assignment05_BasitAbdul

September 30, 2022

1 Assignment 5.1

1.1 1.0.1 Implement the movie review classifier found in section 3.4 of Deep Learning with Python.

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

[2]:
```
# import data
(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 [==============================] - 3s 0us/step
```

[3]:
```
train_data[0]
```

[3]:
```
[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
```

[5]:
```
# No word should exceed 10,000
max([max(sequence) for sequence in train_data])
```

[5]:
```
9999
```

[6]:
```
# decoding reviews back to their text

# dictionary mapping words to an integer index
word_index = imdb.get_word_index()

# reverse it by mapping integer indices to words
reverse_word_index = dict(
    [(value, key) for (key, value) in word_index.items()])

# Decode the review - indices are offset by 3 because 0, 1, 2 are reserved,␣
 ↪indices for "padding", "start of sequence" and "unknown"
decoded_review = " ".join(
    [reverse_word_index.get(i - 3, "?") for i in train_data[0]])

decoded_review
```

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

[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"
```

[7]:
```
# prepare the data
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]:
```
x_train[0]
```

[8]:
```
array([0., 1., 1., ..., 0., 0., 0.])
```

[9]:
```
# vectorize labels so they can be fed into a neural network
y_train = np.asarray(train_labels).astype("float32")
y_test = np.asarray(test_labels).astype("float32")
```

[11]:
```
# Keras implementation
from keras import models
from keras import layers
```

[12]:
```
# build the model
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'))
```

[13]:
```
# compiling the model
model.compile(optimizer="rmsprop",
            loss="binary_crossentropy",
            metrics=["accuracy"])
```

[14]:
```
from keras import optimizers
```

[15]:
```
# configuring the optimizer
model.compile(optimizer=optimizers.RMSprop(lr=0.001),
            loss='binary_crossentropy',
            metrics=['accuracy'])
```

[16]:
```python
# using custom losses & metrics
from keras import losses
from keras import metrics

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

[17]:
```python
# validating the approach
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

[18]:
```python
# train the model
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 [==============================] - 1s 42ms/step - loss: 0.5015 -
binary_accuracy: 0.7805 - val_loss: 0.3704 - val_binary_accuracy: 0.8735
Epoch 2/20
30/30 [==============================] - 1s 29ms/step - loss: 0.2953 -
binary_accuracy: 0.9064 - val_loss: 0.3131 - val_binary_accuracy: 0.8799
Epoch 3/20
30/30 [==============================] - 1s 27ms/step - loss: 0.2176 -
binary_accuracy: 0.9287 - val_loss: 0.2785 - val_binary_accuracy: 0.8907
Epoch 4/20
30/30 [==============================] - 1s 27ms/step - loss: 0.1718 -
binary_accuracy: 0.9448 - val_loss: 0.2860 - val_binary_accuracy: 0.8848
Epoch 5/20
30/30 [==============================] - 1s 27ms/step - loss: 0.1423 -
binary_accuracy: 0.9543 - val_loss: 0.2872 - val_binary_accuracy: 0.8844
Epoch 6/20
30/30 [==============================] - 1s 27ms/step - loss: 0.1150 -
binary_accuracy: 0.9665 - val_loss: 0.3069 - val_binary_accuracy: 0.8837
Epoch 7/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0949 -
binary_accuracy: 0.9726 - val_loss: 0.3126 - val_binary_accuracy: 0.8808
Epoch 8/20
30/30 [==============================] - 1s 31ms/step - loss: 0.0837 -
binary_accuracy: 0.9753 - val_loss: 0.3331 - val_binary_accuracy: 0.8795
Epoch 9/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0662 -
```

