DSC650-T301 Big Data (2235-1)

4/13/2023

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Assignment 5.1

In [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.n
pz
17464789/17464789 [==============================] - 2s 0us/step
```

In [2]:
```
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

# Use function on train and test sets.
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

In [3]:
```
# Vectorize the labels too
y_train = np.asarray(train_labels).astype('float32')
y_test = np.asarray(test_labels).astype('float32')
```

In [4]:
```
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Dense(16, activation = 'relu', input_shape = (10000,)))
model.add(layers.Dense(16, activation = 'relu'))
model.add(layers.Dense(1, activation = 'sigmoid'))

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

In [5]:
```
# Validate your approach
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]

history = model.fit(partial_x_train, partial_y_train, epochs = 20, batch_size = 512, val
```

```
Epoch 1/20
30/30 [==============================] - 2s 31ms/step - loss: 0.5893 - accuracy: 0.7003
- val_loss: 0.4948 - val_accuracy: 0.8133
Epoch 2/20
30/30 [==============================] - 0s 13ms/step - loss: 0.4056 - accuracy: 0.8862
- val_loss: 0.3954 - val_accuracy: 0.8480
Epoch 3/20
30/30 [==============================] - 0s 13ms/step - loss: 0.2911 - accuracy: 0.9211
```

```
- val_loss: 0.3238 - val_accuracy: 0.8808
Epoch 4/20
30/30 [==============================] - 0s 13ms/step - loss: 0.2247 - accuracy: 0.9368
- val_loss: 0.2852 - val_accuracy: 0.8918
Epoch 5/20
30/30 [==============================] - 0s 13ms/step - loss: 0.1822 - accuracy: 0.9482
- val_loss: 0.2774 - val_accuracy: 0.8903
Epoch 6/20
30/30 [==============================] - 0s 13ms/step - loss: 0.1511 - accuracy: 0.9567
- val_loss: 0.3054 - val_accuracy: 0.8786
Epoch 7/20
30/30 [==============================] - 0s 13ms/step - loss: 0.1275 - accuracy: 0.9639
- val_loss: 0.2911 - val_accuracy: 0.8865
Epoch 8/20
30/30 [==============================] - 0s 13ms/step - loss: 0.1066 - accuracy: 0.9714
- val_loss: 0.2956 - val_accuracy: 0.8875
Epoch 9/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0886 - accuracy: 0.9783
- val_loss: 0.3115 - val_accuracy: 0.8843
Epoch 10/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0733 - accuracy: 0.9829
- val_loss: 0.3311 - val_accuracy: 0.8804
Epoch 11/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0599 - accuracy: 0.9873
- val_loss: 0.3769 - val_accuracy: 0.8721
Epoch 12/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0500 - accuracy: 0.9903
- val_loss: 0.3691 - val_accuracy: 0.8779
Epoch 13/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0411 - accuracy: 0.9927
- val_loss: 0.4010 - val_accuracy: 0.8731
Epoch 14/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0332 - accuracy: 0.9950
- val_loss: 0.4325 - val_accuracy: 0.8704
Epoch 15/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0254 - accuracy: 0.9964
- val_loss: 0.4538 - val_accuracy: 0.8712
Epoch 16/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0200 - accuracy: 0.9976
- val_loss: 0.5147 - val_accuracy: 0.8640
Epoch 17/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0147 - accuracy: 0.9987
- val_loss: 0.5623 - val_accuracy: 0.8582
Epoch 18/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0122 - accuracy: 0.9985
- val_loss: 0.5298 - val_accuracy: 0.8715
Epoch 19/20
30/30 [==============================] - 0s 13ms/step - loss: 0.0083 - accuracy: 0.9995
- val_loss: 0.6131 - val_accuracy: 0.8616
Epoch 20/20
30/30 [==============================] - 0s 12ms/step - loss: 0.0072 - accuracy: 0.9993
- val_loss: 0.5968 - val_accuracy: 0.8667
```

In [6]:

```python
# Set the history dict
history_dict = history.history
```

In [7]:

```python
history_dict.keys()
```

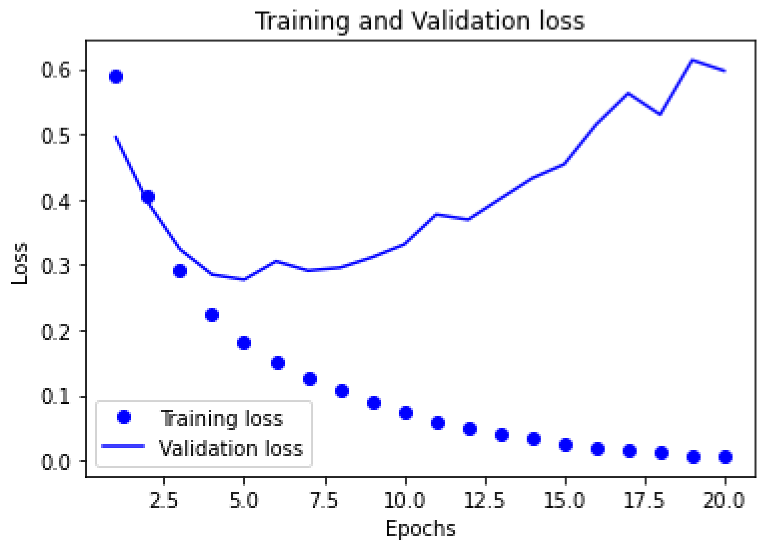
Out[7]:

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

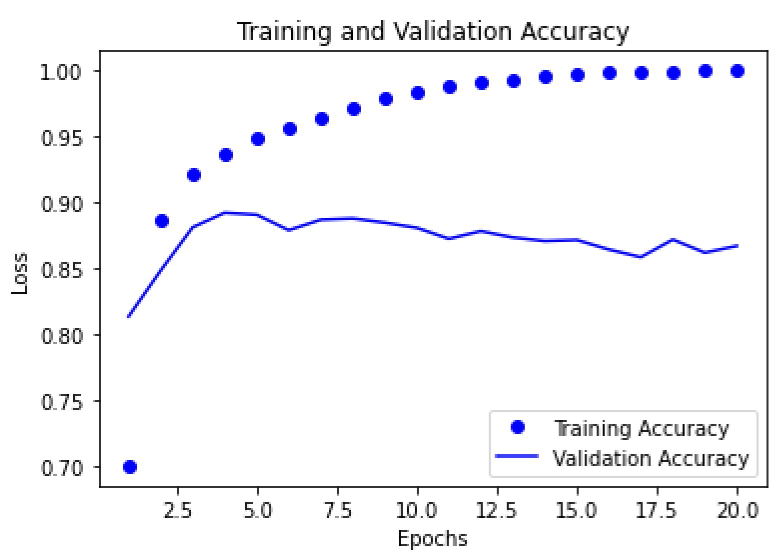
In [10]:

```python
# Plot the training and validation loss.
import matplotlib.pyplot as plt

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()
```



In [13]:
```
# Plot the train data and validation accuracy.
plt.clf()
acc_values = history_dict['accuracy']
val_acc_values = history_dict['val_accuracy']

plt.plot(epochs, acc_values, 'bo', label= 'Training Accuracy')
plt.plot(epochs, val_acc_values, 'b', label = "Validation Accuracy")
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



In [14]:
```
# Retrain 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 9ms/step - loss: 0.5172 - accuracy: 0.7913
Epoch 2/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2995 - accuracy: 0.9045
Epoch 3/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2185 - accuracy: 0.9255
Epoch 4/4
49/49 [==============================] - 0s 9ms/step - loss: 0.1781 - accuracy: 0.9376
782/782 [==============================] - 1s 2ms/step - loss: 0.2889 - accuracy: 0.8842
```

In [15]:

```
results
```

Out[15]:

```
[0.2888578176498413, 0.8841999769210815]
```

In [16]:

```
model.predict(x_test)
```

Out[16]:

```
782/782 [==============================] - 1s 1ms/step
array([[0.23635882],
       [0.99995863],
       [0.966947  ],
       ...,
       [0.12932311],
       [0.13387689],
       [0.73368824]], dtype=float32)
```

Assignment 5.2

In [50]:

```
from keras.datasets import reuters

(train_data, train_labels), (test_data, test_labels) = reuters.load_data(num_words = 100
```

In [51]:

```
len(train_data)
```

Out[51]:

```
8982
```

In [52]:

```
len(test_data)
```

Out[52]:

```
2246
```

In [53]:

```
# Decode the 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
```

Out[53]:

```
'? ? ? 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 pre
tax net should rise to nine to 10 mln dlrs from six mln dlrs in 1986 and rental operatio
n 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'
```

In [54]:

```
# Preparing the data
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

```python
def to_one_hot(labels, dimension = 46):
    results = np.zeros((len(labels), dimension))
    for i, label in enumerate(labels):
        results[i, label] = 1.
    return results

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

In [55]:

```python
from keras.utils.np_utils import to_categorical

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

In [56]:

```python
# Model definition
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 = ['acc'
```

In [57]:

```python
# set aside validation set
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:]
```

In [58]:

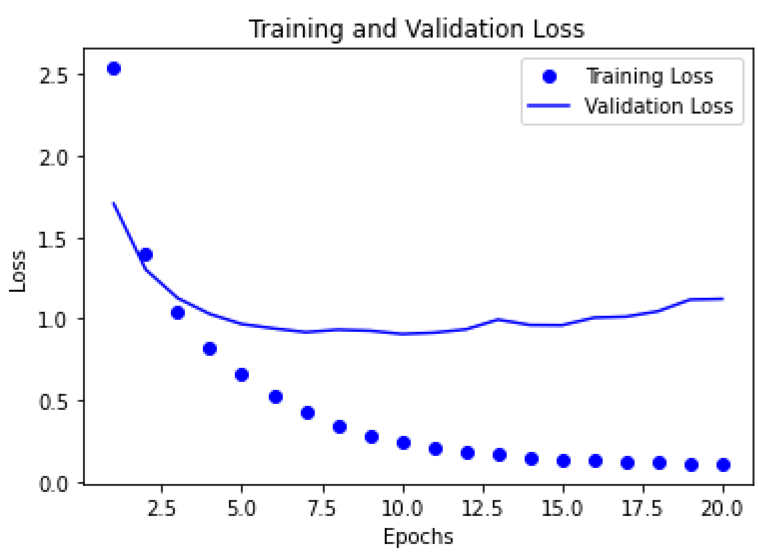
```python
# Train the model
history = model.fit(partial_x_train, partial_y_train, epochs = 20, batch_size = 512, val
```

```
Epoch 1/20
16/16 [==============================] - 1s 38ms/step - loss: 2.5385 - acc: 0.5318 - val
_loss: 1.7057 - val_acc: 0.6330
Epoch 2/20
16/16 [==============================] - 0s 21ms/step - loss: 1.3986 - acc: 0.7065 - val
_loss: 1.3015 - val_acc: 0.7060
Epoch 3/20
16/16 [==============================] - 0s 22ms/step - loss: 1.0482 - acc: 0.7757 - val
_loss: 1.1263 - val_acc: 0.7640
Epoch 4/20
16/16 [==============================] - 0s 22ms/step - loss: 0.8267 - acc: 0.8227 - val
_loss: 1.0292 - val_acc: 0.7850
Epoch 5/20
16/16 [==============================] - 0s 20ms/step - loss: 0.6604 - acc: 0.8598 - val
_loss: 0.9673 - val_acc: 0.7950
Epoch 6/20
16/16 [==============================] - 0s 21ms/step - loss: 0.5301 - acc: 0.8909 - val
_loss: 0.9404 - val_acc: 0.7940
Epoch 7/20
16/16 [==============================] - 0s 21ms/step - loss: 0.4254 - acc: 0.9124 - val
_loss: 0.9175 - val_acc: 0.8070
Epoch 8/20
16/16 [==============================] - 0s 23ms/step - loss: 0.3462 - acc: 0.9273 - val
_loss: 0.9327 - val_acc: 0.8080
Epoch 9/20
16/16 [==============================] - 0s 22ms/step - loss: 0.2861 - acc: 0.9390 - val
_loss: 0.9264 - val_acc: 0.8170
Epoch 10/20
16/16 [==============================] - 0s 21ms/step - loss: 0.2443 - acc: 0.9454 - val
_loss: 0.9063 - val_acc: 0.8170
Epoch 11/20
16/16 [==============================] - 0s 21ms/step - loss: 0.2087 - acc: 0.9494 - val
```

```
_loss: 0.9143 - val_acc: 0.8170
Epoch 12/20
16/16 [==============================] - 0s 21ms/step - loss: 0.1871 - acc: 0.9523 - val
_loss: 0.9349 - val_acc: 0.8110
Epoch 13/20
16/16 [==============================] - 0s 21ms/step - loss: 0.1647 - acc: 0.9534 - val
_loss: 0.9947 - val_acc: 0.8060
Epoch 14/20
16/16 [==============================] - 0s 21ms/step - loss: 0.1498 - acc: 0.9543 - val
_loss: 0.9618 - val_acc: 0.8120
Epoch 15/20
16/16 [==============================] - 0s 22ms/step - loss: 0.1383 - acc: 0.9562 - val
_loss: 0.9603 - val_acc: 0.8110
Epoch 16/20
16/16 [==============================] - 0s 22ms/step - loss: 0.1300 - acc: 0.9553 - val
_loss: 1.0065 - val_acc: 0.8030
Epoch 17/20
16/16 [==============================] - 0s 21ms/step - loss: 0.1257 - acc: 0.9573 - val
_loss: 1.0130 - val_acc: 0.8050
Epoch 18/20
16/16 [==============================] - 0s 24ms/step - loss: 0.1199 - acc: 0.9594 - val
_loss: 1.0458 - val_acc: 0.7990
Epoch 19/20
16/16 [==============================] - 0s 22ms/step - loss: 0.1150 - acc: 0.9588 - val
_loss: 1.1173 - val_acc: 0.7930
Epoch 20/20
16/16 [==============================] - 0s 22ms/step - loss: 0.1101 - acc: 0.9587 - val
_loss: 1.1218 - val_acc: 0.7890
```

In [59]:

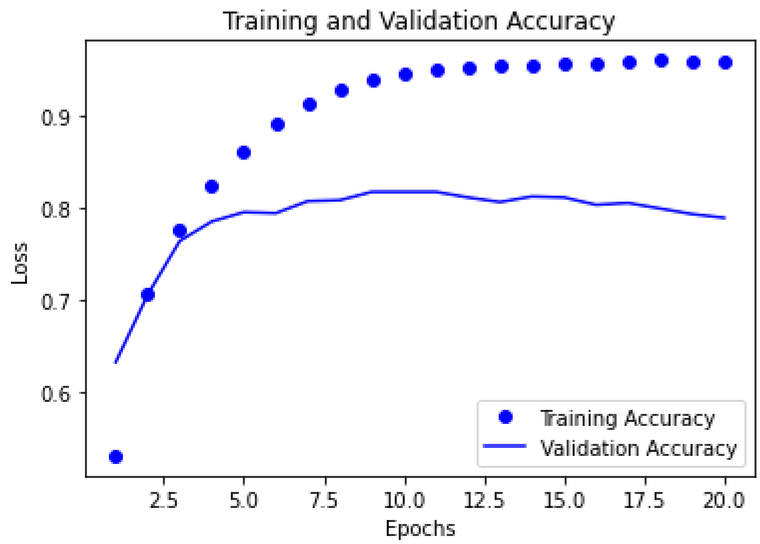
```
# Plotting the training and validation loss
loss = history.history['loss']
val_loss = history.history['val_loss']

