AI & ML

張家瑋 博士

助理教授

國立臺中科技大學資訊工程系

FOUNDATIONS OF NATURAL LANGUAGE PROCESSING
自然語言處理的原理與應用

自然語言處理的主要範疇

- 機器翻譯 (Machine Translation)
- 自然語言理解/語意分析 (Natural Language Understanding / Semantic Analysis)
  1. 問答系統 (Question Answering)
  2. 萃取式摘要 (Extractive Summarization)
  3. 文件分類 (Text Categorization)
- 自然語言生成 (Natural Language Generation)
  1. 進階問答系統 (Advanced Question Answering)
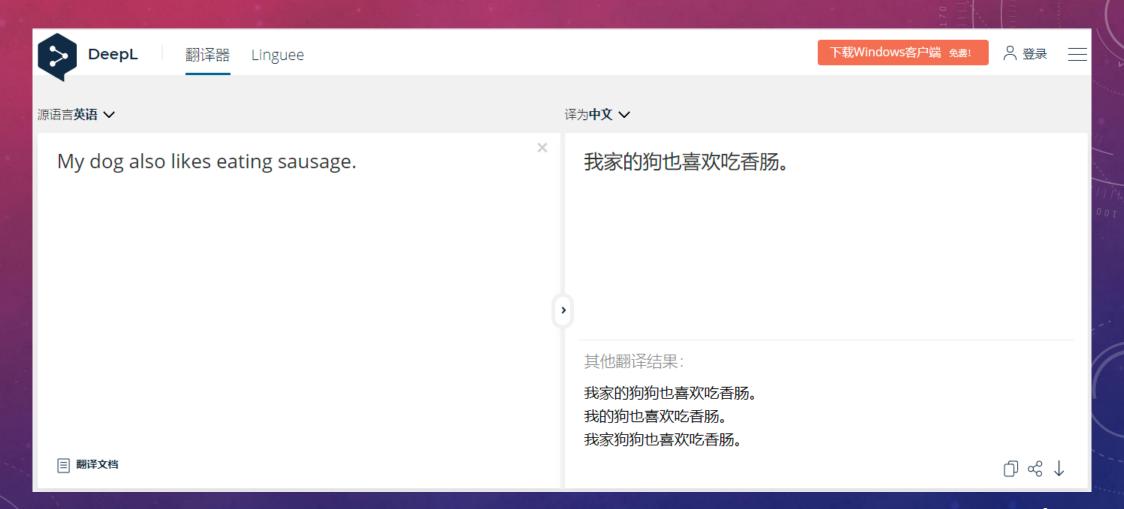 2. 抽象式摘要 (Abstractive Summarization)
  3. 聊天機器人 (Chatbot)

- 語法分析 (Syntactic Parsing)
  1. 中文斷詞 (Chinese word segmentation)
  2. 詞性標註 (Part-of-speech Tagging)
  3. 實體辨識 (Named Entity Recognition)
  4. 詞彙依存 (Typed Dependencies)
  5. 文法樹 (Parse Tree)
- 語音辨識 (Speech Recognition)
- 文字轉語音 (Text to Speech)
- 語音轉文字 (Speech to Text)

機器翻譯
MACHINE TRANSLATION

GOOGLE 翻譯

DEEP L

平行語料

統計式機器翻譯之原理

Quiero ir a la playa más bonita.
I want to go to the beach more pretty.
We just replace each Spanish word with the matching English word.
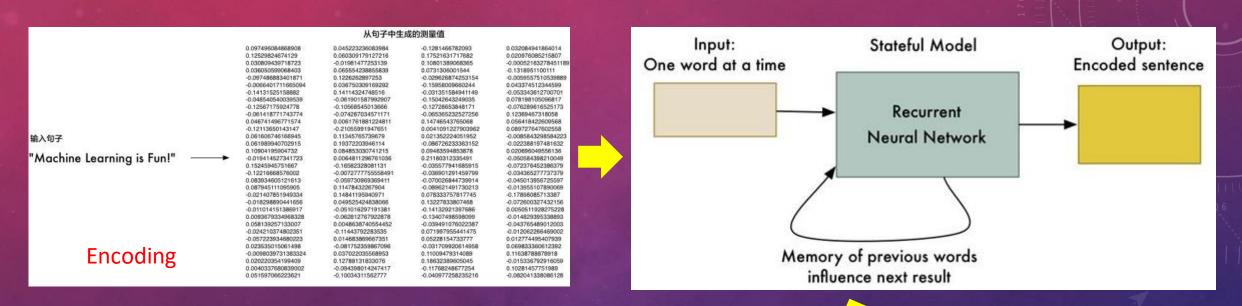
Quiero ir a la playa más bonita.
- I want   - to go   - to   - the beach   - more pretty
- I love   - to work   - at   - the seaside   - most pretty
- I like   - to run   - per   - the open space   - more lovely
- I try   - to appear   - most lovely
- I mean   - to be on   - more tidy
            - to be   - most tidy
            - to leave
            - to pass away
            - to forget
Even the most common phrases have lots of possible translations.
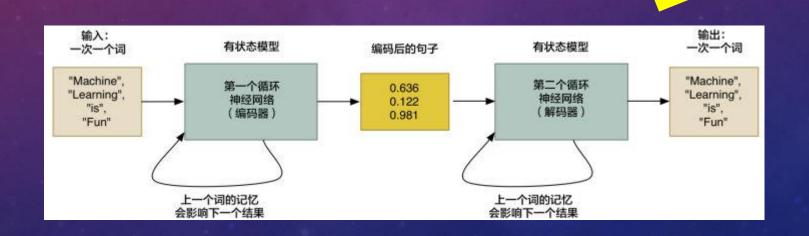
Swap order of nouns and adjectives
Quiero ir a la playa más bonita.
I want   to go   to   the   prettiest beach.

