深度學習教學小計畫

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教材編寫 陳少君

緯育 TibaMe

即學・即戰・即就業

https://www.tibame.com/

學習目標：

- 了解教學方式與進度

Module 0.
教學目的方式與進度

目的方式與進度

深度學習養成班教學目的

為何而學

機器學習利用正確有效的資料訓練模型，並利用驗證資料及測試資料調整其參數，持續改進模型，使其分類、分群、迴歸等演算法能被有效應用

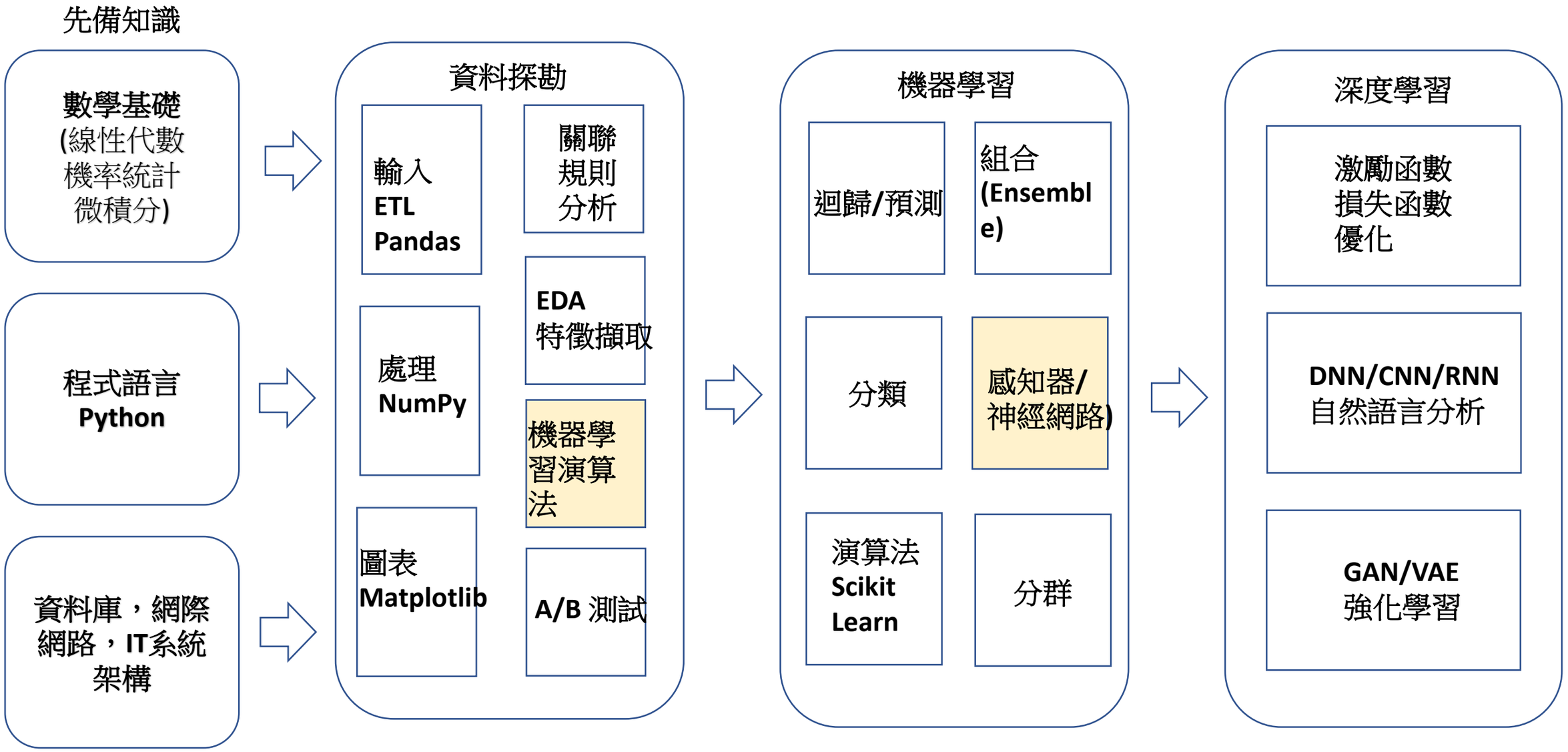
機器學習的一個分支：類神經網路，將成為未來深度學習的基礎。其他各演算法在各行各業也有其廣泛的應用領域。

承先啟後

先備知識：數學概念，Python/R 程式語言，資料探勘，機器學習

進階：深度學習之應用與演進

資料科學知識示意地圖



養成班教學進度

第一天(9月30日)：深度學習介紹
- 深度學習介紹
- Tensorflow 2.0介紹
- 損失函數
- 優化(1)

第二天(10月7日) ：神經網路，CNN
- 優化(2)
- Tensorboard
- CNN原理及應用

養成班教學進度

第三天(10月13日)：CNN應用，文字探勘

- CNN應用：物件偵測
- 文字探勘
- RNN介紹

第四天(10月21日) ：LSTM/GRU，降維，AutoEncoder，風格遷移

- LSTM/GRU
- 降維
- AutoEncoder
- 風格遷移

養成班教學進度

第五天(10月28日)：增強式學習，Keras，複習

- 增強式學習 (Reinforcement Learning)
- Keras
- 深度學習複習
- (Bonus: Transformer/BERT)

第一天

2 小時

深度學習概論
Tensorflow

2 小時

類神經網路
激活函數

2 小時

損失函數
優化演算法

預習：CNN
作業：作業一

從解聯立方程到機器(深度)學習

試解：

5x + 2y = 10

x + 4y = 11

機器學習不是在算參數權重(weight)嗎，把 x, y當成 w_1 w_2，把方程式左邊的係數(5,2) (1,4)定為輸入(x_1 x_2)，
右邊(10,11)為向量y，轉換成感知器的公式：

$5 * w_1 + 2 * w_2 = 10$

$1 * w_1 + 4 * w_2 = 11$

$$\begin{bmatrix}5 & 2\\ 1 & 4\end{bmatrix}\begin{bmatrix}w_1\\ w_2\end{bmatrix}+\begin{bmatrix}-10\\ -11\end{bmatrix}=\begin{bmatrix}0\\ 0\end{bmatrix} \qquad \begin{bmatrix}5 & 2\\ 1 & 4\end{bmatrix}\begin{bmatrix}w_1\\ w_2\end{bmatrix}+\begin{bmatrix}0\\ 0\end{bmatrix}=\begin{bmatrix}10\\ 11\end{bmatrix}$$

如果我們故意不直接求解，而是用更多聯立方程式去逼近，比方$2*w_1 + 2*w_2 = 7$，我們是否也可解出 (w1,w2) ？
這樣作其實就是訓練感知器，如果在感知器後頭接上非線性激勵函數(sigmoid / tanh / relu)，
豈不形成類神經網路之一層？層層疊加就是深度學習網路之前饋(feed forward)部分
機器學習其實是個複雜的**函數映射**，線性代數適合**表述並計算出所需參數w**

看機器學習如何求解多元一次方程？ - 每日頭條 (kknews.cc)

TensorFlow vs PyTorch

兩大陣營各有千秋，簡單的說，TensorFlow 易懂好上手，Pytorch 適合做研究。TensorFlow 有 Tensorboard 的可視化功能，Pytorch 支持動態圖 (Dynamic Graph)。建議未來兩者都學。

以實例比較其不同：

PyTorch vs TensorFlow — spotting the difference | by Kirill Dubovikov | Towards Data Science

Pytorch 學習網站：

Learning PyTorch with Examples — PyTorch Tutorials 1.9.1+cu102 documentation

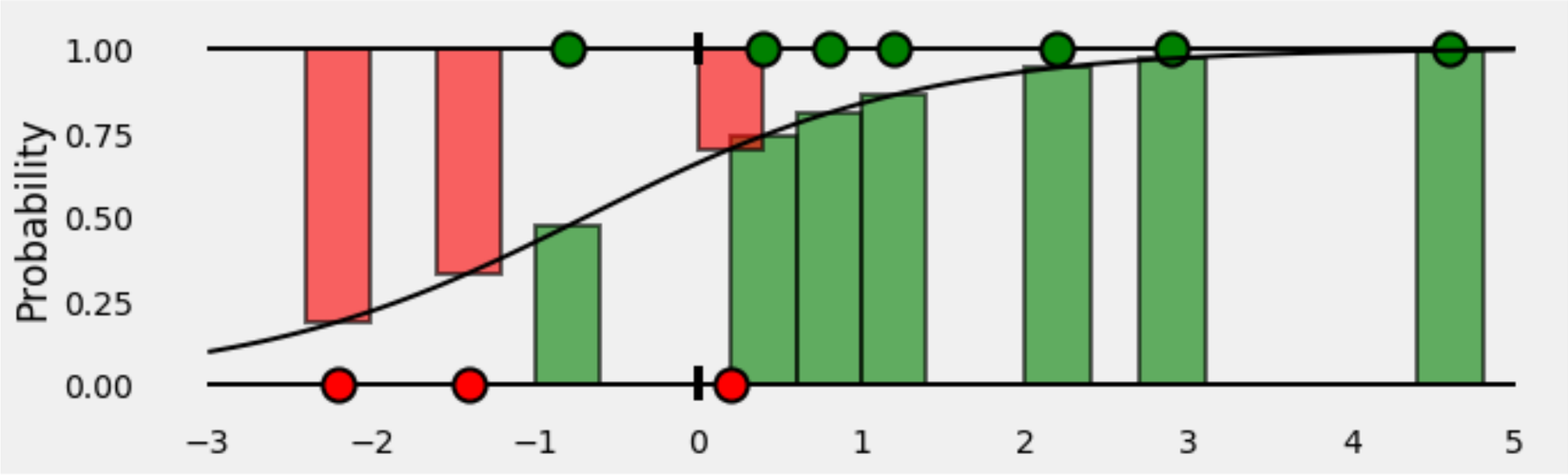
TensorFlow Important Classes

Class	範例/說明
Tensor	運算之主角
Operation	tf.add等運算元
Graph	Tensor的運算圖
Session	執行graph
Variable	像tensor之參數儲存處
Optimizer	以minimize method降低損失
Estimator	逐漸被淘汰之class較難開發卻適於軟體工程
Dataset	處理與載入資料
Iterator	將Dataset依序輸入模型
Saver	儲存參數供繼續訓練

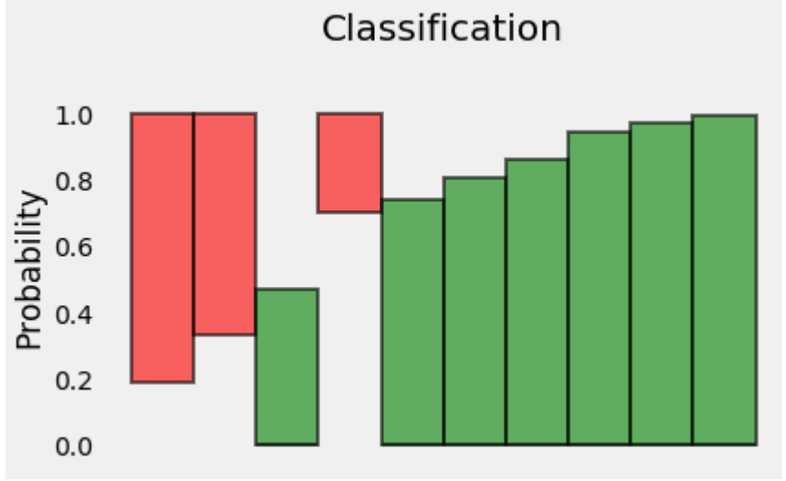
The 10 Most Important TensorFlow Classes - dummies

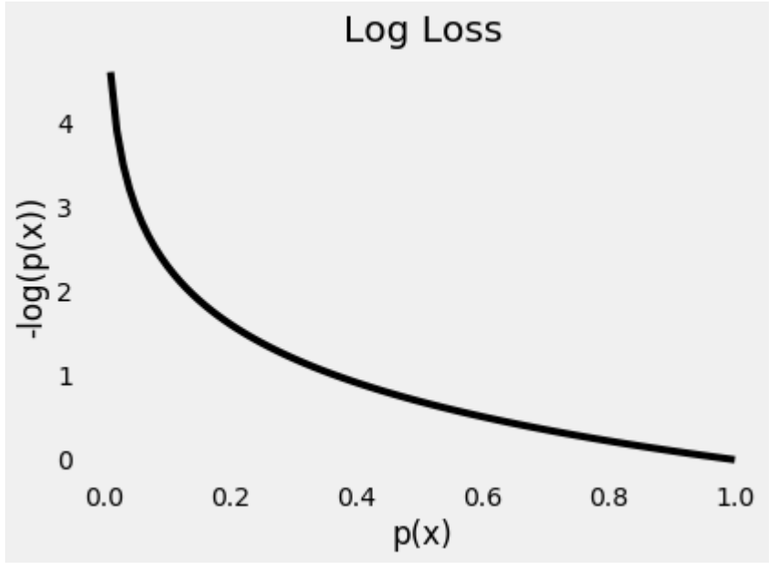
Log Loss (Cross Entropy)計算

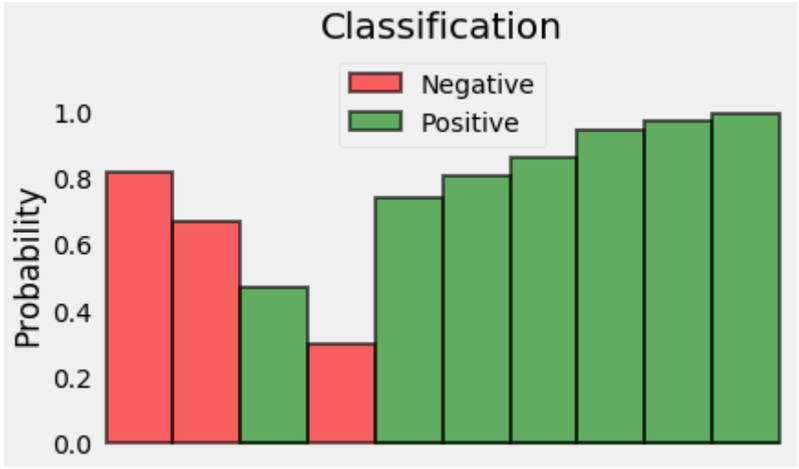
$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

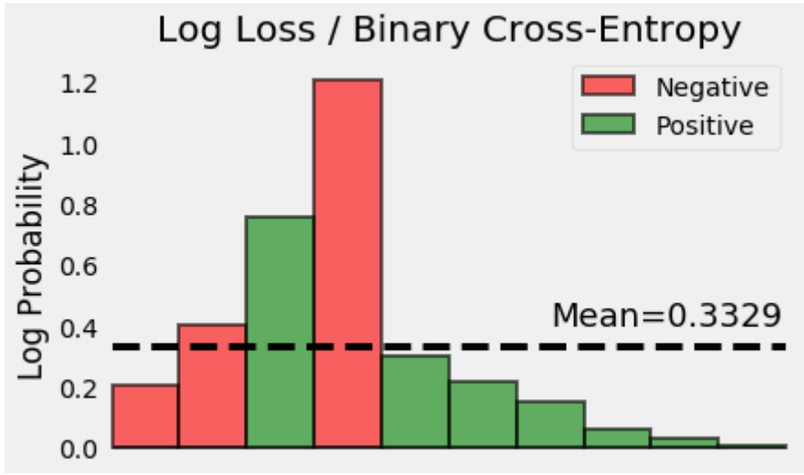


Log Loss (Cross Entropy) 計算









[Understanding binary cross-entropy / log loss: a visual explanation | by Daniel Godoy | Towards Data Science]

Loss Function的種類與選擇

大致分為

Probability Loss:

- Binary Cross Entropy：兩類分類
- Categorical Cross Entropy：多類分類，目標值(label)為獨熱(one hot)編碼
- Sparse Categorical Cross Entropy:(互斥)多類分類，目標值為整數編碼
- Poisson: 取張量元素平均值
- KL Divergence: 取機率對數加總之負數

Regression Loss

- MSE：Mean Squared Error
- MAE：Mean Absolute Error
- Cosine Similarity：向量之角度
- Huber：小的用平方大的用線性

Tensorflow Loss Functions | Loss Function in Tensorflow (analyticsvidhya.com)

稀疏(Sparse)類別不用獨熱(One Hot)

BinaryCrossentropy Loss Function ：

y_true = [0,1,0,0]

y_pred = [-18.6, 0.51, 2.94, -12.8] #這是用 logit, API 可決定

SparseCategoricalCrossentropy Loss Function ：

y_true = [1,2]

y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]] #Probability

CategoricalCrossentropy Loss Function：

y_true = [[0,1,0], [0,0,1]]

y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]] #Probability

Logit 與 Probability

損失函數需要知道 y_pred 是否為 Logit，何謂 Logit？ (機率是 Probability(P))

Odds (賠率) = Probability / (1 –Probability)

Logit = Ln (Odds) = Ln (P/1- P)

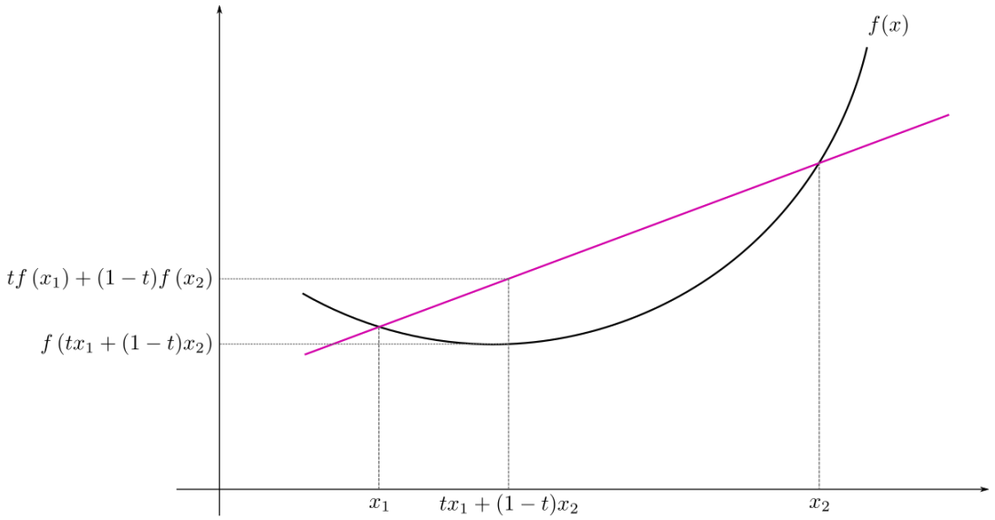
Ln 是底為歐拉數的自然對數

Logit 函數可將 P 轉成 Logit， Logit(0.5) = 0，所以如果 Logit 值 > 0，機率> 0.5
反函數就是 Sigmoid

LOGIT function calculator and graph (medcalc.org)

