CycleGan_Van_Gogh

2018 年 8 月 27 日

1 CycleGAN (梵谷風格轉換)

1.1 CycleGAN 介紹

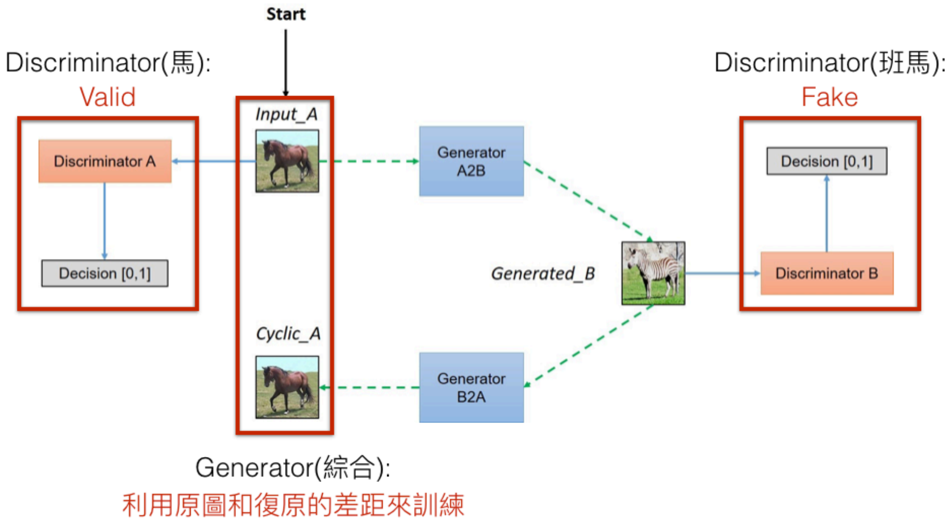
CycleGAN 是一個很有趣的 GAN 的分支，普通的風格轉換你一定要有 Pair 的照片 (未上色和上色)，但 CycleGAN 你可以傳給他非 Pair 的照片，讓他完成兩種領域的互相轉換。

簡單來說，CycleGAN 最重要的就是循環！訓練出兩個 Generator 可以互相轉換對方的領域，也訓練兩個 Discriminator

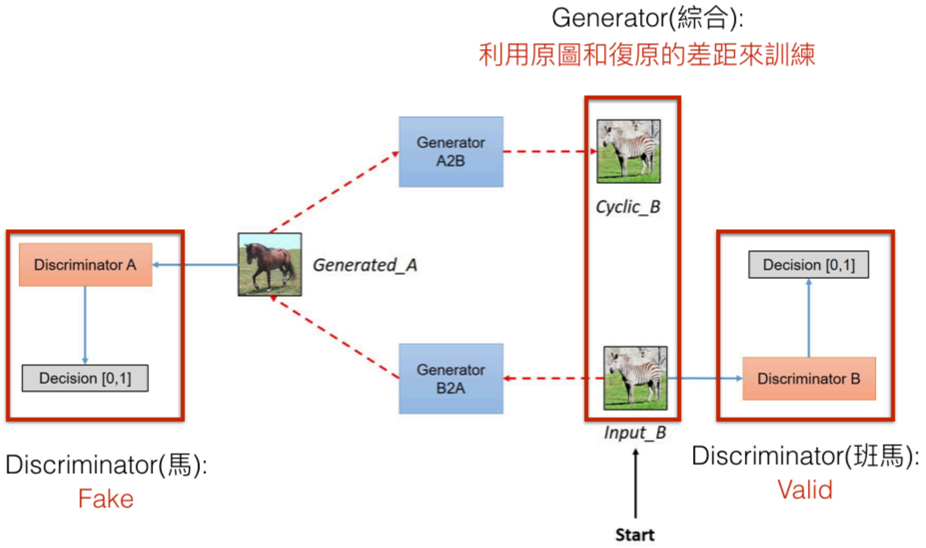
1.2 Model

假設我們現在要完成馬和斑馬的互相轉換

我們先看輪迴的半邊，



再看另外半邊，



你會發現簡單來說！就是給你一張圖 (先拿來訓練 A 分辨器的真)，經過 AB 轉換做出來的 B(訓練 B 分辨器的假)，再把假 B 轉換成 A(拿來訓練偽造器的參數)

再反過來做一次，兩次的循環合成一個完整的 GAN

1.3 Step1. 下載資料集

感謝網路上的梵谷和照片資料集

https://people.eecs.berkeley.edu/~taesung_park/CycleGAN/datasets/vangogh2photo.zip

```
In [1]: from keras.layers import Input
```

```
from keras.models import Model, Sequential
from keras.layers.core import Reshape, Dense, Dropout, Flatten
from keras.layers import Embedding, multiply, BatchNormalization, Concatenate, Input
from keras.layers.convolutional import UpSampling2D, Conv2D
from keras_contrib.layers.normalization import InstanceNormalization
from keras.layers.advanced_activations import LeakyReLU

import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
# 我們會使用到一些內建的資料庫, MAC 需要加入以下兩行, 才不會把對方的 ssl 憑證視為無效
import ssl
ssl._create_default_https_context = ssl._create_unverified_context
```

```
Using TensorFlow backend.
```

```
In [196]: from urllib.request import urlretrieve
          from os.path import exists
          url = "https://people.eecs.berkeley.edu/~taesung_park/" \
                "CycleGAN/datasets/vangogh2photo.zip"
          if not exists("vangogh2photo.zip"):
              print("還未下載過, 幫你下載資料集")
              urlretrieve(url, "vangogh2photo.zip")
          else:
              print("已下載過資料集")
```

```
已下載過資料集
```

```
In [3]: dataset_path = "vangogh2photo"
        from zipfile import ZipFile
        if not exists(dataset_path):
            z = ZipFile("vangogh2photo.zip", "r")
            print("還未解壓縮過, 幫你解壓縮資料集")
            z.extractall()
        else:
            print("已解壓縮過")
```

已解壓縮過

1.4 Step2. 確定資訊

我們先確定一下資料集的資訊 (維度…等等)，順便把資料可視化一下

imageio 函式庫可以幫我們把圖片直接讀取成為 numpy array
所以我在這裡選擇使用 imageio 函式庫幫我閱讀 image，記得安裝一下

```
In [192]: from PIL import Image
          import os
          import numpy as np
          import random
          from imageio import imread

          a_train = []
          a_path = os.path.join(dataset_path, "trainA")
          # 走過 A 分類 (梵谷) 的所有照片
          for fname in os.listdir(a_path):
              img_path = os.path.join(a_path, fname)
              if not fname.startswith("."):
                  a_train.append(img_path)
          # 隨機選一個印出來
          i = random.randint(0, len(a_train) - 1)
          a_img = imread(a_train[i])
          plt.axis("off")
          plt.imshow(a_img)
          print("訓練資料 (梵谷) 維度:", a_img.shape)
```

```
訓練資料 (梵谷) 維度: (256, 256, 3)
```

```
In [195]: b_train = []
          b_path = os.path.join(dataset_path, "trainB")
          # 走過 B 分類 (風景) 的所有照片
          for fname in os.listdir(b_path):
              img_path = os.path.join(b_path, fname)
              if not fname.startswith("."):
                  b_train.append(img_path)

          i = random.randint(0, len(b_train) - 1)
          b_img = imread(b_train[i])
          plt.axis("off")
          plt.imshow(b_img)
          print("訓練資料 (風景) 維度:", b_img.shape)
```

```
訓練資料 (風景) 維度: (256, 256, 3)
```

1.5 Step2. 設計 Discriminator

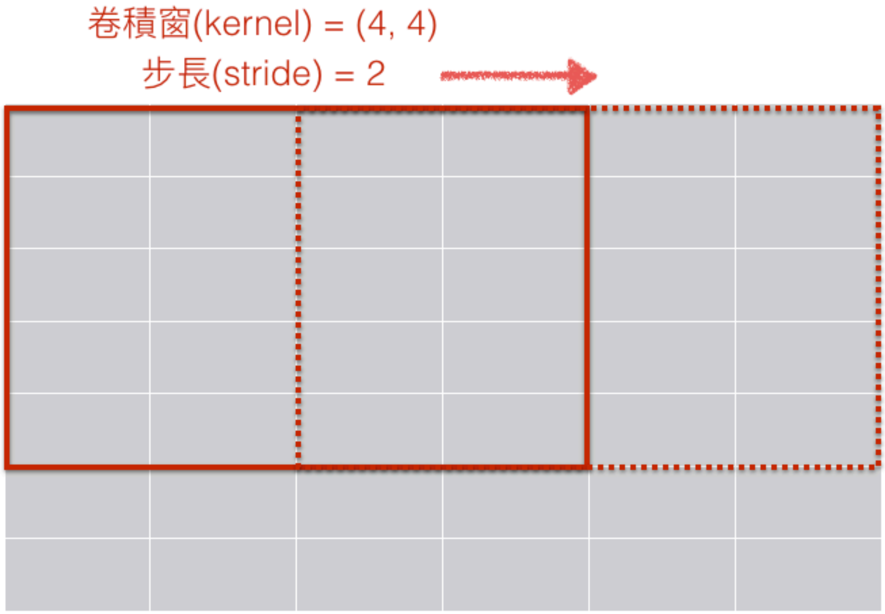
1.5.1 全卷積

這裡使用全卷積，放棄了全連接層，對於圖片來說，全卷積可以正確地抓出圖片的隱含特徵

1.5.2 全卷積步長和視野窗

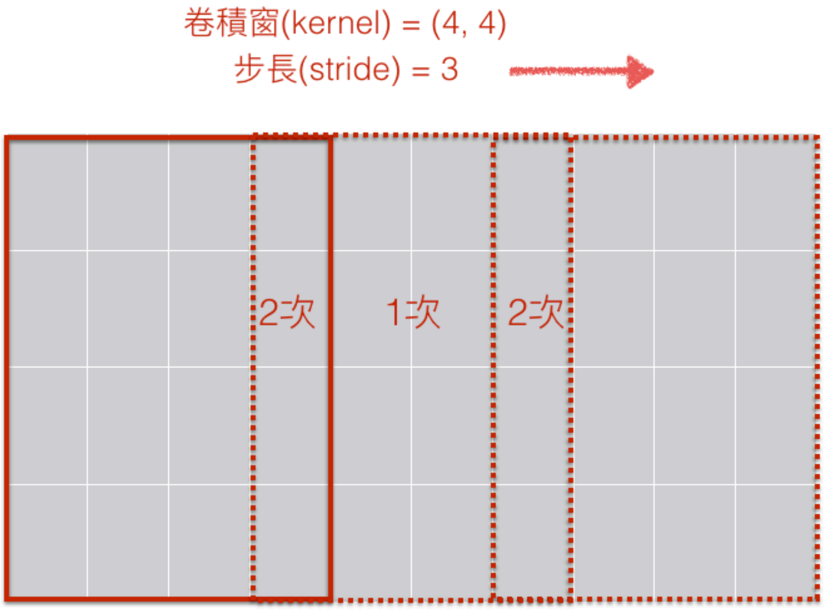
最新的概念裡，我們不使用池化層來減少計算量和縮小圖片了，因為池化其實就意味著放棄資料

我們現在喜歡使用帶步長的卷積層，像下圖的步長 2，一次走兩格，長寬自然就縮小了一半



大家通常會選用 (4, 4) 卷積窗和步長 2

因為如果你的步長不能整除卷積窗的話，會有貢獻不均衡的問題
我們把不均衡的例子放在下面

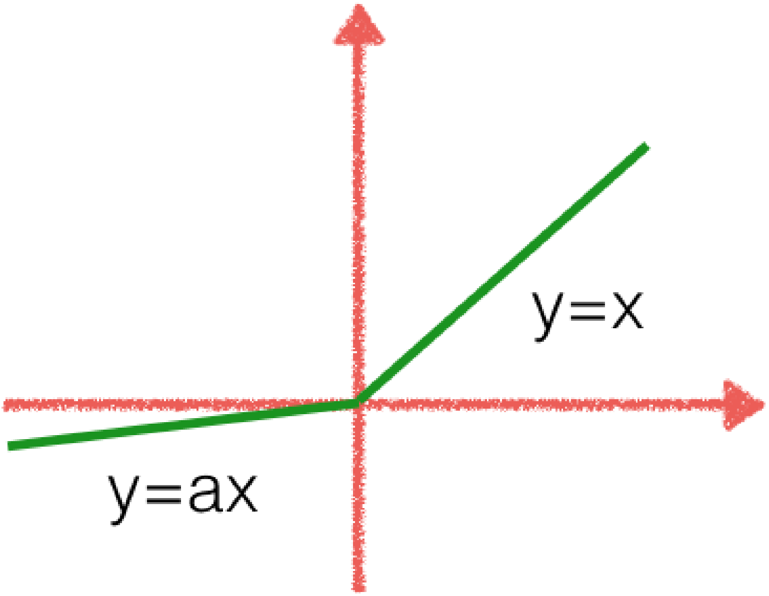


你會發現我們的步長 3 沒辦法整除卷積窗的大小 4
這樣就會有人只貢獻一次，很容易讓我們的特徵抓取變成一個不均衡的抓取

1.5.3 LeakyRelu

激活的函數，以前我們都選擇 relu，但是 relu 有個很嚴重的問題，就是到了死亡區斜率就變 0，那這次梯度下降就是 0，也就是不下降，而且 weights 來到死亡區很容易所有資料來到這神經元都會死亡，這時候我們就稱為這神經元『死亡』了

對於比較複雜的 GAN，網路極其脆弱，所以很容易就死亡了，這裡改進的方法就是改使用 leakyrelu



讓負區的斜率不為 0，但是是一個很小的值就好了

1.5.4 InstanceNormalization

我們上次在標準 GAN 裡有說過 Batch Normalization，簡單來說就是把一個 Batch 所有的資料標準化

目的是為了配合模型的 weights，並且也不會整團資料分佈在一個奇怪的地方

但是我們在做 CycleGAN 的時候，由於每一張圖片差距太大，所以我們改成使用 InstanceNormalization，對於每一張圖片 (而非一個 batch) 做標準化

```
In [7]: # 因為我們需要兩個 Discriminator, 所以我們把它定義成函數
        def build_discriminator():

            def d_layer(layer_input, filters, f_size=(4, 4)):
                d = Conv2D(filters, kernel_size=f_size,
                           strides=2, padding='same')(layer_input)
```

```
            d = LeakyReLU(alpha=0.2)(d)
            d = InstanceNormalization()(d)
            return d

        img = Input(shape=(256, 256, 3))

        d1 = d_layer(img, 64)
        d2 = d_layer(d1, 128)
        d3 = d_layer(d2, 256)
        d4 = d_layer(d3, 512)
        validity = Conv2D(1, kernel_size=4, strides=1, padding='same')(d4)

        return Model(img, validity)
```

1.6 Step2. 設計 Generator

generator 是卷積 (抓出 A 的真正特徵) + 反卷積 (以這些特徵構築 B) 的結果

1.6.1 反卷積

反卷積其實就是卷積的相反，這裡我們使用 UpSampleing 層加上一次的卷積完成一次的反卷積

Size(2, 2) 的 UpSampling 是把每一個數字複製 4 個，變成 2 * 2 的同一數字

記得這裡卷積就必須把步長設定為 1 了
因為並沒有要改變我們的寬度

1.6.2 Concatenate 層

這裡比較特別一點，因為我們並不想讓整個 GAN 產生的結果跟原圖差十萬八千里
所以我們還會順便在反卷積的時候把相對應的卷積層當成 Embedding 傳入，希望這些特徵可以幫我們在 AB 轉換的時候還是維持原圖的特徵

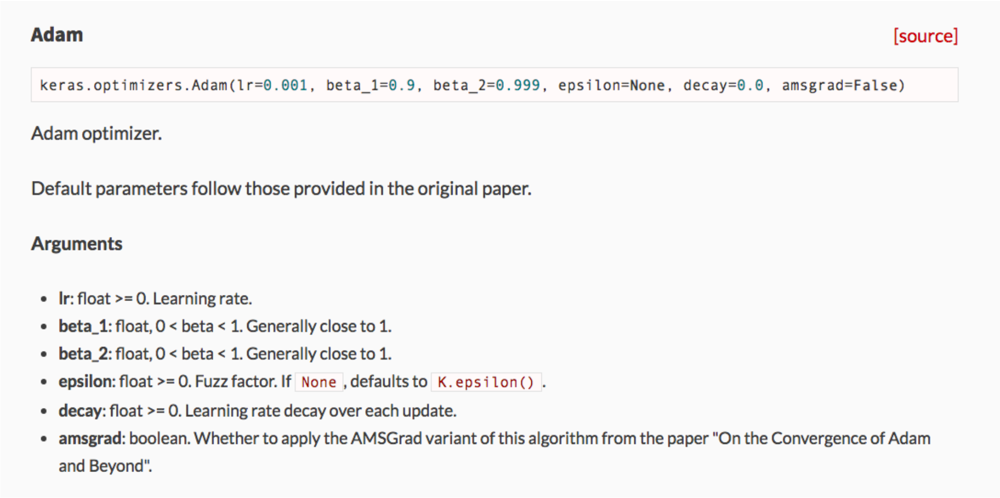
```
In [6]: def build_generator():

        def conv2d(layer_input, filters, f_size=(4, 4)):
            d = Conv2D(filters, kernel_size=f_size,
                       strides=2, padding='same')(layer_input)
            d = LeakyReLU(alpha=0.2)(d)
```

```
        d = InstanceNormalization()(d)
        return d

    def deconv2d(layer_input, skip_input, filters, f_size=(4, 4)):
        u = UpSampling2D(size=(2, 2))(layer_input)
        u = Conv2D(filters, kernel_size=f_size,
                   strides=1, padding='same')(u)
        u = LeakyReLU(alpha=0.2)(u)
        u = InstanceNormalization()(u)
        u = Concatenate()([u, skip_input])
        return u

    d0 = Input(shape=(256, 256, 3))

    d1 = conv2d(d0, 32)
    d2 = conv2d(d1, 64)
    d3 = conv2d(d2, 128)
    d4 = conv2d(d3, 256)

    u1 = deconv2d(d4, d3, 128)
    u2 = deconv2d(u1, d2, 64)
    u3 = deconv2d(u2, d1, 32)
    u3 = deconv2d(d2, d1, 32)


    u4 = UpSampling2D(size=(2, 2))(u3)
    output_img = Conv2D(3, kernel_size=(4, 4),
                        strides=1, padding='same',
                        activation='tanh')(u4)

    return Model(d0, output_img)
```

1.7 Step3. 建立模型並編譯

1.7.1 調整 Adam 優化器

由於我們的 GAN 非常脆弱，所以我希望能稍微讓我們的優化器再調整一下



Adam [source]

`keras.optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0, amsgrad=False)`

Adam optimizer.

Default parameters follow those provided in the original paper.

Arguments

- **lr**: float >= 0. Learning rate.
- **beta_1**: float, 0 < beta < 1. Generally close to 1.
- **beta_2**: float, 0 < beta < 1. Generally close to 1.
- **epsilon**: float >= 0. Fuzz factor. If `None`, defaults to `K.epsilon()`.
- **decay**: float >= 0. Learning rate decay over each update.
- **amsgrad**: boolean. Whether to apply the AMSGrad variant of this algorithm from the paper "On the Convergence of Adam and Beyond".

通常我們不希望我們的 Discriminator 變好的太快，因為 Generator 就會無所適從，不知道如何變好

所以我們會把 learning rate(更新 weights 前面成的常數) 變小一點，根據大家的經驗法則，0.0002 是一個很不錯的學習速率

那這邊我通常也會把動量 (Adam 是基於動量的一個優化器) 調整小一點

總之，我這裡希望放慢一點鑑賞家變慢的速度

1.7.2 Loss

因為我們的 Discriminator 使用的是全卷積，所以最後還是輸出有寬和高

那我們就不能用以往的 Binary CrossEntropy 來判定了，所以我們改用 Mean Square Error(距離平方再開根號) 來當作我們的損失

```
In [8]: from keras.optimizers import Adam
        op = Adam(0.0002, 0.5)
        d_A = build_discriminator()
        d_A.compile(loss='mse',
            optimizer=op,
            metrics=['accuracy'])
        d_A.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 256, 256, 3)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 128, 128, 64)      3136
```

```
_________________________________________________________________
leaky_re_lu_1 (LeakyReLU)    (None, 128, 128, 64)      0

_________________________________________________________________
instance_normalization_1 (In (None, 128, 128, 64)      2

_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 128)       131200

_________________________________________________________________
leaky_re_lu_2 (LeakyReLU)    (None, 64, 64, 128)       0

_________________________________________________________________
instance_normalization_2 (In (None, 64, 64, 128)       2

_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 256)       524544

_________________________________________________________________
leaky_re_lu_3 (LeakyReLU)    (None, 32, 32, 256)       0

_________________________________________________________________
instance_normalization_3 (In (None, 32, 32, 256)       2

_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 512)       2097664

_________________________________________________________________
leaky_re_lu_4 (LeakyReLU)    (None, 16, 16, 512)       0

_________________________________________________________________
instance_normalization_4 (In (None, 16, 16, 512)       2

_________________________________________________________________
conv2d_5 (Conv2D)            (None, 16, 16, 1)         8193
=================================================================
Total params: 2,764,745
Trainable params: 2,764,745
Non-trainable params: 0

_________________________________________________________________
```

```
In [9]: d_B = build_discriminator()
        d_B.compile(loss='mse',
            optimizer=op,
            metrics=['accuracy'])
        d_B.summary()
```

```
_________________________________________________________________
```

```
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         (None, 256, 256, 3)       0
-----------------------------------------------------------------
conv2d_6 (Conv2D)            (None, 128, 128, 64)      3136
-----------------------------------------------------------------
leaky_re_lu_5 (LeakyReLU)    (None, 128, 128, 64)      0
-----------------------------------------------------------------
instance_normalization_5 (In (None, 128, 128, 64)      2
-----------------------------------------------------------------
conv2d_7 (Conv2D)            (None, 64, 64, 128)       131200
-----------------------------------------------------------------
leaky_re_lu_6 (LeakyReLU)    (None, 64, 64, 128)       0
-----------------------------------------------------------------
instance_normalization_6 (In (None, 64, 64, 128)       2
-----------------------------------------------------------------
conv2d_8 (Conv2D)            (None, 32, 32, 256)       524544
-----------------------------------------------------------------
leaky_re_lu_7 (LeakyReLU)    (None, 32, 32, 256)       0
-----------------------------------------------------------------
instance_normalization_7 (In (None, 32, 32, 256)       2
-----------------------------------------------------------------
conv2d_9 (Conv2D)            (None, 16, 16, 512)       2097664
-----------------------------------------------------------------
leaky_re_lu_8 (LeakyReLU)    (None, 16, 16, 512)       0
-----------------------------------------------------------------
instance_normalization_8 (In (None, 16, 16, 512)       2
-----------------------------------------------------------------
conv2d_10 (Conv2D)           (None, 16, 16, 1)         8193
=================================================================
Total params: 2,764,745
Trainable params: 2,764,745
Non-trainable params: 0
-----------------------------------------------------------------
```

1.7.3 合併模型

跟傳統 GAN 一樣，創立一個合併模型，詳細步驟我們註解在程式碼上

```
In [10]: # 建立 Generator, 不過不用編譯, 因為我們沒有要訓練他
         g_AB = build_generator()
         g_BA = build_generator()
         # 輸入圖片的大小
         img_A = Input(shape=(256, 256, 3))
         img_B = Input(shape=(256, 256, 3))

         # 創造偽作
         fake_B = g_AB(img_A)
         fake_A = g_BA(img_B)
         # 偽作再偽造回原作
         reconstr_A = g_BA(fake_B)
         reconstr_B = g_AB(fake_A)
         # 這裡比較特別, 我們希望 A 類的圖片就算丟進 A->B 轉換還是維持
         img_A_id = g_BA(img_A)
         img_B_id = g_AB(img_B)

         # 記得在合併模型的時候我們要固定住 Discriminator
         d_A.trainable = False
         d_B.trainable = False

         # 對兩個偽作接上 Discriminator
         valid_A = d_A(fake_A)
         valid_B = d_B(fake_B)

         # 這裡我們由於有多個 ouput, 所以也要接多個 loss
         # mse 會對預測很差的做很大的懲罰
         # 對於畫, 我們沒有要給很大的懲罰, 所以我們選擇 mae
         combined = Model(inputs=[img_A, img_B],
                          outputs=[ valid_A, valid_B,
                                    reconstr_A, reconstr_B,
                                    img_A_id, img_B_id ])
         combined.compile(loss=['mse', 'mse',
                                'mae', 'mae',
```

```
                                    'mae', 'mae'],
                              loss_weights=[  1, 1,
                                             10, 10,
                                              1, 1],
                              optimizer=op)
         combined.summary()
```

```
________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
================================================================================================
input_6 (InputLayer)            (None, 256, 256, 3)  0
________________________________________________________________________________________________
input_5 (InputLayer)            (None, 256, 256, 3)  0
________________________________________________________________________________________________
model_4 (Model)                 (None, 256, 256, 3)  70281       input_6[0][0]
                                                                 model_3[1][0]
                                                                 input_5[0][0]
________________________________________________________________________________________________
model_3 (Model)                 (None, 256, 256, 3)  70281       input_5[0][0]
                                                                 model_4[1][0]
                                                                 input_6[0][0]
________________________________________________________________________________________________
model_1 (Model)                 (None, 16, 16, 1)    2764745     model_4[1][0]
________________________________________________________________________________________________
model_2 (Model)                 (None, 16, 16, 1)    2764745     model_3[1][0]
================================================================================================
Total params: 5,670,052
Trainable params: 140,562
Non-trainable params: 5,529,490
________________________________________________________________________________________________
```