深度學習於機器翻譯之原理

Encoding

深度學習於機器翻譯之原理

Encoding

Encoder

Decoder
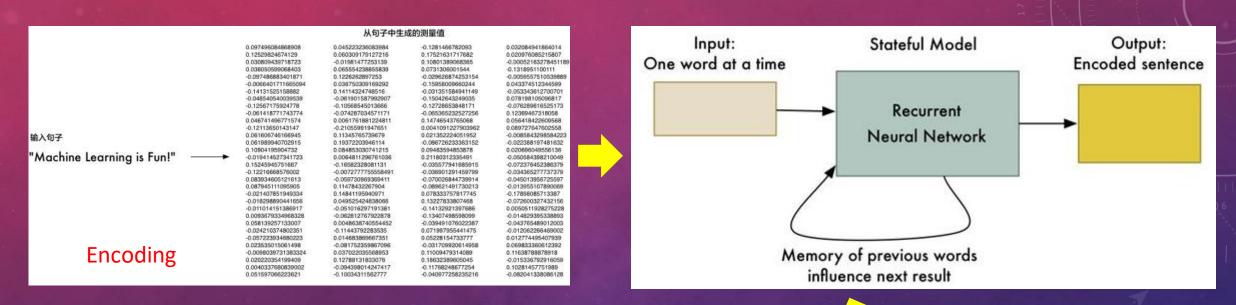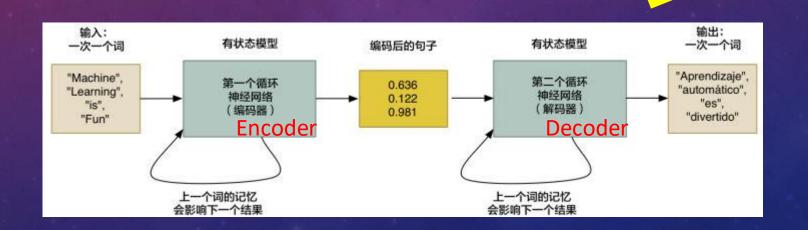
自然語言理解
NATURAL LANGUAGE UNDERSTANDING

VECTOR REPRESENTATION

	w_1	w_2	w_3	..	..	..	w_{n-1}	w_n	label
D_1	0.11	0.23	0	..	..	..	0.57	0	0
D_2	0	0	0	..	..	..	0.29	0.7	1
D_3	0	0.81	0.44	..	..	..	0	0	0
D_4	0	0.37	0	..	..	..	0	0.16	1
..	..	..	..	..	..	..	..	..	..
D_k	..	..	..	..	..	..	..	..	1

TF-IDF

- TF: term frequency: $tf_{i,j} = \dfrac{n_{i,j}}{\sum_k n_{k,j}}$

- IDF: inverse document frequency: $idf_i = \log \dfrac{|D|}{|\{j : t_i \in d_j\}|}$

where:

- |D|: total number of documents in the corpus
- $|\{j : t_i \in d_j\}|$: number of documents where term t_i appears

Then:

- $tfidf_{i,j} = tf_{i,j} \times idf_i$

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Document 1		Document 2	
Term	Term Count	Term	Term Count
this	1	this	1
is	1	is	1
a	2	another	2
sample	1	example	3

- The calculation of tf–idf for the term "this" is performed as follows:
-
$$\text{tf}(''\text{this}'', d_1) = \frac{1}{5} = 0.2$$
$$\text{tf}(''\text{this}'', d_2) = \frac{1}{7} \approx 0.14$$

$$\text{idf}(''\text{this}'', D) = \log\left(\frac{2}{2}\right) = 0$$

- So tf–idf is zero for the word "this", which implies that the word is not very informative as it appears in all documents.

$$\text{tfidf}(''\text{this}'', d_1) = 0.2 \times 0 = 0$$
$$\text{tfidf}(''\text{this}'', d_2) = 0.14 \times 0 = 0$$

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Document 1			Document 2	
Term	Term Count		Term	Term Count
this	1		this	1
is	1		is	1
a	2		another	2
sample	1		example	3

- A slightly more interesting example arises from the word "example", which occurs three times only in the second document:

  -
$$\text{tf}(''\text{example}'', d_1) = \frac{0}{5} = 0$$

  $$\text{idf}(''\text{example}'', D) = \log\left(\frac{2}{1}\right) = 0.301$$

  -
$$\text{tf}(''\text{example}'', d_2) = \frac{3}{7} \approx 0.429$$

$$\text{tfidf}(''\text{example}'', d_1) = \text{tf}(''\text{example}'', d_1) \times \text{idf}(''\text{example}'', D) = 0 \times 0.301 = 0$$
$$\text{tfidf}(''\text{example}'', d_2) = \text{tf}(''\text{example}'', d_2) \times \text{idf}(''\text{example}'', D) = 0.429 \times 0.301 \approx 0.13$$

潛藏語意分析(LSA)

- 奇異值分解
  - Singular Value Decomposition (SVD)

潛藏語意分析(LSA)

- 文件分類/主題探勘
- 語意分析

XY Plot of Words and Titles
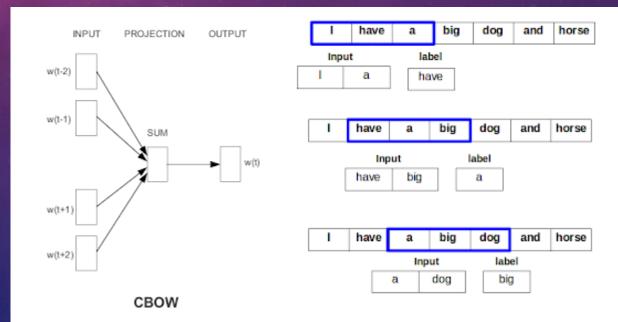
Index Words	Titles								
	T1	T2	T3	T4	T5	T6	T7	T8	T9
book			1	1					
dads						1			1
dummies		1						1	
estate							1		1
guide	1					1			
investing	1	1	1	1	1	1	1	1	1
market	1		1						
real							1		1
rich						2			1
stock	1		1					1	
value				1	1				

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文字檔案

word2vec

將被拆解成多個字元

透過向量比對
找出相似的資料

Input:
one document

Model:

kite

space

dog

netherlands
spain france
belgium italy

water

house

vector space

word
vectors

most_similar('france'):

spain   0.678515
belgium   0.665923
netherlands 0.652428
italy   0.633130

highest cosine
distance values
in vector space
of the nearest
words

解析成多元維度的向量
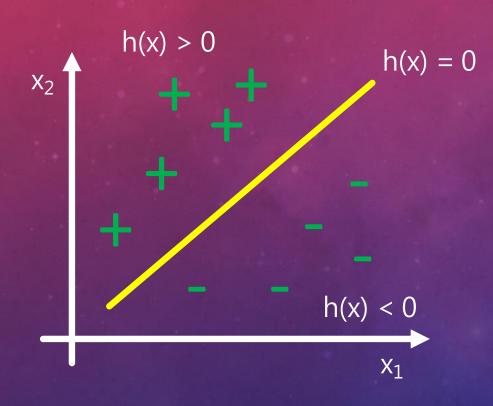
http://zongsoftwarenote.blogspot.com/2017/04/word2vec-model-introduction-skip-gram.html

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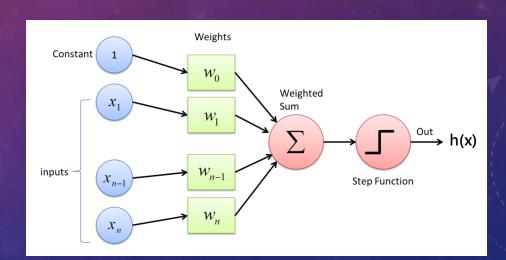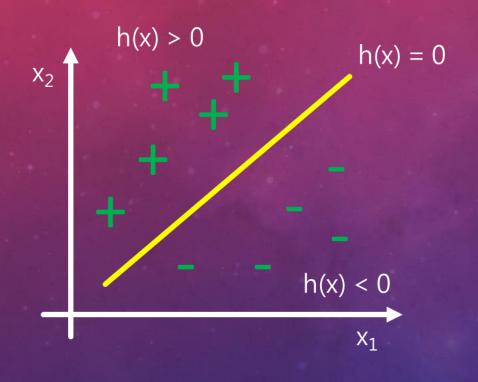
One Hot Encoding

```
The -> [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
cat -> [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
jump -> [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
over -> [0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
the -> [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
dog -> [0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
The -> [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
dog -> [0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
ate -> [0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
my -> [0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
homework -> [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
```

Perceptron Linear Algorithm

$h(x) > 0$

$h(x) = 0$

x_2

$h(x) < 0$

x_1

- Features: $x = (x_1, x_2)$
- Target: $y = +1$ or -1
- $h(x) = w_0 + w_1 x_1 + w_2 x_2$

Weights

Constant 1

w_0

x_1

w_1

Weighted Sum

Σ

Out

$h(x)$

Step Function

inputs

x_{n-1}

w_{n-1}

x_n

w_n

Perceptron Linear Algorithm

$h(x) > 0$

$h(x) = 0$

x_2

$h(x) < 0$

x_1
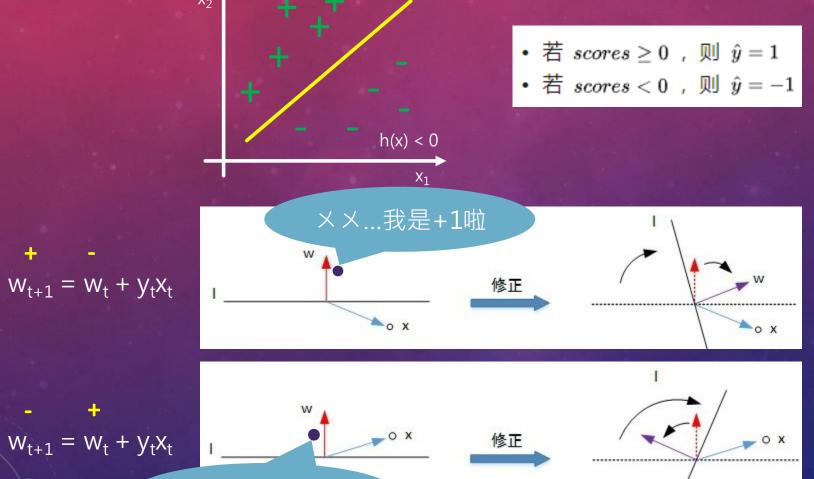
$h(x) = w_0 + w_1x_1 + w_2x_2$

$$scores = \sum_{i}^{N} w_i x_i + b$$

$$scores = \sum_{i}^{N+1} w_i x_i$$

- 若 $scores \geq 0$ ， 则 $\hat{y} = 1$
- 若 $scores < 0$ ， 则 $\hat{y} = -1$
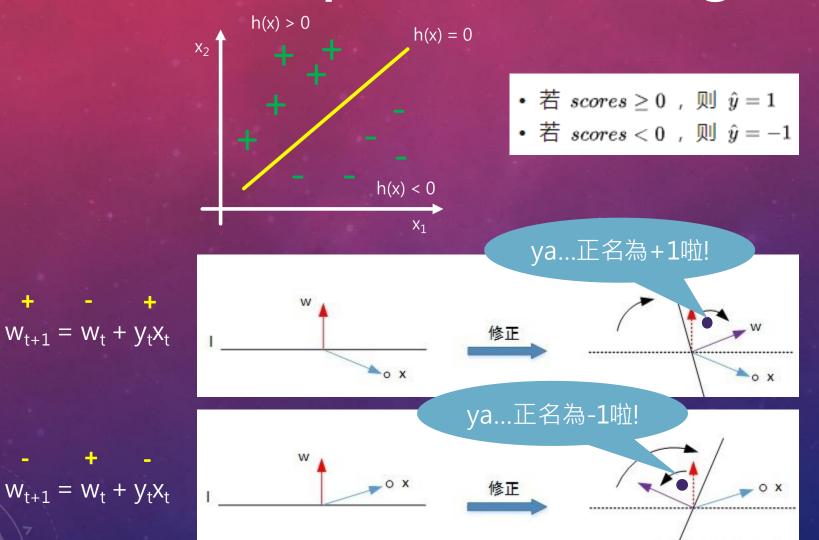
Perceptron Linear Algorithm

x_2

h(x) > 0

h(x) = 0

h(x) < 0

x_1

- 若 $scores \geq 0$ ，則 $\hat{y} = 1$
- 若 $scores < 0$ ，則 $\hat{y} = -1$

ㄨㄨ…我是+1啦

+　**-**

$w_{t+1} = w_t + y_t x_t$

修正

[Case 1]
y = 1 錯分成 y = -1

-　**+**

$w_{t+1} = w_t + y_t x_t$

修正

[Case 2]
y = -1 錯分成 y = 1

ㄨㄨ…我是-1啦

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Perceptron Linear Algorithm

h(x) > 0

x_2

h(x) = 0

h(x) < 0

x_1

- 若 $scores \geq 0$，則 $\hat{y} = 1$
- 若 $scores < 0$，則 $\hat{y} = -1$

+   -   +

$w_{t+1} = w_t + y_t x_t$

ya...正名為+1啦!

[Case 1]
y = 1 錯分成 y = -1

-    +   -

$w_{t+1} = w_t + y_t x_t$

ya...正名為-1啦!

