```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import sqlite3
import csv
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from wordcloud import WordCloud
import re
import os
from flask_sqlalchemy import SQLAlchemy
from sqlalchemy import create_engine # database connection
import sqlalchemy
import datetime as dt
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem.snowball import SnowballStemmer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import SGDClassifier
from sklearn import metrics
from sklearn.metrics import f1_score,precision_score,recall_score
from sklearn import svm
from sklearn.linear_model import LogisticRegression
#from skmultilearn.adapt import mlknn
#from skmultilearn.problem_transform import ClassifierChain
#from skmultilearn.problem_transform import BinaryRelevance
#from skmultilearn.problem_transform import LabelPowerset
#from sklearn.naive_bayes import GaussianNB
from datetime import datetime
print('Done importing all')
```

```
Done importing all
```

2.1.1 Data Overview

Refer: https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data
All of the data is in 2 files: Train and Test.

Train.csv contains 4 columns: Id,Title,Body,Tags.

Test.csv contains the same columns but without the Tags, which you are to predict.

Size of Train.csv - 6.75GB

```
Size of Test.csv - 2GB

Number of rows in Train.csv = 6034195
```

The questions are randomized and contains a mix of verbose text sites as well as sites related to mat
questions from each site may vary, and no filtering has been performed on the questions (such as clo

Data Field Explaination

Dataset contains 6,034,195 rows. The columns in the table are:

```
Id - Unique identifier for each question

Title - The question's title

Body - The body of the question

Tags - The tags associated with the question in a space-seperated format (all lowercase, sho
```

2.1.2 Example Data point

```
Title:  Implementing Boundary Value Analysis of Software Testing in a C++ program?
Body :

        #include<
        iostream>\n
        #include<
        stdlib.h>\n\n
        using namespace std;\n\n
        int main()\n
        {\n
                 int n,a[n],x,c,u[n],m[n],e[n][4];\n
                 cout<<"Enter the number of variables";\n         cin>>n;\n\n
```

```
        cout<<"Enter the Lower, and Upper Limits of the variables";\n
        for(int y=1; y<n+1; y++)\n
        {\n
           cin>>m[y];\n
           cin>>u[y];\n
        }\n
        for(x=1; x<n+1; x++)\n
        {\n
           a[x] = (m[x] + u[x])/2;\n
        }\n
        c=(n*4)-4;\n
        for(int a1=1; a1<n+1; a1++)\n
        {\n\n
           e[a1][0] = m[a1];\n
           e[a1][1] = m[a1]+1;\n
           e[a1][2] = u[a1]-1;\n
           e[a1][3] = u[a1];\n
        }\n
        for(int i=1; i<n+1; i++)\n
        {\n
           for(int l=1; l<=i; l++)\n
           {\n
               if(l!=1)\n
               {\n
                   cout<<a[l]<<"\\t";\n
               }\n
           }\n
           for(int j=0; j<4; j++)\n
           {\n
               cout<<e[i][j];\n
               for(int k=0; k<n-(i+1); k++)\n
               {\n
                   cout<<a[k]<<"\\t";\n
               }\n
               cout<<"\\n";\n
           }\n
        }    \n\n
        system("PAUSE");\n
        return 0;    \n
    }\n


\n\n
```

```
<p>The answer should come in the form of a table like</p>\n\n
<pre><code>
1            50              50\n
2            50              50\n
99           50              50\n
100          50              50\n
50           1               50\n
50           2               50\n
50           99              50\n
50           100             50\n
50           50              1\n
50           50              2\n
50           50              99\n
50           50              100\n
</code></pre>\n\n
<p>if the no of inputs is 3 and their ranges are\n
1,100\n
1,100\n
1,100\n
(could be varied too)</p>\n\n
<p>The output is not coming,can anyone correct the code or tell me what\'s wrong?</p>\n'
```

Tags : 'c++ c'

2.2 Mapping the real-world problem to a Machine Learning Problem

2.2.1 Type of Machine Learning Problem

It is a multi-label classification problem
Multi-label Classification: Multilabel classification assigns to each sample a set of target labels. This
of a data-point that are not mutually exclusive, such as topics that are relevant for a document. A que
of C, Pointers, FileIO and/or memory-management at the same time or none of these.
__Credit__: http://scikit-learn.org/stable/modules/multiclass.html

2.2.2 Performance metric

Micro-Averaged F1-Score (Mean F Score) : The F1 score can be interpreted as a weighted average of
score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recal

the F1 score is:

*F1 = 2 * (precision * recall) / (precision + recall)*

In the multi-class and multi-label case, this is the weighted average of the F1 score of each class.

'Micro f1 score':
Calculate metrics globally by counting the total true positives, false negatives and false positives. Thi
imbalance.

'Macro f1 score':
Calculate metrics for each label, and find their unweighted mean. This does not take label imbalance

https://www.kaggle.com/wiki/MeanFScore
http://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

Hamming loss : The Hamming loss is the fraction of labels that are incorrectly predicted.
https://www.kaggle.com/wiki/HammingLoss

3. Exploratory Data Analysis

3.1 Data Loading and Cleaning

3.1.1 Using Pandas with SQLite to Load the data

```
#Creating db file from csv
start = datetime.now()
disk_engine = create_engine('sqlite:///train.db')

start = dt.datetime.now()
chunksize = 100000
j = 0
index_start = 1
for df in pd.read_csv('Train.csv', names=['Id', 'Title', 'Body', 'Tags'], chunksize=chunksize
    df.index += index_start
    j+=1
    print('{} rows'.format(j*chunksize))
    df.to_sql('train_data_of_stackoverflow', disk_engine, if_exists='append')
    index_start = df.index[-1] + 1
    print("Time taken to run this cell :", datetime.now() - start)
```

```
100000 rows
Time taken to run this cell : 0:00:16.814435
200000 rows
Time taken to run this cell : 0:00:24.448987
300000 rows
Time taken to run this cell : 0:00:32.435646
400000 rows
Time taken to run this cell : 0:00:40.369646
500000 rows
Time taken to run this cell : 0:00:48.488472
600000 rows
Time taken to run this cell : 0:00:56.467731
700000 rows
Time taken to run this cell : 0:01:04.549541
800000 rows
Time taken to run this cell : 0:01:12.471692
900000 rows
Time taken to run this cell : 0:01:20.393455
1000000 rows
Time taken to run this cell : 0:01:28.205321
1100000 rows
Time taken to run this cell : 0:01:35.980612
1200000 rows
Time taken to run this cell : 0:01:43.631223
1300000 rows
Time taken to run this cell : 0:01:51.895985
1400000 rows
Time taken to run this cell : 0:01:59.021229
1500000 rows
Time taken to run this cell : 0:02:06.206323
1600000 rows
Time taken to run this cell : 0:02:13.053242
1700000 rows
Time taken to run this cell : 0:02:19.806309
1800000 rows
Time taken to run this cell : 0:02:26.529283
1900000 rows
Time taken to run this cell : 0:02:33.389793
2000000 rows
Time taken to run this cell : 0:02:40.286096
2100000 rows
Time taken to run this cell : 0:02:47.484527
2200000 rows
Time taken to run this cell : 0:02:54.515509
2300000 rows
Time taken to run this cell : 0:03:02.389808
2400000 rows
Time taken to run this cell : 0:03:09.348553
2500000 rows
Time taken to run this cell : 0:03:16.504127
2600000 rows
Time taken to run this cell : 0:03:23.473060
2700000 rows
Time taken to run this cell : 0:03:30.495699
2800000 rows
Time taken to run this cell : 0:03:37.421675
2900000 rows
```

```
Time taken to run this cell : 0:03:44.619511
3000000 rows
Time taken to run this cell : 0:03:51.736209
3100000 rows
Time taken to run this cell : 0:03:59.100239
3200000 rows
Time taken to run this cell : 0:04:06.150052
3300000 rows
Time taken to run this cell : 0:04:13.417716
3400000 rows
Time taken to run this cell : 0:04:20.678650
3500000 rows
Time taken to run this cell : 0:04:28.218265
3600000 rows
Time taken to run this cell : 0:04:35.977438
3700000 rows
Time taken to run this cell : 0:04:44.146600
3800000 rows
Time taken to run this cell : 0:04:51.271802
3900000 rows
Time taken to run this cell : 0:04:58.699664
4000000 rows
Time taken to run this cell : 0:05:05.817907
4100000 rows
Time taken to run this cell : 0:05:12.953025
4200000 rows
Time taken to run this cell : 0:05:20.199818
4300000 rows
Time taken to run this cell : 0:05:27.687480
4400000 rows
Time taken to run this cell : 0:05:34.998835
4500000 rows
Time taken to run this cell : 0:05:42.185017
4600000 rows
Time taken to run this cell : 0:05:49.634094
4700000 rows
Time taken to run this cell : 0:05:57.294978
4800000 rows
Time taken to run this cell : 0:06:05.639677
4900000 rows
Time taken to run this cell : 0:06:13.564874
5000000 rows
Time taken to run this cell : 0:06:21.073485
5100000 rows
Time taken to run this cell : 0:06:28.415967
5200000 rows
Time taken to run this cell : 0:06:36.274012
5300000 rows
Time taken to run this cell : 0:06:44.149100
5400000 rows
Time taken to run this cell : 0:06:51.557722
5500000 rows
Time taken to run this cell : 0:06:58.869096
5600000 rows
Time taken to run this cell : 0:07:06.003746
5700000 rows
Time taken to run this cell : 0:07:13.543783
5800000 rows
```

```
Time taken to run this cell : 0:07:20.853520
5900000 rows
Time taken to run this cell : 0:07:29.640555
6000000 rows
Time taken to run this cell : 0:07:36.477392
6100000 rows
Time taken to run this cell : 0:07:39.232582
```

3.1.2 Counting the number of rows

```
start = datetime.now()

#*************** Now we have a sqlite database, every time when we have to access it, just us

con = sqlite3.connect('train.db')
num_rows = pd.read_sql_query("""SELECT count(*) FROM train_data_of_stackoverflow""", con)
#Always remember to close the database


print("Number of rows in the database :","\n",num_rows['count(*)'].values[0])
con.close()
print("Time taken to count the number of rows :", datetime.now() - start)
```

```
Number of rows in the database :
 36205176
Time taken to count the number of rows : 0:00:07.908222
```

3.1.3 Checking for duplicates

```
#Learn SQl: https://www.w3schools.com/sql/default.asp
# if os.path.isfile('train.db'):
start = datetime.now()
con = sqlite3.connect('train.db')
df_no_dup = pd.read_sql('SELECT Title, Body, Tags, COUNT(*) as Count_duplicate_questions FROM
con.close()
print("Time taken to run this cell :", datetime.now() - start)
```

```
---------------------------------------------------------------------------
OperationalError                          Traceback (most recent call last)
C:\anaconda\lib\site-packages\pandas\io\sql.py in execute(self, *args, **kwargs)
   1594             else:
-> 1595                 cur.execute(*args)
   1596             return cur

OperationalError: database or disk is full

During handling of the above exception, another exception occurred:

DatabaseError                             Traceback (most recent call last)
<ipython-input-4-44509b173949> in <module>
      3 start = datetime.now()
      4 con = sqlite3.connect('train.db')
----> 5 df_no_dup = pd.read_sql('SELECT Title, Body, Tags, COUNT(*) as Count_duplicate_q
      6 con.close()
      7 print("Time taken to run this cell :", datetime.now() - start)

C:\anaconda\lib\site-packages\pandas\io\sql.py in read_sql(sql, con, index_col, coerce_f
    408             coerce_float=coerce_float,
    409             parse_dates=parse_dates,
--> 410             chunksize=chunksize,
    411         )
    412 

C:\anaconda\lib\site-packages\pandas\io\sql.py in read_query(self, sql, index_col, coerc
   1643 
   1644         args = _convert_params(sql, params)
-> 1645         cursor = self.execute(*args)
   1646         columns = [col_desc[0] for col_desc in cursor.description]
   1647 

C:\anaconda\lib\site-packages\pandas\io\sql.py in execute(self, *args, **kwargs)
   1608                 "Execution failed on sql '{sql}': {exc}".format(sql=args[0], exc
   1609             )
-> 1610             raise_with_traceback(ex)
   1611 
   1612     @staticmethod

C:\anaconda\lib\site-packages\pandas\compat\__init__.py in raise_with_traceback(exc, tra
     42     if traceback == Ellipsis:
     43         _, _, traceback = sys.exc_info()
---> 44     raise exc.with_traceback(traceback)
     45 
     46 

C:\anaconda\lib\site-packages\pandas\io\sql.py in execute(self, *args, **kwargs)
   1593                 cur.execute(*args, **kwargs)
   1594             else:
-> 1595                 cur.execute(*args)
   1596             return cur
   1597         except Exception as exc:

DatabaseError: Execution failed on sql 'SELECT Title, Body, Tags, COUNT(*) as Count_dupl
```

SEARCH STACK OVERFLOW

```
df_no_dup.head()
# we can observe that there are duplicates
```

```
print("number of duplicate questions :", num_rows['count(*)'].values[0]- df_no_dup.shape[0],
      "(",(1-((df_no_dup.shape[0])/(num_rows['count(*)'].values[0])))*100,"% )")
```

```
# From the 6 million  ,1.8 million are duplicates
```

```
# number of times each question appeared in our database
df_no_dup.Count_duplicate_questions.value_counts()
```

```
# only 6 questions that are appear 5 times
# questions that appear 1 times are -> 2.6 millions  .
```

```
df=df_no_dup
df.shape
```

```
sd=[]
start = datetime.now()
for i in range(df_no_dup.shape[0]):
    f=df_no_dup["Tags"][i]# no of characters==0
    if f==None:# when no tag given just remove that datapoint
        df_no_dup=df_no_dup.drop(i,axis=0)     # remove this datapoint
    else:
        d=len(df_no_dup["Tags"][i].split(" "))
        sd.append(d)

print(datetime.now()-start)
```

```
df_no_dup.shape
```

```
df_no_dup["Tag_Count"] = df_no_dup["Tags"].apply(lambda text: len(text.split(" ")))
# adding a new feature number of tags per question
print("Time taken to run this cell :", datetime.now() - start)
df_no_dup.head()
```

```
# distribution of number of tags per question
df_no_dup.Tag_Count.value_counts()
```

Save the Non_duplicate questions in a new database

```
#Creating a new database with no duplicates
if not os.path.isfile('train_no_dup.db'):
    disk_dup = create_engine("sqlite:///train_no_dup.db")
    no_dup = pd.DataFrame(df_no_dup, columns=['Title', 'Body', 'Tags'])
    no_dup.to_sql('no_dup_train',disk_dup)
```

```
#************************************************train_no_dup.db is the new database *********
```

```
#This method seems more appropriate to work with this much data.
#creating the connection with database file.
#if os.path.isfile('train_no_dup.db'):
start = datetime.now()
con = sqlite3.connect('train_no_dup.db')
tag_data = pd.read_sql_query("""SELECT Tags FROM no_dup_train""", con)
    #Always remember to close the database
con.close()

    # Let's now drop unwanted column.
tag_data.drop(tag_data.index[0], inplace=True)
    #Printing first 5 columns from our data frame
tag_data.head()
print(" The Time taken to run this cell is :", datetime.now() - start)
# else:
#     print("Please download the train.db file from drive or run the above cells to genarate
```

```
tag_data.head()
#no_dup.head()
```

