MULTI-LABEL CLASSIFICATION

Feature Engineering

In [1]:

```
!pip install kaggle
"""
To use the Kaggle API, sign up for a Kaggle account at https://www.kaggle.com.
Then go to the 'Account' tab of your user profile (https://www.kaggle.com/<username>/account) and select
This will trigger the download of kaggle.json, a file containing your API credentials.
Upload that file to google colab/google cloud platform
"""
api_token = {"username":"manojkumar83000","key":"a6c354dd1bc5460d07ffb4844b923064"}
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.7/dist-packages (1.5.12)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.7/dist-packages (from kaggle) (2
.8.1)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from kaggle) (4.41.1)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.7/dist-packages (from kaggle) (1.24.3)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.7/dist-packages (from kaggle) (5.
0.2)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from kaggle) (2.23.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.7/dist-packages (from kaggle) (2020.12.5
)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.7/dist-packages (from kaggle) (1.15.0)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.7/dist-packages (from python
-slugify->kaggle) (1.3)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests->kag
gle) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from requests
->kaggle) (3.0.4)
```

In [2]:

```
!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 /root/.kaggle/kaggle.json
!kaggle datasets download -d yekenot/fasttext-crawl-300d-2m
```

```
Downloading fasttext-crawl-300d-2m.zip to /content
 99% 1.43G/1.44G [00:17<00:00, 119MB/s]
100% 1.44G/1.44G [00:17<00:00, 88.5MB/s]
```

In [ ]:

```
!7z e fasttext-crawl-300d-2m.zip -o/content -r
```

```
7-Zip [64] 16.02 : Copyright (c) 1999-2016 Igor Pavlov : 2016-05-21
p7zip Version 16.02 (locale=en_US.UTF-8,Utf16=on,HugeFiles=on,64 bits,2 CPUs Intel(R) Xeon(R) CPU @
2.00GHz (50653),ASM,AES-NI)

Scanning the drive for archives:
  0M Scan                           1 file, 1545551987 bytes (1474 MiB)

Extracting archive: fasttext-crawl-300d-2m.zip
--
Path = fasttext-crawl-300d-2m.zip
Type = zip
Physical Size = 1545551987

  0%              0% - crawl-300d-2M.vec
                          1% - crawl-300d-2M.vec
                2% - crawl-300d-2M.vec
                          3% - crawl-300d-2M.vec
                4% - crawl-300d-2M.vec
                          5% - crawl-300d-2M.vec
                6% - crawl-300d-2M.vec
                          7% - crawl-300d-2M.vec
                8% - crawl-300d-2M.vec
                          9% - crawl-300d-2M.vec
               10% - crawl-300d-2M.vec
                         11% - crawl-300d-2M.vec
                         12% - crawl-300d-2M.vec
                         13% - crawl-300d-2M.vec
                         14% - crawl-300d-2M.vec
                         15% - crawl-300d-2M.vec
                         16% - crawl-300d-2M.vec
```

```
17% - crawl-300d-2M.vec
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40% - crawl-300d-2M.vec
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46% - crawl-300d-2M.vec
47% - crawl-300d-2M.vec
48% - crawl-300d-2M.vec
49% - crawl-300d-2M.vec
50% - crawl-300d-2M.vec
51% - crawl-300d-2M.vec
52% - crawl-300d-2M.vec
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64% - crawl-300d-2M.vec
65% - crawl-300d-2M.vec
66% - crawl-300d-2M.vec
67% - crawl-300d-2M.vec
68% - crawl-300d-2M.vec
69% - crawl-300d-2M.vec
70% - crawl-300d-2M.vec
71% - crawl-300d-2M.vec
72% - crawl-300d-2M.vec
73% - crawl-300d-2M.vec
74% - crawl-300d-2M.vec
75% - crawl-300d-2M.vec
76% - crawl-300d-2M.vec
77% - crawl-300d-2M.vec
78% - crawl-300d-2M.vec
79% - crawl-300d-2M.vec
80% - crawl-300d-2M.vec
81% - crawl-300d-2M.vec
82% - crawl-300d-2M.vec
83% - crawl-300d-2M.vec
84% - crawl-300d-2M.vec
85% - crawl-300d-2M.vec
86% - crawl-300d-2M.vec
87% - crawl-300d-2M.vec
88% - crawl-300d-2M.vec
89% - crawl-300d-2M.vec
90% - crawl-300d-2M.vec
91% - crawl-300d-2M.vec
92% - crawl-300d-2M.vec
93% - crawl-300d-2M.vec
```

```
                   94% - crawl-300d-2M.vec
                   95% - crawl-300d-2M.vec
                   96% - crawl-300d-2M.vec
                   97% - crawl-300d-2M.vec
                   98% - crawl-300d-2M.vec
                   99% - crawl-300d-2M.vec
                  100% - crawl-300d-2M.vec
                  Everything is Ok

Size:       4516698366
Compressed: 1545551987
```

In [6]:

```
!pip install scikit-multilearn
```

```
Collecting scikit-multilearn
  Downloading
https://files.pythonhosted.org/packages/bb/1f/e6ff649c72a1cdf2c7a1d31eb21705110ce1c5d3e7e26b2cc300e163727
kit_multilearn-0.2.0-py3-none-any.whl (89kB)
     |████████████████████████████████| 92kB 10.5MB/s
Installing collected packages: scikit-multilearn
Successfully installed scikit-multilearn-0.2.0
```

In [7]:

```
#importing libraries
import pandas as pd
import numpy as np
import tensorflow as tf
import tqdm
from sklearn.multiclass import OneVsRestClassifier
from skmultilearn.problem_transform import ClassifierChain
from skmultilearn.problem_transform import BinaryRelevance
from skmultilearn.problem_transform import LabelPowerset
```

In [8]:

```
preprocessed_data_train=pd.read_csv("preprocessed_data_train.csv")#loading preprocessed data into panda l
```

In [9]:

```
preprocessed_data_train=preprocessed_data_train.dropna()#removing the nan values
```

In [10]:

```
preprocessed_data_test=pd.read_csv("preprocessed_data_test.csv")
preprocessed_data_test.head(4)
```

Out[10]:

	Unnamed: 0	Description	commenting	ogling	groping	cleaned_text
0	0	During morning, a woman was walking by and thi...	1	1	0	morning woman walking thin guy came around cal...
1	1	A man tried to brush his penis off of a woman'...	0	0	1	man tried brush penis woman shoulder bus
2	2	This happened to a fellow passenger of mine tr...	0	1	0	happened fellow passenger mine travelling metr...
3	3	ogling	0	1	0	ogling

In [ ]:

```
# Reading glove vectors in python: https://stackoverflow.com/a/38230349/4084039
def fasttextModel(gloveFile):
    print ("Loading Fasttext Model")
    f = open(gloveFile,'r', encoding="utf8")
    model = {}#for storing word and the corresponding embedding vector for that word
    for line in f:
        splitLine = line.split()#splitting the line and storing it in a list
        word = splitLine[0]#getting the first element and storing it in word
        embedding = np.array([float(val) for val in splitLine[1:]])#obtaining corresponding vector for th
        model[word] = embedding#storing word as key and embedding vector for that word as value
    print ("Done.",len(model)," words loaded!")
    return model
model = fasttextModel('/content/crawl-300d-2M.vec')
```

```
Loading Fasttext Model
Done. 2000000  words loaded!
```

In [ ]:

```
words = []#for storing all the words in the train data
for i in preprocessed_data_train['cleaned_text']:
    words.extend(str(i).split(' '))
```

```
words = set(words)#getting corresponding unique words in the whole text corpus
print("the unique words in the corpus", len(words))#printing the uniques words length

#here we are obtainig the embeddings for the words that are present in the whole corpus
words_courpus = {}
words_glove = set(model.keys())
for i in words:
    if i in words_glove:
        words_courpus[i] = model[i]
print("fastvec length", len(words_courpus))


# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-save-and-

import pickle
with open('fast_vectors', 'wb') as f:
    pickle.dump(words_courpus, f)
```

```
the unique words in the corpus 7877
fastvec length 6731
```

In [ ]:

```
with open('fast_vectors', 'rb') as f:
    model = pickle.load(f)
    fast_words =  set(model.keys())
```

In [ ]:

```
model['walking']
```

Out[ ]:

```
array([-0.0051, -0.4417, -0.044 , -0.344 , -0.1405, -0.1064,  0.1349,
       -0.0281,  0.3249,  0.0485,  0.1994,  0.1098,  0.5005, -0.0635,
       -0.2376,  0.1094, -0.1058, -0.0696, -0.0585,  0.3074,  0.1115,
       -0.0943, -0.3071, -0.21  ,  0.1331, -0.2107, -0.0882,  0.1755,
       -0.0358,  0.1818,  0.0921,  0.1831, -0.0982, -0.3284, -0.1072,
       -0.384 , -0.0036,  0.3687,  0.1681, -0.0567, -0.1918, -0.337 ,
       -0.206 , -0.1122,  0.0433,  0.0639, -0.0275,  0.2598,  0.1519,
        0.0347, -0.2054, -0.3528,  0.4976, -0.1242,  0.2713,  0.039 ,
       -0.0139, -0.1997,  0.0187,  0.0664, -0.0383, -0.0274, -0.1064,
       -0.0861,  0.0717, -0.0934,  0.3908, -0.2086,  0.1645, -0.6222,
       -0.1018, -0.3692,  0.2942,  0.0502,  0.1019, -0.141 , -0.6319,
       -0.0846,  0.0254, -0.2069, -0.1305, -0.1702, -0.1573,  0.1331,
       -0.4226,  0.0945,  0.139 , -0.4037, -0.1124,  0.2481,  0.188 ,
        0.2011,  0.14  ,  0.147 , -0.031 ,  0.3591, -0.0417, -0.5554,
        0.1189, -0.1325,  0.1368,  0.2906, -0.5972,  0.052 , -0.1006,
       -0.0584, -0.0653, -0.0666, -0.1169, -0.0271,  0.0432, -0.1206,
        0.0199, -0.3453, -0.1691, -0.3068, -0.2882, -0.2942,  0.1618,
       -0.0581,  0.4625, -0.1162,  0.0975,  0.0312,  0.0912,  0.33  ,
        0.261 , -0.148 ,  0.7421, -0.0423, -0.4659, -0.0359,  0.3592,
       -0.2039,  0.0172, -0.0972, -0.1587, -0.203 ,  0.0363, -0.4867,
        0.0126, -0.4184,  0.4007,  0.2412, -0.1529, -0.1228, -0.3334,
        0.1241, -0.0111,  0.2414,  0.3209, -0.0503,  0.0281, -0.0327,
       -0.2649,  0.2701, -0.4573,  0.0662, -0.2451,  0.128 ,  0.3747,
        0.2763,  0.1045, -0.1683, -0.1323, -0.1385,  0.2047, -0.1066,
       -0.1774, -0.0925, -0.2001,  0.1151, -0.1941,  0.0447,  0.2591,
        0.1164, -0.2357,  0.4632,  0.0841, -0.1474, -0.2927,  0.0296,
       -0.3562,  0.2295,  0.1315, -0.0273,  0.1476,  0.0031,  0.3492,
        0.0378, -0.0819,  0.3821, -0.3423,  0.2907, -0.0771, -0.1446,
        0.2536, -0.1516,  0.0664, -0.3455, -0.5454, -0.122 ,  0.0905,
        0.0694, -0.1124, -0.0479, -0.1155,  0.1409,  0.2009,  0.1878,
       -0.095 ,  0.639 , -0.1788,  0.0747, -0.0672,  0.0253, -0.0104,
        0.1096, -0.099 , -0.0519, -0.0343,  0.3933,  0.032 ,  0.0798,
       -0.0046,  0.0959,  0.3037,  0.1986,  0.0757,  0.0569,  0.0112,
        0.0826,  0.2591, -0.2733,  0.1709, -0.0827,  0.3365, -0.0635,
       -0.0898, -0.2455, -0.3057,  0.3218,  0.1993,  0.2337,  0.1879,
       -0.1078,  0.3826,  0.3258, -0.1526, -0.0901,  0.3777,  0.0603,
        0.2405, -0.3783, -0.173 , -0.0061,  0.0276,  0.0265,  0.101 ,
        0.1448, -0.0958,  0.1206,  0.4775,  0.0229,  0.1345, -0.095 ,
       -0.1039, -0.2159, -0.0942, -0.1997, -0.2599,  0.1544,  0.1907,
        0.2654,  0.3778,  0.2622, -0.3729, -0.1306, -0.2838,  0.1407,
        0.1971,  0.3317,  0.0541, -0.0784,  0.0709,  0.0895,  0.4342,
        0.1876, -0.1152, -0.3832,  0.0578, -0.0317, -0.0625,  0.2849,
       -0.0312,  0.1748, -0.2   , -0.1073,  0.1605, -0.1314])
```

In [ ]:

```
text=preprocessed_data_train['cleaned_text'].values
```

In [ ]:

```
fast_text_vectors= [];
```

```
for sentence in text: # for each review/sentence
    sentence=str(sentence)
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in fast_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words#here we are averaging the vectors for individual sentence
    fast_text_vectors.append(vector)

print(len(fast_text_vectors))
print(len(fast_text_vectors[0]))
```

```
7200
300
```

In [ ]:

```
text1=preprocessed_data_test['cleaned_text'].values
```

In [ ]:

```
fast_text_vectors1= [];
for sentence in text1: # for each review/sentence
    sentence=str(sentence)
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in fast_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words#here we are averaging the vectors for individual sentence
    fast_text_vectors1.append(vector)

print(len(fast_text_vectors1))
print(len(fast_text_vectors1[0]))
```

```
1701
300
```

In [ ]:

```
from scipy.sparse import coo_matrix
fasttext_train=coo_matrix(fast_text_vectors)
fasttext_test=coo_matrix(fast_text_vectors1)
```

Adding Extra Features

In [ ]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
from textblob import TextBlob
import nltk
import pandas as pd
import numpy as np
from nltk.corpus import stopwords
```

In [ ]:

```
def length(text):
    return len(str(text))
def word_count(text):
    text=str(text)
    text=text.split()
    return len(text)
def stop_words_count(text):
    text=str(text)
    stop_words=set(stopwords.words('english'))
    text = [word for word in text.split() if word.lower() in stop_words]
    return len(text)
def unique_words(text):
    text=str(text)
    text=text.split()
    length=len(set(text))
    return length
```

In [ ]:

```
#https://www.kaggle.com/shivamb/extensive-text-data-feature-engineering
def get_subjectivity(text):
    try:
        textblob = TextBlob(unicode(text, 'utf-8'))
```

```
        subj = textblob.sentiment.subjectivity
    except:
        subj = 0.0
    return subj
```

In [ ]:

```
nltk.download('stopwords')
```

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

Out[ ]:

```
True
```

In [ ]:

```
#here we are adding some extra features to the dataset
preprocessed_data_train['char_count']=preprocessed_data_train['Description'].apply(length)#counting the n
preprocessed_data_train['word_count']=preprocessed_data_train['Description'].apply(word_count)#counting t
preprocessed_data_train['stopwords_count']=preprocessed_data_train['Description'].apply(stop_words_count)
preprocessed_data_train['unique_words']=preprocessed_data_train['Description'].apply(unique_words)#counti
preprocessed_data_train['word_density']=preprocessed_data_train['char_count']/(preprocessed_data_train['w
preprocessed_data_train['subjectivity']=preprocessed_data_train['cleaned_text'].apply(get_subjectivity)#c
```

In [ ]:

```
#here we are adding some extra features to the dataset
preprocessed_data_test['char_count']=preprocessed_data_test['Description'].apply(length)#counting the no
preprocessed_data_test['word_count']=preprocessed_data_test['Description'].apply(word_count)#counting the
preprocessed_data_test['stopwords_count']=preprocessed_data_test['Description'].apply(stop_words_count)#c
preprocessed_data_test['unique_words']=preprocessed_data_test['Description'].apply(unique_words)#countinc
preprocessed_data_test['word_density']=preprocessed_data_test['char_count']/(preprocessed_data_test['worc
preprocessed_data_test['subjectivity']=preprocessed_data_test['cleaned_text'].apply(get_subjectivity)#cal
```

In [ ]:

```
preprocessed_data_train.head(4)
```

Out[ ]:

	Unnamed: 0	Description	commenting	ogling	groping	cleaned_text	char_count	word_count	stopwords_count	unique_words	word_density	s
0	0	Was walking along crowded street, holding mums...	0	0	1	walking along crowded street holding mum hand ...	183	36	15	35	4.945946	
1	1	This incident took place in the evening.I was ...	0	1	0	incident took place evening metro two guy star...	89	16	7	14	5.235294	
2	2	I WAS WAITING FOR THE BUS. A MAN CAME ON A BIK...	1	0	0	waiting bus man came bike offering liftvto you...	85	18	9	16	4.473684	
3	3	Incident happened inside the train	0	0	0	incident happened inside train	34	5	1	5	5.666667	

In [ ]:

```
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer

import nltk
nltk.download('vader_lexicon')

sid = SentimentIntensityAnalyzer()
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
```

In [ ]:

```
import numpy as np
def sentiment_score(X,feature):#this function is for calculating the sentimental scores of each sentence
    neg=[]#calculating the negative sentimental scores and adding to the list
    neu=[]#calculating the neutral sentimental scores and adding to the list
```

```
    pos=[]#calculating the positive sentimental scores and adding to the list
    compound=[]
    for i in range(len(X)):
        for_sentiment=X[feature].iloc[i]#here we are obtaining the individual sentence
        for_sentiment=str(for_sentiment)
        ss=sid.polarity_scores(for_sentiment)
        neg.append(ss['neg'])
        neu.append(ss['neu'])
        pos.append(ss['pos'])
        compound.append(ss['compound'])
    return np.asarray(neg).reshape(-1,1),np.asarray(neu).reshape(-1,1),np.asarray(pos).reshape(-1,1),np.as
```

In [ ]:

```
p_neg,p_neu,p_pos,p_compound=sentiment_score(preprocessed_data_train,'cleaned_text')
```

In [ ]:

```
#adding polarity scores as features
preprocessed_data_train['neg']=p_neg
preprocessed_data_train['neu']=p_neu
preprocessed_data_train['pos']=p_pos
preprocessed_data_train['compound']=p_compound
```

In [ ]:

```
p_neg1,p_neu1,p_pos1,p_compound1=sentiment_score(preprocessed_data_test,'cleaned_text')
```

In [ ]:

```
#adding polarity scores as features
preprocessed_data_test['neg']=p_neg1
preprocessed_data_test['neu']=p_neu1
preprocessed_data_test['pos']=p_pos1
preprocessed_data_test['compound']=p_compound1
```

In [ ]:

```
preprocessed_data_train.head(4)
```

Out[ ]:

	Unnamed: 0	Description	commenting	ogling	groping	cleaned_text	char_count	word_count	stopwords_count	unique_words	word_density	s
0	0	Was walking along crowded street, holding mums...	0	0	1	walking along crowded street holding mum hand ...	183	36	15	35	4.945946	
1	1	This incident took place in the evening.I was ...	0	1	0	incident took place evening metro two guy star...	89	16	7	14	5.235294	
2	2	I WAS WAITING FOR THE BUS. A MAN CAME ON A BIK...	1	0	0	waiting bus man came bike offering liftvto you...	85	18	9	16	4.473684	
3	3	Incident happened inside the train	0	0	0	incident happened inside train	34	5	1	5	5.666667	

In [ ]:

```
preprocessed_data_train.shape
```

Out[ ]:

```
(7200, 16)
```

Standardizing Numerical Features

In [ ]:

```
#Standardizing the char_count feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['char_count'].values.reshape(-1,1))
char_count_train=scaler.transform(preprocessed_data_train['char_count'].values.reshape(-1,1))
char_count_test=scaler.transform(preprocessed_data_test['char_count'].values.reshape(-1,1))
```

```
char_count_train=char_count_train.reshape(-1,1)
char_count_test=char_count_test.reshape(-1,1)
print(char_count_train.shape)
print(char_count_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the word_count feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['word_count'].values.reshape(-1,1))
word_count_train=scaler.transform(preprocessed_data_train['word_count'].values.reshape(-1,1))
word_count_test=scaler.transform(preprocessed_data_test['word_count'].values.reshape(-1,1))
word_count_train=word_count_train.reshape(-1,1)
word_count_test=word_count_test.reshape(-1,1)
print(word_count_train.shape)
print(word_count_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the stopwords_count feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['stopwords_count'].values.reshape(-1,1))
stopwords_count_train=scaler.transform(preprocessed_data_train['stopwords_count'].values.reshape(-1,1))
stopwords_count_test=scaler.transform(preprocessed_data_test['stopwords_count'].values.reshape(-1,1))
stopwords_count_train=stopwords_count_train.reshape(-1,1)
stopwords_count_test=stopwords_count_test.reshape(-1,1)
print(stopwords_count_train.shape)
print(stopwords_count_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the unique_words feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['unique_words'].values.reshape(-1,1))
unique_words_train=scaler.transform(preprocessed_data_train['unique_words'].values.reshape(-1,1))
unique_words_test=scaler.transform(preprocessed_data_test['unique_words'].values.reshape(-1,1))
unique_words_train=unique_words_train.reshape(-1,1)
unique_words_test=unique_words_test.reshape(-1,1)
print(unique_words_train.shape)
print(unique_words_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the word_density feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['word_density'].values.reshape(-1,1))
word_density_train=scaler.transform(preprocessed_data_train['word_density'].values.reshape(-1,1))
word_density_test=scaler.transform(preprocessed_data_test['word_density'].values.reshape(-1,1))
word_density_train=word_density_train.reshape(-1,1)
word_density_test=word_density_test.reshape(-1,1)
print(word_density_train.shape)
print(word_density_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the subjectivity feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['subjectivity'].values.reshape(-1,1))
subjectivity_train=scaler.transform(preprocessed_data_train['subjectivity'].values.reshape(-1,1))
subjectivity_test=scaler.transform(preprocessed_data_test['subjectivity'].values.reshape(-1,1))
subjectivity_train=subjectivity_train.reshape(-1,1)
subjectivity_test=subjectivity_test.reshape(-1,1)
print(subjectivity_train.shape)
print(subjectivity_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the neg feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['neg'].values.reshape(-1,1))
neg_train=scaler.transform(preprocessed_data_train['neg'].values.reshape(-1,1))
neg_test=scaler.transform(preprocessed_data_test['neg'].values.reshape(-1,1))
neg_train=neg_train.reshape(-1,1)
neg_test=neg_test.reshape(-1,1)
print(neg_train.shape)
print(neg_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the neu feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['neu'].values.reshape(-1,1))
neu_train=scaler.transform(preprocessed_data_train['neu'].values.reshape(-1,1))
neu_test=scaler.transform(preprocessed_data_test['neu'].values.reshape(-1,1))
neu_train=neu_train.reshape(-1,1)
neu_test=neu_test.reshape(-1,1)
print(neu_train.shape)
print(neu_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the pos feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['pos'].values.reshape(-1,1))
pos_train=scaler.transform(preprocessed_data_train['pos'].values.reshape(-1,1))
pos_test=scaler.transform(preprocessed_data_test['pos'].values.reshape(-1,1))
pos_train=pos_train.reshape(-1,1)
pos_test=pos_test.reshape(-1,1)
print(pos_train.shape)
print(pos_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
#Standardizing the compound feature
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()#intializing StandardScaler
scaler.fit(preprocessed_data_train['compound'].values.reshape(-1,1))
compound_train=scaler.transform(preprocessed_data_train['compound'].values.reshape(-1,1))
compound_test=scaler.transform(preprocessed_data_test['compound'].values.reshape(-1,1))
compound_train=compound_train.reshape(-1,1)
compound_test=compound_test.reshape(-1,1)
print(compound_train.shape)
print(compound_test.shape)
```

```
(7200, 1)
(1701, 1)
```

In [ ]:

```
y_train=preprocessed_data_train[['commenting','ogling','groping']]#y_train
y_test=preprocessed_data_test[['commenting','ogling','groping']]#y_test
```

Concating fasttext embeddings and numerical features:

In [ ]:

```
#concating features
from scipy.sparse import hstack
X_train=hstack((fasttext_train,char_count_train,word_count_train,stopwords_count_train,unique_words_train
X_test=hstack((fasttext_test,char_count_test,word_count_test,stopwords_count_test,unique_words_test,word_
print(X_train.shape,y_train.shape)
print(X_test.shape,y_train.shape)
```

```
(7200, 310) (7200, 3)
(1701, 310) (7200, 3)
```

BOW features:

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer=CountVectorizer(ngram_range=(1,4),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
```

```
bow_train=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training poir
bow_test=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

Concating BOW features and numerical features:

In [ ]:

```
#concating features
from scipy.sparse import hstack
X_train1=hstack((bow_train,char_count_train,word_count_train,stopwords_count_train,unique_words_train,wor
X_test1=hstack((bow_test,char_count_test,word_count_test,stopwords_count_test,unique_words_test,word_dens
print(X_train1.shape,y_train.shape)
print(X_test1.shape,y_train.shape)
```

```
(7200, 5010) (7200, 3)
(1701, 5010) (7200, 3)
```

Tfidf Features:

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(1,4),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training pc
tfidf_test=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

Concating Tfidf features and numerical features:

In [ ]:

```
#concating features
from scipy.sparse import hstack
X_train2=hstack((tfidf_train,char_count_train,word_count_train,stopwords_count_train,unique_words_train,w
X_test2=hstack((tfidf_test,char_count_test,word_count_test,stopwords_count_test,unique_words_test,word_de
print(X_train2.shape,y_train.shape)
print(X_test2.shape,y_train.shape)
```

```
(7200, 5010) (7200, 3)
(1701, 5010) (7200, 3)
```

Modelling:

Label Powerset:

GBDT:

In [ ]:

```
import xgboost as xgb
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.linear_model import SGDClassifier
classifier = LabelPowerset(xgb.XGBClassifier())
classifier.fit(X_train, y_train)
predictions = classifier.predict(X_test)
accuracyscore_Xtraingbdt=metrics.accuracy_score(y_test,predictions)
f1score_Xtraingbdt=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtraingbdt=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5755437977660199
micro f1 score : 0.6126760563380282
hamming loss : 0.19400352733686066
```

In [ ]:

```
classifier = LabelPowerset(xgb.XGBClassifier())
classifier.fit(X_train1, y_train)
predictions = classifier.predict(X_test1)
accuracyscore_Xtrain1gbdt=metrics.accuracy_score(y_test,predictions)
f1score_Xtrain1gbdt=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain1gbdt=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6019988242210464
micro f1 score : 0.6230191826522102
hamming loss : 0.17715069566921418
```

In [ ]:

```
classifier = LabelPowerset(xgb.XGBClassifier())
classifier.fit(X_train2, y_train)
```

```
predictions = classifier.predict(X_test2)
accuracyscore_Xtrain2gbdt=metrics.accuracy_score(y_test,predictions)
f1score_Xtrain2gbdt=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain2gbdt=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5984714873603763
micro f1 score : 0.6166174609869253
hamming loss : 0.1781305114638448
```

In [ ]:

```
classifier = LabelPowerset(xgb.XGBClassifier())
classifier.fit(fasttext_train, y_train)
predictions = classifier.predict(fasttext_test)
accuracyscore_fasttexttraingbdt=metrics.accuracy_score(y_test,predictions)
f1score_fasttexttraingbdt=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_fasttexttraingbdt=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5743680188124632
micro f1 score : 0.6125490196078431
hamming loss : 0.19361160101900843
```

In [ ]:

```
classifier = LabelPowerset(xgb.XGBClassifier())
classifier.fit(bow_train, y_train)
predictions = classifier.predict(bow_test)
accuracyscore_bowtraingbdt=metrics.accuracy_score(y_test,predictions)
f1score_bowtraingbdt=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_bowtraingbdt=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5943562610229277
micro f1 score : 0.6142131979695431
hamming loss : 0.17871840094062316
```

In [ ]:

```
classifier = LabelPowerset(xgb.XGBClassifier())
classifier.fit(tfidf_train, y_train)
predictions = classifier.predict(tfidf_test)
accuracyscore_tfidftraingbdt=metrics.accuracy_score(y_test,predictions)
f1score_tfidftraingbdt=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftraingbdt=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5961199294532628
micro f1 score : 0.6140868831716576
hamming loss : 0.17930629041740154
```

Logistic Regression

In [ ]:

```
from skmultilearn.problem_transform import LabelPowerset
from sklearn.linear_model import LogisticRegression
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(X_train, y_train)
predictions = classifier.predict(X_test)
accuracyscore_Xtrainlg=metrics.accuracy_score(y_test,predictions)
f1score_Xtrainlg=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrainlg=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5967078189300411
micro f1 score : 0.6458492003046459
hamming loss : 0.18224573780129336
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(X_train1, y_train)
predictions = classifier.predict(X_test1)
accuracyscore_Xtrain1lg=metrics.accuracy_score(y_test,predictions)
```

```
f1score_Xtrain1lg=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain1lg=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5990593768371546
micro f1 score : 0.6592057761732851
hamming loss : 0.18498922202625906
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(X_train2, y_train)
predictions = classifier.predict(X_test2)
accuracyscore_Xtrain2lg=metrics.accuracy_score(y_test,predictions)
f1score_Xtrain2lg=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain2lg=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6172839506172839
micro f1 score : 0.6617986164488854
hamming loss : 0.17244757985498727
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(fasttext_train, y_train)
predictions = classifier.predict(fasttext_test)
accuracyscore_fasttexttrainlg=metrics.accuracy_score(y_test,predictions)
f1score_fasttexttrainlg=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_fasttexttrainlg=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.588477366255144
micro f1 score : 0.64097672644029
hamming loss : 0.18440133254948068
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(bow_train, y_train)
predictions = classifier.predict(bow_test)
accuracyscore_bowtrainlg=metrics.accuracy_score(y_test,predictions)
f1score_bowtrainlg=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_bowtrainlg=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5943562610229277
micro f1 score : 0.6553713049747658
hamming loss : 0.18734077993337253
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train, y_train)
predictions = classifier.predict(tfidf_test)
accuracyscore_tfidftrainlg=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6208112874779541
micro f1 score : 0.6604578967792007
hamming loss : 0.17146776406035666
```

In [ ]:

```
from prettytable import PrettyTable
table=PrettyTable()
```

In [ ]:

```
table.field_names=['S.NO','MODEL','ACCURACY_SCORE','F1_SCORE','HAMMING_LOSS']
table.add_row([1,'LogisticRegression(numerical features and fasttext embeddings)',accuracyscore_Xtrainlg,
table.add_row([2,'LogisticRegression(numerical features and BOW features)',accuracyscore_Xtrain1lg,f1scor
table.add_row([3,'LogisticRegression(numerical features and Tfidf features)',accuracyscore_Xtrain2lg,f1sc
table.add_row([4,'LogisticRegression(only fasttext embeddings)',accuracyscore_fasttexttrainlg,f1score_fas
table.add_row([5,'LogisticRegression(only BOW featuers)',accuracyscore_bowtrainlg,f1score_bowtrainlg,hamm
table.add_row([6,'LogisticRegression(only Tfidf features)',accuracyscore_tfidftrainlg,f1score_tfidftrainl
```

```
table.add_row([7,'GBDT(numerical features and fasttext embeddings)',accuracyscore_Xtraingbdt,f1score_Xtra
table.add_row([8,'GBDT(numerical features and BOW features)',accuracyscore_Xtrain1gbdt,f1score_Xtrain1gbd
table.add_row([9,'GBDT(numerical features and Tfidf features)',accuracyscore_Xtrain2gbdt,f1score_Xtrain2g
table.add_row([10,'GBDT(only fasttext embeddings)',accuracyscore_fasttexttraingbdt,f1score_fasttexttrainc
table.add_row([11,'GBDT(only BOW featuers)',accuracyscore_bowtraingbdt,f1score_bowtraingbdt,hammingloss_b
table.add_row([12,'GBDT(only Tfidf features)',accuracyscore_tfidftraingbdt,f1score_tfidftraingbdt,hamminc
```

In [ ]:

```
print(table)
```

```
+------+--------------------------------------------------------------+--------------------+-----------
-----+---------------------+
| S.NO |                            MODEL                             |   ACCURACY_SCORE   |
F1_SCORE      |     HAMMING_LOSS    |
+------+--------------------------------------------------------------+--------------------+-----------
-----+---------------------+
|  1   | LogisticRegression(numerical features and fasttext embeddings) | 0.5967078189300411 |
0.6458492003046459 | 0.18224573780129336 |
|  2   |    LogisticRegression(numerical features and BOW features)     | 0.5990593768371546 | 0.65920577
61732851 | 0.18498922202625906 |
|  3   |   LogisticRegression(numerical features and Tfidf features)    | 0.6172839506172839 | 0.66179861
64488854 | 0.17244757985498727 |
|  4   |          LogisticRegression(only fasttext embeddings)          | 0.588477366255144  |
0.64097672644029  | 0.18440133254948068 |
|  5   |             LogisticRegression(only BOW featuers)              | 0.5943562610229277 | 0.65537130
9747658 | 0.18734077993337253 |
|  6   |            LogisticRegression(only Tfidf features)             | 0.6208112874779541 | 0.66045789
7792007 | 0.17146776406035666 |
|  7   |        GBDT(numerical features and fasttext embeddings)        | 0.5755437977660199 |
0.6126760563380282 | 0.19400352733686066 |
|  8   |           GBDT(numerical features and BOW features)            | 0.6019988242210464 |
0.6230191826522102 | 0.17715069566921418 |
|  9   |          GBDT(numerical features and Tfidf features)           | 0.5984714873603763 |
0.6166174609869253 |  0.1781305114638448 |
|  10  |                 GBDT(only fasttext embeddings)                 | 0.5743680188124632 |
0.6125490196078431 | 0.19361160101900843 |
|  11  |                    GBDT(only BOW featuers)                     | 0.5943562610229277 |
0.6142131979695431 | 0.17871840094062316 |
|  12  |                   GBDT(only Tfidf features)                    | 0.5961199294532628 |
0.6140868831716576 | 0.17930629041740154 |
+------+--------------------------------------------------------------+--------------------+-----------
-----+---------------------+
```

Linear SVC:

In [ ]:

```
from sklearn.svm import LinearSVC
classifier = LabelPowerset(LinearSVC())
classifier.fit(X_train, y_train)
predictions = classifier.predict(X_test)
accuracyscore_Xtrainsvc=metrics.accuracy_score(y_test,predictions)
f1score_Xtrainsvc=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrainsvc=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.586713697824809
micro f1 score : 0.6313755795981453
hamming loss : 0.18694885361552027
```

In [ ]:

```
from sklearn.svm import LinearSVC
classifier = LabelPowerset(LinearSVC())
classifier.fit(X_train1, y_train)
predictions = classifier.predict(X_test1)
accuracyscore_Xtrain1svc=metrics.accuracy_score(y_test,predictions)
f1score_Xtrain1svc=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain1svc=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5543797766019988
micro f1 score : 0.6428811847862672
hamming loss : 0.20791691162061532
```

In [ ]:

```
from sklearn.svm import LinearSVC
classifier = LabelPowerset(LinearSVC())
```

```
classifier.fit(X_train2, y_train)
predictions = classifier.predict(X_test2)
accuracyscore_Xtrain2svc=metrics.accuracy_score(y_test,predictions)
f1score_Xtrain2svc=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain2svc=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5961199294532628
micro f1 score : 0.6579898770788142
hamming loss : 0.18538114834411132
```

In [ ]:

```
from sklearn.svm import LinearSVC
classifier = LabelPowerset(LinearSVC())
classifier.fit(fasttext_train, y_train)
predictions = classifier.predict(fasttext_test)
accuracyscore_fasttexttrainsvc=metrics.accuracy_score(y_test,predictions)
f1score_fasttexttrainsvc=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_fasttexttrainsvc=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5831863609641388
micro f1 score : 0.627906976744186
hamming loss : 0.18812463256907702
```

In [ ]:

```
from sklearn.svm import LinearSVC
classifier = LabelPowerset(LinearSVC())
classifier.fit(bow_train, y_train)
predictions = classifier.predict(bow_test)
accuracyscore_bowtrainsvc=metrics.accuracy_score(y_test,predictions)
f1score_bowtrainsvc=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_bowtrainsvc=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5532039976484421
micro f1 score : 0.6424974823766365
hamming loss : 0.2087007642563198
```

In [ ]:

```
from sklearn.svm import LinearSVC
classifier = LabelPowerset(LinearSVC())
classifier.fit(tfidf_train, y_train)
predictions = classifier.predict(tfidf_test)
accuracyscore_tfidftrainsvc=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainsvc=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainsvc=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6014109347442681
micro f1 score : 0.6615831517792302
hamming loss : 0.1826376641191456
```

NaiveBayes:

In [ ]:

```
from sklearn.naive_bayes import GaussianNB
classifier = LabelPowerset(GaussianNB())
classifier.fit(X_train, y_train)
predictions = classifier.predict(X_test)
accuracyscore_Xtrainnb=metrics.accuracy_score(y_test,predictions)
f1score_Xtrainnb=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrainnb=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.44562022339800117
micro f1 score : 0.5350066050198151
hamming loss : 0.27591612776797964
```

In [ ]:

```
from sklearn.naive_bayes import GaussianNB
classifier = LabelPowerset(GaussianNB())
```

```
classifier.fit(X_train1, y_train)
predictions = classifier.predict(X_test1)
accuracyscore_Xtrain1nb=metrics.accuracy_score(y_test,predictions)
f1score_Xtrain1nb=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain1nb=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.3133450911228689
micro f1 score : 0.5184008472332539
hamming loss : 0.3564569860866157
```

In [ ]:

```
from sklearn.naive_bayes import GaussianNB
classifier = LabelPowerset(GaussianNB())
classifier.fit(X_train2, y_train)
predictions = classifier.predict(X_test2)
accuracyscore_Xtrain2nb=metrics.accuracy_score(y_test,predictions)
f1score_Xtrain2nb=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_Xtrain2nb=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.3045267489711934
micro f1 score : 0.5063427800269905
hamming loss : 0.35841661767587696
```

In [ ]:

```
from sklearn.naive_bayes import GaussianNB
classifier = LabelPowerset(GaussianNB())
classifier.fit(fasttext_train, y_train)
predictions = classifier.predict(fasttext_test)
accuracyscore_fasttexttrainnb=metrics.accuracy_score(y_test,predictions)
f1score_fasttexttrainnb=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_fasttexttrainnb=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.43915343915343913
micro f1 score : 0.5256537570340948
hamming loss : 0.2808152067411327
```

In [ ]:

```
from sklearn.naive_bayes import GaussianNB
classifier = LabelPowerset(GaussianNB())
classifier.fit(bow_train, y_train)
predictions = classifier.predict(bow_test)
accuracyscore_bowtrainnb=metrics.accuracy_score(y_test,predictions)
f1score_bowtrainnb=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_bowtrainnb=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.3133450911228689
micro f1 score : 0.5184008472332539
hamming loss : 0.3564569860866157
```

In [ ]:

```
from sklearn.naive_bayes import GaussianNB
classifier = LabelPowerset(GaussianNB())
classifier.fit(tfidf_train, y_train)
predictions = classifier.predict(tfidf_test)
accuracyscore_tfidftrainnb=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainnb=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainnb=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.3045267489711934
micro f1 score : 0.5067240451855837
hamming loss : 0.35939643347050754
```

In [ ]:

```
from prettytable import PrettyTable
table2=PrettyTable()
```

In [ ]:

```
table2.field_names=['S.NO','MODEL','ACCURACY_SCORE','F1_SCORE','HAMMING_LOSS']
table2.add_row([1,'LinearSVC(numerical features and fasttext embeddings)',accuracyscore_Xtrainsvc,f1score
table2.add_row([2,'LinearSVC(numerical features and BOW features)',accuracyscore_Xtrain1svc,f1score_Xtrai
table2.add_row([3,'LinearSVC(numerical features and Tfidf features)',accuracyscore_Xtrain2svc,f1score_Xtr
table2.add_row([4,'LinearSVC(only fasttext embeddings)',accuracyscore_fasttexttrainsvc,f1score_fasttexttr
table2.add_row([5,'LinearSVC(only BOW featuers)',accuracyscore_bowtrainsvc,f1score_bowtrainsvc,hamminglos
table2.add_row([6,'LinearSVC(only Tfidf features)',accuracyscore_tfidftrainsvc,f1score_tfidftrainsvc,hamm
table2.add_row([7,'NB(numerical features and fasttext embeddings)',accuracyscore_Xtrainnb,f1score_Xtrainn
table2.add_row([8,'NB(numerical features and BOW features)',accuracyscore_Xtrain1nb,f1score_Xtrain1nb,ham
table2.add_row([9,'NB(numerical features and Tfidf features)',accuracyscore_Xtrain2nb,f1score_Xtrain2nb,h
table2.add_row([10,'NB(only fasttext embeddings)',accuracyscore_fasttexttrainnb,f1score_fasttexttrainnb,h
table2.add_row([11,'NB(only BOW featuers)',accuracyscore_bowtrainnb,f1score_bowtrainnb,hammingloss_bowtra
table2.add_row([12,'NB(only Tfidf features)',accuracyscore_tfidftrainnb,f1score_tfidftrainnb,hammingloss_
```

In [ ]:

```
print(table2)
```

```
+------+-----------------------------------------------------+---------------------+-------------------
-------------------+
| S.NO |                        MODEL                        |    ACCURACY_SCORE   |      F1_SCORE
HAMMING_LOSS    |
+------+-----------------------------------------------------+---------------------+-------------------
-------------------+
|  1   | LinearSVC(numerical features and fasttext embeddings) |  0.586713697824809  |
0.6313755795981453 | 0.18694885361552027 |
|  2   |     LinearSVC(numerical features and BOW features)    |  0.5543797766019988 | 0.6428811847862672
| 0.20791691162061532 |
|  3   |    LinearSVC(numerical features and Tfidf features)   |  0.5961199294532628 | 0.6579898770788142
| 0.18538114834411132 |
|  4   |          LinearSVC(only fasttext embeddings)          |  0.5831863609641388 | 0.627906976744186
| 0.18812463256907702 |
|  5   |              LinearSVC(only BOW featuers)             |  0.5532039976484421 | 0.6424974823766365
|  0.2087007642563198 |
|  6   |             LinearSVC(only Tfidf features)            |  0.6014109347442681 | 0.6615831517792302
|  0.1826376641191456 |
|  7   |     NB(numerical features and fasttext embeddings)    | 0.44562022339800117 | 0.5350066050198151
| 0.27591612776797964 |
|  8   |        NB(numerical features and BOW features)        |  0.3133450911228689 | 0.5184008472332539
|  0.3564569860866157 |
|  9   |       NB(numerical features and Tfidf features)       |  0.3045267489711934 | 0.5063427800269905
| 0.35841661767587696 |
|  10  |              NB(only fasttext embeddings)             | 0.43915343915343913 | 0.5256537570340948
|  0.2808152067411327 |
|  11  |                 NB(only BOW featuers)                 |  0.3133450911228689 | 0.5184008472332539
|  0.3564569860866157 |
|  12  |                NB(only Tfidf features)                |  0.3045267489711934 | 0.5067240451855837
| 0.35939643347050754 |
+------+-----------------------------------------------------+---------------------+-------------------
-------------------+
```

From this table we can clearly see that Logistic Regression with only Tfidf Features gave better Accuracy,F1Score and HammingLoss.

In [ ]:

```
#now we can just try with other MultiLearn Classifiers
```

OneVsRest Classifier:

In [ ]:

```
classifier = OneVsRestClassifier(LogisticRegression(), n_jobs=-1)
classifier.fit(tfidf_train, y_train)
predictions = classifier.predict(tfidf_test)

print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6102292768959435
micro f1 score : 0.6529481598733677
hamming loss : 0.1718596903782089
```

Classifier Chains:

In [ ]:

```
from skmultilearn.problem_transform import ClassifierChain
classifier = ClassifierChain(LogisticRegression())
classifier.fit(tfidf_train, y_train)
predictions = classifier.predict(tfidf_test)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6149323927101705
micro f1 score : 0.6548463356973996
hamming loss : 0.17166372721928277
```

BinaryRelevance:

In [ ]:

```
from skmultilearn.problem_transform import BinaryRelevance
classifier = BinaryRelevance(LogisticRegression())
classifier.fit(tfidf_train, y_train)
predictions = classifier.predict(tfidf_test)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6102292768959435
micro f1 score : 0.6529481598733677
hamming loss : 0.1718596903782089
```

Changing the ngram_range for TfidfVectorizer and checking for best metric values on one model and of all the models Logistic Regression gave better metrics so we can train on Logistic Regression.

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(1,1),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train1=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training p
tfidf_test1=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(2,2),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train2=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training p
tfidf_test2=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(3,3),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train3=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training p
tfidf_test3=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(4,4),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train4=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training p
tfidf_test4=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(1,2),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train12=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training
tfidf_test12=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(1,3),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train13=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training
tfidf_test13=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(1,4),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train14=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training
tfidf_test14=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(1,5),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
tfidf_train15=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training
tfidf_test15=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer=TfidfVectorizer(ngram_range=(1,6),max_features=5000)
vectorizer.fit(preprocessed_data_train['cleaned_text'].values)#fitting training points
```

```
tfidf_train16=vectorizer.transform(preprocessed_data_train['cleaned_text'].values)#transforming training
tfidf_test16=vectorizer.transform(preprocessed_data_test['cleaned_text'].values)#transforming test points
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train1, y_train)
predictions = classifier.predict(tfidf_test1)
accuracyscore_tfidftrainlg1=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg1=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg1=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6155202821869489
micro f1 score : 0.6531724406383808
hamming loss : 0.1746031746031746
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train2, y_train)
predictions = classifier.predict(tfidf_test2)
accuracyscore_tfidftrainlg2=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg2=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg2=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.5185185185185185
micro f1 score : 0.53629878304658
hamming loss : 0.2165392906133647
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train3, y_train)
predictions = classifier.predict(tfidf_test3)
accuracyscore_tfidftrainlg3=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg3=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg3=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.3903586125808348
micro f1 score : 0.2817047817047817
hamming loss : 0.27082108563590046
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train4, y_train)
predictions = classifier.predict(tfidf_test4)
accuracyscore_tfidftrainlg4=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg4=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg4=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.3321575543797766
micro f1 score : 0.08931804465902234
hamming loss : 0.29570840681951793
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train12, y_train)
predictions = classifier.predict(tfidf_test12)
accuracyscore_tfidftrainlg12=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg12=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg12=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6213991769547325
micro f1 score : 0.6617532971295578
hamming loss : 0.17087987458357828
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train13, y_train)
predictions = classifier.predict(tfidf_test13)
```

```
accuracyscore_tfidftrainlg13=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg13=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg13=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6202233980011758
micro f1 score : 0.6604578967792007
hamming loss : 0.17146776406035666
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train14, y_train)
predictions = classifier.predict(tfidf_test14)
accuracyscore_tfidftrainlg14=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg14=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg14=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6208112874779541
micro f1 score : 0.6604578967792007
hamming loss : 0.17146776406035666
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train15, y_train)
predictions = classifier.predict(tfidf_test15)
accuracyscore_tfidftrainlg15=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg15=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg15=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6225749559082893
micro f1 score : 0.661233993015134
hamming loss : 0.1710758377425044
```

In [ ]:

```
classifier = LabelPowerset(LogisticRegression())
classifier.fit(tfidf_train16, y_train)
predictions = classifier.predict(tfidf_test16)
accuracyscore_tfidftrainlg16=metrics.accuracy_score(y_test,predictions)
f1score_tfidftrainlg16=metrics.f1_score(y_test, predictions, average = 'micro')
hammingloss_tfidftrainlg16=metrics.hamming_loss(y_test,predictions)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6208112874779541
micro f1 score : 0.6596736596736598
hamming loss : 0.17166372721928277
```

In [ ]:

```
from prettytable import PrettyTable
table1=PrettyTable()
```

In [ ]:

```
table1.field_names=['S.NO','MODEL','ACCURACY_SCORE','F1_SCORE','HAMMING_LOSS']
table1.add_row([1,'LogisticRegression(only Tfidf features)ngram_range=(1,1)',accuracyscore_tfidftrainlg1,
table1.add_row([2,'LogisticRegression(only Tfidf features)ngram_range=(2,2)',accuracyscore_tfidftrainlg2,
table1.add_row([3,'LogisticRegression(only Tfidf features)ngram_range=(3,3)',accuracyscore_tfidftrainlg3,
table1.add_row([4,'LogisticRegression(only Tfidf features)ngram_range=(4,4)',accuracyscore_tfidftrainlg4,
table1.add_row([5,'LogisticRegression(only Tfidf features)ngram_range=(1,2)',accuracyscore_tfidftrainlg12
table1.add_row([6,'LogisticRegression(only Tfidf features)ngram_range=(1,3)',accuracyscore_tfidftrainlg13
table1.add_row([7,'LogisticRegression(only Tfidf features)ngram_range=(1,4)',accuracyscore_tfidftrainlg14
table1.add_row([8,'LogisticRegression(only Tfidf features)ngram_range=(1,5)',accuracyscore_tfidftrainlg15
table1.add_row([9,'LogisticRegression(only Tfidf features)ngram_range=(1,6)',accuracyscore_tfidftrainlg16
```

In [ ]:

```
print(table1)
```

```
+-------+------------------------------------------------------------+---------------------+-----------------
+---------------------+
| S.NO |                          MODEL                             |   ACCURACY_SCORE    |       F1_SCORE
|     HAMMING_LOSS    |
+-------+------------------------------------------------------------+---------------------+-----------------
+---------------------+
|  1   | LogisticRegression(only Tfidf features)ngram_range=(1,1) | 0.6155202821869489 |  0.6531724406383
808 |  0.1746031746031746 |
|  2   | LogisticRegression(only Tfidf features)ngram_range=(2,2) | 0.5185185185185185 |   0.536298783046
58  |  0.2165392906133647 |
|  3   | LogisticRegression(only Tfidf features)ngram_range=(3,3) | 0.3903586125808348 |  0.2817047817047
817 | 0.27082108563590046 |
|  4   | LogisticRegression(only Tfidf features)ngram_range=(4,4) | 0.3321575543797766 | 0.08931804465902
234 | 0.29570840681951793 |
|  5   | LogisticRegression(only Tfidf features)ngram_range=(1,2) | 0.6213991769547325 |  0.6617532971295
578 | 0.17087987458357828 |
|  6   | LogisticRegression(only Tfidf features)ngram_range=(1,3) | 0.6202233980011758 |  0.6604578967792
007 | 0.17146776406035666 |
|  7   | LogisticRegression(only Tfidf features)ngram_range=(1,4) | 0.6208112874779541 |  0.6604578967792
007 | 0.17146776406035666 |
|  8   | LogisticRegression(only Tfidf features)ngram_range=(1,5) | 0.6225749559082893 |  0.6612339930151
34  |  0.1710758377425044 |
|  9   | LogisticRegression(only Tfidf features)ngram_range=(1,6) | 0.6208112874779541 |  0.6596736596736
598 | 0.17166372721928277 |
+-------+------------------------------------------------------------+---------------------+-----------------
+---------------------+
```

Hyperparameter Tuning:

In [ ]:

```
from sklearn.model_selection import RandomizedSearchCV
alpha = [0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
params  = {"classifier__C":alpha}
classifier = LabelPowerset(LogisticRegression())
cv = RandomizedSearchCV(estimator=classifier,param_distributions=params,cv=5,refit='accuracy',scoring=['f
cv.fit(tfidf_train15,y_train)
```

Out[ ]:

```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=LabelPowerset(classifier=LogisticRegression(C=1.0,
                                                                         class_weight=None,
                                                                         dual=False,
                                                                         fit_intercept=True,
                                                                         intercept_scaling=1,
                                                                         l1_ratio=None,
                                                                         max_iter=100,
                                                                         multi_class='auto',
                                                                         n_jobs=None,
                                                                         penalty='l2',
                                                                         random_state=None,
                                                                         solver='lbfgs',
                                                                         tol=0.0001,
                                                                         verbose=0,
                                                                         warm_start=False),
                                           require_dense=[True, True]),
                   iid='deprecated', n_iter=10, n_jobs=None,
                   param_distributions={'classifier__C': [1e-06, 1e-05, 0.0001,
                                                          0.001, 0.01, 0.1, 1,
                                                          10, 100, 1000,
                                                          10000]},
                   pre_dispatch='2*n_jobs', random_state=None, refit='accuracy',
                   return_train_score=True, scoring=['f1_micro', 'accuracy'],
                   verbose=0)
```

In [ ]:

```
best_alpha=cv.best_params_
print(cv.best_params_)
```

```
{'classifier__C': 1}
```

This is default alpha so the better metrics is obtained by using

LogisticRegression with ngram_range(1,5)

Accuracy---->0.6225749559082893

Micro f1 score---->0.661233993015134

Hamming loss---->0.1710758377425044

In [ ]:

```
from sklearn.model_selection import RandomizedSearchCV
params={'classifier__eta':[0.0001,0.001,0.01,0.1,0.2,0.3],'classifier__n_estimators':[5,10,50,75,100,200]
classifier = LabelPowerset(xgb.XGBClassifier())
cv = RandomizedSearchCV(estimator=classifier,param_distributions=params,cv=5,refit='accuracy',scoring=['f
cv.fit(tfidf_train15,y_train)
```

Out[ ]:

```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=LabelPowerset(classifier=XGBClassifier(base_score=0.5,
                                                                    booster='gbtree',
                                                                    colsample_bylevel=1,
                                                                    colsample_bynode=1,
                                                                    colsample_bytree=1,
                                                                    gamma=0,
                                                                    learning_rate=0.1,
                                                                    max_delta_step=0,
                                                                    max_depth=3,
                                                                    min_child_weight=1,
                                                                    missing=None,
                                                                    n_estimators=100,
                                                                    n_jobs=1,
                                                                    nthread=None,
                                                                    objective='binary:logistic',
                                                                    random_state=0,
                                                                    re...
                                                                    seed=None,
                                                                    silent=None,
                                                                    subsample=1,
                                                                    verbosity=1),
                                           require_dense=[True, True]),
                   iid='deprecated', n_iter=10, n_jobs=None,
                   param_distributions={'classifier__eta': [0.0001, 0.001, 0.01,
                                                            0.1, 0.2, 0.3],
                                        'classifier__n_estimators': [5, 10, 50,
                                                                     75, 100,
                                                                     200]},
                   pre_dispatch='2*n_jobs', random_state=None, refit='accuracy',
                   return_train_score=True, scoring=['f1_micro', 'accuracy'],
                   verbose=0)
```

In [ ]:

```
best_eta=cv.best_params_['classifier__eta']
best_n_estimators=cv.best_params_['classifier__n_estimators']
print(cv.best_params_)
```

```
{'classifier__n_estimators': 200, 'classifier__eta': 0.3}
```

In [ ]:

```
classifier = LabelPowerset(xgb.XGBClassifier(eta=best_eta,n_estimators=best_n_estimators))
classifier.fit(tfidf_train15, y_train)
predictions = classifier.predict(tfidf_test15)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6119929453262787
micro f1 score : 0.6404539927036886
hamming loss : 0.1738193219674701
```

GBDT with ngram_range(1,5)

Accuracy---->0.6119929453262787

Micro f1 score---->0.6404539927036886

Hamming loss---->0.1738193219674701

In [ ]:

```
from sklearn.model_selection import RandomizedSearchCV
alpha = [0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
```

```
params  = {"classifier__C":alpha}
classifier = LabelPowerset(LinearSVC())
cv = RandomizedSearchCV(estimator=classifier,param_distributions=params,cv=5,refit='accuracy',scoring=['f
cv.fit(tfidf_train15,y_train)
```

Out[ ]:

```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=LabelPowerset(classifier=LinearSVC(C=1.0,
                                                                class_weight=None,
                                                                dual=True,
                                                                fit_intercept=True,
                                                                intercept_scaling=1,
                                                                loss='squared_hinge',
                                                                max_iter=1000,
                                                                multi_class='ovr',
                                                                penalty='l2',
                                                                random_state=None,
                                                                tol=0.0001,
                                                                verbose=0),
                                           require_dense=[True, True]),
                   iid='deprecated', n_iter=10, n_jobs=None,
                   param_distributions={'classifier__C': [1e-06, 1e-05, 0.0001,
                                                          0.001, 0.01, 0.1, 1,
                                                          10, 100, 1000,
                                                          10000]},
                   pre_dispatch='2*n_jobs', random_state=None, refit='accuracy',
                   return_train_score=True, scoring=['f1_micro', 'accuracy'],
                   verbose=0)
```

In [ ]:

```
best_alpha=cv.best_params_['classifier__C']
print(cv.best_params_)
```

```
{'classifier__C': 0.1}
```

In [ ]:

```
classifier = LabelPowerset(LinearSVC(C=best_alpha))
classifier.fit(tfidf_train15, y_train)
predictions = classifier.predict(tfidf_test15)
print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("micro f1 score :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
accuracy : 0.6172839506172839
micro f1 score : 0.6538461538461537
hamming loss : 0.1728395061728395
```

LinearSVC for ngram_range(1,5)

Accuracy---->0.6172839506172839

Micro f1 score---->0.6538461538461537

Hamming loss---->0.1728395061728395

Simple DeepLearning Model:

In [4]:

```
!gdown --id 1CSfnseXxh2H1inuPKmXS4ekacKoB8nCh
```

```
Downloading...
From: https://drive.google.com/uc?id=1CSfnseXxh2H1inuPKmXS4ekacKoB8nCh
To: /content/glove_vectors
128MB [00:03, 33.3MB/s]
```

In [11]:

```
#https://machinelearningmastery.com/use-word-embedding-layers-deep-learning-keras/
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.preprocessing import LabelEncoder,StandardScaler
tokenizer= Tokenizer()
tokenizer.fit_on_texts(preprocessed_data_train['cleaned_text'].tolist())
vocab_size = len(tokenizer.word_index) + 1
encoded_docs = tokenizer.texts_to_sequences(preprocessed_data_train['cleaned_text'])
encoded_docs1 = tokenizer.texts_to_sequences(preprocessed_data_test['cleaned_text'])

l=[]
for i in encoded_docs:
  l.append(len(i))
```

```
max_length=max(l)
```

In [14]:

```
max_length
```

Out[14]:

```
530
```

In [15]:

```
padded_docs = pad_sequences(encoded_docs,maxlen=max_length,padding='post',truncating='post')
padded_docs1 = pad_sequences(encoded_docs1,maxlen=max_length,padding='post',truncating='post')

import pickle
with open('glove_vectors', 'rb') as f:
    model = pickle.load(f)
import numpy as np
embedding_matrix = np.zeros((vocab_size, 300))
for word, i in tokenizer.word_index.items():
    embedding_vector = model.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

In [16]:

```
!pip install tensorflow-addons
import tensorflow_addons as tfa
```

```
Collecting tensorflow-addons
  Downloading
https://files.pythonhosted.org/packages/66/4b/e893d194e626c24b3df2253066aa418f46a432fdb68250cde14bf9bb070
sorflow_addons-0.13.0-cp37-cp37m-manylinux2010_x86_64.whl (679kB)
     |████████████████████████████████| 686kB 27.2MB/s
Requirement already satisfied: typeguard>=2.7 in /usr/local/lib/python3.7/dist-packages (from tensorflow-
addons) (2.7.1)
Installing collected packages: tensorflow-addons
Successfully installed tensorflow-addons-0.13.0
```

In [17]:

```
y_train=preprocessed_data_train[['commenting','ogling','groping']]#y_train
y_test=preprocessed_data_test[['commenting','ogling','groping']]#y_test
```

Model 1:

In [18]:

```
#Input layer
input_layer =tf.keras.layers.Input(shape=(max_length,))
#Embedding layer
embedding=tf.keras.layers.Embedding(vocab_size,300, weights=[embedding_matrix], input_length=max_length,
lstm_layer=tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(128))(embedding)
dense1=tf.keras.layers.Dense(128)(lstm_layer)
output=tf.keras.layers.Dense(3,activation='softmax')(dense1)
model=tf.keras.Model(inputs=input_layer,outputs=output)
```

In [19]:

```
model.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         [(None, 530)]             0         
_________________________________________________________________
embedding (Embedding)        (None, 530, 300)          2363400   
_________________________________________________________________
bidirectional (Bidirectional (None, 256)               439296    
_________________________________________________________________
dense (Dense)                (None, 128)               32896     
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 387       
=================================================================
Total params: 2,835,979
Trainable params: 472,579
Non-trainable params: 2,363,400
_________________________________________________________________
```

In [20]:

```
from tensorflow.keras.callbacks import EarlyStopping,TensorBoard,ModelCheckpoint
import datetime
early_stop = EarlyStopping(monitor='val_accuracy', patience=4, verbose=1)
```

```
log_dir="logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = TensorBoard(log_dir=log_dir, histogram_freq=0, write_graph=True,write_grads=True)
check_point = ModelCheckpoint('best_model_1.h5', monitor='val_accuracy',  verbose=1, save_best_only=True,
model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.Adam(0.00001),metrics=['accu
```

```
WARNING:tensorflow:`write_grads` will be ignored in TensorFlow 2.0 for the `TensorBoard` Callback.
```

In [21]:

```
model.fit(padded_docs,y_train,validation_data=(padded_docs1,y_test),epochs=10,callbacks=[early_stop,tensc
```

```
Epoch 1/10
225/225 [==============================] - ETA: 0s - loss: 0.9709 - accuracy: 0.6692 - f1_score: 0.4032
- hamming_loss: 0.3788
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric
F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The
name `reset_states()` has been deprecated to improve API consistency.
  'consistency.' % (self.__class__.__name__,))
225/225 [==============================] - 23s 64ms/step - loss: 0.9709 - accuracy: 0.6692 - f1_score: 0
.4032 - hamming_loss: 0.3788 - val_loss: 0.9767 - val_accuracy: 0.6808 - val_f1_score: 0.3975 -
val_hamming_loss: 0.3843

Epoch 00001: val_accuracy improved from inf to 0.68078, saving model to best_model_1.h5
Epoch 2/10
225/225 [==============================] - 13s 58ms/step - loss: 0.9561 - accuracy: 0.6964 - f1_score: 0
.4272 - hamming_loss: 0.3636 - val_loss: 0.9630 - val_accuracy: 0.7037 - val_f1_score: 0.4301 -
val_hamming_loss: 0.3635

Epoch 00002: val_accuracy did not improve from 0.68078
Epoch 3/10
225/225 [==============================] - 13s 57ms/step - loss: 0.9457 - accuracy: 0.7092 - f1_score: 0
.4413 - hamming_loss: 0.3547 - val_loss: 0.9490 - val_accuracy: 0.7143 - val_f1_score: 0.4584 -
val_hamming_loss: 0.3455

Epoch 00003: val_accuracy did not improve from 0.68078
Epoch 4/10
225/225 [==============================] - 13s 57ms/step - loss: 0.9297 - accuracy: 0.7051 - f1_score: 0
.4675 - hamming_loss: 0.3380 - val_loss: 0.9356 - val_accuracy: 0.7066 - val_f1_score: 0.4836 -
val_hamming_loss: 0.3294

Epoch 00004: val_accuracy did not improve from 0.68078
Epoch 5/10
225/225 [==============================] - 13s 57ms/step - loss: 0.9163 - accuracy: 0.7136 - f1_score: 0
.5027 - hamming_loss: 0.3157 - val_loss: 0.9236 - val_accuracy: 0.7290 - val_f1_score: 0.5075 -
val_hamming_loss: 0.3141

Epoch 00005: val_accuracy did not improve from 0.68078
Epoch 6/10
225/225 [==============================] - 13s 57ms/step - loss: 0.9042 - accuracy: 0.7286 - f1_score: 0
.5209 - hamming_loss: 0.3041 - val_loss: 0.9125 - val_accuracy: 0.7384 - val_f1_score: 0.5198 -
val_hamming_loss: 0.3063

Epoch 00006: val_accuracy did not improve from 0.68078
Epoch 7/10
225/225 [==============================] - 13s 59ms/step - loss: 0.9010 - accuracy: 0.7149 - f1_score: 0
.5207 - hamming_loss: 0.3042 - val_loss: 0.9294 - val_accuracy: 0.7407 - val_f1_score: 0.4836 -
val_hamming_loss: 0.3294

Epoch 00007: val_accuracy did not improve from 0.68078
Epoch 8/10
225/225 [==============================] - 13s 58ms/step - loss: 0.9042 - accuracy: 0.7289 - f1_score: 0
.5270 - hamming_loss: 0.3002 - val_loss: 0.9072 - val_accuracy: 0.6602 - val_f1_score: 0.5284 -
val_hamming_loss: 0.3008

Epoch 00008: val_accuracy improved from 0.68078 to 0.66020, saving model to best_model_1.h5
Epoch 9/10
225/225 [==============================] - 13s 58ms/step - loss: 0.8796 - accuracy: 0.7056 - f1_score: 0
.5439 - hamming_loss: 0.2895 - val_loss: 0.8947 - val_accuracy: 0.7478 - val_f1_score: 0.5217 -
val_hamming_loss: 0.3051

Epoch 00009: val_accuracy did not improve from 0.66020
Epoch 10/10
225/225 [==============================] - 13s 58ms/step - loss: 0.8667 - accuracy: 0.7004 - f1_score: 0
.5476 - hamming_loss: 0.2872 - val_loss: 0.8710 - val_accuracy: 0.7260 - val_f1_score: 0.5481 -
val_hamming_loss: 0.2883

Epoch 00010: val_accuracy did not improve from 0.66020
```

Out[21]:

```
<tensorflow.python.keras.callbacks.History at 0x7fd728f52550>
```

In [22]:

```
tf.keras.backend.set_value(model.optimizer.lr,0.00002)
```

```
model.fit(padded_docs,y_train,validation_data=(padded_docs1,y_test),epochs=10,callbacks=[early_stop,tensc
```

```
Epoch 1/10
  1/225 [..............................] - ETA: 20s - loss: 1.1901 - accuracy: 0.7812 - f1_score: 0.6479
- hamming_loss: 0.2604
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric
F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The
name `reset_states()` has been deprecated to improve API consistency.
  'consistency.' % (self.__class__.__name__,))
224/225 [============================>.] - ETA: 0s - loss: 0.8471 - accuracy: 0.6906 - f1_score: 0.5511
- hamming_loss: 0.2849
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric
F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The
name `reset_states()` has been deprecated to improve API consistency.
  'consistency.' % (self.__class__.__name__,))
225/225 [==============================] - 14s 62ms/step - loss: 0.8476 - accuracy: 0.6906 - f1_score: 0
.5514 - hamming_loss: 0.2848 - val_loss: 0.8538 - val_accuracy: 0.7002 - val_f1_score: 0.5481 -
val_hamming_loss: 0.2883

Epoch 00001: val_accuracy did not improve from 0.66020
Epoch 2/10
225/225 [==============================] - 13s 57ms/step - loss: 0.8304 - accuracy: 0.7032 - f1_score: 0
.5544 - hamming_loss: 0.2828 - val_loss: 0.8465 - val_accuracy: 0.7049 - val_f1_score: 0.5475 -
val_hamming_loss: 0.2887

Epoch 00002: val_accuracy did not improve from 0.66020
Epoch 3/10
225/225 [==============================] - 13s 58ms/step - loss: 0.8250 - accuracy: 0.7089 - f1_score: 0
.5553 - hamming_loss: 0.2823 - val_loss: 0.8444 - val_accuracy: 0.7160 - val_f1_score: 0.5395 -
val_hamming_loss: 0.2937

Epoch 00003: val_accuracy did not improve from 0.66020
Epoch 4/10
225/225 [==============================] - 13s 58ms/step - loss: 0.8243 - accuracy: 0.7144 - f1_score: 0
.5533 - hamming_loss: 0.2836 - val_loss: 0.8386 - val_accuracy: 0.7014 - val_f1_score: 0.5604 -
val_hamming_loss: 0.2804

Epoch 00004: val_accuracy did not improve from 0.66020
Epoch 5/10
225/225 [==============================] - 13s 58ms/step - loss: 0.8252 - accuracy: 0.6972 - f1_score: 0
.5537 - hamming_loss: 0.2833 - val_loss: 0.8498 - val_accuracy: 0.7384 - val_f1_score: 0.5321 -
val_hamming_loss: 0.2985

Epoch 00005: val_accuracy did not improve from 0.66020
Epoch 6/10
225/225 [==============================] - 13s 59ms/step - loss: 0.8518 - accuracy: 0.6729 - f1_score: 0
.5426 - hamming_loss: 0.2903 - val_loss: 0.8339 - val_accuracy: 0.6661 - val_f1_score: 0.5542 -
val_hamming_loss: 0.2843

Epoch 00006: val_accuracy did not improve from 0.66020
Epoch 7/10
225/225 [==============================] - 13s 58ms/step - loss: 0.8324 - accuracy: 0.6629 - f1_score: 0
.5566 - hamming_loss: 0.2814 - val_loss: 0.8472 - val_accuracy: 0.6808 - val_f1_score: 0.5548 -
val_hamming_loss: 0.2840

Epoch 00007: val_accuracy did not improve from 0.66020
Epoch 8/10
225/225 [==============================] - 13s 57ms/step - loss: 0.8366 - accuracy: 0.7108 - f1_score: 0
.5590 - hamming_loss: 0.2800 - val_loss: 0.8342 - val_accuracy: 0.7284 - val_f1_score: 0.5462 -
val_hamming_loss: 0.2894

Epoch 00008: val_accuracy did not improve from 0.66020
Epoch 9/10
225/225 [==============================] - 13s 57ms/step - loss: 0.8296 - accuracy: 0.7322 - f1_score: 0
.5571 - hamming_loss: 0.2812 - val_loss: 0.8393 - val_accuracy: 0.7178 - val_f1_score: 0.5419 -
val_hamming_loss: 0.2922

Epoch 00009: val_accuracy did not improve from 0.66020
Epoch 00009: early stopping
```

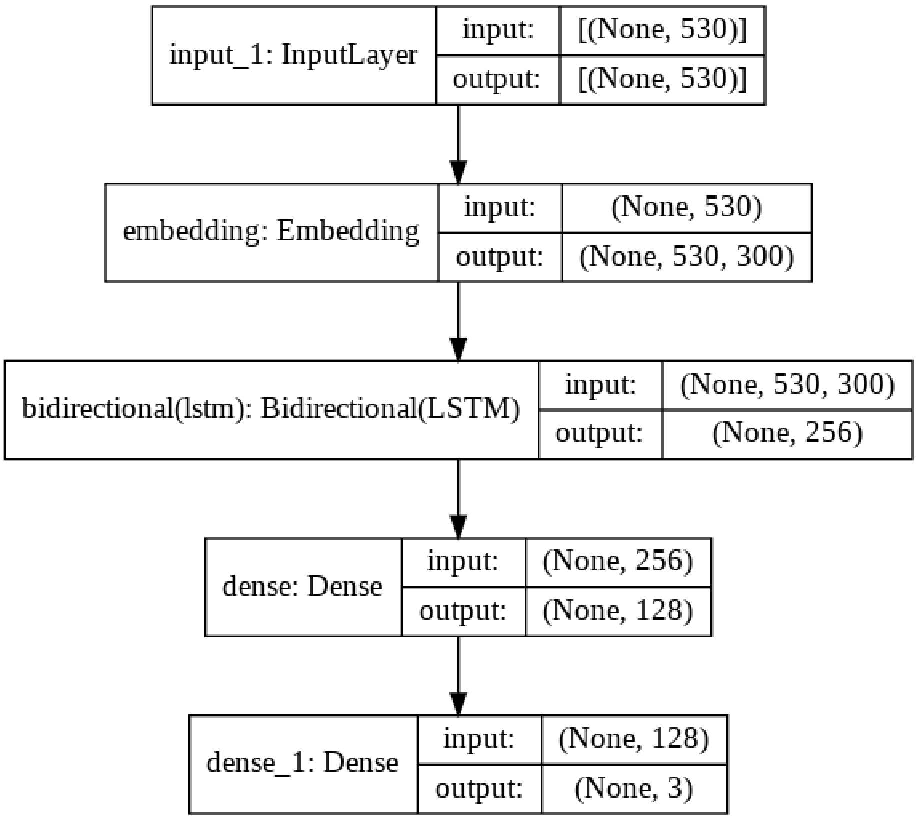
Out[22]:

```
<tensorflow.python.keras.callbacks.History at 0x7fd729f67890>
```

In [23]:

```
tf.keras.utils.plot_model(model, to_file='Model1.png', show_shapes=True)
```

Out[23]:



Model 2:

In [28]:

```
##### from tensorflow.keras.models import Model
#Input layer
input_layer = tf.keras.layers.Input(shape=(max_length,))
#Dense hidden layer
embed=tf.keras.layers.Embedding(vocab_size,300, weights=[embedding_matrix], input_length=max_length, trai
layer11=tf.keras.layers.Conv1D(filters=10,kernel_size=3,activation='relu')(embed)
pool2=tf.keras.layers.MaxPool1D(pool_size=2)(layer11)
flatten=tf.keras.layers.Flatten()(pool2)
drop1=tf.keras.layers.Dropout(0.3)(flatten)
dense1=tf.keras.layers.Dense(32)(drop1)

#Output layer
output=tf.keras.layers.Dense(3,activation='softmax')(dense1)

#Creating a model
model = tf.keras.Model(inputs=input_layer,outputs=output)
```

In [29]:

```
check_point = ModelCheckpoint('best_model_2.h5', monitor='val_accuracy',  verbose=1, save_best_only=True,

model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.Adam(0.0001),metrics=['accura
```

In [30]:

```
model.fit(padded_docs,y_train,validation_data=(padded_docs1,y_test),epochs=10,callbacks=[early_stop,check
```

```
Epoch 1/10
223/225 [============================>.] - ETA: 0s - loss: 0.9771 - accuracy: 0.5533 - f1_score: 0.3840
- hamming_loss: 0.3910
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric
F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The
name `reset_states()` has been deprecated to improve API consistency.
  'consistency.' % (self.__class__.__name__,))
225/225 [==============================] - 3s 9ms/step - loss: 0.9766 - accuracy: 0.5550 - f1_score: 0.3
851 - hamming_loss: 0.3903 - val_loss: 0.9760 - val_accuracy: 0.6767 - val_f1_score: 0.4018 -
val_hamming_loss: 0.3815

Epoch 00001: val_accuracy improved from inf to 0.67666, saving model to best_model_2.h5
Epoch 2/10
225/225 [==============================] - 2s 8ms/step - loss: 0.9589 - accuracy: 0.6187 - f1_score: 0.4
267 - hamming_loss: 0.3639 - val_loss: 0.9633 - val_accuracy: 0.6590 - val_f1_score: 0.4412 -
val_hamming_loss: 0.3565

Epoch 00002: val_accuracy improved from 0.67666 to 0.65902, saving model to best_model_2.h5
Epoch 3/10
225/225 [==============================] - 2s 8ms/step - loss: 0.9713 - accuracy: 0.5733 - f1_score: 0.4
248 - hamming_loss: 0.3651 - val_loss: 0.9772 - val_accuracy: 0.6925 - val_f1_score: 0.4080 -
val_hamming_loss: 0.3776

Epoch 00003: val_accuracy did not improve from 0.65902
Epoch 4/10
225/225 [==============================] - 2s 8ms/step - loss: 0.9845 - accuracy: 0.5690 - f1_score: 0.4
283 - hamming_loss: 0.3629 - val_loss: 0.9705 - val_accuracy: 0.6972 - val_f1_score: 0.4252 -
val_hamming_loss: 0.3666

Epoch 00004: val_accuracy did not improve from 0.65902
Epoch 5/10
225/225 [==============================] - 2s 8ms/step - loss: 1.0054 - accuracy: 0.5472 - f1_score: 0.4
096 - hamming_loss: 0.3748 - val_loss: 0.9813 - val_accuracy: 0.5785 - val_f1_score: 0.4571 -
val_hamming_loss: 0.3463

Epoch 00005: val_accuracy improved from 0.65902 to 0.57848, saving model to best_model_2.h5
Epoch 6/10
225/225 [==============================] - 2s 8ms/step - loss: 1.0235 - accuracy: 0.5396 - f1_score: 0.4
041 - hamming_loss: 0.3783 - val_loss: 0.9881 - val_accuracy: 0.4250 - val_f1_score: 0.4221 -
val_hamming_loss: 0.3686

Epoch 00006: val_accuracy improved from 0.57848 to 0.42504, saving model to best_model_2.h5
Epoch 7/10
225/225 [==============================] - 2s 8ms/step - loss: 1.0332 - accuracy: 0.5379 - f1_score: 0.3
925 - hamming_loss: 0.3856 - val_loss: 0.9933 - val_accuracy: 0.6355 - val_f1_score: 0.3986 -
val_hamming_loss: 0.3837

Epoch 00007: val_accuracy did not improve from 0.42504
Epoch 8/10
225/225 [==============================] - 2s 8ms/step - loss: 1.0512 - accuracy: 0.5315 - f1_score: 0.3
940 - hamming_loss: 0.3847 - val_loss: 1.0113 - val_accuracy: 0.6896 - val_f1_score: 0.4080 -
val_hamming_loss: 0.3776

Epoch 00008: val_accuracy did not improve from 0.42504
Epoch 00008: early stopping
```

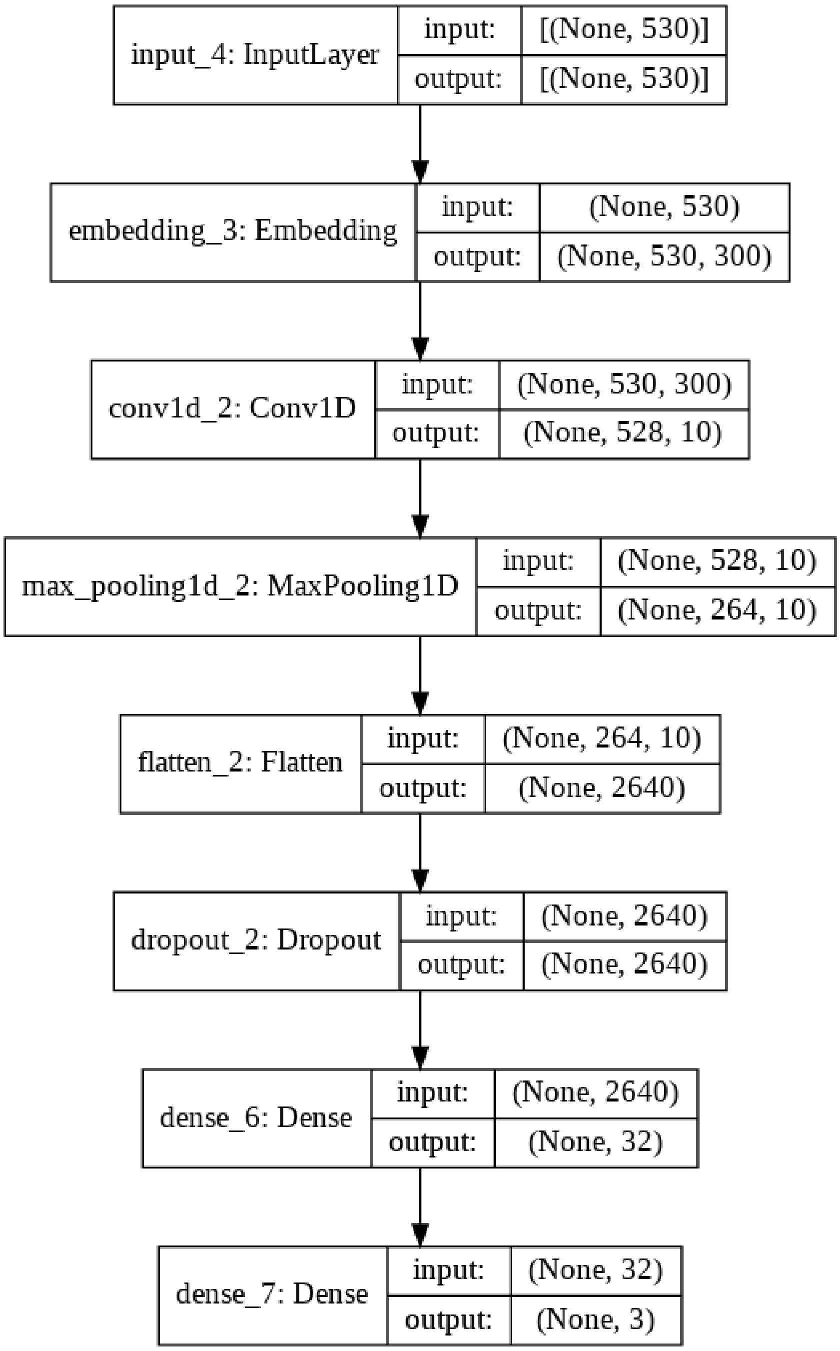
Out[30]:

```
<tensorflow.python.keras.callbacks.History at 0x7fd729a91d90>
```

In [31]:

```
tf.keras.utils.plot_model(model, to_file='Model2.png', show_shapes=True)
```

Out[31]:



Model 3:

In [36]:

```
##### from tensorflow.keras.models import Model
#Input layer
input_layer = tf.keras.layers.Input(shape=(max_length,))
#Dense hidden layer
embed=tf.keras.layers.Embedding(vocab_size,300, weights=[embedding_matrix], input_length=max_length, trai
layer11=tf.keras.layers.Conv1D(filters=32,kernel_size=3,activation='relu')(embed)
pool2=tf.keras.layers.MaxPool1D(pool_size=2)(layer11)
lstm_layer=tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64))(pool2)
dense=tf.keras.layers.Dense(64,activation='relu')(lstm_layer)
output=tf.keras.layers.Dense(3,activation='softmax')(dense)

#Creating a model
model = tf.keras.Model(inputs=input_layer,outputs=output)
```

In [37]:

```
check_point = ModelCheckpoint('best_model_3.h5', monitor='val_accuracy',  verbose=1, save_best_only=True,

model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.Adam(0.0001),metrics=['accura
```

In [38]:

```
model.fit(padded_docs,y_train,validation_data=(padded_docs1,y_test),epochs=10,callbacks=[early_stop,check
```

```
Epoch 1/10
223/225 [============================>.] - ETA: 0s - loss: 0.9619 - accuracy: 0.6103 - f1_score: 0.4055
- hamming_loss: 0.3778
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric
F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The
name `reset_states()` has been deprecated to improve API consistency.
  'consistency.' % (self.__class__.__name__,))
225/225 [==============================] - 9s 30ms/step - loss: 0.9593 - accuracy: 0.6108 - f1_score: 0.
4057 - hamming_loss: 0.3773 - val_loss: 0.9548 - val_accuracy: 0.6884 - val_f1_score: 0.4657 -
val_hamming_loss: 0.3408

Epoch 00001: val_accuracy improved from inf to 0.68842, saving model to best_model_3.h5
Epoch 2/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8758 - accuracy: 0.7287 - f1_score: 0.
5283 - hamming_loss: 0.2994 - val_loss: 0.8567 - val_accuracy: 0.7125 - val_f1_score: 0.5438 -
val_hamming_loss: 0.2910

Epoch 00002: val_accuracy did not improve from 0.68842
Epoch 3/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8189 - accuracy: 0.7251 - f1_score: 0.
5566 - hamming_loss: 0.2814 - val_loss: 0.8388 - val_accuracy: 0.6767 - val_f1_score: 0.5604 -
val_hamming_loss: 0.2804

Epoch 00003: val_accuracy improved from 0.68842 to 0.67666, saving model to best_model_3.h5
Epoch 4/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8183 - accuracy: 0.7021 - f1_score: 0.
5684 - hamming_loss: 0.2739 - val_loss: 0.8552 - val_accuracy: 0.7213 - val_f1_score: 0.5542 -
val_hamming_loss: 0.2843

Epoch 00004: val_accuracy did not improve from 0.67666
Epoch 5/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8393 - accuracy: 0.6933 - f1_score: 0.
5690 - hamming_loss: 0.2736 - val_loss: 0.8527 - val_accuracy: 0.6978 - val_f1_score: 0.5561 -
val_hamming_loss: 0.2832

Epoch 00005: val_accuracy did not improve from 0.67666
Epoch 6/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8315 - accuracy: 0.6931 - f1_score: 0.
5645 - hamming_loss: 0.2764 - val_loss: 0.8512 - val_accuracy: 0.7331 - val_f1_score: 0.5505 -
val_hamming_loss: 0.2867

Epoch 00006: val_accuracy did not improve from 0.67666
Epoch 7/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8386 - accuracy: 0.7035 - f1_score: 0.
5552 - hamming_loss: 0.2824 - val_loss: 0.8498 - val_accuracy: 0.5132 - val_f1_score: 0.5303 -
val_hamming_loss: 0.2996

Epoch 00007: val_accuracy improved from 0.67666 to 0.51323, saving model to best_model_3.h5
Epoch 8/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8364 - accuracy: 0.6907 - f1_score: 0.
5560 - hamming_loss: 0.2818 - val_loss: 0.8495 - val_accuracy: 0.7102 - val_f1_score: 0.5499 -
val_hamming_loss: 0.2871

Epoch 00008: val_accuracy did not improve from 0.51323
Epoch 9/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8432 - accuracy: 0.6818 - f1_score: 0.
5531 - hamming_loss: 0.2837 - val_loss: 0.8758 - val_accuracy: 0.7407 - val_f1_score: 0.5327 -
val_hamming_loss: 0.2981

Epoch 00009: val_accuracy did not improve from 0.51323
Epoch 10/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8529 - accuracy: 0.6778 - f1_score: 0.
5390 - hamming_loss: 0.2926 - val_loss: 0.8754 - val_accuracy: 0.7396 - val_f1_score: 0.5315 -
val_hamming_loss: 0.2988

Epoch 00010: val_accuracy did not improve from 0.51323
```

Out[38]:

```
<tensorflow.python.keras.callbacks.History at 0x7fd7202cc950>
```

In [39]:

```
model.fit(padded_docs,y_train,validation_data=(padded_docs1,y_test),epochs=10,callbacks=[early_stop,check
```

```
Epoch 1/10
  3/225 [..............................] - ETA: 9s - loss: 0.9560 - accuracy: 0.6875 - f1_score: 0.5567
- hamming_loss: 0.2986
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric
F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The
name `reset_states()` has been deprecated to improve API consistency.
  'consistency.' % (self.__class__.__name__,))
224/225 [============================>.] - ETA: 0s - loss: 0.8646 - accuracy: 0.7068 - f1_score: 0.5371
- hamming_loss: 0.2939
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric
F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The
name `reset_states()` has been deprecated to improve API consistency.
  'consistency.' % (self.__class__.__name__,))
225/225 [==============================] - 6s 27ms/step - loss: 0.8648 - accuracy: 0.7067 - f1_score: 0.
5368 - hamming_loss: 0.2940 - val_loss: 0.8868 - val_accuracy: 0.7255 - val_f1_score: 0.5186 -
val_hamming_loss: 0.3071

Epoch 00001: val_accuracy did not improve from 0.51323
Epoch 2/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8602 - accuracy: 0.6949 - f1_score: 0.
5301 - hamming_loss: 0.2983 - val_loss: 0.8917 - val_accuracy: 0.5226 - val_f1_score: 0.5106 -
val_hamming_loss: 0.3122

Epoch 00002: val_accuracy did not improve from 0.51323
Epoch 3/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8664 - accuracy: 0.6574 - f1_score: 0.
5261 - hamming_loss: 0.3008 - val_loss: 0.8870 - val_accuracy: 0.7302 - val_f1_score: 0.5106 -
val_hamming_loss: 0.3122

Epoch 00003: val_accuracy did not improve from 0.51323
Epoch 4/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8676 - accuracy: 0.6804 - f1_score: 0.
5307 - hamming_loss: 0.2979 - val_loss: 0.8881 - val_accuracy: 0.6226 - val_f1_score: 0.5223 -
val_hamming_loss: 0.3047

Epoch 00004: val_accuracy did not improve from 0.51323
Epoch 5/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8706 - accuracy: 0.6892 - f1_score: 0.
5263 - hamming_loss: 0.3007 - val_loss: 0.8896 - val_accuracy: 0.5726 - val_f1_score: 0.5223 -
val_hamming_loss: 0.3047

Epoch 00005: val_accuracy did not improve from 0.51323
Epoch 6/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8711 - accuracy: 0.6644 - f1_score: 0.
5238 - hamming_loss: 0.3023 - val_loss: 0.9024 - val_accuracy: 0.7366 - val_f1_score: 0.4946 -
val_hamming_loss: 0.3224

Epoch 00006: val_accuracy did not improve from 0.51323
Epoch 7/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8763 - accuracy: 0.6751 - f1_score: 0.
5165 - hamming_loss: 0.3069 - val_loss: 0.8877 - val_accuracy: 0.7437 - val_f1_score: 0.5075 -
val_hamming_loss: 0.3141

Epoch 00007: val_accuracy did not improve from 0.51323
Epoch 8/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8728 - accuracy: 0.6699 - f1_score: 0.
5206 - hamming_loss: 0.3044 - val_loss: 0.9174 - val_accuracy: 0.7443 - val_f1_score: 0.4891 -
val_hamming_loss: 0.3259

Epoch 00008: val_accuracy did not improve from 0.51323
Epoch 9/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8765 - accuracy: 0.6913 - f1_score: 0.
5155 - hamming_loss: 0.3075 - val_loss: 0.9182 - val_accuracy: 0.7307 - val_f1_score: 0.4762 -
val_hamming_loss: 0.3341

Epoch 00009: val_accuracy did not improve from 0.51323
Epoch 10/10
225/225 [==============================] - 6s 26ms/step - loss: 0.8800 - accuracy: 0.6837 - f1_score: 0.
5098 - hamming_loss: 0.3112 - val_loss: 0.9137 - val_accuracy: 0.7278 - val_f1_score: 0.5038 -
val_hamming_loss: 0.3165

Epoch 00010: val_accuracy did not improve from 0.51323
```

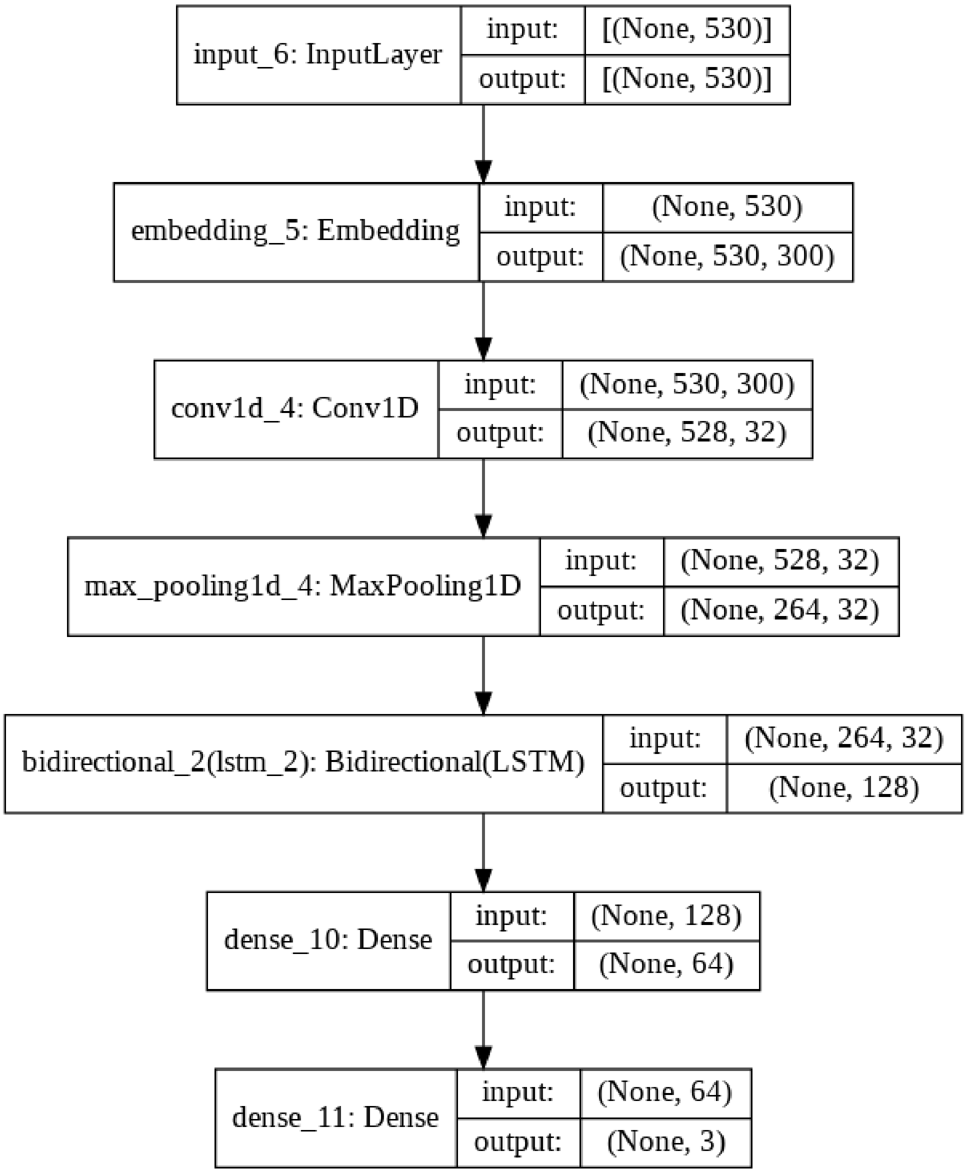
Out[39]:

```
<tensorflow.python.keras.callbacks.History at 0x7fd6d47e2fd0>
```

In [40]:

```
tf.keras.utils.plot_model(model, to_file='Model3.png', show_shapes=True)
```

Out[40]:



input_6: InputLayer
input:
[(None, 530)]
output:
[(None, 530)]
embedding_5: Embedding
input:
(None, 530)
output:
(None, 530, 300)
conv1d_4: Conv1D
input:
(None, 530, 300)
output:
(None, 528, 32)
max_pooling1d_4: MaxPooling1D
input:
(None, 528, 32)
output:
(None, 264, 32)
bidirectional_2(lstm_2): Bidirectional(LSTM)
input:
(None, 264, 32)
output:
(None, 128)
dense_10: Dense
input:
(None, 128)
output:
(None, 64)
dense_11: Dense
input:
(None, 64)
output:
(None, 3)

In [ ]: