assignment05_Muley_Tushar_Week3

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0.0.1 Name: Muley, Tushar

Assignment: Assignment 5 Week 3

Date: Dec 19, 2021

0.1 Assignment 5.1

Implement the movie review classifier found in section 3.4 of Deep Learning with Python.

[1]:
```
from keras.datasets import imdb

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

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/imdb.npz
17465344/17464789 [==============================] - 1s 0us/step
```

```
<__array_function__ internals>:5: VisibleDeprecationWarning: Creating an ndarray
from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or
ndarrays with different lengths or shapes) is deprecated. If you meant to do
this, you must specify 'dtype=object' when creating the ndarray
C:\Users\Tushar\AppData\Roaming\Python\Python38\site-
packages\tensorflow\python\keras\datasets\imdb.py:159:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray
  x_train, y_train = np.array(xs[:idx]), np.array(labels[:idx])
C:\Users\Tushar\AppData\Roaming\Python\Python38\site-
packages\tensorflow\python\keras\datasets\imdb.py:160:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray
  x_test, y_test = np.array(xs[idx:]), np.array(labels[idx:])
```

[2]:
```
train_data[0]
```

```
[2]: [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]
```

[3]:
```
train_labels[0]
```

[3]: 1

[4]:
```
max([max(sequence) for sequence in train_data])
```

[4]: 9999

Decode one of these reviews back to English

[5]:
```
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
```

Encoding the integer sequences into a binary matrix

[6]:
```
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)
```

[7]:
```
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 your network

[9]:
```
from tensorflow import keras
from tensorflow.keras import layers

model = keras.Sequential ([
    layers.Dense(16, activation='relu'),
    layers.Dense(16, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])
```

Complie the model

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

Validation

[11]:
```
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

Training set

[12]:
```
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 [==============================] - 7s 136ms/step - loss: 0.5928 -
accuracy: 0.7062 - val_loss: 0.4317 - val_accuracy: 0.8234
Epoch 2/20
30/30 [==============================] - 1s 18ms/step - loss: 0.3378 - accuracy:
0.8964 - val_loss: 0.3248 - val_accuracy: 0.8748
Epoch 3/20
30/30 [==============================] - 1s 18ms/step - loss: 0.2406 - accuracy:
0.9269 - val_loss: 0.2798 - val_accuracy: 0.8903
Epoch 4/20
30/30 [==============================] - 1s 18ms/step - loss: 0.1856 - accuracy:
0.9417 - val_loss: 0.2827 - val_accuracy: 0.8864
Epoch 5/20
30/30 [==============================] - 1s 26ms/step - loss: 0.1464 - accuracy:
0.9542 - val_loss: 0.2961 - val_accuracy: 0.8831
Epoch 6/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1197 - accuracy:
0.9647 - val_loss: 0.2943 - val_accuracy: 0.8870
Epoch 7/20
30/30 [==============================] - 2s 43ms/step - loss: 0.1016 - accuracy:
0.9707 - val_loss: 0.3267 - val_accuracy: 0.8767
Epoch 8/20
30/30 [==============================] - 1s 30ms/step - loss: 0.0840 - accuracy:
0.9766 - val_loss: 0.3249 - val_accuracy: 0.8811
Epoch 9/20
30/30 [==============================] - 1s 23ms/step - loss: 0.0720 - accuracy:
0.9804 - val_loss: 0.3547 - val_accuracy: 0.8784
Epoch 10/20
30/30 [==============================] - 1s 22ms/step - loss: 0.0586 - accuracy:
0.9853 - val_loss: 0.3711 - val_accuracy: 0.8799
Epoch 11/20
30/30 [==============================] - 1s 18ms/step - loss: 0.0465 - accuracy:
0.9903 - val_loss: 0.4031 - val_accuracy: 0.8761
Epoch 12/20
30/30 [==============================] - 1s 20ms/step - loss: 0.0369 - accuracy:
0.9924 - val_loss: 0.4278 - val_accuracy: 0.8746
Epoch 13/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0288 - accuracy:
0.9953 - val_loss: 0.4565 - val_accuracy: 0.8735
Epoch 14/20
30/30 [==============================] - 1s 19ms/step - loss: 0.0266 - accuracy:
0.9946 - val_loss: 0.4946 - val_accuracy: 0.8702
Epoch 15/20
30/30 [==============================] - 1s 19ms/step - loss: 0.0198 - accuracy:
0.9976 - val_loss: 0.5417 - val_accuracy: 0.8626
Epoch 16/20
```

```
30/30 [==============================] - 1s 18ms/step - loss: 0.0174 - accuracy:
0.9977 - val_loss: 0.5550 - val_accuracy: 0.8685
Epoch 17/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0147 - accuracy:
0.9978 - val_loss: 0.5917 - val_accuracy: 0.8649
Epoch 18/20
30/30 [==============================] - 1s 19ms/step - loss: 0.0108 - accuracy:
0.9992 - val_loss: 0.6251 - val_accuracy: 0.8672
Epoch 19/20
30/30 [==============================] - 1s 20ms/step - loss: 0.0071 - accuracy:
0.9997 - val_loss: 0.6602 - val_accuracy: 0.8663
Epoch 20/20
30/30 [==============================] - 1s 21ms/step - loss: 0.0057 - accuracy:
0.9997 - val_loss: 0.7050 - val_accuracy: 0.8661
```

