In [3]:

```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import sqlite3
import csv
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
#from wordcloud import WordCloud
import re
import os
from sqlalchemy import create_engine # database connection
import datetime as dt
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem.snowball import SnowballStemmer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import SGDClassifier
from sklearn import metrics
from sklearn.metrics import f1_score,precision_score,recall_score
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from skmultilearn.adapt import mlknn
from skmultilearn.problem_transform import ClassifierChain
from skmultilearn.problem_transform import BinaryRelevance
from skmultilearn.problem_transform import LabelPowerset
from sklearn.naive_bayes import GaussianNB
from datetime import datetime
```

# Stack Overflow: Tag Prediction

# 1. Business Problem

## 1.1 Description

### Description

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

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

### Problem Statemtent

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

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

## 1.2 Source / useful links

Data Source : https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data (https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data)
Youtube : https://youtu.be/nNDqbUhtIRg (https://youtu.be/nNDqbUhtIRg)
Research paper : https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/tagging-1.pdf (https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/tagging-1.pdf)
Research paper : https://dl.acm.org/citation.cfm?id=2660970&dl=ACM&coll=DL (https://dl.acm.org/citation.cfm?id=2660970&dl=ACM&coll=DL)

## 1.3 Real World / Business Objectives and Constraints

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

# 2. Machine Learning problem

## 2.1 Data

## 2.1.1 Data Overview

Refer: https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data (https://www.kaggle.com/c/facebook-recruiting-iii-keyword-extraction/data)
All of the data is in 2 files: Train and Test.

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

**Test.csv** contains the same columns but without the Tags, which you are to predict.

**Size of Train.csv** - 6.75GB

**Size of Test.csv** - 2GB

**Number of rows in Train.csv** = 6034195

The questions are randomized and contains a mix of verbose text sites as well as sites related to math and programming. The number of questions from each site may vary, and no filtering has been performed on the questions (such as closed questions).

#### Data Field Explaination

Dataset contains 6,034,195 rows. The columns in the table are:

**Id** - Unique identifier for each question

**Title** - The question's title

**Body** - The body of the question

**Tags** - The tags associated with the question in a space-seperated format (all lowercase, should not contain tabs '\t' or ampersands '&')

## 2.1.2 Example Data point

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

**Body :**

```
#include<
iostream>\n
#include<
stdlib.h>\n\n
using namespace std;\n\n
int main()\n
{\n
        int n,a[n],x,c,u[n],m[n],e[n][4];\n
        cout<<"Enter the number of variables";\n         cin>>
n;\n\n
        cout<<"Enter the Lower, and Upper Limits of the variable
s";\n
        for(int y=1; y<n+1; y++)\n
        {\n
           cin>>m[y];\n
           cin>>u[y];\n
        }\n
        for(x=1; x<n+1; x++)\n
        {\n
           a[x] = (m[x] + u[x])/2;\n
        }\n
        c=(n*4)-4;\n
        for(int a1=1; a1<n+1; a1++)\n
        {\n\n
           e[a1][0] = m[a1];\n
           e[a1][1] = m[a1]+1;\n
           e[a1][2] = u[a1]-1;\n
           e[a1][3] = u[a1];\n
        }\n
        for(int i=1; i<n+1; i++)\n
        {\n
           for(int l=1; l<=i; l++)\n
           {\n
               if(l!=1)\n
               {\n
                   cout<<a[l]<<"\\t";\n
               }\n
           }\n
           for(int j=0; j<4; j++)\n
           {\n
               cout<<e[i][j];\n
               for(int k=0; k<n-(i+1); k++)\n
               {\n
                   cout<<a[k]<<"\\t";\n
               }\n
               cout<<"\\n";\n
           }\n
```

## 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 (https://www.kaggle.com/wiki/MeanFScore)
http://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html (http://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html)

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

# 3. Exploratory Data Analysis

## 3.1 Data Loading and Cleaning

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

In [ ]:

```
#Creating db file from csv
#Learn SQL: https://www.w3schools.com/sql/default.asp
if not os.path.isfile('train.db'):
    start = datetime.now()
    disk_engine = create_engine('sqlite:///train.db')
    start = dt.datetime.now()
    chunksize = 180000
    j = 0
    index_start = 1
    for df in pd.read_csv('Train.csv', names=['Id', 'Title', 'Body', 'Tags'], chunksize
=chunksize, iterator=True, encoding='utf-8', ):
        df.index += index_start
        j+=1
        print('{} rows'.format(j*chunksize))
        df.to_sql('data', disk_engine, if_exists='append')
        index_start = df.index[-1] + 1
    print("Time taken to run this cell :", datetime.now() - start)
```

### 3.1.2 Counting the number of rows

In [ ]:

```
if os.path.isfile('train.db'):
    start = datetime.now()
    con = sqlite3.connect('train.db')
    num_rows = pd.read_sql_query("""SELECT count(*) FROM data""", con)
    #Always remember to close the database
    print("Number of rows in the database :","\n",num_rows['count(*)'].values[0])
    con.close()
    print("Time taken to count the number of rows :", datetime.now() - start)
else:
    print("Please download the train.db file from drive or run the above cell to genara
te train.db file")
```

### 3.1.3 Checking for duplicates

In [ ]:

```
#Learn SQL: https://www.w3schools.com/sql/default.asp
if os.path.isfile('train.db'):
    start = datetime.now()
    con = sqlite3.connect('train.db')
    df_no_dup = pd.read_sql_query('SELECT Title, Body, Tags, COUNT(*) as cnt_dup FROM d
ata GROUP BY Title, Body, Tags', con)
    con.close()
    print("Time taken to run this cell :", datetime.now() - start)
else:
    print("Please download the train.db file from drive or run the first to genarate tr
ain.db file")
```

In [ ]:

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

In [ ]:

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

In [ ]:

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

In [ ]:

```
start = datetime.now()
df_no_dup["tag_count"] = df_no_dup["Tags"].str.count(' ') + 1
# adding a new feature number of tags per question
print("Time taken to run this cell :", datetime.now() - start)
df_no_dup.head()
```

In [ ]:

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

In [ ]:

```
#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 [ ]:

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

    # Let's now drop unwanted column.
    tag_data.drop(tag_data.index[0], inplace=True)
    #Printing first 5 columns from our data frame
    tag_data.head()
    print("Time taken to run this cell :", datetime.now() - start)
else:
    print("Please download the train.db file from drive or run the above cells to genar
ate train.db file")
```

# 3.2 Analysis of Tags

## 3.2.1 Total number of unique tags

In [ ]:

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

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

In [ ]:

```
print("Number of data points :", tag_dtm.shape[0])
print("Number of unique tags :", tag_dtm.shape[1])
```

In [ ]:

```
#'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])
```

### 3.2.3 Number of times a tag appeared

In [ ]:

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

In [ ]:

```
#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()
```

In [ ]:

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

In [ ]:

```
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 [ ]:

```
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])
```

In [ ]:

```
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])
```

In [ ]:

```
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])
```

In [ ]:

```
plt.plot(tag_counts[0:100], c='b')
plt.scatter(x=list(range(0,100,5)), y=tag_counts[0:100:5], c='orange', label="quantiles
with 0.05 intervals")
# quantiles with 0.25 difference
plt.scatter(x=list(range(0,100,25)), y=tag_counts[0:100:25], c='m', label = "quantiles
 with 0.25 intervals")

for x,y in zip(list(range(0,100,25)), tag_counts[0:100:25]):
    plt.annotate(s="({} , {})".format(x,y), xy=(x,y), xytext=(x-0.05, y+500))

plt.title('first 100 tags: Distribution of number of times tag appeared questions')
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.legend()
plt.show()
print(len(tag_counts[0:100:5]), tag_counts[0:100:5])
```

In [ ]:

```
# 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)))
```

**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 [ ]:

```
#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 w
e 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])
```

In [ ]:

```
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_ques
t_count)))
```

In [ ]:

```
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 [ ]:

```
# 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)
```

**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 [ ]:

```
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 [8]:

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

In [4]:

```
#http://www.sqlitetutorial.net/sqlite-python/create-tables/
def create_connection(db_file):
    """ create a database connection to the SQLite database
        specified by db_file
    :param db_file: database file
    :return: Connection object or None
    """
    try:
        conn = sqlite3.connect(db_file)
        return conn
    except Error as e:
        print(e)

    return None

def create_table(conn, create_table_sql):
    """ create a table from the create_table_sql statement
    :param conn: Connection object
    :param create_table_sql: a CREATE TABLE statement
    :return:
    """
    try:
        c = conn.cursor()
        c.execute(create_table_sql)
    except Error as e:
        print(e)

def checkTableExists(dbcon):
    cursr = dbcon.cursor()
    str = "select name from sqlite_master where type='table'"
    table_names = cursr.execute(str)
    print("Tables in the databse:")
    tables =table_names.fetchall()
    print(tables[0][0])
    return(len(tables))

def create_database_table(database, query):
    conn = create_connection(database)
    if conn is not None:
        create_table(conn, query)
        checkTableExists(conn)
    else:
        print("Error! cannot create the database connection.")
    conn.close()

sql_create_table = """CREATE TABLE IF NOT EXISTS QuestionsProcessed (question text NOT
 NULL, code text, tags text, words_pre integer, words_post integer, is_code intege
r);"""
create_database_table("Processed.db", sql_create_table)
```

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

In [ ]:

```
# http://www.sqlitetutorial.net/sqlite-delete/
# https://stackoverflow.com/questions/2279706/select-random-row-from-a-sqlite-table
start = datetime.now()
read_db = 'train_no_dup.db'
write_db = 'Processed.db'
if os.path.isfile(read_db):
    conn_r = create_connection(read_db)
    if conn_r is not None:
        reader =conn_r.cursor()
        reader.execute("SELECT Title, Body, Tags From no_dup_train ORDER BY RANDOM() LI
MIT 1000000;")

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

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

In [ ]:

```
#http://www.bernzilla.com/2008/05/13/selecting-a-random-row-from-an-sqlite-table/

start = datetime.now()
preprocessed_data_list=[]
reader.fetchone()
questions_with_code=0
len_pre=0
len_post=0
questions_proccesed = 0
for row in reader:

    is_code = 0

    title, question, tags = row[0], row[1], row[2]

    if '<code>' in question:
        questions_with_code+=1
        is_code = 1
    x = len(question)+len(title)
    len_pre+=x

    code = str(re.findall(r'<code>(.*?)</code>', question, flags=re.DOTALL))

    question=re.sub('<code>(.*?)</code>', '', question, flags=re.MULTILINE|re.DOTALL)
    question=striphtml(question.encode('utf-8'))

    title=title.encode('utf-8')

    question=str(title)+" "+str(question)
    question=re.sub(r'[^A-Za-z]+',' ',question)
    words=word_tokenize(str(question.lower()))

    #Removing all single letter and and stopwords from question exceptt for the letter
 'c'
    question=' '.join(str(stemmer.stem(j)) for j in words if j not in stop_words and (l
en(j)!=1 or j=='c'))

    len_post+=len(question)
    tup = (question,code,tags,x,len(question),is_code)
    questions_proccesed += 1
    writer.execute("insert into QuestionsProcessed(question,code,tags,words_pre,words_p
ost,is_code) values (?,?,?,?,?,?)",tup)
    if (questions_proccesed%100000==0):
        print("number of questions completed=",questions_proccesed)

no_dup_avg_len_pre=(len_pre*1.0)/questions_proccesed
no_dup_avg_len_post=(len_post*1.0)/questions_proccesed

print( "Avg. length of questions(Title+Body) before processing: %d"%no_dup_avg_len_pre)
print( "Avg. length of questions(Title+Body) after processing: %d"%no_dup_avg_len_post)
print ("Percent of questions containing code: %d"%((questions_with_code*100.0)/question
s_proccesed))

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

In [ ]:

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

In [ ]:

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

In [ ]:

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

In [ ]:

```
preprocessed_data.head()
```

In [ ]:

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

# 4. Machine Learning Models

## 4.1 Converting tags for multilabel problems

| X | y1 | y2 | y3 | y4 |
|---|---|---|---|---|
| x1 | 0 | 1 | 1 | 0 |
| x1 | 1 | 0 | 0 | 0 |
| x1 | 0 | 1 | 0 | 0 |

In [ ]:

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

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

In [17]:

```
def tags_to_choose(n):
    t = multilabel_y.sum(axis=0).tolist()[0]
    sorted_tags_i = sorted(range(len(t)), key=lambda i: t[i], reverse=True)
    multilabel_yn=multilabel_y[:,sorted_tags_i[:n]]
    return multilabel_yn

def questions_explained_fn(n):
    multilabel_yn = tags_to_choose(n)
    x= multilabel_yn.sum(axis=1)
    return (np.count_nonzero(x==0))
```

In [ ]:

```
questions_explained = []
total_tags=multilabel_y.shape[1]
total_qs=preprocessed_data.shape[0]
for i in range(500, total_tags, 100):
    questions_explained.append(np.round(((total_qs-questions_explained_fn(i))/total_qs)
*100,3))
```

In [ ]:

```
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 cov
ers 90% of the tags)
print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
```

In [ ]:

```
multilabel_yx = tags_to_choose(5500)
print("number of questions that are not covered :", questions_explained_fn(5500),"out o
f ", total_qs)
```

In [ ]:

```
print("Number of tags in sample :", multilabel_y.shape[1])
print("number of tags taken :", multilabel_yx.shape[1],"(",(multilabel_yx.shape[1]/mult
ilabel_y.shape[1])*100,"%)")
```

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

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

In [ ]:

```
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 [ ]:

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

## 4.3 Featurizing data

In [ ]:

```
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=0.00009, max_features=200000, smooth_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)
```

In [ ]:

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

In [ ]:

```
# https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-label-classificati
on/
#https://stats.stackexchange.com/questions/117796/scikit-multi-label-classification
# 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.f1_score(y_test, predictions, average = 'macro'))
print(metrics.f1_score(y_test, predictions, average = 'micro'))
print(metrics.hamming_loss(y_test,predictions))

"""
# we are getting memory error because the multilearn package
# is trying to convert the data into dense matrix
# ---------------------------------------------------------------------------
#MemoryError                               Traceback (most recent call last)
#<ipython-input-170-f0e7c7f3e0be> in <module>()
#----> classifier.fit(x_train_multilabel, y_train)
```

## 4.4 Applying Logistic Regression with OneVsRest Classifier

In [ ]:

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

print("accuracy :",metrics.accuracy_score(y_test,predictions))
print("macro f1 score :",metrics.f1_score(y_test, predictions, average = 'macro'))
print("micro f1 scoore :",metrics.f1_score(y_test, predictions, average = 'micro'))
print("hamming loss :",metrics.hamming_loss(y_test,predictions))
print("Precision recall report :\n",metrics.classification_report(y_test, predictions))
```

In [ ]:

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

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

In [5]:

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

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

In [6]:

```
# http://www.sqlitetutorial.net/sqlite-delete/
# https://stackoverflow.com/questions/2279706/select-random-row-from-a-sqlite-table

read_db = 'train_no_dup.db'
write_db = 'Titlemoreweight.db'
train_datasize = 400000
if os.path.isfile(read_db):
    conn_r = create_connection(read_db)
    if conn_r is not None:
        reader =conn_r.cursor()
        # for selecting first 0.5M rows
        reader.execute("SELECT Title, Body, Tags From no_dup_train LIMIT 500001;")
        # for selecting random points
        #reader.execute("SELECT Title, Body, Tags From no_dup_train ORDER BY RANDOM() L
IMIT 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 [9]:

```
#http://www.bernzilla.com/2008/05/13/selecting-a-random-row-from-an-sqlite-table/
start = datetime.now()
preprocessed_data_list=[]
reader.fetchone()
questions_with_code=0
len_pre=0
len_post=0
questions_proccesed = 0
for row in reader:

    is_code = 0

    title, question, tags = row[0], row[1], str(row[2])

    if '<code>' in question:
        questions_with_code+=1
        is_code = 1
    x = len(question)+len(title)
    len_pre+=x

    code = str(re.findall(r'<code>(.*?)</code>', question, flags=re.DOTALL))

    question=re.sub('<code>(.*?)</code>', '', question, flags=re.MULTILINE|re.DOTALL)
    question=striphtml(question.encode('utf-8'))

    title=title.encode('utf-8')

    # adding title three time to the data to increase its weight
    # add tags string to the training data

    question=str(title)+" "+str(title)+" "+str(title)+" "+question

#     if questions_proccesed<=train_datasize:
#         question=str(title)+" "+str(title)+" "+str(title)+" "+question+" "+str(tags)
#     else:
#         question=str(title)+" "+str(title)+" "+str(title)+" "+question

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

    #Removing all single letter and and stopwords from question exceptt for the letter
 'c'
    question=' '.join(str(stemmer.stem(j)) for j in words if j not in stop_words and (l
en(j)!=1 or j=='c'))

    len_post+=len(question)
    tup = (question,code,tags,x,len(question),is_code)
    questions_proccesed += 1
    writer.execute("insert into QuestionsProcessed(question,code,tags,words_pre,words_p
ost,is_code) values (?,?,?,?,?,?)",tup)
    if (questions_proccesed%100000==0):
        print("number of questions completed=",questions_proccesed)

no_dup_avg_len_pre=(len_pre*1.0)/questions_proccesed
no_dup_avg_len_post=(len_post*1.0)/questions_proccesed

print( "Avg. length of questions(Title+Body) before processing: %d"%no_dup_avg_len_pre)
print( "Avg. length of questions(Title+Body) after processing: %d"%no_dup_avg_len_post)
print ("Percent of questions containing code: %d"%((questions_with_code*100.0)/question
```

```
s_proccesed))

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

```
number of questions completed= 100000
number of questions completed= 200000
number of questions completed= 300000
number of questions completed= 400000
Avg. length of questions(Title+Body) before processing: 1239
Avg. length of questions(Title+Body) after processing: 424
Percent of questions containing code: 57
Time taken to run this cell : 0:18:51.052368
```

In [10]:

```
# never forget to close the conections or else we will end up with database locks
conn_r.commit()
conn_w.commit()
conn_r.close()
conn_w.close()
```

**Sample quesitons after preprocessing of data**

In [11]:

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

```
Questions after preprocessed
================================================================================
==========================
('java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index
java.sql.sqlexcept microsoft odbc driver manag invalid descriptor index ja
va.sql.sqlexcept microsoft odbc driver manag invalid descriptor index use
follow code display caus solv',)
--------------------------------------------------------------------------
-------------------------
('better way updat feed fb php sdk better way updat feed fb php sdk better
way updat feed fb php sdk novic facebook api read mani tutori still confus
ed.i find post feed api method like correct second way use curl someth lik
e way better',)
--------------------------------------------------------------------------
-------------------------
('btnadd click event open two window record ad btnadd click event open two
window record ad btnadd click event open two window record ad open window
search.aspx use code hav add button search.aspx nwhen insert record btnadd
click event open anoth window nafter insert record close window',)
--------------------------------------------------------------------------
-------------------------
('sql inject issu prevent correct form submiss php sql inject issu prevent
correct form submiss php sql inject issu prevent correct form submiss php
check everyth think make sure input field safe type sql inject good news s
afe bad news one tag mess form submiss place even touch life figur exact h
tml use templat file forgiv okay entir php script get execut see data post
none forum field post problem use someth titl field none data get post cur
rent use print post see submit noth work flawless statement though also me
ntion script work flawless local machin use host come across problem state
list input test mess',)
--------------------------------------------------------------------------
-------------------------
('countabl subaddit lebesgu measur countabl subaddit lebesgu measur counta
bl subaddit lebesgu measur let lbrace rbrace sequenc set sigma -algebra ma
thcal want show left bigcup right leq sum left right countabl addit measur
defin set sigma algebra mathcal think use monoton properti somewher proof
start appreci littl help nthank ad han answer make follow addit construct
given han answer clear bigcup bigcup cap emptyset neq left bigcup right le
ft bigcup right sum left right also construct subset monoton left right le
q left right final would sum leq sum result follow',)
--------------------------------------------------------------------------
-------------------------
('hql equival sql queri hql equival sql queri hql equival sql queri hql qu
eri replac name class properti name error occur hql error',)
--------------------------------------------------------------------------
-------------------------
('undefin symbol architectur i386 objc class skpsmtpmessag referenc error
undefin symbol architectur i386 objc class skpsmtpmessag referenc error un
defin symbol architectur i386 objc class skpsmtpmessag referenc error impo
rt framework send email applic background import framework i.e skpsmtpmess
ag somebodi suggest get error collect2 ld return exit status import framew
ork correct sorc taken framework follow mfmailcomposeviewcontrol question
lock field updat answer drag drop folder project click copi nthat',)
--------------------------------------------------------------------------
-------------------------
('java.lang.nosuchmethoderror javax.servlet.servletcontext.geteffectiveses
siontrackingmod ljava util set java.lang.nosuchmethoderror javax.servlet.s
ervletcontext.geteffectivesessiontrackingmod ljava util set java.lang.nosu
chmethoderror javax.servlet.servletcontext.geteffectivesessiontrackingmod
ljava util set want servlet process input standalon java program deploy se
rvlet jboss put servlet.class file web-inf class web.xml gave servlet url
```

```
map .do java client program open connect servlet use url object use localh
ost 8080 .do get folow error error org.apache.catalina.connector.coyoteada
pt except error occur contain request process java.lang.nosuchmethoderror
javax.servlet.servletcontext.geteffectivesessiontrackingmod ljava util set
org.apache.catalina.connector.coyoteadapter.postparserequest coyoteadapte
r.java 567 org.apache.catalina.connector.coyoteadapter.servic coyoteadapte
r.java 359 org.apache.coyote.http11.http11processor.process http11processo
r.java 877 org.apache.coyote.http11.http11protocol http11connectionhandle
r.process http11protocol.java 654 org.apache.tomcat.util.net.jioendpoint w
orker.run jioendpoint.java 951 web.xml file content',)
--------------------------------------------------------------------------
-------------------------
('obtain updat locat use gps servic obtain updat locat use gps servic obta
in updat locat use gps servic app two button start track stop track strart
track button click gps start listen locat stop listen use besid toast ever
i new updat locat want thing use background servic alway updat locat even
activ closed.a toast appear everi new updat location.pleas hint link would
appreci',)
--------------------------------------------------------------------------
-------------------------
```

### Saving Preprocessed data to a Database

In [12]:

```
#Taking 0.5 Million entries to a dataframe.
write_db = 'Titlemoreweight.db'
if os.path.isfile(write_db):
    conn_r = create_connection(write_db)
    if conn_r is not None:
        preprocessed_data = pd.read_sql_query("""SELECT question, Tags FROM QuestionsPr
ocessed""", conn_r)
conn_r.commit()
conn_r.close()
```

In [13]:

```
preprocessed_data.head()
```

Out[13]:

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

In [14]:

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

```
number of data points in sample : 499998
number of dimensions : 2
```

### Converting string Tags to multilable output variables

In [15]:

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

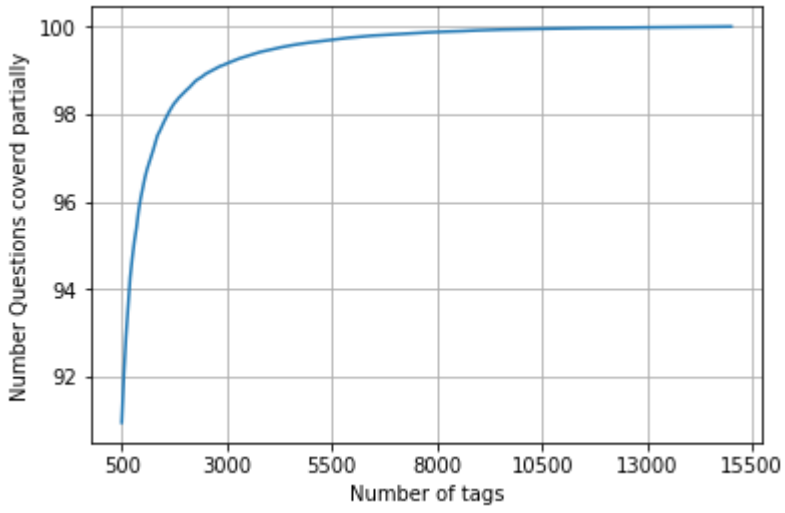
### Selecting 500 Tags

In [18]:

```
questions_explained = []
total_tags=multilabel_y.shape[1]
total_qs=preprocessed_data.shape[0]
for i in range(500, total_tags, 100):
    questions_explained.append(np.round(((total_qs-questions_explained_fn(i))/total_qs)
*100,3))
```

In [19]:

```
fig, ax = plt.subplots()
ax.plot(questions_explained)
xlabel = list(500+np.array(range(-50,450,50))*50)
ax.set_xticklabels(xlabel)
plt.xlabel("Number of tags")
plt.ylabel("Number Questions coverd partially")
plt.grid()
plt.show()
# you can choose any number of tags based on your computing power, minimun is 500(it co
vers 90% of the tags)
print("with ",5500,"tags we are covering ",questions_explained[50],"% of questions")
print("with ",500,"tags we are covering ",questions_explained[0],"% of questions")
```




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

In [20]:

```
# we will be taking 500 tags
multilabel_yx = tags_to_choose(500)
print("number of questions that are not covered :", questions_explained_fn(500),"out of
", total_qs)
```

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

In [21]:

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

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

In [22]:

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

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

### 4.5.2 Featurizing data with Tfidf vectorizer

In [ ]:

```
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=0.00009, max_features=200000, smooth_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)
```

In [23]:

```
from sklearn.feature_extraction.text import CountVectorizer
start = datetime.now()
vectorizer = CountVectorizer(min_df=0.00009, max_features=20000,tokenizer = lambda x: x
.split(),ngram_range=(1,2))
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 : 0:01:42.011543
```

In [24]:

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

```
Dimensions of train data X: (400000, 20000) Y : (400000, 500)
Dimensions of test data X: (99998, 20000) Y: (99998, 500)
```

In [25]:

```
x_train_multilabel=x_train_multilabel[0:160000]
y_train=y_train[0:160000]
```

In [26]:

```
x_test_multilabel=x_test_multilabel[0:40000]
y_test=y_test[0:40000]
```

In [44]:

```
x_train_multilabel=pd.DataFrame.sparse.from_spmatrix(x_train_multilabel)
y_train=pd.DataFrame.sparse.from_spmatrix(y_train)

x_test_multilabel=pd.DataFrame.sparse.from_spmatrix(x_test_multilabel)
y_test=pd.DataFrame.sparse.from_spmatrix(y_test)
```

In [27]:

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

```
Dimensions of train data X: (160000, 20000) Y : (160000, 500)
Dimensions of test data X: (40000, 20000) Y: (40000, 500)
```

In [28]:

```
print(type(x_train_multilabel))
print(type(y_train))
print(type(x_test_multilabel))
print(type(y_test))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
<class 'scipy.sparse.csr.csr_matrix'>
```

### 4.5.3 Applying Logistic Regression with OneVsRest Classifier

In [29]:

```
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l1'
))
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


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


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

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

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

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

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

```
Accuracy : 0.069875
Hamming loss  0.00880855
Micro-average quality numbers
Precision: 0.1881, Recall: 0.4859, F1-measure: 0.2712
Macro-average quality numbers
Precision: 0.1347, Recall: 0.4231, F1-measure: 0.1956
              precision    recall  f1-score   support

           0       0.67      0.80      0.73      1936
           1       0.37      0.40      0.38      3047
           2       0.47      0.52      0.49      2805
           3       0.49      0.66      0.56      1644
           4       0.51      0.57      0.53      2441
           5       0.35      0.46      0.39      1171
           6       0.51      0.62      0.56      1942
           7       0.46      0.64      0.53      1343
           8       0.23      0.28      0.25      1427
           9       0.42      0.64      0.51       587
          10       0.24      0.33      0.28       888
          11       0.40      0.54      0.46      1197
          12       0.31      0.42      0.36       964
          13       0.26      0.46      0.33       696
          14       0.52      0.68      0.59      1102
          15       0.28      0.41      0.33       832
          16       0.18      0.36      0.24       393
          17       0.43      0.70      0.53       790
          18       0.23      0.41      0.30       836
          19       0.17      0.45      0.24       337
          20       0.31      0.53      0.39       522
          21       0.15      0.24      0.19       865
          22       0.22      0.39      0.28       614
          23       0.39      0.70      0.50       313
          24       0.17      0.36      0.23       194
          25       0.14      0.51      0.23       195
          26       0.25      0.50      0.33       344
          27       0.29      0.50      0.37       525
          28       0.32      0.57      0.41       432
          29       0.10      0.34      0.15       151
          30       0.12      0.32      0.18       201
          31       0.10      0.23      0.14       307
          32       0.16      0.47      0.24       130
          33       0.26      0.49      0.34       634
          34       0.17      0.38      0.23       320
          35       0.33      0.67      0.44       297
          36       0.14      0.43      0.21       195
          37       0.32      0.72      0.44        69
          38       0.27      0.57      0.37       332
          39       0.19      0.49      0.27       276
          40       0.23      0.51      0.31       421
          41       0.04      0.27      0.07        77
          42       0.20      0.70      0.31        73
          43       0.28      0.61      0.38       178
          44       0.27      0.57      0.37       367
          45       0.20      0.51      0.29       319
          46       0.24      0.58      0.34       261
          47       0.09      0.35      0.15       121
          48       0.16      0.48      0.24       172
          49       0.42      0.76      0.54       315
          50       0.07      0.23      0.11       122
          51       0.06      0.26      0.10       187
          52       0.06      0.19      0.09        63
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|---|---|---|---|---|
| 53 | 0.21 | 0.46 | 0.29 | 271 |
| 54 | 0.15 | 0.34 | 0.21 | 334 |
| 55 | 0.03 | 0.16 | 0.04 | 58 |
| 56 | 0.15 | 0.39 | 0.22 | 313 |
| 57 | 0.12 | 0.29 | 0.17 | 325 |
| 58 | 0.22 | 0.47 | 0.30 | 270 |
| 59 | 0.43 | 0.82 | 0.56 | 267 |
| 60 | 0.07 | 0.22 | 0.11 | 158 |
| 61 | 0.13 | 0.51 | 0.21 | 67 |
| 62 | 0.46 | 0.85 | 0.60 | 396 |
| 63 | 0.34 | 0.73 | 0.46 | 158 |
| 64 | 0.10 | 0.43 | 0.16 | 46 |
| 65 | 0.06 | 0.25 | 0.09 | 121 |
| 66 | 0.11 | 0.30 | 0.16 | 221 |
| 67 | 0.21 | 0.67 | 0.32 | 105 |
| 68 | 0.33 | 0.66 | 0.44 | 222 |
| 69 | 0.17 | 0.62 | 0.27 | 129 |
| 70 | 0.08 | 0.32 | 0.13 | 135 |
| 71 | 0.11 | 0.38 | 0.18 | 125 |
| 72 | 0.24 | 0.62 | 0.34 | 172 |
| 73 | 0.14 | 0.88 | 0.25 | 26 |
| 74 | 0.10 | 0.55 | 0.16 | 42 |
| 75 | 0.40 | 0.82 | 0.54 | 50 |
| 76 | 0.06 | 0.17 | 0.09 | 158 |
| 77 | 0.08 | 0.45 | 0.13 | 74 |
| 78 | 0.17 | 0.55 | 0.26 | 147 |
| 79 | 0.14 | 0.37 | 0.21 | 187 |
| 80 | 0.12 | 0.45 | 0.19 | 128 |
| 81 | 0.08 | 0.26 | 0.13 | 173 |
| 82 | 0.06 | 0.22 | 0.09 | 103 |
| 83 | 0.20 | 0.58 | 0.30 | 168 |
| 84 | 0.13 | 0.45 | 0.20 | 76 |
| 85 | 0.15 | 0.35 | 0.21 | 212 |
| 86 | 0.09 | 0.27 | 0.13 | 184 |
| 87 | 0.08 | 0.38 | 0.13 | 74 |
| 88 | 0.07 | 0.50 | 0.13 | 38 |
| 89 | 0.06 | 0.27 | 0.10 | 59 |
| 90 | 0.19 | 0.39 | 0.26 | 194 |
| 91 | 0.13 | 0.48 | 0.20 | 164 |
| 92 | 0.26 | 0.66 | 0.37 | 194 |
| 93 | 0.17 | 0.64 | 0.27 | 120 |
| 94 | 0.04 | 0.16 | 0.06 | 49 |
| 95 | 0.08 | 0.33 | 0.13 | 86 |
| 96 | 0.13 | 0.29 | 0.18 | 277 |
| 97 | 0.18 | 0.53 | 0.27 | 116 |
| 98 | 0.20 | 0.73 | 0.32 | 59 |
| 99 | 0.10 | 0.36 | 0.16 | 95 |
| 100 | 0.09 | 0.26 | 0.14 | 178 |
| 101 | 0.46 | 0.76 | 0.58 | 136 |
| 102 | 0.56 | 0.81 | 0.67 | 295 |
| 103 | 0.07 | 0.29 | 0.11 | 70 |
| 104 | 0.05 | 0.17 | 0.08 | 113 |
| 105 | 0.22 | 0.59 | 0.32 | 145 |
| 106 | 0.09 | 0.29 | 0.14 | 118 |
| 107 | 0.24 | 0.64 | 0.35 | 146 |
| 108 | 0.18 | 0.47 | 0.26 | 152 |
| 109 | 0.16 | 0.55 | 0.25 | 114 |
| 110 | 0.04 | 0.16 | 0.07 | 91 |
| 111 | 0.04 | 0.31 | 0.07 | 54 |
| 112 | 0.11 | 0.57 | 0.18 | 60 |
| 113 | 0.10 | 0.43 | 0.16 | 72 |

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|---|---|---|---|---|
| 114 | 0.06 | 0.30 | 0.10 | 82 |
| 115 | 0.14 | 0.47 | 0.22 | 159 |
| 116 | 0.23 | 0.60 | 0.33 | 154 |
| 117 | 0.13 | 0.37 | 0.20 | 142 |
| 118 | 0.08 | 0.38 | 0.13 | 50 |
| 119 | 0.15 | 0.45 | 0.23 | 168 |
| 120 | 0.03 | 0.13 | 0.05 | 92 |
| 121 | 0.30 | 0.68 | 0.41 | 229 |
| 122 | 0.06 | 0.28 | 0.10 | 60 |
| 123 | 0.02 | 0.08 | 0.03 | 95 |
| 124 | 0.36 | 0.79 | 0.50 | 96 |
| 125 | 0.07 | 0.38 | 0.11 | 56 |
| 126 | 0.25 | 0.68 | 0.36 | 157 |
| 127 | 0.02 | 0.20 | 0.04 | 50 |
| 128 | 0.06 | 0.25 | 0.09 | 95 |
| 129 | 0.13 | 0.36 | 0.19 | 42 |
| 130 | 0.07 | 0.43 | 0.12 | 44 |
| 131 | 0.05 | 0.21 | 0.08 | 76 |
| 132 | 0.15 | 0.45 | 0.23 | 137 |
| 133 | 0.41 | 0.76 | 0.54 | 232 |
| 134 | 0.31 | 0.84 | 0.46 | 49 |
| 135 | 0.05 | 0.28 | 0.08 | 40 |
| 136 | 0.05 | 0.46 | 0.10 | 59 |
| 137 | 0.16 | 0.40 | 0.22 | 126 |
| 138 | 0.07 | 0.28 | 0.11 | 116 |
| 139 | 0.11 | 0.40 | 0.17 | 73 |
| 140 | 0.22 | 0.63 | 0.33 | 114 |
| 141 | 0.06 | 0.21 | 0.09 | 84 |
| 142 | 0.19 | 0.56 | 0.28 | 119 |
| 143 | 0.58 | 0.85 | 0.69 | 194 |
| 144 | 0.08 | 0.47 | 0.14 | 66 |
| 145 | 0.15 | 0.55 | 0.24 | 100 |
| 146 | 0.17 | 0.47 | 0.25 | 167 |
| 147 | 0.09 | 0.47 | 0.15 | 36 |
| 148 | 0.07 | 0.28 | 0.11 | 78 |
| 149 | 0.27 | 0.65 | 0.38 | 187 |
| 150 | 0.07 | 0.28 | 0.11 | 156 |
| 151 | 0.09 | 0.78 | 0.15 | 18 |
| 152 | 0.31 | 0.71 | 0.43 | 150 |
| 153 | 0.09 | 0.42 | 0.15 | 38 |
| 154 | 0.09 | 0.30 | 0.14 | 118 |
| 155 | 0.05 | 0.19 | 0.08 | 95 |
| 156 | 0.24 | 0.82 | 0.37 | 66 |
| 157 | 0.09 | 0.27 | 0.14 | 86 |
| 158 | 0.18 | 0.67 | 0.29 | 33 |
| 159 | 0.06 | 0.35 | 0.10 | 49 |
| 160 | 0.06 | 0.28 | 0.11 | 83 |
| 161 | 0.17 | 0.66 | 0.27 | 76 |
| 162 | 0.05 | 0.23 | 0.09 | 91 |
| 163 | 0.18 | 0.49 | 0.26 | 121 |
| 164 | 0.16 | 0.51 | 0.24 | 95 |
| 165 | 0.14 | 0.44 | 0.22 | 122 |
| 166 | 0.12 | 0.55 | 0.19 | 53 |
| 167 | 0.11 | 0.42 | 0.17 | 97 |
| 168 | 0.13 | 0.41 | 0.19 | 135 |
| 169 | 0.12 | 0.33 | 0.18 | 105 |
| 170 | 0.02 | 0.17 | 0.03 | 29 |
| 171 | 0.12 | 0.49 | 0.19 | 43 |
| 172 | 0.09 | 0.51 | 0.16 | 83 |
| 173 | 0.16 | 0.45 | 0.23 | 130 |
| 174 | 0.05 | 0.26 | 0.09 | 66 |

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| 175 | 0.39 | 0.93 | 0.55 | 56 |
| 176 | 0.39 | 0.77 | 0.52 | 159 |
| 177 | 0.26 | 0.67 | 0.38 | 130 |
| 178 | 0.20 | 0.67 | 0.31 | 115 |
| 179 | 0.03 | 0.23 | 0.06 | 60 |
| 180 | 0.08 | 0.61 | 0.13 | 51 |
| 181 | 0.03 | 0.28 | 0.05 | 46 |
| 182 | 0.04 | 0.24 | 0.07 | 51 |
| 183 | 0.18 | 0.54 | 0.27 | 165 |
| 184 | 0.05 | 0.23 | 0.09 | 97 |
| 185 | 0.03 | 0.19 | 0.06 | 32 |
| 186 | 0.07 | 0.27 | 0.11 | 79 |
| 187 | 0.20 | 0.72 | 0.32 | 87 |
| 188 | 0.08 | 0.34 | 0.12 | 80 |
| 189 | 0.16 | 0.57 | 0.25 | 51 |
| 190 | 0.23 | 0.65 | 0.34 | 80 |
| 191 | 0.05 | 0.27 | 0.08 | 83 |
| 192 | 0.18 | 0.61 | 0.27 | 103 |
| 193 | 0.05 | 0.40 | 0.09 | 20 |
| 194 | 0.19 | 0.62 | 0.29 | 89 |
| 195 | 0.04 | 0.17 | 0.06 | 77 |
| 196 | 0.03 | 0.16 | 0.06 | 91 |
| 197 | 0.12 | 0.31 | 0.17 | 112 |
| 198 | 0.11 | 0.29 | 0.16 | 118 |
| 199 | 0.04 | 0.25 | 0.07 | 53 |
| 200 | 0.34 | 0.79 | 0.48 | 86 |
| 201 | 0.13 | 0.43 | 0.20 | 129 |
| 202 | 0.35 | 0.67 | 0.46 | 158 |
| 203 | 0.09 | 0.24 | 0.13 | 111 |
| 204 | 0.09 | 0.32 | 0.14 | 93 |
| 205 | 0.04 | 0.26 | 0.08 | 34 |
| 206 | 0.01 | 0.04 | 0.01 | 50 |
| 207 | 0.10 | 0.45 | 0.17 | 31 |
| 208 | 0.22 | 0.63 | 0.32 | 138 |
| 209 | 0.09 | 0.30 | 0.14 | 106 |
| 210 | 0.15 | 0.44 | 0.22 | 126 |
| 211 | 0.06 | 0.41 | 0.10 | 51 |
| 212 | 0.05 | 0.28 | 0.08 | 32 |
| 213 | 0.05 | 0.43 | 0.09 | 14 |
| 214 | 0.10 | 0.60 | 0.17 | 40 |
| 215 | 0.10 | 0.51 | 0.16 | 57 |
| 216 | 0.20 | 0.42 | 0.27 | 186 |
| 217 | 0.04 | 0.35 | 0.07 | 20 |
| 218 | 0.43 | 0.89 | 0.58 | 100 |
| 219 | 0.19 | 0.51 | 0.27 | 96 |
| 220 | 0.35 | 0.75 | 0.48 | 109 |
| 221 | 0.36 | 0.79 | 0.50 | 129 |
| 222 | 0.12 | 0.55 | 0.20 | 64 |
| 223 | 0.03 | 0.14 | 0.05 | 49 |
| 224 | 0.17 | 0.59 | 0.26 | 85 |
| 225 | 0.10 | 0.59 | 0.18 | 69 |
| 226 | 0.11 | 0.34 | 0.17 | 82 |
| 227 | 0.17 | 0.51 | 0.25 | 69 |
| 228 | 0.04 | 0.19 | 0.07 | 97 |
| 229 | 0.03 | 0.20 | 0.06 | 60 |
| 230 | 0.04 | 0.25 | 0.07 | 77 |
| 231 | 0.10 | 0.50 | 0.16 | 22 |
| 232 | 0.05 | 0.27 | 0.09 | 59 |
| 233 | 0.13 | 0.56 | 0.22 | 77 |
| 234 | 0.09 | 0.32 | 0.14 | 37 |
| 235 | 0.12 | 0.47 | 0.19 | 30 |

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| 236 | 0.27 | 0.77 | 0.40 | 39 |
| 237 | 0.07 | 0.26 | 0.10 | 101 |
| 238 | 0.03 | 0.20 | 0.05 | 50 |
| 239 | 0.01 | 0.05 | 0.01 | 21 |
| 240 | 0.08 | 0.30 | 0.13 | 33 |
| 241 | 0.05 | 0.25 | 0.08 | 88 |
| 242 | 0.07 | 0.42 | 0.12 | 36 |
| 243 | 0.03 | 0.31 | 0.06 | 29 |
| 244 | 0.22 | 0.49 | 0.30 | 112 |
| 245 | 0.06 | 0.30 | 0.10 | 44 |
| 246 | 0.37 | 0.79 | 0.50 | 62 |
| 247 | 0.04 | 0.31 | 0.07 | 26 |
| 248 | 0.02 | 0.12 | 0.04 | 51 |
| 249 | 0.02 | 0.13 | 0.03 | 31 |
| 250 | 0.04 | 0.35 | 0.08 | 23 |
| 251 | 0.12 | 0.47 | 0.19 | 73 |
| 252 | 0.03 | 0.13 | 0.05 | 53 |
| 253 | 0.10 | 0.43 | 0.16 | 44 |
| 254 | 0.05 | 0.26 | 0.09 | 50 |
| 255 | 0.07 | 0.25 | 0.11 | 158 |
| 256 | 0.06 | 0.24 | 0.09 | 83 |
| 257 | 0.07 | 0.45 | 0.12 | 40 |
| 258 | 0.29 | 0.54 | 0.38 | 98 |
| 259 | 0.10 | 0.40 | 0.16 | 63 |
| 260 | 0.14 | 0.41 | 0.21 | 95 |
| 261 | 0.10 | 0.35 | 0.16 | 85 |
| 262 | 0.07 | 0.38 | 0.11 | 42 |
| 263 | 0.22 | 0.41 | 0.29 | 162 |
| 264 | 0.05 | 0.39 | 0.09 | 41 |
| 265 | 0.07 | 0.41 | 0.12 | 34 |
| 266 | 0.04 | 0.33 | 0.07 | 12 |
| 267 | 0.03 | 0.29 | 0.06 | 21 |
| 268 | 0.19 | 0.59 | 0.28 | 92 |
| 269 | 0.05 | 0.38 | 0.08 | 21 |
| 270 | 0.15 | 0.63 | 0.24 | 62 |
| 271 | 0.16 | 0.61 | 0.26 | 77 |
| 272 | 0.10 | 0.37 | 0.16 | 89 |
| 273 | 0.45 | 0.85 | 0.59 | 119 |
| 274 | 0.23 | 0.84 | 0.36 | 37 |
| 275 | 0.04 | 0.23 | 0.07 | 40 |
| 276 | 0.02 | 0.12 | 0.03 | 51 |
| 277 | 0.21 | 0.63 | 0.31 | 54 |
| 278 | 0.16 | 0.68 | 0.26 | 57 |
| 279 | 0.37 | 0.80 | 0.50 | 89 |
| 280 | 0.08 | 0.38 | 0.13 | 29 |
| 281 | 0.27 | 0.64 | 0.38 | 81 |
| 282 | 0.22 | 0.66 | 0.32 | 56 |
| 283 | 0.10 | 0.33 | 0.16 | 137 |
| 284 | 0.13 | 0.52 | 0.20 | 29 |
| 285 | 0.18 | 0.65 | 0.28 | 103 |
| 286 | 0.30 | 0.77 | 0.43 | 100 |
| 287 | 0.13 | 0.57 | 0.22 | 51 |
| 288 | 0.02 | 0.14 | 0.04 | 43 |
| 289 | 0.03 | 0.28 | 0.05 | 32 |
| 290 | 0.03 | 0.24 | 0.06 | 50 |
| 291 | 0.10 | 0.43 | 0.16 | 58 |
| 292 | 0.06 | 0.36 | 0.11 | 33 |
| 293 | 0.13 | 0.62 | 0.21 | 50 |
| 294 | 0.08 | 0.50 | 0.14 | 68 |
| 295 | 0.05 | 0.24 | 0.08 | 37 |
| 296 | 0.01 | 0.17 | 0.03 | 12 |

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| 297 | 0.04 | 0.26 | 0.07 | 47 |
| 298 | 0.08 | 0.53 | 0.14 | 17 |
| 299 | 0.17 | 0.73 | 0.27 | 22 |
| 300 | 0.04 | 0.25 | 0.08 | 60 |
| 301 | 0.01 | 0.08 | 0.02 | 52 |
| 302 | 0.00 | 0.05 | 0.01 | 21 |
| 303 | 0.21 | 0.61 | 0.31 | 90 |
| 304 | 0.32 | 0.83 | 0.46 | 88 |
| 305 | 0.37 | 0.81 | 0.51 | 64 |
| 306 | 0.24 | 0.51 | 0.33 | 101 |
| 307 | 0.04 | 0.18 | 0.07 | 45 |
| 308 | 0.00 | 0.03 | 0.01 | 40 |
| 309 | 0.04 | 0.22 | 0.06 | 41 |
| 310 | 0.13 | 0.50 | 0.21 | 68 |
| 311 | 0.08 | 0.45 | 0.13 | 20 |
| 312 | 0.03 | 0.20 | 0.06 | 20 |
| 313 | 0.03 | 0.27 | 0.05 | 30 |
| 314 | 0.14 | 0.48 | 0.21 | 81 |
| 315 | 0.19 | 0.64 | 0.29 | 59 |
| 316 | 0.06 | 0.33 | 0.10 | 24 |
| 317 | 0.06 | 0.24 | 0.09 | 78 |
| 318 | 0.16 | 0.48 | 0.24 | 60 |
| 319 | 0.17 | 0.57 | 0.26 | 46 |
| 320 | 0.07 | 0.41 | 0.12 | 61 |
| 321 | 0.17 | 0.60 | 0.26 | 48 |
| 322 | 0.14 | 0.55 | 0.22 | 58 |
| 323 | 0.25 | 0.55 | 0.35 | 155 |
| 324 | 0.04 | 0.30 | 0.08 | 37 |
| 325 | 0.03 | 0.24 | 0.06 | 33 |
| 326 | 0.04 | 0.29 | 0.07 | 52 |
| 327 | 0.03 | 0.14 | 0.04 | 59 |
| 328 | 0.28 | 0.79 | 0.41 | 71 |
| 329 | 0.13 | 0.48 | 0.20 | 66 |
| 330 | 0.08 | 0.30 | 0.13 | 50 |
| 331 | 0.03 | 0.28 | 0.06 | 32 |
| 332 | 0.01 | 0.20 | 0.02 | 10 |
| 333 | 0.04 | 0.14 | 0.06 | 81 |
| 334 | 0.04 | 0.23 | 0.07 | 30 |
| 335 | 0.03 | 0.14 | 0.05 | 36 |
| 336 | 0.11 | 0.62 | 0.19 | 21 |
| 337 | 0.02 | 0.23 | 0.03 | 26 |
| 338 | 0.17 | 0.55 | 0.26 | 53 |
| 339 | 0.01 | 0.10 | 0.02 | 29 |
| 340 | 0.23 | 0.62 | 0.33 | 55 |
| 341 | 0.06 | 0.33 | 0.10 | 12 |
| 342 | 0.06 | 0.37 | 0.10 | 19 |
| 343 | 0.08 | 0.50 | 0.14 | 20 |
| 344 | 0.03 | 0.14 | 0.05 | 21 |
| 345 | 0.12 | 0.71 | 0.21 | 21 |
| 346 | 0.01 | 0.20 | 0.03 | 25 |
| 347 | 0.12 | 0.45 | 0.19 | 47 |
| 348 | 0.01 | 0.08 | 0.01 | 25 |
| 349 | 0.18 | 0.79 | 0.30 | 34 |
| 350 | 0.04 | 0.50 | 0.08 | 8 |
| 351 | 0.05 | 0.50 | 0.09 | 10 |
| 352 | 0.22 | 0.56 | 0.31 | 61 |
| 353 | 0.03 | 0.30 | 0.06 | 10 |
| 354 | 0.04 | 0.22 | 0.07 | 58 |
| 355 | 0.09 | 0.54 | 0.16 | 59 |
| 356 | 0.23 | 0.50 | 0.32 | 145 |
| 357 | 0.24 | 0.57 | 0.33 | 135 |

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| 358 | 0.09 | 0.36 | 0.14 | 36 |
| 359 | 0.26 | 0.67 | 0.38 | 67 |
| 360 | 0.07 | 0.34 | 0.11 | 62 |
| 361 | 0.42 | 0.86 | 0.57 | 76 |
| 362 | 0.01 | 0.12 | 0.02 | 24 |
| 363 | 0.33 | 0.81 | 0.46 | 64 |
| 364 | 0.02 | 0.17 | 0.04 | 18 |
| 365 | 0.04 | 0.30 | 0.07 | 27 |
| 366 | 0.28 | 0.85 | 0.42 | 27 |
| 367 | 0.06 | 0.26 | 0.10 | 68 |
| 368 | 0.01 | 0.08 | 0.01 | 13 |
| 369 | 0.02 | 0.25 | 0.04 | 24 |
| 370 | 0.01 | 0.09 | 0.01 | 22 |
| 371 | 0.03 | 0.19 | 0.05 | 36 |
| 372 | 0.22 | 0.43 | 0.29 | 30 |
| 373 | 0.19 | 0.64 | 0.29 | 74 |
| 374 | 0.06 | 0.40 | 0.10 | 30 |
| 375 | 0.02 | 0.15 | 0.03 | 20 |
| 376 | 0.00 | 0.00 | 0.00 | 15 |
| 377 | 0.19 | 0.42 | 0.26 | 79 |
| 378 | 0.01 | 0.09 | 0.02 | 35 |
| 379 | 0.00 | 0.00 | 0.00 | 7 |
| 380 | 0.12 | 0.51 | 0.19 | 57 |
| 381 | 0.04 | 0.20 | 0.06 | 59 |
| 382 | 0.03 | 0.20 | 0.05 | 41 |
| 383 | 0.13 | 0.48 | 0.21 | 69 |
| 384 | 0.03 | 0.21 | 0.06 | 42 |
| 385 | 0.08 | 0.33 | 0.12 | 21 |
| 386 | 0.02 | 0.12 | 0.03 | 24 |
| 387 | 0.05 | 0.29 | 0.09 | 34 |
| 388 | 0.06 | 0.38 | 0.10 | 39 |
| 389 | 0.02 | 0.13 | 0.03 | 45 |
| 390 | 0.35 | 0.68 | 0.46 | 75 |
| 391 | 0.06 | 0.34 | 0.10 | 32 |
| 392 | 0.07 | 0.62 | 0.12 | 8 |
| 393 | 0.01 | 0.07 | 0.02 | 59 |
| 394 | 0.04 | 0.21 | 0.07 | 38 |
| 395 | 0.09 | 0.39 | 0.15 | 61 |
| 396 | 0.07 | 0.34 | 0.12 | 65 |
| 397 | 0.27 | 0.47 | 0.34 | 190 |
| 398 | 0.16 | 0.83 | 0.27 | 36 |
| 399 | 0.02 | 0.22 | 0.04 | 23 |
| 400 | 0.06 | 0.33 | 0.10 | 27 |
| 401 | 0.07 | 0.44 | 0.11 | 36 |
| 402 | 0.11 | 0.42 | 0.17 | 52 |
| 403 | 0.03 | 0.45 | 0.06 | 11 |
| 404 | 0.15 | 0.83 | 0.26 | 6 |
| 405 | 0.07 | 0.33 | 0.11 | 49 |
| 406 | 0.06 | 0.68 | 0.11 | 19 |
| 407 | 0.06 | 0.27 | 0.10 | 11 |
| 408 | 0.11 | 0.52 | 0.18 | 46 |
| 409 | 0.05 | 0.25 | 0.08 | 16 |
| 410 | 0.00 | 0.00 | 0.00 | 5 |
| 411 | 0.08 | 0.29 | 0.13 | 68 |
| 412 | 0.07 | 0.31 | 0.12 | 32 |
| 413 | 0.05 | 0.18 | 0.08 | 61 |
| 414 | 0.02 | 0.19 | 0.03 | 21 |
| 415 | 0.07 | 0.44 | 0.12 | 18 |
| 416 | 0.08 | 0.64 | 0.15 | 25 |
| 417 | 0.01 | 0.12 | 0.02 | 16 |
| 418 | 0.04 | 0.27 | 0.06 | 26 |

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| 419 | 0.12 | 0.50 | 0.19 | 50 |
| 420 | 0.01 | 0.14 | 0.02 | 7 |
| 421 | 0.05 | 0.32 | 0.08 | 28 |
| 422 | 0.07 | 0.41 | 0.12 | 32 |
| 423 | 0.05 | 0.36 | 0.08 | 28 |
| 424 | 0.22 | 0.89 | 0.35 | 9 |
| 425 | 0.00 | 0.00 | 0.00 | 6 |
| 426 | 0.02 | 0.18 | 0.04 | 33 |
| 427 | 0.37 | 0.80 | 0.50 | 64 |
| 428 | 0.21 | 0.86 | 0.34 | 14 |
| 429 | 0.42 | 0.73 | 0.53 | 11 |
| 430 | 0.12 | 0.43 | 0.19 | 61 |
| 431 | 0.05 | 0.24 | 0.08 | 49 |
| 432 | 0.04 | 0.43 | 0.08 | 7 |
| 433 | 0.04 | 0.36 | 0.08 | 11 |
| 434 | 0.24 | 0.67 | 0.36 | 15 |
| 435 | 0.07 | 0.50 | 0.13 | 16 |
| 436 | 0.13 | 0.45 | 0.20 | 42 |
| 437 | 0.02 | 0.10 | 0.04 | 49 |
| 438 | 0.35 | 0.78 | 0.48 | 49 |
| 439 | 0.08 | 0.27 | 0.12 | 55 |
| 440 | 0.05 | 0.22 | 0.08 | 45 |
| 441 | 0.03 | 0.21 | 0.05 | 24 |
| 442 | 0.04 | 0.32 | 0.07 | 31 |
| 443 | 0.06 | 0.24 | 0.10 | 25 |
| 444 | 0.04 | 0.28 | 0.07 | 25 |
| 445 | 0.07 | 0.41 | 0.13 | 22 |
| 446 | 0.05 | 0.31 | 0.08 | 16 |
| 447 | 0.01 | 0.33 | 0.03 | 9 |
| 448 | 0.26 | 0.53 | 0.35 | 43 |
| 449 | 0.12 | 0.43 | 0.19 | 44 |
| 450 | 0.09 | 0.46 | 0.16 | 37 |
| 451 | 0.08 | 0.37 | 0.13 | 30 |
| 452 | 0.02 | 0.23 | 0.04 | 13 |
| 453 | 0.01 | 0.12 | 0.03 | 25 |
| 454 | 0.17 | 0.67 | 0.27 | 39 |
| 455 | 0.13 | 0.47 | 0.21 | 98 |
| 456 | 0.02 | 1.00 | 0.05 | 2 |
| 457 | 0.16 | 0.54 | 0.24 | 54 |
| 458 | 0.02 | 0.30 | 0.04 | 10 |
| 459 | 0.03 | 0.24 | 0.05 | 21 |
| 460 | 0.02 | 0.14 | 0.03 | 29 |
| 461 | 0.12 | 0.50 | 0.20 | 28 |
| 462 | 0.02 | 0.11 | 0.04 | 27 |
| 463 | 0.06 | 0.40 | 0.11 | 40 |
| 464 | 0.14 | 0.37 | 0.21 | 49 |
| 465 | 0.06 | 0.44 | 0.10 | 32 |
| 466 | 0.16 | 0.38 | 0.22 | 90 |
| 467 | 0.17 | 0.67 | 0.27 | 49 |
| 468 | 0.10 | 0.41 | 0.16 | 59 |
| 469 | 0.03 | 0.14 | 0.05 | 35 |
| 470 | 0.27 | 0.83 | 0.41 | 42 |
| 471 | 0.10 | 0.45 | 0.17 | 42 |
| 472 | 0.17 | 0.36 | 0.23 | 64 |
| 473 | 0.08 | 0.41 | 0.14 | 22 |
| 474 | 0.05 | 0.24 | 0.08 | 37 |
| 475 | 0.02 | 0.13 | 0.03 | 30 |
| 476 | 0.20 | 0.66 | 0.31 | 29 |
| 477 | 0.30 | 0.66 | 0.41 | 67 |
| 478 | 0.20 | 0.94 | 0.33 | 16 |
| 479 | 0.03 | 0.16 | 0.05 | 37 |

```
           480       0.19      0.70      0.29        46
           481       0.17      0.43      0.24        56
           482       0.04      0.25      0.07        28
           483       0.34      0.76      0.47        51
           484       0.07      0.28      0.11        32
           485       0.02      0.11      0.03        37
           486       0.07      0.32      0.12        41
           487       0.09      0.46      0.14        24
           488       0.01      0.08      0.02        26
           489       0.10      0.39      0.16        36
           490       0.40      0.83      0.54        29
           491       0.03      0.24      0.06        37
           492       0.00      0.00      0.00        16
           493       0.02      0.12      0.04        41
           494       0.14      0.35      0.20        26
           495       0.15      0.67      0.25        21
           496       0.03      0.17      0.05        12
           497       0.12      0.46      0.18        39
           498       0.05      0.29      0.08        31
           499       0.05      0.31      0.09        45

   micro avg       0.19      0.49      0.27     67448
   macro avg       0.13      0.42      0.20     67448
weighted avg       0.27      0.49      0.33     67448
 samples avg       0.29      0.45      0.30     67448

Time taken to run this cell : 1:10:54.946941
```

## SGD with hinge loss

In [30]:

```
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.00001, penalty='l
1'))
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


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


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

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

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

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

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

```
Accuracy : 0.069
Hamming loss  0.00882585
Micro-average quality numbers
Precision: 0.1871, Recall: 0.4836, F1-measure: 0.2699
Macro-average quality numbers
Precision: 0.1325, Recall: 0.4194, F1-measure: 0.1928
              precision    recall  f1-score   support

           0       0.64      0.79      0.71      1936
           1       0.36      0.39      0.37      3047
           2       0.47      0.51      0.49      2805
           3       0.45      0.66      0.53      1644
           4       0.51      0.55      0.53      2441
           5       0.34      0.47      0.39      1171
           6       0.50      0.62      0.56      1942
           7       0.49      0.66      0.56      1343
           8       0.22      0.25      0.23      1427
           9       0.43      0.64      0.51       587
          10       0.23      0.30      0.26       888
          11       0.40      0.53      0.46      1197
          12       0.29      0.42      0.34       964
          13       0.27      0.46      0.34       696
          14       0.53      0.69      0.60      1102
          15       0.30      0.46      0.37       832
          16       0.19      0.37      0.25       393
          17       0.44      0.70      0.54       790
          18       0.23      0.40      0.29       836
          19       0.16      0.43      0.23       337
          20       0.33      0.57      0.41       522
          21       0.16      0.28      0.20       865
          22       0.22      0.39      0.28       614
          23       0.37      0.66      0.47       313
          24       0.16      0.35      0.22       194
          25       0.13      0.50      0.21       195
          26       0.25      0.50      0.33       344
          27       0.28      0.54      0.37       525
          28       0.31      0.55      0.40       432
          29       0.08      0.28      0.13       151
          30       0.12      0.29      0.17       201
          31       0.09      0.22      0.13       307
          32       0.12      0.38      0.18       130
          33       0.25      0.51      0.34       634
          34       0.17      0.39      0.24       320
          35       0.33      0.67      0.44       297
          36       0.17      0.46      0.24       195
          37       0.33      0.78      0.47        69
          38       0.20      0.49      0.28       332
          39       0.18      0.46      0.26       276
          40       0.22      0.50      0.30       421
          41       0.04      0.29      0.07        77
          42       0.19      0.67      0.30        73
          43       0.26      0.58      0.36       178
          44       0.26      0.57      0.36       367
          45       0.21      0.48      0.29       319
          46       0.26      0.61      0.37       261
          47       0.08      0.30      0.13       121
          48       0.16      0.52      0.24       172
          49       0.40      0.71      0.51       315
          50       0.07      0.27      0.11       122
          51       0.07      0.32      0.12       187
          52       0.06      0.21      0.09        63
```

| | | | | |
|---|---|---|---|---|
| 53 | 0.22 | 0.47 | 0.30 | 271 |
| 54 | 0.17 | 0.36 | 0.23 | 334 |
| 55 | 0.03 | 0.16 | 0.05 | 58 |
| 56 | 0.16 | 0.41 | 0.22 | 313 |
| 57 | 0.13 | 0.30 | 0.18 | 325 |
| 58 | 0.23 | 0.46 | 0.31 | 270 |
| 59 | 0.45 | 0.80 | 0.58 | 267 |
| 60 | 0.09 | 0.26 | 0.13 | 158 |
| 61 | 0.13 | 0.46 | 0.20 | 67 |
| 62 | 0.49 | 0.86 | 0.63 | 396 |
| 63 | 0.36 | 0.75 | 0.48 | 158 |
| 64 | 0.09 | 0.41 | 0.15 | 46 |
| 65 | 0.08 | 0.25 | 0.12 | 121 |
| 66 | 0.11 | 0.33 | 0.17 | 221 |
| 67 | 0.22 | 0.66 | 0.33 | 105 |
| 68 | 0.39 | 0.68 | 0.50 | 222 |
| 69 | 0.21 | 0.60 | 0.31 | 129 |
| 70 | 0.07 | 0.30 | 0.12 | 135 |
| 71 | 0.10 | 0.34 | 0.15 | 125 |
| 72 | 0.26 | 0.61 | 0.36 | 172 |
| 73 | 0.15 | 0.85 | 0.25 | 26 |
| 74 | 0.12 | 0.50 | 0.19 | 42 |
| 75 | 0.25 | 0.80 | 0.38 | 50 |
| 76 | 0.05 | 0.15 | 0.07 | 158 |
| 77 | 0.07 | 0.41 | 0.12 | 74 |
| 78 | 0.17 | 0.56 | 0.27 | 147 |
| 79 | 0.15 | 0.38 | 0.22 | 187 |
| 80 | 0.14 | 0.46 | 0.22 | 128 |
| 81 | 0.09 | 0.25 | 0.13 | 173 |
| 82 | 0.05 | 0.22 | 0.08 | 103 |
| 83 | 0.20 | 0.65 | 0.30 | 168 |
| 84 | 0.13 | 0.39 | 0.20 | 76 |
| 85 | 0.14 | 0.40 | 0.21 | 212 |
| 86 | 0.08 | 0.26 | 0.12 | 184 |
| 87 | 0.08 | 0.41 | 0.13 | 74 |
| 88 | 0.08 | 0.42 | 0.14 | 38 |
| 89 | 0.06 | 0.25 | 0.09 | 59 |
| 90 | 0.18 | 0.44 | 0.25 | 194 |
| 91 | 0.12 | 0.38 | 0.18 | 164 |
| 92 | 0.24 | 0.62 | 0.34 | 194 |
| 93 | 0.19 | 0.63 | 0.29 | 120 |
| 94 | 0.04 | 0.18 | 0.06 | 49 |
| 95 | 0.06 | 0.26 | 0.10 | 86 |
| 96 | 0.13 | 0.29 | 0.18 | 277 |
| 97 | 0.18 | 0.58 | 0.28 | 116 |
| 98 | 0.21 | 0.76 | 0.32 | 59 |
| 99 | 0.14 | 0.46 | 0.22 | 95 |
| 100 | 0.10 | 0.27 | 0.15 | 178 |
| 101 | 0.41 | 0.73 | 0.52 | 136 |
| 102 | 0.56 | 0.81 | 0.66 | 295 |
| 103 | 0.07 | 0.29 | 0.11 | 70 |
| 104 | 0.06 | 0.19 | 0.09 | 113 |
| 105 | 0.18 | 0.59 | 0.28 | 145 |
| 106 | 0.10 | 0.26 | 0.15 | 118 |
| 107 | 0.28 | 0.62 | 0.39 | 146 |
| 108 | 0.18 | 0.55 | 0.27 | 152 |
| 109 | 0.20 | 0.61 | 0.30 | 114 |
| 110 | 0.04 | 0.18 | 0.06 | 91 |
| 111 | 0.03 | 0.20 | 0.05 | 54 |
| 112 | 0.11 | 0.53 | 0.19 | 60 |
| 113 | 0.10 | 0.36 | 0.16 | 72 |

| | | | | |
|---|---|---|---|---|
| 114 | 0.06 | 0.34 | 0.10 | 82 |
| 115 | 0.14 | 0.45 | 0.21 | 159 |
| 116 | 0.23 | 0.56 | 0.33 | 154 |
| 117 | 0.11 | 0.30 | 0.16 | 142 |
| 118 | 0.07 | 0.38 | 0.12 | 50 |
| 119 | 0.14 | 0.43 | 0.21 | 168 |
| 120 | 0.04 | 0.18 | 0.07 | 92 |
| 121 | 0.32 | 0.66 | 0.43 | 229 |
| 122 | 0.06 | 0.32 | 0.10 | 60 |
| 123 | 0.02 | 0.08 | 0.03 | 95 |
| 124 | 0.39 | 0.77 | 0.52 | 96 |
| 125 | 0.06 | 0.29 | 0.09 | 56 |
| 126 | 0.28 | 0.73 | 0.40 | 157 |
| 127 | 0.02 | 0.22 | 0.04 | 50 |
| 128 | 0.05 | 0.23 | 0.08 | 95 |
| 129 | 0.08 | 0.36 | 0.13 | 42 |
| 130 | 0.07 | 0.43 | 0.12 | 44 |
| 131 | 0.03 | 0.14 | 0.05 | 76 |
| 132 | 0.17 | 0.46 | 0.25 | 137 |
| 133 | 0.47 | 0.72 | 0.57 | 232 |
| 134 | 0.26 | 0.90 | 0.41 | 49 |
| 135 | 0.03 | 0.20 | 0.05 | 40 |
| 136 | 0.06 | 0.47 | 0.11 | 59 |
| 137 | 0.15 | 0.40 | 0.22 | 126 |
| 138 | 0.08 | 0.31 | 0.12 | 116 |
| 139 | 0.12 | 0.45 | 0.19 | 73 |
| 140 | 0.21 | 0.57 | 0.31 | 114 |
| 141 | 0.06 | 0.20 | 0.09 | 84 |
| 142 | 0.21 | 0.56 | 0.31 | 119 |
| 143 | 0.59 | 0.87 | 0.70 | 194 |
| 144 | 0.09 | 0.45 | 0.15 | 66 |
| 145 | 0.13 | 0.51 | 0.20 | 100 |
| 146 | 0.19 | 0.51 | 0.27 | 167 |
| 147 | 0.08 | 0.56 | 0.15 | 36 |
| 148 | 0.07 | 0.31 | 0.11 | 78 |
| 149 | 0.27 | 0.63 | 0.37 | 187 |
| 150 | 0.08 | 0.29 | 0.12 | 156 |
| 151 | 0.07 | 0.72 | 0.13 | 18 |
| 152 | 0.26 | 0.66 | 0.38 | 150 |
| 153 | 0.11 | 0.45 | 0.18 | 38 |
| 154 | 0.08 | 0.22 | 0.11 | 118 |
| 155 | 0.04 | 0.18 | 0.07 | 95 |
| 156 | 0.19 | 0.80 | 0.31 | 66 |
| 157 | 0.06 | 0.19 | 0.09 | 86 |
| 158 | 0.15 | 0.64 | 0.24 | 33 |
| 159 | 0.05 | 0.33 | 0.09 | 49 |
| 160 | 0.08 | 0.36 | 0.13 | 83 |
| 161 | 0.14 | 0.61 | 0.22 | 76 |
| 162 | 0.06 | 0.20 | 0.09 | 91 |
| 163 | 0.21 | 0.51 | 0.30 | 121 |
| 164 | 0.16 | 0.57 | 0.25 | 95 |
| 165 | 0.16 | 0.43 | 0.23 | 122 |
| 166 | 0.13 | 0.58 | 0.22 | 53 |
| 167 | 0.08 | 0.35 | 0.13 | 97 |
| 168 | 0.11 | 0.37 | 0.17 | 135 |
| 169 | 0.10 | 0.34 | 0.16 | 105 |
| 170 | 0.02 | 0.24 | 0.04 | 29 |
| 171 | 0.11 | 0.47 | 0.17 | 43 |
| 172 | 0.09 | 0.48 | 0.16 | 83 |
| 173 | 0.16 | 0.51 | 0.24 | 130 |
| 174 | 0.08 | 0.41 | 0.13 | 66 |

| | | | | |
|---|---|---|---|---|
| 175 | 0.37 | 0.93 | 0.53 | 56 |
| 176 | 0.38 | 0.75 | 0.50 | 159 |
| 177 | 0.28 | 0.69 | 0.40 | 130 |
| 178 | 0.22 | 0.66 | 0.33 | 115 |
| 179 | 0.04 | 0.25 | 0.07 | 60 |
| 180 | 0.10 | 0.57 | 0.16 | 51 |
| 181 | 0.02 | 0.22 | 0.04 | 46 |
| 182 | 0.02 | 0.12 | 0.03 | 51 |
| 183 | 0.21 | 0.52 | 0.30 | 165 |
| 184 | 0.04 | 0.23 | 0.07 | 97 |
| 185 | 0.03 | 0.16 | 0.05 | 32 |
| 186 | 0.08 | 0.33 | 0.13 | 79 |
| 187 | 0.24 | 0.71 | 0.36 | 87 |
| 188 | 0.05 | 0.24 | 0.09 | 80 |
| 189 | 0.22 | 0.63 | 0.33 | 51 |
| 190 | 0.23 | 0.66 | 0.34 | 80 |
| 191 | 0.05 | 0.25 | 0.09 | 83 |
| 192 | 0.17 | 0.56 | 0.27 | 103 |
| 193 | 0.06 | 0.50 | 0.11 | 20 |
| 194 | 0.20 | 0.64 | 0.30 | 89 |
| 195 | 0.04 | 0.19 | 0.07 | 77 |
| 196 | 0.03 | 0.16 | 0.05 | 91 |
| 197 | 0.10 | 0.33 | 0.16 | 112 |
| 198 | 0.09 | 0.26 | 0.14 | 118 |
| 199 | 0.06 | 0.26 | 0.10 | 53 |
| 200 | 0.33 | 0.80 | 0.46 | 86 |
| 201 | 0.14 | 0.31 | 0.19 | 129 |
| 202 | 0.28 | 0.66 | 0.40 | 158 |
| 203 | 0.10 | 0.31 | 0.15 | 111 |
| 204 | 0.11 | 0.34 | 0.16 | 93 |
| 205 | 0.05 | 0.26 | 0.08 | 34 |
| 206 | 0.02 | 0.08 | 0.03 | 50 |
| 207 | 0.07 | 0.39 | 0.12 | 31 |
| 208 | 0.25 | 0.62 | 0.35 | 138 |
| 209 | 0.11 | 0.29 | 0.16 | 106 |
| 210 | 0.14 | 0.44 | 0.21 | 126 |
| 211 | 0.07 | 0.45 | 0.12 | 51 |
| 212 | 0.03 | 0.19 | 0.05 | 32 |
| 213 | 0.05 | 0.50 | 0.08 | 14 |
| 214 | 0.11 | 0.57 | 0.18 | 40 |
| 215 | 0.07 | 0.49 | 0.12 | 57 |
| 216 | 0.17 | 0.39 | 0.24 | 186 |
| 217 | 0.02 | 0.30 | 0.04 | 20 |
| 218 | 0.38 | 0.86 | 0.53 | 100 |
| 219 | 0.18 | 0.52 | 0.26 | 96 |
| 220 | 0.30 | 0.75 | 0.43 | 109 |
| 221 | 0.37 | 0.78 | 0.50 | 129 |
| 222 | 0.15 | 0.59 | 0.24 | 64 |
| 223 | 0.04 | 0.20 | 0.06 | 49 |
| 224 | 0.18 | 0.58 | 0.27 | 85 |
| 225 | 0.08 | 0.41 | 0.13 | 69 |
| 226 | 0.10 | 0.35 | 0.16 | 82 |
| 227 | 0.13 | 0.48 | 0.21 | 69 |
| 228 | 0.02 | 0.09 | 0.04 | 97 |
| 229 | 0.03 | 0.17 | 0.05 | 60 |
| 230 | 0.04 | 0.27 | 0.08 | 77 |
| 231 | 0.06 | 0.41 | 0.10 | 22 |
| 232 | 0.05 | 0.20 | 0.08 | 59 |
| 233 | 0.11 | 0.45 | 0.18 | 77 |
| 234 | 0.10 | 0.43 | 0.16 | 37 |
| 235 | 0.10 | 0.47 | 0.16 | 30 |

| | | | | |
|---|---|---|---|---|
| 236 | 0.34 | 0.74 | 0.46 | 39 |
| 237 | 0.07 | 0.24 | 0.10 | 101 |
| 238 | 0.03 | 0.26 | 0.06 | 50 |
| 239 | 0.01 | 0.05 | 0.01 | 21 |
| 240 | 0.11 | 0.39 | 0.17 | 33 |
| 241 | 0.05 | 0.26 | 0.09 | 88 |
| 242 | 0.10 | 0.53 | 0.17 | 36 |
| 243 | 0.03 | 0.24 | 0.05 | 29 |
| 244 | 0.24 | 0.54 | 0.33 | 112 |
| 245 | 0.05 | 0.20 | 0.08 | 44 |
| 246 | 0.29 | 0.79 | 0.43 | 62 |
| 247 | 0.04 | 0.38 | 0.07 | 26 |
| 248 | 0.02 | 0.14 | 0.04 | 51 |
| 249 | 0.01 | 0.03 | 0.01 | 31 |
| 250 | 0.06 | 0.48 | 0.11 | 23 |
| 251 | 0.10 | 0.41 | 0.16 | 73 |
| 252 | 0.04 | 0.15 | 0.06 | 53 |
| 253 | 0.08 | 0.39 | 0.13 | 44 |
| 254 | 0.04 | 0.24 | 0.07 | 50 |
| 255 | 0.08 | 0.27 | 0.12 | 158 |
| 256 | 0.06 | 0.23 | 0.09 | 83 |
| 257 | 0.06 | 0.38 | 0.10 | 40 |
| 258 | 0.23 | 0.55 | 0.33 | 98 |
| 259 | 0.09 | 0.32 | 0.14 | 63 |
| 260 | 0.11 | 0.35 | 0.17 | 95 |
| 261 | 0.09 | 0.32 | 0.14 | 85 |
| 262 | 0.10 | 0.48 | 0.17 | 42 |
| 263 | 0.23 | 0.43 | 0.30 | 162 |
| 264 | 0.05 | 0.34 | 0.08 | 41 |
| 265 | 0.08 | 0.47 | 0.14 | 34 |
| 266 | 0.01 | 0.08 | 0.02 | 12 |
| 267 | 0.04 | 0.29 | 0.07 | 21 |
| 268 | 0.15 | 0.50 | 0.24 | 92 |
| 269 | 0.03 | 0.29 | 0.05 | 21 |
| 270 | 0.15 | 0.61 | 0.24 | 62 |
| 271 | 0.10 | 0.58 | 0.17 | 77 |
| 272 | 0.09 | 0.33 | 0.14 | 89 |
| 273 | 0.43 | 0.85 | 0.57 | 119 |
| 274 | 0.16 | 0.68 | 0.25 | 37 |
| 275 | 0.05 | 0.23 | 0.08 | 40 |
| 276 | 0.03 | 0.18 | 0.06 | 51 |
| 277 | 0.17 | 0.69 | 0.27 | 54 |
| 278 | 0.14 | 0.65 | 0.23 | 57 |
| 279 | 0.25 | 0.83 | 0.38 | 89 |
| 280 | 0.07 | 0.41 | 0.12 | 29 |
| 281 | 0.31 | 0.64 | 0.42 | 81 |
| 282 | 0.20 | 0.64 | 0.30 | 56 |
| 283 | 0.13 | 0.42 | 0.20 | 137 |
| 284 | 0.14 | 0.59 | 0.22 | 29 |
| 285 | 0.21 | 0.63 | 0.31 | 103 |
| 286 | 0.32 | 0.83 | 0.47 | 100 |
| 287 | 0.19 | 0.61 | 0.29 | 51 |
| 288 | 0.03 | 0.23 | 0.05 | 43 |
| 289 | 0.02 | 0.16 | 0.04 | 32 |
| 290 | 0.03 | 0.22 | 0.05 | 50 |
| 291 | 0.11 | 0.45 | 0.17 | 58 |
| 292 | 0.05 | 0.30 | 0.08 | 33 |
| 293 | 0.16 | 0.74 | 0.26 | 50 |
| 294 | 0.09 | 0.43 | 0.14 | 68 |
| 295 | 0.10 | 0.38 | 0.16 | 37 |
| 296 | 0.02 | 0.33 | 0.03 | 12 |

| | | | | |
|---|---|---|---|---|
| 297 | 0.04 | 0.21 | 0.07 | 47 |
| 298 | 0.10 | 0.65 | 0.17 | 17 |
| 299 | 0.17 | 0.73 | 0.28 | 22 |
| 300 | 0.05 | 0.20 | 0.08 | 60 |
| 301 | 0.01 | 0.06 | 0.01 | 52 |
| 302 | 0.02 | 0.14 | 0.03 | 21 |
| 303 | 0.21 | 0.68 | 0.32 | 90 |
| 304 | 0.34 | 0.81 | 0.48 | 88 |
| 305 | 0.36 | 0.77 | 0.49 | 64 |
| 306 | 0.22 | 0.49 | 0.30 | 101 |
| 307 | 0.04 | 0.20 | 0.07 | 45 |
| 308 | 0.00 | 0.03 | 0.01 | 40 |
| 309 | 0.04 | 0.27 | 0.06 | 41 |
| 310 | 0.18 | 0.56 | 0.27 | 68 |
| 311 | 0.08 | 0.50 | 0.14 | 20 |
| 312 | 0.04 | 0.25 | 0.07 | 20 |
| 313 | 0.01 | 0.10 | 0.02 | 30 |
| 314 | 0.16 | 0.49 | 0.24 | 81 |
| 315 | 0.12 | 0.47 | 0.20 | 59 |
| 316 | 0.06 | 0.29 | 0.10 | 24 |
| 317 | 0.06 | 0.26 | 0.09 | 78 |
| 318 | 0.17 | 0.48 | 0.25 | 60 |
| 319 | 0.20 | 0.59 | 0.30 | 46 |
| 320 | 0.09 | 0.48 | 0.15 | 61 |
| 321 | 0.16 | 0.60 | 0.26 | 48 |
| 322 | 0.14 | 0.60 | 0.23 | 58 |
| 323 | 0.27 | 0.55 | 0.36 | 155 |
| 324 | 0.05 | 0.30 | 0.08 | 37 |
| 325 | 0.04 | 0.27 | 0.07 | 33 |
| 326 | 0.04 | 0.27 | 0.06 | 52 |
| 327 | 0.01 | 0.07 | 0.02 | 59 |
| 328 | 0.34 | 0.83 | 0.48 | 71 |
| 329 | 0.12 | 0.45 | 0.19 | 66 |
| 330 | 0.09 | 0.32 | 0.14 | 50 |
| 331 | 0.05 | 0.28 | 0.08 | 32 |
| 332 | 0.01 | 0.20 | 0.03 | 10 |
| 333 | 0.05 | 0.20 | 0.08 | 81 |
| 334 | 0.06 | 0.30 | 0.10 | 30 |
| 335 | 0.07 | 0.33 | 0.12 | 36 |
| 336 | 0.12 | 0.57 | 0.19 | 21 |
| 337 | 0.02 | 0.19 | 0.03 | 26 |
| 338 | 0.16 | 0.47 | 0.23 | 53 |
| 339 | 0.00 | 0.07 | 0.01 | 29 |
| 340 | 0.18 | 0.56 | 0.27 | 55 |
| 341 | 0.05 | 0.42 | 0.10 | 12 |
| 342 | 0.10 | 0.58 | 0.17 | 19 |
| 343 | 0.07 | 0.45 | 0.12 | 20 |
| 344 | 0.10 | 0.48 | 0.17 | 21 |
| 345 | 0.12 | 0.57 | 0.20 | 21 |
| 346 | 0.01 | 0.12 | 0.02 | 25 |
| 347 | 0.14 | 0.55 | 0.22 | 47 |
| 348 | 0.02 | 0.28 | 0.04 | 25 |
| 349 | 0.20 | 0.76 | 0.32 | 34 |
| 350 | 0.07 | 0.75 | 0.12 | 8 |
| 351 | 0.05 | 0.40 | 0.08 | 10 |
| 352 | 0.21 | 0.61 | 0.31 | 61 |
| 353 | 0.04 | 0.50 | 0.07 | 10 |
| 354 | 0.04 | 0.26 | 0.08 | 58 |
| 355 | 0.11 | 0.49 | 0.19 | 59 |
| 356 | 0.23 | 0.57 | 0.33 | 145 |
| 357 | 0.24 | 0.51 | 0.33 | 135 |

| | | | | |
|---|---|---|---|---|
| 358 | 0.11 | 0.53 | 0.18 | 36 |
| 359 | 0.22 | 0.66 | 0.33 | 67 |
| 360 | 0.07 | 0.29 | 0.11 | 62 |
| 361 | 0.38 | 0.87 | 0.53 | 76 |
| 362 | 0.03 | 0.25 | 0.05 | 24 |
| 363 | 0.34 | 0.81 | 0.47 | 64 |
| 364 | 0.06 | 0.33 | 0.10 | 18 |
| 365 | 0.05 | 0.33 | 0.08 | 27 |
| 366 | 0.15 | 0.78 | 0.26 | 27 |
| 367 | 0.07 | 0.28 | 0.12 | 68 |
| 368 | 0.02 | 0.23 | 0.03 | 13 |
| 369 | 0.01 | 0.12 | 0.02 | 24 |
| 370 | 0.01 | 0.09 | 0.02 | 22 |
| 371 | 0.03 | 0.22 | 0.05 | 36 |
| 372 | 0.20 | 0.37 | 0.26 | 30 |
| 373 | 0.21 | 0.62 | 0.32 | 74 |
| 374 | 0.05 | 0.33 | 0.09 | 30 |
| 375 | 0.01 | 0.15 | 0.03 | 20 |
| 376 | 0.00 | 0.00 | 0.00 | 15 |
| 377 | 0.15 | 0.46 | 0.22 | 79 |
| 378 | 0.01 | 0.06 | 0.01 | 35 |
| 379 | 0.00 | 0.00 | 0.00 | 7 |
| 380 | 0.15 | 0.42 | 0.22 | 57 |
| 381 | 0.03 | 0.15 | 0.04 | 59 |
| 382 | 0.04 | 0.24 | 0.07 | 41 |
| 383 | 0.15 | 0.52 | 0.23 | 69 |
| 384 | 0.01 | 0.05 | 0.01 | 42 |
| 385 | 0.05 | 0.19 | 0.08 | 21 |
| 386 | 0.02 | 0.12 | 0.04 | 24 |
| 387 | 0.05 | 0.29 | 0.09 | 34 |
| 388 | 0.07 | 0.38 | 0.11 | 39 |
| 389 | 0.02 | 0.18 | 0.04 | 45 |
| 390 | 0.35 | 0.69 | 0.47 | 75 |
| 391 | 0.06 | 0.31 | 0.10 | 32 |
| 392 | 0.08 | 0.62 | 0.14 | 8 |
| 393 | 0.01 | 0.03 | 0.01 | 59 |
| 394 | 0.03 | 0.16 | 0.05 | 38 |
| 395 | 0.08 | 0.41 | 0.13 | 61 |
| 396 | 0.06 | 0.26 | 0.09 | 65 |
| 397 | 0.26 | 0.58 | 0.36 | 190 |
| 398 | 0.15 | 0.75 | 0.26 | 36 |
| 399 | 0.01 | 0.13 | 0.02 | 23 |
| 400 | 0.05 | 0.33 | 0.09 | 27 |
| 401 | 0.05 | 0.33 | 0.09 | 36 |
| 402 | 0.08 | 0.33 | 0.12 | 52 |
| 403 | 0.02 | 0.36 | 0.04 | 11 |
| 404 | 0.12 | 0.83 | 0.22 | 6 |
| 405 | 0.07 | 0.27 | 0.10 | 49 |
| 406 | 0.06 | 0.58 | 0.11 | 19 |
| 407 | 0.04 | 0.27 | 0.07 | 11 |
| 408 | 0.13 | 0.63 | 0.21 | 46 |
| 409 | 0.01 | 0.06 | 0.02 | 16 |
| 410 | 0.00 | 0.00 | 0.00 | 5 |
| 411 | 0.08 | 0.28 | 0.12 | 68 |
| 412 | 0.05 | 0.28 | 0.09 | 32 |
| 413 | 0.05 | 0.16 | 0.07 | 61 |
| 414 | 0.02 | 0.14 | 0.03 | 21 |
| 415 | 0.04 | 0.33 | 0.07 | 18 |
| 416 | 0.08 | 0.56 | 0.14 | 25 |
| 417 | 0.01 | 0.06 | 0.01 | 16 |
| 418 | 0.03 | 0.31 | 0.06 | 26 |

| | | | | |
|---|---|---|---|---|
| 419 | 0.12 | 0.48 | 0.19 | 50 |
| 420 | 0.03 | 0.29 | 0.05 | 7 |
| 421 | 0.04 | 0.29 | 0.07 | 28 |
| 422 | 0.06 | 0.44 | 0.11 | 32 |
| 423 | 0.06 | 0.43 | 0.11 | 28 |
| 424 | 0.25 | 0.89 | 0.39 | 9 |
| 425 | 0.00 | 0.00 | 0.00 | 6 |
| 426 | 0.03 | 0.21 | 0.05 | 33 |
| 427 | 0.34 | 0.81 | 0.48 | 64 |
| 428 | 0.16 | 0.79 | 0.27 | 14 |
| 429 | 0.36 | 0.73 | 0.48 | 11 |
| 430 | 0.12 | 0.46 | 0.19 | 61 |
| 431 | 0.08 | 0.39 | 0.13 | 49 |
| 432 | 0.00 | 0.00 | 0.00 | 7 |
| 433 | 0.06 | 0.55 | 0.10 | 11 |
| 434 | 0.15 | 0.60 | 0.24 | 15 |
| 435 | 0.05 | 0.38 | 0.09 | 16 |
| 436 | 0.10 | 0.43 | 0.16 | 42 |
| 437 | 0.05 | 0.18 | 0.08 | 49 |
| 438 | 0.35 | 0.76 | 0.47 | 49 |
| 439 | 0.07 | 0.31 | 0.11 | 55 |
| 440 | 0.04 | 0.16 | 0.06 | 45 |
| 441 | 0.03 | 0.21 | 0.06 | 24 |
| 442 | 0.03 | 0.19 | 0.05 | 31 |
| 443 | 0.06 | 0.28 | 0.11 | 25 |
| 444 | 0.04 | 0.36 | 0.08 | 25 |
| 445 | 0.07 | 0.45 | 0.12 | 22 |
| 446 | 0.05 | 0.38 | 0.10 | 16 |
| 447 | 0.02 | 0.44 | 0.04 | 9 |
| 448 | 0.33 | 0.60 | 0.43 | 43 |
| 449 | 0.12 | 0.39 | 0.18 | 44 |
| 450 | 0.09 | 0.38 | 0.15 | 37 |
| 451 | 0.07 | 0.33 | 0.11 | 30 |
| 452 | 0.03 | 0.23 | 0.05 | 13 |
| 453 | 0.02 | 0.16 | 0.03 | 25 |
| 454 | 0.14 | 0.62 | 0.22 | 39 |
| 455 | 0.10 | 0.38 | 0.16 | 98 |
| 456 | 0.02 | 0.50 | 0.03 | 2 |
| 457 | 0.10 | 0.39 | 0.16 | 54 |
| 458 | 0.01 | 0.20 | 0.02 | 10 |
| 459 | 0.04 | 0.24 | 0.06 | 21 |
| 460 | 0.01 | 0.07 | 0.02 | 29 |
| 461 | 0.14 | 0.54 | 0.23 | 28 |
| 462 | 0.03 | 0.15 | 0.05 | 27 |
| 463 | 0.06 | 0.42 | 0.10 | 40 |
| 464 | 0.16 | 0.43 | 0.23 | 49 |
| 465 | 0.09 | 0.47 | 0.15 | 32 |
| 466 | 0.18 | 0.47 | 0.26 | 90 |
| 467 | 0.18 | 0.59 | 0.28 | 49 |
| 468 | 0.10 | 0.41 | 0.16 | 59 |
| 469 | 0.01 | 0.03 | 0.01 | 35 |
| 470 | 0.28 | 0.81 | 0.42 | 42 |
| 471 | 0.11 | 0.38 | 0.17 | 42 |
| 472 | 0.17 | 0.45 | 0.25 | 64 |
| 473 | 0.07 | 0.41 | 0.12 | 22 |
| 474 | 0.04 | 0.19 | 0.06 | 37 |
| 475 | 0.03 | 0.17 | 0.05 | 30 |
| 476 | 0.20 | 0.69 | 0.31 | 29 |
| 477 | 0.27 | 0.70 | 0.39 | 67 |
| 478 | 0.17 | 0.88 | 0.29 | 16 |
| 479 | 0.04 | 0.19 | 0.07 | 37 |

```
           480       0.23      0.67      0.34        46
           481       0.13      0.34      0.19        56
           482       0.05      0.39      0.09        28
           483       0.32      0.76      0.45        51
           484       0.04      0.22      0.06        32
           485       0.02      0.11      0.03        37
           486       0.05      0.29      0.09        41
           487       0.08      0.46      0.14        24
           488       0.01      0.12      0.03        26
           489       0.10      0.42      0.16        36
           490       0.27      0.83      0.40        29
           491       0.04      0.24      0.07        37
           492       0.00      0.06      0.01        16
           493       0.01      0.07      0.02        41
           494       0.08      0.35      0.13        26
           495       0.13      0.67      0.22        21
           496       0.08      0.33      0.13        12
           497       0.10      0.41      0.16        39
           498       0.04      0.23      0.07        31
           499       0.06      0.36      0.10        45

   micro avg       0.19      0.48      0.27     67448
   macro avg       0.13      0.42      0.19     67448
weighted avg       0.27      0.48      0.33     67448
 samples avg       0.29      0.45      0.30     67448

Time taken to run this cell : 1:07:51.576493
```

## Logistic regresssion hyperparameter tuning

In [35]:

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

```
Dimensions of train data X: (40000, 20000) Y : (40000, 500)
Dimensions of test data X: (10000, 20000) Y: (10000, 500)
```

In [34]:

```
x_test_multilabel=x_test_multilabel[0:10000]
y_test=y_test[0:10000]
```

In [41]:

```
#https://stackoverflow.com/questions/12632992/gridsearch-for-an-estimator-inside-a-onevsrestclassifier/12637528
param_grid  = {"estimator__alpha": [10**-5, 10**-3, 10**-1, 10**1, 10**2]}

clf = OneVsRestClassifier(SGDClassifier(loss='log',penalty='l1'))

model = GridSearchCV(clf,param_grid, scoring = 'f1_micro', cv=2,n_jobs=-1)

model.fit(x_train_multilabel, y_train)
```

Out[41]:

```
GridSearchCV(cv=2, error_score=nan,
             estimator=OneVsRestClassifier(estimator=SGDClassifier(alpha=
0.0001,
                                                                   average
=False,
                                                                   class_w
eight=None,
                                                                   early_s
topping=False,
                                                                   epsilon
=0.1,
                                                                   eta0=0.
0,
                                                                   fit_int
ercept=True,
                                                                   l1_rati
o=0.15,
                                                                   learnin
g_rate='optimal',
                                                                   loss='l
og',
                                                                   max_ite
r=1000,
                                                                   n_iter_
no_change=5,
                                                                   n_jobs=
None,
                                                                   penalty
='l1',
                                                                   power_t
=0.5,
                                                                   random_
state=None,
                                                                   shuffle
=True,
                                                                   tol=0.0
01,
                                                                   validat
ion_fraction=0.1,
                                                                   verbose
=0,
                                                                   warm_st
art=False),
                                           n_jobs=None),
             iid='deprecated', n_jobs=-1,
             param_grid={'estimator__alpha': [1e-05, 0.001, 0.1, 10, 10
0]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring='f1_micro', verbose=0)
```

In [47]:

```
#applying the best alpha
start = datetime.now()
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0001, penalty='l1'))
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


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


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

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

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

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

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

```
Accuracy : 0.0693
Hamming loss  0.0070414
Micro-average quality numbers
Precision: 0.2586, Recall: 0.4730, F1-measure: 0.3344
Macro-average quality numbers
Precision: 0.1965, Recall: 0.3564, F1-measure: 0.2354
              precision    recall  f1-score   support

           0       0.62      0.80      0.70       659
           1       0.36      0.34      0.35      1017
           2       0.53      0.55      0.54       895
           3       0.50      0.66      0.57       579
           4       0.52      0.69      0.59       903
           5       0.46      0.53      0.49       453
           6       0.50      0.59      0.54       533
           7       0.43      0.72      0.54       498
           8       0.19      0.26      0.22       384
           9       0.50      0.69      0.58       120
          10       0.18      0.28      0.22       219
          11       0.43      0.47      0.45       333
          12       0.21      0.36      0.27       257
          13       0.27      0.41      0.32       206
          14       0.55      0.74      0.63       313
          15       0.32      0.48      0.38       310
          16       0.25      0.45      0.33       120
          17       0.31      0.76      0.45       127
          18       0.13      0.29      0.18       142
          19       0.27      0.50      0.35       151
          20       0.30      0.56      0.39       142
          21       0.14      0.24      0.17       138
          22       0.16      0.38      0.22       122
          23       0.33      0.57      0.42        72
          24       0.10      0.29      0.15        48
          25       0.38      0.54      0.45        76
          26       0.10      0.46      0.17        59
          27       0.23      0.48      0.31       105
          28       0.42      0.60      0.50       139
          29       0.12      0.35      0.18        26
          30       0.16      0.40      0.23        62
          31       0.04      0.19      0.07        48
          32       0.21      0.56      0.31        32
          33       0.25      0.40      0.31        88
          34       0.13      0.17      0.15        75
          35       0.31      0.62      0.42        69
          36       0.15      0.29      0.20        51
          37       0.36      0.76      0.48        21
          38       0.16      0.50      0.24       107
          39       0.25      0.49      0.33        92
          40       0.41      0.45      0.43        91
          41       0.03      0.22      0.06         9
          42       0.05      0.62      0.10         8
          43       0.36      0.55      0.43        60
          44       0.43      0.67      0.52       221
          45       0.22      0.48      0.30        44
          46       0.47      0.69      0.56        88
          47       0.08      0.12      0.10        34
          48       0.16      0.45      0.24        42
          49       0.31      0.79      0.45        57
          50       0.04      0.14      0.07        21
          51       0.10      0.25      0.14        40
          52       0.07      0.14      0.09        21
```

| | | | | |
|---|---|---|---|---|
| 53 | 0.17 | 0.39 | 0.24 | 31 |
| 54 | 0.15 | 0.43 | 0.22 | 60 |
| 55 | 0.02 | 0.08 | 0.03 | 13 |
| 56 | 0.10 | 0.33 | 0.15 | 33 |
| 57 | 0.13 | 0.26 | 0.17 | 53 |
| 58 | 0.34 | 0.40 | 0.37 | 58 |
| 59 | 0.41 | 0.75 | 0.53 | 64 |
| 60 | 0.09 | 0.23 | 0.13 | 31 |
| 61 | 0.16 | 0.53 | 0.24 | 17 |
| 62 | 0.58 | 0.89 | 0.70 | 156 |
| 63 | 0.10 | 0.58 | 0.16 | 12 |
| 64 | 0.25 | 0.64 | 0.36 | 11 |
| 65 | 0.06 | 0.12 | 0.08 | 26 |
| 66 | 0.12 | 0.18 | 0.14 | 103 |
| 67 | 0.42 | 0.48 | 0.44 | 21 |
| 68 | 0.33 | 0.69 | 0.44 | 58 |
| 69 | 0.22 | 0.38 | 0.28 | 34 |
| 70 | 0.11 | 0.20 | 0.14 | 41 |
| 71 | 0.16 | 0.40 | 0.22 | 25 |
| 72 | 0.19 | 0.60 | 0.28 | 48 |
| 73 | 0.40 | 0.73 | 0.52 | 11 |
| 74 | 0.03 | 0.25 | 0.05 | 8 |
| 75 | 0.81 | 0.93 | 0.87 | 14 |
| 76 | 0.04 | 0.09 | 0.06 | 46 |
| 77 | 0.15 | 0.29 | 0.20 | 17 |
| 78 | 0.47 | 0.55 | 0.51 | 49 |
| 79 | 0.06 | 0.16 | 0.08 | 31 |
| 80 | 0.26 | 0.51 | 0.34 | 41 |
| 81 | 0.09 | 0.34 | 0.14 | 56 |
| 82 | 0.04 | 0.12 | 0.07 | 24 |
| 83 | 0.37 | 0.66 | 0.47 | 59 |
| 84 | 0.17 | 0.38 | 0.24 | 26 |
| 85 | 0.09 | 0.12 | 0.10 | 43 |
| 86 | 0.07 | 0.30 | 0.11 | 73 |
| 87 | 0.08 | 0.75 | 0.15 | 12 |
| 88 | 0.11 | 0.29 | 0.16 | 14 |
| 89 | 0.03 | 0.06 | 0.04 | 18 |
| 90 | 0.16 | 0.33 | 0.22 | 30 |
| 91 | 0.12 | 0.37 | 0.18 | 30 |
| 92 | 0.48 | 0.51 | 0.50 | 55 |
| 93 | 0.19 | 0.58 | 0.29 | 19 |
| 94 | 0.02 | 0.12 | 0.03 | 8 |
| 95 | 0.08 | 0.24 | 0.11 | 17 |
| 96 | 0.13 | 0.21 | 0.16 | 189 |
| 97 | 0.16 | 0.39 | 0.23 | 31 |
| 98 | 0.11 | 0.38 | 0.17 | 13 |
| 99 | 0.28 | 0.56 | 0.38 | 16 |
| 100 | 0.06 | 0.19 | 0.09 | 43 |
| 101 | 0.42 | 0.70 | 0.53 | 30 |
| 102 | 0.50 | 0.72 | 0.59 | 53 |
| 103 | 0.26 | 0.32 | 0.28 | 38 |
| 104 | 0.06 | 0.25 | 0.10 | 36 |
| 105 | 0.23 | 0.62 | 0.33 | 26 |
| 106 | 0.06 | 0.09 | 0.07 | 46 |
| 107 | 0.50 | 0.65 | 0.57 | 40 |
| 108 | 0.07 | 0.22 | 0.10 | 23 |
| 109 | 0.34 | 0.71 | 0.46 | 31 |
| 110 | 0.12 | 0.28 | 0.17 | 32 |
| 111 | 0.09 | 0.26 | 0.14 | 19 |
| 112 | 0.04 | 0.11 | 0.05 | 18 |
| 113 | 0.22 | 0.24 | 0.23 | 17 |

| | | | | |
|---|---|---|---|---|
| 114 | 0.04 | 0.24 | 0.07 | 17 |
| 115 | 0.07 | 0.17 | 0.10 | 36 |
| 116 | 0.13 | 0.45 | 0.20 | 40 |
| 117 | 0.22 | 0.42 | 0.29 | 48 |
| 118 | 0.21 | 0.62 | 0.31 | 8 |
| 119 | 0.24 | 0.39 | 0.30 | 84 |
| 120 | 0.05 | 0.17 | 0.08 | 18 |
| 121 | 0.52 | 0.74 | 0.61 | 77 |
| 122 | 0.18 | 0.16 | 0.17 | 32 |
| 123 | 0.00 | 0.00 | 0.00 | 28 |
| 124 | 0.42 | 0.82 | 0.56 | 17 |
| 125 | 0.01 | 0.07 | 0.02 | 14 |
| 126 | 0.51 | 0.57 | 0.54 | 53 |
| 127 | 0.03 | 0.19 | 0.05 | 16 |
| 128 | 0.07 | 0.22 | 0.10 | 18 |
| 129 | 0.07 | 0.33 | 0.12 | 9 |
| 130 | 0.04 | 0.40 | 0.07 | 5 |
| 131 | 0.05 | 0.18 | 0.08 | 45 |
| 132 | 0.07 | 0.26 | 0.11 | 27 |
| 133 | 0.45 | 0.74 | 0.56 | 50 |
| 134 | 0.62 | 0.88 | 0.73 | 17 |
| 135 | 0.05 | 0.25 | 0.09 | 12 |
| 136 | 0.04 | 0.20 | 0.06 | 15 |
| 137 | 0.14 | 0.20 | 0.16 | 25 |
| 138 | 0.09 | 0.46 | 0.16 | 28 |
| 139 | 0.19 | 0.43 | 0.26 | 21 |
| 140 | 0.18 | 0.55 | 0.27 | 29 |
| 141 | 0.08 | 0.15 | 0.10 | 41 |
| 142 | 0.37 | 0.52 | 0.43 | 29 |
| 143 | 0.48 | 0.77 | 0.59 | 26 |
| 144 | 0.30 | 0.40 | 0.35 | 35 |
| 145 | 0.30 | 0.53 | 0.38 | 19 |
| 146 | 0.20 | 0.50 | 0.29 | 24 |
| 147 | 0.18 | 0.40 | 0.25 | 15 |
| 148 | 0.11 | 0.42 | 0.18 | 12 |
| 149 | 0.75 | 0.78 | 0.76 | 58 |
| 150 | 0.33 | 0.32 | 0.32 | 50 |
| 151 | 0.17 | 0.71 | 0.27 | 7 |
| 152 | 0.30 | 0.89 | 0.44 | 18 |
| 153 | 0.10 | 0.33 | 0.15 | 6 |
| 154 | 0.10 | 0.28 | 0.14 | 18 |
| 155 | 0.02 | 0.06 | 0.03 | 18 |
| 156 | 0.57 | 0.57 | 0.57 | 23 |
| 157 | 0.05 | 0.11 | 0.06 | 18 |
| 158 | 0.41 | 0.78 | 0.54 | 9 |
| 159 | 0.50 | 0.56 | 0.53 | 16 |
| 160 | 0.11 | 0.36 | 0.17 | 22 |
| 161 | 0.23 | 0.60 | 0.33 | 15 |
| 162 | 0.02 | 0.04 | 0.03 | 25 |
| 163 | 0.37 | 0.46 | 0.41 | 28 |
| 164 | 0.12 | 0.26 | 0.17 | 27 |
| 165 | 0.29 | 0.51 | 0.37 | 43 |
| 166 | 0.08 | 0.28 | 0.12 | 25 |
| 167 | 0.20 | 0.21 | 0.21 | 28 |
| 168 | 0.04 | 0.33 | 0.07 | 12 |
| 169 | 0.21 | 0.35 | 0.26 | 23 |
| 170 | 0.07 | 0.22 | 0.11 | 9 |
| 171 | 0.19 | 0.50 | 0.28 | 12 |
| 172 | 0.14 | 0.50 | 0.22 | 12 |
| 173 | 0.21 | 0.37 | 0.27 | 27 |
| 174 | 0.10 | 0.28 | 0.15 | 18 |

| | | | | |
|---|---|---|---|---|
| 175 | 0.77 | 0.91 | 0.83 | 11 |
| 176 | 0.51 | 0.81 | 0.63 | 57 |
| 177 | 0.29 | 0.41 | 0.34 | 32 |
| 178 | 0.27 | 0.70 | 0.39 | 20 |
| 179 | 0.24 | 0.30 | 0.27 | 23 |
| 180 | 0.41 | 0.43 | 0.42 | 21 |
| 181 | 0.06 | 0.31 | 0.09 | 13 |
| 182 | 0.04 | 0.20 | 0.07 | 10 |
| 183 | 0.45 | 0.54 | 0.49 | 96 |
| 184 | 0.15 | 0.10 | 0.12 | 40 |
| 185 | 0.00 | 0.00 | 0.00 | 7 |
| 186 | 0.12 | 0.27 | 0.17 | 11 |
| 187 | 0.17 | 0.50 | 0.25 | 12 |
| 188 | 0.08 | 0.19 | 0.11 | 16 |
| 189 | 0.06 | 0.14 | 0.08 | 7 |
| 190 | 0.52 | 0.59 | 0.55 | 27 |
| 191 | 0.06 | 0.31 | 0.10 | 13 |
| 192 | 0.45 | 0.57 | 0.50 | 37 |
| 193 | 0.08 | 0.22 | 0.12 | 9 |
| 194 | 0.30 | 0.82 | 0.44 | 11 |
| 195 | 0.05 | 0.11 | 0.07 | 27 |
| 196 | 0.06 | 0.25 | 0.10 | 16 |
| 197 | 0.03 | 0.12 | 0.05 | 26 |
| 198 | 0.11 | 0.21 | 0.14 | 29 |
| 199 | 0.02 | 0.12 | 0.03 | 8 |
| 200 | 0.75 | 0.73 | 0.74 | 37 |
| 201 | 0.14 | 0.26 | 0.18 | 31 |
| 202 | 0.25 | 0.62 | 0.36 | 21 |
| 203 | 0.11 | 0.25 | 0.15 | 28 |
| 204 | 0.06 | 0.36 | 0.11 | 11 |
| 205 | 0.16 | 0.29 | 0.20 | 17 |
| 206 | 0.02 | 0.06 | 0.03 | 17 |
| 207 | 0.00 | 0.00 | 0.00 | 4 |
| 208 | 0.60 | 0.77 | 0.67 | 47 |
| 209 | 0.25 | 0.16 | 0.19 | 19 |
| 210 | 0.27 | 0.50 | 0.35 | 54 |
| 211 | 0.10 | 0.29 | 0.15 | 17 |
| 212 | 0.00 | 0.00 | 0.00 | 3 |
| 213 | 0.07 | 0.25 | 0.11 | 4 |
| 214 | 0.03 | 0.17 | 0.06 | 6 |
| 215 | 0.26 | 0.39 | 0.31 | 18 |
| 216 | 0.08 | 0.12 | 0.10 | 25 |
| 217 | 0.00 | 0.00 | 0.00 | 6 |
| 218 | 0.68 | 0.93 | 0.78 | 43 |
| 219 | 0.34 | 0.39 | 0.37 | 33 |
| 220 | 0.40 | 0.54 | 0.46 | 26 |
| 221 | 0.62 | 0.54 | 0.58 | 24 |
| 222 | 0.28 | 0.55 | 0.37 | 20 |
| 223 | 0.03 | 0.11 | 0.05 | 9 |
| 224 | 0.21 | 0.57 | 0.31 | 30 |
| 225 | 0.05 | 0.67 | 0.09 | 6 |
| 226 | 0.19 | 0.55 | 0.28 | 11 |
| 227 | 0.38 | 0.53 | 0.44 | 15 |
| 228 | 0.12 | 0.19 | 0.15 | 16 |
| 229 | 0.03 | 0.14 | 0.05 | 14 |
| 230 | 0.05 | 0.18 | 0.07 | 17 |
| 231 | 0.67 | 0.38 | 0.48 | 16 |
| 232 | 0.03 | 0.07 | 0.04 | 14 |
| 233 | 0.59 | 0.50 | 0.54 | 34 |
| 234 | 0.05 | 0.14 | 0.07 | 7 |
| 235 | 0.43 | 0.30 | 0.35 | 10 |

| | | | | |
|---|---|---|---|---|
| 236 | 0.54 | 0.65 | 0.59 | 20 |
| 237 | 0.11 | 0.13 | 0.12 | 31 |
| 238 | 0.05 | 0.18 | 0.08 | 17 |
| 239 | 0.03 | 0.14 | 0.05 | 7 |
| 240 | 0.38 | 0.53 | 0.44 | 15 |
| 241 | 0.04 | 0.18 | 0.07 | 17 |
| 242 | 0.33 | 0.14 | 0.20 | 14 |
| 243 | 0.00 | 0.00 | 0.00 | 1 |
| 244 | 0.09 | 0.41 | 0.15 | 17 |
| 245 | 0.04 | 0.15 | 0.06 | 13 |
| 246 | 0.62 | 0.80 | 0.70 | 20 |
| 247 | 0.04 | 0.38 | 0.07 | 8 |
| 248 | 0.02 | 0.10 | 0.03 | 10 |
| 249 | 0.00 | 0.00 | 0.00 | 5 |
| 250 | 0.25 | 0.33 | 0.29 | 9 |
| 251 | 0.02 | 0.50 | 0.04 | 6 |
| 252 | 0.00 | 0.00 | 0.00 | 9 |
| 253 | 0.11 | 0.55 | 0.18 | 11 |
| 254 | 0.05 | 0.12 | 0.07 | 8 |
| 255 | 0.13 | 0.17 | 0.15 | 112 |
| 256 | 0.05 | 0.11 | 0.06 | 19 |
| 257 | 0.14 | 0.25 | 0.18 | 8 |
| 258 | 0.52 | 0.79 | 0.62 | 19 |
| 259 | 0.03 | 0.07 | 0.04 | 15 |
| 260 | 0.09 | 0.18 | 0.12 | 22 |
| 261 | 0.08 | 0.26 | 0.13 | 19 |
| 262 | 0.12 | 0.55 | 0.20 | 11 |
| 263 | 0.36 | 0.31 | 0.34 | 147 |
| 264 | 0.03 | 0.33 | 0.06 | 3 |
| 265 | 0.08 | 0.22 | 0.11 | 9 |
| 266 | 0.50 | 0.20 | 0.29 | 5 |
| 267 | 0.05 | 0.17 | 0.07 | 6 |
| 268 | 0.24 | 0.49 | 0.32 | 35 |
| 269 | 0.40 | 0.29 | 0.33 | 7 |
| 270 | 0.21 | 0.50 | 0.30 | 6 |
| 271 | 0.14 | 0.47 | 0.21 | 19 |
| 272 | 0.04 | 0.25 | 0.07 | 12 |
| 273 | 0.77 | 0.79 | 0.78 | 42 |
| 274 | 0.50 | 0.50 | 0.50 | 6 |
| 275 | 0.09 | 0.20 | 0.12 | 10 |
| 276 | 0.07 | 0.11 | 0.09 | 18 |
| 277 | 0.46 | 0.71 | 0.56 | 17 |
| 278 | 0.17 | 0.40 | 0.24 | 15 |
| 279 | 0.54 | 0.88 | 0.67 | 17 |
| 280 | 0.05 | 0.22 | 0.09 | 9 |
| 281 | 0.69 | 0.62 | 0.65 | 29 |
| 282 | 0.42 | 0.81 | 0.55 | 16 |
| 283 | 0.11 | 0.35 | 0.17 | 17 |
| 284 | 0.20 | 0.33 | 0.25 | 3 |
| 285 | 0.58 | 0.79 | 0.67 | 47 |
| 286 | 0.11 | 0.64 | 0.19 | 11 |
| 287 | 0.32 | 0.35 | 0.33 | 17 |
| 288 | 0.11 | 0.12 | 0.12 | 8 |
| 289 | 0.00 | 0.00 | 0.00 | 5 |
| 290 | 0.05 | 0.13 | 0.07 | 15 |
| 291 | 0.19 | 0.50 | 0.28 | 10 |
| 292 | 0.08 | 0.12 | 0.10 | 8 |
| 293 | 0.33 | 0.72 | 0.45 | 18 |
| 294 | 0.14 | 0.13 | 0.14 | 23 |
| 295 | 0.06 | 0.17 | 0.09 | 6 |
| 296 | 0.12 | 0.33 | 0.18 | 3 |

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|---|---|---|---|---|
| 297 | 0.07 | 0.38 | 0.12 | 8 |
| 298 | 0.03 | 1.00 | 0.06 | 1 |
| 299 | 0.07 | 0.50 | 0.12 | 4 |
| 300 | 0.07 | 0.27 | 0.11 | 15 |
| 301 | 0.03 | 0.07 | 0.04 | 14 |
| 302 | 0.00 | 0.00 | 0.00 | 5 |
| 303 | 0.48 | 0.93 | 0.64 | 15 |
| 304 | 0.23 | 0.58 | 0.33 | 12 |
| 305 | 0.73 | 0.73 | 0.73 | 30 |
| 306 | 0.38 | 0.53 | 0.44 | 49 |
| 307 | 0.06 | 0.43 | 0.11 | 7 |
| 308 | 0.00 | 0.00 | 0.00 | 8 |
| 309 | 0.03 | 0.08 | 0.04 | 12 |
| 310 | 0.31 | 0.45 | 0.37 | 20 |
| 311 | 0.14 | 1.00 | 0.24 | 4 |
| 312 | 0.38 | 0.33 | 0.35 | 9 |
| 313 | 0.04 | 0.07 | 0.05 | 14 |
| 314 | 0.35 | 0.29 | 0.32 | 21 |
| 315 | 0.38 | 0.73 | 0.50 | 11 |
| 316 | 0.33 | 0.67 | 0.44 | 3 |
| 317 | 0.11 | 0.21 | 0.15 | 14 |
| 318 | 0.00 | 0.00 | 0.00 | 7 |
| 319 | 0.21 | 0.90 | 0.35 | 10 |
| 320 | 0.16 | 0.21 | 0.18 | 28 |
| 321 | 0.37 | 0.78 | 0.50 | 9 |
| 322 | 0.16 | 0.75 | 0.26 | 8 |
| 323 | 0.52 | 0.48 | 0.49 | 101 |
| 324 | 0.02 | 0.12 | 0.03 | 8 |
| 325 | 0.02 | 0.17 | 0.04 | 6 |
| 326 | 0.06 | 0.15 | 0.09 | 13 |
| 327 | 0.00 | 0.00 | 0.00 | 13 |
| 328 | 0.43 | 0.70 | 0.53 | 37 |
| 329 | 0.19 | 0.62 | 0.29 | 8 |
| 330 | 0.00 | 0.00 | 0.00 | 6 |
| 331 | 0.00 | 0.00 | 0.00 | 4 |
| 332 | 0.00 | 0.00 | 0.00 | 3 |
| 333 | 0.05 | 0.33 | 0.09 | 6 |
| 334 | 0.50 | 0.33 | 0.40 | 9 |
| 335 | 0.17 | 0.25 | 0.20 | 8 |
| 336 | 0.12 | 0.25 | 0.17 | 4 |
| 337 | 0.12 | 0.30 | 0.18 | 10 |
| 338 | 0.22 | 0.80 | 0.35 | 10 |
| 339 | 0.00 | 0.00 | 0.00 | 4 |
| 340 | 0.40 | 0.50 | 0.44 | 16 |
| 341 | 0.00 | 0.00 | 0.00 | 2 |
| 342 | 0.00 | 0.00 | 0.00 | 1 |
| 343 | 0.00 | 0.00 | 0.00 | 7 |
| 344 | 0.00 | 0.00 | 0.00 | 3 |
| 345 | 0.73 | 0.80 | 0.76 | 10 |
| 346 | 0.00 | 0.00 | 0.00 | 5 |
| 347 | 0.42 | 0.57 | 0.48 | 14 |
| 348 | 0.00 | 0.00 | 0.00 | 1 |
| 349 | 0.27 | 0.78 | 0.40 | 9 |
| 350 | 0.00 | 0.00 | 0.00 | 1 |
| 351 | 0.05 | 0.50 | 0.08 | 2 |
| 352 | 0.73 | 0.73 | 0.73 | 26 |
| 353 | 0.50 | 0.33 | 0.40 | 3 |
| 354 | 0.02 | 0.25 | 0.04 | 4 |
| 355 | 0.04 | 0.20 | 0.06 | 10 |
| 356 | 0.04 | 0.07 | 0.05 | 14 |
| 357 | 0.31 | 0.75 | 0.44 | 16 |

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|---|---|---|---|---|
| 358 | 0.17 | 0.22 | 0.19 | 9 |
| 359 | 0.24 | 0.78 | 0.37 | 18 |
| 360 | 0.04 | 0.12 | 0.06 | 16 |
| 361 | 0.30 | 0.79 | 0.43 | 14 |
| 362 | 0.04 | 0.20 | 0.06 | 5 |
| 363 | 0.56 | 1.00 | 0.71 | 5 |
| 364 | 0.00 | 0.00 | 0.00 | 3 |
| 365 | 0.00 | 0.00 | 0.00 | 9 |
| 366 | 0.69 | 0.75 | 0.72 | 12 |
| 367 | 0.20 | 0.56 | 0.29 | 9 |
| 368 | 0.00 | 0.00 | 0.00 | 0 |
| 369 | 0.00 | 0.00 | 0.00 | 7 |
| 370 | 0.00 | 0.00 | 0.00 | 6 |
| 371 | 0.04 | 0.38 | 0.07 | 13 |
| 372 | 0.75 | 0.43 | 0.55 | 7 |
| 373 | 0.30 | 0.35 | 0.32 | 17 |
| 374 | 0.00 | 0.00 | 0.00 | 4 |
| 375 | 0.04 | 0.33 | 0.07 | 3 |
| 376 | 0.00 | 0.00 | 0.00 | 6 |
| 377 | 0.12 | 0.15 | 0.14 | 13 |
| 378 | 0.00 | 0.00 | 0.00 | 8 |
| 379 | 0.00 | 0.00 | 0.00 | 3 |
| 380 | 0.53 | 0.45 | 0.49 | 20 |
| 381 | 0.00 | 0.00 | 0.00 | 16 |
| 382 | 0.00 | 0.00 | 0.00 | 24 |
| 383 | 0.52 | 0.42 | 0.47 | 33 |
| 384 | 0.00 | 0.00 | 0.00 | 17 |
| 385 | 0.00 | 0.00 | 0.00 | 6 |
| 386 | 0.00 | 0.00 | 0.00 | 4 |
| 387 | 0.05 | 0.11 | 0.07 | 9 |
| 388 | 0.25 | 0.33 | 0.29 | 9 |
| 389 | 0.00 | 0.00 | 0.00 | 4 |
| 390 | 0.59 | 0.72 | 0.65 | 18 |
| 391 | 0.15 | 0.30 | 0.20 | 10 |
| 392 | 0.00 | 0.00 | 0.00 | 3 |
| 393 | 0.00 | 0.00 | 0.00 | 17 |
| 394 | 0.00 | 0.00 | 0.00 | 10 |
| 395 | 0.23 | 0.42 | 0.29 | 12 |
| 396 | 0.03 | 0.14 | 0.04 | 7 |
| 397 | 0.28 | 0.37 | 0.32 | 19 |
| 398 | 0.43 | 0.72 | 0.54 | 18 |
| 399 | 0.10 | 0.11 | 0.11 | 9 |
| 400 | 0.19 | 0.60 | 0.29 | 5 |
| 401 | 0.24 | 0.46 | 0.32 | 13 |
| 402 | 0.05 | 0.17 | 0.08 | 6 |
| 403 | 0.10 | 0.50 | 0.17 | 2 |
| 404 | 0.00 | 0.00 | 0.00 | 1 |
| 405 | 0.14 | 0.38 | 0.20 | 8 |
| 406 | 0.13 | 0.40 | 0.20 | 5 |
| 407 | 0.07 | 0.33 | 0.12 | 3 |
| 408 | 0.06 | 0.25 | 0.10 | 4 |
| 409 | 0.00 | 0.00 | 0.00 | 3 |
| 410 | 0.00 | 0.00 | 0.00 | 2 |
| 411 | 0.21 | 0.45 | 0.29 | 11 |
| 412 | 0.17 | 0.50 | 0.25 | 6 |
| 413 | 0.10 | 0.18 | 0.13 | 34 |
| 414 | 0.00 | 0.00 | 0.00 | 8 |
| 415 | 0.08 | 1.00 | 0.14 | 1 |
| 416 | 0.25 | 0.60 | 0.35 | 5 |
| 417 | 0.08 | 0.17 | 0.11 | 6 |
| 418 | 0.00 | 0.00 | 0.00 | 9 |

| | | | | |
|---|---|---|---|---|
| 419 | 0.15 | 0.36 | 0.21 | 14 |
| 420 | 0.00 | 0.00 | 0.00 | 2 |
| 421 | 0.18 | 0.40 | 0.25 | 5 |
| 422 | 0.12 | 0.83 | 0.21 | 6 |
| 423 | 0.00 | 0.00 | 0.00 | 4 |
| 424 | 1.00 | 1.00 | 1.00 | 1 |
| 425 | 0.00 | 0.00 | 0.00 | 2 |
| 426 | 0.14 | 0.38 | 0.20 | 13 |
| 427 | 0.86 | 0.86 | 0.86 | 21 |
| 428 | 0.78 | 0.78 | 0.78 | 9 |
| 429 | 0.00 | 0.00 | 0.00 | 1 |
| 430 | 0.05 | 0.25 | 0.08 | 4 |
| 431 | 0.21 | 0.30 | 0.25 | 23 |
| 432 | 0.00 | 0.00 | 0.00 | 1 |
| 433 | 0.00 | 0.00 | 0.00 | 5 |
| 434 | 0.20 | 0.50 | 0.29 | 2 |
| 435 | 0.14 | 0.50 | 0.22 | 2 |
| 436 | 0.08 | 0.23 | 0.12 | 13 |
| 437 | 0.00 | 0.00 | 0.00 | 7 |
| 438 | 0.29 | 0.67 | 0.40 | 9 |
| 439 | 0.02 | 0.14 | 0.03 | 7 |
| 440 | 0.06 | 0.20 | 0.10 | 10 |
| 441 | 0.17 | 0.33 | 0.22 | 6 |
| 442 | 0.08 | 0.18 | 0.11 | 11 |
| 443 | 0.10 | 0.09 | 0.10 | 11 |
| 444 | 0.05 | 0.07 | 0.06 | 14 |
| 445 | 0.00 | 0.00 | 0.00 | 3 |
| 446 | 0.27 | 1.00 | 0.43 | 3 |
| 447 | 0.02 | 0.25 | 0.03 | 4 |
| 448 | 0.50 | 0.55 | 0.52 | 11 |
| 449 | 0.29 | 0.56 | 0.38 | 9 |
| 450 | 0.12 | 0.33 | 0.17 | 6 |
| 451 | 0.03 | 0.20 | 0.06 | 5 |
| 452 | 0.00 | 0.00 | 0.00 | 3 |
| 453 | 0.00 | 0.00 | 0.00 | 17 |
| 454 | 0.38 | 0.41 | 0.39 | 22 |
| 455 | 0.07 | 0.33 | 0.12 | 12 |
| 456 | 0.00 | 0.00 | 0.00 | 0 |
| 457 | 0.07 | 0.43 | 0.12 | 7 |
| 458 | 0.03 | 0.33 | 0.06 | 3 |
| 459 | 0.05 | 0.33 | 0.08 | 3 |
| 460 | 0.00 | 0.00 | 0.00 | 1 |
| 461 | 0.19 | 0.60 | 0.29 | 5 |
| 462 | 0.00 | 0.00 | 0.00 | 2 |
| 463 | 0.05 | 0.29 | 0.09 | 14 |
| 464 | 0.19 | 0.33 | 0.24 | 9 |
| 465 | 0.18 | 0.33 | 0.24 | 6 |
| 466 | 0.05 | 0.20 | 0.08 | 5 |
| 467 | 0.33 | 0.71 | 0.45 | 7 |
| 468 | 0.33 | 0.10 | 0.15 | 20 |
| 469 | 0.00 | 0.00 | 0.00 | 8 |
| 470 | 0.57 | 1.00 | 0.73 | 8 |
| 471 | 0.36 | 0.56 | 0.43 | 9 |
| 472 | 0.15 | 0.43 | 0.22 | 14 |
| 473 | 0.43 | 0.60 | 0.50 | 5 |
| 474 | 0.00 | 0.00 | 0.00 | 2 |
| 475 | 0.00 | 0.00 | 0.00 | 8 |
| 476 | 0.21 | 0.50 | 0.30 | 6 |
| 477 | 0.33 | 0.67 | 0.44 | 12 |
| 478 | 1.00 | 0.25 | 0.40 | 4 |
| 479 | 0.17 | 0.11 | 0.13 | 9 |

```
           480       0.50      0.80      0.62         5
           481       0.15      0.44      0.23         9
           482       0.00      0.00      0.00         4
           483       0.31      0.77      0.44        13
           484       0.00      0.00      0.00         6
           485       0.06      0.11      0.08         9
           486       0.05      0.20      0.08         5
           487       0.20      0.22      0.21         9
           488       0.07      0.11      0.09         9
           489       0.12      0.50      0.19         6
           490       0.00      0.00      0.00        14
           491       0.06      0.14      0.09        14
           492       0.00      0.00      0.00         3
           493       0.00      0.00      0.00         8
           494       0.19      0.21      0.20        14
           495       0.75      0.50      0.60         6
           496       0.00      0.00      0.00         2
           497       0.07      0.20      0.10         5
           498       0.33      0.20      0.25        10
           499       0.09      0.20      0.13        15

   micro avg       0.26      0.47      0.33     18699
   macro avg       0.20      0.36      0.24     18699
weighted avg       0.33      0.47      0.38     18699
 samples avg       0.34      0.45      0.34     18699

Time taken to run this cell : 0:08:48.564091
```

In [ ]: