Convolution_model_Application

June 9, 2021

1 Convolutional Neural Networks: Application

Welcome to Course 4's second assignment! In this notebook, you will:

- Create a mood classifer using the TF Keras Sequential API
- Build a ConvNet to identify sign language digits using the TF Keras Functional API

After this assignment you will be able to:

- Build and train a ConvNet in TensorFlow for a **binary** classification problem
- Build and train a ConvNet in TensorFlow for a **multiclass** classification problem
- Explain different use cases for the Sequential and Functional APIs

To complete this assignment, you should already be familiar with TensorFlow. If you are not, please refer back to the **TensorFlow Tutorial** of the third week of Course 2 ("**Improving deep neural networks**").

1.1 Table of Contents

1 - Packages

As usual, begin by loading in the packages.

[18]:
```
import math
import numpy as np
import h5py
import matplotlib.pyplot as plt
from matplotlib.pyplot import imread
import scipy
from PIL import Image
import pandas as pd
import tensorflow as tf
import tensorflow.keras.layers as tfl
from tensorflow.python.framework import ops
from cnn_utils import *
from test_utils import summary, comparator

%matplotlib inline
np.random.seed(1)
```

1.1 - Load the Data and Split the Data into Train/Test Sets

You'll be using the Happy House dataset for this part of the assignment, which contains images of peoples' faces. Your task will be to build a ConvNet that determines whether the people in the images are smiling or not – because they only get to enter the house if they're smiling!

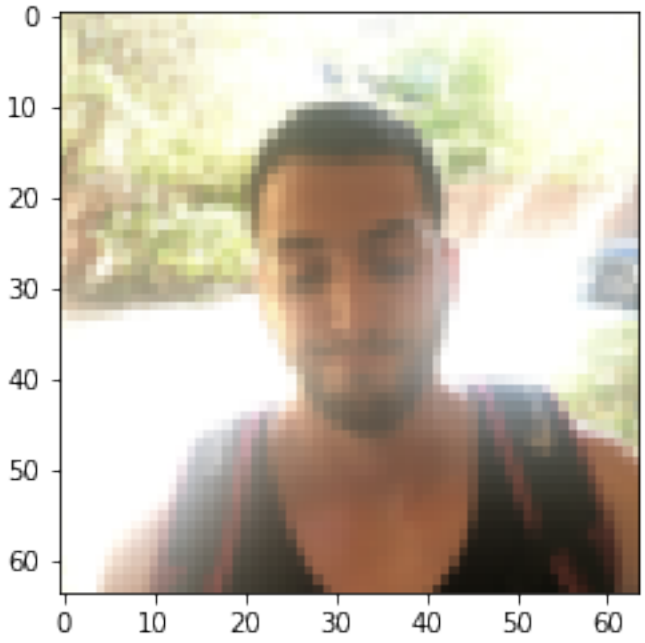
[19]:
```
X_train_orig, Y_train_orig, X_test_orig, Y_test_orig, classes =␣
↪load_happy_dataset()

# Normalize image vectors
X_train = X_train_orig/255.
X_test = X_test_orig/255.

# Reshape
Y_train = Y_train_orig.T
Y_test = Y_test_orig.T

print ("number of training examples = " + str(X_train.shape[0]))
print ("number of test examples = " + str(X_test.shape[0]))
print ("X_train shape: " + str(X_train.shape))
print ("Y_train shape: " + str(Y_train.shape))
print ("X_test shape: " + str(X_test.shape))
print ("Y_test shape: " + str(Y_test.shape))
```

```
number of training examples = 600
number of test examples = 150
X_train shape: (600, 64, 64, 3)
Y_train shape: (600, 1)
X_test shape: (150, 64, 64, 3)
Y_test shape: (150, 1)
```

You can display the images contained in the dataset. Images are **64x64** pixels in RGB format (3

channels).

[20]:
```
index = 124
plt.imshow(X_train_orig[index]) #display sample training image
plt.show()
```



2 - Layers in TF Keras

In the previous assignment, you created layers manually in numpy. In TF Keras, you don't have to write code directly to create layers. Rather, TF Keras has pre-defined layers you can use.

When you create a layer in TF Keras, you are creating a function that takes some input and transforms it into an output you can reuse later. Nice and easy!

