

Neural Network

類神經網路



<https://www.youtube.com/watch?v=bfmFfD2Rlcg>



Facial recognition



Real-time translation



Music composition

Neural Network In 5 Minutes | What Is A Neural Network? | How Neural Networks Work | Simplilearn

Q: Activate functions are threshold functions? 4:50/5:44

A: Activation functions in neural networks are not exactly the same as threshold functions, but they do share some similarities.



Neural networks are inspired by the human brain and are designed to recognize patterns, make predictions, and improve decision-making over time. They are fundamental in applications like image recognition, speech processing, natural language understanding, and autonomous systems.

Here are some real-world case studies that showcase the practical applications of neural networks:

1. ImageNet large-scale visual recognition challenge - Image classification using CNNs
2. Google neural machine translation - Language translation with sequence-to-sequence models
3. Automatic speech recognition systems - Speech recognition with RNNs
4. Detecting diabetic retinopathy - Healthcare diagnosis with deep learning
5. Self-driving cars - Autonomous vehicles with neural networks
6. Netflix movie recommendations - Recommendation systems with collaborative filtering

➤ Computer Vision ; Speech Recognition ; Natural Language Processing (自然語言處理); Recommendation Engine



➤ 電腦視覺 (Computer Vision)

電腦視覺是電腦從影像和影片中擷取資訊和洞察的功能。藉助神經網路，電腦可以區分和識別與人類相似的影像。電腦視覺有多種應用，例如：

- 自動駕駛汽車中的視覺識別，因此它們可以識別道路標誌和其他道路使用者
- 內容審核，可自動從影像和影片封存中移除不安全或不當的內容
- 面部識別，可識別面部，並識別睜眼、眼鏡和面部毛髮等屬性
- 影像標籤，可識別品牌標誌、服裝、安全裝備和其他影像詳細資訊

➤ 語音識別 (Speech Recognition)

儘管語音模式、音調、語氣、語言和口音不同，神經網路仍然可以分析人類語音。Amazon Alexa 和自動轉錄軟體等虛擬助手使用語音識別來執行以下任務：

- 協助呼叫中心客服人員並自動對呼叫分類
- 將臨床對話即時轉化為文件
- 為影片和會議錄音提供準確的字幕，以擴大內容覆蓋範圍



➤ 自然語言處理 (Natural Language Processing)

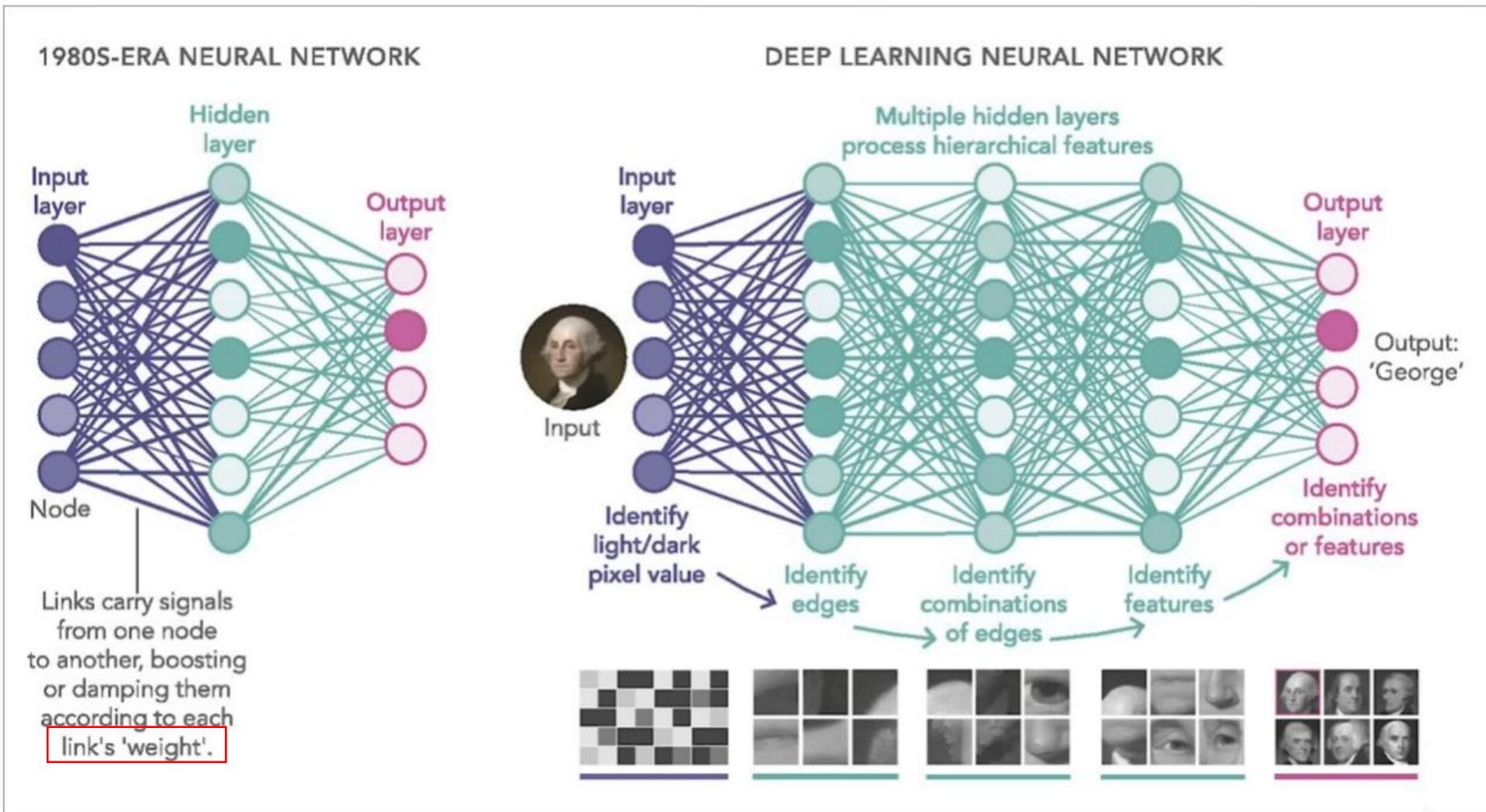
自然語言處理 (NLP) 是處理自然、人工建立文字的功能。神經網路可協助電腦從文字資料和文件中收集洞察和意義。NLP 具有若干使用案例，包括以下功能：

- 自動化虛擬客服人員和聊天機器人 (Chatbot)
- 書面資料的自動整理和分類
- 對電子郵件和表單等長篇文件進行商業智慧分析
- 指示情緒關鍵短語的索引，例如社交媒體上的正面和負面評論
- 指定主題的文件摘要和文章產生

➤ 推薦引擎 (Recommendation Engine)

神經網路可以追蹤使用者活動，以開發個人化推薦。他們還可以分析所有使用者的行為，並探索特定使用者感興趣的新產品或服務。例如，總部位於費城的新創公司 Curalate 可協助品牌將社交媒體帖子轉化為銷售。品牌使用 Curalate 的智慧產品標記 (IPT) 服務，來自動收集和管理使用者產生的社交內容。IPT 使用神經網路，來自動尋找和推薦與使用者社交媒體活動相關的產品。消費者不必透過線上目錄，即可尋找社交媒體影像中的特定產品。而是可以使用 Curalate 的自動產品標記，來輕鬆購買產品。

- An activation function determines whether a neuron should be activated.



- Neurons are connected with weights and biases, which are adjusted during the training process.



Neural networks function through **forward propagation** and **backpropagation**.

- **Forward Propagation:** Data flows from the input layer through hidden layers to the output layer. Each neuron applies its weights and activation functions to transform the input.
- **Backward propagation:** The network calculates the error between the predicted output and the actual output. It then adjusts the weights and biases to minimize this error, using optimization techniques like gradient descent.

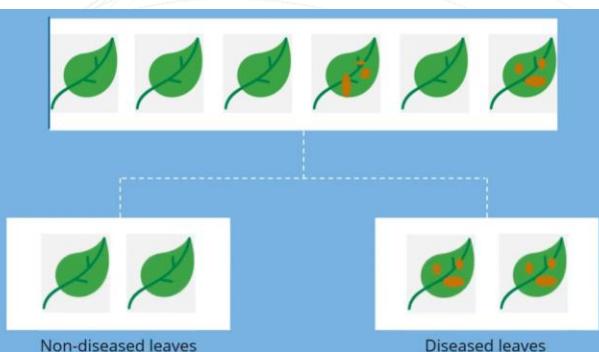
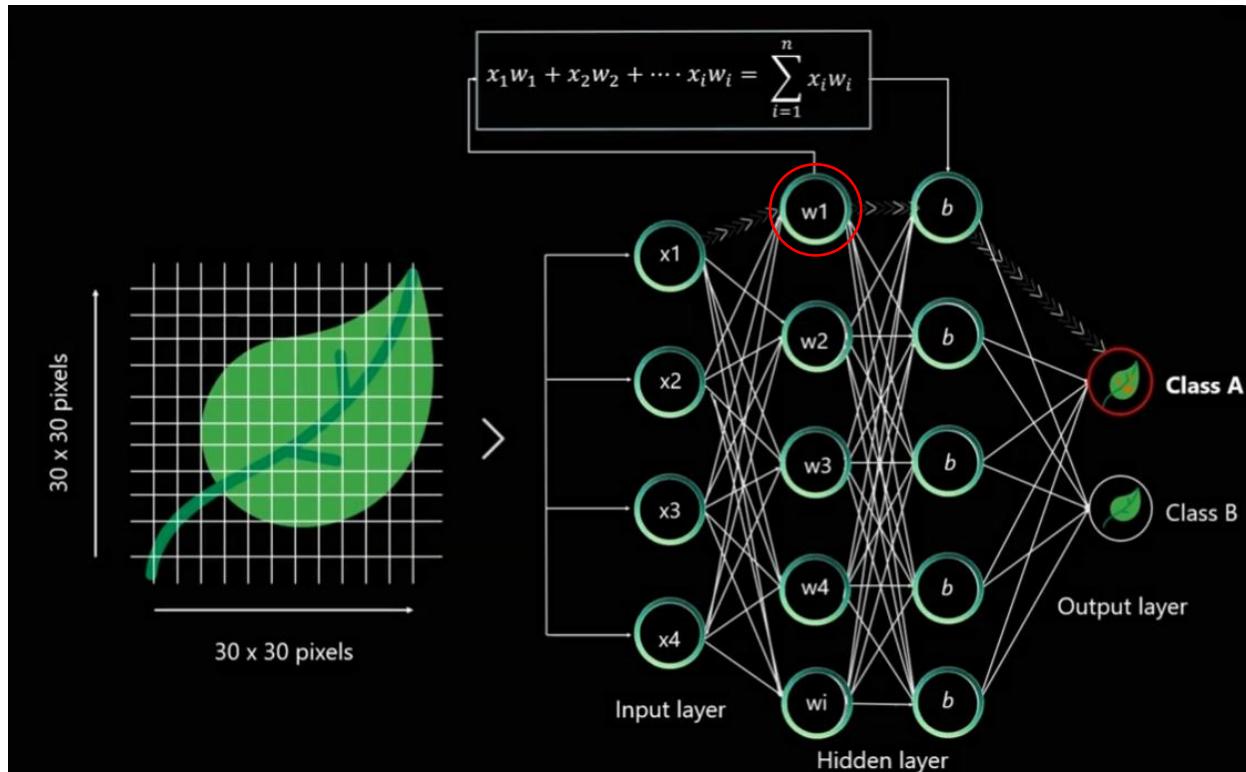
Types of Neural Networks

1. **Feedforward Neural Networks (FNN 前饋):** The simplest type, where data moves only in one direction - from input to output. Suitable for basic prediction tasks.
2. **Convolutional Neural Networks (CNN 卷積):** Specialized for image recognition and computer vision tasks. CNNs use convolutional layers to detect spatial patterns.
3. **Recurrent Neural Networks (RNN 循環):** Designed for sequential data, such as text, speech, or time-series data. RNNs remember previous inputs to make better predictions.
4. **Deep Neural Networks (DNN 深度):** Comprise multiple hidden layers, enabling them to learn highly complex patterns from large datasets.
5. **Other Variants:** GANs (Generative Adversarial Networks) for generating realistic images, autoencoders for feature extraction, and transformers for natural language processing.

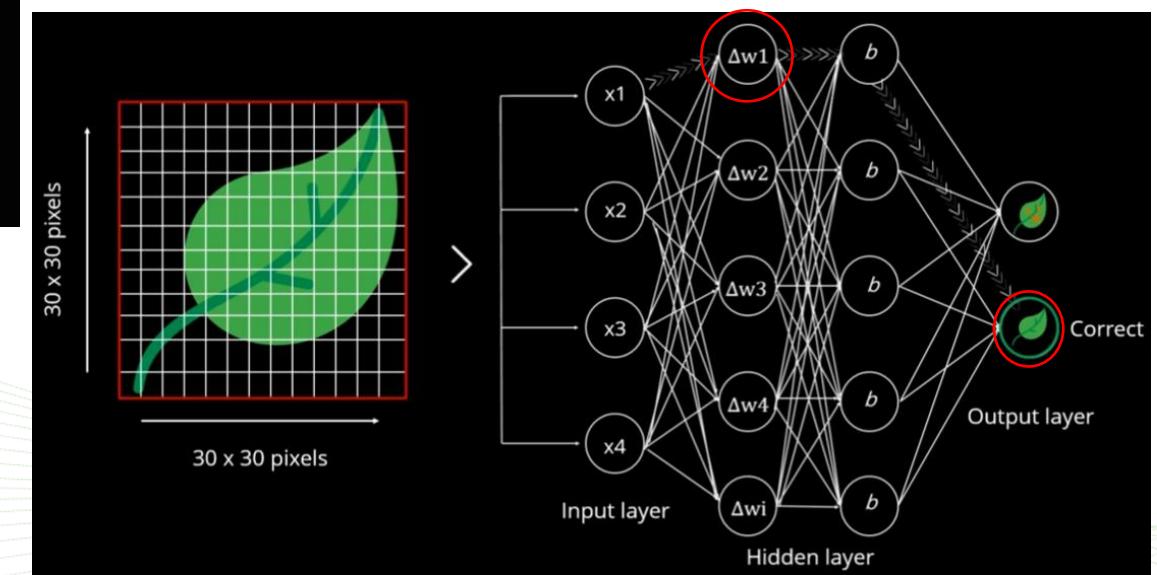
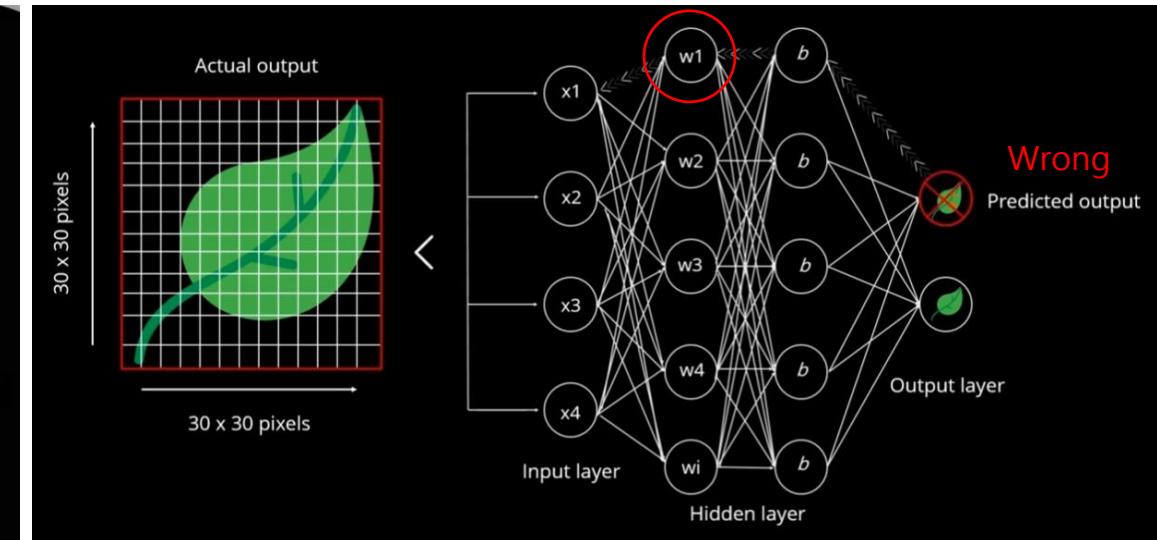


Neural Networks 類神經網路

Forward Propagation



$Wx \rightarrow \Delta Wx$
Adjust Weight

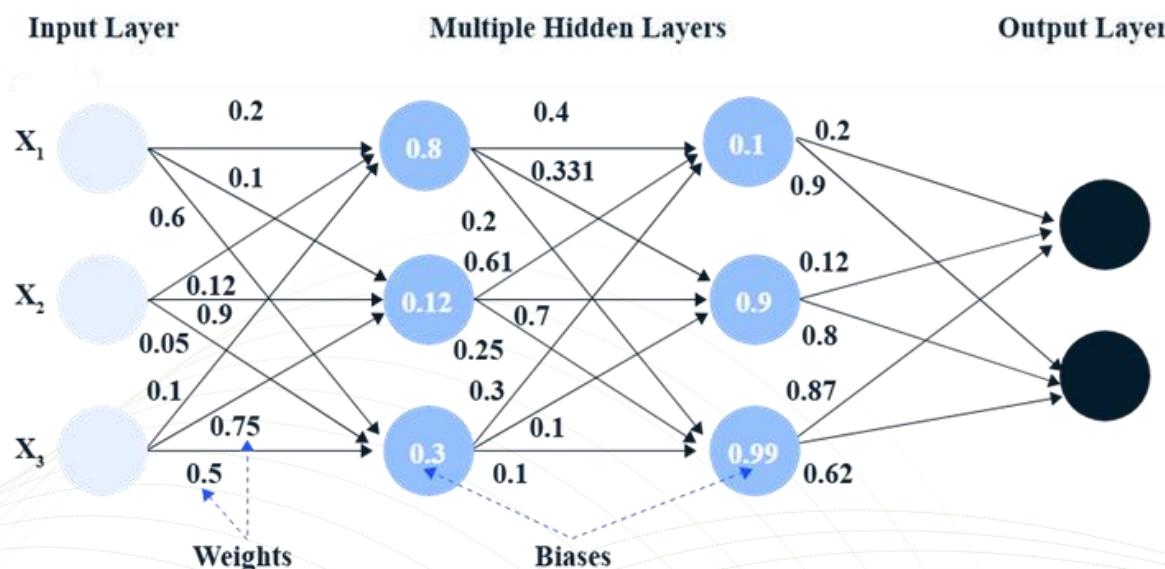




Neural Networks 類神經網路

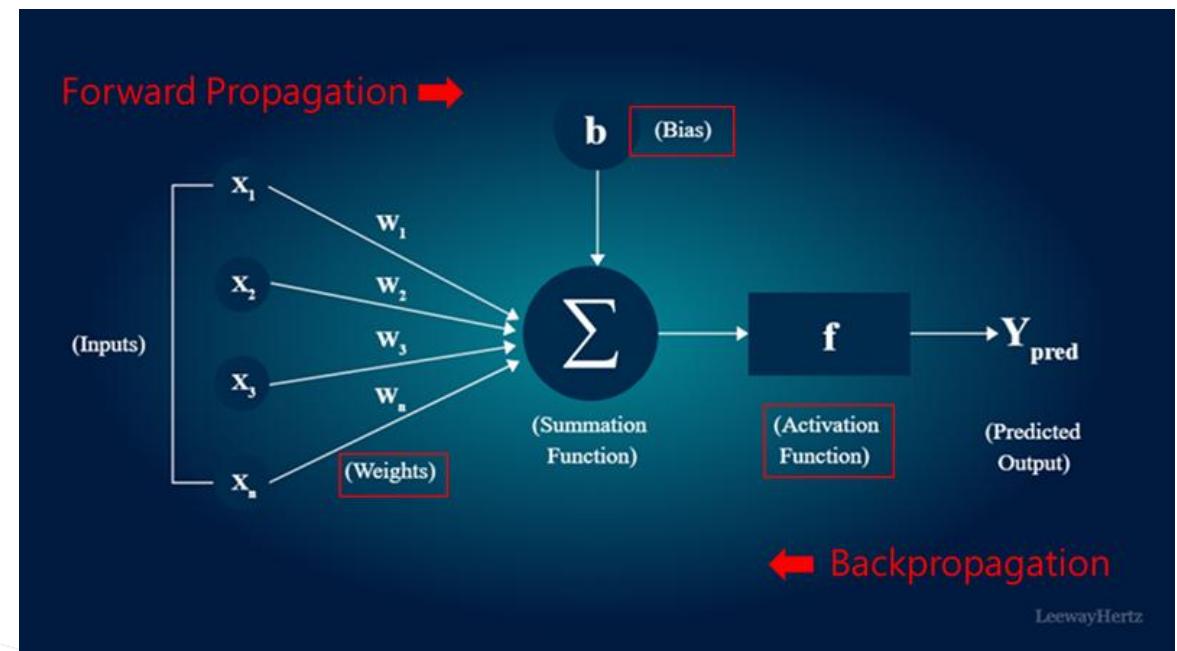
key element of the neural network

1. Input layer
2. Hidden layers
3. Neurons (Nodes)
4. Weights and biases
5. Activation functions
6. Output layer
7. Loss function



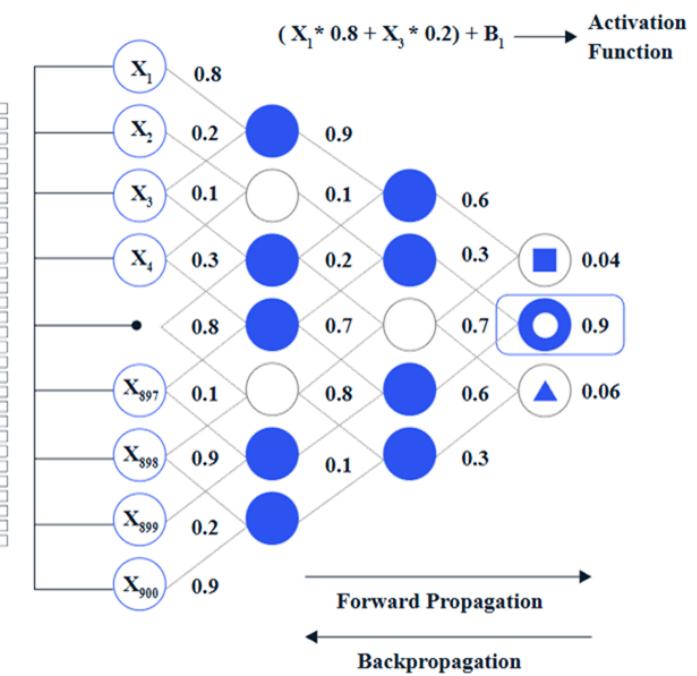
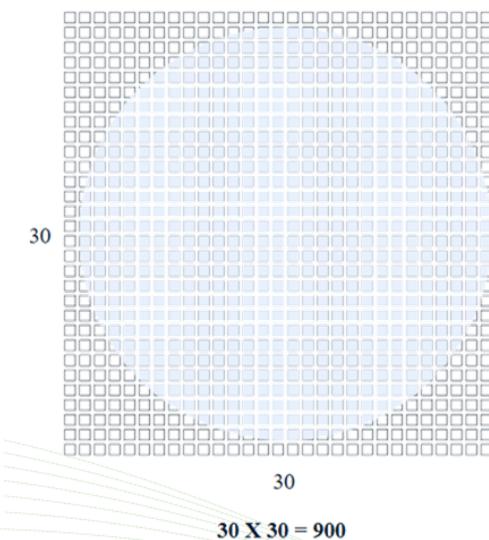
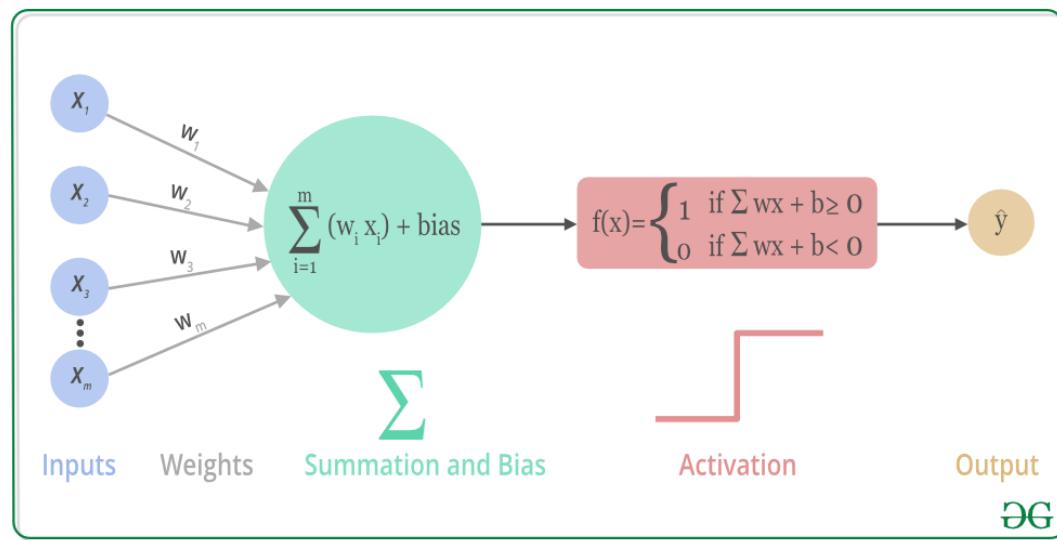
- Neurons are connected with weights and biases, which are adjusted during the training process.
- Biases provide an additional tunable parameter that allows neurons to adjust their activation threshold.
- The loss function measures the discrepancy between the predicted outputs of the neural network and the true values.

- An activation function determines whether a neuron should be activated.
- Common activation functions include sigmoid, tanh, ReLU (Rectified Linear Unit), and softmax.





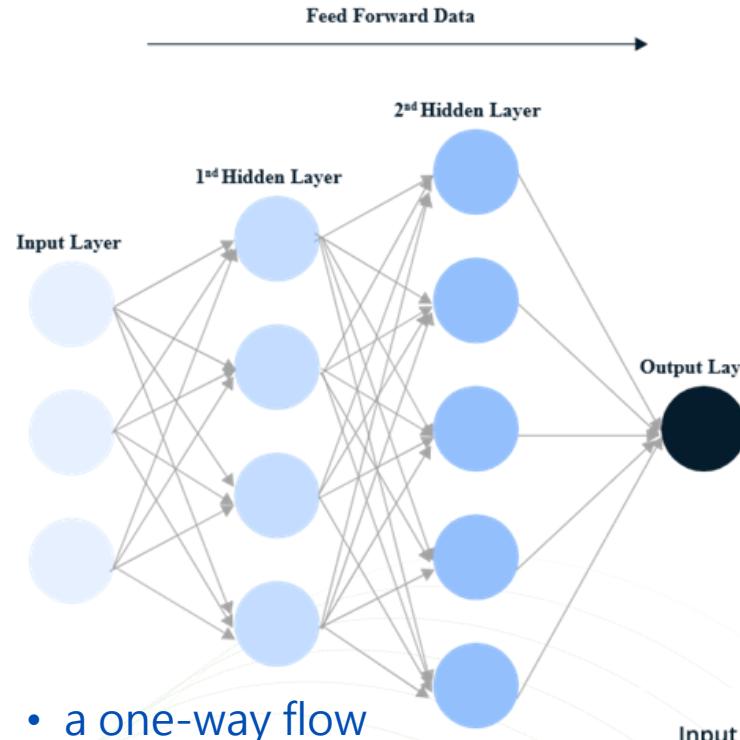
The input values (pixels) are multiplied by the corresponding weights, and their sum is sent as input to the neurons in the hidden layers. Each neuron in the hidden layers also has a numerical value called the bias (e.g., B_1 , B_2 , etc.). The bias is added to the input sum, and the resulting value is passed through a threshold function called the activation function. The activation function determines whether the particular neuron will be activated or not.





Neural Networks 類神經網路

Feedforward Neural Networks (FNN)

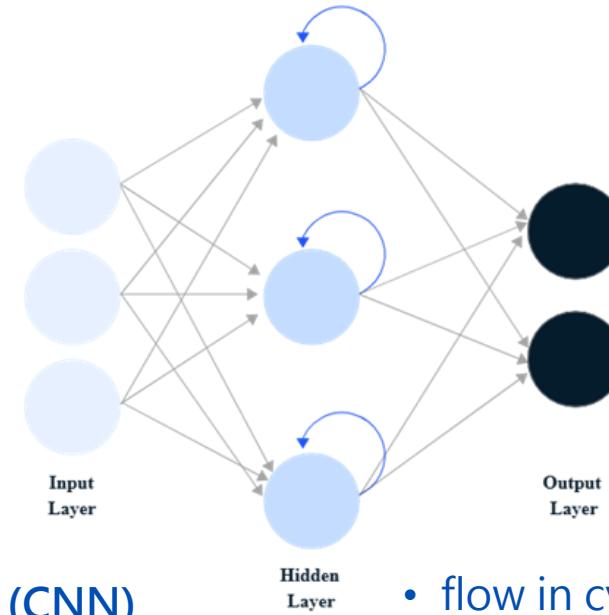


- a one-way flow

A convolutional layer applies a set of learnable filters to the input, performing convolutions to detect local patterns and spatial relationships.

for classification,
regression, and
pattern
recognition tasks

Recurrent Neural Networks (RNN)

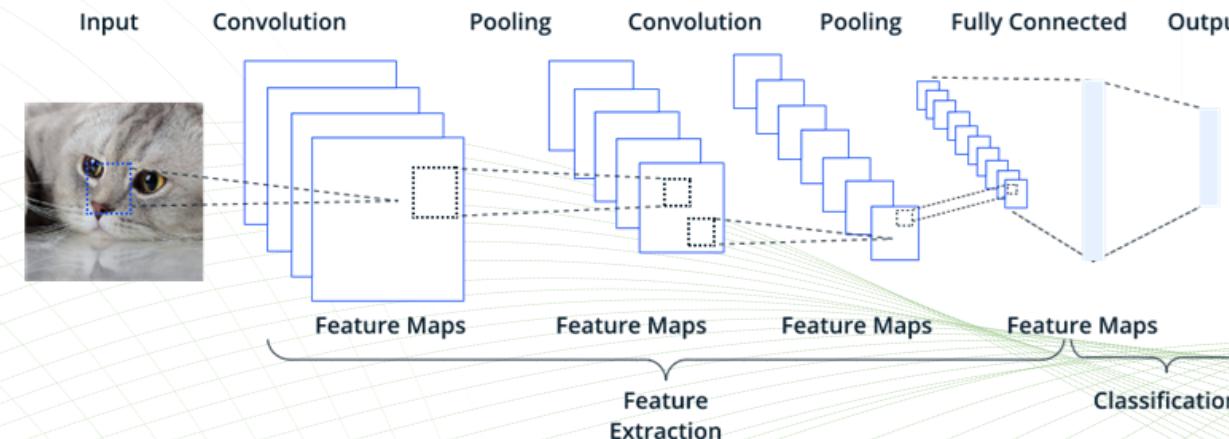


natural language
processing,
speech
recognition and
time series
analysis.

- flow in cycles or loops

Convolutional Neural Networks (CNN)

analyzing visual data, such as images or video

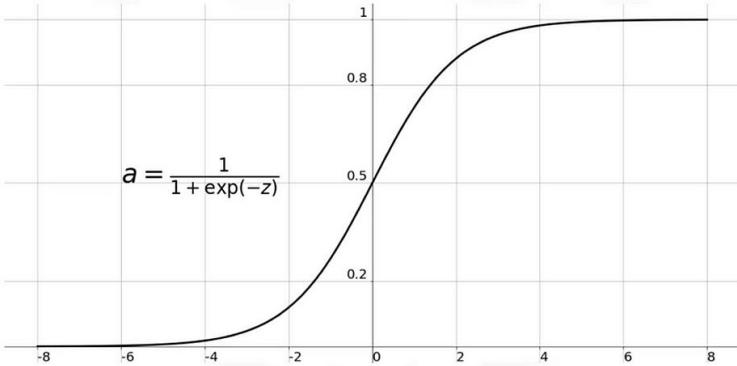


The pooling layers, on the other hand, reduce the dimensionality of the feature maps.

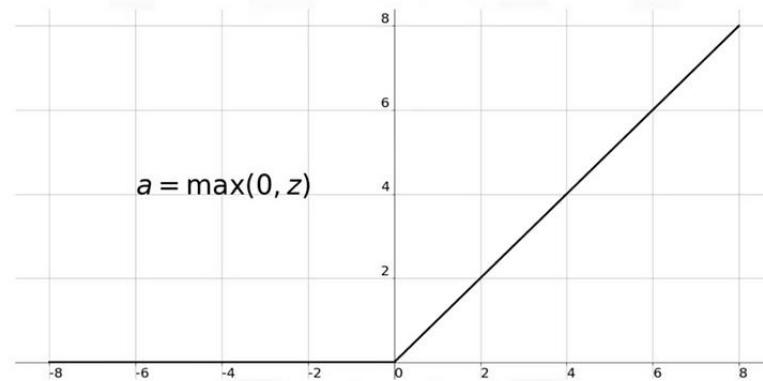


Neural Networks 類神經網路 - Activation function

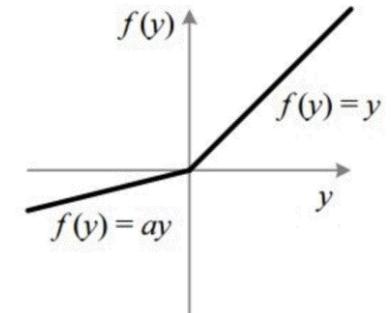
Sigmoid Function For binary classification



ReLU Function For hidden layers

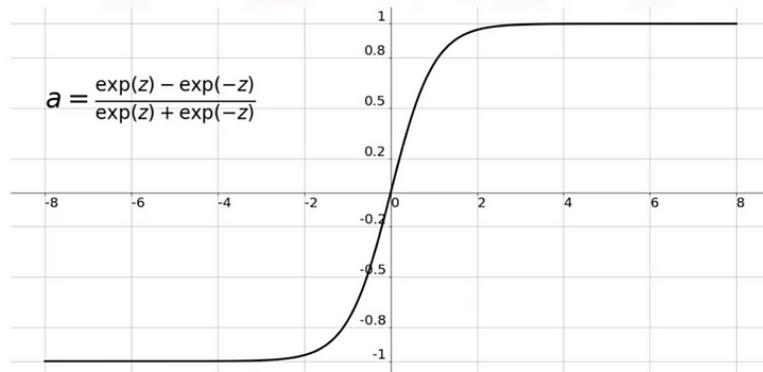


Leaky ReLU Function

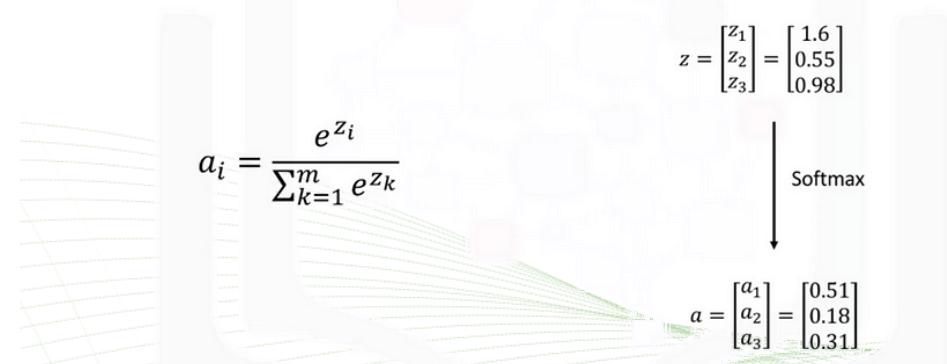


Leaky ReLU is a variation of ReLU that allows a small, non-zero gradient when the input is negative.

Hyperbolic Tangent Function

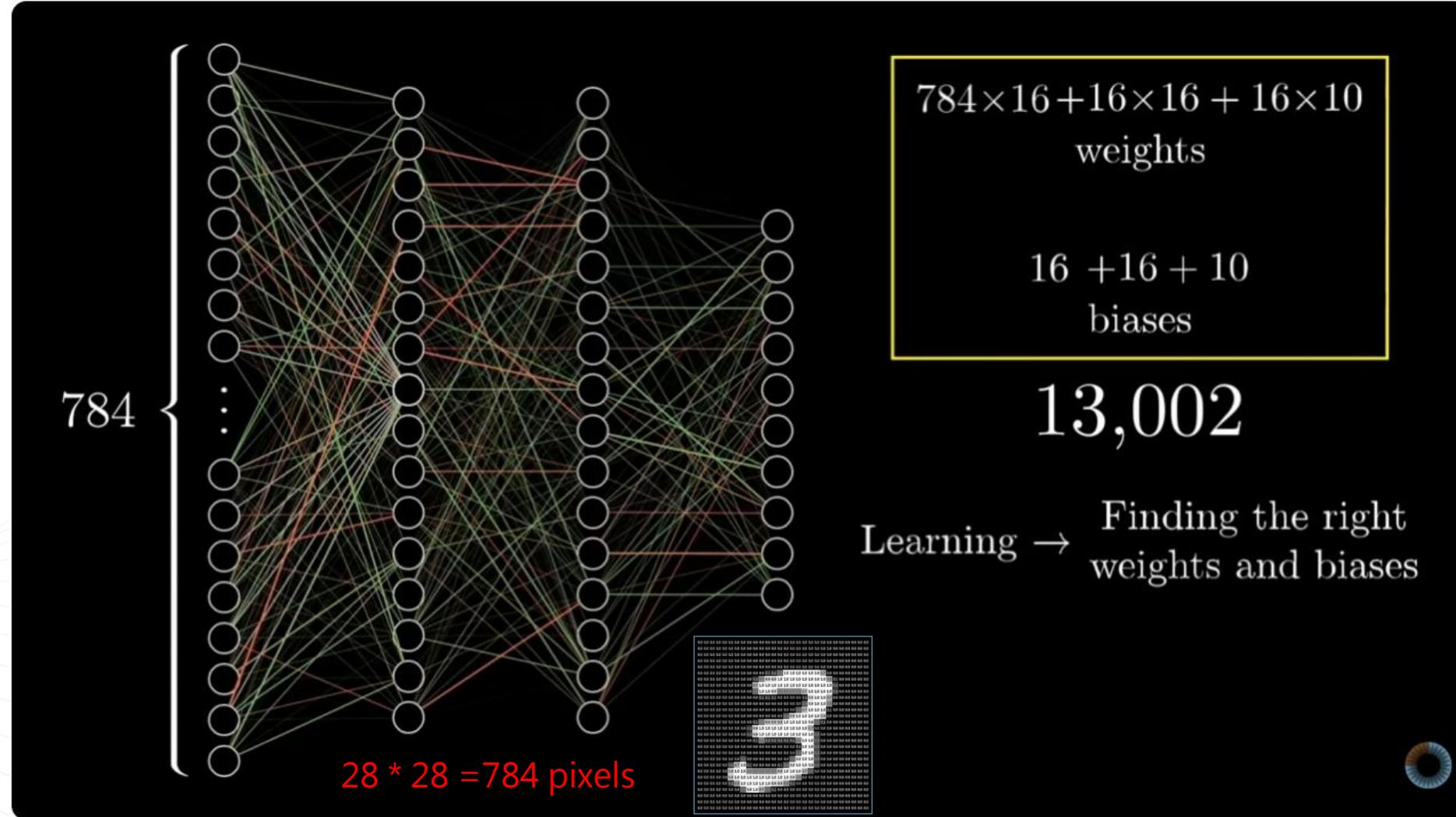


Softmax Function For multi-class classification





<https://www.youtube.com/watch?v=aircArUvnKk&t=695s>

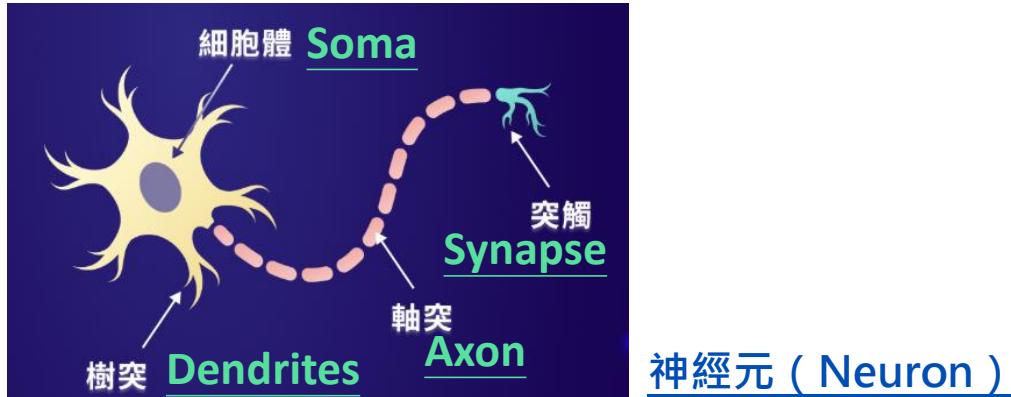


But what is a neural network? | Deep learning chapter 1

Jonathan Chen



Neural Networks 類神經網路



— 7 個神經網路模型 —

1 感知器

2 前饋神經網路

3 卷積神經網路

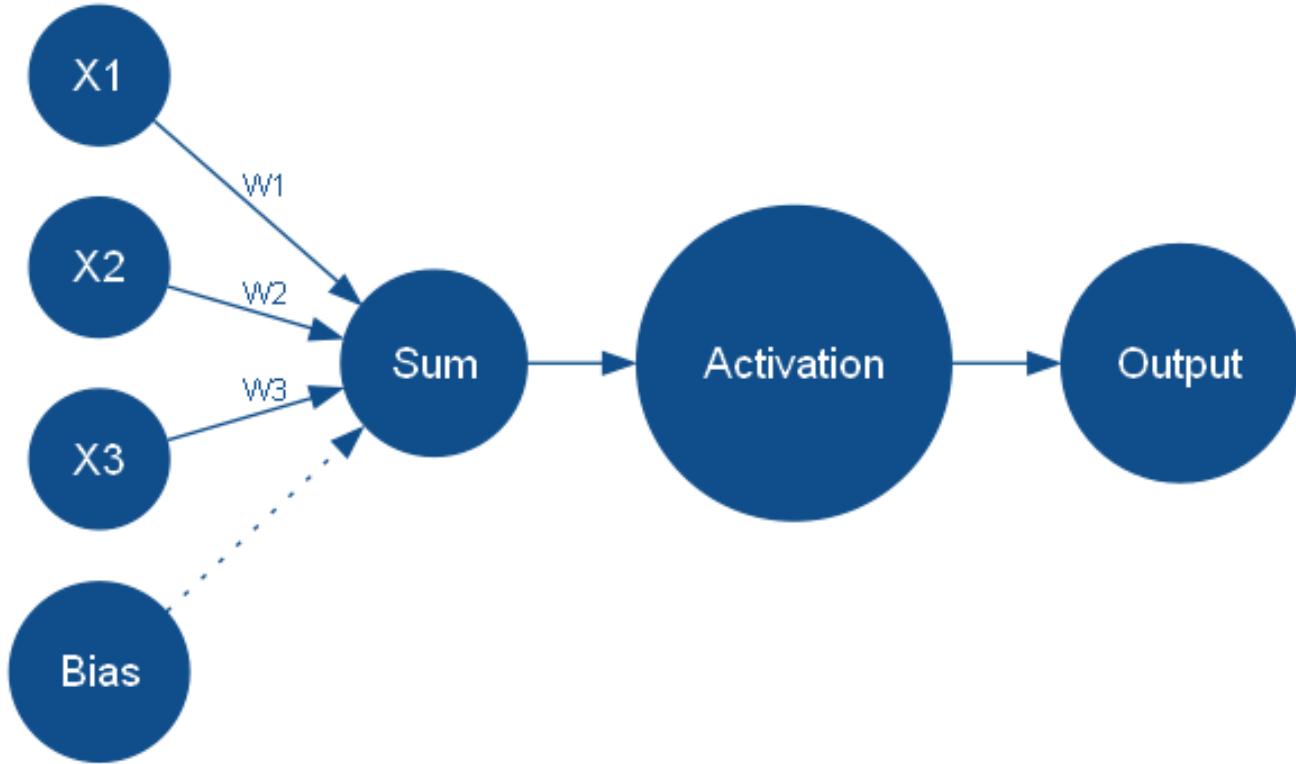
4 循環神經網路

5 生成對抗網路

6 圖神經網路

7 Transformer神經網路

- 感知器 (Perceptron) 的主要功能是處理二元分類問題 (Linear)。
- 前饋神經網路 (FNN) 是多層神經網路中最基本的類型，數據在網路中只能單向傳輸。(MLP: Multi-layer Perceptron)
- 卷積神經網路 (CNN) 是一種擅長處理圖像、影片數據的神經網路，並且提取數據中的空間特徵。CNN 通常包括 3 種主要層次：卷積層、池化層和全連接層。
- 循環神經網路 (RNN) 具有「記憶」功能，能夠利用前一時間步驟的輸出作為當前步驟的輸入，實現對序列數據的依賴建模，因此 RNN 特別適合處理與時間相關的任務，例如金融市場預測、手寫識別。
- GAN 生成對抗網路是透過生成器 (Generator) 和判別器 (Discriminator) 兩部分相互競爭來實現數據生成。生成器專注於創造逼真的數據，而判別器則負責判斷這些數據是否真實，形成一個動態的對抗過程，最終生成器能夠創建出幾乎無法分辨真假數據的成果。
- 圖神經網路 (GNN) 用來分析圖形結構數據的機器學習模型。
- Transformer 模型的核心是「注意力機制」，可以快速抓住數據中各部分的關聯性，

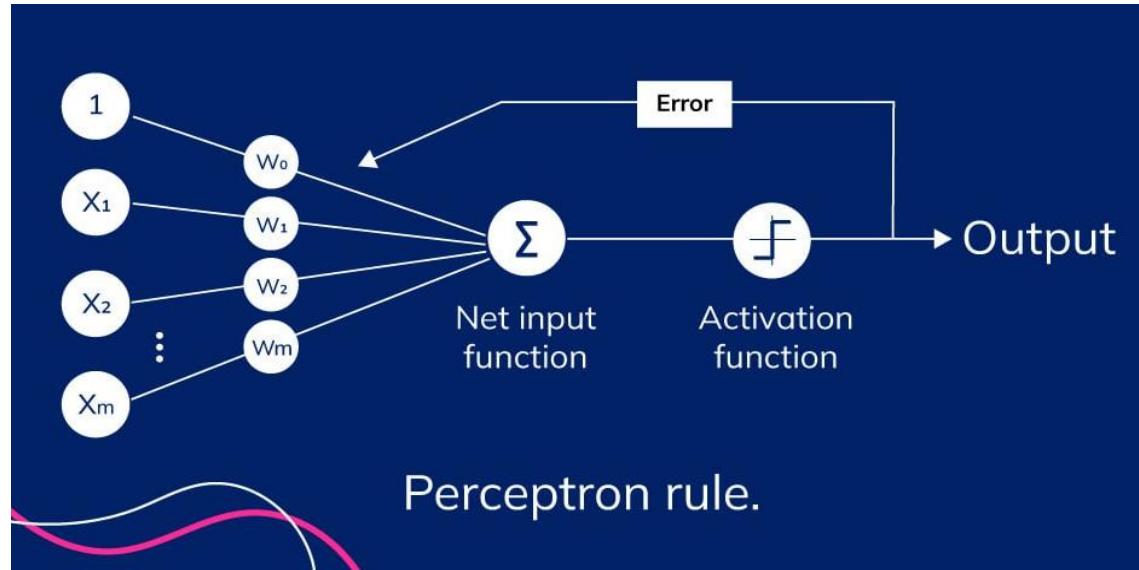


Neural Network Perceptron 感知器



Neural Networks 類神經網路 - Perceptron

A single-layer neural network linear or machine learning approach called a perceptron is used to learn different binary classifiers under supervision.



The difference between the expected and intended outputs serves as the basis for this modification. Through iteratively replicating this learning procedure, the perceptron gradually improves its functionality based on the following equations:

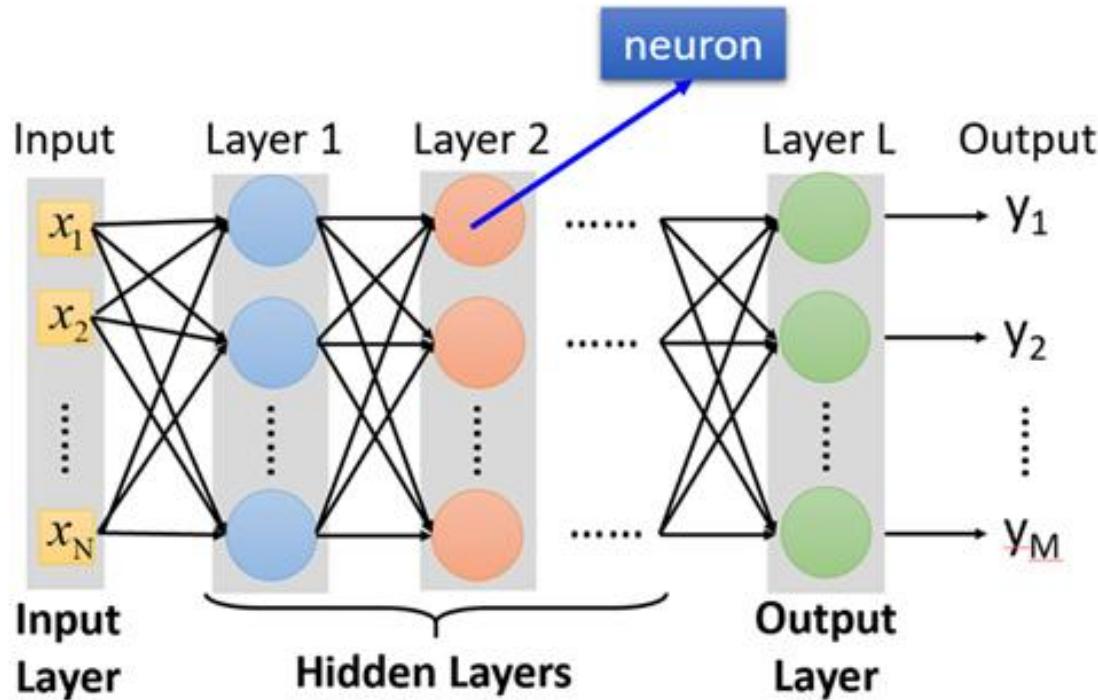
$$\Delta w_i = \alpha(y^T - t)x_i$$

$$\Delta b = \alpha(y^T - t)$$

- The signals x_1, x_2, \dots, x_n are input signals to the perceptron.
 - the **characteristics** or **properties** of the data
- Every input has a corresponding weight, denoted by the characters w_1, w_2, \dots, w_n . - **how important**
- The weighted sum formula serves as a representation of this process: $Z = w^T + w_2x_2 + \dots + w_nx_n$
- To modify the output of the perceptron according to a predetermined threshold, a bias term is frequently added.
- Based on the calculated value, **the activation function decides whether the perceptron will fire or stay dormant**. It has the notation $f(z)$ for example sigmoid function
Equation: $A = 1/(1 + e^{-x})$ and many more like Tanh, RELU, Softmax, etc...
- It displays the judgment or forecast made by the perceptron using the input data. $y = f(z + b)$



Fully Connect Feedforward Network

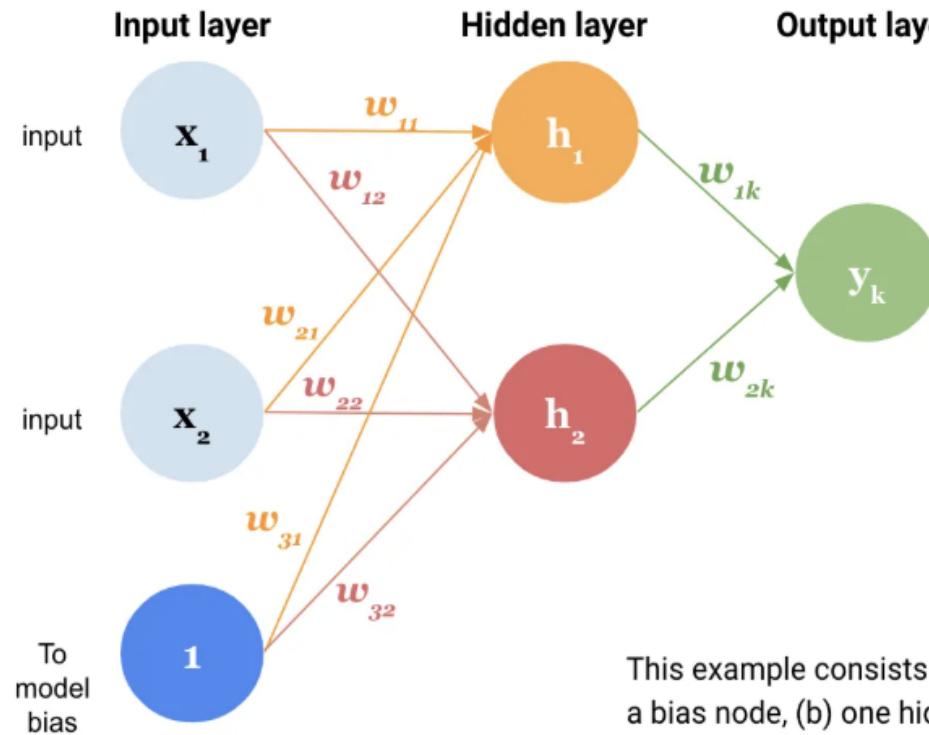


Neural Network
FNN 前饋神經網路



Neural Networks 類神經網路 - FNN

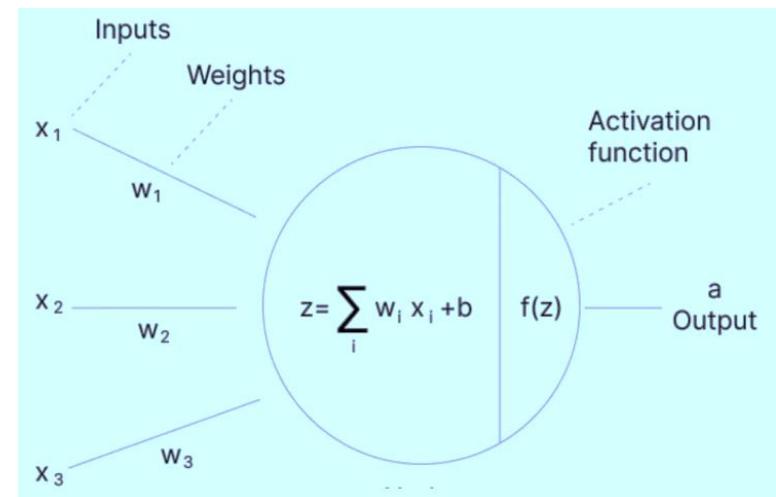
Illustrative example of Multilayer perceptron, a Feedforward neural network



x_1, x_2 : input data features
 w_{ij} : weights of the network
 h_1, h_2 : nodes in the hidden layer
 y_k : output variable

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This example consists of: (a) an input layer with two input nodes and a bias node, (b) one hidden layer with two neurons, and (c) an output layer with one neuron



Depicting input and output to a neuron in hidden layers

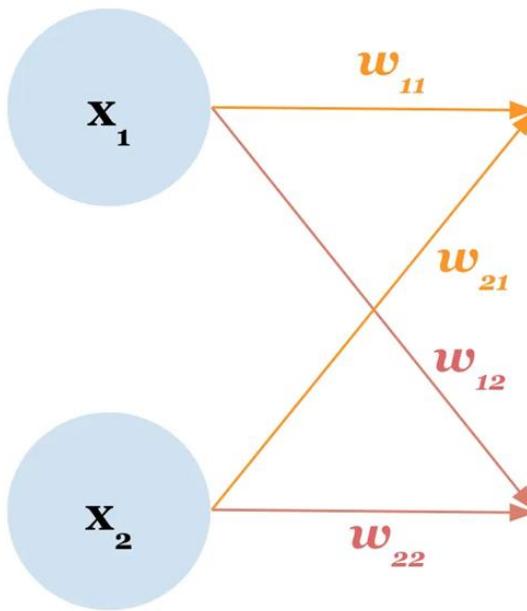
Multilayer perceptron (MLP), a feedforward neural network (FNN)

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Neural Networks 類神經網路 - FNN

Input layer



Hidden layer

Weighted sum of inputs:

$$z_1 = w_{11} * x_1 + w_{21} * x_2$$

Activation function:

$$a_1 = g(z_1)$$

Weighted sum of inputs:

$$z_2 = w_{12} * x_1 + w_{22} * x_2$$

Activation function:

$$a_2 = g(z_2)$$

Activation functions like ReLU, tanh, Maxout can be used

Output layer

Weighted sum of inputs:

$$z_3 = w_{1k} * a_1 + w_{2k} * a_2$$

Activation function:

$$a_3 = g(z_3)$$

Activation functions like Sigmoid, Softmax used in the output layer

Output = a_3
Target = y

$$\text{Loss (L)} = 0.5 * (y - a_3)^2$$

Loss calculation using Mean Squared error

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Forward Propagation

Forward propagation in a Neural Network (Source: AIML.com Research)

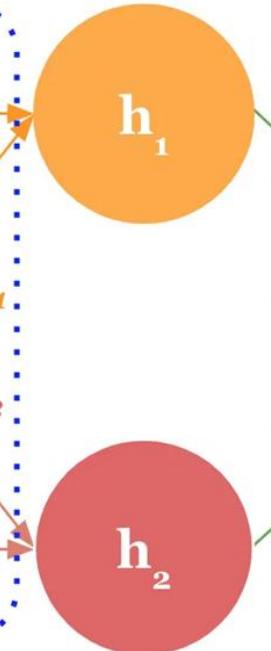
Note: bias term is not shown in the above diagram

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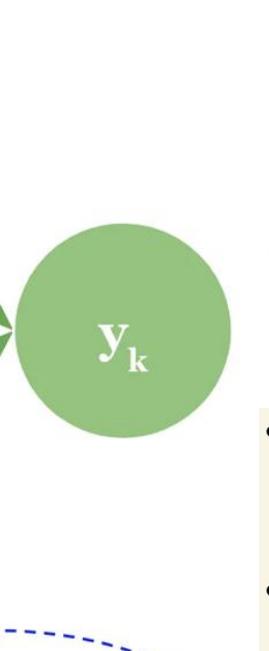
Input layer



Hidden layer



Output layer



- The error is then propagated back through the network (backpropagation), adjusting the weights and biases to minimize the error.

Output = a_3
Target = y

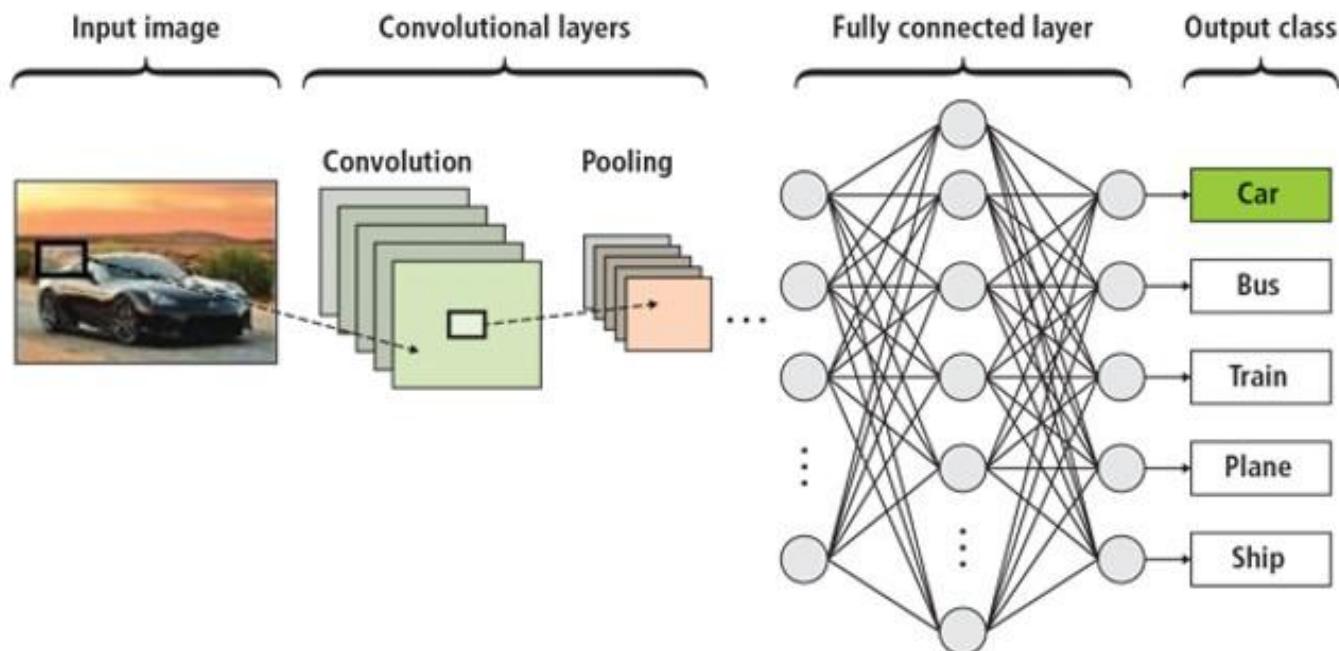
$$\text{Loss (L)} = 0.5 * (y - a_3)^2$$

- In stochastic gradient descent, weights (w_{ij}) are updated as below:
 $w_{ij} := w_{ij} + \Delta w_{ij}$
 $\Delta w_{ij} = -\eta * \partial L(w_{ij}) / \partial w_{ij}$,
 where η is the learning rate and $\partial L(w_{ij}) / \partial w_{ij}$ is the gradient of loss w.r.t the model weights
- Intermediate variables calculated during forward prop ($z_1, z_2, z_3, a_1, a_2, a_3$) are used for gradient calculation $\partial L(w_{ij}) / \partial w_{ij}$

These weights are updated in backprop



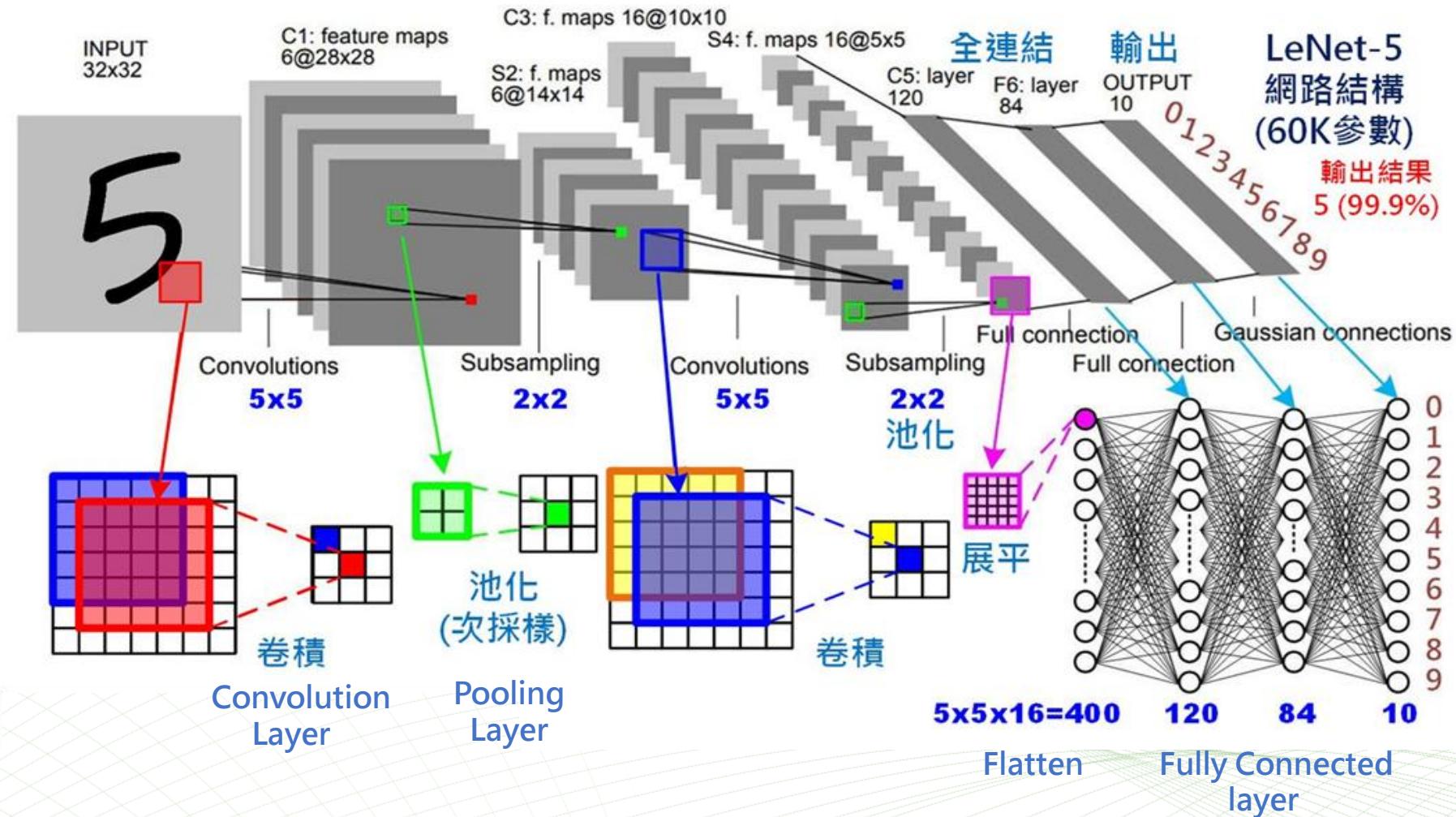
Backward propagation in a neural network (Source: AIML.com research)



Neural Network CNN 卷積神經網路

Neural Networks 類神經網路 - CNN

卷積 (Convolution) 方式來共用權重值 (參數量)，大幅降低記憶體使用量，同時導入二 (多) 維空間提取特徵 (濾波) 概念，讓神經網路更有利於影像 (灰階二維、彩色三維) 類型資料的計算。





Neural Networks 類神經網路 - CNN

卷積(Convolution)

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

移步(Stride)=1

原始資料

$$\begin{matrix} 1 & 0 & 2 & 1 & 3 & 0 \\ 5 & 1 & 6 & 0 & 7 & 1 \\ 9 & 1 & 10 & 0 & 11 & 1 \end{matrix} * \begin{matrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \end{matrix}$$

$$= \begin{matrix} 34 & 39 \\ 54 & 59 \end{matrix}$$

卷積核
(Kernel)

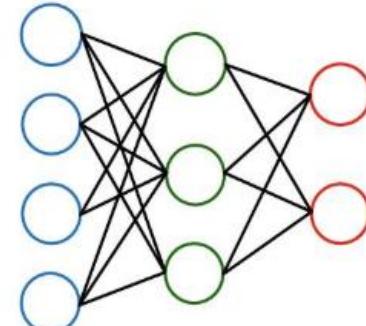
卷積結果

展平(Flatten)

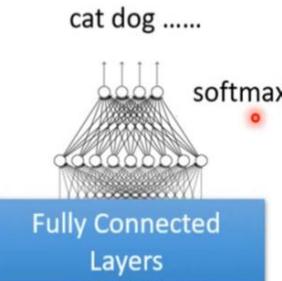
1	2	3
4	5	6
7	8	9



全連結 (Full Connected)



The whole CNN



池化(Pooling)

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

移步(Stride)=2



最大池化 平均池化
(Max. Pooling) (Avg. Pooling)

Softmax 輸出

$$\text{Output layer: } \begin{bmatrix} 1.3 \\ 5.1 \\ 2.2 \\ 0.7 \\ 1.1 \end{bmatrix} \xrightarrow{\text{Softmax activation function}} \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \xrightarrow{\text{Probabilities}} \begin{bmatrix} 0.02 \\ 0.90 \\ 0.05 \\ 0.01 \\ 0.02 \end{bmatrix}$$

卷積神經網路
主要構成元素

所謂**卷積**就是把原始資料乘上卷積核 (Kernel) 後所有位置加總得到的數值，這相當於在**提取特定數值排列的特徵**。

池化的主為目的則為縮小影像，通常以長寬各縮小一半來處理，常見有**最大池化**和**平均池化**。把**重點特徵**保留下來。

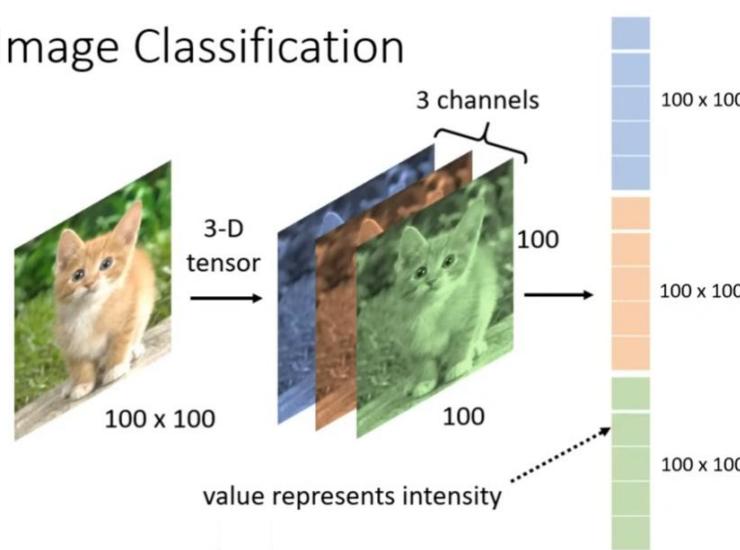


Neural Networks 類神經網路 - CNN

功能	卷積類神經網路 (CNN)	傳統類神經網路
核心架構	由卷積層、活化層、池化層和全連接層組成。	主要由全連接(稠密)層組成。
輸入資料類型	最適合結構化的格狀資料(例如圖像、影片、文字等一維序列)。	可靈活處理各種類型的資料，通常是表格型資料或扁平化向量。
擷取特徵	透過濾波器自動學習階層式特徵(邊緣、紋理、形狀)。	透過直接連接學習特徵，在空間特徵學習方面的成效通常較差。
空間關係	明確保留並運用空間關係(例如圖像中像素之間的鄰近關係)。	獨立處理每個輸入特徵，如果將輸入內容扁平化，空間關係會遺失。
共用參數	是，輸入內容的不同位置會共用權重(濾波器/卷積核)。	否，每個連線都有專屬權重。
參數數量	因為會共用權重和彙整，因此參數通常較少，在處理圖像等高維度輸入內容時更是如此。	參數數量可能非常龐大，尤其是輸入內容維度很多時。
平移不變性	無論特徵在輸入內容中的確切位置為何，都能準確辨識(本身就擅長處理這類工作)。	除非明確使用經過強化的資料進行訓練，否則對輸入特徵的變化會較為敏感。
運算效率	參數較少且有專門的運算作業，因此處理圖像/空間資料的效率較高。	如果輸入內容的維度很多，可能會因為密集連接，而產生極高的運算費用。
主要應用方式	圖像分類、物件偵測、影像分割、影片分析、醫學影像處理、部分自然語言處理工作。	表格型資料分類/迴歸、簡單模式識別、函數逼近、部分自然語言處理工作。
主要優點	非常適合處理視覺資料、學習階層式特徵、平移不變性減少參數，較不易在圖像資料產生過度配適的情形。	可以靈活處理多種資料，適合非空間表格型資料。以基本工作來說，在概念上較容易理解。
重要限制	設計過程可能相當複雜，通常需要大型資料集來進行訓練，對於非空間表格資料的成效較差。	不適合處理高維空間資料，會忽略空間關係。如果輸入內容複雜且參數眾多，容易過度配適。

Neural Networks 類神經網路 - CNN

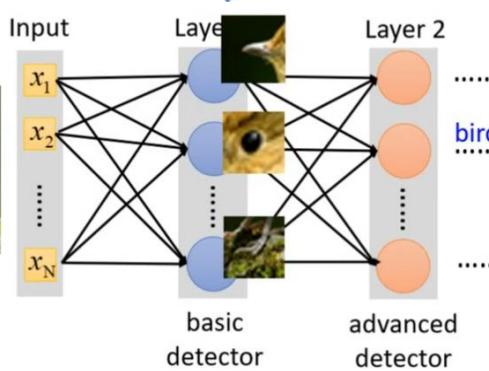
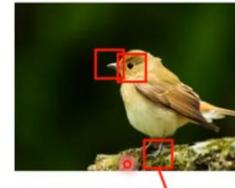
Image Classification



Observation 1

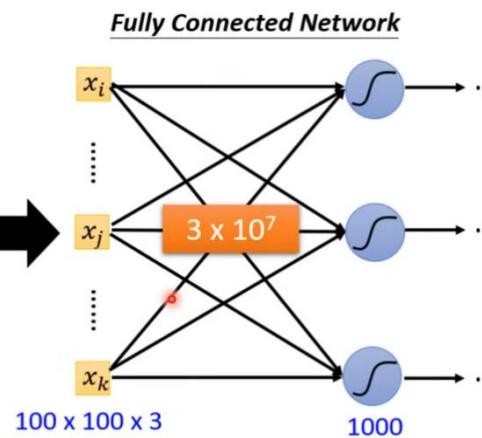
Identifying some critical patterns

Need to see the whole image?

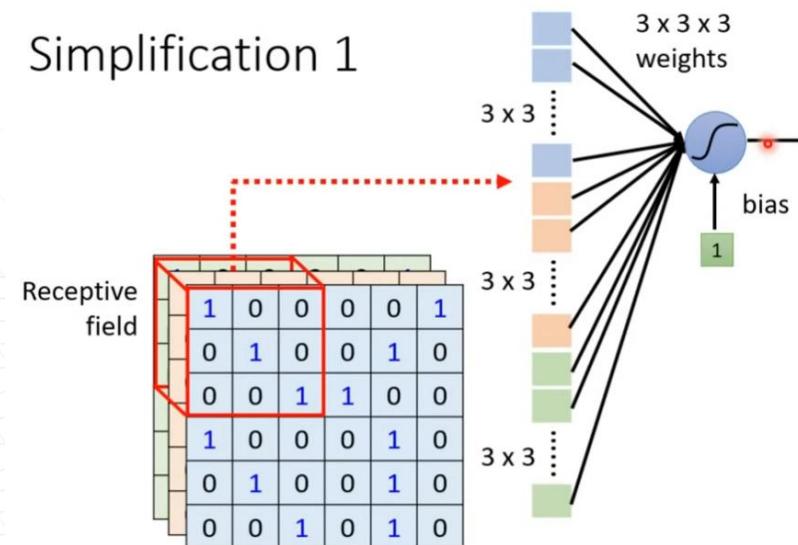


A neuron does not have to see the whole image.

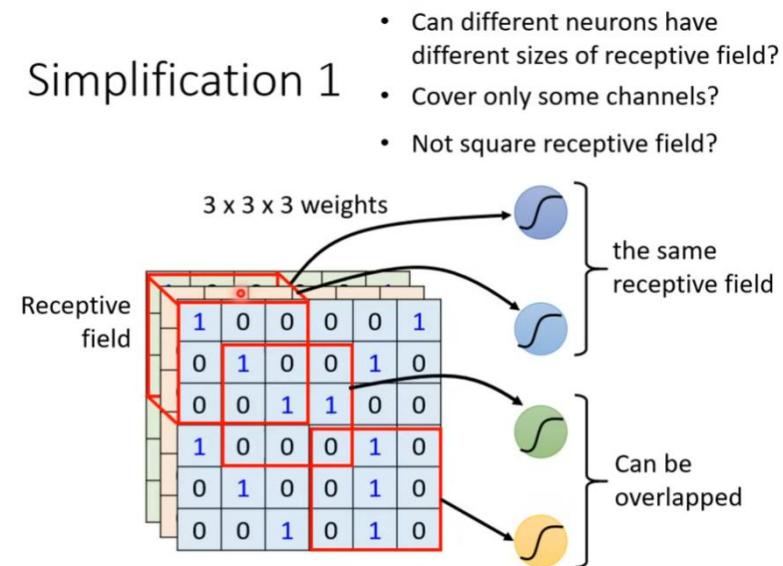
Some patterns are much smaller than the whole image.



Simplification 1



Simplification 1



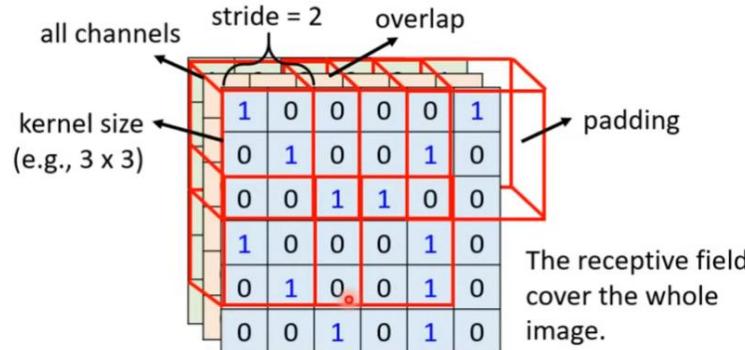
- Can different neurons have different sizes of receptive field?
- Cover only some channels?
- Not square receptive field?



Neural Networks 類神經網路 - CNN

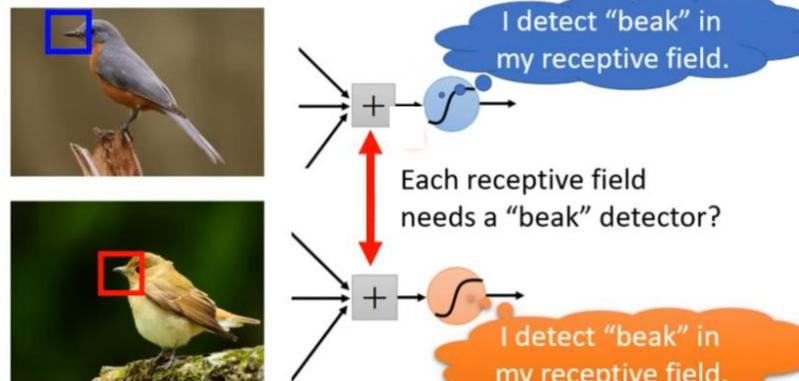
Simplification 1 – Typical Setting

Each receptive field has a set of neurons (e.g., 64 neurons).

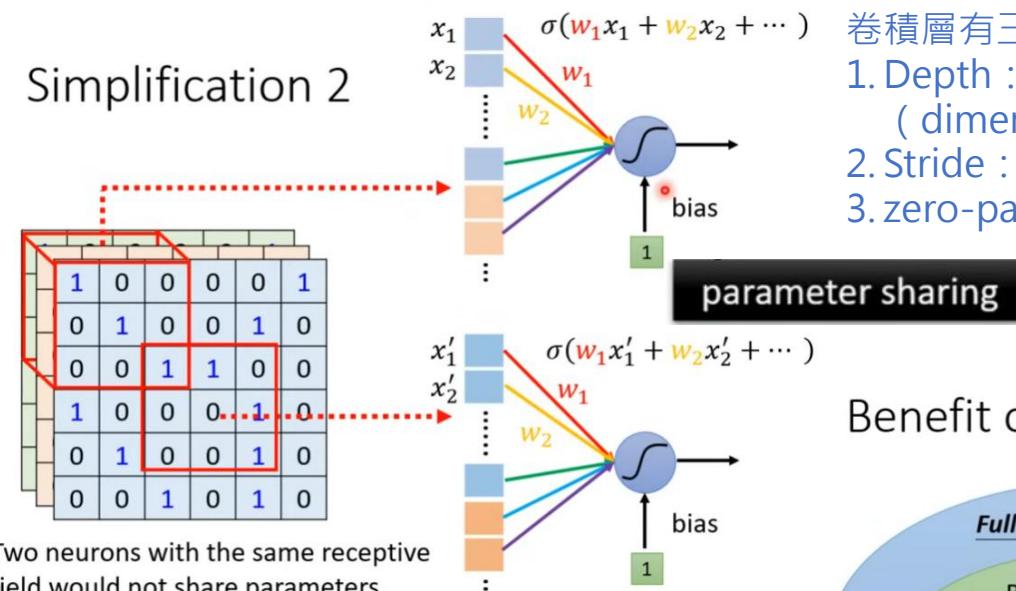


Observation 2

- The same patterns appear in different regions.



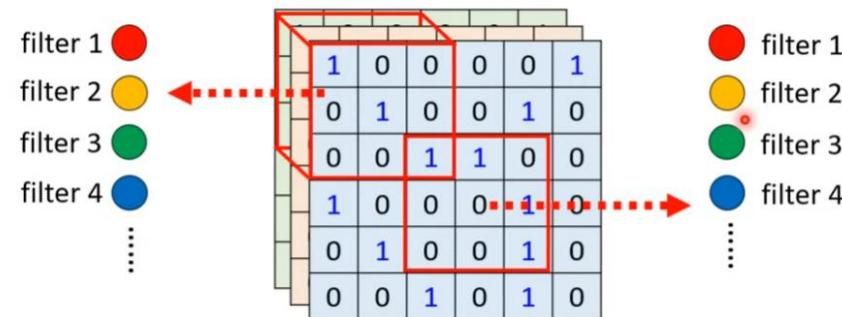
Simplification 2



Simplification 2 – Typical Setting

Each receptive field has a set of neurons (e.g., 64 neurons).

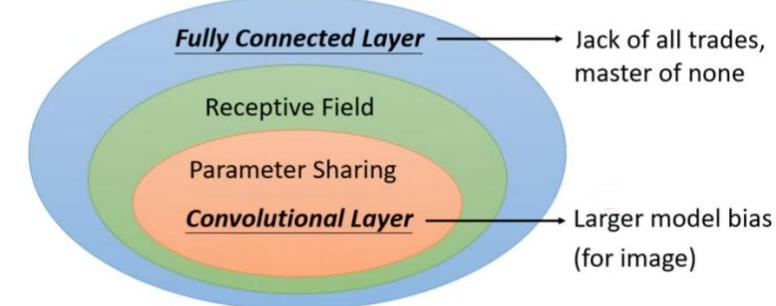
Each receptive field has the neurons with the same set of parameters.



卷積層有三個超參數:

1. Depth : 即輸入圖像的layer數 (dimension)
2. Stride : 即kernel每次移動的格數
3. zero-padding : 外圍補0的大小

Benefit of Convolutional Layer

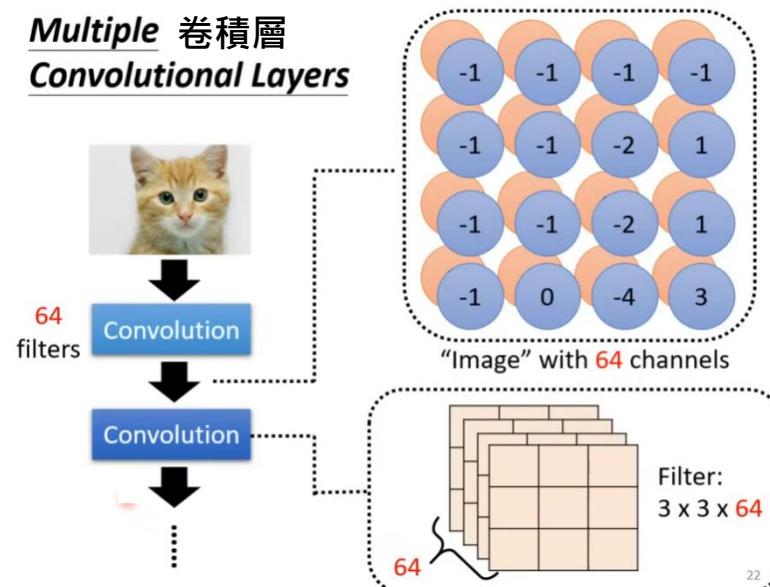


- Some patterns are much smaller than the whole image.
- The same patterns appear in different regions.

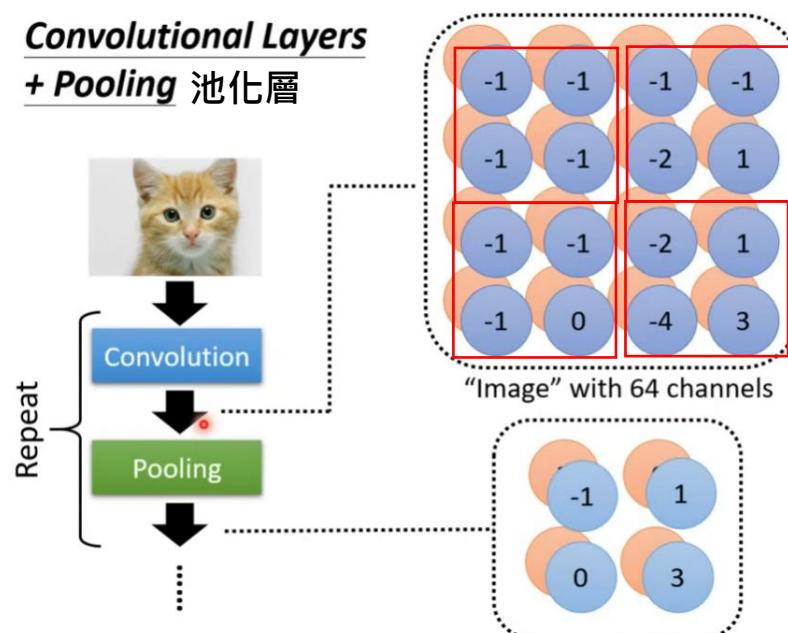


Neural Networks 類神經網路 - CNN

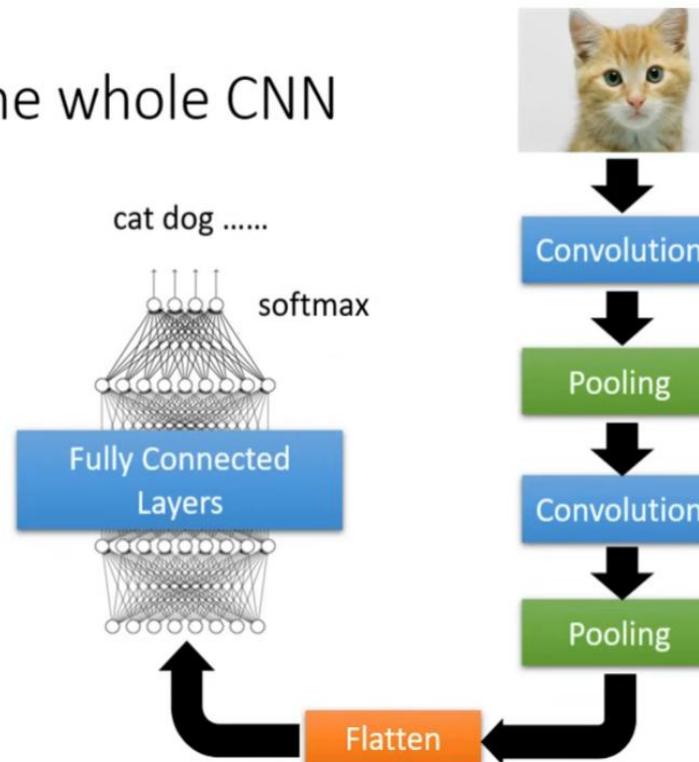
Multiple 卷積層 Convolutional Layers



Convolutional Layers + Pooling 池化層



The whole CNN

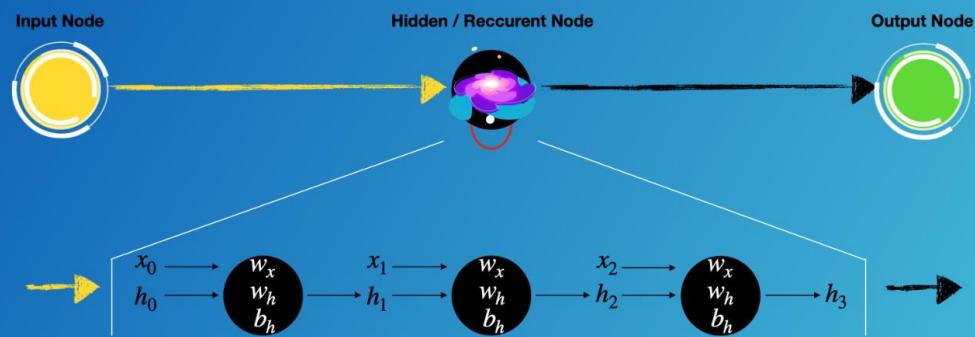


卷積層和池化層，其最主要的目的分別是提取特徵及減少圖像參數，然後將特徵資訊丟到**Full connected layer**來進行分類，其神經元只與上一層kernel的像素連結，而且各連結的權重在同層中是相同且共享的，然而Full connected layer的每個神經元與上層神經元之間彼此相連接，各個連結都有其獨立且相異的權重值，這個現象造成Full connected layer會耗用相當多的運算資源。

- 最大化 (Max-Pooling)
- 平均化 (Mean-Pooling)



RECURRENT NEURAL NETWORKS (RNN)



Neural Network
RNN 循環神經網路



Neural Networks 類神經網路 - RNN

● 什麼是 RNN (Recurrent Neural Network) ?

RNN (循環神經網路) 是一種專門用來處理 序列資料 (sequential data) 的深度學習模型。例如：

- 語音 (Speech)
- 文字 (Text)
- 時間序列 (Time series)
- 影片 (Frame sequence)

其核心概念是「記憶前一步的資訊」，也就是每次輸入都與上一次的隱藏狀態 h_{t-1} 相關。

公式 : $h_t = f(Wx_t + Uh_{t-1} + b)$

這讓 RNN 能理解序列的先後順序，而不是把每一筆資料當成獨立的。

● RNN 的優點

- 1. 適合處理序列與上下文依賴 - 可記住前面資訊，因此能理解像「今天下雨，我沒帶傘」這種需要上下文的資料。
- 2. 參數共享 - 所有時間步共享同一組參數，因此比 CNN、MLP 用更少的參數處理序列。
- 3. 可用於變長序列 - 不像 CNN 需要固定大小輸入。

● RNN 的缺點 (很關鍵)

- 1. 梯度消失 / 梯度爆炸 - 序列長度一長，RNN 很難記住早期的資訊。（這是 RNN 被淘汰的主因之一）
- 2. 訓練速度慢 - 需要按序列步驟逐步處理（不可並行），所以訓練速度比 Transformer 慢非常多。
- 3. 長期依賴問題 (Long-term dependency) - 模型只記得近距離資訊，難以學到「長距離關係」。
- 4. 效能被更好的架構取代

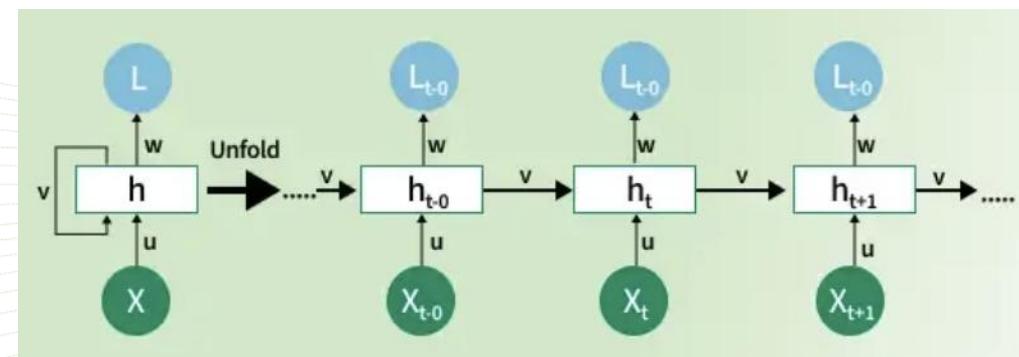
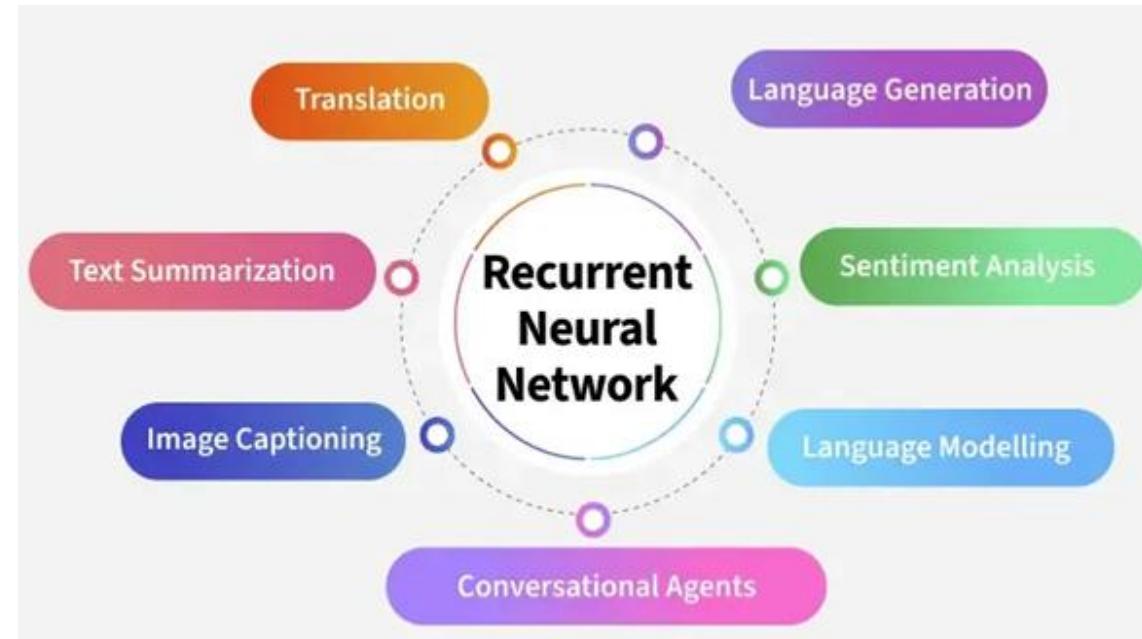
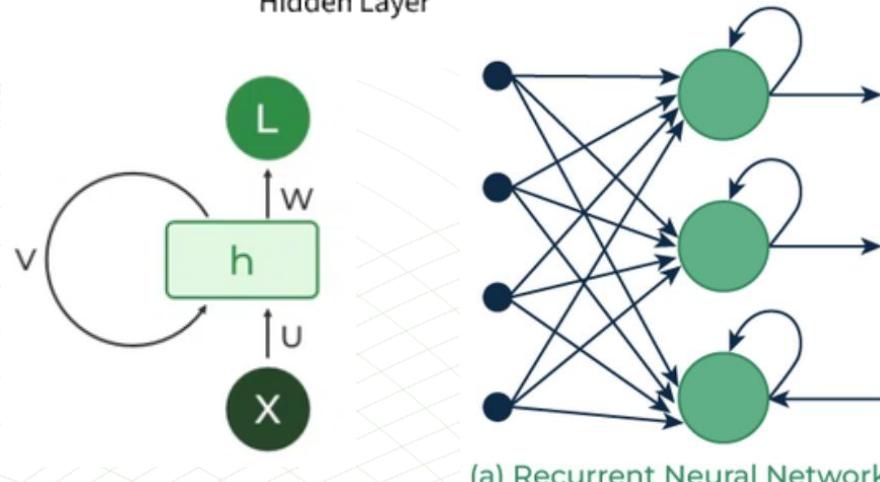
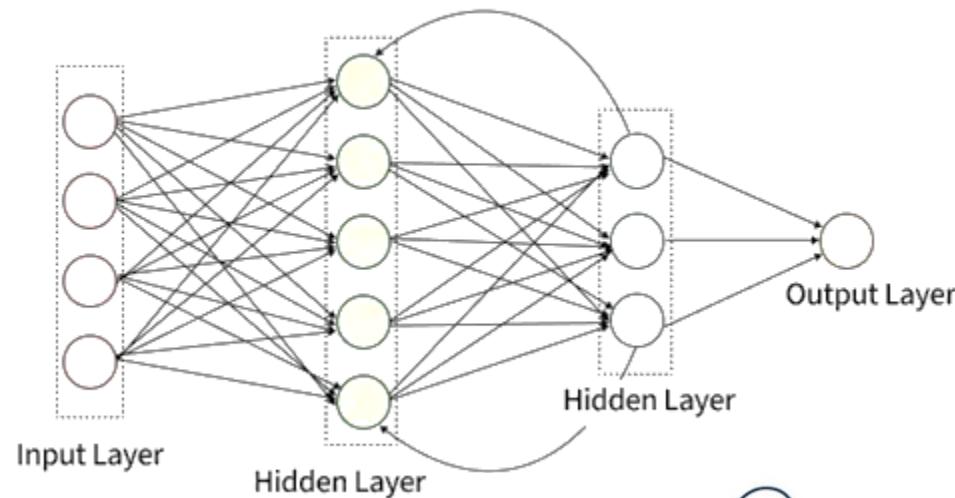
在 NLP、語音等多數領域，RNN 幾乎完全被 LSTM / GRU → 99% 被 Transformer 取代。



Neural Networks 類神經網路 - RNN

循環神經網路 (RNN) 是一種深度學習模型，此模型被訓練來處理並將循序資料輸入轉換為特定的循序資料輸出。循序資料是指其序列組成部分根據複雜的語義和語法規則相互關聯的一種資料，例如單字、文句或時間序列資料。

Recurrent Neural Network



持續地疊加，
就會有權重爆
炸或是梯度消
失的問題

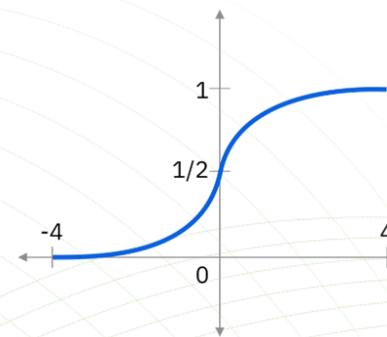


Neural Networks 類神經網路 - RNN

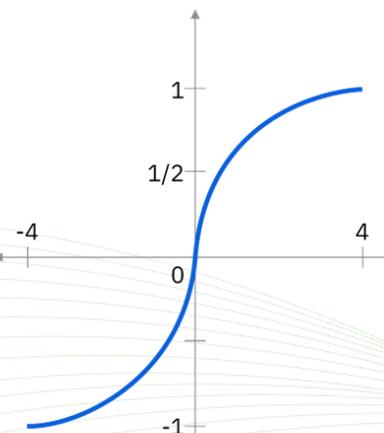
A recurrent neural network or RNN is a deep neural network trained on **sequential or time series** data to create a machine learning (ML) model that can make sequential predictions or conclusions based on sequential inputs. RNNs can also be used to solve **ordinal or temporal** problems such as language translation, natural language processing (NLP), sentiment analysis, speech recognition and image captioning.

They are distinguished by their “**memory**” as they take information from prior inputs to influence the current input and output. Recurrent neural networks **share the same weight parameter within each layer** of the network.

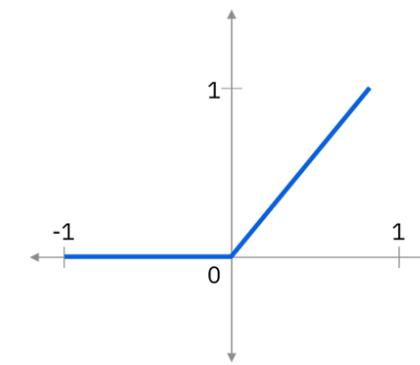
$$g(x) = \frac{1}{1+e^{-x}}$$



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



$$g(x) = \max(0, x)$$



- Common activation functions - Sigmoid, tanh and ReLU

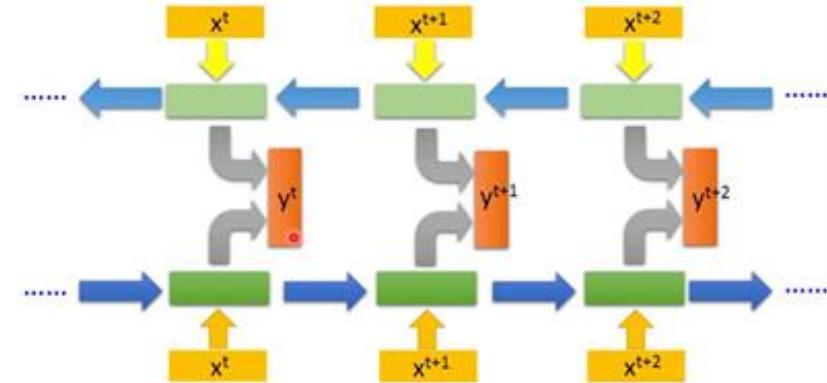


Neural Networks 類神經網路 - RNN

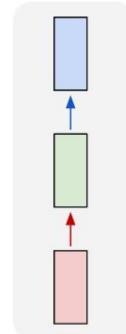
Popular recurrent neural network architecture variants include:

- Standard RNNs
- Bidirectional recurrent neural networks (BRRNs)
- Long short-term memory (LSTM)
- Gated recurrent units (GRUs)
- Encoder-decoder RNN

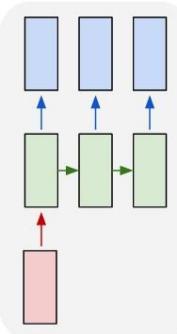
Bidirectional RNN



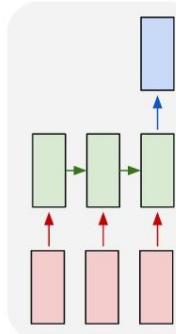
one to one



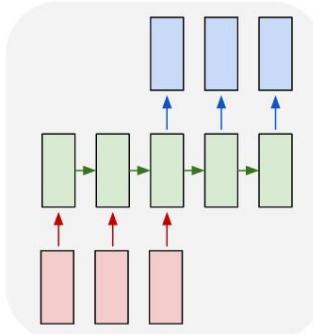
one to many



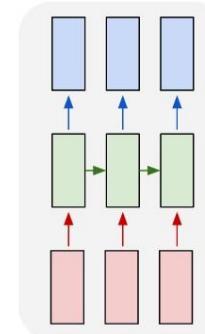
many to one



many to many



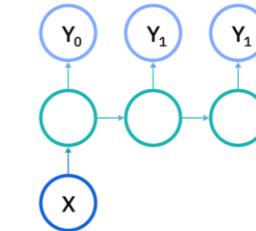
many to many



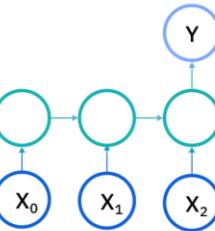
One-to-one



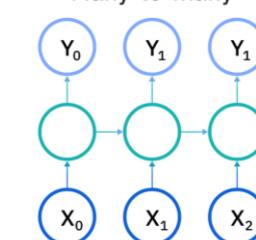
One-to-many



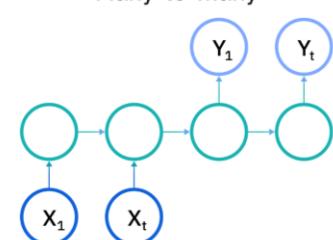
Many-to-one



Many-to-many



Many-to-many

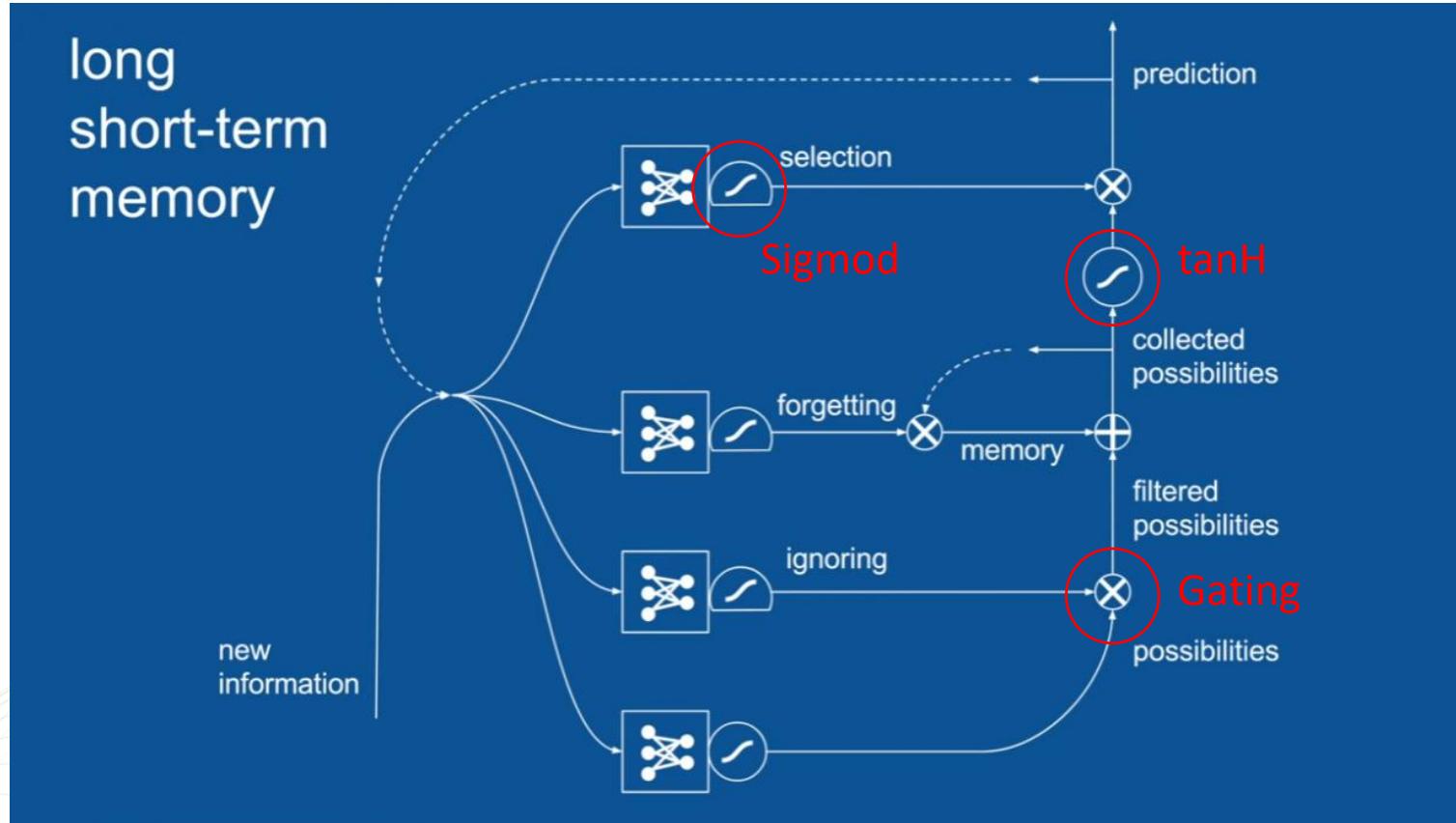


Different types of RNNs



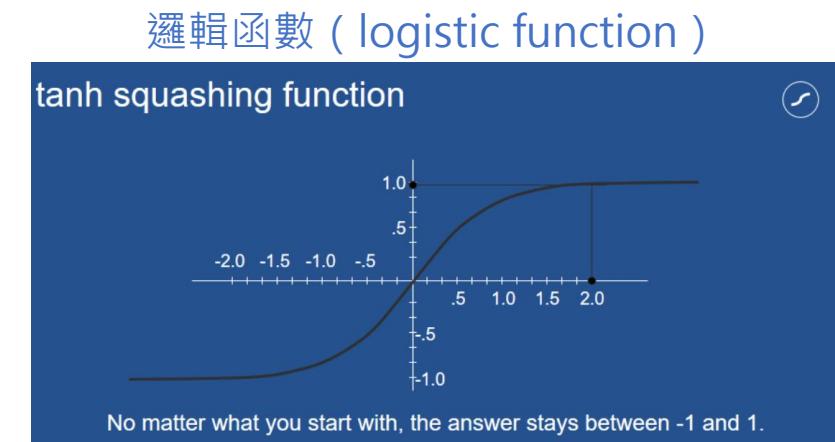
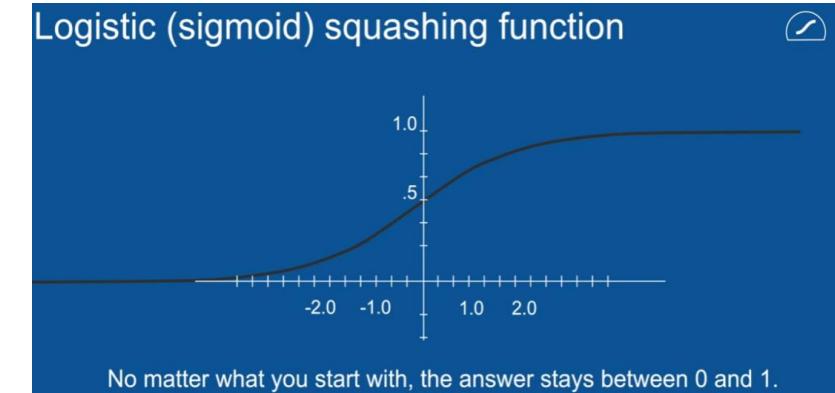
Neural Networks 類神經網路 - RNN

- Long short-term memory (LSTM)



https://brohrer.mcknote.com/zh-Hant/using_machine_learning/

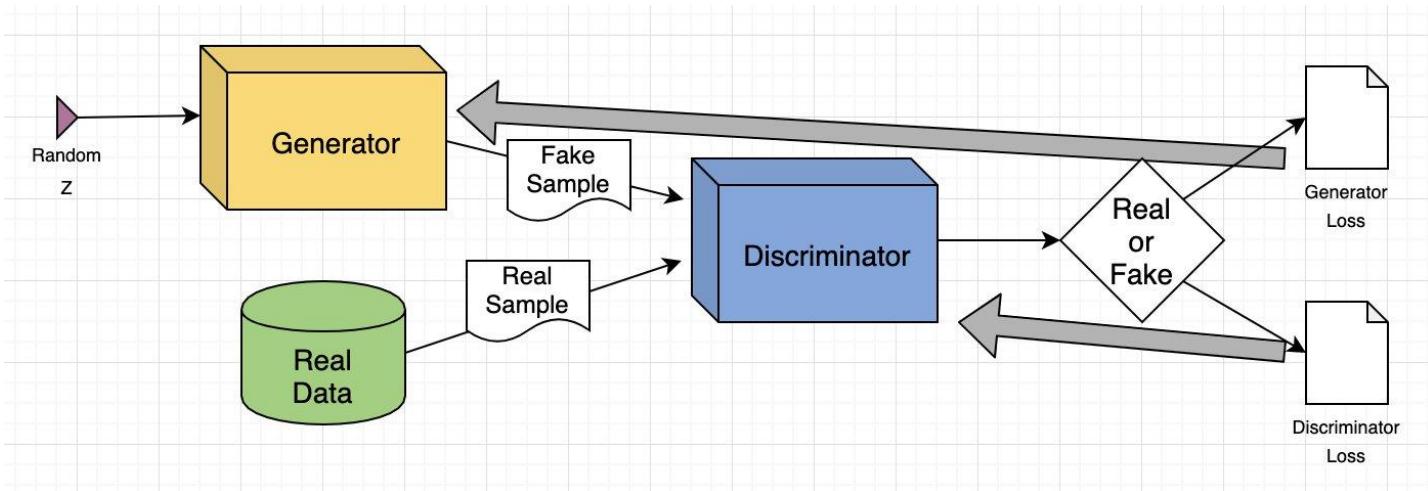
<https://www.youtube.com/watch?v=WCUNPb-5EYI&t=1229s>



擠壓函數 (squashing function · S函數)



Neural Network GAN 生成對抗網路



<https://www.youtube.com/watch?v=TpMlssRdhco>

What are GANs (Generative Adversarial Networks)?

<https://developers.google.com/machine-learning/gan?hl=zh-tw>

Neural Networks 類神經網路 - GAN

Generative adversarial

networks consist of two models:

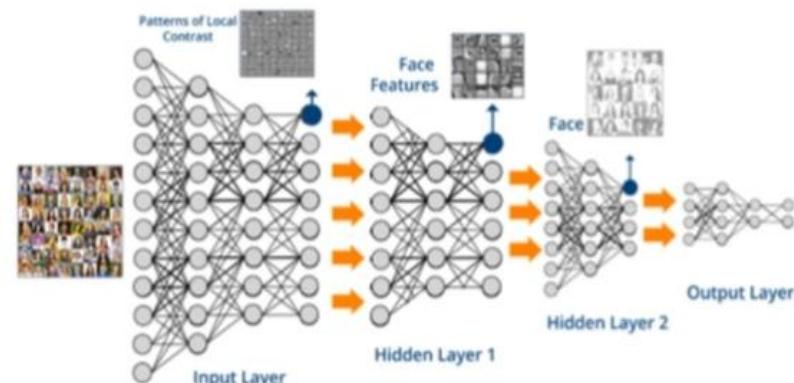
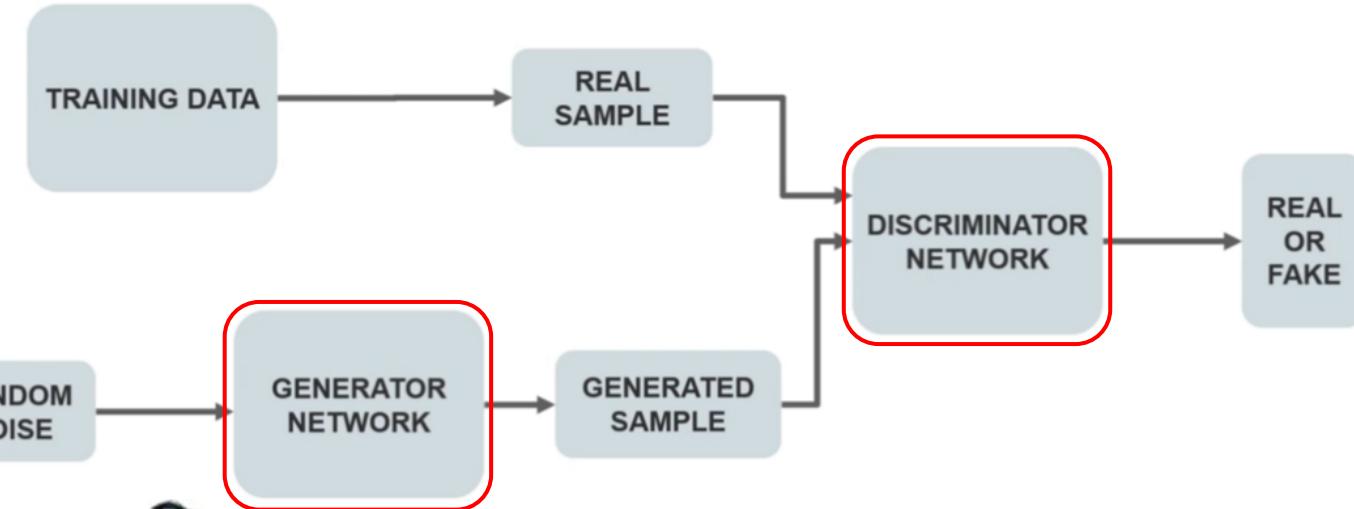
- a **generative model** &
- a **discriminative model**.

Adversarial



Generator and discriminator, each competing to win.

Generator trying to fake and
Discriminator, trying not to
be fooled.



GENERATOR

Generator network that takes a sample and generates a sample of data

DISCRIMINATOR

Discriminator network decides whether the data is generated or taken from the real sample using a binary classification problem with the help of a sigmoid function that gives the output in the range 0 to 1.



Neural Networks 類神經網路 - GAN

以下是有關生成對抗網路的簡要介紹：

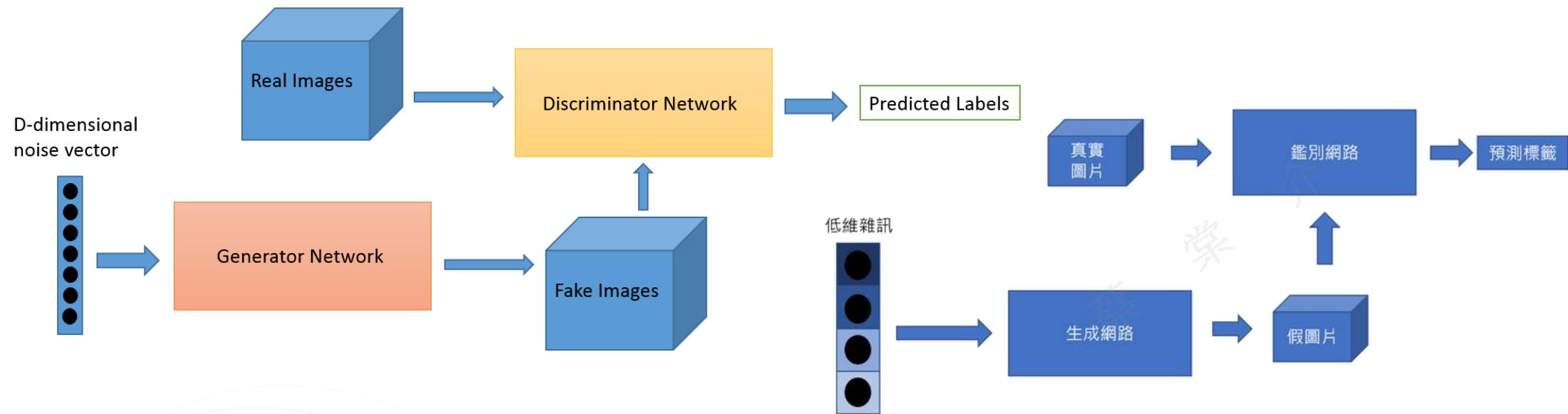
1. 結構：GAN 包含兩個主要組件：**生成器 (Generator) 和判別器 (Discriminator)**。生成器負責生成與真實數據相似的樣本，而判別器則試圖區分真實數據和生成器生成的數據。
2. 對抗過程：訓練過程中，**生成器和判別器進行對抗**。生成器努力生成逼真的樣本以欺騙判別器，同時判別器努力識別出真實數據和生成的數據之間的區別。
3. 最小最大博奕：GAN 的訓練過程可以理解為一種最小最大博奕。**生成器的目標是最小化判別器對其生成的數據的機率估計**，從而生成更逼真的樣本。**判別器的目標是最大化對真實數據的識別能力以及對生成的數據的識別能力**。
4. 生成過程：在訓練完成後，**生成器可以使用隨機雜訊作為輸入**，生成與真實數據相似的新樣本。這種生成過程使得GAN 能夠創造具有高質量的樣本。
5. 應用範疇：GAN 在圖像生成、風格轉換、影像超分辨率、音頻合成、文本生成等多個領域都取得了驚人的成就。它能夠生成逼真的樣本，同時在藝術創作、影視特效等方面也有潛在應用。
6. 變種：GAN 的不同變種包括條件生成對抗網路 (cGAN) 、週期一致性生成對抗網路 (CycleGAN) 、生成對抗自編碼器 (GAN-AE) 等，這些變種擴展了 GAN 的應用範圍。

總之，生成對抗網路 (GAN) 是一種基於對抗訓練的生成模型，透過生成器和判別器的博奕來創造逼真的樣本。



Neural Networks 類神經網路 - GAN

Generative adversarial networks consist of two models: a generative model and a discriminative model.



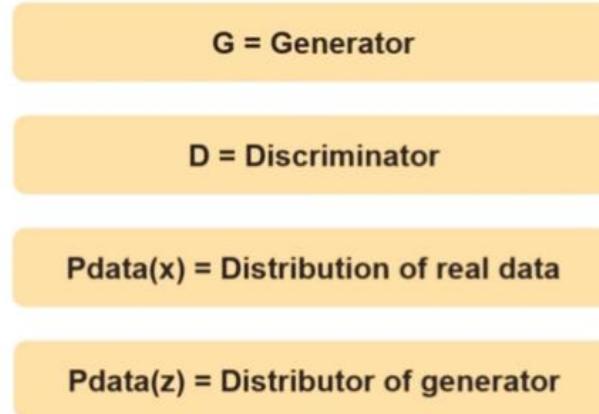
- The discriminator model is a classifier that determines whether a given image looks like a real image from the dataset or like an artificially created image. This is basically a binary classifier that will take the form of a normal convolutional neural network (CNN).
- The generator model takes random input values and transforms them into images through a deconvolutional neural network.
- Over the course of many training iterations, the weights and biases in the discriminator and the generator are trained through backpropagation. The discriminator learns to tell "real" images of handwritten digits apart from "fake" images created by the generator. At the same time, the generator uses feedback from the discriminator to learn how to produce convincing images that the discriminator can't distinguish from real images.



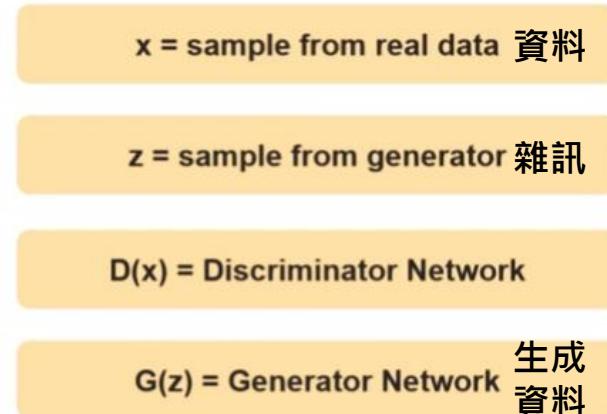
Neural Networks 類神經網路 - GAN

$$\min_G \max_D V(G, D) = E_{x \sim P_{\text{data}}(x)}[\log D(x)] + E_{z \sim P_z(z)} \log[(1 - D(G(z)))]$$

D(x) 真資料的判定結果



D(G(z)) 假資料的判定結果



Define The Problem

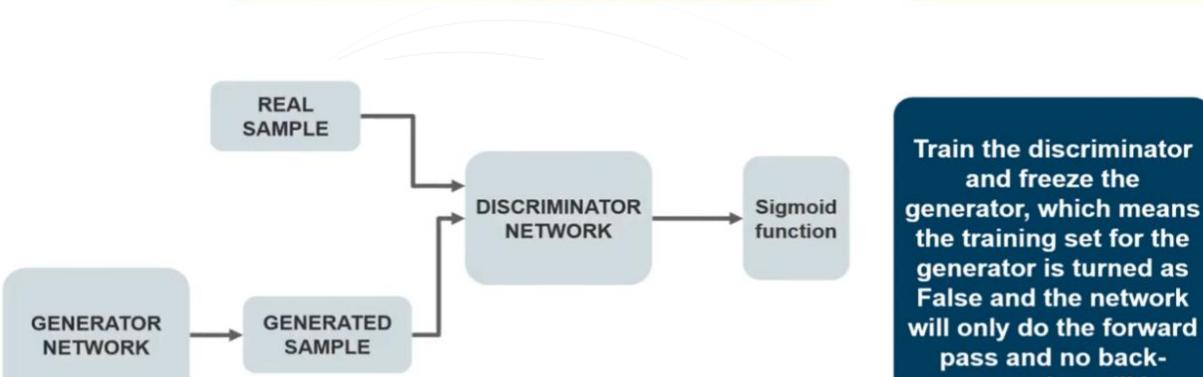
Train Discriminator On Real Data

Train Discriminator On Fake Data

Choose Architecture Of GAN

Generate Fake Inputs For Generator

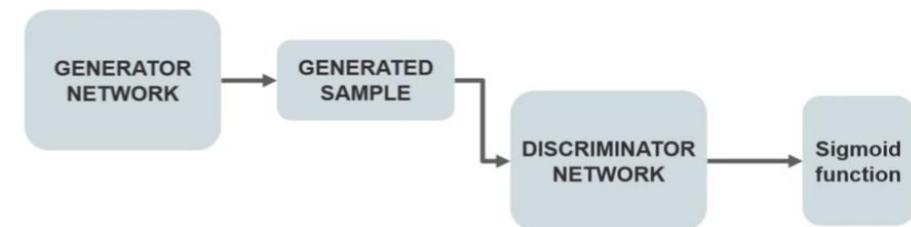
Train Generator With The Output Of Discriminator



G: 亂數 $z \sim p(z) \rightarrow G(z) \rightarrow$ 假樣本

D: 實樣本 $x \sim p_{\text{data}}(x)$

<https://www.youtube.com/watch?v=5g1eXmQtI0E>





Neural Networks 類神經網路 - GAN

$$\min_G \max_D V(G, D) = E_{x \sim P_{\text{data}}(x)} [\log D(x)] + E_{z \sim P_z(z)} \log [1 - D(G(z))]$$

- P_{data} : 真實資料的機率分布。

例：假設一顆天然鑽石 x 輸入到 P_{data} 後得到一個機率值 0.3，記做： $P_{\text{data}}(x)=0.3$ ，代表這顆天然鑽石在實際生活中出現的機率是 0.3。

- P_z : 生成資料的機率分布

當我們隨機加入雜訊 z 到製造機 P_z 後得到一個機率值 0.25，記做 $P_z(z)=0.25$ ，代表這顆合成質石的產出機率是 0.25

- $E_{x \sim P_{\text{data}}(x)}$: 真實資料的期望值

→ 固定G → 變動D → 計算鑑別度 → 選擇「最大」的D

其定義： $E_{x \sim P_{\text{data}}(x)} = \sum x P_{\text{data}}(x)$ 。定義成期望值的原因是有些資料常出現，而有些資料不常出現，故用「平均會出現的資料」來做代表。

- $E_{z \sim P_z(z)}$: 其定義為： $E_{z \sim P_z(z)} = \sum z P_z(z)$

→ 固定D → 變動G → 計算鑑別度 → 選擇「最小」的G

- $V(G, D)$: 鑑別度

一個判別器對於真資料判別結果 $D(x)$ 與 假資料判別結果 $D(G(z))$ 之間的鑑別度，當這兩種資料被視為一致，此值就會很小，反之差異越大則數值越大。

→ 固定G → 變動D → 計算鑑別度 → 選擇「最大」的D

- $\max_D V(G, D)$: 最佳判別器

\max_D 底下的 D 代表「不斷調整 D」，也就是透過調整判別器的參數(θ_d)而產生各種能力的判別器。因為鑑別度 $V(G, D)$ 可以衡量判別器的能力，所以在各種能力的判別器中具備最大鑑別度的判別器就是最佳的判別器。

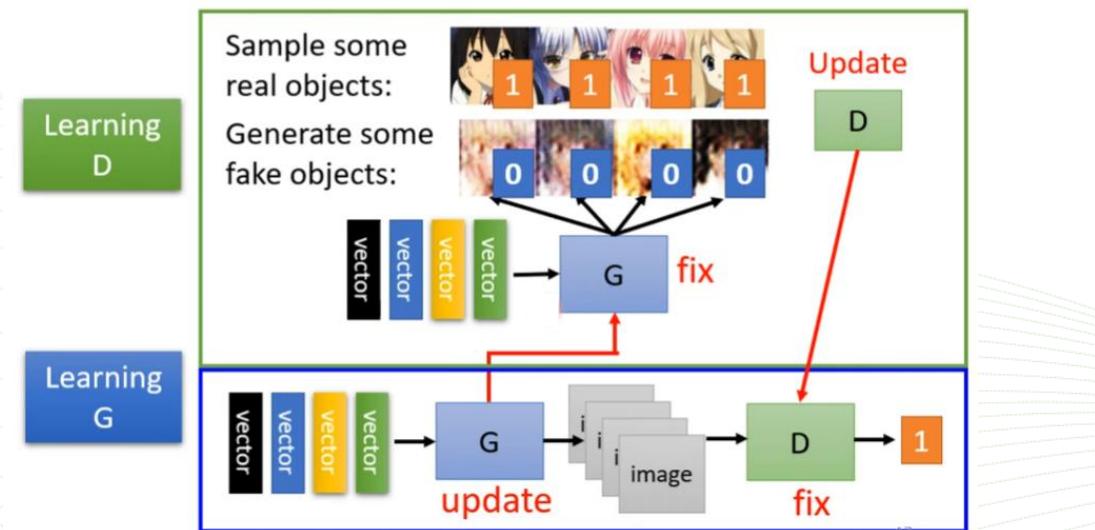
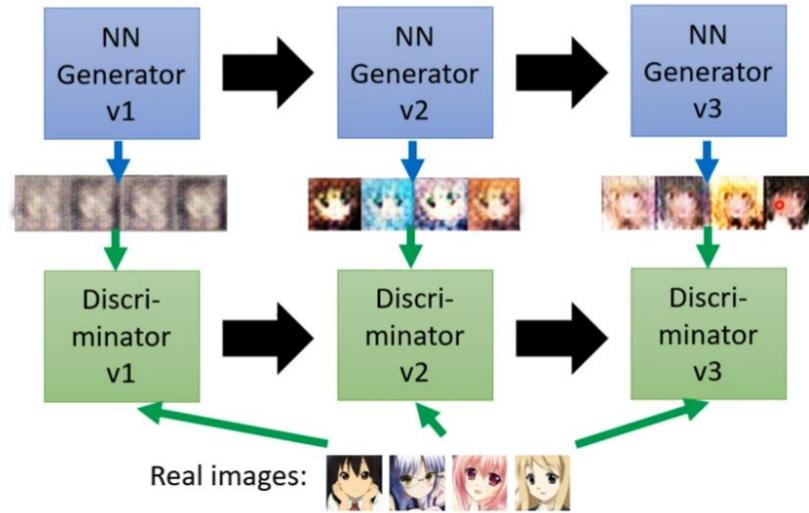
- $\min_G \max_D V(G, D)$: 最佳生成器

\min_G 底下的 G 代表不斷調整 G，也就是透過調整生成器參數(θ_g)來建立多種生成器。當最佳判別器 $\max_D V(G, D)$ 被給定之後，我們會將各種生成器產生的假資料給這個判別器，能使假資料鑑別度最小的成生器就是最佳生成器



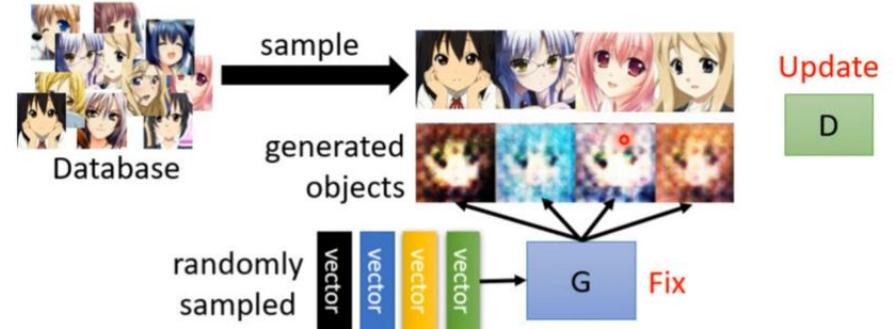
Basic Idea of GAN

This is where the term
“adversarial” comes from.



- Initialize generator and discriminator
 - In each training iteration:

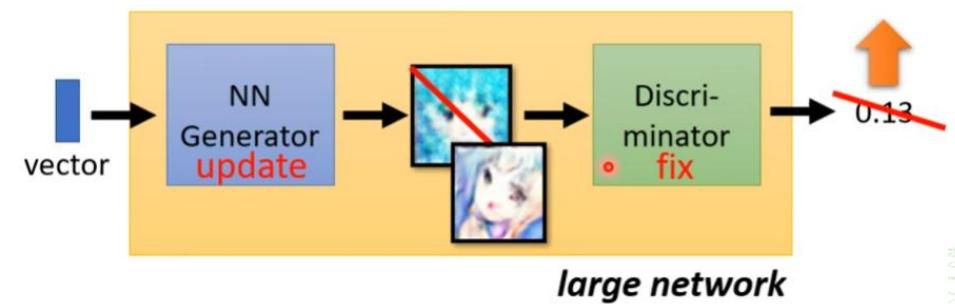
Step 1: Fix generator G, and update discriminator D



Discriminator learns to assign high scores to real objects and low scores to generated objects.

Step 2: Fix discriminator D, and update generator G

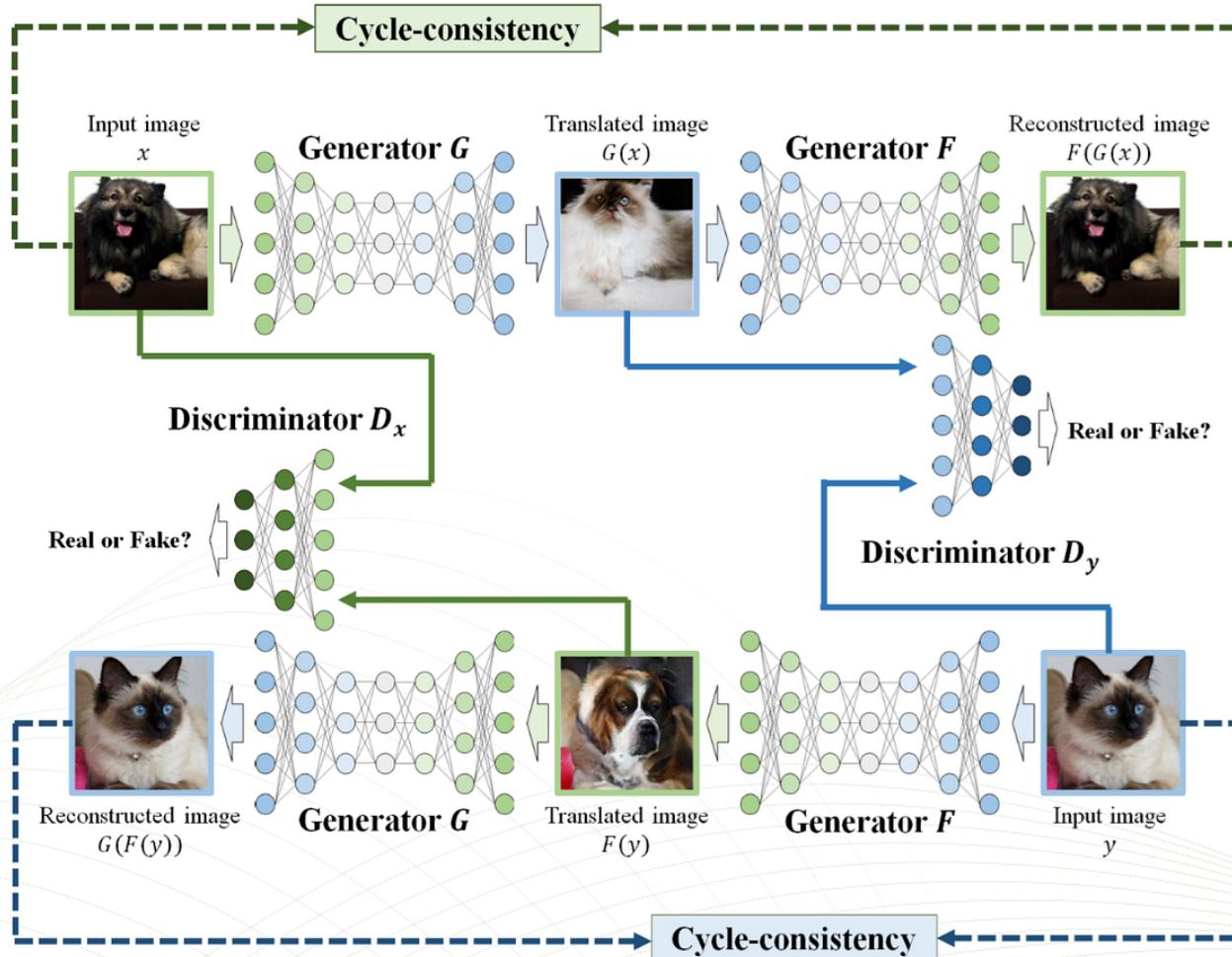
Generator learns to “fool” the discriminator





Neural Networks 類神經網路 - GAN

GAN 生成式對抗網路是一種藉由訓練目前現有的資料集的分布來去生成與其有相關性分布的數據，又稱偽資料。

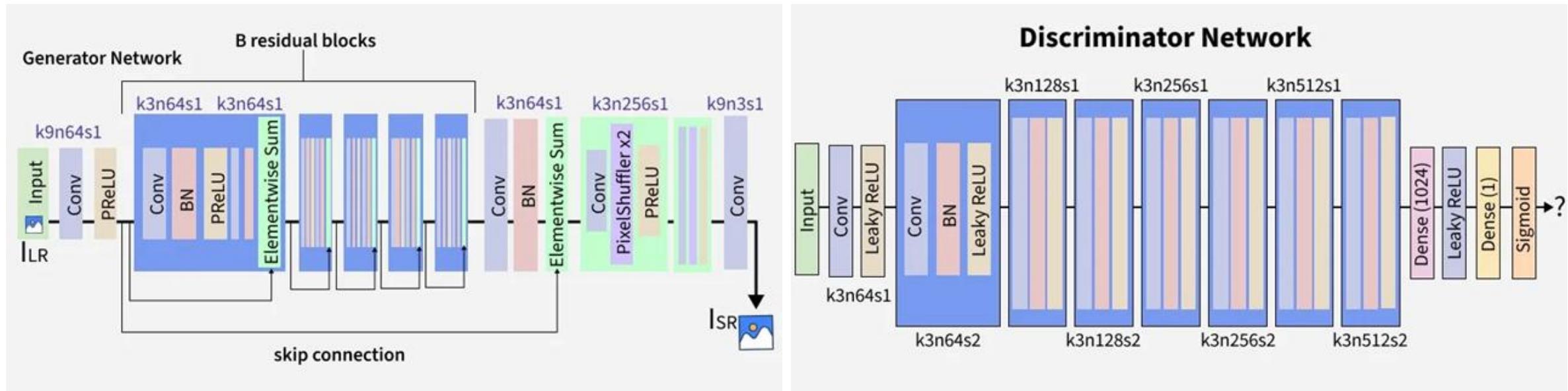


Cycle GAN 則是一個形樣轉變 Style Transfer 的做法

- **Generator G** : 負責把狗的照片(source domain image x) 轉換成貓的照片(target domain image y)
- **Generator F** : 負責把貓的照片(target domain image y) 轉換回狗的照片(source domain image x)
- **Discriminator D_x** : 負責區分真的狗照片 x 和轉換的狗照片 $F(y)$
- **Discriminator D_y** : 負責區分真的貓照片 y 和轉換的貓照片 $G(x)$
- **Cycle-Consistency**
轉換出來的影像，其結構、輪廓、特徵等等是基於其原始的影像

Neural Networks 類神經網路 - GAN

Super-Resolution Generative Adversarial Networks (**SRGAN**) represents an approach to image upscaling that addresses one of the major challenges in computer vision, which is how to recover fine-grained details when enlarging low-resolution images.



Generator Architecture

Each convolutional layer is followed by batch normalization and Parametric ReLU (PReLU) activation
 3×3 kernels and 64 feature maps

Discriminator Architecture

The discriminator follows a structure, using eight convolutional layers with 3×3 kernels with two dense layers and a sigmoid activation function

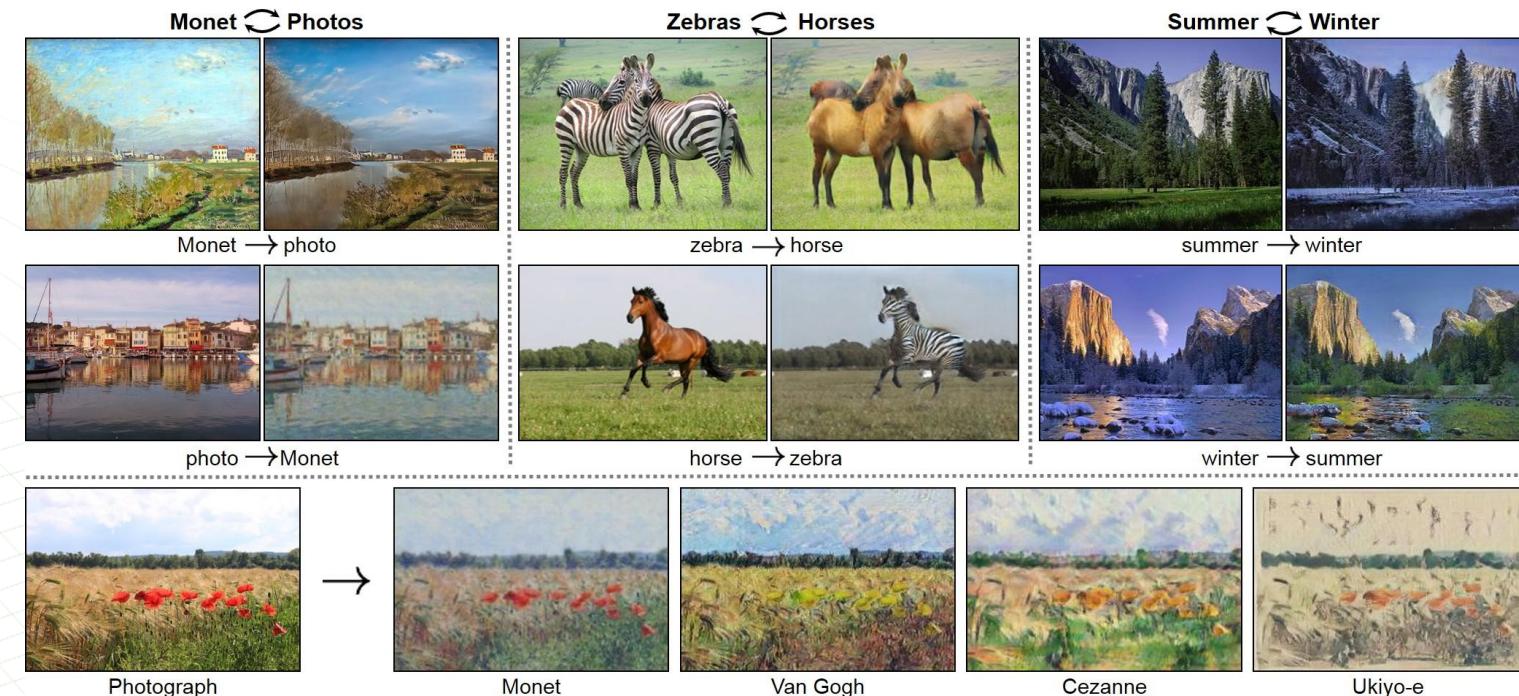


Neural Networks 類神經網路 - GAN

GAN 可以用在甚麼地方：

GAN 可以用於**圖像生成**、**圖像轉換**、**圖像修復**、**圖像超分辨率**、**圖像去噪**、**圖像增強**等。圖像轉換例如把馬的照片與斑馬的照片轉換、把圖片變成畢卡索的畫風等；**圖像修復**即將一張帶有瑕疵或者不完整的圖片給修復成完整圖片；**圖像超分辨率**是將一張低解析度的圖片轉為高解析度的圖片，例如永遠都是144p畫質的尼斯湖水怪可以使用這個技術轉換成1080p高清無碼的尼斯湖水怪（但目前沒有實際圖片，所以生成內容還是會根據餵給AI訓練的資料集生成）。**圖像去噪**就是把圖片噪聲或污染物從圖像中去除，以提高圖像的品質和信噪比。**圖像增強**是將圖像的某些特徵或屬性進行改善或增強，以提高圖像的視覺效果和感知質量，例如把一張爬山的照片中將山上的霧氣消除並且提高照片的色彩與對比度等等。

- 圖片生成
(DeepFake 、人臉生成)
- AI 作畫 (AI 藝術生成)
- 語音合成
(Text-to-Speech , TTS)
- 音樂創作 (AI 自動作曲)
- 數據增強
(Data Augmentation)
- 遊戲場景生成、模擬器生成虛擬環境



Jonathan Chen



Neural Networks 類神經網路 - GAN

GAN可以用在甚麼地方：

Prediction of next frame in a Video



Text to image generation

A Flower With Red Petals And Green Leaves

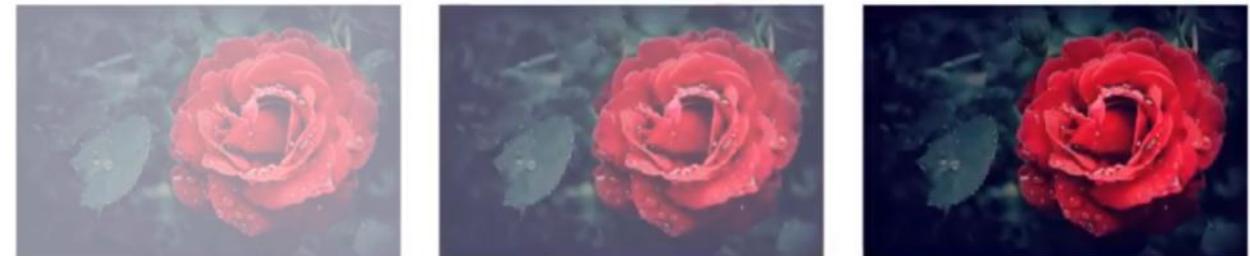


Image to image translation



Real



Generated



Reconstructed

Enhancing the resolution of an image





Neural Networks 類神經網路 - GAN

不同種類的GAN之間的關係

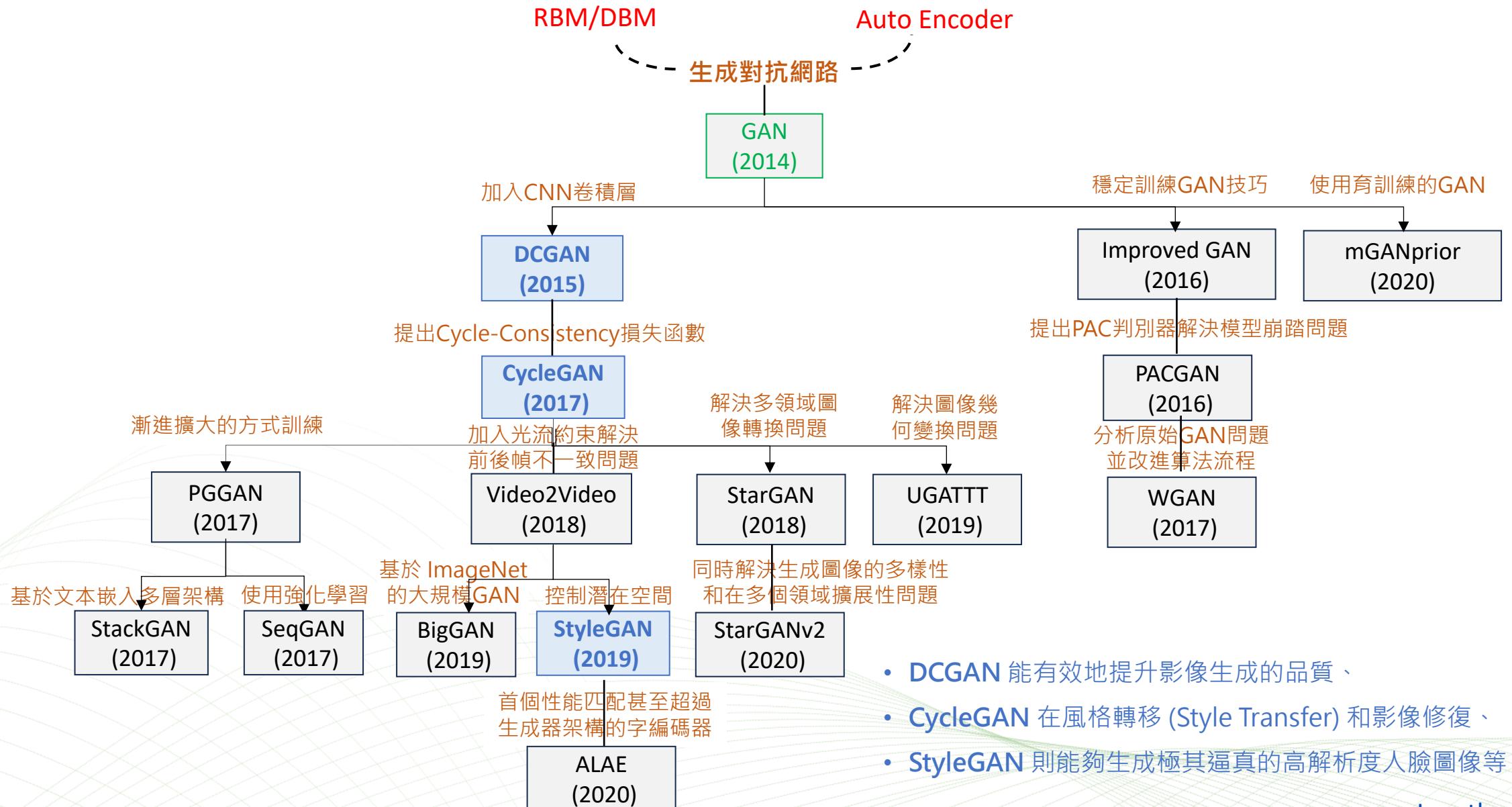
GAN 的代表變體		InfoGAN, cGANs, CycleGAN, f-GAN, WGAN, WGAN-GP, LS-GAN
GAN 的訓練	目標函數	LSGANs, hinge loss based GAN, MDGAN, unrolled GAN, SN-GANs, RGANs
	技巧	ImprovedGANs, AC-GAN
	結構	LAPGAN, DCGANs, PGGAN, StackedGAN, SAGAN, BigGANs, GANs training StyleGAN, hybrids of autoencoders and GANs (EBGAN, BEGAN, BiGAN /ALI, AGE), multi-discriminator learning (D2GAN, GMAN), multi-generator learning (MGAN, MAD-GAN), multi-GAN learning (CoGAN)
任務導向的 GAN	半監督學習	CatGANs, feature matching GANs, VAT, Δ -GAN, Triple-GAN
	遷移學習	DANN, CycleGAN, DiscoGAN, DualGAN, StarGAN, CyCADA, ADDA, FCAN, unsupervised pixel-level domain adaptation (PixelDA)
	強化學習	GAIL

在應用方面，GAN也有不同的種類

領域	子領域	方法
影像處理及電腦視覺	超解析度	SRGAN, ESRGAN, Cycle-in-Cycle GANs, SRDGAN, TGAN
	影像合成和處理	DR-GAN, TP-GAN, PG2, PSGAN, APDrawingGAN, IGAN, introspective adversarial networks, GauGAN
	紋理合成	MGAN, SGAN, PSGAN
	物件偵測	Segan, perceptual GAN, MTGAN
	影片	VGAN, DRNET, Pose-GAN, video2video, MoCoGan
序列資料	自然語言處理	RankGAN, IRGAN, TAC-GAN
	音樂	RNN-GAN (C-RNN-GAN), ORGAN, SeqGAN



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