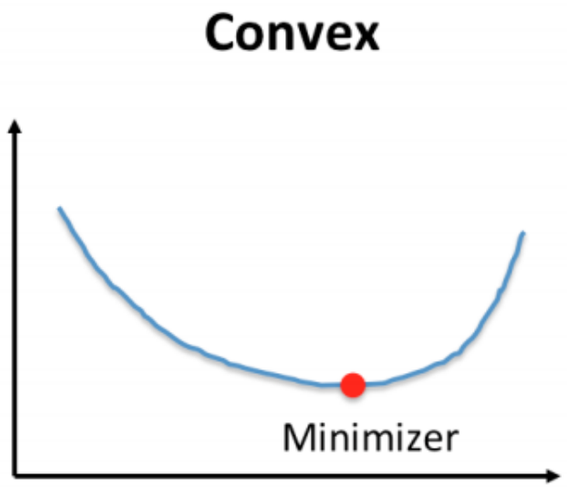
凸函數與優化

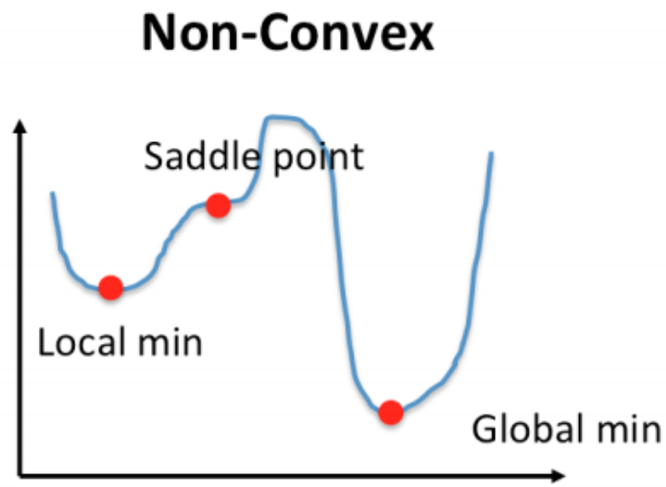
任何一條穿過凸函數曲線的直線，在相交兩點間，直線y之值永遠較凸函數f(x)之值大。



wikipedia.com

非凸函數之優化，可能造成本地優化(local optimum) 或鞍點(saddle point)





printerest.com

Adam 優化器

•**Adam** (Adaptive Moment Estimation) is a replacement optimization algorithm for stochastic gradient descent (**SGD**, fixed learning rate) for training deep learning models.

•Adam combines the best properties of the **AdaGrad** (每個參數都有 learning rate) and **RMSProp** (取每個參數average gradient 當個別 learning rate) algorithms to provide an optimization algorithm that can handle sparse gradients on noisy problems.

•Adam is relatively easy to configure where the default configuration parameters do well on most problems.

•在Tensorflow 的參數設置：learning_rate=0.001, beta1=0.9, beta2=0.999, epsilon=1e-08.

Gentle Introduction to the Adam Optimization Algorithm for Deep Learning (machinelearningmastery.com)

第二天

2 小時

優化演算法(二)

2 小時

Tensorboard
CNN介紹

2 小時

CNN原理架構與應用

預習：Yolo, 文字探勘
作業：作業二

TF2 Beginners 詳細回顧

TensorFlow 2 quickstart for beginners | TensorFlow Core

問題點:

輸入是甚麼：MNIST database – Wikipedia
Load Data 之後是甚麼？2 tuples of NumPy NDArrays for training and testing.
Sequential 是甚麼？ A Fully Connected Neural Network function returning a model.

Data 進入 Dense 時是甚麼？ NumPy NDArray. tf.keras.layers.InputLayer | TensorFlow Core v2.6.0
輸出的結果為何是logit？SoftMax 之後才變成probability？

Data 在 Dense NN 是 Tensor.
Tensor 是甚麼？是不是TensorFlow 才有？ Introduction to Tensors | TensorFlow Core
Tensor 和 Numpy.NDArray 的關係： Tensor 有更多attributes，可利用 GPU/TPU

Model.compile 有哪些 metrics?
Module: tf.keras.metrics | TensorFlow Core v2.6.0

Gradient Descent 回顧

- 由Loss function 得知當時的 loss value L
- 從 Loss Function 對 權重 w 的一次偏微分 $\partial L / \partial w$ ，代入當時的 x, y 得到 梯度 Gradient G(w)
- 將原 w 減去 G(w) 得到新的 w，這就是Descent
- 因為w改變，如果 y = wx + b，斜率是w，則下個x出現時，y的算法會被調整
- 直到w固定下來，回歸直線才固定

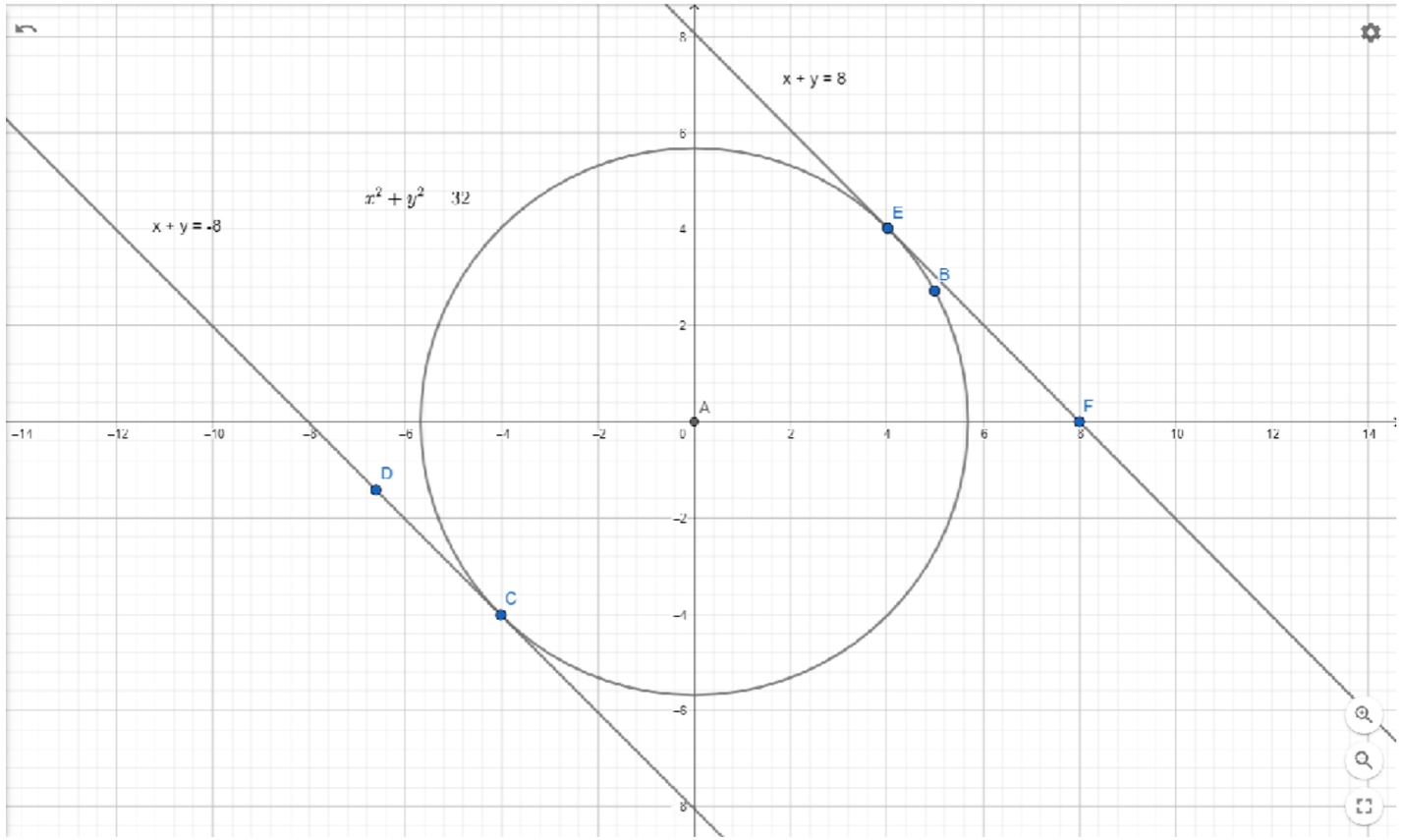
完整觀念

Gradient Descent with Linear Regression | Kaggle

基本觀念

iT 邦幫忙::一起幫忙解決難題，拯救 IT 人的一天 (ithome.com.tw)

Lagrange Multiplier



[A Gentle Introduction To Method Of Lagrange Multipliers (machinelearningmastery.com)]

[Wolfram|Alpha Widgets: "Lagrange Multipliers" - Free Mathematics Widget (wolframalpha.com)]

要求 $f(x,y) = x + y$
限制條件是 $h(x,y) = x^2 + y^2 - 32 = 0$

$L(x, y, \lambda) = f(x,y) + \lambda\, h(x,y)$
對x, y, λ分別取偏微分

$L = x + y + \lambda(x^2 + y^2 - 32)$

$\partial L/\partial x = 1 + 2\lambda x = 0$
$\partial L/\partial y = 1 + 2\lambda y = 0$
$\partial L/\partial \lambda = x^2 + y^2 - 32 = 0$

$x = -1/(2\lambda)$
$y = -1/(2\lambda)$
$1/(4\lambda^2) + 1/(4\lambda^2) - 32 = 0$
$1/(4\lambda^2) = 16$
$\lambda^2 = 1/(16 * 4) = 1/64$
$\lambda = 1/8$
$X = 4$
$Y = 4$

演算法中的正則化(Regularization)

目的：經由調整Loss Function (增加 L1, L2等)達到降低過適(Overfitting)。

L1: (LASSO) $||\mathbf{w}||_1 = |w_1| + |w_2| + ... + |w_N|$

L2: (RIDGE) $\|\mathbf{w}\|_2 = \left(|w_1|^2 + |w_2|^2 + \ldots + |w_N|^2\right)^{\frac{1}{2}}$

$$\hat{y} = w_1 x_1 + w_2 x_2 + ... + w_N x_N + b$$

Logistic Regression Loss Function: L(y_hat,y) = y log y_hat + (1 - y)log(1 - y_hat)

$$Loss = Error(y, \hat{y})$$

$$Loss = Error(y, \hat{y}) + \lambda \sum_{i=1}^{N} |w_i|$$

$$Loss = Error(y, \hat{y}) + \lambda \sum_{i=1}^{N} w_i^2$$

可參考：

[Regularization in Machine Learning - GeeksforGeeks]

Tensorboard

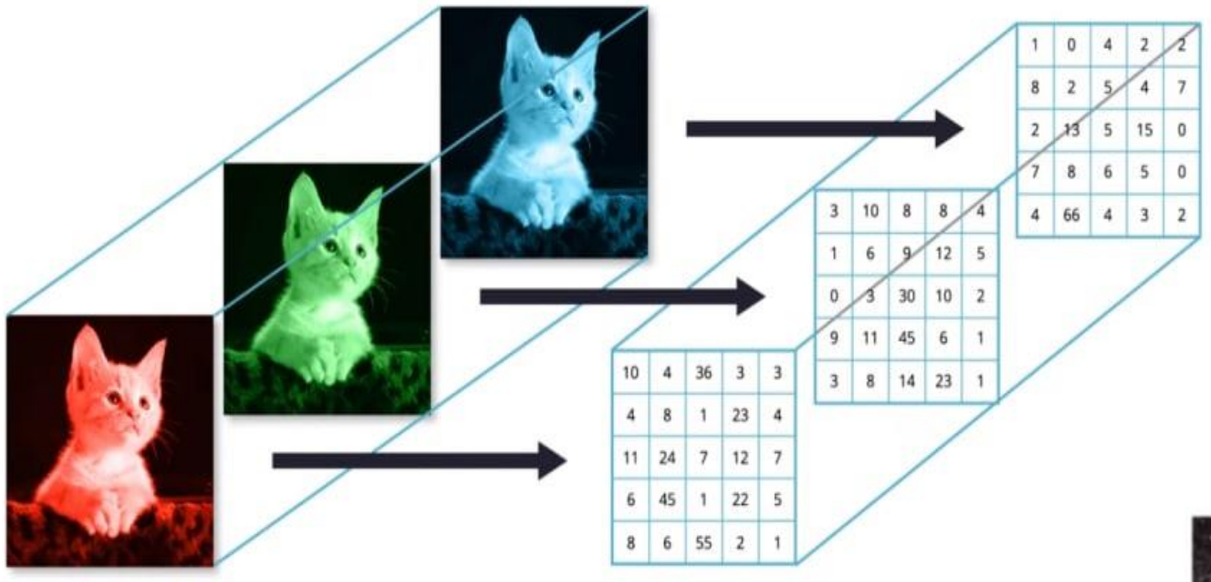
Scaler	純量的變化：loss, accuracy etc
Graph	靜態張量流動圖
Distribution	權重(非純量)之分布 Kernel/bias
Histogram	直方圖表示之(非純量) Kernel/bias etc
Image	使用的影像

Jupyter Notebook Viewer: Tensorboard explanations

Random Number Functions

import	function	parameters	returned type	returned data type	notes
numpy	random.rand	size=shape #(d1, d2)	Array of shape	Float [0.0,1.0)	From **uniform distribution**
random/numpy	randint random.randint	start, end #(0,10)	Integer	Integer between [start, end]	numpy ver. has shape. from **discrete uniform distribution**
numpy	random.random	size=shape #((d1,d2))	Array of shape	Float [0.0,1.0)	From **uniform distribution**
numpy	random.randn	size=shape #(d1, d2)	Array of shape	Normally distributed float number	From **standard normal distribution**
numpy	random.normal	mean, stdev #(d1, d2)	Array of shape	Normally distributed float	From **normal distribution**

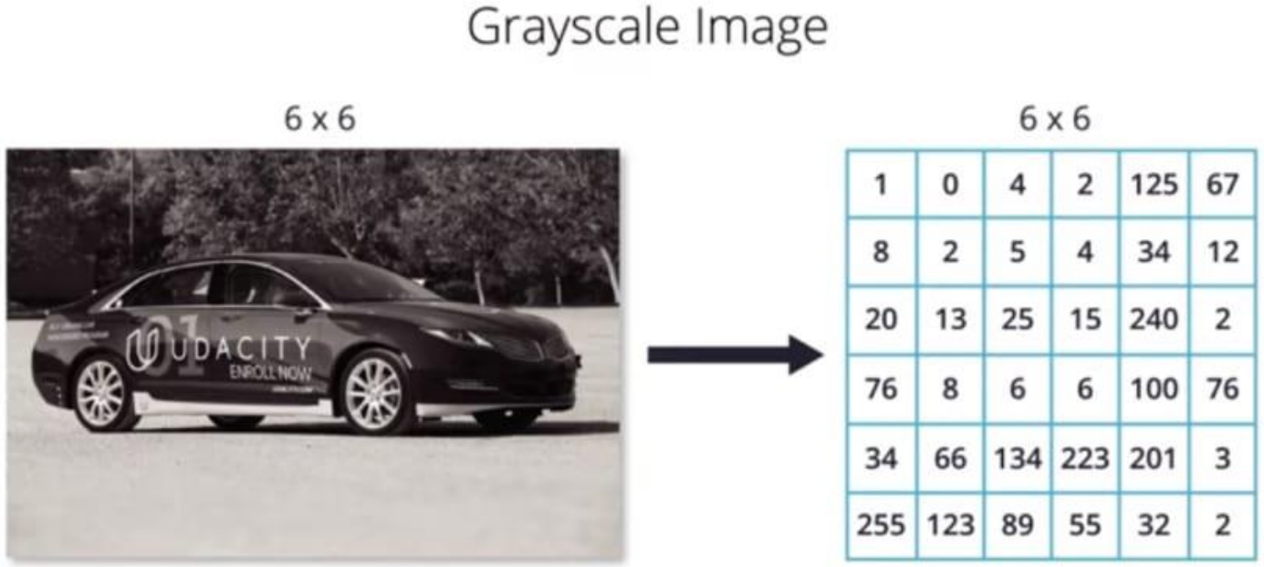
Colored and Gray Images



3D Array of shape (2,2,3):
numpy.array([[[1,2,3],
[3,4,5]],
[[5,6,7],
[7,8,9]]])

3D Array of shape (2,2,1):
numpy.array([[[1],[2]],
[[3],[4]]])

2D Array of shape (2,2):
numpy.array([[1,2],
[3,4]])



CNN Explainer

直接在瀏覽器上展示CNN的各功能

CNN Explainer Introduction (0:00-0:22)
Overview (0:27-0:37)
Convolutional Elastic Explanation View (0:37-0:46)
Convolutional, ReLU, and Pooling Interactive Formula Views (0:46-1:21)
Flatten Elastic Explanation View (1:22-1:41)
Softmax Interactive Formula View (1:41-2:02)
Engaging Learning Experience: Understanding Classification (2:06-2:28)
Interactive Tutorial Article (2:29-2:54)
瀏覽器上展示CNN說明視頻

互動網頁：
CNN Explainer (poloclub.github.io)

Same and Valid Padding

Padding = 'SAME'
Input/Output Same size

Padding = 'Valid'
No Padding

[Same and Valid Padding]

