assignment10_DavisAmie

February 9, 2021

1 File information

File: Assignment_10.ipynb

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Date: 2/9/2021

Course: DSC650 - Big Data

Assignment Number: 10,1, 10.2, 10.3

Purpose: - Transform text input into tokens and convert those tokens into numeric vectors using one-hot encoding and feature hashing. - Build basic text-processing models using recurrent neural networks (RNN) - Understand how word embeddings such as Word2Vec can help improve the performance of text-processing models

2 References:

Bengfort, B., Bilbro, R., & Ojeda, T. (2018). Applied Text Analysis with Python: Enabling Language Aware Data Products with Machine Learning. Sebastopol, CA: OReilly Media, Incorporated.

Chollet, F. (2018). Deep learning with Python. Shelter Island, NY: Manning Publications.

https://keras.io/api/datasets/imdb/

3 Assignment 10.1

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.

3.1 Assignment 10.1a

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

[1]:
```
import sys, unicodedata
def tokenize(sentence):

    # Create a dictionary of punctuation characters
    punctuation = dict.fromkeys(i for i in range(sys.maxunicode)
```

```
                                          if unicodedata.category(chr(i)).startswith('P'))

    # Remove punctuation characters
    sentence = sentence.translate(punctuation)

    # Change to lowercase
    sentence = sentence.lower()

    tokens = []
    # tokenize the sentence
    for word in sentence.split():
        tokens.append(word)

    return tokens

#Test function
tokenize('Create a tokenize function that splits a sentence into words. Ensure␣
 ↪that your tokenizer removes basic punctuation.')
```

[1]:
```
['create',
 'a',
 'tokenize',
 'function',
 'that',
 'splits',
 'a',
 'sentence',
 'into',
 'words',
 'ensure',
 'that',
 'your',
 'tokenizer',
 'removes',
 'basic',
 'punctuation']
```

3.2 Assignment 10.1b

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

[2]:
```
def ngram(tokens, n):

    ngrams = []
    # Create ngrams
    for idx in range(len(tokens)-n+1):
        ngrams.append(tokens[idx:idx+n])
```

```
    return ngrams

# Test function
ngram(['create','a','tokenize','function','that','splits','a','sentence','into','words'],␣
↪5)
```

[2]:
```
[['create', 'a', 'tokenize', 'function', 'that'],
 ['a', 'tokenize', 'function', 'that', 'splits'],
 ['tokenize', 'function', 'that', 'splits', 'a'],
 ['function', 'that', 'splits', 'a', 'sentence'],
 ['that', 'splits', 'a', 'sentence', 'into'],
 ['splits', 'a', 'sentence', 'into', 'words']]
```

3.3 Assignment 10.1c

Implement a one_hot_encode function to create a vector from a numerical vector from a list of tokens.

[3]:
```
import numpy as np
def one_hot_encode(tokens, num_words):

    token_index = {}
    results = ''

    for token in tokens:

        # Assign unique index to each unique token
        if token not in token_index:
            token_index[token] = len(token_index) + 1

    # Initialize vector of zeros
    results = np.zeros(shape=(
                        len(tokens),
#                        num_words,
                        max(token_index.values()) + 1))    # Vectorized tokens

    for i, token in enumerate(tokens):
        index = token_index.get(token)
        results[i, index] = 1.
#        print(i,token)

    return results

# Test function
one_hot_encode(['create','a','tokenize','function','that','splits','a','sentence','into','word
↪3)
```

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

4 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.

```
[4]: # Process the labels of the raw IMDB data
# The Keras imdb dataset is represented by integers
# Need to download dataset to set strings
import os

imdb_dir = 'aclImdb'
train_dir = os.path.join(imdb_dir, 'train')

labels = []
texts = []

# Negative reviews are stored in the neg subdirectory
# Positive reviews are stored in the pos subdirectory
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), encoding="utf8")
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
                labels.append(0)
            else:
                labels.append(1)
```

```
[5]: # Tokenize the text of the raw IMDB data
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import numpy as np
```

```python
maxlen = 100    # Cuts off reviews after 100 words
max_words = 10000    # Considers only the top 10,000 words in the dataset

# Split 10,000 training reviews into training and validation samples (70/30)
training_samples = int(10000 * 0.7)
validation_samples = int(10000 * 0.3)

# Creates vocabulary index based on word frequency
tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(texts)
sequences = tokenizer.texts_to_sequences(texts)

# Transforms to a sequence of integers
word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))

# Pad data since all sequences in a batch must have the same length
data = pad_sequences(sequences, maxlen=maxlen)

labels = np.asarray(labels)
print('Shape of data tensor:', data.shape)
print('Shape of label tensor:', labels.shape)

# Shuffle data before splitting dataset
indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

# Split into train/validation datasets
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]
```

```
Using TensorFlow backend.
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorflow\python\framework\dtypes.py:516: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorflow\python\framework\dtypes.py:517: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\amomu\Anaconda3\lib\site-
```

```
packages\tensorflow\python\framework\dtypes.py:518: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorflow\python\framework\dtypes.py:519: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorflow\python\framework\dtypes.py:520: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorflow\python\framework\dtypes.py:525: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:541: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:542: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:543: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:544: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:545: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\amomu\Anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:550: FutureWarning:
Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future
version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
```

```
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 100)
Shape of label tensor: (25000,)
```

[6]:

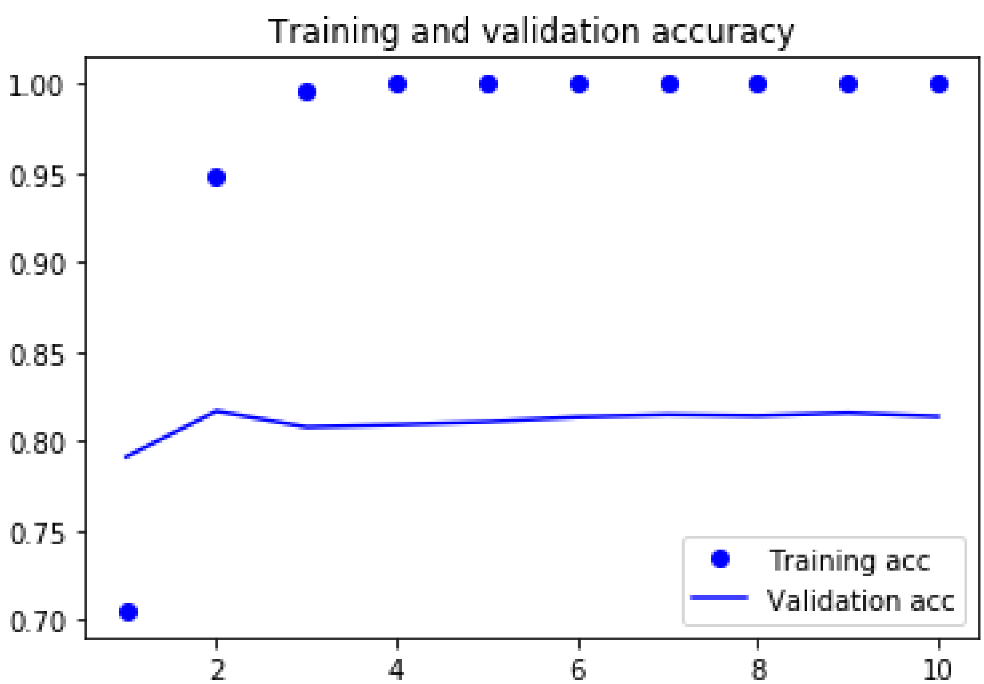
```python
# Train model without pretrained word embeddings
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

embedding_dim = 100

# Instantiate model
model = Sequential()

# Add embedding layer to vectorize words
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))

# Flattens 3D embedded tensor into 2D tensor
model.add(Flatten())

# Binary Classifier Model
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

# Review layers
model.summary()

# Compile and fit 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))
```

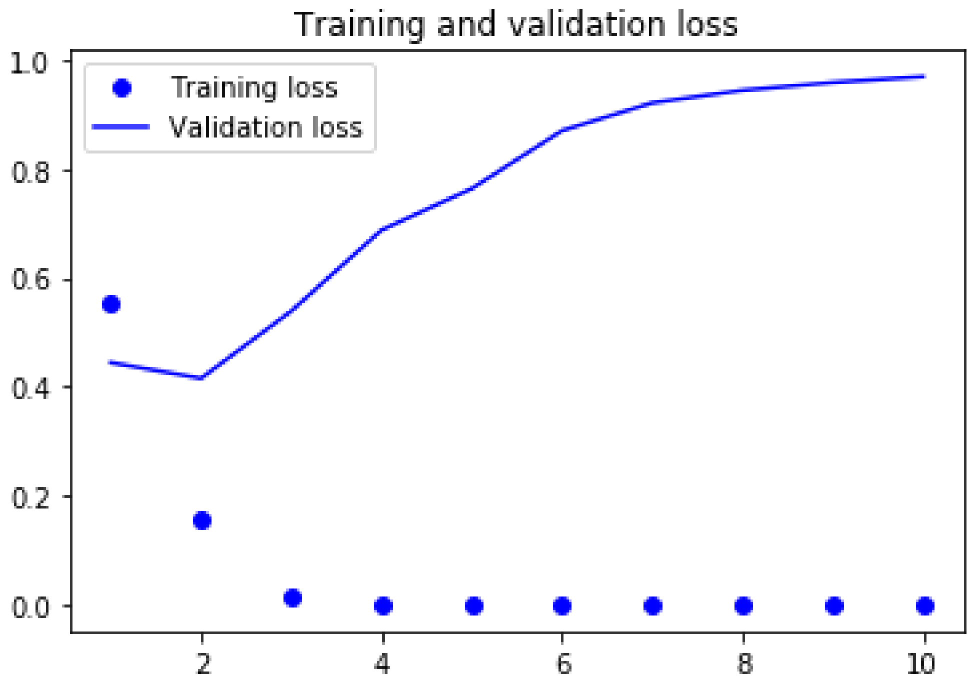
```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 100, 100)          1000000
_________________________________________________________________
flatten_1 (Flatten)          (None, 10000)             0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                320032
_________________________________________________________________
```

```
dense_2 (Dense)              (None, 1)                 33
=================================================================
Total params: 1,320,065
Trainable params: 1,320,065
Non-trainable params: 0
_________________________________________________________________
WARNING:tensorflow:From C:\Users\amomu\Anaconda3\lib\site-
packages\tensorflow\python\ops\nn_impl.py:180:
add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From C:\Users\amomu\Anaconda3\lib\site-
packages\keras\backend\tensorflow_backend.py:422: The name tf.global_variables
is deprecated. Please use tf.compat.v1.global_variables instead.

Train on 7000 samples, validate on 3000 samples
Epoch 1/10
7000/7000 [==============================] - 4s 564us/step - loss: 0.5555 - acc:
0.7049 - val_loss: 0.4442 - val_acc: 0.7910
Epoch 2/10
7000/7000 [==============================] - 4s 547us/step - loss: 0.1561 - acc:
0.9474 - val_loss: 0.4152 - val_acc: 0.8167
Epoch 3/10
7000/7000 [==============================] - 4s 544us/step - loss: 0.0151 - acc:
0.9964 - val_loss: 0.5390 - val_acc: 0.8077
Epoch 4/10
7000/7000 [==============================] - 4s 542us/step - loss: 5.5530e-04 -
acc: 0.9999 - val_loss: 0.6875 - val_acc: 0.8090
Epoch 5/10
7000/7000 [==============================] - 4s 544us/step - loss: 7.7617e-05 -
acc: 1.0000 - val_loss: 0.7638 - val_acc: 0.8107
Epoch 6/10
7000/7000 [==============================] - 4s 555us/step - loss: 1.0333e-06 -
acc: 1.0000 - val_loss: 0.8703 - val_acc: 0.8133
Epoch 7/10
7000/7000 [==============================] - 4s 543us/step - loss: 3.5361e-08 -
acc: 1.0000 - val_loss: 0.9213 - val_acc: 0.8147
Epoch 8/10
7000/7000 [==============================] - 4s 544us/step - loss: 1.1185e-08 -
acc: 1.0000 - val_loss: 0.9444 - val_acc: 0.8140
Epoch 9/10
7000/7000 [==============================] - 4s 544us/step - loss: 7.6962e-09 -
acc: 1.0000 - val_loss: 0.9587 - val_acc: 0.8157
Epoch 10/10
7000/7000 [==============================] - 4s 561us/step - loss: 6.0453e-09 -
acc: 1.0000 - val_loss: 0.9695 - val_acc: 0.8137
```

[7]:

```python
# Plot results
import matplotlib.pyplot as plt

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()
```





A lot of loss on the valdation training set. Accuracy peaks with 4 epochs.

[8]:
```
# Re-run w/ 4 epochs
history = model.fit(x_train, y_train,
                    epochs=4,
                    batch_size=32,
                    validation_data=(x_val, y_val))
```

```
Train on 7000 samples, validate on 3000 samples
Epoch 1/4
7000/7000 [==============================] - 4s 540us/step - loss: 5.1521e-09 -
acc: 1.0000 - val_loss: 0.9779 - val_acc: 0.8133
Epoch 2/4
7000/7000 [==============================] - 4s 545us/step - loss: 4.7075e-09 -
acc: 1.0000 - val_loss: 0.9860 - val_acc: 0.8137
Epoch 3/4
7000/7000 [==============================] - 4s 542us/step - loss: 4.4786e-09 -
acc: 1.0000 - val_loss: 0.9934 - val_acc: 0.8113
Epoch 4/4
7000/7000 [==============================] - 4s 556us/step - loss: 4.3210e-09 -
acc: 1.0000 - val_loss: 0.9983 - val_acc: 0.8113
```

[9]:
```
# Prepare test data
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)
```

[10]:
```
# Evaluate the model on the test set
model.evaluate(x_test, y_test)
```

```
25000/25000 [==============================] - 1s 57us/step
```

[10]:
```
[1.0145229630964994, 0.8131999969482422]
```

81% accuracy, not bad. When originally trainined on the full 25,000 dataset, model was more overfit and only 50% accuracte on validation and test sets.

5 Assignment 10.3

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.

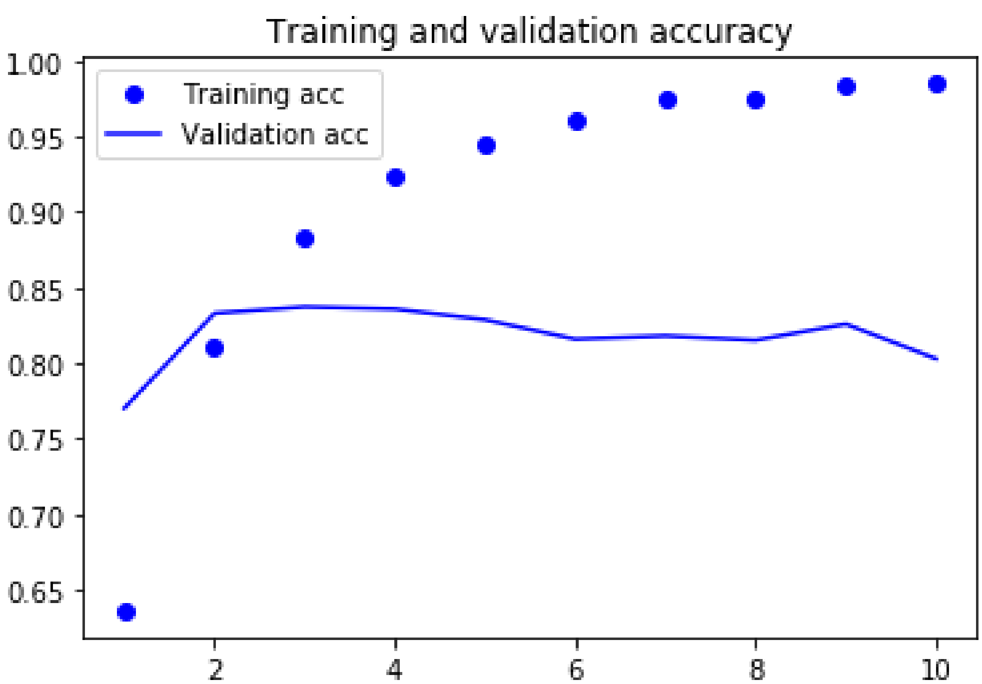
[11]:
```
# Fit the same data with an LSTM layer
from keras.layers import LSTM

# Instantiate model
model = Sequential()

# Add embedding layer to vectorize words
model.add(Embedding(max_words, 32))

# Add LSTM RNN layer
model.add(LSTM(32))
```

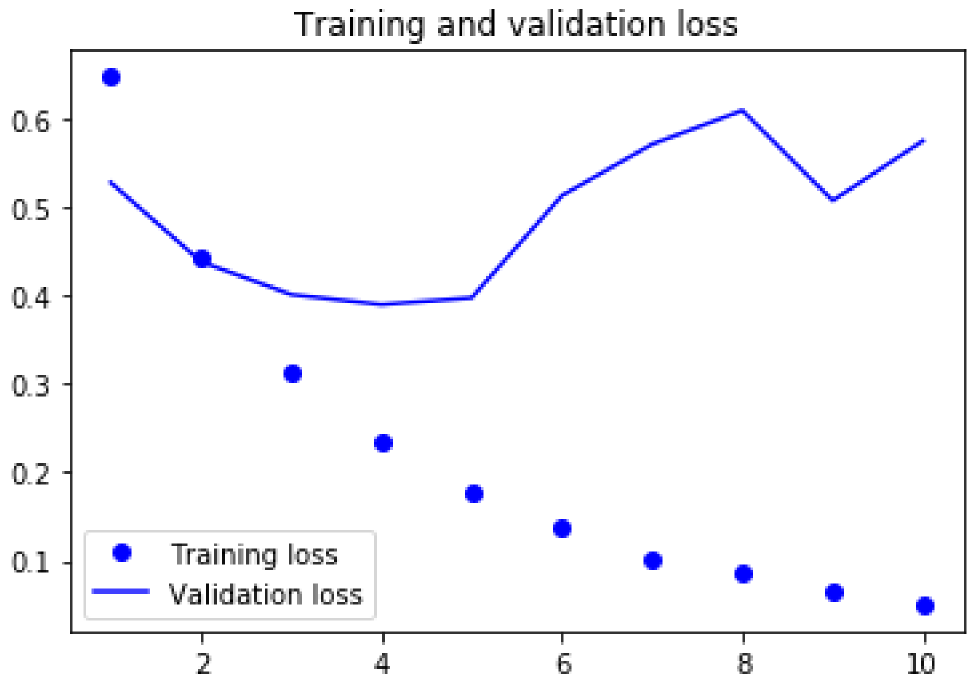
```python
# Binary Classifier Model
model.add(Dense(1, activation='sigmoid'))

# Compile and fit model
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])

# Splits previous training set into 80/20 for validation
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_split=0.2)
```

```
Train on 5600 samples, validate on 1400 samples
Epoch 1/10
5600/5600 [==============================] - 5s 931us/step - loss: 0.6474 - acc:
0.6361 - val_loss: 0.5278 - val_acc: 0.7700
Epoch 2/10
5600/5600 [==============================] - 5s 847us/step - loss: 0.4441 - acc:
0.8100 - val_loss: 0.4380 - val_acc: 0.8329
Epoch 3/10
5600/5600 [==============================] - 5s 854us/step - loss: 0.3120 - acc:
0.8823 - val_loss: 0.4010 - val_acc: 0.8371
Epoch 4/10
5600/5600 [==============================] - 5s 851us/step - loss: 0.2339 - acc:
0.9230 - val_loss: 0.3898 - val_acc: 0.8357
Epoch 5/10
5600/5600 [==============================] - 5s 817us/step - loss: 0.1767 - acc:
0.9450 - val_loss: 0.3974 - val_acc: 0.8286
Epoch 6/10
5600/5600 [==============================] - 5s 862us/step - loss: 0.1366 - acc:
0.9602 - val_loss: 0.5131 - val_acc: 0.8157
Epoch 7/10
5600/5600 [==============================] - 5s 857us/step - loss: 0.1013 - acc:
0.9746 - val_loss: 0.5710 - val_acc: 0.8179
Epoch 8/10
5600/5600 [==============================] - 5s 835us/step - loss: 0.0859 - acc:
0.9757 - val_loss: 0.6091 - val_acc: 0.8150
Epoch 9/10
5600/5600 [==============================] - 5s 845us/step - loss: 0.0659 - acc:
0.9832 - val_loss: 0.5074 - val_acc: 0.8257
Epoch 10/10
5600/5600 [==============================] - 5s 850us/step - loss: 0.0507 - acc:
0.9850 - val_loss: 0.5748 - val_acc: 0.8029
```

[12]:

```python
# Plot results
import matplotlib.pyplot as plt

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()
```





Overfit again!

[13]:
```
# Evaluate the model on the test set
model.evaluate(x_test, y_test)
```

```
25000/25000 [==============================] - 13s 522us/step
```

[13]:
```
[0.5954227439522743, 0.7846400141716003]
```

With the LSTM layer, the accuracy is still around 80%, at 78%.

6 Assignment 10.4

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.

[15]:
```
# Fit the same data with a simple 1D convnet on the IMDB data
from keras import layers
from keras.optimizers import RMSprop

# Instantiate model
model = Sequential()

# Add embedding layer to vectorize words
```

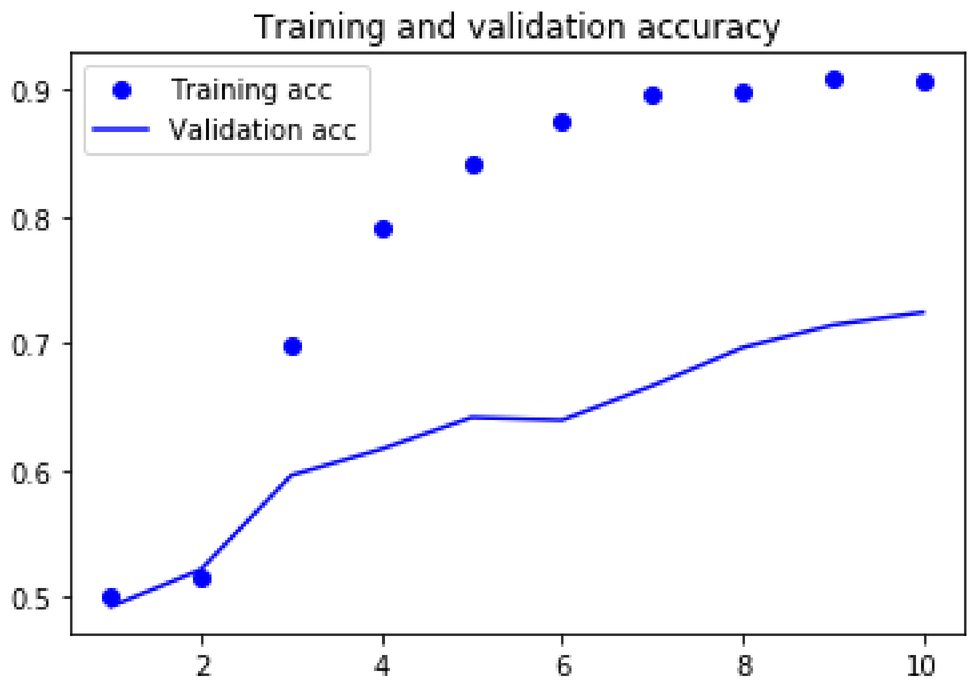
```python
model.add(layers.Embedding(max_words, 128, input_length=maxlen))

# Add 1D Conv RNN layer
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())

# Binary Classifier Model
model.add(layers.Dense(1))

# Review layers
model.summary()

# Compile and fit model
model.compile(optimizer=RMSprop(lr=1e-4),
              loss='binary_crossentropy',
              metrics=['acc'])

# Splits previous training set into 80/20 for validation
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_split=0.2)
```

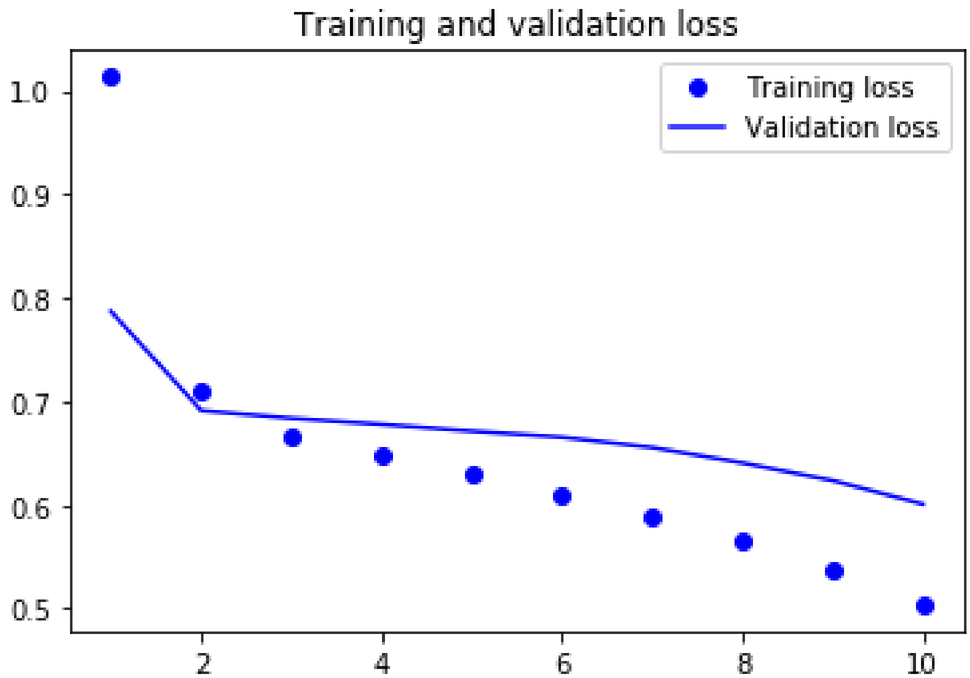
```
WARNING:tensorflow:From C:\Users\amomu\Anaconda3\lib\site-
packages\keras\backend\tensorflow_backend.py:4070: The name tf.nn.max_pool is
deprecated. Please use tf.nn.max_pool2d instead.

Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, 100, 128)          1280000
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 94, 32)            28704
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 18, 32)            0
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 12, 32)            7200
_________________________________________________________________
global_max_pooling1d_1 (Glob (None, 32)                0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 33
=================================================================
Total params: 1,315,937
Trainable params: 1,315,937
```

```
Non-trainable params: 0
_________________________________________________________________
Train on 5600 samples, validate on 1400 samples
Epoch 1/10
5600/5600 [==============================] - 3s 511us/step - loss: 1.0136 - acc:
0.5000 - val_loss: 0.7872 - val_acc: 0.4921
Epoch 2/10
5600/5600 [==============================] - 3s 471us/step - loss: 0.7089 - acc:
0.5157 - val_loss: 0.6913 - val_acc: 0.5214
Epoch 3/10
5600/5600 [==============================] - 3s 498us/step - loss: 0.6673 - acc:
0.6986 - val_loss: 0.6838 - val_acc: 0.5957
Epoch 4/10
5600/5600 [==============================] - 3s 460us/step - loss: 0.6484 - acc:
0.7920 - val_loss: 0.6779 - val_acc: 0.6164
Epoch 5/10
5600/5600 [==============================] - 3s 474us/step - loss: 0.6293 - acc:
0.8409 - val_loss: 0.6714 - val_acc: 0.6414
Epoch 6/10
5600/5600 [==============================] - 3s 466us/step - loss: 0.6099 - acc:
0.8743 - val_loss: 0.6655 - val_acc: 0.6393
Epoch 7/10
5600/5600 [==============================] - 3s 453us/step - loss: 0.5888 - acc:
0.8971 - val_loss: 0.6556 - val_acc: 0.6664
Epoch 8/10
5600/5600 [==============================] - 3s 460us/step - loss: 0.5645 - acc:
0.8982 - val_loss: 0.6407 - val_acc: 0.6964
Epoch 9/10
5600/5600 [==============================] - 3s 457us/step - loss: 0.5370 - acc:
0.9084 - val_loss: 0.6236 - val_acc: 0.7143
Epoch 10/10
5600/5600 [==============================] - 3s 456us/step - loss: 0.5039 - acc:
0.9062 - val_loss: 0.6008 - val_acc: 0.7243
```

[16]:
```python
# Plot results
import matplotlib.pyplot as plt

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()
```





[17]:
```
# Evaluate the model on the test set
model.evaluate(x_test, y_test)
```

```
25000/25000 [==============================] - 3s 119us/step
```

[17]:
```
[0.6050236287117005, 0.7178000211715698]
```

With the 1D convnet, accuracy is a little lower at 71%, but processing time was much faster.