PART 2 TensorFlow

4. Workshop 2 : CIFAR10 資料集 - GAN & CNN 影像處理進階

- < CIFAR10 > : Intro to Generative Adversarial Networks (GAN)
- < CIFAR10 > : Classifying Images with CNNs)

< CIFAR10 > : Intro to Generative Adversarial Networks (GAN)

> **[Reference] :**
>
> - FRANÇOIS CHOLLET, **Deep Learning with Python**, Chapter 8, Section 5, Manning, 2018. (https://tanthiamhuat.files.wordpress.com/2018/03/deeplearningwithpython.pdf (https://tanthiamhuat.files.wordpress.com/2018/03/deeplearningwithpython.pdf))
>
> - Tom Hope, Yehezkel S. Resheff, Itay Lieder, "**Learning TensorFlow - A Guide to building Deep Learning Systems**", `Chapters 5` , O'Reilly (2017) (pdf) https://goo.gl/iEmehh (https://goo.gl/iEmehh)
>   - `[ Code ]` : https://github.com/gigwegbe/Learning-TensorFlow (https://github.com/gigwegbe/Learning-TensorFlow)
>
> - **CIFAR-10 and CIFAR-100 datasets**, https://www.cs.toronto.edu/~kriz/cifar.html (https://www.cs.toronto.edu/~kriz/cifar.html)

In [1]:

```python
import keras
keras.__version__
```

```
Using TensorFlow backend.
```

Out[1]:

```
'2.0.8'
```

[GAN] :

-- a forger network and an expert network, each being trained to best the other.

As such, a GAN is made of two parts:

- `Generator network` — Takes as input a random vector (a random point in the latent space), and decodes it into a synthetic image

- `Discriminator network (or adversary)` — Takes as input an image (real or synthetic), and predicts whether the image came from the training set or was created by the generator network.

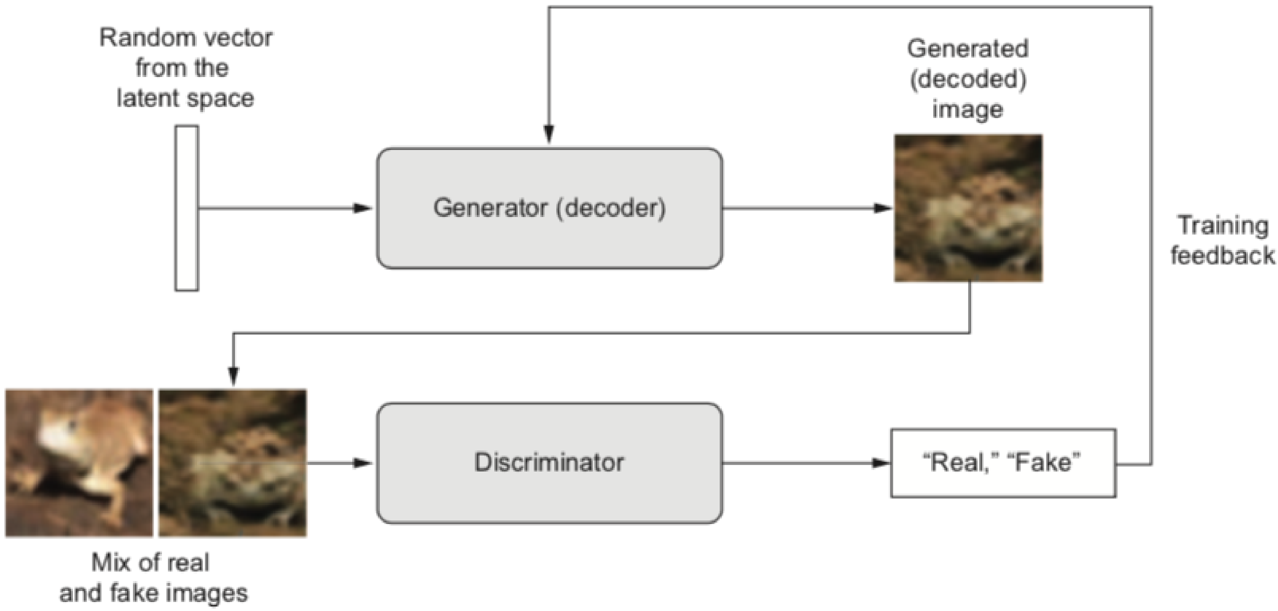

Figure 8.15 A generator transforms random latent vectors into images, and a discriminator seeks to tell real images from generated ones. The generator is trained to fool the discriminator.