3 - The Sequential API

In the previous assignment, you built helper functions using `numpy` to understand the mechanics behind convolutional neural networks. Most practical applications of deep learning today are built using programming frameworks, which have many built-in functions you can simply call. Keras is a high-level abstraction built on top of TensorFlow, which allows for even more simplified and optimized model creation and training.

For the first part of this assignment, you'll create a model using TF Keras' Sequential API, which allows you to build layer by layer, and is ideal for building models where each layer has **exactly one** input tensor and **one** output tensor.

As you'll see, using the Sequential API is simple and straightforward, but is only appropriate for simpler, more straightforward tasks. Later in this notebook you'll spend some time building with a more flexible, powerful alternative: the Functional API.

3.1 - Create the Sequential Model

As mentioned earlier, the TensorFlow Keras Sequential API can be used to build simple models with layer operations that proceed in a sequential order.

You can also add layers incrementally to a Sequential model with the `.add()` method, or remove them using the `.pop()` method, much like you would in a regular Python list.

Actually, you can think of a Sequential model as behaving like a list of layers. Like Python lists, Sequential layers are ordered, and the order in which they are specified matters. If your model is non-linear or contains layers with multiple inputs or outputs, a Sequential model wouldn't be the right choice!

For any layer construction in Keras, you'll need to specify the input shape in advance. This is because in Keras, the shape of the weights is based on the shape of the inputs. The weights are only created when the model first sees some input data. Sequential models can be created by passing a list of layers to the Sequential constructor, like you will do in the next assignment.

Exercise 1 - happyModel

Implement the `happyModel` function below to build the following model: `ZEROPAD2D -> CONV2D -> BATCHNORM -> RELU -> MAXPOOL -> FLATTEN -> DENSE`. Take help from tf.keras.layers

Also, plug in the following parameters for all the steps:

- ZeroPadding2D: padding 3, input shape 64 x 64 x 3
- Conv2D: Use 32 7x7 filters, stride 1
- BatchNormalization: for axis 3
- ReLU
- MaxPool2D: Using default parameters
- Flatten the previous output.
- Fully-connected (Dense) layer: Apply a fully connected layer with 1 neuron and a sigmoid activation.

Hint:

Use **tfl** as shorthand for **tensorflow.keras.layers**

[21]:
```
# GRADED FUNCTION: happyModel

def happyModel():
    """
    Implements the forward propagation for the binary classification model:
    ZEROPAD2D -> CONV2D -> BATCHNORM -> RELU -> MAXPOOL -> FLATTEN -> DENSE

    Note that for simplicity and grading purposes, you'll hard-code all the␣
 ↪values
    such as the stride and kernel (filter) sizes.
    Normally, functions should take these values as function parameters.

    Arguments:
    None
```

```
    Returns:
    model -- TF Keras model (object containing the information for the entire␣
↪training process)
    """
    model = tf.keras.Sequential()
    model.add(tfl.ZeroPadding2D(padding=(3, 3), input_shape=(64, 64, 3)))
    model.add(tfl.Conv2D(32, (7,7), strides=1, input_shape=(64, 64, 3)))
    model.add(tfl.BatchNormalization(axis=3, epsilon=0.00001, name='bn1'))
    model.add(tfl.ReLU())
    model.add(tfl.MaxPooling2D(pool_size=(2,2), strides=None, padding='valid',␣
↪data_format=None))
    model.add(tfl.Flatten())
    model.add(tfl.Dense(1, activation = 'sigmoid'))
    return model
```

[22]:
```
happy_model = happyModel()
# Print a summary for each layer
for layer in summary(happy_model):
    print(layer)

output = [['ZeroPadding2D', (None, 70, 70, 3), 0, ((3, 3), (3, 3))],
            ['Conv2D', (None, 64, 64, 32), 4736, 'valid', 'linear',␣
↪'GlorotUniform'],
            ['BatchNormalization', (None, 64, 64, 32), 128],
            ['ReLU', (None, 64, 64, 32), 0],
            ['MaxPooling2D', (None, 32, 32, 32), 0, (2, 2), (2, 2), 'valid'],
            ['Flatten', (None, 32768), 0],
            ['Dense', (None, 1), 32769, 'sigmoid']]

comparator(summary(happy_model), output)
```

```
['ZeroPadding2D', (None, 70, 70, 3), 0, ((3, 3), (3, 3))]
['Conv2D', (None, 64, 64, 32), 4736, 'valid', 'linear', 'GlorotUniform']
['BatchNormalization', (None, 64, 64, 32), 128]
['ReLU', (None, 64, 64, 32), 0]
['MaxPooling2D', (None, 32, 32, 32), 0, (2, 2), (2, 2), 'valid']
['Flatten', (None, 32768), 0]
['Dense', (None, 1), 32769, 'sigmoid']
All tests passed!
```