[13]:
```
history_dict = history.history
history_dict.keys()
```

[13]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Plotting the training and validation loss

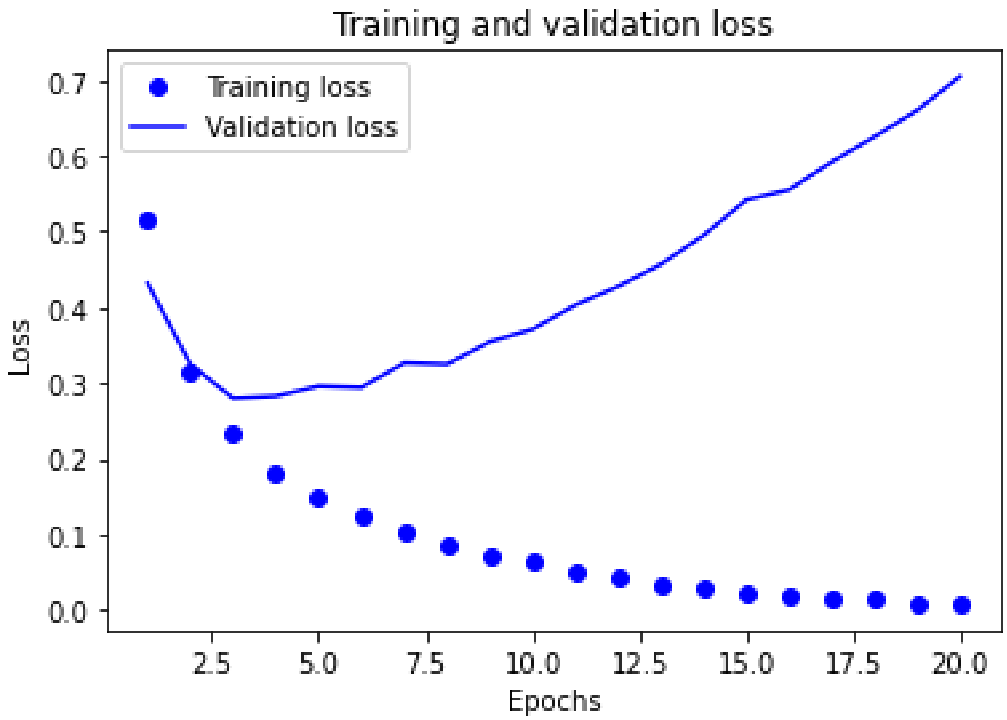
[15]:
```
import matplotlib.pyplot as plt

history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

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

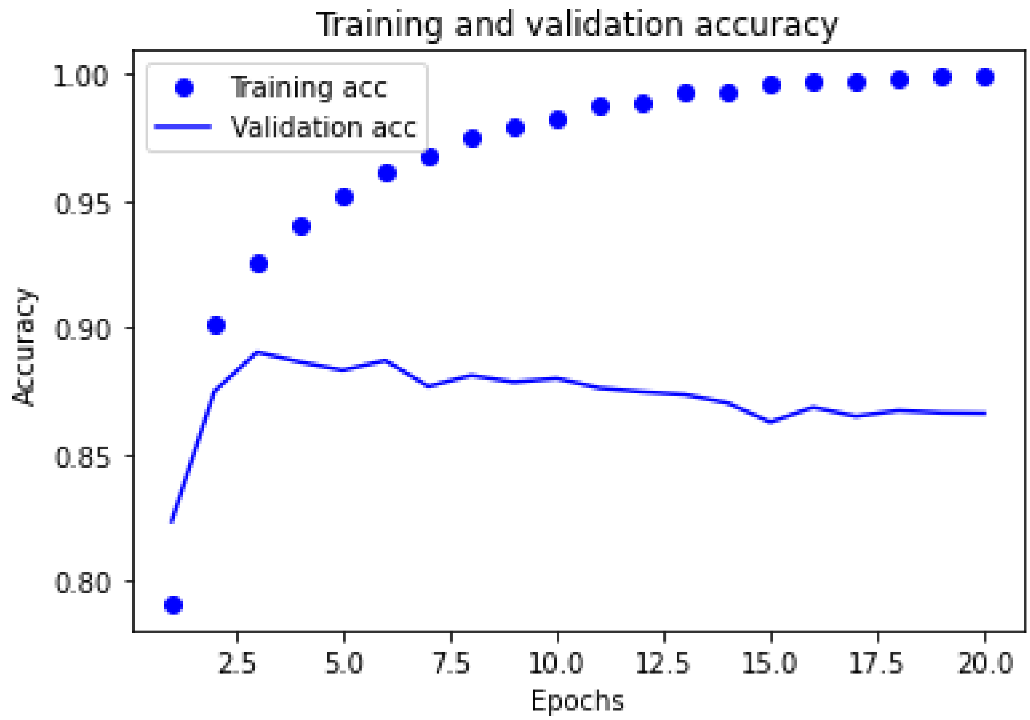


Plotting the training and validation accuracy

[18]:
```
plt.clf()
acc = history_dict['accuracy']
val_acc = history_dict['val_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('Accuracy')
plt.legend()

