


The background is a gradient of red and purple. On the left side, there are several concentric circles and arcs, some with degree markings (40, 150, 160, 170, 180, 190, 200, 210, 220, 230, 240, 250, 260) and arrows indicating a clockwise direction. The main title is centered on the right side.

多媒體數據分析 與應用

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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



翻譯 關閉即時翻譯 

英文 中文 日文 偵測語言 ▾

↔ 中文(繁體) 英文 中文(簡體) ▾ 翻譯

My dog also likes eating sausage.

33/5000

我的狗也喜歡吃香腸。

Wǒ de gǒu yě xǐhuān chī xiāngcháng.

 提出修改建議

DEEP L

 DeepL | 翻译器 | Linguee

下载Windows客户端 免费!  登录 

源语言英语 ▾ 译为中文 ▾

My dog also likes eating sausage.

×

我的狗也喜欢吃香肠。

其他翻译结果:

我家的狗狗也喜欢吃香肠。
我的狗也喜欢吃香肠。
我家狗狗也喜欢吃香肠。

 翻译文档

平行語料

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.

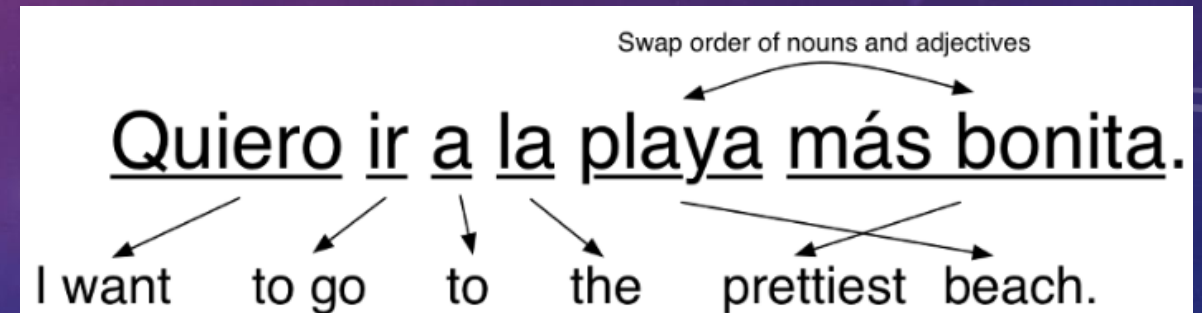
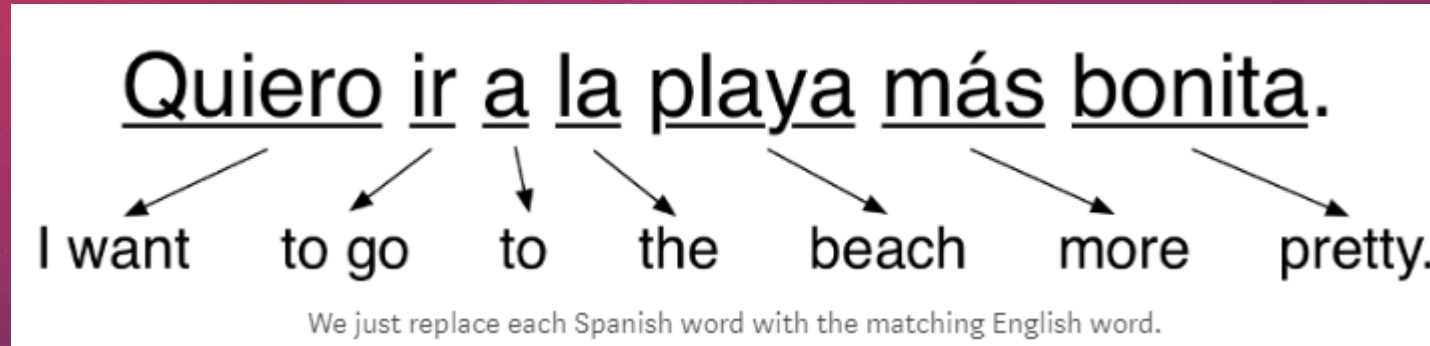


Swap order of nouns and adjectives

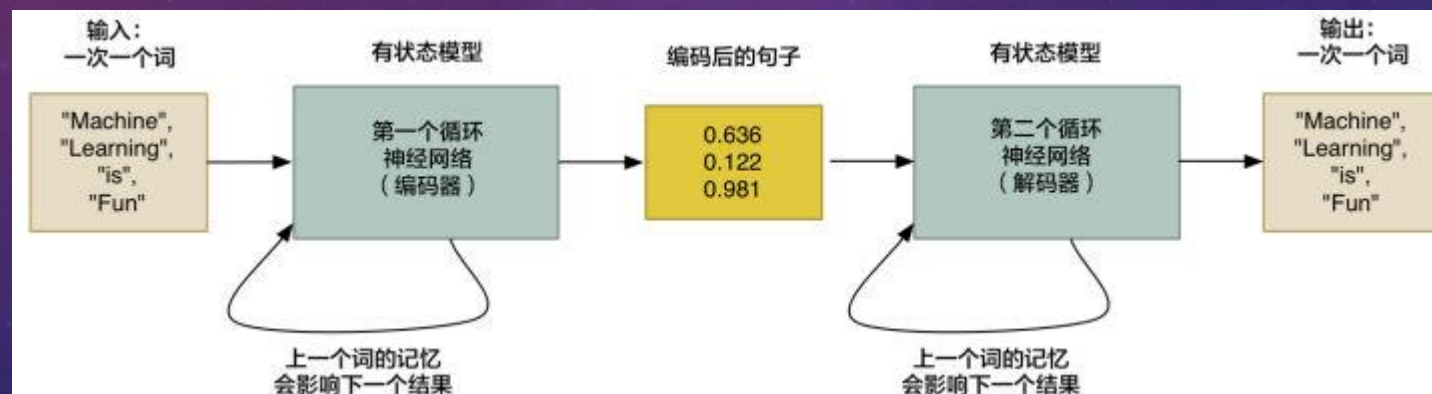
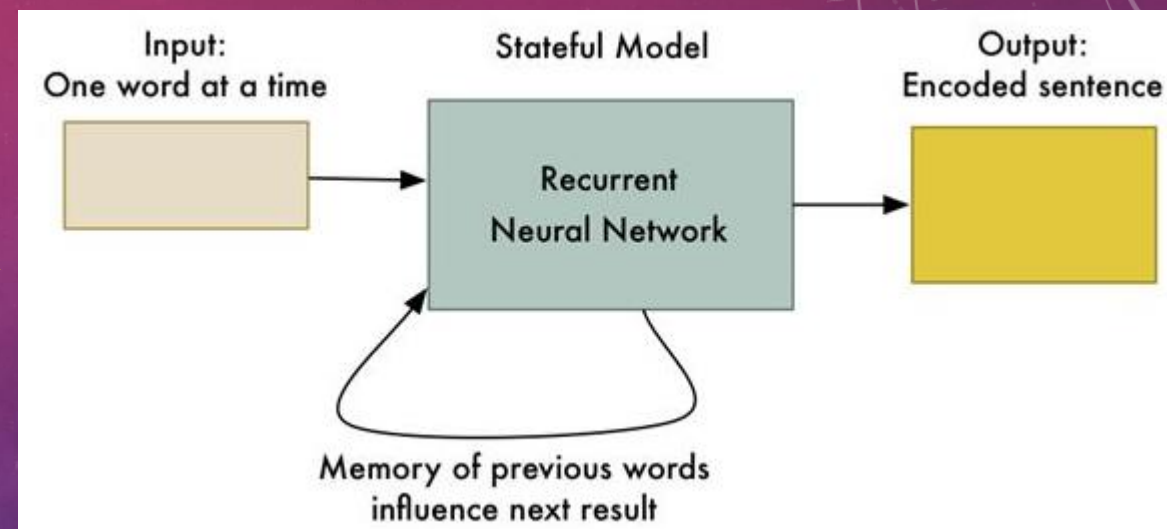
Quiero ir a la playa más bonita.

I want to go to the prettiest beach.

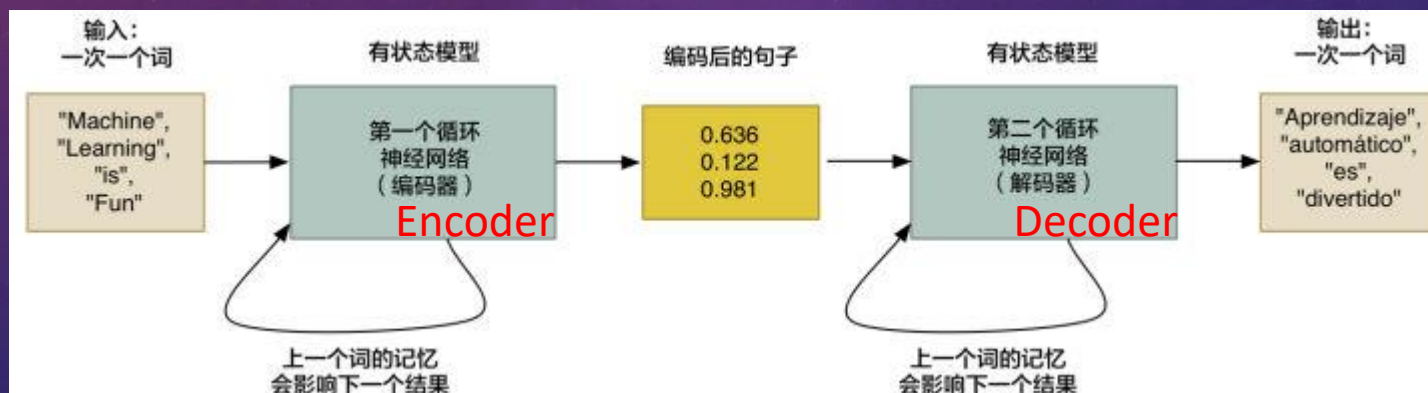
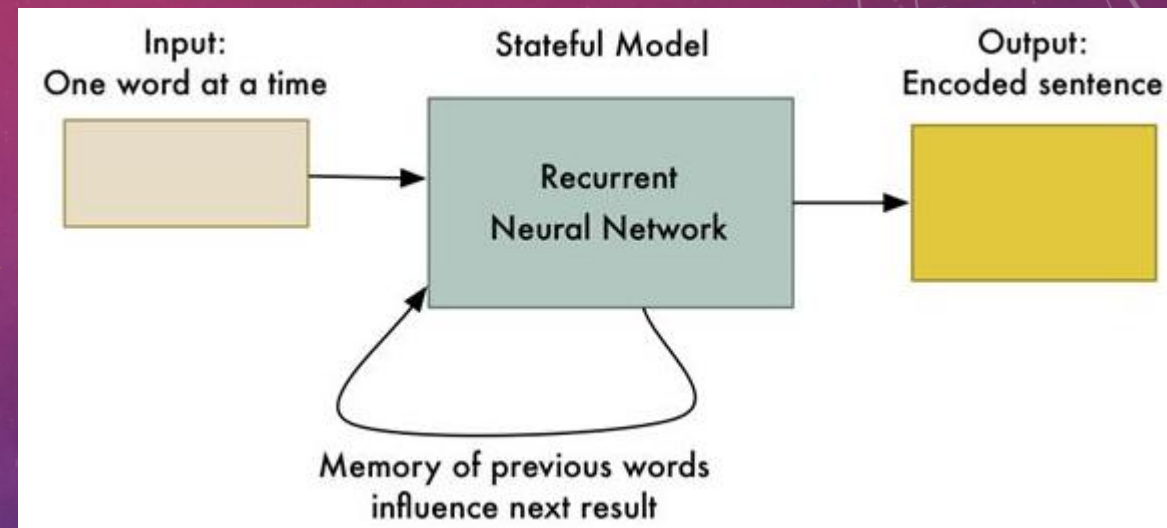
統計式機器翻譯之原理



深度學習於機器翻譯之原理



深度學習於機器翻譯之原理





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:
$$\text{tf}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$
 - IDF: inverse document frequency:
$$\text{idf}_i = \log \frac{|D|}{|\{j : t_i \in d_j\}|}$$
- where:
- $|D|$: total number of documents in the corpus
 - $|\{j : t_i \in d_j\}|$: number of documents where term t_i appears

Then:

- $$\text{tfidf}_{i,j} = \text{tf}_{i,j} \times \text{idf}_i$$

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:

$$\begin{aligned} \text{tf}(\text{"this"}, d_1) &= \frac{1}{5} = 0.2 \\ \text{tf}(\text{"this"}, d_2) &= \frac{1}{7} \approx 0.14 \end{aligned}$$

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

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

$$\begin{aligned} \text{tfidf}(\text{"this"}, d_1) &= 0.2 \times 0 = 0 \\ \text{tfidf}(\text{"this"}, d_2) &= 0.14 \times 0 = 0 \end{aligned}$$

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:

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

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

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

$$\begin{aligned} \text{tfidf}(\text{"example"}, d_1) &= \text{tf}(\text{"example"}, d_1) \times \text{idf}(\text{"example"}, D) = 0 \times 0.301 = 0 \\ \text{tfidf}(\text{"example"}, d_2) &= \text{tf}(\text{"example"}, d_2) \times \text{idf}(\text{"example"}, D) = 0.429 \times 0.301 \approx 0.13 \end{aligned}$$

潛藏語意分析(LSA)

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

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				

=

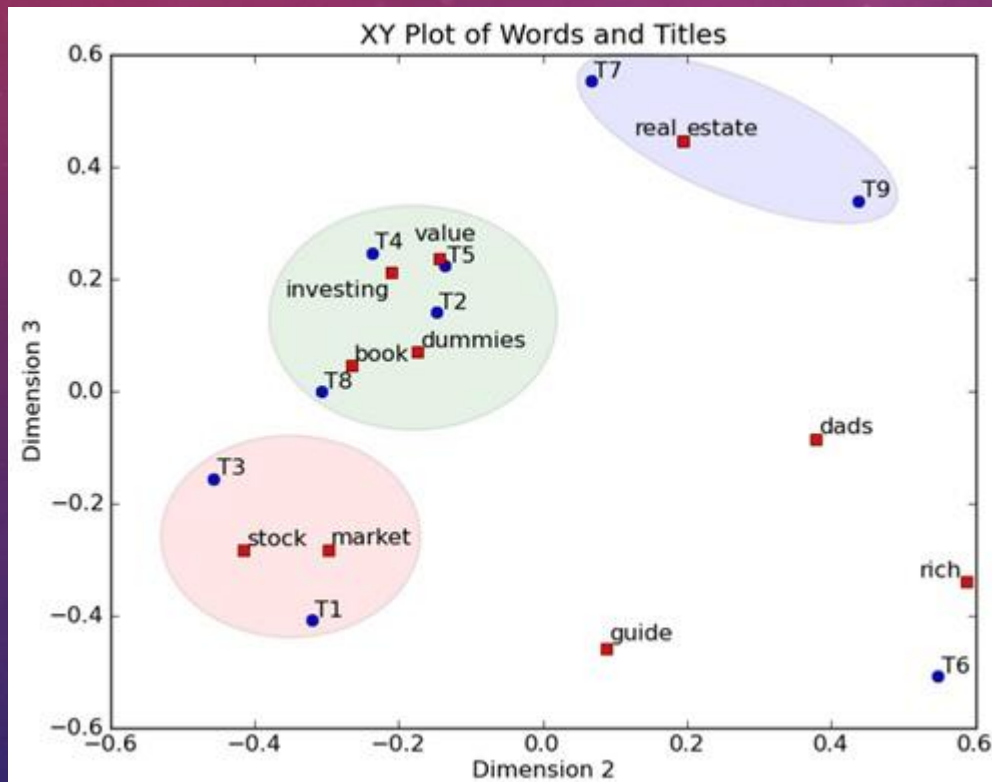
book	0.15	-0.27	0.04
dads	0.24	0.38	-0.09
dummies	0.13	-0.17	0.07
estate	0.18	0.19	0.45
guide	0.22	0.09	-0.46
investing	0.74	-0.21	0.21
market	0.18	-0.30	-0.28
real	0.18	0.19	0.45
rich	0.36	0.59	-0.34
stock	0.25	-0.42	-0.28
value	0.12	-0.14	0.23

3.91	0	0
0	2.61	0
0	0	2.00

T1	T2	T3	T4	T5	T6	T7	T8	T9
0.35	0.22	0.34	0.26	0.22	0.49	0.28	0.29	0.44
-0.32	-0.15	-0.46	-0.24	-0.14	0.55	0.07	-0.31	0.44
-0.41	0.14	-0.16	0.25	0.22	-0.51	0.55	0.00	0.34

潛藏語意分析(LSA)

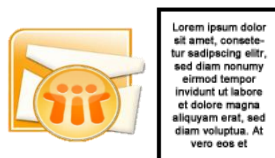
- 文件分類/主題探勘
- 語意分析



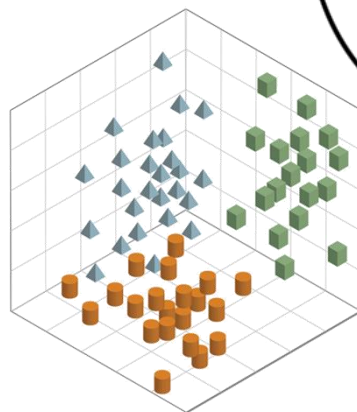
Index Words	Titles								
	T1	T2	T3	T4	T5	T6	T7	T8	T9
book			1	1					
dads						1			1
dummies		1						1	
estate							1		1
guide	1					1			
investing	1	1	1	1	1	1	1	1	1
market	1		1						
real							1		1
rich						2			1
stock	1		1					1	
value				1	1				

文字檔案

Input:
one document



word
vectors



word2vec

將被拆解成多個字元

Model:



vector space

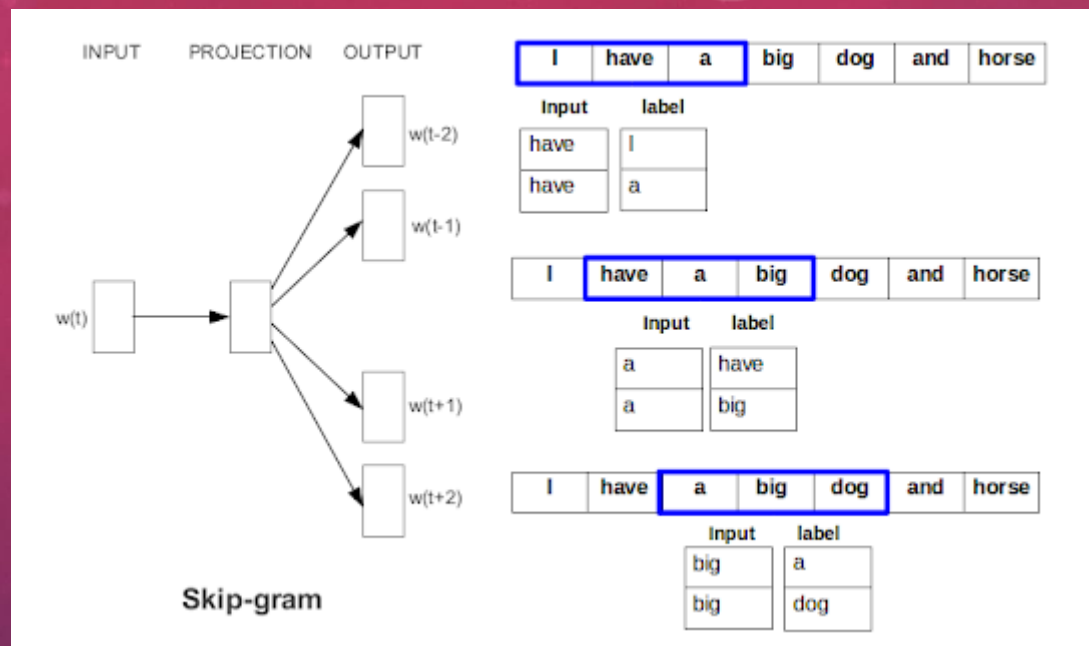
解析成多元維度的向量

透過向量比對
找出相似的資料

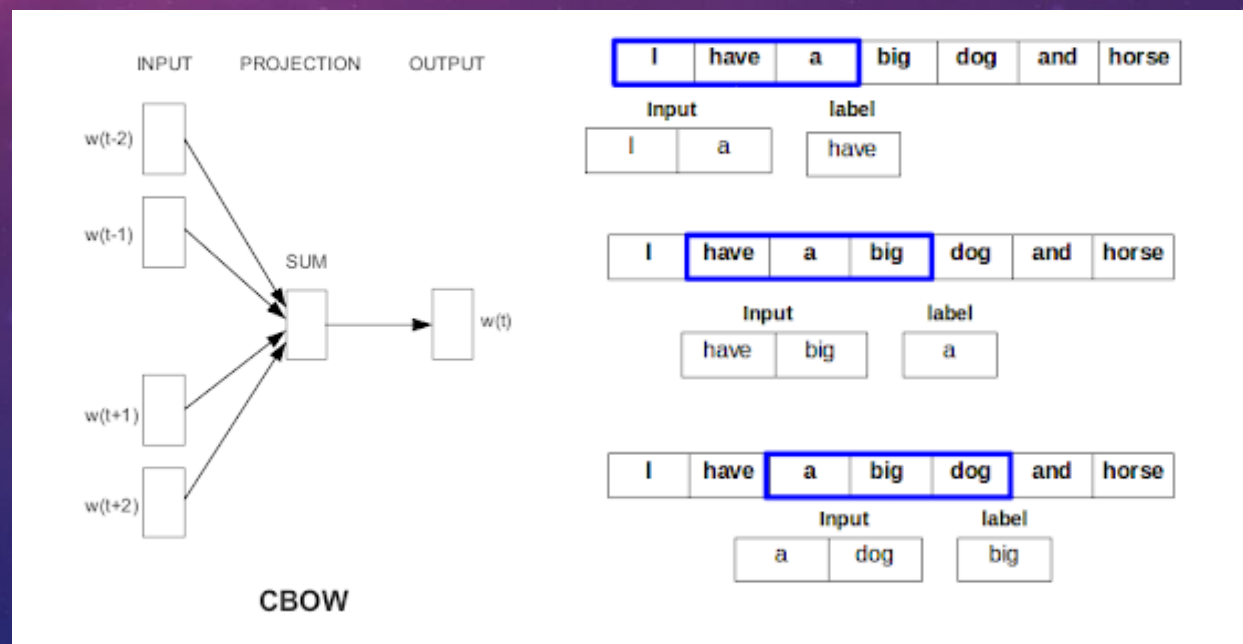
most_similar('france'):

spain	0.678515
belgium	0.665923
netherlands	0.652428
italy	0.633130

highest cosine
distance values
in vector space
of the nearest
words



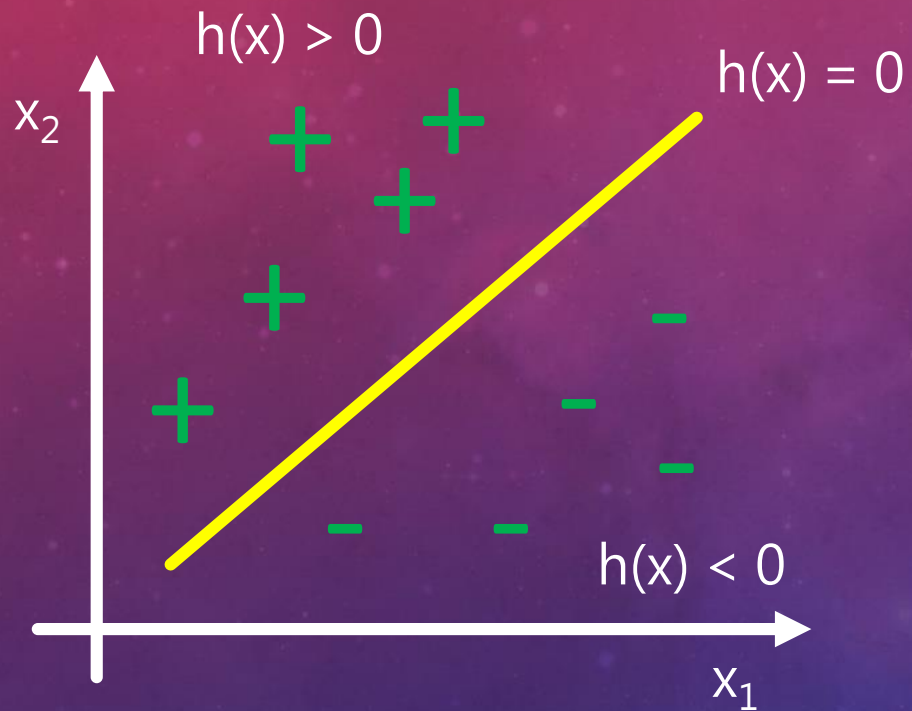
<http://zongsoftwarenote.blogspot.com/2017/04/word2vec-model-introduction-skip-gram.html>



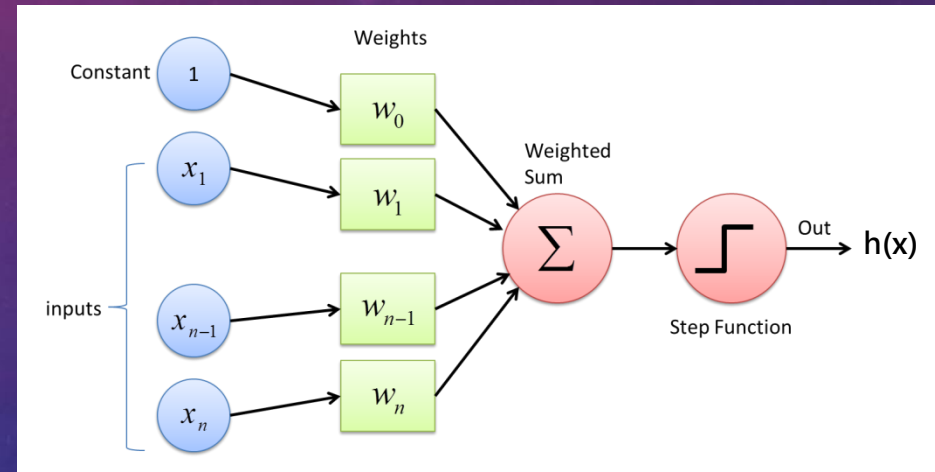
One Hot Encoding

```
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. 0. 1.]
```

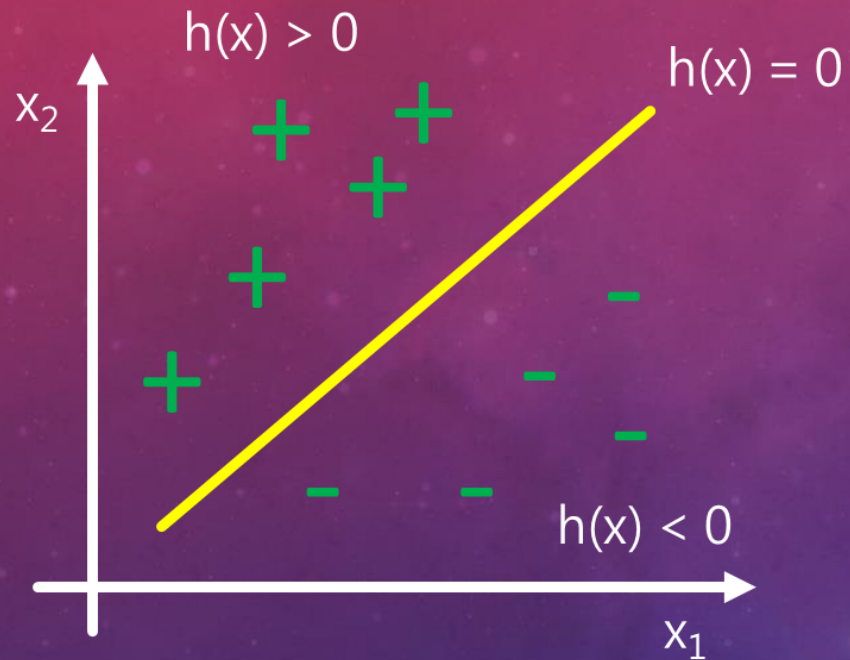

Perceptron Linear Algorithm



- Features: $x = (x_1, x_2)$
- Target: $y = +1$ or -1
- $h(x) = w_0 + w_1x_1 + w_2x_2$



Perceptron Linear Algorithm

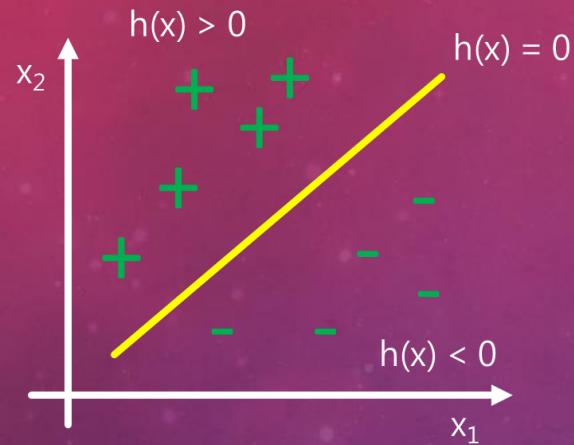


$$scores = \sum_i^N w_i x_i + b$$

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

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

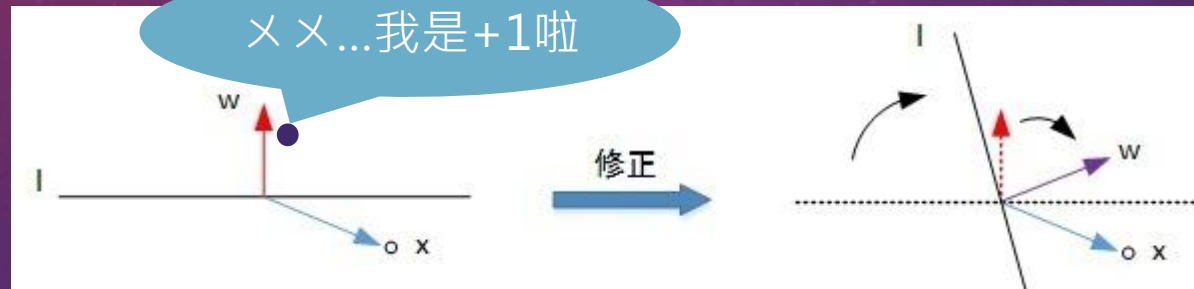
Perceptron Linear Algorithm



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

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

(Note: The '+' sign in the equation is yellow, and the '-' sign is black, corresponding to the labels in the adjacent diagram.)



[Case 1]
 $y = 1$ 錯分成 $y = -1$

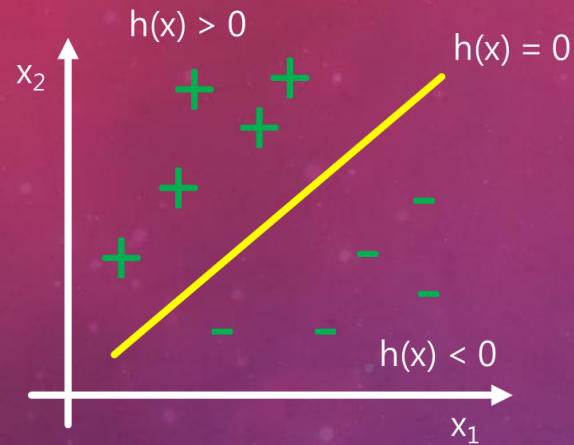
$$w_{t+1} = w_t + y_t x_t$$

(Note: The '-' sign in the equation is yellow, and the '+' sign is black, corresponding to the labels in the adjacent diagram.)



[Case 2]
 $y = -1$ 錯分成 $y = 1$

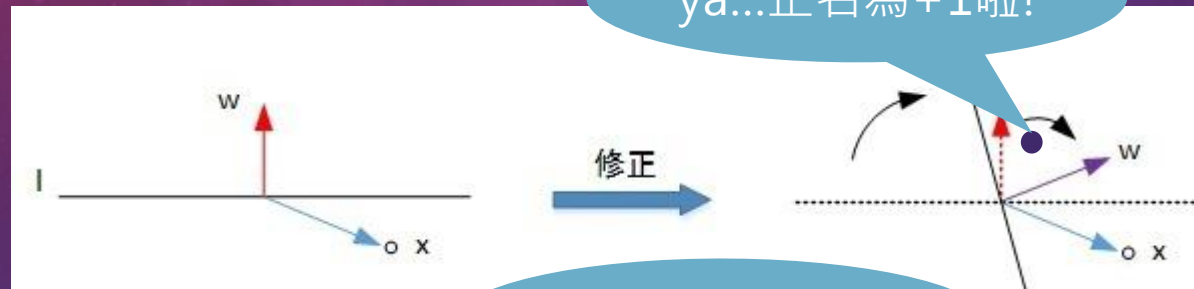
Perceptron Linear Algorithm



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

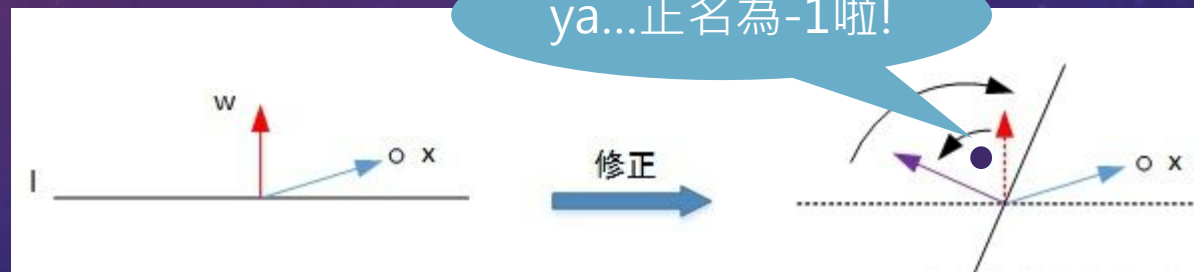
$$\overset{+}{w_{t+1}} = \overset{-}{w_t} + \overset{+}{y_t} x_t$$

$$\overset{-}{w_{t+1}} = \overset{+}{w_t} + \overset{-}{y_t} x_t$$



ya...正名為+1啦!

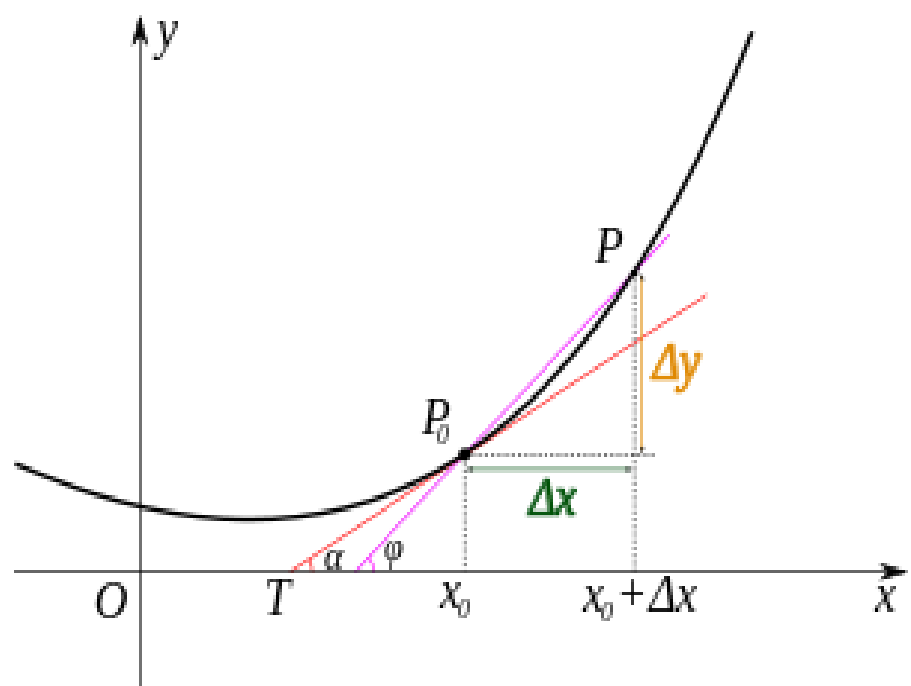
[Case 1]
 $y = 1$ 錯分成 $y = -1$



ya...正名為-1啦!

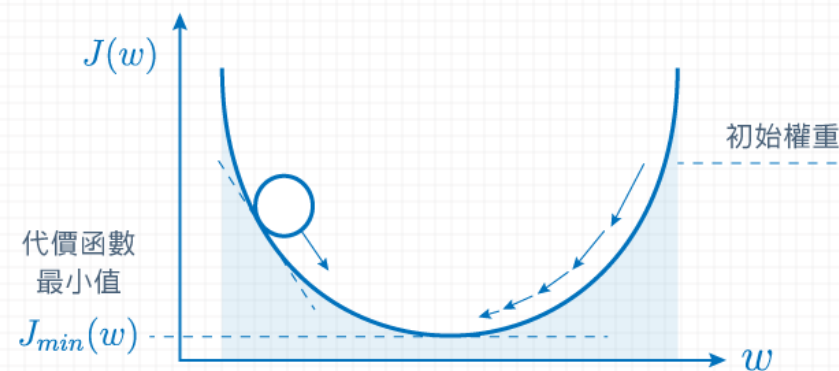
[Case 2]
 $y = -1$ 錯分成 $y = 1$

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

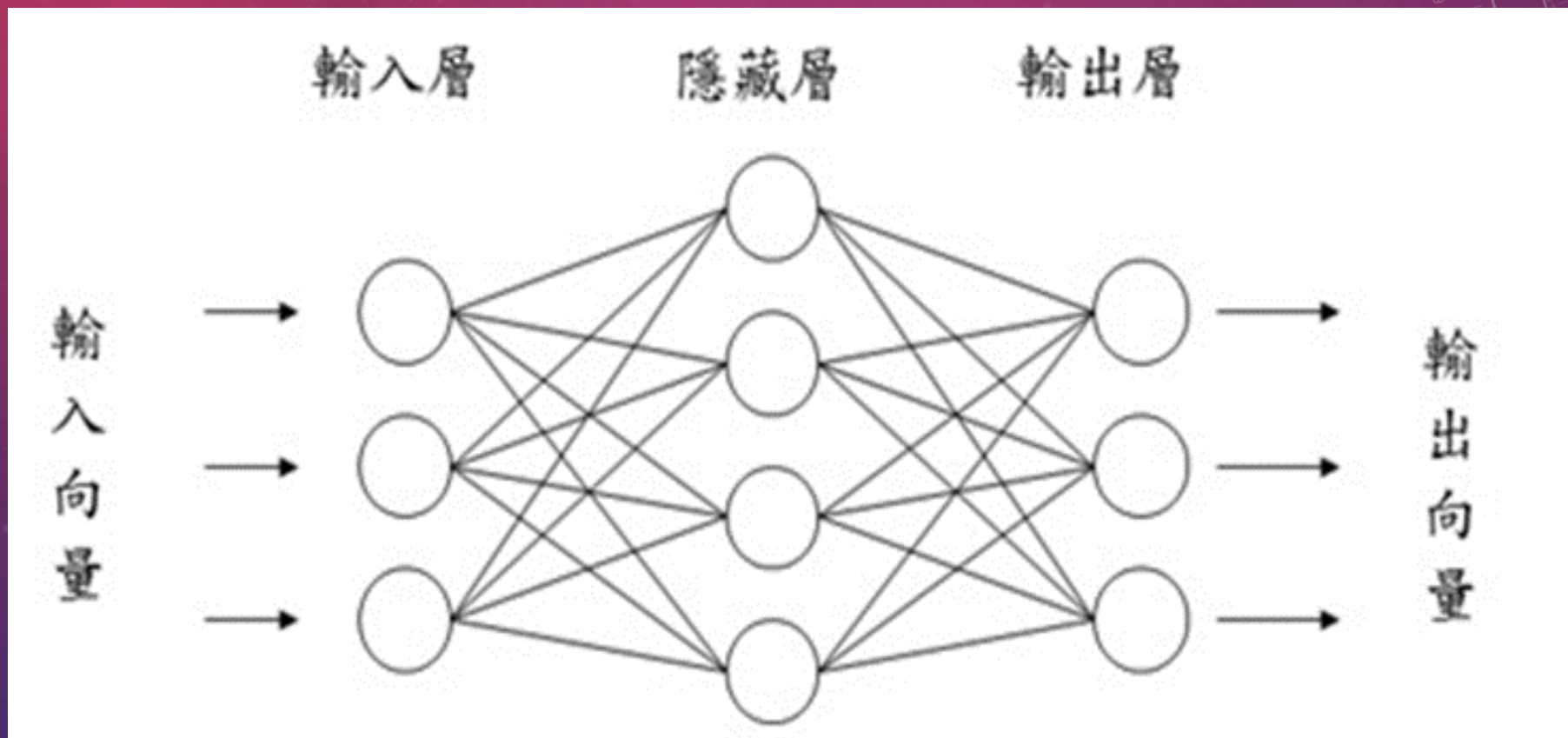


线性關係

代價函數為凸函數
初始值隨機選也能降到全域最小值



Multi-Layer Perceptron (MLP)

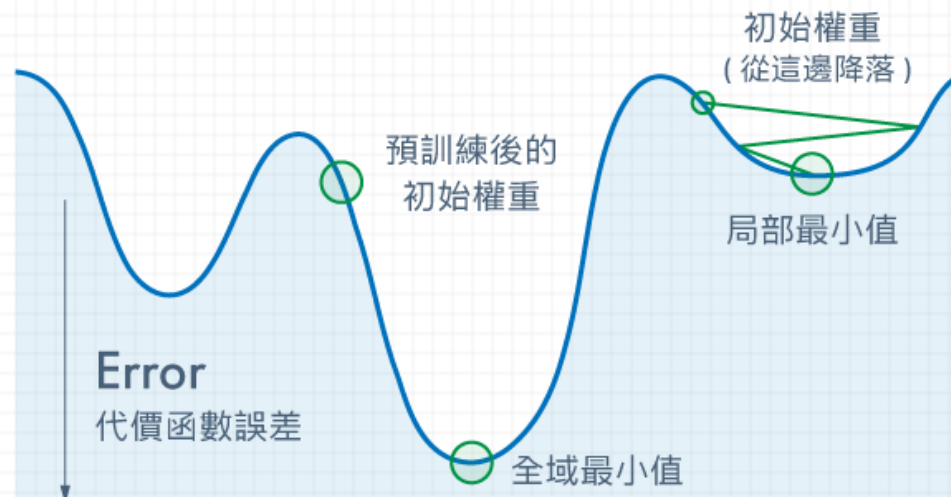


*線性組合 $w = a_1v_1 + a_2v_2 + a_3v_3 + \cdots + a_nv_n$

梯度消失

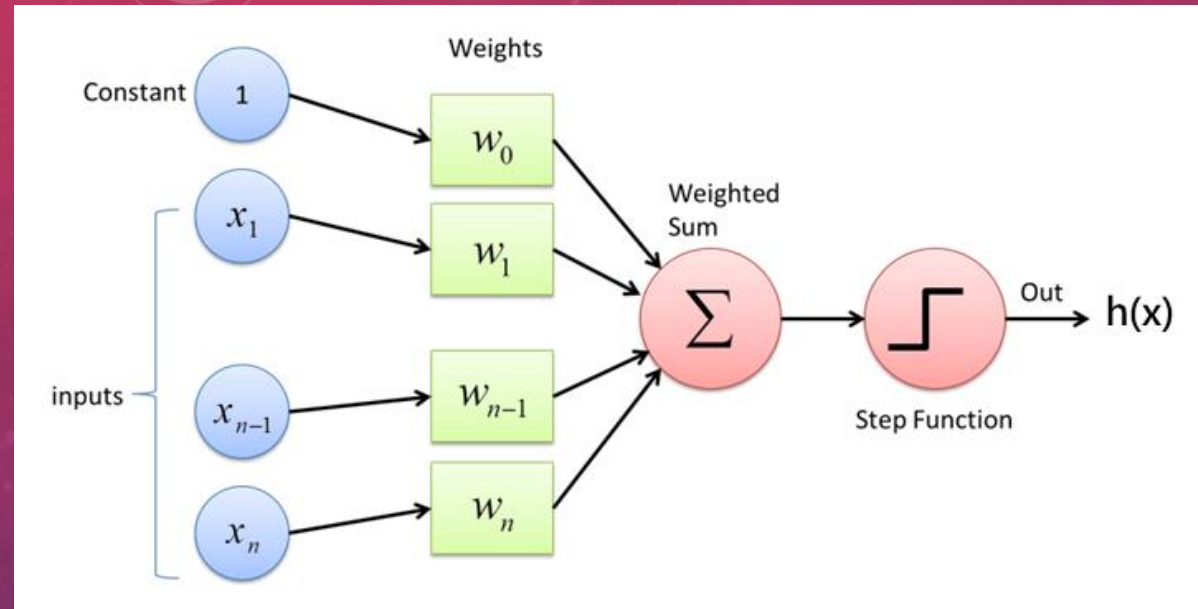
非線性關係

代價函數為非凸函數
初始值隨機選容易降到局部最小值

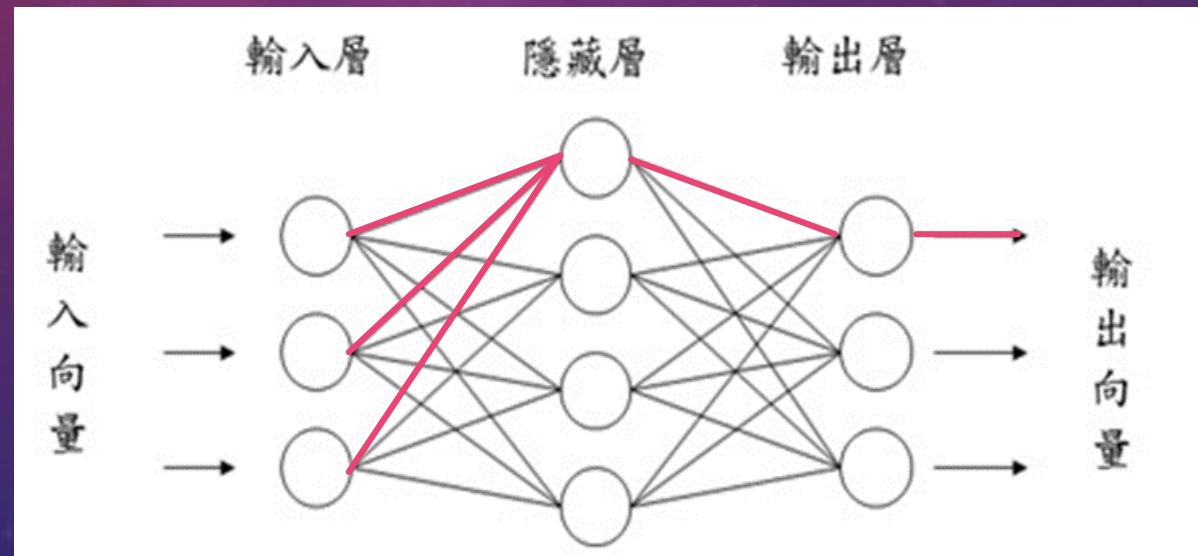


*現實世界的資料多為非線性，因此激活函數通常也是使用非線性函數(非凸函數)傳遞

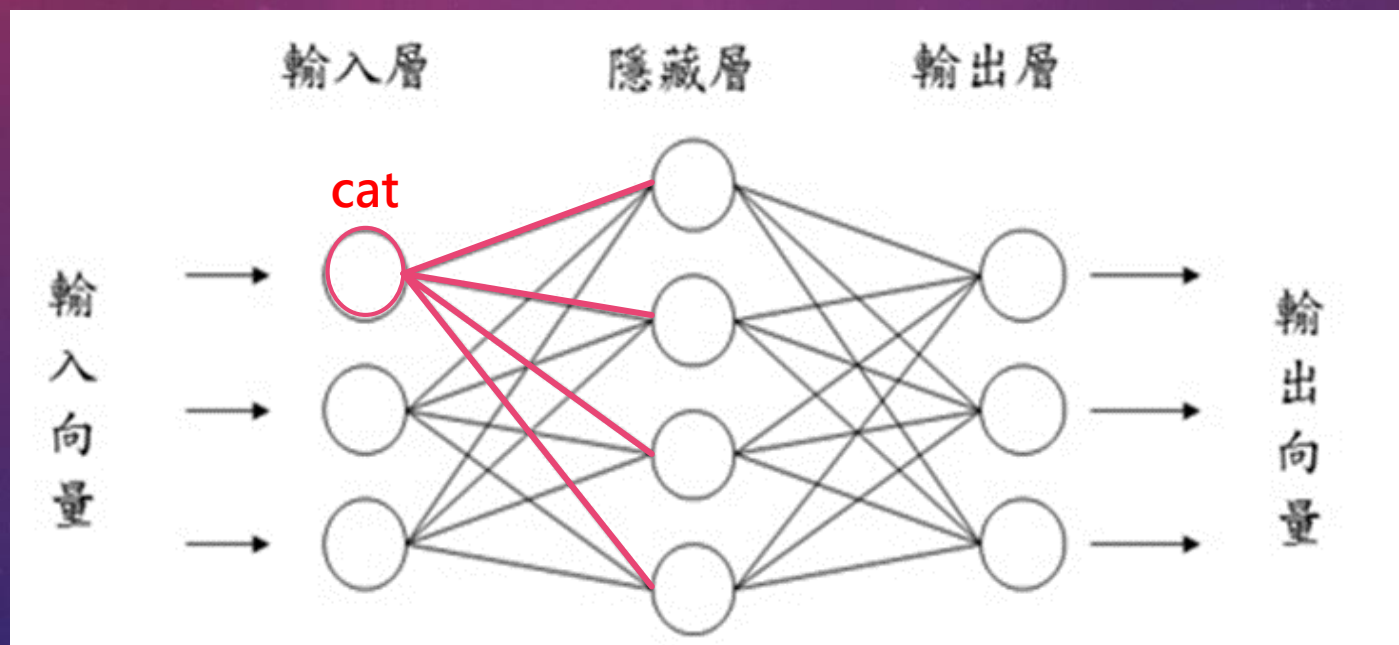
PLA

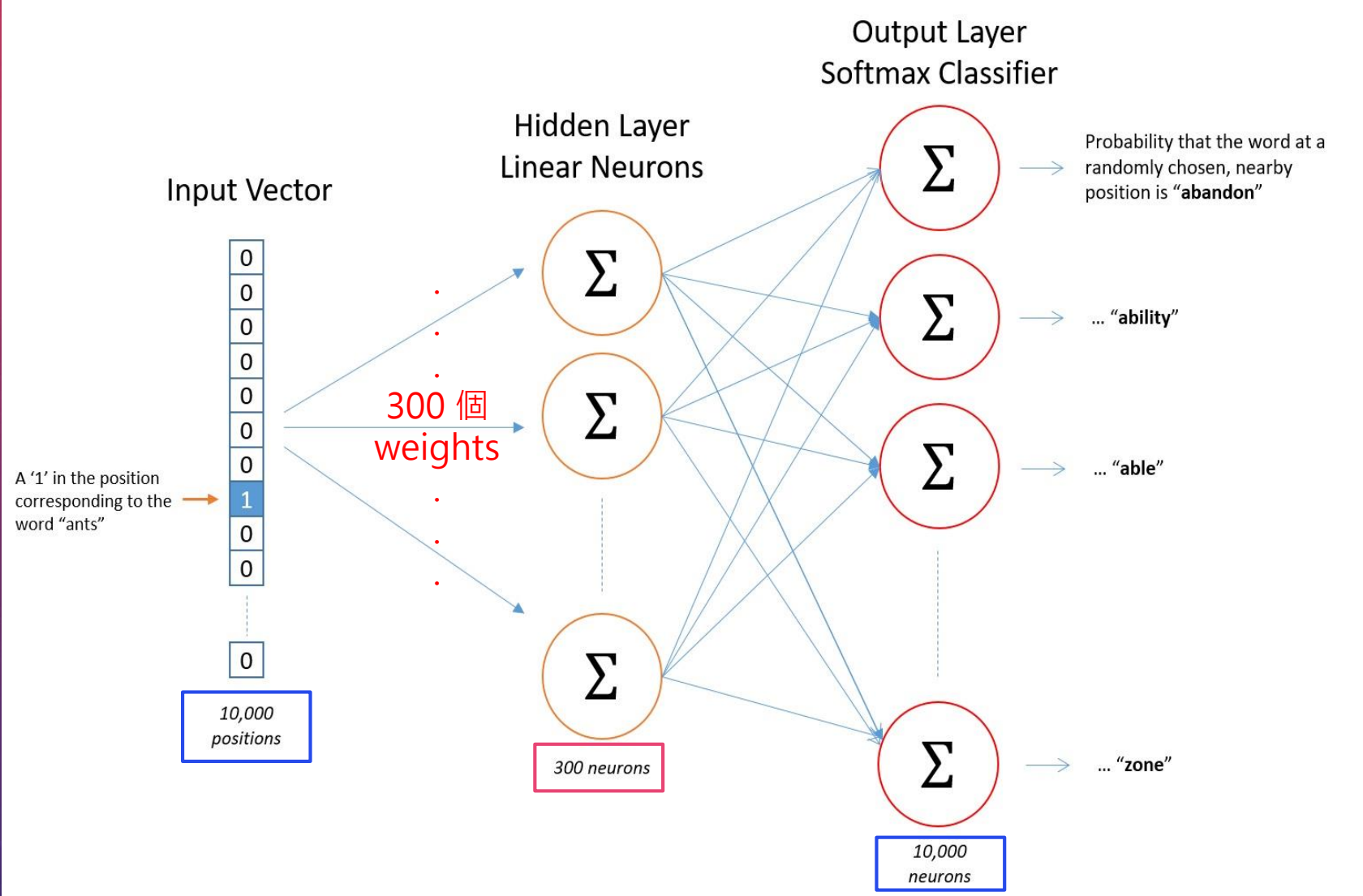


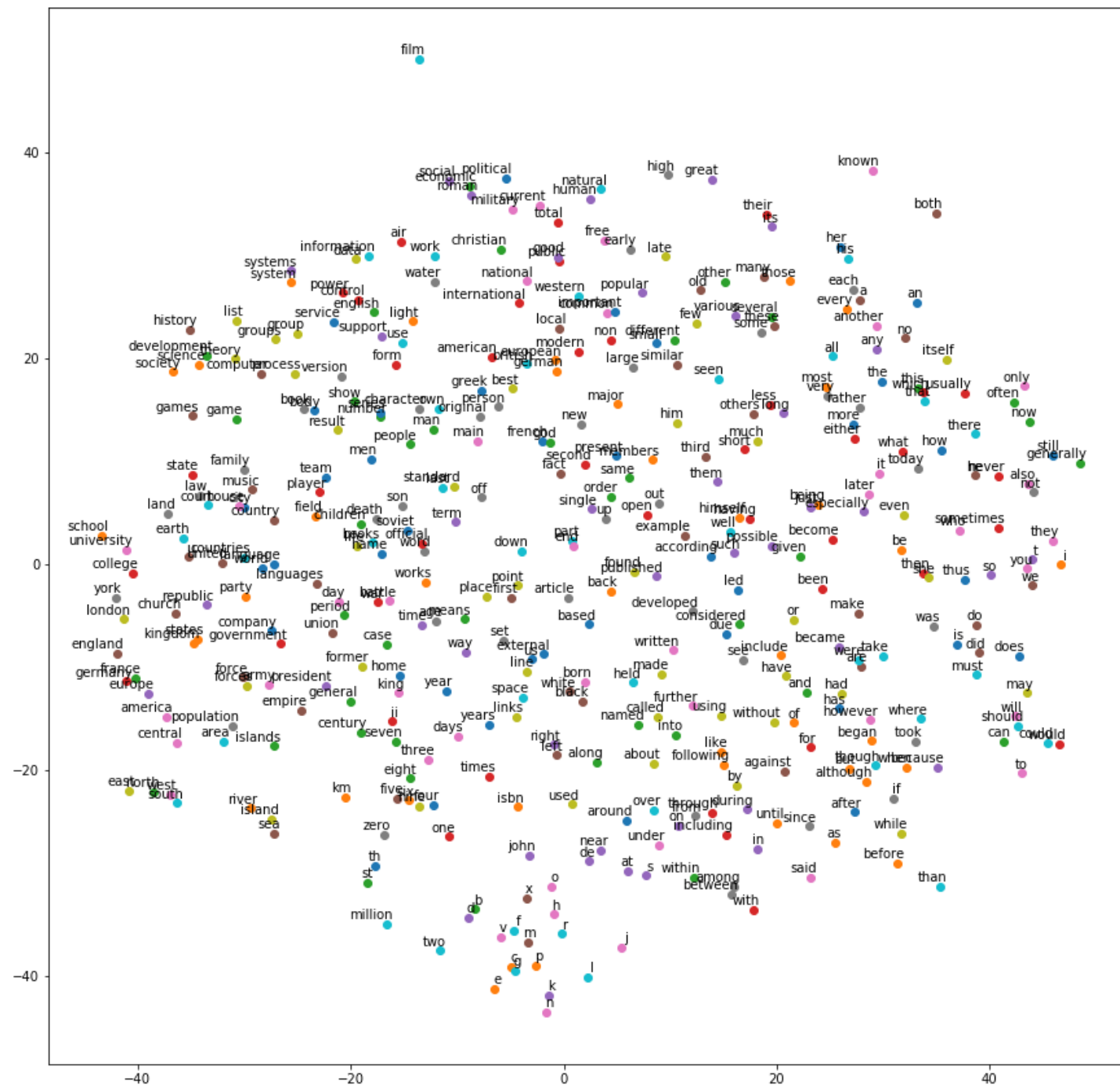
MLP



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.]







The background is a gradient from deep red at the top to dark blue at the bottom, speckled with white dots resembling stars. Overlaid on the left side are several concentric circular patterns. One large circle has a scale from 140 to 260 in increments of 10, with tick marks. Other circles are smaller and some have dashed lines or arrows indicating a clockwise direction.

THINKING TIME

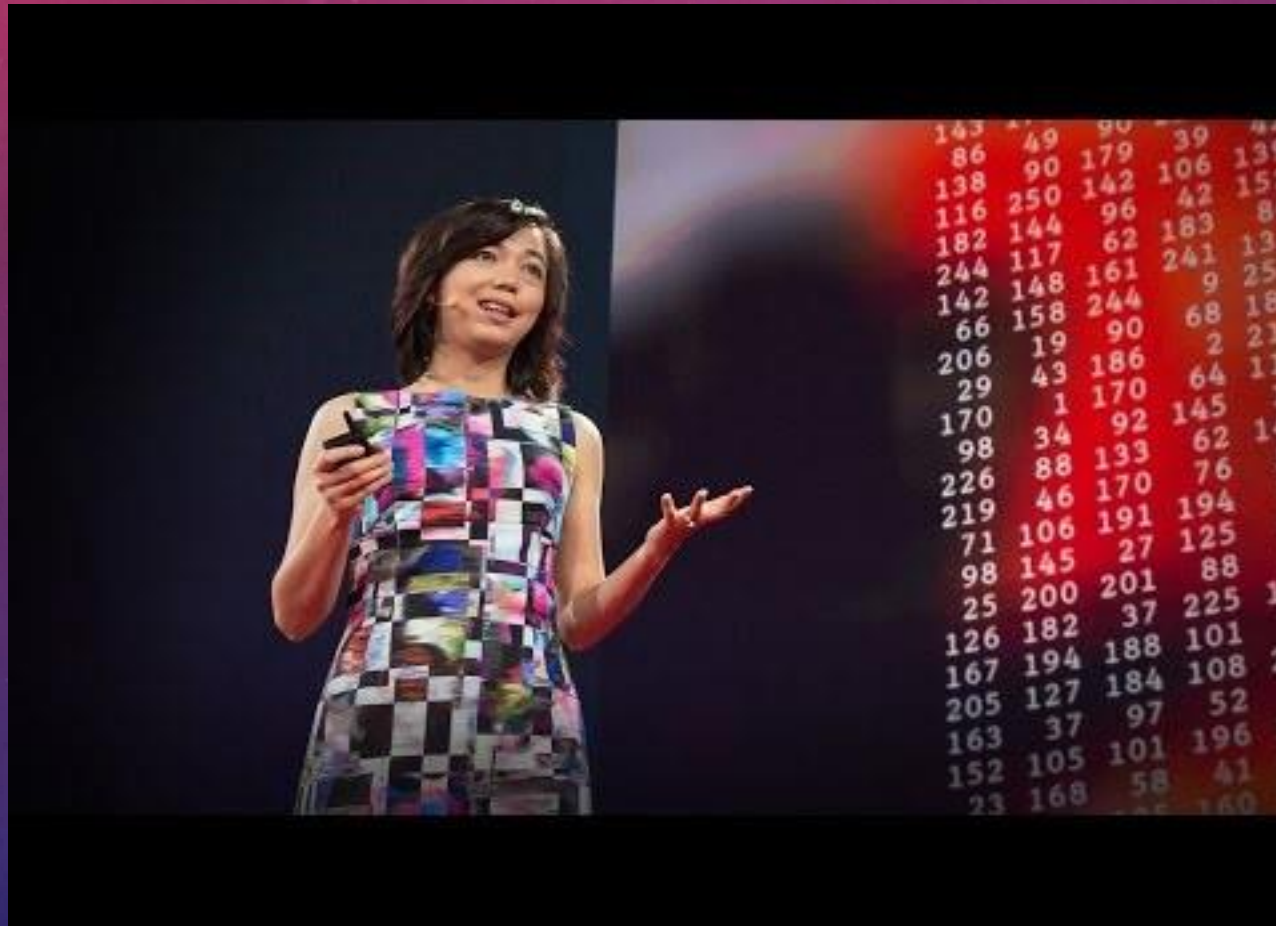
POTENTIAL APPLICATIONS

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

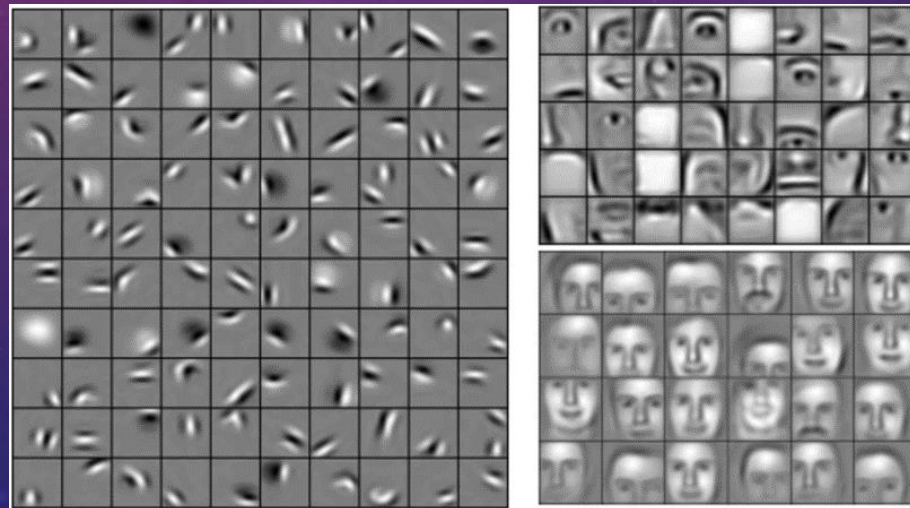
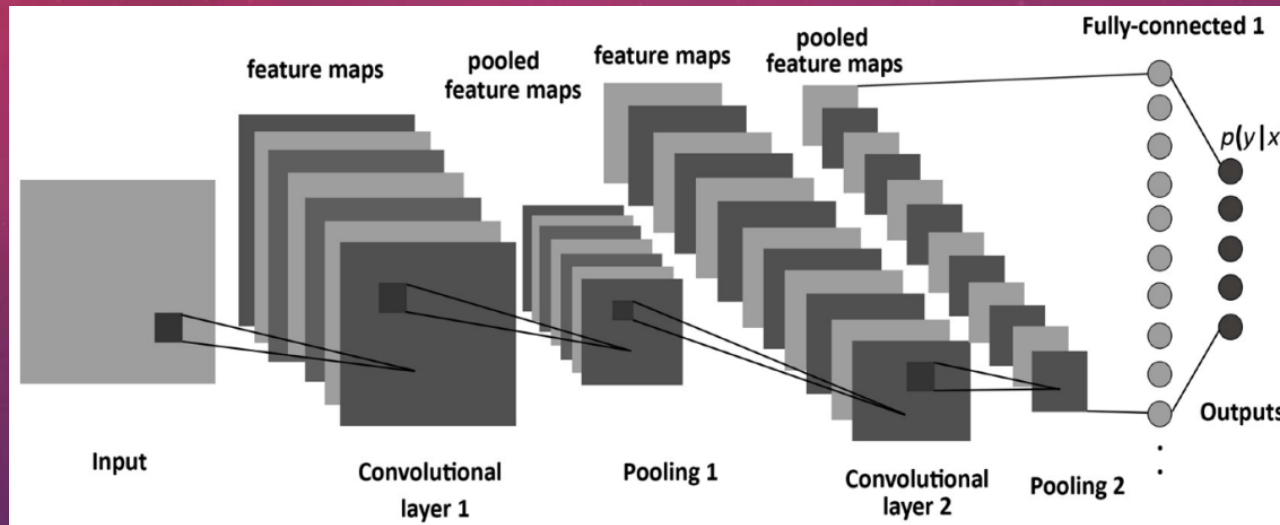
CONVOLUTIONAL NEURAL NETWORK

參考文獻

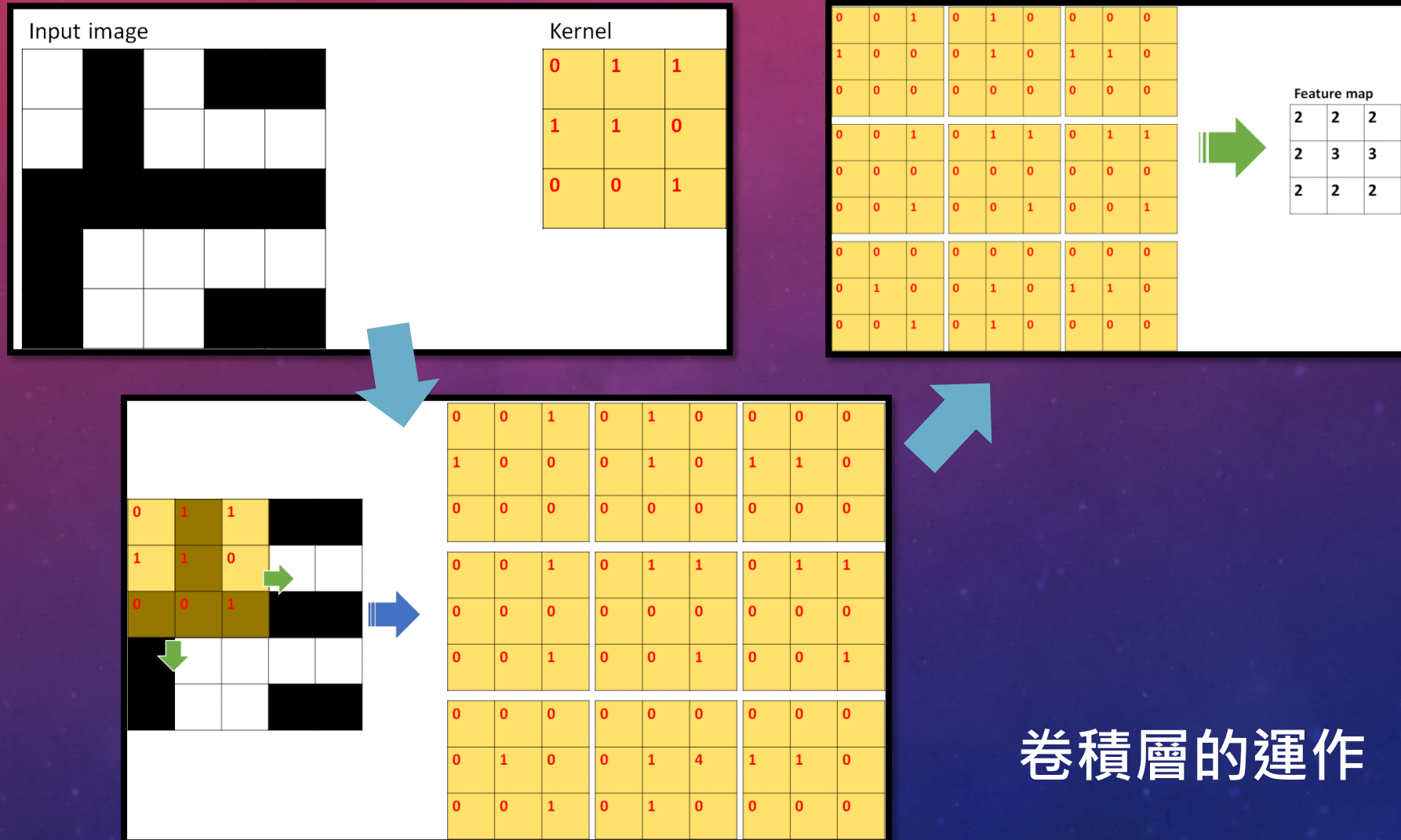
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[HTTPS://GOO.GL/Q5YKPK](https://goo.gl/Q5YKPK)

CONVOLUTIONAL NEURAL NETWORK



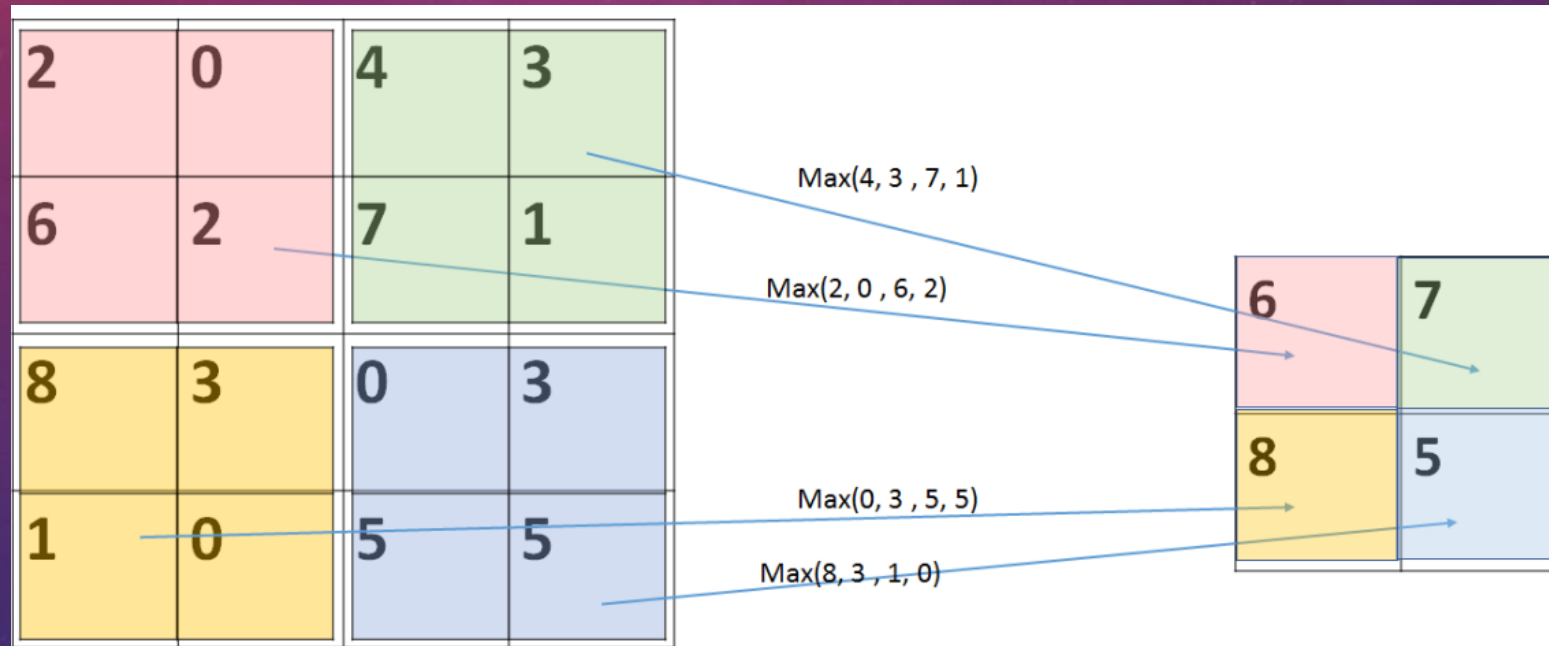
CONVOLUTIONAL NEURAL NETWORK



卷積層的運作

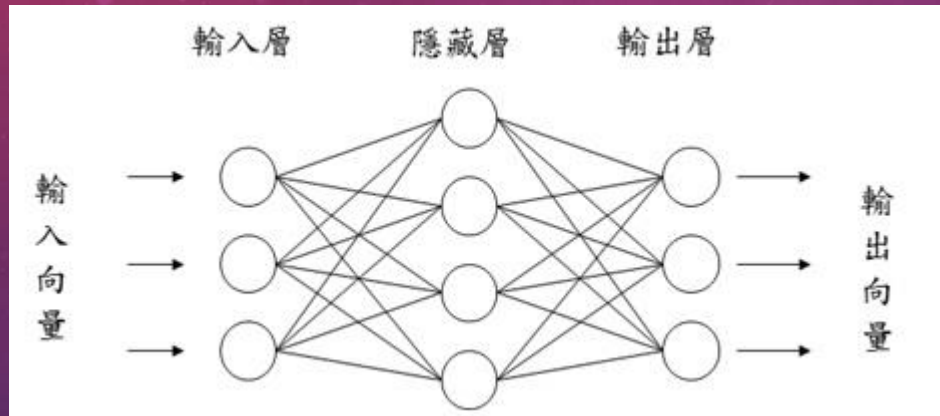
CONVOLUTIONAL NEURAL NETWORK

最大池化層的運作



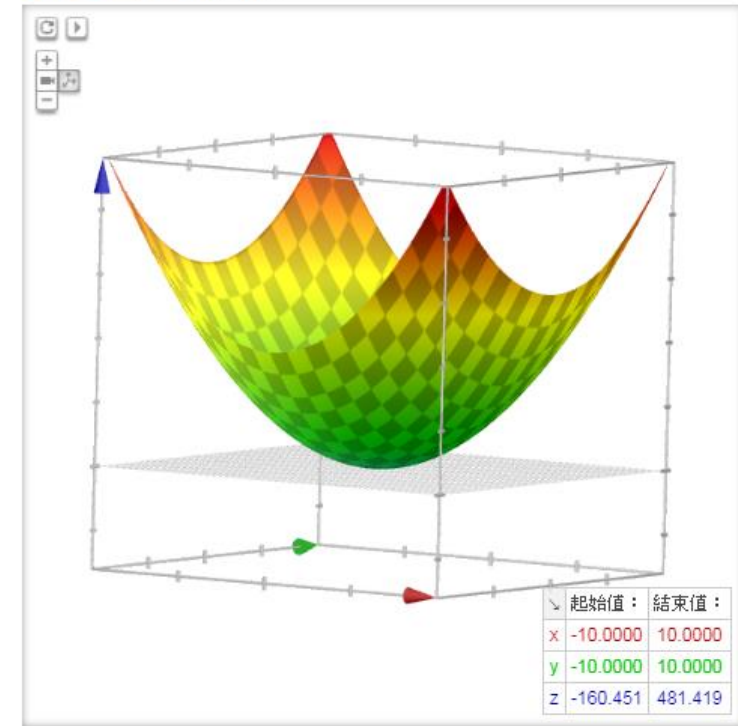
CONVOLUTIONAL NEURAL NETWORK

全連接層的運作



$$3x^2 + 2y^2$$

$3x^2 + 2y^2$ 的圖表

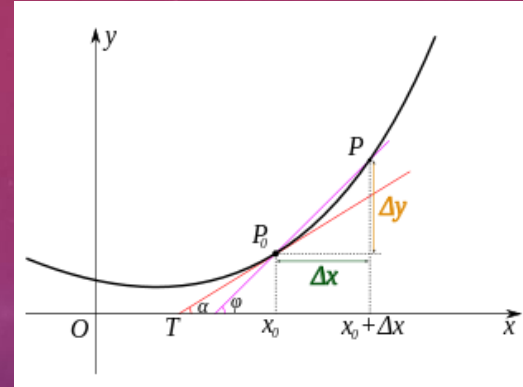
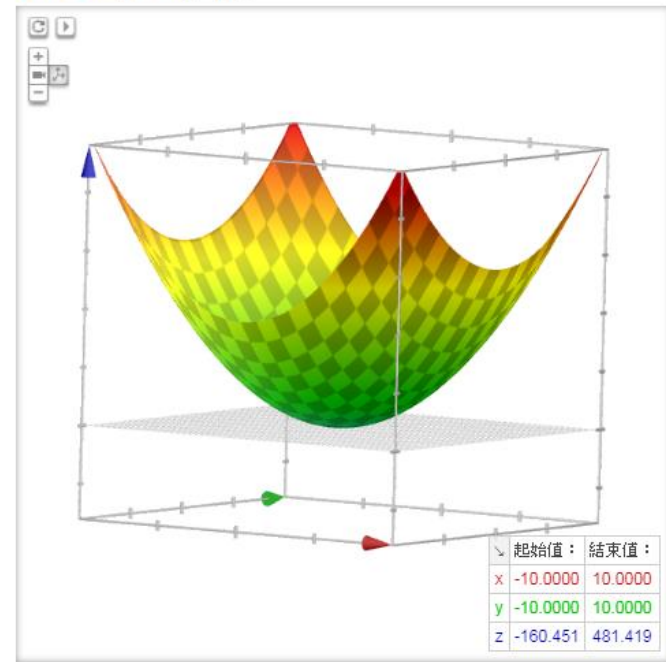


CONVOLUTIONAL NEURAL NETWORK

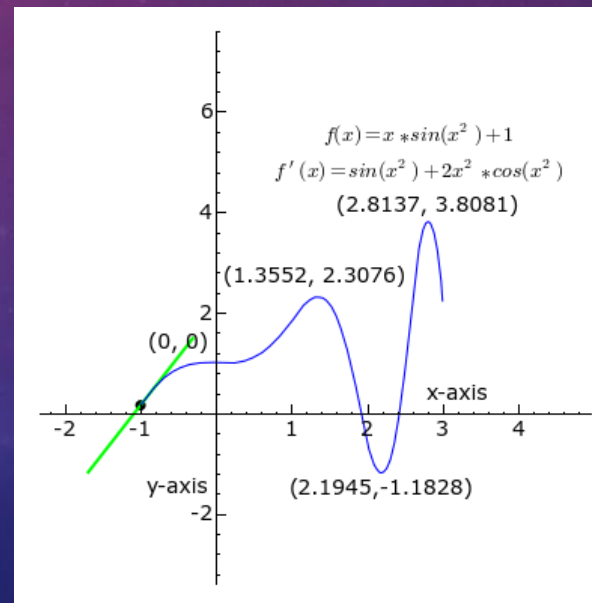
全連接層的運作

$$3x^2 + 2y^2$$

$3x^2 + 2y^2$ 的圖表



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



HOW COMPUTERS LEARN TO RECOGNIZE OBJECTS INSTANTLY



The background is a gradient from deep red at the top to dark blue at the bottom, speckled with white dots resembling stars. Overlaid on this are several faint, white circular and semi-circular lines, some with arrows indicating a clockwise direction. A prominent circular scale with numerical markings from 140 to 260 is visible on the left side.

實際案例

貓狗辨識的結果

[0.14723705	0.98256]
[0.04469623	0.99915826]	
[0.99998796	0.00834211]	
[0.99993527	0.01661933]	
[0.99877125	0.05415697]	
[0.43036035	0.6431105]
[0.20522958	0.95668554]	
[0.8880429	0.28058085]	
[0.08643436	0.9956601]
[0.99908304	0.04826429]	
[0.9999168	0.01841162]	
[0.1397599	0.98483086]	
[0.99558544	0.08876048]	
[0.43750185	0.6269166]
[0.10178897	0.9934009]
[0.10858331	0.9922093]



VIDEO TO VIDEO



VIDEO-TO-VIDEO SYNTHESIS

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



視覺整合信號轉換的體感操控機械手臂





THANK YOU