3.2 Analysis of Tags

3.2.1 Total number of unique tags

```
#****************************************First we have to count (A tag appear how many times)
# this can be done by countvectorizer that can give us Tag_name : Frequency
# Importing & Initializing the "CountVectorizer" object, which
#is scikit-learn's bag of words tool.

#by default 'split()' will tokenize each tag using space.
vectorizer = CountVectorizer(tokenizer = lambda x: x.split())
# fit_transform() does two functions: First, it fits the model
# and learns the vocabulary; second, it transforms our training data
# into feature vectors. The input to fit_transform should be a list of strings.
tag_dtm = vectorizer.fit_transform(tag_data['Tags'])
```

```
print("Number of data points :", tag_dtm.shape[0])
print("Number of unique tags :", tag_dtm.shape[1])
# we have  42048 total  unique tags!

#'get_feature_name()' gives us the vocabulary.
tags = vectorizer.get_feature_names()
#Lets look at the tags we have.
print("Some of the tags we have :", tags[:10])
```

3.2.3 Number of times a tag appeared

```
#    THIS IS THE REPRESENTATION OF THE DATAPOINTS WITH THEIR DIMENSIONS      (SPARCE MATRIX)

'''         TAG1    TAG2     TAG3     .   ..  ..    TAG42048
DP1      1         0               1                            0
DP2      0         0                1                            1
DP3       0        0                0                            1
.
.
DP4206307   0                   1                           1



for calculating how many times a single tag appeared, we have to count the number of one's in
'''




# https://stackoverflow.com/questions/15115765/how-to-access-sparse-matrix-elements
#Lets now store the document term matrix in a dictionary.


'''Each row in the array is one of your original documents (strings), each column is a featur
and the element is the count for that particular word and document.
You can see that if you sum each column you'll get the correct number'''
freqs = tag_dtm.sum(axis=0).A1
result = dict(zip(tags, freqs))


#************************************Saving this dictionary  of tagsto csv files ************

if not os.path.isfile('tag_counts_dict_dtm.csv'):
    with open('tag_counts_dict_dtm.csv', 'w') as csv_file:#   parameter is 'w' this means we
        writer = csv.writer(csv_file)
        for key, value in result.items():
            writer.writerow([key, value])
tag_df = pd.read_csv("tag_counts_dict_dtm.csv", names=['Tags', 'Counts'])
tag_df.head()
```

```
# We are saving each and every thing to database or file, so that if our computer crashes we

# *************************Sort the tags in DESC order, so that we can find the most frequen



tag_df_sorted = tag_df.sort_values(['Counts'], ascending=False)
tag_counts = tag_df_sorted['Counts'].values


plt.plot(tag_counts)
plt.title("Distribution of number of times tag appeared questions")
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()


# first 10k tags

plt.plot(tag_counts[0:10000])
plt.title('first 10k tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
print(len(tag_counts[0:10000:25]), tag_counts[0:10000:25])#  :25 is the step sizes
```

Observations:

- Some Tags appear zero times,but its not much clear how many tags appear zero times, we have to zoom the plot.

```
plt.plot(tag_counts[0:1000])
plt.title('first 1k tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
print(len(tag_counts[0:1000:5]), tag_counts[0:1000:5])         # these are the step sizes


plt.plot(tag_counts[0:500])
plt.title('first 500 tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
print(len(tag_counts[0:500:5]), tag_counts[0:500:5])
```

```
# some tags are very huge in number  , some tags are very less in number.
```

Observations:

- Some Tags appear large number of times and some tags are appear very few times, so we can say micro average 1

measuring performance.

```
plt.plot(tag_counts[0:100], c='b')
plt.scatter(x=list(range(0,100,5)), y=tag_counts[0:100:5], c='orange', label="quantiles with
#quantiles with 0.25 difference
plt.scatter(x=list(range(0,100,25)), y=tag_counts[0:100:25], c='m', label = "quantiles with 0

plt.title('first 100 tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.legend()
plt.show()
print(len(tag_counts[0:100:5]), tag_counts[0:100:5])
```

```
# Store tags greater than 10K in one list
lst_tags_gt_10k = tag_df[tag_df.Counts>10000]
#Print the length of the list
print ('{} Tags are used more than 10000 times'.format(len(lst_tags_gt_10k)))
# Store tags greater than 100K in one list
lst_tags_gt_100k = tag_df[tag_df.Counts>100000]
#Print the length of the list.
print ('{} Tags are used more than 100000 times'.format(len(lst_tags_gt_100k)))
```

Observations:

1. There are total 153 tags which are used more than 10000 times.
2. 14 tags are used more than 100000 times.
3. Most frequent tag (i.e. c#) is used 331505 times.
4. Since some tags occur much more frequenctly than others, Micro-averaged F1-score is the appropriate metri

3.2.4 Tags Per Question

```
#    THIS IS THE REPRESENTATION OF THE DATAPOINTS WITH THEIR DIMENSIONS      (SPARCE MATRIX)

'''         TAG1    TAG2     TAG3     .   ..  ..     TAG42048
DP1      1         0             1                           0
DP2      0         0              1                           1
```

```
DP3       0         0                0                            1
.
.
DP4206307   0                   1                            1



for calculating in one questions how many tags apear, just sum  the numer of ones in the sing
'''

#Storing the count of tag in each question in list 'tag_count'
tag_quest_count = tag_dtm.sum(axis=1).tolist()

#Converting list of lists into single list, we will get [[3], [4], [2], [2], [3]] and we are
tag_quest_count=[int(j) for i in tag_quest_count for j in i]
print ('We have total {} datapoints.'.format(len(tag_quest_count)))

print(tag_quest_count[:5])


print( "Maximum number of tags per question: %d"%max(tag_quest_count))
print( "Minimum number of tags per question: %d"%min(tag_quest_count))
print( "Avg. number of tags per question: %f"% ((sum(tag_quest_count)*1.0)/len(tag_quest_coun


sns.countplot(tag_quest_count, palette='gist_rainbow')
plt.title("Number of tags in the questions ")
plt.xlabel("Number of Tags")
plt.ylabel("Number of questions")
plt.show()
```

Observations:

1. Maximum number of tags per question: 5
2. Minimum number of tags per question: 1
3. Avg. number of tags per question: 2.899
4. Most of the questions are having 2 or 3 tags

3.2.5 Most Frequent Tags

```
# Ploting word cloud
start = datetime.now()

# Lets first convert the 'result' dictionary to 'list of tuples'
tup = dict(result.items())
#Initializing WordCloud using frequencies of tags.
wordcloud = WordCloud(    background_color='black',
                          width=1600,
                          height=800,
```

```
                    ).generate_from_frequencies(tup)

fig = plt.figure(figsize=(30,20))
plt.imshow(wordcloud)
plt.axis('off')
plt.tight_layout(pad=0)
fig.savefig("tag.png")
plt.show()
print("Time taken to run this cell :", datetime.now() - start)
```

Observations:

A look at the word cloud shows that "c#", "java", "php", "asp.net", "javascript", "c++" are some of the mo

3.2.6 The top 20 tags

```
i=np.arange(20)
tag_df_sorted.head(20).plot(kind='bar')
plt.title('Frequency of top 20 tags')
plt.xticks(i, tag_df_sorted['Tags'])
plt.xlabel('Tags')
plt.ylabel('Counts')
plt.show()
```

Observations:

1. Majority of the most frequent tags are programming language.
2. C# is the top most frequent programming language.
3. Android, IOS, Linux and windows are among the top most frequent operating systems.

3.3 Cleaning and preprocessing of Questions

3.3.1 Preprocessing

1. Sample 1M data points
2. Separate out code-snippets from Body
3. Remove Spcial characters from Question title and description (not in code)
4. Remove stop words (Except 'C')
5. Remove HTML Tags
6. Convert all the characters into small letters
7. Use SnowballStemmer to stem the words

```
def striphtml(data):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', str(data))
    return cleantext
stop_words = set(stopwords.words('english'))
stemmer = SnowballStemmer("english")


#****************************************Some functions for databases*********************
#http://www.sqlitetutorial.net/sqlite-python/create-tables/
def create_connection(db_file):
    """ create a database connection to the SQLite database
        specified by db_file
    :param db_file: database file
    :return: Connection object or None
    """
    try:
        conn = sqlite3.connect(db_file)
        return conn
    except Error as e:
        print(e)

    return None

def create_table(conn, create_table_sql):
    """ create a table from the create_table_sql statement
    :param conn: Connection object
    :param create_table_sql: a CREATE TABLE statement
    :return:
    """
    try:
        c = conn.cursor()
        c.execute(create_table_sql)
    except Error as e:
        print(e)

def checkTableExists(dbcon):
    cursr = dbcon.cursor()
    str = "select name from sqlite_master where type='table'"
    table_names = cursr.execute(str)
    print("Tables in the databse:")
    tables =table_names.fetchall()
    print(tables[0][0])
    return(len(tables))

def create_database_table(database, query):
    conn = create_connection(database)
    if conn is not None:
        create_table(conn, query)
        checkTableExists(conn)
    else:
        print("Error! cannot create the database connection.")
```

```
    conn.close()



#**********************************************Create a databse with the empty table********
sql_create_table = """CREATE TABLE IF NOT EXISTS QuestionsProcessed (question text NOT NULL,
create_database_table("Processed.db", sql_create_table)
```

```
Tables in the databse:
QuestionsProcessed
```

```
# http://www.sqlitetutorial.net/sqlite-delete/
# https://stackoverflow.com/questions/2279706/select-random-row-from-a-sqlite-table
start = datetime.now()
read_db = 'train_no_dup.db'     # old database which has all the duplicates rows
write_db = 'Processed.db'        # new database which i make in this it has one table questio
if os.path.isfile(read_db):
    conn_r = create_connection(read_db)
    if conn_r is not None:
        reader =conn_r.cursor()
        reader.execute("SELECT Title, Body, Tags From no_dup_train ORDER BY RANDOM() LIMIT 10



  #****************************We get the 100000 datapoints from the  train_no_dup.db databas

if os.path.isfile(write_db):
    conn_w = create_connection(write_db)
    if conn_w is not None:
        tables = checkTableExists(conn_w)
        writer =conn_w.cursor()
        if tables != 0:
            writer.execute("DELETE FROM QuestionsProcessed WHERE 1")  # rows are empty by the
            print("Cleared All the rows")
print("Time taken to run this cell :", datetime.now() - start)



#**************************Previously we created this table, now we checking if its empty o
```

```
Tables in the database:
QuestionsProcessed
Cleared All the rows
Time taken to run this cell : 0:02:13.422156
```

```
import nltk
nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to
```

__ we create a new data base to store the sampled and preprocessed questions __

```
#http://www.bernzilla.com/2008/05/13/selecting-a-random-row-from-an-sqlite-table/

start = datetime.now()
preprocessed_data_list=[]
reader.fetchone()
questions_with_code=0
len_pre=0
len_post=0
questions_proccesed = 0
for row in reader: # reading one row

    is_code = 0

    title, question, tags = row[0], row[1], row[2]

    if '<code>' in question:
        questions_with_code+=1
        is_code = 1
    x = len(question)+len(title)
    len_pre+=x

    code = str(re.findall(r'<code>(.*?)</code>', question, flags=re.DOTALL))

    question=re.sub('<code>(.*?)</code>', '', question, flags=re.MULTILINE|re.DOTALL)
    question=striphtml(question.encode('utf-8'))

    title=title.encode('utf-8')

    question=str(title)+" "+str(question)
    question=re.sub(r'[^A-Za-z]+',' ',question)
    words=word_tokenize(str(question.lower()))

    #Removing all single letter and and stopwords from question exceptt for the letter 'c'
    question=' '.join(str(stemmer.stem(j)) for j in words if j not in stop_words and (len(j)!

    len_post+=len(question)
    tup = (question,code,tags,x,len(question),is_code)
    questions_proccesed += 1




    #*************************   We are inseting the updated preprocessed data to the new tab


    writer.execute("insert into QuestionsProcessed(question,code,tags,   words_pre,   words_p
    if (questions_proccesed%100000==0):
```

```
        print("number of questions completed=",questions_proccesed)

no_dup_avg_len_pre=(len_pre*1.0)/questions_proccesed
no_dup_avg_len_post=(len_post*1.0)/questions_proccesed

print( "Avg. length of questions(Title+Body) before processing: %d"%no_dup_avg_len_pre)
print( "Avg. length of questions(Title+Body) after processing: %d"%no_dup_avg_len_post)
print ("Percent of questions containing code: %d"%((questions_with_code*100.0)/questions_proc

print("Time taken to run this cell :", datetime.now() - start)
```

```
Avg. length of questions(Title+Body) before processing: 1175
Avg. length of questions(Title+Body) after processing: 326
Percent of questions containing code: 57
Time taken to run this cell : 0:05:20.314822
```

```
# dont forget to close the connections, or else you will end up with locks
conn_r.commit()
conn_w.commit()
conn_r.close()
conn_w.close()
```

```
if os.path.isfile(write_db):
    conn_r = create_connection(write_db)
    if conn_r is not None:
        reader =conn_r.cursor()
        reader.execute("SELECT question From QuestionsProcessed LIMIT 10")
        print("Questions after preprocessed")
        print('='*100)
        reader.fetchone()
        for row in reader:
            print(row)
            print('-'*100)
conn_r.commit()
conn_r.close()
```

```
Questions after preprocessed
==========================================================================================
('c program dump entir hklm registri tree consol tri write simpl consol app dump content
------------------------------------------------------------------------------------------
('android gridview column make ui like net gridview column product name textview product
------------------------------------------------------------------------------------------
('import databas magento want import tecdoc databas magento without success tecdoc msql 
------------------------------------------------------------------------------------------
('exampl libpcap libnet want captur ip packag one server forward packag anoth server lib
------------------------------------------------------------------------------------------
('getscript stylesheet jqueri titl say equival jqueri load stylesheet',)
------------------------------------------------------------------------------------------
('apach truncat static content tri set moinmoin offic wiki window server run apach origi
------------------------------------------------------------------------------------------
('googl map plot multipl marker array tri plot marker array use code pop current locat w
------------------------------------------------------------------------------------------
('perl event loop multipl block watcher tri figur event loop perl current program someth
------------------------------------------------------------------------------------------
('mvvmlight viewmodelloc regist dataservic question might look naiv understand code view
------------------------------------------------------------------------------------------
```

```
#***************************From the Processed.db database select the table 'QuestionsProces
#Taking 1 Million entries to a dataframe.
write_db = 'Processed.db'
if os.path.isfile(write_db):
    conn_r = create_connection(write_db)
    if conn_r is not None:
        preprocessed_data = pd.read_sql_query("""SELECT question, Tags FROM QuestionsProcesse
conn_r.commit()
conn_r.close()
```

```
preprocessed_data.head()
```

	question	tags
0	user unabl access site connect vpn one user un...	networking vpn routing
1	c program dump entir hklm registri tree consol...	c# registry
2	android gridview column make ui like net gridv...	android gridview
3	import databas magento want import tecdoc data...	database magento import
4	exampl libpcap libnet want captur ip packag on...	linux libpcap libnet

```
print("number of data points in sample :", preprocessed_data.shape[0])
print("number of dimensions :", preprocessed_data.shape[1])
```

4. Machine Learning Models

4.1 Converting tags for multilabel problems

X	y1	y2	y3	y4
x1	0	1	1	0
x1	1	0	0	0
x1	0	1	0	0

```
# binary='true' will give a binary vectorizer
vectorizer = CountVectorizer(tokenizer = lambda x: x.split(), binary='true')
multilabel_y = vectorizer.fit_transform(preprocessed_data['tags'])
```

```
multilabel_y.shape# we have the total 18585 labels or tags.
```

```
(99999, 18511)
```

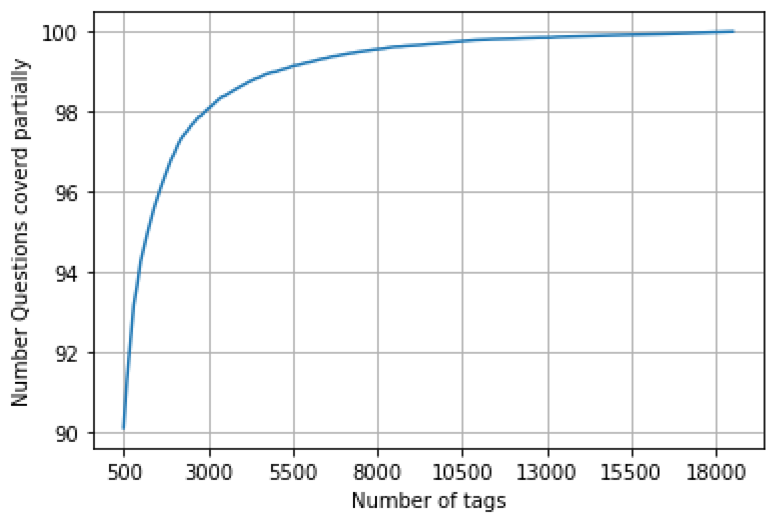
__ We will sample the number of tags instead considering all of them (due to limitation of computing

```
def tags_to_choose(n):
    t = multilabel_y.sum(axis=0).tolist()[0]# Frequency of the particular tag              cou
    #print(len(t))
    sorted_tags_i = sorted(range(len(t)), key=lambda i: t[i], reverse=True)# sort based on th
    #print(sorted_tags_i[:n])
    multilabel_yn=multilabel_y[:,sorted_tags_i[:n]]# questions with  the tags(that get in sec
    #print('**********************************************************************')
    #print(multilabel_yn)
    return multilabel_yn

def questions_explained_fn(n):
    multilabel_yn = tags_to_choose(n)# tags output that i discussed
    x= multilabel_yn.sum(axis=1)#  how many tags a single quesition has !
    #print(x)
    return ((np.count_nonzero(x==0)))# that questions we not able to explain with the labels
```

```
questions_explained = []
total_tags=multilabel_y.shape[1]
total_qs=preprocessed_data.shape[0]
for i in range(500, total_tags, 100):
    questions_explained.append(np.round(((total_qs-questions_explained_fn(i))/total_qs)*100,3
```

```
fig, ax = plt.subplots()
ax.plot(questions_explained)
```

```
xlabel = list(500+np.array(range(-50,450,50))*50)
ax.set_xticklabels(xlabel)
plt.xlabel("Number of tags")
plt.ylabel("Number Questions coverd partially")

plt.grid()
plt.show()
# you can choose any number of tags based on your computing power, minimun is 50(it covers 90
print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
```




```
with  5500 tags we are covering  99.138 % of questions
```

```
multilabel_yx = tags_to_choose(5500)
print("number of questions that are not covered :", questions_explained_fn(5500),"out of ", t
print(multilabel_yx.shape)
preprocessed_data.shape
```

```
number of questions that are not covered : 862 out of  99999
(99999, 5500)
(99999, 2)
```

```
print("Number of tags in sample :", multilabel_y.shape[1])
print("number of tags taken :", multilabel_yx.shape[1],"(",(multilabel_yx.shape[1]/multilabel
```

```
Number of tags in sample : 18511
number of tags taken : 5500 ( 29.71206309761763 %)
```

__ We consider top 15% tags which covers 99% of the questions __

4.2 Split the data into test and train (80:20)

```
# If we given with the time, we will do teh time split. because tags are changing with the ti
# launched asp.2   . so time based splitting will work here,
```

```
total_size=preprocessed_data.shape[0]
train_size=int(0.80*total_size)

x_train=preprocessed_data.head(train_size)
x_test=preprocessed_data.tail(total_size - train_size)
print(x_train.shape)
print(x_test.shape)
y_train = multilabel_yx[0:train_size,:]
y_test = multilabel_yx[train_size:total_size,:]
```

```
(79999, 2)
(20000, 2)
```

```
print("Number of data points in train data :", y_train.shape)
print("Number of data points in test data :", y_test.shape)
```

```
Number of data points in train data : (79999, 5500)
Number of data points in test data : (20000, 5500)
```

4.3 Featurizing data

```
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=0.00009, max_features=50000, smooth_idf=True, norm="l2",
                              sublinear_tf=False, ngram_range=(1,3))
x_train_multilabel = vectorizer.fit_transform(x_train['question'])
x_test_multilabel = vectorizer.transform(x_test['question'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:03.359503
```

```
print("Dimensions of train data X:",x_train_multilabel.shape, "Y :",y_train.shape)
print("Dimensions of test data X:",x_test_multilabel.shape,"Y:",y_test.shape)
```

```
Dimensions of train data X: (79999, 50000) Y : (79999, 5500)
Dimensions of test data X: (20000, 50000) Y: (20000, 5500)
```

```
# https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-label-classification/
#https://stats.stackexchange.com/questions/117796/scikit-multi-label-classification
# classifier = LabelPowerset(GaussianNB())
"""
from skmultilearn.adapt import MLkNN
classifier = MLkNN(k=21)

# train
classifier.fit(x_train_multilabel, y_train)

# predict
predictions = classifier.predict(x_test_multilabel)
```

```
predictions = classifier.predict(x_test_multilabel)
print(accuracy_score(y_test,predictions))
print(metrics.f1_score(y_test, predictions, average = 'macro'))
print(metrics.f1_score(y_test, predictions, average = 'micro'))
print(metrics.hamming_loss(y_test,predictions))

"""
# we are getting memory error because the multilearn package
# is trying to convert the data into dense matrix
# ---------------------------------------------------------------------------
#MemoryError                               Traceback (most recent call last)
#<ipython-input-170-f0e7c7f3e0be> in <module>()
#----> classifier.fit(x_train_multilabel, y_train)
```

```
"\nfrom skmultilearn.adapt import MLkNN\nclassifier = MLkNN(k=21)\n\n# train\nclassifier
```

4.5 Modeling with less data points (0.1M data points) and more weigh

```
# Now we'll repeat all the code from the previous sections
# procedure
#1. Take less datapoints
#2. remove the questions and give the high weitage to the title, by just repeating it 3 times
#3.If we see logically think, users have to write the title so much attractive or Title have
```

```
sql_create_table = """CREATE TABLE IF NOT EXISTS QuestionsProcessed (question text NOT NULL,
create_database_table("Titlemoreweightw.db", sql_create_table)
```

```
Tables in the databse:
QuestionsProcessed
```

```
# http://www.sqlitetutorial.net/sqlite-delete/
# https://stackoverflow.com/questions/2279706/select-random-row-from-a-sqlite-table

read_db = 'train_no_dup.db'
write_db = 'Titlemoreweightw.db'
train_datasize = 400000
if os.path.isfile(read_db):
    conn_r = create_connection(read_db)
    if conn_r is not None:
        reader =conn_r.cursor()
        # for selecting first 0.5M rows
        reader.execute("SELECT Title, Body, Tags From no_dup_train limit 100000;")
        # for selecting random points
        #reader.execute("SELECT Title, Body, Tags From no_dup_train ORDER BY RANDOM() LIMIT 5

if os.path.isfile(write_db):
    conn_w = create_connection(write_db)
    if conn_w is not None:
```

```
        tables = checkTableExists(conn_w)
        writer =conn_w.cursor()
        if tables != 0:
            writer.execute("DELETE FROM QuestionsProcessed WHERE 1")
            print("Cleared All the rows")
```

```
Tables in the databse:
QuestionsProcessed
Cleared All the rows
```

4.5.1 Preprocessing of questions

1. Separate Code from Body
2. Remove Spcial characters from Question title and description (not in code)
3. **Give more weightage to title : Add title three times to the question**

```
<li> Remove stop words (Except 'C') </li>
<li> Remove HTML Tags </li>
<li> Convert all the characters into small letters </li>
<li> Use SnowballStemmer to stem the words </li>
```

```
#http://www.bernzilla.com/2008/05/13/selecting-a-random-row-from-an-sqlite-table/
start = datetime.now()
preprocessed_data_list=[]
reader.fetchone()
questions_with_code=0
len_pre=0
len_post=0
questions_proccesed = 0
for row in reader:

    is_code = 0

    title, question, tags = row[0], row[1], str(row[2])

    if '<code>' in question:
        questions_with_code+=1
        is_code = 1
    x = len(question)+len(title)
    len_pre+=x

    code = str(re.findall(r'<code>(.*?)</code>', question, flags=re.DOTALL))

    question=re.sub('<code>(.*?)</code>', '', question, flags=re.MULTILINE|re.DOTALL)
    question=striphtml(question.encode('utf-8'))

    title=title.encode('utf-8')
```

```
        title=title.encode('utf-8')

        # adding title three time to the data to increase its weight
        # add tags string to the training data

        question=str(title)+" "+str(title)+" "+str(title)+" "+question

#       if questions_proccesed<=train_datasize:
#           question=str(title)+" "+str(title)+" "+str(title)+" "+question+" "+str(tags)
#       else:
#           question=str(title)+" "+str(title)+" "+str(title)+" "+question

        question=re.sub(r'[^A-Za-z0-9#+.\-]+',' ',question)
        words=word_tokenize(str(question.lower()))

        #Removing all single letter and and stopwords from question exceptt for the letter 'c'
        question=' '.join(str(stemmer.stem(j)) for j in words if j not in stop_words and (len(j)!

        len_post+=len(question)
        tup = (question,code,tags,x,len(question),is_code)
        questions_proccesed += 1
        writer.execute("insert into QuestionsProcessed(question,code,tags,words_pre,words_post,is
        if (questions_proccesed%100000==0):
            print("number of questions completed=",questions_proccesed)

    no_dup_avg_len_pre=(len_pre*1.0)/questions_proccesed
    no_dup_avg_len_post=(len_post*1.0)/questions_proccesed

    print( "Avg. length of questions(Title+Body) before processing: %d"%no_dup_avg_len_pre)
    print( "Avg. length of questions(Title+Body) after processing: %d"%no_dup_avg_len_post)
    print ("Percent of questions containing code: %d"%((questions_with_code*100.0)/questions_proc

    print("Time taken to run this cell :", datetime.now() - start)
```

```
Avg. length of questions(Title+Body) before processing: 1232
Avg. length of questions(Title+Body) after processing: 441
Percent of questions containing code: 57
Time taken to run this cell : 0:07:51.700574
```

```
# never forget to close the conections or else we will end up with database locks
conn_r.commit()
conn_w.commit()
conn_r.close()
conn_w.close()
```

__ Sample quesitons after preprocessing of data __

```
if os.path.isfile(write_db):
    conn_r = create_connection(write_db)
    if conn_r is not None:
        reader =conn_r.cursor()
```

```
        reader.execute("SELECT question From QuestionsProcessed LIMIT 10")
        print("Questions after preprocessed")
        print('='*100)
        reader.fetchone()
        for row in reader:
            print(row)
            print('-'*100)
conn_r.commit()
conn_r.close()
```

```
Questions after preprocessed
====================================================================================================
('dynam datagrid bind silverlight dynam datagrid bind silverlight dynam datagrid bind si
----------------------------------------------------------------------------------------------------
('java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid java.lang.nocl
----------------------------------------------------------------------------------------------------
('java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index java.sql.sqlex
----------------------------------------------------------------------------------------------------
('better way updat feed fb php sdk better way updat feed fb php sdk better way updat fee
----------------------------------------------------------------------------------------------------
('btnadd click event open two window record ad btnadd click event open two window record
----------------------------------------------------------------------------------------------------
('sql inject issu prevent correct form submiss php sql inject issu prevent correct form 
----------------------------------------------------------------------------------------------------
('countabl subaddit lebesgu measur countabl subaddit lebesgu measur countabl subaddit le
----------------------------------------------------------------------------------------------------
('hql equival sql queri hql equival sql queri hql equival sql queri hql queri replac nam
----------------------------------------------------------------------------------------------------
('undefin symbol architectur i386 objc class skpsmtpmessag referenc error undefin symbol
----------------------------------------------------------------------------------------------------
```

__ Saving Preprocessed data to a Database __

```
#Taking 0.5 Million entries to a dataframe.
write_db = 'Titlemoreweightw.db'
if os.path.isfile(write_db):
    conn_r = create_connection(write_db)
    if conn_r is not None:
        preprocessed_data = pd.read_sql_query("""SELECT question, Tags FROM QuestionsProcesse
conn_r.commit()
conn_r.close()
```

```
preprocessed_data.shape
```

```
(99999, 2)
```

```
print("number of data points in sample :", preprocessed_data.shape[0])
print("number of dimensions :", preprocessed_data.shape[1])
```

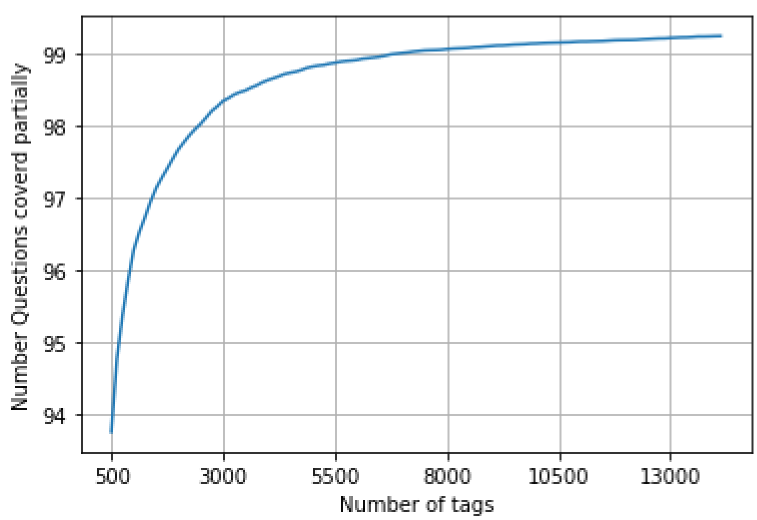
number of data points in sample : 99999

__ Converting string Tags to multilable output variables __

```
vectorizer = CountVectorizer(binary='true')
multilabel_y = vectorizer.fit_transform(preprocessed_data['tags'])
```

__ Selecting 500 Tags __

```
questions_explained = []
total_tags=multilabel_y.shape[1]
total_qs=preprocessed_data.shape[0]
for i in range(500, total_tags, 100):
    questions_explained.append(np.round(((total_qs-questions_explained_fn(i))/total_qs)*100,3

fig, ax = plt.subplots()
ax.plot(questions_explained)
xlabel = list(500+np.array(range(-50,450,50))*50)
ax.set_xticklabels(xlabel)
plt.xlabel("Number of tags")
plt.ylabel("Number Questions coverd partially")
plt.grid()
plt.show()
# you can choose any number of tags based on your computing power, minimun is 500(it covers 9
print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
print("with ",500,"tags we are covering ",questions_explained[0],"% of questions")
```




```
with  5500 tags we are covering  98.986 % of questions
with  500 tags we are covering  93.743 % of questions
```

```
# we will be taking 500 tags
multilabel_yx = tags_to_choose(500)
print("number of questions that are not covered :", questions_explained_fn(500),"out of ", to
```

```
preprocessed_data.shape[0]
```

```
99999
```

```
# If we given with the time, we will do teh time split. because tags are changing with the ti
# launched asp.2   . so time based splitting will work here,


total_size=preprocessed_data.shape[0]
train_size=int(0.80*total_size)


x_train=preprocessed_data.head(train_size)
x_test=preprocessed_data.tail(total_size - train_size)
print(x_train.shape)
print(x_test.shape)
y_train = multilabel_yx[0:train_size,:]
y_test = multilabel_yx[train_size:total_size,:]
```

```
(79999, 2)
(20000, 2)
```

```
print("Number of data points in train data :", y_train.shape)
print("Number of data points in test data :", y_test.shape)
```

```
Number of data points in train data : (79999, 500)
Number of data points in test data : (20000, 500)
```

4.5.2 Featurizing data with TfIdf vectorizer

```
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=0.00009, max_features=10000, smooth_idf=True, norm="l2",
x_train_multilabel = vectorizer.fit_transform(x_train['question'])
x_test_multilabel = vectorizer.transform(x_test['question'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:16.136466
```

```
print("Dimensions of train data X:",x_train_multilabel.shape, "Y :",y_train.shape)
print("Dimensions of test data X:",x_test_multilabel.shape,"Y:",y_test.shape)
```

```
Dimensions of train data X: (79999, 10000) Y : (79999, 500)
Dimensions of test data X: (20000, 10000) Y: (20000, 500)
```

4.5.3 Applying Logistic Regression with OneVsRest Classifier

```
import warnings
```

```
import warnings
warnings.filterwarnings("ignore")
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l1'), n_jo
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


print("Accuracy :",metrics.accuracy_score(y_test, predictions))
print("Hamming loss ",metrics.hamming_loss(y_test,predictions))


precision = precision_score(y_test, predictions, average='micro')
recall = recall_score(y_test, predictions, average='micro')
f1 = f1_score(y_test, predictions, average='micro')

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(precision, recall, f1))

precision = precision_score(y_test, predictions, average='macro')
recall = recall_score(y_test, predictions, average='macro')
f1 = f1_score(y_test, predictions, average='macro')

print("Macro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(precision, recall, f1))

print (metrics.classification_report(y_test, predictions))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Accuracy : 0.1937
Hamming loss  0.0035708
Micro-average quality numbers
Precision: 0.7346, Recall: 0.3800, F1-measure: 0.5009
Macro-average quality numbers
Precision: 0.5558, Recall: 0.2813, F1-measure: 0.3510
              precision    recall  f1-score   support

           0       0.80      0.47      0.59      1805
           1       0.86      0.53      0.65      1186
           2       0.87      0.55      0.68       484
           3       0.82      0.46      0.59      1323
           4       0.87      0.60      0.71       739
           5       0.87      0.48      0.62      1023
           6       0.77      0.39      0.52      1421
           7       0.95      0.62      0.75      1450
           8       0.98      0.82      0.89      1368
           9       0.68      0.45      0.54       914
          10       0.80      0.41      0.55       186
          11       0.77      0.49      0.60       553
          12       0.78      0.40      0.53       644
          13       0.52      0.19      0.28       424
          14       0.70      0.39      0.50        36
          15       0.59      0.37      0.45       352
          16       0.64      0.23      0.34       437
          17       0.76      0.46      0.57       435
          18       0.68      0.56      0.61       153
          19       0.98      0.60      0.75       727
          20       0.63      0.19      0.30       488
          21       0.85      0.62      0.72       272
          22       0.92      0.58      0.71       530
          23       0.95      0.54      0.69       618
          24       0.96      0.55      0.70       614
          25       0.68      0.29      0.40       231
          26       0.53      0.33      0.41       588
          27       0.58      0.40      0.47      1224
          28       0.71      0.45      0.55       165
          29       0.62      0.54      0.58       231
          30       0.72      0.28      0.40       190
          31       0.82      0.59      0.69       296
          32       0.69      0.34      0.46       274
          33       0.56      0.38      0.45       292
          34       0.73      0.27      0.40       190
          35       0.86      0.44      0.59        99
          36       0.88      0.59      0.71       357
          37       0.69      0.38      0.49       870
          38       0.81      0.47      0.60       135
          39       1.00      0.35      0.52        17
          40       0.53      0.08      0.14        99
          41       0.67      0.29      0.40       176
          42       0.29      0.05      0.09       236
          43       0.88      0.32      0.47        22
          44       0.53      0.19      0.28       106
          45       0.56      0.13      0.22       178
          46       0.43      0.24      0.30       241
          47       0.64      0.17      0.27       217
          48       0.64      0.49      0.55       223
```

49	0.67	0.07	0.13	54
50	0.62	0.35	0.44	92
51	0.86	0.59	0.70	203
52	0.71	0.47	0.57	116
53	0.81	0.49	0.61	72
54	0.38	0.20	0.26	15
55	0.25	0.02	0.03	60
56	0.90	0.79	0.84	216
57	0.35	0.08	0.13	74
58	0.35	0.13	0.19	139
59	0.71	0.45	0.55	91
60	0.48	0.10	0.17	156
61	0.42	0.33	0.37	76
62	0.52	0.18	0.27	89
63	0.48	0.17	0.25	173
64	0.53	0.28	0.36	227
65	0.45	0.11	0.18	383
66	0.65	0.22	0.32	148
67	0.56	0.40	0.46	189
68	0.75	0.35	0.48	169
69	0.14	0.06	0.08	50
70	0.68	0.26	0.38	145
71	0.42	0.26	0.32	31
72	0.93	0.72	0.81	141
73	0.88	0.43	0.58	246
74	0.54	0.30	0.39	210
75	0.70	0.10	0.18	159
76	0.49	0.21	0.30	108
77	0.94	0.78	0.86	65
78	0.97	0.70	0.81	145
79	0.91	0.71	0.79	41
80	0.73	0.57	0.64	129
81	0.89	0.53	0.66	76
82	0.63	0.45	0.53	124
83	0.41	0.13	0.20	69
84	0.44	0.16	0.24	91
85	0.49	0.42	0.46	66
86	0.21	0.08	0.12	100
87	0.43	0.26	0.33	38
88	0.73	0.45	0.56	98
89	0.52	0.39	0.45	38
90	0.97	0.68	0.80	154
91	0.88	0.65	0.75	152
92	0.00	0.00	0.00	13
93	0.00	0.00	0.00	47
94	0.80	0.27	0.41	44
95	0.78	0.29	0.43	200
96	0.40	0.24	0.30	25
97	0.61	0.28	0.39	39
98	0.58	0.43	0.49	51
99	0.35	0.26	0.30	43
100	0.33	0.11	0.16	211
101	0.57	0.22	0.32	18
102	0.67	0.50	0.57	32
103	0.77	0.42	0.54	24
104	0.80	0.29	0.42	14
105	0.70	0.48	0.57	96
106	1.00	0.41	0.58	32

```
        107       0.60      0.38      0.46        80
        108       0.74      0.19      0.31       160
        109       0.39      0.07      0.12       123
        110       0.37      0.05      0.09       202
        111       0.56      0.46      0.51        39
        112       0.35      0.07      0.11       123
        113       0.71      0.53      0.60        55
        114       0.45      0.13      0.20        98
        115       0.35      0.16      0.22        50
        116       0.84      0.54      0.65       275
        117       0.40      0.04      0.07       101
        118       0.67      0.12      0.20        50
        119       0.57      0.20      0.29        41
        120       0.62      0.27      0.37        98
        121       0.44      0.13      0.21        30
        122       0.83      0.33      0.47        73
        123       0.91      0.79      0.85       121
        124       0.55      0.38      0.45        29
        125       0.92      0.21      0.34        57
        126       0.50      0.15      0.23        48
        127       0.90      0.75      0.82        24
        128       0.48      0.25      0.33        48
        129       0.75      0.19      0.30        48
        130       0.89      0.51      0.65        99
        131       0.50      0.38      0.43        29
        132       0.45      0.08      0.14        60
        133       0.71      0.74      0.73        89
        134       0.36      0.04      0.08       113
        135       0.38      0.13      0.19        70
        136       0.38      0.07      0.12        68
        137       0.94      0.55      0.70       146
        138       0.79      0.33      0.47        66
        139       0.38      0.06      0.11        49
        140       0.89      0.47      0.62        51
        141       0.56      0.33      0.42        27
        142       0.20      0.04      0.06        54
        143       0.50      0.10      0.16        21
        144       0.40      0.14      0.21        43
        145       0.95      0.41      0.57        49
        146       0.64      0.54      0.58       137
        147       0.84      0.47      0.61        91
        148       0.48      0.34      0.40        29
        149       0.95      0.62      0.75        88
        150       0.70      0.10      0.18        67
        151       0.70      0.41      0.52        46
        152       0.59      0.33      0.42       187
        153       0.81      0.42      0.55        60
        154       0.83      0.38      0.52        40
        155       0.38      0.04      0.08        67
        156       0.33      0.11      0.16        46
        157       0.64      0.30      0.41        23
        158       0.68      0.50      0.57        54
        159       0.46      0.37      0.41        87
        160       0.70      0.21      0.33        66
        161       0.88      0.54      0.67        69
        162       0.41      0.15      0.22        78
        163       0.98      0.82      0.89        50
        164       0.39      0.11      0.18       115
```

164	0.39	0.11	0.18	113
165	0.65	0.18	0.29	71
166	0.12	0.01	0.02	81
167	0.40	0.52	0.45	52
168	0.62	0.36	0.46	22
169	0.00	0.00	0.00	292
170	0.32	0.40	0.35	45
171	0.31	0.03	0.06	146
172	0.00	0.00	0.00	5
173	0.53	0.30	0.38	66
174	0.30	0.14	0.19	21
175	0.50	0.08	0.13	26
176	0.42	0.09	0.15	86
177	0.43	0.17	0.24	18
178	0.12	0.04	0.06	27
179	0.00	0.00	0.00	0
180	1.00	0.71	0.83	7
181	1.00	0.53	0.69	34
182	0.73	0.63	0.68	35
183	0.68	0.51	0.58	51
184	0.89	0.63	0.74	38
185	0.20	0.05	0.08	39
186	0.50	0.08	0.13	13
187	0.60	0.34	0.44	35
188	0.31	0.11	0.17	44
189	0.50	0.11	0.18	46
190	0.69	0.17	0.28	52
191	0.48	0.11	0.18	88
192	0.25	0.02	0.04	41
193	0.96	0.53	0.69	88
194	0.50	0.04	0.07	51
195	0.55	0.20	0.30	127
196	0.00	0.00	0.00	60
197	1.00	0.17	0.29	18
198	0.33	0.03	0.05	36
199	0.19	0.04	0.06	85
200	0.50	0.19	0.27	48
201	0.45	0.29	0.36	17
202	0.40	0.22	0.29	27
203	0.65	0.18	0.29	60
204	0.82	0.50	0.62	105
205	0.64	0.50	0.56	50
206	0.55	0.27	0.36	45
207	0.40	0.32	0.35	19
208	0.57	0.27	0.37	73
209	0.00	0.00	0.00	51
210	0.80	0.20	0.32	20
211	0.00	0.00	0.00	47
212	0.00	0.00	0.00	44
213	0.63	0.35	0.45	34
214	0.72	0.49	0.58	106
215	0.79	0.44	0.57	59
216	0.33	0.10	0.16	87
217	0.80	0.26	0.39	31
218	0.74	0.61	0.67	46
219	0.60	0.11	0.19	27
220	0.27	0.08	0.12	39
221	0.75	0.38	0.51	55

222	0.67	0.12	0.20	34
223	0.67	0.36	0.47	11
224	0.35	0.12	0.18	51
225	0.18	0.07	0.10	46
226	0.50	0.09	0.15	47
227	0.25	0.07	0.11	14
228	0.83	0.24	0.37	21
229	0.62	0.07	0.13	67
230	0.00	0.00	0.00	229
231	0.67	0.11	0.19	54
232	0.77	0.10	0.18	98
233	0.92	0.43	0.59	53
234	0.57	0.22	0.32	36
235	0.68	0.47	0.56	53
236	0.51	0.34	0.41	68
237	0.31	0.13	0.19	38
238	0.46	0.11	0.17	102
239	0.33	0.33	0.33	6
240	0.00	0.00	0.00	5
241	0.50	0.33	0.40	3
242	0.50	0.13	0.21	68
243	0.50	0.43	0.46	91
244	0.92	0.73	0.81	30
245	0.79	0.22	0.34	50
246	1.00	0.25	0.40	4
247	0.65	0.27	0.38	41
248	0.64	0.21	0.32	98
249	0.00	0.00	0.00	0
250	1.00	1.00	1.00	1
251	1.00	0.19	0.32	26
252	0.66	0.29	0.40	66
253	0.79	0.66	0.72	67
254	0.00	0.00	0.00	32
255	0.00	0.00	0.00	2
256	0.60	0.09	0.16	32
257	1.00	0.50	0.67	4
258	0.75	0.08	0.14	39
259	0.85	0.45	0.59	73
260	1.00	0.60	0.75	55
261	0.50	0.33	0.40	12
262	0.44	0.27	0.33	41
263	0.71	0.36	0.48	14
264	0.69	0.16	0.26	56
265	0.86	0.23	0.37	77
266	0.00	0.00	0.00	13
267	0.45	0.31	0.37	16
268	0.00	0.00	0.00	34
269	0.00	0.00	0.00	45
270	1.00	0.07	0.13	43
271	0.44	0.29	0.35	56
272	0.60	0.27	0.37	11
273	0.00	0.00	0.00	42
274	0.85	0.63	0.72	35
275	0.44	0.07	0.12	59
276	0.29	0.10	0.15	49
277	0.63	0.66	0.64	44
278	0.56	0.11	0.18	46
279	0.00	0.00	0.00	7

280	0.88	0.66	0.75	58
281	0.67	0.35	0.46	46
282	0.36	0.40	0.38	10
283	0.58	0.33	0.42	21
284	0.25	0.04	0.07	47
285	0.57	0.17	0.27	23
286	0.92	0.69	0.79	48
287	0.58	0.60	0.59	35
288	0.15	0.02	0.04	81
289	0.73	0.47	0.57	47
290	0.73	0.71	0.72	93
291	0.10	0.02	0.03	61
292	0.70	0.61	0.65	23
293	0.83	0.50	0.62	10
294	0.50	0.03	0.06	30
295	0.00	0.00	0.00	24
296	0.00	0.00	0.00	54
297	0.56	0.65	0.60	34
298	0.37	0.33	0.35	69
299	0.87	0.75	0.80	44
300	0.71	0.38	0.50	13
301	0.88	0.54	0.67	68
302	0.00	0.00	0.00	33
303	0.62	0.44	0.52	18
304	0.20	0.08	0.11	13
305	0.75	0.34	0.47	53
306	0.73	0.21	0.33	75
307	0.88	0.53	0.66	55
308	0.95	0.61	0.74	61
309	0.80	0.41	0.54	90
310	0.56	0.09	0.15	58
311	0.89	0.84	0.86	19
312	0.67	0.06	0.11	34
313	0.40	0.31	0.35	13
314	0.20	0.25	0.22	4
315	0.44	0.10	0.16	41
316	0.81	0.41	0.54	54
317	0.86	0.24	0.38	25
318	0.20	0.25	0.22	4
319	0.40	0.07	0.12	29
320	0.62	0.22	0.32	37
321	1.00	0.17	0.29	6
322	0.14	0.05	0.07	22
323	0.25	0.05	0.09	19
324	0.20	0.25	0.22	4
325	0.54	0.39	0.45	18
326	0.75	0.43	0.55	21
327	0.00	0.00	0.00	26
328	0.72	0.47	0.57	49
329	0.61	0.54	0.58	35
330	1.00	0.05	0.10	19
331	0.60	0.20	0.30	15
332	0.00	0.00	0.00	10
333	0.74	0.53	0.62	38
334	0.14	0.11	0.12	9
335	0.60	0.06	0.10	53
336	1.00	0.56	0.72	32
337	0.33	0.04	0.07	24

337	0.33	0.04	0.07	24
338	1.00	0.67	0.80	3
339	0.00	0.00	0.00	1
340	0.00	0.00	0.00	0
341	0.71	0.45	0.56	11
342	0.68	0.47	0.56	40
343	0.00	0.00	0.00	30
344	0.40	0.08	0.14	24
345	0.50	0.04	0.08	23
346	0.61	0.28	0.38	69
347	0.20	0.06	0.09	18
348	0.17	0.03	0.05	65
349	0.47	0.23	0.31	78
350	1.00	0.08	0.15	12
351	0.50	0.08	0.13	13
352	0.40	0.11	0.17	18
353	1.00	0.63	0.77	46
354	0.82	0.57	0.68	40
355	0.00	0.00	0.00	19
356	0.67	0.08	0.14	26
357	0.53	0.23	0.32	39
358	1.00	0.17	0.29	12
359	0.60	0.19	0.29	16
360	0.70	0.29	0.41	24
361	0.33	0.11	0.16	57
362	0.84	0.80	0.82	20
363	0.83	0.06	0.11	84
364	0.73	0.65	0.69	54
365	0.44	0.12	0.19	33
366	0.67	0.13	0.22	30
367	1.00	0.07	0.12	30
368	0.20	0.05	0.08	19
369	0.00	0.00	0.00	19
370	1.00	0.03	0.06	32
371	0.62	0.42	0.50	12
372	0.50	0.07	0.12	15
373	0.12	0.07	0.09	15
374	0.92	0.65	0.76	17
375	1.00	0.66	0.79	41
376	0.94	0.55	0.70	29
377	0.00	0.00	0.00	28
378	0.50	0.16	0.24	19
379	0.40	0.06	0.11	31
380	0.67	0.14	0.23	29
381	0.29	0.08	0.13	49
382	0.00	0.00	0.00	8
383	0.29	0.08	0.13	24
384	0.50	0.35	0.41	20
385	0.00	0.00	0.00	15
386	0.81	0.57	0.67	37
387	0.00	0.00	0.00	22
388	1.00	0.04	0.07	27
389	0.50	0.38	0.43	29
390	0.00	0.00	0.00	20
391	0.72	0.54	0.62	39
392	0.50	0.10	0.17	10
393	0.38	0.14	0.21	42
394	0.67	0.09	0.15	46

395	0.10	0.10	0.10	10
396	0.75	0.08	0.14	39
397	0.00	0.00	0.00	43
398	0.71	0.30	0.42	50
399	1.00	0.57	0.73	7
400	0.25	0.06	0.10	17
401	1.00	0.17	0.29	6
402	0.00	0.00	0.00	26
403	1.00	0.10	0.18	10
404	0.71	0.36	0.48	14
405	0.00	0.00	0.00	14
406	0.82	0.41	0.55	22
407	0.62	0.17	0.26	60
408	0.39	0.17	0.24	40
409	0.00	0.00	0.00	31
410	0.38	0.33	0.35	9
411	0.42	0.26	0.32	19
412	0.67	0.53	0.59	19
413	0.50	0.20	0.29	5
414	0.33	0.08	0.13	12
415	1.00	0.66	0.79	29
416	0.67	0.06	0.11	33
417	0.33	0.03	0.06	33
418	0.40	0.17	0.24	12
419	0.36	0.10	0.15	42
420	0.50	0.58	0.54	12
421	0.33	0.18	0.24	98
422	0.33	0.12	0.18	8
423	0.00	0.00	0.00	7
424	0.75	0.46	0.57	13
425	0.33	0.08	0.12	13
426	0.33	0.10	0.15	20
427	0.25	0.05	0.09	58
428	0.67	1.00	0.80	2
429	0.38	0.30	0.33	27
430	0.50	0.37	0.42	38
431	0.56	0.23	0.32	40
432	1.00	0.05	0.09	43
433	0.96	0.57	0.72	42
434	0.64	0.29	0.40	24
435	0.33	0.03	0.06	31
436	0.40	0.33	0.36	30
437	0.25	0.06	0.10	16
438	0.67	0.45	0.54	22
439	1.00	1.00	1.00	1
440	0.17	0.11	0.13	19
441	0.67	0.22	0.33	9
442	0.33	0.11	0.17	100
443	0.83	0.36	0.50	28
444	0.75	0.60	0.67	20
445	0.45	0.45	0.45	29
446	0.00	0.00	0.00	21
447	0.80	0.20	0.32	20
448	0.88	0.55	0.68	38
449	0.00	0.00	0.00	22
450	0.61	0.52	0.56	21
451	0.00	0.00	0.00	13
452	0.00	0.00	0.00	24

```
         453       0.55      0.12      0.20        48
         454       0.47      0.11      0.17        75
         455       0.00      0.00      0.00        18
         456       0.00      0.00      0.00         3
         457       0.55      0.46      0.50        13
         458       0.50      0.15      0.24        13
         459       0.27      0.25      0.26        24
         460       0.62      0.28      0.38        36
         461       0.64      0.50      0.56        18
         462       0.50      0.23      0.31        31
         463       0.67      0.07      0.13        28
         464       0.00      0.00      0.00         7
         465       0.89      0.30      0.44        27
         466       1.00      0.83      0.91        12
         467       0.67      0.14      0.24        14
         468       0.00      0.00      0.00         6
         469       0.27      0.18      0.21        17
         470       0.30      0.17      0.21        18
         471       0.67      0.07      0.12        29
         472       0.00      0.00      0.00         2
         473       0.38      0.09      0.14        34
         474       0.00      0.00      0.00         8
         475       0.25      0.25      0.25         4
         476       0.69      0.50      0.58        22
         477       0.50      0.67      0.57         6
         478       0.33      0.24      0.28        17
         479       0.00      0.00      0.00        23
         480       0.86      0.33      0.48        18
         481       0.83      0.45      0.59        11
         482       1.00      0.29      0.44        35
         483       0.59      0.62      0.60        21
         484       0.86      0.64      0.73        28
         485       0.62      0.36      0.45        14
         486       0.90      0.82      0.86        11
         487       1.00      0.13      0.24        15
         488       0.58      0.18      0.28        38
         489       0.08      0.01      0.02        75
         490       0.97      0.57      0.72        51
         491       1.00      0.68      0.81        19
         492       0.50      0.19      0.28        21
         493       0.67      0.12      0.21        16
         494       1.00      0.83      0.91         6
         495       0.40      0.18      0.25        22
         496       0.68      0.35      0.46        37
         497       0.29      0.20      0.24        20
         498       0.70      0.58      0.64        24
         499       0.00      0.00      0.00        17

   micro avg       0.73      0.38      0.50     47151
   macro avg       0.56      0.28      0.35     47151
weighted avg       0.68      0.38      0.47     47151
 samples avg       0.51      0.37      0.40     47151

Time taken to run this cell : 0:02:47.896331
```

```
# For saving the weights or results after run applying model
#joblib.dump(classifier, 'lr_with_more_title_weight.pkl')
```

5. Assignments

1. Use bag of words upto 4 grams and compute the micro f1 score with Logistic regression(OvR)
2. Perform hyperparam tuning on alpha (or lambda) for Logistic regression to improve the performance using G
3. Try OneVsRestClassifier with Linear-SVM (SGDClassifier with loss-hinge)

4.5.2 Featurizing data with BOW vectorizer

```
start = datetime.now()
vectorizer =  CountVectorizer(min_df=0.00009, max_features=10000, ngram_range=(1,4))
x_train_multilabel = vectorizer.fit_transform(x_train['question'])
x_test_multilabel = vectorizer.transform(x_test['question'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:02:01.153712
```

```
print("Dimensions of train data X:",x_train_multilabel.shape, "Y :",y_train.shape)
print("Dimensions of test data X:",x_test_multilabel.shape,"Y:",y_test.shape)
```

```
Dimensions of train data X: (79999, 10000) Y : (79999, 500)
Dimensions of test data X: (20000, 10000) Y: (20000, 500)
```

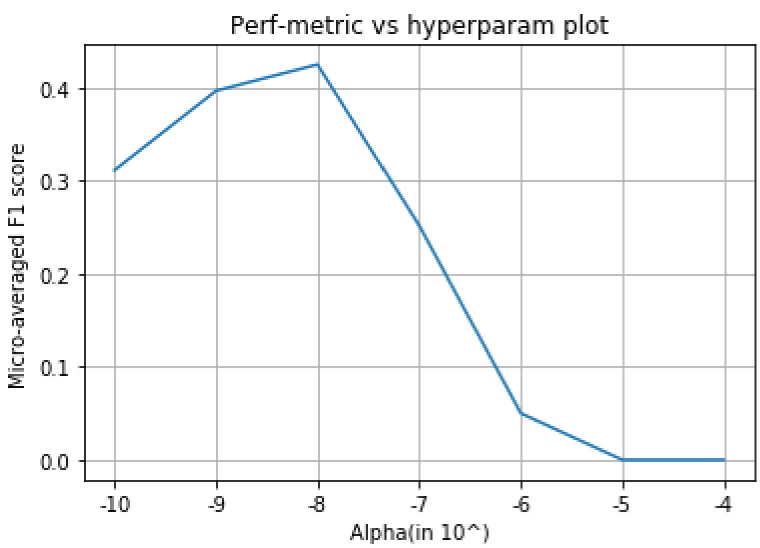
Hyperparameter tuning:

```
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV"
from sklearn.linear_model import LogisticRegression
from tqdm import tqdm

from sklearn.model_selection import learning_curve, GridSearchCV


alpha =[10**-5,10**-4,10**-3,10**-2,10**-1,5,10]
perf_metric = []
for i in tqdm(alpha):

    clf = OneVsRestClassifier(SGDClassifier(loss='log', alpha=i, penalty='l1', random_state=4
    clf.fit(x_train_multilabel, y_train)
    predictions = clf.predict (x_test_multilabel)
    perf_metric.append(f1_score(y_test, predictions, average='micro'))
```

```
    perf_metric.append(f1_score(y_test, predictions, average='micro'))

#print("Time taken to run this cell :", datetime.now() - start)
```

```
100%|████████████████████████████████████████████████████████████████| 7
```

```
# plot the perf metric for each hyperparam(alpha)
fig, ax = plt.subplots()
ax.plot(perf_metric)
xlabel = list(range(-11, -3))
ax.set_xticklabels(xlabel)
plt.title("Perf-metric vs hyperparam plot")
plt.xlabel("Alpha(in 10^)")
plt.ylabel("Micro-averaged F1 score")
plt.grid()
plt.show()
```



Training the model with best hyperparameter

```
start = datetime.now()
# fetching the best alpha
best_alpha = alpha[np.argmax(perf_metric)]
print('Best hyperparam(alpha) : ',best_alpha)

# train the LR model with the best alpha
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=best_alpha, penalty='l1',  r
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)

# print the various performance metrices
print("Accuracy :",metrics.accuracy_score(y_test, predictions))
print("Hamming loss :",metrics.hamming_loss(y_test,predictions))
```

```
precision = precision_score(y_test, predictions, average='micro')
recall = recall_score(y_test, predictions, average='micro')
f1 = f1_score(y_test, predictions, average='micro')

print("\nMicro-average quality numbers -")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(precision, recall, f1))

precision = precision_score(y_test, predictions, average='macro')
recall = recall_score(y_test, predictions, average='macro')
f1 = f1_score(y_test, predictions, average='macro')

print("\nMacro-average quality numbers -")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(precision, recall, f1))

print("\n")
print (metrics.classification_report(y_test, predictions))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Best hyperparam(alpha) :  0.001
Accuracy : 0.1366
Hamming loss : 0.0044873

Micro-average quality numbers -
Precision: 0.5368, Recall: 0.3521, F1-measure: 0.4253

Macro-average quality numbers -
Precision: 0.3906, Recall: 0.2561, F1-measure: 0.2861


              precision    recall  f1-score   support

           0       0.77      0.44      0.56      1805
           1       0.83      0.47      0.60      1186
           2       0.74      0.56      0.64       484
           3       0.81      0.43      0.56      1323
           4       0.86      0.59      0.70       739
           5       0.88      0.47      0.62      1023
           6       0.67      0.41      0.51      1421
           7       0.84      0.64      0.73      1450
           8       0.92      0.57      0.71      1368
           9       0.55      0.41      0.47       914
          10       0.59      0.46      0.52       186
          11       0.73      0.50      0.59       553
          12       0.73      0.39      0.51       644
          13       0.46      0.16      0.24       424
          14       0.51      0.56      0.53        36
          15       0.43      0.43      0.43       352
          16       0.49      0.27      0.34       437
          17       0.62      0.42      0.50       435
          18       0.60      0.42      0.50       153
          19       0.89      0.61      0.73       727
          20       0.46      0.18      0.25       488
          21       0.71      0.37      0.49       272
          22       0.77      0.67      0.71       530
          23       0.89      0.55      0.68       618
          24       0.89      0.54      0.67       614
          25       0.56      0.23      0.33       231
          26       0.60      0.25      0.35       588
          27       0.13      0.21      0.16      1224
          28       0.68      0.41      0.51       165
          29       0.39      0.60      0.47       231
          30       0.56      0.26      0.36       190
          31       0.72      0.70      0.71       296
          32       0.59      0.35      0.44       274
          33       0.50      0.36      0.42       292
          34       0.66      0.34      0.45       190
          35       0.58      0.25      0.35        99
          36       0.86      0.55      0.67       357
          37       0.11      0.12      0.12       870
          38       0.78      0.45      0.57       135
          39       0.60      0.53      0.56        17
          40       0.55      0.06      0.11        99
          41       0.63      0.29      0.40       176
          42       0.16      0.11      0.13       236
          43       0.56      0.41      0.47        22
```

```
          44       0.59      0.23      0.33       106
          45       0.15      0.10      0.12       178
          46       0.31      0.27      0.29       241
          47       0.51      0.18      0.27       217
          48       0.58      0.48      0.52       223
          49       0.50      0.04      0.07        54
          50       0.52      0.33      0.40        92
          51       0.76      0.50      0.60       203
          52       0.34      0.47      0.39       116
          53       0.62      0.54      0.58        72
          54       0.25      0.27      0.26        15
          55       0.00      0.00      0.00        60
          56       0.83      0.88      0.85       216
          57       0.21      0.12      0.15        74
          58       0.23      0.18      0.20       139
          59       0.53      0.44      0.48        91
          60       0.43      0.12      0.19       156
          61       0.44      0.21      0.29        76
          62       0.33      0.25      0.28        89
          63       0.41      0.15      0.22       173
          64       0.38      0.44      0.41       227
          65       0.30      0.19      0.23       383
          66       0.46      0.18      0.25       148
          67       0.50      0.30      0.38       189
          68       0.62      0.20      0.30       169
          69       0.14      0.18      0.16        50
          70       0.60      0.27      0.37       145
          71       0.23      0.39      0.29        31
          72       0.84      0.82      0.83       141
          73       0.66      0.49      0.56       246
          74       0.43      0.29      0.35       210
          75       0.85      0.07      0.13       159
          76       0.45      0.30      0.36       108
          77       0.41      0.75      0.53        65
          78       0.64      0.77      0.70       145
          79       0.74      0.71      0.72        41
          80       0.51      0.75      0.61       129
          81       0.68      0.61      0.64        76
          82       0.48      0.48      0.48       124
          83       0.21      0.23      0.22        69
          84       0.26      0.21      0.23        91
          85       0.40      0.56      0.47        66
          86       0.22      0.21      0.22       100
          87       0.29      0.05      0.09        38
          88       0.53      0.52      0.53        98
          89       0.35      0.18      0.24        38
          90       0.87      0.74      0.80       154
          91       0.82      0.65      0.73       152
          92       0.00      0.00      0.00        13
          93       0.00      0.00      0.00        47
          94       0.81      0.39      0.52        44
          95       0.69      0.40      0.51       200
          96       0.31      0.16      0.21        25
          97       0.42      0.21      0.28        39
          98       0.31      0.37      0.34        51
          99       0.21      0.19      0.20        43
         100       0.17      0.09      0.12       211
         101       0.31      0.28      0.29        18
```

102	0.55	0.34	0.42	32
103	0.71	0.50	0.59	24
104	0.26	0.36	0.30	14
105	0.50	0.28	0.36	96
106	0.36	0.47	0.41	32
107	0.57	0.50	0.53	80
108	0.08	0.01	0.01	160
109	0.24	0.07	0.11	123
110	0.16	0.01	0.03	202
111	0.55	0.56	0.56	39
112	0.19	0.07	0.11	123
113	0.61	0.62	0.61	55
114	0.25	0.19	0.22	98
115	0.32	0.26	0.29	50
116	0.80	0.48	0.60	275
117	0.00	0.00	0.00	101
118	0.40	0.12	0.18	50
119	0.20	0.24	0.22	41
120	0.44	0.38	0.41	98
121	0.31	0.13	0.19	30
122	0.73	0.33	0.45	73
123	0.84	0.81	0.82	121
124	0.35	0.21	0.26	29
125	1.00	0.09	0.16	57
126	0.21	0.15	0.17	48
127	0.50	0.62	0.56	24
128	0.68	0.27	0.39	48
129	0.50	0.25	0.33	48
130	0.82	0.45	0.58	99
131	0.34	0.38	0.36	29
132	0.15	0.08	0.11	60
133	0.56	0.75	0.64	89
134	0.08	0.02	0.03	113
135	0.23	0.24	0.24	70
136	0.21	0.06	0.09	68
137	0.84	0.60	0.70	146
138	0.43	0.48	0.45	66
139	0.24	0.24	0.24	49
140	0.66	0.65	0.65	51
141	0.75	0.22	0.34	27
142	0.21	0.07	0.11	54
143	0.33	0.14	0.20	21
144	0.29	0.28	0.29	43
145	0.89	0.35	0.50	49
146	0.56	0.36	0.44	137
147	0.66	0.41	0.50	91
148	0.27	0.24	0.25	29
149	0.86	0.49	0.62	88
150	0.04	0.03	0.04	67
151	0.76	0.35	0.48	46
152	0.45	0.26	0.33	187
153	0.73	0.45	0.56	60
154	0.31	0.45	0.36	40
155	0.29	0.06	0.10	67
156	0.21	0.30	0.25	46
157	0.33	0.04	0.08	23
158	0.55	0.59	0.57	54
159	0.34	0.22	0.27	87

159	0.34	0.22	0.27	87
160	0.59	0.24	0.34	66
161	0.62	0.45	0.52	69
162	0.29	0.19	0.23	78
163	0.55	0.84	0.67	50
164	0.47	0.06	0.11	115
165	0.39	0.13	0.19	71
166	0.07	0.02	0.04	81
167	0.37	0.44	0.40	52
168	0.47	0.36	0.41	22
169	0.00	0.00	0.00	292
170	0.32	0.56	0.41	45
171	0.14	0.02	0.04	146
172	0.00	0.00	0.00	5
173	0.50	0.23	0.31	66
174	0.04	0.05	0.05	21
175	0.27	0.15	0.20	26
176	0.38	0.10	0.16	86
177	0.50	0.11	0.18	18
178	0.09	0.07	0.08	27
179	0.00	0.00	0.00	0
180	0.06	0.29	0.10	7
181	0.76	0.56	0.64	34
182	0.67	0.57	0.62	35
183	0.51	0.57	0.54	51
184	0.71	0.58	0.64	38
185	0.08	0.03	0.04	39
186	0.00	0.00	0.00	13
187	0.50	0.17	0.26	35
188	0.12	0.16	0.14	44
189	0.16	0.13	0.14	46
190	0.21	0.08	0.11	52
191	0.33	0.19	0.24	88
192	0.11	0.02	0.04	41
193	0.94	0.57	0.71	88
194	0.43	0.06	0.10	51
195	0.47	0.13	0.21	127
196	0.17	0.13	0.15	60
197	0.00	0.00	0.00	18
198	0.10	0.03	0.04	36
199	0.40	0.02	0.04	85
200	0.41	0.27	0.33	48
201	0.44	0.47	0.46	17
202	0.24	0.22	0.23	27
203	0.45	0.22	0.29	60
204	0.46	0.38	0.42	105
205	0.69	0.62	0.65	50
206	0.51	0.42	0.46	45
207	0.17	0.37	0.24	19
208	0.54	0.29	0.38	73
209	0.12	0.02	0.03	51
210	0.00	0.00	0.00	20
211	0.00	0.00	0.00	47
212	0.20	0.05	0.07	44
213	0.37	0.21	0.26	34
214	0.67	0.53	0.59	106
215	0.60	0.10	0.17	59
216	0.09	0.08	0.09	87

```
         217       0.33      0.06      0.11        31
         218       0.66      0.67      0.67        46
         219       0.20      0.15      0.17        27
         220       0.32      0.15      0.21        39
         221       0.41      0.13      0.19        55
         222       0.67      0.06      0.11        34
         223       0.11      0.64      0.19        11
         224       0.10      0.14      0.12        51
         225       0.09      0.13      0.10        46
         226       0.17      0.09      0.11        47
         227       0.06      0.07      0.07        14
         228       0.33      0.10      0.15        21
         229       0.31      0.07      0.12        67
         230       0.00      0.00      0.00       229
         231       0.30      0.11      0.16        54
         232       0.50      0.03      0.06        98
         233       0.91      0.40      0.55        53
         234       0.62      0.28      0.38        36
         235       0.70      0.40      0.51        53
         236       0.41      0.37      0.39        68
         237       0.08      0.21      0.12        38
         238       0.07      0.07      0.07       102
         239       0.07      0.33      0.11         6
         240       0.15      0.40      0.22         5
         241       0.00      0.00      0.00         3
         242       0.03      0.03      0.03        68
         243       0.38      0.32      0.35        91
         244       0.96      0.77      0.85        30
         245       0.50      0.10      0.17        50
         246       0.00      0.00      0.00         4
         247       0.42      0.37      0.39        41
         248       0.60      0.33      0.42        98
         249       0.00      0.00      0.00         0
         250       1.00      1.00      1.00         1
         251       0.67      0.15      0.25        26
         252       0.56      0.29      0.38        66
         253       0.77      0.61      0.68        67
         254       0.12      0.06      0.08        32
         255       0.00      0.00      0.00         2
         256       0.25      0.06      0.10        32
         257       0.25      0.25      0.25         4
         258       0.14      0.03      0.04        39
         259       0.80      0.44      0.57        73
         260       0.90      0.64      0.74        55
         261       0.20      0.58      0.30        12
         262       0.14      0.15      0.14        41
         263       0.50      0.07      0.12        14
         264       0.55      0.11      0.18        56
         265       0.73      0.29      0.41        77
         266       0.00      0.00      0.00        13
         267       0.33      0.25      0.29        16
         268       0.00      0.00      0.00        34
         269       0.00      0.00      0.00        45
         270       0.06      0.02      0.03        43
         271       0.31      0.30      0.31        56
         272       0.60      0.27      0.37        11
         273       0.03      0.02      0.03        42
         274       0.75      0.51      0.61        35
```

275	0.18	0.15	0.17	59
276	0.06	0.06	0.06	49
277	0.63	0.61	0.62	44
278	0.16	0.07	0.09	46
279	0.06	0.14	0.08	7
280	0.83	0.52	0.64	58
281	0.35	0.20	0.25	46
282	0.42	0.50	0.45	10
283	0.55	0.29	0.37	21
284	0.13	0.13	0.13	47
285	0.47	0.30	0.37	23
286	0.80	0.75	0.77	48
287	0.24	0.17	0.20	35
288	0.00	0.00	0.00	81
289	0.63	0.36	0.46	47
290	0.76	0.74	0.75	93
291	0.00	0.00	0.00	61
292	0.48	0.52	0.50	23
293	0.71	0.50	0.59	10
294	0.25	0.03	0.06	30
295	0.00	0.00	0.00	24
296	0.00	0.00	0.00	54
297	0.35	0.24	0.28	34
298	0.26	0.22	0.24	69
299	0.79	0.68	0.73	44
300	0.60	0.23	0.33	13
301	0.80	0.47	0.59	68
302	0.00	0.00	0.00	33
303	0.75	0.33	0.46	18
304	0.14	0.08	0.10	13
305	0.52	0.25	0.33	53
306	0.41	0.21	0.28	75
307	0.77	0.49	0.60	55
308	0.86	0.51	0.64	61
309	0.70	0.37	0.48	90
310	0.00	0.00	0.00	58
311	0.83	0.79	0.81	19
312	0.44	0.12	0.19	34
313	0.21	0.46	0.29	13
314	0.14	0.25	0.18	4
315	0.20	0.02	0.04	41
316	0.72	0.48	0.58	54
317	0.33	0.04	0.07	25
318	0.14	0.25	0.18	4
319	0.20	0.10	0.14	29
320	0.80	0.22	0.34	37
321	1.00	0.50	0.67	6
322	0.17	0.23	0.20	22
323	0.29	0.11	0.15	19
324	0.14	0.25	0.18	4
325	0.86	0.33	0.48	18
326	0.69	0.43	0.53	21
327	0.00	0.00	0.00	26
328	0.70	0.43	0.53	49
329	0.40	0.51	0.45	35
330	0.00	0.00	0.00	19
331	1.00	0.07	0.12	15
332	0.00	0.00	0.00	10

332	0.00	0.00	0.00	10
333	0.68	0.55	0.61	38
334	0.08	0.11	0.10	9
335	0.83	0.09	0.17	53
336	0.83	0.47	0.60	32
337	0.05	0.12	0.07	24
338	0.17	0.33	0.22	3
339	0.00	0.00	0.00	1
340	0.00	0.00	0.00	0
341	0.00	0.00	0.00	11
342	0.54	0.55	0.54	40
343	0.21	0.10	0.14	30
344	0.25	0.08	0.12	24
345	0.17	0.30	0.22	23
346	0.38	0.22	0.28	69
347	0.03	0.06	0.04	18
348	0.04	0.03	0.03	65
349	0.43	0.38	0.41	78
350	1.00	0.08	0.15	12
351	0.14	0.08	0.10	13
352	0.38	0.28	0.32	18
353	1.00	0.54	0.70	46
354	0.62	0.40	0.48	40
355	0.00	0.00	0.00	19
356	0.00	0.00	0.00	26
357	0.38	0.08	0.13	39
358	1.00	0.17	0.29	12
359	0.00	0.00	0.00	16
360	0.22	0.08	0.12	24
361	0.22	0.11	0.14	57
362	0.67	0.90	0.77	20
363	0.00	0.00	0.00	84
364	0.60	0.46	0.52	54
365	0.30	0.09	0.14	33
366	0.03	0.03	0.03	30
367	0.00	0.00	0.00	30
368	0.17	0.05	0.08	19
369	0.00	0.00	0.00	19
370	0.33	0.03	0.06	32
371	0.40	0.67	0.50	12
372	0.00	0.00	0.00	15
373	0.03	0.07	0.05	15
374	0.83	0.59	0.69	17
375	0.83	0.61	0.70	41
376	0.86	0.41	0.56	29
377	0.00	0.00	0.00	28
378	0.50	0.21	0.30	19
379	0.06	0.03	0.04	31
380	0.00	0.00	0.00	29
381	0.13	0.18	0.15	49
382	0.00	0.00	0.00	8
383	0.38	0.12	0.19	24
384	0.33	0.20	0.25	20
385	0.38	0.20	0.26	15
386	0.64	0.49	0.55	37
387	0.00	0.00	0.00	22
388	0.00	0.00	0.00	27
389	0.16	0.17	0.16	29

390	0.17	0.10	0.12	20
391	0.54	0.33	0.41	39
392	0.00	0.00	0.00	10
393	1.00	0.05	0.09	42
394	0.11	0.04	0.06	46
395	0.20	0.30	0.24	10
396	1.00	0.05	0.10	39
397	0.00	0.00	0.00	43
398	0.30	0.20	0.24	50
399	0.33	0.29	0.31	7
400	0.00	0.00	0.00	17
401	1.00	0.17	0.29	6
402	0.00	0.00	0.00	26
403	0.04	0.10	0.06	10
404	0.62	0.36	0.45	14
405	0.11	0.07	0.09	14
406	0.80	0.36	0.50	22
407	0.39	0.12	0.18	60
408	0.15	0.10	0.12	40
409	0.00	0.00	0.00	31
410	0.25	0.22	0.24	9
411	0.62	0.26	0.37	19
412	0.69	0.58	0.63	19
413	1.00	0.20	0.33	5
414	0.17	0.08	0.11	12
415	0.86	0.62	0.72	29
416	0.13	0.15	0.14	33
417	0.00	0.00	0.00	33
418	0.08	0.08	0.08	12
419	0.05	0.02	0.03	42
420	0.33	0.42	0.37	12
421	0.00	0.00	0.00	98
422	0.00	0.00	0.00	8
423	0.75	0.43	0.55	7
424	0.50	0.38	0.43	13
425	0.03	0.08	0.04	13
426	0.00	0.00	0.00	20
427	0.00	0.00	0.00	58
428	0.67	1.00	0.80	2
429	0.29	0.26	0.27	27
430	0.49	0.50	0.49	38
431	0.39	0.30	0.34	40
432	0.00	0.00	0.00	43
433	0.96	0.52	0.68	42
434	0.50	0.33	0.40	24
435	0.25	0.03	0.06	31
436	0.33	0.30	0.32	30
437	0.00	0.00	0.00	16
438	0.56	0.45	0.50	22
439	0.00	0.00	0.00	1
440	0.06	0.05	0.06	19
441	0.25	0.22	0.24	9
442	0.00	0.00	0.00	100
443	0.50	0.32	0.39	28
444	0.60	0.60	0.60	20
445	0.44	0.41	0.43	29
446	0.17	0.05	0.07	21
447	0.00	0.00	0.00	20

```
         448       0.85      0.29      0.43        38
         449       0.00      0.00      0.00        22
         450       0.56      0.48      0.51        21
         451       0.00      0.00      0.00        13
         452       0.00      0.00      0.00        24
         453       0.40      0.04      0.08        48
         454       0.00      0.00      0.00        75
         455       0.00      0.00      0.00        18
         456       0.00      0.00      0.00         3
         457       0.32      0.46      0.37        13
         458       0.00      0.00      0.00        13
         459       0.06      0.04      0.05        24
         460       0.27      0.17      0.21        36
         461       0.20      0.11      0.14        18
         462       0.50      0.03      0.06        31
         463       0.00      0.00      0.00        28
         464       0.25      0.14      0.18         7
         465       0.80      0.30      0.43        27
         466       0.00      0.00      0.00        12
         467       0.00      0.00      0.00        14
         468       0.00      0.00      0.00         6
         469       0.25      0.18      0.21        17
         470       0.15      0.22      0.18        18
         471       0.02      0.03      0.03        29
         472       0.00      0.00      0.00         2
         473       0.33      0.03      0.05        34
         474       0.00      0.00      0.00         8
         475       1.00      0.25      0.40         4
         476       0.22      0.09      0.13        22
         477       0.20      0.50      0.29         6
         478       0.26      0.29      0.28        17
         479       0.20      0.04      0.07        23
         480       1.00      0.06      0.11        18
         481       0.67      0.18      0.29        11
         482       0.93      0.37      0.53        35
         483       0.61      0.52      0.56        21
         484       0.83      0.54      0.65        28
         485       0.33      0.29      0.31        14
         486       0.91      0.91      0.91        11
         487       1.00      0.20      0.33        15
         488       0.00      0.00      0.00        38
         489       0.00      0.00      0.00        75
         490       1.00      0.12      0.21        51
         491       1.00      0.58      0.73        19
         492       0.45      0.24      0.31        21
         493       0.00      0.00      0.00        16
         494       0.44      0.67      0.53         6
         495       0.11      0.09      0.10        22
         496       0.49      0.49      0.49        37
         497       0.17      0.10      0.12        20
         498       0.56      0.42      0.48        24
         499       0.00      0.00      0.00        17

   micro avg       0.54      0.35      0.43     47151
   macro avg       0.39      0.26      0.29     47151
weighted avg       0.55      0.35      0.41     47151
 samples avg       0.42      0.34      0.35     47151
```

```
Time taken to run this cell : 0:03:22.300054
```

Task 3: Apply OneVsRestClassifier with Linear-SVM

Hyperparameter Tuning

```
from tqdm import tqdm
start = datetime.now()
alpha = [10 ** x for x in range(-10, -3, 2)]
perf_metric = []
for i in tqdm(alpha):
    clf = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=i, penalty='l1', random_state
    clf.fit(x_train_multilabel, y_train)
    predictions = clf.predict (x_test_multilabel)
    # append the micro-f1 score for the particular alpha trained classifier
    perf_metric.append(f1_score(y_test, predictions, average='micro'))
print("Time taken to run this cell :", datetime.now() - start)
```

```
100%|
Time taken to run this cell : 0:29:51.230015
```

```
# plot the perf metric for each hyperparam(alpha)
fig, ax = plt.subplots()
ax.plot(perf_metric)
xlabel = list(range(-11, -3))
ax.set_xticklabels(xlabel)
plt.title("Perf-metric vs hyperparam plot - Lin SVM")
plt.xlabel("Alpha(in 10^)")
plt.ylabel("Micro-averaged F1 score")
plt.grid()
plt.show()
```

Perf-metric vs hyperparam plot - Lin SVM

```
start = datetime.now()
# fetching the best alpha
best_alpha = alpha[np.argmax(perf_metric)]
print('Best hyperparam(alpha) : ',best_alpha)

# train the Lin SVM model with the best alpha
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=best_alpha, penalty='l1',
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)

# print the various performance metrices
print("Accuracy :",metrics.accuracy_score(y_test, predictions))
print("Hamming loss :",metrics.hamming_loss(y_test,predictions))


precision = precision_score(y_test, predictions, average='micro')
recall = recall_score(y_test, predictions, average='micro')
f1 = f1_score(y_test, predictions, average='micro')

print("\nMicro-average quality numbers -")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(precision, recall, f1))

precision = precision_score(y_test, predictions, average='macro')
recall = recall_score(y_test, predictions, average='macro')
f1 = f1_score(y_test, predictions, average='macro')

print("\nMacro-average quality numbers -")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(precision, recall, f1))

print("\n")
print (metrics.classification_report(y_test, predictions))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Best hyperparam(alpha) :  0.0001
Accuracy : 0.0877
Hamming loss : 0.006592

Micro-average quality numbers -
Precision: 0.3473, Recall: 0.4527, F1-measure: 0.3931

Macro-average quality numbers -
Precision: 0.2390, Recall: 0.3426, F1-measure: 0.2656


                 precision    recall  f1-score   support

            0       0.59      0.53      0.56      1805
            1       0.64      0.59      0.62      1186
            2       0.52      0.70      0.60       484
            3       0.60      0.51      0.55      1323
            4       0.56      0.65      0.60       739
            5       0.65      0.50      0.56      1023
            6       0.54      0.47      0.50      1421
            7       0.75      0.72      0.74      1450
            8       0.83      0.80      0.82      1368
            9       0.50      0.51      0.51       914
           10       0.25      0.51      0.33       186
           11       0.57      0.53      0.54       553
           12       0.57      0.52      0.54       644
           13       0.34      0.33      0.34       424
           14       0.11      0.47      0.18        36
           15       0.34      0.44      0.38       352
           16       0.30      0.38      0.34       437
           17       0.42      0.51      0.46       435
           18       0.44      0.65      0.53       153
           19       0.78      0.70      0.74       727
           20       0.32      0.44      0.37       488
           21       0.48      0.71      0.58       272
           22       0.58      0.71      0.64       530
           23       0.80      0.63      0.71       618
           24       0.81      0.63      0.70       614
           25       0.22      0.44      0.30       231
           26       0.30      0.66      0.41       588
           27       0.24      0.45      0.31      1224
           28       0.54      0.60      0.57       165
           29       0.32      0.61      0.42       231
           30       0.20      0.42      0.27       190
           31       0.63      0.66      0.64       296
           32       0.33      0.36      0.35       274
           33       0.29      0.42      0.34       292
           34       0.31      0.35      0.33       190
           35       0.47      0.58      0.52        99
           36       0.56      0.65      0.60       357
           37       0.25      0.39      0.30       870
           38       0.50      0.56      0.53       135
           39       0.12      0.47      0.19        17
           40       0.17      0.17      0.17        99
           41       0.25      0.40      0.31       176
           42       0.14      0.19      0.16       236
           43       0.09      0.32      0.14        22
```

```
          44       0.21      0.29      0.25       106
          45       0.19      0.24      0.21       178
          46       0.18      0.31      0.23       241
          47       0.26      0.28      0.27       217
          48       0.44      0.54      0.48       223
          49       0.09      0.11      0.10        54
          50       0.29      0.50      0.37        92
          51       0.65      0.51      0.57       203
          52       0.29      0.51      0.37       116
          53       0.19      0.56      0.29        72
          54       0.04      0.20      0.07        15
          55       0.17      0.15      0.16        60
          56       0.71      0.86      0.78       216
          57       0.28      0.19      0.23        74
          58       0.12      0.06      0.09       139
          59       0.37      0.58      0.45        91
          60       0.15      0.19      0.17       156
          61       0.31      0.37      0.34        76
          62       0.13      0.21      0.16        89
          63       0.15      0.21      0.17       173
          64       0.37      0.51      0.43       227
          65       0.26      0.31      0.28       383
          66       0.18      0.32      0.24       148
          67       0.44      0.53      0.48       189
          68       0.29      0.37      0.33       169
          69       0.06      0.22      0.10        50
          70       0.24      0.42      0.31       145
          71       0.14      0.26      0.18        31
          72       0.57      0.82      0.67       141
          73       0.39      0.59      0.47       246
          74       0.35      0.37      0.36       210
          75       0.26      0.20      0.23       159
          76       0.19      0.29      0.23       108
          77       0.59      0.78      0.67        65
          78       0.63      0.72      0.67       145
          79       0.53      0.76      0.63        41
          80       0.46      0.74      0.56       129
          81       0.28      0.63      0.38        76
          82       0.28      0.50      0.36       124
          83       0.08      0.19      0.11        69
          84       0.14      0.21      0.17        91
          85       0.20      0.53      0.29        66
          86       0.15      0.23      0.18       100
          87       0.22      0.34      0.27        38
          88       0.34      0.28      0.31        98
          89       0.29      0.58      0.38        38
          90       0.55      0.73      0.63       154
          91       0.49      0.72      0.58       152
          92       0.00      0.00      0.00        13
          93       0.02      0.02      0.02        47
          94       0.14      0.45      0.21        44
          95       0.30      0.47      0.36       200
          96       0.21      0.28      0.24        25
          97       0.22      0.36      0.27        39
          98       0.23      0.45      0.31        51
          99       0.13      0.26      0.17        43
         100       0.26      0.22      0.24       211
         101       0.14      0.33      0.20        18
```

102	0.37	0.56	0.44	32
103	0.09	0.58	0.15	24
104	0.03	0.21	0.05	14
105	0.42	0.43	0.42	96
106	0.41	0.53	0.47	32
107	0.46	0.34	0.39	80
108	0.42	0.34	0.37	160
109	0.14	0.11	0.12	123
110	0.13	0.22	0.16	202
111	0.34	0.56	0.43	39
112	0.23	0.26	0.24	123
113	0.39	0.51	0.44	55
114	0.16	0.14	0.15	98
115	0.12	0.30	0.18	50
116	0.34	0.57	0.43	275
117	0.08	0.11	0.09	101
118	0.14	0.24	0.18	50
119	0.19	0.27	0.22	41
120	0.33	0.32	0.32	98
121	0.07	0.20	0.10	30
122	0.29	0.49	0.36	73
123	0.49	0.83	0.62	121
124	0.26	0.55	0.36	29
125	0.43	0.37	0.40	57
126	0.14	0.12	0.13	48
127	0.19	0.79	0.30	24
128	0.20	0.23	0.21	48
129	0.24	0.27	0.25	48
130	0.39	0.62	0.48	99
131	0.09	0.41	0.14	29
132	0.08	0.13	0.10	60
133	0.53	0.62	0.57	89
134	0.07	0.11	0.09	113
135	0.12	0.33	0.18	70
136	0.11	0.22	0.15	68
137	0.59	0.62	0.61	146
138	0.30	0.47	0.36	66
139	0.07	0.22	0.11	49
140	0.20	0.59	0.30	51
141	0.26	0.41	0.32	27
142	0.07	0.13	0.09	54
143	0.05	0.14	0.07	21
144	0.15	0.44	0.22	43
145	0.45	0.37	0.40	49
146	0.36	0.49	0.41	137
147	0.37	0.56	0.45	91
148	0.16	0.41	0.24	29
149	0.50	0.62	0.56	88
150	0.11	0.16	0.13	67
151	0.40	0.41	0.40	46
152	0.24	0.32	0.27	187
153	0.27	0.43	0.33	60
154	0.42	0.40	0.41	40
155	0.17	0.06	0.09	67
156	0.18	0.33	0.23	46
157	0.17	0.43	0.25	23
158	0.41	0.59	0.48	54
159	0.22	0.23	0.22	87

159	0.22	0.23	0.22	87
160	0.37	0.36	0.37	66
161	0.42	0.58	0.48	69
162	0.15	0.36	0.21	78
163	0.65	0.88	0.75	50
164	0.15	0.23	0.18	115
165	0.39	0.15	0.22	71
166	0.05	0.07	0.06	81
167	0.18	0.50	0.26	52
168	0.28	0.59	0.38	22
169	0.50	0.01	0.01	292
170	0.20	0.58	0.30	45
171	0.08	0.03	0.04	146
172	0.00	0.00	0.00	5
173	0.14	0.05	0.07	66
174	0.08	0.29	0.13	21
175	0.10	0.23	0.14	26
176	0.16	0.14	0.15	86
177	0.09	0.17	0.12	18
178	0.04	0.11	0.06	27
179	0.00	0.00	0.00	0
180	0.11	0.57	0.19	7
181	0.54	0.62	0.58	34
182	0.46	0.66	0.54	35
183	0.35	0.57	0.43	51
184	0.41	0.68	0.51	38
185	0.00	0.00	0.00	39
186	0.25	0.38	0.30	13
187	0.34	0.40	0.37	35
188	0.09	0.18	0.12	44
189	0.12	0.24	0.16	46
190	0.17	0.23	0.20	52
191	0.17	0.23	0.20	88
192	0.04	0.07	0.05	41
193	0.86	0.70	0.78	88
194	0.05	0.10	0.07	51
195	0.28	0.32	0.30	127
196	0.07	0.12	0.09	60
197	0.11	0.22	0.15	18
198	0.04	0.06	0.04	36
199	0.09	0.16	0.11	85
200	0.22	0.31	0.26	48
201	0.17	0.71	0.28	17
202	0.21	0.30	0.24	27
203	0.17	0.45	0.25	60
204	0.44	0.51	0.48	105
205	0.42	0.44	0.43	50
206	0.21	0.33	0.25	45
207	0.28	0.58	0.37	19
208	0.22	0.38	0.28	73
209	0.21	0.12	0.15	51
210	0.15	0.25	0.19	20
211	0.08	0.09	0.08	47
212	0.06	0.05	0.05	44
213	0.32	0.35	0.34	34
214	0.46	0.55	0.50	106
215	0.31	0.47	0.37	59
216	0.12	0.22	0.15	87

```
         217       0.23      0.29      0.25        31
         218       0.35      0.72      0.47        46
         219       0.04      0.22      0.06        27
         220       0.09      0.10      0.10        39
         221       0.24      0.35      0.29        55
         222       0.40      0.18      0.24        34
         223       0.16      0.64      0.26        11
         224       0.11      0.14      0.12        51
         225       0.07      0.11      0.08        46
         226       0.11      0.23      0.15        47
         227       0.06      0.14      0.09        14
         228       0.12      0.24      0.16        21
         229       0.15      0.25      0.18        67
         230       0.00      0.00      0.00       229
         231       0.09      0.15      0.11        54
         232       0.36      0.16      0.22        98
         233       0.63      0.45      0.53        53
         234       0.19      0.33      0.24        36
         235       0.25      0.51      0.33        53
         236       0.28      0.40      0.33        68
         237       0.05      0.21      0.09        38
         238       0.14      0.23      0.17       102
         239       0.07      0.33      0.12         6
         240       0.03      0.20      0.06         5
         241       0.15      0.67      0.25         3
         242       0.16      0.16      0.16        68
         243       0.38      0.38      0.38        91
         244       0.35      0.83      0.49        30
         245       0.21      0.32      0.26        50
         246       0.06      0.25      0.10         4
         247       0.25      0.44      0.32        41
         248       0.29      0.26      0.27        98
         249       0.00      0.00      0.00         0
         250       0.10      1.00      0.18         1
         251       0.12      0.27      0.16        26
         252       0.42      0.27      0.33        66
         253       0.44      0.70      0.54        67
         254       0.02      0.06      0.03        32
         255       0.00      0.00      0.00         2
         256       0.07      0.16      0.10        32
         257       0.03      0.50      0.05         4
         258       0.04      0.08      0.05        39
         259       0.51      0.49      0.50        73
         260       0.71      0.55      0.62        55
         261       0.24      0.67      0.36        12
         262       0.11      0.24      0.15        41
         263       0.25      0.29      0.27        14
         264       0.15      0.20      0.17        56
         265       0.37      0.38      0.37        77
         266       0.00      0.00      0.00        13
         267       0.27      0.44      0.33        16
         268       0.02      0.03      0.03        34
         269       0.04      0.02      0.03        45
         270       0.06      0.12      0.08        43
         271       0.27      0.46      0.34        56
         272       0.14      0.27      0.19        11
         273       0.10      0.05      0.06        42
         274       0.69      0.57      0.62        35
```

275	0.04	0.03	0.04	59
276	0.07	0.18	0.11	49
277	0.61	0.64	0.62	44
278	0.11	0.11	0.11	46
279	0.00	0.00	0.00	7
280	0.55	0.66	0.60	58
281	0.48	0.26	0.34	46
282	0.19	0.50	0.27	10
283	0.30	0.33	0.32	21
284	0.07	0.11	0.09	47
285	0.15	0.26	0.19	23
286	0.49	0.77	0.60	48
287	0.39	0.51	0.44	35
288	0.05	0.04	0.04	81
289	0.37	0.53	0.44	47
290	0.62	0.83	0.71	93
291	0.18	0.21	0.19	61
292	0.26	0.70	0.38	23
293	0.23	0.50	0.31	10
294	0.22	0.07	0.10	30
295	0.05	0.08	0.06	24
296	0.08	0.07	0.08	54
297	0.23	0.62	0.34	34
298	0.21	0.39	0.28	69
299	0.63	0.86	0.73	44
300	0.47	0.54	0.50	13
301	0.52	0.56	0.54	68
302	0.02	0.06	0.04	33
303	0.28	0.39	0.33	18
304	0.07	0.38	0.11	13
305	0.19	0.28	0.23	53
306	0.22	0.33	0.26	75
307	0.45	0.62	0.52	55
308	0.79	0.67	0.73	61
309	0.46	0.49	0.47	90
310	0.53	0.16	0.24	58
311	0.28	0.84	0.42	19
312	0.16	0.24	0.19	34
313	0.16	0.38	0.22	13
314	0.11	0.50	0.18	4
315	0.06	0.07	0.07	41
316	0.43	0.52	0.47	54
317	0.18	0.24	0.20	25
318	0.13	0.50	0.21	4
319	0.04	0.14	0.06	29
320	0.10	0.16	0.13	37
321	0.33	0.50	0.40	6
322	0.22	0.50	0.30	22
323	0.08	0.11	0.09	19
324	0.12	0.50	0.20	4
325	0.29	0.56	0.38	18
326	0.35	0.57	0.44	21
327	0.07	0.12	0.09	26
328	0.28	0.55	0.37	49
329	0.43	0.51	0.47	35
330	0.00	0.00	0.00	19
331	0.17	0.20	0.18	15

332	0.08	0.20	0.12	10
333	0.51	0.50	0.51	38
334	0.06	0.22	0.09	9
335	0.39	0.21	0.27	53
336	0.68	0.66	0.67	32
337	0.05	0.08	0.06	24
338	0.03	0.33	0.05	3
339	0.00	0.00	0.00	1
340	0.00	0.00	0.00	0
341	0.12	0.27	0.17	11
342	0.27	0.72	0.39	40
343	0.12	0.07	0.09	30
344	0.11	0.04	0.06	24
345	0.08	0.35	0.13	23
346	0.29	0.25	0.27	69
347	0.10	0.22	0.14	18
348	0.11	0.20	0.14	65
349	0.33	0.27	0.30	78
350	0.00	0.00	0.00	12
351	0.10	0.46	0.16	13
352	0.00	0.00	0.00	18
353	0.76	0.76	0.76	46
354	0.24	0.47	0.32	40
355	0.05	0.11	0.07	19
356	0.08	0.08	0.08	26
357	0.23	0.23	0.23	39
358	0.15	0.17	0.16	12
359	0.00	0.00	0.00	16
360	0.08	0.08	0.08	24
361	0.20	0.18	0.19	57
362	0.55	0.85	0.67	20
363	0.36	0.11	0.17	84
364	0.44	0.67	0.53	54
365	0.15	0.21	0.18	33
366	0.05	0.10	0.07	30
367	0.08	0.03	0.05	30
368	0.00	0.00	0.00	19
369	0.00	0.00	0.00	19
370	0.05	0.06	0.06	32
371	0.15	0.67	0.25	12
372	0.04	0.07	0.05	15
373	0.05	0.13	0.07	15
374	0.61	0.65	0.63	17
375	0.52	0.83	0.64	41
376	0.28	0.62	0.39	29
377	0.04	0.04	0.04	28
378	0.09	0.16	0.12	19
379	0.16	0.16	0.16	31
380	0.18	0.14	0.16	29
381	0.11	0.22	0.14	49
382	0.03	0.12	0.05	8
383	0.08	0.29	0.13	24
384	0.11	0.45	0.17	20
385	0.06	0.13	0.09	15
386	0.52	0.59	0.56	37
387	0.03	0.09	0.05	22
388	0.00	0.00	0.00	27
389	0.20	0.34	0.25	29

390	0.06	0.10	0.07	20
391	0.33	0.56	0.42	39
392	0.06	0.10	0.07	10
393	0.27	0.31	0.29	42
394	0.12	0.13	0.12	46
395	0.03	0.10	0.05	10
396	0.00	0.00	0.00	39
397	0.00	0.00	0.00	43
398	0.27	0.24	0.25	50
399	0.12	0.71	0.21	7
400	0.02	0.06	0.03	17
401	0.08	0.33	0.13	6
402	0.00	0.00	0.00	26
403	0.02	0.10	0.03	10
404	0.17	0.29	0.22	14
405	0.07	0.14	0.10	14
406	0.50	0.55	0.52	22
407	0.22	0.23	0.22	60
408	0.26	0.28	0.27	40
409	0.06	0.13	0.08	31
410	0.17	0.33	0.22	9
411	0.15	0.32	0.20	19
412	0.41	0.63	0.50	19
413	0.17	0.20	0.18	5
414	0.00	0.08	0.01	12
415	0.47	0.59	0.52	29
416	0.04	0.09	0.06	33
417	0.10	0.21	0.13	33
418	0.04	0.08	0.05	12
419	0.11	0.14	0.12	42
420	0.12	0.08	0.10	12
421	0.29	0.32	0.30	98
422	0.06	0.12	0.08	8
423	0.08	0.14	0.10	7
424	0.25	0.62	0.36	13
425	0.08	0.15	0.11	13
426	0.13	0.30	0.18	20
427	0.07	0.12	0.09	58
428	0.25	1.00	0.40	2
429	0.28	0.41	0.33	27
430	0.35	0.39	0.37	38
431	0.22	0.38	0.28	40
432	0.03	0.12	0.05	43
433	0.60	0.67	0.63	42
434	0.21	0.21	0.21	24
435	0.12	0.23	0.16	31
436	0.17	0.17	0.17	30
437	0.06	0.12	0.08	16
438	0.31	0.41	0.35	22
439	0.00	0.00	0.00	1
440	0.09	0.11	0.10	19
441	0.03	0.22	0.05	9
442	0.30	0.20	0.24	100
443	0.44	0.57	0.50	28
444	0.34	0.75	0.47	20
445	0.41	0.62	0.49	29
446	0.04	0.10	0.06	21
447	0.24	0.45	0.32	20

448	0.78	0.55	0.65	38
449	0.05	0.09	0.06	22
450	0.45	0.43	0.44	21
451	0.07	0.23	0.11	13
452	0.03	0.08	0.05	24
453	0.20	0.10	0.14	48
454	0.28	0.32	0.30	75
455	0.14	0.22	0.17	18
456	0.04	0.33	0.07	3
457	0.19	0.46	0.27	13
458	0.00	0.00	0.00	13
459	0.18	0.33	0.24	24
460	0.20	0.36	0.25	36
461	0.31	0.61	0.42	18
462	0.18	0.32	0.23	31
463	0.22	0.14	0.17	28
464	0.00	0.00	0.00	7
465	0.26	0.33	0.30	27
466	0.41	0.75	0.53	12
467	0.12	0.21	0.15	14
468	0.00	0.00	0.00	6
469	0.08	0.12	0.10	17
470	0.11	0.28	0.16	18
471	0.14	0.10	0.12	29
472	0.00	0.00	0.00	2
473	0.35	0.18	0.24	34
474	0.00	0.00	0.00	8
475	0.10	0.50	0.17	4
476	0.28	0.50	0.35	22
477	0.09	0.67	0.15	6
478	0.20	0.24	0.22	17
479	0.25	0.04	0.07	23
480	0.18	0.28	0.22	18
481	0.04	0.18	0.06	11
482	0.32	0.34	0.33	35
483	0.31	0.57	0.40	21
484	0.47	0.61	0.53	28
485	0.11	0.21	0.15	14
486	0.42	0.73	0.53	11
487	0.21	0.33	0.26	15
488	0.16	0.21	0.18	38
489	0.15	0.16	0.15	75
490	0.89	0.49	0.63	51
491	0.74	0.74	0.74	19
492	0.25	0.24	0.24	21
493	0.07	0.25	0.11	16
494	0.31	0.83	0.45	6
495	0.05	0.05	0.05	22
496	0.27	0.49	0.35	37
497	0.03	0.05	0.04	20
498	0.55	0.50	0.52	24
499	0.04	0.12	0.06	17
micro avg	0.35	0.45	0.39	47151
macro avg	0.24	0.34	0.27	47151
weighted avg	0.40	0.45	0.41	47151
samples avg	0.39	0.44	0.37	47151

```
Time taken to run this cell : 0:05:57.704523
```

```
from prettytable import PrettyTable
tb = PrettyTable()
tb.field_names= ("Vectorizer",                        "Model",
tb.add_row(["                tf-idf",                   "Logistic Regression with OVR classif
tb.add_row(["                Bow",                   "Logistic Regression with OVR classifier
tb.add_row(["                Bow",                    "SGD classifier(Logistic loss) with OVR
tb.add_row(["                Bow",                     "SGD classifier(Hinge loss)  with OVR
print(tb.get_string(titles = "KNN - Observations"))
```

```
+------------------------+--------------------------------------------------------------
|       Vectorizer       |                                  Model
+------------------------+--------------------------------------------------------------
|                 tf-idf |                 Logistic Regression with OVR classifier
|                  Bow   |                 Logistic Regression with OVR classifier
|                  Bow   | SGD classifier(Logistic loss) with OVR classifier with parame
|                  Bow   |  SGD classifier(Hinge loss)  with OVR classifier with paramet
+------------------------+--------------------------------------------------------------
```

Step by Step Procedure

- Get the Data from csv file and load into the sqlite database.
- Remove the duplicates rows and load the data in a new database.
- Analysis on tags and save the dictionary(Frequecny of each tag) into csv file.
- Text preprocessing and save the preprocessed text in a new database.
- Now we have 42k tags, now we will reduce the unnecessary tags and use only the most frequer questions.
- Now we have many rows, high dimensions with 5500 tags, even if we apply a simple logistic reg above24 hours with my low ram.
- Now i Took a 0.1 million datapoint From Non_duplicate_Rows_table and again did all the steps -
    - Text Preprocessing and gave high weitage to title by repeating it 3 times.
- Took a first 500 frequent tags that cover the 90% of questions.
- Now apply a logistic regression with tfidf vectorizer.
- Now at last i applied 2 modles logistic regression and linear svm One vs rest classifier with hyp
- Compare all models