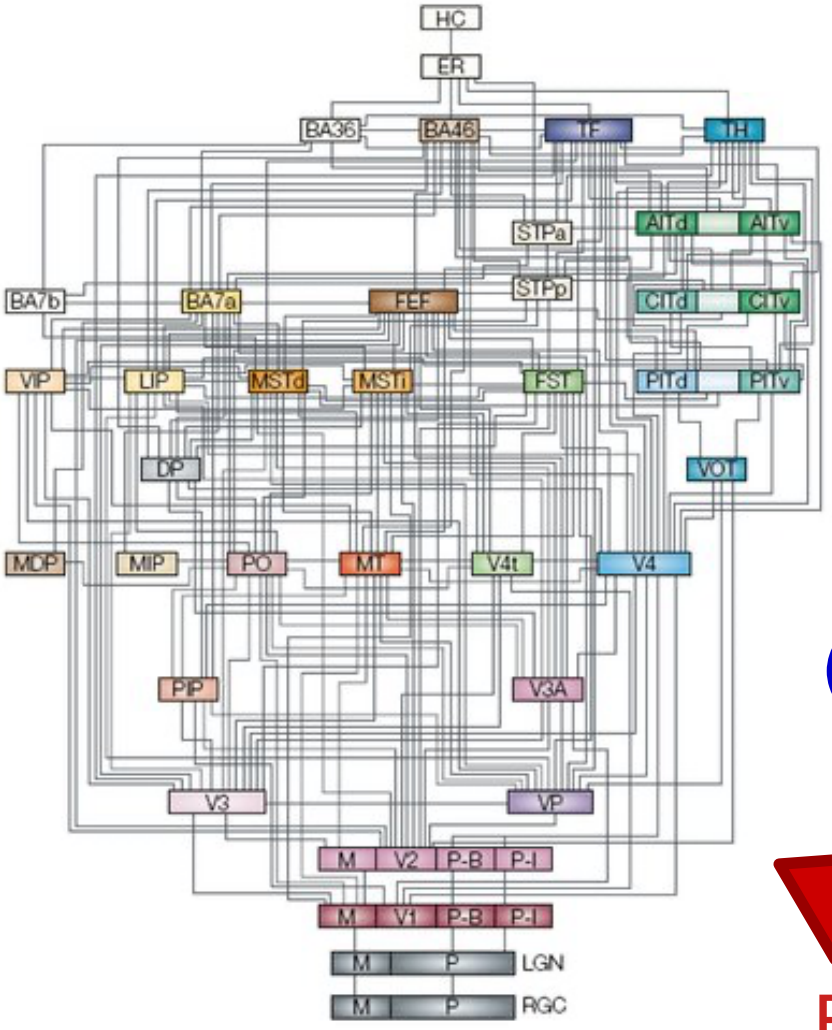
神經與行為模型建構
(Neural & Behavioral Modeling)

課號：Psy7277　　教室： 北 206
識別碼：227M9280　　時間： 五 234

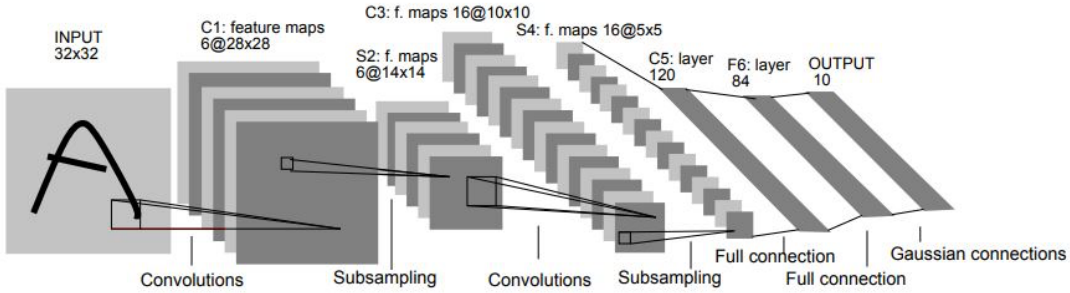
生物神經與類神經的三種關係

預測性模型也可被解釋或幫助解釋



Architectural Metaphors (AM)

(本週開始介紹)



Data Modeling (DM)

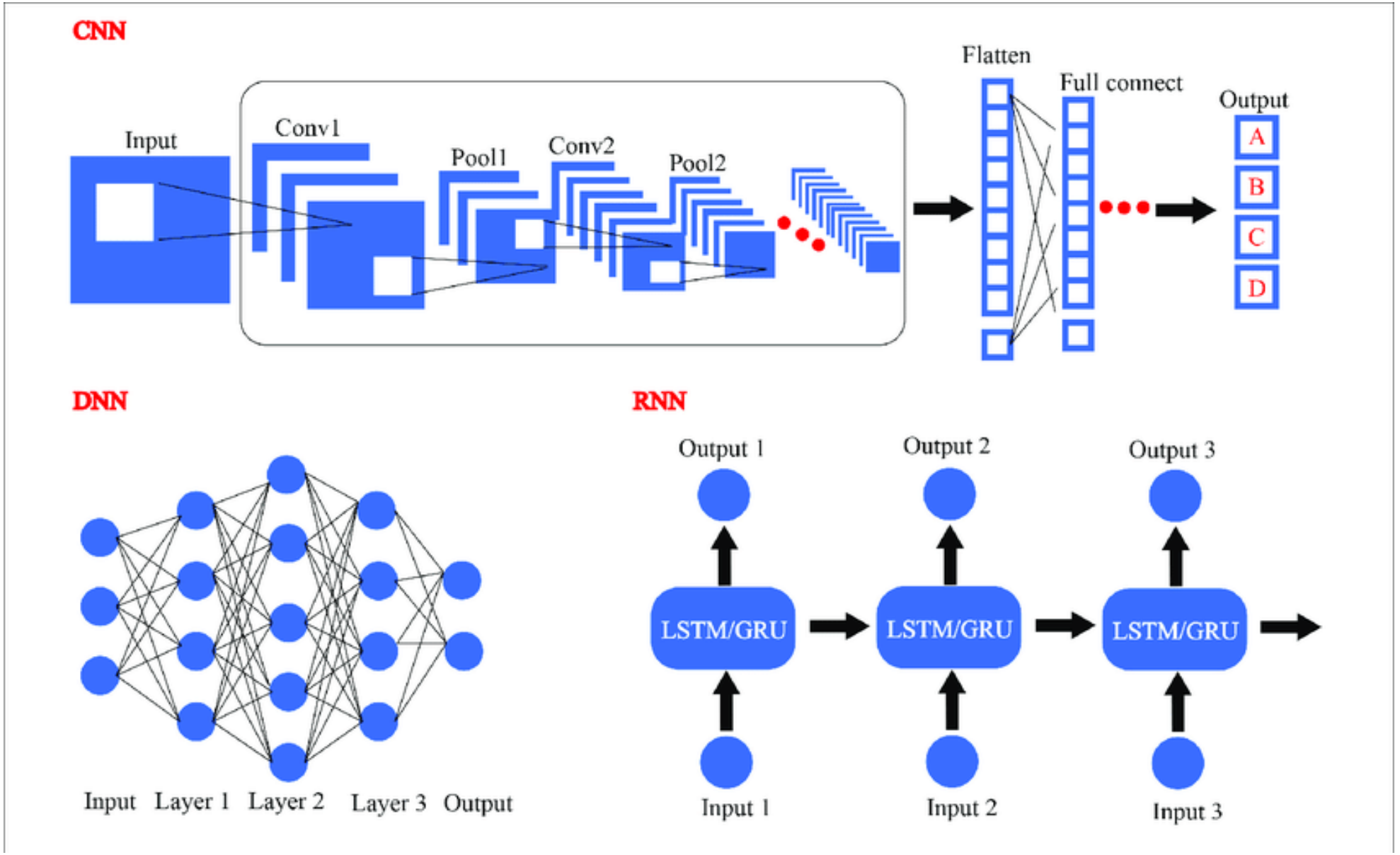
(如 DL 應用在大腦解碼)

Functional Metaphors (FM)

(本來多為計算認知 M, 現在也有深度學習 M)

Deep Neural Networks 的分類

CNN 通常處理影像資料；RNN 通常處理語言資料




本週介紹 CNN
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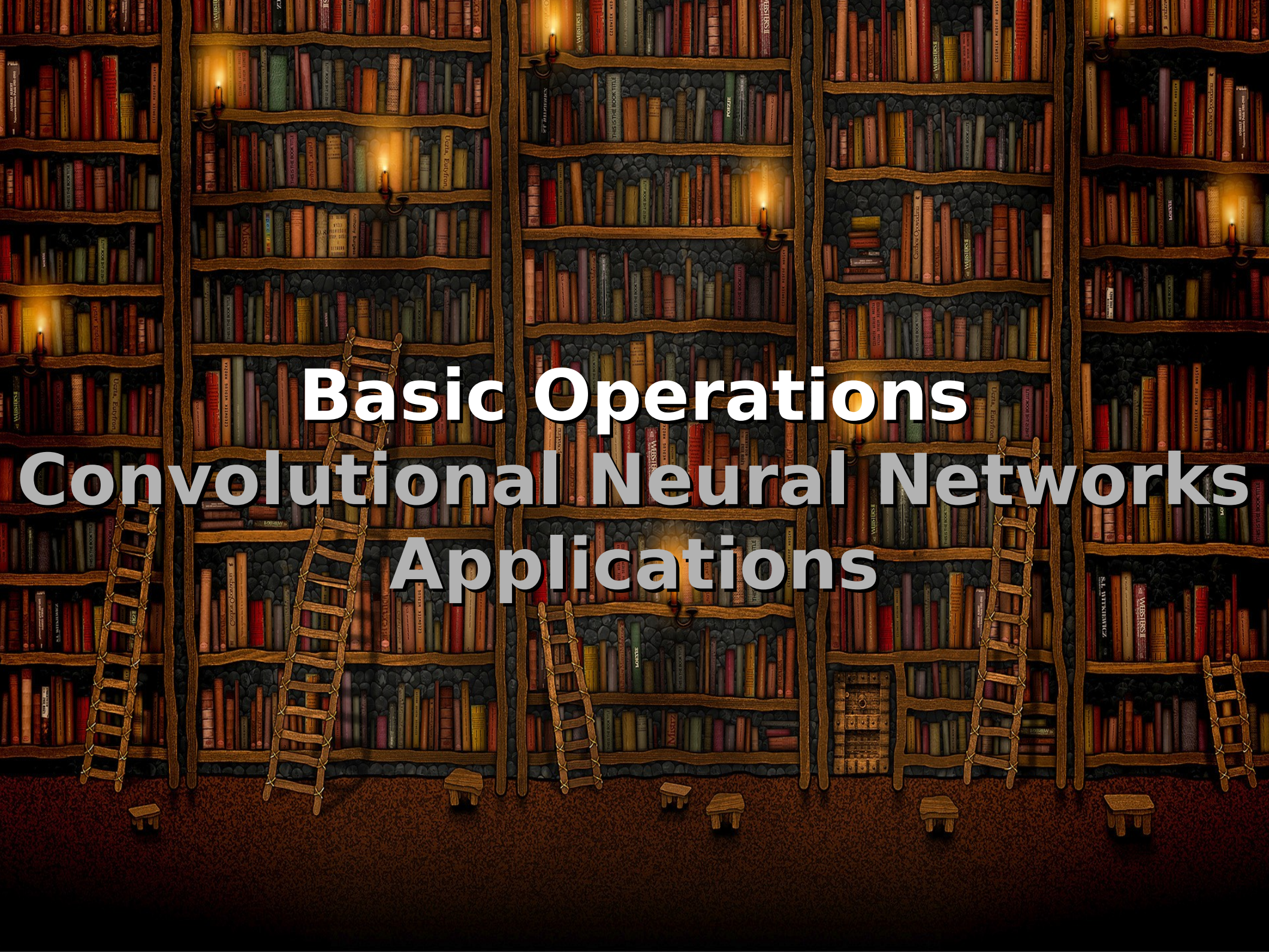
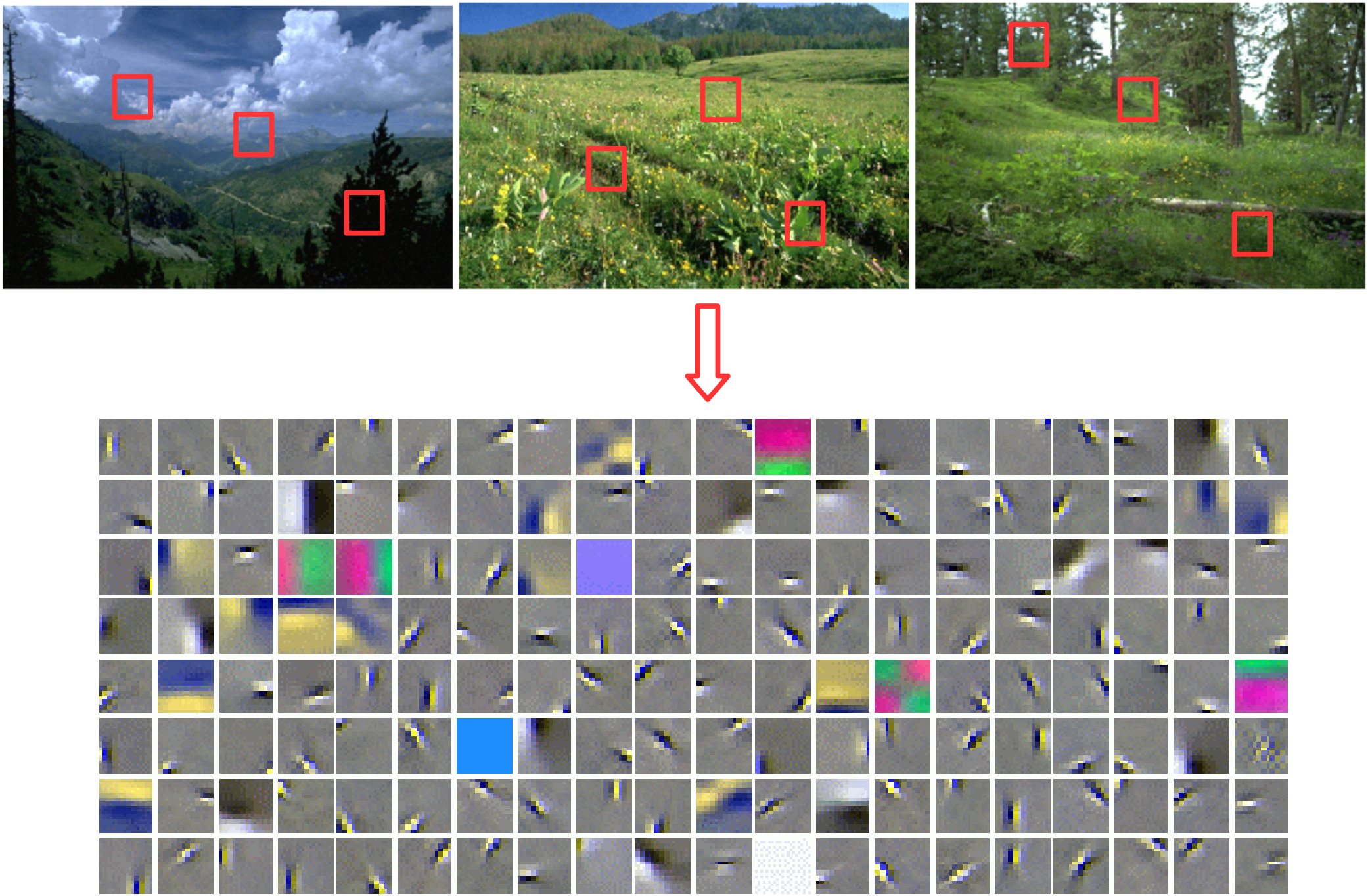

