week_5_assignment 5

April 17, 2022

1 Week5: Assignments

1.0.1 Author: Ganesh Kale

import required packages

[22]:
```
from tensorflow import keras
from keras import models
from keras import layers
from keras.datasets import imdb
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.utils import to_categorical

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = 'all'
```

2 Assignment 5.1: Classifying movie reviews: A binary classification example

[4]:
```
# load the data

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

[6]:
```
# display train and test data sample

print(train_data[0])
train_labels[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]
```

[6]:
```
1
```

2.0.1 Encoding the integer sequences into a binary matrix

[7]:
```python
#  create function to encode sequence

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

[8]:
```python
# display sample of training data after encoding

x_train[0]
```

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

[9]:
```python
# vectorize the lables

y_train = np.asarray(train_labels).astype("float32")
y_test = np.asarray(test_labels).astype("float32")
```

2.0.2 Build the NN Model

[12]:
```python
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
```

Compile the model

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

Splitting data into training and validation

[14]:
```
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

Train the model

[15]:
```
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 45ms/step - loss: 0.5145 - accuracy:
0.7843 - val_loss: 0.4133 - val_accuracy: 0.8416
Epoch 2/20
30/30 [==============================] - 1s 29ms/step - loss: 0.3061 - accuracy:
0.8999 - val_loss: 0.3046 - val_accuracy: 0.8861
Epoch 3/20
30/30 [==============================] - 1s 27ms/step - loss: 0.2234 - accuracy:
0.9269 - val_loss: 0.2809 - val_accuracy: 0.8907
Epoch 4/20
30/30 [==============================] - 1s 29ms/step - loss: 0.1788 - accuracy:
0.9412 - val_loss: 0.2736 - val_accuracy: 0.8909
Epoch 5/20
30/30 [==============================] - 1s 29ms/step - loss: 0.1431 - accuracy:
0.9551 - val_loss: 0.2816 - val_accuracy: 0.8861
Epoch 6/20
30/30 [==============================] - 1s 38ms/step - loss: 0.1169 - accuracy:
0.9638 - val_loss: 0.3234 - val_accuracy: 0.8787
Epoch 7/20
30/30 [==============================] - 1s 42ms/step - loss: 0.0989 - accuracy:
0.9711 - val_loss: 0.3150 - val_accuracy: 0.8816
Epoch 8/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0814 - accuracy:
0.9767 - val_loss: 0.3298 - val_accuracy: 0.8805
Epoch 9/20
30/30 [==============================] - 1s 30ms/step - loss: 0.0659 - accuracy:
0.9834 - val_loss: 0.3539 - val_accuracy: 0.8804
Epoch 10/20
30/30 [==============================] - 1s 30ms/step - loss: 0.0552 - accuracy:
0.9863 - val_loss: 0.3963 - val_accuracy: 0.8706
Epoch 11/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0447 - accuracy:
0.9897 - val_loss: 0.4044 - val_accuracy: 0.8756
Epoch 12/20
30/30 [==============================] - 1s 31ms/step - loss: 0.0358 - accuracy:
```

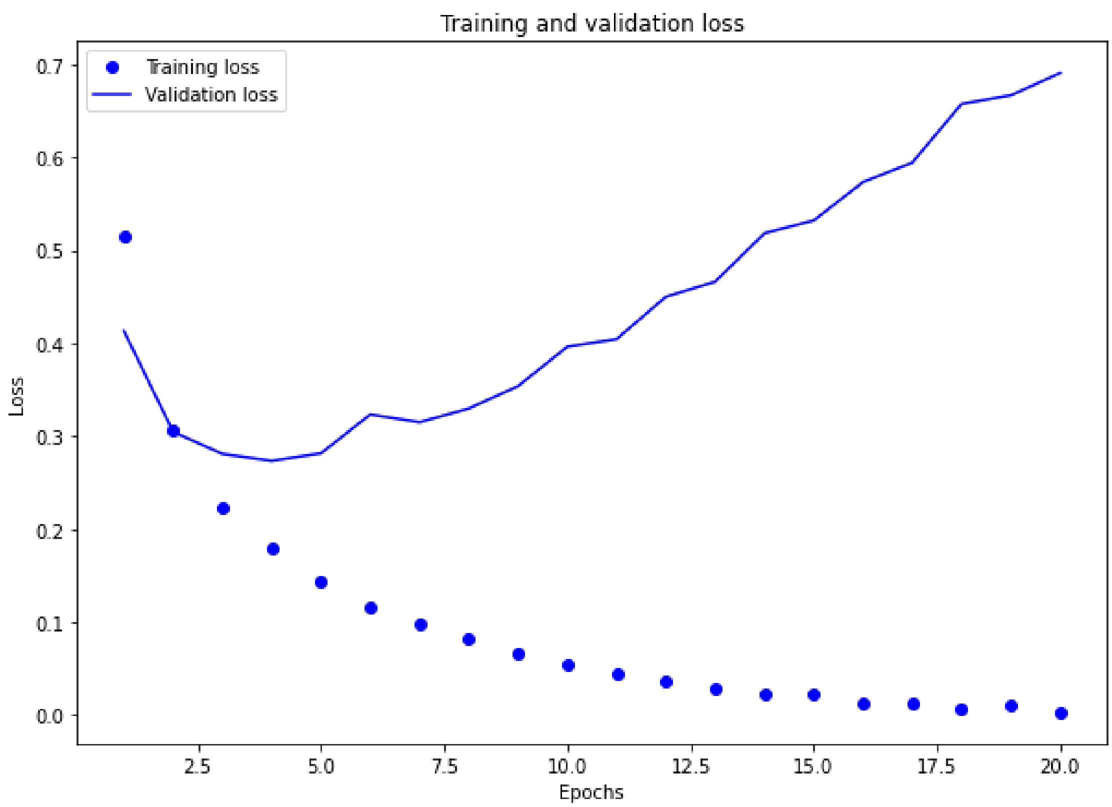
```
0.9927 - val_loss: 0.4500 - val_accuracy: 0.8685
Epoch 13/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0282 - accuracy:
0.9947 - val_loss: 0.4663 - val_accuracy: 0.8726
Epoch 14/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0231 - accuracy:
0.9957 - val_loss: 0.5182 - val_accuracy: 0.8726
Epoch 15/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0218 - accuracy:
0.9950 - val_loss: 0.5320 - val_accuracy: 0.8696
Epoch 16/20
30/30 [==============================] - 1s 29ms/step - loss: 0.0130 - accuracy:
0.9984 - val_loss: 0.5733 - val_accuracy: 0.8700
Epoch 17/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0124 - accuracy:
0.9981 - val_loss: 0.5943 - val_accuracy: 0.8674
Epoch 18/20
30/30 [==============================] - 1s 30ms/step - loss: 0.0068 - accuracy:
0.9997 - val_loss: 0.6573 - val_accuracy: 0.8677
Epoch 19/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0114 - accuracy:
0.9971 - val_loss: 0.6667 - val_accuracy: 0.8669
Epoch 20/20
30/30 [==============================] - 1s 27ms/step - loss: 0.0038 - accuracy:
0.9999 - val_loss: 0.6906 - val_accuracy: 0.8645
```

[16]:
```python
#  see the training history

