Stack Overflow: Tag Prediction

1. Business Problem

Description

Stack Overflow is the largest, most trusted online community for developers to learn, share their programming knowledge, and build their careers.

Stack Overflow is something which every programmer use one way or another. Each month, over 50 million developers come to Stack Overflow to learn, share their knowledge, and build their careers. It features questions and answers on a wide range of topics in computer programming. The website serves as a platform for users to ask and answer questions, and, through membership and active participation, to vote questions and answers up or down and edit questions and answers in a fashion similar to a wiki or Digg. As of April 2014 Stack Overflow has over 4,000,000 registered users, and it exceeded 10,000,000 questions in late August 2015. Based on the type of tags assigned to questions, the top eight most discussed topics on the site are: Java, JavaScript, C#, PHP, Android, jQuery, Python and HTML.

Problem Statement

Suggest the tags based on the content that was there in the question posted on Stackoverflow.

LOAD REQUIRED LIBRARIES

```
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 sqlalchemy import create_engine # database connection
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 sklearn.naive_bayes import GaussianNB
from datetime import datetime
```

CONNECT TO GOOGLE COLAB

```
from google.colab import drive

drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", for
```

LOAD THE DATA FROM CSV FILE TO TRAIN.DB

```
if not os.path.isfile('train.db'):
  start = datetime.now()
  disk_engine = create_engine('sqlite:///train.db')
  start=dt.datetime.now()
  chunksize=180000
  j=0
  index_start=1
  for df in pd.read_csv('/content/drive/My Drive/Colab Notebooks/StackOverflow Tag Predictor/Train.csv',names=['Id
    df.index +=index_start
    j+=1
    df.to_sql('data', disk_engine, if_exists='append')
    index_start = df.index[-1] + 1
  print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:04:30.307245
```

COUNT THE TOTAL NO OF ROWS

```
if os.path.isfile('train.db'):
  start = datetime.now()
  con=sqlite3.connect('train.db')
  num_rows = pd.read_sql_query("""SELECT count(*) FROM data""",con)
  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)
else :
  print("Please download the train.db file from drive or run the above cell to genarate train.db file")
```

```
Number of rows in the database :
 6034196
Time taken to count the number of rows : 0:00:14.149502
```

CHECK FOR DUPLICATES

```
if os.path.isfile('train.db'):
  start = datetime.now()
  con=sqlite3.connect('train.db')
  df_no_duplicate=pd.read_sql_query('SELECT Title, Body, Tags, COUNT(*) as cnt_dup FROM data GROUP BY Title, Body,
  con.close()
  print("Time taken to run this cell :", datetime.now() - start)
else:
  print("Please download the train.db file from drive or run the first to genarate train.db file")
```

```
Time taken to run this cell : 0:05:11.238108
```

```
df_no_duplicate.head()
```

	Title	Body	Tags	cnt_dup
0	Implementing Boundary Value Analysis of S...	<pre> <code>#include<iostream>\n#include&...	c++ c	1

```
print("number of duplicate questions :", num_rows['count(*)'].values[0]- df_no_duplicate.shape[0], "(",(1-((df_no_
```

```
number of duplicate questions : 1827881 ( 30.292038906260256 % )
```

2	Dynamic Datagrid Binding in Silverlight?	<p>I should do binding for datagrid dynamicall...	c# silverlight data-binding columns	1

```
df_no_duplicate.cnt_dup.value_counts()
```

```
1    2656284
2    1272336
3     277575
4         90
5         25
6          5
Name: cnt_dup, dtype: int64
```

```
df_no_duplicate["Tags"].head()
```

```
0                                c++ c
1            c# silverlight data-binding
2    c# silverlight data-binding columns
3                             jsp jstl
4                            java jdbc
Name: Tags, dtype: object
```

```
start = datetime.now()
df_no_duplicate["tag_count"] = df_no_duplicate["Tags"].apply(lambda text: len(str(text).split()))
print("Time taken to run this cell :", datetime.now() - start)
df_no_duplicate.head()
```

```
Time taken to run this cell : 0:00:03.016791
```

	Title	Body	Tags	cnt_dup	tag_count
0	Implementing Boundary Value Analysis of S...	<pre> <code>#include<iostream>\n#include&...	c++ c	1	2
1	Dynamic Datagrid Binding in Silverlight?	<p>I should do binding for datagrid dynamicall...	c# silverlight data-binding	1	3
2	Dynamic Datagrid Binding in Silverlight?	<p>I should do binding for datagrid dynamicall...	c# silverlight data-binding columns	1	4

```
df_no_duplicate.tag_count.value_counts()
```

```
3    1206157
2    1111706
4     814996
1     568298
5     505158
Name: tag_count, dtype: int64
```

```
if not os.path.isfile('train_no_dup.db'):
    disk_dup = create_engine("sqlite:///train_no_dup.db")
    no_dup = pd.DataFrame(df_no_duplicate, columns=['Title', 'Body', 'Tags'])
    no_dup.to_sql('no_dup_train',disk_dup)
```

```
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)
```

```
    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("Time taken to run this cell :", datetime.now() - start)
else:
    print("Please download the train.db file from drive or run the above cells to genarate train.db file")
```

```
Time taken to run this cell : 0:01:54.541361
```

```
tag_data.head()
```

	Tags
1	c# silverlight data-binding
2	c# silverlight data-binding columns
3	jsp jstl
4	java jdbc
5	facebook api facebook-php-sdk

```
tag_data.loc[tag_data['Tags'].isnull(),'Tags'] = ''
```

ANALYSIS OF TAGS --> COUNTVECTORIZER

```
vectorizer=CountVectorizer(tokenizer = lambda x : str(x).split())

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])
```

```
Number of data points : 4206314
Number of unique tags : 42048
```

```
feature_tags=vectorizer.get_feature_names()

print("Some of the tags we have :", feature_tags[:10])
```

```
Some of the tags we have : ['.a', '.app', '.asp.net-mvc', '.aspxauth', '.bash-profile', '.class-file', '.cs-fil
```

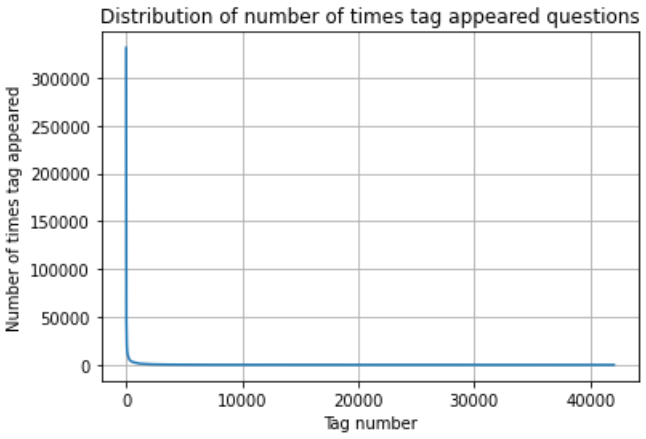
```
freqs = tag_dtm.sum(axis=0).A1
result = dict(zip(feature_tags, freqs))
```

```
if not os.path.isfile('tag_counts_dict_dtm.csv'):
    with open('tag_counts_dict_dtm.csv', 'w') as csv_file:
        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()
```

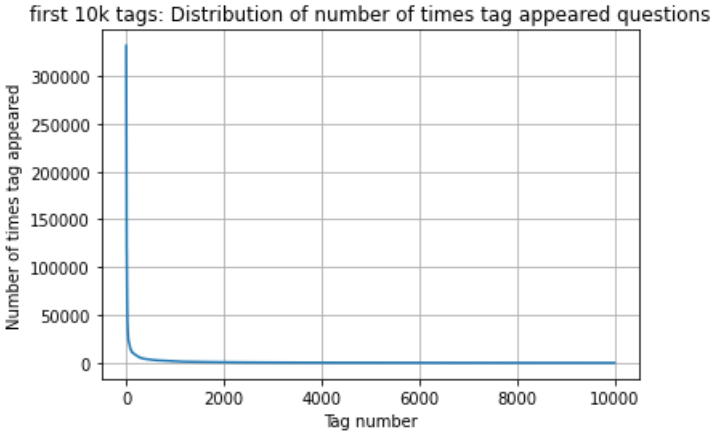
	Tags	Counts
0	.a	18
1	.app	37
2	.asp.net-mvc	1
3	.aspxauth	21

```
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()
```

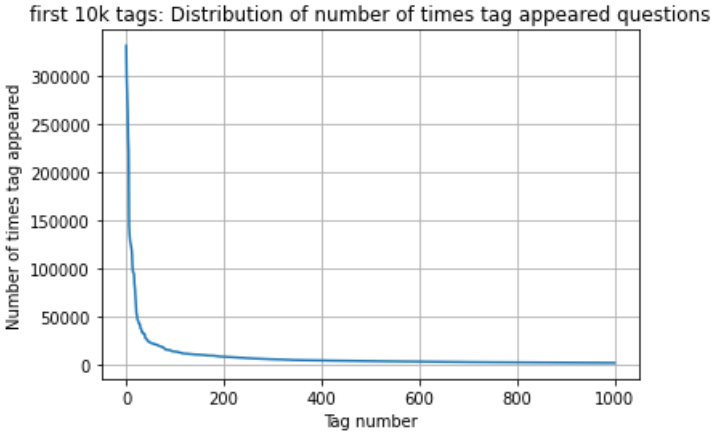



```
plt.plot(tag_counts[0:10000])
plt.title('first 10k tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
```

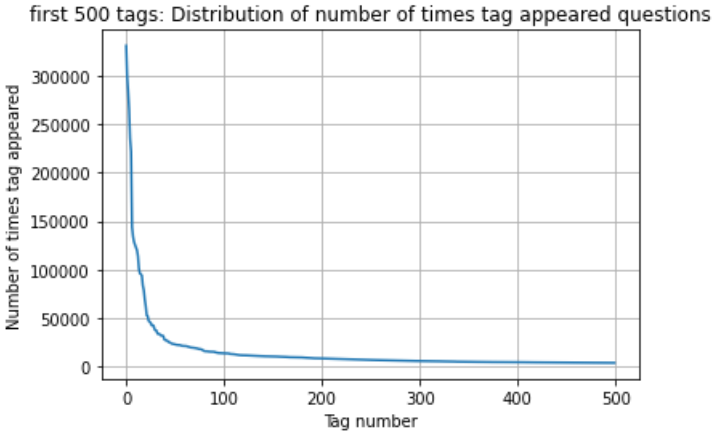



```
plt.plot(tag_counts[0:1000])
plt.title('first 10k tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
```