Now that your model is created, you can compile it for training with an optimizer and loss of your choice. When the string `accuracy` is specified as a metric, the type of accuracy used will be automatically converted based on the loss function used. This is one of the many optimizations built into TensorFlow that make your life easier! If you'd like to read more on how the compiler operates, check the docs here.

[23]:
```
happy_model.compile(optimizer='adam',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])
```

It's time to check your model's parameters with the `.summary()` method. This will display the types of layers you have, the shape of the outputs, and how many parameters are in each layer.

[24]:
```
happy_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
zero_padding2d_1 (ZeroPaddin (None, 70, 70, 3)         0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 64, 64, 32)        4736
_________________________________________________________________
bn1 (BatchNormalization)     (None, 64, 64, 32)        128
_________________________________________________________________
re_lu_3 (ReLU)               (None, 64, 64, 32)        0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 32, 32, 32)        0
_________________________________________________________________
flatten_2 (Flatten)          (None, 32768)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 32769
=================================================================
Total params: 37,633
Trainable params: 37,569
Non-trainable params: 64
_________________________________________________________________
```

3.2 - Train and Evaluate the Model

After creating the model, compiling it with your choice of optimizer and loss function, and doing a sanity check on its contents, you are now ready to build!

Simply call `.fit()` to train. That's it! No need for mini-batching, saving, or complex backpropagation computations. That's all been done for you, as you're using a TensorFlow dataset with the batches specified already. You do have the option to specify epoch number or minibatch size if you like (for example, in the case of an un-batched dataset).

[25]:
```
happy_model.fit(X_train, Y_train, epochs=10, batch_size=16)
```

```
Epoch 1/10
38/38 [==============================] - 3s 87ms/step - loss: 1.4417 - accuracy:
0.6650
Epoch 2/10
38/38 [==============================] - 3s 89ms/step - loss: 0.2608 - accuracy:
```

```
0.8983
Epoch 3/10
38/38 [==============================] - 3s 90ms/step - loss: 0.1784 - accuracy:
0.9300
Epoch 4/10
38/38 [==============================] - 3s 89ms/step - loss: 0.1131 - accuracy:
0.9600
Epoch 5/10
38/38 [==============================] - 3s 87ms/step - loss: 0.1682 - accuracy:
0.9417
Epoch 6/10
38/38 [==============================] - 3s 87ms/step - loss: 0.1253 - accuracy:
0.9567
Epoch 7/10
38/38 [==============================] - 3s 87ms/step - loss: 0.1048 - accuracy:
0.9533
Epoch 8/10
38/38 [==============================] - 3s 87ms/step - loss: 0.1062 - accuracy:
0.9583
Epoch 9/10
38/38 [==============================] - 3s 89ms/step - loss: 0.0912 - accuracy:
0.9600
Epoch 10/10
38/38 [==============================] - 3s 89ms/step - loss: 0.0869 - accuracy:
0.9667
```

[25]:
```
<tensorflow.python.keras.callbacks.History at 0x7f0c6bbaba90>
```

After that completes, just use `.evaluate()` to evaluate against your test set. This function will print the value of the loss function and the performance metrics specified during the compilation of the model. In this case, the `binary_crossentropy` and the `accuracy` respectively.

[26]:
```
happy_model.evaluate(X_test, Y_test)
```

```
5/5 [==============================] - 0s 38ms/step - loss: 0.1613 - accuracy:
0.9133
```

[26]:
```
[0.16131539642810822, 0.9133333563804626]
```

Easy, right? But what if you need to build a model with shared layers, branches, or multiple inputs and outputs? This is where Sequential, with its beautifully simple yet limited functionality, won't be able to help you.

Next up: Enter the Functional API, your slightly more complex, highly flexible friend.

