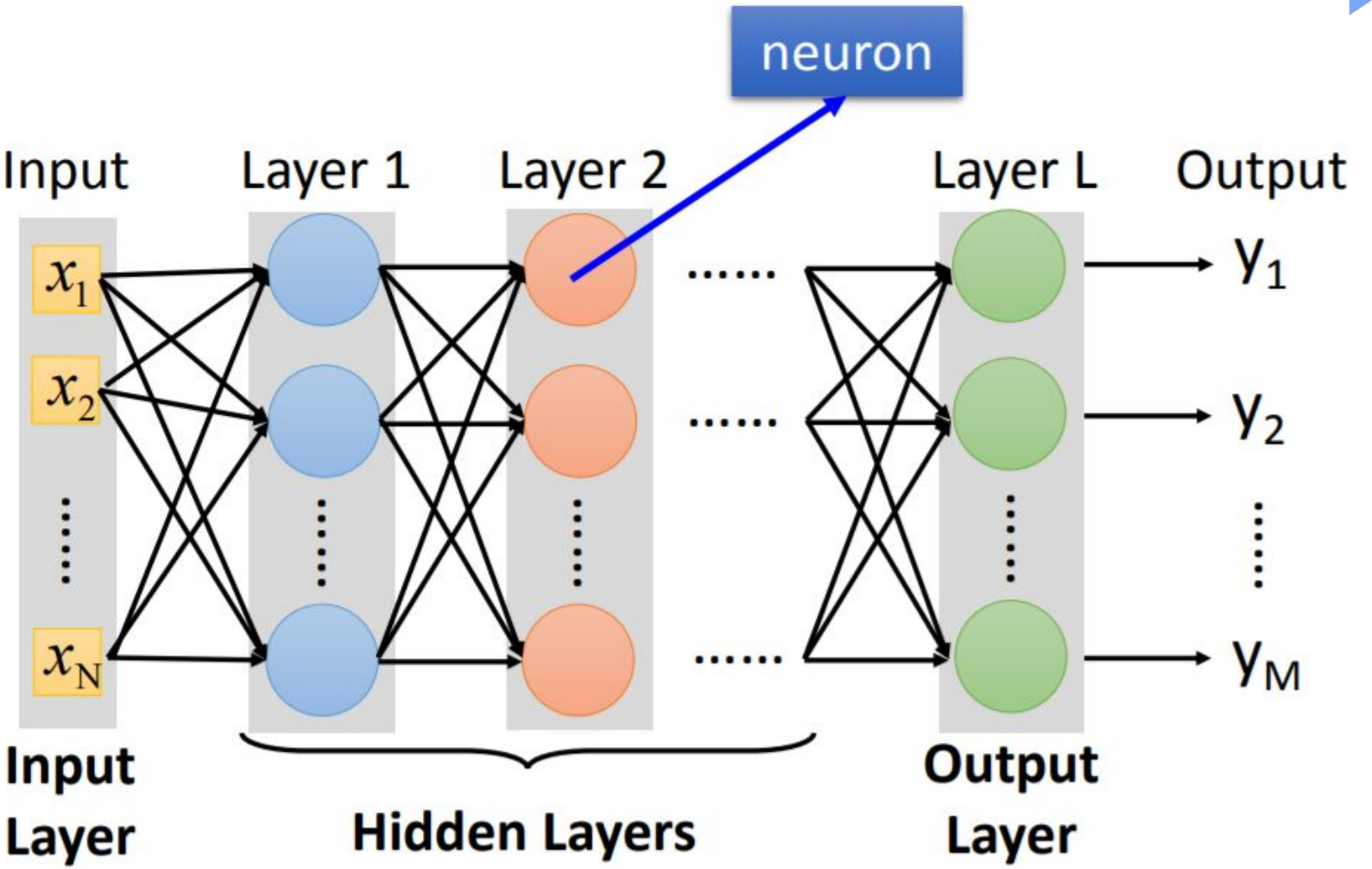




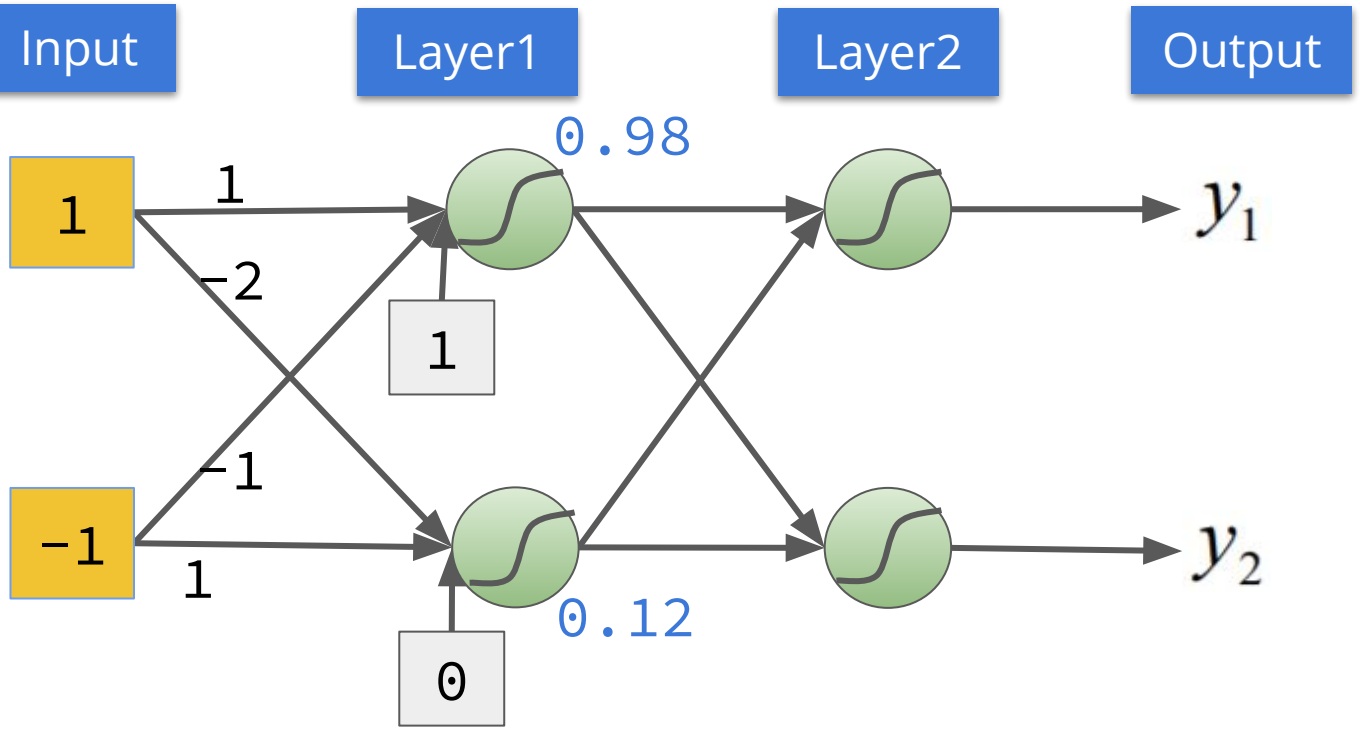
Deep Neural Network(DNN) Tips

- Machine Learning Framework
- Deep Neural Network(DNN) Tips
- Recommedation Engine in Matrix Factorization
- Matrix Factorization with DNN

DNN Structure(Fully Connected)



Matrix Operation



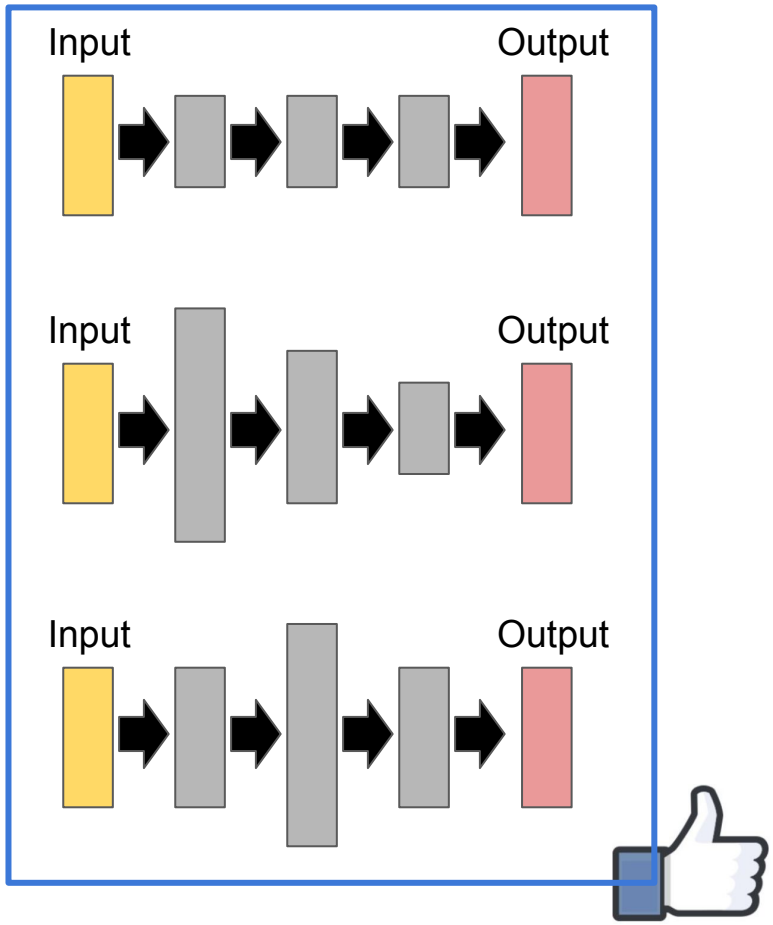
$$\sigma\left(\begin{bmatrix}1 & -1\end{bmatrix}\begin{bmatrix}1 & -1\\ -2 & 1\end{bmatrix}+\begin{bmatrix}1 & 0\end{bmatrix}\right)=\begin{bmatrix}0.98 & 0.12\end{bmatrix}$$

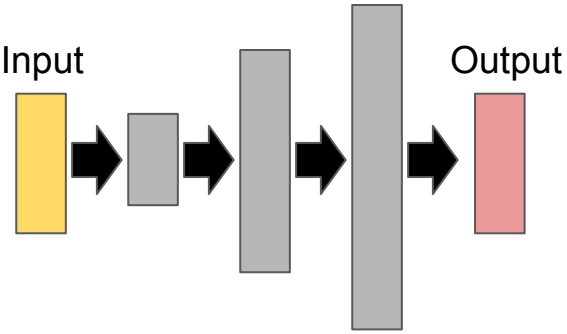
data　weight　bias

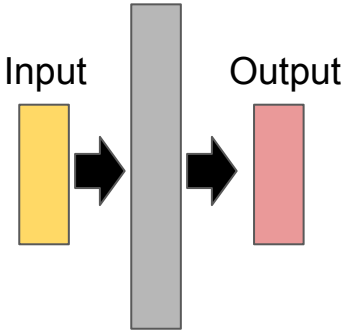
一層Layer的組成元素

σ, w, b

Network的架構(哪種比較好?)



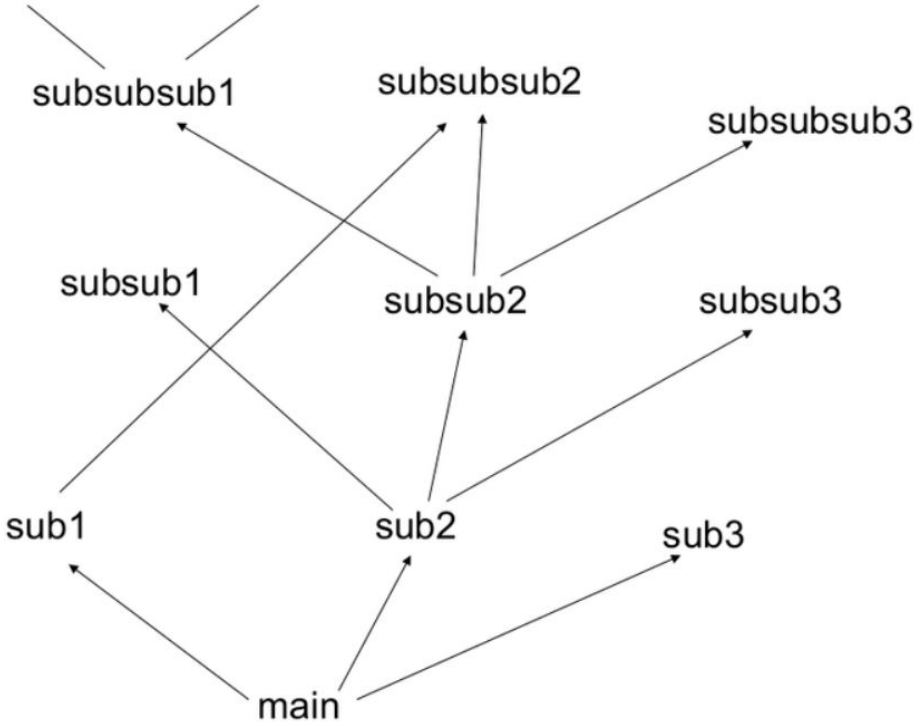




Network的架構

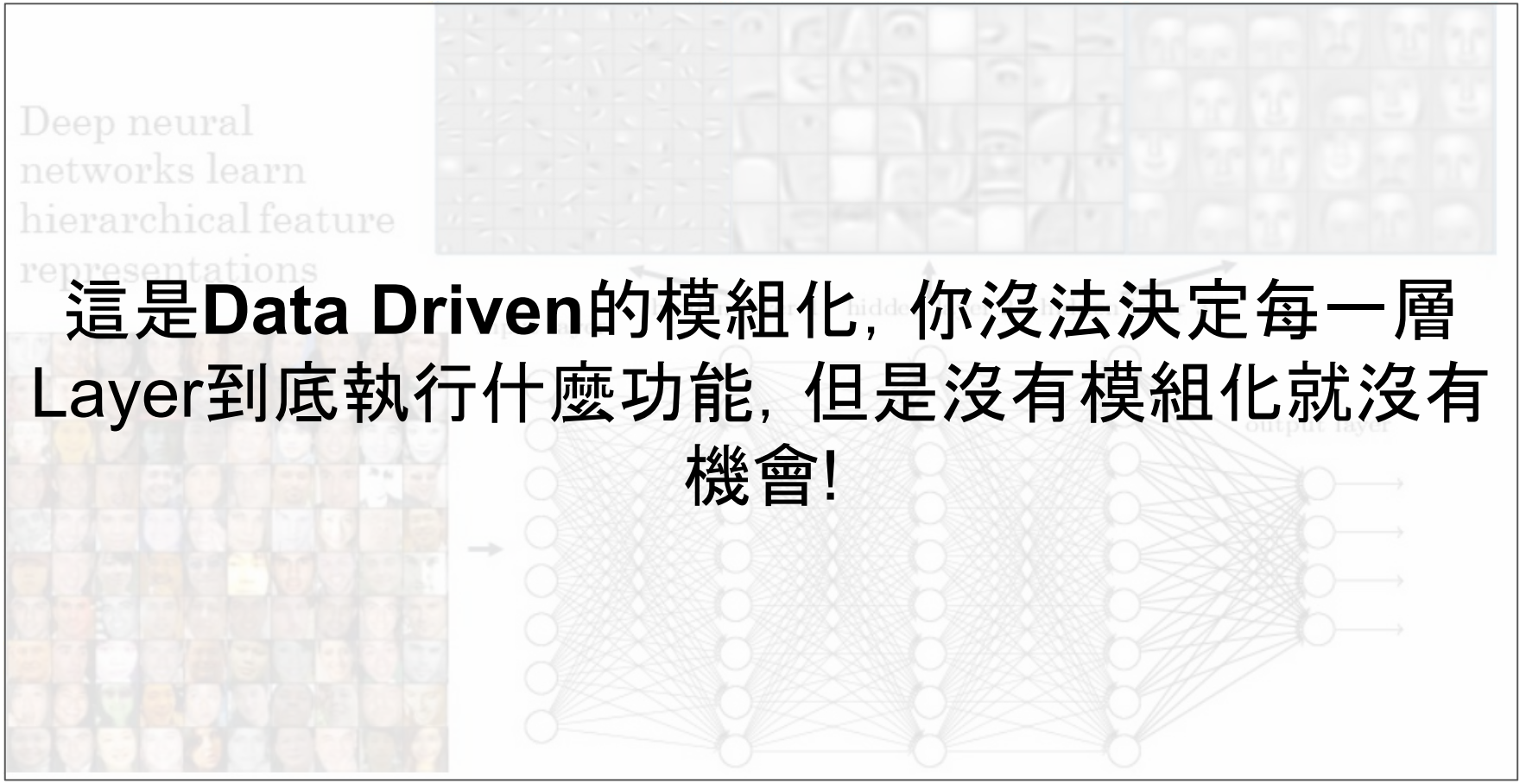
- Deep Neural Network可以想成一種模組化的概念
- 不要一招打天下

Coding的概念:
不要在main重頭寫到尾!



Network的架構

Modularization



這是Data Driven的模組化，你沒法決定每一層Layer到底執行什麼功能，但是沒有模組化就沒有機會!

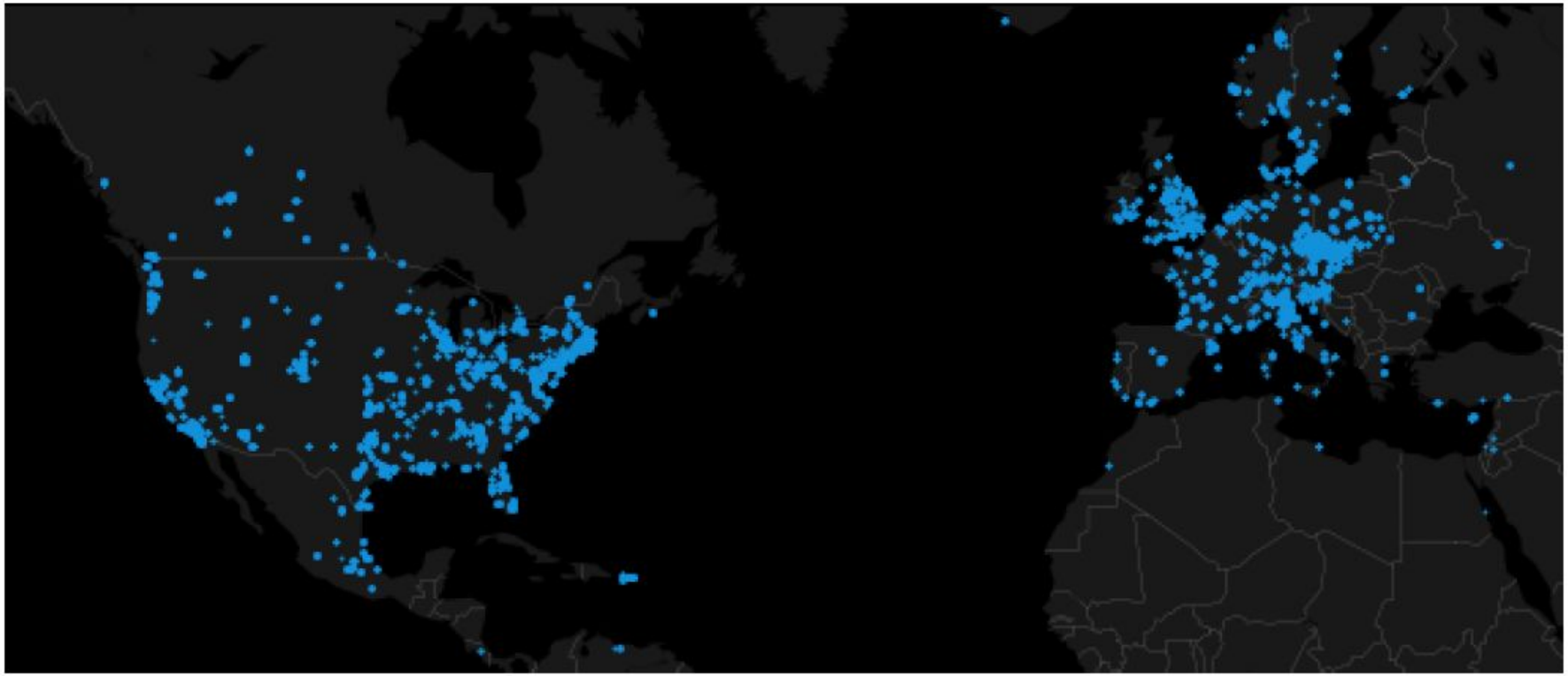
Ref: Deep Learning and Convolutional Neural Networks: RSIP Vision Blogs

Deep Neural Network(DNN) Tips

Classification:
說太多了，動手實作吧！

直接來實作吧！

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

範例資料: 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？

範例資料： 預測會出現哪一隻神奇寶貝？

- 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隻寶可夢
- class 就是我們要預測目標

為了簡化複雜度，我們只挑出五種類別

Data Preprocessing Tips

- Neural network運算只接受數字(numeric)
- 如何處理非數值資料?
  - Categorical variables
  - Ordinal variables
- 不同feature的數值範圍差異是否會有影響?
  - 溫度: 0 ~ 40度
  - 距離: 0 ~ 10000公尺

Data Preprocessing Tips

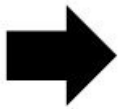
- Categorical variables
  - One Hot Encoding: 回想獵人的系別，強化系、變化系...
    - 避免產生不必要的距離關係!
  - 特殊Case: 地址
    - 台中市大馬路無尾巷

    ⇒ 轉成經緯度 {25.04, 121.61}

Data Preprocessing Tips

- Ordinal variables(順序資料)
  - Def: 跟數值一樣有大小關係(順序關係)卻又像類別變數
  - For example: 衣服size, {S, M, L, XL}
    ⇒ {1, 2, 3, 4}
    ⇒ 當作類別變數One Hot Encoding
      S: [1, 0, 0, 0]
      M: [0, 1, 0, 0]
      ...
  - Create a new feature using mean or median

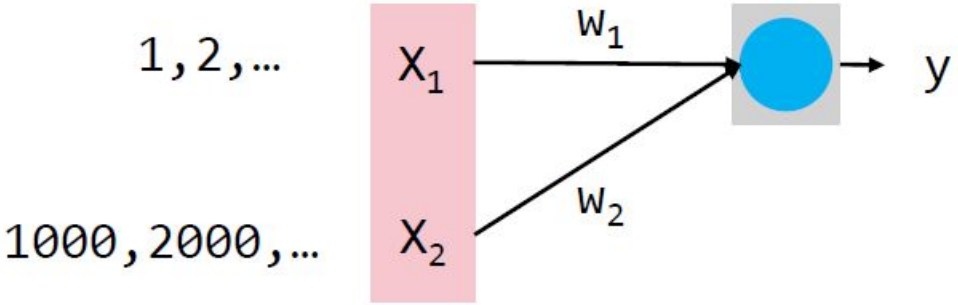
UID	Age
P1	0-17
P2	0-17
P3	55+
P4	26-35

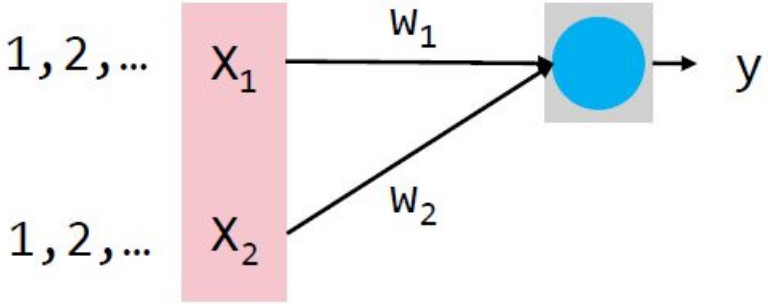


UID	Age
P1	15
P2	15
P3	70
P4	30

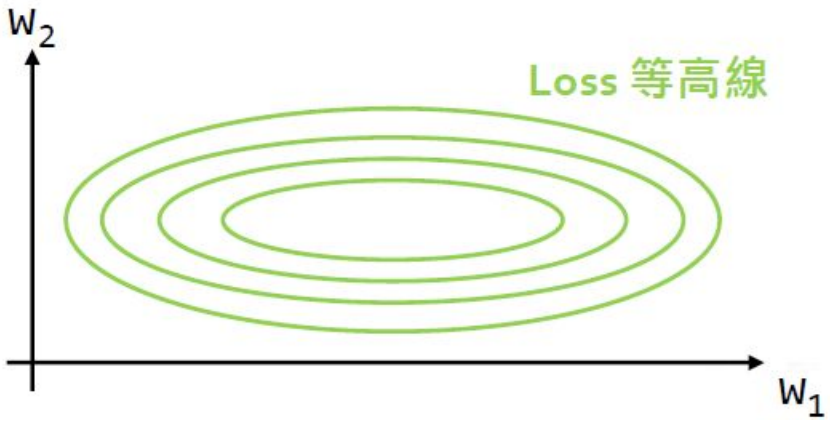
Data Preprocessing Tips

- 對於numeric欄位，處理不同數值範圍
  - 非常建議normalize，不要讓幾個變數主導整個function！





w_2 的修正(ΔW)對於 loss 的影響比較大

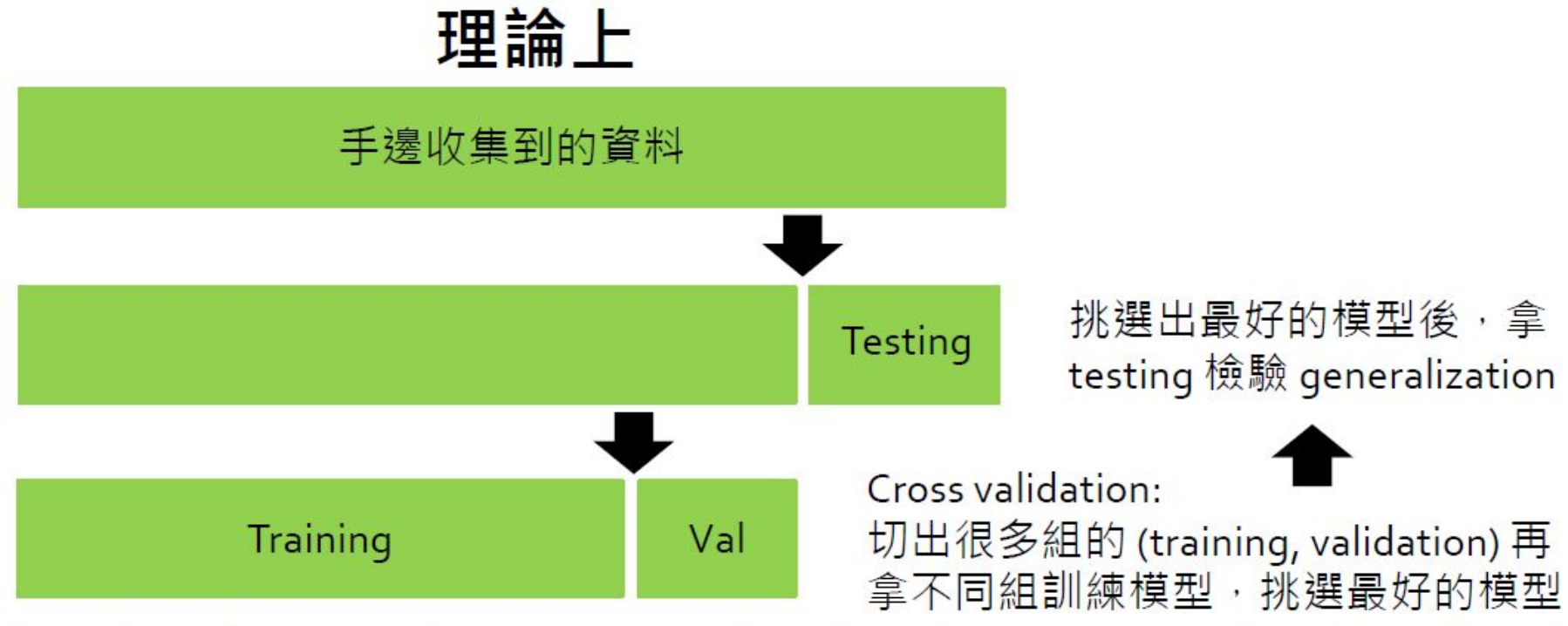


Data Preprocessing Tips

- Normalize methods
  - Min max scaler to [0, 1] $\frac{x_i - min}{max - min}$ **(注意outlier)**
  - Scale to standard normal distribution $\mu = 0,\ \sigma = 1$ (Z-score standardize)
  - 以上兩種方式沒有guideline說什麼狀況下使用最好

How to Treat Your Data?

- Split train, valid, test data
  - Valid data用來挑選model
  - Test data檢驗模型的generalization
- **為簡化複雜度, Demo用traing + valid**



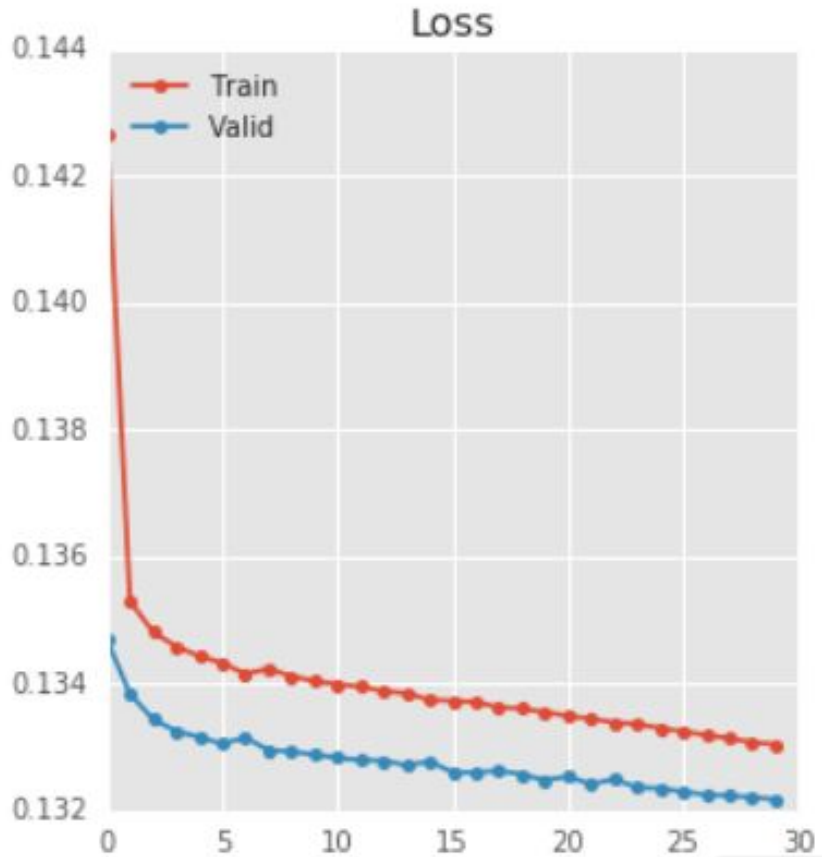
寶可夢Deep Neural Network Tutorial

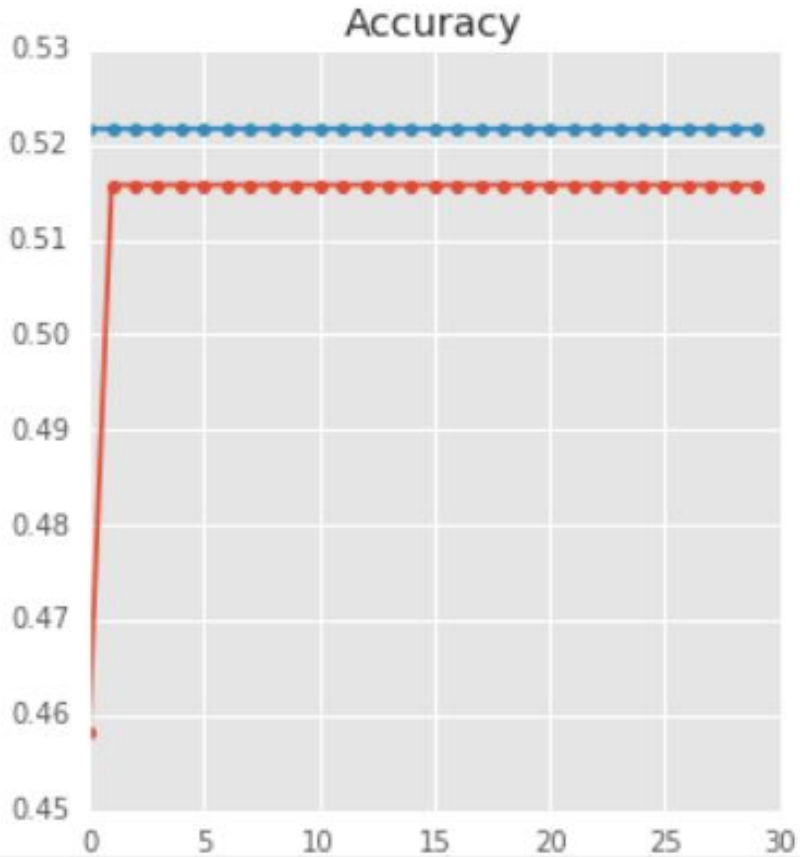
filename	tutorial_dnn_practice.ipynb
lab filename	lab_tutorial_dnn_practice.ipynb
input	200 features
label	5 class
neural network	DNN

Lab File For You

Result of ModelMSE

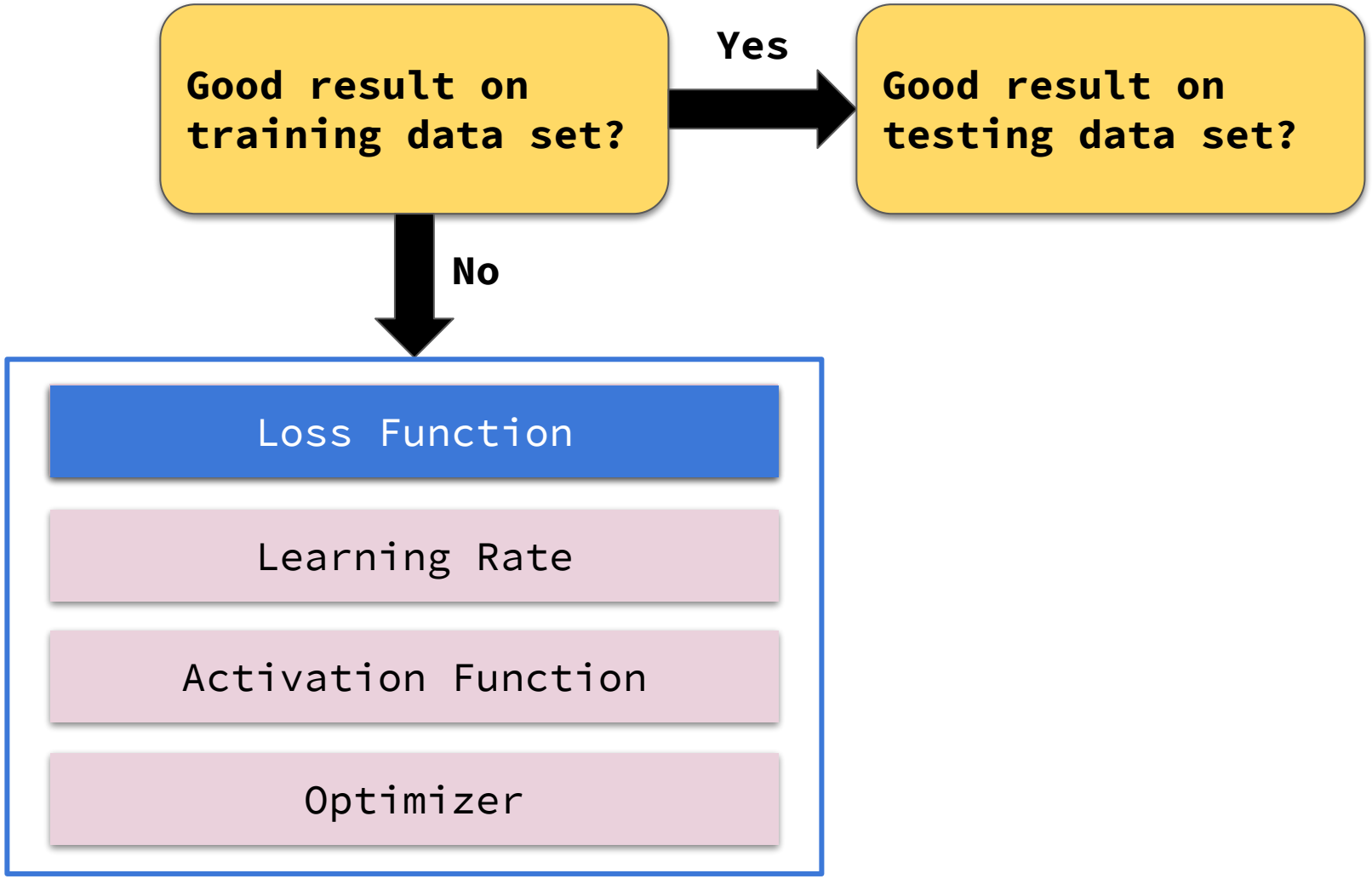
```
mean square error model!
30/30.  train loss: 0.133, valid loss: 0.132, train acc: 0.516, valid acc: 0.522
```





Accuracy about 0.5，好像不太妙啊...

Deep Neural Network(DNN) Tips



Lab: lab_dnn_tutorial_practice.ipynb (15 minutes)

搜尋 ”Do:” 就可以找到可能要修改的位置

lab filename	lab_tutorial_dnn_practice.ipynb
target	將loss function由MSE修改成cross entropy

Classification With Cross Entropy

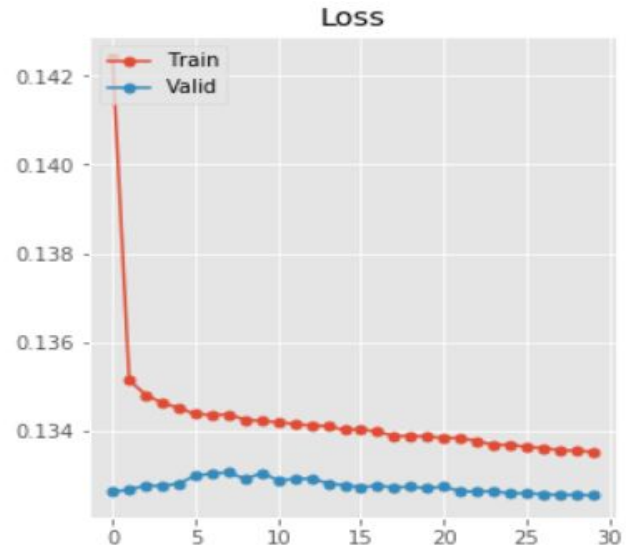
+ learning_rate: 0.01
+ loss function: softmax cross entropy
+ optimizer: 基本款 => GradientDescentOptimizer
+ activation function: sigmoid

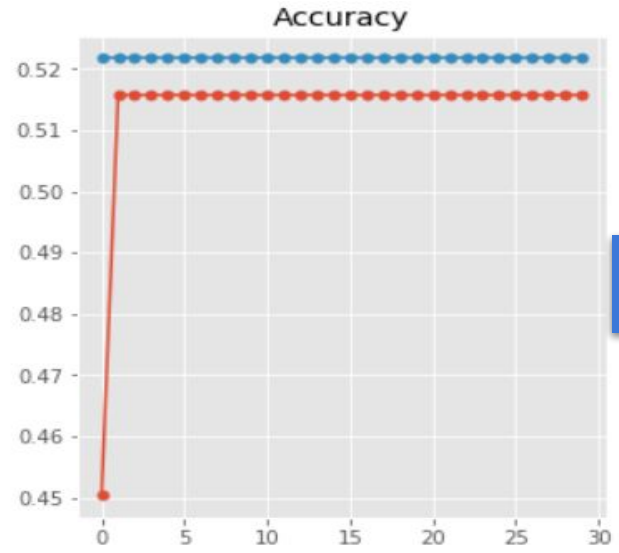
Tensorflow Code(Loss Function)

```
with tf.variable_scope("loss"):
    # loss function 改用 cross entropy
    self.loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=self.labels, logits=nets))
```

- loss function: tf.nn.softmax_cross_entropy_with_logits
  - **這個function會自動幫你的prediction加上softmax**

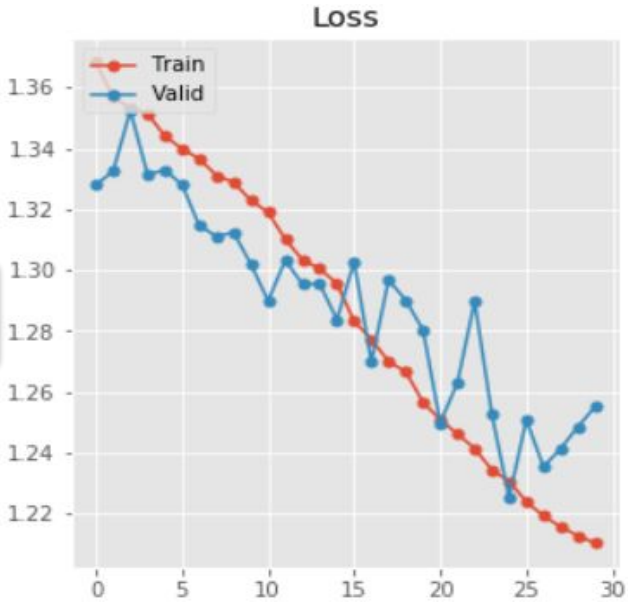
Result - MSE vs Cross Entropy

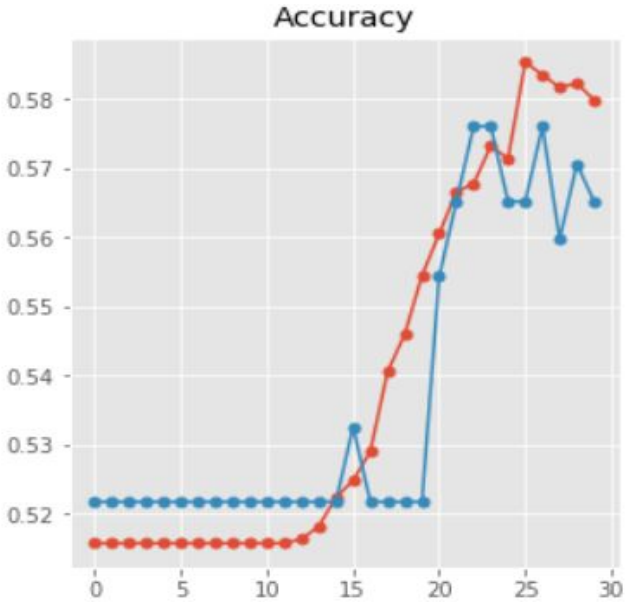




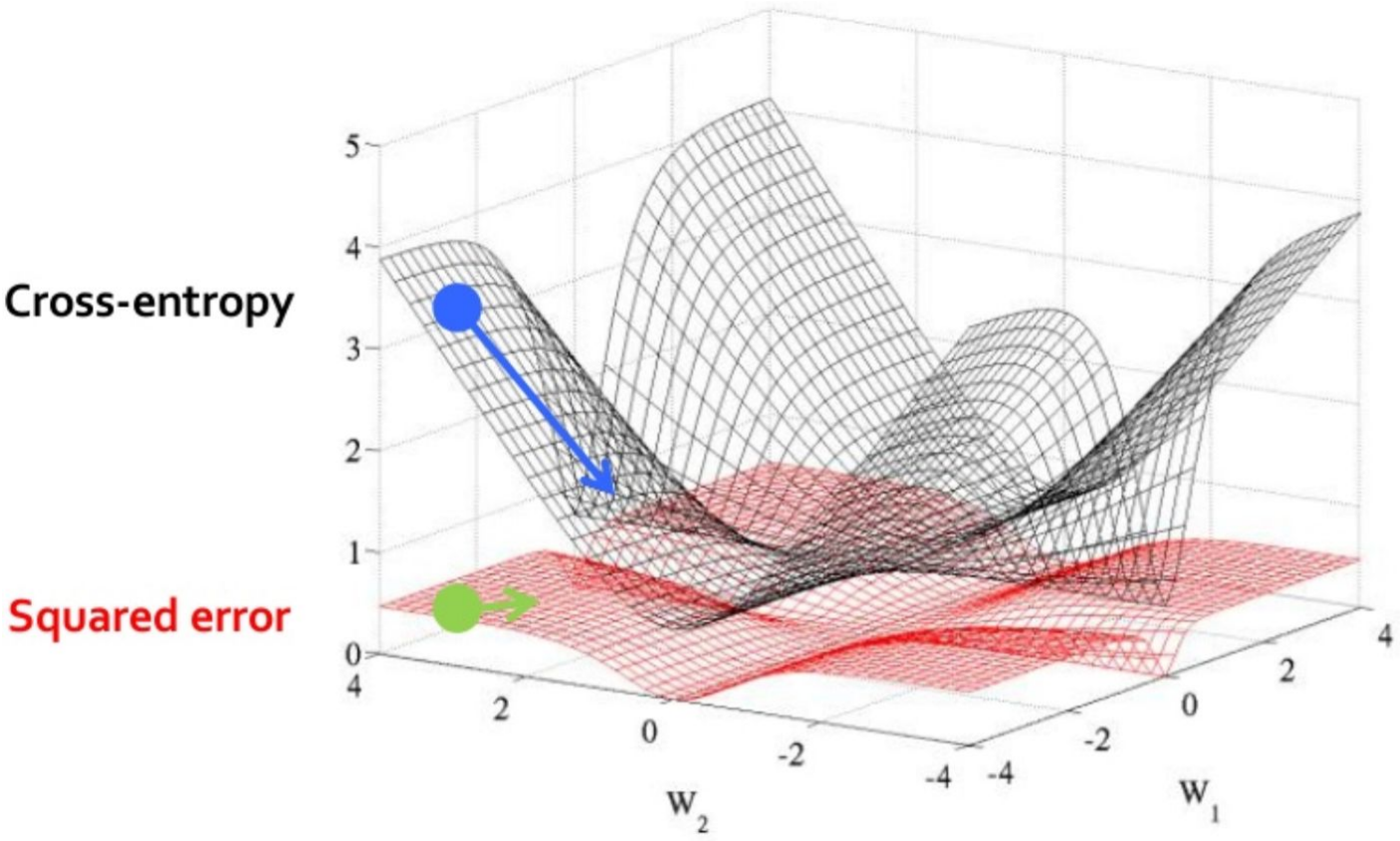
MSE

Cross Entropy





Classification Loss Function: MSE or Cross Entropy



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

How to Select Loss function

- Classification常用cross entropy
  - 搭配softmax or sigmoid當作output layer的activation function

- Regression常用mean squared/absolute error
  - 其他還有...
    - MAPE: mean absolute percentage error
    - SMAPE: symmetric mean absolute percentage error

$$\frac{100}{n}\sum_{i}^{n}\frac{|actual_i - prediction_i|}{actual_i}$$

Lab: lab_dnn_tutorial_practice.ipynb (5 ~ 8 minutes)

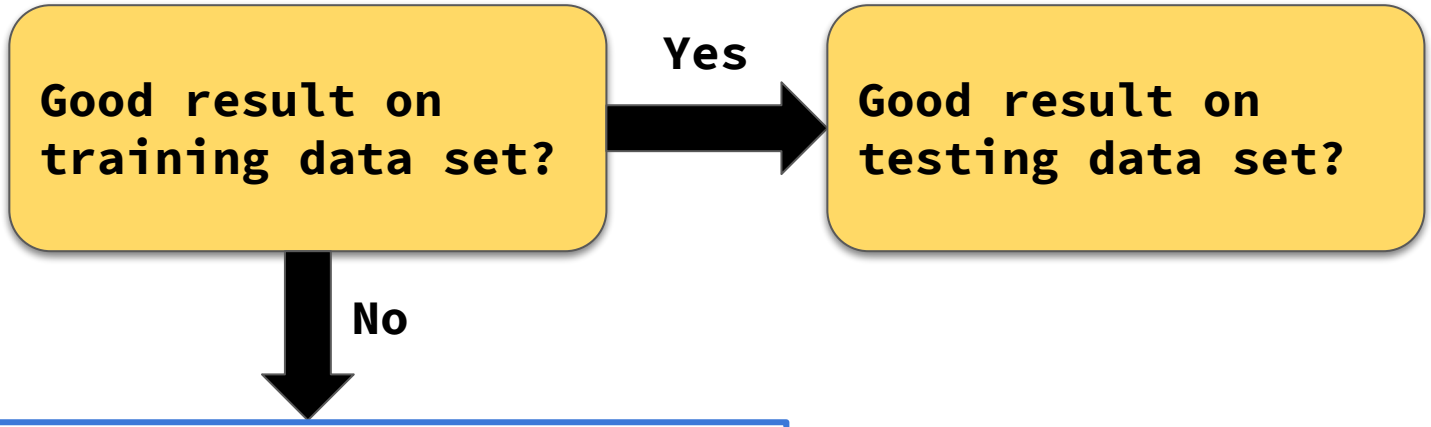
搜尋 ”Do:” 就可以找到可能要修改的位置

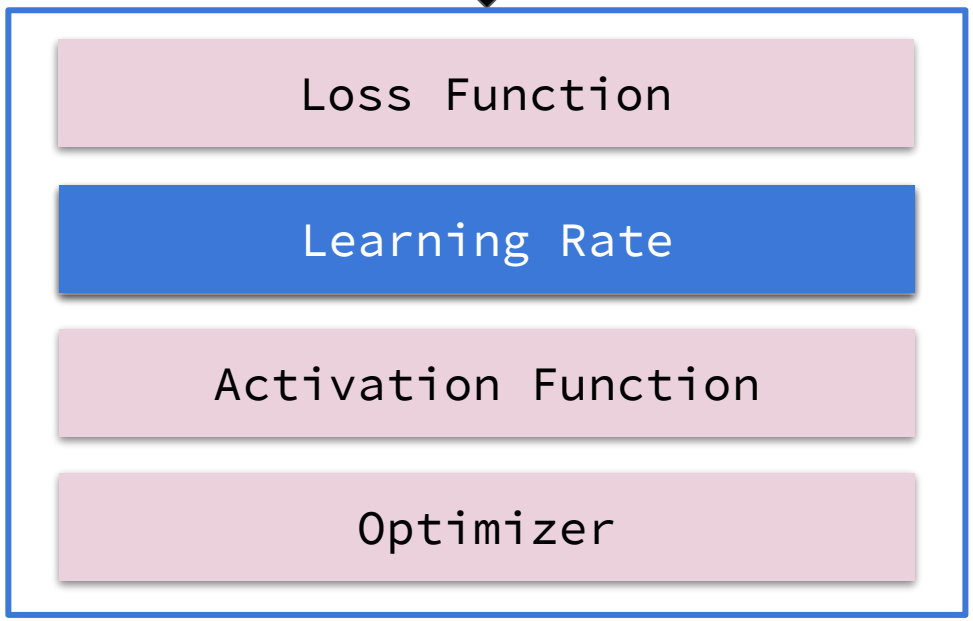
lab filename	lab_tutorial_dnn_practice.ipynb
target	嘗試不同的learning rate: [0.1, 0.01, 0.001]

Try Learning Rate!

+ learning_rate: 0.1, 0.01, 0.001
+ loss function: softmax cross entropy
+ optimizer: 基本款 => GradientDescentOptimizer
+ activation function: sigmoid

Tune Your Learning Rate





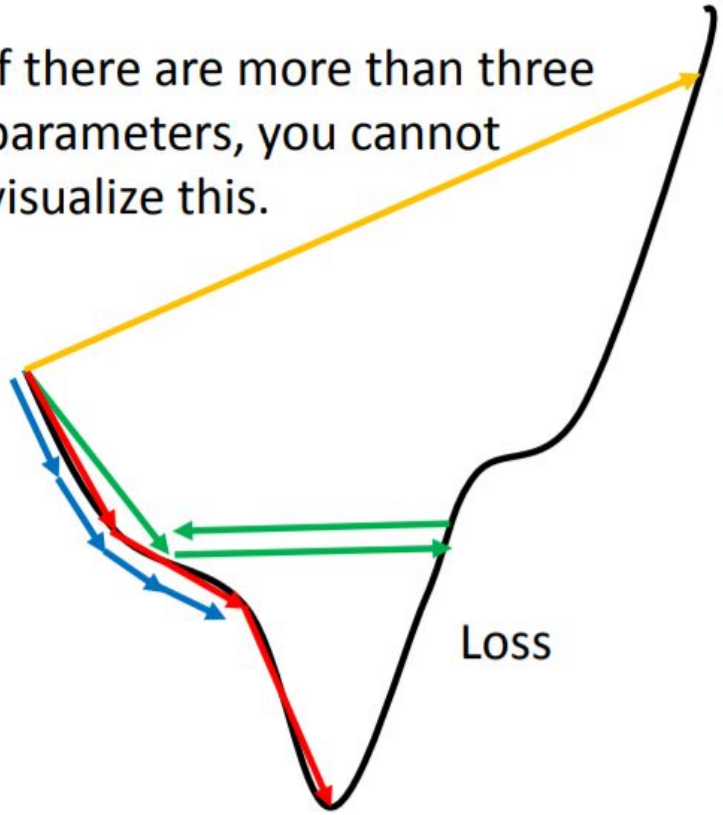
Tune Your Learning Rate

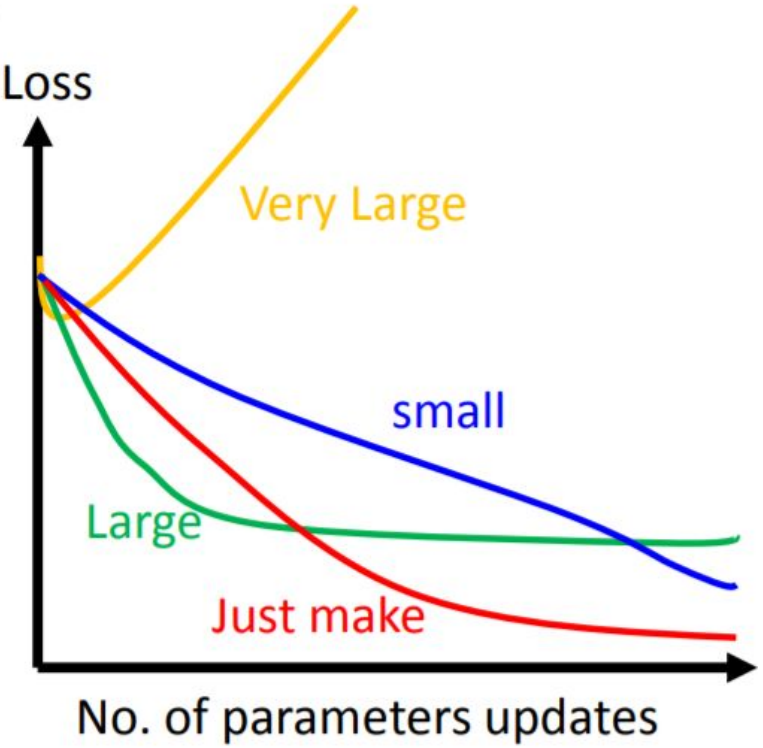
Learning Rate

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

Set the learning rate η carefully

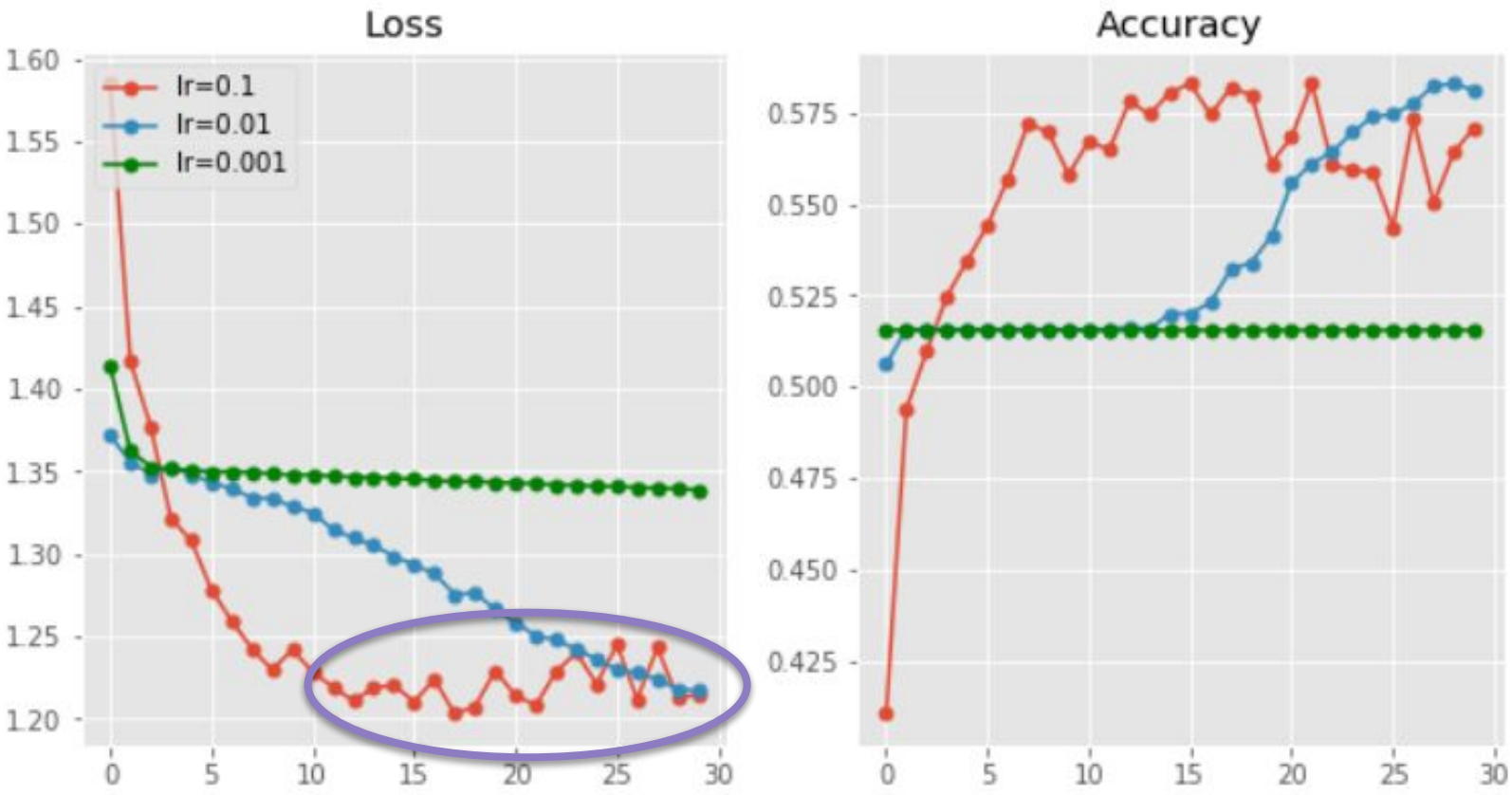
If there are more than three parameters, you cannot visualize this.





But you can always visualize this.

Tune Your Learning Rate

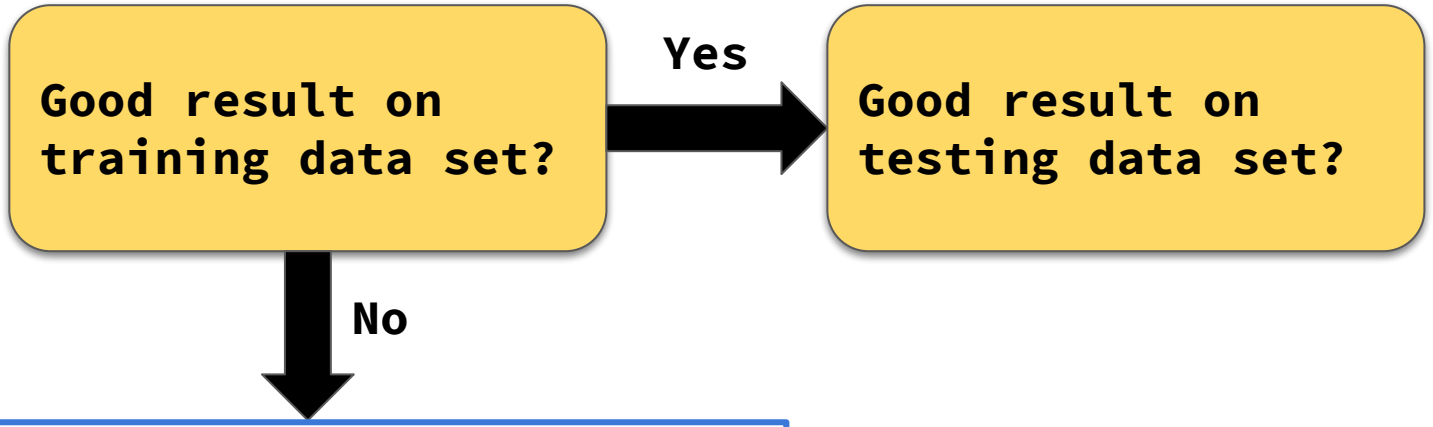


觀察loss，這樣的震盪比表示learning rate可能太大，以這個狀況, 0.01是最好的選擇

Tune Your Learning Rate

- 大多要試試看才知道，通常不會大於0.1
- 調整的步伐大概是一次5 ~ 10倍
  - 0.1 ⇒ 0.01 ⇒ 0.001
  - 0.001 ⇒ 0.01 ⇒ 0.1 ⇒ 0.5
  - ~~0.01 ⇒ 0.012 ⇒ 0.015 ⇒ 最高0.87分不能再高~~

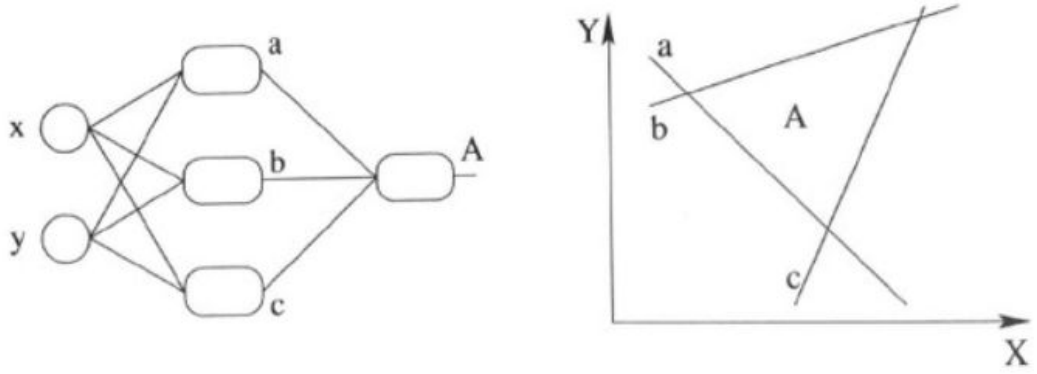
Choose Your Activation Function



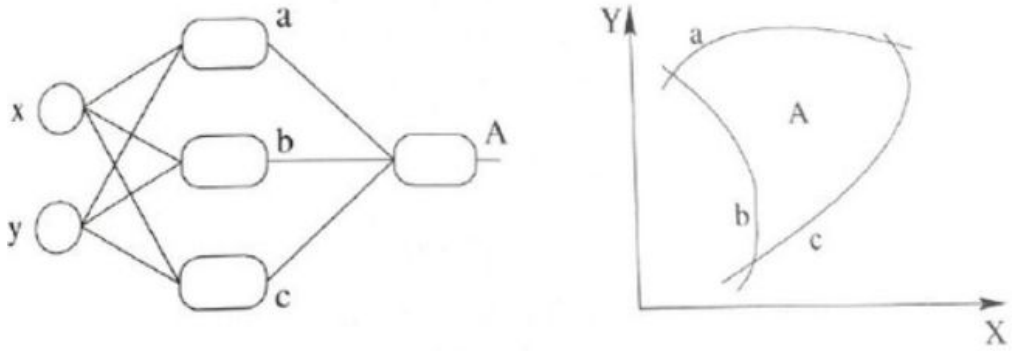
- Loss Function
- Learning Rate
- **Activation Function**
- Optimizer

Activation Function的初衷

- 把你的Neural network變成non-linear，加強fit能力



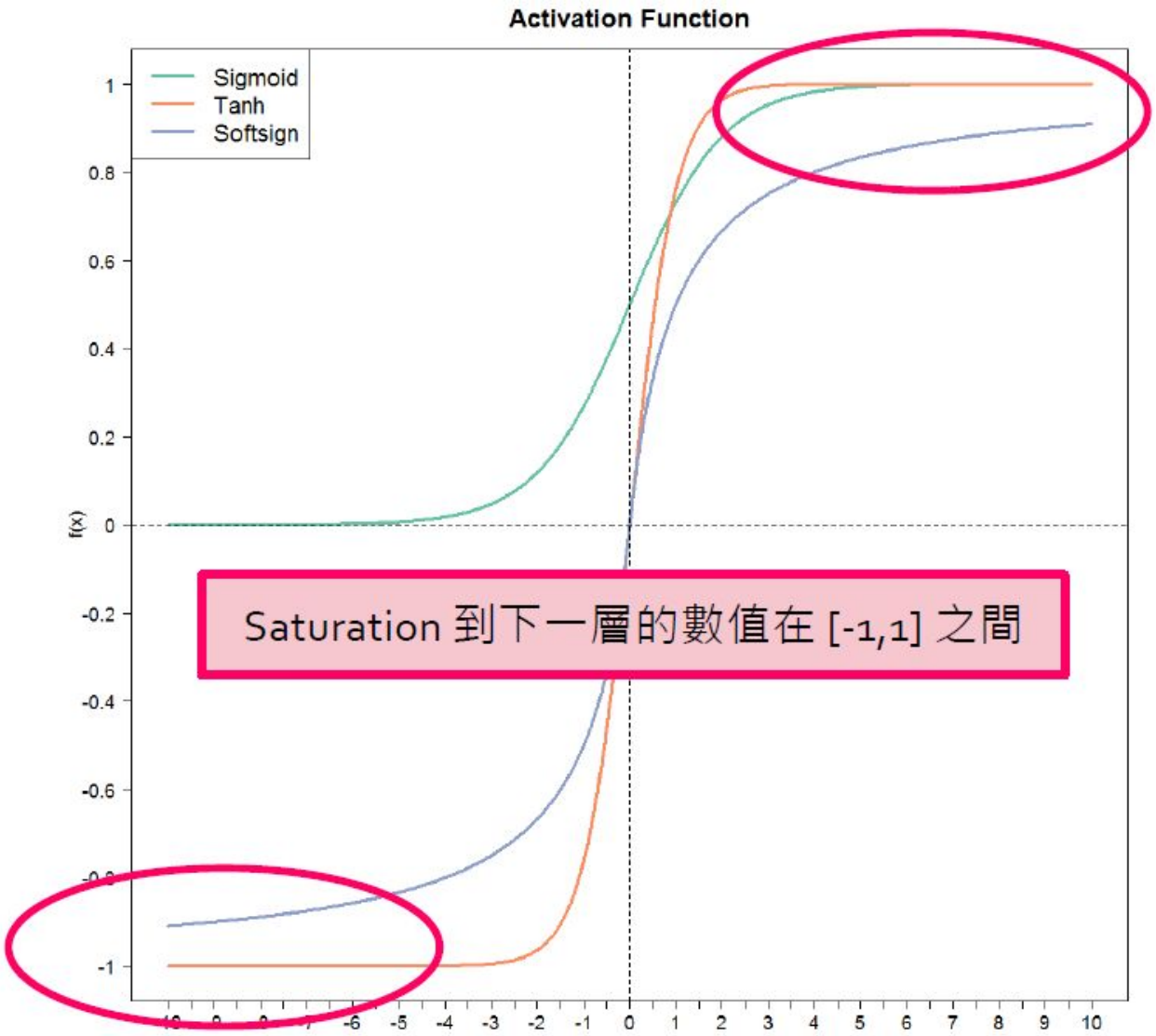
with step activation function



with sigmoid activation function

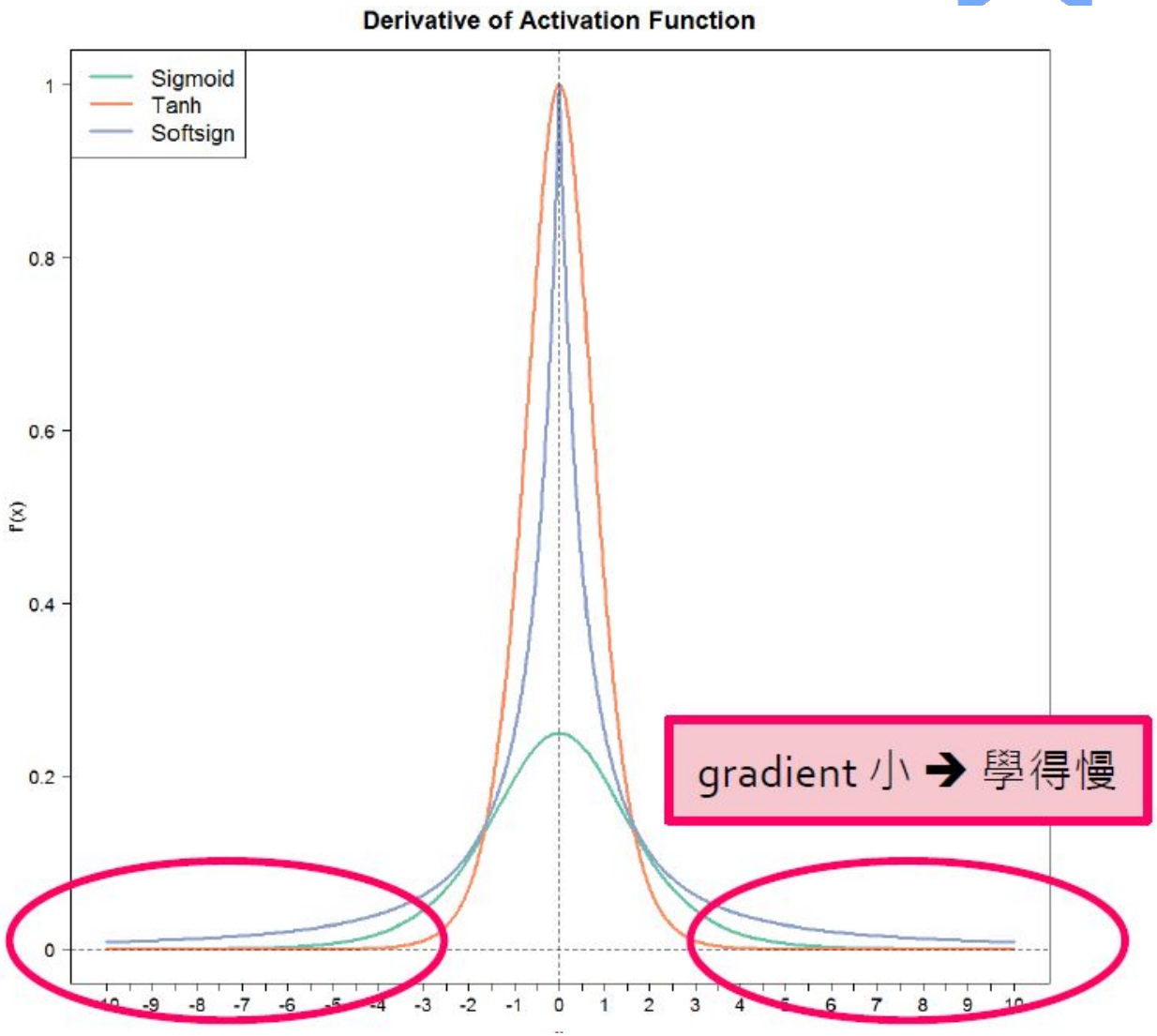
傳統的Activation Function

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



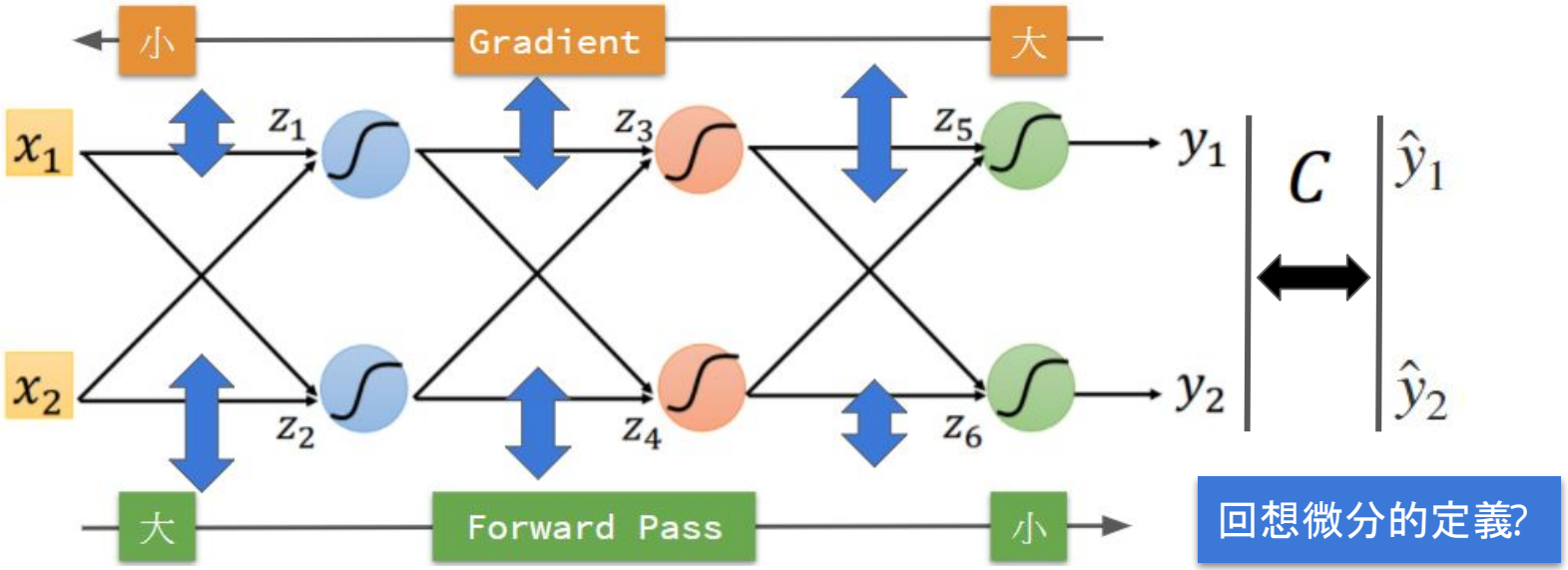
傳統的Activation Function

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



傳統的Activation Function

- Vanishing gradient problem
  - 原因: 每一層的input被壓縮到一個相對很小的output range

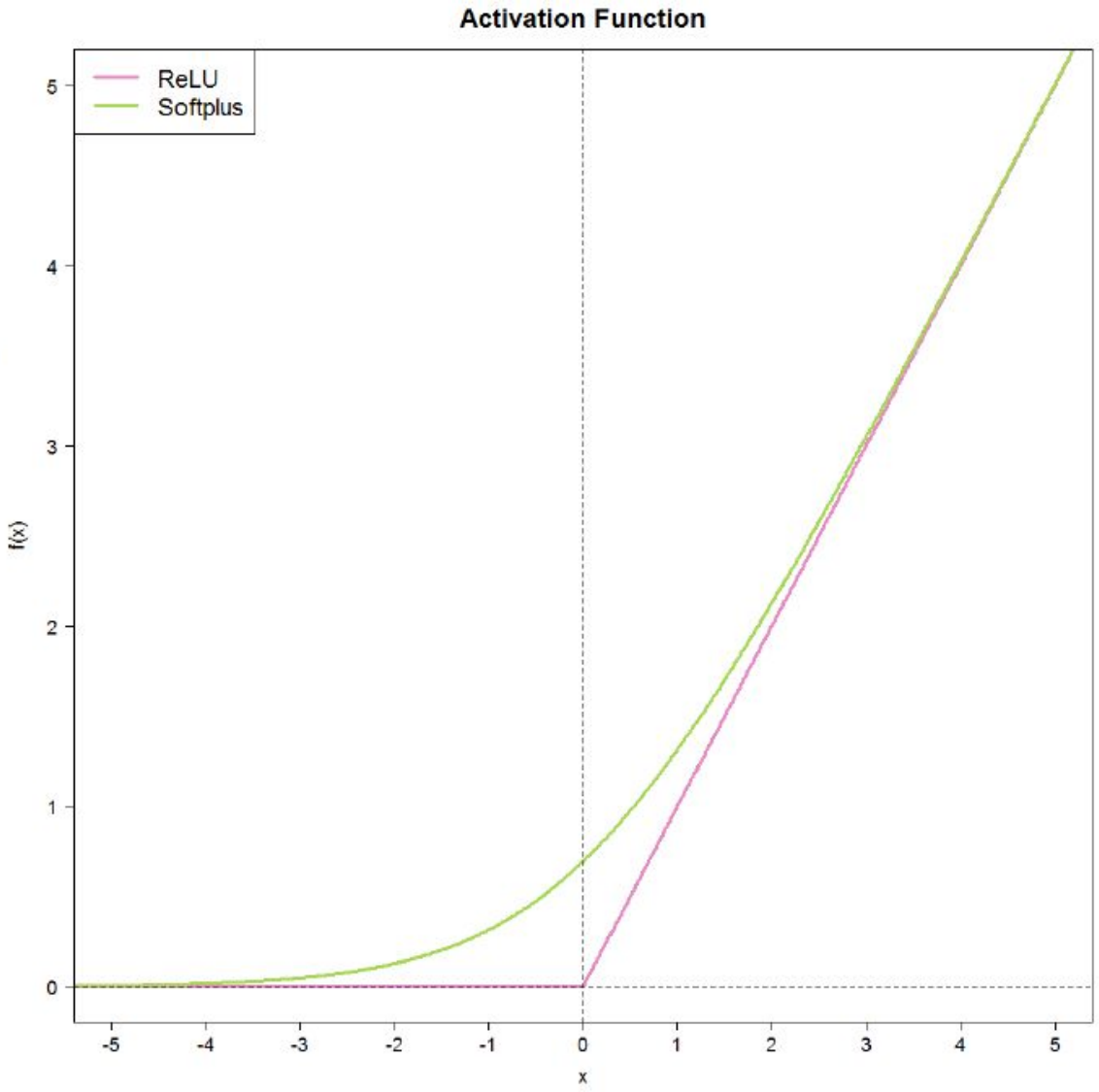


  - 結果: Gradient小無法有效地學習
  - Sigmoid, Tanh, Softsign都有這樣的特性

- **特別不適用於深的深度學習模型**

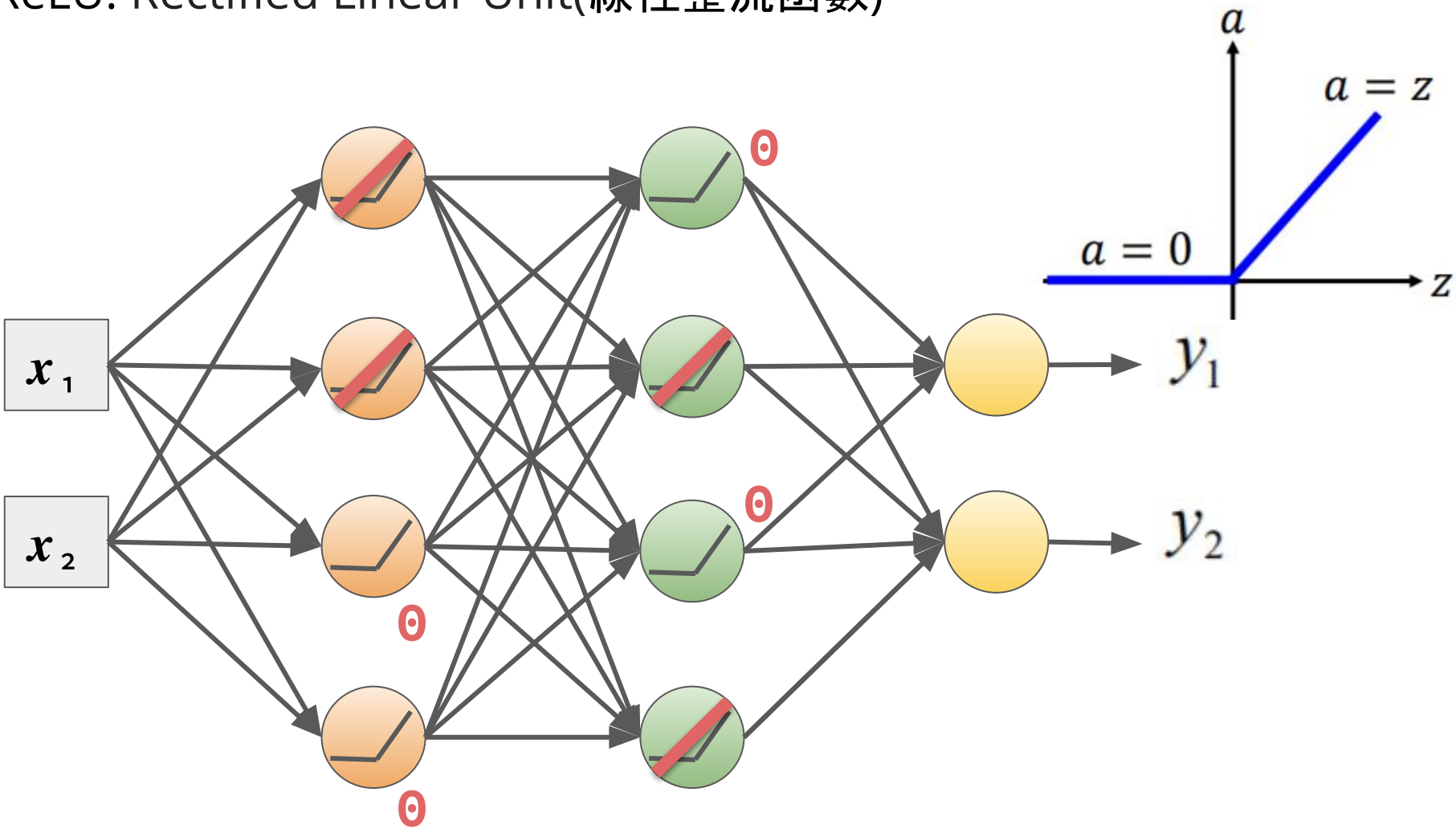
比較潮的Activation Function

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



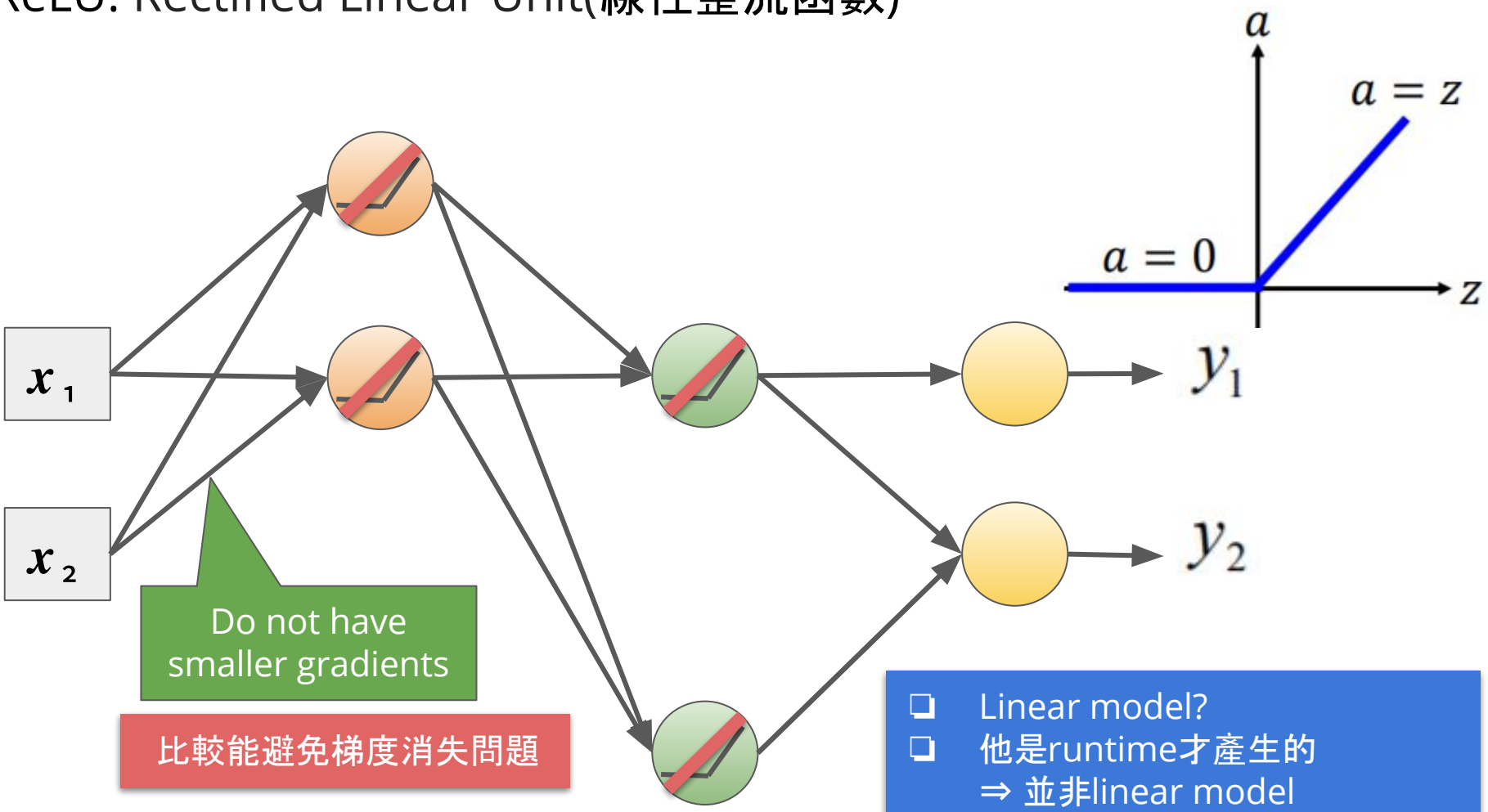
比較潮的Activation Function

ReLU: Rectified Linear Unit(線性整流函數)



比較潮的Activation Function

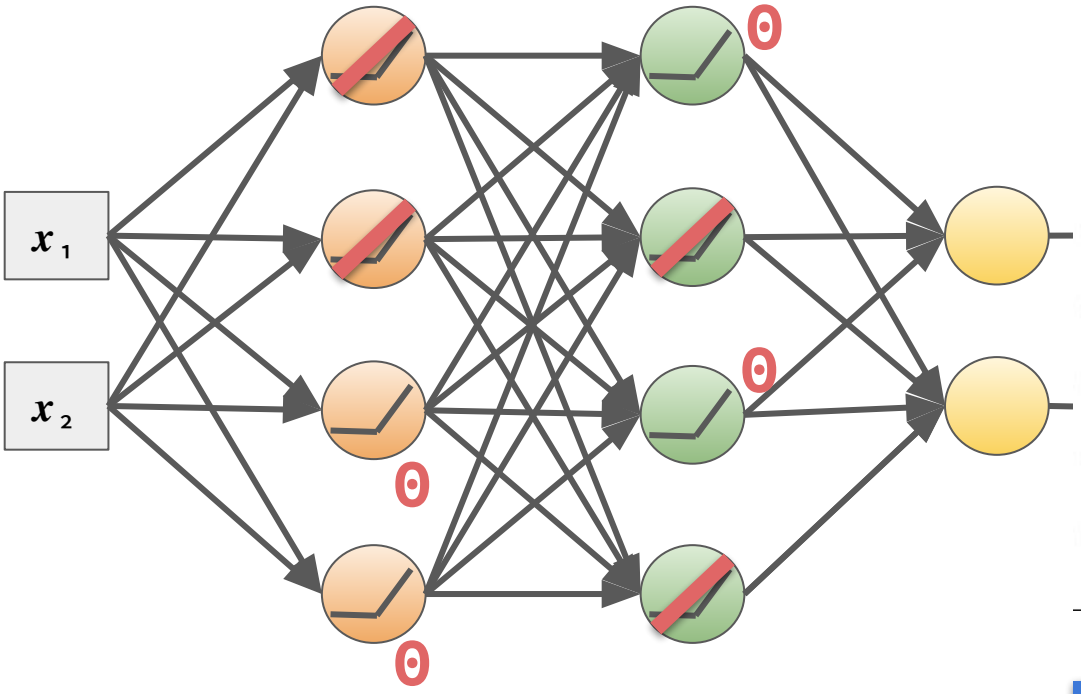
ReLU: Rectified Linear Unit(線性整流函數)

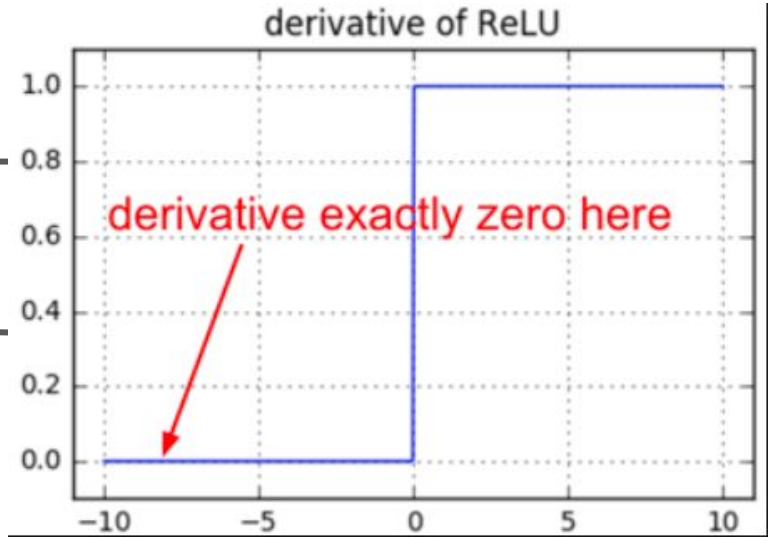


- Linear model?
- 他是runtime才產生的
  ⇒ 並非linear model
- Sparsity, 計算速度快

比較潮的Activation Function

ReLU: 還是有缺點...



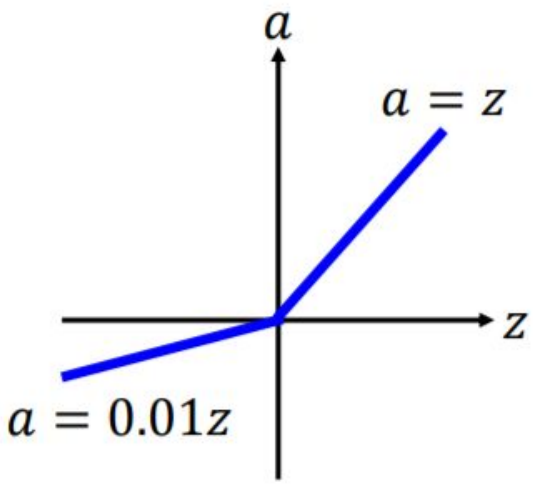


- Dying ReLU problem

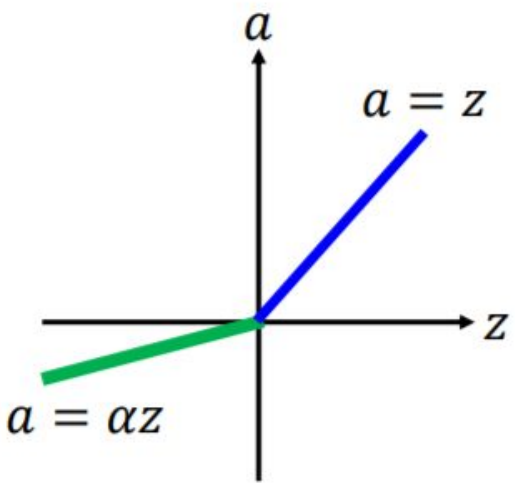
比較潮的Activation Function

ReLU - variant

Leaky ReLU



Parametric ReLU



實際上Dying ReLU problem:

- ❑ 適當的 weight init
- ❑ 適當的 learning rate

α also learned by gradient descent

Lab: lab_dnn_tutorial_practice.ipynb (5 ~ 8 minutes)

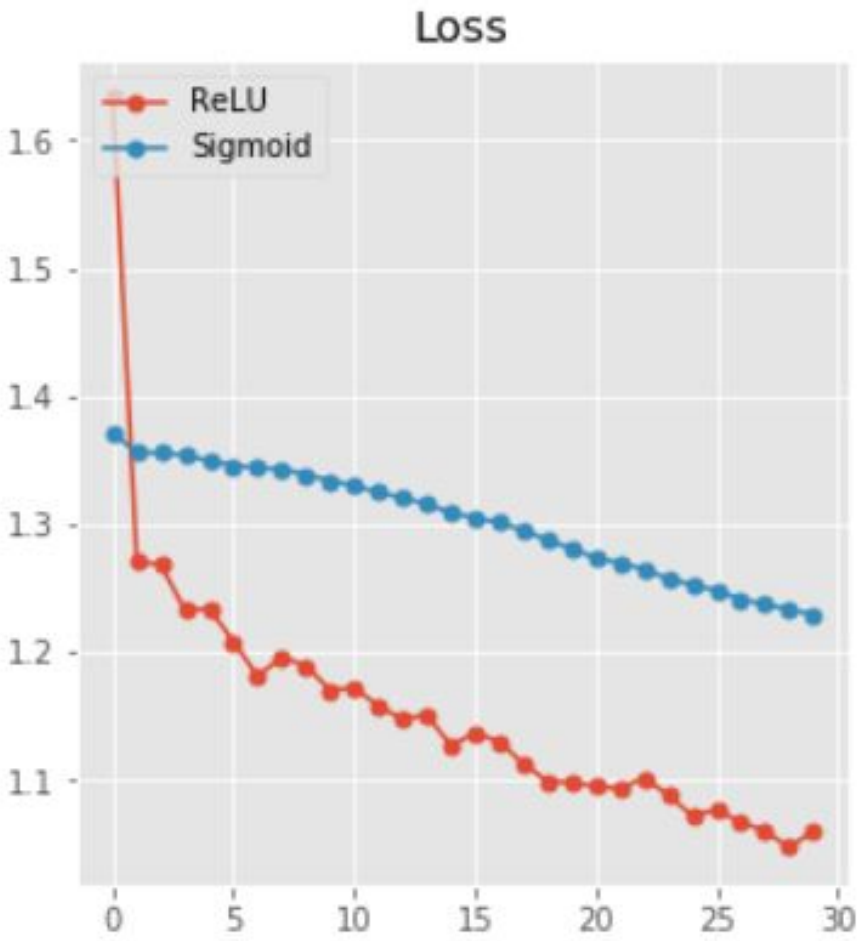
搜尋 ”Do:” 就可以找到可能要修改的位置

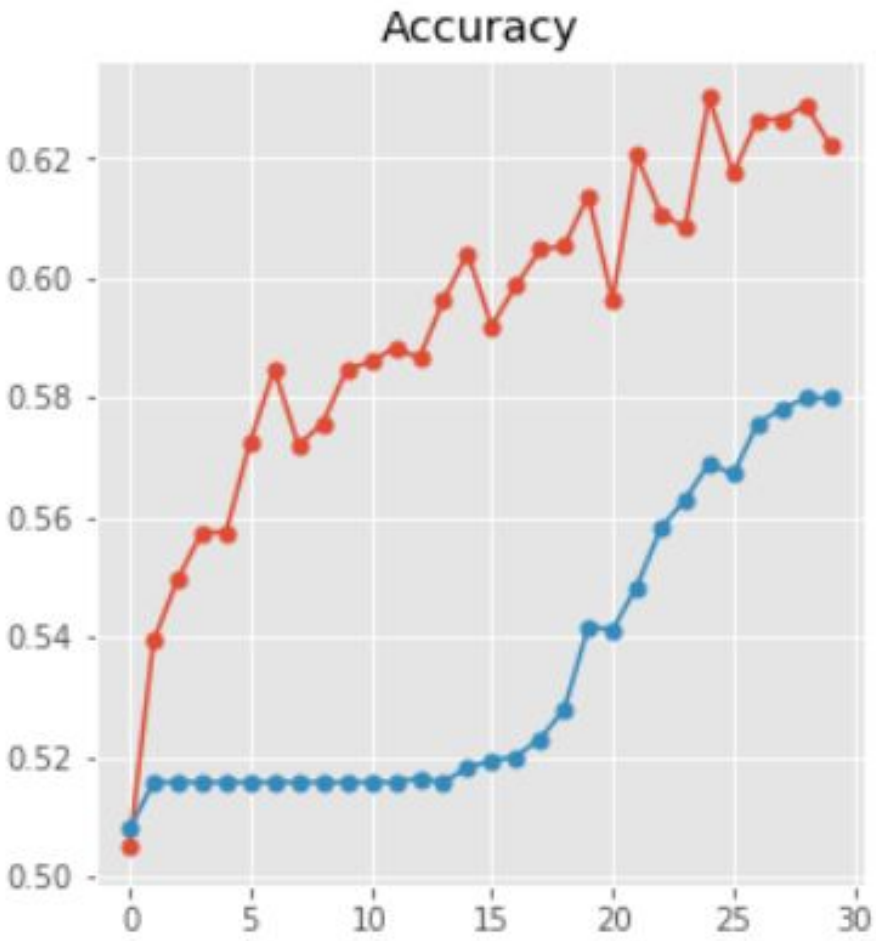
lab filename	lab_tutorial_dnn_practice.ipynb
target	目前是Sigmoid，請嘗試不同的activation function ❑ ReLU、Leaky ReLU ❑ Softplus ❑ Tanh

Try Activation Function

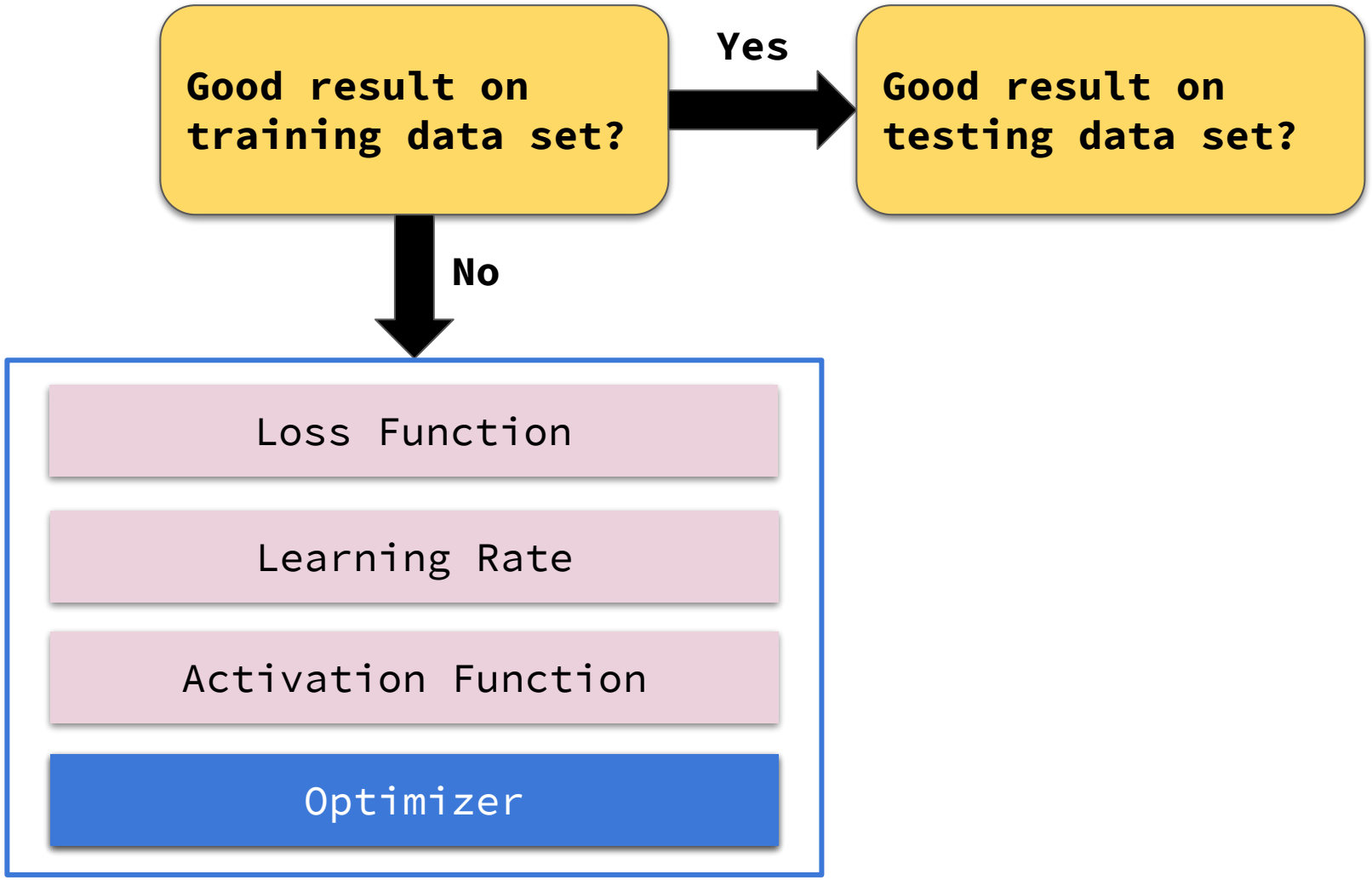
```
+ learning_rate: 0.01
+ loss function: softmax cross entropy
+ optimizer: 基本款 => GradientDescentOptimizer
+ activation function: sigmoid or softplus or relu
```

ReLU vs Sigmoid





Choose Optimizer



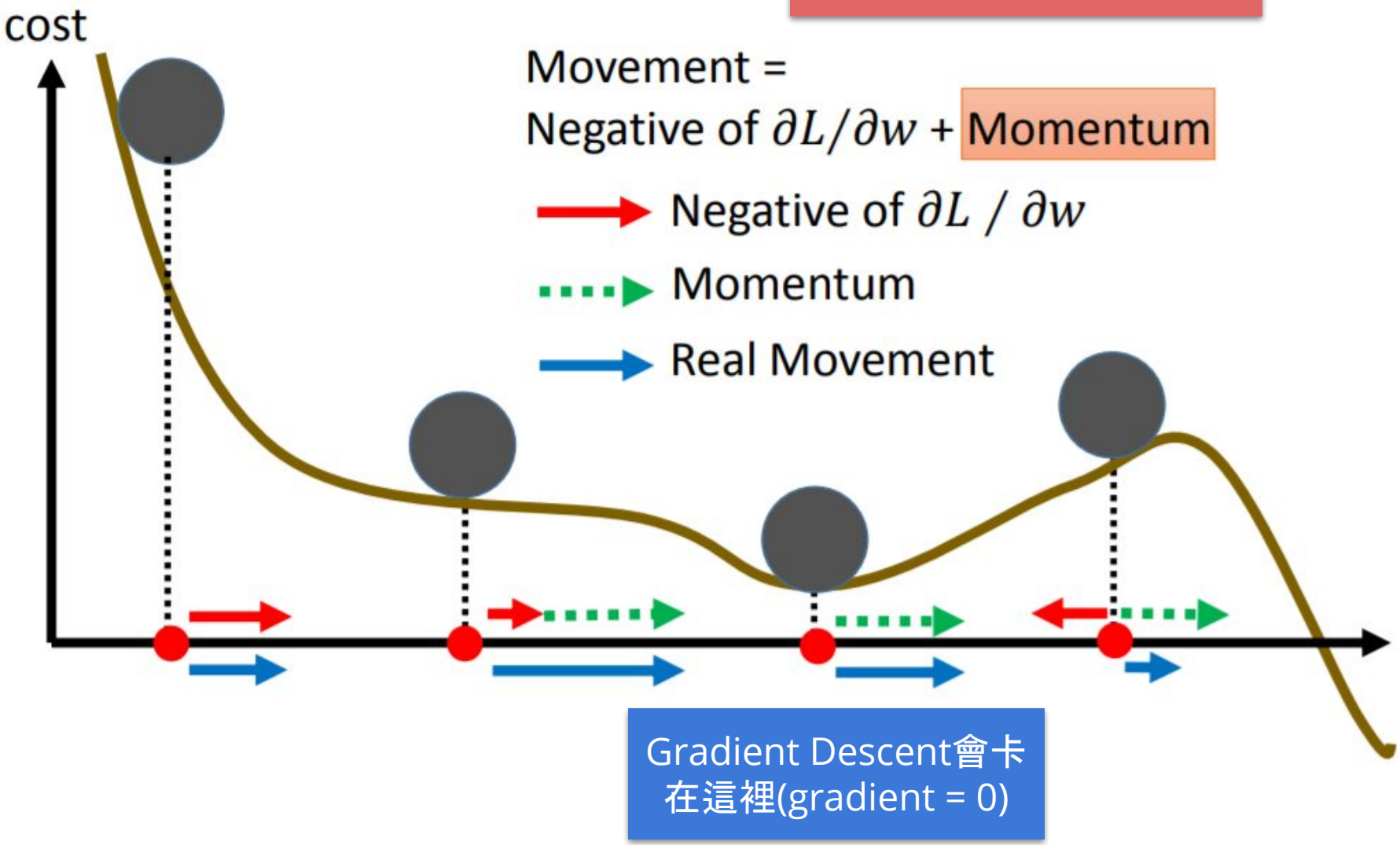
Deep Neural Network(DNN) Tips

Optimizer

- ❏ Gradient Descent
- ❏ Momentum
- ❏ Adagrad – Adaptive Learning Rate
- ❏ RMSprop – Similar with Adagrad
- ❏ Adam – Similar with RMSprop + Momentum

Optimizer – Momentum

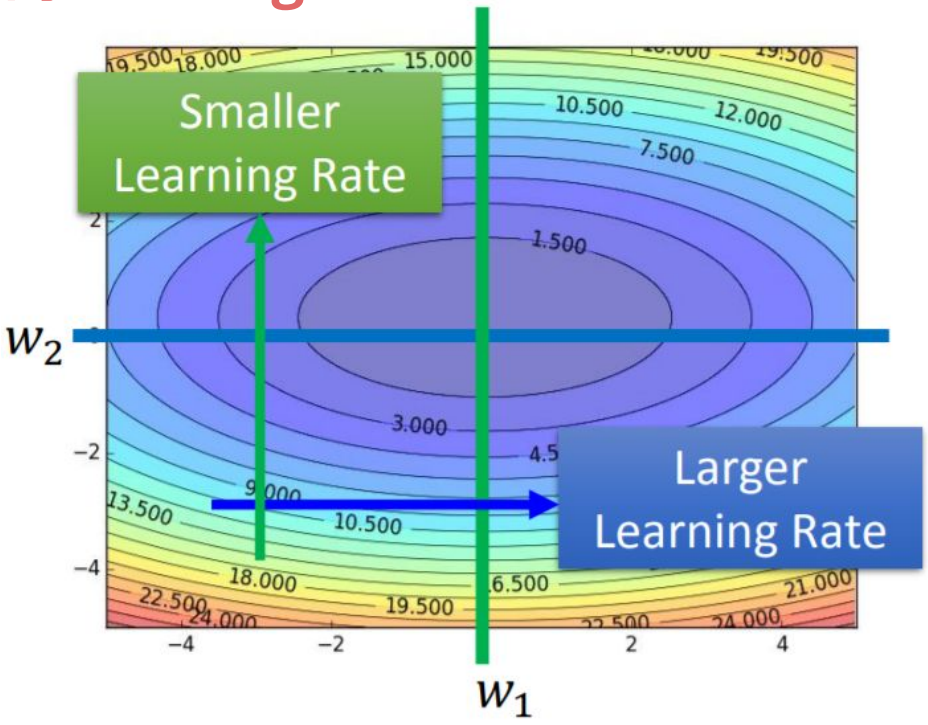
當然沒辦法保證會跑到 global minimum



Optimizer - Adaptive Learning Rate

- 認為一開始離目的很遠，所以用比較大的learning rate
- 在train好幾個epoch之後，離目的越來越近，需要較小的learning rate
- learning rate需要在training runtime調整

- **因材施教：每個參數都有不同的learning rate**



Optimizer - Adagrad

Vanilla Gradient descent

$$\eta^t = \frac{\eta}{\sqrt{t+1}} \qquad g^t = \frac{\partial L(\theta^t)}{\partial w}$$

$$w^{t+1} \leftarrow w^t - \eta^t g^t$$

w is one parameters

Adagrad

$$w^{t+1} \leftarrow w^t - \frac{\eta^t}{\sigma^t} g^t$$

σ^t: ***root mean square*** of the previous derivatives of parameter w

Optimizer - Adagrad

- 直覺的理解

特別大

g^0	g^1	g^2	g^3	g^4	...
0.001	0.001	0.0002	0.0087	0.1	...

g^0	g^1	g^2	g^3	g^4	...
8.7	10.87	18.7	87.7	0.1	...

特別小

$$w^{t+1} \leftarrow w^t - \frac{\eta}{\sqrt{\sum_{i=0}^{t}(g^i)^2}} g^t$$

- 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
- 缺點: learning rate會一直遞減，越train越慢...

Optimizer - RMSProp

Adagrad

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

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

RMSProp

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

$$\sigma^t = \sqrt{\alpha(\sigma^{t-1})^2 + (1-\alpha)(g^t)^2}$$

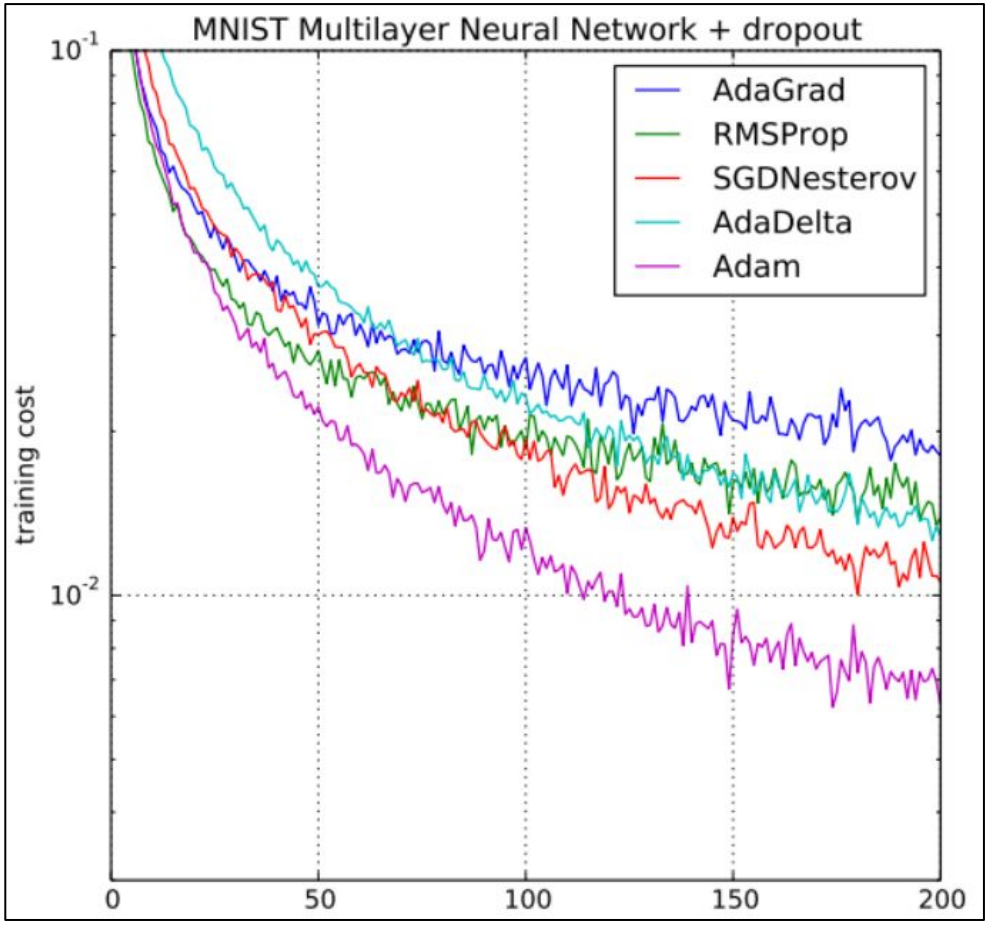
α小: 代表相信當前gradient

α大: 代表相信之前的gradient

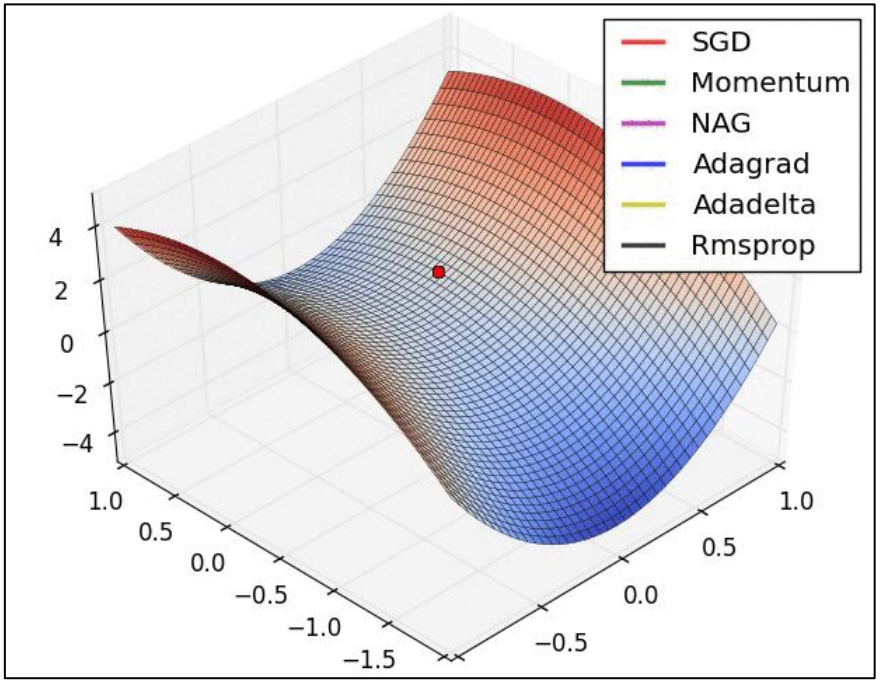
- **另一種參考過去gradient的方式**

Optimizer - Adam

- 綜合 RMSProp + Momentum 的優點
- 個人建議起手式, 先從Adam開始嚐試



實際上Optimizer的效果還是會跟資料有關, 沒有絕對要用什麼工具的規則！



Lab: lab_dnn_tutorial_practice.ipynb (10 ~ 15 minutes)

搜尋 ”Do:” 就可以找到可能要修改的位置

lab filename	lab_tutorial_dnn_practice.ipynb
target	使用不同的Optimizer: ❑ tf.train.AdamOptimizer ❑ tf.train.AdagradOptimizer ❑ tf.train.MomentumOptimizer(momentum=0.9) ❑ tf.train.RMSPropOptimizer

Try Different Optimizer

+ learning_rate: 0.01
+ loss function: softmax cross entropy
+ optimizer: GradientDescentOptimizer or AdamOptimizer
+ activation function: softplus

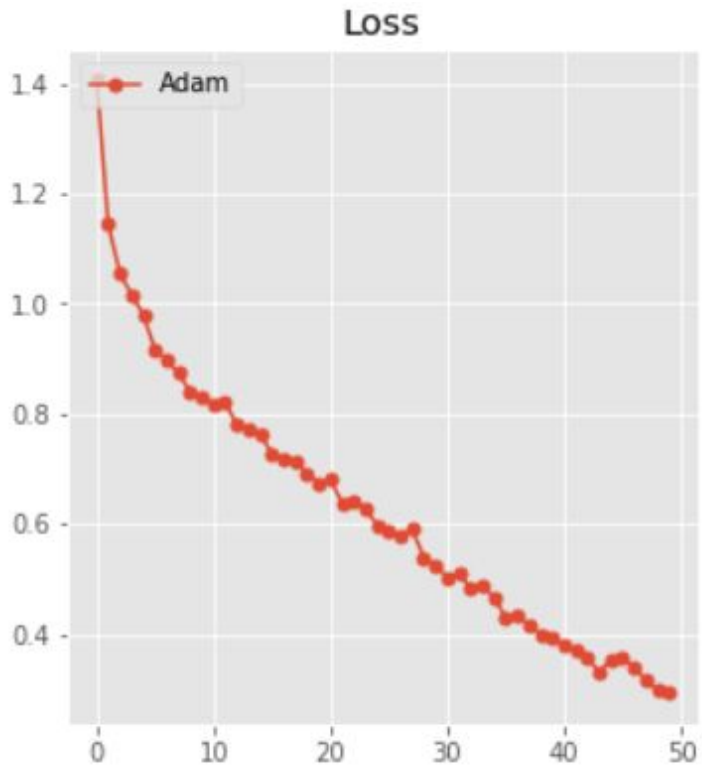
Result: Gradient Descent vs Adam

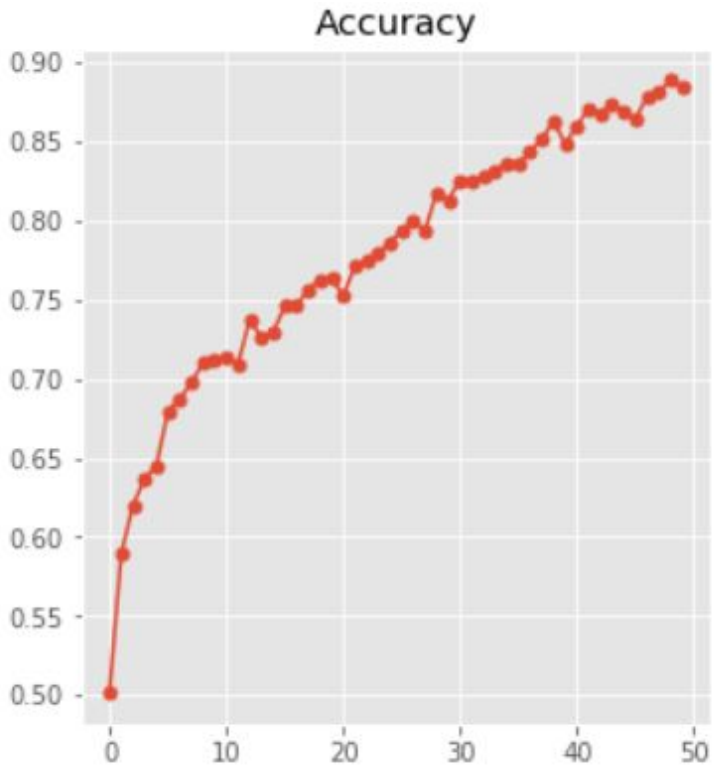
```
model with Adam optimizer!
30/30.  train loss: 0.773, valid loss: 0.975, train acc: 0.732, valid acc: 0.696

model with SGD optimizer!
30/30.  train loss: 1.095, valid loss: 1.434, train acc: 0.605, valid acc: 0.484

<matplotlib.text.Text at 0x7f2ca857d7f0>
```

Current Best Model Configuration

Loss function	**cross entropy**
Activation function	**relu + softmax**
Optimizer	**Adam**

50 epochs後準確率達90%，可以舉杯慶祝了!!!

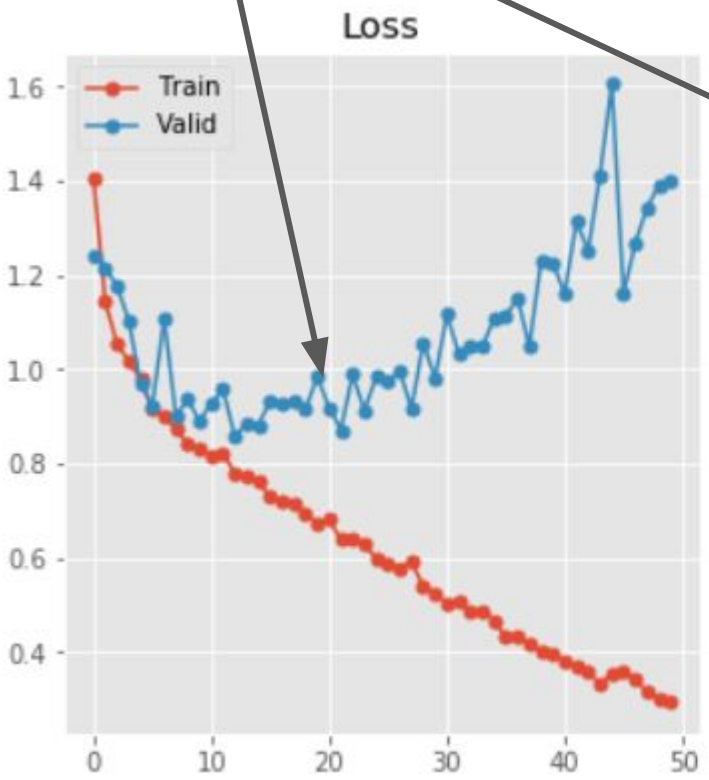


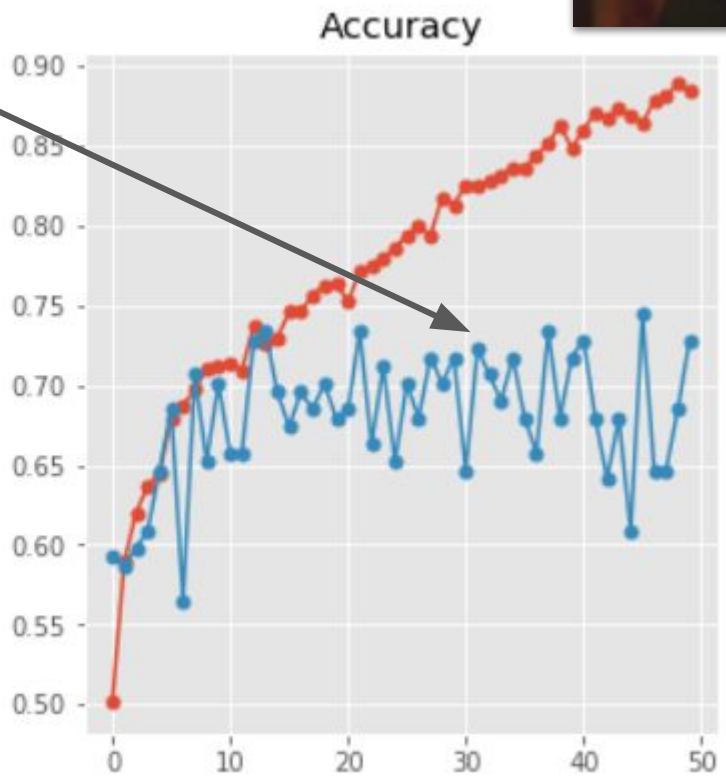


Deep Neural Network(DNN) Tips

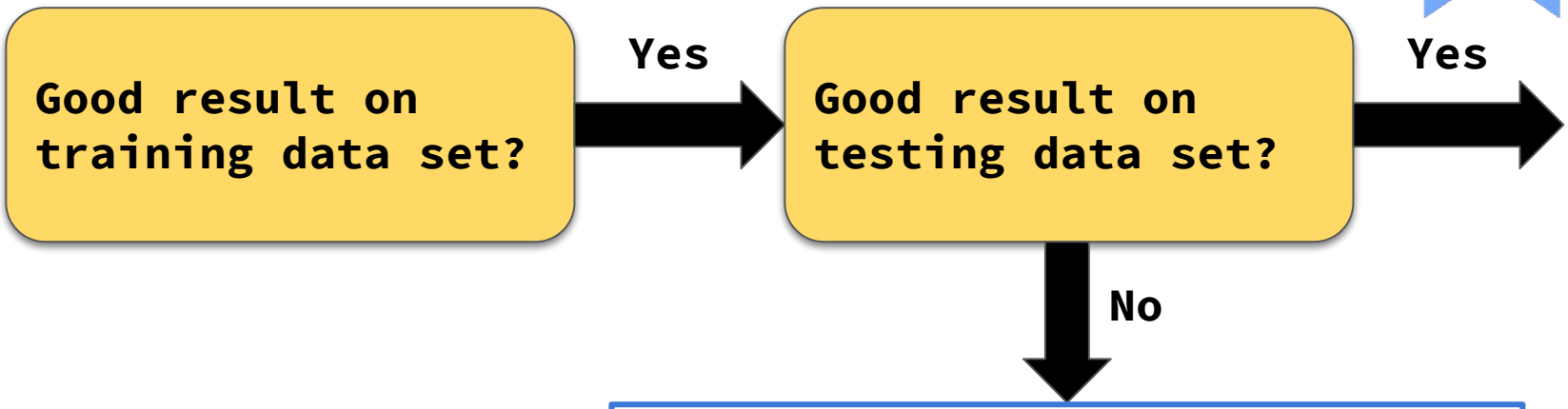
果然...世事難預料!

Overfitting!





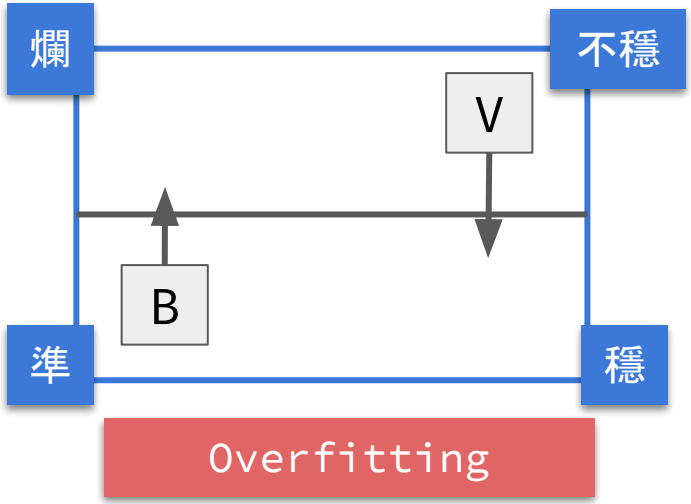
Overfitting

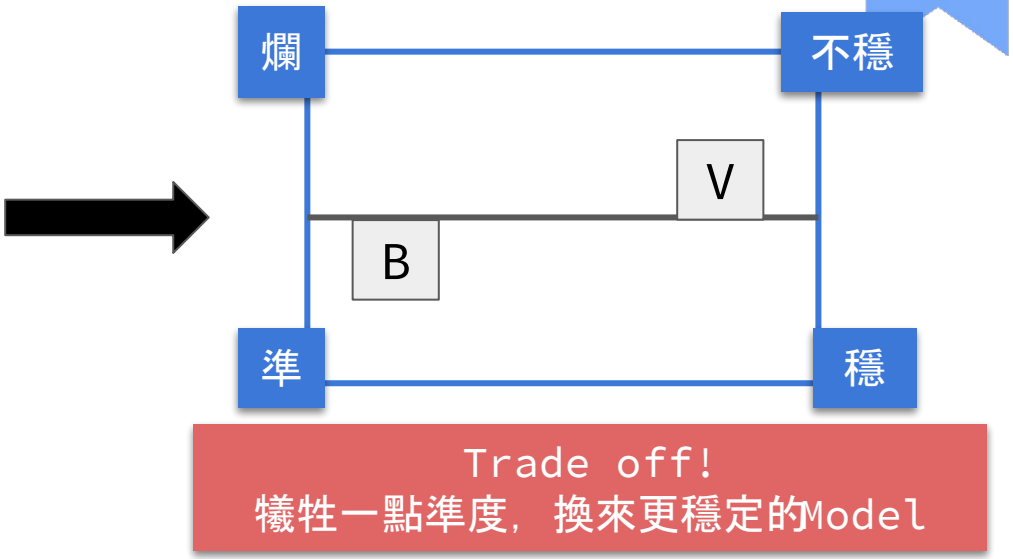


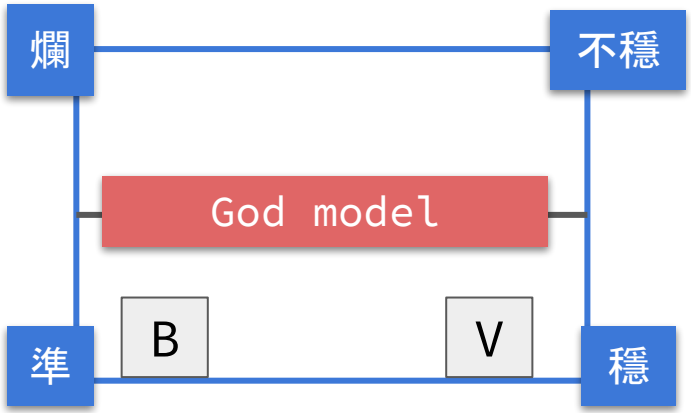
Overfitting的意義:

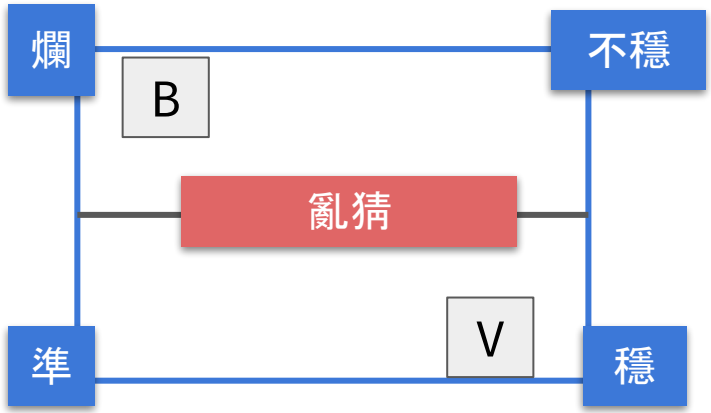
代表model已經太過於擬合data, 必須限制model的能力, **達到generalization的目的**

Model Bias and Variance

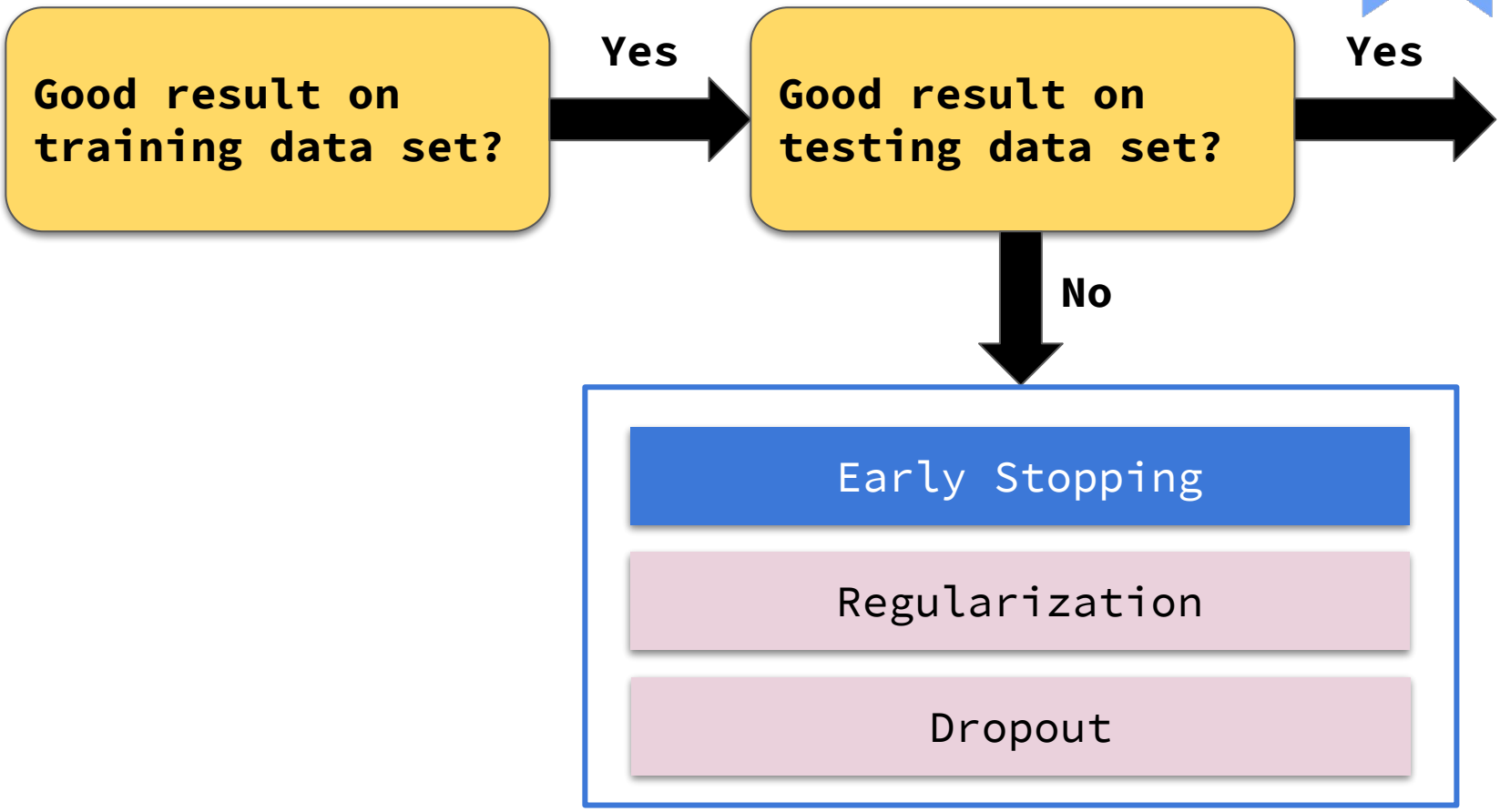






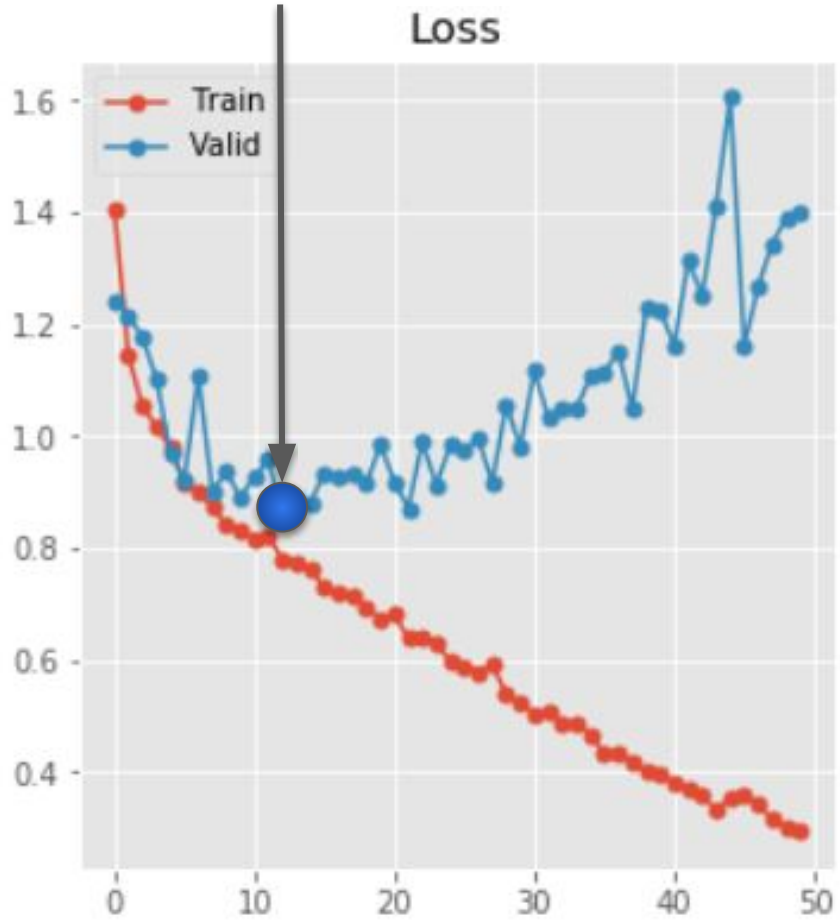


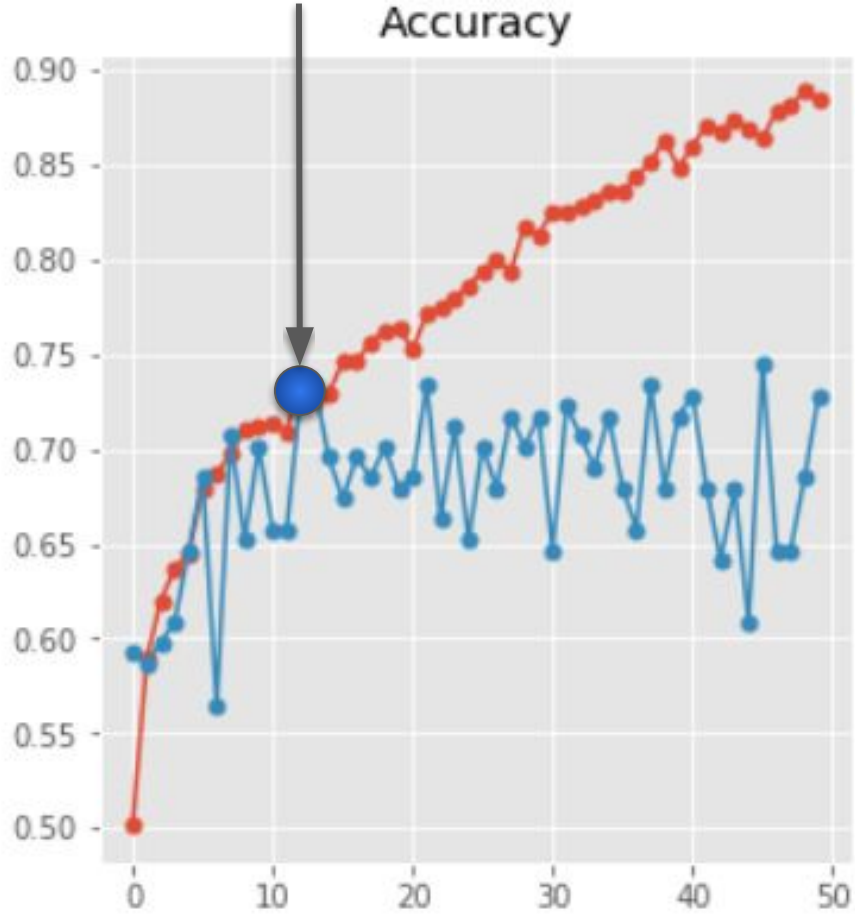
Overfitting



Early Stopping: 懸崖勒馬!

早一點停下來就沒事了!





Early Stopping: 懸崖勒馬!

```
tf.reset_default_graph()
model_adam = ModelAdam()
model_adam.fit(data_fn(X_train, Y_train, n_batch, shuffle=True),
               data_fn(X_valid, Y_valid, n_batch, shuffle=False),
               n_epoch,
               lr=learning_rate,
               callback=EarlyStopping(thres=5))
```

Model fit加上這個callback object即可!

Early Stopping: 懸崖勒馬!

fit 有這麼一段, check callback function on epoch end

```
for ep in range(1, n_epoch + 1):
    training …

    if callback is not None:
        callback(self)
```

```
def __call__(self, model):
    last_vl_loss = model.hist["vl_loss"][-1]
    if self.min_loss > last_vl_loss:
        self.patient = 0
        self.min_loss = last_vl_loss
    else:
        self.patient += 1
    if self.patient >= self.thres:
        raise StopIteration("\nEarly Stopping, valid loss keep increasing for {} times ! "
                            "lowest loss is {:.3f} !"
                            .format(self.patient, self.min_loss))
```

EarlyStopping物件

validation loss是否持續增加?超過一定threshold則停止

Lab: lab_dnn_tutorial_practice.ipynb (5 ~ 10 minutes)

搜尋 ”Do:” 就可以找到可能要修改的位置

lab filename	lab_tutorial_dnn_practice.ipynb
target	加入callback object: EarlyStopping check if overfitting

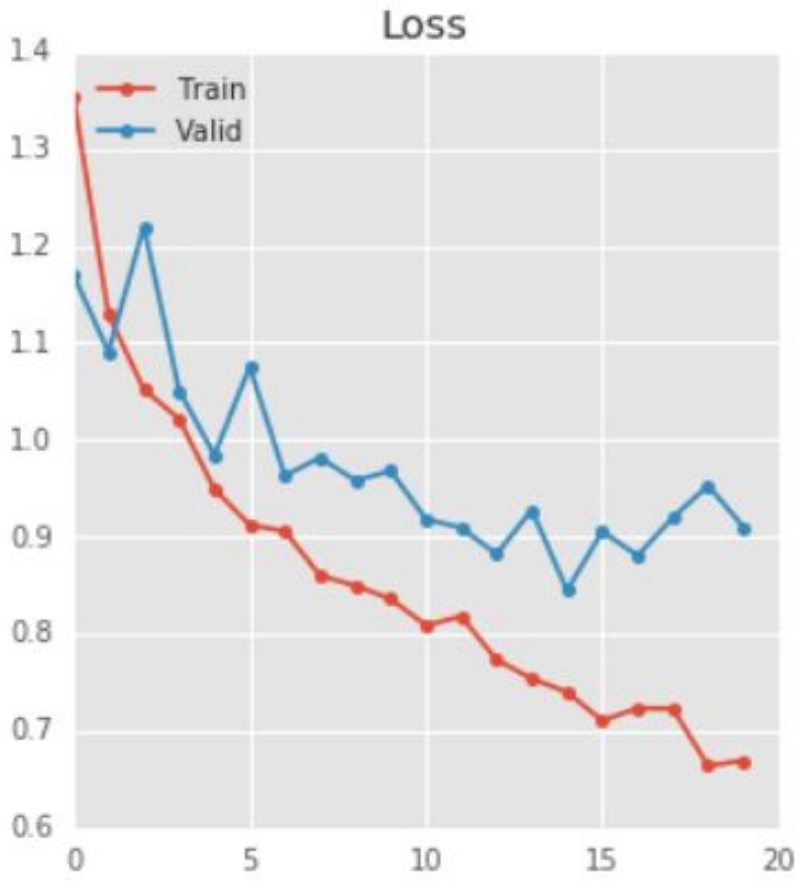
Solve Overfitting: EarlyStopping

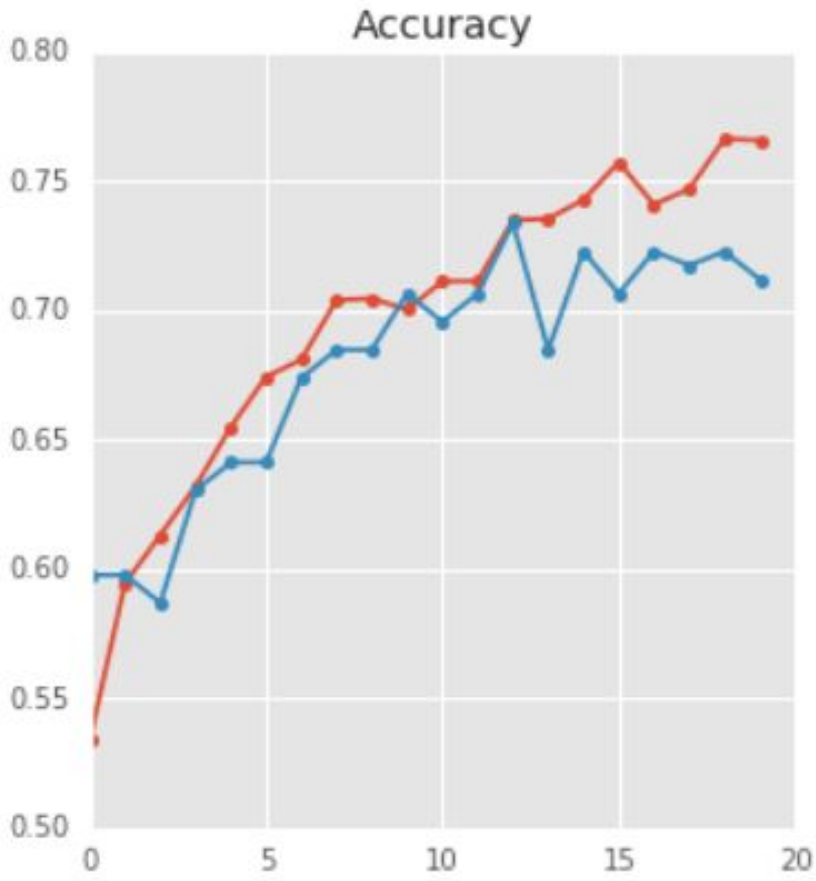
檢查Valid Loss變化, 若發現Loss持續增加超過一定Threshold, 則停止Training

```
+ learning_rate: 0.001
+ loss function: softmax cross entropy
+ optimizer: AdamOptimizer
+ activation function: softplus
+ number of train epoch: 50
```

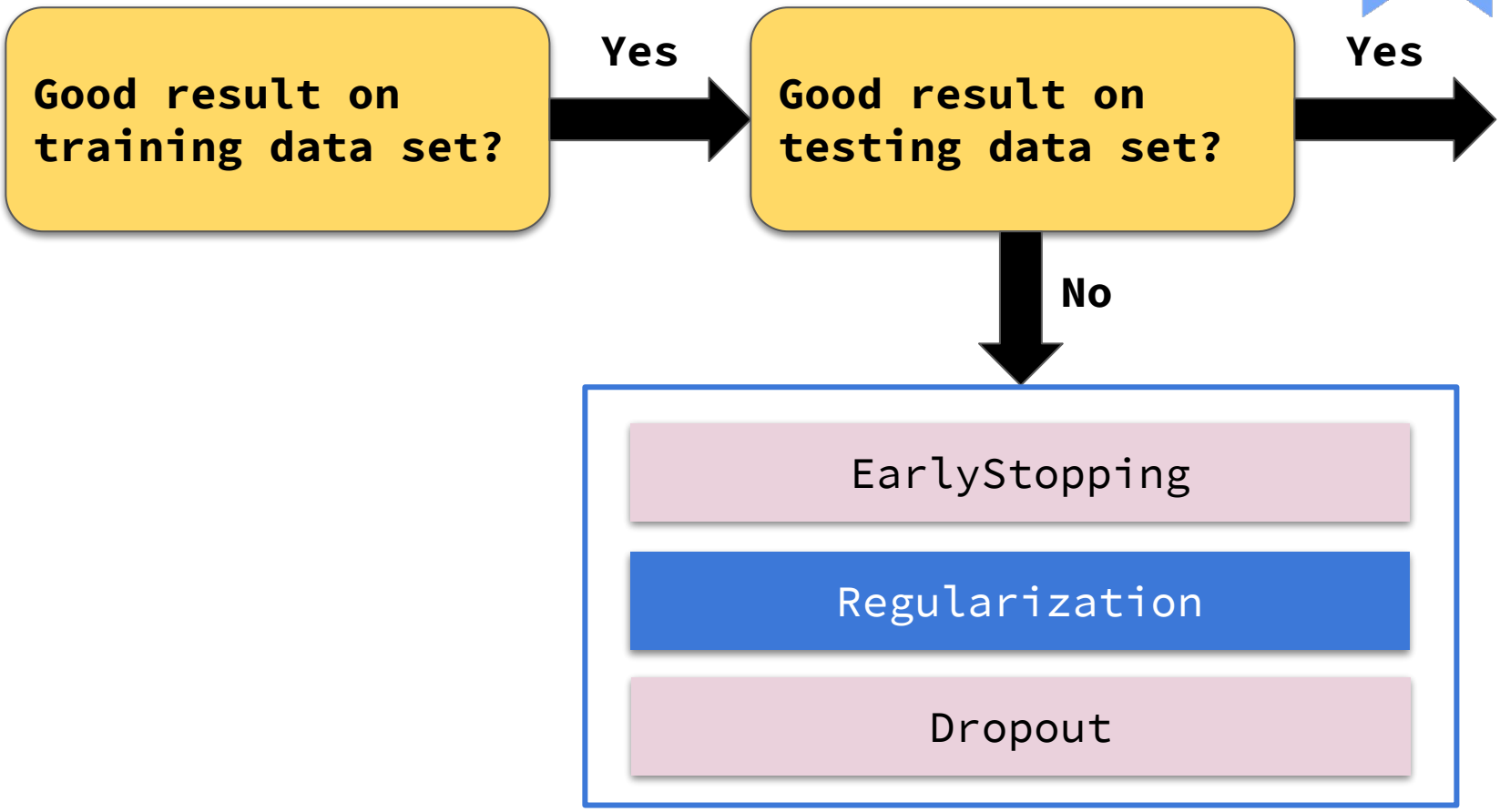
Early Stopping - Threshold=5

```
19/50.  train loss: 0.664, valid loss: 0.953, train acc: 0.766, valid acc: 0.723
Early Stopping, valid loss keep increasing for 5 times ! lowest loss is 0.845 !
```



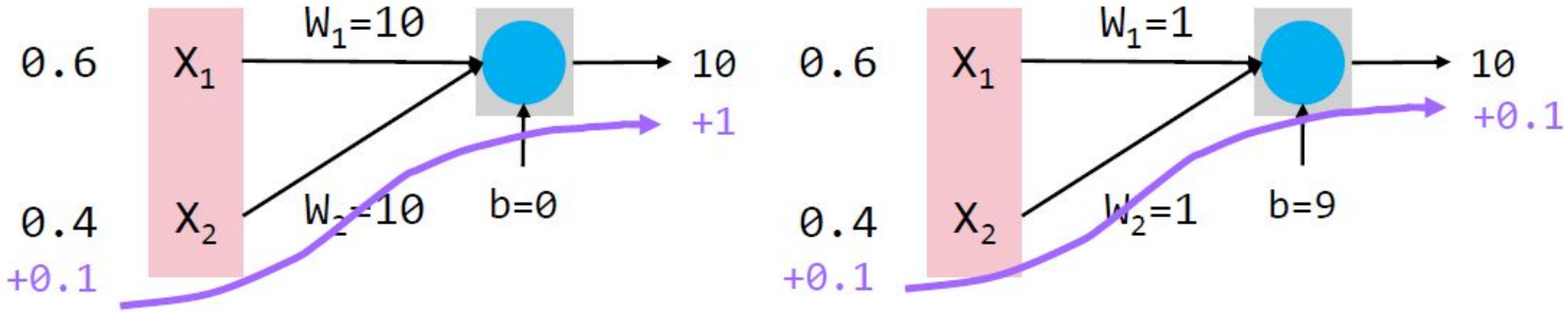


Overfitting



Regularization

- Loss限制weights 的大小讓output 曲線比較平滑



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

- 作法: 加入目標(Loss)函數中，一起優化

$$L'(\theta) = L(\theta) + \lambda(regularizer)$$

- λ是用來調整regularization的比重(通常在0.01以下)
- Regularizer兩種形式: L1 and L2

$$L_1 = \sum_i |w_i|$$

L1 norm: sum of absolute values

$$L_2 = \sum_i |w_i|^2$$

L2 norm: square sum of absolute values

一般狀況是不會加入Bias的參數 (Optional)

Regularization: L2 Norm

L2 regularization:

$$\|\theta\|_2 = (w_1)^2 + (w_2)^2 + \dots$$

$$L'(\theta) = L(\theta) + \lambda \frac{1}{2}\|\theta\|_2$$ Gradient: $$\frac{\partial L'}{\partial w} = \frac{\partial L}{\partial w} + \lambda w$$

Update: $$w^{t+1} \rightarrow w^t - \eta \frac{\partial L'}{\partial w} = w^t - \eta\left(\frac{\partial L}{\partial w} + \lambda w^t\right)$$

$$= (1-\eta\lambda)w^t - \eta \frac{\partial L}{\partial w}$$

接近0

Weight Decay

Lab: lab_dnn_tutorial_practice.ipynb (5 ~ 10 minutes)

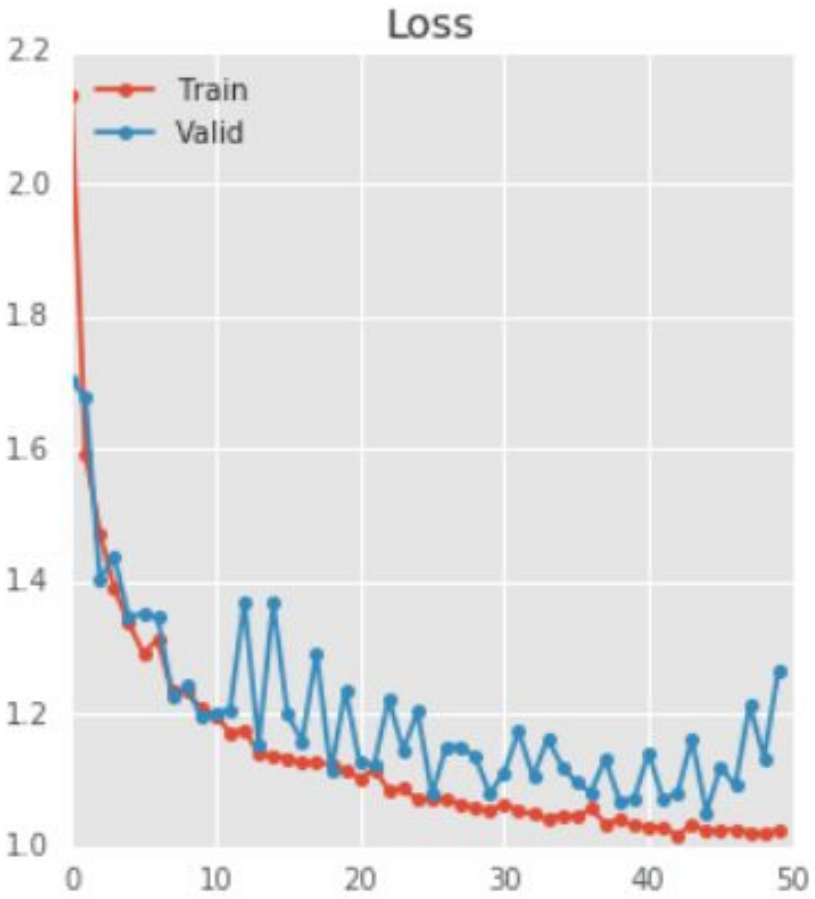
lab filename	lab_tutorial_dnn_practice.ipynb
target	加入l2 regularizer: tf.contrib.layers.l2_regularizer tf.contrib.layers.l1_regularizer

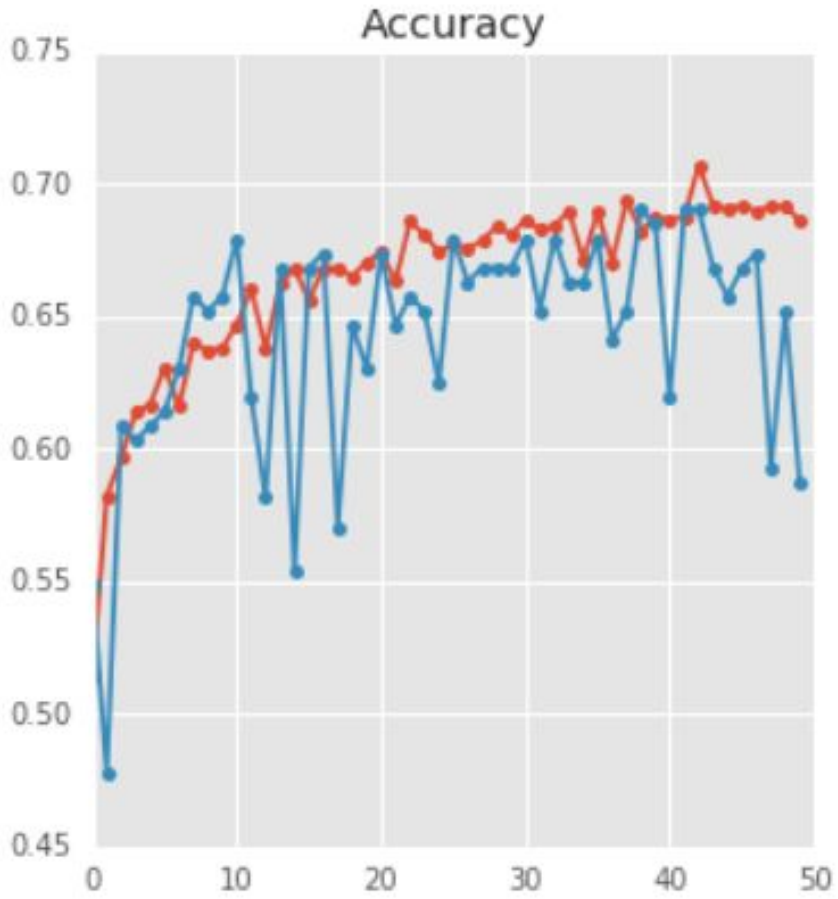
Solve Overfitting: Add Regularizer Term to Loss Function

```
+ learning_rate: 0.001
+ loss function: softmax cross entropy
+ optimizer: AdamOptimizer
+ activation function: softplus
+ number of train epoch: 50

+ >>> add l2 regularizer term to each hidden layers with scale 0.01
```

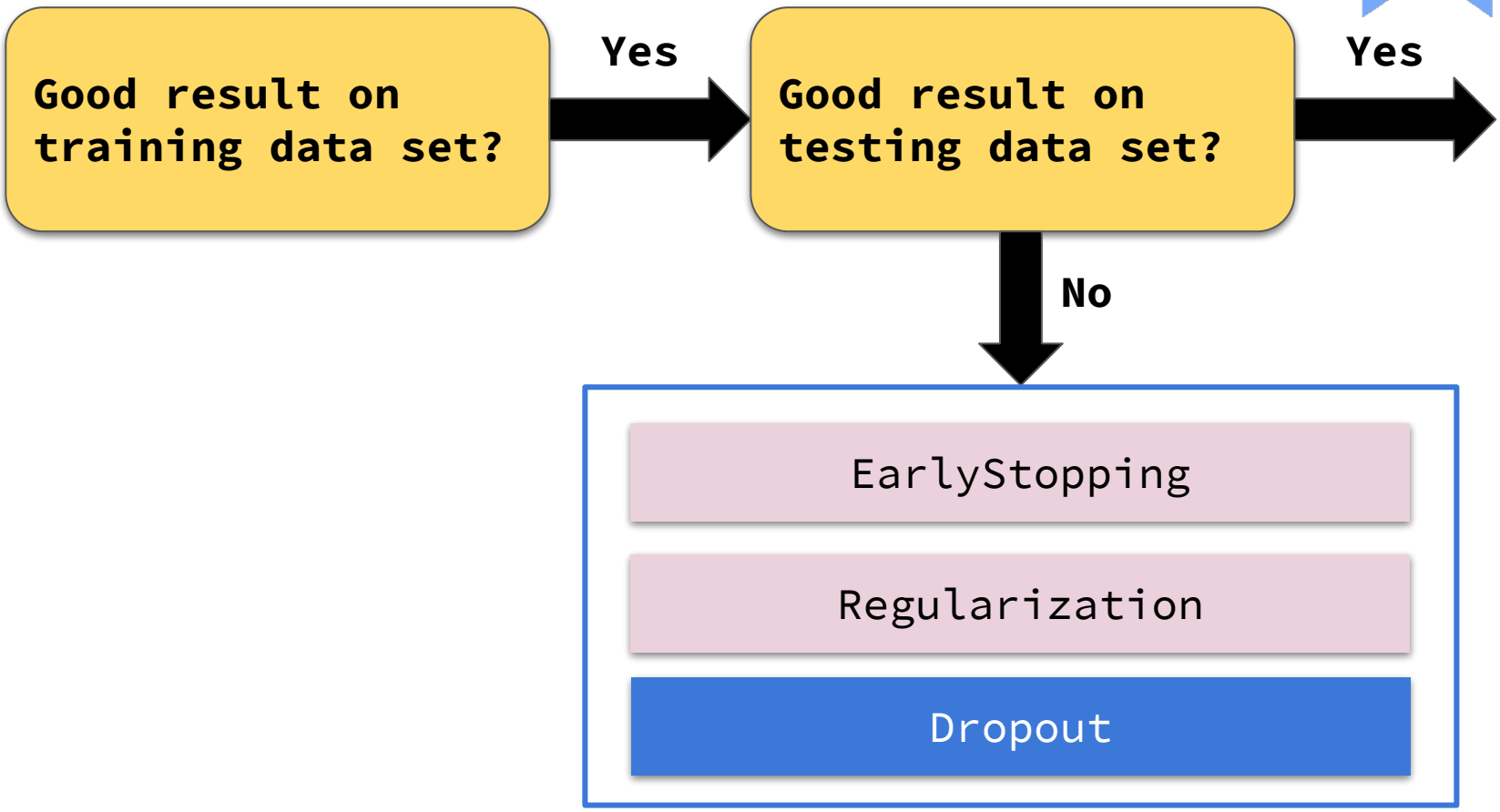
Result - Regularization

```
50/50.  train loss: 1.025, valid loss: 1.268, train acc: 0.686, valid acc: 0.587
```

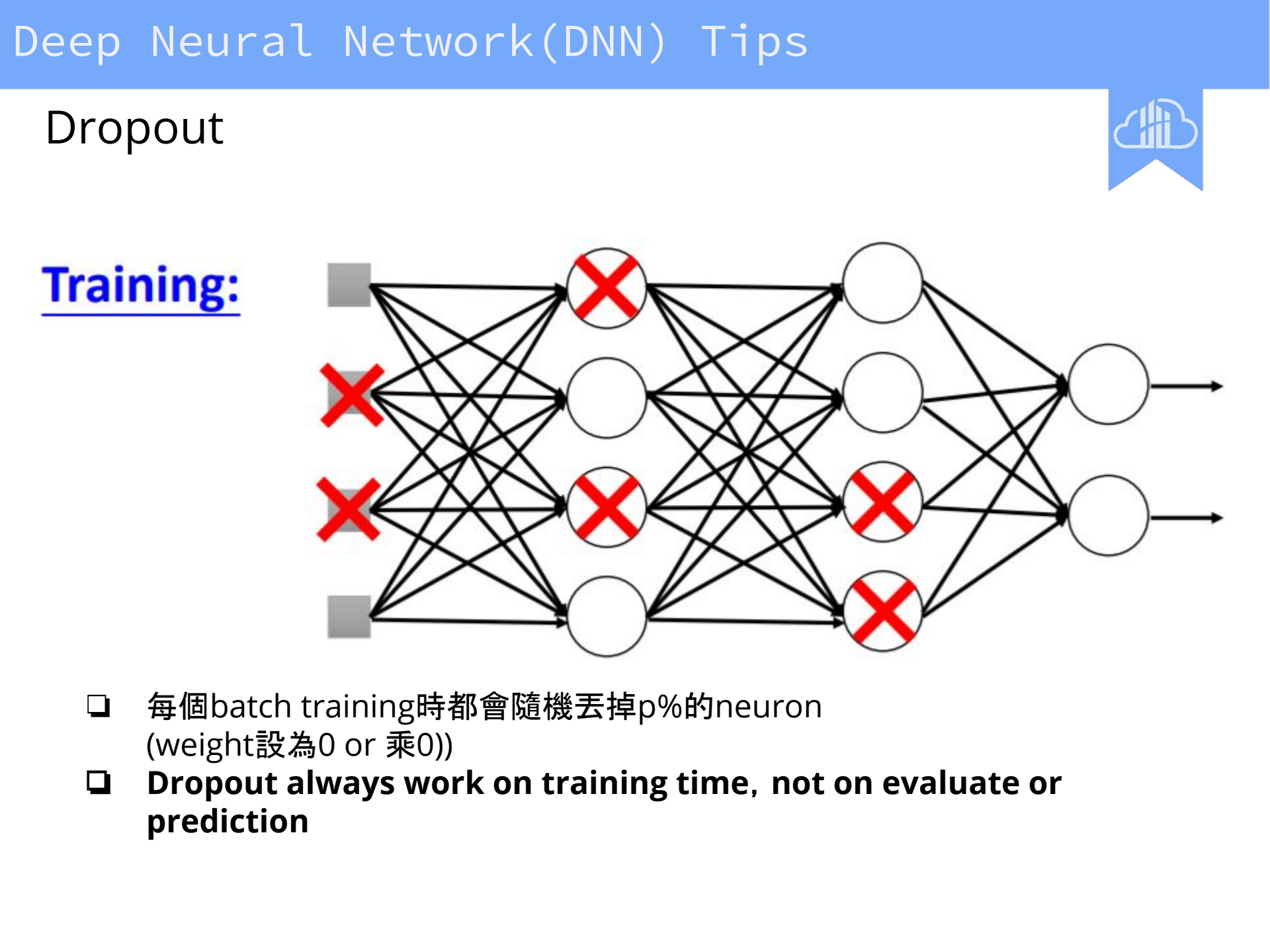




Overfitting



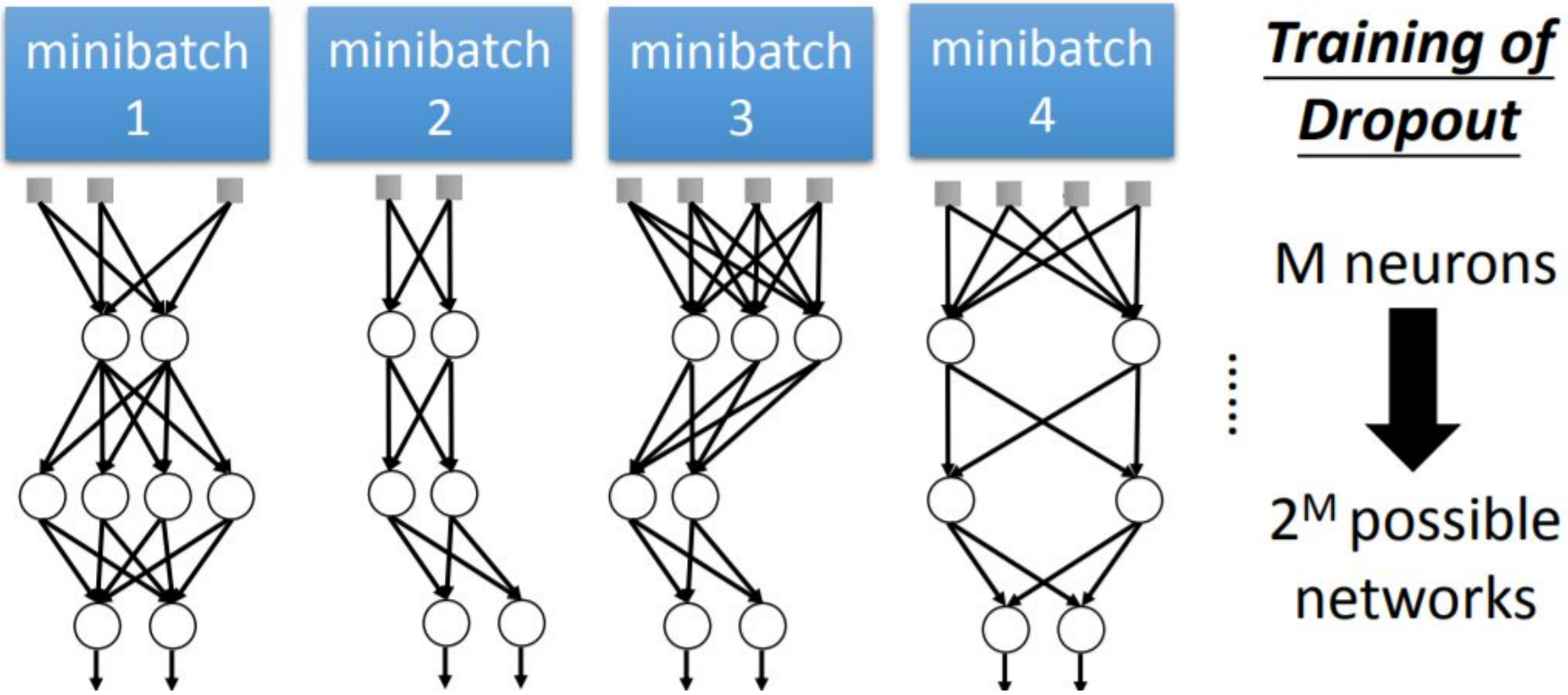
Dropout



Training:

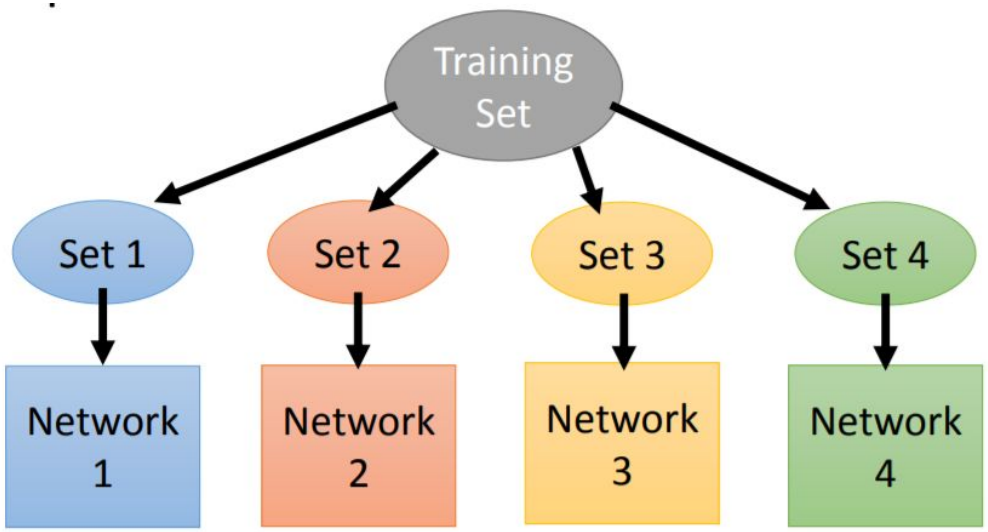
- 每個batch training時都會隨機丟掉p%的neuron (weight設為0 or 乘0))
- **Dropout always work on training time, not on evaluate or prediction**

Dropout - 終極的ensemble方法



- Using one mini-batch to train one network
- Weights in the network are shared

Dropout - 終極的ensemble方法

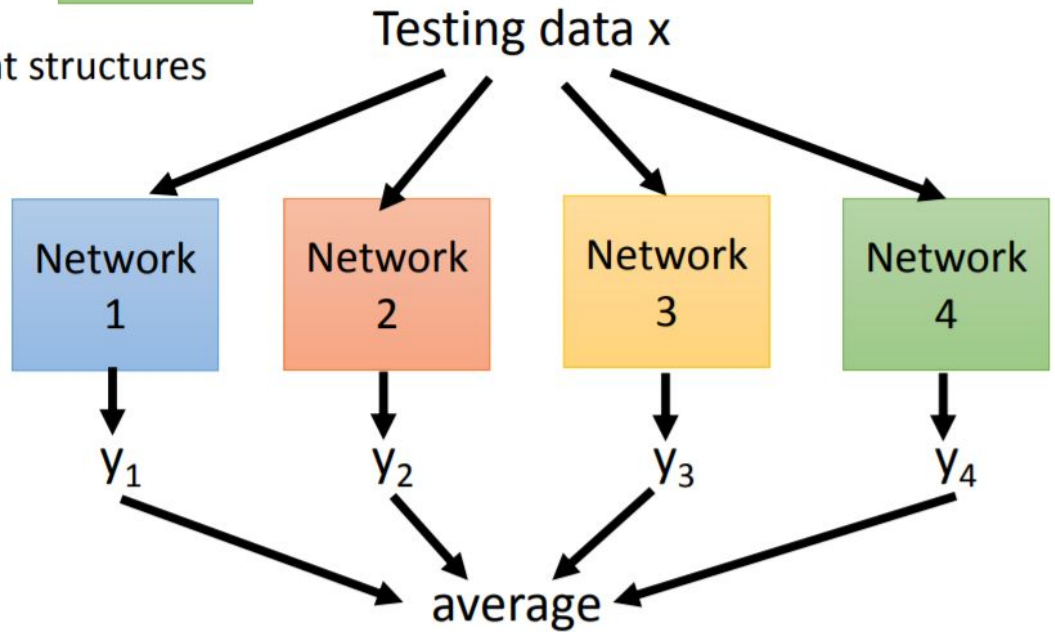


Train a bunch of networks with different structures

Bagging

Decision Tree

Random Forest



直覺的理解

Dropout的結果

- 會讓training performance變差，包含training速度
- **不要一開始就使用dropout!**

Lab: lab_dnn_tutorial_practice.ipynb (5 ~ 10 minutes)

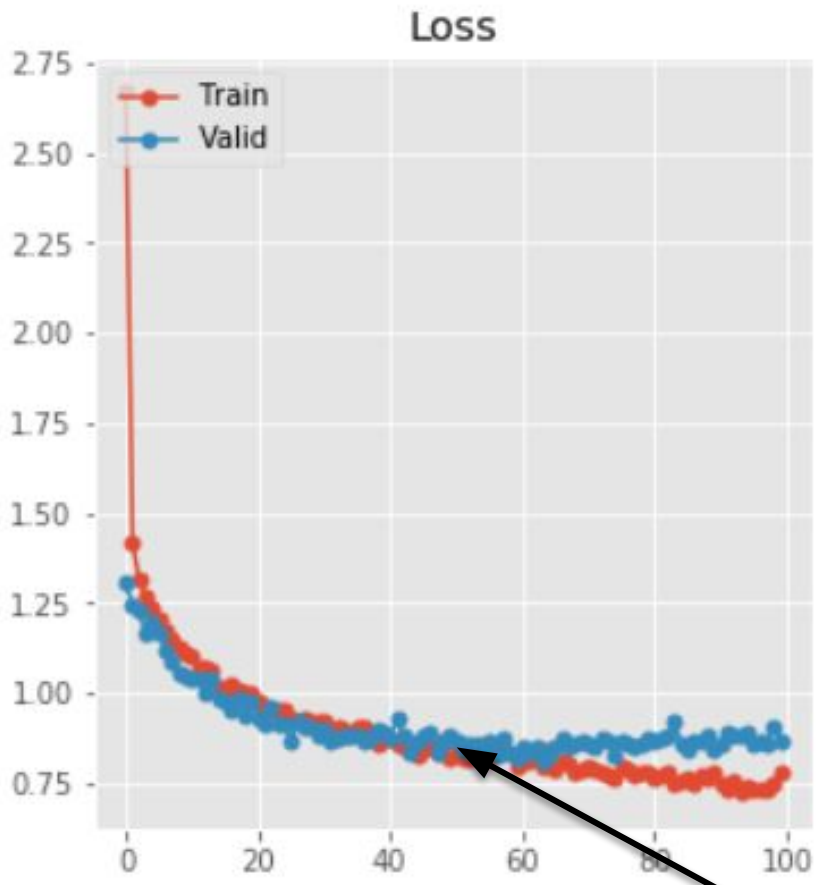
搜尋 ”Do:” 就可以找到可能要修改的位置

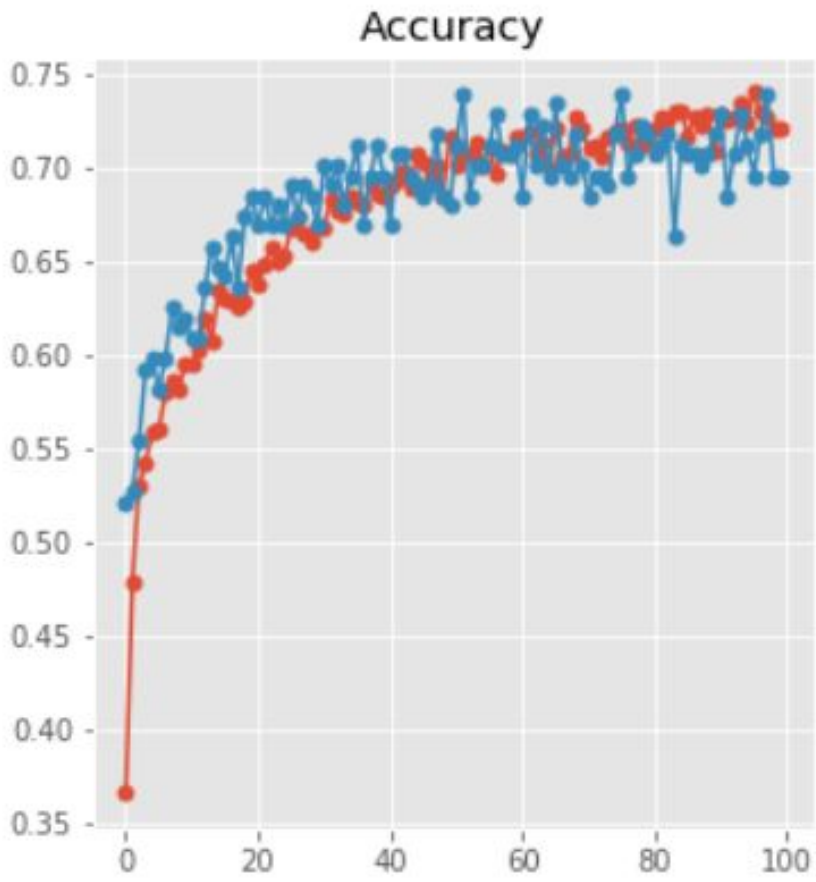
lab filename	**lab_tutorial_dnn_practice.ipynb**
target	**Network加入dropout:** **drop_rate可嘗試 0.3, 0.4, 0.5, 0.6**

Solve Overfitting: Dropout

```
+ learning_rate: 0.001
+ loss function: softmax cross entropy
+ optimizer: AdamOptimizer
+ activation function: relu

+ number of train epoch: 100
>>> Dropout會讓training速度變慢, 增加epoch次數讓分數更好!
```

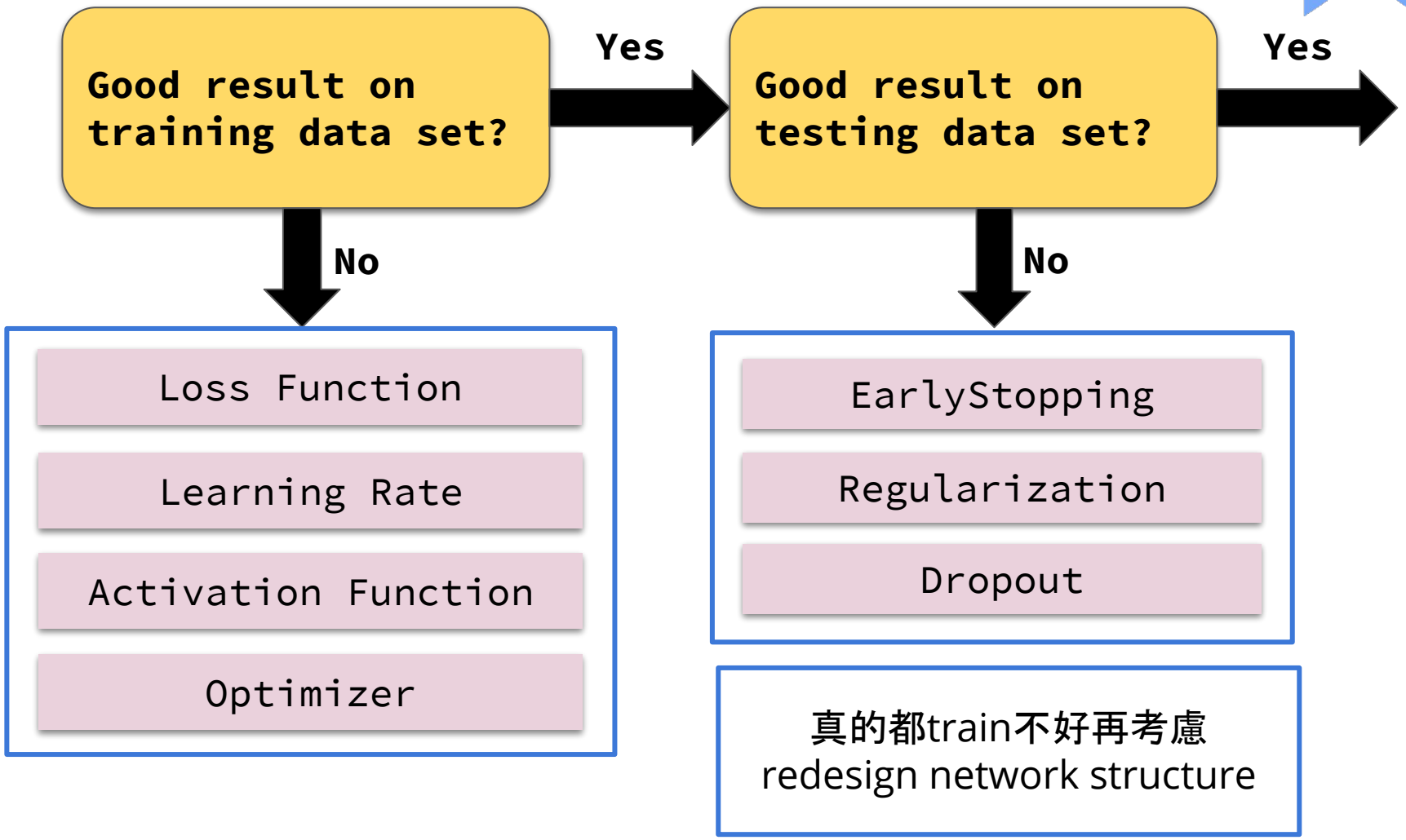
Result - Dropout(After 100 Epochs)





Valid Loss曲線在50 epochs之後已經下降變慢，但並沒有遽增

Recall


Good result on training data set?
Yes
Good result on testing data set?
Yes
No
No
Loss Function
Learning Rate
Activation Function
Optimizer
EarlyStopping
Regularization
Dropout
真的都train不好再考慮
redesign network structure

Recommendation Engine in Matrix Factorization

- Machine Learning Framework
- Deep Neural Network(DNN) Tips
- Recommedation Engine in Matrix Factorization
- Matrix Factorization with DNN

Recommendation Engine in Matrix Factorization

Movielens Data

User Movie Rating

	userId	movieId	rating	timestamp
0	0	30	2.5	1260759144
1	0	833	3.0	1260759179
2	0	859	3.0	1260759182
3	0	906	2.0	1260759185
4	0	931	4.0	1260759205

User Movie Tag

	userId	movieId	tag	timestamp
0	14	304	sandra 'boring' bullock	1138537770
1	14	1517	dentist	1193435061
2	14	5166	Cambodia	1170560997
3	14	6118	Russian	1170626366
4	14	6178	forgettable	1141391765

Movie Metadata

	movieId	title	genres
0	0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	1	Jumanji (1995)	Adventure|Children|Fantasy
2	2	Grumpier Old Men (1995)	Comedy|Romance
3	3	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	4	Father of the Bride Part II (1995)	Comedy

Concept of Latent Factor

U: User, M: Movie, R: Rating(1 ~ 5)

	M1	M2	M3	M4	M5
U1	3	5			1
U2			2	4	
U3	5		1		
U4		3		3	3

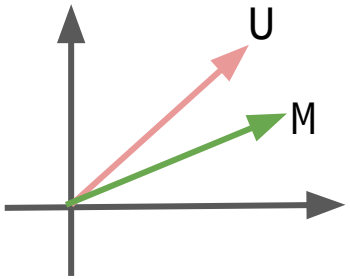
≈

U1	
U2	
U3	
U4	

X

M1	M2	M3	M4	M5

latent factor



User與Movie的距離

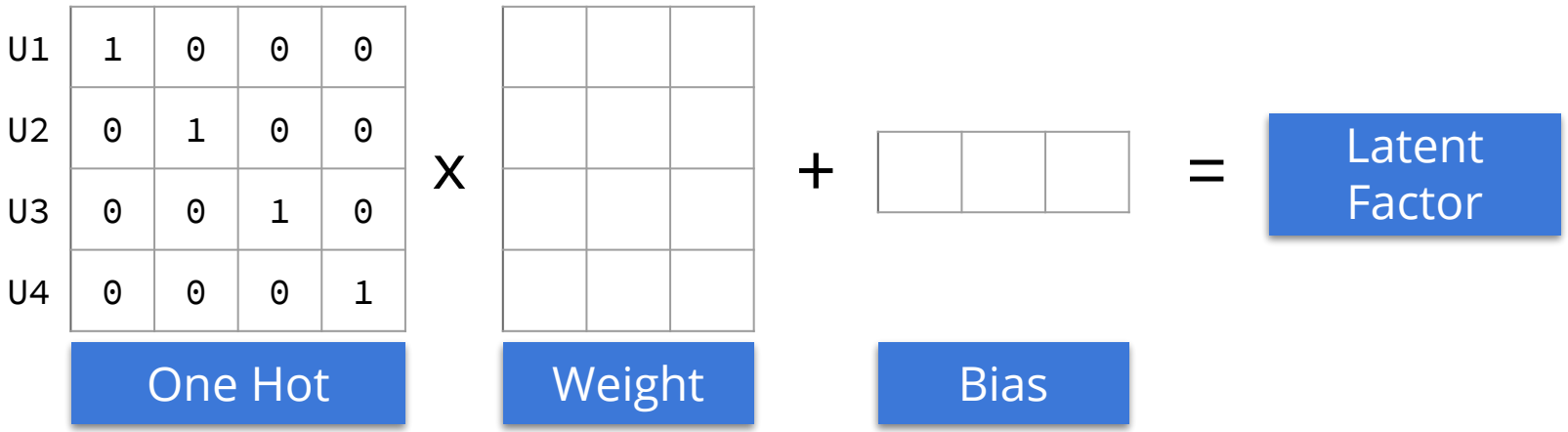
	M2		U1	?	?	?	×	?	≈	5
								?		
								?		

如何將user與movie映射到向量空間?

Relections(Transformation)

user id ⇒ 1263, 1080, 87...
movie id ⇒ 103, 554, 187...

- 把user和movie看成是categorical variable ⇒ One Hot Encoding
- **Recall feature transformation(cascading functions)**



Recommedation Engine in Matrix Factorization

User ID To Embedding

U1	1	0	0	0
U2	0	1	0	0
U3	0	0	1	0
U4	0	0	0	1

One Hot

x

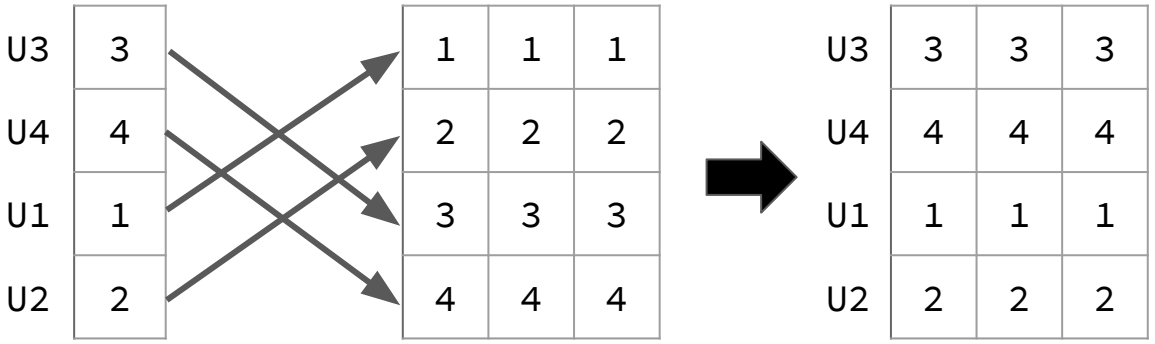
1	1	1
2	2	2
3	3	3
4	4	4

Weights

=

1	1	1
2	2	2
3	3	3
4	4	4

第i號user的latent factor等價於取Weight的第i列 ⇒ **Embedding**



User inputs *Lookup from weights* *User id embedding*

- movie id embedding 也是如法炮製
- 實際都會省略 bias

Model Formulation and Loss Function

U, M ⇒ 透過embedding取得的latent factor

	M1	M2	M3	M4	M5
U1	3	5			1
U2			2	4	
U3	5		1		
U4		3		3	3

$r_{12} \Rightarrow u_1 \cdot m_2 \approx 5$

$r_{33} \Rightarrow u_3 \cdot m_3 \approx 1$

$r_{23} \Rightarrow u_2 \cdot m_3 \approx 2$

$\vdots$

Regression

$$L = \sum_{(i,j)} (u_i \cdot m_j - rij)^2$$

model function

- User rating behavior and movie being rated are highly **biased**
- Recall linear combination ⇒ **wx + b**

$$u_i \cdot m_j + b_u + b_m + b_{global}$$

- 不是U和M的外在影響因素
- Model bias

Minimizing $L = \sum_{(i,j)} (u_i \cdot m_j + b_u + b_m + b_{global} - r_{ij})^2$

model function with bias

Recommendation Engine in Matrix Factorization

Prediction

以向量運算表示 $u_i \cdot m_j + b_u + b_m + b_{global}$

$$Predict =$$

$u_i \cdot m_j$

	M1	M2	M3	M4	M5
U1	3.5	4.7	0.87	1.87	0.8
U2	4.87	5.6	2.1	3.87	4.57
U3	5.87	4.78	1.87	1.2	3.6
U4	1.7	3.2	2.9	2.87	2.6

+

0.8	0.7	0.6	0.5	0.4

b_m Column Wise

+ Row Wise

b_u

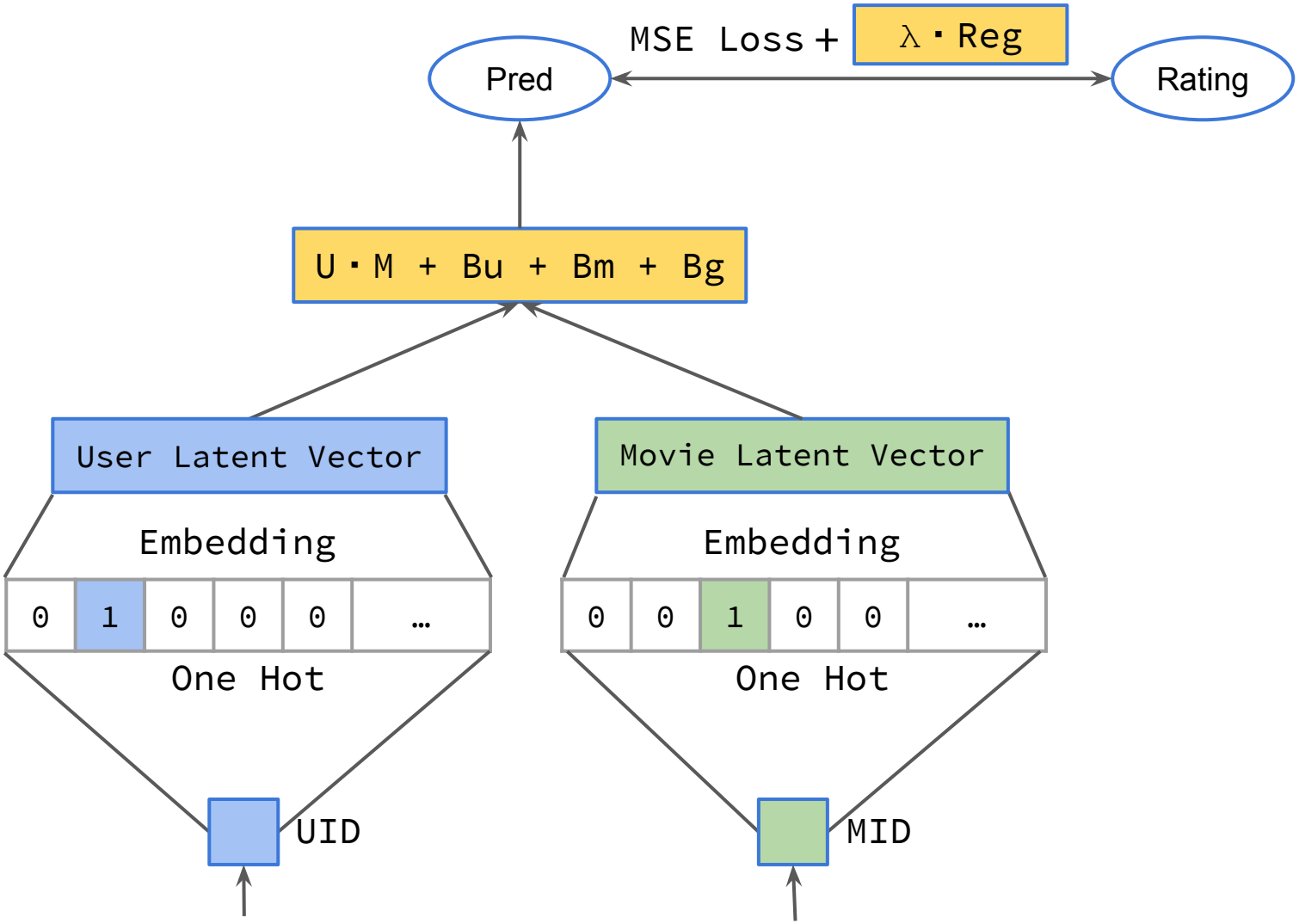
0.1
0.2
0.3
0.4

+ 0.5 b_{global} Element Wise

```
[[ 4.9   6.    2.07  2.97  1.8 ]
 [ 6.37  7.    3.4   5.07  5.67]
 [ 7.47  6.28  3.27  2.5   4.8 ]
 [ 3.4   4.8   4.4   4.27  3.9 ]]
```

這個例子實際跑出來的

First Model - Basic MF



First Model - Basic MF

- Function set formulation

$$f_{u,m}(x) = u_i \cdot m_j + b_u + b_m + b_{global}$$

- Loss function

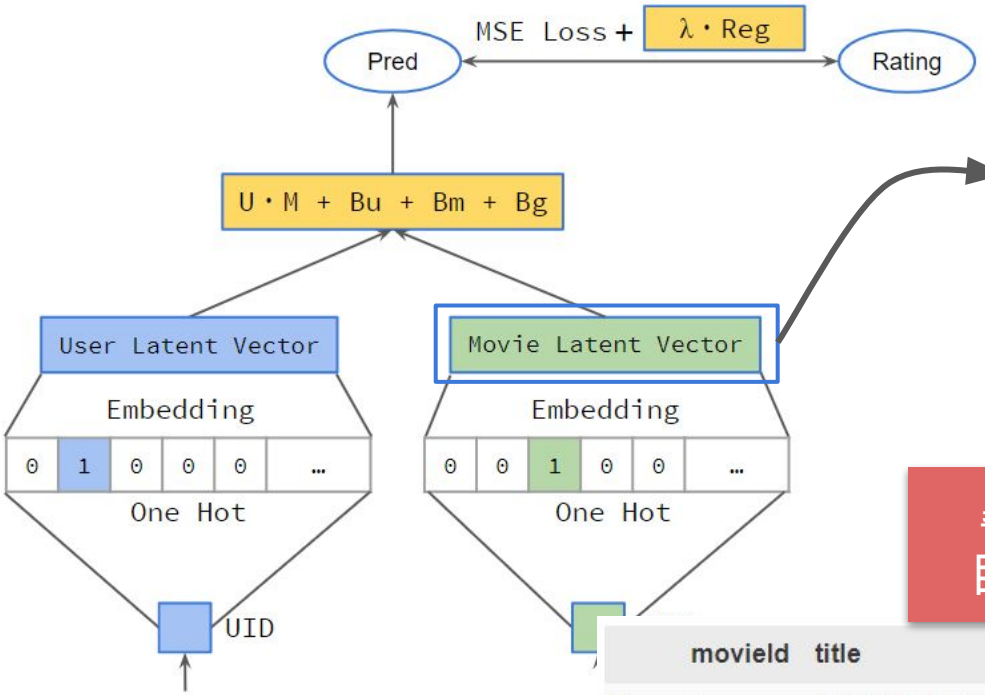
$$L = \sum (f_{u,m}(x) - r_{ij})^2 + \lambda \cdot \frac{1}{2}(\sum u^2 + \sum m^2 + \sum b_u^2 + \sum b_m^2)$$

Basic MF

filename	reco_model_mf.ipynb
lab filename	**lab_reco_model_mf.ipynb**
number of users	671
number of movies	9125
rating range	0.5 ~ 5分, ❑ 4分以上算正評 ❑ 未滿4分認為是負評或是不列入推薦名單
neural network	matrix factorization

Recommendation Engine in Matrix Factorization

Basic MF - 活用Latent Factor(Embedding)!



使用Latent Factor來找出相似的電影

尋找與Toy Story相似的電影
目前來看似乎結果不太合理...

	movieId	title	genres
0	0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
7551	7551	Letters to Juliet (2010)	Drama|Romance
5158	5158	Laws of Attraction (2004)	Comedy|Romance
8473	8473	Lone Survivor (2013)	Action|Drama|Thriller|War
900	900	Perfect Candidate, A (1996)	Documentary
2786	2786	My Chauffeur (1986)	Comedy
6867	6867	To the Left of the Father (Lavoura Arcaica) (2...	Drama
3794	3794	From Hell (2001)	Crime|Horror|Mystery|Thriller
921	921	T-Men (1947)	Film-Noir
4279	4279	The Pumaman (1980)	Action|Adventure|Fantasy|Sci-Fi

Model All Metrics

Model	Dummy Model(亂猜)	Basic MF
RMSE Loss	3.23	0.92
ROC AUC	0.50	0.74
NDCG	strict: 0.45 normal: 0.63	strict: 0.63 normal: 0.76
Precision at 10	strict: 0.37 normal: 0.54	strict: 0.50 normal: 0.63

Recommendation Engine in Matrix Factorization

Lab: lab_reco_model_mf.ipynb (20 minutes)

搜尋 ”Do:” 就可以找到可能要修改的位置

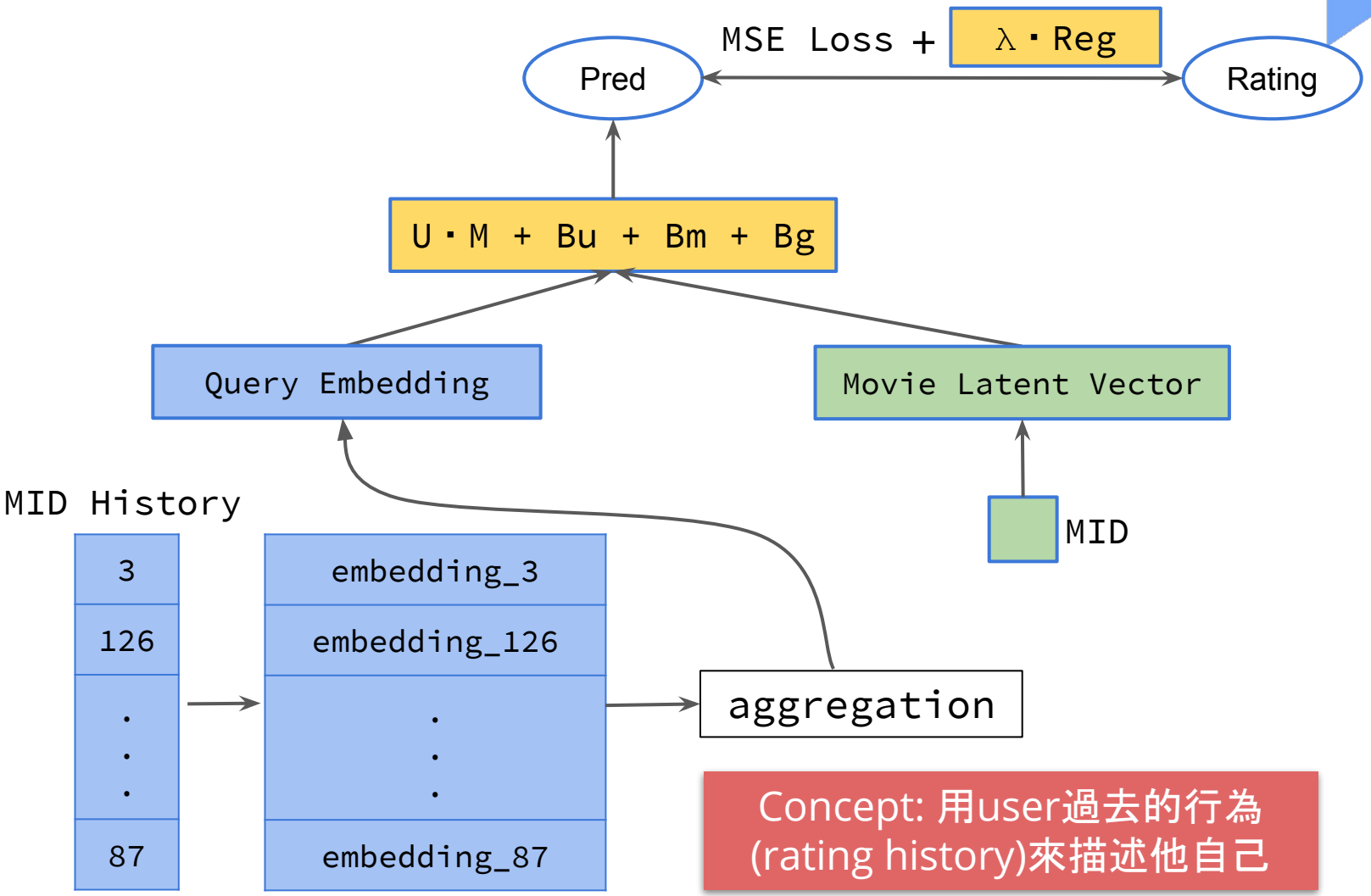
lab filename	lab_reco_model_mf.ipynb
target	您可能要修改的參數: ❑ learning rate ❑ dim: dimension of latent factor(user and movie) ❑ reg: 正規項的強度 ❑ dropout ❑ loss function ❑ optimizer
ideal score	valid loss: 將低到0.92左右 roc auc: 0.74左右 ndcg: strict condition 0.63左右

Model - MF with History

- 如果新的User進來...
  - 假設Profile資訊不足，不知道是男是女...
    - 推薦最受歡迎的電影(完全沒User rating)
  - 就算累積了Rating history，Model還是要重train
    - Fall back to content base recommendation

在不重train的狀況下，希望能夠對新來的user(有rating history)做推薦

Model - MF with History



Model - MF with History

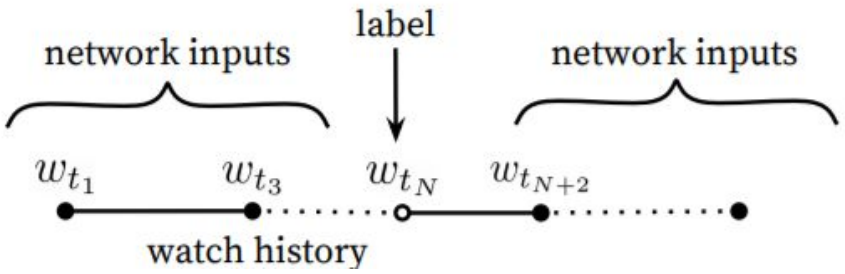
filename	reco_model_mf_with_history.ipynb
lab filename	**lab_reco_model_mf_with_history.ipynb**
number of users	671
number of movies	9125
rating range	0.5 ~ 5分, ❑ 4分以上算正評 ❑ 未滿4分認為是負評或是不列入推薦名單
neural network	matrix factorization

Model - MF with History

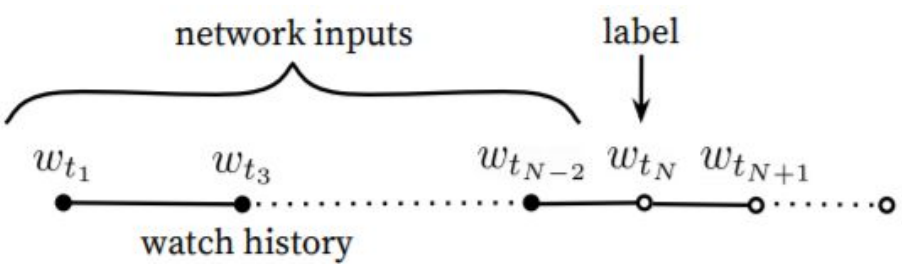
	user_id	query_movie_ids	query_movie_ids_len	candidate_movie_id	rating
0	47	[263, 2860, 3856, 6034, 2409, 2374, 7128, 5339...	357	1393	4.5
1	175	[966, 5026, 4395, 6042, 3871, 6521, 5020, 953,...	177	4002	3.0
2	261	[45, 1104, 154, 4514, 4171, 3801, 3727, 3644, ...	471	3089	2.0

- 觀察47號user
  - query_movie_ids: train data中47號的有rating的movie id，排除1393號
    ⇒ leave one out (這裡的設計也可以只用47號喜歡的電影)

leave one out for predict



leave one out(考慮時間)



Model - MF with History

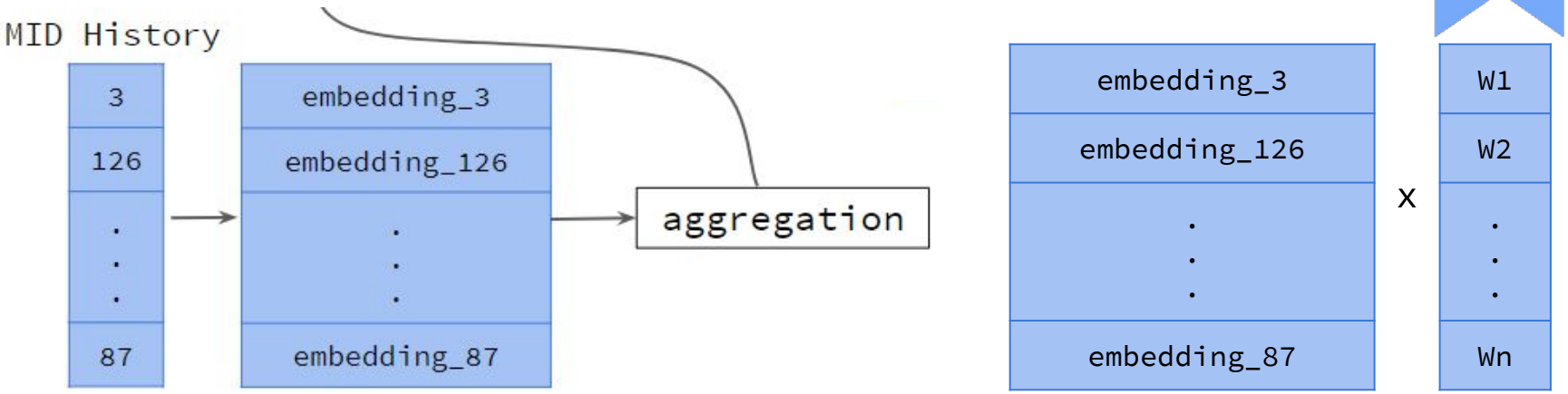
	user_id	query_movie_ids	query_movie_ids_len	candidate_movie_id	rating
0	47	[263, 2860, 3856, 6034, 2409, 2374, 7128, 5339...	357	1393	4.5
1	175	[966, 5026, 4395, 6042, 3871, 6521, 5020, 953,...	177	4002	3.0
2	261	[45, 1104, 154, 4514, 4171, 3801, 3727, 3644, ...	471	3089	2.0

- 觀察47號user
  - query_movie_ids: train data中47號的有rating的movie id，排除1393號
    ⇒ leave one out (這裡的設計也可以只用47號喜歡的電影)
  - query_movie_ids_len: 描述query_movie_ids movie id的個數(tensorflow限制，mini batch裡面的變數長度必須要一致)

所以47號User在train data裡只有一筆資料了?

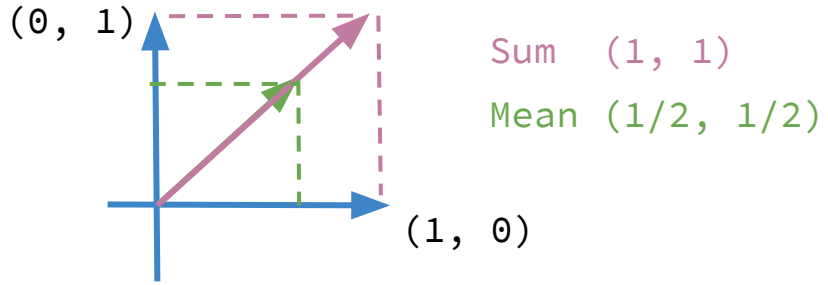
Recommendation Engine in Matrix Factorization

Movie ID Aggregation(Pooling)?



Tensorflow documentation上找到處理multivalent embedding的方式	
Sum	embedding向量相加
Mean	embedding向量相加後平均
SqrtN	將weight normalize後對embedding做weighted sum

在這批資料中效果較好



MF with History - Aggregation(Pooling)

```
with tf.variable_scope("computation"):
    # weighted avg of query embedding
    '''sqrtn aggregation(pooling), X: data, W: weight
           X_1*W_1 + X_2*W_2 + ... + X_n*W_n / sqrt(W_1**2 + W_2**2 + ... W_n**2)
         = weighted sum of X and normalized W
       here data = self.query_emb, weight = weighted '''
    query_emb_mask = tf.sequence_mask(self.query_movie_ids_len)
    weighted = tf.nn.l2_normalize(tf.to_float(query_emb_mask), 1)[:, :, tf.newaxis]
    self.query_emb = tf.reduce_sum(self.query_emb * weighted, 1)
    self.query_bias = tf.matmul(self.query_emb, self.b_query_movie_ids[:, tf.newaxis])
```

```
[2]    [1, 1, 0, 0]      [0.7, 0.7,   0, 0]     [array, array,     0, 0]     [array]
[3]  ➡ [1, 1, 1, 0]   ➡  [0.6, 0.6, 0.6, 0]  X  [array, array, array, 0]  =  [array]
[1]    [1, 0, 0, 0]      [  1,   0,   0, 0]     [array,     0,     0, 0]     [array]
```

query_movie_ids_len *tf.sequence_mask* *normalize* *query_emb*

Weighted Sum!

MF with History - Prediction (graph_computation)

```
infer = tf.reduce_sum(self.query_emb * self.candidate_emb, 1, keep_dims=True)
infer = tf.add(infer, self.b_global)
infer = tf.add(infer, self.query_bias)
self.infer = tf.add(infer, self.candidate_bias, name="infer")
```

```
# one query for all items
self.pred = tf.matmul(self.query_emb, tf.transpose(self.w_candidate_movie_id)) + \
            tf.reshape(tf.matmul(self.w_candidate_movie_id,
                                 self.b_candidate_movie_id[:, tf.newaxis]), (1, -1)) + \
            self.query_bias + \
            self.b_global
```

- infer節點與pred節點做的事情是一樣的，都是帶下列的公式

$$f_{u,m}(x) = u_i \cdot m_j + b_u + b_m + b_{global}$$

- pred節點純粹是為了執行效能而已

MF with History - Metrics and Comparison

Model	MF	MF with history
RMSE Loss	0.92	0.92
ROC AUC	0.74	0.74
NDCG	strict: 0.63 normal: 0.76	strict: 0.63 normal: 0.76
Precision at 10	strict: 0.50 normal: 0.63	strict: 0.51 normal: 0.63

- ❑ MF with history的Model效果沒有進步
- ❑ 但後者的Model較有彈性!

