In [1]:
```
import os
from operator import itemgetter
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
get_ipython().magic(u'matplotlib inline')
plt.style.use('ggplot')

import tensorflow as tf

from keras import models, regularizers, layers, optimizers, losses, metrics
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import to_categorical
```

Sentiment labels indicating positivity or negativity are assigned to movie reviews in the IMDB dataset.

To preprocess the dataset, each review is transformed into a sequence of word embeddings. In this process, each word is represented by a vector of a fixed size.

In [2]:
```
from keras.layers import Embedding

# The Embedding layer requires a minimum of two inputs:
# The maximum word index plus one, or 1000, is the number of potential tokens.
# and the embeddings' dimensions, in this case 64.
embedd_lay = Embedding(1000, 64)
from keras.datasets import imdb
from keras import preprocessing
from keras.utils import pad_sequences
```

A custom-trained embedding layer was created with a training sample size of 100.

In [3]:
```
# The number of words that should be considered as features
fea = 10000
# Remove the text after this number of words(from the top max_features most common
length = 150

# Data Loading to integers
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=fea)

x_train = x_train[:100]
y_train = y_train[:100]

# The integer lists are now transformed into a 2D integer tensor with the shape of
x_train = pad_sequences(x_train, maxlen=length)
x_test = pad_sequences(x_test, maxlen=length)
from keras.models import Sequential
from keras.layers import Flatten, Dense

model1 = Sequential()
# In order to finally flatten the embedded inputs, the maximum length of the input
model1.add(Embedding(10000, 8, input_length=length))
# After the Embedding layer, our activations have shape `(samples, maxlen, 8)`.

# We flatten the 3D tensor of embeddings into a 2D tensor of shape
#`(samples, maxlen * 8)`
model1.add(Flatten())
```

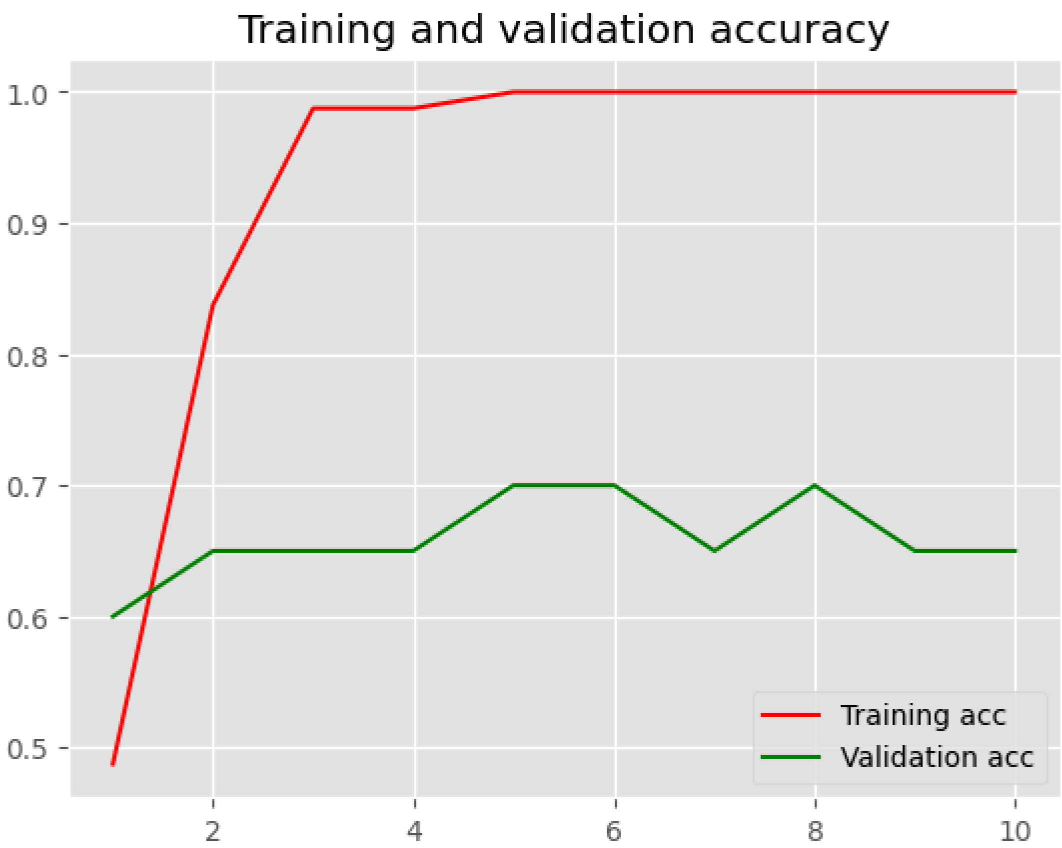
```python
# We add the classifier on top
model1.add(Dense(1, activation='sigmoid'))
model1.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model1.summary()

history1 = model1.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

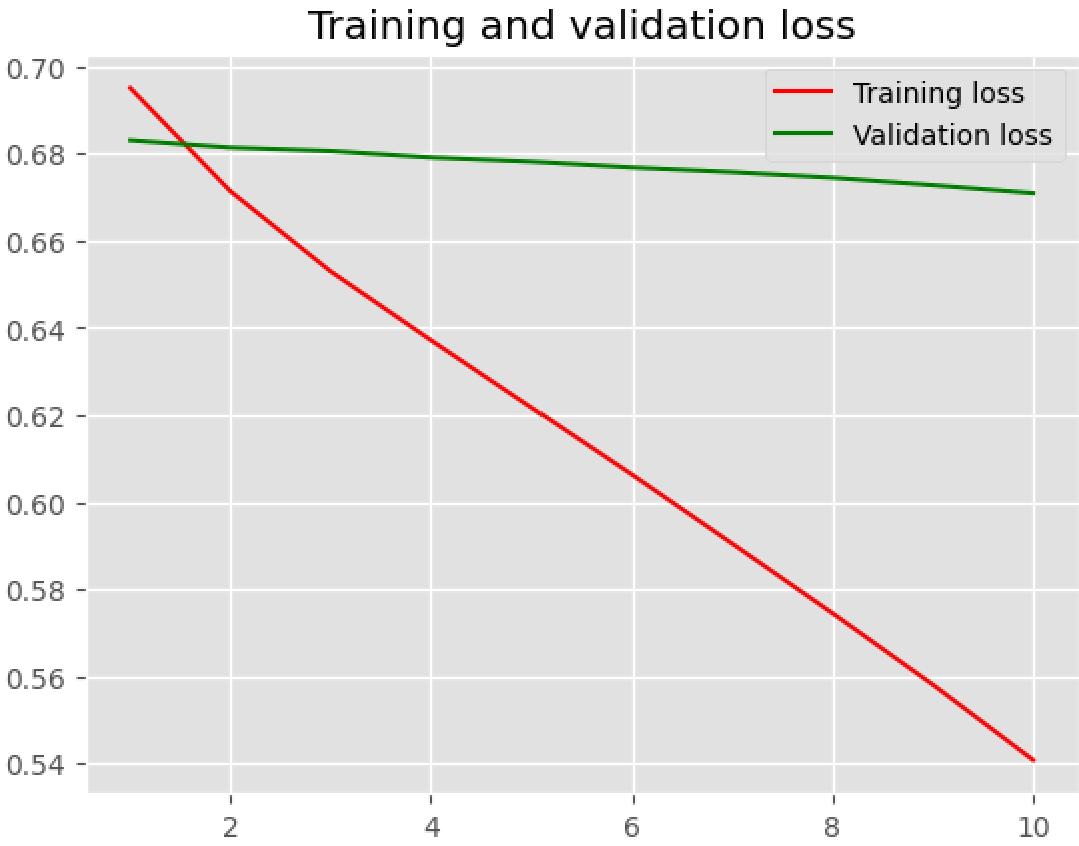
```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/
imdb.npz
17464789/17464789 [==============================] - 1s 0us/step
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              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
3/3 [==============================] - 3s 205ms/step - loss: 0.6951 - acc: 0.4875
- val_loss: 0.6831 - val_acc: 0.6000
Epoch 2/10
3/3 [==============================] - 0s 123ms/step - loss: 0.6714 - acc: 0.8375
- val_loss: 0.6814 - val_acc: 0.6500
Epoch 3/10
3/3 [==============================] - 0s 125ms/step - loss: 0.6530 - acc: 0.9875
- val_loss: 0.6806 - val_acc: 0.6500
Epoch 4/10
3/3 [==============================] - 0s 124ms/step - loss: 0.6372 - acc: 0.9875
- val_loss: 0.6791 - val_acc: 0.6500
Epoch 5/10
3/3 [==============================] - 0s 122ms/step - loss: 0.6217 - acc: 1.0000
- val_loss: 0.6782 - val_acc: 0.7000
Epoch 6/10
3/3 [==============================] - 0s 124ms/step - loss: 0.6063 - acc: 1.0000
- val_loss: 0.6768 - val_acc: 0.7000
Epoch 7/10
3/3 [==============================] - 0s 123ms/step - loss: 0.5904 - acc: 1.0000
- val_loss: 0.6758 - val_acc: 0.6500
Epoch 8/10
3/3 [==============================] - 0s 126ms/step - loss: 0.5744 - acc: 1.0000
- val_loss: 0.6745 - val_acc: 0.7000
Epoch 9/10
3/3 [==============================] - 0s 126ms/step - loss: 0.5581 - acc: 1.0000
- val_loss: 0.6728 - val_acc: 0.6500
Epoch 10/10
3/3 [==============================] - 0s 125ms/step - loss: 0.5408 - acc: 1.0000
- val_loss: 0.6709 - val_acc: 0.6500
```

In [4]:

```python
import matplotlib.pyplot as plt

# Train accuracy
tra_acc = history1.history["acc"]
```

```
# Validation accuracy
val_acc = history1.history["val_acc"]
# Train loss
tra_loss = history1.history["loss"]
# Validation loss
val_loss = history1.history["val_loss"]


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

plt.plot(epochs, tra_acc, "red", label = "Training acc")
plt.plot(epochs, val_acc, "g", label = "Validation acc")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()

plt.plot(epochs, tra_loss, "red", label = "Training loss")
plt.plot(epochs, val_loss, "g", label = "Validation loss")
plt.title("Training and validation loss")
plt.legend()

plt.show()
```





In [5]:
```
test_loss, test_acc = model1.evaluate(x_test, y_test)
print('Test loss:', test_loss)
print('Test accuracy:', test_acc)
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.6936 - acc: 0.502
3
Test loss: 0.693622350692749
Test accuracy: 0.5023199915885925
```

A custom-trained embedding layer was created with a training sample size of 5000

In [6]:
```
fea=10000
length=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=fea)

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

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

x_train = x_train[:5000]
y_train = y_train[:5000]
```

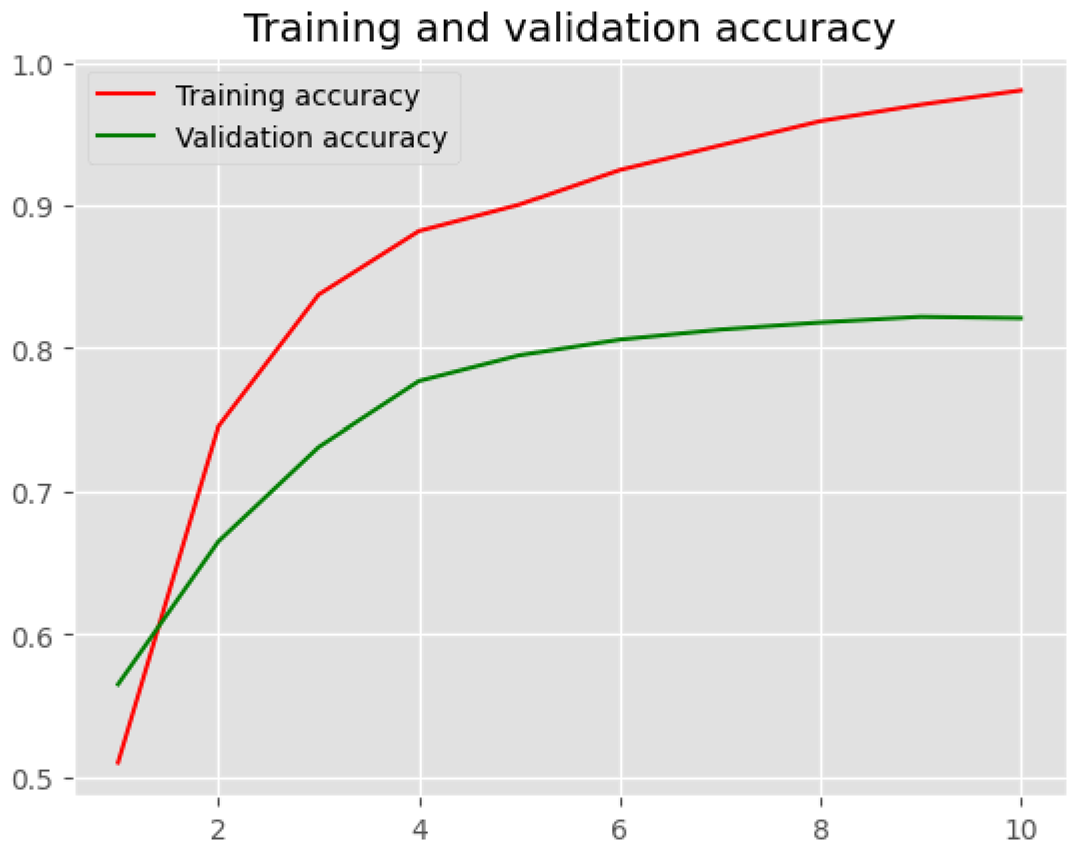
In [7]:
```
model2 = Sequential()
model2.add(Embedding(10000, 8, input_length=length))
model2.add(Flatten())
model2.add(Dense(1, activation='sigmoid'))
model2.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model2.summary()
history2 = model2.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

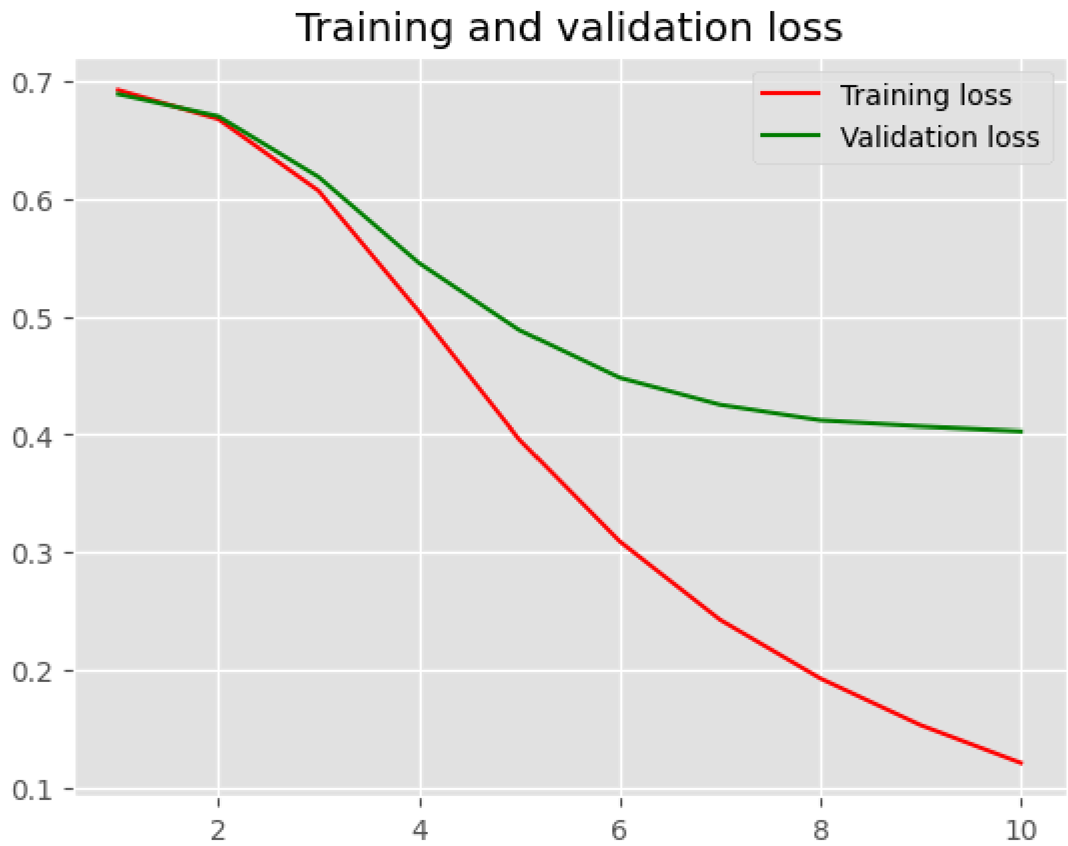
```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_2 (Embedding)     (None, 150, 8)            80000     
                                                                 
 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
125/125 [==============================] - 10s 79ms/step - loss: 0.6925 - acc: 0.5
102 - val_loss: 0.6891 - val_acc: 0.5650
Epoch 2/10
125/125 [==============================] - 5s 39ms/step - loss: 0.6678 - acc: 0.74
52 - val_loss: 0.6702 - val_acc: 0.6650
Epoch 3/10
125/125 [==============================] - 3s 27ms/step - loss: 0.6068 - acc: 0.83
75 - val_loss: 0.6186 - val_acc: 0.7310
Epoch 4/10
125/125 [==============================] - 3s 20ms/step - loss: 0.5043 - acc: 0.88
20 - val_loss: 0.5456 - val_acc: 0.7770
Epoch 5/10
125/125 [==============================] - 2s 15ms/step - loss: 0.3958 - acc: 0.90
05 - val_loss: 0.4885 - val_acc: 0.7950
Epoch 6/10
125/125 [==============================] - 1s 10ms/step - loss: 0.3091 - acc: 0.92
47 - val_loss: 0.4479 - val_acc: 0.8060
Epoch 7/10
125/125 [==============================] - 1s 9ms/step - loss: 0.2426 - acc: 0.942
0 - val_loss: 0.4250 - val_acc: 0.8130
Epoch 8/10
125/125 [==============================] - 1s 10ms/step - loss: 0.1928 - acc: 0.95
90 - val_loss: 0.4118 - val_acc: 0.8180
Epoch 9/10
125/125 [==============================] - 1s 8ms/step - loss: 0.1530 - acc: 0.970
5 - val_loss: 0.4067 - val_acc: 0.8220
Epoch 10/10
125/125 [==============================] - 1s 9ms/step - loss: 0.1209 - acc: 0.980
5 - val_loss: 0.4026 - val_acc: 0.8210
```

In [8]:

```
tra_acc2 = history2.history['acc']
val_acc2 = history2.history['val_acc']
tra_loss2 = history2.history['loss']
val_loss2 = history2.history['val_loss']

epochs = range(1, len(tra_acc2) + 1)

plt.plot(epochs, tra_acc2, 'r', label='Training accuracy')
plt.plot(epochs, val_acc2, 'g', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, tra_loss2, 'r', label='Training loss')
plt.plot(epochs, val_loss2, 'g', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
```

```
plt.show()
```





In [9]:
```
test_loss2, test_accuracy2 = model2.evaluate(x_test, y_test)
print('Test loss:', test_loss2)
print('Test accuracy:', test_accuracy2)
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.3718 - acc: 0.831
0
Test loss: 0.37180960178375244
Test accuracy: 0.8309999704360962
```

A custom-trained embedding layer was created with a training sample size of 1000

In [10]:
```
fea=10000
length=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=fea)

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

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]
```

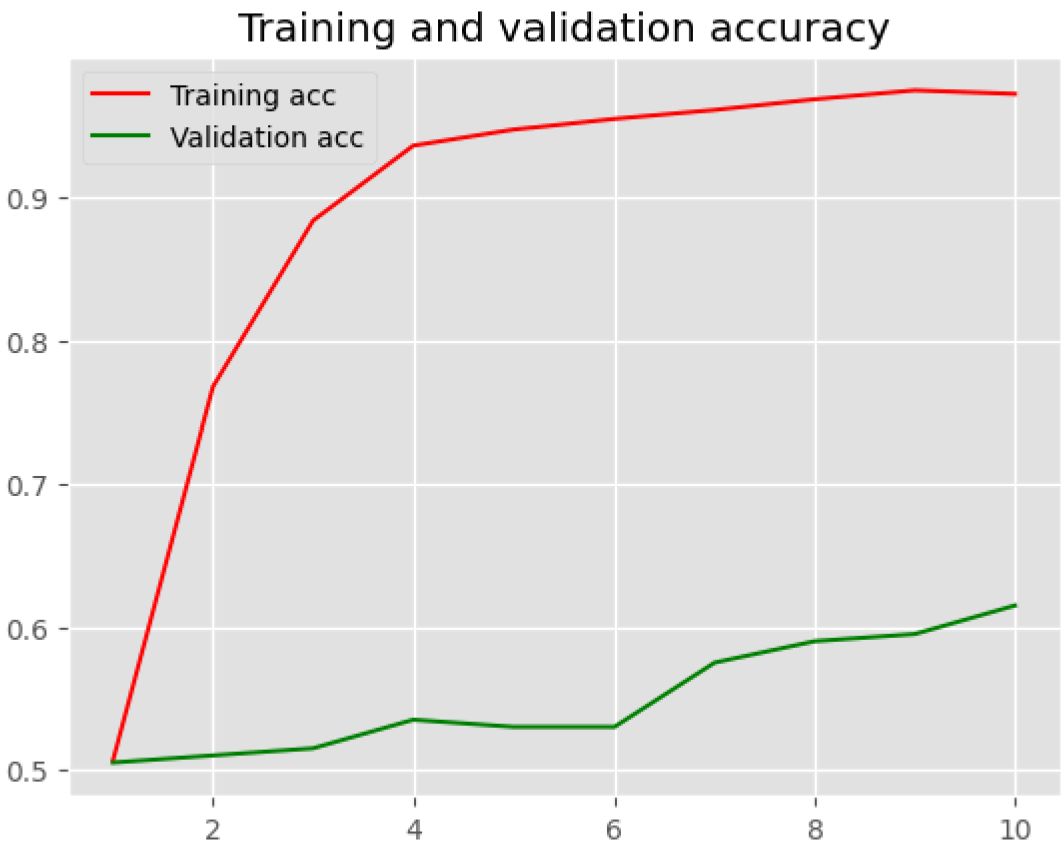
In [11]:
```
model3 = Sequential()
model3.add(Embedding(10000, 8, input_length=length))
model3.add(Flatten())
model3.add(Dense(1, activation='sigmoid'))
model3.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model3.summary()
history3 = model3.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_3 (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
25/25 [==============================] - 2s 71ms/step - loss: 0.6929 - acc: 0.5063
- val_loss: 0.6922 - val_acc: 0.5050
Epoch 2/10
25/25 [==============================] - 2s 64ms/step - loss: 0.6762 - acc: 0.7675
- val_loss: 0.6916 - val_acc: 0.5100
Epoch 3/10
25/25 [==============================] - 1s 31ms/step - loss: 0.6591 - acc: 0.8838
- val_loss: 0.6908 - val_acc: 0.5150
Epoch 4/10
25/25 [==============================] - 1s 48ms/step - loss: 0.6373 - acc: 0.9362
- val_loss: 0.6896 - val_acc: 0.5350
Epoch 5/10
25/25 [==============================] - 2s 63ms/step - loss: 0.6103 - acc: 0.9475
- val_loss: 0.6876 - val_acc: 0.5300
Epoch 6/10
25/25 [==============================] - 1s 34ms/step - loss: 0.5771 - acc: 0.9550
- val_loss: 0.6847 - val_acc: 0.5300
Epoch 7/10
25/25 [==============================] - 1s 29ms/step - loss: 0.5386 - acc: 0.9613
- val_loss: 0.6811 - val_acc: 0.5750
Epoch 8/10
25/25 [==============================] - 1s 33ms/step - loss: 0.4961 - acc: 0.9688
- val_loss: 0.6769 - val_acc: 0.5900
Epoch 9/10
25/25 [==============================] - 1s 26ms/step - loss: 0.4503 - acc: 0.9750
- val_loss: 0.6721 - val_acc: 0.5950
Epoch 10/10
25/25 [==============================] - 0s 19ms/step - loss: 0.4034 - acc: 0.9725
- val_loss: 0.6667 - val_acc: 0.6150
```

In [12]:

```
tra_acc3 = history3.history["acc"]
val_acc3 = history3.history["val_acc"]
tra_loss3 = history3.history["loss"]
val_loss3 = history3.history["val_loss"]

epochs = range(1, len(tra_acc3) + 1)

plt.plot(epochs, tra_acc3, "r", label = "Training acc")
plt.plot(epochs, val_acc3, "g", label = "Validation acc")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()

plt.plot(epochs, tra_loss3, "red", label = "Training loss")
plt.plot(epochs, val_loss3, "g", label = "Validation loss")
plt.title("Training and validation loss")
plt.legend()
```

```
plt.show()
```



In [13]:

```
test_loss3, test_accuracy3 = model3.evaluate(x_test, y_test)
print('Test loss:', test_loss3)
print('Test accuracy:', test_accuracy3)
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.6613 - acc: 0.617
8
Test loss: 0.6613208651542664
Test accuracy: 0.6177600026130676
```

A custom-trained embedding layer was created with a training sample size of 10000

In [14]:
```
fea=10000
length=150
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=fea)

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

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

x_train = x_train[:10000]
y_train = y_train[:10000]
```

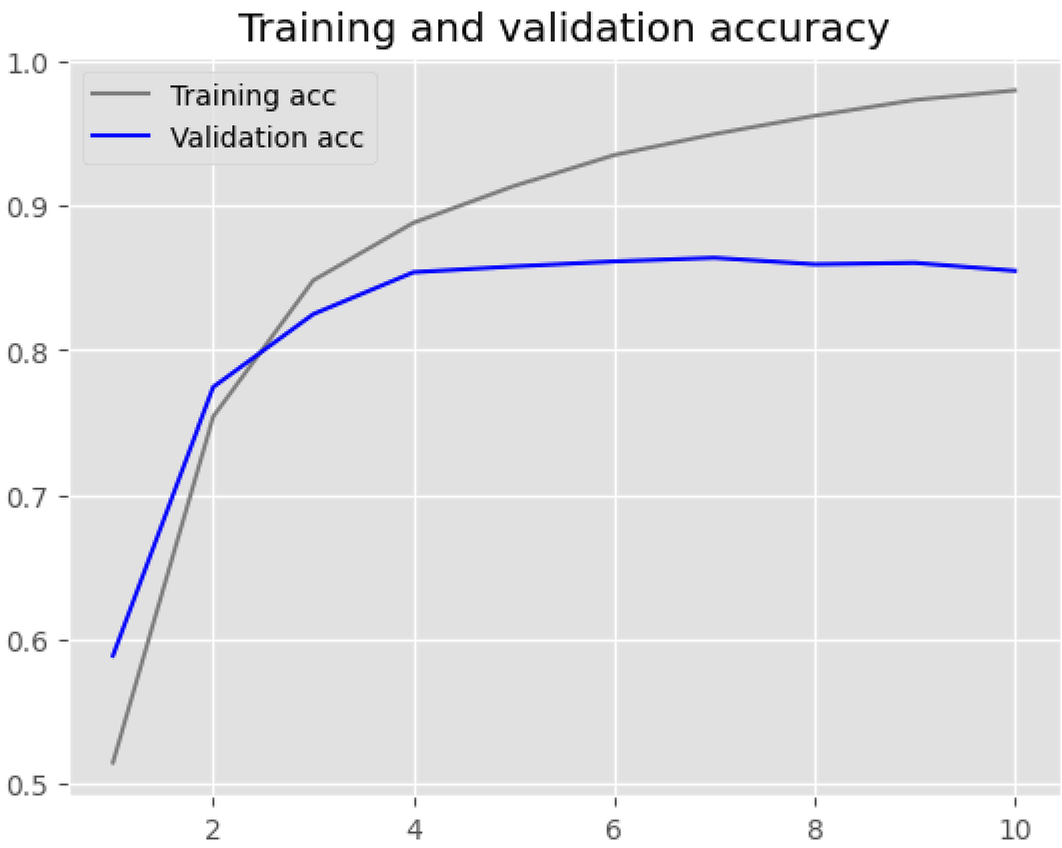
In [15]:
```
model4 = Sequential()
model4.add(Embedding(10000, 8, input_length=length))
model4.add(Flatten())
model4.add(Dense(1, activation='sigmoid'))
model4.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model4.summary()
history4 = model4.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_split=0.2)
```

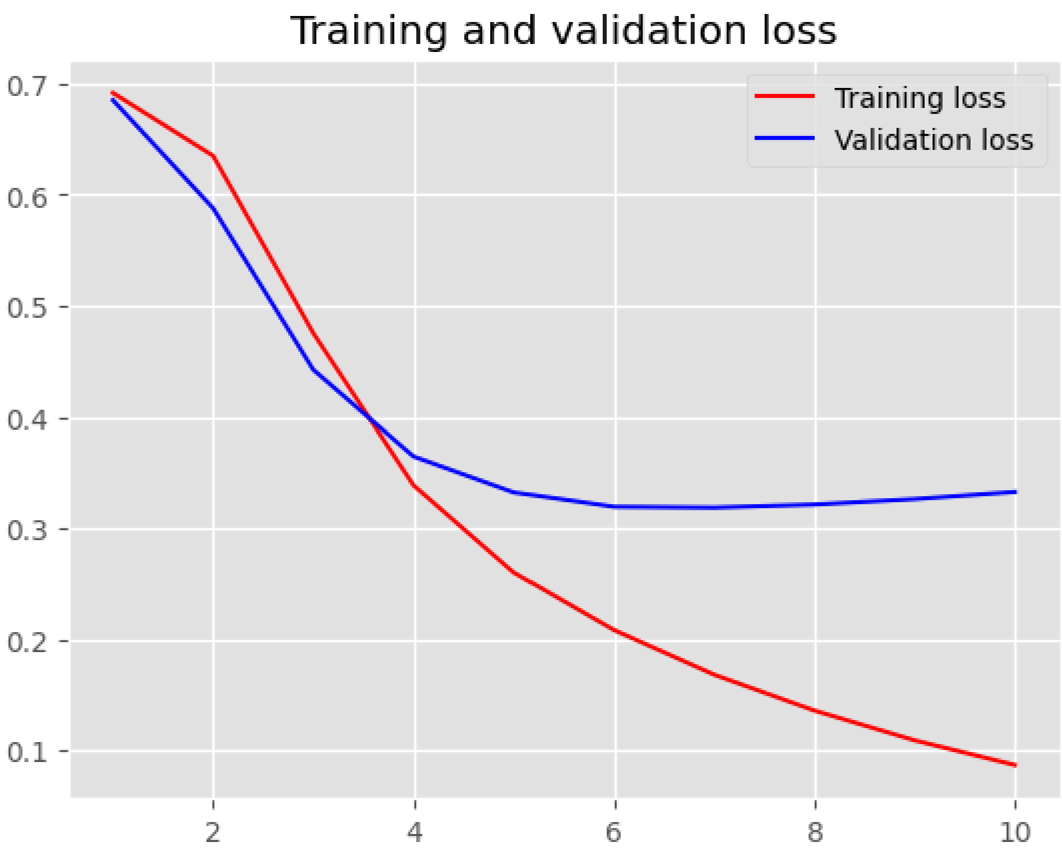
```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_4 (Embedding)     (None, 150, 8)            80000     
                                                                 
 flatten_3 (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
250/250 [==============================] - 11s 42ms/step - loss: 0.6919 - acc: 0.5
150 - val_loss: 0.6853 - val_acc: 0.5890
Epoch 2/10
250/250 [==============================] - 5s 21ms/step - loss: 0.6352 - acc: 0.75
40 - val_loss: 0.5880 - val_acc: 0.7745
Epoch 3/10
250/250 [==============================] - 3s 13ms/step - loss: 0.4755 - acc: 0.84
84 - val_loss: 0.4425 - val_acc: 0.8250
Epoch 4/10
250/250 [==============================] - 2s 6ms/step - loss: 0.3388 - acc: 0.888
2 - val_loss: 0.3647 - val_acc: 0.8540
Epoch 5/10
250/250 [==============================] - 1s 4ms/step - loss: 0.2602 - acc: 0.913
6 - val_loss: 0.3324 - val_acc: 0.8580
Epoch 6/10
250/250 [==============================] - 2s 6ms/step - loss: 0.2082 - acc: 0.935
1 - val_loss: 0.3194 - val_acc: 0.8615
Epoch 7/10
250/250 [==============================] - 2s 7ms/step - loss: 0.1680 - acc: 0.949
6 - val_loss: 0.3187 - val_acc: 0.8640
Epoch 8/10
250/250 [==============================] - 1s 4ms/step - loss: 0.1357 - acc: 0.962
2 - val_loss: 0.3214 - val_acc: 0.8595
Epoch 9/10
250/250 [==============================] - 1s 4ms/step - loss: 0.1089 - acc: 0.973
2 - val_loss: 0.3263 - val_acc: 0.8605
Epoch 10/10
250/250 [==============================] - 1s 5ms/step - loss: 0.0867 - acc: 0.979
9 - val_loss: 0.3328 - val_acc: 0.8550
```

In [16]:

```
tra_acc4 = history4.history["acc"]
val_acc4 = history4.history["val_acc"]
tra_loss4 = history4.history["loss"]
val_loss4 = history4.history["val_loss"]

epochs = range(1, len(tra_acc4) + 1)

plt.plot(epochs, tra_acc4, "grey", label = "Training acc")
plt.plot(epochs, val_acc4, "b", label = "Validation acc")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()

plt.plot(epochs, tra_loss4, "red", label = "Training loss")
plt.plot(epochs, val_loss4, "b", label = "Validation loss")
plt.title("Training and validation loss")
plt.legend()
```

```
plt.show()
```





In [17]:
```
test_loss4, test_accuracy4 = model4.evaluate(x_test, y_test)
print('Test loss:', test_loss4)
print('Test accuracy:', test_accuracy4)
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.3360 - acc: 0.855
0
Test loss: 0.3359987437725067
Test accuracy: 0.8550000190734863
```

In [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  5337k      0  0:00:15  0:00:15 --:--:-- 12.3M
```

In [19]:
```
import os
import shutil

imdb = 'aclImdb'
training = os.path.join(imdb, 'train')

labels = []
texts = []

for label_type in ['neg', 'pos']:
    dir_name = os.path.join(training, label_type)
    for fname in os.listdir(dir_name):
        if fname[-4:] == '.txt':
            f = open(os.path.join(dir_name, fname), encoding='utf-8')
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
                labels.append(0)
            else:
                labels.append(1)
```

If the available training data isn't sufficient to generate word embeddings tailored to the specific problem you're addressing, you can opt for pretrained word embeddings instead.

Tokenizing the data

In [20]:
```
from keras.preprocessing.text import Tokenizer
from keras.utils import pad_sequences
import numpy as np

length2 = 150 # cut off review after 150 words
tra_info = 100 # Training sample 100
val_info = 10000 # Validation sample 10000
words = 10000 # Considers only the top 10000 words in the dataset

tokenizer1 = Tokenizer(num_words=words)
tokenizer1.fit_on_texts(texts)
sequences = tokenizer1.texts_to_sequences(texts)
word_index = tokenizer1.word_index
print("Found %s unique tokens." % len(word_index))

data = pad_sequences(sequences, maxlen=length2)

labels = np.asarray(labels)
print("Shape of data tensor:", data.shape)
print("Shape of label tensor:", labels.shape)
# Splits data into training and validation set, but shuffles is, since samples are
# all negatives first, then all positive
indices = np.arange(data.shape[0])
np.random.shuffle(indices)
```

```
data = data[indices]
labels = labels[indices]

x_train = data[:tra_info] # (200, 100)
y_train = labels[:tra_info] # shape (200,)
x_validation = data[tra_info:tra_info+val_info] # shape (10000, 100)
y_validation = labels[tra_info:tra_info+val_info] # shape (10000,)
```

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

Setting up and installing the GloVe word embedding.

In [21]:

```
import numpy as np
import requests
from io import BytesIO
import zipfile

glove_url = 'https://nlp.stanford.edu/data/glove.6B.zip'  # URL to download GloVe e
glove_zip = requests.get(glove_url)

# Unzip the contents
with zipfile.ZipFile(BytesIO(glove_zip.content)) as z:
    z.extractall('/content/glove')

# Loading GloVe embeddings into memory
embeddings_index = {}
with open('/content/glove/glove.6B.100d.txt', 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))
```

```
Found 400000 word vectors.
```

We utilized the 6B version of the GloVe model, trained on a combination of Wikipedia data and Gigaword 5 corpus, comprising 6 billion tokens and encompassing 400,000 words.

Creating the GloVe word embeddings matrix.

Using a pretrained word embedding layer with a training sample size of 100.

In [22]:

```
embedding_di = 100

embedding_matrix = np.zeros((words, embedding_di))
for word, i in word_index.items():
    embedd_vector = embeddings_index.get(word)
    if i < words:
        if embedd_vector is not None:
            # Words not found in embedding index will be all-zeros.
            embedding_matrix[i] = embedd_vector
```

In [23]:

```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(words, embedding_di, input_length=length2))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
```

```
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_5 (Embedding)     (None, 150, 100)          1000000   
                                                                 
 flatten_4 (Flatten)         (None, 15000)             0         
                                                                 
 dense_4 (Dense)             (None, 32)                480032    
                                                                 
 dense_5 (Dense)             (None, 1)                 33        
                                                                 
=================================================================
Total params: 1480065 (5.65 MB)
Trainable params: 1480065 (5.65 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [24]:

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

The Embedding layer loads the pretrained word embedding. By setting it to False when invoking the Embedding layer, it ensures that the embedding is not trainable. If you set trainable = True, the optimization method might alter the word embedding values. It's advisable to keep pretrained sections unchanged during student training to prevent them from forgetting previously learned information.

In [25]:

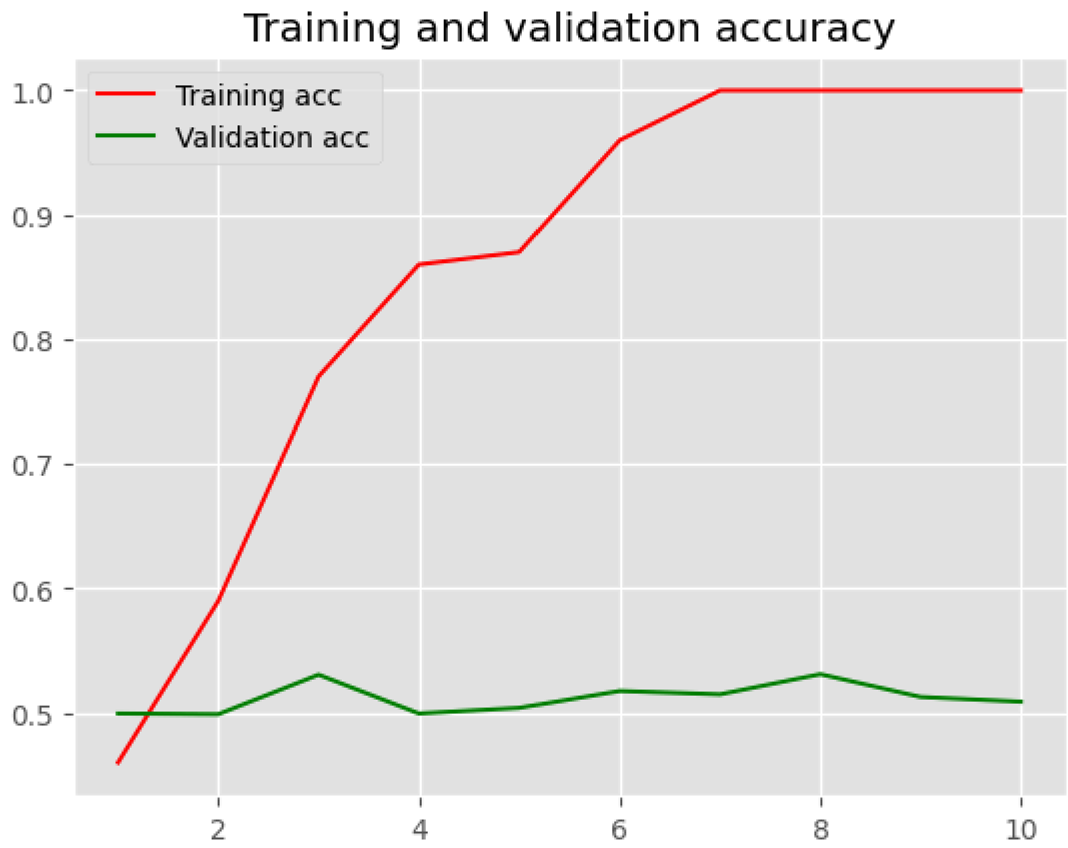
```
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_validation, y_validation))
model.save_weights('pre_trained_glove_model.h5')
```

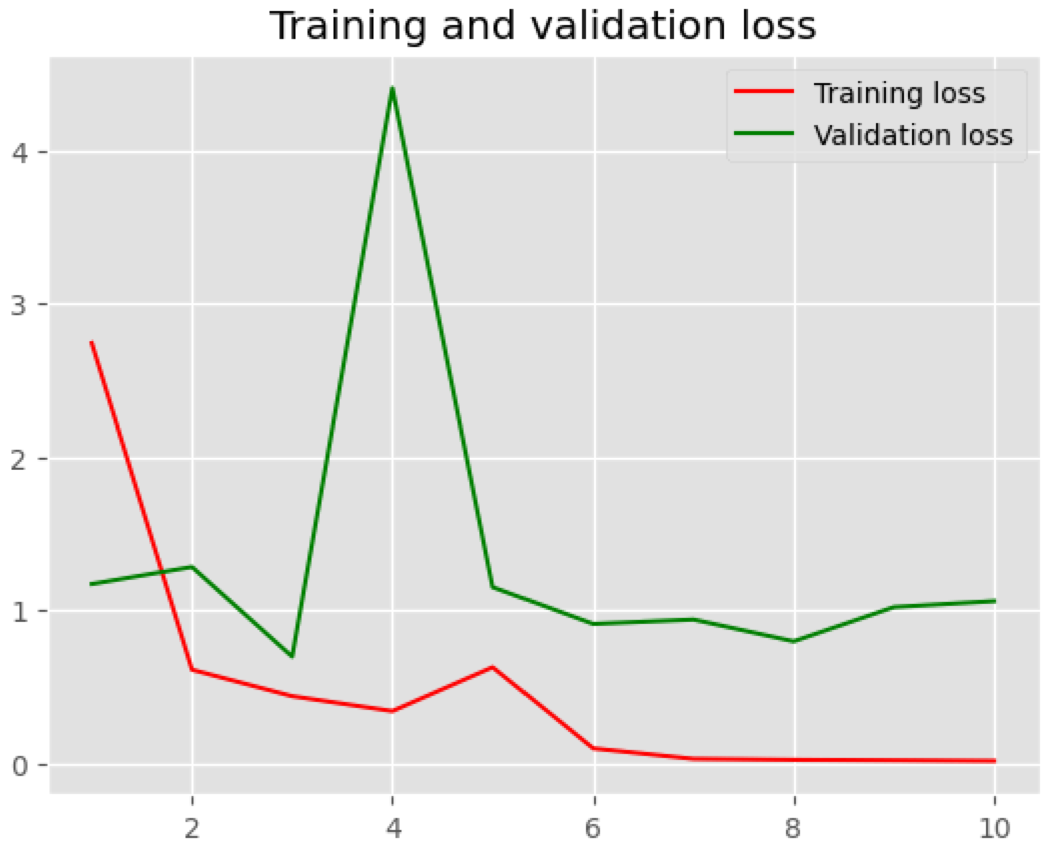
```
Epoch 1/10
4/4 [==============================] - 2s 233ms/step - loss: 2.7435 - acc: 0.4600
- val_loss: 1.1707 - val_acc: 0.4994
Epoch 2/10
4/4 [==============================] - 1s 181ms/step - loss: 0.6100 - acc: 0.5900
- val_loss: 1.2823 - val_acc: 0.4988
Epoch 3/10
4/4 [==============================] - 1s 180ms/step - loss: 0.4371 - acc: 0.7700
- val_loss: 0.6956 - val_acc: 0.5306
Epoch 4/10
4/4 [==============================] - 1s 182ms/step - loss: 0.3394 - acc: 0.8600
- val_loss: 4.4112 - val_acc: 0.4994
Epoch 5/10
4/4 [==============================] - 1s 184ms/step - loss: 0.6264 - acc: 0.8700
- val_loss: 1.1500 - val_acc: 0.5039
Epoch 6/10
4/4 [==============================] - 1s 183ms/step - loss: 0.0955 - acc: 0.9600
- val_loss: 0.9095 - val_acc: 0.5175
Epoch 7/10
4/4 [==============================] - 1s 184ms/step - loss: 0.0272 - acc: 1.0000
- val_loss: 0.9383 - val_acc: 0.5148
Epoch 8/10
4/4 [==============================] - 1s 190ms/step - loss: 0.0208 - acc: 1.0000
- val_loss: 0.7957 - val_acc: 0.5310
Epoch 9/10
4/4 [==============================] - 1s 188ms/step - loss: 0.0177 - acc: 1.0000
- val_loss: 1.0197 - val_acc: 0.5127
Epoch 10/10
4/4 [==============================] - 1s 188ms/step - loss: 0.0138 - acc: 1.0000
- val_loss: 1.0587 - val_acc: 0.5089
```

Due to the limited training data, it's anticipated that the model will overfit rapidly. This phenomenon is evident in the wide range of validation accuracy.

In [26]:

```
import matplotlib.pyplot as plt

tra_acc = history.history['acc']
val_acc = history.history['val_acc']
tra_loss = history.history['loss']
val_loss = history.history['val_loss']

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

plt.plot(epochs, tra_acc, 'r', label='Training acc')
plt.plot(epochs, val_acc, 'g', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

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

plt.show()
```





In [27]:

```
test_loss, test_accuracy= model.evaluate(x_test, y_test)
print('Test loss:', test_loss)
print('Test accuracy:', test_accuracy)
```

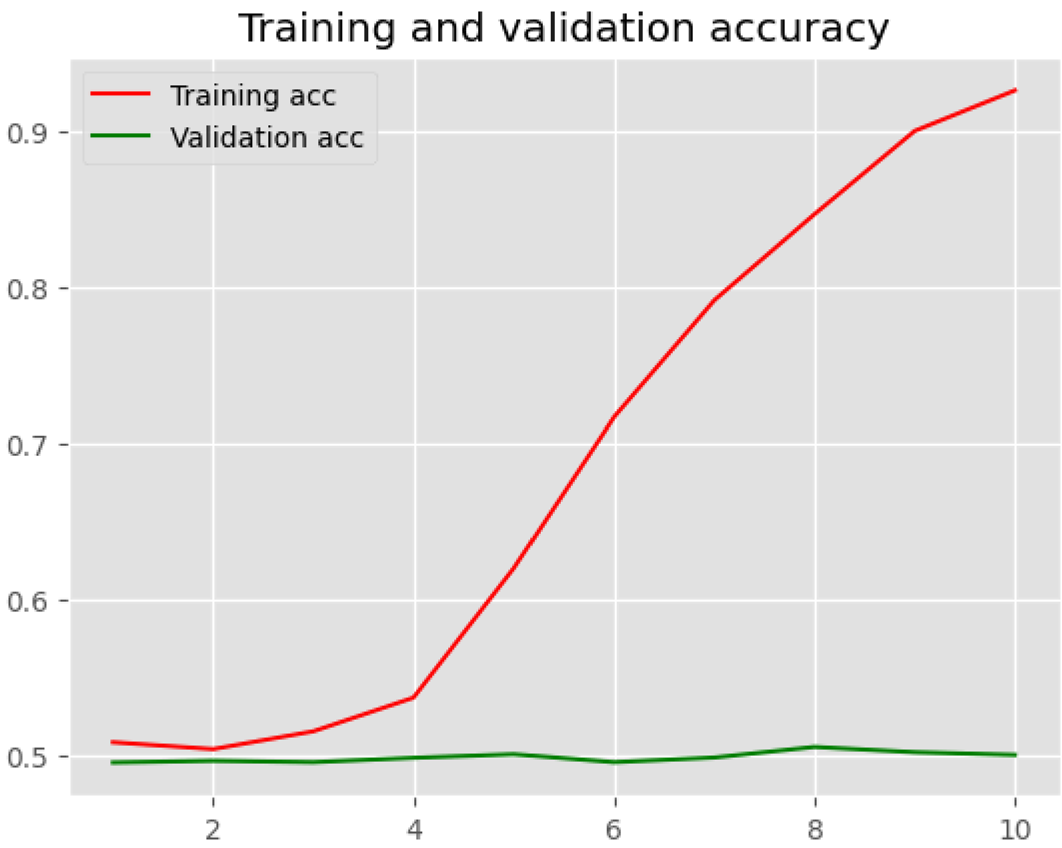
```
782/782 [==============================] - 2s 2ms/step - loss: 1.1559 - acc: 0.493
2
Test loss: 1.15593683719635
Test accuracy: 0.4931600093841553
```

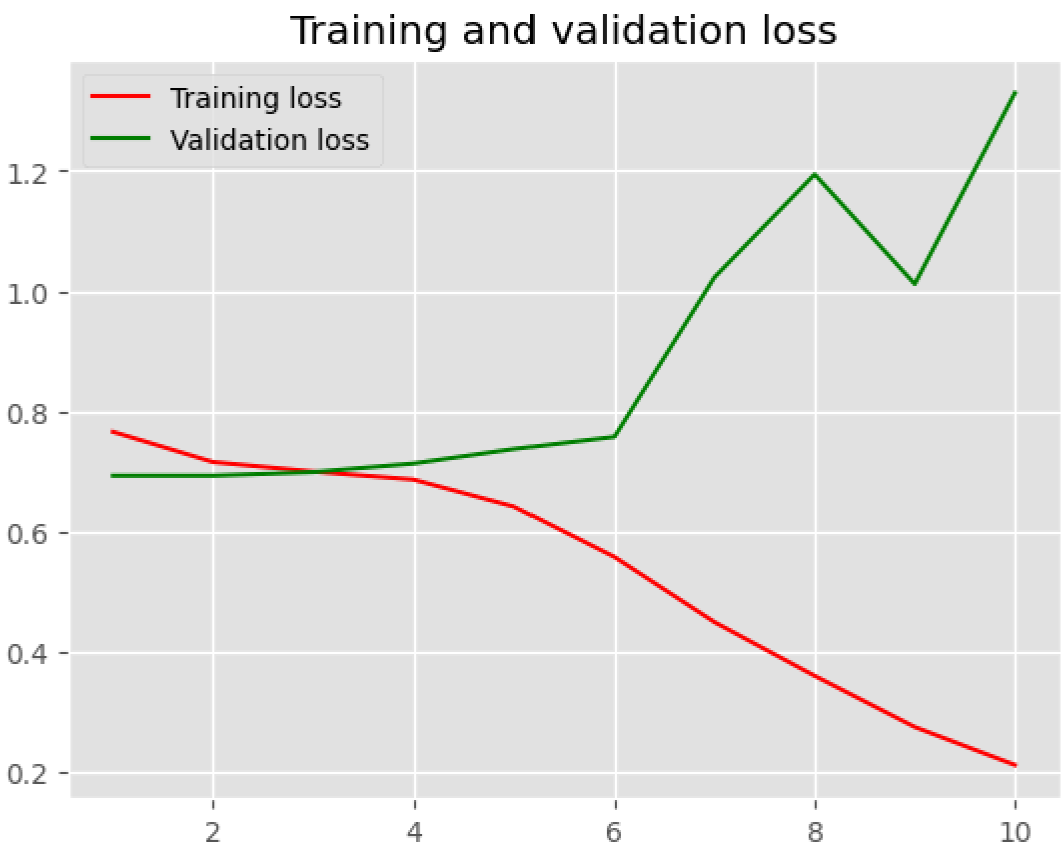
Using a pretrained word embedding layer with a training sample size of 5000.

In [28]:
```
from keras.preprocessing.text import Tokenizer
from keras.utils import pad_sequences
import numpy as np

length2 = 150
tra_info = 5000 # Training sample is 5000
val_info = 10000
words = 10000

tokenizer2 = Tokenizer(num_words=words)
tokenizer2.fit_on_texts(texts)
sequences = tokenizer2.texts_to_sequences(texts)
word_index = tokenizer2.word_index
print("Found %s unique tokens." % len(word_index))

data = pad_sequences(sequences, maxlen=length2)

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

indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

x_train = data[:tra_info]
y_train = labels[:tra_info]
x_validation = data[tra_info:tra_info+val_info]
y_validation = labels[tra_info:tra_info+val_info]
embedding_di = 100

embedd_matrix = np.zeros((words, embedding_di))
for word, i in word_index.items():
    embedd_vector = embeddings_index.get(word)
    if i < words:
        if embedd_vector is not None:

            embedd_matrix[i] = embedd_vector

from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model11 = Sequential()
model11.add(Embedding(words, embedding_di, input_length=length2))
model11.add(Flatten())
model11.add(Dense(32, activation='relu'))
model11.add(Dense(1, activation='sigmoid'))
model11.summary()

model11.layers[0].set_weights([embedding_matrix])
model11.layers[0].trainable = False
model11.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history11 = model11.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_validation, y_validation))
model11.save_weights('pre_trained_glove_model.h5')
import matplotlib.pyplot as plt
```

```
tra_acc1 = history11.history['acc']
val_acc11 = history11.history['val_acc']
tra_loss11 = history11.history['loss']
val_loss11 = history11.history['val_loss']

epochs = range(1, len(tra_acc1) + 1)

plt.plot(epochs, tra_acc1, 'r', label='Training acc')
plt.plot(epochs, val_acc11, 'g', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, tra_loss11, 'red', label='Training loss')
plt.plot(epochs, val_loss11, 'g', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 150)
Shape of label tensor: (25000,)
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_6 (Embedding)     (None, 150, 100)          1000000   
                                                                 
 flatten_5 (Flatten)         (None, 15000)             0         
                                                                 
 dense_6 (Dense)             (None, 32)                480032    
                                                                 
 dense_7 (Dense)             (None, 1)                 33        
                                                                 
=================================================================
Total params: 1480065 (5.65 MB)
Trainable params: 1480065 (5.65 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
157/157 [==============================] - 2s 7ms/step - loss: 0.7662 - acc: 0.508
2 - val_loss: 0.6933 - val_acc: 0.4952
Epoch 2/10
157/157 [==============================] - 1s 6ms/step - loss: 0.7159 - acc: 0.503
8 - val_loss: 0.6933 - val_acc: 0.4963
Epoch 3/10
157/157 [==============================] - 1s 7ms/step - loss: 0.7000 - acc: 0.515
2 - val_loss: 0.6992 - val_acc: 0.4954
Epoch 4/10
157/157 [==============================] - 1s 7ms/step - loss: 0.6868 - acc: 0.536
8 - val_loss: 0.7134 - val_acc: 0.4982
Epoch 5/10
157/157 [==============================] - 1s 7ms/step - loss: 0.6420 - acc: 0.619
8 - val_loss: 0.7375 - val_acc: 0.5005
Epoch 6/10
157/157 [==============================] - 1s 7ms/step - loss: 0.5581 - acc: 0.716
8 - val_loss: 0.7578 - val_acc: 0.4954
Epoch 7/10
157/157 [==============================] - 1s 7ms/step - loss: 0.4497 - acc: 0.791
6 - val_loss: 1.0232 - val_acc: 0.4984
Epoch 8/10
157/157 [==============================] - 1s 7ms/step - loss: 0.3605 - acc: 0.846
8 - val_loss: 1.1942 - val_acc: 0.5052
Epoch 9/10
157/157 [==============================] - 1s 7ms/step - loss: 0.2754 - acc: 0.900
2 - val_loss: 1.0119 - val_acc: 0.5018
Epoch 10/10
157/157 [==============================] - 1s 7ms/step - loss: 0.2123 - acc: 0.926
2 - val_loss: 1.3295 - val_acc: 0.5001
```





In [29]:

```
test_loss11, test_accuracy11 = model11.evaluate(x_test, y_test)
print('Test loss:', test_loss11)
print('Test accuracy:', test_accuracy11)
```

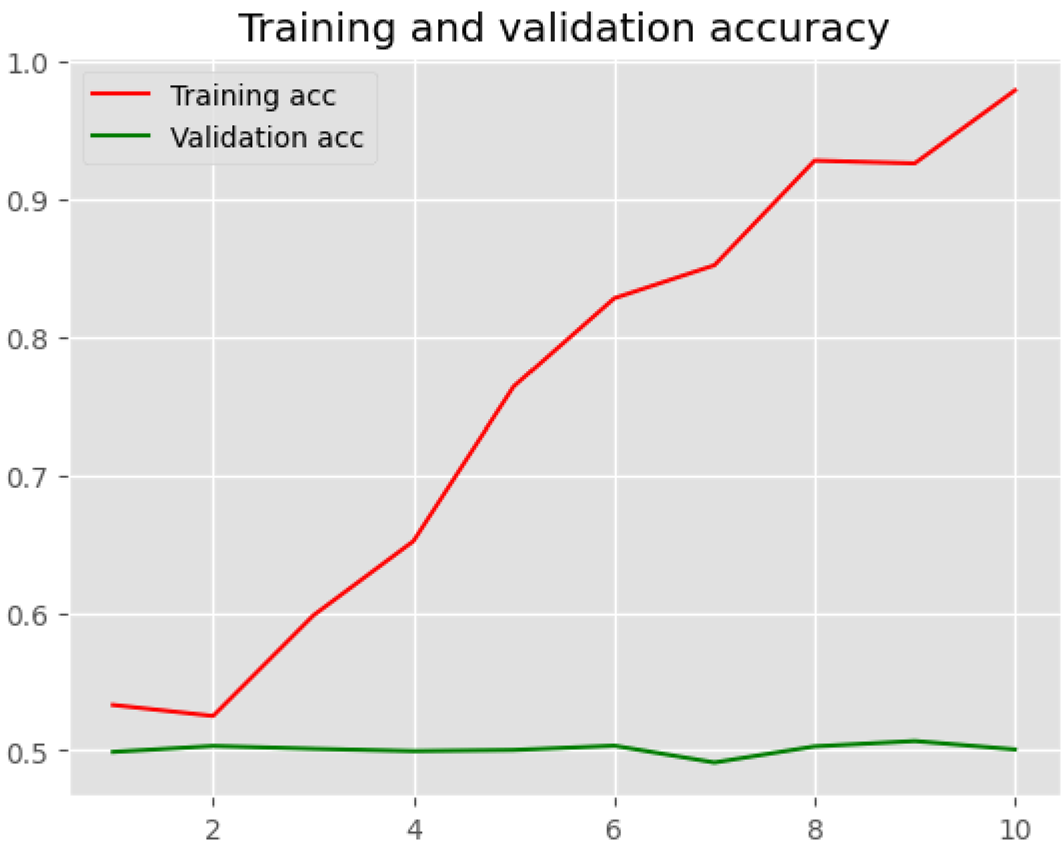
```
782/782 [==============================] - 2s 2ms/step - loss: 1.3064 - acc: 0.499
4
Test loss: 1.3064237833023071
Test accuracy: 0.49935999512672424
```

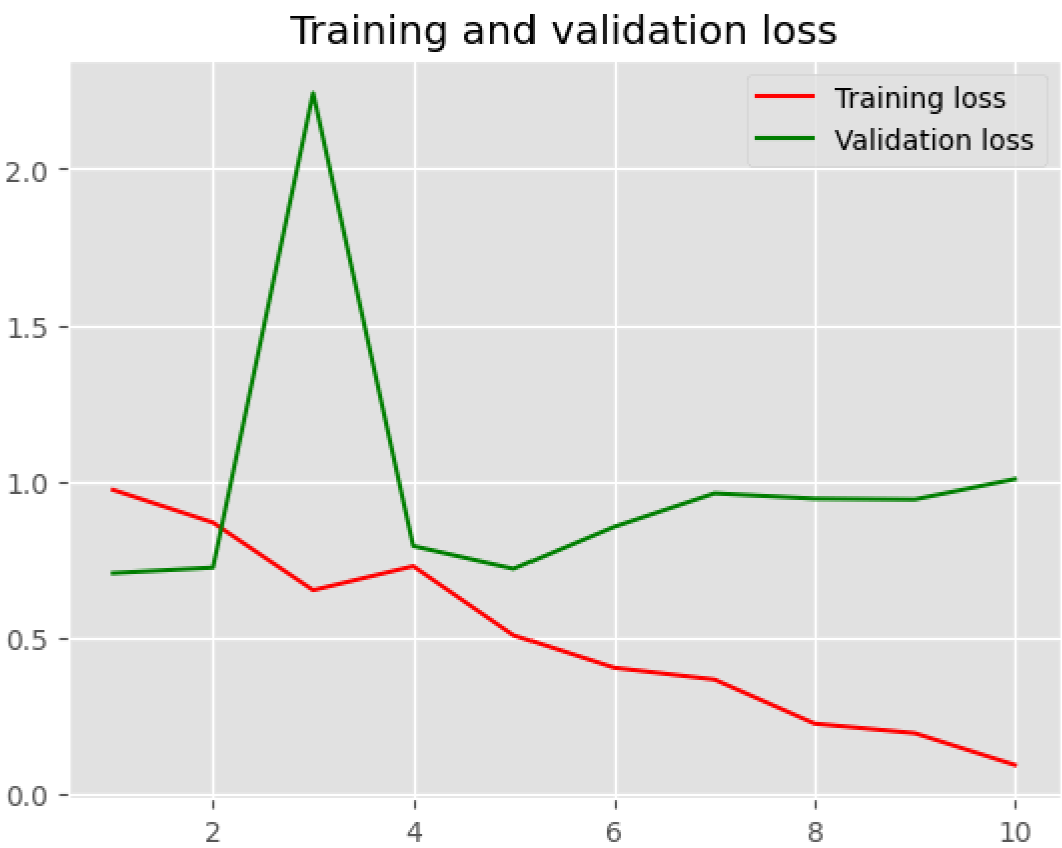
Utilizing a pretrained word embedding layer with a training sample size of 1000.

In [30]:
```
from keras.preprocessing.text import Tokenizer
from keras.utils import pad_sequences
import numpy as np

length = 150
tra_info = 1000 #Trains on 1000 samples
val_info = 10000
words = 10000

tokenizer3 = Tokenizer(num_words=words)
tokenizer3.fit_on_texts(texts)
sequences = tokenizer3.texts_to_sequences(texts)
word_index = tokenizer3.word_index
print("Found %s unique tokens." % len(word_index))

data = pad_sequences(sequences, maxlen=length)

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

indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

x_train = data[:tra_info]
y_train = labels[:tra_info]
x_val = data[tra_info:tra_info+val_info]
y_val = labels[tra_info:tra_info+val_info]
embedding_di = 100

embedd_matrix = np.zeros((words, embedding_di))
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word)
    if i < words:
        if embedding_vector is not None:

            embedd_matrix[i] = embedding_vector

from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model12 = Sequential()
model12.add(Embedding(words, embedding_di, input_length=length))
model12.add(Flatten())
model12.add(Dense(32, activation='relu'))
model12.add(Dense(1, activation='sigmoid'))
model12.summary()

model12.layers[0].set_weights([embedding_matrix])
model12.layers[0].trainable = False
model12.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history12 = model12.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_val, y_val))
model12.save_weights('pre_trained_glove_model.h5')
import matplotlib.pyplot as plt
```

```
tra_acc12 = history12.history['acc']
val_acc12 = history12.history['val_acc']
loss12 = history12.history['loss']
val_loss12 = history12.history['val_loss']

epochs = range(1, len(tra_acc12) + 1)

plt.plot(epochs, tra_acc12, 'r', label='Training acc')
plt.plot(epochs, val_acc12, 'g', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss12, 'red', label='Training loss')
plt.plot(epochs, val_loss12, 'g', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 150)
Shape of label tensor: (25000,)
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_7 (Embedding)     (None, 150, 100)          1000000   
                                                                 
 flatten_6 (Flatten)         (None, 15000)             0         
                                                                 
 dense_8 (Dense)             (None, 32)                480032    
                                                                 
 dense_9 (Dense)             (None, 1)                 33        
                                                                 
=================================================================
Total params: 1480065 (5.65 MB)
Trainable params: 1480065 (5.65 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
32/32 [==============================] - 1s 26ms/step - loss: 0.9727 - acc: 0.5330
- val_loss: 0.7059 - val_acc: 0.4989
Epoch 2/10
32/32 [==============================] - 1s 21ms/step - loss: 0.8679 - acc: 0.5250
- val_loss: 0.7238 - val_acc: 0.5032
Epoch 3/10
32/32 [==============================] - 1s 20ms/step - loss: 0.6514 - acc: 0.5980
- val_loss: 2.2432 - val_acc: 0.5012
Epoch 4/10
32/32 [==============================] - 1s 20ms/step - loss: 0.7282 - acc: 0.6520
- val_loss: 0.7928 - val_acc: 0.4995
Epoch 5/10
32/32 [==============================] - 1s 21ms/step - loss: 0.5070 - acc: 0.7640
- val_loss: 0.7199 - val_acc: 0.5003
Epoch 6/10
32/32 [==============================] - 1s 21ms/step - loss: 0.4030 - acc: 0.8280
- val_loss: 0.8545 - val_acc: 0.5034
Epoch 7/10
32/32 [==============================] - 1s 21ms/step - loss: 0.3653 - acc: 0.8520
- val_loss: 0.9615 - val_acc: 0.4912
Epoch 8/10
32/32 [==============================] - 1s 21ms/step - loss: 0.2242 - acc: 0.9280
- val_loss: 0.9443 - val_acc: 0.5029
Epoch 9/10
32/32 [==============================] - 1s 20ms/step - loss: 0.1936 - acc: 0.9260
- val_loss: 0.9419 - val_acc: 0.5068
Epoch 10/10
32/32 [==============================] - 1s 20ms/step - loss: 0.0918 - acc: 0.9790
- val_loss: 1.0071 - val_acc: 0.5007
```





In [31]:

```
test_loss12, test_accuracy12 = model12.evaluate(x_test, y_test)
print('Test loss:', test_loss12)
print('Test accuracy:', test_accuracy12)
```

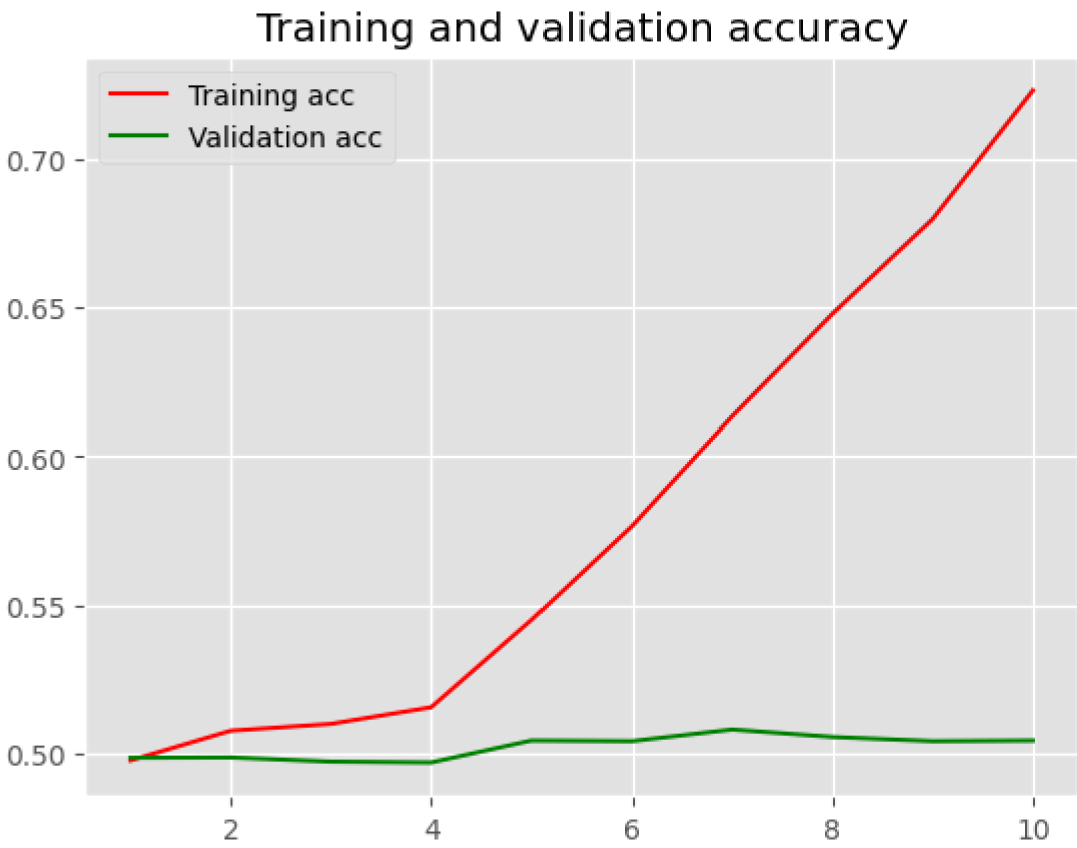
```
782/782 [==============================] - 2s 2ms/step - loss: 1.0084 - acc: 0.498
0
Test loss: 1.0084171295166016
Test accuracy: 0.49796000123023987
```

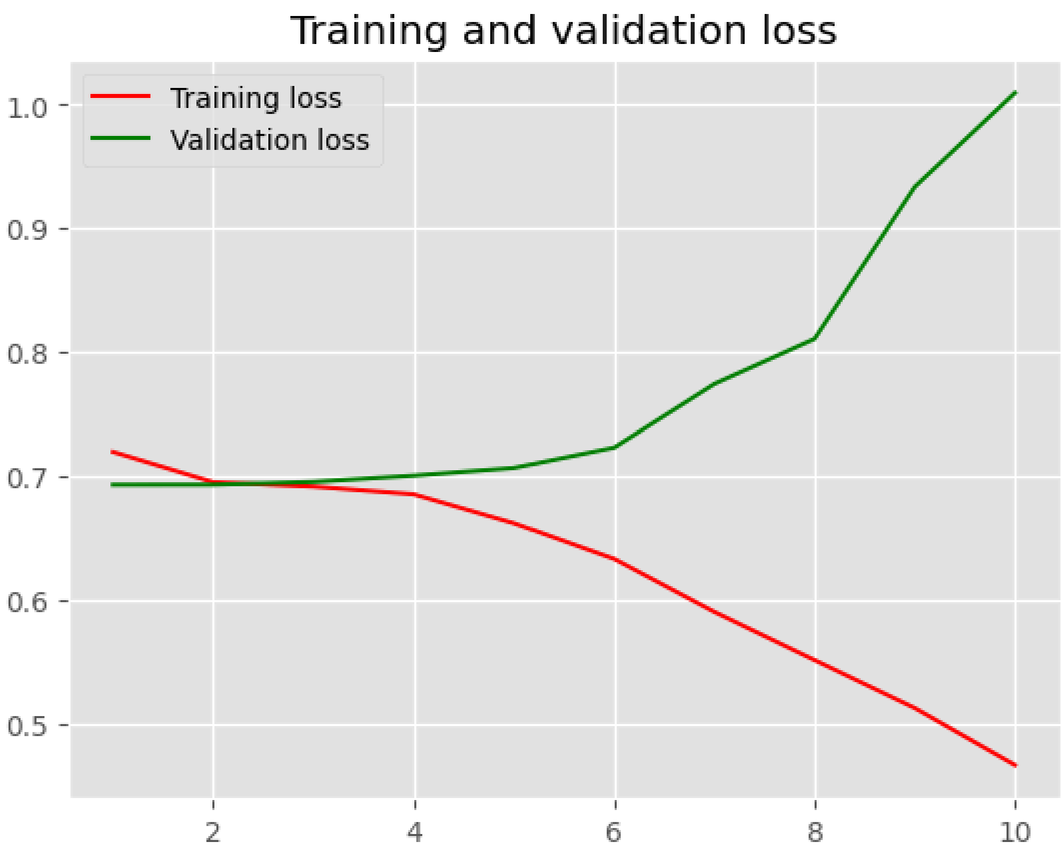
Employing a pretrained word embedding layer with a training sample size of 10,000.

In [32]:
```
from keras.preprocessing.text import Tokenizer
from keras.utils import pad_sequences
import numpy as np

length = 150
tra_info = 10000 # Trains on 10000 samples
val_info = 10000
words = 10000

tokenizer4 = Tokenizer(num_words=words)
tokenizer4.fit_on_texts(texts)
sequences = tokenizer4.texts_to_sequences(texts)
word_index = tokenizer4.word_index
print("Found %s unique tokens." % len(word_index))

data = pad_sequences(sequences, maxlen=length)

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

indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]

x_train = data[:tra_info]
y_train = labels[:tra_info]
x_val = data[tra_info:tra_info+val_info]
y_val = labels[tra_info:tra_info+val_info]
embedding_di = 100

embedd_matrix = np.zeros((words, embedding_di))
for word, i in word_index.items():
    embedd_vector = embeddings_index.get(word)
    if i < words:
        if embedd_vector is not None:

            embedd_matrix[i] = embedd_vector

from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model13 = Sequential()
model13.add(Embedding(words, embedding_di, input_length=length))
model13.add(Flatten())
model13.add(Dense(32, activation='relu'))
model13.add(Dense(1, activation='sigmoid'))
model13.summary()

model13.layers[0].set_weights([embedding_matrix])
model13.layers[0].trainable = False
model13.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['acc'])
history13 = model13.fit(x_train, y_train,
                    epochs=10,
                    batch_size=32,
                    validation_data=(x_val, y_val))
model13.save_weights('pre_trained_glove_model.h5')
import matplotlib.pyplot as plt
```

```
tra_acc13 = history13.history['acc']
val_acc13 = history13.history['val_acc']
tra_loss13 = history13.history['loss']
val_loss13 = history13.history['val_loss']

epochs = range(1, len(tra_acc13) + 1)

plt.plot(epochs, tra_acc13, 'r', label='Training acc')
plt.plot(epochs, val_acc13, 'g', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, tra_loss13, 'r', label='Training loss')
plt.plot(epochs, val_loss13, 'g', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```

```
Found 88582 unique tokens.
Shape of data tensor: (25000, 150)
Shape of label tensor: (25000,)
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_8 (Embedding)     (None, 150, 100)          1000000   
                                                                 
 flatten_7 (Flatten)         (None, 15000)             0         
                                                                 
 dense_10 (Dense)            (None, 32)                480032    
                                                                 
 dense_11 (Dense)            (None, 1)                 33        
                                                                 
=================================================================
Total params: 1480065 (5.65 MB)
Trainable params: 1480065 (5.65 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
313/313 [==============================] - 2s 5ms/step - loss: 0.7196 - acc: 0.497
8 - val_loss: 0.6931 - val_acc: 0.4987
Epoch 2/10
313/313 [==============================] - 1s 4ms/step - loss: 0.6952 - acc: 0.507
8 - val_loss: 0.6932 - val_acc: 0.4988
Epoch 3/10
313/313 [==============================] - 1s 4ms/step - loss: 0.6917 - acc: 0.510
1 - val_loss: 0.6955 - val_acc: 0.4974
Epoch 4/10
313/313 [==============================] - 1s 4ms/step - loss: 0.6854 - acc: 0.515
7 - val_loss: 0.7005 - val_acc: 0.4971
Epoch 5/10
313/313 [==============================] - 1s 4ms/step - loss: 0.6620 - acc: 0.545
1 - val_loss: 0.7066 - val_acc: 0.5045
Epoch 6/10
313/313 [==============================] - 1s 5ms/step - loss: 0.6331 - acc: 0.576
7 - val_loss: 0.7230 - val_acc: 0.5043
Epoch 7/10
313/313 [==============================] - 1s 5ms/step - loss: 0.5903 - acc: 0.613
5 - val_loss: 0.7743 - val_acc: 0.5082
Epoch 8/10
313/313 [==============================] - 1s 5ms/step - loss: 0.5513 - acc: 0.647
9 - val_loss: 0.8108 - val_acc: 0.5057
Epoch 9/10
313/313 [==============================] - 1s 5ms/step - loss: 0.5125 - acc: 0.679
8 - val_loss: 0.9337 - val_acc: 0.5043
Epoch 10/10
313/313 [==============================] - 1s 5ms/step - loss: 0.4664 - acc: 0.723
1 - val_loss: 1.0097 - val_acc: 0.5045
```





In [33]:
```
test_loss13, test_accuracy13 = model13.evaluate(x_test, y_test)
print('Test loss:', test_loss13)
print('Test accuracy:', test_accuracy13)
```

```
782/782 [==============================] - 2s 2ms/step - loss: 0.9962 - acc: 0.506
8
Test loss: 0.9962033033370972
Test accuracy: 0.5067600011825562
```