assignment05_SafsafiAchraf

April 17, 2021

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DSC650

Assignment 5

Assignment 5.1 : Classifying movie reviews

The IMDB dataset

Loading the IMDB dataset

[1]:
```
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
from keras.datasets import imdb

(train_data, train_labels), (test_data, test_labels) = imdb.
↪load_data(num_words=10000)
```

[3]:
```
print(train_data[0])
```

```
[1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941, 4, 173, 36,
256, 5, 25, 100, 43, 838, 112, 50, 670, 2, 9, 35, 480, 284, 5, 150, 4, 172, 112,
167, 2, 336, 385, 39, 4, 172, 4536, 1111, 17, 546, 38, 13, 447, 4, 192, 50, 16,
6, 147, 2025, 19, 14, 22, 4, 1920, 4613, 469, 4, 22, 71, 87, 12, 16, 43, 530,
38, 76, 15, 13, 1247, 4, 22, 17, 515, 17, 12, 16, 626, 18, 2, 5, 62, 386, 12, 8,
316, 8, 106, 5, 4, 2223, 5244, 16, 480, 66, 3785, 33, 4, 130, 12, 16, 38, 619,
5, 25, 124, 51, 36, 135, 48, 25, 1415, 33, 6, 22, 12, 215, 28, 77, 52, 5, 14,
407, 16, 82, 2, 8, 4, 107, 117, 5952, 15, 256, 4, 2, 7, 3766, 5, 723, 36, 71,
43, 530, 476, 26, 400, 317, 46, 7, 4, 2, 1029, 13, 104, 88, 4, 381, 15, 297, 98,
32, 2071, 56, 26, 141, 6, 194, 7486, 18, 4, 226, 22, 21, 134, 476, 26, 480, 5,
144, 30, 5535, 18, 51, 36, 28, 224, 92, 25, 104, 4, 226, 65, 16, 38, 1334, 88,
12, 16, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32]
```

[4]:
```
train_labels[0]
```

[4]: 1

No word ndex will exceed 10,000

[5]:
```
max([max(sequence) for sequence in train_data])
```

[5]: 9999

Decode one of these reviews back to English words

[6]:
```
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]])
decoded_review
```

[6]: "? this film was just brilliant casting location scenery story direction everyone's really suited the part they played and you could just imagine being there robert ? is an amazing actor and now the same being director ? father came from the same scottish island as myself so i loved the fact there was a real connection with this film the witty remarks throughout the film were great it was just brilliant so much that i bought the film as soon as it was released for ? and would recommend it to everyone to watch and the fly fishing was amazing really cried at the end it was so sad and you know what they say if you cry at a film it must have been good and this definitely was also ? to the two little boy's that played the ? of norman and paul they were just brilliant children are often left out of the ? list i think because the stars that play them all grown up are such a big profile for the whole film but these children are amazing and should be praised for what they have done don't you think the whole story was so lovely because it was true and was someone's life after all that was shared with us all"

Preparing the data

Encoding the integer sequences into a binary matrix

[7]:
```
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)

x_train[0]
```

[7]: array([0., 1., 1., …, 0., 0., 0.])

[8]:
```
y_train = np.asarray(train_labels).astype('float32')
y_test = np.asarray(test_labels).astype('float32')
```

Building our network

The model definition

[9]:
```
from keras import models
from keras import layers

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'))
```

Compiling the model

[10]:
```
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

Configuring the optimizer

[11]:
```
from keras import optimizers

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

Using custom losses and metrics

[12]:
```
from keras import losses
from keras import metrics

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

Validating our approach

Setting aside a validation set

[13]:
```
x_val = x_train[:10000]
partial_x_train = x_train[10000:]

y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

Training our model

```
[14]: 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 47ms/step - loss: 0.6099 -
binary_accuracy: 0.6801 - val_loss: 0.3972 - val_binary_accuracy: 0.8700
Epoch 2/20
30/30 [==============================] - 0s 14ms/step - loss: 0.3336 -
binary_accuracy: 0.9005 - val_loss: 0.3558 - val_binary_accuracy: 0.8578
Epoch 3/20
30/30 [==============================] - 0s 12ms/step - loss: 0.2402 -
binary_accuracy: 0.9264 - val_loss: 0.3086 - val_binary_accuracy: 0.8749
Epoch 4/20
30/30 [==============================] - 0s 13ms/step - loss: 0.1872 -
binary_accuracy: 0.9401 - val_loss: 0.2730 - val_binary_accuracy: 0.8916
Epoch 5/20
30/30 [==============================] - 0s 13ms/step - loss: 0.1453 -
binary_accuracy: 0.9564 - val_loss: 0.3039 - val_binary_accuracy: 0.8803
Epoch 6/20
30/30 [==============================] - 0s 12ms/step - loss: 0.1189 -
binary_accuracy: 0.9652 - val_loss: 0.2917 - val_binary_accuracy: 0.8858
Epoch 7/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0975 -
binary_accuracy: 0.9723 - val_loss: 0.3244 - val_binary_accuracy: 0.8825
Epoch 8/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0818 -
binary_accuracy: 0.9783 - val_loss: 0.3298 - val_binary_accuracy: 0.8825
Epoch 9/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0655 -
binary_accuracy: 0.9854 - val_loss: 0.3941 - val_binary_accuracy: 0.8730
Epoch 10/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0585 -
binary_accuracy: 0.9856 - val_loss: 0.3770 - val_binary_accuracy: 0.8801
Epoch 11/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0458 -
binary_accuracy: 0.9895 - val_loss: 0.4018 - val_binary_accuracy: 0.8756
Epoch 12/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0359 -
binary_accuracy: 0.9932 - val_loss: 0.4294 - val_binary_accuracy: 0.8778
Epoch 13/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0262 -
binary_accuracy: 0.9956 - val_loss: 0.5375 - val_binary_accuracy: 0.8543
Epoch 14/20
```

```
30/30 [==============================] - 0s 12ms/step - loss: 0.0246 -
binary_accuracy: 0.9962 - val_loss: 0.5165 - val_binary_accuracy: 0.8634
Epoch 15/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0180 -
binary_accuracy: 0.9978 - val_loss: 0.5300 - val_binary_accuracy: 0.8672
Epoch 16/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0134 -
binary_accuracy: 0.9986 - val_loss: 0.5569 - val_binary_accuracy: 0.8702
Epoch 17/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0099 -
binary_accuracy: 0.9995 - val_loss: 0.5906 - val_binary_accuracy: 0.8694
Epoch 18/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0077 -
binary_accuracy: 0.9996 - val_loss: 0.6274 - val_binary_accuracy: 0.8658
Epoch 19/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0062 -
binary_accuracy: 0.9996 - val_loss: 0.6620 - val_binary_accuracy: 0.8655
Epoch 20/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0040 -
binary_accuracy: 0.9999 - val_loss: 0.6933 - val_binary_accuracy: 0.8665
```

[15]:
```
history_dict = history.history
history_dict.keys()
```

[15]:
```
dict_keys(['loss', 'binary_accuracy', 'val_loss', 'val_binary_accuracy'])
```

Plotting the training and validation loss

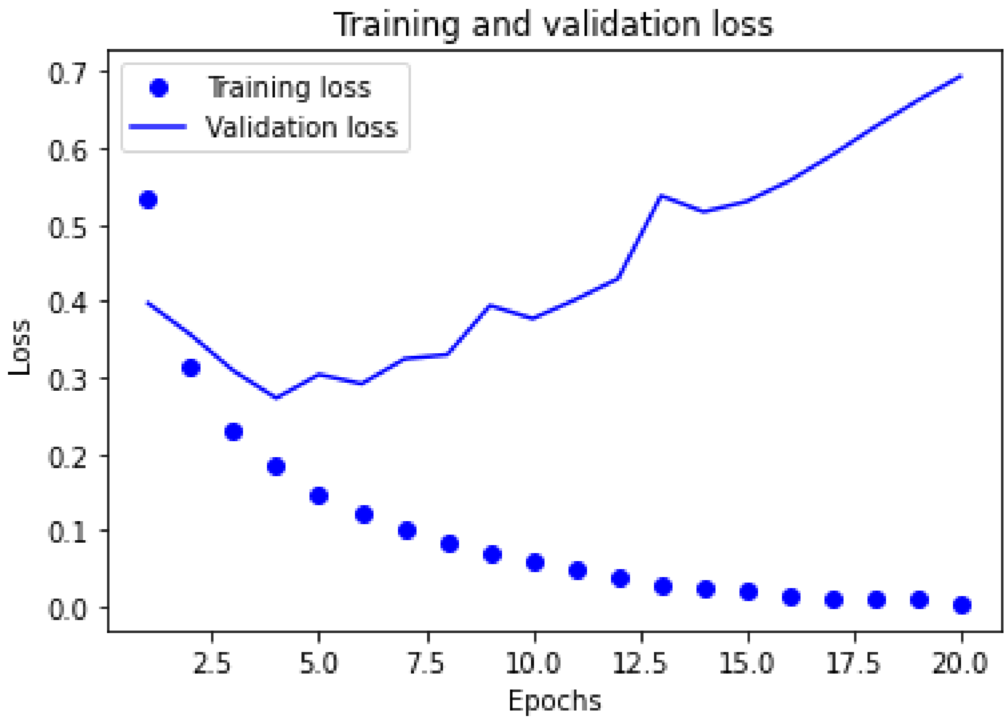
[16]:
```
import matplotlib.pyplot as plt

acc = history.history['binary_accuracy']
val_acc = history.history['val_binary_accuracy']
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()
```

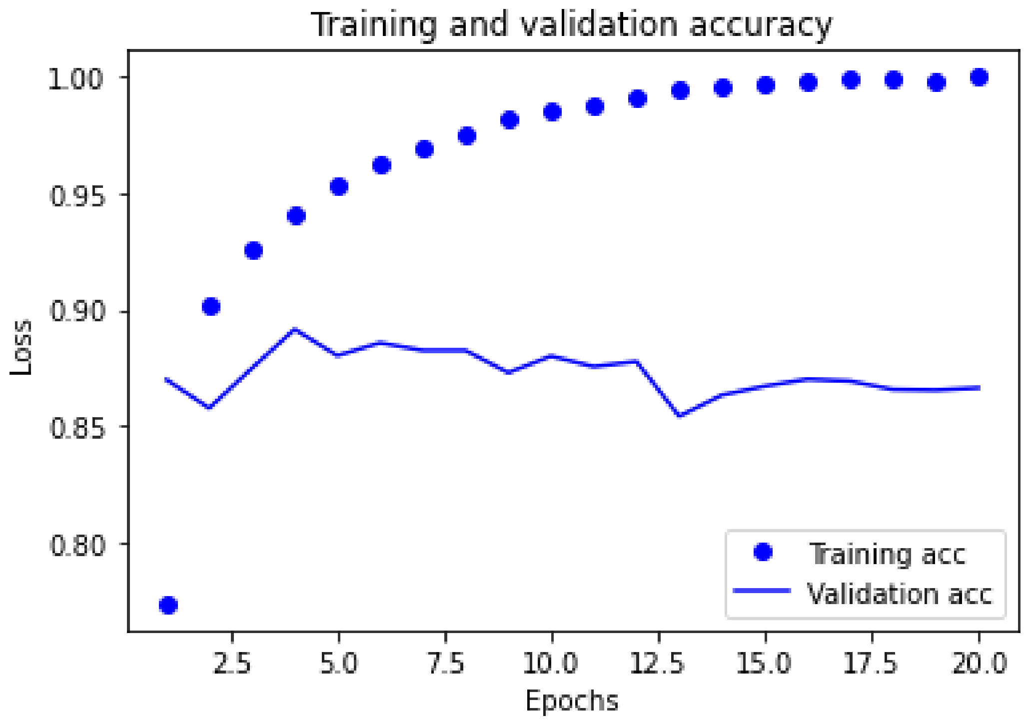


Plotting the training and validation accuracy

[17]:
```
plt.clf()
acc_values = history_dict['binary_accuracy']
val_acc_values = history_dict['val_binary_accuracy']

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()
```



Retraining a model from scratch

[18]:
```
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 13ms/step - loss: 0.5778 - accuracy:
0.7230
Epoch 2/4
49/49 [==============================] - 1s 11ms/step - loss: 0.2876 - accuracy:
0.9055
Epoch 3/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2098 - accuracy:
0.9262
Epoch 4/4
```

```
49/49 [==============================] - 0s 8ms/step - loss: 0.1693 - accuracy:
0.9398
782/782 [==============================] - 1s 2ms/step - loss: 0.2996 -
accuracy: 0.8798
```

[19]:
```python
results
```

[19]:
```
[0.29959574341773987, 0.8797600269317627]
```

Using a trained network to generate predictions on new data

[20]:
```python
model.predict(x_test)
```

[20]:
```
array([[0.16862705],
       [0.9999273 ],
       [0.8069594 ],
       …,
       [0.07418606],
       [0.06543425],
       [0.4470158 ]], dtype=float32)
```

Assignment 5.2 : Classifying newswires

The Reuters dataset

Loading the Reuters dataset

[21]:
```python
from keras.datasets import reuters

(train_data, train_labels), (test_data, test_labels) = reuters.
↪load_data(num_words=10000)
```

[22]:
```python
len(train_data)
```

[22]:
```
8982
```

[23]:
```python
len(test_data)
```

[23]:
```
2246
```

[24]:
```python
print(train_data[10])
```

```
[1, 245, 273, 207, 156, 53, 74, 160, 26, 14, 46, 296, 26, 39, 74, 2979, 3554,
14, 46, 4689, 4329, 86, 61, 3499, 4795, 14, 61, 451, 4329, 17, 12]
```

Decoding newswires back to text

[25]:
```python
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]])
decoded_newswire
```

[25]:
```
'? ? ? said as a result of its december acquisition of space co it expects
earnings per share in 1987 of 1 15 to 1 30 dlrs per share up from 70 cts in 1986
the company said pretax net should rise to nine to 10 mln dlrs from six mln dlrs
in 1986 and rental operation revenues to 19 to 22 mln dlrs from 12 5 mln dlrs it
said cash flow per share this year should be 2 50 to three dlrs reuter 3'
```

[26]:
```python
train_labels[10]
```

[26]:
```
3
```

Preparing the data

Encoding the data

[27]:
```python
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]:
```python
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]:
```python
from keras.utils.np_utils import to_categorical

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

Building our network

Model definition

[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'))
```

Compiling the model

[31]:
```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Validating our approach

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:]
```

Training the model

[33]:
```
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 29ms/step - loss: 3.0710 - accuracy:
0.4364 - val_loss: 1.6837 - val_accuracy: 0.6370
Epoch 2/20
16/16 [==============================] - 0s 17ms/step - loss: 1.4674 - accuracy:
0.6899 - val_loss: 1.2818 - val_accuracy: 0.7150
Epoch 3/20
16/16 [==============================] - 0s 16ms/step - loss: 1.0750 - accuracy:
0.7643 - val_loss: 1.1426 - val_accuracy: 0.7390
Epoch 4/20
16/16 [==============================] - 0s 16ms/step - loss: 0.8202 - accuracy:
0.8278 - val_loss: 1.0368 - val_accuracy: 0.7700
Epoch 5/20
16/16 [==============================] - 0s 21ms/step - loss: 0.6546 - accuracy:
0.8640 - val_loss: 0.9590 - val_accuracy: 0.7940
Epoch 6/20
```

```
16/16 [==============================] - 0s 17ms/step - loss: 0.5272 - accuracy:
0.8964 - val_loss: 0.9218 - val_accuracy: 0.7990
Epoch 7/20
16/16 [==============================] - 0s 15ms/step - loss: 0.4383 - accuracy:
0.9109 - val_loss: 0.9115 - val_accuracy: 0.8080
Epoch 8/20
16/16 [==============================] - 0s 16ms/step - loss: 0.3454 - accuracy:
0.9268 - val_loss: 0.9344 - val_accuracy: 0.7910
Epoch 9/20
16/16 [==============================] - 0s 15ms/step - loss: 0.2834 - accuracy:
0.9405 - val_loss: 0.9008 - val_accuracy: 0.8040
Epoch 10/20
16/16 [==============================] - 0s 15ms/step - loss: 0.2435 - accuracy:
0.9439 - val_loss: 1.0188 - val_accuracy: 0.7780
Epoch 11/20
16/16 [==============================] - 0s 15ms/step - loss: 0.2132 - accuracy:
0.9504 - val_loss: 0.9124 - val_accuracy: 0.8040
Epoch 12/20
16/16 [==============================] - 0s 14ms/step - loss: 0.1784 - accuracy:
0.9536 - val_loss: 0.9277 - val_accuracy: 0.8010
Epoch 13/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1532 - accuracy:
0.9571 - val_loss: 0.9558 - val_accuracy: 0.8130
Epoch 14/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1391 - accuracy:
0.9598 - val_loss: 0.9694 - val_accuracy: 0.8060
Epoch 15/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1305 - accuracy:
0.9614 - val_loss: 0.9987 - val_accuracy: 0.8050
Epoch 16/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1146 - accuracy:
0.9621 - val_loss: 1.0329 - val_accuracy: 0.7930
Epoch 17/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1232 - accuracy:
0.9570 - val_loss: 1.0481 - val_accuracy: 0.8010
Epoch 18/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1140 - accuracy:
0.9594 - val_loss: 1.1128 - val_accuracy: 0.7920
Epoch 19/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1091 - accuracy:
0.9637 - val_loss: 1.1062 - val_accuracy: 0.7900
Epoch 20/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1016 - accuracy:
0.9656 - val_loss: 1.0945 - val_accuracy: 0.7950
```

Plotting the training and validation loss

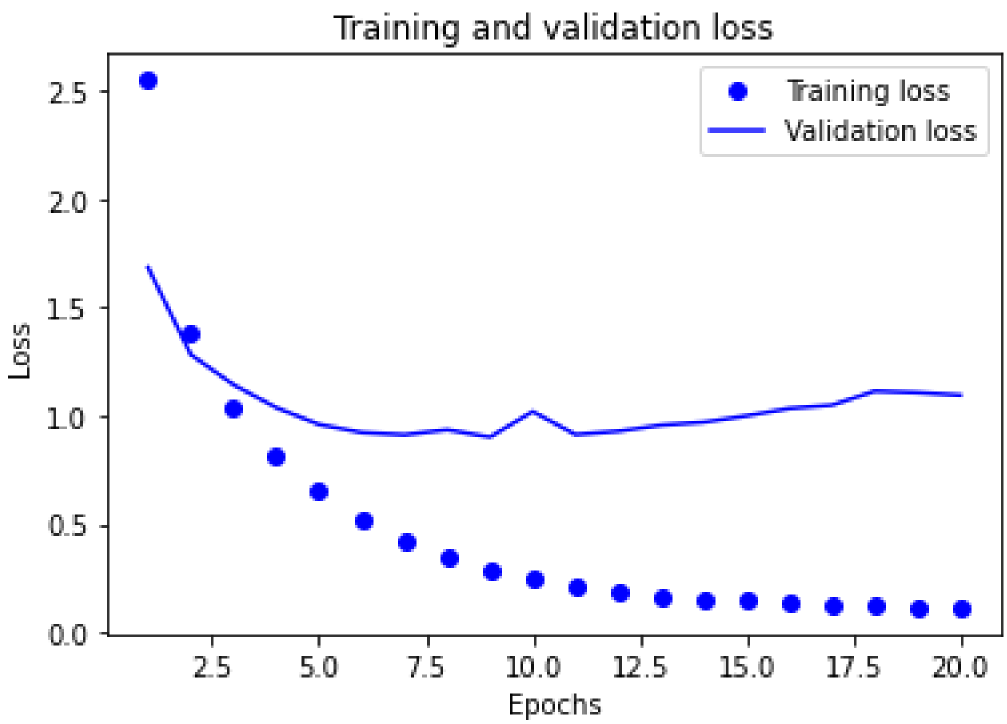
[34]:
```
import matplotlib.pyplot as plt

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()
```



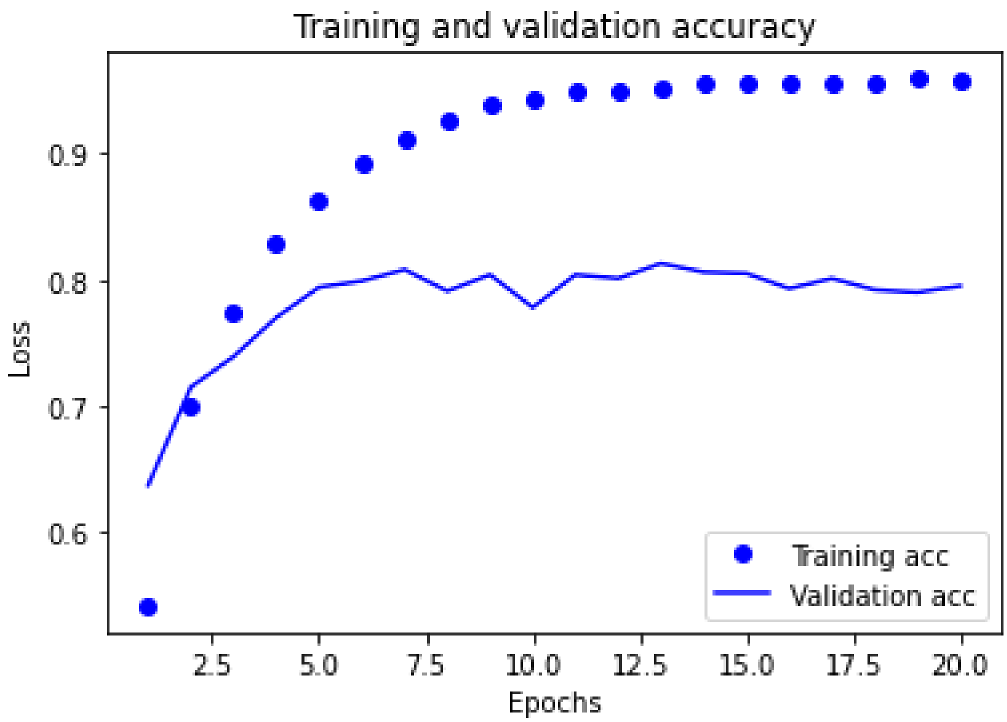
Plotting the training and validation accuracy

[35]:
```
plt.clf()
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
```

```python
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



Retraining a model from scratch

[36]:
```python
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=8,
          batch_size=512,
          validation_data=(x_val, y_val))
results = model.evaluate(x_test, one_hot_test_labels)
```

```
Epoch 1/8
16/16 [==============================] - 1s 25ms/step - loss: 3.1525 - accuracy:
0.3970 - val_loss: 1.7930 - val_accuracy: 0.6240
Epoch 2/8
16/16 [==============================] - 0s 16ms/step - loss: 1.5477 - accuracy:
0.6829 - val_loss: 1.3402 - val_accuracy: 0.6980
Epoch 3/8
16/16 [==============================] - 0s 16ms/step - loss: 1.1257 - accuracy:
0.7537 - val_loss: 1.1730 - val_accuracy: 0.7380
Epoch 4/8
16/16 [==============================] - 0s 18ms/step - loss: 0.8850 - accuracy:
0.8123 - val_loss: 1.0582 - val_accuracy: 0.7710
Epoch 5/8
16/16 [==============================] - 0s 15ms/step - loss: 0.7280 - accuracy:
0.8466 - val_loss: 0.9824 - val_accuracy: 0.7870
Epoch 6/8
16/16 [==============================] - 0s 16ms/step - loss: 0.5632 - accuracy:
0.8823 - val_loss: 0.9400 - val_accuracy: 0.8100
Epoch 7/8
16/16 [==============================] - 0s 16ms/step - loss: 0.4505 - accuracy:
0.9103 - val_loss: 0.8879 - val_accuracy: 0.8200
Epoch 8/8
16/16 [==============================] - 0s 14ms/step - loss: 0.3563 - accuracy:
0.9276 - val_loss: 0.8959 - val_accuracy: 0.8210
71/71 [==============================] - 0s 2ms/step - loss: 0.9783 - accuracy:
0.7872
```

[37]:
```
results
```

[37]:
```
[0.9783440828323364, 0.7871772050857544]
```

The accuracy reached by the random classifier is about 19%

[38]:
```
import copy

test_labels_copy = copy.copy(test_labels)
np.random.shuffle(test_labels_copy)
float(np.sum(np.array(test_labels) == np.array(test_labels_copy))) /␣
 ↪len(test_labels)
```

[38]:
```
0.19545859305431879
```

Generating predictions on new data

Generating predictions for new data

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

Each entry in predictions is a vector of length 46:

[40]:
```
predictions[0].shape
```

[40]: (46,)

The coefficients in this vector sum to 1:

[41]:
```
np.sum(predictions[0])
```

[41]: 0.9999999

The largest entry is the predicted class—the class with the highest probability:

[42]:
```
np.argmax(predictions[0])
```

[42]: 3

A different way to handle the labels and the loss

[43]:
```
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

[44]:
```
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['acc'])
```

The importance of having sufficiently large intermediate layers

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 14ms/step - loss: 3.5529 - accuracy:
0.1590 - val_loss: 2.7013 - val_accuracy: 0.2520
Epoch 2/20
63/63 [==============================] - 0s 6ms/step - loss: 2.4127 - accuracy:
```

```
0.3419 - val_loss: 1.8286 - val_accuracy: 0.5450
Epoch 3/20
63/63 [==============================] - 0s 7ms/step - loss: 1.6928 - accuracy:
0.5567 - val_loss: 1.5804 - val_accuracy: 0.5720
Epoch 4/20
63/63 [==============================] - 0s 6ms/step - loss: 1.3713 - accuracy:
0.6072 - val_loss: 1.4630 - val_accuracy: 0.6480
Epoch 5/20
63/63 [==============================] - 0s 6ms/step - loss: 1.2216 - accuracy:
0.6859 - val_loss: 1.3901 - val_accuracy: 0.6760
Epoch 6/20
63/63 [==============================] - 0s 7ms/step - loss: 1.0505 - accuracy:
0.7205 - val_loss: 1.3382 - val_accuracy: 0.6910
Epoch 7/20
63/63 [==============================] - 0s 6ms/step - loss: 0.9709 - accuracy:
0.7533 - val_loss: 1.3063 - val_accuracy: 0.7030
Epoch 8/20
63/63 [==============================] - 0s 7ms/step - loss: 0.8349 - accuracy:
0.7954 - val_loss: 1.3540 - val_accuracy: 0.7050
Epoch 9/20
63/63 [==============================] - 0s 7ms/step - loss: 0.7643 - accuracy:
0.8046 - val_loss: 1.3584 - val_accuracy: 0.6980
Epoch 10/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6983 - accuracy:
0.8252 - val_loss: 1.3388 - val_accuracy: 0.7130
Epoch 11/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6577 - accuracy:
0.8301 - val_loss: 1.3590 - val_accuracy: 0.7200
Epoch 12/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6226 - accuracy:
0.8393 - val_loss: 1.3927 - val_accuracy: 0.7120
Epoch 13/20
63/63 [==============================] - 0s 6ms/step - loss: 0.5623 - accuracy:
0.8580 - val_loss: 1.4391 - val_accuracy: 0.7190
Epoch 14/20
63/63 [==============================] - 0s 7ms/step - loss: 0.5325 - accuracy:
0.8610 - val_loss: 1.4704 - val_accuracy: 0.7180
Epoch 15/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4871 - accuracy:
0.8758 - val_loss: 1.5119 - val_accuracy: 0.7230
Epoch 16/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4781 - accuracy:
0.8766 - val_loss: 1.5572 - val_accuracy: 0.7160
Epoch 17/20
63/63 [==============================] - 0s 6ms/step - loss: 0.4555 - accuracy:
0.8790 - val_loss: 1.6022 - val_accuracy: 0.7170
Epoch 18/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4328 - accuracy:
```

```
0.8860 - val_loss: 1.6134 - val_accuracy: 0.7220
Epoch 19/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4052 - accuracy:
0.8881 - val_loss: 1.6638 - val_accuracy: 0.7140
Epoch 20/20
63/63 [==============================] - 0s 6ms/step - loss: 0.4018 - accuracy:
0.8941 - val_loss: 1.7169 - val_accuracy: 0.7210
```

[45]:
```
<tensorflow.python.keras.callbacks.History at 0x7f4a341dc220>
```

Assignment 5.3 : Predicting house prices

The Boston Housing Price dataset

Loading the Boston housing dataset

[46]:
```
from keras.datasets import boston_housing

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

[47]:
```
train_data.shape
```

[47]:
```
(404, 13)
```

[48]:
```
test_data.shape
```

[48]:
```
(102, 13)
```

[49]:
```
train_targets
```

[49]:
```
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])
```

Preparing the data

Normalizing the data

[50]:
```python
mean = train_data.mean(axis=0)
train_data -= mean
std = train_data.std(axis=0)
train_data /= std

test_data -= mean
test_data /= std
```

Building our network

Model definition

[51]:
```python
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
```

Validating our approach using K-fold validation

K-fold validation

[52]:
```
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
```

[53]:
```
all_scores
```

[53]: [2.2719955444335938, 2.6824657917022705, 2.980651617050171, 2.458961248397827]

[54]:
```
np.mean(all_scores)
```

[54]: 2.5985185503959656

Saving the validation logs at each fold

```python
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
```

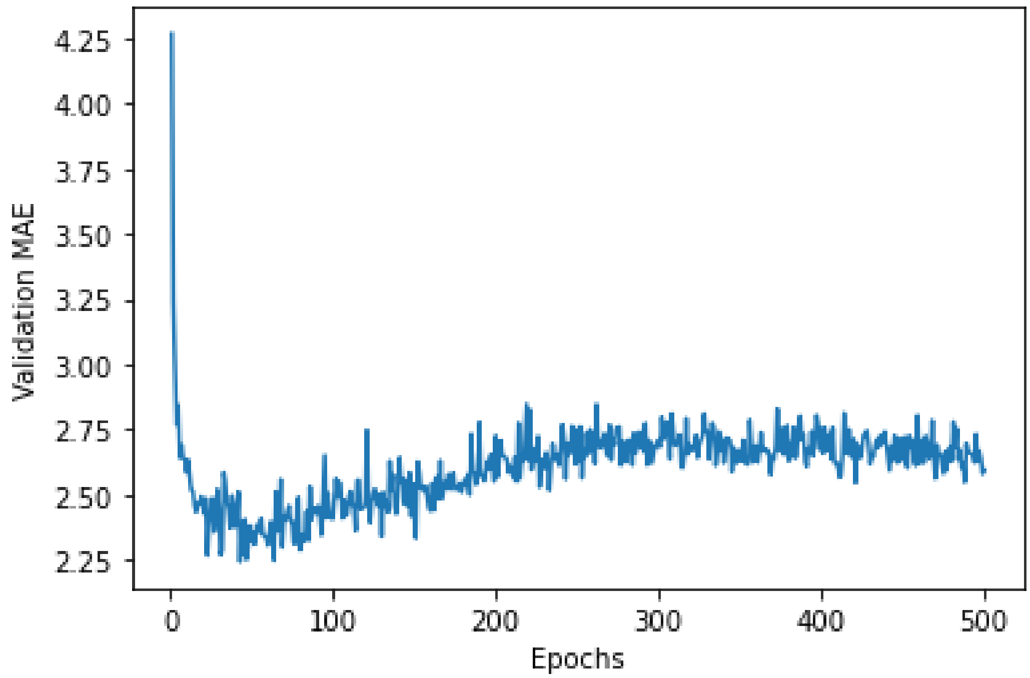
Building the history of successive mean K-fold validation scores

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

Plotting validation scores

```python
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()
```

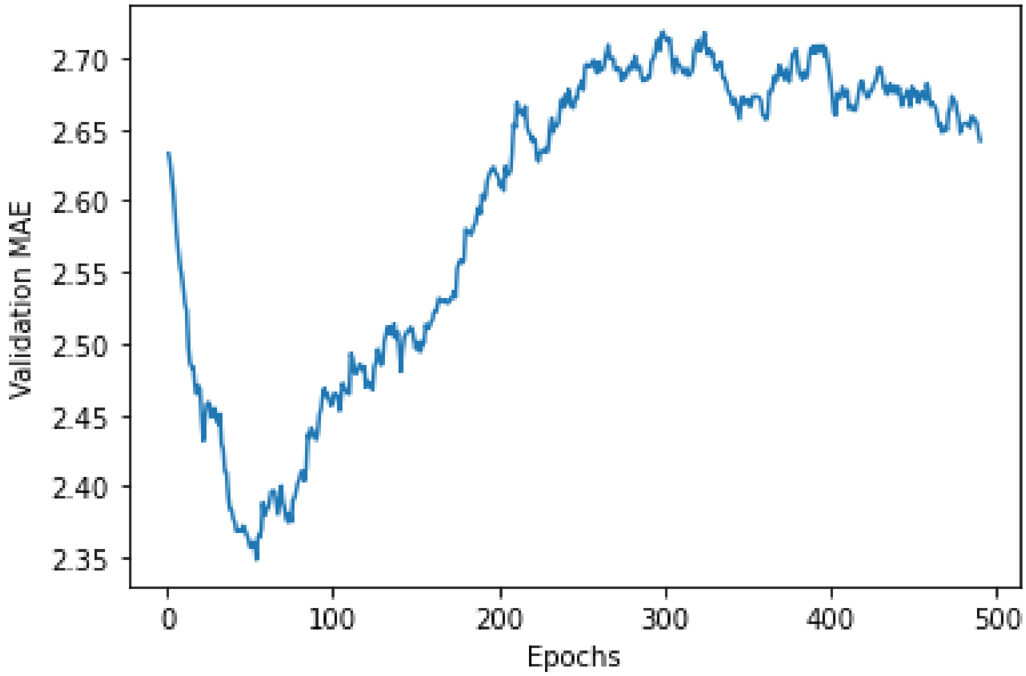


Plotting validation scores, excluding the first 10 data points

[58]:
```
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()
```



Training the final model

[59]:
```
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 1ms/step - loss: 18.5483 - mae: 2.6491
```

[60]:
```
test_mae_score
```

[60]: 2.6490962505340576