modelNotebook

May 15, 2019

[74]:
```
#!/usr/bin/env python3
import scipy.io.wavfile
from python_speech_features import mfcc, delta
import numpy as np
import math

import tensorflow as tf
from tensorflow.keras import layers
from keras.utils import to_categorical
from keras.utils import plot_model
import IPython.display
import matplotlib.pyplot as plt
```

[75]:
```
np.random.seed(1234)

# Audio pre-processing cell


files = [ 'cousinhenry_01_trollope_8khz.wav',
'siegeofcorinth_2_byron_8khz.wav',
'upperroom_16_ryle_8khz.wav',
'vorst_14_machiavelli_8khz.wav',
]

# This constant is the number of entries of the all_examples list below that
# correspond to one training example.
# * The 13 is magic -- it's the default number of mfcc... frequencies(?)␣
↪calculated
#   by many places on the web and in the python library we used.
# * The 49 comes from a combination of our sample size and mfcc window. Our␣
↪sample
#   size is half second and we calculate mfccs in a 25ms window with a 10ms␣
↪stride.
#   (0.5 - 0.01) / 0.01 = 49
# * Multiply that * 2 because we are also calculating the first derivative of␣
↪the
```

```
#   mfcc... cepstrum(?), which seems to be common (further adding 2nd␣
↪derivative
#   is also common).
# * The + 1 is because the label for each sample comes right after the above.
height_of_one_training_example = 49 * 13 * 2 + 1

label = 0
all_examples = []
for one_file in files:
  label += 1
  rate, data = scipy.io.wavfile.read(one_file)
  total_length_of_wave = data.shape[0]
  print ("just read file number %d which contains %d audio samples and is named␣
↪%s Now analying it:" %
        (label, total_length_of_wave, one_file))
  assert rate == 8000, "rate was %d" % rate

  half_second_length = 4000
  start_index_of_half_second = 0
  num_training_example_in_this_file = 0
  while total_length_of_wave - start_index_of_half_second >= half_second_length:
    num_training_example_in_this_file += 1

    # The class with the least data has 752, so let's do 750 samples each for␣
↪class balance.
    if num_training_example_in_this_file == 751:
      break;

    if num_training_example_in_this_file % 500 == 0:
      print ("\t analyzing training sample number %d" %␣
↪num_training_example_in_this_file)

    this_training_example_raw = data[start_index_of_half_second:
↪start_index_of_half_second + half_second_length]
    start_index_of_half_second += half_second_length
    assert len(this_training_example_raw) == 4000,␣
↪len(this_training_example_raw)
    mfccs = mfcc(this_training_example_raw, 8000)
    assert mfccs.shape == (49, 13), mfccs.shape

    # Alfredo used 2 here, and changing it doesn't change the output size, so␣
↪*shrug*.
    first_derivative = delta(mfccs, 2)
    assert first_derivative.shape == (49, 13), first_derivative.shape
    all_examples.extend(mfccs.flatten().tolist())
    all_examples.extend(first_derivative.flatten().tolist())
```

```
    all_examples.append(label)
    assert len(all_examples) % height_of_one_training_example == 0, (
        "num_training_example_in_this_file = %d" %␣
 ↪num_training_example_in_this_file)
```

```
just read file number 1 which contains 7305509 audio samples and is named
cousinhenry_01_trollope_8khz.wav Now analying it:
         analyzing training sample number 500
just read file number 2 which contains 12400013 audio samples and is named
siegeofcorinth_2_byron_8khz.wav Now analying it:
         analyzing training sample number 500
just read file number 3 which contains 36554719 audio samples and is named
upperroom_16_ryle_8khz.wav Now analying it:
         analyzing training sample number 500
just read file number 4 which contains 3008270 audio samples and is named
vorst_14_machiavelli_8khz.wav Now analying it:
         analyzing training sample number 500
```