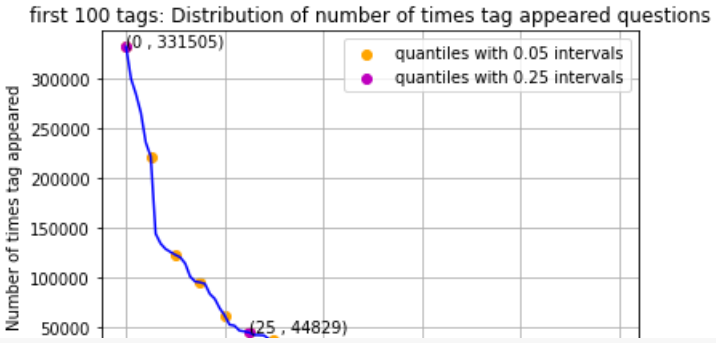
```
plt.ylabel("Number of times tag appeared")
plt.show()
```




```
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()
```




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

for x,y in zip(list(range(0,100,25)), tag_counts[0:100:25]):
    plt.annotate(s="({} , {})".format(x,y), xy=(x,y), xytext=(x-0.05, y+500))

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].Tags
#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].Tags
#Print the length of the list.
print ('{} Tags are used more than 100000 times'.format(len(lst_tags_gt_100k)))
```

```
153 Tags are used more than 10000 times
14 Tags are used more than 100000 times
```

Observations:

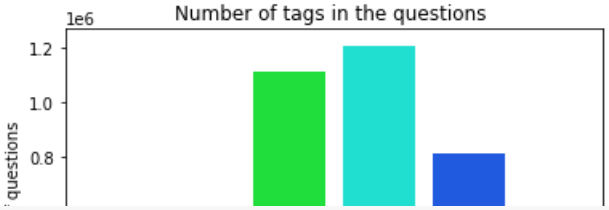
1. There are total 153 tags which are used more than 10000 times.
2. 14 tags are used more than 100000 times.
3. Most frequent tag (i.e. c#) is used 331505 times.
4. Since some tags occur much more frequenctly than others
5. Micro-averaged. F1-score is the appropriate metric for this probelm.

TAGS PER QUESTION

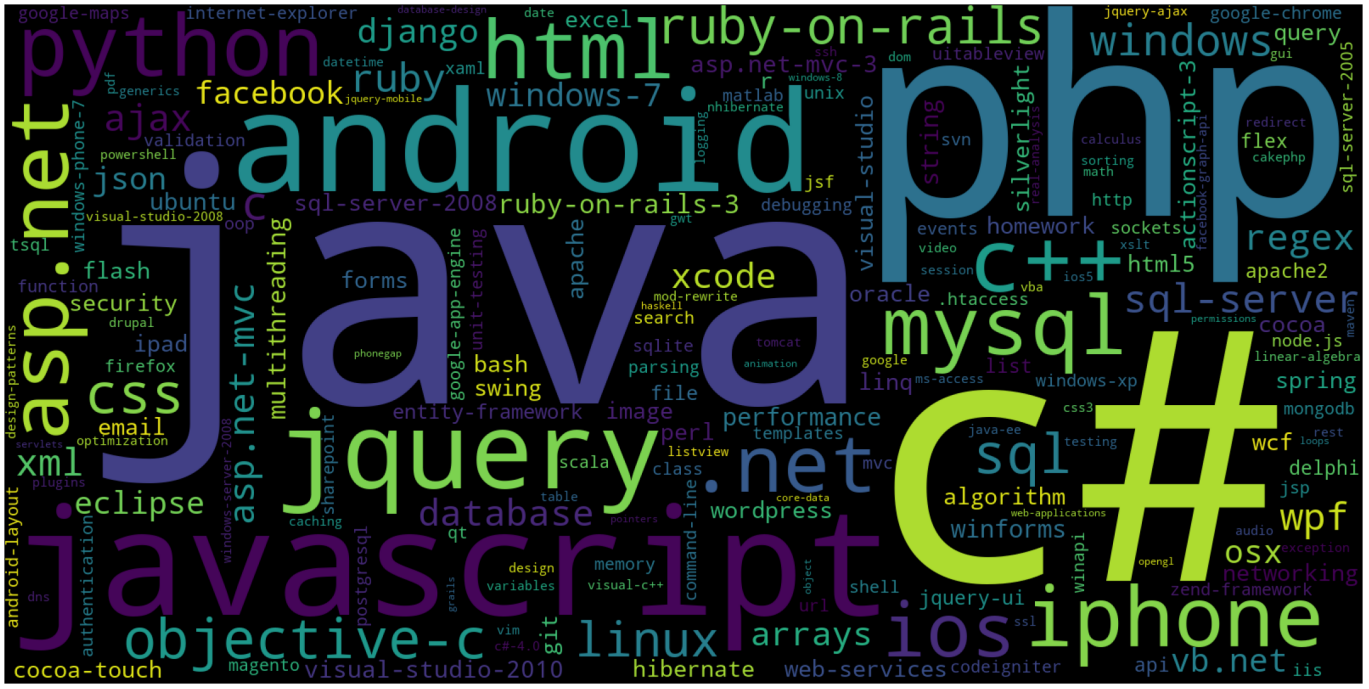
```
tag_quest_count = tag_dtm.sum(axis=1).tolist()

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])
```

```
We have total 4206314 datapoints.
[3, 4, 2, 2, 3]
```

```
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()
```



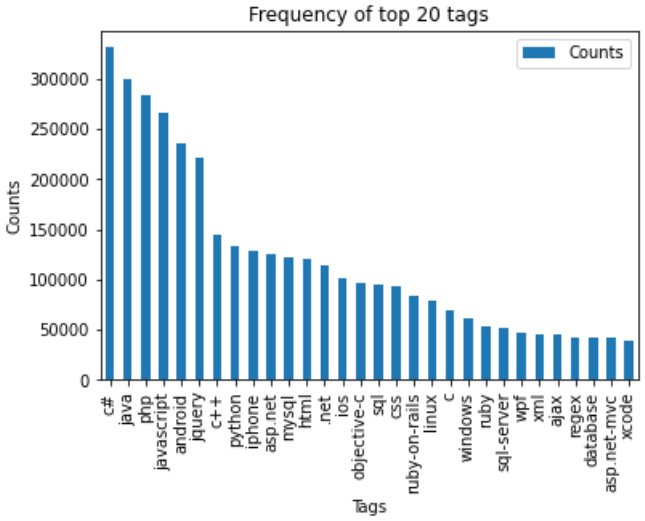

```
start = datetime.now()

# 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)
```




```
Time taken to run this cell : 0:00:05.589744
```

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

```
i=np.arange(30)
tag_df_sorted.head(30).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.

CLEANING & PREPROCESSING OF QUESTIONS

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

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

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

```
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()

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

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

```
start = datetime.now()
read_db = 'train_no_dup.db'
write_db = 'Processed.db'
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 1000000;")

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

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

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

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
True
```

```
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], 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)!=1 or j=='c'))

    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_code) values (?,?,?,
    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_proccesed))

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

```
number of questions completed= 100000
number of questions completed= 200000
number of questions completed= 300000
number of questions completed= 400000
number of questions completed= 500000
number of questions completed= 600000
number of questions completed= 700000
```

```
conn_r.commit()
conn_w.commit()
conn_r.close()
conn_w.close()
```

```
Time taken to run this cell : 0:25:27.369922
```

```
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
====================================================================================================
('right wrong practic use statement foo foo true throughout short career far program mere student work internsh
----------------------------------------------------------------------------------------------------
('java anim import imag netbean hi want ask move import jpg imag left right bottom beginn java pleas help thank
----------------------------------------------------------------------------------------------------
('help sql inner join tri inner join temp tabl ni know done done complet forgot npleas advis queri tri execut f
----------------------------------------------------------------------------------------------------
('possibl pitfal use extens method base shorthand regular want access properti possibl null object use often sn
----------------------------------------------------------------------------------------------------
('chrome extens run background file function everi sec extens need synch data server everi second also backgrou
----------------------------------------------------------------------------------------------------
('iphon xcode mutablecopi still immut look place regard problem tri creat nsuser default object add mutabl arra
----------------------------------------------------------------------------------------------------
('could due servic endpoint bind use http protocol wcf servic run fine local machin put server receiv follow er
----------------------------------------------------------------------------------------------------
('gotoandstop bug reason one instanc get gotoandstop go stop second frame movi clip two frame load ad movieclip
----------------------------------------------------------------------------------------------------
('traffic shape tp ipsec vpn via account connect need abl control amount bandwidth specif user account use vpn
----------------------------------------------------------------------------------------------------
```

```
start = datetime.now()
con=sqlite3.connect('/content/drive/My Drive/Colab Notebooks/StackOverflow Tag Predictor/Processed.db')
preprocessed_data  = pd.read_sql_query("""SELECT question, Tags FROM QuestionsProcessed""",con)
con.close()
print("Time taken to count the number of rows :", datetime.now() - start)
```

```
Time taken to count the number of rows : 0:00:21.968940
```

```
preprocessed_data.head()
```

	question	tags
0	macport gcc select error tri exec appl darwin ...	macports selection gcc
1	right wrong practic use statement foo foo true	validation if-statement logic

MACHINE LEARNING MODELS

Converting Tags to MultiLabel Problems

```
preprocessed_data[preprocessed_data.isnull().any(axis=1)]
```

	question	tags
642062	handl nullobject done quit bit research best w...	None

```
preprocessed_data.loc[preprocessed_data['tags'].isnull(),'tags'] = ''
```

```
# binary = true  , means it will return binary vector
count_vectorizer=CountVectorizer(tokenizer = lambda x : str(x).split() , binary='true')

multilabel_y=count_vectorizer.fit_transform(preprocessed_data['tags'])
```

```
def tags_to_choose(n):
    t = multilabel_y.sum(axis=0).tolist()[0]
    sorted_tags_i = sorted(range(len(t)), key=lambda i: t[i], reverse=True)
    multilabel_yn=multilabel_y[:,sorted_tags_i[:n]]
    return multilabel_yn

def questions_explained_fn(n):
    multilabel_yn = tags_to_choose(n)
    x= multilabel_yn.sum(axis=1)
    return (np.count_nonzero(x==0))
```

```
multilabel_y.shape[1]
```

```
35388
```

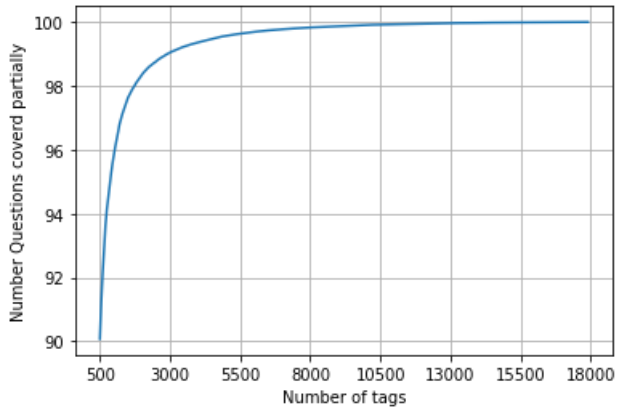
```
preprocessed_data.shape[0]
```

```
999997
```

```
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% of the tags)
```

```
print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
```




```
with  5500 tags we are covering  99.048 % of questions
```

