```
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/

#### 1.2 Source / useful links

Data Source: <a href="https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data">https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data</a>

Youtube: https://youtu.be/nNDqbUhtlRq

Research paper: https://www.microsoft.com/en-us/research/wp-

content/uploads/2016/02/tagging-1.pdf

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

## 1.3 Real World / Business Objectives and Constraints

- 1. Predict as many tags as possible with high precision and recall.
- 2. Incorrect tags could impact customer experience on StackOverflow.
- 3. No strict latency constraints.

## 2. Machine Learning problem

## **2.1 Data**

#### 2.1.1 Data Overview

Refer: <a href="https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data">https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data</a>

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 y ou 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-seperate d format (all lowercase, should not contain tabs '\t' or ampersa nds '&')

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

```
{\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</pre>
                            for(int k=0; k< n-(i+1); k++) \setminus 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
```

for(int l=1; l<=i; l++)\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
                                         50\n
                         100
           50
                         50
                                         1\n
           50
                                         2\n
                         50
           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, FilelO and/or memory-management at the same time or none of these.

\_\_Credit\_\_: http://scikit-learn.org/stable/modules/multiclass.html

#### 2.2.2 Performance metric

**Micro-Averaged F1-Score (Mean F Score)**: The F1 score can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal. The formula for the F1 score is:

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

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

#### 'Micro f1 score':

Calculate metrics globally by counting the total true positives, false negatives and false positives. This is a better metric when we have class imbalance.

#### 'Macro f1 score':

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

https://www.kaggle.com/wiki/MeanFScore http://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1 score.html

**Hamming loss**: The Hamming loss is the fraction of labels that are incorrectly predicted. <a href="https://www.kaggle.com/wiki/HammingLoss">https://www.kaggle.com/wiki/HammingLoss</a>

# 3. Exploratory Data Analysis

## 3.1 Data Loading and Cleaning

#### 3.1.1 Using Pandas with SQLite to Load the data

```
In [5]: #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
            i = 0
            index start = 1
            for df in pd.read csv('Train.csv', names=['Id', 'Title', 'Body', 'T
        ags'], chunksize=chunksize, iterator=True, encoding='utf-8', ):
                df.index += index start
                i+=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 [6]: 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 abov
e cell to genarate train.db file")
```

Number of rows in the database : 6034196
Time taken to count the number of rows : 0:01:49.292997

## 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(*) a
    s cnt_dup FROM data GROUP BY Title, Body, Tags', con)
        con.close()
        print("Time taken to run this cell :", datetime.now() - start)
else:
    print("Please download the train.db file from drive or run the firs
    t to genarate train.db file")
```

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

In [0]: df\_no\_dup.head()
# we can observe that there are duplicates

Out[0]:

	Title	Body	Tags	С
•	Implementing Boundary Value Analysis of S	<pre><pre><code>#include&lt;iostream&gt;\n#include&amp;</code></pre></pre>	C++ C	1

	Title	Body	Tags	С				
1	Dynamic Datagrid Binding in Silverlight?							
2	Dynamic Datagrid Binding in Silverlight?	c# silverlight data- binding columns	1					
3	java.lang.NoClassDefFoundError: javax/serv	jsp jstl	1					
4	java.sql.SQLException:[Microsoft] I use the following code\n\n <pre>code&gt;</pre>							
-	<pre>df_no_dup.shape[0], "(",(1</pre>	<pre>uestions :", num_rows['count(*)'].v -((df_no_dup.shape[0])/(num_rows['double.come))</pre>						
	values[0])))*100,"% )") mber of duplicate question	s : 1827881 ( 30.2920389063 % )						
# number of times each question appeared in our database df no dup.cnt dup.value counts()								
1 2656284 2 1272336 3 277575 4 90 5 25 6 5 Name: cnt_dup, dtype: int64								
<pre>start = datetime.now()</pre>								

In [0]:

In [0]:

In [0]:

Out[0]:

```
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[0]: \_\_\_\_\_

	Title	Body	Tags	С
0	Implementing Boundary Value Analysis of S	<pre><pre><code>#include&lt;iostream&gt;\n#include&amp;</code></pre></pre>	C++ C	1
1	Dynamic Datagrid Binding in Silverlight?	I should do binding for datagrid dynamicall	c# silverlight data- binding	1
2	Dynamic Datagrid Binding in Silverlight?	I should do binding for datagrid dynamicall	c# silverlight data- binding columns	1
3	java.lang.NoClassDefFoundError: javax/serv	I followed the guide in		

In [0]: # distribution of number of tags per question
df\_no\_dup.tag\_count.value\_counts()

Out[0]: 3 1206157 2 1111706 4 814996 1 568298

```
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""", c
        on)
            #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 abov
        e cells to genarate train.db file")
```

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

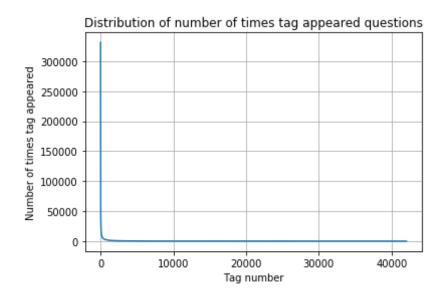
```
#is scikit-learn's bag of words tool.
        #by default 'split()' will tokenize each tag using space.
        vectorizer = CountVectorizer(tokenizer = lambda x: x.split())
        # fit transform() does two functions: First, it fits the model
        # and learns the vocabulary; second, it transforms our training data
        # into feature vectors. The input to fit transform should be a list of
         strinas.
        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',
        '.bash-profile', '.class-file', '.cs-file', '.doc', '.drv', '.ds-stor
        e'l
        3.2.3 Number of times a tag appeared
In [0]: # https://stackoverflow.com/questions/15115765/how-to-access-sparse-mat
        rix-elements
        #Lets now store the document term matrix in a dictionary.
        freqs = tag dtm.sum(axis=0).A1
        result = dict(zip(tags, fregs))
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)
```

#### Out[0]:

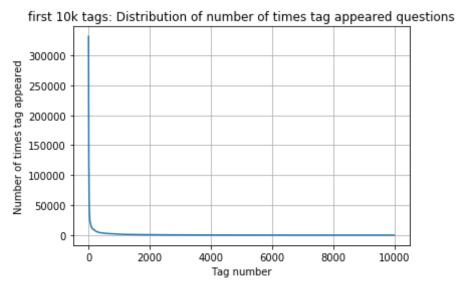
	Tags	Counts
0	.a	18
1	.арр	37
2	.asp.net-mvc	1
3	.aspxauth	21
4	.bash-profile	138

```
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])
```

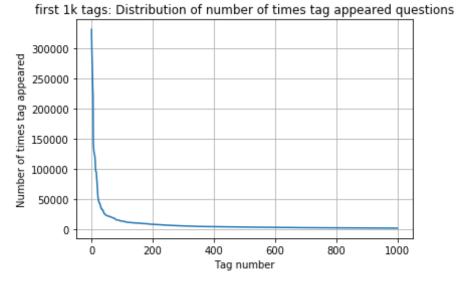


	0 [3315	05 4	4829	22429	17728	13364	1116	2 100	29 9	9148	8054
71	6466	5865	5370	9 498	3 45	26 4	281	4144	3929	3750	359
3	3453	3299	3123	3 298	9 28	91 2	738	2647	2527	2431	. 233
1	2259	2186	209	7 202	0 19	59 1	900	1828	1770	1723	167
3	1631	1574	1532	2 147	9 14	48 1	406	1365	1328	1300	126
6	1245	1222	119	7 118	1 11	.58 1	139	1121	1101	1076	105
6	1038	1023	1000	5 98	3 9	66	952	938	926	911	. 89
1	882	869	850	5 84	1 8	30	816	804	789	779	77
0	752	743	733	3 72	5 7	'12	702	688	678	671	. 65
8	650	643	634	4 62	7 6	16	607	598	589	583	57
7	568	559	552	2 54	5 5	40	533	526	518	512	50
6	500	495	490	9 48	5 4	80	477	469	465	457	45

0			407	400	40.0	400	4.5.0		400	
3	447	442	437	432	426	422	418	413	408	40
5	398	393	388	385	381	378	374	370	367	36
	361	357	354	350	347	344	342	339	336	33
2	330	326	323	319	315	312	309	307	304	30
1	299	296	293	291	289	286	284	281	278	27
6	275	272	270	268	265	262	260	258	256	25
4	252	250	249	247	245	243	241	239	238	23
6	234	233	232	230	228	226	224	222	220	21
9	217	215	214	212	210	209	207	205	204	20
3	201	200	199	198	196	194	193	192	191	18
9	188	186	185	183	182	181	180	179	178	17
7	175	174	172	171	170	169	168	167	166	16
5	164	162	161	160	159	158	157	156	156	15
5	154	153	152	151	150	149	149	148	147	14
6	145	144	143	142	142	141	140	139	138	13
7	137	136	135	134	134	133	132	131	130	13
0	129	128	128	127	126	126	125	124	124	12
3	123	122	122	121	120	120	119	118	118	11
7	117	116	116	115	115	114	113	113	112	11
1										

```
111
                  109
                                 108
                                        108
                                               107
                                                                     10
           110
                          109
                                                       106
                                                              106
6
    105
           105
                  104
                          104
                                 103
                                        103
                                               102
                                                       102
                                                              101
                                                                     10
1
           100
                   99
                           99
                                  98
                                         98
                                                97
                                                        97
                                                               96
    100
                                                                       9
6
     95
            95
                   94
                           94
                                  93
                                         93
                                                 93
                                                        92
                                                               92
                                                                       9
1
     91
            90
                   90
                           89
                                  89
                                         88
                                                 88
                                                        87
                                                               87
                                                                       8
6
     86
            86
                   85
                           85
                                  84
                                         84
                                                 83
                                                        83
                                                               83
                                                                       8
2
     82
            82
                   81
                           81
                                  80
                                         80
                                                 80
                                                        79
                                                               79
                                                                       7
8
     78
            78
                   78
                           77
                                  77
                                         76
                                                76
                                                        76
                                                               75
                                                                      7
5
            74
                   74
                           74
                                  73
                                         73
                                                73
                                                        73
                                                               72
     75
                                                                       7
2]
```

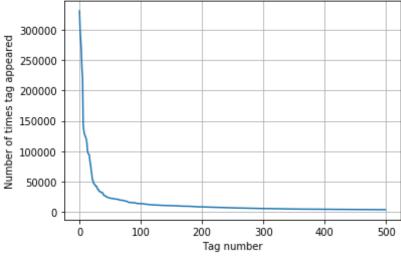
```
In [0]: plt.plot(tag_counts[0:1000])
   plt.title('first lk tags: Distribution of number of times tag appeared
        questions')
   plt.grid()
   plt.xlabel("Tag number")
   plt.ylabel("Number of times tag appeared")
   plt.show()
   print(len(tag_counts[0:1000:5]), tag_counts[0:1000:5])
```



200 [331 537	505 221	533 122	769 95	160 62	2023	44	829	37	170	31	897	26	925	24
22429	21820	20957	19758	18905	1772	28	1553	33	1509	7	148	84	137	03
13364	13157	12407	11658	11228	1110	_	1086		1066		103	_	102	
10029	9884	9719	9411	9252	914		904		861		83			63
8054	7867	7702	7564	7274	71!		70!	52	684		66			53
6466	6291	6183	6093	5971	580	65	576	50	557	77	54	90	54	11
5370	5283	5207	5107	5066	498	83	489	91	478	35	46.	58	45	49
4526	4487	4429	4335	4310	428	81	423	39	422	28	41	95	41	59
4144	4088	4050	4002	3957	392	29	387	74	384	19	38	18	37	97
3750	3703	3685	3658	3615	359	93	356	64	352	21	35	95	34	83
3453	3427	3396	3363	3326	329	99	327	72	323	32	31	96	31	68
3123	3094	3073	3050	3012	298	89	298	34	295	3	29	34	29	03
2891	2844	2819	2784	2754	27	38	272	26	276	8(	26	81	26	69
2647	2621	2604	2594	2556	252	27	25	10	248	32	24	60	24	44
2431	2409	2395	2380	2363	233	31	23	12	229	97	22	90	22	81
2259	2246	2222	2211	2198	218	86	216	52	214	12	21.	32	21	07
2097	2078	2057	2045	2036	202		20		199		19			65
1959	1952	1940	1932	1912	190		187		186		18.			41
1828	1821	1813	1801	1782	17	_	176		174		17			34
1723	1707	1697	1688	1683	16	73	166	55	165	6	16	46	16	39]

```
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])

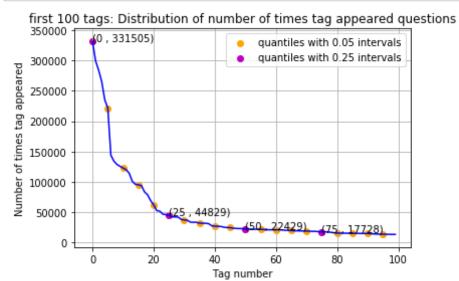
   first 500 tags: Distribution of number of times tag appeared questions
```



```
100 [331505 221533 122769 95160 62023 44829 37170 31897 26925 24
537
  22429
         21820
                20957
                       19758
                               18905
                                      17728
                                             15533
                                                     15097
                                                            14884
                                                                   13703
                       11658
                                             10863
                                                     10600
                                                            10350
                                                                   10224
  13364
         13157
                12407
                               11228
                                      11162
  10029
                                9252
                                       9148
                                              9040
          9884
                 9719
                         9411
                                                      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
          4487
                 4429
                        4335
                                              4239
                                                      4228
                                                                    4159
   4526
                                4310
                                       4281
                                                             4195
          4088
                 4050
                        4002
                                3957
                                       3929
                                               3874
                                                      3849
                                                             3818
                                                                    3797
   4144
   3750
                                                      3521
          3703
                 3685
                         3658
                                3615
                                       3593
                                               3564
                                                             3505
                                                                    34831
```

```
In [0]: plt.plot(tag_counts[0:100], c='b')
```

```
plt.scatter(x=list(range(0,100,5)), y=tag counts[0:100:5], c='orange',
label="quantiles with 0.05 intervals")
# quantiles with 0.25 difference
plt.scatter(x=list(range(0,100,25)), y=tag counts[0:100:25], c='m', lab
el = "quantiles with 0.25 intervals")
for x,y in zip(list(range(0,100,25)), tag counts[0:100:25]):
    plt.annotate(s="(\{\}, \{\}))".format(x,y), xy=(x,y), xytext=(x-0.05, y
+500))
plt.title('first 100 tags: Distribution of number of times tag appeared
questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.legend()
plt.show()
print(len(tag counts[0:100:5]), tag_counts[0:100:5])
```



20 [331505 221533 122769 95160 62023 44829 37170 31897 26925 245 37 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

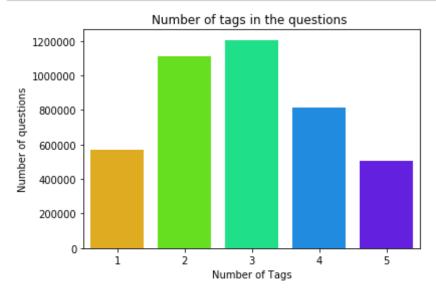
```
In [0]: #Storing the count of tag in each question in list 'tag_count'
    tag_quest_count = tag_dtm.sum(axis=1).tolist()
    #Converting list of lists into single list, we will get [[3], [4], [2],
        [2], [3]] and we are converting this to [3, 4, 2, 2, 3]
    tag_quest_count=[int(j) for i in tag_quest_count for j in i]
    print ('We have total {} datapoints.'.format(len(tag_quest_count)))
    print(tag_quest_count[:5])

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

```
In [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_count)))
```

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()
```

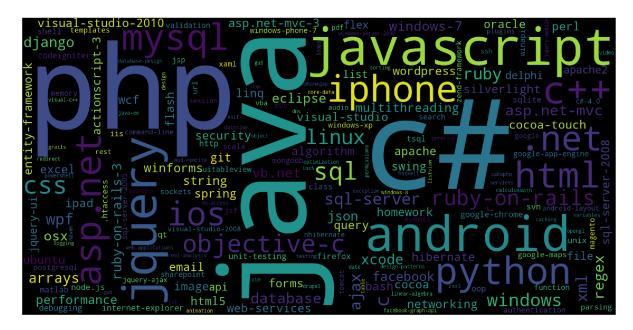


#### Observations:

- 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)
```



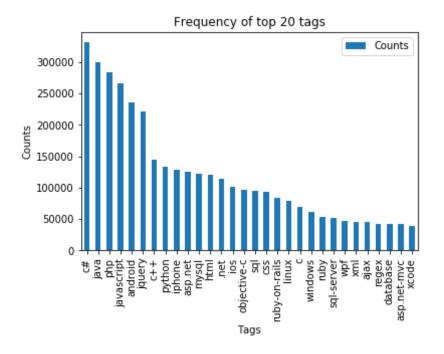
Time taken to run this cell : 0:00:05.470788

#### **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

## 3.3.1 Preprocessing

- 1. Sample 1M data points
- 2. Separate out code-snippets from Body
- 3. Remove Spcial characters from Question title and description (not in code)
- 4. Remove stop words (Except 'C')

- 5. Remove HTML Tags
- 6. Convert all the characters into small letters
- 7. Use SnowballStemmer to stem the words

```
In [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 [3]: #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:
            0.00
            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, guery):
            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 (qu
        estion text NOT NULL, code text, tags text, words pre integer, words po
        st integer, is code integer);"""
        create database table("Processed.db", sql create table)
        Tables in the databse:
        OuestionsProcessed
In [7]: # http://www.sglitetutorial.net/sglite-delete/
        # https://stackoverflow.com/questions/2279706/select-random-row-from-a-
        salite-table
        start = datetime.now()
        read db = 'train no dup.db'
        write db = 'Processed.db'
        if os.path.isfile(read db):
            conn r = create connection(read db)
            if conn r is not None:
                reader =conn r.cursor()
                reader.execute("SELECT Title, Body, Tags From no dup train ORDE
        R BY RANDOM() LIMIT 1000000;")
```

```
if os.path.isfile(write db):
    conn_w = create_connection(write db)
    if conn w is not None:
        tables = checkTableExists(conn w)
        writer =conn w.cursor()
        if tables != 0:
            writer.execute("DELETE FROM QuestionsProcessed WHERE 1")
            print("Cleared All the rows")
print("Time taken to run this cell :", datetime.now() - start)
Tables in the databse:
OuestionsProcessed
Cleared All the rows
Time taken to run this cell: 1:21:57.873387
```

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

```
In [10]: #http://www.bernzilla.com/2008/05/13/selecting-a-random-row-from-an-sql
         ite-table/
         start = datetime.now()
         preprocessed data list=[]
         reader.fetchone()
         questions with code=0
         len pre=0
         len post=0
         questions proccesed = 0
         for row in reader:
             is code = 0
             title, question, tags = row[0], row[1], row[2]
             if '<code>' in guestion:
                 questions_with_code+=1
                 is code = 1
             x = len(question) + len(title)
             len pre+=x
```

```
code = str(re.findall(r'<code>(.*?)</code>', guestion, flags=re.DOT
ALL))
    question=re.sub('<code>(.*?)</code>', '', question, flags=re.MULTIL
INE|re.DOTALL)
    question=striphtml(question.encode('utf-8'))
    title=title.encode('utf-8')
    question=str(title)+" "+str(question)
    question=re.sub(r'[^A-Za-z]+',' ',question)
    words=word tokenize(str(question.lower()))
    #Removing all single letter and and stopwords from question exceptt
for the letter 'c'
    question=' '.join(str(stemmer.stem(j)) for j in words if j not in s
top words and (len(j)!=1 or j=='c'))
    len post+=len(question)
    tup = (question,code,tags,x,len(question),is_code)
    questions processed += 1
    writer.execute("insert into QuestionsProcessed(question,code,tags,w
ords pre, words post, is code) values (?,?,?,?,?)", tup)
    if (questions proccesed%100000==0):
        print("number of questions completed=",questions proccesed)
no dup avg len pre=(len pre*1.0)/questions proccesed
no dup avg len post=(len post*1.0)/questions proccesed
print( "Avg. length of questions(Title+Body) before processing: %d"%no
dup avg len pre)
print( "Avg. length of questions(Title+Body) after processing: %d"%no d
up avg len post)
print ("Percent of questions containing code: %d"%((questions with code
*100.0)/questions proccesed))
print("Time taken to run this cell :", datetime.now() - start)
number of questions completed= 100000
number of questions completed= 200000
```

```
number of questions completed= 300000
         number of questions completed= 400000
         number of questions completed= 500000
         number of questions completed= 600000
         number of questions completed= 700000
         number of questions completed= 800000
         number of questions completed= 900000
         Avg. length of guestions(Title+Body) before processing: 1170
         Avg. length of questions(Title+Body) after processing: 326
         Percent of questions containing code: 57
         Time taken to run this cell: 0:52:38.852891
In [11]: # dont forget to close the connections, or else you will end up with lo
         cks
         conn r.commit()
         conn w.commit()
         conn_r.close()
         conn w.close()
In [12]: 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 1
         0")
                 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
         ('use gt librari librari integr gtk functionn decid switch gt nso creat
         test cmake file tri integr qt work load libari dynam use execut get und
```

i relev file use',)
('store document variabl wonder store document variabl whether would sp eed enhanc know exampl make much differ think variabl would act pointer document script would need tri refer back document',)
('delet record databas work first datagridview event creat simpl projec t learn function c databas within window form datagridview updat add re cord event doubl mous click row header datagrid view delet record datagridview well databas work great first attempt form load attempt delet m ulitpl record datagridview delet databas close reopen work one record d elet stop far',)
('see queri fire hibern see queri fire hibern hibern applic run tomca t',)
('tri split sentenc regex tri figur day reliabl split next line follow order passiv mark enemi isol nearbi alli activ deal physic damag target isol amount increas evolv enlarg claw increas damag isol enemi miss hea lth max vs monster increas rang tast fear kha zix basic attack get past mid sentenc period',)
('best way implement piec wise period function object c need implement kind illustr function ratio somefunct time object c languag actual matt er task seem pure algorithm common way thing like nnext thing easili ad just process design number small interv per period exampl chang simpl f unction like sin say ratio work vs work adjust',)
('jqueri ajax return youtub ifram src jsfiddl http jsfiddl net zxdys cr eat blogger post summari use jqueri although return element ifram attr src find blog refer done wrong pleas help',)

('xml cach issu tri figur data show ui present think may due xml cach i ssu much experi aspect ui seem util xml display content look like anyon know work could explain way refresh thank',)

-----

-----

('differ meego android stack meego android stack share relev librari us erspac top linux kernel look android stack guess meego share compon lin ux kernel includ display driver flash memori driver ipc driver usb driv er keypad driver audio driver power manag wifi driver camera driver blu etooth driver read cyanogenmod complain tri cm run wonki devic seem wif i camera bluetooth mean android specif part share meego otherwis anoth linux base platform part android stack guess applic framework part android specif also librari like media framework other',)

-----

-----

## In [14]: preprocessed\_data.head()

#### Out[14]:

	question	tags		
0	extrem low prioriti select queri mysql possibl	mysql select priority-queue		
1	use qt librari librari integr gtk functionn de	c++ cmake shared-libraries qt5		
2	store document variabl wonder store document v	javascript		
3	delet record databas work first datagridview e	datagridview delete record		

	question		tags
4	see queri fire hibern see queri fire hibern hi	java hibernate tomcat	

```
In [15]: 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 : 999997
    number of dimensions : 2
```

# 4. Machine Learning Models

## 4.1 Converting tags for multilabel problems

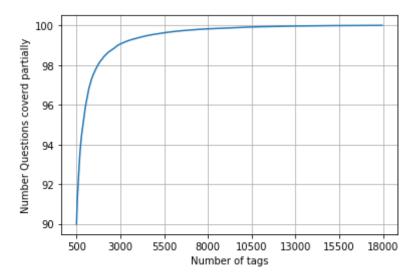
X	y1	y2	у3	y4
x1	0	1	1	0
x1	1	0	0	0
x1	0	1	0	0

```
In [32]: # binary='true' will give a binary vectorizer
    vectorizer = CountVectorizer(tokenizer = lambda x: x.split(), binary='t
    rue')
    multilabel_y = vectorizer.fit_transform(preprocessed_data['tags'])
```

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

```
In [13]: 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=T
```

```
rue)
             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 [34]: questions explained = []
         total tags=multilabel y.shape[1]
         total qs=preprocessed data.shape[0]
         for i in range(500, total tags, 100):
             questions explained.append(np.round(((total qs-questions explained
         fn(i))/total qs)*100,3))
In [35]: 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, mini
         mun is 50(it covers 90% of the tags)
         print("with ",5500,"tags we are covering ",questions explained[50],"% o
         f questions")
```



with 5500 tags we are covering 99.058 % of questions

```
In [36]: multilabel_yx = tags_to_choose(5500)
    print("number of questions that are not covered :", questions_explained
    _fn(5500),"out of ", total_qs)
```

number of questions that are not covered : 9419 out of 999996

Number of tags in sample : 35413 number of tags taken : 5500 ( 15.53101968203767 %)

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

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

```
In [38]: total size=preprocessed data.shape[0]
         train size=int(0.80*total size)
         x train=preprocessed data.head(train size)
         x test=preprocessed data.tail(total size - train size)
         y train = multilabel yx[0:train size,:]
         y test = multilabel yx[train size:total size,:]
In [39]: 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: (799996, 5500)
         Number of data points in test data: (200000, 5500)
         4.3 Featurizing data
In [0]: start = datetime.now()
         vectorizer = TfidfVectorizer(min df=0.00009, max features=200000, smoot
         h idf=True, norm="l2", \
                                      tokenizer = lambda x: x.split(), sublinear
         tf=False, ngram range=(1,3)
         x train multilabel = vectorizer.fit transform(x train['question'])
         x test multilabel = vectorizer.transform(x test['question'])
         print("Time taken to run this cell :", datetime.now() - start)
         Time taken to run this cell: 0:09:50.460431
In [0]: print("Dimensions of train data X:",x train multilabel.shape, "Y:",y t
         rain.shape)
         print("Dimensions of test data X:",x test multilabel.shape,"Y:",y test.
         shape)
         Diamensions of train data X: (799999, 88244) Y: (799999, 5500)
         Diamensions of test data X: (200000, 88244) Y: (200000, 5500)
In [0]: # https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-la
```

```
bel-classification/
#https://stats.stackexchange.com/questions/117796/scikit-multi-label-cl
assification
# classifier = LabelPowerset(GaussianNB())
from skmultilearn.adapt import MLkNN
classifier = MLkNN(k=21)
# train
classifier.fit(x train multilabel, y train)
# predict
predictions = classifier.predict(x test multilabel)
print(accuracy score(y test,predictions))
print(metrics.fl score(y test, predictions, average = 'macro'))
print(metrics.fl score(y test, predictions, average = 'micro'))
print(metrics.hamming loss(y test,predictions))
# we are getting memory error because the multilearn package
# is trying to convert the data into dense matrix
#MemoryError
                                           Traceback (most recent call
last)
#<ipython-input-170-f0e7c7f3e0be> in <module>()
#----> classifier.fit(x train multilabel, y train)
```

# 4.4 Applying Logistic Regression with OneVsRest Classifier

```
In [0]: # this will be taking so much time try not to run it, download the lr w
        ith equal weight.pkl file and use to predict
        # This takes about 6-7 hours to run.
        classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0000
        1, penalty='ll'), n jobs=-1)
        classifier.fit(x train multilabel, y train)
        predictions = classifier.predict(x test multilabel)
        print("accuracy :",metrics.accuracy score(y test,predictions))
        print("macro f1 score :", metrics.f1 score(y test, predictions, average
        = 'macro'))
        print("micro fl scoore :", metrics.fl score(y test, predictions, average
         = 'micro'))
        print("hamming loss :", metrics.hamming loss(y test, predictions))
        print("Precision recall report :\n", metrics.classification report(y tes
        t. predictions))
        accuracy : 0.081965
        macro f1 score : 0.0963020140154
        micro f1 scoore : 0.374270748817
        hamming loss: 0.00041225090909090907
        Precision recall report :
                                    recall f1-score
                       precision
                                                       support
                  0
                           0.62
                                     0.23
                                               0.33
                                                        15760
                           0.79
                                     0.43
                                               0.56
                                                        14039
                           0.82
                                     0.55
                                               0.66
                                                        13446
                  3
                          0.76
                                     0.42
                                               0.54
                                                        12730
                  4
                           0.94
                                     0.76
                                               0.84
                                                        11229
                           0.85
                                     0.64
                                               0.73
                                                        10561
                                               0.42
                  6
                           0.70
                                     0.30
                                                         6958
                           0.87
                                     0.61
                                               0.72
                                                         6309
                  8
                           0.70
                                               0.50
                                                         6032
                                     0.40
                  9
                           0.78
                                     0.43
                                               0.55
                                                         6020
                 10
                          0.86
                                     0.62
                                               0.72
                                                         5707
                          0.52
                                               0.25
                                     0.17
                                                         5723
                 11
                 12
                           0.55
                                                         5521
                                     0.10
                                               0.16
                 13
                           0.59
                                     0.25
                                               0.35
                                                         4722
                           0.61
                                     0.22
                                               0.32
                                                         4468
                 14
                 15
                           0.79
                                     0.52
                                               0.63
                                                         4536
                                               ^ ~=
```

5438	0.00	0.00	0.00	7
5439	0.00	0.00	0.00	9
5440	0.00	0.00	0.00	12
5441	0.00	0.00	0.00	10
5442	0.00	0.00	0.00	7
5443	0.00	0.00	0.00	12
5444	0.00	0.00	0.00	7
5445	0.00	0.00	0.00	9
5446	0.00	0.00	0.00	7
5447	0.00	0.00	0.00	6
5448	0.00	0.00	0.00	12
5449	0.00	0.00	0.00	9
5450	0.00	0.00	0.00	10
5451	0.00	0.00	0.00	6
5452	0.00	0.00	0.00	11
5453	0.00	0.00	0.00	7
5454	0.00	0.00	0.00	9
5455	0.00	0.00	0.00	11
5456	0.00	0.00	0.00	7
5457	0.00	0.00	0.00	9
5458	0.00	0.00	0.00	8
5459	0.00	0.00	0.00	11
5460	0.00	0.00	0.00	7
5461	0.00	0.00	0.00	11
5462	0.00	0.00	0.00	10
5463	0.00	0.00	0.00	9
5464	0.00	0.00	0.00	9
5465	0.00	0.00	0.00	7
5466	0.00	0.00	0.00	9
5467	0.00	0.00	0.00	14
5468	0.00	0.00	0.00	9
5469	0.00	0.00	0.00	12
5470	0.00	0.00	0.00	11
5471	0.00	0.00	0.00	8
5472	0.00	0.00	0.00	15
5473	0.00	0.00	0.00	4
5474	0.00	0.00	0.00	8
5475	0.00	0.00	0.00	9
5476	0.00	0.00	0.00	11

```
0.00
                                         0.00
       5477
                              0.00
                                                       8
       5478
                   0.00
                              0.00
                                         0.00
                                                       6
       5479
                   0.00
                                                       7
                              0.00
                                         0.00
       5480
                   0.00
                              0.00
                                         0.00
                                                       7
       5481
                   0.00
                              0.00
                                         0.00
                                                      10
                                                      12
       5482
                   0.00
                              0.00
                                         0.00
       5483
                   0.00
                              0.00
                                         0.00
                                                       6
       5484
                   0.00
                              0.00
                                         0.00
                                                       9
                   0.00
       5485
                              0.00
                                         0.00
                                                       8
                   0.00
                                                       8
       5486
                              0.00
                                         0.00
       5487
                   0.00
                              0.00
                                         0.00
                                                       9
                   0.00
       5488
                              0.00
                                         0.00
                                                       7
       5489
                   0.00
                              0.00
                                         0.00
                                                      10
       5490
                   0.00
                              0.00
                                         0.00
                                                      12
       5491
                   0.00
                              0.00
                                         0.00
                                                       6
       5492
                   0.00
                              0.00
                                         0.00
                                                       8
       5493
                   0.00
                              0.00
                                         0.00
                                                      13
       5494
                   0.00
                              0.00
                                         0.00
                                                       6
       5495
                   0.00
                              0.00
                                         0.00
                                                      10
       5496
                   0.00
                              0.00
                                         0.00
                                                       7
       5497
                   0.00
                              0.00
                                         0.00
                                                       9
       5498
                   0.00
                              0.00
                                         0.00
                                                       6
       5499
                   0.00
                                         0.00
                                                      13
                              0.00
avg / total
                   0.53
                              0.26
                                         0.33
                                                  530065
```

```
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 [47]: sql_create_table = """CREATE TABLE IF NOT EXISTS QuestionsProcessed (question text NOT NULL, code text, tags text, words_pre integer, words_po
```

```
st integer, is code integer);"""
        create database table("Titlemoreweight.db", sql create table)
        Tables in the databse:
        OuestionsProcessed
In [4]: # http://www.sqlitetutorial.net/sqlite-delete/
        # https://stackoverflow.com/questions/2279706/select-random-row-from-a-
        sglite-table
        read db = 'train no dup.db'
        write db = 'Titlemoreweight.db'
        train datasize = 75000
        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 LIMI
        T 100001;")
                # for selecting random points
                #reader.execute("SELECT Title, Body, Tags From no dup train ORD
        ER BY RANDOM() LIMIT 500001;")
        if os.path.isfile(write db):
            conn w = create connection(write db)
            if conn w is not None:
                tables = checkTableExists(conn w)
                writer =conn w.cursor()
                if tables != 0:
                    writer.execute("DELETE FROM QuestionsProcessed WHERE 1")
                    print("Cleared All the rows")
        Tables in the databse:
```

**OuestionsProcessed** 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 [5]: #http://www.bernzilla.com/2008/05/13/selecting-a-random-row-from-an-sql
        ite-table/
        start = datetime.now()
        preprocessed data list=[]
        reader.fetchone()
        questions with code=0
        len pre=0
        len post=0
        questions proccesed = 0
        for row in reader:
            is code = 0
            title, question, tags = row[0], row[1], str(row[2])
            if '<code>' in question:
                questions with code+=1
                is code = 1
            x = len(question) + len(title)
            len pre+=x
            code = str(re.findall(r'<code>(.*?)</code>', question, flags=re.DOT
        ALL))
            question=re.sub('<code>(.*?)</code>', '', question, flags=re.MULTIL
        INE|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:</pre>
          question=str(title)+" "+str(title)+" "+str(title)+" "+questio
n+" "+str(tags)
      else:
          question=str(title)+" "+str(title)+" "+str(title)+" "+questio
    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 s
top_words and (len(j)!=1 or j=='c'))
    len post+=len(question)
    tup = (question,code,tags,x,len(question),is code)
    questions processed += 1
    writer.execute("insert into QuestionsProcessed(question,code,tags,w
ords pre, words post, is code) values (?,?,?,?,?)", tup)
    if (questions proccesed%100000==0):
        print("number of questions completed=",questions proccesed)
no dup avg len pre=(len pre*1.0)/questions proccesed
no dup avg len post=(len post*1.0)/questions proccesed
print( "Avg. length of questions(Title+Body) before processing: %d"%no
dup avg len pre)
print( "Avg. length of questions(Title+Body) after processing: %d"%no d
up avg len post)
print ("Percent of questions containing code: %d"%((questions with code
*100.0)/questions proccesed))
```

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

number of questions completed= 100000
Avg. length of questions(Title+Body) before processing: 1232
Avg. length of questions(Title+Body) after processing: 441
Percent of questions containing code: 57
Time taken to run this cell : 0:05:17.346340
In [6]: # never forget to close the conections or else we will end up with data base locks
conn_r.commit()
conn_w.commit()
conn_r.close()
conn_w.close()
```

#### Sample quesitons after preprocessing of data

```
In [7]:
    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 1
0")
        print("Questions after preprocessed")
        print('='*100)
        reader.fetchone()
        for row in reader:
            print(row)
            print('-'*100)
        conn_r.commit()
        conn_r.close()
```

Questions after preprocessed

\_\_\_\_\_\_

\_\_\_\_\_

('dynam datagrid bind silverlight dynam datagrid bind silverlight dynam datagrid bind silverlight bind datagrid dynam code wrote code debug cod e block seem bind correct grid come column form come grid column althou

gh necessari bind nthank repli advance..',) ('java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryval id java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryva lid java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryv alid follow guid link instal jstl got follow error tri launch jsp page java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid taglib declar instal jstl 1.1 tomcat webapp tri project work also tri v ersion 1.2 istl still messag caus solv'.) ('java.sql.sqlexcept microsoft odbc driver manag invalid descriptor ind ex java.sql.sqlexcept microsoft odbc driver manag invalid descriptor in dex java.sql.sqlexcept microsoft odbc driver manag invalid descriptor i ndex use follow code display caus solv',) ('better way updat feed fb php sdk better way updat feed fb php sdk bet ter way 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 s ometh like way better'.) ('btnadd click event open two window record ad btnadd click event open two window record ad btnadd click event open two window record ad open window search.aspx use code hav add button search.aspx nwhen insert rec ord btnadd click event open anoth window nafter insert record close win dow',) ('sql inject issu prevent correct form submiss php sql inject issu prev ent correct form submiss php sql inject issu prevent correct form submi ss php check everyth think make sure input field safe type sql inject g ood news safe bad news one tag mess form submiss place even touch life figur exact html use templat file forgiv okay entir php script get exec ut see data post none forum field post problem use someth titl field no ne data get post current use print post see submit noth work flawless s tatement though also mention script work flawless local machin use host

```
come across problem state list input test mess',)
        ('countabl subaddit lebesqu measur countabl subaddit lebesqu measur cou
        ntabl subaddit lebesgu measur let lbrace rbrace sequenc set sigma -alge
        bra mathcal want show left bigcup right leg sum left right countabl add
        it measur defin set sigma algebra mathcal think use monoton properti so
        mewher proof start appreci littl help nthank ad han answer make follow
        addit construct given han answer clear bigcup bigcup cap emptyset neg l
        eft bigcup right left bigcup right sum left right also construct subset
        monoton left right leg left right final would sum leg sum result follo
        ('hql equival sql queri hql equival sql queri hql equival sql queri hql
        queri replac name class properti name error occur hql error',)
        ('undefin symbol architectur i386 objc class skpsmtpmessag referenc err
        or undefin symbol architectur i386 objc class skpsmtpmessag referenc er
        ror undefin symbol architectur i386 objc class skpsmtpmessag referenc e
        rror import framework send email applic background import framework i.e
        skpsmtpmessag somebodi suggest get error collect2 ld return exit status
        import framework correct sorc taken framework follow mfmailcomposeviewc
        ontrol question lock field updat answer drag drop folder project click
        copi nthat'.)
        Saving Preprocessed data to a Database
In [8]: #Taking 0.5 Million entries to a dataframe.
        write db = 'Titlemoreweight.db'
        if os.path.isfile(write db):
            conn r = create connection(write db)
            if conn r is not None:
                preprocessed data = pd.read sql query("""SELECT question, Tags
```

```
FROM QuestionsProcessed""", conn_r)
conn_r.commit()
conn_r.close()
```

### In [9]: preprocessed\_data.head()

#### Out[9]:

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

```
In [10]: 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 : 100000 number of dimensions : 2

#### **Converting String Tags to multilable output variables**

```
In [11]: vectorizer = CountVectorizer(tokenizer = lambda x: x.split(), binary='t
    rue')
    multilabel_y = vectorizer.fit_transform(preprocessed_data['tags'])
```

#### **Selecting 500 Tags**

```
In [14]:          questions_explained = []
          total_tags=multilabel_y.shape[1]
          total_qs=preprocessed_data.shape[0]
          for i in range(500, total_tags, 100):
```

```
questions explained.append(np.round(((total qs-questions explained
         fn(i))/total qs)*100,3))
In [15]: 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, mini
         mun is 500(it covers 90% of the tags)
         print("with ",5500,"tags we are covering ",questions explained[50],"% o
         f questions")
          print("with ",500,"tags we are covering ",questions explained[0],"% of
          questions")
            100
          Number Questions coverd partially
             98
             97
             96
             95
             94
             93
                500 3000 5500 8000 10500 13000 15500 18000 20500
                                Number of tags
         with 5500 tags we are covering 99.481 % of questions
         with 500 tags we are covering 92.5 % of questions
In [16]: # we will be taking 500 tags
```

multilabel yx = tags to choose(500)

```
print("number of questions that are not covered:", questions explained
         fn(500), "out of ", total qs)
         number of questions that are not covered : 7500 out of 100000
In [21]: x train=preprocessed data.head(train datasize)
         x test=preprocessed data.tail(preprocessed data.shape[0] - 75000)
         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: (75000, 500)
         Number of data points in test data: (25000, 500)
         4.5.2 Featurizing data with Tfldf vectorizer
In [23]: start = datetime.now()
         vectorizer = TfidfVectorizer(min df=0.00009, max features=200000, smoot
         h idf=True, norm="l2", \
                                      tokenizer = lambda x: x.split(), sublinear
         tf=False, ngram range=(1,3)
         x train multilabel = vectorizer.fit transform(x train['question'])
         x test multilabel = vectorizer.transform(x test['question'])
         print("Time taken to run this cell :", datetime.now() - start)
         Time taken to run this cell: 0:00:57.894613
         print("Dimensions of train data X:",x train multilabel.shape, "Y :",y t
In [24]:
         rain.shape)
         print("Dimensions of test data X:",x test multilabel.shape,"Y:",y test.
         shape)
         Dimensions of train data X: (75000, 110254) Y: (75000, 500)
         Dimensions of test data X: (25000, 110254) Y: (25000, 500)
```

#### 4.5.3 Applying Logistic Regression with OneVsRest Classifier

```
In [0]: start = datetime.now()
        classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0000
        1, penalty='ll'), n jobs=-1)
        classifier.fit(x train multilabel, y train)
        predictions = classifier.predict (x test multilabel)
        print("Accuracy :",metrics.accuracy score(y test, predictions))
        print("Hamming loss ", metrics.hamming loss(y test, predictions))
        precision = precision_score(y_test, predictions, average='micro')
        recall = recall score(y test, predictions, average='micro')
        f1 = f1 score(y test, predictions, average='micro')
        print("Micro-average quality numbers")
        print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(pr
        ecision, 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(pr
        ecision, recall, f1))
        print (metrics.classification report(y test, predictions))
        print("Time taken to run this cell :", datetime.now() - start)
        Accuracy : 0.23623
        Hamming loss 0.00278088
        Micro-average quality numbers
        Precision: 0.7216, Recall: 0.3256, F1-measure: 0.4488
        Macro-average quality numbers
        Precision: 0.5473 Recall: 0.2572 Flampasure: 0.3330
```

LICCTOTOII O	.J4/J, NECALI		ı T-IIICasaı	בי הייים
	precision	recall	f1-score	support
•	0.04	0.64	0.76	5510
0	0.94	0.64	0.76	5519
1	0.69	0.26	0.38	8190
2	0.81	0.37	0.51	6529
3	0.81	0.43	0.56	3231
4	0.81	0.40	0.54	6430
5	0.82	0.33	0.47	2879
6	0.87	0.50	0.63	5086
7	0.87	0.54	0.67	4533
8	0.60	0.13	0.22	3000
9	0.81	0.53	0.64	2765
10	0.59	0.17	0.26	3051
11	0.70	0.33	0.45	3009
12	0.64	0.24	0.35	2630
13	0.71	0.23	0.35	1426
14	0.90	0.53	0.67	2548
15	0.66	0.18	0.28	2371
16	0.65	0.23	0.34	873
17	0.89	0.61	0.72	2151
18	0.62	0.23	0.33	2204
19	0.71	0.40	0.51	831
20	0.77	0.41	0.53	1860
21	0.27	0.07	0.11	2023
22	0.49	0.23	0.31	1513
23	0.91	0.49	0.64	1207
24	0.56	0.29	0.38	506
25	0.68	0.30	0.42	425
26	0.65	0.40	0.49	793
27	0.60	0.32	0.42	1291
28	0.75	0.36	0.48	1208
29	0.42	0.09	0.15	406
30	0.75	0.18	0.29	504
31	0.29	0.10	0.14	732
32	0.59	0.24	0.35	441
33	0.56	0.18	0.27	1645
34	0.71	0.25	0.37	1058
35	0.83	0.54	0.66	946
36	A 60	A 71	N 32	6//

<del>-</del> UJ	0.50	0.11	0.10	υ <del>τ</del>
466	0.56	0.28	0.37	173
467	0.81	0.36	0.50	107
468	0.82	0.11	0.20	126
469	0.00	0.00	0.00	114
470	0.94	0.79	0.86	140
471	0.92	0.28	0.43	79
472	0.41	0.30	0.35	143
473	0.69	0.30	0.42	158
474	0.36	0.07	0.11	138
475	0.00	0.00	0.00	59
476	0.57	0.30	0.39	88
477	0.86	0.56	0.68	176
478	0.94	0.71	0.81	24
479	0.09	0.01	0.02	92
480	0.82	0.50	0.62	100
481	0.47	0.17	0.26	103
482	0.47	0.23	0.31	74
483	0.85	0.57	0.68	105
484	0.25	0.02	0.04	83
485	0.17	0.01	0.02	82
486	0.36	0.11	0.17	71
487	0.43	0.18	0.26	120
488	0.33	0.02	0.04	105
489	0.72	0.30	0.42	87
490	1.00	0.81	0.90	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	0.52	0.18	0.27	61
495	0.98	0.65	0.78	344
496	0.36	0.19	0.25	52
497	0.60	0.18	0.28	137
498	0.33	0.04	0.07	98
499	0.65	0.16	0.26	79
total	0.67	0.33	0.43	173812

Time taken to run this cell : 0:10:14.264591

avg /

```
In [0]: | joblib.dump(classifier, 'lr with more title weight.pkl')
Out[0]: ['lr with more title weight.pkl']
In [0]: start = datetime.now()
        classifier 2 = OneVsRestClassifier(LogisticRegression(penalty='ll'), n
        iobs=-1)
        classifier 2.fit(x train multilabel, y train)
        predictions 2 = classifier 2.predict(x test multilabel)
        print("Accuracy :", metrics.accuracy score(y test, predictions 2))
        print("Hamming loss ", metrics.hamming loss(y test, predictions 2))
        precision = precision score(y test, predictions 2, average='micro')
        recall = recall score(y test, predictions 2, average='micro')
        f1 = f1 score(y test, predictions 2, average='micro')
        print("Micro-average quality numbers")
        print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(pr
        ecision, recall, f1))
        precision = precision score(y test, predictions 2, average='macro')
        recall = recall score(y test, predictions 2, average='macro')
        f1 = f1 score(y test, predictions 2, average='macro')
        print("Macro-average quality numbers")
        print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(pr
        ecision, recall, f1))
        print (metrics.classification report(y test, predictions 2))
        print("Time taken to run this cell :", datetime.now() - start)
        Accuracy : 0.25108
        Hamming loss 0.00270302
        Micro-average quality numbers
        Precision: 0.7172, Recall: 0.3672, F1-measure: 0.4858
        Macro-average quality numbers
        Precision: 0.5570, Recall: 0.2950, F1-measure: 0.3710
                                  recall f1-score
                     precision
                                                     support
```

0	0.94	0.72	0.82	5519
1	0.70	0.34	0.45	8190
2	0.80	0.42	0.55	6529
3	0.82	0.49	0.61	3231
4	0.80	0.44	0.57	6430
5	0.82	0.38	0.52	2879
6	0.86	0.53	0.66	5086
7	0.87	0.58	0.70	4533
8	0.60	0.13	0.22	3000
9	0.82	0.57	0.67	2765
10	0.60	0.20	0.30	3051
11	0.68	0.38	0.49	3009
12	0.62	0.29	0.40	2630
13	0.73	0.30	0.43	1426
14	0.89	0.57	0.70	2548
15	0.65	0.23	0.34	2371
16	0.65	0.25	0.37	873
17	0.89	0.63	0.74	2151
18	0.60	0.25	0.35	2204
19	0.71	0.41	0.52	831
20	0.76	0.47	0.58	1860
21	0.29	0.09	0.14	2023
22	0.52	0.24	0.33	1513
23	0.89	0.55	0.68	1207
24	0.56	0.28	0.38	506
25	0.69	0.34	0.45	425
26	0.65	0.43	0.52	793
27	0.62	0.38	0.47	1291
28	0.74	0.39	0.51	1208
29	0.46	0.10	0.17	406
30	0.76	0.21	0.33	504
31	0.26	0.08	0.12	732
32	0.60	0.29	0.39	441
33	0.60	0.27	0.38	1645
34	0.69	0.26	0.38	1058
35	0.83	0.58	0.68	946
36	0.65	0.24	0.35	644
37	0.98	0.65	0.78	136
38	0.62	0.38	0.47	570

468	0.56	0.26	0.36	126
469	0.20	0.01	0.02	114
470	0.93	0.81	0.87	140
471	0.85	0.42	0.56	79
472	0.40	0.35	0.37	143
473	0.67	0.37	0.47	158
474	0.48	0.10	0.17	138
475	0.00	0.00	0.00	59
476	0.63	0.33	0.43	88
477	0.83	0.65	0.73	176
478	0.95	0.79	0.86	24
479	0.22	0.04	0.07	92
480	0.79	0.50	0.61	100
481	0.51	0.28	0.36	103
482	0.40	0.22	0.28	74
483	0.78	0.63	0.69	105
484	0.20	0.02	0.04	83
485	0.20	0.02	0.04	82
486	0.48	0.15	0.23	71
487	0.45	0.21	0.29	120
488	0.50	0.06	0.10	105
489	0.73	0.37	0.49	87
490	1.00	0.81	0.90	32
491	0.33	0.03	0.05	69
492	0.33	0.02	0.04	49
493	0.11	0.02	0.03	117
494	0.52	0.23	0.32	61
495	0.95	0.79	0.87	344
496	0.32	0.13	0.19	52
497	0.59	0.28	0.38	137
498	0.31	0.10	0.15	98
499	0.48	0.20	0.29	79
avg / total	0.67	0.37	0.46	173812

Time taken to run this cell : 1:09:41.236859

## 5. Assignments

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

### 5.1 Bag of words for train and test data

```
In [43]: # used 100000 data points due to memory constraint
         # https://scikit-learn.org/stable/modules/generated/sklearn.model selec
         tion.GridSearchCV.html
In [25]: start = datetime.now()
         vectorizer = CountVectorizer(min df=0.00009, max features=200000, \
                                      tokenizer = lambda x: x.split(), ngram ra
         nge=(1,4)
         x train multilabel = vectorizer.fit transform(x train['question'])
         x test multilabel = vectorizer.transform(x test['question'])
         print("Time taken to run this cell :", datetime.now() - start)
         print("Dimensions of train data X:",x train multilabel.shape, "Y :",y t
         rain.shape)
         print("Dimensions of test data X:",x test multilabel.shape,"Y:",y test.
         shape)
         Time taken to run this cell: 0:01:35.174754
         Dimensions of train data X: (75000, 112005) Y: (75000, 500)
         Dimensions of test data X: (25000, 112005) Y: (25000, 500)
```

### **5.2.1 Applying Logistic Regression**

```
In [36]: start = datetime.now()
         classifier = OneVsRestClassifier(LogisticRegression(penalty='l1'))
         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(pr
         ecision, 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(pr
         ecision, recall, f1))
         print (metrics.classification report(y test, predictions))
         print("Time taken to run this cell :", datetime.now() - start)
         Accuracy : 0.17252
         Hamming loss 0.00344696
         Micro-average quality numbers
         Precision: 0.5824, Recall: 0.3802, F1-measure: 0.4600
         Macro-average quality numbers
         Precision: 0.4266, Recall: 0.2940, F1-measure: 0.3368
                       precision recall f1-score support
                    0
                                      0.67
                                                0.73
                                                          2641
                            0.81
                    1
                            0.49
                                      0.32
                                                0.39
                                                          2585
                    2
                            0.31
                                      0.15
                                                0.20
                                                           702
                                      0.58
                                                0.62
                                                           899
                            0.67
                            0.68
                                      0.51
                                                0.58
                                                          1436
```

434	0.00	0.00	0.00	0
435	0.00	0.00	0.00	2
436	0.23	0.09	0.13	35
437	0.31	0.11	0.16	37
438	0.73	0.55	0.63	20
439	0.27	0.08	0.13	36
440	0.27	0.18	0.22	22
441	0.40	0.53	0.45	19
442	0.69	0.65	0.67	17
443	0.00	0.00	0.00	35
444	0.50	0.14	0.22	7
445	0.68	0.62	0.65	24
446	0.79	0.55	0.65	49
447	0.17	0.04	0.07	70
448	0.00	0.00	0.00	9
449	0.40	0.10	0.16	20
450	0.13	0.04	0.06	52
451	0.09	0.05	0.06	21
452	0.79	0.47	0.59	40
453	0.00	0.00	0.00	14
454	0.33	0.15	0.21	13
455	0.00	0.00	0.00	18
456	0.12	0.17	0.14	6
457	0.11	0.05	0.07	19
458	0.00	0.00	0.00	17
459	0.78	0.62	0.69	29
460	0.11	0.04	0.06	23
461	0.33	0.29	0.31	14
462	0.30	0.12	0.17	26
463	0.00	0.00	0.00	22
464	0.96	0.57	0.72	40
465	0.17	0.13	0.15	23
466	0.20	0.07	0.11	42
467	0.27	0.13	0.17	31
468	0.25	0.03	0.05	37
469	0.00	0.00	0.00	5
470	0.22	0.17	0.19	12
471	0.63	0.28	0.39	43
472	0.00	0.00	0.00	51

	473	0.38	0.45	0.41	29
	474	0.84	0.67	0.74	24
	475	0.56	0.64	0.60	66
	476	0.33	0.18	0.24	38
	477	0.60	0.32	0.41	19
	478	0.40	0.29	0.33	14
	479	0.17	0.12	0.14	24
	480	0.70	0.11	0.19	62
	481	0.27	0.12	0.16	26
	482	0.17	0.29	0.21	7
	483	0.00	0.00	0.00	9
	484	0.83	0.43	0.57	23
	485	0.62	0.43	0.51	23
	486	0.70	0.39	0.50	18
	487	0.92	0.39	0.55	31
	488	0.40	0.40	0.40	10
	489	0.22	0.10	0.13	21
	490	0.14	0.08	0.11	12
	491	0.50	0.08	0.14	12
	492	0.11	0.18	0.14	11
	493	0.45	0.40	0.43	25
	494	0.14	0.10	0.12	10
	495	0.43	0.38	0.40	8
	496	0.19	0.16	0.17	19
	497	0.35	0.11	0.17	72
	498	0.45	0.33	0.38	15
	499	0.54	0.41	0.46	32
micro	_	0.58	0.38	0.46	48283
macro	avg	0.43	0.29	0.34	48283
weighted	avg	0.55	0.38	0.44	48283
samples	avg	0.45	0.38	0.38	48283

Time taken to run this cell : 0:28:33.945710

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn\_for)

```
L:\Anaconda\lip\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in la
bels with no true samples.
  'recall', 'true', average, warn_for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l
abels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l
abels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in samples with no predicted labels.
```

```
'precision', 'predicted', average, warn_tor)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in samples with no true labels.
   'recall', 'true', average, warn_for)
```

# 5.2.2 Applying Logistic Regression with hyperparameter tuning

```
In [ ]: from sklearn.model selection import GridSearchCV
         from sklearn.linear model import LogisticRegression
         from sklearn.multiclass import OneVsRestClassifier
         tuned parameters = [{'estimator C': [100, 10, 1, 0.1, 0.01, 0.001, 0.0
         0011}1
         Classifier = OneVsRestClassifier(LogisticRegression(penalty='l1'))
         grid = GridSearchCV(Classifier, tuned parameters, scoring = 'f1 micro',
         cv=3)
         grid.fit(x train multilabel, y train)
In [39]: print(grid.best estimator )
         OneVsRestClassifier(estimator=LogisticRegression(C=1, class weight=Non
         e,
                                                           dual=False, fit interc
         ept=True,
                                                           intercept scaling=1,
                                                           ll ratio=None, max_ite
         r=100,
                                                           multi class='warn',
                                                           n jobs=None, penalty
         ='l1',
                                                           random state=None,
                                                           solver='warn', tol=0.0
```

```
001.
                                                          verbose=0, warm start=
         False),
                             n jobs=None)
In [40]: start = datetime.now()
         classifier = OneVsRestClassifier(estimator=LogisticRegression(C=1.penal
         ty='l1'))
         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(pr
         ecision, 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(pr
         ecision, recall, f1))
         print (metrics.classification report(y test, predictions))
         print("Time taken to run this cell :", datetime.now() - start)
         Accuracy : 0.17252
         Hamming loss 0.00344688
         Micro-average quality numbers
         Precision: 0.5825, Recall: 0.3802, F1-measure: 0.4601
         Macro-average quality numbers
         Precision: 0.4265, Recall: 0.2941, F1-measure: 0.3369
                                    recall f1-score support
                       precision
```

0         0.81         0.67         0.73         2641           1         0.49         0.32         0.39         2585           2         0.31         0.15         0.20         702           3         0.67         0.58         0.62         899           4         0.68         0.51         0.58         1436           5         0.73         0.52         0.60         1087           6         0.64         0.43         0.52         1476           7         0.71         0.58         0.64         827           8         0.86         0.63         0.73         1515           9         0.74         0.68         0.71         1041           10         0.71         0.57         0.63         861           11         0.52         0.35         0.42         245           12         0.58         0.38         0.46         37           13         0.65         0.35         0.46         914           14         0.38         0.22         0.28         460           15         0.55         0.36         0.44         423           16					
2       0.31       0.15       0.20       702         3       0.67       0.58       0.62       899         4       0.68       0.51       0.58       1436         5       0.73       0.52       0.60       1087         6       0.64       0.43       0.52       1476         7       0.71       0.58       0.64       827         8       0.86       0.63       0.73       1515         9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62					
3       0.67       0.58       0.62       899         4       0.68       0.51       0.58       1436         5       0.73       0.52       0.60       1087         6       0.64       0.43       0.52       1476         7       0.71       0.58       0.64       827         8       0.86       0.63       0.73       1515         9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.76       0.42 <td></td> <td></td> <td></td> <td></td> <td></td>					
4       0.68       0.51       0.58       1436         5       0.73       0.52       0.60       1087         6       0.64       0.43       0.52       1476         7       0.71       0.58       0.64       827         8       0.86       0.63       0.73       1515         9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62 <td>2</td> <td></td> <td></td> <td></td> <td></td>	2				
5       0.73       0.52       0.60       1087         6       0.64       0.43       0.52       1476         7       0.71       0.58       0.64       827         8       0.86       0.63       0.73       1515         9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42 <td></td> <td></td> <td></td> <td></td> <td></td>					
6       0.64       0.43       0.52       1476         7       0.71       0.58       0.64       827         8       0.86       0.63       0.73       1515         9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28 <td></td> <td></td> <td></td> <td></td> <td></td>					
7       0.71       0.58       0.64       827         8       0.86       0.63       0.73       1515         9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37 <td></td> <td></td> <td></td> <td></td> <td></td>					
8       0.86       0.63       0.73       1515         9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
9       0.74       0.68       0.71       1041         10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
10       0.71       0.57       0.63       861         11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
11       0.52       0.35       0.42       245         12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
12       0.58       0.38       0.46       37         13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
13       0.65       0.35       0.46       914         14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.64       0.54<					
14       0.38       0.22       0.28       460         15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40<					
15       0.55       0.36       0.44       423         16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
16       0.56       0.20       0.30       792         17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
17       0.57       0.25       0.35       700         18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
18       0.70       0.62       0.66       308         19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
19       0.84       0.62       0.71       541         20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
20       0.49       0.33       0.39       535         21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74					
21       0.79       0.59       0.67       330         22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74					
22       0.76       0.42       0.54       548         23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74					
23       0.46       0.28       0.35       304         24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74					
24       0.50       0.37       0.42       331         25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74					
25       0.46       0.32       0.37       365         26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74	23				
26       0.53       0.28       0.37       292         27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74		0.50			
27       0.26       0.11       0.15       375         28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74	25	0.46		0.37	
28       0.34       0.24       0.28       105         29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74					
29       0.36       0.25       0.30       138         30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74					
30       0.63       0.46       0.54       755         31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74	28			0.28	
31       0.55       0.40       0.46       15         32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74	29	0.36	0.25		
32       0.64       0.58       0.61       223         33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74	30	0.63	0.46	0.54	
33       0.55       0.31       0.40       212         34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74		0.55	0.40	0.46	
34       0.57       0.32       0.41       275         35       0.75       0.56       0.64       230         36       0.16       0.08       0.11       74	32	0.64	0.58	0.61	223
35 0.75 0.56 0.64 230 36 0.16 0.08 0.11 74	33	0.55	0.31	0.40	212
36 0.16 0.08 0.11 74	34	0.57	0.32	0.41	275
	35	0.75	0.56	0.64	
37 0.25 0.17 0.20 236	36	0.16	0.08	0.11	74
	37	0.25	0.17	0.20	236

#### Time taken to run this cell : 0:29:44.224812

```
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in la
bels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l
abels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l
abels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
```

```
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
   'recall', 'true', average, warn_for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in samples with no predicted labels.
   'precision', 'predicted', average, warn_for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in samples with no true labels.
   'recall', 'true', average, warn_for)
```

# 5.2.3 Applying Logistic Regression(SGD with log loss) with hyperparameter tuning

```
In []: from sklearn.model_selection import GridSearchCV
    from sklearn.linear_model import LogisticRegression
    from sklearn.multiclass import OneVsRestClassifier

    tuned_parameters = [{'estimator_alpha': [100, 10, 1, 0.1, 0.01, 0.001, 0.0001]}]

    Classifier = OneVsRestClassifier(SGDClassifier(loss='log', penalty='ll'))

    grid = GridSearchCV(Classifier, tuned_parameters,scoring = 'fl_micro', cv=3)

    grid.fit(x_train_multilabel, y_train)

In [31]: print(grid.best_estimator_)

OneVsRestClassifier(estimator=SGDClassifier(alpha=0.001, average=False, class_weight=None, early_stopping=False, epsil on=0.1,
```

```
eta0=0.0, fit intercept=Tru
         e,
                                                      l1 ratio=0.15.
                                                      learning rate='optimal', lo
         ss='log',
                                                      max iter=1000, n iter no ch
         ange=5,
                                                      n jobs=None, penalty='l1',
                                                      power t=0.5, random state=N
         one,
                                                      shuffle=True, tol=0.001,
                                                      validation fraction=0.1, ve
         rbose=0,
                                                      warm start=False),
                             n jobs=None)
In [34]: start = datetime.now()
         classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001,
          penalty='l1'))
         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(pr
         ecision, 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(pr
```

```
ecision, recall, f1))
print (metrics.classification report(y test, predictions))
print("Time taken to run this cell :", datetime.now() - start)
Accuracy : 0.13604
Hamming loss 0.0037132
Micro-average quality numbers
Precision: 0.5377, Recall: 0.2761, F1-measure: 0.3648
Macro-average quality numbers
Precision: 0.3502, Recall: 0.2047, F1-measure: 0.2364
                           recall f1-score
              precision
                                               support
                   0.85
                             0.64
                                        0.73
                                                  2641
           0
           1
                             0.11
                                        0.19
                                                  2585
                   0.52
                             0.10
                                        0.16
                                                   702
           2
                   0.41
                                                   899
                   0.66
                             0.58
                                        0.62
           4
                   0.79
                                        0.55
                                                  1436
                             0.42
                   0.70
                             0.55
                                        0.62
                                                  1087
                   0.73
                             0.38
                                        0.51
                                                  1476
                   0.76
                             0.56
                                        0.65
                                                   827
           8
                   0.83
                                        0.67
                                                  1515
                             0.56
           9
                   0.85
                             0.15
                                        0.25
                                                  1041
                                        0.21
                                                   861
          10
                   0.69
                             0.12
          11
                   0.61
                             0.42
                                        0.50
                                                   245
          12
                   0.51
                             0.51
                                        0.51
                                                    37
          13
                   0.67
                             0.37
                                        0.48
                                                   914
          14
                   0.46
                             0.10
                                        0.16
                                                   460
          15
                                        0.31
                   0.60
                             0.21
                                                   423
          16
                             0.17
                                        0.27
                                                   792
                   0.61
          17
                             0.12
                                        0.21
                                                   700
                   0.62
          18
                   0.53
                                        0.49
                                                   308
                             0.45
          19
                   0.80
                                        0.70
                                                   541
                             0.62
          20
                   0.50
                             0.15
                                        0.23
                                                   535
          21
                   0.78
                             0.57
                                        0.66
                                                   330
                   0.80
                             0.46
                                        0.58
                                                   548
          22
          23
                                                   304
                   0.24
                             0.35
                                        0.28
          24
                                        0.24
                   0.63
                             0.15
                                                   331
                                        0.26
          25
                   0.40
                             0.19
                                                   365
          26
                             0.30
                                        0.41
                                                   292
                   0.63
```

```
0.25
                                        0.36
         495
                   0.67
                                                      8
                   0.14
                              0.05
                                        0.08
         496
                                                     19
         497
                   0.00
                              0.00
                                        0.00
                                                     72
                   0.25
                              0.13
                                        0.17
                                                     15
         498
                   0.00
                                        0.00
                                                     32
         499
                              0.00
                                                 48283
   micro avq
                   0.54
                              0.28
                                        0.36
                   0.35
                              0.20
                                        0.24
                                                 48283
  macro avq
weighted avg
                                                 48283
                   0.51
                              0.28
                                        0.34
samples avq
                   0.36
                              0.28
                                        0.29
                                                 48283
```

Time taken to run this cell: 0:11:31.703597

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U ndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in la bels with no true samples.

'recall', 'true', average, warn\_for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l abels with no predicted samples.

'precision', 'predicted', average, warn for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l abels with no true samples.

'recall', 'true', average, warn\_for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U ndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true samples.

'recall', 'true', average, warn for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: Precision and F-score are ill-defined and being

set to 0 0 in labels with no predicted samples

```
SEL LU U.U III LADELS WILII IIU PLEUICLEU SAMPLES.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in samples with no true labels.
  'recall', 'true', average, warn for)
```

# 5.2.4 Applying SVM (SGD with hinge loss) with hyperparameter tuning

```
In [ ]: from sklearn.model_selection import GridSearchCV

tuned_parameters = [{'estimator_alpha': [100, 10, 1, 0.1, 0.01, 0.001, 0.0001]}]

Classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', penalty='l 1'))

grid = GridSearchCV(Classifier, tuned_parameters,scoring = 'fl_micro', cv=3)

grid.fit(x_train_multilabel, y_train)
```

```
In [33]: print(grid.best estimator )
         OneVsRestClassifier(estimator=SGDClassifier(alpha=0.001, average=False,
                                                      class weight=None,
                                                      early stopping=False, epsil
         on=0.1,
                                                      eta0=0.0, fit intercept=Tru
         e,
                                                      l1 ratio=0.15,
                                                      learning rate='optimal',
                                                      loss='hinge', max iter=100
         Θ,
                                                      n iter no change=5, n jobs=
         None,
                                                      penalty='l1', power t=0.5,
                                                      random state=None, shuffle=
         True,
                                                      tol=0.001, validation fract
         ion=0.1,
                                                      verbose=0, warm start=Fals
         e),
                             n jobs=None)
In [35]: start = datetime.now()
         classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.00
         1, penalty='l1'))
         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(pr
```

```
ecision, 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(pr
ecision, recall, f1))
print (metrics.classification report(y test, predictions))
print("Time taken to run this cell :", datetime.now() - start)
Accuracy : 0.1424
Hamming loss 0.00361368
Micro-average quality numbers
Precision: 0.5613, Recall: 0.2953, F1-measure: 0.3870
Macro-average quality numbers
Precision: 0.2889, Recall: 0.2076, F1-measure: 0.2178
                           recall f1-score
              precision
                                              support
           0
                             0.63
                                       0.71
                                                  2641
                   0.81
           1
                   0.46
                             0.07
                                       0.13
                                                 2585
                   0.40
                             0.14
                                       0.21
                                                  702
           3
                   0.69
                             0.63
                                       0.66
                                                  899
                   0.77
                             0.39
                                       0.52
                                                 1436
                   0.76
                             0.55
                                       0.64
                                                  1087
                   0.70
                             0.40
                                       0.51
                                                  1476
                   0.77
                             0.60
                                       0.68
                                                  827
           8
                   0.93
                             0.55
                                       0.69
                                                  1515
                                       0.70
           9
                   0.71
                             0.69
                                                  1041
          10
                   0.65
                             0.42
                                       0.51
                                                  861
          11
                                       0.48
                                                  245
                   0.47
                             0.49
          12
                   0.22
                                       0.31
                                                   37
                             0.51
          13
                   0.69
                             0.35
                                       0.47
                                                  914
          14
                   0.50
                                       0.02
                                                  460
                             0.01
          15
                   0.72
                             0.29
                                       0.41
                                                  423
          16
                   0.51
                             0.16
                                       0.24
                                                  792
          17
                   0.69
                             0.11
                                       0.19
                                                   700
          18
                   0.58
                             0.41
                                       0.48
                                                  308
                             ^ ^^
```

	TU /	0.00	0.00	0.00	J.1
	488	0.00	0.00	0.00	10
	489	0.44	0.19	0.27	21
	490	0.08	0.08	0.08	12
	491	0.00	0.00	0.00	12
	492	0.00	0.00	0.00	11
	493	0.23	0.44	0.30	25
	494	0.00	0.00	0.00	10
	495	0.57	0.50	0.53	8
	496	0.25	0.21	0.23	19
	497	0.00	0.00	0.00	72
	498	0.29	0.33	0.31	15
	499	0.00	0.00	0.00	32
micro	avg	0.56	0.30	0.39	48283
macro	avg	0.29	0.21	0.22	48283
weighted	avg	0.47	0.30	0.34	48283
samples	avg	0.39	0.29	0.31	48283

Time taken to run this cell: 0:09:46.105604

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U ndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in la bels with no true samples.

'recall', 'true', average, warn for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l abels with no predicted samples.

'precision', 'predicted', average, warn\_for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U ndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in l abels with no true samples.

'recall', 'true', average, warn for)

C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U ndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.

```
'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in labels with no true samples.
  'recall', 'true', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1437: U
ndefinedMetricWarning: Precision and F-score are ill-defined and being
set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn for)
C:\Anaconda\lib\site-packages\sklearn\metrics\classification.py:1439: U
ndefinedMetricWarning: Recall and F-score are ill-defined and being set
to 0.0 in samples with no true labels.
  'recall', 'true', average, warn for)
```

### 5.3 Observations

- 1. Used 4 gram bag of words to prepare train and test data
- 2. Logistic regression without hyperparameter tuning gives F1 score of 0.4600
- 3. Logistic regression with hyperparameter tuning gives F1 score of 0.4601
- 4. Logistic regression with hyperparameter tuning gives best F1 score

- 5. SGD Classifier(with hyperparameter tuning) with log loss and hinge loss gives F1 score of 0.3648 and 0.3870
- 6. Results may improve if we use more data points, compared the results with pretty library

```
In [45]: from prettytable import PrettyTable
        x = PrettyTable(["Model", "F1 Score"])
        x.add row(["Logistic Regression","0.4600"])
        x.add row(["Logistic Regression with hyperparameter tuning", "0.4601"])
        x.add row(["Logistic Regression(SGD with log loss) with hyperparameter
         tuning", "0.3648"])
        x.add row(["Linear SVM(SGD with hinge loss) with hyperparameter tuning"
         ,"0.3\overline{6}48"])
        print(x)
                                      Model
                                                                        l F
        1 Score I
                   -----
                                Logistic Regression
        0.4600
                   Logistic Regression with hyperparameter tuning
        0.4601
          Logistic Regression(SGD with log loss) with hyperparameter tuning |
        0.3648
              Linear SVM(SGD with hinge loss) with hyperparameter tuning
        0.3648 I
```