Alyssa Weber DSC 650 Week 5

5.1 - Movie Review Classifier

Deep Learning with Python: Section 3.4, pg 68-77

In [1]:
```
# import the movie review dataset

from keras.datasets import imdb

# only loads the most frequent 10,000 words
# the data sets are loaded as lists
# the labels are loaded as 0- negative and 1- positive
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=10000)
```

```
2023-07-09 23:37:18.786902: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not find cuda drivers on your machine, GPU
will not be used.
2023-07-09 23:37:18.911416: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not find cuda drivers on your machine, GPU
will not be used.
2023-07-09 23:37:18.914305: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized t
o use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX512F FMA, in other operations, rebuild TensorFlow with the appropriate c
ompiler flags.
2023-07-09 23:37:20.326561: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find Ten
sorRT
```

In [2]:
```
# Cannot feed lists into Neural Networks. Use On-hot encoding to change lists into vectors of 0s and 1s

import numpy as np

def vectorize_sequences (sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension)) #creates an all-zero matrix of shape (len(sequences), dimension)
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1 #sets specific indicies of results[i] to 1's
    return results

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

In [3]:
```
# Vectorize labels

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

In [4]:
```
# Define 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'))
```

In [5]:
```
# Set 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 [6]:
```
# Compile and train the model
# note: binary_crossentropy is the usually the best choice when dealing with output probabilities

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
```

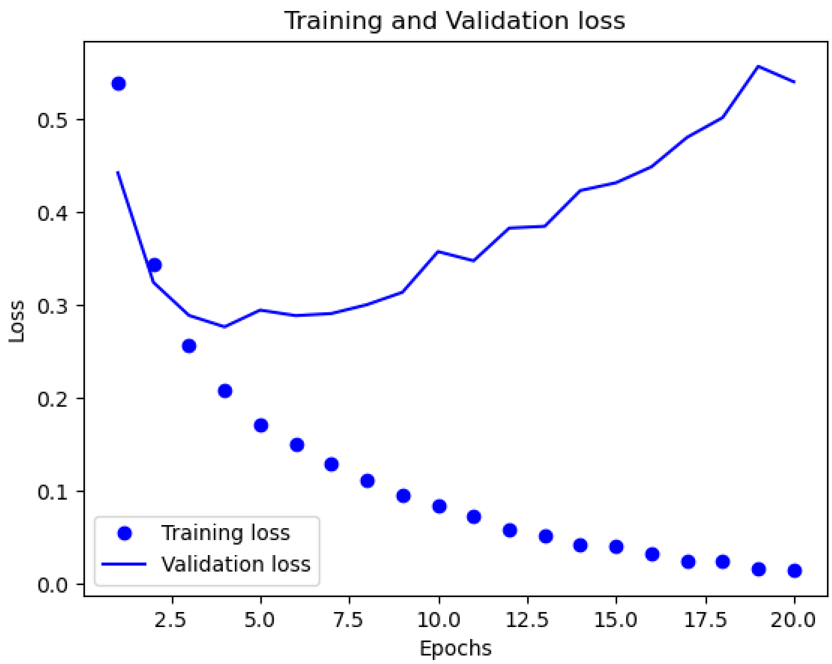
```
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
30/30 [==============================] - 2s 48ms/step - loss: 0.5386 - acc: 0.7803 - val_loss: 0.4423 - val_acc: 0.832
9
Epoch 2/20
30/30 [==============================] - 0s 15ms/step - loss: 0.3434 - acc: 0.8897 - val_loss: 0.3243 - val_acc: 0.880
7
Epoch 3/20
30/30 [==============================] - 0s 14ms/step - loss: 0.2566 - acc: 0.9129 - val_loss: 0.2888 - val_acc: 0.890
3
Epoch 4/20
30/30 [==============================] - 0s 15ms/step - loss: 0.2077 - acc: 0.9297 - val_loss: 0.2765 - val_acc: 0.890
1
Epoch 5/20
30/30 [==============================] - 1s 17ms/step - loss: 0.1719 - acc: 0.9425 - val_loss: 0.2945 - val_acc: 0.882
4
Epoch 6/20
30/30 [==============================] - 0s 14ms/step - loss: 0.1497 - acc: 0.9511 - val_loss: 0.2885 - val_acc: 0.883
7
Epoch 7/20
30/30 [==============================] - 0s 14ms/step - loss: 0.1292 - acc: 0.9585 - val_loss: 0.2908 - val_acc: 0.886
1
Epoch 8/20
30/30 [==============================] - 0s 16ms/step - loss: 0.1116 - acc: 0.9655 - val_loss: 0.3003 - val_acc: 0.884
2
Epoch 9/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0953 - acc: 0.9723 - val_loss: 0.3137 - val_acc: 0.882
3
Epoch 10/20
30/30 [==============================] - 0s 16ms/step - loss: 0.0840 - acc: 0.9775 - val_loss: 0.3574 - val_acc: 0.877
4
Epoch 11/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0732 - acc: 0.9802 - val_loss: 0.3475 - val_acc: 0.878
6
Epoch 12/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0588 - acc: 0.9862 - val_loss: 0.3827 - val_acc: 0.870
8
Epoch 13/20
30/30 [==============================] - 0s 16ms/step - loss: 0.0526 - acc: 0.9877 - val_loss: 0.3847 - val_acc: 0.875
5
Epoch 14/20
30/30 [==============================] - 0s 16ms/step - loss: 0.0430 - acc: 0.9916 - val_loss: 0.4231 - val_acc: 0.869
0
Epoch 15/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0403 - acc: 0.9909 - val_loss: 0.4315 - val_acc: 0.870
5
Epoch 16/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0318 - acc: 0.9930 - val_loss: 0.4487 - val_acc: 0.874
1
Epoch 17/20
30/30 [==============================] - 0s 14ms/step - loss: 0.0252 - acc: 0.9961 - val_loss: 0.4803 - val_acc: 0.875
4
Epoch 18/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0240 - acc: 0.9961 - val_loss: 0.5016 - val_acc: 0.867
1
Epoch 19/20
30/30 [==============================] - 0s 15ms/step - loss: 0.0169 - acc: 0.9985 - val_loss: 0.5567 - val_acc: 0.860
8
Epoch 20/20
30/30 [==============================] - 0s 16ms/step - loss: 0.0149 - acc: 0.9985 - val_loss: 0.5401 - val_acc: 0.869
0
```

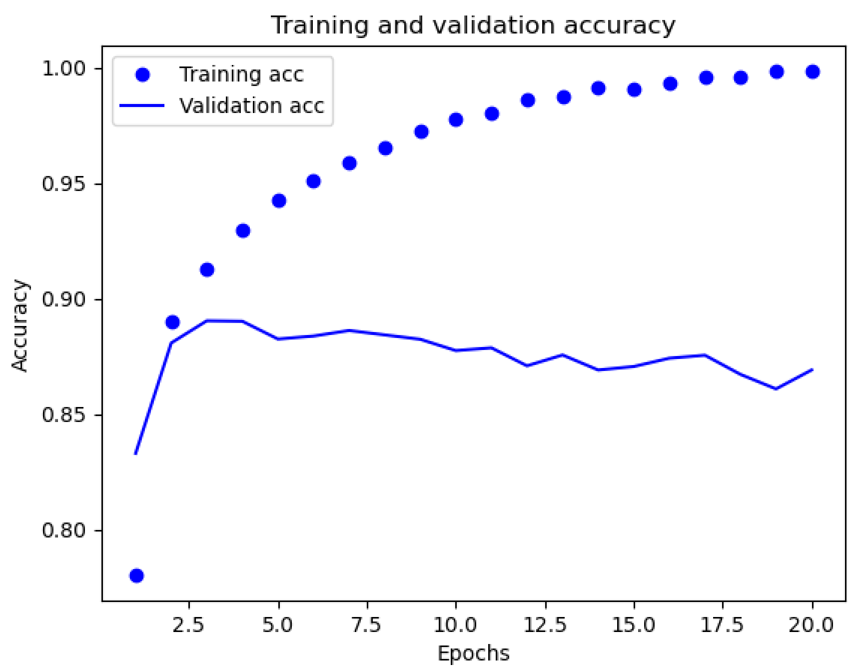
In [7]:

```
# Plot the training and validation loss

import matplotlib.pyplot as plt

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') #'bo' is for blue dot
plt.plot(epochs, val_loss_values, 'b', label = 'Validation loss') #'b' is for solid blue line
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



In [8]:
```
# Plot the taining and validation accuracy

plt.clf()
acc = history_dict['acc']
val_acc = history_dict['val_acc']
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()
```



note: The visuals above show an overfitting. "After the second epoch, you're overoptimizing on the training data, and you end up learning representations that are specific to the traioning data and don't generalize to the data outside of the training set."

In [9]:
```
# Retrain a new 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)

results
```

```
Epoch 1/4
49/49 [==============================] - 1s 9ms/step - loss: 0.4534 - accuracy: 0.8113
Epoch 2/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2630 - accuracy: 0.9069
Epoch 3/4
49/49 [==============================] - 0s 9ms/step - loss: 0.2089 - accuracy: 0.9238
Epoch 4/4
49/49 [==============================] - 0s 9ms/step - loss: 0.1741 - accuracy: 0.9376
782/782 [==============================] - 2s 2ms/step - loss: 0.3023 - accuracy: 0.8795
```

Out[9]:
```
[0.3023304045200348, 0.8795199990272522]
```

note: Achieves an accuracy of about 88%

5.2 - News Classifier

Deep Learning with Python: Section 3.5, pg 78-84

In [10]:
```
# Import the news classsifier dataset

from keras.datasets import reuters

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

In [11]:
```
# Encode the data

import numpy as np
```

```
def vectorize_sequences (sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension)) #creates an all-zero matrix of shape (len(sequences), dimension)
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1 #sets specific indicies of results[i] to 1's
    return results

x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)

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 [12]:
```
# Define the model

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 [13]:
```
# Compile the model

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

In [14]:
```
# set 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:]
```

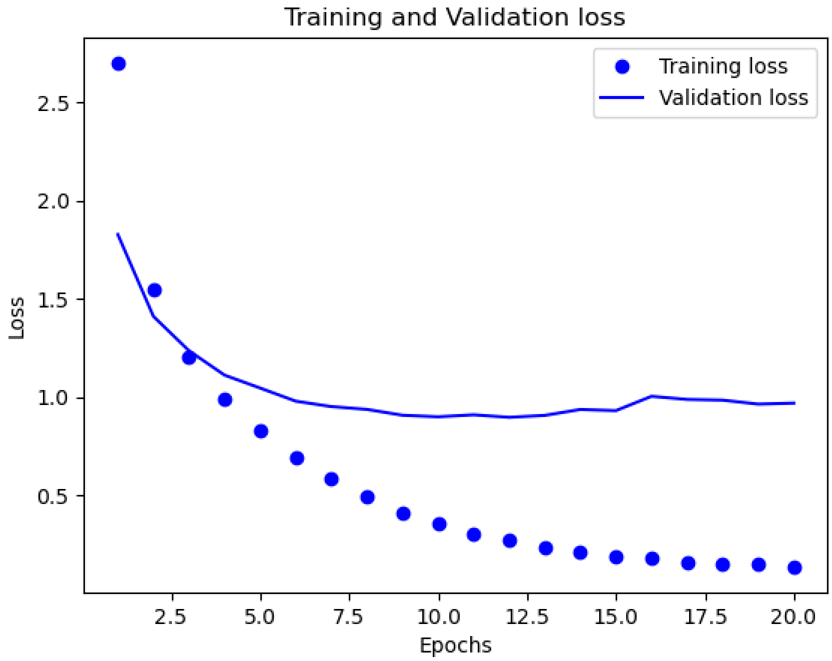
In [15]:
```
# Train the model

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

```
Epoch 1/20
16/16 [==============================] - 1s 41ms/step - loss: 2.6985 - accuracy: 0.4587 - val_loss: 1.8259 - val_accur
acy: 0.6090
Epoch 2/20
16/16 [==============================] - 0s 22ms/step - loss: 1.5458 - accuracy: 0.6733 - val_loss: 1.4098 - val_accur
acy: 0.6850
Epoch 3/20
16/16 [==============================] - 0s 21ms/step - loss: 1.2013 - accuracy: 0.7339 - val_loss: 1.2351 - val_accur
acy: 0.7180
Epoch 4/20
16/16 [==============================] - 0s 21ms/step - loss: 0.9905 - accuracy: 0.7828 - val_loss: 1.1110 - val_accur
acy: 0.7450
Epoch 5/20
16/16 [==============================] - 0s 21ms/step - loss: 0.8275 - accuracy: 0.8172 - val_loss: 1.0454 - val_accur
acy: 0.7780
Epoch 6/20
16/16 [==============================] - 0s 24ms/step - loss: 0.6919 - accuracy: 0.8500 - val_loss: 0.9787 - val_accur
acy: 0.7950
Epoch 7/20
16/16 [==============================] - 0s 22ms/step - loss: 0.5823 - accuracy: 0.8755 - val_loss: 0.9512 - val_accur
acy: 0.7990
Epoch 8/20
16/16 [==============================] - 0s 21ms/step - loss: 0.4905 - accuracy: 0.8948 - val_loss: 0.9369 - val_accur
acy: 0.8040
Epoch 9/20
16/16 [==============================] - 0s 23ms/step - loss: 0.4139 - accuracy: 0.9085 - val_loss: 0.9072 - val_accur
acy: 0.8100
Epoch 10/20
16/16 [==============================] - 0s 21ms/step - loss: 0.3577 - accuracy: 0.9228 - val_loss: 0.8993 - val_accur
acy: 0.8110
Epoch 11/20
16/16 [==============================] - 0s 23ms/step - loss: 0.3067 - accuracy: 0.9334 - val_loss: 0.9094 - val_accur
acy: 0.8110
Epoch 12/20
16/16 [==============================] - 0s 21ms/step - loss: 0.2697 - accuracy: 0.9386 - val_loss: 0.8966 - val_accur
acy: 0.8130
Epoch 13/20
16/16 [==============================] - 0s 23ms/step - loss: 0.2376 - accuracy: 0.9459 - val_loss: 0.9064 - val_accur
acy: 0.8180
Epoch 14/20
16/16 [==============================] - 0s 24ms/step - loss: 0.2091 - accuracy: 0.9506 - val_loss: 0.9365 - val_accur
acy: 0.8040
Epoch 15/20
16/16 [==============================] - 0s 24ms/step - loss: 0.1910 - accuracy: 0.9516 - val_loss: 0.9306 - val_accur
acy: 0.8010
Epoch 16/20
16/16 [==============================] - 0s 24ms/step - loss: 0.1789 - accuracy: 0.9524 - val_loss: 1.0034 - val_accur
acy: 0.7940
Epoch 17/20
16/16 [==============================] - 0s 23ms/step - loss: 0.1604 - accuracy: 0.9554 - val_loss: 0.9875 - val_accur
acy: 0.7990
Epoch 18/20
16/16 [==============================] - 0s 22ms/step - loss: 0.1543 - accuracy: 0.9557 - val_loss: 0.9839 - val_accur
acy: 0.7990
Epoch 19/20
16/16 [==============================] - 0s 23ms/step - loss: 0.1499 - accuracy: 0.9569 - val_loss: 0.9639 - val_accur
acy: 0.8050
Epoch 20/20
16/16 [==============================] - 0s 21ms/step - loss: 0.1363 - accuracy: 0.9551 - val_loss: 0.9687 - val_accur
acy: 0.8080
```

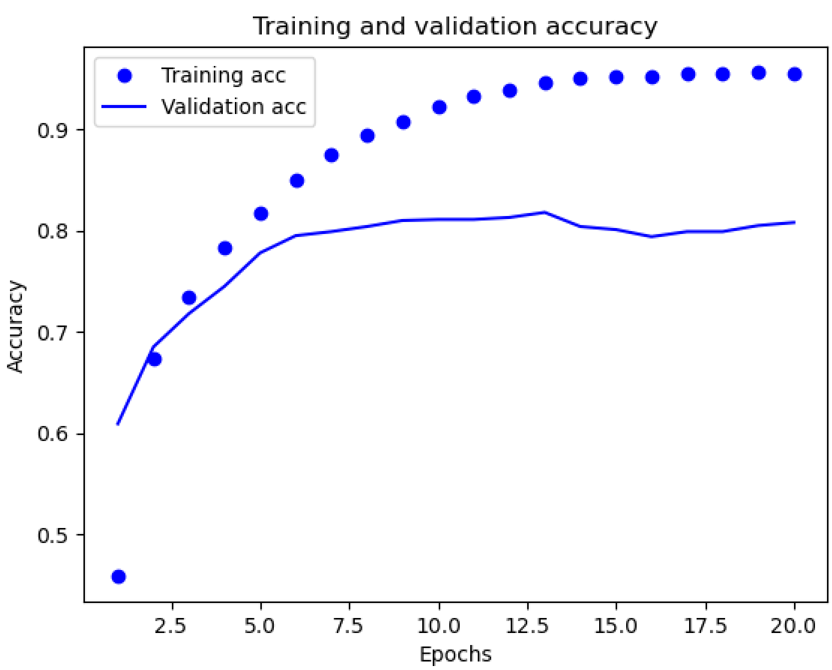
In [16]:

```python
# Plot 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') #'bo' is for blue dot
plt.plot(epochs, val_loss, 'b', label = 'Validation loss') #'b' is for solid blue line
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
```

```
plt.legend()

plt.show()
```



In [17]:
```
# Plot the training and validation accuracy

plt.clf() #clears the figure

acc = history.history['accuracy'] #note: used 'accuracy' instead of 'acc' as shown in the text
val_acc = history.history['val_accuracy'] #note: used 'val_accuracy' instead of 'val_acc' as shown in the text

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()
```



note: The text says that it peaks after 9 epochs, however, this round of modeling seems to peak later. I will continue to use 9 as suggested by the text.

In [18]:
```
# Retrain 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)

results
```

```
Epoch 1/9
16/16 [==============================] - 1s 40ms/step - loss: 2.7251 - accuracy: 0.4880 - val_loss: 1.8092 - val_accur
acy: 0.6250
Epoch 2/9
16/16 [==============================] - 0s 20ms/step - loss: 1.5366 - accuracy: 0.6842 - val_loss: 1.3856 - val_accur
acy: 0.6830
Epoch 3/9
16/16 [==============================] - 0s 22ms/step - loss: 1.1842 - accuracy: 0.7433 - val_loss: 1.2007 - val_accur
acy: 0.7430
Epoch 4/9
16/16 [==============================] - 0s 22ms/step - loss: 0.9779 - accuracy: 0.7918 - val_loss: 1.1277 - val_accur
acy: 0.7640
Epoch 5/9
16/16 [==============================] - 0s 21ms/step - loss: 0.8098 - accuracy: 0.8309 - val_loss: 1.0412 - val_accur
acy: 0.7710
Epoch 6/9
16/16 [==============================] - 0s 20ms/step - loss: 0.6726 - accuracy: 0.8578 - val_loss: 0.9899 - val_accur
acy: 0.7890
Epoch 7/9
16/16 [==============================] - 0s 20ms/step - loss: 0.5635 - accuracy: 0.8837 - val_loss: 0.9294 - val_accur
acy: 0.7980
Epoch 8/9
16/16 [==============================] - 0s 21ms/step - loss: 0.4796 - accuracy: 0.9004 - val_loss: 0.9027 - val_accur
acy: 0.8060
Epoch 9/9
16/16 [==============================] - 0s 23ms/step - loss: 0.4004 - accuracy: 0.9178 - val_loss: 0.8972 - val_accur
acy: 0.8220
71/71 [==============================] - 0s 3ms/step - loss: 0.9660 - accuracy: 0.7858
```

Out[18]:
```
[0.965984582901001, 0.7858415246009827]
```

The accuracy of this model is just above 78%

5.3 - Housing Price Regression Model

Deep Learning with Python: Section 3.6, pg 85-91

In [34]:
```
from keras.datasets import boston_housing

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

In [35]:
```
# 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 [36]:
```
# Define the model

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 [37]:
```
# 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)
    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
```

In [38]:
```
# print scores
all_scores
```

Out[38]: `[1.8084664344787598, 2.2307748794555664, 2.705993890762329, 2.4515841007232666]`

In [39]:
```
# print mean of the scores
np.mean(all_scores)
```

Out[39]: `2.2992048263549805`

note: the average validation score was 2.3, meaning that we're off by $2,300.

In [42]:
```
# 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['val_mae'] #note: used 'val_mae' rather than 'val_mean_absuolute_error' as indicate
    all_mae_histories.append(mae_history)
```

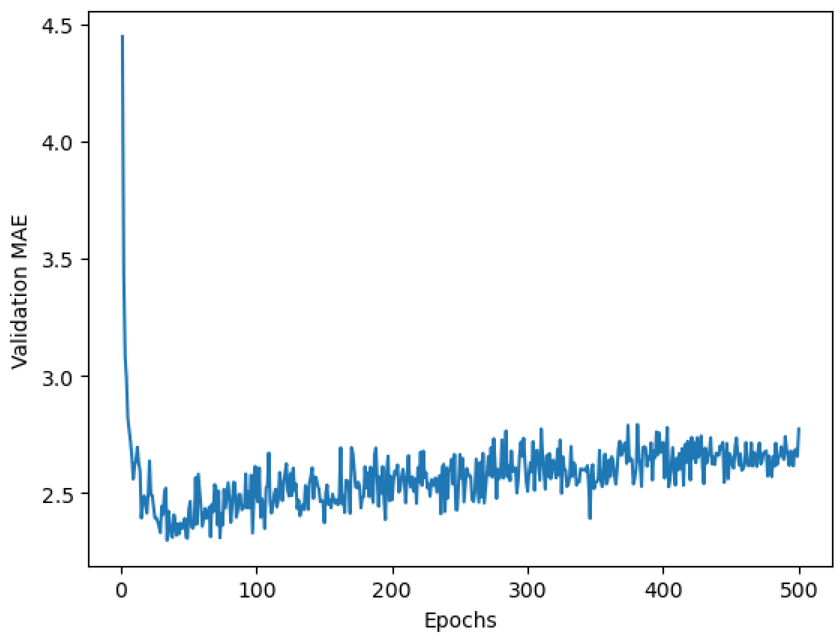
```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3
```

In [44]:

```
# Build 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_epochs)]
```

In [45]:

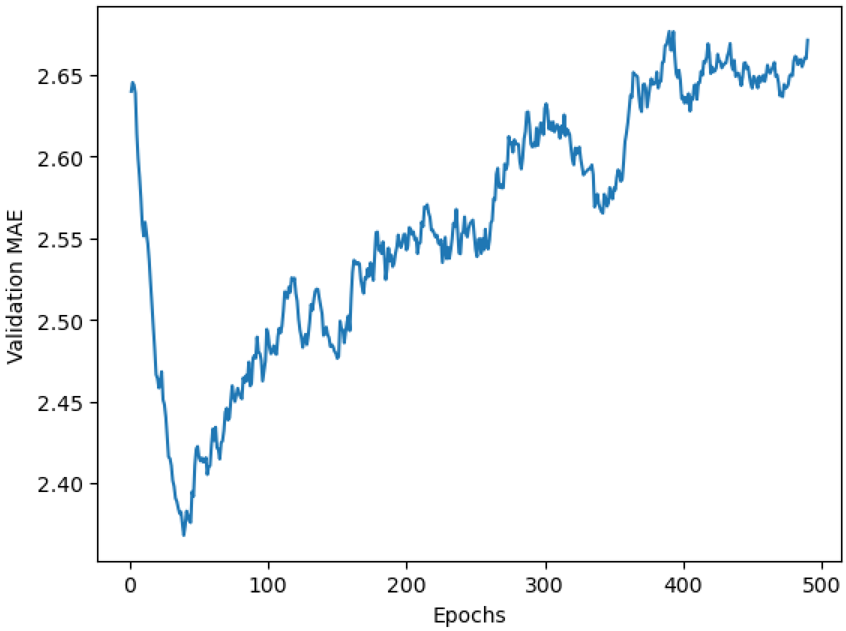
```
# Plot validation scores

import matplotlib.pyplot as plt

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



In [46]:

```
# plot the 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()
```



note: In the text the graph shos that that the MAE stops improving significantly after 80 epochs. My graph looks closer to 40 or 50. I will continue with the text's example of 80.

In [47]:
```
# 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)

test_mae_score
```

```
4/4 [==============================] - 0s 3ms/step - loss: 17.0829 - mae: 2.5729
```

Out[47]: 2.5729193687438965

This model is off by about $2,570, which is slightly worse than the average I had previously. I'm going to shy away from the text and run the model one more time at 45 epochs.

In [48]:
```
# NOT IN TEXT
# Testing the model at 45 epochs instead of 80 based on the results my graph showed.

model = build_model()
model.fit(train_data, train_targets,
          epochs=45, batch_size=16, verbose=0)

test_mse_score, test_mae_score = model.evaluate(test_data, test_targets)

test_mae_score
```

```
4/4 [==============================] - 0s 3ms/step - loss: 21.8970 - mae: 2.8650
```

Out[48]: 2.8650147914886475

note: This was not an improvement.