# **Assignment 10**

#### **DSC 650**

#### Jake Meyer

#### 05/20/2023

Using code examples from Chapter 6 of First Edition: deep-learning-with-python-notebooks

```
In [1]:
         ## Import the necessary modules for the assignment.
        import csv
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import tensorflow as tf
        import keras
        import sklearn
        import itertools
        import string
        import nltk
        from numpy import array
        from numpy import argmax
        from sklearn.model selection import train test split
        from pathlib import Path
        from contextlib import redirect stdout
        import time
        import os
        ## Import the necessary keras components.
        from keras import layers, models, preprocessing
        from keras.datasets import imdb
        from keras.preprocessing.text import Tokenizer
        from keras preprocessing.sequence import pad sequences
        from keras.preprocessing import sequence
        from keras.utils import to categorical, np utils
        from keras.models import Sequential, load model
        from keras.layers import LSTM
        from keras.layers.core import Dense, Dropout, Activation, Flatten, Embedding
        from keras.optimizers import RMSprop
        import tensorflow.compat.v1 as tf
        tf.disable v2 behavior()
        WARNING:tensorflow:From C:\Users\jkmey\anaconda3\lib\site-packages\tensorflow\python\compa
        t\v2 compat.py:107: disable resource variables (from tensorflow.python.ops.variable scope)
        is deprecated and will be removed in a future version.
        Instructions for updating:
        non-resource variables are not supported in the long term
In [2]:
        ## Print versions of essential packages
        print("keras version: {}".format(keras. version ))
        print("tensorflow version: {}".format(tf. version ))
        print("pandas version: {}".format(pd. version ))
        print("numpy version: {}".format(np. version ))
        keras version: 2.9.0
        tensorflow version: 2.9.1
        pandas version: 1.3.4
        numpy version: 1.20.3
```

## **Assignment 10.1**

In the first part of the assignment, you will implement basic text-preprocessing functions in Python. These functions do not need to scale to large text documents and will only need to handle small inputs.

#### Assignment 10.1.a

Create a tokenize function that splits a sentence into words. Ensure that your tokenizer removes basic punctuation.

```
In [3]:
         1.1.1
        Purpose: As specified in the instructions, function will split a sentence into words and
        Argument: sentence
        Returns: tokens
         1.1.1
        def tokenize(sentence):
            ## Sentence broken down into words by spaces.
            words = sentence.split()
            ## Remove punctuation from the sentence
            punctuation removal table = str.maketrans('', '', string.punctuation)
            tokens = [word.translate(punctuation removal table) for word in words]
            return tokens
In [4]:
        ## Show that the tokenize() function is working as expected.
        sentence = "Currently, I am working on assignment 10 and trying to see if this function we
        word list = tokenize(sentence)
        print(word list)
        ['Currently', 'I', 'am', 'working', 'on', 'assignment', '10', 'and', 'trying', 'to', 'se
        e', 'if', 'this', 'function', 'works']
```

### Assignment 10.1.b

```
Implement an 'ngram' function that splits tokens into N-grams.
In [5]:
         1.1.1
         Purpose: As specified in the instructions, function will split tokens into N-grams.
        Arguments: tokens and n
        Returns: n grams
        def ngrams(tokens, n):
            n grams = nltk.ngrams(tokens, n)
             return n grams
In [6]:
         ## Show that ngrams() function is working as expected.
        sentence = "Currently, I am working on assignment 10 and trying to see if this function we
        tokens = tokenize(sentence)
         ## print(tokens)
        n grams = ngrams(tokens, 3)
        print(type(n grams))
        print(n grams)
        <class 'zip'>
        <zip object at 0x0000027FAF2CEC00>
In [7]:
         ## Show the contents of n grams to validate it is working as expected.
         for gram in n grams:
```

```
print(gram)
 ('Currently', 'I', 'am')
 ('I', 'am', 'working')
 ('am', 'working', 'on')
 ('working', 'on', 'assignment')
 ('on', 'assignment', '10')
 ('assignment', '10', 'and')
 ('10', 'and', 'trying')
 ('and', 'trying', 'to')
 ('trying', 'to', 'see')
 ('to', 'see', 'if')
 ('see', 'if', 'this')
 ('if', 'this', 'function')
 ('this', 'function', 'works')
Assignment 10.1.c
Implement an one_hot_encode function to create a vector from a numerical vector from a list of tokens.
```

```
In [8]:
         1.1.1
        Purpose: As specified in the instructions, function will create a vector from a numerical
        Tried following example 6.1 from text for word-level one-hot encoding (toy example)
        Arguments: tokens and number of words
        Returns: results
        def one hot encode(tokens, num words):
             token index = {}
             for sample in tokens:
                 for word in sample.split():
                     if word in sample.split():
                         if word not in token index:
                             token index[word] = len(token index) + 1
            max length = 10
            results = np.zeros(shape = (len(tokens), max length, max(token index.values()) + 1))
             for i, sample in enumerate(tokens):
                 for j, word in list(enumerate(sample.split()))[:max length]:
                     index = token index.get(word)
                     results[i, j, index] = 1
             return results
In [9]:
         ## Show that the one hot encode() function is working correctly.
        sentence = "Currently, I am working on assignment 10 and trying to see if this function wo
        tokens = tokenize(sentence)
         ## print(tokens)
        one hot example = one hot encode (tokens, 15)
        print(type(one hot example))
        print(one hot example)
        <class 'numpy.ndarray'>
        [[[0. 1. 0. ... 0. 0. 0.]]
          [0. 0. 0. ... 0. 0. 0.]
          [0. 0. 0. ... 0. 0. 0.]
          [0. 0. 0. ... 0. 0. 0.]
          [0. 0. 0. ... 0. 0. 0.]
          [0. 0. 0. ... 0. 0. 0.]]
         [[0. 0. 1. ... 0. 0. 0.]
          [0. 0. 0. ... 0. 0. 0.]
          [0. 0. 0. ... 0. 0. 0.]
```

[0. 0. 0. ... 0. 0. 0.]

```
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]]
. . .
[[0. 0. 0. ... 1. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]]
[[0. 0. 0. ... 0. 1. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]]
[[0. 0. 0. ... 0. 0. 1.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]]]
```

### **Assignment 10.2**

Using listings 6.16, 6.17, and 6.18 in Deep Learning with Python as a guide, train a sequential model with embeddings on the IMDB data found in data/external/imdb/. Produce the model performance metrics and training and validation accuracy curves within the Jupyter notebook.

```
In [10]:
         ## Define directories for storing results and loading the data (train and test).
         imdb dir = Path('C:/Users/jkmey/Documents/Github/DSC650 Course Assignments/dsc650/data/ext
         results dir = Path('C:/Users/jkmey/Documents/Github/DSC650 Course Assignments/'
                             'dsc650/dsc650/assignments/assignment10/').joinpath('results').joinpath
         results dir.mkdir(parents = True, exist ok = True)
         test dir = os.path.join(imdb dir, 'test')
         train dir = os.path.join(imdb dir, 'train')
In [11]:
         ## Using 6.8 as an additional reference from Deep Learning with Python code.
         ## Code will process the labels of the raw IMDB data.
         labels = []
         texts = []
         for label type in ['neg', 'pos']:
             dir name = os.path.join(train dir, label type)
             for fname in sorted(os.listdir(dir name)):
                 if fname[-4:] == '.txt':
                      f = open(os.path.join(dir name, fname), encoding = "utf8")
                     texts.append(f.read())
```

```
else:
                         labels.append(1)
In [12]:
         ## Using 6.9 as an additional reference from Deep Learning with Python code.
         ## Code will Tokenize text of the raw IMDB data.
         maxlen = 100 # We will cut reviews after 100 words
         training samples = 200 # We will be training on 200 samples
         validation samples = 10000 # We will be validating on 10000 samples
         max words = 10000 # We will only consider the top 10,000 words in the dataset
         embedding dim = 100
         tokenizer = Tokenizer(num words=max words)
         tokenizer.fit on texts(texts)
         sequences = tokenizer.texts to sequences(texts)
         word index = tokenizer.word index
         print('Found %s unique tokens.' % len(word index))
         data = pad sequences(sequences, maxlen=maxlen)
         labels = np.asarray(labels)
         print('Shape of data tensor:', data.shape)
         print('Shape of label tensor:', labels.shape)
         # Split the data into a training set and a validation set
         # But first, shuffle the data, since we started from data
         # where sample are ordered (all negative first, then all positive).
         indices = np.arange(data.shape[0])
         np.random.shuffle(indices)
         data = data[indices]
         labels = labels[indices]
         x train = data[:training samples]
         y train = labels[:training samples]
         x val = data[training samples: training samples + validation samples]
         y val = labels[training samples: training samples + validation samples]
        Found 88582 unique tokens.
        Shape of data tensor: (25000, 100)
        Shape of label tensor: (25000,)
In [13]:
         ## Using 6.16 as reference from Deep Learning with Python code.
         ## Code will define the model.
         model = Sequential()
         model.add(Embedding(max_words, embedding dim, input length=maxlen))
         model.add(Flatten())
         model.add(Dense(32, activation='relu'))
         model.add(Dense(1, activation='sigmoid'))
         model.summary()
        WARNING:tensorflow:From C:\Users\jkmey\anaconda3\lib\site-packages\keras\initializers\init
        ializers_v1.py:277: calling RandomUniform.__init__ (from tensorflow.python.ops.init_ops) w
        ith dtype is deprecated and will be removed in a future version.
        Instructions for updating:
```

Call initializer instance with the dtype argument instead of passing it to the constructor

Param #

Output Shape

\_\_\_\_\_\_

f.close()

Model: "sequential"

Layer (type)

if label\_type == 'neg':
 labels.append(0)

```
dense 1 (Dense)
                         (None, 1)
                                           33
     ______
     Total params: 1,320,065
     Trainable params: 1,320,065
     Non-trainable params: 0
In [14]:
      ## Save the summary for this model to the results directory.
      summary file = results dir.joinpath('assignment 10-2 Model Summary.txt')
      with open(summary file, 'w') as f:
         with redirect stdout(f):
           model.summary()
In [15]:
      ## Train and Evaluate the model.
      model.compile(optimizer='rmsprop',
               loss='binary crossentropy',
               metrics=['acc'])
      history = model.fit(x train, y train,
                    epochs=10,
                    batch size=32,
                    validation data=(x val, y val))
      result model file = results dir.joinpath('model 10-2.h5')
      model.save weights(result model file)
     Train on 200 samples, validate on 10000 samples
     WARNING: tensorflow: OMP NUM THREADS is no longer used by the default Keras config. To confi
     gure the number of threads, use tf.config.threading APIs.
     Epoch 1/10
      32/200 [===>.....] - ETA: 0s - loss: 0.6951 - acc: 0.4375
     C:\Users\jkmey\anaconda3\lib\site-packages\keras\engine\training v1.py:2045: UserWarning:
      `Model.state updates` will be removed in a future version. This property should not be use
     d in TensorFlow 2.0, as `updates` are applied automatically.
       updates = self.state updates
     l loss: 0.6940 - val acc: 0.4985
     Epoch 2/10
     l loss: 0.7003 - val acc: 0.4977
     Epoch 3/10
     l loss: 0.7077 - val acc: 0.5038
     Epoch 4/10
     1 loss: 0.7038 - val acc: 0.5086
     Epoch 5/10
     l loss: 0.7089 - val acc: 0.5124
     Epoch 6/10
     l loss: 0.7173 - val acc: 0.5107
     Epoch 7/10
     l loss: 0.7303 - val acc: 0.5075
```

(None, 100, 100)

(None, 10000)

(None, 32)

1000000

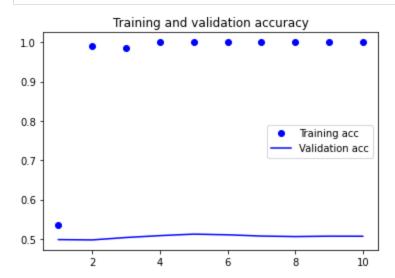
320032

embedding (Embedding)

flatten (Flatten)

dense (Dense)

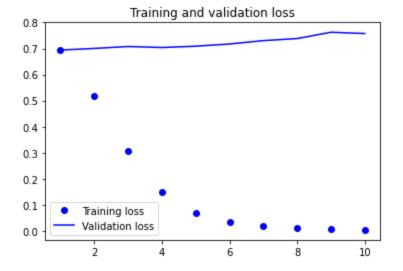
```
Epoch 8/10
       1 loss: 0.7382 - val acc: 0.5062
       Epoch 9/10
       l loss: 0.7624 - val acc: 0.5072
       Epoch 10/10
       200/200 [============= ] - 0s 1ms/sample - loss: 0.0042 - acc: 1.0000 - va
       l loss: 0.7574 - val acc: 0.5070
In [16]:
       result model file = results dir.joinpath('model 10-2.h5')
       model.save weights(result model file)
In [17]:
       ## Plotting the accuracy and results.
       acc = history.history['acc']
       val acc = history.history['val acc']
       loss = history.history['loss']
       val loss = history.history['val loss']
       epochs = range(1, len(acc) + 1)
       plt.plot(epochs, acc, 'bo', label='Training acc')
       plt.plot(epochs, val acc, 'b', label='Validation acc')
       plt.title('Training and validation accuracy')
       plt.legend()
       plt.figure()
       plt.plot(epochs, loss, 'bo', label='Training loss')
```



plt.title('Training and validation loss')

plt.legend()
plt.show()

plt.plot(epochs, val loss, 'b', label='Validation loss')



## Using 6.17 as reference Tokenize the data of the test set.

```
test dir = os.path.join(imdb dir, 'test')
         labels = []
         texts = []
         for label type in ['neg', 'pos']:
             dir name = os.path.join(test dir, label type)
              for fname in sorted(os.listdir(dir name)):
                  if fname[-4:] == '.txt':
                      f = open(os.path.join(dir name, fname), encoding = "utf8")
                      texts.append(f.read())
                      f.close()
                      if label type == 'neg':
                          labels.append(0)
                      else:
                          labels.append(1)
         sequences = tokenizer.texts to sequences(texts)
         x test = pad sequences(sequences, maxlen=maxlen)
         y test = np.asarray(labels)
In [19]:
          ## Load and evaluate the model.
         model.load weights(result model file)
         eval = model.evaluate(x test, y test)
In [20]:
          \#\# Show the x test and y test accuracy results.
         print(eval)
```

### Assignment 10.3

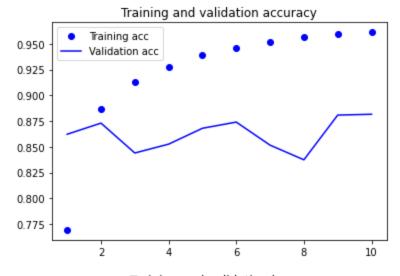
[0.7548423609542847, 0.51572]

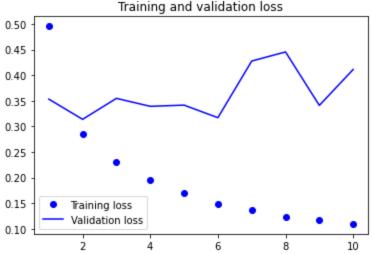
In [18]:

Using listing 6.27 in Deep Learning with Python as a guide, fit the same data with an LSTM layer. Produce the model performance metrics and training and validation accuracy curves within the Jupyter notebook.

```
In [22]: | ## Preprocess the data.
      max features = 10000 # number of words to consider as features
      maxlen = 500 # cut texts after this number of words (among top max features most common v
      batch size = 32
      print('Loading data...')
      (input train, y train), (input test, y test) = imdb.load data(num words=max features)
      print(len(input train), 'train sequences')
      print(len(input test), 'test sequences')
      print('Pad sequences (samples x time)')
      input train = pad sequences(input train, maxlen=maxlen)
      input test = pad sequences(input test, maxlen=maxlen)
      print('input train shape:', input train.shape)
      print('input test shape:', input test.shape)
     Loading data...
     25000 train sequences
     25000 test sequences
     Pad sequences (samples x time)
     input train shape: (25000, 500)
     input test shape: (25000, 500)
In [34]:
      ## Use 6.27 as a referece for code.
      ## Use the LSTM layer in Keras.
      model 2 = Sequential()
      model 2.add(Embedding(max features, 32))
      model 2.add(LSTM(32))
      model 2.add(Dense(1, activation='sigmoid'))
      model 2.compile(optimizer='rmsprop',
               loss='binary_crossentropy',
               metrics=['acc'])
      history 2 = model 2.fit(input train, y train,
                    epochs=10,
                    batch size=128,
                     validation split=0.2)
     Train on 20000 samples, validate on 5000 samples
     Epoch 1/10
     - val loss: 0.3534 - val acc: 0.8622
     - val loss: 0.3139 - val acc: 0.8730
     Epoch 3/10
     - val loss: 0.3548 - val acc: 0.8440
     Epoch 4/10
     - val loss: 0.3393 - val acc: 0.8526
     - val loss: 0.3416 - val acc: 0.8680
     Epoch 6/10
     - val loss: 0.3171 - val acc: 0.8740
     Epoch 7/10
     - val loss: 0.4277 - val acc: 0.8516
     Epoch 8/10
     - val loss: 0.4455 - val acc: 0.8374
     Epoch 9/10
```

```
- val loss: 0.3411 - val acc: 0.8808
       Epoch 10/10
       - val loss: 0.4113 - val acc: 0.8816
In [35]:
       ## Save the summary for this model to the results directory.
        summary file 2 = results dir2.joinpath('assignment 10-3 Model Summary.txt')
        with open(summary file 2, 'w') as f:
           with redirect stdout(f):
               model 2.summary()
In [36]:
       model 2.summary()
       Model: "sequential 2"
                               Output Shape
       Layer (type)
                                                     Param #
       ______
        embedding 2 (Embedding) (None, None, 32)
                                                      320000
        lstm 1 (LSTM)
                               (None, 32)
                                                      8320
                                (None, 1)
        dense 3 (Dense)
                                                       33
       ______
       Total params: 328,353
       Trainable params: 328,353
       Non-trainable params: 0
In [37]:
       result model file 2 = results dir2.joinpath('model 10-3.h5')
        model 2.save weights(result model file 2)
In [38]:
       ## Plotting the accuracy and results.
        acc 2 = history 2.history['acc']
        val acc 2 = history 2.history['val acc']
        loss 2 = history 2.history['loss']
        val loss 2 = history 2.history['val loss']
        epochs = range(1, len(acc) + 1)
        plt.plot(epochs, acc 2, 'bo', label='Training acc')
        plt.plot(epochs, val acc 2, 'b', label='Validation acc')
        plt.title('Training and validation accuracy')
        plt.legend()
        plt.figure()
        plt.plot(epochs, loss 2, 'bo', label='Training loss')
        plt.plot(epochs, val loss 2, 'b', label='Validation loss')
        plt.title('Training and validation loss')
        plt.legend()
        plt.show()
```





```
In [40]: ## Load and evaluate the model_2.
    model_2.load_weights(result_model_file_2)
    eval_2 = model_2.evaluate(x_test, y_test)
In [41]: ## Show the x_test and y_test accuracy results.
    print(eval_2)
[1.780648521823883, 0.52356]
```

### **Assignment 10.4**

print(len(x\_train), 'train sequences')
print(len(x test), 'test sequences')

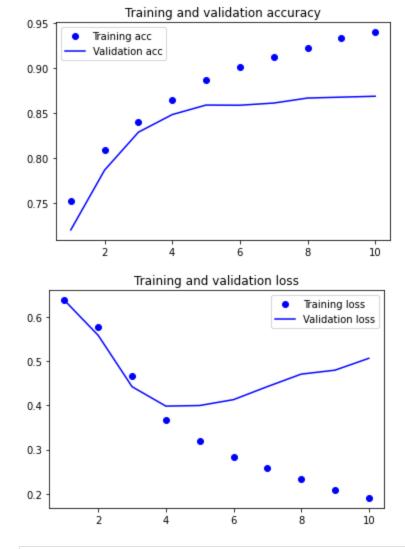
Using listing 6.46 in Deep Learning with Python as a guide, fit the same data with a simple 1D convnet. Produce the model performance metrics and training and validation accuracy curves within the Jupyter notebook.

(x\_train, y\_train), (x\_test, y\_test) = imdb.load data(num words=max features)

```
print('Pad sequences (samples x time)')
        x train = pad sequences(x train, maxlen=max len)
        x test = pad sequences(x test, maxlen=max len)
        print('x train shape:', x train.shape)
        print('x test shape:', x test.shape)
        Loading data...
        25000 train sequences
        25000 test sequences
        Pad sequences (samples x time)
        x train shape: (25000, 500)
        x test shape: (25000, 500)
In [46]:
        ## Use code from 6.46 to Train and Evaluate a Simple 1D Convnet.
        model 3 = Sequential()
        model 3.add(layers.Embedding(max features, 128, input length=max len))
        model 3.add(layers.Conv1D(32, 7, activation='relu'))
        model 3.add(layers.MaxPooling1D(5))
        model 3.add(layers.Conv1D(32, 7, activation='relu'))
        model 3.add(layers.GlobalMaxPooling1D())
        model 3.add(layers.Dense(1))
        model 3.summary()
        model 3.compile(optimizer=RMSprop(lr=1e-4),
                     loss='binary crossentropy',
                     metrics=['acc'])
        history 3 = model.fit(x train, y train,
                           epochs=10,
                           batch size=128,
                           validation split=0.2)
        Model: "sequential 4"
        Layer (type) Output Shape
                                                  Param #
        ______
         embedding 4 (Embedding) (None, 500, 128)
                                                           1280000
        conv1d 2 (Conv1D)
                                 (None, 494, 32)
                                                          28704
        max pooling1d 1 (MaxPooling (None, 98, 32)
```

```
conv1d 3 (Conv1D) (None, 92, 32)
                                7200
global max pooling1d 1 (Glo (None, 32)
balMaxPooling1D)
dense 5 (Dense)
                (None, 1)
                                33
______
Total params: 1,315,937
Trainable params: 1,315,937
Non-trainable params: 0
Train on 20000 samples, validate on 5000 samples
Epoch 1/10
24 - val loss: 0.6372 - val acc: 0.7200
Epoch 2/10
95 - val loss: 0.5578 - val acc: 0.7866
Epoch 3/10
```

```
04 - val loss: 0.4420 - val acc: 0.8288
     Epoch 4/10
     51 - val loss: 0.3982 - val acc: 0.8484
     Epoch 5/10
     65 - val loss: 0.3996 - val acc: 0.8590
     Epoch 6/10
     09 - val loss: 0.4128 - val acc: 0.8588
     Epoch 7/10
     29 - val loss: 0.4422 - val acc: 0.8612
     Epoch 8/10
     22 - val loss: 0.4704 - val acc: 0.8668
     Epoch 9/10
     31 - val loss: 0.4793 - val acc: 0.8678
     Epoch 10/10
     01 - val loss: 0.5061 - val acc: 0.8688
In [47]:
      ## Save the summary for this model to the results directory.
      summary file 3 = results dir3.joinpath('assignment 10-4 Model Summary.txt')
      with open(summary file 3, 'w') as f:
         with redirect stdout(f):
           model 3.summary()
In [48]:
      result model file 3 = results dir3.joinpath('model 10-4.h5')
      model 3.save weights(result model file 3)
In [50]:
      ## Plotting the accuracy and results.
      acc 3 = history 3.history['acc']
      val acc 3 = history 3.history['val acc']
      loss 3 = history 3.history['loss']
      val loss 3 = history 3.history['val loss']
      epochs = range(1, len(acc) + 1)
      plt.plot(epochs, acc 3, 'bo', label='Training acc')
      plt.plot(epochs, val acc 3, 'b', label='Validation acc')
      plt.title('Training and validation accuracy')
      plt.legend()
      plt.figure()
      plt.plot(epochs, loss 3, 'bo', label='Training loss')
      plt.plot(epochs, val loss 3, 'b', label='Validation loss')
      plt.title('Training and validation loss')
      plt.legend()
      plt.show()
```



```
In [51]: ## Load and evaluate the model_3.
model_3.load_weights(result_model_file_3)
eval_3 = model_3.evaluate(x_test, y_test)
```

```
In [52]: ## Show the x_test and y_test accuracy results.
    print(eval_3)
```

[1.3791219604492186, 0.5]