history_dict = history.history
history_dict.keys()
```

[16]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Plotting the training and validation loss

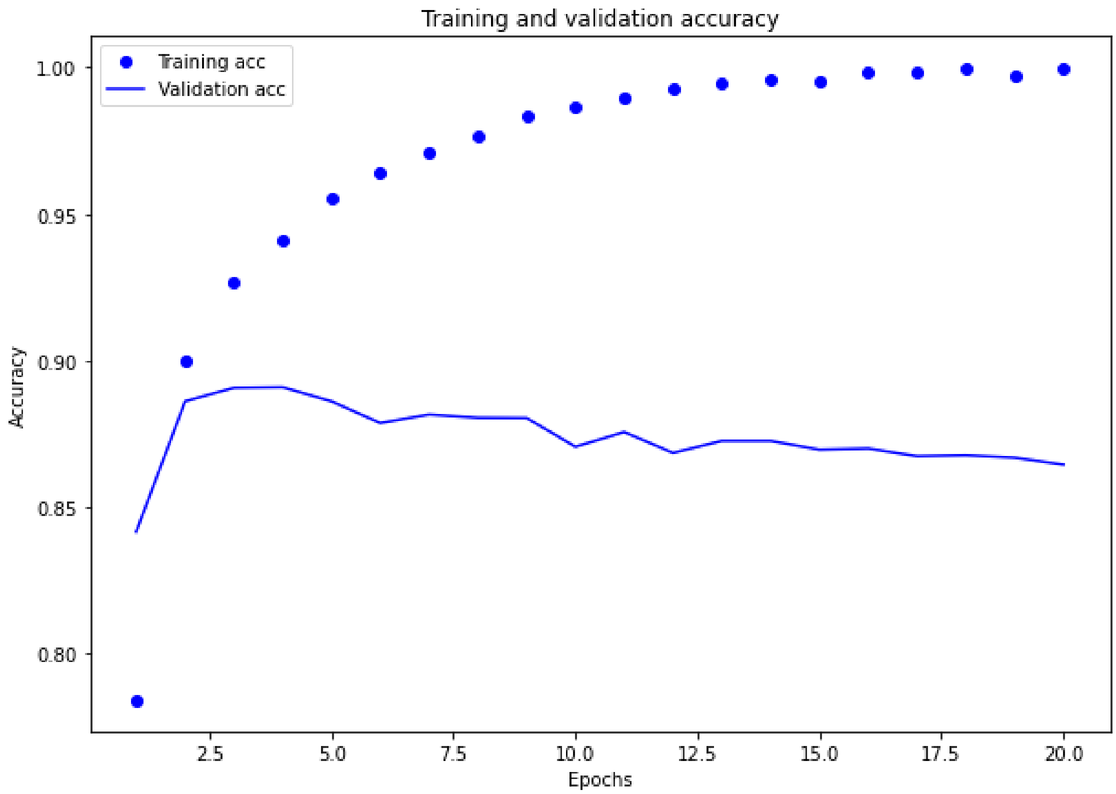
[20]:
```python
plt.figure(figsize=(10,7))