plt.show()
```



Retraining a model from scratch

[21]:
```
model = keras.Sequential([
    layers.Dense(16, activation='relu'),
    layers.Dense(16, activation='relu'),
    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 [==============================] - 2s 13ms/step - loss: 0.5546 - accuracy:
0.7265
Epoch 2/4
49/49 [==============================] - 1s 13ms/step - loss: 0.2702 - accuracy:
0.9123
Epoch 3/4
49/49 [==============================] - 1s 14ms/step - loss: 0.1997 - accuracy:
0.9313
Epoch 4/4
```

```
49/49 [==============================] - 1s 13ms/step - loss: 0.1605 - accuracy:
0.9444
782/782 [==============================] - 2s 2ms/step - loss: 0.3289 -
accuracy: 0.8707: 0s - loss:
```

[22]:
```
results
```

[22]:
```
[0.3288571238517761, 0.8706799745559692]
```

Using a trained network to generate predictions on new data

[23]:
```
model.predict(x_test)
```

[23]:
```
array([[0.22420892],
       [0.9990783 ],
       [0.9645244 ],
       …,
       [0.185489  ],
       [0.12515825],
       [0.80406165]], dtype=float32)
```

0.2 Assignment 5.2 -

Classifying newswires: a multiclass classification example Implement the news classifier found in section 3.5 of Deep Learning with Python.

Load data

[1]:
```
from keras.datasets import reuters

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

```
C:\Users\Tushar\AppData\Roaming\Python\Python38\site-
packages\tensorflow\python\keras\datasets\reuters.py:148:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray
  x_train, y_train = np.array(xs[:idx]), np.array(labels[:idx])
C:\Users\Tushar\AppData\Roaming\Python\Python38\site-
packages\tensorflow\python\keras\datasets\reuters.py:149:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray
  x_test, y_test = np.array(xs[idx:]), np.array(labels[idx:])
```

[2]:
```
len(train_data)
```

[2]: 8982

[3]:
```
len(test_data)
```

[3]: 2246

[4]:
```
train_data[10]
```

[4]:
```
[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

[5]:
```
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]])
```

[6]:
```
train_labels[10]
```

[6]: 3

Preparing the data

[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)
```

[8]:
```
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)
```

[9]:
```
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 your network

[10]:
```
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

[11]:
```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Validating your approach

[12]:
```
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

[13]:
```
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 [==============================] - 8s 206ms/step - loss: 3.2135 -
accuracy: 0.3811 - val_loss: 1.8512 - val_accuracy: 0.6290
Epoch 2/20
16/16 [==============================] - 1s 39ms/step - loss: 1.6128 - accuracy:
0.6666 - val_loss: 1.3601 - val_accuracy: 0.7090
Epoch 3/20
16/16 [==============================] - 1s 41ms/step - loss: 1.1183 - accuracy:
0.7668 - val_loss: 1.1756 - val_accuracy: 0.7570
Epoch 4/20
16/16 [==============================] - 1s 46ms/step - loss: 0.9017 - accuracy:
0.8116 - val_loss: 1.0637 - val_accuracy: 0.7770
Epoch 5/20
16/16 [==============================] - 1s 45ms/step - loss: 0.6961 - accuracy:
0.8586 - val_loss: 0.9799 - val_accuracy: 0.7990
Epoch 6/20
16/16 [==============================] - 1s 42ms/step - loss: 0.5594 - accuracy:
0.8881 - val_loss: 0.9449 - val_accuracy: 0.8020
Epoch 7/20
16/16 [==============================] - 1s 38ms/step - loss: 0.4525 - accuracy:
0.9135 - val_loss: 0.9265 - val_accuracy: 0.8020
Epoch 8/20
16/16 [==============================] - 1s 39ms/step - loss: 0.3553 - accuracy:
0.9325 - val_loss: 0.8982 - val_accuracy: 0.8170
Epoch 9/20
16/16 [==============================] - 1s 37ms/step - loss: 0.3046 - accuracy:
0.9385 - val_loss: 0.9095 - val_accuracy: 0.8150
Epoch 10/20
16/16 [==============================] - 1s 37ms/step - loss: 0.2458 - accuracy:
0.9472 - val_loss: 0.9551 - val_accuracy: 0.8010
Epoch 11/20
16/16 [==============================] - 1s 37ms/step - loss: 0.2092 - accuracy:
0.9552 - val_loss: 0.9322 - val_accuracy: 0.8200
Epoch 12/20
16/16 [==============================] - 1s 33ms/step - loss: 0.1874 - accuracy:
0.9561 - val_loss: 0.9483 - val_accuracy: 0.8100
Epoch 13/20
```

```
16/16 [==============================] - 1s 34ms/step - loss: 0.1601 - accuracy:
0.9601 - val_loss: 0.9672 - val_accuracy: 0.8150
Epoch 14/20
16/16 [==============================] - 1s 39ms/step - loss: 0.1451 - accuracy:
0.9595 - val_loss: 1.0671 - val_accuracy: 0.8050
Epoch 15/20
16/16 [==============================] - 1s 36ms/step - loss: 0.1327 - accuracy:
0.9599 - val_loss: 1.0189 - val_accuracy: 0.8110
Epoch 16/20
16/16 [==============================] - 1s 35ms/step - loss: 0.1259 - accuracy:
0.9619 - val_loss: 1.0720 - val_accuracy: 0.8030
Epoch 17/20
16/16 [==============================] - 1s 35ms/step - loss: 0.1163 - accuracy:
0.9626 - val_loss: 1.0739 - val_accuracy: 0.8020
Epoch 18/20
16/16 [==============================] - 1s 38ms/step - loss: 0.1099 - accuracy:
0.9602 - val_loss: 1.0494 - val_accuracy: 0.8130
Epoch 19/20
16/16 [==============================] - 1s 35ms/step - loss: 0.1023 - accuracy:
0.9639 - val_loss: 1.1001 - val_accuracy: 0.8000
Epoch 20/20
16/16 [==============================] - 1s 36ms/step - loss: 0.0996 - accuracy:
0.9656 - val_loss: 1.1330 - val_accuracy: 0.8070
```

Plotting the training and validation loss

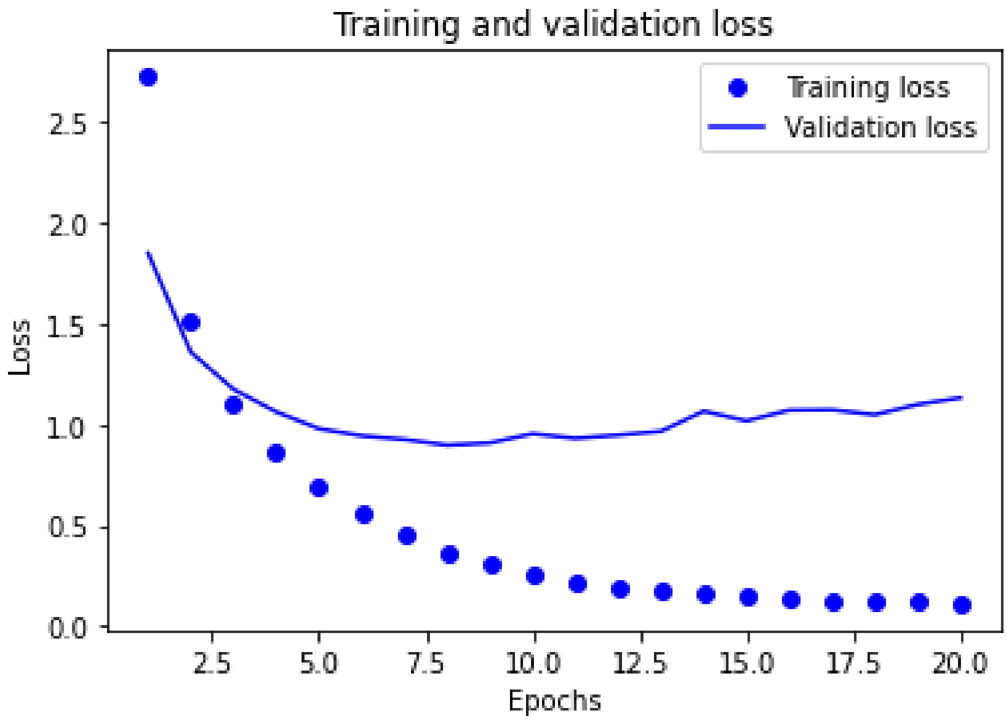
[14]:
```
import matplotlib.pyplot as plt

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()
```



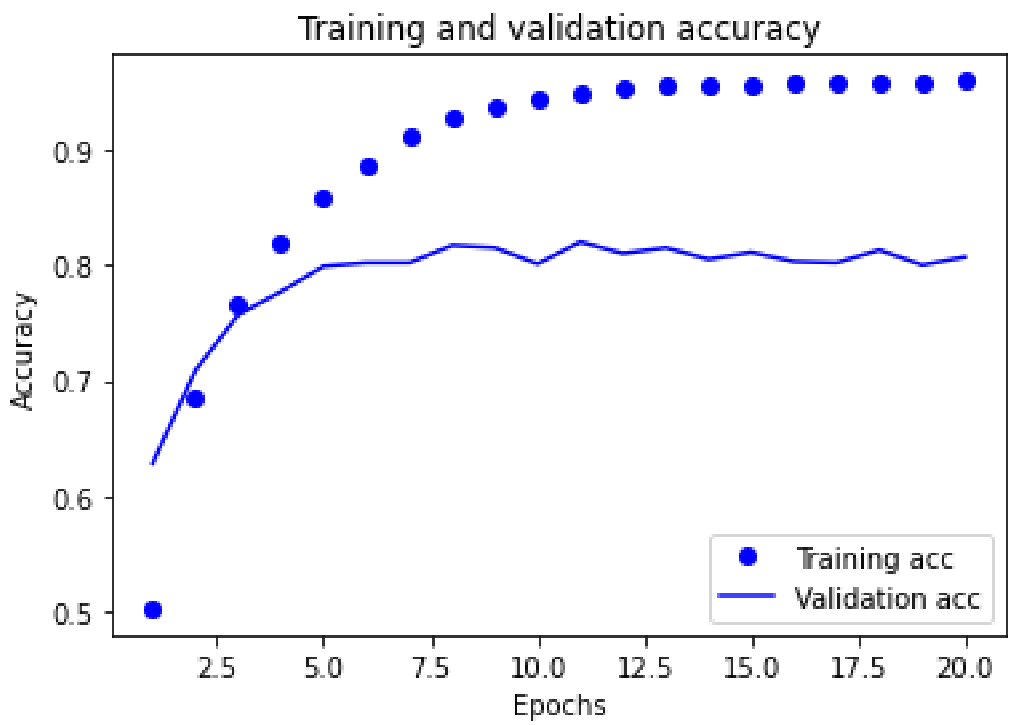
Plotting the training and validation accuracy

[16]:
```
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')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



Retraining a model from scratch

[17]:
```
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 [==============================] - 2s 66ms/step - loss: 3.0504 - accuracy:
0.4232 - val_loss: 1.7205 - val_accuracy: 0.6410
Epoch 2/9
16/16 [==============================] - 1s 41ms/step - loss: 1.5002 - accuracy:
0.6956 - val_loss: 1.3097 - val_accuracy: 0.7100
Epoch 3/9
16/16 [==============================] - 1s 45ms/step - loss: 1.0782 - accuracy:
```

```
0.7692 - val_loss: 1.1295 - val_accuracy: 0.7500
Epoch 4/9
16/16 [==============================] - 1s 46ms/step - loss: 0.8361 - accuracy:
0.8212 - val_loss: 1.0276 - val_accuracy: 0.7800
Epoch 5/9
16/16 [==============================] - 1s 47ms/step - loss: 0.6682 - accuracy:
0.8611 - val_loss: 0.9737 - val_accuracy: 0.7910
Epoch 6/9
16/16 [==============================] - 1s 49ms/step - loss: 0.5204 - accuracy:
0.8938 - val_loss: 0.9255 - val_accuracy: 0.8090
Epoch 7/9
16/16 [==============================] - ETA: 0s - loss: 0.4221 - accuracy: 0.91
- 1s 46ms/step - loss: 0.4214 - accuracy: 0.9141 - val_loss: 0.9039 -
val_accuracy: 0.8070
Epoch 8/9
16/16 [==============================] - 1s 77ms/step - loss: 0.3331 - accuracy:
0.9286 - val_loss: 0.9156 - val_accuracy: 0.8090
Epoch 9/9
16/16 [==============================] - 1s 48ms/step - loss: 0.2814 - accuracy:
0.9378 - val_loss: 0.8833 - val_accuracy: 0.8150
71/71 [==============================] - 0s 5ms/step - loss: 0.9773 - accuracy:
0.7832
```

[18]:
```
results
```

[18]: [0.9773288369178772, 0.7831701040267944]

[20]:
```
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)
```

[20]: 0.19412288512911843

Generating predictions on new data

[21]:
```
predictions = model.predict(x_test)
```

[22]:
```
predictions[0].shape
```

[22]: (46,)

[23]:
```
np.sum(predictions[0])
```

[23]: 1.0

[24]:
```
np.argmax(predictions[0])
```

[24]: 3

A different way to handle the labels and the loss

[25]:
```
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

[26]:
```
model.compile(optimizer='rmsprop',
              loss='sparse_categorical_crossentropy',
              metrics=['acc'])
```

The importance of having sufficiently large intermediate layers

[27]:
```
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 [==============================] - 3s 20ms/step - loss: 3.6646 - accuracy:
0.0873 - val_loss: 3.1689 - val_accuracy: 0.2580
Epoch 2/20
63/63 [==============================] - 1s 14ms/step - loss: 2.9481 - accuracy:
0.2650 - val_loss: 2.5934 - val_accuracy: 0.2940
Epoch 3/20
63/63 [==============================] - 1s 16ms/step - loss: 2.3941 - accuracy:
0.3167 - val_loss: 2.1410 - val_accuracy: 0.3460
Epoch 4/20
63/63 [==============================] - 1s 13ms/step - loss: 1.8790 - accuracy:
0.3711 - val_loss: 1.7268 - val_accuracy: 0.4880
Epoch 5/20
63/63 [==============================] - 1s 15ms/step - loss: 1.5390 - accuracy:
0.5170 - val_loss: 1.6470 - val_accuracy: 0.4750
Epoch 6/20
63/63 [==============================] - 5s 73ms/step - loss: 1.4122 - accuracy:
0.5441 - val_loss: 1.5302 - val_accuracy: 0.6410
Epoch 7/20
63/63 [==============================] - 1s 20ms/step - loss: 1.2311 - accuracy:
0.6838 - val_loss: 1.4330 - val_accuracy: 0.6650
Epoch 8/20
```

```
63/63 [==============================] - 1s 19ms/step - loss: 1.0729 - accuracy:
0.7224 - val_loss: 1.4012 - val_accuracy: 0.6650
Epoch 9/20
63/63 [==============================] - 1s 23ms/step - loss: 0.9657 - accuracy:
0.7502 - val_loss: 1.4317 - val_accuracy: 0.6750
Epoch 10/20
63/63 [==============================] - 1s 22ms/step - loss: 0.9137 - accuracy:
0.7533 - val_loss: 1.4498 - val_accuracy: 0.6730
Epoch 11/20
63/63 [==============================] - 1s 15ms/step - loss: 0.8862 - accuracy:
0.7634 - val_loss: 1.4923 - val_accuracy: 0.6750
Epoch 12/20
63/63 [==============================] - 1s 15ms/step - loss: 0.8291 - accuracy:
0.7802 - val_loss: 1.5320 - val_accuracy: 0.6690
Epoch 13/20
63/63 [==============================] - 1s 13ms/step - loss: 0.8111 - accuracy:
0.7818 - val_loss: 1.5888 - val_accuracy: 0.6700
Epoch 14/20
63/63 [==============================] - 1s 15ms/step - loss: 0.7676 - accuracy:
0.7955 - val_loss: 1.5891 - val_accuracy: 0.6790
Epoch 15/20
63/63 [==============================] - 1s 14ms/step - loss: 0.7723 - accuracy:
0.7937 - val_loss: 1.6605 - val_accuracy: 0.6720
Epoch 16/20
63/63 [==============================] - 1s 15ms/step - loss: 0.7140 - accuracy:
0.8067 - val_loss: 1.7169 - val_accuracy: 0.6750
Epoch 17/20
63/63 [==============================] - 1s 16ms/step - loss: 0.7127 - accuracy:
0.8121 - val_loss: 1.7745 - val_accuracy: 0.6740
Epoch 18/20
63/63 [==============================] - 1s 14ms/step - loss: 0.6930 - accuracy:
0.8142 - val_loss: 1.8306 - val_accuracy: 0.6800
Epoch 19/20
63/63 [==============================] - 1s 15ms/step - loss: 0.6749 - accuracy:
0.8178 - val_loss: 1.8679 - val_accuracy: 0.6780
Epoch 20/20
63/63 [==============================] - 1s 14ms/step - loss: 0.6562 - accuracy:
0.8202 - val_loss: 1.9090 - val_accuracy: 0.6770
```

```
[27]: <tensorflow.python.keras.callbacks.History at 0x25786e132b0>
```

0.3 Assignment 5.3

Implement the housing price regression model found in section 3.6 of Deep Learning with Python.

The Boston Housing Price dataset

[28]:
```
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
```

[29]:
```
train_data.shape
```

[29]:
```
(404, 13)
```

[30]:
```
test_data.shape
```

[30]:
```
(102, 13)
```

[31]:
```
train_targets
```

[31]:
```
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

[32]:
```
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 your network