4 - The Functional API

Welcome to the second half of the assignment, where you'll use Keras' flexible Functional API to build a ConvNet that can differentiate between 6 sign language digits.

The Functional API can handle models with non-linear topology, shared layers, as well as layers with multiple inputs or outputs. Imagine that, where the Sequential API requires the model to move in a linear fashion through its layers, the Functional API allows much more flexibility. Where Sequential is a straight line, a Functional model is a graph, where the nodes of the layers can connect in many more ways than one.

In the visual example below, the one possible direction of the movement Sequential model is shown in contrast to a skip connection, which is just one of the many ways a Functional model can be constructed. A skip connection, as you might have guessed, skips some layer in the network and feeds the output to a later layer in the network. Don't worry, you'll be spending more time with skip connections very soon!

4.1 - Load the SIGNS Dataset

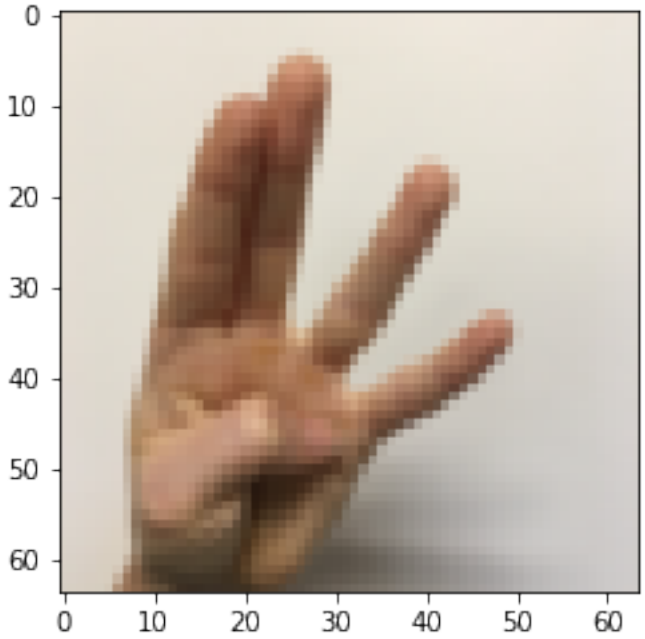
As a reminder, the SIGNS dataset is a collection of 6 signs representing numbers from 0 to 5.

[27]:
```
# Loading the data (signs)
X_train_orig, Y_train_orig, X_test_orig, Y_test_orig, classes =␣
↪load_signs_dataset()
```

The next cell will show you an example of a labelled image in the dataset. Feel free to change the value of `index` below and re-run to see different examples.

[28]:
```
# Example of an image from the dataset
index = 9
plt.imshow(X_train_orig[index])
print ("y = " + str(np.squeeze(Y_train_orig[:, index])))
```

```
y = 4
```



4.2 - Split the Data into Train/Test Sets

In Course 2, you built a fully-connected network for this dataset. But since this is an image dataset, it is more natural to apply a ConvNet to it.

To get started, let's examine the shapes of your data.

[29]:
```
X_train = X_train_orig/255.
X_test = X_test_orig/255.
Y_train = convert_to_one_hot(Y_train_orig, 6).T
Y_test = convert_to_one_hot(Y_test_orig, 6).T
print ("number of training examples = " + str(X_train.shape[0]))
print ("number of test examples = " + str(X_test.shape[0]))
print ("X_train shape: " + str(X_train.shape))
print ("Y_train shape: " + str(Y_train.shape))
print ("X_test shape: " + str(X_test.shape))
print ("Y_test shape: " + str(Y_test.shape))
```

```
number of training examples = 1080
number of test examples = 120
X_train shape: (1080, 64, 64, 3)
Y_train shape: (1080, 6)
X_test shape: (120, 64, 64, 3)
Y_test shape: (120, 6)
```

4.3 - Forward Propagation

In TensorFlow, there are built-in functions that implement the convolution steps for you. By now, you should be familiar with how TensorFlow builds computational graphs. In the Functional API, you create a graph of layers. This is what allows such great flexibility.

However, the following model could also be defined using the Sequential API since the information flow is on a single line. But don't deviate. What we want you to learn is to use the functional API.

