IMDB MOVIES - SENTIMENT ANALYSIS USING RNN

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1. Data uploading

In [1]:

```
import numpy as np
import pandas as pd
import re
import nltk
from nltk.corpus import stopwords
from numpy import array
from keras.preprocessing.text import one_hot
from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers.core import Activation , Dense , Dropout
from keras.layers import Flatten
from keras.layers import GlobalMaxPooling1D
from keras.layers.embeddings import Embedding
from sklearn.model_selection import train_test_split
from keras.preprocessing.text import Tokenizer
```

In [2]:

```
movie_reviews = pd.read_csv("/content/IMDB Dataset.csv",engine='python',encoding='utf-8')
```

2. Data exploring

In [3]:

```
movie_reviews.head()
```

Out[3]:

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. <br /><br />The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive

In [4]:

```
movie_reviews.isnull().values.any()
```

Out[4]:

```
False
```

In [5]:

```
movie_reviews.shape
```

Out[5]:

```
(50000, 2)
```

In [6]:

```
movie_reviews['review'][4]
```

Out[6]:

```
'Petter Mattei\'s "Love in the Time of Money" is a visually stunning film to watch. Mr. Mattei offers us a
vivid portrait about human relations. This is a movie that seems to be telling us what money, power and su
ccess do to people in the different situations we encounter. <br /><br />This being a variation on the Art
hur Schnitzler\'s play about the same theme, the director transfers the action to the present time New York
where all these different characters meet and connect. Each one is connected in one way, or another to the
```

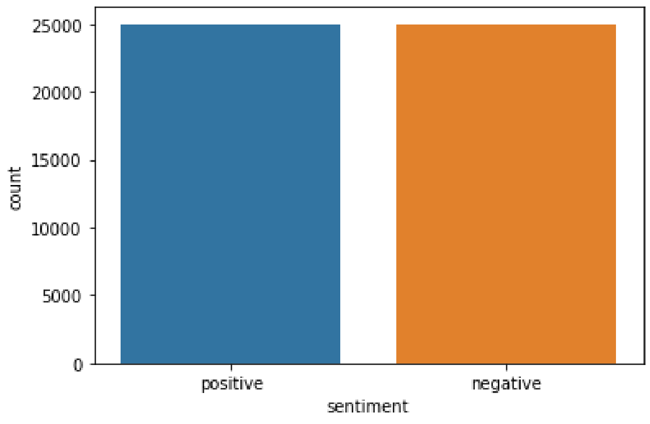
```
next person, but no one seems to know the previous point of contact. Stylishly, the film has a sophisticat
ed luxurious look. We are taken to see how these people live and the world they live in their own habitat.
<br /><br />The only thing one gets out of all these souls in the picture is the different stages of lonel
iness each one inhabits. A big city is not exactly the best place in which human relations find sincere fu
lfillment, as one discerns is the case with most of the people we encounter.<br /><br />The acting is good
under Mr. Mattei\'s direction. Steve Buscemi, Rosario Dawson, Carol Kane, Michael Imperioli, Adrian Grenie
r, and the rest of the talented cast, make these characters come alive.<br /><br />We wish Mr. Mattei good
luck and await anxiously for his next work.'
```

In [7]:

```python
import seaborn as sns
sns.countplot(x='sentiment',data=movie_reviews)
```

Out[7]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd77afa3210>
```



3. Data preprocessing

In [39]:

```python
#Data Preprocessing and Cleaning
def preprocess_text(sen):
  #Removing Html tags
  sentence = remove_tags(sen)

  #Removing punctuations and numbers
  sentence = re.sub('[^a-zA-Z]',' ',sentence)

  #Single character removal
  sentence = re.sub(r"\s+[a-zA-Z]\s"," ",sentence)

  #Removing Multiple Spaces
  sentence = re.sub(r'\s+',' ', sentence)

  pattern = re.compile('<.*?>')
  sentence = re.sub(pattern,' ',sentence)

  return sentence
```

In [40]:

```python
TAG_RE = re.compile(r'<[^>]+.>')

def remove_tags(text):
  return TAG_RE.sub('',text)
```

In [41]:

```python
review = []
sentences  = list(movie_reviews['review'])
for sen in sentences:
  review.append(preprocess_text(sen))
```

In [42]:

```python
review[4]
```

Out[42]:

```
'Petter Mattei Love in the Time of Money is visually stunning film to watch Mr Mattei offers us vivid port
rait about human relations This is movie that seems to be telling us what money power and success do to pe
ople in the different situations we encounter This being variation on the Arthur Schnitzler play about the
same theme the director transfers the action to the present time New York where all these different charac
```

```
ters meet and connect Each one is connected in one way or another to the next person but no one seems to k
now the previous point of contact Stylishly the film has sophisticated luxurious look We are taken to see
how these people live and the world they live in their own habitat The only thing one gets out of all thes
e souls in the picture is the different stages of loneliness each one inhabits big city is not exactly the
best place in which human relations find sincere fulfillment as one discerns is the case with most of the
people we encounter The acting is good under Mr Mattei direction Steve Buscemi Rosario Dawson Carol Kane M
ichael Imperioli Adrian Grenier and the rest of the talented cast make these characters come alive We wish
Mr Mattei good luck and await anxiously for his next work '
```

In [43]:

```
converted = movie_reviews['sentiment']
converted = np.array(list(map(lambda x: 1 if x=='positive'  else 0,converted)))
```

4. Train-test split

In [44]:

```
review_train , review_test , converted_train , converted_test = train_test_split(review,converted,test_si
ze = 0.20 , random_state= 0 )
```

In [45]:

```
print(len(review_train))
print(len(review_test))
```

```
40000
10000
```

5. Word embeddings

In [46]:

```
tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(review_train)

review_train = tokenizer.texts_to_sequences(review_train)
review_test = tokenizer.texts_to_sequences(review_test)
```

In [47]:

```
vocab_size = len(tokenizer.word_index)+1

maxlen = 100

review_train = pad_sequences(review_train , maxlen=maxlen , padding='post')
review_test = pad_sequences(review_test , maxlen=maxlen , padding='post')
```

In [48]:

```
!wget -c http://nlp.stanford.edu/data/glove.840B.300d.zip
```

```
--2021-11-26 06:38:31--  http://nlp.stanford.edu/data/glove.840B.300d.zip
Resolving nlp.stanford.edu (nlp.stanford.edu)... 171.64.67.140
Connecting to nlp.stanford.edu (nlp.stanford.edu)|171.64.67.140|:80... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://nlp.stanford.edu/data/glove.840B.300d.zip [following]
--2021-11-26 06:38:31--  https://nlp.stanford.edu/data/glove.840B.300d.zip
Connecting to nlp.stanford.edu (nlp.stanford.edu)|171.64.67.140|:443... connected.
HTTP request sent, awaiting response... 301 Moved Permanently
Location: http://downloads.cs.stanford.edu/nlp/data/glove.840B.300d.zip [following]
--2021-11-26 06:38:31--  http://downloads.cs.stanford.edu/nlp/data/glove.840B.300d.zip
Resolving downloads.cs.stanford.edu (downloads.cs.stanford.edu)... 171.64.64.22
Connecting to downloads.cs.stanford.edu (downloads.cs.stanford.edu)|171.64.64.22|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 2176768927 (2.0G) [application/zip]
Saving to: ‘glove.840B.300d.zip’

glove.840B.300d.zip 100%[===================>]   2.03G  5.02MB/s    in 6m 52s

2021-11-26 06:45:23 (5.04 MB/s) - ‘glove.840B.300d.zip’ saved [2176768927/2176768927]
```

In [49]:

```
import zipfile
with zipfile.ZipFile("/content/glove.840B.300d.zip", "r") as zipread:
  zipread.extractall("/content/")
  zipread.close
```

In [50]:

```
from numpy import zeros
from numpy import asarray

embeddings_dictionary = dict()
glove_file = open('/content/glove.6B.100d.txt',encoding='utf8')

for line in glove_file:
  records = line.split()
  word = records[0]
  vector_dimensions = asarray(records[1:],dtype = 'float32')
  embeddings_dictionary[word]=vector_dimensions
glove_file.close()
```

In [51]:

```
embedding_matrix = zeros((vocab_size , 100))
for word , index in tokenizer.word_index.items():
  embedding_vector = embeddings_dictionary.get(word)
  if embedding_vector is not None:
    embedding_matrix[index] = embedding_vector
```

6. RNN Model

In [64]:

```
from keras.layers import LSTM

model = Sequential()
embedding_layer  = Embedding(vocab_size,100,input_length=maxlen , trainable=False , weights = [embedding_
matrix])

model.add(embedding_layer)
model.add(LSTM(128))

model.add(Dense(1,activation='sigmoid'))
model.summary()
model.compile(optimizer = 'adam' , loss = 'binary_crossentropy',metrics =['acc'])
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_2 (Embedding)     (None, 100, 100)          9228500   
                                                                 
 lstm_2 (LSTM)               (None, 128)               117248    
                                                                 
 dense_2 (Dense)             (None, 1)                 129       
                                                                 
=================================================================
Total params: 9,345,877
Trainable params: 117,377
Non-trainable params: 9,228,500
_________________________________________________________________
```

In [65]:

```
history = model.fit(review_train , converted_train , batch_size=128 , epochs=10 , verbose=1 , validation
_split=0.2)
```

```
Epoch 1/10
250/250 [==============================] - 74s 290ms/step - loss: 0.5500 - acc: 0.7109 - val_loss: 0.4467
- val_acc: 0.7952
Epoch 2/10
250/250 [==============================] - 71s 285ms/step - loss: 0.4411 - acc: 0.7944 - val_loss: 0.3954
- val_acc: 0.8186
Epoch 3/10
250/250 [==============================] - 71s 285ms/step - loss: 0.3935 - acc: 0.8207 - val_loss: 0.3881
- val_acc: 0.8276
Epoch 4/10
250/250 [==============================] - 71s 285ms/step - loss: 0.3674 - acc: 0.8349 - val_loss: 0.3636
- val_acc: 0.8394
Epoch 5/10
250/250 [==============================] - 71s 286ms/step - loss: 0.3448 - acc: 0.8466 - val_loss: 0.3681
- val_acc: 0.8335
Epoch 6/10
250/250 [==============================] - 72s 287ms/step - loss: 0.3295 - acc: 0.8558 - val_loss: 0.3421
- val_acc: 0.8468
Epoch 7/10
```

```
250/250 [==============================] - 71s 285ms/step - loss: 0.3088 - acc: 0.8665 - val_loss: 0.3611
- val_acc: 0.8401
Epoch 8/10
250/250 [==============================] - 71s 285ms/step - loss: 0.2970 - acc: 0.8696 - val_loss: 0.3347
- val_acc: 0.8540
Epoch 9/10
250/250 [==============================] - 71s 285ms/step - loss: 0.2792 - acc: 0.8829 - val_loss: 0.3359
- val_acc: 0.8546
Epoch 10/10
250/250 [==============================] - 71s 286ms/step - loss: 0.2582 - acc: 0.8924 - val_loss: 0.3324
- val_acc: 0.8599
```

7. Model Evaluation

In [66]:

```
score  = model.evaluate(review_test , converted_test , verbose= 1)
print("Test Score: ",score[0])
print("Test Accuracy: ",score[1])
```

```
313/313 [==============================] - 9s 30ms/step - loss: 0.3574 - acc: 0.8521
Test Score:  0.3573628067970276
Test Accuracy:  0.8521000146865845
```

In [67]:

```
instance = review[60]
print(instance)
```

```
What happened What we have here is basically solid and plausible premise and with decent and talented cast
but somewhere the movie loses it Actually it never really got going There was little excitement when we fi
nd out that Angie is not really pregnant then find out that she is after all but that was it Steve Martin w
ho is very talented person and usually brings lot to movie was dreadful and his entire character was not ev
en close to being important to this movie other than to make it longer really would have liked to see more
interactions between the main characters Kate and Angie and maybe try not for pure comedy which unfortunat
ely it was not but maybe drama with comedic elements think if the movie did this it could have been very f
unny since both actresses are quite funny in their own ways and sitting here can think of numerous scenari
os that would have been riot
```

In [68]:

```
instance = tokenizer.texts_to_sequences(instance)

flat_list =[]

for sublist in instance:
  for item in sublist:
    flat_list.append(item)

flat_list=[flat_list]
instance = pad_sequences(flat_list , padding='post',maxlen=maxlen)

model.predict(instance)
```

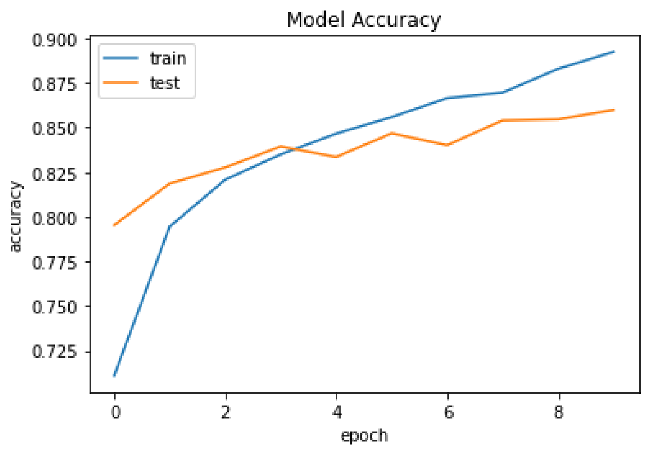
Out[68]:

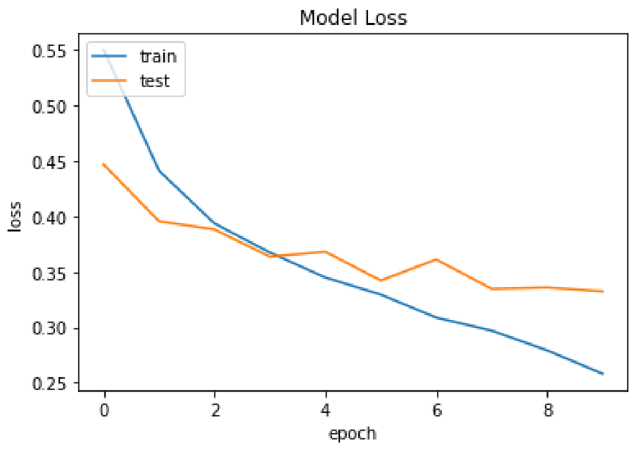
```
array([[0.21861425]], dtype=float32)
```

8. Plotting the model performance

In [69]:

```
import matplotlib.pyplot as plt

plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])

plt.title("Model Accuracy")
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','test'],loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.title("Model Loss")
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','test'],loc='upper left')
plt.show()
```





9. Testing the model

In [70]:

```
pred=np.where(model.predict(review_test))
```

In [71]:

```
samp=pad_sequences(tokenizer.texts_to_sequences(['I hate this movie.There is no story in it']),maxlen=maxl
en)
```

In [72]:

```
np.where(model.predict(samp)>0.5,'Positive review','Negative review')[0][0]
```

Out[72]:

```
'Negative review'
```

In [73]:

```
samp_2=pad_sequences(tokenizer.texts_to_sequences(['I love this movie.There is nice story in it']),maxlen=
maxlen)
```

In [74]:

```
np.where(model.predict(samp_2)>0.5,'Positive review','Negative review')[0][0]
```

Out[74]:

```
'Positive review'
```