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()
```



In [60]:

```
# plotting the training and validation accuracy
plt.clf()
```

```
acc = history.history['acc']
val_acc = history.history['val_acc']

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('Loss')
plt.legend()

plt.show()
```



In [61]:

```
# Train a new model from scratch
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 = ['acc'

model.fit(partial_x_train, partial_y_train, epochs = 9, batch_size = 512, validation_dat
results = model.evaluate(x_test, one_hot_test_labels)
```

```
Epoch 1/9
16/16 [==============================] - 1s 35ms/step - loss: 2.8303 - acc: 0.4891 - val
_loss: 1.8465 - val_acc: 0.6390
Epoch 2/9
16/16 [==============================] - 0s 21ms/step - loss: 1.4929 - acc: 0.6937 - val
_loss: 1.3620 - val_acc: 0.6840
Epoch 3/9
16/16 [==============================] - 0s 21ms/step - loss: 1.1015 - acc: 0.7661 - val
_loss: 1.1682 - val_acc: 0.7430
Epoch 4/9
16/16 [==============================] - 0s 21ms/step - loss: 0.8769 - acc: 0.8168 - val
_loss: 1.0641 - val_acc: 0.7730
Epoch 5/9
16/16 [==============================] - 0s 21ms/step - loss: 0.7030 - acc: 0.8507 - val
_loss: 0.9928 - val_acc: 0.8010
Epoch 6/9
16/16 [==============================] - 0s 21ms/step - loss: 0.5689 - acc: 0.8777 - val
_loss: 0.9680 - val_acc: 0.7950
Epoch 7/9
16/16 [==============================] - 0s 21ms/step - loss: 0.4552 - acc: 0.9037 - val
_loss: 0.9289 - val_acc: 0.8070
Epoch 8/9
16/16 [==============================] - 0s 21ms/step - loss: 0.3721 - acc: 0.9212 - val
_loss: 0.8983 - val_acc: 0.8140
```

```
Epoch 9/9
16/16 [==============================] - 0s 20ms/step - loss: 0.3084 - acc: 0.9350 - val
_loss: 0.8900 - val_acc: 0.8260
71/71 [==============================] - 0s 2ms/step - loss: 0.9607 - acc: 0.7854
```

In [62]:
```python
results
```

Out[62]:
```
[0.9606949687004089, 0.7853962779045105]
```

In [63]:
```python
# test against random
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)
```

Out[63]:
```
0.1856634016028495
```

In [64]:
```python
# Generating predictions
predictions = model.predict(x_test)
```

```
71/71 [==============================] - 0s 2ms/step
```

In [65]:
```python
np.sum(predictions[0])
```

Out[65]:
```
0.99999994
```

In [66]:
```python
np.argmax(predictions[0])
```

Out[66]:
```
3
```

In [67]:
```python
# A model with an information bottleneck
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 = ['accu

model.fit(partial_x_train, partial_y_train, epochs = 20, batch_size = 128, validation_da
```

```
Epoch 1/20
63/63 [==============================] - 2s 13ms/step - loss: 2.5799 - accuracy: 0.4826
- val_loss: 1.8618 - val_accuracy: 0.5750
Epoch 2/20
63/63 [==============================] - 1s 9ms/step - loss: 1.5852 - accuracy: 0.6143 -
val_loss: 1.5305 - val_accuracy: 0.6150
Epoch 3/20
63/63 [==============================] - 1s 9ms/step - loss: 1.3116 - accuracy: 0.6460 -
val_loss: 1.4312 - val_accuracy: 0.6420
Epoch 4/20
63/63 [==============================] - 1s 10ms/step - loss: 1.1422 - accuracy: 0.6958
- val_loss: 1.3817 - val_accuracy: 0.6740
Epoch 5/20
63/63 [==============================] - 1s 9ms/step - loss: 1.0150 - accuracy: 0.7397 -
val_loss: 1.3496 - val_accuracy: 0.6920
Epoch 6/20
63/63 [==============================] - 1s 9ms/step - loss: 0.9157 - accuracy: 0.7588 -
val_loss: 1.3517 - val_accuracy: 0.7070
Epoch 7/20
63/63 [==============================] - 1s 10ms/step - loss: 0.8380 - accuracy: 0.7737
- val_loss: 1.3629 - val_accuracy: 0.7010
Epoch 8/20
```

```
63/63 [==============================] - 1s 9ms/step - loss: 0.7722 - accuracy: 0.7883 -
val_loss: 1.3999 - val_accuracy: 0.7090
Epoch 9/20
63/63 [==============================] - 1s 9ms/step - loss: 0.7120 - accuracy: 0.8036 -
val_loss: 1.4359 - val_accuracy: 0.7040
Epoch 10/20
63/63 [==============================] - 1s 10ms/step - loss: 0.6632 - accuracy: 0.8203
- val_loss: 1.4672 - val_accuracy: 0.7200
Epoch 11/20
63/63 [==============================] - 1s 9ms/step - loss: 0.6176 - accuracy: 0.8390 -
val_loss: 1.4942 - val_accuracy: 0.7180
Epoch 12/20
63/63 [==============================] - 1s 9ms/step - loss: 0.5778 - accuracy: 0.8462 -
val_loss: 1.5400 - val_accuracy: 0.7190
Epoch 13/20
63/63 [==============================] - 1s 9ms/step - loss: 0.5455 - accuracy: 0.8562 -
val_loss: 1.6165 - val_accuracy: 0.7140
Epoch 14/20
63/63 [==============================] - 1s 9ms/step - loss: 0.5175 - accuracy: 0.8599 -
val_loss: 1.6383 - val_accuracy: 0.7200
Epoch 15/20
63/63 [==============================] - 1s 9ms/step - loss: 0.4934 - accuracy: 0.8627 -
val_loss: 1.7053 - val_accuracy: 0.7280
Epoch 16/20
63/63 [==============================] - 1s 9ms/step - loss: 0.4718 - accuracy: 0.8647 -
val_loss: 1.7340 - val_accuracy: 0.7210
Epoch 17/20
63/63 [==============================] - 1s 9ms/step - loss: 0.4533 - accuracy: 0.8670 -
val_loss: 1.8751 - val_accuracy: 0.7200
Epoch 18/20
63/63 [==============================] - 1s 10ms/step - loss: 0.4359 - accuracy: 0.8713
- val_loss: 1.8528 - val_accuracy: 0.7220
Epoch 19/20
63/63 [==============================] - 1s 9ms/step - loss: 0.4223 - accuracy: 0.8758 -
val_loss: 1.9876 - val_accuracy: 0.7180
Epoch 20/20
63/63 [==============================] - 1s 10ms/step - loss: 0.4102 - accuracy: 0.8797
- val_loss: 1.9674 - val_accuracy: 0.7160
```

Out[67]:

```
<keras.callbacks.History at 0x1819ab13760>
```

Assignment 5.3

In [68]:

```python
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
57026/57026 [==============================] - 0s 1us/step
```

In [69]:

```python
train_data.shape
```

Out[69]:

```
(404, 13)
```

In [70]:

```python
test_data.shape
```

Out[70]:

```
(102, 13)
```

In [71]:

```python
train_targets
```

Out[71]:

```
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])
```

In [72]:
```python
# Prepare the 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
```

In [73]:
```python
# model definition
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
```

In [74]:
```python
# K-fold validation
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
    partial_train_targets = np.concatenate([train_targets[:i * num_val_samples], train_t

    model = build_model()
    model.fit(partial_train_data, partial_train_targets, epochs = num_epochs, batch_size
    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
```

In [75]:

```
all_scores
```

Out[75]:

```
[1.9039514064788818, 2.5413460731506348, 2.7545762062072754, 2.315114736557007]
```

In [76]:

```
np.mean(all_scores)
```

Out[76]:

```
2.3787471055984497
```

In [78]:

```
# Saving the validation logs at 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
    partial_train_targets = np.concatenate([train_targets[:i * num_val_samples], train_t

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

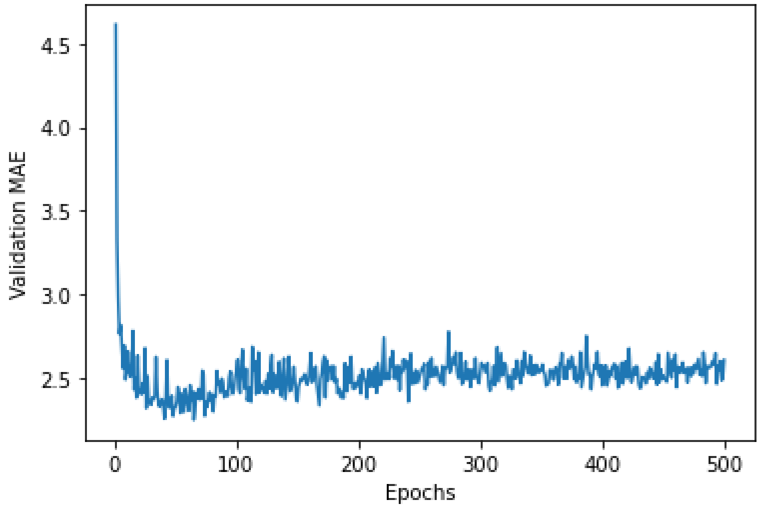
```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3
```

In [79]:

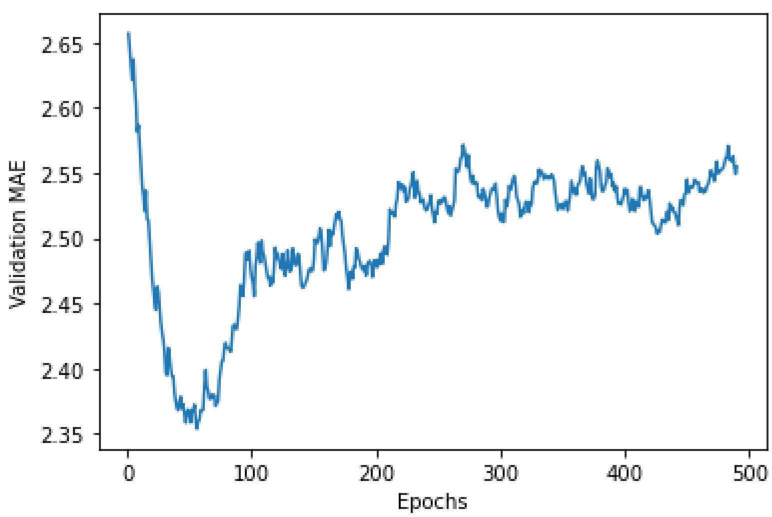
```
# Building a history of successive k-fold validation scores
average_mae_history = [np.mean([x[i] for x in all_mae_histories]) for i in range(num_epo
```

In [80]:

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



In [81]:
```
# Plotting validation scores, excluding first 10 data points.
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()
```



In [83]:
```
# Training the final 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 2ms/step - loss: 17.0257 - mae: 2.7760
```

In [84]:
```
test_mae_score
```

Out[84]:
```
2.775958299636841
```