Begin building your graph of layers by creating an input node that functions as a callable object:

- **input_img = tf.keras.Input(shape=input_shape):**

Then, create a new node in the graph of layers by calling a layer on the `input_img` object:

- **tf.keras.layers.Conv2D(filters= ... , kernel_size= ... , padding='same')(input_img):** Read the full documentation on Conv2D.
- **tf.keras.layers.MaxPool2D(pool_size=(f, f), strides=(s, s), padding='same'):** `MaxPool2D()` downsamples your input using a window of size (f, f) and strides of size (s, s) to carry out max pooling over each window. For max pooling, you usually operate on a single example at a time and a single channel at a time. Read the full documentation on MaxPool2D.
- **tf.keras.layers.ReLU():** computes the elementwise ReLU of Z (which can be any shape). You can read the full documentation on ReLU.

- **tf.keras.layers.Flatten()**: given a tensor "P", this function takes each training (or test) example in the batch and flattens it into a 1D vector.
  - If a tensor P has the shape (batch_size,h,w,c), it returns a flattened tensor with shape (batch_size, k), where $k = h \times w \times c$. "k" equals the product of all the dimension sizes other than the first dimension.
  - For example, given a tensor with dimensions [100, 2, 3, 4], it flattens the tensor to be of shape [100, 24], where 24 = 2 * 3 * 4. You can read the full documentation on Flatten.
- **tf.keras.layers.Dense(units= ... , activation='softmax')(F):** given the flattened input F, it returns the output computed using a fully connected layer. You can read the full documentation on Dense.

In the last function above (`tf.keras.layers.Dense()`), the fully connected layer automatically initializes weights in the graph and keeps on training them as you train the model. Hence, you did not need to initialize those weights when initializing the parameters.

Lastly, before creating the model, you'll need to define the output using the last of the function's compositions (in this example, a Dense layer):

- **outputs = tf.keras.layers.Dense(units=6, activation='softmax')(F)**

Window, kernel, filter, pool The words "kernel" and "filter" are used to refer to the same thing. The word "filter" accounts for the amount of "kernels" that will be used in a single convolution layer. "Pool" is the name of the operation that takes the max or average value of the kernels.

This is why the parameter `pool_size` refers to `kernel_size`, and you use `(f,f)` to refer to the filter size.

Pool size and kernel size refer to the same thing in different objects - They refer to the shape of the window where the operation takes place.

Exercise 2 - convolutional_model

Implement the `convolutional_model` function below to build the following model: `CONV2D -> RELU -> MAXPOOL -> CONV2D -> RELU -> MAXPOOL -> FLATTEN -> DENSE`. Use the functions above!

Also, plug in the following parameters for all the steps:

- Conv2D: Use 8 4 by 4 filters, stride 1, padding is "SAME"
- ReLU
- MaxPool2D: Use an 8 by 8 filter size and an 8 by 8 stride, padding is "SAME"
- **Conv2D**: Use 16 2 by 2 filters, stride 1, padding is "SAME"
- **ReLU**
- **MaxPool2D**: Use a 4 by 4 filter size and a 4 by 4 stride, padding is "SAME"
- Flatten the previous output.
- Fully-connected (Dense) layer: Apply a fully connected layer with 6 neurons and a softmax activation.