A schematic GAN implementation

In what follows, we explain how to implement a GAN in Keras, in its barest form -- since GANs are quite advanced, diving deeply into the technical details would be out of scope for us. Our specific implementation will be a deep convolutional GAN, or DCGAN: a GAN where the generator and discriminator are deep convnets. In particular, it leverages a `Conv2DTranspose` layer for image upsampling in the generator.

We will **train our GAN on images from CIFAR10, a dataset of 50,000 32x32 RGB images belong to 10 classes (5,000 images per class).** To make things even easier, we will only use images belonging to the class "frog".

Schematically, our GAN looks like this:

- A `generator` network maps vectors of shape `(latent_dim,)` to images of shape `(32, 32, 3)`.
- A `discriminator` network maps images of shape (32, 32, 3) to a binary score estimating the probability that the image is real.
- A `gan` network chains the generator and the discriminator together: `gan(x) = discriminator(generator(x))`. Thus this `gan` network maps latent space vectors to the discriminator's assessment of the realism of these latent vectors as decoded by the generator.
- We train the discriminator using examples of real and fake images along with "real"/"fake" labels, as we would train any regular image classification model.
- To train the generator, we use the gradients of the generator's weights with regard to the loss of the `gan` model. This means that, at every step, we move the weights of the generator in a direction that will make the discriminator more likely to classify as "real" the images decoded by the generator. I.e. we train the generator to fool the discriminator.

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The generator

First, we develop a `generator` model, which turns a vector (from the latent space -- during training it will sampled at random) into a candidate image. One of the many issues that commonly arise with GANs is that the generator gets stuck with generated images that look like noise. A possible solution is to use dropout on both the discriminator and generator.

In [1]:

```python
import keras
from keras import layers
import numpy as np

latent_dim = 32
height = 32
width = 32
channels = 3

generator_input = keras.Input(shape=(latent_dim,))

# First, transform the input into a 16x16 128-channels feature map
x = layers.Dense(128 * 16 * 16)(generator_input)
x = layers.LeakyReLU()(x)
x = layers.Reshape((16, 16, 128))(x)

# Then, add a convolution layer
x = layers.Conv2D(256, 5, padding='same')(x)
x = layers.LeakyReLU()(x)

# Upsample to 32x32
x = layers.Conv2DTranspose(256, 4, strides=2, padding='same')(x)
x = layers.LeakyReLU()(x)

# Few more conv layers
x = layers.Conv2D(256, 5, padding='same')(x)
x = layers.LeakyReLU()(x)
x = layers.Conv2D(256, 5, padding='same')(x)
x = layers.LeakyReLU()(x)

# Produce a 32x32 1-channel feature map
x = layers.Conv2D(channels, 7, activation='tanh', padding='same')(x)
generator = keras.models.Model(generator_input, x)
generator.summary()
```

```
Using TensorFlow backend.

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 32768)             1081344
_________________________________________________________________
leaky_re_lu_1 (LeakyReLU)    (None, 32768)             0
_________________________________________________________________
reshape_1 (Reshape)          (None, 16, 16, 128)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 16, 16, 256)       819456
_________________________________________________________________
leaky_re_lu_2 (LeakyReLU)    (None, 16, 16, 256)       0
_________________________________________________________________
conv2d_transpose_1 (Conv2DTr (None, 32, 32, 256)       1048832
_________________________________________________________________
leaky_re_lu_3 (LeakyReLU)    (None, 32, 32, 256)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 32, 256)       1638656
_________________________________________________________________
leaky_re_lu_4 (LeakyReLU)    (None, 32, 32, 256)       0
```

```
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 256)       1638656
_________________________________________________________________
leaky_re_lu_5 (LeakyReLU)    (None, 32, 32, 256)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 32, 32, 3)         37635
=================================================================
Total params: 6,264,579
Trainable params: 6,264,579
Non-trainable params: 0
_________________________________________________________________
```

The discriminator

Then, we develop a `discriminator` model, that takes as input a candidate image (real or synthetic) and classifies it into one of two classes, either "generated image" or "real image that comes from the training set".

In [2]:

```
discriminator_input = layers.Input(shape=(height, width, channels))
x = layers.Conv2D(128, 3)(discriminator_input)
x = layers.LeakyReLU()(x)
x = layers.Conv2D(128, 4, strides=2)(x)
x = layers.LeakyReLU()(x)
x = layers.Conv2D(128, 4, strides=2)(x)
x = layers.LeakyReLU()(x)
x = layers.Conv2D(128, 4, strides=2)(x)
x = layers.LeakyReLU()(x)
x = layers.Flatten()(x)

# One dropout layer - important trick!
x = layers.Dropout(0.4)(x)

# Classification layer
x = layers.Dense(1, activation='sigmoid')(x)

discriminator = keras.models.Model(discriminator_input, x)
discriminator.summary()

# To stabilize training, we use learning rate decay
# and gradient clipping (by value) in the optimizer.
discriminator_optimizer = keras.optimizers.RMSprop(lr=0.0008, clipvalue=1.0, decay=1e-
discriminator.compile(optimizer=discriminator_optimizer, loss='binary_crossentropy')
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_2 (InputLayer)         (None, 32, 32, 3)         0         
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 30, 30, 128)       3584      
_________________________________________________________________
leaky_re_lu_6 (LeakyReLU)    (None, 30, 30, 128)       0         
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 14, 14, 128)       262272    
_________________________________________________________________
leaky_re_lu_7 (LeakyReLU)    (None, 14, 14, 128)       0         
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 6, 6, 128)         262272    
_________________________________________________________________
leaky_re_lu_8 (LeakyReLU)    (None, 6, 6, 128)         0         
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 2, 2, 128)         262272    
_________________________________________________________________
leaky_re_lu_9 (LeakyReLU)    (None, 2, 2, 128)         0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 512)               0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 513       
=================================================================
Total params: 790,913
Trainable params: 790,913
Non-trainable params: 0
_________________________________________________________________
```

The adversarial network

- **Finally, we setup the GAN, which chains the generator and the discriminator.**
- This is the model that, when trained, will move the generator in a direction that improves its ability to fool the discriminator.
- This model turns latent space points into a classification decision, "fake" or "real", and it is meant to be trained with labels that are always "these are real images". So training `gan` will updates the weights of `generator` in a way that makes `discriminator` more likely to predict "real" when looking at fake images.
- Very importantly, we set the discriminator to be frozen during training (non-trainable): its weights will not be updated when training `gan` .
- If the discriminator weights could be updated during this process, then we would be training the discriminator to always predict "real", which is not what we want!

In [3]:

```
# Set discriminator weights to non-trainable
# (will only apply to the `gan` model)
discriminator.trainable = False

gan_input = keras.Input(shape=(latent_dim,))
gan_output = discriminator(generator(gan_input))
gan = keras.models.Model(gan_input, gan_output)

gan_optimizer = keras.optimizers.RMSprop(lr=0.0004, clipvalue=1.0, decay=1e-8)
gan.compile(optimizer=gan_optimizer, loss='binary_crossentropy')
```

How to train your DCGAN

Now we can start training. To recapitulate, this is schematically what the training loop looks like:

```
for each epoch:
    * Draw random points in the latent space (random noise).
    * Generate images with `generator` using this random noise.
    * Mix the generated images with real ones.
    * Train `discriminator` using these mixed images, with corresponding targets,
 either "real" (for the real images) or "fake" (for the generated images).
    * Draw new random points in the latent space.
    * Train `gan` using these random vectors, with targets that all say "these are
real images". This will update the weights of the generator (only, since discrimin
ator is frozen inside `gan`) to move them towards getting the discriminator to pre
dict "these are real images" for generated images, i.e. this trains the generator
 to fool the discriminator.
```

Let's implement it:

In [4]:

```
import os
from keras.preprocessing import image

# Load CIFAR10 data
(x_train, y_train), (_, _) = keras.datasets.cifar10.load_data()

# Select frog images (class 6)
x_train = x_train[y_train.flatten() == 6]

# Normalize data
x_train = x_train.reshape(
    (x_train.shape[0],) + (height, width, channels)).astype('float32') / 255.

iterations = 10000
batch_size = 20
save_dir = './'

# Start training loop
start = 0
for step in range(iterations):
    # Sample random points in the latent space
    random_latent_vectors = np.random.normal(size=(batch_size, latent_dim))

    # Decode them to fake images
    generated_images = generator.predict(random_latent_vectors)

    # Combine them with real images
    stop = start + batch_size
    real_images = x_train[start: stop]
    combined_images = np.concatenate([generated_images, real_images])

    # Assemble labels discriminating real from fake images
    labels = np.concatenate([np.ones((batch_size, 1)),
                             np.zeros((batch_size, 1))])
    # Add random noise to the labels - important trick!
    labels += 0.05 * np.random.random(labels.shape)

    # Train the discriminator
    d_loss = discriminator.train_on_batch(combined_images, labels)

    # sample random points in the latent space
    random_latent_vectors = np.random.normal(size=(batch_size, latent_dim))

    # Assemble labels that say "all real images"
    misleading_targets = np.zeros((batch_size, 1))

    # Train the generator (via the gan model,
    # where the discriminator weights are frozen)
    a_loss = gan.train_on_batch(random_latent_vectors, misleading_targets)

    start += batch_size
    if start > len(x_train) - batch_size:
      start = 0

    # Occasionally save / plot
    if step % 100 == 0:
        # Save model weights
        gan.save_weights('gan.h5')

```

```
        # Print metrics
        print('discriminator loss at step %s: %s' % (step, d_loss))
        print('adversarial loss at step %s: %s' % (step, a_loss))

        # Save one generated image
        img = image.array_to_img(generated_images[0] * 255., scale=False)
        img.save(os.path.join(save_dir, 'generated_frog' + str(step) + '.png'))

        # Save one real image, for comparison
        img = image.array_to_img(real_images[0] * 255., scale=False)
        img.save(os.path.join(save_dir, 'real_frog' + str(step) + '.png'))
```

```
discriminator loss at step 0: 0.685675
adversarial loss at step 0: 0.667591
discriminator loss at step 100: 0.756201
adversarial loss at step 100: 0.820905
discriminator loss at step 200: 0.699047
adversarial loss at step 200: 0.776581
discriminator loss at step 300: 0.684602
adversarial loss at step 300: 0.513813
discriminator loss at step 400: 0.707092
adversarial loss at step 400: 0.716778
discriminator loss at step 500: 0.686278
adversarial loss at step 500: 0.741214
discriminator loss at step 600: 0.692786
adversarial loss at step 600: 0.745891
discriminator loss at step 700: 0.69771
adversarial loss at step 700: 0.781026
discriminator loss at step 800: 0.69236
adversarial loss at step 800: 0.748769
discriminator loss at step 900: 0.663193
```

Let's display a few of our fake images:

In [5]:

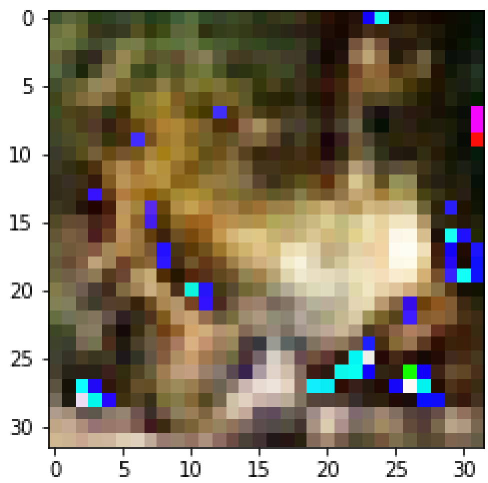
```
import matplotlib.pyplot as plt

# Sample random points in the latent space
random_latent_vectors = np.random.normal(size=(10, latent_dim))

# Decode them to fake images
generated_images = generator.predict(random_latent_vectors)

for i in range(generated_images.shape[0]):
    img = image.array_to_img(generated_images[i] * 255., scale=False)
    plt.figure()
    plt.imshow(img)

plt.show()
```



Froggy with some pixellated artifacts.

Figure 8.18 Play the discriminator: in each row, two images were dreamed up by the GAN, and one image comes from the training set. Can you tell them apart? (Answers: the real images in each column are middle, top, bottom, middle.)

< CIFAR10 > : Classifying Images with CNNs by TensorFlow

[Reference] :

- Tom Hope, Yehezkel S. Resheff, Itay Lieder, "**Learning TensorFlow - A Guide to building Deep Learning Systems**", `Chapters 4` , O'Reilly (2017) (pdf) https://goo.gl/iEmehh (https://goo.gl/iEmehh)
  - `[ Code ]` : https://github.com/gigwegbe/Learning-TensorFlow (https://github.com/gigwegbe/Learning-TensorFlow)
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In [ ]:

```

```