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

```
number of questions that are not covered : 9517 out of  999997
```

```
print("Number of tags in sample :", multilabel_y.shape[1])
print("number of tags taken :", multilabel_yx.shape[1],"(",(multilabel_yx.shape[1]/multilabel_y.shape[1])*100,"%)"
```

```
Number of tags in sample : 35388
number of tags taken : 5500 ( 15.541991635582683 %)
```

Split the Data into Test & Train

```
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)

y_train = multilabel_yx[0:train_size,:]
y_test = multilabel_yx[train_size:total_size,:]
```

```
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 : (799997, 5500)
Number of data points in test data : (200000, 5500)
```

Featurizing of data

TF-IDF Featurization Vector

```
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=0.00009, max_features=200000, smooth_idf=True, norm="l2", \
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram_range=(1,1))
```

```
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 : 0:00:37.624874
```

```
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: (799997, 9366) Y : (799997, 5500)
Dimensions of test data X: (200000, 9366) Y: (200000, 5500)
```

```
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l1'), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict(x_test_multilabel)

print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("macro f1 score :",metrics.f1_score(y_test, predictions, average = 'macro'))
print("micro f1 scoore :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
print("Precision recall report :\n",metrics.classification_report(y_test, predictions))
```

```
start = datetime.now()
con=sqlite3.connect('/content/drive/My Drive/Colab Notebooks/StackOverflow Tag Predictor/Titlemoreweight.db')
preprocessed_data  = pd.read_sql_query("""SELECT question, Tags FROM QuestionsProcessed LIMIT 200000""",con)
con.close()
print("Time taken to count the number of rows :", datetime.now() - start)
```

```
Time taken to count the number of rows : 0:34:27.679654
```

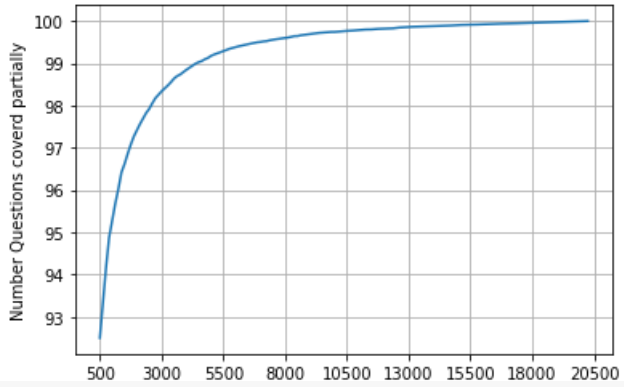
```
print("number of data points in sample :", preprocessed_data.shape[0])
print("number of dimensions :", preprocessed_data.shape[1])
```

```
number of data points in sample : 200000
number of dimensions : 2
```

```
vectorizer = CountVectorizer(tokenizer = lambda x: x.split(), binary='true')
multilabel_y = vectorizer.fit_transform(preprocessed_data['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 90% of the tags)
print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
print("with ",500,"tags we are covering ",questions_explained[0],"% of questions")
```




```
multilabel_yx = tags_to_choose(500)
print("number of questions that are not covered :", questions_explained_fn(500),"out of ", total_qs)
```

```
number of questions that are not covered : 15045 out of  200000
```

```
train_datasize = 130000
x_train=preprocessed_data.head(train_datasize)
x_test=preprocessed_data.tail(preprocessed_data.shape[0] - 130000)

y_train = multilabel_yx[0:train_datasize,:]
y_test = multilabel_yx[train_datasize:preprocessed_data.shape[0],:]
```

```
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 : (130000, 500)
Number of data points in test data : (70000, 500)
```

```
start = datetime.now()
vectorizer = CountVectorizer(min_df=0.00009, max_features=200000,
                             tokenizer = lambda x: str(x).split(),ngram_range=(1,4))
x_train_multilabel_bow = vectorizer.fit_transform(x_train['question'])
x_test_multilabel_bow = vectorizer.transform(x_test['question'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:02:35.063394
```

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

```
Dimensions of train data X: (130000, 100181) Y : (130000, 500)
Dimensions of test data X: (70000, 100181) Y: (70000, 500)
```

```
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l1'), n_jobs=1)
classifier.fit(x_train_multilabel_bow, y_train)
predictions = classifier.predict (x_test_multilabel_bow)


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 : 0.11258571428571429
Hamming loss  0.006103285714285714
Micro-average quality numbers
Precision: 0.3424, Recall: 0.5517, F1-measure: 0.4225
Macro-average quality numbers
Precision: 0.1623, Recall: 0.3566, F1-measure: 0.2083
              precision    recall  f1-score   support

           0       0.97      0.96      0.96     42802
           1       0.25      0.32      0.28      1764
           2       0.27      0.41      0.33       942
           3       0.24      0.28      0.26      6539
           4       0.35      0.45      0.40      2540
           5       0.50      0.58      0.54      2156
           6       0.47      0.54      0.50      1990
           7       0.13      0.21      0.16       611
           8       0.20      0.33      0.25       324
           9       0.69      0.74      0.71      2335
          10       0.27      0.43      0.33       736
          11       0.23      0.38      0.29      1199
          12       0.31      0.48      0.38       842
          13       0.30      0.44      0.36       770
          14       0.40      0.63      0.49       975
          15       0.22      0.33      0.26       523
          16       0.09      0.36      0.14       143
          17       0.34      0.57      0.43       428
          18       0.39      0.60      0.47       552
          19       0.44      0.59      0.50       708
          20       0.26      0.63      0.37        89
          21       0.17      0.39      0.24       219
          22       0.29      0.29      0.29       662
          23       0.18      0.20      0.19      1965
          24       0.23      0.38      0.29      1046
          25       0.23      0.34      0.27       488
          26       0.26      0.38      0.31       458
          27       0.25      0.39      0.31      1193
          28       0.51      0.44      0.47      1492
          29       0.09      0.22      0.13       354
          30       0.10      0.47      0.17       159
          31       0.09      0.34      0.15       157
          32       0.17      0.26      0.21       740
          33       0.40      0.44      0.42      1337
          34       0.21      0.38      0.27       226
          35       0.25      0.50      0.33       535
          36       0.22      0.37      0.28       315
          37       0.12      0.28      0.17       167
          38       0.39      0.62      0.48      1074
          39       0.23      0.33      0.27       336
          40       0.13      0.45      0.21       312
          41       0.13      0.19      0.15       682
          42       0.36      0.65      0.46       265
          43       0.46      0.65      0.54       478
          44       0.22      0.42      0.29       598
          45       0.19      0.33      0.24      1054
          46       0.26      0.42      0.32       253
          47       0.14      0.21      0.17       936
          48       0.10      0.28      0.15       133
          49       0.09      0.23      0.13       152
          50       0.35      0.42      0.38       943
          51       0.10      0.18      0.13       243
          52       0.13      0.36      0.19       135
          53       0.92      0.84      0.88       969
          54       0.13      0.19      0.16       801
          55       0.13      0.72      0.22        50
          56       0.12      0.40      0.18       142
          57       0.13      0.36      0.19       125
          58       0.02      0.15      0.03        39
          59       0.10      0.50      0.16        36
          60       0.22      0.42      0.29       205
          61       0.11      0.21      0.14       354
          62       0.10      0.20      0.13       266
          63       0.17      0.54      0.26       178
```

64	0.36	0.76	0.49	163
65	0.13	0.48	0.21	46
66	0.13	0.25	0.17	269
67	0.29	0.79	0.43	133
68	0.18	0.33	0.23	577
69	0.12	0.23	0.16	212
70	0.31	0.70	0.43	120
71	0.09	0.20	0.13	258
72	0.13	0.23	0.17	354
73	0.42	0.58	0.49	159
74	0.07	0.31	0.11	89
75	0.22	0.37	0.28	125
76	0.08	0.24	0.12	94
77	0.37	0.37	0.37	456
78	0.20	0.31	0.24	712
79	0.15	0.22	0.18	299
80	0.06	0.23	0.10	53
81	0.12	0.40	0.18	275
82	0.21	0.40	0.28	623
83	0.18	0.43	0.25	75
84	0.01	0.22	0.02	27
85	0.24	0.39	0.29	230
86	0.26	0.42	0.32	177
87	0.03	0.27	0.06	30
88	0.32	0.62	0.42	655
89	0.06	0.21	0.10	126
90	0.31	0.30	0.31	422
91	0.05	0.12	0.07	130
92	0.53	0.87	0.66	451
93	0.05	0.17	0.08	77
94	0.04	0.12	0.06	461
95	0.26	0.50	0.34	104
96	0.07	0.15	0.10	454
97	0.20	0.49	0.28	345
98	0.17	0.49	0.26	125
99	0.25	0.47	0.33	144
100	0.09	0.22	0.12	279
101	0.08	0.25	0.12	99
102	0.34	0.53	0.42	553
103	0.12	0.34	0.18	123
104	0.05	0.12	0.07	542
105	0.11	0.18	0.14	542
106	0.07	0.18	0.10	118
107	0.18	0.58	0.27	73
108	0.07	0.24	0.11	191
109	0.06	0.13	0.08	180
110	0.10	0.30	0.15	121
111	0.05	0.24	0.08	41
112	0.07	0.16	0.10	254
113	0.06	0.18	0.10	146
114	0.38	0.41	0.39	279
115	0.13	0.22	0.17	245
116	0.14	0.29	0.19	102
117	0.37	0.35	0.36	469
118	0.08	0.10	0.09	248
119	0.15	0.28	0.19	98
120	0.20	0.40	0.27	105
121	0.07	0.24	0.10	164
122	0.12	0.42	0.19	95
123	0.19	0.42	0.26	208
124	0.23	0.41	0.29	85
125	0.18	0.48	0.26	98
126	0.03	0.27	0.05	41
127	0.32	0.41	0.36	431
128	0.23	0.37	0.28	111
129	0.10	0.35	0.16	74
130	0.10	0.27	0.15	116
131	0.14	0.49	0.21	126
132	0.23	0.46	0.31	270
133	0.05	0.43	0.10	35
134	0.07	0.30	0.11	64
135	0.15	0.59	0.23	243

135	0.19	0.39	0.25	249
136	0.75	0.81	0.78	345
137	0.12	0.25	0.16	174
138	0.11	0.34	0.17	183
139	0.50	0.43	0.46	454
140	0.52	0.74	0.61	302
141	0.16	0.40	0.23	82
142	0.34	0.82	0.48	82
143	0.18	0.37	0.24	98
144	0.41	0.72	0.52	137
145	0.22	0.32	0.26	412
146	0.02	0.10	0.03	224
147	0.11	0.25	0.15	153
148	0.25	0.70	0.37	64
149	0.17	0.51	0.26	68
150	0.08	0.25	0.12	126
151	0.07	0.10	0.09	202
152	0.02	0.31	0.04	39
153	0.09	0.39	0.15	36
154	0.20	0.49	0.28	136
155	0.07	0.13	0.09	212
156	0.23	0.45	0.31	51
157	0.17	0.45	0.25	94
158	0.04	0.13	0.06	286
159	0.28	0.48	0.35	350
160	0.07	0.36	0.12	22
161	0.05	0.20	0.07	120
162	0.06	0.17	0.09	144
163	0.24	0.50	0.33	119
164	0.07	0.29	0.11	42
165	0.66	0.83	0.73	361
166	0.11	0.24	0.15	206
167	0.16	0.40	0.23	87
168	0.06	0.35	0.10	112
169	0.15	0.27	0.20	298
170	0.19	0.24	0.21	191
171	0.17	0.44	0.24	91
172	0.22	0.52	0.31	100
173	0.04	0.14	0.07	167
174	0.32	0.31	0.32	344
175	0.03	0.07	0.04	76
176	0.06	0.17	0.08	198
177	0.09	0.27	0.13	127
178	0.08	0.26	0.12	102
179	0.10	0.52	0.16	31
180	0.23	0.42	0.30	139
181	0.17	0.51	0.25	63
182	0.17	0.28	0.21	367
183	0.19	0.55	0.28	67
184	0.01	0.04	0.01	46
185	0.46	0.16	0.24	381
186	0.04	0.17	0.06	29
187	0.11	0.26	0.16	111
188	0.14	0.38	0.21	121
189	0.01	0.02	0.02	82
190	0.15	0.36	0.21	118
191	0.13	0.43	0.20	77
192	0.19	0.53	0.28	118
193	0.05	0.15	0.07	159
194	0.26	0.30	0.28	269
195	0.25	0.67	0.36	81
196	0.22	0.43	0.29	299
197	0.04	0.11	0.06	47
198	0.30	0.77	0.43	47
199	0.08	0.27	0.12	62
200	0.01	0.08	0.02	24
201	0.18	0.42	0.25	86
202	0.29	0.27	0.28	308
203	0.40	0.55	0.46	321
204	0.03	0.06	0.04	67
205	0.06	0.25	0.09	28
206	0.17	0.61	0.26	59
207	0.14	0.31	0.19	245

207	0.14	0.91	0.19	249
208	0.25	0.68	0.37	53
209	0.03	0.11	0.05	274
210	0.02	0.38	0.04	8
211	0.20	0.46	0.28	95
212	0.18	0.37	0.24	129
213	0.13	0.50	0.20	34
214	0.17	0.30	0.22	89
215	0.14	0.43	0.21	67
216	0.07	0.36	0.12	25
217	0.49	0.80	0.61	109
218	0.09	0.16	0.11	134
219	0.20	0.46	0.28	70
220	0.14	0.42	0.21	67
221	0.14	0.32	0.20	79
222	0.22	0.44	0.29	50
223	0.34	0.75	0.47	93
224	0.13	0.35	0.19	94
225	0.04	0.11	0.06	180
226	0.03	0.14	0.05	79
227	0.13	0.45	0.20	64
228	0.03	0.10	0.05	50
229	0.21	0.64	0.31	53
230	0.08	0.34	0.13	44
231	0.11	0.28	0.16	61
232	0.11	0.59	0.19	49
233	0.40	0.75	0.52	72
234	0.12	0.18	0.14	233
235	0.11	0.16	0.13	166
236	0.21	0.60	0.31	58
237	0.06	0.20	0.10	152
238	0.23	0.30	0.26	302
239	0.19	0.52	0.28	42
240	0.25	0.52	0.34	269
241	0.05	0.13	0.07	54
242	0.08	0.25	0.12	162
243	0.06	0.30	0.10	23
244	0.24	0.44	0.31	66
245	0.05	0.33	0.09	40
246	0.22	0.42	0.29	73
247	0.49	0.71	0.58	78
248	0.08	0.18	0.11	131
249	0.10	0.26	0.14	82
250	0.30	0.65	0.41	57
251	0.15	0.18	0.16	296
252	0.13	0.24	0.17	87
253	0.13	0.27	0.18	96
254	0.38	0.30	0.34	280
255	0.03	0.21	0.05	24
256	0.10	0.24	0.14	88
257	0.04	0.57	0.07	7
258	0.08	0.21	0.11	136
259	0.28	0.51	0.36	73
260	0.42	0.19	0.26	268
261	0.30	0.91	0.45	11
262	0.39	0.55	0.46	82
263	0.04	0.60	0.07	5
264	0.13	0.32	0.18	108
265	0.26	0.63	0.36	78
266	0.06	0.20	0.09	69
267	0.05	0.19	0.08	80
268	0.13	0.43	0.20	28
269	0.03	0.14	0.05	44
270	0.23	0.60	0.33	42
271	0.14	0.34	0.20	114
272	0.08	0.17	0.11	59
273	0.09	0.23	0.13	130
274	0.10	0.33	0.15	48
275	0.04	0.20	0.07	227
276	0.30	0.73	0.43	75
277	0.13	0.22	0.16	68
278	0.40	0.56	0.46	143
279	0.04	0.23	0.07	78

279	0.04	0.25	0.07	78
280	0.30	0.63	0.41	78
281	0.30	0.52	0.39	61
282	0.04	0.11	0.06	61
283	0.08	0.27	0.12	52
284	0.02	0.12	0.03	24
285	0.03	0.10	0.05	125
286	0.11	0.25	0.15	138
287	0.11	0.25	0.15	171
288	0.38	0.50	0.43	157
289	0.09	0.43	0.14	30
290	0.02	0.17	0.04	30
291	0.21	0.47	0.29	64
292	0.02	0.33	0.04	9
293	0.13	0.30	0.18	123
294	0.08	0.29	0.13	35
295	0.01	0.05	0.01	22
296	0.24	0.47	0.32	184
297	0.18	0.30	0.23	140
298	0.19	0.29	0.23	224
299	0.19	0.46	0.27	97
300	0.05	0.12	0.07	65
301	0.04	0.16	0.06	44
302	0.09	0.39	0.14	38
303	0.22	0.30	0.26	98
304	0.08	0.42	0.13	31
305	0.30	0.40	0.34	235
306	0.39	0.73	0.51	249
307	0.13	0.10	0.11	247
308	0.12	0.45	0.19	122
309	0.13	0.20	0.16	230
310	0.09	0.23	0.13	166
311	0.05	0.28	0.09	40
312	0.05	0.24	0.08	17
313	0.06	0.31	0.10	36
314	0.27	0.47	0.34	109
315	0.00	0.01	0.01	67
316	0.35	0.67	0.46	79
317	0.10	0.15	0.12	197
318	0.10	0.49	0.17	47
319	0.47	0.39	0.43	222
320	0.11	0.59	0.19	27
321	0.50	0.63	0.56	207
322	0.42	0.39	0.40	240
323	0.20	0.15	0.18	215
324	0.20	0.43	0.27	120
325	0.12	0.37	0.18	130
326	0.23	0.57	0.33	28
327	0.07	0.16	0.10	166
328	0.32	0.60	0.42	45
329	0.33	0.54	0.41	180
330	0.04	0.24	0.06	62
331	0.10	0.24	0.14	105
332	0.23	0.69	0.34	39
333	0.06	1.00	0.12	4
334	0.13	0.41	0.19	113
335	0.13	0.47	0.20	78
336	0.08	0.22	0.11	51
337	0.20	0.18	0.19	147
338	0.01	0.03	0.02	135
339	0.04	0.15	0.07	27
340	0.06	0.14	0.08	79
341	0.39	0.73	0.51	30
342	0.10	0.30	0.15	54
343	0.26	0.31	0.28	195
344	0.13	0.36	0.19	39
345	0.11	0.89	0.19	9
346	0.47	0.69	0.56	86
347	0.05	0.16	0.08	44
348	0.25	0.42	0.32	185
349	0.21	0.62	0.31	66
350	0.03	0.67	0.06	3
351	0.10	0.40	0.15	35

352	0.37	0.38	0.38	216
353	0.22	0.40	0.28	42
354	0.04	0.50	0.08	6
355	0.02	1.00	0.04	3
356	0.03	0.36	0.05	14
357	0.09	0.55	0.15	31
358	0.11	0.33	0.16	204
359	0.05	0.05	0.05	211
360	0.30	0.26	0.28	184
361	0.18	0.25	0.21	108
362	0.02	0.06	0.03	54
363	0.05	0.27	0.08	56
364	0.09	0.21	0.12	97
365	0.12	0.40	0.19	72
366	0.02	0.17	0.03	12
367	0.29	0.22	0.25	185
368	0.12	0.16	0.13	193
369	0.03	0.12	0.05	34
370	0.18	0.34	0.23	164
371	0.14	0.83	0.24	18
372	0.08	0.29	0.13	65
373	0.07	0.35	0.11	20
374	0.01	0.03	0.01	29
375	0.27	0.42	0.33	71
376	0.04	0.05	0.04	164
377	0.17	0.53	0.25	185
378	0.05	0.21	0.08	24
379	0.09	0.33	0.14	52
380	0.02	0.14	0.04	57
381	0.09	0.17	0.12	59
382	0.11	0.29	0.16	117
383	0.17	0.62	0.27	39
384	0.28	0.45	0.34	125
385	0.07	0.25	0.11	130
386	0.26	0.61	0.37	74
387	0.19	0.66	0.29	35
388	0.10	0.67	0.17	21
389	0.20	0.25	0.22	175
390	0.07	0.11	0.09	54
391	0.00	0.00	0.00	29
392	0.07	0.14	0.09	63
393	0.10	0.47	0.17	34
394	0.20	0.66	0.31	38
395	0.05	0.27	0.09	15
396	0.01	0.10	0.01	10
397	0.08	0.27	0.13	49
398	0.24	0.31	0.27	169
399	0.08	0.30	0.13	33
400	0.35	0.56	0.43	84
401	0.27	0.61	0.37	31
402	0.10	0.54	0.17	24
403	0.57	0.26	0.36	187
404	0.03	0.50	0.06	6
405	0.12	0.33	0.18	33
406	0.02	0.18	0.04	17
407	0.03	0.19	0.05	21
408	0.07	0.21	0.10	62
409	0.07	0.14	0.09	78
410	0.46	0.47	0.46	147
411	0.06	0.29	0.10	31
412	0.00	0.00	0.00	14
413	0.19	0.31	0.23	103
414	0.42	0.75	0.53	36
415	0.28	0.57	0.38	68
416	0.02	0.19	0.04	43
417	0.18	0.45	0.26	73
418	0.51	0.56	0.54	62
419	0.06	0.23	0.10	97
420	0.06	0.21	0.09	42
421	0.17	0.41	0.24	41
422	0.01	0.05	0.02	38
423	0.00	0.03	0.01	36

424	0.04	0.23	0.07	13
425	0.06	0.33	0.10	24
426	0.00	0.33	0.01	3
427	0.07	0.30	0.11	94
428	0.27	0.26	0.27	151
429	0.34	0.71	0.46	63
430	0.02	0.25	0.04	40
431	0.23	0.43	0.30	49
432	0.01	0.03	0.01	34
433	0.27	0.78	0.40	37
434	0.10	0.35	0.15	34
435	0.06	1.00	0.11	1
436	0.03	0.17	0.05	29
437	0.06	0.18	0.09	50
438	0.00	0.00	0.00	104
439	0.00	0.00	0.00	29
440	0.06	0.35	0.11	23
441	0.03	0.09	0.04	46
442	0.05	0.15	0.07	39
443	0.17	0.34	0.23	56
444	0.18	0.47	0.27	80
445	0.03	0.10	0.05	30
446	0.04	0.17	0.06	30
447	0.13	0.30	0.18	37
448	0.02	0.05	0.03	39
449	0.07	0.16	0.10	83
450	0.06	0.39	0.10	23
451	0.06	0.44	0.10	9
452	0.06	0.23	0.10	44
453	0.25	0.17	0.20	166
454	0.19	0.66	0.30	32
455	0.06	0.26	0.10	53
456	0.14	0.63	0.23	41
457	0.05	0.12	0.07	78
458	0.13	0.19	0.16	133
459	0.05	0.20	0.08	25
460	0.11	0.34	0.16	103
461	0.10	0.21	0.14	53
462	0.07	0.30	0.12	30
463	0.03	0.50	0.05	4
464	0.06	0.08	0.07	66
465	0.03	0.28	0.05	47
466	0.06	0.26	0.10	31
467	0.14	0.49	0.22	35
468	0.01	0.04	0.02	50
469	0.34	0.35	0.34	155
470	0.06	0.26	0.10	27
471	0.36	0.50	0.42	58
472	0.03	0.08	0.05	159

```
start = datetime.now()
classifier_2 = OneVsRestClassifier(LogisticRegression(penalty='l1',solver='liblinear'), n_jobs=1)
classifier_2.fit(x_train_multilabel_bow, y_train)
predictions_2 = classifier_2.predict(x_test_multilabel_bow)
print("Accuracy :",metrics.accuracy_score(y_test, predictions_2))
print("Hamming loss ",metrics.hamming_loss(y_test,predictions_2))


precision = precision_score(y_test, predictions_2, average='micro')
recall = recall_score(y_test, predictions_2, average='micro')
f1 = f1_score(y_test, predictions_2, 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_2, average='macro')
recall = recall_score(y_test, predictions_2, average='macro')
f1 = f1_score(y_test, predictions_2, 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_2))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Accuracy : 0.2359
Hamming loss  0.002942057142857143
Micro-average quality numbers
Precision: 0.6777, Recall: 0.5207, F1-measure: 0.5889
Macro-average quality numbers
Precision: 0.4122, Recall: 0.3021, F1-measure: 0.3397
              precision    recall  f1-score   support

           0       0.98      0.97      0.97     42802
           1       0.42      0.26      0.32      1764
           2       0.56      0.38      0.46       942
           3       0.34      0.19      0.25      6539
           4       0.48      0.41      0.45      2540
           5       0.65      0.54      0.59      2156
           6       0.66      0.50      0.57      1990
           7       0.31      0.17      0.22       611
           8       0.55      0.24      0.34       324
           9       0.76      0.78      0.77      2335
          10       0.48      0.40      0.44       736
          11       0.40      0.29      0.34      1199
          12       0.55      0.40      0.46       842
          13       0.54      0.36      0.43       770
          14       0.61      0.56      0.58       975
          15       0.37      0.21      0.27       523
          16       0.40      0.27      0.32       143
          17       0.71      0.56      0.62       428
          18       0.71      0.53      0.61       552
          19       0.67      0.55      0.60       708
          20       0.81      0.61      0.69        89
          21       0.48      0.25      0.33       219
          22       0.43      0.27      0.33       662
          23       0.23      0.13      0.17      1965
          24       0.50      0.28      0.36      1046
          25       0.44      0.29      0.35       488
          26       0.47      0.31      0.37       458
          27       0.52      0.38      0.44      1193
          28       0.68      0.48      0.56      1492
          29       0.23      0.16      0.19       354
          30       0.49      0.41      0.45       159
          31       0.47      0.29      0.36       157
          32       0.31      0.19      0.24       740
          33       0.53      0.40      0.46      1337
          34       0.57      0.32      0.41       226
          35       0.66      0.49      0.57       535
          36       0.46      0.28      0.35       315
          37       0.33      0.20      0.25       167
          38       0.74      0.64      0.68      1074
          39       0.44      0.26      0.33       336
          40       0.49      0.37      0.42       312
          41       0.22      0.13      0.16       682
          42       0.74      0.57      0.65       265
          43       0.77      0.61      0.68       478
          44       0.63      0.36      0.46       598
          45       0.45      0.27      0.34      1054
          46       0.51      0.30      0.38       253
          47       0.27      0.17      0.21       936
          48       0.32      0.23      0.27       133
          49       0.38      0.18      0.24       152
          50       0.43      0.37      0.40       943
          51       0.17      0.11      0.13       243
          52       0.43      0.28      0.34       135
          53       0.98      0.90      0.94       969
          54       0.24      0.13      0.17       801
          55       0.58      0.64      0.61        50
          56       0.55      0.36      0.44       142
          57       0.49      0.27      0.35       125
          58       0.24      0.13      0.17        39
          59       0.38      0.36      0.37        36
          60       0.51      0.33      0.40       205
          61       0.29      0.21      0.24       354
          62       0.28      0.20      0.24       266
          63       0.58      0.47      0.52       178
```

64	0.90	0.68	0.77	163
65	0.53	0.46	0.49	46
66	0.36	0.20	0.26	269
67	0.78	0.74	0.76	133
68	0.32	0.20	0.24	577
69	0.23	0.09	0.13	212
70	0.82	0.66	0.73	120
71	0.29	0.16	0.21	258
72	0.19	0.12	0.14	354
73	0.72	0.58	0.64	159
74	0.50	0.27	0.35	89
75	0.37	0.29	0.32	125
76	0.26	0.20	0.23	94
77	0.52	0.36	0.43	456
78	0.42	0.38	0.40	712
79	0.29	0.11	0.16	299
80	0.28	0.17	0.21	53
81	0.43	0.32	0.37	275
82	0.53	0.23	0.32	623
83	0.53	0.39	0.45	75
84	0.12	0.07	0.09	27
85	0.62	0.34	0.44	230
86	0.49	0.36	0.41	177
87	0.45	0.33	0.38	30
88	0.60	0.69	0.64	655
89	0.14	0.10	0.12	126
90	0.50	0.37	0.42	422
91	0.15	0.04	0.06	130
92	0.82	0.86	0.84	451
93	0.29	0.06	0.11	77
94	0.13	0.05	0.07	461
95	0.71	0.38	0.50	104
96	0.18	0.09	0.12	454
97	0.39	0.37	0.38	345
98	0.44	0.44	0.44	125
99	0.52	0.33	0.41	144
100	0.20	0.06	0.09	279
101	0.49	0.18	0.26	99
102	0.78	0.62	0.69	553
103	0.52	0.24	0.32	123
104	0.14	0.08	0.10	542
105	0.21	0.14	0.17	542
106	0.33	0.11	0.16	118
107	0.52	0.40	0.45	73
108	0.27	0.14	0.19	191
109	0.29	0.12	0.17	180
110	0.48	0.27	0.35	121
111	0.28	0.17	0.21	41
112	0.14	0.06	0.08	254
113	0.19	0.13	0.15	146
114	0.60	0.36	0.45	279
115	0.33	0.17	0.22	245
116	0.49	0.21	0.29	102
117	0.56	0.39	0.46	469
118	0.20	0.06	0.09	248
119	0.37	0.24	0.29	98
120	0.56	0.47	0.51	105
121	0.23	0.11	0.15	164
122	0.48	0.31	0.37	95
123	0.48	0.27	0.35	208
124	0.59	0.39	0.47	85
125	0.60	0.53	0.57	98
126	0.27	0.15	0.19	41
127	0.79	0.34	0.47	431
128	0.59	0.33	0.43	111
129	0.39	0.22	0.28	74
130	0.42	0.20	0.27	116
131	0.52	0.42	0.47	126
132	0.35	0.40	0.37	270
133	0.36	0.29	0.32	35
134	0.34	0.27	0.30	64
135	0.59	0.66	0.62	243

136	0.96	0.79	0.87	345
137	0.41	0.18	0.25	174
138	0.32	0.27	0.29	183
139	0.73	0.39	0.50	454
140	0.81	0.72	0.76	302
141	0.68	0.34	0.46	82
142	0.77	0.77	0.77	82
143	0.50	0.37	0.42	98
144	0.86	0.74	0.79	137
145	0.41	0.25	0.31	412
146	0.21	0.09	0.12	224
147	0.29	0.13	0.18	153
148	0.60	0.62	0.61	64
149	0.61	0.41	0.49	68
150	0.20	0.08	0.11	126
151	0.15	0.09	0.12	202
152	0.26	0.28	0.27	39
153	0.56	0.39	0.46	36
154	0.50	0.46	0.48	136
155	0.20	0.06	0.09	212
156	0.49	0.39	0.43	51
157	0.45	0.44	0.44	94
158	0.20	0.08	0.12	286
159	0.52	0.45	0.48	350
160	0.45	0.41	0.43	22
161	0.10	0.07	0.08	120
162	0.24	0.12	0.16	144
163	0.59	0.50	0.55	119
164	0.37	0.26	0.31	42
165	0.82	0.81	0.81	361
166	0.28	0.15	0.19	206
167	0.60	0.29	0.39	87
168	0.29	0.29	0.29	112
169	0.24	0.11	0.15	298
170	0.40	0.23	0.29	191
171	0.44	0.48	0.46	91
172	0.67	0.49	0.57	100
173	0.10	0.05	0.07	167
174	0.47	0.34	0.40	344
175	0.07	0.04	0.05	76
176	0.17	0.09	0.12	198
177	0.40	0.24	0.30	127
178	0.33	0.20	0.25	102
179	0.65	0.35	0.46	31
180	0.51	0.46	0.48	139
181	0.65	0.56	0.60	63
182	0.46	0.24	0.32	367
183	0.52	0.70	0.59	67
184	0.00	0.00	0.00	46
185	0.57	0.16	0.25	381
186	0.90	0.31	0.46	29
187	0.33	0.26	0.29	111
188	0.26	0.17	0.20	121
189	0.21	0.04	0.06	82
190	0.58	0.42	0.49	118
191	0.70	0.52	0.60	77
192	0.59	0.53	0.56	118
193	0.26	0.09	0.14	159
194	0.43	0.38	0.41	269
195	0.76	0.64	0.70	81
196	0.41	0.31	0.35	299
197	0.31	0.09	0.13	47
198	0.76	0.74	0.75	47
199	0.40	0.26	0.31	62
200	0.31	0.17	0.22	24
201	0.53	0.27	0.36	86
202	0.53	0.22	0.31	308
203	0.67	0.56	0.61	321
204	0.08	0.03	0.04	67
205	0.16	0.18	0.17	28
206	0.58	0.49	0.53	59

