assignment05_FoxAndrea

April 18, 2021

0.1 5.1 Implement the movie review classifier found in section 3.4 of Deep Learning with Python [pages 68-78]

[1]:
```
#Load libraries
import numpy as np
from keras.datasets import imdb
```

3.1 Loading the IMDB dataset

[2]:
```
#From Robert Zacchigna to turn off warnings
np.warnings.filterwarnings('ignore', category = np.VisibleDeprecationWarning)

#Argument num_words = 10,000 means we only keep the top 10,000 most frequently␣
↪occurring words
#The variables train_data and test_data are lists of reviews which are a list␣
↪of word indices
#The variables train_labels and test_labels are lists of 0s and 1s. 0 =␣
↪negative, 1 = positive
(train_data, train_labels), (test_data, test_labels) = imdb.
↪load_data(num_words=10000)
```

[3]:
```
#Because restricting to the top 10,000  most frequent words, no word index will␣
↪exceed 10,000
max([max(sequence) for sequence in train_data])
```

[3]: 9999

[4]:
```
#Decode one of these reviews back to English words
word_index = imdb.get_word_index()
reverse_word_index = dict(
    [(value, key) for (key, value) in word_index.items()])
decoded_review = ' '.join(
    [reverse_word_index.get(i - 3, '?') for i in train_data[0]])
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/imdb_word_index.json
1646592/1641221 [==============================] - 0s 0us/step
```

3.2 Encoding the integer sequences into a binary matrix

[6]:
```
#Encoding the integer sequences into a binary matrix
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.
    return results

x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)

#Here is what the samples look like now
x_train[0]
```

[6]:
```
array([0., 1., 1., …, 0., 0., 0.])
```

[7]:
```
#Vectorize your labels
y_train = np.asarray(train_labels).astype('float32')
y_test = np.asarray(test_labels).astype('float32')

#Now the data is ready to be fed into a neural network
```

3.3 The model definition

[10]:
```
#Load in libraries
from keras import models
from keras import layers
```

[11]:
```
model = models.Sequential()
model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

3.4 Compiling the model

[12]:
```
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

3.5 Configuring the optimizer

[13]:
```
from keras import optimizers

model.compile(optimizer=optimizers.RMSprop(lr=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

3.6 Using custom losses and metrics

[14]:
```python
from keras import losses
from keras import metrics

model.compile(optimizer=optimizers.RMSprop(lr=0.001),
              loss=losses.binary_crossentropy,
              metrics=[metrics.binary_accuracy])
```

3.7 Setting aside a validation set

[15]:
```python
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

3.8 Training your model

[16]:
```python
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])

history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 45ms/step - loss: 0.5997 - acc:
0.7059 - val_loss: 0.3998 - val_acc: 0.8711
Epoch 2/20
30/30 [==============================] - 0s 12ms/step - loss: 0.3397 - acc:
0.9018 - val_loss: 0.3202 - val_acc: 0.8774
Epoch 3/20
30/30 [==============================] - 0s 11ms/step - loss: 0.2409 - acc:
0.9255 - val_loss: 0.3092 - val_acc: 0.8751
Epoch 4/20
30/30 [==============================] - 0s 13ms/step - loss: 0.1915 - acc:
0.9359 - val_loss: 0.2767 - val_acc: 0.8884
Epoch 5/20
30/30 [==============================] - 0s 12ms/step - loss: 0.1445 - acc:
0.9592 - val_loss: 0.3001 - val_acc: 0.8782
Epoch 6/20
30/30 [==============================] - 0s 12ms/step - loss: 0.1191 - acc:
0.9664 - val_loss: 0.2990 - val_acc: 0.8847
Epoch 7/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0996 - acc:
0.9715 - val_loss: 0.3197 - val_acc: 0.8791
Epoch 8/20
```

```
30/30 [==============================] - 0s 11ms/step - loss: 0.0813 - acc:
0.9773 - val_loss: 0.3257 - val_acc: 0.8830
Epoch 9/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0631 - acc:
0.9843 - val_loss: 0.3567 - val_acc: 0.8741
Epoch 10/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0477 - acc:
0.9901 - val_loss: 0.4273 - val_acc: 0.8689
Epoch 11/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0426 - acc:
0.9923 - val_loss: 0.4089 - val_acc: 0.8766
Epoch 12/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0328 - acc:
0.9940 - val_loss: 0.4268 - val_acc: 0.8756
Epoch 13/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0235 - acc:
0.9972 - val_loss: 0.5070 - val_acc: 0.8621
Epoch 14/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0197 - acc:
0.9972 - val_loss: 0.4989 - val_acc: 0.8709
Epoch 15/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0121 - acc:
0.9994 - val_loss: 0.5631 - val_acc: 0.8624
Epoch 16/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0124 - acc:
0.9990 - val_loss: 0.5645 - val_acc: 0.8683
Epoch 17/20
30/30 [==============================] - 0s 16ms/step - loss: 0.0095 - acc:
0.9989 - val_loss: 0.5999 - val_acc: 0.8690
Epoch 18/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0054 - acc:
0.9998 - val_loss: 0.7234 - val_acc: 0.8502
Epoch 19/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0065 - acc:
0.9995 - val_loss: 0.6660 - val_acc: 0.8644
Epoch 20/20
30/30 [==============================] - 1s 19ms/step - loss: 0.0040 - acc:
0.9997 - val_loss: 0.7071 - val_acc: 0.8652
```

3.9 Ploting the training and validation less

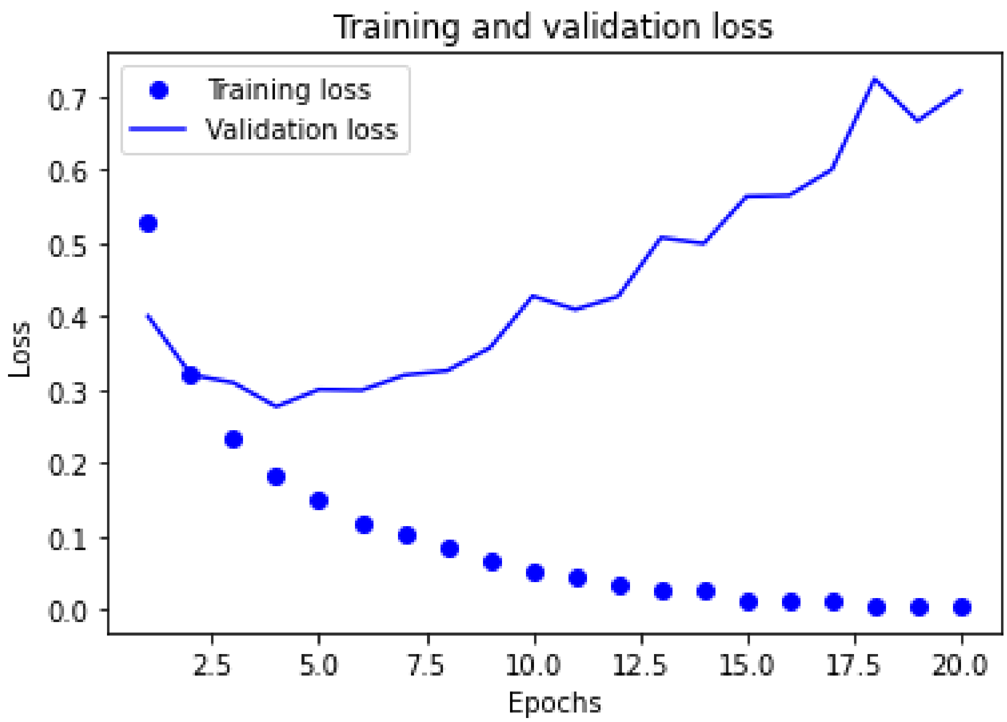
[17]:
```python
import matplotlib.pyplot as plt

acc = history.history['acc'] #came from general chat
history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
```

```
epochs = range(1, len(acc) + 1)

plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

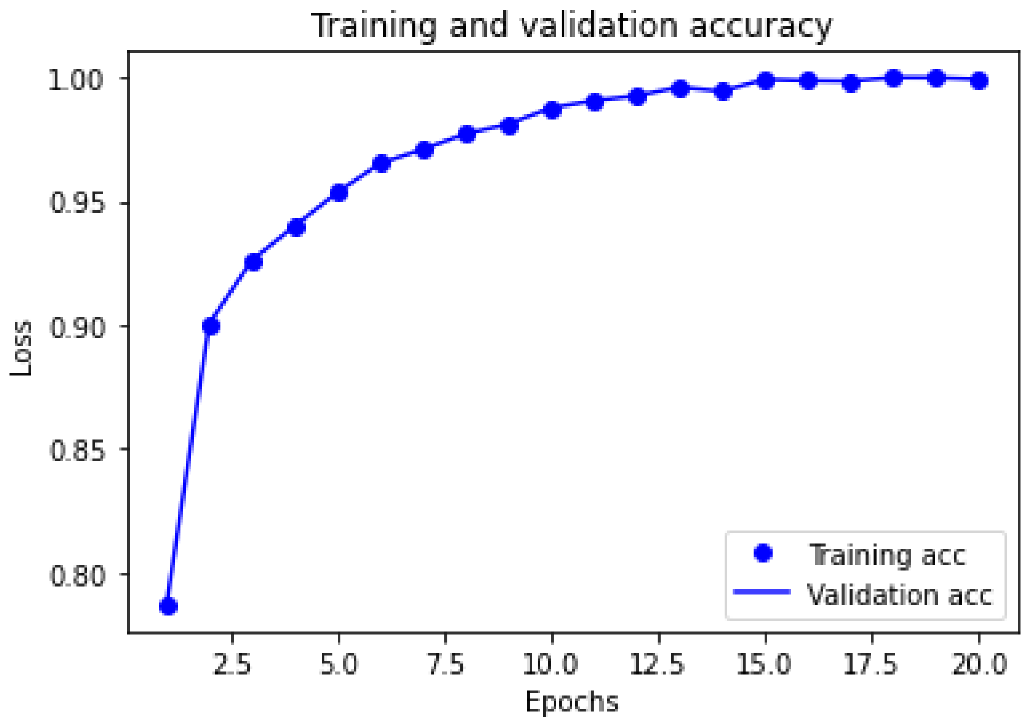


3.10 Plotting the training and validation accuracy

[18]:
```
plt.clf()
val_acc = history.history['acc'] #Came from chat
acc_values = history_dict['acc']
val_acc_values = history_dict['val_acc']

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

```
plt.show()
```



The training loss decreases with every epoch, and the training accuracy increases with every ep

3.11 Retraining a model from scratch

[19]:
```
model = models.Sequential()
model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=4, batch_size=512)
results = model.evaluate(x_test, y_test)
```

```
Epoch 1/4
49/49 [==============================] - 1s 11ms/step - loss: 0.5480 - accuracy:
0.7358
Epoch 2/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2690 - accuracy:
0.9150
```

```
Epoch 3/4
49/49 [==============================] - 0s 9ms/step - loss: 0.1953 - accuracy:
0.9331
Epoch 4/4
49/49 [==============================] - 0s 8ms/step - loss: 0.1648 - accuracy:
0.9438
782/782 [==============================] - 2s 2ms/step - loss: 0.3016 -
accuracy: 0.8806
```

[20]:
```
results #achieves 88% accuracy
```

[20]:
```
[0.30164003372192383, 0.8805599808692932]
```

[21]:
```
#Using a trained network to generate predictions on new data
model.predict(x_test)
```

[21]:
```
array([[0.15626568],
       [0.99988985],
       [0.65604335],
       …,
       [0.09303167],
       [0.05772743],
       [0.47996917]], dtype=float32)
```

0.2 Implement the news classifier found in section 3.5 of Deep Learning with Python [pages 78-84]

3.12 Loading the Reuters dataset

[22]:
```
from keras.datasets import reuters

#From Robert Zacchigna to turn off warnings
np.warnings.filterwarnings('ignore', category=np.VisibleDeprecationWarning)

#argument num_words = 10,000 restricts the data to the 10,000 most frequently␣
↪occuring words found in the data
(train_data, train_labels), (test_data, test_labels) = reuters.load_data(
    num_words=10000)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/reuters.npz
2113536/2110848 [==============================] - 0s 0us/step
```

[24]:
```
len(train_data) #8,982 training examples
```

[24]:
```
8982
```

[25]:
```
len(test_data) #2,246 test examples
```

[25]: 2246

3.13 Decoding newswires back to text

[26]:
```
word_index = reuters.get_word_index()
reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])
decoded_newswire = ' '.join([reverse_word_index.get(i - 3, '?') for i in
    train_data[0]])

#Now can vectorize the data with the exact same code as in the previous example
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/reuters_word_index.json
557056/550378 [==============================] - 0s 0us/step
```

3.14 Encoding the data

[27]:
```
import numpy as np

def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.
    return results

x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

[28]:
```
#To vectorize the labels, can cast the label list as an integer tensor or␣
↪one-hot encoding
def to_one_hot(labels, dimension=46):
    results = np.zeros((len(labels), dimension))
    for i, label in enumerate(labels):
        results[i, label] = 1.
    return results

one_hot_train_labels = to_one_hot(train_labels)
one_hot_test_labels = to_one_hot(test_labels)
```

[29]:
```
#Built-in way to do this in keras
from keras.utils.np_utils import to_categorical

one_hot_train_labels = to_categorical(train_labels)
one_hot_test_labels = to_categorical(test_labels)
```

3.15 Model delinition

[30]:
```
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))

#2 things to note:
#You end the network with a Dense layer of size 46. Each entry will encode a␣
↪different output class
#The last layer uses a softmax activation
```

3.16 Compiling the model

[31]:
```
#best loss function to use in this case is categorical_crossentropy
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

3.17 Setting aside a validation set

[32]:
```
x_val = x_train[:1000]
partial_x_train = x_train[1000:]

y_val = one_hot_train_labels[:1000]
partial_y_train = one_hot_train_labels[1000:]
```

3.18 Training the model

[33]:
```
#train the network for 20 epochs
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
16/16 [==============================] - 1s 32ms/step - loss: 3.1442 - accuracy:
0.4243 - val_loss: 1.7107 - val_accuracy: 0.6580
Epoch 2/20
16/16 [==============================] - 0s 18ms/step - loss: 1.4678 - accuracy:
0.7042 - val_loss: 1.2925 - val_accuracy: 0.7130
Epoch 3/20
16/16 [==============================] - 0s 19ms/step - loss: 1.0479 - accuracy:
0.7748 - val_loss: 1.1108 - val_accuracy: 0.7700
Epoch 4/20
16/16 [==============================] - 0s 18ms/step - loss: 0.8201 - accuracy:
```

```
0.8328 - val_loss: 1.0116 - val_accuracy: 0.7880
Epoch 5/20
16/16 [==============================] - 0s 17ms/step - loss: 0.6545 - accuracy:
0.8603 - val_loss: 0.9319 - val_accuracy: 0.8000
Epoch 6/20
16/16 [==============================] - 0s 18ms/step - loss: 0.4989 - accuracy:
0.8971 - val_loss: 0.9159 - val_accuracy: 0.8020
Epoch 7/20
16/16 [==============================] - 0s 15ms/step - loss: 0.4048 - accuracy:
0.9117 - val_loss: 0.8882 - val_accuracy: 0.8130
Epoch 8/20
16/16 [==============================] - 0s 16ms/step - loss: 0.3325 - accuracy:
0.9300 - val_loss: 0.9248 - val_accuracy: 0.8090
Epoch 9/20
16/16 [==============================] - 0s 15ms/step - loss: 0.2755 - accuracy:
0.9399 - val_loss: 0.8952 - val_accuracy: 0.8130
Epoch 10/20
16/16 [==============================] - 0s 17ms/step - loss: 0.2209 - accuracy:
0.9489 - val_loss: 0.9220 - val_accuracy: 0.8120
Epoch 11/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1938 - accuracy:
0.9526 - val_loss: 0.9352 - val_accuracy: 0.8100
Epoch 12/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1747 - accuracy:
0.9554 - val_loss: 0.9176 - val_accuracy: 0.8110
Epoch 13/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1520 - accuracy:
0.9599 - val_loss: 0.9387 - val_accuracy: 0.8040
Epoch 14/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1400 - accuracy:
0.9583 - val_loss: 0.9654 - val_accuracy: 0.8160
Epoch 15/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1319 - accuracy:
0.9608 - val_loss: 1.0122 - val_accuracy: 0.8000
Epoch 16/20
16/16 [==============================] - 0s 18ms/step - loss: 0.1214 - accuracy:
0.9613 - val_loss: 0.9796 - val_accuracy: 0.8150
Epoch 17/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1184 - accuracy:
0.9568 - val_loss: 1.0511 - val_accuracy: 0.8030
Epoch 18/20
16/16 [==============================] - 0s 19ms/step - loss: 0.1059 - accuracy:
0.9610 - val_loss: 1.0269 - val_accuracy: 0.8130
Epoch 19/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1044 - accuracy:
0.9606 - val_loss: 1.0676 - val_accuracy: 0.7970
Epoch 20/20
16/16 [==============================] - 0s 19ms/step - loss: 0.1013 - accuracy:
```

0.9617 - val_loss: 1.0756 - val_accuracy: 0.8050

3.19 Plotting the training and validation loss

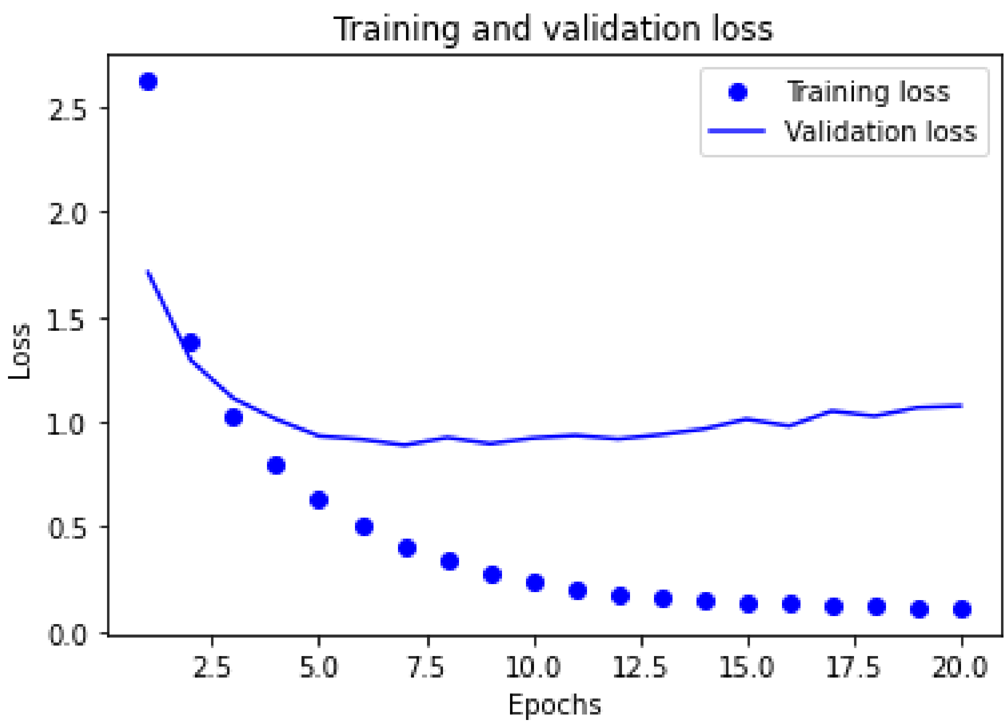
[34]:
```python
import matplotlib.pyplot as plt

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(loss) + 1)

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



3.20 Plotting the training and validation accuracy

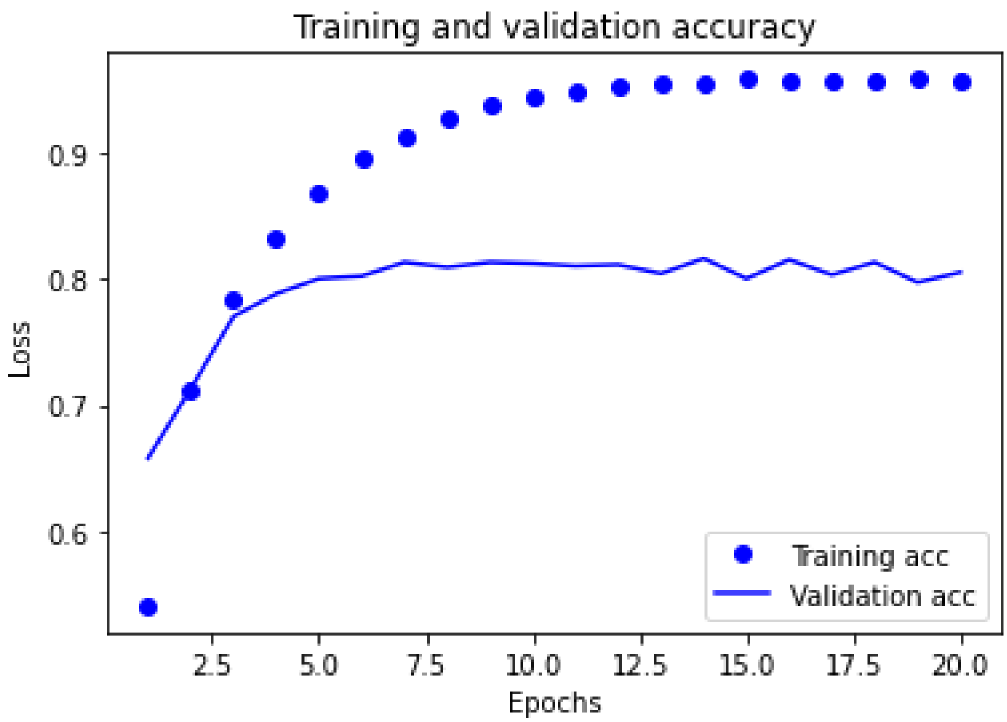
[35]:
```python
plt.clf()

acc = history.history['accuracy'] #Per general chat
```

```
val_acc = history.history['val_accuracy'] #Per general chat

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



The network begins to overfit after nine epochs

3.21 Retraining a model from scratch

[36]:
```
model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))

model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit(partial_x_train,
```

```
          partial_y_train,
          epochs=9,
          batch_size=512,
          validation_data=(x_val, y_val))
results = model.evaluate(x_test, one_hot_test_labels)
```

```
Epoch 1/9
16/16 [==============================] - 1s 28ms/step - loss: 3.0867 - accuracy:
0.4097 - val_loss: 1.7388 - val_accuracy: 0.6370
Epoch 2/9
16/16 [==============================] - 0s 16ms/step - loss: 1.5174 - accuracy:
0.6908 - val_loss: 1.3284 - val_accuracy: 0.7030
Epoch 3/9
16/16 [==============================] - 0s 15ms/step - loss: 1.0981 - accuracy:
0.7646 - val_loss: 1.1547 - val_accuracy: 0.7390
Epoch 4/9
16/16 [==============================] - 0s 18ms/step - loss: 0.8617 - accuracy:
0.8154 - val_loss: 1.0278 - val_accuracy: 0.7920
Epoch 5/9
16/16 [==============================] - 0s 16ms/step - loss: 0.6705 - accuracy:
0.8630 - val_loss: 0.9763 - val_accuracy: 0.7970
Epoch 6/9
16/16 [==============================] - 0s 17ms/step - loss: 0.5439 - accuracy:
0.8893 - val_loss: 0.9204 - val_accuracy: 0.8100
Epoch 7/9
16/16 [==============================] - 0s 14ms/step - loss: 0.4302 - accuracy:
0.9139 - val_loss: 0.8873 - val_accuracy: 0.8190
Epoch 8/9
16/16 [==============================] - 0s 14ms/step - loss: 0.3434 - accuracy:
0.9281 - val_loss: 0.9224 - val_accuracy: 0.8120
Epoch 9/9
16/16 [==============================] - 0s 18ms/step - loss: 0.2925 - accuracy:
0.9380 - val_loss: 0.9058 - val_accuracy: 0.8070
71/71 [==============================] - 0s 2ms/step - loss: 1.0207 - accuracy:
0.7792
```

[37]:
```
#Final results
results #About 79% accuracy
```

[37]: [1.020650863647461, 0.7791629433631897]

[38]:
```
import copy
test_labels_copy = copy.copy(test_labels)
np.random.shuffle(test_labels_copy)
hits_array = np.array(test_labels) == np.array(test_labels_copy)
float(np.sum(hits_array)) / len(test_labels)
```

```
#Closer to 18%, which book says is good, compared to random baseline
```

[38]: 0.17764915405164738

3.22 Generating predictions for new data

[39]:
```
predictions = model.predict(x_test)
```

[40]:
```
#Each entry in predictions is a vector of length 46
predictions[0].shape
```

[40]: (46,)

[41]:
```
#The coefficients in this vector sum to 1
np.sum(predictions[0])
```

[41]: 1.0000001

[42]:
```
#largest entry is the predicted class-the class with the highest probability
np.argmax(predictions[0])
```

[42]: 3

[43]:
```
#different way to handle the labels and loss
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

[44]:
```
#With integer labels, you should use sparse_categorical_crossentropy
model.compile(optimizer='rmsprop',
              loss='sparse_categorical_crossentropy',
              metrics=['acc'])
```

3.23 A model with an information bottleneck

[45]:
```
model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(4, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))

model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit(partial_x_train,
          partial_y_train,
          epochs=20,
          batch_size=128,
          validation_data=(x_val, y_val))
```

```
Epoch 1/20
63/63 [==============================] - 1s 10ms/step - loss: 3.4776 - accuracy:
0.3450 - val_loss: 3.0492 - val_accuracy: 0.4860
Epoch 2/20
63/63 [==============================] - 0s 6ms/step - loss: 2.9496 - accuracy:
0.4010 - val_loss: 2.7116 - val_accuracy: 0.2350
Epoch 3/20
63/63 [==============================] - 0s 6ms/step - loss: 2.4706 - accuracy:
0.2552 - val_loss: 1.9842 - val_accuracy: 0.2990
Epoch 4/20
63/63 [==============================] - 0s 6ms/step - loss: 1.6627 - accuracy:
0.5485 - val_loss: 1.5187 - val_accuracy: 0.6180
Epoch 5/20
63/63 [==============================] - 0s 6ms/step - loss: 1.3035 - accuracy:
0.6515 - val_loss: 1.4565 - val_accuracy: 0.6370
Epoch 6/20
63/63 [==============================] - 0s 7ms/step - loss: 1.2048 - accuracy:
0.6702 - val_loss: 1.4408 - val_accuracy: 0.6330
Epoch 7/20
63/63 [==============================] - 0s 7ms/step - loss: 1.0936 - accuracy:
0.6906 - val_loss: 1.4512 - val_accuracy: 0.6580
Epoch 8/20
63/63 [==============================] - 0s 6ms/step - loss: 0.9890 - accuracy:
0.7272 - val_loss: 1.4672 - val_accuracy: 0.6650
Epoch 9/20
63/63 [==============================] - 0s 6ms/step - loss: 0.9791 - accuracy:
0.7511 - val_loss: 1.4921 - val_accuracy: 0.6630
Epoch 10/20
63/63 [==============================] - 0s 7ms/step - loss: 0.9156 - accuracy:
0.7598 - val_loss: 1.4909 - val_accuracy: 0.6810
Epoch 11/20
63/63 [==============================] - 0s 6ms/step - loss: 0.8494 - accuracy:
0.7817 - val_loss: 1.6247 - val_accuracy: 0.6670
Epoch 12/20
63/63 [==============================] - 0s 7ms/step - loss: 0.8064 - accuracy:
0.7970 - val_loss: 1.5679 - val_accuracy: 0.6830
Epoch 13/20
63/63 [==============================] - 0s 7ms/step - loss: 0.7853 - accuracy:
0.8035 - val_loss: 1.6078 - val_accuracy: 0.6880
Epoch 14/20
63/63 [==============================] - 0s 6ms/step - loss: 0.7213 - accuracy:
0.8196 - val_loss: 1.6844 - val_accuracy: 0.6840
Epoch 15/20
63/63 [==============================] - 0s 6ms/step - loss: 0.7129 - accuracy:
0.8159 - val_loss: 1.7183 - val_accuracy: 0.6860
Epoch 16/20
63/63 [==============================] - 0s 7ms/step - loss: 0.7019 - accuracy:
0.8156 - val_loss: 1.8153 - val_accuracy: 0.6810
```

```
Epoch 17/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6791 - accuracy:
0.8226 - val_loss: 1.8214 - val_accuracy: 0.6970
Epoch 18/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6849 - accuracy:
0.8238 - val_loss: 1.9814 - val_accuracy: 0.6900
Epoch 19/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6284 - accuracy:
0.8292 - val_loss: 2.0153 - val_accuracy: 0.6900
Epoch 20/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6344 - accuracy:
0.8310 - val_loss: 2.1518 - val_accuracy: 0.6800
```

[45]: <tensorflow.python.keras.callbacks.History at 0x7f774f566a90>

Now at 71% validation accuracy. Drop is due to fact that trying to compress a lot of informatic

0.3 5.3 Implement the housing price regression model found in section 3.6 of Deep Learning with Python [pages 85-90]

3.24 Loading the Boston housing dataset

[47]:
```
from keras.datasets import boston_housing

(train_data, train_targets), (test_data, test_targets) = boston_housing.
↪load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/boston_housing.npz
57344/57026 [==============================] - 0s 1us/step
```

[48]:
```
#Look at train data
train_data.shape
```

[48]: (404, 13)

[49]:
```
#Look at test data
test_data.shape
```

[49]: (102, 13)

[50]:
```
#Targets
train_targets
```

[50]:
```
array([15.2, 42.3, 50. , 21.1, 17.7, 18.5, 11.3, 15.6, 15.6, 14.4, 12.1,
       17.9, 23.1, 19.9, 15.7,  8.8, 50. , 22.5, 24.1, 27.5, 10.9, 30.8,
       32.9, 24. , 18.5, 13.3, 22.9, 34.7, 16.6, 17.5, 22.3, 16.1, 14.9,
       23.1, 34.9, 25. , 13.9, 13.1, 20.4, 20. , 15.2, 24.7, 22.2, 16.7,
```

```
12.7, 15.6, 18.4, 21. , 30.1, 15.1, 18.7,  9.6, 31.5, 24.8, 19.1,
22. , 14.5, 11. , 32. , 29.4, 20.3, 24.4, 14.6, 19.5, 14.1, 14.3,
15.6, 10.5,  6.3, 19.3, 19.3, 13.4, 36.4, 17.8, 13.5, 16.5,  8.3,
14.3, 16. , 13.4, 28.6, 43.5, 20.2, 22. , 23. , 20.7, 12.5, 48.5,
14.6, 13.4, 23.7, 50. , 21.7, 39.8, 38.7, 22.2, 34.9, 22.5, 31.1,
28.7, 46. , 41.7, 21. , 26.6, 15. , 24.4, 13.3, 21.2, 11.7, 21.7,
19.4, 50. , 22.8, 19.7, 24.7, 36.2, 14.2, 18.9, 18.3, 20.6, 24.6,
18.2,  8.7, 44. , 10.4, 13.2, 21.2, 37. , 30.7, 22.9, 20. , 19.3,
31.7, 32. , 23.1, 18.8, 10.9, 50. , 19.6,  5. , 14.4, 19.8, 13.8,
19.6, 23.9, 24.5, 25. , 19.9, 17.2, 24.6, 13.5, 26.6, 21.4, 11.9,
22.6, 19.6,  8.5, 23.7, 23.1, 22.4, 20.5, 23.6, 18.4, 35.2, 23.1,
27.9, 20.6, 23.7, 28. , 13.6, 27.1, 23.6, 20.6, 18.2, 21.7, 17.1,
 8.4, 25.3, 13.8, 22.2, 18.4, 20.7, 31.6, 30.5, 20.3,  8.8, 19.2,
19.4, 23.1, 23. , 14.8, 48.8, 22.6, 33.4, 21.1, 13.6, 32.2, 13.1,
23.4, 18.9, 23.9, 11.8, 23.3, 22.8, 19.6, 16.7, 13.4, 22.2, 20.4,
21.8, 26.4, 14.9, 24.1, 23.8, 12.3, 29.1, 21. , 19.5, 23.3, 23.8,
17.8, 11.5, 21.7, 19.9, 25. , 33.4, 28.5, 21.4, 24.3, 27.5, 33.1,
16.2, 23.3, 48.3, 22.9, 22.8, 13.1, 12.7, 22.6, 15. , 15.3, 10.5,
24. , 18.5, 21.7, 19.5, 33.2, 23.2,  5. , 19.1, 12.7, 22.3, 10.2,
13.9, 16.3, 17. , 20.1, 29.9, 17.2, 37.3, 45.4, 17.8, 23.2, 29. ,
22. , 18. , 17.4, 34.6, 20.1, 25. , 15.6, 24.8, 28.2, 21.2, 21.4,
23.8, 31. , 26.2, 17.4, 37.9, 17.5, 20. ,  8.3, 23.9,  8.4, 13.8,
 7.2, 11.7, 17.1, 21.6, 50. , 16.1, 20.4, 20.6, 21.4, 20.6, 36.5,
 8.5, 24.8, 10.8, 21.9, 17.3, 18.9, 36.2, 14.9, 18.2, 33.3, 21.8,
19.7, 31.6, 24.8, 19.4, 22.8,  7.5, 44.8, 16.8, 18.7, 50. , 50. ,
19.5, 20.1, 50. , 17.2, 20.8, 19.3, 41.3, 20.4, 20.5, 13.8, 16.5,
23.9, 20.6, 31.5, 23.3, 16.8, 14. , 33.8, 36.1, 12.8, 18.3, 18.7,
19.1, 29. , 30.1, 50. , 50. , 22. , 11.9, 37.6, 50. , 22.7, 20.8,
23.5, 27.9, 50. , 19.3, 23.9, 22.6, 15.2, 21.7, 19.2, 43.8, 20.3,
33.2, 19.9, 22.5, 32.7, 22. , 17.1, 19. , 15. , 16.1, 25.1, 23.7,
28.7, 37.2, 22.6, 16.4, 25. , 29.8, 22.1, 17.4, 18.1, 30.3, 17.5,
24.7, 12.6, 26.5, 28.7, 13.3, 10.4, 24.4, 23. , 20. , 17.8,  7. ,
11.8, 24.4, 13.8, 19.4, 25.2, 19.4, 19.4, 29.1])
```

3.25 Normalizing the data

[51]:
```
mean = train_data.mean(axis=0)
train_data -= mean
std = train_data.std(axis=0)
train_data /= std

test_data -= mean
test_data /= std
```

3.26 Model definition

[53]:
```python
#Using less training data causes worse overfitting. Using a small network is␣
↪one way to mitigate overfitting

from keras import models
from keras import layers

def build_model():
    model = models.Sequential()
    model.add(layers.Dense(64, activation='relu',
                           input_shape=(train_data.shape[1],)))
    model.add(layers.Dense(64, activation='relu'))
    model.add(layers.Dense(1))
    model.compile(optimizer='rmsprop', loss='mse', metrics=['mae'])
    return model
```

3.27 K-fold validation

[54]:
```python
import numpy as np

k = 4
num_val_samples = len(train_data) // k
num_epochs = 100
all_scores = []
for i in range(k):
    print('processing fold #', i)
    val_data = train_data[i * num_val_samples: (i + 1) * num_val_samples]
    val_targets = train_targets[i * num_val_samples: (i + 1) * num_val_samples]

    partial_train_data = np.concatenate(
        [train_data[:i * num_val_samples],
         train_data[(i + 1) * num_val_samples:]],
        axis=0)
    partial_train_targets = np.concatenate(
        [train_targets[:i * num_val_samples],
         train_targets[(i + 1) * num_val_samples:]],
        axis=0)

    model = build_model()
    model.fit(partial_train_data, partial_train_targets,
              epochs=num_epochs, batch_size=1, verbose=0)
    val_mse, val_mae = model.evaluate(val_data, val_targets, verbose=0)
    all_scores.append(val_mae)
```

```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3
```

[55]:
```
#Ran with 100 epochs gives us the following results
all_scores
```

[55]:
```
[2.3203392028808594,
 2.8495006561279297,
 2.7895870208740234,
 2.3913373947143555]
```

[56]:
```
np.mean(all_scores) #mean is 2.59
```

[56]:
```
2.587691068649292
```

3.28 Saving the validation logs at each fold

[58]:
```
#Now using 500 epochs
num_epochs = 500
all_mae_histories = []
for i in range(k):
    print('processing fold #', i)
    val_data = train_data[i * num_val_samples: (i + 1) * num_val_samples]
    val_targets = train_targets[i * num_val_samples: (i + 1) * num_val_samples]
    partial_train_data = np.concatenate(
        [train_data[:i * num_val_samples],
         train_data[(i + 1) * num_val_samples:]],
        axis=0)
    partial_train_targets = np.concatenate(
        [train_targets[:i * num_val_samples],
         train_targets[(i + 1) * num_val_samples:]],
        axis=0)

    model = build_model()
    history = model.fit(partial_train_data, partial_train_targets,
                        validation_data=(val_data, val_targets),
                        epochs=num_epochs, batch_size=1, verbose=0)
    mae_history = history.history['val_mae']
    all_mae_histories.append(mae_history)
```

```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3
```

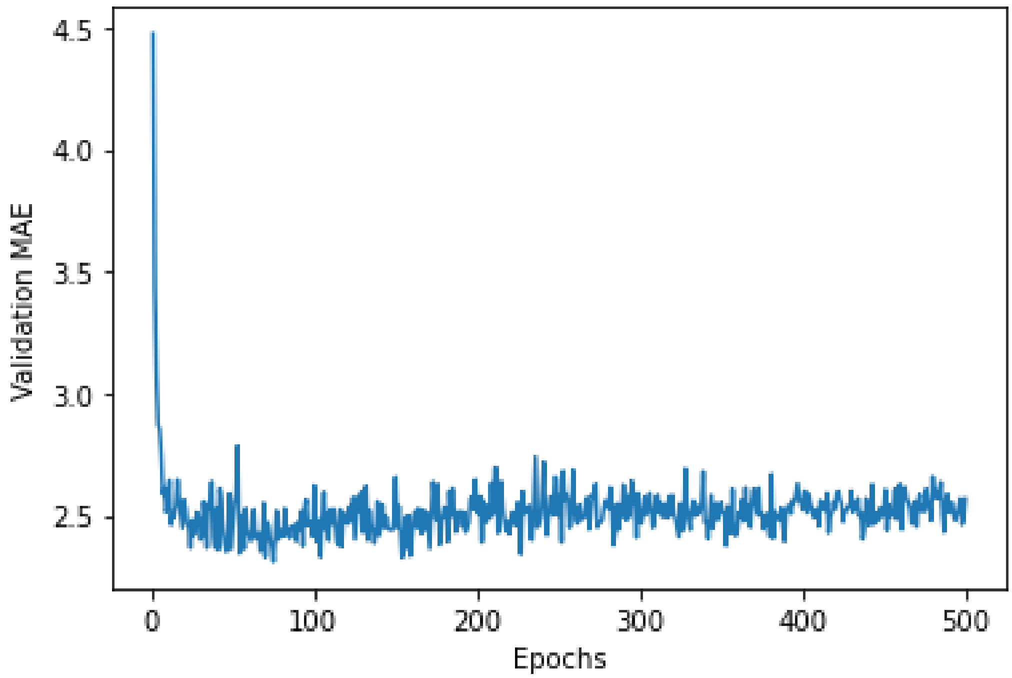
3.29 Building the history of successive mean K-fold validation scores

[59]:
```
average_mae_history = [
    np.mean([x[i] for x in all_mae_histories]) for i in range(num_epochs)]
```

3.30 Plotting validation scores

[60]:
```
import matplotlib.pyplot as plt

plt.plot(range(1, len(average_mae_history) + 1), average_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()
```



Plot looks odd because of scaling issues and high variance. To solve this need to omit the firs

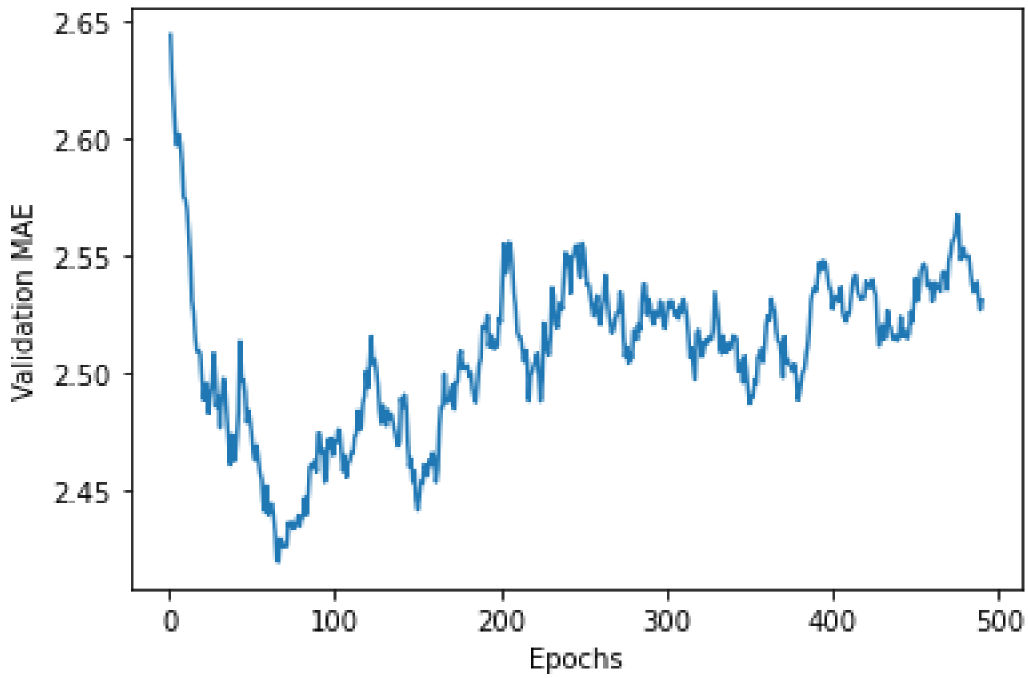
3.31 Plotting validation scores, excluding the first 10 data points

[61]:
```
def smooth_curve(points, factor=0.9):
  smoothed_points = []
  for point in points:
    if smoothed_points:
      previous = smoothed_points[-1]
      smoothed_points.append(previous * factor + point * (1 - factor))
    else:
      smoothed_points.append(point)
  return smoothed_points

smooth_mae_history = smooth_curve(average_mae_history[10:])

plt.plot(range(1, len(smooth_mae_history) + 1), smooth_mae_history)
plt.xlabel('Epochs')
```

```
plt.ylabel('Validation MAE')
plt.show()
```



This plot shows MAE stops improving after 80 epochs. Past that is overfitting.

3.32 Training the final model

[62]:
```
model = build_model()
model.fit(train_data, train_targets,
          epochs=80, batch_size=16, verbose=0)
test_mse_score, test_mae_score = model.evaluate(test_data, test_targets)
```

```
4/4 [==============================] - 0s 2ms/step - loss: 17.5328 - mae: 2.8139
```

[63]:
```
#final result
test_mae_score
```

[63]: 2.8138980865478516