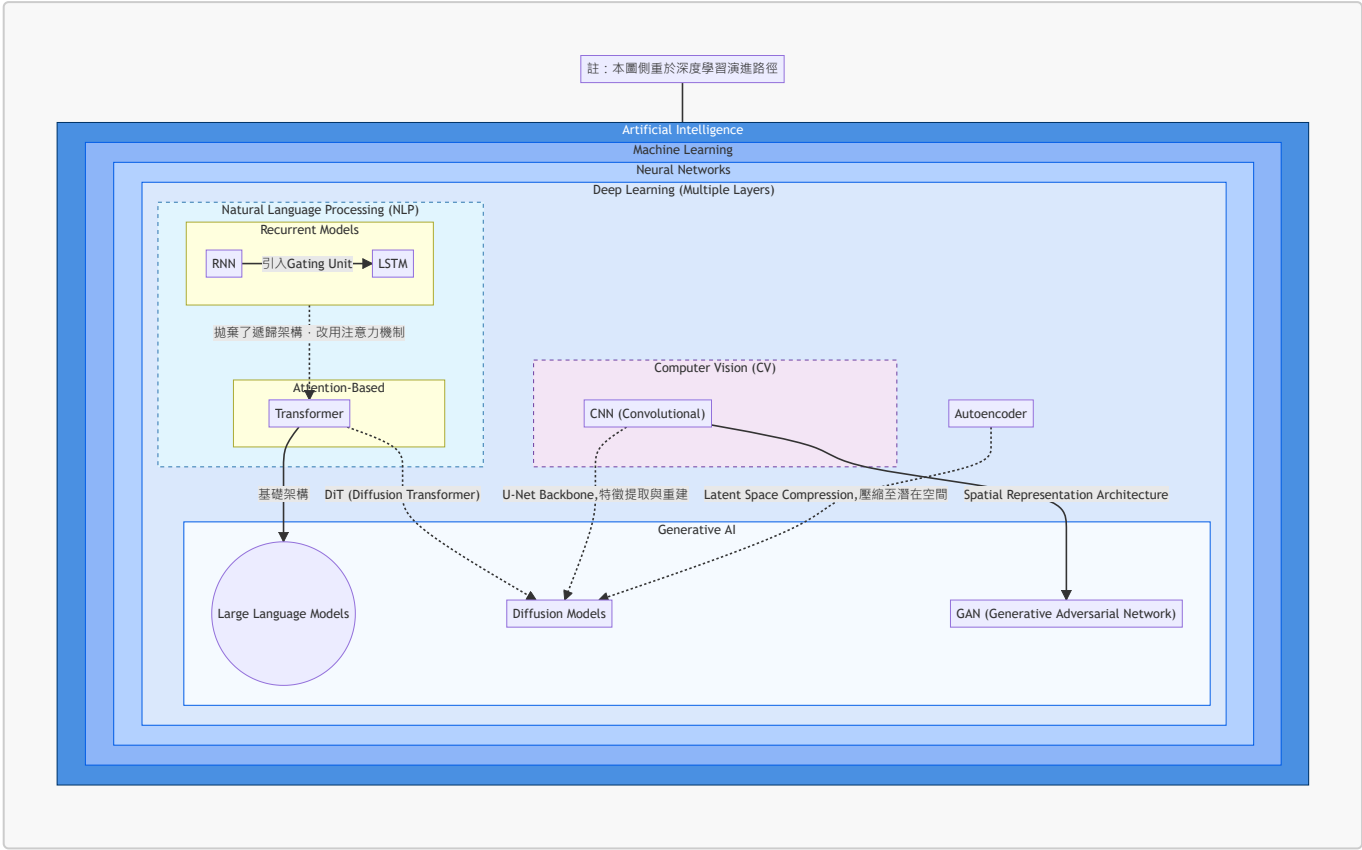
AI outline graph



Definition: Generative AI

讓computer學會產生複雜而有結構的物件, 就是Classification, 因為Generative AI就是給一個未完成的句子, 去猜接下來接哪一個token

- 複雜 : 無限可能
- 有結構 : 由有限的基本單位(toekn)所構成
- 基本單位(token) :
    - 影像 : 是由像素構成的. 每個像素又由RGB三個子像素組成,而每個子像素的可能值範圍為0-255. 影像只考慮兩個維度: width, height
    - 聲音訊號 : 是由取樣點構成的. 遠看是聲音訊號,拉進後則可以看到一個一個的取樣點.一秒鐘有多少取樣點,取決於取樣率(sampling rate);比如, 16kHz的取樣率意味著一秒鐘有16000個取樣點. 而每個取樣點有多少種可能的數值,則取決於取樣解析度(bit resolution);常見的16-bit解析度有65,536種可能的數值
    - 影片 : 就是一連串的圖片, 每一張圖片又叫Frame. 需考慮三個維度: width, height, time

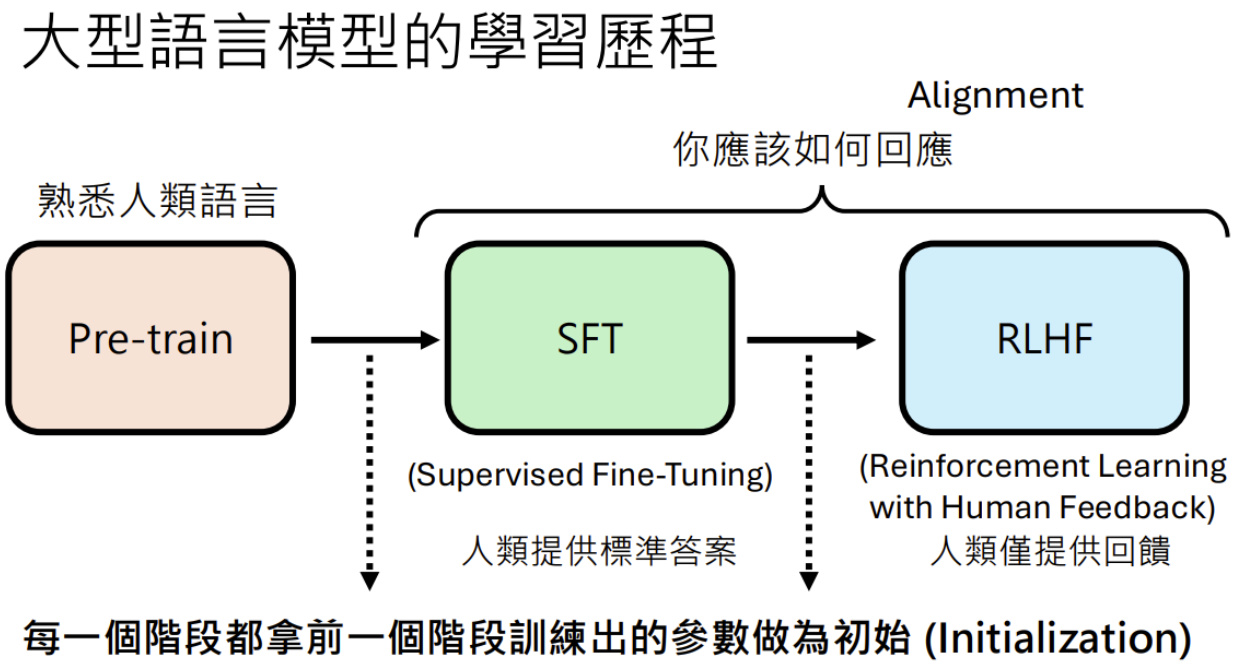
Retrieval Augmented Generation(RAG)

Context Engineering的核心目標

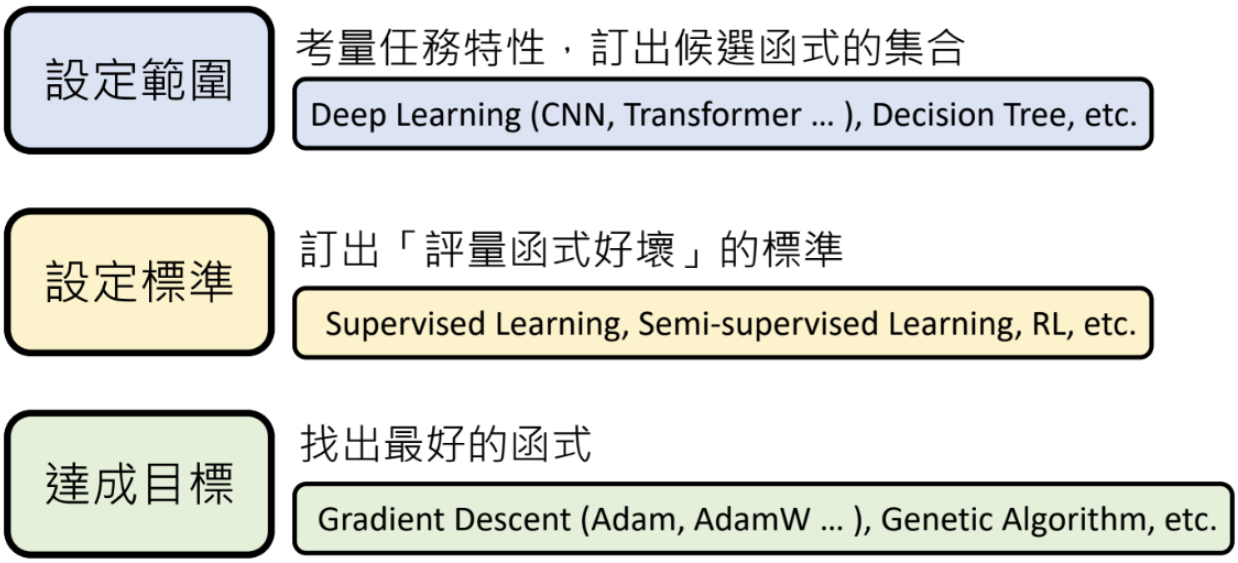
- 避免塞爆Context(把需要的放進去,不需要的清出來)

- 常用招數
    - Select
        - 挑選需要的內容, e.g. RAG, Tool RAG, Memory RAG
    - Compress
    - Multi-Agent

