In [1]:
```
Vaibhav Rokade
Roll No :54
```

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

In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

In [5]:
```
import string
import re
from os import listdir
from nltk.corpus import stopwords
from keras.preprocessing.text import Tokenizer
from keras.utils import plot_model
from keras.models import Sequential
from keras.layers import Dense, Flatten, Embedding
import numpy as np
import nltk
from keras.layers import Conv1D, MaxPooling1D
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[5]:
```
True
```

In [6]:
```
# load doc into memory
def load_doc(filename):
  # open the file as read only
  file = open(filename, 'r' )
  # read all text
  text = file.read()
  # close the file
  file.close()
  return text
```

In [7]:
```
text = load_doc('drive/MyDrive/review_polarity
/txt_sentoken/pos/cv026_29325.txt')
```

In [8]:
```
text
```

Out[8]:
```
'for those of us who weren\'t yet born when the 1960\'s rock \'n\' rolled aro
und , monterey pop affords an affectionate glimpse of the music that influenc
ed our parents to be hippies . \nfrom otis redding to jimi hendrix , janis jo
plin to the mamas and the papas , and jefferson airplane to the who , this do
cumentary is jam-packed with contagious energy . \nbut i give fair warning th
at i will reveal the ending , which does not do the rest of the film the just
ice it deserves . \nshot in 1969 at an outdoor concert that precluded woodsto
ck , the film defies the stereotype of the general population at the time .
\nsure , some have painted their faces and smoke joints , but d . a . \npenne
baker ( the war room , moon over broadway ) surprisingly chooses to show a br
oad spectrum of the audience . \nno matter who is watching , it all comes bac
k to the talented musicians that stir your soul . \nthe excitement starts bef
ore the music even begins . \na young girl is cleaning thousands of seats and
when asked why by an interviewer , she replies that she feels lucky to do so
. \nthere are moments of organized craziness as john phillips , leader of the
mamas and the papas and one of the concert organizers , tries to get in touch
with dionne warwick . \nand when one band is tuning up , a member remarks , "
finally , a decent sound system ! " \nyou can tell just by watching these fir
st few moments that this show isn\'t about vanity , it\'s about playing the m
usic you love to those who have an appreciation for it , a two-way street .
\nthis interaction between audience and performer continues throughout the fi
lm and becomes infectious to the audience . \nit\'s impossible to tear your e
yes away from janis joplin as she belts out her ballad about love being a bal
l and chain . \nand while the lyrics to " wild thing " may not be all that co
mplicated , watching jimi hendrix mime having sex with his guitar is as capti
vating as otis redding singing about love . \neven if you don\'t recognize ev
ery band you see on stage , you can imagine being as enthralled by their work
as the public sitting in those seats . \nthe only drawback to the film is the
ending , which unfortunately i must reveal . \nall the other bands , big name
s then and still today , got approximately 7 to 10 minutes of screen time .
\nin contrast , the last band on camera , a wholly forgettable one , gets an
entire 18 minutes of screen time . \nfor a film that\'s only 78 minutes long
, that\'s too large of a chunk , especially when previous acts are much more
stimulating . \nall in all , monterey pop is a precious , rare look at a time
period that still holds sway over us . \nthe variety of music , as well as th
e beautifully shot performances , are easy to become immersed in . \nif there
was ever any question as to why most of these bands were so popular , this is
quickly dispelled . \nit\'s almost depressing to think that music this moving
doesn\'t get made much anymore . \ninstead we\'re stuck with * nsync , the ba
ckstreet boys , and jennifer lopez , all of whom should have stuck with model
ing . \n'
```

In [10]:
```
# turn a doc into clean tokens
def clean_doc(doc):
  # split into tokens by white space
  tokens = doc.split()
  # prepare regex for char filtering
  re_punc = re.compile( '[%s]' % re.escape(string.punctuation))
  # remove punctuation from each word
  tokens = [re_punc.sub( '' , w) for w in tokens]
  # remove remaining tokens that are not alphabetic
  tokens = [word for word in tokens if word.isalpha()]
  # filter out stop words
  stop_words = set(stopwords.words( 'english' ))
  tokens = [w for w in tokens if not w in stop_words]
  # filter out short tokens
  tokens = [word for word in tokens if len(word) > 1]
  return tokens
```

In [11]:
```
clean_doc(text)
```

Out[11]:
```
['us',
 'werent',
 'yet',
 'born',
 'rock',
 'rolled',
 'around',
 'monterey',
 'pop',
 'affords',
 'affectionate',
 'glimpse',
 'music',
 'influenced',
 'parents',
 'hippies',
 'otis',
 'redding',
 'jimi',
```

In [12]:
```
# load doc, clean and return line of tokens
def doc_to_line(filename, vocab):
  # load the doc
  doc = load_doc(filename)
  # clean doc
  tokens = clean_doc(doc)
  # filter by vocab
  tokens = [w for w in tokens if w in vocab]
  return ' ' .join(tokens)
```

In [13]:
```
vocab = open('vocab.txt')
vocab = vocab.read().split()
```

In [14]:
```
text = doc_to_line('drive/MyDrive/review_polarity/txt_sentoken/pos/cv026_29325.
                   vocab)
```

In [15]:
```
text
```

Out[15]:
```
'us werent yet born rock rolled around monterey pop affectionate glimpse musi
c influenced parents hippies otis redding jimi hendrix janis joplin mamas pap
as jefferson airplane documentary jampacked contagious energy give fair warni
ng reveal ending rest film justice deserves shot outdoor concert film defies
stereotype general population time sure painted faces smoke joints war room m
oon broadway surprisingly chooses show broad spectrum audience matter watchin
g comes back talented musicians stir soul excitement starts music even begins
young girl cleaning thousands seats asked interviewer replies feels lucky mom
ents organized craziness john phillips leader mamas papas one concert tries g
et touch one band tuning member remarks finally decent sound system tell watc
hing first moments show isnt vanity playing music love appreciation street in
teraction audience performer continues throughout film becomes infectious aud
ience impossible tear eyes away janis joplin belts ballad love ball chain lyr
ics wild thing may complicated watching jimi hendrix mime sex guitar captivat
ing otis redding singing love even dont recognize every band see stage imagin
e enthralled work public sitting seats drawback film ending unfortunately mus
t reveal bands big names still today got approximately minutes screen time co
ntrast last band camera wholly forgettable one gets entire minutes screen tim
e film thats minutes long thats large chunk especially previous acts much sti
mulating monterey pop precious rare look time period still holds sway us vari
ety music well beautifully shot performances easy become immersed ever questi
on bands popular quickly almost depressing think music moving doesnt get made
much anymore instead stuck backstreet boys jennifer lopez stuck modeling'
```

In [ ]:
```
# load all docs in a directory
def process_train(directory, vocab):
  documents = list()
  for filename in listdir(directory):
    if not filename.startswith( 'cv9' ):
      path = directory + '/' + filename
      doc = load_doc(path)
      tokens = clean_doc(doc, vocab)
      documents.append(tokens)
  return documents

