How to Implement CycleGAN Models From Scratch With Keras

by **Jason Brownlee** on August 7, 2019 in **Generative Adversarial Networks**

The Cycle Generative adversarial Network, or CycleGAN for short, is a generator model for converting images from one domain to another domain.

For example, the model can be used to translate images of horses to images of zebras, or photographs of city landscapes at night to city landscapes during the day.

The benefit of the CycleGAN model is that it can be trained without paired examples. That is, it does not require examples of photographs before and after the translation in order to train the model, e.g. photos of the same city landscape during the day and at night. Instead, it is able to use a collection of photographs from each domain and extract and harness the underlying style of images in the collection in order to perform the translation.

The model is very impressive but has an architecture that appears quite complicated to implement for beginners.

In this tutorial, you will discover how to implement the CycleGAN architecture from scratch using the Keras deep learning framework.

After completing this tutorial, you will know:

- How to implement the discriminator and generator models.
- How to define composite models to train the generator models via adversarial and cycle loss.
- How to implement the training process to update model weights each training iteration.

Discover how to develop DCGANs, conditional GANs, Pix2Pix, CycleGANs, and more with Keras in my new GANs book, with 29 step-by-step tutorials and full source code.

Let's get started.

How to Develop CycleGAN Models From Scratch With Keras
Photo by anokarina, some rights reserved.

Tutorial Overview

This tutorial is divided into five parts; they are:

1. What Is the CycleGAN Architecture?
2. How to Implement the CycleGAN Discriminator Model
3. How to Implement the CycleGAN Generator Model
4. How to Implement Composite Models for Least Squares and Cycle Loss
5. How to Update Discriminator and Generator Models

What Is the CycleGAN Architecture?

The CycleGAN model was described by Jun-Yan Zhu, et al. in their 2017 paper titled "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks."

The model architecture is comprised of two generator models: one generator (Generator-A) for generating images for the first domain (Domain-A) and the second generator (Generator-B) for generating images for the second domain (Domain-B).

- Generator-A -> Domain-A
- Generator-B -> Domain-B

The generator models perform image translation, meaning that the image generation process is conditional on an input image, specifically an image from the other domain. Generator-A takes an image from Domain-B as input and Generator-B takes an image from Domain-A as input.

- Domain-B -> Generator-A -> Domain-A
- Domain-A -> Generator-B -> Domain-B

Each generator has a corresponding discriminator model.

The first discriminator model (Discriminator-A) takes real images from Domain-A and generated images from Generator-A and predicts whether they are real or fake. The second discriminator model (Discriminator-B) takes real images from Domain-B and generated images from Generator-B and predicts whether they are real or fake.

- Domain-A -> Discriminator-A -> [Real/Fake]
- Domain-B -> Generator-A -> Discriminator-A -> [Real/Fake]
- Domain-B -> Discriminator-B -> [Real/Fake]
- Domain-A -> Generator-B -> Discriminator-B -> [Real/Fake]

The discriminator and generator models are trained in an adversarial zero-sum process, like normal GAN models.

The generators learn to better fool the discriminators and the discriminators learn to better detect fake images. Together, the models find an equilibrium during the training process.

Additionally, the generator models are regularized not just to create new images in the target domain, but instead create translated versions of the input images from the source domain. This is achieved by using generated images as input to the corresponding generator model and comparing the output image to the original images.

Passing an image through both generators is called a cycle. Together, each pair of generator models are trained to better reproduce the original source image, referred to as cycle consistency.

- Domain-B -> Generator-A -> Domain-A -> Generator-B -> Domain-B
- Domain-A -> Generator-B -> Domain-B -> Generator-A -> Domain-A

There is one further element to the architecture referred to as the identity mapping.

This is where a generator is provided with images as input from the target domain and is expected to generate the same image without change. This addition to the architecture is optional, although it results in a better matching of the color profile of the input image.

- Domain-A -> Generator-A -> Domain-A
- Domain-B -> Generator-B -> Domain-B

Now that we are familiar with the model architecture, we can take a closer look at each model in turn and how they can be implemented.

The paper provides a good description of the models and training process, although the official Torch implementation was used as the definitive description for each model and training process and provides the basis for the the model implementations described below.

How to Implement the CycleGAN Discriminator Model

The discriminator model is responsible for taking a real or generated image as input and predicting whether it is real or fake.

The discriminator model is implemented as a PatchGAN model.

> *For the discriminator networks we use 70 × 70 PatchGANs, which aim to classify whether 70 × 70 overlapping image patches are real or fake.*

— Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.

The PatchGAN was described in the 2016 paper titled "Precomputed Real-time Texture Synthesis With Markovian Generative Adversarial Networks" and was used in the pix2pix model for image translation described in the 2016 paper titled "Image-to-Image Translation with Conditional Adversarial Networks."

The architecture is described as discriminating an input image as real or fake by averaging the prediction for nxn squares or patches of the source image.

> *… we design a discriminator architecture – which we term a PatchGAN – that only penalizes structure at the scale of patches. This discriminator tries to classify if each NxN patch in an image is real or fake. We run this discriminator convolutionally across the image, averaging all responses to provide the ultimate output of D.*

— Image-to-Image Translation with Conditional Adversarial Networks, 2016.

This can be implemented directly by using a somewhat standard deep convolutional discriminator model.

Instead of outputting a single value like a traditional discriminator model, the PatchGAN discriminator model can output a square or one-channel feature map of predictions. The 70×70 refers to the effective receptive field of the model on the input, not the actual shape of the output feature map.

The receptive field of a convolutional layer refers to the number of pixels that one output of the layer maps to in the input to the layer. The effective receptive field refers to the mapping of one pixel in the output of a deep convolutional model (multiple layers) to the input image. Here, the PatchGAN is an approach to designing a deep convolutional network based on the effective receptive field, where one output activation of the model maps to a 70×70 patch of the input image, regardless of the size of the input image.

The PatchGAN has the effect of predicting whether each 70×70 patch in the input image is real or fake. These predictions can then be averaged to give the output of the model (if needed) or compared directly to a matrix (or a vector if flattened) of expected values (e.g. 0 or 1 values).

The discriminator model described in the paper takes 256×256 color images as input and defines an explicit architecture that is used on all of the test problems. The architecture uses blocks of Conv2D-InstanceNorm-LeakyReLU layers, with 4×4 filters and a 2×2 stride.

> *Let Ck denote a 4×4 Convolution-InstanceNorm-LeakyReLU layer with k filters and stride 2. After the last layer, we apply a convolution to produce a 1-dimensional output. We do not use InstanceNorm for the first C64 layer. We use leaky ReLUs with a slope of 0.2.*

— Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.

The architecture for the discriminator is as follows:

- C64-C128-C256-C512

This is referred to as a 3-layer PatchGAN in the CycleGAN and Pix2Pix nomenclature, as excluding the first hidden layer, the model has three hidden layers that could be scaled up or down to give different sized PatchGAN models.

Not listed in the paper, the model also has a final hidden layer C512 with a 1×1 stride, and an output layer C1, also with a 1×1 stride with a linear activation function. Given the model is mostly used with 256×256 sized images as input, the size of the output feature map of activations is 16×16. If 128×128 images were used as input, then the size of the output feature map of activations would be 8×8.

The model does not use batch normalization; instead, instance normalization is used.

Instance normalization was described in the 2016 paper titled "Instance Normalization: The Missing Ingredient for Fast Stylization." It is a very simple type of normalization and involves standardizing (e.g. scaling to a standard Gaussian) the values on each feature map.

The intent is to remove image-specific contrast information from the image during image generation, resulting in better generated images.

> *The key idea is to replace batch normalization layers in the generator architecture with instance normalization layers, and to keep them at test time (as opposed to freeze and simplify them out as done for batch normalization). Intuitively, the normalization process allows to remove*

> *instance-specific contrast information from the content image, which simplifies generation. In practice, this results in vastly improved images.*

— Instance Normalization: The Missing Ingredient for Fast Stylization, 2016.

Although designed for generator models, it can also prove effective in discriminator models.

An implementation of instance normalization is provided in the keras-contrib project that provides early access to community-supplied Keras features.

The keras-contrib library can be installed via *pip* as follows:

```
sudo pip install git+https://www.github.com/keras-team/keras-contrib.git
```

Or, if you are using an Anaconda virtual environment, such as on EC2:

```
git clone https://www.github.com/keras-team/keras-contrib.git
cd keras-contrib
sudo ~/anaconda3/envs/tensorflow_p36/bin/python setup.py install
```

The new *InstanceNormalization* layer can then be used as follows:

```
...
from keras_contrib.layers.normalization.instancenormalization import InstanceNormalization
# define layer
layer = InstanceNormalization(axis=-1)
...
```

The *"axis"* argument is set to -1 to ensure that features are normalized per feature map.

The network weights are initialized to Gaussian random numbers with a standard deviation of 0.02, as is described for DCGANs more generally.

> *Weights are initialized from a Gaussian distribution N (0, 0.02).*

— Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.

The discriminator model is updated using a least squares loss (L2), a so-called Least-Squared Generative Adversarial Network, or LSGAN.

> *… we replace the negative log likelihood objective by a least-squares loss. This loss is more stable during training and generates higher quality results.*

— Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.

This can be implemented using "mean squared error" between the target values of class=1 for real images and class=0 for fake images.

Additionally, the paper suggests dividing the loss for the discriminator by half during training, in an effort to slow down updates to the discriminator relative to the generator.