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

[22]:
```
plt.clf()

plt.figure(figsize=(10,7))

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();
```

```
<Figure size 432x288 with 0 Axes>
```



Retraining a model from scratch - for 4 epochs

[23]:
```
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 [==============================] - 0s 10ms/step - loss: 0.5049 - accuracy:
0.7966
Epoch 2/4
49/49 [==============================] - 0s 8ms/step - loss: 0.2975 - accuracy:
0.9072
Epoch 3/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2170 - accuracy:
0.9286
```

```
Epoch 4/4
49/49 [==============================] - 0s 8ms/step - loss: 0.1783 - accuracy:
0.9394
```

[23]:
```
<tensorflow.python.keras.callbacks.History at 0x7f2911e17880>
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.3007 -
accuracy: 0.8813
```

[25]:
```python
# display the result

results
```

[25]:
```
[0.3007475733757019, 0.8813199996948242]
```

[26]:
```python
print(f"The accuracy of the model is {round(results[1],2)*100}%")
```

```
The accuracy of the model is 88.0%
```

2.0.3 END

3 Assignment 5.2: Classifying newswires: A multiclass classification example

[8]:
```python
# loading the Reuters dataset

from tensorflow.keras.datasets import reuters
(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
```

[9]:
```python
# display  records in each data set train and test

len(train_data)
len(test_data)
```

[9]:
```
8982
```

[9]:
```
2246
```

[11]:
```python
# display train data sample

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]
```

[12]:
```python
# Decoding newswires 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]])

decoded_newswire
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/reuters_word_index.json
557056/550378 [==============================] - 0s 1us/step
```

[12]:
```
'? ? ? 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'
```

[13]:
```python
# label associated with an example is an integer between 0 and 45

train_labels[10]
```

[13]:
```
3
```

Encoding the input data

[18]:
```python
 def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1
    return results
```

[19]:
```python
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

Encoding the labels

[20]:
```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
y_train = to_one_hot(train_labels)
y_test = to_one_hot(test_labels)
```

[23]:
```python
y_train = to_categorical(train_labels)
y_test = to_categorical(test_labels)
```

Building your model

[25]:
```python
model = keras.Sequential([
    layers.Dense(64, activation="relu"),
    layers.Dense(64, activation="relu"),
    layers.Dense(46, activation="softmax")
])
```

Compiling the model

[26]:
```python
model.compile(optimizer="rmsprop",
              loss="categorical_crossentropy",
              metrics=["accuracy"])
```

Setting aside a validation set

[27]:
```python
x_val = x_train[:1000]
partial_x_train = x_train[1000:]
y_val = y_train[:1000]
partial_y_train = y_train[1000:]
```

[28]:
```python
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

