Support Vector Machine on Amazon Food Reviews

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

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

Objective: Given Amazon Food reviews, convert all the reviews into a vector using four techniques:
1. TFIDF.
2. Average W2V.
3. Average TFIDF-W2V.

Then perform following tasks under each technique:
Task 1. Split train and test data in a ratio of 80:20.
Task 2. Perform GridSearch Cross Validation and Random Search Cross Validation to find optimal Value of C and Gamma.
Task 3. Apply Support Vector Machine using RBF kernel and report accuracy.
Task 4. Check for train error.

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

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

Loading the data

SQLite Database

In order to load the data, We have used the SQLITE dataset as it 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 id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [6]:
```
import sqlite3
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plot

from gensim.models import Word2Vec
import gensim
from sklearn.metrics import accuracy_score, confusion_matrix

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler

from sklearn.svm import SVC
from sklearn import linear_model
from sklearn.cross_validation import train_test_split
from sklearn.grid_search import GridSearchCV
from sklearn.grid_search import RandomizedSearchCV

from wordcloud import WordCloud
```

In [7]:
```
connection = sqlite3.connect('FinalAmazonFoodReviewsDataset.sqlite')
```

In [8]:
```
data = pd.read_sql_query("SELECT * FROM Reviews", connection)
```

In [9]:
```
data.head()
```

Out[9]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	Positive	1303862400	Good Quality Dog Food	se
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	Negative	1346976000	Not as Advertised	lal
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	Positive	1219017600	"Delight" says it all	F . cc a
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	Positive	1350777600	Great taffy	t
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	Positive	1342051200	Nice Taffy	

In [10]:
```
data.shape
```

Out[10]: (364171, 12)

In [11]:
```
data["Score"].value_counts()
```

Out[11]:
```
Positive    307061
Negative     57110
Name: Score, dtype: int64
```

In [12]:
```
def changingScores(score):
    if score == "Positive":
        return 1
    else:
        return -1
```

In [13]:
```
# changing score
# Positive = 1
# Negative = -1
actualScore = list(data["Score"])
positiveNegative = list(map(changingScores, actualScore)) #map(function, list of numbers)
data['Score'] = positiveNegative
```

In [14]:
```
data.head()
```

Out[14]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food	I b seve V ca
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	-1	1346976000	Not as Advertised	Pr a label J S Pea
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all	Thi confe tha aro
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	1	1350777600	Great taffy	taff
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	1	1342051200	Nice Taffy	I wil fo or tl

In [15]:
```
allPositiveReviews = data[(data["Score"] == 1)]
```

In [16]:
```
allPositiveReviews.shape
```

Out[16]:
```
(307061, 12)
```

In [17]:
```
positiveReviews_5000 = allPositiveReviews[:5000]
```

In [18]:
```
positiveReviews_5000.shape
```

Out[18]:
```
(5000, 12)
```

In [19]:
```
positiveReviews_5000.head()
```

Out[19]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food	I bo seve V ca
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all	Thi confe tha arou
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	1	1350777600	Great taffy	(taffy I T v
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	1	1342051200	Nice Taffy	I wild for ord th
5	6	7	B006K2ZZ7K	A1SP2KVKFXXRU1	David C. Sullivan	0	0	1	1340150400	Great! Just as good as the expensive brands!	salty taffy fla and v

In [20]:
```
allNegativeReviews = data[(data["Score"] == -1)]
```

In [21]:
```
allNegativeReviews.shape
```
Out[21]:
```
(57110, 12)
```

In [22]:
```
negativeReviews_5000 = allNegativeReviews[:5000]
```

In [23]:
```
negativeReviews_5000.shape
```
Out[23]:
```
(5000, 12)
```

In [24]:
```
negativeReviews_5000.head()
```

Out[24]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	T
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	-1	1346976000	Not as Advertised	Prod arri labe Jun Sal Peanu
11	12	13	B0009XLVG0	A327PCT23YH90	LT	1	1	-1	1339545600	My Cats Are Not Fans of the New Food	My c ha be hap eat Felic Pla
15	16	17	B001GVISJM	A3KLWF6WQ5BNYO	Erica Neathery	0	0	-1	1348099200	poor taste	I l eat th and tl are g watc
25	26	27	B001GVISJM	A3RXAU2N8KV45G	lady21	0	1	-1	1332633600	Nasty No flavor	- cand just re No fla . J pla
45	47	51	B001EO5QW8	A108P30XVUFKXY	Roberto A	0	7	-1	1203379200	Don't like it	T oatm is good. mus so

In [25]:
```
frames_10000 = [positiveReviews_5000, negativeReviews_5000]
```

In [26]:
```
FinalPositiveNegative = pd.concat(frames_10000)
```

In [27]:
```
FinalPositiveNegative.shape
```

Out[27]:
```
(10000, 12)
```

In [28]:
```
#Sorting FinalDataframe by "Time"
FinalSortedPositiveNegative_10000 = FinalPositiveNegative.sort_values('Time', axis=0, ascending=True, inplace=False)
```

In [29]:
```
FinalSortedPositiveNegativeScore_10000 = FinalSortedPositiveNegative_10000["Score"]
```

In [30]:
```
FinalSortedPositiveNegative_10000.shape
```

Out[30]:
```
(10000, 12)
```

In [31]:
```
FinalSortedPositiveNegativeScore_10000.shape
```

Out[31]:
```
(10000,)
```

In [32]:
```
Data = FinalSortedPositiveNegative_10000
```

In [33]:
```
Data_Labels = FinalSortedPositiveNegativeScore_10000
```

In [34]:
```
print(Data.shape)
print(Data_Labels.shape)
```

```
(10000, 12)
(10000,)
```

In [35]:
```
Data.head()
```

Out[35]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
772	1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	7	1	961718400	Great Product
771	1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	10	1	962236800	WOW Make your own 'slickers' !
5822	7427	8111	B0000EIE2Z	A3M174IC0VXOS2	Gail Cooke	3	3	1	1075420800	BEST BLUEBERRIES
2418	3481	3783	B00016UX0K	AF1PV3DIC0XM7	Robert Ashton	1	2	1	1081555200	Classic Condiment
5206	6790	7432	B0001E1IME	A2IKCTD1I73PLW	Adeba	2	8	1	1083456000	amazon monopoly/ripoff

1. TFIDF

In [36]:
```
positive_reviews = Data[(Data["Score"] == 1)]
negative_reviews = Data[(Data["Score"] == -1)]
```

In [37]:
```
positive_reviews.shape, negative_reviews.shape
```

Out[37]: ((5000, 12), (5000, 12))

In [38]:
```
Positive_tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), stop_words = "english")
Positive_tf_idf = Positive_tf_idf_vect.fit_transform(positive_reviews["ProcessedText"].values)
```

In [39]:
```
Positive_tf_idf.shape
```

Out[39]: (5000, 114651)

In [40]:
```
features = Positive_tf_idf_vect.get_feature_names()
```

In [41]:
```
idfValues = Positive_tf_idf_vect.idf_
```

In [45]:
```
d = dict(zip(features, 9 - idfValues))
```

In [46]:
```
sortedDict = sorted(d.items(), key = lambda d: d[1], reverse = True)
```

In [47]:
```
for i in range(200):
    print(sortedDict[i])
```

```
('like', 6.809072442421418)
('tast', 6.765368008186689)
('great', 6.763992492151379)
('good', 6.73466078043391)
('love', 6.689725684788852)
('flavor', 6.590032302691801)
('use', 6.568508292946707)
('just', 6.50636578331954)
('veri', 6.503690792870237)
('product', 6.470097075582087)
('tri', 6.467323148699362)
('make', 6.391361607896317)
('buy', 6.114608605976726)
('onli', 6.072907876777782)
('time', 6.060468186302143)
('realli', 6.049279258384337)
('best', 5.968767617525185)
('price', 5.95030555468545)
('littl', 5.909095286038787)
('dont', 5.886181026515912)
('order', 5.886181026515912)
('amazon', 5.849077276312534)
('store', 5.833492545295836)
('eat', 5.817661080079155)
('coffe', 5.8141086784747875)
('becaus', 5.806965790962407)
('recommend', 5.797964830103432)
('better', 5.790705270090627)
('mix', 5.726773729244833)
('ive', 5.650123319469437)
('ani', 5.631075124498743)
('high', 5.624644234168453)
('food', 5.594074168083775)
('bag', 5.591854411345462)
('drink', 5.580681110747337)
('year', 5.569381555493403)
('delici', 5.544063747509114)
('want', 5.529979007627374)
```

```
('work', 5.515693050379898)
('look', 5.501200043077331)
('favorit', 5.474071375689078)
('pack', 5.47156824547096)
('nice', 5.458957737879031)
('enjoy', 5.448753567704788)
('sweet', 5.441031521610878)
('day', 5.433249381168823)
('purchas', 5.428027437187671)
('sugar', 5.3879686766356665)
('say', 5.379760696217836)
('tea', 5.379760696217836)
('perfect', 5.377009662845947)
('snack', 5.377009662845947)
('brand', 5.371484786913977)
('bought', 5.3603426103607354)
('easi', 5.357537559433126)
('way', 5.349074885514393)
('sinc', 5.337678750783524)
('mani', 5.3290456036388205)
('thing', 5.3290456036388205)
('fresh', 5.302689758933458)
('need', 5.302689758933458)
('cup', 5.281699483041622)
('differ', 5.281699483041622)
('bit', 5.278664579346469)
('lot', 5.278664579346469)
('box', 5.269504209947804)
('think', 5.269504209947804)
('free', 5.254047951711112)
('packag', 5.247797931365941)
('add', 5.2094545761682935)
('come', 5.2094545761682935)
('regular', 5.2094545761682935)
('wonder', 5.1963396340904655)
('chip', 5.189717093329972)
('water', 5.189717093329972)
('alway', 5.166186595919777)
('local', 5.1627794375981635)
('everi', 5.155930095752589)
('got', 5.152487751561615)
('right', 5.135096008849747)
```

```
('know', 5.131581066742303)
('ship', 5.12451389951921)
('tasti', 5.120961497914842)
('calori', 5.113818610402461)
('review', 5.077318208182936)
('definit', 5.066103137362795)
('hard', 5.058555931727413)
('excel', 5.050951332342193)
('did', 5.039434890280634)
('befor', 5.031682913476317)
('qualiti', 5.027784273060659)
('healthi', 5.000059725045804)
('natur', 5.000059725045804)
('sure', 5.000059725045804)
('stuff', 4.975668271921645)
('famili', 4.971544554737783)
('high recommend', 4.967403762071751)
('someth', 4.963245751923088)
('ad', 4.954877502252571)
('doe', 4.954877502252571)
('chocol', 4.950666969716227)
('hot', 4.950666969716227)
('long', 4.933645282146797)
('happi', 4.929344200247407)
('small', 4.911952457535537)
('thank', 4.911952457535537)
('treat', 4.898707230785517)
('doesnt', 4.894252880436136)
('milk', 4.894252880436136)
('ingredi', 4.876234374933458)
('serv', 4.867101891370185)
('actual', 4.857885236265261)
('feel', 4.857885236265261)
('far', 4.853244856708759)
('howev', 4.843898994290521)
('month', 4.839193103253109)
('problem', 4.839193103253109)
('size', 4.839193103253109)
('didnt', 4.824941080545907)
('quick', 4.820144908282414)
('light', 4.800726822425313)
('usual', 4.800726822425313)
```

```
('pancak', 4.795812807622884)
('veri good', 4.795812807622884)
('help', 4.7859117366401716)
('groceri', 4.780924195129133)
('expens', 4.770873859275632)
('varieti', 4.770873859275632)
('start', 4.750464987644424)
('contain', 4.745297017485981)
('old', 4.745297017485981)
('pretti', 4.745297017485981)
('salt', 4.745297017485981)
('quit', 4.740102200608877)
('bake', 4.734880256627726)
('cook', 4.724353843640738)
('friend', 4.724353843640738)
('big', 4.719048791411046)
('gluten', 4.719048791411046)
('sauc', 4.7137154454356835)
('came', 4.7083535022942975)
('worth', 4.697542586190082)
('juic', 4.692092981422517)
('thought', 4.686613515657892)
('dog', 4.664390378873181)
('pleas', 4.664390378873181)
('recip', 4.664390378873181)
('peopl', 4.653090823619248)
('reason', 4.653090823619248)
('open', 4.64739280250461)
('arriv', 4.641662127795625)
('bean', 4.641662127795625)
('kid', 4.641662127795625)
('low', 4.641662127795625)
('abl', 4.635898423078875)
('anyth', 4.635898423078875)
('home', 4.635898423078875)
('case', 4.6301013053945494)
('new', 4.6301013053945494)
('altern', 4.618405265631358)
('groceri store', 4.618405265631358)
('strong', 4.606570807984355)
('expect', 4.600600640997851)
('diet', 4.5945946169376395)
```

```
('save', 4.588552302481677)
('tast like', 4.588552302481677)
('husband', 4.582473256405295)
('real', 4.582473256405295)
('anoth', 4.576357029387859)
('bad', 4.576357029387859)
('absolut', 4.57020316381348)
('organ', 4.57020316381348)
('tast great', 4.564011193565559)
('item', 4.551511030801327)
('especi', 4.538852633929404)
('smell', 4.532462835830634)
('textur', 4.532462835830634)
('chicken', 4.519559430994725)
('instead', 4.519559430994725)
('sever', 4.519559430994725)
('week', 4.513044749973531)
('oil', 4.506487349427372)
('amaz', 4.499886665396021)
('blend', 4.486553134526556)
('fruit', 4.486553134526556)
('theyr', 4.486553134526556)
('bottl', 4.479819102345211)
('butter', 4.479819102345211)
('kind', 4.479819102345211)
('onc', 4.479819102345211)
('orang', 4.479819102345211)
('wont', 4.459340571001671)
('cat', 4.445451458841004)
('fat', 4.445451458841004)
('prefer', 4.445451458841004)
('ago', 4.438433886182358)
('avail', 4.438433886182358)
('gluten free', 4.438433886182358)
('soda', 4.438433886182358)
('wish', 4.438433886182358)
```

In [50]:
```
def PlotWordCloud(frequency):
    worcloudPlot = WordCloud(background_color="white", width=1500, height=1000)
    worcloudPlot.generate_from_frequencies(frequencies=frequency)
    plot.figure(figsize=(15,10))
    plot.imshow(worcloudPlot, interpolation="bilinear")
    plot.axis("off")
    plot.show()
```

In [51]:
```
PlotWordCloud(d)
```

This is a Word Cloud for all the positive reviews in the corpus.
This Word Cloud plot correponds to the most frequent words in all positive reviews based on IDF values. More is the IDF Value for a word the less frequent is the word in the corpus.

How I have plotted this word cloud. Now formulae for IDF(D,Wi) = (ln(N+1 / ni+1) + 1) where 'N' is total number of documents in a corpus and 'ni' is the total number of documents where word 'Wi' occurs. Hence, I got all the idf values from idf_ attribute and I got corresponding features from get_features_names() function. Now since, the highest possible idf value can be 8.88, hence, I subtracted all the idf values from '9' which leads to the highest idf value of the most frequently occuring word. Now I created dictionary where features are the keys and modified idf value are the values and I feeded this to the word cloud and plot the same. The same is done for negative reviews as well.

In [52]:
```
Negative_tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), stop_words = "english")
Negative_tf_idf = Negative_tf_idf_vect.fit_transform(negative_reviews["ProcessedText"].values)
```

In [53]:
```
Negative_tf_idf.shape
```

Out[53]:
```
(5000, 139161)
```

In [54]:
```
features_neg = Negative_tf_idf_vect.get_feature_names()
```

In [55]:
```
negIDF = Negative_tf_idf_vect.idf_
```

In [56]:
```
NegD = dict(zip(features_neg, 9 - negIDF))
```

In [57]:
```
sortedDictNeg = sorted(NegD.items(), key = lambda NegD: NegD[1], reverse = True)
```

In [58]:
```
for i in range(200):
    print(sortedDictNeg[i])
```

```
('tast', 7.0050070599682215)
('like', 7.004466080782725)
('product', 6.762615081465285)
('just', 6.6496447054933165)
('veri', 6.595748937288184)
('tri', 6.565994676206391)
('good', 6.44957396719508)
('flavor', 6.4170040385096545)
('use', 6.376263183183732)
('buy', 6.343270500029383)
('dont', 6.271578571573267)
('becaus', 6.170961542527858)
('onli', 6.1211746177476165)
('make', 6.113290214223468)
('time', 6.082477327793933)
('order', 6.054889371275104)
('realli', 6.047871798616457)
('look', 6.009101688151887)
('love', 5.951857145376868)
('food', 5.95030555468545)
('eat', 5.9314962227279535)
('bought', 5.923553369214017)
('disappoint', 5.889486814650411)
('ani', 5.862729365480861)
('packag', 5.861033012232683)
('better', 5.8473575854330075)
('review', 5.8473575854330075)
('did', 5.835236224900663)
('think', 5.828243189409692)
('purchas', 5.822966132308848)
('amazon', 5.810543612310291)
('box', 5.794341637734011)
('want', 5.783392623244341)
('bad', 5.781556075437039)
('say', 5.751703112287357)
('didnt', 5.742188292646019)
('know', 5.7287135940626595)
('thought', 5.720931453620604)
```

```
('bag', 5.713088276159578)
('drink', 5.674969318055968)
('great', 5.66881545248159)
('way', 5.645921632615737)
('price', 5.618171719662835)
('littl', 5.613833318064237)
('got', 5.609476012695281)
('ive', 5.5761765986262315)
('someth', 5.5761765986262315)
('coffe', 5.564825738957542)
('tast like', 5.557952859669781)
('thing', 5.555651362681502)
('water', 5.548714918684844)
('dog', 5.544063747509114)
('store', 5.520477748503234)
('mix', 5.513292088842359)
('money', 5.5036301779306225)
('befor', 5.484021706542246)
('receiv', 5.484021706542246)
('differ', 5.456416440450358)
('open', 5.443612168204369)
('smell', 5.443612168204369)
('away', 5.441031521610878)
('brand', 5.438444198045927)
('doe', 5.4358501628688805)
('ingredi', 5.430641817761742)
('recommend', 5.409532854551507)
('tea', 5.3879686766356665)
('item', 5.382504182163588)
('sugar', 5.382504182163588)
('howev', 5.365929217069375)
('sinc', 5.357537559433126)
('cup', 5.349074885514393)
('old', 5.337678750783524)
('sweet', 5.331931608527956)
('come', 5.314489305864614)
('doesnt', 5.314489305864614)
('year', 5.311552446191303)
('pack', 5.305652724064116)
('work', 5.302689758933458)
('day', 5.29074931856154)
('sure', 5.284725203958159)
```

```
('need', 5.266432010910833)
('chocol', 5.263350344373426)
('mani', 5.250927824374869)
('actual', 5.244658211361273)
('hope', 5.222399740760331)
('anoth', 5.219179126060288)
('expect', 5.2094545761682935)
('mayb', 5.193033845955966)
('hard', 5.189717093329972)
('lot', 5.183050401971783)
('ship', 5.166186595919777)
('stuff', 5.159360630849378)
('problem', 5.155930095752589)
('return', 5.152487751561615)
('compani', 5.149033516693528)
('contain', 5.145567308717043)
('wast', 5.135096008849747)
('enjoy', 5.131581066742303)
('anyth', 5.117396431750346)
('bit', 5.106624334768435)
('high', 5.0993779262476675)
('month', 5.095734934969167)
('peopl', 5.088408894877094)
('ill', 5.084725649460797)
('small', 5.077318208182936)
('wont', 5.073593809091953)
('hot', 5.069855486981346)
('noth', 5.069855486981346)
('new', 5.054760860758861)
('star', 5.050951332342193)
('ad', 5.04712723590379)
('read', 5.031682913476317)
('qualiti', 5.019941095599632)
('whi', 5.015996317308616)
('strong', 5.00805976771288)
('treat', 4.996035574746079)
('natur', 4.971544554737783)
('dri', 4.963245751923088)
('textur', 4.963245751923088)
('local', 4.946438633606706)
('right', 4.946438633606706)
('pretti', 4.9379279439387975)
```

```
('said', 4.933645282146797)
('kind', 4.929344200247407)
('big', 4.916328832135337)
('gave', 4.916328832135337)
('best', 4.903141827853382)
('real', 4.889778600041215)
('worth', 4.889778600041215)
('chew', 4.885284210453376)
('regular', 4.885284210453376)
('chang', 4.871678558397598)
('feel', 4.871678558397598)
('list', 4.867101891370185)
('half', 4.862504182121556)
('probabl', 4.862504182121556)
('end', 4.839193103253109)
('instead', 4.834464962057163)
('size', 4.834464962057163)
('far', 4.824941080545907)
('came', 4.810482997370677)
('guess', 4.810482997370677)
('arriv', 4.800726822425313)
('free', 4.795812807622884)
('veri disappoint', 4.795812807622884)
('wasnt', 4.795812807622884)
('piec', 4.790874525982302)
('unfortun', 4.780924195129133)
('bitter', 4.770873859275632)
('decid', 4.770873859275632)
('horribl', 4.770873859275632)
('care', 4.765810557319085)
('long', 4.765810557319085)
('everi', 4.7607214878116135)
('sever', 4.7607214878116135)
('start', 4.7607214878116135)
('went', 4.7607214878116135)
('fine', 4.745297017485981)
('usual', 4.740102200608877)
('isnt', 4.734880256627726)
('label', 4.729630900741583)
('case', 4.719048791411046)
('expens', 4.719048791411046)
('aw', 4.7137154454356835)
```

```
('notic', 4.7137154454356835)
('throw', 4.7137154454356835)
('bottl', 4.7083535022942975)
('mouth', 4.7083535022942975)
('save', 4.7083535022942975)
('terribl', 4.702962653659421)
('plastic', 4.697542586190082)
('week', 4.697542586190082)
('minut', 4.686613515657892)
('organ', 4.686613515657892)
('wouldnt', 4.686613515657892)
('left', 4.681103859846922)
('complet', 4.675563679471306)
('stick', 4.675563679471306)
('milk', 4.669992634421851)
('let', 4.664390378873181)
('juic', 4.653090823619248)
('second', 4.64739280250461)
('definit', 4.635898423078875)
('took', 4.6301013053945494)
('groceri', 4.61250554350417)
('wast money', 4.61250554350417)
('add', 4.600600640997851)
('low', 4.600600640997851)
('believ', 4.5945946169376395)
('quit', 4.5945946169376395)
('alway', 4.588552302481677)
('onc', 4.588552302481677)
('custom', 4.582473256405295)
('worst', 4.576357029387859)
('ginger', 4.557780643814923)
('nice', 4.557780643814923)
('fact', 4.551511030801327)
('fresh', 4.551511030801327)
('wrong', 4.545201861608064)
('wonder', 4.538852633929404)
```

In [59]:
```
PlotWordCloud(NegD)
```

This is a Word Cloud for all the negative reviews in the corpus.

This Word Cloud plot correponds to the most frequent words in all negative reviews based on IDF values. More is the IDF Value for a word the less frequent is the word in the corpus.

In [66]:
```
tfidf_vect = TfidfVectorizer(ngram_range = (1,2))
```

In [67]:
```
Data_TFIDF = tfidf_vect.fit_transform(Data["ProcessedText"].values)
```

In [68]:
```
Data_TFIDF.shape
```

Out[68]:
```
(10000, 237703)
```

In [69]:
```
type(Data_TFIDF)
```

Out[69]:
```
scipy.sparse.csr.csr_matrix
```

In [70]:
```
Data_TFIDF_Std = StandardScaler(with_mean = False).fit_transform(Data_TFIDF)
```

In [71]:
```
print(Data_TFIDF_Std.shape)
print(type(Data_TFIDF_Std))
```

```
(10000, 237703)
<class 'scipy.sparse.csr.csr_matrix'>
```

Task 1. Split train and test data in a ratio of 80:20.

In [72]:
```
train_TFIDF, test_TFIDF, train_labels_TFIDF, test_labels_TFIDF = train_test_split(Data_TFIDF_Std, Data_Labels, test_size
```

In [73]:
```
train_TFIDF.shape, test_TFIDF.shape, train_labels_TFIDF.shape, test_labels_TFIDF.shape
```

Out[73]:
```
((8000, 237703), (2000, 237703), (8000,), (2000,))
```

Task 2. Perform GridSearch Cross Validation and Random Search Cross Validation to find optimal Value of C and Gamma.

In [135]:
```
#when gamma value decreases then RBF kernel increases
clf = SVC()

hyper_parameters = {'kernel': ['rbf'], 'gamma': [10**-8, 10**-6, 10**-4], 'C': [100, 500, 1000, 2000]}
bestCV = GridSearchCV(clf, hyper_parameters, scoring = "accuracy", cv = 3)
bestCV.fit(train_TFIDF, train_labels_TFIDF)

print(bestCV.best_estimator_)
```

```
SVC(C=2000, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=1e-08, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [136]:
```
best_parameter = bestCV.best_params_
best_parameter
```

Out[136]:
```
{'C': 2000, 'gamma': 1e-08, 'kernel': 'rbf'}
```

In [137]:
```
scoreData = bestCV.grid_scores_
scoreData
```

Out[137]:
```
[mean: 0.52800, std: 0.00495, params: {'C': 100, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.82188, std: 0.01049, params: {'C': 100, 'gamma': 1e-06, 'kernel': 'rbf'},
 mean: 0.50338, std: 0.00015, params: {'C': 100, 'gamma': 0.0001, 'kernel': 'rbf'},
 mean: 0.81688, std: 0.01265, params: {'C': 500, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.82188, std: 0.01049, params: {'C': 500, 'gamma': 1e-06, 'kernel': 'rbf'},
 mean: 0.50338, std: 0.00015, params: {'C': 500, 'gamma': 0.0001, 'kernel': 'rbf'},
 mean: 0.84237, std: 0.01116, params: {'C': 1000, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.82188, std: 0.01049, params: {'C': 1000, 'gamma': 1e-06, 'kernel': 'rbf'},
 mean: 0.50338, std: 0.00015, params: {'C': 1000, 'gamma': 0.0001, 'kernel': 'rbf'},
 mean: 0.84500, std: 0.00992, params: {'C': 2000, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.82188, std: 0.01049, params: {'C': 2000, 'gamma': 1e-06, 'kernel': 'rbf'},
 mean: 0.50338, std: 0.00015, params: {'C': 2000, 'gamma': 0.0001, 'kernel': 'rbf'}]
```

In [138]:
```
error = []
eachError = []
for i in range(12):
    eachError.append(1 - scoreData[i][1])
    if i == 2 or i == 5 or i == 8 or i == 11:
        error.append(eachError)
        eachError = []
```

In [139]:
```
error
```

Out[139]:
```
[[0.472, 0.17812499999999998, 0.496625],
 [0.18312499999999998, 0.17812499999999998, 0.496625],
 [0.15762500000000002, 0.17812499999999998, 0.496625],
 [0.15500000000000003, 0.17812499999999998, 0.496625]]
```

In [140]:
```
columnNames = [10**-8, 10**-6, 10**-4]
```

In [141]:
```
errorFrame = pd.DataFrame(error, columns = columnNames)
```

In [142]:
```
errorFrame
```

Out[142]:

	1e-08	1e-06	0.0001
0	0.472000	0.178125	0.496625
1	0.183125	0.178125	0.496625
2	0.157625	0.178125	0.496625
3	0.155000	0.178125	0.496625

In [143]:
```
indexNames = [100, 500, 1000, 2000]
errorFrame["C"] = indexNames
```

In [144]:
```
errorFrame
```

Out[144]:

	1e-08	1e-06	0.0001	C
0	0.472000	0.178125	0.496625	100
1	0.183125	0.178125	0.496625	500
2	0.157625	0.178125	0.496625	1000
3	0.155000	0.178125	0.496625	2000

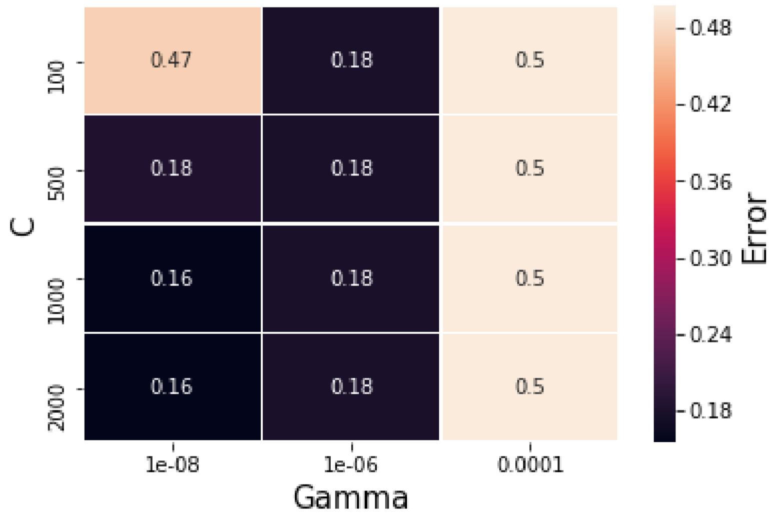
In [145]:
```
errorFrame.set_index("C", append = False, drop = True, inplace = True)
```

In [146]:
```
errorFrame
```

Out[146]:

	1e-08	1e-06	0.0001
C			
100	0.472000	0.178125	0.496625
500	0.183125	0.178125	0.496625
1000	0.157625	0.178125	0.496625
2000	0.155000	0.178125	0.496625

In [147]:
```
ax = sns.heatmap(errorFrame, annot = True, linewidths=.5)
ax.figure.axes[0].set_xlabel('Gamma', size = 15)
ax.figure.axes[0].set_ylabel('C', size = 15)
ax.figure.axes[-1].set_ylabel('Error', size = 15)
plot.show()
```



Here above in heatmap you can see that the error is minimum when gamma value is 10^-8 and C value is 2000. Therefore, from grid search we are considering our C value as 2000 and Gamma Value as 10^-8

In [148]:
```
n = list(np.random.normal(loc=2000, scale=500, size = 100))  #taking 100 numbers which are distributed normally with mean
                                                             #and std-dev = 500
```

In [149]:
```
k = []
for i in n:
    k.append(abs(i))
```

In [150]:
```
#when gamma value decreases then RBF kernel increases
clf = SVC()

hyper_parameters2 = {'kernel': ['rbf'], 'gamma': [10**-8, 10**-6], 'C': k}

bestCV_random = RandomizedSearchCV(clf, hyper_parameters2, n_iter = 4, scoring = "accuracy", cv = 3)

bestCV_random.fit(train_TFIDF, train_labels_TFIDF)
print(bestCV_random.best_estimator_)
```

```
SVC(C=2447.5558059680925, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=1e-08, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [151]:
```
best_random_parameter = bestCV_random.best_params_
best_random_parameter["C"]
```

Out[151]:
```
2447.5558059680925
```

In [152]:
```
scoreRandomData = bestCV_random.grid_scores_
scoreRandomData
```

Out[152]:
```
[mean: 0.84575, std: 0.00976, params: {'kernel': 'rbf', 'gamma': 1e-08, 'C': 2447.5558059680925},
 mean: 0.84500, std: 0.00940, params: {'kernel': 'rbf', 'gamma': 1e-08, 'C': 1636.881474751077},
 mean: 0.82188, std: 0.01049, params: {'kernel': 'rbf', 'gamma': 1e-06, 'C': 1645.657293928913},
 mean: 0.82188, std: 0.01049, params: {'kernel': 'rbf', 'gamma': 1e-06, 'C': 1460.31104996981}]
```

Here, above as you can see that error becomes least at C value 2447.555 and gamma value 10^-8.

In [153]:
```
# We are taking our hyper-parameter C as the average of best C computed from gridSearchCV and RandomSearchCV
FinalHP = (best_parameter["C"] + best_random_parameter["C"]) / 2
FinalHP
```

Out[153]:
```
2223.7779029840462
```

Task 3. Apply Support Vector Machine using RBF kernel and report accuracy.

In [161]:
```
model = SVC(C = FinalHP, kernel = "rbf", gamma = 10**-9)

model.fit(train_TFIDF, train_labels_TFIDF)

prediction = model.predict(test_TFIDF)

AccuracyScore = accuracy_score(test_labels_TFIDF, prediction) * 100

print("Accuracy score of SVC = "+str(AccuracyScore)+"%")
```

```
Accuracy score of SVC = 79.9%
```

Task 4. Check for train error.

In [163]:
```
model = SVC(C = FinalHP, kernel = "rbf", gamma = 10**-9)

model.fit(train_TFIDF, train_labels_TFIDF)

prediction2 = model.predict(train_TFIDF)

AccuracyScore2 = accuracy_score(train_labels_TFIDF, prediction2)

print("Train error of SVC = "+str(1 - AccuracyScore2))
```

```
Train error of SVC = 0.0018749999999996
```

By gamma value of 10^-8, our model was over-fitting, therefore, we have decided to change the value of gamma to 10^-9

2. Avg W2V

In [32]:
```
i = 0
listOfSentences = []
for sentence in Data["ProcessedText"].values:
    subSentence = []
    for word in sentence.split():
        subSentence.append(word)

    listOfSentences.append(subSentence)
```

In [33]:
```
print(Data['ProcessedText'].values[0])
print("\n")
print(listOfSentences[0:2])
print("\n")
print(type(listOfSentences))
```

```
this was realli good idea and the final product outstand use the decal car window and everybodi ask where bought the de
cal made two thumb


[['this', 'was', 'realli', 'good', 'idea', 'and', 'the', 'final', 'product', 'outstand', 'use', 'the', 'decal', 'car',
'window', 'and', 'everybodi', 'ask', 'where', 'bought', 'the', 'decal', 'made', 'two', 'thumb'], ['just', 'receiv', 'sh
ipment', 'and', 'could', 'hard', 'wait', 'tri', 'this', 'product', 'love', 'which', 'what', 'call', 'them', 'instead',
'sticker', 'becaus', 'they', 'can', 'remov', 'easili', 'daughter', 'design', 'sign', 'print', 'revers', 'use', 'her',
'car', 'window', 'they', 'print', 'beauti', 'have', 'the', 'print', 'shop', 'program', 'go', 'have', 'lot', 'fun', 'wit
h', 'this', 'product', 'becaus', 'there', 'are', 'window', 'everywher', 'and', 'other', 'surfac', 'like', 'screen', 'an
d', 'comput', 'monitor']]


<class 'list'>
```

In [34]:
```
w2vModel = gensim.models.Word2Vec(listOfSentences, size=300, min_count=5, workers=4)
```

In [35]:
```
# compute average word2vec for each review.
sentenceAsW2V = []
for sentence in listOfSentences:
    sentenceVector = np.zeros(300)
    TotalWordsPerSentence = 0
    for word in sentence:
        try:
            vect = w2vModel.wv[word]
            sentenceVector += vect
            TotalWordsPerSentence += 1
        except:
            pass
    sentenceVector /= TotalWordsPerSentence
    sentenceAsW2V.append(sentenceVector)

print(type(sentenceAsW2V))
print(len(sentenceAsW2V))
print(len(sentenceAsW2V[0]))
```

```
<class 'list'>
10000
300
```

In [36]:
```
standardized_Avg_w2v = StandardScaler().fit_transform(sentenceAsW2V)
print(standardized_Avg_w2v.shape)
print(type(standardized_Avg_w2v))
```

```
(10000, 300)
<class 'numpy.ndarray'>
```

Task 1. Split train and test data in a ratio of 80:20.

In [37]:
```
train_AvgW2V, test_AvgW2V, train_labels_AvgW2V, test_labels_AvgW2V = train_test_split(standardized_Avg_w2v, Data_Labels,
```

In [38]:
```
train_AvgW2V.shape, test_AvgW2V.shape, train_labels_AvgW2V.shape, test_labels_AvgW2V.shape
```

Out[38]:
```
((8000, 300), (2000, 300), (8000,), (2000,))
```

Task 2. Perform GridSearch Cross Validation and Random Search Cross Validation to find optimal Value of C and Gamma.

In [80]:
```
#when gamma value decreases then RBF kernel increases
clf = SVC()

hyper_parameters = {'kernel': ['rbf'], 'gamma': [10**-8, 10**-7, 10**-5], 'C': [10, 100, 500, 1000]}
bestCV = GridSearchCV(clf, hyper_parameters, scoring = "accuracy", cv = 3)
bestCV.fit(train_AvgW2V, train_labels_AvgW2V)

print(bestCV.best_estimator_)
```

```
SVC(C=1000, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=1e-05, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [81]:
```
best_parameter = bestCV.best_params_
best_parameter["C"]
```

Out[81]:
```
1000
```

In [82]:
```
scoreData = bestCV.grid_scores_
scoreData
```

Out[82]:
```
[mean: 0.50138, std: 0.00009, params: {'C': 10, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.50187, std: 0.00055, params: {'C': 10, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.77587, std: 0.00996, params: {'C': 10, 'gamma': 1e-05, 'kernel': 'rbf'},
 mean: 0.50187, std: 0.00055, params: {'C': 100, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.75200, std: 0.01030, params: {'C': 100, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.78738, std: 0.01295, params: {'C': 100, 'gamma': 1e-05, 'kernel': 'rbf'},
 mean: 0.73938, std: 0.01336, params: {'C': 500, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.76987, std: 0.01005, params: {'C': 500, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.79438, std: 0.01080, params: {'C': 500, 'gamma': 1e-05, 'kernel': 'rbf'},
 mean: 0.75175, std: 0.01012, params: {'C': 1000, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.77563, std: 0.01059, params: {'C': 1000, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.79863, std: 0.00705, params: {'C': 1000, 'gamma': 1e-05, 'kernel': 'rbf'}]
```

In [83]:
```
error2 = []
eachError2 = []
for i in range(12):
    eachError2.append(1 - scoreData[i][1])
    if i == 2 or i == 5 or i == 8 or i == 11:
        error2.append(eachError2)
        eachError2 = []
error2
```

Out[83]:
```
[[0.498625, 0.49812500000000004, 0.22412500000000002],
 [0.49812500000000004, 0.248, 0.21262499999999995],
 [0.260625, 0.23012500000000002, 0.20562499999999995],
 [0.24824999999999997, 0.224375, 0.20137499999999997]]
```

In [84]:
```
columnNames2 = [10**-8, 10**-7, 10**-5]
errorFrame2 = pd.DataFrame(error2, columns = columnNames2)
errorFrame2
```

Out[84]:

	1e-08	1e-07	1e-05
0	0.498625	0.498125	0.224125
1	0.498125	0.248000	0.212625
2	0.260625	0.230125	0.205625
3	0.248250	0.224375	0.201375

In [85]:
```
indexNames2 = [10, 100, 500, 1000]
errorFrame2["C"] = indexNames2
errorFrame2
```

Out[85]:

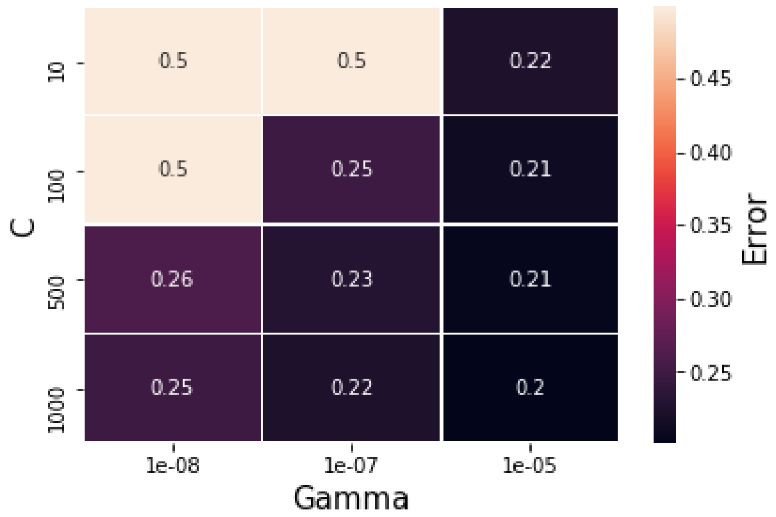
	1e-08	1e-07	1e-05	C
0	0.498625	0.498125	0.224125	10
1	0.498125	0.248000	0.212625	100
2	0.260625	0.230125	0.205625	500
3	0.248250	0.224375	0.201375	1000

In [86]:
```
errorFrame2.set_index("C", append = False, drop = True, inplace = True)
errorFrame2
```

Out[86]:

C	1e-08	1e-07	1e-05
10	0.498625	0.498125	0.224125
100	0.498125	0.248000	0.212625
500	0.260625	0.230125	0.205625
1000	0.248250	0.224375	0.201375

In [87]:
```
ax2 = sns.heatmap(errorFrame2, annot = True, linewidths=.5)
ax2.figure.axes[0].set_xlabel('Gamma', size = 15)
ax2.figure.axes[0].set_ylabel('C', size = 15)
ax2.figure.axes[-1].set_ylabel('Error', size = 15)
plot.show()
```



Here above in heatmap you can see that the error is minimum when gamma value is 10^-5 and C value is 1000. Therefore, from grid search we are considering our C value as 1000 and Gamma Value as 10^-5

In [90]:
```
n = list(np.random.normal(loc=1000, scale=400, size = 100))  #taking 100 numbers which are distributed normally with mean
                                                             #and std-dev = 400
```

In [97]:
```
#when gamma value decreases then RBF kernel increases
clf = SVC()

hyper_parameters3 = {'kernel': ['rbf'], 'gamma': [10**-6, 10**-5], 'C': n}

bestCV_random2 = RandomizedSearchCV(clf, hyper_parameters3, n_iter = 4, scoring = "accuracy", cv = 3)

bestCV_random2.fit(train_AvgW2V, train_labels_AvgW2V)
print(bestCV_random2.best_estimator_)
```

```
SVC(C=1302.608385476245, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=1e-05, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [98]:
```
best_random_parameter2 = bestCV_random2.best_params_
best_random_parameter2["C"]
```

Out[98]:
```
1302.608385476245
```

In [99]:
```
scoreRandomData2 = bestCV_random2.grid_scores_
scoreRandomData2
```

Out[99]:
```
[mean: 0.79975, std: 0.00796, params: {'kernel': 'rbf', 'gamma': 1e-05, 'C': 1467.1596660697855},
 mean: 0.80012, std: 0.00771, params: {'kernel': 'rbf', 'gamma': 1e-05, 'C': 1302.608385476245},
 mean: 0.79837, std: 0.00717, params: {'kernel': 'rbf', 'gamma': 1e-05, 'C': 1073.1100023854217},
 mean: 0.78625, std: 0.01277, params: {'kernel': 'rbf', 'gamma': 1e-06, 'C': 772.5827460396076}]
```

Here, above as you can see that error becomes least at C value 1302.608 and gamma value 10^-5.

In [100]:
```
# We are taking our hyper-parameter C as the average of best C computed from gridSearchCV and RandomSearchCV
FinalHP2 = (best_parameter["C"] + best_random_parameter2["C"]) / 2
FinalHP2
```

Out[100]:
```
1151.3041927381225
```

Task 3. Apply Support Vector Machine using RBF kernel and report accuracy.

In [101]:
```
model = SVC(C = FinalHP2, kernel = "rbf", gamma = 10**-5)

model.fit(train_AvgW2V, train_labels_AvgW2V)

prediction3 = model.predict(test_AvgW2V)

AccuracyScore3 = accuracy_score(test_labels_AvgW2V, prediction3) * 100

print("Accuracy score of SVC = "+str(AccuracyScore3)+"%")
```

```
Accuracy score of SVC = 81.25%
```

In [102]:
```
Confusion_Matrix = confusion_matrix(test_labels_AvgW2V, prediction3)
print("Confusion Matrix on L2 regularization  \n"+str(Confusion_Matrix))
```

```
Confusion Matrix on L2 regularization
[[834 155]
 [220 791]]
```

In [103]:
```
tn, fp, fn, tp = confusion_matrix(test_labels_AvgW2V, prediction3).ravel()
tn, fp, fn, tp
```

Out[103]:
```
(834, 155, 220, 791)
```

Trying SGD Classifier on SVM

In [54]:
```
clf = linear_model.SGDClassifier(loss="hinge")

clf.fit(train_AvgW2V, train_labels_AvgW2V)

prediction_SGD = clf.predict(test_AvgW2V)

AccuracyScore_SGD = accuracy_score(test_labels_AvgW2V, prediction_SGD) * 100

print("Accuracy score of SVC on SGDClassifier = "+str(AccuracyScore_SGD)+"%")
```

```
Accuracy score of SVC on SGDClassifier = 78.2%

C:\Users\GauravP\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:128: FutureWarning: max_iter a
nd tol parameters have been added in <class 'sklearn.linear_model.stochastic_gradient.SGDClassifier'> in 0.19. If both
are left unset, they default to max_iter=5 and tol=None. If tol is not None, max_iter defaults to max_iter=1000. From
0.21, default max_iter will be 1000, and default tol will be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

Task 4. Check for train error.

In [104]:
```
model = SVC(C = FinalHP, kernel = "rbf", gamma = 10**-5)

model.fit(train_AvgW2V, train_labels_AvgW2V)

prediction3 = model.predict(train_AvgW2V)

AccuracyScore3 = accuracy_score(train_labels_AvgW2V, prediction3)

print("Train error of SVC = "+str(1 - AccuracyScore3))
```

```
Train error of SVC = 0.19625000000000004
```

3. TFIDF-W2V

In [39]:
```
tfidf_vect = TfidfVectorizer(ngram_range = (1,2))
tfidf = tfidf_vect.fit_transform(Data["ProcessedText"].values)
```

In [40]:
```
w2v_Model = gensim.models.Word2Vec(listOfSentences, size=300, min_count=5, workers=4)
```

In [41]:
```
print(tfidf.shape)
print(type(tfidf))
```

```
(10000, 237703)
<class 'scipy.sparse.csr.csr_matrix'>
```

In [42]:
```
# TF-IDF weighted Word2Vec
tfidf_features = tfidf_vect.get_feature_names()

tfidf_w2v = []
reviews = 0

for sentence in listOfSentences:
    sentenceVector = np.zeros(300)
    weightTfidfSum = 0
    for word in sentence:
        try:
            W2V_Vector = w2v_Model.wv[word]
            tfidfVector = tfidf[reviews, tfidf_features.index(word)]
            sentenceVector += (W2V_Vector * tfidfVector)
            weightTfidfSum += tfidfVector
        except:
            pass
    sentenceVector /= weightTfidfSum
    tfidf_w2v.append(sentenceVector)
    reviews += 1
```

In [43]:
```
standardized_tfidf_w2v = StandardScaler().fit_transform(tfidf_w2v)
print(standardized_tfidf_w2v.shape)
print(type(standardized_tfidf_w2v))
```

```
(10000, 300)
<class 'numpy.ndarray'>
```

Task 1. Split train and test data in a ratio of 80:20.

In [45]:
```
train_TFIDF_W2V, test_TFIDF_W2V, train_labels_TFIDF_W2V, test_labels_TFIDF_W2V = train_test_split(standardized_tfidf_w2v,
```

In [46]:
```
train_TFIDF_W2V.shape, test_TFIDF_W2V.shape, train_labels_TFIDF_W2V.shape, test_labels_TFIDF_W2V.shape
```

Out[46]:
```
((8000, 300), (2000, 300), (8000,), (2000,))
```

Task 2. Perform GridSearch Cross Validation and Random Search Cross Validation to find optimal Value of C and Gamma.

In [47]:
```
#when gamma value decreases then RBF kernel increases
clf = SVC()

hyper_parameters = {'kernel': ['rbf'], 'gamma': [10**-8, 10**-7, 10**-5], 'C': [10, 100, 500, 1000]}
bestCV = GridSearchCV(clf, hyper_parameters, scoring = "accuracy", cv = 3)
bestCV.fit(train_TFIDF_W2V, train_labels_TFIDF_W2V)

print(bestCV.best_estimator_)
```

```
SVC(C=1000, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=1e-05, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [48]:
```
best_parameter = bestCV.best_params_
best_parameter["C"]
```

Out[48]:
```
1000
```

In [49]:
```
scoreData = bestCV.grid_scores_
scoreData
```

Out[49]:
```
[mean: 0.50200, std: 0.00009, params: {'C': 10, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.50225, std: 0.00027, params: {'C': 10, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.75125, std: 0.00521, params: {'C': 10, 'gamma': 1e-05, 'kernel': 'rbf'},
 mean: 0.50225, std: 0.00027, params: {'C': 100, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.72850, std: 0.00621, params: {'C': 100, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.76338, std: 0.00674, params: {'C': 100, 'gamma': 1e-05, 'kernel': 'rbf'},
 mean: 0.70937, std: 0.00428, params: {'C': 500, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.74600, std: 0.00536, params: {'C': 500, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.77550, std: 0.01129, params: {'C': 500, 'gamma': 1e-05, 'kernel': 'rbf'},
 mean: 0.72825, std: 0.00616, params: {'C': 1000, 'gamma': 1e-08, 'kernel': 'rbf'},
 mean: 0.75138, std: 0.00582, params: {'C': 1000, 'gamma': 1e-07, 'kernel': 'rbf'},
 mean: 0.78075, std: 0.01280, params: {'C': 1000, 'gamma': 1e-05, 'kernel': 'rbf'}]
```

In [51]:
```
error = []
eachError = []
for i in range(12):
    eachError.append(1 - scoreData[i][1])
    if i == 2 or i == 5 or i == 8 or i == 11:
        error.append(eachError)
        eachError = []
error
```

Out[51]:
```
[[0.498, 0.49775, 0.24875000000000003],
 [0.49775, 0.27149999999999996, 0.23662499999999997],
 [0.290625, 0.254, 0.22450000000000003],
 [0.27175000000000005, 0.24862499999999998, 0.21924999999999994]]
```

In [52]:
```
columnNames = [10**-8, 10**-7, 10**-5]
errorFrame = pd.DataFrame(error, columns = columnNames)
errorFrame
```

Out[52]:

	1e-08	1e-07	1e-05
0	0.498000	0.497750	0.248750
1	0.497750	0.271500	0.236625
2	0.290625	0.254000	0.224500
3	0.271750	0.248625	0.219250

In [53]:
```
indexNames = [10, 100, 500, 1000]
errorFrame["C"] = indexNames
errorFrame
```

Out[53]:

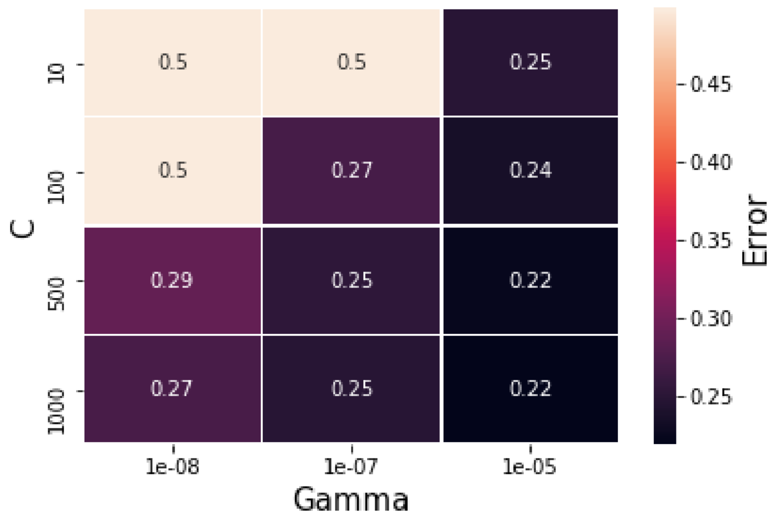
	1e-08	1e-07	1e-05	C
0	0.498000	0.497750	0.248750	10
1	0.497750	0.271500	0.236625	100
2	0.290625	0.254000	0.224500	500
3	0.271750	0.248625	0.219250	1000

In [54]:
```
errorFrame.set_index("C", append = False, drop = True, inplace = True)
errorFrame
```

Out[54]:

	1e-08	1e-07	1e-05
C			
10	0.498000	0.497750	0.248750
100	0.497750	0.271500	0.236625
500	0.290625	0.254000	0.224500
1000	0.271750	0.248625	0.219250

In [55]:
```
ax = sns.heatmap(errorFrame, annot = True, linewidths=.5)
ax.figure.axes[0].set_xlabel('Gamma', size = 15)
ax.figure.axes[0].set_ylabel('C', size = 15)
ax.figure.axes[-1].set_ylabel('Error', size = 15)
plot.show()
```



Here above in heatmap you can see that the error is minimum when gamma value is 10^-5 and C value is 1000. Therefore, from grid search we are considering our C value as 1000 and Gamma Value as 10^-5

In [56]:
```
n = list(np.random.normal(loc=1000, scale=3000, size = 100))  #taking 100 numbers which are distributed normally with mea
                                                              #and std-dev = 300
```

In [58]:
```
#when gamma value decreases then RBF kernel increases
clf = SVC()

hyper_parameters = {'kernel': ['rbf'], 'gamma': [10**-6, 10**-5], 'C': n}

bestCV_random = RandomizedSearchCV(clf, hyper_parameters, n_iter = 4, scoring = "accuracy", cv = 3)

bestCV_random.fit(train_TFIDF_W2V, train_labels_TFIDF_W2V)
print(bestCV_random.best_estimator_)
```

```
SVC(C=967.8423171725512, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=1e-05, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [59]:
```
best_random_parameter = bestCV_random.best_params_
best_random_parameter["C"]
```

Out[59]:
```
967.8423171725512
```

In [60]:
```
best_random_parameter = bestCV_random.best_params_
best_random_parameter
```

Out[60]:
```
{'C': 967.8423171725512, 'gamma': 1e-05, 'kernel': 'rbf'}
```

Here, above as you can see that error becomes least at C value 967.842 and gamma value 10^-5.

In [61]:
```
# We are taking our hyper-parameter C as the average of best C computed from gridSearchCV and RandomSearchCV
FinalHP = (best_parameter["C"] + best_random_parameter["C"]) / 2
FinalHP
```

Out[61]:
```
983.9211585862756
```

Task 3. Apply Support Vector Machine using RBF kernel and report accuracy.

In [62]:
```
model = SVC(C = FinalHP, kernel = "rbf", gamma = 10**-5)

model.fit(train_TFIDF_W2V, train_labels_TFIDF_W2V)

prediction = model.predict(test_TFIDF_W2V)

AccuracyScore = accuracy_score(test_labels_TFIDF_W2V, prediction) * 100

print("Accuracy score of SVC = "+str(AccuracyScore)+"%")
```

```
Accuracy score of SVC = 78.95%
```

In [63]:
```
Confusion_Matrix = confusion_matrix(test_labels_TFIDF_W2V, prediction)
print("Confusion Matrix on L2 regularization  \n"+str(Confusion_Matrix))
```

```
Confusion Matrix on L2 regularization
[[795 189]
 [232 784]]
```

In [64]:
```
tn, fp, fn, tp = confusion_matrix(test_labels_TFIDF_W2V, prediction).ravel()
tn, fp, fn, tp
```

Out[64]:
```
(795, 189, 232, 784)
```

Task 4. Check for train error.

In [65]:
```
model = SVC(C = FinalHP, kernel = "rbf", gamma = 10**-5)

model.fit(train_TFIDF_W2V, train_labels_TFIDF_W2V)

prediction = model.predict(train_TFIDF_W2V)

AccuracyScore = accuracy_score(train_labels_TFIDF_W2V, prediction)

print("Train error of SVC = "+str(1 - AccuracyScore))
```

```
Train error of SVC = 0.20375
```

Summary

TFIDF

1. Optimal Value of C from Grid Search = 2000
2. Optimal Value of gamma from Grid Search = 10^-8
3. Optimal Value of C from Random Search = 2447.555
4. Optimal Value of gamma from Random Search = 10^-8
5. Final C and gamma value for model are 2223.777 & 10^-9 respectively
6. Accuracy = 79.9%
7. Train Error = 0.00187499

Avg W2V

1. Optimal Value of C from Grid Search = 1000
2. Optimal Value of gamma from Grid Search = 10^-5
3. Optimal Value of C from Random Search = 1302.608
4. Optimal Value of gamma from Random Search = 10^-5
5. Final C and gamma value for model are 1151.304 & 10^-5 respectively
6. Accuracy = 81.25%
7. Train Error = 0.196

TFIDF-W2V

1. Optimal Value of C from Grid Search = 1000
2. Optimal Value of gamma from Grid Search = 10^-5
3. Optimal Value of C from Random Search = 967.842
4. Optimal Value of gamma from Random Search = 10^-5
5. Final C and gamma value for model are 983.921 & 10^-5 respectively
6. Accuracy = 78.95%
7. Train Error = 0.20375