assignment-4-text-and-sequence

May 6, 2024

Assignment 4**

Gayathri Yenigalla Harshith Reddy Suram

Text and sequence

Two required parameters are passed to Keras while initializing the Embedding layer: the greatest word index in the dataset plus one, which is the usual definition of the number of potential tokens. The size of the embedding vectors is represented by the dimensionality of the embeddings. For example, you may create an Embedding layer with 1000 potential tokens and 64 dimensions by doing the following:

[5]:
```
from keras.layers import Embedding
embedding_layer = Embedding(1000, 64)
```

[6]:
```
from keras.models import Sequential
from keras.layers import Flatten, Dense
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.callbacks import ModelCheckpoint
from keras.models import Sequential
from keras.layers import Flatten, Dense, Embedding, LSTM,  Conv1D,␣
↪MaxPooling1D, GlobalMaxPooling1D, Dropout
from keras.models import load_model
from keras.preprocessing.text import Tokenizer
from sklearn.model_selection import train_test_split
from keras.optimizers import RMSprop
from google.colab import files
import re, os
from keras.datasets import imdb
from keras import preprocessing
from keras.utils import pad_sequences
```

Model 1 From Scratch

[7]:
```python
# The number of terms considered to be qualities
max_features = 10000
#Delete texts with 150 words or less.
maxlen = 150
# Load the data as lists of integers.
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
#preprocessing.sequence.pad_sequences
x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)
```

[8]:
```python
model = Sequential()

# We set the maximum input length for our Embedding layer.
# in order to subsequently flatten the embedded inputs

model.add(Embedding(10000, 8, input_length=maxlen))

# The 3D tensor of embeddings is flattened.
# into a 2D tensor of shape `(samples, maxlen * 8)`
model.add(Flatten())

# The classifier is added on top.
model.add(Dense(1, activation='sigmoid'))

#assembling the model
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model.summary()

history_1 = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

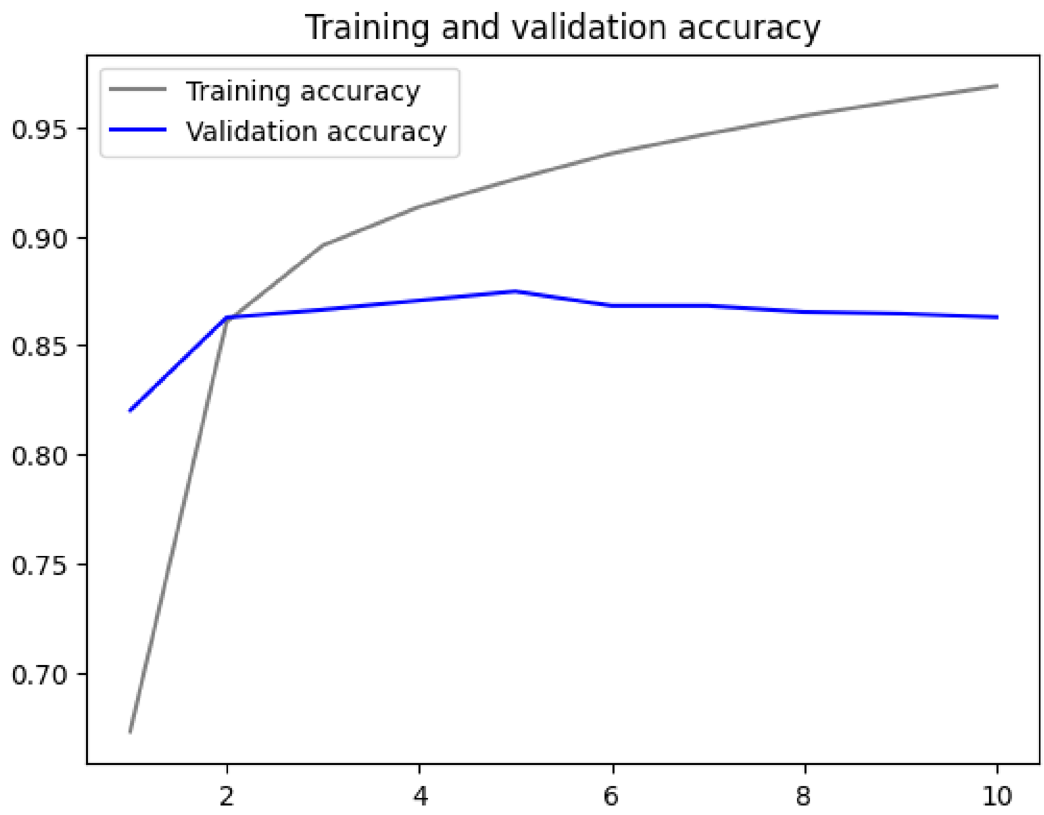
```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_3 (Embedding)     (None, 150, 8)            80000

 flatten_1 (Flatten)         (None, 1200)              0

 dense_1 (Dense)             (None, 1)                 1201

=================================================================
Total params: 81201 (317.19 KB)
Trainable params: 81201 (317.19 KB)
Non-trainable params: 0 (0.00 Byte)
```

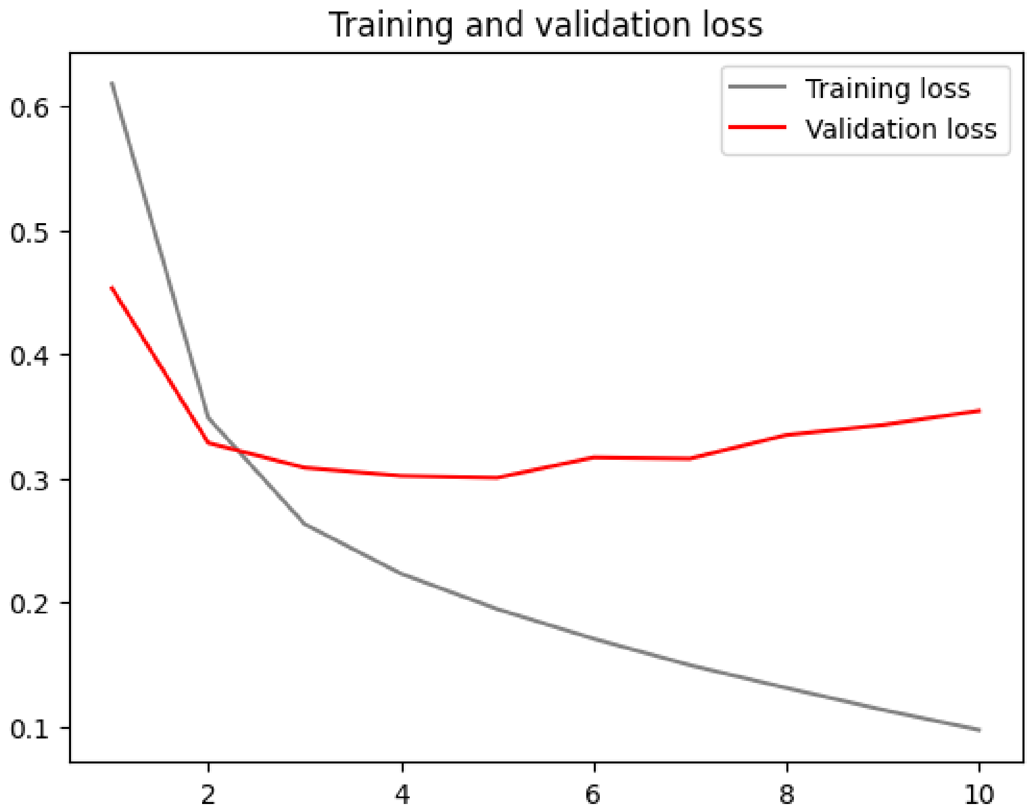
```
-----------------------------------------------------------------
Epoch 1/10
625/625 [==============================] - 18s 28ms/step - loss: 0.6181 - acc:
0.6727 - val_loss: 0.4532 - val_acc: 0.8200
Epoch 2/10
625/625 [==============================] - 5s 8ms/step - loss: 0.3487 - acc:
0.8605 - val_loss: 0.3284 - val_acc: 0.8626
Epoch 3/10
625/625 [==============================] - 4s 6ms/step - loss: 0.2630 - acc:
0.8957 - val_loss: 0.3085 - val_acc: 0.8662
Epoch 4/10
625/625 [==============================] - 4s 6ms/step - loss: 0.2230 - acc:
0.9133 - val_loss: 0.3019 - val_acc: 0.8704
Epoch 5/10
625/625 [==============================] - 3s 6ms/step - loss: 0.1945 - acc:
0.9261 - val_loss: 0.3004 - val_acc: 0.8746
Epoch 6/10
625/625 [==============================] - 3s 5ms/step - loss: 0.1705 - acc:
0.9378 - val_loss: 0.3168 - val_acc: 0.8680
Epoch 7/10
625/625 [==============================] - 3s 4ms/step - loss: 0.1493 - acc:
0.9468 - val_loss: 0.3158 - val_acc: 0.8680
Epoch 8/10
625/625 [==============================] - 4s 6ms/step - loss: 0.1309 - acc:
0.9552 - val_loss: 0.3348 - val_acc: 0.8652
Epoch 9/10
625/625 [==============================] - 3s 5ms/step - loss: 0.1133 - acc:
0.9621 - val_loss: 0.3430 - val_acc: 0.8644
Epoch 10/10
625/625 [==============================] - 2s 4ms/step - loss: 0.0971 - acc:
0.9688 - val_loss: 0.3543 - val_acc: 0.8628
```

This plots training and validation accuracy along with training and validation loss using matplotlib. The first plot shows accuracy, where grey represents training accuracy and blue represents validation accuracy. The second plot displays loss, with grey for training and red for validation.

[9]:
```python
import matplotlib.pyplot as plt

accuracy = history_1.history['acc']
val_accuracy = history_1.history['val_acc']
loss = history_1.history['loss']
val_loss = history_1.history['val_loss']

epochs = range(1, len(accuracy) + 1)

plt.plot(epochs, accuracy, 'grey', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
```

```
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'grey', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[10]:
```
test_loss, test_acc = model.evaluate(x_test, y_test)
print('Test loss:', test_loss)
print('Test accuracy:', test_acc)
```

```
782/782 [==============================] - 2s 3ms/step - loss: 0.3530 - acc:
0.8617
Test loss: 0.35300153493881226
Test accuracy: 0.8616799712181091
```

Training for Model 2: 100 samples

[11]:
```
max_features=10000
maxlen=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)

texts = np.concatenate((x_train, x_test), axis=0)
labels = np.concatenate((x_train, x_test), axis=0)

x_train = x_train[:100]
```

```
y_train = y_train[:100]
```

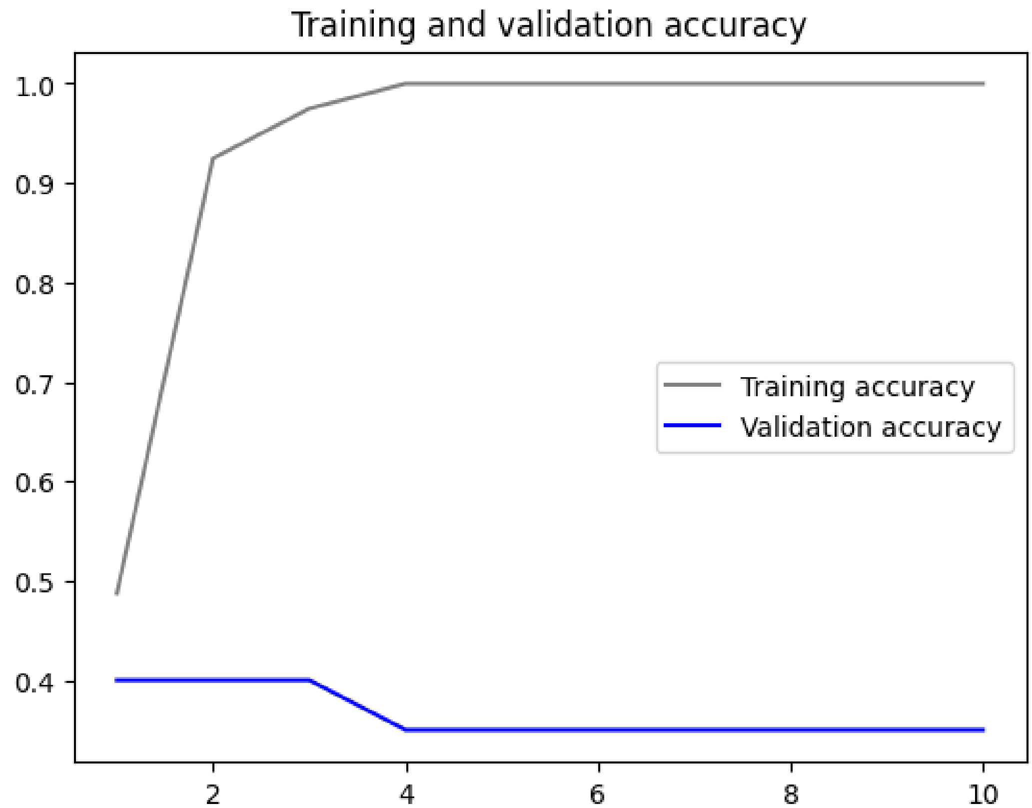
[12]:
```
model = Sequential()
model.add(Embedding(10000, 8, input_length=maxlen))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model.summary()
history_2 = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

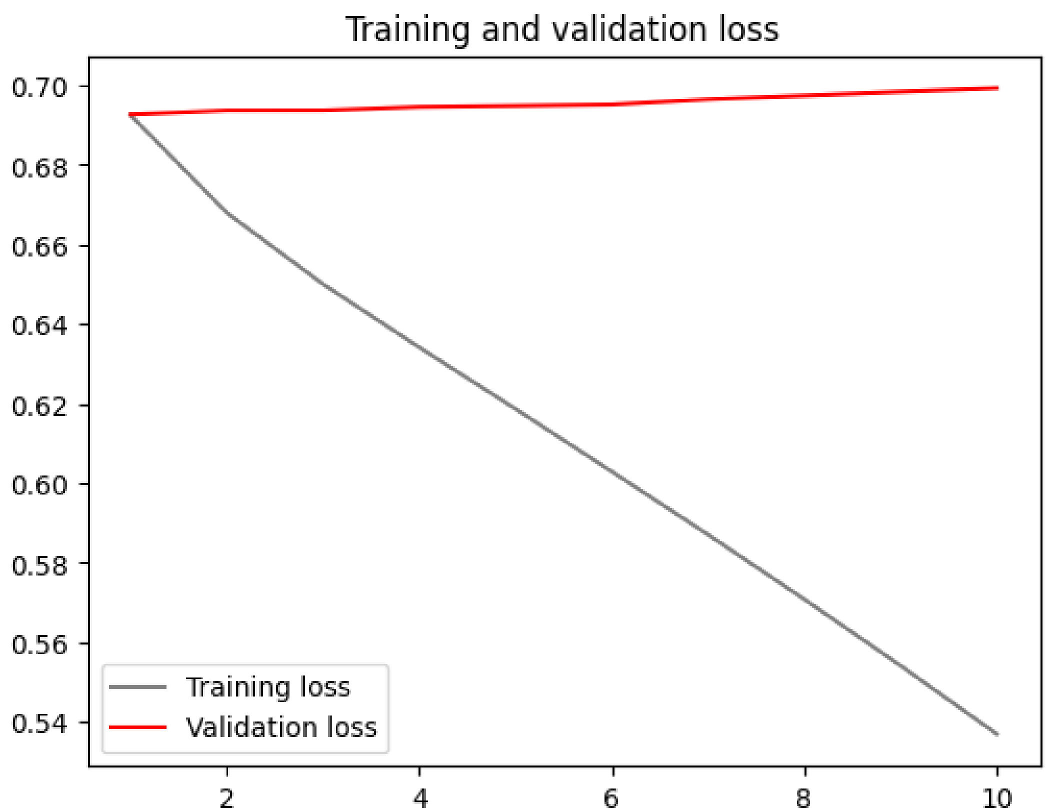
```
Model: "sequential_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_4 (Embedding)     (None, 150, 8)            80000

 flatten_2 (Flatten)         (None, 1200)              0

 dense_2 (Dense)             (None, 1)                 1201

=================================================================
Total params: 81201 (317.19 KB)
Trainable params: 81201 (317.19 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
3/3 [==============================] - 1s 287ms/step - loss: 0.6925 - acc:
0.4875 - val_loss: 0.6926 - val_acc: 0.4000
Epoch 2/10
3/3 [==============================] - 0s 175ms/step - loss: 0.6680 - acc:
0.9250 - val_loss: 0.6936 - val_acc: 0.4000
Epoch 3/10
3/3 [==============================] - 0s 92ms/step - loss: 0.6500 - acc: 0.9750
- val_loss: 0.6937 - val_acc: 0.4000
Epoch 4/10
3/3 [==============================] - 0s 118ms/step - loss: 0.6341 - acc:
1.0000 - val_loss: 0.6945 - val_acc: 0.3500
Epoch 5/10
3/3 [==============================] - 0s 119ms/step - loss: 0.6187 - acc:
1.0000 - val_loss: 0.6948 - val_acc: 0.3500
Epoch 6/10
3/3 [==============================] - 0s 117ms/step - loss: 0.6029 - acc:
1.0000 - val_loss: 0.6951 - val_acc: 0.3500
Epoch 7/10
```

```
3/3 [==============================] - 0s 117ms/step - loss: 0.5871 - acc:
1.0000 - val_loss: 0.6965 - val_acc: 0.3500
Epoch 8/10
3/3 [==============================] - 0s 68ms/step - loss: 0.5708 - acc: 1.0000
- val_loss: 0.6974 - val_acc: 0.3500
Epoch 9/10
3/3 [==============================] - 0s 109ms/step - loss: 0.5542 - acc:
1.0000 - val_loss: 0.6983 - val_acc: 0.3500
Epoch 10/10
3/3 [==============================] - 0s 54ms/step - loss: 0.5370 - acc: 1.0000
- val_loss: 0.6993 - val_acc: 0.3500
```

This plots training and validation accuracy, along with training and validation loss over epochs. It uses grey for training accuracy, blue for validation accuracy, grey for training loss, and red for validation loss. Finally, both plots are displayed using plt.show().

[13]:
```python
accuracy = history_2.history['acc']
val_accuracy = history_2.history['val_acc']
loss = history_2.history['loss']
val_loss = history_2.history['val_loss']

epochs = range(1, len(accuracy) + 1)

plt.plot(epochs, accuracy, 'grey', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'grey', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```


Training and validation accuracy
1.0
0.9
0.8
0.7
0.6
0.5
0.4
2
4
6
8
10
Training accuracy
Validation accuracy



[14]:
```
test_loss, test_acc = model.evaluate(x_test, y_test)
print('Test loss:', test_loss)
print('Test accuracy:', test_acc)
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.6940 - acc:
0.5006
Test loss: 0.6940385699272156
Test accuracy: 0.5006399750709534
```

1 Using Pre-Trained word embeddings

We now adjust the quantity of training samples to ascertain the point at which the embedding layer performs better.

Get the IMDB data in raw text format.

Model 3: Pre-trained model with 100 samples for training

[16]:
```
content = "/content/IMDB-Movie-Data.csv"
```

[17]:
```
import os
```

[18]:
```
!curl -O https://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz
!tar -xf aclImdb_v1.tar.gz

!rm -r aclImdb/train/unsup
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 80.2M  100 80.2M    0     0  14.2M      0  0:00:05  0:00:05 --:--:-- 18.8M
```

[31]:
```
imdb_dir = "/content/aclImdb"
```

[32]:
```
train_dir = os.path.join(imdb_dir, 'train')
```

[33]:
```
labels = []
texts = []
```

[34]:
```
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)
```

Tokenizing the data

[35]:
```
maxlen = 150  #Reviews will be trimmed after 100 words.
training_samples = 100 # 100 samples will be used for our training.
validation_samples = 10000  # We'll be using 10,000 samples for validation.
max_words = 10000  # Only the top 10,000 terms in the dataset will be taken␣
 ↪into account.

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)


# Divide the data into two sets: a validation set and a training set.
# However, since we began with data, first shuffle the data.
# in which the samples are arranged (all positive samples come first, followed
 ↪by all negative samples). provide in a single paragraph
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, 150)
Shape of label tensor: (25000,)
```

Get the GloVe word embeddings here.

Processing the embeddings beforehand

[37]:
```
import numpy as np
import os

# Define the directory containing the GloVe embeddings
glove_file = "/content/glove.6B.100d.txt"
```

[38]:
```
# Define the directory containing the GloVe embeddings
glove_file = "/content/glove.6B.100d.txt"

# Load the pre-trained word embeddings
embeddings_index = {}
with open(glove_file, encoding="utf-8") as f:
    for line in f:
        values = line.split()
        word = values[0]
        try:
            coefs = np.asarray(values[1:], dtype='float32')
            embeddings_index[word] = coefs
        except ValueError:
            print(f"Issue with word: {word}. Skipping...")
            continue

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

```
Issue with word: altham. Skipping…
Found 169139 word vectors.
```

[39]:
```
embedding_dim = 100

embedding_matrix = np.zeros((max_words, embedding_dim))
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word)
    if i < max_words:
        if embedding_vector is not None:
            # All-zero words are those that cannot be located in the embedding␣
 ↪index.
            embedding_matrix[i] = embedding_vector
```

Building the model

[40]:
```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_5 (Embedding)     (None, 150, 100)          1000000

 lstm (LSTM)                 (None, 32)                17024

 dense_3 (Dense)             (None, 1)                 33

=================================================================
Total params: 1017057 (3.88 MB)
Trainable params: 1017057 (3.88 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Loading the GloVe embeddings in the model

[41]:
```
model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False
```

[42]:
```
print("Training data shape:", y_train.shape)
```

```
Training data shape: (100,)
```

Train and evaluate

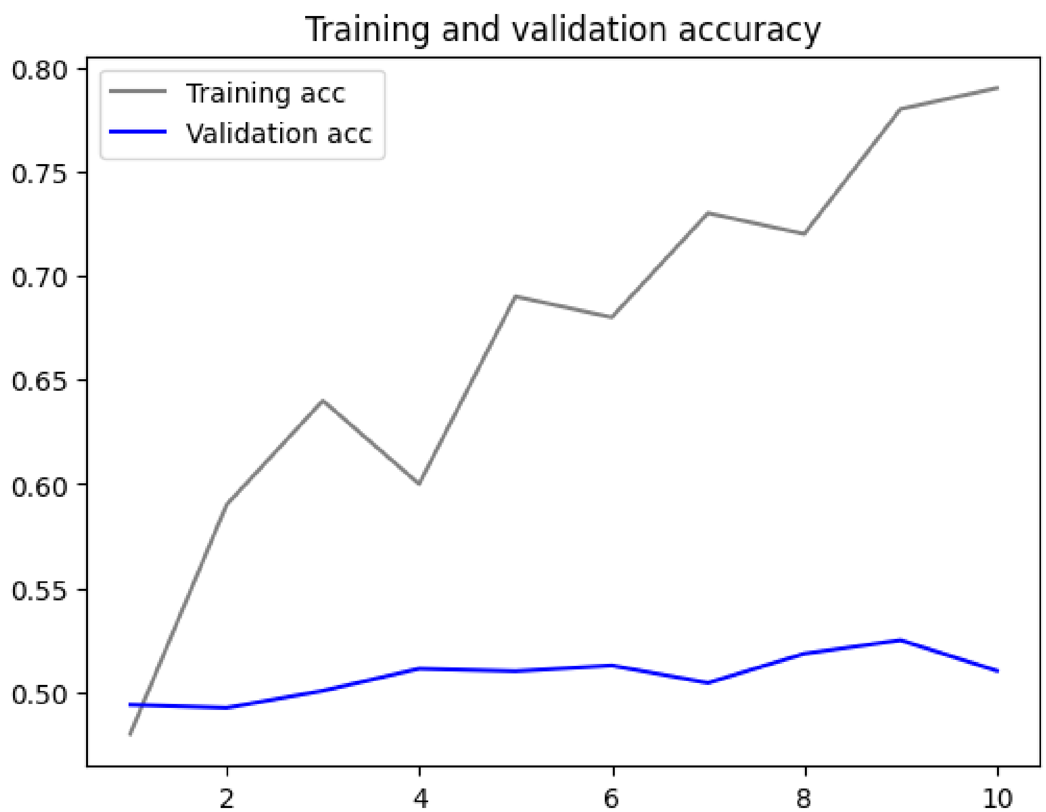
[43]:
```
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history_3 = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_val, y_val))
model.save_weights('pre_trained_glove_model.3a')
```

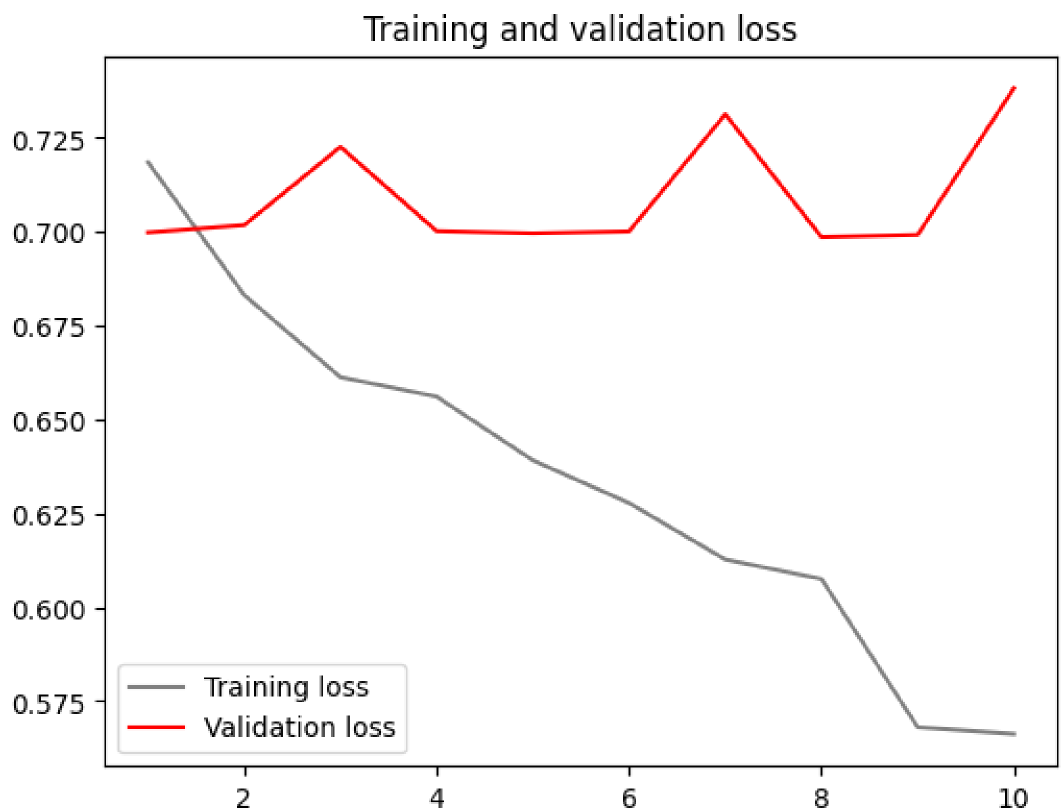
```
Epoch 1/10
4/4 [==============================] - 4s 590ms/step - loss: 0.7185 - acc:
0.4800 - val_loss: 0.6998 - val_acc: 0.4940
Epoch 2/10
4/4 [==============================] - 1s 388ms/step - loss: 0.6831 - acc:
0.5900 - val_loss: 0.7018 - val_acc: 0.4925
Epoch 3/10
4/4 [==============================] - 3s 864ms/step - loss: 0.6613 - acc:
0.6400 - val_loss: 0.7226 - val_acc: 0.5007
Epoch 4/10
4/4 [==============================] - 3s 873ms/step - loss: 0.6561 - acc:
0.6000 - val_loss: 0.7002 - val_acc: 0.5113
Epoch 5/10
4/4 [==============================] - 1s 390ms/step - loss: 0.6391 - acc:
0.6900 - val_loss: 0.6996 - val_acc: 0.5101
Epoch 6/10
4/4 [==============================] - 1s 400ms/step - loss: 0.6278 - acc:
0.6800 - val_loss: 0.7001 - val_acc: 0.5128
Epoch 7/10
4/4 [==============================] - 1s 402ms/step - loss: 0.6127 - acc:
0.7300 - val_loss: 0.7313 - val_acc: 0.5045
Epoch 8/10
4/4 [==============================] - 1s 437ms/step - loss: 0.6075 - acc:
0.7200 - val_loss: 0.6986 - val_acc: 0.5185
Epoch 9/10
4/4 [==============================] - 1s 393ms/step - loss: 0.5680 - acc:
0.7800 - val_loss: 0.6992 - val_acc: 0.5250
Epoch 10/10
4/4 [==============================] - 1s 436ms/step - loss: 0.5662 - acc:
0.7900 - val_loss: 0.7383 - val_acc: 0.5103
```

This visualizes the training and validation accuracy, and loss over epochs using matplotlib. It extracts accuracy and loss values from history_3, plots them separately for training and validation, and displays the plots with corresponding labels.

[44]:
```
import matplotlib.pyplot as plt
```

```
acc = history_3.history['acc']
val_acc = history_3.history['val_acc']
loss = history_3.history['loss']
val_loss = history_3.history['val_loss']

epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, 'grey', 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, 'grey', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[45]:
```
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))
            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)
```

[46]:
```
model.load_weights('pre_trained_glove_model.3a')
model.evaluate(x_test, y_test)
```

```
782/782 [==============================] - 4s 5ms/step - loss: 0.7350 - acc:
0.5130
```

[46]:
```
[0.7349625825881958, 0.5129600167274475]
```

We now adjust the quantity of training samples to ascertain the point at which the embedding layer performs better.

Model 4 training sample size - 1000 using embedding layer

[47]:
```
max_features=10000
maxlen=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)

texts = np.concatenate((x_train, x_test), axis=0)
labels = np.concatenate((x_train, x_test), axis=0)

x_train = x_train[:1000]
y_train = y_train[:1000]
```

[48]:
```
model = Sequential()
model.add(Embedding(10000, 8, input_length=maxlen))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model.summary()
history_4 = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

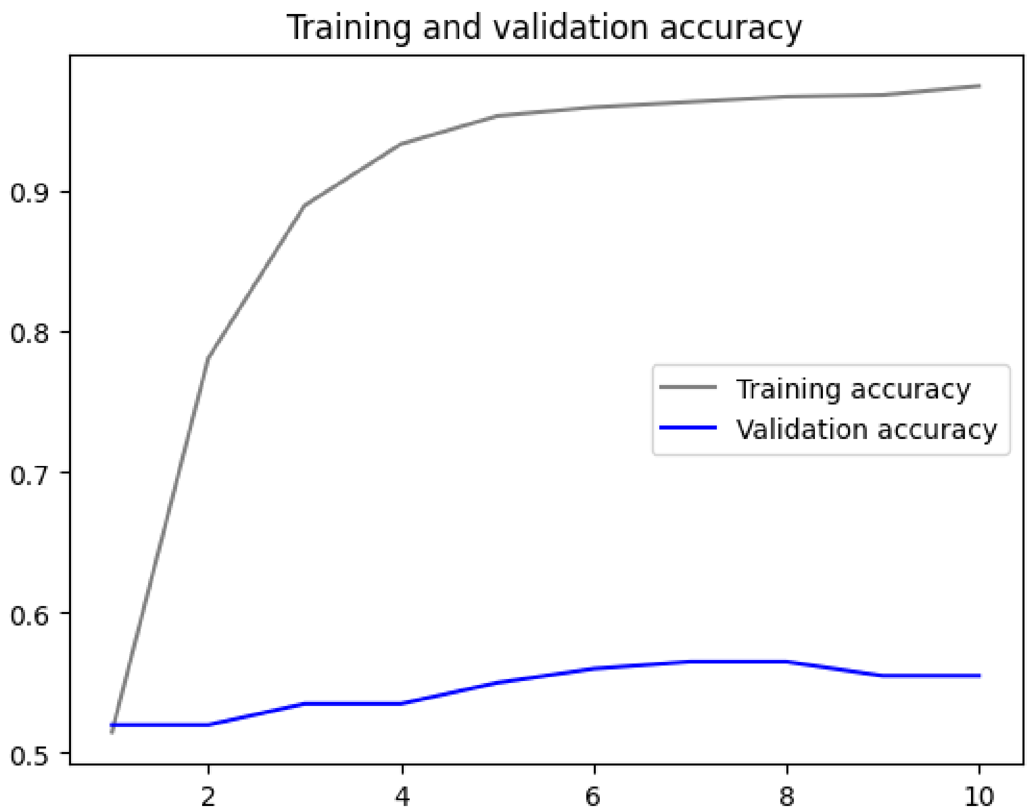
```
Model: "sequential_4"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_6 (Embedding)     (None, 150, 8)            80000

 flatten_3 (Flatten)         (None, 1200)              0

 dense_4 (Dense)             (None, 1)                 1201

=================================================================
```

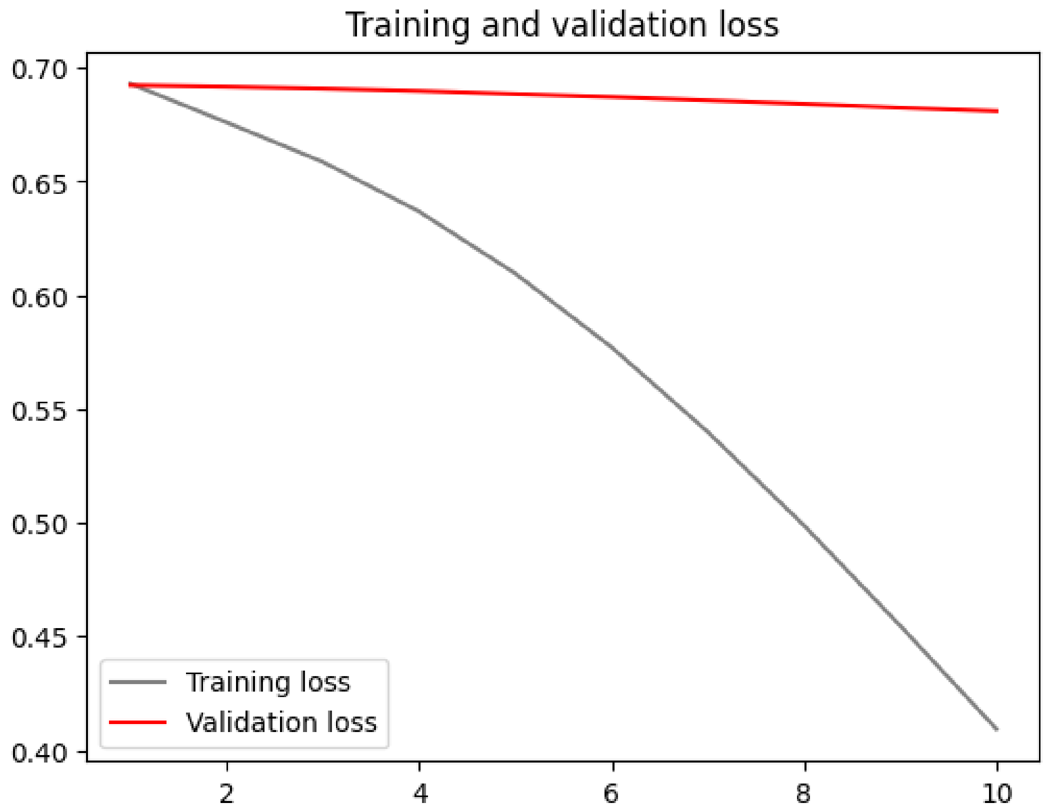
```
Total params: 81201 (317.19 KB)
Trainable params: 81201 (317.19 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
25/25 [==============================] - 4s 131ms/step - loss: 0.6931 - acc:
0.5150 - val_loss: 0.6923 - val_acc: 0.5200
Epoch 2/10
25/25 [==============================] - 3s 110ms/step - loss: 0.6760 - acc:
0.7812 - val_loss: 0.6917 - val_acc: 0.5200
Epoch 3/10
25/25 [==============================] - 3s 98ms/step - loss: 0.6587 - acc:
0.8900 - val_loss: 0.6909 - val_acc: 0.5350
Epoch 4/10
25/25 [==============================] - 1s 39ms/step - loss: 0.6369 - acc:
0.9337 - val_loss: 0.6899 - val_acc: 0.5350
Epoch 5/10
25/25 [==============================] - 1s 47ms/step - loss: 0.6096 - acc:
0.9538 - val_loss: 0.6885 - val_acc: 0.5500
Epoch 6/10
25/25 [==============================] - 1s 33ms/step - loss: 0.5772 - acc:
0.9600 - val_loss: 0.6872 - val_acc: 0.5600
Epoch 7/10
25/25 [==============================] - 1s 38ms/step - loss: 0.5400 - acc:
0.9638 - val_loss: 0.6857 - val_acc: 0.5650
Epoch 8/10
25/25 [==============================] - 1s 25ms/step - loss: 0.4989 - acc:
0.9675 - val_loss: 0.6841 - val_acc: 0.5650
Epoch 9/10
25/25 [==============================] - 1s 27ms/step - loss: 0.4548 - acc:
0.9688 - val_loss: 0.6825 - val_acc: 0.5550
Epoch 10/10
25/25 [==============================] - 1s 30ms/step - loss: 0.4094 - acc:
0.9750 - val_loss: 0.6810 - val_acc: 0.5550
```

This visualizes training and validation accuracy, as well as training and validation loss over epochs using Matplotlib. It plots training and validation accuracy separately, with grey for training and blue for validation, and similarly for training and validation loss with grey and red respectively, then displays both plots.

[49]:
```
accuracy = history_4.history['acc']
val_accuracy = history_4.history['val_acc']
loss = history_4.history['loss']
val_loss = history_4.history['val_loss']

epochs = range(1, len(accuracy) + 1)

plt.plot(epochs, accuracy, 'grey', label='Training accuracy')
```

```
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'grey', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[50]:
```
test_loss, test_acc = model.evaluate(x_test, y_test)
print('Test loss:', test_loss)
print('Test accuracy:', test_acc)
```

```
782/782 [==============================] - 2s 3ms/step - loss: 0.6798 - acc:
0.5645
Test loss: 0.6798288822174072
Test accuracy: 0.564520001411438
```

Model 5 Taining sample - 15000 using both embedding layer and Conv1D

[51]:
```
max_features=10000
maxlen=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)

texts = np.concatenate((x_train, x_test), axis=0)
labels = np.concatenate((x_train, x_test), axis=0)

x_train = x_train[:15000]
```

```python
y_train = y_train[:15000]
```

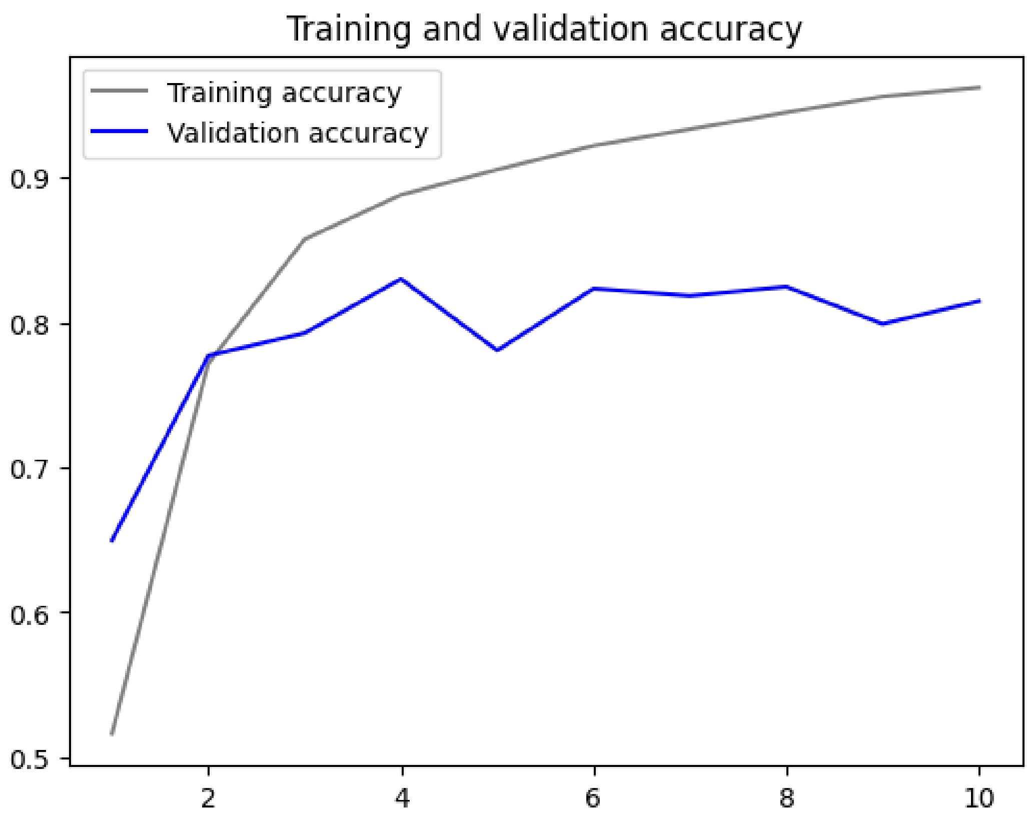
[52]:
```python
model = Sequential()
model.add(Embedding(10000, 10, input_length=maxlen))
model.add(Conv1D(512, 3, activation='relu'))
model.add(MaxPooling1D(3))

model.add(Conv1D(256, 3, activation='relu'))
model.add(MaxPooling1D(3))

model.add(Conv1D(256, 3, activation='relu'))
model.add(Dropout(0.8))
model.add(MaxPooling1D(3))

model.add(GlobalMaxPooling1D())
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model.summary()
history_5 = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

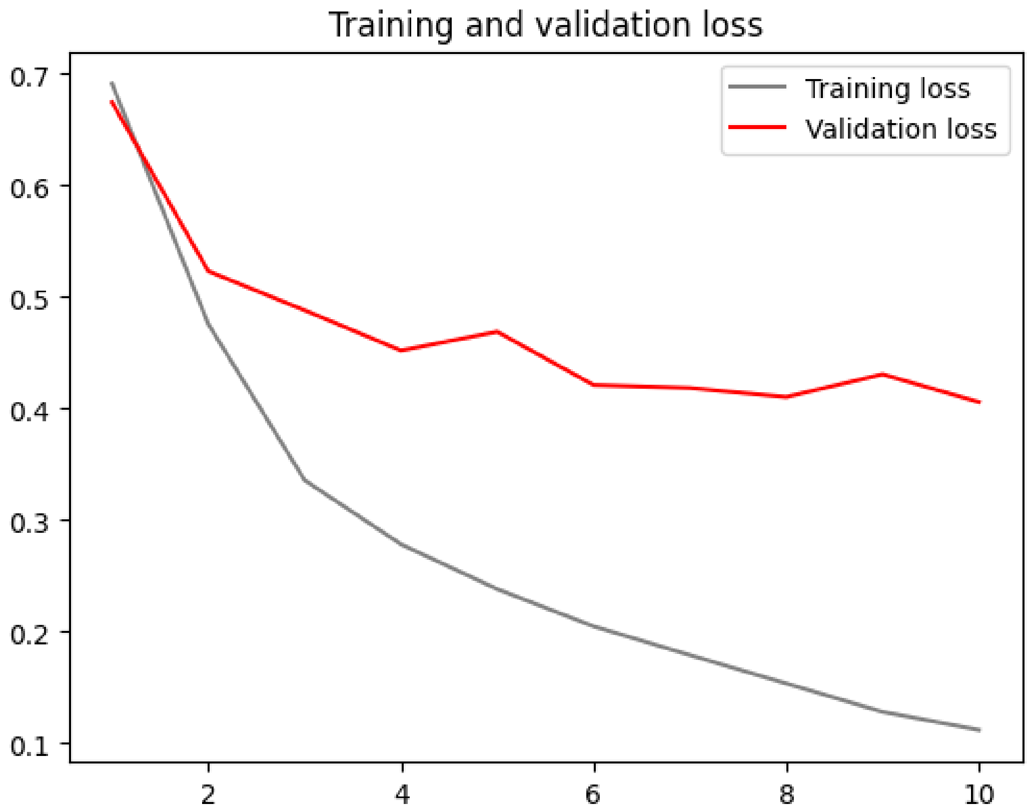
```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_7 (Embedding)     (None, 150, 10)           100000

 conv1d (Conv1D)             (None, 148, 512)          15872

 max_pooling1d (MaxPooling1  (None, 49, 512)           0
 D)

 conv1d_1 (Conv1D)           (None, 47, 256)           393472

 max_pooling1d_1 (MaxPoolin  (None, 15, 256)           0
 g1D)

 conv1d_2 (Conv1D)           (None, 13, 256)           196864

 dropout (Dropout)           (None, 13, 256)           0

 max_pooling1d_2 (MaxPoolin  (None, 4, 256)            0
 g1D)
```

```
 global_max_pooling1d (Glob  (None, 256)               0
 alMaxPooling1D)

 flatten_4 (Flatten)         (None, 256)               0

 dense_5 (Dense)             (None, 1)                 257

=================================================================
Total params: 706465 (2.69 MB)
Trainable params: 706465 (2.69 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
375/375 [==============================] - 30s 68ms/step - loss: 0.6912 - acc:
0.5163 - val_loss: 0.6746 - val_acc: 0.6497
Epoch 2/10
375/375 [==============================] - 7s 19ms/step - loss: 0.4757 - acc:
0.7717 - val_loss: 0.5231 - val_acc: 0.7770
Epoch 3/10
375/375 [==============================] - 6s 17ms/step - loss: 0.3358 - acc:
0.8574 - val_loss: 0.4881 - val_acc: 0.7927
Epoch 4/10
375/375 [==============================] - 4s 10ms/step - loss: 0.2784 - acc:
0.8881 - val_loss: 0.4521 - val_acc: 0.8300
Epoch 5/10
375/375 [==============================] - 3s 9ms/step - loss: 0.2382 - acc:
0.9055 - val_loss: 0.4689 - val_acc: 0.7807
Epoch 6/10
375/375 [==============================] - 4s 11ms/step - loss: 0.2048 - acc:
0.9220 - val_loss: 0.4211 - val_acc: 0.8233
Epoch 7/10
375/375 [==============================] - 3s 9ms/step - loss: 0.1791 - acc:
0.9334 - val_loss: 0.4184 - val_acc: 0.8183
Epoch 8/10
375/375 [==============================] - 3s 7ms/step - loss: 0.1537 - acc:
0.9449 - val_loss: 0.4104 - val_acc: 0.8247
Epoch 9/10
375/375 [==============================] - 3s 7ms/step - loss: 0.1281 - acc:
0.9559 - val_loss: 0.4307 - val_acc: 0.7990
Epoch 10/10
375/375 [==============================] - 3s 9ms/step - loss: 0.1120 - acc:
0.9621 - val_loss: 0.4059 - val_acc: 0.8147
```

[53]:
```python
accuracy = history_5.history['acc']
val_accuracy = history_5.history['val_acc']
loss = history_5.history['loss']
val_loss = history_5.history['val_loss']
```

```
epochs = range(1, len(accuracy) + 1)

plt.plot(epochs, accuracy, 'grey', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'grey', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[54]:
```
test_loss, test_acc = model.evaluate(x_test, y_test)
print('Test loss:', test_loss)
print('Test accuracy:', test_acc)
```

```
782/782 [==============================] - 3s 4ms/step - loss: 0.4239 - acc:
0.8036
Test loss: 0.42388579249382
Test accuracy: 0.8035600185394287
```

As we've seen, the accuracy was still low in the prior model even after increasing the training sample size. However, when we combined Con1D with the larger training sample size, the accuracy rose to 81%.

Model 6 Training sample 30000 with Conv1D and embedding layers

[55]:
```
max_features=10000
maxlen=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)
```

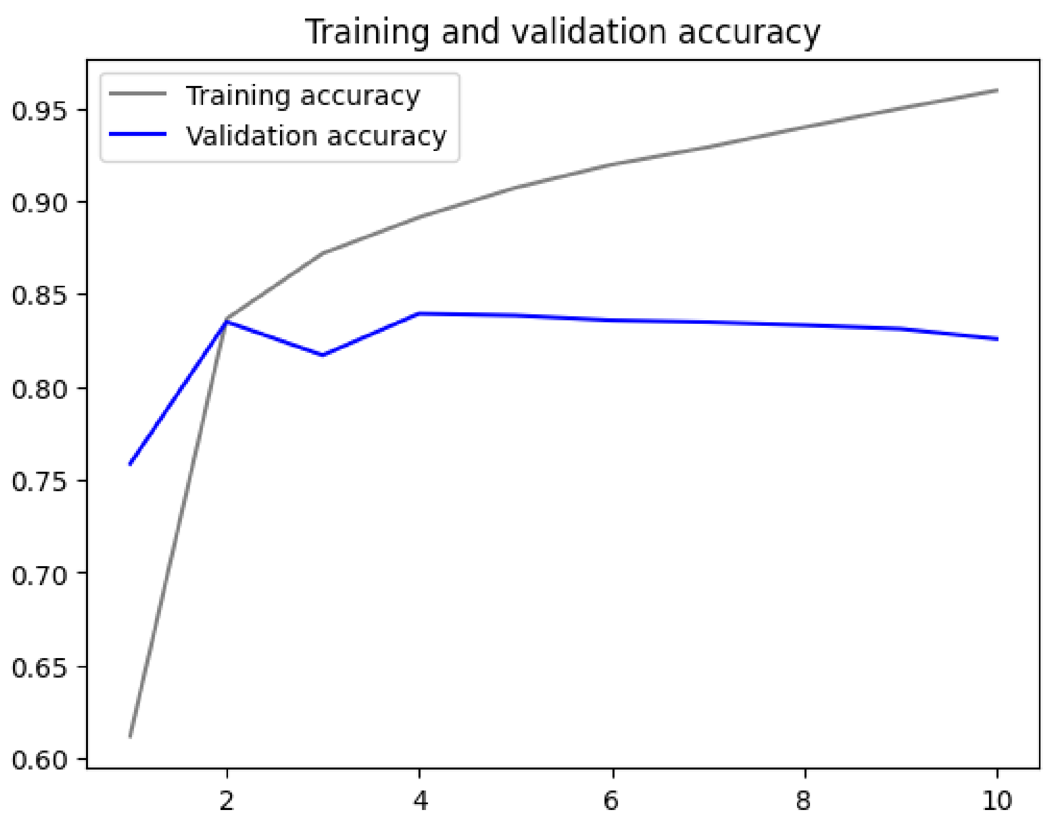
```
texts = np.concatenate((x_train, x_test), axis=0)
labels = np.concatenate((x_train, x_test), axis=0)

x_train = x_train[:30000]
y_train = y_train[:30000]
```

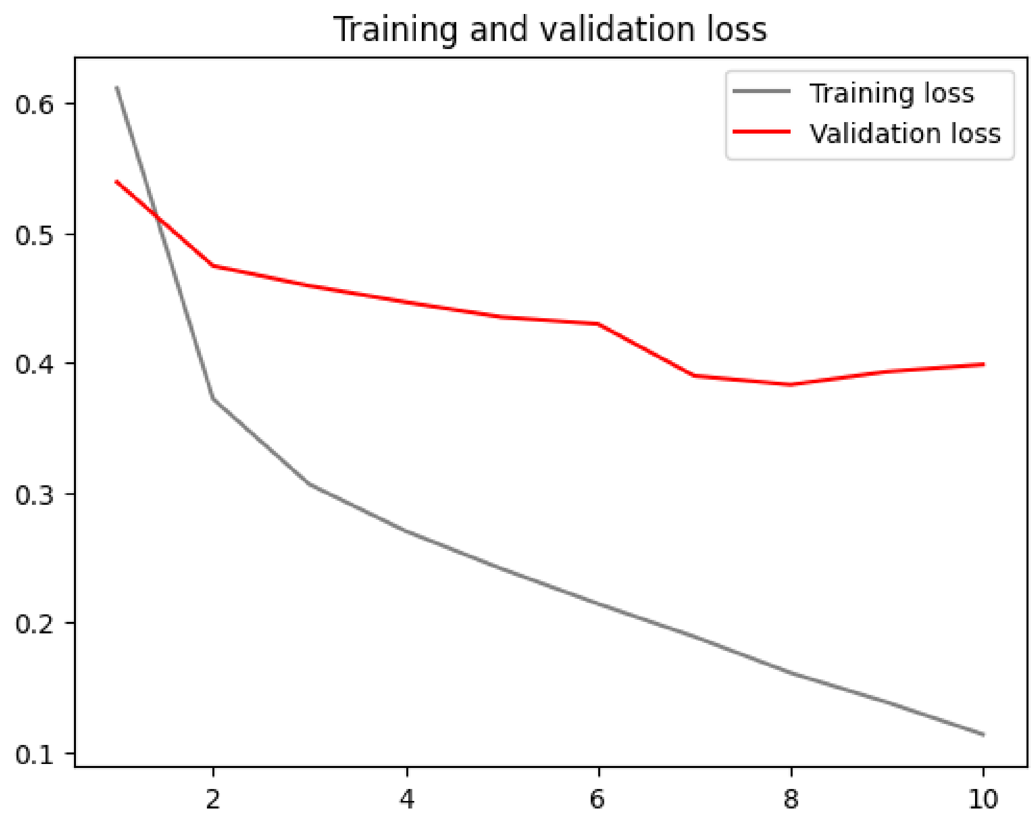
[56]:
```
model = Sequential()
model.add(Embedding(10000, 12, input_length=maxlen))
model.add(Conv1D(512, 3, activation='relu'))
model.add(MaxPooling1D(3))

model.add(Conv1D(256, 3, activation='relu'))
model.add(MaxPooling1D(3))

model.add(Conv1D(256, 3, activation='relu'))
model.add(Dropout(0.8))
model.add(MaxPooling1D(3))

model.add(GlobalMaxPooling1D())
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model.summary()
history_6 = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_8 (Embedding)     (None, 150, 12)           120000

 conv1d_3 (Conv1D)           (None, 148, 512)          18944

 max_pooling1d_3 (MaxPoolin  (None, 49, 512)           0
 g1D)

 conv1d_4 (Conv1D)           (None, 47, 256)           393472

 max_pooling1d_4 (MaxPoolin  (None, 15, 256)           0
 g1D)

 conv1d_5 (Conv1D)           (None, 13, 256)           196864

 dropout_1 (Dropout)         (None, 13, 256)           0
```

```
 max_pooling1d_5 (MaxPoolin  (None, 4, 256)            0
 g1D)

 global_max_pooling1d_1 (Gl  (None, 256)               0
 obalMaxPooling1D)

 flatten_5 (Flatten)         (None, 256)               0

 dense_6 (Dense)             (None, 1)                 257

=================================================================
Total params: 729537 (2.78 MB)
Trainable params: 729537 (2.78 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
625/625 [==============================] - 31s 48ms/step - loss: 0.6112 - acc:
0.6122 - val_loss: 0.5390 - val_acc: 0.7586
Epoch 2/10
625/625 [==============================] - 8s 14ms/step - loss: 0.3720 - acc:
0.8365 - val_loss: 0.4744 - val_acc: 0.8350
Epoch 3/10
625/625 [==============================] - 8s 13ms/step - loss: 0.3064 - acc:
0.8718 - val_loss: 0.4591 - val_acc: 0.8170
Epoch 4/10
625/625 [==============================] - 6s 9ms/step - loss: 0.2704 - acc:
0.8912 - val_loss: 0.4465 - val_acc: 0.8394
Epoch 5/10
625/625 [==============================] - 7s 11ms/step - loss: 0.2413 - acc:
0.9071 - val_loss: 0.4351 - val_acc: 0.8384
Epoch 6/10
625/625 [==============================] - 5s 8ms/step - loss: 0.2144 - acc:
0.9196 - val_loss: 0.4297 - val_acc: 0.8358
Epoch 7/10
625/625 [==============================] - 5s 8ms/step - loss: 0.1891 - acc:
0.9289 - val_loss: 0.3899 - val_acc: 0.8348
Epoch 8/10
625/625 [==============================] - 6s 9ms/step - loss: 0.1613 - acc:
0.9396 - val_loss: 0.3830 - val_acc: 0.8332
Epoch 9/10
625/625 [==============================] - 4s 7ms/step - loss: 0.1387 - acc:
0.9498 - val_loss: 0.3930 - val_acc: 0.8312
Epoch 10/10
625/625 [==============================] - 5s 7ms/step - loss: 0.1139 - acc:
0.9594 - val_loss: 0.3985 - val_acc: 0.8258
```

[57]:
```
accuracy = history_6.history['acc']
val_accuracy = history_6.history['val_acc']
loss = history_6.history['loss']
val_loss = history_6.history['val_loss']

epochs = range(1, len(accuracy) + 1)

plt.plot(epochs, accuracy, 'grey', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'grey', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[58]:
```
test_loss, test_acc = model.evaluate(x_test, y_test)
print('Test loss:', test_loss)
print('Test accuracy:', test_acc)
```

```
782/782 [==============================] - 4s 5ms/step - loss: 0.4031 - acc:
0.8184
Test loss: 0.4030909836292267
Test accuracy: 0.8184000253677368
```

Model 7 pretrained model. Training - 15000 samples

[61]:
```
import os
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import numpy as np

# Define the directory containing the IMDb dataset
imdb_dir = '/content/aclImdb'

texts = []
labels = []
```

```python
# Load the IMDb dataset
for label_type in ['neg', 'pos']:
    dir_name = os.path.join(imdb_dir, 'train', 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)

# Define parameters for tokenization and padding
maxlen = 150
training_samples = 15000
validation_samples = 10000
max_words = 10000

# Tokenize the text data
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))

# Pad sequences to ensure uniform 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 the data
indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

# Split the data into training and validation sets
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, 150)
Shape of label tensor: (25000,)
```

[62]:
```
model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_9 (Embedding)     (None, 150, 100)          1000000

 lstm_1 (LSTM)               (None, 32)                17024

 dense_7 (Dense)             (None, 1)                 33

=================================================================
Total params: 1017057 (3.88 MB)
Trainable params: 1017057 (3.88 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[63]:
```
model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False
```

[64]:
```
print("Training data shape:", y_train.shape)
```

```
Training data shape: (15000,)
```

[65]:
```
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history_7 = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_val, y_val))
model.save_weights('pre_trained_glove_model.7a')
```

```
Epoch 1/10
469/469 [==============================] - 8s 11ms/step - loss: 0.5950 - acc:
0.6823 - val_loss: 0.4955 - val_acc: 0.7717
Epoch 2/10
469/469 [==============================] - 6s 13ms/step - loss: 0.4811 - acc:
0.7738 - val_loss: 0.4466 - val_acc: 0.7962
Epoch 3/10
```

```
469/469 [==============================] - 5s 12ms/step - loss: 0.4165 - acc:
0.8132 - val_loss: 0.4107 - val_acc: 0.8113
Epoch 4/10
469/469 [==============================] - 5s 10ms/step - loss: 0.3841 - acc:
0.8294 - val_loss: 0.3961 - val_acc: 0.8209
Epoch 5/10
469/469 [==============================] - 6s 13ms/step - loss: 0.3555 - acc:
0.8462 - val_loss: 0.3717 - val_acc: 0.8344
Epoch 6/10
469/469 [==============================] - 5s 10ms/step - loss: 0.3336 - acc:
0.8550 - val_loss: 0.3686 - val_acc: 0.8418
Epoch 7/10
469/469 [==============================] - 5s 10ms/step - loss: 0.3165 - acc:
0.8683 - val_loss: 0.3606 - val_acc: 0.8448
Epoch 8/10
469/469 [==============================] - 6s 13ms/step - loss: 0.2989 - acc:
0.8720 - val_loss: 0.3478 - val_acc: 0.8492
Epoch 9/10
469/469 [==============================] - 5s 10ms/step - loss: 0.2870 - acc:
0.8781 - val_loss: 0.4278 - val_acc: 0.8199
Epoch 10/10
469/469 [==============================] - 6s 13ms/step - loss: 0.2742 - acc:
0.8827 - val_loss: 0.3428 - val_acc: 0.8511
```

[66]:

```
model.load_weights('pre_trained_glove_model.7a')
model.evaluate(x_test, y_test)
```

```
782/782 [==============================] - 4s 5ms/step - loss: 1.0577 - acc:
0.4964
```

[66]:

```
[1.0577056407928467, 0.49636000394821167]
```

Pre Trained model with 30,000 samples

[67]:

```
maxlen = 150  #Reviews will be trimmed after 100 words.
training_samples = 30000 # We'll be using 30,000 samples for training.
validation_samples = 10000  # We'll be using 10,000 samples for validation.
max_words = 10000   # Only the top 10,000 terms in the dataset will be taken␣
↪into account.

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)

# Divide the data into two sets: a validation set and a training set.
# However, since we began with data, first shuffle the data.
# in which the samples are arranged (all positive samples come first, followed␣
↪by all negative samples).
indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

x_train = data[:30000]
y_train = labels[:30000]
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, 150)
Shape of label tensor: (25000,)
```

[68]:
```
model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(LSTM(128))
model.add(Dropout(0.3))

model.add(Dense(256, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))

model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False
```

[69]:
```
model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False
```

[70]:
```
print("Training data shape:", y_train.shape)
```

```
Training data shape: (25000,)
```

[72]:
```
from keras.preprocessing.sequence import pad_sequences
from keras.preprocessing.text import Tokenizer
from keras.models import Sequential
from keras.layers import Embedding, LSTM, Dense
import numpy as np
```

```
maxlen = 150  # Cut texts after 150 words
training_samples = 15000  # Train on 15000 samples
validation_samples = 10000  # Validate on 10000 samples
max_words = 10000  # Consider only the top 10,000 words in the dataset

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)

# Shuffle data
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]

# Define the model
model = Sequential()
model.add(Embedding(max_words, 64))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
model.summary()

# Train the model
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_val, y_val))

# Save the model weights
```

```python
model.save_weights('pre_trained_glove_model.8a')
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 150)
Shape of label tensor: (25000,)
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_11 (Embedding)    (None, None, 64)          640000

 lstm_3 (LSTM)               (None, 32)                12416

 dense_10 (Dense)            (None, 1)                 33

=================================================================
Total params: 652449 (2.49 MB)
Trainable params: 652449 (2.49 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
469/469 [==============================] - 32s 65ms/step - loss: 0.6935 - acc:
0.4986 - val_loss: 0.6936 - val_acc: 0.4934
Epoch 2/10
469/469 [==============================] - 12s 26ms/step - loss: 0.6898 - acc:
0.5431 - val_loss: 0.6946 - val_acc: 0.5080
Epoch 3/10
469/469 [==============================] - 8s 16ms/step - loss: 0.6761 - acc:
0.5811 - val_loss: 0.7041 - val_acc: 0.5092
Epoch 4/10
469/469 [==============================] - 8s 17ms/step - loss: 0.6452 - acc:
0.6303 - val_loss: 0.7267 - val_acc: 0.5106
Epoch 5/10
469/469 [==============================] - 6s 13ms/step - loss: 0.5938 - acc:
0.6785 - val_loss: 0.8062 - val_acc: 0.5043
Epoch 6/10
469/469 [==============================] - 8s 16ms/step - loss: 0.5257 - acc:
0.7347 - val_loss: 0.8303 - val_acc: 0.5037
Epoch 7/10
469/469 [==============================] - 6s 12ms/step - loss: 0.4503 - acc:
0.7915 - val_loss: 0.9550 - val_acc: 0.5003
Epoch 8/10
469/469 [==============================] - 8s 18ms/step - loss: 0.3762 - acc:
0.8370 - val_loss: 1.1117 - val_acc: 0.4958
Epoch 9/10
469/469 [==============================] - 6s 12ms/step - loss: 0.3020 - acc:
0.8723 - val_loss: 1.1767 - val_acc: 0.5021
```

```
Epoch 10/10
469/469 [==============================] - 6s 14ms/step - loss: 0.2324 - acc:
0.9109 - val_loss: 1.3844 - val_acc: 0.4954
```

[73]:

```
model.load_weights('pre_trained_glove_model.8a')
model.evaluate(x_test, y_test)
```

```
782/782 [==============================] - 3s 4ms/step - loss: 1.3654 - acc:
0.5095
```

[73]:

```
[1.365393877029419, 0.5094799995422363]
```