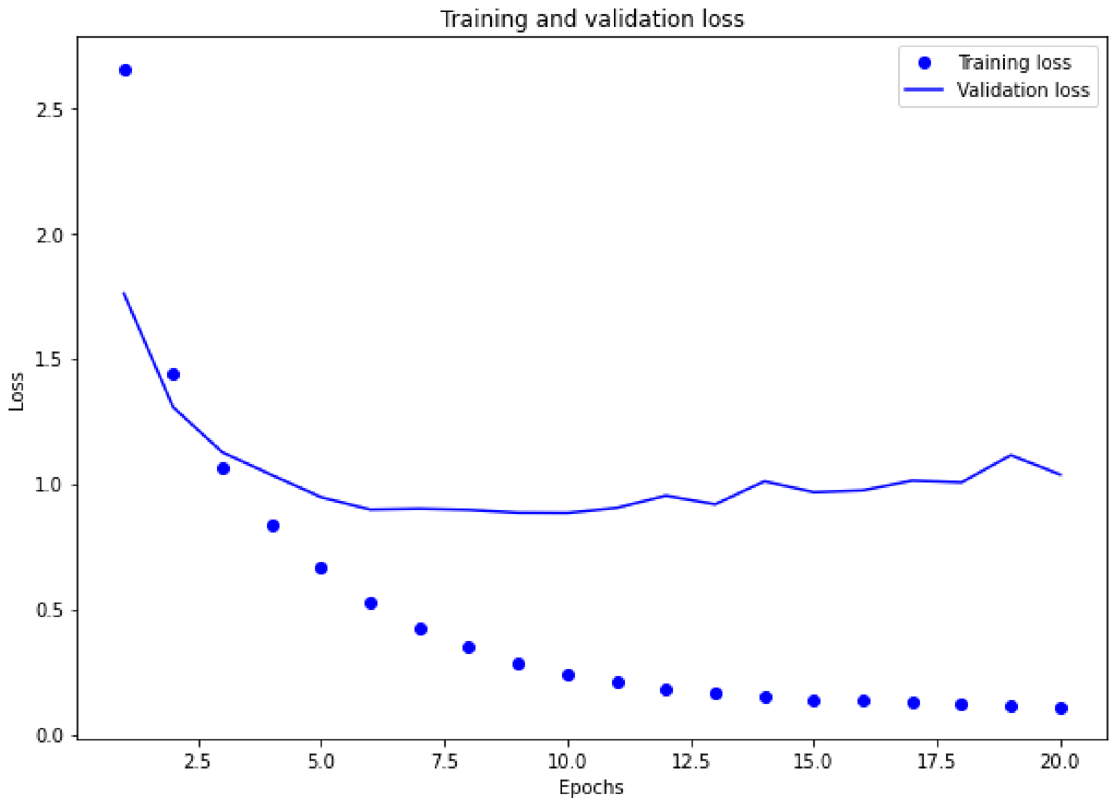
```
Epoch 1/20
16/16 [==============================] - 1s 35ms/step - loss: 2.6546 - accuracy:
0.5004 - val_loss: 1.7578 - val_accuracy: 0.6500
Epoch 2/20
16/16 [==============================] - 1s 44ms/step - loss: 1.4382 - accuracy:
0.7015 - val_loss: 1.3042 - val_accuracy: 0.7170
Epoch 3/20
16/16 [==============================] - 1s 45ms/step - loss: 1.0600 - accuracy:
0.7776 - val_loss: 1.1244 - val_accuracy: 0.7550
Epoch 4/20
16/16 [==============================] - 1s 44ms/step - loss: 0.8344 - accuracy:
0.8217 - val_loss: 1.0341 - val_accuracy: 0.7860
Epoch 5/20
16/16 [==============================] - 0s 20ms/step - loss: 0.6638 - accuracy:
0.8602 - val_loss: 0.9458 - val_accuracy: 0.7990
Epoch 6/20
16/16 [==============================] - 0s 19ms/step - loss: 0.5292 - accuracy:
0.8910 - val_loss: 0.8961 - val_accuracy: 0.8110
```

```
Epoch 7/20
16/16 [==============================] - 0s 18ms/step - loss: 0.4262 - accuracy:
0.9137 - val_loss: 0.8996 - val_accuracy: 0.8090
Epoch 8/20
16/16 [==============================] - 0s 19ms/step - loss: 0.3465 - accuracy:
0.9286 - val_loss: 0.8951 - val_accuracy: 0.8090
Epoch 9/20
16/16 [==============================] - 0s 17ms/step - loss: 0.2855 - accuracy:
0.9382 - val_loss: 0.8836 - val_accuracy: 0.8210
Epoch 10/20
16/16 [==============================] - 0s 16ms/step - loss: 0.2423 - accuracy:
0.9451 - val_loss: 0.8826 - val_accuracy: 0.8230
Epoch 11/20
16/16 [==============================] - 0s 16ms/step - loss: 0.2070 - accuracy:
0.9506 - val_loss: 0.9029 - val_accuracy: 0.8210
Epoch 12/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1823 - accuracy:
0.9521 - val_loss: 0.9517 - val_accuracy: 0.8090
Epoch 13/20
16/16 [==============================] - 0s 18ms/step - loss: 0.1664 - accuracy:
0.9533 - val_loss: 0.9173 - val_accuracy: 0.8130
Epoch 14/20
16/16 [==============================] - 1s 34ms/step - loss: 0.1526 - accuracy:
0.9546 - val_loss: 1.0090 - val_accuracy: 0.7960
Epoch 15/20
16/16 [==============================] - 1s 39ms/step - loss: 0.1366 - accuracy:
0.9560 - val_loss: 0.9653 - val_accuracy: 0.8130
Epoch 16/20
16/16 [==============================] - 1s 50ms/step - loss: 0.1333 - accuracy:
0.9569 - val_loss: 0.9726 - val_accuracy: 0.8190
Epoch 17/20
16/16 [==============================] - 1s 34ms/step - loss: 0.1273 - accuracy:
0.9557 - val_loss: 1.0120 - val_accuracy: 0.8000
Epoch 18/20
16/16 [==============================] - 0s 26ms/step - loss: 0.1205 - accuracy:
0.9567 - val_loss: 1.0046 - val_accuracy: 0.8150
Epoch 19/20
16/16 [==============================] - 0s 23ms/step - loss: 0.1172 - accuracy:
0.9572 - val_loss: 1.1131 - val_accuracy: 0.7870
Epoch 20/20
16/16 [==============================] - 0s 22ms/step - loss: 0.1106 - accuracy:
0.9563 - val_loss: 1.0359 - val_accuracy: 0.8060
```

Plotting the training and validation loss

[30]:
```
plt.figure(figsize=(10,7))

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();
```

