In [46]:

```
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.model_selection import GridSearchCV
from sklearn import metrics
from sklearn.metrics import f1_score,precision_score,recall_score
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from skmultilearn.adapt import mlknn
from skmultilearn.problem_transform import ClassifierChain
from skmultilearn.problem_transform import BinaryRelevance
from skmultilearn.problem_transform import LabelPowerset
from sklearn.naive_bayes import GaussianNB
from datetime import datetime
```

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

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

\n\n

The answer should come in the form of a table like
\n\n

```
1            50              50\n
2            50              50\n
99           50              50\n
100          50              50\n
50           1               50\n
```

```
            50          2               50\n
            50          99              50\n
            50          100             50\n
            50          50              1\n
            50          50              2\n
            50          50              99\n
            50          50              100\n


\n\n


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)
\n\n


The output is not coming,can anyone correct the code or tell me what\'s wrong?
\n'
```
Tags : 'c++ c'

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

2.2.1 Type of Machine Learning Problem

It is a multi-label classification problem
Multi-label Classification: Multilabel classification assigns to each sample a set of target labels. This 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]:

```
#Creating db file from csv
#Learn SQL: https://www.w3schools.com/sql/default.asp
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('Train.csv', names=['Id', 'Title', 'Body', 'Tags'], chunksize=chunksize, iterator=True, encoding='utf-8', ):
        df.index += index_start
        j+=1
        print('{} rows'.format(j*chunksize))
        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()
    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])
    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 : 0:02:08.946018
```

3.1.3 Checking for duplicates

In [4]:

```
#Learn SQl: https://www.w3schools.com/sql/default.asp
if os.path.isfile('train.db'):
    start = datetime.now()
    con = sqlite3.connect('train.db')
    df_no_dup = pd.read_sql_query('SELECT Title, Body, Tags, COUNT(*) as cnt_dup FROM data GROUP BY Title, Body, Tags', con)
    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 : 0:49:06.283803
```

In [5]:

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

Out[5]:

Title	Body	Tags	cnt_dup

	Title	Body	Tags	cnt_dup
0	Implementing Boundary Value Analysis of S...	<pre><code>#include<iostream>\n#include&...	c++ c	1
1	Dynamic Datagrid Binding in Silverlight?	<p>I should do binding for datagrid dynamicall...	c# silverlight data-binding	1
2	Dynamic Datagrid Binding in Silverlight?	<p>I should do binding for datagrid dynamicall...	c# silverlight data-binding columns	1
3	java.lang.NoClassDefFoundError: javax/serv...	<p>I followed the guide in <a href="http://sta...	jsp jstl	1
4	java.sql.SQLException:[Microsoft][ODBC Dri...	I use the following code \n\n<pre><code>...	java jdbc	2

In [6]:

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

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

In [10]:

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

Out[10]:

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

In [7]:

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

```
Time taken to run this cell : 0:00:04.904542
```

Out[7]:

	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
3	java.lang.NoClassDefFoundError: javax/serv...	<p>I followed the guide in <a href="http://sta...	jsp jstl	1	2
4	java.sql.SQLException:[Microsoft][ODBC Dri...	I use the following code \n\n<pre><code>...	java jdbc	2	2

In [14]:

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

Out[14]:

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

```
Name: tag_count, dtype: int64
```

In [8]:

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

In [9]:

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

    # Let's now drop unwanted column.
    tag_data.drop(tag_data.index[0], inplace=True)
    #Printing first 5 columns from our data frame
    tag_data.head()
    print("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.d
b file")
```

```
Time taken to run this cell : 0:04:08.094781
```

3.2 Analysis of Tags

3.2.1 Total number of unique tags

In [10]:

```
# Importing & Initializing the "CountVectorizer" object, which
#is scikit-learn's bag of words tool.

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

In [11]:

```
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
```

In [12]:

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

```
Some of the tags we have : ['.a', '.app', '.asp.net-mvc', '.aspxauth', '.bash-profile', '.class-fi
le', '.cs-file', '.doc', '.drv', '.ds-store']
```

3.2.3 Number of times a tag appeared

In [13]:

```
# 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 [14]:

```
#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[14]:

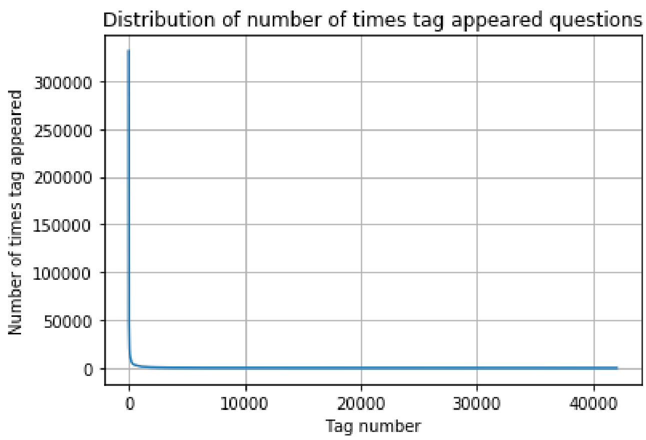
	Tags	Counts
0	.a	18
1	.app	37
2	.asp.net-mvc	1
3	.aspxauth	21
4	.bash-profile	138

In [15]:

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

In [0]:

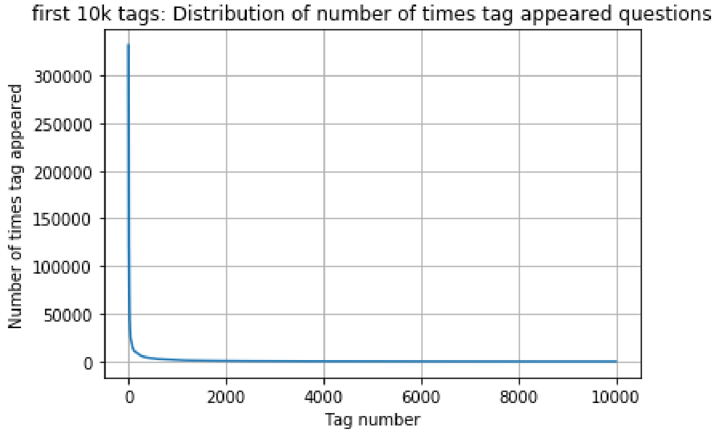
```
plt.plot(tag_counts)
plt.title("Distribution of number of times tag appeared questions")
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
```



In [0]:

```
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")
```

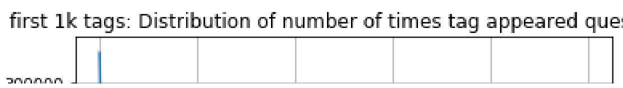
```
plt.show()
print(len(tag_counts[0:10000:25]), tag_counts[0:10000:25])
```

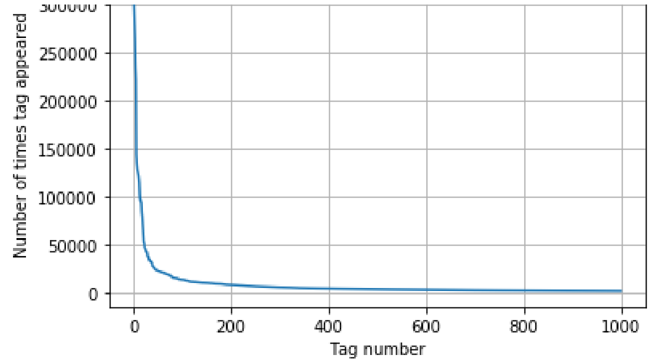



```
400 [331505  44829  22429  17728  13364  11162  10029   9148   8054   7151
   6466   5865   5370   4983   4526   4281   4144   3929   3750   3593
   3453   3299   3123   2989   2891   2738   2647   2527   2431   2331
   2259   2186   2097   2020   1959   1900   1828   1770   1723   1673
   1631   1574   1532   1479   1448   1406   1365   1328   1300   1266
   1245   1222   1197   1181   1158   1139   1121   1101   1076   1056
   1038   1023   1006    983    966    952    938    926    911    891
    882    869    856    841    830    816    804    789    779    770
    752    743    733    725    712    702    688    678    671    658
    650    643    634    627    616    607    598    589    583    577
    568    559    552    545    540    533    526    518    512    506
    500    495    490    485    480    477    469    465    457    450
    447    442    437    432    426    422    418    413    408    403
    398    393    388    385    381    378    374    370    367    365
    361    357    354    350    347    344    342    339    336    332
    330    326    323    319    315    312    309    307    304    301
    299    296    293    291    289    286    284    281    278    276
    275    272    270    268    265    262    260    258    256    254
    252    250    249    247    245    243    241    239    238    236
    234    233    232    230    228    226    224    222    220    219
    217    215    214    212    210    209    207    205    204    203
    201    200    199    198    196    194    193    192    191    189
    188    186    185    183    182    181    180    179    178    177
    175    174    172    171    170    169    168    167    166    165
    164    162    161    160    159    158    157    156    156    155
    154    153    152    151    150    149    149    148    147    146
    145    144    143    142    142    141    140    139    138    137
    137    136    135    134    134    133    132    131    130    130
    129    128    128    127    126    126    125    124    124    123
    123    122    122    121    120    120    119    118    118    117
    117    116    116    115    115    114    113    113    112    111
    111    110    109    109    108    108    107    106    106    106
    105    105    104    104    103    103    102    102    101    101
    100    100     99     99     98     98     97     97     96     96
     95     95     94     94     93     93     93     92     92     91
     91     90     90     89     89     88     88     87     87     86
     86     86     85     85     84     84     83     83     83     82
     82     82     81     81     80     80     80     79     79     78
     78     78     78     77     77     76     76     76     75     75
     75     74     74     74     73     73     73     73     72     72]
```

In [0]:

```
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])
```

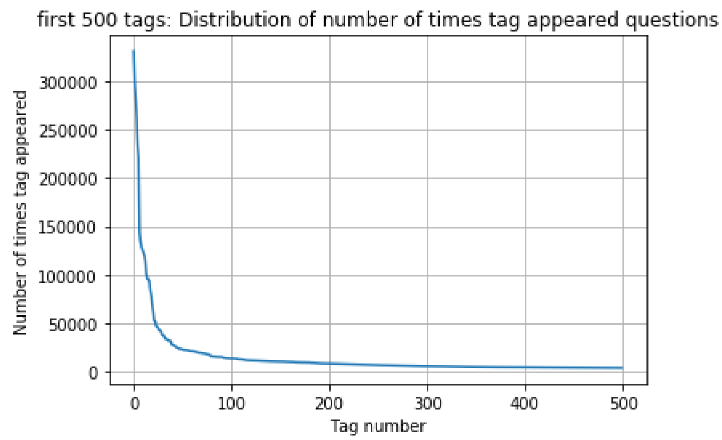





```
200 [331505 221533 122769  95160  62023  44829  37170  31897  26925  24537
  22429  21820  20957  19758  18905  17728  15533  15097  14884  13703
  13364  13157  12407  11658  11228  11162  10863  10600  10350  10224
  10029   9884   9719   9411   9252   9148   9040   8617   8361   8163
   8054   7867   7702   7564   7274   7151   7052   6847   6656   6553
   6466   6291   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
   3750   3703   3685   3658   3615   3593   3564   3521   3505   3483
   3453   3427   3396   3363   3326   3299   3272   3232   3196   3168
   3123   3094   3073   3050   3012   2989   2984   2953   2934   2903
   2891   2844   2819   2784   2754   2738   2726   2708   2681   2669
   2647   2621   2604   2594   2556   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   1971   1965
   1959   1952   1940   1932   1912   1900   1879   1865   1855   1841
   1828   1821   1813   1801   1782   1770   1760   1747   1741   1734
   1723   1707   1697   1688   1683   1673   1665   1656   1646   1639]
```

In [0]:

```
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])
```



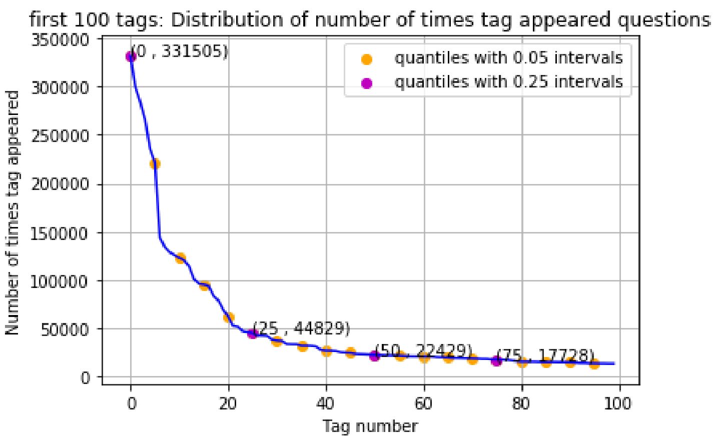

```
100 [331505 221533 122769  95160  62023  44829  37170  31897  26925  24537
  22429  21820  20957  19758  18905  17728  15533  15097  14884  13703
  13364  13157  12407  11658  11228  11162  10863  10600  10350  10224
  10029   9884   9719   9411   9252   9148   9040   8617   8361   8163
   8054   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
   3750   3703   3685   3658   3615   3593   3564   3521   3505   3483]
```

In [0]:

```
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 i
ntervals")
# 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 in
tervals")

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])
```




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

In [16]:

```
# 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, Micro-averaged F1-score is the appropriate metric for this probelm.

3.2.4 Tags Per Question

In [17]:

```
#Storing the count of tag in each question in list 'tag_count'
tag_quest_count = tag_dtm.sum(axis=1).tolist()
#Converting list of lists into single list, we will get [[3], [4], [2], [2], [3]] and we are conve
rting this to [3, 4, 2, 2, 3]
```

```
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]
```

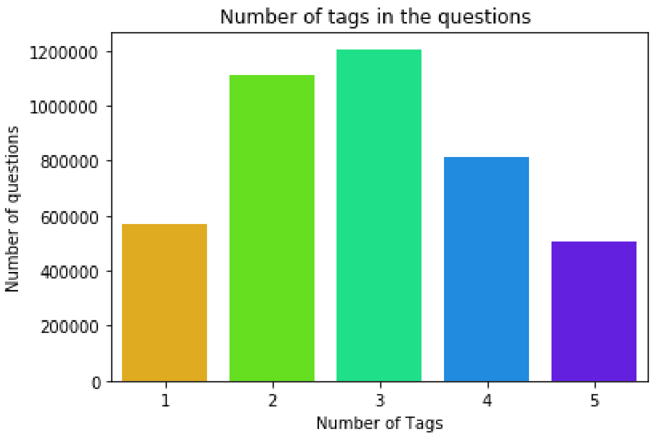
In [17]:

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

```
Maximum number of tags per question: 5
Minimum number of tags per question: 0
Avg. number of tags per question: 2.899438
```

In [0]:

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



Observations:

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

3.2.5 Most Frequent Tags

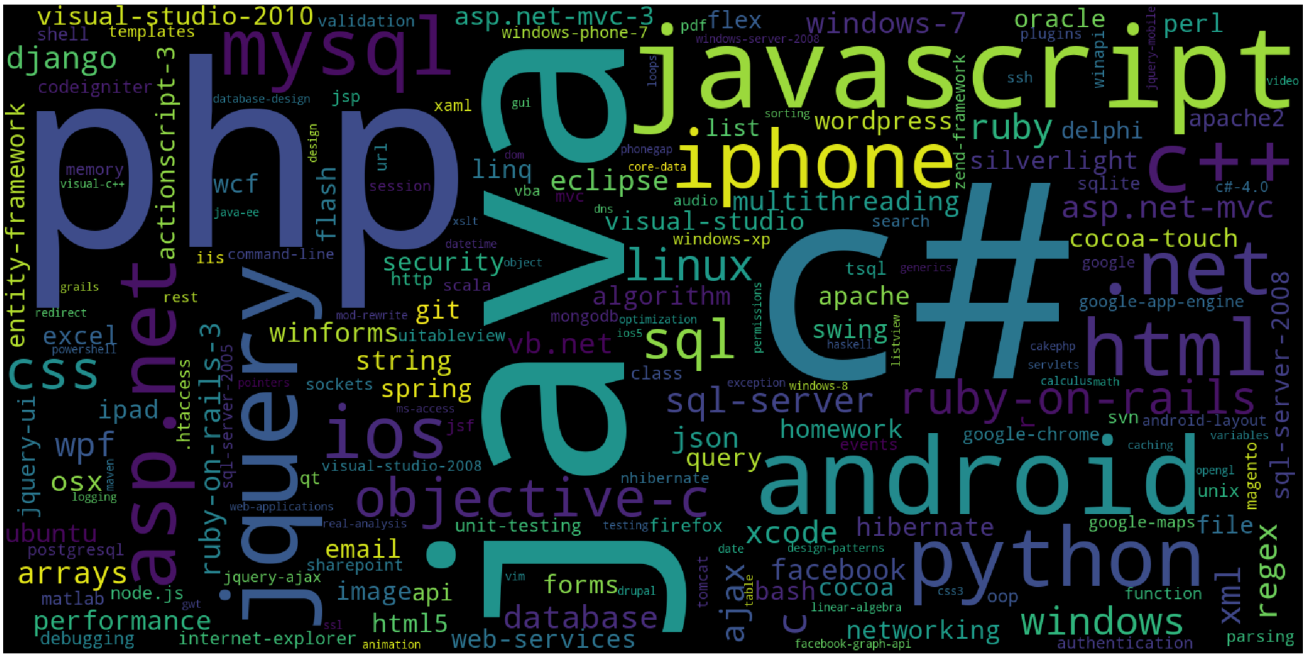
In [0]:

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

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

fig = plt.figure(figsize=(30,20))
plt.imshow(wordcloud)
plt.axis('off')
plt.tight_layout(pad=0)
```

```
fig.savefig("tag.png")
plt.show()
print("Time taken to run this cell :", datetime.now() - start)
```




```
Time taken to run this cell : 0:00:05.470788
```

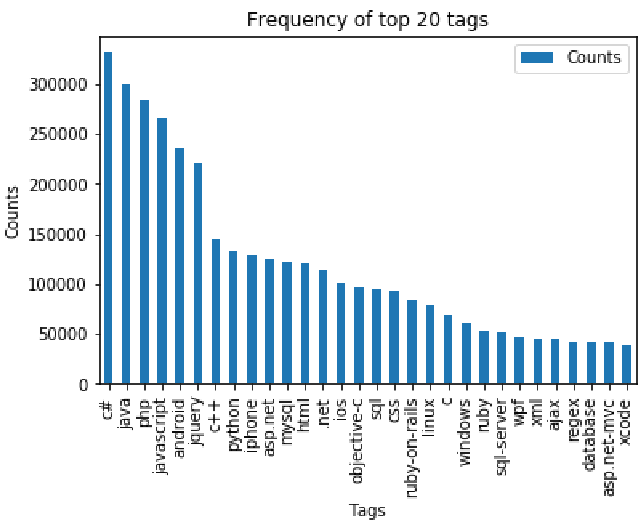
Observations:

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 [0]:

```
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.

3.3 Cleaning and preprocessing of Questions

3.3.1 Preprocessing

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

In [4]:

```
def striphtml(data):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', str(data))
    return cleantext
stop_words = set(stopwords.words('english'))
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:
        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, words_pre integer, words_post integer, is_code integer);"""
create_database_table("Processed.db", sql_create_table)
```

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

In [20]:

```
# 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'
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
100000;")

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
Cleared All the rows
Time taken to run this cell : 0:45:30.018750
```

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

In [2]:

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

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\ACER\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Out[2]:

```
True
```

In [22]:

```
#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 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 (?,?,?,?,?,?)",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)
```

```
Avg. length of questions(Title+Body) before processing: 1173
Avg. length of questions(Title+Body) after processing: 328
Percent of questions containing code: 57
Time taken to run this cell : 0:13:36.858055
```

In [23]:

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

In [24]:

```
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
====================================================================================================

('pass paramet ibact access ibact programat amp want pass two paramet ibact call ncan one suggest
easi way',)
----------------------------------------------------------------------------------------------------
('good tutori use sharekit anyon know good tutori easi understand sharekit look found noth pretti
new xcode',)
```

```
----------------------------------------------------------------------------------------------------
('scroll differ element time element element scroll one time scroll want want use pure javascript
simpl code possibl ty',)
----------------------------------------------------------------------------------------------------
('tooltip show even though posit track work one slideshow rotat imag insid file tri add tooltip ba
se coordin actual need show littl tooltip anchor one imag insid slideshow figur wrong code see anc
hor tooltip specif coordin insert html ad plugin trace coordin mous trace coord posit tooltip work
correct anchor tooltip element show wrong code code tooltip',)
----------------------------------------------------------------------------------------------------
('vmware player virtualbox bridg network work window nat connect work tri run ubuntu server insid
virtual machin window bit laptop develop need run server softwar ubuntu virtual machin ubuntu also
need go internet git updat etc far tell use nat abl host server ubuntu client window host connect
server also believ sort intern host network sinc ubuntu virtual machin need access internet packag
manag git etc leav bridg network select bridg network vmware player virtual box abl connect intern
et ubuntu virtual machin abl connect net network set nat true vmware player virtualbox heck resolv
issu inform need provid',)
----------------------------------------------------------------------------------------------------
('fusion loader find dll actual unabl load one request type retriev loaderexcept properti inform a
nyon idea would caus fusion loader simpli skip dll warn acknowledg see problem attempt c assembl l
oadfrom c deploy bin webservic dll command line applic dll depend platform dll load depend fail li
ne code throw except check fusion assembl load messag see pre bind state inform nlog displaynam pl
atform version cultur neutral publickeytoken null fulli specifi nlog bind start loadfrom load
context nwrn nativ imag probe loadfrom context nativ imag probe default load context like assembl
load nlog applic configur file found nlog use machin configur file c window microsoft net framewor
k config machin config nlog polici appli refer time privat custom partial locat base assembl bind
nlog attempt download new url file c project bin debug platform dll nlog attempt download new url
file c project bin debug platform platform dll nlog attempt download new url file c project bin de
bug platform exe nlog attempt download new url file c project bin debug platform platform exe nlog
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y bin platform platform dll nlog attempt download new url file c deploy bin platform exe nlog atte
mpt download new url file c deploy bin platform platform exe thing dll present c deploy bin platfo
rm dll proper version sign public key thing thought mayb realli depend platform dll broken caus be
havior chase depend tree reflector found miss dlls mayb releas debug mismatch bit vs bit everyth b
uilt machin mayb misread log stop hit dll find see either success unsuccess messag log know fail e
xcept thank help nsteve ps tech detail nmachin environ window bit net amp instal nthis applic run
fine anoth machin vista bit directori structur dlls although built machin',)
----------------------------------------------------------------------------------------------------
('facebook oauth rate limit tri extract facebook id list email use url around id extract get error
remot server return error bad request facebook api search rate limit doc',)
----------------------------------------------------------------------------------------------------
('sampl line across blob perpendicular angl python opencv unless suggest switch someth els work pr
ogram trace dot center binari blob resembl curv confetti piec later fit point cubic spline trace c
urv part program need creat vector sampl angl line across binari imag calcul angl use posit along
confetti blob exampl imag sketch point trace might look like find center vertic section black
confetti straightforward provid black pixel find left right white edg middl half distanc easi
vector use make calcul row imag confetti piec alway line straight vertic sometim curv align horizo
nt need vector cut section confetti angl effici way sampl angl vector imag practic imag process li
brari python pil opencv oper get vector line angl imag make one take care make sure effici effici
way calcul angl vector need one way get appropri angl find angl result minimum width black segment
return vector need exhaust cycl degre degre increment anoth way get appropri angl might find
tangent curv confetti piec use line perpendicular might complic thought better tackl problem would
help specif suggest regard fetch line across imag effici way get perpendicular angl would also gre
at',)
----------------------------------------------------------------------------------------------------
('show gl mathbb bullet group let mathbb text invert time text matric mathbb want show mathbb bull
et group bullet multipl matric think group bullet associ exampl c set ab c equal bc',)
----------------------------------------------------------------------------------------------------
```

In [6]:

```python
#Taking 1 Million entries to a dataframe.
write_db = 'Processed.db'
if os.path.isfile(write_db):
    conn_r = create_connection(write_db)
    if conn_r is not None:
        preprocessed_data = pd.read_sql_query("""SELECT question, Tags FROM QuestionsProcessed""",
conn_r)
conn_r.commit()
conn_r.close()
```

In [7]:

```python
preprocessed_data.head()
```

Out[7]:

	question	tags
0	appengin applic make cooki onlin work fine loc...	python google-app-engine
1	pass paramet ibact access ibact programat amp ...	iphone objective-c cocoa ibaction
2	good tutori use sharekit anyon know good tutor...	objective-c ios sharekit
3	scroll differ element time element element scr...	javascript dom
4	tooltip show even though posit track work one ...	javascript jquery tooltip anchor

In [8]:

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

```
number of data points in sample : 99999
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 [9]:

```
# binary='true' will give a binary vectorizer
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 [10]:

```
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))
```

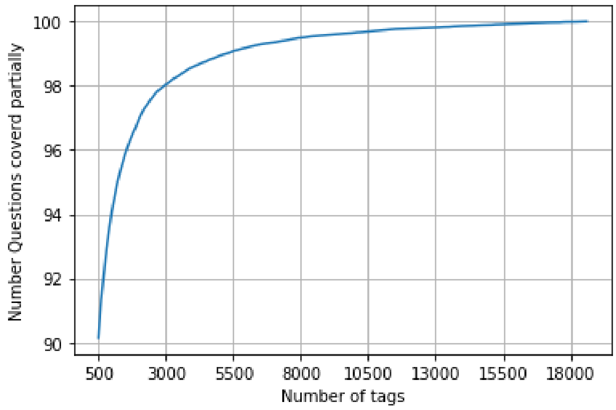
In [11]:

```
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 [12]:

```
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")
print("with ",500,"tags we are covering ",questions_explained[0],"% of questions")
```




```
with  5500 tags we are covering  99.078 % of questions
with  500 tags we are covering  90.142 % of questions
```

In [13]:

```
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 : 9858 out of  99999
```

In [14]:

```
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 : 18659
number of tags taken : 500 ( 2.679672008146203 %)
```

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

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

In [15]:

```
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,:]
```

In [16]:

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

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

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

4.3 Featurizing data

In [17]:

```
start = datetime.now()
vectorizer = CountVectorizer(min_df=0.00009, max_features=20000, \
                             tokenizer = lambda x: x.split(), ngram_range=(1,4))
x_train_multilabel = vectorizer.fit_transform(x_train['question'])
x_test_multilabel = vectorizer.transform(x_test['question'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:30.541573
```

In [18]:

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

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

In [22]:

```
from sklearn.externals import joblib
joblib.dump(x_train_multilabel, 'x_train_BOW_80k_.pkl')

joblib.dump(x_test_multilabel, 'x_test_BOW_20k.pkl')

joblib.dump(y_train, 'y_train_80k.pkl')

joblib.dump(y_test, 'y_test_20k.pkl')
```

```
c:\users\acer\appdata\local\programs\python\python37\lib\site-
packages\sklearn\externals\joblib\__init__.py:15: DeprecationWarning: sklearn.externals.joblib is
deprecated in 0.21 and will be removed in 0.23. Please import this functionality directly from job
lib, which can be installed with: pip install joblib. If this warning is raised when loading
pickled models, you may need to re-serialize those models with scikit-learn 0.21+.
  warnings.warn(msg, category=DeprecationWarning)
```

Out[22]:

```
['y_test_20k.pkl']
```

In [23]:

```
x_train_multilabel = joblib.load('x_train_BOW_80k_.pkl')

x_test_multilabel = joblib.load('x_test_BOW_20k.pkl')

y_train = joblib.load('y_train_80k.pkl')

y_test = joblib.load('y_test_20k.pkl')
```

4.4 Applying Logistic Regression with OneVsRest Classifier

In [26]:

```
# this will be taking so much time try not to run it, download the lr_with_equal_weight.pkl file a
nd use to predict
# This takes about 6-7 hours to run.
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l1'), n_jobs=-1)
classifier.fit(x_train_multilabel.copy(), 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))
```

```
accuracy : 0.0841
macro f1 score : 0.24957170393020744
micro f1 scoore : 0.3317445185891325
hamming loss : 0.006309
Precision recall report :
              precision    recall  f1-score   support

           0       0.37      0.41      0.39      1512
           1       0.46      0.52      0.49      1400
           2       0.54      0.60      0.57      1367
           3       0.45      0.51      0.48      1249
           4       0.72      0.83      0.77      1059
           5       0.60      0.65      0.62      1024
           6       0.38      0.43      0.40       702
           7       0.58      0.66      0.62       652
           8       0.43      0.51      0.47       602
           9       0.42      0.51      0.46       612
          10       0.56      0.66      0.61       573
          11       0.26      0.30      0.28       591
          12       0.17      0.24      0.19       498
          13       0.29      0.32      0.30       479
          14       0.31      0.36      0.34       463
          15       0.33      0.39      0.36       463
          16       0.49      0.60      0.54       442
          17       0.50      0.60      0.55       420
          18       0.32      0.39      0.35       406
          19       0.26      0.30      0.28       355
          20       0.16      0.24      0.19       299
          21       0.34      0.43      0.38       267
          22       0.29      0.42      0.35       240
          23       0.36      0.51      0.42       221
          24       0.27      0.43      0.33       209
          25       0.56      0.76      0.64       202
          26       0.42      0.66      0.51       173
          27       0.27      0.42      0.33       217
          28       0.12      0.21      0.15       199
          29       0.24      0.33      0.28       190
          30       0.64      0.85      0.73       186
          31       0.29      0.46      0.35       194
          32       0.34      0.57      0.42       153
          33       0.27      0.43      0.33       147
          34       0.21      0.37      0.27       142
          35       0.19      0.33      0.24       153
          36       0.54      0.59      0.56       164
          37       0.41      0.56      0.47       157
          38       0.17      0.25      0.20       152
          39       0.13      0.24      0.17       117
          40       0.12      0.17      0.14       124
          41       0.11      0.22      0.15       124
          42       0.25      0.46      0.32       124
          43       0.23      0.39      0.29       114
          44       0.13      0.25      0.17       120
          45       0.15      0.28      0.20       111
          46       0.21      0.33      0.26       108
          47       0.11      0.21      0.14       105
          48       0.14      0.24      0.18       108
          49       0.14      0.24      0.18       108
          50       0.14      0.26      0.19       118
          51       0.12      0.23      0.16       108
          52       0.41      0.53      0.46       129
          53       0.53      0.72      0.61        99
          54       0.58      0.78      0.67        88
          55       0.36      0.57      0.44       102
          56       0.07      0.13      0.09       108
          57       0.33      0.55      0.41       108
          58       0.10      0.21      0.14       104
          59       0.17      0.41      0.24        90
          60       0.36      0.53      0.43       101
          61       0.45      0.67      0.54       102
          62       0.19      0.44      0.27        87
          63       0.36      0.54      0.43        96
```

64	0.17	0.28	0.21	92
65	0.19	0.45	0.26	93
66	0.23	0.33	0.27	93
67	0.14	0.26	0.18	98
68	0.12	0.29	0.17	84
69	0.05	0.11	0.07	82
70	0.51	0.71	0.59	89
71	0.17	0.31	0.22	81
72	0.35	0.59	0.44	79
73	0.26	0.48	0.34	73
74	0.29	0.43	0.35	91
75	0.13	0.21	0.16	85
76	0.23	0.35	0.28	85
77	0.16	0.28	0.21	75
78	0.27	0.43	0.34	76
79	0.11	0.20	0.15	89
80	0.19	0.31	0.23	86
81	0.28	0.47	0.35	77
82	0.41	0.65	0.51	66
83	0.42	0.63	0.50	83
84	0.40	0.54	0.46	79
85	0.36	0.56	0.44	87
86	0.14	0.30	0.19	77
87	0.32	0.49	0.39	72
88	0.21	0.33	0.26	75
89	0.48	0.64	0.55	76
90	0.19	0.38	0.25	73
91	0.25	0.45	0.32	67
92	0.29	0.51	0.37	69
93	0.19	0.30	0.23	84
94	0.11	0.27	0.16	64
95	0.08	0.13	0.10	68
96	0.23	0.34	0.27	71
97	0.10	0.23	0.14	65
98	0.13	0.25	0.17	64
99	0.48	0.66	0.56	68
100	0.10	0.16	0.12	57
101	0.39	0.62	0.47	68
102	0.18	0.27	0.22	63
103	0.03	0.09	0.04	43
104	0.43	0.69	0.53	61
105	0.21	0.46	0.29	56
106	0.05	0.10	0.07	58
107	0.18	0.47	0.26	53
108	0.45	0.63	0.53	57
109	0.28	0.47	0.35	59
110	0.08	0.22	0.12	49
111	0.11	0.24	0.15	54
112	0.61	0.80	0.69	64
113	0.15	0.25	0.19	59
114	0.18	0.32	0.23	66
115	0.20	0.40	0.26	57
116	0.09	0.23	0.13	48
117	0.46	0.73	0.56	60
118	0.05	0.11	0.07	57
119	0.27	0.72	0.39	47
120	0.43	0.62	0.51	61
121	0.13	0.25	0.17	59
122	0.65	0.84	0.73	50
123	0.14	0.27	0.18	48
124	0.03	0.08	0.05	62
125	0.10	0.24	0.14	50
126	0.33	0.59	0.42	58
127	0.44	0.79	0.56	52
128	0.56	0.77	0.65	57
129	0.05	0.16	0.08	44
130	0.14	0.23	0.17	66
131	0.08	0.14	0.10	50
132	0.24	0.46	0.32	46
133	0.23	0.41	0.29	54
134	0.28	0.36	0.32	55
135	0.00	0.00	0.00	50
136	0.14	0.39	0.21	41
137	0.04	0.13	0.06	52
138	0.15	0.22	0.18	58
139	0.09	0.16	0.12	55
140	0.28	0.44	0.35	52
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

141	0.13	0.27	0.18	49
142	0.18	0.41	0.25	44
143	0.11	0.21	0.15	58
144	0.29	0.48	0.36	44
145	0.19	0.42	0.26	48
146	0.06	0.12	0.08	51
147	0.31	0.43	0.36	49
148	0.48	0.74	0.59	43
149	0.52	0.91	0.66	56
150	0.08	0.20	0.12	41
151	0.34	0.46	0.39	59
152	0.41	0.54	0.46	56
153	0.08	0.20	0.11	41
154	0.27	0.55	0.36	44
155	0.13	0.22	0.17	59
156	0.15	0.33	0.21	43
157	0.22	0.45	0.29	47
158	0.20	0.36	0.26	50
159	0.14	0.28	0.18	39
160	0.26	0.53	0.35	45
161	0.27	0.58	0.37	43
162	0.21	0.38	0.27	50
163	0.49	0.85	0.63	48
164	0.16	0.31	0.21	45
165	0.04	0.10	0.06	41
166	0.03	0.09	0.04	46
167	0.20	0.38	0.26	48
168	0.03	0.07	0.04	44
169	0.31	0.56	0.40	48
170	0.14	0.32	0.20	50
171	0.25	0.38	0.30	45
172	0.62	0.83	0.71	47
173	0.09	0.12	0.10	57
174	0.11	0.22	0.14	51
175	0.05	0.10	0.06	52
176	0.05	0.16	0.07	37
177	0.31	0.43	0.36	44
178	0.57	0.80	0.67	51
179	0.10	0.21	0.13	43
180	0.48	0.66	0.56	47
181	0.07	0.24	0.11	37
182	0.22	0.50	0.30	32
183	0.52	0.67	0.58	39
184	0.12	0.24	0.16	42
185	0.10	0.33	0.16	33
186	0.12	0.30	0.17	44
187	0.53	0.68	0.60	38
188	0.11	0.26	0.15	43
189	0.11	0.32	0.17	37
190	0.11	0.17	0.14	47
191	0.09	0.18	0.12	50
192	0.15	0.33	0.20	27
193	0.06	0.16	0.09	43
194	0.13	0.33	0.19	39
195	0.07	0.19	0.11	37
196	0.01	0.03	0.01	34
197	0.28	0.58	0.38	36
198	0.34	0.54	0.42	39
199	0.23	0.61	0.34	31
200	0.47	0.68	0.55	41
201	0.07	0.14	0.09	36
202	0.38	0.51	0.44	45
203	0.17	0.30	0.22	40
204	0.22	0.41	0.29	37
205	0.06	0.20	0.09	30
206	0.22	0.52	0.31	29
207	0.28	0.46	0.35	39
208	0.33	0.47	0.39	34
209	0.08	0.21	0.12	29
210	0.17	0.37	0.24	38
211	0.12	0.30	0.17	43
212	0.06	0.13	0.08	39
213	0.43	0.77	0.55	35
214	0.08	0.18	0.11	44
215	0.29	0.43	0.35	42
216	0.15	0.31	0.20	35
217	0.00	0.00	0.00	39

218	0.29	0.41	0.34	44
219	0.25	0.47	0.33	45
220	0.12	0.32	0.17	28
221	0.10	0.26	0.15	34
222	0.07	0.15	0.09	33
223	0.07	0.18	0.10	34
224	0.36	0.62	0.46	29
225	0.21	0.42	0.28	33
226	0.18	0.28	0.22	46
227	0.30	0.42	0.35	31
228	0.15	0.31	0.20	32
229	0.04	0.17	0.07	24
230	0.05	0.14	0.07	29
231	0.13	0.37	0.20	35
232	0.22	0.37	0.27	38
233	0.10	0.22	0.14	27
234	0.31	0.59	0.41	37
235	0.05	0.22	0.09	23
236	0.19	0.45	0.27	29
237	0.23	0.42	0.30	38
238	0.03	0.11	0.05	28
239	0.11	0.30	0.16	27
240	0.45	0.89	0.60	27
241	0.44	0.82	0.57	33
242	0.15	0.29	0.19	35
243	0.13	0.35	0.19	34
244	0.28	0.59	0.38	27
245	0.11	0.52	0.19	25
246	0.20	0.43	0.27	30
247	0.24	0.56	0.34	25
248	0.33	0.57	0.42	28
249	0.57	0.72	0.64	39
250	0.06	0.14	0.08	28
251	0.23	0.52	0.31	31
252	0.11	0.27	0.16	26
253	0.32	0.62	0.42	29
254	0.12	0.41	0.19	17
255	0.08	0.27	0.12	22
256	0.13	0.29	0.18	28
257	0.10	0.24	0.14	33
258	0.14	0.26	0.18	31
259	0.10	0.23	0.14	30
260	0.55	0.93	0.69	30
261	0.01	0.03	0.02	35
262	0.04	0.11	0.06	28
263	0.17	0.47	0.25	32
264	0.14	0.40	0.21	25
265	0.07	0.28	0.11	25
266	0.09	0.24	0.13	29
267	0.31	0.75	0.44	20
268	0.22	0.39	0.28	28
269	0.22	0.35	0.27	31
270	0.06	0.15	0.09	26
271	0.21	0.39	0.28	28
272	0.02	0.07	0.03	28
273	0.00	0.00	0.00	31
274	0.04	0.12	0.06	26
275	0.11	0.16	0.13	32
276	0.21	0.48	0.29	31
277	0.31	0.47	0.38	36
278	0.04	0.07	0.05	30
279	0.03	0.07	0.04	28
280	0.15	0.40	0.22	20
281	0.30	0.50	0.38	32
282	0.10	0.18	0.13	34
283	0.19	0.39	0.26	23
284	0.12	0.35	0.18	26
285	0.33	0.64	0.44	22
286	0.25	0.42	0.32	31
287	0.23	0.48	0.31	25
288	0.12	0.25	0.17	28
289	0.16	0.26	0.20	31
290	0.17	0.50	0.26	22
291	0.00	0.00	0.00	27
292	0.01	0.04	0.02	23
293	0.38	0.69	0.49	26
294	0.04	0.15	0.06	20

295	0.13	0.27	0.18	22
296	0.01	0.03	0.02	30
297	0.15	0.24	0.19	25
298	0.17	0.42	0.25	26
299	0.05	0.16	0.07	25
300	0.00	0.00	0.00	24
301	0.10	0.24	0.14	25
302	0.02	0.11	0.04	18
303	0.15	0.24	0.18	25
304	0.05	0.11	0.07	27
305	0.61	0.88	0.72	25
306	0.03	0.07	0.05	27
307	0.13	0.48	0.21	23
308	0.05	0.14	0.08	22
309	0.05	0.17	0.08	23
310	0.02	0.05	0.03	21
311	0.07	0.18	0.10	22
312	0.06	0.13	0.08	31
313	0.10	0.35	0.15	20
314	0.31	0.50	0.38	28
315	0.07	0.17	0.10	23
316	0.01	0.04	0.02	26
317	0.02	0.05	0.02	22
318	0.32	0.45	0.37	29
319	0.19	0.35	0.25	23
320	0.05	0.17	0.08	23
321	0.12	0.21	0.15	28
322	0.08	0.13	0.10	31
323	0.12	0.26	0.16	27
324	0.20	0.30	0.24	27
325	0.35	0.60	0.44	25
326	0.05	0.10	0.07	29
327	0.03	0.06	0.04	34
328	0.24	0.63	0.35	19
329	0.20	0.50	0.29	16
330	0.10	0.16	0.12	32
331	0.15	0.26	0.19	27
332	0.16	0.35	0.21	26
333	0.11	0.33	0.16	21
334	0.24	0.39	0.30	23
335	0.04	0.13	0.06	15
336	0.03	0.10	0.05	21
337	0.15	0.24	0.18	29
338	0.12	0.25	0.16	32
339	0.00	0.00	0.00	24
340	0.05	0.19	0.08	21
341	0.29	0.56	0.38	25
342	0.24	0.57	0.34	21
343	0.28	0.73	0.40	11
344	0.31	0.38	0.34	26
345	0.40	0.59	0.48	17
346	0.11	0.19	0.14	27
347	0.35	0.75	0.47	24
348	0.03	0.08	0.05	25
349	0.43	0.59	0.50	27
350	0.01	0.07	0.02	14
351	0.18	0.50	0.26	18
352	0.17	0.38	0.24	24
353	0.15	0.36	0.21	22
354	0.09	0.18	0.12	17
355	0.15	0.38	0.22	16
356	0.16	0.47	0.24	15
357	0.03	0.11	0.04	18
358	0.21	0.35	0.26	31
359	0.23	0.41	0.30	22
360	0.05	0.12	0.07	24
361	0.03	0.10	0.04	21
362	0.11	0.29	0.16	21
363	0.17	0.47	0.25	17
364	0.18	0.35	0.24	20
365	0.13	0.29	0.18	17
366	0.28	0.48	0.35	23
367	0.02	0.05	0.03	22
368	0.48	0.50	0.49	30
369	0.03	0.12	0.05	16
370	0.07	0.33	0.12	12
371	0.14	0.29	0.18	21

372	0.09	0.22	0.12	18
373	0.02	0.05	0.02	22
374	0.23	0.58	0.33	19
375	0.02	0.05	0.02	21
376	0.24	0.59	0.34	17
377	0.21	0.26	0.24	23
378	0.57	0.76	0.65	17
379	0.09	0.21	0.12	19
380	0.20	0.40	0.27	20
381	0.30	0.37	0.33	19
382	0.12	0.26	0.16	23
383	0.11	0.24	0.15	21
384	0.05	0.19	0.08	21
385	0.07	0.24	0.11	21
386	0.16	0.31	0.21	26
387	0.01	0.07	0.02	15
388	0.08	0.16	0.10	19
389	0.19	0.39	0.26	23
390	0.22	0.28	0.25	29
391	0.20	0.43	0.27	14
392	0.02	0.03	0.03	31
393	0.17	0.45	0.24	22
394	0.45	0.64	0.53	22
395	0.08	0.22	0.12	18
396	0.02	0.06	0.03	17
397	0.19	0.36	0.25	28
398	0.21	0.35	0.26	20
399	0.08	0.22	0.12	18
400	0.11	0.22	0.14	18
401	0.32	0.67	0.43	15
402	0.06	0.15	0.08	20
403	0.04	0.09	0.05	22
404	0.04	0.16	0.06	19
405	0.52	0.50	0.51	30
406	0.42	0.53	0.47	19
407	0.06	0.30	0.10	10
408	0.28	0.45	0.35	20
409	0.33	0.50	0.39	26
410	0.06	0.25	0.10	20
411	0.11	0.47	0.18	17
412	0.10	0.38	0.16	16
413	0.20	0.56	0.29	18
414	0.02	0.05	0.03	19
415	0.08	0.16	0.11	25
416	0.22	0.42	0.29	19
417	0.13	0.31	0.18	13
418	0.02	0.06	0.03	17
419	0.07	0.31	0.12	16
420	0.06	0.14	0.08	22
421	0.44	0.67	0.53	24
422	0.04	0.17	0.06	12
423	0.29	0.52	0.38	23
424	0.07	0.20	0.11	20
425	0.02	0.04	0.02	25
426	0.38	0.48	0.42	23
427	0.02	0.12	0.04	16
428	0.09	0.27	0.13	15
429	0.17	0.35	0.23	20
430	0.34	0.60	0.44	20
431	0.47	0.67	0.55	24
432	0.37	0.67	0.47	21
433	0.44	0.55	0.49	20
434	0.03	0.07	0.04	14
435	0.07	0.19	0.10	16
436	0.39	0.44	0.42	25
437	0.10	0.27	0.15	15
438	0.08	0.24	0.12	17
439	0.23	0.36	0.28	25
440	0.04	0.23	0.06	13
441	0.09	0.19	0.12	21
442	0.50	0.72	0.59	18
443	0.05	0.16	0.07	19
444	0.02	0.05	0.03	20
445	0.52	0.78	0.62	18
446	0.15	0.23	0.18	22
447	0.32	0.60	0.42	20
448	0.17	0.47	0.25	19

```
        449       0.10      0.25      0.14        12
        450       0.04      0.07      0.05        29
        451       0.20      0.33      0.25        21
        452       0.32      0.75      0.45        16
        453       0.08      0.21      0.12        19
        454       0.07      0.16      0.10        19
        455       0.05      0.14      0.08        22
        456       0.06      0.14      0.08        22
        457       0.08      0.23      0.12        13
        458       0.11      0.27      0.16        22
        459       0.11      0.27      0.15        15
        460       0.11      0.25      0.15        16
        461       0.08      0.16      0.11        19
        462       0.06      0.20      0.09        15
        463       0.15      0.30      0.20        20
        464       0.15      0.25      0.18        24
        465       0.10      0.40      0.16        15
        466       0.13      0.24      0.17        17
        467       0.50      0.62      0.56        16
        468       0.14      0.33      0.19        15
        469       0.31      0.69      0.43        13
        470       0.07      0.29      0.11        14
        471       0.00      0.00      0.00        17
        472       0.11      0.24      0.15        17
        473       0.06      0.20      0.09        15
        474       0.05      0.11      0.07        19
        475       0.21      0.62      0.31        13
        476       0.35      0.74      0.47        19
        477       0.27      0.42      0.33        26
        478       0.11      0.15      0.13        20
        479       0.09      0.25      0.14        24
        480       0.12      0.17      0.14        23
        481       0.02      0.06      0.02        16
        482       0.26      0.38      0.31        24
        483       0.04      0.21      0.07        14
        484       0.33      0.67      0.44        21
        485       0.13      0.26      0.17        19
        486       0.00      0.00      0.00        21
        487       0.07      0.21      0.11        14
        488       0.12      0.22      0.16        18
        489       0.19      0.38      0.25        21
        490       0.11      0.50      0.18        10
        491       0.11      0.27      0.15        15
        492       0.62      0.65      0.63        20
        493       0.42      0.78      0.55        18
        494       0.02      0.06      0.03        17
        495       0.04      0.17      0.06        12
        496       0.02      0.07      0.03        15
        497       0.44      0.55      0.49        20
        498       0.10      0.24      0.14        17
        499       0.12      0.39      0.19        18

  micro avg       0.27      0.43      0.33     36138
  macro avg       0.20      0.35      0.25     36138
weighted avg      0.32      0.43      0.36     36138
 samples avg      0.34      0.42      0.33     36138
```

In [0]:

```python
from sklearn.externals import joblib
joblib.dump(classifier, 'lr_with_equal_weight.pkl')
```

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

In [0]:

```python
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:
```

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

In [0]:

```
# 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 databse:
QuestionsProcessed
Cleared All the rows
```

4.5.1 Preprocessing of questions

1. Separate Code from Body
2. Remove Spcial characters from Question title and description (not in code)
3. **Give more weightage to title : Add title three times to the question**
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 [0]:

```
#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_proccesed<=train_datasize:
#         question=str(title)+" "+str(title)+" "+str(title)+" "+question+" "+str(tags)
#     else:
#         question=str(title)+" "+str(title)+" "+str(title)+" "+question

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

    #Removing all single letter and and stopwords from question exceptt for the letter 'c'
    question=' '.join(str(stemmer.stem(j)) for j in words if j not in stop_words and (len(j)!=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 (?,?,?,?,?,?)",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: 424
Percent of questions containing code: 57
Time taken to run this cell : 0:23:12.329039
```

In [0]:

```
# 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 [0]:

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

```
Questions after preprocessed
====================================================================================================

('dynam datagrid bind silverlight dynam datagrid bind silverlight dynam datagrid bind silverlight
bind datagrid dynam code wrote code debug code block seem bind correct grid come column form come
grid column although necessari bind nthank repli 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 guid link instal js
tl got follow error tri launch jsp page java.lang.noclassdeffounderror javax servlet jsp tagext ta
glibraryvalid taglib declar instal jstl 1.1 tomcat webapp tri project work also tri version 1.2 js
tl still messag caus solv',)
----------------------------------------------------------------------------------------------------
('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 follow code display caus solv',)
----------------------------------------------------------------------------------------------------
('better way updat feed fb php sdk better way updat feed fb php sdk better way updat feed fb php s
dk novic facebook api read mani tutori still confused.i find post feed api method like correct sec
ond way use curl someth like way better',)
----------------------------------------------------------------------------------------------------
('btnadd click event open two window record ad btnadd click event open two window record ad btnadd
click event open two window record ad open window search.aspx use code hav add button search.aspx
nwhen insert record btnadd click event open anoth window nafter insert record close window',)
----------------------------------------------------------------------------------------------------
('sql inject issu prevent correct form submiss php sql inject issu prevent correct form submiss ph
p sql inject issu prevent correct form submiss php check everyth think make sure input field safe
type sql inject good news safe bad news one tag mess form submiss place even touch life figur exac
t html use templat file forgiv okay entir php script get execut see data post none forum field pos
t problem use someth titl field none data get post current use print post see submit noth work fla
wless statement though also mention script work flawless local machin use host come across problem
state list input test mess',)
----------------------------------------------------------------------------------------------------
('countabl subaddit lebesgu measur countabl subaddit lebesgu measur countabl subaddit lebesgu meas
ur let lbrace rbrace sequenc set sigma -algebra mathcal want show left bigcup right leq sum left r
ight countabl addit measur defin set sigma algebra mathcal think use monoton properti somewher pro
of start appreci littl help nthank ad han answer make follow addit construct given han answer clea
r bigcup bigcup cap emptyset neq left bigcup right left bigcup right sum left right also construct
subset monoton left right leq left right final would sum leq sum result follow',)
----------------------------------------------------------------------------------------------------
('hql equival sql queri hql equival sql queri hql equival sql queri hql queri replac name class pr
operti name error occur hql error',)
----------------------------------------------------------------------------------------------------
('undefin symbol architectur i386 objc class skpsmtpmessag referenc error undefin symbol
architectur i386 objc class skpsmtpmessag referenc error undefin symbol architectur i386 objc
class skpsmtpmessag referenc error import framework send email applic background import framework
i.e skpsmtpmessag somebodi suggest get error collect2 ld return exit status import framework corre
ct sorc taken framework follow mfmailcomposeviewcontrol question lock field updat answer drag drop
folder project click copi nthat',)
----------------------------------------------------------------------------------------------------
```

Saving Preprocessed data to a Database

In [27]:

```
#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 [28]:

```
preprocessed_data.head()
```

Out[28]:

	question	tags

	question	tags
0	dynam datagrid bind silverlight dynam datagrid...	c# silverlight data-binding
1	dynam datagrid bind silverlight dynam datagrid...	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 updat feed fb php sdk better way up...	facebook api facebook-php-sdk

In [29]:

```
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
```

Converting string Tags to multilable output variables

In [30]:

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

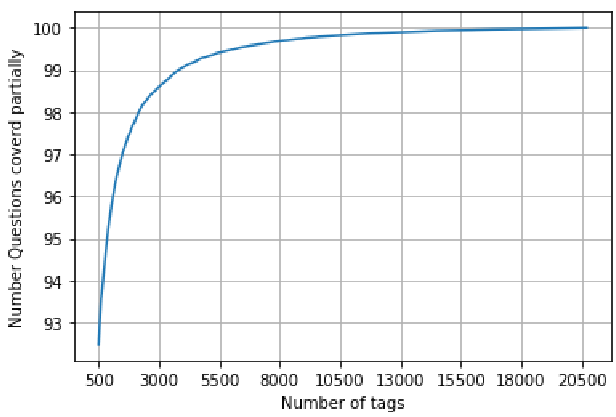
Selecting 500 Tags

In [31]:

```
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 [53]:

```
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")
```




```
with  5500 tags we are covering  99.41 % of questions
with  500 tags we are covering  92.478 % of questions
```

In [32]:

```
# 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_q
s)
```

```
number of questions that are not covered : 15044 out of  200000
```

Splitting the data into (80:20)

In [33]:

```
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,:]
```

In [34]:

```
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 : (160000, 500)
Number of data points in test data : (40000, 500)
```

4.5.2 Featurizing data with BOW vectorizer (4 grams)

In [35]:

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

```
Time taken to run this cell : 0:04:06.282163
```

In [36]:

```
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: (160000, 96789) Y : (160000, 500)
Dimensions of test data X: (40000, 96789) Y: (40000, 500)
```

In [38]:

```
from sklearn.externals import joblib
joblib.dump(x_train_multilabel, 'x_train_BOW_160k_.pkl')

joblib.dump(x_test_multilabel, 'x_test_BOW_40k.pkl')

joblib.dump(y_train, 'y_train_160k.pkl')

joblib.dump(y_test, 'y_test_40k.pkl')
```

Out[38]:

```
['y_test_40k.pkl']
```

In [39]:

```
x_train_multilabel = joblib.load('x_train_BOW_160k_.pkl')

x_test_multilabel = joblib.load('x_test_BOW_40k.pkl')

y_train = joblib.load('y_train_160k.pkl')

y_test = joblib.load('y_test_40k.pkl')
```

Task 1 : Applying Logistic Regression with OneVsRest Classifier

In [42]:

```
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l1'), n_jobs=-1)
classifier.fit(x_train_multilabel.copy(), 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 : 0.138125
Hamming loss  0.00456645
Micro-average quality numbers
Precision: 0.4722, Recall: 0.6226, F1-measure: 0.5371
Macro-average quality numbers
Precision: 0.1588, Recall: 0.2637, F1-measure: 0.1849
              precision    recall  f1-score   support

           0       0.98      0.97      0.98     36915
           1       0.17      0.19      0.18       140
           2       0.07      0.22      0.11        37
           3       0.20      0.25      0.22      4486
           4       0.29      0.39      0.33       784
           5       0.56      0.57      0.57       486
           6       0.36      0.45      0.40       220
           7       0.05      0.21      0.09        33
           8       0.03      0.14      0.05         7
           9       0.12      0.27      0.17        44
          10       0.34      0.54      0.42       244
          11       0.11      0.28      0.16       255
          12       0.25      0.43      0.32       121
          13       0.45      0.47      0.46       272
          14       0.23      0.40      0.29       189
          15       0.24      0.30      0.27       158
          16       0.11      0.46      0.18        24
          17       0.13      0.53      0.21        17
          18       0.20      0.31      0.24        45
          19       0.30      0.52      0.38       101
          20       0.00      0.00      0.00         3
          21       0.00      0.00      0.00         6
          22       0.16      0.30      0.21       137
```

23	0.15	0.23	0.18	1654
24	0.22	0.33	0.26	740
25	0.11	0.18	0.13	82
26	0.13	0.20	0.16	65
27	0.24	0.39	0.30	971
28	0.03	0.15	0.05	13
29	0.00	0.00	0.00	51
30	0.15	0.52	0.23	50
31	0.03	0.29	0.05	7
32	0.23	0.27	0.25	428
33	0.35	0.42	0.38	1150
34	0.03	0.20	0.05	5
35	0.37	0.58	0.45	323
36	0.16	0.17	0.16	18
37	0.07	0.25	0.11	40
38	0.50	0.65	0.56	910
39	0.13	0.25	0.17	125
40	0.29	0.47	0.36	179
41	0.14	0.22	0.17	496
42	0.48	0.72	0.58	94
43	0.67	0.67	0.67	310
44	0.30	0.48	0.37	429
45	0.20	0.36	0.26	878
46	0.07	0.12	0.09	16
47	0.14	0.29	0.19	758
48	0.12	0.05	0.07	22
49	0.00	0.00	0.00	4
50	0.39	0.51	0.44	863
51	0.11	0.06	0.08	17
52	0.16	0.50	0.24	8
53	0.97	0.82	0.89	957
54	0.16	0.24	0.19	647
55	0.00	0.00	0.00	1
56	0.06	0.32	0.10	19
57	0.00	0.00	0.00	5
58	0.00	0.00	0.00	0
59	0.00	0.00	0.00	1
60	0.03	0.02	0.03	44
61	0.12	0.28	0.16	175
62	0.11	0.16	0.13	129
63	0.29	0.33	0.31	6
64	0.32	0.67	0.43	12
65	0.00	0.00	0.00	0
66	0.18	0.32	0.23	88
67	0.15	0.83	0.25	23
68	0.20	0.31	0.24	470
69	0.04	0.15	0.06	34
70	0.72	0.62	0.67	37
71	0.09	0.20	0.12	104
72	0.00	0.00	0.00	8
73	0.60	0.52	0.56	29
74	0.00	0.00	0.00	4
75	0.00	0.00	0.00	0
76	0.10	0.11	0.11	9
77	0.05	0.20	0.08	5
78	0.20	0.39	0.26	636
79	0.17	0.20	0.18	152
80	0.03	0.15	0.04	13
81	0.21	0.38	0.27	146
82	0.29	0.38	0.33	507
83	0.00	0.00	0.00	0
84	0.08	0.25	0.12	12
85	0.41	0.46	0.43	170
86	0.27	0.34	0.30	35
87	0.00	0.00	0.00	0
88	0.42	0.49	0.45	586
89	0.08	0.30	0.13	50
90	0.34	0.49	0.40	334
91	0.05	0.11	0.07	65
92	0.00	0.00	0.00	5
93	0.08	0.06	0.07	16
94	0.06	0.11	0.08	375
95	0.23	0.17	0.19	18
96	0.08	0.15	0.11	375
97	0.23	0.37	0.28	249
98	0.18	0.38	0.24	16
99	0.00	0.00	0.00	0

100	0.12	0.23	0.16	188
101	0.11	0.13	0.12	23
102	0.39	0.61	0.47	520
103	0.13	0.28	0.18	18
104	0.07	0.14	0.09	460
105	0.16	0.24	0.19	477
106	0.35	0.18	0.24	49
107	0.11	0.18	0.14	11
108	0.10	0.21	0.14	127
109	0.09	0.17	0.12	81
110	0.08	0.15	0.10	40
111	0.00	0.00	0.00	0
112	0.11	0.16	0.13	185
113	0.08	0.14	0.10	81
114	0.49	0.44	0.46	236
115	0.10	0.20	0.14	130
116	0.08	1.00	0.15	1
117	0.32	0.50	0.39	398
118	0.06	0.09	0.07	183
119	0.00	0.00	0.00	2
120	0.11	0.38	0.17	8
121	0.12	0.19	0.15	97
122	0.34	0.49	0.40	35
123	0.25	0.43	0.32	94
124	0.00	0.00	0.00	0
125	0.22	0.60	0.32	30
126	0.03	0.33	0.06	3
127	0.34	0.48	0.40	365
128	0.09	1.00	0.16	2
129	0.00	0.00	0.00	19
130	0.00	0.00	0.00	2
131	0.29	0.44	0.35	70
132	0.31	0.50	0.38	207
133	0.00	0.00	0.00	1
134	0.09	0.33	0.15	27
135	0.22	0.52	0.31	211
136	0.26	0.50	0.34	12
137	0.23	0.22	0.22	86
138	0.25	0.31	0.27	134
139	0.43	0.49	0.46	406
140	0.70	0.74	0.72	215
141	0.20	0.50	0.29	4
142	0.18	0.33	0.24	12
143	0.35	0.58	0.44	12
144	0.62	0.75	0.68	102
145	0.23	0.35	0.28	340
146	0.03	0.09	0.05	148
147	0.18	0.30	0.22	60
148	0.00	0.00	0.00	0
149	0.00	0.00	0.00	2
150	0.00	0.00	0.00	1
151	0.11	0.20	0.14	131
152	0.01	0.25	0.01	4
153	0.00	0.00	0.00	1
154	0.30	0.50	0.38	117
155	0.21	0.28	0.24	40
156	0.00	0.00	0.00	0
157	0.22	0.55	0.31	31
158	0.09	0.17	0.12	217
159	0.38	0.47	0.42	302
160	0.00	0.00	0.00	0
161	0.07	0.20	0.10	81
162	0.10	0.10	0.10	49
163	0.35	0.61	0.44	51
164	0.00	0.00	0.00	1
165	0.71	0.80	0.75	317
166	0.16	0.21	0.18	136
167	0.00	0.00	0.00	0
168	0.14	0.35	0.20	54
169	0.11	0.28	0.16	241
170	0.11	0.15	0.13	66
171	0.24	0.36	0.29	25
172	0.50	0.83	0.62	6
173	0.07	0.19	0.10	63
174	0.26	0.44	0.33	300
175	0.06	0.18	0.09	17
176	0.06	0.14	0.09	102

177	0.07	0.14	0.09	29
178	0.05	0.14	0.08	14
179	0.17	0.56	0.26	9
180	0.36	0.54	0.43	84
181	0.27	0.60	0.37	5
182	0.21	0.37	0.27	313
183	0.00	0.00	0.00	1
184	0.00	0.00	0.00	2
185	0.40	0.49	0.44	335
186	0.00	0.00	0.00	0
187	0.09	0.28	0.14	29
188	0.00	0.00	0.00	1
189	0.00	0.00	0.00	44
190	0.23	0.51	0.32	55
191	0.64	0.26	0.37	34
192	0.36	0.48	0.41	63
193	0.06	0.11	0.08	106
194	0.29	0.42	0.34	205
195	0.00	0.00	0.00	0
196	0.28	0.41	0.34	229
197	0.05	0.12	0.07	17
198	0.14	0.50	0.22	2
199	0.13	0.12	0.13	16
200	0.00	0.00	0.00	1
201	0.26	0.78	0.39	9
202	0.33	0.38	0.35	269
203	0.56	0.55	0.56	291
204	0.11	0.09	0.10	32
205	0.00	0.00	0.00	0
206	0.05	0.50	0.08	2
207	0.20	0.35	0.25	185
208	0.06	0.33	0.10	3
209	0.04	0.08	0.05	233
210	0.00	0.00	0.00	0
211	0.39	0.40	0.39	48
212	0.36	0.48	0.41	33
213	0.29	1.00	0.44	2
214	0.37	0.24	0.29	42
215	0.00	0.00	0.00	4
216	0.00	0.00	0.00	0
217	0.43	0.75	0.55	12
218	0.16	0.41	0.22	79
219	0.11	0.17	0.13	6
220	0.26	0.38	0.31	21
221	0.20	0.34	0.25	32
222	0.00	0.00	0.00	2
223	0.17	1.00	0.29	1
224	0.00	0.00	0.00	0
225	0.07	0.13	0.09	120
226	0.05	0.22	0.08	23
227	0.17	0.44	0.25	18
228	0.03	0.13	0.05	15
229	0.14	0.17	0.15	6
230	0.08	0.11	0.09	9
231	0.00	0.00	0.00	0
232	0.17	1.00	0.29	1
233	0.36	0.50	0.42	8
234	0.10	0.25	0.14	188
235	0.15	0.25	0.19	126
236	0.09	0.33	0.14	3
237	0.09	0.13	0.11	63
238	0.34	0.51	0.40	229
239	0.00	0.00	0.00	0
240	0.35	0.41	0.38	224
241	0.17	0.33	0.22	3
242	0.13	0.18	0.15	129
243	0.00	0.00	0.00	0
244	0.48	0.59	0.53	22
245	0.09	0.06	0.07	16
246	0.49	0.58	0.53	38
247	0.55	0.59	0.57	29
248	0.08	0.19	0.12	26
249	0.15	0.20	0.17	35
250	0.71	0.62	0.67	8
251	0.16	0.20	0.17	258
252	0.30	0.24	0.27	55
253	0.06	0.23	0.09	13

254	0.34	0.41	0.37	246
255	0.00	0.00	0.00	1
256	0.00	0.00	0.00	0
257	0.00	0.00	0.00	1
258	0.07	0.17	0.10	69
259	0.33	0.29	0.31	17
260	0.46	0.64	0.53	217
261	0.00	0.00	0.00	0
262	0.20	1.00	0.33	1
263	0.00	0.00	0.00	0
264	0.22	0.44	0.29	63
265	0.21	0.50	0.30	14
266	0.00	0.00	0.00	1
267	0.00	0.00	0.00	13
268	0.00	0.00	0.00	1
269	0.00	0.00	0.00	2
270	0.00	0.00	0.00	2
271	0.25	0.36	0.30	74
272	0.14	0.14	0.14	28
273	0.07	0.11	0.09	47
274	0.00	0.00	0.00	8
275	0.09	0.23	0.13	195
276	0.58	0.79	0.67	62
277	0.46	0.26	0.33	42
278	0.41	0.56	0.47	118
279	0.09	0.25	0.13	51
280	1.00	0.44	0.62	9
281	0.38	0.55	0.44	11
282	0.06	0.20	0.10	25
283	0.05	0.10	0.07	10
284	0.00	0.00	0.00	11
285	0.04	0.04	0.04	80
286	0.21	0.18	0.19	34
287	0.11	0.15	0.13	143
288	0.00	0.00	0.00	0
289	0.00	0.00	0.00	0
290	0.20	0.11	0.14	18
291	0.38	0.71	0.50	14
292	0.00	0.00	0.00	0
293	0.21	0.13	0.16	71
294	0.14	1.00	0.25	1
295	0.00	0.00	0.00	2
296	0.25	0.46	0.32	138
297	0.25	0.41	0.31	107
298	0.28	0.32	0.30	198
299	0.16	0.43	0.23	44
300	0.00	0.00	0.00	30
301	0.00	0.00	0.00	12
302	0.29	0.22	0.25	18
303	0.00	0.00	0.00	4
304	0.00	0.00	0.00	0
305	0.08	0.50	0.14	10
306	0.60	0.81	0.69	36
307	0.16	0.34	0.22	208
308	0.19	0.42	0.26	93
309	0.02	0.03	0.03	29
310	0.13	0.19	0.16	143
311	0.03	0.33	0.05	3
312	0.00	0.00	0.00	0
313	0.00	0.00	0.00	10
314	0.29	0.50	0.37	60
315	0.00	0.00	0.00	31
316	0.49	0.65	0.56	48
317	0.13	0.18	0.15	175
318	0.23	0.43	0.30	7
319	0.31	0.45	0.37	192
320	0.20	0.20	0.20	5
321	0.53	0.61	0.57	164
322	0.21	0.55	0.31	115
323	0.19	0.37	0.25	192
324	0.24	0.40	0.30	20
325	0.17	0.41	0.24	97
326	0.44	0.44	0.44	18
327	0.00	0.00	0.00	0
328	0.17	1.00	0.29	1
329	0.41	0.41	0.41	156
330	0.02	0.08	0.03	36

331	0.00	0.00	0.00	5
332	0.00	0.00	0.00	0
333	0.00	0.00	0.00	0
334	0.30	0.45	0.36	87
335	0.30	0.43	0.35	51
336	0.12	0.14	0.13	29
337	0.20	0.19	0.20	98
338	0.00	0.00	0.00	3
339	0.00	0.00	0.00	8
340	0.16	0.20	0.18	49
341	0.33	1.00	0.50	1
342	0.05	0.17	0.08	12
343	0.20	0.33	0.25	160
344	0.11	0.50	0.18	2
345	0.00	0.00	0.00	0
346	0.56	0.85	0.68	53
347	0.11	0.19	0.14	21
348	0.28	0.53	0.36	156
349	0.55	0.75	0.63	8
350	0.00	0.00	0.00	0
351	0.00	0.00	0.00	0
352	0.26	0.30	0.28	102
353	0.00	0.00	0.00	0
354	0.06	0.50	0.11	2
355	0.00	0.00	0.00	1
356	0.00	0.00	0.00	0
357	0.14	0.60	0.23	5
358	0.21	0.32	0.26	177
359	0.06	0.15	0.09	189
360	0.22	0.15	0.18	154
361	0.25	0.30	0.27	90
362	0.01	0.05	0.01	20
363	0.00	0.00	0.00	0
364	0.16	0.20	0.18	64
365	0.12	0.31	0.18	39
366	0.00	0.00	0.00	0
367	0.30	0.46	0.36	147
368	0.12	0.12	0.12	169
369	0.00	0.00	0.00	11
370	0.31	0.54	0.40	125
371	0.08	0.50	0.14	2
372	0.06	0.26	0.10	19
373	0.00	0.00	0.00	0
374	0.02	0.11	0.03	9
375	0.23	0.37	0.28	52
376	0.05	0.09	0.07	144
377	0.18	0.25	0.21	169
378	0.00	0.00	0.00	0
379	0.16	0.41	0.23	39
380	0.00	0.00	0.00	6
381	0.09	0.07	0.08	40
382	0.11	0.30	0.16	77
383	0.70	0.44	0.54	16
384	0.44	0.49	0.46	117
385	0.22	0.30	0.25	101
386	0.58	0.41	0.48	34
387	0.09	0.20	0.13	5
388	0.00	0.00	0.00	0
389	0.20	0.29	0.24	157
390	0.08	0.13	0.10	30
391	0.04	0.05	0.04	22
392	0.06	0.03	0.04	35
393	0.15	0.45	0.22	11
394	0.13	1.00	0.23	4
395	0.00	0.00	0.00	5
396	0.00	0.00	0.00	0
397	0.00	0.00	0.00	2
398	0.20	0.41	0.27	146
399	0.00	0.00	0.00	0
400	0.35	0.61	0.44	57
401	0.08	0.33	0.13	3
402	0.00	0.00	0.00	1
403	0.29	0.47	0.36	152
404	0.00	0.00	0.00	1
405	0.20	0.45	0.28	20
406	0.00	0.00	0.00	0
407	0.14	0.14	0.14	7

408	0.08	0.21	0.12	33
409	0.05	0.08	0.07	48
410	0.32	0.49	0.39	126
411	0.00	0.00	0.00	0
412	0.00	0.00	0.00	11
413	0.29	0.36	0.32	66
414	0.15	1.00	0.27	2
415	0.00	0.00	0.00	0
416	0.03	0.05	0.04	21
417	0.20	1.00	0.33	1
418	0.33	1.00	0.50	2
419	0.03	0.03	0.03	73
420	0.10	0.08	0.09	24
421	0.00	0.00	0.00	2
422	0.00	0.00	0.00	19
423	0.00	0.00	0.00	22
424	0.00	0.00	0.00	2
425	0.00	0.00	0.00	2
426	0.00	0.00	0.00	0
427	0.11	0.16	0.13	68
428	0.27	0.23	0.25	131
429	0.00	0.00	0.00	0
430	0.05	0.07	0.06	28
431	0.30	0.69	0.42	13
432	0.00	0.00	0.00	14
433	0.00	0.00	0.00	0
434	0.00	0.00	0.00	0
435	0.00	0.00	0.00	0
436	0.06	0.07	0.06	15
437	0.10	0.27	0.14	30
438	0.07	0.09	0.08	82
439	0.00	0.00	0.00	0
440	0.33	0.33	0.33	6
441	0.05	0.17	0.08	12
442	0.05	0.12	0.07	8
443	0.60	0.39	0.47	46
444	0.41	0.37	0.39	54
445	0.00	0.00	0.00	0
446	0.04	0.17	0.06	6
447	0.00	0.00	0.00	0
448	0.00	0.00	0.00	6
449	0.21	0.12	0.16	32
450	0.10	0.33	0.15	3
451	0.00	0.00	0.00	1
452	0.00	0.00	0.00	6
453	0.18	0.33	0.23	127
454	0.00	0.00	0.00	2
455	0.09	0.17	0.12	23
456	0.13	0.33	0.19	21
457	0.16	0.13	0.14	47
458	0.13	0.28	0.17	112
459	0.00	0.00	0.00	0
460	0.20	0.36	0.26	97
461	0.15	0.08	0.11	25
462	0.25	0.17	0.20	6
463	0.00	0.00	0.00	1
464	0.08	0.04	0.05	55
465	0.07	0.42	0.11	24
466	0.00	0.00	0.00	1
467	0.34	0.62	0.44	16
468	0.00	0.00	0.00	16
469	0.46	0.54	0.50	136
470	0.00	0.00	0.00	9
471	0.39	0.44	0.41	27
472	0.10	0.24	0.14	134
473	0.00	0.00	0.00	5
474	0.44	0.51	0.47	96
475	0.16	0.25	0.19	120
476	0.16	0.50	0.24	6
477	0.25	1.00	0.40	1
478	0.00	0.00	0.00	6
479	0.09	0.48	0.15	42
480	0.00	0.00	0.00	0
481	0.00	0.00	0.00	0
482	0.22	0.29	0.25	7
483	0.00	0.00	0.00	24
484	0.00	0.00	0.00	2

```
         485       0.03      0.11      0.05        27
         486       0.07      0.16      0.10       112
         487       0.00      0.00      0.00         0
         488       0.35      0.53      0.42        53
         489       0.00      0.00      0.00        16
         490       0.21      0.22      0.22        89
         491       0.00      0.00      0.00         0
         492       0.14      0.43      0.21        21
         493       0.16      0.33      0.21        21
         494       0.00      0.00      0.00         1
         495       0.33      0.50      0.40         4
         496       0.00      0.00      0.00         0
         497       0.14      0.22      0.17        79
         498       0.00      0.00      0.00         6
         499       0.00      0.00      0.00        10

   micro avg       0.47      0.62      0.54     85094
   macro avg       0.16      0.26      0.18     85094
weighted avg       0.57      0.62      0.59     85094
 samples avg       0.62      0.69      0.58     85094

Time taken to run this cell : 0:52:09.065298
```

In [43]:

```
joblib.dump(classifier, 'lr_with_more_title_weight.pkl')
```

Out[43]:

```
['lr_with_more_title_weight.pkl']
```

In [44]:

```
start = datetime.now()
classifier_2 = OneVsRestClassifier(LogisticRegression(penalty='l1'), n_jobs=-1)
classifier_2.fit(x_train_multilabel, y_train)
predictions_2 = classifier_2.predict(x_test_multilabel)
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 : 0.25835
Hamming loss  0.00269665
Micro-average quality numbers
Precision: 0.7180, Recall: 0.6031, F1-measure: 0.6555
Macro-average quality numbers
Precision: 0.3018, Recall: 0.2338, F1-measure: 0.2508
              precision    recall  f1-score   support

           0       0.98      0.98      0.98     36915
           1       0.22      0.13      0.16       140
           2       0.31      0.22      0.25        37
           3       0.25      0.18      0.21      4486
           4       0.46      0.43      0.44       784
           5       0.75      0.57      0.65       486
           6       0.58      0.44      0.50       220
           7       0.16      0.15      0.16        33
```

8	0.12	0.14	0.13	7
9	0.45	0.30	0.36	44
10	0.43	0.44	0.44	244
11	0.29	0.21	0.24	255
12	0.35	0.41	0.38	121
13	0.53	0.36	0.43	272
14	0.41	0.38	0.39	189
15	0.36	0.22	0.27	158
16	0.38	0.33	0.36	24
17	0.45	0.53	0.49	17
18	0.62	0.56	0.59	45
19	0.57	0.50	0.53	101
20	0.00	0.00	0.00	3
21	0.20	0.17	0.18	6
22	0.23	0.28	0.25	137
23	0.22	0.13	0.17	1654
24	0.41	0.29	0.34	740
25	0.33	0.20	0.24	82
26	0.28	0.20	0.23	65
27	0.48	0.37	0.42	971
28	0.00	0.00	0.00	13
29	0.07	0.02	0.03	51
30	0.49	0.48	0.48	50
31	0.50	0.29	0.36	7
32	0.35	0.21	0.26	428
33	0.52	0.47	0.50	1150
34	0.17	0.20	0.18	5
35	0.73	0.58	0.65	323
36	0.27	0.17	0.21	18
37	0.10	0.05	0.07	40
38	0.73	0.65	0.69	910
39	0.41	0.22	0.29	125
40	0.49	0.31	0.38	179
41	0.25	0.17	0.20	496
42	0.82	0.64	0.72	94
43	0.78	0.70	0.74	310
44	0.59	0.40	0.48	429
45	0.42	0.30	0.35	878
46	0.14	0.06	0.09	16
47	0.28	0.23	0.25	758
48	0.50	0.09	0.15	22
49	0.00	0.00	0.00	4
50	0.43	0.42	0.42	863
51	0.17	0.06	0.09	17
52	0.38	0.38	0.38	8
53	0.98	0.91	0.94	957
54	0.26	0.16	0.20	647
55	0.00	0.00	0.00	1
56	0.55	0.32	0.40	19
57	0.00	0.00	0.00	5
58	0.00	0.00	0.00	0
59	0.00	0.00	0.00	1
60	0.19	0.09	0.12	44
61	0.34	0.26	0.29	175
62	0.24	0.16	0.20	129
63	1.00	0.17	0.29	6
64	0.88	0.58	0.70	12
65	0.00	0.00	0.00	0
66	0.38	0.17	0.23	88
67	0.61	0.74	0.67	23
68	0.33	0.22	0.26	470
69	0.40	0.12	0.18	34
70	0.85	0.59	0.70	37
71	0.13	0.09	0.10	104
72	0.00	0.00	0.00	8
73	0.83	0.52	0.64	29
74	0.00	0.00	0.00	4
75	0.00	0.00	0.00	0
76	0.50	0.11	0.18	9
77	0.40	0.40	0.40	5
78	0.41	0.36	0.38	636
79	0.37	0.25	0.30	152
80	0.40	0.15	0.22	13
81	0.49	0.34	0.40	146
82	0.52	0.37	0.43	507
83	0.00	0.00	0.00	0
84	0.20	0.08	0.12	12

85	0.62	0.41	0.50	170
86	0.48	0.34	0.40	35
87	0.00	0.00	0.00	0
88	0.61	0.59	0.60	586
89	0.13	0.16	0.15	50
90	0.49	0.40	0.44	334
91	0.17	0.08	0.11	65
92	0.50	0.40	0.44	5
93	0.25	0.06	0.10	16
94	0.13	0.04	0.06	375
95	0.75	0.33	0.46	18
96	0.21	0.13	0.16	375
97	0.39	0.35	0.37	249
98	0.17	0.12	0.14	16
99	0.00	0.00	0.00	0
100	0.23	0.12	0.16	188
101	0.44	0.17	0.25	23
102	0.78	0.64	0.70	520
103	0.50	0.22	0.31	18
104	0.16	0.10	0.12	460
105	0.22	0.13	0.16	477
106	0.43	0.12	0.19	49
107	0.50	0.18	0.27	11
108	0.31	0.16	0.21	127
109	0.32	0.12	0.18	81
110	0.47	0.17	0.25	40
111	0.00	0.00	0.00	0
112	0.24	0.10	0.14	185
113	0.20	0.10	0.13	81
114	0.58	0.40	0.47	236
115	0.35	0.22	0.27	130
116	0.00	0.00	0.00	1
117	0.56	0.46	0.50	398
118	0.21	0.07	0.11	183
119	0.00	0.00	0.00	2
120	0.00	0.00	0.00	8
121	0.24	0.09	0.13	97
122	0.71	0.43	0.54	35
123	0.56	0.37	0.45	94
124	0.00	0.00	0.00	0
125	0.68	0.57	0.62	30
126	0.14	0.33	0.20	3
127	0.77	0.49	0.60	365
128	0.00	0.00	0.00	2
129	0.50	0.16	0.24	19
130	0.00	0.00	0.00	2
131	0.57	0.46	0.51	70
132	0.41	0.43	0.42	207
133	0.00	0.00	0.00	1
134	0.35	0.26	0.30	27
135	0.59	0.57	0.58	211
136	0.75	0.25	0.38	12
137	0.47	0.20	0.28	86
138	0.39	0.26	0.31	134
139	0.70	0.46	0.55	406
140	0.86	0.63	0.73	215
141	0.67	0.50	0.57	4
142	0.54	0.58	0.56	12
143	0.78	0.58	0.67	12
144	0.79	0.81	0.80	102
145	0.41	0.29	0.34	340
146	0.15	0.05	0.08	148
147	0.19	0.15	0.17	60
148	0.00	0.00	0.00	0
149	0.00	0.00	0.00	2
150	0.00	0.00	0.00	1
151	0.13	0.12	0.13	131
152	0.25	0.50	0.33	4
153	0.00	0.00	0.00	1
154	0.55	0.43	0.48	117
155	0.19	0.07	0.11	40
156	0.00	0.00	0.00	0
157	0.58	0.45	0.51	31
158	0.20	0.09	0.12	217
159	0.53	0.50	0.51	302
160	0.00	0.00	0.00	0
161	0.12	0.07	0.09	81

162	0.29	0.10	0.15	49
163	0.60	0.57	0.59	51
164	0.00	0.00	0.00	1
165	0.82	0.78	0.80	317
166	0.27	0.11	0.16	136
167	0.00	0.00	0.00	0
168	0.50	0.39	0.44	54
169	0.21	0.14	0.17	241
170	0.33	0.24	0.28	66
171	0.29	0.16	0.21	25
172	0.75	0.50	0.60	6
173	0.24	0.14	0.18	63
174	0.47	0.38	0.42	300
175	0.00	0.00	0.00	17
176	0.12	0.07	0.09	102
177	0.23	0.17	0.20	29
178	0.12	0.07	0.09	14
179	1.00	0.44	0.62	9
180	0.53	0.56	0.55	84
181	1.00	0.40	0.57	5
182	0.44	0.32	0.37	313
183	0.50	1.00	0.67	1
184	0.00	0.00	0.00	2
185	0.52	0.29	0.37	335
186	0.00	0.00	0.00	0
187	0.17	0.10	0.13	29
188	0.00	0.00	0.00	1
189	0.00	0.00	0.00	44
190	0.65	0.47	0.55	55
191	0.74	0.68	0.71	34
192	0.65	0.57	0.61	63
193	0.24	0.08	0.12	106
194	0.38	0.39	0.38	205
195	0.00	0.00	0.00	0
196	0.45	0.31	0.37	229
197	0.00	0.00	0.00	17
198	0.17	0.50	0.25	2
199	0.00	0.00	0.00	16
200	0.00	0.00	0.00	1
201	0.62	0.56	0.59	9
202	0.53	0.33	0.41	269
203	0.68	0.56	0.62	291
204	0.00	0.00	0.00	32
205	0.00	0.00	0.00	0
206	0.00	0.00	0.00	2
207	0.31	0.25	0.28	185
208	0.50	0.33	0.40	3
209	0.13	0.09	0.10	233
210	0.00	0.00	0.00	0
211	0.58	0.38	0.46	48
212	0.30	0.18	0.23	33
213	0.67	1.00	0.80	2
214	0.29	0.38	0.33	42
215	0.00	0.00	0.00	4
216	0.00	0.00	0.00	0
217	0.73	0.67	0.70	12
218	0.41	0.28	0.33	79
219	0.50	0.33	0.40	6
220	0.44	0.33	0.38	21
221	0.37	0.22	0.27	32
222	0.00	0.00	0.00	2
223	1.00	1.00	1.00	1
224	0.00	0.00	0.00	0
225	0.13	0.04	0.06	120
226	0.18	0.09	0.12	23
227	0.33	0.39	0.36	18
228	0.00	0.00	0.00	15
229	0.67	0.67	0.67	6
230	0.14	0.11	0.12	9
231	0.00	0.00	0.00	0
232	0.25	1.00	0.40	1
233	0.33	0.38	0.35	8
234	0.19	0.20	0.19	188
235	0.48	0.24	0.32	126
236	0.33	0.33	0.33	3
237	0.08	0.05	0.06	63
238	0.54	0.49	0.51	229

239	0.00	0.00	0.00	0
240	0.56	0.32	0.41	224
241	0.00	0.00	0.00	3
242	0.26	0.12	0.17	129
243	0.00	0.00	0.00	0
244	0.92	0.55	0.69	22
245	0.00	0.00	0.00	16
246	0.74	0.37	0.49	38
247	0.80	0.55	0.65	29
248	0.33	0.12	0.17	26
249	0.33	0.14	0.20	35
250	0.83	0.62	0.71	8
251	0.28	0.21	0.24	258
252	0.48	0.22	0.30	55
253	0.44	0.31	0.36	13
254	0.48	0.37	0.42	246
255	0.00	0.00	0.00	1
256	0.00	0.00	0.00	0
257	0.20	1.00	0.33	1
258	0.27	0.25	0.26	69
259	1.00	0.47	0.64	17
260	0.58	0.57	0.58	217
261	0.00	0.00	0.00	0
262	0.33	1.00	0.50	1
263	0.00	0.00	0.00	0
264	0.38	0.16	0.22	63
265	0.58	0.50	0.54	14
266	0.00	0.00	0.00	1
267	0.20	0.08	0.11	13
268	0.00	0.00	0.00	1
269	0.00	0.00	0.00	2
270	0.33	0.50	0.40	2
271	0.39	0.18	0.24	74
272	0.13	0.14	0.14	28
273	0.17	0.11	0.13	47
274	0.00	0.00	0.00	8
275	0.20	0.15	0.17	195
276	0.70	0.81	0.75	62
277	0.57	0.31	0.40	42
278	0.59	0.54	0.57	118
279	0.17	0.16	0.16	51
280	0.83	0.56	0.67	9
281	0.78	0.64	0.70	11
282	0.17	0.08	0.11	25
283	0.33	0.10	0.15	10
284	0.00	0.00	0.00	11
285	0.05	0.01	0.02	80
286	0.23	0.09	0.13	34
287	0.18	0.09	0.12	143
288	0.00	0.00	0.00	0
289	0.00	0.00	0.00	0
290	0.33	0.06	0.10	18
291	0.62	0.57	0.59	14
292	0.00	0.00	0.00	0
293	0.17	0.07	0.10	71
294	0.00	0.00	0.00	1
295	0.00	0.00	0.00	2
296	0.43	0.40	0.42	138
297	0.59	0.36	0.44	107
298	0.48	0.32	0.38	198
299	0.52	0.32	0.39	44
300	0.06	0.03	0.04	30
301	0.00	0.00	0.00	12
302	0.50	0.28	0.36	18
303	0.00	0.00	0.00	4
304	0.00	0.00	0.00	0
305	0.50	0.40	0.44	10
306	0.88	0.83	0.86	36
307	0.32	0.27	0.29	208
308	0.46	0.30	0.36	93
309	0.06	0.03	0.04	29
310	0.43	0.16	0.23	143
311	0.00	0.00	0.00	3
312	0.00	0.00	0.00	0
313	0.25	0.10	0.14	10
314	0.49	0.37	0.42	60
315	0.00	0.00	0.00	31

316	0.74	0.58	0.65	48
317	0.12	0.06	0.08	175
318	0.11	0.43	0.17	7
319	0.52	0.35	0.42	192
320	0.50	0.20	0.29	5
321	0.67	0.65	0.66	164
322	0.57	0.60	0.58	115
323	0.20	0.15	0.17	192
324	0.52	0.55	0.54	20
325	0.48	0.35	0.40	97
326	0.73	0.61	0.67	18
327	0.00	0.00	0.00	0
328	0.00	0.00	0.00	1
329	0.49	0.40	0.44	156
330	0.33	0.11	0.17	36
331	0.33	0.20	0.25	5
332	0.00	0.00	0.00	0
333	0.00	0.00	0.00	0
334	0.57	0.34	0.43	87
335	0.38	0.39	0.39	51
336	0.23	0.10	0.14	29
337	0.29	0.14	0.19	98
338	0.00	0.00	0.00	3
339	0.00	0.00	0.00	8
340	0.33	0.16	0.22	49
341	0.50	1.00	0.67	1
342	0.33	0.08	0.13	12
343	0.51	0.29	0.37	160
344	1.00	0.50	0.67	2
345	0.00	0.00	0.00	0
346	0.86	0.79	0.82	53
347	0.21	0.14	0.17	21
348	0.68	0.60	0.64	156
349	0.60	0.75	0.67	8
350	0.00	0.00	0.00	0
351	0.00	0.00	0.00	0
352	0.44	0.27	0.34	102
353	0.00	0.00	0.00	0
354	1.00	0.50	0.67	2
355	0.00	0.00	0.00	1
356	0.00	0.00	0.00	0
357	0.14	0.40	0.21	5
358	0.30	0.12	0.18	177
359	0.20	0.10	0.13	189
360	0.34	0.16	0.21	154
361	0.39	0.27	0.32	90
362	0.00	0.00	0.00	20
363	0.00	0.00	0.00	0
364	0.24	0.08	0.12	64
365	0.47	0.23	0.31	39
366	0.00	0.00	0.00	0
367	0.50	0.43	0.46	147
368	0.14	0.07	0.09	169
369	0.00	0.00	0.00	11
370	0.53	0.50	0.52	125
371	0.25	0.50	0.33	2
372	0.08	0.05	0.06	19
373	0.00	0.00	0.00	0
374	0.00	0.00	0.00	9
375	0.64	0.58	0.61	52
376	0.20	0.09	0.12	144
377	0.43	0.31	0.36	169
378	0.00	0.00	0.00	0
379	0.24	0.13	0.17	39
380	0.00	0.00	0.00	6
381	0.18	0.05	0.08	40
382	0.33	0.19	0.25	77
383	0.80	0.50	0.62	16
384	0.61	0.50	0.55	117
385	0.29	0.16	0.21	101
386	0.63	0.50	0.56	34
387	0.25	0.20	0.22	5
388	0.00	0.00	0.00	0
389	0.36	0.18	0.24	157
390	0.29	0.17	0.21	30
391	0.00	0.00	0.00	22
392	0.18	0.06	0.09	35

393	0.20	0.18	0.19	11
394	0.80	1.00	0.89	4
395	0.00	0.00	0.00	5
396	0.00	0.00	0.00	0
397	0.00	0.00	0.00	2
398	0.61	0.38	0.47	146
399	0.00	0.00	0.00	0
400	0.46	0.49	0.47	57
401	0.40	0.67	0.50	3
402	0.00	0.00	0.00	1
403	0.60	0.55	0.57	152
404	0.00	0.00	0.00	1
405	0.33	0.25	0.29	20
406	0.00	0.00	0.00	0
407	0.00	0.00	0.00	7
408	0.29	0.18	0.22	33
409	0.09	0.06	0.07	48
410	0.61	0.55	0.58	126
411	0.00	0.00	0.00	0
412	0.00	0.00	0.00	11
413	0.53	0.30	0.38	66
414	0.67	1.00	0.80	2
415	0.00	0.00	0.00	0
416	0.25	0.05	0.08	21
417	0.00	0.00	0.00	1
418	1.00	1.00	1.00	2
419	0.06	0.03	0.04	73
420	0.00	0.00	0.00	24
421	0.00	0.00	0.00	2
422	0.12	0.05	0.07	19
423	0.00	0.00	0.00	22
424	0.00	0.00	0.00	2
425	0.00	0.00	0.00	2
426	0.00	0.00	0.00	0
427	0.40	0.15	0.22	68
428	0.43	0.16	0.23	131
429	0.00	0.00	0.00	0
430	0.17	0.04	0.06	28
431	0.41	0.54	0.47	13
432	0.00	0.00	0.00	14
433	0.00	0.00	0.00	0
434	0.00	0.00	0.00	0
435	0.00	0.00	0.00	0
436	0.00	0.00	0.00	15
437	0.41	0.30	0.35	30
438	0.05	0.01	0.02	82
439	0.00	0.00	0.00	0
440	0.50	0.17	0.25	6
441	0.00	0.00	0.00	12
442	0.10	0.12	0.11	8
443	0.67	0.39	0.49	46
444	0.64	0.46	0.54	54
445	0.00	0.00	0.00	0
446	0.20	0.17	0.18	6
447	0.00	0.00	0.00	0
448	0.12	0.17	0.14	6
449	0.20	0.06	0.10	32
450	0.25	0.33	0.29	3
451	0.00	0.00	0.00	1
452	0.00	0.00	0.00	6
453	0.42	0.36	0.39	127
454	0.33	0.50	0.40	2
455	0.30	0.13	0.18	23
456	0.60	0.57	0.59	21
457	0.26	0.11	0.15	47
458	0.31	0.17	0.22	112
459	0.00	0.00	0.00	0
460	0.54	0.36	0.43	97
461	0.43	0.12	0.19	25
462	0.22	0.33	0.27	6
463	0.00	0.00	0.00	1
464	0.23	0.09	0.13	55
465	0.26	0.21	0.23	24
466	0.33	1.00	0.50	1
467	0.60	0.75	0.67	16
468	0.00	0.00	0.00	16
469	0.62	0.49	0.55	136

```
        469       0.62      0.49      0.55       [illegible]
        470       0.00      0.00      0.00         9
        471       0.56      0.37      0.44        27
        472       0.22      0.19      0.20       134
        473       0.00      0.00      0.00         5
        474       0.49      0.38      0.42        96
        475       0.41      0.26      0.32       120
        476       0.33      0.33      0.33         6
        477       0.33      1.00      0.50         1
        478       0.00      0.00      0.00         6
        479       0.32      0.43      0.37        42
        480       0.00      0.00      0.00         0
        481       0.00      0.00      0.00         0
        482       0.40      0.29      0.33         7
        483       0.00      0.00      0.00        24
        484       0.00      0.00      0.00         2
        485       0.11      0.04      0.06        27
        486       0.16      0.09      0.12       112
        487       0.00      0.00      0.00         0
        488       0.77      0.51      0.61        53
        489       0.18      0.12      0.15        16
        490       0.26      0.10      0.15        89
        491       0.00      0.00      0.00         0
        492       0.17      0.10      0.12        21
        493       0.55      0.29      0.37        21
        494       0.00      0.00      0.00         1
        495       0.00      0.00      0.00         4
        496       0.00      0.00      0.00         0
        497       0.12      0.08      0.09        79
        498       0.00      0.00      0.00         6
        499       0.00      0.00      0.00        10

   micro avg       0.72      0.60      0.66     85094
   macro avg       0.30      0.23      0.25     85094
weighted avg       0.66      0.60      0.63     85094
 samples avg       0.79      0.68      0.68     85094

Time taken to run this cell : 1:16:59.418203
```

Task 2 : Hyperparameter Tuning using GridSearch

In [47]:

```
start = datetime.now()
parameters = [(10**i) for i in range(2,-5,-1)]
params = {'estimator__C':parameters}

lr = OneVsRestClassifier(LogisticRegression())
grid = GridSearchCV(lr, params, cv=3, scoring='f1_micro', n_jobs=-1)
grid.fit(x_train_multilabel, y_train)

print("best C = ", grid.best_params_)
print("Accuracy on train data = ", grid.best_score_*100)
a = grid.best_params_
optimal_c = a.get('estimator__C')
print("Time taken to run this cell :", datetime.now() - start)
```

```
best C =  {'estimator__C': 1}
Accuracy on train data =  46.99556222594188
Time taken to run this cell : 14:53:14.713315
```

In [48]:

```
print(grid)
```

```
GridSearchCV(cv=3, error_score='raise-deprecating',
             estimator=OneVsRestClassifier(estimator=LogisticRegression(C=1.0,
                                                                        class_weight=None,
                                                                        dual=False,
                                                                        fit_intercept=True,
                                                                        intercept_scaling=1,
                                                                        l1_ratio=None,
                                                                        max_iter=100,
```

```
                                                            multi_class='warn',
                                                            n_jobs=None,
                                                            penalty='l2',
                                                            random_state=None,
                                                            solver='warn',
                                                            tol=0.0001,
                                                            verbose=0,
                                                            warm_start=False),
                                  n_jobs=None),
             iid='warn', n_jobs=-1,
             param_grid={'estimator__C': [100, 10, 1, 0.1, 0.01, 0.001,
                                          0.0001]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='f1_micro', verbose=0)
```

In [49]:

```
start = datetime.now()
classifier_3 =
OneVsRestClassifier(LogisticRegression(C=1.0,class_weight=None,dual=False,fit_intercept=True,interc
ept_scaling=1,l1_ratio=None,max_iter=100,multi_class='warn',n_jobs=None,penalty='l2',random_state=N
one,solver='warn',tol=0.0001,verbose=0,warm_start=False))
classifier_3.fit(x_train_multilabel, y_train)
predictions_3 = classifier_3.predict(x_test_multilabel)
print("Accuracy :",metrics.accuracy_score(y_test, predictions_3))
print("Hamming loss ",metrics.hamming_loss(y_test,predictions_3))


precision = precision_score(y_test, predictions_3, average='micro')
recall = recall_score(y_test, predictions_3, average='micro')
f1 = f1_score(y_test, predictions_3, 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_3, average='macro')
recall = recall_score(y_test, predictions_3, average='macro')
f1 = f1_score(y_test, predictions_3, 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_3))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Accuracy : 0.274475
Hamming loss  0.00251835
Micro-average quality numbers
Precision: 0.7733, Recall: 0.5774, F1-measure: 0.6611
Macro-average quality numbers
Precision: 0.3450, Recall: 0.1931, F1-measure: 0.2347
              precision    recall  f1-score   support

           0       0.98      0.98      0.98     36915
           1       0.43      0.11      0.17       140
           2       0.30      0.16      0.21        37
           3       0.26      0.17      0.21      4486
           4       0.48      0.39      0.43       784
           5       0.81      0.55      0.65       486
           6       0.73      0.45      0.56       220
           7       0.28      0.15      0.20        33
           8       0.20      0.14      0.17         7
           9       0.36      0.27      0.31        44
          10       0.45      0.43      0.44       244
          11       0.41      0.15      0.21       255
          12       0.39      0.40      0.40       121
          13       0.56      0.37      0.44       272
          14       0.43      0.34      0.38       189
          15       0.37      0.20      0.26       158
          16       0.44      0.29      0.35        24
          17       0.43      0.35      0.39        17
          18       0.75      0.47      0.58        45
          19       0.64      0.47      0.54       101
          20       0.00      0.00      0.00         3
          21       0.00      0.00      0.00         6
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22	0.27	0.22	0.24	137
23	0.25	0.12	0.17	1654
24	0.47	0.27	0.34	740
25	0.35	0.16	0.22	82
26	0.24	0.18	0.21	65
27	0.55	0.36	0.43	971
28	0.00	0.00	0.00	13
29	0.00	0.00	0.00	51
30	0.57	0.40	0.47	50
31	0.29	0.29	0.29	7
32	0.38	0.20	0.26	428
33	0.53	0.41	0.46	1150
34	0.25	0.20	0.22	5
35	0.76	0.54	0.63	323
36	0.38	0.17	0.23	18
37	0.05	0.03	0.03	40
38	0.76	0.63	0.69	910
39	0.45	0.19	0.27	125
40	0.56	0.31	0.40	179
41	0.26	0.14	0.18	496
42	0.83	0.64	0.72	94
43	0.80	0.71	0.75	310
44	0.64	0.37	0.47	429
45	0.46	0.26	0.34	878
46	0.25	0.06	0.10	16
47	0.33	0.19	0.24	758
48	0.67	0.09	0.16	22
49	0.00	0.00	0.00	4
50	0.42	0.38	0.40	863
51	0.12	0.06	0.08	17
52	0.38	0.38	0.38	8
53	0.99	0.68	0.81	957
54	0.27	0.13	0.17	647
55	0.00	0.00	0.00	1
56	0.75	0.32	0.44	19
57	0.00	0.00	0.00	5
58	0.00	0.00	0.00	0
59	0.00	0.00	0.00	1
60	0.33	0.09	0.14	44
61	0.38	0.21	0.27	175
62	0.25	0.13	0.17	129
63	1.00	0.17	0.29	6
64	1.00	0.42	0.59	12
65	0.00	0.00	0.00	0
66	0.46	0.14	0.21	88
67	0.79	0.83	0.81	23
68	0.36	0.19	0.25	470
69	0.50	0.12	0.19	34
70	0.85	0.62	0.72	37
71	0.15	0.08	0.10	104
72	0.00	0.00	0.00	8
73	0.88	0.52	0.65	29
74	0.00	0.00	0.00	4
75	0.00	0.00	0.00	0
76	0.33	0.11	0.17	9
77	1.00	0.40	0.57	5
78	0.48	0.33	0.39	636
79	0.30	0.16	0.21	152
80	0.00	0.00	0.00	13
81	0.64	0.34	0.44	146
82	0.53	0.33	0.41	507
83	0.00	0.00	0.00	0
84	0.50	0.08	0.14	12
85	0.69	0.35	0.46	170
86	0.57	0.23	0.33	35
87	0.00	0.00	0.00	0
88	0.63	0.50	0.56	586
89	0.15	0.14	0.15	50
90	0.50	0.37	0.43	334
91	0.18	0.06	0.09	65
92	0.00	0.00	0.00	5
93	0.50	0.06	0.11	16
94	0.19	0.04	0.07	375
95	0.50	0.11	0.18	18
96	0.26	0.11	0.15	375
97	0.39	0.33	0.36	249
98	0.25	0.19	0.21	16

99	0.00	0.00	0.00	0
100	0.35	0.14	0.20	188
101	0.43	0.13	0.20	23
102	0.87	0.53	0.66	520
103	0.60	0.17	0.26	18
104	0.24	0.07	0.10	460
105	0.23	0.09	0.13	477
106	0.46	0.12	0.19	49
107	0.00	0.00	0.00	11
108	0.44	0.17	0.24	127
109	0.30	0.07	0.12	81
110	0.56	0.12	0.20	40
111	0.00	0.00	0.00	0
112	0.30	0.08	0.12	185
113	0.26	0.06	0.10	81
114	0.65	0.36	0.46	236
115	0.35	0.18	0.23	130
116	0.00	0.00	0.00	1
117	0.61	0.38	0.47	398
118	0.21	0.03	0.06	183
119	0.00	0.00	0.00	2
120	0.67	0.25	0.36	8
121	0.32	0.07	0.12	97
122	0.73	0.31	0.44	35
123	0.57	0.34	0.43	94
124	0.00	0.00	0.00	0
125	0.75	0.50	0.60	30
126	0.33	0.33	0.33	3
127	0.84	0.38	0.53	365
128	0.00	0.00	0.00	2
129	0.43	0.16	0.23	19
130	0.00	0.00	0.00	2
131	0.62	0.41	0.50	70
132	0.38	0.32	0.35	207
133	0.00	0.00	0.00	1
134	0.50	0.26	0.34	27
135	0.67	0.54	0.59	211
136	0.80	0.33	0.47	12
137	0.55	0.13	0.21	86
138	0.43	0.22	0.29	134
139	0.77	0.38	0.51	406
140	0.91	0.57	0.70	215
141	1.00	0.50	0.67	4
142	0.56	0.42	0.48	12
143	0.64	0.58	0.61	12
144	0.92	0.76	0.83	102
145	0.51	0.24	0.32	340
146	0.14	0.03	0.05	148
147	0.21	0.12	0.15	60
148	0.00	0.00	0.00	0
149	0.00	0.00	0.00	2
150	0.00	0.00	0.00	1
151	0.11	0.07	0.08	131
152	0.67	0.50	0.57	4
153	0.00	0.00	0.00	1
154	0.65	0.40	0.50	117
155	0.33	0.07	0.12	40
156	0.00	0.00	0.00	0
157	0.61	0.45	0.52	31
158	0.24	0.05	0.08	217
159	0.54	0.42	0.47	302
160	0.00	0.00	0.00	0
161	0.21	0.07	0.11	81
162	0.38	0.10	0.16	49
163	0.64	0.59	0.61	51
164	0.00	0.00	0.00	1
165	0.85	0.71	0.77	317
166	0.35	0.12	0.18	136
167	0.00	0.00	0.00	0
168	0.54	0.35	0.43	54
169	0.24	0.12	0.16	241
170	0.26	0.14	0.18	66
171	0.33	0.20	0.25	25
172	1.00	0.33	0.50	6
173	0.38	0.13	0.19	63
174	0.49	0.32	0.39	300
175	0.00	0.00	0.00	17

176	0.21	0.07	0.10	102
177	0.36	0.14	0.20	29
178	0.33	0.07	0.12	14
179	0.75	0.33	0.46	9
180	0.60	0.50	0.55	84
181	0.67	0.40	0.50	5
182	0.49	0.22	0.31	313
183	0.00	0.00	0.00	1
184	0.00	0.00	0.00	2
185	0.55	0.29	0.38	335
186	0.00	0.00	0.00	0
187	0.22	0.07	0.11	29
188	0.00	0.00	0.00	1
189	0.00	0.00	0.00	44
190	0.69	0.44	0.53	55
191	0.83	0.44	0.58	34
192	0.65	0.51	0.57	63
193	0.53	0.08	0.13	106
194	0.38	0.32	0.35	205
195	0.00	0.00	0.00	0
196	0.50	0.28	0.35	229
197	0.00	0.00	0.00	17
198	0.33	0.50	0.40	2
199	0.00	0.00	0.00	16
200	0.00	0.00	0.00	1
201	0.67	0.44	0.53	9
202	0.55	0.25	0.34	269
203	0.72	0.51	0.60	291
204	0.00	0.00	0.00	32
205	0.00	0.00	0.00	0
206	0.00	0.00	0.00	2
207	0.34	0.21	0.26	185
208	0.00	0.00	0.00	3
209	0.17	0.05	0.07	233
210	0.00	0.00	0.00	0
211	0.64	0.33	0.44	48
212	0.28	0.15	0.20	33
213	0.67	1.00	0.80	2
214	0.29	0.36	0.32	42
215	0.00	0.00	0.00	4
216	0.00	0.00	0.00	0
217	0.88	0.58	0.70	12
218	0.44	0.20	0.28	79
219	0.67	0.33	0.44	6
220	0.55	0.29	0.37	21
221	0.45	0.16	0.23	32
222	0.00	0.00	0.00	2
223	1.00	1.00	1.00	1
224	0.00	0.00	0.00	0
225	0.17	0.03	0.06	120
226	0.20	0.04	0.07	23
227	0.31	0.22	0.26	18
228	0.00	0.00	0.00	15
229	1.00	0.50	0.67	6
230	0.50	0.11	0.18	9
231	0.00	0.00	0.00	0
232	1.00	1.00	1.00	1
233	0.50	0.38	0.43	8
234	0.19	0.12	0.15	188
235	0.56	0.15	0.24	126
236	1.00	0.33	0.50	3
237	0.09	0.03	0.05	63
238	0.60	0.36	0.45	229
239	0.00	0.00	0.00	0
240	0.57	0.31	0.40	224
241	0.00	0.00	0.00	3
242	0.36	0.10	0.16	129
243	0.00	0.00	0.00	0
244	0.77	0.45	0.57	22
245	0.00	0.00	0.00	16
246	0.83	0.39	0.54	38
247	0.88	0.48	0.62	29
248	0.20	0.04	0.06	26
249	0.45	0.14	0.22	35
250	0.83	0.62	0.71	8
251	0.30	0.12	0.17	258
252	0.56	0.16	0.25	55

253	0.50	0.23	0.32	13
254	0.46	0.23	0.31	246
255	0.00	0.00	0.00	1
256	0.00	0.00	0.00	0
257	0.50	1.00	0.67	1
258	0.36	0.19	0.25	69
259	1.00	0.29	0.45	17
260	0.59	0.56	0.58	217
261	0.00	0.00	0.00	0
262	0.50	1.00	0.67	1
263	0.00	0.00	0.00	0
264	0.41	0.11	0.18	63
265	0.71	0.36	0.48	14
266	0.00	0.00	0.00	1
267	0.50	0.08	0.13	13
268	0.00	0.00	0.00	1
269	0.00	0.00	0.00	2
270	1.00	0.50	0.67	2
271	0.48	0.18	0.26	74
272	0.12	0.07	0.09	28
273	0.11	0.02	0.04	47
274	0.00	0.00	0.00	8
275	0.31	0.10	0.15	195
276	0.79	0.81	0.80	62
277	0.64	0.21	0.32	42
278	0.67	0.54	0.60	118
279	0.21	0.12	0.15	51
280	1.00	0.44	0.62	9
281	1.00	0.55	0.71	11
282	0.00	0.00	0.00	25
283	1.00	0.10	0.18	10
284	0.00	0.00	0.00	11
285	0.00	0.00	0.00	80
286	0.45	0.15	0.22	34
287	0.15	0.04	0.07	143
288	0.00	0.00	0.00	0
289	0.00	0.00	0.00	0
290	0.00	0.00	0.00	18
291	0.78	0.50	0.61	14
292	0.00	0.00	0.00	0
293	0.23	0.07	0.11	71
294	0.00	0.00	0.00	1
295	0.00	0.00	0.00	2
296	0.46	0.33	0.38	138
297	0.62	0.33	0.43	107
298	0.50	0.23	0.31	198
299	0.76	0.30	0.43	44
300	0.14	0.03	0.05	30
301	0.00	0.00	0.00	12
302	0.60	0.17	0.26	18
303	0.00	0.00	0.00	4
304	0.00	0.00	0.00	0
305	0.80	0.40	0.53	10
306	0.96	0.72	0.83	36
307	0.34	0.20	0.25	208
308	0.41	0.18	0.25	93
309	0.10	0.03	0.05	29
310	0.52	0.09	0.15	143
311	0.00	0.00	0.00	3
312	0.00	0.00	0.00	0
313	0.50	0.10	0.17	10
314	0.59	0.32	0.41	60
315	0.00	0.00	0.00	31
316	0.86	0.50	0.63	48
317	0.16	0.03	0.05	175
318	0.05	0.29	0.09	7
319	0.65	0.32	0.43	192
320	0.50	0.20	0.29	5
321	0.72	0.60	0.65	164
322	0.60	0.48	0.53	115
323	0.22	0.10	0.14	192
324	0.69	0.45	0.55	20
325	0.55	0.25	0.34	97
326	0.85	0.61	0.71	18
327	0.00	0.00	0.00	0
328	0.00	0.00	0.00	1
329	0.53	0.40	0.46	156

330	0.50	0.06	0.10	36
331	0.00	0.00	0.00	5
332	0.00	0.00	0.00	0
333	0.00	0.00	0.00	0
334	0.60	0.17	0.27	87
335	0.47	0.33	0.39	51
336	0.08	0.03	0.05	29
337	0.28	0.07	0.11	98
338	0.00	0.00	0.00	3
339	0.00	0.00	0.00	8
340	0.44	0.14	0.22	49
341	1.00	1.00	1.00	1
342	1.00	0.17	0.29	12
343	0.56	0.25	0.35	160
344	0.00	0.00	0.00	2
345	0.00	0.00	0.00	0
346	0.88	0.72	0.79	53
347	0.14	0.05	0.07	21
348	0.76	0.39	0.52	156
349	1.00	0.75	0.86	8
350	0.00	0.00	0.00	0
351	0.00	0.00	0.00	0
352	0.51	0.20	0.28	102
353	0.00	0.00	0.00	0
354	0.00	0.00	0.00	2
355	0.00	0.00	0.00	1
356	0.00	0.00	0.00	0
357	0.33	0.40	0.36	5
358	0.36	0.09	0.14	177
359	0.26	0.05	0.09	189
360	0.45	0.12	0.19	154
361	0.40	0.21	0.28	90
362	0.33	0.05	0.09	20
363	0.00	0.00	0.00	0
364	0.36	0.06	0.11	64
365	0.67	0.15	0.25	39
366	0.00	0.00	0.00	0
367	0.57	0.31	0.41	147
368	0.22	0.04	0.07	169
369	0.00	0.00	0.00	11
370	0.66	0.33	0.44	125
371	0.50	0.50	0.50	2
372	0.12	0.05	0.07	19
373	0.00	0.00	0.00	0
374	0.00	0.00	0.00	9
375	0.74	0.50	0.60	52
376	0.26	0.06	0.09	144
377	0.50	0.25	0.33	169
378	0.00	0.00	0.00	0
379	0.26	0.15	0.19	39
380	0.00	0.00	0.00	6
381	0.30	0.07	0.12	40
382	0.29	0.10	0.15	77
383	0.80	0.50	0.62	16
384	0.69	0.42	0.52	117
385	0.28	0.11	0.16	101
386	0.58	0.41	0.48	34
387	0.50	0.20	0.29	5
388	0.00	0.00	0.00	0
389	0.44	0.17	0.24	157
390	0.38	0.17	0.23	30
391	0.00	0.00	0.00	22
392	0.00	0.00	0.00	35
393	0.25	0.18	0.21	11
394	0.80	1.00	0.89	4
395	0.00	0.00	0.00	5
396	0.00	0.00	0.00	0
397	0.00	0.00	0.00	2
398	0.69	0.27	0.39	146
399	0.00	0.00	0.00	0
400	0.51	0.46	0.48	57
401	0.50	0.33	0.40	3
402	0.00	0.00	0.00	1
403	0.55	0.23	0.32	152
404	0.00	0.00	0.00	1
405	0.50	0.30	0.37	20
406	0.00	0.00	0.00	0

407	0.00	0.00	0.00	7
408	0.36	0.15	0.21	33
409	0.14	0.04	0.06	48
410	0.77	0.40	0.52	126
411	0.00	0.00	0.00	0
412	0.00	0.00	0.00	11
413	0.62	0.24	0.35	66
414	0.50	0.50	0.50	2
415	0.00	0.00	0.00	0
416	1.00	0.05	0.09	21
417	0.00	0.00	0.00	1
418	1.00	1.00	1.00	2
419	0.09	0.03	0.04	73
420	0.00	0.00	0.00	24
421	0.00	0.00	0.00	2
422	0.00	0.00	0.00	19
423	0.00	0.00	0.00	22
424	0.00	0.00	0.00	2
425	0.00	0.00	0.00	2
426	0.00	0.00	0.00	0
427	0.31	0.07	0.12	68
428	0.48	0.11	0.17	131
429	0.00	0.00	0.00	0
430	0.00	0.00	0.00	28
431	0.53	0.62	0.57	13
432	0.00	0.00	0.00	14
433	0.00	0.00	0.00	0
434	0.00	0.00	0.00	0
435	0.00	0.00	0.00	0
436	0.00	0.00	0.00	15
437	0.62	0.27	0.37	30
438	0.00	0.00	0.00	82
439	0.00	0.00	0.00	0
440	1.00	0.17	0.29	6
441	0.00	0.00	0.00	12
442	0.00	0.00	0.00	8
443	0.81	0.28	0.42	46
444	0.81	0.39	0.53	54
445	0.00	0.00	0.00	0
446	0.00	0.00	0.00	6
447	0.00	0.00	0.00	0
448	0.25	0.17	0.20	6
449	0.00	0.00	0.00	32
450	0.50	0.33	0.40	3
451	0.00	0.00	0.00	1
452	0.00	0.00	0.00	6
453	0.47	0.24	0.31	127
454	0.00	0.00	0.00	2
455	0.43	0.13	0.20	23
456	0.56	0.48	0.51	21
457	0.19	0.06	0.10	47
458	0.30	0.11	0.16	112
459	0.00	0.00	0.00	0
460	0.68	0.29	0.41	97
461	0.67	0.08	0.14	25
462	0.50	0.33	0.40	6
463	0.00	0.00	0.00	1
464	0.31	0.09	0.14	55
465	0.67	0.17	0.27	24
466	0.00	0.00	0.00	1
467	0.71	0.62	0.67	16
468	0.00	0.00	0.00	16
469	0.70	0.29	0.41	136
470	0.00	0.00	0.00	9
471	0.82	0.33	0.47	27
472	0.33	0.12	0.17	134
473	0.00	0.00	0.00	5
474	0.53	0.32	0.40	96
475	0.48	0.17	0.25	120
476	0.00	0.00	0.00	6
477	1.00	1.00	1.00	1
478	0.00	0.00	0.00	6
479	0.50	0.40	0.45	42
480	0.00	0.00	0.00	0
481	0.00	0.00	0.00	0
482	0.40	0.29	0.33	7
483	0.00	0.00	0.00	24

```
         484       0.00      0.00      0.00         2
         485       0.00      0.00      0.00        27
         486       0.12      0.04      0.05       112
         487       0.00      0.00      0.00         0
         488       0.83      0.45      0.59        53
         489       0.00      0.00      0.00        16
         490       0.35      0.12      0.18        89
         491       0.00      0.00      0.00         0
         492       0.22      0.10      0.13        21
         493       0.50      0.19      0.28        21
         494       0.00      0.00      0.00         1
         495       1.00      0.25      0.40         4
         496       0.00      0.00      0.00         0
         497       0.25      0.08      0.12        79
         498       0.00      0.00      0.00         6
         499       0.00      0.00      0.00        10

   micro avg       0.77      0.58      0.66     85094
   macro avg       0.35      0.19      0.23     85094
weighted avg       0.68      0.58      0.61     85094
 samples avg       0.82      0.66      0.68     85094

Time taken to run this cell : 3:32:41.854259
```

Task 3 : Applying Linear SVM with OneVsRest Classifier

In [50]:

```python
start = datetime.now()
classifier_4 = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.00001, penalty='l2'),
n_jobs=-1)
classifier_4.fit(x_train_multilabel.copy(), y_train)
predictions_4 = classifier_4.predict (x_test_multilabel)


print("Accuracy :",metrics.accuracy_score(y_test, predictions_4))
print("Hamming loss ",metrics.hamming_loss(y_test,predictions_4))


precision = precision_score(y_test, predictions_4, average='micro')
recall = recall_score(y_test, predictions_4, average='micro')
f1 = f1_score(y_test, predictions_4, 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_4, average='macro')
recall = recall_score(y_test, predictions_4, average='macro')
f1 = f1_score(y_test, predictions_4, 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_4))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Accuracy : 0.21535
Hamming loss  0.00306385
Micro-average quality numbers
Precision: 0.6553, Recall: 0.5906, F1-measure: 0.6213
Macro-average quality numbers
Precision: 0.2811, Recall: 0.2149, F1-measure: 0.2263
              precision    recall  f1-score   support

           0       0.98      0.96      0.97     36915
           1       0.09      0.16      0.11       140
           2       0.18      0.19      0.18        37
           3       0.20      0.27      0.23      4486
           4       0.39      0.32      0.35       784
           5       0.60      0.56      0.58       486
           6       0.49      0.50      0.49       220
           7       0.07      0.18      0.10        33
           8       0.20      0.14      0.17         7
           9       0.22      0.34      0.27        44
```

10	0.36	0.41	0.38	244
11	0.16	0.22	0.18	255
12	0.16	0.35	0.21	121
13	0.36	0.35	0.36	272
14	0.31	0.33	0.32	189
15	0.28	0.21	0.24	158
16	0.25	0.33	0.29	24
17	0.13	0.24	0.17	17
18	0.45	0.49	0.47	45
19	0.39	0.54	0.45	101
20	0.00	0.00	0.00	3
21	0.17	0.33	0.22	6
22	0.20	0.34	0.25	137
23	0.24	0.14	0.18	1654
24	0.33	0.28	0.30	740
25	0.19	0.22	0.20	82
26	0.14	0.23	0.18	65
27	0.29	0.48	0.36	971
28	0.04	0.08	0.06	13
29	0.03	0.02	0.02	51
30	0.28	0.44	0.34	50
31	0.08	0.29	0.12	7
32	0.29	0.27	0.28	428
33	0.51	0.43	0.47	1150
34	0.12	0.20	0.15	5
35	0.67	0.56	0.61	323
36	0.04	0.06	0.05	18
37	0.03	0.03	0.03	40
38	0.74	0.62	0.67	910
39	0.31	0.18	0.23	125
40	0.43	0.35	0.39	179
41	0.23	0.23	0.23	496
42	0.75	0.55	0.64	94
43	0.78	0.69	0.73	310
44	0.52	0.43	0.47	429
45	0.39	0.29	0.34	878
46	0.07	0.06	0.07	16
47	0.26	0.30	0.28	758
48	0.17	0.09	0.12	22
49	0.00	0.00	0.00	4
50	0.42	0.46	0.44	863
51	0.03	0.06	0.04	17
52	0.22	0.50	0.31	8
53	0.98	0.81	0.89	957
54	0.24	0.16	0.19	647
55	0.00	0.00	0.00	1
56	0.20	0.26	0.23	19
57	0.00	0.00	0.00	5
58	0.00	0.00	0.00	0
59	0.00	0.00	0.00	1
60	0.12	0.05	0.07	44
61	0.35	0.31	0.33	175
62	0.23	0.12	0.16	129
63	0.50	0.50	0.50	6
64	0.75	0.50	0.60	12
65	0.00	0.00	0.00	0
66	0.41	0.17	0.24	88
67	0.60	0.78	0.68	23
68	0.30	0.22	0.25	470
69	0.18	0.12	0.14	34
70	0.83	0.51	0.63	37
71	0.14	0.15	0.15	104
72	0.00	0.00	0.00	8
73	0.78	0.48	0.60	29
74	0.00	0.00	0.00	4
75	0.00	0.00	0.00	0
76	0.50	0.11	0.18	9
77	0.29	0.40	0.33	5
78	0.35	0.36	0.35	636
79	0.22	0.20	0.21	152
80	0.00	0.00	0.00	13
81	0.36	0.30	0.33	146
82	0.45	0.34	0.38	507
83	0.00	0.00	0.00	0
84	0.17	0.08	0.11	12
85	0.62	0.56	0.59	170
86	0.39	0.34	0.36	35

87	0.00	0.00	0.00	0
88	0.63	0.49	0.56	586
89	0.10	0.14	0.12	50
90	0.48	0.34	0.40	334
91	0.12	0.12	0.12	65
92	0.17	0.20	0.18	5
93	0.25	0.06	0.10	16
94	0.22	0.04	0.06	375
95	0.36	0.22	0.28	18
96	0.16	0.17	0.16	375
97	0.33	0.37	0.35	249
98	0.25	0.19	0.21	16
99	0.00	0.00	0.00	0
100	0.20	0.15	0.17	188
101	0.33	0.09	0.14	23
102	0.87	0.51	0.64	520
103	0.33	0.22	0.27	18
104	0.18	0.12	0.14	460
105	0.14	0.02	0.03	477
106	0.31	0.16	0.21	49
107	0.20	0.09	0.13	11
108	0.25	0.23	0.24	127
109	0.23	0.10	0.14	81
110	0.19	0.07	0.11	40
111	0.00	0.00	0.00	0
112	0.27	0.11	0.15	185
113	0.25	0.09	0.13	81
114	0.58	0.39	0.47	236
115	0.31	0.20	0.24	130
116	0.00	0.00	0.00	1
117	0.49	0.42	0.45	398
118	0.11	0.05	0.07	183
119	0.00	0.00	0.00	2
120	0.10	0.12	0.11	8
121	0.24	0.11	0.15	97
122	0.35	0.37	0.36	35
123	0.51	0.32	0.39	94
124	0.00	0.00	0.00	0
125	0.71	0.50	0.59	30
126	0.00	0.00	0.00	3
127	0.65	0.52	0.58	365
128	0.00	0.00	0.00	2
129	0.43	0.16	0.23	19
130	0.00	0.00	0.00	2
131	0.59	0.49	0.53	70
132	0.36	0.35	0.36	207
133	0.00	0.00	0.00	1
134	0.17	0.22	0.19	27
135	0.61	0.55	0.57	211
136	0.67	0.33	0.44	12
137	0.38	0.26	0.31	86
138	0.38	0.25	0.30	134
139	0.73	0.32	0.45	406
140	0.89	0.59	0.71	215
141	0.50	0.25	0.33	4
142	0.36	0.67	0.47	12
143	0.75	0.75	0.75	12
144	0.82	0.71	0.76	102
145	0.43	0.29	0.34	340
146	0.09	0.07	0.08	148
147	0.26	0.10	0.14	60
148	0.00	0.00	0.00	0
149	0.00	0.00	0.00	2
150	0.00	0.00	0.00	1
151	0.14	0.17	0.15	131
152	0.08	0.25	0.12	4
153	0.00	0.00	0.00	1
154	0.53	0.42	0.47	117
155	0.20	0.12	0.15	40
156	0.00	0.00	0.00	0
157	0.50	0.42	0.46	31
158	0.17	0.08	0.11	217
159	0.51	0.59	0.54	302
160	0.00	0.00	0.00	0
161	0.21	0.20	0.20	81
162	0.27	0.14	0.19	49
163	0.57	0.67	0.61	51

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
164	0.00	0.00	0.00	1
165	0.82	0.75	0.78	317
166	0.28	0.12	0.16	136
167	0.00	0.00	0.00	0
168	0.35	0.35	0.35	54
169	0.24	0.09	0.13	241
170	0.17	0.09	0.12	66
171	0.33	0.28	0.30	25
172	1.00	0.33	0.50	6
173	0.31	0.19	0.24	63
174	0.47	0.44	0.46	300
175	0.00	0.00	0.00	17
176	0.12	0.09	0.10	102
177	0.46	0.21	0.29	29
178	0.27	0.29	0.28	14
179	0.75	0.33	0.46	9
180	0.51	0.37	0.43	84
181	0.25	0.40	0.31	5
182	0.45	0.18	0.26	313
183	0.00	0.00	0.00	1
184	0.00	0.00	0.00	2
185	0.48	0.47	0.47	335
186	0.00	0.00	0.00	0
187	0.00	0.00	0.00	29
188	0.00	0.00	0.00	1
189	0.11	0.02	0.04	44
190	0.35	0.47	0.40	55
191	0.92	0.35	0.51	34
192	0.55	0.44	0.49	63
193	0.31	0.10	0.16	106
194	0.37	0.39	0.38	205
195	0.00	0.00	0.00	0
196	0.45	0.38	0.41	229
197	0.33	0.06	0.10	17
198	0.33	0.50	0.40	2
199	0.25	0.06	0.10	16
200	0.00	0.00	0.00	1
201	0.67	0.67	0.67	9
202	0.49	0.39	0.43	269
203	0.63	0.48	0.55	291
204	0.05	0.03	0.04	32
205	0.00	0.00	0.00	0
206	0.00	0.00	0.00	2
207	0.24	0.18	0.20	185
208	0.00	0.00	0.00	3
209	0.08	0.19	0.12	233
210	0.00	0.00	0.00	0
211	0.56	0.48	0.52	48
212	0.28	0.15	0.20	33
213	0.25	0.50	0.33	2
214	0.26	0.45	0.33	42
215	0.00	0.00	0.00	4
216	0.00	0.00	0.00	0
217	0.89	0.67	0.76	12
218	0.36	0.35	0.36	79
219	0.00	0.00	0.00	6
220	0.19	0.29	0.23	21
221	0.25	0.44	0.32	32
222	0.00	0.00	0.00	2
223	0.50	1.00	0.67	1
224	0.00	0.00	0.00	0
225	0.08	0.06	0.07	120
226	0.43	0.13	0.20	23
227	0.25	0.33	0.29	18
228	0.00	0.00	0.00	15
229	0.80	0.67	0.73	6
230	0.25	0.11	0.15	9
231	0.00	0.00	0.00	0
232	0.17	1.00	0.29	1
233	0.44	0.50	0.47	8
234	0.19	0.19	0.19	188
235	0.52	0.18	0.27	126
236	0.50	0.33	0.40	3
237	0.10	0.05	0.06	63
238	0.55	0.44	0.49	229
239	0.00	0.00	0.00	0
240	0.53	0.34	0.42	224

240	0.55	0.34	0.42	224
241	0.00	0.00	0.00	3
242	0.25	0.27	0.26	129
243	0.00	0.00	0.00	0
244	1.00	0.45	0.62	22
245	0.50	0.19	0.27	16
246	0.82	0.24	0.37	38
247	0.74	0.48	0.58	29
248	0.09	0.04	0.05	26
249	0.50	0.11	0.19	35
250	1.00	0.62	0.77	8
251	0.24	0.06	0.09	258
252	0.41	0.25	0.31	55
253	0.33	0.15	0.21	13
254	0.38	0.14	0.20	246
255	0.00	0.00	0.00	1
256	0.00	0.00	0.00	0
257	0.00	0.00	0.00	1
258	0.23	0.19	0.21	69
259	1.00	0.35	0.52	17
260	0.57	0.35	0.44	217
261	0.00	0.00	0.00	0
262	0.33	1.00	0.50	1
263	0.00	0.00	0.00	0
264	0.44	0.19	0.27	63
265	0.50	0.50	0.50	14
266	0.00	0.00	0.00	1
267	0.40	0.15	0.22	13
268	0.00	0.00	0.00	1
269	0.00	0.00	0.00	2
270	0.50	0.50	0.50	2
271	0.41	0.22	0.28	74
272	0.25	0.07	0.11	28
273	0.10	0.02	0.04	47
274	0.00	0.00	0.00	8
275	0.21	0.12	0.15	195
276	0.82	0.79	0.80	62
277	0.59	0.38	0.46	42
278	0.63	0.69	0.66	118
279	0.13	0.10	0.11	51
280	1.00	0.44	0.62	9
281	0.83	0.45	0.59	11
282	0.33	0.04	0.07	25
283	0.50	0.10	0.17	10
284	0.00	0.00	0.00	11
285	0.13	0.09	0.11	80
286	0.30	0.21	0.25	34
287	0.19	0.18	0.18	143
288	0.00	0.00	0.00	0
289	0.00	0.00	0.00	0
290	0.12	0.06	0.08	18
291	0.50	0.57	0.53	14
292	0.00	0.00	0.00	0
293	0.27	0.11	0.16	71
294	0.00	0.00	0.00	1
295	0.00	0.00	0.00	2
296	0.41	0.28	0.33	138
297	0.42	0.31	0.36	107
298	0.39	0.37	0.38	198
299	0.58	0.32	0.41	44
300	0.00	0.00	0.00	30
301	0.00	0.00	0.00	12
302	0.71	0.28	0.40	18
303	0.00	0.00	0.00	4
304	0.00	0.00	0.00	0
305	0.43	0.30	0.35	10
306	0.88	0.81	0.84	36
307	0.28	0.29	0.29	208
308	0.48	0.39	0.43	93
309	0.21	0.10	0.14	29
310	0.36	0.15	0.22	143
311	0.00	0.00	0.00	3
312	0.00	0.00	0.00	0
313	0.20	0.10	0.13	10
314	0.50	0.43	0.46	60
315	0.00	0.00	0.00	31
316	0.72	0.58	0.64	48
317	0.12	0.06	0.08	175

317	0.12	0.06	0.08	175
318	0.07	0.43	0.12	7
319	0.63	0.41	0.50	192
320	1.00	0.20	0.33	5
321	0.67	0.65	0.66	164
322	0.49	0.45	0.47	115
323	0.19	0.10	0.13	192
324	0.40	0.30	0.34	20
325	0.52	0.24	0.33	97
326	0.77	0.56	0.65	18
327	0.00	0.00	0.00	0
328	0.00	0.00	0.00	1
329	0.49	0.42	0.45	156
330	0.29	0.06	0.09	36
331	0.17	0.20	0.18	5
332	0.00	0.00	0.00	0
333	0.00	0.00	0.00	0
334	0.67	0.11	0.20	87
335	0.51	0.41	0.46	51
336	0.17	0.14	0.15	29
337	0.28	0.11	0.16	98
338	0.00	0.00	0.00	3
339	0.00	0.00	0.00	8
340	0.18	0.04	0.07	49
341	0.33	1.00	0.50	1
342	0.50	0.17	0.25	12
343	0.56	0.22	0.32	160
344	0.00	0.00	0.00	2
345	0.00	0.00	0.00	0
346	0.63	0.75	0.69	53
347	0.12	0.05	0.07	21
348	0.73	0.46	0.56	156
349	0.86	0.75	0.80	8
350	0.00	0.00	0.00	0
351	0.00	0.00	0.00	0
352	0.41	0.19	0.26	102
353	0.00	0.00	0.00	0
354	0.25	0.50	0.33	2
355	0.00	0.00	0.00	1
356	0.00	0.00	0.00	0
357	0.15	0.40	0.22	5
358	0.31	0.05	0.09	177
359	0.16	0.15	0.16	189
360	0.42	0.21	0.28	154
361	0.41	0.28	0.33	90
362	0.00	0.00	0.00	20
363	0.00	0.00	0.00	0
364	0.24	0.08	0.12	64
365	0.44	0.31	0.36	39
366	0.00	0.00	0.00	0
367	0.37	0.24	0.29	147
368	0.24	0.04	0.07	169
369	0.00	0.00	0.00	11
370	0.60	0.26	0.36	125
371	0.33	0.50	0.40	2
372	0.06	0.05	0.05	19
373	0.00	0.00	0.00	0
374	0.00	0.00	0.00	9
375	0.49	0.54	0.51	52
376	0.10	0.06	0.08	144
377	0.38	0.33	0.35	169
378	0.00	0.00	0.00	0
379	0.38	0.31	0.34	39
380	0.00	0.00	0.00	6
381	0.20	0.05	0.08	40
382	0.35	0.09	0.14	77
383	0.70	0.44	0.54	16
384	0.62	0.45	0.52	117
385	0.22	0.12	0.15	101
386	0.58	0.44	0.50	34
387	0.33	0.20	0.25	5
388	0.00	0.00	0.00	0
389	0.35	0.25	0.30	157
390	0.50	0.10	0.17	30
391	0.00	0.00	0.00	22
392	0.31	0.14	0.20	35
393	0.27	0.27	0.27	11
394	0.80	1.00	0.89	4

394	0.80	1.00	0.89	4
395	0.00	0.00	0.00	5
396	0.00	0.00	0.00	0
397	0.00	0.00	0.00	2
398	0.40	0.43	0.42	146
399	0.00	0.00	0.00	0
400	0.49	0.49	0.49	57
401	0.40	0.67	0.50	3
402	0.00	0.00	0.00	1
403	0.42	0.23	0.30	152
404	0.00	0.00	0.00	1
405	0.42	0.25	0.31	20
406	0.00	0.00	0.00	0
407	0.00	0.00	0.00	7
408	0.29	0.18	0.22	33
409	0.10	0.06	0.08	48
410	0.63	0.41	0.50	126
411	0.00	0.00	0.00	0
412	0.20	0.09	0.13	11
413	0.69	0.30	0.42	66
414	0.50	0.50	0.50	2
415	0.00	0.00	0.00	0
416	0.33	0.05	0.08	21
417	0.00	0.00	0.00	1
418	1.00	1.00	1.00	2
419	0.10	0.05	0.07	73
420	0.00	0.00	0.00	24
421	0.00	0.00	0.00	2
422	0.00	0.00	0.00	19
423	0.00	0.00	0.00	22
424	0.00	0.00	0.00	2
425	0.00	0.00	0.00	2
426	0.00	0.00	0.00	0
427	0.23	0.13	0.17	68
428	0.42	0.15	0.22	131
429	0.00	0.00	0.00	0
430	0.50	0.04	0.07	28
431	0.50	0.69	0.58	13
432	0.00	0.00	0.00	14
433	0.00	0.00	0.00	0
434	0.00	0.00	0.00	0
435	0.00	0.00	0.00	0
436	0.00	0.00	0.00	15
437	0.33	0.20	0.25	30
438	0.05	0.01	0.02	82
439	0.00	0.00	0.00	0
440	1.00	0.17	0.29	6
441	0.00	0.00	0.00	12
442	0.00	0.00	0.00	8
443	0.83	0.22	0.34	46
444	0.71	0.28	0.40	54
445	0.00	0.00	0.00	0
446	1.00	0.17	0.29	6
447	0.00	0.00	0.00	0
448	0.00	0.00	0.00	6
449	0.00	0.00	0.00	32
450	0.33	0.33	0.33	3
451	0.17	1.00	0.29	1
452	0.33	0.17	0.22	6
453	0.32	0.33	0.33	127
454	0.33	0.50	0.40	2
455	0.45	0.22	0.29	23
456	0.55	0.52	0.54	21
457	0.06	0.02	0.03	47
458	0.26	0.22	0.24	112
459	0.00	0.00	0.00	0
460	0.40	0.26	0.31	97
461	0.50	0.04	0.07	25
462	1.00	0.17	0.29	6
463	0.00	0.00	0.00	1
464	0.21	0.07	0.11	55
465	0.28	0.21	0.24	24
466	0.00	0.00	0.00	1
467	0.67	0.62	0.65	16
468	0.00	0.00	0.00	16
469	0.59	0.30	0.40	136
470	0.00	0.00	0.00	9
471	0.61	0.41	0.49	27

```
         471       0.61      0.41      0.49        27
         472       0.30      0.07      0.12       134
         473       0.00      0.00      0.00         5
         474       0.59      0.23      0.33        96
         475       0.33      0.12      0.18       120
         476       0.17      0.17      0.17         6
         477       1.00      1.00      1.00         1
         478       0.00      0.00      0.00         6
         479       0.39      0.31      0.35        42
         480       0.00      0.00      0.00         0
         481       0.00      0.00      0.00         0
         482       0.30      0.43      0.35         7
         483       0.00      0.00      0.00        24
         484       0.00      0.00      0.00         2
         485       0.07      0.04      0.05        27
         486       0.24      0.07      0.11       112
         487       0.00      0.00      0.00         0
         488       0.66      0.55      0.60        53
         489       0.00      0.00      0.00        16
         490       0.23      0.13      0.17        89
         491       0.00      0.00      0.00         0
         492       0.19      0.14      0.16        21
         493       0.36      0.24      0.29        21
         494       0.00      0.00      0.00         1
         495       1.00      0.50      0.67         4
         496       0.00      0.00      0.00         0
         497       0.20      0.09      0.12        79
         498       0.00      0.00      0.00         6
         499       0.00      0.00      0.00        10

   micro avg       0.66      0.59      0.62     85094
   macro avg       0.28      0.21      0.23     85094
weighted avg       0.64      0.59      0.61     85094
 samples avg       0.73      0.66      0.64     85094

Time taken to run this cell : 0:04:38.244261
```

5. Prettytable

In [58]:

```
from prettytable import PrettyTable
pt = PrettyTable()
pt.field_names = ["Index","Model", "Vectorizer", "Accuracy", "Hamming loss","Precision","Recall","F
1 Measure"]
pt.add_row(["1","SGDClassifier with Log Loss",'BOW', 0.1381, 0.0045, 0.4722, 0.6226, 0.5371])
pt.add_row(["2","Logistic Regression",'BOW', 0.2583, 0.0026, 0.7180, 0.6031, 0.6555])
pt.add_row(["3","Logistic Regression",'BOW', 0.2744, 0.0025, 0.7733, 0.5774, 0.6611])
pt.add_row(["4","Linear SVM",'BOW', 0.2153, 0.0030, 0.6553, 0.5906, 0.6213])
print(pt)
```

```
+-------+-----------------------------+------------+----------+--------------+-----------+--------+
---------+
| Index |            Model            | Vectorizer | Accuracy | Hamming loss | Precision | Recall |
F1 Measure |
+-------+-----------------------------+------------+----------+--------------+-----------+--------+
---------+
|   1   | SGDClassifier with Log Loss |    BOW     |  0.1381  |    0.0045    |   0.4722  | 0.6226 |
0.5371   |
|   2   |     Logistic Regression     |    BOW     |  0.2583  |    0.0026    |   0.718   | 0.6031 |
0.6555   |
|   3   |     Logistic Regression     |    BOW     |  0.2744  |    0.0025    |   0.7733  | 0.5774 |
0.6611   |
|   4   |          Linear SVM         |    BOW     |  0.2153  |    0.003     |   0.6553  | 0.5906 |
0.6213   |
+-------+-----------------------------+------------+----------+--------------+-----------+--------+
---------+
```

Conclusions

1. For Modeling we have taken 0.5 million datapoints and 500 tags.

2. Logistic Regression with Hyperparameter tuning gives us best accuracy of 0.2744.
3. SGDClassifier with log loss gives less accuracy than SGDClassifier with hinge loss.
4. It almost took 15 hours to do hyperparameter tuning using GridSearch

In [ ]:

```

```