> *In practice, we divide the objective by 2 while optimizing D, which slows down the rate at which D learns, relative to the rate of G.*

— Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.

This can be achieved by setting the "*loss_weights*" argument to 0.5 when compiling the model. Note that this weighting does not appear to be implemented in the official Torch implementation when updating discriminator models are defined in the fDx_basic() function.

We can tie all of this together in the example below with a *define_discriminator()* function that defines the PatchGAN discriminator. The model configuration matches the description in the appendix of the paper with additional details from the official Torch implementation defined in the defineD_n_layers() function.

```
# example of defining a 70x70 patchgan discriminator model
from keras.optimizers import Adam
from keras.initializers import RandomNormal
from keras.models import Model
from keras.models import Input
from keras.layers import Conv2D
from keras.layers import LeakyReLU
from keras.layers import Activation
from keras.layers import Concatenate
from keras.layers import BatchNormalization
from keras_contrib.layers.normalization.instancenormalization import InstanceNormalization
from keras.utils.vis_utils import plot_model

# define the discriminator model
def define_discriminator(image_shape):
    # weight initialization
    init = RandomNormal(stddev=0.02)
    # source image input
    in_image = Input(shape=image_shape)
    # C64
    d = Conv2D(64, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(in_image)
    d = LeakyReLU(alpha=0.2)(d)
    # C128
    d = Conv2D(128, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # C256
    d = Conv2D(256, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # C512
    d = Conv2D(512, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # second last output layer
    d = Conv2D(512, (4,4), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # patch output
    patch_out = Conv2D(1, (4,4), padding='same', kernel_initializer=init)(d)
    # define model
```

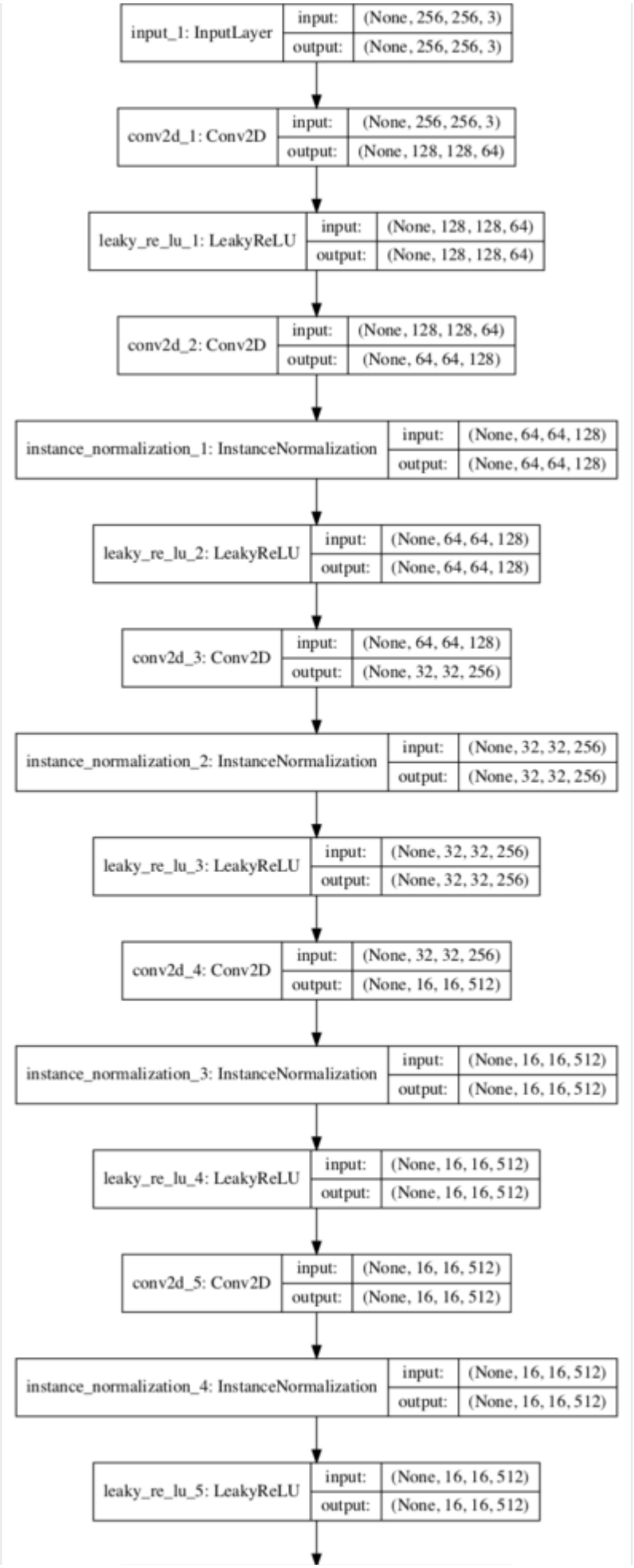
```
    model = Model(in_image, patch_out)
    # compile model
    model.compile(loss='mse', optimizer=Adam(lr=0.0002, beta_1=0.5), loss_weights=[0.5])
    return model

# define image shape
image_shape = (256,256,3)
# create the model
model = define_discriminator(image_shape)
# summarize the model
model.summary()
# plot the model
plot_model(model, to_file='discriminator_model_plot.png', show_shapes=True, show_layer_names=Tr
```

Note: the *plot_model()* function requires that both the pydot and pygraphviz libraries are installed. If this is a problem, you can comment out both the import and call to this function.

Running the example summarizes the model showing the size inputs and outputs for each layer.

```
_________________________________________________________________
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
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 128)       131200
_________________________________________________________________
instance_normalization_1 (In (None, 64, 64, 128)       256
_________________________________________________________________
leaky_re_lu_2 (LeakyReLU)    (None, 64, 64, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 256)       524544
_________________________________________________________________
instance_normalization_2 (In (None, 32, 32, 256)       512
_________________________________________________________________
leaky_re_lu_3 (LeakyReLU)    (None, 32, 32, 256)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 512)       2097664
_________________________________________________________________
instance_normalization_3 (In (None, 16, 16, 512)       1024
_________________________________________________________________
leaky_re_lu_4 (LeakyReLU)    (None, 16, 16, 512)       0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 16, 16, 512)       4194816
_________________________________________________________________
instance_normalization_4 (In (None, 16, 16, 512)       1024
_________________________________________________________________
leaky_re_lu_5 (LeakyReLU)    (None, 16, 16, 512)       0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 16, 16, 1)         8193
=================================================================
Total params: 6,962,369
Trainable params: 6,962,369
Non-trainable params: 0
_________________________________________________________________
```

A plot of the model architecture is also created to help get an idea of the inputs, outputs, and transitions of the image data through the model.


input_1: InputLayer
input: (None, 256, 256, 3)
output: (None, 256, 256, 3)
conv2d_1: Conv2D
input: (None, 256, 256, 3)
output: (None, 128, 128, 64)
leaky_re_lu_1: LeakyReLU
input: (None, 128, 128, 64)
output: (None, 128, 128, 64)
conv2d_2: Conv2D
input: (None, 128, 128, 64)
output: (None, 64, 64, 128)
instance_normalization_1: InstanceNormalization
input: (None, 64, 64, 128)
output: (None, 64, 64, 128)
leaky_re_lu_2: LeakyReLU
input: (None, 64, 64, 128)
output: (None, 64, 64, 128)
conv2d_3: Conv2D
input: (None, 64, 64, 128)
output: (None, 32, 32, 256)
instance_normalization_2: InstanceNormalization
input: (None, 32, 32, 256)
output: (None, 32, 32, 256)
leaky_re_lu_3: LeakyReLU
input: (None, 32, 32, 256)
output: (None, 32, 32, 256)
conv2d_4: Conv2D
input: (None, 32, 32, 256)
output: (None, 16, 16, 512)
instance_normalization_3: InstanceNormalization
input: (None, 16, 16, 512)
output: (None, 16, 16, 512)
leaky_re_lu_4: LeakyReLU
input: (None, 16, 16, 512)
output: (None, 16, 16, 512)
conv2d_5: Conv2D
input: (None, 16, 16, 512)
output: (None, 16, 16, 512)
instance_normalization_4: InstanceNormalization
input: (None, 16, 16, 512)
output: (None, 16, 16, 512)
leaky_re_lu_5: LeakyReLU
input: (None, 16, 16, 512)
output: (None, 16, 16, 512)

conv2d_6: Conv2D	input:	(None, 16, 16, 512)
	output:	(None, 16, 16, 1)

Plot of the PatchGAN Discriminator Model for the CycleGAN

How to Implement the CycleGAN Generator Model

The CycleGAN Generator model takes an image as input and generates a translated image as output.

The model uses a sequence of downsampling convolutional blocks to encode the input image, a number of residual network (ResNet) convolutional blocks to transform the image, and a number of upsampling convolutional blocks to generate the output image.

> *Let c7s1-k denote a 7×7 Convolution-InstanceNormReLU layer with k filters and stride 1. dk denotes a 3×3 Convolution-InstanceNorm-ReLU layer with k filters and stride 2. Reflection padding was used to reduce artifacts. Rk denotes a residual block that contains two 3 × 3 convolutional layers with the same number of filters on both layer. uk denotes a 3 × 3 fractional-strided-ConvolutionInstanceNorm-ReLU layer with k filters and stride 1/2.*

— Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.

The architecture for the 6-resnet block generator for 128×128 images is as follows:

- c7s1-64,d128,d256,R256,R256,R256,R256,R256,R256,u128,u64,c7s1-3

First, we need a function to define the ResNet blocks. These are blocks comprised of two 3×3 CNN layers where the input to the block is concatenated to the output of the block, channel-wise.

This is implemented in the *resnet_block()* function that creates two Conv-InstanceNorm blocks with 3×3 filters and 1×1 stride and without a ReLU activation after the second block, matching the official Torch implementation in the build_conv_block() function. Same padding is used instead of reflection padded recommended in the paper for simplicity.

```
# generator a resnet block
def resnet_block(n_filters, input_layer):
    # weight initialization
    init = RandomNormal(stddev=0.02)
    # first layer convolutional layer
    g = Conv2D(n_filters, (3,3), padding='same', kernel_initializer=init)(input_layer)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # second convolutional layer
    g = Conv2D(n_filters, (3,3), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    # concatenate merge channel-wise with input layer
    g = Concatenate()([g, input_layer])
    return g
```

Next, we can define a function that will create the 9-resnet block version for 256×256 input images. This can easily be changed to the 6-resnet block version by setting *image_shape* to (128x128x3) and *n_resnet* function argument to 6.

Importantly, the model outputs pixel values with the shape as the input and pixel values are in the range [-1, 1], typical for GAN generator models.

```
# define the standalone generator model
def define_generator(image_shape=(256,256,3), n_resnet=9):
    # weight initialization
    init = RandomNormal(stddev=0.02)
    # image input
    in_image = Input(shape=image_shape)
    # c7s1-64
    g = Conv2D(64, (7,7), padding='same', kernel_initializer=init)(in_image)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # d128
    g = Conv2D(128, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # d256
    g = Conv2D(256, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # R256
    for _ in range(n_resnet):
        g = resnet_block(256, g)
    # u128
    g = Conv2DTranspose(128, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # u64
    g = Conv2DTranspose(64, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # c7s1-3
    g = Conv2D(3, (7,7), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    out_image = Activation('tanh')(g)
    # define model
    model = Model(in_image, out_image)
    return model
```

The generator model is not compiled as it is trained via a composite model, seen in the next section.

Tying this together, the complete example is listed below.

```
# example of an encoder-decoder generator for the cyclegan
from keras.optimizers import Adam
from keras.models import Model
from keras.models import Input
from keras.layers import Conv2D
from keras.layers import Conv2DTranspose
from keras.layers import Activation
from keras.initializers import RandomNormal
from keras.layers import Concatenate
from keras_contrib.layers.normalization.instancenormalization import InstanceNormalization
from keras.utils.vis_utils import plot_model

# generator a resnet block
def resnet_block(n_filters, input_layer):
    # weight initialization
    init = RandomNormal(stddev=0.02)
    # first layer convolutional layer
    g = Conv2D(n_filters, (3,3), padding='same', kernel_initializer=init)(input_layer)
```

```
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # second convolutional layer
    g = Conv2D(n_filters, (3,3), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    # concatenate merge channel-wise with input layer
    g = Concatenate()([g, input_layer])
    return g

# define the standalone generator model
def define_generator(image_shape=(256,256,3), n_resnet=9):
    # weight initialization
    init = RandomNormal(stddev=0.02)
    # image input
    in_image = Input(shape=image_shape)
    # c7s1-64
    g = Conv2D(64, (7,7), padding='same', kernel_initializer=init)(in_image)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # d128
    g = Conv2D(128, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # d256
    g = Conv2D(256, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # R256
    for _ in range(n_resnet):
        g = resnet_block(256, g)
    # u128
    g = Conv2DTranspose(128, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # u64
    g = Conv2DTranspose(64, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # c7s1-3
    g = Conv2D(3, (7,7), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    out_image = Activation('tanh')(g)
    # define model
    model = Model(in_image, out_image)
    return model

# create the model
model = define_generator()
# summarize the model
model.summary()
# plot the model
plot_model(model, to_file='generator_model_plot.png', show_shapes=True, show_layer_names=True)
```

Running the example first summarizes the model.

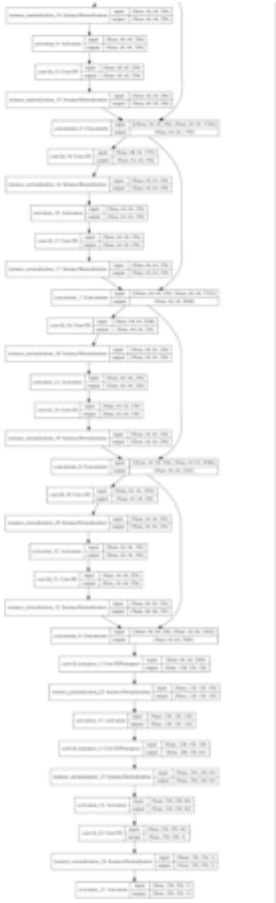
```
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            (None, 256, 256, 3)  0
__________________________________________________________________________________________________
conv2d_1 (Conv2D)               (None, 256, 256, 64) 9472        input_1[0][0]
__________________________________________________________________________________________________
instance_normalization_1 (Insta (None, 256, 256, 64) 128         conv2d_1[0][0]
__________________________________________________________________________________________________
```

```
activation_1 (Activation)       (None, 256, 256, 64) 0           instance_normalization_1[0][0
__________________________________________________________________________________________
conv2d_2 (Conv2D)               (None, 128, 128, 128 73856       activation_1[0][0]
__________________________________________________________________________________________
instance_normalization_2 (Insta (None, 128, 128, 128 256         conv2d_2[0][0]
__________________________________________________________________________________________
activation_2 (Activation)       (None, 128, 128, 128 0           instance_normalization_2[0][0
__________________________________________________________________________________________
conv2d_3 (Conv2D)               (None, 64, 64, 256)  295168      activation_2[0][0]
__________________________________________________________________________________________
instance_normalization_3 (Insta (None, 64, 64, 256)  512         conv2d_3[0][0]
__________________________________________________________________________________________
activation_3 (Activation)       (None, 64, 64, 256)  0           instance_normalization_3[0][0
__________________________________________________________________________________________
conv2d_4 (Conv2D)               (None, 64, 64, 256)  590080      activation_3[0][0]
__________________________________________________________________________________________
instance_normalization_4 (Insta (None, 64, 64, 256)  512         conv2d_4[0][0]
__________________________________________________________________________________________
activation_4 (Activation)       (None, 64, 64, 256)  0           instance_normalization_4[0][0
__________________________________________________________________________________________
conv2d_5 (Conv2D)               (None, 64, 64, 256)  590080      activation_4[0][0]
__________________________________________________________________________________________
instance_normalization_5 (Insta (None, 64, 64, 256)  512         conv2d_5[0][0]
__________________________________________________________________________________________
concatenate_1 (Concatenate)     (None, 64, 64, 512)  0           instance_normalization_5[0][0
                                                                 activation_3[0][0]
__________________________________________________________________________________________
conv2d_6 (Conv2D)               (None, 64, 64, 256)  1179904     concatenate_1[0][0]
__________________________________________________________________________________________
instance_normalization_6 (Insta (None, 64, 64, 256)  512         conv2d_6[0][0]
__________________________________________________________________________________________
activation_5 (Activation)       (None, 64, 64, 256)  0           instance_normalization_6[0][0
__________________________________________________________________________________________
conv2d_7 (Conv2D)               (None, 64, 64, 256)  590080      activation_5[0][0]
__________________________________________________________________________________________
instance_normalization_7 (Insta (None, 64, 64, 256)  512         conv2d_7[0][0]
__________________________________________________________________________________________
concatenate_2 (Concatenate)     (None, 64, 64, 768)  0           instance_normalization_7[0][0
                                                                 concatenate_1[0][0]
__________________________________________________________________________________________
conv2d_8 (Conv2D)               (None, 64, 64, 256)  1769728     concatenate_2[0][0]
__________________________________________________________________________________________
instance_normalization_8 (Insta (None, 64, 64, 256)  512         conv2d_8[0][0]
__________________________________________________________________________________________
activation_6 (Activation)       (None, 64, 64, 256)  0           instance_normalization_8[0][0
__________________________________________________________________________________________
conv2d_9 (Conv2D)               (None, 64, 64, 256)  590080      activation_6[0][0]
__________________________________________________________________________________________
instance_normalization_9 (Insta (None, 64, 64, 256)  512         conv2d_9[0][0]
__________________________________________________________________________________________
concatenate_3 (Concatenate)     (None, 64, 64, 1024) 0           instance_normalization_9[0][0
                                                                 concatenate_2[0][0]
__________________________________________________________________________________________
conv2d_10 (Conv2D)              (None, 64, 64, 256)  2359552     concatenate_3[0][0]
__________________________________________________________________________________________
instance_normalization_10 (Inst (None, 64, 64, 256)  512         conv2d_10[0][0]
__________________________________________________________________________________________
activation_7 (Activation)       (None, 64, 64, 256)  0           instance_normalization_10[0][
__________________________________________________________________________________________
conv2d_11 (Conv2D)              (None, 64, 64, 256)  590080      activation_7[0][0]
__________________________________________________________________________________________
instance_normalization_11 (Inst (None, 64, 64, 256)  512         conv2d_11[0][0]
__________________________________________________________________________________________
concatenate_4 (Concatenate)     (None, 64, 64, 1280) 0           instance_normalization_11[0][
                                                                 concatenate_3[0][0]
```

```
__________________________________________________________________________________________________
conv2d_12 (Conv2D)              (None, 64, 64, 256)  2949376     concatenate_4[0][0]
__________________________________________________________________________________________________
instance_normalization_12 (Inst (None, 64, 64, 256)  512         conv2d_12[0][0]
__________________________________________________________________________________________________
activation_8 (Activation)       (None, 64, 64, 256)  0           instance_normalization_12[0][
__________________________________________________________________________________________________
conv2d_13 (Conv2D)              (None, 64, 64, 256)  590080      activation_8[0][0]
__________________________________________________________________________________________________
instance_normalization_13 (Inst (None, 64, 64, 256)  512         conv2d_13[0][0]
__________________________________________________________________________________________________
concatenate_5 (Concatenate)     (None, 64, 64, 1536) 0           instance_normalization_13[0][
                                                                 concatenate_4[0][0]
__________________________________________________________________________________________________
conv2d_14 (Conv2D)              (None, 64, 64, 256)  3539200     concatenate_5[0][0]
__________________________________________________________________________________________________
instance_normalization_14 (Inst (None, 64, 64, 256)  512         conv2d_14[0][0]
__________________________________________________________________________________________________
activation_9 (Activation)       (None, 64, 64, 256)  0           instance_normalization_14[0][
__________________________________________________________________________________________________
conv2d_15 (Conv2D)              (None, 64, 64, 256)  590080      activation_9[0][0]
__________________________________________________________________________________________________
instance_normalization_15 (Inst (None, 64, 64, 256)  512         conv2d_15[0][0]
__________________________________________________________________________________________________
concatenate_6 (Concatenate)     (None, 64, 64, 1792) 0           instance_normalization_15[0][
                                                                 concatenate_5[0][0]
__________________________________________________________________________________________________
conv2d_16 (Conv2D)              (None, 64, 64, 256)  4129024     concatenate_6[0][0]
__________________________________________________________________________________________________
instance_normalization_16 (Inst (None, 64, 64, 256)  512         conv2d_16[0][0]
__________________________________________________________________________________________________
activation_10 (Activation)      (None, 64, 64, 256)  0           instance_normalization_16[0][
__________________________________________________________________________________________________
conv2d_17 (Conv2D)              (None, 64, 64, 256)  590080      activation_10[0][0]
__________________________________________________________________________________________________
instance_normalization_17 (Inst (None, 64, 64, 256)  512         conv2d_17[0][0]
__________________________________________________________________________________________________
concatenate_7 (Concatenate)     (None, 64, 64, 2048) 0           instance_normalization_17[0][
                                                                 concatenate_6[0][0]
__________________________________________________________________________________________________
conv2d_18 (Conv2D)              (None, 64, 64, 256)  4718848     concatenate_7[0][0]
__________________________________________________________________________________________________
instance_normalization_18 (Inst (None, 64, 64, 256)  512         conv2d_18[0][0]
__________________________________________________________________________________________________
activation_11 (Activation)      (None, 64, 64, 256)  0           instance_normalization_18[0][
__________________________________________________________________________________________________
conv2d_19 (Conv2D)              (None, 64, 64, 256)  590080      activation_11[0][0]
__________________________________________________________________________________________________
instance_normalization_19 (Inst (None, 64, 64, 256)  512         conv2d_19[0][0]
__________________________________________________________________________________________________
concatenate_8 (Concatenate)     (None, 64, 64, 2304) 0           instance_normalization_19[0][
                                                                 concatenate_7[0][0]
__________________________________________________________________________________________________
conv2d_20 (Conv2D)              (None, 64, 64, 256)  5308672     concatenate_8[0][0]
__________________________________________________________________________________________________
instance_normalization_20 (Inst (None, 64, 64, 256)  512         conv2d_20[0][0]
__________________________________________________________________________________________________
activation_12 (Activation)      (None, 64, 64, 256)  0           instance_normalization_20[0][
__________________________________________________________________________________________________
conv2d_21 (Conv2D)              (None, 64, 64, 256)  590080      activation_12[0][0]
__________________________________________________________________________________________________
instance_normalization_21 (Inst (None, 64, 64, 256)  512         conv2d_21[0][0]
__________________________________________________________________________________________________
concatenate_9 (Concatenate)     (None, 64, 64, 2560) 0           instance_normalization_21[0][
                                                                 concatenate_8[0][0]
```

```
140 __________________________________________________________________________________________________
141 conv2d_transpose_1 (Conv2DTrans (None, 128, 128, 128 2949248     concatenate_9[0][0]
142 __________________________________________________________________________________________________
143 instance_normalization_22 (Inst (None, 128, 128, 128 256         conv2d_transpose_1[0][0]
144 __________________________________________________________________________________________________
145 activation_13 (Activation)      (None, 128, 128, 128 0           instance_normalization_22[0][
146 __________________________________________________________________________________________________
147 conv2d_transpose_2 (Conv2DTrans (None, 256, 256, 64) 73792       activation_13[0][0]
148 __________________________________________________________________________________________________
149 instance_normalization_23 (Inst (None, 256, 256, 64) 128         conv2d_transpose_2[0][0]
150 __________________________________________________________________________________________________
151 activation_14 (Activation)      (None, 256, 256, 64) 0           instance_normalization_23[0][
152 __________________________________________________________________________________________________
153 conv2d_22 (Conv2D)              (None, 256, 256, 3)  9411        activation_14[0][0]
154 __________________________________________________________________________________________________
155 instance_normalization_24 (Inst (None, 256, 256, 3)  6           conv2d_22[0][0]
156 __________________________________________________________________________________________________
157 activation_15 (Activation)      (None, 256, 256, 3)  0           instance_normalization_24[0][
158 ==================================================================================================
159 Total params: 35,276,553
160 Trainable params: 35,276,553
161 Non-trainable params: 0
162 __________________________________________________________________________________________________
```

A Plot of the generator model is also created, showing the skip connections in the ResNet blocks.



Plot of the Generator Model for the CycleGAN

How to Implement Composite Models for Least Squares and Cycle Loss

The generator models are not updated directly. Instead, the generator models are updated via composite models.

An update to each generator model involves changes to the model weights based on four concerns:

- Adversarial loss (L2 or mean squared error).
- Identity loss (L1 or mean absolute error).
- Forward cycle loss (L1 or mean absolute error).
- Backward cycle loss (L1 or mean absolute error).

The adversarial loss is the standard approach for updating the generator via the discriminator, although in this case, the least squares loss function is used instead of the negative log likelihood (e.g. binary cross entropy).

First, we can use our function to define the two generators and two discriminators used in the CycleGAN.

```
...
# input shape
image_shape = (256,256,3)
```

```
# generator: A -> B
g_model_AtoB = define_generator(image_shape)
# generator: B -> A
g_model_BtoA = define_generator(image_shape)
# discriminator: A -> [real/fake]
d_model_A = define_discriminator(image_shape)
# discriminator: B -> [real/fake]
d_model_B = define_discriminator(image_shape)
```

A composite model is required for each generator model that is responsible for only updating the weights of that generator model, although it is required to share the weights with the related discriminator model and the other generator model.

This can be achieved by marking the weights of the other models as not trainable in the context of the composite model to ensure we are only updating the intended generator.

```
...
# ensure the model we're updating is trainable
g_model_1.trainable = True
# mark discriminator as not trainable
d_model.trainable = False
# mark other generator model as not trainable
g_model_2.trainable = False
```

The model can be constructed piecewise using the Keras functional API.

The first step is to define the input of the real image from the source domain, pass it through our generator model, then connect the output of the generator to the discriminator and classify it as real or fake.

```
...
# discriminator element
input_gen = Input(shape=image_shape)
gen1_out = g_model_1(input_gen)
output_d = d_model(gen1_out)
```

Next, we can connect the identity mapping element with a new input for the real image from the target domain, pass it through our generator model, and output the (hopefully) untranslated image directly.

```
...
# identity element
input_id = Input(shape=image_shape)
output_id = g_model_1(input_id)
```

So far, we have a composite model with two real image inputs and a discriminator classification and identity image output. Next, we need to add the forward and backward cycles.

The forward cycle can be achieved by connecting the output of our generator to the other generator, the output of which can be compared to the input to our generator and should be identical.

```
...
# forward cycle
output_f = g_model_2(gen1_out)
```

The backward cycle is more complex and involves the input for the real image from the target domain passing through the other generator, then passing through our generator, which should match the real image from the target domain.

```
...
# backward cycle
gen2_out = g_model_2(input_id)
output_b = g_model_1(gen2_out)
```

That's it.

We can then define this composite model with two inputs: one real image for the source and the target domain, and four outputs, one for the discriminator, one for the generator for the identity mapping, one for the other generator for the forward cycle, and one from our generator for the backward cycle.

```
...
# define model graph
model = Model([input_gen, input_id], [output_d, output_id, output_f, output_b])
```

The adversarial loss for the discriminator output uses least squares loss which is implemented as L2 or mean squared error. The outputs from the generators are compared to images and are optimized using L1 loss implemented as mean absolute error.

The generator is updated as a weighted average of the four loss values. The adversarial loss is weighted normally, whereas the forward and backward cycle loss is weighted using a parameter called *lambda* and is set to 10, e.g. 10 times more important than adversarial loss. The identity loss is also weighted as a fraction of the lambda parameter and is set to 0.5 * 10 or 5 in the official Torch implementation.

```
...
# compile model with weighting of least squares loss and L1 loss
model.compile(loss=['mse', 'mae', 'mae', 'mae'], loss_weights=[1, 5, 10, 10], optimizer=opt)
```

We can tie all of this together and define the function *define_composite_model()* for creating a composite model for training a given generator model.

```
# define a composite model for updating generators by adversarial and cycle loss
def define_composite_model(g_model_1, d_model, g_model_2, image_shape):
    # ensure the model we're updating is trainable
    g_model_1.trainable = True
    # mark discriminator as not trainable
    d_model.trainable = False
    # mark other generator model as not trainable
    g_model_2.trainable = False
    # discriminator element
    input_gen = Input(shape=image_shape)
    gen1_out = g_model_1(input_gen)
    output_d = d_model(gen1_out)
    # identity element
    input_id = Input(shape=image_shape)
    output_id = g_model_1(input_id)
    # forward cycle
    output_f = g_model_2(gen1_out)
    # backward cycle
    gen2_out = g_model_2(input_id)
    output_b = g_model_1(gen2_out)
    # define model graph
    model = Model([input_gen, input_id], [output_d, output_id, output_f, output_b])
    # define optimization algorithm configuration
    opt = Adam(lr=0.0002, beta_1=0.5)
    # compile model with weighting of least squares loss and L1 loss
    model.compile(loss=['mse', 'mae', 'mae', 'mae'], loss_weights=[1, 5, 10, 10], optimizer=opt
    return model
```

This function can then be called to prepare a composite model for training both the *g_model_AtoB* generator model and the *g_model_BtoA* model; for example:

```
...
# composite: A -> B -> [real/fake, A]
c_model_AtoBtoA = define_composite_model(g_model_AtoB, d_model_B, g_model_BtoA, image_shape)
# composite: B -> A -> [real/fake, B]
c_model_BtoAtoB = define_composite_model(g_model_BtoA, d_model_A, g_model_AtoB, image_shape)
```

Summarizing and plotting the composite model is a bit of a mess as it does not help to see the inputs and outputs of the model clearly.

We can summarize the inputs and outputs for each of the composite models below. Recall that we are sharing or reusing the same set of weights if a given model is used more than once in the composite model.

Generator-A Composite Model

Only Generator-A weights are trainable and weights for other models and not trainable.

- **Adversarial Loss**: Domain-B -> Generator-A -> Domain-A -> Discriminator-A -> [real/fake]
- **Identity Loss**: Domain-A -> Generator-A -> Domain-A
- **Forward Cycle Loss**: Domain-B -> Generator-A -> Domain-A -> Generator-B -> Domain-B
- **Backward Cycle Loss**: Domain-A -> Generator-B -> Domain-B -> Generator-A -> Domain-A

Generator-B Composite Model

Only Generator-B weights are trainable and weights for other models are not trainable.

- **Adversarial Loss**: Domain-A -> Generator-B -> Domain-B -> Discriminator-B -> [real/fake]
- **Identity Loss**: Domain-B -> Generator-B -> Domain-B
- **Forward Cycle Loss**: Domain-A -> Generator-B -> Domain-B -> Generator-A -> Domain-A
- **Backward Cycle Loss**: Domain-B -> Generator-A -> Domain-A -> Generator-B -> Domain-B

A complete example of creating all of the models is listed below for completeness.

```
# example of defining composite models for training cyclegan generators
from keras.optimizers import Adam
from keras.models import Model
from keras.models import Sequential
from keras.models import Input
from keras.layers import Conv2D
from keras.layers import Conv2DTranspose
from keras.layers import Activation
from keras.layers import LeakyReLU
from keras.initializers import RandomNormal
from keras.layers import Concatenate
from keras_contrib.layers.normalization.instancenormalization import InstanceNormalization
from keras.utils.vis_utils import plot_model

# define the discriminator model
def define_discriminator(image_shape):
    # weight initialization
    init = RandomNormal(stddev=0.02)
```

```
    # source image input
    in_image = Input(shape=image_shape)
    # C64
    d = Conv2D(64, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(in_image)
    d = LeakyReLU(alpha=0.2)(d)
    # C128
    d = Conv2D(128, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # C256
    d = Conv2D(256, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # C512
    d = Conv2D(512, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # second last output layer
    d = Conv2D(512, (4,4), padding='same', kernel_initializer=init)(d)
    d = InstanceNormalization(axis=-1)(d)
    d = LeakyReLU(alpha=0.2)(d)
    # patch output
    patch_out = Conv2D(1, (4,4), padding='same', kernel_initializer=init)(d)
    # define model
    model = Model(in_image, patch_out)
    # compile model
    model.compile(loss='mse', optimizer=Adam(lr=0.0002, beta_1=0.5), loss_weights=[0.5])
    return model

# generator a resnet block
def resnet_block(n_filters, input_layer):
    # weight initialization
    init = RandomNormal(stddev=0.02)
    # first layer convolutional layer
    g = Conv2D(n_filters, (3,3), padding='same', kernel_initializer=init)(input_layer)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # second convolutional layer
    g = Conv2D(n_filters, (3,3), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    # concatenate merge channel-wise with input layer
    g = Concatenate()([g, input_layer])
    return g

# define the standalone generator model
def define_generator(image_shape, n_resnet=9):
    # weight initialization
    init = RandomNormal(stddev=0.02)
    # image input
    in_image = Input(shape=image_shape)
    # c7s1-64
    g = Conv2D(64, (7,7), padding='same', kernel_initializer=init)(in_image)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # d128
    g = Conv2D(128, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # d256
    g = Conv2D(256, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # R256
    for _ in range(n_resnet):
        g = resnet_block(256, g)
```

```
    # u128
    g = Conv2DTranspose(128, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # u64
    g = Conv2DTranspose(64, (3,3), strides=(2,2), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    g = Activation('relu')(g)
    # c7s1-3
    g = Conv2D(3, (7,7), padding='same', kernel_initializer=init)(g)
    g = InstanceNormalization(axis=-1)(g)
    out_image = Activation('tanh')(g)
    # define model
    model = Model(in_image, out_image)
    return model

# define a composite model for updating generators by adversarial and cycle loss
def define_composite_model(g_model_1, d_model, g_model_2, image_shape):
    # ensure the model we're updating is trainable
    g_model_1.trainable = True
    # mark discriminator as not trainable
    d_model.trainable = False
    # mark other generator model as not trainable
    g_model_2.trainable = False
    # discriminator element
    input_gen = Input(shape=image_shape)
    gen1_out = g_model_1(input_gen)
    output_d = d_model(gen1_out)
    # identity element
    input_id = Input(shape=image_shape)
    output_id = g_model_1(input_id)
    # forward cycle
    output_f = g_model_2(gen1_out)
    # backward cycle
    gen2_out = g_model_2(input_id)
    output_b = g_model_1(gen2_out)
    # define model graph
    model = Model([input_gen, input_id], [output_d, output_id, output_f, output_b])
    # define optimization algorithm configuration
    opt = Adam(lr=0.0002, beta_1=0.5)
    # compile model with weighting of least squares loss and L1 loss
    model.compile(loss=['mse', 'mae', 'mae', 'mae'], loss_weights=[1, 5, 10, 10], optimizer=op
    return model

# input shape
image_shape = (256,256,3)
# generator: A -> B
g_model_AtoB = define_generator(image_shape)
# generator: B -> A
g_model_BtoA = define_generator(image_shape)
# discriminator: A -> [real/fake]
d_model_A = define_discriminator(image_shape)
# discriminator: B -> [real/fake]
d_model_B = define_discriminator(image_shape)
# composite: A -> B -> [real/fake, A]
c_model_AtoB = define_composite_model(g_model_AtoB, d_model_B, g_model_BtoA, image_shape)
# composite: B -> A -> [real/fake, B]
c_model_BtoA = define_composite_model(g_model_BtoA, d_model_A, g_model_AtoB, image_shape)
```

How to Update Discriminator and Generator Models

Training the defined models is relatively straightforward.

First, we must define a helper function that will select a batch of real images and the associated target (1.0).

```
# select a batch of random samples, returns images and target
def generate_real_samples(dataset, n_samples, patch_shape):
    # choose random instances
    ix = randint(0, dataset.shape[0], n_samples)
    # retrieve selected images
    X = dataset[ix]
    # generate 'real' class labels (1)
    y = ones((n_samples, patch_shape, patch_shape, 1))
    return X, y
```

Similarly, we need a function to generate a batch of fake images and the associated target (0.0).

```
# generate a batch of images, returns images and targets
def generate_fake_samples(g_model, dataset, patch_shape):
    # generate fake instance
    X = g_model.predict(dataset)
    # create 'fake' class labels (0)
    y = zeros((len(X), patch_shape, patch_shape, 1))
    return X, y
```

Now, we can define the steps of a single training iteration. We will model the order of updates based on the implementation in the official Torch implementation in the OptimizeParameters() function (**Note**: the official code uses a more confusing inverted naming convention).

1. Update Generator-B (A->B)
2. Update Discriminator-B
3. Update Generator-A (B->A)
4. Update Discriminator-A

First, we must select a batch of real images by calling *generate_real_samples()* for both Domain-A and Domain-B.

Typically, the batch size (*n_batch*) is set to 1. In this case, we will assume 256×256 input images, which means the *n_patch* for the PatchGAN discriminator will be 16.

```
...
# select a batch of real samples
X_realA, y_realA = generate_real_samples(trainA, n_batch, n_patch)
X_realB, y_realB = generate_real_samples(trainB, n_batch, n_patch)
```

Next, we can use the batches of selected real images to generate corresponding batches of generated or fake images.

```
...
# generate a batch of fake samples
X_fakeA, y_fakeA = generate_fake_samples(g_model_BtoA, X_realB, n_patch)
X_fakeB, y_fakeB = generate_fake_samples(g_model_AtoB, X_realA, n_patch)
```

The paper describes using a pool of previously generated images from which examples are randomly selected and used to update the discriminator model, where the pool size was set to 50 images.

> *… [we] update the discriminators using a history of generated images rather than the ones produced by the latest generators. We keep an image buffer that stores the 50 previously created images.*

— Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.

This can be implemented using a list for each domain and a using a function to populate the pool, then randomly replace elements from the pool once it is at capacity.

The *update_image_pool()* function below implements this based on the official Torch implementation in image_pool.lua.

```
# update image pool for fake images
def update_image_pool(pool, images, max_size=50):
    selected = list()
    for image in images:
        if len(pool) < max_size:
            # stock the pool
            pool.append(image)
            selected.append(image)
        elif random() < 0.5:
            # use image, but don't add it to the pool
            selected.append(image)
        else:
            # replace an existing image and use replaced image
            ix = randint(0, len(pool))
            selected.append(pool[ix])
            pool[ix] = image
    return asarray(selected)
```

We can then update our image pool with generated fake images, the results of which can be used to train the discriminator models.

```
...
# update fakes from pool
X_fakeA = update_image_pool(poolA, X_fakeA)
X_fakeB = update_image_pool(poolB, X_fakeB)
```

Next, we can update Generator-A.

The *train_on_batch()* function will return a value for each of the four loss functions, one for each output, as well as the weighted sum (first value) used to update the model weights which we are interested in.

```
...
# update generator B->A via adversarial and cycle loss
g_loss2, _, _, _, _  = c_model_BtoA.train_on_batch([X_realB, X_realA], [y_realA, X_realA, X_real
```

We can then update the discriminator model using the fake images that may or may not have come from the image pool.

```
...
# update discriminator for A -> [real/fake]
dA_loss1 = d_model_A.train_on_batch(X_realA, y_realA)
dA_loss2 = d_model_A.train_on_batch(X_fakeA, y_fakeA)
```

We can then do the same for the other generator and discriminator models.

```
...
# update generator A->B via adversarial and cycle loss
g_loss1, _, _, _, _ = c_model_AtoB.train_on_batch([X_realA, X_realB], [y_realB, X_realB, X_realA
# update discriminator for B -> [real/fake]
dB_loss1 = d_model_B.train_on_batch(X_realB, y_realB)
dB_loss2 = d_model_B.train_on_batch(X_fakeB, y_fakeB)
```

At the end of the training run, we can then report the current loss for the discriminator models on real and fake images and of each generator model.

```
...
# summarize performance
print('>%d, dA[%.3f,%.3f] dB[%.3f,%.3f] g[%.3f,%.3f]' % (i+1, dA_loss1,dA_loss2, dB_loss1,dB_los
```

Tying this all together, we can define a function named *train()* that takes an instance of each of the defined models and a loaded dataset (list of two NumPy arrays, one for each domain) and trains the model.

A batch size of 1 is used as is described in the paper and the models are fit for 100 training epochs.

```
# train cyclegan models
def train(d_model_A, d_model_B, g_model_AtoB, g_model_BtoA, c_model_AtoB, c_model_BtoA, dataset
    # define properties of the training run
    n_epochs, n_batch, = 100, 1
    # determine the output square shape of the discriminator
    n_patch = d_model_A.output_shape[1]
    # unpack dataset
    trainA, trainB = dataset
    # prepare image pool for fakes
    poolA, poolB = list(), list()
    # calculate the number of batches per training epoch
    bat_per_epo = int(len(trainA) / n_batch)
    # calculate the number of training iterations
    n_steps = bat_per_epo * n_epochs
    # manually enumerate epochs
    for i in range(n_steps):
        # select a batch of real samples
        X_realA, y_realA = generate_real_samples(trainA, n_batch, n_patch)
        X_realB, y_realB = generate_real_samples(trainB, n_batch, n_patch)
        # generate a batch of fake samples
        X_fakeA, y_fakeA = generate_fake_samples(g_model_BtoA, X_realB, n_patch)
        X_fakeB, y_fakeB = generate_fake_samples(g_model_AtoB, X_realA, n_patch)
        # update fakes from pool
        X_fakeA = update_image_pool(poolA, X_fakeA)
        X_fakeB = update_image_pool(poolB, X_fakeB)
        # update generator B->A via adversarial and cycle loss
        g_loss2, _, _, _, _  = c_model_BtoA.train_on_batch([X_realB, X_realA], [y_realA, X_real
        # update discriminator for A -> [real/fake]
        dA_loss1 = d_model_A.train_on_batch(X_realA, y_realA)
        dA_loss2 = d_model_A.train_on_batch(X_fakeA, y_fakeA)
        # update generator A->B via adversarial and cycle loss
        g_loss1, _, _, _, _ = c_model_AtoB.train_on_batch([X_realA, X_realB], [y_realB, X_realB
        # update discriminator for B -> [real/fake]
        dB_loss1 = d_model_B.train_on_batch(X_realB, y_realB)
        dB_loss2 = d_model_B.train_on_batch(X_fakeB, y_fakeB)
        # summarize performance
        print('>%d, dA[%.3f,%.3f] dB[%.3f,%.3f] g[%.3f,%.3f]' % (i+1, dA_loss1,dA_loss2, dB_los
```

The train function can then be called directly with our defined models and loaded dataset.

```
...
# load a dataset as a list of two numpy arrays
dataset = ...
# train models
train(d_model_A, d_model_B, g_model_AtoB, g_model_BtoA, c_model_AtoB, c_model_BtoA, dataset)
```

As an improvement, it may be desirable to combine the update to each discriminator model into a single operation as is performed in the fDx_basic() function of the official implementation.

Additionally, the paper describes updating the models for another 100 epochs (200 in total), where the learning rate is decayed to 0.0. This too can be added as a minor extension to the training process.

Further Reading

This section provides more resources on the topic if you are looking to go deeper.

Papers

- Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 2017.
- Perceptual Losses for Real-Time Style Transfer and Super-Resolution, 2016.
- Image-to-Image Translation with Conditional Adversarial Networks, 2016.
- Least Squares Generative Adversarial Networks, 2016.
- Precomputed Real-time Texture Synthesis With Markovian Generative Adversarial Networks, 2016.
- Instance Normalization: The Missing Ingredient for Fast Stylization
- Layer Normalization

API

- Keras API.
- keras-contrib : Keras community contributions, GitHub.

Projects

- CycleGAN Project (official), GitHub
- pytorch-CycleGAN-and-pix2pix (official), GitHub.
- CycleGAN Project Page (official)
- Keras-GAN: Keras implementations of Generative Adversarial Networks.
- CycleGAN-Keras: Keras implementation of CycleGAN using a tensorflow backend.
- cyclegan-keras: keras implementation of cycle-gan

Articles

- Question: PatchGAN Discriminator.
- Receptive Field Calculator

Summary

In this tutorial, you discovered how to implement the CycleGAN architecture from scratch using the Keras deep learning framework.

Specifically, you learned:

- How to implement the discriminator and generator models.
- How to define composite models to train the generator models via adversarial and cycle loss.
- How to implement the training process to update model weights each training iteration.

Do you have any questions?
Ask your questions in the comments below and I will do my best to answer.

About Jason Brownlee

Jason Brownlee, PhD is a machine learning specialist who teaches developers how to get results with modern machine learning methods via hands-on tutorials.
View all posts by Jason Brownlee →

‹ A Gentle Introduction to CycleGAN for Image Translation

How to Develop a CycleGAN for Image-to-Image Translation with Keras ›

67 Responses to *How to Implement CycleGAN Models From Scratch With Keras*

Dilip Rajkumar August 8, 2019 at 8:59 pm #

REPLY

Hi Jason, thanks for this great tutorial about CycleGAN. I have a physics-based regression problem (~8 input features and 1 response variable) with only 35 data points from the real world lab test results. We have a 1D simulation tool with which we can generate any number of low fidelity artificial data points. Unfortunately, the low fidelity artificial synthesised data points are not having the same distribution as the real world lab test results and there are differences due to domain shift between real world lab test and simulated data.

Can you please give some tips on applying CycleGAN for a numeric dataset (regression problem) to make the low fidelity (synthesised data) to appear more like the real world lab test data but still being physically consistent?

Jason Brownlee August 9, 2019 at 8:10 am #

REPLY

Good question.

Perhaps you can try adapting the above example for your data?

Perhaps try a gaussian process or kde approach to modeling the distribution of points and sample it randomly?

Dilip Rajkumar October 11, 2019 at 10:14 pm #

REPLY

Hi Jason,
In my case, the 35 lab test points can be said to represent data from Domain A and the 1000s (or seemingly infinite) of points from the 1D Physics Simulator can be said to be from Domain B. I believe the scenario is similar to the case of CycleGANs generating Van Gogh style dog paintings (https://dmitryulyanov.github.io/feed-forward-neural-doodle/) by combining seemingly large number of Dog photos (which are theoretically unlimited) with Van Gogh paintings which are limited in number, so I think CycleGANs are a good choice for my problem. I do have a few simple questions though:
For my scenario synthesizing numeric data is the `update_image_pool` function needed to keep track of fake samples created by the generator?
Do I have to employ `Instance normalization` or `batch normalization` in the architecture of the generator and discriminator?
Since I am only synthesizing numeric data, I am planning to use a simple architecture for the generator and discriminator as below, is this appropriate?

```
def define_discriminator(n_inputs=nr_features):
model = Sequential()
model.add(Dense(n_inputs, activation='relu', kernel_initializer='he_uniform', input_dim=n_inputs))
model.add(Dense(32,activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
return model

def define_generator(nr_features):
model = Sequential()
model.add(Dense(nr_features, activation='LeakyReLU',input_shape=(nr_features,)))
model.add(Dense(32, activation='LeakyReLU'))
model.add(Dense(1, activation='linear'))
model.compile(loss='mse', optimizer=Adam(lr=0.0002, beta_1=0.5), loss_weights=[0.5])
return model
```

Jason Brownlee October 12, 2019 at 6:58 am #

REPLY

If it is just numerical data, perhaps use a gaussian process or other much simpler generative model?

Prisilla August 9, 2019 at 10:21 am #

REPLY

Hi Jason,

Can you elaborate about batch normalization and instance normalization? Why in instance normalization, axis is set to -1.

Thanks,
Prisilla

Jason Brownlee August 9, 2019 at 2:21 pm #

REPLY

Excellent question.

Basically, batch norm normalizes (standardizes) across the batch, instance norm normalizes (standardizes) across the instance only.

This paper explains it:
https://arxiv.org/abs/1607.08022

The axis of -1 indicates we are normalizing over channels for one image, assuming a channels-last image format. You can see this from the API documentation here:

https://github.com/keras-team/keras-contrib/blob/master/keras_contrib/layers/normalization/instancenormalization.py

I hope that helps.

Jonathan August 20, 2019 at 10:52 pm #

REPLY

Hi Jason,

Thanks for the nice post. Just one question regarding update_image_pool function, wouldn't be a possible issue to reach an index out of range of pool?

++ max_size is set to 50 (if len(pool) < max_size) , hence pool index are from 0 to 49.
++ ix = randint(0, len(pool)), will return an integer between 0 to 50

So there may be a possibility to access pool[50] which is out of range?

Jason Brownlee August 21, 2019 at 6:44 am #

REPLY

Nice catch!

I should do len(pool)-1.

Nevertheless, python does not do out of bounds, an index of 50 will become an index of 0.

Radu September 1, 2019 at 5:58 am #

REPLY

Hi Jason,

First of all, I want o thank you. I really appreciate your post, it really helped me understand the whole "CycleGan" thing, you really did a great thing explaining everything.

Secondly, I want to ask you something. Your training loop is quite different from the other implementations that I have seen(PyTorch official, Keras). Mainly, I reffer to the way you are updating the models G1, D1, G2, D2 instead of G1,G2, D1, D2. Is there any specific reason you have decided to do it this way, or it was just modified for simplicity?

Thank you,
Radu

Jason Brownlee September 2, 2019 at 5:22 am #

REPLY

Thanks Radu.

Yes, the update order of the models is based on the official implementation provided with the paper.

Jon September 18, 2019 at 12:34 am #

REPLY

Hey Jason! Thanks for the wonderful and in-depth explanation of this complex topic.
I feel a little stupid asking this but can you please tell me how we are passing the images to the code? We are supposed to feed them as lists but are those lists supposed to be made of 3-dim image data?
Thank you.

Jason Brownlee September 18, 2019 at 6:13 am #

REPLY

No stupid questions here!

Images are loaded as numpy arrays, to learn more about this see this tutorial:
https://machinelearningmastery.com/how-to-load-and-manipulate-images-for-deep-learning-in-python-with-pil-pillow/

And here:
https://machinelearningmastery.com/how-to-load-convert-and-save-images-with-the-keras-api/

Raghu September 18, 2019 at 5:17 am #

REPLY

Thanks for the well explained article.

I was trying to save and load the model using Keras' save & load_model but on loading it fails to recognize the InstanceNormalization layer. Can you suggest a workaround?
Also, any way to visualize the training images after some iterations?

Jason Brownlee September 18, 2019 at 6:32 am #

REPLY

Good question, use:

```
...
cust = {'InstanceNormalization': InstanceNormalization}
model = load_model('model.h5', cust)
```

dtri November 14, 2019 at 4:29 am #

REPLY

Hello and thanks for the very nice tutorials! Could you please make a tutorial on how to implement a recycleGAN model for video retargeting in keras? Thanks

Jason Brownlee November 14, 2019 at 8:07 am #

REPLY

Thanks for the suggestion!

Clancy November 15, 2019 at 8:44 am #

REPLY

Hi Jason, thanks for the excellent walkthrough.

Due to a bug not allowing me to correctly import tensorflow addons (undefined symbol error) which I hope to figure out at some stage, I cannot use the Instance normalization layer.

Can I just replace this with BatchNormalization (with axis -1 same as here) or do I have to do anything special in addition?

Thanks

Jason Brownlee November 16, 2019 at 7:14 am #

REPLY

Not really.

You can install InstanceNormalziation as a Keras extension, not a tensorflow extension.

Or perhaps try just skipping the layer?

Kenny November 21, 2019 at 3:13 pm #

REPLY

Hi,

I have some questions about Res-Net architecture in the Generator model. Seems like in your res netblock, are you downsampling and upsampling every time? In the first res block, you feed in 256 x64x64 to the block and concatenate it. The result is 512x64x64. Then you feed that into the rest netblock. It becomes 256x64x64 then for concatenation it becomes 768x54x64. Usually, I thought res-net block would do elt-wise adding not concatenation.

Jason Brownlee November 22, 2019 at 5:58 am #

REPLY

Yes, it is modified to match what was implemented in the cyclegan paper.

David J. December 6, 2019 at 5:21 am #

REPLY

Hi,

Thanks alot for the very helpful tutorial. This helped me alot in understanding how to perform sequential training of different parts of a single model in Keras.

I have a few questions, and these might be a little stupid given the lack of my expertise in Keras:

1) If you set the discriminator as trainable=FALSE when you create the composite model, don't you need to set it back to trainable=TRUE before running the train_on_batch of discriminator.

2) Can you expand a little bit more on how the weights are updated for layers shared between multiple models i.e the layers of the generator model which are also part of composite model. Are the layers in Keras global entities and hence can be updated as part of different models, or are the layers specific to each model?

3) When compiling the composite model, there are 4 different loss functions, i.e mae , mse.. . I wanted to ask how the order of these 4 loss functions was decided?

I am trying to use the above tutorial to write another architecture of my own which requires sequential training of various parts of the model and hence my questions.

Jason Brownlee December 6, 2019 at 5:31 am #

REPLY

You're welcome.

No, the trainability only affects the scope of the model – to each call to compile(). It is trainable standalone, not trainable as part of the discriminator.

Yes, I cover this in another post, this one I think:
https://machinelearningmastery.com/how-to-develop-a-generative-adversarial-network-for-a-1-dimensional-function-from-scratch-in-keras/

The order matters, but is the linear order we specified.

It's a fun model this one! Hang in there!

Tempa February 1, 2020 at 9:44 pm #

REPLY

Hi,
Thank you for your in-depth explanations of the model!
I'm trying to a use the related Pix2pix model with Tensorflow and I have a question about your usage of Instance Normalization.

Tensorflow Pix2Pix tutorial uses Batch Normalization on every down(or up)sampling steps instead of Instance Normalization.

On the other hand, their tutorial code on github (https://github.com/tensorflow/examples/blob/master/tensorflow_examples/models/pix2pix/pix2pix.py) offer an Instance Normalization option (disabled by default) which is similar to your implementation.

From what I understood, Instance Normalization is better than Batch Normalization for image generation, so should I use Instance Normalization in my model?

I mean, is there a reason to not use Instance Normalization over Batch Normalization (I'll be always using a batch size of 1, if that matters)?

Thank you for your help!

Jason Brownlee February 2, 2020 at 6:24 am # REPLY

I'm not familiar with the tensorflow implementation, sorry. Perhaps contact the authors.

I implemented the model based on the paper.

To see if it matters, perhaps test with each and compare the results?

Tempa February 2, 2020 at 6:43 am # REPLY

I think it's what I'm going to do, it's just that it will take quite some time to train so I'm trying to get things right before training. I'll compare with some simpler datasets first then.
Thank you again for all the articles you made on this subject!

Jason Brownlee February 3, 2020 at 5:42 am # REPLY

Sounds like a good plan!

harsh saxena February 26, 2020 at 8:53 pm # REPLY

0%| | 0/533 [00:00<?, ?it/s]C:\Users\acer\Anaconda3\lib\site-packages\keras\engine\training.py:297: UserWarning: Discrepancy between trainable weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?
'Discrepancy between trainable weights and collected trainable'
C:\Users\acer\Anaconda3\lib\site-packages\keras\engine\training.py:297: UserWarning: Discrepancy between trainable weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?
'Discrepancy between trainable weights and collected trainable'
C:\Users\acer\Anaconda3\lib\site-packages\keras\engine\training.py:297: UserWarning: Discrepancy between trainable weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?
'Discrepancy between trainable weights and collected trainable'
C:\Users\acer\Anaconda3\lib\site-packages\keras\engine\training.py:297: UserWarning: Discrepancy

between trainable weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?
'Discrepancy between trainable weights and collected trainable'

While training the model I got this warning. Do I need to take care of this or is it fine?

REPLY

Jason Brownlee February 27, 2020 at 5:44 am #

You can ignore the warnings.

REPLY

harsh saxena February 26, 2020 at 8:56 pm #

In the above tutorial, you have used a batch size of 1 but I am using 2, so do I need to change anything else also in the model architecture to make it give good results or changing batch_size won,t affect the results?

REPLY

Jason Brownlee February 27, 2020 at 5:46 am #

The code is developed for a batch size of 1, I believe. You may need to make large changes to support other batch sizes.

REPLY

harsh saxena February 27, 2020 at 5:15 pm #

Actually I changed some parts of code and batch size to 4 and also the size of the image to 128. The model is getting trained and has reached the 20th epoch. I just wanted to know if the model will give good results with my batch size also?

I also did one more change to the code. Instead of loading the whole data at once I have created a custom data generator to give 4 images at a time and not using the whole memory to store the whole dataset.

So does these two changes will give me good results or not?

REPLY

Jason Brownlee February 28, 2020 at 5:59 am #

I don’t know, I would think a batch size of 1 is important.

Test and compare.

harsh saxena February 26, 2020 at 10:24 pm #

REPLY

I am getting a resource exhausted error. So do I need to upgrade my RAM or GPU?

Jason Brownlee February 27, 2020 at 5:49 am #

REPLY

Perhaps, or try running on AWS EC2.

harsh saxena February 27, 2020 at 6:01 pm #

REPLY

So the resource exhausted error is because of RAM or because of GPU?

Jason Brownlee February 28, 2020 at 6:01 am #

REPLY

I don't know, sorry. It has never happened to me. Perhaps post your question to stackoverflow.

Shuvam Ghosal April 12, 2020 at 12:03 am #

REPLY

Hi Jason,

I am very glad and benefited by this post of yours on CycleGAN implementation. You have very lucidly explained this quite complex topic and I very much appreciate it.

I have a small doubt. In the Resnet Block creation function, while you are doing the concatenation of Input layer and g, you have written:

g = Concatenate()[g, input_layer]

Shouldn't the argument list be [input_layer, g]? Because otherwise the input layer will come after g in the merged layer. But, it should come before g according to the architecture in the paper, isn't it? Can u kindly clear my doubt?

Many Thanks,
Shuvam Ghosal

Jason Brownlee April 12, 2020 at 6:21 am #

REPLY

Thanks.

Doesn't matter I believe. Perhaps test and confirm.

REPLY

Shuvam Ghosal April 12, 2020 at 3:11 pm #

Ok, Jason. Thank you.

REPLY

RJ April 21, 2020 at 1:42 am #

Hi Jason,

many thanks for this great tutorial, it really helps to understand the basic idea behind a CycleGAN. I have one question regarding the outputs of the CycleGAN:

When I apply your implementation on the apples2oranges dataset from the official paper and inspect the outputs of the predict() method, the output quality never changes. It starts with a noisy image where the original input image used for prediction can still slightly be seen. However, even after 200 epochs, it appears the same. Despite that, the loss values decrease early but start to stagnate after 30-50 epochs.

Do you have an idea what could cause this issue?

Many thanks again and in advance!

REPLY

Jason Brownlee April 21, 2020 at 6:02 am #

You're welcome.

Very cool!

You might need to tune the model and learning algorithm for the change in the dataset.

REPLY

nir ben zikri May 1, 2020 at 11:22 pm #

hey,

thank you so much for the article!
the g_loss1,g_loss2 are huge (around 3000) and it doesnt converge, did you ran into this situation? i havent change the code, just fixed some import issues (random etc.)

thanks!

REPLY

nir ben zikri May 1, 2020 at 11:23 pm #

forgot to mansion that i used the horse2zebra dataset, so far i ran 1000 iteration and its still huge, mybe it should be trained for a couple of days?

RJ May 2, 2020 at 8:40 pm #

REPLY

If the generator losses are very high, you should check the color values of the images. If they're in the range of [0..255], the losses are typically very large, whereas for normalized color values to [-1..1] or [0..1] (depending on your activation function) already reduces the loss values for the generator.

Another issue that I encountered when working with composite models was that I accidentally trained the wrong model, i.e. I used the wrong model for generating fake images.

Jason Brownlee May 3, 2020 at 6:09 am #

REPLY

Great tip!

Jason Brownlee May 2, 2020 at 5:47 am #

REPLY

GANs do not converge:
https://machinelearningmastery.com/faq/single-faq/why-is-my-gan-not-converging

Viswajith May 8, 2020 at 4:11 pm #

REPLY

My question might be trivial: I am training the above model (a version inspired by yours but my own code) in Google Colab. Since there are 1200 or so images in the train A folder and if I were to use 100 epochs of training, I will have to run 120000 steps of training. Now even with GPU I most likely will need at least 24 hours of model training for this model. But with the 12 hour GPU limit on Colab this seems to be impossible. So I am thinking of using model checkpoints and also note down the step at which training stopped. Would it be right if I load the model weights at the saved point and start the remaining training from the step at which it stopped?

Jason Brownlee May 9, 2020 at 6:09 am #

REPLY

That sounds like a great solution!

Viswajith May 9, 2020 at 10:50 am #

REPLY

Once I use predict after training the image pixel values are between 0-1. Is this right?

Jason Brownlee May 9, 2020 at 1:51 pm #

REPLY

Any input to the model must be prepared in an identical manner as the training data.

KK96 May 13, 2020 at 6:00 am #

REPLY

Hi Jason, great article! Thanks for sharing it online. One doubt, why is the training pattern trains generators first and not the discriminators first, like the simple GAN models.

Jason Brownlee May 13, 2020 at 6:47 am #

REPLY

You're welcome.

Guillaume Delacroix May 16, 2020 at 4:22 pm #

REPLY

Hi Jason, I have read many of your articles but can you please include your own results from running this code so people can see what the end result is like and able to assess if this one is worth reading at all?

Jason Brownlee May 17, 2020 at 6:29 am #

REPLY

I always do (use the blog search)! For example:
https://machinelearningmastery.com/cyclegan-tutorial-with-keras/

Neil May 17, 2020 at 6:23 am #

REPLY

I can't get over how helpful your articles are. I will be buying the book to help support what you are doing.

Mahsa May 21, 2020 at 8:49 am #

REPLY

Hi,
Thank you for your informative article.
I am running it on my 3D data and the problem is the discriminator accuracy after number of steps reaches 100% which I guess is bad. Is this something common? Do you know what can be done in this case?

Jason Brownlee May 21, 2020 at 1:39 pm #

REPLY

Accuracy is a poor metric of generate image quality. Ignore it.

Generate images along the way and look at them to see if it is a good time to stop training.

M May 28, 2020 at 5:11 am #

REPLY

Except in the case of having unpaired images, what are the benefits of using CycleGAN in comparison to plain GAN? If we have paired images, is it better to use GAN?
I am asking this question because when CycleGAN used in translation tasks, it often leads to results which lack sharpness and fine-detailed structures.

Jason Brownlee May 28, 2020 at 6:22 am #

REPLY

Paired images you would use pix2pix
Unpaired you would use cyclegan.

A plain gan cannot do conditional image generation.

Neil May 31, 2020 at 9:58 pm #

REPLY

There is a MAJOR mistake in the construction of the ResNet. ResNet does not concatenate the input and the output, it adds them together. Concatenation leads to feature maps that are thousands of channels deep which slows down learning significantly. To change this all you have to do is replace concatenate with add. It is also missing a Relu at the end (the input to the next res block needs to be activated). This change makes the network have about 1/3 the number of parameters which is extremely significant.

Jason Brownlee June 1, 2020 at 6:20 am #

REPLY

Sure, but we are not implementing resnet. The implementation here matches the modified resnet blocks from the cyclegan paper.

Neil June 1, 2020 at 12:02 pm #

REPLY

I would definitely take another look to make sure. The paper only says it uses residual blocks. All the implementations on github that I can find for cycleGan use addition like in the ResNet paper.

Jason Brownlee June 1, 2020 at 1:43 pm #

REPLY

Thanks for the tip.

Looks like an add:
https://github.com/junyanz/CycleGAN/blob/master/models/architectures.lua#L221

I'll look into updating it.

Neil June 1, 2020 at 10:05 pm #

It's confusing because the torch implementation uses "concatTable" to do the skip connection while the pytorch implementation uses a straightforward + operator. Other keras implementations I've seen use an Add layer. Im not familiar with torch and lua, but maybe concatTable is a misleading name? Anyways, thanks for looking into it and providing a great tutorial.

Jason Brownlee June 2, 2020 at 6:12 am #

Agreed.

You're welcome.

Xingdong Cao June 4, 2020 at 2:59 am #

REPLY

Hi, when using PathchGAN as Discriminator, why sometimes the loss function is mse, and sometimes the loss function is binary_crossenropy?

Here, you use mse as lossfuction, but in pix2pix model, you use binary_crossentropy.

Jason Brownlee June 4, 2020 at 6:25 am #

REPLY

Yes, different approaches to defining the adversarial loss.

Leave a Reply

Name (required)

Email (will not be published) (required)

Website

SUBMIT COMMENT

Welcome!

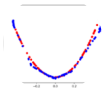
My name is *Jason Brownlee* PhD, and I **help developers** get results with **machine learning**.

Read more

Never miss a tutorial:

Picked for you:

How to Develop a Pix2Pix GAN for Image-to-Image Translation



How to Develop a 1D Generative Adversarial Network From Scratch in Keras

How to Develop a CycleGAN for Image-to-Image Translation with Keras

How to Develop a Conditional GAN (cGAN) From Scratch

How to Develop a GAN to Generate CIFAR10 Small Color Photographs