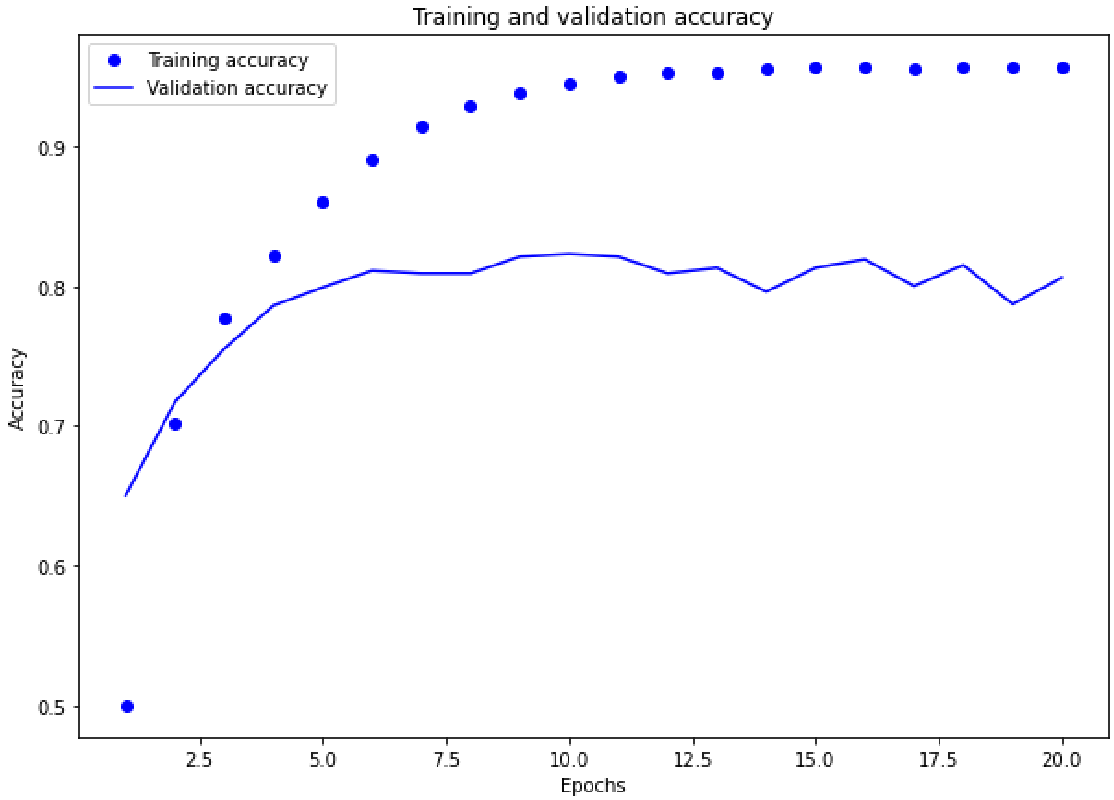


Plotting the training and validation accuracy

[31]:
```
plt.clf()

plt.figure(figsize=(10,7))

acc = history.history["accuracy"]
val_acc = history.history["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training accuracy")
plt.plot(epochs, val_acc, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
```

```
plt.ylabel("Accuracy")
plt.legend()
plt.show();
```

```
<Figure size 432x288 with 0 Axes>
```



Retraining a model from scratch

[32]:
```
model = keras.Sequential([
  layers.Dense(64, activation="relu"),
  layers.Dense(64, activation="relu"),
  layers.Dense(46, activation="softmax")
])
model.compile(optimizer="rmsprop",
              loss="categorical_crossentropy",
              metrics=["accuracy"])
model.fit(x_train,
          y_train,
          epochs=9,
          batch_size=512)
results = model.evaluate(x_test, y_test)
```

```
Epoch 1/9
18/18 [==============================] - 0s 16ms/step - loss: 2.6042 - accuracy:
0.4963
Epoch 2/9
18/18 [==============================] - 0s 13ms/step - loss: 1.4033 - accuracy:
0.7088
Epoch 3/9
18/18 [==============================] - 0s 12ms/step - loss: 1.0273 - accuracy:
0.7808
Epoch 4/9
18/18 [==============================] - 0s 13ms/step - loss: 0.7990 - accuracy:
0.8292
Epoch 5/9
18/18 [==============================] - 0s 12ms/step - loss: 0.6345 - accuracy:
0.8661
Epoch 6/9
18/18 [==============================] - 0s 13ms/step - loss: 0.5035 - accuracy:
0.8965
Epoch 7/9
18/18 [==============================] - 0s 13ms/step - loss: 0.4030 - accuracy:
0.9144
Epoch 8/9
18/18 [==============================] - 0s 13ms/step - loss: 0.3334 - accuracy:
0.9259
Epoch 9/9
18/18 [==============================] - 0s 15ms/step - loss: 0.2758 - accuracy:
0.9378
```

[32]:
```
<tensorflow.python.keras.callbacks.History at 0x7fcde67db550>
```

```
71/71 [==============================] - 0s 2ms/step - loss: 0.9557 - accuracy:
0.7907
```

[33]:
```
# display the result

results
```

[33]:
```
[0.9557026028633118, 0.790739119052887]
```

[34]:
```
print(f"The accuracy of the model is {round(results[1],2)*100}%")
```

```
The accuracy of the model is 79.0%
```

predictions on new data

[35]:
```
# predictions is a vector of length 46

predictions = model.predict(x_test)
```

```
predictions[0].shape
```

[35]: (46,)

[36]:
```
# The coefficients in this vector sum to 1

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

[36]: 0.99999994

[37]:
```
# the class with the highest probability

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

[37]: 3

different way to handle the labels and the loss

[38]:
```
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

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

importance of having sufficiently large intermediate layers

[40]:
```
model = keras.Sequential([
    layers.Dense(64, activation="relu"),
    layers.Dense(4, 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=20,
          batch_size=128,
          validation_data=(x_val, y_val))
```

```
Epoch 1/20
63/63 [==============================] - 1s 9ms/step - loss: 3.0746 - accuracy:
0.2279 - val_loss: 2.5696 - val_accuracy: 0.2740
Epoch 2/20
63/63 [==============================] - 1s 8ms/step - loss: 1.9711 - accuracy:
0.5382 - val_loss: 1.6253 - val_accuracy: 0.6230
Epoch 3/20
```

```
63/63 [==============================] - 1s 11ms/step - loss: 1.4587 - accuracy:
0.6419 - val_loss: 1.4765 - val_accuracy: 0.6360
Epoch 4/20
63/63 [==============================] - 1s 9ms/step - loss: 1.2913 - accuracy:
0.6704 - val_loss: 1.4255 - val_accuracy: 0.6600
Epoch 5/20
63/63 [==============================] - 1s 8ms/step - loss: 1.1830 - accuracy:
0.7005 - val_loss: 1.4011 - val_accuracy: 0.6620
Epoch 6/20
63/63 [==============================] - 0s 7ms/step - loss: 1.0987 - accuracy:
0.7076 - val_loss: 1.3835 - val_accuracy: 0.6610
Epoch 7/20
63/63 [==============================] - 1s 9ms/step - loss: 1.0299 - accuracy:
0.7103 - val_loss: 1.4036 - val_accuracy: 0.6570
Epoch 8/20
63/63 [==============================] - 1s 8ms/step - loss: 0.9731 - accuracy:
0.7210 - val_loss: 1.4025 - val_accuracy: 0.6680
Epoch 9/20
63/63 [==============================] - 0s 8ms/step - loss: 0.9242 - accuracy:
0.7388 - val_loss: 1.4112 - val_accuracy: 0.6780
Epoch 10/20
63/63 [==============================] - 1s 8ms/step - loss: 0.8834 - accuracy:
0.7523 - val_loss: 1.4567 - val_accuracy: 0.6750
Epoch 11/20
63/63 [==============================] - 1s 9ms/step - loss: 0.8461 - accuracy:
0.7602 - val_loss: 1.4977 - val_accuracy: 0.6790
Epoch 12/20
63/63 [==============================] - 1s 8ms/step - loss: 0.8124 - accuracy:
0.7669 - val_loss: 1.5203 - val_accuracy: 0.6800
Epoch 13/20
63/63 [==============================] - 0s 7ms/step - loss: 0.7838 - accuracy:
0.7750 - val_loss: 1.5645 - val_accuracy: 0.6700
Epoch 14/20
63/63 [==============================] - 1s 8ms/step - loss: 0.7546 - accuracy:
0.7830 - val_loss: 1.6169 - val_accuracy: 0.6750
Epoch 15/20
63/63 [==============================] - 0s 7ms/step - loss: 0.7325 - accuracy:
0.7908 - val_loss: 1.6323 - val_accuracy: 0.6690
Epoch 16/20
63/63 [==============================] - 0s 8ms/step - loss: 0.7074 - accuracy:
0.7984 - val_loss: 1.6979 - val_accuracy: 0.6720
Epoch 17/20
63/63 [==============================] - 1s 8ms/step - loss: 0.6895 - accuracy:
0.8029 - val_loss: 1.7345 - val_accuracy: 0.6670
Epoch 18/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6701 - accuracy:
0.8112 - val_loss: 1.7949 - val_accuracy: 0.6680
Epoch 19/20
```

```
63/63 [==============================] - 0s 7ms/step - loss: 0.6530 - accuracy:
0.8142 - val_loss: 1.8719 - val_accuracy: 0.6690
Epoch 20/20
63/63 [==============================] - 0s 7ms/step - loss: 0.6363 - accuracy:
0.8167 - val_loss: 1.8490 - val_accuracy: 0.6830
```

[40]:
```
<tensorflow.python.keras.callbacks.History at 0x7fcde76fa970>
```

4 END

5 Assignment 5.3:Predicting house prices: A regression example

[41]:
```python
# Loading the Boston housing dataset


from tensorflow.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
```

[42]:
```python
# display shape of datset


train_data.shape
test_data.shape
```

[42]:
```
(404, 13)
```

[42]:
```
(102, 13)
```

[44]:
```python
# display targets - sample

train_targets[:5]
```

[44]:
```
array([15.2, 42.3, 50. , 21.1, 17.7])
```

Normalizing the data

[45]:
```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 the model

[46]:
```
def build_model():
    model = keras.Sequential([
        layers.Dense(64, activation="relu"),
        layers.Dense(64, activation="relu"),
        layers.Dense(1)
    ])
    model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
    return model
```

Validating approach using K-fold validation

[47]:
```
k = 4
num_val_samples = len(train_data) // k
num_epochs = 100
all_scores = []
for i in range(k):
    print(f"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
```

[47]:
```
<tensorflow.python.keras.callbacks.History at 0x7fcde5fdbcd0>
```

```
Processing fold #1
```

[47]:
```
<tensorflow.python.keras.callbacks.History at 0x7fcde62af0a0>
```

```
Processing fold #2
```

[47]:
```
<tensorflow.python.keras.callbacks.History at 0x7fcde4ba7ac0>
```

```
Processing fold #3
```

