Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/)

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [63]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

from sklearn.cross_validation import train_test_split
from sklearn.preprocessing import StandardScaler
import sklearn.preprocessing as preprocessing
from sklearn.linear_model import SGDClassifier

from sklearn.cross_validation import train_test_split
import pandas as pd

from sklearn.metrics import confusion_matrix, classification_report, accuracy_
score
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from datetime import datetime
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
import scikitplot as skplt
from sklearn.cross_validation import train_test_split
```

```
from sklearn.preprocessing import StandardScaler
import sklearn.preprocessing as preprocessing
from sklearn.svm import SVC
from wordcloud import WordCloud
from sklearn.calibration import CalibratedClassifierCV
```

In [90]:

```
# using the SQLite Table to read data.
con = sqlite3.connect('database.sqlite')



#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3
 """, con)


#parti
def partition(x):
    if x < 3:
        return 'negative'
    return 'positive'

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
```

In [91]:
```
print(filtered_data.shape) #looking at the number of attributes and size of th
e data
filtered_data.head()
```

```
(525814, 10)
```

Out[91]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulne
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [92]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[92]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [93]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inp
lace=False, kind='quicksort', na_position='last')
```

In [94]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"
}, keep='first', inplace=False)
final.shape
```

Out[94]: (364173, 10)

In [95]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[95]: 69.25890143662969

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [96]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[96]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [97]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [98]:
```
#Before starting the next phase of preprocessing lets see the number of entrie
s left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(364171, 10)
```

Out[98]:
```
positive    307061
negative     57110
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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 [99]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks i
s good, but I prefer bolder taste.... imagine my surprise when I ordered 2 bo
xes - both were expired! One expired back in 2005 for gosh sakes.  I admit th
at Amazon agreed to credit me for cost plus part of shipping, but geez, 2 yea
rs expired!!!  I'm hoping to find local San Diego area shoppe that carries po
ds so that I can try something different than starbucks.
==================================================
Great ingredients although, chicken should have been 1st rather than chicken
broth, the only thing I do not think belongs in it is Canola oil. Canola or r
apeseed is not someting a dog would ever find in nature and if it did find ra
peseed in nature and eat it, it would poison them. Today's Food industries ha
ve convinced the masses that Canola oil is a safe and even better oil than ol
ive or virgin coconut, facts though say otherwise. Until the late 70's it was
poisonous until they figured out a way to fix that. I still like it but it co
uld be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the
excellence of this product.<br /><br />Thick, delicious.  Perfect.  3 ingredi
ents: Water, Maltitol, Natural Maple Flavor.  PERIOD.  No chemicals.  No garb
age.<br /><br />Have numerous friends & family members hooked on this stuff.
My husband & son, who do NOT like "sugar free" prefer this over major label r
egular syrup.<br /><br />I use this as my SWEETENER in baking: cheesecakes, w
hite brownies, muffins, pumpkin pies, etc... Unbelievably delicious...<br /><
br />Can you tell I like it? :)
==================================================
```

In [100]:
```
# 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)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
```

In [101]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-rem
ove-all-tags-from-an-element
from bs4 import BeautifulSoup

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

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks i
s good, but I prefer bolder taste.... imagine my surprise when I ordered 2 bo
xes - both were expired! One expired back in 2005 for gosh sakes.  I admit th
at Amazon agreed to credit me for cost plus part of shipping, but geez, 2 yea
rs expired!!!  I'm hoping to find local San Diego area shoppe that carries po
ds so that I can try something different than starbucks.
==================================================
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broth, the only thing I do not think belongs in it is Canola oil. Canola or r
apeseed is not someting a dog would ever find in nature and if it did find ra
peseed in nature and eat it, it would poison them. Today's Food industries ha
ve convinced the masses that Canola oil is a safe and even better oil than ol
ive or virgin coconut, facts though say otherwise. Until the late 70's it was
poisonous until they figured out a way to fix that. I still like it but it co
uld be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the
excellence of this product.Thick, delicious.  Perfect.  3 ingredients: Water,
Maltitol, Natural Maple Flavor.  PERIOD.  No chemicals.  No garbage.Have nume
rous friends & family members hooked on this stuff.  My husband & son, who do
NOT like "sugar free" prefer this over major label regular syrup.I use this a
s my SWEETENER in baking: cheesecakes, white brownies, muffins, pumpkin pies,
etc... Unbelievably delicious...Can you tell I like it? :)
```

In [102]:
```
# 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 [103]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Great ingredients although, chicken should have been 1st rather than chicken
broth, the only thing I do not think belongs in it is Canola oil. Canola or r
apeseed is not someting a dog would ever find in nature and if it did find ra
peseed in nature and eat it, it would poison them. Today is Food industries h
ave convinced the masses that Canola oil is a safe and even better oil than o
live or virgin coconut, facts though say otherwise. Until the late 70 is it w
as poisonous until they figured out a way to fix that. I still like it but it
could be better.
==================================================
```

In [104]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/408403
9
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
```

In [105]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Great ingredients although chicken should have been 1st rather than chicken b
roth the only thing I do not think belongs in it is Canola oil Canola or rape
seed is not someting a dog would ever find in nature and if it did find rapes
eed in nature and eat it it would poison them Today is Food industries have c
onvinced the masses that Canola oil is a safe and even better oil than olive 
or virgin coconut facts though say otherwise Until the late 70 is it was pois
onous until they figured out a way to fix that I still like it but it could b
e better
```

In [106]:
```
# 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',
'ourselves', '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', 'it
self', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 't
hat', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have',
'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'becau
se', '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', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'a
ll', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'tha
n', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "shoul
d've", 'now', '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", 'm
a', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shoul
dn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [107]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].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 i
n stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|
| 364171/364171 [02:11<00:00, 2765.24it/s]
```

In [108]:
```
final['CleanedText']=preprocessed_reviews #adding a column of CleanedText whic
h displays the data after pre-processing of the review
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
```

In [109]:
```
conn = sqlite3.connect('final.sqlite')
c=conn.cursor()
conn.text_factory = str
final.to_sql('Reviews', conn,  schema=None, if_exists='replace', index=True, i
ndex_label=None, chunksize=None, dtype=None)
```

In [110]:
```
con = sqlite3.connect("final.sqlite")
final = pd.read_sql_query("""SELECT * FROM Reviews""",con)
```

In [111]:
```
final.sort_values("Time",ascending=True, inplace=True, kind='quicksort')
```

In [112]:
```
final['Score'].replace(['negative', 'positive'],[0,1],inplace=True)
```

In [113]:
```
final = final.to_csv("final.csv")
```

[3.2] Preprocessing Review Summary

- create column of cleanedtext and save preprocessed_reviews.
- sort data with time.
- convert negative class with 0 and positive class with 1.
- then we save in sqlite.
- then convert sqlite file to csv file.

In [6]:
```
final = pd.read_csv("final.csv") # reading csv file
```

In [7]:
```
final = final.iloc[:100000] #taking 100k point
```

In [8]:
```
X = final["CleanedText"]
y = final["Score"]
```

Function

1.SGD with hinge-loss

In [9]:
```
def SGD(X_train, X_test, y_train, y_test):

    start=datetime.now()

    #Normalize Data
    X_train = preprocessing.normalize(X_train)
    print ("Train Data Size: ",X_train.shape)
    #Normalize Data
    X_test = preprocessing.normalize(X_test)
    print ("Test Data Size: ",X_test.shape)

    print("SGD Classifier")
    model=SGDClassifier()
    penalty=['l1', 'l2']
    param={'alpha': [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,0.5,1,5,10,50, 10
0,500,1000], 'penalty':penalty}
    gsv =GridSearchCV(estimator=model, param_grid=param,  n_jobs=-1, verbose=1
)
    gsv.fit(X_train,y_train)

    penalty=model.get_params()['penalty']
    alpha=model.get_params()['alpha']
    print('best alpha=',alpha)
    print('best penalty=',penalty)

    model1 = SGDClassifier(penalty= penalty, alpha=alpha)

    model1.fit(X_train,y_train)
    y_pred = model1.predict(X_test)
    print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100
))
    print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
    print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
    print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))

    test=CalibratedClassifierCV(model)
    test.fit(X_train,y_train)
    print('ROC curve--')
    y_pred_proba=test.predict_proba(X_test)
    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_proba[:,1], pos_la
bel=1)
    auc = metrics.roc_auc_score(y_test, y_pred_proba[:,1])
    plt.plot(fpr,tpr,label="auc="+str(auc))
    plt.plot([0,1],[0,1],linestyle='--')
    plt.legend(loc=4)
    plt.title('ROC curve')
    plt.show()


    confusion = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(
2))
    sns.set(font_scale=1.4)#for label size
    sns.heatmap(confusion, annot=True,annot_kws={"size": 16}, fmt='g')
    #skplt.plot_confusion_matrix(y_test ,y_pred)

    end=datetime.now()
```

```
    print('duration = ',(end-start))

    return penalty,alpha
```

2.Word cloud

In [10]:
```
##code borrowed from  https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-for-scikit-learn-classifiers
def show_cloud(vectorizer, w, n=50):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(w[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    positive = []
    negative = []
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        #print("\t%.4f\t%-15s\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))
        positive.append(fn_2)
        negative.append(fn_1)
    positive = ' '.join(positive)

    #wordcloud for postitve word

    wordcloud  = WordCloud(max_font_size=40).generate(positive)
    plt.figure()
    plt.title("wordcloud for positive class words")
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()

    print('*****************************************************')

    negative = ' '.join(negative)

    #wordcloud for negative word

    wordcloud  = WordCloud(max_font_size=40).generate(negative)
    plt.figure()
    plt.title("wordcloud for negative class words")
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()
```

[4] Featurization

[4.1] BAG OF WORDS

In [11]:
```
# split the data set into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

In [12]:
```
#Bow
count = CountVectorizer()

Bow_train = count.fit_transform(X_train)

Bow_test = count.transform(X_test)
```

In [13]:
```
Bow_train = preprocessing.normalize(Bow_train)
print("Train Data Size: ",Bow_train.shape)

#Normalize Data
Bow_test = preprocessing.normalize(Bow_test)
print("Train Data Size: ",Bow_test.shape)
```

```
Train Data Size:  (70000, 31561)
Train Data Size:  (30000, 31561)
```

[4.3] TF-IDF

In [14]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_train = tf_idf_vect.fit_transform(X_train)
tf_idf_test = tf_idf_vect.transform(X_test)
```

In [15]:
```
tf_idf_train = preprocessing.normalize(tf_idf_train)
print("Train Data Size: ",tf_idf_train.shape)

#Normalize Data
tf_idf_test = preprocessing.normalize(tf_idf_test)
print("Train Data Size: ",tf_idf_test.shape)
```

```
Train Data Size:  (70000, 40525)
Train Data Size:  (30000, 40525)
```

[4.4] Word2Vec

In [17]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in X_train:
    list_of_sentance.append(sentance.split())
```

In [18]:
```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sentance,min_count=5,size=200, workers=4)
```

In [19]:
```
w2v_words = list(w2v_model.wv.vocab)
```

In [20]:
```
i=0
list_of_sent_test=[]
for sent in X_test.values:
    list_of_sent_test.append(sent.split())
```

In [21]:
```
w2v_model_test=Word2Vec(list_of_sent_test,min_count=5,size=200, workers=4)
```

In [22]:
```
w2v_words_test = list(w2v_model_test.wv.vocab)
```

[4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [23]:
```
# average Word2Vec for train data
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
st
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length 50, you migh
t need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|████████████████████████████████████████████████████████████████████
██| 70000/70000 [01:00<00:00, 1151.26it/s]

70000
200
```

In [24]:
```
# average Word2Vec for test data
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in th
is list
for sent in tqdm(list_of_sent_test): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length 50, you migh
t need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_test:
            vec = w2v_model_test.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
100%|████████████████████████████████████████████████████████████████████████
██| 30000/30000 [00:22<00:00, 1327.80it/s]

30000
200
```

In [25]:
```
#Normalize Data
avg_train = preprocessing.normalize(sent_vectors)
print("Train Data Size: ",avg_train.shape)

avg_test = preprocessing.normalize(sent_vectors_test)
print("Train Data Size: ",avg_test.shape)
```

```
Train Data Size:  (70000, 200)
Train Data Size:  (30000, 200)
```

[4.4.1.2] TFIDF weighted W2v

In [26]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix_train = model.fit_transform(X_train)
tf_idf_matrix_test = model.transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [27]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review is sto
red in this list
row=0;
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix_train[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
print(len(tfidf_sent_vectors_train))
print(len(tfidf_sent_vectors_train[0]))
```

```
100%|████████████████████████████████████████████████████████████████████████
███| 70000/70000 [11:36<00:00, 100.53it/s]

70000
200
```

In [28]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stor
ed in this list
row=0;
for sent in tqdm(list_of_sent_test): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_test and word in tfidf_feat:
            vec = w2v_model_test.wv[word]
#             tf_idf = tf_idf_matrix_test[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1

print(len(tfidf_sent_vectors_test))
print(len(tfidf_sent_vectors_test[0]))
```

```
100%|██████████████████████████████████████████████████████████████████████
████| 30000/30000 [05:04<00:00, 98.49it/s]

30000
200
```

In [29]:
```
#Normalize Data
w2v_tfidf_train = preprocessing.normalize(tfidf_sent_vectors_train)
print("Train Data Size: ",w2v_tfidf_train.shape)

w2v_tfidf_test = preprocessing.normalize(tfidf_sent_vectors_test)
print("Train Data Size: ",w2v_tfidf_test.shape)
```

```
Train Data Size:  (70000, 200)
Train Data Size:  (30000, 200)
```

Taking 40K point for RBF kernel

In [37]:
```
final = pd.read_csv("final.csv")
```

In [38]:
```
final = final.iloc[:40000] #taking 40k point
```

In [39]:
```
X = final["CleanedText"]
y = final["Score"]
```

Function

In [40]:
```
# defining model function that does cross validation , accuracy, test accuracy

# and confusion matrix
# this function takes 'search', 'X_train', 'X_test', 'y_train', 'y_test' as ar
guments
def SVM(X_train, X_test, y_train, y_test):

    start=datetime.now()

    #Normalize Data

    print ("Train Data Size: ",X_train.shape)
    #Normalize Data
    X_test = preprocessing.normalize(X_test)
    print ("Test Data Size: ",X_test.shape)


    #params we need to try on classifier

    print("SVC GridSearch")
    model =SVC()
    gamma=[0.0001, 0.001,  0.01, 0.05, 0.1, 0.5, 1, 5, 10]
    param={'C': [0.001,  0.01, 0.05, 0.1, 0.5, 1, 5, 10], 'gamma':gamma}
    gsv = CV=GridSearchCV(estimator=model, param_grid=param, verbose=1, n_jobs
=-1)
    gsv.fit(X_train,y_train)


    c=gsv.best_estimator_.get_params()['C']
    gamma=gsv.best_estimator_.get_params()['gamma']
    print("Best HyperParameter: ",gsv.best_params_)
    print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))

    test = SVC(C=c,gamma=gamma,probability=True)
    test.fit(X_train,y_train)
    y_pred = test.predict(X_test)
    print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100
))
    print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
    print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
    print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))

    print('ROC curve--')
    y_pred_proba=test.predict_proba(X_test)
    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_proba[:,1], pos_la
bel=1)
    auc = metrics.roc_auc_score(y_test, y_pred_proba[:,1])
    plt.plot(fpr,tpr,label="auc="+str(auc))
    plt.plot([0,1],[0,1],linestyle='--')
    plt.legend(loc=4)
    plt.title('ROC curve')
    plt.show()


    confusion = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(
2))
```

```
    sns.set(font_scale=1.4)#for label size
    sns.heatmap(confusion, annot=True,annot_kws={"size": 16}, fmt='g')
    #skplt.plot_confusion_matrix(y_test ,y_pred)

    end=datetime.now()
    print('duration = ',(end-start))
```

[4.1] BAG OF WORDS

In [41]:
```
# split the data set into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=0)
```

In [42]:
```
#Bow
count = CountVectorizer(min_df = 10, max_features = 500)

Bow_train = count.fit_transform(X_train)

Bow_test = count.transform(X_test)
```

In [43]:
```
Bow_train = preprocessing.normalize(Bow_train)
print("Train Data Size: ",Bow_train.shape)

#Normalize Data
Bow_test = preprocessing.normalize(Bow_test)
print("Train Data Size: ",Bow_test.shape)
```

```
Train Data Size:  (28000, 500)
Train Data Size:  (12000, 500)
```

[4.2] TF-IDF

In [44]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10,max_features = 500)
tf_idf_train = tf_idf_vect.fit_transform(X_train)
tf_idf_test = tf_idf_vect.transform(X_test)
```

In [45]:
```
tf_idf_train = preprocessing.normalize(tf_idf_train)
print("Train Data Size: ",tf_idf_train.shape)

#Normalize Data
tf_idf_test = preprocessing.normalize(tf_idf_test)
print("Train Data Size: ",tf_idf_test.shape)
```

```
Train Data Size:  (28000, 500)
Train Data Size:  (12000, 500)
```

[4.4] Word2Vec

In [46]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in X_train:
    list_of_sentance.append(sentance.split())
```

In [47]:
```
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(list_of_sentance,min_count=5,size=200, workers=4)
```

In [48]:
```
w2v_words = list(w2v_model.wv.vocab)
```

In [49]:
```
i=0
list_of_sent_test=[]
for sent in X_test.values:
    list_of_sent_test.append(sent.split())
```

In [50]:
```
w2v_model_test=Word2Vec(list_of_sent_test,min_count=5,size=200, workers=4)
```

In [51]:
```
w2v_words_test = list(w2v_model_test.wv.vocab)
```

[4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [52]:
```
# average Word2Vec for train data
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
st
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length 50, you migh
t need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████████████████████████████████████
█| 28000/28000 [00:21<00:00, 1291.72it/s]

28000
200
```

In [53]:
```
# average Word2Vec for test data
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in th
is list
for sent in tqdm(list_of_sent_test): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length 50, you migh
t need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_test:
            vec = w2v_model_test.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
100%|████████████████████████████████████████████████████████████████████
██| 12000/12000 [00:08<00:00, 1453.98it/s]

12000
200
```

In [54]:
```
#Normalize Data
avg_train = preprocessing.normalize(sent_vectors)
print("Train Data Size: ",avg_train.shape)

avg_test = preprocessing.normalize(sent_vectors_test)
print("Train Data Size: ",avg_test.shape)
```

```
Train Data Size:  (28000, 200)
Train Data Size:  (12000, 200)
```

[4.4.1.2] TFIDF weighted W2v

In [55]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix_train = model.fit_transform(X_train)
tf_idf_matrix_test = model.transform(X_test)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [56]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review is sto
red in this list
row=0;
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix_train[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
print(len(tfidf_sent_vectors_train))
print(len(tfidf_sent_vectors_train[0]))
```

```
100%|████████████████████████████████████████████████████████████
███| 28000/28000 [03:32<00:00, 131.99it/s]

28000
200
```

In [57]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stor
ed in this list
row=0;
for sent in tqdm(list_of_sent_test): # for each review/sentence
    sent_vec = np.zeros(200) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words_test and word in tfidf_feat:
            vec = w2v_model_test.wv[word]
#             tf_idf = tf_idf_matrix_test[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1

print(len(tfidf_sent_vectors_test))
print(len(tfidf_sent_vectors_test[0]))
```

```
100%|████████████████████████████████████████████████████████████████████
███| 12000/12000 [01:22<00:00, 145.51it/s]

12000
200
```

In [58]:
```
#Normalize Data
w2v_tfidf_train = preprocessing.normalize(tfidf_sent_vectors_train)
print("Train Data Size: ",w2v_tfidf_train.shape)

w2v_tfidf_test = preprocessing.normalize(tfidf_sent_vectors_test)
print("Train Data Size: ",w2v_tfidf_test.shape)
```

```
Train Data Size:  (28000, 200)
Train Data Size:  (12000, 200)
```

[5] Assignment 7: SVM

Applying SVM

[5.1] Linear SVM

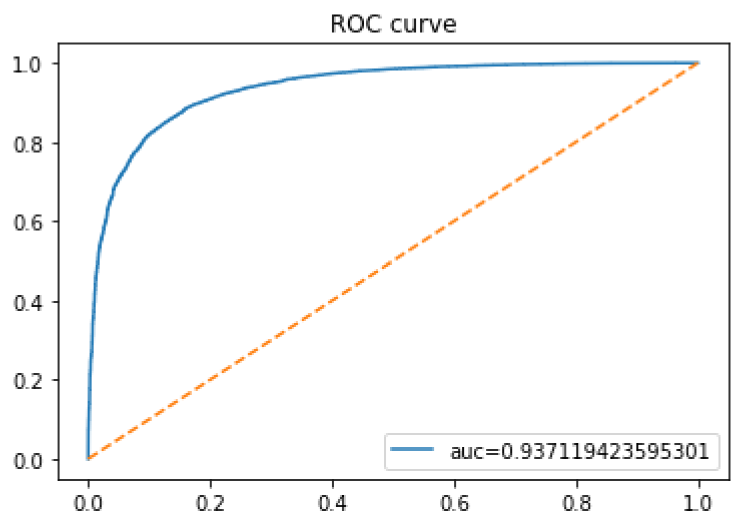
[5.1.1] Applying Linear SVM on BOW, SET 1

In [30]:
```
penalty,alpha = SGD(X_train=Bow_train,X_test=Bow_test,y_train=y_train,y_test=y
_test)
```

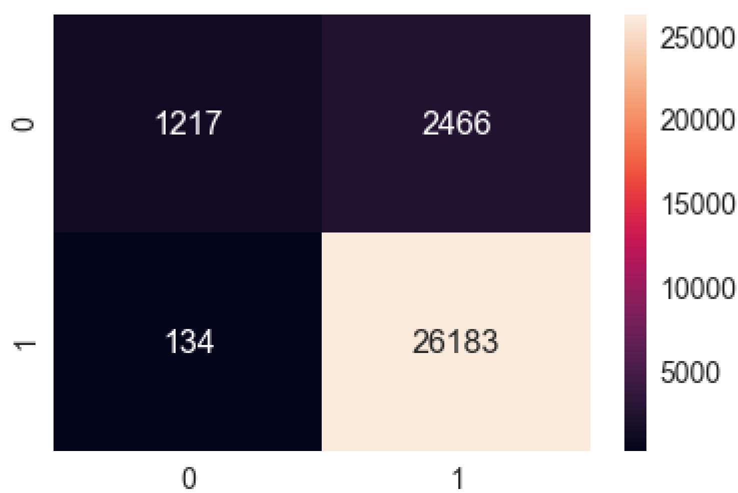
```
Train Data Size:  (70000, 31561)
Test Data Size:  (30000, 31561)
SGD Classifier
Fitting 3 folds for each of 30 candidates, totalling 90 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    8.2s
[Parallel(n_jobs=-1)]: Done  90 out of  90 | elapsed:   12.9s finished

best alpha= 0.0001
best penalty= l2
Accuracy on test set: 91.333%
Precision on test set: 0.914
Recall on test set: 0.995
F1-Score on test set: 0.953
ROC curve--
```




```
duration =  0:00:14.530640
```

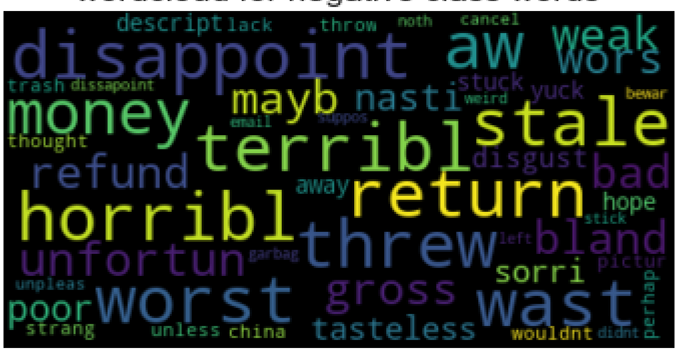


In [31]:
```
clf = SGDClassifier(penalty= penalty, alpha=alpha)
clf.fit(Bow_train,y_train)
show_cloud(count, clf.coef_)
```

wordcloud for positive class words

****

wordcloud for negative class words



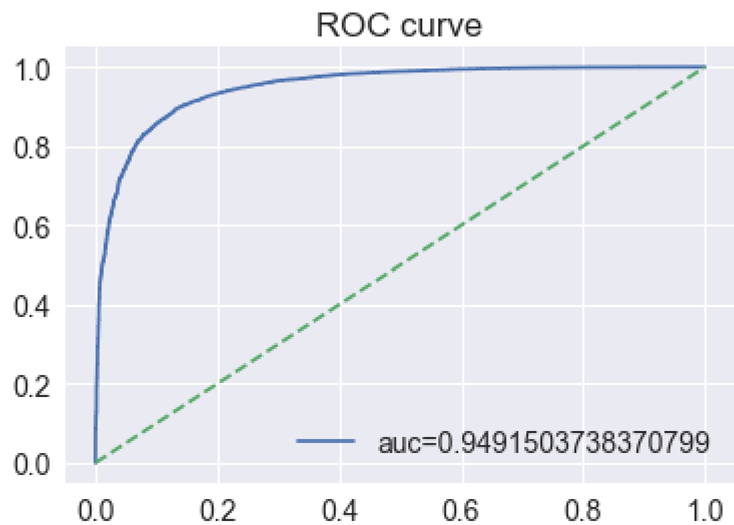
[5.1.2] Applying Linear SVM on TFIDF, SET 2

In [32]:
```
penalty,alpha = SGD(X_train=tf_idf_train,X_test=tf_idf_test,y_train=y_train,y_test=y_test)
```

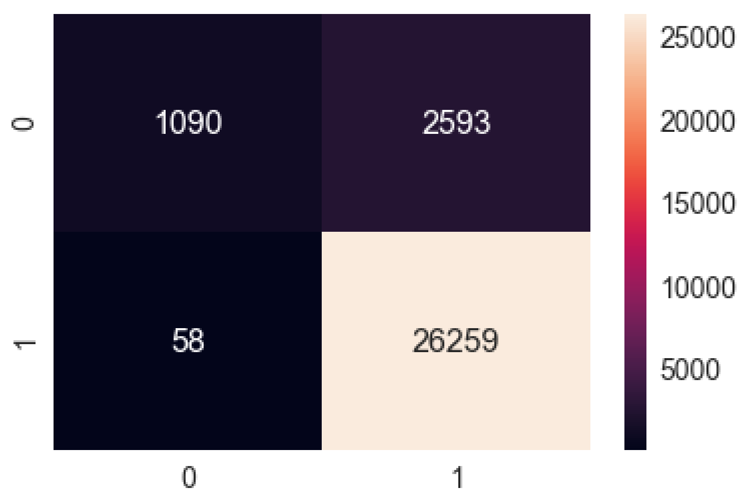
```
Train Data Size:  (70000, 40525)
Test Data Size:  (30000, 40525)
SGD Classifier
Fitting 3 folds for each of 30 candidates, totalling 90 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    9.1s
[Parallel(n_jobs=-1)]: Done  90 out of  90 | elapsed:   15.1s finished

best alpha= 0.0001
best penalty= l2
Accuracy on test set: 91.163%
Precision on test set: 0.910
Recall on test set: 0.998
F1-Score on test set: 0.952
ROC curve--
```




```
duration =  0:00:16.738014
```

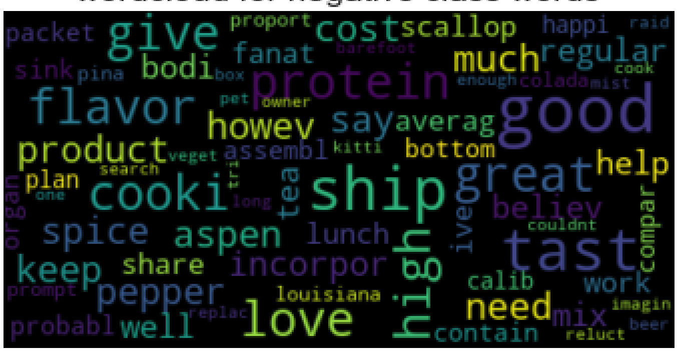


In [33]:
```
clf = SGDClassifier(penalty= penalty, alpha=alpha)
clf.fit(Bow_train,y_train)
show_cloud(tf_idf_vect, clf.coef_)
```

wordcloud for positive class words

****

wordcloud for negative class words



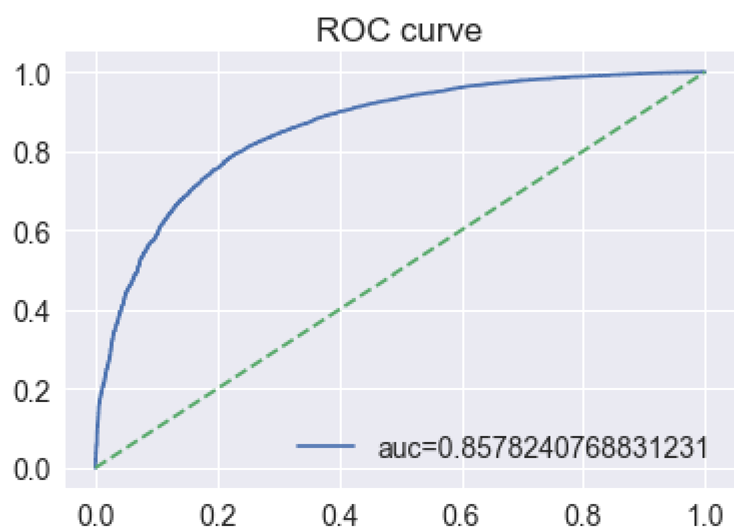
[5.1.3] Applying Linear SVM on AVG W2V, SET 3

In [34]:
```
penalty,alpha = SGD(X_train=avg_train,X_test=avg_test,y_train=y_train,y_test=y
_test)
```

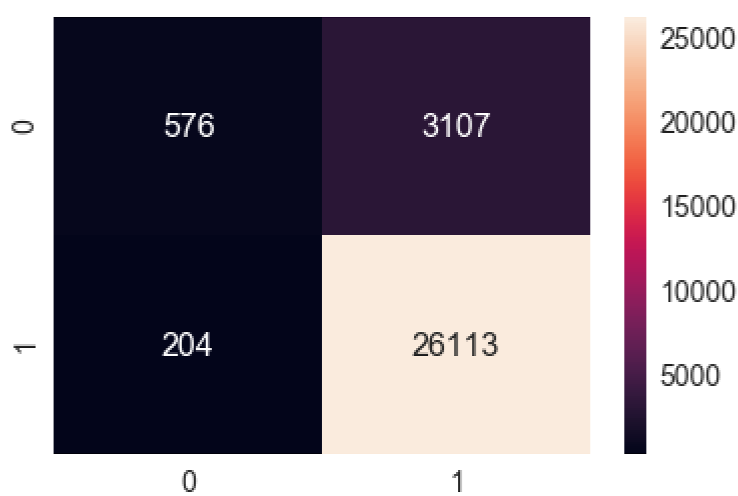
```
Train Data Size:  (70000, 200)
Test Data Size:  (30000, 200)
SGD Classifier
Fitting 3 folds for each of 30 candidates, totalling 90 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   12.1s
[Parallel(n_jobs=-1)]: Done  90 out of  90 | elapsed:   24.9s finished

best alpha= 0.0001
best penalty= l2
Accuracy on test set: 88.963%
Precision on test set: 0.894
Recall on test set: 0.992
F1-Score on test set: 0.940
ROC curve--
```




```
duration =  0:00:27.322994
```



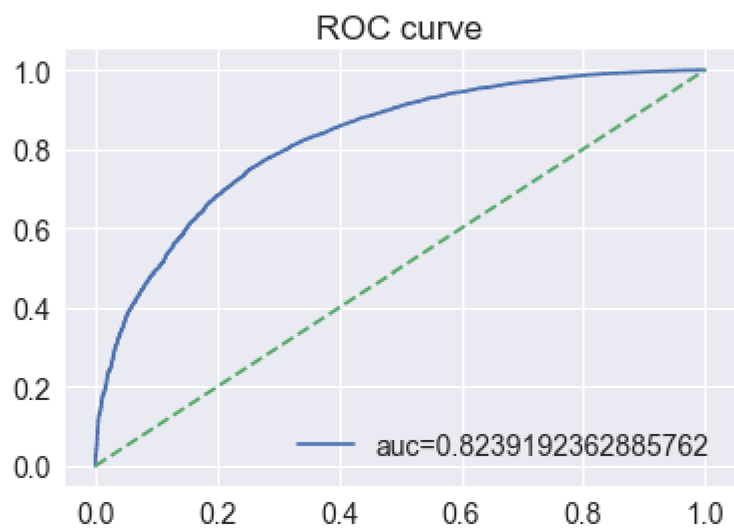
[5.1.4] Applying Linear SVM on TFIDF W2V, SET 4

In [35]:
```
penalty,alpha = SGD(X_train=w2v_tfidf_train,X_test=w2v_tfidf_test,y_train=y_tr
ain,y_test=y_test)
```

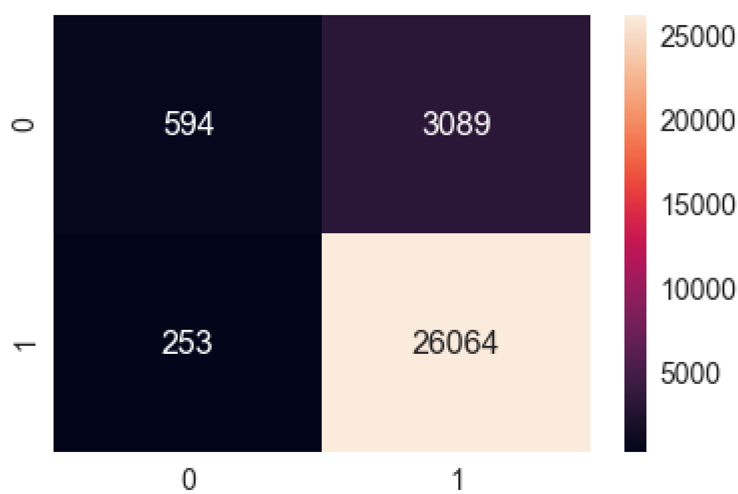
```
Train Data Size:  (70000, 200)
Test Data Size:  (30000, 200)
SGD Classifier
Fitting 3 folds for each of 30 candidates, totalling 90 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   12.1s
[Parallel(n_jobs=-1)]: Done  90 out of  90 | elapsed:   24.9s finished

best alpha= 0.0001
best penalty= l2
Accuracy on test set: 88.860%
Precision on test set: 0.894
Recall on test set: 0.990
F1-Score on test set: 0.940
ROC curve--
```




```
duration =  0:00:26.944971
```



[5.2] RBF SVM

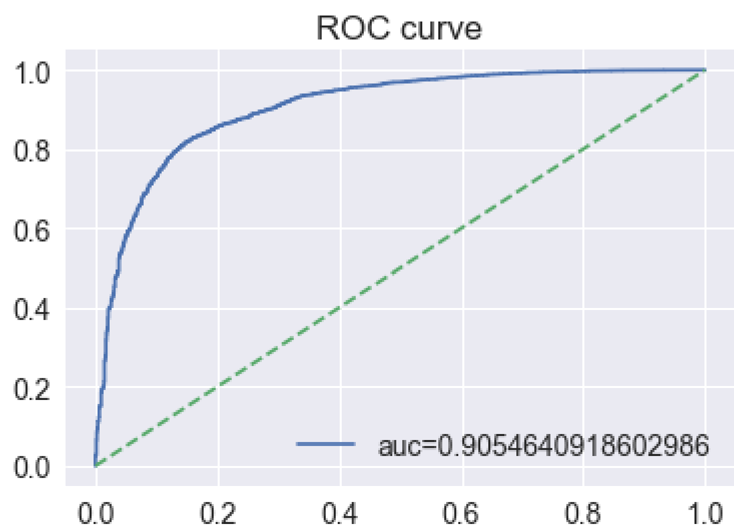
[5.2.1] Applying RBF SVM on BOW, SET 1

In [59]:
```
SVM(X_train=Bow_train,X_test=Bow_test,y_train=y_train,y_test=y_test)
```

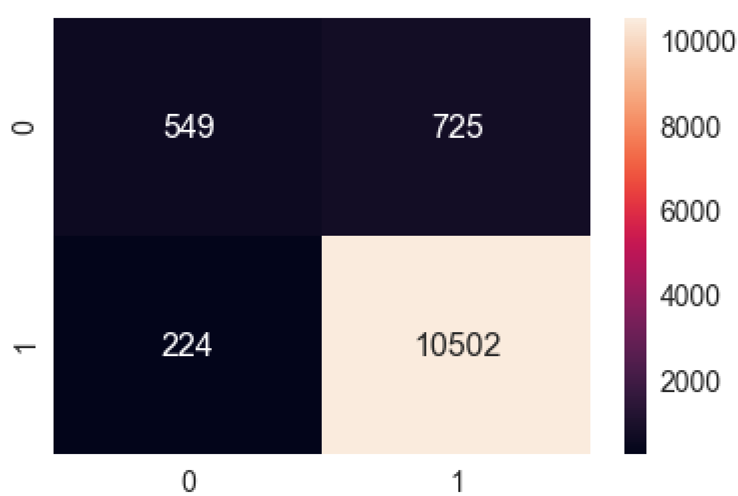
```
Train Data Size:  (28000, 500)
Test Data Size:  (12000, 500)
SVC GridSearch
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  6.5min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed: 65.9min
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed: 91.8min finished

Best HyperParameter:  {'C': 5, 'gamma': 0.5}
Best Accuracy: 91.37%
Accuracy on test set: 92.092%
Precision on test set: 0.935
Recall on test set: 0.979
F1-Score on test set: 0.957
ROC curve--
```




```
duration =  1:50:25.266501
```



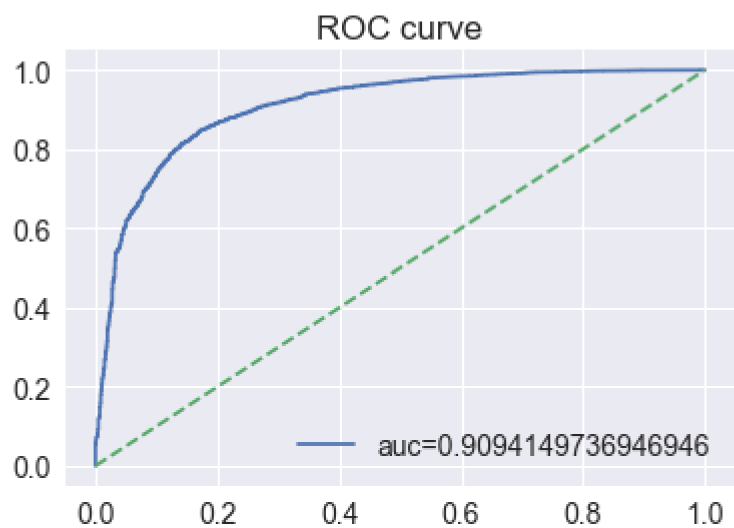
[5.2.2] Applying RBF SVM on TFIDF, SET 2

In [60]:
```
SVM(X_train=tf_idf_train,X_test=tf_idf_test,y_train=y_train,y_test=y_test)
```

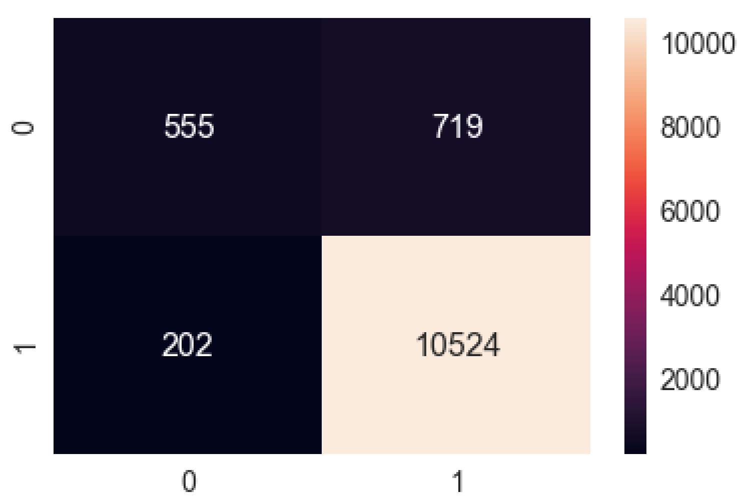
```
Train Data Size:  (28000, 500)
Test Data Size:  (12000, 500)
SVC GridSearch
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  6.6min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed: 68.7min
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed: 94.2min finished

Best HyperParameter:  {'C': 5, 'gamma': 0.5}
Best Accuracy: 91.48%
Accuracy on test set: 92.325%
Precision on test set: 0.936
Recall on test set: 0.981
F1-Score on test set: 0.958
ROC curve--
```




```
duration =  1:53:53.598457
```



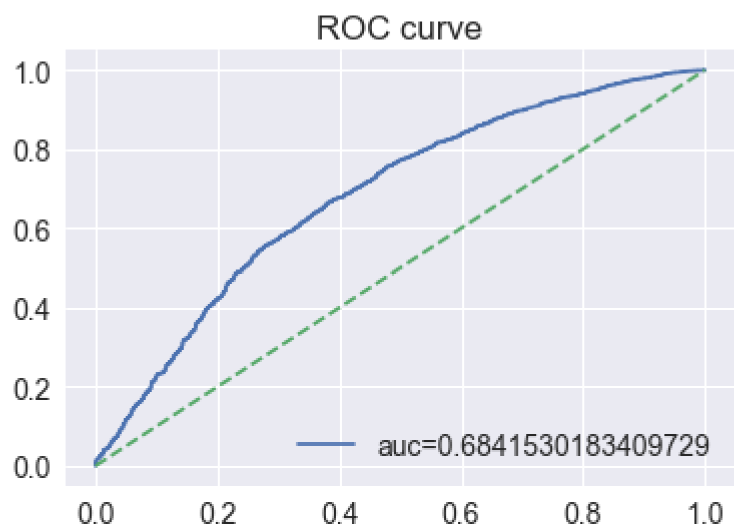
[5.2.3] Applying RBF SVM on AVG W2V, SET 3

In [61]:
```
SVM(X_train=avg_train,X_test=avg_test,y_train=y_train,y_test=y_test)
```

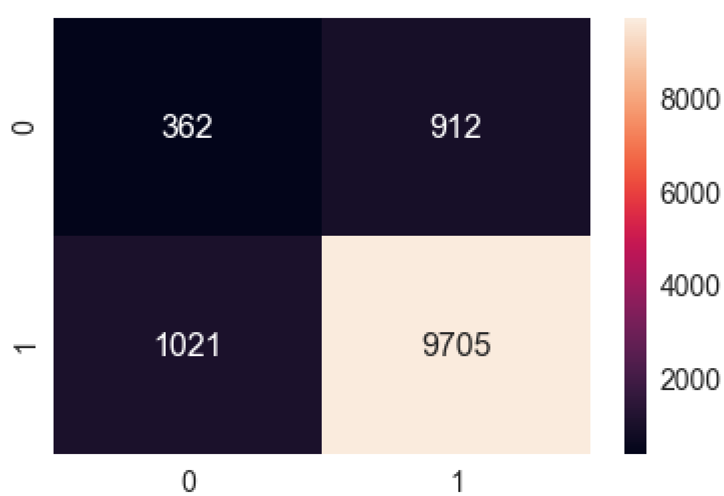
```
Train Data Size:  (28000, 200)
Test Data Size:  (12000, 200)
SVC GridSearch
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed: 14.0min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed: 95.9min
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed: 121.8min finished

Best HyperParameter:  {'C': 10, 'gamma': 1}
Best Accuracy: 91.20%
Accuracy on test set: 83.892%
Precision on test set: 0.914
Recall on test set: 0.905
F1-Score on test set: 0.909
ROC curve--
```




```
duration =  2:13:45.760831
```



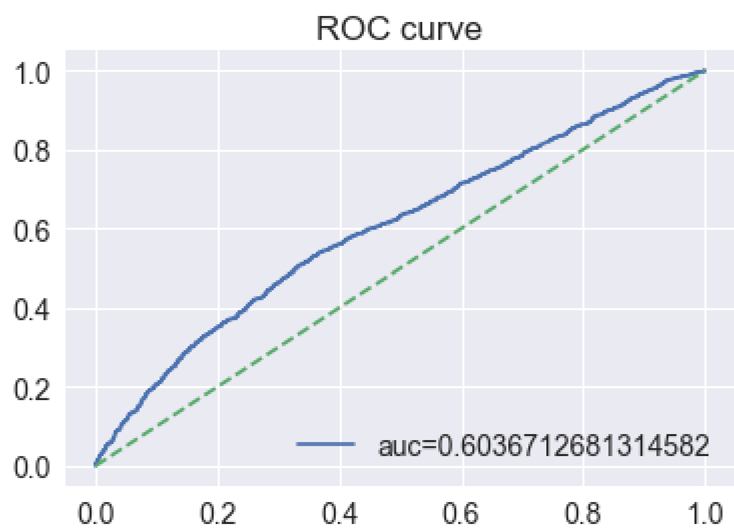
[5.2.4] Applying RBF SVM on TFIDF W2V, SET 4

In [62]:
```
SVM(X_train=w2v_tfidf_train,X_test=w2v_tfidf_test,y_train=y_train,y_test=y_tes
t)
```

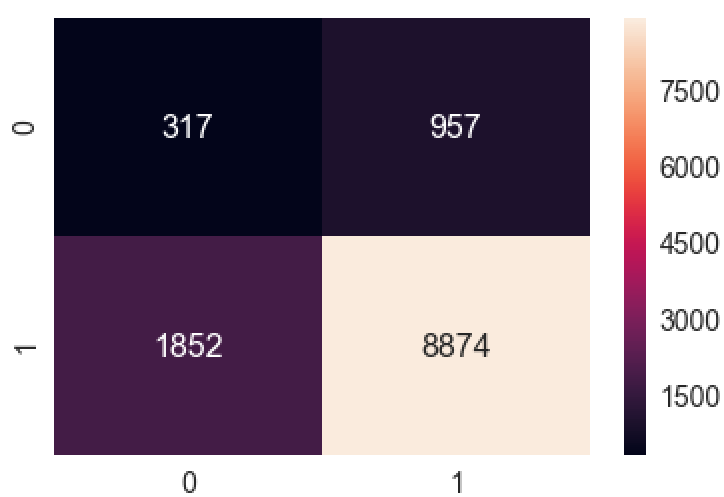
```
Train Data Size:  (28000, 200)
Test Data Size:  (12000, 200)
SVC GridSearch
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed: 14.0min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed: 97.2min
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed: 124.4min finished

Best HyperParameter:  {'C': 10, 'gamma': 1}
Best Accuracy: 90.51%
Accuracy on test set: 76.592%
Precision on test set: 0.903
Recall on test set: 0.827
F1-Score on test set: 0.863
ROC curve--
```




```
duration =  2:17:33.815122
```



[6] Conclusions

[5.1] Linear SVM Performance Table 100K points

sno	featurization	best alpha	best penalty	Accuracy	Precision	Recall	F1-Score
1	Bow	0.0001	l2	91.333%	0.914	0.995	0.953
2	Tfidf	0.0001	l2	91.163%	0.910	0.998	0.952
3	Avg w2v	0.0001	l2	88.963%	0.894	0.992	0.940
4	Tfidf w2v	0.0001	l2	88.860%	0.894	0.990	0.940

[5.2] RBF SVM Performance Table 40K points

sno	featurization	best C	best gamma	Accuracy	Precision	Recall	F1-Score
1	BOW	5	0.5	92.092%	0.935	0.979	0.957
2	Tfidf	5	0.5	92.325%	0.936	0.981	0.958
3	avg w2v	10	1	83.892%	0.914	0.905	0.909
4	tfidf w2v	10	1	76.592%	0.903	0.942	0.863

- SVC works well in case of Bow and Tfidf.
- In both cases Bow and tfidf work well.
- SVM with RBF kernal take more time than SGD with Hinge-loss.