[76]:
```
np.random.seed(123456)

# This cell massages the audio features into a format Keras likes and splits␣
 ↪into test/dev sets.

# TODO(dgrogan): Parts of the first half and last half of this cell are␣
 ↪inverses and can be combined.
all_examples_np = np.array(all_examples)
all_examples_np = all_examples_np.reshape((height_of_one_training_example, -1),␣
 ↪order='F')

#print ("all_examples_np.shape = %s, so we have %d training samples" % (
#        all_examples_np.shape, all_examples_np.shape[1]))
assert all_examples_np[-1, 0] == 1, (
    "make sure the last row labels the first column as belonging to file number␣
 ↪1 %s" % all_examples_np[-1, 0])

shuffled_examples = all_examples_np.T
np.random.shuffle(shuffled_examples)
shuffled_examples = shuffled_examples.T

# I changed to 0.9 when I thought we might not have enough data. We can change␣
 ↪it back to whatever.
training_pct = 0.9

number_of_training_examples = int(math.ceil(all_examples_np.shape[1] *␣
 ↪training_pct))

# The labels are the last entry in each of the columns, hence the -1 below.
```

```python
X_train = shuffled_examples[0:-1, 0:number_of_training_examples]
Y_train = shuffled_examples[-1:, 0:number_of_training_examples]
X_dev   = shuffled_examples[0:-1, number_of_training_examples:]
Y_dev   = shuffled_examples[-1:, number_of_training_examples:]

# The labels in Y are an integer corresponding to the speaker number.
# In Keras, you want (number of data, attributes). So we reshape.
# Want: (see coursera M4 - Keras Tutorial)
# if training_pct = 0.8, (11853, 1274) (11853, 1) (2963, 1274) (2963, 1)
X_train = X_train.T
Y_train = Y_train.T
X_dev = X_dev.T
Y_dev = Y_dev.T

# Sanity check the train/dev shapes.
print(X_train.shape, Y_train.shape, X_dev.shape, Y_dev.shape)

# Sanity check the one-hot encoding.
print(Y_train[0:5])
print(Y_dev[0:5])
Y_train = to_categorical(Y_train - 1) # -1 because to_categorical seems to␣
 ↪expect labels to start at 0
Y_dev = to_categorical(Y_dev - 1)
print(Y_train[0:5])
print(Y_dev[0:5])
```

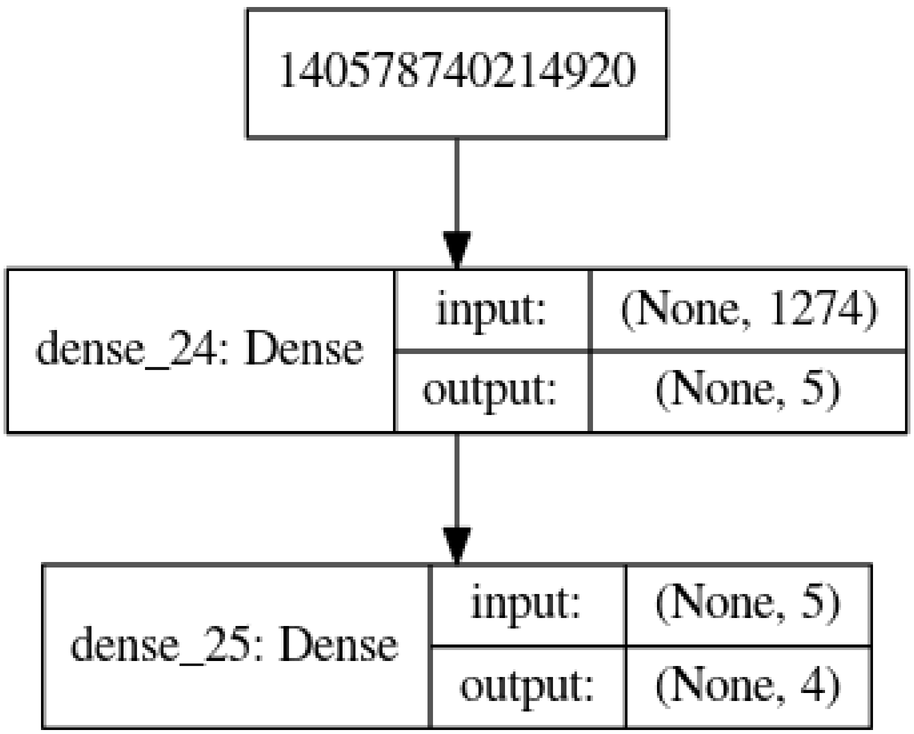
```
(2700, 1274) (2700, 1) (300, 1274) (300, 1)
[[3.]
 [3.]
 [4.]
 [2.]
 [2.]]
[[3.]
 [4.]
 [2.]
 [4.]
 [4.]]
[[0. 0. 1. 0.]
 [0. 0. 1. 0.]
 [0. 0. 0. 1.]
 [0. 1. 0. 0.]
 [0. 1. 0. 0.]]
[[0. 0. 1. 0.]
 [0. 0. 0. 1.]
 [0. 1. 0. 0.]
 [0. 0. 0. 1.]
 [0. 0. 0. 1.]]
```

[77]:
```python
#Keras
model = tf.keras.Sequential()

#hidden layers
model.add(layers.Dense(5, activation='relu', input_dim=X_train.shape[1]))
model.add(layers.Dense(4, activation='softmax'))

model.compile(optimizer=tf.train.AdamOptimizer(0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

keras.utils.plot_model(model, to_file='test_keras_plot_model.png',␣
 ↪show_shapes=True)
display(IPython.display.Image('test_keras_plot_model.png'))
print(model.summary())
# I don't know where 140240419526080 in the picture came from
```




```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_24 (Dense)             (None, 5)                 6375
_________________________________________________________________
dense_25 (Dense)             (None, 4)                 24
```

```
=================================================================
Total params: 6,399
Trainable params: 6,399
Non-trainable params: 0
_________________________________________________________________
None
```

[78]:
```
%%time
history_object = model.fit(X_train, Y_train, epochs=30, batch_size=128,␣
 ↪verbose=2, shuffle=True,
         validation_data=(X_dev, Y_dev))
```

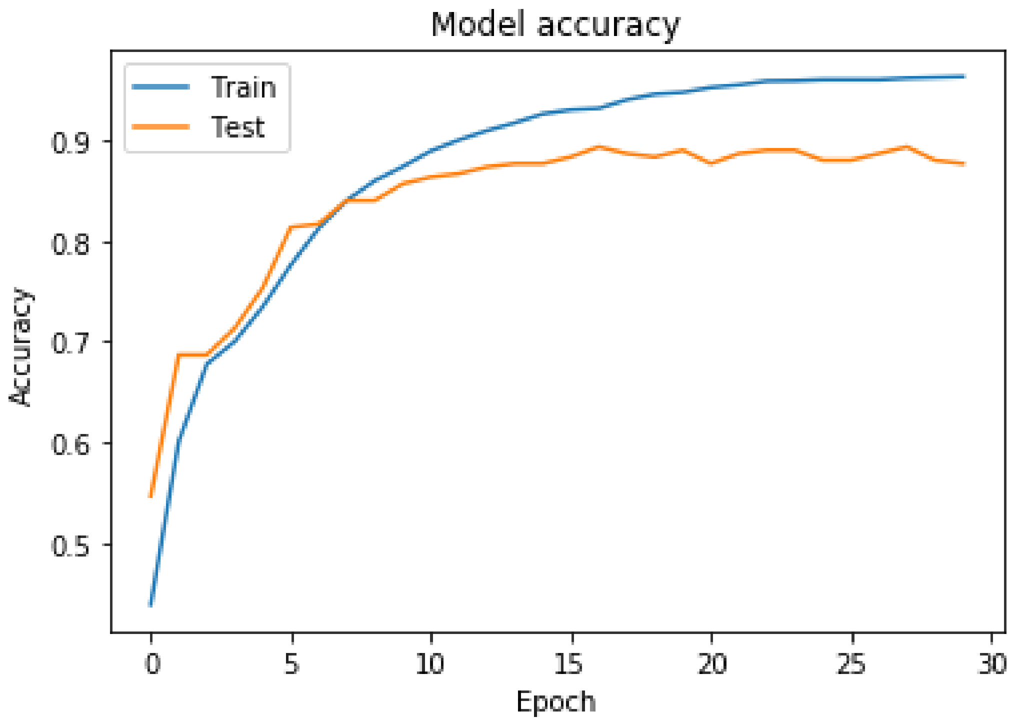
```
Train on 2700 samples, validate on 300 samples
Epoch 1/30
 - 1s - loss: 2.5111 - acc: 0.4389 - val_loss: 1.0546 - val_acc: 0.5467
Epoch 2/30
 - 0s - loss: 0.9688 - acc: 0.6007 - val_loss: 0.8933 - val_acc: 0.6867
Epoch 3/30
 - 0s - loss: 0.8344 - acc: 0.6774 - val_loss: 0.8103 - val_acc: 0.6867
Epoch 4/30
 - 0s - loss: 0.7470 - acc: 0.7000 - val_loss: 0.7668 - val_acc: 0.7133
Epoch 5/30
 - 0s - loss: 0.6878 - acc: 0.7344 - val_loss: 0.7254 - val_acc: 0.7533
Epoch 6/30
 - 0s - loss: 0.6404 - acc: 0.7759 - val_loss: 0.5987 - val_acc: 0.8133
Epoch 7/30
 - 0s - loss: 0.5762 - acc: 0.8122 - val_loss: 0.6358 - val_acc: 0.8167
Epoch 8/30
 - 0s - loss: 0.5258 - acc: 0.8400 - val_loss: 0.5887 - val_acc: 0.8400
Epoch 9/30
 - 0s - loss: 0.4873 - acc: 0.8596 - val_loss: 0.6414 - val_acc: 0.8400
Epoch 10/30
 - 0s - loss: 0.4495 - acc: 0.8737 - val_loss: 0.6300 - val_acc: 0.8567
Epoch 11/30
 - 0s - loss: 0.4238 - acc: 0.8893 - val_loss: 0.6425 - val_acc: 0.8633
Epoch 12/30
 - 0s - loss: 0.4073 - acc: 0.9000 - val_loss: 0.6198 - val_acc: 0.8667
Epoch 13/30
 - 0s - loss: 0.3838 - acc: 0.9093 - val_loss: 0.6009 - val_acc: 0.8733
Epoch 14/30
 - 0s - loss: 0.3631 - acc: 0.9170 - val_loss: 0.5837 - val_acc: 0.8767
Epoch 15/30
 - 0s - loss: 0.3531 - acc: 0.9259 - val_loss: 0.6393 - val_acc: 0.8767
Epoch 16/30
 - 0s - loss: 0.3371 - acc: 0.9300 - val_loss: 0.5929 - val_acc: 0.8833
Epoch 17/30
 - 0s - loss: 0.3226 - acc: 0.9315 - val_loss: 0.5897 - val_acc: 0.8933
```