[47]: <tensorflow.python.keras.callbacks.History at 0x7fcde4a73880>

[48]:
```
all_scores
```

[48]:
```
[1.9127342700958252,
 2.2901790142059326,
 2.5055272579193115,
 2.2678756713867188]
```

[49]:
```
np.mean(all_scores)
```

[49]:
```
2.244079053401947
```

Saving the validation logs at each fold

[50]:
```
num_epochs = 500
all_mae_histories = []
for i in range(k):
    print(f"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)
```

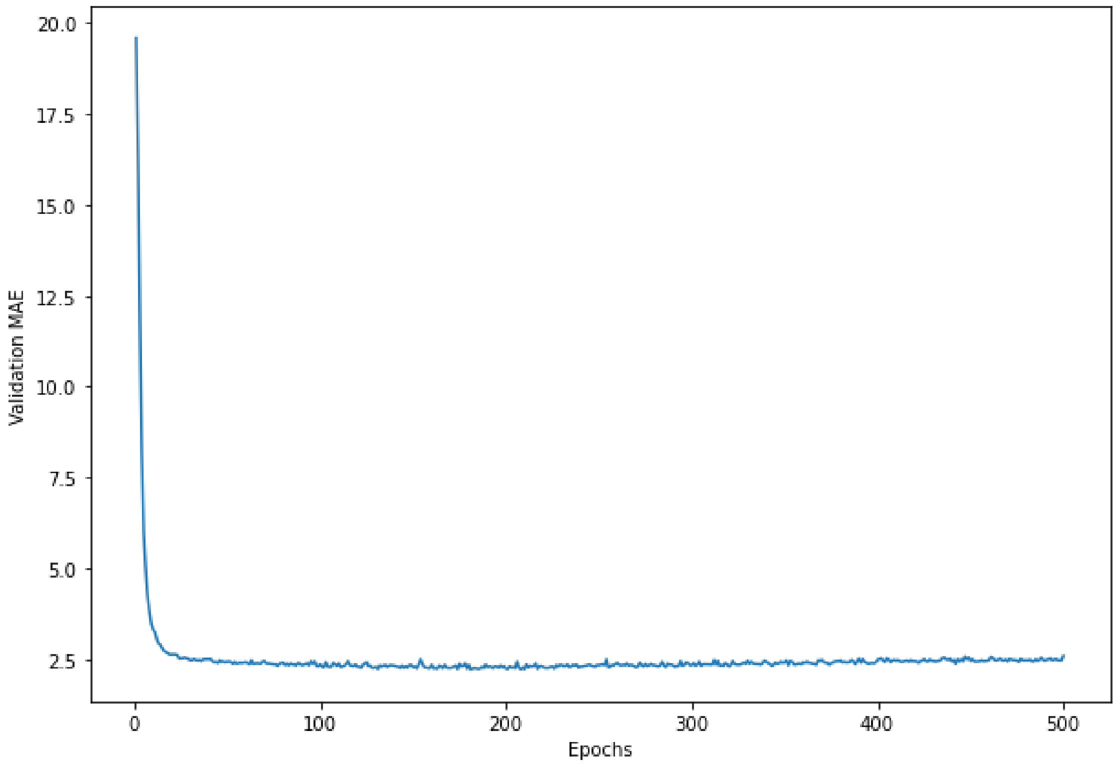
```
Processing fold #0
Processing fold #1
Processing fold #2
Processing fold #3
```

Building the history of successive mean K-fold validation scores

[51]:
```
average_mae_history = [
    np.mean([x[i] for x in all_mae_histories]) for i in range(num_epochs)]
p
```

