

```
In [1]: import warnings
        warnings.filterwarnings("ignore")
        import pandas as pd
        pd.set option('display.max colwidth',100)
        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
        os.chdir('./Dataset/')
        from sqlalchemy import create engine # database connection
        import datetime as dt
        import nltk
        from nltk.corpus import stopwords
        nltk.download('stopwords')
        nltk.download('punkt')
        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 fl 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
from sklearn.model selection import GridSearchCV
[nltk data] Downloading package stopwords to
[nltk data] /home/rushabh6792/nltk data...
[nltk data] Package stopwords is already up-to-date!
[nltk data] Downloading package punkt to
[nltk data] /home/rushabh6792/nltk data...
[nltk data]
             Package punkt is already up-to-date!
```

Stack Overflow: Tag Prediction

1. Business Problem

1.1 Description

Description

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

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

Problem Statemtent

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

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

1.2 Source / useful links

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

Youtube: https://youtu.be/nNDqbUhtIRq

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

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

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

1.3 Real World / Business Objectives and Constraints

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

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

2. Machine Learning problem

2.1 Data

2.1.1 Data Overview

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

All of the data is in 2 files: Train and Test.

Train.csv contains 4 columns: Id, Title, Body, Tags.

Test.csv contains the same columns but without the Tags, which 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
                   for(int l=1; l<=i; l++)\n
                   {\n
                       if(l!=1)\n
                        {\n
                            cout<<a[l]<<"\\t";\n
                       }\n
                   }\n
                   for(int j=0; j<4; j++)\n
                   {\n
```

```
cout<<e[i][j];\n
                           for(int k=0; k<n-(i+1); k++)\n
                           {\n
                               cout<<a[k]<<"\\t";\n
                           }\n
                           cout<<"\\n";\n
                       }\n
                         n\n
                    system("PAUSE");\n
                    return 0;
                               \n
           }\n
n\n
The answer should come in the form of a table like
n\n
           1
                        50
                                        50\n
           2
                        50
                                        50\n
           99
                        50
                                        50\n
           100
                        50
                                        50\n
           50
                        1
                                        50\n
           50
                        2
                                        50\n
           50
                        99
                                        50\n
           50
                        100
                                        50\n
           50
                        50
                                        1\n
           50
                        50
                                        2\n
           50
                        50
                                        99\n
```

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

2.2.1 Type of Machine Learning Problem

It is a multi-label classification problem

Multi-label Classification: Multilabel classification assigns to each sample a set of target labels. This can be thought as predicting properties of a data-point that are not mutually exclusive, such as topics that are relevant for a document. A question on Stackoverflow might be about any of C, Pointers, FileIO and/or memory-management at the same time or none of these.

__Credit__: http://scikit-learn.org/stable/modules/multiclass.html

2.2.2 Performance metric

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

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

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

'Micro f1 score':

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

'Macro f1 score':

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

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

Hamming loss: The Hamming loss is the fraction of labels that are incorrectly predicted. https://www.kaggle.com/wiki/HammingLoss

3. Exploratory Data Analysis

3.1 Data Loading and Cleaning

3.1.1 Using Pandas with SQLite to Load the data

```
In [2]: |#Creating db file from csv
        #Learn SOL: 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 [3]: if os.path.isfile('train.db'):
            start = datetime.now()
            con = sqlite3.connect('train.db')
            num_rows = pd.read_sql_query("""SELECT count(*) FROM data""", con)
            #Always remember to close the database
            print("Number of rows in the database :","\n",num rows['count(*)'].
        values[0])
            con.close()
            print("Time taken to count the number of rows :", datetime.now() -
        start)
        else:
            print("Please download the train.db file from drive or run the abov
        e cell to genarate train.db file")
        Number of rows in the database :
         6034196
        Time taken to count the number of rows: 0:01:41.252723
```

3.1.3 Checking for duplicates

```
In [4]: #Learn SQl: https://www.w3schools.com/sql/default.asp
          if os.path.isfile('train.db'):
               start = datetime.now()
               con = sqlite3.connect('train.db')
               df no dup = pd.read sql query('SELECT Title, Body, Tags, COUNT(*) 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: 0:02:49.410350
In [5]: df no dup.head()
          # we can observe that there are duplicates
Out[5]:
                                             Title
                                                                                                   Bod<sup>1</sup>
               Implementing Boundary Value Analysis of
                                                   <code>#include&lt;iostream&gt;\n#include&lt;stdlib.h&gt;\n\nusin
                    Software Testing in a C++ program?
                                                                                 namespace std;\n\nint mai.
                                                     I should do binding for datagrid dynamically at code. I wrote
                Dynamic Datagrid Binding in Silverlight?
                                                                           the code as below. When I debug.
                                                     I should do binding for datagrid dynamically at code. I wrote
                Dynamic Datagrid Binding in Silverlight?
                                                                           the code as below. When I debug.
                     java.lang.NoClassDefFoundError:
                                                                                I followed the guide in <</p>
              javax/servlet/jsp/tagext/TagLibraryValidator
                                                    href="http://stackoverflow.com/tags/jstl/info">this link</a> to in.
                java.sql.SQLException:[Microsoft][ODBC
                                                           I use the following code\n\n<code>try {\
                 Driver Manager] Invalid descriptor index
                                                                   Class.forName("sun.jdbc.odbc.JdbcOdbcDr.
```

```
print("number of duplicate questions :", num_rows['count(*)'].values[0]
In [6]:
          - df no dup.shape[0], "(",(1-((df no dup.shape[0])/(num rows['count(*)'
          ].values[0])))*100,"% )")
          number of duplicate questions: 1827881 ( 30.292038906260256 % )
In [7]: # number of times each question appeared in our database
          df no dup.cnt dup.value counts()
Out[7]: 1
                2656284
                1272336
          3
                 277575
                       90
          5
                      25
          6
          Name: cnt dup, dtype: int64
          df no dup[df no dup.isnull().any(axis=1)]
In [8]:
Out[8]:
                                            Title
                                                                               Body Tags cnt_dup
                                                      777547
                           Do we really need NULL?
                                                            Duplicate:</strong><br>\n <a
                                                                                    None
                                                          href="http://stackoverflow.com...
                                                     I am running into a problem which
                    Find all values that are not null and
            962680
                                                    results in an ORA-01722 error. I have a None
                                                                                                 1
                                not in another table
                                                                    table that contain...
                                                   I have done guite a bit of research on
           1126558
                                Handle NullObjects
                                                   best ways to deal with null objects.\nThe None
                                                                        best I came ...
                                                    In german null means 0, so how do
                           How do Germans call null
           1256102
                                                   they call null (like null reference) ?\n
                         Page cannot be null. Please
                                                         I get this error when i remove
                     ensure that this operation is being
           2430668
                                                    dynamically telerik raddock and raddock None
                    performed in the context of an A...
                                                                zone controls and add...
```

<pre>In [9]: df_no_dup = df_no_dup[~df_no_dup.isnull().any(axis=1)] In [10]: start = datetime.now() df_no_dup["tag_count"] = df_no_dup["Tags"].apply(lambda text: len(text.split(" "))) # adding a new feature number of tags per question print("Time taken to run this cell :", datetime.now() - start) df_no_dup.head() Time taken to run this cell : 0:00:03.162973</pre> Out[10]: Title Bo			Title	Body	Tags	cnt_dup					
In [9]: df_no_dup = df_no_dup[~df_no_dup.isnull().any(axis=1)] In [10]: start = datetime.now() df_no_dup["tag_count"] = df_no_dup["Tags"].apply(lambda text: len(text.split(""))) # adding a new feature number of tags per question print("Time taken to run this cell :", datetime.now() - start) df_no_dup.head() Time taken to run this cell : 0:00:03.162973 Out[10]: In [10]: start = datetime.now() df_no_dup["tag_count"] = df_no_dup["Tags"].apply(lambda text: len(text.split(""))) # adding a new feature number of tags per question print("Time taken to run this cell :", datetime.now() - start) df_no_dup.head() Time taken to run this cell : 0:00:03.162973 Out[10]: Out[10]: Out[10]: Out[10]: Title Dynamic Datagrid Binding in Silverlight? Software Testing in a C++ program? The code as below. When I debute the code as below.		3329908		"0"?\n\nExample:\n\n <pre></pre>	None	1					
In [10]: start = datetime.now() df_no_dup["tag_count"] = df_no_dup["Tags"].apply(lambda text: len(text.split(" "))) # adding a new feature number of tags per question print("Time taken to run this cell : ", datetime.now() - start) df_no_dup.head() Time taken to run this cell : 0:00:03.162973 Out[10]: Title Bo Implementing Boundary Value Analysis of Software Testing in a C++ program? 1 Dynamic Datagrid Binding in Silverlight? * Code>#include⁢iostream>\n#include⁢stdlib.h>\n\n\n\n\n\n\n\n\n\n\n\n\n\n\n\n\n\n\n		3551595		quote\n\n <blockquote>\n And don't</blockquote>	None	2					
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 : 0:00:03.162973 Out[10]: Title Bo Implementing Boundary Value Analysis of Software Testing in a C++ program?	In [9]:	df_no_d	up = df_no_dup[~df_no_du	up.isnull().any(axis=1)]							
Out [10]: Title Bo Implementing Boundary Value Analysis of Software Testing in a C++ program? Code>#include <iostream>\n#include<stdlib.h>\n\nus namespace std;\n\nint material and state of the code as below. When I debut Title Out [10]: Code>#include<iostream>\n#include<stdlib.h>\n\nus namespace std;\n\nint material and state of the code as below. When I debut Title Out [10]: Code>#include<iostream>\n#include<stdlib.h>\n\nus namespace std;\n\nint material and state of the code as below. When I debut Code>#include<iostream>\n#include<stdlib.h>\n\nus namespace std;\n\nint material and state of the code as below. When I debut Code>#include<iostream>\n#include<stdlib.h>\n\nus namespace std;\n\nint material and state of the code as below. When I debut Code>#include<iostream>\n#include<stdlib.h>\n\nint material and state of the code as below. When I debut Code>#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#include<iostream>\n#in</iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></iostream></stdlib.h></iostream></stdlib.h></iostream></stdlib.h></iostream></stdlib.h></iostream></stdlib.h></iostream></stdlib.h></iostream>		<pre>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)</pre>									
Implementing Boundary Value Analysis of Software Testing in a C++ program?		lime ta	ken to run this cell : 0	1:00:03.1629/3							
 1 Dynamic Datagrid Binding in Silverlight? 2 Dynamic Datagrid Rinding in Silverlight? 1 Software Testing in a C++ program? 2 Code>#include<iostream>\n#include<stdlib.h>\n\nus namespace std;\n\nint material code. I wrote the code as below. When I debute the code as below. When I debute the code as below. When I debute the code as below. I wrote the code as below. 	out[10]:			Bod							
the code as below. When I debute the code as below.											
		1 Dyn	namic Datagrid Binding in Silverlight?								
		2 Dyn	namic Datagrid Binding in Silverlight?								
java.lang.NoClassDefFoundError: sp> followed the guide in javax/servlet/jsp/tagext/TagLibraryValidator href="http://stackoverflow.com/tags/jstl/info">this link to i		3 javax/s									
java.sql.SQLException:[Microsoft][ODBC I use the following code\n\n <pre>pre><code>try</code></pre>											

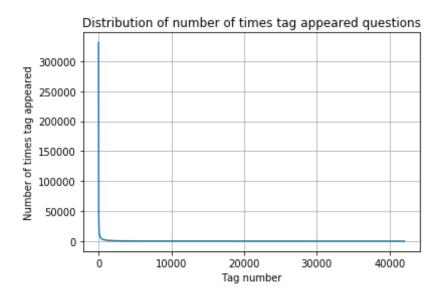
```
In [11]: # distribution of number of tags per question
         df no dup.tag count.value counts()
Out[11]: 3
              1206157
              1111706
         4
              814996
         1
               568291
         5
               505158
         Name: tag count, dtype: int64
In [12]: #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 [13]: #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 = sglite3.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: 0:00:50.063605
```

3.2 Analysis of Tags

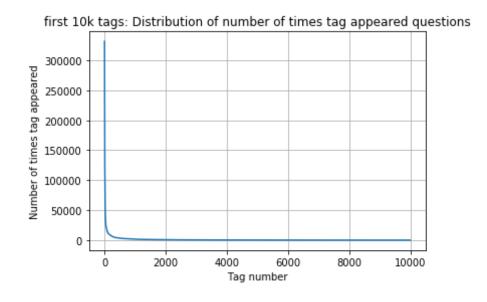
3.2.1 Total number of unique tags

```
In [14]: # 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 [15]: print("Number of data points :", tag dtm.shape[0])
         print("Number of unique tags :", tag dtm.shape[1])
         Number of data points : 4206307
         Number of unique tags: 42048
In [16]: #'get feature name()' gives us the vocabulary.
         tags = vectorizer.get feature names()
         #Lets look at the tags we have.
         print("Some of the tags we have :", tags[:10])
         Some of the tags we have : ['.a', '.app', '.asp.net-mvc', '.aspxauth',
         '.bash-profile', '.class-file', '.cs-file', '.doc', '.drv', '.ds-stor
         e']
         3.2.3 Number of times a tag appeared
In [17]: # 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 [18]: #Saving this dictionary to csv files.
         if not os.path.isfile('tag counts dict dtm.csv'):
              with open('tag counts dict dtm.csv', 'w') as csv file:
                 writer = csv.writer(csv file)
                  for key, value in result.items():
                      writer.writerow([key, value])
         tag df = pd.read csv("tag counts dict dtm.csv", names=['Tags', 'Counts'
         tag df.head()
Out[18]:
                        Tags Counts
          0 hyper-v-server-2008-r2
                                223
                                 2
                        rmail
             django-generic-views
                                109
                       asm.js
                       menhir
In [19]: tag df sorted = tag df.sort values(['Counts'], ascending=False)
         tag counts = tag df sorted['Counts'].values
In [20]: 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()
```



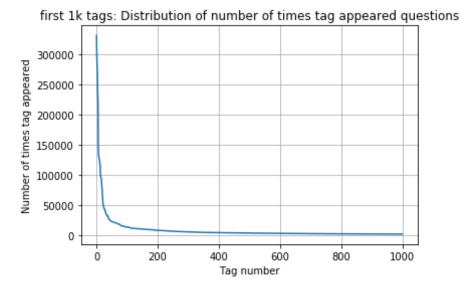
```
In [21]: plt.plot(tag_counts[0:10000])
   plt.title('first 10k tags: Distribution of number of times tag appeared
        questions')
   plt.grid()
   plt.xlabel("Tag number")
   plt.ylabel("Number of times tag appeared")
   plt.show()
   print(len(tag_counts[0:10000:25]), tag_counts[0:10000:25])
```



400 151	[3315	505 4	4829	22429	17728	13364	11162	10029	9148	805	54 7
	6466	5865	537	0 49	983 4	526 42	281 41	L44 3	929 3	3750	3593
	3453	3299									2331
	2259	2186	209	7 20	920 1	959 19	000 18	328 1	.770	1723	1673
	1631	1574	153	2 14	479 1	448 14	06 13	365 1	.328	1300	1266
	1245	1222	119	7 1	181 1	158 11	.39 11	L21 1	.101	1076	1056
	1038	1023	100	6 9	983	966 9	52	938	926	911	891
	882	869	85	6 8	841	830 8	316 8	304	789	779	770
	752	743						886	678	671	658
	650	643						598	589	583	577
	568	559						526	518	512	506
	500	495		_				169	465	457	450
	447	442				_		118	413	408	403
	398	393						374	370	367	365
	361	357						342	339	336	332
	330	326						309	307	304	301
	299	296						284	281	278	276
	275	272						260	258	256	254
	252	250						241	239	238	236
	234	233	23	52 .	230	228 2	226 2	224	222	220	219

217	215	214	212	210	209	207	205	204	203
201	200	199	198	196	194	193	192	191	189
188	186	185	183	182	181	180	179	178	177
175	174	172	171	170	169	168	167	166	165
164	162	161	160	159	158	157	156	156	155
154	153	152	151	150	149	149	148	147	146
145	144	143	142	142	141	140	139	138	137
137	136	135	134	134	133	132	131	130	130
129	128	128	127	126	126	125	124	124	123
123	122	122	121	120	120	119	118	118	117
117	116	116	115	115	114	113	113	112	111
111	110	109	109	108	108	107	106	106	106
105	105	104	104	103	103	102	102	101	101
100	100	99	99	98	98	97	97	96	96
95	95	94	94	93	93	93	92	92	91
91	90	90	89	89	88	88	87	87	86
86	86	85	85	84	84	83	83	83	82
82	82	81	81	80	80	80	79	79	78
78	78	78	77	77	76	76	76	75	75
75	74	74	74	73	73	73	73	72	72]

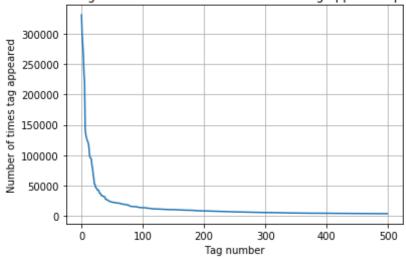
```
In [22]: plt.plot(tag_counts[0:1000])
   plt.title('first 1k tags: Distribution of number of times tag appeared
        questions')
   plt.grid()
   plt.xlabel("Tag number")
   plt.ylabel("Number of times tag appeared")
   plt.show()
   print(len(tag_counts[0:1000:5]), tag_counts[0:1000:5])
```



200 [33 537	1505 221	533 122	769 95	160 62	2023 4	14829	371	70 3	1897	26925	5 24
22429	21820	20957	19758	18905	17728	3 155	33	15097	1488	4 13	3703
13364	13157	12407	11658	11228	11162	2 108	63	10600	1035	0 10)224
10029	9884	9719	9411	9252	9148	3 90	40	8617	836	1 8	3163
8054	7867	7702	7564	7274	715	1 70	52	6847	665	6 6	5553
6466	6291	6183	6093	5971	5865	5 57	60	5577	549	0 5	5411
5370	5283	5207	5107	5066	4983	3 48	91	4785	465	8 4	1549
4526	4487	4429	4335	4310	4282	1 42	39	4228	419	5 4	159
4144	4088	4050	4002	3957	3929	9 38	74	3849	381	.8 3	3797
3750	3703	3685	3658	3615	3593	35	64	3521	350	5 3	3483
3453	3427	3396	3363	3326	3299	9 32	72	3232	319	6 3	3168
3123	3094	3073	3050	3012	2986		83	2953			2903
2891	2844	2819	2784	2754	2738		26	2708			2669
2647	2621	2604	2594	2556	2527	7 25	10	2482			2444
2431	2409	2395	2380	2363	233		12	2297	229		2281
2259	2246	2222	2211	2198	2186	5 21	62	2142	213	2 2	2107
2097	2078	2057	2045	2036	2020		11	1994			.965
1959		1940	1932	1912	1900		79	1865			.841
1828		1813	1801	1782	1770		60	1747	174		.734
1723	1707	1697	1688	1683	1673	3 16	65	1656	164	6 1	.639]

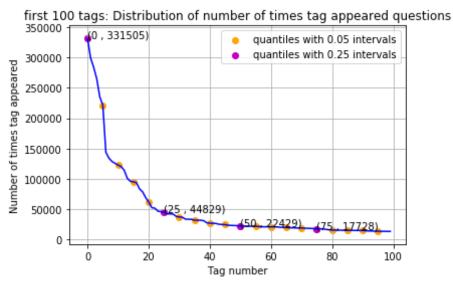
```
In [23]: plt.plot(tag_counts[0:500])
   plt.title('first 500 tags: Distribution of number of times tag appeared
        questions')
   plt.grid()
   plt.xlabel("Tag number")
   plt.ylabel("Number of times tag appeared")
   plt.show()
   print(len(tag_counts[0:500:5]), tag_counts[0:500:5])
```

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



100 [331	505 221	533 122	769 95	160 62	023 44	1829 37	170 31	.897 26	925 24
537									
22429	21820	20957	19758	18905	17728	15533	15097	14884	13703
13364	13157	12407	11658	11228	11162	10863	10600	10350	10224
10029	9884	9719	9411	9252	9148	9040	8617	8361	8163
8054	7867	7702	7564	7274	7151	7052	6847	6656	6553
6466	6291	6183	6093	5971	5865	5760	5577	5490	5411
5370	5283	5207	5107	5066	4983	4891	4785	4658	4549
4526	4487	4429	4335	4310	4281	4239	4228	4195	4159
4144	4088	4050	4002	3957	3929	3874	3849	3818	3797
3750	3703	3685	3658	3615	3593	3564	3521	3505	3483]

```
In [24]: 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

```
In [25]: # 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 [26]: #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])
```

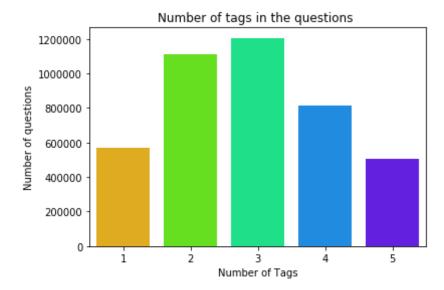
We have total 4206307 datapoints.

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

```
In [27]: 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: 2.899443

```
In [28]: 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()
```



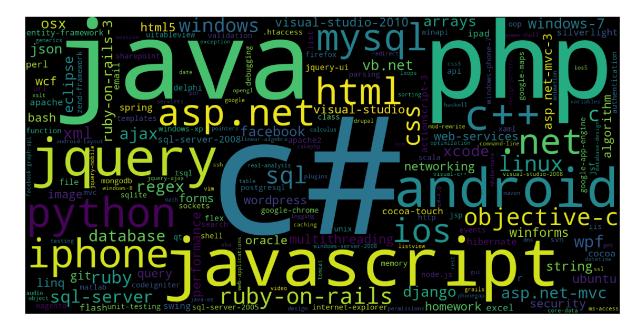
Observations:

- 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 [29]: # 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)
```



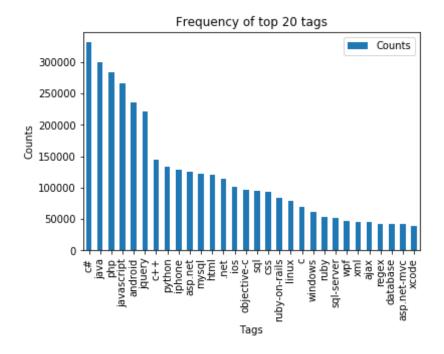
Time taken to run this cell: 0:00:04.672499

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 [30]: 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 [31]: def striphtml(data):
             cleanr = re.compile('<.*?>')
             cleantext = re.sub(cleanr, ' ', str(data))
             return cleantext
         stop words = set(stopwords.words('english'))
         stemmer = SnowballStemmer("english")
In [32]: #http://www.sqlitetutorial.net/sqlite-python/create-tables/
         def create connection(db file):
             """ create a database connection to the SQLite database
                 specified by db file
             :param db file: database file
             :return: Connection object or None
             try:
                 conn = sqlite3.connect(db file)
                 return conn
             except Error as e:
                 print(e)
             return None
         def create table(conn, create table sql):
             """ create a table from the create table sql statement
             :param conn: Connection object
             :param create table sql: a CREATE TABLE statement
             :return:
             try:
                 c = conn.cursor()
                 c.execute(create table sql)
             except Error as e:
```

```
print(e)
         def checkTableExists(dbcon):
             cursr = dbcon.cursor()
             str = "select name from sqlite master where type='table'"
             table names = cursr.execute(str)
             print("Tables in the databse:")
             tables =table names.fetchall()
             print(tables[0][0])
             return(len(tables))
         def create database table(database, 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 [33]: # 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
```

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

Tables in the databse: QuestionsProcessed Cleared All the rows Time taken to run this cell: 0:00:30.674447

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

```
In [34]: #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 question:
        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)
         Avg. length of questions(Title+Body) before processing: 1173
         Avg. length of questions(Title+Body) after processing: 327
         Percent of questions containing code: 57
         Time taken to run this cell: 0:02:25.423838
In [35]: # 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 [36]: #Taking 1 Million entries to a dataframe.
         write db = 'Processed.db'
         if os.path.isfile(write db):
             conn r = create connection(write db)
             if conn r is not None:
                 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
         ('check variabl type primit mayb question bit stupid know check variabl
         primit java like thank',)
         (Inst missingmethodoxsont assur and thousand and usar machin insight is
```

(net missingmethodexcept occur one thousand end user machin insight is su baffl affect singl user knowledg reproduc us user receiv missingmeth odexcept trace file indic occur creat new instanc compon call initi set up method prepar work initializeworkerbyargu exampl method specifi erro r interfac method base class implement class deriv base class overrid n eed user latest releas applic provid code ship within singl assembl dis til version compon',) ('updat listview delet oper display data pull android os sqlite databas success get item delet click howev issu refresh updat listview oper cod e delet contact updatelist method includ method three way tri refresh n one work idea might achiev edit chang code think would solut work eithe r dbadapt class delet method getallcontactslist thought get new cursor delet contact would updat list accord unfortun made differ idea',) ('specifi visual studio instal condit visual studio instal project want instal creat specif folder check box checkbox form ad project ui check name properti checkbox checkboxa idea put condit properti folder get cr eat checkbox check',) ('stop black box oper use asynchron deleg invok method load xml file xp athdocu xml big fit memori never finish load code work xml file success

load xpathdocu abl use timer event execut asyncxpath endinvok result st atement work end createdocu method stop xpathdocu load conclus thing is su applic end statement kill applic anyon know stop blackbox oper load

xpathdocu',)

('mirror drive extent found plex instal window ultim system two disk dr ive window partit disk mb system reserv rest c incl boot page file cras h dump want mirror disk setup disk mirror disk window softwar raid chan g disk dynam disk add mirror disk surpris grab hunk disk mirror c mirro r mb system well good disk die want abl boot disk put new disk resync b ack busi minimum fuss click system reserv partit say add mirror ask sel ect disk select disk give error extent found plex disk look like though t mayb round issu perhap even shrink system reserv mb still give error disk complet mirror disk disk die disk readi run',)

('jqueri pagin plugin asp net gridview implement pagin asp gridview num ber record retriev databas use jqueri pagin plug implement',) ('apach ubuntu return known caus note question resolv pleas see solut c ase similar issu background php mysql base databas driven applic make h eavi use ajax near request server occur way request get request instanc server respond via ison user work inward data set return finer finer re sult applic stabl product abil debug platform develop laptop osx hous u buntu server product ubuntu server ubuntu server run mysql server copi apach develop laptop connect mysql server run hous ubuntu server run ap ach server ubuntu server fulli date via offici sourc apach php fun part applic return result correct case except one subsect data set request d ata within subsect alway return instead result set subsect guestion mer e queri return result base known id record known exist contain corrupt data debug log turn apach set php log file occur see follow apach error log mask impli lack data howev error log php error log whatsoev time re turn result elsewher data set issu might think problem must databas how ev use develop laptop copi apach connect mysql server hous network run request generat error run applic apach server laptop everyth cool perfo rm request data within databas databas server instead use server local copi apach fail utter baffl help would great appreci point',) ('remov work copi creat via git new workdir without hose origin repo us e git new workdir script present contrib section git codebas https gith ub com git git tree master contrib workdir work multipl branch code bas e simultan window use msysgit repo git svn repo pure git ni problem cre at work copi use command say longer interest branch want get rid work c opi also hose origin work copi hind sight kinda obvious given git new w orkdir use hard link share git repo multipl work copi good way clean wo rk copi creat way longer want machin',)

In [37]: 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()
           preprocessed data.head()
In [38]:
Out[38]:
                                                                 question
                                                                                                tags
               inherit parent constructor argument brows discuss similar topic find situat
                                                                                   javascript inheritance
                                                        tri call parent cons...
                                                                                  constructor arguments
                  check variabl type primit mayb question bit stupid know check variabl
            1
                                                                                              python
                                                        primit java like thank
                 net missingmethodexcept occur one thousand end user machin insight
                                                                                         .net exception
                                                   issu baffl affect singl user ...
                                                                                missingmethodexception
                    updat listview delet oper display data pull android os sqlite databas
            3
                                                                            android sqlite android-listview
                                                   success get item delet cli...
                 specifi visual studio instal condit visual studio instal project want instal
                                                                             visual-studio-2008 windows-
                                                         creat specif folder...
                                                                                             installer
           print("number of data points in sample :", preprocessed data.shape[0])
In [39]:
           print("number of dimensions :", preprocessed data.shape[1])
           number of data points in sample: 99999
           number of dimensions: 2
           4. Machine Learning Models
           global report = pd.DataFrame(columns=['Vectorizer', 'Model', 'NGram',
            'Parameter', 'Precision', 'Recall', 'F1 Score Micro'])
```

4.1 Converting tags for multilabel problems

```
    X
    y1
    y2
    y3
    y4

    x1
    0
    1
    1
    0

    x1
    1
    0
    0
    0

    x1
    0
    1
    0
    0
```

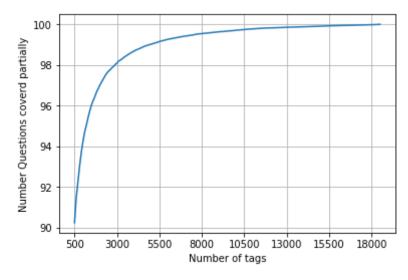
```
In [41]: # binary='true' will give a binary vectorizer
  vectorizer = CountVectorizer(tokenizer = lambda x: x.split(), binary='t
    rue')
  multilabel_y = vectorizer.fit_transform(preprocessed_data['tags'])
```

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

```
In [42]: 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 [44]: fig, ax = plt.subplots()
    ax.plot(questions_explained)
    xlabel = list(500+np.array(range(-50,450,50))*50)
    ax.set_xticklabels(xlabel)
    plt.xlabel("Number of tags")
    plt.ylabel("Number Questions coverd partially")
    plt.grid()
    plt.show()
    # you can choose any number of tags based on your computing power, minimun is 50(it covers 90% of the tags)
    print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
```



with 5500 tags we are covering 99.154 % of questions

```
In [45]: 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 : 846 out of 99999

```
In [46]: print("Number of tags in sample :", multilabel_y.shape[1])
print("number of tags taken :", multilabel_yx.shape[1],"(",(multilabel_
```

```
yx.shape[1]/multilabel_y.shape[1])*100,"%)")

Number of tags in sample : 18587
number of tags taken : 5500 ( 29.59057405713671 %)
```

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

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

```
In [47]: 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 [48]: print("Number of data points in train data :", y_train.shape)
print("Number of data points in test data :", y_test.shape)
```

Number of data points in train data : (79999, 5500) Number of data points in test data : (20000, 5500)

4.3 Featurizing data

```
In [50]: # print("Dimensions of train data X:",x train multilabel.shape, "Y:",y
          train.shape)
         # print("Dimensions of test data X:",x test multilabel.shape,"Y:",y tes
         t.shape)
In [51]: # 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)
Out[51]: "\nfrom skmultilearn.adapt import MLkNN\nclassifier = MLkNN(k=21)\n\n#
         train\nclassifier.fit(x train multilabel, y train)\n\n# predict\npredic
         tions = classifier.predict(x test multilabel)\nprint(accuracy score(y t
         est,predictions))\nprint(metrics.fl score(y test, predictions, average
         = 'macro'))\nprint(metrics.fl score(y test, predictions, average = 'mic
```

4.4 Applying Logistic Regression with OneVsRest Classifier

```
In [52]: # # this will be taking so much time try not to run it, download the lr
         with equal weight.pkl file and use to predict
         # # This takes about 6-7 hours to run.
         # classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00
         001, penalty='l1'), n jobs=-1)
         # classifier.fit(x train multilabel, y train)
         # predictions = classifier.predict(x test multilabel)
         # print("accuracy :", metrics.accuracy score(y test, predictions))
         # print("macro f1 score :", metrics.f1 score(v test, predictions, averag
         e = 'macro'))
         # print("micro f1 scoore :", metrics.f1 score(y test, predictions, avera
         ge = 'micro'))
         # print("hamming loss:", metrics.hamming loss(y test, predictions))
         # print("Precision recall report :\n", metrics.classification report(y t
         est, predictions))
In [53]: # from sklearn.externals import joblib
```

```
# joblib.dump(classifier, 'lr with equal weight.pkl')
```

4.5 Modeling with less data points (0.15M data points) and more weight to title and 500 tags only.

```
In [54]: | 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("Titlemoreweight.db", sql create table)
```

Tables in the databse: **OuestionsProcessed**

```
In [55]: # http://www.sqlitetutorial.net/sqlite-delete/
         # https://stackoverflow.com/questions/2279706/select-random-row-from-a-
         sqlite-table
         read db = 'train no dup.db'
         write db = 'Titlemoreweight.db'
         # train datasize = 100000
         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 150001;")
                 # 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: QuestionsProcessed Cleared All the rows

4.5.1 Preprocessing of questions

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

- 4. Remove stop words (Except 'C')
- 5. Remove HTML Tags
- 6. Convert all the characters into small letters
- 7. Use SnowballStemmer to stem the words

```
In [56]: #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 guestion:
                 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: 1222
Avg. length of questions(Title+Body) after processing: 430
```

```
Percent of questions containing code: 57
Time taken to run this cell: 0:05:33.648006
```

```
In [57]: # 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 [58]: 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 taglibraryvalid java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryv

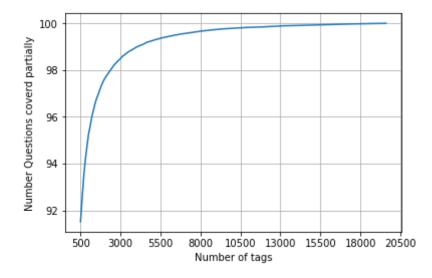
juvarianginociassacirounaciroi juvan scrvice jsp tagent tagitariyv alid follow guid link instal jstl got follow error tri launch jsp page java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid taglib declar instal jstl 1.1 tomcat webapp tri project work also tri v ersion 1.2 jstl still 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 wav 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 q 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 lebesgu measur countabl subaddit lebesgu measur cou ntabl subaddit lebesqu 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 hal 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 [59]: #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 [60]: preprocessed data.head()

```
Out[60]:
                                                                     question
                                                                                                tags
               dynam datagrid bind silverlight dynam datagrid bind silverlight dynam datagrid
                                                                                c# silverlight data-binding
                                                               bind silverlight ...
               dynam datagrid bind silverlight dynam datagrid bind silverlight dynam datagrid
                                                                                c# silverlight data-binding
                                                               bind silverlight ...
                                                                                             columns
                      java.lang.noclassdeffounderror javax servlet jsp tagext taglibraryvalid
                                                                                              isp istl
                                                       java.lang.noclassdeffoun...
                     java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index
            3
                                                                                            java jdbc
                                                        java.sql.sqlexcept micro...
                better way updat feed fb php sdk better way updat feed fb php sdk better way
                                                                                 facebook api facebook-
                                                            updat feed fb php s...
                                                                                             php-sdk
           print("number of data points in sample :", preprocessed data.shape[0])
In [61]:
           print("number of dimensions :", preprocessed data.shape[1])
           number of data points in sample : 150000
           number of dimensions : 2
           Converting string Tags to multilable output variables
           vectorizer = CountVectorizer(tokenizer = lambda x: x.split(), binary='t
In [62]:
            rue')
           multilabel y = vectorizer.fit transform(preprocessed data['tags'])
           Selecting 500 Tags
           questions explained = []
In [63]:
           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 [64]: 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],"% of questions")
print("with ",500,"tags we are covering ",questions_explained[0],"% of questions")
```



with 5500 tags we are covering 99.363 % of questions with 500 tags we are covering 91.515 % of questions

```
In [65]: # 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 : 12728 out of 150000

```
In [66]: preprocessed data.shape
Out[66]: (150000, 2)
In [67]: train datasize=120000
         x train=preprocessed data.head(train datasize)
         x test=preprocessed data.tail(preprocessed data.shape[0] - train datasi
         ze)
         y train = multilabel yx[0:train datasize,:]
         y test = multilabel yx[train datasize:preprocessed data.shape[0],:]
         print("Number of data points in y train data :", y train.shape)
In [68]:
         print("Number of data points in y test data :", y test.shape)
         print("Number of data points in x train data :", x train.shape)
         print("Number of data points in x test data :", x test.shape)
         Number of data points in y train data: (120000, 500)
         Number of data points in v test data: (30000, 500)
         Number of data points in x train data: (120000, 2)
         Number of data points in x test data : (30000, 2)
         4.5.2 Featurizing data with Tfldf vectorizer
In [69]: 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 : 0:01:49.784085
In [70]: 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)

Dimensions of train data X: (120000, 101362) Y: (120000, 500)
Dimensions of test data X: (30000, 101362) Y: (30000, 500)
```

4.5.3 Applying Logistic Regression with OneVsRest Classifier

```
In [71]: start = datetime.now()
         classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0000
         1, penalty='l1'), n jobs=-1)
         classifier.fit(x train multilabel, y train)
         predictions = classifier.predict (x test multilabel)
         print("Accuracy :",metrics.accuracy score(y test, predictions))
         print("Hamming loss ", metrics.hamming loss(y test, predictions))
         precision = precision score(y test, predictions, average='micro')
         recall = recall score(y test, predictions, average='micro')
         f1 = f1 score(y test, predictions, average='micro')
         global report = global report.append({
                                  'Vectorizer': 'Tf-IDF',
                                  'Model': 'Logistic Regression (SGD with log los
         s)',
                                  'NGram': '(1,3)',
                                  'Parameter': 0.00001.
                                  'Precision': precision,
                                  'Recall': recall,
                                  'F1 Score Micro':f1
                              },
                             ignore index=True)
         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 : 0.2045
Hamming loss 0.0030292
Micro-average quality numbers
Precision: 0.7131, Recall: 0.3144, F1-measure: 0.4364
Macro-average quality numbers
Precision: 0.5388, Recall: 0.2350, F1-measure: 0.3075
                           recall f1-score
              precision
                                            support
           0
                   0.80
                             0.32
                                       0.45
                                                 1111
           1
                   0.73
                             0.17
                                       0.28
                                                 2052
           2
                   0.67
                             0.36
                                       0.47
                                                 2388
                   0.75
                             0.50
                                       0.60
                                                 2226
           4
                   0.82
                             0.43
                                       0.57
                                                 2014
                   0.57
                             0.11
                                       0.18
                                                  642
                   0.83
                             0.35
                                       0.49
                                                 1756
           7
                                                 1690
                   0.93
                             0.62
                                       0.74
           8
                   0.65
                             0.19
                                       0.29
                                                  341
                   0.78
                             0.77
                                       0.78
                                                 2344
                             0.35
                                       0.46
                                                  821
          10
                   0.68
          11
                   0.57
                             0.21
                                       0.30
                                                 1143
          12
                   0.85
                             0.32
                                       0.46
                                                  768
          13
                   0.64
                             0.26
                                       0.37
                                                  745
          14
                   0.80
                             0.55
                                       0.65
                                                  952
          15
                   0.56
                             0.25
                                       0.34
                                                  314
          16
                   0.59
                             0.19
                                       0.29
                                                  624
```

17	0.80	0.53	0.64	535
18	0.88	0.44	0.59	631
19	0.94	0.46	0.61	101
20	0.74	0.20	0.32	245
21	0.83	0.49	0.62	694
22	0.60	0.24	0.34	568
23	0.73	0.26	0.38	423
24	0.75	0.24	0.36	406
25	0.69	0.29	0.41	1373
26	0.60	0.27	0.37	253
27	0.28	0.06	0.09	357
28	0.84	0.23	0.37	222
29	0.69	0.25	0.36	273
30	0.60	0.22	0.33	308
31	0.63	0.25	0.35	256
32	0.76	0.38	0.51	295
33	0.36	0.06	0.10	263
34	0.88	0.45	0.59	256
35	0.51	0.28	0.36	280
36	0.46	0.20	0.28	290
37	0.21	0.05	0.08	200
38	0.38	0.19	0.26	109
39	0.70	0.41	0.52	209
40	0.63	0.40	0.49	113
41	0.73	0.21	0.32	197
42	0.81	0.42	0.56	52
43	0.50	0.01	0.02	179
44	0.83	0.42	0.56	431
45 46	0.40	0.09	0.14	47
46	0.79	0.30	0.43	37
47	0.68	0.28	0.40	155
48	0.69	0.48	0.56	254
49	0.61	0.25	0.35	201
50	0.69	0.30	0.41	61
51 52	0.96	0.70	0.81	246
52 53	0.72	0.60	0.66	146 516
53 54	0.94 0.86	0.89 0.60	0.91	516 170
54 55	0.86	0.00	0.71 0.12	234
رر	و د ، ه	ש.ט/	U.12	234

0.27	0.04	0.07	357
			78
			102
			122
			138
			36
			172
			60
			106
			34
			101
			38
			104
			144
			135
			190
			139
			69
			133
0.81	0.35	0.49	181
0.53	0.37	0.44	113
0.70	0.20	0.31	158
0.41	0.11	0.17	142
0.54	0.22	0.31	96
0.50	0.15	0.23	101
0.75		0.33	56
			62
0.66	0.45	0.54	77
0.90	0.09	0.16	100
0.49	0.33	0.40	54
0.44	0.09	0.15	79
0.61	0.22	0.32	92
0.72	0.23	0.34	124
0.67	0.40	0.50	101
0.33	0.03	0.05	40
0.58	0.27	0.37	66
0.44	0.26	0.33	58
0.83	0.12	0.21	161
0.61	0.18	0.27	130
	0.74 0.92 0.55 0.86 0.64 0.57 0.09 0.33 0.32 0.57 0.64 0.53 0.70 0.14 0.81 0.53 0.70 0.41 0.54 0.55 0.75 0.41 0.54 0.66 0.90 0.49 0.44 0.67 0.67 0.33 0.44 0.81	0.74 0.22 0.92 0.68 0.55 0.19 0.86 0.54 0.64 0.25 0.57 0.09 0.09 0.02 0.70 0.47 0.33 0.12 0.57 0.21 0.64 0.33 0.53 0.13 0.51 0.21 0.26 0.09 0.78 0.32 1.00 0.01 0.14 0.01 0.81 0.35 0.53 0.37 0.70 0.20 0.41 0.11 0.54 0.22 0.50 0.15 0.75 0.21 0.14 0.02 0.45 0.90 0.49 0.33 0.44 0.09 0.49 0.33 0.40 0.33 0.44 0.09 0.44 0.09 0.44 0.26 0.44 0.26 0.83	0.74 0.22 0.34 0.92 0.68 0.78 0.55 0.19 0.28 0.86 0.54 0.67 0.64 0.25 0.36 0.57 0.09 0.16 0.09 0.02 0.03 0.70 0.47 0.56 0.33 0.12 0.17 0.32 0.12 0.17 0.57 0.21 0.31 0.64 0.33 0.43 0.53 0.13 0.21 0.51 0.21 0.30 0.26 0.09 0.14 0.78 0.32 0.46 1.00 0.01 0.03 0.14 0.01 0.01 0.81 0.35 0.49 0.53 0.37 0.44 0.70 0.20 0.31 0.41 0.11 0.17 0.54 0.22 0.31 0.54 0.22 0.31 0.54 0.22 0.33 0.75 0.21

95	0.55	0.13	0.21	47
96	0.75	0.51	0.61	107
97	0.56	0.23	0.33	39
98	0.20	0.03	0.05	111
99	0.71	0.11	0.18	95
100	0.34	0.16	0.22	129
101	0.91	0.34	0.50	91
102	0.50	0.19	0.27	27
103	0.93	0.78	0.85	90
104	0.40	0.02	0.03	124
105	0.41	0.16	0.23	76
106	0.25	0.04	0.06	371
107	0.72	0.33	0.46	114
108	0.59	0.31	0.40	98
109	0.83	0.30	0.44	63
110	0.62	0.33	0.43	24
111	0.74	0.32	0.45	53
112	0.43	0.09	0.15	65
113	0.53	0.26	0.35	70
114	0.75	0.44	0.56	27
115	0.33	0.01	0.03	72
116	0.57	0.30	0.39	27
117	0.79	0.17	0.28	90
118	0.68	0.34	0.45	95
119	0.30	0.15	0.20	92
120	0.39	0.21	0.27	87
121	0.58	0.31	0.41	45
122	0.33	0.01	0.01	182
123	0.41	0.12	0.18	94
124	0.77	0.32	0.45	62
125	0.86	0.42	0.56	91
126	0.89	0.35	0.50	69
127	0.63	0.42	0.51	73
128	0.88	0.28	0.42	25
129	0.00	0.00	0.00	68
130	0.33	0.12	0.18	123
131	0.18	0.12	0.18	84
132	0.00	0.00	0.00	67
133	0.64	0.11	0.19	127
TOO	0.04	0.11	0.19	14/

104	0 00	0 40	0 55	4-
134	0.90	0.40	0.55	45
135	0.49	0.31	0.38	88
136	0.00	0.00	0.00	63
137	0.93	0.72	0.81	96
138	0.62	0.07	0.13	71
139	0.93	0.54	0.68	92
140	1.00	0.04	0.08	23
141	0.62	0.14	0.23	90
142	0.33	0.10	0.15	10
143	0.50	0.16	0.24	44
144	0.61	0.21	0.31	67
145	0.72	0.40	0.52	131
146	0.28	0.10	0.14	83
147	0.00	0.00	0.00	32
148	0.54	0.06	0.11	115
149	0.48	0.21	0.29	63
150	0.76	0.30	0.43	83
151	0.70	0.39	0.50	101
152	0.20	0.03	0.06	29
153	0.94	0.84	0.89	191
154	0.97	0.56	0.71	54
155	0.68	0.30	0.41	84
156	0.54	0.19	0.28	37
157	0.38	0.28	0.32	65
158	0.53	0.17	0.26	46
159	0.87	0.41	0.56	80
160	0.00	0.00	0.00	66
161	0.00	0.00	0.00	56
162	0.50	0.17	0.25	127
163	0.80	0.46	0.58	111
164	0.27	0.09	0.14	32
165	0.44	0.14	0.22	28
166	0.33	0.02	0.04	98
167	0.76	0.53	0.63	88
168	0.87	0.46	0.60	59
169	0.00	0.00	0.00	42
170	0.67	0.50	0.57	4
171	0.75	0.43	0.55	95
172	0.67	0.04	0.07	54
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173	0.84	0.49	0.62	65
174	0.58	0.35	0.44	31
175	0.62	0.25	0.36	32
176	0.64	0.31	0.42	58
177	0.79	0.14	0.24	76
178	0.25	0.02	0.03	55
179	0.89	0.76	0.82	74
180	0.95	0.55	0.69	64
181	1.00	0.09	0.16	57
182	0.31	0.11	0.16	36
183	0.64	0.27	0.38	52
184	0.75	0.38	0.50	48
185	0.67	0.12	0.21	16
186	0.00	0.00	0.00	28
187	0.33	0.08	0.13	36
188	0.67	0.38	0.49	26
189	0.33	0.14	0.19	44
190	0.57	0.17	0.27	46
191	0.29	0.08	0.12	75
192	0.50	0.08	0.14	50
193	0.75	0.45	0.56	20
194	0.50	0.07	0.13	27
195	0.60	0.50	0.55	6
196	0.25	0.04	0.07	68
197	0.59	0.59	0.59	29
198	0.82	0.09	0.16	104
199	0.57	0.33	0.42	36
200	1.00	0.75	0.86	4
201	1.00	0.25	0.40	4
202	0.38	0.03	0.06	96
203	0.94	0.54	0.69	61
204	0.40	0.07	0.12	82
205	0.47	0.26	0.34	34
206	0.79	0.35	0.48	66
207	0.27	0.07	0.11	97
208	0.22	0.04	0.07	89
209	0.76	0.53	0.62	55
210	0.82	0.36	0.50	78
211	0.75	0.04	0.07	78

212	0.00	0 17	0 27	150
212	0.68	0.17	0.27	158
213	0.29	0.05	0.08	44
214	0.65	0.49	0.56	35
215	0.90	0.58	0.71	48
216	0.69	0.58	0.63	62
217	1.00	0.18	0.31	11
218	0.96	0.38	0.55	68
219	0.35	0.12	0.17	60
220	0.50	0.08	0.14	25
221	0.43	0.18	0.25	57
222	0.94	0.42	0.58	36
223	0.46	0.07	0.12	88
224	0.44	0.09	0.15	46
225	0.57	0.07	0.12	60
226	0.52	0.17	0.26	65
227	1.00	0.43	0.60	7
228	0.14	0.08	0.11	12
229	0.27	0.04	0.08	68
230	0.67	0.15	0.24	40
231	0.22	0.08	0.11	26
232	0.81	0.57	0.67	30
233	0.80	0.10	0.17	41
234	0.27	0.06	0.09	53
235	0.65	0.49	0.56	35
236	0.40	0.11	0.17	18
237	0.00	0.00	0.00	22
238	0.73	0.54	0.62	59
239	0.78	0.42	0.55	43
240	0.43	0.13	0.20	45
241	0.60	0.07	0.12	46
242	0.33	0.05	0.09	38
243	0.86	0.34	0.49	56
244	0.27	0.09	0.13	35
245	0.50	0.02	0.05	42
246	0.25	0.06	0.10	33
247	0.39	0.15	0.22	47
248	0.64	0.28	0.39	25
249	0.77	0.51	0.62	39
250	1.00	0.06	0.12	77

251	0.79	0.41	0.54	56
252	0.11	0.03	0.04	72
253	1.00	1.00	1.00	4
254	0.71	0.41	0.52	29
255	0.35	0.06	0.11	113
256	0.82	0.61	0.70	59
257	0.00	0.00	0.00	59
258	0.93	0.64	0.76	39
259	0.82	0.75	0.78	12
260	0.75	0.67	0.71	9
261	0.96	0.55	0.70	44
262	0.78	0.56	0.65	32
263	0.25	0.01	0.01	156
264	1.00	0.40	0.57	5
265	0.09	0.02	0.03	198
266	0.00	0.00	0.00	40
267	0.33	0.03	0.06	29
268	0.00	0.00	0.00	39
269	0.00	0.00	0.00	6
270	0.75	0.60	0.67	5
271	0.00	0.00	0.00	17
272	0.25	0.04	0.06	54
273	0.38	0.13	0.19	23
274	0.00	0.00	0.00	126
275	0.77	0.31	0.44	32
276	0.67	0.60	0.63	10
277	0.83	0.52	0.64	67
278	0.48	0.19	0.27	53
279	0.67	0.12	0.21	16
280	0.77	0.53	0.62	19
281	0.67	0.07	0.12	61
282	0.50	0.02	0.05	81
283	0.66	0.20	0.31	94
284	0.70	0.23	0.34	31
285	0.40	0.05	0.08	43
286	0.60	0.11	0.19	79
287	0.30	0.40	0.34	20
288	0.78	0.82	0.80	17
289	0.82	0.48	0.61	56

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			59
			48
			45
			29
0.50			37
		0.14	38
0.82	0.52	0.64	44
0.72	0.32	0.44	41
0.00	0.00	0.00	25
0.00	0.00	0.00	4
1.00	0.09	0.17	11
1.00	1.00	1.00	3
0.62	0.16	0.25	32
0.60	0.24	0.34	50
0.14	0.02	0.04	46
	0.00 0.00 1.00 1.00 0.62 0.60	0.44 0.17 0.65 0.30 0.50 0.12 0.83 0.19 0.50 0.03 0.40 0.16 0.00 0.00 0.00 0.00 0.73 0.45 0.25 0.03 0.50 0.12 0.00 0.00 0.43 0.16 0.78 0.39 0.44 0.31 0.67 0.20 0.17 0.08 1.00 0.38 0.50 0.05 0.43 0.08 0.91 0.58 0.62 0.14 0.45 0.26 0.92 0.59 0.87 0.56 0.33 0.07 0.50 0.38 0.50 0.38 0.50 0.08 0.82 0.52 0.72 0.32 0.00 0.00 1.00 0.09 1.00 0.09 1.00	0.44 0.17 0.25 0.65 0.30 0.41 0.50 0.12 0.19 0.83 0.19 0.30 0.50 0.03 0.06 0.40 0.16 0.23 0.00 0.00 0.00 0.00 0.00 0.00 0.73 0.45 0.56 0.25 0.03 0.05 0.50 0.12 0.20 0.00 0.00 0.00 0.43 0.16 0.23 0.78 0.39 0.52 0.44 0.31 0.36 0.67 0.20 0.31 0.17 0.08 0.11 1.00 0.38 0.55 0.50 0.05 0.10 0.43 0.08 0.14 0.91 0.58 0.71 0.62 0.14 0.23 0.45 0.26 0.33 0.92 0.59 0.72 0.87 0.56 0.68 0.33 0.07

329	0.96	0.55	0.70	47
330	1.00	0.58	0.73	31
331	0.00	0.00	0.00	11
332	0.00	0.00	0.00	31
333	1.00	0.08	0.14	26
334	0.00	0.00	0.00	41
335	0.00	0.00	0.00	39
336	0.79	0.38	0.51	40
337	0.27	0.08	0.12	37
338	1.00	0.30	0.46	10
339	0.00	0.00	0.00	38
340	1.00	0.78	0.88	23
341	0.17	0.06	0.09	33
342	0.31	0.10	0.15	40
343	0.60	0.17	0.27	35
344	0.56	0.33	0.42	30
345	0.00	0.00	0.00	33
346	0.86	0.24	0.38	25
347	0.50	0.22	0.31	9
348	0.50	0.50	0.50	2
349	0.81	0.38	0.52	34
350	0.33	0.13	0.19	38
351	0.50	0.16	0.25	49
352	0.00	0.00	0.00	22
353	0.47	0.21	0.29	39
354	0.25	0.06	0.09	18
355	0.43	0.10	0.16	31
356	0.50	0.10	0.10	17
357	0.92	0.34	0.50	35
358	0.25	0.02	0.04	43
359	0.68	0.45	0.54	47
360	0.50	0.03	0.06	29
361	0.74	0.61	0.67	38
362	0.47	0.22	0.30	36
363	0.36	0.22	0.27	55
364	0.73	0.24	0.36	34
365	0.46	0.25	0.32	24
366	0.00	0.00	0.00	19
367	0.30	0.60	0.40	5

368	0.50	0.09	0.15	33
369	0.78	0.53	0.63	34
370	0.43	0.15	0.22	20
371	0.00	0.00	0.00	17
372	0.47	0.23	0.30	31
373	0.00	0.00	0.00	34
374	0.25	0.04	0.07	23
375	0.50	0.26	0.34	31
376	0.62	0.18	0.28	28
377	0.83	0.68	0.75	22
378	1.00	0.33	0.50	9
379 380	1.00	0.07	0.13	29 20
381	0.47 0.85	0.27 0.63	0.34 0.72	30 35
382	0.69	0.03	0.72	36
383	1.00	0.25	0.37	4
384	0.94	0.23	0.40	24
385	0.58	0.28	0.38	25
386	0.00	0.00	0.00	27
387	0.55	0.17	0.26	36
388	0.75	0.39	0.51	31
389	0.87	0.35	0.50	37
390	0.46	0.22	0.30	27
391	0.59	0.35	0.44	46
392	0.33	0.25	0.29	4
393	0.17	0.11	0.13	19
394	0.00	0.00	0.00	12
395	0.44	0.27	0.33	26
396	0.24	0.06	0.09	69
397	1.00	0.16	0.28	25
398	0.25	0.03	0.06	32
399	0.40	0.12	0.19	33
400	0.00	0.00	0.00	38
401	0.50	0.18	0.26	17
402	0.00	0.00	0.00	24
403	1.00	0.31	0.48	16
404 405	1.00	0.27	0.42	15
405	0.50	0.05	0.09	20 15
406	0.33	0.07	0.11	15

407	0.60	0.12	0.20	25
408	0.33	0.26	0.29	19
409	0.60	0.26	0.36	46
410	0.00	0.00	0.00	45
411	0.67	0.10	0.17	21
412	0.00	0.00	0.00	8
413	0.58	0.40	0.47	35
414	0.00	0.00	0.00	34
415	1.00	0.50	0.67	14
416	0.10	0.03	0.05	29
417	0.44	0.14	0.22	28
418	0.40	0.10	0.15	21
419	1.00	0.04	0.07	26
420	0.58	0.29	0.39	38
421	0.00	0.00	0.00	131
422	0.50	0.12	0.19	26
423	0.58	0.28	0.38	25
424	0.78	0.38	0.51	48
425	0.00	0.00	0.00	24
426	0.33	0.05	0.08	42
427	0.40	0.31	0.35	26
428	0.00	0.00	0.00	10
429	0.56	0.41	0.47	54
430	0.70	0.22	0.33	32
431	0.40	0.17	0.24	48
432	0.27	0.11	0.16	35
433	1.00	0.05	0.09	22
434	0.50	0.12	0.20	24
435	1.00	0.46	0.63	59
436	0.00	0.00	0.00	35
437	0.00	0.00	0.00	12
438	0.61	0.28	0.38	50
439	0.25	0.06	0.09	36
440	0.00	0.00	0.00	35
441	0.00	0.00	0.00	8
442	0.00	0.00	0.00	48
443	1.00	0.44	0.62	18
444	0.77	0.19	0.31	52
445	0.67	0.20	0.31	20
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446	0.00	0.00	0.00	18
447	0.00	0.00	0.00	6
448	0.33	0.04	0.06	28
449	0.29	0.05	0.09	38
450	0.00	0.00	0.00	129
451	0.94	0.55	0.70	29
452	0.17	0.02	0.03	58
453	0.20	0.03	0.05	32
454	0.75	0.38	0.50	16
455	0.95	0.53	0.68	34
456	0.29	0.44	0.35	9
457	0.96	0.73	0.83	30
458	0.60	0.15	0.24	40
459	0.57	0.11	0.18	37
460	0.90	0.60	0.72	30
461	1.00	0.22	0.36	27
462	0.29	0.17	0.21	12
463	0.50	0.35	0.41	17
464	0.88	0.25	0.39	56
465	0.80	0.44	0.57	9
466	0.00	0.00	0.00	22
467	0.17	0.11	0.13	9
468	0.00	0.00	0.00	15
469	0.00	0.00	0.00	14
470	0.67	0.25	0.36	16
471	0.86	0.33	0.48	18
472	0.25	0.12	0.17	16
473	0.73	0.50	0.59	22
474	0.12	0.08	0.10	12
475	1.00	0.47	0.64	110
476	0.50	0.45	0.47	20
477	0.70	0.45	0.55	31
478	0.71	0.12	0.20	42
479	0.00	0.00	0.00	4
480	0.45	0.11	0.17	47
481	1.00	0.33	0.50	30
482	0.00	0.00	0.00	35
483	0.11	0.03	0.05	30
484	0.33	0.10	0.15	20

```
485
                   0.71
                             0.33
                                        0.45
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         486
                   1.00
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                             0.26
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                   0.17
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                                        0.24
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                             0.18
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                                                 55953
                   0.71
                             0.31
                                        0.44
   micro avq
                   0.54
                             0.24
                                        0.31
                                                 55953
   macro avq
                   0.65
                             0.31
                                        0.40
                                                 55953
weighted avg
 samples avg
                   0.41
                             0.30
                                        0.32
                                                 55953
```

Time taken to run this cell: 0:01:56.473712

```
'Model': 'Logistic Regression',
                        'NGram': '(1,3)',
                        'Parameter': 1,
                        'Precision': precision,
                        'Recall': recall,
                        'F1 Score Micro':f1
                     },
                    ignore index=True)
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: 0.21033333333333334
Hamming loss 0.003007
Micro-average quality numbers
Precision: 0.7086, Recall: 0.3293, F1-measure: 0.4496
Macro-average quality numbers
Precision: 0.5460, Recall: 0.2565, F1-measure: 0.3290
                           recall f1-score support
              precision
                   0.80
                             0.33
                                       0.47
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                             0.35
                                       0.49
                                                 1756
                   0.93
                             0.65
                                       0.77
                                                 1690
```

8	0.64	0.19	0.30	341
9	0.78	0.78	0.78	2344
10	0.68	0.36	0.47	821
11	0.58	0.22	0.31	1143
12	0.84	0.33	0.47	768
13	0.62	0.27	0.38	745
14	0.79	0.55	0.65	952
15	0.56	0.25	0.34	314
16	0.58	0.18	0.28	624
17	0.80	0.53	0.64	535
18	0.87	0.47	0.61	631
19	0.94	0.50	0.66	101
20	0.76	0.20	0.32	245
21	0.83	0.49	0.62	694
22	0.59	0.25	0.35	568
23	0.71	0.26	0.39	423
24	0.73	0.25	0.37	406
25	0.70	0.29	0.41	1373
26	0.58	0.25	0.35	253
27	0.29	0.08	0.12	357
28	0.83	0.24	0.38	222
29	0.65	0.25	0.36	273
30	0.62	0.25	0.36	308
31	0.62	0.25	0.35	256
32	0.75	0.40	0.52	295
33	0.39	0.07	0.12	263
34	0.88	0.47	0.61	256
35	0.52	0.29	0.37	280
36	0.47	0.22	0.30	290
37 38	0.18	0.04	0.07	200
30 39	0.42	0.21	0.28 0.53	109
40	0.69 0.67	0.43 0.38	0.33	209 113
41	0.73	0.38	0.49	113
42	0.79	0.22	0.57	52
43	0.79	0.44	0.03	179
43 44	0.82	0.02	0.55	431
45	0.45	0.41	0.33	47
46	0.78	0.38	0.51	37
47	0.70	0.30	0.51	155

4/	0.68	0.29	0.41	155
48	0.70	0.48	0.57	254
49	0.61	0.27	0.37	201
50	0.75	0.34	0.47	61
51	0.96	0.71	0.82	246
52	0.71	0.60	0.65	146
53	0.94	0.89	0.91	516
54	0.84	0.58	0.69	170
55	0.32	0.06	0.10	234
56	0.27	0.04	0.08	357
57	0.70	0.21	0.32	78
58	0.92	0.70	0.79	102
59	0.54	0.18	0.27	122
60	0.86	0.54	0.66	138
61	0.60	0.25	0.35	36
62	0.49	0.10	0.16	172
63	0.11	0.02	0.03	60
64	0.69	0.51	0.59	106
65	0.38	0.15	0.21	34
66	0.31	0.13	0.18	101
67	0.62	0.21	0.31	38
68	0.65	0.34	0.44	104
69	0.45	0.13	0.20	144
70	0.53	0.23	0.32	135
71	0.32	0.12	0.18	190
72	0.76	0.32	0.45	139
73	0.50	0.01	0.03	69
74	0.14	0.01	0.01	133
75	0.78	0.38	0.51	181
76	0.52	0.35	0.41	113
77	0.67	0.20	0.30	158
78	0.39	0.13	0.20	142
79	0.56	0.20	0.29	96
80	0.59	0.17	0.26	101
81	0.67	0.21	0.32	56
82	0.17	0.02	0.03	62
83	0.67	0.44	0.53	77
84	0.92	0.12	0.21	100
85	0.51	0.35	0.42	54
0.0	^ 47	^ ^^	A 1F	70

გი	0.4/	0.09	0.15	/9
87	0.70	0.21	0.32	92
88	0.67	0.21	0.32	124
89	0.71	0.40	0.51	101
90	0.33	0.05	0.09	40
91	0.61	0.30	0.40	66
92	0.42	0.24	0.31	58
93	0.95	0.24	0.38	161
94	0.66	0.18	0.28	130
95	0.62	0.17	0.27	47
96	0.77	0.50	0.61	107
97	0.62	0.26	0.36	39
98	0.33	0.05	0.08	111
99	0.67	0.15	0.24	95
100	0.33	0.12	0.18	129
101	0.84	0.40	0.54	91
102	0.44	0.15	0.22	27
103	0.92	0.79	0.85	90
104	0.30	0.02	0.04	124
105	0.39	0.16	0.22	76
106	0.29	0.09	0.14	371
107	0.70	0.35	0.47	114
108	0.58	0.33	0.42	98
109	0.87	0.32	0.47	63
110	0.69	0.38	0.49	24
111	0.75	0.34	0.47	53
112	0.38	0.08	0.13	65
113	0.58	0.30	0.40	70
114	0.81	0.48	0.60	27
115	0.25	0.01	0.03	72
116	0.60	0.33	0.43	27
117	0.80	0.22	0.35	90
118	0.67	0.35	0.46	95
119	0.29	0.14	0.19	92
120	0.43	0.28	0.34	87
121	0.57	0.29	0.38	45
122	0.25	0.01	0.02	182
123	0.43	0.14	0.21	94
124	0.80	0.32	0.46	62

125	0.83	0.43	0.5/	91
126	0.81	0.38	0.51	69
127	0.64	0.44	0.52	73
128	0.89	0.32	0.47	25
129	1.00	0.01	0.03	68
130	0.36	0.13	0.19	123
131	0.24	0.06	0.10	84
132	0.00	0.00	0.00	67
133	0.52	0.12	0.19	127
134	0.80	0.44	0.57	45
135	0.52	0.34	0.41	88
136	0.00	0.00	0.00	63
137	0.92	0.72	0.81	96
138	0.62	0.07	0.13	71
139	0.93	0.58	0.71	92
140	1.00	0.04	0.08	23
141	0.64	0.16	0.25	90
142	0.50	0.10	0.17	10
143	0.47	0.16	0.24	44
144	0.64	0.24	0.35	67
145	0.76	0.42	0.54	131
146	0.26	0.08	0.13	83
147	0.17	0.03	0.05	32
148	0.48	0.11	0.18	115
149	0.63	0.27	0.38	63
150	0.77	0.33	0.46	83
151	0.69	0.35	0.46	101
152	0.17	0.03	0.06	29
153	0.93	0.86	0.90	191
154	0.94	0.59	0.73	54
155	0.63	0.26	0.37	84
156	0.63	0.32	0.43	37
157	0.33	0.25	0.28	65
158	0.50	0.17	0.26	46
159	0.83	0.44	0.57	80
160	0.11	0.02	0.03	66
161	0.00	0.00	0.00	56
162	0.50	0.19	0.27	127
163	0.73	0.57	0.64	111

164	0.22	0.06	Θ.10	32
165	0.50	0.11	0.18	28
166	0.29	0.02	0.04	98
167	0.76	0.55	0.64	88
168	0.88	0.47	0.62	59
169	0.00	0.00	0.00	42
170	0.50	0.50	0.50	4
171	0.75	0.42	0.54	95
172	0.50	0.06	0.10	54
173	0.85	0.52	0.65	65
174	0.60	0.39	0.47	31
175	0.64	0.28	0.39	32
176	0.65	0.34	0.45	58
177	0.65	0.14	0.24	76
178	0.50	0.04	0.07	55
179	0.88	0.78	0.83	74
180	0.90	0.56	0.69	64
181	1.00	0.09	0.16	57
182	0.36	0.11	0.17	36
183	0.56	0.27	0.36	52
184	0.70	0.40	0.51	48
185	0.57	0.25	0.35	16
186	0.00	0.00	0.00	28
187	0.31	0.11	0.16	36
188	0.56	0.38	0.45	26
189	0.38	0.14	0.20	44
190	0.47	0.15	0.23	46
191	0.29	0.09	0.14	75
192	0.58	0.14	0.23	50
193	0.82	0.45	0.58	20
194	0.50	0.07	0.13	27
195	0.50	0.50	0.50	6
196	0.29	0.07	0.12	68
197	0.54	0.52	0.53	29
198	0.79	0.11	0.19	104
199	0.57	0.33	0.42	36
200	1.00	0.75	0.86	4
201	1.00	0.25	0.40	4
202	0.43	0.03	0.06	96
	^ ^	^ -	^ 7^	<i>-</i>

203	0.92	0.59	0./2	ρΤ
204	0.36	0.06	0.10	82
205	0.48	0.29	0.36	34
206	0.81	0.39	0.53	66
207	0.21	0.06	0.10	97
208	0.26	0.07	0.11	89
209	0.76	0.53	0.62	55
210	0.81	0.44	0.57	78
211	0.50	0.05	0.09	78
212	0.74	0.34	0.46	158
213	0.38	0.07	0.12	44
214	0.69	0.51	0.59	35
215	0.91	0.67	0.77	48
216	0.74	0.65	0.69	62
217	1.00	0.09	0.17	11
218	1.00	0.43	0.60	68
219	0.33	0.10	0.15	60
220	0.40	0.08	0.13	25
221	0.44	0.19	0.27	57
222	0.83	0.42	0.56	36
223	0.67	0.09	0.16	88
224	0.33	0.07	0.11	46
225	0.56	0.08	0.14	60
226	0.52	0.17	0.26	65
227	0.80	0.57	0.67	7
228	0.25	0.17	0.20	12
229	0.36	0.06	0.10	68
230	0.88	0.17	0.29	40
231	0.22	0.08	0.11	26
232	0.81	0.57	0.67	30
233	0.86	0.15	0.25	41
234	0.27	0.08	0.12	53
235	0.61	0.49	0.54	35
236	0.50	0.11	0.18	18
237	0.14	0.05	0.07	22
238	0.70	0.54	0.61	59
239	0.78	0.42	0.55	43
240	0.41	0.16	0.23	45
241	0.67	0.09	0.15	46
				• • •

242	0.33	0.05	0.09	38
243	0.87	0.36	0.51	56
244	0.27	0.11	0.16	35
245	0.25	0.02	0.04	42
246	0.33	0.06	0.10	33
247	0.42	0.17	0.24	47
248	0.70	0.28	0.40	25
249	0.76	0.49	0.59	39
250	1.00	0.10	0.19	77
251	0.79	0.48	0.60	56
252	0.26	0.07	0.11	72
253	1.00	1.00	1.00	4
254	0.67	0.41	0.51	29
255	0.53	0.16	0.24	113
256	0.80	0.66	0.72	59
257	0.00	0.00	0.00	59
258	0.93	0.67	0.78	39
259	0.82	0.75	0.78	12
260	0.86	0.67	0.75	9
261	0.97	0.64	0.77	44
262	0.78	0.56	0.65	32
263	0.11	0.01	0.01	156
264	1.00	0.40	0.57	5
265	0.12	0.06	0.08	198
266	0.00	0.00	0.00	40
267	0.33	0.03	0.06	29
268	0.00	0.00	0.00	39
269	0.00	0.00	0.00	6
270	0.75	0.60	0.67	5
271	0.00	0.00	0.00	17
272	0.30	0.06	0.09	54
273	0.40	0.17	0.24	23
274	0.00	0.00	0.00	126
275	0.71	0.31	0.43	32
276	0.60	0.60	0.60	10
277	0.85	0.61	0.71	67
278	0.50	0.21	0.29	53
279	0.67	0.12	0.21	16
280	0.80	0.63	0.71	19
201	^ ^7	^ ^7	^ 17	C 1

281	0.6/	0.0/	0.12	ρΙ
282	0.54	0.09	0.15	81
283	0.56	0.20	0.30	94
284	0.70	0.23	0.34	31
285	0.40	0.05	0.08	43
286	0.58	0.18	0.27	79
287	0.29	0.35	0.32	20
288	0.78	0.82	0.80	17
289	0.82	0.59	0.69	56
290	0.10	0.02	0.03	63
291	0.44	0.17	0.25	46
292	0.62	0.30	0.41	50
293	0.60	0.18	0.27	17
294	0.83	0.19	0.30	27
295	0.50	0.03	0.06	63
296	0.33	0.12	0.18	25
297	0.00	0.00	0.00	38
298	0.14	0.02	0.03	62
299	0.77	0.49	0.60	49
300	0.38	0.08	0.13	39
301	0.67	0.25	0.36	8
302	0.00	0.00	0.00	18
303	0.33	0.21	0.26	19
304	0.67	0.44	0.53	18
305	0.56	0.35	0.43	26
306	0.67	0.20	0.31	10
307	0.14	0.08	0.11	12
308	0.75	0.38	0.50	8
309	0.44	0.07	0.12	57
310	0.57	0.11	0.18	37
311	0.85	0.66	0.74	50
312	0.50	0.17	0.25	36
313	0.42	0.26	0.32	19
314	0.91	0.69	0.79	59 40
315	0.84	0.65	0.73	48 45
316	0.36	0.11	0.17	45 20
317	0.56	0.17	0.26	29 37
318 319	0.50 0.50	0.38 0.08	0.43 0.14	37 38
219	0.50	0.00	0.14	30

320	0.81	0.5/	0.6/	44
321	0.79	0.37	0.50	41
322	0.00	0.00	0.00	25
323	0.00	0.00	0.00	4
324	0.33	0.09	0.14	11
325	0.75	1.00	0.86	3
326	0.62	0.16	0.25	32
327	0.55	0.22	0.31	50
328	0.14	0.02	0.04	46
329	0.97	0.64	0.77	47
330	0.95	0.61	0.75	31
331	0.00	0.00	0.00	11
332	0.00	0.00	0.00	31
333	0.80	0.15	0.26	26
334	0.00	0.00	0.00	41
335	0.00	0.00	0.00	39
336	0.76	0.40	0.52	40
337	0.23	0.08	0.12	37
338	1.00	0.50	0.67	10
339	0.00	0.00	0.00	38
340	1.00	0.74	0.85	23
341	0.22	0.06	0.10	33
342	0.31	0.10	0.15	40
343	0.67	0.17	0.27	35
344	0.48	0.33	0.39	30
345	0.00	0.00	0.00	33
346	0.83	0.40	0.54	25
347	0.50	0.22	0.31	9
348	0.50	0.50	0.50	2
349	0.86	0.56	0.68	34
350	0.42	0.21	0.28	38
351	0.47	0.14	0.22	49
352	0.00	0.00	0.00	22
353	0.48	0.26	0.33	39
354	0.50	0.22	0.31	18
355	0.38	0.10	0.15	31
356	0.00	0.00	0.00	17
357	0.93	0.40	0.56	35
358	0.25	0.02	0.04	43

359	0.56	0.62	0.59	4/
360	0.67	0.07	0.12	29
361	0.77	0.61	0.68	38
362	0.45	0.25	0.32	36
363	0.31	0.27	0.29	55
364	0.64	0.26	0.37	34
365	0.50	0.29	0.37	24
366	0.00	0.00	0.00	19
367	0.38	0.60	0.46	5
368	0.57	0.12	0.20	33
369	0.79	0.56	0.66	34
370	0.75	0.15	0.25	20
371	0.00	0.00	0.00	17
372	0.46	0.19	0.27	31
373	0.25	0.03	0.05	34
374	0.20	0.04	0.07	23
375	0.50	0.29	0.37	31
376	0.50	0.18	0.26	28
377	0.88	0.64	0.74	22
378	1.00	0.33	0.50	9
379	1.00	0.10	0.19	29
380	0.33	0.23	0.27	30
381	0.85	0.63	0.72	35
382	0.56	0.28	0.37	36
383	0.00	0.00	0.00	4
384	0.94	0.67	0.78	24
385	0.62	0.32	0.42	25
386	0.25	0.04	0.06	27
387	0.58	0.19	0.29	36
388	0.72	0.42	0.53	31
389	0.88	0.38	0.53	37
390	0.50	0.30	0.37	27
391	0.68	0.41	0.51	46
392	0.33	0.25	0.29	4
393	0.14	0.11	0.12	19
394	0.00	0.00	0.00	12
395	0.50	0.31	0.38	26
396	0.29	0.07	0.12	69
397	0.87	0.52	0.65	25

398	⊎.33	0.06	0.11	32
399	0.42	0.15	0.22	33
400	0.00	0.00	0.00	38
401	0.50	0.18	0.26	17
402	0.00	0.00	0.00	24
403	0.80	0.50	0.62	16
404	1.00	0.33	0.50	15
405	0.25	0.05	0.08	20
406	0.25	0.07	0.11	15
407	0.43	0.12	0.19	25
408	0.38	0.26	0.31	19
409	0.58	0.24	0.34	46
410	0.00	0.00	0.00	45
411	0.40	0.10	0.15	21
412	0.00	0.00	0.00	8
413	0.64	0.40	0.49	35
414	0.00	0.00	0.00	34
415	1.00	0.50	0.67	14
416	0.18	0.07	0.10	29
417	0.33	0.11	0.16	28
418	0.25	0.05	0.08	21
419	1.00	0.08	0.14	26
420	0.58	0.29	0.39	38
421	0.00	0.00	0.00	131
422	0.25	0.08	0.12	26
423	0.54	0.28	0.37	25
424	0.84	0.33	0.48	48
425	0.33	0.04	0.07	24
426	0.45	0.12	0.19	42
427	0.44	0.31	0.36	26
428	1.00	0.10	0.18	10
429	0.58	0.41	0.48	54
430	0.69	0.28	0.40	32
431	0.43	0.19	0.26	48
432	0.28	0.14	0.19	35
433	1.00	0.05	0.09	22
434	0.57	0.17	0.26	24
435	0.94	0.54	0.69	59
436	0.11	0.03	0.05	35
427	^ ^^	^ ^^	^ ^^	1 7

43/	0.00	0.00	0.00	12
438	0.59	0.26	0.36	50
439	0.22	0.06	0.09	36
440	0.00	0.00	0.00	35
441	0.00	0.00	0.00	8
442	0.00	0.00	0.00	48
443	0.90	0.50	0.64	18
444	0.80	0.23	0.36	52
445	0.80	0.20	0.32	20
446	0.00	0.00	0.00	18
447	0.00	0.00	0.00	6
448	0.40	0.07	0.12	28
449	0.43	0.08	0.13	38
450	0.97	0.53	0.68	129
451	0.84	0.72	0.78	29
452	0.27	0.05	0.09	58
453	0.20	0.03	0.05	32
454	0.67	0.38	0.48	16
455	0.95	0.59	0.73	34
456	0.33	0.44	0.38	9
457	0.96	0.77	0.85	30
458	0.67	0.20	0.31	40
459	0.43	0.08	0.14	37
460	0.83	0.67	0.74	30
461	1.00	0.26	0.41	27
462	0.33	0.17	0.22	12
463	0.42	0.29	0.34	17
464	0.90	0.34	0.49	56
465	1.00	0.67	0.80	9
466	1.00	0.05	0.09	22
467	0.17	0.11	0.13	9
468	0.00	0.00	0.00	15
469	0.50	0.07	0.12	14
470	0.67	0.25	0.36	16
471	0.91	0.56	0.69	18
472	0.33	0.25	0.29	16
473	0.69	0.50	0.58	22
474	0.12	0.08	0.10	12
475	1.00	0.75	0.86	110
				• • •

	4/6	⊎.58	⊎.55	0.56	20
	477	0.68	0.48	0.57	31
	478	0.67	0.14	0.24	42
	479	0.00	0.00	0.00	4
	480	0.50	0.17	0.25	47
	481	1.00	0.37	0.54	30
	482	0.00	0.00	0.00	35
	483	0.22	0.07	0.10	30
	484	0.33	0.15	0.21	20
	485	0.80	0.53	0.64	15
	486	1.00	0.06	0.11	17
	487	0.50	0.09	0.15	11
	488	0.50	0.14	0.22	36
	489	0.12	0.03	0.05	32
	490	0.80	0.29	0.42	14
	491	0.73	0.32	0.44	25
	492	0.37	0.57	0.45	23
	493	0.00	0.00	0.00	9
	494	0.46	0.16	0.24	37
	495	0.00	0.00	0.00	24
	496	0.82	0.26	0.40	34
	497	0.12	0.04	0.06	25
	498	1.00	0.11	0.20	9
	499	0.67	0.24	0.35	17
micro	avg	0.71	0.33	0.45	55953
macro	avg	0.55	0.26	0.33	55953
weighted	avg	0.65	0.33	0.42	55953
samples	avg	0.42	0.31	0.34	55953

Time taken to run this cell : 0:05:16.940751

4.5.4 Featurizing data with BoW vectorizer

```
qe=(1,4)
x train multilabel bow = vectorizer bow.fit transform(x train['questio
n'1)
x test multilabel bow = vectorizer bow.transform(x test['question'])
print("Time taken to run this cell :", datetime.now() - start)
```

Time taken to run this cell: 0:03:25.682941

```
In [74]: print("Dimensions of train data X:",x train multilabel bow.shape, "Y:"
         ,y train.shape)
         print("Dimensions of test data X:",x test multilabel bow.shape,"Y:",y t
         est.shape)
```

Dimensions of train data X: (120000, 102634) Y: (120000, 500) Dimensions of test data X: (30000, 102634) Y: (30000, 500)

4.5.5 Applying Logistic Regression with OneVsRest Classifier

```
In [75]: | start = datetime.now()
         classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0000
         1, penalty='l1'))
         classifier.fit(x train multilabel_bow, y_train)
         predictions = classifier.predict (x test multilabel bow)
         print("Accuracy :",metrics.accuracy score(y test, predictions))
         print("Hamming loss ", metrics.hamming loss(y test, predictions))
         precision = precision score(y test, predictions, average='micro')
         recall = recall score(y test, predictions, average='micro')
         f1 = f1 score(y test, predictions, average='micro')
         global report = global report.append({
                                  'Vectorizer': 'BoW',
                                  'Model': 'Logistic Regression (SGD with log los
         s)',
                                  'NGram': '(1,4)',
```

```
'Parameter': 0.00001,
                        'Precision': precision,
                        'Recall': recall,
                        'F1 Score Micro':f1
                     },
                    ignore index=True)
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 : 0.0765
Hamming loss 0.007617333333333333
Micro-average quality numbers
Precision: 0.2297, Recall: 0.4427, F1-measure: 0.3024
Macro-average quality numbers
Precision: 0.1552, Recall: 0.3670, F1-measure: 0.2071
              precision
                           recall f1-score support
           0
                   0.35
                             0.45
                                       0.39
                                                 1111
           1
                   0.32
                             0.37
                                       0.34
                                                 2052
           2
                   0.43
                             0.48
                                       0.45
                                                 2388
                                       0.56
                                                 2226
                   0.52
                             0.60
                   0.46
                             0.55
                                       0.50
                                                 2014
                   0.12
                             0.22
                                       0.16
                                                 642
                   0.41
                             0.49
                                       0.44
                                                 1756
                   0.68
                             0.73
                                       0.71
                                                 1690
                                                  341
           8
                   0.22
                             0.31
                                       0.26
                   0.66
                             0.74
                                       0.70
                                                 2344
```

10	0.38	0.45	0.41	821
11	0.27	0.33	0.30	1143
12	0.39	0.47	0.43	768
13	0.29	0.42	0.35	745
14	0.48	0.62	0.54	952
15	0.21	0.37	0.27	314
16	0.26	0.39	0.31	624
17	0.38	0.58	0.46	535
18	0.44	0.60	0.51	631
19	0.35	0.66	0.46	101
20	0.21	0.35	0.26	245
21	0.47	0.59	0.52	694
22	0.29	0.43	0.35	568
23	0.26	0.39	0.31	423
24	0.26	0.43	0.33	406
25	0.55	0.48	0.51	1373
26	0.18	0.42	0.26	253
27	0.14	0.26	0.18	357
28	0.16	0.36	0.22	222
29	0.28	0.40	0.33	273
30	0.22	0.39	0.28	308
31	0.19	0.36	0.25	256
32	0.28	0.42	0.34	295
33	0.09	0.19	0.12	263
34	0.34	0.57	0.43	256
35	0.21	0.37	0.27	280
36	0.31	0.45	0.37	290
37	0.19	0.28	0.23	200
38	0.11	0.39	0.18	109
39	0.22	0.38	0.28	209
40	0.16	0.43	0.23	113
41	0.21	0.37	0.27	197
42	0.14	0.63	0.23	52
43	0.06	0.15	0.08	179
44	0.53	0.53	0.53	431
45	0.05	0.17	0.07	47
46	0.10	0.51	0.17	37
47	0.19	0.35	0.25	155
48	0.35	0.48	0.41	254
49	0.20	0.37	0.26	201

50	0.11	0.43	0.17	61
51	0.52	0.79	0.63	246
52	0.34	0.68	0.46	146
53	0.74	0.91	0.81	516
54	0.33	0.58	0.42	170
55	0.10	0.17	0.12	234
56	0.12	0.19	0.14	357
57	0.07	0.29	0.11	78
58	0.40	0.71	0.51	102
59	0.12	0.31	0.18	122
60	0.38	0.62	0.48	138
61	0.04	0.22	0.07	36
62	0.11	0.27	0.16	172
63	0.01	0.05	0.02	60
64	0.19	0.49	0.27	106
65	0.19	0.44	0.27	34
66	0.08	0.28	0.13	101
67	0.07	0.26	0.11	38
68	0.17	0.43	0.25	104
69	0.09	0.17	0.12	144
70	0.17	0.30	0.22	135
71	0.11	0.20	0.14	190
72	0.25	0.44	0.32	139
73	0.04	0.16	0.07	69
74	0.08	0.16	0.11	133
75	0.38	0.47	0.42	181
76	0.19	0.47	0.27	113
77	0.15	0.37	0.21	158
78	0.11	0.23	0.15	142
79	0.13	0.23	0.17	96
80	0.26	0.50	0.34	101
81	0.10	0.27	0.14	56
82	0.05	0.21	0.08	62
83	0.17	0.43	0.25	77
84	0.10	0.28	0.15	100
85	0.14	0.52	0.22	54
86	0.07	0.27	0.11	79
87	0.18	0.37	0.24	92
88	0.16	0.34	0.21	124

89	0.23	0.48	0.31	101
90	0.03	0.12	0.04	40
91	0.20	0.36	0.26	66
92	0.08	0.43	0.13	58
93	0.34	0.52	0.41	161
94	0.12	0.28	0.17	130
95	0.14	0.23	0.18	47
96	0.24	0.52	0.33	107
97	0.09	0.44	0.15	39
98	0.07	0.20	0.11	111
99	0.12	0.25	0.16	95
100	0.11	0.22	0.14	129
101	0.26	0.51	0.35	91
102	0.03	0.19	0.05	27
103	0.43	0.86	0.57	90
104	0.09	0.21	0.12	124
105	0.06	0.18	0.09	76
106	0.26	0.32	0.29	371
107	0.25	0.41	0.31	114
108	0.17	0.44	0.25	98
109	0.11	0.35	0.16	63
110	0.11	0.46	0.18	24
111	0.15	0.43	0.22	53
112	0.07	0.18	0.10	65
113	0.11	0.36	0.17	70
114	0.12	0.59	0.20	27
115	0.11	0.29	0.16	72 27
116	0.16	0.33	0.22	27 90
117 118	0.19 0.16	0.39 0.39	0.25 0.22	95
119	0.16	0.39	0.22	92
120	0.15	0.40	0.23	87
121	0.13	0.34	0.21	45
121	0.17	0.12	0.24	182
123	0.12	0.12	0.03	94
124	0.22	0.48	0.30	62
125	0.18	0.48	0.27	91
126	0.13	0.45	0.21	69
127	0.22	0.47	0.30	73

128	0.12	0.44	0.19	25
129	0.02	0.09	0.04	68
130	0.12	0.26	0.16	123
131	0.06	0.21	0.10	84
132	0.04	0.10	0.05	67
133	0.11	0.33	0.16	127
134	0.10	0.42	0.16	45
135	0.18	0.43	0.25	88
136	0.04	0.16	0.07	63
137	0.60	0.79	0.68	96
138	0.06	0.24	0.10	71
139	0.34	0.71	0.46	92
140	0.03	0.13	0.05	23
141	0.12	0.34	0.17	90
142	0.02	0.30	0.04	10
143	0.07	0.25	0.11	44
144	0.20	0.51	0.28	67
145	0.42	0.44	0.43	131
146	0.08	0.18	0.11	83
147	0.08	0.25	0.12	32
148	0.13	0.24	0.17	115
149	0.19	0.44	0.26	63
150	0.24	0.48	0.32	83
151	0.33	0.43	0.37	101
152	0.06	0.21	0.09	29
153	0.76	0.79	0.78	191
154	0.34	0.67	0.45	54
155	0.20	0.39	0.27	84
156	0.16	0.57	0.25	37
157	0.10	0.34	0.15	65
158	0.10	0.37	0.15	46
159	0.21	0.53	0.30	80
160	0.05	0.20	0.08	66
161	0.05	0.14	0.07	56
162	0.16	0.20	0.18	127
163	0.44	0.65	0.52	111
164 165	0.05	0.19	0.07	32 28
165 166	0.02	0.11	0.03	28 98
166	0.05	0.12	0.07	90

167	0.30	0.62	0.41	88
168	0.27	0.53	0.36	59
169	0.05	0.21	0.08	42
170	0.05	0.50	0.09	4
171	0.19	0.45	0.27	95
172	0.03	0.15	0.05	54
173	0.29	0.58	0.39	65
174	0.16	0.52	0.24	31
175	0.09	0.47	0.16	32
176	0.14	0.38	0.21	58
177	0.10	0.24	0.14	76
178	0.03	0.13	0.04	55
179	0.55	0.81	0.66	74
180	0.31	0.70	0.43	64
181	0.07	0.16	0.09	57
182	0.07	0.39	0.12	36
183	0.13	0.44	0.20	52
184	0.20	0.46	0.28	48
185	0.20	0.56	0.29	16
186	0.03	0.18	0.06	28
187	0.12	0.28	0.17	36
188	0.10	0.35	0.16	26
189	0.09	0.30	0.13	44
190	0.15	0.33	0.21	46
191	0.09	0.27	0.14	75 50
192	0.05	0.28	0.09	50
193	0.17	0.40	0.24	20
194	0.03	0.15	0.05	27
195	0.06	0.50	0.10	6
196	0.14	0.24	0.18	68
197	0.14	0.48	0.21	29
198	0.12	0.28	0.17	104
199	0.08	0.39	0.14	36
200	0.17	1.00	0.29	4
201	0.07	0.50	0.12	4 06
202 203	0.05	0.16 0.64	0.08	96 61
203	0.41 0.11	0.04	0.50 0.15	82
204	0.11	0.28	0.15	82 34
Z 0 J	0.13	0.55	0.24	24

206	0.30	0.52	0.38	66
207	0.09	0.38	0.15	97
208	0.05	0.13	0.08	89
209	0.34	0.62	0.44	55
210	0.28	0.63	0.38	78
211	0.06	0.18	0.09	78
212	0.38	0.52	0.44	158
213	0.04	0.18	0.07	44
214	0.17	0.54	0.26	35
215	0.37	0.73	0.49	48
216	0.31	0.63	0.42	62
217	0.00	0.00	0.00	11
218	0.28	0.54	0.37	68
219	0.13	0.38	0.20	60
220	0.02	0.16	0.04	25
221	0.13	0.37	0.19	57
222	0.08	0.50	0.14	36
223	0.08	0.23	0.12	88
224	0.05	0.22	0.08	46
225	0.04	0.18	0.06	60
226	0.10	0.28	0.15	65
227	0.05	0.57	0.09	7
228	0.14	0.67	0.24	12
229	0.02	0.09	0.04	68
230	0.06	0.23	0.10	40
231	0.04	0.15	0.07	26
232	0.17	0.70	0.28	30
233	0.11	0.27	0.15	41
234	0.08	0.28	0.13	53
235	0.12	0.54	0.20	35
236	0.04	0.17	0.07	18
237	0.02	0.09	0.03	22
238	0.24	0.68	0.36	59
239	0.24	0.51	0.32	43
240	0.08	0.24	0.12	45 46
241	0.04	0.15	0.06	46
242	0.04	0.21	0.07	38
243	0.23	0.38	0.28	56
244	0.05	0.29	0.09	35

245	0.03	0.14	0.05	42
246	0.03	0.12	0.05	33
247	0.14	0.34	0.20	47
248	0.05	0.36	0.08	25
249	0.15	0.62	0.25	39
250	0.21	0.45	0.29	77
251	0.34	0.61	0.44	56
252	0.09	0.22	0.13	72
253	0.18	1.00	0.31	4
254	0.13	0.59	0.21	29
255	0.18	0.23	0.20	113
256	0.34	0.71	0.46	59
257	0.04	0.10	0.06	59
258	0.32	0.62	0.42	39
259	0.11	0.75	0.19	12
260	0.06	0.56	0.12	9
261	0.38	0.80	0.51	44
262	0.14	0.44	0.21	32
263	0.08	0.27	0.13	156
264	0.10	0.60	0.18	5
265	0.14	0.27	0.18	198
266	0.04	0.12	0.05	40
267	0.08	0.38	0.13	29
268	0.00	0.00	0.00	39
269	0.01	0.17	0.02	6
270	0.06	0.60	0.11	5
271	0.05	0.41	0.09	17
272	0.10	0.33	0.16	54
273	0.05	0.30	0.09	23
274	0.02	0.03	0.02	126
275	0.12	0.41	0.19	32
276	0.08	0.60	0.15	10
277	0.29	0.51	0.37	67
278	0.21	0.38	0.27	53
279	0.01	0.06	0.02	16
280	0.18	0.63	0.28	19
281	0.05	0.13	0.07	61
282	0.11	0.25	0.15	81
283	0.19	0.39	0.26	94

284	0.15	0.42	0.22	31
285	0.06	0.26	0.09	43
286	0.13	0.29	0.18	79
287	0.16	0.50	0.24	20
288	0.19	0.88	0.32	17
289	0.35	0.61	0.45	56
290	0.04	0.14	0.06	63
291	0.10	0.30	0.15	46
292	0.08	0.28	0.12	50
293	0.05	0.35	0.08	17
294	0.07	0.33	0.11	27
295	0.02	0.08	0.04	63
296	0.08	0.28	0.12	25
297	0.01	0.03	0.01	38
298	0.04	0.13	0.06	62
299	0.35	0.63	0.45	49
300	0.04	0.23	0.07	39
301	0.01	0.12	0.02	8
302	0.03	0.22	0.05	18
303	0.09	0.32	0.14	19
304	0.12	0.44	0.19	18
305	0.14	0.69	0.23	26
306	0.04	0.30	0.07	10
307	0.06	0.17	0.09	12
308	0.09	0.50	0.15	8
309	0.12	0.33	0.18	57
310	0.08	0.22	0.12	37
311	0.42	0.68	0.52	50
312	0.12	0.33	0.17	36
313	0.02	0.16	0.04	19 50
314 315	0.42 0.38	0.76 0.62	0.54 0.47	59 48
316	0.38	0.02	0.47	46 45
317	0.09	0.22	0.12	43 29
318	0.09	0.43	0.14	37
319	0.14	0.43	0.21	38
320	0.36	0.59	0.10	44
321	0.30	0.59	0.37	41
322	0.29	0.04	0.37	25
J	0.01	0.04	0.01	23

323	0.00	0.00	0.00	4
324	0.02	0.09	0.03	11
325	0.23	1.00	0.38	3
326	0.09	0.31	0.14	32
327	0.16	0.36	0.22	50
328	0.07	0.26	0.12	46
329	0.56	0.74	0.64	47
330	0.42	0.81	0.56	31
331	0.00	0.00	0.00	11
332	0.02	0.10	0.04	31
333	0.03	0.12	0.04	26
334	0.00	0.00	0.00	41
335	0.06	0.21	0.09	39
336	0.14	0.33	0.20	40
337	0.09	0.27	0.14	37
338	0.14	0.50	0.22	10
339	0.00	0.00	0.00	38
340	0.57	0.87	0.69	23
341	0.05	0.24	0.09	33
342	0.03	0.17	0.06	40
343	0.05	0.14	0.07	35
344	0.10	0.30	0.15	30
345	0.02	0.09	0.04	33
346	0.12	0.52	0.19	25
347	0.07	0.44	0.11	9
348	0.03	0.50	0.05	2
349	0.26	0.65	0.37	34
350	0.09	0.37	0.14	38
351	0.19	0.41	0.26	49
352	0.01	0.09	0.02	22
353	0.07	0.18	0.10	39
354	0.06	0.28	0.10	18
355	0.05	0.19	0.08	31
356	0.02	0.12	0.03	17
357	0.25	0.54	0.34	35
358	0.04	0.09	0.05	43
359	0.21	0.66	0.32	47
360	0.04	0.17	0.07	29
361	0.37	0.66	0.48	38

362	0.16	0.39	0.23	36
363	0.22	0.44	0.29	55
364	0.09	0.24	0.13	34
365	0.08	0.25	0.13	24
366	0.03	0.21	0.05	19
367	0.04	0.60	0.08	5
368	0.07	0.27	0.11	33
369	0.21	0.62	0.31	34
370	0.16	0.50	0.24	20
371	0.02	0.18	0.04	17
372	0.07	0.26	0.11	31
373	0.04	0.12	0.06	34
374	0.03	0.13	0.05	23
375	0.15	0.39	0.22	31
376	0.08	0.32	0.13	28
377	0.26	0.77	0.39	22
378	0.01	0.11	0.02	9
379	0.09	0.24	0.14	29
380	0.11	0.33	0.16	30
381	0.19	0.74	0.30	35
382	0.18	0.42	0.25	36
383	0.01	0.25	0.03	4
384	0.37	0.88	0.52	24
385	0.10	0.36	0.15	25
386	0.06	0.22	0.10	27
387	0.14	0.39	0.21	36
388	0.19	0.45	0.27	31
389	0.21	0.49	0.30	37
390	0.17	0.41	0.24	27
391	0.19	0.46	0.26	46
392	0.03	0.50	0.06	4
393 394	0.11 0.03	0.42 0.33	0.17	19 12
			0.06	
395	0.10	0.38	0.16	26 60
396 307	0.15	0.29	0.20	69 25
397 398	0.15 0.06	0.44 0.25	0.23 0.10	25 32
399	0.06	0.23	0.10	33
400	0.05	0.21	0.10	38
400	כטיט	0.10	0.00	20

401	0.09	0.29	0.14	17
402	0.03	0.21	0.05	24
403	0.10	0.62	0.17	16
404	0.16	0.53	0.25	15
405	0.06	0.25	0.10	20
406	0.02	0.20	0.04	15
407	0.07	0.32	0.11	25
408	0.04	0.16	0.07	19
409	0.09	0.33	0.14	46
410	0.00	0.00	0.00	45
411	0.05	0.29	0.08	21
412	0.00	0.00	0.00	8
413	0.25	0.57	0.35	35
414	0.02	0.09	0.04	34
415	0.24	0.79	0.37	14
416	0.07	0.21	0.11	29
417	0.05	0.14	0.07	28
418	0.14	0.19	0.16	21
419	0.05	0.15	0.07	26
420	0.21	0.32	0.25	38
421	0.19	0.31	0.24	131
422	0.03	0.19	0.05	26
423	0.11	0.32	0.17	25
424	0.59	0.56	0.57	48
425	0.03	0.17	0.05	24
426	0.08	0.31	0.13	42
427	0.13	0.35	0.19	26
428	0.03	0.20	0.05	10
429	0.27	0.54	0.36	54
430	0.11	0.31	0.16	32
431	0.22	0.46	0.30	48
432	0.12	0.31	0.17	35
433	0.02	0.14	0.04	22
434	0.05	0.21	0.08	24
435	0.40	0.61	0.49	59
436	0.03	0.11	0.05	35
437 438	0.00	0.00	0.00	12 50
438 439	0.26	0.32 0.17	0.29	50 36
439	0.05	U. 1/	0.07	20

440	0.06	0.14	0.09	35
441	0.00	0.00	0.00	8
442	0.10	0.23	0.14	48
443	0.14	0.50	0.22	18
444	0.25	0.37	0.30	52
445	0.08	0.30	0.12	20
446	0.07	0.22	0.10	18
447	0.02	0.17	0.04	6
448	0.10	0.21	0.13	28
449	0.06	0.16	0.09	38
450	0.98	0.63	0.76	129
451	0.33	0.72	0.45	29
452	0.09	0.14	0.11	58
453	0.00	0.00	0.00	32
454	0.22	0.62	0.33	16
455	0.37	0.65	0.47	34
456	0.08	0.44	0.13	9
457	0.45	0.87	0.59	30
458	0.12	0.33	0.18	40
459	0.13	0.30	0.18	37
460	0.35	0.77	0.48	30
461	0.08	0.33	0.13	27
462	0.05	0.25	0.09	12
463	0.08	0.41	0.13	17
464	0.31	0.59	0.41	56
465	0.21	0.44	0.29	9
466	0.16	0.45	0.24	22
467	0.04	0.33	0.08	9
468	0.04	0.33	0.07	15
469	0.01	0.07	0.02	14
470 471	0.07	0.50 0.67	0.13 0.28	16 18
471	0.17 0.05	0.07	0.28	16
472	0.03	0.50	0.32	22
473 474	0.06	0.25	0.32	12
474	0.92	0.23	0.10	110
475	0.24	0.79	0.35	20
477	0.22	0.55	0.33	31
478	0.11	0.36	0.32	42
		5.55	· · - /	

```
479
                   0.01
                              0.25
                                        0.02
                                                      4
         480
                    0.16
                              0.43
                                        0.24
                                                     47
                    0.25
                              0.53
                                        0.34
                                                     30
         481
         482
                   0.03
                              0.11
                                        0.05
                                                     35
         483
                    0.11
                              0.23
                                        0.15
                                                     30
         484
                   0.08
                              0.40
                                        0.14
                                                     20
                              0.53
                                        0.28
                                                     15
         485
                    0.19
         486
                    0.04
                              0.12
                                        0.05
                                                     17
                              0.09
                                        0.02
                                                     11
         487
                   0.01
         488
                                        0.14
                                                     36
                   0.09
                              0.25
         489
                   0.08
                              0.22
                                        0.12
                                                     32
         490
                              0.43
                                        0.17
                                                     14
                    0.11
                              0.40
                                        0.21
                                                     25
         491
                    0.14
                   0.20
                              0.48
                                        0.28
                                                     23
         492
         493
                   0.00
                              0.00
                                        0.00
                                                      9
         494
                    0.14
                                        0.17
                                                     37
                              0.22
         495
                   0.03
                              0.12
                                        0.04
                                                     24
         496
                    0.18
                              0.44
                                        0.25
                                                     34
                              0.20
                                        0.10
         497
                    0.06
                                                     25
         498
                                        0.02
                    0.01
                              0.11
                                                      9
                    0.10
                              0.35
                                        0.15
                                                     17
         499
   micro avq
                    0.23
                              0.44
                                        0.30
                                                  55953
                   0.16
                              0.37
                                        0.21
                                                  55953
   macro avg
weighted avg
                   0.31
                              0.44
                                        0.35
                                                  55953
 samples avq
                   0.32
                              0.42
                                        0.32
                                                  55953
```

Time taken to run this cell: 1:15:27.156165

```
In [76]: start = datetime.now()
    classifier_2 = OneVsRestClassifier(LogisticRegression(penalty='l1'))
    classifier_2.fit(x_train_multilabel_bow, y_train)
    predictions_2 = classifier_2.predict(x_test_multilabel_bow)
    print("Accuracy :",metrics.accuracy_score(y_test, predictions_2))
    print("Hamming loss ",metrics.hamming_loss(y_test,predictions_2))

precision = precision_score(y_test, predictions_2, average='micro')
```

```
recall = recall score(y test, predictions 2, average='micro')
f1 = f1 score(y test, predictions 2, average='micro')
global report = global report.append({
                       'Vectorizer': 'BoW',
                       'Model': 'Logistic Regression',
                       'NGram': '(1,4)',
                       'Parameter': 1,
                       'Precision': precision,
                       'Recall': recall.
                       'F1 Score Micro':f1
                    },
                   ignore index=True)
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: 0.18633333333333333
Micro-average quality numbers
Precision: 0.5644, Recall: 0.3887, F1-measure: 0.4604
Macro-average quality numbers
Precision: 0.4320, Recall: 0.3112, F1-measure: 0.3527
             precision recall f1-score support
                           0.40
                                      0.48
                  0.61
                                                1111
                                               2052
          1
                  0.47
                            0.30
                                      0.36
                  0.54
                            0.42
                                      0.47
                                               2388
```

3	0.66	0.56	0.60	2226
4	0.66	0.50	0.57	2014
5	0.30	0.14	0.19	642
6	0.64	0.41	0.50	1756
7	0.89	0.72	0.79	1690
8	0.55	0.24	0.34	341
9	0.77	0.78	0.78	2344
10	0.57	0.40	0.47	821
11	0.43	0.29	0.34	1143
12	0.64	0.40	0.49	768
13	0.55	0.37	0.44	745
14	0.69	0.56	0.62	952
15	0.46	0.27	0.34	314
16	0.41	0.26	0.32	624
17	0.72	0.56	0.63	535
18	0.73	0.54	0.62	631
19	0.88	0.57	0.69	101
20	0.53	0.26	0.35	245
21	0.73	0.54	0.62	694
22	0.48	0.32	0.38	568
23	0.52	0.32	0.40	423
24	0.53	0.34	0.42	406
25	0.70	0.49	0.58	1373
26	0.52	0.34	0.41	253
27	0.24	0.16	0.19	357
28	0.50	0.28	0.36	222
29	0.58	0.30	0.40	273
30	0.48	0.32	0.38	308
31	0.45	0.30	0.36	256
32	0.69	0.41	0.52	295
33	0.22	0.11	0.15	263
34	0.74	0.53	0.62	256
35	0.42	0.34	0.37	280
36	0.47	0.32	0.38	290
37	0.36	0.17	0.23	200
38	0.34	0.29	0.32	109
39	0.62	0.39	0.48	209
40	0.52	0.39	0.45	113
41	0.54	0.28	0.37	197

42	0.51	0.56	0.53	52
43 44	0.17 0.77	0.10 0.50	0.13 0.61	179 431
45	0.77	0.11	0.16	431 47
46	0.44	0.38	0.41	37
47	0.54	0.34	0.41	155
48	0.65	0.50	0.57	254
49	0.50	0.34	0.41	201
50	0.40	0.28	0.33	61
51	0.92	0.73	0.82	246
52	0.67	0.62	0.64	146
53	0.92	0.91	0.92	516
54	0.75	0.55	0.64	170
55	0.21	0.10	0.13	234
56	0.19	0.11	0.14	357
57	0.55	0.27	0.36	78
58	0.87	0.68	0.76	102
59	0.35	0.24	0.28	122
60	0.72	0.57	0.64	138
61	0.22	0.17	0.19	36
62	0.35	0.19	0.25	172
63	0.08	0.03	0.05	60
64 65	0.59 0.35	0.51 0.32	0.55 0.34	106 34
66	0.29	0.32	0.34	101
67	0.29	0.23	0.38	38
68	0.45	0.34	0.46	104
69	0.32	0.17	0.22	144
70	0.38	0.24	0.29	135
71	0.24	0.14	0.17	190
72	0.56	0.36	0.44	139
73	0.21	0.04	0.07	69
74	0.07	0.04	0.05	133
75	0.73	0.46	0.57	181
76	0.43	0.43	0.43	113
77	0.42	0.22	0.29	158
78	0.28	0.15	0.19	142
79	0.45	0.18	0.25	96
80	0.52	0.25	0.34	101

81	0.42	0.18	0.25	56
82	0.13	0.05	0.07	62
83	0.58	0.44	0.50	77
84	0.45	0.15	0.23	100
85	0.55	0.43	0.48	54
86	0.30	0.16	0.21	79
87	0.44	0.24	0.31	92
88	0.45	0.31	0.37	124
89	0.60	0.39	0.47	101
90	0.27	0.10	0.15	40
91	0.56	0.44	0.49	66
92	0.42	0.31	0.36	58
93	0.67	0.42	0.51	161
94	0.40	0.25	0.30	130
95	0.44	0.26	0.32	47
96	0.64	0.50	0.57	107
97	0.50	0.31	0.38	39
98	0.22	0.12	0.15	111
99	0.39	0.22	0.28	95
100	0.29	0.22	0.25	129
101	0.74	0.46	0.57	91
102	0.19	0.19	0.19	27
103	0.85	0.84	0.85	90
104	0.20	0.07	0.11	124
105	0.30	0.17	0.22	76
106	0.35	0.18	0.24	371
107	0.67	0.40	0.50	114
108	0.49	0.37	0.42	98
109	0.60	0.40	0.48	63
110	0.63	0.50	0.56	24
111	0.54	0.28	0.37	53
112	0.16	0.09	0.12	65
113	0.53	0.36	0.43	70
114	0.50	0.56	0.53	27
115	0.31	0.12	0.18	72
116	0.33	0.19	0.24	27
117	0.54	0.32	0.40	90
118	0.50	0.40	0.44	95
119	0.37	0.27	0.31	92

120	0.28	0.21	0.24	87
121	0.57	0.36	0.44	45
122	0.18	0.08	0.11	182
123	0.31	0.12	0.17	94
124	0.72	0.42	0.53	62
125	0.73	0.44	0.55	91
126	0.69	0.51	0.58	69
127	0.49	0.48	0.48	73
128	1.00	0.52	0.68	25
129	0.20	0.03	0.05	68
130	0.31	0.19	0.23	123
131	0.25	0.15	0.19	84
132	0.00	0.00	0.00	67
133	0.30	0.20	0.24	127
134	0.47	0.60	0.52	45
135	0.49	0.42	0.45	88
136	0.00	0.00	0.00	63
137	0.89	0.77	0.83	96
138	0.19	0.08	0.12	71
139	0.84	0.64	0.73	92
140	0.23	0.13	0.17	23
141	0.42	0.23	0.30	90
142	0.15	0.20	0.17	10
143	0.27	0.18	0.22	44
144	0.59	0.43	0.50	67
145	0.65	0.46	0.54	131
146	0.17	0.07	0.10	83
147	0.27	0.12	0.17	32
148	0.30	0.15	0.20	115
149	0.47	0.29	0.36	63
150	0.62	0.35	0.45	83
151	0.73	0.47	0.57	101
152	0.27	0.10	0.15	29
153	0.92	0.85	0.89	191
154	0.86	0.69	0.76	54
155	0.58	0.35	0.43	84
156	0.50	0.38	0.43	37
157	0.32	0.38	0.35	65
158	0.33	0.20	0.25	46

0.79	0.53	0.63	80
0.19	0.11	0.14	66
0.17	0.07	0.10	56
0.41	0.23	0.29	127
0.67	0.59	0.63	111
0.17	0.06	0.09	32
0.25	0.14	0.18	28
0.03	0.01	0.02	98
0.68	0.58	0.63	88
0.76	0.54	0.63	59
	0.02	0.03	42
0.29	0.50	0.36	4
0.58	0.40	0.47	95
0.27	0.17	0.21	54
0.74	0.54	0.62	65
0.60	0.48	0.54	31
0.62	0.47	0.54	32
0.54	0.34	0.42	58
0.42	0.21	0.28	76
0.05	0.02	0.03	55
0.80	0.85	0.82	74
0.78	0.62	0.70	64
0.35	0.12	0.18	57
0.47	0.25	0.33	36
0.35	0.42	0.38	52
0.49	0.44	0.46	48
0.25	0.31	0.28	16
0.12	0.07	0.09	28
0.16	0.17	0.16	36
0.28	0.31	0.29	26
0.19	0.09	0.12	44
0.55	0.35	0.43	46
0.32	0.20	0.25	75
0.21	0.24	0.22	50
0.50	0.45	0.47	20
0.31	0.19	0.23	27
0.38	0.50	0.43	6
0.17	0.13	0.15	68
0.33	0.41	0.37	29
	0.19 0.17 0.41 0.67 0.17 0.25 0.03 0.68 0.76 0.05 0.29 0.58 0.27 0.60 0.62 0.54 0.42 0.05 0.80 0.78 0.35 0.47 0.35 0.49 0.25 0.16 0.28 0.19 0.55 0.31 0.38 0.17	0.19 0.11 0.17 0.07 0.41 0.23 0.67 0.59 0.17 0.06 0.25 0.14 0.03 0.01 0.68 0.58 0.76 0.54 0.05 0.02 0.29 0.50 0.58 0.40 0.27 0.17 0.74 0.54 0.60 0.48 0.62 0.47 0.54 0.34 0.42 0.21 0.05 0.02 0.80 0.85 0.78 0.62 0.35 0.12 0.47 0.25 0.35 0.42 0.49 0.44 0.25 0.31 0.12 0.07 0.16 0.17 0.28 0.31 0.19 0.09 0.55 0.35 0.32 0.20 0.21 0.24 0.50 0.45 0.31	0.19 0.11 0.14 0.17 0.07 0.10 0.41 0.23 0.29 0.67 0.59 0.63 0.17 0.06 0.09 0.25 0.14 0.18 0.03 0.01 0.02 0.68 0.58 0.63 0.76 0.54 0.63 0.05 0.02 0.03 0.29 0.50 0.36 0.58 0.40 0.47 0.27 0.17 0.21 0.74 0.54 0.62 0.60 0.48 0.54 0.62 0.47 0.54 0.54 0.34 0.42 0.42 0.21 0.28 0.05 0.02 0.03 0.80 0.85 0.82 0.78 0.62 0.70 0.35 0.12 0.18 0.47 0.25 0.33 0.35 0.12 0.18 0.47 0.25 0.33 0.49 0.44

198	0.33	0.17	0.23	104
199	0.45	0.25	0.32	36
200	1.00	1.00	1.00	4
201	0.75	0.75	0.75	4
202	0.25	0.07	0.11	96
203	0.82	0.61	0.70	61
204	0.45	0.17	0.25	82
205	0.46	0.35	0.40	34
206	0.66	0.41	0.50	66
207	0.17	0.09	0.12	97
208	0.14	0.06	0.08	89
209	0.78	0.53	0.63	55
210	0.72	0.54	0.62	78
211	0.22	0.08	0.11	78
212	0.68	0.47	0.56	158
213	0.24	0.09	0.13	44
214	0.62	0.60	0.61	35
215	0.87	0.71	0.78	48
216	0.66	0.66	0.66	62
217	0.50	0.36	0.42	11
218	0.81	0.44	0.57	68
219	0.31	0.22	0.25	60
220	0.33	0.08	0.13	25
221	0.31	0.14	0.19	57
222	0.59	0.53	0.56	36
223	0.37	0.17	0.23	88
224	0.26	0.15	0.19	46
225	0.32	0.10	0.15	60
226	0.26	0.14	0.18	65
227	0.50	0.57	0.53	7
228	0.41	0.58	0.48	12
229	0.18	0.13	0.15	68
230	0.44	0.28	0.34	40
231	0.08	0.04	0.05	26
232	0.72	0.60	0.65	30
233	0.33	0.20	0.25	41
234	0.18	0.08	0.11	53
235	0.51	0.54	0.53	35
236	0.62	0.28	0.38	18

237	0.17	0.09	0.12	22
238	0.67	0.56	0.61	59
239	0.67	0.56	0.61	43
240	0.34	0.27	0.30	45
241	0.33	0.13	0.19	46
242	0.13	0.05	0.08	38
243	0.94	0.29	0.44	56
244	0.24	0.17	0.20	35
245	0.10	0.05	0.06	42
246	0.07	0.03	0.04	33
247	0.38	0.28	0.32	47
248	0.62	0.20	0.30	25
249	0.56	0.59	0.57	39
250	0.56	0.19	0.29	77
251	0.74	0.55	0.63	56
252	0.20	0.06	0.09	72
253	0.67	1.00	0.80	4
254	0.50	0.38	0.43	29
255	0.41	0.27	0.32	113
256	0.75	0.71	0.73	59
257	0.18	0.05	0.08	59
258	0.83	0.62	0.71	39
259	0.64	0.58	0.61	12
260	0.56	0.56	0.56	9
261	0.94	0.66	0.77	44
262	0.76	0.50	0.60	32
263	0.18	0.17	0.17	156
264	1.00	0.60	0.75	5
265	0.18	0.07	0.10	198
266	0.07	0.03	0.04	40
267	0.20	0.14	0.16	29
268	0.00	0.00	0.00	39
269	0.11	0.17	0.13	6
270	0.75	0.60	0.67	5
271	0.40	0.12	0.18	17
272	0.30	0.13	0.18	54
273	0.38	0.26	0.31	23
274	0.00	0.00	0.00	126
275	0.44	0.34	0.39	32

276	0.40	0.60	0.48	10
277	0.82	0.61	0.70	67
278	0.47	0.36	0.41	53
279	0.33	0.12	0.18	16
280	0.72	0.68	0.70	19
281	0.30	0.13	0.18	61
282	0.38	0.21	0.27	81
283	0.41	0.34	0.37	94
284	0.46	0.35	0.40	31
285	0.31	0.21	0.25	43
286	0.35	0.22	0.27	79
287	0.29	0.40	0.33	20
288	0.83	0.88	0.86	17
289	0.73	0.64	0.69	56
290	0.15	0.08	0.10	63
291	0.48	0.33	0.39	46
292	0.43	0.36	0.39	50
293	0.62	0.29	0.40	17
294	0.36	0.15	0.21	27
295	0.04	0.02	0.02	63
296	0.23	0.12	0.16	25
297	0.04	0.03	0.03	38
298	0.25	0.10	0.14	62
299	0.67	0.59	0.63	49
300	0.19	0.15	0.17	39
301	0.00	0.00	0.00	8
302	0.17	0.11	0.13	18
303	0.15	0.11	0.12	19
304	0.60	0.67	0.63	18
305	0.44	0.46	0.45	26
306	0.23	0.30	0.26	10
307	0.17	0.17	0.17	12
308	0.60	0.38	0.46	8
309	0.37	0.12	0.18	57
310	0.31	0.22	0.25	37
311	0.80	0.72	0.76	50
312	0.38	0.31	0.34	36
313	0.24	0.26	0.25	19
314	0.88	0.71	0.79	59

315	0.79	0.71	0.75	48
316	0.22	0.13	0.17	45
317	0.62	0.34	0.44	29
318	0.33	0.32	0.33	37
319	0.24	0.11	0.15	38
320	0.81	0.68	0.74	44
321	0.64	0.39	0.48	41
322	0.15	0.08	0.11	25
323	0.25	0.25	0.25	4
324	0.12	0.09	0.11	11
325	0.75	1.00	0.86	3
326	0.45	0.28	0.35	32
327	0.49	0.34	0.40	50
328	0.26	0.11	0.15	46
329	0.90	0.74	0.81	47
330	0.91	0.68	0.78	31
331	0.00	0.00	0.00	11
332	0.00	0.00	0.00	31
333	0.08	0.04	0.05	26
334	0.07	0.02	0.04	41
335	0.08	0.03	0.04	39
336	0.69	0.45	0.55	40
337	0.28	0.22	0.24	37
338	0.83	0.50	0.62	10
339	0.00	0.00	0.00	38
340	0.94	0.70	0.80	23
341	0.26	0.15	0.19	33
342	0.16	0.07	0.10	40
343	0.38	0.17	0.24	35
344	0.52	0.40	0.45	30
345	0.08	0.03	0.04	33
346	0.65	0.44	0.52	25
347	0.75	0.33	0.46	9
348	0.50	0.50	0.50	2
349	0.79	0.68	0.73	34
350	0.36	0.47	0.41	38
351	0.57	0.27	0.36	49
352	0.00	0.00	0.00	22
353	0.35	0.23	0.28	39

354	0.50	0.17	0.25	18
355	0.21	0.13	0.16	31
356	0.14	0.06	0.08	17
357	0.73	0.69	0.71	35
358	0.44	0.09	0.15	43
359	0.56	0.64	0.59	47
360	0.20	0.10	0.14	29
361	0.65	0.58	0.61	38
362	0.41	0.31	0.35	36
363	0.36	0.36	0.36	55
364	0.29	0.21	0.24	34
365	0.27	0.17	0.21	24
366	0.12	0.11	0.11	19
367	0.22	0.40	0.29	5
368	0.20	0.12	0.15	33
369	0.69	0.65	0.67	34
370	0.42	0.40	0.41	20
371	0.07	0.06	0.06	17
372	0.31	0.13	0.18	31
373	0.11	0.03	0.05	34
374	0.15	0.13	0.14	23
375	0.41	0.39	0.40	31
376	0.62	0.29	0.39	28
377	0.78	0.64	0.70	22
378	0.36	0.56	0.43	9
379	0.33	0.21	0.26	29
380	0.26	0.27	0.26	30
381	0.72	0.60	0.66	35
382	0.41	0.31	0.35	36
383	0.17	0.25	0.20	4
384	0.90	0.79	0.84	24
385	0.60	0.36	0.45	25
386	0.08	0.04	0.05	27
387	0.75	0.33	0.46	36
388	0.61	0.45	0.52	31
389	0.65	0.46	0.54	37
390	0.39	0.33	0.36	27
391	0.58	0.41	0.48	46
392	0.25	0.50	0.33	4

0.26	0.32	0.29	19
0.00	0.00	0.00	12
0.50	0.42	0.46	26
0.19	0.04	0.07	69
0.67	0.72	0.69	25
0.14	0.06	0.09	32
0.32	0.18	0.23	33
0.32	0.18	0.23	38
0.50	0.29	0.37	17
0.12	0.04	0.06	24
0.73	0.50	0.59	16
0.83	0.33	0.48	15
0.00	0.00	0.00	20
0.00	0.00	0.00	15
0.21	0.12	0.15	25
0.29	0.26	0.28	19
0.53	0.37	0.44	46
0.00	0.00	0.00	45
0.17	0.10	0.12	21
0.00	0.00	0.00	8
0.50	0.51	0.51	35
0.00	0.00	0.00	34
1.00		0.73	14
0.23			29
0.33			28
0.43	0.14	0.21	21
0.25	0.15	0.19	26
0.52	0.29	0.37	38
0.17	0.02	0.04	131
0.29	0.23	0.26	26
0.40	0.40	0.40	25
0.81	0.62	0.71	48
0.17	0.08	0.11	24
0.29	0.14	0.19	42
0.39	0.35	0.37	26
0.11	0.10	0.11	10
0.54	0.39	0.45	54
0.55	0.34	0.42	32
0.39	0.27	0.32	48
	0.00 0.50 0.19 0.67 0.14 0.32 0.50 0.12 0.73 0.83 0.00 0.21 0.29 0.53 0.00 0.21 0.29 0.53 0.00 0.21 0.29 0.50 0.17 0.00 0.23 0.33 0.43 0.25 0.52 0.17 0.29 0.55 0.55	0.00 0.00 0.50 0.42 0.19 0.04 0.67 0.72 0.14 0.06 0.32 0.18 0.32 0.18 0.50 0.29 0.12 0.04 0.73 0.50 0.83 0.33 0.00 0.00 0.21 0.12 0.29 0.26 0.53 0.37 0.00 0.00 0.17 0.10 0.00 0.00 0.50 0.51 0.00 0.00 1.00 0.57 0.23 0.10 0.33 0.14 0.43 0.14 0.43 0.14 0.25 0.29 0.17 0.02 0.29 0.23 0.40 0.40 0.81 0.62 0.17 0.08 0.29 0.14 0.39 0.35 0.11 0.10 0.54	0.00 0.00 0.00 0.50 0.42 0.46 0.19 0.04 0.07 0.67 0.72 0.69 0.14 0.06 0.09 0.32 0.18 0.23 0.50 0.29 0.37 0.12 0.04 0.06 0.73 0.50 0.59 0.83 0.33 0.48 0.00 0.00 0.00 0.21 0.12 0.15 0.29 0.26 0.28 0.53 0.37 0.44 0.00 0.00 0.00 0.17 0.10 0.12 0.00 0.00 0.00 0.17 0.10 0.12 0.00 0.00 0.00 0.17 0.10 0.12 0.00 0.00 0.00 0.51 0.51 0.51 0.00 0.57 0.73 0.23 0.10 0.14 0.33 0.14 0.20 0.43 0.14

432	0.44	0.20	0.27	35
433	0.38	0.14	0.20	22
434	0.18	0.12	0.15	24
435	0.78	0.59	0.67	59
436	0.22	0.14	0.17	35
437	0.00	0.00	0.00	12
438	0.61	0.38	0.47	50
439	0.09	0.03	0.04	36
440	0.21	0.14	0.17	35
441	0.43	0.38	0.40	8
442	0.21	0.19	0.20	48
443	0.75	0.50	0.60	18
444	0.64	0.35	0.45	52
445	0.60	0.15	0.24	20
446	0.14	0.06	0.08	18
447	0.00	0.00	0.00	6
448	0.27	0.14	0.19	28
449	0.25	0.13	0.17	38
450	0.98	0.84	0.91	129
451	0.72	0.72	0.72	29
452	0.26	0.12	0.16	58
453	0.10	0.03	0.05	32
454	0.43	0.38	0.40	16
455	0.92	0.68	0.78	34
456	0.40	0.44	0.42	9
457	0.86	0.83	0.85	30
458	0.36	0.23	0.28	40
459	0.47	0.22	0.30	37
460	0.81	0.73	0.77	30
461	0.55	0.41	0.47	27
462	0.14	0.08	0.11	12
463	0.33	0.29	0.31	17
464	0.80	0.50	0.62	56
465	0.44	0.44	0.44	9
466	0.38	0.23	0.29	22
467	0.40	0.22	0.29	9
468	0.00	0.00	0.00	15
469	0.25	0.07	0.11	14
470	0.55	0.38	0.44	16

	471	0.85	0.61	0.71	18
	472	0.29	0.31	0.30	16
	473	0.46	0.55	0.50	22
	474	0.40	0.17	0.27	12
	474	1.00	0.17	0.27	110
	475				20
		0.48	0.70	0.57	
	477	0.62	0.52	0.56	31
	478	0.44	0.17	0.24	42
	479	0.00	0.00	0.00	4
	480	0.52	0.26	0.34	47
	481	0.75	0.40	0.52	30
	482	0.00	0.00	0.00	35
	483	0.00	0.00	0.00	30
	484	0.38	0.15	0.21	20
	485	0.80	0.53	0.64	15
	486	0.33	0.18	0.23	17
	487	0.33	0.09	0.14	11
	488	0.43	0.17	0.24	36
	489	0.18	0.09	0.12	32
	490	0.36	0.36	0.36	14
	491	0.50	0.24	0.32	25
	492	0.37	0.57	0.45	23
	493	0.00	0.00	0.00	9
	494	0.26	0.14	0.18	37
	495	0.12	0.08	0.10	24
	496	0.80	0.35	0.49	34
	497	0.20	0.12	0.15	25
	498	0.12	0.11	0.12	9
	499	0.47	0.41	0.44	17
	133	0117	0111	0111	_,
micro	avg	0.56	0.39	0.46	55953
macro	avg	0.43	0.31	0.35	55953
weighted	avg	0.54	0.39	0.45	55953
samples	avg	0.43	0.37	0.37	55953
adilib rea	uvy	0.75	0.57	0.57	

Time taken to run this cell: 0:50:37.329590

4.5.6 Applying Hyperparameter tuning using GridSearch Logistic

Regression with OneVsRest Classifier

```
In [77]: start = datetime.now()
         parameters = {'estimator alpha': [10**i for i in range(-6, 4, 1)]}
         classifier = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l1'
         ), n jobs=-1
         g clf = GridSearchCV(classifier, parameters, n jobs=-1, verbose=50, sco
         ring='f1 micro', cv=5)
         q clf.fit(x train multilabel bow, y train)
         predictions = q clf.predict (x test multilabel bow)
         print("Optimal Parameters: ", g clf.best params )
         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')
         global report = global report.append({
                                  'Vectorizer': 'BoW'.
                                  'Model': 'Logistic Regression (SGD with log los
         s) - Hypertuned',
                                  'NGram': '(1,4)',
                                 'Parameter': q clf.best params ['estimator alp
         ha'],
                                 'Precision': precision,
                                  'Recall': recall.
                                  'F1 Score Micro':f1
                             ignore index=True)
         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)
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
ers.
[Parallel(n jobs=-1)]: Done
                              1 tasks
                                             elapsed: 96.6min
[Parallel(n jobs=-1)]: Done
                              2 tasks
                                             elapsed: 107.5min
[Parallel(n jobs=-1)]: Done
                                             elapsed: 112.2min
                              3 tasks
[Parallel(n jobs=-1)]: Done
                              4 tasks
                                             elapsed: 118.8min
[Parallel(n jobs=-1)]: Done
                              5 tasks
                                             elapsed: 121.6min
[Parallel(n jobs=-1)]: Done
                              6 tasks
                                             elapsed: 127.4min
[Parallel(n jobs=-1)]: Done
                                             elapsed: 128.7min
                              7 tasks
[Parallel(n jobs=-1)]: Done
                              8 tasks
                                             elapsed: 141.1min
[Parallel(n jobs=-1)]: Done
                              9 tasks
                                             elapsed: 170.0min
[Parallel(n jobs=-1)]: Done 10 tasks
                                             elapsed: 180.5min
[Parallel(n jobs=-1)]: Done 11 tasks
                                             elapsed: 186.8min
[Parallel(n jobs=-1)]: Done 12 tasks
                                             elapsed: 188.8min
[Parallel(n jobs=-1)]: Done 13 tasks
                                             elapsed: 201.5min
[Parallel(n jobs=-1)]: Done 14 tasks
                                             elapsed: 203.3min
[Parallel(n jobs=-1)]: Done 15 tasks
                                             elapsed: 204.8min
[Parallel(n jobs=-1)]: Done 16 tasks
                                             elapsed: 207.3min
[Parallel(n iobs=-1)]: Done 17 tasks
                                             elapsed: 217.4min
[Parallel(n jobs=-1)]: Done 18 tasks
                                             elapsed: 220.6min
[Parallel(n jobs=-1)]: Done 19 tasks
                                             elapsed: 220.9min
[Parallel(n jobs=-1)]: Done 20 tasks
                                             elapsed: 221.1min
[Parallel(n jobs=-1)]: Done 21 tasks
                                             elapsed: 222.2min
[Parallel(n jobs=-1)]: Done 22 tasks
                                             elapsed: 223.8min
[Parallel(n jobs=-1)]: Done 23 tasks
                                             elapsed: 226.7min
[Parallel(n jobs=-1)]: Done 24 tasks
                                             elapsed: 231.8min
[Parallel(n jobs=-1)]: Done 25 tasks
                                             elapsed: 237.1min
[Parallel(n jobs=-1)]: Done 26 tasks
                                             elapsed: 242.1min
[Parallel(n jobs=-1)]: Done 27 tasks
                                             elapsed: 242.7min
```

```
[Parallel(n jobs=-1)]: Done 28 tasks
                                            elapsed: 243.0min
[Parallel(n jobs=-1)]: Done 29 tasks
                                            elapsed: 245.6min
[Parallel(n jobs=-1)]: Done 30 tasks
                                            elapsed: 245.8min
[Parallel(n jobs=-1)]: Done 31 tasks
                                            elapsed: 246.3min
[Parallel(n jobs=-1)]: Done 32 tasks
                                            elapsed: 250.9min
[Parallel(n jobs=-1)]: Done 33 tasks
                                            elapsed: 255.6min
[Parallel(n jobs=-1)]: Done 34 tasks
                                            elapsed: 258.1min
[Parallel(n jobs=-1)]: Done 35 tasks
                                            elapsed: 260.4min
[Parallel(n jobs=-1)]: Done 37 out of 50 |
                                            elapsed: 260.7min remainin
a: 91.6min
[Parallel(n jobs=-1)]: Done 39 out of 50 | elapsed: 261.4min remainin
a: 73.7min
[Parallel(n jobs=-1)]: Done 41 out of 50 | elapsed: 270.4min remainin
q: 59.4min
[Parallel(n jobs=-1)]: Done 43 out of 50 | elapsed: 274.8min remainin
q: 44.7min
[Parallel(n jobs=-1)]: Done 45 out of 50 | elapsed: 275.3min remainin
q: 30.6min
[Parallel(n jobs=-1)]: Done 47 out of 50 | elapsed: 275.6min remainin
q: 17.6min
[Parallel(n jobs=-1)]: Done 50 out of 50 | elapsed: 278.1min finished
Optimal Parameters: {'estimator alpha': 0.001}
Accuracy : 0.1647
Hamming loss 0.0034135333333333334
Micro-average quality numbers
Precision: 0.5805, Recall: 0.3062, F1-measure: 0.4009
Macro-average quality numbers
Precision: 0.3810, Recall: 0.2136, F1-measure: 0.2544
              precision
                          recall f1-score
                                             support
           0
                   0.64
                            0.28
                                      0.39
                                                1111
           1
                   0.56
                            0.10
                                      0.17
                                                2052
                                                2388
           2
                            0.31
                   0.65
                                      0.42
                            0.49
                  0.73
                                      0.59
                                                2226
           4
                   0.78
                            0.44
                                      0.57
                                                2014
                   0.46
                            0.11
                                      0.18
                                                 642
                            0.37
                   0.68
                                      0.48
                                                1756
                  0.83
                            0.59
                                      0.69
                                                1690
                   0.56
                            0.23
                                      0.33
                                                 341
```

9 10	0.77 0.61	0.77 0.32	0.77 0.42	2344 821
11	0.53	0.18	0.27	1143
12	0.69	0.38	0.49	768
13	0.73	0.23	0.35	745
14	0.77	0.46	0.57	952
15	0.41	0.27	0.32	314
16	0.55	0.15	0.24	624
17	0.73	0.59	0.65	535
18	0.80	0.51	0.63	631
19	0.65	0.49	0.56	101
20	0.41	0.32	0.36	245
21	0.73	0.51	0.60	694
22	0.51	0.23	0.31	568
23	0.66	0.20	0.31	423
24	0.78	0.06	0.11	406
25	0.66	0.40	0.50	1373
26	0.46	0.40	0.42	253
27	0.21	0.14	0.17	357
28	0.53	0.36	0.43	222
29	0.58	0.46	0.51	273
30	0.41	0.21	0.28	308
31	0.59	0.22	0.32	256
32	0.71	0.38	0.50	295
33	0.23	0.09	0.13	263
34	0.85	0.48	0.61	256
35	0.40	0.29	0.33	280
36 27	0.22	0.20	0.21	290
37 38	0.31 0.29	0.12 0.21	0.17 0.25	200 109
39	0.29	0.21	0.45	209
40	0.03	0.40	0.43	113
41	0.50	0.28	0.36	197
42	0.32	0.19	0.24	52
43	0.00	0.00	0.00	179
44	0.83	0.44	0.57	431
45	0.29	0.15	0.20	47
46	0.47	0.22	0.30	37
47	0.49	0.16	0.24	155

48 49	0.59 0.55	0.51 0.18	0.55 0.27	254 201
50 51	0.61 0.93	0.28 0.79	0.38 0.86	61 246
52	0.67	0.54	0.60	146
53	0.94	0.83	0.88	516
54	0.85	0.55	0.67	170
55	0.34	0.18	0.24	234
56	0.12	0.07	0.09	357
57	0.48	0.27	0.34	78
58	0.70	0.70	0.70	102
59	0.45	0.17	0.25	122
60	0.81	0.62	0.70	138
61	0.26	0.22	0.24	36
62	0.26	0.11	0.16	172
63	0.25	0.03	0.06	60
64	0.67	0.38	0.48	106
65	0.20	0.03	0.05	34
66 67	0.31	0.15	0.20	101
67 69	0.20 0.42	0.21	0.20	38 104
68 69	0.42	0.36 0.12	0.38 0.18	104 144
70	0.12	0.12	0.15	135
70 71	0.12	0.19	0.13	190
71 72	0.72	0.32	0.20	139
73	0.23	0.10	0.14	69
74	0.00	0.00	0.00	133
75	0.88	0.13	0.22	181
76	0.46	0.47	0.46	113
77	0.37	0.30	0.33	158
78	0.18	0.08	0.11	142
79	0.21	0.18	0.19	96
80	0.19	0.22	0.20	101
81	0.55	0.20	0.29	56
82	0.06	0.02	0.03	62
83	0.42	0.64	0.50	77
84	0.50	0.01	0.02	100
85	0.53	0.46	0.50	54
86	0.37	0.18	0.24	79

87 88	0.33 0.63	0.16 0.23	0.22 0.34	92 124
89	0.64	0.50	0.56	101
90	0.20	0.03	0.04	40
91	0.41	0.27	0.33	66
92	0.39	0.28	0.32	58
93	0.25	0.01	0.01	161
94	0.43	0.10	0.16	130
95	0.00	0.00	0.00	47
96	0.75	0.64	0.69	107
97	0.38	0.38	0.38	39
98	0.14	0.04	0.06	111
99	0.67	0.11	0.18	95 120
100	0.16	0.13	0.14	129
101	0.74	0.43	0.54	91 27
102	0.20	0.07	0.11	27
103	0.91	0.71	0.80	90
104	0.00	0.00	0.00	124
105	0.10	0.20	0.13	76
106	0.00	0.00	0.00 0.48	371 114
107 108	0.71 0.54	0.36	0.46	98
100	0.84	0.40 0.33	0.48	63
110	0.75	0.25	0.48	24
111	0.73	0.23	0.38	53
112	0.45	0.43	0.43	65
113	0.15	0.11	0.12	70
114	0.34	0.24	0.36	27
115	0.50	0.01	0.03	72
116	0.19	0.30	0.23	27
117	0.39	0.23	0.29	90
118	0.64	0.22	0.33	95
119	0.30	0.30	0.30	92
120	0.22	0.34	0.27	87
121	0.42	0.44	0.43	45
122	0.00	0.00	0.00	182
123	0.23	0.12	0.15	94
124	0.81	0.27	0.41	62
125	0.80	0.45	0.58	91

126 127	0.76 0.53	0.41 0.44	0.53 0.48	69 73
128 129	0.33 0.00	0.32 0.00	0.33 0.00	25 68
130	0.44	0.20	0.00	123
131	0.13	0.11	0.12	84
132	0.00	0.00	0.00	67
133	0.16	0.06	0.08	127
134	0.28	0.22	0.25	45
135	0.51	0.41	0.45	88
136	0.03	0.05	0.04	63
137	0.90	0.78	0.84	96
138	0.00	0.00	0.00	71
139	0.85	0.75	0.80	92
140	0.20	0.04	0.07	23
141	0.39	0.10	0.16	90
142	0.22	0.20	0.21	10
143	0.14	0.02	0.04	44
144	0.62	0.31	0.42	67
145	0.66	0.40	0.50	131
146	0.16	0.11	0.13	83
147	0.12	0.06	0.08	32
148	0.42	0.04	0.08	115
149	0.44	0.30	0.36	63
150	0.57	0.41	0.48	83
151	0.70	0.30	0.42	101
152	0.12	0.03	0.05	29
153	0.88	0.71	0.78	191
154 155	0.82	0.59	0.69	54 84
155 156	0.43	0.33	0.38	84 37
156 157	0.23 0.20	0.08 0.22	0.12 0.21	65
157	0.30	0.22	0.21	46
158	0.78	0.17	0.59	80
160	0.10	0.47	0.05	66
161	0.00	0.00	0.00	56
162	0.33	0.20	0.25	127
163	0.77	0.40	0.52	111
164	0.11	0.03	0.05	32

165 166	0.20 0.35	0.07 0.06	0.11 0.10	28 98
167	0.69	0.57	0.62	88
168	0.59	0.49	0.54	59
169	0.20	0.05	0.08	42
170	0.60	0.75	0.67	4
171	0.80	0.37	0.50	95
172	0.00	0.00	0.00	54
173	0.65	0.31	0.42	65
174	0.50	0.35	0.42	31
175	0.58	0.22	0.32	32
176	0.22	0.29	0.25	58
177	0.33	0.16	0.21	76
178	0.40	0.04	0.07	55
179	0.92	0.59	0.72	74
180	0.74	0.62	0.68	64
181	1.00	0.02	0.03	57
182	0.17	0.25	0.20	36
183	0.50	0.21	0.30	52
184	0.58	0.40	0.47	48
185	0.00	0.00	0.00	16
186	0.00	0.00	0.00	28
187	0.00	0.00	0.00	36
188	0.22	0.08	0.11	26
189	0.15	0.09	0.11	44
190	0.16	0.09	0.11	46
191	0.22	0.11	0.14	75
192	0.00	0.00	0.00	50
193	0.45	0.25	0.32	20
194	0.33	0.04	0.07	27
195	0.40	0.33	0.36	6
196	0.20	0.03	0.05	68
197	0.50	0.52	0.51	29
198	0.00	0.00	0.00	104
199	0.59	0.36	0.45	36
200	1.00	0.75	0.86	4
201	1.00	0.50	0.67	4
202	0.50	0.04	0.08	96
203	0.59	0.66	0.62	61

204	0.41	0.11	0.17	82
205	0.50	0.29	0.37	34
203	0.50	0.23	0.57	34
206	0.73	0.50	0.59	66
207	0.42	0.16	0.24	97
208	0.15	0.03	0.06	89
209	0.78	0.51	0.62	55
210	0.71	0.47	0.57	78
211	0.08	0.03	0.04	78
212	1.00	0.01	0.01	158
213	0.00	0.00	0.00	44
214	0.59	0.49	0.53	35
215	0.84	0.44	0.58	48
216	0.63	0.53	0.58	62
217	0.00	0.00	0.00	11
218	0.88	0.43	0.57	68
219	0.34	0.20	0.25	60
220	0.00	0.00	0.00	25
221	0.46	0.21	0.29	57
222	0.50	0.31	0.38	36
223	0.33	0.05	0.08	88
224	0.24	0.24	0.24	46
225	0.38	0.08	0.14	60
226	0.39	0.14	0.20	65
227	1.00	0.43	0.60	7
228	0.07	0.08	0.08	12
229	0.27	0.04	0.08	68
230	0.70	0.17	0.28	40
231	0.14	0.12	0.12	26
232	0.94	0.57	0.71	30
233	0.00	0.00	0.00	41
234	0.28	0.17	0.21	53
235	0.30	0.17	0.22	35
236	0.31	0.22	0.26	18
237	0.00	0.00	0.00	22
238	0.73	0.51	0.60	59
239	0.48	0.51	0.49	43
240	0.21	0.11	0.14	45
241	0.00	0.00	0.00	46
242	0.20	0.08	0.11	38

243 244	0.72 0.13	0.32 0.20	0.44 0.16	56 35
245	0.01	0.02	0.01	42
246	0.20	0.03	0.05	33
247	0.28	0.26	0.27	47
248	0.23	0.12	0.16	25
249	0.20	0.41	0.27	39
250	0.00	0.00	0.00	77
251	0.72	0.55	0.63	56
252	0.00	0.00	0.00	72
253	0.67	1.00	0.80	4
254	0.60	0.31	0.41	29
255	0.35	0.08	0.13	113
256	0.80	0.56	0.66	59
257	0.09	0.05	0.07	59
258	0.97	0.72	0.82	39
259	0.54	0.58	0.56	12
260	0.57	0.44	0.50	9
261	0.96	0.61	0.75	44
262	0.65	0.41	0.50	32
263	0.00	0.00	0.00	156
264	0.60	0.60	0.60	5
265	0.00	0.00	0.00	198
266	0.00	0.00	0.00	40
267	0.00	0.00	0.00	29
268	0.00	0.00	0.00	39
269	0.00	0.00	0.00	6
270	0.75	0.60	0.67	5
271	0.50	0.12	0.19	17 54
272 273	0.00	0.00	0.00	23
273 274	0.17 0.00	0.09	$\begin{array}{c} \textbf{0.11} \\ \textbf{0.00} \end{array}$	23 126
274	0.55	0.00 0.38	0.44	32
275	0.50	0.30	0.44	10
277	0.82	0.60	0.69	67
278	0.44	0.08	0.03	53
279	0.60	0.19	0.13	16
280	0.64	0.15	0.73	19
281	0.32	0.11	0.17	61

282	0.00	0.00	0.00	81
283	0.51	0.23	0.32	94
284	0.67	0.13	0.22	31
285	0.25	0.09	0.14	43
286	0.07	0.03	0.04	79
287	0.38	0.40	0.39	20
288	0.81	0.76	0.79	17
289	0.78	0.52	0.62	56
290	0.00	0.00	0.00	63
291	0.38	0.20	0.26	46
292	0.36	0.20	0.26	50
293	0.40	0.24	0.30	17
294	0.29	0.07	0.12	27
295	0.14	0.03	0.05	63
296	0.29	0.36	0.32	25
297	0.00	0.00	0.00	38
298	0.00	0.00	0.00	62
299	0.73	0.39	0.51	49
300	0.00	0.00	0.00	39
301	0.17	0.25	0.20	8
302	0.09	0.17	0.12	18
303	0.00	0.00	0.00	19
304	1.00	0.22	0.36	18 26
305	0.47	0.35	0.40	26 10
306 207	0.67	0.20	0.31	10 12
307 308	1.00 1.00	0.08 0.12	0.15 0.22	8
309	0.33	0.12	0.22	57
310	0.33	0.08	0.13	37 37
311	0.86	0.60	0.71	50
312	0.50	0.08	0.14	36
313	0.08	0.05	0.06	19
314	0.84	0.36	0.50	59
315	0.90	0.38	0.53	48
316	0.35	0.13	0.19	45
317	0.09	0.07	0.08	29
318	0.35	0.19	0.25	37
319	0.57	0.11	0.18	38
320	0.81	0.68	0.74	44

321 322	0.61 0.00	0.27 0.00	0.37 0.00	41 25
323	0.00	0.00	0.00	4
324	0.20	0.09	0.13	11
325	0.25	0.67	0.36	3
326	0.35	0.19	0.24	32
327	0.56	0.20	0.29	50
328	0.11	0.02	0.04	46
329	0.96	0.47	0.63	47
330	0.85	0.74	0.79	31
331	0.00	0.00	0.00	11
332	0.00	0.00	0.00	31
333	0.43	0.12	0.18	26
334	0.00	0.00	0.00	41
335	0.08	0.05	0.06	39
336	0.78	0.17	0.29	40
337	0.11	0.05	0.07	37
338	0.50	0.20	0.29	10
339	0.00	0.00	0.00	38
340	0.70	0.70	0.70	23
341	0.16	0.09	0.12	33
342	0.10	0.05	0.07	40
343	0.36	0.11	0.17	35
344	0.50	0.30	0.37	30
345	0.00	0.00	0.00	33
346	0.00	0.00	0.00	25
347 348	0.11 0.50	0.44 0.50	0.17 0.50	9 2
340 349	0.85	0.65	0.73	34
350	0.83	0.05	0.73	3 4 38
351	0.42	0.16	0.08	49
352	0.42	0.10	0.24	22
353	0.00	0.13	0.18	39
354	0.29	0.13	0.10	18
355	0.00	0.03	0.05	31
356	0.11	0.00	0.00	17
357	0.82	0.26	0.39	35
358	0.02	0.20	0.00	43
359	0.00	0.00	0.00	43 47
	0.00	0.00		

360 361	0.00 0.75	0.00 0.63	0.00 0.69	29 38
362	0.25	0.19	0.22	36
363	0.48	0.22	0.30	55
364	0.23	0.24	0.23	34
365	0.31	0.17	0.22	24
366	0.33	0.11	0.16	19
367	0.20	0.20	0.20	5
368	0.12	0.09	0.10	33
369	0.75	0.35	0.48	34
370	0.17	0.05	0.08	20
371	0.00	0.00	0.00	17
372	0.14	0.32	0.20	31
373 374	0.00 0.25	0.00	0.00	34 23
	0.25	0.04 0.16	0.07 0.20	31
375 376	0.25	0.18	0.20	28
370 377	0.74	0.18	0.21	20
378	1.00	0.77	0.70	9
379	0.00	0.00	0.00	29
380	0.19	0.27	0.22	30
381	0.71	0.71	0.71	35
382	0.55	0.17	0.26	36
383	0.00	0.00	0.00	4
384	0.95	0.75	0.84	24
385	0.43	0.12	0.19	25
386	0.00	0.00	0.00	27
387	0.28	0.31	0.29	36
388	0.55	0.35	0.43	31
389	0.57	0.11	0.18	37
390	0.33	0.04	0.07	27
391	0.00	0.00	0.00	46
392	1.00	0.50	0.67	4
393	0.33	0.16	0.21	19
394	0.00	0.00	0.00	12
395	0.27	0.15	0.20	26
396	0.00	0.00	0.00	69
397	0.00	0.00	0.00	25
398	0.36	0.12	0.19	32

399	0.30	0.09	0.14	33
400	0.17	0.03	0.05	38
400	0.17	0.05	0.05	30
401	0.50	0.12	0.19	17
402	0.00	0.00	0.00	24
403	1.00	0.12	0.22	16
404	0.00	0.00	0.00	15
405	0.00	0.00	0.00	20
406	0.00	0.00	0.00	15
407	0.38	0.12	0.18	25
408	0.23	0.16	0.19	19
409	0.50	0.20	0.28	46
410	0.00	0.00	0.00	45
411	0.00	0.00	0.00	21
412	0.33	0.12	0.18	8
413	0.57	0.46	0.51	35
414	0.20	0.06	0.09	34
415	1.00	0.43	0.60	14
416	0.29	0.24	0.26	29
417	0.00	0.00	0.00	28
418	0.00	0.00	0.00	21
419	0.00	0.00	0.00	26
420	0.62	0.34	0.44	38
421	0.00	0.00	0.00	131
422	0.00	0.00	0.00	26
423	0.00	0.00	0.00	25
424	0.79	0.31	0.45	48
425	0.00	0.00	0.00	24
426	0.00	0.00	0.00	42
427	0.31	0.15	0.21	26
428	0.00	0.00	0.00	10
429	0.48	0.28	0.35	54
430	0.00	0.00	0.00	32
431	0.25	0.10	0.15	48
432	0.16	0.09	0.11	35
433	0.00	0.00	0.00	22
434	0.00	0.00	0.00	24
435	1.00	0.10	0.18	59
436	0.00	0.00	0.00	35
437	0.05	0.17	0.07	12

440 0.00 0.00 0.00 35 441 0.00 0.00 0.00 8 442 0.26 0.15 0.19 48 443 1.00 0.22 0.36 18 444 0.78 0.13 0.23 52 445 1.00 0.10 0.18 20 446 0.33 0.06 0.10 18 447 0.00 0.00 0.00 6 448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 58 452 0.00 0.00 0.00 58	438 439	0.69 0.25	0.18 0.11	0.29 0.15	50 36
442 0.26 0.15 0.19 48 443 1.00 0.22 0.36 18 444 0.78 0.13 0.23 52 445 1.00 0.10 0.18 20 446 0.33 0.06 0.10 18 447 0.00 0.00 0.00 6 448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					35
443 1.00 0.22 0.36 18 444 0.78 0.13 0.23 52 445 1.00 0.10 0.18 20 446 0.33 0.06 0.10 18 447 0.00 0.00 0.00 6 448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
444 0.78 0.13 0.23 52 445 1.00 0.10 0.18 20 446 0.33 0.06 0.10 18 447 0.00 0.00 0.00 6 448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
445 1.00 0.10 0.18 20 446 0.33 0.06 0.10 18 447 0.00 0.00 0.00 6 448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
446 0.33 0.06 0.10 18 447 0.00 0.00 0.00 6 448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
447 0.00 0.00 0.00 6 448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
448 0.00 0.00 0.00 28 449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
449 0.08 0.05 0.06 38 450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
450 0.00 0.00 0.00 129 451 0.00 0.00 0.00 29					
451 0.00 0.00 0.00 29					
452 0.00 0.00 0.00 58					
					32
					16
					34
					9
					30
					40
					37
					30
					27
					12
					17
		0.00			56
					9
					22
					9
					15
					14
					16
471 0.83 0.28 0.42 18	471	0.83	0.28	0.42	18
	472	0.20	0.19	0.19	16
			0.45	0.43	22
		0.25	0.17	0.20	12
		0.00	0.00	0.00	110
476 0.45 0.45 0.45 20	476	0.45	0.45	0.45	20

	477	0.75	0.10	0.17	31
	478	0.29	0.05	0.08	42
	479	0.00	0.00	0.00	4
	480	0.36	0.17	0.23	47
	481	0.00	0.00	0.00	30
	482	0.00	0.00	0.00	35
	483	0.10	0.03	0.05	30
	484	0.20	0.10	0.13	20
	485	1.00	0.33	0.50	15
	486	0.50	0.12	0.19	17
	487	0.33	0.09	0.14	11
	488	0.50	0.11	0.18	36
	489	0.14	0.06	0.09	32
	490	0.57	0.29	0.38	14
	491	0.80	0.16	0.27	25
	492	0.28	0.30	0.29	23
	493	0.00	0.00	0.00	9
	494	0.00	0.00	0.00	37
	495	0.00	0.00	0.00	24
	496	0.88	0.21	0.33	34
	497	0.00	0.00	0.00	25
	498	0.00	0.00	0.00	9
	499	0.00	0.00	0.00	17
micro	avg	0.58	0.31	0.40	55953
macro		0.38	0.21	0.25	55953
weighted	avg	0.54	0.31	0.37	55953
samples	-	0.37	0.29	0.30	55953

Time taken to run this cell : 4:41:47.328133

4.5.7 Applying Linear SVM with OneVsRest Classifier - TFIDF Vectorizer

```
In [78]: start = datetime.now()
  classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.00
  001, 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')
global report = global report.append({
                        'Vectorizer': 'Tf-IDF',
                        'Model': 'Linear SVM (SGD with hinge loss)',
                        'NGram': '(1,3)',
                        'Parameter': 0.00001,
                        'Precision': precision,
                        'Recall': recall,
                        'F1 Score Micro':f1
                     },
                    ignore index=True)
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: 0.2189333333333334 Hamming loss 0.002922733333333334 Micro-average quality numbers Precision: 0.7923, Recall: 0.2934, F1-measure: 0.4282 Macro-average quality numbers Precision: 0.4256, Recall: 0.2180, F1-measure: 0.2638 precision recall f1-score support 0 0.80 0.35 0.49 1111 0.73 0.14 0.24 2052 1 2 0.78 0.28 0.42 2388 0.82 0.45 0.58 2226 0.84 0.42 0.56 2014 0.61 0.14 0.23 642 0.81 0.35 0.49 1756 0.80 1690 0.93 0.71 8 0.71 0.20 0.32 341 9 0.77 0.87 0.82 2344 0.70 0.44 821 10 0.32 11 0.73 0.01 0.03 1143 12 0.85 0.33 0.48 768 13 0.76 0.21 0.33 745 14 0.83 0.51 0.63 952 15 0.74 0.21 0.32 314 16 0.16 0.26 624 0.68 535 17 0.80 0.60 0.68 18 0.85 0.51 0.63 631 19 0.88 0.56 0.69 101 20 0.36 0.72 0.24 245 21 0.86 0.47 0.61 694 22 0.76 0.06 0.10 568 23 0.75 0.35 423 0.23 24 0.82 0.14 0.24 406 25 1.00 0.00 0.00 1373 253 26 0.58 0.30 0.40 27 0.00 0.00 0.00 357 28 0.76 0.31 0.44 222 29 0.81 0.25 0.38 273 30 0.65 0.13 0.21 308 31 0.67 0.27 0.38 256 32 0.75 0.44 0.56 295

33 34	0.00 0.86	0.00 0.54	0.00 0.66	263 256
35	0.52	0.05	0.10	280
36	0.20	0.00	0.01	290
37	1.00	0.01	0.01	200
38	1.00	0.01	0.02	109
39	0.66	0.41	0.50	209
40	0.58	0.41	0.48	113
41	0.82	0.21	0.33	197
42	0.69	0.46	0.55	52
43	0.00	0.00	0.00	179
44	0.84	0.52	0.64	431
45	0.38	0.11	0.17	47
46	0.82	0.38	0.52	37
47	0.80	0.13	0.22	155
48	0.71	0.50	0.59	254
49	0.72	0.15	0.25	201
50	0.88	0.23	0.36	61
51	0.93	0.78	0.85	246
52	0.69	0.69	0.69	146
53	0.94	0.91	0.93	516
54	0.85	0.59	0.70	170
55	0.00	0.00	0.00	234
56	0.00	0.00	0.00	357
57	0.00	0.00	0.00	78
58	0.92	0.69	0.79	102
59	0.00	0.00	0.00	122
60	0.88	0.57	0.69	138
61	0.67	0.06	0.10	36
62	0.00	0.00	0.00	172
63	0.00	0.00	0.00	60
64	0.66	0.46	0.54	106
65	1.00	0.06	0.11	34
66	1.00	0.01	0.02	101
67	0.60	0.32	0.41	38
68	0.66	0.34	0.45	104
69 70	0.00 0.00	0.00 0.00	0.00 0.00	144 135
70	0.00	0.00	0.00	133
71	0.00	0.00	0.00	190

72	0.82	0.30	0.44	139
73	0.00	0.00	0.00	69
74	0.00	0.00	0.00	133
75	0.84	0.51	0.63	181
76	0.59	0.35	0.44	113
77	0.70	0.22	0.34	158
78	0.00	0.00	0.00	142
79	0.00	0.00	0.00	96
80	0.00	0.00	0.00	101
81	0.69	0.20	0.31	56
82	0.00	0.00	0.00	62
83	0.64	0.55	0.59	77
84	0.92	0.11	0.20	100
85	0.53	0.48	0.50	54
86	0.00	0.00	0.00	79
87	0.67	0.02	0.04	92
88	0.71	0.24	0.36	124
89	0.77	0.46	0.57	101
90	0.56	0.12	0.20	40
91	0.74	0.26	0.38	66
92	0.50	0.03	0.06	58
93	0.96	0.27	0.43	161
94	0.83	0.15	0.25	130
95	1.00	0.02	0.04	47
96	0.74	0.55	0.63	107
97	0.79	0.28	0.42	39
98	0.00	0.00	0.00	111
99	0.71	0.16	0.26	95
100	0.00	0.00	0.00	129
101	0.94	0.37	0.54	91
102	0.35	0.22	0.27	27
103	0.94	0.81	0.87	90
104	0.00	0.00	0.00	124
105	0.00	0.00	0.00	76
106	0.00	0.00	0.00	371
107	0.71	0.36	0.48	114
108	0.61	0.32	0.42	98
109	0.80	0.38	0.52	63
110	0.80	0.33	0.47	24

111	0.75	0.17	0.28	53
112	0.00	0.00	0.00	65
113	0.50	0.07	0.12	70
114	0.90	0.33	0.49	27
115	0.00	0.00	0.00	72
116	0.55	0.22	0.32	27
117	0.00	0.00	0.00	90
118	0.69	0.37	0.48	95
119	1.00	0.01	0.02	92
120	0.00	0.00	0.00	87
121	0.56	0.20	0.30	45
122	0.00	0.00	0.00	182
123	0.00	0.00	0.00	94
124	0.82	0.45	0.58	62
125	0.84	0.46	0.60	91
126	0.73	0.51	0.60	69
127	0.64	0.41	0.50	73
128	1.00	0.40	0.57	25
129	0.00	0.00	0.00	68
130	0.00	0.00	0.00	123
131	0.00	0.00	0.00	84
132	0.00	0.00	0.00	67
133	0.00	0.00	0.00	127
134	0.78	0.47	0.58	45
135	0.50	0.40	0.44	88
136	0.00	0.00	0.00	63
137	0.92	0.79	0.85	96
138	0.70	0.10	0.17	71
139	0.84	0.71	0.77	92
140	0.00	0.00	0.00	23
141	0.67	0.07	0.12	90
142	0.50	0.20	0.29	10
143	0.00	0.00	0.00	44
144	0.61	0.28	0.39	67
145	0.81	0.32	0.46	131
146	0.00	0.00	0.00	83
147	0.00	0.00	0.00	32
148	0.00	0.00	0.00	115
149	0.43	0.05	0.09	63

150	0.74	0.34	0.46	83
151	0.84	0.38	0.52	101
152	0.00	0.00	0.00	29
153	0.91	0.94	0.93	191
154	0.91	0.59	0.72	54
155	0.00	0.00	0.00	84
156	0.62	0.27	0.38	37
157	0.50	0.03	0.06	65
158	0.62	0.11	0.19	46
159	0.84	0.54	0.66	80
160	0.00	0.00	0.00	66
161	0.00	0.00	0.00	56
162	0.00	0.00	0.00	127
163	0.69	0.82	0.75	111
164	0.00	0.00	0.00	32
165	1.00	0.04	0.07	28
166	0.00	0.00	0.00	98
167	0.77	0.65	0.70	88
168	0.85	0.47	0.61	59
169	0.00	0.00	0.00	42
170	0.67	0.50	0.57	4
171	0.75	0.47	0.58	95
172	0.00	0.00	0.00	54
173	0.77	0.57	0.65	65
174	0.63	0.39	0.48	31
175	1.00	0.09	0.17	32
176	0.78	0.12	0.21	58
177	0.90	0.12	0.21	76
178	0.00	0.00	0.00	55
179	0.84	0.80	0.82	74
180	0.89	0.61	0.72	64
181	0.00	0.00	0.00	57
182	0.00	0.00	0.00	36
183	0.67	0.23	0.34	52
184	0.83	0.31	0.45	48
185	0.33	0.06	0.11	16
186	0.00	0.00	0.00	28
187	0.40	0.06	0.10	36
188	0.75	0.12	0.20	26

189	0.00	0.00	0.00	44
190	0.80	0.09	0.16	46
191	0.00	0.00	0.00	75
192	0.56	0.10	0.17	50
193	0.80	0.40	0.53	20
194	0.00	0.00	0.00	27
195	0.57	0.67	0.62	6
196	0.67	0.03	0.06	68
197	0.50	0.55	0.52	29
198	0.84	0.15	0.26	104
199	0.67	0.33	0.44	36
200	1.00	0.75	0.86	4
201	1.00	0.75	0.86	4
202	0.00	0.00	0.00	96
203	0.86	0.62	0.72	61
204	0.00	0.00	0.00	82
205	0.00	0.00	0.00	34
206	0.76	0.42	0.54	66
207	0.00	0.00	0.00	97
208	0.00	0.00	0.00	89
209	0.78	0.65	0.71	55
210	0.79	0.49	0.60	78
211	0.00	0.00	0.00	78
212	0.88	0.39	0.54	158
213	0.50	0.09	0.15	44
214	0.66	0.66	0.66	35
215	0.76	0.79	0.78	48
216	0.71	0.74	0.72	62
217	0.00	0.00	0.00	11
218	0.97	0.49	0.65	68
219	0.00	0.00	0.00	60
220	0.00	0.00	0.00	25
221	1.00	0.02	0.03	57
222	0.90	0.50	0.64	36
223	0.00	0.00	0.00	88
224	0.00	0.00	0.00	46
225	0.00	0.00	0.00	60
226	0.00	0.00	0.00	65
227	0.50	0.43	0.46	7
227	0.50	0.43	0.46	7

228	0.50	0.25	0.33	12
229	0.00	0.00	0.00	68
230	1.00	0.10	0.18	40
231	0.00	0.00	0.00	26
232	0.81	0.57	0.67	30
233	0.80	0.10	0.17	41
234	0.00	0.00	0.00	53
235	0.64	0.46	0.53	35
236	0.57	0.22	0.32	18
237	0.00	0.00	0.00	22
238	0.73	0.59	0.65	59
239	0.76	0.51	0.61	43
240	0.00	0.00	0.00	45
241	0.50	0.02	0.04	46
242	0.00	0.00	0.00	38
243	0.84	0.38	0.52	56
244	0.00	0.00	0.00	35
245	0.00	0.00	0.00	42
246	0.00	0.00	0.00	33
247	0.00	0.00	0.00	47
248	0.75	0.24	0.36	25
249	0.70	0.49	0.58	39
250	0.00	0.00	0.00	77
251	0.79	0.61	0.69	56
252	0.00	0.00	0.00	72
253	1.00	1.00	1.00	4
254	0.69	0.38	0.49	29
255	0.00	0.00	0.00	113
256	0.71	0.69	0.70	59
257	0.00	0.00	0.00	59
258	0.93	0.69	0.79	39
259	0.75	0.75	0.75	12
260	0.60	0.67	0.63	9
261	0.92	0.75	0.83	44
262	0.79	0.59	0.68	32
263	0.00	0.00	0.00	156
264	1.00	0.40	0.57	5
265	0.00	0.00	0.00	198
266	0.00	0.00	0.00	40

267	0.00	0.00	0.00	29
268	0.00	0.00	0.00	39
269	0.00	0.00	0.00	6
270	0.75	0.60	0.67	5
271	0.00	0.00	0.00	17
272	0.33	0.04	0.07	54
273	0.00	0.00	0.00	23
274	0.00	0.00	0.00	126
275	0.79	0.34	0.48	32
276	0.60	0.30	0.40	10
277	0.83	0.58	0.68	67
278	0.00	0.00	0.00	53
279	0.00	0.00	0.00	16
280	0.75	0.63	0.69	19
281	0.00	0.00	0.00	61
282	1.00	0.01	0.02	81
283	0.50	0.01	0.02	94
284	0.75	0.19	0.31	31
285	0.00	0.00	0.00	43
286	0.00	0.00	0.00	79
287	0.00	0.00	0.00	20
288	0.79	0.88	0.83	17
289	0.82	0.59	0.69	56
290	0.00	0.00	0.00	63
291	0.00	0.00	0.00	46
292	0.00	0.00	0.00	50
293	0.67	0.24	0.35	17
294	0.00	0.00	0.00	27
295	0.00	0.00	0.00	63
296	0.00	0.00	0.00	25
297	0.00	0.00	0.00	38
298	0.25	0.02	0.03	62
299	0.72	0.59	0.65	49
300	0.00	0.00	0.00	39
301	0.00	0.00	0.00	8
302	0.00	0.00	0.00	18
303	0.50	0.16	0.24	19
304	0.85	0.61	0.71	18
305	0.48	0.46	0.47	26

306	0.00	0.00	0.00	10
307 308	0.33 1.00	0.08 0.38	0.13 0.55	12 8
309	0.40	0.38	0.06	57
310	0.00	0.04	0.00	37
311	0.80	0.74	0.77	50
312	0.00	0.00	0.00	36
313	0.00	0.00	0.00	19
314	0.86	0.73	0.79	59
315	0.79	0.65	0.71	48
316	0.00	0.00	0.00	45
317	0.00	0.00	0.00	29
318	0.67	0.05	0.10	37
319	0.00	0.00	0.00	38
320	0.85	0.75	0.80	44
321	0.81	0.32	0.46	41
322	0.00	0.00	0.00	25
323	0.00	0.00	0.00	4
324	0.00	0.00	0.00	11
325	0.75	1.00	0.86	3
326	0.00	0.00	0.00	32
327	0.50	0.08	0.14	50
328	0.00	0.00	0.00	46
329	0.95	0.74	0.83	47
330	0.95	0.61	0.75	31
331	0.00	0.00	0.00	11
332	0.00	0.00	0.00	31
333	0.00	0.00	0.00	26
334	0.00	0.00	0.00	41
335	0.00	0.00	0.00	39 40
336 337	0.80 0.00	0.40 0.00	0.53	40 37
338	0.75	0.60	0.00 0.67	10
339	0.00	0.00	0.07	38
340	0.86	0.78	0.82	23
341	0.00	0.78	0.02	33
342	0.00	0.00	0.00	40
343	0.75	0.00	0.15	35
J-7-J	0.75	0.03	0.15	33
344	0.00	0.00	0.00	30

345	0.00	0.00	0.00	33
346	0.86	0.24	0.38	25
347	0.57	0.44	0.50	9
348	0.50	0.50	0.50	2
349	0.83	0.71	0.76	34
350	0.00	0.00	0.00	38
351	0.00	0.00	0.00	49
352	0.00	0.00	0.00	22
353	0.00	0.00	0.00	39
354	0.00	0.00	0.00	18
355	0.00	0.00	0.00	31
356	0.00	0.00	0.00	17
357	0.78	0.71	0.75	35
358	0.00	0.00	0.00	43
359	0.51	0.53	0.52	47
360	0.00	0.00	0.00	29
361	0.69	0.63	0.66	38
362	0.57	0.11	0.19	36
363	0.31	0.07	0.12	55
364	0.00	0.00	0.00	34
365	0.00	0.00	0.00	24
366	0.00	0.00	0.00	19
367	0.43	0.60	0.50	5
368	0.00	0.00	0.00	33
369	0.76	0.65	0.70	34
370	0.00	0.00	0.00	20
371	0.00	0.00	0.00	17
372	0.00	0.00	0.00	31
373	1.00	0.03	0.06	34
374	0.00	0.00	0.00	23
375	0.00	0.00	0.00	31
376	0.00	0.00	0.00	28
377	0.80	0.73	0.76	22
378	0.00	0.00	0.00	9
379	0.00	0.00	0.00	29
380	0.00	0.00	0.00	30
381	0.83	0.71	0.77	35
382	0.67	0.17	0.27	36
383	0.00	0.00	0.00	4

384	0.95	0.75	0.84	24
385	0.62	0.32	0.42	25
386	0.00	0.00	0.00	27
387	0.59	0.28	0.38	36
388	0.72	0.42	0.53	31
389	0.73	0.43	0.54	37
390	0.61	0.41	0.49	27
391	0.56	0.39	0.46	46
392	0.50	0.50	0.50	4
393	0.00	0.00	0.00	19
394	0.00	0.00	0.00	12
395	0.75	0.12	0.20	26
396	0.00	0.00	0.00	69
397	0.79	0.44	0.56	25
398	0.00	0.00	0.00	32
399	0.00	0.00	0.00	33
400	0.00	0.00	0.00	38
401	0.71	0.29	0.42	17
402	0.00	0.00	0.00	24
403	0.69	0.56	0.62	16
404	1.00	0.33	0.50	15
405	0.00	0.00	0.00	20
406	0.00	0.00	0.00	15
407	0.00	0.00	0.00	25
408	1.00	0.05	0.10	19
409	0.67	0.17	0.28	46
410	0.00	0.00	0.00	45
411	0.00	0.00	0.00	21
412	0.00	0.00	0.00	8
413	0.60	0.09	0.15	35
414	0.00	0.00	0.00	34
415	0.89	0.57	0.70	14
416	0.00	0.00	0.00	29
417	0.00	0.00	0.00	28
418	0.00	0.00	0.00	21
419	0.67	0.08	0.14	26
420	0.00	0.00	0.00	38
421	0.00	0.00	0.00	131
422	0.00	0.00	0.00	26

423	0.79	0.44	0.56	25
424	0.77	0.50	0.61	48
425	0.50	0.08	0.14	24
426	0.20	0.02	0.04	42
427	0.00	0.00	0.00	26
428	0.00	0.00	0.00	10
429	0.75	0.06	0.10	54
430	0.00	0.00	0.00	32
431	0.00	0.00	0.00	48
432	0.00	0.00	0.00	35
433	0.00	0.00	0.00	22
434	1.00	0.04	0.08	24
435	0.90	0.63	0.74	59
436	0.00	0.00	0.00	35
437	0.00	0.00	0.00	12
438	0.61	0.40	0.48	50
439	0.00	0.00	0.00	36
440	0.00	0.00	0.00	35
441	1.00	0.25	0.40	8
442	0.00	0.00	0.00	48
443	0.90	0.50	0.64	18
444	0.61	0.27	0.37	52
445	0.00	0.00	0.00	20
446	0.00	0.00	0.00	18
447	0.00	0.00	0.00	6
448	0.00	0.00	0.00	28
449	0.00	0.00	0.00	38
450	0.98	0.93	0.96	129
451	0.81	0.72	0.76	29
452	0.00	0.00	0.00	58
453	0.00	0.00	0.00	32
454	0.86	0.38	0.52	16
455	0.88	0.65	0.75	34
456	0.00	0.00	0.00	9
457	0.90	0.87	0.88	30
458	0.70	0.17	0.28	40
459	0.50	0.05	0.10	37
460	0.91	0.70	0.79	30
461	1.00	0.26	0.41	27

462	0.20	0.25	0.20	10
462 463	0.38	0.25	0.30	12 17
464	0.53 0.85	0.47 0.52	0.50 0.64	56
465	0.60	0.52	0.63	9
466	0.00	0.00	0.00	22
467	0.50	0.00	0.31	9
468	0.00	0.22	0.00	15
469	0.00	0.00	0.00	14
470	0.78	0.44	0.56	16
470	0.78	0.44	0.69	18
471	0.33	0.19	0.09	16
472	0.62	0.19	0.24	22
473 474	0.02	0.39	0.17	12
475	1.00	0.17	0.17	110
475	0.67	0.20	0.31	20
477	0.71	0.65	0.51	31
477	0.71	0.03	0.00	42
478 479	0.73	0.14	0.24	42
480	0.00	0.00	0.00	47
481		0.40	0.57	30
482	1.00 0.00	0.40	0.00	35
483	0.00	0.00	0.00	30
484		0.10	0.15	20
485	0.29 1.00	0.10	0.13	15
486	0.00	0.47	0.04	17
487	0.00	0.00	0.00	11
488	0.50	0.11	0.18	36
489	0.00	0.11	0.18	32
499	0.75	0.43	0.55	14
490	0.73	0.43	0.51	25
491	0.45	0.57	0.50	23
492	0.43	0.00	0.00	9
494	0.00	0.00	0.00	37
495	0.00	0.00	0.00	24
495		0.26		34
490 497	0.82 0.00	0.20	0.40 0.00	25
497 498	0.00	0.00	0.00	9
490 499				17
433	0.00	0.00	0.00	1/

```
0.79
  micro avq
                            0.29
                                      0.43
                                               55953
  macro avg
                  0.43
                            0.22
                                      0.26
                                               55953
                  0.62
                            0.29
                                      0.36
                                               55953
weighted avg
samples avg
                  0.42
                            0.28
                                      0.32
                                               55953
```

Time taken to run this cell: 0:01:41.415308

4.5.8 Applying Linear SVM with OneVsRest Classifier BOW Vectorizer

```
In [80]: start = datetime.now()
         classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.00
         001, penalty='l1'), n jobs=-1)
         classifier.fit(x train multilabel bow, y train)
         predictions = classifier.predict (x test multilabel bow)
         print("Accuracy :",metrics.accuracy score(y test, predictions))
         print("Hamming loss ",metrics.hamming loss(y test,predictions))
         precision = precision score(y test, predictions, average='micro')
         recall = recall score(y test, predictions, average='micro')
         f1 = f1 score(y test, predictions, average='micro')
         global report = global report.append({
                                  'Vectorizer': 'BoW',
                                  'Model': 'Linear SVM (SGD with hinge loss)',
                                  'NGram': '(1,4)',
                                  'Parameter': 0.00001.
                                  'Precision': precision,
                                  'Recall': recall.
                                  'F1 Score Micro':f1
                              },
                             ignore index=True)
         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)
Micro-average quality numbers
Precision: 0.2304, Recall: 0.4430, F1-measure: 0.3032
Macro-average quality numbers
Precision: 0.1532, Recall: 0.3646, F1-measure: 0.2044
                         recall f1-score
             precision
                                          support
          0
                  0.33
                           0.48
                                     0.39
                                               1111
          1
                  0.32
                           0.38
                                     0.35
                                               2052
                                               2388
          2
                  0.43
                           0.49
                                     0.46
                  0.52
                           0.59
                                     0.55
                                               2226
                  0.49
                           0.55
                                     0.52
                                               2014
          5
                  0.12
                           0.19
                                     0.15
                                               642
                  0.44
                           0.47
                                     0.45
                                               1756
                                     0.74
                  0.71
                           0.79
                                               1690
                           0.30
                                     0.21
                                               341
                  0.16
          9
                  0.68
                           0.74
                                     0.71
                                               2344
                                     0.42
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                  0.40
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                                               821
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                                               1143
         12
                  0.37
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                                     0.42
                                                768
         13
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                                               745
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                  0.29
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                                     0.45
         18
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                           0.58
                                     0.49
                                                631
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```

20 21 22 23	0.25 0.18 0.46 0.29 0.30	0.35 0.58 0.40 0.37	0.24 0.52 0.33 0.33	245 694 568 423
24	0.30	0.41	0.35	406
25	0.54	0.52	0.53	1373 253
26 27	0.22 0.14	0.48 0.25	0.30 0.18	357
28	0.13	0.23	0.19	222
29	0.23	0.39	0.29	273
30	0.22	0.40	0.29	308
31	0.20	0.36	0.26	256
32	0.29	0.45	0.35	295
33	0.09	0.20	0.12	263
34	0.43	0.58	0.49	256
35	0.25	0.42	0.31	280
36	0.26	0.42	0.32	290
37	0.15	0.25	0.18	200
38	0.12	0.36	0.19	109
39 40	0.21 0.18	0.39 0.39	0.27 0.24	209 113
41	0.22	0.39	0.24	113
42	0.10	0.60	0.17	52
43	0.07	0.16	0.09	179
44	0.44	0.57	0.49	431
45	0.04	0.19	0.07	47
46	0.11	0.51	0.18	37
47	0.15	0.32	0.21	155
48	0.33	0.51	0.40	254
49	0.23	0.40	0.29	201
50	0.11	0.41	0.17	61
51	0.56	0.80	0.66	246
52	0.32	0.66	0.43	146
53 54	0.64 0.32	0.91 0.58	0.75 0.41	516 170
55	0.11	0.38	0.41	234
56	0.13	0.23	0.15	357
57	0.13	0.40	0.18	78
52	U 33	A 65	A 11	107

98	0.09	0.33	0.14	59 111
99	0.10	0.29	0.15	95
100	0.13	0.24	0.13	129
101	0.13	0.51	0.32	91
102	0.03	0.19	0.06	27
103	0.42	0.90	0.57	90
104	0.07	0.18	0.10	124
105	0.05	0.12	0.07	76
106	0.25	0.29	0.27	371
107	0.23	0.40	0.29	114
108	0.17	0.35	0.23	98
109	0.14	0.33	0.20	63
110	0.12	0.54	0.20	24
111	0.12	0.45	0.20	53
112	0.10	0.25	0.15	65
113	0.14	0.37	0.21	70
114	0.17	0.56	0.26	27
115	0.08	0.24	0.12	72
116	0.18	0.44	0.25	27
117	0.13	0.36	0.19	90
118	0.16	0.38	0.23	95
119	0.16	0.35	0.22	92
120	0.11	0.36	0.17	87
121	0.11	0.47	0.18	45
122	0.09	0.13	0.10	182
123	0.12	0.24	0.16	94
124	0.21	0.52	0.29	62
125	0.29	0.51	0.37	91
126	0.20	0.48	0.28	69
127	0.20	0.41	0.27	73
128	0.17	0.56	0.26	25
129	0.02	0.06	0.03	68
130	0.09	0.27	0.13	123
131	0.10	0.27	0.14	84
132	0.04	0.10	0.06	67
133	0.09	0.20	0.13	127
134	0.19	0.40	0.25	45
135	0.26	0.48	0.34	88
136	U U3	ค 1२	A A5	63

130 137	0.62	0.10	0.05	96
138	0.02	0.35	0.70	71
139	0.31	0.65	0.42	92
140	0.02	0.09	0.03	23
141	0.14	0.28	0.19	90
142	0.03	0.40	0.05	10
143	0.07	0.18	0.10	44
144	0.13	0.43	0.21	67
145	0.37	0.45	0.40	131
146	0.09	0.16	0.11	83
147	0.07	0.22	0.10	32
148	0.15	0.23	0.18	115
149	0.14	0.46	0.22	63
150	0.19	0.45	0.27	83
151	0.34	0.48	0.40	101
152	0.07	0.31	0.12	29
153	0.74	0.82	0.78	191
154	0.39	0.65	0.49	54
155	0.18	0.46	0.26	84
156	0.15	0.46	0.23	37
157	0.14	0.37	0.20	65
158	0.07	0.22	0.11	46
159	0.23	0.53	0.32	80
160	0.04	0.12	0.05	66
161	0.03	0.07	0.05	56
162	0.15	0.24	0.18	127
163	0.45	0.68	0.54	111
164	0.05	0.22	0.08	32
165	0.04	0.25	0.06	28
166	0.03	0.10	0.05	98
167	0.28	0.60	0.38	88
168	0.26	0.58	0.36	59
169	0.04	0.17	0.06	42
170	0.03	0.50	0.05	4
171	0.22	0.38	0.28	95
172	0.04	0.15	0.06	54
173	0.24	0.55	0.33	65 21
174	0.17	0.55	0.25	31
175	A 17	A 17	A 10	37

173	0.14	0.4/	0.19	J2
176	0.14	0.34	0.20	58
177	0.11	0.21	0.15	76
178	0.03	0.15	0.05	55
179	0.48	0.84	0.61	74
180	0.27	0.62	0.37	64
181	0.09	0.19	0.13	57
182	0.06	0.33	0.10	36
183	0.07	0.46	0.13	52
184	0.18	0.44	0.25	48
185	0.19	0.56	0.28	16
186	0.04	0.18	0.06	28
187	0.12	0.31	0.17	36
188	0.14	0.38	0.20	26
189	0.07	0.32	0.12	44
190	0.16	0.35	0.22	46
191	0.10	0.19	0.13	75 50
192	0.08	0.26	0.12	50
193	0.12	0.45	0.20	20
194	0.02	0.11	0.03	27
195	0.03	0.33	0.06	6
196	0.15	0.25	0.19	68
197	0.12	0.48	0.19	29
198	0.14	0.29	0.19	104
199	0.15	0.42	0.22	36
200	0.07	1.00	0.14	4
201	0.10	0.75	0.17	4
202	0.06	0.18	0.09	96
203	0.35	0.59	0.44	61
204	0.07	0.29	0.11	82
205	0.15	0.50	0.23	34
206	0.25	0.53	0.34	66
207	0.15	0.37	0.21	97
208	0.05	0.11	0.07	89
209	0.37	0.60	0.46	55
210	0.34	0.64	0.44	78
211	0.08	0.23	0.12	78
212	0.35	0.51	0.42	158
213	0.05	0.16	0.07	44
21/	ค 12	A 16	A 26	35

214 215 216 217 218 219 220 221 222 223 224 225 226 227 228	0.15 0.41 0.35 0.02 0.39 0.15 0.03 0.15 0.12 0.06 0.04 0.06 0.11 0.03 0.12	0.40 0.75 0.65 0.18 0.57 0.33 0.16 0.30 0.44 0.17 0.22 0.22 0.26 0.43 0.58	0.20 0.53 0.45 0.03 0.47 0.21 0.05 0.20 0.19 0.09 0.07 0.10 0.16 0.06 0.19	48 62 11 68 60 25 57 36 88 46 60 65 7
229	0.03	0.15	0.05	68
230	0.10	0.30	0.15	40
231	0.07	0.23	0.11	26
232	0.20	0.63	0.30	30
233	0.06	0.20	0.09	41
234	0.06	0.26	0.10	53 35
235 236	0.15 0.06	0.51 0.22	0.24 0.09	33 18
230	0.00	0.22	0.09	22
238	0.02	0.18	0.04	59
239	0.29	0.53	0.40	43
240	0.13	0.33	0.18	45
241	0.04	0.20	0.07	46
242	0.05	0.18	0.07	38
243	0.21	0.50	0.29	56
244	0.07	0.23	0.11	35
245	0.03	0.14	0.05	42
246	0.01	0.06	0.02	33
247	0.11	0.30	0.16	47
248	0.06	0.28	0.10	25
249	0.17	0.54	0.26	39
250	0.30	0.47	0.37	77
251	0.34	0.59	0.43	56
252	0.08	0.18	0.11	72
252	ค 1ว	A 75	A 71	1

254	0.12	0.75	0.21	29
255	0.13	0.20	0.16	113
256	0.37	0.69	0.48	59
257	0.06	0.14	0.08	59
258	0.31	0.64	0.42	39
259	0.14	0.83	0.23	12
260	0.10	0.67	0.17	9
261	0.31	0.66	0.42	44
262	0.18	0.56	0.27	32
263	0.07	0.18	0.10	156
264	0.06	0.40	0.11	5
265	0.16	0.38	0.23	198
266	0.02	0.07	0.03	40
267	0.04	0.28	0.08	29
268	0.00	0.00	0.00	39
269	0.02	0.33	0.05	6
270	0.11	0.60	0.18	5
271	0.03	0.29	0.06	17
272	0.09	0.22	0.12	54
273	0.06	0.35	0.10	23
274	0.03	0.06	0.04	126
275	0.12	0.47	0.20	32
276	0.07	0.50	0.12	10
277	0.31	0.58	0.40	67
278	0.16	0.40	0.23	53
279	0.01	0.06	0.02	16
280	0.35	0.79	0.48	19
281	0.09	0.18	0.12	61
282	0.09	0.19	0.12	81
283	0.17	0.39	0.24	94
284	0.11	0.39	0.17	31
285	0.08	0.30	0.12	43
286	0.05	0.20	0.09	79
287	0.11	0.40	0.18	20
288	0.33	0.76	0.46	17
289	0.35	0.62	0.45	56
290	0.03	0.11	0.05	63
291	0.08	0.28	0.12	46
202	A A2	A 36	A 1/	50

292 293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322	0.06 0.06 0.05 0.01 0.05 0.31 0.04 0.01 0.03 0.10 0.17 0.02 0.02 0.02 0.06 0.11 0.10 0.42 0.10 0.42 0.10 0.42 0.05	0.35 0.35 0.22 0.06 0.28 0.08 0.13 0.61 0.15 0.12 0.32 0.44 0.65 0.20 0.08 0.50 0.25 0.27 0.72 0.31 0.37 0.69 0.62 0.41 0.32 0.41 0.32 0.41 0.57 0.54 0.54	0.14 0.10 0.09 0.04 0.08 0.02 0.07 0.41 0.06 0.01 0.06 0.15 0.17 0.26 0.04 0.03 0.11 0.15 0.15 0.15 0.15 0.15 0.15 0.15 0.15 0.15 0.17 0.26 0.01	17 27 63 25 38 62 49 39 8 18 19 18 26 10 12 8 57 37 50 36 19 59 48 45 29 37 38 44 41 25
316	0.07	0.24	0.11	45
318	0.09	0.32	0.14	37
320	0.43	0.57	0.49	44
322	0.05	0.24	0.09	25
323 324	0.01 0.02	0.25 0.18	0.01 0.04	4 11
325 326	0.09 0.10	1.00 0.41	0.17 0.16	3 32
327 328	0.13 0.07	0.38 0.26	0.19 0.12	50 46
329 330	0.46 0.37	0.74 0.81	0.57 0.51	47 31
221	A AA	A AA	A AA	11

332 333 334 335 336 337 338 339 340 341 342 343 344 345 346 347 348 349 350 351 352 353 354 355 356 357 358 359 360 361 362 363 363 363 363 363 363 363 363 363	0.02 0.07 0.00 0.03 0.16 0.05 0.09 0.01 0.04 0.07 0.03 0.06 0.09 0.05 0.03 0.09 0.23 0.09 0.23 0.01 0.02 0.04 0.01 0.02 0.04 0.01 0.02 0.03 0.03 0.03 0.03 0.03 0.09 0.23 0.01 0.02 0.03 0.03 0.03 0.03 0.04 0.09 0.23 0.01 0.02 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.09 0.05 0.09 0.01 0.02 0.04 0.09 0.09 0.03 0.09 0.03 0.09 0.03 0.09	0.00 0.06 0.27 0.00 0.08 0.38 0.14 0.40 0.03 0.24 0.12 0.09 0.33 0.27 0.44 0.22 0.50 0.62 0.34 0.39 0.39 0.11 0.13 0.06 0.49 0.07 0.62 0.62 0.62 0.62 0.62 0.62 0.63 0.64 0.7 0.62 0.62 0.62 0.63 0.63 0.64 0.7 0.62 0.63 0.64 0.65 0.	0.00 0.03 0.12 0.00 0.04 0.23 0.08 0.14 0.05 0.05 0.04 0.15 0.10 0.15 0.08 0.05 0.16 0.02 0.04 0.02 0.04 0.02 0.16 0.04 0.09 0.18 0.09 0.10 0.10 0.10 0.10 0.11 0.01	31 26 41 39 40 37 10 38 23 33 40 35 30 33 25 9 2 34 38 49 22 39 18 31 17 35 43 47 29 38 36 55 34 47 29 36 47 29 36 47 37 47 47 47 47 47 47 47 47 47 47 47 47 47
370	ค 11	A 35	A 17	20

371 372 373 374 375 376 377 378 379 380 381 382 383 384 385 386 387 388 389 390 391 392 393 394 395 396 397 398 399 400 401 402	0.11 0.02 0.10 0.04 0.02 0.14 0.08 0.16 0.01 0.06 0.10 0.22 0.17 0.01 0.45 0.08 0.04 0.12 0.15 0.26 0.14 0.17 0.04 0.12 0.01 0.02 0.14 0.01 0.05 0.01 0.05 0.01 0.05 0.01 0.05 0.01 0.05	0.12 0.29 0.24 0.13 0.42 0.21 0.73 0.11 0.40 0.74 0.36 0.25 0.83 0.24 0.15 0.36 0.55 0.49 0.56 0.49 0.50 0.53 0.49 0.50 0.16 0.16 0.16 0.16 0.16 0.18	0.17 0.04 0.15 0.08 0.04 0.12 0.26 0.01 0.09 0.16 0.34 0.23 0.02 0.59 0.12 0.06 0.17 0.23 0.24 0.07 0.20 0.10 0.10 0.10 0.17 0.20 0.10	17 31 34 23 31 28 22 9 29 30 35 36 4 24 25 27 36 31 37 27 46 4 19 12 26 69 25 32 33 33 31 24 25 27 36 40 40 40 40 40 40 40 40 40 40 40 40 40
396	0.07	0.16	0.10	69
403	0.11	0.69	0.19	16
404	0.08	0.47	0.14	15
405	0.06	0.30	0.11	20
406	0.03	0.20	0.06	15
407	0.05	0.20	0.08	25
408	0.05	0.26	0.09	19
100	ค 16	A 35	A 22	16

409 410	0.10	0.33 0.02	0.22	45
411	0.06	0.38	0.11	21
412	0.00	0.00	0.00	8
413	0.26	0.63	0.37	35
414	0.02	0.06	0.03	34
415	0.26	0.64	0.37	14
416	0.05	0.21	0.08	29
417	0.04	0.14	0.07	28
418	0.07	0.19	0.11	21
419	0.04	0.12	0.05	26
420	0.26	0.45	0.33	38
421	0.23	0.26	0.24	131
422	0.07	0.27	0.11	26
423	0.12	0.36	0.18	25
424	0.52	0.67	0.58	48
425	0.03	0.17	0.05	24
426	0.08	0.21	0.11	42
427	0.08	0.31	0.13	26
428	0.00	0.00	0.00	10
429	0.30	0.56	0.39	54
430	0.11	0.28	0.15	32
431	0.17	0.38	0.24	48
432	0.09	0.23	0.13	35
433	0.02	0.18	0.04	22
434	0.05	0.29	0.08	24
435	0.49	0.58	0.53	59
436	0.06	0.23	0.09	35
437	0.01	0.08	0.02	12
438	0.27	0.44	0.33	50
439	0.06	0.19	0.10	36
440	0.05	0.14	0.07	35
441	0.02	0.12	0.04	8
442	0.11	0.21	0.15	48
443	0.17	0.56	0.26	18
444	0.24	0.35	0.29	52
445	0.10	0.40	0.16	20
446	0.03	0.11	0.05	18
447	0.00	0.00	0.00	6
112	A A7	A 12	A 1A	28

449 450 451	0.07 0.05 0.97 0.22	0.10 0.26 0.65 0.66	0.10 0.08 0.78 0.33	38 129 29
452 453	0.07 0.03	0.10 0.09	0.08 0.05	58 32
454 455	0.15 0.48	0.56 0.65	0.24 0.55	16 34
456	0.06	0.03	0.10	9
457	0.42	0.77	0.54	30
458	0.09	0.23	0.12	40
459	0.11	0.22	0.15	37
460	0.29	0.77	0.43	30
461	0.10	0.41	0.16	27
462	0.08	0.33	0.12	12
463	0.10	0.47	0.16	17
464	0.29	0.48	0.36	56
465	0.14	0.56	0.22	9
466	0.22	0.36	0.27	22
467	0.02	0.22	0.04	9
468 460	0.02	0.13 0.07	0.03	15 14
469 470	0.01 0.08	0.44	0.02 0.13	16
470	0.14	0.44	0.13	18
472	0.02	0.19	0.23	16
473	0.16	0.68	0.27	22
474	0.05	0.17	0.08	12
475	0.94	0.55	0.69	110
476	0.20	0.75	0.32	20
477	0.21	0.55	0.31	31
478	0.13	0.26	0.18	42
479	0.01	0.25	0.02	4
480	0.18	0.36	0.24	47
481	0.32	0.60	0.42	30
482	0.03	0.14	0.05	35
483	0.09	0.30	0.14	30
484	0.09	0.25	0.13	20
485	0.24	0.53	0.33	15 17
486	0.05	0.24	0.09	17
127	A A1	A 12	ค คร	11

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                   0.08
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         491
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         492
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         493
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                   0.04
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         497
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                                       0.07
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                                       0.02
         498
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                             0.11
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                             0.53
                                       0.26
                                                    17
         499
                   0.17
   micro ava
                   0.23
                             0.44
                                        0.30
                                                 55953
                   0.15
                             0.36
  macro avg
                                        0.20
                                                 55953
weighted avg
                   0.31
                             0.44
                                                 55953
                                        0.35
samples avg
                   0.32
                             0.42
                                       0.32
                                                 55953
```

Time taken to run this cell: 0:12:51.098087

4.5.9 Applying Hyperparameter tuning using GridSearch Logistic Regression(LR) with OneVsRest Classifier

```
In [82]: start = datetime.now()
    parameters = {'estimator__C': [10**i for i in range(-6, 4, 1)]}
    classifier = OneVsRestClassifier(LogisticRegression(penalty='l1'))
    g_clf = GridSearchCV(classifier, parameters, n_jobs=-1, verbose=50, sco
    ring='f1_micro', cv=5)
    g_clf.fit(x_train_multilabel_bow, y_train)
    predictions = g_clf.predict (x_test_multilabel_bow)

    print("Optimal Parameters: ", g_clf.best_params_)

    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')
global report = global report.append({
                        'Vectorizer': 'BoW',
                        'Model': 'Logistic Regression - Hypertuned',
                        'NGram': '(1.4)'.
                        'Parameter': q clf.best params ['estimator C'
],
                        'Precision': precision,
                        'Recall': recall,
                        'F1 Score Micro':f1
                    },
                    ignore index=True)
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)
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
ers.
[Parallel(n jobs=-1)]: Done
                             1 tasks
                                            elapsed: 6.1min
[Parallel(n jobs=-1)]: Done
                             2 tasks
                                            elapsed: 6.1min
[Parallel(n jobs=-1)]: Done
                             3 tasks
                                            elapsed: 6.1min
[Parallel(n jobs=-1)]: Done
                              4 tasks
                                            elapsed: 6.1min
                                            elapsed: 6.2min
[Parallel(n jobs=-1)]: Done
                              5 tasks
[Parallel(n jobs=-1)]: Done
                              6 tasks
                                            elapsed: 6.2min
```

```
| elapsed: 6.2min
[Parallel(n jobs=-1)]: Done
                             7 tasks
[Parallel(n jobs=-1)]: Done
                             8 tasks
                                            elapsed: 6.3min
[Parallel(n jobs=-1)]: Done
                             9 tasks
                                            elapsed: 12.0min
[Parallel(n jobs=-1)]: Done 10 tasks
                                            elapsed: 12.8min
[Parallel(n jobs=-1)]: Done 11 tasks
                                            elapsed: 20.1min
[Parallel(n jobs=-1)]: Done 12 tasks
                                            elapsed: 20.6min
                                            elapsed: 21.5min
[Parallel(n jobs=-1)]: Done 13 tasks
[Parallel(n jobs=-1)]: Done 14 tasks
                                            elapsed: 25.7min
[Parallel(n jobs=-1)]: Done 15 tasks
                                            elapsed: 26.8min
[Parallel(n jobs=-1)]: Done 16 tasks
                                            elapsed: 27.8min
[Parallel(n jobs=-1)]: Done 17 tasks
                                            elapsed: 31.5min
[Parallel(n jobs=-1)]: Done 18 tasks
                                            elapsed: 33.1min
[Parallel(n jobs=-1)]: Done 19 tasks
                                            elapsed: 38.3min
[Parallel(n jobs=-1)]: Done 20 tasks
                                            elapsed: 41.3min
[Parallel(n jobs=-1)]: Done 21 tasks
                                            elapsed: 47.3min
[Parallel(n jobs=-1)]: Done 22 tasks
                                            elapsed: 52.0min
[Parallel(n jobs=-1)]: Done 23 tasks
                                            elapsed: 52.1min
[Parallel(n jobs=-1)]: Done 24 tasks
                                            elapsed: 52.8min
[Parallel(n jobs=-1)]: Done 25 tasks
                                            elapsed: 56.5min
[Parallel(n jobs=-1)]: Done 26 tasks
                                            elapsed: 66.4min
[Parallel(n jobs=-1)]: Done 27 tasks
                                            elapsed: 74.7min
[Parallel(n jobs=-1)]: Done 28 tasks
                                            elapsed: 76.3min
[Parallel(n jobs=-1)]: Done 29 tasks
                                            elapsed: 83.6min
[Parallel(n jobs=-1)]: Done 30 tasks
                                            elapsed: 89.3min
[Parallel(n jobs=-1)]: Done 31 tasks
                                            elapsed: 119.8min
[Parallel(n jobs=-1)]: Done 32 tasks
                                            elapsed: 121.2min
[Parallel(n jobs=-1)]: Done 33 tasks
                                            elapsed: 122.8min
[Parallel(n jobs=-1)]: Done 34 tasks
                                            elapsed: 130.9min
[Parallel(n jobs=-1)]: Done 35 tasks
                                            elapsed: 145.6min
[Parallel(n iobs=-1)]: Done 37 out of 50 |
                                            elapsed: 162.8min remainin
q: 57.2min
[Parallel(n jobs=-1)]: Done 39 out of 50 | elapsed: 198.9min remainin
a: 56.1min
[Parallel(n jobs=-1)]: Done 41 out of 50 | elapsed: 208.7min remainin
q: 45.8min
[Parallel(n jobs=-1)]: Done 43 out of 50 | elapsed: 222.6min remainin
q: 36.2min
[Parallel(n jobs=-1)]: Done 45 out of 50 | elapsed: 236.9min remainin
q: 26.3min
[Parallel(n iobs=-1)]: Done 47 out of 50 | elapsed: 257.1min remainin
```

q: 16.4min [Parallel(n jobs=-1)]: Done 50 out of 50 | elapsed: 266.2min finished Optimal Parameters: {'estimator C': 1} Accuracy: 0.186366666666668 Hamming loss 0.003399266666666665 Micro-average quality numbers Precision: 0.5644, Recall: 0.3888, F1-measure: 0.4604 Macro-average quality numbers Precision: 0.4321, Recall: 0.3113, F1-measure: 0.3528 precision recall f1-score support 0 0.40 0.48 0.61 1111 0.47 0.30 0.36 2052 1 0.54 2388 2 0.42 0.48 0.66 0.56 0.60 2226 0.66 0.50 0.57 2014 0.30 0.19 642 5 0.14 1756 0.64 0.41 0.50 0.89 0.72 0.79 1690 0.55 0.24 0.34 341 0.78 0.77 2344 9 0.77 821 10 0.57 0.39 0.46 11 0.43 0.29 0.34 1143 12 0.64 0.49 768 0.40 13 0.44 0.55 0.37 745 14 0.69 0.56 0.62 952 15 0.46 0.27 0.34 314 0.27 0.32 624 16 0.42 17 0.72 0.56 0.63 535 0.54 0.62 631 18 0.73 19 0.88 0.57 0.69 101 20 0.53 0.26 0.35 245 0.54 0.62 694 21 0.73 22 0.48 0.32 0.38 568 23 0.51 0.32 0.39 423 24 0.52 0.34 0.41 406 25 0.70 0.49 0.58 1373 26 0.52 0.34 0.41 253

357

27

0.24

0.16

0.19

	··-·	J. 25	J. 25	JJ.
28	0.50	0.28	0.36	222
29	0.58	0.30	0.40	273
30	0.48	0.32	0.39	308
31	0.45	0.30	0.36	256
32	0.69	0.41	0.52	295
33	0.22	0.11	0.15	263
34	0.74	0.53	0.62	256
35	0.42	0.34	0.37	280
36	0.47	0.32	0.38	290
37	0.36	0.17	0.23	200
38	0.34	0.29	0.32	109
39	0.62	0.39	0.48	209
40	0.53	0.40	0.45	113
41	0.54	0.28	0.37	197
42	0.51	0.56	0.53	52
43	0.17	0.10	0.13	179
44	0.77	0.50	0.61	431
45	0.29	0.11	0.16	47
46	0.44	0.38	0.41	37
47	0.54	0.34	0.41	155
48	0.65	0.50	0.57	254
49	0.50	0.34	0.41	201
50	0.40	0.28	0.33	61
51	0.92	0.73	0.82	246
52	0.67	0.62	0.64	146
53	0.92	0.91	0.92	516
54	0.75	0.55	0.64	170
55	0.21	0.10	0.13	234
56	0.19	0.11	0.14	357
57	0.57	0.27	0.37	78
58	0.87	0.68	0.76	102
59	0.35	0.24	0.28	122
60	0.72	0.57	0.64	138
61	0.22	0.17	0.19	36
62	0.35	0.19	0.25	172
63	0.08	0.03	0.05	60
64	0.59	0.51	0.55	106
65	0.35	0.32	0.34	34
66	0.29	0.25	0.27	101

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67	0.43	0.34	0.38	38
68	0.56	0.39	0.46	104
69	0.32	0.17	0.22	144
70	0.38	0.24	0.29	135
71	0.24	0.14	0.17	190
72	0.56	0.36	0.44	139
73	0.21	0.04	0.07	69
74	0.07	0.04	0.05	133
75	0.73	0.46	0.57	181
76	0.43	0.43	0.43	113
77	0.42	0.22	0.29	158
78	0.28	0.15	0.19	142
79	0.45	0.18	0.25	96
80	0.52	0.25	0.34	101
81	0.44	0.20	0.27	56
82	0.12	0.05	0.07	62
83	0.58	0.44	0.50	77
84	0.45	0.15	0.23	100
85	0.55	0.43	0.48	54
86	0.30	0.16	0.21	79
87	0.44	0.24	0.31	92
88	0.45	0.31	0.37	124
89	0.60	0.39	0.47	101
90	0.27	0.10	0.15	40
91	0.56	0.44	0.49	66
92	0.42	0.31	0.36	58
93	0.67	0.42	0.51	161
94	0.40	0.25	0.30	130
95 06	0.44	0.26	0.32	47
96 07	0.64	0.50	0.57	107
97	0.50	0.31	0.38	39
98	0.22	0.12	0.15	111
99	0.39	0.22	0.28	95 120
100	0.29	0.22	0.25 0.57	129 91
101	0.74	0.46		91 27
102 103	0.19 0.86	0.19 0.86	0.19 0.86	
103	0.20	0.00	0.80	90 124
104	0.20	0.07	0.11	76
TAN	טניט	0.17	U.ZZ	7 U

	0.50	··-·	· ·	
106	0.35	0.18	0.24	371
107	0.68	0.40	0.51	114
108	0.49	0.37	0.42	98
109	0.60	0.40	0.48	63
110	0.63	0.50	0.56	24
111	0.54	0.28	0.37	53
112	0.16	0.09	0.12	65
113	0.53	0.36	0.43	70
114	0.50	0.56	0.53	27
115	0.31	0.12	0.18	72
116	0.33	0.19	0.24	27
117	0.54	0.32	0.40	90
118	0.50	0.40	0.44	95
119	0.37	0.27	0.31	92
120	0.28	0.21	0.24	87
121	0.57	0.36	0.44	45
122	0.18	0.08	0.11	182
123	0.31	0.12	0.17	94
124	0.72	0.42	0.53	62
125	0.73	0.44	0.55	91
126	0.69	0.51	0.58	69
127	0.49	0.48	0.48	73
128	1.00	0.52	0.68	25
129	0.20	0.03	0.05	68
130	0.31	0.19	0.23	123
131	0.25	0.15	0.19	84
132	0.00	0.00	0.00	67
133	0.30	0.20	0.24	127
134	0.47	0.60	0.52	45
135	0.49	0.41	0.44	88
136	0.00	0.00	0.00	63
137	0.89	0.77	0.83	96
138	0.19	0.08	0.12	71
139	0.84	0.64	0.73	92
140	0.21	0.13	0.16	23
141	0.42	0.23	0.30	90
142	0.15	0.20	0.17	10
143	0.27	0.18	0.22	44
144	0.59	0.43	0.50	67

	0.55	٠٥	0.55	∵ .
145	0.65	0.46	0.54	131
146	0.17	0.07	0.10	83
147	0.27	0.12	0.17	32
148	0.30	0.15	0.20	115
149	0.47	0.29	0.36	63
150	0.62	0.35	0.45	83
151	0.73	0.47	0.57	101
152	0.27	0.10	0.15	29
153	0.92	0.85	0.89	191
154	0.86	0.69	0.76	54
155	0.58	0.35	0.43	84
156	0.50	0.38	0.43	37
157	0.32	0.38	0.35	65
158	0.33	0.20	0.25	46
159	0.79	0.53	0.63	80
160	0.19	0.11	0.14	66
161	0.17	0.07	0.10	56
162	0.41	0.23	0.29	127
163	0.67	0.59	0.63	111
164	0.17	0.06	0.09	32
165	0.25	0.14	0.18	28
166	0.03	0.01	0.02	98
167	0.68	0.58	0.63	88
168	0.76	0.54	0.63	59
169	0.05	0.02	0.03	42
170	0.29	0.50	0.36	4
171	0.58	0.40	0.47	95
172	0.27	0.17	0.21	54
173	0.74	0.54	0.62	65
174	0.60	0.48	0.54	31
175	0.62	0.47	0.54	32
176	0.54	0.34	0.42	58
177	0.42	0.21	0.28	76
178	0.05	0.02	0.03	55
179	0.80	0.85	0.82	74
180	0.78	0.62	0.70	64
181	0.35	0.12	0.18	57
182	0.50	0.25	0.33	36
183	0.35	0.42	0.38	52

	0.00	· · · -	٠.٠٠	J_
184	0.49	0.44	0.46	48
185	0.25	0.31	0.28	16
186	0.12	0.07	0.09	28
187	0.16	0.17	0.16	36 36
188	0.28	0.31	0.29	26 44
189	0.19	0.09	0.12	44
190 191	0.55	0.35	0.43 0.25	75
191	0.32 0.21	0.20 0.24	0.23	75 50
192	0.50	0.45	0.22	20
193	0.31	0.43	0.47	27
195	0.31	0.19	0.23	6
196	0.30	0.13	0.45	68
190	0.17	0.13	0.13	29
198	0.33	0.17	0.23	104
199	0.45	0.25	0.32	36
200	1.00	1.00	1.00	4
201	0.75	0.75	0.75	4
202	0.75	0.07	0.11	96
203	0.82	0.61	0.70	61
204	0.45	0.17	0.25	82
205	0.46	0.35	0.40	34
206	0.66	0.41	0.50	66
207	0.17	0.09	0.12	97
208	0.14	0.06	0.08	89
209	0.78	0.53	0.63	55
210	0.72	0.54	0.62	78
211	0.22	0.08	0.11	78
212	0.68	0.48	0.57	158
213	0.24	0.09	0.13	44
214	0.62	0.60	0.61	35
215	0.89	0.71	0.79	48
216	0.66	0.66	0.66	62
217	0.50	0.36	0.42	11
218	0.81	0.44	0.57	68
219	0.31	0.22	0.25	60
220	0.33	0.08	0.13	25
221	0.31	0.14	0.19	57
222	0.59	0.53	0.56	36

	0.55	٠.٥٥	0.50	
223	0.37	0.17	0.23	88
224	0.26	0.15	0.19	46
225	0.32	0.10	0.15	60
226	0.26	0.14	0.18	65
227	0.50	0.57	0.53	7
228	0.41	0.58	0.48	12
229	0.18	0.13	0.15	68
230	0.44	0.28	0.34	40
231	0.08	0.04	0.05	26
232	0.72	0.60	0.65	30
233	0.33	0.20	0.25	41
234	0.19	0.08	0.11	53
235	0.51	0.54	0.53	35
236	0.62	0.28	0.38	18
237	0.17	0.09	0.12	22
238	0.67	0.56	0.61	59
239	0.67	0.56	0.61	43
240	0.34	0.27	0.30	45
241	0.33	0.13	0.19	46
242	0.13	0.05	0.08	38
243	0.94	0.29	0.44	56
244	0.24	0.17	0.20	35 42
245 246	0.10	0.05	0.06	42 33
240	0.07 0.38	0.03 0.28	0.04 0.32	47
247	0.62	0.20	0.32	25
249	0.56	0.59	0.57	39
250	0.56	0.19	0.29	77
251	0.74	0.55	0.63	56
252	0.20	0.06	0.09	72
253	0.67	1.00	0.80	4
254	0.48	0.34	0.40	29
255	0.41	0.27	0.32	113
256	0.75	0.71	0.73	59
257	0.18	0.05	0.08	59
258	0.83	0.62	0.71	39
259	0.64	0.58	0.61	12
260	0.56	0.56	0.56	9
261	0.94	0.66	0.77	44

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262	0.76	0.50	0.60	32
263	0.18	0.17	0.17	156
264	1.00	0.60	0.75	5
265	0.18	0.07	0.10	198
266	0.07	0.03	0.04	40
267	0.20	0.14	0.16	29
268	0.00	0.00	0.00	39
269	0.11	0.17	0.13	6
270	0.75	0.60	0.67	5
271	0.40	0.12	0.18	17
272	0.30	0.13	0.18	54
273	0.38	0.26	0.31	23
274	0.00	0.00	0.00	126
275	0.44	0.34	0.39	32
276	0.40	0.60	0.48	10
277	0.82	0.61	0.70	67
278	0.47	0.36	0.41	53
279	0.33	0.12	0.18	16
280	0.72	0.68	0.70	19
281	0.30	0.13	0.18	61
282	0.38	0.21	0.27	81
283	0.41	0.34	0.37	94
284	0.46	0.35	0.40	31
285	0.31	0.21	0.25	43
286	0.35	0.22	0.27	79
287	0.29	0.40	0.33	20
288	0.83	0.88	0.86	17
289	0.73	0.64	0.69	56
290	0.15	0.08	0.10	63
291	0.48	0.33	0.39	46
292	0.43	0.36	0.39	50
293	0.62	0.29	0.40	17
294	0.36	0.15	0.21	27
295	0.04	0.02	0.02	63
296	0.23	0.12	0.16	25
297	0.04	0.03	0.03	38
298	0.25	0.10	0.14	62
299	0.67	0.59	0.63	49
300	0.19	0.15	0.17	39

	J. 25	·	· · · ·	
301	0.00	0.00	0.00	8
302	0.17	0.11	0.13	18
303	0.15	0.11	0.12	19
304	0.60	0.67	0.63	18
305	0.44	0.46	0.45	26
306	0.23	0.30	0.26	10
307	0.17	0.17	0.17	12
308	0.60	0.38	0.46	8
309	0.37	0.12	0.18	57
310	0.31	0.22	0.25	37
311	0.80	0.72	0.76	50
312	0.38	0.31	0.34	36
313	0.24	0.26	0.25	19
314	0.88	0.71	0.79	59
315	0.79	0.71	0.75	48
316	0.22	0.13	0.17	45
317	0.62	0.34	0.44	29
318	0.33	0.32	0.33	37
319	0.24	0.11	0.15	38
320	0.81	0.68	0.74	44
321	0.64	0.39	0.48	41
322	0.15	0.08	0.11	25
323	0.25	0.25	0.25	4
324	0.12	0.09	0.11	11
325	0.75	1.00	0.86	3
326	0.45	0.28	0.35	32
327	0.49	0.34	0.40	50
328	0.26	0.11	0.15	46
329	0.90	0.74	0.81	47
330	0.91	0.68	0.78	31
331	0.00	0.00	0.00	11
332	0.00	0.00	0.00	31
333	0.08	0.04	0.05	26
334	0.07	0.02	0.04	41
335	0.08	0.03	0.04	39
336	0.69	0.45	0.55	40
337	0.28	0.22	0.24	37
338	0.83	0.50	0.62	10
339	0.00	0.00	0.00	38

	٠.٠٠	0.00	0.00	
340	0.94	0.70	0.80	23
341	0.26	0.15	0.19	33
342	0.16	0.07	0.10	40
343	0.38	0.17	0.24	35
344	0.52	0.40	0.45	30
345	0.08	0.03	0.04	33
346	0.65	0.44	0.52	25
347	0.75	0.33	0.46	9
348	0.50	0.50	0.50	2
349	0.79	0.68	0.73	34
350	0.36	0.47	0.41	38
351	0.57	0.27	0.36	49
352	0.00	0.00	0.00	22
353	0.35	0.23	0.28	39
354	0.50	0.17	0.25	18
355	0.21	0.13	0.16	31
356	0.14	0.06	0.08	17
357	0.73	0.69	0.71	35
358	0.44	0.09	0.15	43
359	0.56	0.64	0.59	47
360	0.20	0.10	0.14	29
361	0.65	0.58	0.61	38
362	0.41	0.31	0.35	36
363	0.36	0.36	0.36	55
364	0.29	0.21	0.24	34
365	0.27	0.17	0.21	24
366	0.12	0.11	0.11	19
367	0.22	0.40	0.29	5
368	0.20	0.12	0.15	33
369	0.69	0.65	0.67	34
370	0.42	0.40	0.41	20
371	0.07	0.06	0.06	17
372	0.31	0.13	0.18	31
373	0.11	0.03	0.05	34
374	0.15	0.13	0.14	23
375	0.41	0.39	0.40	31
376 277	0.62	0.29	0.39	28 22
377 270	0.78 0.36	0.64 0.56	0.70 0.43	22 9
378	מב. ט	מכ.ט	ช.45	9

٠.٠	0.00	0.50	· · · ·	_
379	0.33	0.21	0.26	29
380	0.26	0.27	0.26	30
381	0.72	0.60	0.66	35
382	0.41	0.31	0.35	36
383	0.17	0.25	0.20	4
384	0.90	0.79	0.84	24
385	0.60	0.36	0.45	25
386	0.08	0.04	0.05	27
387	0.75	0.33	0.46	36
388	0.61	0.45	0.52	31
389	0.65	0.46	0.54	37 27
390 301	0.39	0.33	0.36	27 46
391 392	0.58 0.25	0.41 0.50	0.48 0.33	46 4
392	0.25	0.30	0.29	19
393 394	0.20	0.00	0.29	19
395	0.50	0.42	0.46	26
396	0.19	0.42	0.40	69
397	0.67	0.72	0.69	25
398	0.14	0.06	0.09	32
399	0.32	0.18	0.23	33
400	0.32	0.18	0.23	38
401	0.50	0.29	0.37	17
402	0.12	0.04	0.06	24
403	0.73	0.50	0.59	16
404	0.83	0.33	0.48	15
405	0.00	0.00	0.00	20
406	0.00	0.00	0.00	15
407	0.21	0.12	0.15	25
408	0.29	0.26	0.28	19
409	0.53	0.37	0.44	46
410	0.00	0.00	0.00	45
411	0.17	0.10	0.12	21
412	0.00	0.00	0.00	8
413	0.50	0.51	0.51	35
414	0.00	0.00	0.00	34
415	1.00	0.57	0.73	14
416	0.23	0.10	0.14	29
417	0.33	0.14	0.20	28

	0.00	··-·	··	
418	0.43	0.14	0.21	21
419	0.25	0.15	0.19	26
420	0.52	0.29	0.37	38
421	0.17	0.02	0.04	131
422	0.29	0.23	0.26	26
423	0.40	0.40	0.40	25
424	0.81	0.62	0.71	48
425	0.17	0.08	0.11	24
426	0.29	0.14	0.19	42
427	0.39	0.35	0.37	26
428	0.11	0.10	0.11	10
429	0.54	0.39	0.45	54
430	0.55	0.34	0.42	32
431	0.39	0.27	0.32	48
432	0.44	0.20	0.27	35
433	0.38	0.14	0.20	22
434	0.18	0.12	0.15	24
435	0.78	0.59	0.67	59
436	0.22	0.14	0.17	35
437	0.00	0.00	0.00	12
438	0.61	0.38	0.47	50
439	0.09	0.03	0.04	36
440	0.21	0.14	0.17	35
441	0.43	0.38	0.40	8
442	0.21	0.19	0.20	48
443	0.75	0.50	0.60	18
444	0.64	0.35	0.45	52
445	0.60	0.15	0.24	20
446	0.14	0.06	0.08	18
447	0.00	0.00	0.00	6
448	0.27	0.14	0.19	28
449	0.25	0.13	0.17	38
450	0.98	0.84	0.91	129
451	0.72	0.72	0.72	29
452	0.26	0.12	0.16	58
453	0.10	0.03	0.05	32
454	0.43	0.38	0.40	16
455	0.92	0.68	0.78	34
456	0.40	0.44	0.42	9

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457	0.86	0.83	0.85	30
458	0.36	0.23	0.28	40
459	0.47	0.22	0.30	37
460	0.81	0.73	0.77	30
461	0.55	0.41	0.47	27
462	0.14	0.08	0.11	12
463	0.33	0.29	0.31	17
464	0.80	0.50	0.62	56
465	0.40	0.44	0.42	9
466	0.38	0.23	0.29	22
467	0.40	0.22	0.29	9
468	0.00	0.00	0.00	15
469	0.25	0.07	0.11	14
470	0.55	0.38	0.44	16
471	0.85	0.61	0.71	18
472	0.29	0.31	0.30	16
473	0.48	0.59	0.53	22
474	0.67	0.17	0.27	12
475	1.00	0.97	0.99	110
476	0.48	0.70	0.57	20
477	0.62	0.52	0.56	31
478	0.41	0.17	0.24	42
479	0.00	0.00	0.00	4
480	0.52	0.26	0.34	47
481	0.75	0.40	0.52	30
482	0.00	0.00	0.00	35
483	0.00	0.00	0.00	30
484	0.38	0.15	0.21	20
485	0.80	0.53	0.64	15
486	0.33	0.18	0.23	17
487	0.33	0.09	0.14	11
488	0.43	0.17	0.24	36
489	0.18	0.09	0.12	32
490	0.36	0.36	0.36	14
491	0.50	0.24	0.32	25
492	0.37	0.57	0.45	23
493	0.00	0.00	0.00	9
494	0.26	0.14	0.18	37
495	0.12	0.08	0.10	24

		··	J. J.	· · · ·	
	496	0.80	0.35	0.49	34
	497	0.20	0.12	0.15	25
	498	0.12	0.11	0.12	9
	499	0.47	0.41	0.44	17
micro	avg	0.56	0.39	0.46	55953
macro	_	0.43	0.31	0.35	55953
weighted	avg	0.54	0.39	0.45	55953
samples	avg	0.43	0.37	0.37	55953

Time taken to run this cell : 5:20:04.315891

Conclusions

In [83]: global_report

Out[83]:

	Vectorizer	Model	NGram	Parameter	Precision	Recall	F1_Score_Micro
0	Tf-IDF	Logistic Regression (SGD with log loss)	(1,3)	0.00001	0.713139	0.314389	0.436393
1	Tf-IDF	Logistic Regression	(1,3)	1.00000	0.708631	0.329258	0.449610
2	BoW	Logistic Regression (SGD with log loss)	(1,4)	0.00001	0.229672	0.442675	0.302433
3	BoW	Logistic Regression	(1,4)	1.00000	0.564393	0.388719	0.460366
4	BoW	Logistic Regression (SGD with log loss) - Hypertuned	(1,4)	0.00100	0.580476	0.306168	0.400889
5	Tf-IDF	Linear SVM (SGD with hinge loss)	(1,3)	0.00001	0.792334	0.293353	0.428178
6	BoW	Linear SVM (SGD with hinge loss)	(1,4)	0.00001	0.230407	0.443033	0.303153
7	BoW	Logistic Regression - Hypertuned	(1,4)	1.00000	0.564387	0.388826	0.460440

Summarized Conclusion -

This is the StackOverflow Tag Prediction problem which is a multi-label classification based problem.

For multilabel classification, we used OneVsRest Classifier technique to solve.

Dataset size - ~6M However, due to memory constraints & performance issues, we tried to limit the dataset size to 0.15M that is, 150K points only.

Performance metric we used - Micro F1 Score as the dataset is quite imbalanced.

We tried 2 different Vectorizer - Term Frequency-Inverse Document Frequency(TF-IDF) and Bag Of Words.

The Feature Engineering which we used was to use 3-gram and 4-gram vectorizer.

Since this involves high features in the dataset, we tried to limit ourselves with Logistic Regression and SVM only. Since these algorithms tend to perform well with high feature dataset.

Result -

Logistic Regression with Lasso regression penalty tuned with 'C' hyperparameter and cross validation set to 5, we got the highest micro f1 score of 0.46 with best parameter to 1.

However, this F1Score can be increased by two ways.

- 1. Increasing the dataset size from 0.15M to atleast 5M or 10M or 15M.
- 2. Increasing the output tag limit from 500 to atleast 3k.