[Case 2]
y = -1 錯分成 y = 1

$$\tan \alpha = \lim_{\Delta x \to 0} \tan \varphi = \lim_{\Delta x \to 0} \frac{f(x_0 + \Delta x) - f(x_0)}{\Delta x}$$

線性關係

代價函數為凸函數
初始值隨機選也能降到全域最小值

$J(w)$

初始權重

代價函數
最小值

$J_{min}(w)$

w
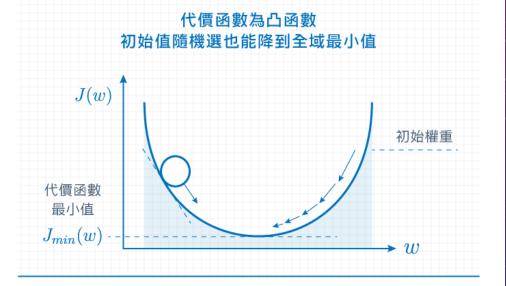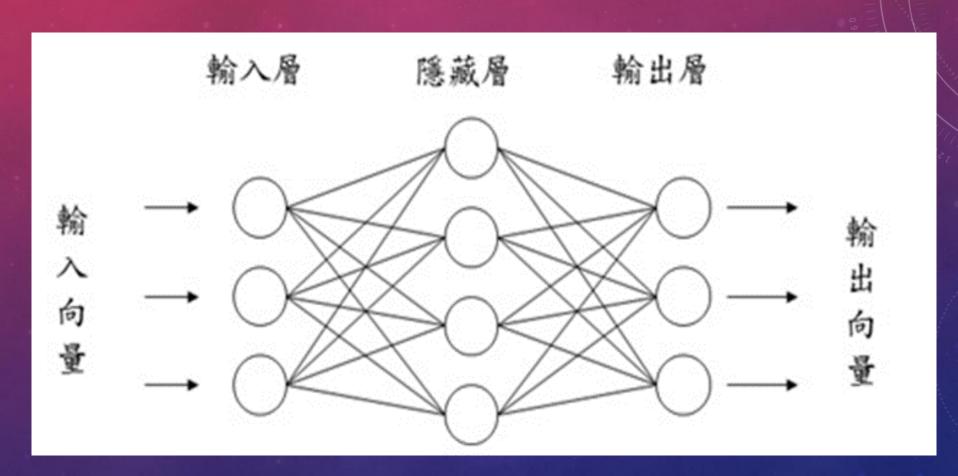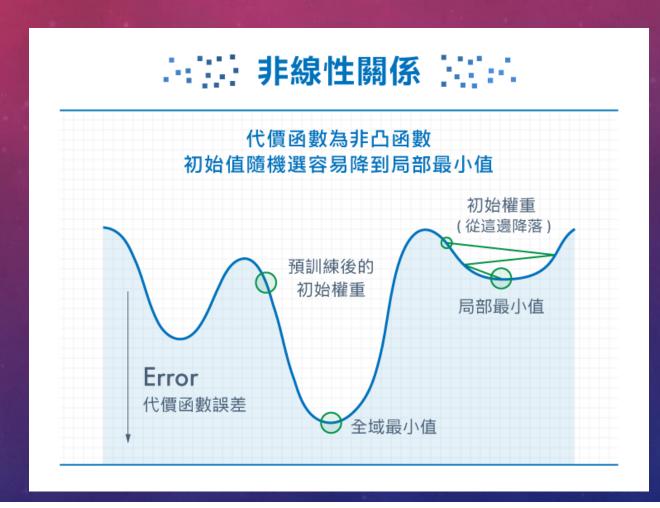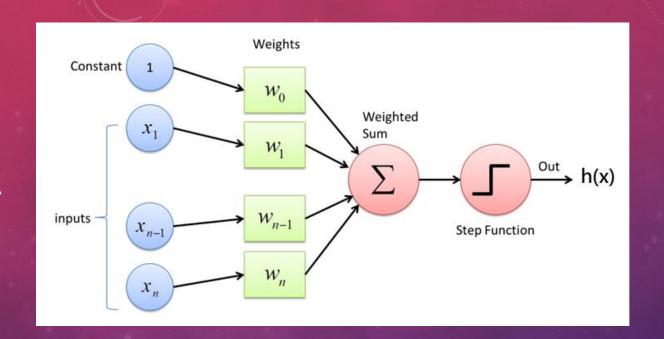
Multi-Layer Perceptron (MLP)
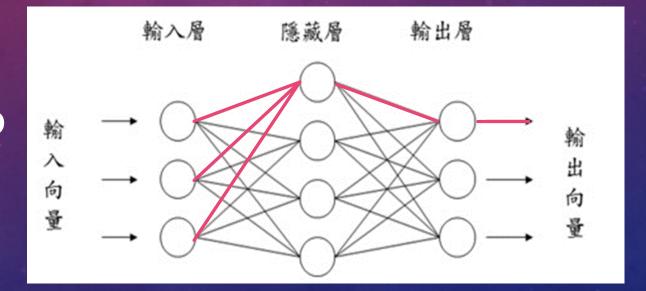
*線性組合 $w = a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_n v_n$

梯度消失

*現實世界的資料多為非線性，因此激活函數通常也是使用非線性函數(非凸函數)傳遞

PLA

MLP

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```
The -> [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
cat -> [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
jump -> [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
over -> [0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
the -> [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
dog -> [0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
The -> [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
dog -> [0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
ate -> [0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
my -> [0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
homework -> [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
```
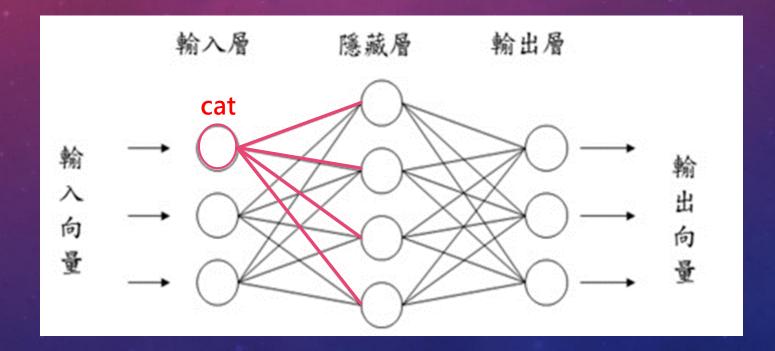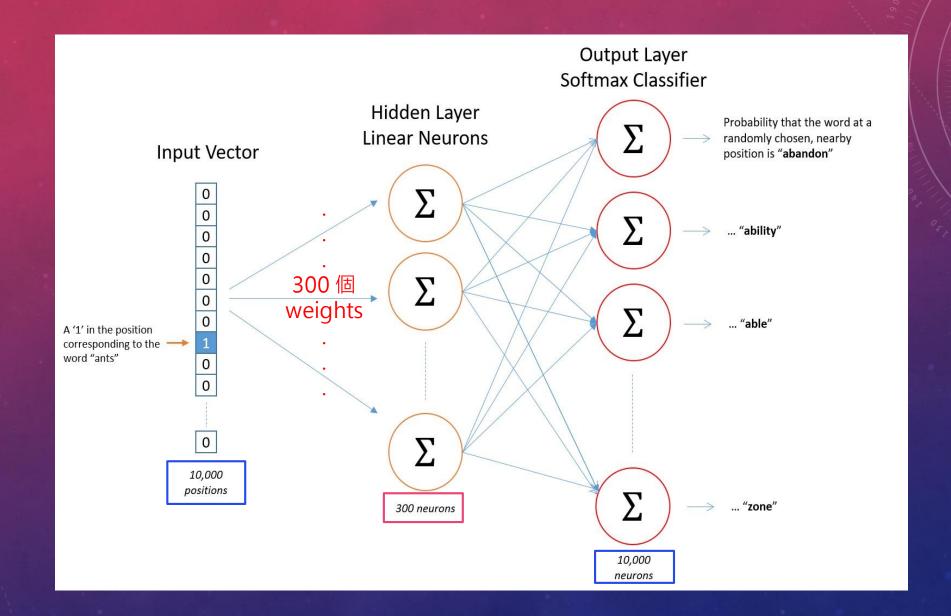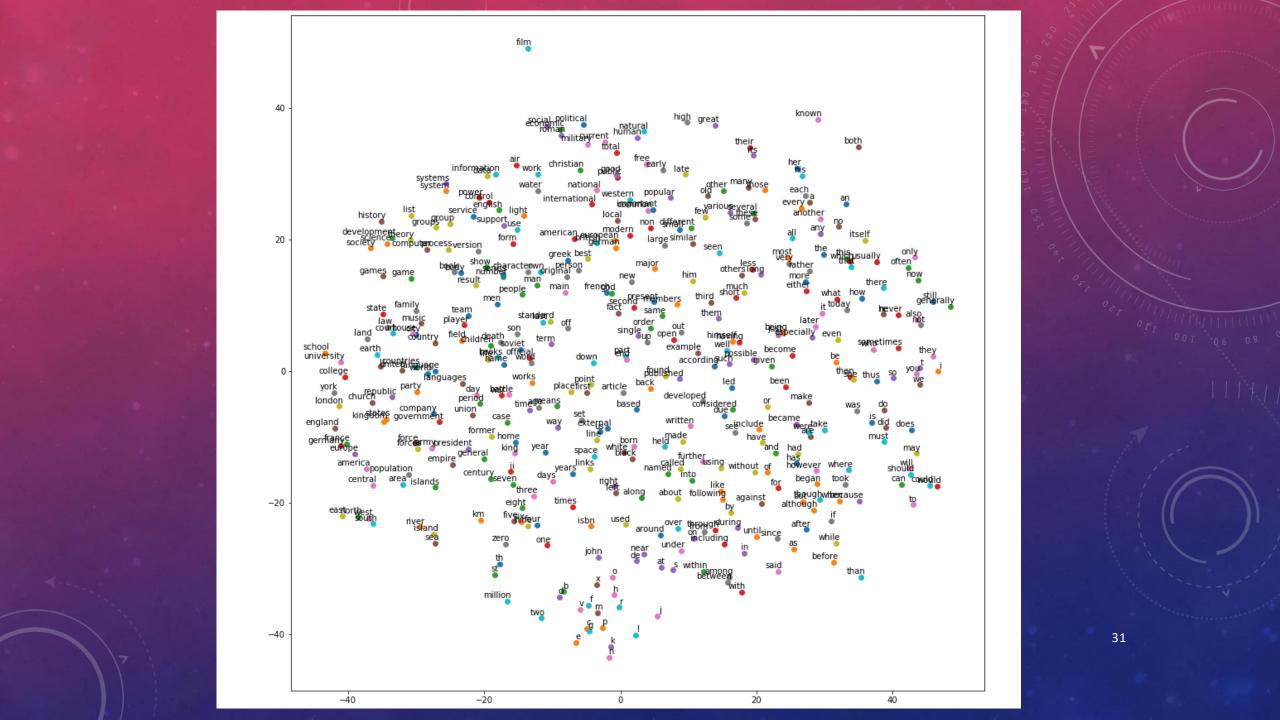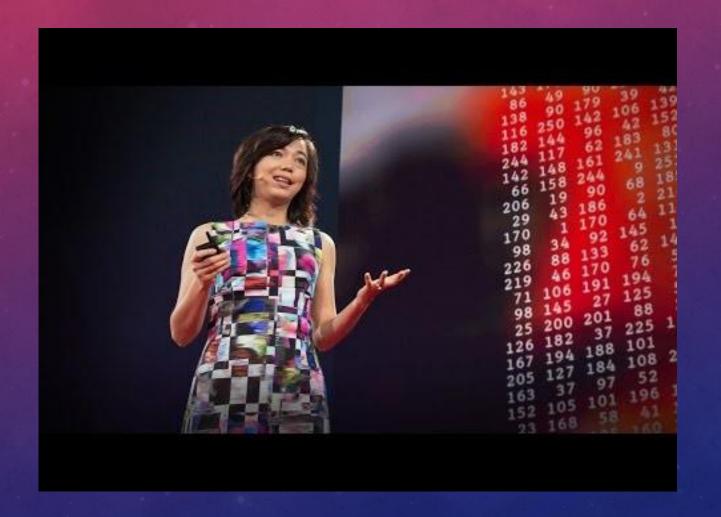
FOUNDATIONS OF COMPUTER VISION
電腦視覺的原理與應用

HOW WE TEACH COMPUTERS TO UNDERSTAND PICTURES

電腦視覺
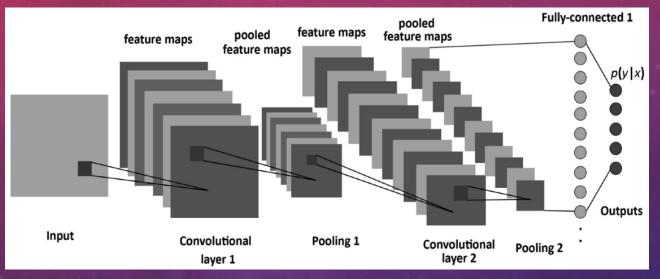
- 利用攝影機和電腦代替人眼對目標進行識別、跟蹤和測量等機器視覺，並做圖像處理，用電腦處理為更適合人眼觀察或傳送給儀器檢測的圖像。
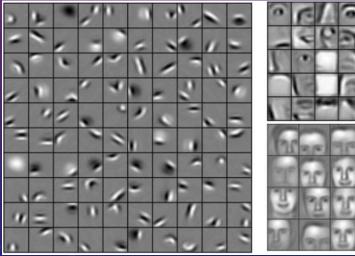
- 人工智慧的主要研究問題是：如何讓系統具備「計劃」和「決策能力」，使之完成特定的動作，如移動機器人通過特定環境。
  - 此問題中，電腦視覺可作為感知器，為決策提供資訊。其中研究方向包括模式識別和機器學習，因此電腦視覺被看作人工智慧的分支。
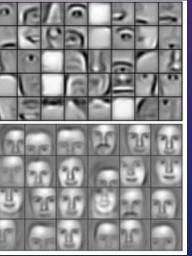
電腦視覺應用
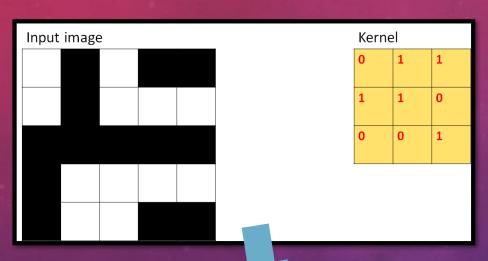
- 作為一個工程學科，電腦視覺基於相關理論來建立電腦視覺系統。這類系統的組成部分包括：
  1. 過程控制(Process Control)（如工業機器人和無人駕駛車）
  2. 事件監測(Event Monitoring)（如圖像監測）
  3. 資訊組織(Information Organization)（如圖像資料庫和圖像序列的索引建立）
  4. 物體與環境建模（如工業檢查，醫學圖像分析和拓撲建模）
  5. 交感互動（如人機互動的輸入裝置）
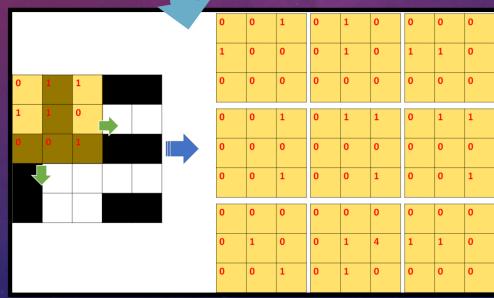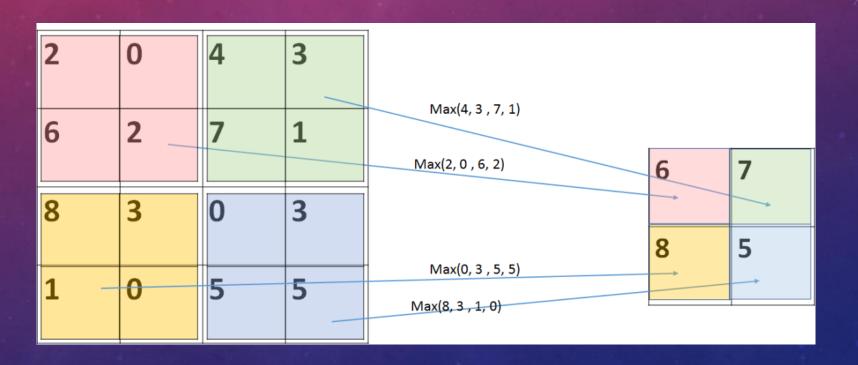
卷積神經網路
CONVOLUTIONAL NEURAL NETWORK

參考文獻

