DEEP LEARNING MODELS

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

```
Mounted at /content/gdrive
```

```
import pandas as pd
import numpy as np
import re

import matplotlib.pyplot as plt
import seaborn as sns

import nltk
nltk.download('punkt')
nltk.download('wordnet')
nltk.download('stopwords')

from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk import WordPunctTokenizer
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from textblob import TextBlob
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
sto_word = list(set(stopwords.words('english')))
from nltk.stem import WordNetLemmatizer  # lemmatizer

from wordcloud import WordCloud
from nltk.tokenize import word_tokenize
from nltk.util import ngrams

pd.set_option('mode.chained_assignment', None)

from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.cluster import MiniBatchKMeans
import plotly.express as px
```

```
import pickle

from sklearn.metrics import hamming_loss, recall_score, precision_score,
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
import pickle
#pickle.dump((combined_data_fe), open('/content/gdrive/MyDrive/cs1/combir
combined_data_fe = pickle.load(open('/content/gdrive/MyDrive/cs1/combinec
fastext_dict     = pickle.load(open('/content/gdrive/MyDrive/cs1/data/ft/
```

```
combined_data_fe.head()
```

	description	commenting	ogling	grouping	noun_count	punctuation
0	walking along crowded street holding mum hand ...	0	0	1	8	
1	incident took place evening metro two guy star...	0	1	0	5	
2	waiting bus man came bike offering liftvto you...	1	0	0	5	
3	incident happened inside train	0	0	0	2	
4	witnessed incident chain brutally snatched eld...	0	0	0	7	

```
y = combined_data_fe[['commenting', 'ogling', 'grouping']]
combined_data_fe.drop(['commenting', 'ogling', 'grouping'], axis=1, inpla
x = combined_data_fe
```

```
x.shape, y.shape
```

```
((9193, 11), (9193, 3))
```

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, stratify=y, tes
```

```
print(f'x train shape {x_train.shape}')
print(f'y train shape {y_train.shape}')
print(f'x test shape  {x_test.shape}')
print(f'y test shape  {y_test.shape}')
```

```
x train shape (7354, 11)
y train shape (7354, 3)
x test shape  (1839, 11)
y test shape  (1839, 3)
```

```
def exact_match_ratio(y_true, y_pred):
  emr = np.all(y_true == y_pred, axis=1).mean()
  return emr
```

```
from sklearn.metrics import hamming_loss, recall_score, precision_score,

def metrics(y_true, y_pred,):

  print("Hamming Loss      : ", hamming_loss(y_true, y_pred))
  print("Exact Match Ratio : ", exact_match_ratio(y_true, y_pred))
  print("Recall micro      : ", recall_score(y_true, y_pred, average='mic
  print("Precision micro   : ", precision_score(y_true, y_pred, average='
  print("Fl score micro    : ", f1_score(y_true, y_pred, average='micro')
  print(" ")
  print("Recall macro      : ", recall_score(y_true, y_pred, average='mac
  print("Precision macro   : ", precision_score(y_true, y_pred, average='
  print("Fl score macro    : ", f1_score(y_true, y_pred, average='macro')
```

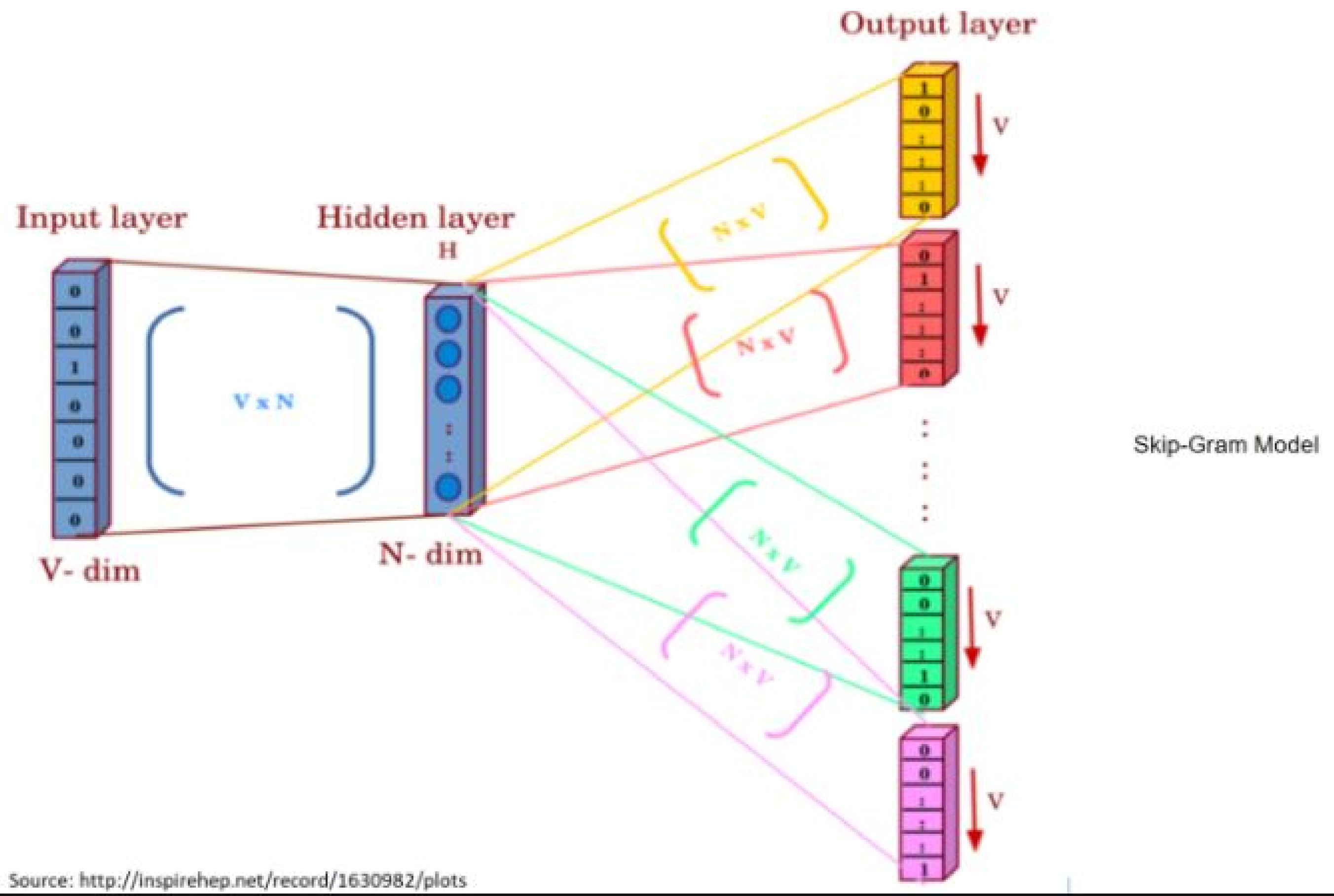
```
import tensorflow as tf
```

```
from keras.preprocessing.text import Tokenizer
from keras_preprocessing.sequence import pad_sequences

def pad_vocab(train, test, column):

  '''train/test : frame
     column     : text column
     returns    : trian/test values, train/test padding, vocab size, word

  # text data
  train_text =list(train[column].values)
  test_text = list(test[column].values)

  # tokenize the Text data
  tokenizer = Tokenizer()
  # fit on train data
  tokenizer.fit_on_texts(train_text)
  # transform train and test data
  train_description_sequences = tokenizer.texts_to_sequences(train_text)
  test_description_sequences = tokenizer.texts_to_sequences(test_text)

  # vocabulary size
  vocab_size = len(tokenizer.word_index) + 1

  word_index_e = tokenizer.word_index
  # pad the sequnce

  train_pad = pad_sequences(
        train_description_sequences, maxlen=300, dtype='int32', padding='
        truncating='post')

  test_pad = pad_sequences(
        test_description_sequences, maxlen=300, dtype='int32', padding='p
        truncating='post')

  return train_text, test_text, train_pad, test_pad, vocab_size, word_inc


train_text, test_text, train_pad, test_pad, vocab_size, word_index, toker
```

FASTEXT

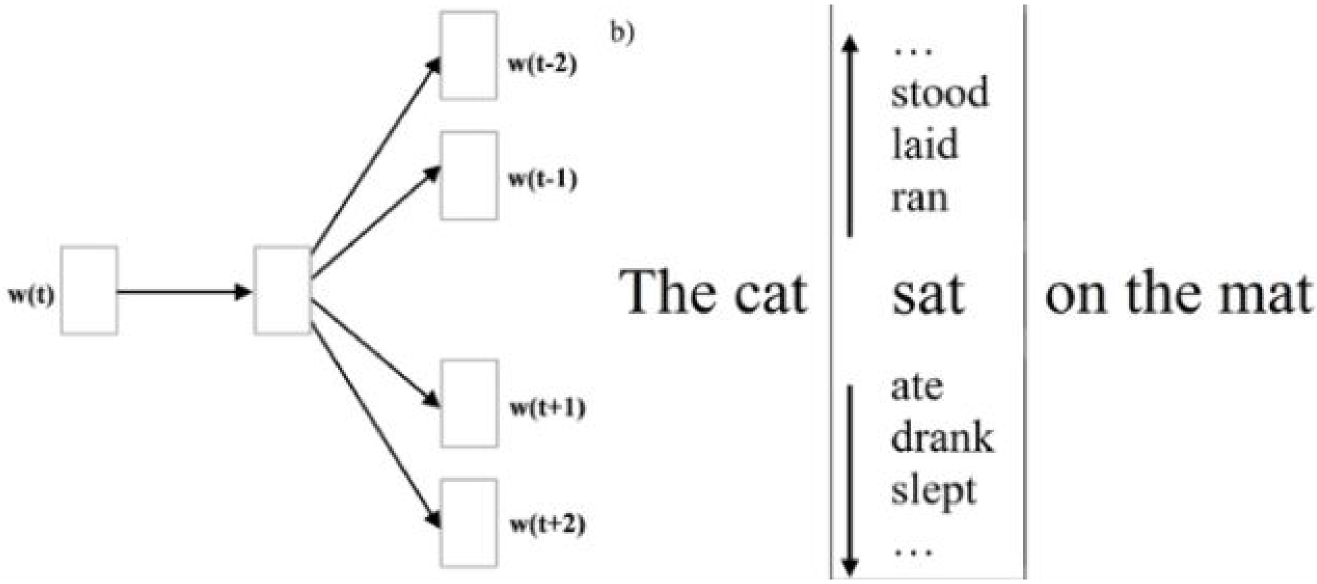
Fastext THEORY

1. Fastext allows to learn representation of words and sentences which can be used for various task, here we used it as transfer learning (embedding of words/sentences to fed into model).
2. in fastext each word is represented as bag of character n-grams in addition to the word itself ex word sponge with n = 3, fastext representation are <sp, spo, pon, ong, nge, ge>, if pon is part of vocablary it is represented as < pon > i.e distinguishing word and its ngram this helps to preserves word whichare short and can be occur later in sentences so its ngram can be used as reference, during traning it learns weights for ngrams (subwords) as well for entire word token.
3. models on which fastext trained is skipgram or cbow, here used is skipgram skipgram is used to predict the context word for a given target word. Here, target word is input while context words are output, simply put it tries to find most relatable word for a given word.



Skip-Gram Model

example



4. fastext supports negative sampling, or hierarchical softmax as loss functions, here used is negative sampling.
5. Why need negative sampling?

Let suppose vocab = 10000 and hidden layer is 300 dimesions total parameter we will have for single token update is 10000x300 = 3M, and updating 3M parameter for every token is computationally expensive, so negative sampling addresses this issue by updating only a small fraction of the output neurons for each training sample, typicall range for this is 5-20.

it encompasses sigmod function as binary classification task of actual context word (positive) and randomly drawn word (negative), simple idea is that if able to seperate postive to negative word vectors learned are good enough.

with negative sampling objective becomes, whether the word (c) is in the context window of the the center word (w) or not.

The probability of a word (c) appearing within the context of the center word (w) can be defined as,

$$p(D=1|w,c;\theta) = \frac{1}{1+exp(-\bar{c}_{output_{(j)}} \cdot w)} \in \mathbb{R}^1$$

where c is word came from postive or negative word context, w = input center word, thetha = weight matrix having dim. of input x hidden layer (no. of neurons), c_output = wt. embedding matrix of output word since vanilla skipgram have v(vocab words) so complexity is o(v) but negative sampling has complexity of o(k+1) where k is negative samples which is less than v, i.e. why negative sampling saves a significant amount of computational cost per iteration.

6. algo rejects words based on certain threshold calculated as, p(w) = sqrt(t/f(w)) + t/f(w), where f(w) = count/total no. of tokens, normally t is takena as 10e-5
7. negative words are taken following the distribution as below

$$P_n(w) = \left(\frac{U(w)}{Z}\right)^{\alpha}$$

where U(w) is unigram distribution i.e how many times each word appeared in a corpus, z = normalization factor, each word w divides by no. of time it appear in corpus (normaliztion), alpha = hyperparam normally taken as 3/4 accor. to paper.

8. derivative of negative sampling in network

where, c_pos = words that actually appear within the context window of the center word (w)

c_neg = words that are randomly drawn from a noise distribution Pn(w) or negative sampling,

w = word vector of input word which is equal to hidden layer (neuron) h, i.e. h is obtained by multiplying the input word embedding matrix (let, 3) with the V-dim input vector (let, 10) so final shape is (10,) x (10,3) = 3 (hidden state).

theta = concat of input and output wt. matrices

$$\theta = [W_{input} \quad W_{output}] = \begin{bmatrix} u_{the} \\ u_{passes} \\ \vdots \\ u_{who} \\ v_{the} \\ v_{passes} \\ \vdots \\ v_{who} \end{bmatrix} \in \mathbb{R}^{2NV}$$

u is a word vector from w_input and v is a word vector from w_output.

WORKING

```
from gensim.models.fasttext import FastText
import nltk
def fast_model(embed_size, window_size, min_words, down_sampling):

  """embedding_size :  size of the embedding vector.
  window_size      :  size of the number of words occurring before and a
  min_word         :  minimum frequency of a word in the corpus for whic
  down_sampling    :  most frequently occurring word will be down-sample

  word_punctuation_tokenizer = nltk.WordPunctTokenizer()
  word_tokenized_corpus = [word_punctuation_tokenizer.tokenize(sent) for
  model = FastText(word_tokenized_corpus, size=embed_size, window=window_

  embedding_matrix_fast_text = np.zeros((vocab_size, embed_size))
  for word, i in tokenizer.word_index.items():
    try:
      embedding_vector = model.wv[word] # getting the vector for each wor
    except:
      embedding_vector = np.zeros(300)

  if embedding_vector is not None:
    embedding_matrix_fast_text[i] = embedding_vector

  return embedding_matrix_fast_text
```

```
  return embedding_matrix_fast_text
```

```
%%time
embedding_matrix_ft = fast_model(300, 20, 5, 1e-2)
```

```
CPU times: user 6min 48s, sys: 1.11 s, total: 6min 49s
Wall time: 3min 31s
```

```
#pickle.dump((embedding_matrix_ft), open('/content/gdrive/MyDrive/cs1/dee
embedding_matrix_ft = pickle.load(open('/content/gdrive/MyDrive/cs1/deep
```

```
import sys, os, re, csv, codecs
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Dense, Input, LSTM, Embedding, Conv1D
from tensorflow.keras.layers import  BatchNormalization, Dropout, Activat
from tensorflow.keras.layers import Bidirectional, GlobalMaxPool1D
from tensorflow.keras.models import Model
from tensorflow.keras import initializers, regularizers, constraints, opt

from sklearn.metrics import hamming_loss
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score

import numpy as np
import pandas as pd
```

bi dir. lstm

```
def model(embed_matrix, vocab_size, embedd_size,input_length):

  '''embed_matrix   : matrix weight from embedding,
     vocab_size     : length of vocab,
     embedd_size    : size of embedding,
     input lenght   : maximum/custom lenght of text,
     returns        : model'''
```

```
    input = Input(shape=(input_length,), name='Descripton text')  # input
    embedding = Embedding(vocab_size, embedd_size, weights=[embed_matrix],
    x = SpatialDropout1D(0.5)(embedding)
    x0 = Bidirectional(LSTM(128, return_sequences=True, dropout=0.2, recurr

    #1
    x = Dense(100, activation="relu")(x0)
    #x = GlobalMaxPool1D()(x)
    x = BatchNormalization()(x)
    x = Dropout(0.5)(x)

    #2
    x1 = Dense(100, activation="relu")(x0)
    x1 = BatchNormalization()(x1)
    x1 = Dropout(0.5)(x1)

    x_con =  Concatenate(axis=1)([x,x1])
    x_ = GlobalMaxPool1D()(x_con)
    x_ = Dropout(0.5)(x_)

    output = Dense(3, activation="sigmoid")(x_)

    model = Model(inputs=input, outputs=output)
    return model

#model.summary()


model_1_ft = model(embedding_matrix_ft, vocab_size, 300, 300)
model_1_ft.summary()
```

```
Model: "model"
_____________________________________________________________________________
Layer (type)                    Output Shape         Param #     Conn
=============================================================================
Descripton text (InputLayer)    [(None, 300)]        0
_____________________________________________________________________________
embedding (Embedding)           (None, 300, 300)     2420100     Desc
_____________________________________________________________________________
spatial_dropout1d (SpatialDropo (None, 300, 300)     0           embe
_____________________________________________________________________________
bidirectional (Bidirectional)   (None, 300, 256)     439296      spat
_____________________________________________________________________________
dense (Dense)                   (None, 300, 100)     25700       bidi
_____________________________________________________________________________
dense_1 (Dense)                 (None, 300, 100)     25700       bidi
_____________________________________________________________________________
batch_normalization (BatchNorma (None, 300, 100)     400         dens
```

```
batch_normalization_1 (BatchNor (None, 300, 100)     400          dens
_________________________________________________________________________
dropout (Dropout)               (None, 300, 100)     0            batc
_________________________________________________________________________
dropout_1 (Dropout)             (None, 300, 100)     0            batc
_________________________________________________________________________
concatenate (Concatenate)       (None, 600, 100)     0            drop
                                                                  drop
_________________________________________________________________________
global_max_pooling1d (GlobalMax (None, 100)          0            conc
_________________________________________________________________________
dropout_2 (Dropout)             (None, 100)          0            glob
_________________________________________________________________________
dense_2 (Dense)                 (None, 3)            303          drop
=========================================================================
Total params: 2,911,899
Trainable params: 491,399
Non-trainable params: 2,420,500
_________________________________________________________________________
```

```
def class_conversion(array):

  '''take array as input convert probablity to label based on threshold c

  row, column = array.shape
  predict =np.zeros((row, column))
  for i in range(row):
    for j in range(column):
      if array[i,j]>0.5:
        predict[i,j] = 1
  return predict
```

```
from tensorflow.keras.callbacks import *

filepath = '/content/gdrive/MyDrive/cs1/deep_model1_ft.hdf5'
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_loss', verbo

optimizer = tf.keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, bet
model_1_ft.compile(loss='binary_crossentropy', optimizer = optimizer, met

hstry = model_1_ft.fit(train_pad, y_train, batch_size=64, epochs=12, vali
```

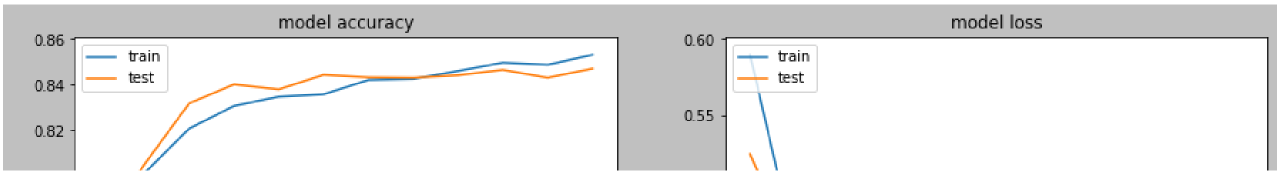
```
Epoch 1/12
115/115 [==============================] - 397s 3s/step - loss: 2.518
```

```
Epoch 00001: val_loss improved from inf to 0.59733, saving model to /
Epoch 2/12
115/115 [==============================] - 387s 3s/step - loss: 0.680

Epoch 00002: val_loss did not improve from 0.59733
Epoch 3/12
115/115 [==============================] - 390s 3s/step - loss: 0.625

Epoch 00003: val_loss did not improve from 0.59733
Epoch 4/12
115/115 [==============================] - 388s 3s/step - loss: 0.598

Epoch 00004: val_loss improved from 0.59733 to 0.57774, saving model
Epoch 5/12
115/115 [==============================] - 389s 3s/step - loss: 0.566

Epoch 00005: val_loss improved from 0.57774 to 0.54573, saving model
Epoch 6/12
115/115 [==============================] - 390s 3s/step - loss: 0.559

Epoch 00006: val_loss improved from 0.54573 to 0.53606, saving model
Epoch 7/12
115/115 [==============================] - 387s 3s/step - loss: 0.541

Epoch 00007: val_loss improved from 0.53606 to 0.49998, saving model
Epoch 8/12
115/115 [==============================] - 391s 3s/step - loss: 0.523

Epoch 00008: val_loss did not improve from 0.49998
Epoch 9/12
115/115 [==============================] - 389s 3s/step - loss: 0.516

Epoch 00009: val_loss improved from 0.49998 to 0.49320, saving model
Epoch 10/12
115/115 [==============================] - 390s 3s/step - loss: 0.511

Epoch 00010: val_loss did not improve from 0.49320
Epoch 11/12
115/115 [==============================] - 388s 3s/step - loss: 0.502

Epoch 00011: val_loss improved from 0.49320 to 0.48856, saving model
Epoch 12/12
115/115 [==============================] - 387s 3s/step - loss: 0.498

Epoch 00012: val_loss improved from 0.48856 to 0.48764, saving model
```

```
score = model_1_ft.evaluate(test_pad, y_test, verbose=1)
print("Loss         :", score[0])
print("Bin. Accuracy:", score[1])
```

```
58/58 [==============================] - 18s 317ms/step - loss: 0.487
Loss         : 0.48764151334762573
Bin. Accuracy: 0.8294363021850586
```

```
import matplotlib.pyplot as plt

def plot_los():
  fig = plt.figure(figsize=(15, 5)).patch.set_facecolor('silver')
  plt.subplot(121)

  plt.plot(hstry.history['binary_accuracy'])
  plt.plot(hstry.history['val_binary_accuracy'])
  plt.title('model accuracy')
  plt.ylabel('accuracy')
  plt.xlabel('epoch')
  plt.legend(['train','test'], loc='upper left')

  plt.subplot(122)
  plt.plot(hstry.history['loss'])
  plt.plot(hstry.history['val_loss'])

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

plot_los()
```



OBSERVATION

1. initially in epoch loss curve training loss is higher than validation loss that means underftting, which is quite evident as it is starting stage, but after epoch 7, validation loss is higher than training loss indicates model starts overftting, but epoch 7 is the best balance we are looking for.

```
y_pred = model_1_ft.predict(test_pad, batch_size=64)
y_class = class_conversion(y_pred)
```

```
y_class
```

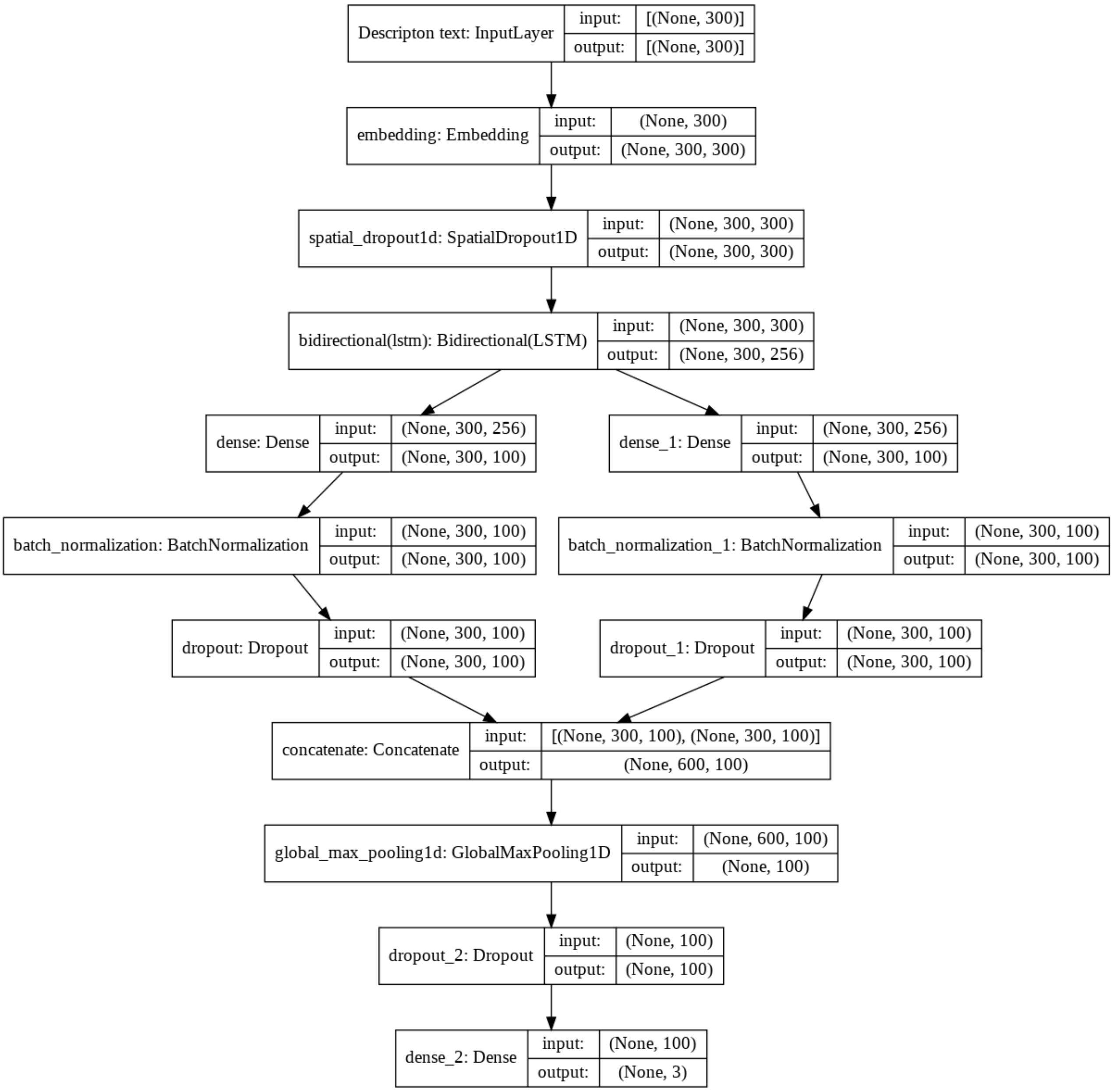
```
array([[1., 0., 0.],
       [0., 0., 1.],
       [0., 0., 0.],
       ...,
       [0., 0., 0.],
       [0., 0., 0.],
       [0., 0., 0.]])
```

```
metrics(y_test, y_class)
```

```
Hamming Loss      :  0.1705637121624071
Exact Match Ratio :  0.610657966286025
Recall micro      :  0.5003043213633597
Precision micro   :  0.8726114649681529
Fl score micro    :  0.6359767891682785

Recall macro      :  0.4707705417414137
Precision macro   :  0.861443355701792
Fl score macro    :  0.5954439073166472
```

```
model_1_ft.save('/content/gdrive/MyDrive/cs1/model1_ft_deepl.h5')
```

```
tf.keras.utils.plot_model( model_1_ft, show_shapes=True, show_layer_names
```


Descripton text: InputLayer
input: [(None, 300)]
output: [(None, 300)]
embedding: Embedding
input: (None, 300)
output: (None, 300, 300)
spatial_dropout1d: SpatialDropout1D
input: (None, 300, 300)
output: (None, 300, 300)
bidirectional(lstm): Bidirectional(LSTM)
input: (None, 300, 300)
output: (None, 300, 256)
dense: Dense
input: (None, 300, 256)
output: (None, 300, 100)
dense_1: Dense
input: (None, 300, 256)
output: (None, 300, 100)
batch_normalization: BatchNormalization
input: (None, 300, 100)
output: (None, 300, 100)
batch_normalization_1: BatchNormalization
input: (None, 300, 100)
output: (None, 300, 100)
dropout: Dropout
input: (None, 300, 100)
output: (None, 300, 100)
dropout_1: Dropout
input: (None, 300, 100)
output: (None, 300, 100)
concatenate: Concatenate
input: [(None, 300, 100), (None, 300, 100)]
output: (None, 600, 100)
global_max_pooling1d: GlobalMaxPooling1D
input: (None, 600, 100)
output: (None, 100)
dropout_2: Dropout
input: (None, 100)
output: (None, 100)
dense_2: Dense
input: (None, 100)
output: (None, 3)

cnn 1d

```
def model2ft(embed_matrix, vocab_size, embedd_size,input_length):
  input = Input(shape=(300,), name='Descripton text cnn1d')  # input

  embedding = Embedding(vocab_size, embedd_size, weights=[embed_matrix],

  x = SpatialDropout1D(0.5)(embedding)
  conv0 = Conv1D(128, 6, activation="relu")(x)
  z = GlobalMaxPool1D()(conv0)

  conv1 = Conv1D(128, 6, activation="relu")(x)
  x1 = GlobalMaxPool1D()(conv1)

  x1 = Concatenate()([x1,z])

  x2 = Dropout(0.5)(x1)

  output = Dense(3, activation="sigmoid")(x2)

  model_2_ft = Model(inputs=input, outputs=output)

  return model_2_ft

  #model_2_ft.summary()
```

```
model_2_ft = model2ft(embedding_matrix_ft, vocab_size, 300, 300)
```

```
model_2_ft.summary()
```

```
Model: "model_1"
__________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Conn
==========================================================================================
Descripton text cnn1d (InputLay [(None, 300)]        0
__________________________________________________________________________________________
embedding_1 (Embedding)         (None, 300, 300)     2420100     Desc
__________________________________________________________________________________________
spatial_dropout1d_1 (SpatialDro (None, 300, 300)     0           embe
__________________________________________________________________________________________
conv1d_1 (Conv1D)               (None, 295, 128)     230528      spat
__________________________________________________________________________________________
conv1d (Conv1D)                 (None, 295, 128)     230528      spat
__________________________________________________________________________________________
global_max_pooling1d_2 (GlobalM (None, 128)          0           conv
__________________________________________________________________________________________
global_max_pooling1d_1 (GlobalM (None, 128)          0           conv
__________________________________________________________________________________________
concatenate_1 (Concatenate)     (None, 256)          0           glob
                                                                 glob
__________________________________________________________________________________________
dropout_3 (Dropout)             (None, 256)          0           conc
__________________________________________________________________________________________
dense_3 (Dense)                 (None, 3)            771         drop
==========================================================================================
Total params: 2,881,927
Trainable params: 461,827
Non-trainable params: 2,420,100
__________________________________________________________________________________________
```

```
from tensorflow.keras.callbacks import *

filepath = '/content/gdrive/MyDrive/cs1/deep_model2_ft.hdf5'
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_loss', verbo

optimizer = tf.keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, bet
model_2_ft.compile(loss='binary_crossentropy', optimizer = optimizer, met

hstry1 = model_2_ft.fit(train_pad, y_train, batch_size=64, epochs=12, val
```

```
Epoch 1/12
115/115 [==============================] - 96s 825ms/step - loss: 0.5

Epoch 00001: val_loss improved from inf to 0.46864, saving model to /
Epoch 2/12
115/115 [==============================] - 94s 822ms/step - loss: 0.4
```

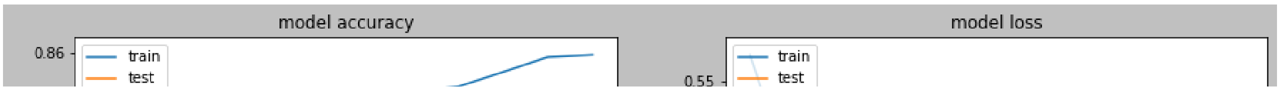
```
Epoch 00002: val_loss improved from 0.46864 to 0.44287, saving model
Epoch 3/12
115/115 [==============================] - 94s 820ms/step - loss: 0.4

Epoch 00003: val_loss improved from 0.44287 to 0.42810, saving model
Epoch 4/12
115/115 [==============================] - 95s 823ms/step - loss: 0.4

Epoch 00004: val_loss improved from 0.42810 to 0.42214, saving model
Epoch 5/12
115/115 [==============================] - 94s 820ms/step - loss: 0.4

Epoch 00005: val_loss improved from 0.42214 to 0.41765, saving model
Epoch 6/12
115/115 [==============================] - 94s 821ms/step - loss: 0.3

Epoch 00006: val_loss improved from 0.41765 to 0.41134, saving model
Epoch 7/12
115/115 [==============================] - 94s 822ms/step - loss: 0.3

Epoch 00007: val_loss improved from 0.41134 to 0.40930, saving model
Epoch 8/12
115/115 [==============================] - 94s 822ms/step - loss: 0.3

Epoch 00008: val_loss did not improve from 0.40930
Epoch 9/12
115/115 [==============================] - 95s 823ms/step - loss: 0.3

Epoch 00009: val_loss improved from 0.40930 to 0.40898, saving model
Epoch 10/12
115/115 [==============================] - 95s 823ms/step - loss: 0.3

Epoch 00010: val_loss did not improve from 0.40898
Epoch 11/12
115/115 [==============================] - 95s 823ms/step - loss: 0.3

Epoch 00011: val_loss did not improve from 0.40898
Epoch 12/12
115/115 [==============================] - 94s 822ms/step - loss: 0.3

Epoch 00012: val_loss did not improve from 0.40898
```

```
score = model_2_ft.evaluate(test_pad, y_test, verbose=1)
print("Loss         :", score[0])
print("Bin. Accuracy:", score[1])
```

```
58/58 [==============================] - 9s 157ms/step - loss: 0.4107
```

```
Loss          : 0.4107370674610138
Bin. Accuracy: 0.8394055366516113
```

```
import matplotlib.pyplot as plt

def plot_los():
  fig = plt.figure(figsize=(15, 5)).patch.set_facecolor('silver')
  plt.subplot(121)

  plt.plot(hstry1.history['binary_accuracy'])
  plt.plot(hstry1.history['val_binary_accuracy'])
  plt.title('model accuracy')
  plt.ylabel('accuracy')
  plt.xlabel('epoch')
  plt.legend(['train','test'], loc='upper left')

  plt.subplot(122)
  plt.plot(hstry1.history['loss'])
  plt.plot(hstry1.history['val_loss'])

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

plot_los()
```



OBSERVATION

1. initially in epoch loss curve training loss is higher than validation loss that means underftting, which is quite evident as it is starting stage, but after epoch 3, validation loss higher than training loss indicates model starts overftting, but epoch 3 is the best balance we are looking for.

```
y_pred = model_2_ft.predict(test_pad, batch_size=64)
y_class = class_conversion(y_pred)
```

```
y_class
```

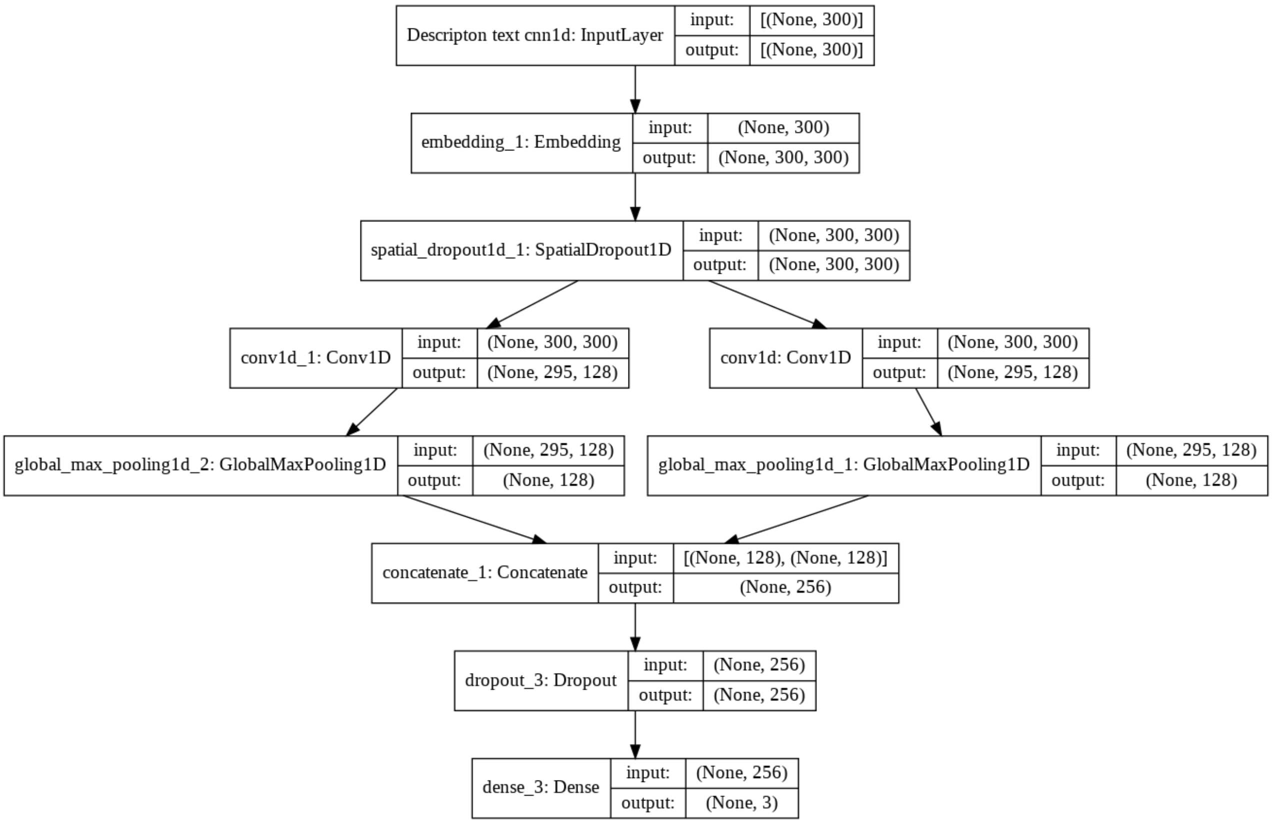
```
array([[1., 0., 0.],
       [0., 0., 1.],
       [0., 0., 0.],
       ...,
       [1., 0., 0.],
       [0., 0., 0.],
       [0., 0., 0.]])
```

```
metrics(y_test, y_class)
```

```
Hamming Loss       :  0.16059452601051297
Exact Match Ratio :  0.6296900489396411
Recall micro       :  0.5709068776628119
Precision micro    :  0.838248436103664
Fl score micro     :  0.6792179580014481

Recall macro       :  0.543709772250049
Precision macro    :  0.8158412600797383
Fl score macro     :  0.6473652706173126
```

```
model_2_ft.save('/content/gdrive/MyDrive/cs1/model2_ft_deepl.h5')
```

```
tf.keras.utils.plot_model( model_2_ft, show_shapes=True, show_layer_names
```



bi dir. and cnn1d

```
def model3ft(embed_matrix, vocab_size, embedd_size,input_length):
  input = Input(shape=(input_length,))  # input
  embedding = Embedding(vocab_size, embedd_size, weights=[embed_matrix]
```

```
    embedding = Embedding(vocab_size, embedd_size, weights=[embed_matrix],

    x = SpatialDropout1D(0.2)(embedding)

    x = Bidirectional(LSTM(128, return_sequences=True, dropout=0.15, recurr
    x = Conv1D(64, kernel_size=3, padding='valid', kernel_initializer='glor

    avg_pool = GlobalAveragePooling1D()(x)
    max_pool = GlobalMaxPooling1D()(x)

    x = concatenate([avg_pool, max_pool])
    x = BatchNormalization()(x)
    x = Dropout(0.2)(x)
    x = Dense(128, activation='relu')(x)
    x = Dense(64, activation='relu')(x)
    out = Dropout(0.2)(x)

    output = Dense(3, activation="sigmoid")(out)
    model_3_ft = Model(inputs=input, outputs=output)

    return model_3_ft
```

```
model_3_ft = model3ft(embedding_matrix_ft, vocab_size, 300, 300)
model_3_ft.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #	Conn
input_1 (InputLayer)	[(None, 300)]	0	
embedding (Embedding)	(None, 300, 300)	2420100	inpu
spatial_dropout1d (SpatialDropo	(None, 300, 300)	0	embe
bidirectional (Bidirectional)	(None, 300, 256)	439296	spat
conv1d (Conv1D)	(None, 298, 64)	49216	bidi
global_average_pooling1d (Globa	(None, 64)	0	conv
global_max_pooling1d (GlobalMax	(None, 64)	0	conv
concatenate (Concatenate)	(None, 128)	0	glob glob

```
batch_normalization (BatchNorma (None, 128)          512         conc
_________________________________________________________________________
dropout (Dropout)               (None, 128)          0           batc
_________________________________________________________________________
dense (Dense)                   (None, 128)          16512       drop
_________________________________________________________________________
dense_1 (Dense)                 (None, 64)           8256        dens
_________________________________________________________________________
dropout_1 (Dropout)             (None, 64)           0           dens
_________________________________________________________________________
dense_2 (Dense)                 (None, 3)            195         drop
=========================================================================
Total params: 2,934,087
Trainable params: 513,731
Non-trainable params: 2,420,356
_________________________________________________________________________
```

```
from tensorflow.keras.callbacks import *

filepath = '/content/gdrive/MyDrive//cs1/deep_model3_ft.hdf5'
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_loss', verbo

optimizer = tf.keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, bet
model_3_ft.compile(loss='binary_crossentropy', optimizer = optimizer, met

hstry2 = model_3_ft.fit(train_pad, y_train, batch_size=64, epochs=12, val
```

```
Epoch 1/12
115/115 [==============================] - 388s 3s/step - loss: 0.505

Epoch 00001: val_loss improved from inf to 0.54016, saving model to /
Epoch 2/12
115/115 [==============================] - 379s 3s/step - loss: 0.432

Epoch 00002: val_loss improved from 0.54016 to 0.45533, saving model
Epoch 3/12
115/115 [==============================] - 378s 3s/step - loss: 0.412

Epoch 00003: val_loss improved from 0.45533 to 0.40136, saving model
Epoch 4/12
115/115 [==============================] - 375s 3s/step - loss: 0.395

Epoch 00004: val_loss improved from 0.40136 to 0.39075, saving model
Epoch 5/12
115/115 [==============================] - 376s 3s/step - loss: 0.383

Epoch 00005: val_loss improved from 0.39075 to 0.38528, saving model
Epoch 6/12
```

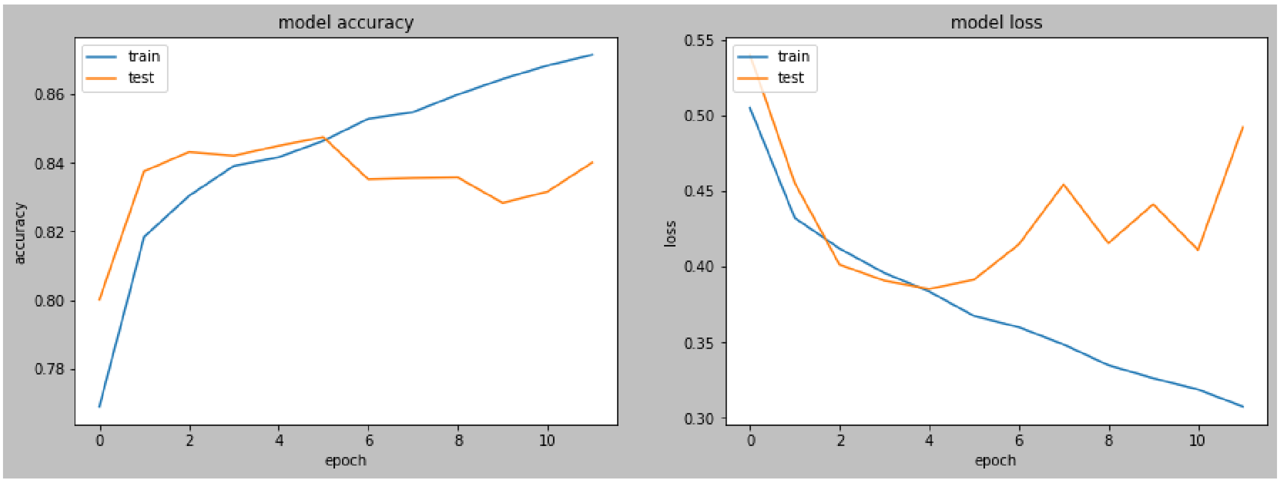
```
115/115 [==============================] - 375s 3s/step - loss: 0.367

Epoch 00006: val_loss did not improve from 0.38528
Epoch 7/12
115/115 [==============================] - 374s 3s/step - loss: 0.360

Epoch 00007: val_loss did not improve from 0.38528
Epoch 8/12
115/115 [==============================] - 381s 3s/step - loss: 0.348

Epoch 00008: val_loss did not improve from 0.38528
Epoch 9/12
115/115 [==============================] - 375s 3s/step - loss: 0.334

Epoch 00009: val_loss did not improve from 0.38528
Epoch 10/12
115/115 [==============================] - 375s 3s/step - loss: 0.326

Epoch 00010: val_loss did not improve from 0.38528
Epoch 11/12
115/115 [==============================] - 373s 3s/step - loss: 0.318

Epoch 00011: val_loss did not improve from 0.38528
Epoch 12/12
115/115 [==============================] - 375s 3s/step - loss: 0.307

Epoch 00012: val_loss did not improve from 0.38528
```

```
score = model_3_ft.evaluate(test_pad, y_test, verbose=1)
print("Loss         :", score[0])
print("Bin. Accuracy:", score[1])
```

```
58/58 [==============================] - 18s 308ms/step - loss: 0.492
Loss         : 0.4922749996185303
Bin. Accuracy: 0.8401304483413696
```

```
import matplotlib.pyplot as plt

def plot_los():
  fig = plt.figure(figsize=(15, 5)).patch.set_facecolor('silver')
  plt.subplot(121)

  plt.plot(hstry2.history['binary_accuracy'])
  plt.plot(hstry2.history['val_binary_accuracy'])
  plt.title('model accuracy')
  plt.ylabel('accuracy')
```

```
    plt.xlabel('epoch')
    plt.legend(['train','test'], loc='upper left')

    plt.subplot(122)
    plt.plot(hstry2.history['loss'])
    plt.plot(hstry2.history['val_loss'])

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

plot_los()
```



OBSERVATION

1. initially in epoch loss curve training loss is lower than validation loss that means overfitting, but after epoch 4, validation loss is higher than training loss indicates model starts overftting, at epoch 2-3 test loss higher than train which indicates marginally underfit but epoch 4 is the best balance we are looking for.

```
y_pred = model_3_ft.predict(test_pad, batch_size=64)
```

```
y_class = class_conversion(y_pred)
```

```
y_class
```

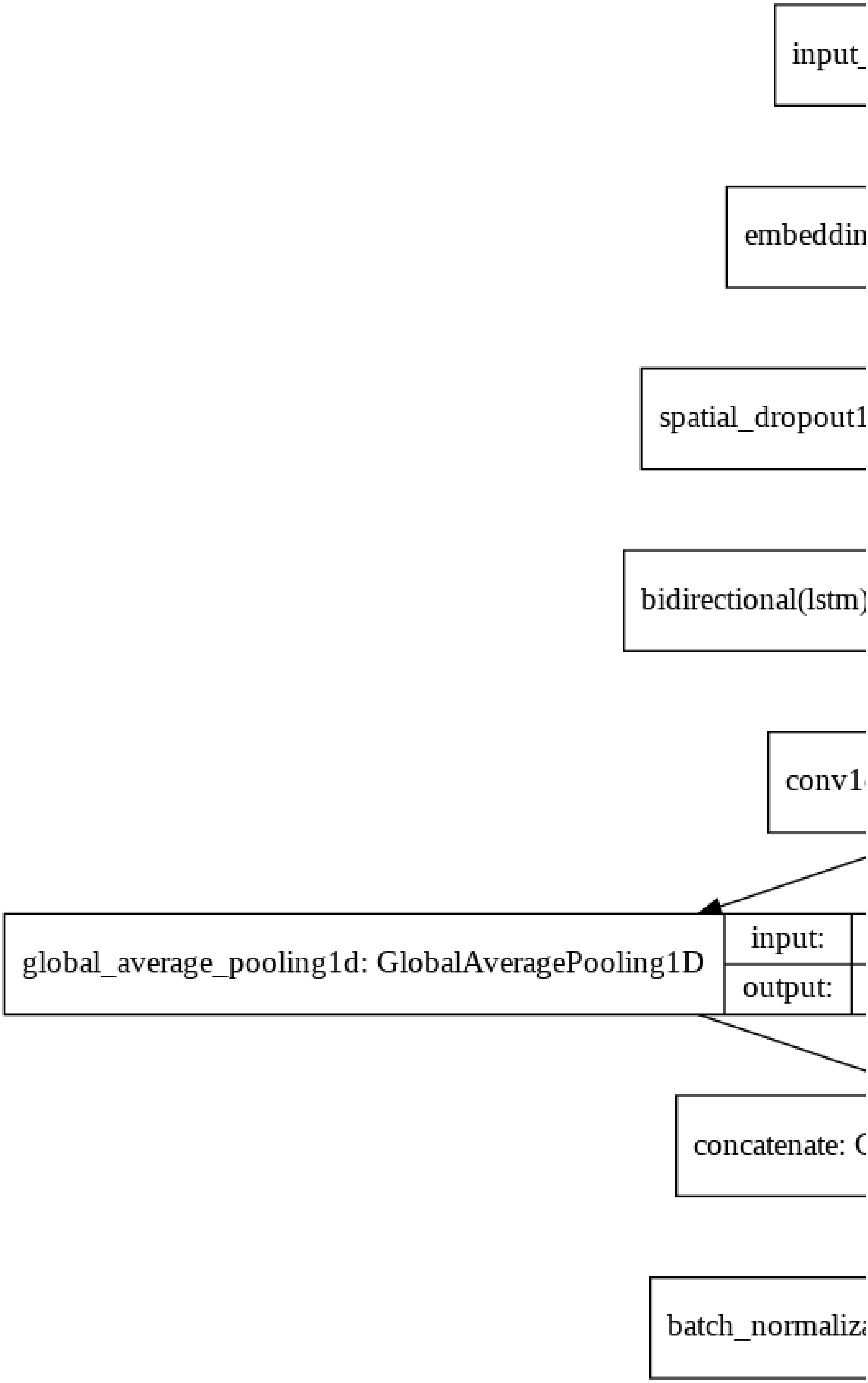
```
array([[1., 0., 0.],
       [0., 0., 1.],
       [0., 0., 0.],
       ...,
       [0., 0., 0.],
       [0., 0., 1.],
       [0., 0., 0.]])
```

```
metrics(y_test, y_class)
```

```
Hamming Loss      :  0.1598694942903752
Exact Match Ratio :  0.6247960848287113
Recall micro      :  0.5721241631162508
Precision micro   :  0.8400357462019661
Fl score micro    :  0.6806661839246924

Recall macro      :  0.5373421564979804
Precision macro   :  0.8200479052453645
Fl score macro    :  0.6345582336404335
```

```
model_3_ft.save('/content/gdrive/MyDrive/cs1/model3_ft_deepl.h5')
```

```
tf.keras.utils.plot_model( model_3_ft, show_shapes=True, show_layer_names
```


input_
embeddin
spatial_dropout1
bidirectional(lstm)
conv1
global_average_pooling1d: GlobalAveragePooling1D
input:
output:
concatenate: C
batch_normaliz

GLOVE

GLOVE THEORY

1. glove captures global context by using conditional probablity (co-occurance based matrix), i.e. using co-occurance probablity as ratio and use it as word representation.

2. $$F(w_i, w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}}, \qquad (1)$$

here, w_i, w_j = words in context, w_tilda_k = whose embedd to be learn, P_ik = prob. of word i in context of k, P_jk = prob. of word j in context of k.

aim = learn function F which encapsulates information on right hand side of equation, which info is there in corpus.

3. $$F(w_i - w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}}. \qquad (2)$$

since w_'s are vector, i.e having linear structure as it is vector, so use difference, but other operation can also be used, but it also restricts to differnce of two word (i,j).

4. since in eq 2 rhs is scaler, to have the same dim. we convert lhs also to scaler by taking dot product, which also help to clearly defining loss function.

$$F\left((w_i - w_j)^T \tilde{w}_k\right) = \frac{P_{ik}}{P_{jk}}, \qquad (3)$$

5. in eq3 let w_tilda_k = pot, i.e. we are learning various word embedding given pot, but this can also be the case that we need embedding of pot w.r.t different w_tilda_k (say sky), so to encode this inter-changibilty we require function F to be homomorphic i.e. we can express as below

$$F\left((w_i - w_j)^T \tilde{w}_k\right) = \frac{F(w_i^T \tilde{w}_k)}{F(w_j^T \tilde{w}_k)}, \qquad (4)$$

$$F(w_i^T \tilde{w}_k) = P_{ik} = \frac{X_{ik}}{X_i}. \qquad (5)$$

where, X_ik = number of times any word appears (k) in context of word i, X = word-word co-occurance count mat.

6. after taking log of eq. 5 and adding baises we get

$$w_i^T \tilde{w}_k + b_i + \tilde{b}_k = \log(X_{ik}). \qquad (7)$$

7. on eq 6 using least square regression as loss function (F), and multiplying by weighing function (f(X_ij)) gives overall cost function

$$J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2, \qquad (8)$$

where V = size of vocab aim of giving weighing function that it should not measure all co-occurances equally i.e not treating same which occurs rarely.

from the paper f(X) is as below

$$f(x) = \begin{cases} (x/x_{\max})^\alpha & \text{if } x < x_{\max} \\ 1 & \text{otherwise} \end{cases} . \quad (9)$$

with x_max = 3/4.

properties of f(X) should kept in mind are

1. at f(0) = 0.
2. f(X) continous function vanishes as x tends to 0.
3. f(X) non decreasing so that co-occurrences not overweighted.
4. f(X) small for large value of x, so that frequent co-occurences are not overweigth.

WORKING MODEL

```
import os
path_glove = os.path.join(os.path.expanduser('~'), '/content/gdrive/MyDri

def glove_embedding(word_index):
  embedding_index = {}
  hit = 0
  miss = 0
  embedding_matrix = np.zeros((len(word_index)+1, 300))

  with open(path_glove) as f:
    for line in f:
      word, coef = line.split(maxsplit=1)
      coef = np.fromstring(coef, 'float', sep=' ')
      embedding_index[word] = coef

  print('Found %s word vectors.' % len(embedding_index))

  for word, i in word_index.items():
    embedding_vector = embedding_index.get(word)
    if embedding_vector is not None:
      ## words not found in embedding index will be all zeros
      embedding_matrix[i] = embedding_vector
      hit += 1
    else:
      miss += 1

  print(f'Converted {hit} words, misses {miss}')
```

```
    print(f'Converted {hit} words, misses {miss}')

    return embedding_matrix
```

```
glove_embed = glove_embedding(word_index)
```

```
Found 400000 word vectors.
Converted 6428 words, misses 1638
```

bi dir. lstm

[ ] ↳ 12 cells hidden

cnn 1d

[ ] ↳ 11 cells hidden

bi dir. lstm and cnn 1d

[ ] ↳ 11 cells hidden

OVER VIEW

```
from prettytable import PrettyTable
k6 = PrettyTable()
print(' Best from Dl ')
print('-'*15)
print(' ')
k6.field_names = ["Model","Embedding","Hamming loss","EMR","Recall","Prec
k6.add_row(["Bidir. Lstm",'FASTEXT',0.1706, 0.6107, 0.5003, 0.8726, 0.636
k6.add_row(["CNN1D",'FASTEXT',0.1606, 0.6297, 0.5709, 0.8382, 0.6792])
k6.add_row(["Bidir. Lstm  + CNN1D",'FASTEXT',0.1599, 0.6248, 0.5721, 0.84
k6.add_row(["Bidir. Lstm",'GLOVE',0.1787, 0.5808, 0.4760, 0.8622, 0.6133]
k6.add_row(["CNN1D",'GLOVE',0.1579, 0.6351, 0.5971, 0.8244, 0.6926])
k6.add_row(["Bidir. Lstm  + CNN1D",'GLOVE',0.1791, 0.5889, 0.4960, 0.835
print(k6)
```

```
 Best from Dl
```

```
---------------

+----------------------+-----------+--------------+--------+--------+
|        Model         | Embedding | Hamming loss |  EMR   | Recall |
+----------------------+-----------+--------------+--------+--------+
|     Bidir. Lstm      |  FASTEXT  |    0.1706    | 0.6107 | 0.5003 |
|        CNN1D         |  FASTEXT  |    0.1606    | 0.6297 | 0.5709 |
| Bidir. Lstm  + CNN1D |  FASTEXT  |    0.1599    | 0.6248 | 0.5721 |
|     Bidir. Lstm      |   GLOVE   |    0.1787    | 0.5808 | 0.476  |
|        CNN1D         |   GLOVE   |    0.1579    | 0.6351 | 0.5971 |
| Bidir. Lstm  + CNN1D |   GLOVE   |    0.1791    | 0.5889 | 0.496  |
+----------------------+-----------+--------------+--------+--------+
```

```
k7 = PrettyTable()
print(' Best from Ml ')
print('-'*15)
print(' ')
k7.field_names = ["Model","Embedding","Hamming loss","EMR","Recall","Prec
k7.add_row(["bow word + Numerical",'LOGISTIC REGRESSION',0.1684, 0.6145,
k7.add_row(["tf-idf word + Numerical",'LINEAR SVM',0.1727, 0.6057, 0.5879
k7.add_row(["tf-idf char + Numerical",'LINEAR SVM',0.1731, 0.6074, 0.5618
k7.add_row(["fastext + Numerical",'LOGISTIC REGRESSION',0.2021, 0.5416, 0
k7.add_row(["dl features + Numerical",'LINEAR SVM',0.2623, 0.4279, 0.4437
k7.add_row(["bert + Numerical",'LOGISTIC REGRESSION',0.1990, 0.5579, 0.55
print(k7)
```

```
 Best from Ml
---------------

+-------------------------+---------------------+--------------+-----
|          Model          |      Embedding      | Hamming loss |  EMR
+-------------------------+---------------------+--------------+-----
|   bow word + Numerical  | LOGISTIC REGRESSION |    0.1684    | 0.61
| tf-idf word + Numerical |      LINEAR SVM     |    0.1727    | 0.60
| tf-idf char + Numerical |      LINEAR SVM     |    0.1731    | 0.60
|   fastext + Numerical   | LOGISTIC REGRESSION |    0.2021    | 0.54
| dl features + Numerical |      LINEAR SVM     |    0.2623    | 0.42
|     bert + Numerical    | LOGISTIC REGRESSION |    0.199     | 0.55
+-------------------------+---------------------+--------------+-----
```

```
##chossing cnn1 d glove
```

OBSERVATION

Q. reason why hamming loss has decreased but with no increase in F1 score?

The reason hamming loss is decreasing but not substantial increase in f1 is due to reason that hamming loss evaluates row wise at a time (i.e change in row element row wise) there is no compulsion of tp,fp,fn in hamming loss its just bit of 0's and 1's, the bits might have change in any order it is still considered in hamming loss, but f1-micro considers comparison of actual and predicted with individual column wise (which have tp, fp, fn), i.e investigates label wise relationship (which is much stricter than previous one).

e.x.

actual	predicted	hamming loss	p,	r,	f1-micro
[1,0,1]	[1,1,1]	1 bit 0.337	2/2+0=1	2/2+1 = 0.667	0.80
[1,0,0]	[1,1,1]	2 bit 0.667	1/1+0=1	1/1+2 = 0.667	0.80
		avg 1/2 = 0.5			avg 0.80

from the above example it is clear that individual and avg hamming loss is less than f1-micro (individual and avg) is almost same i.e avg hamming loss decrease but no increase in f1-micro.

END 2 END PIPLINE

```
lemmatizer = WordNetLemmatizer()
def preprocess(text):

    """performs common expansion of english words, preforms preprocessing

    text = re.sub(r"won\'t", "will not", text)   # decontracting the wor
    text = re.sub(r"can\'t", "can not", text)
    text = re.sub(r"n\'t", " not", text)
    text = re.sub(r"\'re", " are", text)
    text = re.sub(r"\'s", " is", text)
    text = re.sub(r"\'d", " would", text)
    text = re.sub(r"\'ll", " will", text)
    text = re.sub(r"\'t", " not", text)
    text = re.sub(r"\'ve", " have", text)
```

```
    text = re.sub(r"\'m", " am", text)

    text = re.sub(r'\w+:\s?','',text)
    text = re.sub('[([].*?[\)]', '', text)
    text = re.sub('[<[].*?[\>]', '', text)
    text = re.sub('[{[].*?[\}]', '', text)

    text = ' '.join([lemmatizer.lemmatize(word) for word in text.split()]

    text = re.sub(r'\W', ' ', str(text))
    text = re.sub(r'\s+[a-zA-Z]\s+', ' ', text)
    text = re.sub(r"[^A-Za-z0-9]", " ", text)
    text = re.sub(r'[^\w\s]','',text)
    text = ' '.join(e for e in text.split() if e.lower() not in set(stopw
    # convert to lower and remove stopwords discard words whose len < 2

    text = re.sub("\s\s+" , " ", text)
    text = text.lower().strip()

    return text



pickle.dump((tokenizer), open('/content/gdrive/MyDrive/cs1/tokenizer.pkl'


##load from pickle tokenizer model
##load tensorflow keras numpy pandas, padd sequences
def end_to_end_pipeline(string):
  path = '/content/gdrive/MyDrive/cs1/deep model final/model2_gv_deepl.h5
  result = []
  x = preprocess(string)
  sent_token = tokenizer.texts_to_sequences([x])

  sent_token_padd = pad_sequences(sent_token, maxlen=300, dtype='int32',
  model = tf.keras.models.load_model(path)
  pred = model.predict(sent_token_padd)

  row, column = pred.shape
  predict = np.zeros((row, column))
  for i in range(row):
    for j in range(column):
      if pred[i,j]>0.5:
        predict[i,j] = 1

  for k in range(predict.shape[0]):
    if predict[k][0] == 1.0:
```

```
        result.append('commenting')
      if predict[k][1] == 1.0:
        result.append('ogling')
      if predict[k][2] == 1.0:
        result.append('groping')
      if np.sum(predict) == 0.0:
        result.append('None')

    print(f'possible action : {result}')
```

```
query_1 = 'During morning, a woman was walking and thin guy came around a
end_to_end_pipeline(query_1)
```

```
possible action : ['commenting']
```

```
query_2 = 'During morning, a woman was walking by and thin guy came and g
end_to_end_pipeline(query_2)
```

```
possible action : ['groping']
```

```
query_3 = 'During morning, a woman was walking by and thin guy was starin
end_to_end_pipeline(query_3)
```

```
possible action : ['ogling']
```

```
query_4 = 'During morning, a woman was walking by and thin guy came and c
end_to_end_pipeline(query_4)
```

```
possible action : ['None']
```

```
query_5 = 'Catcalls and passing comments were two of the ghastly things t
end_to_end_pipeline(query_5)
```

```
possible action : ['commenting']
```

```
query_6 = 'This incident took place in the evening.I was in the metro whe
end_to_end_pipeline(query_6)
```

```
possible action : ['ogling']
```

```
query_7 = 'Was walking along crowded street, holding mums hand, when an e
end_to_end_pipeline(query_7)
```

```
possible action : ['groping']
```

```
query_8 = 'chain snatching evening punjabi bagh bus stop'
end_to_end_pipeline(query_8)
```

```
possible action : ['None']
```

```
query_9 = 'Was walking along crowded street, holding mums hand, when an e
end_to_end_pipeline(query_9)
```

```
possible action : ['groping']
```

```
query_10 = 'witnEsseD incident chaIn9 brutALLy snatched elderly lady inci
end_to_end_pipeline(query_10)
```

```
possible action : ['None']
```

```
query_11 = 'incident kap0Pened inMide tRaI*n'
end_to_end_pipeline(query_11)
```

```
possible action : ['None']
```

LIME

LIME THEORY

↳ 1 cell hidden

WORKING

```
pip install lime
```

```
Collecting lime
  Downloading lime-0.2.0.1.tar.gz (275 kB)
```

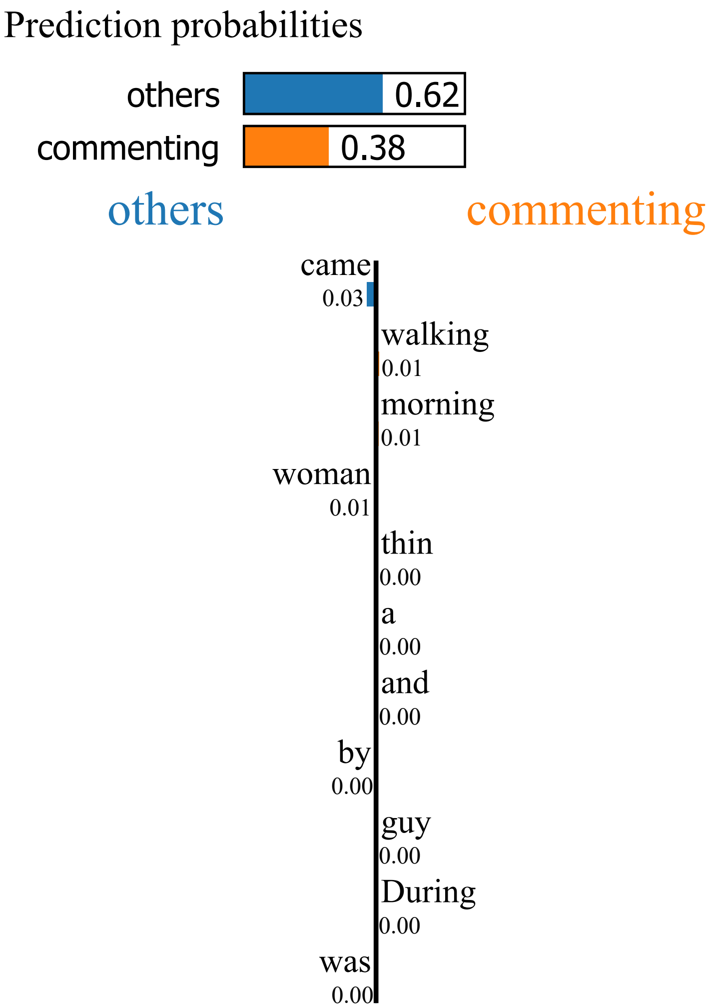
```
     |████████████████████████████████| 275 kB 8.8 MB/s
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/p
Requirement already satisfied: scikit-image>=0.12 in /usr/local/lib/p
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/pytho
Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python
Requirement already satisfied: PyWavelets>=0.4.0 in /usr/local/lib/py
Requirement already satisfied: pillow>=4.3.0 in /usr/local/lib/python
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/py
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: decorator<5,>=4.3 in /usr/local/lib/py
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3
Building wheels for collected packages: lime
  Building wheel for lime (setup.py) ... done
  Created wheel for lime: filename=lime-0.2.0.1-py3-none-any.whl size
  Stored in directory: /root/.cache/pip/wheels/ca/cb/e5/ac701e12d365a
Successfully built lime
Installing collected packages: lime
Successfully installed lime-0.2.0.1
```

```
model = tf.keras.models.load_model('/content/gdrive/MyDrive/cs1/deep mo
#k = model.predict(test_pad)
```

```
def raw_to_probab(pred):

  '''take prediction and return mormalized value for its row'''

  p0 = []
  for j in range(pred.shape[0]):
    for i in pred[j]:
      p0.append(i/sum(pred[j]))

  return np.array(p0, dtype='float32').reshape(-1,3)



#https://github.com/marcotcr/lime/issues/409

from lime.lime_text import LimeTextExplainer
model = tf.keras.models.load_model('/content/gdrive/MyDrive/cs1/deep mode
def multi_label_explain(text, labels, features, samples):
```

```
    '''take text : string of info,
    labels       : labels,
    features     : no. of features to be consider while explaining,
    sample       : no. of neighbourhood samples to be tken for lime expla
    each label and give explaintion for that label with focused words'''


    for label in labels:
        class_names = ['others', label]

        def make_classifier_pipeline(label=label):
          label_index = labels.index(label)
          # pick the corresponding output node
          def lime_explainer_pipeline(texts):
            x_sequence = tokenizer.texts_to_sequences(texts)
            x_sequence = pad_sequences(x_sequence, maxlen=300, padding='p
            predict_probs = model.predict(x_sequence)
            prd_p = raw_to_probab(predict_probs)
            prob_true = prd_p[:, label_index]
            result = np.transpose(np.vstack(([1-prob_true, prob_true])))
            result  = result.reshape(-1, 2)
            print(result.shape)
            return result

          return lime_explainer_pipeline

        classifer_fn = make_classifier_pipeline(label=label)
        explainer = LimeTextExplainer(class_names=class_names, kernel_wic
        exp = explainer.explain_instance(text, classifer_fn, num_features
        exp.show_in_notebook(text=True, predict_proba=True)



labels = ['commenting', 'ogling', 'groping']
r = 'During morning, a woman was walking by and thin guy came.'
mle = multi_label_explain(r, labels, 20, 500)
```

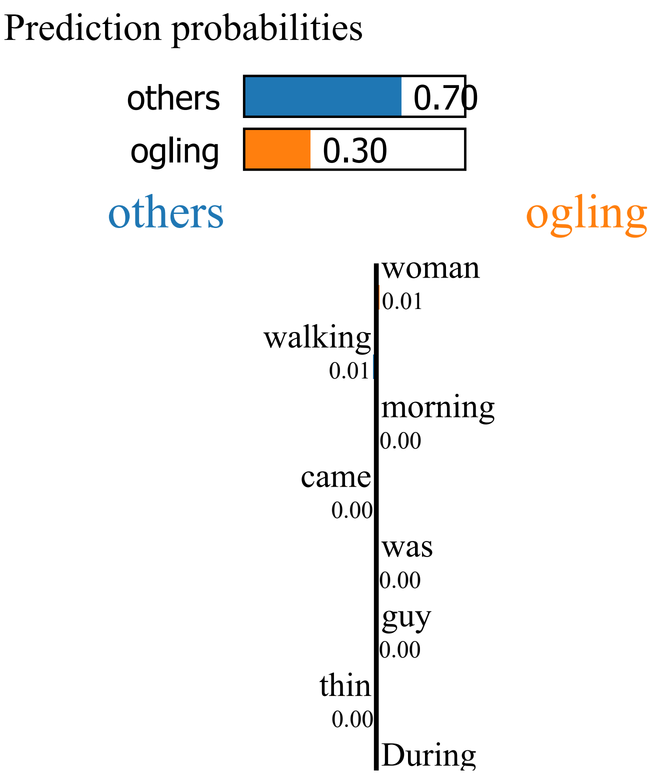
```
(500, 2)
```



Text with highlighted words

During morning, a woman was walking by and thin guy came.

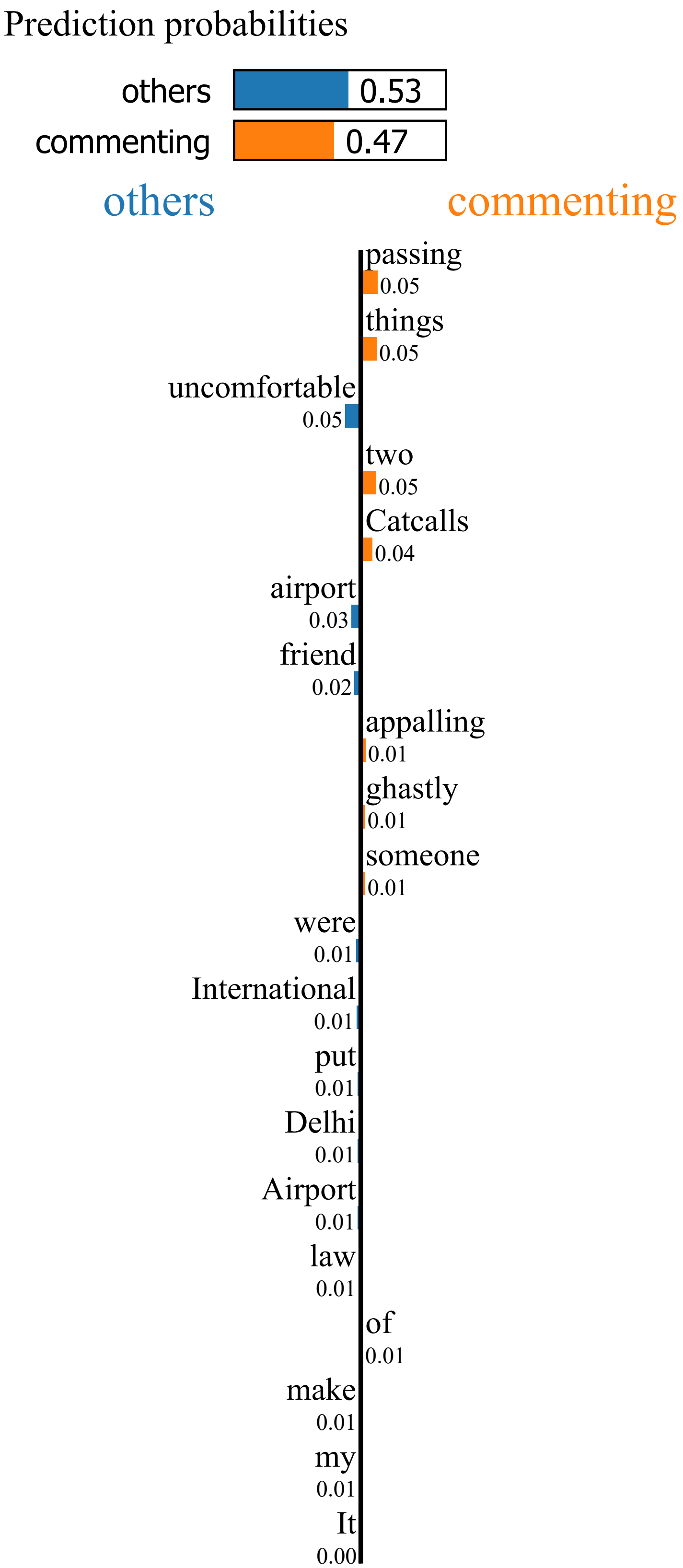
```
(500, 2)
```



0.00
and
0.00
a
0.00

```
r0 = 'Catcalls and passing were two of the ghastly things the Delhi polic
labels = ['commenting', 'ogling', 'groping']
mle = multi_label_explain(r0, labels, 20, 500)
```

```
(500, 2)
```



Text with highlighted words

Catcalls and passing were two of the ghastly things the Delhi police at the International Airport put me and my friend through. It is appalling that the protectors and law enforcers at the airport can make someone so uncomfortable.

```
(500, 2)
```

Prediction probabilities


```
r = 'Was walking along crowded street, holding mums hand, when an elderly
x_sequen = tokenizer.texts_to_sequences([r])
x_sequen = pad_sequences(x_sequen, maxlen=300, padding='post', truncating
pdt = model.predict(x_sequen)
pdt
```

```
array([[0.02093241, 0.06269768, 0.9715594 ]], dtype=float32)
```

```
pdt.shape
```

```
(1, 3)
```

```
pt = raw_to_probab(pdt)
pt
```

```
array([[0.01983758, 0.05941841, 0.920744  ]], dtype=float32)
```

OBSERVATION

1. since we have used sigmoid as final layer, to get probablity for each class/label we have to normalize each entry by its row sum, that is what function raw to probablity is doing.
2. other label indictes labels other than which is present on right side. ex if right side commenting, than others will have ogling and groping (we cannot determine individual percentage in others).

3. in first output, During morning, a woman was walking by and thin guy came.

```
            percent  word model think imp.
commenting - 38% -    walking, morning
ogling     - 30% -    women, mornng
groping    - 32% -    came
```