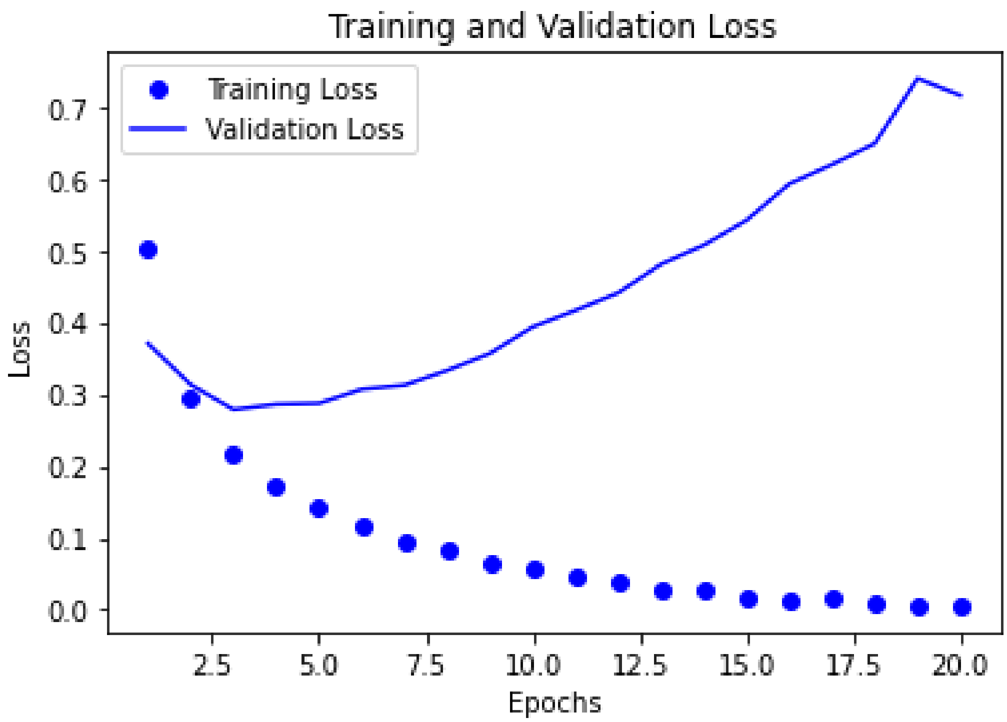
```
binary_accuracy: 0.9820 - val_loss: 0.3567 - val_binary_accuracy: 0.8760
Epoch 10/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0560 -
binary_accuracy: 0.9852 - val_loss: 0.3936 - val_binary_accuracy: 0.8704
Epoch 11/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0453 -
binary_accuracy: 0.9897 - val_loss: 0.4166 - val_binary_accuracy: 0.8718
Epoch 12/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0388 -
binary_accuracy: 0.9904 - val_loss: 0.4410 - val_binary_accuracy: 0.8755
Epoch 13/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0279 -
binary_accuracy: 0.9953 - val_loss: 0.4808 - val_binary_accuracy: 0.8695
Epoch 14/20
30/30 [==============================] - 1s 26ms/step - loss: 0.0261 -
binary_accuracy: 0.9942 - val_loss: 0.5071 - val_binary_accuracy: 0.8704
Epoch 15/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0182 -
binary_accuracy: 0.9972 - val_loss: 0.5417 - val_binary_accuracy: 0.8684
Epoch 16/20
30/30 [==============================] - 1s 31ms/step - loss: 0.0145 -
binary_accuracy: 0.9980 - val_loss: 0.5924 - val_binary_accuracy: 0.8692
Epoch 17/20
30/30 [==============================] - 1s 42ms/step - loss: 0.0148 -
binary_accuracy: 0.9968 - val_loss: 0.6194 - val_binary_accuracy: 0.8693
Epoch 18/20
30/30 [==============================] - 1s 50ms/step - loss: 0.0099 -
binary_accuracy: 0.9982 - val_loss: 0.6485 - val_binary_accuracy: 0.8695
Epoch 19/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0058 -
binary_accuracy: 0.9998 - val_loss: 0.7390 - val_binary_accuracy: 0.8552
Epoch 20/20
30/30 [==============================] - 1s 30ms/step - loss: 0.0069 -
binary_accuracy: 0.9991 - val_loss: 0.7156 - val_binary_accuracy: 0.8678
```

