Assignment 5.1

In [1]:
```
# lOad necessary libraries
from keras.datasets import imdb
import numpy as np

import matplotlib.pyplot as plt
```

In [2]:
```
#Loading the IMDB Dataset
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=10000)
```

In [3]:
```
print(train_data[0],'\n\n----------', train_labels[0],'\n\n----------',test_data[0],'\n\
```

```
[1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941, 4, 173, 36, 256, 5, 2
5, 100, 43, 838, 112, 50, 670, 2, 9, 35, 480, 284, 5, 150, 4, 172, 112, 167, 2, 336, 38
5, 39, 4, 172, 4536, 1111, 17, 546, 38, 13, 447, 4, 192, 50, 16, 6, 147, 2025, 19, 14, 2
2, 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, 376
6, 5, 723, 36, 71, 43, 530, 476, 26, 400, 317, 46, 7, 4, 2, 1029, 13, 104, 88, 4, 381, 1
5, 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, 1
6, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32]

---------- 1

---------- [1, 591, 202, 14, 31, 6, 717, 10, 10, 2, 2, 5, 4, 360, 7, 4, 177, 5760, 394,
354, 4, 123, 9, 1035, 1035, 1035, 10, 10, 13, 92, 124, 89, 488, 7944, 100, 28, 1668, 14,
31, 23, 27, 7479, 29, 220, 468, 8, 124, 14, 286, 170, 8, 157, 46, 5, 27, 239, 16, 179,
2, 38, 32, 25, 7944, 451, 202, 14, 6, 717]

---------- 0
```

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

Out[4]:
```
1
```

In [5]:
```
# Test to see a review
word_index = imdb.get_word_index()
reverse_word_index = dict([(value, key) for (key, value) in word_index.items()]) # Rever
decoded_review = ' '.join([reverse_word_index.get(i - 3, '?') for i in train_data[0]])
```

In [6]:
```
decoded_review
```

Out[6]:
```
"? this film was just brilliant casting location scenery story direction everyone's real
ly suited the part they played and you could just imagine being there robert ? is an ama
zing actor and now the same being director ? father came from the same scottish island a
s myself so i loved the fact there was a real connection with this film the witty remark
s 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 fi
shing was amazing really cried at the end it was so sad and you know what they say if yo
u 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 l
eft out of the ? list i think because the stars that play them all grown up are such a b
ig profile for the whole film but these children are amazing and should be praised for w
hat 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"
```

In [7]:
```
# Encoding the integer sequences into a binary matrix
```

```
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)
```

In [8]:
```
# sample train data
x_train[0]
```

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

In [9]:
```
#Vectorize the label
y_train = np.asarray(train_labels).astype('float32')
y_test = np.asarray(test_labels).astype('float32')
```

In [10]:
```
# The model definition
#The Keras implementation
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'))
```

In [11]:
```
# Compiling the model
model.compile(optimizer='rmsprop',
loss='binary_crossentropy',
metrics=['accuracy'])
```

In [12]:
```
# Configuring the optimizer
from keras import optimizers
model.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),
loss='binary_crossentropy',
metrics=['accuracy'])
from keras import losses
from keras import metrics
model.compile(optimizer=optimizers.RMSprop(learning_rate=0.001),
loss=losses.binary_crossentropy,
metrics=[metrics.binary_accuracy])
```

In [13]:
```
# Setting aside a validation set
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

In [14]:
```
# Training the model
#model.compile(optimizer='rmsprop',loss='binary_crossentropy',metrics=['accuracy'])
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 23ms/step - loss: 0.5231 - binary_accuracy:
0.7790 - val_loss: 0.4368 - val_binary_accuracy: 0.8140
Epoch 2/20
30/30 [==============================] - 0s 11ms/step - loss: 0.3163 - binary_accuracy:
```