HTTPS://GOO.GL/FJVJG1

HTTPS://GOO.GL/Q5YKPK

CONVOLUTIONAL NEURAL NETWORK

CONVOLUTIONAL NEURAL NETWORK

卷積層的運作

CONVOLUTIONAL NEURAL NETWORK

最大池化層的運作

CONVOLUTIONAL NEURAL NETWORK
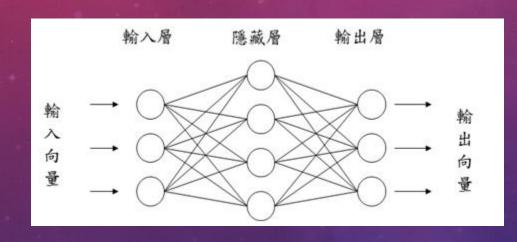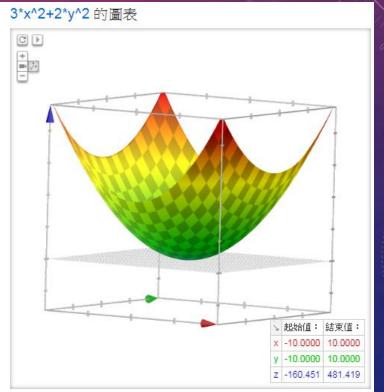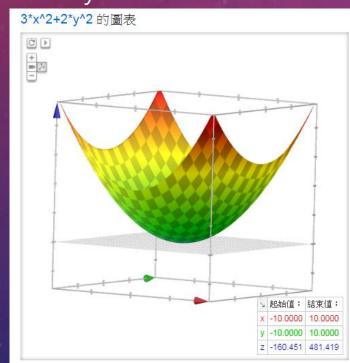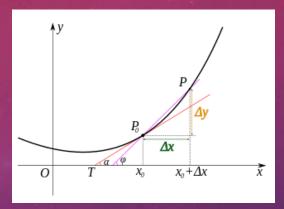
全連接層的運作

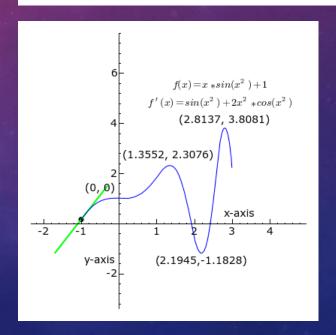$3x^2 + 2y^2$

全連接層的運作

$3x^2 + 2y^2$

$$\tan \alpha = \lim_{\Delta x \to 0} \tan \varphi = \lim_{\Delta x \to 0} \frac{f(x_0 + \Delta x) - f(x_0)}{\Delta x}$$

HOW COMPUTERS LEARN TO RECOGNIZE OBJECTS INSTANTLY

http://mropengate.blogspot.com/2018/06/yolo-yolov3.html

實際案例

貓狗辨識的結果

VIDEO TO VIDEO

The paper "Video-to-Video Synthesis" and its source code is available here:
https://tcwang0509.github.io/vid2vid/
https://github.com/NVIDIA/vid2vid

智慧視覺系統機器人

IVS可以偵測咖啡杯內的水位狀況

視覺整合信號轉換的體感操控機械手臂