[1] Amazon Fine Food Reviews Analysis

Data Source: 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. 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 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

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 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".

Task to be performed:

1. We need to work with 2 versions of SVM a. Linear kernel b. RBF kernel
2. When we are working with linear kernel, if want a computationally less expensive algorithm we can go with ‘SGDClassifier’ with hinge loss.
3. When we are working with ‘SGDClassifier’ with hinge loss and trying to find the AUC score, we might need to use CalibratedClassifierCV
4. Similarly, like kdtree of knn, when we are working with RBF kernel it's better to reduce the number of dimensions.
5. When we are working on the linear kernel with BOW or TFIDF please print the best feature for each of the positive and negative classes.

6. Try to introduce some features, and work more on featurizations so that our model can do better.

In [1]:
```
import numpy
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from sklearn.cross_validation import train_test_split
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
import re
import sqlite3
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\cros
s_validation.py:41: DeprecationWarning: This module was deprecated in v
ersion 0.18 in favor of the model_selection module into which all the r
efactored classes and functions are moved. Also note that the interface
of the new CV iterators are different from that of this module. This mo
dule will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:
```
con = sqlite3.connect("./amazon-fine-food-reviews/database.sqlite")
data = pd.read_sql_query('''
SELECT *
FROM REVIEWS
WHERE SCORE != 3''', con)
data.shape
```

Out[2]:
```
(525814, 10)
```

Data Cleaning

In [3]:
```
data = data[data.HelpfulnessNumerator <= data.HelpfulnessDenominator]
```

```
data.shape
```

Out[3]: (525812, 10)

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 [4]:
```
data['Score'] = data["Score"].apply(lambda x: "positive" if x > 3 else "negative")
sorted_data = data.sort_values('ProductId',axis = 0, inplace = False, kind = 'quicksort',ascending = True)
sorted_data.head()
```

Out[4]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
138693	150511	0006641040	A1C9K534BCI9GO	Laura Purdie Salas	0	0
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	18
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	2

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0	0

In [5]:
```
filtered_data = sorted_data.drop_duplicates(subset = {'UserId','Profile
Name','Time'} ,keep = 'first', inplace = False)
filtered_data.shape
```

Out[5]:
```
(328770, 10)
```

In [6]:
```
filtered_data['Score'].value_counts()
```

Out[6]:
```
positive    275650
negative     53120
Name: Score, dtype: int64
```

In [7]:
```
final = filtered_data.copy()
```

In [8]:
```
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to C:\Users\manish
[nltk_data]     dogra\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[8]:
```
True
```

In [9]:
```
stop = set(stopwords.words("english"))
st = PorterStemmer()
st.stem('burned')
```

Out[9]: 'burn'

Text Preprocessing: Stemming, stop-word removal and Lemmatization.

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 [10]:
```
def cleanhtml(sent):
    cleanr = re.compile('<.*?>')
    cleaned = re.sub(cleanr,' ',sent)
    return cleaned
def cleanpunc(sent):
    clean = re.sub(r'[?|!|$|#|\'|"|:]',r'',sent)
    clean = re.sub(r'[,|(|)|.|\|/]',r' ',clean)
    return clean
```

In [11]:
```
i=0
all_positive_reviews =[]
all_negative_reviews = []
final_string = []
stem_data = " "
for p in final['Text'].values:
    filtered_sens = []#filtered word
    p = cleanhtml(p)
    for w in p.split():
       # print(w)
        punc = cleanpunc(w)
        for s in punc.split():
            #print(w)
            if (s.isalpha()) & (len(s)>2):
                if s.lower() not in stop:
                    stem_data = (st.stem(s.lower())).encode('utf8')
                    #can we use lemmatizer and stemming altogether??
                    filtered_sens.append(stem_data)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_reviews.append(stem_data)
                    if (final['Score'].values)[i] == 'negative':
                        all_negative_reviews.append(stem_data)
                else:
                    continue
            else:
                continue
    #print(filtered_sens)
    str1 = b" ".join(filtered_sens)
    #print(str1)
    final_string.append(str1)
    i+=1
```

In [12]:
```
final['CleanedText'] = final_string
final.head()
```

Out[12]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
138693	150511	0006641040	A1C9K534BCI9GO	Laura Purdie Salas	0	0
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	18
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	2
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0	0

In [13]:
```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.feature_extraction.text import CountVectorizer
```

In [14]:
```
final = final.sort_values('Time',axis= 0,inplace = False , na_position
= 'last',ascending = True)
X = final['CleanedText'].values
X = X[:100000]
y = final['Score'].values
y = y[:100000]
```

In [15]:
```
X_train ,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3,s
tratify = y)
```

SGD Classifier on Bow

In [16]:
```
count_vect = CountVectorizer() #in scikit-learn
bow_train = count_vect.fit_transform(X_train)
bow_test = count_vect.transform(X_test)
```

In [17]:
```
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
```

In [19]:
```
from sklearn.linear_model import SGDClassifier
from sklearn.svm import SVC
alp = {'alpha' : [10**i for i in range(-4,5)]}
gd = GridSearchCV(SGDClassifier(class_weight = 'balanced', loss = 'hing
e'),alp,scoring = 'accuracy',cv = 4,n_jobs = -1,refit = True)
gd.fit(bow_train,y_train)
print(gd.best_estimator_)
pred = gd.predict(bow_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\line
ar_model\stochastic_gradient.py:128: FutureWarning: max_iter and tol pa
```

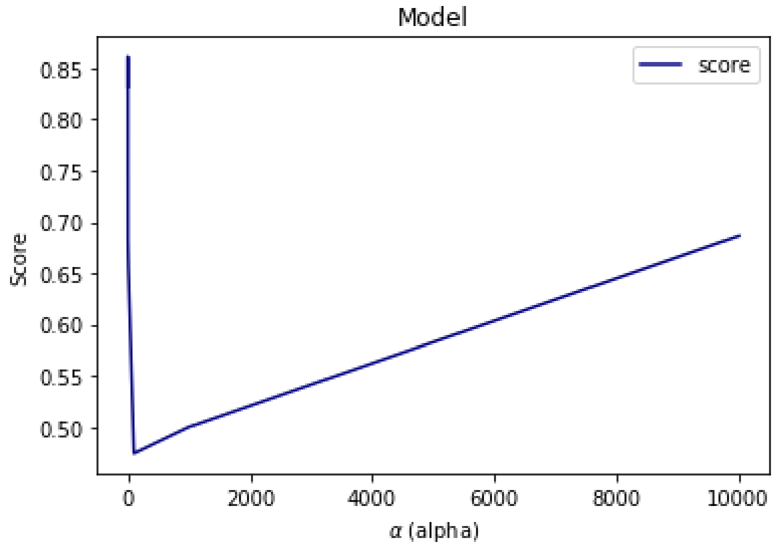
```
rameters have been added in <class 'sklearn.linear_model.stochastic_gra
dient.SGDClassifier'> in 0.19. If both are left unset, they default to
max_iter=5 and tol=None. If tol is not None, max_iter defaults to max_i
ter=1000. From 0.21, default max_iter will be 1000, and default tol wil
l be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

```
SGDClassifier(alpha=0.01, average=False, class_weight='balanced', epsil
on=0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', max_iter=None, n_iter=Non
e,
       n_jobs=1, penalty='l2', power_t=0.5, random_state=None,
       shuffle=True, tol=None, verbose=0, warm_start=False)
Accuracy is 85.5533333333
```

In [23]:

```
scores = [x[1] for x in gd.grid_scores_]
plt.figure()
plt.title('Model')
plt.xlabel('$\\alpha$ (alpha)')
plt.ylabel('Score')
a = [10**i for i in range(-4,5)]
plt.plot(a,scores, label='score',color='navy')
plt.legend()
plt.show()
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\mode
l_selection\_search.py:761: DeprecationWarning: The grid_scores_ attrib
ute was deprecated in version 0.18 in favor of the more elaborate cv_re
sults_ attribute. The grid_scores_ attribute will not be available from
0.20
  DeprecationWarning)
```



In [24]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.46      0.85      0.60      3811
   positive       0.98      0.86      0.91     26189

avg / total       0.91      0.86      0.87     30000
```

```
Recall for positive 0.855740959945
Recall for negative 0.854106533718


Precision for postive 0.975791352811
Precision for negative 0.46281814304
```

Top 10 important features

In [25]:
```
index = gd.best_estimator_.coef_.argsort()[:,:-1]
```

In [27]:
```
import numpy as np
top_10 = np.take(count_vect.get_feature_names(),index)
print(top_10[0])
```

```
['disappoint' 'worst' 'terribl' ..., 'excel' 'delici' 'great']
```

SGD Classifier on BOW with hinge loss

- Optimal alpha = 0.01
- Accuracy = 85.5
- Precision = 0.98(positive), 0.46(negative)
- Recall = 0.86 ,0.85

SGD Classifier on tfidf

In [35]:
```
tfidf_vect = TfidfVectorizer()
tfidf_train = tfidf_vect.fit_transform (X_train)
tfidf_test = tfidf_vect.transform(X_test)
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler(with_mean = False)
X_tr = sc.fit_transform(tfidf_train)
X_te = sc.transform(tfidf_test)
gd_tf = GridSearchCV(SGDClassifier(class_weight = 'balanced', loss = 'h
inge'),alp,scoring = 'accuracy',cv = 5,n_jobs = -1)
gd_tf.fit(X_tr,y_train)
print(gd_tf.best_params_)
pred = gd_tf.predict(X_te)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

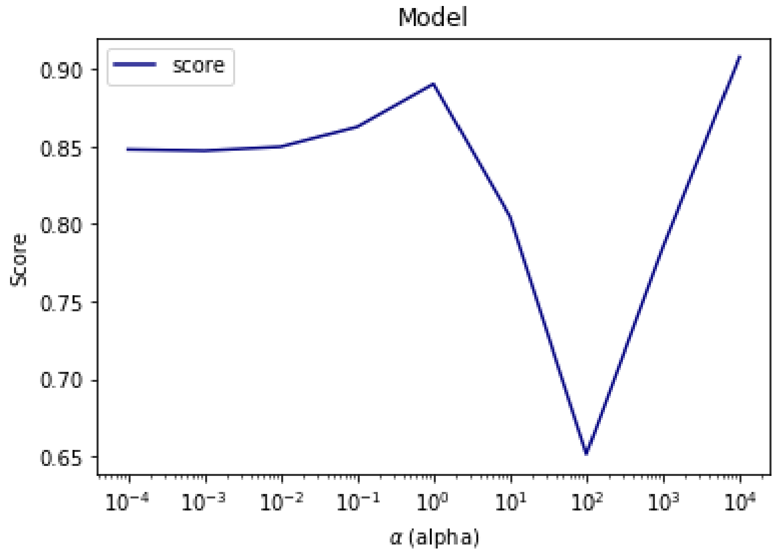
```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\line
ar_model\stochastic_gradient.py:128: FutureWarning: max_iter and tol pa
rameters have been added in <class 'sklearn.linear_model.stochastic_gra
dient.SGDClassifier'> in 0.19. If both are left unset, they default to
max_iter=5 and tol=None. If tol is not None, max_iter defaults to max_i
ter=1000. From 0.21, default max_iter will be 1000, and default tol wil
l be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

```
{'alpha': 10000}
Accuracy is 90.2233333333
```

In [36]:

```
scores = [x[1] for x in gd_tf.grid_scores_]
plt.figure()
plt.title('Model')
plt.xlabel('$\\alpha$ (alpha)')
plt.ylabel('Score')
a = [10**i for i in range(-4,5)]
plt.semilogx(a,scores, label='score',color='navy')
plt.legend()
plt.show()
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\mode
l_selection\_search.py:761: DeprecationWarning: The grid_scores_ attrib
ute was deprecated in version 0.18 in favor of the more elaborate cv_re
sults_ attribute. The grid_scores_ attribute will not be available from
0.20
  DeprecationWarning)
```



In [37]:
```
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.69      0.42      0.52      3811
   positive       0.92      0.97      0.95     26189

avg / total       0.89      0.90      0.89     30000
```

```
Recall for positive 0.972736645156
Recall for negative 0.417738126476


Precision for postive 0.919874341012
Precision for negative 0.690372940156
```

Top 10 important features

In [38]:
```
index = gd_tf.best_estimator_.coef_.argsort()[::-1]
top_10 = np.take(tfidf_vect.get_feature_names(),index)
print(top_10[0])
```

```
['disappoint' 'worst' 'wast' ..., 'best' 'love' 'great']
```

SGD Classifier on TFIDF with hinge loss

- Optimal alpha = 10000
- Accuracy = 90.22
- Precision = 0.92(positive), 0.69(negative)
- Recall = 0.97 ,0.42

SGD Classifier on avg w2v

In [39]:
```
list_of_sent_train = []
for i in X_train:
    sent = []
    for word in i.split():
        sent.append(word.decode('utf-8'))
    list_of_sent_train.append(sent)
```

In [40]:
```
from gensim.models import Word2Vec
```

```
w2v_model = Word2Vec(list_of_sent_train,min_count = 5,size = 50,workers
 = 4)
sent_vectors_train = []
for sent in list_of_sent_train:
    sent_vec = np.zeros(50)
    cnt_word = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_word += 1
        except:
            pass
    sent_vec /= cnt_word
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\gensim\util
s.py:1197: UserWarning: detected Windows; aliasing chunkize to chunkize
_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

```
70000
```

In [41]:

```
list_of_sent_test = []
for i in X_test:
    sent = []
    for word in i.split():
        sent.append(word.decode('utf-8'))
    list_of_sent_test.append(sent)
```

In [42]:

```
import warnings
warnings.filterwarnings("ignore")
from gensim.models import Word2Vec
w2v_model = Word2Vec(list_of_sent_test,min_count = 5,size = 50,workers
= 4)
sent_vectors_test = []
for sent in list_of_sent_test:
```

```
    sent_vec = np.zeros(50)
    cnt_word = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_word += 1
        except:
            pass
    sent_vec /= cnt_word
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
```

```
30000
```

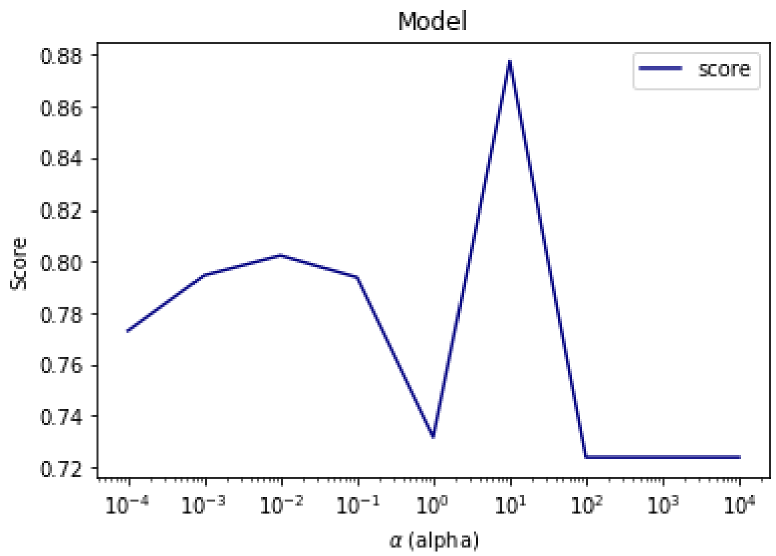
In [43]:
```
np.where(np.isnan(sent_vectors_test))
```

Out[43]:
```
(array([], dtype=int64), array([], dtype=int64))
```

In [44]:
```
sc = StandardScaler()
w2v_train = sc.fit_transform(sent_vectors_train)
w2v_test = sc.transform(sent_vectors_test)
gd_w2v = GridSearchCV(SGDClassifier(class_weight = 'balanced', loss =
'hinge'),alp,scoring = 'accuracy',cv = 5,n_jobs = -1)
gd_w2v.fit(w2v_train,y_train)
print(gd_w2v.best_estimator_)
pred = gd_w2v.predict(w2v_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
SGDClassifier(alpha=10, average=False, class_weight='balanced', epsilon
=0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', max_iter=None, n_iter=Non
e,
       n_jobs=1, penalty='l2', power_t=0.5, random_state=None,
       shuffle=True, tol=None, verbose=0, warm_start=False)
Accuracy is 87.2933333333
```

In [45]:
```
scores = [x[1] for x in gd_w2v.grid_scores_]
plt.figure()
plt.title('Model')
plt.xlabel('$\\alpha$ (alpha)')
plt.ylabel('Score')
a = [10**i for i in range(-4,5)]
plt.semilogx(a,scores, label='score',color='navy')
plt.legend()
plt.show()
```



In [46]:
```
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
              precision    recall  f1-score   support

   negative       0.00      0.00      0.00      3811
   positive       0.87      1.00      0.93     26189

avg / total       0.76      0.87      0.81     30000



Recall for positive 0.99996181603
Recall for negative 0.0


Precision for postive 0.872962432081
Precision for negative 0.0
```

SGD Classifier on Avg w2vec with hinge loss

- Optimal alpha = 10
- Accuracy = 87.29
- Precision = 0.87(positive), 0.0(negative)
- Recall = 1.0 ,0.0

SGD Classifier on Tfidf w2vec

In [47]:

```
tf_idf_feat = tfidf_vect.get_feature_names()
tfidf_sent_vec_train = []
row = 0
for sent in list_of_sent_train:
    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
```

```
            tfidf = tfidf_train[row,tf_idf_feat.index(word)]
            sent_vec += (vec*tfidf)
            weight_sum += tfidf
        except:
            pass
    sent_vec/= weight_sum
    tfidf_sent_vec_train.append(sent_vec)
    row += 1
```

In [48]:
```
tf_idf_feat = tfidf_vect.get_feature_names()
tfidf_sent_vec_test = []
row = 0
for sent in list_of_sent_test:
    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            tfidf = tfidf_test[row,tf_idf_feat.index(word)]
            sent_vec += (vec*tfidf)
            weight_sum += tfidf
        except:
            pass
    sent_vec/= weight_sum
    tfidf_sent_vec_test.append(sent_vec)
    row += 1
```

In [49]:
```
np.where(np.isnan(tfidf_sent_vec_train))
```

Out[49]:
```
(array([ 8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,
         8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,
         8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,
         8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,
         8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,  8797,
         8797,  8797,  8797,  8797,  8797, 44257, 44257, 44257, 44257,
        44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257,
        44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257,
        44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257,
        44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257,
```

```
         44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257, 44257,
44257], dtype=int64),
 array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15,
16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32,
33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49,
  0,
         1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
17,
        18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
34,
        35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49], dt
ype=int64))
```

In [50]:

```
y_tr = y_train
```

In [51]:

```
del tfidf_sent_vec_train[8797]
y_train = np.delete(y_train,8797)
```

In [55]:

```
del tfidf_sent_vec_train[44256]
y_train = np.delete(y_train,44256)
```

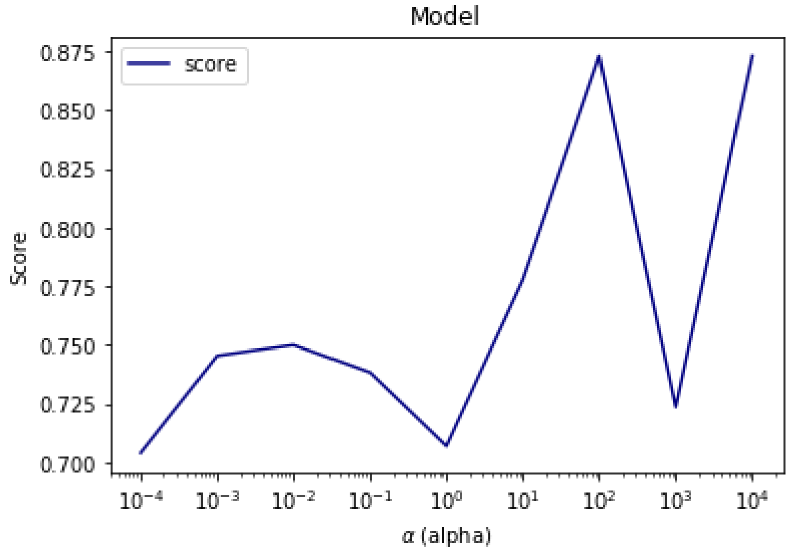
In [56]:

```
sc =  StandardScaler()
tfidf_w2v_train = sc.fit_transform(tfidf_sent_vec_train)
tfidf_w2v_test = sc.transform(tfidf_sent_vec_test)
gd_wtf = GridSearchCV(SGDClassifier(class_weight = 'balanced', loss =
'hinge'),alp,scoring = 'accuracy',cv = 10,n_jobs = -1)
gd_wtf.fit(tfidf_w2v_train,y_train)
print(gd_wtf.best_params_)
pred = gd_wtf.predict(tfidf_w2v_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
{'alpha': 100}
Accuracy is 87.2966666667
```

In [57]:

```
scores = [x[1] for x in gd_wtf.grid_scores_]
plt.figure()
plt.title('Model')
plt.xlabel('$\\alpha$ (alpha)')
plt.ylabel('Score')
a = [10**i for i in range(-4,5)]
plt.semilogx(a,scores, label='score',color='navy')
plt.legend()
plt.show()
```



In [58]:

```
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00      3811
   positive       0.87      1.00      0.93     26189

avg / total       0.76      0.87      0.81     30000



Recall for positive 1.0
Recall for negative 0.0


Precision for postive 0.872966666667
Precision for negative 0.0
```

SGD Classifier on Tfidf w2vec with hinge loss

- Optimal alpha = 100
- Accuracy = 87.29
- Precision = 0.87(positive), 0.0(negative)
- Recall = 1.0 ,0.0

As we came to know that SGD with hinge loss performed well on tfidf so we can apply the SVC with Rbf kernel on Tfidf

SVC with Rbf kernel on Tfidf

In [59]:
```
Cs = [0.001, 0.01, 0.1, 1, 10]
gammas = [0.001, 0.01]
param_grid = {'C': Cs, 'gamma' : gammas}
grid_search = GridSearchCV(SVC(kernel='rbf',class_weight = 'balanced'),
 param_grid, cv=2,scoring = 'accuracy',n_jobs = -1)
```

```
grid_search.fit(X_tr, y_tr)
print(grid_search.best_params_)
```

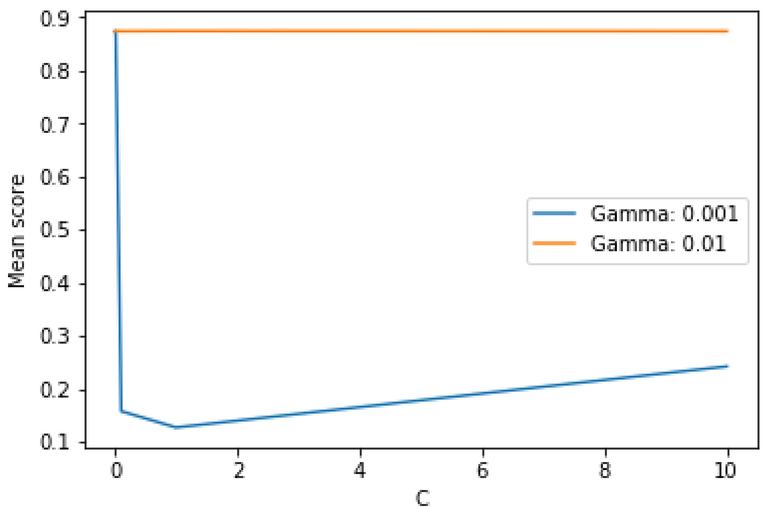
{'C': 1, 'gamma': 0.001}

In [60]:
```
pred = grid_search.predict(X_te)
acc = accuracy_score(y_test,pred)
print("Accuracy is",acc*100)
```

Accuracy is 87.45

In [65]:
```
scores = [x[1] for x in grid_search.grid_scores_]
scores = np.array(scores).reshape(len(gammas), len(Cs))

for ind, i in enumerate(gammas):
    plt.plot(Cs, scores[ind], label='Gamma: ' + str(i))
plt.legend()
plt.xlabel('C')
plt.ylabel('Mean score')
plt.show()
```



In [66]:
```
print(classification_report(y_test,pred))
```

```
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.81      0.02      0.03      3811
   positive       0.87      1.00      0.93     26189

avg / total       0.87      0.87      0.82     30000



Recall for positive 0.999465424415
Recall for negative 0.015743899239


Precision for postive 0.874657488472
Precision for negative 0.810810810811
```

SVC on Tfidf with rbf kernel

- Optimal C and gamma = .001
- Accuracy = 87.45
- Precision = 0.87(positive), 0.81(negative)
- Recall = 1 ,0.02