[19]:
```
history_dict = history.history
history_dict.keys()
```

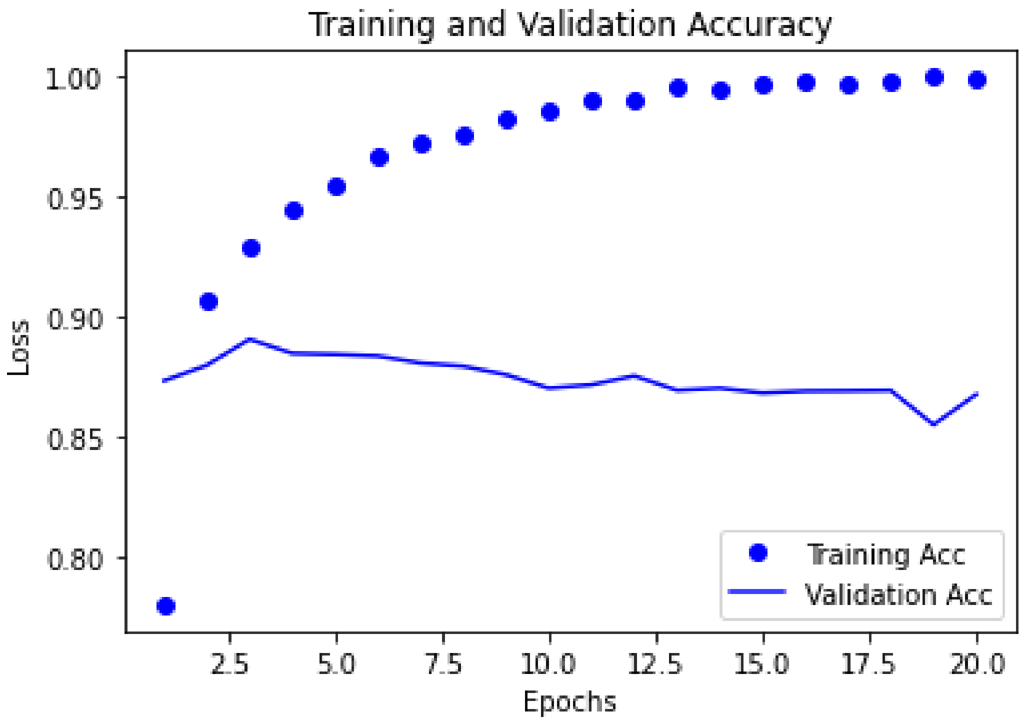
[19]:
```
dict_keys(['loss', 'binary_accuracy', 'val_loss', 'val_binary_accuracy'])
```

[20]:
```
# plot training & validation loss
import matplotlib.pyplot as plt
history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
acc = history_dict["binary_accuracy"]
```

```
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()
```



[21]:
```
# plot training & validation accuracy
plt.clf() # clears figure
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_values, 'b', label='Validation Acc')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



[22]:
```python
# retraining a model from scratch
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: 0.5153 - accuracy:
0.7828
Epoch 2/4
49/49 [==============================] - 0s 9ms/step - loss: 0.3003 - accuracy:
0.9066
Epoch 3/4
49/49 [==============================] - 0s 10ms/step - loss: 0.2181 - accuracy:
0.9271
Epoch 4/4
49/49 [==============================] - 0s 8ms/step - loss: 0.1774 - accuracy:
```

```
0.9389
782/782 [==============================] - 2s 2ms/step - loss: 0.2889 -
accuracy: 0.8858
```

[23]:
```
# view results
results
```

[23]:
```
[0.2889421582221985, 0.8858399987220764]
```

[24]:
```
# predict with model
model.predict(x_test)
```

[24]:
```
array([[0.2081638 ],
       [0.99562436],
       [0.86532116],
       …,
       [0.16729161],
       [0.06938234],
       [0.5782353 ]], dtype=float32)
```

2 Assignment 5.2

2.1 1.0.1 Implement the news classifier found in section 3.5 of Deep Learning with Python.

[25]:
```
import keras
```

[26]:
```
from keras.datasets import reuters
```

[27]:
```
(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
```

[28]:
```
len(train_data)
```

[28]:
```
8982
```

[29]:
```
len(test_data)
```

[29]:
```
2246
```

[30]:
```
train_data[10]
```

[30]:

```
[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]
```

[31]:

```python
# decode back to text
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]])
```

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

[32]:

```python
decoded_newswire
```

[32]:

```
'? ? ? 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'

[33]:
```
# prepare the data
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)
```

[34]:
```
# one hot encode
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

y_train = to_one_hot(train_labels)
y_test = to_one_hot(test_labels)
```

[35]:
```
from keras.utils.np_utils import to_categorical
```

[36]:
```
one_hot_train_labels = to_categorical(train_labels)
one_hot_test_labels = to_categorical(test_labels)
```

[37]:
```
# Build the model
from keras import models, layers
```

[38]:
```
model = keras.Sequential([
    layers.Dense(64, activation="relu", input_shape = (10000,)),
    layers.Dense(64, activation="relu"),
    layers.Dense(46, activation="softmax")
])
```

[39]:
```
model.compile(optimizer="rmsprop",
              loss="categorical_crossentropy",
              metrics=["accuracy"])
```

[40]:
```
# validate approach
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:]
```

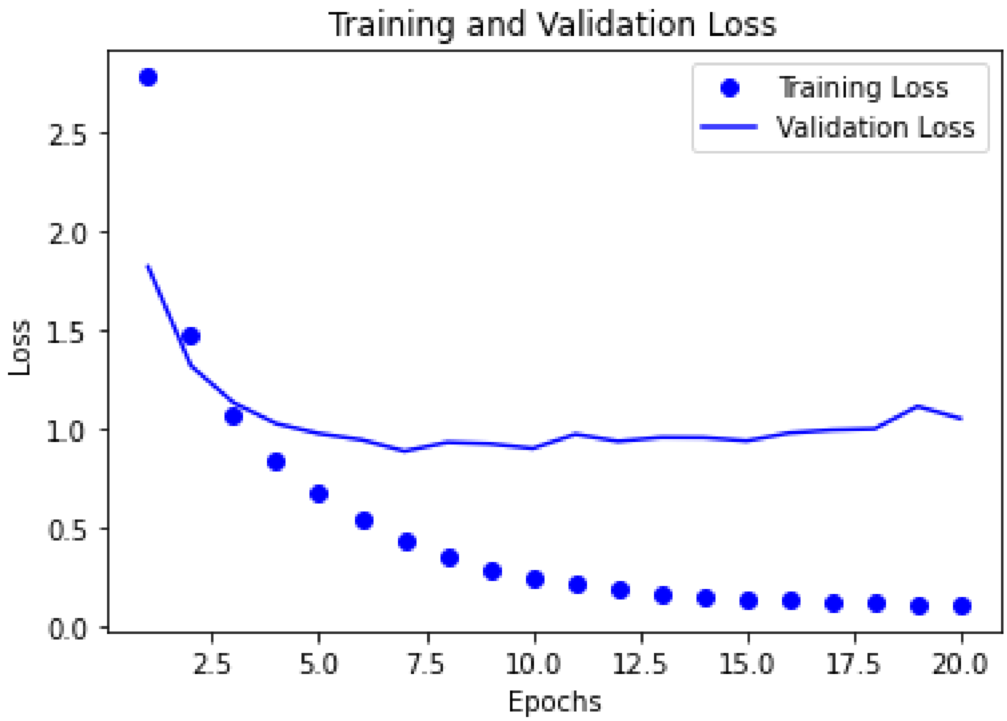
[41]:
```
# train the network for 20 epochs
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs = 20,
                    batch_size = 512,
                    validation_data = (x_val, y_val))
```

```
Epoch 1/20
16/16 [==============================] - 0s 23ms/step - loss: 2.7810 - accuracy:
0.5150 - val_loss: 1.8202 - val_accuracy: 0.6570
Epoch 2/20
16/16 [==============================] - 0s 18ms/step - loss: 1.4707 - accuracy:
0.7041 - val_loss: 1.3203 - val_accuracy: 0.7230
Epoch 3/20
16/16 [==============================] - 0s 18ms/step - loss: 1.0729 - accuracy:
0.7727 - val_loss: 1.1329 - val_accuracy: 0.7570
Epoch 4/20
16/16 [==============================] - 0s 18ms/step - loss: 0.8464 - accuracy:
0.8244 - val_loss: 1.0268 - val_accuracy: 0.7760
Epoch 5/20
16/16 [==============================] - 0s 17ms/step - loss: 0.6758 - accuracy:
0.8562 - val_loss: 0.9765 - val_accuracy: 0.7900
Epoch 6/20
16/16 [==============================] - 0s 15ms/step - loss: 0.5411 - accuracy:
0.8869 - val_loss: 0.9449 - val_accuracy: 0.8000
Epoch 7/20
16/16 [==============================] - 0s 18ms/step - loss: 0.4359 - accuracy:
0.9105 - val_loss: 0.8873 - val_accuracy: 0.8100
Epoch 8/20
16/16 [==============================] - 0s 17ms/step - loss: 0.3570 - accuracy:
0.9271 - val_loss: 0.9321 - val_accuracy: 0.8050
Epoch 9/20
16/16 [==============================] - 0s 14ms/step - loss: 0.2909 - accuracy:
0.9365 - val_loss: 0.9246 - val_accuracy: 0.8060
Epoch 10/20
16/16 [==============================] - 0s 18ms/step - loss: 0.2476 - accuracy:
0.9437 - val_loss: 0.9014 - val_accuracy: 0.8190
Epoch 11/20
16/16 [==============================] - 0s 16ms/step - loss: 0.2125 - accuracy:
0.9494 - val_loss: 0.9732 - val_accuracy: 0.7980
Epoch 12/20
16/16 [==============================] - 0s 19ms/step - loss: 0.1860 - accuracy:
0.9526 - val_loss: 0.9371 - val_accuracy: 0.8100
Epoch 13/20
```

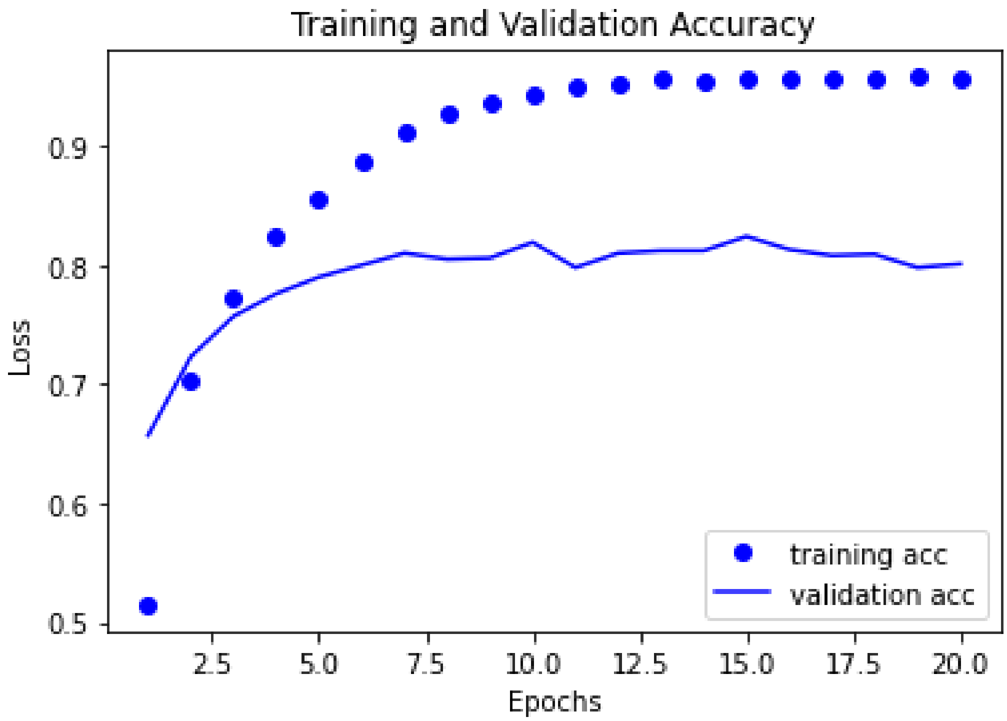
```
16/16 [==============================] - 0s 18ms/step - loss: 0.1678 - accuracy:
0.9554 - val_loss: 0.9575 - val_accuracy: 0.8120
Epoch 14/20
16/16 [==============================] - 0s 18ms/step - loss: 0.1492 - accuracy:
0.9553 - val_loss: 0.9565 - val_accuracy: 0.8120
Epoch 15/20
16/16 [==============================] - 0s 20ms/step - loss: 0.1416 - accuracy:
0.9564 - val_loss: 0.9395 - val_accuracy: 0.8240
Epoch 16/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1350 - accuracy:
0.9567 - val_loss: 0.9795 - val_accuracy: 0.8130
Epoch 17/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1262 - accuracy:
0.9557 - val_loss: 0.9946 - val_accuracy: 0.8080
Epoch 18/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1208 - accuracy:
0.9569 - val_loss: 1.0004 - val_accuracy: 0.8090
Epoch 19/20
16/16 [==============================] - 0s 20ms/step - loss: 0.1133 - accuracy:
0.9582 - val_loss: 1.1145 - val_accuracy: 0.7980
Epoch 20/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1121 - accuracy:
0.9568 - val_loss: 1.0528 - val_accuracy: 0.8010
```

[42]:

```python
# display loss & accuracy plots
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()
```



[43]:
```
plt.clf() # clear figure

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('Loss')
plt.legend()
plt.show()
```



[44]:
```
# retrain model from scratch
model = models.Sequential([
  layers.Dense(64, activation="relu", input_shape = (10000,)),
  layers.Dense(64, activation="relu"),
  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 [==============================] - 0s 25ms/step - loss: 2.5708 - accuracy:
0.5327 - val_loss: 1.7150 - val_accuracy: 0.6570
Epoch 2/9
16/16 [==============================] - 0s 17ms/step - loss: 1.3807 - accuracy:
```

```
0.7115 - val_loss: 1.2966 - val_accuracy: 0.7120
Epoch 3/9
16/16 [==============================] - 0s 17ms/step - loss: 1.0260 - accuracy:
0.7819 - val_loss: 1.1406 - val_accuracy: 0.7550
Epoch 4/9
16/16 [==============================] - 0s 17ms/step - loss: 0.8056 - accuracy:
0.8317 - val_loss: 1.0263 - val_accuracy: 0.7820
Epoch 5/9
16/16 [==============================] - 0s 15ms/step - loss: 0.6386 - accuracy:
0.8622 - val_loss: 0.9632 - val_accuracy: 0.8000
Epoch 6/9
16/16 [==============================] - 0s 17ms/step - loss: 0.5114 - accuracy:
0.8916 - val_loss: 0.9114 - val_accuracy: 0.8070
Epoch 7/9
16/16 [==============================] - 0s 16ms/step - loss: 0.4068 - accuracy:
0.9136 - val_loss: 0.9183 - val_accuracy: 0.8090
Epoch 8/9
16/16 [==============================] - 0s 15ms/step - loss: 0.3310 - accuracy:
0.9297 - val_loss: 0.9088 - val_accuracy: 0.8100
Epoch 9/9
16/16 [==============================] - 0s 16ms/step - loss: 0.2731 - accuracy:
0.9405 - val_loss: 0.9078 - val_accuracy: 0.8110
71/71 [==============================] - 0s 2ms/step - loss: 0.9904 - accuracy:
0.7863
```

[45]:
```
results
```

[45]: [0.9904041886329651, 0.7862867116928101]

[46]:
```
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)
```

[46]: 0.18432769367764915

[47]:
```
predictions = model.predict(x_test)
```

[48]:
```
predictions[0].shape
```

[48]: (46,)

[49]:
```
# each entry in predictions is a vector of length 46
```

[50]:
```
np.sum(predictions[0])
```

[50]: 1.0

[51]:
```
# the coefficients in the vector sum to 1
```

[52]:
```
np.argmax(predictions[0])
```

[52]: 3

[53]:
```
# different way to handle labels & the loss
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

[54]:
```
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
```

[55]:
```
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: 2.9545 - accuracy:
0.4377 - val_loss: 2.2940 - val_accuracy: 0.5440
Epoch 2/20
63/63 [==============================] - 1s 9ms/step - loss: 1.8669 - accuracy:
0.5811 - val_loss: 1.7047 - val_accuracy: 0.5990
Epoch 3/20
63/63 [==============================] - 0s 8ms/step - loss: 1.4180 - accuracy:
0.6596 - val_loss: 1.5177 - val_accuracy: 0.6570
Epoch 4/20
63/63 [==============================] - 0s 7ms/step - loss: 1.2196 - accuracy:
0.6912 - val_loss: 1.4587 - val_accuracy: 0.6490
Epoch 5/20
63/63 [==============================] - 1s 8ms/step - loss: 1.0952 - accuracy:
0.7140 - val_loss: 1.3867 - val_accuracy: 0.6690
Epoch 6/20
63/63 [==============================] - 1s 8ms/step - loss: 0.9957 - accuracy:
0.7348 - val_loss: 1.3890 - val_accuracy: 0.6860
```