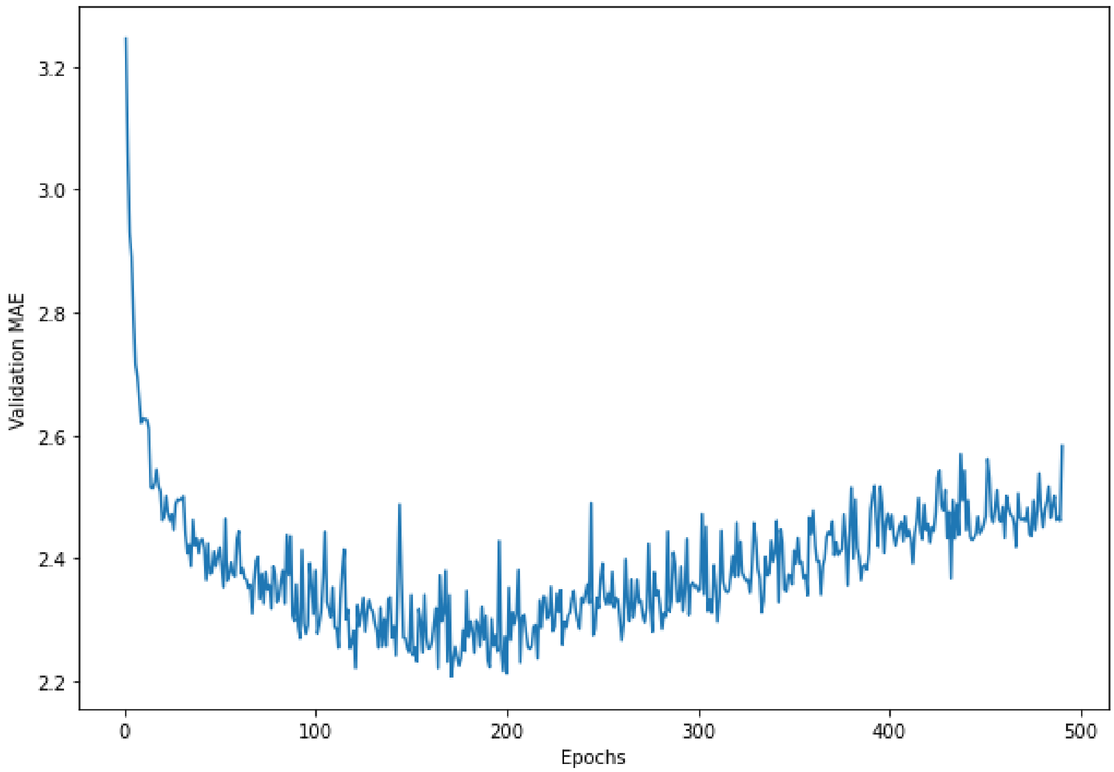
Plotting validation scores

[54]:
```
plt.figure(figsize=(10,7))

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



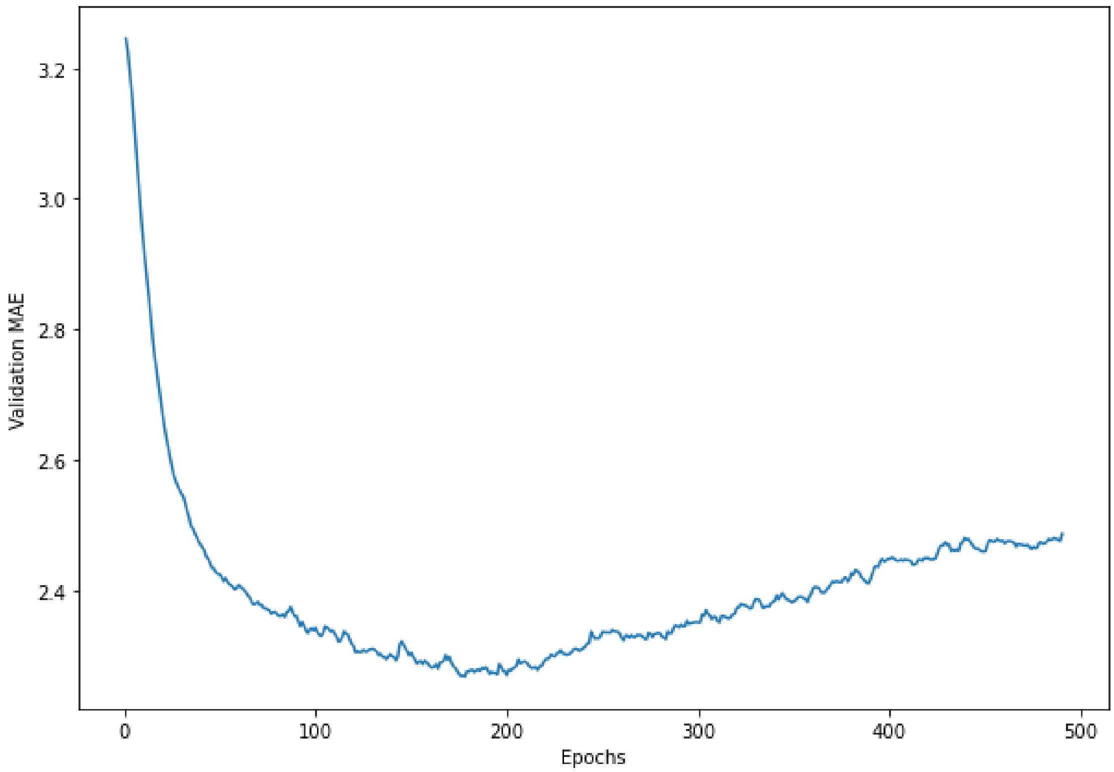
Plotting validation scores, excluding the first 10 data points

[56]:
```
truncated_mae_history = average_mae_history[10:]
plt.figure(figsize=(10,7))

plt.plot(range(1, len(truncated_mae_history) + 1), truncated_mae_history)
plt.xlabel("Epochs")
plt.ylabel("Validation MAE")
plt.show();
```



[62]:
```
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
```

[64]:
```
smooth_mae_history = smooth_curve(average_mae_history[10:])
plt.figure(figsize=(10,7))

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

[57]:
```
model = build_model()
model.fit(train_data, train_targets,
          epochs=130, batch_size=16, verbose=0)
test_mse_score, test_mae_score = model.evaluate(test_data, test_targets)
```

[57]:
```
<tensorflow.python.keras.callbacks.History at 0x7fcdefa8dd00>
```

```
4/4 [==============================] - 0s 1ms/step - loss: 13.5448 - mae: 2.4619
```

[58]:
```
test_mae_score
```

[58]:
```
2.461940288543701
```

predictions on new data

[59]:
```
predictions = model.predict(test_data)
predictions[0]
```

[59]:
```
array([7.760147], dtype=float32)
```

6 END