Machine Learning

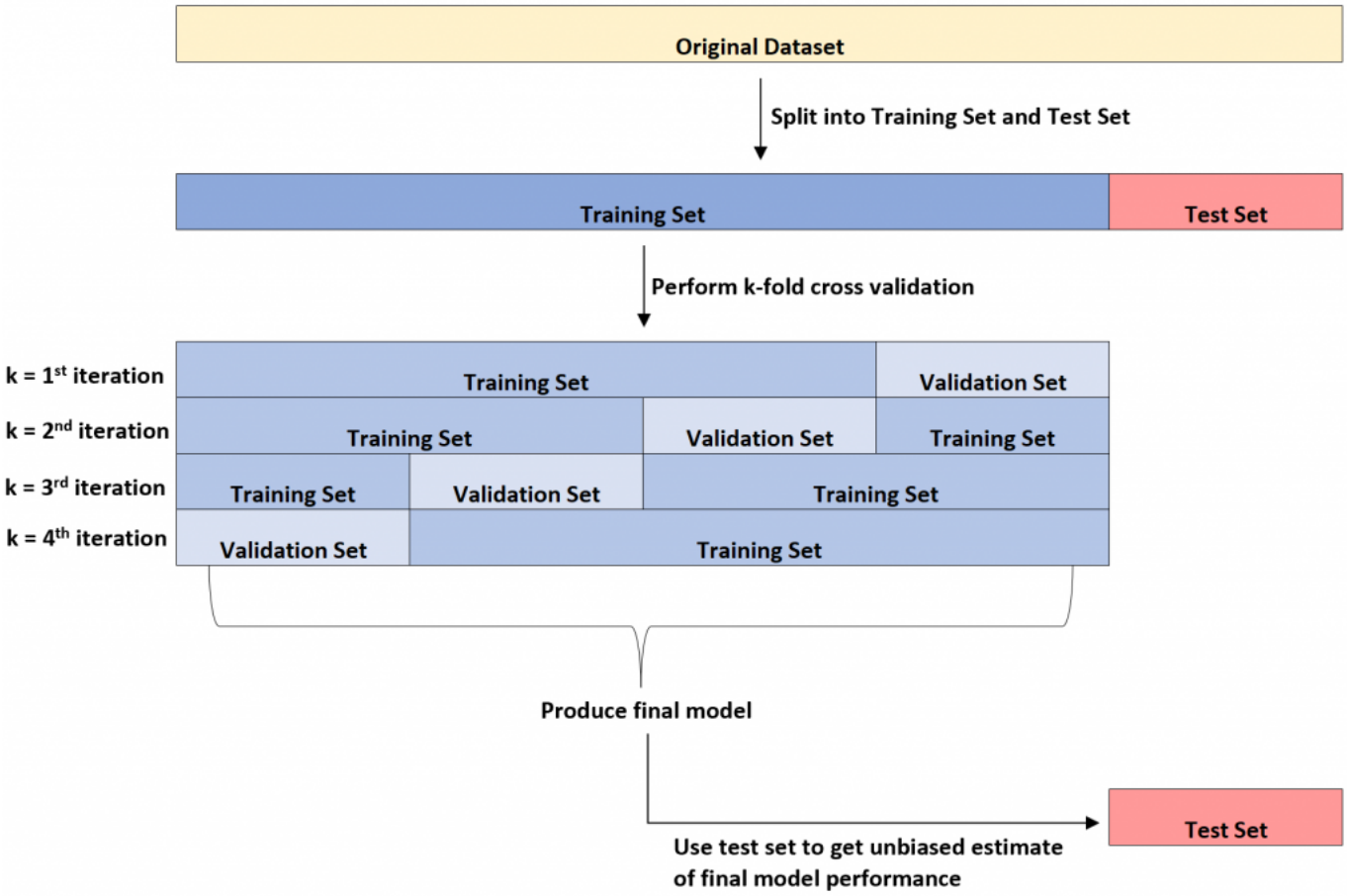


0. ML三步驟



1. prepare data

- split data into
  i. **training data** 98%
  ii. **validation data** 1%
  iii. **public test data** 0.5%
  iv. **private test data** 0.5%

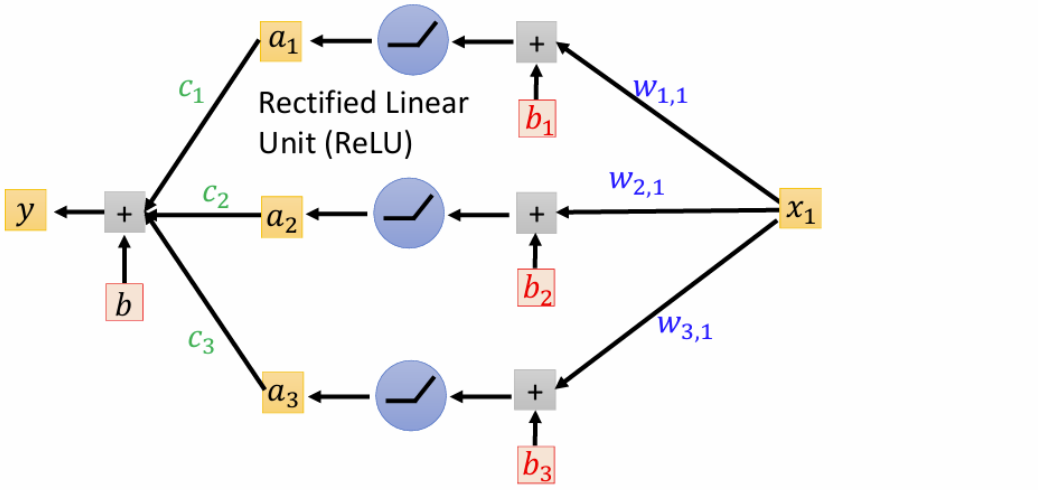


2. set a model

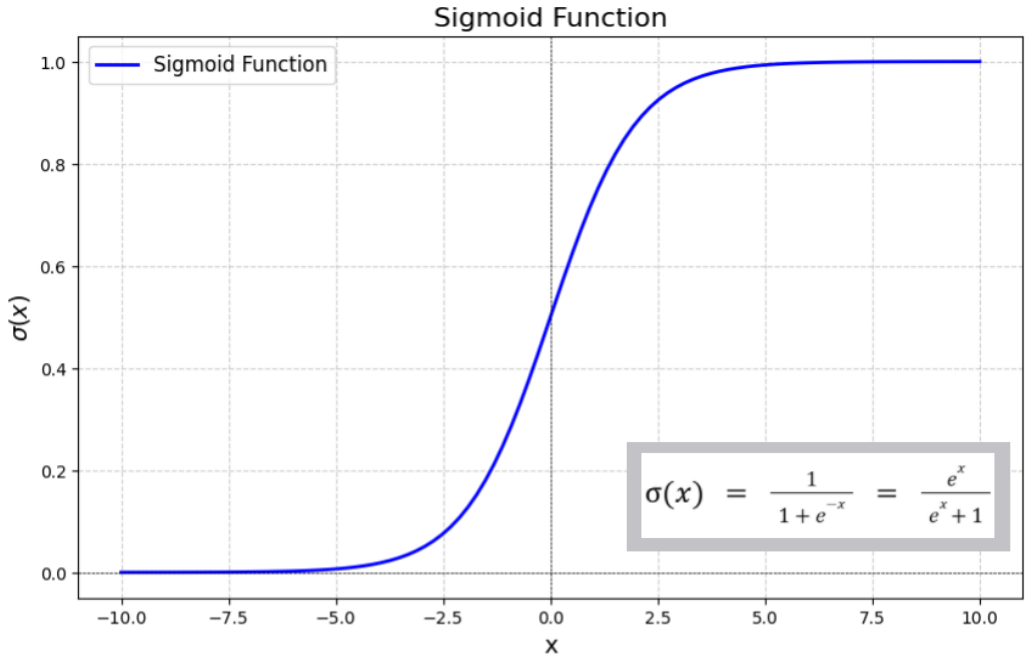
- 根據domain knowledge
  - Simple Linear Regression
    - $y = \beta_0 + \beta_1 x + \epsilon$
      - 其中 β_0 為截距，β_1 為斜率，ϵ 為隨機誤差。
      - y, x is feature.$\beta 1$ is weight.$\beta 0$ is bias
  - Multiple Linear Regression
    - $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon$

- Piecewise Linear Curves

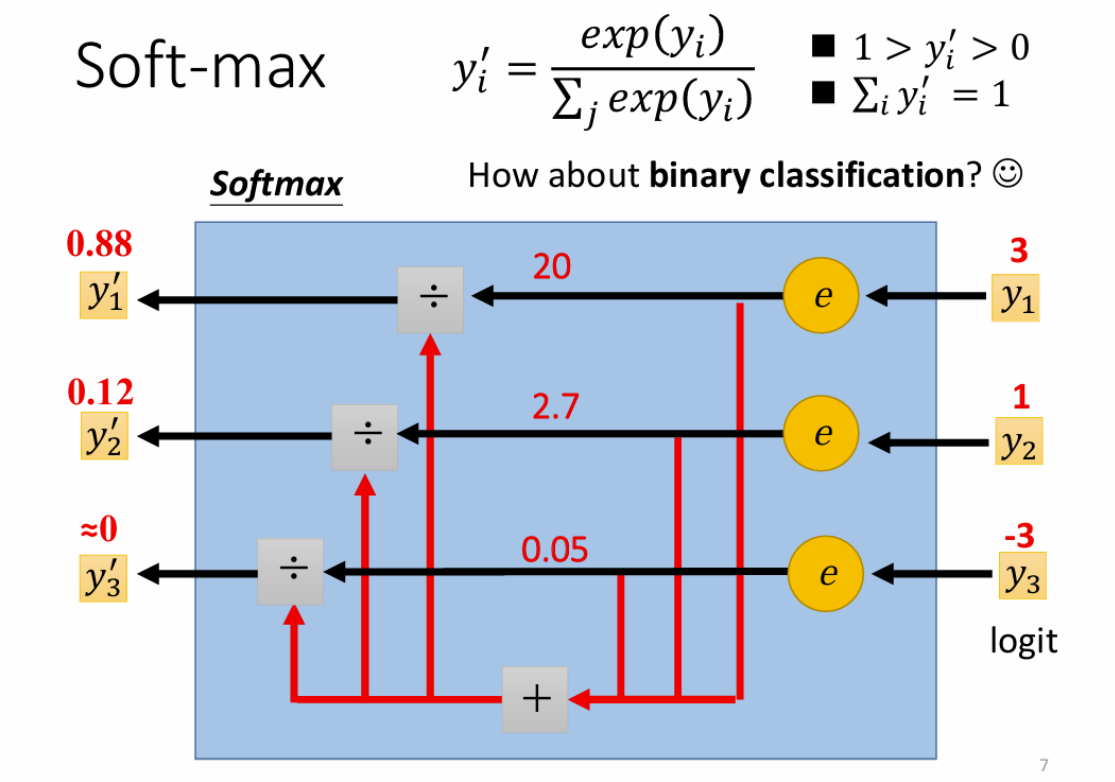
$$y = b + \sum_{i=1}^{H} c_i \underbrace{max(0, w_{i,1}x_1 + b_i)}_{a_i}$$



- Classification
  - Binary Classification(Sigmoid=Logistic Function)
    - $P(y=1|x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\cdots+\beta_n x_n)}}$

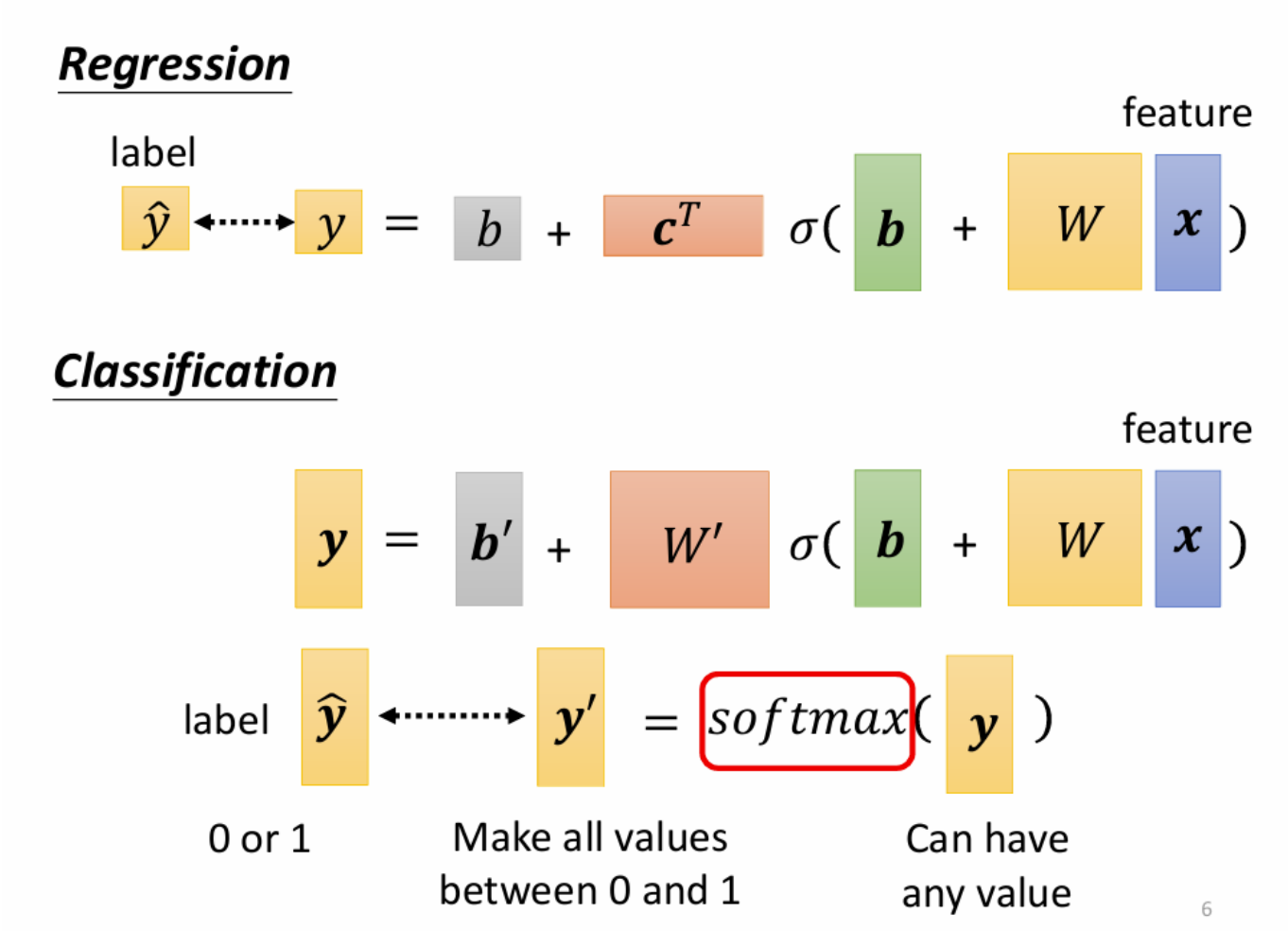


- Multi-class Classification(Softmax)



  - Structured Learning
    - **create** something with structure(e.g. image, document)

compare regression and classification



- σ is called **activation function**
  - Regression
    - σ is Relu
  - Classification
    - σ is sigmoid/softmax
- $\sigma(\mathbf{b}+\mathbf{W}\mathbf{x})$ is a **neuron**
- $f(\mathbf{x})=b+\mathbf{c}^T\sigma(\mathbf{b}+\mathbf{W}\mathbf{x})$ is **1-Hidden Layer Neural Network**

3. set Cost function/Loss function

- Mean Squared Error, MSE
  - $MSE=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
    - n : 訓練資料的總數 (Train Data Size / Batch Size).
    - y_i : 第 i 筆資料的真實標籤 (Ground Truth).
    - $\hat{y}_i$: 模型對第 i 筆資料的預測值 (Prediction)。
- Mean Absolute Error, MAE
  - $MAE=\frac{1}{n}\sum_{i=1}^{n}|(y_i-\hat{y}_i)|$
    - n : 訓練資料的總數 (Train Data Size / Batch Size).
    - y_i : 第 i 筆資料的真實標籤 (Ground Truth).
    - $\hat{y}_i$: 模型對第 i 筆資料的預測值 (Prediction)。
- Cross-Entropy(classification)
  - if $y,\hat{y}$ are both probability distributions
  - $Cross-Entropy=H(y,\hat{y})=-\sum_{i=1}^{c}y_i\log(\hat{y}_i)$
    - c: The total number of classes or categories.
    - **Minimizing cross-entropy** is equivalent to **maximizing likelihood**
    - y_i: The probability of the i-th class in the true distribution (often a one-hot encoded vector where only one $y_i=1$ and others are 0).
    - $\hat{y}_i$: The probability of the i-th class predicted by the model (usually the output of a Softmax function($0\leq\hat{y}_i\leq 1$ and $\sum\hat{y}_i=1$.)).

4. set optimizer

- Gradient Descent(Vanilla Gradient Descent)
  - $\theta^{t+1}=\theta^t-\eta\cdot\nabla L(\theta^t)$
    - $\nabla L(\theta^t)$ 代表損失函數 L 在當前參數 θ^t 位置的「斜率」或「坡度」
    - η(Eta) : The Learning Rate
  - 問題 : 只根據當下算出來的g^t來決定方向
    - 解法 : Gradient Descent + Optimizer
      - 根據$g^0,g^1,g^2,\ldots,g^t$ 一起來決定方向(調整learning rate)
        - Adagrad
          - for each dimension i : $\eta=\frac{\eta}{\sigma_i^t}$, $\sigma_i^t=\sqrt{\sum_{i=0}^{t}(g_i^t)^2}$
          - 問題 : 每一個維度權重相同
        - RMSProp
          - 解決Adagrad : 最近算出來的gradient給比較大的影響
          - use α
  - 可以用 Momentum (下滑之物體會有動量繼續前行, 不會直接殺停)來繼續找 global minimum用以脫離saddle point or local minimum

- for each dimension i : $\theta_i^{t+1} = \theta_i^t - \eta \cdot m_i^t$ ， $m_i^t = g_i^0 + g_i^1 + g_i^2 + \ldots + g^t$

- Adam : RMSProp + Momentum

  ➢ Compute gradient $\boldsymbol{g}^t = \nabla L(\boldsymbol{\theta}^t)$

  Momentum

  For each dimension i: $m_i^t = \beta m_i^{t-1} + (1-\beta) g_i^t$ $\theta_i^{t+1} \leftarrow \theta_i^t - \eta m_i^t$

  RMSProp

  For each dimension i: $\sigma_i^t = \sqrt{\alpha (\sigma_i^{t-1})^2 + (1-\alpha)(g_i^t)^2}$ $\theta_i^{t+1} \leftarrow \theta_i^t - \frac{\eta}{\sigma_i^t} g_i^t$

  Adam

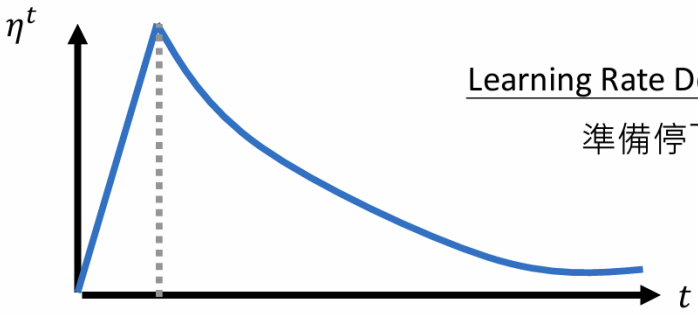
  $\theta_i^{t+1} \leftarrow \theta_i^t - \frac{\eta}{\sigma_i^t} m_i^t$ Adam has bias-corrected terms, which are omitted here for simplicity.

- 也可以用Learning Rate Scheduling來調整learning rate

$$\theta_i^{t+1} \leftarrow \theta_i^t - \frac{\eta}{\sigma_i^t} m_i^t \quad \Rightarrow \quad \theta_i^{t+1} \leftarrow \theta_i^t - \frac{\eta^t}{\sigma_i^t} m_i^t$$

Warm Up

探索地形

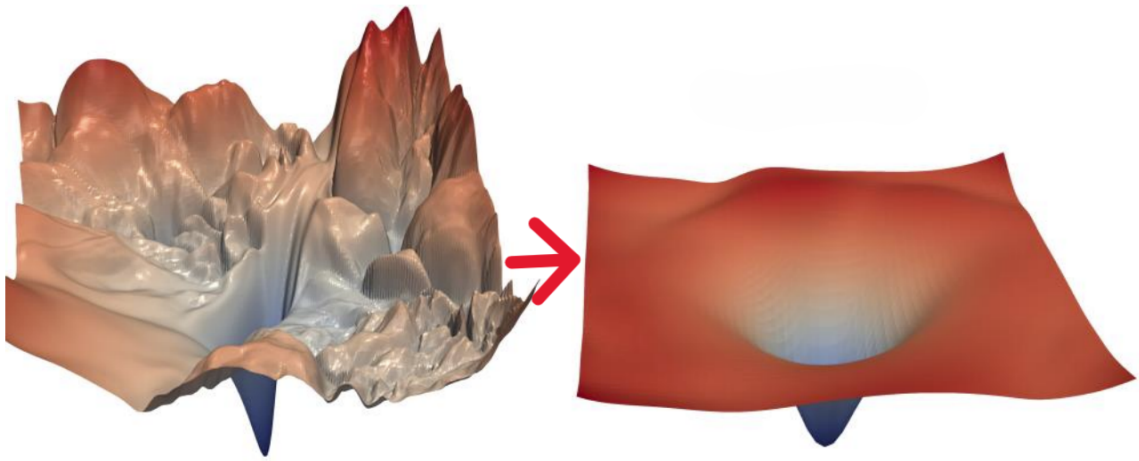


Learning Rate Decay

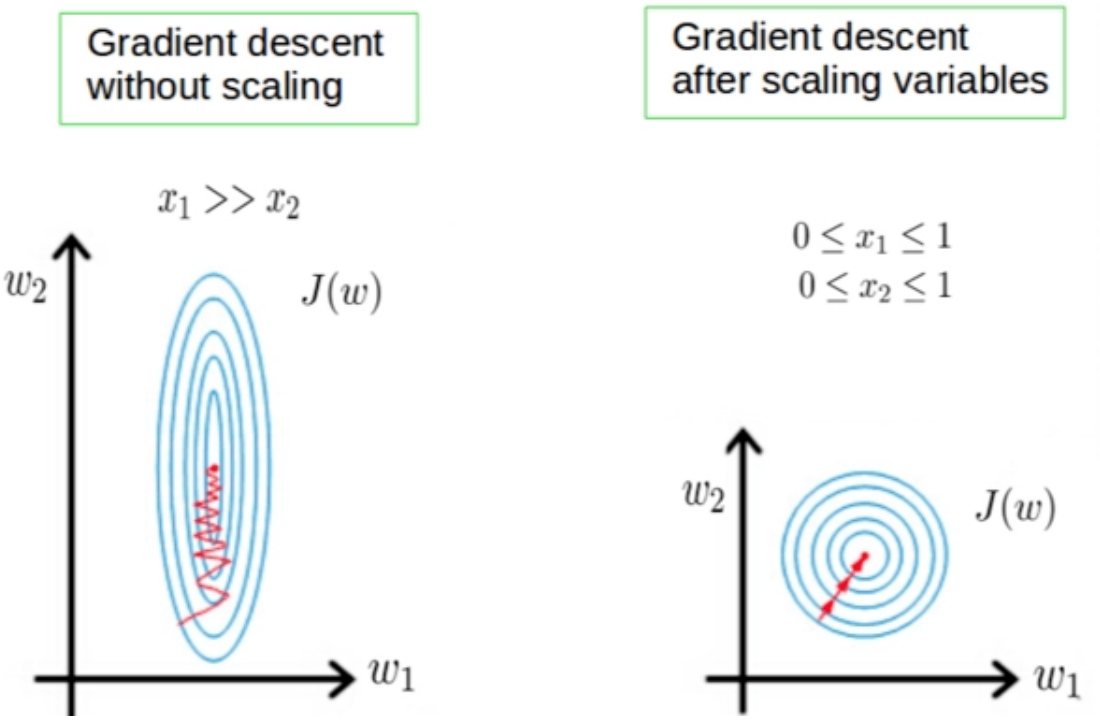
準備停下來

  - warp up : 給optimizer探索地形的機會, 因為剛進入一個新地圖, 不知道地圖有什麼, 設定一個大的learning rate, 讓參數亂跑, 可以大概知道地圖長什麼樣

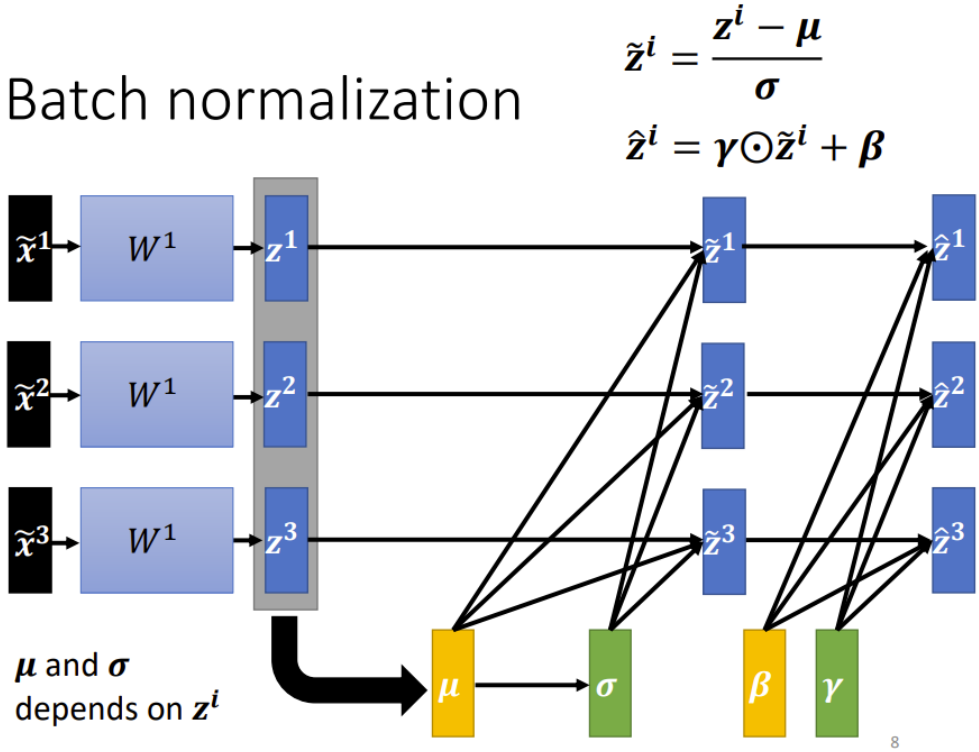
- Feature Scaling(夷平error surface)



- accelerate gradient descent



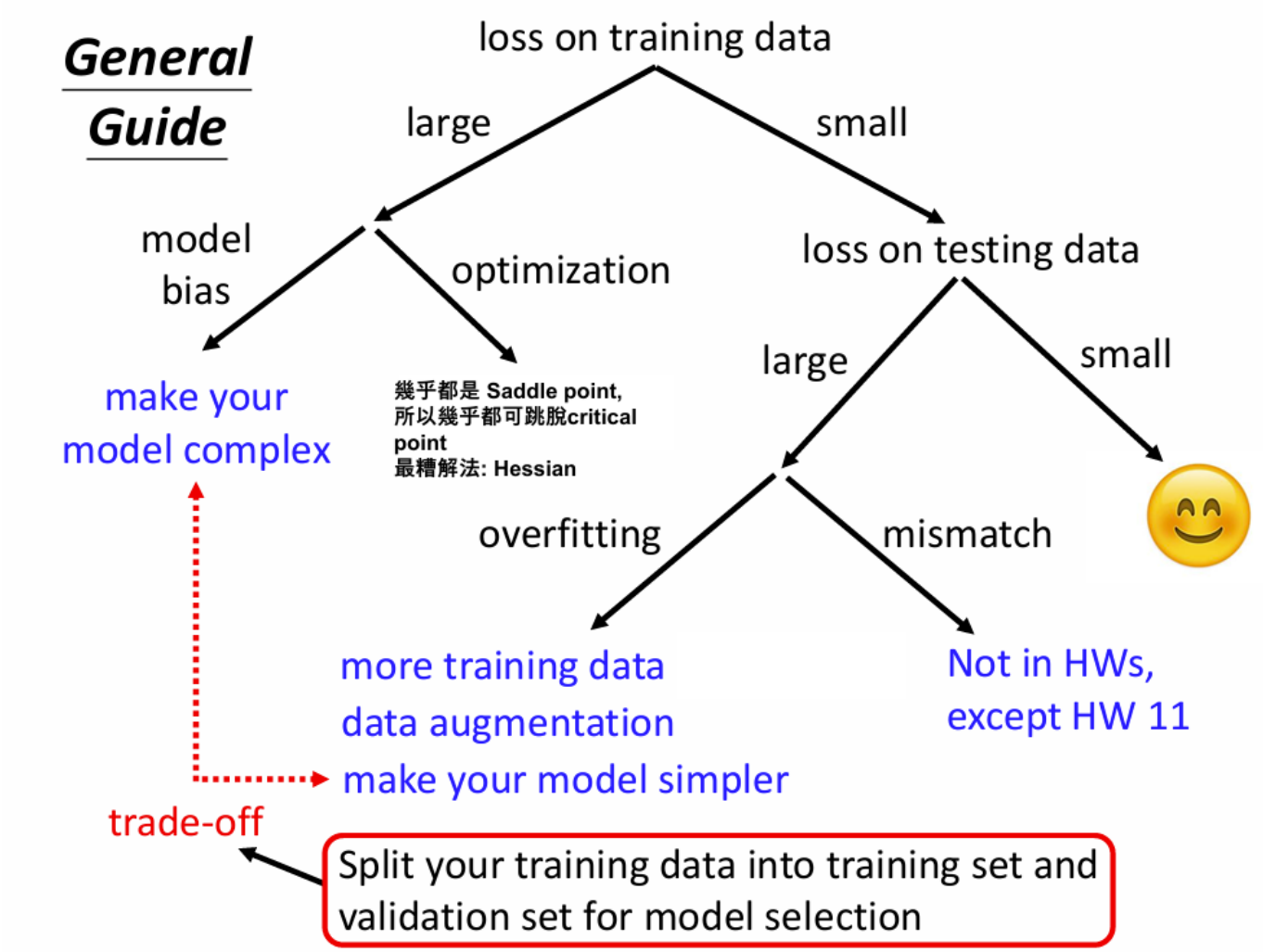
- Normalization
  - Batch Normalization



    - γ, β are another network parameters, 另外再被learned出來的;因為normalization完後,$\tilde{z}^1, \tilde{z}^2, \tilde{z}^3, \ldots$ 之平均為0, 可能會對模型產生限制,所以加上 γ, β
    - γ initialize to $[1, 1, \ldots, 1]^T$
    - β initialize to $[0, 0, \ldots, 0]^T$
  - Layer Normalization
- Standardizatoin

5.Train the model

- Initialization
    - Kaiming Initialization
- **Use gradient descent to train the model, accelerating convergence to the minimum loss and yielding the optimal model(Find the best $\beta_0, \beta_1, \beta_2, \beta_3, \ldots, \epsilon$).**
- general guide



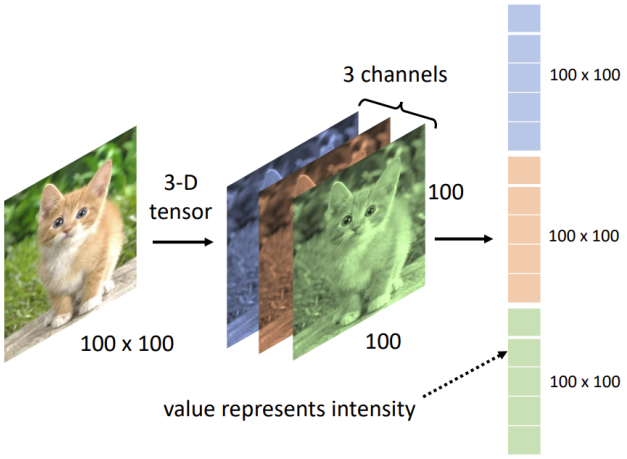
6. use validation data to evaluate your model

- be aware of overfitting

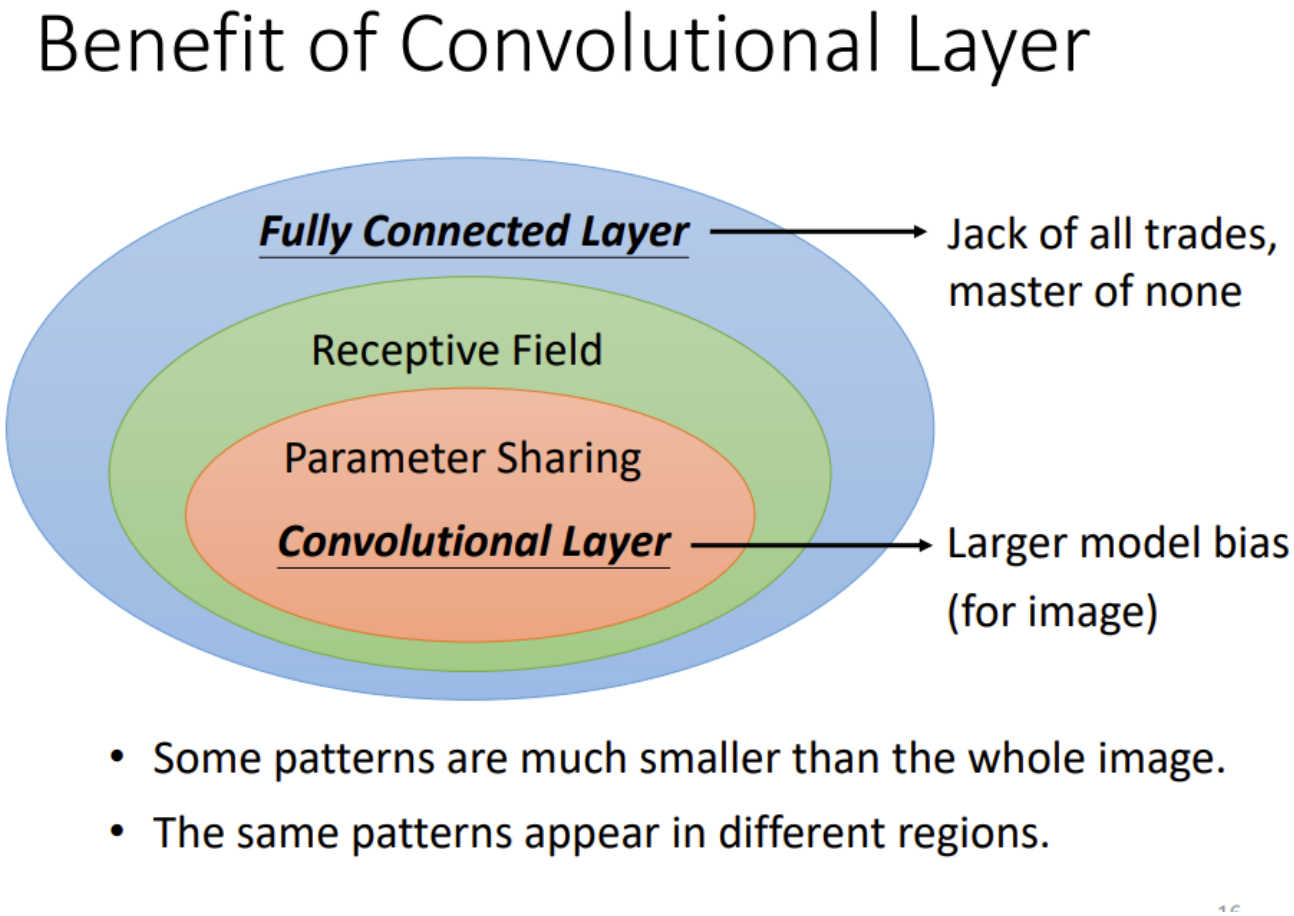
7. use test data to test/inference your model

- public test data
    - be aware of overfitting
- private test data

Convolutional Neural Networks, CNN



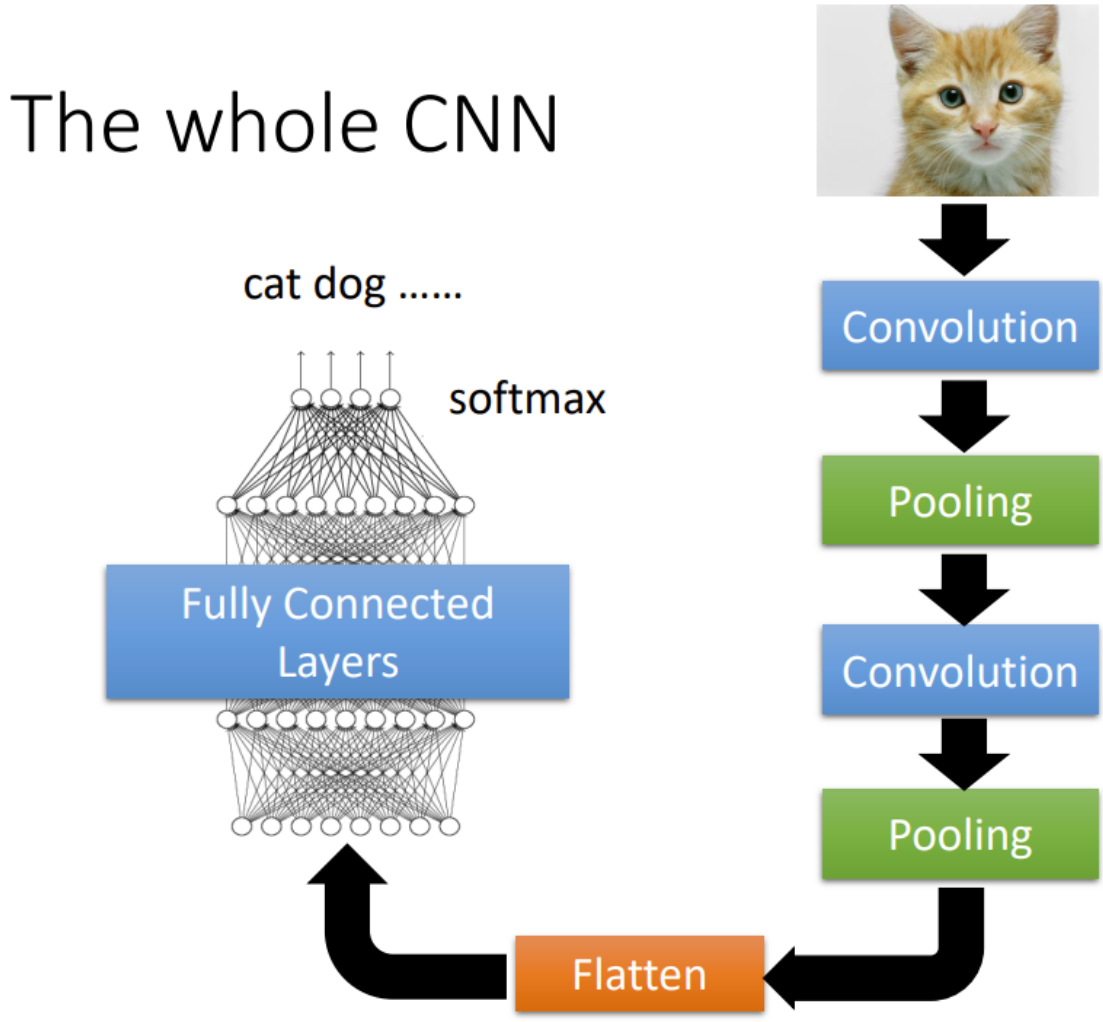
channel : R, G, B



不需Fully Connected Network, weight太龐大了, 用Receptive Field

鳥嘴可能在任何地方, 所以可以parameters sharing, called **Filter**

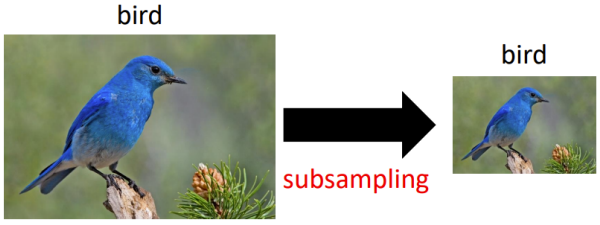
The Whole CNN



Pooling :

e.g. 把奇數rows, columns拿掉, 讓圖變小

- Subsampling the pixels will not change the object



Flatten :

把matrix變成column