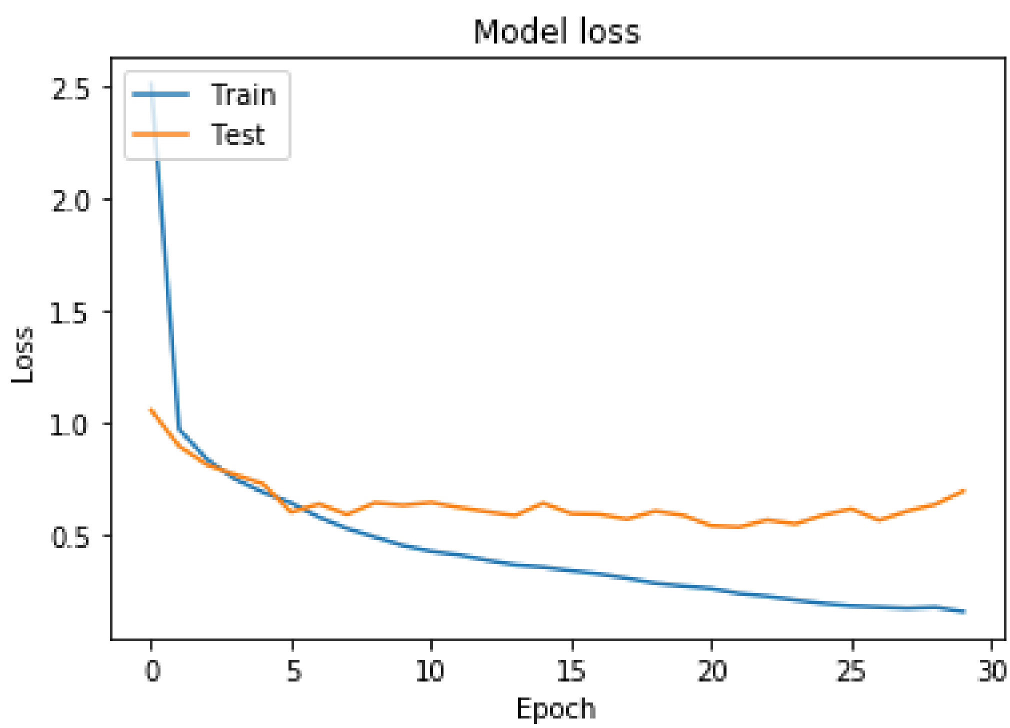
```
Epoch 18/30
 - 0s - loss: 0.3033 - acc: 0.9400 - val_loss: 0.5675 - val_acc: 0.8867
Epoch 19/30
 - 0s - loss: 0.2811 - acc: 0.9456 - val_loss: 0.6041 - val_acc: 0.8833
Epoch 20/30
 - 0s - loss: 0.2687 - acc: 0.9474 - val_loss: 0.5846 - val_acc: 0.8900
Epoch 21/30
 - 0s - loss: 0.2571 - acc: 0.9522 - val_loss: 0.5383 - val_acc: 0.8767
Epoch 22/30
 - 0s - loss: 0.2354 - acc: 0.9548 - val_loss: 0.5320 - val_acc: 0.8867
Epoch 23/30
 - 0s - loss: 0.2225 - acc: 0.9585 - val_loss: 0.5644 - val_acc: 0.8900
Epoch 24/30
 - 0s - loss: 0.2059 - acc: 0.9589 - val_loss: 0.5460 - val_acc: 0.8900
Epoch 25/30
 - 0s - loss: 0.1907 - acc: 0.9600 - val_loss: 0.5855 - val_acc: 0.8800
Epoch 26/30
 - 0s - loss: 0.1798 - acc: 0.9600 - val_loss: 0.6136 - val_acc: 0.8800
Epoch 27/30
 - 0s - loss: 0.1745 - acc: 0.9600 - val_loss: 0.5624 - val_acc: 0.8867
Epoch 28/30
 - 0s - loss: 0.1692 - acc: 0.9615 - val_loss: 0.6035 - val_acc: 0.8933
Epoch 29/30
 - 0s - loss: 0.1741 - acc: 0.9622 - val_loss: 0.6336 - val_acc: 0.8800
Epoch 30/30
 - 0s - loss: 0.1542 - acc: 0.9630 - val_loss: 0.6929 - val_acc: 0.8767
CPU times: user 6.98 s, sys: 1.31 s, total: 8.29 s
Wall time: 4.73 s
```

[79]:

```
# Plot training & validation accuracy values
plt.plot(history_object.history['acc'])
plt.plot(history_object.history['val_acc'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()

# Plot training & validation loss values
plt.plot(history_object.history['loss'])
plt.plot(history_object.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```


Model accuracy
Train
Test
Accuracy
0.9
0.8
0.7
0.6
0.5
0
5
10
15
20
25
30
Epoch


Model loss
Train
Test
Loss
2.5
2.0
1.5
1.0
0.5
0
5
10
15
20
25
30
Epoch

```
[ ]:
```