```
# Importing necessary libraries
```

import warnings

warnings.filterwarnings('ignore')

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import csv

import sqlite3

import os

import re

import datetime as dt

from datetime import datetime

from wordcloud import WordCloud

import pickle

import nltk

from sqlalchemy import create_engine # database connection

from nltk.corpus import stopwords

from nltk.tokenize import word_tokenize

from nltk.stem.snowball import SnowballStemmer

from sklearn.metrics import f1_score,precision_score,recall_score

from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

from sklearn.multiclass import OneVsRestClassifier

from sklearn.linear_model import SGDClassifier, LogisticRegression

from sklearn.naive_bayes import GaussianNB

from sklearn import metrics

from sklearn import svm

from skmultilearn.adapt import mlknn

from skmultilearn.problem_transform import ClassifierChain, BinaryRelevance, LabelPowerset

Stack Overflow: Tag Prediction

1. Business Problem

1.1 Description

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 Statemtent

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

Source: https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/

1.2 Source / useful links

Data Source: https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data

Youtube: https://youtu.be/nNDqbUhtIRg

 $Research\ paper: \underline{https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/tagging-1.pdf}$

Research paper: https://dl.acm.org/citation.cfm?id=2660970&dl=ACM&coll=DL

1.3 Real World / Business Objectives and Constraints

1. Predict as many tags as possible with high precision and recall.

- 2. Incorrect tags could impact customer experience on StackOverflow.
- 3. No strict latency constraints.

2. Machine Learning problem

2.1 Data

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 math and programming. The number of questions from each site may vary, and no filtering has been performed on the questions (such as closed questions).

__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, should not contain tabs '\t' or ampersands '&')

2.1.2 Example Data point

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

```
#include<
iostream>\n
```

{\n

```
#include<
stdlib.h>\n\n
using namespace std;\n\n
int main()\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
      for(x=1; x< n+1; x++) \ 
       a[x] = (m[x] + u[x])/2; n
      c=(n*4)-4;\n
      for(int a1=1; a1<n+1; a1++)\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
               for(int i=1; i<n+1; i++)\n
                 for(int l=1; l<=i; l++)\n
                 {\n
                    if(I!=1)\n
                      cout << a[l] << "\t";\n
                    }\n
                 for(int j=0; j<4; j++)n
                    cout<<e[i][j];\n
                    for(int k=0; k< n-(i+1); k++) n
                      cout << a[k] << "\t";\n
                    }\n
                    cout<<"\\n";\n
                 }\n
               } \n\n
               system("PAUSE");\n
               return 0; \n
         }\n
The answer should come in the form of a table like
         1
                  50
                              50\n
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                              50\n
                  50
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                              99\n
                              100\n
         50
                   50
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)
```

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

The output is not coming, can anyone correct the code or tell me what\'s wrong?

2.2.1 Type of Machine Learning Problem

It is a multi-label classification problem

 $n\n$

 $n\n$

\n\n

 $n\n$

\n'

Tags : 'c++ c'

Multi-label Classification: Multilabel classification assigns to each sample a set of target labels. This can be thought as predicting properties of a data-point that are not mutually exclusive, such as topics that are relevant for a document. A question on Stackoverflow might be about any 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 the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal. The formula for 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. This is a better metric when we have class imbalance.

'Macro f1 score':

Calculate metrics for each label, and find their unweighted mean. This does not take label imbalance into account.

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

In [2]:

```
# Train file unzipping
import zipfile
with zipfile.ZipFile('Train.zip', 'r') as zip_ref:
    zip_ref.extractall('lab')

# Test File unzipping
with zipfile.ZipFile('Test.zip', 'r') as zip_ref:
    zip_ref.extractall('lab')
```

Out[2]:

"\n# https://stackoverflow.com/a/3451150/10219869\n\n# Train file unzipping\nimport zipfile\nwith zipfile.ZipFile('Train.zip', 'r') as zip_ref:\n zip_ref.e xtractall('lab')\n\n# Test File unzipping\nwith zipfile.ZipFile('Test.zip', 'r') as zip_ref.\n zip_ref.extractall('lab')\n\n"

In [3]:

```
#Creating db file from csv
#Learn SQL: https://www.w3schools.com/sql/default.asp
from datetime import datetime
if not os.path.isfile('train.db'):
  start = datetime.now()
   # creating new SQLite database engine
  disk_engine = create_engine('sqlite:///train.db')
  start = dt.datetime.now()
  chunksize = 180000
  \mathbf{i} = 0
  index_start = 1
   # importing data into SQLite from CSV
  for df in pd.read_csv('Train.csv', names=['Id', 'Title', 'Body', 'Tags'], chunksize=chunksize, iterator=True, encoding='utf-8', ):
     df.index += index_start
     i += 1
     print('{} rows'.format(j*chunksize))
     # 'data' is the name given to the table which consists of above 4 columns
     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)
```

3.1.2 Counting the number of rows

```
In [3]:
```

```
if os.path.isfile('train.db'):
    start = datetime.now()

# connecting to database
    con = sqlite3.connect('train.db')
    num_rows = pd.read_sql_query("SELECT count(*) FROM data", con)

#Always remember to close the database
    print("Number of rows in the database :","\n",num_rows['count(*)'].values[0])

# disconnecting from database
    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: 0:03:13.509836

3.1.3 Checking for duplicates

In [5]:

```
#Learn SQI: https://www.w3schools.com/sql/default.asp

if os.path.isfile('train.db'):
    start = datetime.now()

# connecting to database
    con = sqlite3.connect('train.db')

# creating "no duplicates" DataFrame
    df_no_dup = pd.read_sql_query('SELECT Title, Body, Tags, COUNT(*) as cnt_dup FROM data GROUP BY Title, Body, Tags', con)

# disconnecting from database
    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: 0:02:45.507073

In [6]:

df_no_dup.head()
After grouping all 3 columns except 'ld' (as it is unique obviously), we observe there are duplicates and its count.

Out[6]:

	Title	Body	Tags	cnt_dup
0	Implementing Boundary Value Analysis of S	<pre><code>#include<iostream>\n#include&</code></pre>	C++ C	1
1	Dynamic Datagrid Binding in Silverlight?	I should do binding for datagrid dynamicall	c# silverlight data-binding	1
2	Dynamic Datagrid Binding in Silverlight?	I should do binding for datagrid dynamicall	c# silverlight data-binding columns	1
3	java.lang. No Class Def Found Error: javax/serv	I followed the guide in		

In [7]:

```
# Total number of questions which are repeated more than once
df_no_dup[df_no_dup['cnt_dup'] >1 ].count()
```

Out[7]:

Body 1550031 Tags 1550030 cnt_dup 1550031 dtype: int64

In [8]:

Total number of duplicate questions
print(num_rows['count(*)'].values[0] - df_no_dup.shape[0], 'and its percentage is ', ((num_rows['count(*)'].values[0] - df_no_dup.shape[0]) / num_row s['count(*)'].values[0]) * 100,'%')

1827881 and its percentage is 30.292038906260256 %

In [9]:

number of times each question appeared in our database 'data' df_no_dup['cnt_dup'].value_counts()

Out[9]:

- 1 2656284
- 2 1272336
- 3 277575
- 4 90
- 5 25
- 6 5

Name: cnt_dup, dtype: int64

3.1.4 Checking for NaN values

In [10]:

Found no duplicate rows in 'Title' feature df_no_dup[df_no_dup['Title'].isna()]

Out[10]:

Title Body Tags cnt_dup

In [11]:

Found no duplicate rows in 'Body' feature df_no_dup[df_no_dup['Body'].isna()]

Out[11]:

Title Body Tags cnt_dup

In [12]:

Found 7 duplicate rows in 'Tags' feature df_no_dup[df_no_dup['Tags'].isna()]

Out[12]:

	Title	Body	Tags	cnt_dup
777547	Do we really need NULL?	<pre><blookledge< pre=""></blookledge<></pre> <pre> possible Duplicate:</pre>	None	1
962680	Find all values that are not null and not in a	I am running into a problem which results i	None	1
1126558	Handle NullObjects	I have done quite a bit of research on best	None	1
1256102	How do Germans call null	In german null means 0, so how do they call	None	1
2430668	Page cannot be null. Please ensure that this 0	I get this error when i remove dynamically	None	1
3329908	What is the difference between NULL and "0"?	What is the difference from NULL and "0"? </th <th>None</th> <th>1</th>	None	1
3551595	a bit of difference between null and space	I was just reading this quote\n\n <block< th=""><th>None</th><th>2</th></block<>	None	2

as there are 7 rows of empty Tags, we remove them df_no_dup.dropna(inplace=**True**)

In [14]:

```
start = datetime.now()

# adding a new feature number of tags per question
a=[]

for i in df_no_dup["Tags"]:
    i = i.split(' ')
    a.append(len(i))

df_no_dup["tag_count"]= a

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

Time taken to run this cell: 0:00:03.892881

Out[14]:

	Title	Body	Tags	cnt_dup	tag_count	
0	Implementing Boundary Value Analysis of S	<pre><code>#include<iostream>\n#include&</code></pre>	C++ C	1	2	
1	Dynamic Datagrid Binding in Silverlight?	I should do binding for datagrid dynamicall	c# silverlight data-binding	1	3	
2	Dynamic Datagrid Binding in Silverlight?	I should do binding for datagrid dynamicall	c# silverlight data-binding columns	1	4	
3	java.lang. No Class Def Found Error: javax/serv	I followed the guide in <a block"="" href="http://sta</td><td>jsp jstl</td><td>1</td><td>2</td></tr><tr><td>4</td><td><math display=">java.sql. SQLException: [Microsoft] [ODBC\ Dri	I use the following code\n\n <pre>pre><code></code></pre>	java jdbc	2	2

In [15]:

```
# distribution of no. of tags per question
df_no_dup['tag_count'].value_counts()
```

Out[15]:

- 3 1206157
- 2 1111706
- 4 814996
- 1 568291
- 5 505158

Name: tag_count, dtype: int64

In [16]:

```
#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')
  # making dataframe with no duplicates
  # 'no_dup_train' is table name in database of train_no_dup
  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)
  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: 0:00:50.115210

3.2 Analysis of Tags

```
3.2.1 Total number of unique tags
In [17]:
# Importing & Initializing the "CountVectorizer" object, which is scikit-learn's bag of words (bow) 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'])
In [18]:
# BOW representation of sparse vectors.
tag_dtm.shape
Out[18]:
(4206314, 42048)
In [19]:
print("Number of data points :", tag_dtm.shape[0])
print("Number of unique tags :", tag_dtm.shape[1])
Number of data points: 4206314
```

```
In [20]:

#'get_feature_names()' used on vectorizer, gives us the vocabulary.

tags = vectorizer.get_feature_names()

#Lets look at the tags we have.

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

Some of the tags we have :

Number of unique tags: 42048

['.a', '.app', '.asp.net-mvc', '.aspxauth', '.bash-profile', '.class-file', '.cs-file', '.doc', '.drv', '.ds-store']

3.2.3 Number of times a tag appeared

In [21]:

```
# https://stackoverflow.com/questions/15115765/how-to-access-sparse-matrix-elements
#Lets now store the document term matrix in a dictionary.
freqs = tag_dtm.sum(axis=0).A1
result = dict(zip(tags, freqs))
```

In [22]:

```
freqs[:10]
```

Out[22]:

array([18, 37, 1, 21, 138, 53, 14, 47, 1, 8], dtype=int64)

In [23]:

```
#Saving this dictionary to csv files.
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()
```

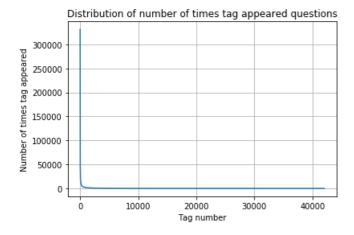
Out[23]

Tags Counts 0 urlbinding 5 1 mongovue 11 2 createitem 3 3 ipython-notebook 63 4 rubyosa 2

In [24]:

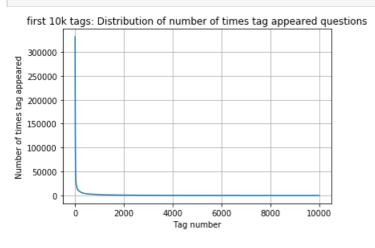
```
tag_df_sorted = tag_df.sort_values(['Counts'], ascending=False)
tag_counts = tag_df_sorted['Counts'].values

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()
```



In [25]:

```
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])
```

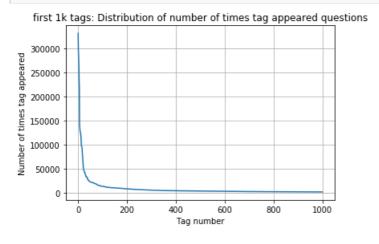


```
400 [331505 44829 22429 17728 13364 11162 10029 9148 8054 7151
 6466 5865 5370 4983
                            4281 4144 3929 3750 3593
                      4526
 3453 3299
            3123
                 2989
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```

In [26]:

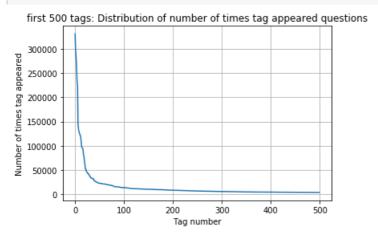
```
plt.plot(tag_counts[0:1000])
plt.title('first 1k tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
print(len(tag_counts[0:1000:5]), tag_counts[0:1000:5])
```



```
200 [331505 221533 122769 95160 62023 44829 37170 31897 26925 24537
 22429 21820 20957 19758 18905 17728 15533 15097 14884 13703
 13364 13157 12407 11658 11228 11162 10863 10600 10350 10224
 10029
       9884 9719
                    9411
                          9252
                               9148
                                      9040
                                            8617
                                                  8361
                                                        8163
 8054
       7867
             7702
                   7564
                          7274
                               7151
                                      7052
                                           6847
                                                  6656
                                                        6553
 6466
       6291
                    6093
             6183
                          5971
                                5865
                                      5760
                                            5577
                                                  5490
                                                        5411
 5370
       5283
             5207
                    5107
                          5066
                                4983
                                            4785
                                                  4658
                                      4891
                                                        4549
                                            4228
 4526
       4487
             4429
                    4335
                         4310
                                4281
                                      4239
                                                  4195
                                                        4159
 4144
       4088
                    4002
                         3957
                                            3849
                                                  3818
             4050
                               3929
                                      3874
                                                        3797
 3750
       3703
                    3658
                          3615
                                3593
                                      3564
                                            3521
                                                  3505
                                                        3483
             3685
 3453
             3396
                    3363
                          3326
                               3299
                                      3272
                                            3232
                                                  3196
       3427
                                                        3168
 3123
       3094
             3073
                    3050
                          3012
                                2989
                                      2984
                                            2953
                                                  2934
                                                        2903
 2891
       2844
             2819
                    2784
                          2754
                                2738
                                      2726
                                            2708
                                                  2681
                                                        2669
       2621
                         2556
 2647
             2604
                   2594
                               2527
                                      2510
                                            2482
                                                  2460
                                                        2444
 2431
       2409
             2395
                   2380
                         2363
                               2331
                                      2312
                                            2297
                                                  2290
                                                        2281
 2259
       2246
             2222
                    2211
                          2198
                               2186
                                      2162
                                            2142
                                                  2132
                                                        2107
 2097
       2078
             2057
                    2045
                         2036
                               2020
                                      2011
                                            1994
                                                        1965
                                                  1971
 1959
       1952
             1940
                    1932
                          1912
                                1900
                                      1879
                                            1865
                                                  1855
                                                        1841
 1828
       1821
             1813
                    1801
                          1782
                                1770
                                      1760
                                            1747
                                                  1741
                                                        1734
                                                  1646
                                                        1639]
 1723
       1707
             1697
                   1688
                         1683
                               1673
                                     1665
                                           1656
```

In [27]:

```
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])
```



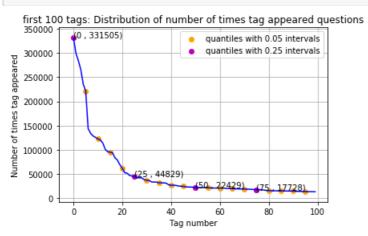
```
100 [331505 221533 122769 95160 62023 44829 37170 31897 26925 24537
22429 21820 20957 19758 18905 17728 15533 15097 14884 13703
13364 13157 12407 11658 11228 11162 10863 10600 10350 10224
 10029 9884 9719 9411
                       9252 9148 9040 8617
 8054
      7867
            7702 7564
                      7274
                            7151
                                  7052 6847
                                             6656
                                                  6553
 6466
      6291
            6183
                 6093
                       5971
                            5865
                                  5760
                                       5577
                                             5490
                                                  5411
 5370
      5283
            5207
                 5107
                       5066
                            4983
                                  4891
                                       4785
                                             4658
                                                  4549
 4526
      4487
            4429
                 4335
                      4310
                            4281
                                  4239
                                       4228
                                             4195
                                                  4159
 4144 4088
           4050 4002
                       3957
                            3929
                                  3874
                                       3849 3818 3797
                                       3521
 3750
      3703 3685 3658 3615 3593 3564
                                             3505 3483]
```

In [28]:

```
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.legend()
plt.legend()
plt.show()
print(len(tag_counts[0:100:5]), tag_counts[0:100:5])
```



20 [331505 221533 122769 95160 62023 44829 37170 31897 26925 24537 22429 21820 20957 19758 18905 17728 15533 15097 14884 13703]

In [29]:

tag_df.columns

Out[29]:

Index(['Tags', 'Counts'], dtype='object')

In [30]:

```
#Print the length of the list
print ('{{}} Tags are used more than 10000 times'.format(len(tag_df[tag_df['Counts'] > 10000])))

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

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, Micro-averaged F1-score is the appropriate metric for this probelem.

3.2.4 Tags Per Question

In [31]:

```
#Storing the count of tag in each question in list 'tag_count'
# if not .tolist() then the o/p will be in the form of matrix bcoz tag_dtm is a sparse matrix(a result of count vectorizer)
tag_quest_count = tag_dtm.sum(axis=1).tolist()

tag_quest_count[:10]
```

Out[31]:

[[3], [4], [2], [2], [3], [3], [2], [2], [2], [2]

In [32]:

```
#Converting list of lists into single list, we will get [[3], [4], [2], [2], [3]] and we are converting this to [3, 4, 2, 2, 3] tag_quest_counts=[]

for i in tag_quest_count:
    for j in i:
        tag_quest_counts.append(j)
    print ('We have total {} datapoints:'.format(len(tag_quest_counts)))

print(tag_quest_counts[:5])
```

We have total 4206314 datapoints.

[3, 4, 2, 2, 3]

In [33]:

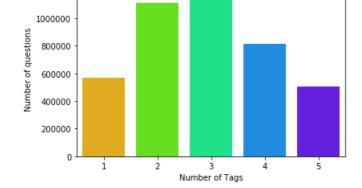
```
print( "Maximum number of tags per question: ", max(tag_quest_counts))
print( "Minimum number of tags per question: ", min(tag_quest_counts))
print( "Avg. number of tags per question: ",((sum(tag_quest_counts)*1.0)/len(tag_quest_counts)))
```

Maximum number of tags per question: 5 Minimum number of tags per question: 1

Avg. number of tags per question: 2.8994395092710623

In [34]:

```
sns.countplot(tag_quest_counts, 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

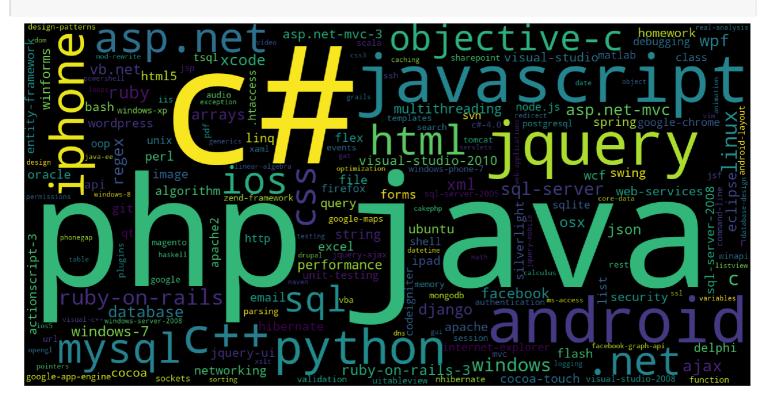
In [35]:

```
# 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)
wordcloud.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: 0:00:05.045855

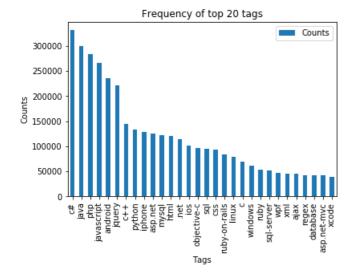
Observations:

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

3.2.6 The top 20 tags

In [36]:

```
i=np.arange(30)
tag_df_sorted['Counts'][: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.legend()
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 HTML Tags
- 5. Convert all the characters into small letters
- 6. Use SnowballStemmer to stem the words

In [4]:

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

In [5]:

```
#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:
    connect = sqlite3.connect(db_file)
    return connect
except Error as e:
    print(e)

return None
```

```
def create_table(connect, create_table_sql):
   """ create a table from the create_table_sql statement
  :param connect: Connection object
  :param create table sql: a CREATE TABLE statement
   :return:
  try:
    c = connect.cursor()
    c.execute(create_table_sql)
  except Error as e:
    print(e)
def checkTableExists(dbcon):
  cursor = dbcon.cursor()
  str = "select name from sqlite_master where type='table'"
  table_names = cursor.execute(str)
  print("Tables in the database:")
  tables =table names.fetchall()
  print(tables[0][0])
  return(len(tables))
def create_database_table(database, query):
  connect = create_connection(database)
  if connect is not None:
     create_table(connect, query)
     checkTableExists(connect)
  else:
     print("Error! cannot create the database connection.")
  connect.close()
sgl create table = "CREATE TABLE IF NOT EXISTS Questions Processed (question text NOT NULL, code text, tags text, words pre integer, words
post integer, is code integer);"
create database table("Processed.db", sql create table)
Tables in the database:
QuestionsProcessed
In [39]:
# 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'
if os.path.isfile(read db):
  connect_read = create_connection(read_db)
  if connect_read is not None:
    reader =connect read.cursor()
     # took 1 million random datapoints
    reader.execute("SELECT Title, Body, Tags From no_dup_train ORDER BY RANDOM() LIMIT 1000000;")
write_db = 'Processed.db'
if os.path.isfile(write db):
  connect_write = create_connection(write_db)
  if connect_write is not None:
     tables = checkTableExists(connect write)
     writer =connect_write.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 database: QuestionsProcessed Cleared All the rows

Time taken to run this cell: 0:02:18.028313

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

In [40]:

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

[nltk_data] Downloading package punkt to
[nltk_data] /home/passionateguy_bharat/nltk_data...
```

[mik_data] Fackage punkt is already up-to-date:

Out[40]:

True

In [41]:

```
#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], 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 from question
  question = ''.join(str(stemmer.stem(j)) for j in words)
  question = ''.join([i for i in question.split() if (len(i)>1 or i == '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 (?,?,?,?,?)",tup)
  if (questions processed%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
number of questions completed = 800000
number of questions completed = 900000
Avg. length of questions(Title+Body) before processing: 1171
Avg. length of questions(Title+Body) after processing: 490
Percent of questions containing code: 57
Time taken to run this cell: 0:32:06.224758
```

In [42]:

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

connect_write.close()

In [43]:

```
if os.path.isfile(write_db):
    connect_read = create_connection(write_db)
    if connect_read is not None:
        reader =connect_read.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)
        connect_read.commit()
        connect_read.close()
```

Questions after preprocessed

('javascript div slider no jqueri am look to write javascript div slider tri jqueri plugin for div slide howev sinc our applic is dynam generat somehow the c urrent jqueri plugin don seem to render the slider correct henc thought to see if could write simpl slider that will toggl two div in slider way basic would have two div and one left button and one right bottom so when click the right button the first content should slide to the second horizont same way co uld flip it back with the left button have an abil to have second delay between transit would be help ani pointer on how to write this will be realli help th x',)

('howto disabl format dection on date how do disabl format detect on date on iphon mobil webapp ni ve tri which doesn work after all it date not phone numb',)

('whi is javascript math floor the slowest way to calcul floor in javascript general not fan of microbenchmark but this one has veri interest result http er nestdelgado com archiv benchmark on the floor it suggest that is the slowest way to calcul floor in javascript all be faster nthis seem pretti shock as w ould expect that peopl implement javascript in today modern browser would be some pretti smart peopl doe floor do someth import that the other met hod fail to do is there ani reason to use it',)

('no modul name fcntl am tri to execut this method with ironpython on net use ironpython am use window c code can someon tell me what am do wro ng keep gettin that do not have fcntl modul',)

('run regex replac on regex in javascript have the regex which valid csv file but want to be abl to modifi the delimit with ani delimit is it possibl to run re gex replac on regex exampl use backtick as the delimit',)

('how do generat breadcrumb for my melt app have use the melt framework to build web applic with the follow structur now want to generat breadcrumb to show in the layout php abov the content of each view what would be the best way to implement breadcrumb in melt',)

('document properti demot from listitem field is not work have content type in librari configur with word document as templat it is the default content type nwhen creat via the ui from new item enter inform into the dip set valu in the document via quick part document properti nthese entri are reflect on the under sharepoint list item and in the bodi of the document if re open the document the chang in the dip do not get reflect in the document bodi if creat document via code use the templat file set the list item field the list item properti are not reflect in the document at all they can be found when inspect the xml but they never get demot into the bodi of the document ani bodi got ani pointer as to how we can tri and ensur that the document and the list item properti are kept in sync',)

('how to appli devexpress skin to devexpress textbox control use devexpress theme builder in order to creat theme success appli the theme the probl em aris when had differ width aspx textbox decid to creat skin in theme builder and onli chang the width use skinid properti to set the skin on textbox but don see the effect regist my theme with the follow code should do similar registr for my skin',)

('reset video progress bar on click have video progress bar that move to new div when you click on said div and show the play progress of current pla y video would like to know how can reset the bar when click on the new div instead of when the new video start to play basic click first div video play click anoth div progress bar reset move to new place new video play and bar show have the follow script but as ve not had to work with this befor my grasp of it is littl tenuous ani help would be great appreci',)

In [44]:

```
#Taking 2 Million entries to a dataframe.
write_db = 'Processed.db'
if os.path.isfile(write_db):
    connect_read = create_connection(write_db)
    if connect_read is not None:
        preprocessed_data = pd.read_sql_query("SELECT question, Tags FROM QuestionsProcessed", connect_read)
connect_read.commit()
connect_read.close()
```

In [45]:

preprocessed_data.head()

Out[45]:

question tags

0	question unix termin pager use on os and prefer the uni	tags r less readline
1	javascript div slider no jqueri am look to wri	javascript jquery slider
2	howto disabl format dection on date how do dis	iphone mobile-web
3	whi is javascript math floor the slowest way t	javascript optimization
4	no modul name fcntl am tri to execut this meth	c# module compiler-errors ironpython fcntl

In [46]:

```
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 : 999999

number of dimensions: 2

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
```

In [47]:

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

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

In [6]:

```
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))
```

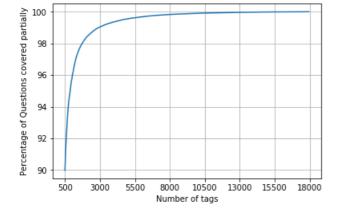
In [49]:

```
questions_explained = []
total_qs= preprocessed_data.shape[0]
total_tags= multilabel_y.shape[1]

for i in range(500, total_tags, 100):
    questions_explained.append(np.round(((total_qs-questions_explained_fn(i))/total_qs)*100,3))
```

In [50]:

```
fig, ax = plt.subplots()
ax.plot(questions_explained)
xlabel = list(500+np.array(range(-50,450,50))*50) # [-2000, 500, 3000, 5500, 8000, 10500, 13000, 15500, 18000, 20500]
ax.set_xticklabels(xlabel)
plt.xlabel("Number of tags")
plt.ylabel("Percentage of Questions covered 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 99.035 % of questions

In [51]:

```
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: 9650 out of 999999

In [52]:

```
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 : 35490 number of tags taken : 5500 (15.497323189630881 %)

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

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

In [53]:

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

x_train=preprocessed_data.head(train_size) # considering top (head) 80% (train_size)

x_test=preprocessed_data.tail(total_size - train_size)

# sparse matrices of top 5500 features
y_train = multilabel_yx[0:train_size,:]
y_test = multilabel_yx[train_size:total_size,:]
```

In [54]:

```
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 : (799999, 5500) Number of data points in test data : (200000, 5500)

4.3 Featurizing data

In [55]:

```
start = datetime.now()

vectorizer = TfidfVectorizer(min_df=0.00009, tokenizer = lambda x: x.split(), 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: 0:11:56.544073

In [56]:

```
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: (799999, 181427) Y: (799999, 5500) Dimensions of test data X: (200000, 181427) Y: (200000, 5500)

In [57]:

```
# 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)
classifier.fit(x_train_multilabel, y_train)
# predict
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
#MemorvError
                                  Traceback (most recent call last)
#<ipython-input-170-f0e7c7f3e0be> in <module>()
#----> classifier.fit(x_train_multilabel, y_train)
```

Out[57]:

"\nfrom skmultilearn.adapt import MLkNN\nclassifier = MLkNN(k=21)\n\n# train\nclassifier.fit(x_train_multilabel, y_train)\n\n# predict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npredict\npr

4.5 Modeling with less data points (0.5M data points) and more weight to title and 500 tags only.

In [7]:

sql_create_table = "CREATE TABLE IF NOT EXISTS QuestionsProcessed (question text NOT NULL, code text, tags text, words_pre integer, words _post integer, is_code integer);"
create_database_table("Titlemoreweight.db", sql_create_table)

Tables in the database:

QuestionsProcessed

In [8]:

```
# 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 = 'Titlemoreweight.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 500001;")
    # for selecting random points
     #reader.execute("SELECT Title, Body, Tags From no dup train ORDER BY RANDOM() LIMIT 500001;")
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 database: 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
- 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

In [9]:

```
#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')
   # 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 proceesed<=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)
  question = ".join([i \ \textbf{for} \ i \ \textbf{in} \ question.split() \ \textbf{if} \ (len(i)>1 \ \textbf{or} \ i == '\textbf{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 (?,?,?,?,?)",tup)
  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
Avg. length of questions(Title+Body) before processing: 1239
Avg. length of questions(Title+Body) after processing: 607
Percent of questions containing code: 57
Time taken to run this cell: 0:22:43.404308
```

In [10]:

```
# 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

In [11]:

```
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('-1*100)
        conn_r.commit()
        conn_r.close()
```

Questions after preprocessed

('dynam datagrid bind in silverlight dynam datagrid bind in silverlight dynam datagrid bind in silverlight should do bind for datagrid dynam at code wrot e the code as below when debug this code block it seem that it doe bind correct but grid come with no column on form whi doesn come grid with column although did necessari bind nthank for the repli in advance..',)

('java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid follow the guid in this link to instal jstl but got the follow error when tri to launch my jsp page java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid the taglib declar is instal jstl 1.1 under in tomcat webapp and tri to do the same in my project but it didn work also tri version 1.2 of jstl and still the same messag how is this caus and how can solv it',)

('java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index use the follow code it display how is this caus and how can solv it',)

('better way to updat feed on fb with php sdk better way to updat feed on fb with php sdk better way to updat feed on fb with php sdk am novic with t he facebook api have read so mani tutori and am still confused.i find that can post to the feed with api method like this and that is correct second way is use curl someth like this which way is better',)

('btnadd click event open two window after record ad btnadd click event open two window after record ad btnadd click event open two window after record ad open window search.aspx use below code hav add button in search.aspx nwhen insert record from btnadd click event then it open anoth window nafter insert record have to close that window how can do that',)

('sql inject issu prevent correct form submiss php sql inject issu prevent correct form submiss php sql inject issu prevent correct form submiss php so ve been check everyth can think of to make sure my input field are all safe from ani type of sql inject the good news is they are safe the bad news is there is one tag that mess up the form submiss in place that it shouldneven touch and can for the life of me figur out whit his is the exact html use it in templat file so forgiv the okay this is the entir php script that get execut until it see that there is no data post none of the forum field are be post the problem is when use someth such as or in the titl field none of the data get post am current use print post to see what is be submit and noth is it work flawless for ani other statement though and should also mention that this script work flawless on my local machin but when use my host come across the problem state abov this is list of all the input test that mess it up',)

('countabl subaddit of the lebesgu measur countabl subaddit of the lebesgu measur let Ibrace rbrace be se quenc of set in sigma -algebra mathcal want to show that left bigcup right leq sum left right where is countabl addit measur defin for all set in sigma a lgebra mathcal think have to use the monoton properti somewher in the proof but don how to start it appreci littl help nthank ad from han answer mak e the follow addit from the construct given in han answer it is clear the bigcup bigcup and cap emptyset for all neq so left bigcup right left bigcup right sum left right also from the construct we have subset for all and so by monoton we have left right leq left right final we would have sum leq sum and the result follow',)

(that equival to this sal queri hat equival to this sal queri hat equival to this sal queri what is hat queri for the show replaced my name with class and

roperti name but error occur hql error',)

('undefin symbol for architectur i386 objc class skpsmtpmessag referenc from error undefin symbol for architectur i386 objc class skpsmtpmessag referenc from error undefin symbol for architectur i386 objc class skpsmtpmessag referenc from error have import framework for send email from applic in background have import framework i.e skpsmtpmessag can somebodi suggest me whi am get this error collect2 ld return exit status have import framework correct sorc from which have taken framework and follow is mfmailcomposeviewcontrol question lock the field updat answer is you just dra g and drop folder over the project and click copi nthat it',)

4

10 . 1

Saving Preprocessed data to a Database

In [12]:

```
#Taking 0.5 Million entries to a dataframe.
write_db = 'Titlemoreweight.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 QuestionsProcessed""", conn_r)
conn_r.commit()
conn_r.close()
```

In [13]:

preprocessed_data.head()

Out[13]:

	question	tags
0	dynam datagrid bind in silverlight dynam datag	c# silverlight data-binding
1	dynam datagrid bind in silverlight dynam datag	c# silverlight data-binding columns
2	java.lang.noclassdeffounderror javax servlet j	jsp jstl
3	java.sql.sqlexcept microsoft odbc driver manag	java jdbc
4	better way to updat feed on fb with php sdk be	facebook api facebook-php-sdk

In [14]:

```
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 : 500000 number of dimensions : 2

Converting string Tags to multilable output variables

In [15]:

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

Selecting 500 Tags

In [16]:

```
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))
```

In [17]:

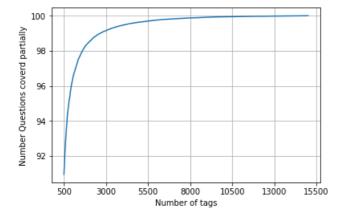
```
fig, ax = plt.subplots()
ax.plot(questions_explained)
xlabel = list(500+np.array(range(-50,450,50))*50)
ax.set_xticklabels(xlabel)
plt.xlabel("Number of tags")
plt.ylabel("Number Questions coverd partially")
```

plt.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")



with 5500 tags we are covering 99.157 % of questions with 500 tags we are covering 90.956 % of questions

In [18]:

```
# 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 ", total_qs)
```

number of questions that are not covered: 45221 out of 500000

In [19]:

```
x_train=preprocessed_data.head(train_datasize)
x_test=preprocessed_data.tail(preprocessed_data.shape[0] - 400000)

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

In [20]:

```
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 : (400000, 500) Number of data points in test data : (100000, 500)

4.5.2 Featurizing data with Tfldf vectorizer

In [21]:

```
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=0.00009, smooth_idf=True, norm="I2", tokenizer = lambda x: x.split(), 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: 0:05:48.254292

In [22]:

```
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: (400000, 192729) Y: (400000, 500) Dimensions of test data X: (100000, 192729) Y: (100000, 500)

4.5.3 Applying SGD Classifier with loss='log' with OneVsRest Classifier

In [23]:

```
metrics.SCORERS.keys()
```

Out[23]:

dict_keys(['max_error', 'average_precision', 'jaccard_samples', 'jaccard', 'f1_macro', 'precision_macro', 'f1_micro', 'r2', 'neg_mean_absolute_error', 're call_micro', 'f1_weighted', 'explained_variance', 'jaccard_micro', 'precision_micro', 'fowlkes_mallows_score', 'adjusted_rand_score', 'balanced_accura cy', 'neg_log_loss', 'f1', 'completeness_score', 'roc_auc', 'precision_weighted', 'recall_samples', 'precision', 'recall_macro', 'jaccard_weighted', 'recall', 'precision_samples', 'normalized_mutual_info_score', 'neg_median_absolute_error', 'recall_weighted', 'neg_mean_squared_error', 'neg_mean_squared_error', 'adjusted_mutual_info_score', 'brier_score_loss', 'accuracy', 'v_measure_score', 'jaccard_macro', 'homogeneity_score', 'mutual_info_score', 'f1_samples'])

(a) 11_camples y

In [24]:

from sklearn.model_selection import RandomizedSearchCV, GridSearchCV

In [32]:

Time taken to run this cell: 5:20:54.521809

In [34]:

```
print('Best parameters: \n', rscv.best_estimator_)
print()
print('ROC AUC Score: ', rscv.score(x_test_multilabel, y_test))
```

Best parameters:

```
OneVsRestClassifier(estimator=SGDClassifier(alpha=0.001, average=False, class_weight=None, early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True, l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter=1000, n_iter_no_change=5, n_jobs=-1, penalty='l1', power_t=0.5, random_state=None, shuffle=True, tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False), n_jobs=None)
```

ROC AUC Score: 0.03726603243900106

In [27]:

```
start = datetime.now()
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("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')
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: 0.22845 Hamming loss 0.00281536 Micro-average quality numbers

Precision: 0.7291, Recall: 0.3025, F1-measure: 0.4276

Macro-average quality numbers

Precision: 0.5457, Recall: 0.2320, F1-measure: 0.3085

precision recall f1-score support

69
$\begin{array}{c} 0.83 \\ 0.68 \\ 0.28 \\ 0.51 \\ 0.77 \\ 0.98 \\ 0.77 \\ 0.98 \\ 0.77 \\ 0.98 \\ 0.77 \\ 0.98 \\ 0.77 \\ 0.98 \\ 0.77 \\ 0.98 \\ 0.77 \\ 0.98 \\ 0.77 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.98 \\ 0.$
0.50 0.43 0.06 0.17 0.45 0.73 0.33 0.68 0.00 0.18 0.24 0.28 0.16 0.21 0.29 0.27 0.23 0.50 0.43 0.29 0.27 0.23 0.50 0.40 0.20 0.50 0.27 0.50 0.40 0.20 0.50 0.40 0.20 0.50 0.40 0.20 0.50 0.40 0.20 0.50 0.40 0.40 0.40 0.40 0.40 0.40 0.4
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63 59 63 81 62 83 19 24 1 43 160 50 19 175 25 7 88 84 91 90 37 66 33 76 1 150 29 82 66 33 76 1 150 29 82 66 33 76 1 150 29 82 66 32 76 1 160 160 160 160 160 160 160 160 160

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480
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            0.24
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                                     71
     487
            0.40
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     488
            0.00
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     489
            0.79
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                                     87
     490
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     491
             1.00
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     492
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     493
             0.17
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                                    117
     494
            0.57
                    0.20
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                                     61
     495
             1.00
                    0.15
                            0.26
                                    344
     496
            0.30
                    0.13
                            0.19
                                     52
     497
            0.61
                    0.14
                            0.23
                                    137
     498
            0.36
                    0.04
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                                     98
     499
            0.75
                    0.15
                            0.25
                                     79
               0.73
                      0.30
                              0.43 173812
 micro avg
 macro avg
               0.55
                       0.23
                               0.31 173812
                        0.30
                                0.40 173812
                0.67
weighted avg
samples avg
                0.39
                        0.29
                                0.31
                                      173812
```

Time taken to run this cell : 0:19:03.567914

4.5.4 Applying SGD Classifier with loss='hinge' with OneVsRest Classifier

In [25]:

Time taken to run this cell: 2:42:20.782226

In [26]:

```
print('Best parameters: \n', rscv.best_estimator_)
print()
print('ROC AUC Score: ', rscv.score(x_test_multilabel, y_test))
```

Best parameters:

```
OneVsRestClassifier(estimator=SGDClassifier(alpha=0.001, average=False, class_weight=None, early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True, 11_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=1000, n_iter_no_change=5, n_jobs=-1, penalty='11', power_t=0.5, random_state=None, shuffle=True, tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False), n_jobs=None)
```

ROC AUC Score: 0.1138582559024317

In [27]:

```
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', 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("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: 0.24237
Hamming loss 0.0027244
Micro-average quality numbers
Precision: 0.8137, Recall: 0.2805, F1-measure: 0.4172
Macro-average quality numbers
Precision: 0.3977, Recall: 0.2025, F1-measure: 0.2472
        precision recall f1-score support
       0
            0.95
                    0.66
                            0.77
                                     5519
            0.70
                    0.20
                            0.31
                                     8190
       1
       2
            0.85
                    0.34
                            0.48
                                     6529
       3
            0.81
                    0.40
                            0.53
                                     3231
       4
            0.86
                    0.35
                                     6430
                            0.50
       5
            0.82
                    0.34
                            0.48
                                     2879
      6
            0.87
                    0.51
                            0.64
                                     5086
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            0.90
                    0.53
                                     4533
                            0.67
       8
            0.62
                            0.23
                                     3000
                    0.14
      9
            0.83
                    0.49
                            0.62
                                     2765
      10
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                     0.01
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                                     3051
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                     0.30
                             0.43
                                      3009
      12
             0.74
                     0.21
                             0.33
                                     2630
      13
             0.73
                     0.16
                             0.26
                                      1426
      14
             0.91
                     0.55
                             0.69
                                      2548
                     0.14
                                     2371
      15
             0.82
                             0.25
      16
             0.67
                     0.22
                             0.33
                                      873
```

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0.69

0.77

0.00

0.63

0.88

1.00

0.73

0.63

0.67

0.81

0.50

0.79

0.00

0.64

0.00

0.72

0.83

0.76

0.94

0.64

0.87

0.72

0.37

0.75

0.78

0.68

0.82

0.81

1.00

0.74

0.78

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0.00

0.00

0.68

0.00

0.00

0.59

0.18

0.48

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0.53

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0.06

0.57

0.42

0.55

0.19

0.22

0.01

0.56

0.69

0.00

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0.00

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0.28

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0.00

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0.00

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0.65

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0.61

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0.43

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1207

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425

793

1291

1208

406

504

732

441

1645

1058

946

644

136

570

766

1132

174

210

433

626

852

534

350

496

785

475

305

251

914

728

258

56 57 58 59 60 61 62 63 64 65 66 67 77 77 77 78 79 81 82 83 84 85 86 77 88 89 99 91 91 91 91 91 91 91 91 91 91 91 91
0.00 0.00 0.00 0.80 0.91 0.75 0.89 0.91 0.82 0.50 0.00 0.00 0.76 0.83 0.66 0.00 0.83 0.94 0.81 0.88 0.00 0.76 0.76 0.76 0.76 0.76 0.76 0.76
0.00 0.00 0.26 0.67 0.01 0.20 0.74 0.66 0.33 0.00 0.00 0.54 0.57 0.51 0.00 0.50 0.78 0.43 0.74 0.00 0.50 0.78 0.43 0.74 0.00 0.51 0.02 0.00 0.01 0.00 0.00 0.00 0.00 0.0
0.00 0.00 0.40 0.77 0.02 0.33 0.81 0.73 0.40 0.00 0.00 0.63 0.68 0.57 0.00 0.02 0.85 0.57 0.80 0.00 0.04 0.63 0.35 0.29 0.35 0.00 0.01 0.05 0.04 0.05 0.00 0.00 0.00 0.00 0.00
821 541 748 724 660 235 718 461 473 474 401 401 403 403 403 404 404 405 407 407 408 409 409 409 409 409 409 409 409

140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 166 167 168 169 170 171 172 173 174 175 176 177 178 180 181 182 183 184 185 186 187 188 189 190 191 192 203 204 205 206 207 208 209 210 211 212 213 214 215 216 217 218
0.74 0.00 0.65 0.86 0.00 0.62 0.00 0.65 0.00 0.94 0.91 0.82 0.81 0.46 1.00 0.02 0.00 0.85 0.00 0.87 0.66 0.00 0.00 0.00 0.00 0.00 0.00 0.0
0.54 0.00 0.45 0.78 0.00 0.42 0.00 0.53 0.00 0.56 0.03 0.67 0.44 0.00 0.67 0.00 0.67 0.32 0.00 0.62 0.00 0.45 0.37 0.28 0.31 0.00 0.00 0.00 0.00 0.00 0.00 0.00
0.63 0.00 0.53 0.82 0.00 0.50 0.00 0.58 0.00 0.70 0.06 0.74 0.57 0.07 0.01 0.00 0.59 0.39 0.44 0.00 0.00 0.00 0.00 0.00 0.00 0.0
318 159 274 262 118 164 165 360 265 375 150 265 375 376 376 376 376 376 377 377 378 379 379 379 379 379 379 379 379

221	0.93	0.69	0.79	266
222	0.78	0.40	0.53	290
223	0.00	0.00	0.00	128
224	0.82	0.43	0.56	159
225	0.68	0.27	0.39	164
226	0.62	0.40	0.49	144
227	0.00	0.00	0.00	276
228 229	0.00 0.00	0.00	0.00	235 216
230	0.00	0.00	0.00	228
231	0.74	0.62	0.68	64
232	0.00	0.00	0.00	103
233	0.73	0.35	0.47	216
234	0.00	0.00	0.00	116
235	0.57	0.45	0.51	77
236	0.87	0.72	0.79	67
237	0.70	0.07	0.13	218
238 239	0.00 0.00	0.00	0.00	139 94
240	0.55	0.21	0.30	77
241	0.00	0.00	0.00	167
242	0.80	0.33	0.46	86
243	0.00	0.00	0.00	58
244	0.74	0.13	0.22	269
245	0.00	0.00	0.00	112
246	0.94	0.79	0.86	255
247	0.53	0.14	0.22	58
248 249	0.00	0.00	0.00	81 131
250	0.00	0.00	0.00	93
251	0.00	0.00	0.00	154
252	0.00	0.00	0.00	129
253	0.66	0.25	0.37	83
254	0.00	0.00	0.00	191
255	0.00	0.00	0.00	219
256	0.00	0.00	0.00	130
257	0.00	0.00	0.00	93
258	0.67	0.53	0.59	217
259	0.00	0.00	0.00	141
260	0.81	0.15	0.26	143
261	0.00	0.00	0.00	219
262 263	0.00 0.00	0.00	0.00	107 236
264 265	0.25 0.33	0.01	0.02	119 72
266 267	0.00	0.00	0.00	70 107
268 269	0.67	0.45	0.54	169 129
270	0.71	0.62	0.66	159
271	0.90	0.44	0.59	190
272	0.00	0.00	0.00	248
273		0.78	0.83	264
274 275	0.89	0.70	0.78	105 104
276	0.00	0.00	0.00	115
277	0.83		0.75	170
278	0.67	0.23	0.35	145
279	0.91	0.68	0.78	230
280	0.52	0.15	0.23	80
281	0.67	0.72	0.69	217
282	0.74	0.62	0.68	175
283 284	0.74 0.00 0.52	0.02 0.00 0.19	0.00 0.28	269 74
285 286	0.83 0.89	0.19 0.51 0.65	0.64 0.75	206 227
287 288	0.89 0.90 0.00	0.83 0.34 0.00	0.75 0.49 0.00	130 129
289 290	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	80 99
291 292	0.00 0.78 0.00	0.00 0.30 0.00	0.43 0.00	208 67
292 293 294	0.00 0.95 0.00	0.00 0.36 0.00	0.52 0.00	109 140
295 296	0.00 0.00 0.00	0.00 0.00 0.00	0.00	241 72
297 298	0.00 0.00 0.81	0.00 0.00 0.28	0.00 0.00 0.41	107 61
299 300	0.86	0.26 0.31 0.00	0.46 0.00	77 111
301 302	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	126 73
302	0.00	0.00	0.00	73
303	0.64		0.49	176

304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 331 332 333 344 345 346 347 348 349 340 341 342 343 344 345 346 347 348 349 340 341 342 343 344 345 346 347 348 349 340 341 342 343 344 345 346 347 348 349 340 341 341 342 343 344 345 346 347 348 349 340 341 341 342 343 344 345 346 347 348 349 340 341 342 343 344 345 346 347 348 349 340 340 341 342 343 344 345 346 347 348 349 340 340 341 342 343 344 345 346 347 348 349 340 340 340 340 340 340 340 340	0.93 0.91 0.00 0.00 0.00 0.57 1.00 0.76 0.50 0.00 0.43 0.00 0.83 0.00 0.84 0.67 0.00 0.00 0.00 0.00 0.00 0.00 0.00	0.74 0.74 0.70 0.00 0.00 0.00 0.13 0.02 0.59 0.33 0.00 0.22 0.00 0.01 0.06 0.00 0.55 0.00 0.00 0.00 0.00 0.00	0.83 0.82 0.00 0.00 0.00 0.21 0.04 0.66 0.40 0.00 0.29 0.00 0.03 0.11 0.00 0.66 0.00 0.00 0.00 0.00 0.00	230 156 146 98 78 94 162 116 57 65 138 195 197 126 115 198 125 197 126 115 198 125 197 126 117 198 197 198 197 198 197 198 198 198 198 198 198 198 198 198 198
352	0.90	0.49	0.63	136
353	0.00	0.00	0.00	54
354	0.00	0.00	0.00	134

386	0.00	0.00	0.00	64
387 388	0.00	0.00	0.00	93 102
388 389	0.00	0.00	0.00	102
390 391	0.94	0.70	0.80	178
391	0.00 0.88	0.00 0.50	0.00 0.64	115 42
393	0.00	0.00	0.00	134
394 395	0.00	0.00	0.00	112 176
396	0.00	0.00	0.00	125
397 398	0.73 0.76	0.23 0.71	0.35 0.74	224 63
399	0.76	0.71	0.74	59
400	0.50	0.02	0.03	63
401 402	0.00	0.00	0.00	98 162
403	0.00	0.00	0.00	83
404 405	0.64 0.00	0.84 0.00	0.73 0.00	19 92
406	0.86	0.15	0.25	41
407 408	0.90 0.76	0.21 0.32	0.34 0.45	43 160
409	0.00	0.00	0.00	50
410 411	0.00	0.00	0.00	19 175
412	0.00	0.00	0.00	72
413 414	0.00	0.00	0.00	95
414	0.00	0.00	0.00	97 48
416	0.33	0.02	0.04	83
417 418	0.00	0.00	0.00	40 91
419	0.00	0.00	0.00	90
420 421	0.00	0.00	0.00	37 66
422	0.00	0.00	0.00	73
423 424	0.42 0.91	0.23 0.88	0.30 0.89	56 33
424 425	0.00	0.00	0.09	33 76
426	0.00	0.00	0.00	81
427 428	0.97 0.91	0.75 0.72	0.85 0.81	150 29
429	0.99	0.92	0.96	389
430 431	0.69 0.00	0.31 0.00	0.43 0.00	167 123
432	0.00	0.00	0.00	39
433 434	0.00 0.96	0.00 0.71	0.00 0.82	82 66
435	0.60	0.19	0.29	93
436 437	0.69 0.00	0.23 0.00	0.34 0.00	87 86
438	0.78	0.45	0.57	104
439	0.00	0.00	0.00	100
440 441	0.00	0.00	0.00	141 110
442	0.00	0.00	0.00	123
443 444	0.25 0.00	0.03 0.00	0.05 0.00	71 109
445	0.00	0.00	0.00	48
446 447	0.00 0.00	0.00 0.00	0.00	76 38
448	0.65	0.65	0.65	81
449 450	1.00 0.00	0.05 0.00	0.09 0.00	132 81
451	0.87	0.34	0.49	76
452 453	0.00 0.00	0.00	0.00	44 44
454	0.82	0.47	0.60	70
455 450	0.00	0.00	0.00	155
456 457	1.00 0.00	0.02 0.00	0.05 0.00	43 72
458	0.00	0.00	0.00	62
459 460	0.88 0.00	0.10 0.00	0.18 0.00	69 119
461	0.00	0.00	0.00	79
462 463	0.00	0.00	0.00	47 104
464	0.00	0.00	0.00	106
465 466	0.00	0.00	0.00	64 173
466 467	0.00 0.71	0.00 0.33	0.00 0.45	173
468	0.89	0.06	0.12	126

```
469
           0.00
                  0.00
                          0.00
                                  114
   470
           0.93
                  0.81
                          0.87
                                  140
   471
           1.00
                  0.37
                          0.54
                                   79
   472
           0.00
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                          0.00
                                  143
   473
           0.71
                  0.34
                          0.46
                                  158
   474
           0.00
                  0.00
                          0.00
                                  138
   475
           0.00
                  0.00
                          0.00
                                   59
   476
           0.63
                  0.14
                          0.22
                                   88
   477
           0.83
                  0.67
                          0.74
                                  176
   478
                                   24
           0.90
                  0.79
                          0.84
   479
                          0.00
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                  0.00
                                   92
   480
           0.79
                  0.55
                          0.65
                                  100
   481
                                  103
           0.54
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   482
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                  0.00
                          0.00
                                   74
   483
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   492
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                          0.00
                                   49
   493
           0.00
                  0.00
                          0.00
                                  117
   494
           0.52
                  0.26
                          0.35
                                   61
   495
           0.97
                  0.75
                          0.85
                                  344
   496
           0.00
                  0.00
                          0.00
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   497
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                  0.00
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   498
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   499
           0.65
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                          0.29
                                   79
                    0.28
                            0.42 173812
             0.81
micro avg
             0.40
                     0.20
                             0.25 173812
              0.60
                      0.28
                             0.36
                                   173812
              0.40
                      0.27
                              0.31
                                    173812
```

macro avg weighted avg samples avg

Time taken to run this cell: 0:11:50.750816

Conclusions

In [29]:

In []:

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["SNo", 'Classifier', 'Penalty', 'hyperparameter', "F1_micro average"]
x.add_row(["1", 'SGDC(loss=log)', 'L1', 'C = 0.00001', "0.43" ]) x.add_row(["2", 'SGDC(loss=hinge)', 'L1', 'C = 0.00001', "0.42" ])
print(x)
+----+
| SNo | Classifier | Penalty | hyperparameter | F1_micro average |
+----+
| 1 | SGDC(loss=log) | L1 | C = 0.00001 |
| 2 | SGDC(loss=hinge) | L1 | C = 0.00001 | 0.42
```