
In [1]:

```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import sqlite3
import csv
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from wordcloud import WordCloud
import re
import os
from sqlalchemy import create_engine # database connection
import datetime as dt
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem.snowball import SnowballStemmer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import SGDClassifier
from sklearn import metrics
from sklearn.metrics import f1_score,precision_score,recall_score
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from 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/ (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 (https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data)
Youtube : https://youtu.be/nNDqbUhtIRg (https://youtu.be/nNDqbUhtIRg)
Research paper : https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/tagging-1.pdf (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 (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 (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 lowe
rcase, should not contain tabs '\t' or ampersands '&')
```

## 2.1.2 Example Data point

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

```
        #include<
        iostream>\n
        #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 variable
s";\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 (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 (https://www.kaggle.com/wiki/MeanFScore)
http://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html (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 (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 [0]:

```
#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=chu
        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 [0]:

```
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 t
```

```
Number of rows in the database :
 6034196
Time taken to count the number of rows : 0:01:15.750352
```

### 3.1.3 Checking for duplicates

In [0]:

```
#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
    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.
```

```
Time taken to run this cell : 0:04:33.560122
```

In [0]:

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

Out[6]:

| | 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... | <p>I use the following code</p>\n\n<pre><code>... | java jdbc | 2 |

In [0]:

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

```
number of duplicate questions : 1827881 ( 30.2920389063 % )
```

In [0]:

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

Out[8]:

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

In [0]:

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

```
Time taken to run this cell : 0:00:03.169523
```

Out[9]:

| | Title | Body | Tags | cnt_dup | t |
|---|---|---|---|---|---|
| **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... | <p>I use the following code</p>\n\n<pre> <code>... | java jdbc | 2 | |

In [0]:

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

Out[10]:

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

In [0]:

```
#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 [0]:

```
#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
```

```
Time taken to run this cell : 0:00:52.992676
```

# 3.2 Analysis of Tags

## 3.2.1 Total number of unique tags

In [0]:

```
# 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 [0]:

```
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 [0]:

```
#'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 tages we have : ['.a', '.app', '.asp.net-mvc', '.aspxauth', '.ba
sh-profile', '.class-file', '.cs-file', '.doc', '.drv', '.ds-store']
```

## 3.2.3 Number of times a tag appeared

In [0]:

```
# 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 [0]:

```
#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[17]:

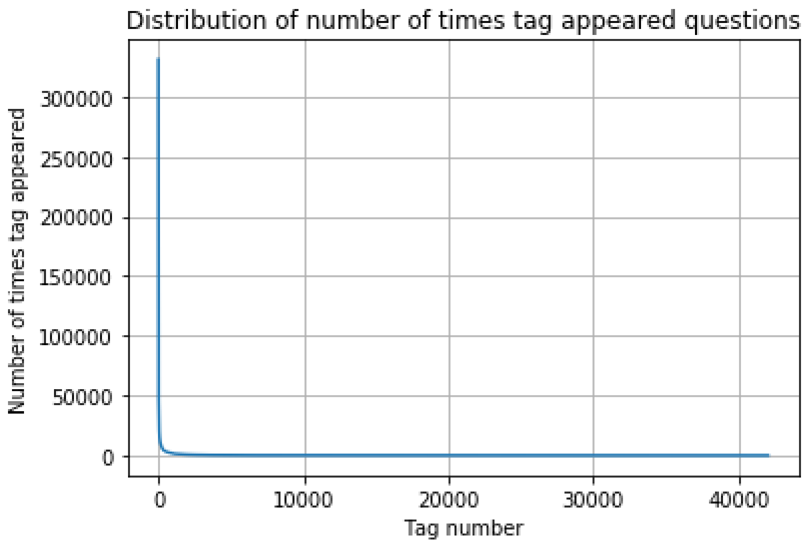
| | Tags | Counts |
|---|---|---|
| **0** | .a | 18 |
| **1** | .app | 37 |
| **2** | .asp.net-mvc | 1 |
| **3** | .aspxauth | 21 |
| **4** | .bash-profile | 138 |

In [0]:

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

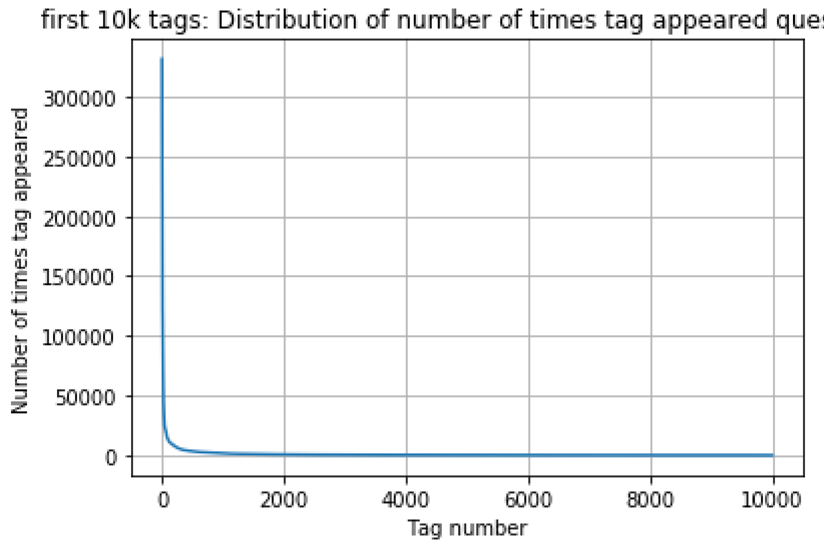
In [0]:

```
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])
```

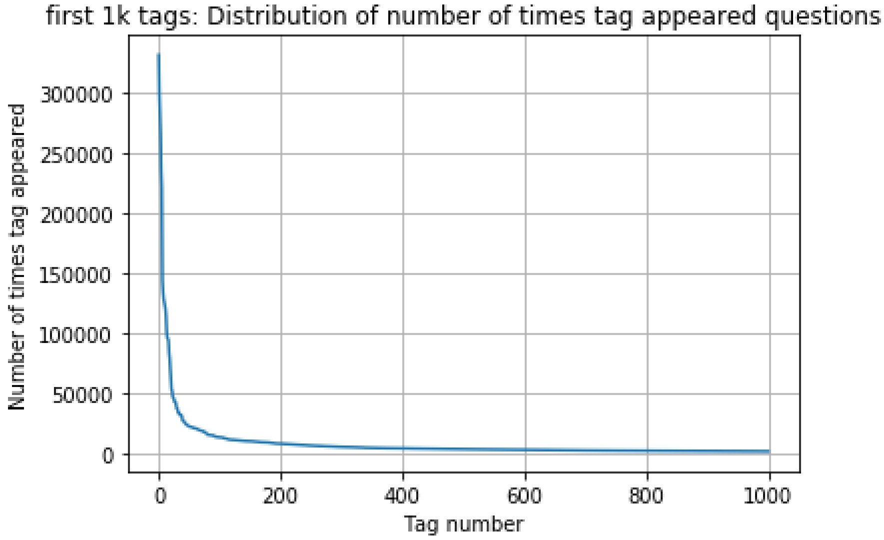



```
400 [331505  44829  22429  17728  13364  11162  10029   9148   8054   7151
   6466   5865   5370   4983   4526   4281   4144   3929   3750   3593
   3453   3299   3123   2989   2891   2738   2647   2527   2431   2331
   2259   2186   2097   2020   1959   1900   1828   1770   1723   1673
   1631   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]:

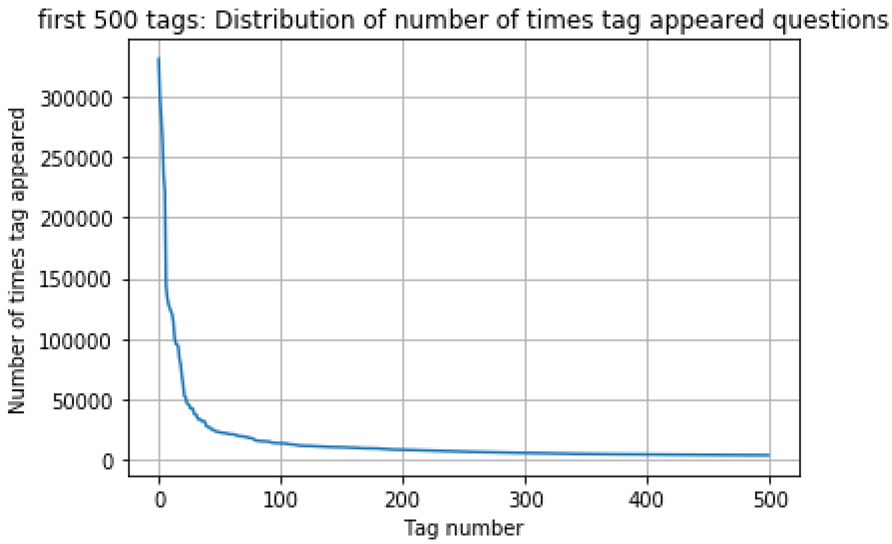
```
plt.plot(tag_counts[0:1000])
plt.title('first 1k tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
print(len(tag_counts[0:1000:5]), tag_counts[0:1000:5])
```




```
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])
```



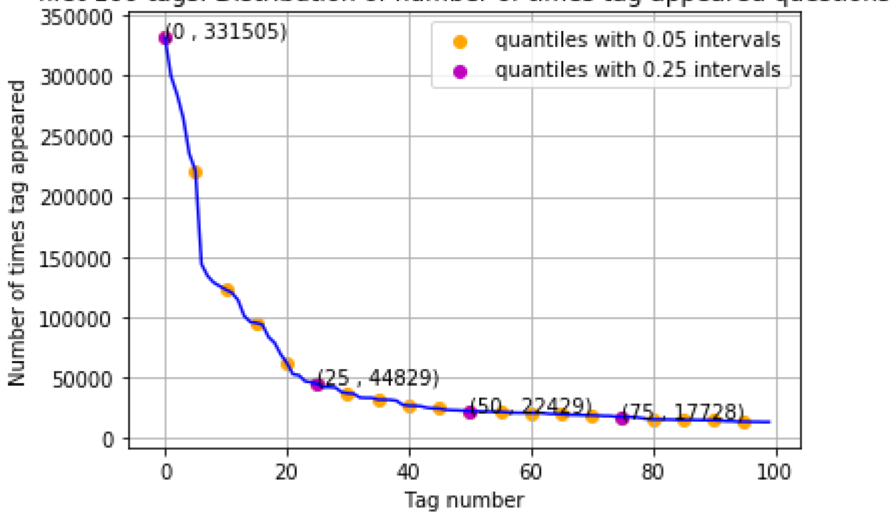

```
100 [331505 221533 122769  95160  62023  44829  37170  31897  26925  24537
  22429  21820  20957  19758  18905  17728  15533  15097  14884  13703
  13364  13157  12407  11658  11228  11162  10863  10600  10350  10224
  10029   9884   9719   9411   9252   9148   9040   8617   8361   8163
   8054   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 wit
# quantiles with 0.25 difference
plt.scatter(x=list(range(0,100,25)), y=tag_counts[0:100:25], c='m', label = "quantiles with

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 [0]:

```
# 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 [0]:

```
#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 ar
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]
```

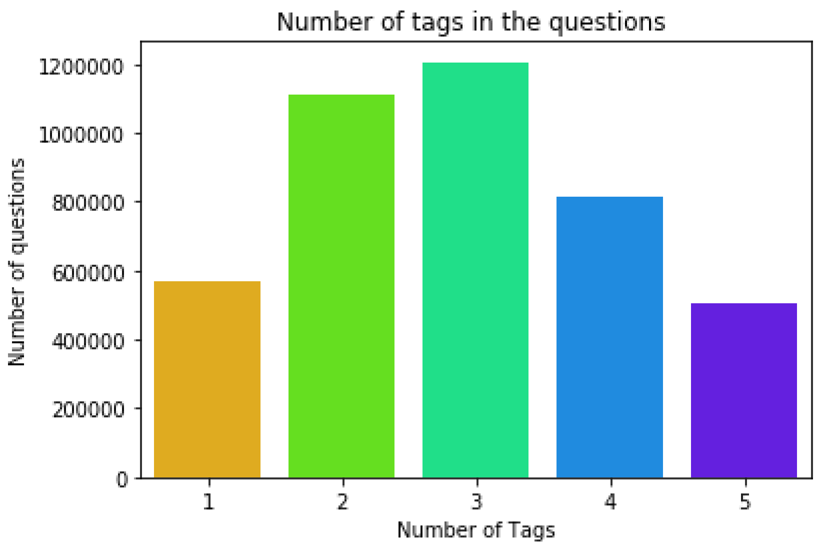
In [0]:

```
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_cc
```

```
Maximum number of tags per question: 5
Minimum number of tags per question: 1
Avg. number of tags per question: 2.899440
```

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

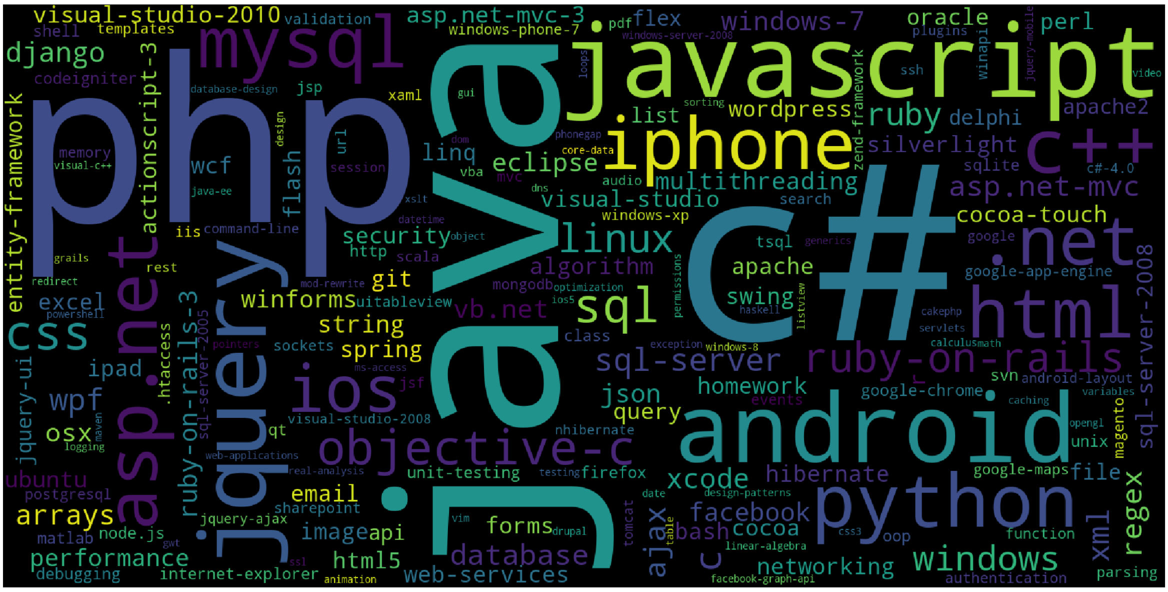
### 3.2.5 Most Frequent Tags

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)
```



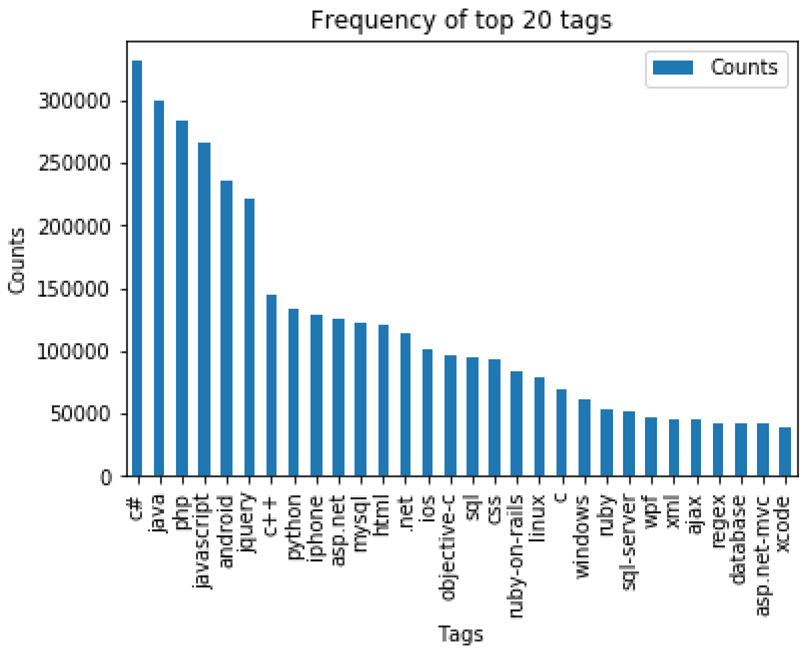

```
Time taken to run this cell : 0:00:05.470788
```

**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

In [2]:

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

In [16]:

```
#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
create_database_table("Processed.db", sql_create_table)
```

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

# 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 |

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

In [15]:

```
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 [0]:

```
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 [4]:

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

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

In [5]:

```
# 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

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 [7]:

```
#http://www.bernzilla.com/2008/05/13/selecting-a-random-row-from-an-sqlite-table/
import nltk
nltk.download('punkt')

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

    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,
    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_pr
```

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

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\hp\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping tokenizers\punkt.zip.
number of questions completed= 100000
number of questions completed= 200000
number of questions completed= 300000
number of questions completed= 400000
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 : 0:19:23.878200
```

In [8]:

```
# 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 [9]:

```
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
============================================================================
========================
('java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index ja
va.sql.sqlexcept microsoft odbc driver manag invalid descriptor index java.s
ql.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 w
ay updat feed fb php sdk novic facebook api read mani tutori still confused.
i find post feed api method like correct second way use curl someth like way
better',)
----------------------------------------------------------------------------
------------------------
('btnadd click event open two window record ad btnadd click event open two w
indow record ad btnadd click event open two window record ad open window sea
rch.aspx use code hav add button search.aspx nwhen insert record btnadd clic
k event open anoth window nafter insert record close window',)
----------------------------------------------------------------------------
------------------------
('sql inject issu prevent correct form submiss php sql inject issu prevent c
orrect form submiss php sql inject issu prevent correct form submiss php che
ck everyth think make sure input field safe type sql inject good news safe b
ad news one tag mess form submiss place even touch life figur exact html use
templat file forgiv okay entir php script get execut see data post none foru
m field post problem use someth titl field none data get post current use pr
int post see submit noth work flawless statement though also mention script
work flawless local machin use host come across problem state list input tes
t mess',)
----------------------------------------------------------------------------
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('countabl subaddit lebesgu measur countabl subaddit lebesgu measur countabl
subaddit lebesgu measur let lbrace rbrace sequenc set sigma -algebra mathcal
want show left bigcup right leq sum left right countabl addit measur defin s
et sigma algebra mathcal think use monoton properti somewher proof start app
reci littl help nthank ad han answer make follow addit construct given han a
nswer clear bigcup bigcup cap emptyset neq left bigcup right left bigcup rig
ht sum left right also construct subset monoton left right leq left right fi
nal would sum leq sum result follow',)
----------------------------------------------------------------------------
------------------------
('hql equival sql queri hql equival sql queri hql equival sql queri hql quer
i replac name class properti name error occur hql error',)
----------------------------------------------------------------------------
```

```
------------------------
('undefin symbol architectur i386 objc class skpsmtpmessag referenc error un
defin symbol architectur i386 objc class skpsmtpmessag referenc error undefi
n symbol architectur i386 objc class skpsmtpmessag referenc error import fra
mework send email applic background import framework i.e skpsmtpmessag someb
odi suggest get error collect2 ld return exit status import framework correc
t sorc taken framework follow mfmailcomposeviewcontrol question lock field u
pdat answer drag drop folder project click copi nthat',)
----------------------------------------------------------------------------
------------------------
('java.lang.nosuchmethoderror javax.servlet.servletcontext.geteffectivesessi
ontrackingmod ljava util set java.lang.nosuchmethoderror javax.servlet.servl
etcontext.geteffectivesessiontrackingmod ljava util set java.lang.nosuchmeth
oderror javax.servlet.servletcontext.geteffectivesessiontrackingmod ljava ut
il set want servlet process input standalon java program deploy servlet jbos
s put servlet.class file web-inf class web.xml gave servlet url map .do java
client program open connect servlet use url object use localhost 8080 .do ge
t folow error error org.apache.catalina.connector.coyoteadapt except error o
ccur contain request process java.lang.nosuchmethoderror javax.servlet.servl
etcontext.geteffectivesessiontrackingmod ljava util set org.apache.catalina.
connector.coyoteadapter.postparserequest coyoteadapter.java 567 org.apache.c
atalina.connector.coyoteadapter.servic coyoteadapter.java 359 org.apache.coy
ote.http11.http11processor.process http11processor.java 877 org.apache.coyot
e.http11.http11protocol http11connectionhandler.process http11protocol.java
654 org.apache.tomcat.util.net.jioendpoint worker.run jioendpoint.java 951 w
eb.xml file content',)
----------------------------------------------------------------------------
------------------------
('obtain updat locat use gps servic obtain updat locat use gps servic obtain
updat locat use gps servic app two button start track stop track strart trac
k button click gps start listen locat stop listen use besid toast everi new
updat locat want thing use background servic alway updat locat even activ cl
osed.a toast appear everi new updat location.pleas hint link would apprec
i',)
----------------------------------------------------------------------------
------------------------
```

### Saving Preprocessed data to a Database

In [10]:

```
#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 QuestionsProces
conn_r.commit()
conn_r.close()
```

In [11]:

```
preprocessed_data.head()
```

Out[11]:

| | question | tags |
|---|---|---|
| **0** | java.lang.noclassdeffounderror javax servlet j... | jsp jstl |
| **1** | java.sql.sqlexcept microsoft odbc driver manag... | java jdbc |
| **2** | better way updat feed fb php sdk better way up... | facebook api facebook-php-sdk |
| **3** | btnadd click event open two window record ad b... | javascript asp.net web |
| **4** | sql inject issu prevent correct form submiss p... | php forms |

In [12]:

```
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 : 499998
number of dimensions : 2
```

#### Converting string Tags to multilable output variables

In [13]:

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

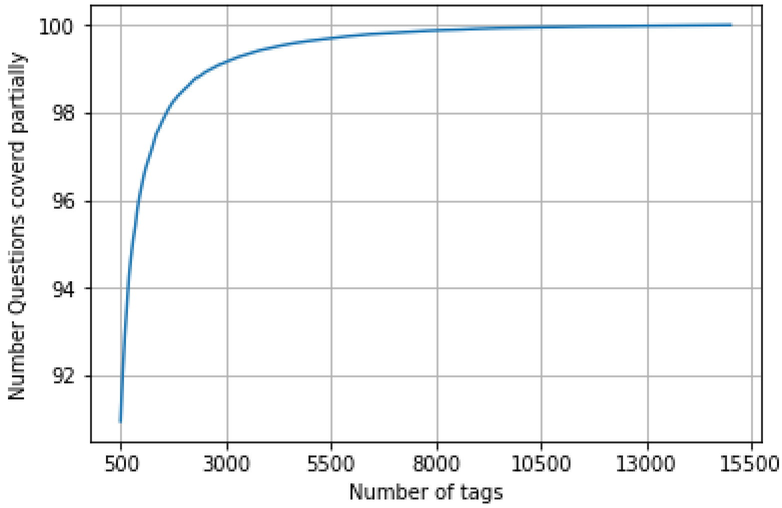
#### Selecting 500 Tags

In [17]:

```
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
```

In [19]:

```
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
print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
print("with ",500,"tags we are covering ",questions_explained[0],"% of questions")
```




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

In [20]:

```
# 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 ",
```

```
number of questions that are not covered : 45221 out of  499998
```

In [21]:

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

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

In [22]:

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

```
Number of data points in train data : (400000, 500)
Number of data points in test data : (99998, 500)
```

# 5. Assignments

# USE BoW WITH UPTO 4 GRAMS AND COMPUTE micro F1 score with L.R(1 Vs Rest)

## 5.1 Featurizing data with Count vectorizer

In [28]:

```
start = datetime.now()
vectorizer = CountVectorizer(min_df=0.00009, max_features=200000, tokenizer = lambda x: x.s

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 : 0:06:31.754828
```

In [30]:

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

```
Dimensions of train data X: (400000, 95586) Y : (400000, 500)
Dimensions of test data X: (99998, 95586) Y: (99998, 500)
```

# Logistic Regression with OneVsRestClassifier using count vectorizer

### Hyperparameter tuning(Using grid search) :-

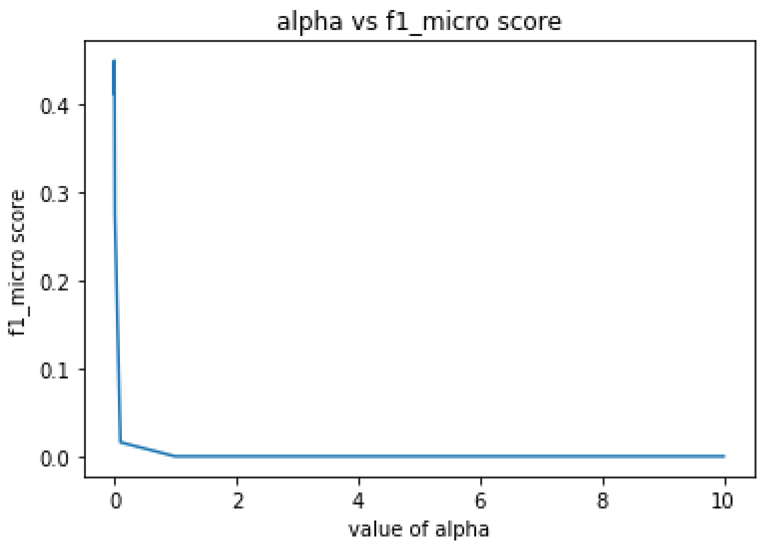
In [32]:

```
from sklearn.model_selection import GridSearchCV
param={'estimator__alpha': [10**-9, 10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1]}
classifier = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l1'))
gsv = GridSearchCV(estimator = classifier, param_grid=param, verbose=0, scoring='f1_micro',
gsv.fit(x_train_multilabel, y_train)

best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
print('value of alpha after hyperparameter tuning : ',best_alpha)
print('--------------------------------------------------------------')
# plotting C vs f1_micro_score
x_1=[]
y_1=[]
for x in gsv.grid_scores_:
    x_1.append(x[0]['estimator__alpha'])
    y_1.append(x[1])
plt.plot(x_1,y_1)
plt.xlabel('value of alpha')
plt.ylabel('f1_micro score')
plt.title('alpha vs f1_micro score')
plt.show()
```

```
value of alpha after hyperparameter tuning :  0.001
--------------------------------------------------------------

C:\Users\hp\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:7
61: DeprecationWarning: The grid_scores_ attribute was deprecated in version
0.18 in favor of the more elaborate cv_results_ attribute. The grid_scores_
attribute will not be available from 0.20
  DeprecationWarning)
```




## Applying model using best hyperparameter:-

In [33]:

```
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l1'), n_jo
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


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


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

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

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

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

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

```
Accuracy : 0.1868137362747255
Hamming loss  0.003220684413688274
Micro-average quality numbers
Precision: 0.5624, Recall: 0.3312, F1-measure: 0.4169
Macro-average quality numbers
Precision: 0.4101, Recall: 0.2382, F1-measure: 0.2832
              precision    recall  f1-score   support

           0       0.78      0.66      0.71      5519
           1       0.40      0.36      0.38      8189
           2       0.77      0.35      0.48      6529
           3       0.56      0.48      0.52      3231
           4       0.67      0.47      0.55      6430
           5       0.71      0.29      0.42      2878
           6       0.72      0.56      0.63      5086
           7       0.76      0.61      0.68      4533
           8       0.57      0.14      0.22      3000
           9       0.68      0.57      0.62      2765
          10       0.45      0.18      0.26      3051
          11       0.67      0.36      0.47      3009
          12       0.56      0.25      0.35      2630
          13       0.56      0.18      0.27      1425
          14       0.80      0.61      0.69      2548
          15       0.73      0.09      0.15      2371
          16       0.52      0.34      0.41       873
          17       0.78      0.65      0.71      2151
          18       0.47      0.27      0.34      2204
          19       0.47      0.45      0.46       831
          20       0.79      0.35      0.48      1860
          21       0.24      0.12      0.16      2023
          22       0.38      0.21      0.27      1513
          23       0.83      0.56      0.67      1207
```