[34]:
```
# GRADED FUNCTION: convolutional_model
```

```
def convolutional_model(input_shape):
    """
    Implements the forward propagation for the model:
    CONV2D -> RELU -> MAXPOOL -> CONV2D -> RELU -> MAXPOOL -> FLATTEN -> DENSE

    Note that for simplicity and grading purposes, you'll hard-code some values
    such as the stride and kernel (filter) sizes.
    Normally, functions should take these values as function parameters.

    Arguments:
    input_img -- input dataset, of shape (input_shape)

    Returns:
    model -- TF Keras model (object containing the information for the entire␣
↪training process)
    """

    input_img = tf.keras.Input(shape=input_shape)
    ## CONV2D: 8 filters 4x4, stride of 1, padding 'SAME'
    # Z1 = None
    ## RELU
    # A1 = None
    ## MAXPOOL: window 8x8, stride 8, padding 'SAME'
    # P1 = None
    ## CONV2D: 16 filters 2x2, stride 1, padding 'SAME'
    # Z2 = None
    ## RELU
    # A2 = None
    ## MAXPOOL: window 4x4, stride 4, padding 'SAME'
    # P2 = None
    ## FLATTEN
    # F = None
    ## Dense layer
    ## 6 neurons in output layer. Hint: one of the arguments should be␣
↪"activation='softmax'"
    # outputs = None
    # YOUR CODE STARTS HERE


    Z1 = tfl.Conv2D(8, (4,4), strides=1, padding="same")(input_img)
    A1 = tfl.ReLU(max_value=None, negative_slope=0, threshold=0)(input_img)
    P1 = tfl.MaxPooling2D(pool_size=(8, 8), strides=(8, 8),␣
↪padding='same')(input_img)
    Z2 = tfl.Conv2D(16, (2,2), strides=1, padding="same")(input_img)
    A2 = tfl.ReLU(max_value=None, negative_slope=0, threshold=0)(input_img)
    P2 = tfl.MaxPooling2D(pool_size=(4, 4), strides=(4, 4),␣
↪padding='same')(input_img)
```

```
    F = tfl.Flatten()
    outputs = tfl.Conv2D(8, (4,4), strides=1, activation='linear',␣
 ↪padding="same")(input_img)

    # YOUR CODE ENDS HERE
    model = tf.keras.Model(inputs=input_img, outputs=outputs)
    return model
```

[35]:
```
conv_model = convolutional_model((64, 64, 3))
conv_model.compile(optimizer='adam',
                   loss='categorical_crossentropy',
                   metrics=['accuracy'])
conv_model.summary()

output = [['InputLayer', [(None, 64, 64, 3)], 0],
        ['Conv2D', (None, 64, 64, 8), 392, 'same', 'linear', 'GlorotUniform'],
        ['ReLU', (None, 64, 64, 8), 0],
        ['MaxPooling2D', (None, 8, 8, 8), 0, (8, 8), (8, 8), 'same'],
        ['Conv2D', (None, 8, 8, 16), 528, 'same', 'linear', 'GlorotUniform'],
        ['ReLU', (None, 8, 8, 16), 0],
        ['MaxPooling2D', (None, 2, 2, 16), 0, (4, 4), (4, 4), 'same'],
        ['Flatten', (None, 64), 0],
        ['Dense', (None, 6), 390, 'softmax']]

comparator(summary(conv_model), output)
```

```
Model: "functional_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         [(None, 64, 64, 3)]       0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 64, 64, 8)         392
=================================================================
Total params: 392
Trainable params: 392
Non-trainable params: 0
_________________________________________________________________
All tests passed!
```

Both the Sequential and Functional APIs return a TF Keras model object. The only difference is how inputs are handled inside the object model!

