AI 新手村指南

初學技能--深度學習

對你來
說....

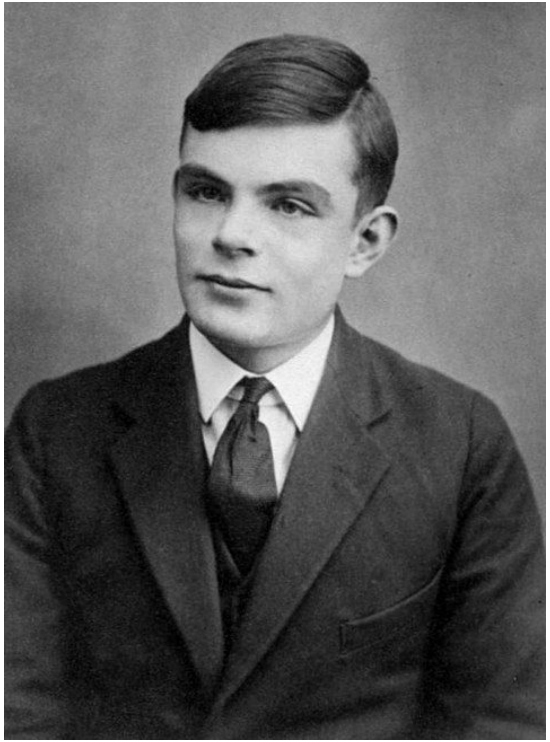
什麼是 AI ??

什麼東西叫 AI ??

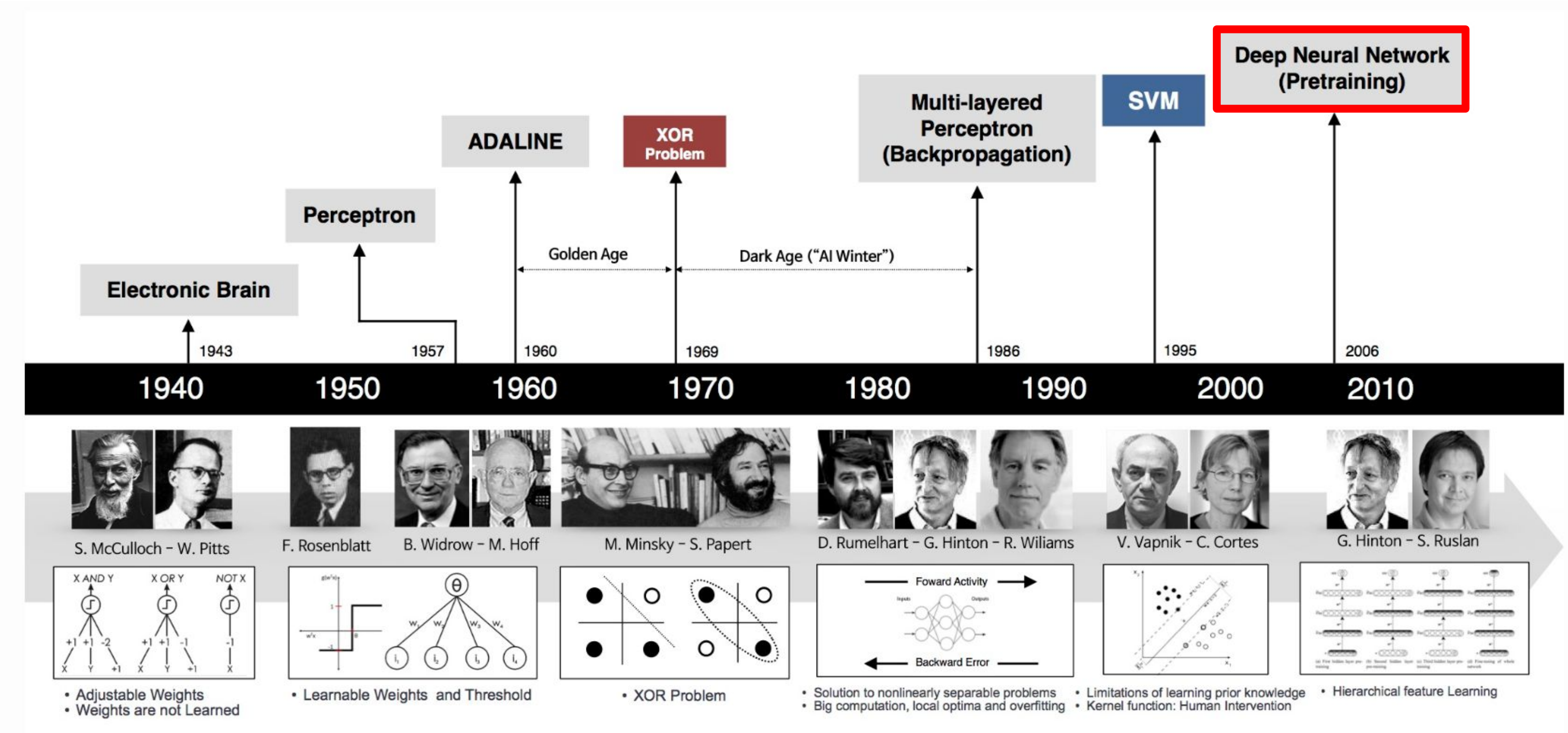
其實 AI 是種演算法

Alan Mathison Turing (1912-1954)

- 是計算機科學家、數學家、邏輯學家、密碼分析學家和理論生物學家
- 被譽為「計算機科學之父」、「人工智慧之父」
- 著名的文章--- *Computing machinery and intelligence*，提出「Can Machines Think?」
- Turing Test 圖靈測試(1950)



站在巨人的肩膀--AI 人工智慧的里程碑



https://beamandrew.github.io/deeplearning/2017/02/23/deep_learning_101_part1.html

哪時候你開始發現....

AI 離我好像很近....