207	0.90	0.29	0.28	249
208	0.85	0.64	0.73	53
209	0.11	0.09	0.10	274
210	0.12	0.12	0.12	8
211	0.48	0.26	0.34	95
212	0.29	0.22	0.25	129
213	0.64	0.47	0.54	34
214	0.29	0.34	0.31	89
215	0.55	0.36	0.43	67
216	0.36	0.20	0.26	25
217	0.62	0.63	0.63	109
218	0.40	0.15	0.22	134
219	0.62	0.49	0.54	70
220	0.53	0.40	0.46	67
221	0.39	0.22	0.28	79
222	0.50	0.40	0.44	50
223	0.72	0.71	0.71	93
224	0.27	0.26	0.26	94
225	0.14	0.05	0.07	180
226	0.10	0.06	0.08	79
227	0.31	0.36	0.33	64
228	0.15	0.06	0.09	50
229	0.65	0.64	0.65	53
230	0.52	0.34	0.41	44
231	0.24	0.21	0.23	61
232	0.39	0.39	0.39	49
233	0.73	0.75	0.74	72
234	0.20	0.14	0.16	233
235	0.33	0.10	0.16	166
236	0.67	0.52	0.58	58
237	0.16	0.07	0.09	152
238	0.52	0.27	0.35	302
239	0.49	0.55	0.52	42
240	0.46	0.34	0.39	269
241	0.26	0.11	0.16	54
242	0.21	0.07	0.11	162
243	0.50	0.39	0.44	23
244	0.65	0.30	0.41	66
245	0.19	0.10	0.13	40
246	0.67	0.59	0.63	73
247	0.83	0.62	0.71	78
248	0.35	0.17	0.23	131
249	0.26	0.11	0.16	82
250	0.67	0.58	0.62	57
251	0.19	0.06	0.09	296
252	0.39	0.18	0.25	87
253	0.27	0.16	0.20	96
254	0.44	0.14	0.21	280
255	0.25	0.21	0.23	24
256	0.31	0.19	0.24	88
257	0.23	0.43	0.30	7
258	0.24	0.15	0.19	136
259	0.72	0.56	0.63	73
260	0.63	0.43	0.51	268
261	1.00	0.82	0.90	11
262	0.69	0.51	0.59	82
263	0.50	0.80	0.62	5
264	0.37	0.24	0.29	108
265	0.67	0.50	0.57	78
266	0.16	0.10	0.12	69
267	0.34	0.12	0.18	80
268	0.37	0.25	0.30	28
269	0.12	0.05	0.07	44
270	0.66	0.60	0.62	42
271	0.47	0.25	0.32	114
272	0.10	0.08	0.09	59
273	0.27	0.21	0.24	130
274	0.26	0.21	0.23	48
275	0.17	0.11	0.13	227
276	0.72	0.77	0.74	75
277	0.71	0.32	0.44	68
278	0.59	0.48	0.53	143
279	0.16	0.15	0.16	78

279	0.10	0.13	0.10	78
280	0.69	0.56	0.62	78
281	0.72	0.59	0.65	61
282	0.06	0.02	0.03	61
283	0.43	0.25	0.32	52
284	0.20	0.08	0.12	24
285	0.06	0.02	0.02	125
286	0.35	0.19	0.24	138
287	0.18	0.09	0.12	171
288	0.68	0.45	0.54	157
289	0.52	0.40	0.45	30
290	0.18	0.10	0.13	30
291	0.77	0.31	0.44	64
292	0.14	0.22	0.17	9
293	0.20	0.12	0.15	123
294	0.45	0.29	0.35	35
295	0.25	0.09	0.13	22
296	0.41	0.46	0.43	184
297	0.64	0.21	0.32	140
298	0.38	0.19	0.25	224
299	0.63	0.45	0.53	97
300	0.07	0.03	0.04	65
301	0.11	0.05	0.06	44
302	0.43	0.26	0.33	38
303	0.37	0.18	0.24	98
304	0.48	0.48	0.48	31
305	0.38	0.25	0.30	235
306	0.98	0.93	0.95	249
307	0.40	0.09	0.15	247
308	0.40	0.30	0.34	122
309	0.20	0.08	0.11	230
310	0.37	0.16	0.22	166
311	0.23	0.15	0.18	40
312	0.56	0.29	0.38	17
313	0.27	0.19	0.23	36
314	0.55	0.33	0.41	109
315	0.00	0.00	0.00	67
316	0.63	0.58	0.61	79
317	0.08	0.02	0.03	197
318	0.27	0.53	0.36	47
319	0.62	0.35	0.45	222
320	0.47	0.56	0.51	27
321	0.68	0.56	0.61	207
322	0.69	0.38	0.49	240
323	0.26	0.18	0.21	215
324	0.42	0.33	0.37	120
325	0.42	0.23	0.30	130
326	0.68	0.54	0.60	28
327	0.15	0.16	0.15	166
328	0.66	0.56	0.60	45
329	0.45	0.45	0.45	180
330	0.17	0.08	0.11	62
331	0.44	0.23	0.30	105
332	0.81	0.67	0.73	39
333	0.67	1.00	0.80	4
334	0.54	0.28	0.37	113
335	0.39	0.40	0.39	78
336	0.27	0.14	0.18	51
337	0.42	0.17	0.24	147
338	0.07	0.02	0.03	135
339	0.29	0.33	0.31	27
340	0.29	0.13	0.18	79
341	0.92	0.73	0.81	30
342	0.26	0.15	0.19	54
343	0.59	0.23	0.33	195
344	0.35	0.31	0.33	39
345	0.75	0.67	0.71	9
346	0.75	0.78	0.77	86
347	0.39	0.20	0.27	44
348	0.68	0.39	0.50	185
349	0.68	0.61	0.64	66
350	1.00	0.67	0.80	3
351	0.39	0.31	0.35	35

352	0.57	0.42	0.48	216
353	0.41	0.38	0.40	42
354	0.67	0.33	0.44	6
355	0.06	0.33	0.10	3
356	0.22	0.14	0.17	14
357	0.34	0.35	0.35	31
358	0.32	0.06	0.10	204
359	0.12	0.01	0.02	211
360	0.38	0.19	0.25	184
361	0.29	0.20	0.24	108
362	0.06	0.02	0.03	54
363	0.21	0.18	0.19	56
364	0.21	0.10	0.14	97
365	0.29	0.21	0.24	72
366	0.17	0.08	0.11	12
367	0.64	0.41	0.50	185
368	0.18	0.06	0.09	193
369	0.27	0.12	0.16	34
370	0.57	0.34	0.43	164
371	0.62	0.72	0.67	18
372	0.22	0.11	0.14	65
373	0.60	0.30	0.40	20
374	0.00	0.00	0.00	29
375	0.64	0.42	0.51	71
376	0.14	0.12	0.13	164
377	0.37	0.34	0.35	185
378	0.19	0.21	0.20	24
379	0.24	0.17	0.20	52
380	0.21	0.12	0.15	57
381	0.20	0.07	0.10	59
382	0.23	0.09	0.13	117
383	0.58	0.54	0.56	39
384	0.57	0.53	0.55	125
385	0.35	0.14	0.20	130
386	0.66	0.58	0.62	74
387	0.71	0.63	0.67	35
388	0.48	0.62	0.54	21
389	0.35	0.24	0.28	175
390	0.19	0.09	0.12	54
391	0.00	0.00	0.00	29
392	0.35	0.11	0.17	63
393	0.28	0.32	0.30	34
394	0.81	0.66	0.72	38
395	0.20	0.20	0.20	15
396	0.29	0.20	0.24	10
397	0.33	0.18	0.24	49
398	0.51	0.20	0.29	169
399	0.29	0.24	0.26	33
400	0.45	0.35	0.39	84
401	0.72	0.58	0.64	31
402	0.38	0.42	0.40	24
403	0.67	0.36	0.47	187
404	0.40	0.33	0.36	6
405	0.50	0.30	0.38	33
406	0.21	0.24	0.22	17
407	0.20	0.10	0.13	21
408	0.42	0.16	0.23	62
409	0.20	0.06	0.10	78
410	0.70	0.50	0.58	147
411	0.30	0.26	0.28	31
412	0.00	0.00	0.00	14
413	0.41	0.12	0.18	103
414	0.74	0.64	0.69	36
415	0.58	0.59	0.58	68
416	0.07	0.05	0.05	43
417	0.45	0.38	0.41	73
418	0.73	0.60	0.65	62
419	0.04	0.02	0.03	97
420	0.03	0.02	0.03	42
421	0.63	0.46	0.54	41
422	0.07	0.05	0.06	38
423	0.04	0.03	0.03	36

424	0.14	0.08	0.10	13
425	0.42	0.33	0.37	24
426	0.10	0.33	0.15	3
427	0.37	0.23	0.29	94
428	0.38	0.22	0.28	151
429	0.60	0.54	0.57	63
430	0.09	0.05	0.06	40
431	0.53	0.41	0.46	49
432	0.00	0.00	0.00	34
433	0.78	0.76	0.77	37
434	0.36	0.29	0.32	34
435	1.00	1.00	1.00	1
436	0.13	0.07	0.09	29
437	0.20	0.18	0.19	50
438	0.00	0.00	0.00	104
439	0.00	0.00	0.00	29
440	0.33	0.22	0.26	23
441	0.05	0.02	0.03	46
442	0.12	0.08	0.09	39
443	0.57	0.30	0.40	56
444	0.54	0.49	0.51	80
445	0.09	0.03	0.05	30
446	0.11	0.10	0.11	30
447	0.32	0.30	0.31	37
448	0.19	0.10	0.13	39
449	0.21	0.14	0.17	83
450	0.47	0.39	0.43	23
451	0.40	0.67	0.50	9
452	0.38	0.20	0.26	44
453	0.48	0.36	0.41	166
454	0.64	0.56	0.60	32
455	0.37	0.25	0.30	53
456	0.52	0.59	0.55	41
457	0.18	0.09	0.12	78
458	0.29	0.11	0.16	133
459	0.25	0.16	0.20	25
460	0.51	0.37	0.43	103
461	0.53	0.15	0.24	53
462	0.34	0.33	0.34	30
463	0.11	0.25	0.15	4
464	0.11	0.06	0.08	66

LINEAR SVM

468	0.00	0.00	0.00	50

```
from sklearn.model_selection import GridSearchCV
from scipy.stats import randint as sp_randint
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import SGDClassifier


LinearSVM = OneVsRestClassifier(SGDClassifier(loss='hinge',penalty='l2',random_state=None, class_weight=None), n_j
LinearSVM.fit(x_train_multilabel_bow, y_train)
predictions_svm = LinearSVM.predict(x_test_multilabel_bow)
print("Accuracy :",metrics.accuracy_score(y_test, predictions_svm))
print("Hamming loss ",metrics.hamming_loss(y_test,predictions_svm))


precision = precision_score(y_test, predictions_svm, average='micro')
recall = recall_score(y_test, predictions_svm, average='micro')
f1 = f1_score(y_test, predictions_svm, 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_svm, average='macro')
recall = recall_score(y_test, predictions_svm, average='macro')
f1 = f1_score(y_test, predictions_svm, average='macro')
```

```
24
25 print("Macro-average quality numbers")
26 print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(precision, recall, f1))
27
28 print (metrics.classification_report(y_test, predictions_svm))
29 print("Time taken to run this cell :", datetime.now() - start)
```

```
Accuracy : 0.2384
Hamming loss  0.002897085714285714
Micro-average quality numbers
Precision: 0.7029, Recall: 0.4923, F1-measure: 0.5790
Macro-average quality numbers
Precision: 0.4318, Recall: 0.2714, F1-measure: 0.3184
              precision    recall  f1-score   support

           0       0.98      0.95      0.96     42802
           1       0.36      0.23      0.28      1764
           2       0.55      0.32      0.40       942
           3       0.36      0.17      0.23      6539
           4       0.46      0.37      0.41      2540
           5       0.64      0.53      0.58      2156
           6       0.64      0.49      0.56      1990
           7       0.29      0.18      0.22       611
           8       0.43      0.25      0.32       324
           9       0.76      0.79      0.78      2335
          10       0.44      0.38      0.41       736
          11       0.37      0.25      0.29      1199
          12       0.49      0.36      0.42       842
          13       0.52      0.30      0.38       770
          14       0.55      0.53      0.54       975
          15       0.32      0.17      0.23       523
          16       0.38      0.25      0.30       143
          17       0.64      0.54      0.59       428
          18       0.71      0.50      0.59       552
          19       0.62      0.53      0.57       708
          20       0.84      0.60      0.70        89
          21       0.47      0.18      0.26       219
          22       0.41      0.24      0.30       662
          23       0.25      0.12      0.16      1965
          24       0.49      0.27      0.35      1046
          25       0.42      0.26      0.32       488
          26       0.42      0.27      0.33       458
          27       0.53      0.38      0.45      1193
          28       0.69      0.42      0.52      1492
          29       0.24      0.13      0.17       354
          30       0.43      0.36      0.39       159
          31       0.33      0.24      0.28       157
          32       0.32      0.22      0.26       740
          33       0.55      0.40      0.46      1337
          34       0.57      0.30      0.39       226
          35       0.69      0.44      0.54       535
          36       0.48      0.18      0.27       315
          37       0.28      0.15      0.20       167
          38       0.76      0.59      0.67      1074
          39       0.39      0.21      0.28       336
          40       0.43      0.35      0.39       312
          41       0.24      0.16      0.19       682
          42       0.81      0.54      0.65       265
          43       0.76      0.63      0.68       478
          44       0.67      0.25      0.36       598
          45       0.53      0.25      0.34      1054
          46       0.49      0.28      0.36       253
          47       0.31      0.13      0.18       936
          48       0.33      0.20      0.25       133
          49       0.31      0.10      0.15       152
          50       0.45      0.24      0.31       943
          51       0.19      0.09      0.12       243
          52       0.41      0.30      0.35       135
          53       0.98      0.74      0.85       969
          54       0.23      0.04      0.07       801
          55       0.62      0.58      0.60        50
          56       0.60      0.30      0.40       142
          57       0.39      0.24      0.30       125
          58       0.12      0.08      0.09        39
          59       0.44      0.33      0.38        36
          60       0.51      0.27      0.36       205
          61       0.31      0.19      0.23       354
          62       0.27      0.15      0.19       266
          63       0.66      0.38      0.48       178
```

64	0.85	0.63	0.72	163
65	0.54	0.43	0.48	46
66	0.39	0.15	0.22	269
67	0.72	0.74	0.73	133
68	0.34	0.09	0.14	577
69	0.15	0.04	0.06	212
70	0.77	0.67	0.71	120
71	0.25	0.14	0.18	258
72	0.17	0.19	0.18	354
73	0.72	0.57	0.63	159
74	0.44	0.25	0.32	89
75	0.48	0.29	0.36	125
76	0.32	0.26	0.29	94
77	0.56	0.28	0.37	456
78	0.48	0.27	0.35	712
79	0.25	0.07	0.11	299
80	0.18	0.15	0.16	53
81	0.54	0.27	0.36	275
82	0.53	0.11	0.19	623
83	0.55	0.37	0.44	75
84	0.10	0.07	0.08	27
85	0.63	0.39	0.48	230
86	0.51	0.32	0.39	177
87	0.50	0.33	0.40	30
88	0.61	0.50	0.55	655
89	0.18	0.12	0.14	126
90	0.49	0.38	0.43	422
91	0.08	0.02	0.03	130
92	0.83	0.80	0.82	451
93	0.19	0.05	0.08	77
94	0.08	0.00	0.01	461
95	0.68	0.40	0.51	104
96	0.19	0.09	0.12	454
97	0.39	0.41	0.40	345
98	0.43	0.40	0.42	125
99	0.54	0.39	0.45	144
100	0.27	0.11	0.15	279
101	0.47	0.09	0.15	99
102	0.79	0.55	0.65	553
103	0.71	0.20	0.32	123
104	0.22	0.07	0.10	542
105	0.17	0.05	0.08	542
106	0.32	0.14	0.20	118
107	0.58	0.40	0.47	73
108	0.29	0.14	0.18	191
109	0.30	0.12	0.17	180
110	0.47	0.17	0.25	121
111	0.39	0.22	0.28	41
112	0.12	0.02	0.04	254
113	0.17	0.10	0.13	146
114	0.66	0.34	0.45	279
115	0.35	0.12	0.18	245
116	0.51	0.23	0.31	102
117	0.57	0.36	0.44	469
118	0.23	0.03	0.06	248
119	0.38	0.23	0.29	98
120	0.57	0.41	0.48	105
121	0.18	0.05	0.08	164
122	0.39	0.28	0.33	95
123	0.47	0.37	0.42	208
124	0.53	0.35	0.42	85
125	0.65	0.51	0.57	98
126	0.23	0.07	0.11	41
127	0.79	0.39	0.52	431
128	0.57	0.29	0.38	111
129	0.41	0.27	0.33	74
130	0.44	0.22	0.30	116
131	0.54	0.31	0.39	126
132	0.37	0.37	0.37	270
133	0.35	0.20	0.25	35
134	0.41	0.23	0.30	64
135	0.62	0.65	0.64	243

135	0.62	0.69	0.64	245
136	0.93	0.75	0.83	345
137	0.41	0.18	0.25	174
138	0.34	0.28	0.31	183
139	0.76	0.27	0.39	454
140	0.86	0.64	0.73	302
141	0.62	0.39	0.48	82
142	0.74	0.80	0.77	82
143	0.42	0.35	0.38	98
144	0.87	0.64	0.73	137
145	0.48	0.21	0.30	412
146	0.24	0.10	0.14	224
147	0.26	0.08	0.12	153
148	0.62	0.64	0.63	64
149	0.54	0.38	0.45	68
150	0.18	0.07	0.10	126
151	0.15	0.07	0.10	202
152	0.21	0.15	0.18	39
153	0.55	0.33	0.41	36
154	0.69	0.43	0.53	136
155	0.21	0.04	0.07	212
156	0.50	0.43	0.46	51
157	0.49	0.48	0.49	94
158	0.18	0.07	0.10	286
159	0.49	0.49	0.49	350
160	0.41	0.32	0.36	22
161	0.15	0.07	0.10	120
162	0.24	0.14	0.18	144
163	0.59	0.55	0.57	119
164	0.50	0.19	0.28	42
165	0.85	0.73	0.79	361
166	0.35	0.14	0.20	206
167	0.60	0.17	0.27	87
168	0.39	0.26	0.31	112
169	0.33	0.10	0.15	298
170	0.45	0.15	0.23	191
171	0.55	0.44	0.49	91
172	0.88	0.50	0.64	100
173	0.22	0.07	0.10	167
174	0.47	0.41	0.44	344
175	0.14	0.04	0.06	76
176	0.25	0.09	0.13	198
177	0.42	0.19	0.26	127
178	0.38	0.22	0.28	102
179	0.67	0.26	0.37	31
180	0.57	0.47	0.52	139
181	0.74	0.41	0.53	63
182	0.47	0.25	0.32	367
183	0.49	0.64	0.55	67
184	0.00	0.00	0.00	46
185	0.54	0.11	0.18	381
186	0.56	0.17	0.26	29
187	0.31	0.16	0.21	111
188	0.22	0.12	0.15	121
189	0.17	0.01	0.02	82
190	0.50	0.36	0.42	118
191	0.79	0.34	0.47	77
192	0.61	0.53	0.57	118
193	0.38	0.07	0.12	159
194	0.44	0.24	0.31	269
195	0.78	0.58	0.67	81
196	0.44	0.20	0.27	299
197	0.09	0.02	0.03	47
198	0.79	0.70	0.74	47
199	0.36	0.16	0.22	62
200	0.00	0.00	0.00	24
201	0.60	0.30	0.40	86
202	0.52	0.15	0.24	308
203	0.77	0.45	0.57	321
204	0.00	0.00	0.00	67
205	0.21	0.21	0.21	28
206	0.51	0.44	0.47	59
207	0.33	0.19	0.24	245

207	0.55	0.19	0.24	249
208	0.65	0.58	0.61	53
209	0.06	0.01	0.01	274
210	0.25	0.12	0.17	8
211	0.53	0.38	0.44	95
212	0.30	0.25	0.27	129
213	0.58	0.44	0.50	34
214	0.35	0.30	0.33	89
215	0.51	0.37	0.43	67
216	0.42	0.20	0.27	25
217	0.67	0.53	0.59	109
218	0.45	0.10	0.16	134
219	0.60	0.47	0.53	70
220	0.63	0.36	0.46	67
221	0.50	0.18	0.26	79
222	0.57	0.40	0.47	50
223	0.75	0.71	0.73	93
224	0.33	0.22	0.27	94
225	0.10	0.06	0.07	180
226	0.22	0.09	0.13	79
227	0.35	0.38	0.36	64
228	0.25	0.04	0.07	50
229	0.72	0.55	0.62	53
230	0.55	0.27	0.36	44
231	0.18	0.26	0.21	61
232	0.38	0.51	0.43	49
233	0.82	0.75	0.78	72
234	0.23	0.17	0.19	233
235	0.34	0.06	0.10	166
236	0.84	0.45	0.58	58
237	0.12	0.01	0.02	152
238	0.61	0.23	0.33	302
239	0.49	0.48	0.48	42
240	0.56	0.42	0.48	269
241	0.25	0.07	0.11	54
242	0.20	0.02	0.03	162
243	0.53	0.39	0.45	23
244	0.78	0.38	0.51	66
245	0.14	0.05	0.07	40
246	0.69	0.49	0.58	73
247	0.86	0.55	0.67	78
248	0.28	0.13	0.18	131
249	0.37	0.13	0.20	82
250	0.86	0.56	0.68	57
251	0.21	0.01	0.03	296
252	0.49	0.20	0.28	87
253	0.25	0.15	0.18	96
254	0.52	0.26	0.34	280
255	0.36	0.17	0.23	24
256	0.38	0.14	0.20	88
257	0.30	0.43	0.35	7
258	0.26	0.12	0.16	136
259	0.76	0.47	0.58	73
260	0.62	0.51	0.56	268
261	0.82	0.82	0.82	11
262	0.67	0.43	0.52	82
263	0.33	0.40	0.36	5
264	0.36	0.25	0.30	108
265	0.80	0.47	0.60	78
266	0.24	0.09	0.13	69
267	0.41	0.11	0.18	80
268	0.57	0.29	0.38	28
269	0.22	0.05	0.08	44
270	0.71	0.57	0.63	42
271	0.41	0.29	0.34	114
272	0.15	0.07	0.09	59
273	0.43	0.20	0.27	130
274	0.23	0.19	0.21	48
275	0.28	0.10	0.14	227
276	0.77	0.61	0.68	75
277	0.65	0.38	0.48	68
278	0.66	0.51	0.57	143
279	0.26	0.15	0.19	78

279	0.20	0.13	0.15	75
280	0.81	0.44	0.57	78
281	0.75	0.49	0.59	61
282	0.00	0.00	0.00	61
283	0.69	0.21	0.32	52
284	0.25	0.12	0.17	24
285	0.11	0.02	0.03	125
286	0.35	0.17	0.23	138
287	0.17	0.05	0.07	171
288	0.72	0.31	0.43	157
289	0.62	0.33	0.43	30
290	0.17	0.07	0.10	30
291	0.74	0.31	0.44	64
292	0.15	0.22	0.18	9
293	0.36	0.13	0.19	123
294	0.55	0.34	0.42	35
295	0.20	0.05	0.07	22
296	0.40	0.44	0.42	184
297	0.63	0.29	0.40	140
298	0.39	0.10	0.16	224
299	0.80	0.44	0.57	97
300	0.12	0.03	0.05	65
301	0.14	0.05	0.07	44
302	0.50	0.32	0.39	38
303	0.45	0.26	0.32	98
304	0.52	0.42	0.46	31
305	0.32	0.25	0.28	235
306	0.99	0.76	0.86	249
307	0.31	0.23	0.26	247
308	0.47	0.29	0.36	122
309	0.24	0.06	0.10	230
310	0.40	0.13	0.19	166
311	0.19	0.10	0.13	40
312	0.44	0.24	0.31	17
313	0.27	0.19	0.23	36
314	0.53	0.39	0.44	109
315	0.00	0.00	0.00	67
316	0.72	0.68	0.70	79
317	0.19	0.06	0.09	197
318	0.16	0.47	0.23	47
319	0.68	0.32	0.44	222
320	0.63	0.44	0.52	27
321	0.70	0.57	0.63	207
322	0.74	0.29	0.41	240
323	0.32	0.06	0.09	215
324	0.47	0.29	0.36	120
325	0.44	0.16	0.24	130
326	0.82	0.64	0.72	28
327	0.12	0.15	0.13	166
328	0.76	0.49	0.59	45
329	0.51	0.48	0.49	180
330	0.23	0.11	0.15	62
331	0.28	0.25	0.26	105
332	0.96	0.56	0.71	39
333	0.50	1.00	0.67	4
334	0.61	0.40	0.48	113
335	0.64	0.29	0.40	78
336	0.21	0.08	0.11	51
337	0.40	0.18	0.25	147
338	0.00	0.00	0.00	135
339	0.30	0.37	0.33	27
340	0.12	0.01	0.02	79
341	0.95	0.63	0.76	30
342	0.25	0.06	0.09	54
343	0.59	0.20	0.30	195
344	0.30	0.33	0.31	39
345	0.86	0.67	0.75	9
346	0.78	0.65	0.71	86
347	0.31	0.11	0.17	44
348	0.76	0.28	0.40	185
349	0.83	0.53	0.65	66
350	0.33	0.33	0.33	3
351	0.53	0.29	0.37	35

352	0.51	0.31	0.39	216
353	0.52	0.33	0.41	42
354	0.67	0.33	0.44	6
355	0.07	0.67	0.12	3
356	0.20	0.07	0.11	14
357	0.42	0.35	0.39	31
358	0.39	0.09	0.14	204
359	0.00	0.00	0.00	211
360	0.48	0.17	0.26	184
361	0.29	0.18	0.22	108
362	0.00	0.00	0.00	54
363	0.31	0.18	0.23	56
364	0.32	0.09	0.14	97
365	0.41	0.17	0.24	72
366	0.00	0.00	0.00	12
367	0.60	0.22	0.32	185
368	0.20	0.02	0.03	193
369	0.17	0.06	0.09	34
370	0.57	0.27	0.37	164
371	0.67	0.67	0.67	18
372	0.29	0.15	0.20	65
373	0.42	0.25	0.31	20
374	0.00	0.00	0.00	29
375	0.52	0.34	0.41	71
376	0.12	0.01	0.01	164
377	0.53	0.14	0.22	185
378	0.12	0.12	0.12	24
379	0.26	0.25	0.25	52
380	0.08	0.02	0.03	57
381	0.29	0.03	0.06	59
382	0.33	0.02	0.03	117
383	0.65	0.56	0.60	39
384	0.65	0.44	0.53	125
385	0.27	0.12	0.16	130
386	0.66	0.58	0.62	74
387	0.66	0.54	0.59	35
388	0.52	0.57	0.55	21
389	0.49	0.13	0.20	175
390	0.00	0.00	0.00	54
391	0.00	0.00	0.00	29
392	0.46	0.10	0.16	63
393	0.33	0.38	0.36	34
394	0.75	0.63	0.69	38
395	0.50	0.20	0.29	15
396	0.25	0.20	0.22	10
397	0.33	0.12	0.18	49
398	0.67	0.05	0.09	169
399	0.33	0.30	0.32	33
400	0.56	0.45	0.50	84
401	0.80	0.52	0.63	31
402	0.44	0.46	0.45	24
403	0.72	0.16	0.26	187
404	0.50	0.33	0.40	6
405	0.58	0.33	0.42	33
406	0.17	0.12	0.14	17
407	0.50	0.05	0.09	21
408	0.32	0.10	0.15	62
409	0.19	0.04	0.06	78
410	0.67	0.48	0.56	147
411	0.35	0.23	0.27	31
412	0.00	0.00	0.00	14
413	0.69	0.19	0.30	103
414	0.88	0.61	0.72	36
415	0.51	0.59	0.54	68
416	0.16	0.07	0.10	43
417	0.44	0.37	0.40	73
418	0.89	0.52	0.65	62
419	0.00	0.00	0.00	97
420	0.08	0.05	0.06	42
421	0.73	0.39	0.51	41
422	0.33	0.05	0.09	38
423	0.50	0.03	0.05	36

424	0.20	0.08	0.11	13
425	0.33	0.12	0.18	24
426	0.00	0.00	0.00	3
427	0.40	0.22	0.29	94
428	0.37	0.16	0.22	151
429	0.73	0.59	0.65	63
430	0.25	0.07	0.12	40
431	0.47	0.31	0.37	49
432	0.00	0.00	0.00	34
433	0.87	0.70	0.78	37
434	0.39	0.32	0.35	34
435	1.00	1.00	1.00	1
436	0.14	0.03	0.06	29
437	0.17	0.14	0.15	50
438	0.00	0.00	0.00	104
439	0.00	0.00	0.00	29
440	0.20	0.04	0.07	23
441	0.00	0.00	0.00	46
442	0.27	0.10	0.15	39
443	0.61	0.30	0.40	56
444	0.61	0.35	0.44	80
445	0.14	0.07	0.09	30
446	0.10	0.07	0.08	30
447	0.33	0.24	0.28	37
448	0.62	0.13	0.21	39
449	0.19	0.10	0.13	83
450	0.67	0.26	0.38	23
451	0.31	0.56	0.40	9
452	0.47	0.16	0.24	44
453	0.55	0.10	0.17	166
454	0.68	0.47	0.56	32
455	0.29	0.11	0.16	53
456	0.60	0.51	0.55	41
457	0.14	0.08	0.10	78
458	0.25	0.05	0.09	133
459	0.33	0.12	0.18	25
460	0.50	0.17	0.26	103
461	0.62	0.09	0.16	53
462	0.38	0.30	0.33	30
463	1.00	0.25	0.40	4
464	0.17	0.05	0.07	66
465	0.25	0.11	0.15	47
466	0.33	0.19	0.24	31

CONCLUSION USING PRETTY TABLE

470	0.17	0.11	0.13	27

```
pip install -U PTable
```

```
Collecting PTable
  Downloading https://files.pythonhosted.org/packages/ab/b3/b54301811173ca94119eb474634f120a49cd370f257d1aae5a4
Building wheels for collected packages: PTable
  Building wheel for PTable (setup.py) ... done
  Created wheel for PTable: filename=PTable-0.9.2-cp36-none-any.whl size=22908 sha256=f93098ba6d1e52cdfd0e51e86
  Stored in directory: /root/.cache/pip/wheels/22/cc/2e/55980bfe86393df3e9896146a01f6802978d09d7ebcba5ea56
Successfully built PTable
Installing collected packages: PTable
Successfully installed PTable-0.9.2
```

```
from prettytable import PrettyTable
x= PrettyTable()
x.title = "TF-IDF Featurization"
x.field_names = ["Algorithm" , "Macro F1 Score Precision", "Micro F1 Score", "Hamming Loss"]
x.add_row(["Logistic Regression with OneVsRest",0.5473,0.7216,0.002708])
print(x)
y= PrettyTable()
y.add_row(["Logistic Regression with OneVsRest",0.4122,0.6777,0.002942])
y.add_row(["Linear SVM with OneVsRest",0.4318,0.7029,0.00289])
y.title = "CountVectorizer BIGRAM"
```

```
y.title = "CountVectorizer BIGRAM"
y.field_names = ["Algorithm" , "Macro F1 Score Precision", "Micro F1 Score", "Hamming Loss"]
print(y)
```

```
+-----------------------------------------------------------------------------------------+
|                                  TF-IDF Featurization                                   |
+----------------------------------+-------------------------+----------------+-------------+
|            Algorithm             | Macro F1 Score Precision | Micro F1 Score | Hamming Loss |
+----------------------------------+-------------------------+----------------+-------------+
| Logistic Regression with OneVsRest |         0.5473          |     0.7216     |   0.002708   |
+----------------------------------+-------------------------+----------------+-------------+
+-----------------------------------------------------------------------------------------+
|                                 CountVectorizer BIGRAM                                  |
+----------------------------------+-------------------------+----------------+-------------+
|            Algorithm             | Macro F1 Score Precision | Micro F1 Score | Hamming Loss |
+----------------------------------+-------------------------+----------------+-------------+
| Logistic Regression with OneVsRest |         0.4122          |     0.6777     |   0.002942   |
|     Linear SVM with OneVsRest      |         0.4318          |     0.7029     |   0.00289    |
+----------------------------------+-------------------------+----------------+-------------+
```

CONCLUSION : LOGISTIC REGRESSION WITH ONEVSREST HAVE GOOD PRECISION : 0.6777 AS MICRO F1 SCORE

```
1
```