def process_test(directory, vocab):
  documents = list()
  for filename in listdir(directory):
    if filename.startswith( 'cv9' ):
      path = directory + '/' + filename
      doc = load_doc(path)
      tokens = clean_doc(doc, vocab)
      documents.append(tokens)
  return documents
```

In [ ]:
```
# load all docs in a directory
def process_docs(directory, vocab, is_train):
  documents = list()
  # walk through all files in the folder
  for filename in listdir(directory):
    # skip any reviews in the test set
    if is_train and filename.startswith( 'cv9' ):
      continue
    if not is_train and not filename.startswith( 'cv9' ):
      continue
    # create the full path of the file to open
    path = directory + '/' + filename
    # load the doc
    doc = load_doc(path)
    # clean doc
    tokens = clean_doc(doc)
    # add to list
    documents.append(tokens)
  return documents
```

In [ ]:
```
lines = process_docs('drive/MyDrive/review_polarity/txt_sentoken/pos',
                     vocab, False)
```

In [ ]:
```
len(lines)
```

Out[61]: 100

In [ ]:
```
# load and clean a dataset
def load_clean_dataset(vocab, is_train):
  # load documents
  neg = process_docs('drive/MyDrive/review_polarity/txt_sentoken/neg', vocab, i
  pos = process_docs('drive/MyDrive/review_polarity/txt_sentoken/pos', vocab, i
  docs = neg + pos
  # prepare labels
  labels = [0 for _ in range(len(neg))] + [1 for _ in range(len(pos))]
  return docs, labels
```

In [ ]:
```
train, train_labels = load_clean_dataset(vocab, True)
test, test_labels = load_clean_dataset(vocab, False)
```

In [ ]:
```
len(train), len(test)
```

Out[70]: (1800, 200)

In [ ]:
```
len(l)
```

Out[19]: 2000

In [ ]:
```
from collections import Counter
Counter(l)
```

Out[20]:
```
Counter({0: 1000, 1: 1000})
```

Build the DNN model

In [ ]:
```
# define the model
def define_model(n_words):
  # define network
  model = Sequential()
  model.add(Dense(50, input_shape=(n_words,), activation= 'relu' ))
  model.add(Dense(1, activation= 'sigmoid' ))
  # compile network
  model.compile(loss= 'binary_crossentropy' , optimizer= 'adam' ,
                metrics=[ 'accuracy' ])
  # summarize defined model
  model.summary()
  plot_model(model, to_file= 'model.png' , show_shapes=True)
  return model
```

In [ ]:
```
# fit a tokenizer
def create_tokenizer(lines):
  tokenizer = Tokenizer()
  tokenizer.fit_on_texts(lines)
  return tokenizer
```

In [ ]:
```
# create the tokenizer
tokenizer = create_tokenizer(d)
```

In [ ]:
```
# encode data
x_train = tokenizer.texts_to_matrix(d, mode= 'binary' )
```

In [ ]:
```
x_train
```

Out[31]:
```
array([[0., 1., 1., ..., 0., 0., 0.],
       [0., 0., 1., ..., 0., 0., 0.],
       [0., 1., 1., ..., 0., 0., 0.],
       ...,
       [0., 1., 1., ..., 0., 0., 0.],
       [0., 1., 1., ..., 0., 0., 0.],
       [0., 1., 1., ..., 0., 0., 0.]])
```

In [ ]:
```
x_train.shape
```

Out[33]:
```
(2000, 25768)
```

In [ ]:
```
tokenizer.word_docs
```

Out[34]:
```
defaultdict(int,
            {'officer': 96,
             'little': 916,
             'wig': 18,
             'goers': 7,
             'designer': 34,
             'overthetop': 50,
             'frances': 18,
             'successful': 164,
             'shaken': 9,
             'always': 434,
             'however': 653,
             'winds': 31,
             'comes': 581,
             'glenn': 38,
             'ben': 103,
             'eric': 48,
             'years': 677,
             'tape': 35,
```

In [ ]:
```
# define network
n_words = x_train.shape[1]
model = define_model(n_words)
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_2 (Dense)             (None, 50)                1288450

 dense_3 (Dense)             (None, 1)                 51

=================================================================
Total params: 1,288,501
Trainable params: 1,288,501
Non-trainable params: 0
_________________________________________________________________
```

Train the model

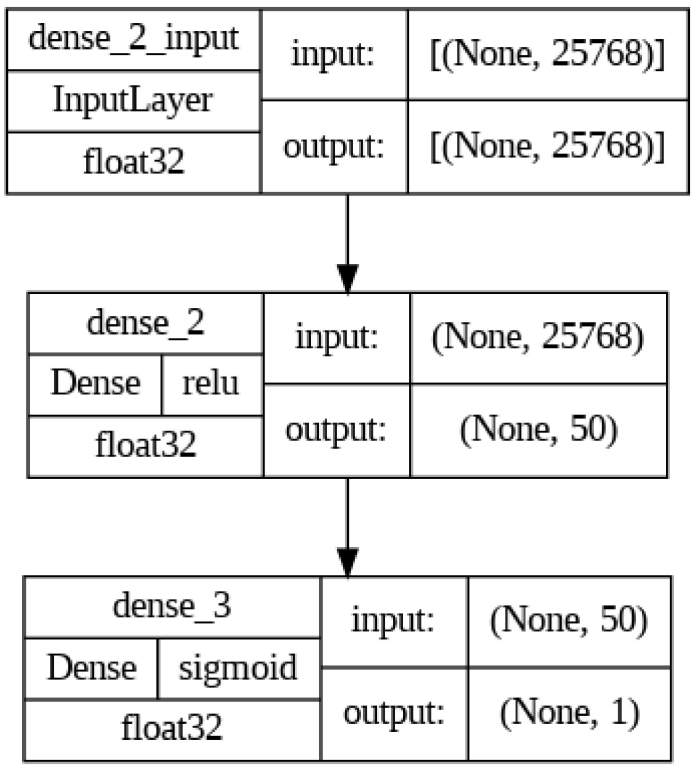
In [ ]:
```
# fit network
model.fit(x_train, np.array(l), epochs=10, batch_size=10)
```

```
Epoch 1/10
200/200 [==============================] - 5s 18ms/step - loss: 0.4138 - accu
racy: 0.8195
Epoch 2/10
200/200 [==============================] - 4s 19ms/step - loss: 0.0277 - accu
racy: 0.9970
Epoch 3/10
200/200 [==============================] - 4s 20ms/step - loss: 0.0053 - accu
racy: 1.0000
Epoch 4/10
200/200 [==============================] - 4s 18ms/step - loss: 0.0018 - accu
racy: 1.0000
Epoch 5/10
200/200 [==============================] - 3s 17ms/step - loss: 8.0094e-04 -
accuracy: 1.0000
Epoch 6/10
200/200 [==============================] - 4s 21ms/step - loss: 4.5061e-04 -
accuracy: 1.0000
Epoch 7/10
200/200 [==============================] - 4s 20ms/step - loss: 2.8474e-04 -
accuracy: 1.0000
Epoch 8/10
200/200 [==============================] - 4s 18ms/step - loss: 1.9553e-04 -
accuracy: 1.0000
Epoch 9/10
200/200 [==============================] - 4s 18ms/step - loss: 1.4216e-04 -
accuracy: 1.0000
Epoch 10/10
200/200 [==============================] - 4s 22ms/step - loss: 1.0766e-04 -
accuracy: 1.0000
```

Out[36]:
```
<keras.callbacks.History at 0x7f12b83554e0>
```

In [ ]:
```
plot_model(model, show_dtype=True, show_layer_activations=True,
           show_shapes=True, show_layer_names=True )
```

Out[37]:



In [ ]:
```
# classify a review as negative or positive
def predict_sentiment(review):
  # clean
  tokens = clean_doc(review)
  # filter by vocab
  tokens = [w for w in tokens if w in vocab]
  # convert to line
  line = ' ' .join(tokens)
  # encode
  encoded = tokenizer.texts_to_matrix([line], mode= 'binary' )
  # predict sentiment
  yhat = model.predict(encoded, verbose=0)
  # retrieve predicted percentage and label
  percent_pos = yhat[0,0]
  if round(percent_pos) == 0:
    return (1-percent_pos), 'NEGATIVE'
  return percent_pos, 'POSITIVE'
```

In [ ]:
```
# test positive text
text = ' Best movie ever! It was great, I will definitely recommend it. '
percent, sentiment = predict_sentiment(text)
print( ' Review: [%s]\nSentiment: %s (%.3f%%) ' % (text, sentiment, percent*100
```

```
 Review: [ Best movie ever! It was great, I will definitely recommend it. ]
Sentiment: POSITIVE (62.977%)
```

In [ ]:
```
# test negative text
text = ' This is a bad movie. '
percent, sentiment = predict_sentiment(text)
print( ' Review: [%s]\nSentiment: %s (%.3f%%) ' % (text, sentiment, percent*100
```

```
 Review: [ This is a bad movie. ]
Sentiment: NEGATIVE (66.968%)
```

In [ ]:
```

```