The Milestone of the Deep Learning

2006 Netflix | **2010 ImageNet** | **2016 Alpha Go**

Important Milestone

2006 RBM (Hinton)
- Deep Learning Base Recommandation

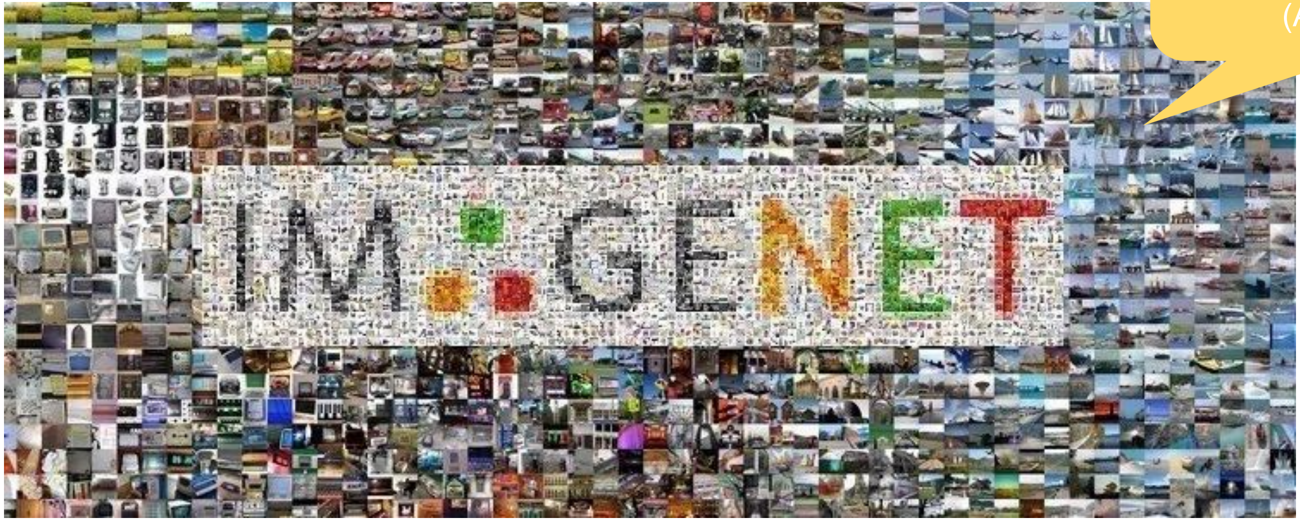
哪時候開始關注「深度學習」的呢？

2006
Netflix

2010
ImageNet

2016
Alpha Go

ILSVR（ImageNet Large Scale Visual Recognition Competition）



Important Milestone

2012 AlexNet
(Alex, Hinton)

哪時候開始關注「深度學習」的呢？

2006
Netflix

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ImageNet

2016
Alpha Go

<u>Important Milestone</u>

2016 AlphaGo
對戰世界冠軍李世石

讓機器下圍棋有多厲害？

棋類名稱	棋局所有變化可能	程式擊敗職業棋士紀錄	程式作者
西洋跳棋 Checkers	10^{32}	Chinook，6 平手 Marion Timsley (1994)	Jonathan Schaeffer (Alberta University)
黑白棋 Othello	10^{58}	Logistello，6:0 勝村上健 (1997)	Michael Buro (Othello strong player)
九路圍棋 9 X 9 Go	10^{85}	東華七號，七番賽 4:3 勝職業棋時黨希昀 (2013/6) 七番賽 4:1 勝職業棋士蕭愛霖 (2014/6)	周政緯、顏士淨 (東華大學)
西洋棋 Chess	10^{123}	DeepBlue，3.5-2.5 勝卡斯帕羅夫 (1997/5)	許峰雄深藍團隊 (IBM)
象棋 Chinese Chess	10^{150}	Shiga，紅先勝陳振國八段 (2006/ 11)	鄭明政、顏士淨 (東華大學)
日本將棋 Shogi	10^{226}	Tsutsukana 勝森下卓九段 (2014/4)	一丸貴則 (名古屋大學)
圍棋 19 X 19 Go	10^{400}	AlphaGo，4:1 勝李世九段 (2016/3)	谷歌 DeepMind 團隊

2019 兩大史事

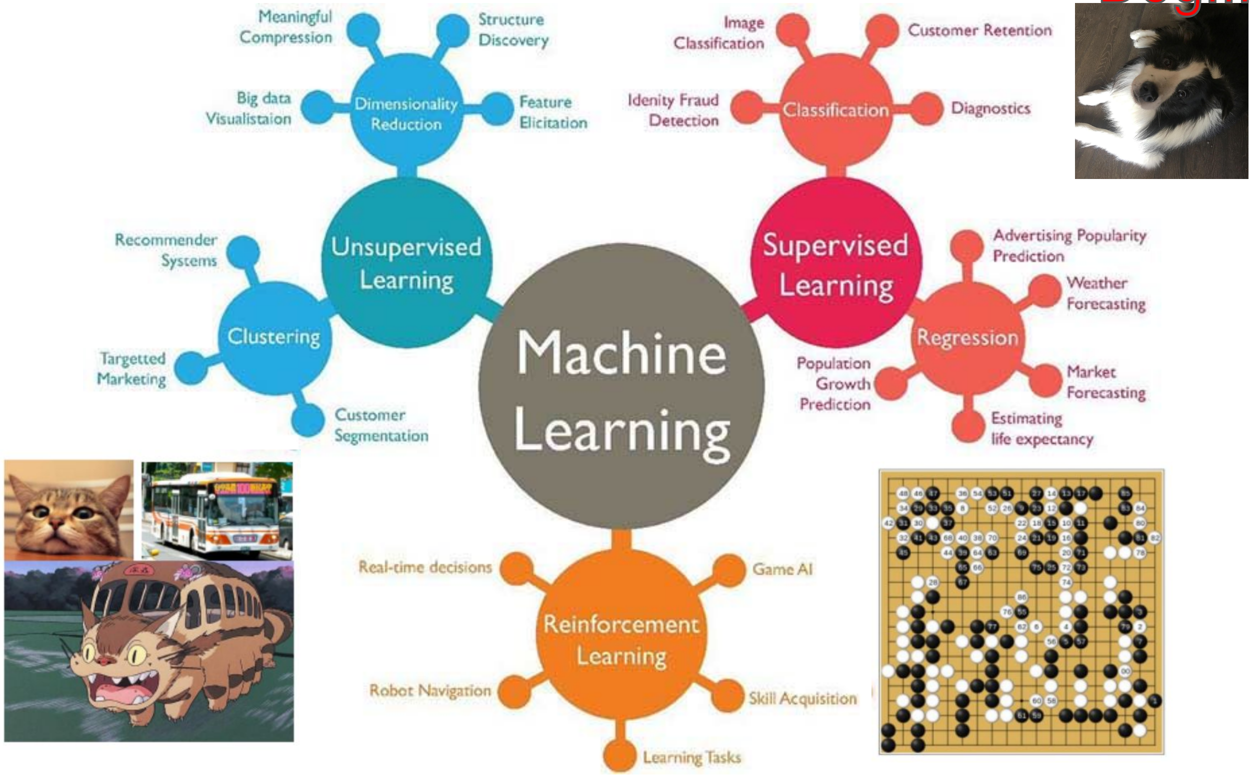
Deep Mind -- AlphaStar

Microsoft -- Suphx 天鳳

什麼問題都用 AI
就好了嗎??

機器學習的問題種類

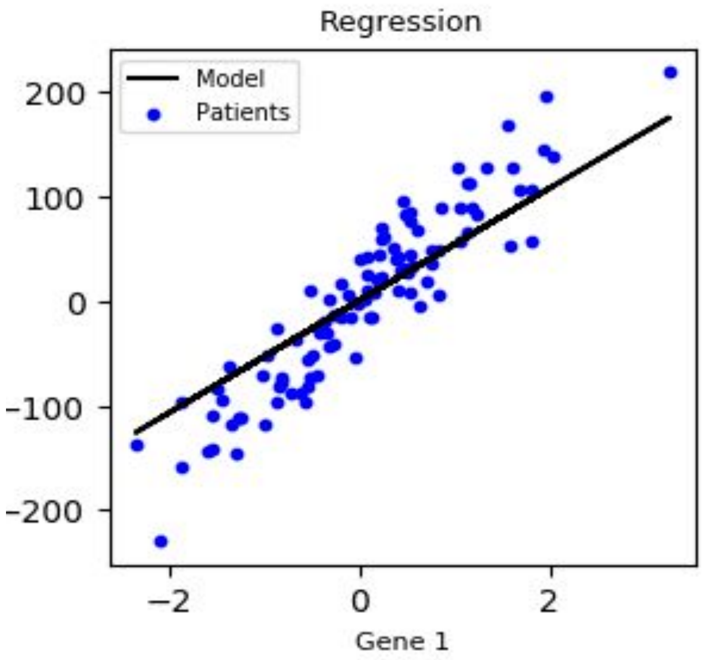
- 監督式學習
  Supervised Learning
  - Regression 迴歸
  - Classification 分類
- 非監督式學習
  Unsupervied Learning
  - Clustering 分群
  - Dimensionality Reduction
    維度縮減
- 強化式學習
  Reinforcement Learning

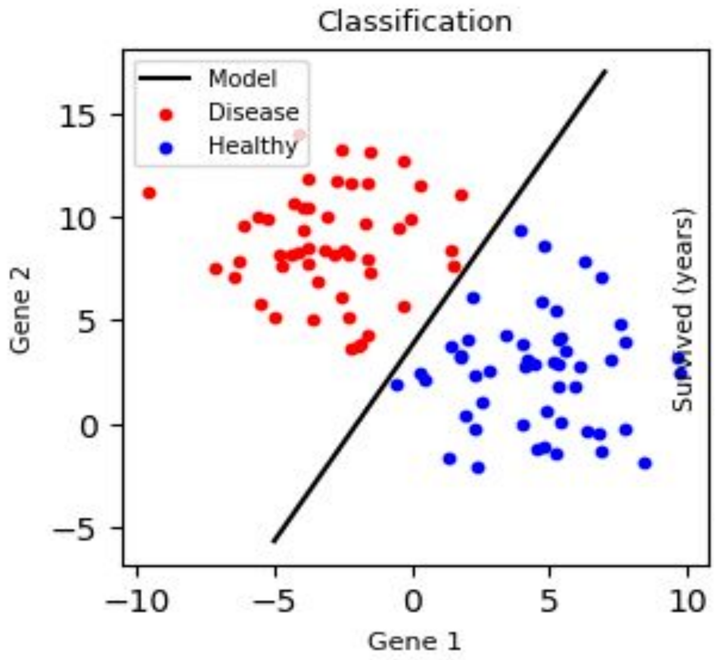


Dog!!!

https://www.techleer.com/articles/203-machine-learning-algorithm-backbone-of-emerging-technologies/

了解問題--迴歸與分類問題

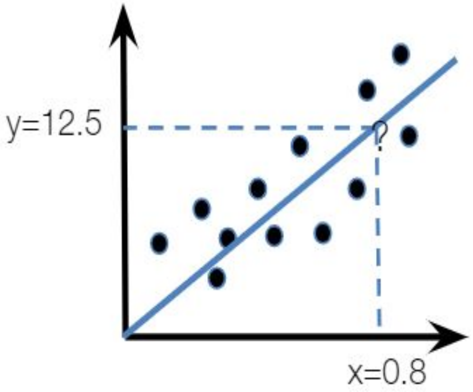




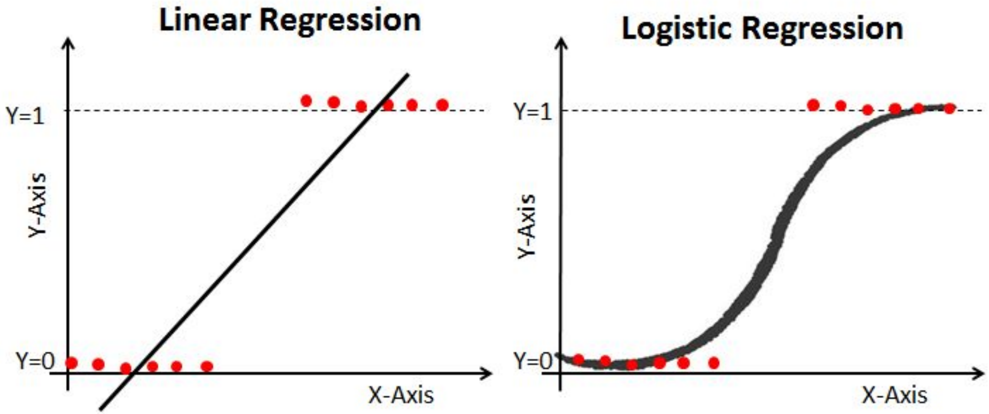
了解問題--迴歸與分類問題

線性迴歸
Linear Regression

$$y = wx + b$$

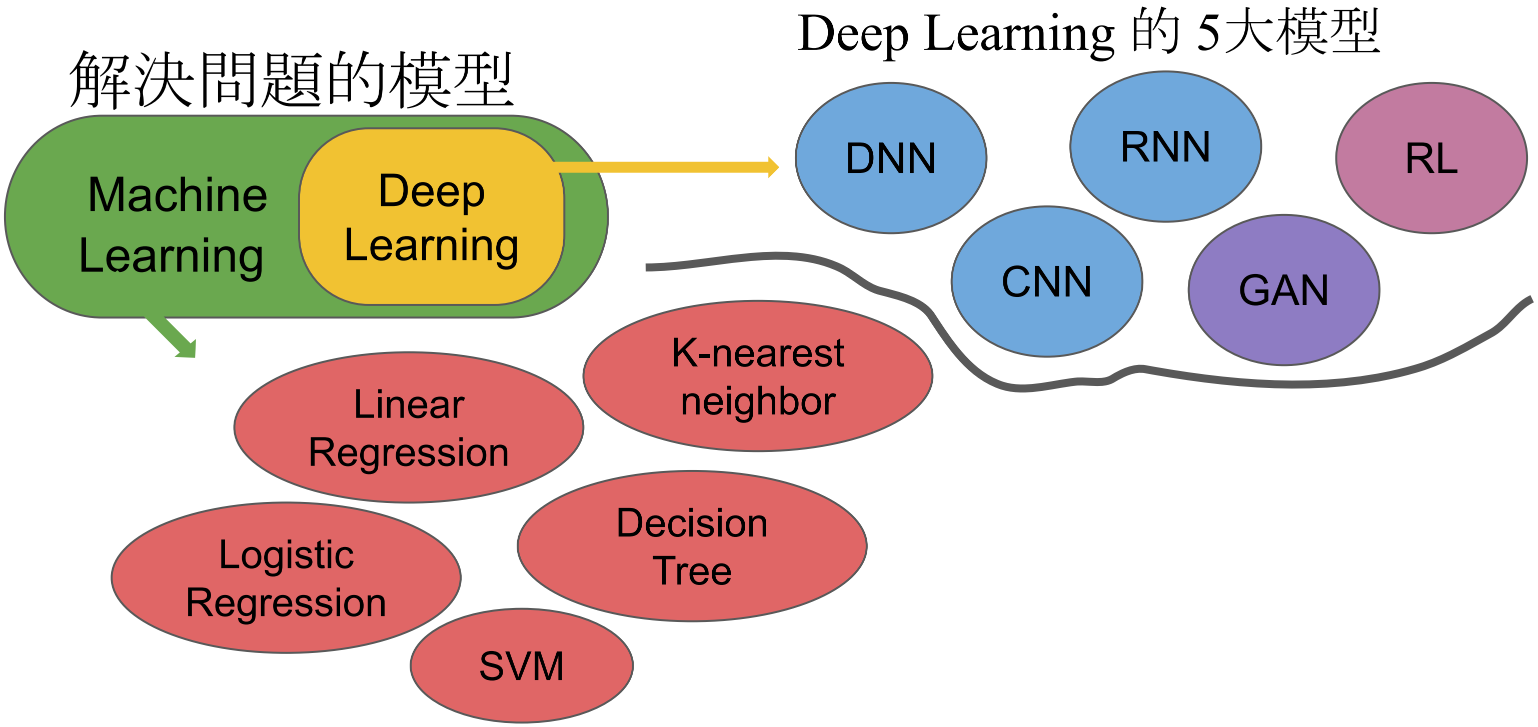


邏輯斯迴歸
Logistic Regression



$$f(x) = \frac{1}{1 + e^{-(wx+b)}}$$

機器學習方法百百種



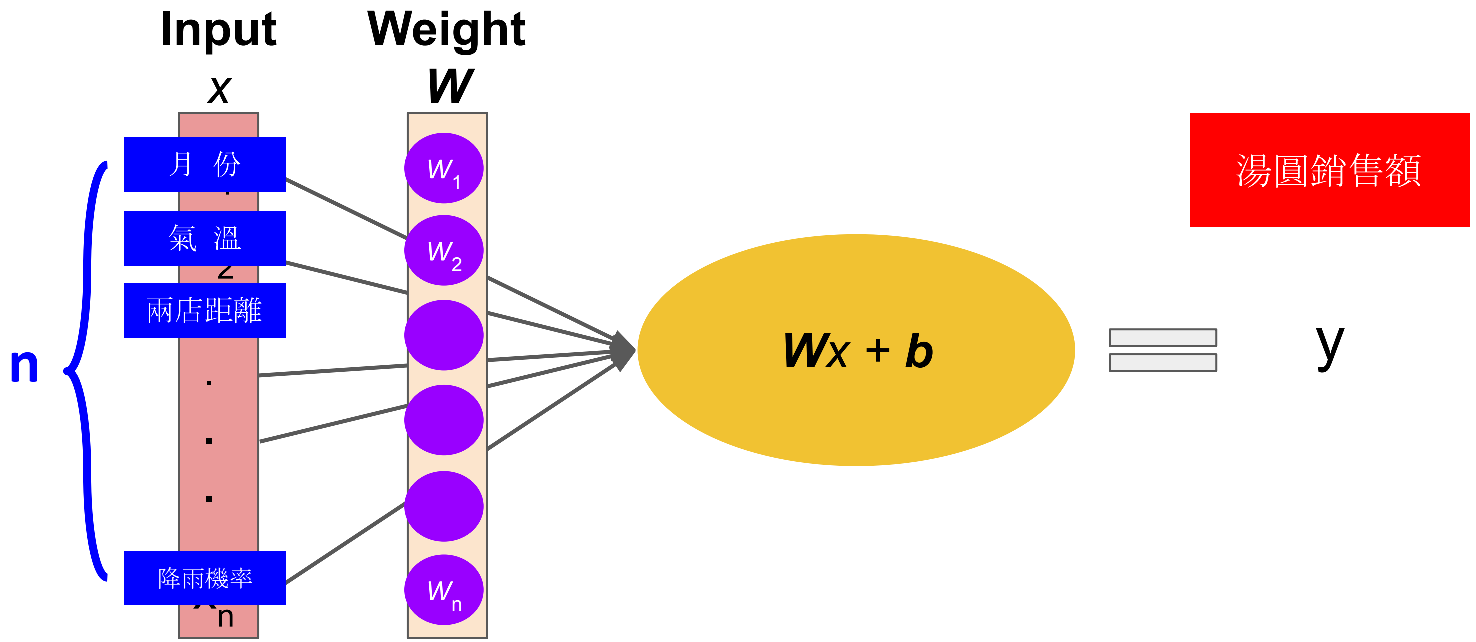
解決問題的模型
Deep Learning 的 5大模型
Machine Learning
Deep Learning
DNN
RNN
RL
CNN
GAN
K-nearest neighbor
Linear Regression
Decision Tree
Logistic Regression
SVM

小試一下身手～～

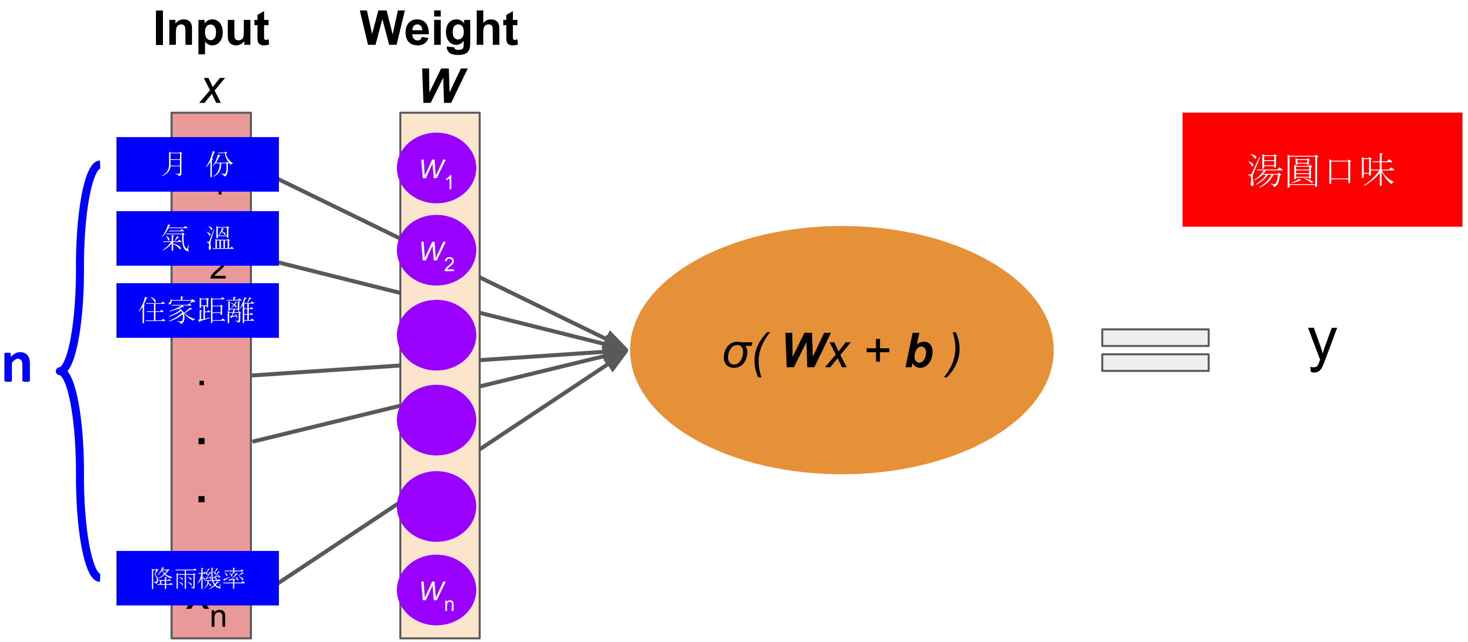
Deep Learning 深度學習

神奇的....
類神經網路模型

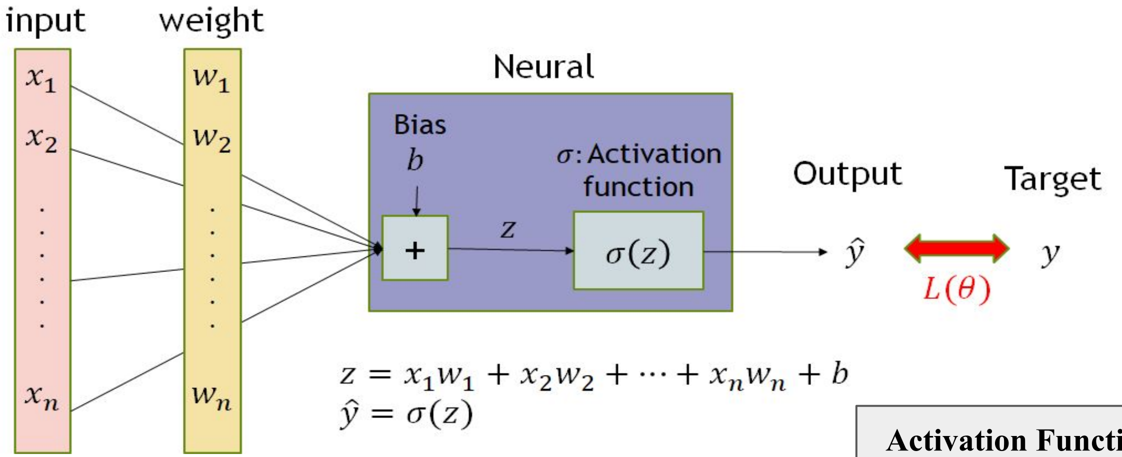
實際的迴歸問題....



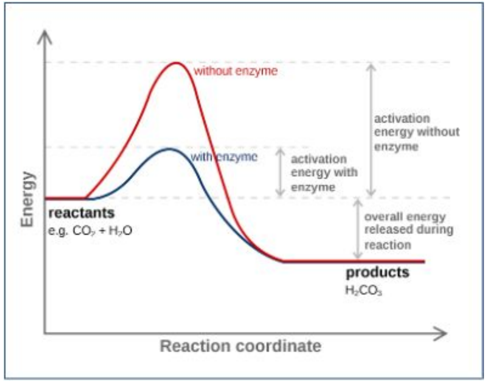
實際的分類問題....

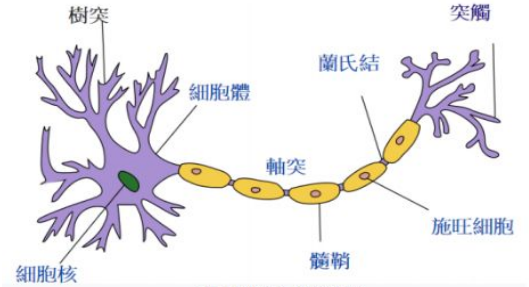


Neural Network 類神經網路 --- A Neuron



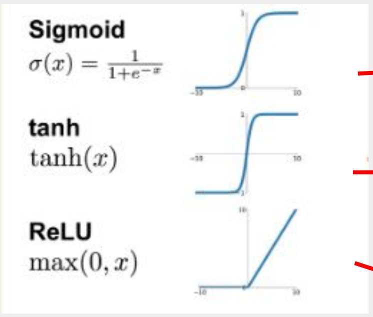
$$z = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n + b$$
$$\hat{y} = \sigma(z)$$





典型神經元的結構

Activation Function 基本款

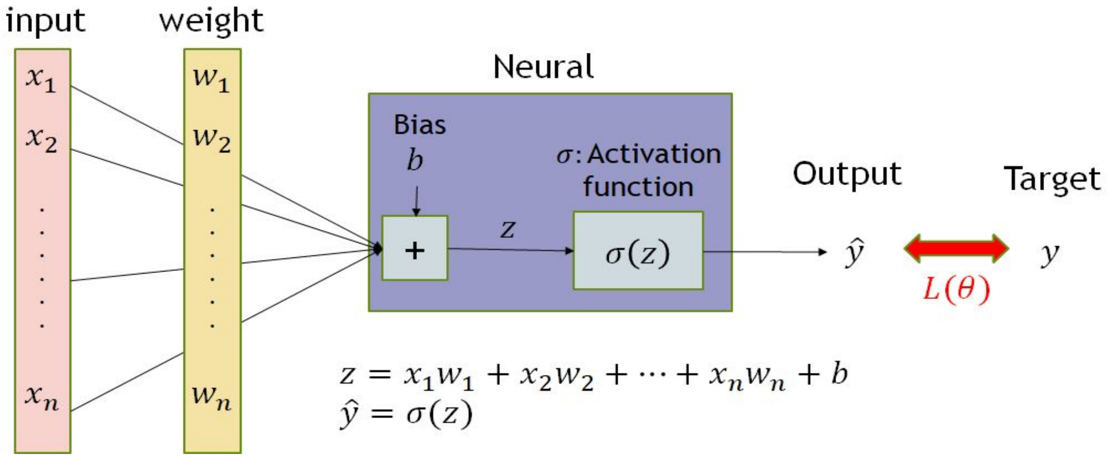


$$\sigma'(x) = \sigma(x)(1 - \sigma(x))$$

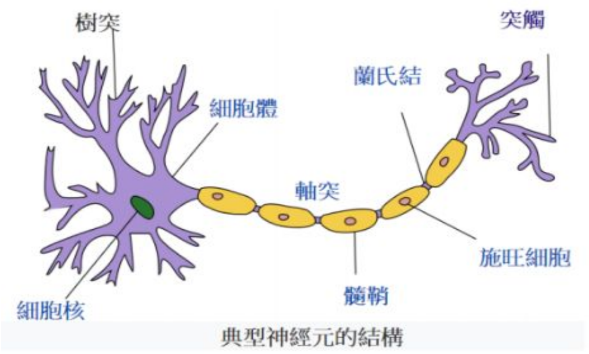
$$\sigma'(x) = 1 - \sigma(x)^2$$

$$\sigma'(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

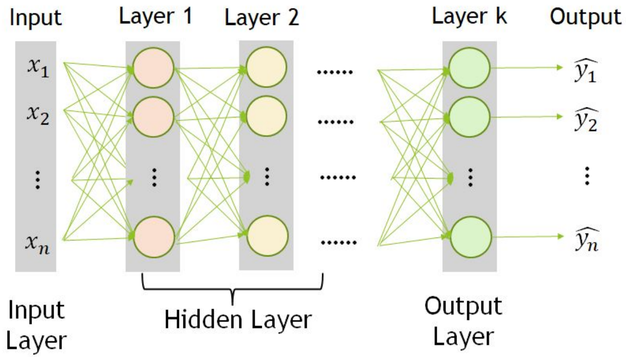
何謂 “Deep” Neural Network？



$$z = x_1w_1 + x_2w_2 + \cdots + x_nw_n + b$$
$$\hat{y} = \sigma(z)$$



x	input	從不同來源來的資訊
w	weight	對來源的訊號強弱敏感程度
b	bias	對某件事情的成見
z	$z = wx + b$	綜合所有來源資訊
σ	Activation Func.	資訊分析的條件
y	$y = \sigma(z)$	最後的結果



三大神經元、三個積木塊

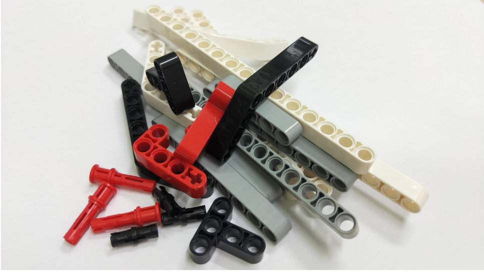
CNN

視覺神經

RNN

遞迴神經

DNN



大腦神經

定義模型好不好

評估模型好壞的指標---Loss Function

- mean absolute error

$$L(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{N}\|y_i - \hat{y}_i\|$$

- mean square error

$$L(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

- R^2 score

$$L(y,\hat{y}) = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

- binary crossentropy

$$\hat{y} = \sigma(z) = \frac{1}{1 + \mathrm{e}^{-wz+b}}$$

$$L(y,\hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[\,y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\,]$$

- categorical crossentropy

$$\hat{s}_i = \frac{\mathrm{e}^{\hat{y}_i}}{\sum_j \mathrm{e}^{\hat{z}_j}}$$

$$L(y,\hat{s}) = -\frac{1}{N}\sum_{i=1}^{N} s_{i1}\log\hat{s}_{i1} + \cdots + s_{im}\log\hat{s}_{im}$$

- $F1$-score

$$Precision(y,\hat{y}) = \frac{I(y_i = \hat{y}_i = 1)}{I(\hat{y}_i)} = \frac{TP}{TP + FP}$$

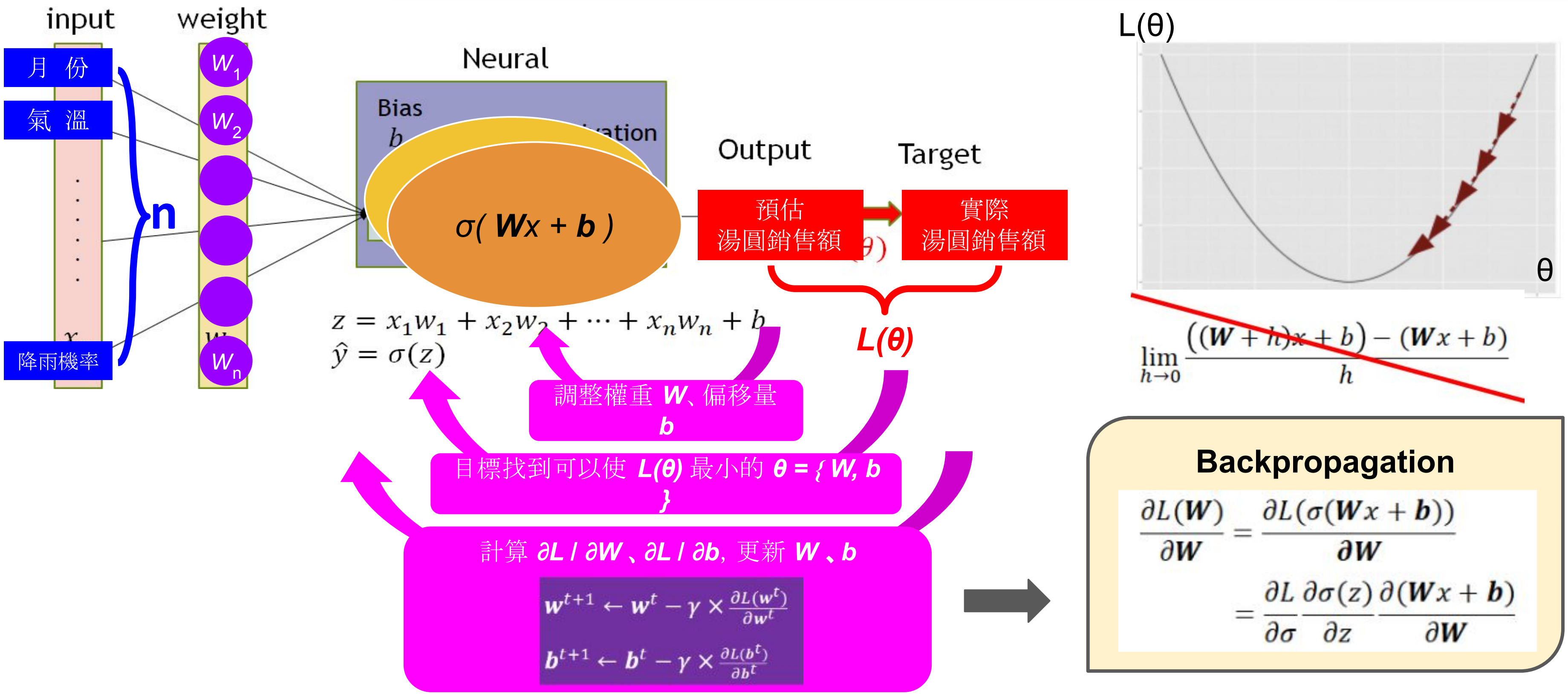
$$Recall(y,\hat{y}) = \frac{I(y_i = \hat{y}_i = 1)}{I(y_i)} = \frac{TP}{TP + FN}$$

$$F1(y,\hat{y}) = \frac{2pr}{p + r}$$

		predicted condition	
	total population	prediction positive	prediction negative
true condition	condition positive	True Positive (TP) 真陽性	False Negative (FN) (type II error) 偽陰性
	condition negative	False Positive (FP) (Type I error) 偽陽性	True Negative (TN) 真陰性

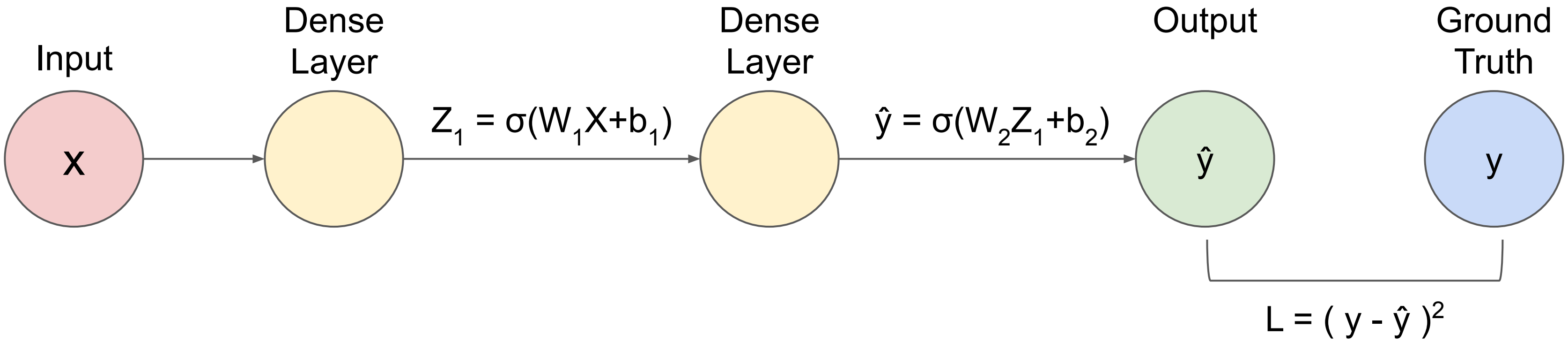
訓練神經網路....

什麼是訓練模型？



input
weight
月 份
氣 溫
降雨機率
n
W_1
W_2
W_n
Neural
Bias
b
σ(**W**x + **b**)
Output
Target
預估
湯圓銷售額
實際
湯圓銷售額
$z = x_1w_1 + x_2w_2 + \cdots + x_nw_n + b$
$\hat{y} = \sigma(z)$
L(θ)
調整權重 **W**、偏移量 **b**
目標找到可以使 **L(θ)** 最小的 **θ = { W, b }**
計算 ∂L / ∂W、∂L / ∂b，更新 **W**、**b**
$\boldsymbol{w}^{t+1} \leftarrow \boldsymbol{w}^t - \gamma \times \frac{\partial L(\boldsymbol{w}^t)}{\partial \boldsymbol{w}^t}$
$\boldsymbol{b}^{t+1} \leftarrow \boldsymbol{b}^t - \gamma \times \frac{\partial L(\boldsymbol{b}^t)}{\partial \boldsymbol{b}^t}$
L(θ)
θ
$\cancel{\lim_{h \to 0} \frac{((\boldsymbol{W}+h)x+b)-(\boldsymbol{W}x+b)}{h}}$
Backpropagation
$\frac{\partial L(\boldsymbol{W})}{\partial \boldsymbol{W}} = \frac{\partial L(\sigma(\boldsymbol{W}x+\boldsymbol{b}))}{\partial \boldsymbol{W}}$
$= \frac{\partial L}{\partial \sigma}\frac{\partial \sigma(z)}{\partial z}\frac{\partial(\boldsymbol{W}x+\boldsymbol{b})}{\partial \boldsymbol{W}}$

算個來看看....微積分記得多少



Question:

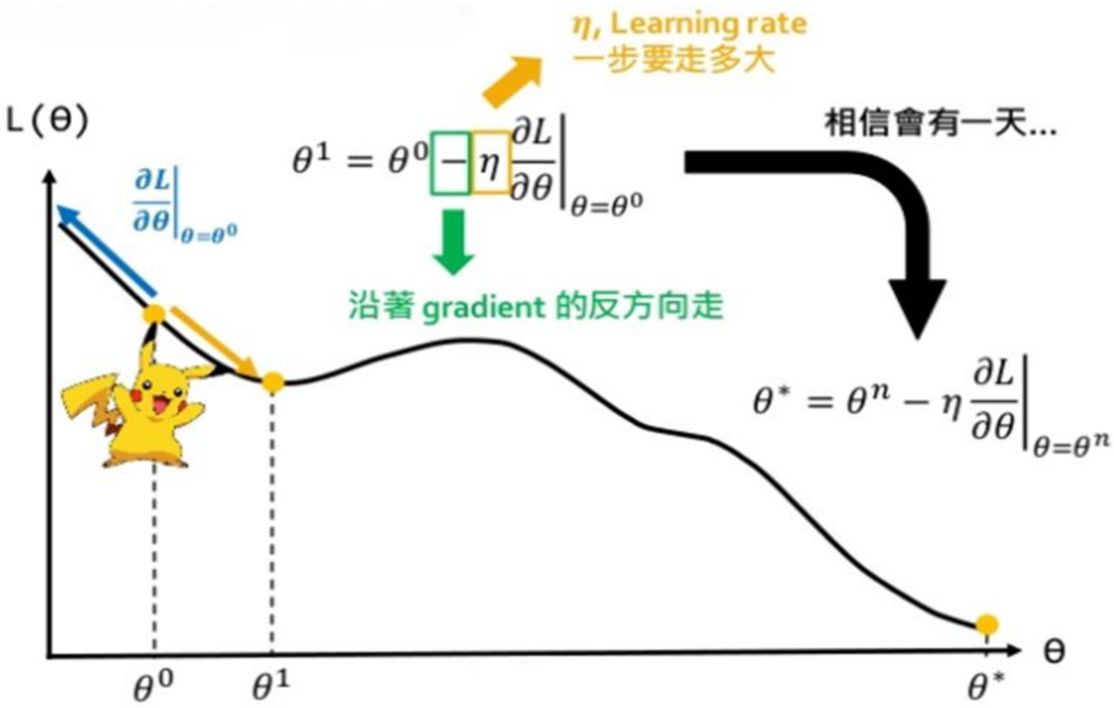
1. $\frac{\partial L}{\partial W_2}$ 、 $\frac{\partial L}{\partial b_2}$ = ?
2. $\frac{\partial L}{\partial W_1}$ 、 $\frac{\partial L}{\partial b_1}$ = ?

Activation Function:

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

2. $relu(x) = \max(x, 0)$

如何學到最強攻略？



$z = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n + b$

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

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

1.受loss function 影響

2.受activation影響

Optimizer 優化器

- Gradient Descent (GD)
  - 模型看完一輪所有資料，更新一次權重

  - 優點
    - 根據所有資料的訊息，更新模型
  - 缺點
    - 結果好壞很依賴起始點
    - 很容易掉進去 Local Minimum 就限制住找 Global Minimum 的可能

- Stochastic Gradient Descent (SGD)
  - 模型看完一小堆(batch)資料，更新權重一次

  - 優點
    - 收斂速度上，比 GD 快
  - 缺點
    - 可能會抽到極端的擾動值資料，偏離了 Global Minimum 的收斂方向

Optimizer 優化器

- RMSProp

  - 模型看完一小堆(batch)資料，更新權重一次

  - 優點
    - 不僅有依照當次計算的梯度做更新，還有參考過去的梯度做更新依據
  - 缺點
    - 還是有掉進去 Local Minimum 的可能

$$w^1 \leftarrow w^0 - \frac{\eta}{\sigma^0} g^0 \qquad \sigma^0 = g^0$$

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

$$w^3 \leftarrow w^2 - \frac{\eta}{\sigma^2} g^2 \qquad \sigma^2 = \sqrt{\alpha(\sigma^1)^2 + (1-\alpha)(g^2)^2}$$

$$\vdots$$

$$w^{t+1} \leftarrow w^t - \frac{\eta}{\sigma^t} g^t \qquad \sigma^t = \sqrt{\alpha(\sigma^{t-1})^2 + (1-\alpha)(g^t)^2}$$

- ADAM

  - 模型看完一小堆(batch)資料，更新權重一次
  - 加了 Momentum 的 RMSProp

  - 優點
    - 給予一點點小小的擾動 (Momentum)，協助翻出 Local Minimum 的小峽谷，找到 Global Minimum 的可能
    - 適合大部分的優化狀況使用

Require: θ_0: Initial parameter vector
$m_0 \leftarrow 0$ (Initialize 1st moment vector)
$v_0 \leftarrow 0$ (Initialize 2nd moment vector)
$t \leftarrow 0$ (Initialize timestep)
while θ_t not converged **do**
$t \leftarrow t + 1$
$g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)
$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)
$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)
$\widehat{m}_t \leftarrow m_t/(1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)
$\widehat{v}_t \leftarrow v_t/(1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)
$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t/(\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)
end while
return θ_t (Resulting parameters)