```
          24       0.44      0.35      0.39       506
          25       0.68      0.37      0.48       425
          26       0.52      0.41      0.46       793
          27       0.54      0.33      0.41      1291
          28       0.72      0.30      0.43      1208
          29       0.27      0.07      0.11       406
          30       0.57      0.15      0.24       504
          31       0.26      0.17      0.20       732
          32       0.56      0.30      0.39       441
          33       0.28      0.19      0.22      1645
          34       0.50      0.40      0.44      1058
          35       0.69      0.66      0.68       946
          36       0.51      0.26      0.35       644
          37       0.77      0.82      0.79       136
          38       0.56      0.38      0.45       570
          39       0.81      0.31      0.45       766
          40       0.51      0.27      0.35      1132
          41       0.32      0.29      0.30       174
          42       0.64      0.48      0.55       210
          43       0.55      0.50      0.52       433
          44       0.42      0.53      0.47       626
          45       0.52      0.35      0.42       852
          46       0.66      0.38      0.48       534
          47       0.24      0.18      0.21       350
          48       0.71      0.46      0.56       496
          49       0.78      0.55      0.64       785
          50       0.18      0.10      0.13       475
          51       0.24      0.12      0.16       305
          52       0.29      0.06      0.10       251
          53       0.66      0.38      0.49       914
          54       0.29      0.18      0.22       728
          55       0.00      0.00      0.00       258
          56       0.36      0.13      0.19       821
          57       0.40      0.08      0.14       541
          58       0.80      0.25      0.38       748
          59       0.91      0.64      0.75       724
          60       0.24      0.06      0.10       660
          61       0.84      0.25      0.38       235
          62       0.84      0.81      0.82       718
          63       0.83      0.55      0.66       468
          64       0.53      0.45      0.49       191
          65       0.22      0.11      0.14       429
          66       0.16      0.10      0.13       415
          67       0.73      0.49      0.59       274
          68       0.78      0.57      0.66       510
          69       0.51      0.53      0.52       466
          70       0.27      0.09      0.13       305
          71       0.38      0.16      0.23       247
          72       0.59      0.58      0.58       401
          73       0.92      0.78      0.84        86
          74       0.37      0.41      0.39       120
          75       0.83      0.78      0.80       129
          76       0.07      0.01      0.01       473
          77       0.28      0.28      0.28       143
          78       0.76      0.45      0.56       347
          79       0.64      0.27      0.38       479
          80       0.36      0.33      0.34       279
          81       0.81      0.12      0.20       461
          82       0.09      0.01      0.02       298
          83       0.75      0.41      0.53       396
          84       0.38      0.35      0.36       184
```

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|---|---|---|---|---|
| 85 | 0.48 | 0.17 | 0.25 | 573 |
| 86 | 0.24 | 0.08 | 0.12 | 325 |
| 87 | 0.50 | 0.23 | 0.31 | 273 |
| 88 | 0.28 | 0.20 | 0.23 | 135 |
| 89 | 0.20 | 0.19 | 0.19 | 232 |
| 90 | 0.40 | 0.39 | 0.39 | 409 |
| 91 | 0.46 | 0.44 | 0.45 | 420 |
| 92 | 0.65 | 0.64 | 0.64 | 408 |
| 93 | 0.62 | 0.45 | 0.52 | 241 |
| 94 | 0.30 | 0.09 | 0.13 | 211 |
| 95 | 0.21 | 0.14 | 0.17 | 277 |
| 96 | 0.21 | 0.04 | 0.07 | 410 |
| 97 | 0.88 | 0.22 | 0.35 | 501 |
| 98 | 0.53 | 0.62 | 0.57 | 136 |
| 99 | 0.48 | 0.25 | 0.33 | 239 |
| 100 | 0.40 | 0.07 | 0.12 | 324 |
| 101 | 0.91 | 0.55 | 0.68 | 277 |
| 102 | 0.91 | 0.67 | 0.78 | 613 |
| 103 | 0.43 | 0.19 | 0.26 | 157 |
| 104 | 0.16 | 0.21 | 0.18 | 295 |
| 105 | 0.65 | 0.36 | 0.46 | 334 |
| 106 | 0.51 | 0.08 | 0.14 | 335 |
| 107 | 0.76 | 0.47 | 0.58 | 389 |
| 108 | 0.45 | 0.21 | 0.29 | 251 |
| 109 | 0.51 | 0.42 | 0.46 | 317 |
| 110 | 0.41 | 0.05 | 0.09 | 187 |
| 111 | 0.24 | 0.11 | 0.15 | 140 |
| 112 | 0.11 | 0.04 | 0.06 | 154 |
| 113 | 0.45 | 0.37 | 0.41 | 332 |
| 114 | 0.33 | 0.23 | 0.27 | 323 |
| 115 | 0.32 | 0.14 | 0.19 | 344 |
| 116 | 0.71 | 0.44 | 0.54 | 370 |
| 117 | 0.47 | 0.17 | 0.25 | 313 |
| 118 | 0.79 | 0.52 | 0.63 | 874 |
| 119 | 0.36 | 0.19 | 0.25 | 293 |
| 120 | 0.00 | 0.00 | 0.00 | 200 |
| 121 | 0.66 | 0.47 | 0.55 | 463 |
| 122 | 0.18 | 0.20 | 0.19 | 119 |
| 123 | 0.00 | 0.00 | 0.00 | 256 |
| 124 | 0.89 | 0.71 | 0.79 | 195 |
| 125 | 0.33 | 0.22 | 0.26 | 138 |
| 126 | 0.73 | 0.47 | 0.57 | 376 |
| 127 | 0.13 | 0.07 | 0.09 | 122 |
| 128 | 0.12 | 0.11 | 0.11 | 252 |
| 129 | 0.00 | 0.00 | 0.00 | 144 |
| 130 | 0.10 | 0.02 | 0.03 | 150 |
| 131 | 0.17 | 0.01 | 0.02 | 210 |
| 132 | 0.17 | 0.14 | 0.15 | 361 |
| 133 | 0.89 | 0.52 | 0.66 | 453 |
| 134 | 0.67 | 0.83 | 0.74 | 124 |
| 135 | 0.00 | 0.00 | 0.00 | 91 |
| 136 | 0.32 | 0.26 | 0.28 | 128 |
| 137 | 0.41 | 0.35 | 0.38 | 218 |
| 138 | 0.00 | 0.00 | 0.00 | 243 |
| 139 | 0.32 | 0.24 | 0.28 | 149 |
| 140 | 0.77 | 0.37 | 0.50 | 318 |
| 141 | 0.10 | 0.18 | 0.13 | 159 |
| 142 | 0.58 | 0.32 | 0.41 | 274 |
| 143 | 0.69 | 0.81 | 0.75 | 362 |
| 144 | 0.51 | 0.21 | 0.30 | 118 |
| 145 | 0.52 | 0.35 | 0.42 | 164 |

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|---|---|---|---|---|
| 146 | 0.56 | 0.25 | 0.35 | 461 |
| 147 | 0.62 | 0.43 | 0.51 | 159 |
| 148 | 0.33 | 0.14 | 0.20 | 166 |
| 149 | 0.95 | 0.52 | 0.67 | 346 |
| 150 | 0.43 | 0.09 | 0.14 | 350 |
| 151 | 0.80 | 0.60 | 0.69 | 55 |
| 152 | 0.75 | 0.44 | 0.55 | 387 |
| 153 | 0.35 | 0.06 | 0.10 | 150 |
| 154 | 0.69 | 0.07 | 0.13 | 281 |
| 155 | 0.23 | 0.14 | 0.18 | 202 |
| 156 | 0.62 | 0.69 | 0.65 | 130 |
| 157 | 0.26 | 0.10 | 0.14 | 245 |
| 158 | 0.86 | 0.48 | 0.62 | 177 |
| 159 | 0.45 | 0.25 | 0.32 | 130 |
| 160 | 0.46 | 0.19 | 0.27 | 336 |
| 161 | 0.84 | 0.65 | 0.73 | 220 |
| 162 | 0.10 | 0.03 | 0.05 | 229 |
| 163 | 0.84 | 0.47 | 0.60 | 316 |
| 164 | 0.57 | 0.16 | 0.25 | 283 |
| 165 | 0.30 | 0.38 | 0.33 | 197 |
| 166 | 0.12 | 0.08 | 0.09 | 101 |
| 167 | 0.24 | 0.24 | 0.24 | 231 |
| 168 | 0.30 | 0.14 | 0.19 | 370 |
| 169 | 0.39 | 0.24 | 0.29 | 258 |
| 170 | 0.13 | 0.06 | 0.08 | 101 |
| 171 | 0.36 | 0.20 | 0.26 | 89 |
| 172 | 0.31 | 0.28 | 0.29 | 193 |
| 173 | 0.33 | 0.36 | 0.35 | 309 |
| 174 | 0.41 | 0.09 | 0.15 | 172 |
| 175 | 0.92 | 0.73 | 0.81 | 95 |
| 176 | 0.94 | 0.50 | 0.65 | 346 |
| 177 | 0.97 | 0.29 | 0.44 | 322 |
| 178 | 0.47 | 0.50 | 0.48 | 232 |
| 179 | 0.56 | 0.04 | 0.07 | 125 |
| 180 | 0.42 | 0.19 | 0.26 | 145 |
| 181 | 0.08 | 0.16 | 0.11 | 77 |
| 182 | 0.12 | 0.05 | 0.07 | 182 |
| 183 | 0.57 | 0.30 | 0.39 | 257 |
| 184 | 0.13 | 0.05 | 0.07 | 216 |
| 185 | 0.20 | 0.05 | 0.07 | 242 |
| 186 | 0.27 | 0.18 | 0.22 | 165 |
| 187 | 0.76 | 0.51 | 0.61 | 263 |
| 188 | 0.29 | 0.11 | 0.16 | 174 |
| 189 | 0.60 | 0.09 | 0.15 | 136 |
| 190 | 0.93 | 0.43 | 0.59 | 202 |
| 191 | 0.30 | 0.10 | 0.15 | 134 |
| 192 | 0.76 | 0.32 | 0.45 | 230 |
| 193 | 0.28 | 0.18 | 0.22 | 90 |
| 194 | 0.56 | 0.44 | 0.50 | 185 |
| 195 | 0.11 | 0.07 | 0.08 | 156 |
| 196 | 0.14 | 0.01 | 0.01 | 160 |
| 197 | 0.00 | 0.00 | 0.00 | 266 |
| 198 | 0.22 | 0.14 | 0.17 | 284 |
| 199 | 0.14 | 0.18 | 0.15 | 145 |
| 200 | 0.91 | 0.66 | 0.76 | 212 |
| 201 | 0.51 | 0.25 | 0.33 | 317 |
| 202 | 0.72 | 0.41 | 0.52 | 427 |
| 203 | 0.19 | 0.10 | 0.13 | 232 |
| 204 | 0.32 | 0.19 | 0.24 | 217 |
| 205 | 0.46 | 0.34 | 0.39 | 527 |
| 206 | 0.04 | 0.01 | 0.01 | 124 |

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|---|---|---|---|---|
| 207 | 0.25 | 0.01 | 0.02 | 103 |
| 208 | 0.73 | 0.61 | 0.67 | 287 |
| 209 | 0.13 | 0.10 | 0.11 | 193 |
| 210 | 0.43 | 0.32 | 0.37 | 220 |
| 211 | 0.67 | 0.01 | 0.03 | 140 |
| 212 | 0.08 | 0.07 | 0.08 | 161 |
| 213 | 0.48 | 0.18 | 0.26 | 72 |
| 214 | 0.60 | 0.43 | 0.51 | 396 |
| 215 | 0.49 | 0.32 | 0.39 | 134 |
| 216 | 0.00 | 0.00 | 0.00 | 400 |
| 217 | 0.51 | 0.28 | 0.36 | 75 |
| 218 | 0.94 | 0.76 | 0.84 | 219 |
| 219 | 0.66 | 0.35 | 0.46 | 210 |
| 220 | 0.30 | 0.24 | 0.27 | 298 |
| 221 | 0.96 | 0.52 | 0.68 | 266 |
| 222 | 0.83 | 0.25 | 0.38 | 290 |
| 223 | 0.10 | 0.12 | 0.11 | 128 |
| 224 | 0.76 | 0.32 | 0.45 | 159 |
| 225 | 0.38 | 0.19 | 0.25 | 164 |
| 226 | 0.51 | 0.38 | 0.43 | 144 |
| 227 | 0.37 | 0.47 | 0.42 | 276 |
| 228 | 0.05 | 0.02 | 0.03 | 235 |
| 229 | 0.29 | 0.04 | 0.07 | 216 |
| 230 | 0.31 | 0.21 | 0.25 | 228 |
| 231 | 0.52 | 0.56 | 0.54 | 64 |
| 232 | 0.09 | 0.06 | 0.07 | 103 |
| 233 | 0.71 | 0.24 | 0.35 | 216 |
| 234 | 0.00 | 0.00 | 0.00 | 116 |
| 235 | 0.66 | 0.51 | 0.57 | 77 |
| 236 | 0.92 | 0.67 | 0.78 | 67 |
| 237 | 0.00 | 0.00 | 0.00 | 218 |
| 238 | 0.09 | 0.04 | 0.06 | 139 |
| 239 | 0.17 | 0.02 | 0.04 | 94 |
| 240 | 0.35 | 0.18 | 0.24 | 77 |
| 241 | 0.40 | 0.02 | 0.05 | 167 |
| 242 | 0.51 | 0.29 | 0.37 | 86 |
| 243 | 0.24 | 0.19 | 0.21 | 58 |
| 244 | 0.22 | 0.09 | 0.12 | 269 |
| 245 | 0.11 | 0.05 | 0.07 | 112 |
| 246 | 0.95 | 0.62 | 0.75 | 255 |
| 247 | 0.37 | 0.19 | 0.25 | 58 |
| 248 | 0.30 | 0.04 | 0.07 | 81 |
| 249 | 0.00 | 0.00 | 0.00 | 131 |
| 250 | 0.28 | 0.12 | 0.17 | 93 |
| 251 | 0.43 | 0.23 | 0.30 | 154 |
| 252 | 0.21 | 0.05 | 0.08 | 129 |
| 253 | 0.45 | 0.28 | 0.34 | 83 |
| 254 | 0.23 | 0.09 | 0.13 | 191 |
| 255 | 0.00 | 0.00 | 0.00 | 219 |
| 256 | 0.11 | 0.03 | 0.05 | 130 |
| 257 | 0.39 | 0.35 | 0.37 | 93 |
| 258 | 0.65 | 0.46 | 0.54 | 217 |
| 259 | 0.15 | 0.06 | 0.09 | 141 |
| 260 | 0.94 | 0.10 | 0.19 | 143 |
| 261 | 0.50 | 0.10 | 0.17 | 219 |
| 262 | 0.47 | 0.26 | 0.34 | 107 |
| 263 | 0.31 | 0.28 | 0.29 | 236 |
| 264 | 0.14 | 0.11 | 0.12 | 119 |
| 265 | 0.05 | 0.18 | 0.08 | 72 |
| 266 | 0.13 | 0.04 | 0.06 | 70 |
| 267 | 0.18 | 0.04 | 0.06 | 107 |

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|---|---|---|---|---|
| 268 | 0.65 | 0.33 | 0.43 | 169 |
| 269 | 0.18 | 0.08 | 0.11 | 129 |
| 270 | 0.59 | 0.63 | 0.61 | 159 |
| 271 | 0.63 | 0.18 | 0.28 | 190 |
| 272 | 0.41 | 0.09 | 0.15 | 248 |
| 273 | 0.90 | 0.64 | 0.75 | 264 |
| 274 | 0.63 | 0.69 | 0.66 | 105 |
| 275 | 0.00 | 0.00 | 0.00 | 104 |
| 276 | 0.09 | 0.02 | 0.03 | 115 |
| 277 | 0.63 | 0.63 | 0.63 | 170 |
| 278 | 0.50 | 0.30 | 0.37 | 145 |
| 279 | 0.66 | 0.51 | 0.57 | 230 |
| 280 | 0.58 | 0.38 | 0.45 | 80 |
| 281 | 0.68 | 0.52 | 0.59 | 217 |
| 282 | 0.74 | 0.56 | 0.64 | 175 |
| 283 | 0.48 | 0.05 | 0.09 | 269 |
| 284 | 0.60 | 0.36 | 0.45 | 74 |
| 285 | 0.79 | 0.47 | 0.59 | 206 |
| 286 | 0.89 | 0.54 | 0.67 | 227 |
| 287 | 0.59 | 0.44 | 0.50 | 130 |
| 288 | 0.24 | 0.07 | 0.11 | 129 |
| 289 | 0.08 | 0.01 | 0.02 | 80 |
| 290 | 0.15 | 0.12 | 0.13 | 99 |
| 291 | 0.75 | 0.27 | 0.40 | 208 |
| 292 | 0.28 | 0.07 | 0.12 | 67 |
| 293 | 0.60 | 0.28 | 0.39 | 109 |
| 294 | 0.17 | 0.26 | 0.21 | 140 |
| 295 | 0.17 | 0.14 | 0.15 | 241 |
| 296 | 0.19 | 0.18 | 0.18 | 72 |
| 297 | 0.28 | 0.10 | 0.15 | 107 |
| 298 | 0.83 | 0.16 | 0.27 | 61 |
| 299 | 0.74 | 0.38 | 0.50 | 77 |
| 300 | 0.12 | 0.05 | 0.07 | 111 |
| 301 | 0.00 | 0.00 | 0.00 | 126 |
| 302 | 0.00 | 0.00 | 0.00 | 73 |
| 303 | 0.51 | 0.45 | 0.48 | 176 |
| 304 | 0.96 | 0.61 | 0.74 | 230 |
| 305 | 0.93 | 0.67 | 0.78 | 156 |
| 306 | 0.36 | 0.56 | 0.44 | 146 |
| 307 | 0.19 | 0.08 | 0.11 | 98 |
| 308 | 0.05 | 0.03 | 0.03 | 78 |
| 309 | 0.67 | 0.02 | 0.04 | 94 |
| 310 | 0.69 | 0.26 | 0.38 | 162 |
| 311 | 0.69 | 0.41 | 0.51 | 116 |
| 312 | 0.53 | 0.30 | 0.38 | 57 |
| 313 | 0.00 | 0.00 | 0.00 | 65 |
| 314 | 0.29 | 0.39 | 0.34 | 138 |
| 315 | 0.36 | 0.30 | 0.33 | 195 |
| 316 | 0.45 | 0.39 | 0.42 | 69 |
| 317 | 0.00 | 0.00 | 0.00 | 134 |
| 318 | 0.30 | 0.19 | 0.23 | 148 |
| 319 | 0.80 | 0.45 | 0.57 | 161 |
| 320 | 0.16 | 0.17 | 0.17 | 104 |
| 321 | 0.70 | 0.63 | 0.66 | 156 |
| 322 | 0.49 | 0.23 | 0.31 | 134 |
| 323 | 0.54 | 0.31 | 0.39 | 232 |
| 324 | 0.21 | 0.11 | 0.14 | 92 |
| 325 | 0.30 | 0.09 | 0.13 | 197 |
| 326 | 0.04 | 0.01 | 0.01 | 126 |
| 327 | 0.33 | 0.01 | 0.02 | 115 |
| 328 | 0.97 | 0.57 | 0.71 | 198 |

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|---|---|---|---|---|
| 329 | 0.52 | 0.26 | 0.35 | 125 |
| 330 | 0.67 | 0.10 | 0.17 | 81 |
| 331 | 0.18 | 0.03 | 0.05 | 94 |
| 332 | 0.00 | 0.00 | 0.00 | 56 |
| 333 | 0.03 | 0.00 | 0.01 | 260 |
| 334 | 0.00 | 0.00 | 0.00 | 60 |
| 335 | 0.25 | 0.14 | 0.18 | 110 |
| 336 | 0.58 | 0.39 | 0.47 | 71 |
| 337 | 0.20 | 0.21 | 0.21 | 66 |
| 338 | 0.46 | 0.31 | 0.37 | 150 |
| 339 | 0.00 | 0.00 | 0.00 | 54 |
| 340 | 0.82 | 0.45 | 0.58 | 195 |
| 341 | 0.00 | 0.00 | 0.00 | 79 |
| 342 | 0.32 | 0.32 | 0.32 | 38 |
| 343 | 0.36 | 0.23 | 0.28 | 43 |
| 344 | 0.20 | 0.01 | 0.03 | 68 |
| 345 | 0.52 | 0.40 | 0.45 | 73 |
| 346 | 0.15 | 0.06 | 0.09 | 116 |
| 347 | 0.48 | 0.38 | 0.42 | 111 |
| 348 | 0.11 | 0.05 | 0.07 | 63 |
| 349 | 0.89 | 0.49 | 0.63 | 104 |
| 350 | 0.59 | 0.43 | 0.50 | 44 |
| 351 | 0.00 | 0.00 | 0.00 | 40 |
| 352 | 1.00 | 0.20 | 0.33 | 136 |
| 353 | 0.42 | 0.31 | 0.36 | 54 |
| 354 | 0.00 | 0.00 | 0.00 | 134 |
| 355 | 0.30 | 0.12 | 0.17 | 120 |
| 356 | 0.27 | 0.06 | 0.10 | 228 |
| 357 | 0.55 | 0.09 | 0.15 | 269 |
| 358 | 0.64 | 0.29 | 0.40 | 80 |
| 359 | 0.79 | 0.27 | 0.40 | 140 |
| 360 | 0.18 | 0.04 | 0.07 | 125 |
| 361 | 0.92 | 0.34 | 0.50 | 169 |
| 362 | 0.07 | 0.04 | 0.05 | 56 |
| 363 | 0.93 | 0.56 | 0.70 | 154 |
| 364 | 0.33 | 0.02 | 0.03 | 58 |
| 365 | 0.11 | 0.20 | 0.14 | 71 |
| 366 | 0.96 | 0.50 | 0.66 | 54 |
| 367 | 0.06 | 0.01 | 0.01 | 116 |
| 368 | 1.00 | 0.02 | 0.04 | 54 |
| 369 | 0.00 | 0.00 | 0.00 | 71 |
| 370 | 0.11 | 0.02 | 0.03 | 61 |
| 371 | 0.57 | 0.06 | 0.10 | 71 |
| 372 | 0.73 | 0.42 | 0.54 | 52 |
| 373 | 0.60 | 0.06 | 0.11 | 150 |
| 374 | 0.30 | 0.31 | 0.30 | 93 |
| 375 | 0.03 | 0.03 | 0.03 | 67 |
| 376 | 0.00 | 0.00 | 0.00 | 76 |
| 377 | 0.91 | 0.09 | 0.17 | 106 |
| 378 | 0.20 | 0.01 | 0.02 | 86 |
| 379 | 0.11 | 0.07 | 0.09 | 14 |
| 380 | 1.00 | 0.23 | 0.37 | 122 |
| 381 | 0.10 | 0.06 | 0.07 | 104 |
| 382 | 0.22 | 0.11 | 0.14 | 66 |
| 383 | 0.48 | 0.29 | 0.36 | 110 |
| 384 | 0.00 | 0.00 | 0.00 | 155 |
| 385 | 0.07 | 0.06 | 0.06 | 50 |
| 386 | 0.19 | 0.19 | 0.19 | 64 |
| 387 | 0.00 | 0.00 | 0.00 | 93 |
| 388 | 0.31 | 0.27 | 0.29 | 102 |
| 389 | 0.00 | 0.00 | 0.00 | 108 |

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|---|---|---|---|---|
| 390 | 0.85 | 0.51 | 0.63 | 178 |
| 391 | 0.58 | 0.10 | 0.16 | 115 |
| 392 | 0.92 | 0.26 | 0.41 | 42 |
| 393 | 0.00 | 0.00 | 0.00 | 134 |
| 394 | 0.00 | 0.00 | 0.00 | 112 |
| 395 | 0.25 | 0.01 | 0.01 | 176 |
| 396 | 0.00 | 0.00 | 0.00 | 125 |
| 397 | 0.37 | 0.35 | 0.36 | 224 |
| 398 | 0.79 | 0.35 | 0.48 | 63 |
| 399 | 0.00 | 0.00 | 0.00 | 59 |
| 400 | 0.39 | 0.30 | 0.34 | 63 |
| 401 | 0.16 | 0.04 | 0.07 | 98 |
| 402 | 0.32 | 0.05 | 0.09 | 162 |
| 403 | 0.29 | 0.14 | 0.19 | 83 |
| 404 | 0.75 | 0.63 | 0.69 | 19 |
| 405 | 0.10 | 0.05 | 0.07 | 92 |
| 406 | 0.33 | 0.15 | 0.20 | 41 |
| 407 | 0.22 | 0.28 | 0.25 | 43 |
| 408 | 0.00 | 0.00 | 0.00 | 160 |
| 409 | 0.16 | 0.16 | 0.16 | 50 |
| 410 | 0.00 | 0.00 | 0.00 | 19 |
| 411 | 0.32 | 0.12 | 0.18 | 175 |
| 412 | 0.12 | 0.01 | 0.02 | 72 |
| 413 | 0.17 | 0.09 | 0.12 | 95 |
| 414 | 0.11 | 0.07 | 0.09 | 97 |
| 415 | 0.27 | 0.15 | 0.19 | 48 |
| 416 | 0.38 | 0.25 | 0.30 | 83 |
| 417 | 0.00 | 0.00 | 0.00 | 40 |
| 418 | 0.15 | 0.09 | 0.11 | 91 |
| 419 | 0.39 | 0.23 | 0.29 | 90 |
| 420 | 0.22 | 0.16 | 0.19 | 37 |
| 421 | 0.05 | 0.02 | 0.02 | 66 |
| 422 | 0.55 | 0.29 | 0.38 | 73 |
| 423 | 0.35 | 0.20 | 0.25 | 56 |
| 424 | 0.88 | 0.67 | 0.76 | 33 |
| 425 | 0.08 | 0.01 | 0.02 | 76 |
| 426 | 0.03 | 0.02 | 0.03 | 81 |
| 427 | 0.99 | 0.63 | 0.77 | 150 |
| 428 | 0.82 | 0.79 | 0.81 | 29 |
| 429 | 0.00 | 0.00 | 0.00 | 389 |
| 430 | 0.59 | 0.20 | 0.30 | 167 |
| 431 | 0.00 | 0.00 | 0.00 | 123 |
| 432 | 0.31 | 0.49 | 0.38 | 39 |
| 433 | 0.34 | 0.24 | 0.29 | 82 |
| 434 | 0.94 | 0.73 | 0.82 | 66 |
| 435 | 0.53 | 0.32 | 0.40 | 93 |
| 436 | 0.27 | 0.03 | 0.06 | 87 |
| 437 | 0.17 | 0.10 | 0.13 | 86 |
| 438 | 0.53 | 0.34 | 0.41 | 104 |
| 439 | 0.00 | 0.00 | 0.00 | 100 |
| 440 | 0.33 | 0.01 | 0.01 | 141 |
| 441 | 0.30 | 0.27 | 0.28 | 110 |
| 442 | 0.21 | 0.09 | 0.12 | 123 |
| 443 | 0.00 | 0.00 | 0.00 | 71 |
| 444 | 0.28 | 0.05 | 0.08 | 109 |
| 445 | 0.20 | 0.12 | 0.15 | 48 |
| 446 | 0.44 | 0.21 | 0.29 | 76 |
| 447 | 0.10 | 0.05 | 0.07 | 38 |
| 448 | 0.60 | 0.49 | 0.54 | 81 |
| 449 | 0.44 | 0.06 | 0.11 | 132 |
| 450 | 0.45 | 0.25 | 0.32 | 81 |

```
         451       0.00      0.00      0.00        76
         452       0.00      0.00      0.00        44
         453       0.00      0.00      0.00        44
         454       0.73      0.39      0.50        70
         455       0.17      0.04      0.06       155
         456       0.21      0.16      0.18        43
         457       0.31      0.22      0.26        72
         458       0.21      0.10      0.13        62
         459       0.24      0.07      0.11        69
         460       0.21      0.03      0.06       119
         461       0.62      0.16      0.26        79
         462       0.15      0.04      0.07        47
         463       0.18      0.02      0.03       104
         464       0.50      0.27      0.35       106
         465       0.20      0.02      0.03        64
         466       0.51      0.18      0.27       173
         467       0.77      0.32      0.45       107
         468       0.50      0.01      0.02       126
         469       0.00      0.00      0.00       114
         470       0.93      0.61      0.74       140
         471       0.00      0.00      0.00        79
         472       0.27      0.36      0.31       143
         473       0.23      0.03      0.06       158
         474       0.57      0.03      0.06       138
         475       0.11      0.07      0.08        59
         476       0.62      0.33      0.43        88
         477       0.69      0.74      0.71       176
         478       0.11      0.54      0.19        24
         479       0.00      0.00      0.00        92
         480       0.80      0.33      0.47       100
         481       0.50      0.02      0.04       103
         482       0.09      0.23      0.13        74
         483       0.76      0.48      0.58       105
         484       0.07      0.02      0.04        83
         485       0.11      0.01      0.02        82
         486       0.18      0.06      0.09        71
         487       0.38      0.23      0.28       120
         488       0.00      0.00      0.00       105
         489       0.46      0.53      0.49        87
         490       1.00      0.66      0.79        32
         491       0.00      0.00      0.00        69
         492       0.00      0.00      0.00        49
         493       0.00      0.00      0.00       117
         494       0.16      0.05      0.07        61
         495       0.00      0.00      0.00       344
         496       0.00      0.00      0.00        52
         497       0.67      0.12      0.20       137
         498       0.00      0.00      0.00        98
         499       0.00      0.00      0.00        79

 avg / total       0.54      0.33      0.39    173809

Time taken to run this cell : 0:14:06.786004

C:\Users\hp\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
35: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
35: UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l
abels with no predicted samples.
```

```
  'precision', 'predicted', average, warn_for)
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
35: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

# Linear SVM with OneVsRestClassifier (With Hinge loss):-

## Hyperparameter tuning:-

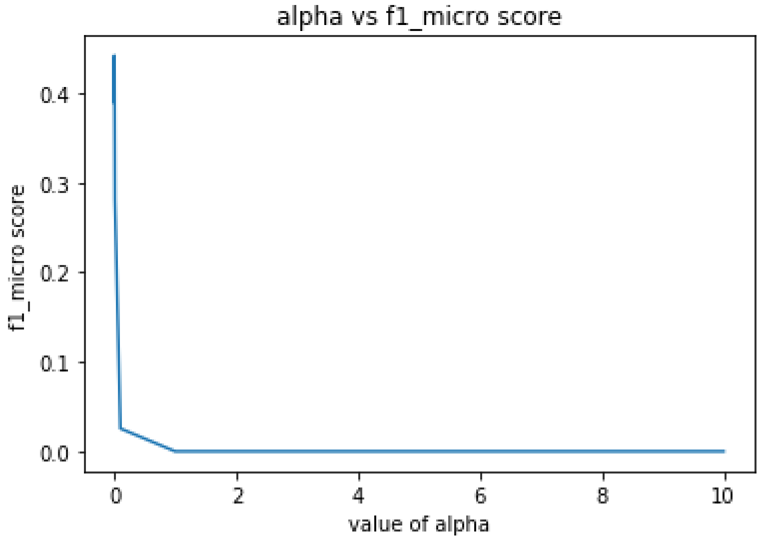
In [34]:

```
param={'estimator__alpha': [10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1]}
classifier = OneVsRestClassifier(SGDClassifier( loss='hinge', penalty='l1'))
gsv = GridSearchCV(estimator = classifier, param_grid=param,  verbose=0, scoring='f1_micro'
gsv.fit(x_train_multilabel, y_train)

best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
print('value of alpha after hyperparameter tuning : ',best_alpha)
print('-------------------------------------------------------------')
# plotting C vs f1_micro_score
x_1=[]
y_1=[]
for x in gsv.grid_scores_:
    x_1.append(x[0]['estimator__alpha'])
    y_1.append(x[1])
plt.plot(x_1,y_1)
plt.xlabel('value of alpha')
plt.ylabel('f1_micro score')
plt.title('alpha vs f1_micro score')
plt.show()
```

```
value of alpha after hyperparameter tuning :  0.001
-------------------------------------------------------------

C:\Users\hp\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:7
61: DeprecationWarning: The grid_scores_ attribute was deprecated in version
0.18 in favor of the more elaborate cv_results_ attribute. The grid_scores_
attribute will not be available from 0.20
  DeprecationWarning)
```




## Applying model using best hyperparameter:-

In [35]:

```
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.001, penalty='l1'), n_
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


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


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

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

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

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

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

```
Accuracy : 0.181013620272240545
Hamming loss  0.0032552451049020982
Micro-average quality numbers
Precision: 0.5552, Recall: 0.3199, F1-measure: 0.4059
Macro-average quality numbers
Precision: 0.3223, Recall: 0.2400, F1-measure: 0.2587
             precision    recall  f1-score   support

          0       0.81      0.67      0.73      5519
          1       0.45      0.19      0.26      8189
          2       0.68      0.38      0.49      6529
          3       0.58      0.47      0.52      3231
          4       0.71      0.42      0.52      6430
          5       0.59      0.39      0.47      2878
          6       0.73      0.56      0.63      5086
          7       0.82      0.56      0.66      4533
          8       0.50      0.17      0.26      3000
          9       0.69      0.58      0.63      2765
         10       0.42      0.11      0.17      3051
         11       0.72      0.32      0.44      3009
         12       0.58      0.27      0.37      2630
         13       0.24      0.29      0.26      1425
         14       0.75      0.62      0.68      2548
         15       0.65      0.13      0.21      2371
         16       0.51      0.30      0.38       873
         17       0.70      0.72      0.71      2151
         18       0.57      0.19      0.29      2204
         19       0.47      0.49      0.48       831
         20       0.73      0.48      0.58      1860
         21       0.00      0.00      0.00      2023
         22       0.08      0.00      0.00      1513
         23       0.65      0.61      0.63      1207
```

| | | | | |
|---|---|---|---|---|
| 24 | 0.67 | 0.07 | 0.12 | 506 |
| 25 | 0.70 | 0.35 | 0.46 | 425 |
| 26 | 0.40 | 0.45 | 0.42 | 793 |
| 27 | 0.55 | 0.31 | 0.40 | 1291 |
| 28 | 0.60 | 0.37 | 0.46 | 1208 |
| 29 | 0.26 | 0.17 | 0.20 | 406 |
| 30 | 0.58 | 0.27 | 0.36 | 504 |
| 31 | 0.10 | 0.04 | 0.05 | 732 |
| 32 | 0.44 | 0.33 | 0.38 | 441 |
| 33 | 0.27 | 0.02 | 0.04 | 1645 |
| 34 | 0.52 | 0.36 | 0.42 | 1058 |
| 35 | 0.63 | 0.59 | 0.61 | 946 |
| 36 | 0.49 | 0.29 | 0.37 | 644 |
| 37 | 0.77 | 0.82 | 0.80 | 136 |
| 38 | 0.37 | 0.46 | 0.41 | 570 |
| 39 | 0.68 | 0.36 | 0.47 | 766 |
| 40 | 0.52 | 0.26 | 0.34 | 1132 |
| 41 | 0.21 | 0.28 | 0.24 | 174 |
| 42 | 0.47 | 0.64 | 0.55 | 210 |
| 43 | 0.58 | 0.52 | 0.55 | 433 |
| 44 | 0.48 | 0.47 | 0.48 | 626 |
| 45 | 0.40 | 0.29 | 0.34 | 852 |
| 46 | 0.50 | 0.46 | 0.48 | 534 |
| 47 | 0.04 | 0.02 | 0.02 | 350 |
| 48 | 0.55 | 0.55 | 0.55 | 496 |
| 49 | 0.68 | 0.59 | 0.64 | 785 |
| 50 | 0.00 | 0.00 | 0.00 | 475 |
| 51 | 0.10 | 0.06 | 0.08 | 305 |
| 52 | 0.00 | 0.00 | 0.00 | 251 |
| 53 | 0.65 | 0.34 | 0.45 | 914 |
| 54 | 0.06 | 0.00 | 0.00 | 728 |
| 55 | 0.00 | 0.00 | 0.00 | 258 |
| 56 | 0.24 | 0.23 | 0.24 | 821 |
| 57 | 0.28 | 0.05 | 0.08 | 541 |
| 58 | 0.70 | 0.29 | 0.41 | 748 |
| 59 | 0.85 | 0.74 | 0.79 | 724 |
| 60 | 0.00 | 0.00 | 0.00 | 660 |
| 61 | 0.73 | 0.26 | 0.38 | 235 |
| 62 | 0.81 | 0.82 | 0.82 | 718 |
| 63 | 0.72 | 0.66 | 0.69 | 468 |
| 64 | 0.42 | 0.46 | 0.44 | 191 |
| 65 | 0.18 | 0.14 | 0.16 | 429 |
| 66 | 0.00 | 0.00 | 0.00 | 415 |
| 67 | 0.64 | 0.66 | 0.65 | 274 |
| 68 | 0.73 | 0.61 | 0.66 | 510 |
| 69 | 0.41 | 0.32 | 0.36 | 466 |
| 70 | 0.20 | 0.14 | 0.17 | 305 |
| 71 | 0.22 | 0.19 | 0.20 | 247 |
| 72 | 0.63 | 0.50 | 0.56 | 401 |
| 73 | 0.81 | 0.74 | 0.78 | 86 |
| 74 | 0.46 | 0.43 | 0.45 | 120 |
| 75 | 0.30 | 0.76 | 0.43 | 129 |
| 76 | 0.00 | 0.00 | 0.00 | 473 |
| 77 | 0.23 | 0.34 | 0.27 | 143 |
| 78 | 0.63 | 0.56 | 0.59 | 347 |
| 79 | 0.53 | 0.39 | 0.45 | 479 |
| 80 | 0.32 | 0.35 | 0.33 | 279 |
| 81 | 0.63 | 0.16 | 0.26 | 461 |
| 82 | 0.00 | 0.00 | 0.00 | 298 |
| 83 | 0.67 | 0.47 | 0.55 | 396 |
| 84 | 0.32 | 0.21 | 0.25 | 184 |

| | | | | |
|---|---|---|---|---|
| 85 | 0.71 | 0.09 | 0.16 | 573 |
| 86 | 0.33 | 0.08 | 0.13 | 325 |
| 87 | 0.50 | 0.18 | 0.27 | 273 |
| 88 | 0.28 | 0.31 | 0.29 | 135 |
| 89 | 0.00 | 0.00 | 0.00 | 232 |
| 90 | 0.29 | 0.36 | 0.32 | 409 |
| 91 | 0.45 | 0.39 | 0.41 | 420 |
| 92 | 0.65 | 0.58 | 0.61 | 408 |
| 93 | 0.46 | 0.50 | 0.48 | 241 |
| 94 | 0.00 | 0.00 | 0.00 | 211 |
| 95 | 0.00 | 0.00 | 0.00 | 277 |
| 96 | 0.00 | 0.00 | 0.00 | 410 |
| 97 | 0.82 | 0.17 | 0.29 | 501 |
| 98 | 0.58 | 0.58 | 0.58 | 136 |
| 99 | 0.46 | 0.22 | 0.30 | 239 |
| 100 | 0.09 | 0.06 | 0.07 | 324 |
| 101 | 0.89 | 0.73 | 0.80 | 277 |
| 102 | 0.81 | 0.74 | 0.77 | 613 |
| 103 | 0.53 | 0.18 | 0.27 | 157 |
| 104 | 0.00 | 0.00 | 0.00 | 295 |
| 105 | 0.36 | 0.36 | 0.36 | 334 |
| 106 | 0.00 | 0.00 | 0.00 | 335 |
| 107 | 0.50 | 0.47 | 0.49 | 389 |
| 108 | 0.34 | 0.14 | 0.19 | 251 |
| 109 | 0.43 | 0.50 | 0.46 | 317 |
| 110 | 0.00 | 0.00 | 0.00 | 187 |
| 111 | 0.61 | 0.10 | 0.17 | 140 |
| 112 | 0.36 | 0.27 | 0.31 | 154 |
| 113 | 0.42 | 0.29 | 0.34 | 332 |
| 114 | 0.00 | 0.00 | 0.00 | 323 |
| 115 | 0.10 | 0.01 | 0.01 | 344 |
| 116 | 0.50 | 0.54 | 0.52 | 370 |
| 117 | 0.49 | 0.26 | 0.34 | 313 |
| 118 | 0.71 | 0.48 | 0.57 | 874 |
| 119 | 0.25 | 0.25 | 0.25 | 293 |
| 120 | 0.00 | 0.00 | 0.00 | 200 |
| 121 | 0.58 | 0.56 | 0.57 | 463 |
| 122 | 0.20 | 0.14 | 0.17 | 119 |
| 123 | 0.00 | 0.00 | 0.00 | 256 |
| 124 | 0.58 | 0.81 | 0.67 | 195 |
| 125 | 0.15 | 0.27 | 0.19 | 138 |
| 126 | 0.53 | 0.39 | 0.45 | 376 |
| 127 | 0.00 | 0.00 | 0.00 | 122 |
| 128 | 0.00 | 0.00 | 0.00 | 252 |
| 129 | 0.00 | 0.00 | 0.00 | 144 |
| 130 | 0.00 | 0.00 | 0.00 | 150 |
| 131 | 0.04 | 0.02 | 0.03 | 210 |
| 132 | 0.31 | 0.06 | 0.10 | 361 |
| 133 | 0.76 | 0.66 | 0.70 | 453 |
| 134 | 0.72 | 0.91 | 0.80 | 124 |
| 135 | 0.00 | 0.00 | 0.00 | 91 |
| 136 | 0.68 | 0.10 | 0.18 | 128 |
| 137 | 0.35 | 0.28 | 0.31 | 218 |
| 138 | 0.00 | 0.00 | 0.00 | 243 |
| 139 | 0.11 | 0.25 | 0.15 | 149 |
| 140 | 0.63 | 0.48 | 0.55 | 318 |
| 141 | 0.00 | 0.00 | 0.00 | 159 |
| 142 | 0.58 | 0.41 | 0.48 | 274 |
| 143 | 0.72 | 0.72 | 0.72 | 362 |
| 144 | 0.22 | 0.34 | 0.27 | 118 |
| 145 | 0.41 | 0.49 | 0.45 | 164 |

| | | | | |
|---|---|---|---|---|
| 146 | 0.46 | 0.30 | 0.37 | 461 |
| 147 | 0.49 | 0.40 | 0.44 | 159 |
| 148 | 0.00 | 0.00 | 0.00 | 166 |
| 149 | 0.92 | 0.54 | 0.68 | 346 |
| 150 | 0.17 | 0.11 | 0.13 | 350 |
| 151 | 0.29 | 0.58 | 0.39 | 55 |
| 152 | 0.62 | 0.52 | 0.56 | 387 |
| 153 | 0.00 | 0.00 | 0.00 | 150 |
| 154 | 0.50 | 0.07 | 0.12 | 281 |
| 155 | 0.36 | 0.02 | 0.05 | 202 |
| 156 | 0.49 | 0.70 | 0.58 | 130 |
| 157 | 0.16 | 0.16 | 0.16 | 245 |
| 158 | 0.74 | 0.74 | 0.74 | 177 |
| 159 | 0.37 | 0.33 | 0.35 | 130 |
| 160 | 0.28 | 0.21 | 0.24 | 336 |
| 161 | 0.75 | 0.65 | 0.70 | 220 |
| 162 | 0.00 | 0.00 | 0.00 | 229 |
| 163 | 0.78 | 0.51 | 0.62 | 316 |
| 164 | 0.67 | 0.29 | 0.40 | 283 |
| 165 | 0.67 | 0.03 | 0.06 | 197 |
| 166 | 0.19 | 0.20 | 0.19 | 101 |
| 167 | 0.00 | 0.00 | 0.00 | 231 |
| 168 | 0.13 | 0.10 | 0.11 | 370 |
| 169 | 0.32 | 0.31 | 0.32 | 258 |
| 170 | 0.00 | 0.00 | 0.00 | 101 |
| 171 | 0.22 | 0.22 | 0.22 | 89 |
| 172 | 0.22 | 0.40 | 0.29 | 193 |
| 173 | 0.35 | 0.35 | 0.35 | 309 |
| 174 | 0.20 | 0.18 | 0.19 | 172 |
| 175 | 0.71 | 0.88 | 0.79 | 95 |
| 176 | 0.80 | 0.58 | 0.67 | 346 |
| 177 | 0.83 | 0.32 | 0.46 | 322 |
| 178 | 0.52 | 0.45 | 0.48 | 232 |
| 179 | 0.27 | 0.14 | 0.19 | 125 |
| 180 | 0.38 | 0.28 | 0.32 | 145 |
| 181 | 0.26 | 0.12 | 0.16 | 77 |
| 182 | 0.00 | 0.00 | 0.00 | 182 |
| 183 | 0.31 | 0.35 | 0.33 | 257 |
| 184 | 0.00 | 0.00 | 0.00 | 216 |
| 185 | 0.19 | 0.13 | 0.16 | 242 |
| 186 | 0.22 | 0.21 | 0.22 | 165 |
| 187 | 0.56 | 0.58 | 0.57 | 263 |
| 188 | 0.00 | 0.00 | 0.00 | 174 |
| 189 | 0.22 | 0.06 | 0.09 | 136 |
| 190 | 0.78 | 0.45 | 0.57 | 202 |
| 191 | 0.00 | 0.00 | 0.00 | 134 |
| 192 | 0.63 | 0.45 | 0.53 | 230 |
| 193 | 0.40 | 0.11 | 0.17 | 90 |
| 194 | 0.43 | 0.55 | 0.48 | 185 |
| 195 | 0.08 | 0.04 | 0.05 | 156 |
| 196 | 0.00 | 0.00 | 0.00 | 160 |
| 197 | 0.00 | 0.00 | 0.00 | 266 |
| 198 | 0.19 | 0.11 | 0.14 | 284 |
| 199 | 0.23 | 0.08 | 0.11 | 145 |
| 200 | 0.80 | 0.79 | 0.79 | 212 |
| 201 | 0.10 | 0.02 | 0.03 | 317 |
| 202 | 0.62 | 0.57 | 0.59 | 427 |
| 203 | 0.00 | 0.00 | 0.00 | 232 |
| 204 | 0.00 | 0.00 | 0.00 | 217 |
| 205 | 0.45 | 0.44 | 0.45 | 527 |
| 206 | 0.00 | 0.00 | 0.00 | 124 |

| | | | | |
|---|---|---|---|---|
| 207 | 0.26 | 0.17 | 0.21 | 103 |
| 208 | 0.70 | 0.56 | 0.62 | 287 |
| 209 | 0.00 | 0.00 | 0.00 | 193 |
| 210 | 0.41 | 0.25 | 0.32 | 220 |
| 211 | 0.90 | 0.06 | 0.12 | 140 |
| 212 | 0.00 | 0.00 | 0.00 | 161 |
| 213 | 0.09 | 0.21 | 0.13 | 72 |
| 214 | 0.55 | 0.34 | 0.42 | 396 |
| 215 | 0.81 | 0.29 | 0.43 | 134 |
| 216 | 0.00 | 0.00 | 0.00 | 400 |
| 217 | 0.31 | 0.28 | 0.30 | 75 |
| 218 | 0.89 | 0.67 | 0.76 | 219 |
| 219 | 0.05 | 0.05 | 0.05 | 210 |
| 220 | 0.83 | 0.61 | 0.70 | 298 |
| 221 | 0.92 | 0.58 | 0.71 | 266 |
| 222 | 0.73 | 0.46 | 0.56 | 290 |
| 223 | 0.00 | 0.00 | 0.00 | 128 |
| 224 | 0.54 | 0.47 | 0.50 | 159 |
| 225 | 0.47 | 0.17 | 0.25 | 164 |
| 226 | 0.40 | 0.48 | 0.43 | 144 |
| 227 | 0.52 | 0.19 | 0.28 | 276 |
| 228 | 0.00 | 0.00 | 0.00 | 235 |
| 229 | 0.00 | 0.00 | 0.00 | 216 |
| 230 | 0.00 | 0.00 | 0.00 | 228 |
| 231 | 0.60 | 0.64 | 0.62 | 64 |
| 232 | 0.00 | 0.00 | 0.00 | 103 |
| 233 | 0.37 | 0.35 | 0.36 | 216 |
| 234 | 0.00 | 0.00 | 0.00 | 116 |
| 235 | 0.53 | 0.48 | 0.50 | 77 |
| 236 | 0.84 | 0.73 | 0.78 | 67 |
| 237 | 0.00 | 0.00 | 0.00 | 218 |
| 238 | 0.00 | 0.00 | 0.00 | 139 |
| 239 | 0.00 | 0.00 | 0.00 | 94 |
| 240 | 0.36 | 0.35 | 0.36 | 77 |
| 241 | 0.00 | 0.00 | 0.00 | 167 |
| 242 | 0.75 | 0.31 | 0.44 | 86 |
| 243 | 0.16 | 0.21 | 0.18 | 58 |
| 244 | 0.17 | 0.07 | 0.10 | 269 |
| 245 | 0.00 | 0.00 | 0.00 | 112 |
| 246 | 0.91 | 0.73 | 0.81 | 255 |
| 247 | 0.34 | 0.22 | 0.27 | 58 |
| 248 | 0.00 | 0.00 | 0.00 | 81 |
| 249 | 0.00 | 0.00 | 0.00 | 131 |
| 250 | 0.38 | 0.20 | 0.27 | 93 |
| 251 | 0.32 | 0.29 | 0.30 | 154 |
| 252 | 0.00 | 0.00 | 0.00 | 129 |
| 253 | 0.25 | 0.31 | 0.28 | 83 |
| 254 | 0.11 | 0.23 | 0.15 | 191 |
| 255 | 0.00 | 0.00 | 0.00 | 219 |
| 256 | 0.00 | 0.00 | 0.00 | 130 |
| 257 | 0.19 | 0.40 | 0.26 | 93 |
| 258 | 0.61 | 0.62 | 0.61 | 217 |
| 259 | 0.25 | 0.02 | 0.04 | 141 |
| 260 | 0.66 | 0.17 | 0.28 | 143 |
| 261 | 0.60 | 0.11 | 0.19 | 219 |
| 262 | 0.30 | 0.36 | 0.33 | 107 |
| 263 | 0.25 | 0.34 | 0.29 | 236 |
| 264 | 0.17 | 0.12 | 0.14 | 119 |
| 265 | 0.16 | 0.25 | 0.19 | 72 |
| 266 | 0.14 | 0.14 | 0.14 | 70 |
| 267 | 0.30 | 0.03 | 0.05 | 107 |

| | | | | |
|---|---|---|---|---|
| 268 | 0.50 | 0.49 | 0.50 | 169 |
| 269 | 0.00 | 0.00 | 0.00 | 129 |
| 270 | 0.48 | 0.67 | 0.56 | 159 |
| 271 | 0.00 | 0.00 | 0.00 | 190 |
| 272 | 0.25 | 0.19 | 0.21 | 248 |
| 273 | 0.83 | 0.69 | 0.76 | 264 |
| 274 | 0.59 | 0.69 | 0.63 | 105 |
| 275 | 0.00 | 0.00 | 0.00 | 104 |
| 276 | 0.00 | 0.00 | 0.00 | 115 |
| 277 | 0.72 | 0.62 | 0.67 | 170 |
| 278 | 0.50 | 0.41 | 0.45 | 145 |
| 279 | 0.83 | 0.54 | 0.66 | 230 |
| 280 | 0.38 | 0.28 | 0.32 | 80 |
| 281 | 0.56 | 0.63 | 0.59 | 217 |
| 282 | 0.65 | 0.51 | 0.57 | 175 |
| 283 | 0.00 | 0.00 | 0.00 | 269 |
| 284 | 0.52 | 0.46 | 0.49 | 74 |
| 285 | 0.61 | 0.49 | 0.54 | 206 |
| 286 | 0.85 | 0.72 | 0.78 | 227 |
| 287 | 0.59 | 0.44 | 0.50 | 130 |
| 288 | 0.38 | 0.02 | 0.04 | 129 |
| 289 | 0.00 | 0.00 | 0.00 | 80 |
| 290 | 0.00 | 0.00 | 0.00 | 99 |
| 291 | 0.73 | 0.31 | 0.44 | 208 |
| 292 | 0.00 | 0.00 | 0.00 | 67 |
| 293 | 0.43 | 0.20 | 0.28 | 109 |
| 294 | 0.22 | 0.08 | 0.12 | 140 |
| 295 | 0.14 | 0.16 | 0.15 | 241 |
| 296 | 0.13 | 0.17 | 0.14 | 72 |
| 297 | 0.00 | 0.00 | 0.00 | 107 |
| 298 | 0.73 | 0.18 | 0.29 | 61 |
| 299 | 0.83 | 0.19 | 0.32 | 77 |
| 300 | 0.00 | 0.00 | 0.00 | 111 |
| 301 | 0.00 | 0.00 | 0.00 | 126 |
| 302 | 0.00 | 0.00 | 0.00 | 73 |
| 303 | 0.32 | 0.59 | 0.42 | 176 |
| 304 | 0.89 | 0.58 | 0.71 | 230 |
| 305 | 0.90 | 0.66 | 0.76 | 156 |
| 306 | 0.37 | 0.27 | 0.32 | 146 |
| 307 | 0.09 | 0.15 | 0.11 | 98 |
| 308 | 0.00 | 0.00 | 0.00 | 78 |
| 309 | 0.23 | 0.20 | 0.22 | 94 |
| 310 | 0.00 | 0.00 | 0.00 | 162 |
| 311 | 0.63 | 0.61 | 0.62 | 116 |
| 312 | 0.37 | 0.60 | 0.46 | 57 |
| 313 | 0.00 | 0.00 | 0.00 | 65 |
| 314 | 0.32 | 0.33 | 0.32 | 138 |
| 315 | 0.34 | 0.26 | 0.30 | 195 |
| 316 | 0.33 | 0.41 | 0.36 | 69 |
| 317 | 0.33 | 0.09 | 0.14 | 134 |
| 318 | 0.35 | 0.09 | 0.15 | 148 |
| 319 | 0.78 | 0.52 | 0.62 | 161 |
| 320 | 0.00 | 0.00 | 0.00 | 104 |
| 321 | 0.47 | 0.55 | 0.51 | 156 |
| 322 | 0.40 | 0.48 | 0.43 | 134 |
| 323 | 0.39 | 0.34 | 0.36 | 232 |
| 324 | 0.00 | 0.00 | 0.00 | 92 |
| 325 | 0.00 | 0.00 | 0.00 | 197 |
| 326 | 0.00 | 0.00 | 0.00 | 126 |
| 327 | 0.00 | 0.00 | 0.00 | 115 |
| 328 | 0.97 | 0.45 | 0.62 | 198 |

| | | | | |
|---|---|---|---|---|
| 329 | 0.29 | 0.41 | 0.34 | 125 |
| 330 | 0.38 | 0.19 | 0.25 | 81 |
| 331 | 0.00 | 0.00 | 0.00 | 94 |
| 332 | 0.00 | 0.00 | 0.00 | 56 |
| 333 | 0.00 | 0.00 | 0.00 | 260 |
| 334 | 0.08 | 0.02 | 0.03 | 60 |
| 335 | 0.00 | 0.00 | 0.00 | 110 |
| 336 | 0.36 | 0.42 | 0.39 | 71 |
| 337 | 0.08 | 0.06 | 0.07 | 66 |
| 338 | 0.24 | 0.40 | 0.30 | 150 |
| 339 | 0.00 | 0.00 | 0.00 | 54 |
| 340 | 0.75 | 0.47 | 0.58 | 195 |
| 341 | 0.00 | 0.00 | 0.00 | 79 |
| 342 | 0.20 | 0.24 | 0.21 | 38 |
| 343 | 0.58 | 0.33 | 0.42 | 43 |
| 344 | 0.00 | 0.00 | 0.00 | 68 |
| 345 | 0.44 | 0.45 | 0.45 | 73 |
| 346 | 0.00 | 0.00 | 0.00 | 116 |
| 347 | 0.77 | 0.53 | 0.63 | 111 |
| 348 | 0.03 | 0.05 | 0.04 | 63 |
| 349 | 0.76 | 0.50 | 0.60 | 104 |
| 350 | 0.57 | 0.48 | 0.52 | 44 |
| 351 | 0.00 | 0.00 | 0.00 | 40 |
| 352 | 0.82 | 0.36 | 0.50 | 136 |
| 353 | 0.27 | 0.37 | 0.31 | 54 |
| 354 | 0.11 | 0.07 | 0.09 | 134 |
| 355 | 0.23 | 0.17 | 0.20 | 120 |
| 356 | 0.00 | 0.00 | 0.00 | 228 |
| 357 | 0.00 | 0.00 | 0.00 | 269 |
| 358 | 0.35 | 0.36 | 0.36 | 80 |
| 359 | 0.69 | 0.26 | 0.37 | 140 |
| 360 | 0.00 | 0.00 | 0.00 | 125 |
| 361 | 0.79 | 0.71 | 0.75 | 169 |
| 362 | 0.15 | 0.14 | 0.15 | 56 |
| 363 | 0.76 | 0.74 | 0.75 | 154 |
| 364 | 0.00 | 0.00 | 0.00 | 58 |
| 365 | 0.00 | 0.00 | 0.00 | 71 |
| 366 | 0.93 | 0.46 | 0.62 | 54 |
| 367 | 0.00 | 0.00 | 0.00 | 116 |
| 368 | 0.00 | 0.00 | 0.00 | 54 |
| 369 | 0.00 | 0.00 | 0.00 | 71 |
| 370 | 0.04 | 0.07 | 0.05 | 61 |
| 371 | 0.36 | 0.13 | 0.19 | 71 |
| 372 | 0.40 | 0.40 | 0.40 | 52 |
| 373 | 0.49 | 0.31 | 0.38 | 150 |
| 374 | 0.29 | 0.28 | 0.28 | 93 |
| 375 | 0.00 | 0.00 | 0.00 | 67 |
| 376 | 0.00 | 0.00 | 0.00 | 76 |
| 377 | 0.83 | 0.09 | 0.17 | 106 |
| 378 | 0.00 | 0.00 | 0.00 | 86 |
| 379 | 0.00 | 0.00 | 0.00 | 14 |
| 380 | 0.82 | 0.15 | 0.25 | 122 |
| 381 | 0.00 | 0.00 | 0.00 | 104 |
| 382 | 0.24 | 0.15 | 0.19 | 66 |
| 383 | 0.26 | 0.26 | 0.26 | 110 |
| 384 | 0.00 | 0.00 | 0.00 | 155 |
| 385 | 0.00 | 0.00 | 0.00 | 50 |
| 386 | 0.17 | 0.27 | 0.20 | 64 |
| 387 | 0.00 | 0.00 | 0.00 | 93 |
| 388 | 0.26 | 0.13 | 0.17 | 102 |
| 389 | 0.00 | 0.00 | 0.00 | 108 |

| | | | | |
|---|---|---|---|---|
| 390 | 0.84 | 0.66 | 0.74 | 178 |
| 391 | 0.41 | 0.19 | 0.26 | 115 |
| 392 | 0.74 | 0.33 | 0.46 | 42 |
| 393 | 0.00 | 0.00 | 0.00 | 134 |
| 394 | 0.02 | 0.02 | 0.02 | 112 |
| 395 | 0.00 | 0.00 | 0.00 | 176 |
| 396 | 0.00 | 0.00 | 0.00 | 125 |
| 397 | 0.54 | 0.37 | 0.44 | 224 |
| 398 | 0.60 | 0.43 | 0.50 | 63 |
| 399 | 0.00 | 0.00 | 0.00 | 59 |
| 400 | 0.25 | 0.43 | 0.32 | 63 |
| 401 | 0.00 | 0.00 | 0.00 | 98 |
| 402 | 0.00 | 0.00 | 0.00 | 162 |
| 403 | 0.24 | 0.34 | 0.28 | 83 |
| 404 | 0.70 | 0.84 | 0.76 | 19 |
| 405 | 0.00 | 0.00 | 0.00 | 92 |
| 406 | 0.38 | 0.51 | 0.44 | 41 |
| 407 | 0.25 | 0.51 | 0.33 | 43 |
| 408 | 0.00 | 0.00 | 0.00 | 160 |
| 409 | 0.19 | 0.26 | 0.22 | 50 |
| 410 | 0.00 | 0.00 | 0.00 | 19 |
| 411 | 0.00 | 0.00 | 0.00 | 175 |
| 412 | 0.00 | 0.00 | 0.00 | 72 |
| 413 | 0.00 | 0.00 | 0.00 | 95 |
| 414 | 0.00 | 0.00 | 0.00 | 97 |
| 415 | 0.00 | 0.00 | 0.00 | 48 |
| 416 | 0.28 | 0.42 | 0.34 | 83 |
| 417 | 0.00 | 0.00 | 0.00 | 40 |
| 418 | 0.00 | 0.00 | 0.00 | 91 |
| 419 | 0.31 | 0.12 | 0.18 | 90 |
| 420 | 0.14 | 0.19 | 0.16 | 37 |
| 421 | 0.00 | 0.00 | 0.00 | 66 |
| 422 | 0.44 | 0.29 | 0.35 | 73 |
| 423 | 0.25 | 0.27 | 0.26 | 56 |
| 424 | 0.86 | 0.91 | 0.88 | 33 |
| 425 | 0.00 | 0.00 | 0.00 | 76 |
| 426 | 0.00 | 0.00 | 0.00 | 81 |
| 427 | 0.99 | 0.57 | 0.72 | 150 |
| 428 | 0.79 | 0.76 | 0.77 | 29 |
| 429 | 0.00 | 0.00 | 0.00 | 389 |
| 430 | 0.44 | 0.32 | 0.37 | 167 |
| 431 | 0.00 | 0.00 | 0.00 | 123 |
| 432 | 0.32 | 0.41 | 0.36 | 39 |
| 433 | 0.25 | 0.32 | 0.28 | 82 |
| 434 | 0.94 | 0.70 | 0.80 | 66 |
| 435 | 0.46 | 0.40 | 0.43 | 93 |
| 436 | 0.00 | 0.00 | 0.00 | 87 |
| 437 | 0.00 | 0.00 | 0.00 | 86 |
| 438 | 0.46 | 0.44 | 0.45 | 104 |
| 439 | 0.06 | 0.09 | 0.07 | 100 |
| 440 | 0.00 | 0.00 | 0.00 | 141 |
| 441 | 0.00 | 0.00 | 0.00 | 110 |
| 442 | 0.13 | 0.11 | 0.12 | 123 |
| 443 | 0.40 | 0.03 | 0.05 | 71 |
| 444 | 0.00 | 0.00 | 0.00 | 109 |
| 445 | 0.00 | 0.00 | 0.00 | 48 |
| 446 | 0.38 | 0.33 | 0.35 | 76 |
| 447 | 0.00 | 0.00 | 0.00 | 38 |
| 448 | 0.52 | 0.60 | 0.56 | 81 |
| 449 | 0.32 | 0.10 | 0.15 | 132 |
| 450 | 0.00 | 0.00 | 0.00 | 81 |

```
         451       0.58      0.14      0.23        76
         452       0.00      0.00      0.00        44
         453       0.00      0.00      0.00        44
         454       0.49      0.39      0.43        70
         455       0.57      0.03      0.05       155
         456       0.00      0.00      0.00        43
         457       0.37      0.22      0.28        72
         458       0.10      0.16      0.12        62
         459       0.00      0.00      0.00        69
         460       0.00      0.00      0.00       119
         461       0.00      0.00      0.00        79
         462       0.08      0.21      0.12        47
         463       0.00      0.00      0.00       104
         464       0.41      0.32      0.36       106
         465       0.00      0.00      0.00        64
         466       0.37      0.15      0.21       173
         467       0.64      0.23      0.34       107
         468       0.00      0.00      0.00       126
         469       0.00      0.00      0.00       114
         470       0.65      0.80      0.72       140
         471       0.00      0.00      0.00        79
         472       0.41      0.13      0.19       143
         473       0.71      0.16      0.26       158
         474       0.00      0.00      0.00       138
         475       0.00      0.00      0.00        59
         476       0.56      0.10      0.17        88
         477       0.72      0.53      0.61       176
         478       0.94      0.67      0.78        24
         479       0.00      0.00      0.00        92
         480       0.59      0.43      0.50       100
         481       0.17      0.02      0.03       103
         482       0.08      0.20      0.12        74
         483       0.64      0.58      0.61       105
         484       0.00      0.00      0.00        83
         485       0.00      0.00      0.00        82
         486       0.00      0.00      0.00        71
         487       0.32      0.17      0.23       120
         488       0.00      0.00      0.00       105
         489       0.65      0.30      0.41        87
         490       0.95      0.62      0.75        32
         491       0.00      0.00      0.00        69
         492       0.00      0.00      0.00        49
         493       0.00      0.00      0.00       117
         494       0.59      0.16      0.26        61
         495       0.00      0.00      0.00       344
         496       0.00      0.00      0.00        52
         497       0.00      0.00      0.00       137
         498       0.00      0.00      0.00        98
         499       0.43      0.25      0.32        79

 avg / total       0.48      0.32      0.37    173809

Time taken to run this cell : 0:11:26.150570

C:\Users\hp\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
35: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
35: UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l
abels with no predicted samples.
```

```
  'precision', 'predicted', average, warn_for)
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
35: UndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

# ---------------------------------------------CONCLUSION------------------------------------------------

## --------------------------------- PrettyTable for model comparisions:-----------------------------------------

### -----------------------------------Micro-average quality numbers(Precision, Recall, F1-measure)------------------------------

In [12]:

```
# Creating table using PrettyTable library
from prettytable import PrettyTable

# Names of models
names =['Logistic Regression(1VsRestClassifier)','Linear SVM(1VsRestClassifier)']

alpha=[0.001, 0.001]

Precision = [0.5624,0.5552]


Recall = [0.3312,0.3199]

F1_measure = [0.4169, 0.4059]


Accuracy=[0.186 ,0.181 ]


Hamming_loss=[0.00322068,0.003255245]

penalty=['L1','L1']

# Initializing prettytable
ptable = PrettyTable()

# Adding columns

ptable.add_column("MODEL",names)
ptable.add_column("Penalty",penalty)
ptable.add_column("Hyperparameter",alpha)
ptable.add_column("Precision",Precision)
ptable.add_column("Recall",Recall)
ptable.add_column("F1-measure",F1_measure)
ptable.add_column("Hamming loss",Hamming_loss)
ptable.add_column("Accuracy",Accuracy)


# Printing the Table
print(ptable)
```

```
+----------------------------------------+---------+----------------+-------
----+--------+------------+-------------+----------+
|                 MODEL                  | Penalty | Hyperparameter | Precis
ion | Recall | F1-measure | Hamming loss | Accuracy |
+----------------------------------------+---------+----------------+-------
----+--------+------------+-------------+----------+
| Logistic Regression(1VsRestClassifier) |    L1   |     0.001      |   0.56
24  | 0.3312 |   0.4169   |  0.00322068  |  0.186   |
|     Linear SVM(1VsRestClassifier)      |    L1   |     0.001      |   0.55
52  | 0.3199 |   0.4059   | 0.003255245  |  0.181   |
+----------------------------------------+---------+----------------+-------
----+--------+------------+-------------+----------+
```

## -----------------------------------Macro-average quality numbers(Precision, Recall, F1-measure)-----------------------------

In [14]:

```
# Creating table using PrettyTable library
from prettytable import PrettyTable

# Names of models
names =['Logistic Regression(1VsRestClassifier)','Linear SVM(1VsRestClassifier)']

alpha=[0.001, 0.001]

Precision = [ 0.4101,0.3223]


Recall = [0.2382, 0.2400]

F1_measure = [0.2832, 0.2587]


Accuracy=[0.186 ,0.181 ]


Hamming_loss=[0.00322068,0.003255245]

penalty=['L1','L1']

# Initializing prettytable
ptable = PrettyTable()

# Adding columns

ptable.add_column("MODEL",names)
ptable.add_column("Penalty",penalty)
ptable.add_column("Hyperparameter",alpha)
ptable.add_column("Precision",Precision)
ptable.add_column("Recall",Recall)
ptable.add_column("F1-measure",F1_measure)
ptable.add_column("Hamming loss",Hamming_loss)
ptable.add_column("Accuracy",Accuracy)


# Printing the Table
print(ptable)
```

```
+----------------------------------------+---------+----------------+-------
----+--------+------------+--------------+----------+
|                 MODEL                  | Penalty | Hyperparameter | Precis
ion | Recall | F1-measure | Hamming loss | Accuracy |
+----------------------------------------+---------+----------------+-------
----+--------+------------+--------------+----------+
| Logistic Regression(1VsRestClassifier) |    L1   |     0.001      |   0.41
01  | 0.2382 |   0.2832   |  0.00322068  |  0.186   |
|     Linear SVM(1VsRestClassifier)      |    L1   |     0.001      |   0.32
23  |  0.24  |   0.2587   | 0.003255245  |  0.181   |
+----------------------------------------+---------+----------------+-------
----+--------+------------+--------------+----------+
```

# STEPS FOLLOWED:

**1----->> Exploratory Data Analysis.**

```
            A: Data Loading and Cleaning.

            B: Analysis of Tags.

            C: Checking for duplicates.
```

**2----->> Machine Learning Models.**

```
                A: Converting tags for multilabel problems.

                B: Preprocessing of questions.

                C: Separate Code from Body.

                D: Remove Spcial characters from Question title and description (not i
n code).

                E: Give more weightage to title : Add title three times to the questio
n.

                F: Remove stop words (Except 'C').

                G: Remove HTML Tags.

                H: Convert all the characters into small letters.

                I: Use SnowballStemmer to stem the words.
```

**3----->> USE BoW WITH UPTO 4 GRAMS AND COMPUTE micro F1 score with Logistic Regression(1 Vs Rest)**

**4----->> USE BoW WITH UPTO 4 GRAMS AND COMPUTE micro F1 score with Linear SVM(1 Vs Rest)(With Hinge loss)**

# OBSERVATIONS:

## note: HERE WE HAVE TAKEN ONLY 500 TAGS AND VERY LESS NO OF QUESTION PAIRS i.e .5M because we have low configration system and limited time.

1:Here we have taken linear models i.e logistic regression and linear svm because they works very well with high dimension data, so we use tfidf featurization for these models.

2:Here we have taken v.less no.of points and tags If we take more data points and all tags our performance matric can improve much.

3:As we observed the most important thing is time taken by our simple linear model which are v.fast as compair to other models here, i.e they also take decent much amount of time.

4:If we take time into consideration model(Logistic Regression,Linear SVM) are best for productization in these type of real world problems(i.e multilabel classification).

In [ ]:

```

```