assignment10_FoxAndrea

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```
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Date: 5-16-2021
Course: DSC650 - T301 Big Data
Assignment: Assignment 10
```

0.1 Assignment 10.1

In the first part of the assignment, you will implement basic text-preprocessing functions in I

0.1.1 10.1.a

Create a tokenize function that splits a sentence into words. Ensure that your tokenizer remove

[1]:
```python
def tokenize(sentence):
    #create punctuations variable and loop to remove punctuation from
    #https://www.programiz.com/python-programming/examples/remove-punctuation
    punctuations = '''!()-[]{};:'"\,<>./?@#$%^&*_~'''
    no_punc = ""
    for char in sentence:
        if char not in punctuations:
            no_punc = no_punc + char
    #change case to lower (Sam Loyd called it out in 10.1 chat)
    no_punc = no_punc.lower()
    #create variable to split sentence into separate tokens
    words = no_punc.split()
    return words

sentence = 'All code is guilty, until proven innocent.'
tokens = tokenize(sentence)
print(tokens)
```

```
['all', 'code', 'is', 'guilty', 'until', 'proven', 'innocent']
```

0.1.2 10.1.b

Implement an `ngram` function that splits tokens into N-grams.

[9]:
```python
def ngram(tokens, n):
    #create ngram variable using zip. Found here: https://albertauyeung.github.
↪io/2018/06/03/generating-ngrams.html
```

```
    ngrams = zip(*[tokens[i:] for i in range(n)])
    return [" ".join(ngram) for ngram in ngrams]

n = 4
sentence = 'All code is guilty, until proven innocent.'
ngram(tokens, n)
```

[9]:
```
['all code is guilty',
 'code is guilty until',
 'is guilty until proven',
 'guilty until proven innocent']
```

0.1.3 10.1.c

Implement an one_hot_encode function to create a vector from a numerical vector from a list of

[12]:
```
#load helper library
import numpy as np

#used listing 6.1 from book page - 182 for guidance
def one_hot_encode(tokens, num_words):
    token_index = {}
    for sample in samples:
        for word in sample.split():
            if word not in token_index:
                token_index[word] = len(token_index) + 1
    results = np.zeros(shape = (len(samples), num_words, max(token_index.
 ↪values()) + 1))
    for i, sample in enumerate(samples):
        for j, word in list(enumerate(sample.split()))[ :num_words]:
            index = token_index.get(word)
            results[i, j, index] = 1
    return results

#made the assumption that num_words was the same as max_length
num_words = 10
samples = ['I have a lovely bunch of coconuts.', 'Sally sold seashells by the␣
 ↪seashore.']
one_hot_encode(tokens, num_words)
```

[12]:
```
array([[[0., 1., 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., 1., 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., 1., 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., 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., 1., 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., 1., 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., 1., 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.]]])
```

0.2 10.2

Using listings 6.16, 6.17, and 6.18 in Deep Learning with Python as a guide, train a sequential

[51]:

```
#load libraries
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import numpy as np
import matplotlib.pyplot as plt
import os
from pathlib import Path

#create directories
current_dir = Path(os.getcwd()).absolute()
imdb_dir = Path('/home/jovyan/dsc650/data/external/imdb/aclImdb/')
test_dir = os.path.join(imdb_dir, 'test')
train_dir = os.path.join(imdb_dir, 'train')
```

[45]:

```
#Listing 6.8 - Processing 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 os.listdir(dir_name):
        if fname[-4:] == '.txt':
            f = open(os.path.join(dir_name, fname))
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
```

```
                labels.append(0)
            else:
                labels.append(1)
```

[46]:
```
#Listing 6.9 - Tokenizing the text of the raw IMDB data
maxlen = 100
training_samples = 200
validation_samples = 10000
max_words = 10000

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)

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,)
```

[47]:
```
#Listing 6.10 - Parsing the GloVe word-embeddings file
#Opened website listed in book and downloaded glove.6B.100 then moved to␣
 ↪assignment10 folder
embeddings_index = {}
f = open('glove.6B.100d.txt')
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
```

```python
f.close()

print('Found %s word vectors.' % len(embeddings_index))
```

```
Found 400000 word vectors.
```

[48]:
```python
#Listing 6.11 - Preparing the GloVe word-embeddings matrix
embedding_dim = 100

embedding_matrix = np.zeros((max_words, embedding_dim))
for word, i in word_index.items():
    if i < max_words:
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector

#Listing 6.12 - Model Definition
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()
```

```
Model: "sequential_5"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, 100, 100)          1000000

_________________________________________________________________
flatten_3 (Flatten)          (None, 10000)             0

_________________________________________________________________
dense_6 (Dense)              (None, 32)                320032

_________________________________________________________________
dense_7 (Dense)              (None, 1)                 33
=================================================================
Total params: 1,320,065
Trainable params: 1,320,065
Non-trainable params: 0

_________________________________________________________________
```

[50]:
```python
#Listing 6.13 - Loading pretrained word embeddings into the Embedding layer
model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False

#Listing 6.14 - Training and evaluation
model.compile(optimizer='rmsprop',
```

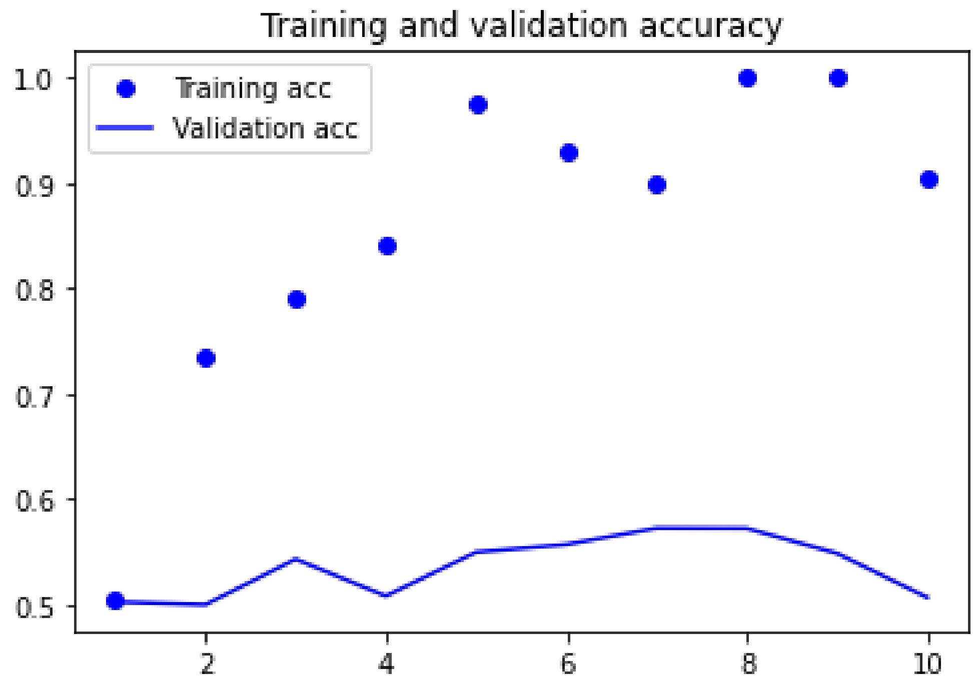
```
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_val, y_val))
model.save_weights('pre_trained_glove_model.h5')
```

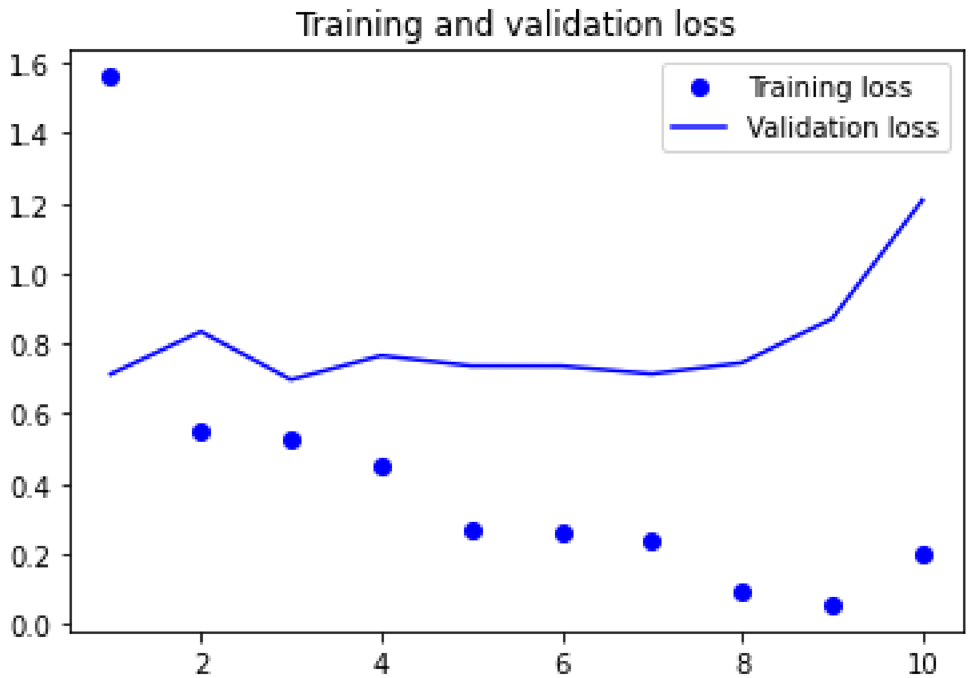
```
Epoch 1/10
7/7 [==============================] - 1s 120ms/step - loss: 1.8968 - acc:
0.4993 - val_loss: 0.7131 - val_acc: 0.5024
Epoch 2/10
7/7 [==============================] - 1s 102ms/step - loss: 0.5673 - acc:
0.7323 - val_loss: 0.8341 - val_acc: 0.4997
Epoch 3/10
7/7 [==============================] - 1s 98ms/step - loss: 0.5884 - acc: 0.7163
- val_loss: 0.6973 - val_acc: 0.5428
Epoch 4/10
7/7 [==============================] - 1s 100ms/step - loss: 0.4380 - acc:
0.8772 - val_loss: 0.7660 - val_acc: 0.5079
Epoch 5/10
7/7 [==============================] - 1s 99ms/step - loss: 0.2808 - acc: 0.9770
- val_loss: 0.7366 - val_acc: 0.5494
Epoch 6/10
7/7 [==============================] - 1s 93ms/step - loss: 0.2493 - acc: 0.9546
- val_loss: 0.7362 - val_acc: 0.5567
Epoch 7/10
7/7 [==============================] - 1s 99ms/step - loss: 0.1945 - acc: 0.9424
- val_loss: 0.7138 - val_acc: 0.5722
Epoch 8/10
7/7 [==============================] - 1s 98ms/step - loss: 0.0985 - acc: 1.0000
- val_loss: 0.7454 - val_acc: 0.5720
Epoch 9/10
7/7 [==============================] - 1s 100ms/step - loss: 0.0556 - acc:
1.0000 - val_loss: 0.8705 - val_acc: 0.5483
Epoch 10/10
7/7 [==============================] - 1s 98ms/step - loss: 0.1279 - acc: 0.9598
- val_loss: 1.2084 - val_acc: 0.5066
```

[52]:

```
#Listing 6.15 - Plotting the 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)
```

```python
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.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[53]:
```
#Listing 6.16 - Training the same model without pretrained word embeddings
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()

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))
```

```
Model: "sequential_6"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_4 (Embedding)      (None, 100, 100)          1000000
_________________________________________________________________
flatten_4 (Flatten)          (None, 10000)             0
_________________________________________________________________
dense_8 (Dense)              (None, 32)                320032
```

```
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 33
=================================================================
Total params: 1,320,065
Trainable params: 1,320,065
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
7/7 [==============================] - 1s 120ms/step - loss: 0.6947 - acc:
0.4768 - val_loss: 0.6923 - val_acc: 0.5206
Epoch 2/10
7/7 [==============================] - 1s 107ms/step - loss: 0.5252 - acc:
0.9963 - val_loss: 0.6937 - val_acc: 0.5233
Epoch 3/10
7/7 [==============================] - 1s 101ms/step - loss: 0.3219 - acc:
0.9894 - val_loss: 0.7089 - val_acc: 0.5154
Epoch 4/10
7/7 [==============================] - 1s 105ms/step - loss: 0.1537 - acc:
1.0000 - val_loss: 0.6970 - val_acc: 0.5317
Epoch 5/10
7/7 [==============================] - 1s 102ms/step - loss: 0.0734 - acc:
1.0000 - val_loss: 0.7063 - val_acc: 0.5315
Epoch 6/10
7/7 [==============================] - 1s 105ms/step - loss: 0.0357 - acc:
1.0000 - val_loss: 0.7119 - val_acc: 0.5324
Epoch 7/10
7/7 [==============================] - 1s 107ms/step - loss: 0.0199 - acc:
1.0000 - val_loss: 0.7096 - val_acc: 0.5371
Epoch 8/10
7/7 [==============================] - 1s 98ms/step - loss: 0.0107 - acc: 1.0000
- val_loss: 0.7170 - val_acc: 0.5370
Epoch 9/10
7/7 [==============================] - 1s 107ms/step - loss: 0.0064 - acc:
1.0000 - val_loss: 0.7224 - val_acc: 0.5403
Epoch 10/10
7/7 [==============================] - 1s 97ms/step - loss: 0.0039 - acc: 1.0000
- val_loss: 0.7311 - val_acc: 0.5405
```

[54]:

```python
#Listing 6.17 - Tokenizing the data of the test set
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))
```

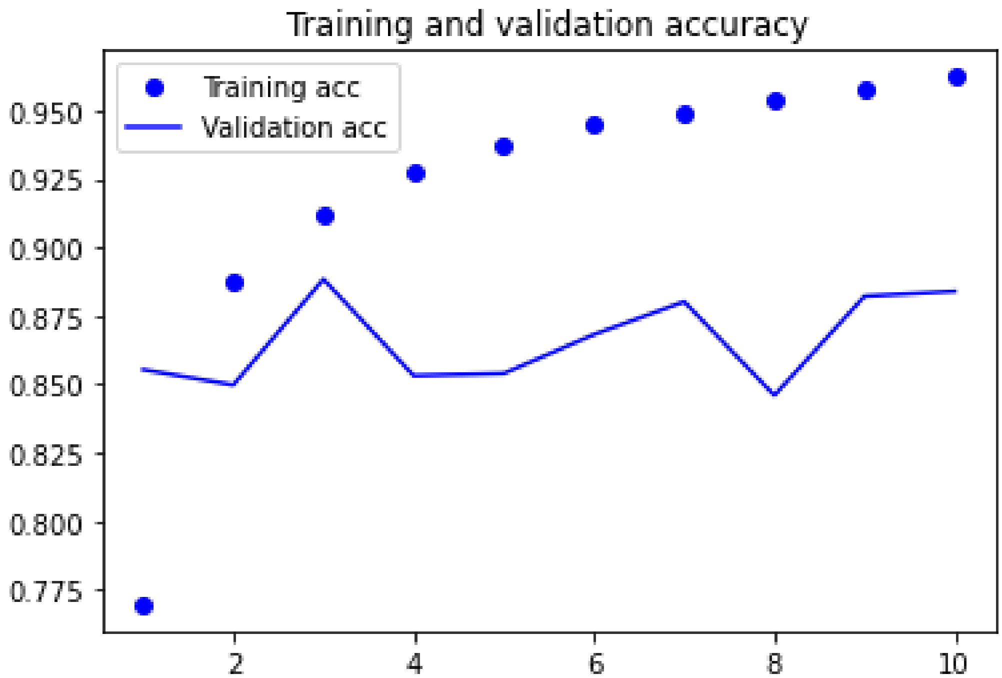
```
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
                labels.append(0)
            else:
                labels.append(1)

sequences = tokenizer.texts_to_sequences(texts)
x_test = pad_sequences(sequences, maxlen=maxlen)
y_test = np.asarray(labels)
```

[55]:
```
#Listing 6.18 - Evaluating the model on the test set
model.load_weights('pre_trained_glove_model.h5')
model.evaluate(x_test, y_test)
```

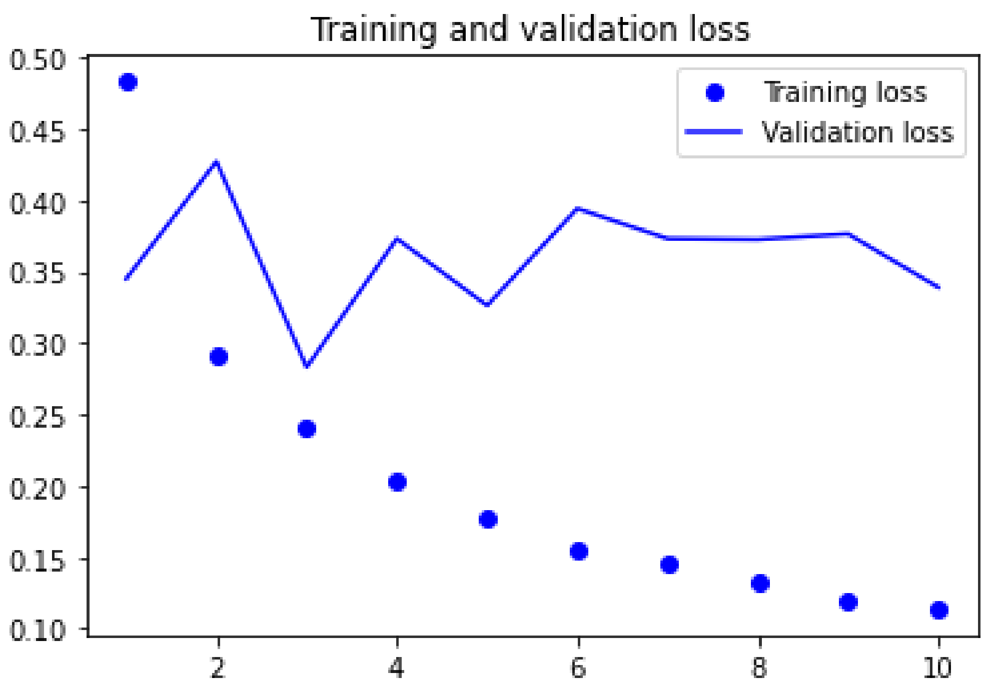
```
782/782 [==============================] - 2s 2ms/step - loss: 1.2161 - acc:
0.5061
```

[55]: [1.2160563468933105, 0.5061200261116028]

[69]:
```
#Plot metrics
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.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```



Training and validation accuracy
Training acc
Validation acc
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.775
2
4
6
8
10



Training and validation loss
Training loss
Validation loss
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
2
4
6
8
10

0.3 10.3

Using listing 6.27 in Deep Learning with Python as a guide, fit the same data with an LSTM laye

[67]:
```
#load libraries
from keras.layers import LSTM
from keras.datasets import imdb
from keras.preprocessing import sequence
from keras.layers import Dense
import matplotlib.pyplot as plt
```

[64]:
```
#Listing 6.22 - Preparing the IMDB data
max_features = 10000
maxlen = 500
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 = sequence.pad_sequences(input_train, maxlen=maxlen)
input_test = sequence.pad_sequences(input_test, maxlen=maxlen)
print('input_train shape:', input_train.shape)
print('input_test shape:', input_test.shape)
```

```
Loading data…
```

```
<__array_function__ internals>:5: VisibleDeprecationWarning: Creating an ndarray
from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or
ndarrays with different lengths or shapes) is deprecated. If you meant to do
this, you must specify 'dtype=object' when creating the ndarray
/opt/conda/lib/python3.8/site-
packages/tensorflow/python/keras/datasets/imdb.py:159:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray
  x_train, y_train = np.array(xs[:idx]), np.array(labels[:idx])
/opt/conda/lib/python3.8/site-
packages/tensorflow/python/keras/datasets/imdb.py:160:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray
  x_test, y_test = np.array(xs[idx:]), np.array(labels[idx:])
```

```
25000 train sequences
25000 test sequences
Pad sequences (samples x time)
input_train shape: (25000, 500)
input_test shape: (25000, 500)
```

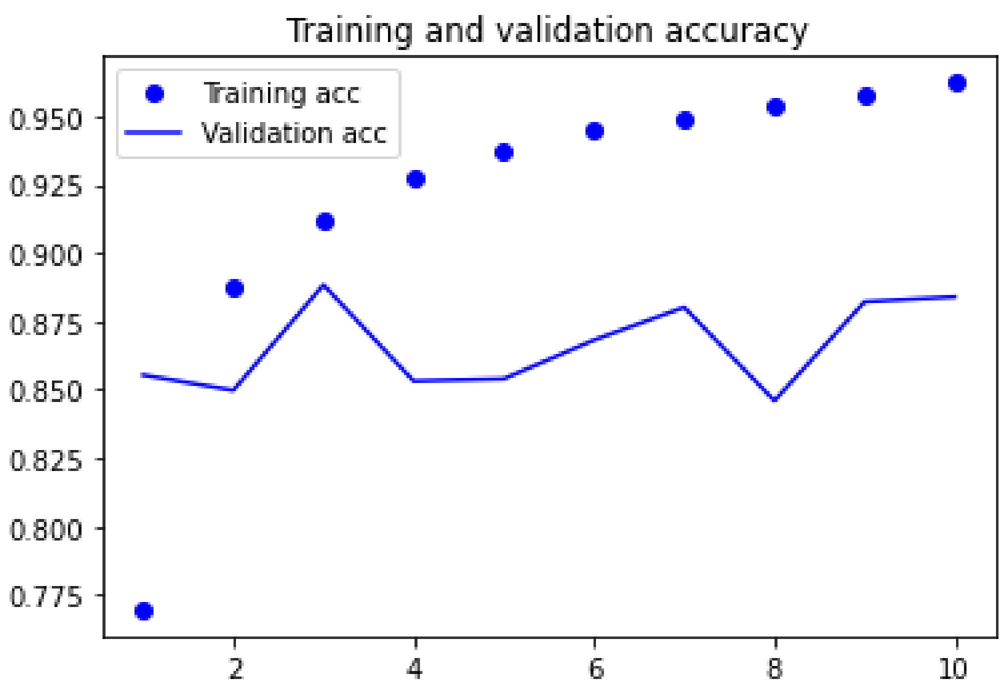
[66]:

```
#Listing 6.27 - Using the LSTM layer in Keras
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(input_train, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_split=0.2)
```

```
Epoch 1/10
157/157 [==============================] - 65s 405ms/step - loss: 0.5842 - acc:
0.6786 - val_loss: 0.3451 - val_acc: 0.8554
Epoch 2/10
157/157 [==============================] - 61s 389ms/step - loss: 0.2969 - acc:
0.8868 - val_loss: 0.4273 - val_acc: 0.8498
Epoch 3/10
157/157 [==============================] - 61s 386ms/step - loss: 0.2437 - acc:
0.9110 - val_loss: 0.2832 - val_acc: 0.8884
Epoch 4/10
157/157 [==============================] - 61s 389ms/step - loss: 0.1961 - acc:
0.9318 - val_loss: 0.3733 - val_acc: 0.8532
Epoch 5/10
157/157 [==============================] - 60s 384ms/step - loss: 0.1720 - acc:
0.9409 - val_loss: 0.3264 - val_acc: 0.8540
Epoch 6/10
157/157 [==============================] - 60s 382ms/step - loss: 0.1488 - acc:
0.9495 - val_loss: 0.3944 - val_acc: 0.8682
Epoch 7/10
157/157 [==============================] - 61s 386ms/step - loss: 0.1351 - acc:
0.9531 - val_loss: 0.3732 - val_acc: 0.8802
Epoch 8/10
157/157 [==============================] - 60s 382ms/step - loss: 0.1222 - acc:
0.9591 - val_loss: 0.3727 - val_acc: 0.8460
Epoch 9/10
157/157 [==============================] - 59s 378ms/step - loss: 0.1153 - acc:
0.9592 - val_loss: 0.3766 - val_acc: 0.8822
Epoch 10/10
```

```
157/157 [==============================] - 61s 386ms/step - loss: 0.1053 - acc:
0.9665 - val_loss: 0.3392 - val_acc: 0.8840
```

[68]:
```python
#Plotting metrics
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.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```



0.4 10.4

Using listing 6.46 in Deep Learning with Python as a guide, fit the same data with a simple 1D

[73]:
```
#load libraries
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop
from keras.datasets import imdb
from keras.preprocessing import sequence
```

[72]:
```
#Listing 6.45 - Preparing the IMDB data
max_features = 10000
max_len = 500

print('Loading data...')
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
print(len(x_train), 'train sequences')
print(len(x_test), 'test sequences')

print('Pad sequences (samples x time)')
x_train = sequence.pad_sequences(x_train, maxlen=max_len)
x_test = sequence.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)
```

[74]:

```
#Listing 6.46 - Training and evaluating a simple 1D convnet on the IMDB data
model = Sequential()
model.add(layers.Embedding(max_features, 128, input_length=max_len))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.MaxPooling1D(5))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(1))

model.summary()

model.compile(optimizer=RMSprop(lr=1e-4),
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_split=0.2)
```

```
Model: "sequential_13"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_10 (Embedding)     (None, 500, 128)          1280000
_________________________________________________________________
conv1d (Conv1D)              (None, 494, 32)           28704
_________________________________________________________________
max_pooling1d (MaxPooling1D) (None, 98, 32)            0
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 92, 32)            7200
_________________________________________________________________
global_max_pooling1d (Global (None, 32)                0
_________________________________________________________________
dense_15 (Dense)             (None, 1)                 33
=================================================================
Total params: 1,315,937
Trainable params: 1,315,937
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
157/157 [==============================] - 11s 66ms/step - loss: 2.9626 - acc:
```

```
0.4982 - val_loss: 0.6926 - val_acc: 0.5222
Epoch 2/10
157/157 [==============================] - 10s 63ms/step - loss: 0.6837 - acc:
0.5844 - val_loss: 0.6717 - val_acc: 0.6602
Epoch 3/10
157/157 [==============================] - 10s 65ms/step - loss: 0.6479 - acc:
0.7507 - val_loss: 0.6309 - val_acc: 0.7336
Epoch 4/10
157/157 [==============================] - 10s 64ms/step - loss: 0.5842 - acc:
0.8148 - val_loss: 0.5244 - val_acc: 0.7996
Epoch 5/10
157/157 [==============================] - 10s 66ms/step - loss: 0.4634 - acc:
0.8435 - val_loss: 0.4473 - val_acc: 0.8244
Epoch 6/10
157/157 [==============================] - 10s 66ms/step - loss: 0.3678 - acc:
0.8679 - val_loss: 0.4094 - val_acc: 0.8456
Epoch 7/10
157/157 [==============================] - 10s 65ms/step - loss: 0.3116 - acc:
0.8895 - val_loss: 0.4022 - val_acc: 0.8530
Epoch 8/10
157/157 [==============================] - 10s 65ms/step - loss: 0.2786 - acc:
0.9009 - val_loss: 0.3938 - val_acc: 0.8598
Epoch 9/10
157/157 [==============================] - 10s 65ms/step - loss: 0.2441 - acc:
0.9167 - val_loss: 0.4128 - val_acc: 0.8664
Epoch 10/10
157/157 [==============================] - 10s 65ms/step - loss: 0.2268 - acc:
0.9245 - val_loss: 0.4265 - val_acc: 0.8720
```

[75]:
```python
#Plotting the data
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.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
```

```
plt.legend()

plt.show()
```