1.8 Step4. 訓練模型

由於我們是全卷積，所以必須把寬高都填滿 1，那最後輸出只有一個通道，所以是 (16, 16, 1)

```
In [197]: patch = int(256 / 2**4)
          disc_patch = (patch, patch, 1)
          disc_patch
```

```
Out[197]: (16, 16, 1)
```

因為一次訓練一張圖，所以我們只需要 (1, 16, 16, 1) -> (一張圖, 寬, 高, 通道數)

```
In [199]: valid = np.ones((1,) + disc_patch)
          fake = np.zeros((1,) + disc_patch)
```

大概訓練了數萬次，只取最後的幾次

```
In [189]: batch_size = 1
          train_count = 5
          d_loss_list = []
          g_loss_list = []
          for train in range(0, train_count):
              dash = "-" * 15
              print(dash, "Train", train, dash)


              ida = np.random.randint(0, len(a_train), batch_size)
              idb = np.random.randint(0, len(b_train), batch_size)



              imgs_A = []
              imgs_B = []
              for i in ida:
                  imgs_A.append((imread(a_train[i]) - 127.5)/127.5)
              for i in idb:
                  imgs_B.append((imread(b_train[i]) - 127.5)/127.5)
              imgs_A = np.array(imgs_A)
              imgs_B = np.array(imgs_B)

              fake_B = g_AB.predict(imgs_A)
              fake_A = g_BA.predict(imgs_B)

              d_A.trainable = True
              d_B.trainable = True
              dA_loss_real = d_A.train_on_batch(imgs_A, valid)
              dA_loss_fake = d_A.train_on_batch(fake_A, fake)
              dA_loss = 0.5 * np.add(dA_loss_real, dA_loss_fake)
```

```
            dB_loss_real = d_B.train_on_batch(imgs_B, valid)
            dB_loss_fake = d_B.train_on_batch(fake_B, fake)
            dB_loss = 0.5 * np.add(dB_loss_real, dB_loss_fake)

            # Total discriminator loss
            d_loss = 0.5 * np.add(dA_loss, dB_loss)


            d_A.trainable = False
            d_B.trainable = False
            g_loss = combined.train_on_batch([imgs_A, imgs_B],
                                                    [valid, valid,
                                                    imgs_A, imgs_B,
                                                    imgs_A, imgs_B])

            dash = "-" * 15
            print("Discriminator loss:", d_loss)
            print("Generator loss:", g_loss)
            d_loss_list.append(d_loss)
            g_loss_list.append(g_loss)
```

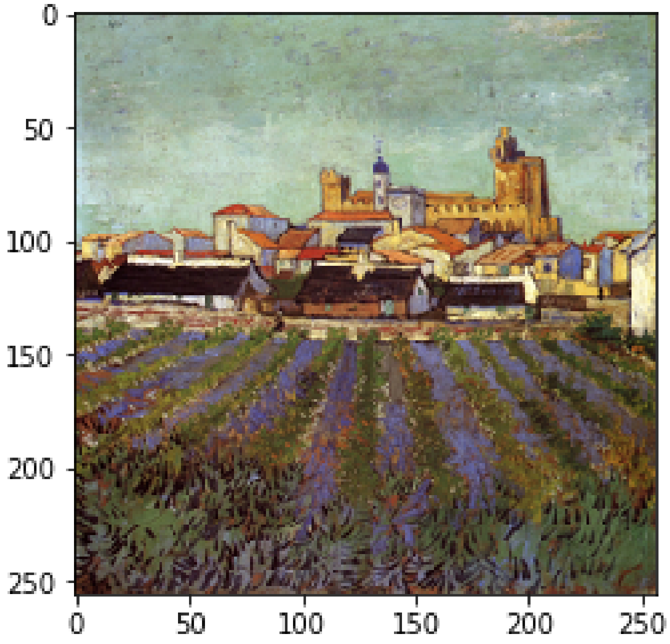
```
--------------- Train 0 ---------------
Discriminator loss: [0.02281462 1.        ]
Generator loss: [3.9857652, 0.89864177, 0.7574793, 0.101250775, 0.072771996, 0.2323237, 0.3570
--------------- Train 1 ---------------
Discriminator loss: [0.2055629 0.75      ]
Generator loss: [3.002908, 0.97745234, 0.105900034, 0.09675653, 0.07022899, 0.1215199, 0.12818
--------------- Train 2 ---------------
Discriminator loss: [0.02731891 1.        ]
Generator loss: [3.7201955, 1.074858, 0.77537143, 0.05991071, 0.09943257, 0.14868948, 0.127843
--------------- Train 3 ---------------
Discriminator loss: [0.10703883 0.79589844]
Generator loss: [3.515755, 1.0189565, 0.6486736, 0.09558727, 0.058565624, 0.22159313, 0.085002
--------------- Train 4 ---------------
Discriminator loss: [0.10798818 0.86328125]
Generator loss: [3.2700064, 1.074095, 0.349965, 0.06928012, 0.07942289, 0.2272602, 0.13165641]
```

1.9 Step5. 看看結果

原本的畫

```
In [63]: idx = random.randint(0, len(a_train) - 1)
         drawing = imread(a_train[idx])
         plt.imshow(drawing)
```

```
Out[63]: <matplotlib.image.AxesImage at 0x1355bb208>
```

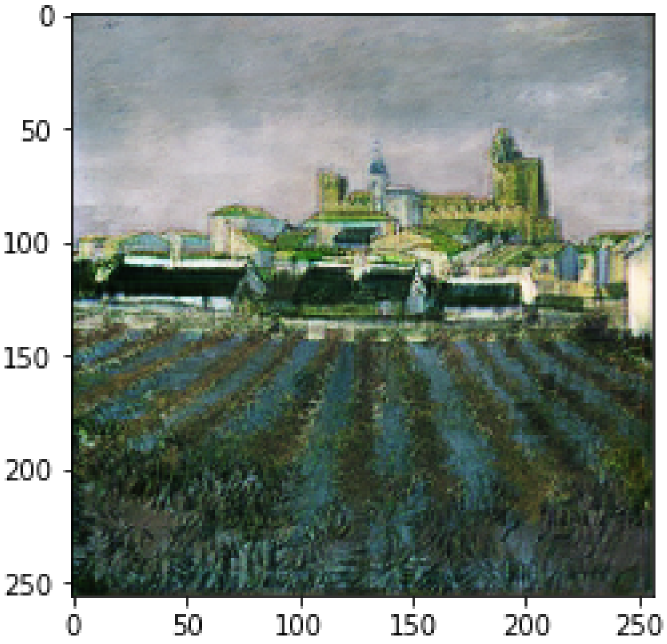


```
In [64]: drawing_shaped = (drawing - 127.5)/127.5
```

轉換成風景後

```
In [190]: fake_scenery = g_AB.predict(np.array([drawing_shaped]))
          fake_scenery = 0.5 * fake_scenery + 0.5
          plt.imshow(fake_scenery[0])
```

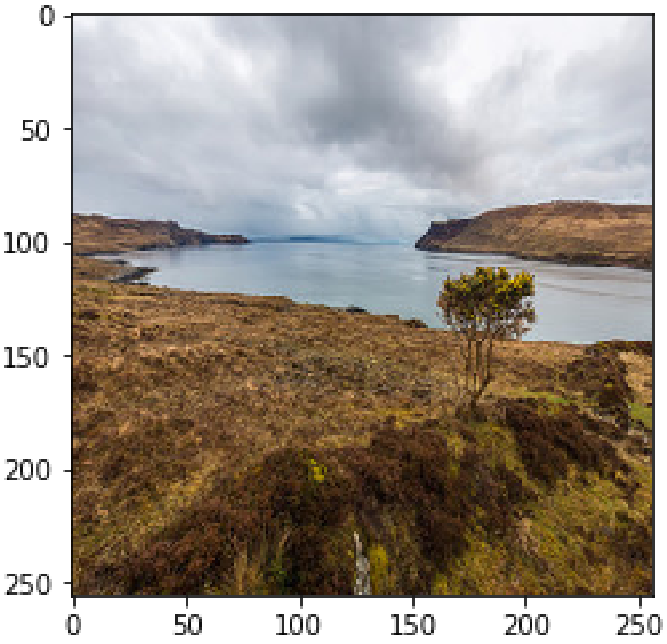
```
Out[190]: <matplotlib.image.AxesImage at 0x11e49b9e8>
```



原本的風景

```
In [128]: idx = random.randint(0, len(b_train) - 1)
          scenery = imread(b_train[idx])
          plt.imshow(scenery)
```

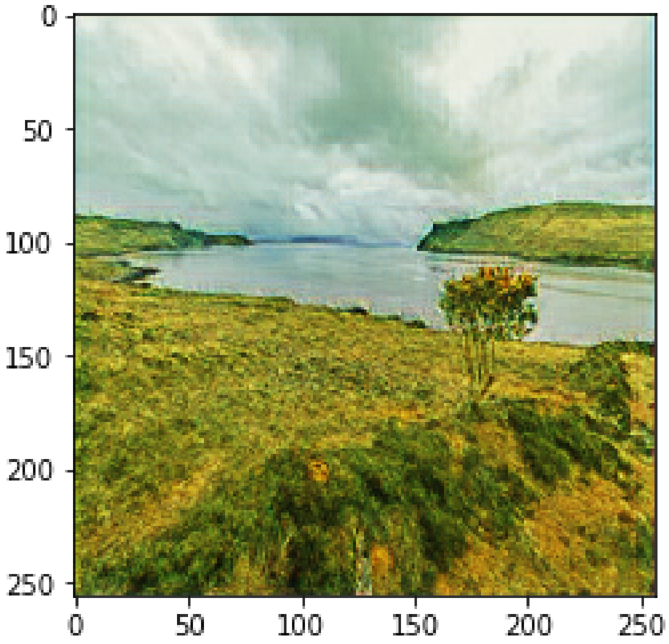
```
Out[128]: <matplotlib.image.AxesImage at 0x135fcb208>
```



```
In [129]: scenery_shaped = (scenery - 127.5)/127.5
```

轉換成梵谷風

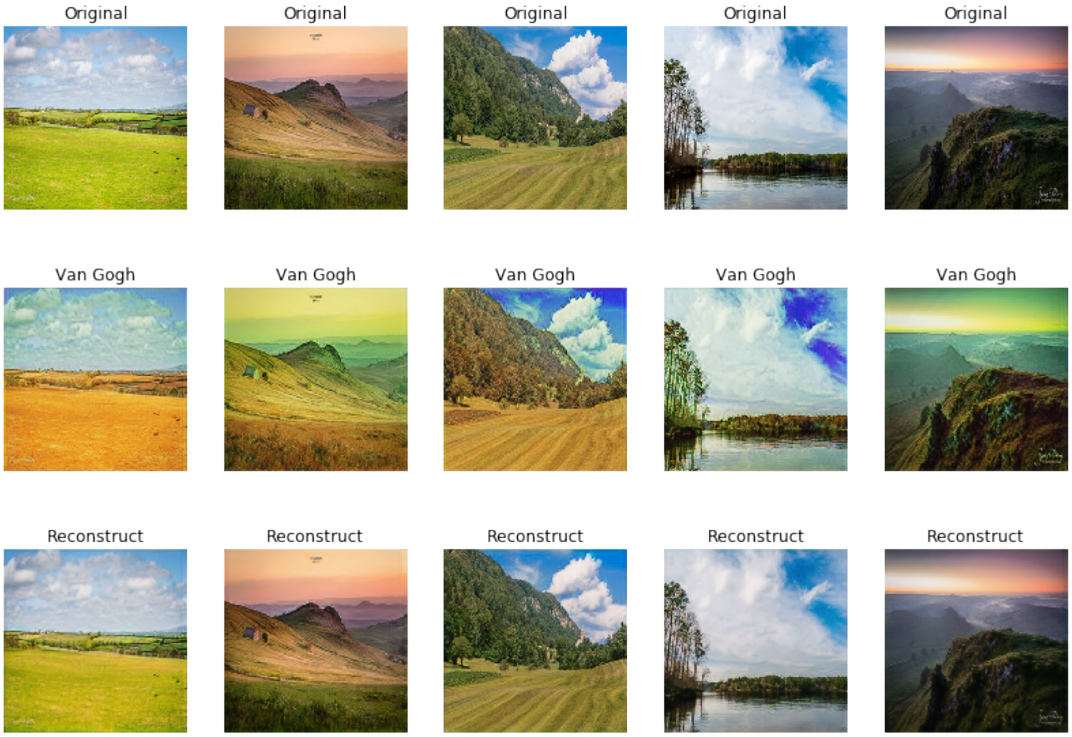
```
In [191]: fake_drawing = g_BA.predict(np.array([scenery_shaped]))
          fake_drawing = 0.5 * fake_drawing + 0.5
          plt.imshow(fake_drawing[0])

Out[191]: <matplotlib.image.AxesImage at 0x139cb5390>
```



列出多一點，你可以看得出，有些轉換隱隱有梵谷的影子了

```
In [181]: drawbatch = 5
          idx = np.random.randint(0, len(b_train), drawbatch)

          scenery_batch = []
          drawing_batch = []
          reconstruct_batch = []

          for i in idx:
              scenery_i = imread(b_train[i])
              scenery_i_shaped = (scenery_i - 127.5)/127.5
              scenery_batch.append(scenery_i)
              fake_drawing_i = g_BA.predict(np.array([scenery_i_shaped]))
              reconstruct_i = g_AB.predict(fake_drawing_i)
              fake_drawing_i = 0.5 * fake_drawing_i + 0.5
              drawing_batch.append(fake_drawing_i[0])
              reconstruct_i = 0.5 * reconstruct_i + 0.5
              reconstruct_batch.append(reconstruct_i[0])
```

```
plt.figure(figsize = (14,10))
for (i, draw) in enumerate(scenery_batch):
    plt.subplot(3, drawbatch, i + 1)
    plt.title("Original")
    plt.axis("off")
    plt.imshow(draw)
for (i, draw) in enumerate(drawing_batch):
    plt.subplot(3, drawbatch, drawbatch + (i + 1))
    plt.title("Van Gogh")
    plt.axis("off")
    plt.imshow(draw)
for (i, draw) in enumerate(reconstruct_batch):
    plt.subplot(3, drawbatch, 2 * drawbatch + (i + 1))
    plt.title("Reconstruct")
    plt.axis("off")
    plt.imshow(draw)
```



```
In [20]: d_A.save("davangogh.h5")
         d_B.save("dbvangogh.h5")
         g_AB.save("gabvangogh.h5")
         g_BA.save("gbavangogh.h5")
         combined.save("combinedvangogh.h5")
```