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How to Develop a Conditional GAN (cGAN) From Scratch

by **Jason Brownlee** on July 5, 2019 in **Generative Adversarial Networks**

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Generative Adversarial Networks, or GANs, are an architecture for training generative models, such as deep convolutional neural networks for generating images.

Although GAN models are capable of generating new random plausible examples for a given dataset, there is no way to control the types of images that are generated other than trying to figure out the complex relationship between the latent space input to the generator and the generated images.

The conditional generative adversarial network, or cGAN for short, is a type of GAN that involves the conditional generation of images by a generator model. Image generation can be conditional on a class label, if available, allowing the targeted generated of images of a given type.

In this tutorial, you will discover how to develop a conditional generative adversarial network for the targeted generation of items of clothing.

After completing this tutorial, you will know:

- The limitations of generating random samples with a GAN that can be overcome with a conditional generative adversarial network.
- How to develop and evaluate an unconditional generative adversarial network for generating photos of items of clothing.
- How to develop and evaluate a conditional generative adversarial network for generating photos of items of clothing.

Kick-start your project with my new book Generative Adversarial Networks with Python, including *step-by-step tutorials* and the *Python source code* files for all examples.

Let's get started.

How to Develop a Conditional Generative Adversarial Network From Scratch
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Tutorial Overview

This tutorial is divided into five parts; they are:

1. Conditional Generative Adversarial Networks
2. Fashion-MNIST Clothing Photograph Dataset
3. Unconditional GAN for Fashion-MNIST
4. Conditional GAN for Fashion-MNIST
5. Conditional Clothing Generation

Conditional Generative Adversarial Networks

A generative adversarial network, or GAN for short, is an architecture for training deep learning-based generative models.

The architecture is comprised of a generator and a discriminator model. The generator model is responsible for generating new plausible examples that ideally are indistinguishable from real examples in the dataset. The discriminator model is responsible for classifying a given image as either real (drawn from the dataset) or fake (generated).

The models are trained together in a zero-sum or adversarial manner, such that improvements in the discriminator come at the cost of a reduced capability of the generator, and vice versa.

GANs are effective at image synthesis, that is, generating new examples of images for a target dataset. Some datasets have additional information, such as a class label, and it is desirable to make use of this information.

For example, the MNIST handwritten digit dataset has class labels of the corresponding integers, the CIFAR-10 small object photograph dataset has class labels for the corresponding objects in the

photographs, and the Fashion-MNIST clothing dataset has class labels for the corresponding items of clothing.

There are two motivations for making use of the class label information in a GAN model.

1. Improve the GAN.
2. Targeted Image Generation.

Additional information that is correlated with the input images, such as class labels, can be used to improve the GAN. This improvement may come in the form of more stable training, faster training, and/or generated images that have better quality.

Class labels can also be used for the deliberate or targeted generation of images of a given type.

A limitation of a GAN model is that it may generate a random image from the domain. There is a relationship between points in the latent space to the generated images, but this relationship is complex and hard to map.

Alternately, a GAN can be trained in such a way that both the generator and the discriminator models are conditioned on the class label. This means that when the trained generator model is used as a standalone model to generate images in the domain, images of a given type, or class label, can be generated.

> *Generative adversarial nets can be extended to a conditional model if both the generator and discriminator are conditioned on some extra information y. […] We can perform the conditioning by feeding y into the both the discriminator and generator as additional input layer.*

— Conditional Generative Adversarial Nets, 2014.

For example, in the case of MNIST, specific handwritten digits can be generated, such as the number 9; in the case of CIFAR-10, specific object photographs can be generated such as '*frogs*'; and in the case of the Fashion MNIST dataset, specific items of clothing can be generated, such as '*dress*.'

This type of model is called a Conditional Generative Adversarial Network, CGAN or cGAN for short.

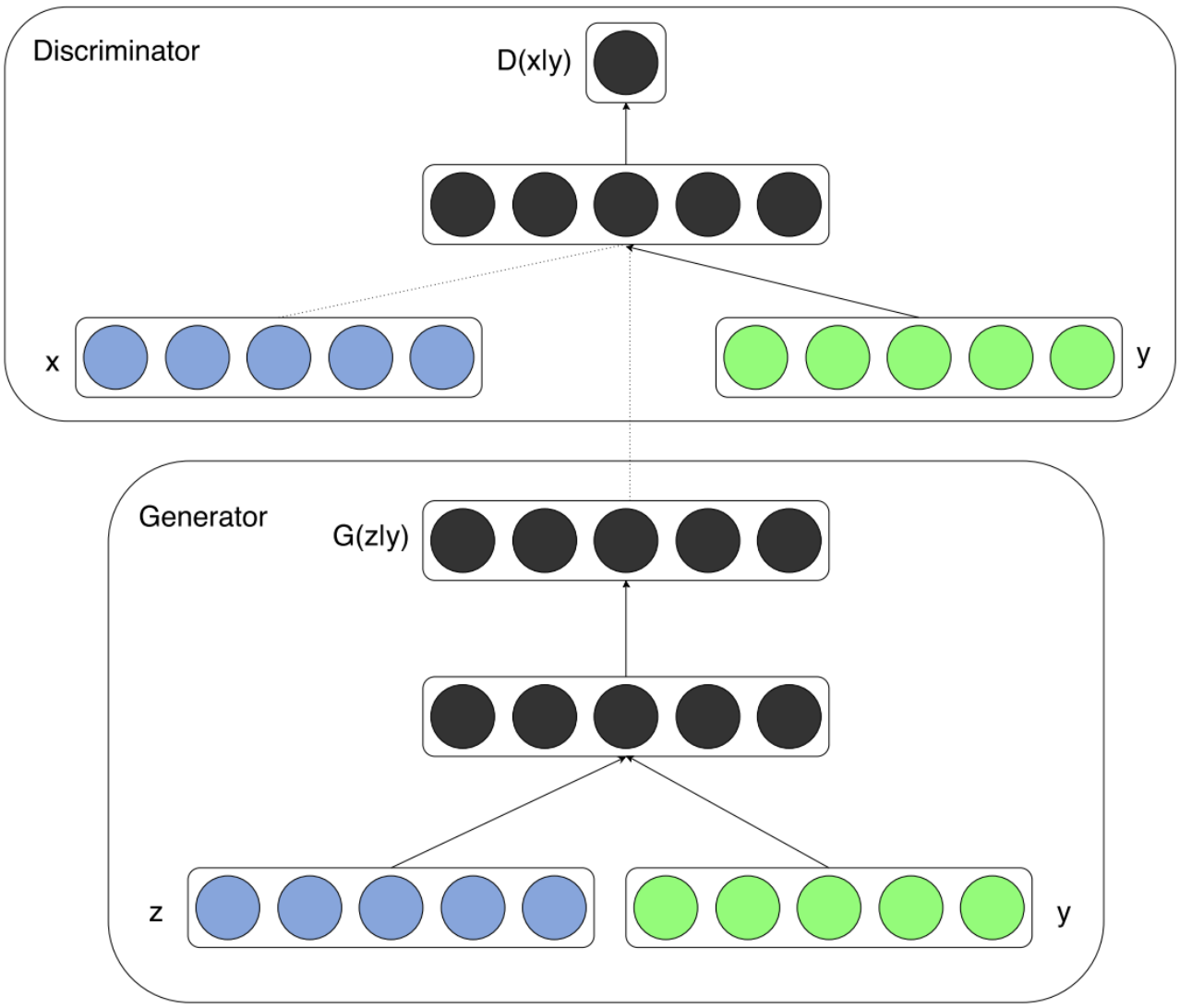
The cGAN was first described by Mehdi Mirza and Simon Osindero in their 2014 paper titled "Conditional Generative Adversarial Nets." In the paper, the authors motivate the approach based on the desire to direct the image generation process of the generator model.

> *… by conditioning the model on additional information it is possible to direct the data generation process. Such conditioning could be based on class labels*

— Conditional Generative Adversarial Nets, 2014.

Their approach is demonstrated in the MNIST handwritten digit dataset where the class labels are one hot encoded and concatenated with the input to both the generator and discriminator models.

The image below provides a summary of the model architecture.



Example of a Conditional Generator and a Conditional Discriminator in a Conditional Generative Adversarial Network. Taken from Conditional Generative Adversarial Nets, 2014.

There have been many advancements in the design and training of GAN models, most notably the deep convolutional GAN, or DCGAN for short, that outlines the model configuration and training procedures that reliably result in the stable training of GAN models for a wide variety of problems. The conditional training of the DCGAN-based models may be referred to as CDCGAN or cDCGAN for short.

There are many ways to encode and incorporate the class labels into the discriminator and generator models. A best practice involves using an embedding layer followed by a fully connected layer with a linear activation that scales the embedding to the size of the image before concatenating it in the model as an additional channel or feature map.

A version of this recommendation was described in the 2015 paper titled "Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks."

> *… we also explore a class conditional version of the model, where a vector c encodes the label. This is integrated into Gk & Dk by passing it through a linear layer whose output is*

reshaped into a single plane feature map which is then concatenated with the 1st layer maps.

— Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks, 2015.

This recommendation was later added to the 'GAN Hacks' list of heuristic recommendations when designing and training GAN models, summarized as:

> *16: Discrete variables in Conditional GANs*
> *– Use an Embedding layer*
> *– Add as additional channels to images*
> *– Keep embedding dimensionality low and upsample to match image channel size*

— GAN Hacks

Although GANs can be conditioned on the class label, so-called class-conditional GANs, they can also be conditioned on other inputs, such as an image, in the case where a GAN is used for image-to-image translation tasks.

In this tutorial, we will develop a GAN, specifically a DCGAN, then update it to use class labels in a cGAN, specifically a cDCGAN model architecture.

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Fashion-MNIST Clothing Photograph Dataset

The Fashion-MNIST dataset is proposed as a more challenging replacement dataset for the MNIST dataset.

It is a dataset comprised of 60,000 small square 28×28 pixel grayscale images of items of 10 types of clothing, such as shoes, t-shirts, dresses, and more.

Keras provides access to the Fashion-MNIST dataset via the fashion_mnist.load_dataset() function. It returns two tuples, one with the input and output elements for the standard training dataset, and another with the input and output elements for the standard test dataset.

The example below loads the dataset and summarizes the shape of the loaded dataset.

Note: the first time you load the dataset, Keras will automatically download a compressed version of the images and save them under your home directory in *~/.keras/datasets/*. The download is fast as the dataset is only about 25 megabytes in its compressed form.

```
# example of loading the fashion_mnist dataset
from keras.datasets.fashion_mnist import load_data
# load the images into memory
(trainX, trainy), (testX, testy) = load_data()
# summarize the shape of the dataset
print('Train', trainX.shape, trainy.shape)
print('Test', testX.shape, testy.shape)
```

Running the example loads the dataset and prints the shape of the input and output components of the train and test splits of images.

We can see that there are 60K examples in the training set and 10K in the test set and that each image is a square of 28 by 28 pixels.

```
Train (60000, 28, 28) (60000,)
Test (10000, 28, 28) (10000,)
```

The images are grayscale with a black background (0 pixel value) and the items of clothing are in white (pixel values near 255). This means if the images were plotted, they would be mostly black with a white item of clothing in the middle.

We can plot some of the images from the training dataset using the matplotlib library with the imshow() function and specify the color map via the '*cmap*' argument as '*gray*' to show the pixel values correctly.

```
# plot raw pixel data
pyplot.imshow(trainX[i], cmap='gray')
```

Alternately, the images are easier to review when we reverse the colors and plot the background as white and the clothing in black.

They are easier to view as most of the image is now white with the area of interest in black. This can be achieved using a reverse grayscale color map, as follows:

```
# plot raw pixel data
pyplot.imshow(trainX[i], cmap='gray_r')
```

The example below plots the first 100 images from the training dataset in a 10 by 10 square.

```
# example of loading the fashion_mnist dataset
from keras.datasets.fashion_mnist import load_data
from matplotlib import pyplot
# load the images into memory
(trainX, trainy), (testX, testy) = load_data()
# plot images from the training dataset
for i in range(100):
    # define subplot
    pyplot.subplot(10, 10, 1 + i)
    # turn off axis
    pyplot.axis('off')
    # plot raw pixel data
    pyplot.imshow(trainX[i], cmap='gray_r')
pyplot.show()
```

Running the example creates a figure with a plot of 100 images from the MNIST training dataset, arranged in a 10×10 square.

Plot of the First 100 Items of Clothing From the Fashion MNIST Dataset.

We will use the images in the training dataset as the basis for training a Generative Adversarial Network.

Specifically, the generator model will learn how to generate new plausible items of clothing using a discriminator that will try to distinguish between real images from the Fashion MNIST training dataset and new images output by the generator model.

This is a relatively simple problem that does not require a sophisticated generator or discriminator model, although it does require the generation of a grayscale output image.

Unconditional GAN for Fashion-MNIST

In this section, we will develop an unconditional GAN for the Fashion-MNIST dataset.

The first step is to define the models.

The discriminator model takes as input one 28×28 grayscale image and outputs a binary prediction as to whether the image is real (class=1) or fake (class=0). It is implemented as a modest convolutional neural network using best practices for GAN design such as using the LeakyReLU activation function with a slope of 0.2, using a 2×2 stride to downsample, and the adam version of stochastic gradient descent with a learning rate of 0.0002 and a momentum of 0.5

The define_discriminator() function below implements this, defining and compiling the discriminator model and returning it. The input shape of the image is parameterized as a default function argument in case you want to re-use the function for your own image data later.

```
# define the standalone discriminator model
def define_discriminator(in_shape=(28,28,1)):
    model = Sequential()
    # downsample
    model.add(Conv2D(128, (3,3), strides=(2,2), padding='same', input_shape=in_shape))
    model.add(LeakyReLU(alpha=0.2))
    # downsample
    model.add(Conv2D(128, (3,3), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    # classifier
    model.add(Flatten())
    model.add(Dropout(0.4))
    model.add(Dense(1, activation='sigmoid'))
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])
    return model
```

The generator model takes as input a point in the latent space and outputs a single 28×28 grayscale image. This is achieved by using a fully connected layer to interpret the point in the latent space and provide sufficient activations that can be reshaped into many copies (in this case 128) of a low-resolution version of the output image (e.g. 7×7). This is then upsampled twice, doubling the size and quadrupling the area of the activations each time using transpose convolutional layers. The model uses best practices such as the LeakyReLU activation, a kernel size that is a factor of the stride size, and a hyperbolic tangent (tanh) activation function in the output layer.

The *define_generator()* function below defines the generator model, but intentionally does not compile it as it is not trained directly, then returns the model. The size of the latent space is parameterized as a function argument.

```
# define the standalone generator model
def define_generator(latent_dim):
    model = Sequential()
    # foundation for 7x7 image
    n_nodes = 128 * 7 * 7
    model.add(Dense(n_nodes, input_dim=latent_dim))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Reshape((7, 7, 128)))
    # upsample to 14x14
    model.add(Conv2DTranspose(128, (4,4), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    # upsample to 28x28
    model.add(Conv2DTranspose(128, (4,4), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    # generate
    model.add(Conv2D(1, (7,7), activation='tanh', padding='same'))
    return model
```

Next, a GAN model can be defined that combines both the generator model and the discriminator model into one larger model. This larger model will be used to train the model weights in the generator, using the output and error calculated by the discriminator model. The discriminator model is trained separately, and as such, the model weights are marked as not trainable in this larger GAN model to ensure that only the weights of the generator model are updated. This change to the trainability of the discriminator weights only has an effect when training the combined GAN model, not when training the discriminator standalone.

This larger GAN model takes as input a point in the latent space, uses the generator model to generate an image which is fed as input to the discriminator model, then is output or classified as real or fake.

The *define_gan()* function below implements this, taking the already-defined generator and discriminator models as input.

```
# define the combined generator and discriminator model, for updating the generator
def define_gan(generator, discriminator):
    # make weights in the discriminator not trainable
    discriminator.trainable = False
    # connect them
    model = Sequential()
    # add generator
    model.add(generator)
    # add the discriminator
    model.add(discriminator)
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt)
    return model
```

Now that we have defined the GAN model, we need to train it. But, before we can train the model, we require input data.

The first step is to load and prepare the Fashion MNIST dataset. We only require the images in the training dataset. The images are black and white, therefore we must add an additional channel dimension to transform them to be three dimensional, as expected by the convolutional layers of our models. Finally, the pixel values must be scaled to the range [-1,1] to match the output of the generator model.

The *load_real_samples()* function below implements this, returning the loaded and scaled Fashion MNIST training dataset ready for modeling.

```
# load fashion mnist images
def load_real_samples():
    # load dataset
    (trainX, _), (_, _) = load_data()
    # expand to 3d, e.g. add channels
    X = expand_dims(trainX, axis=-1)
    # convert from ints to floats
    X = X.astype('float32')
    # scale from [0,255] to [-1,1]
    X = (X - 127.5) / 127.5
    return X
```

We will require one batch (or a half) batch of real images from the dataset each update to the GAN model. A simple way to achieve this is to select a random sample of images from the dataset each time.

The *generate_real_samples()* function below implements this, taking the prepared dataset as an argument, selecting and returning a random sample of Fashion MNIST images and their corresponding class label for the discriminator, specifically class=1, indicating that they are real images.

```
# select real samples
def generate_real_samples(dataset, n_samples):
    # choose random instances
    ix = randint(0, dataset.shape[0], n_samples)
    # select images
    X = dataset[ix]
    # generate class labels
    y = ones((n_samples, 1))
```

```
    return X, y
```

Next, we need inputs for the generator model. These are random points from the latent space, specifically Gaussian distributed random variables.

The *generate_latent_points()* function implements this, taking the size of the latent space as an argument and the number of points required and returning them as a batch of input samples for the generator model.

```
# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    x_input = x_input.reshape(n_samples, latent_dim)
    return x_input
```

Next, we need to use the points in the latent space as input to the generator in order to generate new images.

The *generate_fake_samples()* function below implements this, taking the generator model and size of the latent space as arguments, then generating points in the latent space and using them as input to the generator model. The function returns the generated images and their corresponding class label for the discriminator model, specifically class=0 to indicate they are fake or generated.

```
# use the generator to generate n fake examples, with class labels
def generate_fake_samples(generator, latent_dim, n_samples):
    # generate points in latent space
    x_input = generate_latent_points(latent_dim, n_samples)
    # predict outputs
    X = generator.predict(x_input)
    # create class labels
    y = zeros((n_samples, 1))
    return X, y
```

We are now ready to fit the GAN models.

The model is fit for 100 training epochs, which is arbitrary, as the model begins generating plausible items of clothing after perhaps 20 epochs. A batch size of 128 samples is used, and each training epoch involves 60,000/128, or about 468 batches of real and fake samples and updates to the model.

First, the discriminator model is updated for a half batch of real samples, then a half batch of fake samples, together forming one batch of weight updates. The generator is then updated via the composite gan model. Importantly, the class label is set to 1 or real for the fake samples. This has the effect of updating the generator toward getting better at generating real samples on the next batch.

The *train()* function below implements this, taking the defined models, dataset, and size of the latent dimension as arguments and parameterizing the number of epochs and batch size with default arguments. The generator model is saved at the end of training.

```
# train the generator and discriminator
def train(g_model, d_model, gan_model, dataset, latent_dim, n_epochs=100, n_batch=128):
    bat_per_epo = int(dataset.shape[0] / n_batch)
    half_batch = int(n_batch / 2)
    # manually enumerate epochs
    for i in range(n_epochs):
        # enumerate batches over the training set
        for j in range(bat_per_epo):
```

```
            # get randomly selected 'real' samples
            X_real, y_real = generate_real_samples(dataset, half_batch)
            # update discriminator model weights
            d_loss1, _ = d_model.train_on_batch(X_real, y_real)
            # generate 'fake' examples
            X_fake, y_fake = generate_fake_samples(g_model, latent_dim, half_batch)
            # update discriminator model weights
            d_loss2, _ = d_model.train_on_batch(X_fake, y_fake)
            # prepare points in latent space as input for the generator
            X_gan = generate_latent_points(latent_dim, n_batch)
            # create inverted labels for the fake samples
            y_gan = ones((n_batch, 1))
            # update the generator via the discriminator's error
            g_loss = gan_model.train_on_batch(X_gan, y_gan)
            # summarize loss on this batch
            print('>%d, %d/%d, d1=%.3f, d2=%.3f g=%.3f' %
                (i+1, j+1, bat_per_epo, d_loss1, d_loss2, g_loss))
    # save the generator model
    g_model.save('generator.h5')
```

We can then define the size of the latent space, define all three models, and train them on the loaded fashion MNIST dataset.

```
# size of the latent space
latent_dim = 100
# create the discriminator
discriminator = define_discriminator()
# create the generator
generator = define_generator(latent_dim)
# create the gan
gan_model = define_gan(generator, discriminator)
# load image data
dataset = load_real_samples()
# train model
train(generator, discriminator, gan_model, dataset, latent_dim)
```

Tying all of this together, the complete example is listed below.

```
# example of training an unconditional gan on the fashion mnist dataset
from numpy import expand_dims
from numpy import zeros
from numpy import ones
from numpy.random import randn
from numpy.random import randint
from keras.datasets.fashion_mnist import load_data
from keras.optimizers import Adam
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Reshape
from keras.layers import Flatten
from keras.layers import Conv2D
from keras.layers import Conv2DTranspose
from keras.layers import LeakyReLU
from keras.layers import Dropout

# define the standalone discriminator model
def define_discriminator(in_shape=(28,28,1)):
    model = Sequential()
    # downsample
    model.add(Conv2D(128, (3,3), strides=(2,2), padding='same', input_shape=in_shape))
    model.add(LeakyReLU(alpha=0.2))
    # downsample
    model.add(Conv2D(128, (3,3), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    # classifier
    model.add(Flatten())
    model.add(Dropout(0.4))
    model.add(Dense(1, activation='sigmoid'))
```

```
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])
    return model

# define the standalone generator model
def define_generator(latent_dim):
    model = Sequential()
    # foundation for 7x7 image
    n_nodes = 128 * 7 * 7
    model.add(Dense(n_nodes, input_dim=latent_dim))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Reshape((7, 7, 128)))
    # upsample to 14x14
    model.add(Conv2DTranspose(128, (4,4), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    # upsample to 28x28
    model.add(Conv2DTranspose(128, (4,4), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    # generate
    model.add(Conv2D(1, (7,7), activation='tanh', padding='same'))
    return model

# define the combined generator and discriminator model, for updating the generator
def define_gan(generator, discriminator):
    # make weights in the discriminator not trainable
    discriminator.trainable = False
    # connect them
    model = Sequential()
    # add generator
    model.add(generator)
    # add the discriminator
    model.add(discriminator)
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt)
    return model

# load fashion mnist images
def load_real_samples():
    # load dataset
    (trainX, _), (_, _) = load_data()
    # expand to 3d, e.g. add channels
    X = expand_dims(trainX, axis=-1)
    # convert from ints to floats
    X = X.astype('float32')
    # scale from [0,255] to [-1,1]
    X = (X - 127.5) / 127.5
    return X

# select real samples
def generate_real_samples(dataset, n_samples):
    # choose random instances
    ix = randint(0, dataset.shape[0], n_samples)
    # select images
    X = dataset[ix]
    # generate class labels
    y = ones((n_samples, 1))
    return X, y

# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    x_input = x_input.reshape(n_samples, latent_dim)
    return x_input

# use the generator to generate n fake examples, with class labels
```

```
def generate_fake_samples(generator, latent_dim, n_samples):
    # generate points in latent space
    x_input = generate_latent_points(latent_dim, n_samples)
    # predict outputs
    X = generator.predict(x_input)
    # create class labels
    y = zeros((n_samples, 1))
    return X, y

# train the generator and discriminator
def train(g_model, d_model, gan_model, dataset, latent_dim, n_epochs=100, n_batch=128):
    bat_per_epo = int(dataset.shape[0] / n_batch)
    half_batch = int(n_batch / 2)
    # manually enumerate epochs
    for i in range(n_epochs):
        # enumerate batches over the training set
        for j in range(bat_per_epo):
            # get randomly selected 'real' samples
            X_real, y_real = generate_real_samples(dataset, half_batch)
            # update discriminator model weights
            d_loss1, _ = d_model.train_on_batch(X_real, y_real)
            # generate 'fake' examples
            X_fake, y_fake = generate_fake_samples(g_model, latent_dim, half_batch)
            # update discriminator model weights
            d_loss2, _ = d_model.train_on_batch(X_fake, y_fake)
            # prepare points in latent space as input for the generator
            X_gan = generate_latent_points(latent_dim, n_batch)
            # create inverted labels for the fake samples
            y_gan = ones((n_batch, 1))
            # update the generator via the discriminator's error
            g_loss = gan_model.train_on_batch(X_gan, y_gan)
            # summarize loss on this batch
            print('>%d, %d/%d, d1=%.3f, d2=%.3f g=%.3f' %
                (i+1, j+1, bat_per_epo, d_loss1, d_loss2, g_loss))
    # save the generator model
    g_model.save('generator.h5')

# size of the latent space
latent_dim = 100
# create the discriminator
discriminator = define_discriminator()
# create the generator
generator = define_generator(latent_dim)
# create the gan
gan_model = define_gan(generator, discriminator)
# load image data
dataset = load_real_samples()
# train model
train(generator, discriminator, gan_model, dataset, latent_dim)
```

Running the example may take a long time on modest hardware.

I recommend running the example on GPU hardware. If you need help, you can get started quickly by using an AWS EC2 instance to train the model. See the tutorial:

- How to Setup Amazon AWS EC2 GPUs to Train Keras Deep Learning Models (step-by-step)

The loss for the discriminator on real and fake samples, as well as the loss for the generator, is reported after each batch.

Note: Your results may vary given the stochastic nature of the algorithm or evaluation procedure, or differences in numerical precision. Consider running the example a few times and compare the average outcome.

In this case, the discriminator and generator loss both sit around values of about 0.6 to 0.7 over the course of training.

```
...
>100, 464/468, d1=0.681, d2=0.685 g=0.693
>100, 465/468, d1=0.691, d2=0.700 g=0.703
>100, 466/468, d1=0.691, d2=0.703 g=0.706
>100, 467/468, d1=0.698, d2=0.699 g=0.699
>100, 468/468, d1=0.699, d2=0.695 g=0.708
```

At the end of training, the generator model will be saved to file with the filename '*generator.h5*'.

This model can be loaded and used to generate new random but plausible samples from the fashion MNIST dataset.

The example below loads the saved model and generates 100 random items of clothing.

```
# example of loading the generator model and generating images
from keras.models import load_model
from numpy.random import randn
from matplotlib import pyplot

# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    x_input = x_input.reshape(n_samples, latent_dim)
    return x_input

# create and save a plot of generated images (reversed grayscale)
def show_plot(examples, n):
    # plot images
    for i in range(n * n):
        # define subplot
        pyplot.subplot(n, n, 1 + i)
        # turn off axis
        pyplot.axis('off')
        # plot raw pixel data
        pyplot.imshow(examples[i, :, :, 0], cmap='gray_r')
    pyplot.show()

# load model
model = load_model('generator.h5')
# generate images
latent_points = generate_latent_points(100, 100)
# generate images
X = model.predict(latent_points)
# plot the result
show_plot(X, 10)
```

Running the example creates a plot of 100 randomly generated items of clothing arranged into a 10×10 grid.

Note: Your results may vary given the stochastic nature of the algorithm or evaluation procedure, or differences in numerical precision. Consider running the example a few times and compare the average outcome.

In this case, we can see an assortment of clothing items such as shoes, sweaters, and pants. Most items look quite plausible and could have come from the fashion MNIST dataset. They are not perfect, however, as there are some sweaters with a single sleeve and shoes that look like a mess.

Example of 100 Generated items of Clothing using an Unconditional GAN.

Conditional GAN for Fashion-MNIST

In this section, we will develop a conditional GAN for the Fashion-MNIST dataset by updating the unconditional GAN developed in the previous section.

The best way to design models in Keras to have multiple inputs is by using the Functional API, as opposed to the Sequential API used in the previous section. We will use the functional API to re-implement the discriminator, generator, and the composite model.

Starting with the discriminator model, a new second input is defined that takes an integer for the class label of the image. This has the effect of making the input image conditional on the provided class label.

The class label is then passed through an Embedding layer with the size of 50. This means that each of the 10 classes for the Fashion MNIST dataset (0 through 9) will map to a different 50-element vector representation that will be learned by the discriminator model.

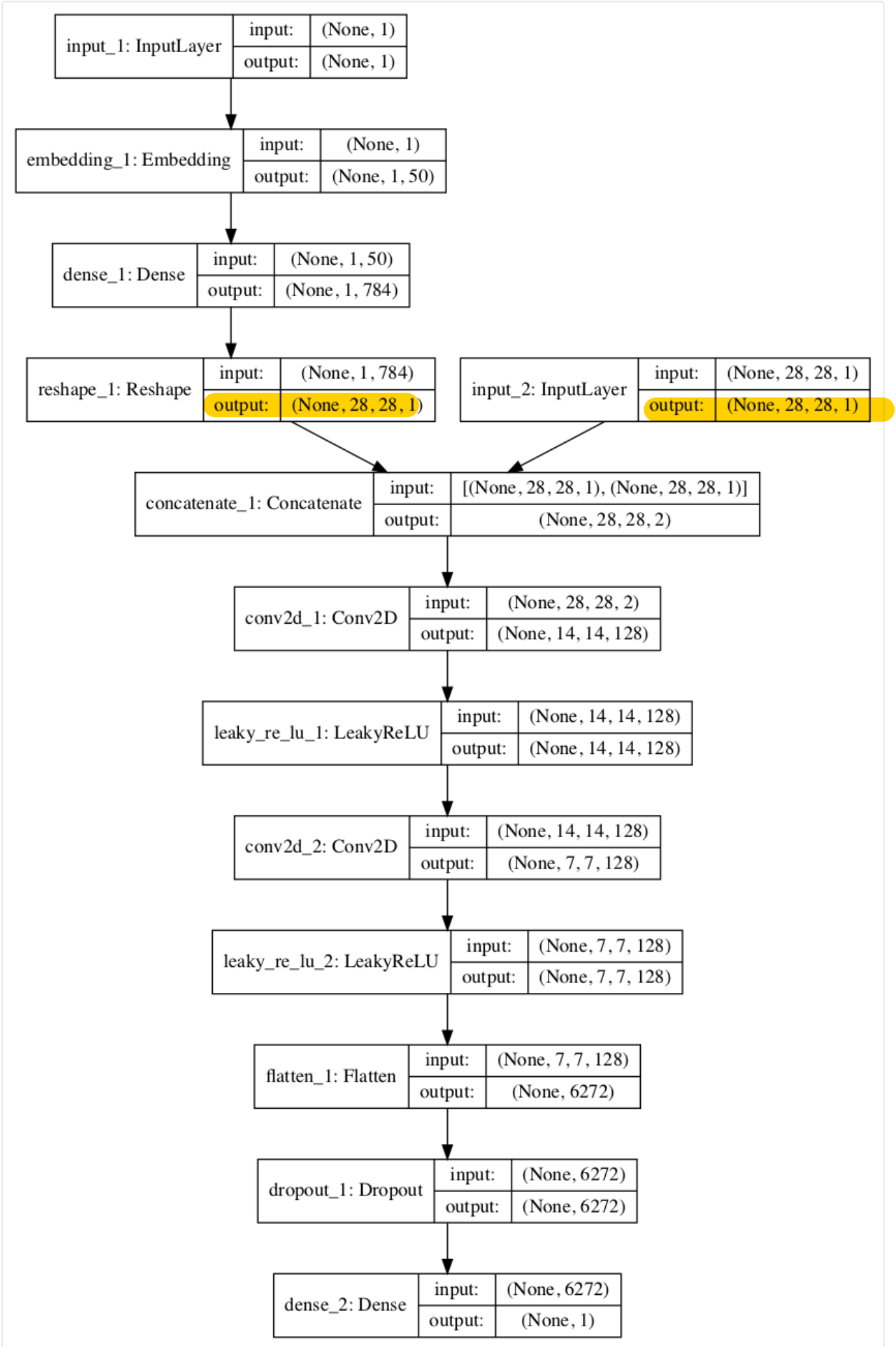
The output of the embedding is then passed to a fully connected layer with a linear activation. Importantly, the fully connected layer has enough activations that can be reshaped into one channel of a 28×28 image. The activations are reshaped into single 28×28 activation map and concatenated with the input image. This has the effect of looking like a two-channel input image to the next convolutional layer.

The *define_discriminator()* below implements this update to the discriminator model. The parameterized shape of the input image is also used after the embedding layer to define the number of activations for the fully connected layer to reshape its output. The number of classes in the problem is also parameterized in the function and set.

```
# define the standalone discriminator model
def define_discriminator(in_shape=(28,28,1), n_classes=10):
    # label input
    in_label = Input(shape=(1,))
    # embedding for categorical input
    li = Embedding(n_classes, 50)(in_label)
    # scale up to image dimensions with linear activation
    n_nodes = in_shape[0] * in_shape[1]
    li = Dense(n_nodes)(li)
    # reshape to additional channel
    li = Reshape((in_shape[0], in_shape[1], 1))(li)
    # image input
    in_image = Input(shape=in_shape)
    # concat label as a channel
    merge = Concatenate()([in_image, li])
    # downsample
    fe = Conv2D(128, (3,3), strides=(2,2), padding='same')(merge)
    fe = LeakyReLU(alpha=0.2)(fe)
    # downsample
    fe = Conv2D(128, (3,3), strides=(2,2), padding='same')(fe)
    fe = LeakyReLU(alpha=0.2)(fe)
    # flatten feature maps
    fe = Flatten()(fe)
    # dropout
    fe = Dropout(0.4)(fe)
    # output
    out_layer = Dense(1, activation='sigmoid')(fe)
    # define model
    model = Model([in_image, in_label], out_layer)
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])
    return model
```

In order to make the architecture clear, below is a plot of the discriminator model.

The plot shows the two inputs: first the class label that passes through the embedding (left) and the image (right), and their concatenation into a two-channel 28×28 image or feature map (middle). The rest of the model is the same as the discriminator designed in the previous section.


input_1: InputLayer
input: (None, 1)
output: (None, 1)
embedding_1: Embedding
input: (None, 1)
output: (None, 1, 50)
dense_1: Dense
input: (None, 1, 50)
output: (None, 1, 784)
reshape_1: Reshape
input: (None, 1, 784)
output: (None, 28, 28, 1)
input_2: InputLayer
input: (None, 28, 28, 1)
output: (None, 28, 28, 1)
concatenate_1: Concatenate
input: [(None, 28, 28, 1), (None, 28, 28, 1)]
output: (None, 28, 28, 2)
conv2d_1: Conv2D
input: (None, 28, 28, 2)
output: (None, 14, 14, 128)
leaky_re_lu_1: LeakyReLU
input: (None, 14, 14, 128)
output: (None, 14, 14, 128)
conv2d_2: Conv2D
input: (None, 14, 14, 128)
output: (None, 7, 7, 128)
leaky_re_lu_2: LeakyReLU
input: (None, 7, 7, 128)
output: (None, 7, 7, 128)
flatten_1: Flatten
input: (None, 7, 7, 128)
output: (None, 6272)
dropout_1: Dropout
input: (None, 6272)
output: (None, 6272)
dense_2: Dense
input: (None, 6272)
output: (None, 1)

Plot of the Discriminator Model in the Conditional Generative Adversarial Network

Next, the generator model must be updated to take the class label. This has the effect of making the point in the latent space conditional on the provided class label.

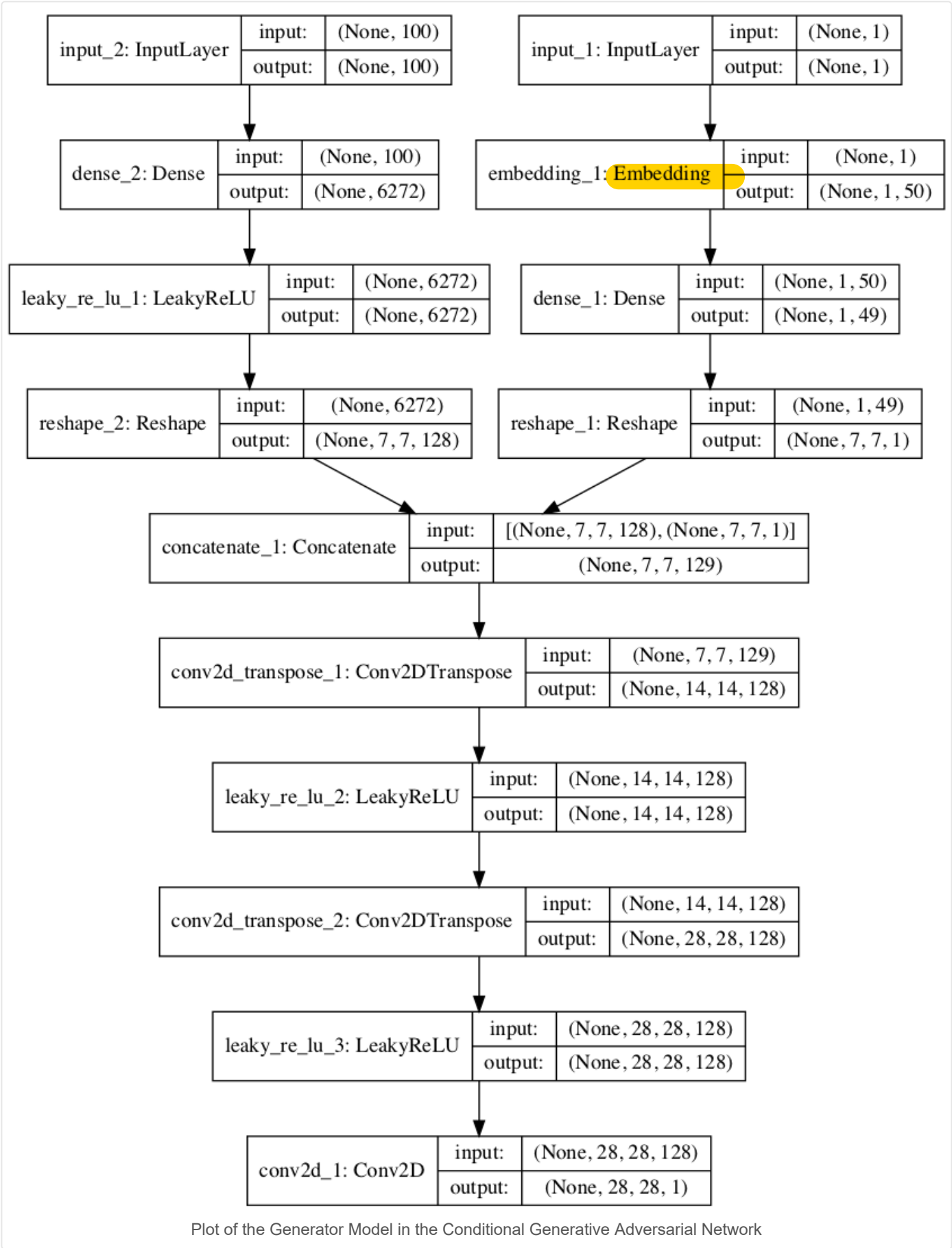
As in the discriminator, the class label is passed through an embedding layer to map it to a unique 50-element vector and is then passed through a fully connected layer with a linear activation before being resized. In this case, the activations of the fully connected layer are resized into a single 7×7 feature map. This is to match the 7×7 feature map activations of the unconditional generator model. The new 7×7 feature map is added as one more channel to the existing 128, resulting in 129 feature maps that are then upsampled as in the prior model.

The *define_generator()* function below implements this, again parameterizing the number of classes as we did with the discriminator model.

```
# define the standalone generator model
def define_generator(latent_dim, n_classes=10):
    # label input
    in_label = Input(shape=(1,))
    # embedding for categorical input
    li = Embedding(n_classes, 50)(in_label)
    # linear multiplication
    n_nodes = 7 * 7
    li = Dense(n_nodes)(li)
    # reshape to additional channel
    li = Reshape((7, 7, 1))(li)
    # image generator input
    in_lat = Input(shape=(latent_dim,))
    # foundation for 7x7 image
    n_nodes = 128 * 7 * 7
    gen = Dense(n_nodes)(in_lat)
    gen = LeakyReLU(alpha=0.2)(gen)
    gen = Reshape((7, 7, 128))(gen)
    # merge image gen and label input
    merge = Concatenate()([gen, li])
    # upsample to 14x14
    gen = Conv2DTranspose(128, (4,4), strides=(2,2), padding='same')(merge)
    gen = LeakyReLU(alpha=0.2)(gen)
    # upsample to 28x28
    gen = Conv2DTranspose(128, (4,4), strides=(2,2), padding='same')(gen)
    gen = LeakyReLU(alpha=0.2)(gen)
    # output
    out_layer = Conv2D(1, (7,7), activation='tanh', padding='same')(gen)
    # define model
    model = Model([in_lat, in_label], out_layer)
    return model
```

To help understand the new model architecture, the image below provides a plot of the new conditional generator model.

In this case, you can see the 100-element point in latent space as input and subsequent resizing (left) and the new class label input and embedding layer (right), then the concatenation of the two sets of feature maps (center). The remainder of the model is the same as the unconditional case.



Plot of the Generator Model in the Conditional Generative Adversarial Network

Finally, the composite GAN model requires updating.

The new GAN model will take a point in latent space as input and a class label and generate a prediction of whether input was real or fake, as before.

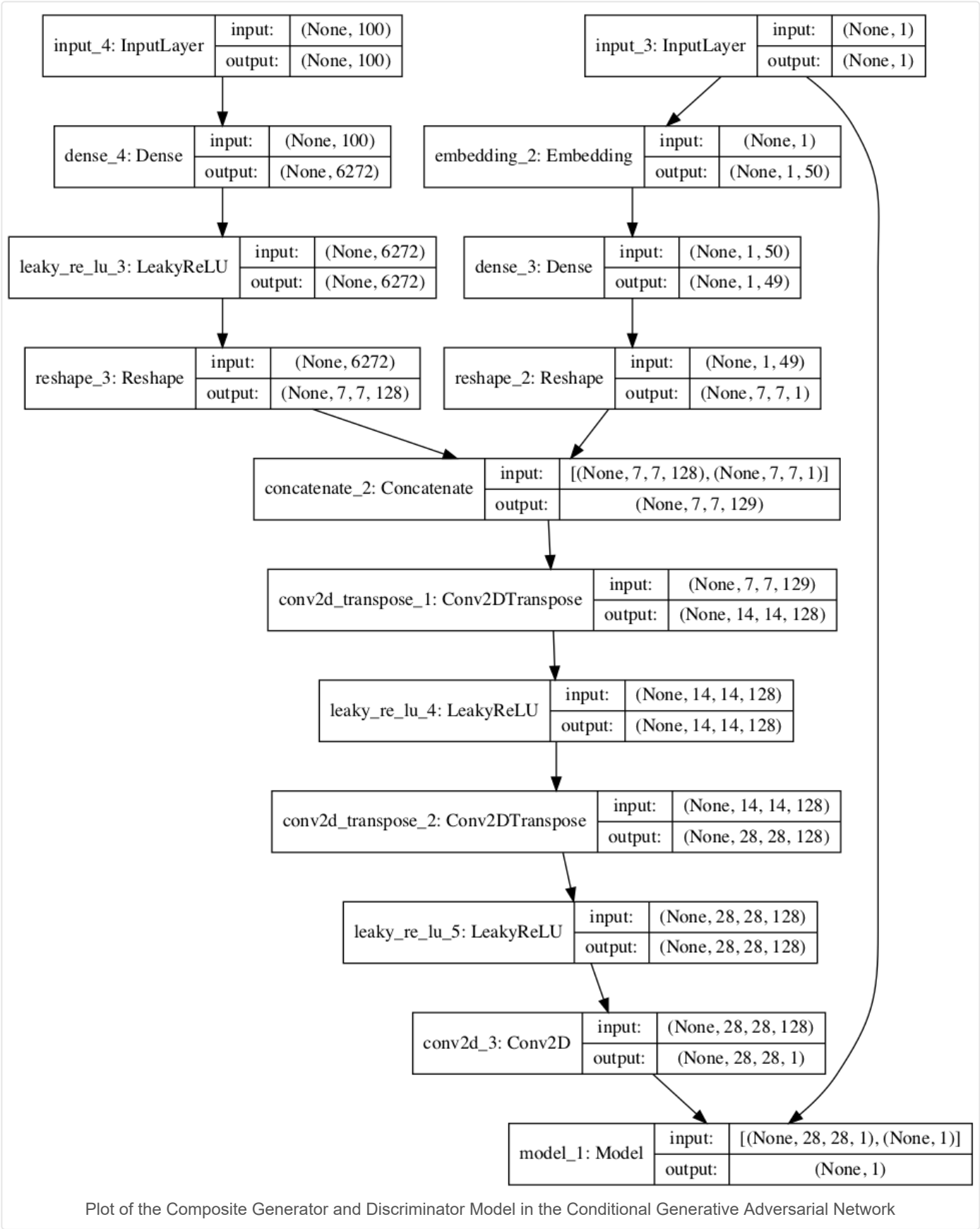
Using the functional API to design the model, it is important that we explicitly connect the image generated output from the generator as well as the class label input, both as input to the discriminator model. This allows the same class label input to flow down into the generator and down into the discriminator.

The *define_gan()* function below implements the conditional version of the GAN.

```
# define the combined generator and discriminator model, for updating the generator
def define_gan(g_model, d_model):
    # make weights in the discriminator not trainable
    d_model.trainable = False
    # get noise and label inputs from generator model
    gen_noise, gen_label = g_model.input
    # get image output from the generator model
    gen_output = g_model.output
    # connect image output and label input from generator as inputs to discriminator
    gan_output = d_model([gen_output, gen_label])
    # define gan model as taking noise and label and outputting a classification
    model = Model([gen_noise, gen_label], gan_output)
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt)
    return model
```

The plot below summarizes the composite GAN model.

Importantly, it shows the generator model in full with the point in latent space and class label as input, and the connection of the output of the generator and the same class label as input to the discriminator model (last box at the bottom of the plot) and the output of a single class label classification of real or fake.



Plot of the Composite Generator and Discriminator Model in the Conditional Generative Adversarial Network

The hard part of the conversion from unconditional to conditional GAN is done, namely the definition and configuration of the model architecture.

Next, all that remains is to update the training process to also use class labels.

First, the *load_real_samples()* and *generate_real_samples()* functions for loading the dataset and selecting a batch of samples respectively must be updated to make use of the real class labels from the

training dataset. Importantly, the *generate_real_samples()* function now returns images, clothing labels, and the class label for the discriminator (class=1).

```
# load fashion mnist images
def load_real_samples():
    # load dataset
    (trainX, trainy), (_, _) = load_data()
    # expand to 3d, e.g. add channels
    X = expand_dims(trainX, axis=-1)
    # convert from ints to floats
    X = X.astype('float32')
    # scale from [0,255] to [-1,1]
    X = (X - 127.5) / 127.5
    return [X, trainy]

# select real samples
def generate_real_samples(dataset, n_samples):
    # split into images and labels
    images, labels = dataset
    # choose random instances
    ix = randint(0, images.shape[0], n_samples)
    # select images and labels
    X, labels = images[ix], labels[ix]
    # generate class labels
    y = ones((n_samples, 1))
    return [X, labels], y
```

Next, the *generate_latent_points()* function must be updated to also generate an array of randomly selected integer class labels to go along with the randomly selected points in the latent space.

Then the *generate_fake_samples()* function must be updated to use these randomly generated class labels as input to the generator model when generating new fake images.

```
# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples, n_classes=10):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    z_input = x_input.reshape(n_samples, latent_dim)
    # generate labels
    labels = randint(0, n_classes, n_samples)
    return [z_input, labels]

# use the generator to generate n fake examples, with class labels
def generate_fake_samples(generator, latent_dim, n_samples):
    # generate points in latent space
    z_input, labels_input = generate_latent_points(latent_dim, n_samples)
    # predict outputs
    images = generator.predict([z_input, labels_input])
    # create class labels
    y = zeros((n_samples, 1))
    return [images, labels_input], y
```

Finally, the *train()* function must be updated to retrieve and use the class labels in the calls to updating the discriminator and generator models.

```
# train the generator and discriminator
def train(g_model, d_model, gan_model, dataset, latent_dim, n_epochs=100, n_batch=128):
    bat_per_epo = int(dataset[0].shape[0] / n_batch)
    half_batch = int(n_batch / 2)
    # manually enumerate epochs
    for i in range(n_epochs):
        # enumerate batches over the training set
        for j in range(bat_per_epo):
            # get randomly selected 'real' samples
```

```
            [X_real, labels_real], y_real = generate_real_samples(dataset, half_batch)
            # update discriminator model weights
            d_loss1, _ = d_model.train_on_batch([X_real, labels_real], y_real)
            # generate 'fake' examples
            [X_fake, labels], y_fake = generate_fake_samples(g_model, latent_dim, half_batch)
            # update discriminator model weights
            d_loss2, _ = d_model.train_on_batch([X_fake, labels], y_fake)
            # prepare points in latent space as input for the generator
            [z_input, labels_input] = generate_latent_points(latent_dim, n_batch)
            # create inverted labels for the fake samples
            y_gan = ones((n_batch, 1))
            # update the generator via the discriminator's error
            g_loss = gan_model.train_on_batch([z_input, labels_input], y_gan)
            # summarize loss on this batch
            print('>%d, %d/%d, d1=%.3f, d2=%.3f g=%.3f' %
                (i+1, j+1, bat_per_epo, d_loss1, d_loss2, g_loss))
    # save the generator model
    g_model.save('cgan_generator.h5')
```

Tying all of this together, the complete example of a conditional deep convolutional generative adversarial network for the Fashion MNIST dataset is listed below.

```
# example of training an conditional gan on the fashion mnist dataset
from numpy import expand_dims
from numpy import zeros
from numpy import ones
from numpy.random import randn
from numpy.random import randint
from keras.datasets.fashion_mnist import load_data
from keras.optimizers import Adam
from keras.models import Model
from keras.layers import Input
from keras.layers import Dense
from keras.layers import Reshape
from keras.layers import Flatten
from keras.layers import Conv2D
from keras.layers import Conv2DTranspose
from keras.layers import LeakyReLU
from keras.layers import Dropout
from keras.layers import Embedding
from keras.layers import Concatenate

# define the standalone discriminator model
def define_discriminator(in_shape=(28,28,1), n_classes=10):
    # label input
    in_label = Input(shape=(1,))
    # embedding for categorical input
    li = Embedding(n_classes, 50)(in_label)
    # scale up to image dimensions with linear activation
    n_nodes = in_shape[0] * in_shape[1]
    li = Dense(n_nodes)(li)
    # reshape to additional channel
    li = Reshape((in_shape[0], in_shape[1], 1))(li)
    # image input
    in_image = Input(shape=in_shape)
    # concat label as a channel
    merge = Concatenate()([in_image, li])
    # downsample
    fe = Conv2D(128, (3,3), strides=(2,2), padding='same')(merge)
    fe = LeakyReLU(alpha=0.2)(fe)
    # downsample
    fe = Conv2D(128, (3,3), strides=(2,2), padding='same')(fe)
    fe = LeakyReLU(alpha=0.2)(fe)
    # flatten feature maps
    fe = Flatten()(fe)
    # dropout
    fe = Dropout(0.4)(fe)
    # output
```

```
    out_layer = Dense(1, activation='sigmoid')(fe)
    # define model
    model = Model([in_image, in_label], out_layer)
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])
    return model

# define the standalone generator model
def define_generator(latent_dim, n_classes=10):
    # label input
    in_label = Input(shape=(1,))
    # embedding for categorical input
    li = Embedding(n_classes, 50)(in_label)
    # linear multiplication
    n_nodes = 7 * 7
    li = Dense(n_nodes)(li)
    # reshape to additional channel
    li = Reshape((7, 7, 1))(li)
    # image generator input
    in_lat = Input(shape=(latent_dim,))
    # foundation for 7x7 image
    n_nodes = 128 * 7 * 7
    gen = Dense(n_nodes)(in_lat)
    gen = LeakyReLU(alpha=0.2)(gen)
    gen = Reshape((7, 7, 128))(gen)
    # merge image gen and label input
    merge = Concatenate()([gen, li])
    # upsample to 14x14
    gen = Conv2DTranspose(128, (4,4), strides=(2,2), padding='same')(merge)
    gen = LeakyReLU(alpha=0.2)(gen)
    # upsample to 28x28
    gen = Conv2DTranspose(128, (4,4), strides=(2,2), padding='same')(gen)
    gen = LeakyReLU(alpha=0.2)(gen)
    # output
    out_layer = Conv2D(1, (7,7), activation='tanh', padding='same')(gen)
    # define model
    model = Model([in_lat, in_label], out_layer)
    return model

# define the combined generator and discriminator model, for updating the generator
def define_gan(g_model, d_model):
    # make weights in the discriminator not trainable
    d_model.trainable = False
    # get noise and label inputs from generator model
    gen_noise, gen_label = g_model.input
    # get image output from the generator model
    gen_output = g_model.output
    # connect image output and label input from generator as inputs to discriminator
    gan_output = d_model([gen_output, gen_label])
    # define gan model as taking noise and label and outputting a classification
    model = Model([gen_noise, gen_label], gan_output)
    # compile model
    opt = Adam(lr=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt)
    return model

# load fashion mnist images
def load_real_samples():
    # load dataset
    (trainX, trainy), (_, _) = load_data()
    # expand to 3d, e.g. add channels
    X = expand_dims(trainX, axis=-1)
    # convert from ints to floats
    X = X.astype('float32')
    # scale from [0,255] to [-1,1]
    X = (X - 127.5) / 127.5
    return [X, trainy]

```

```
# # select real samples
def generate_real_samples(dataset, n_samples):
    # split into images and labels
    images, labels = dataset
    # choose random instances
    ix = randint(0, images.shape[0], n_samples)
    # select images and labels
    X, labels = images[ix], labels[ix]
    # generate class labels
    y = ones((n_samples, 1))
    return [X, labels], y

# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples, n_classes=10):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    z_input = x_input.reshape(n_samples, latent_dim)
    # generate labels
    labels = randint(0, n_classes, n_samples)
    return [z_input, labels]

# use the generator to generate n fake examples, with class labels
def generate_fake_samples(generator, latent_dim, n_samples):
    # generate points in latent space
    z_input, labels_input = generate_latent_points(latent_dim, n_samples)
    # predict outputs
    images = generator.predict([z_input, labels_input])
    # create class labels
    y = zeros((n_samples, 1))
    return [images, labels_input], y

# train the generator and discriminator
def train(g_model, d_model, gan_model, dataset, latent_dim, n_epochs=100, n_batch=128):
    bat_per_epo = int(dataset[0].shape[0] / n_batch)
    half_batch = int(n_batch / 2)
    # manually enumerate epochs
    for i in range(n_epochs):
        # enumerate batches over the training set
        for j in range(bat_per_epo):
            # get randomly selected 'real' samples
            [X_real, labels_real], y_real = generate_real_samples(dataset, half_batch)
            # update discriminator model weights
            d_loss1, _ = d_model.train_on_batch([X_real, labels_real], y_real)
            # generate 'fake' examples
            [X_fake, labels], y_fake = generate_fake_samples(g_model, latent_dim, half_bat
            # update discriminator model weights
            d_loss2, _ = d_model.train_on_batch([X_fake, labels], y_fake)
            # prepare points in latent space as input for the generator
            [z_input, labels_input] = generate_latent_points(latent_dim, n_batch)
            # create inverted labels for the fake samples
            y_gan = ones((n_batch, 1))
            # update the generator via the discriminator's error
            g_loss = gan_model.train_on_batch([z_input, labels_input], y_gan)
            # summarize loss on this batch
            print('>%d, %d/%d, d1=%.3f, d2=%.3f g=%.3f' %
                (i+1, j+1, bat_per_epo, d_loss1, d_loss2, g_loss))
    # save the generator model
    g_model.save('cgan_generator.h5')

# size of the latent space
latent_dim = 100
# create the discriminator
d_model = define_discriminator()
# create the generator
g_model = define_generator(latent_dim)
# create the gan
gan_model = define_gan(g_model, d_model)
# load image data
```

```
dataset = load_real_samples()
# train model
train(g_model, d_model, gan_model, dataset, latent_dim)
```

Running the example may take some time, and GPU hardware is recommended, but not required.

At the end of the run, the model is saved to the file with name '*cgan_generator.h5*'.

Conditional Clothing Generation

In this section, we will use the trained generator model to conditionally generate new photos of items of clothing.

We can update our code example for generating new images with the model to now generate images conditional on the class label. We can generate 10 examples for each class label in columns.

The complete example is listed below.

```
# example of loading the generator model and generating images
from numpy import asarray
from numpy.random import randn
from numpy.random import randint
from keras.models import load_model
from matplotlib import pyplot

# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples, n_classes=10):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    z_input = x_input.reshape(n_samples, latent_dim)
    # generate labels
    labels = randint(0, n_classes, n_samples)
    return [z_input, labels]

# create and save a plot of generated images
def save_plot(examples, n):
    # plot images
    for i in range(n * n):
        # define subplot
        pyplot.subplot(n, n, 1 + i)
        # turn off axis
        pyplot.axis('off')
        # plot raw pixel data
        pyplot.imshow(examples[i, :, :, 0], cmap='gray_r')
    pyplot.show()

# load model
model = load_model('cgan_generator.h5')
# generate images
latent_points, labels = generate_latent_points(100, 100)
# specify labels
labels = asarray([x for _ in range(10) for x in range(10)])
# generate images
X  = model.predict([latent_points, labels])
# scale from [-1,1] to [0,1]
X = (X + 1) / 2.0
# plot the result
save_plot(X, 10)
```

Running the example loads the saved conditional GAN model and uses it to generate 100 items of clothing.

The clothing is organized in columns. From left to right, they are "*t-shirt*", '*trouser*', '*pullover*', '*dress*', '*coat*', '*sandal*', '*shirt*', '*sneaker*', '*bag*', and '*ankle boot*'.

We can see not only are the randomly generated items of clothing plausible, but they also match their expected category.

Example of 100 Generated items of Clothing using a Conditional GAN.

Extensions

This section lists some ideas for extending the tutorial that you may wish to explore.

- **Latent Space Size**. Experiment by varying the size of the latent space and review the impact on the quality of generated images.
- **Embedding Size**. Experiment by varying the size of the class label embedding, making it smaller or larger, and review the impact on the quality of generated images.
- **Alternate Architecture**. Update the model architecture to concatenate the class label elsewhere in the generator and/or discriminator model, perhaps with different dimensionality, and review the impact on the quality of generated images.

If you explore any of these extensions, I'd love to know.
Post your findings in the comments below.

Further Reading

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

Posts

- Chapter 20. Deep Generative Models, Deep Learning, 2016.
- Chapter 8. Generative Deep Learning, Deep Learning with Python, 2017.

Papers

- Generative Adversarial Networks, 2014.
- Tutorial: Generative Adversarial Networks, NIPS, 2016.
- Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, 2015
- Conditional Generative Adversarial Nets, 2014.
- Image-To-Image Translation With Conditional Adversarial Networks, 2017.
- Conditional Generative Adversarial Nets For Convolutional Face Generation, 2015.

API

- Keras Datasets API.
- Keras Sequential Model API
- Keras Convolutional Layers API
- How can I “freeze” Keras layers?
- MatplotLib API
- NumPy Random sampling (numpy.random) API
- NumPy Array manipulation routines

Articles

- How to Train a GAN? Tips and tricks to make GANs work
- Fashion-MNIST Project, GitHub.
- Training a Conditional DC-GAN on CIFAR-10 (code), 2018.
- GAN: From Zero to Hero Part 2 Conditional Generation by GAN, 2018.
- Keras-GAN Project. Keras implementations of Generative Adversarial Networks, GitHub.
- Conditional Deep Convolutional GAN (CDCGAN) – Keras Implementation, GitHub.

Summary

In this tutorial, you discovered how to develop a conditional generative adversarial network for the targeted generation of items of clothing.

Specifically, you learned:

- The limitations of generating random samples with a GAN that can be overcome with a conditional generative adversarial network.
- How to develop and evaluate an unconditional generative adversarial network for generating photos of items of clothing.
- How to develop and evaluate a conditional generative adversarial network for generating photos of items of clothing.

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

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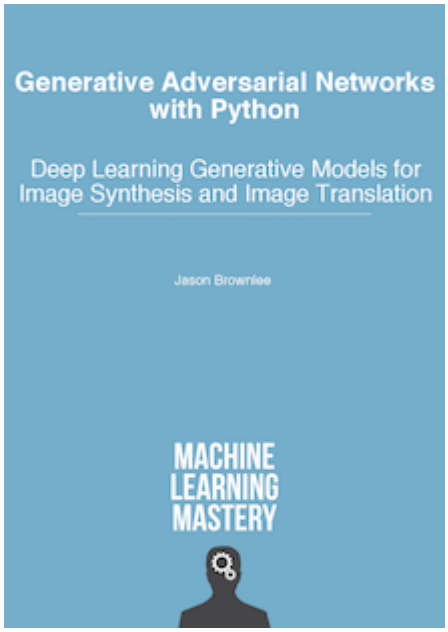

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About Jason Brownlee

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 →

‹ How to Explore the GAN Latent Space When Generating Faces
How to Identify and Diagnose GAN Failure Modes ›

127 Responses to *How to Develop a Conditional GAN (cGAN) From Scratch*

Keith Beaudoin July 5, 2019 at 8:52 am #

REPLY

cool ty.

Jason Brownlee July 5, 2019 at 8:54 am #

REPLY

Thanks Keith.

Shravan Kumar Parunandula July 5, 2019 at 11:47 am #

REPLY

This is fantastic. Thanks for disseminating great knowledge.

What if I wanted to train the discriminator as well, as we are only training generator in the current model. Please correct me if I am wrong.

Help me understand how many samples it requires to train a generator, for it to generate new samples that resembles original distribution. Is there any constraint on minimum number of input samples for gans.

Thanks
Shravan

Jason Brownlee July 6, 2019 at 8:19 am #

REPLY

No, both the generator and discriminator are trained at the same time.

There is great work with the semi-supervised GAN on training a classifier with very few real samples.

Shabnam July 7, 2019 at 9:40 pm #

REPLY

Nice blog.
Do you have any blog on deployment of pytorch or tensorflow based gan model on Android?
I am desperately in need of it.

Jason Brownlee July 8, 2019 at 8:41 am #

REPLY

No, sorry.

Raja August 9, 2020 at 1:04 am #

REPLY

Hi Jason , But you are setting the discriminator weights trainable as False
# make weights in the discriminator not trainable
d_model.trainable = False

I don’t understand it now .

Jason Brownlee August 9, 2020 at 5:45 am #

REPLY

Only in the context of the composite model.

To learn more about freezing weights in different contexts, see:

– How can I freeze layers and do fine-tuning?
https://keras.io/getting_started/faq/

Ken July 5, 2019 at 1:01 pm #

REPLY

A ton of great blog posts! I'm really excited for your book on GAN's. I think bugged you about writing one a couple years ago! – A fan of your books.

Jason Brownlee July 6, 2019 at 8:21 am #

REPLY

Thanks! And thanks for bugging me Ken!

I'm really excited about it.

Partha S July 5, 2019 at 4:23 pm #

REPLY

Ken

Request you to put the title of the book here please

Regards
Partha

Jason Brownlee July 6, 2019 at 8:24 am #

REPLY

Ken is referring to my upcoming book on GANs.

The title will be "Generative Adversarial Networks with Python".

It should be available in a week or two.

Hitarth July 5, 2019 at 6:24 pm #

REPLY

I didn't understand that how the generator will produce good results while training composite unconscious GAN by passing ones as output label, shouldn't it be zeros?

Hitarth July 5, 2019 at 6:25 pm #

REPLY

In the unconditional GAN training.

Jason Brownlee July 6, 2019 at 8:31 am #

REPLY

The unconditional GAN is trained.

Perhaps I don't understand your question?

Jason Brownlee July 6, 2019 at 8:31 am #

REPLY

It is crazy stuff.

Basically, we are training the generator to fool the discriminator, and in this case, the generator is conditional on the specific class label. The discriminator causes the discriminator to associate specific generated images with class labels.

If this is all new to you, perhaps start here:
https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/

Yasser March 22, 2020 at 2:14 am #

REPLY

Hello sir ,
I really appreciate your work .I have a question,I want to work with this technique but as an input I have an Image and then I feed it to the generator to have another image and then feed it to the descriminator but the problem is all tutorials are starting from a random input .
Do you have any blog or code you can help me with

Jason Brownlee March 22, 2020 at 6:58 am #

REPLY

It sounds like you might be interested in image to image translation.

This will help:
https://machinelearningmastery.com/a-gentle-introduction-to-pix2pix-generative-adversarial-network/

Howard July 12, 2019 at 9:31 am #

REPLY

Great article, thank you! I have two questions.

First, you use an embedding layer on the labels in both the discriminator and generator. I don't see what the embedding is doing for you. With just 10 labels, why is a 50-dimensional vector any more useful than a normal one-hot vector (after all, the ten one-hot vectors are orthonormal, so they're as distinct as can be). So what is the algorithmic motivation for having an embedding layer?

Second, why then follow that with a dense layer? Again, the one-hot label vectors seem to be all we need, but here we've already turned them into 50-dimensional vectors. What necessary job is the dense layer accomplishing?

Thank you!

REPLY

Jason Brownlee July 13, 2019 at 6:47 am #

Great questions.

The embedding layer provides a projection of the class label, a distributed representation that can be used to condition the image generation and classification.

The distributed representation can be scaled up and inserted nicely into the model as a filter map like structure.

There are other ways of getting the class label into the model, but this approach is reported to be more effective. Why? That's a hard question and might be intractable right now. Most of the GAN finding are empirical.

Try the alternate of just a one hot encoded vector concat with the z for G and a secondary input for D and compare results.

REPLY

M October 23, 2019 at 11:13 am #

Hi Jason,

Thank you for this very useful and detailed. Do you have any references that explain the embedding idea more thoroughly, or can you offer any more intuition? I understand why you might use an embedding for words/sentences as there is an idea of semantic similarity there, but not following why in a dataset like this (or simple MNIST) an embedding layer makes sense. Is it effectively just a way of reshaping the one-hot? Thanks!

REPLY

Jason Brownlee October 23, 2019 at 1:49 pm #

An embedding is an alternate to one hot encoding for categorical data.

It is popular for words, but can be used for any categorical or ordinal data.

REPLY

Chuanliang Jiang July 14, 2019 at 7:56 am #

In unconditional GAN codes, why discriminator model weights can be updated separately for exclusive real and fake sample ?

```
# update discriminator model weights
d_loss1, _ = d_model.train_on_batch(X_real, y_real)
```

```
# update discriminator model weights
d_loss2, _ = d_model.train_on_batch(X_fake, y_fake)
```

Basically discriminator is binary classification. If all samples are real (=1) or faked(=0) exclusively , the binary classification is unable to be converged. Why not combined X_real and X_fake together and then input the sample into discriminator which will classify real and faked sample, e.g.

d_loss, _ = d_model.train_on_batch([X_real, X_fake], [y_real, y_fake])

Jason Brownlee July 14, 2019 at 8:19 am #

REPLY

You can, but it has been reported that separate batch updates keep the D model stable with respect to the performance of the generator (e.g. it does not get better – faster).

More here:
https://machinelearningmastery.com/how-to-code-generative-adversarial-network-hacks/

Kristof August 30, 2019 at 12:02 am #

REPLY

Thanks for the very useful tutorial!
I always get these kind of warnings:

“W0829 11:18:47.925395 14568 training.py:2197] Discrepancy between trainable weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?”

Does it mean I did something different, or is this something you see as well. The model runs, so does it matter?

Jason Brownlee August 30, 2019 at 6:25 am #

REPLY

You can safely ignore that warning – we are abusing Keras a little 🙂

Yue September 8, 2019 at 10:42 pm #

REPLY

Hi Janson, very nice tutorial< I was stuck somewhere when running your code:

we define "define_discriminator(in_shape=(28,28,1))" with shape (28,28,1), and then we call it to do "d_model.train_on_batch(X_real, y_real)", where the sample size is 64 (error message as follows):

ValueError: Error when checking model input: the list of Numpy arrays that you are passing to your model is not the size the model expected. Expected to see 1 array(s), but instead got the following list of 64 arrays: [, , …

I am new to deep learning so do not know how to fix it..

Yue September 9, 2019 at 2:12 am #

REPLY

Sorry, I found out I made a mistake when I tried to copy your code< Ignore my question please.

Jason Brownlee September 9, 2019 at 5:16 am #

REPLY

No problem!

Jason Brownlee September 9, 2019 at 5:15 am #

REPLY

Sorry to hear that, I have some suggestions here that might help:
https://machinelearningmastery.com/faq/single-faq/why-does-the-code-in-the-tutorial-not-work-for-me

Umair Khan September 26, 2019 at 10:01 pm #

REPLY

How is the discriminator model instance ‘d_model’ trained in the training loop, when the same instance is set to trainable=False in the ‘define_GAN’ method?

Jason Brownlee September 27, 2019 at 8:01 am #

REPLY

Setting trainable=False only effects the generator, it does not effect the discriminator.

See this:
https://keras.io/getting-started/faq/#how-can-i-freeze-keras-layers

W. Jin October 19, 2019 at 7:23 am #

REPLY

Thank you very much! This is a clearly written, nicely structured and most inspiring tutorial. I love all the detailed explainations as well as the attached code. Excellent!

Jason Brownlee October 20, 2019 at 6:12 am #

REPLY

Thanks!

Venugopal Shah October 22, 2019 at 3:09 pm #

REPLY

Thank you Jason! This is a really good tutorial. I went on to do some further experiments and I am facing some issues. I am trying to implement a cSAGAN with spectral normalization and for some reason, the discriminator throws up an error 'NoneType' object has no attribute '_inbound_nodes'.

This has been bothering me because the same attention layer worked well with an unconditioned SAGAN which works using Keras Sequential(). The problem is arising only when attention is added to this functional Keras model.

I need some insight from you on what could be wrong.

Jason Brownlee October 23, 2019 at 6:30 am #

REPLY

Not sure I can help you with your custom code, sorry. Perhaps try posting to stackoverflow?

Venugopal Shah October 26, 2019 at 11:59 am #

REPLY

I managed to figure it out eventually! It was a really silly mistake on my part. However I would still like to thank you again for this post which was the founding base for my project. You are doing a wonderful job!

Jason Brownlee October 27, 2019 at 5:37 am #

REPLY

Happy to hear that, well done!

Jordan November 10, 2019 at 6:58 am #

REPLY

Hi,

Does using an Embedding layer segment the latent space for each class? What I mean is can you use this method to get the generator to produce, for instance, a t-shirt+shoe combination?

Jason Brownlee November 10, 2019 at 8:28 am #

REPLY

Yes! Probably.

Dang Tuan Hoang December 3, 2019 at 1:14 pm #

REPLY

Hi, Jason

Do you think it is possible to train Conditional GAN with more than 1 condition? For example, I want to train a painter, which color the input picture, conditioned by non-color input picture and color label

REPLY

Jason Brownlee December 3, 2019 at 1:36 pm #

Yes. I think infogan has multiple conditions.

Yes, sounds like a little image to image translation and a little conditional gan. Give it a try! Let me know how you go.

REPLY

Dang Tuan Hoang December 3, 2019 at 3:35 pm #

I'm currently following MC-GAN paper, but Info GAN look interesting as well. Definitely, gonna try it later

REPLY

Jason Brownlee December 4, 2019 at 5:28 am #

Very cool. Eager to hear how you go.

REPLY

Marcin December 17, 2019 at 6:40 pm #

An awesome article Jason! Thank you for your effort.

REPLY

Jason Brownlee December 18, 2019 at 6:00 am #

You're welcome.

REPLY

tvtaerum January 4, 2020 at 9:36 am #

As always, some beautiful work Brownlee. I realize this will be no surprise to you but you can run an almost identical cgan against the mnist (number) dataset by changing the following lines:

1. replace:
from tensorflow.keras.datasets.fashion_mnist import load_data
with:
from tensorflow.keras.datasets.mnist import load_data
Note: I personally use the tensorflow version of keras
2. replace all instances of:
opt = Adam(lr=0.0002, beta_1=0.5)

with:
opt = Adam(lr=0.0001, beta_1=0.5) # learning rate just needs to be slowed down

The reason I mention this (almost obvious) fact is for me, cgan produces better and more interesting results than a simple gan. Other people's tutorials give some code and then with a wave of the hands suggest that, "it's apparent something recognizable as numbers are being produced".

In particular I appreciated your explanations for the Keras functional API approach.

What I do wish is there was some easy way to graphically illustrate the equivalent of first and second derivative estimates in order to better "see" why some attempts fail and other succeed. I realize that an approximation to an approximation is difficult to visualize but something along those lines would be great since single number measures tell me almost nothing diagnostic about what's going on internally. For instance, (for illustration purposes only), it might be doing well with noses and chins but doing a poor job with eyes and ears. I'm sure there are many searching for better ways to have more science and less art in these weight estimations. I'm sure you have some great insights on this.

Again, beautiful work and thank you for your great explanations.

Jason Brownlee January 5, 2020 at 7:01 am #

REPLY

Thanks for your feedback and kind words.

Evaluating GANs remains challenging, some of the metrics here might give you ideas:
https://machinelearningmastery.com/how-to-evaluate-generative-adversarial-networks/

tvtaerum January 13, 2020 at 4:14 pm #

REPLY

Thanks for your reply and pointing me to your tutorial. You may consider me to be a mathematical barbarian after you see some of the things I've attempted but my interest is in "what works". If there are useful observations to make, I'm sure you'll do a much more elegant job than I can. My observations are based on a limited number of experiments – I am amazed at how much you accomplish every month.

Simply for interest sake, I have a set of learning rates and betas which consistently produce good results for both the MNIST and the FASHION_MNIST dataset for me. I realize learning rates and betas are not the bleeding edge of GANS research but I am surprised the narrow range over which there is convergence:
define_discriminator opt as:
opt = Adam(lr=0.0008, beta_1=0.1)
define_gan opt as:
opt = Adam(lr=0.0006, beta_1=0.05)

I read your outline about measuring the goodness of results for gans. The tutorial is interesting but it seems to me you make your best point where you indicate that d1 and d2 ought to be about 0.6 while g ought to have values around 0.8. My general limited experience is, if I can keep my values for d1, d2 and g within reasonable bounds of those values, then I am soon going to have convergence. And if I am going to have convergence, then I need to first obtain good estimates of learning rate and momentum.

In keeping with this, you make the point in your tutorial about exploration of latent space that you may have to restart the analysis if the values of loss go out of bounds. In keeping with this view, I attempted the following which I've added to the training function of your tutorial on exploring latent space. Substantially, it saves a recent copy of the models where the values of loss are under 1.0 and recovers the models when the losses go out of an arbitrary bound and "tries again". Surprisingly, it does seem to carry on from where it left off and it does appear to prevent having to restart the whole analysis.

```
            if (d_loss1 > 1.4 or d_loss2 > 1.4 or g_loss > 1.4):
                qReSet = True
                g_model = g_model_save
                d_model = d_model_save
                gan_model = gan_model_save
            # summarize loss on this batch
            if (j+1) % 5==0 or d_loss1 > 1.0 or d_loss2 > 1.0 or g_loss > 1.0:
                diff = int(time.time()-now)
                print('>%d/%d, %d/%d, d1=%.3f, d2=%.3f, g=%.3f, secs=%d' %
                    (i+1, n_epochs, j+1, bat_per_epo, d_loss1, d_loss2, g_loss, diff),
                if d_loss1 <= 1.0 and d_loss2 <= 1.0 and g_loss <= 1.0:
                    g_model_save = g_model
                    d_model_save = d_model
                    gan_model_save = gan_model
```

I'm also attempting to understand what is the "maximum clarity" possible with respect to images generated. As in any statistical analysis, knowing the "maximum" is critical to understanding how far we've gotten or might theoretically go. While I recognize the mathematical usefulness of using normally distributed numbers to represent latent space, it doesn't appear to be important in practice – uniform between -3.0 and 3.0 (platykurtic) works as well as normal. I've found the following works quite well:

```
    initX = -3.0
    rangeX = 2.0*abs(initX)
    stepX = rangeX / (latent_dim * n_samples)
    x_input = asarray([initX + stepX*(float(i)) for i in range(0,latent_dim * n_samples
    shuffle(x_input)
```

It's not terribly clever but it demonstrates, I think, that the points in the latent space do not have to be random spaced but different and spread out, and there may be some benefit in insuring that the latent space is uniformly covered as illustrated in the code and that the latent space does not have to be Gaussian. I haven't determined, for myself, whether or not this is the case in practice over a wide range of problems – you would obviously know better.

Finally, for the exploration of latent space, my GPU doesn't appear to have enough memory to use n_batch = 128 so I'm using n_batch = 64.

If I'm doing anything really dumb, feel free to let me know. 🙂

Jason Brownlee January 14, 2020 at 7:19 am #

REPLY

Very impressive, thanks for sharing!

You should consider writing up your findings more fully in a blog post.

tvtaerum January 16, 2020 at 4:47 am #

REPLY

I apologize for putting so much in the comment section of your site. Your work is amazingly good and a person realizes this only after trying out different approaches and searching for better material on the Internet. My plan is, as you suggest, to put something up as a blog post once I resolve a couple of issues.

But yes, I did do and report something really dumb in my last comment which I'd like to correct… I copied the address rather than using the 'copy' module and creating a backup. And, of course, I can only do this easily with the generator and the gan function. The compiled discriminator continues to work in the background gradually improving on its ability to tell the difference between real and fake, while in front the generator model jiggers its way to creating better fakes. In some ways this is how humans learn – the "slow" discriminator gradually improves over time, and the generator catches up.

By "backing up" the generator and gan models, I'm able to give every analysis many "second chances" at converging (not going out of bounds). In the interest of forcing convergence (irrespective of how really good the final model is) I used the following code:

```
            if (d_loss1 > 0.95 or d_loss2 > 0.95 or g_loss > 0.95):
                      nTrips+=1
                      g_model = copy.copy(g_model_save)
                      gan_model = copy.copy(gan_model_save)
            # summarize loss on this batch
            if (j+1) % 5==0 or d_loss1 > 1.0 or d_loss2 > 1.0 or g_loss > 1.0:
                      diff = int(time.time()-now)
                      print('>%d/%d, %d/%d, d1=%.3f, d2=%.3f, g=%.3f, secs=%d, trips=%d'
                                (i+1, n_epochs, j+1, bat_per_epo, d_loss1, d_loss2, g_lo
            if d_loss1 <= 0.90 and d_loss2 <= 0.90 and g_loss <= 0.90:
                      g_model_save = copy.copy(g_model)
                      gan_model_save = copy.copy(gan_model)
```

I will put up a blog post and make many references to your great work once I better understand the limits.

Jason Brownlee January 16, 2020 at 6:25 am #

REPLY

Thanks for sharing.

San February 10, 2020 at 11:42 pm #

REPLY

GANs can be used for non-image data?

Jason Brownlee February 11, 2020 at 5:13 am #

REPLY

Yes, but they are not as effective as specialized generative models, at least from what I have seen.

marpuri ganesh March 4, 2020 at 12:25 am #

REPLY

your model fails while running it with mnist dataset but it works perfectly fine with fashion_mnist dataset I can not understand what is going wrong. Both d1_loss and d2_loss becomes 0.00 and gan_loss skyrockets could you give a hint in what's going wrong here

REPLY

Jason Brownlee March 4, 2020 at 5:56 am #

If you change the dataset, you may need to tune the model to the change.

REPLY

pratik korat July 19, 2020 at 11:43 pm #

can you told me how to do that ? kindly
i build both model manually and bigger then this still both loss goes to zero and i used mnist digit data

i don't know what i'm missing !!!!kindly help with this

REPLY

Jason Brownlee July 20, 2020 at 6:14 am #

Yes, this is a big topic, perhaps start here:
https://machinelearningmastery.com/start-here/#gans

REPLY

CJAY March 4, 2020 at 6:46 pm #

Hey thank you Jason. Very impreesive article.

I'm wondering if CGAN can be used in a regression problem. Since among many GAN, only CGAN have the y label. But I'm not sure how to apply it to non-image problem. For example, I want to generate some synthetic data. I have some real data points of y,x. y = f(x1,x2,x3,x4). y is a non-linear function of x1~x4. I have few hundreds of [x1,x2, x3, x4, y] data. However, I want to have more data since the real data is hard to obtain. So basically I want to generate x1_fake, x2_fake, x3_fake, x4_fake, and y_fake where y_fake is still the same non-linear function of x1_fake~x4_fake, i.e., y_fake = f(x1_fake, x2_fake, x3_fake, x4_fake). Is it possible to generate such synthetic dataset using CGAN?

REPLY

Jason Brownlee March 5, 2020 at 6:31 am #

Thanks.

Yes, you could condition on a numerical variable. A different loss function and activation function would be need. I recommend experimenting.

marpuri ganesh March 7, 2020 at 2:21 pm #

REPLY

I tunned the learning rate,batch size, epochs of the model but no use

Jason Brownlee March 8, 2020 at 6:04 am #

REPLY

Perhaps try some of the suggestions here:
https://machinelearningmastery.com/how-to-code-generative-adversarial-network-hacks/

mupumefo March 11, 2020 at 5:02 am #

REPLY

Jason, have patience for this beginner question.
I'm having trouble understanding some of the syntax when you implement your cGANs
In both define_discriminator() and define_generator(), you have paired parenthesis:
examples:
define_discriminator()
line 6: li = Embedding(n_classes, 50)(in_label)
line 9: li = Dense(n_nodes)(li)

define_generator()
line 16: gen = Dense(n_nodes)(in_lat)
line 17: gen = LeakyReLU(alpha=0.2)(gen)

What is the meaning of the extra (in_label), (li), (in_lat), (gen) on the end of each of these lines?
You did not need this in your GANs code.

Jason Brownlee March 11, 2020 at 5:29 am #

REPLY

This is the functional API, perhaps start here:
https://machinelearningmastery.com/keras-functional-api-deep-learning/

Tobias April 4, 2020 at 2:45 am #

REPLY

Hi Jason!

As usual, a great explanation!

How would you modify the GAN to create n discrete values, i.e. categories, with different classes. Let's say: n_class1=10, n_class2=15,n_class=18?

Any first thoughts or examples?

Thanks in advance,
Tobias

Jason Brownlee April 4, 2020 at 6:26 am #

REPLY

Thanks.

It would be a much better idea to use a bayesian model instead. This is just a demonstration for how GANs work and a bad example of a generative model for tabular data.

salman razzaq April 17, 2020 at 1:10 pm #

REPLY

Please guide me how can i modify this code to use it for celebA data set. can i implement the same as that is RGB and there are various labels for a single picture.

Jason Brownlee April 17, 2020 at 1:32 pm #

REPLY

This is a common question that I answer here:
https://machinelearningmastery.com/faq/single-faq/can-you-change-the-code-in-the-tutorial-to-___

Joel April 19, 2020 at 10:36 am #

REPLY

Hi Jason!

Very nice explanation! Thank you!

I just wonder if there is any pre-trained CGAN or GAN model out there so we can directly use as transfer learning? Specifically, I am interested in Celebra face data.

Thanks again,

Joel

Jason Brownlee April 19, 2020 at 1:17 pm #

REPLY

Thanks!

Pre-trained, perhaps – I don't have any sorry.

Nobita Kun April 20, 2020 at 8:29 pm #

REPLY

Thank you Jason, very clear and really useful for a beginner like me.
I have a question about the implementation of the training part.
why should you use half batch for generating real and fake samples but use full_batch (n_batch) in preparing latent point for the input to the generator.

```
X_real, y_real = generate_real_samples(dataset, half_batch)
X_fake, y_fake = generate_fake_samples(g_model, latent_dim, half_batch)

X_gan = generate_latent_points(latent_dim, n_batch)
```

Jason Brownlee April 21, 2020 at 5:53 am #

REPLY

Thanks.

This is a common heuristic when training GANs, you can learn more here:
https://machinelearningmastery.com/how-to-train-stable-generative-adversarial-networks/

Nobita Kun April 21, 2020 at 10:30 am #

REPLY

Thank you for your quick response. I checked the link you gave me, I didn't find information about using half-batch and n-batch. Would you please explain a bit here.

Jason Brownlee April 21, 2020 at 11:46 am #

REPLY

From that post:

Use mini batches of all real or all fake

Nobita Kun April 22, 2020 at 12:49 am #

Thank you very much for your help, Jason.

Jason Brownlee April 22, 2020 at 6:00 am #

You're welcome.

pratik korat July 20, 2020 at 12:49 pm #

REPLY

it is functional api that can be used to create branches in your model
in sequential model you can't do that

Jason Brownlee July 20, 2020 at 1:53 pm #

REPLY

Agreed.

Akshay June 21, 2020 at 6:36 pm #

REPLY

Hi Jason!
Very Nice explanation . Helped me a lot in clarifying my doubts.
But I have a request – Can U make same kind Of Explanation for “Context Encoder : Feature learning by Inpainting” .

Thanks!!

Jason Brownlee June 22, 2020 at 6:11 am #

REPLY

Thanks!

Great suggestion.

Cornelia July 1, 2020 at 7:49 am #

REPLY

Thanks for the Tutorial, I’ve been working my way through all the GAN tutorials you provided, it has been super helpful!

I tried training this conditional GAN on different data sets and it worked well. Now I’m trying to train it on a data set with a different number of classes (3 and 5). I changed the n_classes in every method as well as the label generation after the training and loading of the network of course. However, I get an IndexError and have been unable to solve it. Could you quickly suggest which changes need to be made to change the number of classes in the data set?

Cheers!

Jason Brownlee July 1, 2020 at 11:18 am #

REPLY

Thanks, I’m happy to hear that.

Sorry to hear that you’re having trouble adapting the example.

Perhaps confirm that the number of nodes in the output layer matches the number of classes in the target variable and that the target variable was appropriately one hot encoded.

Alex July 6, 2020 at 12:19 pm #

REPLY

Hi Jason, Thanks for the Tutorial ! I have a question below:

If each label represents the length, width and height of the product, how to not only put the label but also put the length, width and height into the model? Because I want to see the changes of different length, width and height on the model generation results. Thanks!

Jason Brownlee July 6, 2020 at 2:09 pm #

REPLY

Interesting idea, you might want to explore using an infogan and have a parameter for each element.

Alex July 6, 2020 at 5:16 pm #

REPLY

Thank you. I'll read your infogan article. (https://machinelearningmastery.com/how-to-develop-an-information-maximizing-generative-adversarial-network-infogan-in-keras/)

Alex July 16, 2020 at 5:28 pm #

REPLY

At present, the model I want to generate is supervised learning, but using InfoGAN should be unsupervised model. Maybe I still use CGAN to generate and control the results?

Jason Brownlee July 17, 2020 at 6:03 am #

REPLY

I recommend using the techniques you think are the most appropriate to your project.

Alex July 16, 2020 at 5:33 pm #

REPLY

For example, I input geometric features x, y, z of various products, then output the process parameters of the product. ex: INPUT (x,y,z) and OUTPUT (temp,pressure,speed),

Is it possible for the model to predict the process parameters of the product when the geometric characteristics x, y, z of the new product are input?

Jason Brownlee July 17, 2020 at 6:04 am #

REPLY

It depends on the data, but yes, this is what supervised learning is designed to achieve.

Perhaps this framework will help:
http://machinelearningmastery.com/how-to-define-your-machine-learning-problem/

Shaoxuan July 13, 2020 at 11:30 pm #

REPLY

Hi, Jason,
I have question about the labels in conditional GAN. Instead of several categories, like integers from 0 to 9, can the labels be generated by continuous Uniform distribution(0,1)? So there will be hundreds of labels inputted to the generator or discriminator.
Do you think it is reasonable or doable? Thank you very much!

Jason Brownlee July 14, 2020 at 6:24 am #

REPLY

I don't see why not.

Jay July 25, 2020 at 10:51 am #

REPLY

What changes do I have to make to be able to train with 3 channel images? I changed the input_shape to (dim, dim, 3) but I still get the error: ValueError: Input 0 of layer conv2d is incompatible with the layer: expected axis -1 of input shape to have value 4 but received input with shape [None, dim, dim, 2]

Jason Brownlee July 26, 2020 at 6:13 am #

REPLY

Perhaps start with this model and adapt it to be conditional:
https://machinelearningmastery.com/how-to-develop-a-generative-adversarial-network-for-a-cifar-10-small-object-photographs-from-scratch/

Richard Macwan August 27, 2020 at 4:36 am #

REPLY

I had to change the Embedding layer's dimensions for the conditional Gan otherwise tf complained that it could not reshape (32,1,50) to (32,7,7).
I changed the 50 to 49 as li = Embedding(n_classes,49)(in_label).
Am I missing something or it was a typo?

Jason Brownlee August 27, 2020 at 6:25 am #

REPLY

That is odd, sorry to hear that.

Did you copy all other code examples as-is without modification?
Are your libraries up to date?

Do these tips help:
https://machinelearningmastery.com/faq/single-faq/why-does-the-code-in-the-tutorial-not-work-for-

me

Richard Macwan August 27, 2020 at 8:56 pm #

REPLY

No since I haven't purchased the book, I don't have the code. I did find the problem though, and I was silly to ask the question! It was obvious that I had missed adding a Dense layer before Reshaping in the generator!

Thanks for your prompt reply.

Jason Brownlee August 28, 2020 at 6:42 am #

REPLY

I'm happy to hear that you solved your problem!

Nir Regev September 2, 2020 at 12:59 am #

REPLY

Hi Jason,
great post (again).
How would the conditional DCGAN would change if instead of label (condition) input, I have a facial landmark image of some dimension (e.g. a grayscale of 28,28) ? The generator, in this case, should generate an image that corresponds to the landmark image, and so is the discriminator should "judge" the image according to the landmark condition.
Specifically I'm struggling to understand what should be in the in_label and li in the define_discriminator method. thanks

Jason Brownlee September 2, 2020 at 6:31 am #

REPLY

Not dramatically, perhaps just adjustments to the model for the new input shape.

Omar September 22, 2020 at 1:15 am #

REPLY

Hello,
Thanks a lot for this tutorial! I really needed this.

Only one question, what are the changes needed in the generator and the discriminator if I am using a custom dataset, with dimensions (64,64,3) not (28,28,1)?
This is really bugging me, I know it's simple but I think I might be overseeing something.

Thanks for your help.

Jason Brownlee September 22, 2020 at 6:51 am #

REPLY

Change the expected input shape for the discriminator and perhaps add more layers to support the larger images.

Add more layers to the generator to ensure the output shape matches the expected size.

How many layers and what types – you will have to discover the answer via trial and error.

Omar September 22, 2020 at 6:43 pm #

REPLY

Thanks, will have a look into this.
One more thing, my dataset is loaded as a tf batch dataset (using keras image dataset from directory). How can adjust the code to train this instead of the MNIST fashion?

Jason Brownlee September 23, 2020 at 6:35 am #

REPLY

Sorry, I don't know about "tf batch dataset".

Kim Quinto October 2, 2020 at 9:55 pm #

REPLY

Hello,
Thanks for the detailed blogs! I am trying to improve a classifier that was trained on a small imbalance dataset, and I am considering using CGAN to extend my dataset and making it a balanced one, but here comes the question: Can I use the whole dataset (train, validation and test) to train my CGAN and then use the generated images to extend and balance my classifier? or should I use the training set only? I am a little bit confused if using the whole dataset is completely fine since the generated images will be from a different distribution. I couldn't find any answer for my confusion, so what do you think?

Kim Quinto October 2, 2020 at 9:58 pm #

REPLY

I am confused because in that case, my classifier will be validated and tested on generated images that were trained on these datasets to be generated.

Tiwalade Usman December 25, 2020 at 1:57 am #

REPLY

You apply it only to your training data

Jason Brownlee October 3, 2020 at 6:07 am #

REPLY

No, I think it would be valid to only the training dataset to train the GAN as part of your experiment.

REPLY

Sang Young Lim October 6, 2020 at 1:19 am #

In regard of your nice post below,
https://machinelearningmastery.com/generative-adversarial-network-loss-functions/

My question is that is lower g_loss better?
Because I think your code and explanations imply following statement
“In practice, this is also implemented as a binary classification problem, like the discriminator. Instead of maximizing the loss, we can flip the labels for real and fake images and minimize the cross-entropy.”

I am trying to use Bayesian Optimization method on this cDCGAN above, and I got lost deciding to define the evaluation function to look for bigger g_loss or smaller g_loss (on average).

I have done 500 epoch on this code above, but could not find g_loss is going down or up.
Thank you for the post by the way. Great work!

REPLY

Jason Brownlee October 6, 2020 at 6:57 am #

In general, for GANs, no:
https://machinelearningmastery.com/faq/single-faq/why-is-my-gan-not-converging

REPLY

Eoin Kenny October 7, 2020 at 8:39 pm #

Hi Jason thanks for this.

Quick question, does the embedding work with floating point numbers? I dont’ want to only have ints for input here, I want a float too, is that possible?

Thanks you.

REPLY

Jason Brownlee October 8, 2020 at 8:30 am #

Embedding layers in general? Yes.

REPLY

Harshi Rao November 22, 2020 at 1:07 am #

Hi Jason,
I’ve been following your blogs, posts and newsletters for the past few years!
Do you have any advice on how to apply GANs for document generation?
Thanks in advance.

Jason Brownlee November 22, 2020 at 6:56 am #

REPLY

Thanks!

I would recommend “language models” for document generation, not GANs:
https://machinelearningmastery.com/?s=language+models&post_type=post&submit=Search

Ali November 23, 2020 at 8:45 pm #

REPLY

Hi Jason,
My question is naive, but would appreciate if you answer it.
Assume that I have 1D data and want to have only dense layers in both models. Here is the code for my disc model definition:

```
def define_discriminator(in_shape=(10,1), n_classes=8):
# label input
in_label = Input(shape=(1,))

li = Embedding(n_classes, 50)(in_label)

n_nodes = in_shape[0]
li = Dense(n_nodes)(li)
# reshape to additional channel
li = Reshape((n_nodes, 1))(li)

in_data = Input(shape=in_shape)
# concat label as a channel
merge = Concatenate()([in_data, li])
hidden1 = Dense(64, activation='relu')(merge)
hidden2 = Dense(64, activation='relu')(hidden1)
# output
out_layer = Dense(1, activation='sigmoid')(hidden2)
# define model
model = Model([in_data, in_label], out_layer)
# compile model
opt = Adam(lr=0.0002, beta_1=0.5)
model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])

return model
```

The problem is that when I use d_model.predict(), the output has 3 dimensions instead of 2. In fact, the shape should be (64, 1), but it is (64, 10, 1) where 10 is the input dimension. Please let me know what I am missing here.

Jason Brownlee November 24, 2020 at 6:19 am #

REPLY

Perhaps review a plot or summary of the model to confirm it was constructed the way you intended.

Tiwalade Usman December 25, 2020 at 2:00 am #

REPLY

How do I apply cGAN to augment images with multi-labels?

Jason Brownlee December 25, 2020 at 5:26 am #

REPLY

Good question. I have not explored this, perhaps use a little trial and error to see what works well.

Let me know how you go.

Ali Sedaghatbaf December 26, 2020 at 8:44 pm #

REPLY

Hi Jason,

I am interested to know if it is possible to checkpoint your gan model. Since typical metrics e.g. loss and accuracy do not work for GANs, we have to define custom metrics. Using keras, we can easily do this for a classifier like the disc model, but I don;t know how to do this with the gen model. Please assume that we have a metric to analyze the quality of the generated images.

Jason Brownlee December 27, 2020 at 5:00 am #

REPLY

Not really as loss does not relate to image quality.

You can save after each manually executed epoch if you like.

Nadjib December 28, 2020 at 12:06 pm #

REPLY

Hi, thank you for this great tutorial. Is there a way of using more than one condition vector ? could we use multiple condition vectors then concatenate them ?

Jason Brownlee December 28, 2020 at 1:16 pm #

REPLY

You're welcome.

Perhaps. You may need to experiment and/or check the literature for related approaches.

Morne January 4, 2021 at 8:57 am #

REPLY

Thanks for teaching me ML. 2 Questions:
I notice train_on_batch is passed a half_batch real & half_batch fake data. Are weights somehow only updated on loading a full batch?
Why would we use such high 50d Embedding for mapping only10 classes?

REPLY

Jason Brownlee January 4, 2021 at 1:38 pm #

Weights are updated after each batch update.

50d embedding is common, you can try alternatives.

REPLY

Gili January 5, 2021 at 8:45 pm #

Hi Jason, thanks for the great tutorial!
I'm trying to create a conditional gan for time series data so my model is using LSTMs instead of CNNs.
I'm having trouble understanding how to reshape my input and the labels embeddings.
In my case, instead of a 28×28 image, I have a time-series sample of shape: time_steps, n_features
As you know, an LSTM needs the input to be [n_samples, time_steps, n_features]
but now I also need to add the labels and I will get 4 dimensions instead of 3.
do you have any suggestions on how to do this right?
thanks a lot!

REPLY

Jason Brownlee January 6, 2021 at 6:28 am #

Perhaps this will help:
https://machinelearningmastery.com/faq/single-faq/what-is-the-difference-between-samples-timesteps-and-features-for-lstm-input

REPLY

Dennis February 16, 2021 at 3:51 pm #

Hi Jason,
Thanks for your great post.
In you code when generate fake image;

```
def generate_fake_samples(generator, latent_dim, n_samples):
    # generate points in latent space
    z_input, labels_input = generate_latent_points(latent_dim, n_samples)
    # predict outputs
    images = generator.predict([z_input, labels_input])
    # create class labels
    y = zeros((n_samples, 1))
    return [images, labels_input], y
```

But based on the paper, I see other people use real label inputs(same as from real image sample) and z_input to generator fake image, then test d model weights based on this fake image. But it seems this won't influence the model. I want to ask which one is correct? Is there any difference?

Thank you!

Jason Brownlee February 17, 2021 at 5:25 am #

REPLY

There are many different types of models.

Perhaps experiment with small modifications and see what works well for your application.

Leave a Reply

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I'm *Jason Brownlee* PhD
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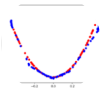

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