Recommendation Engine in Matrix Factorization

Lab: lab_reco_model_mf_with_history.ipynb (20 minutes)

搜尋 ”Do:” 就可以找到可能要修改的位置

lab filename	lab_reco_model_mf_with_history.ipynb
target	您可能要修改的參數: ❑ learning rate ❑ dim: dimension of latent factor(user and movie) ❑ reg: 正規項的強度 ❑ dropout ❑ loss function ❑ optimizer
ideal score	valid loss: 降低到0.92左右 roc auc: 0.74左右 ndcg: strict condition 0.63左右

Recommendation Engine with DNN

- Machine Learning Framework
- Deep Neural Network(DNN) Tips
- Recommedation Engine in Matrix Factorization
- Matrix Factorization with DNN

Model - MF with DNN

- 同樣的想法，也來改進一下**Movie Latent Factor**

	userId	movieId	title	genres	rating
0	0	30	Dangerous Minds (1995)	Drama	2.5
1	0	833	Dumbo (1941)	Animation|Children|Drama|Musical	3.0
2	0	859	Sleepers (1996)	Thriller	3.0
3	0	906	Escape from New York (1981)	Action|Adventure|Sci-Fi|Thriller	2.0
4	0	931	Cinema Paradiso (Nuovo cinema Paradiso) (1989)	Drama	4.0

- Movie Meta好像太少了點
  - title欄位有**年份資料**
  - genres告訴我們一部電影可以有多種類型
  - rating是user對電影的評分，一部電影被多個user評分
    ⇒ 可以算出**平均評分**

Model - MF with DNN

- 於是電影可以用下列Meta來描述

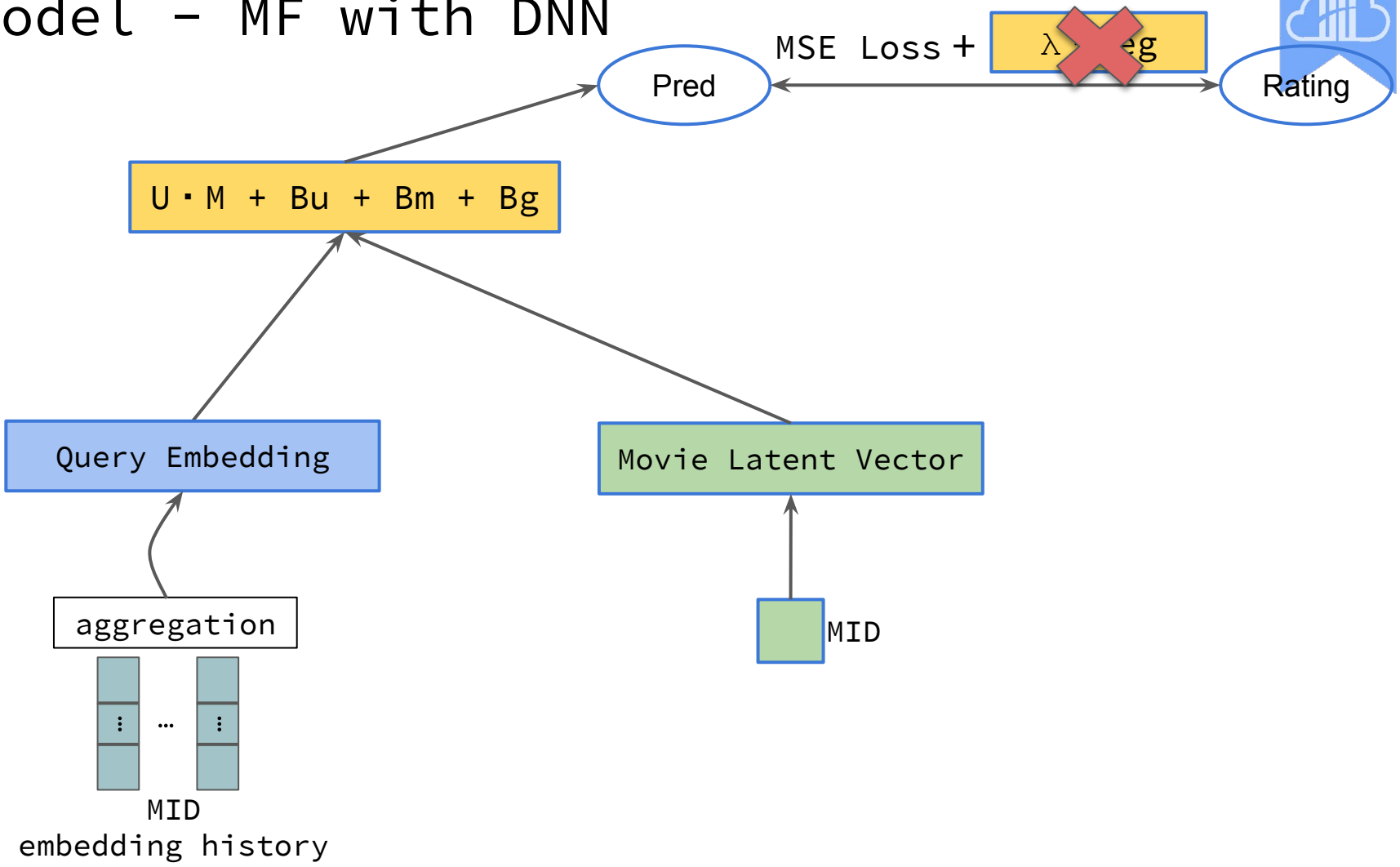
genres	genres_len	avg_rating	year	candidate_movie_id	rating
[1, 0, 3, 0]	3	0.716049	0.833333	1393	4.5
[5, 13, 10, 1]	4	0.643739	0.877193	4002	3.0
[0, 7, 2, 0]	3	0.545752	0.859649	3089	2.0
[7, 11, 2, 0]	3	0.448148	0.833333	1308	3.0
[1, 0, 0, 0]	1	0.779449	0.736842	2340	1.5

- genres: multivalent variable ⇒ embedding ⇒ average
- genres_len: 描述genres長度
- avg_rating: 電影的平均評分(已normalize to 0 ~ 1之間)
- year: 從title extract出來(已normalize to 0 ~ 1之間)

Enrich movie metadata
- 還可以Crawler搜尋電影導演、演員、票房等等..

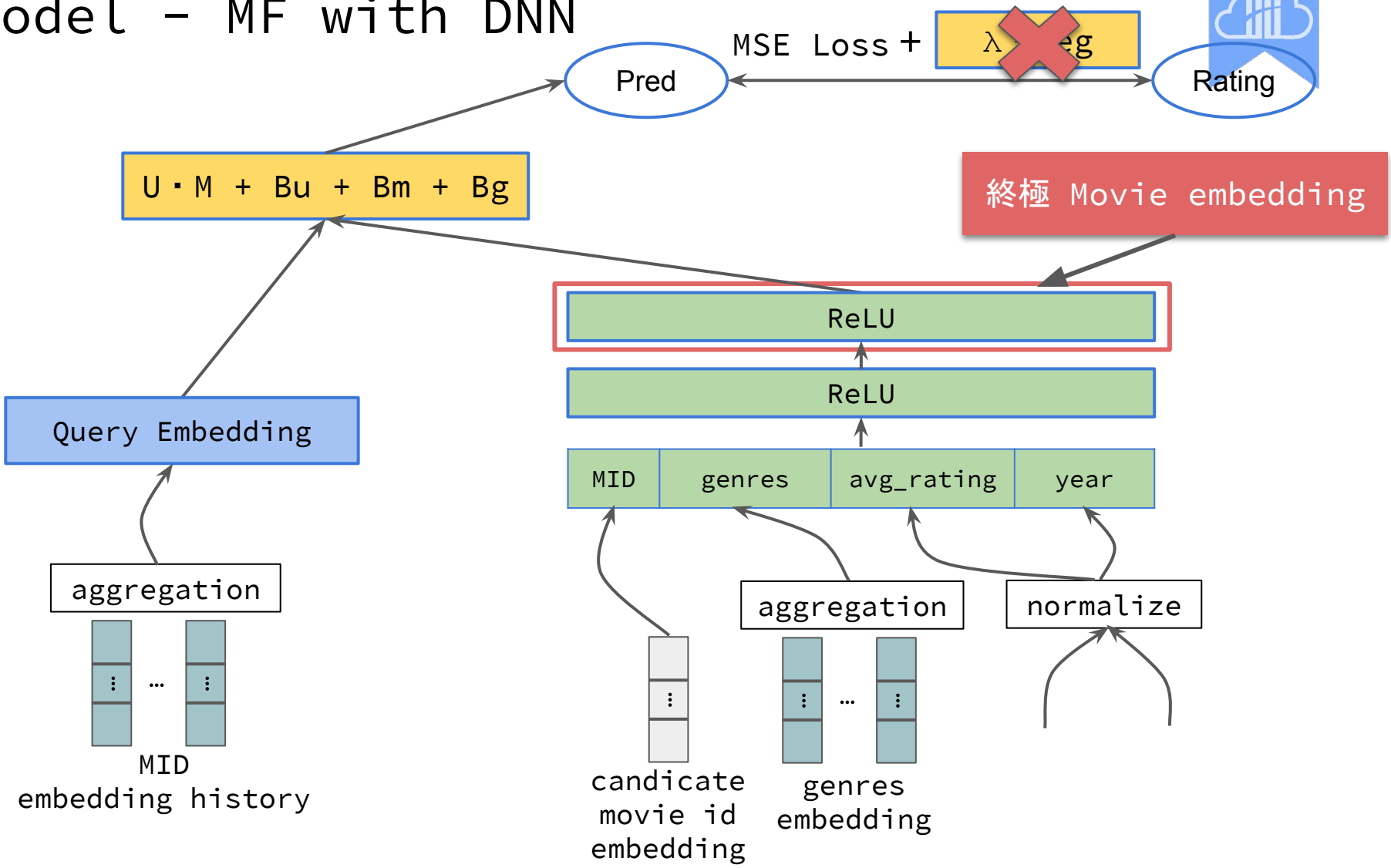
Recommendation Engine with DNN

Model – MF with DNN



Recommendation Engine with DNN

Model – MF with DNN



Model - MF with DNN

filename	reco_model_mf_dnn.ipynb
lab filename	**lab_reco_model_mf_dnn.ipynb**
number of users	671
number of movies	9125
rating range	0.5 ~ 5分, ❑ 4分以上算正評 ❑ 未滿4分認為是負評或是不列入推薦名單
neural network	matrix factorization with dnn

Model - MF with DNN(graph_dnn)

```
with tf.variable_scope("dnn"):
    # encode [item embedding + item metadata]
    self.item_repr = tf.concat([self.candidate_emb, self.genres_emb, self.avg_rating[:, tf.newaxis], self.year[:, tf.newaxis]], 1)
    self.candidate_bias = tf.matmul(self.item_repr, self.b_candidate_movie_id[:, tf.newaxis])

    # dp_scale = 0.5
    self.item_repr = tf.layers.dense(self.item_repr, dim, kernel_initializer=init_fn, activation=tf.nn.relu)
    # self.item_repr = tf.layers.dropout(self.item_repr, dp_scale, training=self.isTrain)
    self.item_repr = tf.layers.dense(self.item_repr, dim, kernel_initializer=init_fn, activation=tf.nn.relu)
    # self.item_repr = tf.layers.dropout(self.item_repr, dp_scale, training=self.isTrain)
```

- item_repr: concat metadata
  - candidate movie id embedding (16) +
  - genres embedding (8) +
  - 平均分數 (1) +
  - 年份 (1)

  ⇒ shape = 16 + 8 + 1 + 1 = 26

- 兩層DNN(fully connected layer) + ReLU ⇒ encoding
- **這裡的Network structure可以自行調整(增加層數 or 調整neuron數)**

Model - MF with DNN

Trainging

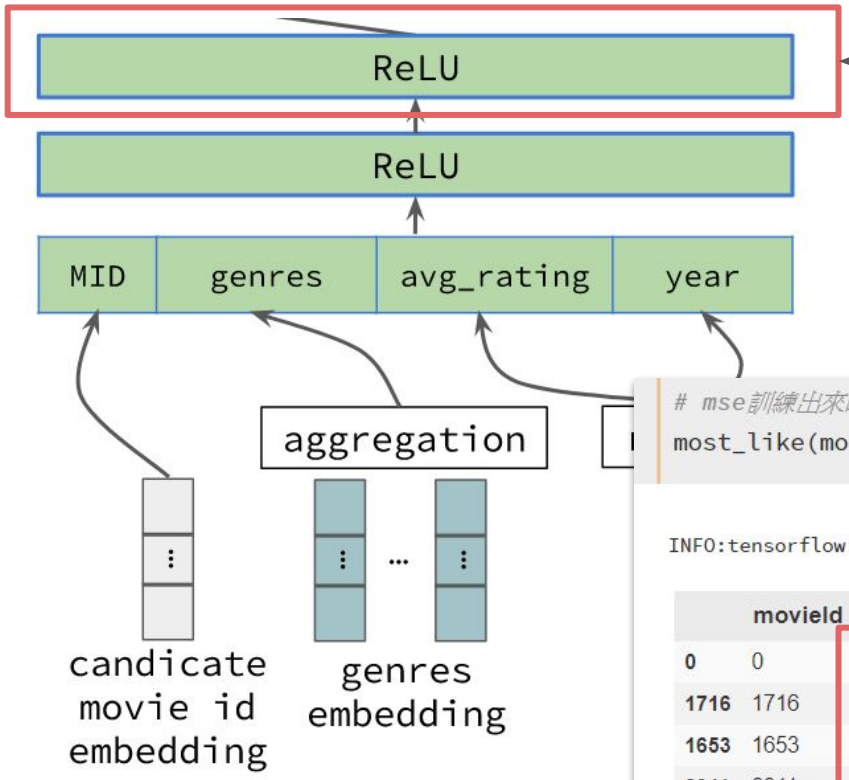
```
# !cp -a ./model/model_mf_with_dnn_bak/* ./model/mode
# 每個batch的數量
n_batch = 128
with tf.Session(graph=model.graph) as sess:
    model.fit(sess, dataFn(trProcessed, n_batch=n_bat
```

```
reset model: clean model dir: ./model/model_mf_with_dnn ...
Epoch    Train Error     Val Error       Elapsed Time
01       1.096           0.934           14.236 secs, saving ...
02       0.961           0.894           15.311 secs, saving ...
03       0.931           0.870           14.697 secs, saving ...
04       0.910           0.854           13.682 secs, saving ...
05       0.894           0.844
06       0.881           0.835
07       0.870           0.827
08       0.862           0.823           15.012 secs, saving ...
09       0.856           0.818           13.786 secs, saving ...
10       0.851           0.820           13.758 secs
```

Valid RMSE error已經可以低達0.81

Recommendation Engine with DNN

MF with DNN - 活用Laten Factor(Embedding)!



找出跟Toy Story相似的電影

- ❏ Indide Out
- ❏ Toy Story2
- ❏ Antz(螞蟻雄兵)

...

```
# mse訓練出來的model
most_like(model, 0, k=11)
```

```
INFO:tensorflow:Restoring parameters from ./model/model_mf_with_dnn/model-9
```

	movieId	title	genres
0	0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1716	1716	NeverEnding Story, The (1984)	Adventure|Children|Fantasy
1653	1653	Return to Oz (1985)	Adventure|Children|Fantasy
8911	8911	Inside Out (2015)	Adventure|Animation|Children|Comedy|Drama|Fantasy
1815	1815	Antz (1998)	Adventure|Animation|Children|Comedy|Fantasy
3217	3217	Emperor's New Groove, The (2000)	Adventure|Animation|Children|Comedy|Fantasy
7945	7945	Asterix and the Vikings (Astérix et les Viking...	Adventure|Animation|Children|Comedy|Fantasy
2506	2506	Toy Story 2 (1999)	Adventure|Animation|Children|Comedy|Fantasy
3079	3079	The Spiral Staircase (1945)	Horror|Mystery|Thriller
813	813	Escape to Witch Mountain (1975)	Adventure|Children|Fantasy
6246	6246	MirrorMask (2005)	Adventure|Children|Drama|Fantasy

Model - 實際上使用Embedding的例子

使用User embedding找出該user偏好的衣服類型

甚至可以找不同類型的搭配(馬克思禮服找到一堆寬腿褲)

https://making.dia.com/embedding-everything-for-anything2anything-recommendations-fca7f58f53ff

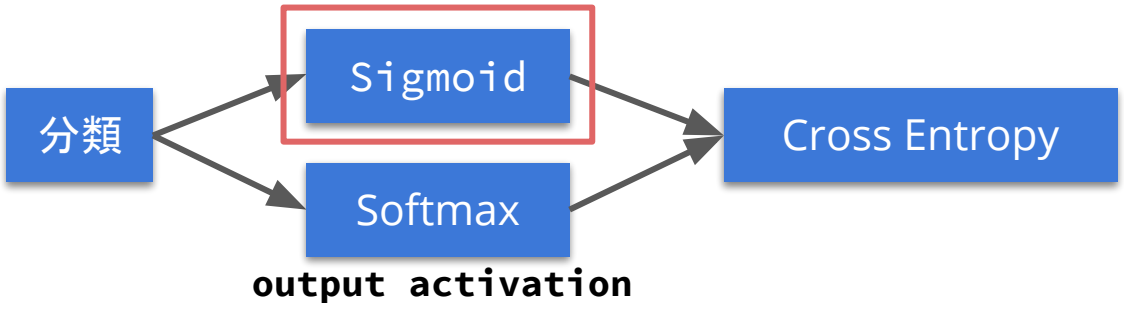
MF with DNN - Metrics and Comparison

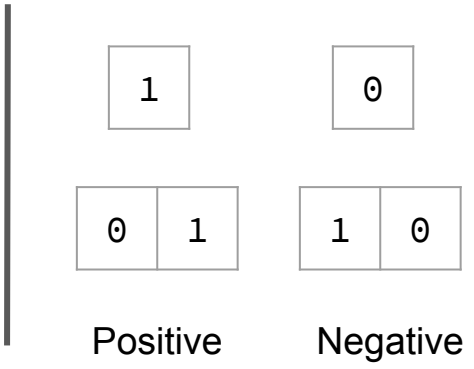
Model	MF	MF with history	MF with DNN
RMSE Loss	0.92	0.92	**0.82**
ROC AUC	0.74	0.74	**0.80**
NDCG	strict: 0.63 normal: 0.76	strict: 0.63 normal: 0.76	**strict: 0.73** **normal: 0.86**
Precision at 10	strict: 0.50 normal: 0.63	strict: 0.51 normal: 0.63	**strict: 0.59** **normal: 0.68**

Model - MF with DNN(Classification)

- Movie rating: explicit feedback
- **通常User不會這麼熱心的對你的商品評價**
  - implicit feedback
    - 商品點閱次數
    - Youtube影片觀看時間
    - ...

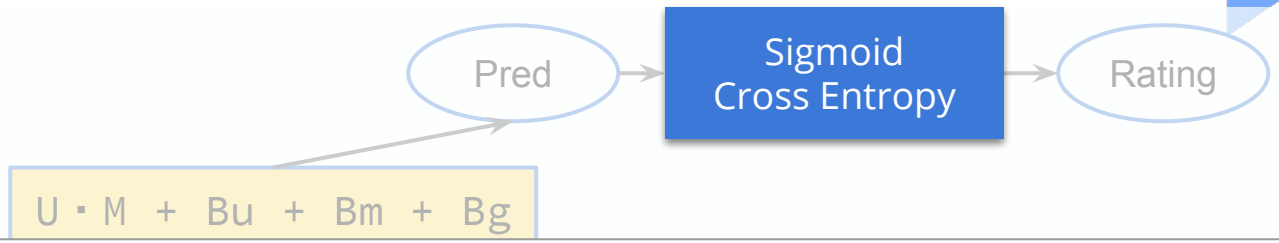
    ⇒ 通常只能得到1(Positive), 0(Negtive)
- **Label 0.5 ~ 5 ⇒ 1 or 0 (這裡4分以上 = 1 others 0)**
  - Regression ⇒ Binary classification
  - P(使用者A 喜歡 電影B) = ??





Recommendation Engine with DNN

Model - MF with DNN(Classification)

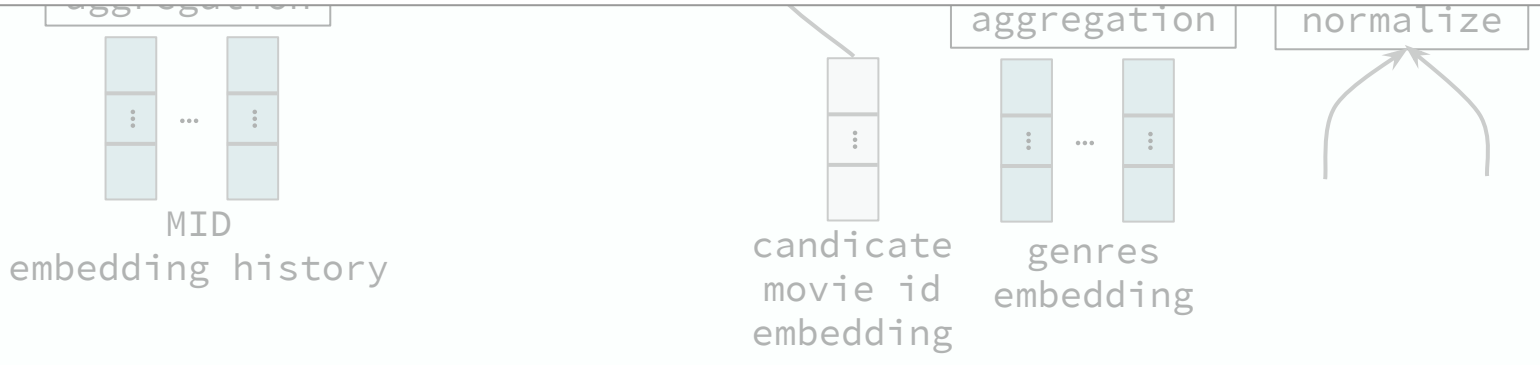


- Function set

$$f_{u,m}(x) = \sigma(u_i \cdot m_j + b_u + b_m + b_{global})$$

- Loss function: cross entropy

$$L = -\sum(\hat{y} \cdot lnf_{u,m}(x) + (1 - \hat{y})(1 - lnf_{u,m}(x)))$$



Recommendation Engine with DNN

Model – MF with DNN

```
with tf.variable_scope("loss"):
    # if rating >= 4 then 1 else 0
    self.alter_rating = tf.to_float(self.rating >= 4)
    self.loss = tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(labels=self.alter_rating[:, np.newaxis], logits=self.infer))

    # for eval
    self.rmse_loss = tf.sqrt(tf.losses.mean_squared_error(labels=self.alter_rating[:, tf.newaxis], predictions=self.infer))
    self.mae_loss = tf.reduce_mean(tf.abs(self.infer - self.alter_rating[:, tf.newaxis]))
    pass
```

- alter_rating: **在tensorflow裡轉換label**
  - if rating >= 4 ⇒ 1, else 0

Model – MF with DNN

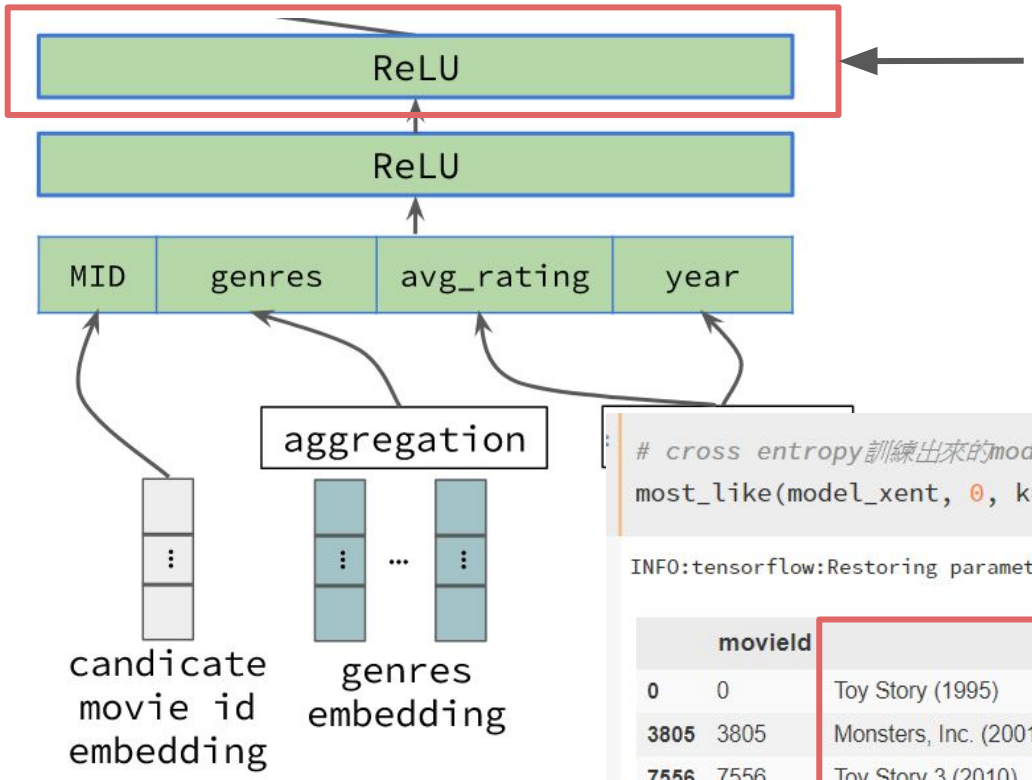
Trainging

```
n_batch = 128
with tf.Session(graph=model_xent.graph) as sess:
    model_xent.fit(sess, dataFn(trProcessed, n_batch=n_batch, sh
```

```
reset model: clean model dir: ./model/model_mf_with_dnn_xent ...
Epoch   XEntropy Error  Val XENT Error  Val RMSE Error  Elapsed Time
01      0.653           0.622           0.745           15.133 secs, saving ...
02      0.607           0.590           0.888           15.839 secs, saving ...
03      0.580           0.571           0.930           15.542 secs, saving ...
04      0.562           0.559           0.986           14.085 secs, saving ...
05      0.551           0.566           1.271           14.290 secs
06      0.542           0.552           1.190           17.491 secs, saving ...
07      0.536           0.547           1.241           14.598 secs, saving ...
08      0.530           0.539           1.200           15.505 secs, saving ...
09      0.524           0.534           1.271           14.136 secs, saving ...
10      0.520           0.535           1.447
```

- 最佳化cross entropy
- RMSE的分數與之前的Model相比是無意義的 ⇒ Label值域已經轉變!

MF with DNN(Cross Entropy)，活用Embedding



找出跟Toy Story相似的電影
- ❏ Monsters, Inc
- ❏ Toy Story3
- ❏ Toy Story2

...

```
# cross entropy訓練出來的model
most_like(model_xent, 0, k=11)
```

```
INFO:tensorflow:Restoring parameters from ./model/model_mf_with_dnn_xent\model-11
```

	movieId	title	genres
0	0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
3805	3805	Monsters, Inc. (2001)	Adventure|Animation|Children|Comedy|Fantasy
7556	7556	Toy Story 3 (2010)	Adventure|Animation|Children|Comedy|Fantasy|IMAX
7373	7373	Black Dynamite (2009)	Action|Comedy
7343	7343	Haunted World of El Superbeasto, The (2009)	Action|Animation|Comedy|Horror|Thriller
3419	3419	Shrek (2001)	Adventure|Animation|Children|Comedy|Fantasy|Ro...
215	215	Gordy (1995)	Children|Comedy|Fantasy
7653	7653	Red (2010)	Action|Comedy
7525	7525	Exit Through the Gift Shop (2010)	Comedy|Documentary
2506	2506	Toy Story 2 (1999)	Adventure|Animation|Children|Comedy|Fantasy
1656	1656	Sleeping Beauty (1959)	Animation|Children|Musical

MF with DNN - Metrics and Comparison

Model	MF	MF with history	MF with DNN(MSE)	MF with DNN (Cross Entropy)
RMSE Loss	0.92	0.92	**0.82**	~~1.44~~ **cross entropy loss: 0.53(無法與RMSE相比)**
ROC AUC	0.74	0.74	0.80	**0.81**
NDCG	strict: 0.63 normal: 0.76	strict: 0.63 normal: 0.76	**strict: 0.73** **normal: 0.83**	strict: 0.72 normal: 0.82
Precision at 10	strict: 0.50 normal: 0.63	strict: 0.51 normal: 0.63	**strict: 0.59** **normal: 0.68**	**strict: 0.59** **normal: 0.68**

Lab: lab_reco_model_mf_dnn.ipynb (20 minutes)

搜尋 ”Do:” 就可以找到可能要修改的位置

lab filename	lab_reco_model_mf_dnn.ipynb
target	您可能要修改的參數: ❑ learning rate ❑ dim: dimension of latent factor(user and movie) ❑ dropout ❑ loss function ❑ optimizer ❑ DNN structure
ideal score	valid rmse loss: 降低到0.82左右 roc auc: 0.80左右 ndcg: strict condition 0.60左右

Model MF with DNN 彈性的應用

- 對於新的user
  - 無使用紀錄
    - 推薦最受歡迎商品
  - 一點點使用紀錄
    - Content base recommendation(trained item embedding)
  - 大量使用紀錄
    - Model recommendation

- 對於新進來的電影
  - 將metadata帶入model取得embedding就可以使用
    - ex: genres、avg_rating、year、director、actors(actresses)...
  - 不使用指向性的Feature ⇒ Ex: Movie ID

Ending

- 若有課程上的建議，歡迎來信
  - gary.chen@mile.cloud
  - johann.chu@mile.cloud
  - jeff.liu@mile.cloud

填寫問卷
便可索取課堂參考資料連結

CloudMile 萬里雲