```
0.9035 - val_loss: 0.3159 - val_binary_accuracy: 0.8819
Epoch 3/20
30/30 [==============================] - 0s 10ms/step - loss: 0.2298 - binary_accuracy:
0.9284 - val_loss: 0.2958 - val_binary_accuracy: 0.8833
Epoch 4/20
30/30 [==============================] - 0s 11ms/step - loss: 0.1813 - binary_accuracy:
0.9427 - val_loss: 0.2742 - val_binary_accuracy: 0.8907
Epoch 5/20
30/30 [==============================] - 0s 11ms/step - loss: 0.1484 - binary_accuracy:
0.9539 - val_loss: 0.2904 - val_binary_accuracy: 0.8852
Epoch 6/20
30/30 [==============================] - 0s 11ms/step - loss: 0.1205 - binary_accuracy:
0.9631 - val_loss: 0.3200 - val_binary_accuracy: 0.8749
Epoch 7/20
30/30 [==============================] - 0s 11ms/step - loss: 0.1033 - binary_accuracy:
0.9690 - val_loss: 0.3301 - val_binary_accuracy: 0.8794
Epoch 8/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0839 - binary_accuracy:
0.9757 - val_loss: 0.3245 - val_binary_accuracy: 0.8834
Epoch 9/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0693 - binary_accuracy:
0.9813 - val_loss: 0.3450 - val_binary_accuracy: 0.8811
Epoch 10/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0570 - binary_accuracy:
0.9852 - val_loss: 0.4337 - val_binary_accuracy: 0.8640
Epoch 11/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0480 - binary_accuracy:
0.9883 - val_loss: 0.3946 - val_binary_accuracy: 0.8798
Epoch 12/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0376 - binary_accuracy:
0.9925 - val_loss: 0.4234 - val_binary_accuracy: 0.8775
Epoch 13/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0290 - binary_accuracy:
0.9944 - val_loss: 0.5560 - val_binary_accuracy: 0.8526
Epoch 14/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0264 - binary_accuracy:
0.9945 - val_loss: 0.4805 - val_binary_accuracy: 0.8743
Epoch 15/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0169 - binary_accuracy:
0.9979 - val_loss: 0.5126 - val_binary_accuracy: 0.8695
Epoch 16/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0145 - binary_accuracy:
0.9982 - val_loss: 0.5403 - val_binary_accuracy: 0.8710
Epoch 17/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0112 - binary_accuracy:
0.9987 - val_loss: 0.5763 - val_binary_accuracy: 0.8692
Epoch 18/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0101 - binary_accuracy:
0.9986 - val_loss: 0.6074 - val_binary_accuracy: 0.8677
Epoch 19/20
30/30 [==============================] - 0s 11ms/step - loss: 0.0049 - binary_accuracy:
0.9999 - val_loss: 0.6687 - val_binary_accuracy: 0.8621
Epoch 20/20
30/30 [==============================] - 0s 10ms/step - loss: 0.0069 - binary_accuracy:
0.9992 - val_loss: 0.6673 - val_binary_accuracy: 0.8681
```

In [15]:

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

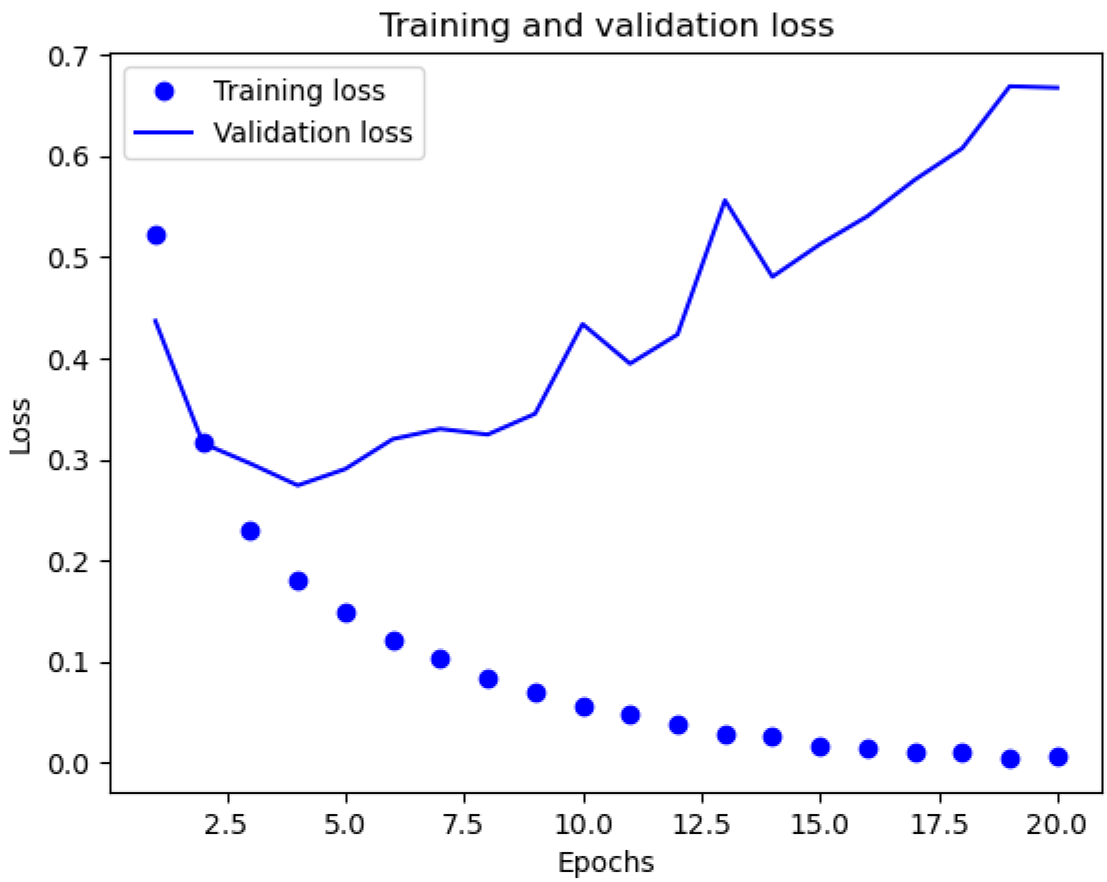
Out[15]:

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

In [16]:

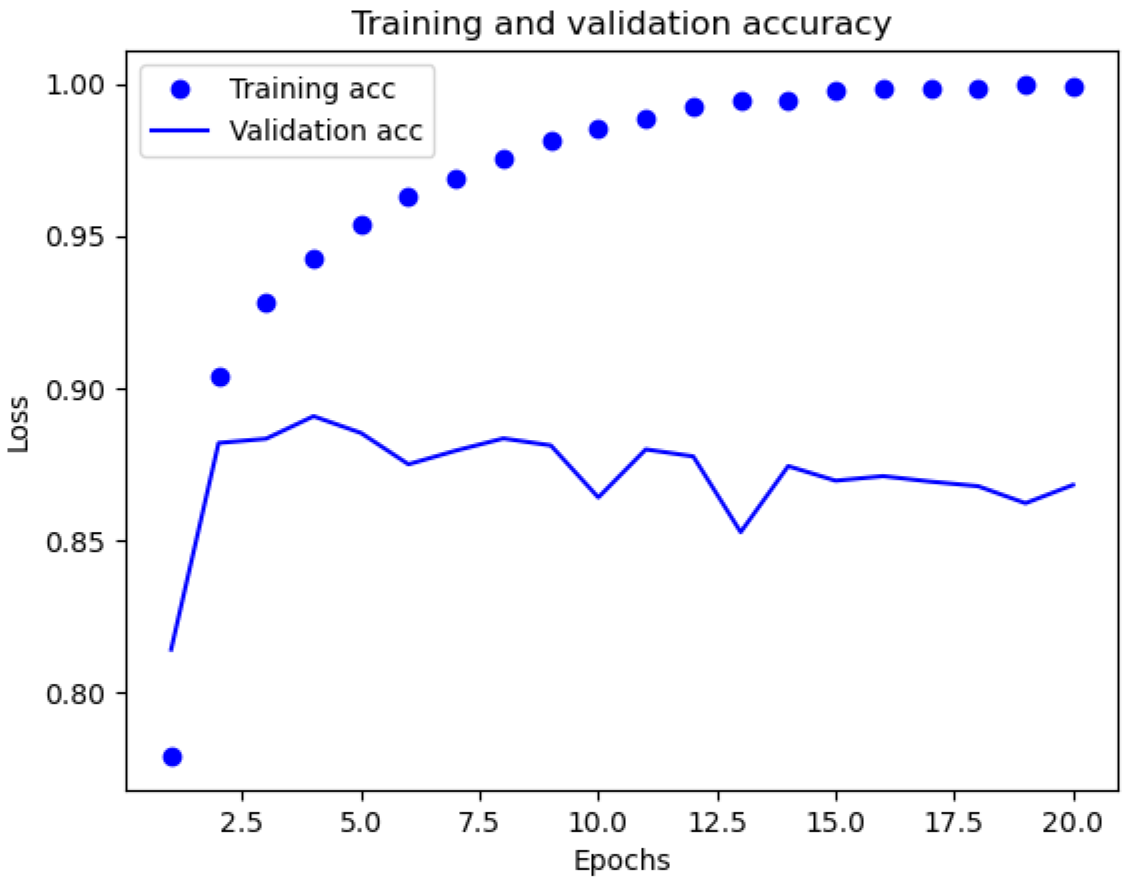
```python
# Plotting training and validation loss
import matplotlib.pyplot as plt
acc = history.history['binary_accuracy']
val_acc = history.history['val_binary_accuracy']
```

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(acc) + 1)
# "bo" for the "blue dot"
plt.plot(epochs, loss, 'bo', label='Training loss')
# b for the "solid blue line"
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 [17]:

```
#  Plotting training and validation accuracy
plt.clf() # clear figure
acc = history.history['binary_accuracy']
val_acc = history.history['val_binary_accuracy']
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [18]:
```
#  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'])

# Fit Model
model.fit(x_train, y_train, epochs=4, batch_size=512)
# Evaluate the model
results = model.evaluate(x_test, y_test)
```

```
Epoch 1/4
49/49 [==============================] - 1s 7ms/step - loss: 0.4736 - accuracy: 0.8073
Epoch 2/4
49/49 [==============================] - 0s 7ms/step - loss: 0.2783 - accuracy: 0.9007
Epoch 3/4
49/49 [==============================] - 0s 7ms/step - loss: 0.2143 - accuracy: 0.9228
Epoch 4/4
49/49 [==============================] - 0s 7ms/step - loss: 0.1842 - accuracy: 0.9336
782/782 [==============================] - 1s 1ms/step - loss: 0.2840 - accuracy: 0.8870
```

In [19]:
```
results = model.evaluate(x_test,y_test)
```

```
782/782 [==============================] - 1s 2ms/step - loss: 0.2840 - accuracy: 0.8870
```

Accuray around 88.6%

In [20]:
```
#  Using a trained network to generate predictions on new data
model.predict(x_test)
```

```
782/782 [==============================] - 1s 1ms/step
```

Out[20]:
```
array([[0.201202  ],
```

```
       [0.9996977 ],
       [0.7996492 ],
       ...,
       [0.14773846],
       [0.08682977],
       [0.6919805 ]], dtype=float32)
```

Assignment 5.2

In [21]:
```
 # Loading the Reuters dataset
from keras.datasets import reuters

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

In [22]:
```
# Decoding newswires back to text (for testing)
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]])
```

In [23]:
```
decoded_newswire
```

Out[23]:
```
'? ? ? 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 [24]:
```
# Encoding 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

#Vectorizing training and test data
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

In [25]:
```
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

#Vectorizing training and test data
one_hot_train_labels = to_one_hot(train_labels)
one_hot_test_labels = to_one_hot(test_labels)
```

In [26]:
```
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 [27]:
```
# Model definition
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'))
```

In [28]:
```
# Compiling the model
model.compile(optimizer='rmsprop',
loss='categorical_crossentropy',
metrics=['accuracy'])
```

In [29]:
```
#  Setting aside a 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 [30]:
```
# Training 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
16/16 [==============================] - 1s 30ms/step - loss: 2.7009 - accuracy: 0.5088
- val_loss: 1.7623 - val_accuracy: 0.6290
Epoch 2/20
16/16 [==============================] - 0s 18ms/step - loss: 1.4789 - accuracy: 0.6880
- val_loss: 1.3671 - val_accuracy: 0.7040
Epoch 3/20
16/16 [==============================] - 0s 18ms/step - loss: 1.1348 - accuracy: 0.7583
- val_loss: 1.1865 - val_accuracy: 0.7340
Epoch 4/20
16/16 [==============================] - 0s 19ms/step - loss: 0.9316 - accuracy: 0.8037
- val_loss: 1.0800 - val_accuracy: 0.7720
Epoch 5/20
16/16 [==============================] - 0s 18ms/step - loss: 0.7821 - accuracy: 0.8314
- val_loss: 1.0315 - val_accuracy: 0.7730
Epoch 6/20
16/16 [==============================] - 0s 18ms/step - loss: 0.6572 - accuracy: 0.8543
- val_loss: 0.9645 - val_accuracy: 0.8020
Epoch 7/20
16/16 [==============================] - 0s 18ms/step - loss: 0.5506 - accuracy: 0.8809
- val_loss: 0.9346 - val_accuracy: 0.8030
Epoch 8/20
16/16 [==============================] - 0s 19ms/step - loss: 0.4682 - accuracy: 0.8991
- val_loss: 0.9209 - val_accuracy: 0.8010
Epoch 9/20
16/16 [==============================] - 0s 18ms/step - loss: 0.3966 - accuracy: 0.9156
- val_loss: 0.8945 - val_accuracy: 0.8120
Epoch 10/20
16/16 [==============================] - 0s 17ms/step - loss: 0.3373 - accuracy: 0.9253
- val_loss: 0.8815 - val_accuracy: 0.8230
Epoch 11/20
16/16 [==============================] - 0s 17ms/step - loss: 0.2984 - accuracy: 0.9337
- val_loss: 0.8874 - val_accuracy: 0.8160
Epoch 12/20
16/16 [==============================] - 0s 20ms/step - loss: 0.2559 - accuracy: 0.9431
- val_loss: 0.9073 - val_accuracy: 0.8120
Epoch 13/20
16/16 [==============================] - 0s 17ms/step - loss: 0.2293 - accuracy: 0.9469
- val_loss: 0.8775 - val_accuracy: 0.8160
Epoch 14/20
16/16 [==============================] - 0s 18ms/step - loss: 0.2051 - accuracy: 0.9496
- val_loss: 0.8903 - val_accuracy: 0.8220
Epoch 15/20
16/16 [==============================] - 0s 19ms/step - loss: 0.1883 - accuracy: 0.9520
- val_loss: 0.9055 - val_accuracy: 0.8210
Epoch 16/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1692 - accuracy: 0.9543
```

```
- val_loss: 0.9239 - val_accuracy: 0.8090
Epoch 17/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1601 - accuracy: 0.9551
- val_loss: 0.9498 - val_accuracy: 0.8080
Epoch 18/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1539 - accuracy: 0.9529
- val_loss: 0.9751 - val_accuracy: 0.8020
Epoch 19/20
16/16 [==============================] - 0s 18ms/step - loss: 0.1406 - accuracy: 0.9577
- val_loss: 0.9663 - val_accuracy: 0.8190
Epoch 20/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1396 - accuracy: 0.9568
- val_loss: 0.9560 - val_accuracy: 0.8090
```

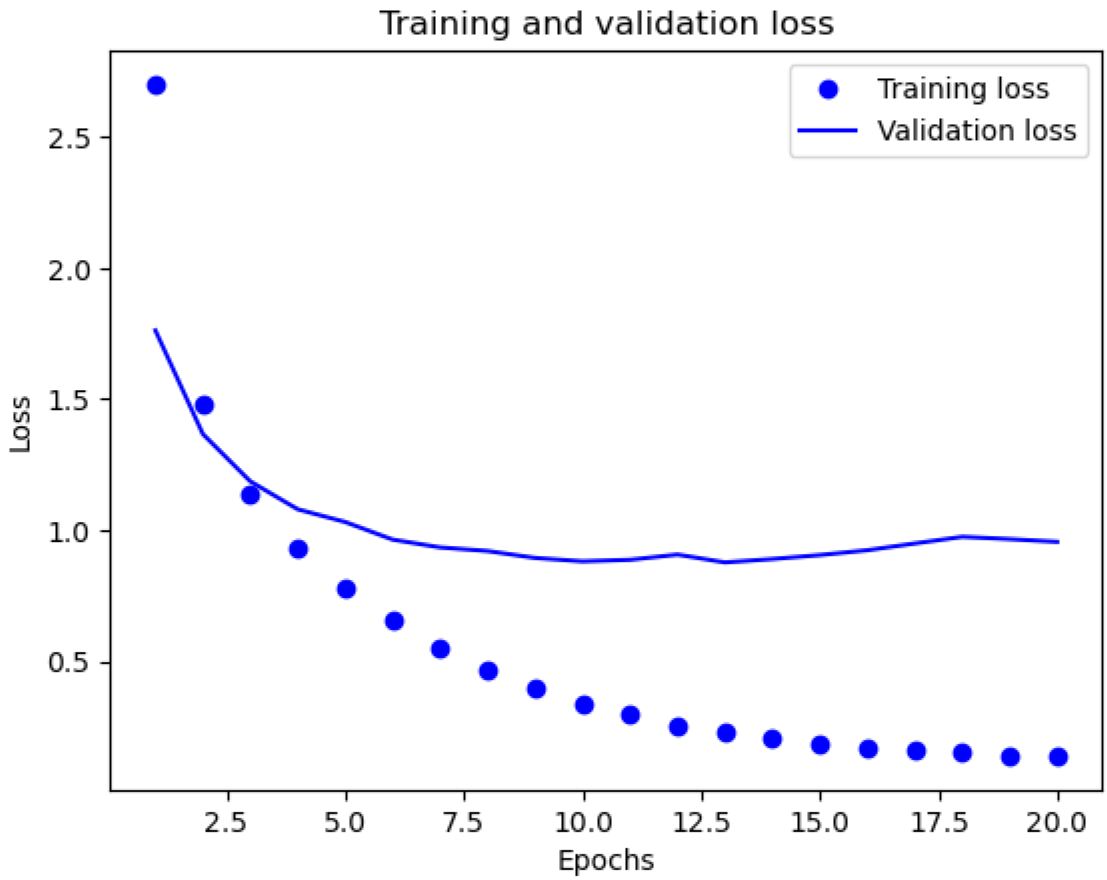
In [31]:
```
history.history
```

Out[31]:
```
{'loss': [2.7009339332580566,
  1.4788738489151,
  1.1347589492797852,
  0.9315976500511169,
  0.782071135864258,
  0.6572456955909729,
  0.5506003499031067,
  0.4682437479496002,
  0.39662355184555054,
  0.3373497724533081,
  0.2983768582344055,
  0.2558958828449249,
  0.2292533814907074,
  0.20509150624275208,
  0.18831995129585266,
  0.16919584572315216,
  0.16012796759605408,
  0.1539221554994583,
  0.14059589803218842,
  0.13959212601184845],
 'accuracy': [0.5087697505950928,
  0.6880481243133545,
  0.7583312392234802,
  0.8036832809448242,
  0.8313705921173096,
  0.8542971611022949,
  0.8808569312095642,
  0.8991481065750122,
  0.9155600070953369,
  0.9253320097923279,
  0.933725893497467,
  0.9431220293045044,
  0.9468804597854614,
  0.949636697769165,
  0.9520170092582703,
  0.9542720913887024,
  0.9551491141319275,
  0.9528940320014954,
  0.9576547145843506,
  0.9567777514457703],
 'val_loss': [1.7622895240783691,
  1.3671013116836548,
  1.1865359544754028,
  1.0800073146820068,
  1.0315494537353516,
  0.9644616842269897,
  0.934642672538757 3,
  0.9209083318710327,
  0.894510209560394 3,
  0.8815388083457947,
```

```
 0.8874248266220093,
 0.9073402285575867,
 0.8774551749229431,
 0.8903384804725647,
 0.905495285987854,
 0.9238684773445129,
 0.9498202800750732,
 0.9751138687133789,
 0.9662750363349915,
 0.9559662938117981],
'val_accuracy': [0.6290000081062317,
 0.7039999961853027,
 0.734000027179718,
 0.7720000147819519,
 0.7730000019073486,
 0.8019999861717224,
 0.8029999732971191,
 0.8009999990463257,
 0.8119999766349792,
 0.8230000138282776,
 0.8159999847412109,
 0.8119999766349792,
 0.8159999847412109,
 0.8220000267028809,
 0.8209999799728394,
 0.8090000152587891,
 0.8080000281333923,
 0.8019999861717224,
 0.8190000057220459,
 0.8090000152587891]}
```

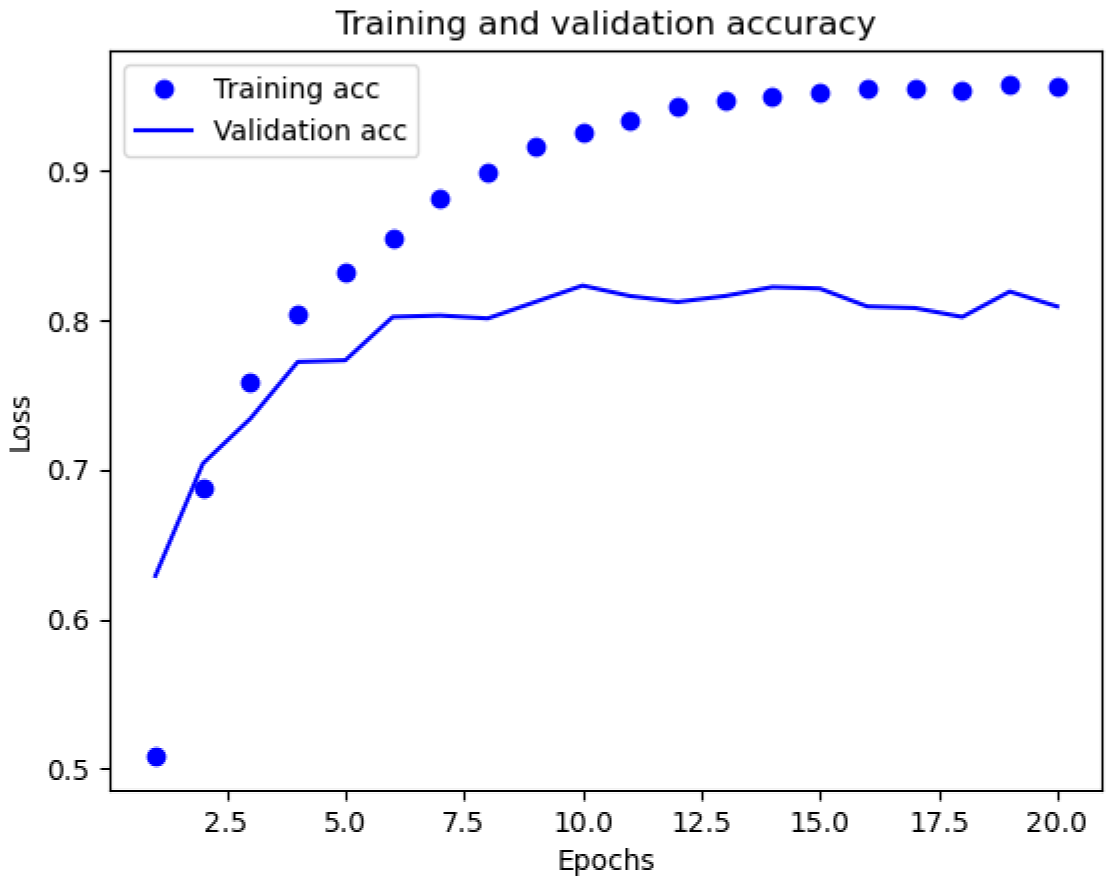
In [32]:

```
#  Plotting the training and validation loss

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()
```



In [33]:

```
# Plotting the training and validation accuracy

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



In [34]:
```
# Retraining a 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=['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 [==============================] - 1s 25ms/step - loss: 2.8159 - accuracy: 0.5040
- val_loss: 1.8757 - val_accuracy: 0.6360
Epoch 2/9
16/16 [==============================] - 0s 18ms/step - loss: 1.5573 - accuracy: 0.6891
- val_loss: 1.3694 - val_accuracy: 0.7020
Epoch 3/9
16/16 [==============================] - 0s 17ms/step - loss: 1.1739 - accuracy: 0.7511
- val_loss: 1.1751 - val_accuracy: 0.7440
Epoch 4/9
16/16 [==============================] - 0s 16ms/step - loss: 0.9544 - accuracy: 0.7990
- val_loss: 1.0680 - val_accuracy: 0.7720
Epoch 5/9
16/16 [==============================] - 0s 17ms/step - loss: 0.7945 - accuracy: 0.8358
- val_loss: 1.0015 - val_accuracy: 0.7770
Epoch 6/9
16/16 [==============================] - 0s 19ms/step - loss: 0.6646 - accuracy: 0.8601
- val_loss: 0.9728 - val_accuracy: 0.7970
Epoch 7/9
16/16 [==============================] - 0s 17ms/step - loss: 0.5595 - accuracy: 0.8800
```

```
- val_loss: 0.9014 - val_accuracy: 0.8110
Epoch 8/9
16/16 [==============================] - 0s 17ms/step - loss: 0.4675 - accuracy: 0.8971
- val_loss: 0.9093 - val_accuracy: 0.8040
Epoch 9/9
16/16 [==============================] - 0s 17ms/step - loss: 0.4016 - accuracy: 0.9126
- val_loss: 0.9143 - val_accuracy: 0.8020
71/71 [==============================] - 0s 2ms/step - loss: 0.9991 - accuracy: 0.7649
```

In [35]:
```
results
```

Out[35]:
```
[0.9991289973258972, 0.764915406703949]
```

Accuracy of around 78%

In [36]:
```
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)
```

Out[36]:
```
0.18165627782724844
```

In [37]:
```
#  Generating predictions for new data
predictions = model.predict(x_test)
```

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

In [38]:
```
predictions[0].shape, np.sum(predictions[0]),  np.argmax(predictions[0])
```

Out[38]:
```
((46,), 1.0000001, 4)
```

In [39]:
```
# Different way of handling lables and loss
y_train = np.array(train_labels)
y_test = np.array(test_labels)
```

In [40]:
```
model.compile(optimizer='rmsprop',
loss='sparse_categorical_crossentropy', #categorical_crossentropy, expects the labels to
metrics=['acc'])
```

In [41]:
```
# 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=['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: 3.4378 - accuracy: 0.1531
- val_loss: 3.1022 - val_accuracy: 0.2330
Epoch 2/20
63/63 [==============================] - 1s 9ms/step - loss: 2.8414 - accuracy: 0.2303 -
val_loss: 2.6608 - val_accuracy: 0.2480
Epoch 3/20
63/63 [==============================] - 1s 8ms/step - loss: 2.3632 - accuracy: 0.2623 -
val_loss: 2.0956 - val_accuracy: 0.3100
```

```
Epoch 4/20
63/63 [==============================] - 1s 8ms/step - loss: 1.6963 - accuracy: 0.5733 -
val_loss: 1.5737 - val_accuracy: 0.6000
Epoch 5/20
63/63 [==============================] - 1s 8ms/step - loss: 1.3920 - accuracy: 0.6320 -
val_loss: 1.4764 - val_accuracy: 0.6190
Epoch 6/20
63/63 [==============================] - 1s 9ms/step - loss: 1.2708 - accuracy: 0.6600 -
val_loss: 1.4493 - val_accuracy: 0.6290
Epoch 7/20
63/63 [==============================] - 1s 8ms/step - loss: 1.1873 - accuracy: 0.6907 -
val_loss: 1.4511 - val_accuracy: 0.6460
Epoch 8/20
63/63 [==============================] - 1s 8ms/step - loss: 1.1192 - accuracy: 0.7105 -
val_loss: 1.4196 - val_accuracy: 0.6740
Epoch 9/20
63/63 [==============================] - 0s 8ms/step - loss: 1.0601 - accuracy: 0.7404 -
val_loss: 1.4572 - val_accuracy: 0.6810
Epoch 10/20
63/63 [==============================] - 1s 8ms/step - loss: 1.0098 - accuracy: 0.7507 -
val_loss: 1.4422 - val_accuracy: 0.6770
Epoch 11/20
63/63 [==============================] - 0s 8ms/step - loss: 0.9614 - accuracy: 0.7580 -
val_loss: 1.4539 - val_accuracy: 0.6720
Epoch 12/20
63/63 [==============================] - 1s 8ms/step - loss: 0.9216 - accuracy: 0.7620 -
val_loss: 1.4454 - val_accuracy: 0.6840
Epoch 13/20
63/63 [==============================] - 1s 8ms/step - loss: 0.8837 - accuracy: 0.7706 -
val_loss: 1.5043 - val_accuracy: 0.6870
Epoch 14/20
63/63 [==============================] - 1s 8ms/step - loss: 0.8508 - accuracy: 0.7816 -
val_loss: 1.4821 - val_accuracy: 0.6830
Epoch 15/20
63/63 [==============================] - 1s 8ms/step - loss: 0.8216 - accuracy: 0.7880 -
val_loss: 1.5166 - val_accuracy: 0.6830
Epoch 16/20
63/63 [==============================] - 1s 9ms/step - loss: 0.7935 - accuracy: 0.7940 -
val_loss: 1.5910 - val_accuracy: 0.6760
Epoch 17/20
63/63 [==============================] - 1s 9ms/step - loss: 0.7706 - accuracy: 0.7964 -
val_loss: 1.6410 - val_accuracy: 0.6690
Epoch 18/20
63/63 [==============================] - 1s 8ms/step - loss: 0.7517 - accuracy: 0.8002 -
val_loss: 1.6623 - val_accuracy: 0.6760
Epoch 19/20
63/63 [==============================] - 1s 9ms/step - loss: 0.7306 - accuracy: 0.8028 -
val_loss: 1.6723 - val_accuracy: 0.6800
Epoch 20/20
63/63 [==============================] - 0s 8ms/step - loss: 0.7132 - accuracy: 0.8048 -
val_loss: 1.6837 - val_accuracy: 0.6790
```

Out[41]:
```
<keras.callbacks.History at 0x26e179ae610>
```

Assignment 5.3

In [42]:
```python
# Loading the Boston housing dataset

from keras.datasets import boston_housing

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

In [43]:
```python
# Normalizing 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 [44]:
```
#  Model definition
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
```

In [45]:
```
# K-fold validation

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)
    # Prepare the validation data: data from partition #k
    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)
    #Evaluates the model on the validation data
    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 [46]:
```
all_scores
```

Out[46]:
```
[2.101060628890991, 2.39310359954834, 2.691499710083008, 2.4688401222229004]
```

In [47]:
```
np.mean(all_scores)
```

Out[47]:
```
2.41362601518631
```

In [48]:
```
from keras import backend as K
# Some memory clean-up
K.clear_session()
```

In [49]:

```
# 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 + 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['mae']
    all_mae_histories.append(mae_history)
```

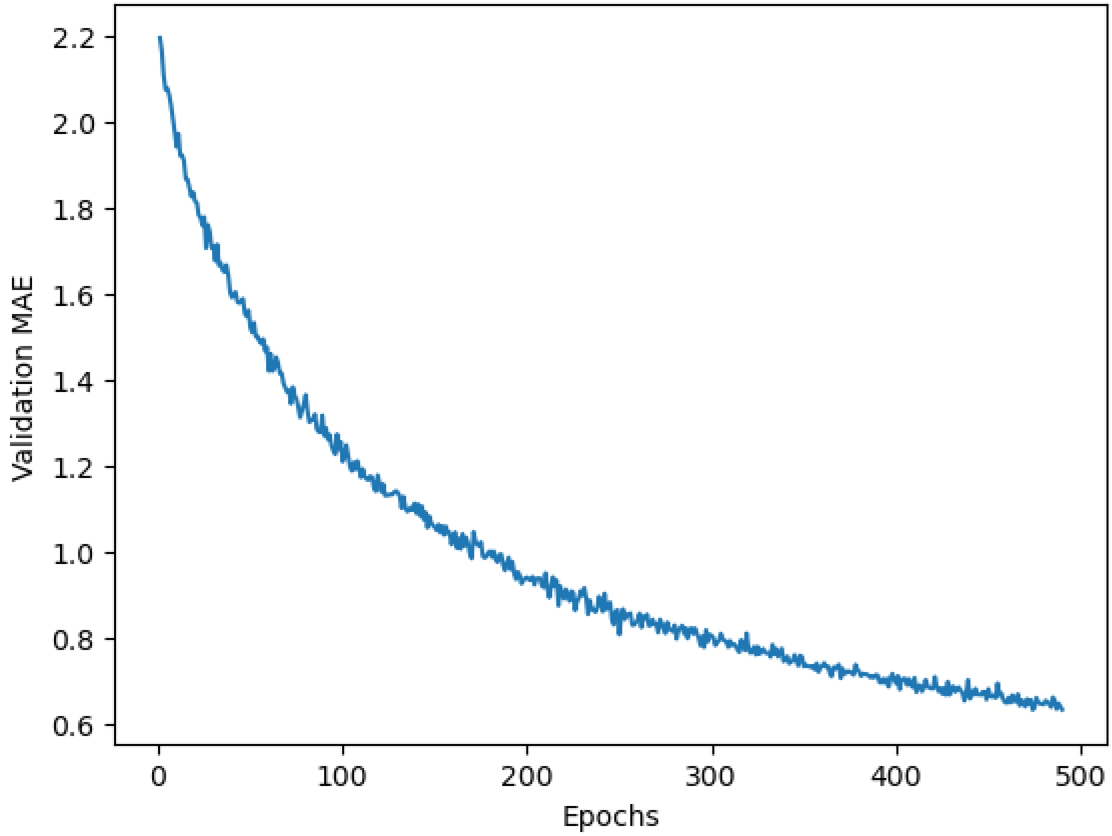
```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3
```

In [50]:

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

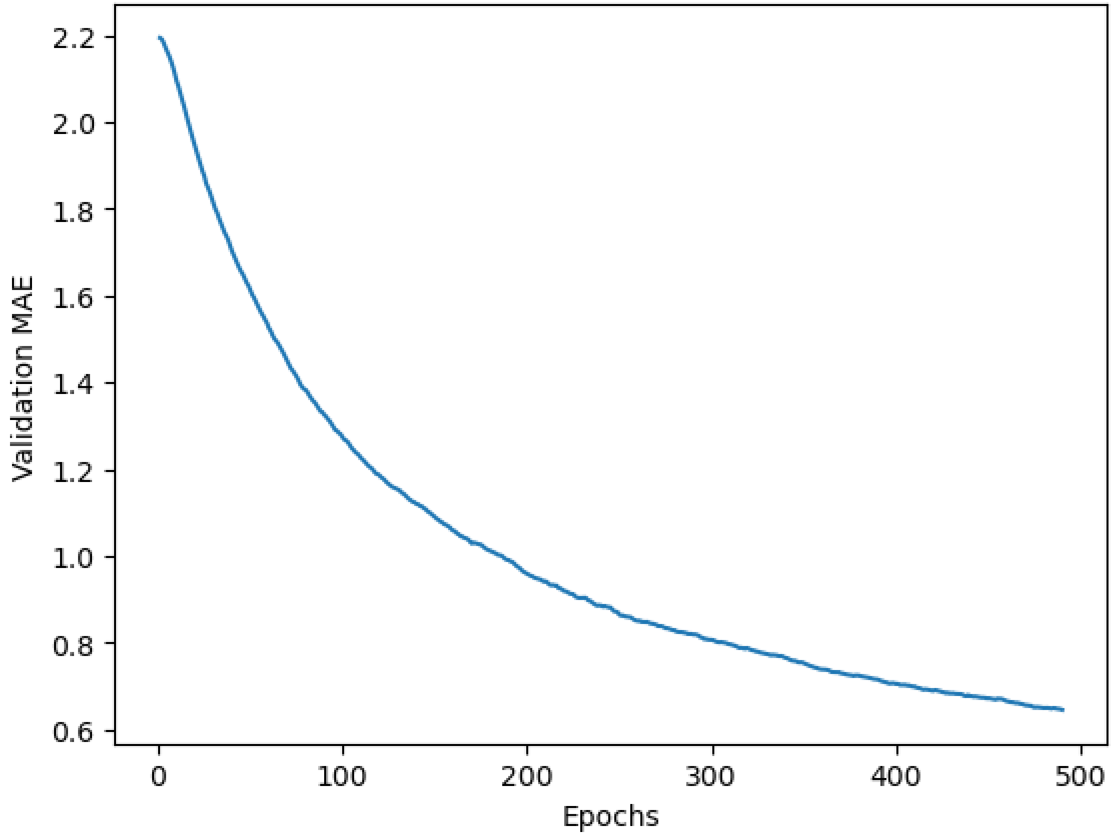
In [51]:

```
# Plotting validation scores
import matplotlib.pyplot as plt
plt.plot(range(1, len(average_mae_history[10:]) + 1), average_mae_history[10:])
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()
```



In [52]:

```
# Plotting validation scores, excluding the 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 [53]:
```
# 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 3ms/step - loss: 18.6953 - mae: 2.6824
```

In [54]:
```
test_mae_score
```

Out[54]:
```
2.682408571243286
```

In [55]:
```
#Generating predictions on new data
predictions = model.predict(test_data)
predictions[0]
```

```
4/4 [==============================] - 0s 2ms/step
```

Out[55]:
```
array([8.047043], dtype=float32)
```