Basic Operations
Convolutional Neural Networks
Applications

Patterns shared by Patches

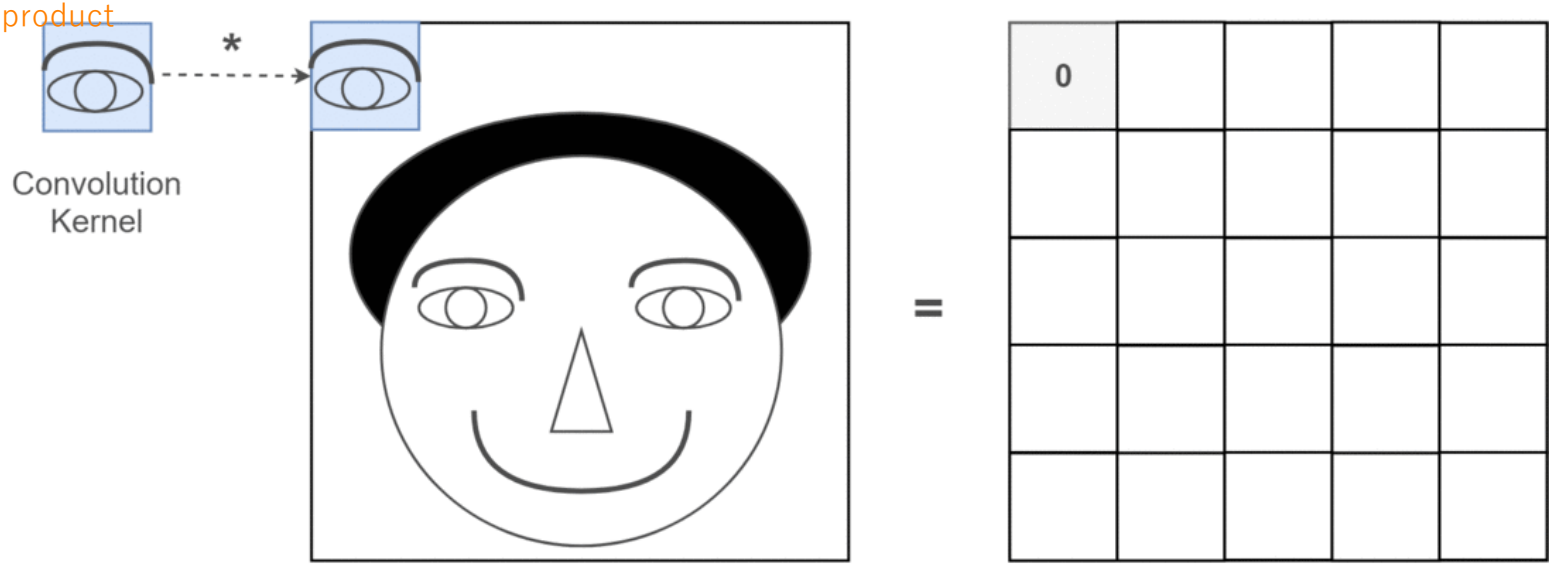


2D Spatial Convolution

x11*w11 + ... + x22w22

Convolution與 Correlation 傻傻分不清楚

實際上 convolution 會先將 weight matrix 上下顛倒在左右相反
之後再與 x 做 dot product



X_{11}	X_{12}	X_{13}
X_{21}	X_{22}	X_{23}
X_{31}	X_{32}	X_{33}

W_{11}	W_{12}
W_{21}	W_{22}

2D Spatial Filtering

例如找橫向的特徵

垂直就很少

這張圖就有很多

Padding & Stride

Input 與 Output 的維度關係一定要會算

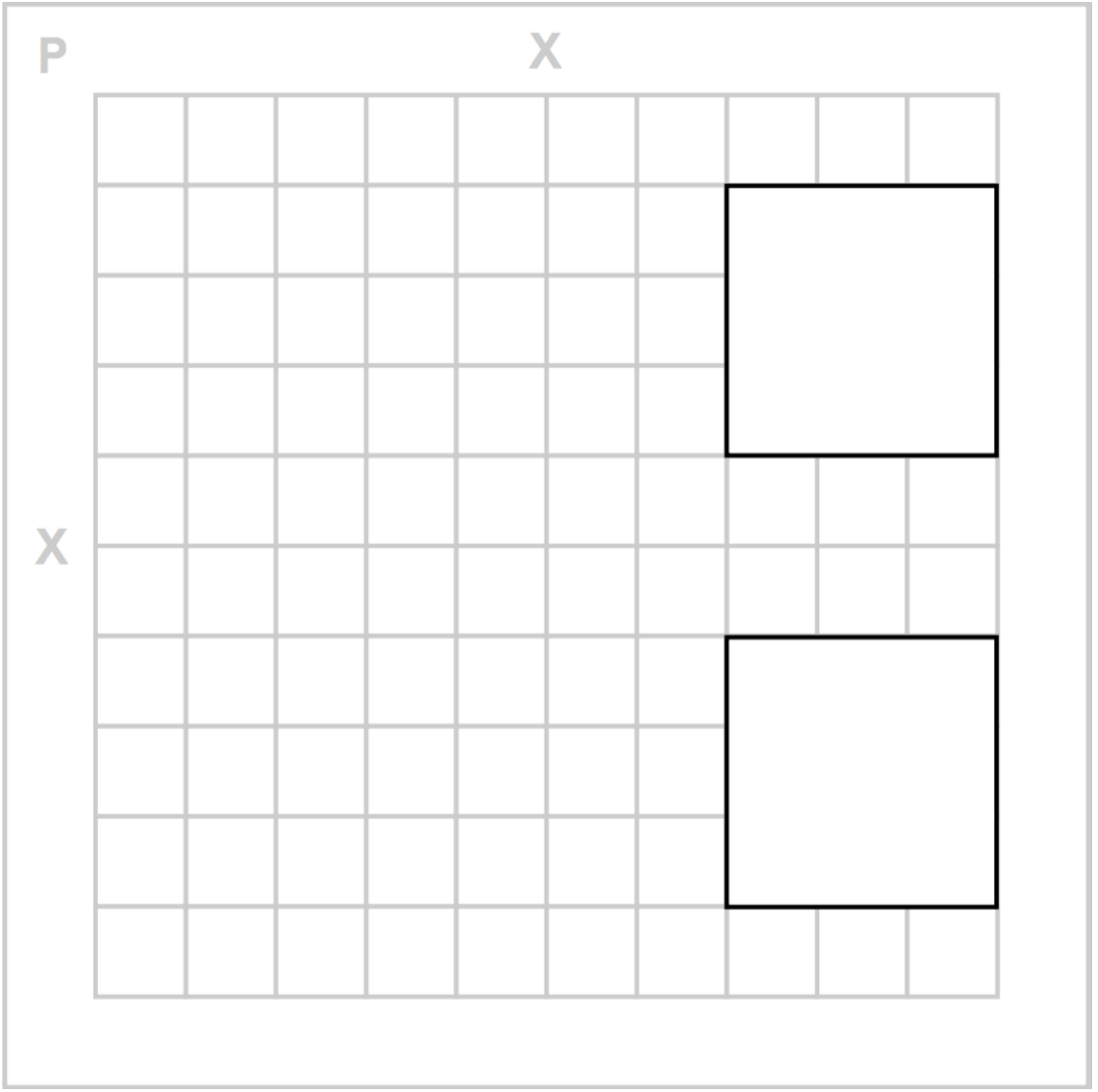
$$1 + \frac{X - F + 2P}{S}$$

X = image size

F = filter size

P = padding

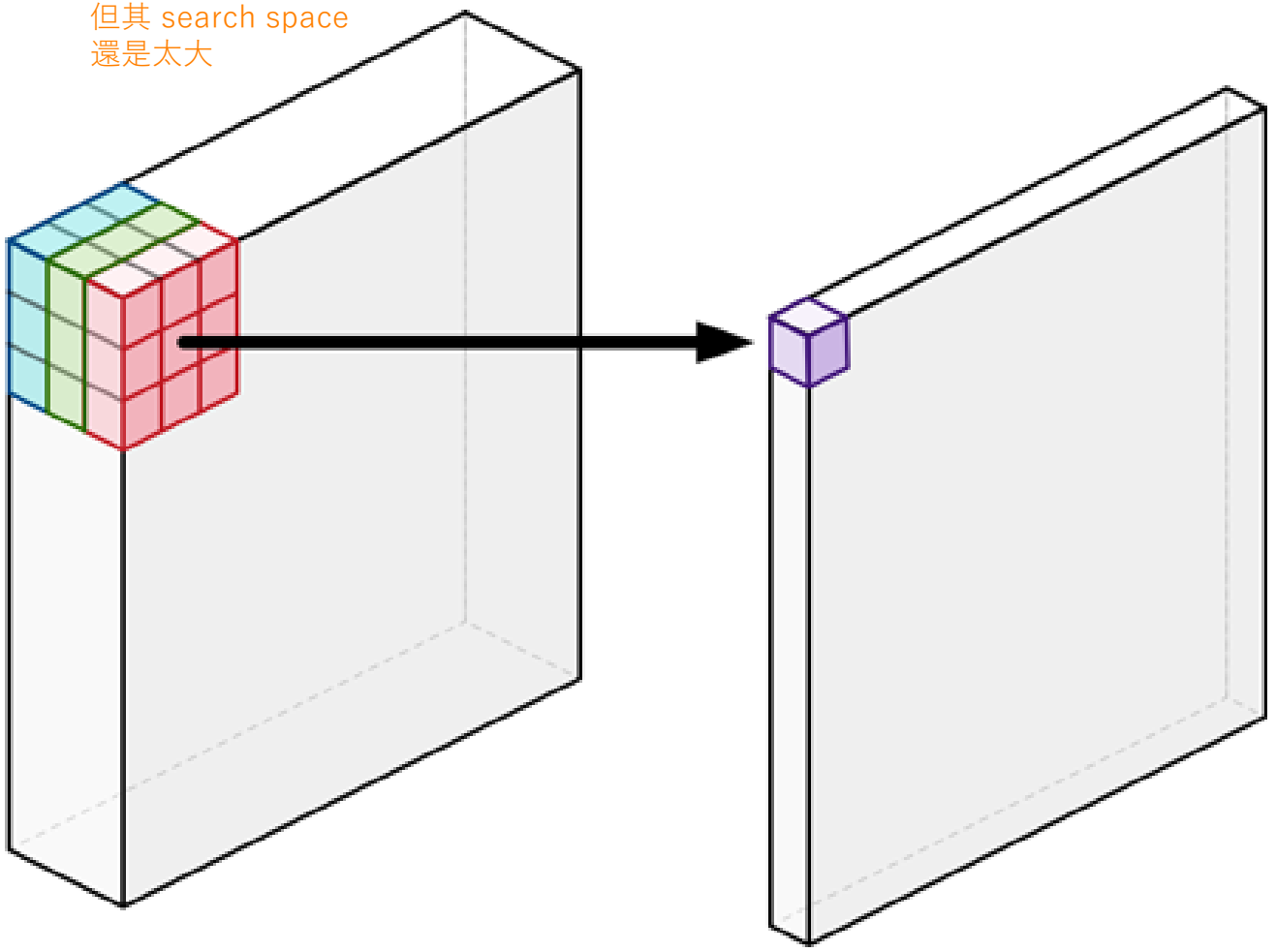
S = stride



3D Spatial Convolution

和 2D 一樣就是 template matching

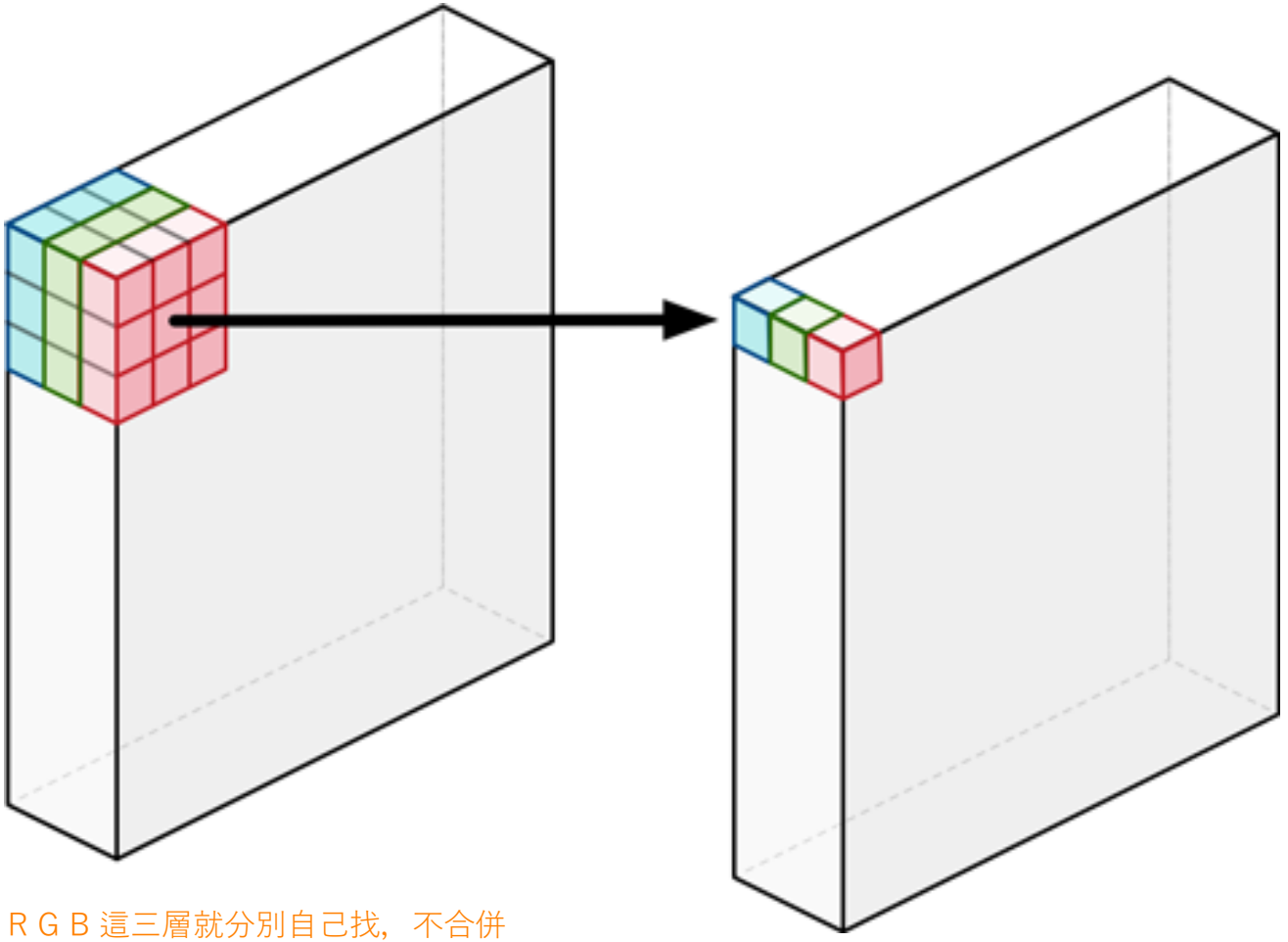
RGB 轉為 灰階
但其 search space
還是太大



Search Space 大小 : 2^(3*3*3)=2^27

Depthwise Separable Conv.

出現在 Xception Net 及其後繼的 Mobile Net 中



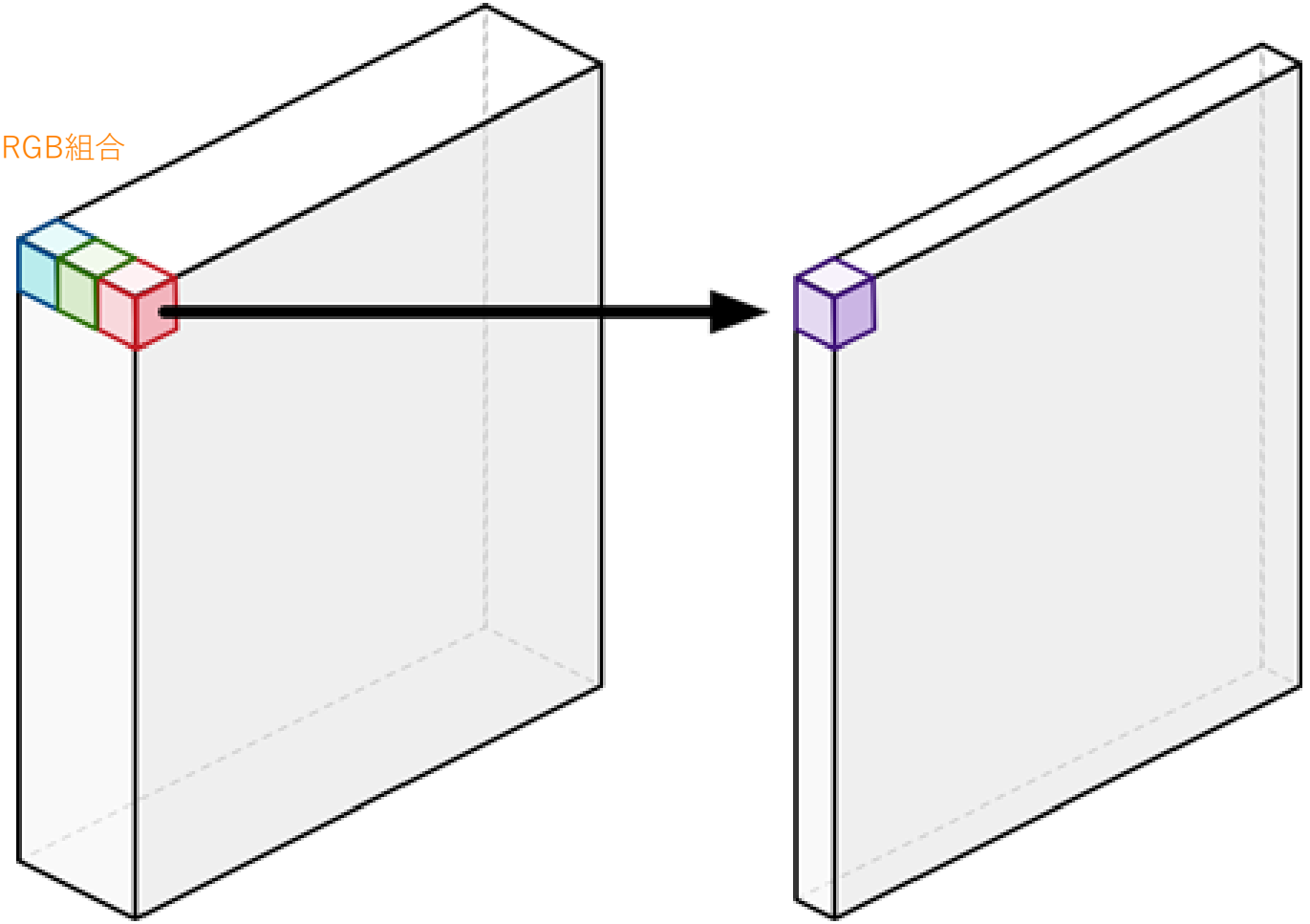
R G B 這三層就分別自己找，不合併
使 search space 變少

Search Space 大小 : 2^(3*3)*3=2^9*3

Pointwise Convolution

Inception, Xception, Squeeze, Mobile Nets 皆有

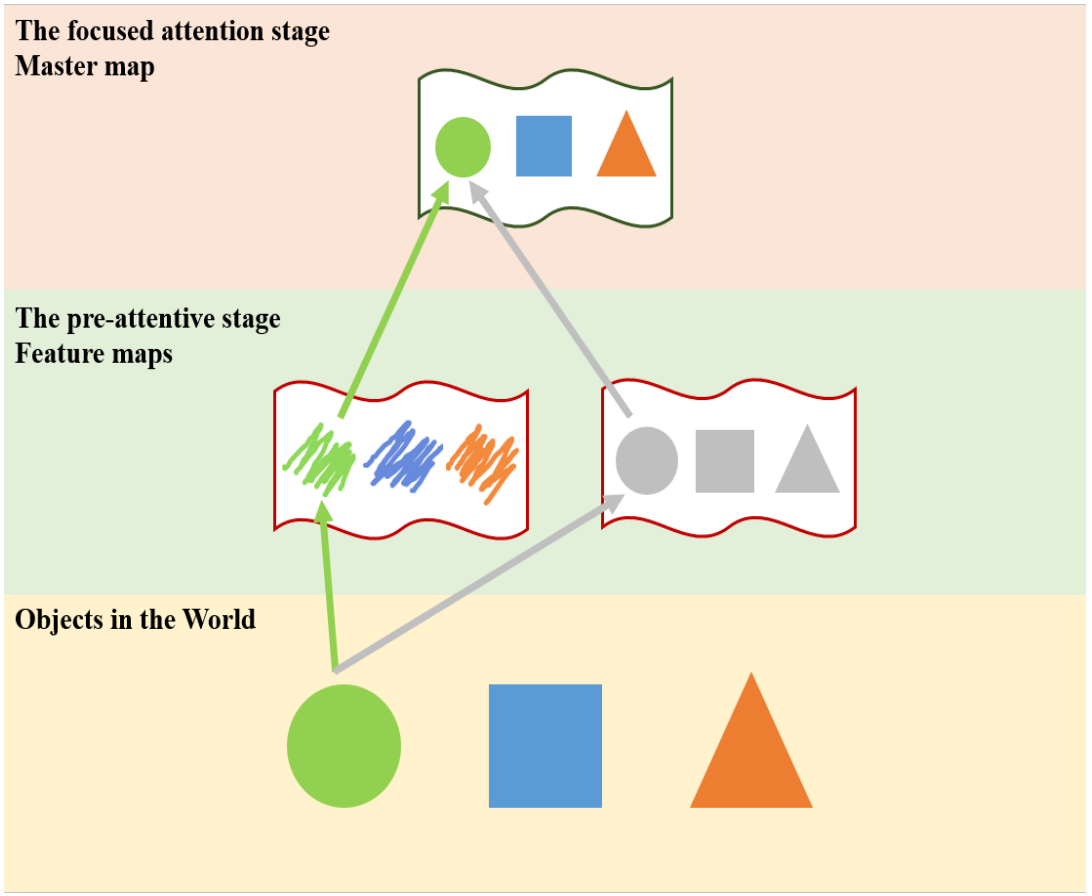
只特別找特別的RGB組合
pointwise

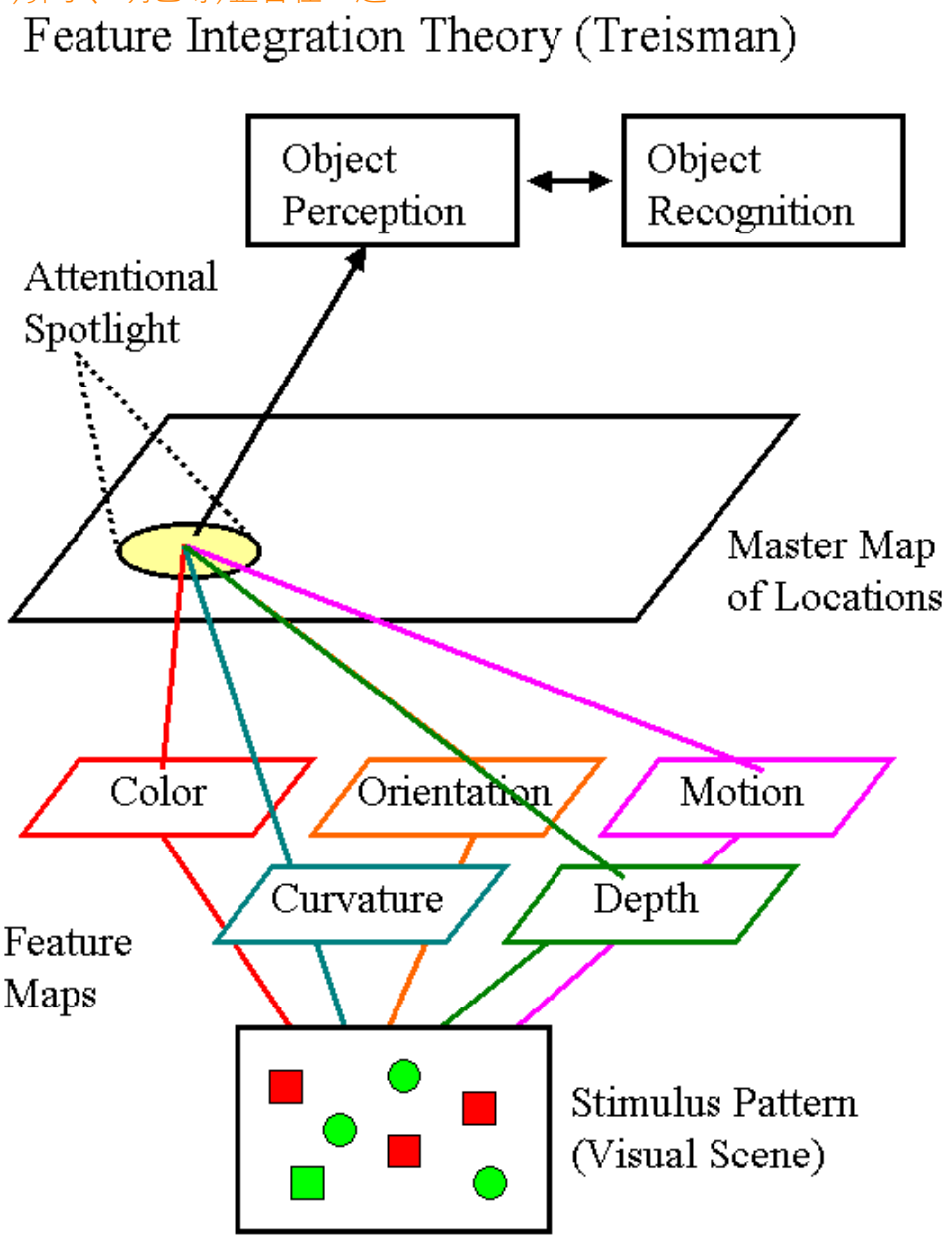


Feature Integration Theory

就是 Features 分開處理再整合

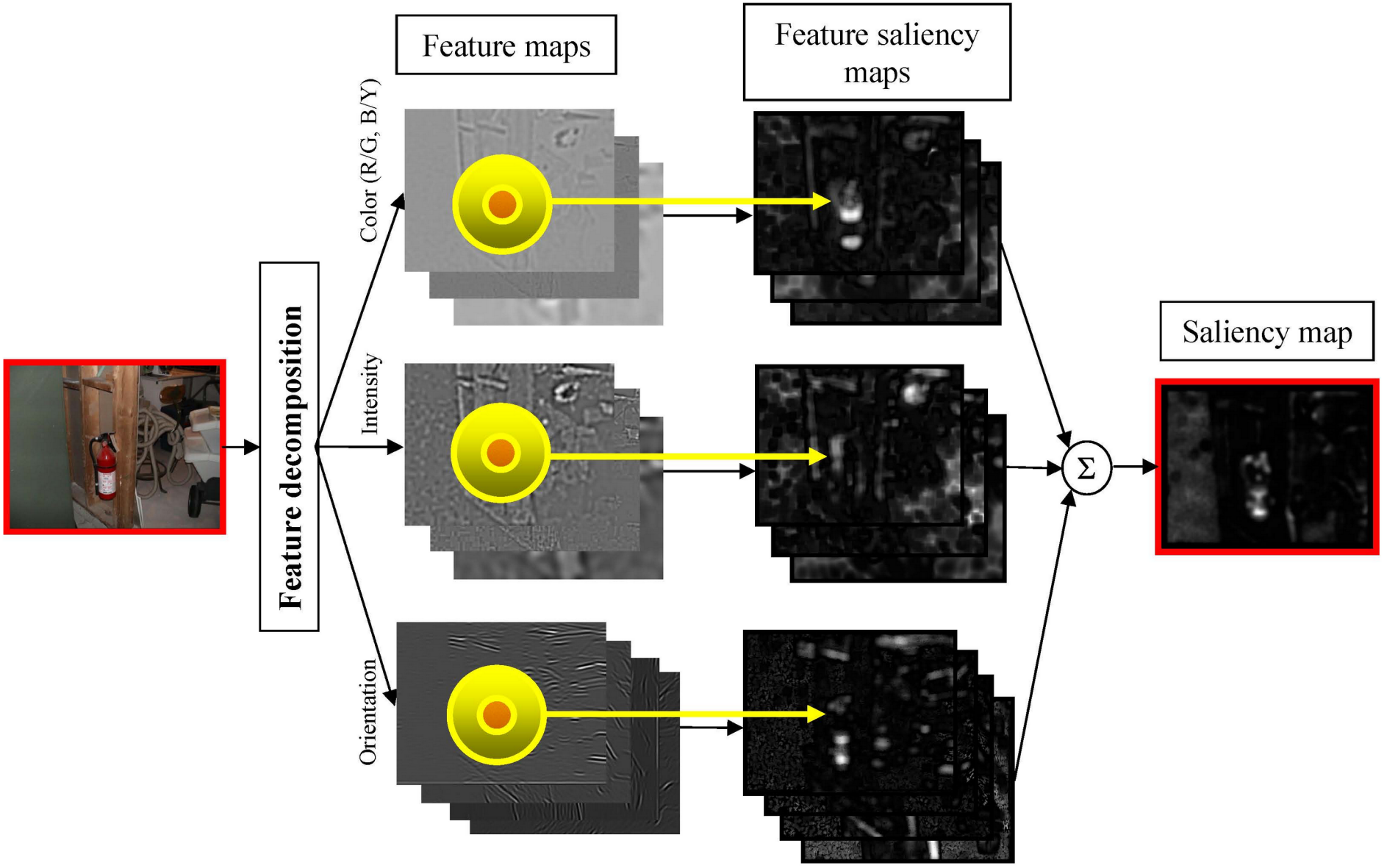
如何將各種的 feature maps (眼睛、)鼻子、嘴巴等)整合在一起





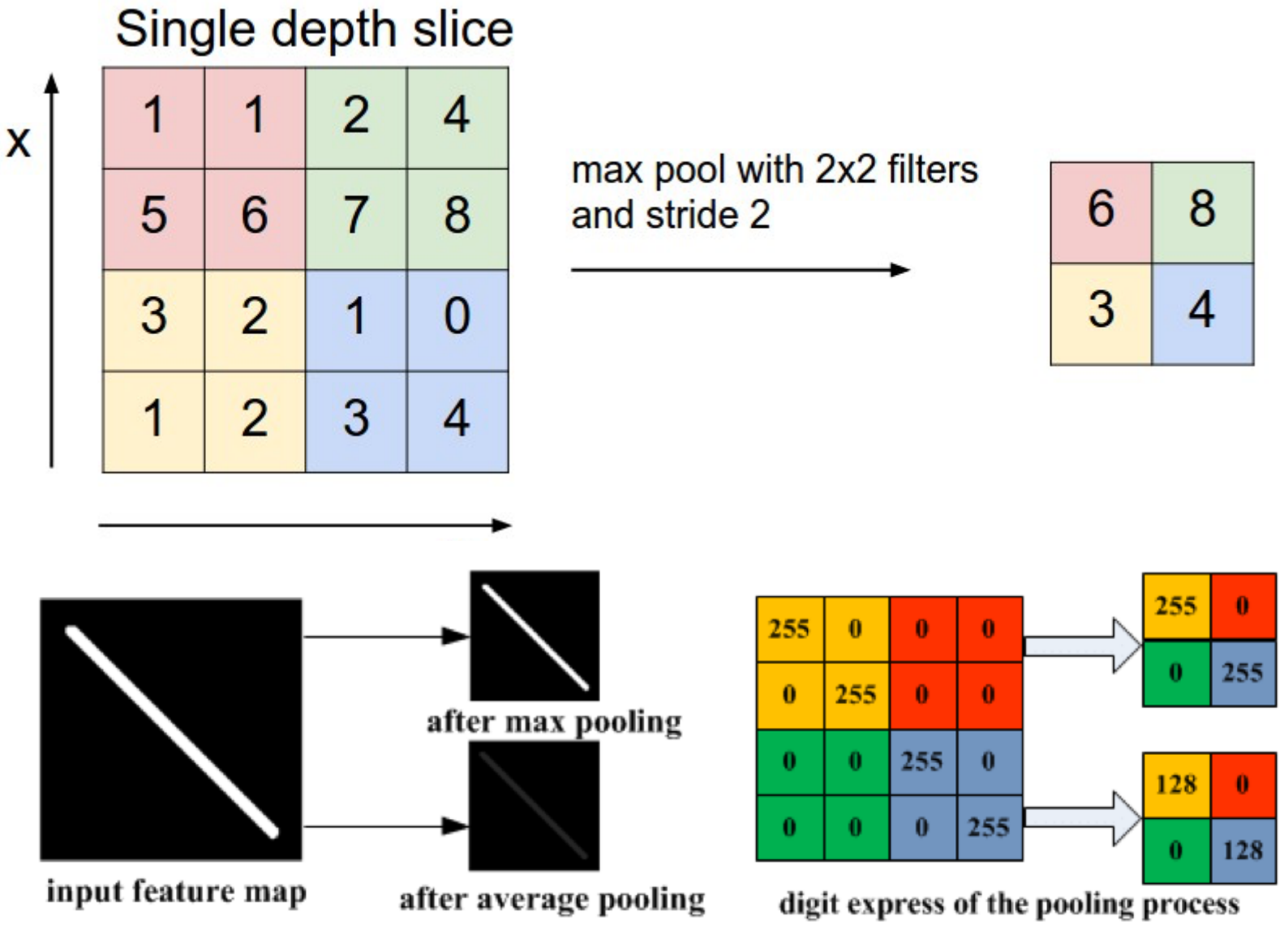
Saliency Map

只是 Feature Integration Theory 的實境版



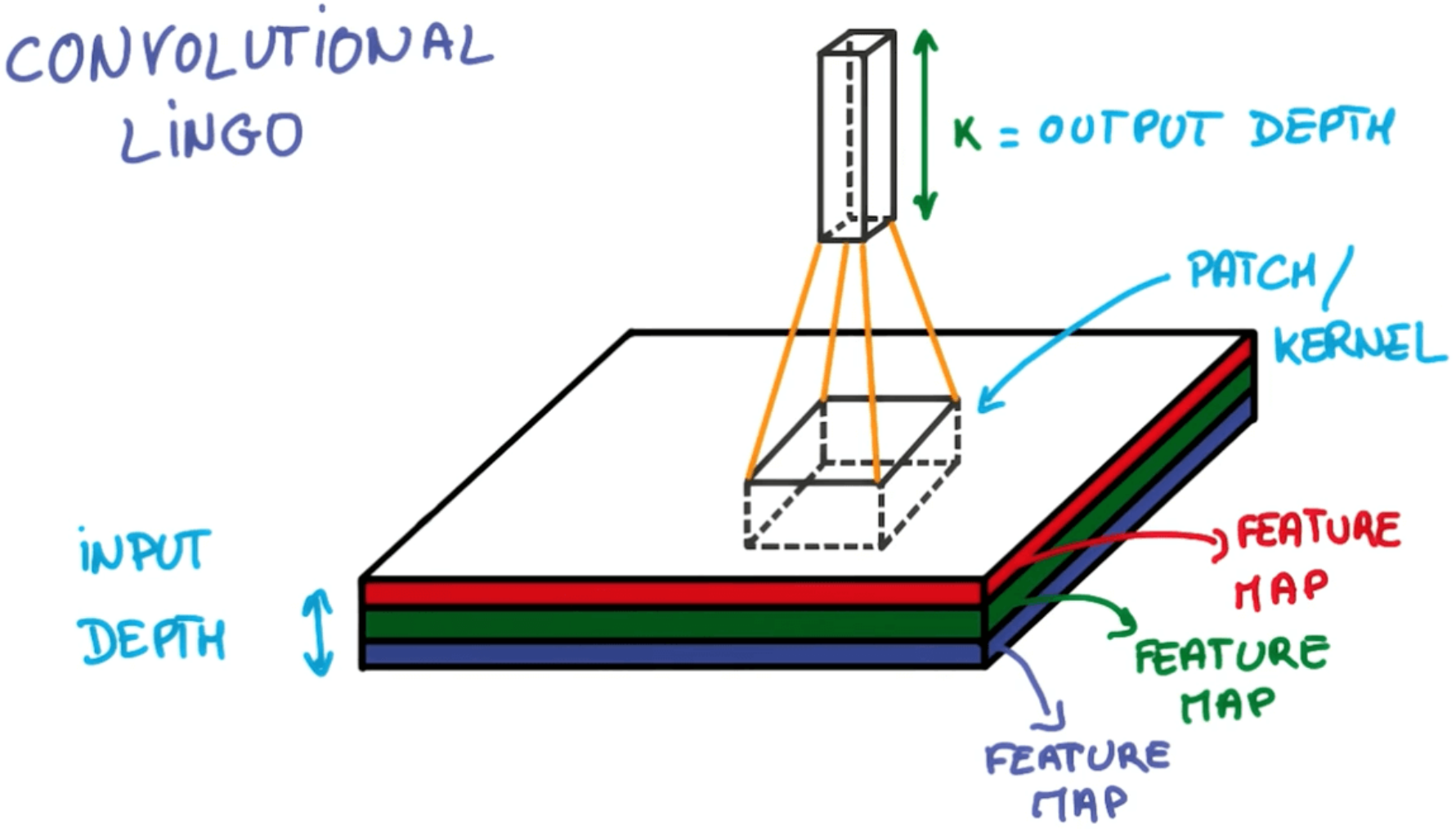
(Max) Pooling

就是 downsampling



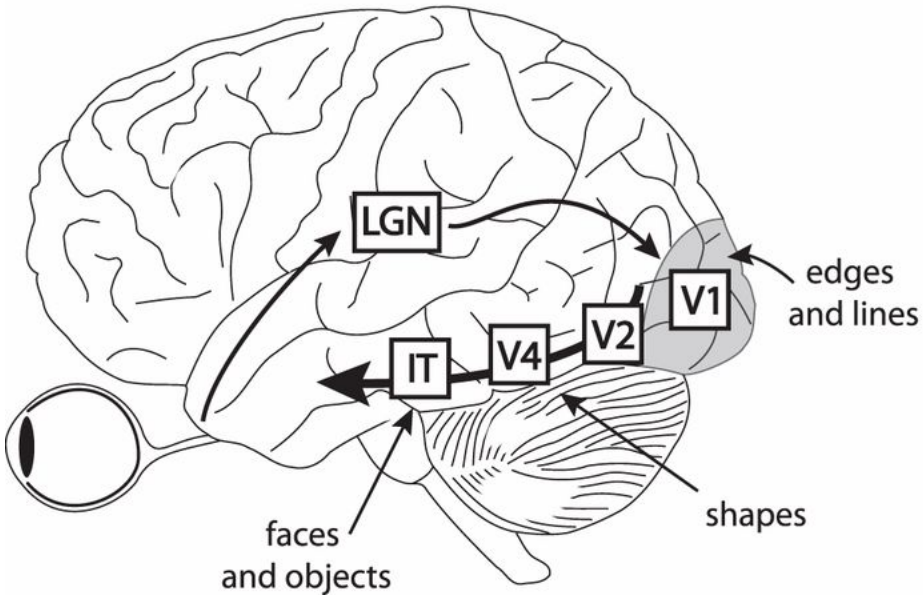
CNN Terms

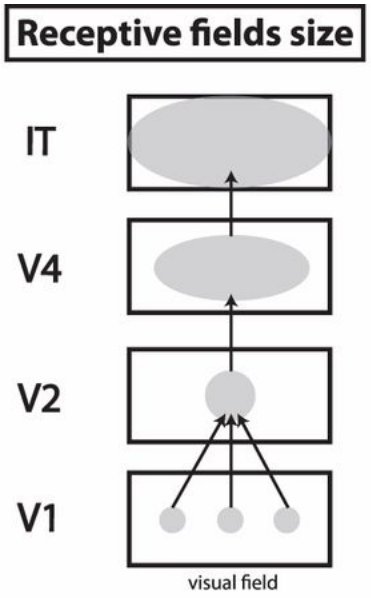
Kernel 對應到的就是生物上的 Receptive Field

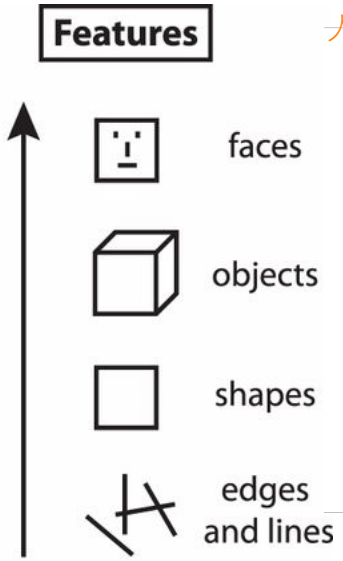


CNN 的金字塔結構

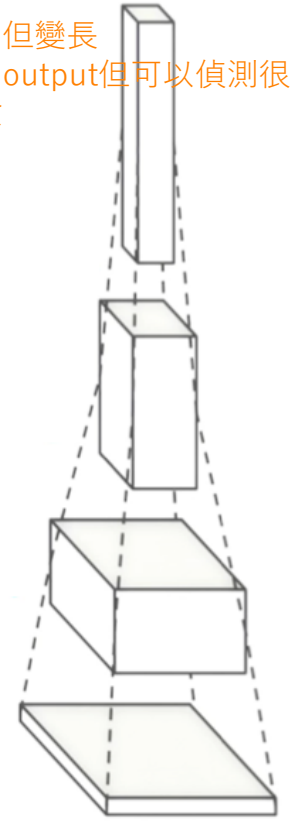
是在仿 ventral visual pathway in the brain

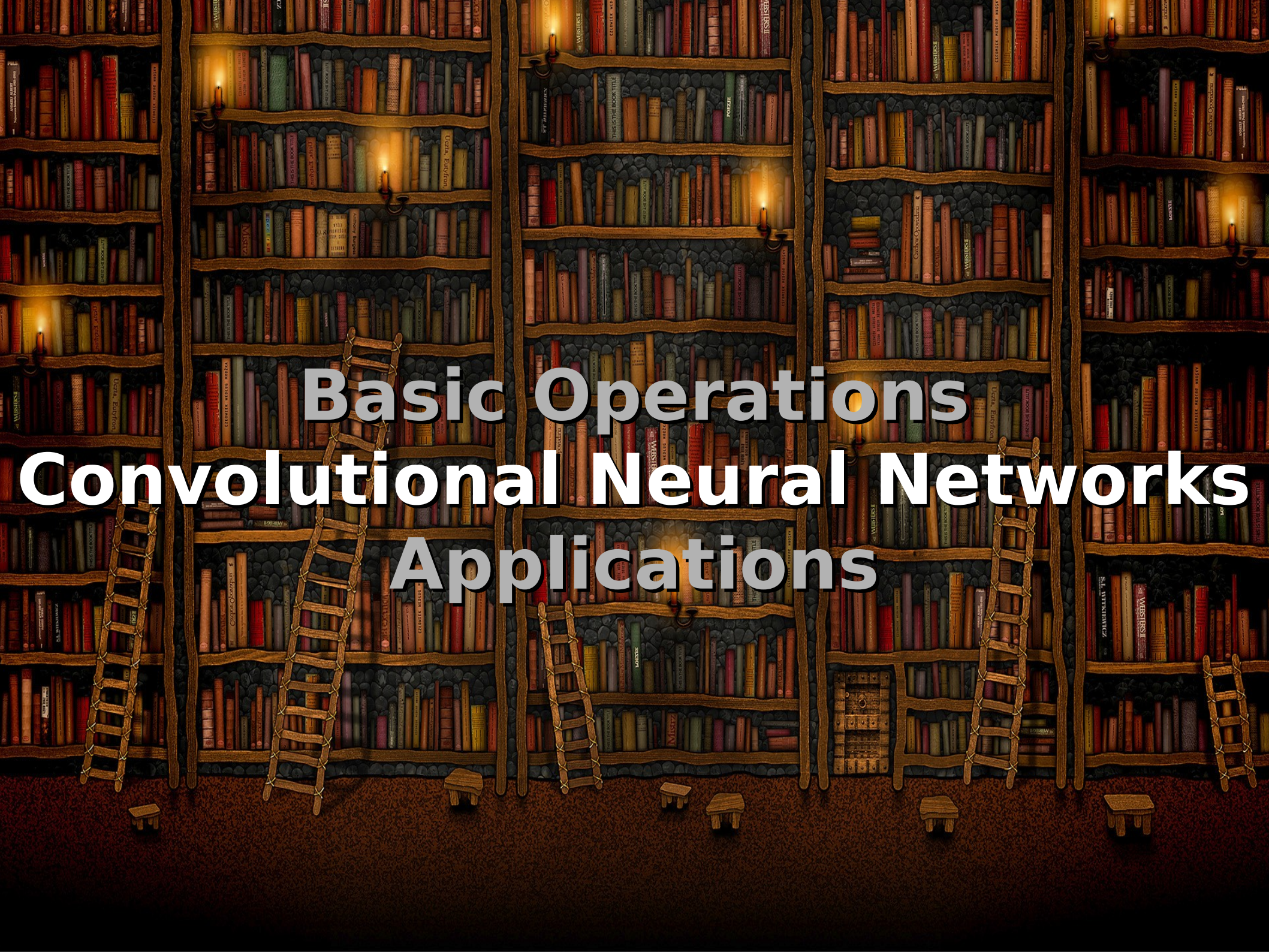






變窄但變長
一個output但可以偵測很多種
人臉



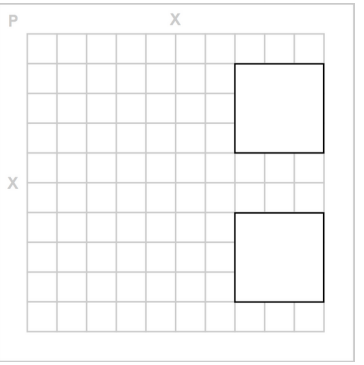

Basic Operations
Convolutional Neural Networks
Applications

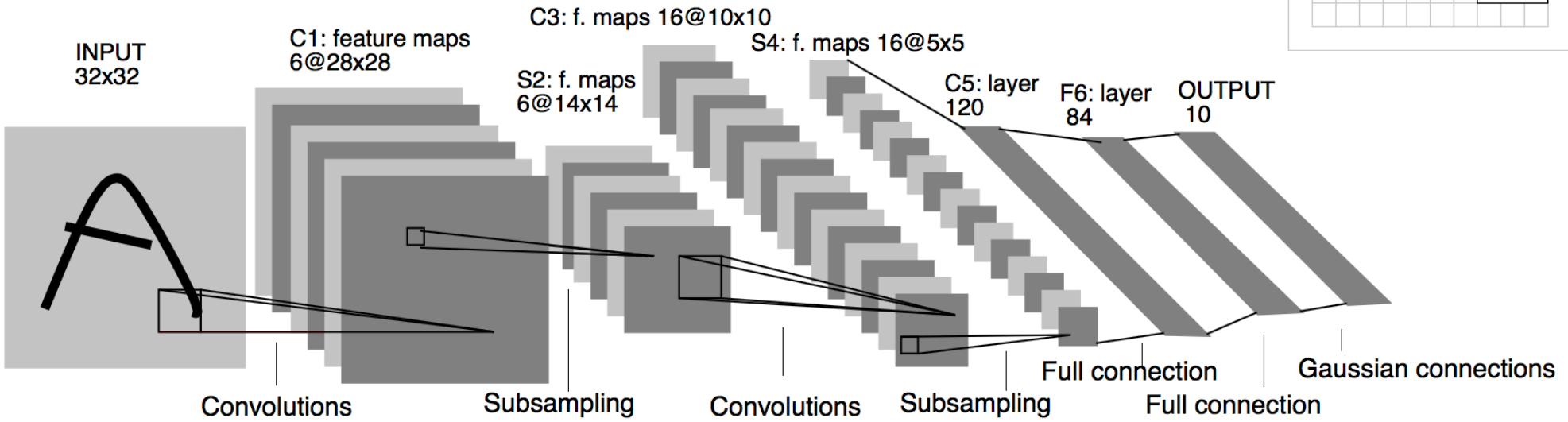
LeNet (1998)

有 convolution 有 pooling

$$1 + \frac{X - F + 2P}{S}$$

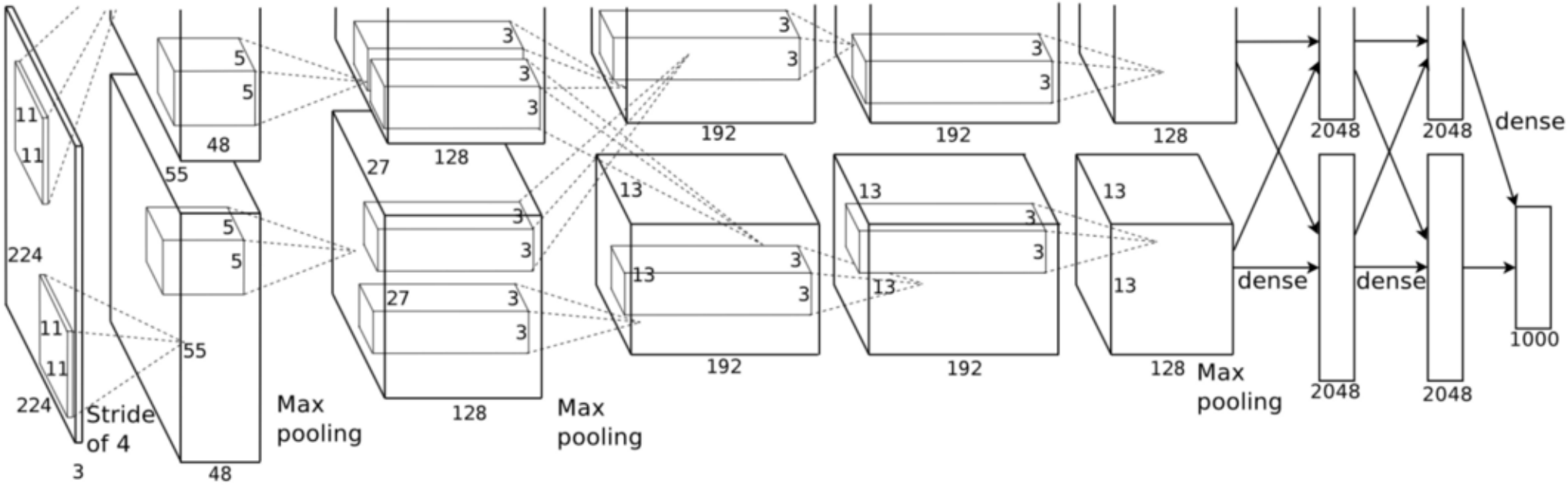
X = image size
F = filter size
P = padding
S = stride





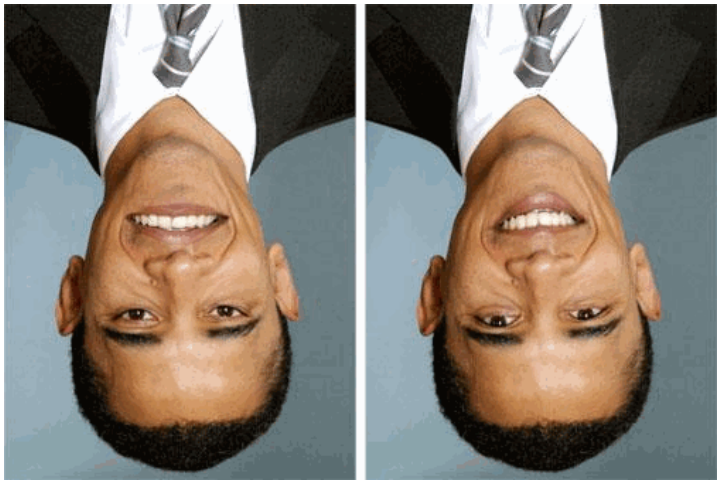
AlexNet (2012)

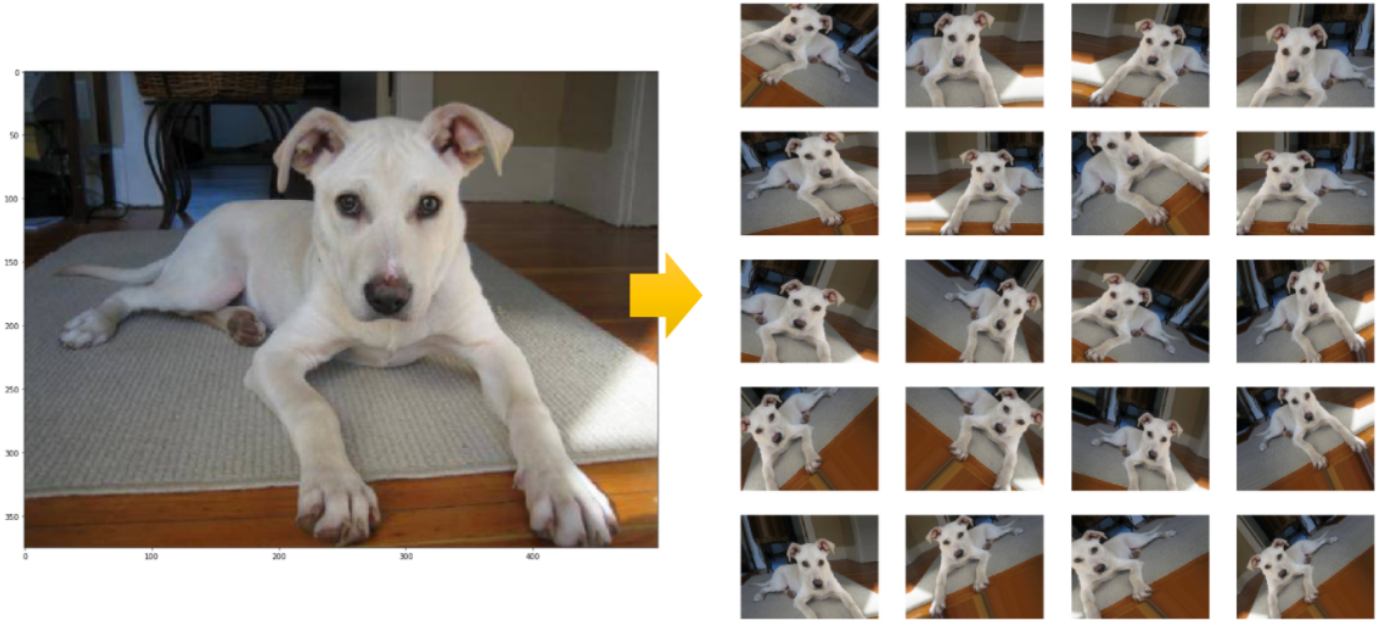
引入 Relu, LRN, Data Augmentation, Dropout
並用兩顆 Nvidia GTX580 訓練 6 天



Data Augmentation

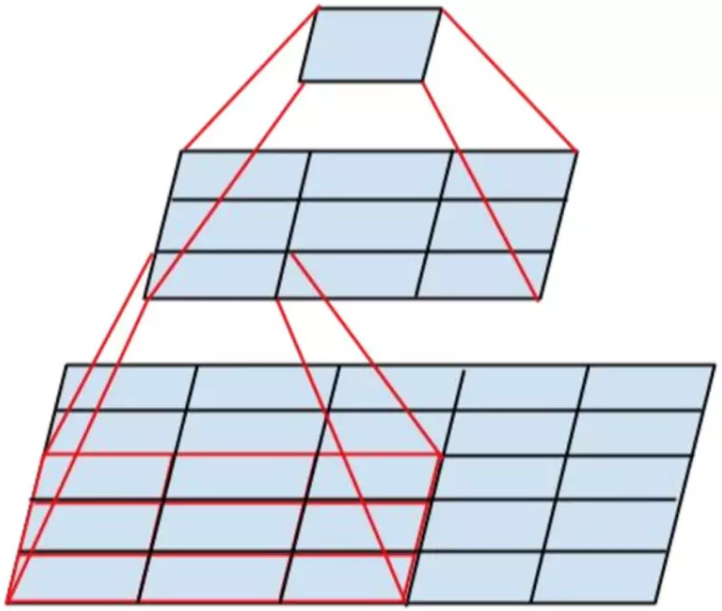
把資料集變大：仿造視覺的 tolerance(“invariance”)





VGG Net (2014)

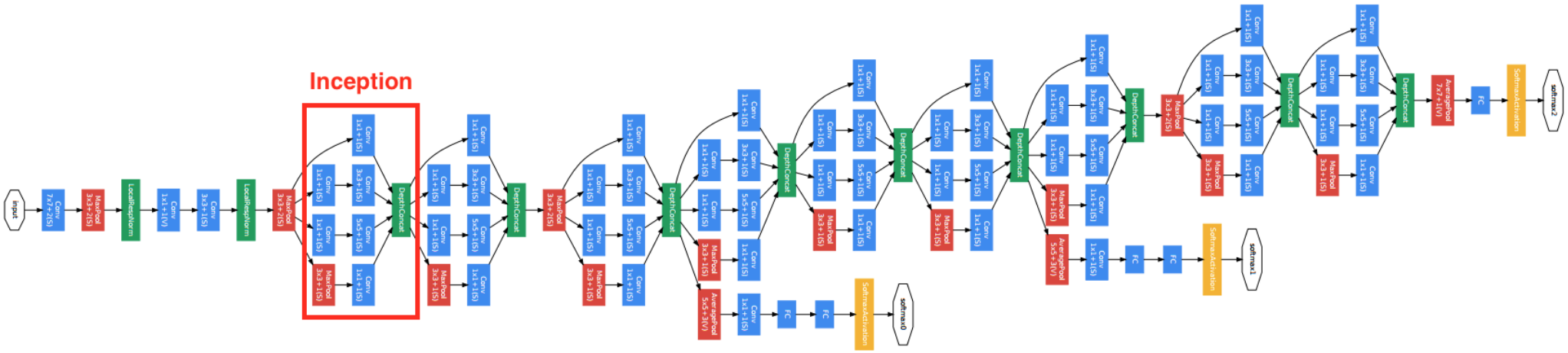
闡明下游 convolution kernels 只要 3x3

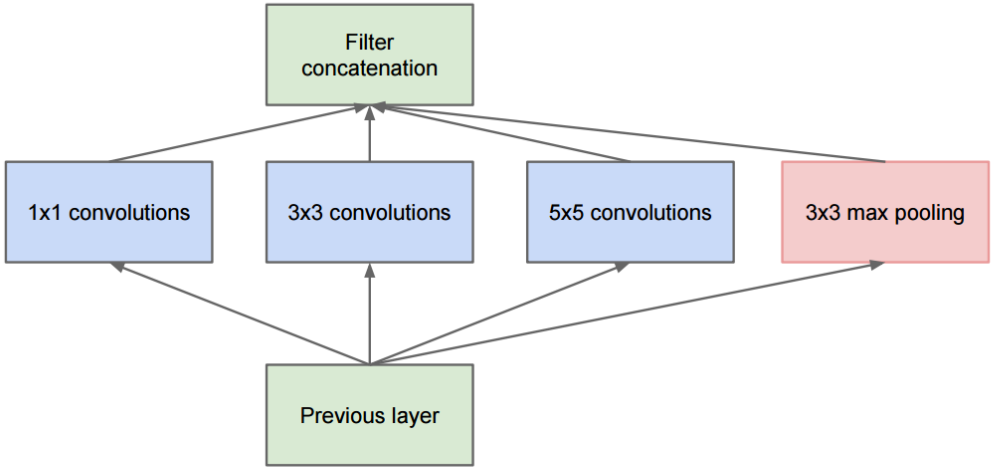


ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

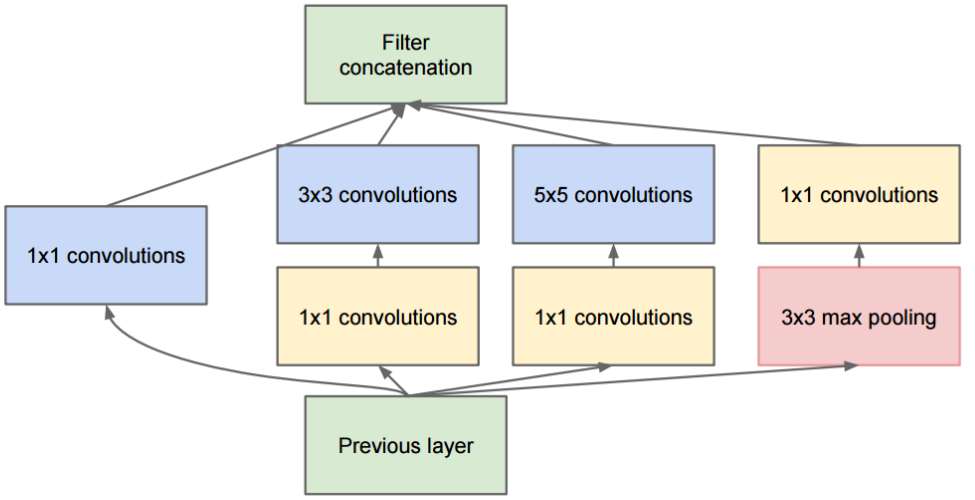
GoogLeNet (2015)

Inception module 主要仿製 multiscale vision





(a) Inception module, naïve version

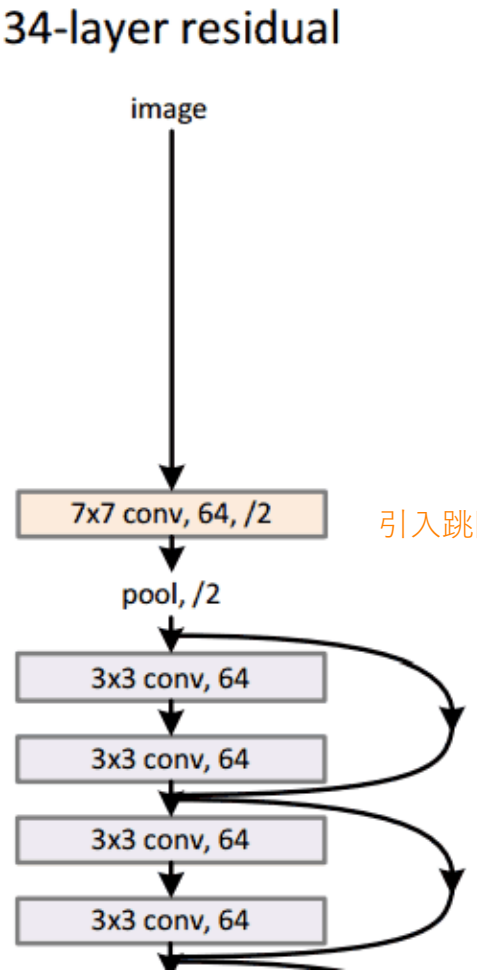


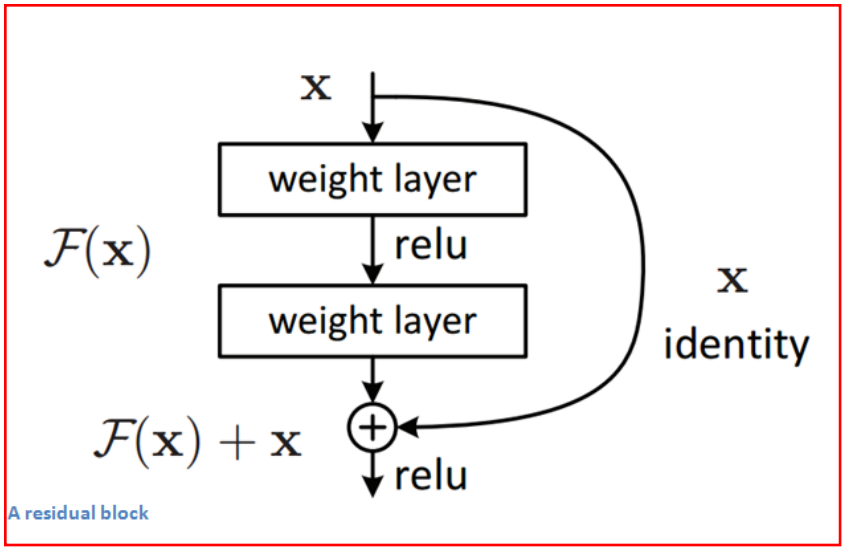
(b) Inception module with dimension reductions

ResNet (2015)

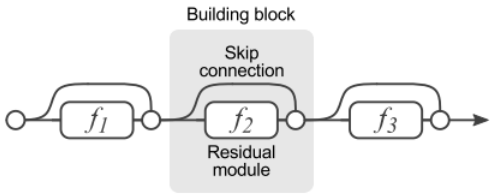
後來有一陣子深層網路到19曾就衝不上去了

$$f(x)=a_0+a_1x+a_2x^2+a_3x^3+\ldots$$



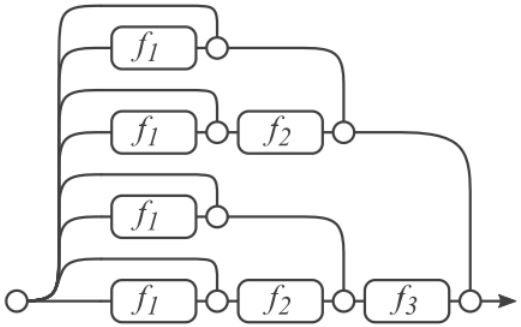


引入跳階的結構來解決深層的問題



(a) Conventional 3-block residual network

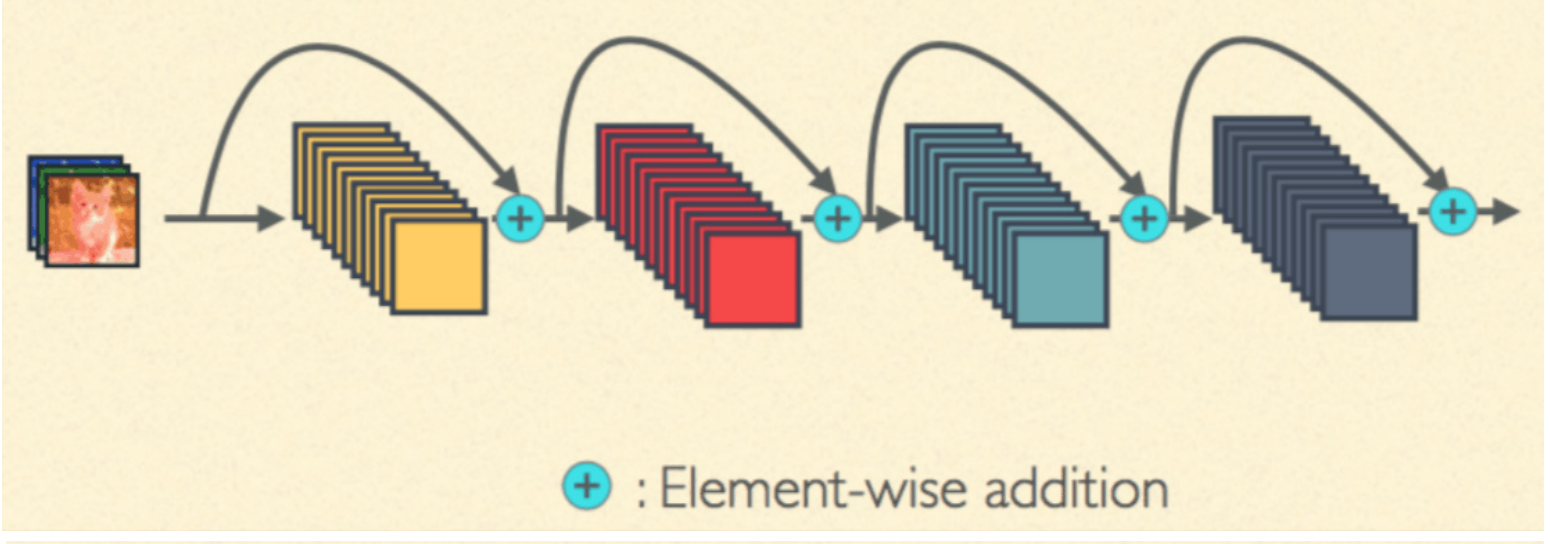
=

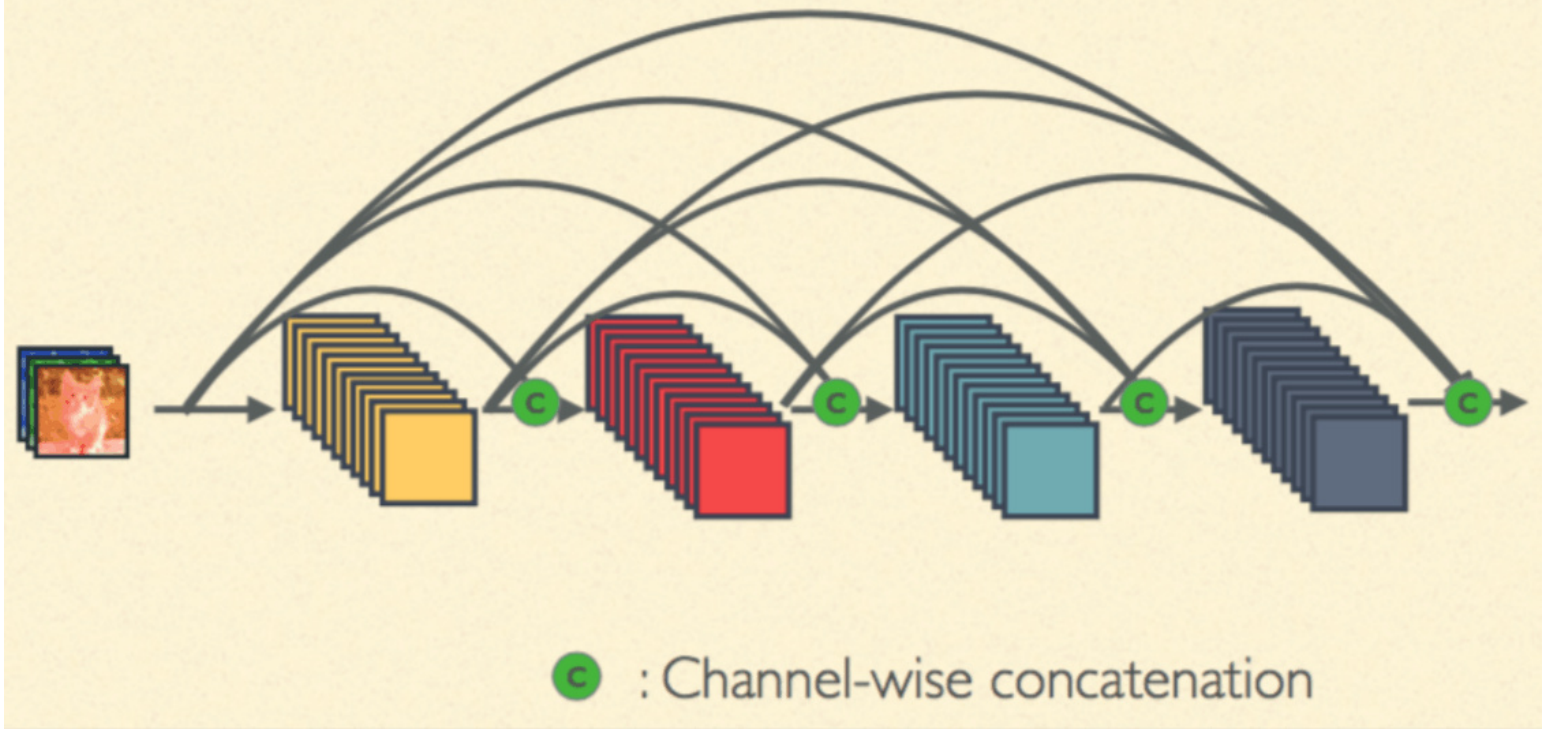


(b) Unraveled view of (a)

DenseNet (2017)

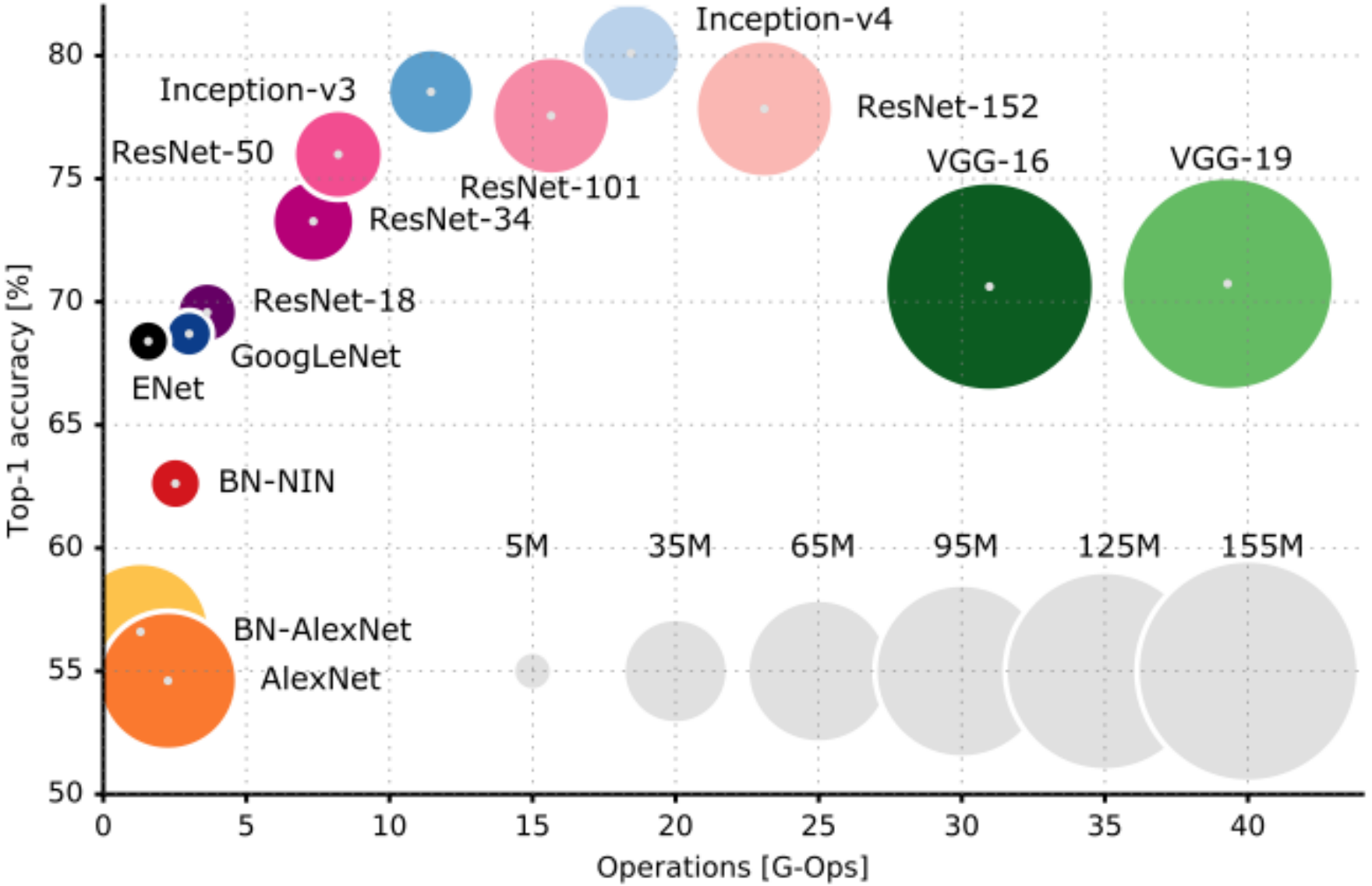
比 ResNet 加入更多跳接

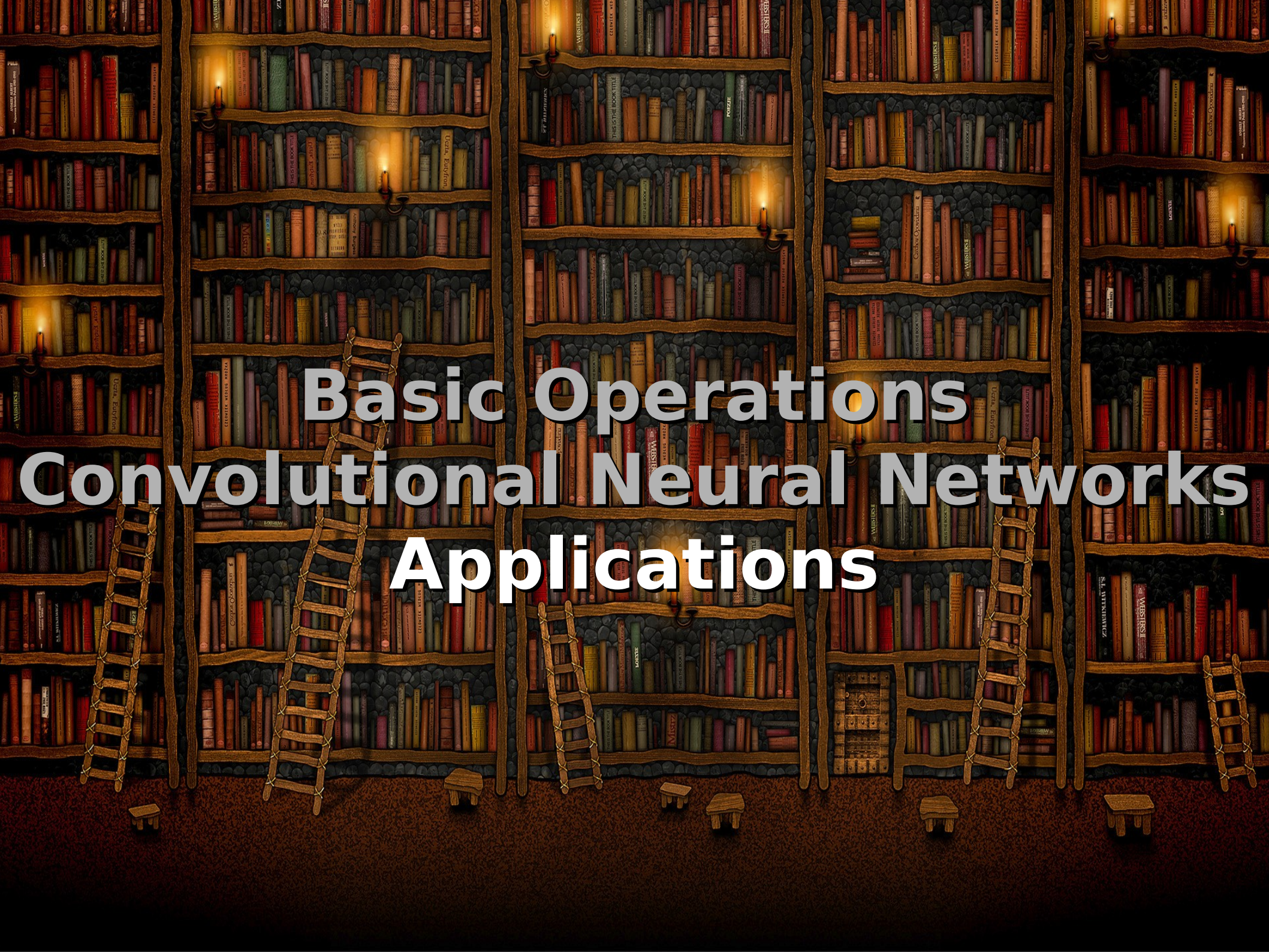




CNN 模型比較

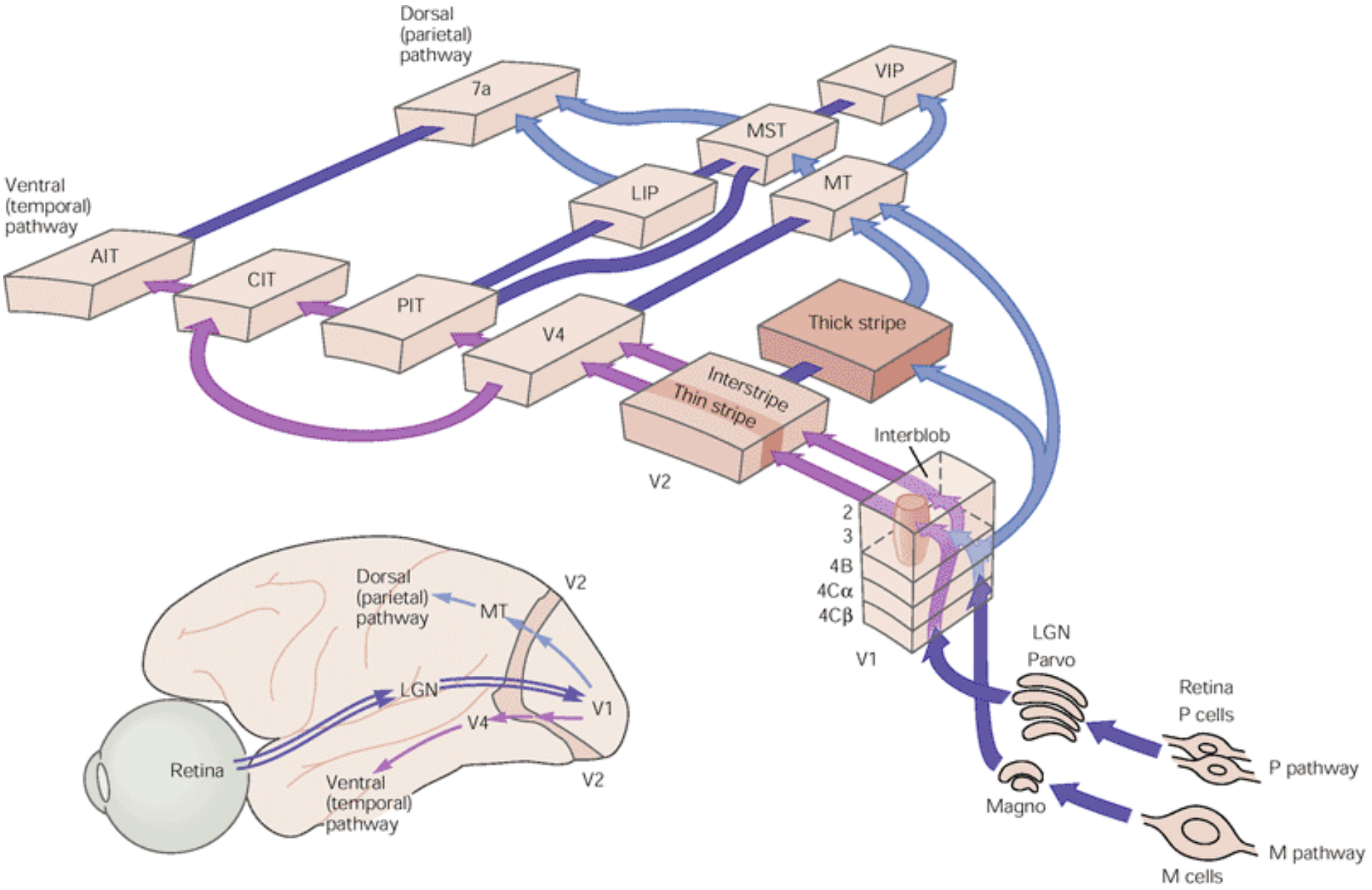
有些雖強大但計算太重




Basic Operations
Convolutional Neural Networks
Applications

CNN 只模仿了 What Pathway

但還有 Where Pathway

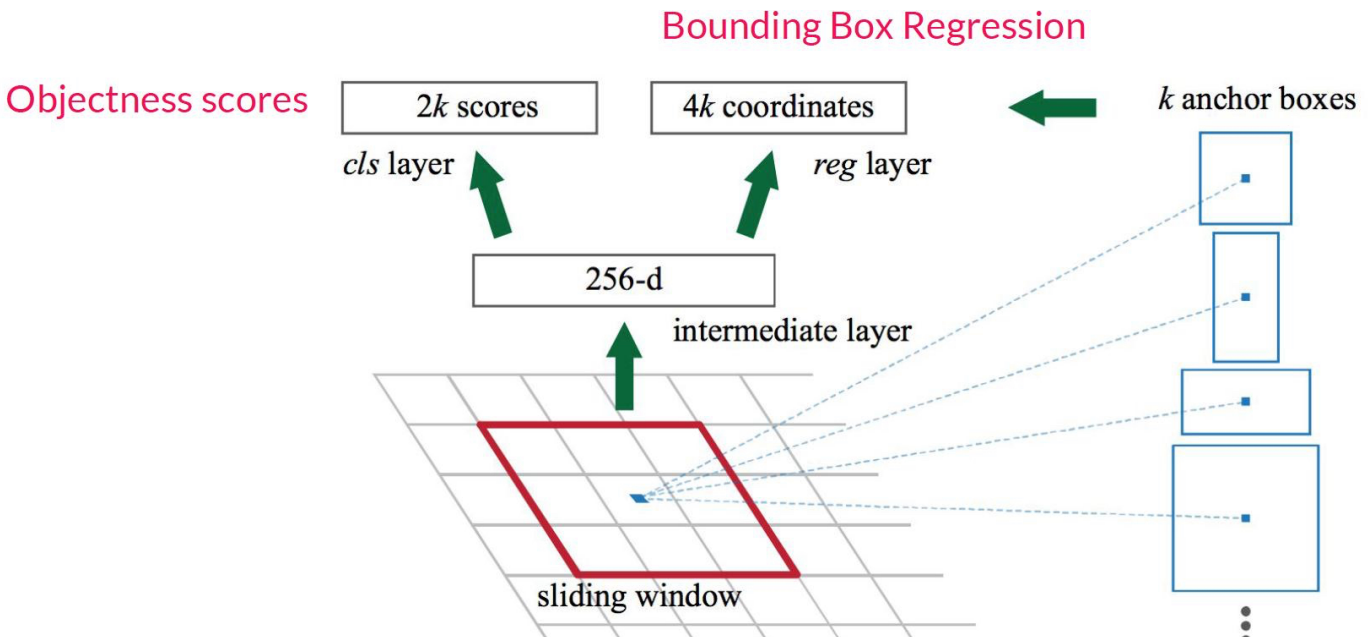


只模仿 What Pathway 的不足

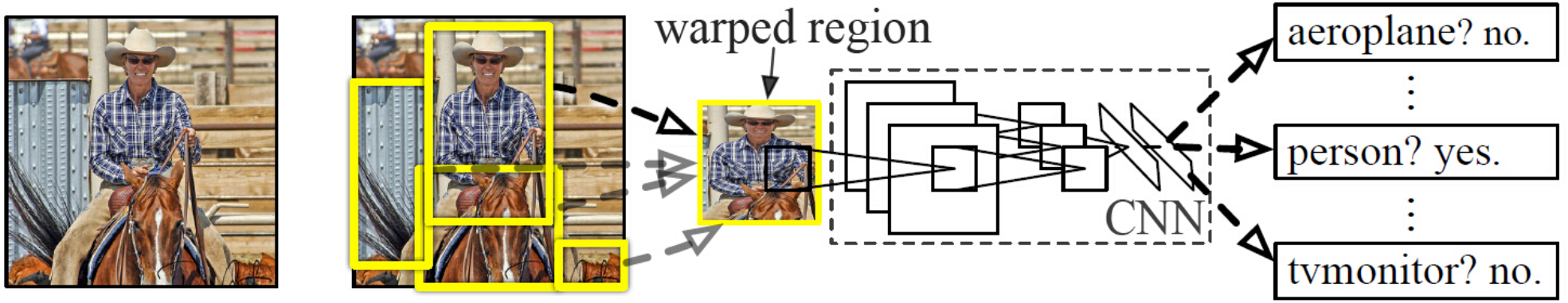
無法分解問題來各個擊破

where passwate 的問題
需sequential attention

Region-based CNN (R-CNN)



R-CNN: *Regions with CNN features*



1. Input image

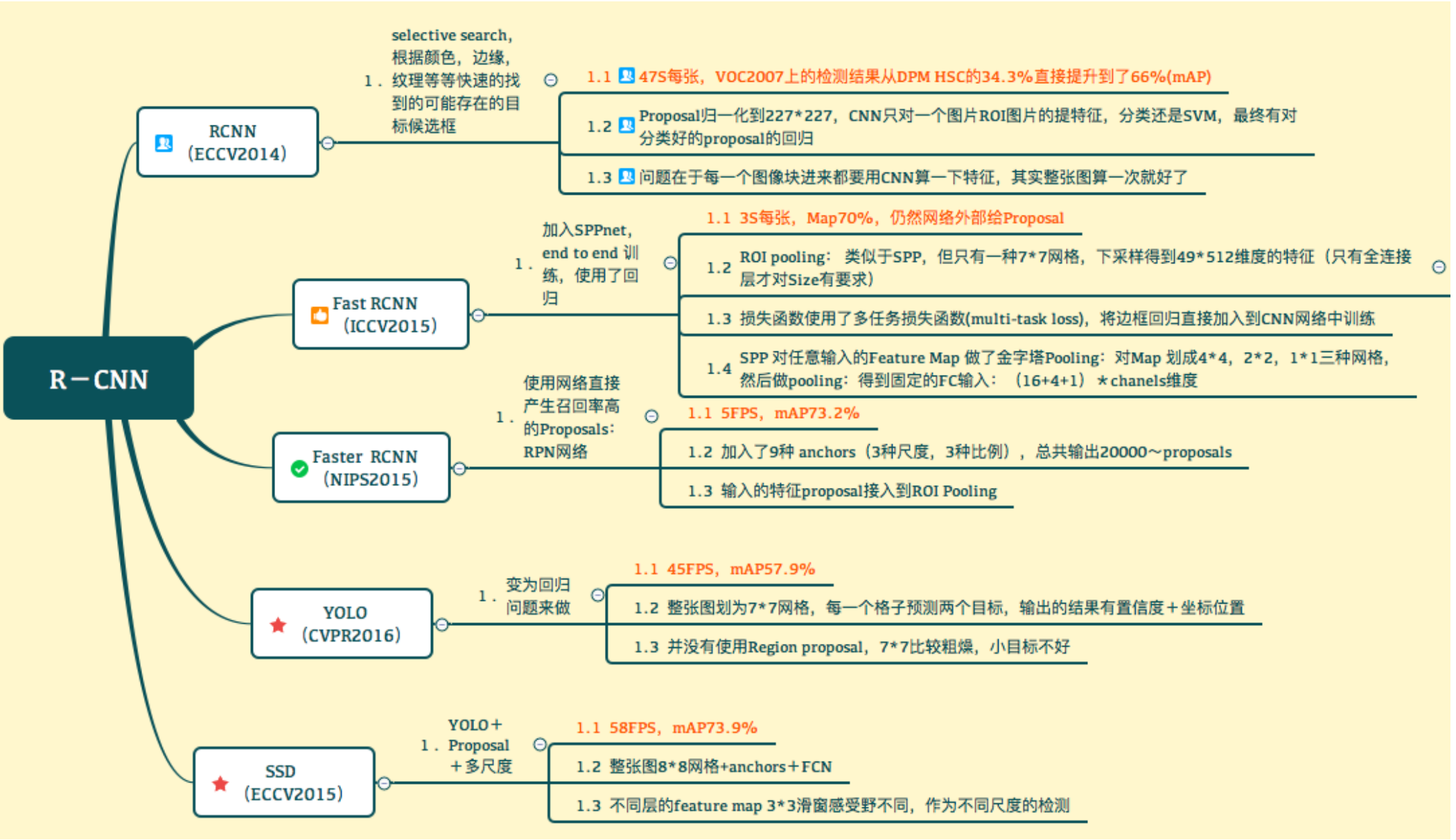
2. Extract region proposals (~2k)

3. Compute CNN features

4. Classify regions

R-CNN 的徒子徒孫

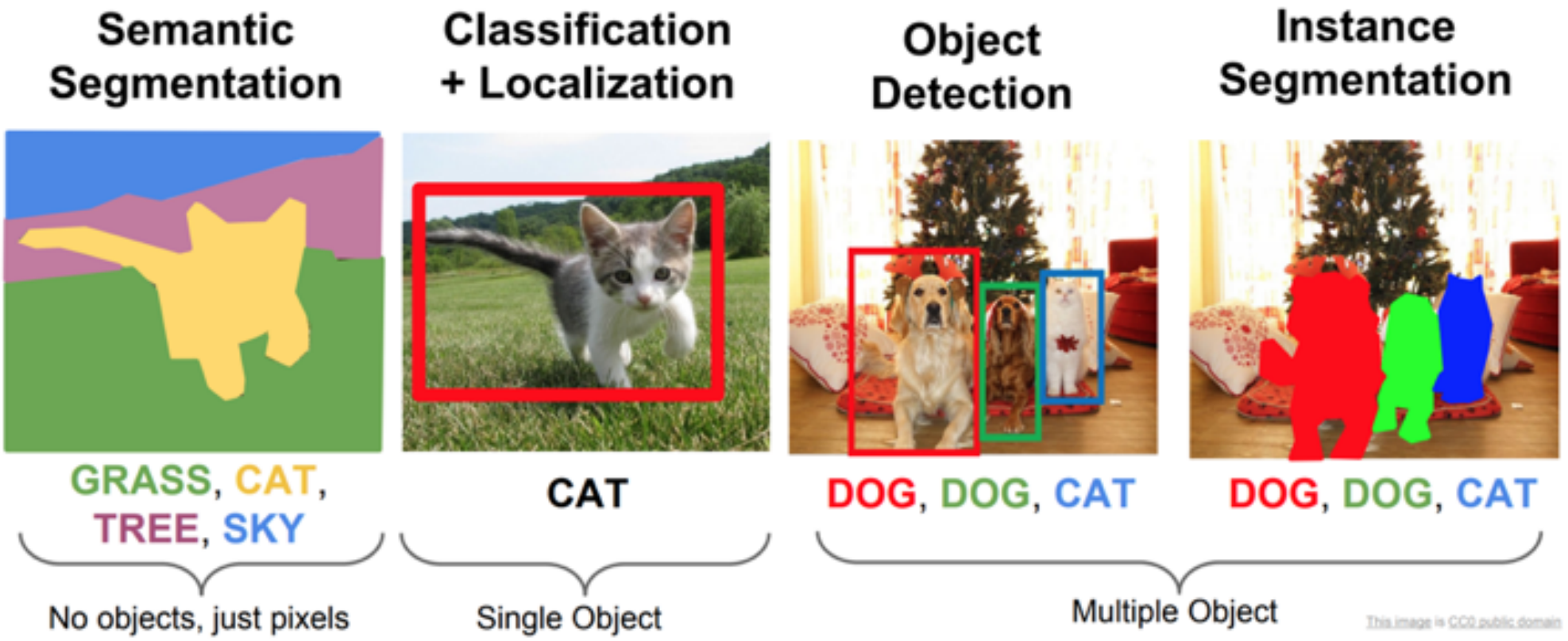
族繁不及備載



電腦視覺的幾類問題

computational vision 的單位是 objects!
image processing 的單位是 pixel

都是用 CNN 來處理



在生醫影像的應用中也都是這幾類問題

Object Classification (1/2)

如判斷大腦是否有腫瘤

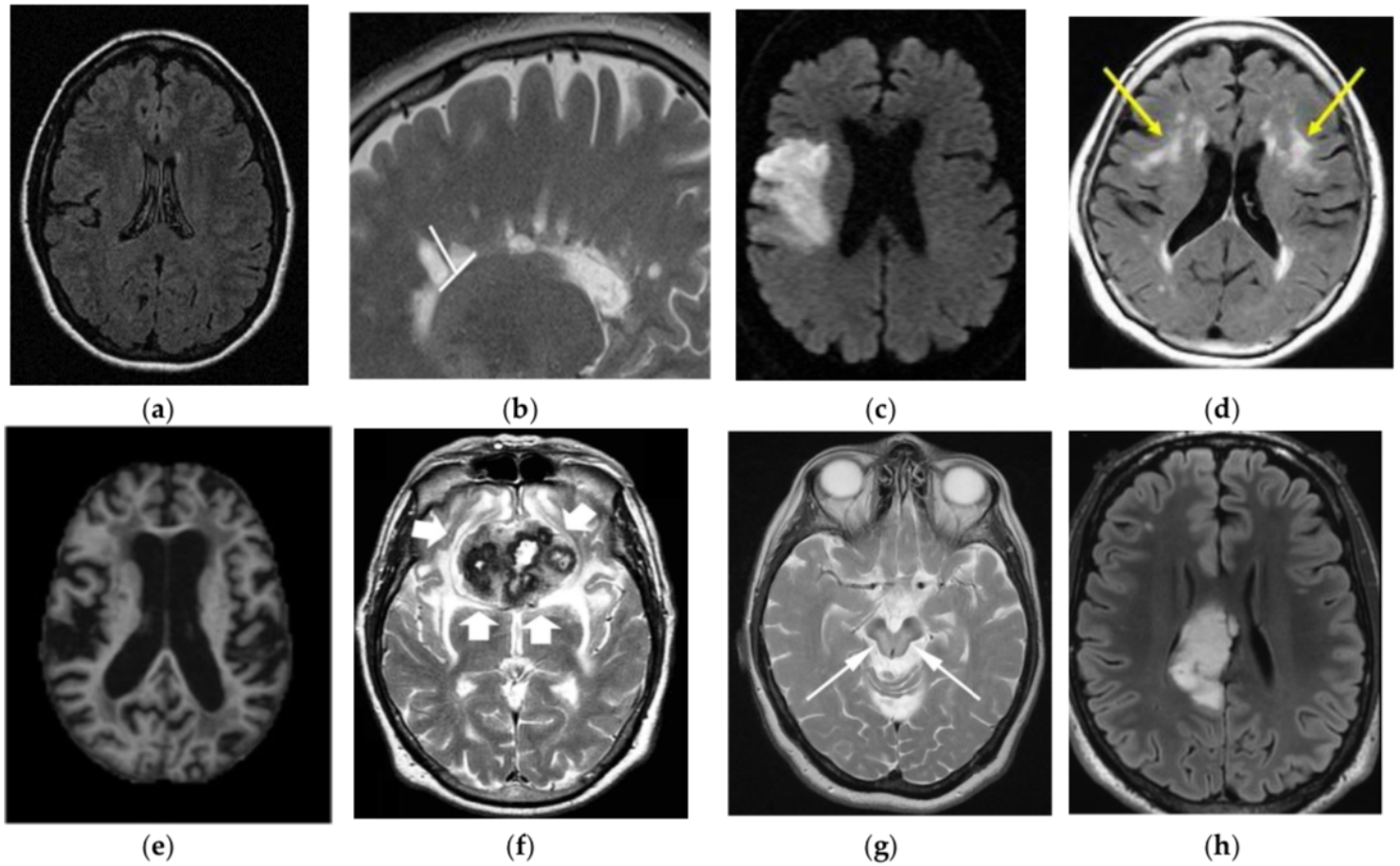


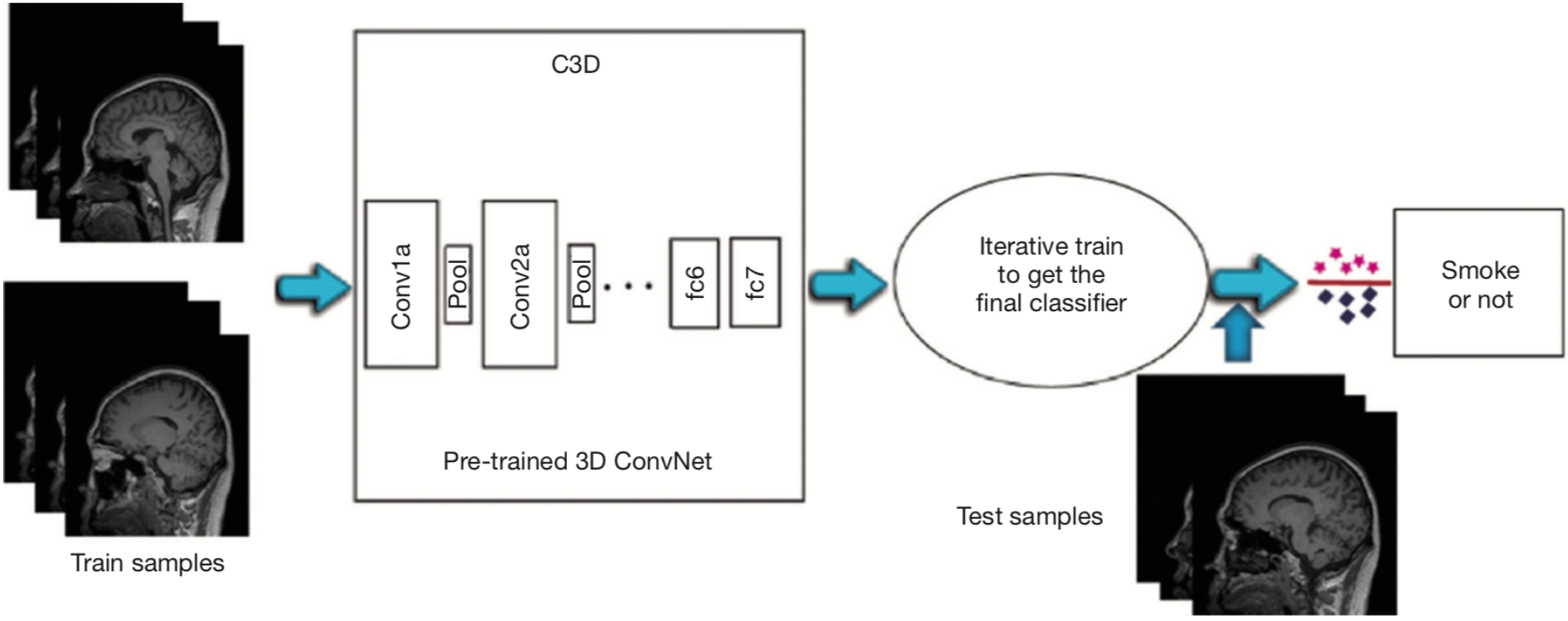
Figure 17. Comparison of brain tumor with other brain disorders (image permission requested from sources). (**a**) Normal Brain [AtheroPoint^{TM}]; (**b**) Multiple Sclerosis [113]; (**c**) Stroke [114]; (**d**) Leukoaraiosis [115]; (**e**) Alzheimer's Disease [116]; (**f**) Parkinson's Disease [117]; (**g**) Wilson'sDisease [118]; (**h**) Brain Tumor [119].

Tandel et al., 2019

Object Classification (2/2)

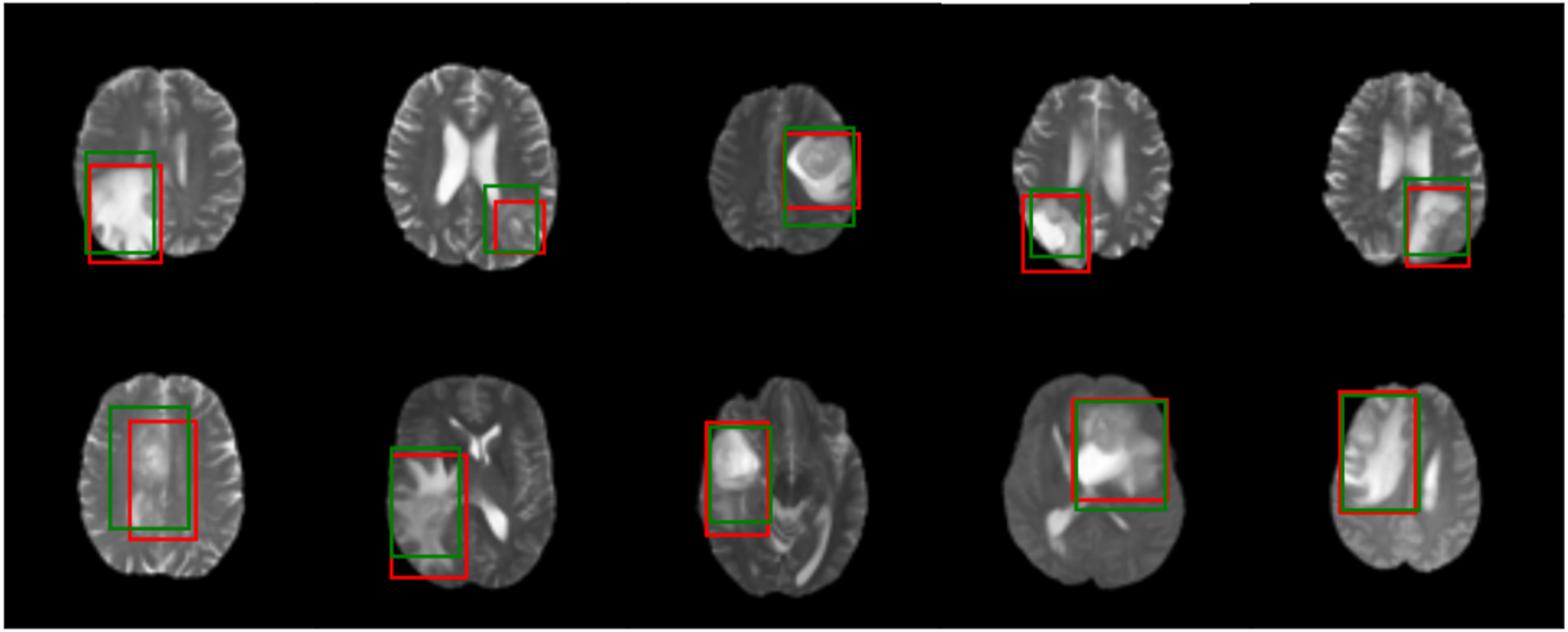
如判斷一個人是否有抽煙

Methods	Conv3D (%)	SVM (%)	ConvLSTM (%)
Sensitivity	80.0	84.0	93.33
Specificity	81.3	83.75	93.75
Overall accuracy	80.6	83.8	93.5



Object Detection

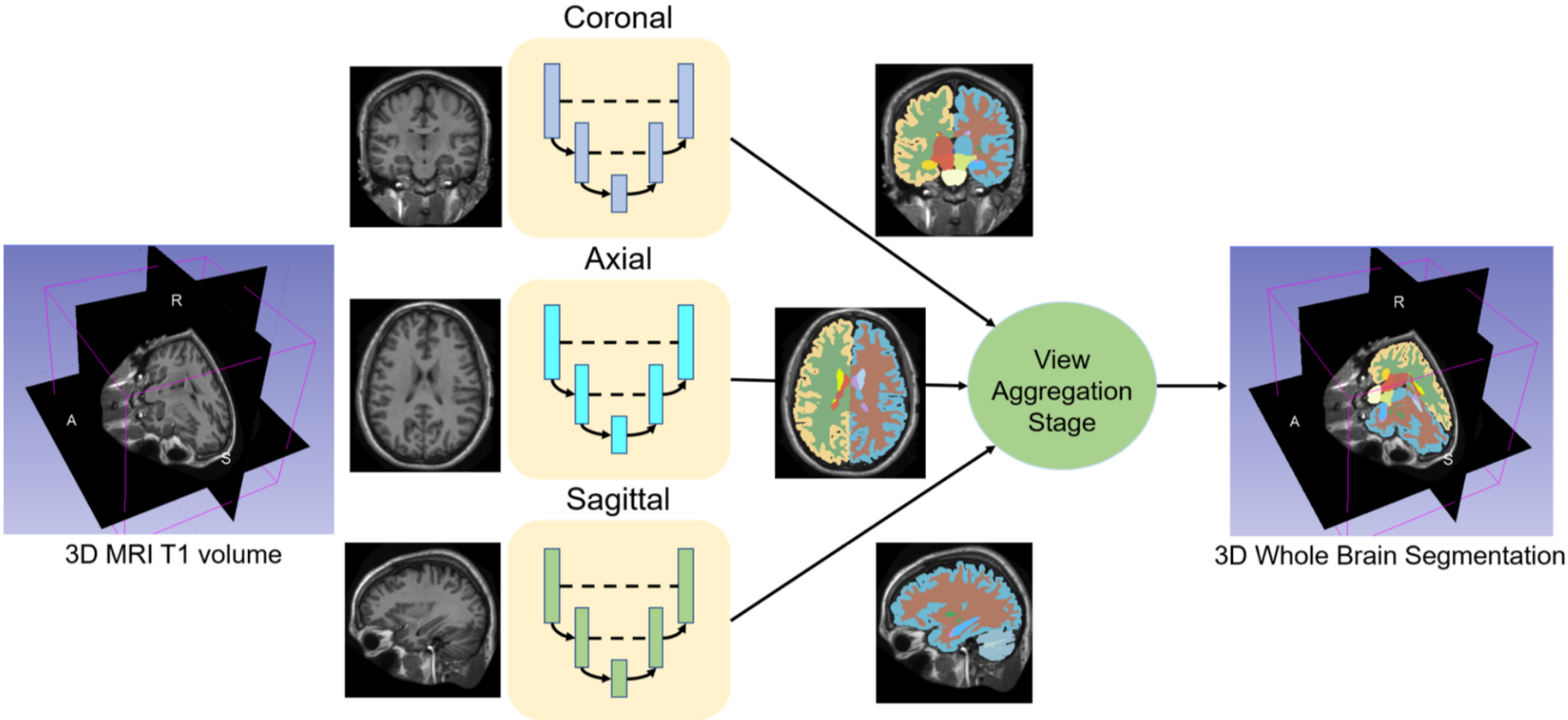
有沒有辦法能 localize?



Banerjee et al., 2018

Semantic Segmentation (1/3)

QuickNAT 使用 U-net

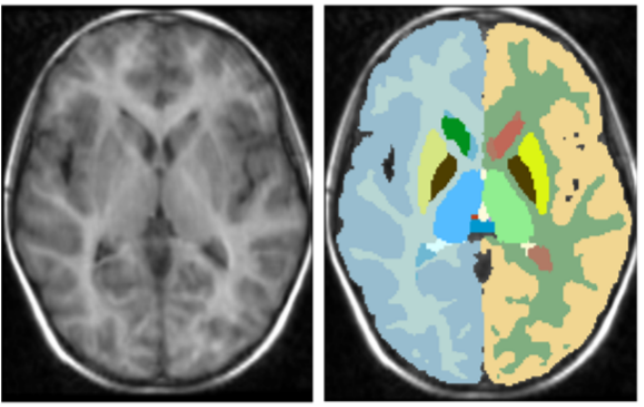


Roy et al., 2019

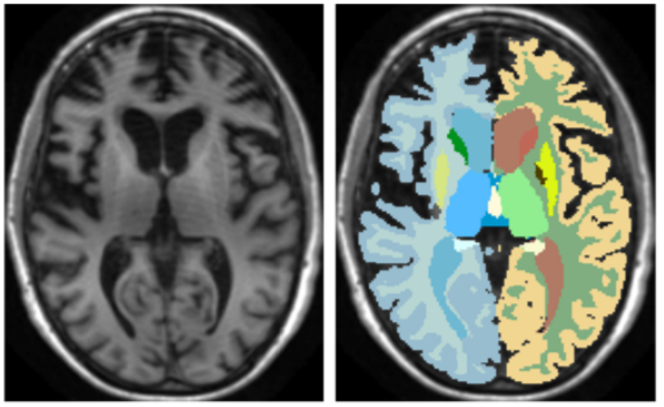
Semantic Segmentation (2/2)

QuickNAT 可以快速且精準地做區域分割

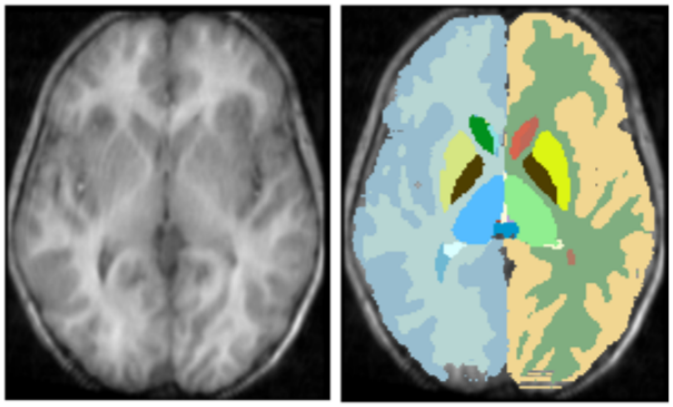
	Method	ADNI-29	CANDI	IBSR
All scans	**QuickNAT**	$\mathbf{0.825 \pm 0.027}$	$\mathbf{0.819 \pm 0.028}$	$\mathbf{0.820 \pm 0.035}$
	FreeSurfer	0.745 ± 0.042	0.780 ± 0.025	0.776 ± 0.025
	FSL	0.643 ± 0.290	0.647 ± 0.369	0.461 ± 0.419
	Failure of FSL	5 out of 29 (17%)	3 out of 13 (23%)	8 out of 18 (44%)
Scans where FSL succeeded	**QuickNAT**	$\mathbf{0.823 \pm 0.027}$	0.817 ± 0.032	0.817 ± 0.035
	FreeSurfer	0.745 ± 0.045	0.775 ± 0.027	0.772 ± 0.022
	FSL	0.775 ± 0.024	$\mathbf{0.841 \pm 0.013}$	$\mathbf{0.825 \pm 0.013}$



(a) IBSR dataset



(b) ADNI dataset



(c) CANDI dataset

Roy et al., 2019

Game Over