[Implementing 'SAME' and 'VALID' padding of Tensorflow in Python]

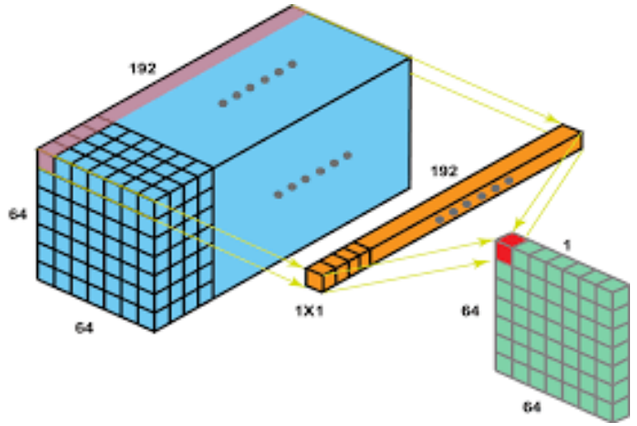
1 x 1 Convolution

背景: 每個 FILTER 產生一個 CHANNEL，太多 LAYERS 產生太多 CHANNEL
造成 運算資源浪費且減慢速度，1 x 1 FILTER 可解決此問題

做法：1 x 1 FILTER 跨越所有 CHANNELS 做 CONVOLUTION，並將其映射(PROJECT)為單一CHANNEL。所以是一個有效的改變(增加或減少)CHANNEL數目的工具。

用途：常用在GOOGLE INCEPTION/RESNET 環境中

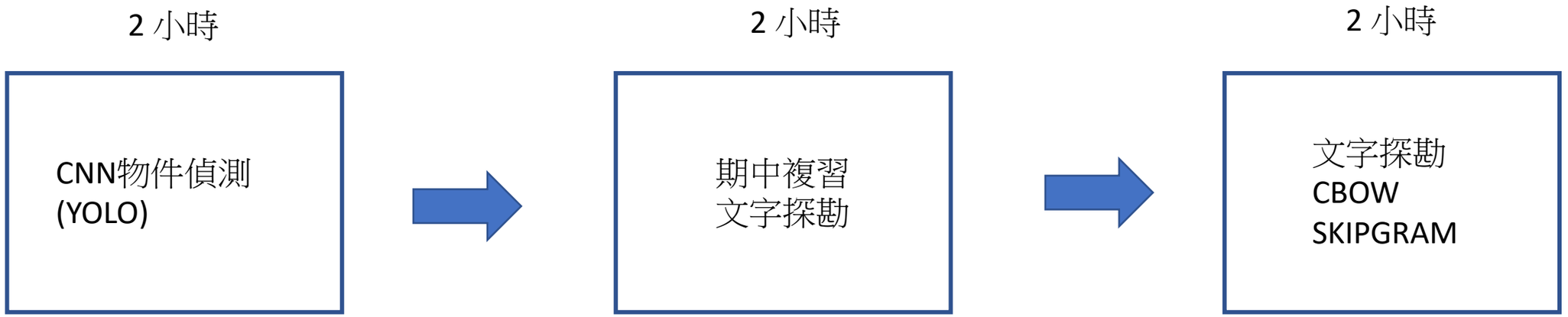
RESNET: match channel numbers between input and output
INCEPTION: reduce channel numbers



#parameters = #CH(I) * #CH(O) + #CH(O)
#CH : number of channels

[A Gentle Introduction to 1x1 Convolutions to Manage Model Complexity (machinelearningmastery.com)]

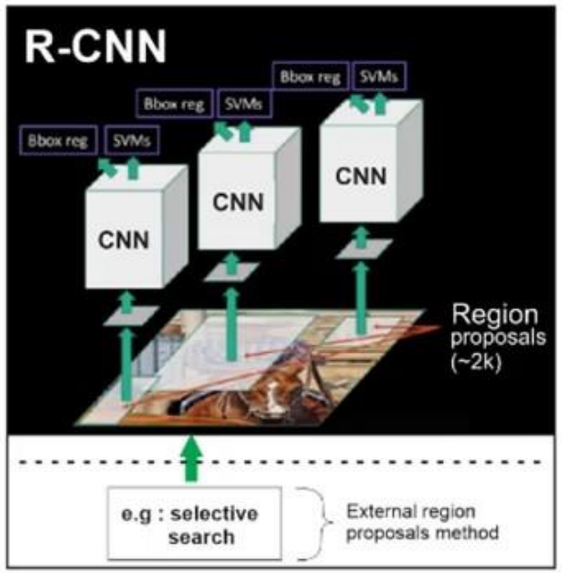
第三天

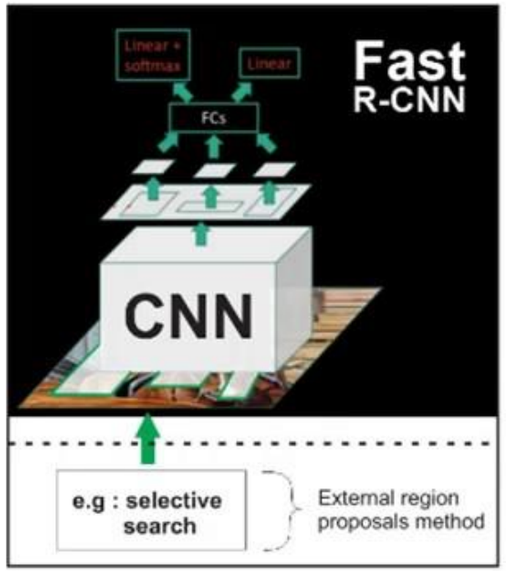


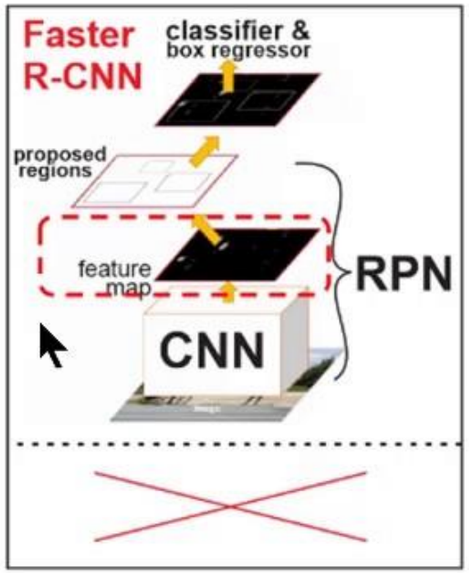
預習：LSTM/GRU, 降維, AutoEncoder
作業：作業三

R-CNN, Fast and Faster

1. Introduction#02







	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image	50 seconds	2 seconds	0.2 seconds
Speed-up	1x	25x	250x
mAP (VOC 2007)	66.0%	66.9%	66.9%

* Standford lecture notes on CNN by Fei Fei Li and Andrej Karpathy

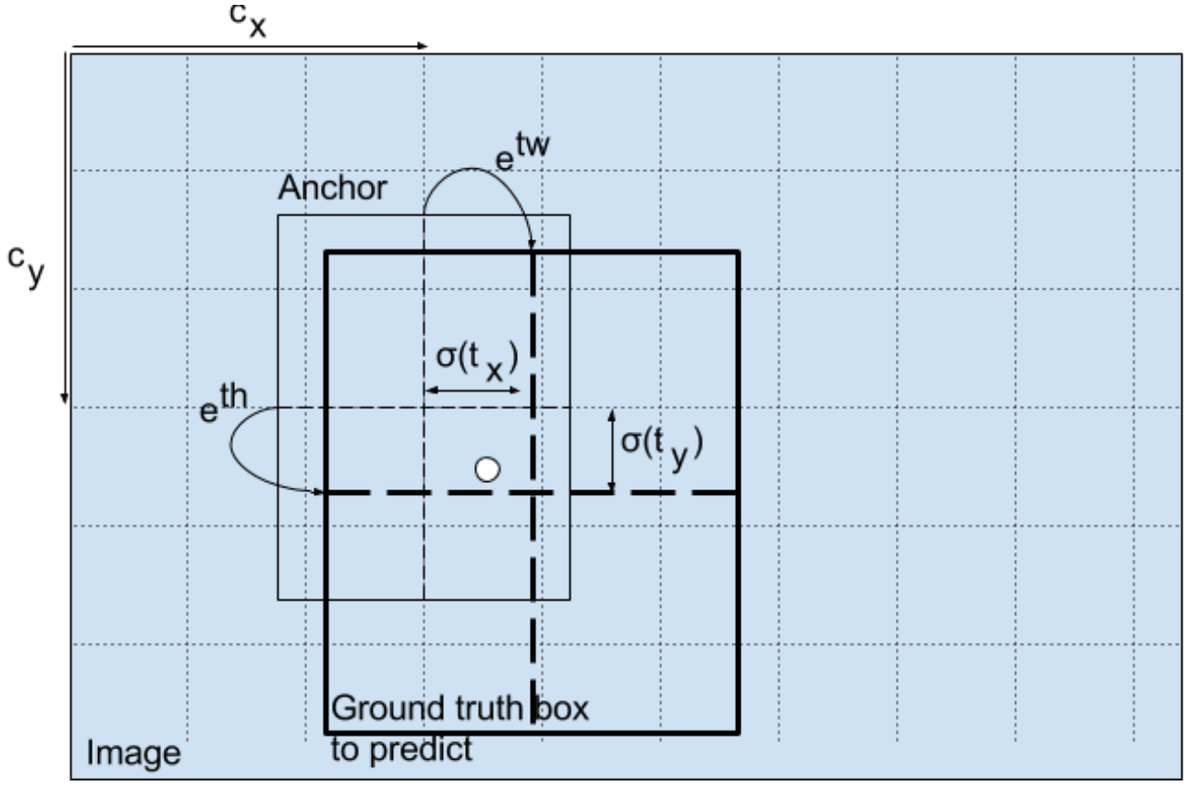
5

By Ardian Umam

https://jhui.github.io/2017/03/15/Fast-R-CNN-and-Faster-R-CNN

Why Anchor Box?

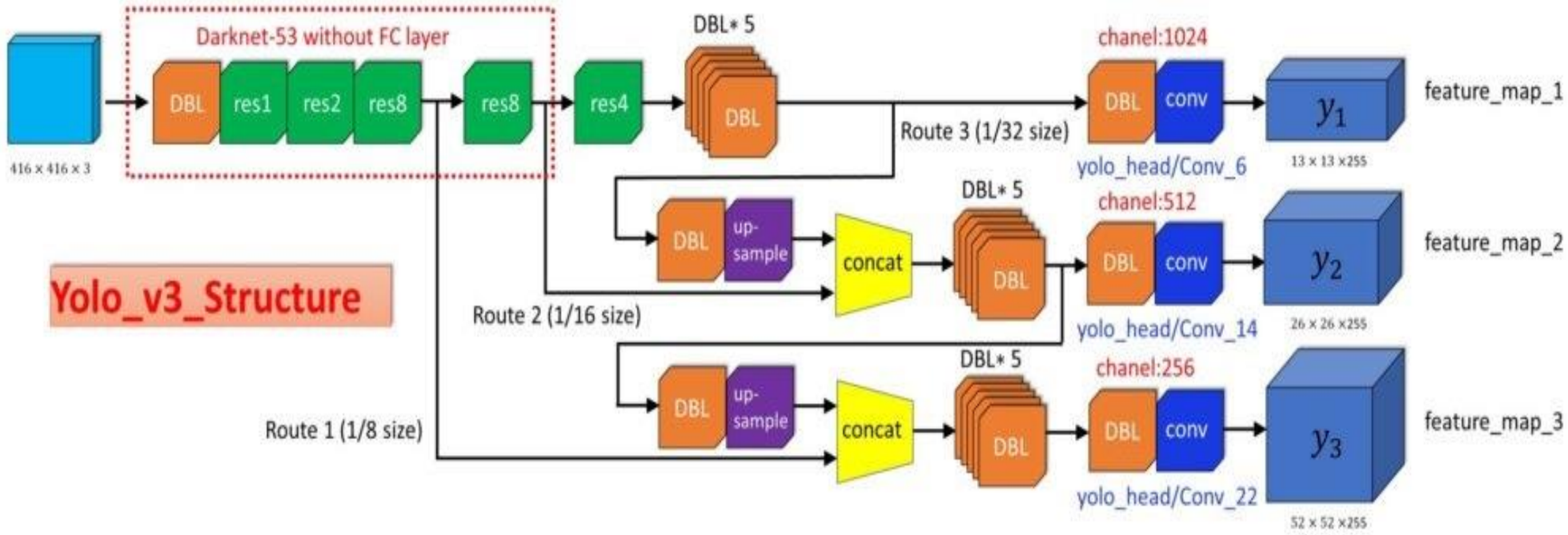
YOLO V3 的每個GRID CELL 都有 3x3個 以此CELL質心為中心的錨點框 (ANCHOR BOX)。利用他們預測此GRID CELL所負責的所有QUALIFIED BOUNDING BOXES。大中小加起來理論上有((13x13)+(26x26)+(52x52))x3 = 10647 個候選框

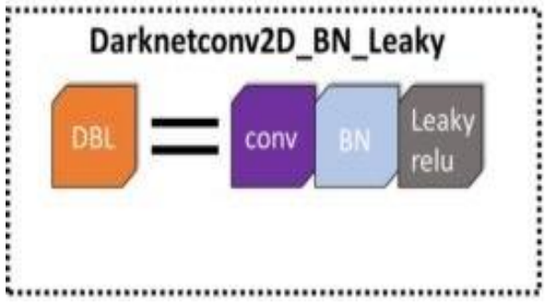


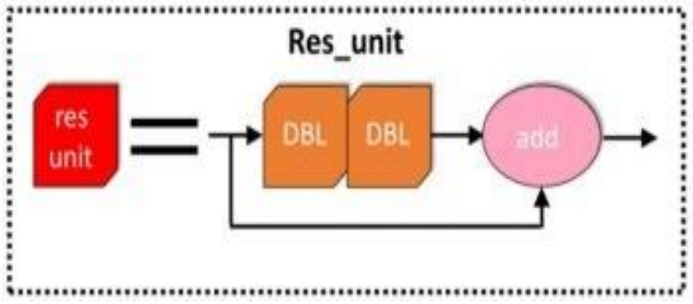
$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w e^{t_w}$$
$$b_h = p_h e^{t_h}$$

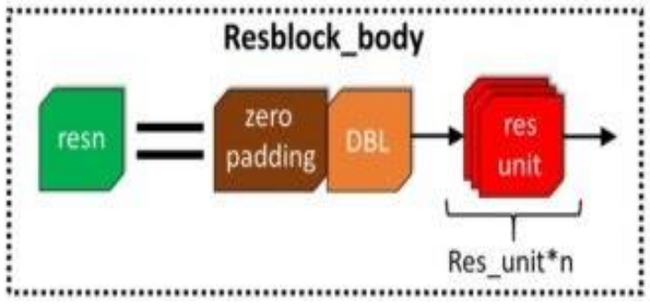
How to Implement a YOLO (v3) Object Detector from Scratch in PyTorch: Part 1 - KDnuggets

Yolo v3 Prediction



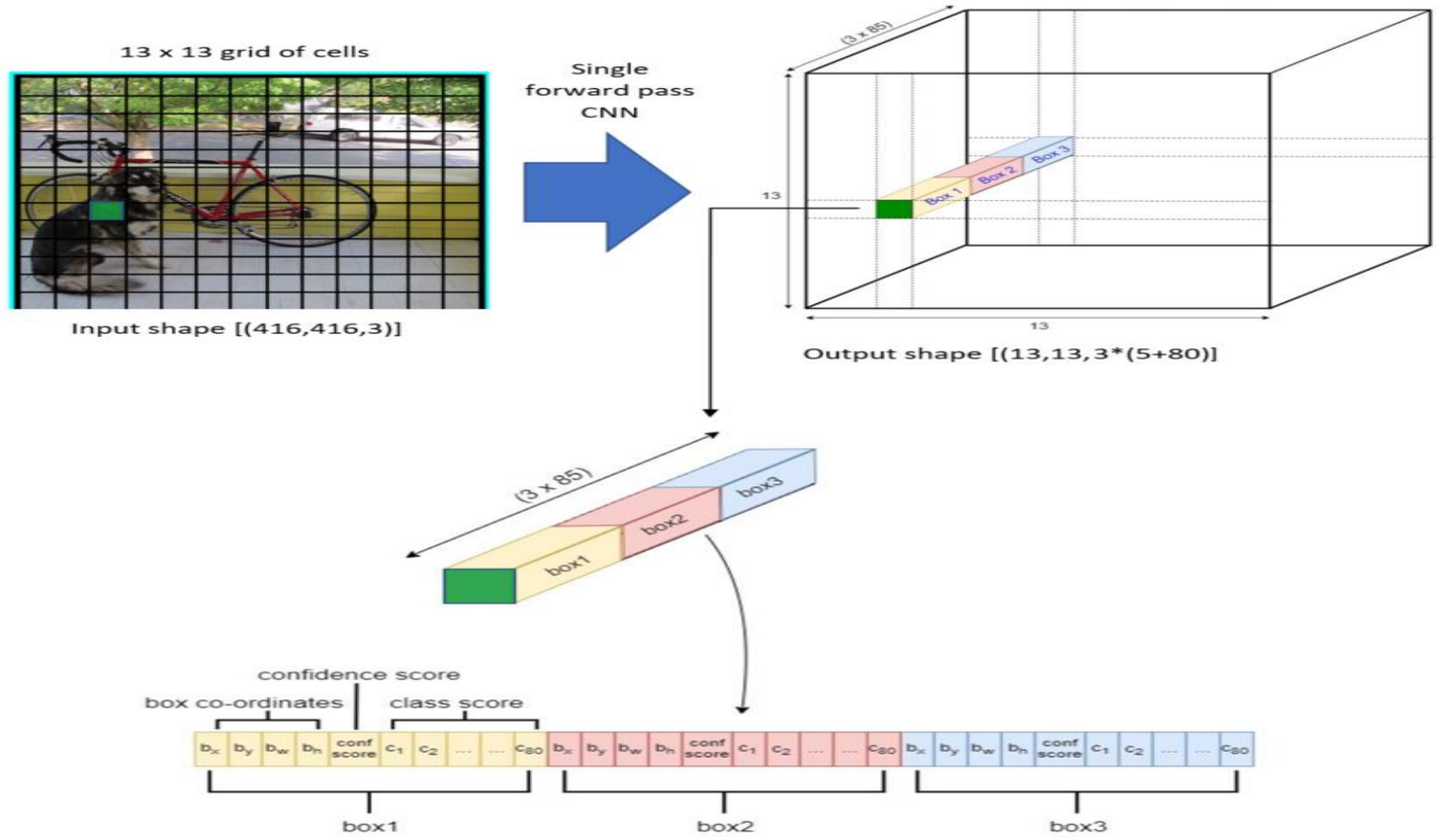






#011 TF YOLO V3 Object Detection in TensorFlow 2.0 (datahacker.rs)

Yolo v3 data structure



https://machinelearningspace.com/yolov3-tensorflow-2-part-1/)

Yolo loss function

Regression loss

$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

Confidence loss

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

Classification loss

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

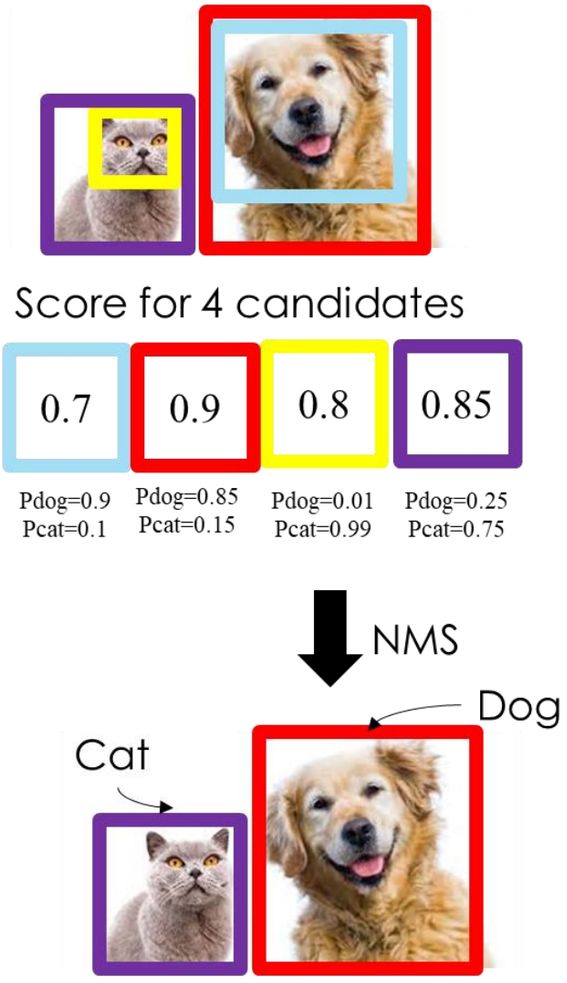
NMS演算法

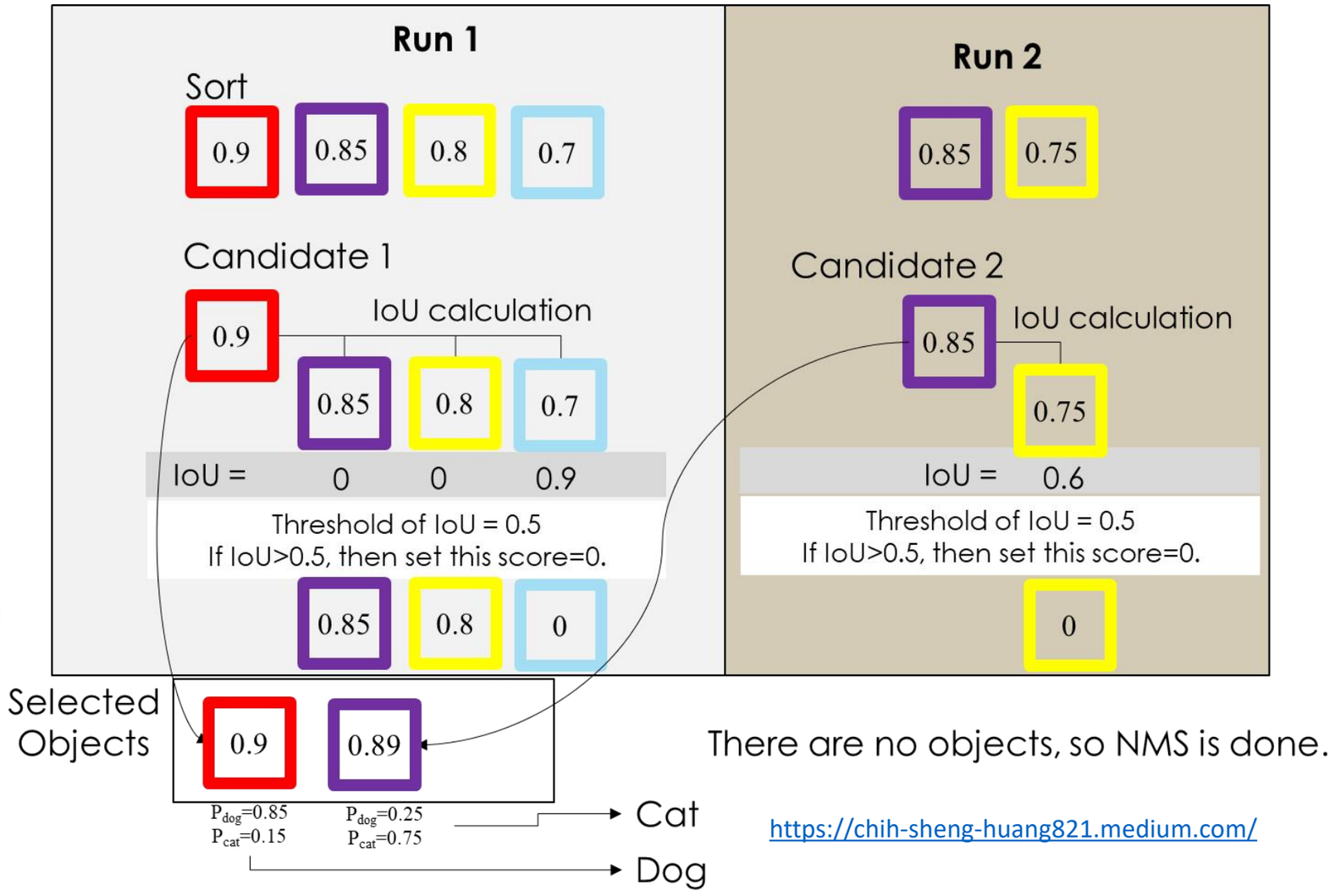
Input : $\mathcal{B} = \{b_1, .., b_N\}, \mathcal{S} = \{s_1, .., s_N\}, N_t$
$\mathcal{B}$ is the list of initial detection boxes
$\mathcal{S}$ contains corresponding detection scores
N_t is the NMS threshold

begin
  $\mathcal{D} \leftarrow \{\}$
  while $\mathcal{B} \neq empty$ **do**
    $m \leftarrow$ argmax $\mathcal{S}$
    $\mathcal{M} \leftarrow b_m$
    $\mathcal{D} \leftarrow \mathcal{D} \bigcup \mathcal{M}; \mathcal{B} \leftarrow \mathcal{B} - \mathcal{M}$
    for b_i *in* $\mathcal{B}$ **do**
      if $iou(\mathcal{M}, b_i) \geq N_t$ **then**
        $\mathcal{B} \leftarrow \mathcal{B} - b_i; \mathcal{S} \leftarrow \mathcal{S} - s_i$
      end
    end
  end
  return $\mathcal{D}, \mathcal{S}$
end

NMS

NMS: 2 classes, Threshold 0.5





https://chih-sheng-huang821.medium.com/

何謂 Word Embedding

Embedding: 文字轉向量，為什麼要轉向量？幾度空間的向量？

為了要計算距離，字與字，句與句，段與段，文與文。

有了這些，就可以用向量距離，以三角幾何學計算相似度。(GenSim = Generate Similarity)

字彙的空間，叫做文句集 (Corpus)，和當時的應用範圍有關，並非全世界所有的字。

轉向量的方法？One Hot Encoding, Label Encoding (Index), Word2Vec

Word2Vec最精簡(dense)，可指定向量維度(dim)，且向量最接近人類賦予的意義(Why?)。

可以Gensim 為工具，以CBOW 和 SkipGram為演算法實現 Word2Vec

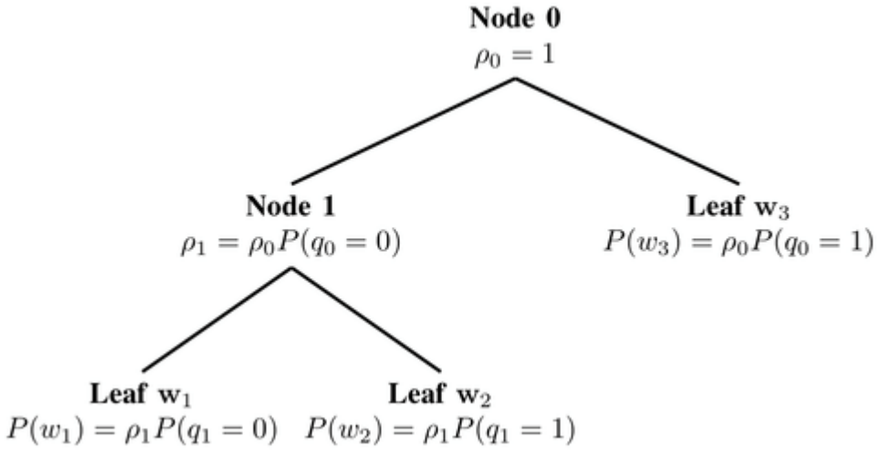
Tf.keras.layers.embedding 這一層就像NN，每個參數都得用Corpus訓練，才能得到vectors

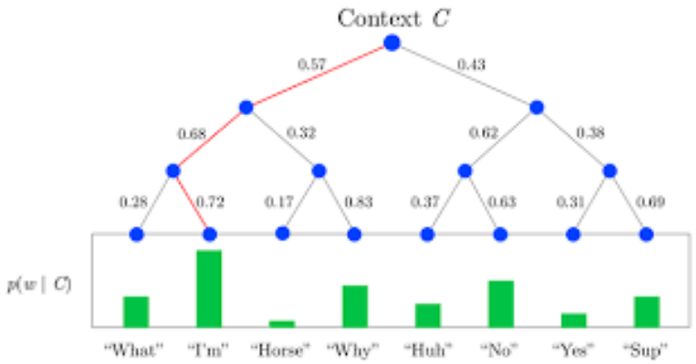
https://www.tensorflow.org/text/guide/word_embeddings

Hierarchical Softmax

Softmax 是用來分類出是哪個字，但Corpus有太多的字，比方100000個，CBOW的單層Softmax根本做不到，要分層以加速。

Hierarchical softmax (H-Softmax) is an approximation inspired by binary trees that was proposed by Morin and Bengio (2005) [3]. H-Softmax essentially replaces the flat softmax layer with a hierarchical layer that has the words as leaves, as can be seen in Figure 1.





Negative Sampling

在Skip-Gram 的演算法中，因要產生字對表達是否為周圍字(context word)，因此需要產生Negtive Samples。但是理論上所有Corpus 裡非在 windows內的全是Negative ，難道將所有的非鄰接字都做成樣本嗎?當然不可能。如果我們真的那樣做，每次運算要調整的權數就太多了。所以我們往往只取4,5到20個當做negative samples，以適當的損失函數來完成正確的訓練

以下文件對Skip-Gram 的 Negative Sampling 有詳細說明
https://www.tensorflow.org/tutorials/text/word2vec

Skipgram

shalt	not	make	a	machine

input	output
make	shalt
make	not
make	a
make	machine

Negative Sampling

input word	output word	target
make	shalt	1
make	aaron	0
make	taco	0

Gensim

Gensim = Generate Similarity (產生類似的文件)

主要優點：
- 毋須將整個文件庫(Corpus)載入主記憶體中，可見進批次進行分析整理
- 可利用計算機硬體之多核結構加速運行
- 非監督式學習無須標籤
- 可與多種作業環境及平台整合

應用舉例：
- Word2Vec：文字轉向量技術
- TF-IDF (Term frequency–inverse document frequency)：文字轉向量技術
- 潛在語意分析(LSA : Latent Semantec Analysis)

學習：

Gensim - Introduction – Tutorialspoint

gensim: Core Concepts (radimrehurek.com)

TF-IDF

TF-IDF (Term frequency–inverse document frequency)：

目的就是要以一個數字表達在文件集的特異/重要程度

TF: **在本句(文件)出現次數**(頻率 = 次數/總次數)**除以本句(文件)總字數**
IDF:**在Corpus出現的句(文件)數**除以**有此字出現的句(文件)數**
TF代表在該句的 分量，IDF代表在該文件集的特異程度
TF * IDF 之值 即為該字在該句中的TF-IDF 值

實際公式IDF有時用log，稍有不同

TF = (Frequency of the word in the sentence) / (Total number of words in the sentence)
IDF: log((Total number of sentences (documents))/(Number of sentences (documents) containing the word))

某字的TF-IDF向量 可以說是這個字在該文件集中的特徵向量，可用來做相似度運算

https://stackabuse.com/python-for-nlp-creating-tf-idf-model-from-scratch/

第四天

2 小時

RNN原理
LSTM與GRU

2 小時

RNN進階應用
PCA 與 t-SNE

2 小時

AutoEncoder
圖像風格

預習：GAN，強化學習
作業：作業四

RNN Weights Saving/Sharing

T = 100 D = 10 M = 15 K = 1	輸入層 (Input Layer)	隱藏層 (Hidden Layer)	輸出層 (Output Layer)	總數
DNN	輸入攤平(flatten)	輸入(T*D) * 隱藏(M) * 步數(T)	步數(T) * 隱藏(M)	1.5M
DNN 權數公式	T * D = 1000	(T * D) * M * T = 1.5 Million	T * M * K = 1500	1.5M
RNN	W_{xh} = D * M = 150	W_{hh} = M * M = 225	W_{ho} = M * K = 15	385

Spam Detection in RNN

DEMO19_SPAM_DETECTION RNN.ipynb 說明

RNN 必須有 N x T x D
我們設定 T = data_train.shape[1]也就是整句話

我們希望Embedding的維數(Dimensionality) = 20，RNN 隱藏神經元 = 15
D = 20
M = 15
#先將所有字彙轉成20維度向量，然後再做LSTM/RNN訓練

```
i = Input(shape=(T,))
x = Embedding(V + 1, D)(i)
x = LSTM(M, return_sequences=True)(x)
x = GlobalMaxPooling1D()(x)
x = Dense(1, activation='sigmoid')(x)

model = Model(i, x)
```

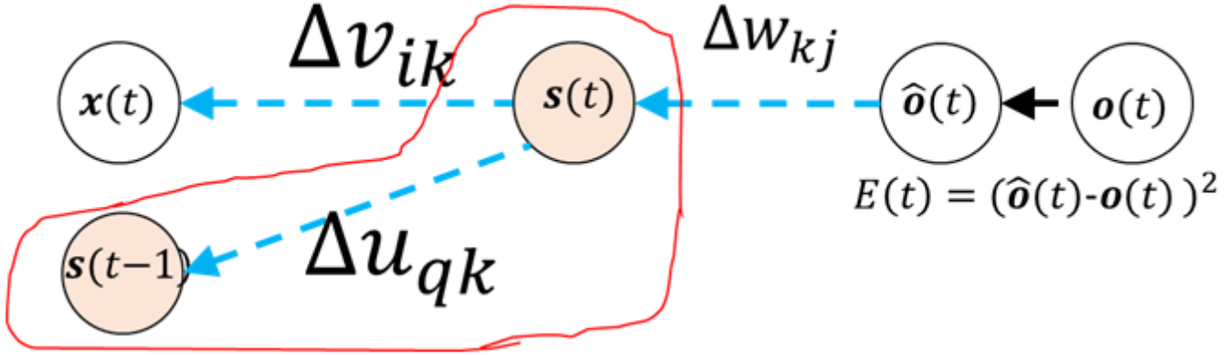
Spam Detection in RNN

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 162)]             0
_________________________________________________________________
embedding (Embedding)        (None, 162, 20)           145960
_________________________________________________________________
lstm (LSTM)                  (None, 162, 15)           2160
_________________________________________________________________
global_max_pooling1d (Global (None, 15)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 16
=================================================================
Total params: 148,136
Trainable params: 148,136
Non-trainable params: 0
```

= **V+1 * D** = 7298 * 20 = **145960**

= **4(D*M + M*M + M)=**4(300+225+15)=**2160**

RNN BPTT 的解釋



RNN所用到的Back-propagation Through Time，所謂的Through Time其實跟MLP用的Back-propagation差別最大就是多了△*u_qk*這一項

$$\Delta u_{qk} = \sum_{i=1}^{n} \left\{ \left[\sum_{j=0}^{m} \left(\hat{o}_j{}^{(i)}(t) - o_j{}^{(i)}(t) \right) f_2'(z_j^{(i)}(t)) \right] \left[w_{kj} f_1'(h_k(t)) s_k(t-1) \right] \right\}$$

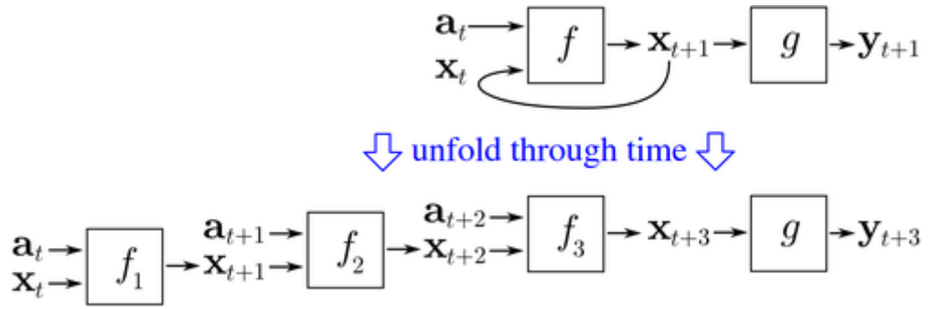
但換個角度想，時間t-1的state(*sk*(*t*-1))這個部分，你把這部分想像它只是單純的input node，這樣整個網路跟MLP基本上是完全一樣的。

遞歸神經網路(Recurrent Neural Network): Back-propagation Through Time | by Tommy Huang | Medium

Backpropagation Through Time

演算法：

1.Present a sequence of timesteps of input and output pairs to the network.
2.Unroll the network then calculate and accumulate errors across each timestep.
3.Roll-up the network and update weights.
4.Repeat.

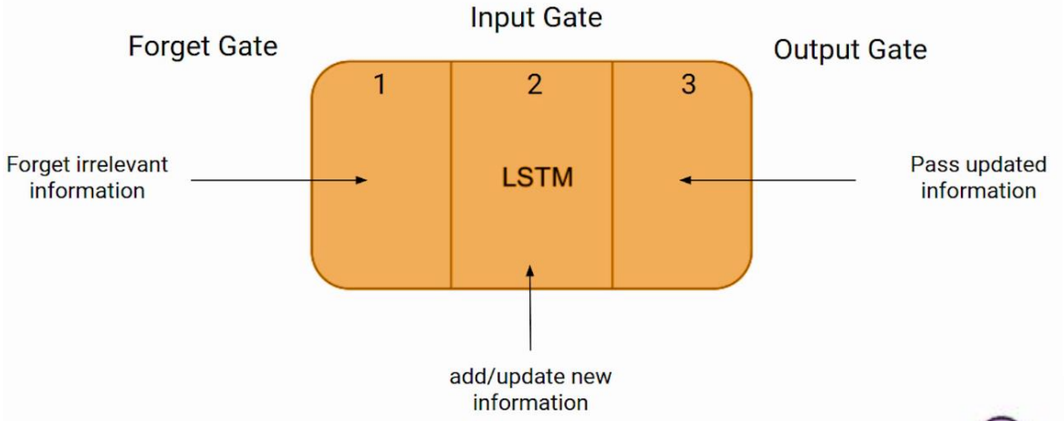


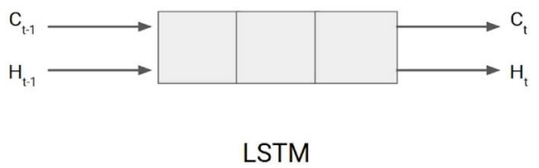
缺點：

One of the main problems of BPTT is the high cost of a single parameter update, which makes it impossible to use a large number of iterations.

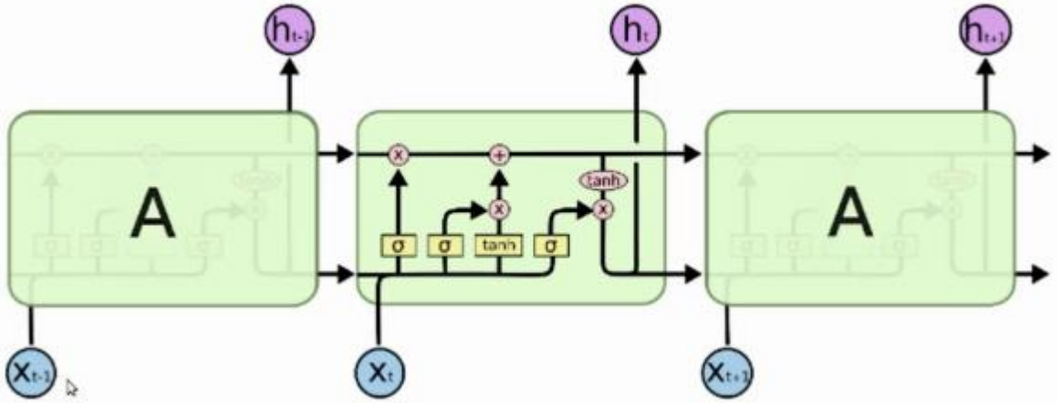
A Gentle Introduction to Backpropagation Through Time (machinelearningmastery.com)

The secret of LSTM





Forget: Bob is a nice person. Dan on the other hand is evil.



$C_t = f_t * C_{t-1} + i_t * N_t$ (updating cell state)

$H_t = o_t * \tanh(C_t)$

$\text{Output} = \text{Softmax}(H_t)$

Input: Bob knows swimming. He told me over the phone that he had served the navy for four long years.

Output: Bob single-handedly fought the enemy and died for his country. For his contributions, brave_____ .

LSTM | Introduction to LSTM | Long Short Term Memor (analyticsvidhya.com)

Bidirectional LSTM

Traditionally, LSTMs have been one-way models, also called unidirectional ones. In other words, sequences such as tokens (i.e. words) are read in a left-to-right or right-to-left fashion.

This does not necessarily reflect good practice, as more recent Transformer based approaches like BERT suggest.

In fact, *bidirectionality* – or processing the input in a left-to-right *and* a right-to-left fashion, can improve the performance of your Machine Learning model.

While conceptually bidirectional LSTMs work in a bidirectional fashion, they are not bidirectional in practice. Rather, they are just two unidirectional LSTMs for which the output is combined.

Fox example: model.add(Bidirectional(LSTM(10), merge_mode='sum'))

Bidirectional LSTMs with TensorFlow 2.0 and Keras – MachineCurve

LSTM vs GRU by IEEE

Long short-term memory networks(LSTM) and **gate recurrent unit networks(GRU)** are two popular variants of recurrent neural networks(RNN) with long-term memory.

This study compares the performance differences of these two deep learning models, involving two dimensions: **dataset size** for training, long/short text, and **quantitative evaluation** on five indicators including running **speed, accuracy, recall, F1 value, and AUC**. The corpus uses the datasets officially released by Yelp Inc.

In terms of model **training speed**, GRU is 29.29% faster than LSTM for processing the same dataset; and in terms of **performance**, GRU performance will surpass LSTM in the scenario of **long text and small dataset**, and inferior to LSTM in other scenarios.

Considering the two dimensions of both performance and computing power cost, the performance-cost ratio of GRU is higher than that of LSTM, which is 23.45%, 27.69%, and 26.95% higher in accuracy ratio, recall ratio, and F1 ratio respectively.

LSTM and GRU Neural Network Performance Comparison Study: Taking Yelp Review Dataset as an Example | IEEE Conference Publication | IEEE Xplore

機器翻譯：What is BLEU score

BLEU, or the **Bilingual Evaluation Understudy**, is a score for comparing a candidate translation of text to one or more reference translations.

Although developed for translation, it can be used to evaluate text generated for a suite of natural language processing tasks.

BLEU Score	Interpretation
< 10	Almost useless
10 - 19	Hard to get the gist
20 - 29	The gist is clear, but has significant grammatical errors
30 - 40	Understandable to good translations
40 - 50	High quality translations
50 - 60	Very high quality, adequate, and fluent translations
> 60	Quality often better than human

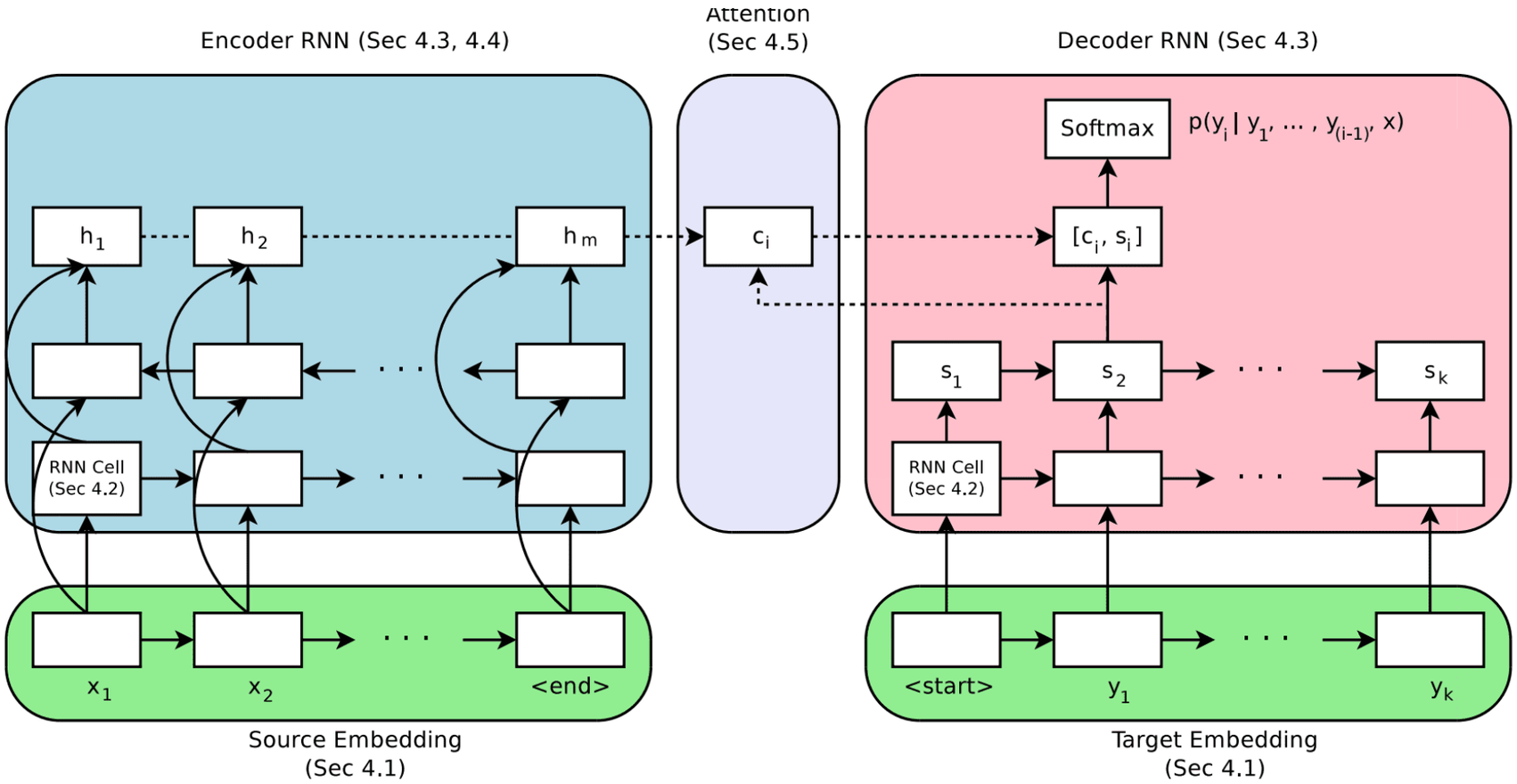
機器翻譯：What is Beam size

Beam size, or beam width, is a parameter in the beam search algorithm which determines how many of the best partial solutions to evaluate. In an LSTM model of melody generation, for example, beam size limits the number of candidates to take as input for the decoder.

A beam size of 1 is a best-first search - only the most probable candidate is chosen as input for the decoder. A beam size of k will decode and evaluate the top k candidates. A large beam size means a more extensive search - not only the single best candidate is evaluated.

機器翻譯：A detailed example

Encoder/Decoder with RNN Model + Attention



[How to Configure an Encoder-Decoder Model for Neural Machine Translation (machinelearningmastery.com)]

PCA 降維步驟

Steps Involved in the PCA

Step 1: Standardize the dataset.
Step 2: Calculate the covariance matrix for the features in the dataset.
Step 3: Calculate the eigenvalues and eigenvectors for the covariance matrix.
Step 4: Sort eigenvalues and their corresponding eigenvectors.
Step 5: Pick k eigenvalues and form a matrix of eigenvectors.
Step 6: Transform the original matrix.

Understanding Principle Component Analysis(PCA) step by step. | by The Nobles | Analytics Vidhya | Medium

t-SNE 演算法的步驟

The t-SNE algorithm comprises two main stages.

First, t-SNE constructs a probability distribution over pairs of high-dimensional objects in such a way that similar objects are assigned a higher probability while dissimilar points are assigned a lower probability. 在每對高維的物件上建立機率分布，給予相似的物件較高機率，不同的則給予較低機率

Second, t-SNE defines a similar probability distribution over the points in the low-dimensional map, and it minimizes the Kullback–Leibler divergence (KL divergence) between the two distributions with respect to the locations of the points in the map.其次，在相對應的低維地圖上建立類似分布，並且將兩分布的KL divergence在低維地圖的點極小化

While the original algorithm uses the Euclidean distance between objects as the base of its similarity metric, this can be changed as appropriate.
此演算法不一定要用歐式距離來量度。

GMM-CVAE and AG-CVAE

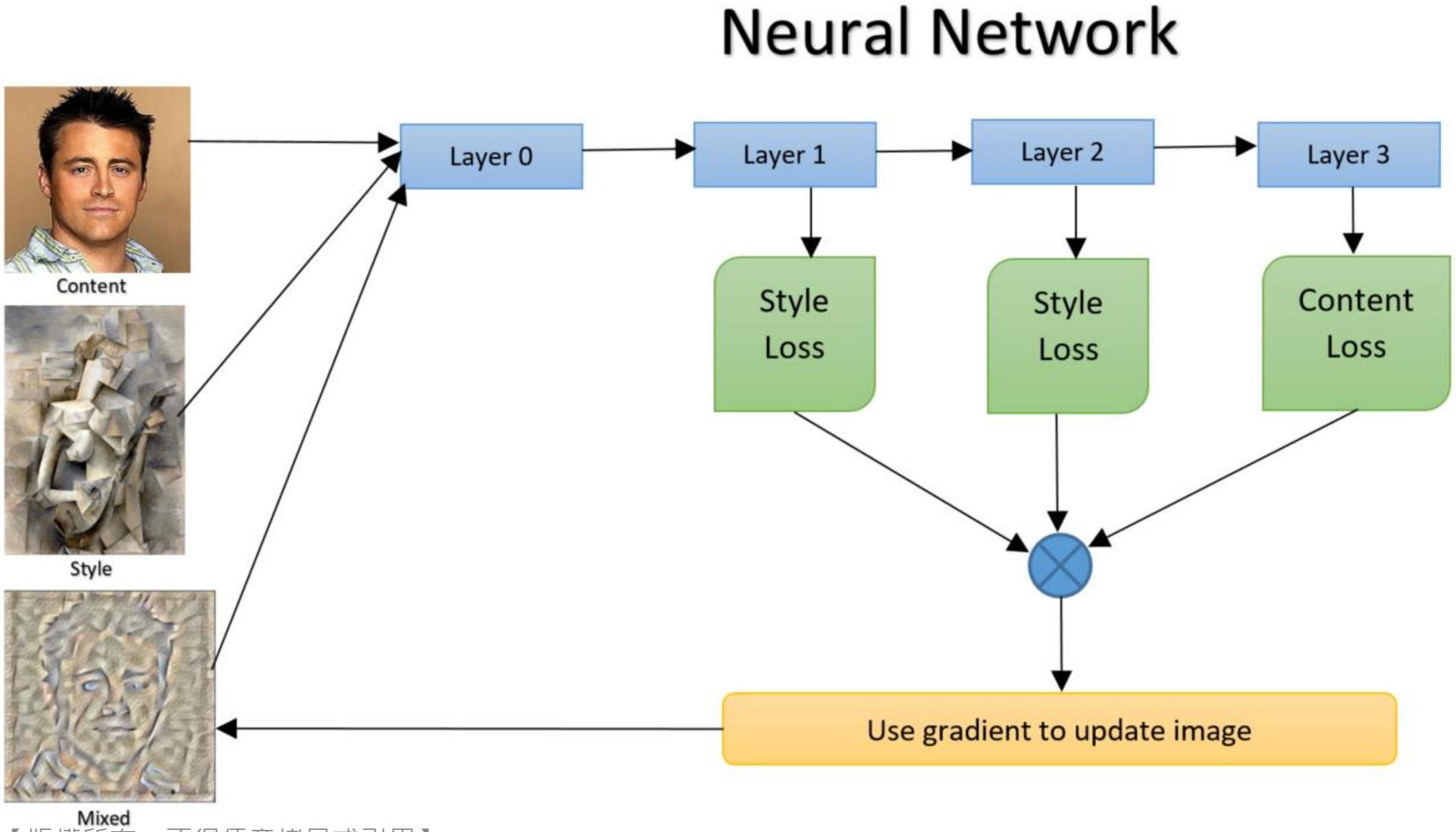
Standard CVAEs with a fixed Gaussian prior yield descriptions with too little variability. Instead, we propose two models that explicitly structure the latent space around K components corresponding to different types of image content, and combine components to create priors for images that contain multiple types of content simultaneously (e.g., several kinds of objects).

Our first model uses a **Gaussian Mixture model (GMM)** prior, while the second one defines a novel **Additive Gaussian (AG)** prior that linearly combines component means. We show that both models produce captions that are more diverse and more accurate than a strong LSTM baseline or a "vanilla" CVAE with a fixed Gaussian prior, with AG-CVAE showing particular promise.

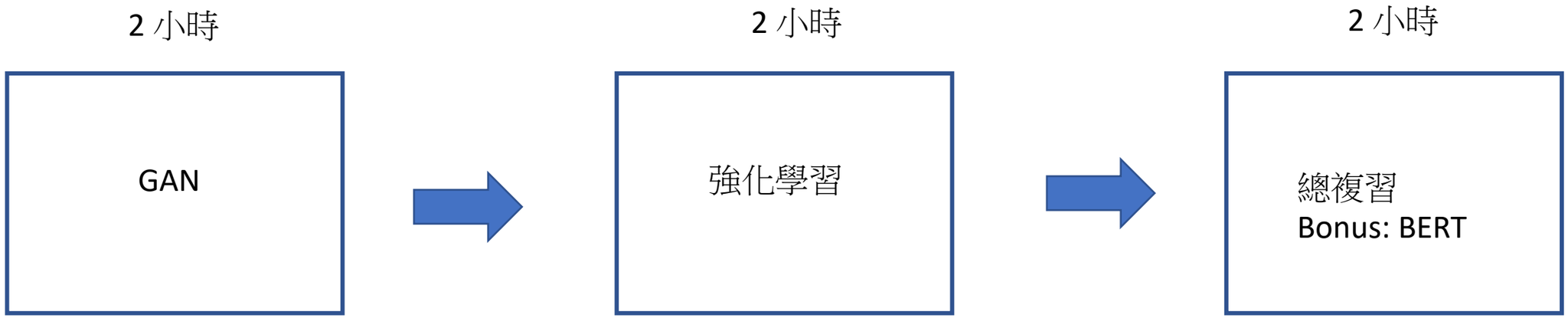
r the single-best-caption output.

Diversity metrics for multi-candidate models		
	Diversity within candidates	Novelty within candidates
CVAE [29]	11.8	**82.0**
GMM-CVAE [29]	59.4	80.9
AG-CVAE [29]	**76.4**	79.5

Neural Style Transfer



第五天



預習：GAN，強化學習
作業：作業五

Cycle GAN Example

原理：將兩個互相映射的GAN，以強迫loss consistent (一致) 的方式造成來源和目的影像在轉換過程中擁有類似的風格或結構。

CycleGAN最大的特色是不需要成對的影像，就可以學習到風格是如何轉換的。如果一匹棕色的馬映射到一批斑馬，那麼一群棕色的馬就可以轉換成一群斑馬，不同情境下的馬，都會映射成類似情境的斑馬。維持轉換(映射)的一致性。

CycleGAN和Pix2Pix十分類似，不同點在於：

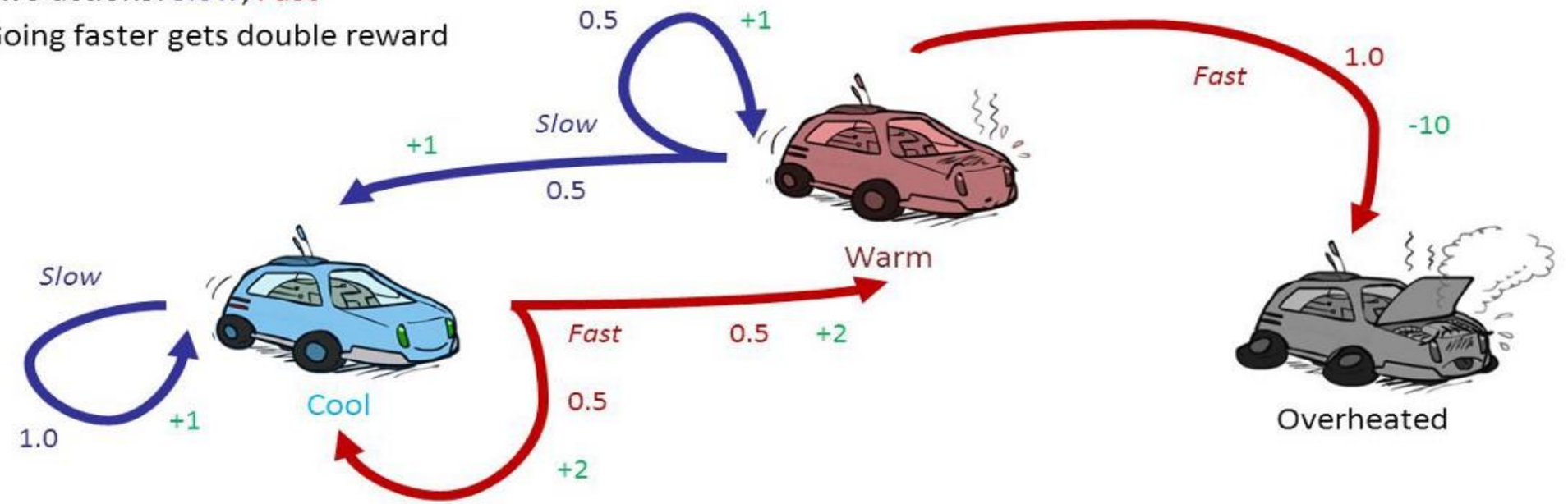
- CycleGAN 使用 Instance Normalization 而非 Batch Normalization
- CycleGAN 使用 ResNet Image Generator

CycleGAN | TensorFlow Core

馬可夫決策過程

Example: Racing

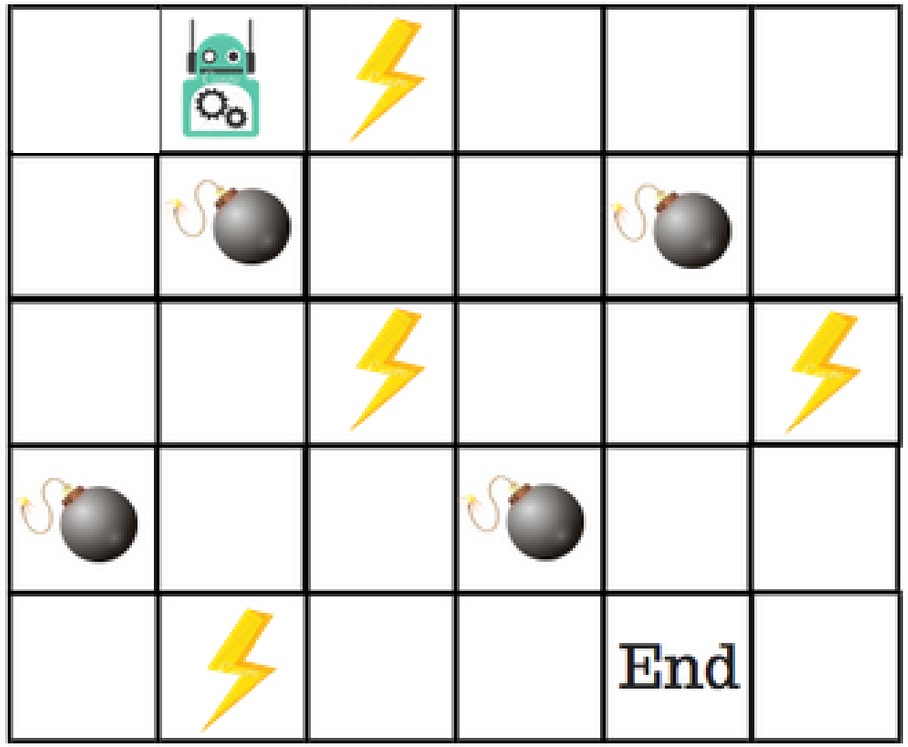
- A robot car wants to travel far, quickly
- Three states: Cool, Warm, Overheated
- Two actions: *Slow*, *Fast*
- Going faster gets double reward



medium.com

Markov 鍊模型：決策過程與過去無關，只和現在有關

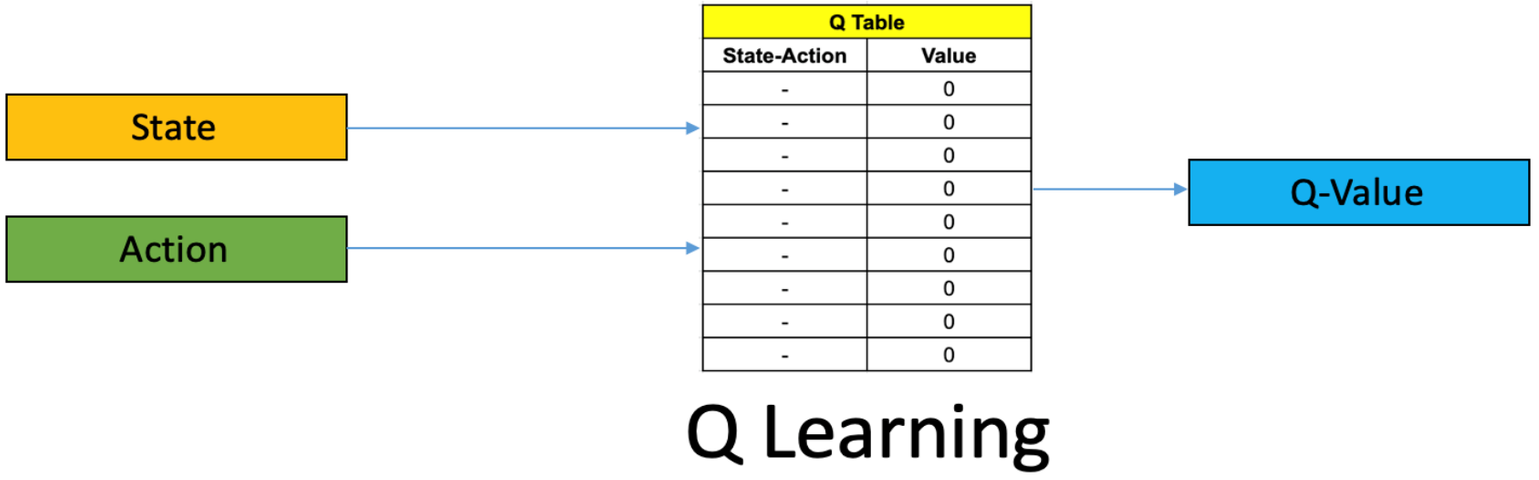
Q-Learning Table

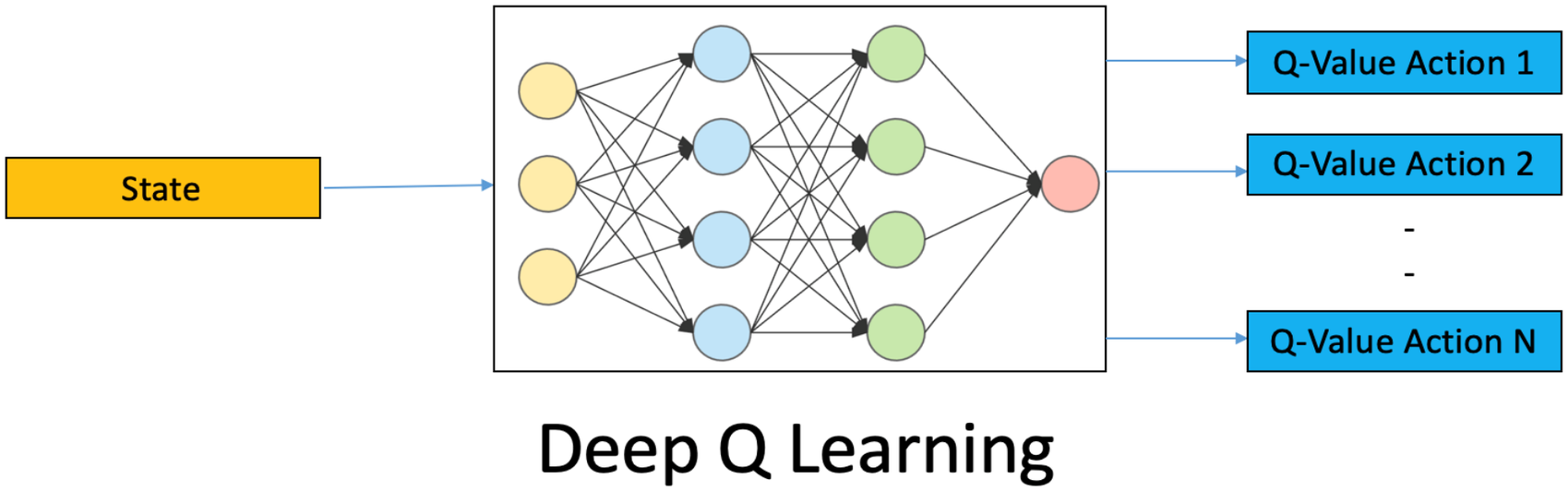


Actions :	↑	→	↓	←
Start	0	0	0	0
Nothing / Blank	0	0	0	0
Power	0	0	0	0
Mines	0	0	0	0
END	0	0	0	0

[An introduction to Q-Learning: reinforcement learning (freecodecamp.org)]

從 Q-table 到 DQN





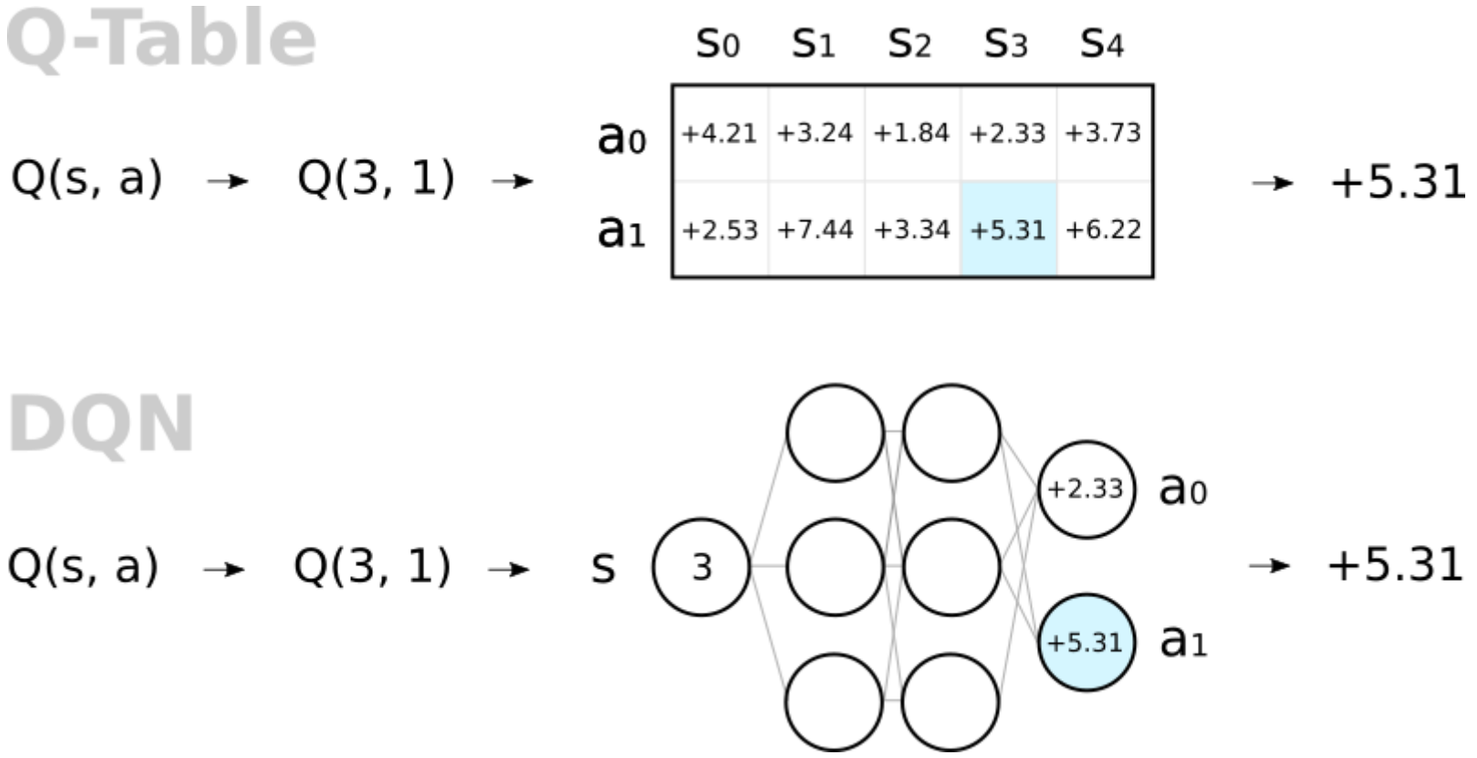
DQN其實就是用神經網路去模擬(逼近)Q-Table，DQN 直接產生各action再取最大值，而Q-Table 則找產生最大Q值的action。

一旦action被(policy)決定，Environment就會提供 reward 和下一個 state。Q-table 會根據新的state 去衡量所有可能的action，DQN則 輸入state 即可產生下一個action.

當State數變成無窮大時，Q-table將不敷使用，DQN經由訓練，其w與b的值將可取代被訓練後的Q(s,a)而達到同樣效果

Analyticsvidhya.com

從 Q-table 到 DQN：例子



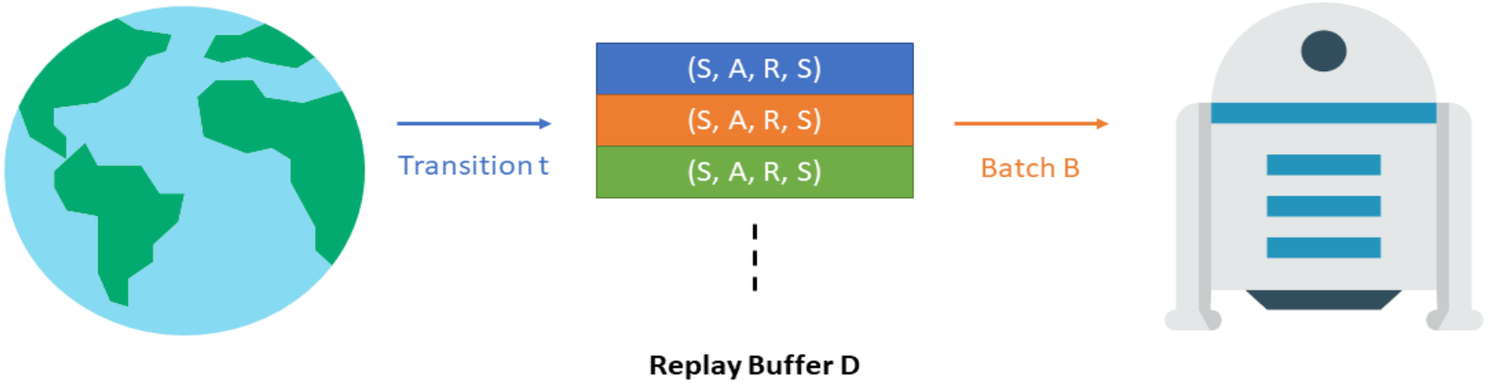
valohai.com

Experience Replay(經驗回放)

訓練時有效而多元，無須真實世界的模擬或執行，只雖機重覆回放(s,a,r,s’)值
收斂較快因而結果穩定

Experience Replay

- Save transitions $(S_t, A_t, R_{t+1}, S_{t+1})$ into buffer and sample batch B
- Use batch B to train the agent



endtoend.ai

學習目標：

- 了解Transformer
- 了解BERT

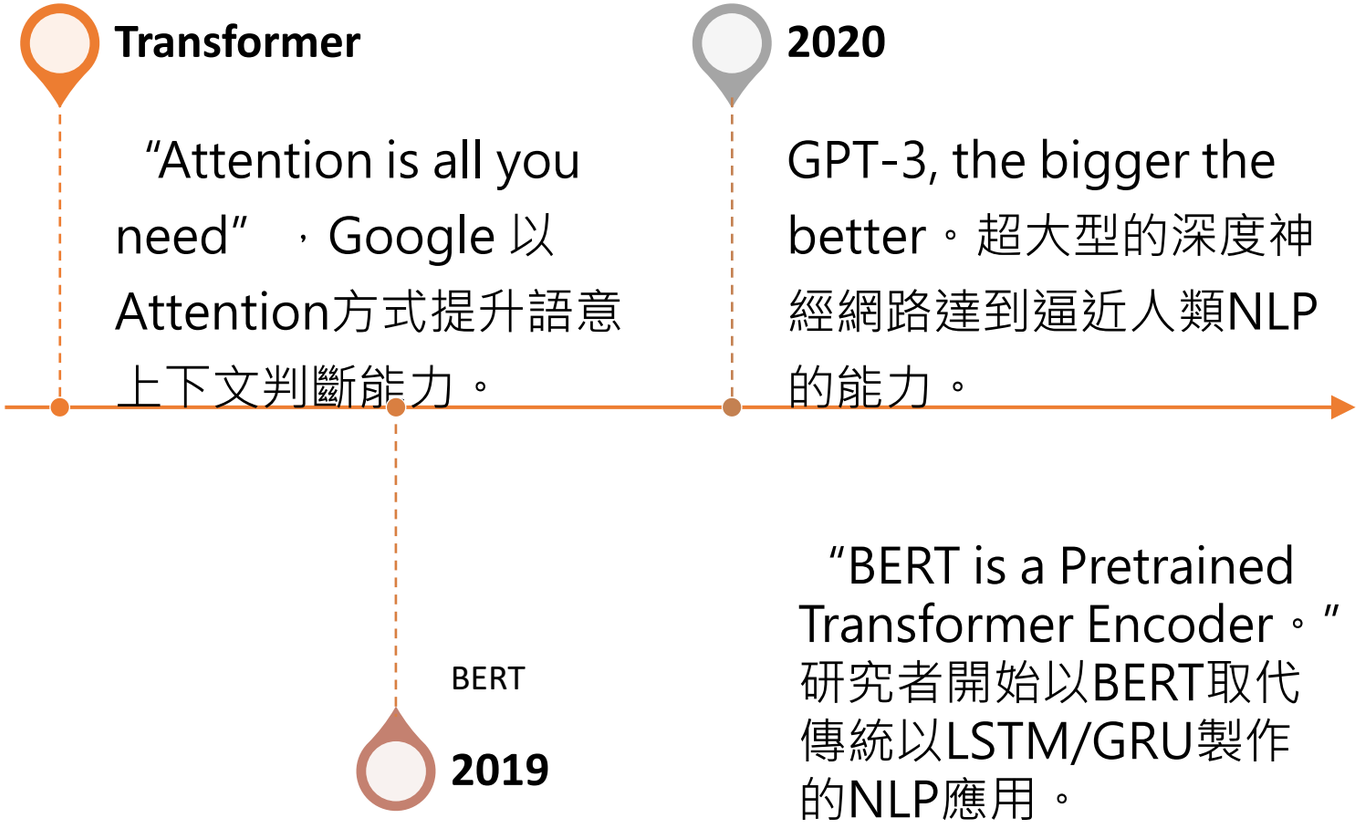
Bonus: BERT的原理與應用

BERT的原理與應用

內容大綱

- BERT的歷史淵源
- BERT的簡介
- BERT的應用：假新聞分類器
- BERT的其他應用

BERT的歷史淵源



BERT的簡介：BERT之前

- Elmo：雙向預訓LSTM based context-based Language Model
- ULM-FiT：在RNN/NLP 領域開始Transfer Learning 就像 CNN在 Computer Vision領域
- Transformer: 包括 Encoder和 Decoder，主要是建立自然語言翻譯的語言模型，他完全揚棄了 LSTM 模式而採用 Attention 模式。他的 Encoder-Deoder模式可用來做許多 downstream applications.
- OpenAI Transformer：利用 Transformer Decoder 做 Predicting Future Tokens。Encoder只留下self-attention layer. 應用包括 分類，蘊涵(entailment)，相似 (similarity)，選擇等。But it is forward direction only.

BERT的簡介： BERT的背景

- BERT (Bidirectional Encoder Representations from Transformers), 是一個 Pretrained Transformer 的 Encoder。Transformer 源自 Attention is all you need 的構想，揚棄傳統的RNN/LSTM/GRU的作法，不以順序(sequence)而以位置(position)達到平行訓練的目的，同時以一套Self-Attention的計算法更準地抓到了文句的上下文(Context)，進而提高幾乎所有NLP應用的準確度，包括分類與預測等等。

- 由於BERT系統龐大，即使是BASE model也有上億個神經元，非普通系統所能承受。我們一般都用Pretrained BERT Model再接上Fine Tuning Model來完成分類或其他應用，效果比起用RNN/LSTM好很多。

BERT的簡介： BERT的原理

- BERT的輸入有三個Embeddings，分別是 Token Embeddings (可能由Word2Vec, Glove等產生)，Position Embeddings紀錄順序位置，以及Segment Embeddings 紀錄相關或隨機字句。

- 在預訓時，BERT嘗試同時預測(15%)被掩蓋的字(Masked Language Model，MLM)以及下一句子預測 (Next Sentence Prediction)。

- BERT其實就是 預訓過的 Transformer Encoder，因為同時保有 字義，位置 和 段落 輸入的 embeddings，運用 Transformer Self-Attention 的能力，只要在後頭接上簡單的Linear Classifier or Regressor，就可完成許多NLP的應用。

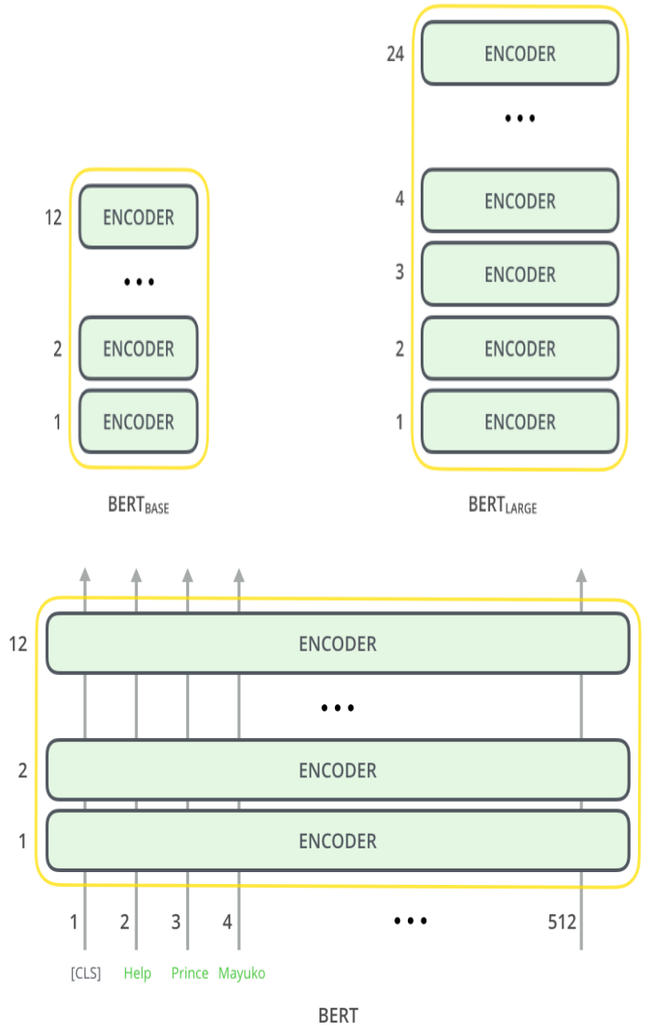
BERT的簡介：架構 – 輸入

常用的 BERT模型有兩種:

BERT BASE – 和OpenAI Transformer 大小差不多(12層)
BERT LARGE – 研發用非常大的模型(24層)

前面說過 BERT 基本上就是一個訓練過的 Transformer Encoder如右圖。BASE/LARGE 有 12/16 Attention Head， 784/1024 Hidden Unit。

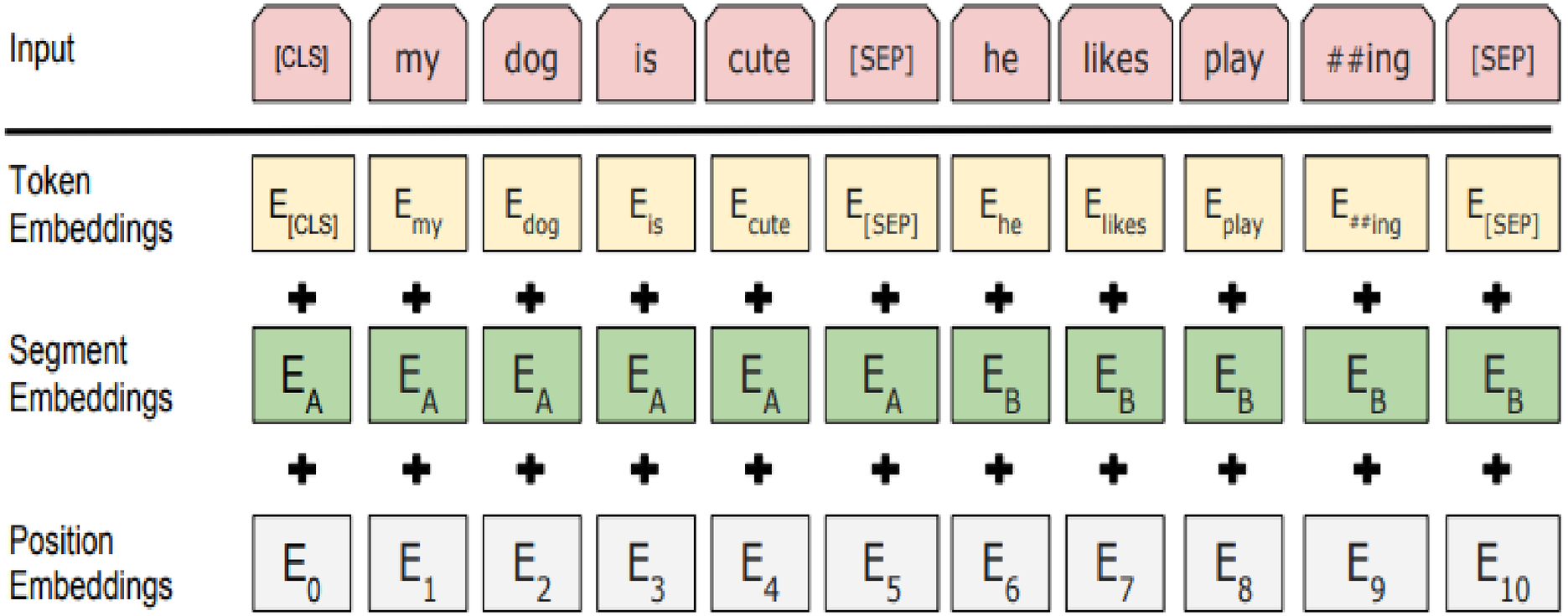
第一個input token 有一個特殊的 Classification Token [CLS]，Input token 不斷往上走，每一層都有self-attention層和Feed-forward層，然後在交給下一個Encoder.



BERT的簡介：輸入Embeddings

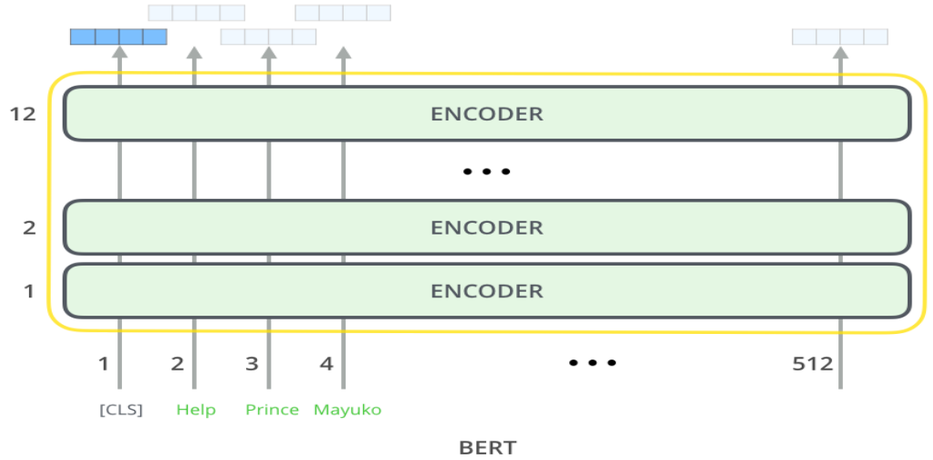
- BERT的輸入Embeddings其實是三個Embeddings的組合：
- Token Embedding: 就是你提供文章的句子加上[CLS][SEP][MASK]等特殊字符的向量，[CLS]代表句子的開端；[SEP]是相鄰(關)句子的間隔，像是句號；[MASK]是掩蓋掉的字符。
- Segment Embedding: 和[SEP]配合，表示第幾個句子。
- Position Embedding:輸入中的第幾個位置。

BERT的簡介：輸入Embeddings



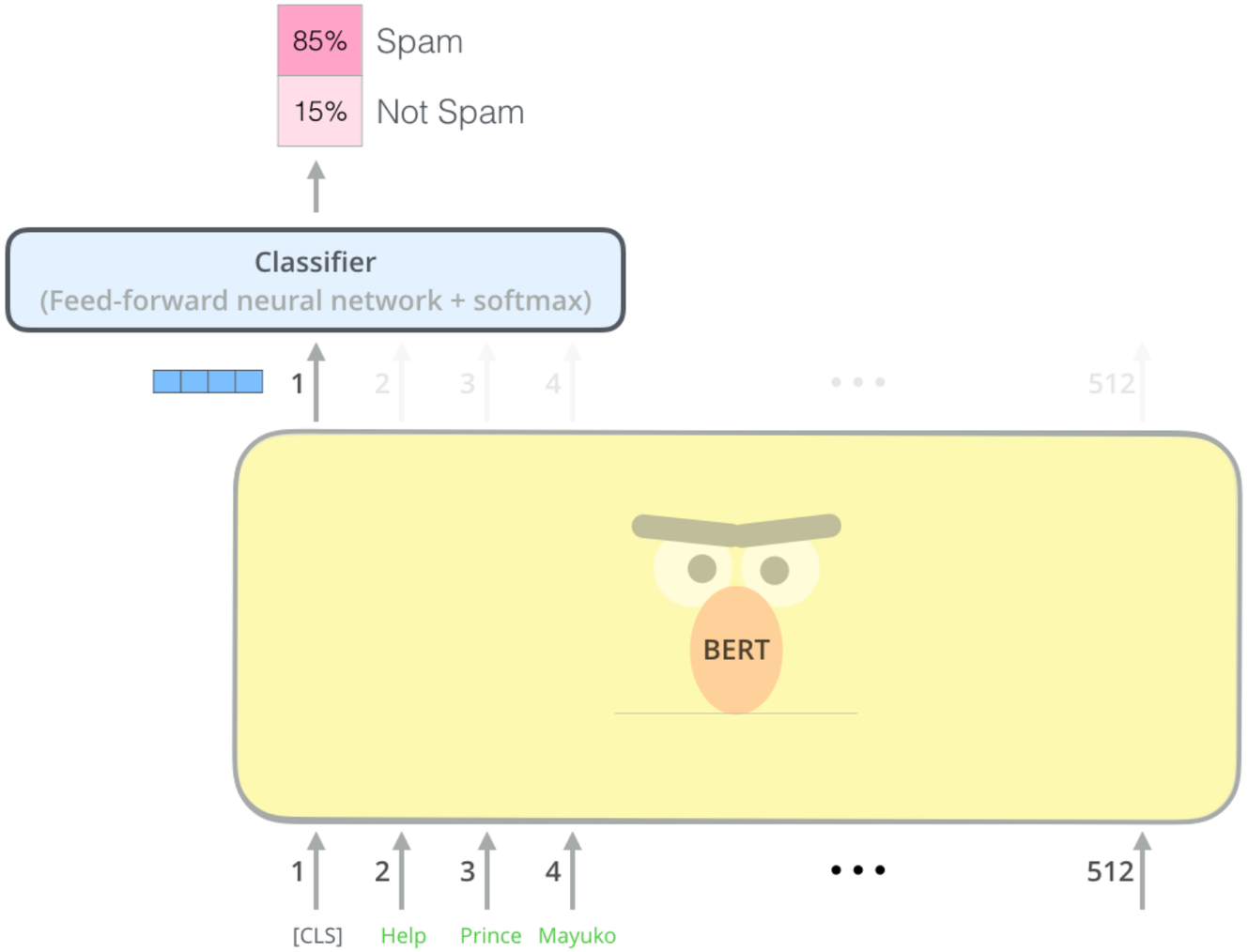
BERT的簡介：架構 – 輸出

輸出部分，512個輸出每個都有一個hidden_size=768(BERT Base)的向量，如果是做句子分類，其實只須注意第一個位置即可，也就是相對於[CLS]位置的那個。



這個向量可以輸入到我們設計的分類器. BERT作者僅用了單層的NN分類器即達到良好效果.

BERT的應用：假新聞分類器(圖示)



BERT的應用：假新聞分類器(簡述)

- 以新聞真偽這個應用的分類例題來說，我們主要在做dataset preprocessing以及 Classifier Model的 Fine Tune Training，中間主要的分類引擎是BERT BASE UNCASED。一旦將Label好的Real News 和 Fake News 的 Training Set, Test Set 和 Validation Set 分好，Preprocess就算完成。我們的PyTorch Fine Tune Python 程式主要就是將接口定義好，超參數設好，其實和其他的Classifier沒有甚麼不同。

- 例題：https://towardsdatascience.com/bert-text-classification-using-pytorch-723dfb8b6b5b
- **BERT fine-tune on fake news detection.ipynb**
- Use: PyTorch interface for BERT by Hugging Face

BERT的應用：假新聞分類器(前處理)

- 1. 下載Kaggle的Real/Fake News Dataset news.csv，放在Google Drive /transformers/data 裡：
  https ://www.kaggle.com/nopdev/real-and-fake-news-dataset

- 2. 在Colab 執行 **Preprocessing of Fake News Dataset.ipynb**

- 3. 要將Goggle Drive Mount 到 Colab的 Container，中間需要 Authorization Code

```
from google.colab import drive
drive.mount('/content/drive’  )
```

- 4. 按比例寫入 train.csv, test.csv 和 valid.csv

BERT的應用：假新聞分類器(載入資料)

- **tokenizer** = BertTokenizer.from_pretrained('bert-base-uncased’)
- text_field = Field(use_vocab=False, tokenize=**tokenizer**.encode, lower=False,
- include_lengths=False, batch_first=True,.....
- **train**, valid, test = TabularDataset.splits(path=source_folder, train='train.csv’ ……
- # Iterators
- train_iter = BucketIterator(**train**, batch_size=16, sort_key=lambda x: len(x.text),
- ……
- test_iter = ...
- valid_iter =……

.

BERT的應用：假新聞分類器(建模)

```
class BERT(nn.Module):

    def __init__(self):
        super(BERT, self).__init__()

        options_name = "bert-base-uncased"
        self.encoder = BertForSequenceClassification.from_pretrained(options_name)

    def forward(self, text, label):
        loss, text_fea = self.encoder(text, labels=label)[:2]

        return loss, text_fea
```

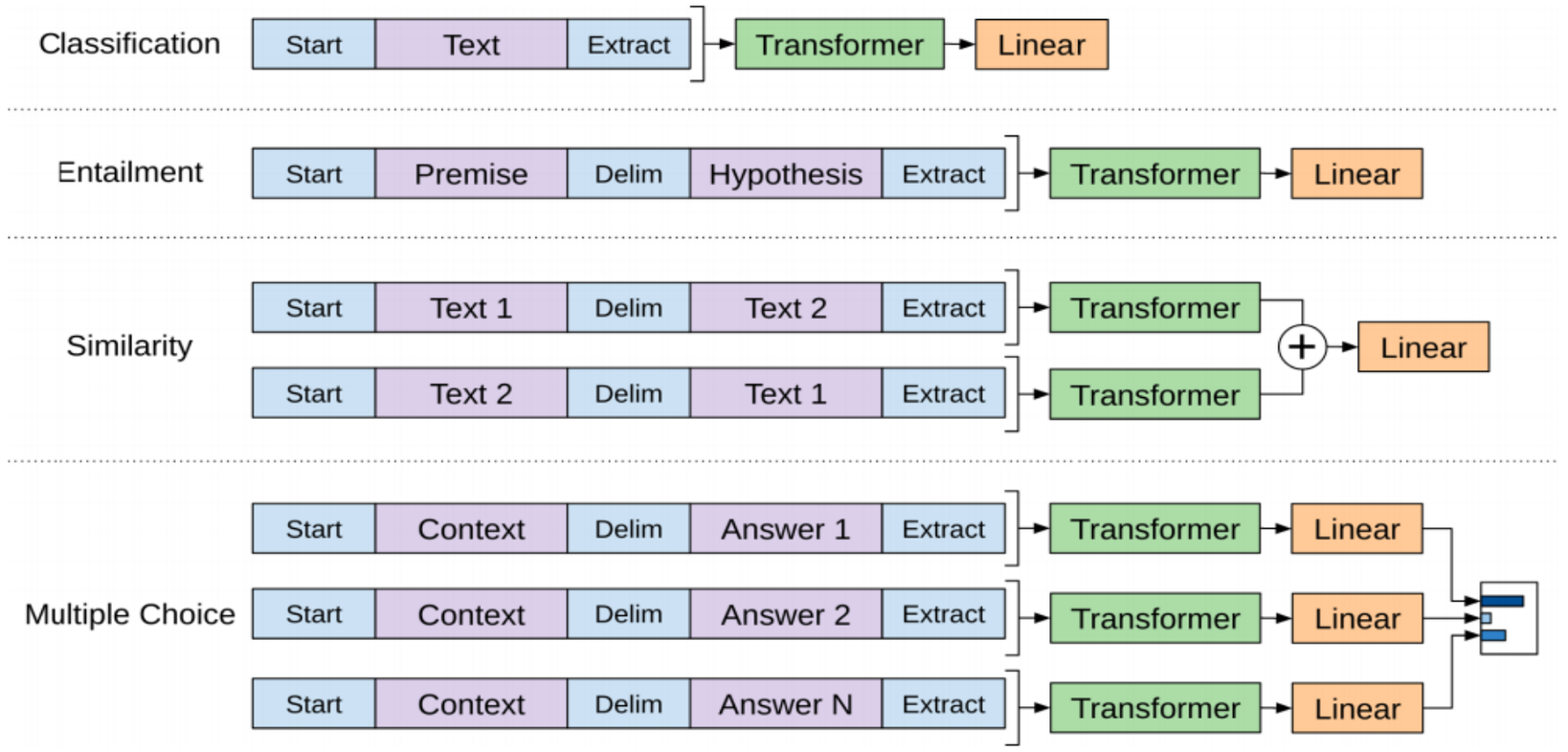
BERT的應用：假新聞分類器(訓練)

- model = BERT().to(device)
- optimizer = optim.Adam(model.parameters(), lr=2e-5)
- train(model=model, optimizer=optimizer)

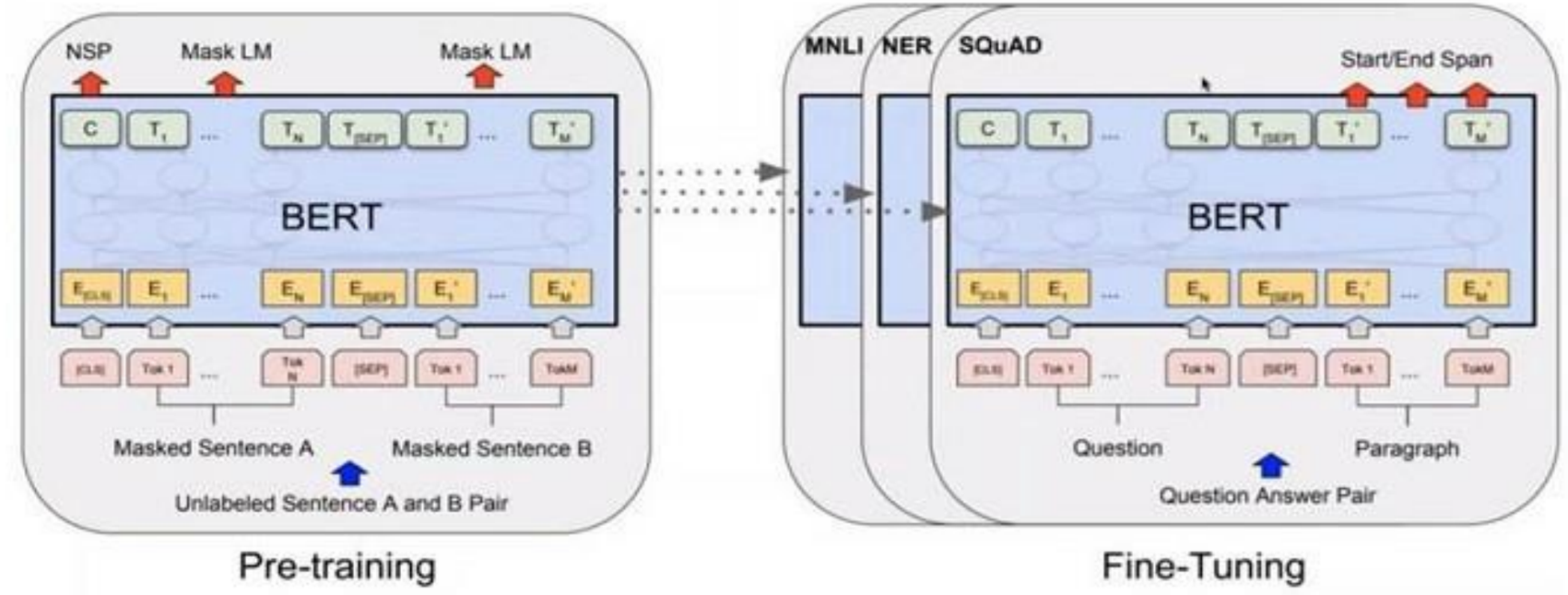
- # show loss, accuracy…
- # Evaluate
- 作業檔案: BERT fine-tune on fake news detection.ipynb

BERT的其他應用

BERT的作者號稱還可做以下這些NLP應用：分類，蘊涵，相似度比較，多選等，以下是簡單架構示意圖



BERT的的其他應用：模式



左邊是pre-trained: **NSP: Next Sentence Prediction, Mask LM: Masked Language Model**

右邊是fine-tuning應用：NER: Named Entity Recognition, SQuAD: 回答系統, MNLI：自然語言介面, 以及最常見的分類

BERT的其他應用：延伸練習

- 延伸學習任務一，用BERT MLM pretrained model 做**中間字的預測**，比方輸入
- text = "[CLS] Who was Jim Henson ? [SEP] Jim Henson was a puppeteer [SEP] "
- masked_index = 8
- tokenized_text[masked_index] = '[MASK]'
- 然後猜出是 Henson
- https://github.com/aniruddhachoudhury/BERT-Tutorials/tree/master/Blog%201
- 程式檔名：BERT_Tutorial_1.ipynb

- 延伸學習任務二，用 The Corpus of Linguistic Acceptability (CoLA) dataset **判斷文法是否正確**
- 程式檔名： BERT_Fine_Tuning_Sentence_Classification.ipynb

學習目標：

- 了解轉換學習
- 了解 TFLite

Bonus: Transfer Learning

轉換學習：TFLite 與 AIoT

Tensorflow Lite:

能夠讓行動(Mobile)和嵌入式(Embedded)應用使用機器學習(ML)的一組軟體工具，這些應用因而可在 iOS, Android, Raspberry Pi上執行。

但是如何將訓練好的模型輸出給行動應用開發者呢？

遷移學習：TFLITE與AIOT

高階步驟: (訓練端Training Side)
#1 正常訓練模型
從server/desktop訓練模型
把model 和 weights 遷移到行動裝置
一旦在行動裝置，model即可做
prediction/inference
#2 用Tensorflow Lite Converter 轉換模型
到.tflite 檔.
假設是 Keras API
.tflite 只是一個檔案模式, 就像 model.save() 產生 .h5 檔一樣
在 “import tensorflow as tf” 之後加幾行 code

遷移學習：TFLITE與AIOT

高階步驟: (行動開發者端)

#3 在行動開發者端, 使用 Tensorflow lite 庫.
支持 Java/C++ (Android) 和 Swift/Objective-C (iOS)
用 Tensorflow Lite Interpreter 載入 .tflite 檔並且用現有模型做預測。
數據需要和Tensorflow Lite interpreter相匹配.

遷移學習：TFLITE與AIOT

要改變的程式，訓練端

```
#convert the model to TFLite format

converter =
tf.lite.TFLiteConverter.from_keras_model(model)

tflite.model = converter.convert()

with open(  “converted_model.tffile”  , wb) as f:
      f.write(tflite_model)
```

遷移學習：TFLITE與AIOT

TFLite vs TF Serving

行動裝置也可用Serving直接對server做API calls.
TF Lite 讓你直接在行動/嵌入裝置使用模型，無需使用網路.
如果在地鐵或通訊不良處，依賴雲端不是很好的選擇。
但如果模型複雜需大量運算TF Lite 就不是很好的選擇.

遷移學習：TFLITE與AIOT

對無ML背景的行動裝置開發者:
預訓練好的模型包括: Object detection, pose estimation, smart reply.

https://www.tensorflow.org/lite/models

學習目標：

- 了解 推薦系統
- 實作推薦系統

Bonus: Recommender System

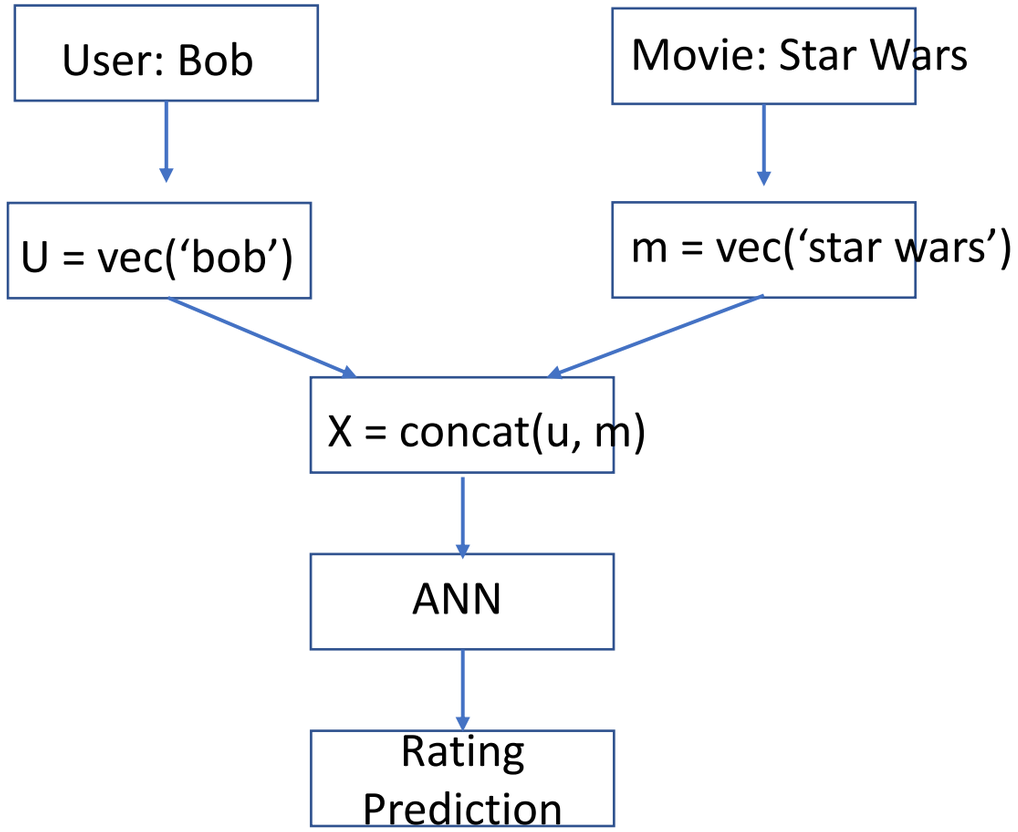
推薦系統的製作

推薦系統的製作

推薦系統三元素：(User, Item, Rating)通常以電影為例
Ratings 數據一定非完整
運用機器學習去趨近 f(user, item) → rating
如果我們已有預測函數 f(), 我們只需選擇user尚未看過的項目(比方說電影)從最高依降序推薦.
但 (user, item) 非數值而是範疇型(categorical), 然而NN需要做矩陣運算
在NLP中我們已得到靈感，用 embedding，將(user, item)轉成相關的向量

推薦系統的製作

推薦系統流程：



推薦系統的製作

Pseudocode：

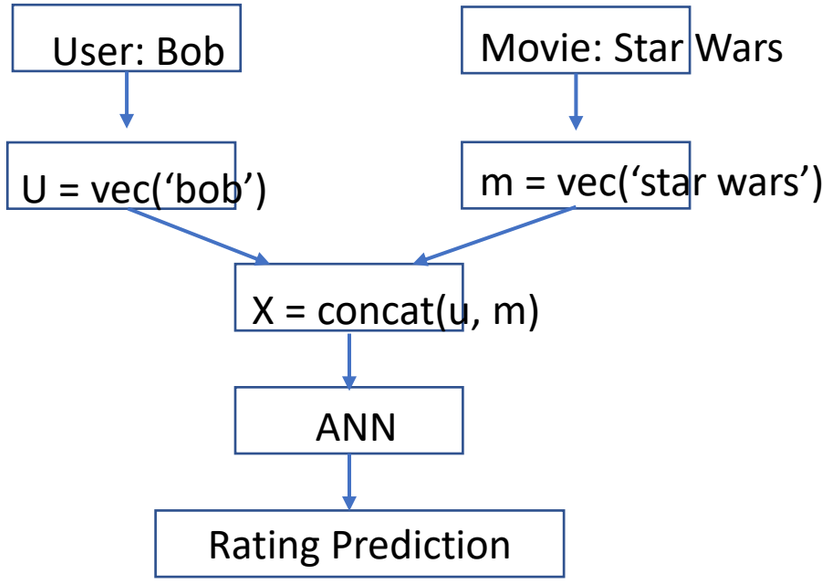
```
u = Input(shape((1,))
m = Input(shape((1,))
u_emb = Embedding(num_users, embedding_dim)(u)
m_emb = Embedding(num_movies, embedding_dim)(m)
#combine into a single feature factor
x=Concat(u_emb, m_emb)
#ANN
x=Dense(512, activation= ‘relu’ )(x)
X=Dense(1)(x)
```

推薦系統的製作

用Functional API, 而非 sequential API

Sequential API 無法合併兩個模型，
因為每一層只能連接到另一層.

Functional API 提供NN的彈性，
比方GAN的設計.



推薦系統的製作

Demo21_Recommender System.ipynb

Note: The ID 需要連續，因為它是對向量的索引.

需要先扁平化(flatten)再接續 (concatenate): Nx1xD → NxD

Homework: 在老師示範此檔案之後，嘗試尋求改進val_loss的任何方法。
Hint: 改變 hyper parameter.