4.4 - Train the Model

[37]:
```
train_dataset = tf.data.Dataset.from_tensor_slices((X_train, Y_train)).batch(64)
test_dataset = tf.data.Dataset.from_tensor_slices((X_test, Y_test)).batch(64)
```

```
history = conv_model.fit(train_dataset, epochs=100,␣
 ↪validation_data=test_dataset)
```

```
Epoch 1/100
```

```
      ␣
↪---------------------------------------------------------------------------

       ValueError                                Traceback (most recent call␣
↪last)

       <ipython-input-37-c0adbdb469a4> in <module>
         1 train_dataset = tf.data.Dataset.from_tensor_slices((X_train,␣
↪Y_train)).batch(64)
         2 test_dataset = tf.data.Dataset.from_tensor_slices((X_test, Y_test)).
↪batch(64)
   ----> 3 history = conv_model.fit(train_dataset, epochs=100,␣
↪validation_data=test_dataset)


       /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/
↪training.py in _method_wrapper(self, *args, **kwargs)
       106   def _method_wrapper(self, *args, **kwargs):
       107     if not self._in_multi_worker_mode():  # pylint:␣
↪disable=protected-access
   --> 108       return method(self, *args, **kwargs)
       109
       110     # Running inside `run_distribute_coordinator` already.


       /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/
↪training.py in fit(self, x, y, batch_size, epochs, verbose, callbacks,␣
↪validation_split, validation_data, shuffle, class_weight, sample_weight,␣
↪initial_epoch, steps_per_epoch, validation_steps, validation_batch_size,␣
↪validation_freq, max_queue_size, workers, use_multiprocessing)
      1096                 batch_size=batch_size):
      1097               callbacks.on_train_batch_begin(step)
   -> 1098               tmp_logs = train_function(iterator)
      1099               if data_handler.should_sync:
      1100                 context.async_wait()


       /opt/conda/lib/python3.7/site-packages/tensorflow/python/eager/
↪def_function.py in __call__(self, *args, **kwds)
       778       else:
       779         compiler = "nonXla"
```

```
   --> 780         result = self._call(*args, **kwds)
       781
       782       new_tracing_count = self._get_tracing_count()


       /opt/conda/lib/python3.7/site-packages/tensorflow/python/eager/
↪def_function.py in _call(self, *args, **kwds)
       812       # In this case we have not created variables on the first call.
↪ So we can
       813       # run the first trace but we should fail if variables are␣
↪created.
   --> 814       results = self._stateful_fn(*args, **kwds)
       815       if self._created_variables:
       816         raise ValueError("Creating variables on a non-first call to␣
↪a function"


       /opt/conda/lib/python3.7/site-packages/tensorflow/python/eager/function.
↪py in __call__(self, *args, **kwargs)
      2826     """Calls a graph function specialized to the inputs."""
      2827     with self._lock:
   -> 2828       graph_function, args, kwargs = self.
↪_maybe_define_function(args, kwargs)
      2829     return graph_function._filtered_call(args, kwargs)  # pylint:␣
↪disable=protected-access
      2830


       /opt/conda/lib/python3.7/site-packages/tensorflow/python/eager/function.
↪py in _maybe_define_function(self, args, kwargs)
      3208           and self.input_signature is None
      3209           and call_context_key in self._function_cache.missed):
   -> 3210         return self._define_function_with_shape_relaxation(args,␣
↪kwargs)
      3211
      3212       self._function_cache.missed.add(call_context_key)


       /opt/conda/lib/python3.7/site-packages/tensorflow/python/eager/function.
↪py in _define_function_with_shape_relaxation(self, args, kwargs)
      3140
      3141     graph_function = self._create_graph_function(
   -> 3142         args, kwargs, override_flat_arg_shapes=relaxed_arg_shapes)
      3143     self._function_cache.arg_relaxed[rank_only_cache_key] =␣
↪graph_function
      3144
```

```
      /opt/conda/lib/python3.7/site-packages/tensorflow/python/eager/function.
↪py in _create_graph_function(self, args, kwargs, override_flat_arg_shapes)
     3073             arg_names=arg_names,
     3074             override_flat_arg_shapes=override_flat_arg_shapes,
  -> 3075             capture_by_value=self._capture_by_value),
     3076         self._function_attributes,
     3077         function_spec=self.function_spec,


      /opt/conda/lib/python3.7/site-packages/tensorflow/python/framework/
↪func_graph.py in func_graph_from_py_func(name, python_func, args, kwargs,␣
↪signature, func_graph, autograph, autograph_options, add_control_dependencies,␣
↪arg_names, op_return_value, collections, capture_by_value,␣
↪override_flat_arg_shapes)
      984         _, original_func = tf_decorator.unwrap(python_func)
      985
  --> 986       func_outputs = python_func(*func_args, **func_kwargs)
      987
      988       # invariant: `func_outputs` contains only Tensors,␣
↪CompositeTensors,


      /opt/conda/lib/python3.7/site-packages/tensorflow/python/eager/
↪def_function.py in wrapped_fn(*args, **kwds)
      598         # __wrapped__ allows AutoGraph to swap in a converted␣
↪function. We give
      599         # the function a weak reference to itself to avoid a␣
↪reference cycle.
  --> 600         return weak_wrapped_fn().__wrapped__(*args, **kwds)
      601     weak_wrapped_fn = weakref.ref(wrapped_fn)
      602


      /opt/conda/lib/python3.7/site-packages/tensorflow/python/framework/
↪func_graph.py in wrapper(*args, **kwargs)
      971           except Exception as e:  # pylint:disable=broad-except
      972             if hasattr(e, "ag_error_metadata"):
  --> 973               raise e.ag_error_metadata.to_exception(e)
      974             else:
      975               raise


      ValueError: in user code:

      /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/
↪training.py:806 train_function  *
```

```
            return step_function(self, iterator)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/
↪training.py:796 step_function  **
            outputs = model.distribute_strategy.run(run_step, args=(data,))
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/distribute/
↪distribute_lib.py:1211 run
            return self._extended.call_for_each_replica(fn, args=args,␣
↪kwargs=kwargs)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/distribute/
↪distribute_lib.py:2585 call_for_each_replica
            return self._call_for_each_replica(fn, args, kwargs)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/distribute/
↪distribute_lib.py:2945 _call_for_each_replica
            return fn(*args, **kwargs)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/
↪training.py:789 run_step  **
            outputs = model.train_step(data)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/
↪training.py:749 train_step
            y, y_pred, sample_weight, regularization_losses=self.losses)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/
↪compile_utils.py:204 __call__
            loss_value = loss_obj(y_t, y_p, sample_weight=sw)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/losses.py:
↪149 __call__
            losses = ag_call(y_true, y_pred)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/losses.py:
↪253 call  **
            return ag_fn(y_true, y_pred, **self._fn_kwargs)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/util/dispatch.
↪py:201 wrapper
            return target(*args, **kwargs)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/losses.py:
↪1535 categorical_crossentropy
            return K.categorical_crossentropy(y_true, y_pred,␣
↪from_logits=from_logits)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/util/dispatch.
↪py:201 wrapper
            return target(*args, **kwargs)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/backend.
↪py:4687 categorical_crossentropy
            target.shape.assert_is_compatible_with(output.shape)
        /opt/conda/lib/python3.7/site-packages/tensorflow/python/framework/
↪tensor_shape.py:1134 assert_is_compatible_with
            raise ValueError("Shapes %s and %s are incompatible" % (self, other))
```

```
ValueError: Shapes (None, 6) and (None, 64, 64, 8) are incompatible
```

5 - History Object

The history object is an output of the `.fit()` operation, and provides a record of all the loss and metric values in memory. It's stored as a dictionary that you can retrieve at `history.history`:

[33]:
```
history.history
```

```
␣
↪---------------------------------------------------------------------------

NameError                                 Traceback (most recent call␣
↪last)

<ipython-input-33-6cd13d6a221b> in <module>
----> 1 history.history


NameError: name 'history' is not defined
```

Now visualize the loss over time using `history.history`:

[38]:
```
# The history.history["loss"] entry is a dictionary with as many values as␣
 ↪epochs that the
# model was trained on.
df_loss_acc = pd.DataFrame(history.history)
df_loss= df_loss_acc[['loss','val_loss']]
df_loss.rename(columns={'loss':'train','val_loss':'validation'},inplace=True)
df_acc= df_loss_acc[['accuracy','val_accuracy']]
df_acc.rename(columns={'accuracy':'train','val_accuracy':
 ↪'validation'},inplace=True)
df_loss.plot(title='Model loss',figsize=(12,8)).
 ↪set(xlabel='Epoch',ylabel='Loss')
df_acc.plot(title='Model Accuracy',figsize=(12,8)).
 ↪set(xlabel='Epoch',ylabel='Accuracy')
```

```
␣
↪---------------------------------------------------------------------------

NameError                                 Traceback (most recent call␣
↪last)

<ipython-input-38-55f5ebfbfb89> in <module>
```

```
        1 # The history.history["loss"] entry is a dictionary with as many␣
↪values as epochs that the
        2 # model was trained on.
  ----> 3 df_loss_acc = pd.DataFrame(history.history)
        4 df_loss= df_loss_acc[['loss','val_loss']]
        5 df_loss.rename(columns={'loss':'train','val_loss':
↪'validation'},inplace=True)


      NameError: name 'history' is not defined
```

Congratulations! You've finished the assignment and built two models: One that recognizes smiles, and another that recognizes SIGN language with almost 80% accuracy on the test set. In addition to that, you now also understand the applications of two Keras APIs: Sequential and Functional. Nicely done!

By now, you know a bit about how the Functional API works and may have glimpsed the possibilities. In your next assignment, you'll really get a feel for its power when you get the opportunity to build a very deep ConvNet, using ResNets!

6 - Bibliography

You're always encouraged to read the official documentation. To that end, you can find the docs for the Sequential and Functional APIs here:

https://www.tensorflow.org/guide/keras/sequential_model

https://www.tensorflow.org/guide/keras/functional