MPST: Movie Plot Synopses with Tags

1. Business Problem

1.1 Sources and Refernces:

Data Source : https://www.kaggle.com/cryptexcode/mpst-movie-plot-synopses-with-tags#mpst_full_data.csv (https://www.kaggle.com/cryptexcode/mpst-movie-plot-synopses-with-tags#mpst_full_data.csv)

Research paper : https://www.aclweb.org/anthology/L18-1274 (https://www.aclweb.org/anthology/L18-1274)

Research paper : http://ritual.uh.edu/mpst-2018/ (http://ritual.uh.edu/mpst-2018/)

1.2 Business Constraints:

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

2. Machine Learning Problem:

Contains all the IMDB id, title, plot synopsis, tags for the movies. There are 14,828 movies' data in total. The split column indicates where the data instance resides in the Train/Dev/Test split.

Columns imdb_id

IMDB id of the movie title:- Title of the move

plot_synopsis:- Plot Synopsis of the move

tags:- Tags assigned to the move

split:-Position of the movie in the standard data split

synopsis_source:-From where the plot synopsis was collected

3. Exploratory Data Analysis:

3.1 Data Loading and Cleaning

In [0]:

```
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
```

In [1]:

```
pip install scikit-multilearn
```

```
Collecting scikit-multilearn
  Downloading https://files.pythonhosted.org/packages/bb/1f/e6ff649c72a1cd
f2c7a1d31eb21705110ce1c5d3e7e26b2cc300e1637272/scikit_multilearn-0.2.0-py3
-none-any.whl (89kB)
     |████████████████████████████████| 92kB 4.3MB/s
Installing collected packages: scikit-multilearn
Successfully installed scikit-multilearn-0.2.0
```

In [0]:

```
data = pd.read_csv('mpst_full_data.csv')
data.columns
```

Out[0]:

```
Index(['imdb_id', 'title', 'plot_synopsis', 'tags', 'split',
       'synopsis_source'],
      dtype='object')
```

In [0]:

```
data.head()
```

Out[0]:

	imdb_id	title	plot_synopsis	tags	split	synopsis_source
0	tt0057603	I tre volti della paura	Note: this synopsis is for the orginal Italian...	cult, horror, gothic, murder, atmospheric	train	imdb
1	tt1733125	Dungeons & Dragons: The Book of Vile Darkness	Two thousand years ago, Nhagruul the Foul, a s...	violence	train	imdb
2	tt0033045	The Shop Around the Corner	Matuschek's, a gift store in Budapest, is the ...	romantic	test	imdb
3	tt0113862	Mr. Holland's Opus	Glenn Holland, not a morning person by anyone'...	inspiring, romantic, stupid, feel-good	train	imdb
4	tt0086250	Scarface	In May 1980, a Cuban man named Tony Montana (A...	cruelty, murder, dramatic, cult, violence, atm...	val	imdb

In [0]:

```
#Creating db file from csv
if not os.path.isfile('train.db'):
    start = datetime.now()
    disk_engine = create_engine('sqlite:///train.db')
    start = dt.datetime.now()
    chunksize = 50000
    j=0
    index_start = 1
    for df in pd.read_csv('mpst_full_data.csv', chunksize=chunksize, iterator=True, enc
oding='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)
```

In [0]:

```
# Counting number of rows

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)
    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("Run the above cell to genarate train.db file")
```

```
Number of rows in the database :
 14828
Time taken to count the number of rows : 0:00:00
```

Number of train, test and validation data:

In [0]:

```
con = sqlite3.connect('train.db')
no_dup = pd.read_sql_query('SELECT split, COUNT(*) AS num FROM data GROUP BY split', co
n)
con.close()
```

In [0]:

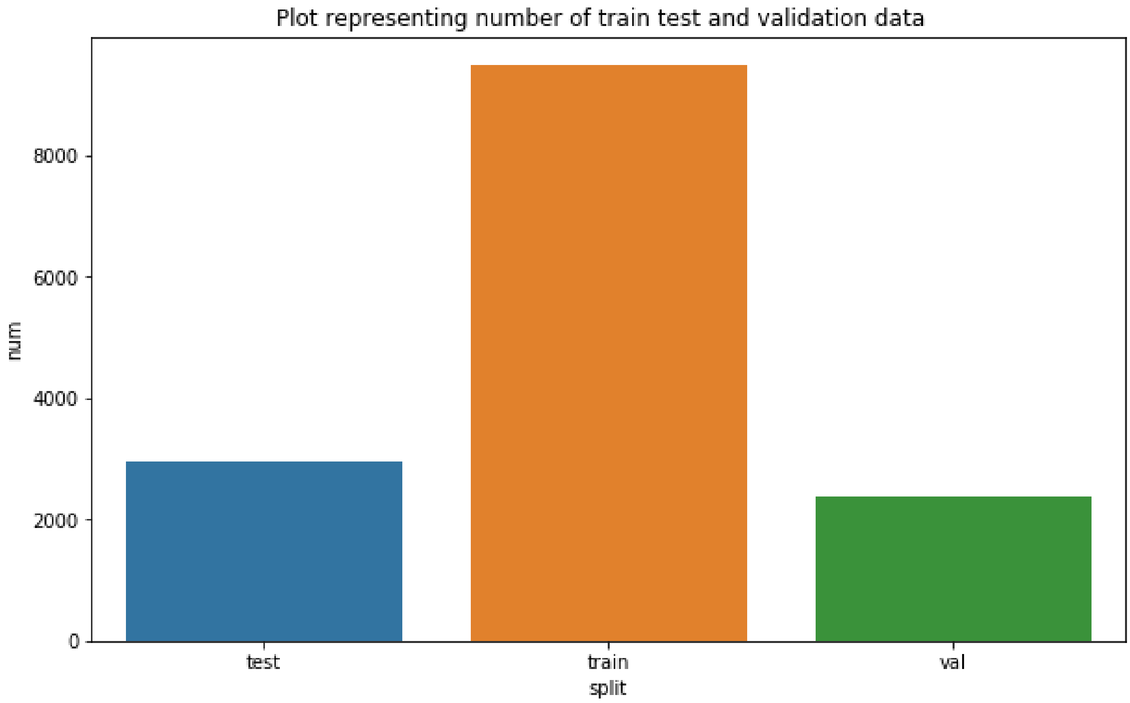
```
no_dup
```

Out[0]:

	split	num
0	test	2966
1	train	9489
2	val	2373

In [0]:

```
plt.figure(figsize=(10, 6))
plt.title ("Plot representing number of train test and validation data  ")
sns.barplot(no_dup['split'],no_dup['num'])
plt.show()
```



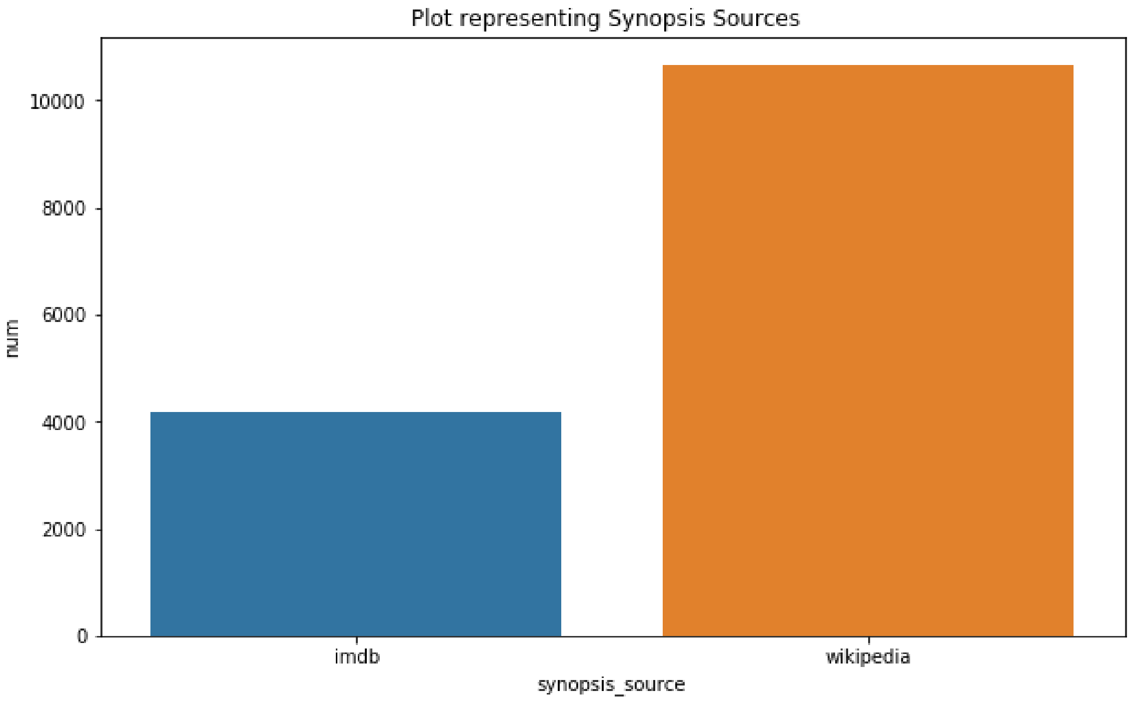
Data Sources:

In [0]:

```
con = sqlite3.connect('train.db')
no_dup = pd.read_sql_query('SELECT synopsis_source, COUNT(*) AS num FROM data GROUP BY
 synopsis_source', con)
con.close()
```

In [0]:

```
plt.figure(figsize=(10, 6))
plt.title ("Plot representing Synopsis Sources  ")
sns.barplot(no_dup['synopsis_source'],no_dup['num'])
plt.show()
```



3.1.2 Checking for duplicates

In [0]:

```
if os.path.isfile('train.db'):
    start = datetime.now()
    con = sqlite3.connect('train.db')
    df_no_dup = pd.read_sql_query('SELECT Title, plot_synopsis, Tags, split, COUNT(*) a
s cnt_dup FROM data GROUP BY title, plot_synopsis, tags, split', con)
    con.close()
    print("Time taken to run this cell :", datetime.now() - start)
else:
    print("Run the first to genarate train.db file")
```

```
Time taken to run this cell : 0:00:00.546881
```

In [0]:

```
df_no_dup.head()
```

Out[0]:

	title	plot_synopsis	tags	split	cnt_dup
0	$	Set in Hamburg, West Germany, several criminal...	murder	test	1
1	$windle	A 6th grader named Griffin Bing decides to gat...	flashback	train	1
2	'71	Gary Hook, a new recruit to the British Army, ...	suspenseful, neo noir, murder, violence	train	1
3	'A' gai wak	Sergeant Dragon Ma (Jackie Chan) is part of th...	cult, violence	train	1
4	'Breaker' Morant	In Pretoria, South Africa, in 1902, Major Char...	murder, anti war, violence, flashback, tragedy...	train	1

In [0]:

```
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,"% )")
```

```
number of duplicate questions : 47 ( 0.3169678985702751 % )
```

In [0]:

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

Out[0]:

```
1    14743
2       32
3        4
5        1
4        1
Name: cnt_dup, dtype: int64
```

In [0]:

```
# number of tags per movie title.
df_no_dup["tag_count"] = df_no_dup['tags'].apply(lambda text: len(text.split(",")))
df_no_dup.head()
```

Out[0]:

	title	plot_synopsis	tags	split	cnt_dup	tag_count
0	$	Set in Hamburg, West Germany, several criminal...	murder	test	1	1
1	$windle	A 6th grader named Griffin Bing decides to gat...	flashback	train	1	1
2	'71	Gary Hook, a new recruit to the British Army, ...	suspenseful, neo noir, murder, violence	train	1	4
3	'A' gai wak	Sergeant Dragon Ma (Jackie Chan) is part of th...	cult, violence	train	1	2
4	'Breaker' Morant	In Pretoria, South Africa, in 1902, Major Char...	murder, anti war, violence, flashback, tragedy...	train	1	6

In [0]:

```
df_no_dup.tag_count.value_counts()
```

Out[0]:

```
1     5478
2     3115
3     1959
4     1238
5      916
6      606
7      478
8      316
9      223
10     135
11     107
13      52
12      51
14      33
15      28
16      16
18      11
17       9
21       3
23       2
20       2
19       2
25       1
Name: tag_count, dtype: int64
```

In [0]:

```
# 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', 'plot_synopsis', 'tags', 'spli
t'])
    no_dup.to_sql('no_dup_train', disk_dup)
```

In [0]:

```
# Loading again
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("Run the above cells to genarate train_no_dup.db file")
```

```
Time taken to run this cell : 0:00:00.125001
```

3.2 Analysis of Tags

3.2.1 Total number of unique tags

In [0]:

```
# using count vectorizer
vectorizer = CountVectorizer(tokenizer = lambda x: x.split(','))

tag_dtm = vectorizer.fit_transform(tag_data['tags'])
```

In [0]:

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

```
Number of data points : 14780
Number of unique tags : 142
```

In [0]:

```
# some of the tags
tags = vectorizer.get_feature_names()

print("Some of the tags we have :", tags[:10])
```

```
Some of the tags we have : [' absurd', ' action', ' adult comedy', ' alleg
ory', ' alternate history', ' alternate reality', ' anti war', ' atmospher
ic', ' autobiographical', ' avant garde']
```

3.2.3 Number of times a tag appeared

In [0]:

```
#Lets now store the document term matrix in a dictionary.
freqs = tag_dtm.sum(axis=0).A1
result = dict(zip(tags, freqs))
```

In [0]:

```
#Saving this dictionary to csv files.
if not os.path.isfile('tag_counts_dict_dtm.csv'):
    with open('tag_counts_dict_dtm.csv', 'w') as csv_file:
        writer = csv.writer(csv_file)
        for key, value in result.items():
            writer.writerow([key, value])
tag_df = pd.read_csv("tag_counts_dict_dtm.csv", names=['Tags', 'Counts'])
tag_df.head()
```

Out[0]:

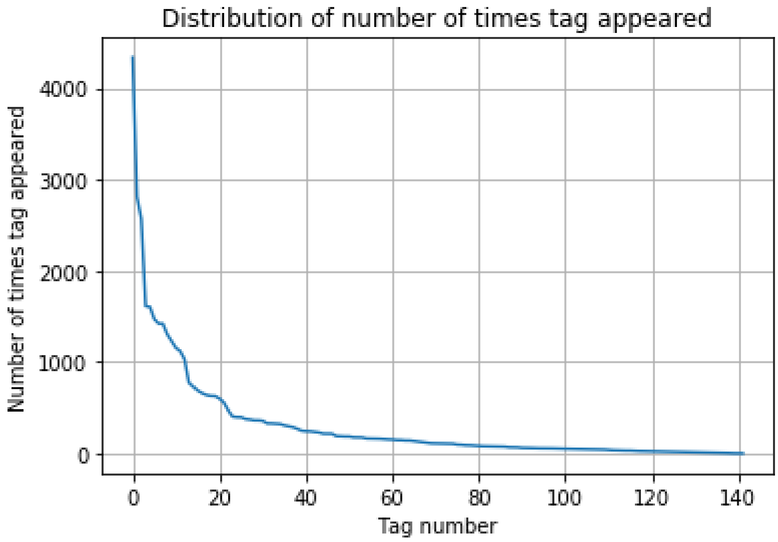
	Tags	Counts
0	absurd	178
1	action	599
2	adult comedy	110
3	allegory	82
4	alternate history	79

In [0]:

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

In [0]:

```
plt.plot(tag_counts[:1000])
plt.title("Distribution of number of times tag appeared")
plt.grid()
plt.xlabel("Tag number")
plt.ylabel("Number of times tag appeared")
plt.show()
```

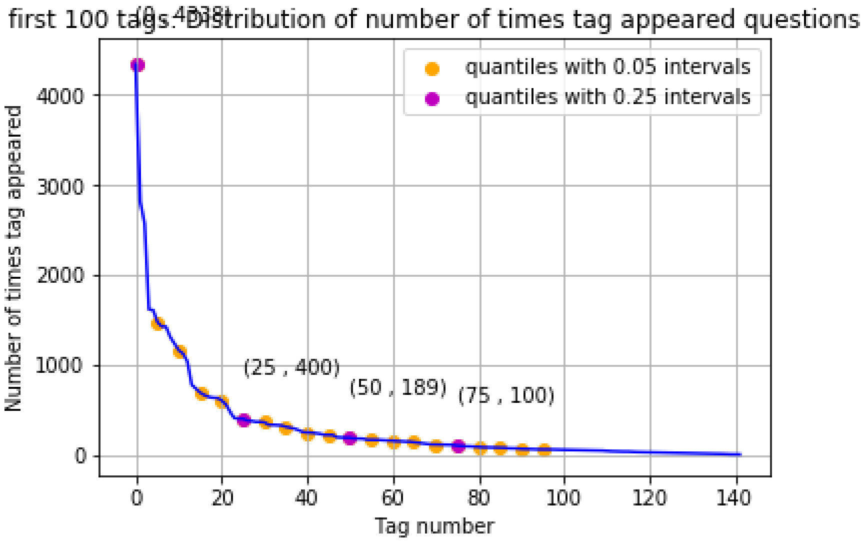


In [0]:

```
plt.plot(tag_counts, 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])
```




```
20 [4338 1473 1157  686  599  400  361  311  247  219  189  165  155  139
  113  100   84   78   64   59]
```

3.2.4 Tags Per Question

In [0]:

```
# Storing the count of tag in each question in the 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])
```

```
We have total 14780 datapoints.
[1, 4, 2, 6, 1]
```

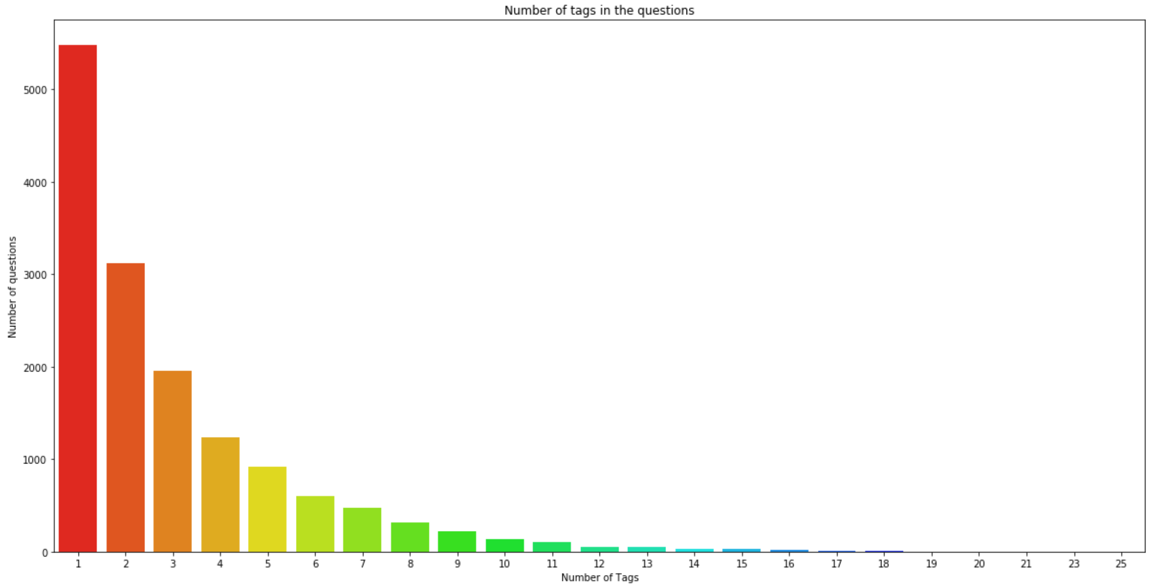
In [0]:

```
print ("Maximum no of tag per question: %d"%max(tag_quest_count))
print ("Minimum no of tags per quest: %d"%min(tag_quest_count))
print ("Avg number of tags per qudestion: %f"% ((sum(tag_quest_count)*1.0)/len(tag_ques
t_count)))
```

```
Maximum no of tag per question: 25
Minimum no of tags per quest: 1
Avg number of tags per qudestion: 2.987077
```

In [0]:

```
fig = plt.figure(figsize=(20,10))
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: 1
2. Minimum number of tags per question: 1
3. Avg. number of tags per question: 2.99

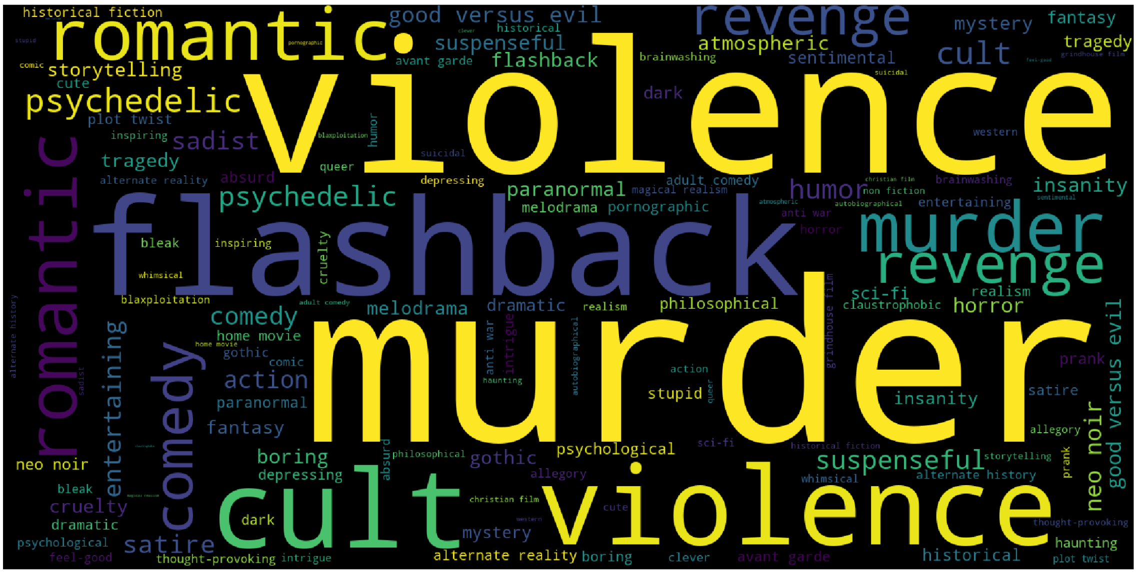
3.2.5 Most Frequent Tags

In [0]:

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

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

fig = plt.figure(figsize=(30,20))
plt.imshow(wordcloud)
plt.axis('off')
plt.tight_layout(pad=0)
fig.savefig("tag.png")
plt.show()
print("Time taken to run this cell :", datetime.now() - start)
```




```
Time taken to run this cell : 0:00:04.417730
```

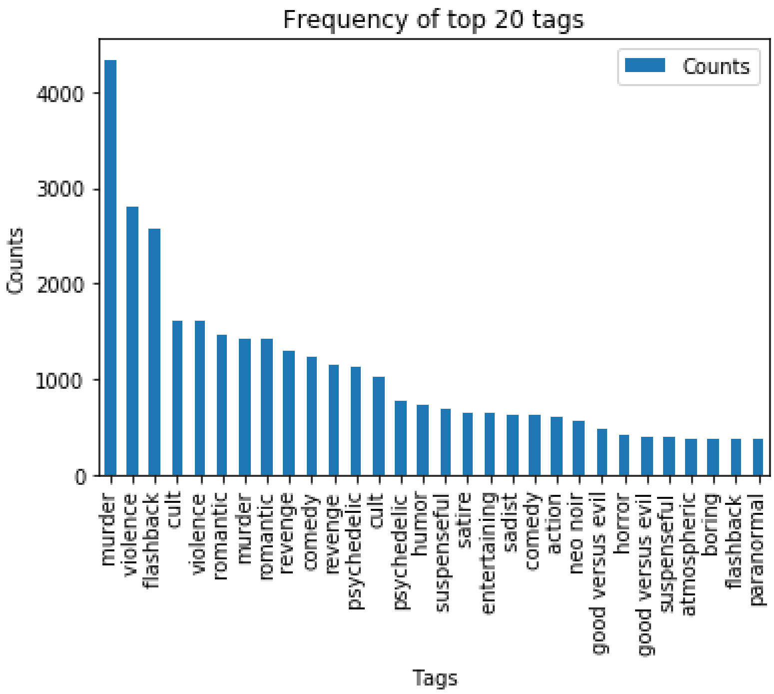
Observations:
A look at the word cloud shows that "violence", "murder", "flashback", "romantic", "cult" are some of the most frequent tags.

3.2.6 The top 20 tags

In [0]:

```
i=np.arange(30)
fig = plt.figure(figsize=(20,10))
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()
```

<Figure size 1440x720 with 0 Axes>



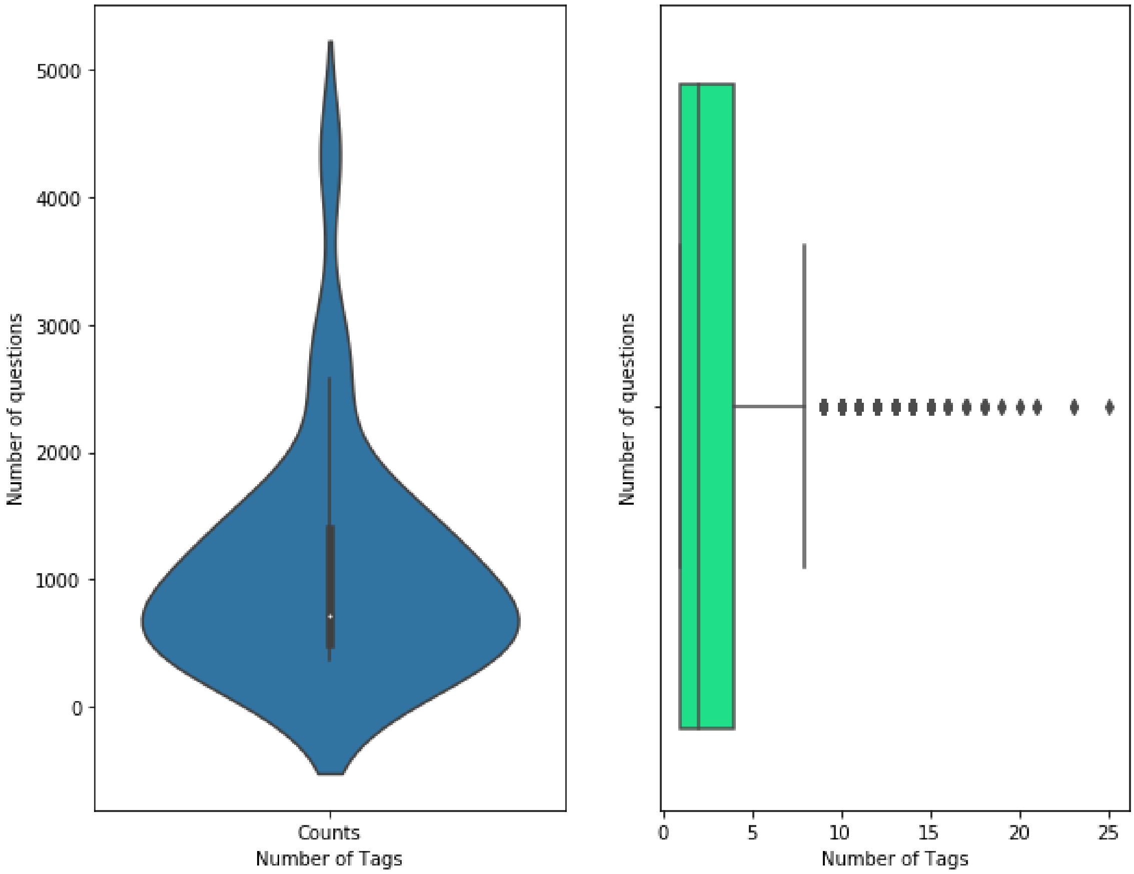
In [0]:

```
# Obsetving the quantiles using the violin plot and box .

plt.figure(figsize=(10, 8))

plt.subplot(1,2,1)
sns.violinplot(data = tag_df_sorted.head(30) , )
plt.xlabel("Number of Tags")
plt.ylabel("Number of questions")

plt.subplot(1,2,2)
sns.boxplot(tag_quest_count, palette='gist_rainbow')
plt.xlabel("Number of Tags")
plt.ylabel("Number of questions")
plt.show()
```

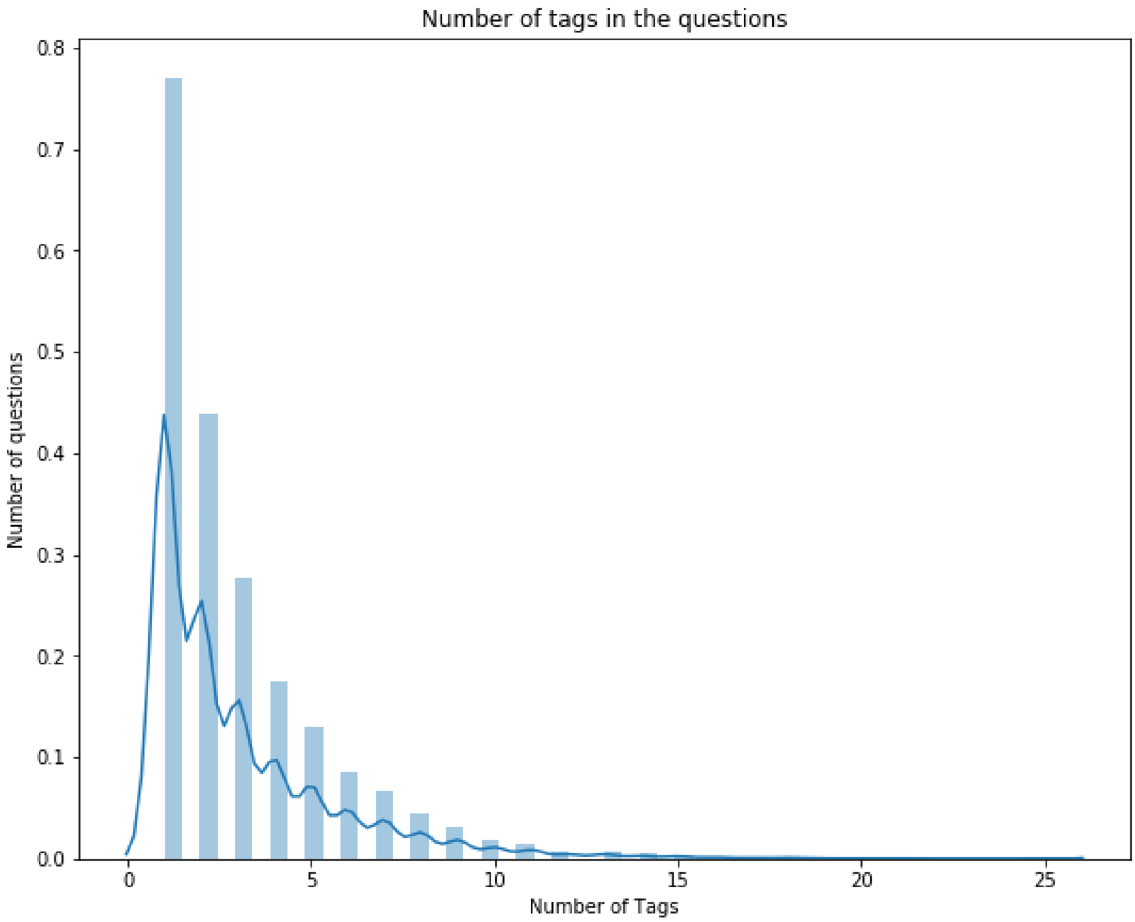


Observation: Most of the tags are acquired by 800 questions and has 1 tags.

In [0]:

```
# plot for average no of tags per question

plt.figure(figsize=(10, 8))
plt.subplot()
sns.distplot(tag_quest_count)
plt.title("Number of tags in the questions")
plt.xlabel("Number of Tags")
plt.ylabel("Number of questions")
plt.show()
```



Observation: Most of the questions have 1 tags in average and there is an average of 450 questions with 1 tags, 250 questions with 2 tag and so on.

3.3 Cleaning and preprocessing of Questions

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [0]:

```
if os.path.isfile('train_no_dup.db'):
    start = datetime.now()
    con = sqlite3.connect('train_no_dup.db')
    my_data = pd.read_sql_query("""SELECT * FROM no_dup_train""", con)
    #Always remember to close the database
    con.close()

    # Let's now drop unwanted column.
    my_data.drop(my_data.index[0], inplace=True)
    #Printing first 5 columns from our data frame
    my_data.head()
    print("Time taken to run this cell :", datetime.now() - start)
else:
    print("Run the above cells to genarate train_no_dup.db file")
```

```
Time taken to run this cell : 0:00:01.500045
```

In [0]:

```
# printing some random reviews
sent_0 = my_data['plot_synopsis'].values[0]
print(sent_0)
print("="*50)

sent_1000 = my_data['plot_synopsis'].values[1000]
print(sent_1000)
print("="*50)
```

A 6th grader named Griffin Bing decides to gather their entire grade in a sleepover protest in an old house about to be demolished after their plan for using a new space in their town was thrown out because of their youth. However, only Griffin and his best friend Ben Slovak show up. Griffin discovers a Babe Ruth baseball card that, unbeknownst to him, is worth huge amounts of money. Excited that the card could help his family, which is struggling financially, Griffin takes it to the local collectibles dealer, S. Wendell Palomino. S. Wendell tells the boys that the card is an old counterfeit of a valuable one, worth only one hundred dollars. A dejected Griffin later chances upon Palomino on television, stating that the card he stole was worth at least a million dollars. Enraged, Griffin and Ben try to steal it back from Swindle's shop, only to find that it has gone, and they have to break into Swindle's house. Now, in order to get the card back, Griffin must gather a team of local students with unique skills to break into Palomino's heavily guarded home to retrieve the card before the big auction where Swindle plans to sell the card. The team consists of seven people (including Ben and Griffin): Savannah the Dog whisperer, to get past Swindle's massive, violent Guard Dog Luthor; Logan the actor, to distract Swindle's eagle-eyed neighbor who spends his days watching the entire street's goings-on; Antonia "Pitch" Benson the "born to climb" girl, to scale the skylight in Swindle's house; Darren Vader who the others had no choice but to add to the team, for he threatened to rat them out (But Darren proved to be useful pulling people up the skylight); Melissa the unsociable computer genius, who was used to break into Swindle's UltraTech alarm system. The tension is piled with an unexpected visit from the auctioneer, yet another even more menacing guard dog, and a betrayal from the person who begged to be in the group. The book was followed by multiple sequels, titled Zoobreak, Framed!, Showoff, Hideout , Jackpot and Unleashed.

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Aos 11 anos de idade, relatam os especialistas, a criança tem um senso de justiça bastante aflorado. É também nesta fase em que o olhar crítico se acentua. Rita (Mel Maia), a protagonista desta história, tem exatos 11 anos quando sofre um duro golpe e vê o seu mundo virar ao avesso. Esta rasteira lhe deixa marcas profundas, chaga que Rita carregará pela vida inteira.A menina, órfã de mãe, é criada pelo pai. Amoroso, Genésio (Tony Ramos) jamais imaginou que a sua segunda esposa pudesse representar o pior de seus pesadelos. Carminha (Adriana Esteves), a madrasta, rouba tudo da enteada: os sonhos, a casa, a família e a esperança. Rita conhece um modelo de vida sem esperança, de muitas perdas e solidão. Ela sente, na pele, a amargura da decepção.Mas enganam-se aqueles que subestimam a capacidade de sobrevivência de Rita. A menina não sucumbe ao longo dos anos. De tudo o que lhe foi tirado, restou apenas um único e vital sentimento: a sede por um acerto de contas. É neste momento em que o limite para que os fins justifiquem os meios entra em discussão. Esse limite, por diversas vezes, não se encaixa no formato simples e dicotômico de certo ou errado.Na saga pela sua própria justiça, Rita deixa para trás o passado frágil e se transforma em Nina (Débora Falabella), uma mulher obstinada, firme e blindada para as surpresas que o destino lhe reserva. A vida se encarregou desta metamorfose. Está feito, não há como voltar.Alternative Synopsis in English by Yosra_in_EgyptIn Brazil, a young girl, Rita, knew her father's new wife, Carminha (Adriana Esteves), was up to no good. She tried to warn her father that the same woman, who could mistreat her, planned to rob him. What she didn't know is that her father would wind up dead.Without that good man to protect her, the girl is brought to the garbage dump and abandoned. Rita is befriended by an urchin with the nickname of Potato and is then brought to a kind woman everyone calls Mama Lucinda (Vera Holtz).Rita and Potato have a kind of young love which even includes a pretend wedding ceremony. When Rita gets adopted by a well-to-do couple, she leaves Brazil for Argentina but she does not forget those who helped her and those who hurt both her and her father.As soon as she is old enough to handle the challenge, she returns for revenge against her evil stepmother by using her culinary skills to get a jo

```
b in her mansion. Carminha has done well for herself by marrying a former
soccer star. She's fooling everyone she's a goody-goody but she is a cruel
witch to her chubby daughter Ágatha (Ana Karolina Lannes) and anyone who g
ets in her way.Potato is there too at the mansion but under the name Jorgi
nho (Cauã Reymond) because he was somehow adopted from the dump by Carminh
a and her new husband Tufão (Jorge Araújo). Rita (Débora Falabella) of cou
rse can't use her real name and goes by the name Nina for her ruseCan she
exact sweet revenge while at the same time rekindle her first love?
==================================================
```

In [0]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)

print(sent_0)
```

```
A 6th grader named Griffin Bing decides to gather their entire grade in a
sleepover protest in an old house about to be demolished after their plan
for using a new space in their town was thrown out because of their youth.
However, only Griffin and his best friend Ben Slovak show up. Griffin disc
overs a Babe Ruth baseball card that, unbeknownst to him, is worth huge am
ounts of money. Excited that the card could help his family, which is stru
ggling financially, Griffin takes it to the local collectibles dealer, S.
Wendell Palomino. S. Wendell tells the boys that the card is an old counte
rfeit of a valuable one, worth only one hundred dollars. A dejected Griffi
n later chances upon Palomino on television, stating that the card he stol
e was worth at least a million dollars. Enraged, Griffin and Ben try to st
eal it back from Swindle's shop, only to find that it has gone, and they h
ave to break into Swindle's house. Now, in order to get the card back, Gri
ffin must gather a team of local students with unique skills to break into
Palomino's heavily guarded home to retrieve the card before the big auctio
n where Swindle plans to sell the card. The team consists of seven people
(including Ben and Griffin): Savannah the Dog whisperer, to get past Swind
le's massive, violent Guard Dog Luthor; Logan the actor, to distract Swind
le's eagle-eyed neighbor who spends his days watching the entire street's
goings-on; Antonia "Pitch" Benson the "born to climb" girl, to scale the s
kylight in Swindle's house; Darren Vader who the others had no choice but
to add to the team, for he threatened to rat them out (But Darren proved t
o be useful pulling people up the skylight); Melissa the unsociable comput
er genius, who was used to break into Swindle's UltraTech alarm system. Th
e tension is piled with an unexpected visit from the auctioneer, yet anoth
er even more menacing guard dog, and a betrayal from the person who begged
to be in the group. The book was followed by multiple sequels, titled Zoob
reak, Framed!, Showoff, Hideout , Jackpot and Unleashed.
```

In [0]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all-t
ags-from-an-element
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)
```

```
A 6th grader named Griffin Bing decides to gather their entire grade in a
sleepover protest in an old house about to be demolished after their plan
for using a new space in their town was thrown out because of their youth.
However, only Griffin and his best friend Ben Slovak show up. Griffin disc
overs a Babe Ruth baseball card that, unbeknownst to him, is worth huge am
ounts of money. Excited that the card could help his family, which is stru
ggling financially, Griffin takes it to the local collectibles dealer, S.
Wendell Palomino. S. Wendell tells the boys that the card is an old counte
rfeit of a valuable one, worth only one hundred dollars. A dejected Griffi
n later chances upon Palomino on television, stating that the card he stol
e was worth at least a million dollars. Enraged, Griffin and Ben try to st
eal it back from Swindle's shop, only to find that it has gone, and they h
ave to break into Swindle's house. Now, in order to get the card back, Gri
ffin must gather a team of local students with unique skills to break into
Palomino's heavily guarded home to retrieve the card before the big auctio
n where Swindle plans to sell the card. The team consists of seven people
(including Ben and Griffin): Savannah the Dog whisperer, to get past Swind
le's massive, violent Guard Dog Luthor; Logan the actor, to distract Swind
le's eagle-eyed neighbor who spends his days watching the entire street's
goings-on; Antonia "Pitch" Benson the "born to climb" girl, to scale the s
kylight in Swindle's house; Darren Vader who the others had no choice but
to add to the team, for he threatened to rat them out (But Darren proved t
o be useful pulling people up the skylight); Melissa the unsociable comput
er genius, who was used to break into Swindle's UltraTech alarm system. Th
e tension is piled with an unexpected visit from the auctioneer, yet anoth
er even more menacing guard dog, and a betrayal from the person who begged
to be in the group. The book was followed by multiple sequels, titled Zoob
reak, Framed!, Showoff, Hideout , Jackpot and Unleashed.
==================================================
```

In [0]:

```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [0]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselve
s', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him',
'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 't
hey', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "th
at'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'ha
d', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as'
, 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through'
, 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'ov
er', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'an
y', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too'
, 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'no
w', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't",
'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'migh
tn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'w
asn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [0]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(my_data['plot_synopsis'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwor
ds)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████| 14780/14780 [00:35<00:00, 415.57
it/s]
```

In [0]:

```
preprocessed_reviews[1500]
```

Out[0]:

```
'william nessen american freelance journalist travels aceh indonesia cover
conflict taking place time shot period four years black road follows nesse
n transforms objective journalist supporter free aceh movement gerakan ace
h merdeka gam tsunami made aceh indonesian province northern tip sumatra w
ell known across world people remain ignorant struggle independence willia
m nessen first travelled aceh print journalist point nessen no plans film
recorded footage intended sell television networks began visit general bam
bang darmono leader indonesian military aceh gaining trust general darmono
nessen able obtain information shooting opportunities would unavailable jo
urnalists period fell love trusted military translator sya diah syeh marha
ban spy separatist movement worked together continuing extract sensitive i
nformation general darmono nessen collection footage grew thought making f
ilm idea would later evolve black road nessen marhaban married aceh days w
edding nessen best man human rights activist kidnapped murdered indonesian
security forces became clear nessen independence movement supported majori
ty acehnese personal experiences began influence began support gam went li
ve front lines rebels many times travelling general darmono guerrillas sec
ret total nessen spent year gam military realised hunted almost killed ind
onesian military accused espionage ordered stop reporting rebel held areas
nessen spent weeks running authorities many near death experiences turned
military imprisoned forty days following deported singapore banned enterin
g indonesia one year ban renewed year since'
```

In [0]:

```
my_data['preprocessed_data'] = preprocessed_reviews
```

In [0]:

```
import pickle
my_data.to_pickle("final_data")
```

In [0]:

```
new_data = pd.read_pickle("final_data")
```

In [0]:

```
new_data.head()
```

Out[0]:

	index	title	plot_synopsis	tags	split	preprocessed_data
1	1	$windle	A 6th grader named Griffin Bing decides to gat...	flashback	train	grader named griffin bing decides gather entir...
2	2	'71	Gary Hook, a new recruit to the British Army, ...	suspenseful, neo noir, murder, violence	train	gary hook new recruit british army takes leave...
3	3	'A' gai wak	Sergeant Dragon Ma (Jackie Chan) is part of th...	cult, violence	train	sergeant dragon jackie chan part hong kong mar...
4	4	'Breaker' Morant	In Pretoria, South Africa, in 1902, Major Char...	murder, anti war, violence, flashback, tragedy...	train	pretoria south africa major charles bolton rod...
5	5	'C'-Man	Customs Investigator Cliff Holden (Dean Jagger...	murder	train	customs investigator cliff holden dean jagger ...

4. Machine Learning Models

4.1 Split the data into test and train

In [0]:

```
x_train=new_data.loc[(new_data['split'] == 'train') | (new_data['split'] == 'val')]
x_test=new_data.loc[(new_data['split'] == 'test')]
```

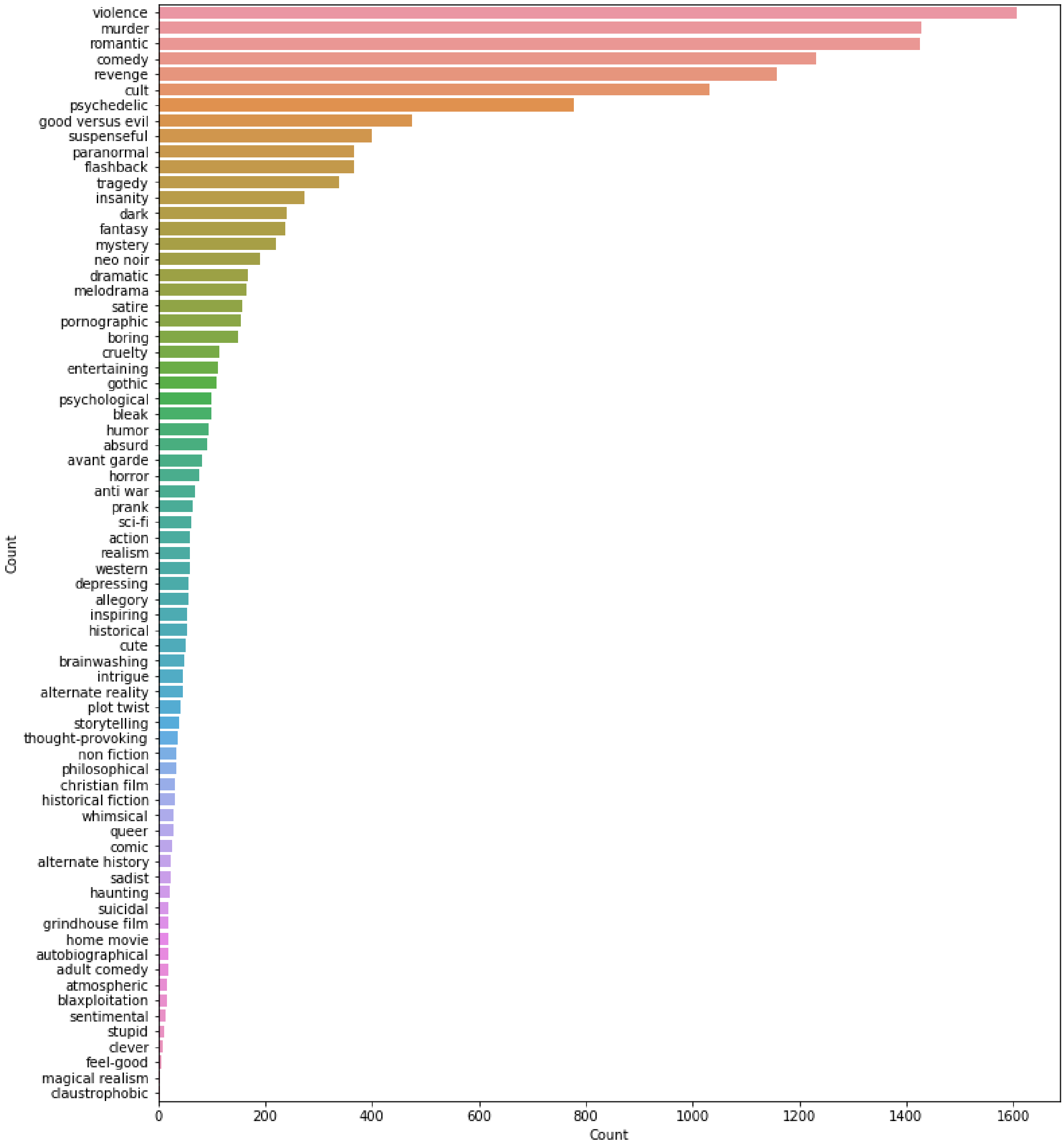
Analysing Tags one more time:

In [0]:

```
import nltk
all_genres = nltk.FreqDist(new_data['tags'].apply(lambda x: x.split(',')[0]))
all_genres_df = pd.DataFrame({'Genre': list(all_genres.keys()), 'Count': list(all_genre
s.values())})
```

In [0]:

```
g = all_genres_df.nlargest(columns="Count", n = 100)
plt.figure(figsize=(12,15))
ax = sns.barplot(data=g, x= "Count", y = "Genre")
ax.set(ylabel = 'Count')
plt.show()
```



OBSERVATION:
The number of tags are completely unbalanced.

4.3 Featurizing data

Pipeline and One Vs Rest classifier:

In [0]:

```
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfTransformer

X_train = np.array(x_train['preprocessed_data'])
Y_train = np.array(x_train['tags'])
X_test = np.array(x_test['preprocessed_data'])
Y_test = np.array(x_test['tags'])

model = Pipeline([('vect', CountVectorizer()),
                      ('tfidf', TfidfTransformer()),
                      ('clf', OneVsRestClassifier(SGDClassifier(loss='log', penalty='l
1', class_weight="balanced"), n_jobs=-1))
                      ])
model.fit(X_train, Y_train)
```

In [0]:

```
from sklearn.externals import joblib
joblib.dump(model, "pipeline1.pkl", compress=9)
""" Predict the test dataset using Naive Bayes"""
prediction = model.predict(X_test)
```

In [0]:

```
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))
```

```
Accuracy : 0.005398110661268556
Hamming loss  0.05500038014863812
Micro-average quality numbers
Precision: 0.1586, Recall: 0.3639, F1-measure: 0.2209
Macro-average quality numbers
Precision: 0.0733, Recall: 0.1752, F1-measure: 0.0969
              precision    recall  f1-score   support

           0       0.07      0.09      0.08        35
           1       0.14      0.42      0.21       117
           2       0.10      0.12      0.11        26
           3       0.07      0.18      0.10        11
           4       0.14      0.38      0.20        13
           5       0.04      0.08      0.05        26
           6       0.03      0.07      0.04        15
           7       0.07      0.17      0.10        75
           8       0.00      0.00      0.00         4
           9       0.04      0.03      0.04        31
          10       0.03      0.12      0.05         8
          11       0.04      0.05      0.05        20
          12       0.09      0.15      0.11        79
          13       0.03      0.11      0.05         9
          14       0.00      0.00      0.00         3
          15       0.09      0.13      0.11        15
          16       0.03      0.09      0.05        11
          17       0.09      0.22      0.12       120
          18       0.06      0.17      0.09        24
          19       0.08      0.17      0.11        72
          20       0.23      0.46      0.30       351
          21       0.00      0.00      0.00        32
          22       0.06      0.09      0.07        35
          23       0.06      0.07      0.06        29
          24       0.03      0.06      0.04        49
          25       0.14      0.38      0.20       142
          26       0.17      0.29      0.21        65
          27       0.03      0.10      0.05        10
          28       0.26      0.42      0.32       515
          29       0.20      0.41      0.27        90
          30       0.18      0.49      0.26        65
          31       0.02      0.11      0.04         9
          32       0.17      0.38      0.23        21
          33       0.09      0.13      0.10        54
          34       0.15      0.26      0.19        19
          35       0.03      0.04      0.03        26
          36       0.22      0.51      0.31        78
          37       0.13      0.30      0.19       150
          38       0.13      0.24      0.17        82
          39       0.02      0.05      0.03        19
          40       0.02      0.04      0.03        28
          41       0.00      0.00      0.00         5
          42       0.05      0.10      0.07        60
          43       0.49      0.69      0.57       885
          44       0.11      0.24      0.15        66
          45       0.20      0.53      0.29       111
          46       0.00      0.00      0.00         1
          47       0.07      0.13      0.09        38
          48       0.05      0.10      0.06        31
          49       0.04      0.06      0.04        33
          50       0.00      0.00      0.00         0
          51       0.07      0.07      0.07        42
          52       0.15      0.30      0.20       229
```

53	0.06	0.09	0.07	47
54	0.00	0.00	0.00	8
55	0.02	0.04	0.03	24
56	0.17	0.38	0.23	268
57	0.19	0.34	0.24	311
58	0.16	0.33	0.21	142
59	0.14	0.29	0.19	138
60	0.18	0.38	0.24	53
61	0.07	0.10	0.08	49
62	0.03	0.05	0.03	61
63	0.03	0.05	0.04	37
64	0.01	0.17	0.03	6
65	0.13	0.37	0.19	153
66	0.06	0.10	0.08	20
67	0.02	0.04	0.03	52
68	0.39	0.63	0.48	593
69	0.02	0.25	0.04	4
70	0.00	0.00	0.00	6
71	0.06	0.05	0.05	21
72	0.03	0.08	0.05	12
73	0.02	0.50	0.03	2
74	0.00	0.00	0.00	11
75	0.04	0.40	0.07	5
76	0.03	0.22	0.06	9
77	0.08	0.20	0.12	15
78	0.00	0.00	0.00	4
79	0.00	0.00	0.00	4
80	0.00	0.00	0.00	14
81	0.00	0.00	0.00	3
82	0.04	0.05	0.04	20
83	0.00	0.00	0.00	36
84	0.00	0.00	0.00	9
85	0.00	0.00	0.00	6
86	0.00	0.00	0.00	0
87	0.00	0.00	0.00	2
88	0.16	0.37	0.22	248
89	0.02	0.33	0.04	3
90	0.00	0.00	0.00	25
91	0.11	0.26	0.15	200
92	0.02	0.11	0.04	9
93	0.05	0.08	0.06	50
94	0.03	0.08	0.04	13
95	0.06	0.09	0.07	34
96	0.00	0.00	0.00	17
97	0.26	0.43	0.33	47
98	0.01	1.00	0.01	1
99	0.06	0.07	0.07	81
100	0.18	0.44	0.25	100
101	0.13	0.39	0.19	18
102	0.03	0.67	0.05	3
103	0.01	0.20	0.02	5
104	0.05	0.10	0.07	10
105	0.03	0.33	0.05	6
106	0.00	0.00	0.00	3
107	0.11	0.29	0.15	14
108	0.06	0.05	0.05	22
109	0.09	0.19	0.12	54
110	0.03	0.08	0.04	13
111	0.02	0.08	0.03	12
112	0.00	0.00	0.00	0
113	0.02	0.03	0.03	33

```
         114       0.17      0.43      0.24       269
         115       0.03      0.04      0.04        51
         116       0.05      0.09      0.06        34
         117       0.00      0.00      0.00         4
         118       0.19      0.31      0.23        91
         119       0.00      0.00      0.00         5
         120       0.02      0.09      0.03        11
         121       0.10      0.14      0.11        28
         122       0.00      0.00      0.00         9
         123       0.38      0.47      0.42       166
         124       0.00      0.00      0.00        18
         125       0.00      0.00      0.00         7
         126       0.00      0.00      0.00        13
         127       0.17      0.39      0.24       239
         128       0.31      0.63      0.41       276
         129       0.01      0.17      0.02         6
         130       0.11      0.06      0.07        35
         131       0.09      0.31      0.14        13
         132       0.00      0.00      0.00         2
         133       0.00      0.00      0.00         5
         134       0.00      0.00      0.00         2
         135       0.00      0.00      0.00         2
         136       0.09      0.28      0.13        75
         137       0.00      0.00      0.00         7
         138       0.08      0.15      0.11        67
         139       0.21      0.45      0.28       318
         140       0.12      0.30      0.18        10
         141       0.00      0.00      0.00         7

avg / total       0.20      0.36      0.25      9020
```

Applying Logistic Regression with OneVsRest Classifier

In [0]:

```
start = datetime.now()
vectorizer = CountVectorizer(min_df=0.00009, max_features=50000, tokenizer = lambda x:
x.split())
vectorizer.fit(x_train['preprocessed_data'])
x_train_multilabel = vectorizer.transform(x_train['preprocessed_data'])
x_test_multilabel = vectorizer.transform(x_test['preprocessed_data'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:09.106299
```

In [0]:

```
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: (11816, 50000) Y : (11816, 142)
Dimensions of test data X: (2964, 50000) Y: (2964, 142)
```

In [0]:

```
#from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import GridSearchCV
start = datetime.now()
model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l1', class_weight
="balanced"))

parameters = {
    "estimator__alpha": [10**-5,10**-4,  10**-3, 10**-1, 10**1]
}
model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabel, y_train)

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

```
0.10172648121582308
{'estimator__alpha': 1e-05}
Time taken to run this cell : 0:05:36.648090
```

In [0]:

```
start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l1',
class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)

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


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

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(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 : 0.0006747638326585695
Hamming loss  0.12262644694075384
Micro-average quality numbers
Precision: 0.0678, Recall: 0.3704, F1-measure: 0.1146
Macro-average quality numbers
Precision: 0.0471, Recall: 0.3029, F1-measure: 0.0717
              precision    recall  f1-score   support

           0       0.02      0.20      0.03        35
           1       0.12      0.36      0.18       117
           2       0.03      0.54      0.06        26
           3       0.01      0.27      0.01        11
           4       0.02      0.62      0.04        13
           5       0.02      0.23      0.03        26
           6       0.02      0.47      0.04        15
           7       0.04      0.23      0.07        75
           8       0.00      0.25      0.01         4
           9       0.03      0.23      0.05        31
          10       0.02      0.62      0.03         8
          11       0.00      0.05      0.01        20
          12       0.04      0.29      0.08        79
          13       0.01      0.44      0.02         9
          14       0.00      0.33      0.01         3
          15       0.01      0.27      0.03        15
          16       0.01      0.27      0.01        11
          17       0.06      0.20      0.09       120
          18       0.02      0.29      0.05        24
          19       0.05      0.24      0.08        72
          20       0.20      0.39      0.26       351
          21       0.03      0.31      0.06        32
          22       0.02      0.14      0.03        35
          23       0.02      0.17      0.04        29
          24       0.04      0.37      0.08        49
          25       0.10      0.34      0.16       142
          26       0.08      0.35      0.13        65
          27       0.01      0.20      0.02        10
          28       0.21      0.35      0.26       515
          29       0.09      0.47      0.16        90
          30       0.12      0.57      0.19        65
          31       0.00      0.00      0.00         9
          32       0.05      0.52      0.09        21
          33       0.05      0.39      0.09        54
          34       0.03      0.32      0.05        19
          35       0.02      0.19      0.03        26
          36       0.12      0.51      0.20        78
          37       0.08      0.31      0.13       150
          38       0.08      0.33      0.13        82
          39       0.01      0.26      0.03        19
          40       0.03      0.29      0.05        28
          41       0.00      0.00      0.00         5
          42       0.04      0.28      0.07        60
          43       0.43      0.63      0.51       885
          44       0.05      0.33      0.09        66
          45       0.15      0.54      0.23       111
          46       0.00      0.00      0.00         1
          47       0.04      0.32      0.07        38
          48       0.02      0.26      0.04        31
          49       0.02      0.27      0.04        33
          50       0.00      0.00      0.00         0
          51       0.05      0.38      0.09        42
          52       0.12      0.29      0.17       229
```

53	0.04	0.30	0.07	47
54	0.02	0.50	0.03	8
55	0.02	0.17	0.03	24
56	0.15	0.34	0.21	268
57	0.15	0.29	0.20	311
58	0.12	0.39	0.18	142
59	0.11	0.34	0.16	138
60	0.09	0.58	0.16	53
61	0.05	0.33	0.08	49
62	0.03	0.15	0.05	61
63	0.02	0.19	0.04	37
64	0.00	0.17	0.01	6
65	0.10	0.33	0.16	153
66	0.02	0.55	0.04	20
67	0.04	0.25	0.07	52
68	0.35	0.49	0.41	593
69	0.01	0.75	0.02	4
70	0.00	0.17	0.01	6
71	0.01	0.10	0.02	21
72	0.02	0.25	0.03	12
73	0.00	0.50	0.01	2
74	0.01	0.09	0.01	11
75	0.01	0.40	0.02	5
76	0.01	0.22	0.02	9
77	0.03	0.53	0.05	15
78	0.00	0.00	0.00	4
79	0.01	0.50	0.02	4
80	0.01	0.14	0.02	14
81	0.00	0.00	0.00	3
82	0.02	0.25	0.04	20
83	0.01	0.06	0.01	36
84	0.00	0.11	0.01	9
85	0.02	0.50	0.03	6
86	0.00	0.00	0.00	0
87	0.00	0.50	0.00	2
88	0.11	0.24	0.15	248
89	0.01	0.33	0.02	3
90	0.02	0.16	0.03	25
91	0.10	0.26	0.15	200
92	0.01	0.33	0.02	9
93	0.03	0.28	0.06	50
94	0.01	0.08	0.01	13
95	0.02	0.21	0.04	34
96	0.01	0.12	0.01	17
97	0.09	0.51	0.15	47
98	0.00	1.00	0.00	1
99	0.05	0.17	0.07	81
100	0.13	0.40	0.20	100
101	0.04	0.50	0.08	18
102	0.01	1.00	0.02	3
103	0.00	0.00	0.00	5
104	0.01	0.30	0.02	10
105	0.01	0.33	0.02	6
106	0.00	0.67	0.01	3
107	0.03	0.43	0.05	14
108	0.01	0.09	0.02	22
109	0.05	0.31	0.09	54
110	0.01	0.31	0.03	13
111	0.02	0.42	0.03	12
112	0.00	0.00	0.00	0
113	0.03	0.30	0.06	33

114	0.17	0.33	0.22	269
115	0.04	0.24	0.06	51
116	0.03	0.32	0.06	34
117	0.01	0.25	0.01	4
118	0.12	0.36	0.18	91
119	0.00	0.00	0.00	5
120	0.00	0.09	0.01	11
121	0.04	0.29	0.07	28
122	0.00	0.00	0.00	9
123	0.28	0.46	0.35	166
124	0.01	0.17	0.02	18
125	0.01	0.14	0.01	7
126	0.00	0.00	0.00	13
127	0.15	0.28	0.19	239
128	0.25	0.57	0.35	276
129	0.00	0.17	0.01	6
130	0.04	0.17	0.06	35
131	0.04	0.46	0.07	13
132	0.00	0.50	0.00	2
133	0.00	0.00	0.00	5
134	0.00	0.50	0.01	2
135	0.00	0.00	0.00	2
136	0.07	0.35	0.11	75
137	0.01	0.29	0.01	7
138	0.07	0.34	0.12	67
139	0.19	0.33	0.24	318
140	0.04	0.60	0.08	10
141	0.00	0.14	0.01	7
avg / total	0.16	0.37	0.21	9020

Time taken to run this cell : 0:00:30.039634

In [0]:

```
start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(LogisticRegression(C=0.00001, class_weight="balanced"
), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)

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


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

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(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 : 0.0
Hamming loss  0.1783134705669917
Micro-average quality numbers
Precision: 0.0807, Recall: 0.7040, F1-measure: 0.1447
Macro-average quality numbers
Precision: 0.0484, Recall: 0.4170, F1-measure: 0.0796
              precision    recall  f1-score   support

           0       0.02      0.40      0.04        35
           1       0.07      0.94      0.14       117
           2       0.05      0.58      0.09        26
           3       0.01      0.18      0.01        11
           4       0.03      0.77      0.05        13
           5       0.03      0.65      0.06        26
           6       0.04      0.60      0.07        15
           7       0.04      0.83      0.07        75
           8       0.01      0.25      0.03         4
           9       0.02      0.29      0.04        31
          10       0.04      0.50      0.08         8
          11       0.01      0.30      0.02        20
          12       0.03      0.91      0.06        79
          13       0.01      0.33      0.02         9
          14       0.00      0.00      0.00         3
          15       0.02      0.33      0.03        15
          16       0.00      0.09      0.01        11
          17       0.07      0.57      0.12       120
          18       0.04      0.21      0.06        24
          19       0.04      0.47      0.07        72
          20       0.14      0.95      0.24       351
          21       0.03      0.62      0.06        32
          22       0.02      0.46      0.04        35
          23       0.02      0.41      0.04        29
          24       0.03      0.82      0.05        49
          25       0.07      0.87      0.12       142
          26       0.06      0.68      0.12        65
          27       0.01      0.30      0.02        10
          28       0.18      0.98      0.30       515
          29       0.06      0.91      0.10        90
          30       0.05      0.85      0.10        65
          31       0.01      0.22      0.02         9
          32       0.04      0.67      0.08        21
          33       0.04      0.74      0.08        54
          34       0.04      0.47      0.07        19
          35       0.02      0.46      0.04        26
          36       0.08      0.91      0.14        78
          37       0.07      0.87      0.13       150
          38       0.05      0.68      0.09        82
          39       0.02      0.21      0.04        19
          40       0.05      0.50      0.09        28
          41       0.00      0.00      0.00         5
          42       0.05      0.62      0.09        60
          43       0.40      0.87      0.55       885
          44       0.04      0.77      0.08        66
          45       0.10      0.91      0.18       111
          46       0.00      0.00      0.00         1
          47       0.03      0.66      0.06        38
          48       0.02      0.55      0.05        31
          49       0.02      0.45      0.04        33
          50       0.00      0.00      0.00         0
          51       0.05      0.62      0.10        42
          52       0.09      0.87      0.16       229
```

53	0.03	0.49	0.06	47
54	0.01	0.25	0.02	8
55	0.01	0.46	0.02	24
56	0.11	0.94	0.20	268
57	0.13	0.86	0.23	311
58	0.08	0.80	0.15	142
59	0.09	0.69	0.16	138
60	0.06	0.81	0.10	53
61	0.04	0.80	0.07	49
62	0.03	0.48	0.05	61
63	0.02	0.49	0.04	37
64	0.00	0.00	0.00	6
65	0.08	0.90	0.15	153
66	0.02	0.55	0.04	20
67	0.02	0.73	0.05	52
68	0.27	0.93	0.42	593
69	0.09	0.50	0.15	4
70	0.00	0.00	0.00	6
71	0.01	0.05	0.02	21
72	0.03	0.25	0.06	12
73	0.00	0.00	0.00	2
74	0.02	0.09	0.04	11
75	0.07	0.40	0.12	5
76	0.02	0.22	0.03	9
77	0.04	0.60	0.07	15
78	0.00	0.00	0.00	4
79	0.00	0.00	0.00	4
80	0.01	0.14	0.02	14
81	0.00	0.00	0.00	3
82	0.02	0.10	0.04	20
83	0.01	0.22	0.02	36
84	0.02	0.11	0.03	9
85	0.04	0.33	0.08	6
86	0.00	0.00	0.00	0
87	0.00	0.00	0.00	2
88	0.10	0.87	0.18	248
89	0.00	0.00	0.00	3
90	0.03	0.52	0.06	25
91	0.11	0.39	0.17	200
92	0.03	0.33	0.06	9
93	0.03	0.74	0.06	50
94	0.00	0.00	0.00	13
95	0.03	0.38	0.05	34
96	0.01	0.12	0.02	17
97	0.08	0.70	0.14	47
98	0.00	0.00	0.00	1
99	0.06	0.35	0.10	81
100	0.11	0.68	0.19	100
101	0.06	0.67	0.11	18
102	0.07	1.00	0.13	3
103	0.00	0.00	0.00	5
104	0.02	0.20	0.03	10
105	0.03	0.33	0.05	6
106	0.00	0.00	0.00	3
107	0.04	0.57	0.08	14
108	0.01	0.05	0.01	22
109	0.06	0.50	0.10	54
110	0.02	0.15	0.03	13
111	0.05	0.17	0.07	12
112	0.00	0.00	0.00	0
113	0.05	0.52	0.09	33

```
         114       0.17      0.47      0.25       269
         115       0.04      0.53      0.07        51
         116       0.04      0.56      0.08        34
         117       0.03      0.25      0.06         4
         118       0.10      0.46      0.17        91
         119       0.00      0.00      0.00         5
         120       0.03      0.09      0.04        11
         121       0.09      0.25      0.13        28
         122       0.01      0.11      0.02         9
         123       0.50      0.37      0.42       166
         124       0.01      0.11      0.02        18
         125       0.00      0.00      0.00         7
         126       0.00      0.00      0.00        13
         127       0.16      0.49      0.24       239
         128       0.29      0.61      0.39       276
         129       0.00      0.00      0.00         6
         130       0.08      0.23      0.12        35
         131       0.07      0.77      0.13        13
         132       0.00      0.00      0.00         2
         133       0.01      0.20      0.02         5
         134       0.00      0.00      0.00         2
         135       0.00      0.00      0.00         2
         136       0.05      0.67      0.09        75
         137       0.00      0.00      0.00         7
         138       0.05      0.27      0.08        67
         139       0.20      0.56      0.29       318
         140       0.07      0.70      0.13        10
         141       0.00      0.00      0.00         7

 avg / total       0.15      0.70      0.22      9020

Time taken to run this cell : 0:01:18.687766
```

Linear SVM :-

In [0]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()
model_to_set = OneVsRestClassifier(SGDClassifier(loss='hinge', penalty='l1'))

parameters = {
    "estimator__alpha": [10**-5, 10**-3, 10**-2, 10**1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabel, y_train)

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

```
0.17046158034897937
{'estimator__alpha': 1e-05}
Time taken to run this cell : 0:10:13.612452
```

In [0]:

```
start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.00001, penalty='l
1', class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)

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


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

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(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 : 0.0
Hamming loss  0.12170696242230712
Micro-average quality numbers
Precision: 0.0656, Recall: 0.3532, F1-measure: 0.1106
Macro-average quality numbers
Precision: 0.0480, Recall: 0.3006, F1-measure: 0.0724
              precision    recall  f1-score   support

           0       0.02      0.23      0.04        35
           1       0.11      0.38      0.17       117
           2       0.04      0.46      0.08        26
           3       0.01      0.18      0.01        11
           4       0.02      0.69      0.04        13
           5       0.02      0.31      0.05        26
           6       0.02      0.47      0.04        15
           7       0.03      0.15      0.05        75
           8       0.00      0.25      0.01         4
           9       0.02      0.19      0.04        31
          10       0.02      0.62      0.05         8
          11       0.01      0.15      0.02        20
          12       0.05      0.35      0.09        79
          13       0.01      0.56      0.02         9
          14       0.00      0.33      0.01         3
          15       0.02      0.33      0.04        15
          16       0.01      0.27      0.01        11
          17       0.05      0.19      0.08       120
          18       0.02      0.17      0.04        24
          19       0.06      0.21      0.09        72
          20       0.19      0.39      0.26       351
          21       0.02      0.25      0.04        32
          22       0.02      0.14      0.03        35
          23       0.03      0.24      0.05        29
          24       0.04      0.29      0.06        49
          25       0.10      0.34      0.16       142
          26       0.08      0.38      0.13        65
          27       0.01      0.30      0.02        10
          28       0.21      0.35      0.26       515
          29       0.12      0.48      0.19        90
          30       0.11      0.63      0.19        65
          31       0.01      0.33      0.02         9
          32       0.05      0.52      0.09        21
          33       0.04      0.33      0.08        54
          34       0.03      0.42      0.06        19
          35       0.03      0.23      0.05        26
          36       0.13      0.62      0.22        78
          37       0.09      0.32      0.15       150
          38       0.08      0.33      0.13        82
          39       0.02      0.32      0.03        19
          40       0.03      0.50      0.06        28
          41       0.00      0.00      0.00         5
          42       0.04      0.22      0.07        60
          43       0.45      0.49      0.47       885
          44       0.05      0.27      0.08        66
          45       0.14      0.57      0.23       111
          46       0.00      0.00      0.00         1
          47       0.04      0.42      0.08        38
          48       0.03      0.29      0.05        31
          49       0.02      0.18      0.04        33
          50       0.00      0.00      0.00         0
          51       0.05      0.36      0.09        42
          52       0.12      0.31      0.17       229
```

53	0.04	0.23	0.06	47
54	0.01	0.38	0.03	8
55	0.01	0.21	0.02	24
56	0.16	0.37	0.22	268
57	0.14	0.32	0.20	311
58	0.14	0.36	0.20	142
59	0.12	0.34	0.18	138
60	0.08	0.49	0.13	53
61	0.03	0.24	0.06	49
62	0.03	0.13	0.05	61
63	0.02	0.19	0.03	37
64	0.00	0.33	0.01	6
65	0.09	0.27	0.13	153
66	0.02	0.45	0.04	20
67	0.03	0.19	0.05	52
68	0.35	0.46	0.40	593
69	0.01	0.50	0.02	4
70	0.00	0.00	0.00	6
71	0.01	0.10	0.03	21
72	0.03	0.33	0.05	12
73	0.01	1.00	0.02	2
74	0.01	0.09	0.01	11
75	0.01	0.40	0.02	5
76	0.01	0.33	0.03	9
77	0.03	0.53	0.05	15
78	0.00	0.00	0.00	4
79	0.00	0.25	0.01	4
80	0.02	0.29	0.03	14
81	0.00	0.00	0.00	3
82	0.03	0.30	0.05	20
83	0.01	0.06	0.01	36
84	0.01	0.22	0.02	9
85	0.02	0.50	0.04	6
86	0.00	0.00	0.00	0
87	0.00	0.50	0.00	2
88	0.13	0.29	0.18	248
89	0.01	0.33	0.02	3
90	0.02	0.24	0.04	25
91	0.10	0.24	0.14	200
92	0.01	0.33	0.03	9
93	0.04	0.26	0.07	50
94	0.01	0.08	0.01	13
95	0.03	0.21	0.05	34
96	0.01	0.18	0.02	17
97	0.09	0.51	0.15	47
98	0.00	1.00	0.00	1
99	0.04	0.14	0.06	81
100	0.12	0.38	0.19	100
101	0.04	0.44	0.07	18
102	0.01	1.00	0.03	3
103	0.00	0.00	0.00	5
104	0.01	0.30	0.02	10
105	0.01	0.33	0.01	6
106	0.01	0.67	0.01	3
107	0.03	0.50	0.05	14
108	0.02	0.23	0.03	22
109	0.05	0.24	0.08	54
110	0.01	0.31	0.03	13
111	0.02	0.42	0.03	12
112	0.00	0.00	0.00	0
113	0.04	0.30	0.07	33

```
        114       0.15      0.31      0.20       269
        115       0.03      0.18      0.05        51
        116       0.03      0.24      0.05        34
        117       0.00      0.00      0.00         4
        118       0.11      0.34      0.17        91
        119       0.00      0.00      0.00         5
        120       0.01      0.18      0.01        11
        121       0.03      0.25      0.06        28
        122       0.00      0.00      0.00         9
        123       0.30      0.42      0.35       166
        124       0.02      0.39      0.05        18
        125       0.01      0.14      0.01         7
        126       0.00      0.00      0.00        13
        127       0.16      0.29      0.21       239
        128       0.26      0.49      0.34       276
        129       0.00      0.00      0.00         6
        130       0.05      0.29      0.08        35
        131       0.03      0.46      0.05        13
        132       0.00      0.00      0.00         2
        133       0.00      0.00      0.00         5
        134       0.00      0.00      0.00         2
        135       0.00      0.00      0.00         2
        136       0.06      0.31      0.10        75
        137       0.00      0.14      0.01         7
        138       0.07      0.31      0.11        67
        139       0.18      0.35      0.24       318
        140       0.05      0.70      0.10        10
        141       0.01      0.29      0.02         7

avg / total       0.16      0.35      0.21      9020

Time taken to run this cell : 0:00:30.975755
```

Featurizing data with TfIdf vectorizer

In [0]:

```
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=0.0009, max_features=50000, 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['preprocessed_data'])
x_test_multilabel = vectorizer.transform(x_test['preprocessed_data'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:30.167028
```

In [0]:

```
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: (11816, 50000) Y : (11816, 142)
Dimensions of test data X: (2964, 50000) Y: (2964, 142)
```

Applying Logistic Regression with OneVsRest Classifier

In [0]:

```
#from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import GridSearchCV
start = datetime.now()

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

parameters = {
    "estimator__alpha": [10**-5, 10**-3, 10**-1, 10**1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabel, y_train)

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

```
0.15835410206450806
{'estimator__alpha': 1e-05}
Time taken to run this cell : 0:01:34.344331
```

In [0]:

```
start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0001, penalty='l2',
class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)

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


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

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(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 : 0.005398110661268556
Hamming loss  0.05500038014863812
Micro-average quality numbers
Precision: 0.1586, Recall: 0.3639, F1-measure: 0.2209
Macro-average quality numbers
Precision: 0.0733, Recall: 0.1752, F1-measure: 0.0969
```

	precision	recall	f1-score	support
0	0.07	0.09	0.08	35
1	0.14	0.42	0.21	117
2	0.10	0.12	0.11	26
3	0.07	0.18	0.10	11
4	0.14	0.38	0.20	13
5	0.04	0.08	0.05	26
6	0.03	0.07	0.04	15
7	0.07	0.17	0.10	75
8	0.00	0.00	0.00	4
9	0.04	0.03	0.04	31
10	0.03	0.12	0.05	8
11	0.04	0.05	0.05	20
12	0.09	0.15	0.11	79
13	0.03	0.11	0.05	9
14	0.00	0.00	0.00	3
15	0.09	0.13	0.11	15
16	0.03	0.09	0.05	11
17	0.09	0.22	0.12	120
18	0.06	0.17	0.09	24
19	0.08	0.17	0.11	72
20	0.23	0.46	0.30	351
21	0.00	0.00	0.00	32
22	0.06	0.09	0.07	35
23	0.06	0.07	0.06	29
24	0.03	0.06	0.04	49
25	0.14	0.38	0.20	142
26	0.17	0.29	0.21	65
27	0.03	0.10	0.05	10
28	0.26	0.42	0.32	515
29	0.20	0.41	0.27	90
30	0.18	0.49	0.26	65
31	0.02	0.11	0.04	9
32	0.17	0.38	0.23	21
33	0.09	0.13	0.10	54
34	0.15	0.26	0.19	19
35	0.03	0.04	0.03	26
36	0.22	0.51	0.31	78
37	0.13	0.30	0.19	150
38	0.13	0.24	0.17	82
39	0.02	0.05	0.03	19
40	0.02	0.04	0.03	28
41	0.00	0.00	0.00	5
42	0.05	0.10	0.07	60
43	0.49	0.69	0.57	885
44	0.11	0.24	0.15	66
45	0.20	0.53	0.29	111
46	0.00	0.00	0.00	1
47	0.07	0.13	0.09	38
48	0.05	0.10	0.06	31
49	0.04	0.06	0.04	33
50	0.00	0.00	0.00	0
51	0.07	0.07	0.07	42
52	0.15	0.30	0.20	229

53	0.06	0.09	0.07	47
54	0.00	0.00	0.00	8
55	0.02	0.04	0.03	24
56	0.17	0.38	0.23	268
57	0.19	0.34	0.24	311
58	0.16	0.33	0.21	142
59	0.14	0.29	0.19	138
60	0.18	0.38	0.24	53
61	0.07	0.10	0.08	49
62	0.03	0.05	0.03	61
63	0.03	0.05	0.04	37
64	0.01	0.17	0.03	6
65	0.13	0.37	0.19	153
66	0.06	0.10	0.08	20
67	0.02	0.04	0.03	52
68	0.39	0.63	0.48	593
69	0.02	0.25	0.04	4
70	0.00	0.00	0.00	6
71	0.06	0.05	0.05	21
72	0.03	0.08	0.05	12
73	0.02	0.50	0.03	2
74	0.00	0.00	0.00	11
75	0.04	0.40	0.07	5
76	0.03	0.22	0.06	9
77	0.08	0.20	0.12	15
78	0.00	0.00	0.00	4
79	0.00	0.00	0.00	4
80	0.00	0.00	0.00	14
81	0.00	0.00	0.00	3
82	0.04	0.05	0.04	20
83	0.00	0.00	0.00	36
84	0.00	0.00	0.00	9
85	0.00	0.00	0.00	6
86	0.00	0.00	0.00	0
87	0.00	0.00	0.00	2
88	0.16	0.37	0.22	248
89	0.02	0.33	0.04	3
90	0.00	0.00	0.00	25
91	0.11	0.26	0.15	200
92	0.02	0.11	0.04	9
93	0.05	0.08	0.06	50
94	0.03	0.08	0.04	13
95	0.06	0.09	0.07	34
96	0.00	0.00	0.00	17
97	0.26	0.43	0.33	47
98	0.01	1.00	0.01	1
99	0.06	0.07	0.07	81
100	0.18	0.44	0.25	100
101	0.13	0.39	0.19	18
102	0.03	0.67	0.05	3
103	0.01	0.20	0.02	5
104	0.05	0.10	0.07	10
105	0.03	0.33	0.05	6
106	0.00	0.00	0.00	3
107	0.11	0.29	0.15	14
108	0.06	0.05	0.05	22
109	0.09	0.19	0.12	54
110	0.03	0.08	0.04	13
111	0.02	0.08	0.03	12
112	0.00	0.00	0.00	0
113	0.02	0.03	0.03	33

```
        114       0.17      0.43      0.24       269
        115       0.03      0.04      0.04        51
        116       0.05      0.09      0.06        34
        117       0.00      0.00      0.00         4
        118       0.19      0.31      0.23        91
        119       0.00      0.00      0.00         5
        120       0.02      0.09      0.03        11
        121       0.10      0.14      0.11        28
        122       0.00      0.00      0.00         9
        123       0.38      0.47      0.42       166
        124       0.00      0.00      0.00        18
        125       0.00      0.00      0.00         7
        126       0.00      0.00      0.00        13
        127       0.17      0.39      0.24       239
        128       0.31      0.63      0.41       276
        129       0.01      0.17      0.02         6
        130       0.11      0.06      0.07        35
        131       0.09      0.31      0.14        13
        132       0.00      0.00      0.00         2
        133       0.00      0.00      0.00         5
        134       0.00      0.00      0.00         2
        135       0.00      0.00      0.00         2
        136       0.09      0.28      0.13        75
        137       0.00      0.00      0.00         7
        138       0.08      0.15      0.11        67
        139       0.21      0.45      0.28       318
        140       0.12      0.30      0.18        10
        141       0.00      0.00      0.00         7

avg / total       0.20      0.36      0.25      9020

Time taken to run this cell : 0:00:20.134000
```

Linear SVM :-

In [0]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()
model_to_set = OneVsRestClassifier(SGDClassifier(loss='hinge', penalty='l1'))

parameters = {
    "estimator__alpha": [10**-5, 10**-3, 10**-2, 10**1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_jobs=-1)

model_tunning.fit(x_train_multilabel, y_train)

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

```
0.15155415487444512
{'estimator__alpha': 1e-05}
Time taken to run this cell : 0:09:01.232018
```

In [0]:

```
start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=0.0001, penalty='l2'
, class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict(x_test_multilabel)

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


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

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(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 : 0.0023616734143049934
Hamming loss  0.0660840888787516
Micro-average quality numbers
Precision: 0.1254, Recall: 0.3488, F1-measure: 0.1845
Macro-average quality numbers
Precision: 0.0641, Recall: 0.2168, F1-measure: 0.0883
              precision    recall  f1-score   support

           0       0.05      0.09      0.06        35
           1       0.17      0.35      0.23       117
           2       0.03      0.12      0.05        26
           3       0.04      0.18      0.07        11
           4       0.08      0.54      0.15        13
           5       0.02      0.08      0.03        26
           6       0.03      0.40      0.05        15
           7       0.06      0.24      0.10        75
           8       0.00      0.00      0.00         4
           9       0.03      0.03      0.03        31
          10       0.03      0.38      0.06         8
          11       0.03      0.05      0.04        20
          12       0.09      0.22      0.12        79
          13       0.02      0.22      0.04         9
          14       0.02      0.67      0.04         3
          15       0.03      0.13      0.05        15
          16       0.00      0.00      0.00        11
          17       0.09      0.17      0.11       120
          18       0.05      0.12      0.07        24
          19       0.06      0.11      0.08        72
          20       0.22      0.41      0.29       351
          21       0.03      0.06      0.04        32
          22       0.06      0.09      0.07        35
          23       0.04      0.07      0.05        29
          24       0.02      0.04      0.03        49
          25       0.14      0.35      0.20       142
          26       0.13      0.35      0.19        65
          27       0.01      0.10      0.02        10
          28       0.25      0.43      0.32       515
          29       0.19      0.41      0.26        90
          30       0.16      0.51      0.24        65
          31       0.01      0.33      0.03         9
          32       0.13      0.52      0.21        21
          33       0.09      0.20      0.13        54
          34       0.06      0.32      0.10        19
          35       0.02      0.04      0.02        26
          36       0.18      0.46      0.26        78
          37       0.12      0.27      0.17       150
          38       0.11      0.27      0.16        82
          39       0.02      0.11      0.04        19
          40       0.03      0.07      0.04        28
          41       0.00      0.00      0.00         5
          42       0.02      0.03      0.02        60
          43       0.48      0.62      0.54       885
          44       0.10      0.14      0.12        66
          45       0.16      0.44      0.24       111
          46       0.00      0.00      0.00         1
          47       0.08      0.24      0.12        38
          48       0.03      0.03      0.03        31
          49       0.06      0.06      0.06        33
          50       0.00      0.00      0.00         0
          51       0.07      0.12      0.09        42
          52       0.14      0.28      0.18       229
```

53	0.04	0.04	0.04	47
54	0.00	0.00	0.00	8
55	0.01	0.04	0.02	24
56	0.16	0.32	0.22	268
57	0.16	0.33	0.22	311
58	0.17	0.35	0.22	142
59	0.18	0.25	0.20	138
60	0.15	0.42	0.22	53
61	0.07	0.12	0.09	49
62	0.01	0.03	0.02	61
63	0.03	0.05	0.04	37
64	0.01	0.17	0.03	6
65	0.13	0.30	0.18	153
66	0.03	0.10	0.05	20
67	0.03	0.06	0.04	52
68	0.36	0.63	0.46	593
69	0.03	0.75	0.06	4
70	0.00	0.00	0.00	6
71	0.02	0.05	0.03	21
72	0.02	0.25	0.04	12
73	0.01	0.50	0.02	2
74	0.01	0.09	0.02	11
75	0.02	0.40	0.03	5
76	0.02	0.22	0.03	9
77	0.05	0.40	0.08	15
78	0.00	0.00	0.00	4
79	0.00	0.00	0.00	4
80	0.02	0.07	0.03	14
81	0.00	0.33	0.01	3
82	0.02	0.05	0.03	20
83	0.00	0.00	0.00	36
84	0.00	0.00	0.00	9
85	0.01	0.17	0.02	6
86	0.00	0.00	0.00	0
87	0.00	0.00	0.00	2
88	0.15	0.35	0.21	248
89	0.01	0.33	0.02	3
90	0.00	0.00	0.00	25
91	0.10	0.26	0.15	200
92	0.01	0.22	0.03	9
93	0.05	0.12	0.07	50
94	0.02	0.08	0.03	13
95	0.05	0.09	0.07	34
96	0.00	0.00	0.00	17
97	0.22	0.43	0.29	47
98	0.00	1.00	0.01	1
99	0.06	0.11	0.08	81
100	0.18	0.47	0.26	100
101	0.07	0.44	0.11	18
102	0.03	1.00	0.05	3
103	0.01	0.20	0.02	5
104	0.02	0.30	0.03	10
105	0.02	0.33	0.04	6
106	0.01	0.33	0.01	3
107	0.07	0.43	0.11	14
108	0.03	0.05	0.03	22
109	0.07	0.15	0.10	54
110	0.01	0.08	0.02	13
111	0.02	0.25	0.03	12
112	0.00	0.00	0.00	0
113	0.02	0.06	0.03	33

```
        114       0.16      0.38      0.22       269
        115       0.06      0.12      0.08        51
        116       0.06      0.15      0.09        34
        117       0.00      0.00      0.00         4
        118       0.19      0.30      0.23        91
        119       0.00      0.00      0.00         5
        120       0.01      0.09      0.03        11
        121       0.07      0.14      0.09        28
        122       0.00      0.00      0.00         9
        123       0.41      0.43      0.42       166
        124       0.02      0.11      0.03        18
        125       0.03      0.57      0.05         7
        126       0.00      0.00      0.00        13
        127       0.17      0.38      0.24       239
        128       0.29      0.59      0.39       276
        129       0.01      0.17      0.01         6
        130       0.08      0.11      0.09        35
        131       0.08      0.77      0.14        13
        132       0.00      0.00      0.00         2
        133       0.00      0.00      0.00         5
        134       0.00      0.00      0.00         2
        135       0.00      0.00      0.00         2
        136       0.07      0.24      0.11        75
        137       0.00      0.00      0.00         7
        138       0.07      0.16      0.10        67
        139       0.19      0.33      0.24       318
        140       0.08      0.70      0.14        10
        141       0.00      0.00      0.00         7

avg / total       0.19      0.35      0.24      9020

Time taken to run this cell : 0:00:19.604080
```

Performance of baseline Models:

In [0]:

```
from prettytable import PrettyTable
ptable = PrettyTable()

ptable.title = " Comparison of Performances "
ptable.field_names = ['Model','Hyperparameter', 'Precession','Recall','F1-Score']
ptable.add_row(["Logistic Regression (BOW)","0.00001","0.19", "0.18", '0.19'])
ptable.add_row(["Linear SVM (BOW)", "0.00001", "0.18", "0.17", '0.18'])
ptable.add_row(["Logistic Regression (Tfidf)", "0.00001", "0.26", "0.11", '0.15'])
ptable.add_row(["Linear SVM (Tfidf)", "0.00001", "0.22", "0.14", '0.16'])

print(ptable)
```

```
+-----------------------------+----------------+------------+--------+----
------+
|            Model            | Hyperparameter | Precession | Recall | F1-
Score |
+-----------------------------+----------------+------------+--------+----
------+
|  Logistic Regression (BOW)  |    0.00001     |    0.19    |  0.18  |
0.19   |
|       Linear SVM (BOW)      |    0.00001     |    0.18    |  0.17  |
0.18   |
| Logistic Regression (Tfidf) |    0.00001     |    0.26    |  0.11  |
0.15   |
|      Linear SVM (Tfidf)     |    0.00001     |    0.22    |  0.14  |
0.16   |
+-----------------------------+----------------+------------+--------+----
------+
```

Model not performing well so considering more feature engineering

Feature Engineering:

In [3]:

```
# Code to read csv file into Colaboratory from google drive:

!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

```
     |████████████████████████████████| 993kB 3.4MB/s
  Building wheel for PyDrive (setup.py) ... done
```

In [0]:

```
final = 'https://drive.google.com/open?id=15aSHHI7Fys2OuSoZGe3iPpOgEpOKGfRj'
```

In [5]:

```
fluff, id5 = final.split('=')

print (id5)
```

```
15aSHHI7Fys2OuSoZGe3iPpOgEpOKGfRj
```

In [0]:

```
downloaded5 = drive.CreateFile({'id':id5})
downloaded5.GetContentFile('final_data')
```

In [0]:

```
new_data = pd.read_pickle("final_data")
```

In [0]:

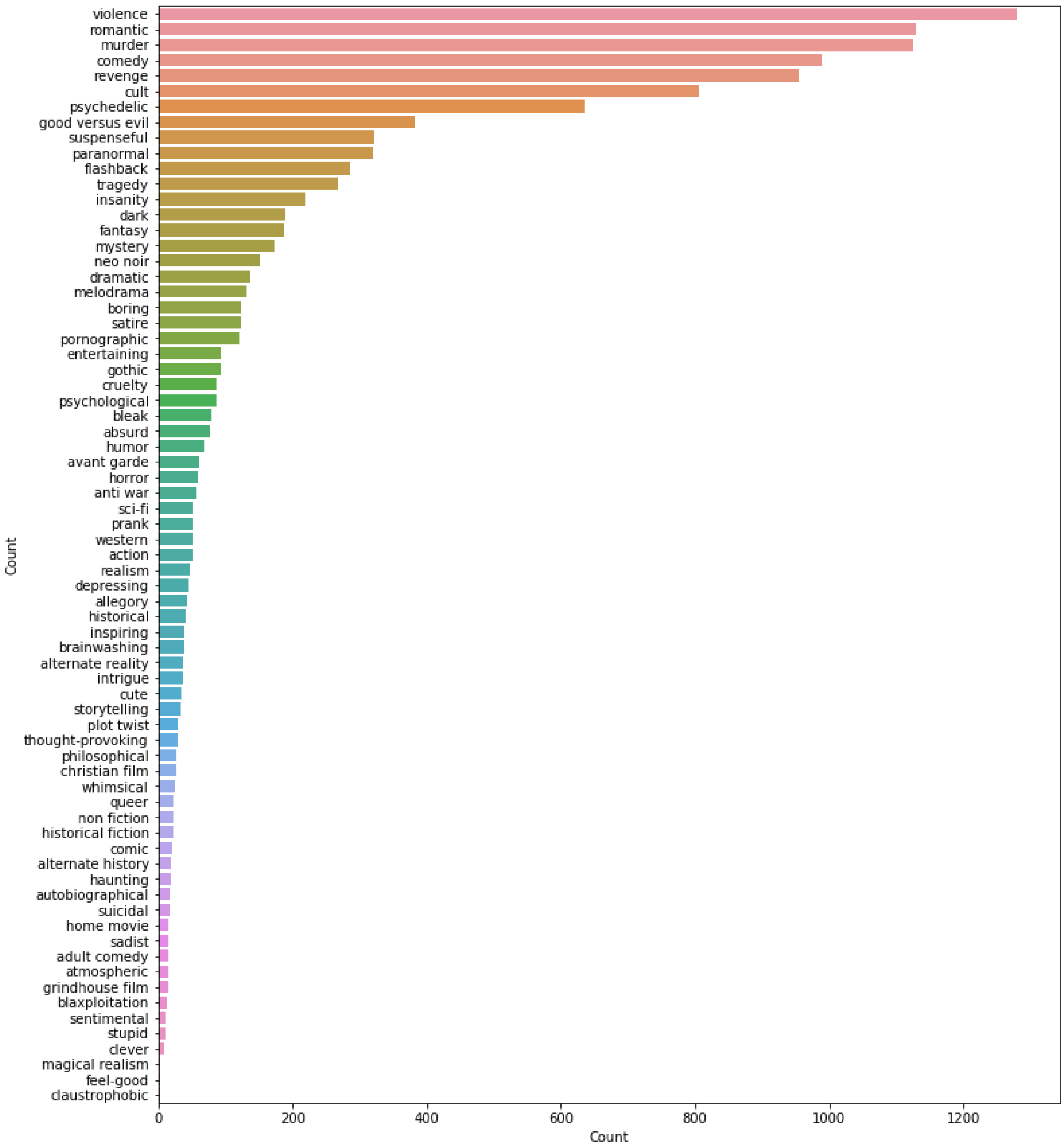
```
X = new_data['preprocessed_data']
y = new_data['tags']
```

In [0]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, random_state=
42)
```

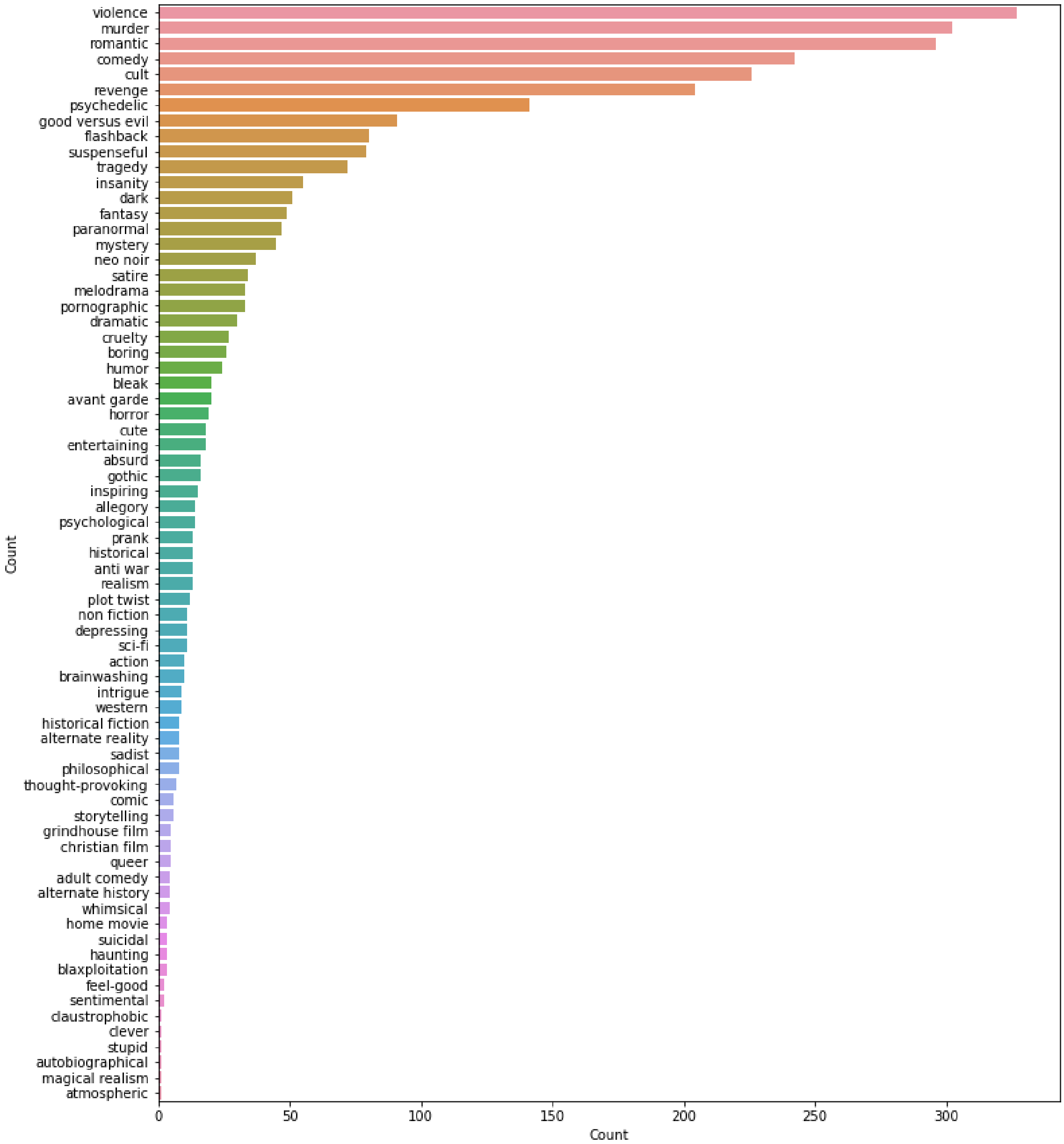
In [15]:

```
# checking the uniformity of the tags

import nltk
all_genres = nltk.FreqDist(y_train.apply(lambda x: x.split(',')[0]))
all_genres_df = pd.DataFrame({'Genre': list(all_genres.keys()), 'Count': list(all_genre
s.values())})

g = all_genres_df.nlargest(columns="Count", n = 100)
plt.figure(figsize=(12,15))
ax = sns.barplot(data=g, x= "Count", y = "Genre")
ax.set(ylabel = 'Count')
plt.show()
```


violence
romantic
murder
comedy
revenge
cult
psychedelic
good versus evil
suspenseful
paranormal
flashback
tragedy
insanity
dark
fantasy
mystery
neo noir
dramatic
melodrama
boring
satire
pornographic
entertaining
gothic
cruelty
psychological
bleak
absurd
humor
avant garde
horror
anti war
sci-fi
prank
western
action
realism
depressing
allegory
historical
inspiring
brainwashing
alternate reality
intrigue
cute
storytelling
plot twist
thought-provoking
philosophical
christian film
whimsical
queer
non fiction
historical fiction
comic
alternate history
haunting
autobiographical
suicidal
home movie
sadist
adult comedy
atmospheric
grindhouse film
blaxploitation
sentimental
stupid
clever
magical realism
feel-good
claustrophobic
Count
0
200
400
600
800
1000
1200
Count

In [16]:

```
import nltk
all_genres = nltk.FreqDist(y_test.apply(lambda x: x.split(',')[0]))
all_genres_df = pd.DataFrame({'Genre': list(all_genres.keys()), 'Count': list(all_genre
s.values())})
g = all_genres_df.nlargest(columns="Count", n = 100)
plt.figure(figsize=(12,15))
ax = sns.barplot(data=g, x= "Count", y = "Genre")
ax.set(ylabel = 'Count')
plt.show()
```



Since the number of tags are completely unbalanced and few of them are not of that importance. So we would try to reduce the number of tags by analysing them.

Converting tags for multilabel problems

We have seen above that the distribution of tags per synopsis isn't uniform. Some of the synopsis have >20 tags wheras some have 1 tag. But the in an average the number of tags per synopsis is 2.9 (see EDA). So we would consider 4 tags per plot synopsis.

In [0]:

```
## Analysing tags

vectorizer = CountVectorizer(tokenizer = lambda x: x.split(','), binary='true', max_fea
tures = 4)
multilabel_y_train = vectorizer.fit_transform(y_train)
multilabel_y_test = vectorizer.transform(y_test)
```

Unigram

In [49]:

```
# unigram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2",
\
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram
_range=(1,1))
x_train_multilabe_uni = vectorizer.fit_transform(X_train)
x_test_multilabel_uni = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:03.874541
```

In [62]:

```
#from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l
2', class_weight="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabe_uni, multilabel_y_train)

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

```
0.4297968028569633
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:03.524394
```

In [63]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabe_uni, multilabel_y_train)
predictions = classifier.predict (x_test_multilabel_uni)

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


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

```
Accuracy : 0.3318673883626522
Hamming loss  0.30294316644113667
Micro-average quality numbers
Precision: 0.3311, Recall: 0.6079, F1-measure: 0.4287
Macro-average quality numbers
Precision: 0.3223, Recall: 0.5954, F1-measure: 0.4118
              precision    recall  f1-score   support

           0       0.20      0.54      0.29       308
           1       0.25      0.53      0.34       507
           2       0.48      0.64      0.55       844
           3       0.36      0.68      0.47       552

   micro avg       0.33      0.61      0.43      2211
   macro avg       0.32      0.60      0.41      2211
weighted avg       0.36      0.61      0.44      2211
 samples avg       0.19      0.26      0.20      2211

Time taken to run this cell : 0:00:00.391169
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Bigram:

In [52]:

```
# bigram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2",
\
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram
_range=(2,2))
x_train_multilabe_bi = vectorizer.fit_transform(X_train)
x_test_multilabel_bi = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:31.653510
```

In [53]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l
2', class_weight="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabe_bi, multilabel_y_train)

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

```
0.40495992259001856
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:01.122359
```

In [67]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabe_bi, multilabel_y_train)
predictions = classifier.predict (x_test_multilabel_bi)

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


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

```
Accuracy : 0.37516914749661706
Hamming loss  0.2790933694181326
Micro-average quality numbers
Precision: 0.3450, Recall: 0.5482, F1-measure: 0.4235
Macro-average quality numbers
Precision: 0.3304, Recall: 0.5309, F1-measure: 0.4038
              precision    recall  f1-score   support

           0       0.21      0.46      0.29       308
           1       0.28      0.48      0.35       507
           2       0.46      0.59      0.52       844
           3       0.37      0.59      0.46       552

   micro avg       0.35      0.55      0.42      2211
   macro avg       0.33      0.53      0.40      2211
weighted avg       0.36      0.55      0.43      2211
 samples avg       0.17      0.23      0.18      2211

Time taken to run this cell : 0:00:00.104916

/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Trigram:

In [65]:

```python
# trigram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2", \
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram_range=(3,3))
x_train_multilabe_tri = vectorizer.fit_transform(X_train)
x_test_multilabel_tri = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:43.848315
```

In [66]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.00001, penalty='l
2', class_weight="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabe_tri, multilabel_y_train)

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

```
0.320370968053034
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:00.389017
```

In [68]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabe_tri, multilabel_y_train)
predictions = classifier.predict (x_test_multilabel_tri)

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


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

```
Accuracy : 0.2774018944519621
Hamming loss  0.35597090663058184
Micro-average quality numbers
Precision: 0.2381, Recall: 0.4107, F1-measure: 0.3014
Macro-average quality numbers
Precision: 0.2354, Recall: 0.4053, F1-measure: 0.2911
              precision    recall  f1-score   support

           0       0.13      0.37      0.19       308
           1       0.21      0.43      0.28       507
           2       0.35      0.42      0.38       844
           3       0.25      0.40      0.31       552

   micro avg       0.24      0.41      0.30      2211
   macro avg       0.24      0.41      0.29      2211
weighted avg       0.26      0.41      0.31      2211
 samples avg       0.14      0.18      0.14      2211

Time taken to run this cell : 0:00:00.062588

/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

ngram:

In [69]:

```
# 1 to 3 gram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2",
\
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram
_range=(1,3))
x_train_1 = vectorizer.fit_transform(X_train)
x_test_1 = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:25.980471
```

In [75]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_1, multilabel_y_train)

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

```
0.435374988842312106
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:04.791252
```

In [76]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_1, multilabel_y_train)
predictions = classifier.predict (x_test_1)

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


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

```
Accuracy : 0.33558863328822736
Hamming loss  0.2987144790257104
Micro-average quality numbers
Precision: 0.3353, Recall: 0.6083, F1-measure: 0.4323
Macro-average quality numbers
Precision: 0.3264, Recall: 0.5954, F1-measure: 0.4155
              precision    recall  f1-score   support

           0       0.20      0.54      0.29       308
           1       0.26      0.54      0.35       507
           2       0.48      0.64      0.55       844
           3       0.36      0.66      0.47       552

   micro avg       0.34      0.61      0.43      2211
   macro avg       0.33      0.60      0.42      2211
weighted avg       0.36      0.61      0.45      2211
 samples avg       0.19      0.26      0.20      2211

Time taken to run this cell : 0:00:00.389888


/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Unigram + bigram + ngram:

In [0]:

```
# combining features
from scipy.sparse import coo_matrix, hstack
train_1 = hstack((x_train_multilabe_uni, x_train_multilabe_bi),format="csr",dtype='floa
t64')
test_1 = hstack((x_test_multilabel_uni, x_test_multilabel_bi),format="csr",dtype='float
64')
```

In [0]:

```
train_2 = hstack((train_1, x_train_1),format="csr",dtype='float64')
test_2 = hstack((test_1, x_test_1),format="csr",dtype='float64')
```

In [84]:

```
#from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(train_2, multilabel_y_train)

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

```
0.44795244711069937
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:11.382344
```

In [88]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(train_2, multilabel_y_train)
predictions = classifier.predict (test_2)

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


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

```
Accuracy : 0.3623139377537212
Hamming loss  0.2834066305818674
Micro-average quality numbers
Precision: 0.3509, Recall: 0.6065, F1-measure: 0.4446
Macro-average quality numbers
Precision: 0.3358, Recall: 0.5894, F1-measure: 0.4232
              precision    recall  f1-score   support

           0       0.21      0.55      0.30       308
           1       0.28      0.47      0.35       507
           2       0.48      0.67      0.56       844
           3       0.38      0.68      0.48       552

   micro avg       0.35      0.61      0.44      2211
   macro avg       0.34      0.59      0.42      2211
weighted avg       0.37      0.61      0.46      2211
 samples avg       0.20      0.26      0.21      2211

Time taken to run this cell : 0:00:00.922825
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Char 3-gram:

In [89]:

```
vectorizer = TfidfVectorizer(sublinear_tf=True, strip_accents='unicode', analyzer='cha
r', ngram_range=(3, 3),  max_features=20000)
x_train_3char = vectorizer.fit_transform(X_train)
x_test_3char = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:07:23.299955
```

In [90]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_3char, multilabel_y_train)

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

```
0.46544995286032065
{'estimator__alpha': 0.0001}
Time taken to run this cell : 0:00:15.799001
```

In [94]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0001, penalty='l2',
class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_3char, multilabel_y_train)
predictions = classifier.predict (x_test_3char)

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


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

```
Accuracy : 0.3457374830852503
Hamming loss  0.2873815967523681
Micro-average quality numbers
Precision: 0.3567, Recall: 0.6680, F1-measure: 0.4651
Macro-average quality numbers
Precision: 0.3408, Recall: 0.6407, F1-measure: 0.4418
              precision    recall  f1-score   support

           0       0.22      0.52      0.31       308
           1       0.28      0.62      0.38       507
           2       0.49      0.74      0.59       844
           3       0.38      0.68      0.49       552

   micro avg       0.36      0.67      0.47      2211
   macro avg       0.34      0.64      0.44      2211
weighted avg       0.37      0.67      0.48      2211
 samples avg       0.21      0.28      0.23      2211

Time taken to run this cell : 0:00:01.148391

/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Char 4-gram:

In [95]:

```
vectorizer = TfidfVectorizer(sublinear_tf=True, strip_accents='unicode', analyzer='cha
r', ngram_range=(4, 4),  max_features=20000)
x_train_4char = vectorizer.fit_transform(X_train)
x_test_4char = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:38.516180
```

In [96]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_4char, multilabel_y_train)

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

```
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning

0.476084480394257
{'estimator__alpha': 0.0001}
Time taken to run this cell : 0:00:26.063463
```

In [104]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0001, penalty='l2',
class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_4char, multilabel_y_train)
predictions = classifier.predict (x_test_4char)

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


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

```
Accuracy : 0.38836265223274696
Hamming loss  0.25431326116373476
Micro-average quality numbers
Precision: 0.3917, Recall: 0.6508, F1-measure: 0.4890
Macro-average quality numbers
Precision: 0.3674, Recall: 0.6100, F1-measure: 0.4583
              precision    recall  f1-score   support

           0       0.28      0.44      0.34       308
           1       0.31      0.56      0.40       507
           2       0.48      0.77      0.59       844
           3       0.40      0.68      0.50       552

   micro avg       0.39      0.65      0.49      2211
   macro avg       0.37      0.61      0.46      2211
weighted avg       0.39      0.65      0.49      2211
 samples avg       0.22      0.28      0.23      2211

Time taken to run this cell : 0:00:01.852960
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Char (3-6gram) :

In [105]:

```
vectorizer = TfidfVectorizer(sublinear_tf=True, strip_accents='unicode', analyzer='cha
r', ngram_range=(3, 6),  max_features=20000)
x_train_36char = vectorizer.fit_transform(X_train)
x_test_36char = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:04:27.433399
```

In [106]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_36char, multilabel_y_train)

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

```
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning

0.47566124329486026
{'estimator__alpha': 0.0001}
Time taken to run this cell : 0:00:56.720863
```

In [111]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0001, penalty='l2',
class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_36char, multilabel_y_train)
predictions = classifier.predict (x_test_36char)

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


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

```
Accuracy : 0.34100135317997293
Hamming loss  0.2922868741542625
Micro-average quality numbers
Precision: 0.3557, Recall: 0.6943, F1-measure: 0.4704
Macro-average quality numbers
Precision: 0.3471, Recall: 0.6839, F1-measure: 0.4528
              precision    recall  f1-score   support

           0       0.20      0.70      0.32       308
           1       0.30      0.58      0.40       507
           2       0.49      0.76      0.60       844
           3       0.39      0.70      0.50       552

   micro avg       0.36      0.69      0.47      2211
   macro avg       0.35      0.68      0.45      2211
weighted avg       0.38      0.69      0.49      2211
 samples avg       0.21      0.29      0.23      2211

Time taken to run this cell : 0:00:03.987050
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Char 3gram + Char 4gram:

In [0]:

```
# combining features
from scipy.sparse import coo_matrix, hstack
train_10 = hstack((x_train_3char, x_train_4char),format="csr",dtype='float64')
test_10 = hstack((x_test_3char, x_test_4char),format="csr",dtype='float64')
```

In [0]:

```
train_11 = hstack((train_10, x_train_36char),format="csr",dtype='float64')
test_11 = hstack((test_10, x_test_36char),format="csr",dtype='float64')
```

In [118]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-2, 10**-1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(train_11, multilabel_y_train)

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

```
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
/usr/local/lib/python3.6/dist-packages/sklearn/externals/joblib/externals/
loky/process_executor.py:706: UserWarning: A worker stopped while some job
s were given to the executor. This can be caused by a too short worker tim
eout or by a memory leak.
  "timeout or by a memory leak.", UserWarning

0.46743534533011887
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:01:37.283418
```

In [127]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(train_11, multilabel_y_train)
predictions = classifier.predict (test_11)

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


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

```
Accuracy : 0.35182679296346414
Hamming loss  0.2868741542625169
Micro-average quality numbers
Precision: 0.3598, Recall: 0.6852, F1-measure: 0.4718
Macro-average quality numbers
Precision: 0.3514, Recall: 0.6693, F1-measure: 0.4551
              precision    recall  f1-score   support

           0       0.24      0.60      0.34       308
           1       0.27      0.68      0.39       507
           2       0.49      0.73      0.59       844
           3       0.41      0.67      0.51       552

   micro avg       0.36      0.69      0.47      2211
   macro avg       0.35      0.67      0.46      2211
weighted avg       0.38      0.69      0.49      2211
 samples avg       0.22      0.29      0.23      2211

Time taken to run this cell : 0:00:07.139096
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Combining all:

In [0]:

```
train_20 = hstack((train_11, train_2),format="csr",dtype='float64')
test_20 = hstack((test_11, test_2),format="csr",dtype='float64')
```

In [137]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(train_20, multilabel_y_train)
predictions = classifier.predict (test_20)

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


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

```
Accuracy : 0.36028416779431666
Hamming loss  0.2807848443843031
Micro-average quality numbers
Precision: 0.3648, Recall: 0.6766, F1-measure: 0.4740
Macro-average quality numbers
Precision: 0.3501, Recall: 0.6596, F1-measure: 0.4528
              precision    recall  f1-score   support

           0       0.23      0.63      0.33       308
           1       0.30      0.56      0.39       507
           2       0.49      0.75      0.59       844
           3       0.38      0.71      0.50       552

   micro avg       0.36      0.68      0.47      2211
   macro avg       0.35      0.66      0.45      2211
weighted avg       0.38      0.68      0.49      2211
 samples avg       0.21      0.29      0.23      2211

Time taken to run this cell : 0:00:08.722892
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
143: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in samples with no predicted labels.
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1
145: UndefinedMetricWarning: Recall and F-score are ill-defined and being
set to 0.0 in samples with no true labels.
  'recall', 'true', average, warn_for)
```

Models with 3 tags:

We have seen above that the distribution of tags per synopsis isn't uniform. Some of the synopsis have >20 tags wheras some have 1 tag. But the in an average the number of tags per synopsis is 2.9 (see EDA). So now we would consider 3 tags per plot synopsis.

In [0]:

```
## Analysing tags

vectorizer = CountVectorizer(tokenizer = lambda x: x.split(','), binary='true', max_fea
tures = 3)
multilabel_y_train = vectorizer.fit_transform(y_train)
multilabel_y_test = vectorizer.transform(y_test)
```

Unigram

In [141]:

```
# unigram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2",
\
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram
_range=(1,1))
x_train_multilabe_uni = vectorizer.fit_transform(X_train)
x_test_multilabel_uni = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:04.266203
```

In [142]:

```
#from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log',  penalty='l2', class_weigh
t="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabe_uni, multilabel_y_train)

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

```
0.46210357714474454
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:04.238473
```

In [144]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabe_uni, multilabel_y_train)
predictions = classifier.predict (x_test_multilabel_uni)

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


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

```
Accuracy : 0.3876860622462788
Hamming loss  0.3126973387460532
Micro-average quality numbers
Precision: 0.3664, Recall: 0.6269, F1-measure: 0.4625
Macro-average quality numbers
Precision: 0.3622, Recall: 0.6197, F1-measure: 0.4538
              precision    recall  f1-score   support

           0       0.26      0.52      0.34       507
           1       0.47      0.65      0.55       844
           2       0.36      0.68      0.47       552

   micro avg       0.37      0.63      0.46      1903
   macro avg       0.36      0.62      0.45      1903
weighted avg       0.38      0.63      0.47      1903
 samples avg       0.21      0.26      0.21      1903

Time taken to run this cell : 0:00:00.309143
```

Bigram:

In [145]:

```
# bigram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2", \
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram_range=(2,2))
x_train_multilabe_bi = vectorizer.fit_transform(X_train)
x_test_multilabel_bi = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:33.847608
```

In [146]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log',  penalty='l2', class_weight="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_jobs=-1)

model_tunning.fit(x_train_multilabe_bi, multilabel_y_train)

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

```
0.45157734638310426
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:01.016492
```

In [147]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabe_bi, multilabel_y_train)
predictions = classifier.predict (x_test_multilabel_bi)

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


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

```
Accuracy : 0.40933694181326 12
Hamming loss  0.3005187189896256
Micro-average quality numbers
Precision: 0.3704, Recall: 0.5723, F1-measure: 0.4497
Macro-average quality numbers
Precision: 0.3657, Recall: 0.5652, F1-measure: 0.4417
              precision    recall  f1-score   support

           0       0.27      0.50      0.35       507
           1       0.46      0.60      0.52       844
           2       0.37      0.60      0.46       552

   micro avg       0.37      0.57      0.45      1903
   macro avg       0.37      0.57      0.44      1903
weighted avg       0.38      0.57      0.46      1903
 samples avg       0.19      0.23      0.19      1903

Time taken to run this cell : 0:00:00.121753
```

Trigram:

In [148]:

```
# trigram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2",
\
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram
_range=(3,3))
x_train_multilabe_tri = vectorizer.fit_transform(X_train)
x_test_multilabel_tri = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:45.430605
```

In [149]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log',penalty='l2', class_weight=
"balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_multilabe_tri, multilabel_y_train)

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

```
0.34785314753950863
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:00.538062
```

In [150]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_multilabe_tri, multilabel_y_train)
predictions = classifier.predict (x_test_multilabel_tri)

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


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

```
Accuracy : 0.32949932341001353
Hamming loss  0.36682453766350925
Micro-average quality numbers
Precision: 0.2715, Recall: 0.4214, F1-measure: 0.3302
Macro-average quality numbers
Precision: 0.2707, Recall: 0.4207, F1-measure: 0.3258
              precision    recall  f1-score   support

           0       0.21      0.43      0.28       507
           1       0.35      0.43      0.39       844
           2       0.25      0.41      0.31       552

   micro avg       0.27      0.42      0.33      1903
   macro avg       0.27      0.42      0.33      1903
weighted avg       0.28      0.42      0.34      1903
 samples avg       0.14      0.17      0.15      1903

Time taken to run this cell : 0:00:00.060931
```

ngram:

In [151]:

```
# 1 to 3 gram for plot_synopsis
start = datetime.now()
vectorizer = TfidfVectorizer(min_df=10, max_features=20000, smooth_idf=True, norm="l2",
\
                             tokenizer = lambda x: x.split(), sublinear_tf=False, ngram
_range=(1,3))
x_train_1 = vectorizer.fit_transform(X_train)
x_test_1 = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:26.807438
```

In [152]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_1, multilabel_y_train)

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

```
0.4645703712686341
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:03.901196
```

In [154]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_1, multilabel_y_train)
predictions = classifier.predict (x_test_1)

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


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

```
Accuracy : 0.391407307171853 85
Hamming loss  0.3092016238159675
Micro-average quality numbers
Precision: 0.3704, Recall: 0.6301, F1-measure: 0.4665
Macro-average quality numbers
Precision: 0.3648, Recall: 0.6206, F1-measure: 0.4571
              precision    recall  f1-score   support

           0       0.26      0.53      0.35       507
           1       0.47      0.67      0.55       844
           2       0.36      0.66      0.47       552

   micro avg       0.37      0.63      0.47      1903
   macro avg       0.36      0.62      0.46      1903
weighted avg       0.38      0.63      0.47      1903
 samples avg       0.21      0.26      0.22      1903

Time taken to run this cell : 0:00:00.388091
```

Unigram + bigram + ngram:

In [0]:

```
# combining features
from scipy.sparse import coo_matrix, hstack
train_1 = hstack((x_train_multilabe_uni, x_train_multilabe_bi),format="csr",dtype='floa
t64')
test_1 = hstack((x_test_multilabel_uni, x_test_multilabel_bi),format="csr",dtype='float
64')
```

In [0]:

```
train_2 = hstack((train_1, x_train_1),format="csr",dtype='float64')
test_2 = hstack((test_1, x_test_1),format="csr",dtype='float64')
```

In [157]:

```
#from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-1, 10**0]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(train_2, multilabel_y_train)

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

```
0.47434746646522724
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:08.344420
```

In [158]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(train_2, multilabel_y_train)
predictions = classifier.predict (test_2)

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


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

```
Accuracy : 0.40798376184032475
Hamming loss  0.2963464140730717
Micro-average quality numbers
Precision: 0.3817, Recall: 0.6148, F1-measure: 0.4710
Macro-average quality numbers
Precision: 0.3770, Recall: 0.6085, F1-measure: 0.4623
              precision    recall  f1-score   support

           0       0.27      0.51      0.35       507
           1       0.49      0.64      0.55       844
           2       0.38      0.68      0.48       552

   micro avg       0.38      0.61      0.47      1903
   macro avg       0.38      0.61      0.46      1903
weighted avg       0.40      0.61      0.48      1903
 samples avg       0.21      0.25      0.21      1903

Time taken to run this cell : 0:00:00.811268
```

Char 3-gram:

In [159]:

```
vectorizer = TfidfVectorizer(sublinear_tf=True, strip_accents='unicode', analyzer='cha
r', ngram_range=(3, 3),  max_features=20000)
x_train_3char = vectorizer.fit_transform(X_train)
x_test_3char = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:39.854711
```

In [160]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-2, 10**-1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_3char, multilabel_y_train)

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

```
0.49214003181988253
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:00:13.676614
```

In [163]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_3char, multilabel_y_train)
predictions = classifier.predict (x_test_3char)

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


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

```
Accuracy : 0.42354533152909335
Hamming loss  0.29093369418132614
Micro-average quality numbers
Precision: 0.3939, Recall: 0.6605, F1-measure: 0.4935
Macro-average quality numbers
Precision: 0.3871, Recall: 0.6454, F1-measure: 0.4819
              precision    recall  f1-score   support

           0       0.28      0.58      0.38       507
           1       0.50      0.73      0.59       844
           2       0.39      0.63      0.48       552

   micro avg       0.39      0.66      0.49      1903
   macro avg       0.39      0.65      0.48      1903
weighted avg       0.41      0.66      0.50      1903
 samples avg       0.21      0.27      0.22      1903

Time taken to run this cell : 0:00:01.049600
```

Char 4-gram:

In [164]:

```
vectorizer = TfidfVectorizer(sublinear_tf=True, strip_accents='unicode', analyzer='cha
r', ngram_range=(4, 4),  max_features=20000)
x_train_4char = vectorizer.fit_transform(X_train)
x_test_4char = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:00:49.548791
```

In [165]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_4char, multilabel_y_train)

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

```
0.5012929936983989
{'estimator__alpha': 0.0001}
Time taken to run this cell : 0:00:24.060838
```

In [166]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0001, penalty='l2',
class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_4char, multilabel_y_train)
predictions = classifier.predict (x_test_4char)

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


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

```
Accuracy : 0.43403247631935505
Hamming loss  0.2771763644564727
Micro-average quality numbers
Precision: 0.4110, Recall: 0.6737, F1-measure: 0.5106
Macro-average quality numbers
Precision: 0.4067, Recall: 0.6621, F1-measure: 0.5012
              precision    recall  f1-score   support

           0       0.30      0.61      0.40       507
           1       0.50      0.73      0.60       844
           2       0.42      0.64      0.51       552

   micro avg       0.41      0.67      0.51      1903
   macro avg       0.41      0.66      0.50      1903
weighted avg       0.42      0.67      0.52      1903
 samples avg       0.22      0.28      0.23      1903

Time taken to run this cell : 0:00:01.678374
```

Char (3-6gram) :

In [167]:

```
vectorizer = TfidfVectorizer(sublinear_tf=True, strip_accents='unicode', analyzer='cha
r', ngram_range=(3, 6),  max_features=20000)
x_train_36char = vectorizer.fit_transform(X_train)
x_test_36char = vectorizer.transform(X_test)
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:03:08.151874
```

In [168]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-2, 10**-1,1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(x_train_36char, multilabel_y_train)

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

```
0.5026521726173548
{'estimator__alpha': 0.0001}
Time taken to run this cell : 0:00:57.277825
```

In [169]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.0001, penalty='l2', class_weight="balanced"), n_jobs=-1)
classifier.fit(x_train_36char, multilabel_y_train)
predictions = classifier.predict (x_test_36char)

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


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

```
Accuracy : 0.42625169147496617
Hamming loss  0.2836039693279206
Micro-average quality numbers
Precision: 0.4053, Recall: 0.6879, F1-measure: 0.5100
Macro-average quality numbers
Precision: 0.3988, Recall: 0.6757, F1-measure: 0.4997
              precision    recall  f1-score   support

           0       0.29      0.61      0.40       507
           1       0.49      0.74      0.59       844
           2       0.41      0.68      0.51       552

   micro avg       0.41      0.69      0.51      1903
   macro avg       0.40      0.68      0.50      1903
weighted avg       0.42      0.69      0.52      1903
 samples avg       0.23      0.28      0.24      1903

Time taken to run this cell : 0:00:04.089585
```

Char 3gram + Char 4gram:

In [0]:

```
# combining features
from scipy.sparse import coo_matrix, hstack
train_10 = hstack((x_train_3char, x_train_4char),format="csr",dtype='float64')
test_10 = hstack((x_test_3char, x_test_4char),format="csr",dtype='float64')
```

In [0]:

```
train_11 = hstack((train_10, x_train_36char),format="csr",dtype='float64')
test_11 = hstack((test_10, x_test_36char),format="csr",dtype='float64')
```

In [172]:

```
from sklearn.model_selection import GridSearchCV
start = datetime.now()

model_to_set = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l2', class_weight
="balanced" ))

parameters = {
    "estimator__alpha": [10**-5, 10**-4, 10**-3, 10**-2, 10**-1]
}

model_tunning = GridSearchCV(model_to_set, param_grid=parameters, scoring='f1_micro',n_
jobs=-1)

model_tunning.fit(train_11, multilabel_y_train)

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

```
0.5071430797128947
{'estimator__alpha': 0.001}
Time taken to run this cell : 0:01:17.810360
```

In [173]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(train_11, multilabel_y_train)
predictions = classifier.predict (test_11)

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


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

```
Accuracy : 0.39309878213802435
Hamming loss  0.3077356788452864
Micro-average quality numbers
Precision: 0.3835, Recall: 0.7141, F1-measure: 0.4990
Macro-average quality numbers
Precision: 0.3812, Recall: 0.7038, F1-measure: 0.4911
              precision    recall  f1-score   support

           0       0.27      0.66      0.39       507
           1       0.48      0.77      0.59       844
           2       0.39      0.68      0.50       552

   micro avg       0.38      0.71      0.50      1903
   macro avg       0.38      0.70      0.49      1903
weighted avg       0.40      0.71      0.51      1903
 samples avg       0.23      0.29      0.24      1903

Time taken to run this cell : 0:00:06.486245
```

Combining all:

In [0]:

```
train_20 = hstack((train_11, train_2),format="csr",dtype='float64')
test_20 = hstack((test_11, test_2),format="csr",dtype='float64')
```

In [177]:

```
# train model

start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=0.001, penalty='l2', c
lass_weight="balanced"), n_jobs=-1)
classifier.fit(train_20, multilabel_y_train)
predictions = classifier.predict (test_20)

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


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

```
Accuracy : 0.38836265223274696
Hamming loss  0.3062697338746053
Micro-average quality numbers
Precision: 0.3862, Recall: 0.7252, F1-measure: 0.5040
Macro-average quality numbers
Precision: 0.3928, Recall: 0.7180, F1-measure: 0.5007
              precision    recall  f1-score   support

           0       0.27      0.73      0.39       507
           1       0.48      0.77      0.59       844
           2       0.43      0.66      0.52       552

   micro avg       0.39      0.73      0.50      1903
   macro avg       0.39      0.72      0.50      1903
weighted avg       0.41      0.73      0.52      1903
 samples avg       0.23      0.30      0.25      1903

Time taken to run this cell : 0:00:07.687658
```

Pretty Table after feature engineering:

In [185]:

```
from prettytable import PrettyTable
ptable = PrettyTable()
print ("Comparison of models using 4 TAGS:")
ptable.field_names = ['Model', 'Weighted Precession','Weighted Recall','Weighted F1-Sco
re']
ptable.add_row(["Unigram","0.36", "0.61", '0.44'])
ptable.add_row(["bigram",  "0.36", "0.55", '0.43'])
ptable.add_row(["trigram",  "0.26", "0.41", '0.31'])
ptable.add_row(["ngram (1,3)",  "0.36", "0.61", '0.45'])
ptable.add_row(["unigram + bigram + ngram",  "0.37", "0.61", '0.46'])
ptable.add_row(["Char 3-gram",  "0.37", "0.67", '0.48'])
ptable.add_row(["Char 4-gram",  "0.39", "0.65", '0.49'])
ptable.add_row(["Char (3-6) gram",  "0.38", "0.69", '0.49'])
ptable.add_row(["Char 3gram + 4gram",  "0.38", "0.69", '0.49'])
ptable.add_row(["Combining all",  "0.38", "0.68", '0.49'])

print(ptable)


ptable = PrettyTable()
print ("Comparison of models using 3 TAGS:")
ptable.field_names = ['Model', 'Weighted Precession','Weighted Recall','Weighted F1-Sco
re']
ptable.add_row(["Unigram","0.38", "0.63", '0.47'])
ptable.add_row(["bigram",  "0.38", "0.57", '0.46'])
ptable.add_row(["trigram",  "0.28", "0.42", '0.34'])
ptable.add_row(["ngram (1,3)",  "0.38", "0.63", '0.47'])
ptable.add_row(["unigram + bigram + ngram",  "0.40", "0.61", '0.48'])
ptable.add_row(["Char 3-gram",  "0.41", "0.66", '0.50'])
ptable.add_row(["Char 4-gram",  "0.42", "0.67", '0.52'])
ptable.add_row(["Char (3-6) gram",  "0.42", "0.69", '0.52'])
ptable.add_row(["Char 3gram + 4gram",  "0.40", "0.71", '0.51'])
ptable.add_row(["Combining all 4TAG + 3TAG features",  "0.41", "0.73", '0.52'])

print(ptable)
```

Comparison of models using 4 TAGS:

Model	Weighted Precession	Weighted Recall	Weighted F1-Score
Unigram	0.36	0.61	0.44
bigram	0.36	0.55	0.43
trigram	0.26	0.41	0.31
ngram (1,3)	0.36	0.61	0.45
unigram + bigram + ngram	0.37	0.61	0.46
Char 3-gram	0.37	0.67	0.48
Char 4-gram	0.39	0.65	0.49
Char (3-6) gram	0.38	0.69	0.49
Char 3gram + 4gram	0.38	0.69	0.49
Combining all	0.38	0.68	0.49

Comparison of models using 3 TAGS:

Model	Weighted Precession	Weighted Recall	Weighted F1-Score
Unigram	0.38	0.63	0.47
bigram	0.38	0.57	0.46
trigram	0.28	0.42	0.34
ngram (1,3)	0.38	0.63	0.47
unigram + bigram + ngram	0.40	0.61	0.48
Char 3-gram	0.41	0.66	0.50
Char 4-gram	0.42	0.67	0.52
Char (3-6) gram	0.42	0.69	0.52
Char 3gram + 4gram	0.40	0.71	0.51
Combining all 4TAG + 3TAG features	0.41	0.73	0.52

OBSERVATION & STEPS FOLLOWED:

EDA:
1. First of all we stored the data from csv file to sql database to make the data exploration easy and more effective. 2. Analysed the data as per split column. We observed that there are 9489 train and 2966 test data, which are quite less. 3. We have seen that wikipedia dominates imdb as the source of data. 4. Then we plotted no of tags per movie. We observed that most of the movie had 1 tag. 5. The most frequent tags were violence, murder, flashback, romantic, cult etc. 6. Then we tried to clean the data, plot_synopsis preciselt using nltk library.

BASELINE MODEL:
1. First of all we observed that the tags are unbalanced. 2. We splitted the data into test and train as per the split column of the dataset. 3. We built models using count and tfidf vectorization. 4. We applied logistic reression and linear SVM on top of one vs rest classifier as its multi class classification problem. 5. The tfidf model using linear SVM performed the best. 6. After all the analysis we observed that the models had unbalanced data, unbalanced no of tags and lesser number of data. Hence it couldn't perform the best.

FEATURE ENGINEERED MODELS:

1. I went through the actual reasearch paper of this experiment/project which is :- [https://arxiv.org/pdf/1802.07858.pdf (https://arxiv.org/pdf/1802.07858.pdf)](https://arxiv.org/pdf/1802.07858.pdf)
2. What i observed is that they experimented on lexical features like TFIDF using weighted vectors like unigram, bigram, ngrams. They also performed character level featurization which was unique thing for me and fascinating.
3. The main problem which the baseline models was that the plot synopses were imbalanced and number of tags per synopses were varying by great margin.
4. In EDA we observed that in an average each movie had 2.9 tags. So we did choose 4tags and 3tags to build 2 sets of models and analysed them.
5. In case of 4tag models (3char + 4char gram) model performed the best with micro-f1 score of 49% which is significant increase from the baseline models.
6. In case of 3tag models again (3char + 4char gram) model performed the best with micro-f1 score of 51% which is significant increase from the baseline models.
7. When i combined both the features of 3 tag and 4tag i got a micro f1-score of 52 % which is our best performance. The precesion and recall of the same were 41% and 73% respectively which is very good.
8. One thing i noticed that my models performed way better than the models they used in research paper which is a matter of satisfaction.