Customizing Keras

In this appendix we will look briefly in more details at the code we have used to build a GAN. If you have studied the chapter, you will have realized that we have not used the compile()/fit() approach, but that we have built a custom training loop. It is important that you understand the fundamental concepts on how this work with Keras. This appendix is here exactly for this reason.

We will not cover here material as custom loss functions, custom layers or custom activation functions. In case you are interested you will find plenty of examples in the official documentation.

This chapter is intended as a very short reference that I hope will help you to quickly understand how to customize Keras and understand better the code of this book and especially the chapter on GANs. I added for reference (since is useful) a short section on how to customize callback classes, I hope it is useful.

A complete overview on how to customize Keras would require a book on its own[[1]](#footnote-1) and is not the goal of this book.

# Custom callback class

In the previous appendix you have seen what callback functions are. In this section we will see how you can customize them for your purposes, since this is a really useful thing even if you are using the compile()/fit() approach. To do this we need to understand how the abstract base class keras.callbacks.Callback is working.

The abstract base class Callback can be found at the moment of writing at

[tensorflow/python/keras/callbacks.py](https://www.tensorflow.org/code/stable/tensorflow/python/keras/callbacks.py).

To start customizing you need simply to define a custom class that inherit from keras.callbacks.Callback. The main methods you want to redefine are the following

* on\_train\_begin 🡪 Called at the beginning of training
* on\_train\_end 🡪 Called at the end of training
* on\_epoch\_begin 🡪 Called at the start of an epoch
* on\_epoch\_end 🡪 Called at the end of an epoch
* on\_batch\_begin 🡪 Called right before processing a batch
* on\_batch\_end 🡪 Called at the end of a batch

This can be done with the code

from tensorflow import keras

class My\_Callback(keras.callbacks.Callback):

    def on\_train\_begin(self, logs={}):

# Your code here

       return

    def on\_train\_end(self, logs={}):

# Your code here

        return

    def on\_epoch\_begin(self, epoch, logs={}):

# Your code here

return

    def on\_epoch\_end(self, epoch, logs={}):

# Your code here

return

    def on\_batch\_begin(self, batch, logs={}):

# Your code here

return

    def on\_batch\_end(self, batch, logs={}):

# Your code here

self.losses.append(logs.get('loss'))

return

Each of the methods have slightly different inputs that you may use in your class. Let's look at them briefly:

on\_epoch\_begin, on\_epoch\_end

|  |
| --- |
| Arguments: |
|  | epoch: integer, index of epoch. |
|  | logs: dictionary of logs. |

on\_train\_begin, on\_train\_end

|  |
| --- |
| Arguments: |
|  | logs: dictionary of logs. |

on\_batch\_begin, on\_batch\_end

|  |
| --- |
| Arguments: |
|  | batch: integer, index of batch within the current epoch. |
|  | logs: dictionary of logs. |

Let's see with an example how we can use this class.

## Example of a custom callback class

Let's again consider the MNIST example. Same code you have already seen by now many times:

import tensorflow as tf

from tensorflow import keras

(train\_images, train\_labels), (test\_images, test\_labels) = tf.keras.datasets.mnist.load\_data()

train\_labels = train\_labels[:5000]

test\_labels = test\_labels[:5000]

train\_images = train\_images[:5000].reshape(-1, 28 \* 28) / 255.0

test\_images = test\_images[:5000].reshape(-1, 28 \* 28) / 255.0

and then let's define a Sequential model for our example

model = tf.keras.models.Sequential([

keras.layers.Dense(512, activation=tf.keras.activations.relu, input\_shape=(784,)),

keras.layers.Dropout(0.2),

keras.layers.Dense(10, activation=tf.keras.activations.softmax)

])

model.compile(optimizer='adam',

loss=tf.keras.losses.sparse\_categorical\_crossentropy,

metrics=['accuracy'])

Now let's write a custom callback class, redefining only one of the methods to see what the inputs are. For example, let's what the variable logs contains at the beginning of the training

class CustomCallback1(keras.callbacks.Callback):

def on\_train\_begin(self, logs={}):

print (logs)

return

you can then use it with

CC1 = CustomCallback1()

model.fit(train\_images, train\_labels, epochs = 2,

validation\_data = (test\_images,test\_labels),

callbacks = [CC1]) # pass callback to training

Remember to always instantiate the class and pass the CC1 variable, and not the class itself. You will get

Train on 5000 samples, validate on 5000 samples

{}

Epoch 1/2

5000/5000 [==============================] - 1s 274us/step - loss: 0.0976 - acc: 0.9746 - val\_loss: 0.2690 - val\_acc: 0.9172

Epoch 2/2

5000/5000 [==============================] - 1s 275us/step - loss: 0.0650 - acc: 0.9852 - val\_loss: 0.2925 - val\_acc: 0.9114

{}

<tensorflow.python.keras.callbacks.History at 0x7f795d750208>

The logs dictionary is empty, as you can see from the {}. Let's expand our class a bit

class CustomCallback2(keras.callbacks.Callback):

def on\_train\_begin(self, logs={}):

print (logs)

return

def on\_epoch\_end(self, epoch, logs={}):

print ("Just finished epoch", epoch)

print (logs)

return

now training the network with

CC2 = CustomCallback2()

model.fit(train\_images, train\_labels, epochs = 2,

validation\_data = (test\_images,test\_labels),

callbacks = [CC2]) # pass callback to training

will give the output (reported here for just one epoch for brevity)

Train on 5000 samples, validate on 5000 samples

{}

Epoch 1/2

4864/5000 [============================>.] - ETA: 0s - loss: 0.0511 - acc: 0.9879

Just finished epoch 0

{'val\_loss': 0.2545496598124504, 'val\_acc': 0.9244, 'loss': 0.05098680723309517, 'acc': 0.9878}

Now things are starting to get interesting. The logs dictionary contains a lot more information now that we can access and use. In the dictionary now we have val\_loss, val\_acc and acc. Let's customize our output a bit. Let's set verbose = 0 in the fit() call to suppress the standard output and let's generate our own.

Our new class will be

class CustomCallback3(keras.callbacks.Callback):

def on\_train\_begin(self, logs={}):

print (logs)

return

def on\_epoch\_end(self, epoch, logs={}):

print ("Just finished epoch", epoch)

print ('Loss evaluated on the validation dataset =',logs.get('val\_loss'))

print ('Accuracy reached is', logs.get('acc'))

return

and we can train our network with

CC3 = CustomCallback3()

model.fit(train\_images, train\_labels, epochs = 2,

validation\_data = (test\_images,test\_labels),

callbacks = [CC3], verbose = 0) # pass callback to training

and we will get

{}

Just finished epoch 0

Loss evaluated on the validation dataset = 0.2546206972360611

The empty {} is simply the empty logs dictionary that on\_train\_begin received. Of course, you can simply print information every few epochs. For example by simply modifying the on\_epoch\_end() function as

def on\_epoch\_end(self, epoch, logs={}):

if (epoch % 10 == 0):

print ("Just finished epoch", epoch)

print ('Loss evaluated on the validation dataset =',logs.get('val\_loss'))

print ('Accuracy reached is', logs.get('acc'))

return

this will give you the following output if you train your network for 30 epochs

{}

Just finished epoch 0

Loss evaluated on the validation dataset = 0.3692033936366439

Accuracy reached is 0.9932

Just finished epoch 10

Loss evaluated on the validation dataset = 0.3073081444747746

Accuracy reached is 1.0

Just finished epoch 20

Loss evaluated on the validation dataset = 0.31566708440929653

Accuracy reached is 0.9992

<tensorflow.python.keras.callbacks.History at 0x7f796083c4e0>

Now you should start to get an idea on how you can perform several things during the training. You can for example save accuracy values in lists to be able to plot them later, or simply plot metrics to check how your training is going. The possibility are almost endless and callbacks are a great way of customizing what happens during training.

# Custom training loops

The easiest way of training a network with Keras, is to use the compile()/fit() approach. That makes building and training a network very easy. But the downside of this approach is that you don’t have much flexibility on how the training is implemented. For example suppose you want to train two networks in alternate fashion (as you have learned in the chapter about GANs), in this case the standard fit() call is not enough anymore and you need to implement a custom training loop. Let’s see how to do that.

# Calculation of gradients

As you know, the fit() function will evaluate the gradients of the loss function and, by using the appropriate optimizer, use them to update the weights. The first step in implementing a custom training loop, is to understand how to evaluate the gradients of a given function manually. Let us consider the function . How can we calculate the gradient of it at with TensorFlow? By simply taking manually the derivative we can immediately see that

And therefore

With Keras we can simply do the same calculation this way

x = tf.constant(2.0)  
with tf.GradientTape() as g:  
  g.watch(x)  
  y = x \* x  
dy\_dx = g.gradient(y, x)

The variable dy\_dx will be a Tensor that will have a single value of 4:

tf.Tensor(4.0, shape=(), dtype=float32)

What happens is that TensorFlow operations are “recorded” in sequence, like on a tape (from here the name GradientTape), if they are executed within this context manager. TensorFlow checks all the operations called, and save all the gradients of the operations that are evaluated in the context. Note that everything that happens outside the context is ignored. In TensorFlow language every operation and variable that is recorded is said is being “watched”. Luckily when dealing with neural networks, all trainable variables (the weights and bias typically) are automatically watched. But you can manually ask TensorFlow to watch other tensors by manually using the watch() call, as we have done in our example with the code g.watch(x).

To understand what is going on in the background, you would need to understand autodifferentiation. But intuitively you can think of the process in this way: when TensorFlow evaluates an operation it will also save in memory its gradient. By using the gradientTape you are simply asking TensorFlow to keep in memory the evaluated gradients of specific operations so that they can be used and combined properly to get the right result at the end.

Note that as soon as you call the gradient() function, all the resources held by the GradientTape() are released. If you want, for example, to calculate the second derivative you must do it differently than our example above. You will need to use the parameter persistent=True in the creation of the GradientTape(). For example, suppose you want the second derivative of the function

At The result is 12 since

With Keras the code would look like this

x = tf.constant(2.0)  
with tf.GradientTape(persistent=True) as g:  
  g.watch(x)  
  y = x \* x \* x

dy\_dx = g.gradient(y, x)     
dy\_dx = g.gradient(y, x)

That will give you the expected result

tf.Tensor(12.0, shape=(), dtype=float32)

Running the same code without the persistent=True parameter will give you an error message when calling the function gradient() a second time. There is also another important point to note. Consider the following code where I have removed the g.watch(x) call.

x = tf.constant(2.0)

with tf.GradientTape() as g:

y = x \* x \* x

dy\_dx = g.gradient(y, x)

print(dy\_dx)

The result of this code will be None. No gradient can be evaluated since the variable x is not being “watched” by the GradientTape(). Now let’s see how to implement a custom training loop with a neural network.

## Custom Training Loop for a Neural Network

Now consider a very small FFNN with two layers, each having 64 neurons.

inputs = keras.Input(shape=(784,), name="digits")

x1 = layers.Dense(64, activation="relu")(inputs)

x2 = layers.Dense(64, activation="relu")(x1)

outputs = layers.Dense(10, name="predictions")(x2)

model = keras.Model(inputs=inputs, outputs=outputs)

As a second step we need to specify optimizer and loss function (remember that now we will not use the compile() function, so we need to use the Keras functions explicitly):

optimizer = keras.optimizers.Adam(learning\_rate=1e-2)

loss\_fn = keras.losses.SparseCategoricalCrossentropy(from\_logits=True)

Another thing that you will need to specify (by using the Keras functions) are the metrics you want to track, since you will not be able to specify the metrics in the fit() call.

train\_acc\_metric = keras.metrics.SparseCategoricalAccuracy()

val\_acc\_metric = keras.metrics.SparseCategoricalAccuracy()

At this point we have all the ingredients we need. The loop can now be implemented easily

epochs = 200

for epoch in range(epochs):

with tf.GradientTape() as tape:

# Run the forward pass of the layer.

logits = model(x\_train, training=True) # Logits for this minibatch

# Compute the loss funtion

loss\_value = loss\_fn(y\_train, logits)

grads = tape.gradient(loss\_value, model.trainable\_weights)

optimizer.apply\_gradients(zip(grads, model.trainable\_weights))

# Update training metric.

train\_acc\_metric.update\_state(y\_train, logits)

# Display metrics at the end of each epoch.

train\_acc = train\_acc\_metric.result()

if epoch % 20 == 0:

print(

"Training loss (for one batch) at step %d: %.4f"

% (epoch, float(loss\_value))

)

print("Training acc over epoch: %.4f" % (float(train\_acc),))

In the GradientTape() context you need the following steps:

* the forward pass: easily done with model(x\_train, training=True).
* The loss function: loss\_value = loss\_fn(y\_train, logits)
* And then you need to calculate the gradients and apply them to update the weights: grads = tape.gradient(loss\_value, model.trainable\_weights)  
  optimizer.apply\_gradients(zip(grads, model.trainable\_weights))

The tape.gradient() calculate the gradient of the loss function (that is being watched in the GradientTape context), and the second (apply\_gradients())apply the gradients with the optimizers to update the network weights.

After that you need to keep track of the metrics. The call train\_acc\_metric.update\_state(y\_train, logits) update the metrics we defined, and then the call train\_acc = train\_acc\_metric.result() save its value in a variable (train\_acc) that you can display during training. This very basic loop should let you understand how you can build your own custom training loops. Of course, there is much more you can do and, as usual, the best place to get all information is the official Keras documentation[[2]](#footnote-2). Note that there at least two things that are important but that we have not discussed:

* How to train with mini-batches (the training loop we discussed uses all the data). To do that you could use   
  train\_dataset = tf.data.Dataset.from\_tensor\_slices((x\_train, y\_train)  
  train\_dataset = train\_dataset.shuffle(buffer\_size=1024).batch(batch\_size)  
  and then add a loop over the batches with  
  for step, (x\_batch\_train, y\_batch\_train) in enumerate(train\_dataset):
* How to speed up your training by using @tf.function. But this is a more advanced topic that would require a long discussion and goes beyond the scope of this book.

Remember that the goal of this book is not to make you a Keras expert, but to let you understand how neural networks work and how easy is to implement them. The goal of this appendix is to give just enough information that you can follow the book. To better understand customization of Keras, your best chance is to use the official documentation and work through the examples.

1. In case you are looking for such a book, a very good introduction is the book by Jojo Moolayil, *Learn Keras for Deep Neural Networks: A Fast-Track Approach to Modern Deep Learning with Python* published by APRESS. [↑](#footnote-ref-1)
2. A good place to start is https://www.tensorflow.org/guide/keras/writing\_a\_training\_loop\_from\_scratch [↑](#footnote-ref-2)