

神經與行為模型建構 (Neural & Behavioral Modeling)

課號：Psy5352

識別碼：227U2810

教室：普 101

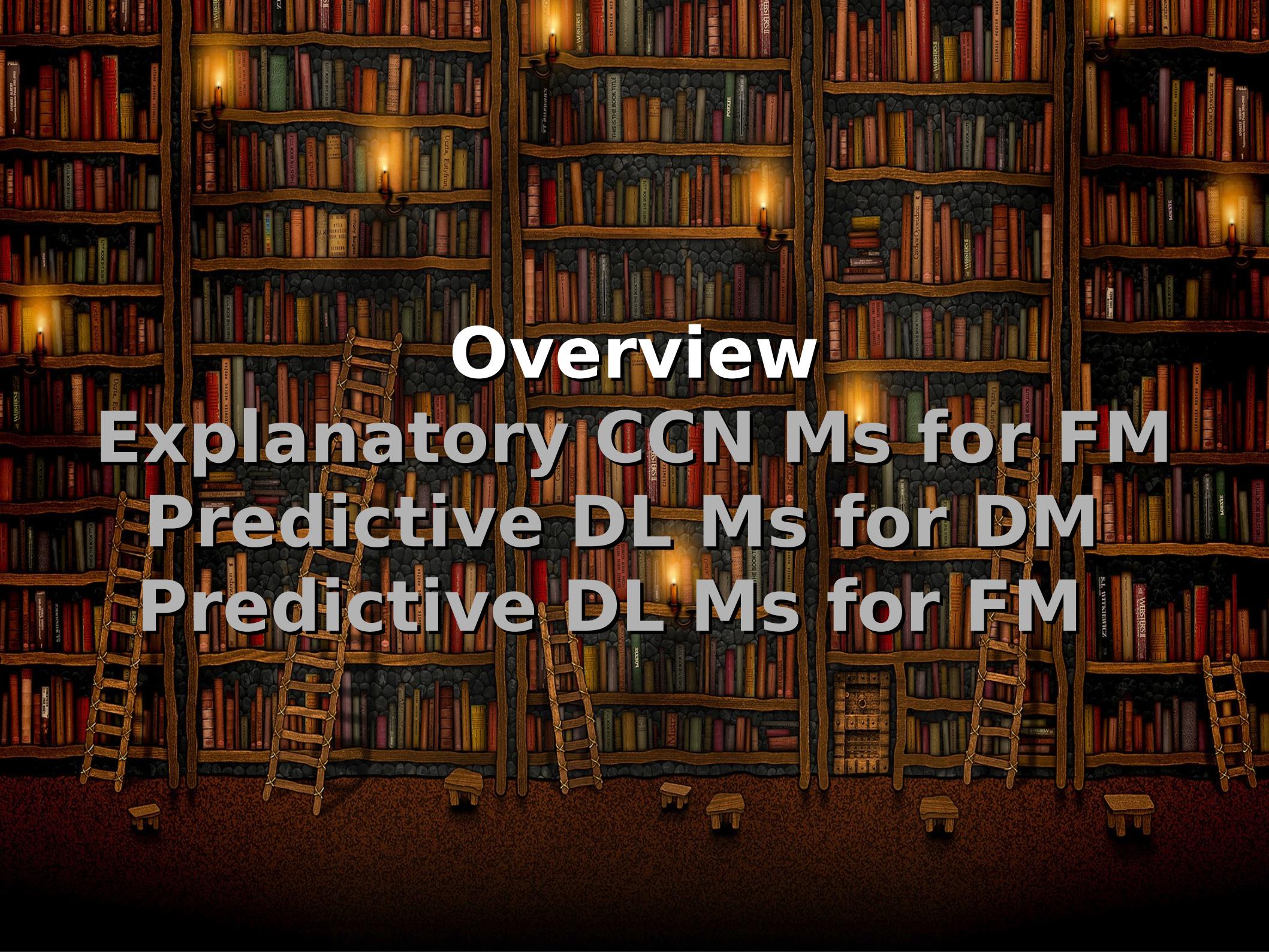
時間：— 234





終於來到了深度學習
！





Overview

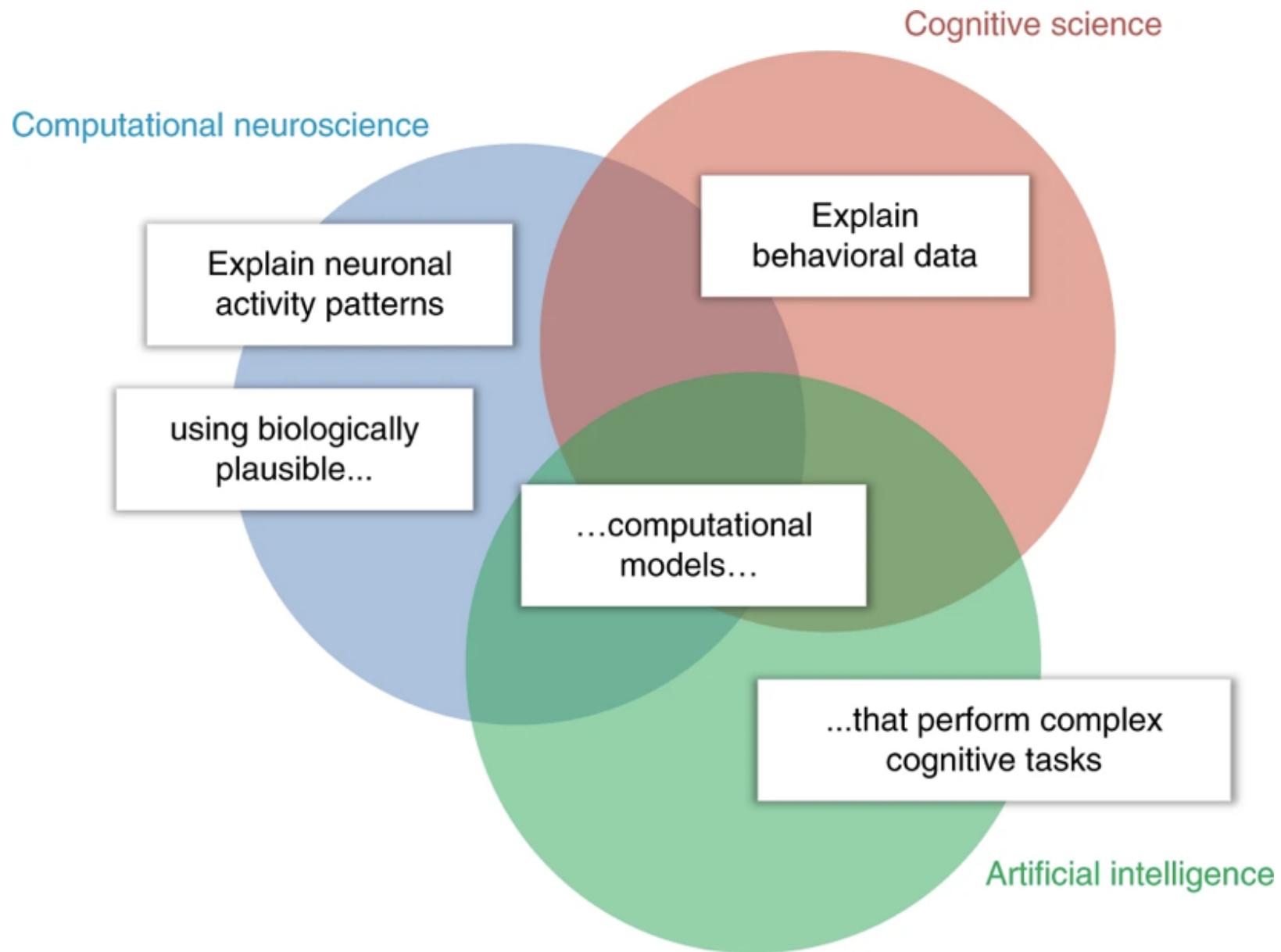
Explanatory CCN Ms for FM

Predictive DL Ms for DM

Predictive DL Ms for FM

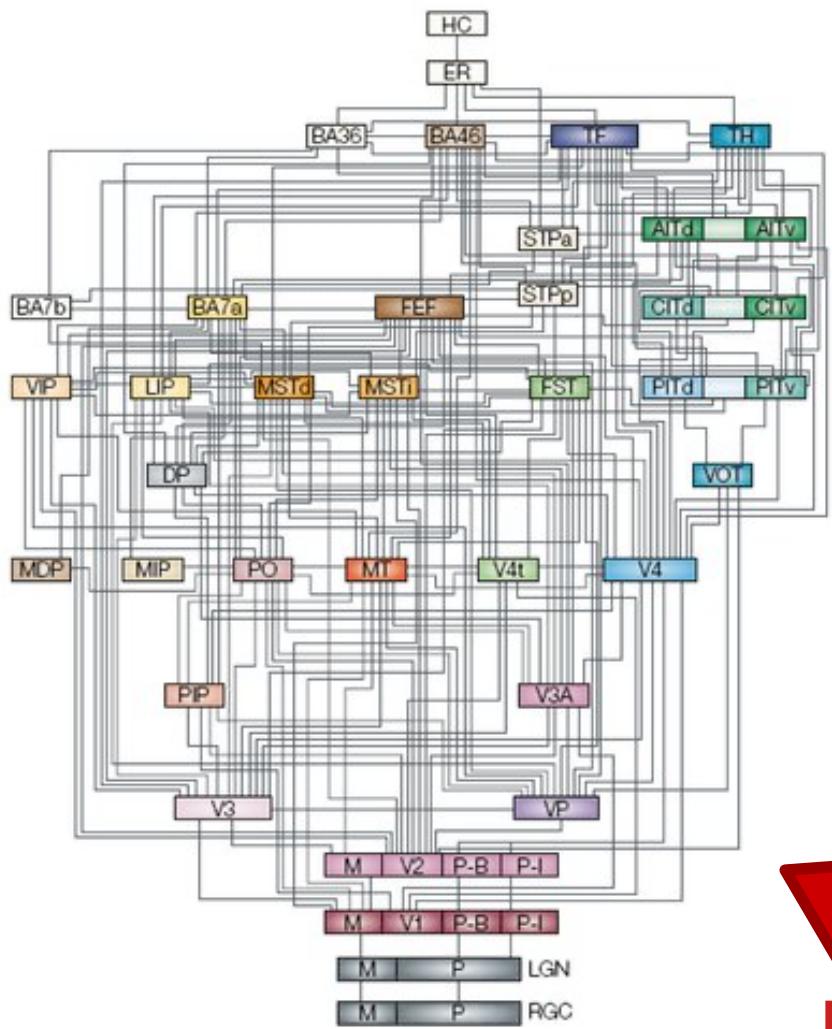
解釋性模型 vs. 預測性模型

迴歸：機器學習 :: 計算認知神經科學：深度學習

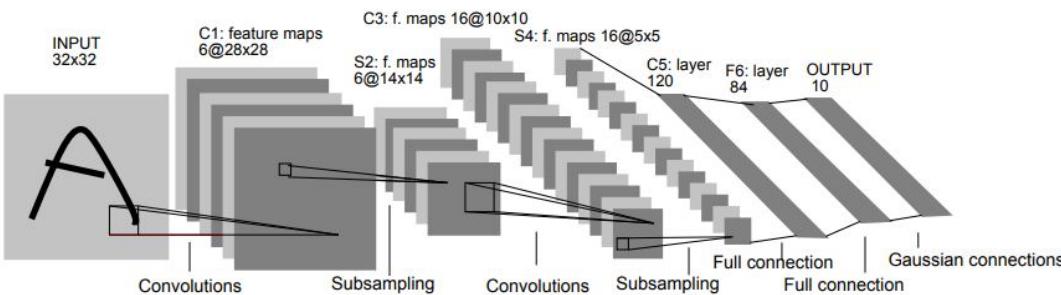
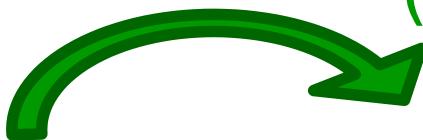


生物神經與類神經的三種關係

預測性模型也可被解釋或幫助解釋



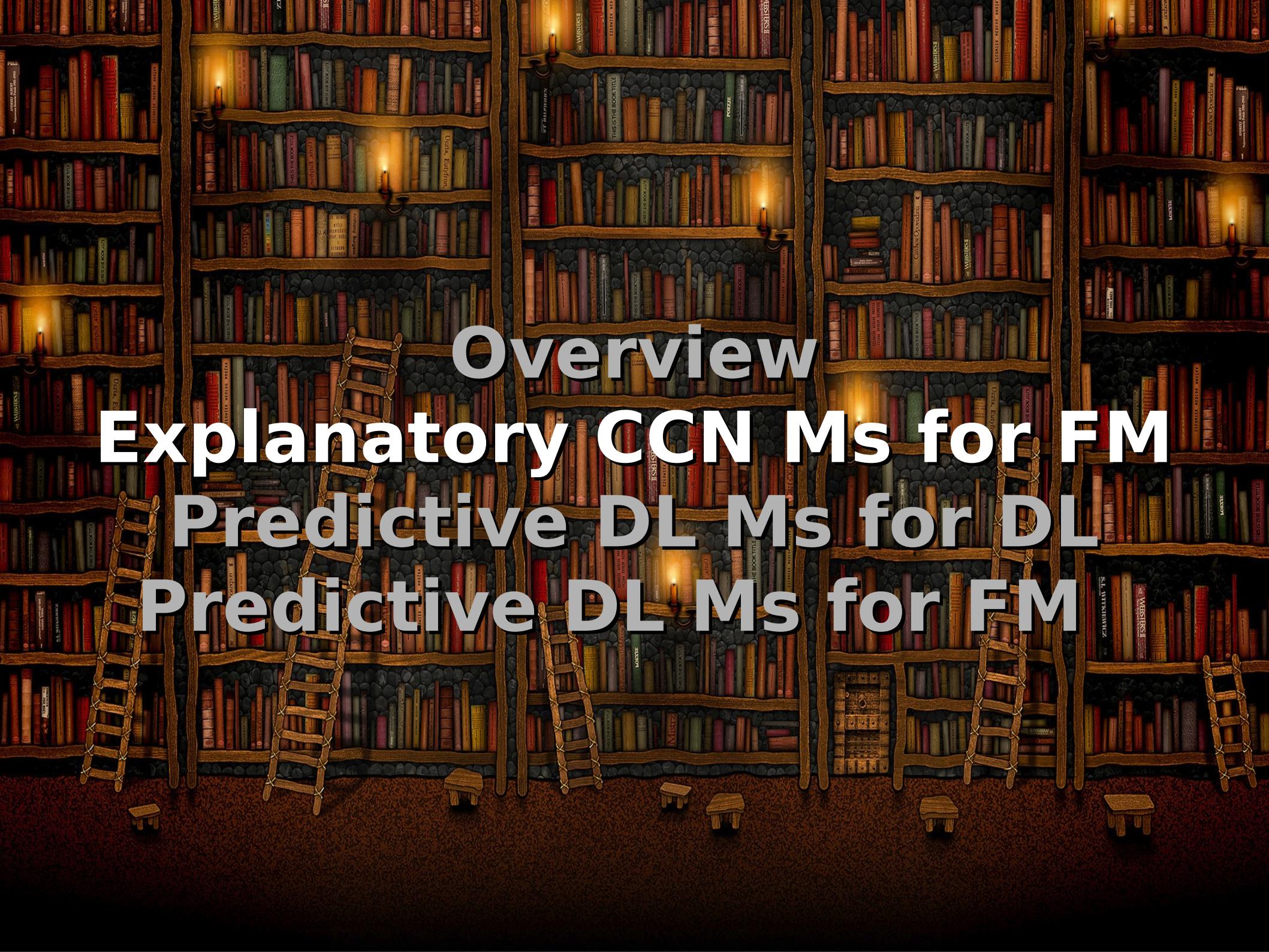
Architectural Metaphors (AM)
(下幾週介紹)



Data Modeling (DM)
(如 DL 應用在大腦解碼)



Functional Metaphors (FM)
(本來多為計算認知 M, 現在也有深度學習 M)



Overview

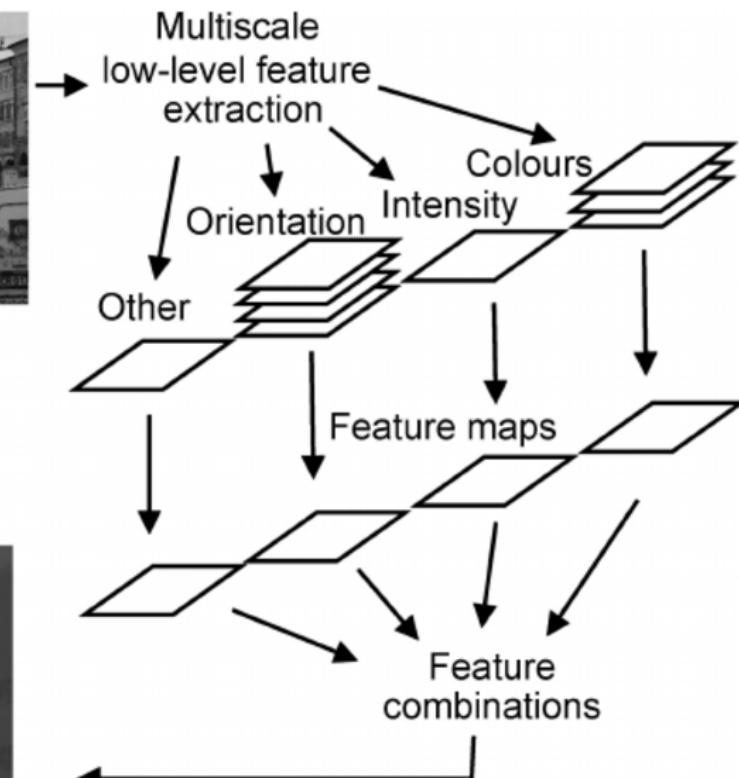
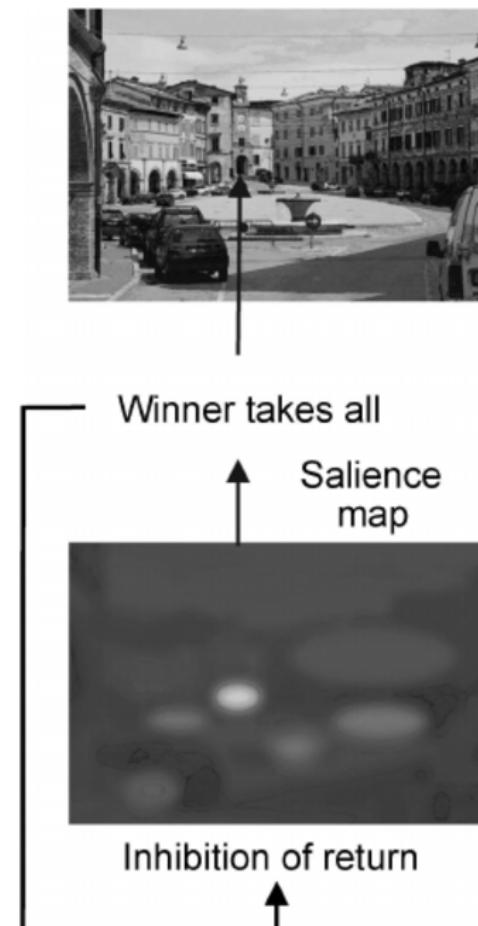
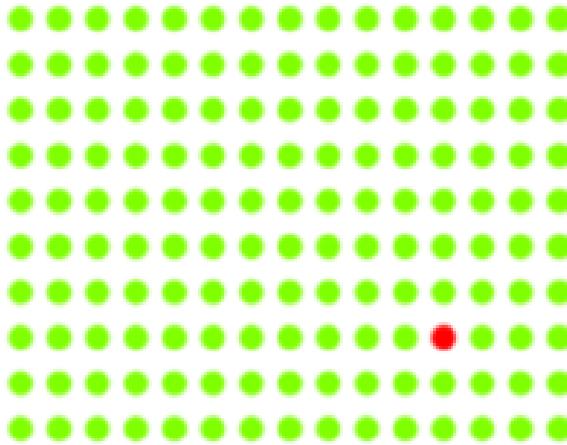
Explanatory CCN Ms for FM

Predictive DL Ms for DL

Predictive DL Ms for FM

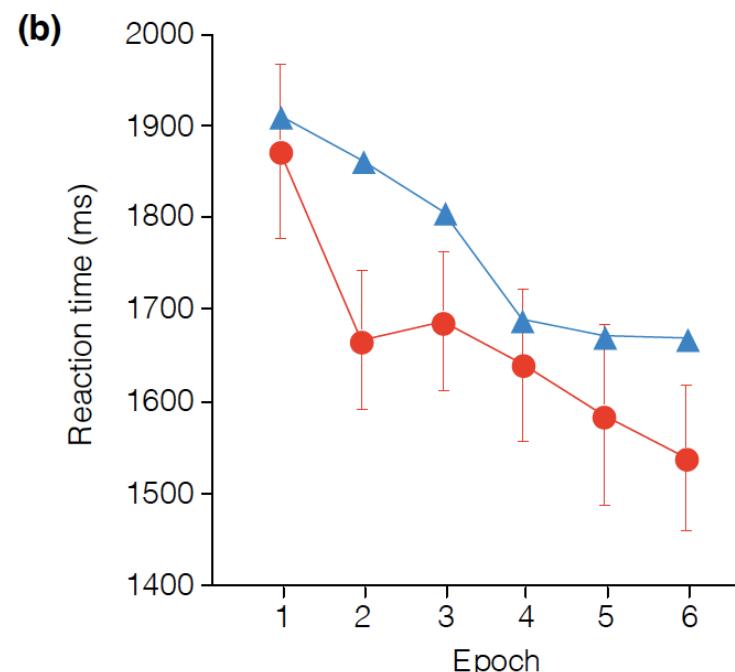
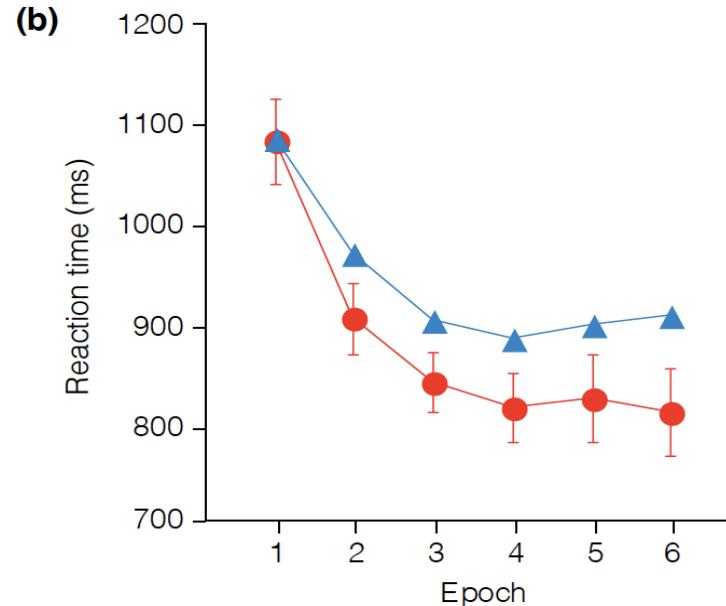
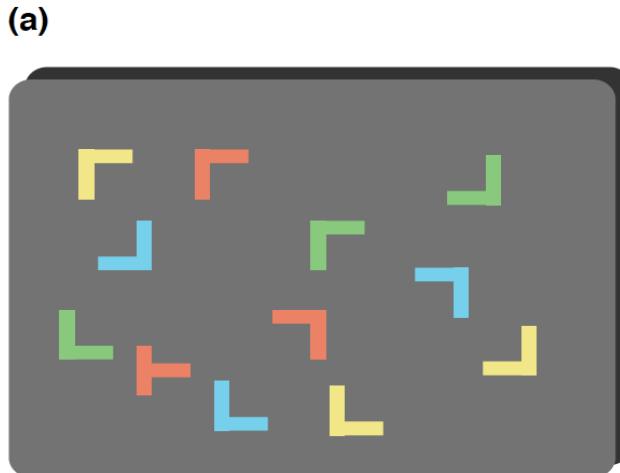
Functional Metaphor 範例 A(1/3)

視覺搜尋時我們要先看哪裡？



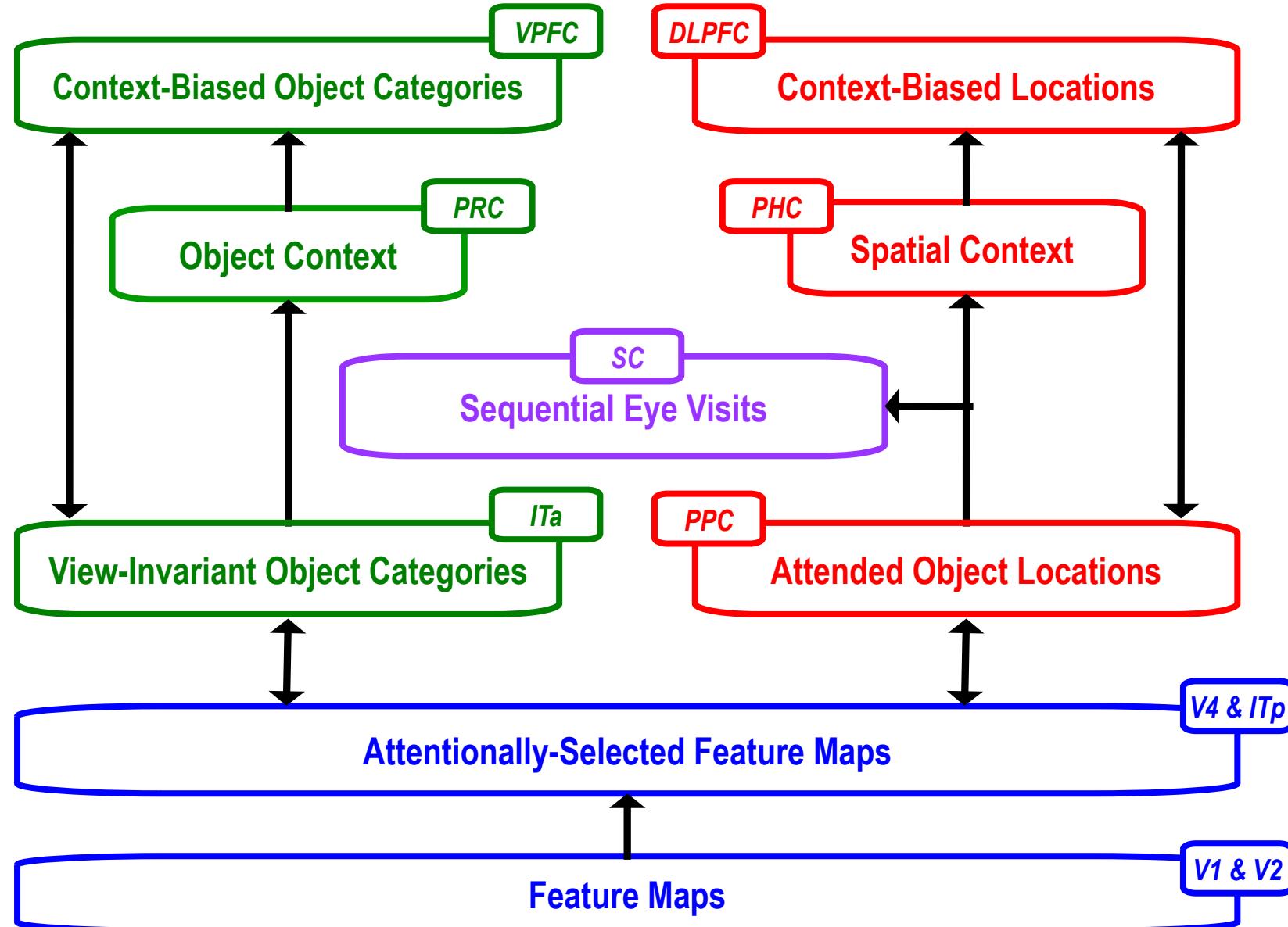
Functional Metaphor 範例 A(2/3)

但搜尋時有 bottom-up & top-down 的訊號



Functional Metaphor 範例 A(3/3)

Bottom-up signals as memory retrieval cues



Functional Metaphor 範例 B(1/3)

我們是怎麼學習 / 使用指導語的？



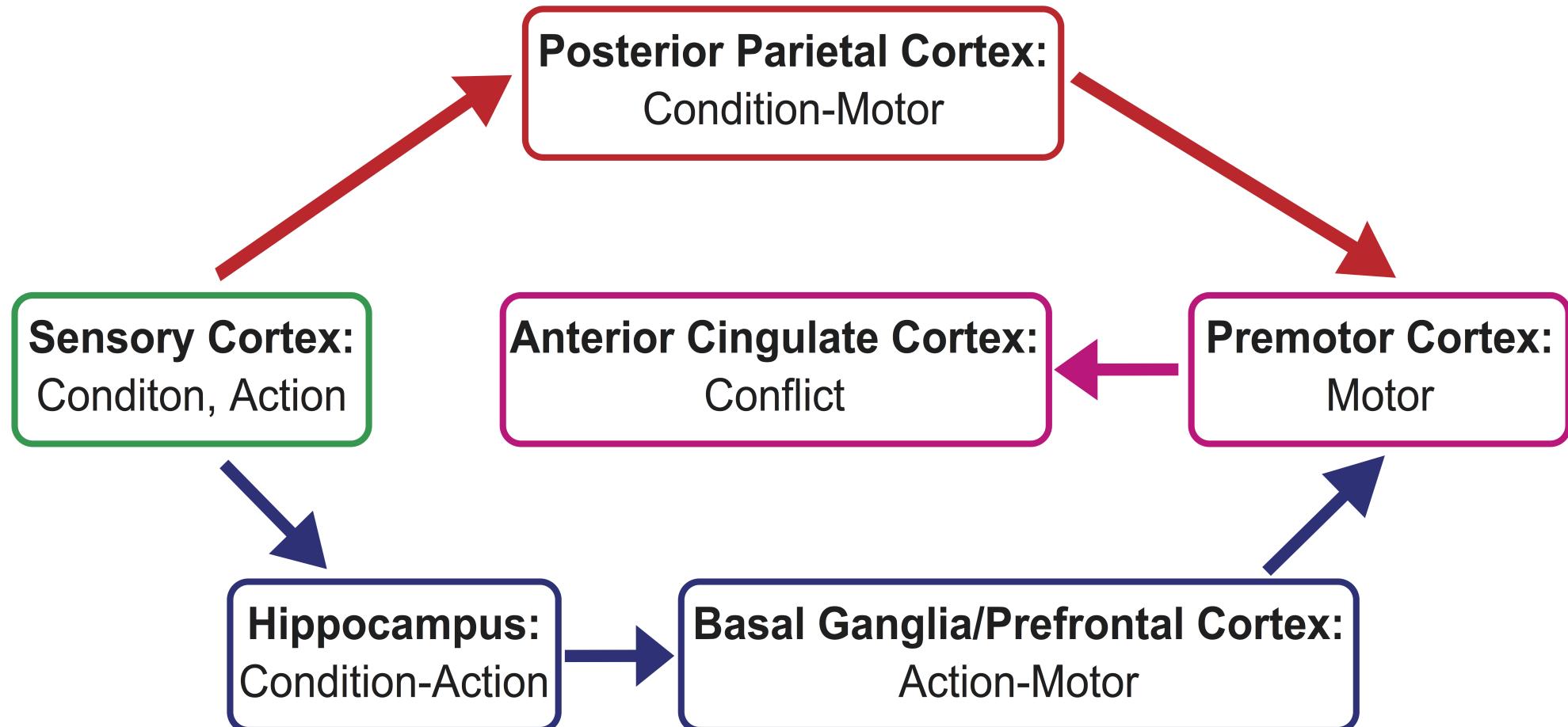
"At that traffic light, turn right."

S → R

Functional Metaphor 範例 B(2/3)

指導語要能夠暫時地蓋掉習慣

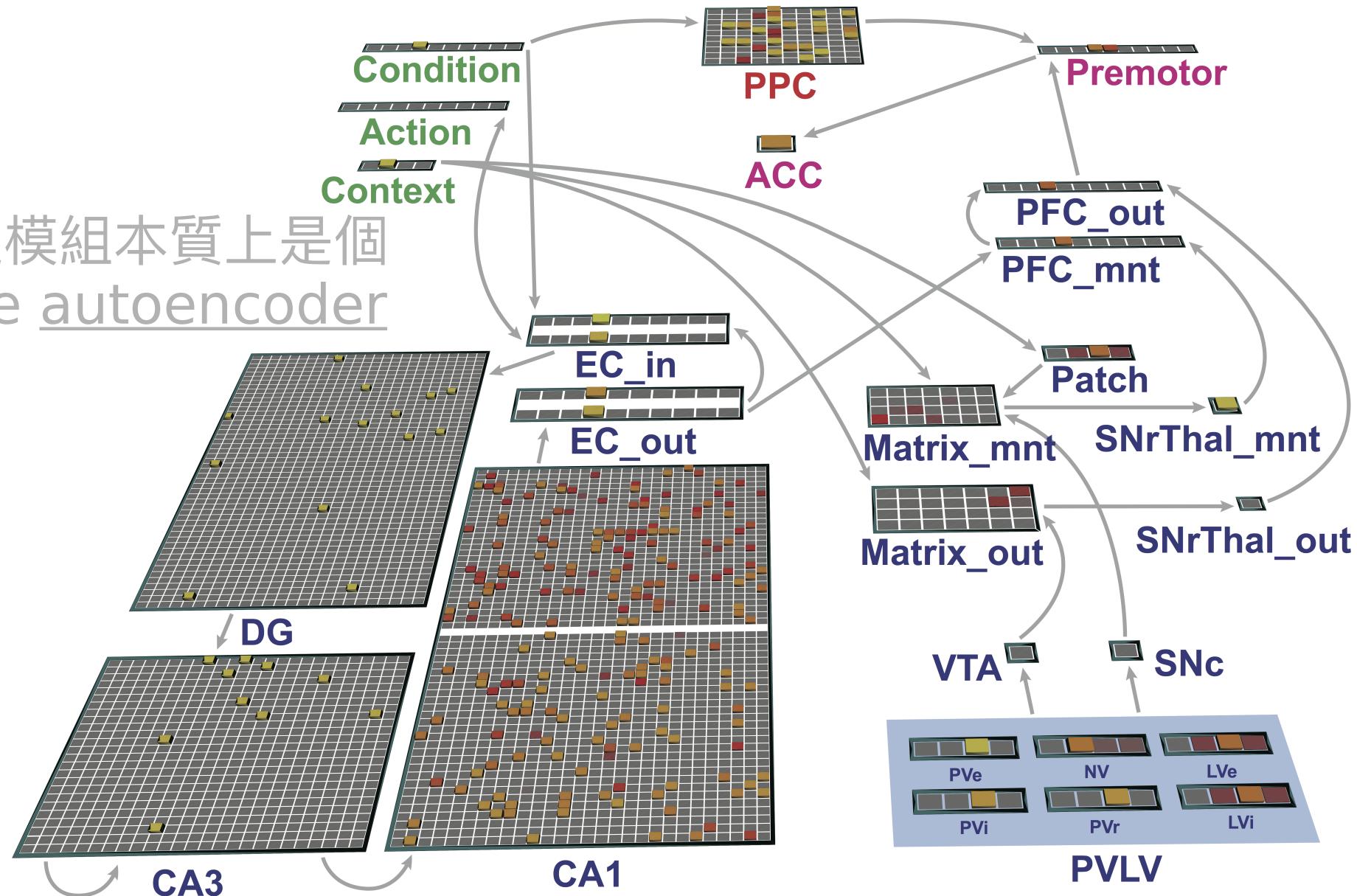
Habitual Pathway (slow learning; fast processing)

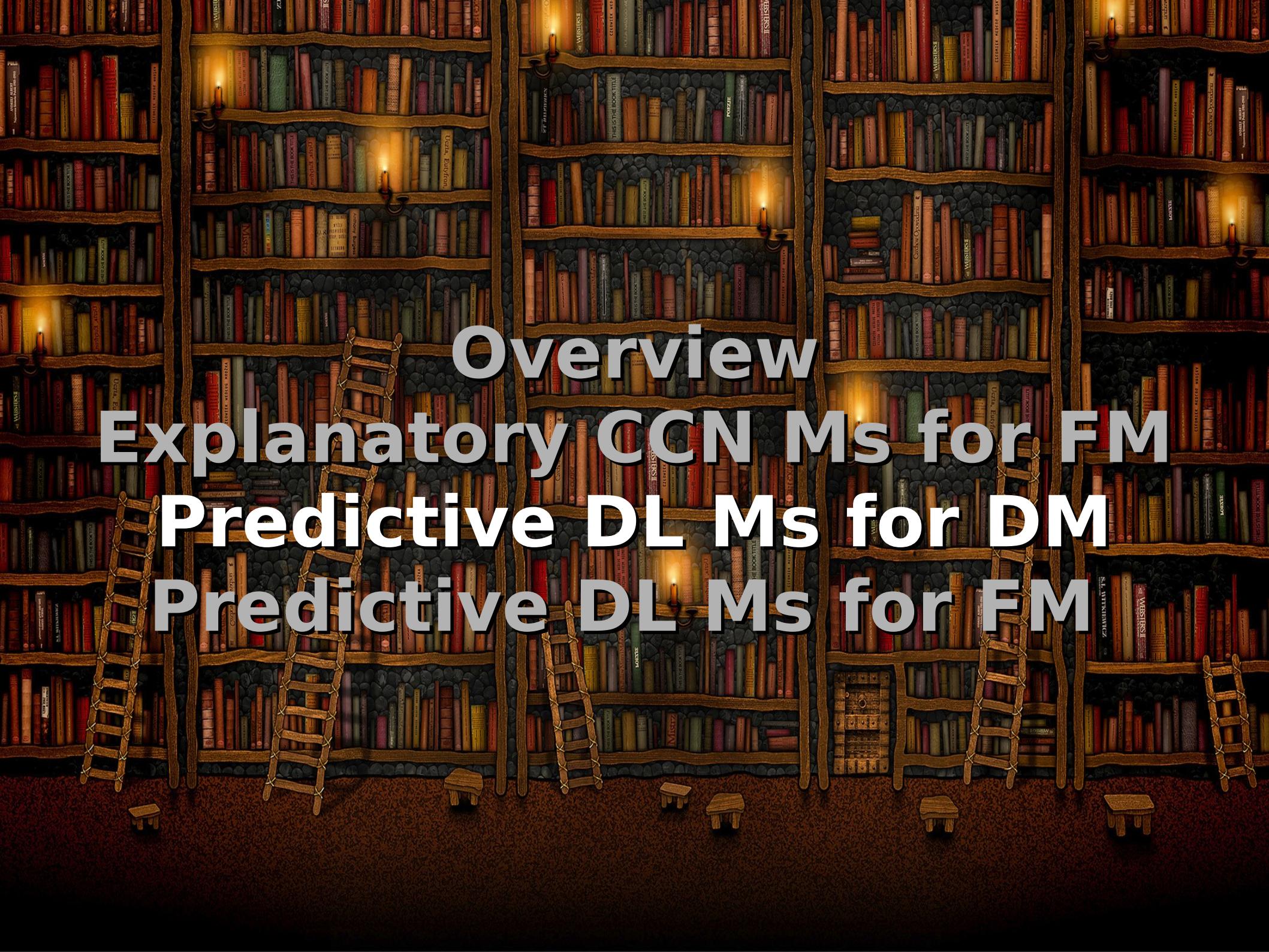


Instructable Pathway (fast learning; slow processing)

Functional Metaphor 範例 B(3/3)

海馬做 S-R 的指導語回想後傳給 PFC 做控制





Overview

Explanatory CCN Ms for FM

Predictive DL Ms for DM

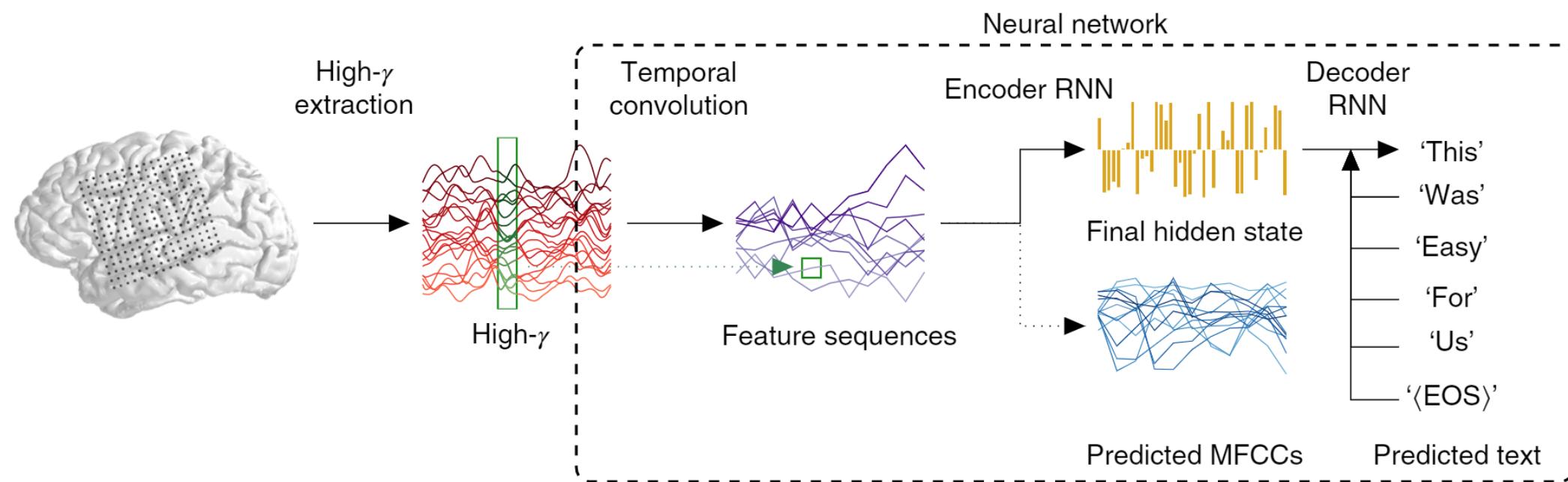
Predictive DL Ms for FM

Data Modeling 範例

利用循環神經網路 (RNN) 來做 Brain Decoding

Machine translation of cortical activity to text with an encoder-decoder framework

Joseph G. Makin^{ID}^{1,2}✉, David A. Moses^{1,2} and Edward F. Chang^{ID}^{1,2}✉



預測性模型為何比較會預測 (1/2)

因為沒有錯誤的模型結構假設

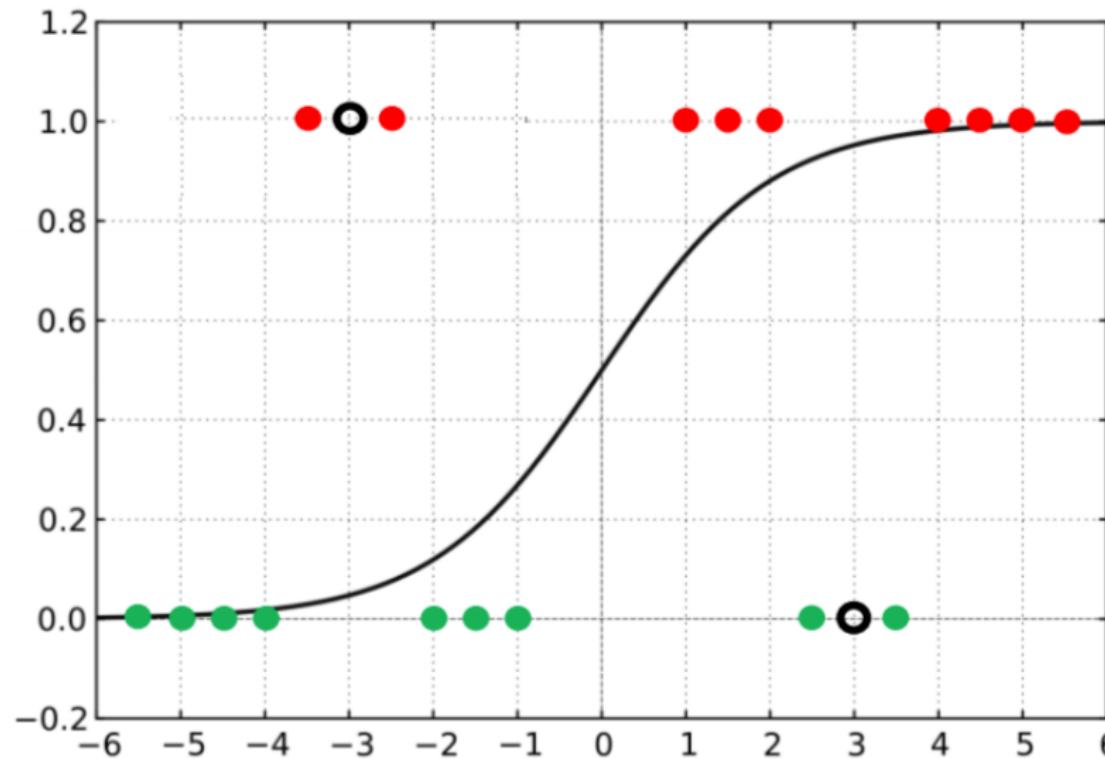
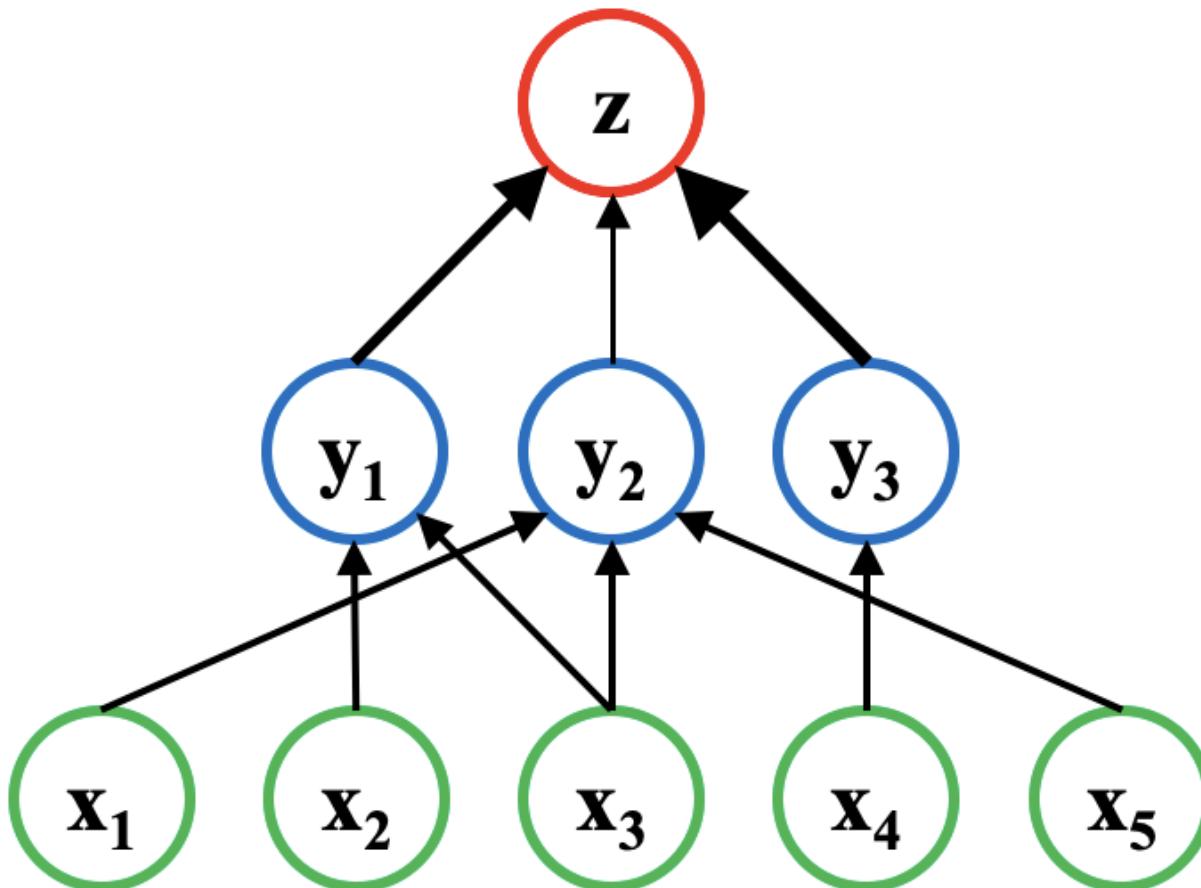


圖 2. 邏輯迴歸與 K-近鄰演算法的預測差異。邏輯迴歸對空心兩點的 y 值估計會根據連續的邏輯函數而預測 $y(x=-3)=0$ 與 $y(x=3)=1$ ；2-近鄰演算法則會利用 $x=-3$ 或 $x=3$ 旁左右兩個 y 值來投票預測 $y(x=-3)=1$ 與 $y(x=3)=0$ 。

預測性模型為何比較會預測 (2/2)

下圖 y_2 可視為是一個代表 $x_1x_3x_5$ 的三階交互作用項



Universal Approximation Theorem

3層網路就可以逼近任何連續函數 (cf. 泰勒展開式)

輸出層

神經元 : $F(x) = \sum_{i=1}^N v_i \varphi(w_i^T \mathbf{x} + b_i)$

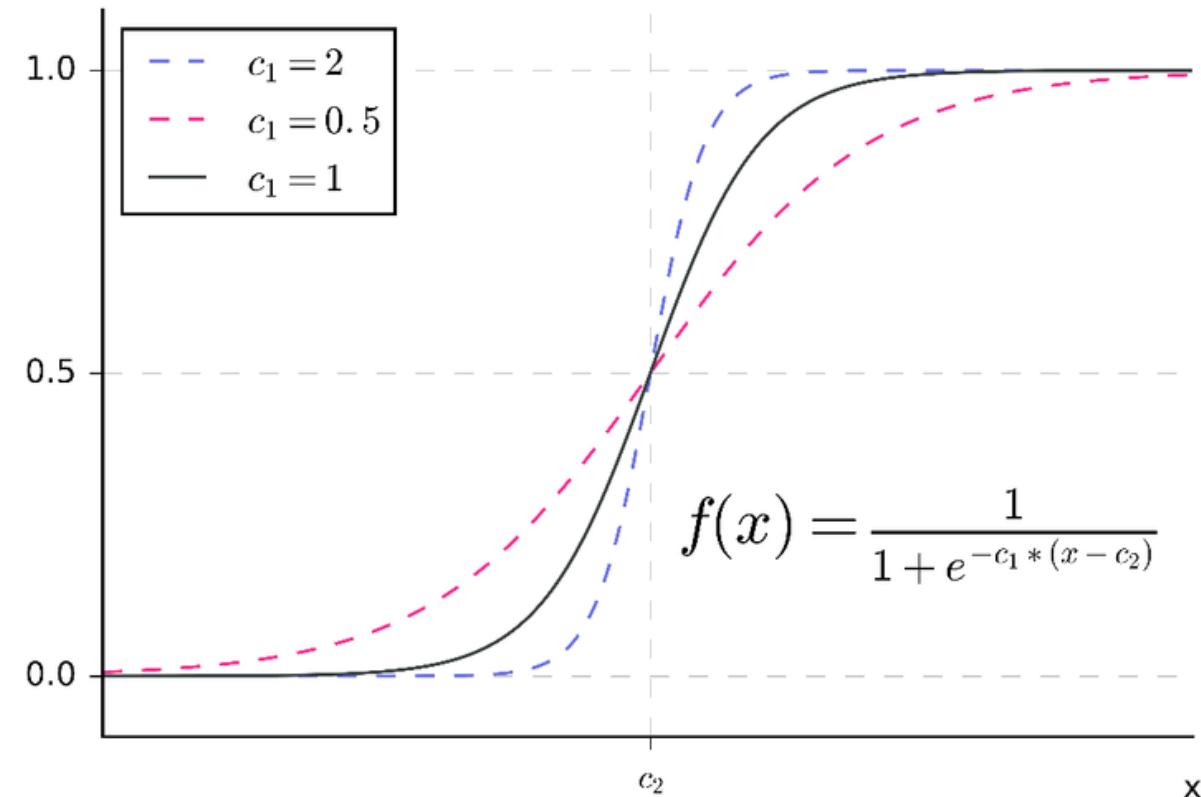
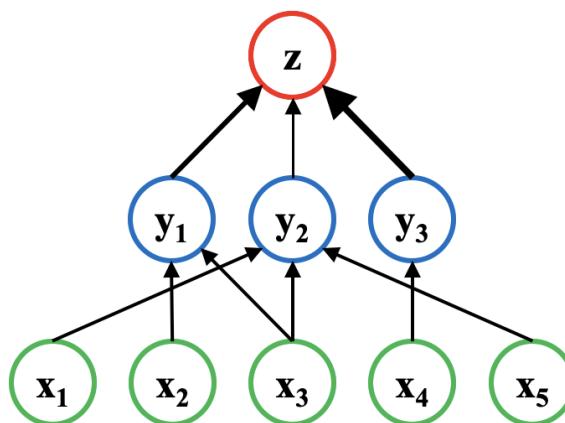
輸入層神經元

隱藏層神經元的
激發函數當基底函數

as an approximate realization of the function f where f is independent of φ ;
that is,

$$|F(x) - f(x)| < \varepsilon$$

for all $x \in I_m$. In other words,



Q1: 淺碟網路還是深度網路好？

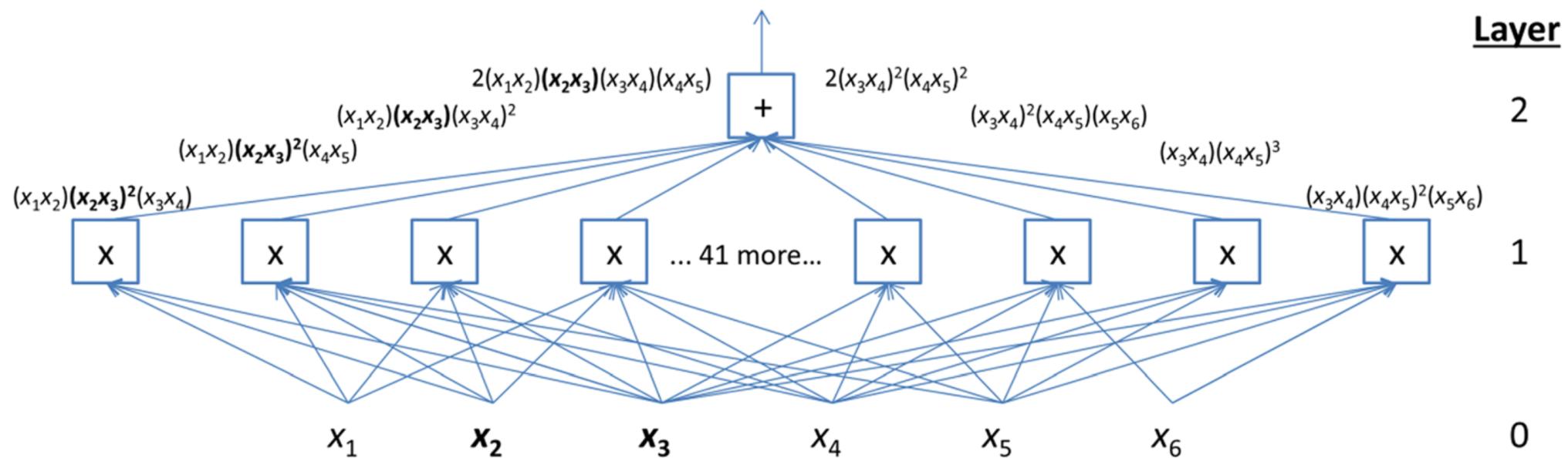
若兩者的參數量一樣誰學得快？

or

要解決同一個問題誰參數量較少？

Shallow Architecture

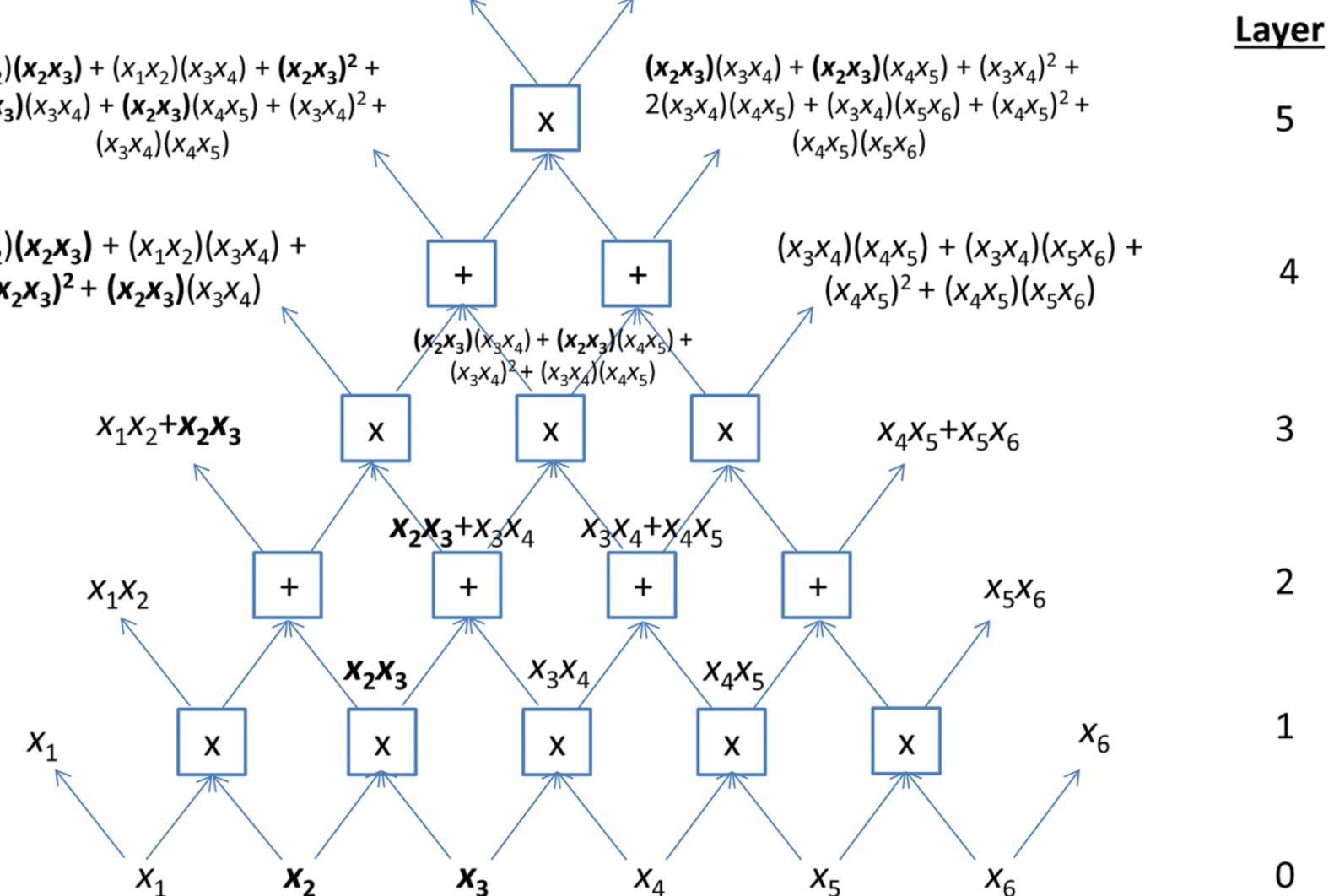
$$\begin{aligned} & (x_1x_2)(x_2x_3)^2(x_3x_4) + (x_1x_2)(x_2x_3)^2(x_4x_5) + (x_1x_2)(x_2x_3)(x_3x_4)^2 + 2(x_1x_2)(x_2x_3)(x_3x_4)(x_4x_5) + (x_1x_2)(x_2x_3)(x_3x_4)(x_5x_6) + (x_1x_2)(x_2x_3)(x_4x_5)^2 + (x_1x_2)(x_3x_4)(x_4x_5) + (x_1x_2)(x_3x_4)^3 + 2(x_1x_2)(x_3x_4)^2(x_4x_5) + (x_1x_2)(x_3x_4)^2(x_5x_6) + (x_1x_2)(x_3x_4)(x_4x_5)^2 + (x_1x_2)(x_3x_4)(x_5x_6) + \\ & (x_2x_3)^3(x_3x_4) + (x_2x_3)^3(x_4x_5) + (x_2x_3)^2(x_3x_4)^2 + 2(x_2x_3)^2(x_3x_4)(x_4x_5) + (x_2x_3)^2(x_3x_4)(x_5x_6) + (x_2x_3)^2(x_4x_5)^2 + (x_2x_3)^2(x_4x_5)(x_5x_6) + \\ & 2(x_2x_3)^2(x_3x_4)^2 + 2(x_2x_3)^2(x_3x_4)(x_4x_5) + 2(x_2x_3)(x_3x_4)^3 + 4(x_2x_3)(x_3x_4)^2(x_4x_5) + 2(x_2x_3)(x_3x_4)^2(x_5x_6) + 2(x_2x_3)(x_3x_4)(x_4x_5)^2 + 2(x_2x_3)(x_3x_4)(x_4x_5)(x_5x_6) + \\ & (x_2x_3)^2(x_4x_5)(x_3x_4) + (x_2x_3)^2(x_4x_5)(x_4x_5)^2 + (x_2x_3)(x_4x_5)(x_3x_4)^2 + 2(x_2x_3)(x_4x_5)^2(x_3x_4) + (x_2x_3)(x_4x_5)(x_3x_4)(x_5x_6) + (x_2x_3)(x_4x_5)^3 + (x_2x_3)(x_4x_5)^2(x_5x_6) + \\ & (x_3x_4)^3(x_2x_3) + (x_3x_4)^2(x_2x_3)(x_4x_5) + (x_3x_4)^4 + 2(x_3x_4)^3(x_4x_5) + (x_3x_4)^3(x_5x_6) + (x_3x_4)^2(x_4x_5)^2 + (x_3x_4)^2(x_4x_5)(x_5x_6) + \\ & (x_3x_4)^2(x_4x_5)(x_2x_3) + (x_3x_4)(x_4x_5)^2(x_2x_3) + (x_4x_5)(x_3x_4)^3 + 2(x_3x_4)^2(x_4x_5)^2 + (x_3x_4)^2(x_4x_5)(x_5x_6) + (x_3x_4)(x_4x_5)^3 + (x_3x_4)(x_4x_5)^2(x_5x_6) \end{aligned}$$



深度網路能更有效率地表徵階層結構的資料

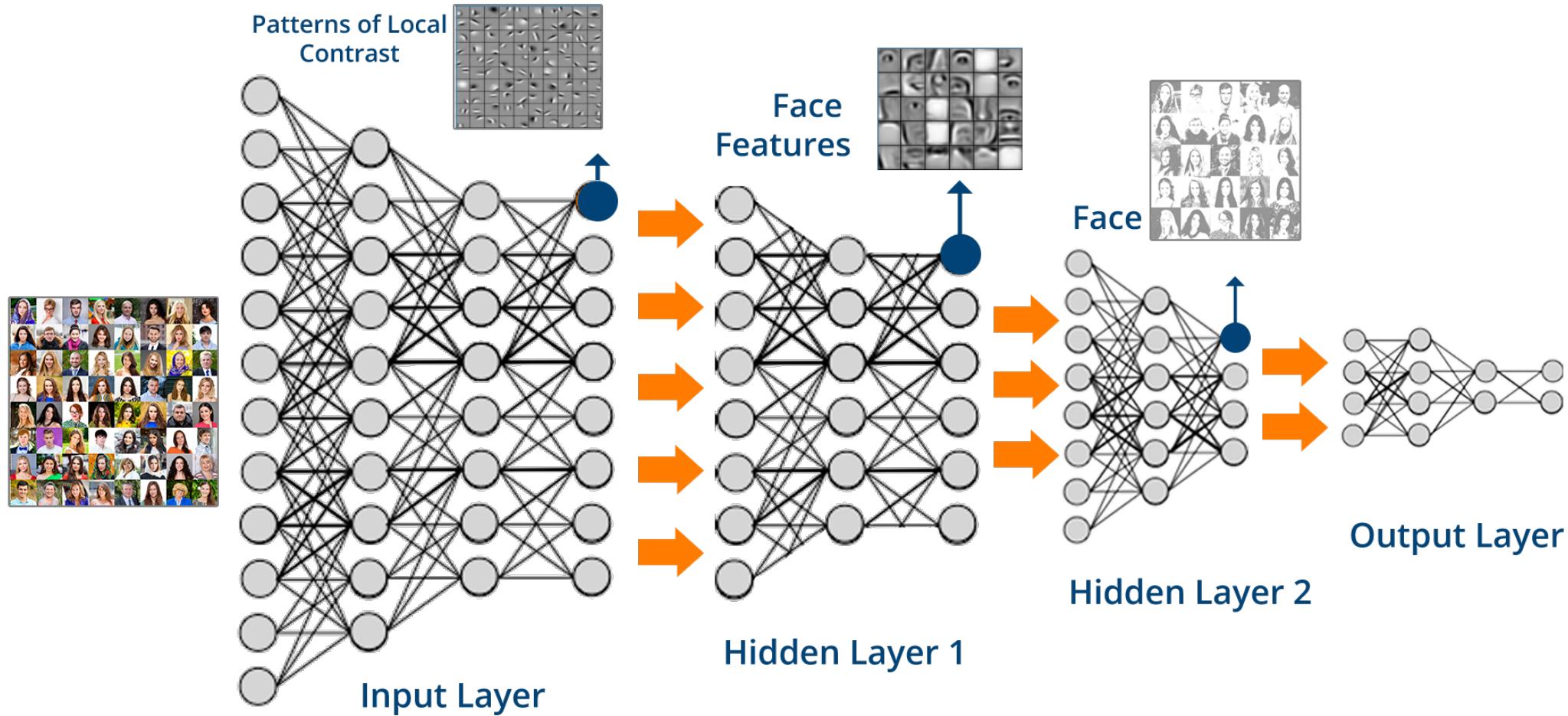
Deep Architecture

$$\begin{aligned}
 & (x_1x_2)(x_2x_3)^2(x_3x_4) + (x_1x_2)(x_2x_3)^2(x_4x_5) + (x_1x_2)(x_2x_3)(x_3x_4)^2 + 2(x_1x_2)(x_2x_3)(x_3x_4)(x_4x_5) + (x_1x_2)(x_2x_3)(x_3x_4)(x_5x_6) + \\
 & (x_1x_2)(x_2x_3)(x_3x_4)^2 + (x_1x_2)(x_3x_4)(x_2x_3)(x_4x_5) + (x_1x_2)(x_3x_4)^3 + 2(x_1x_2)(x_3x_4)^2(x_4x_5) + (x_1x_2)(x_3x_4)^2(x_5x_6) + \\
 & (x_2x_3)^3(x_3x_4) + (x_2x_3)^3(x_4x_5) + (x_2x_3)^2(x_3x_4)^2 + 2(x_2x_3)^2(x_3x_4)(x_4x_5) + (x_2x_3)^2(x_3x_4)(x_5x_6) + \\
 & 2(x_2x_3)^2(x_3x_4)^2 + 2(x_2x_3)^2(x_3x_4)(x_4x_5) + 2(x_2x_3)(x_3x_4)^3 + 4(x_2x_3)(x_3x_4)^2(x_4x_5) + 2(x_2x_3)(x_3x_4)^2(x_5x_6) + \\
 & 2(x_2x_3)(x_3x_4)(x_4x_5) + 2(x_2x_3)(x_3x_4)^2 + 2(x_2x_3)(x_3x_4)(x_4x_5)^2 + 2(x_2x_3)(x_3x_4)(x_5x_6) + \\
 & (x_2x_3)^2(x_4x_5)(x_3x_4) + (x_2x_3)^2(x_4x_5)(x_4x_5)^2 + (x_2x_3)(x_4x_5)(x_3x_4)^2 + 2(x_2x_3)(x_4x_5)^2(x_3x_4) + (x_2x_3)(x_4x_5)(x_5x_6) + \\
 & (x_3x_4)^3(x_2x_3) + (x_3x_4)^2(x_2x_3)(x_4x_5) + (x_3x_4)^4 + 2(x_3x_4)^3(x_4x_5) + (x_3x_4)^3(x_5x_6) + (x_3x_4)^2(x_4x_5)^2 + (x_3x_4)^2(x_4x_5)(x_5x_6) + \\
 & (x_3x_4)^2(x_4x_5)(x_2x_3) + (x_3x_4)(x_4x_5)^2(x_2x_3) + (x_4x_5)(x_3x_4)^3 + 2(x_3x_4)^2(x_4x_5)^2 + (x_3x_4)^2(x_4x_5)(x_5x_6) + (x_3x_4)(x_4x_5)^3 + (x_3x_4)(x_4x_5)^2(x_5x_6)
 \end{aligned}$$



Q2: 咩是一組數目有限但最好的基底函數？

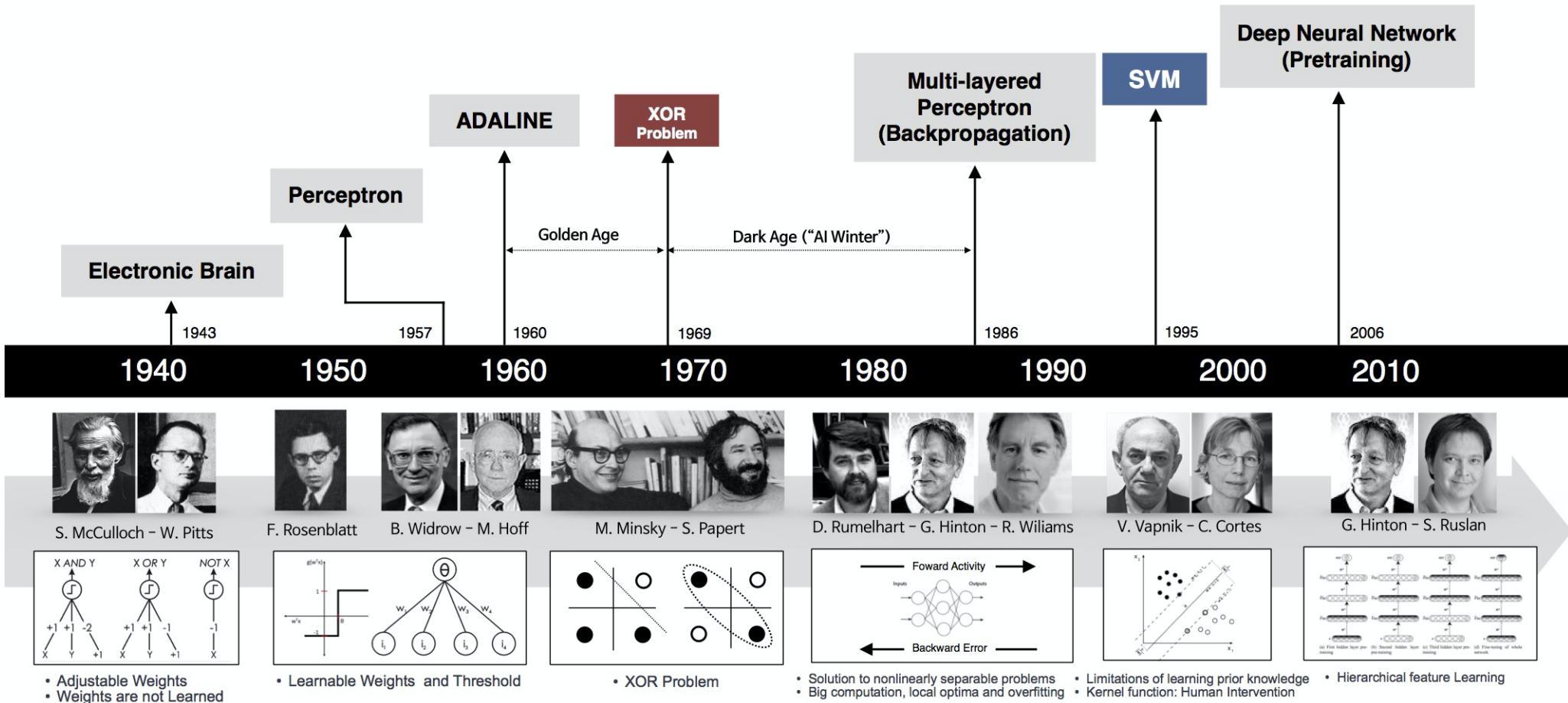
依照計算問題學來的：即偵測最能解決該問題的特徵



如同樣的資料集是要分類性別還是要分類種族？

Deep Neural Networks 的發展

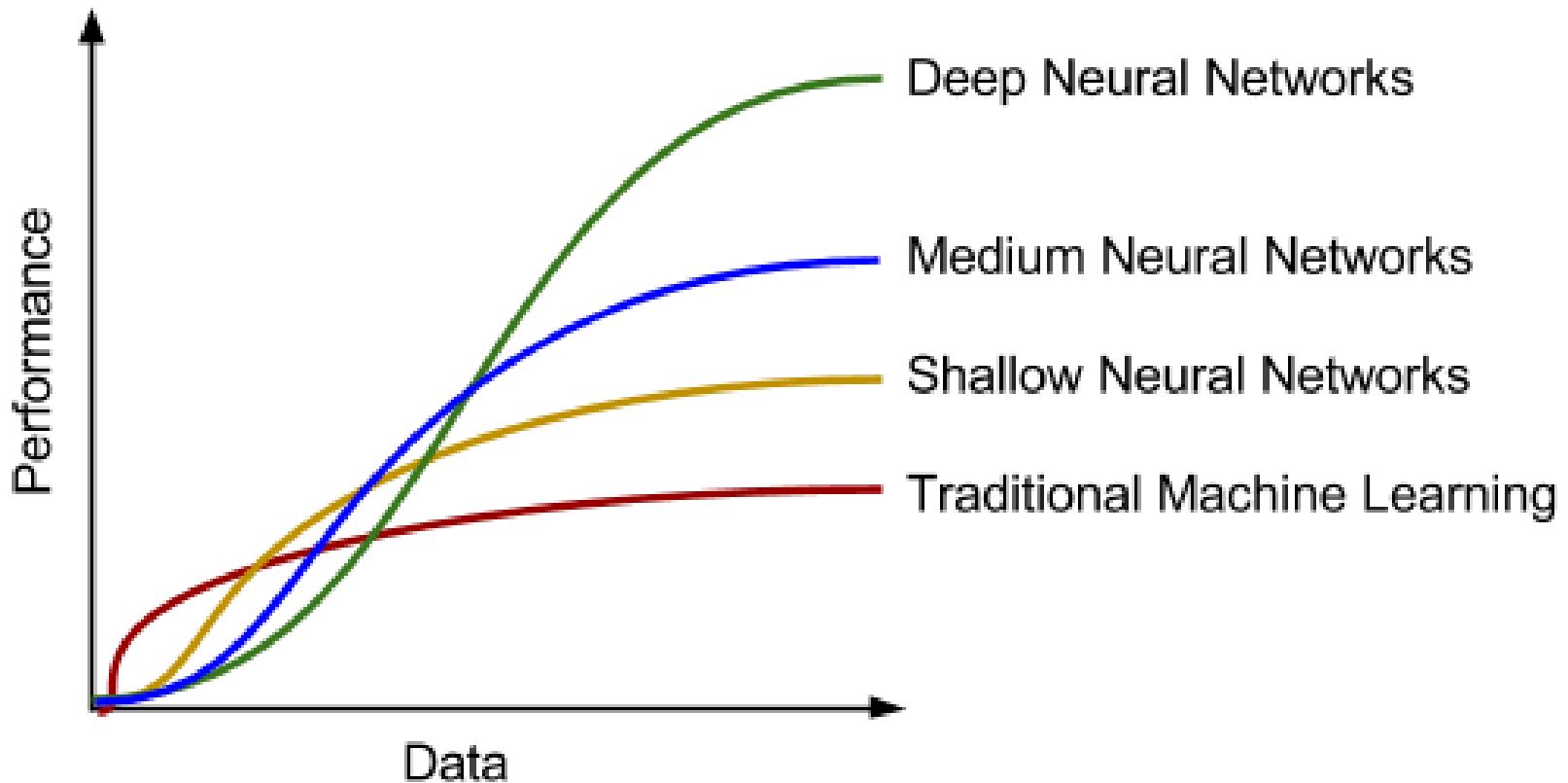
模組加深加寬；整體模型加深加寬



本質上都是在增加 1. 學習效率 & 2. 模型複雜度

模型複雜度 vs. 資料量

簡單模型在資料少的情況表現更好

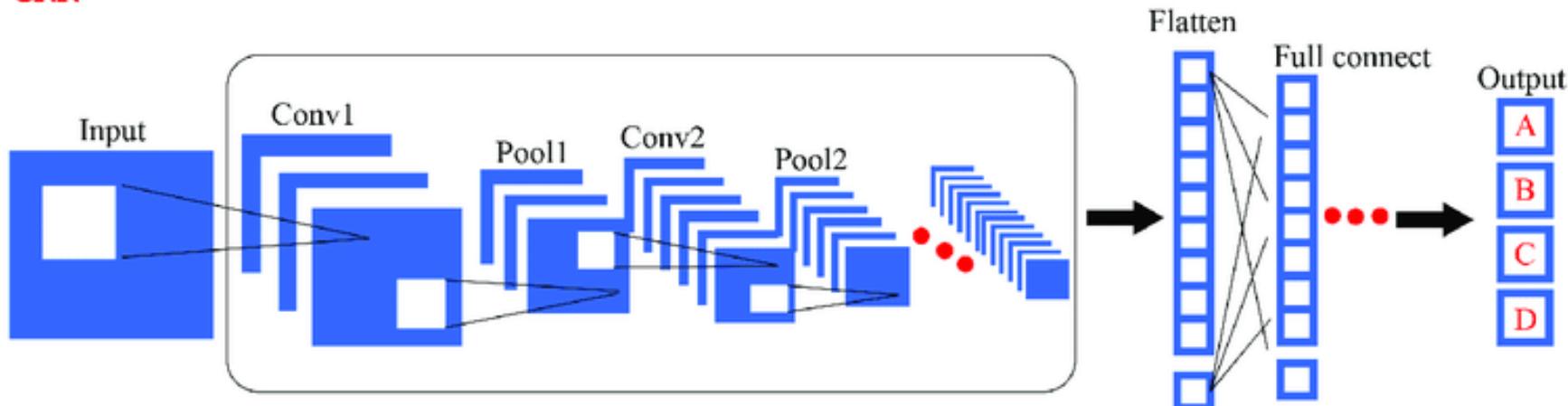


所以 DNN 裡面才有這麼多 hyperparameter tuning

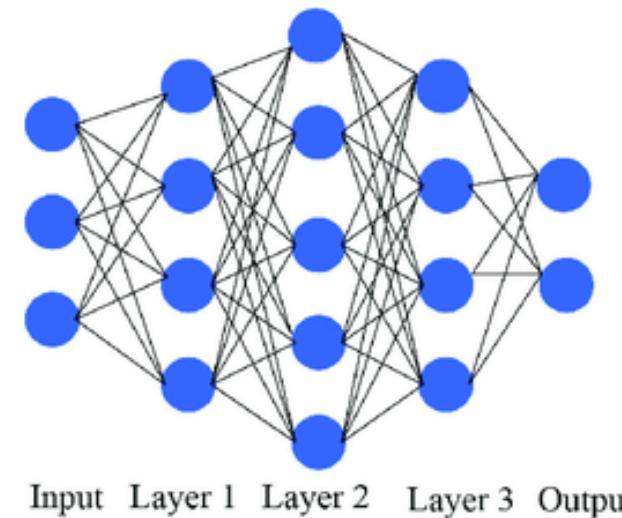
Deep Neural Networks 的分類

CNN 通常處理影像資料；RNN 通常處理語言資料

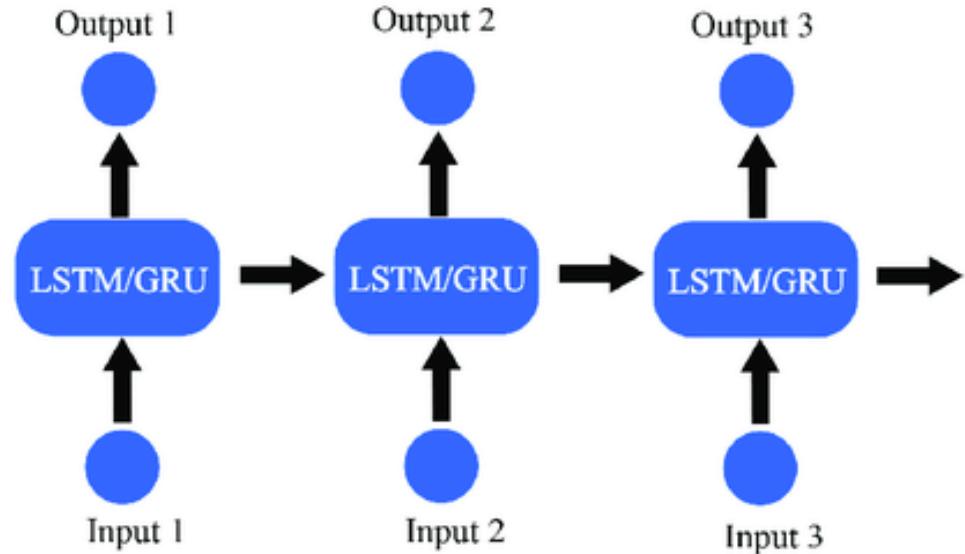
CNN



DNN

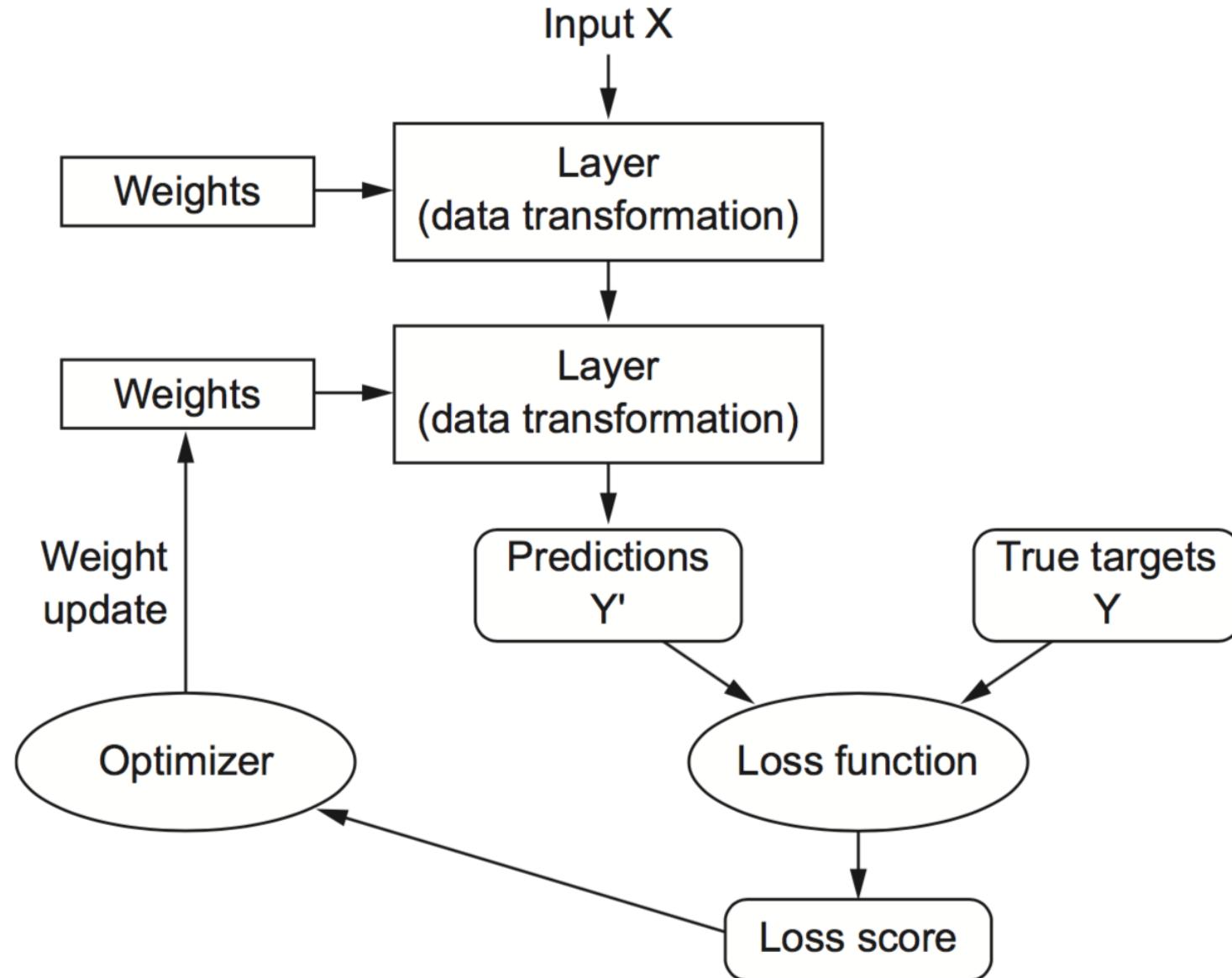


RNN



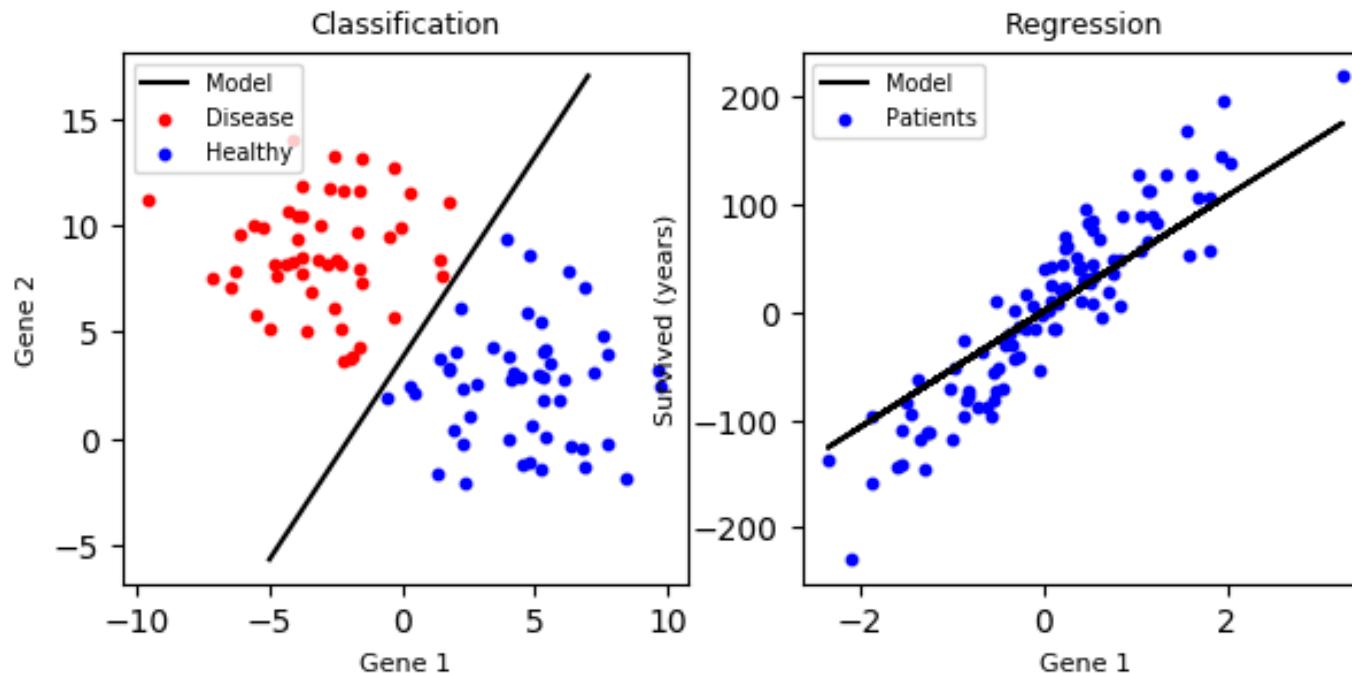
Deep Supervised Learning

和 Shallow Supervised Learning 程序一樣



Loss: Cross-entropy vs. MSE

分類分對就好，確切數值不對沒關係；迴歸錯必較



$$\hat{y} \quad y$$

$$D(\hat{y}, y) = - \sum_j y_j \ln \hat{y}_j$$

$$\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

$$MSE = \frac{1}{m} \sum_{i=1}^m (y_i - h_i)^2 \text{ (迴歸用)}$$

$$\text{分類用: } CE = -\frac{1}{m} \sum_{i=1}^m [y_i \log(h_i) + (1 - y_i) \log(1 - h_i)]$$

更新 W: Backpropagation

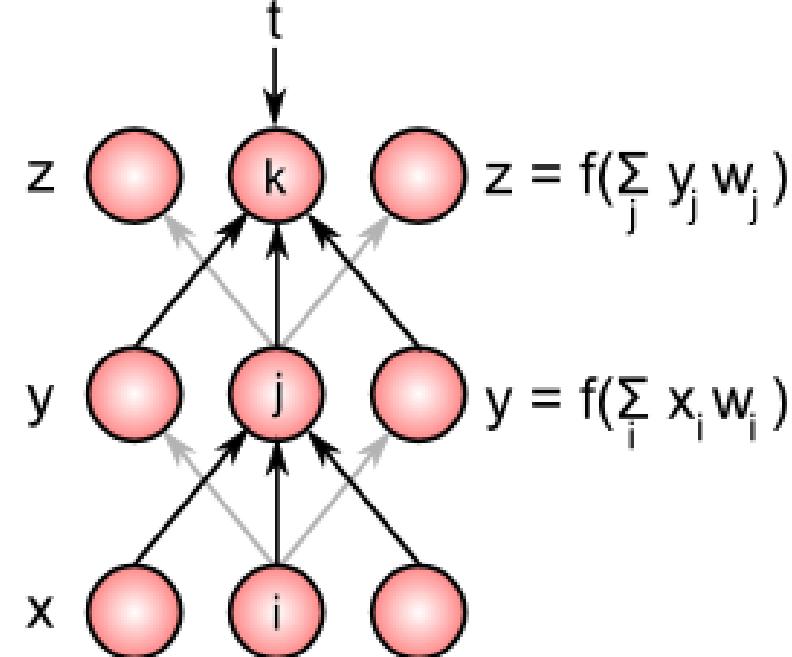
多層 NNs 常用的非生物性演算法（因違反 locality）

Target

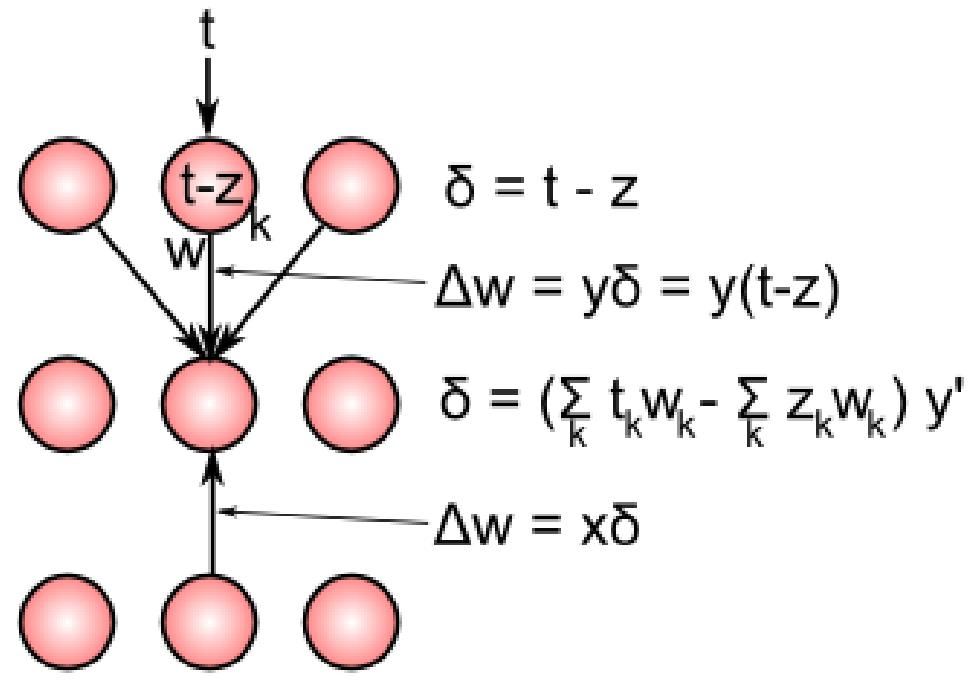
Output

Hidden

Input



a) Feedforward Activation

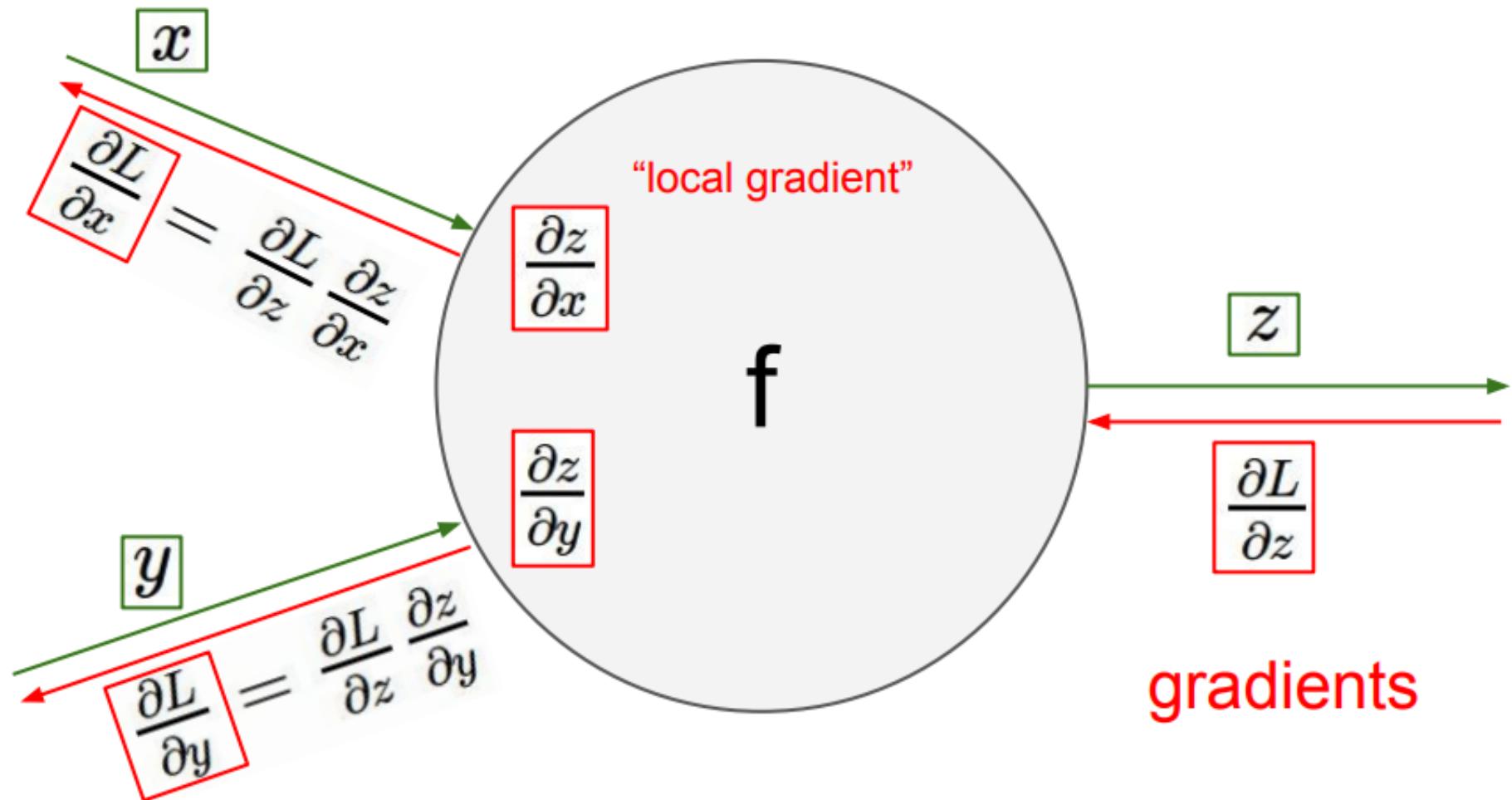


b) Error Backpropagation

當激發函數是 sigmoid 時 BP 的推証請參考這裡

更新 W: Deep Backpropagation

看似複雜但每個映射只要管好計算自己的梯度即可



Overview

Explanatory CCN Ms for FM

Predictive DL Ms for DM

Predictive DL Ms for FM

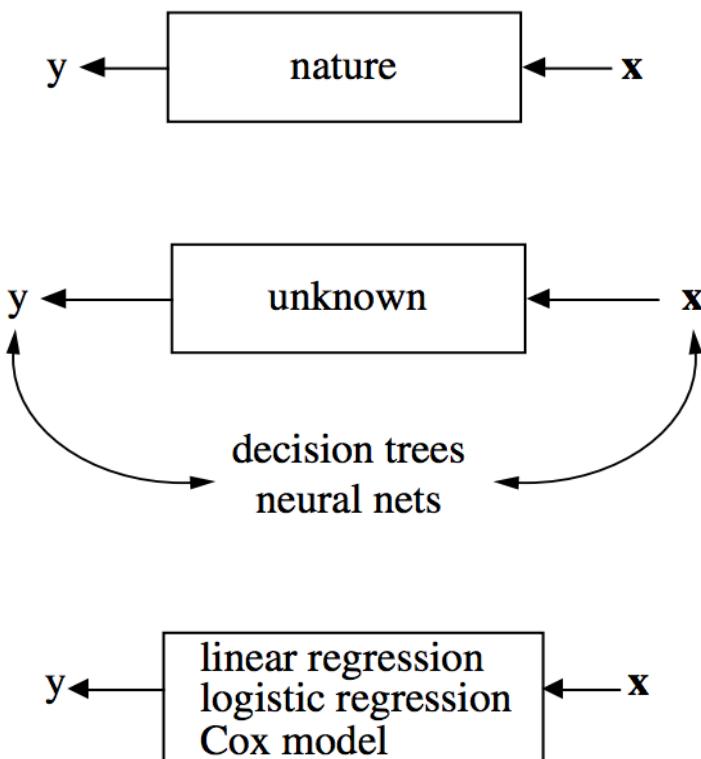
解釋性模型 vs. 預測性模型 (1/4)

科學需要透明盒；科技暗黑也沒關係

Statistical Science
2001, Vol. 16, No. 3, 199–231

Statistical Modeling: The Two Cultures

Leo Breiman



解釋性模型 vs. 預測性模型 (2/4)

先把模型做對 > 講一個不真確的故事

Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning

Perspectives on Psychological Science
2017, Vol. 12(6) 1100–1122

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DOI: 10.1177/1745691617693393
www.psychologicalscience.org/PPS



Tal Yarkoni and Jacob Westfall

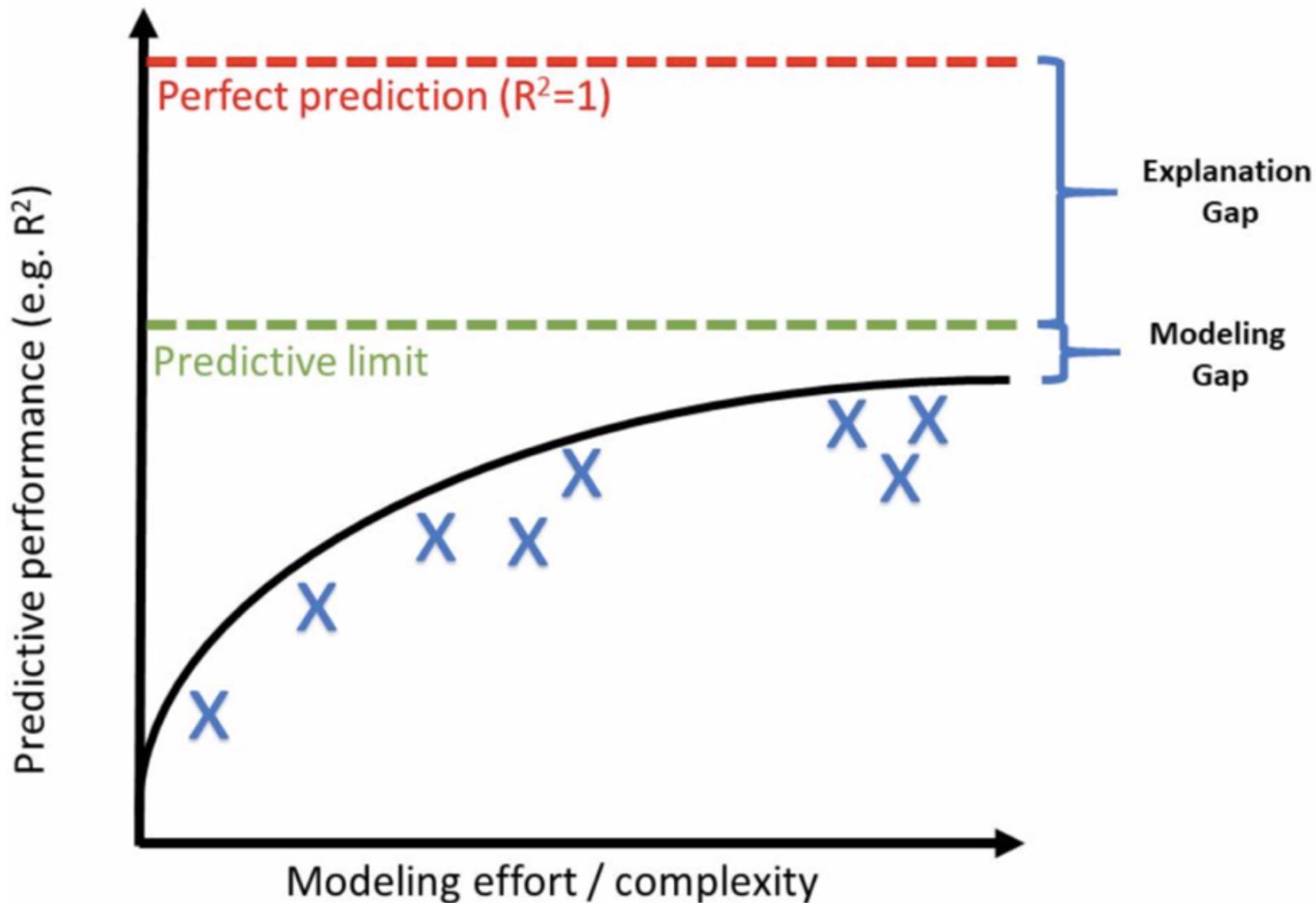
University of Texas at Austin

Abstract

Psychology has historically been concerned, first and foremost, with explaining the causal mechanisms that give rise to behavior. Randomized, tightly controlled experiments are enshrined as the gold standard of psychological research, and there are endless investigations of the various mediating and moderating variables that govern various behaviors. We argue that psychology's near-total focus on explaining the causes of behavior has led much of the field to be populated by research programs that provide intricate theories of psychological mechanism but that have little (or unknown) ability to predict future behaviors with any appreciable accuracy. We propose that principles and techniques from the field of machine learning can help psychology become a more predictive science. We review some of the fundamental concepts and tools of machine learning and point out examples where these concepts have been used to conduct interesting and important psychological research that focuses on predictive research questions. We suggest that an increased focus on prediction, rather than explanation, can ultimately lead us to greater understanding of behavior.

解釋性模型 vs. 預測性模型 (3/4)

先把模型做對 > 講一個不真確的故事

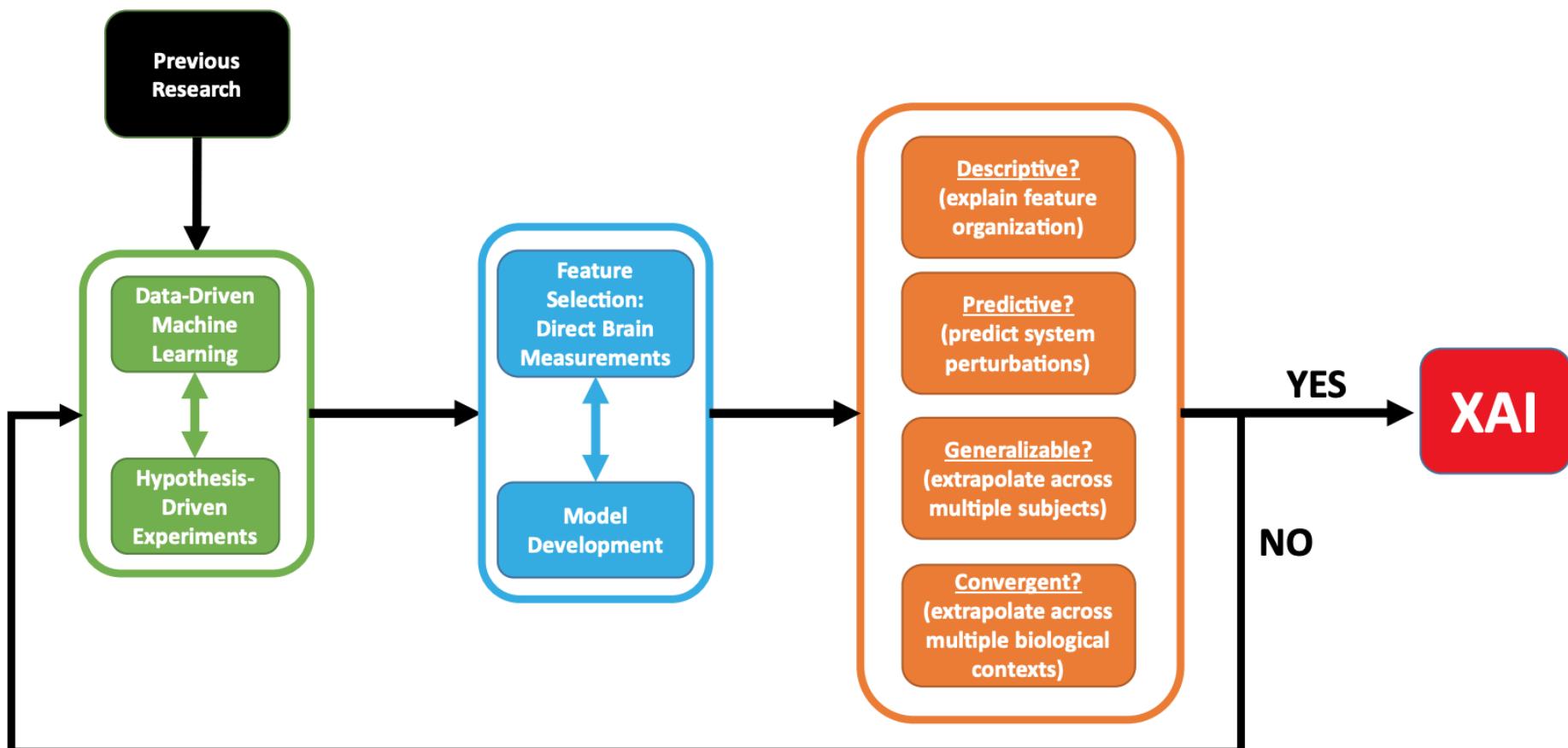


解釋性模型 vs. 預測性模型 (4/4)

先把模型做對 > 講一個不真確的故事

A Shared Vision for Machine Learning in Neuroscience

✉ Mai-Anh T. Vu,¹ ✉ Tülay Adalı,⁸ Demba Ba,⁹ György Buzsáki,¹⁰ ✉ David Carlson,^{3,4} Katherine Heller,⁵ Conor Liston,¹¹ ✉ Cynthia Rudin,^{6,7} ✉ Vikaas S. Sohal,¹² ✉ Alik S. Widge,¹³ ✉ Helen S. Mayberg,¹⁴ Guillermo Sapiro,⁶ and Kafui Dzirasa^{1,2}



Functional Metaphor 範例 C (1/3)

為何成人感知 50% 合成臉為外國人？One-drop rule?

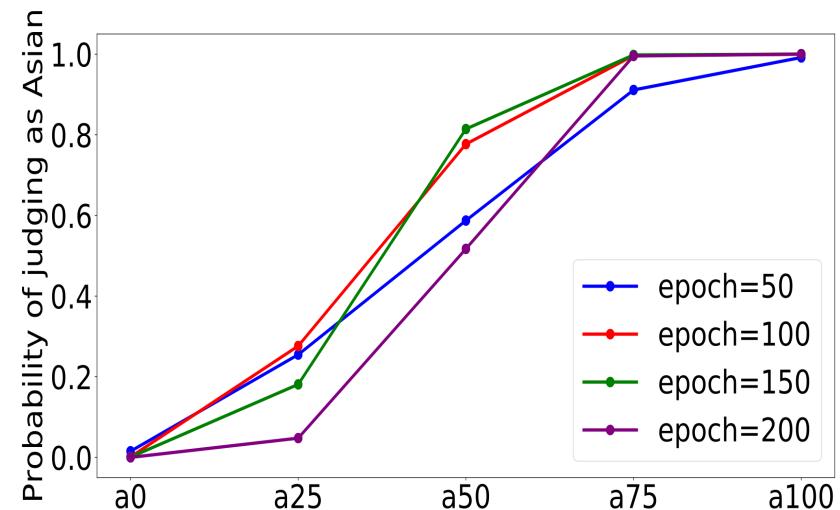
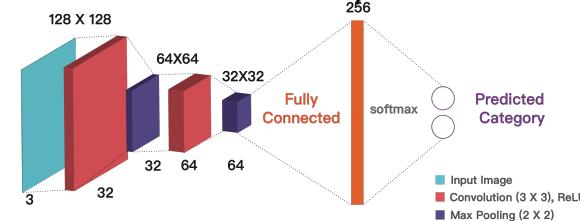
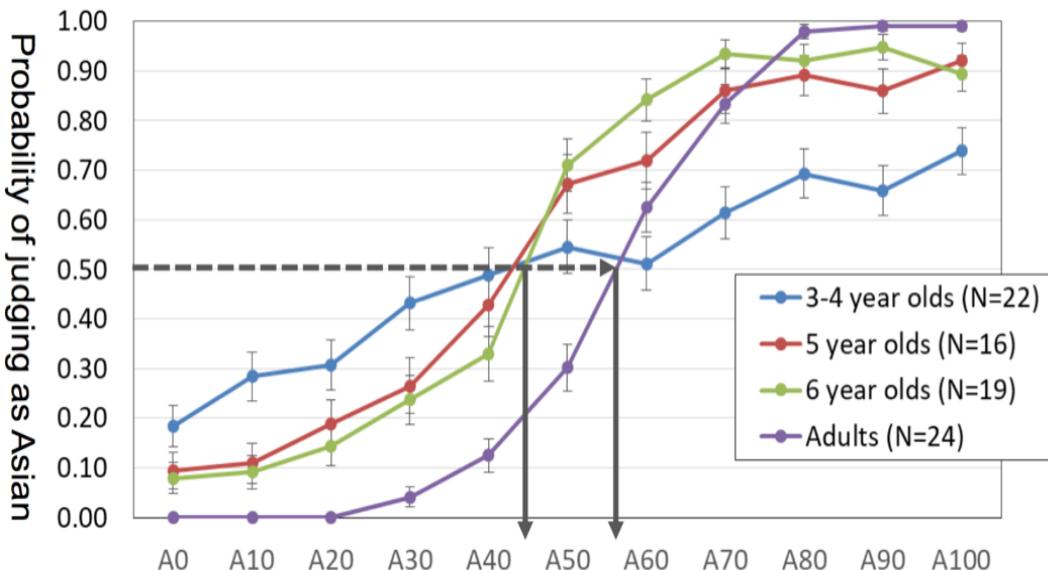


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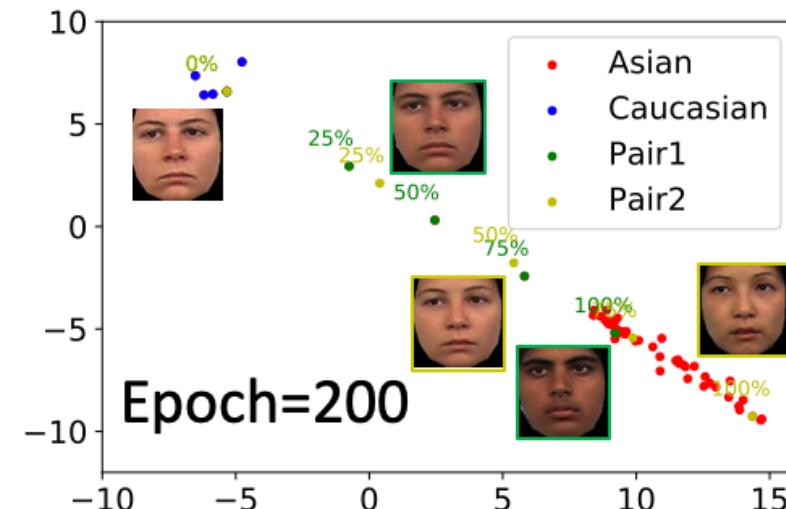
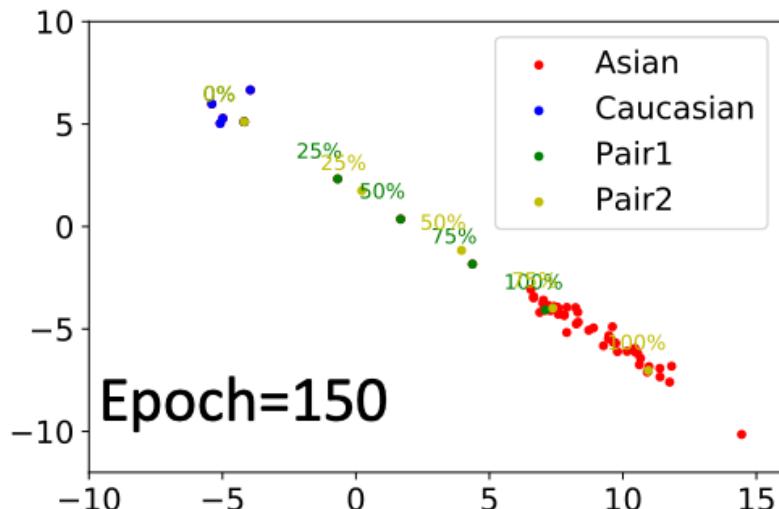
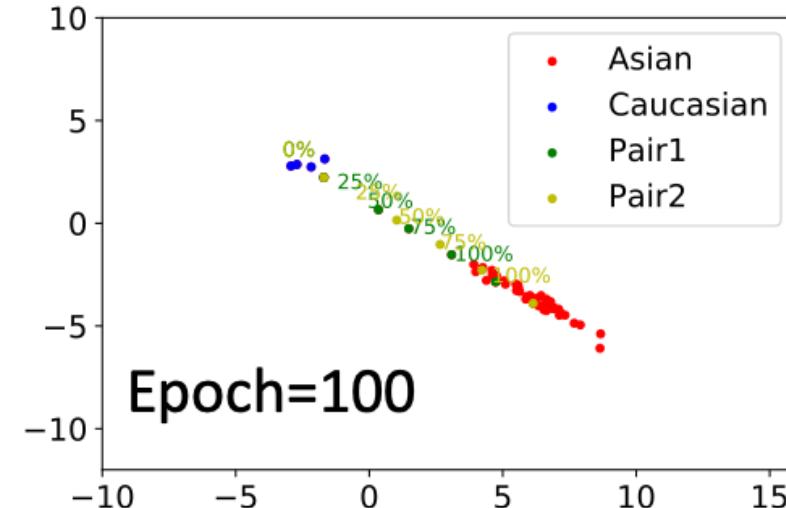
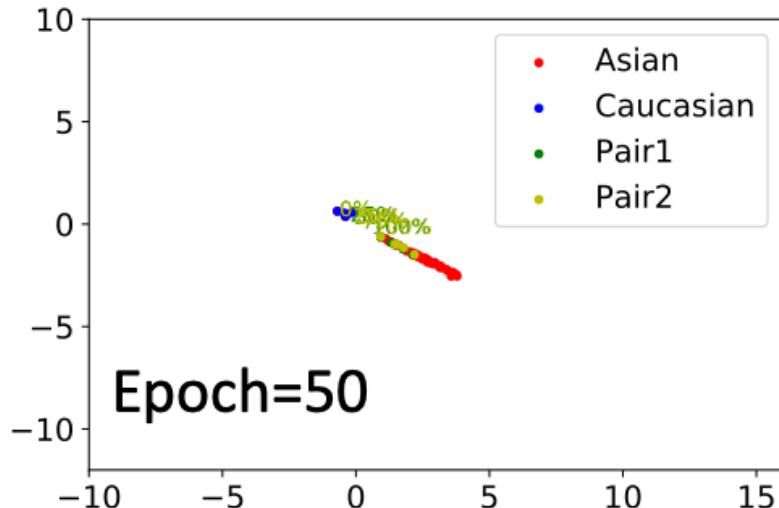
² MOST AI Biomedical Research Center

³ Graduate Institute of Biomedical Sciences, China Medical University



Functional Metaphor 範例 C (2/2)

種族判斷的實驗資料能被經驗學習解釋



Game Over