```
Epoch 7/20
63/63 [==============================] - 0s 8ms/step - loss: 0.9124 - accuracy:
0.7595 - val_loss: 1.3815 - val_accuracy: 0.6860
Epoch 8/20
63/63 [==============================] - 0s 7ms/step - loss: 0.8408 - accuracy:
0.7809 - val_loss: 1.3805 - val_accuracy: 0.6910
Epoch 9/20
63/63 [==============================] - 0s 7ms/step - loss: 0.7761 - accuracy:
0.7969 - val_loss: 1.3941 - val_accuracy: 0.7010
Epoch 10/20
63/63 [==============================] - 0s 8ms/step - loss: 0.7197 - accuracy:
0.8126 - val_loss: 1.4102 - val_accuracy: 0.6930
Epoch 11/20
63/63 [==============================] - 1s 8ms/step - loss: 0.6715 - accuracy:
0.8242 - val_loss: 1.4503 - val_accuracy: 0.6980
Epoch 12/20
63/63 [==============================] - 0s 8ms/step - loss: 0.6286 - accuracy:
0.8378 - val_loss: 1.4759 - val_accuracy: 0.7090
Epoch 13/20
63/63 [==============================] - 0s 7ms/step - loss: 0.5915 - accuracy:
0.8504 - val_loss: 1.5322 - val_accuracy: 0.7080
Epoch 14/20
63/63 [==============================] - 0s 7ms/step - loss: 0.5589 - accuracy:
0.8567 - val_loss: 1.5789 - val_accuracy: 0.7080
Epoch 15/20
63/63 [==============================] - 0s 7ms/step - loss: 0.5276 - accuracy:
0.8603 - val_loss: 1.6187 - val_accuracy: 0.7070
Epoch 16/20
63/63 [==============================] - 0s 7ms/step - loss: 0.5041 - accuracy:
0.8647 - val_loss: 1.6996 - val_accuracy: 0.7040
Epoch 17/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4819 - accuracy:
0.8710 - val_loss: 1.7236 - val_accuracy: 0.7020
Epoch 18/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4624 - accuracy:
0.8773 - val_loss: 1.8066 - val_accuracy: 0.7020
Epoch 19/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4427 - accuracy:
0.8795 - val_loss: 1.8394 - val_accuracy: 0.7090
Epoch 20/20
63/63 [==============================] - 0s 7ms/step - loss: 0.4267 - accuracy:
0.8850 - val_loss: 1.8972 - val_accuracy: 0.7070
```

[55]:
```
<tensorflow.python.keras.callbacks.History at 0x7f47687c27c0>
```

[56]:
```python
# ~70% accuracy
# ~ 9% drop due to compressing a lot of info
```

3 Assignment 5.3

3.1 1.0.1 Implement the housing price regression model found in section 3.6 of Deep Learning with Python.

[57]:
```
from keras.datasets import boston_housing
```

[58]:
```
(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
```

[59]:
```
train_data.shape
```

[59]:
```
(404, 13)
```

[60]:
```
test_data.shape
```

[60]:
```
(102, 13)
```

[61]:
```
train_targets
```

[61]:
```
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])
```

[62]:
```
# prepare data
mean = train_data.mean(axis=0)
train_data -= mean
std = train_data.std(axis=0)
train_data /= std
test_data -= mean
test_data /= std
```

[63]:
```
# build model
from keras import models, layers
```

[65]:
```
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
```

[66]:
```
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=16, 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
```

[67]:
```
all_scores
```

[67]: [1.9824161529541016, 2.5980234146118164, 2.496790647506714, 2.3545424938201904]

[68]:
```
np.mean(all_scores)
```

[68]: 2.3579431772232056

[69]:
```
# save validation logs for each fold
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=16, verbose=0)
    mae_history = history.history["val_mae"]
    all_mae_histories.append(mae_history)
```

```
processing fold # 0
```

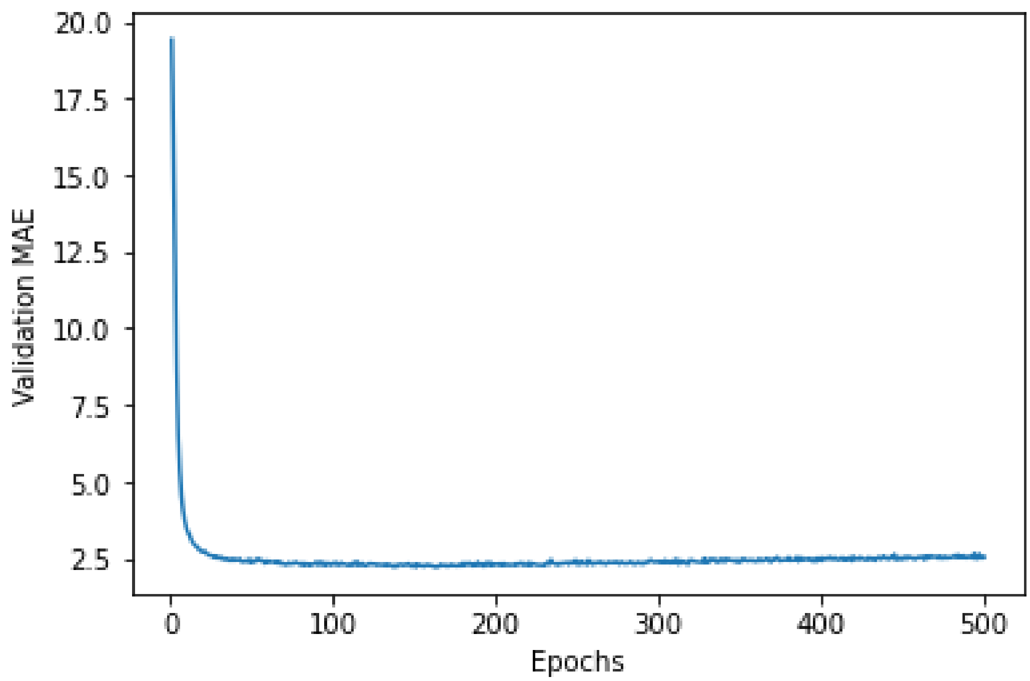
```
processing fold # 1
processing fold # 2
processing fold # 3
```

[70]:

```
# compute average of the per-epoch MAE scores for all folds
average_mae_history = [np.mean([x[i] for x in all_mae_histories]) for i in␣
↪range(num_epochs)]
```

[71]:

```
# plot validation scores
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()
```

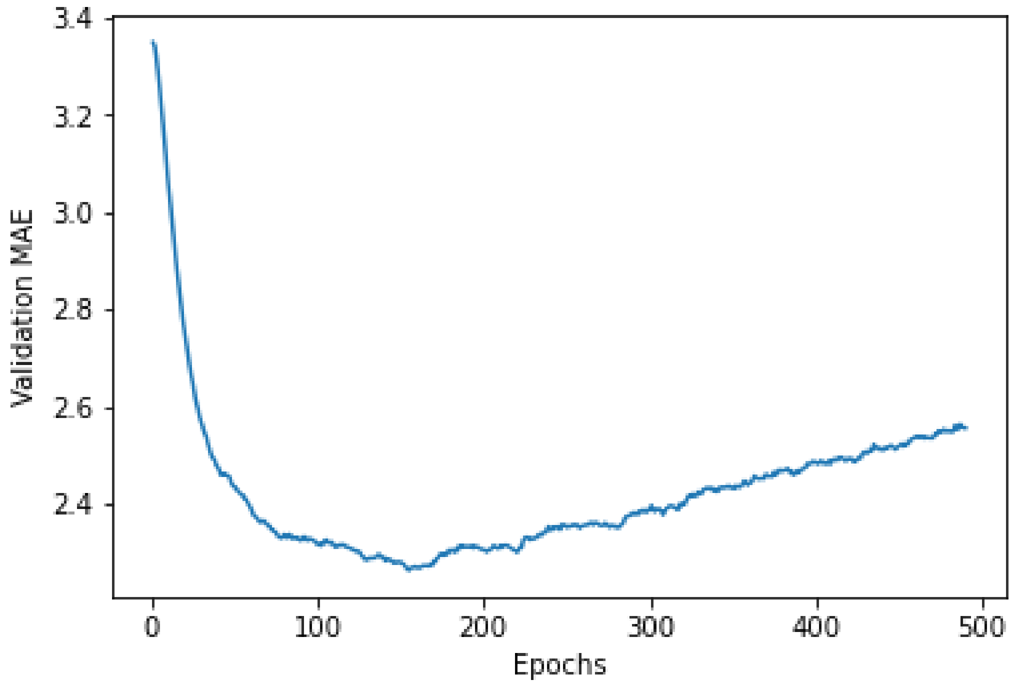


[73]:

```
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:])
```

[74]:
```
# plot validation scores but excluding first 10 data points
plt.plot(range(1, len(smooth_mae_history) + 1), smooth_mae_history)
plt.xlabel("Epochs")
plt.ylabel("Validation MAE")
plt.show()
```



[75]:
```
# train the model
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 930us/step - loss: 18.3195 - mae:
2.6116
```

[76]:
```
test_mae_score
```

[76]: 2.611565351486206

[ ]:
```
# still off by about -$2.611
```