[33]:
```
import keras
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 your approach using K-fold validation

[35]:
```
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
```

[36]:
```
all_scores
```

[36]:
```
[1.982920527458191, 2.484312057495117, 2.6799979209899902, 2.448901891708374]
```

[37]:
```
np.mean(all_scores)
```

[37]:
```
2.399033099412918
```

Saving the validation logs at each fold

[39]:
```
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
```

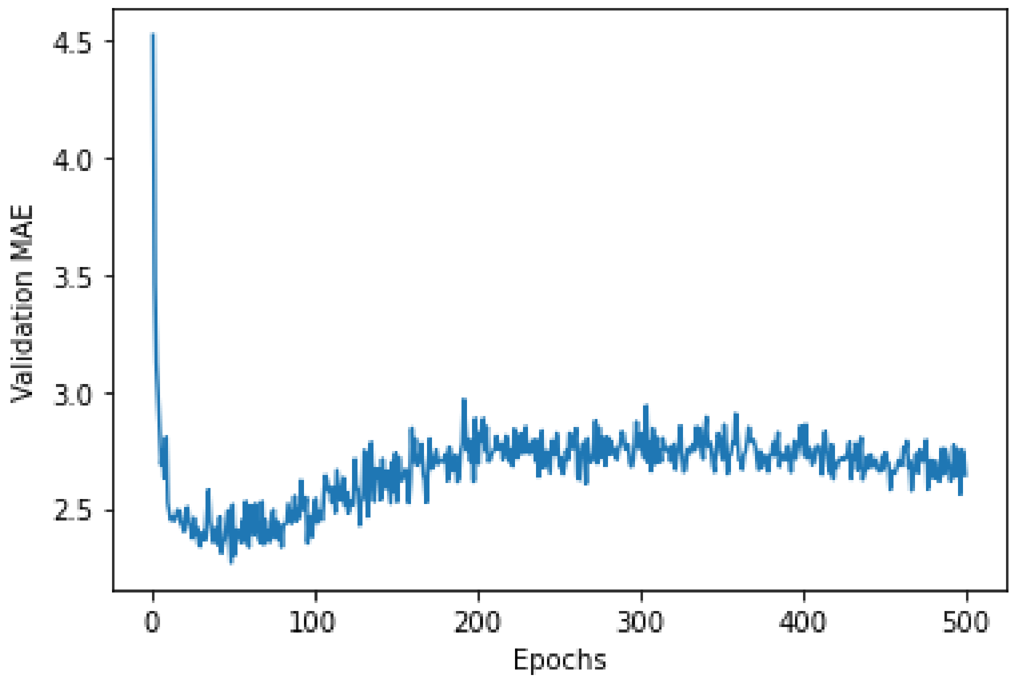
Building the history of successive mean K-fold validation scores

[40]:
```
average_mae_history = [
    np.mean([x[i] for x in all_mae_histories]) for i in range(num_epochs)]
```

Plotting validation scores

[41]:
```
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()
```



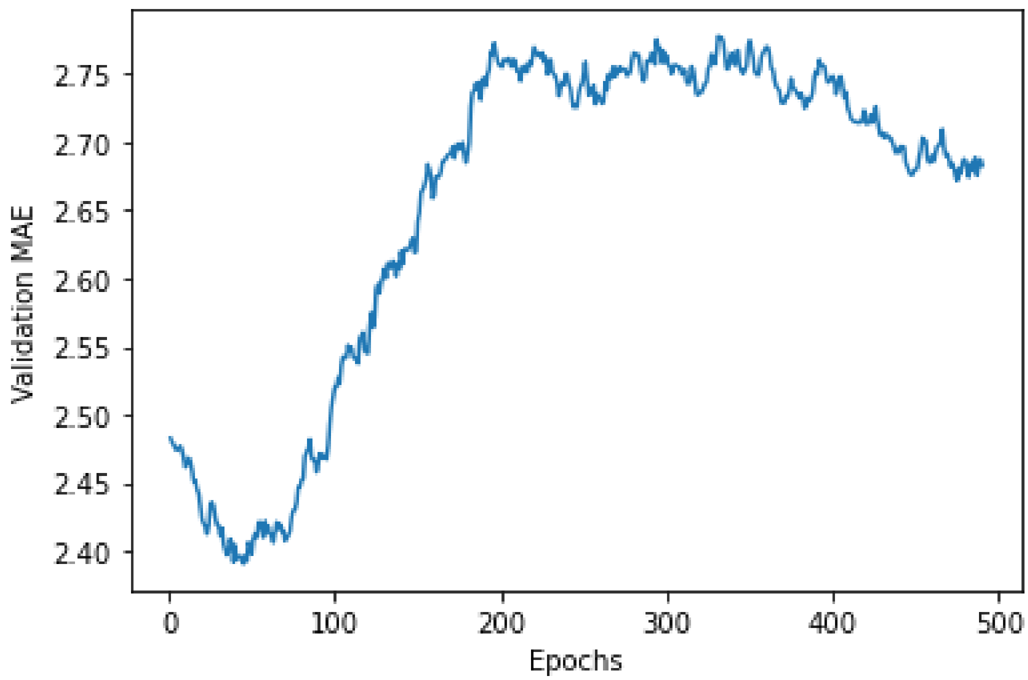
Plotting validation scores, excluding the first 10 data points

[42]:
```
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

[44]:
```
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 3ms/step - loss: 16.6004 - mae: 2.6129
```

[45]:
```
test_mae_score
```

[45]: 2.612933874130249

Generating predictions on new data

[46]:
```
predictions = model.predict(test_data)
predictions[0]
```

[46]:
```
array([8.1121025], dtype=float32)
```

[ ]: