Assignment 4

Text and sequence

```
from keras.layers import Embedding
# The Embedding layer takes at least two arguments:
# the number of possible tokens, here 1000 (1 + maximum word index),
# and the dimensionality of the embeddings, here 64.
embedding_layer = Embedding(1000, 64)
```

```
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,
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

```
# Number of words to consider as features
max_features = 10000
# Cut texts after 150 words
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)
```

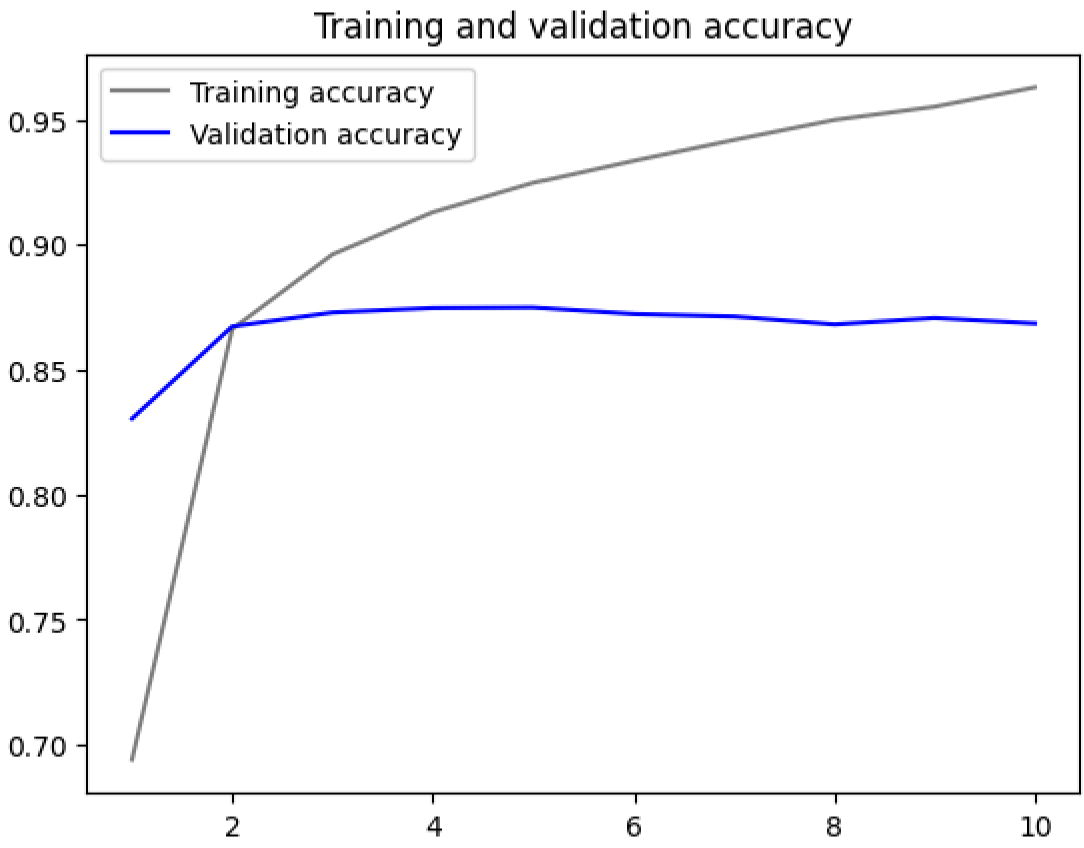
```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-data
17464789/17464789 [==============================] - 1s 0us/step
```

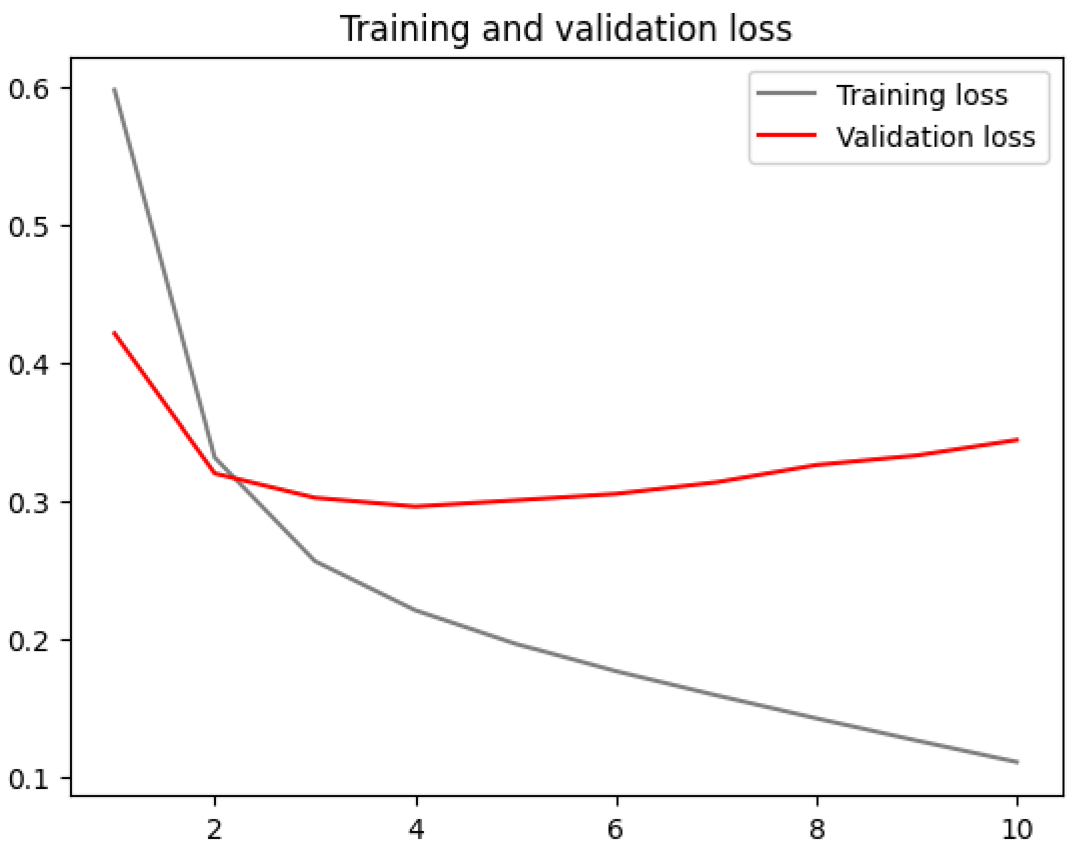
```
model = Sequential()

# We specify the maximum input length to our Embedding layer
# so we can later flatten the embedded inputs

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

# We flatten the 3D tensor of embeddings
# into a 2D tensor of shape `(samples, maxlen * 8)`
model.add(Flatten())

# We add the classifier on top
model.add(Dense(1, activation='sigmoid'))

#compiling 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"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_1 (Embedding)     (None, 150, 8)            80000     
                                                                 
 flatten (Flatten)           (None, 1200)              0         
                                                                 
 dense (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 [==============================] - 26s 39ms/step - loss: 0.5974 - acc
Epoch 2/10
625/625 [==============================] - 6s 9ms/step - loss: 0.3316 - acc: (
Epoch 3/10
625/625 [==============================] - 4s 7ms/step - loss: 0.2566 - acc: (
Epoch 4/10
625/625 [==============================] - 4s 6ms/step - loss: 0.2211 - acc: (
Epoch 5/10
625/625 [==============================] - 4s 6ms/step - loss: 0.1968 - acc: (
Epoch 6/10
625/625 [==============================] - 3s 5ms/step - loss: 0.1769 - acc: (
Epoch 7/10
625/625 [==============================] - 3s 4ms/step - loss: 0.1595 - acc: (
Epoch 8/10
625/625 [==============================] - 2s 4ms/step - loss: 0.1428 - acc: (
Epoch 9/10
625/625 [==============================] - 2s 4ms/step - loss: 0.1267 - acc: (
```

```
Epoch 10/10
625/625 [==============================] - 3s 5ms/step - loss: 0.1112 - acc: (
```

```
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()
```






```
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: 0.3465 - acc: (
Test loss: 0.34654125571250916
Test accuracy: 0.8657600283622742
```

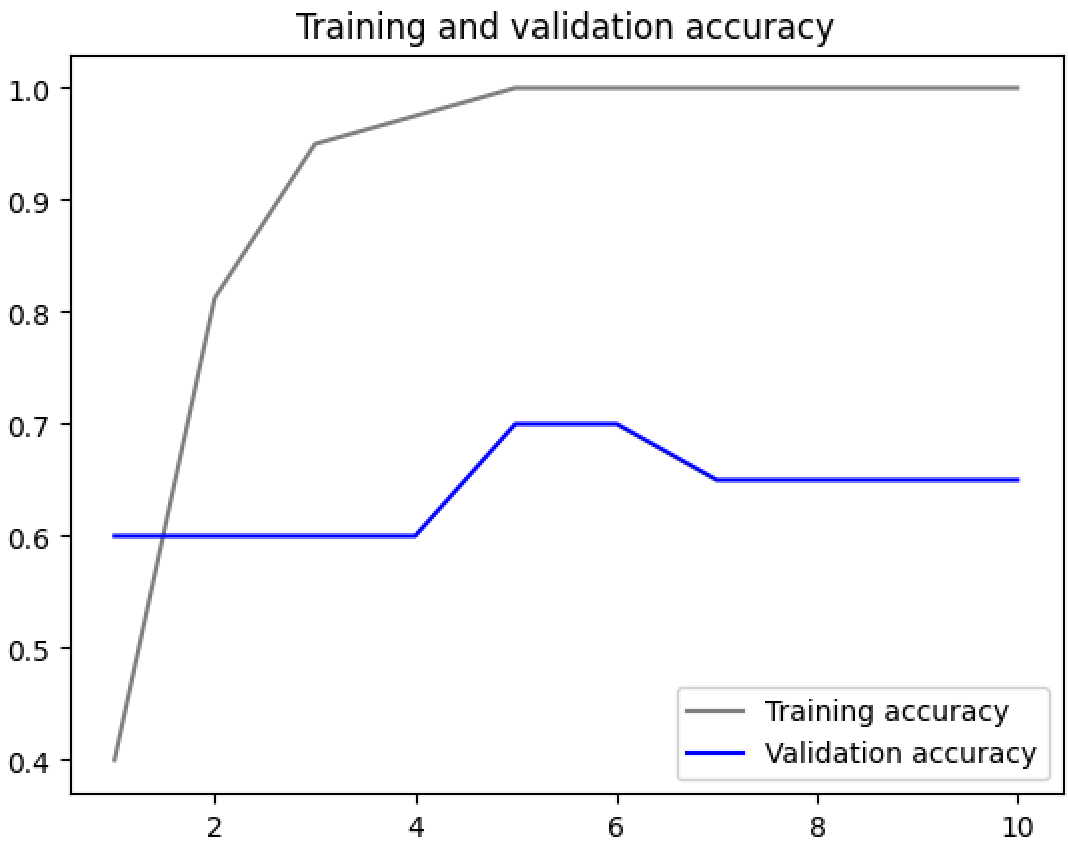
Model 2 Training - 100 samples

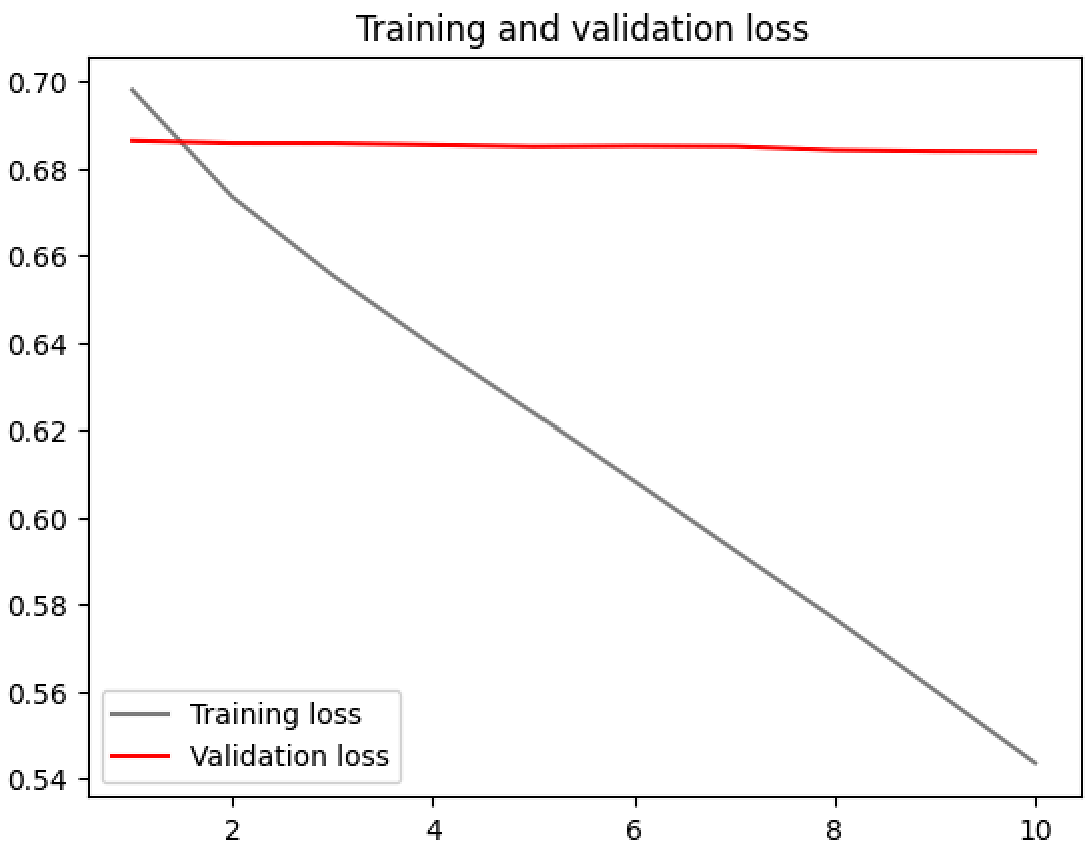
```
max_features=10000
maxlen=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

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]


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_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (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
3/3 [==============================] - 2s 440ms/step - loss: 0.6980 - acc: 0.
Epoch 2/10
3/3 [==============================] - 1s 243ms/step - loss: 0.6734 - acc: 0.
Epoch 3/10
3/3 [==============================] - 1s 276ms/step - loss: 0.6554 - acc: 0.
Epoch 4/10
3/3 [==============================] - 1s 286ms/step - loss: 0.6392 - acc: 0.
Epoch 5/10
3/3 [==============================] - 1s 226ms/step - loss: 0.6239 - acc: 1.
Epoch 6/10
3/3 [==============================] - 0s 175ms/step - loss: 0.6083 - acc: 1.
Epoch 7/10
3/3 [==============================] - 1s 207ms/step - loss: 0.5924 - acc: 1.
```

```
Epoch 8/10
3/3 [==============================] - 0s 171ms/step - loss: 0.5767 - acc: 1.(
Epoch 9/10
3/3 [==============================] - 1s 189ms/step - loss: 0.5602 - acc: 1.(
Epoch 10/10
3/3 [==============================] - 0s 142ms/step - loss: 0.5435 - acc: 1.(
```

```
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()
```






```
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: 0.6944 - acc: (
Test loss: 0.6943621039390564
Test accuracy: 0.49375998973846436
```

Using Pre-Trained word embeddings

Download the IMDB data as raw text

Model 3 Pre-Trained model, Training- 100 samples

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
%cd /content/drive/MyDrive/
```

```
/content/drive/MyDrive
```

```
import os
```

```
!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  Curre
                                 Dload  Upload   Total   Spent    Left  Speed
100 80.2M  100 80.2M    0     0  7175k      0  0:00:11  0:00:11 --:--:-- 14.3M
```

```
imdb_dir = '/content/drive/MyDrive/aclImdb'
```

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

```
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)
```

Tokenizing the data

```
maxlen = 150  # We will cut reviews after 100 words
training_samples = 100 # We will be training on 100 samples
validation_samples = 10000  # We will be validating on 10000 samples
max_words = 10000  # We will only consider the top 10,000 words in the dataset

tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(texts)
sequences = tokenizer.texts_to_sequences(texts)

word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))

data = pad_sequences(sequences, maxlen=maxlen)

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

# Split the data into a training set and a validation set
# But first, shuffle the data, since we started from data
# where sample are ordered (all negative first, then all positive).
indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

x_train = data[:training_samples]
y_train = labels[:training_samples]
x_val = data[training_samples: training_samples + validation_samples]
y_val = labels[training_samples: training_samples + validation_samples]
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 150)
Shape of label tensor: (25000,)
```

Download the GloVe word embeddings

Pre-Processing the embeddings

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

```
from google.colab import drive
import os
import numpy as np

# Mount Google Drive
drive.mount('/content/drive')

# Specify the path to the GloVe embeddings file in your Google Drive
glove_dir = '/content/drive/MyDrive/glove.6B'
drive.mount("/content/drive", force_remount=True)
glove_file_path = os.path.join(glove_dir, 'glove.6B.100d.txt')

# Load GloVe embeddings into a dictionary
embeddings_index = {}
with open(glove_file_path, 'r', encoding='utf-8') as f:
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embeddings_index[word] = coefs

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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
Mounted at /content/drive
```

```
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:
            # Words not found in embedding index will be all-zeros.
            embedding_matrix[i] = embedding_vector
```

Building the model

```
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_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 embedding_3 (Embedding)     (None, 150, 100)          1000000

 lstm (LSTM)                 (None, 32)                17024

 dense_2 (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

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

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

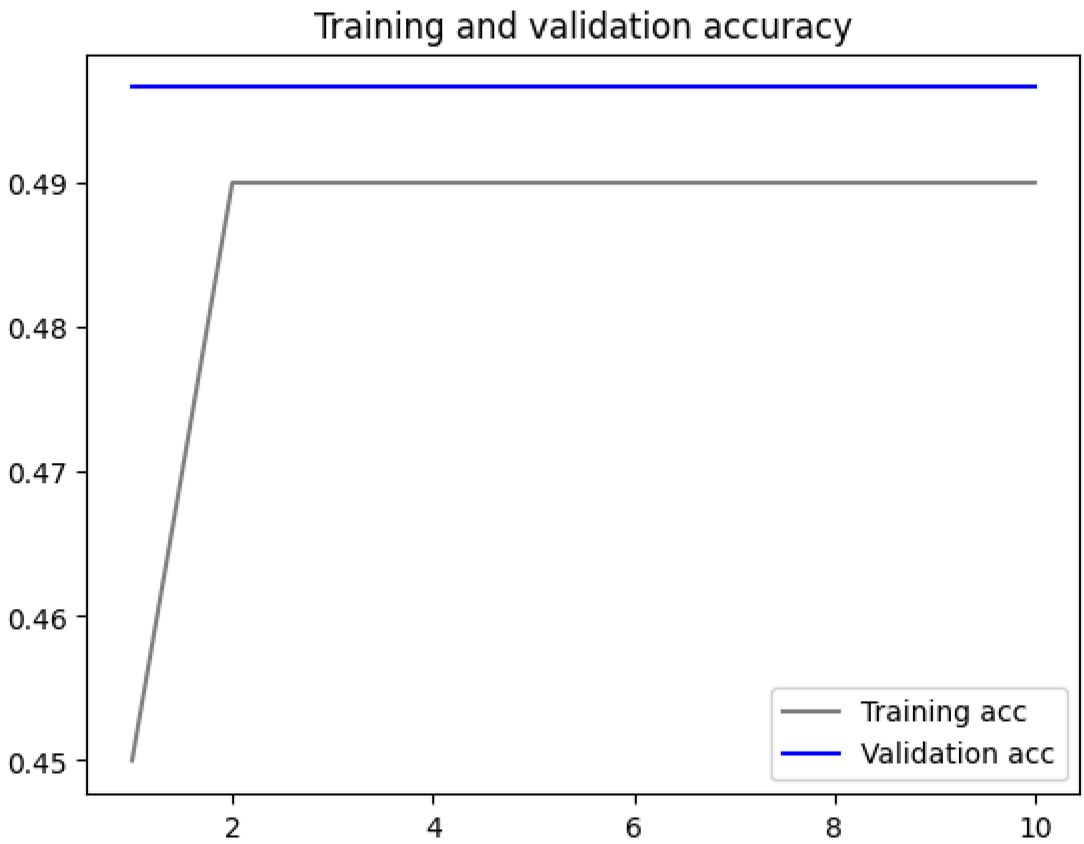
```
Training data shape: (100,)
```

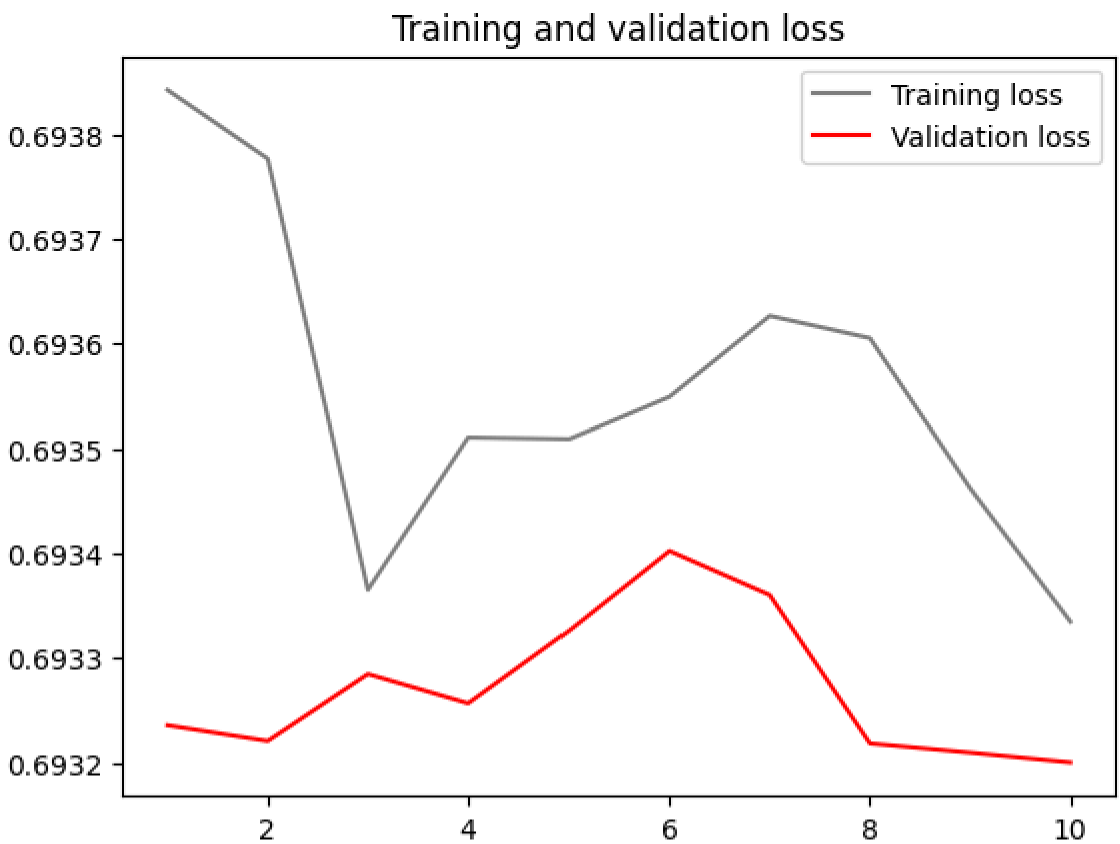
Train and evaluate

```
import tensorflow as tf

# Check if Google Drive is mounted
if not tf.io.gfile.exists('/content/drive'):
    from google.colab import drive
    drive.mount('/content/drive')

# Retry saving the model weights
try:
    model.save_weights('/content/drive/MyDrive/pre_trained_glove_model.3a')
    print("Model weights saved successfully.")
except Exception as e:
    print("Error occurred while saving model weights:", e)
```

```
Model weights saved successfully.
```

```
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()
```


Training and validation accuracy
0.49
0.48
0.47
0.46
0.45
2
4
6
8
10
Training acc
Validation acc


Training and validation loss
0.6938
0.6937
0.6936
0.6935
0.6934
0.6933
0.6932
2
4
6
8
10
Training loss
Validation loss

```
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)


try:
    model.load_weights('pre_trained_glove_model.3a')
    print("Model weights loaded successfully.")
except Exception as e:
    print("Error occurred while loading model weights:", e)
```

```
Error occurred while loading model weights: Unsuccessful TensorSliceReader co
```

Now we change the number of training samples to determine at what point the embedding layer gives better performance

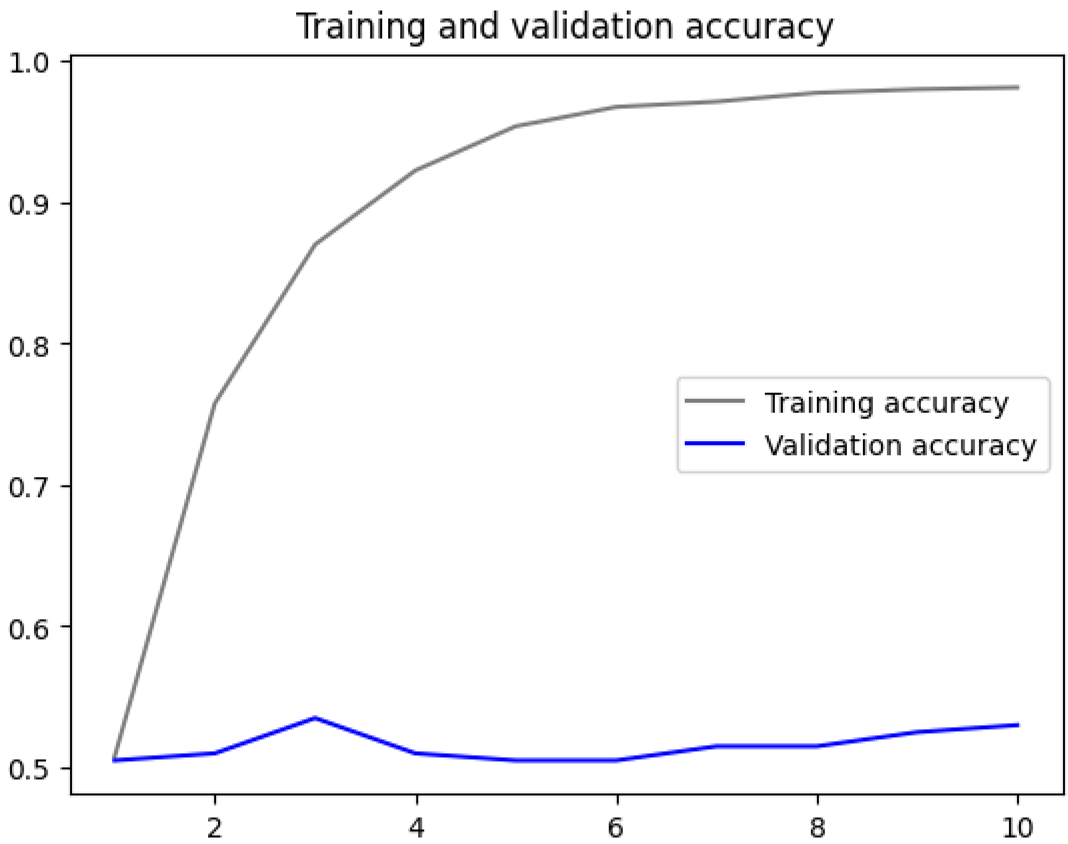
Model 4 training sample size - 1000 using embedding layer

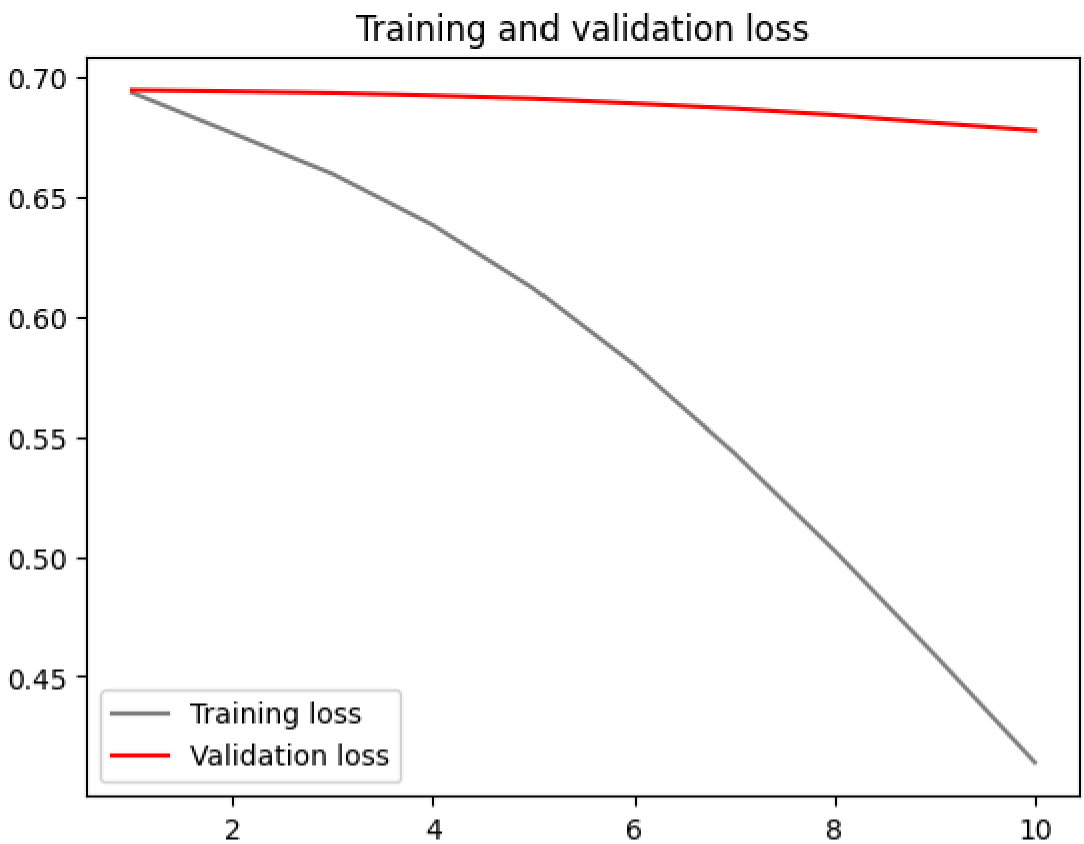
```
max_features=10000
maxlen=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

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]


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_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_4 (Embedding)     (None, 150, 8)            80000

 flatten_2 (Flatten)         (None, 1200)              0

 dense_3 (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 [==============================] - 2s 62ms/step - loss: 0.6934 - acc: 0
Epoch 2/10
25/25 [==============================] - 1s 51ms/step - loss: 0.6765 - acc: 0
Epoch 3/10
25/25 [==============================] - 1s 39ms/step - loss: 0.6595 - acc: 0
Epoch 4/10
25/25 [==============================] - 1s 45ms/step - loss: 0.6382 - acc: 0
Epoch 5/10
25/25 [==============================] - 2s 62ms/step - loss: 0.6118 - acc: 0
Epoch 6/10
25/25 [==============================] - 1s 48ms/step - loss: 0.5799 - acc: 0
Epoch 7/10
25/25 [==============================] - 1s 26ms/step - loss: 0.5432 - acc: 0
Epoch 8/10
25/25 [==============================] - 1s 29ms/step - loss: 0.5025 - acc: 0
Epoch 9/10
25/25 [==============================] - 1s 25ms/step - loss: 0.4591 - acc: 0
```

```
Epoch 10/10
25/25 [==============================] - 0s 17ms/step - loss: 0.4141 - acc: 0
```

```
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()
```






```
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: 0.6711 - acc: (
Test loss: 0.6710591912269592
Test accuracy: 0.5905600190162659
```

Double-click (or enter) to edit

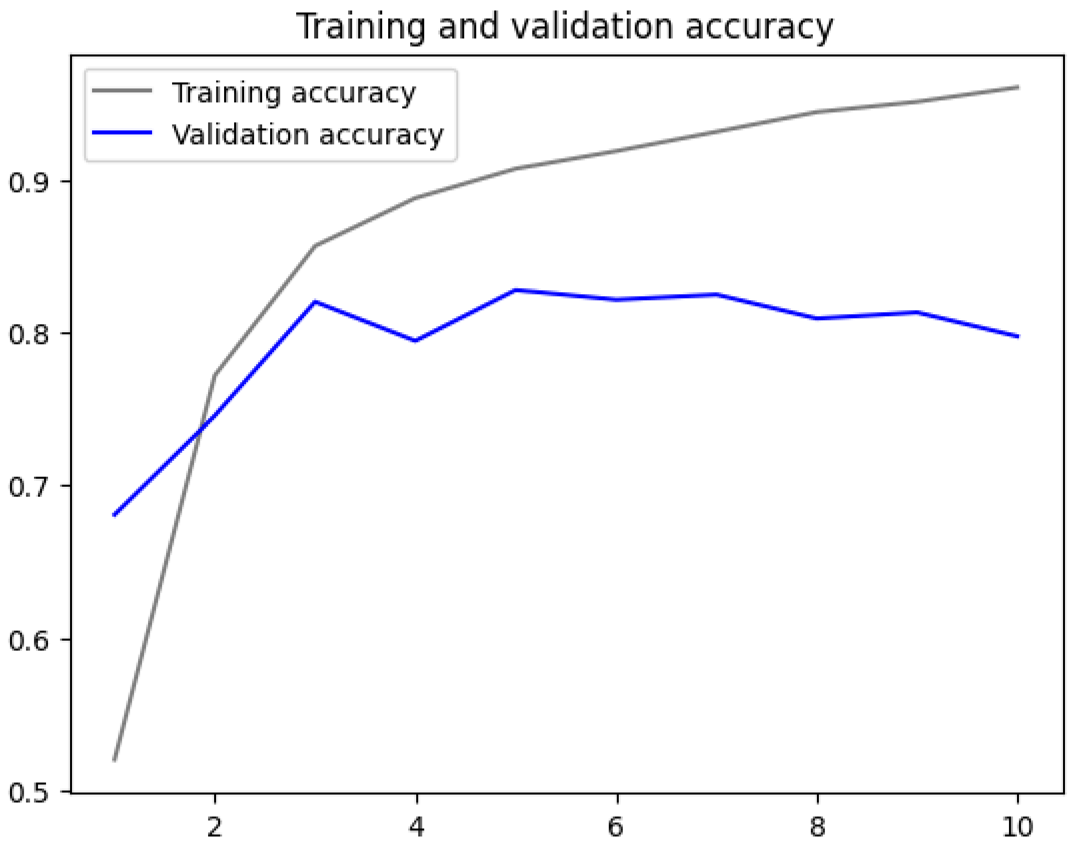
Model 5 Taining sample - 15000 using both embedding layer and Conv1D

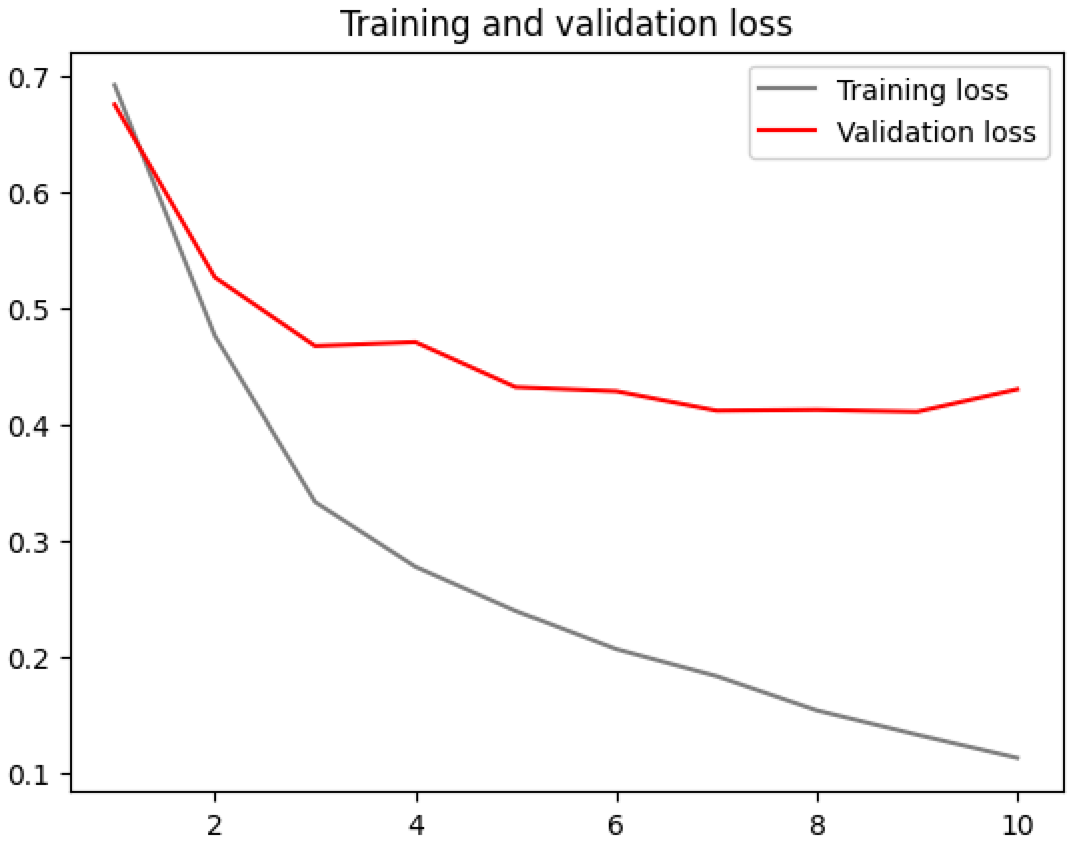
```
max_features=10000
maxlen=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

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]
y_train = y_train[:15000]


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_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_5 (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_3 (Flatten)         (None, 256)               0

 dense_4 (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 [==============================] - 27s 56ms/step - loss: 0.6919 - acc
Epoch 2/10
375/375 [==============================] - 8s 21ms/step - loss: 0.4760 - acc:
Epoch 3/10
375/375 [==============================] - 5s 12ms/step - loss: 0.3332 - acc:
Epoch 4/10
375/375 [==============================] - 5s 14ms/step - loss: 0.2775 - acc:
Epoch 5/10
375/375 [==============================] - 4s 10ms/step - loss: 0.2394 - acc:
Epoch 6/10
375/375 [==============================] - 3s 8ms/step - loss: 0.2065 - acc: (
Epoch 7/10
375/375 [==============================] - 5s 12ms/step - loss: 0.1832 - acc:
Epoch 8/10
375/375 [==============================] - 4s 11ms/step - loss: 0.1537 - acc:
Epoch 9/10
375/375 [==============================] - 3s 8ms/step - loss: 0.1328 - acc: (
Epoch 10/10
375/375 [==============================] - 3s 7ms/step - loss: 0.1128 - acc: (
```

```
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()
```






```
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: 0.4450 - acc: (
Test loss: 0.44504714012145996
Test accuracy: 0.7938799858093262
```

As we have seen in the previous model even though we increased the training sample size the accuracy was still low but when we used Con1D along with increased training sample size the accuracy improved to 81%

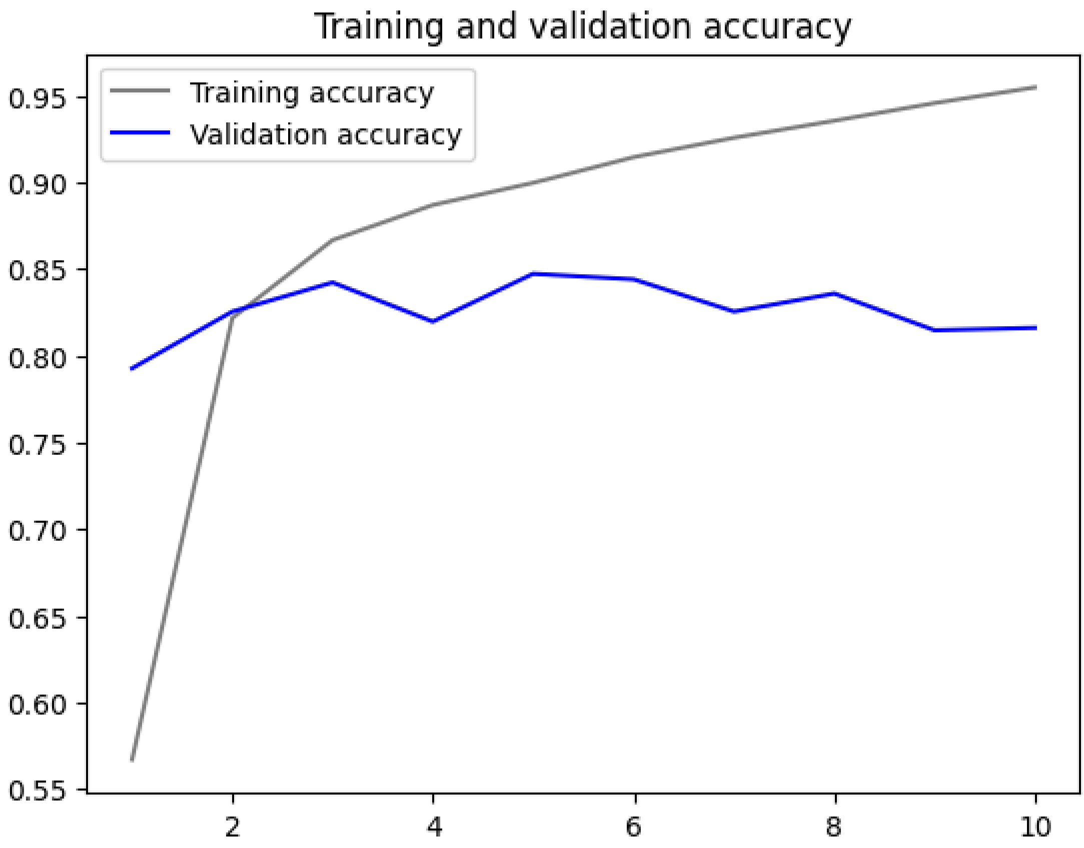
Model 6 Training sample 30000 using both embedding layers and Conv1D

```
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]


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_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_11 (Embedding)    (None, 150, 12)           120000

 conv1d_12 (Conv1D)          (None, 148, 512)          18944

 max_pooling1d_12 (MaxPooli  (None, 49, 512)           0
 ng1D)
```

```
 conv1d_13 (Conv1D)          (None, 47, 256)           393472

 max_pooling1d_13 (MaxPooli  (None, 15, 256)           0
 ng1D)

 conv1d_14 (Conv1D)          (None, 13, 256)           196864

 dropout_4 (Dropout)         (None, 13, 256)           0

 max_pooling1d_14 (MaxPooli  (None, 4, 256)            0
 ng1D)

 global_max_pooling1d_4 (Gl  (None, 256)               0
 obalMaxPooling1D)

 flatten_7 (Flatten)         (None, 256)               0

 dense_10 (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 [==============================] - 18s 28ms/step - loss: 0.6481 - acc
Epoch 2/10
625/625 [==============================] - 8s 12ms/step - loss: 0.3968 - acc:
Epoch 3/10
625/625 [==============================] - 5s 9ms/step - loss: 0.3205 - acc: (
Epoch 4/10
625/625 [==============================] - 6s 9ms/step - loss: 0.2810 - acc: (
Epoch 5/10
625/625 [==============================] - 4s 7ms/step - loss: 0.2525 - acc: (
Epoch 6/10
625/625 [==============================] - 4s 7ms/step - loss: 0.2262 - acc: (
Epoch 7/10
625/625 [==============================] - 5s 9ms/step - loss: 0.1999 - acc: (
Epoch 8/10
625/625 [==============================] - 5s 7ms/step - loss: 0.1770 - acc: (
Epoch 9/10
625/625 [==============================] - 4s 7ms/step - loss: 0.1540 - acc: (
Epoch 10/10
625/625 [==============================] - 5s 8ms/step - loss: 0.1278 - acc: (
```

```
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()
```




```
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: 0.4130 - acc: (
Test loss: 0.41296547651290894
Test accuracy: 0.8127999901771545
```

Model 7 pretrained model. Training - 15000 samples

```
maxlen = 150  # We will cut reviews after 150 words
training_samples = 15000  # We will be training on 15000 samples
validation_samples = 10000  # We will be validating on 10000 samples
max_words = 10000  # We will only consider the top 10,000 words in the dataset

tokenizer = Tokenizer(num_words=max_words)

# Convert any non-string elements in the texts list to strings
texts = [str(text) for text in texts]

# Fit the tokenizer on the texts
tokenizer.fit_on_texts(texts)
sequences = tokenizer.texts_to_sequences(texts)

word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))

data = pad_sequences(sequences, maxlen=maxlen)

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

# Split the data into a training set and a validation set
# But first, shuffle the data, since we started from data
# where samples are ordered (all negative first, then all positive).
indices = np.arange(data.shape[0])
np.random.shuffle(indices)

data = data[indices]
```