assignment05_LewisRebecca

January 16, 2021

1 Assignment 5.1

1.1 Binary Classifier

1.1.1 Rebecca Lewis

[1]:
```
import numpy as np
```

[2]:
```
#load the imdb dataset
from keras.datasets import imdb

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

[3]:
```
#validated training and testing sets
#train_data[0]
#train_labels[0]
max([max(sequence) for sequence in train_data])
```

[3]:
```
9999
```

[4]:
```
#decode review back to English
word_index = imdb.get_word_index()
reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])
decoded_review = ' '.join([reverse_word_index.get(i-3,'?') for i in␣
↪train_data[0]])
```

[5]:
```
decoded_review
```

[5]:
```
"? 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"
```

[6]:
```
#encode the integer dequences 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)
```

[7]:
```
#validate
#x_train[0]
```

[8]:
```
#vectorize labels
y_train = np.asarray(train_labels).astype('float32')
y_test = np.asarray(test_labels).astype('float32')
```

[9]:
```
#implement the model
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'])

#to configure optimization or loss parameters
# import keras import optimizers
# model.compile(optimizer=optimizers.RMSprop(lr=0.001),
#               loss='binary_crossentropy',
#               metrics=['accuracy'])

# import keras import optimizers
# model.compile(optimizer=optimizers.RMSprop(lr=0.001),
#               loss=losses.binary_crossentropy,
```

```
#               metrics=['accuracy'])
```

[10]:
```
#set aside validation set
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

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

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 [==============================] - 2s 58ms/step - loss: 0.5075 - acc:
0.7884 - val_loss: 0.3838 - val_acc: 0.8641
Epoch 2/20
30/30 [==============================] - 1s 29ms/step - loss: 0.3001 - acc:
0.9045 - val_loss: 0.3262 - val_acc: 0.8702
Epoch 3/20
30/30 [==============================] - 1s 28ms/step - loss: 0.2196 - acc:
0.9286 - val_loss: 0.2761 - val_acc: 0.8899
Epoch 4/20
30/30 [==============================] - 1s 27ms/step - loss: 0.1754 - acc:
0.9428 - val_loss: 0.2729 - val_acc: 0.8898
Epoch 5/20
30/30 [==============================] - 1s 41ms/step - loss: 0.1398 - acc:
0.9563 - val_loss: 0.3051 - val_acc: 0.8817
Epoch 6/20
30/30 [==============================] - 1s 36ms/step - loss: 0.1174 - acc:
0.9623 - val_loss: 0.2995 - val_acc: 0.8844
Epoch 7/20
30/30 [==============================] - 1s 37ms/step - loss: 0.0961 - acc:
0.9711 - val_loss: 0.3334 - val_acc: 0.8776
Epoch 8/20
30/30 [==============================] - 1s 36ms/step - loss: 0.0797 - acc:
0.9760 - val_loss: 0.3410 - val_acc: 0.8817
Epoch 9/20
30/30 [==============================] - 1s 34ms/step - loss: 0.0654 - acc:
0.9819 - val_loss: 0.3651 - val_acc: 0.8786
Epoch 10/20
```

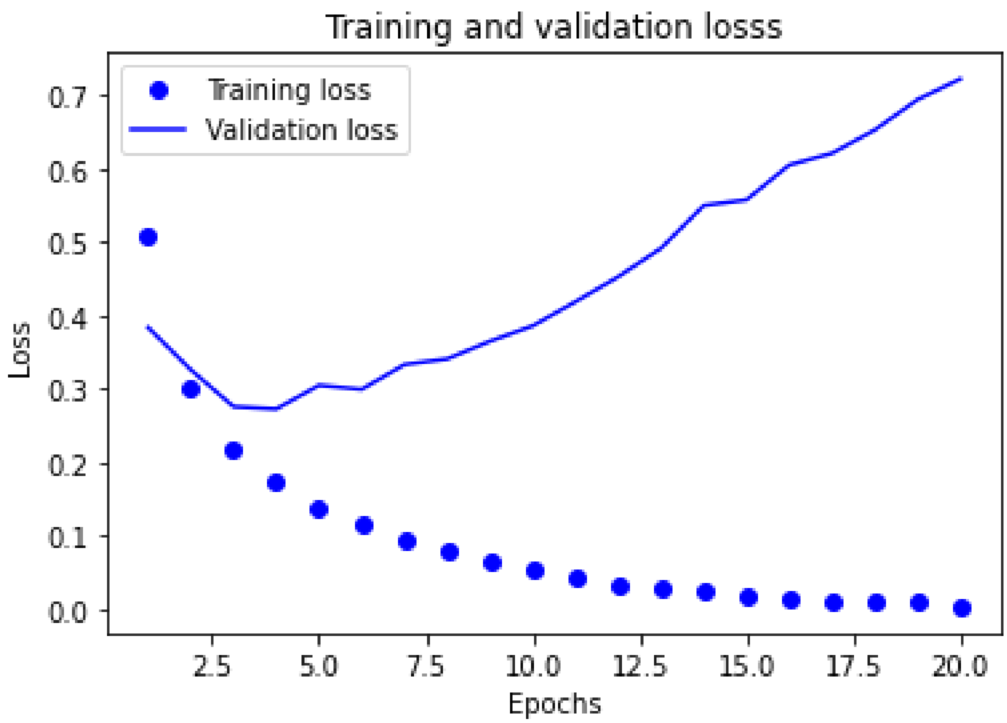
```
30/30 [==============================] - 1s 45ms/step - loss: 0.0555 - acc:
0.9848 - val_loss: 0.3860 - val_acc: 0.8779
Epoch 11/20
30/30 [==============================] - 1s 42ms/step - loss: 0.0433 - acc:
0.9892 - val_loss: 0.4188 - val_acc: 0.8771
Epoch 12/20
30/30 [==============================] - 1s 31ms/step - loss: 0.0344 - acc:
0.9926 - val_loss: 0.4527 - val_acc: 0.8753
Epoch 13/20
30/30 [==============================] - 1s 35ms/step - loss: 0.0278 - acc:
0.9947 - val_loss: 0.4914 - val_acc: 0.8735
Epoch 14/20
30/30 [==============================] - 1s 32ms/step - loss: 0.0249 - acc:
0.9949 - val_loss: 0.5496 - val_acc: 0.8650
Epoch 15/20
30/30 [==============================] - 1s 33ms/step - loss: 0.0189 - acc:
0.9967 - val_loss: 0.5572 - val_acc: 0.8700
Epoch 16/20
30/30 [==============================] - 1s 39ms/step - loss: 0.0147 - acc:
0.9981 - val_loss: 0.6047 - val_acc: 0.8676
Epoch 17/20
30/30 [==============================] - 1s 19ms/step - loss: 0.0122 - acc:
0.9984 - val_loss: 0.6205 - val_acc: 0.8686
Epoch 18/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0094 - acc:
0.9990 - val_loss: 0.6522 - val_acc: 0.8673
Epoch 19/20
30/30 [==============================] - 1s 29ms/step - loss: 0.0101 - acc:
0.9981 - val_loss: 0.6937 - val_acc: 0.8691
Epoch 20/20
30/30 [==============================] - 1s 28ms/step - loss: 0.0041 - acc:
0.9999 - val_loss: 0.7215 - val_acc: 0.8660
```

[12]:
```
history_dict = history.history
history_dict.keys()
```

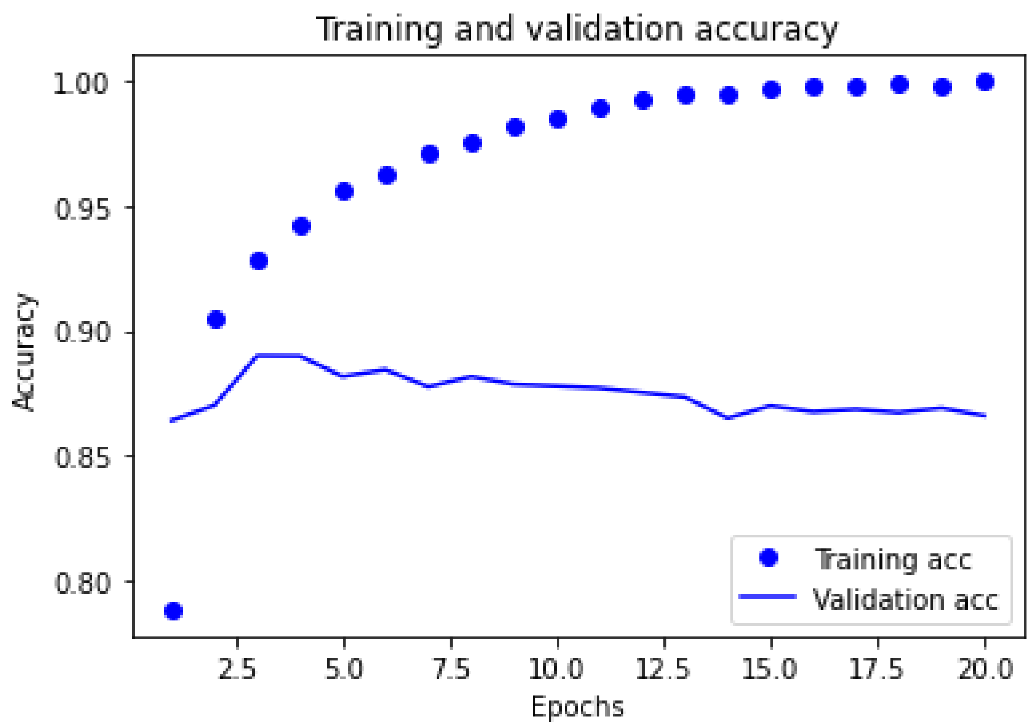
[12]:
```
dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
```

[13]:
```
#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(history_dict['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 losss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



[14]:
```
#plot the training and validation accuracy
plt.clf()
acc_values = history_dict['acc']
val_acc_values = history_dict['val_acc']


plt.plot(epochs, acc_values, '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('Accuracy')
plt.legend()

plt.show()
```



[15]:
```
#retraining from scratch on 4 epochs
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 [==============================] - 0s 8ms/step - loss: 0.4657 - accuracy:
0.8248
Epoch 2/4
49/49 [==============================] - 0s 8ms/step - loss: 0.2681 - accuracy:
0.9076
Epoch 3/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2041 - accuracy:
0.9285
Epoch 4/4
49/49 [==============================] - 0s 7ms/step - loss: 0.1728 - accuracy:
```

```
0.9381
782/782 [==============================] - 2s 2ms/step - loss: 0.2934 -
accuracy: 0.8850
```

[16]:
```python
model.predict(x_test)
```

[16]:
```
array([[0.21150035],
       [0.99972636],
       [0.7833364 ],
       …,
       [0.10918015],
       [0.06057188],
       [0.53854114]], dtype=float32)
```

[17]:
```python
#experiment with three hidden 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(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 [==============================] - 0s 10ms/step - loss: 0.4558 - accuracy:
0.8107
Epoch 2/4
49/49 [==============================] - 0s 10ms/step - loss: 0.2444 - accuracy:
0.9108
Epoch 3/4
49/49 [==============================] - 0s 9ms/step - loss: 0.1909 - accuracy:
0.9325
Epoch 4/4
49/49 [==============================] - 0s 7ms/step - loss: 0.1633 - accuracy:
0.9412
782/782 [==============================] - 1s 2ms/step - loss: 0.3123 -
accuracy: 0.8799
```

[18]:
```python
#this does not perform as well as two hidden layers  - try one
#experiment with three hidden layers
model = models.Sequential()
model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
```

```
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 [==============================] - 0s 8ms/step - loss: 0.4406 - accuracy:
0.8291
Epoch 2/4
49/49 [==============================] - 0s 8ms/step - loss: 0.2712 - accuracy:
0.9099
Epoch 3/4
49/49 [==============================] - 0s 8ms/step - loss: 0.2151 - accuracy:
0.9263
Epoch 4/4
49/49 [==============================] - 0s 7ms/step - loss: 0.1816 - accuracy:
0.9380
782/782 [==============================] - 2s 2ms/step - loss: 0.2855 -
accuracy: 0.8838
```

[19]:
```
#performance is slightly better
#using this number of layers alter units
model = models.Sequential()
model.add(layers.Dense(32, activation='relu', input_shape=(10000,)))
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 [==============================] - 0s 8ms/step - loss: 0.4261 - accuracy:
0.8187
Epoch 2/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2518 - accuracy:
0.9111
Epoch 3/4
49/49 [==============================] - 0s 8ms/step - loss: 0.2015 - accuracy:
0.9285
Epoch 4/4
49/49 [==============================] - 0s 8ms/step - loss: 0.1700 - accuracy:
```

```
0.9398
782/782 [==============================] - 1s 2ms/step - loss: 0.2977 -
accuracy: 0.8821
```

[20]:
```
#performance is not improved
#try mse loss function

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

model.compile(optimizer='rmsprop',
             loss='mean_squared_error',
             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 8ms/step - loss: 0.1555 - accuracy:
0.8294
Epoch 2/4
49/49 [==============================] - 0s 8ms/step - loss: 0.0905 - accuracy:
0.9039
Epoch 3/4
49/49 [==============================] - 0s 7ms/step - loss: 0.0685 - accuracy:
0.9229
Epoch 4/4
49/49 [==============================] - 0s 7ms/step - loss: 0.0567 - accuracy:
0.9372
782/782 [==============================] - 1s 2ms/step - loss: 0.0843 -
accuracy: 0.8896
```

[21]:
```
#performance is not improved - try tanh activation
model = models.Sequential()
model.add(layers.Dense(16, activation='tanh', input_shape=(10000,)))
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 [==============================] - 0s 7ms/step - loss: 0.4442 - accuracy:
0.8307
```

```
Epoch 2/4
49/49 [==============================] - 0s 7ms/step - loss: 0.2740 - accuracy:
0.9091
Epoch 3/4
49/49 [==============================] - 0s 8ms/step - loss: 0.2142 - accuracy:
0.9270
Epoch 4/4
49/49 [==============================] - 0s 6ms/step - loss: 0.1794 - accuracy:
0.9376
782/782 [==============================] - 1s 2ms/step - loss: 0.2813 -
accuracy: 0.8863
```

2 Assignment 5.2

2.1 Multiclassifier Example

2.1.1 Rebecca Lewis

[22]:
```
from keras.datasets import reuters

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

len(train_data), len(test_data)
```

[22]:
```
(8982, 2246)
```

[23]:
```
#decode back to words
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
```

[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 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'
```

[24]:
```
train_labels[10]
```

[24]:
```
3
```

[25]:
```
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)
```

[26]:
```
#one hot encoding example for labels
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)

#keras built in function
# from keras.utils.np_utils import to_categorical
# one_hot_train_labels = to_categorical(train_labels)
# one_hot_test_labels = to_categorical(test_labels)
```

[27]:
```
#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=['accuracy'])
```

[28]:
```
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:]
```

[29]:
```
history = model.fit(partial_x_train,
                   partial_y_train,
                   epochs=20,
                   batch_size=512,
                   validation_data=(x_val, y_val))
```

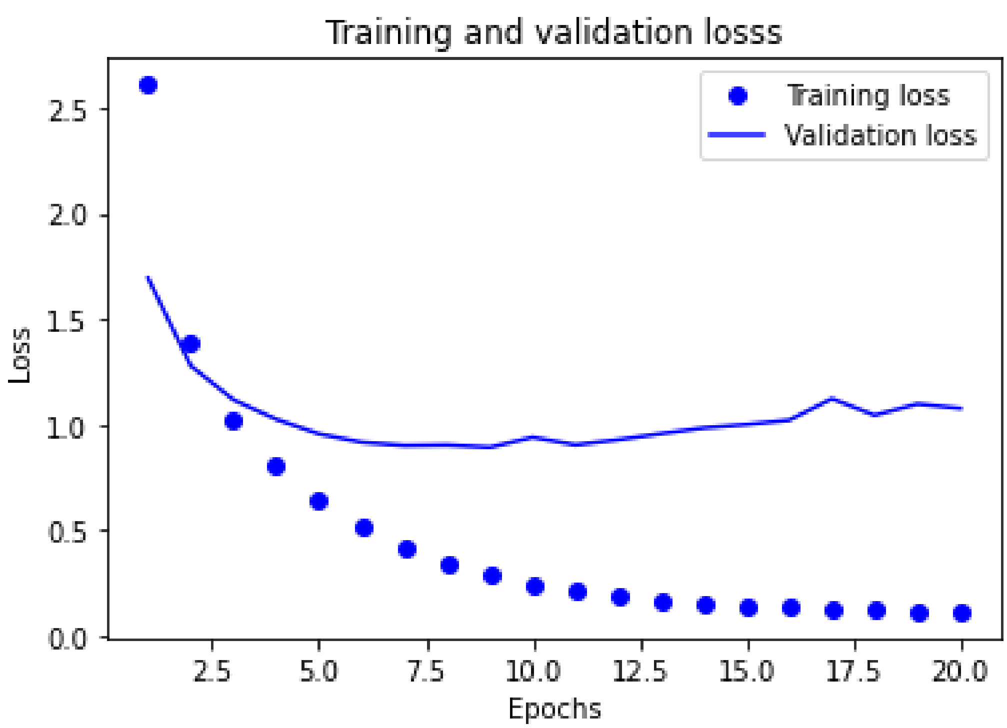
```
Epoch 1/20
16/16 [==============================] - 1s 49ms/step - loss: 2.6112 - accuracy:
0.5331 - val_loss: 1.6936 - val_accuracy: 0.6400
Epoch 2/20
16/16 [==============================] - 0s 17ms/step - loss: 1.3830 - accuracy:
```

```
0.7119 - val_loss: 1.2778 - val_accuracy: 0.7190
Epoch 3/20
16/16 [==============================] - 0s 18ms/step - loss: 1.0216 - accuracy:
0.7783 - val_loss: 1.1165 - val_accuracy: 0.7590
Epoch 4/20
16/16 [==============================] - 0s 14ms/step - loss: 0.8055 - accuracy:
0.8281 - val_loss: 1.0241 - val_accuracy: 0.7820
Epoch 5/20
16/16 [==============================] - 0s 16ms/step - loss: 0.6451 - accuracy:
0.8639 - val_loss: 0.9548 - val_accuracy: 0.8020
Epoch 6/20
16/16 [==============================] - 0s 18ms/step - loss: 0.5134 - accuracy:
0.8924 - val_loss: 0.9151 - val_accuracy: 0.8080
Epoch 7/20
16/16 [==============================] - 0s 19ms/step - loss: 0.4185 - accuracy:
0.9121 - val_loss: 0.8997 - val_accuracy: 0.8100
Epoch 8/20
16/16 [==============================] - 0s 18ms/step - loss: 0.3414 - accuracy:
0.9276 - val_loss: 0.9022 - val_accuracy: 0.8140
Epoch 9/20
16/16 [==============================] - 0s 15ms/step - loss: 0.2823 - accuracy:
0.9366 - val_loss: 0.8913 - val_accuracy: 0.8170
Epoch 10/20
16/16 [==============================] - 0s 16ms/step - loss: 0.2405 - accuracy:
0.9441 - val_loss: 0.9387 - val_accuracy: 0.8010
Epoch 11/20
16/16 [==============================] - 0s 18ms/step - loss: 0.2084 - accuracy:
0.9509 - val_loss: 0.9028 - val_accuracy: 0.8150
Epoch 12/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1833 - accuracy:
0.9520 - val_loss: 0.9272 - val_accuracy: 0.8160
Epoch 13/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1629 - accuracy:
0.9515 - val_loss: 0.9560 - val_accuracy: 0.8180
Epoch 14/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1522 - accuracy:
0.9546 - val_loss: 0.9834 - val_accuracy: 0.8070
Epoch 15/20
16/16 [==============================] - 0s 18ms/step - loss: 0.1382 - accuracy:
0.9551 - val_loss: 0.9995 - val_accuracy: 0.8040
Epoch 16/20
16/16 [==============================] - 0s 17ms/step - loss: 0.1344 - accuracy:
0.9545 - val_loss: 1.0200 - val_accuracy: 0.8040
Epoch 17/20
16/16 [==============================] - 0s 19ms/step - loss: 0.1228 - accuracy:
0.9577 - val_loss: 1.1220 - val_accuracy: 0.7960
Epoch 18/20
16/16 [==============================] - 0s 16ms/step - loss: 0.1191 - accuracy:
```

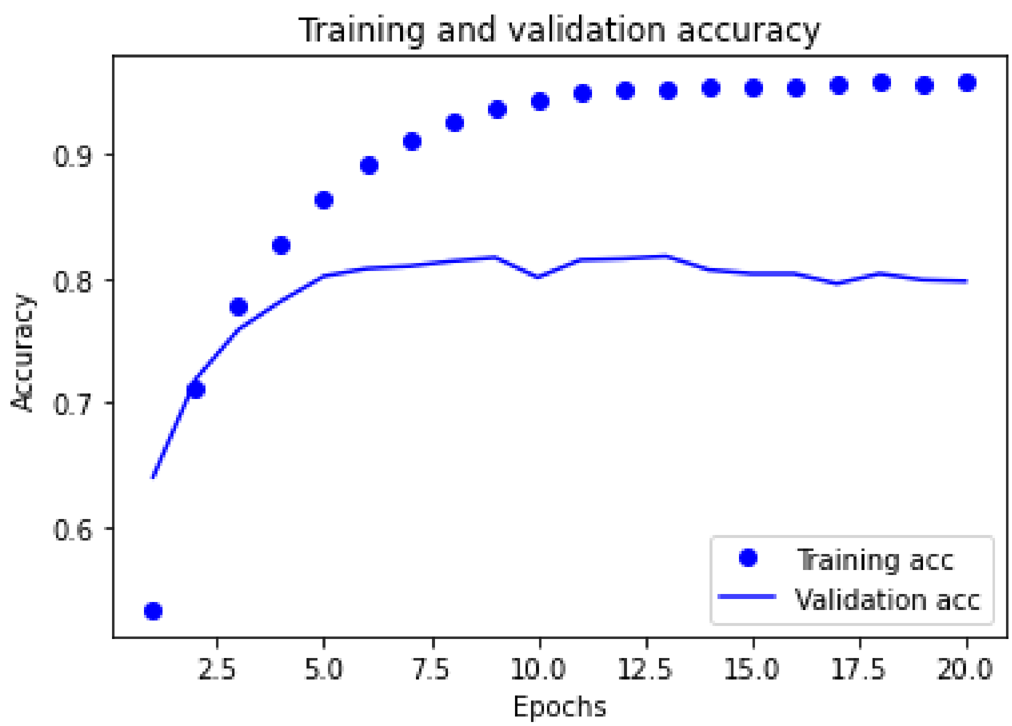
```
0.9583 - val_loss: 1.0435 - val_accuracy: 0.8040
Epoch 19/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1123 - accuracy:
0.9570 - val_loss: 1.0972 - val_accuracy: 0.7990
Epoch 20/20
16/16 [==============================] - 0s 15ms/step - loss: 0.1129 - accuracy:
0.9584 - val_loss: 1.0762 - val_accuracy: 0.7980
```

[30]:

```
plt.clf()

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 losss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



[31]:
```
#plot 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('Accuracy')
plt.legend()

plt.show()
```



[32]:
```
history.history.keys()
```

[32]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

[33]:
```
#retrain the model
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 [==============================] - 0s 21ms/step - loss: 2.6492 - accuracy:
0.5371 - val_loss: 1.7450 - val_accuracy: 0.6460
Epoch 2/9
16/16 [==============================] - 0s 20ms/step - loss: 1.4068 - accuracy:
0.7167 - val_loss: 1.2937 - val_accuracy: 0.7250
Epoch 3/9
16/16 [==============================] - 0s 18ms/step - loss: 1.0193 - accuracy:
0.7848 - val_loss: 1.1172 - val_accuracy: 0.7630
Epoch 4/9
16/16 [==============================] - 0s 17ms/step - loss: 0.7941 - accuracy:
0.8311 - val_loss: 1.0176 - val_accuracy: 0.7840
Epoch 5/9
16/16 [==============================] - 0s 14ms/step - loss: 0.6344 - accuracy:
0.8652 - val_loss: 0.9467 - val_accuracy: 0.8000
Epoch 6/9
16/16 [==============================] - 0s 17ms/step - loss: 0.5079 - accuracy:
0.8955 - val_loss: 0.9302 - val_accuracy: 0.8090
Epoch 7/9
16/16 [==============================] - 0s 15ms/step - loss: 0.4160 - accuracy:
0.9117 - val_loss: 0.9000 - val_accuracy: 0.8120
Epoch 8/9
16/16 [==============================] - 0s 17ms/step - loss: 0.3346 - accuracy:
0.9285 - val_loss: 0.9913 - val_accuracy: 0.7890
Epoch 9/9
16/16 [==============================] - 0s 15ms/step - loss: 0.2823 - accuracy:
0.9392 - val_loss: 0.8990 - val_accuracy: 0.8220
71/71 [==============================] - 0s 2ms/step - loss: 0.9910 - accuracy:
0.7841
```

[34]:
```
results
```

[34]: [0.9909918904304504, 0.784060537815094]

[35]:
```
#generating predictions for new data
predictions = model.predict(x_test)
```

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

[35]: (46,)

[36]:
```
np.sum(predictions[0])
```

[36]: 0.9999999

[37]:
```
np.argmax(predictions[0])
```

[37]: 3

3 Assignment 5.3

3.1 Regression Example

3.1.1 Rebecca Lewis

[71]:
```
from keras.datasets import boston_housing

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

train_data.shape, test_data.shape
```

[71]: ((404, 13), (102, 13))

[72]:
```
#normalize 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
```

[73]:
```
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
```

[74]:
```
#set up 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+1) * num_val_samples:]], axis=0)

    partial_train_targets = np.concatenate(
        [train_targets[:i * num_val_samples],
        train_targets[(i+1) * num_val_samples:]], axis=0)

    model = build_model()
    model.fit(partial_train_data, partial_train_targets, epochs=num_epochs,␣
 ↪batch_size=1, verbose=0)
    val_mse, val_mae = model.evaluate(val_data, val_targets, verbose=0)
    all_scores.append(val_mae)
```

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

[75]:
```
all_scores
```

[75]:
```
[2.288649082183838, 3.0874688625335693, 2.7066917419433594, 2.5108232498168945]
```

[76]:
```
np.mean(all_scores)
```

[76]:
```
2.6484082341194153
```

[77]:
```
from keras import backend as K

# Some memory clean-up
K.clear_session()
```

[78]:
```
#modify k fold for saving the history
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)
```

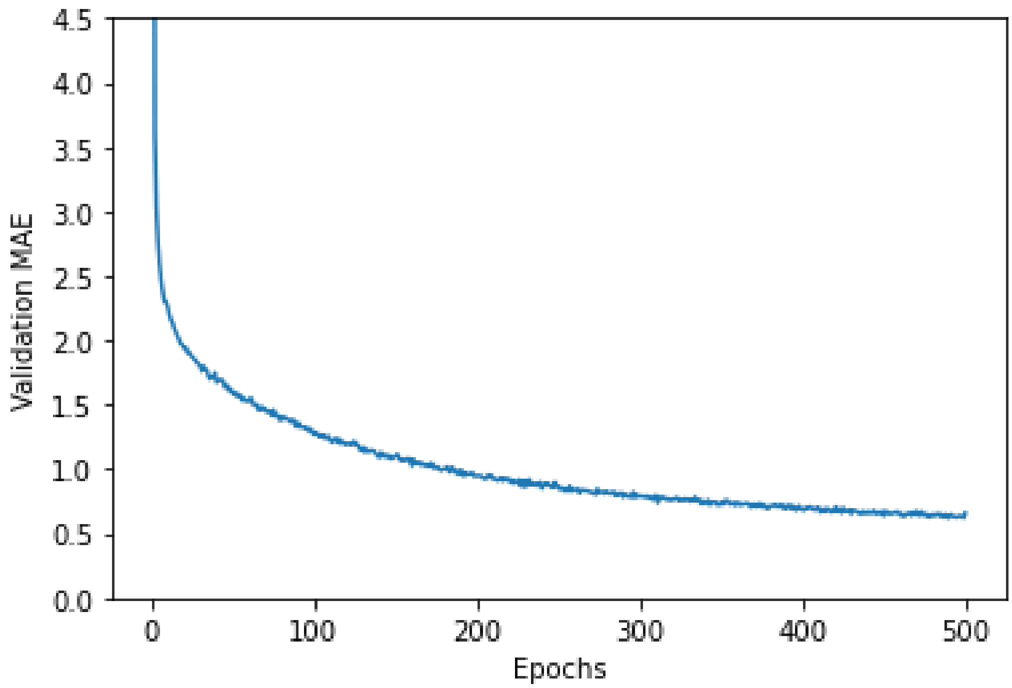
```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3
```

[79]:
```
history.history.keys()
```

[79]:
```
dict_keys(['loss', 'mae', 'val_loss', 'val_mae'])
```

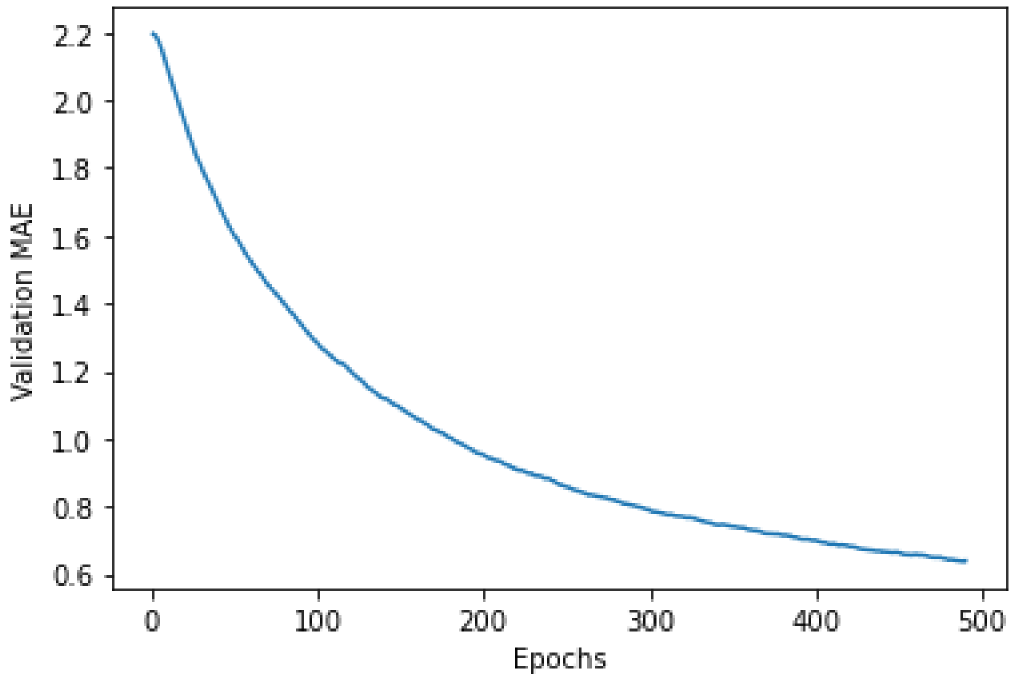
[80]:
```
average_mae_history = [np.mean([x[i] for x in all_mae_histories]) for i in␣
↪range(num_epochs)]
```

[82]:
```
# plot validation scores
plt.clf
plt.plot(range(1, len(average_mae_history) + 1), average_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.ylim(0,4.5)
plt.show()
```



[85]:

```
#modify plot
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()
```



[86]:
```
#train 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 1ms/step - loss: 19.8521 - mae: 2.8411
```

[87]:
```
test_mae_score
```

[87]: 2.841092586517334

[ ]:
```
```