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 [3]:

```
# Importing libraries
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
%matplotlib inline
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 nltk.stem.porter import PorterStemmer

import re

import nltk
nltk.download('stopwords')
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
```

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

In [4]:

```python
# using sqlite 3 to load the data
con1 = sqlite3.connect('database.sqlite')

# Eliminating the reviews which are equal to 3
filtered_data = pd.read_sql_query("SELECT * FROM Reviews WHERE Score !=3", con1)

#Defining polarity
def polarity(x):
    if x < 3:
        return 'negative'
    else:
        return 'positive'

filtered_data['Score']=filtered_data['Score'].map(polarity)
print(filtered_data.shape)
filtered_data.head()
```

(525814, 10)

Out[4]:

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

In [5]:

```
#sorting product id in ascending order
sorted_data = filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fa
lse, kind='quicksort', na_position='last')

#Deduplication
final = sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep
='first',inplace=False)

print(final.shape)
final.head(3)
```

```
(364173, 10)
```

Out[5]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulr
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	

In [6]:

```
(final.shape[0]/sorted_data.shape[0])*100
```

Out[6]:

```
69.25890143662969
```

In [7]:

```
# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]
print(final.shape)
```

```
(364171, 10)
```

Text Preprocessing: Stemming, stop-word removal and Lemmatization

In [8]:

```
#importing the stopwords
from nltk.corpus import stopwords
stop=set(stopwords.words('english'))
words_to_keep = set(('not'))
stop -= words_to_keep

#initialising snowball stemmer
sno = nltk.stem.SnowballStemmer('english')

#function to clean html-tags
def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

#function to clean the word of any punctuation or special characters
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [9]:

```
#Code for removing HTML tags , punctuations . Code for removing stopwords . Code for ch
ecking if word is not alphanumeric and
# also greater than 2 . Code for stemmimg and also to convert them to lowercase letters
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTML tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describ
e positive reviews
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describ
e negative reviews reviews
                else:
                    continue
            else:
                continue

    str1 = b" ".join(filtered_sentence) #final string of cleaned words


    final_string.append(str1)
    i+=1
```

In [10]:

```
#adding a column of CleanedText which displays the data after pre-processing of the rev
iew
final['CleanedText']=final_string
final['CleanedText']=final['CleanedText'].str.decode("utf-8")

#below the processed review can be seen in the CleanedText Column
print('Shape of final',final.shape)
final.head()
```

```
Shape of final (364171, 11)
```

Out[10]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	
138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	

In [57]:

```
from sklearn.model_selection import train_test_split
# sorting based on time
time_sorted_data = final.sort_values('Time', axis=0, ascending = True, inplace=False, k
ind='quicksort', na_position = 'last' )

x=time_sorted_data['CleanedText']
y=time_sorted_data['Score']

X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.3, random_state=0
)
```

[4] Featurization

[4.1] BAG OF WORDS

In [58]:

```
count_vect = CountVectorizer(min_df=10)
X_train_vec = count_vect.fit_transform(X_train)
X_test_vec = count_vect.transform(X_test)

print("the type of count vectorizer :",type(X_train_vec))
print("the shape of out text BOW vectorizer : ",X_train_vec.get_shape())
print("the number of unique words :", X_train_vec.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (254919, 12709)
the number of unique words : 12709
```

Tasks

1. **Apply Multinomial NaiveBayes on these feature sets**

    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

2. **The hyper paramter tuning(find best Alpha)**

    - Find the best hyper parameter which will give the maximum AUC (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
    - Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Feature importance**

    - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using values of `feature_log_prob_` parameter of MultinomialNB (https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.MultinomialNB.html) and print their corresponding feature names

4. **Feature engineering**

    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.
        - Considering some features from review summary as well.

5. **Representation of results**

    - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure. Here on X-axis you will have alpha values, since they have a wide range, just to represent those alpha values on the graph, apply log function on those alpha values.
      Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
      Along with plotting ROC curve, you need to print the confusion matrix (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-tnr-1/) with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.
      (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
      (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
    (https://seaborn.pydata.org/generated/seaborn.heatmap.html)

    (https://seaborn.pydata.org/generated/seaborn.heatmap.html)

6. **Conclusion** (https://seaborn.pydata.org/generated/seaborn.heatmap.html)

    (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
    - You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library (https://seaborn.pydata.org/generated/seaborn.heatmap.html) link (http://zetcode.com/python/prettytable/)

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this [link. (https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)](https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf)

Applying Multinomial Naive Bayes

[5.1] Applying Naive Bayes on BOW, SET 1

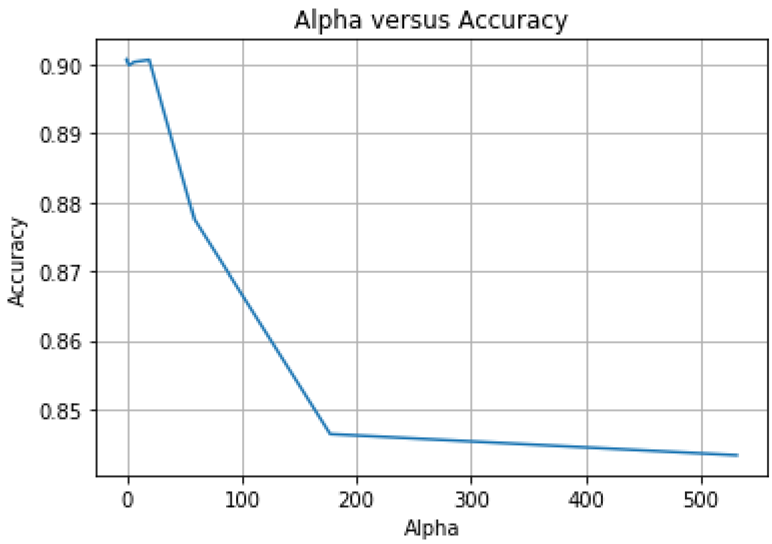
In [59]:

```
#Applying 10-fold CV
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import MultinomialNB

#creating alpha values in range of 10(power=-3) to 10(power=3)
neighbors = []
i=0.001
while(i<=1000):
    neighbors.append(np.round(i,3))
    i *= 3

#empty list for cv scores
cv_scores=[]

#perform 10 fold cv
for k in neighbors:
    bn=MultinomialNB(alpha=k)
    scores=cross_val_score(bn,X_train_vec, Y_train, cv=10, scoring='accuracy', n_jobs =
-1)
    cv_scores.append(scores.mean())

#determine best alpha
optimal_alpha=neighbors[cv_scores.index(max(cv_scores))]
print('\nThe optimal value of alpha is %.3f.' % optimal_alpha)
```

```
The optimal value of alpha is 0.009.
```

In [66]:

```
plt.plot(neighbors,cv_scores)
plt.xlabel("Alpha")
plt.ylabel("Accuracy")
plt.title("Alpha versus Accuracy")
plt.grid()
plt.show()

print("\n Alpha values", neighbors)
print("\n Accuracy values", np.round(cv_scores,5))
```




```
 Alpha values [0.001, 0.003, 0.009, 0.027, 0.081, 0.243, 0.729, 2.187, 6.5
61, 19.683, 59.049, 177.147, 531.441]

 Accuracy values [0.90071 0.90077 0.90079 0.90079 0.90067 0.90058 0.9003
0.89991 0.90037
 0.90068 0.87746 0.84643 0.84335]
```

In [61]:

```
from sklearn.metrics import accuracy_score
# NB plot for optimal alpha
bn_optimal = MultinomialNB(alpha = optimal_alpha)

bn_optimal.fit(X_train_vec,Y_train)

predictions = bn_optimal.predict(X_test_vec)

acc = accuracy_score(Y_test,predictions) * 100
print('Test acc of this NB model with alpha = %.3f is %f' % (optimal_alpha, acc))

# Variables that will be used for  making table in Conclusion part of this assignment
bow_multinomial_alpha = optimal_alpha
bow_multinomial_train_acc = max(cv_scores)*100
bow_multinomial_test_acc = acc
```

```
Test acc of this NB model with alpha = 0.009 is 89.915974
```

[5.1.1] Top 10 important features of positive class from SET 1

In [62]:

```
bn_optimal.classes_
```

Out[62]:

```
array(['negative', 'positive'], dtype='<U8')
```

In [68]:

```
class_features = bn_optimal.feature_log_prob_

# row 0 is for negative and row 1 is positive
negative_features = class_features[0]
positive_features = class_features[1]

#Getting all feature names
feature_names = count_vect.get_feature_names()

#Sorting by argsort
sorted_negative_features = np.argsort(negative_features[::-1])
sorted_positive_features = np.argsort(positive_features[::-1])

print('\033[1m  Top 10 positive features are \033[0m')
for i in list(sorted_positive_features[0:10]):
        print("%s = %f" % (feature_names[i] , positive_features[i]))
```

```
  Top 10 positive features are
beaten = -11.356869
shipe = -13.066517
rda = -10.622099
satisfactori = -10.958553
satur = -9.239673
sandwhich = -12.162376
refresh = -7.871150
satan = -12.904077
overkil = -12.071423
long = -6.497812
```

[5.1.2] Top 10 important features of negative class from SET 1

In [67]:

```
class_features = bn_optimal.feature_log_prob_

# row 0 is for negative and row 1 is positive
negative_features = class_features[0]
positive_features = class_features[1]

#Getting all feature names
feature_names = count_vect.get_feature_names()

#Sorting by argsort
sorted_negative_features = np.argsort(negative_features[::-1])
sorted_positive_features = np.argsort(positive_features[::-1])

print('\033[1m  Top 10 negative features are \033[0m')
for i in list(sorted_negative_features[0:10]):
        print("%s = %f" % (feature_names[i] , negative_features[i]))
```

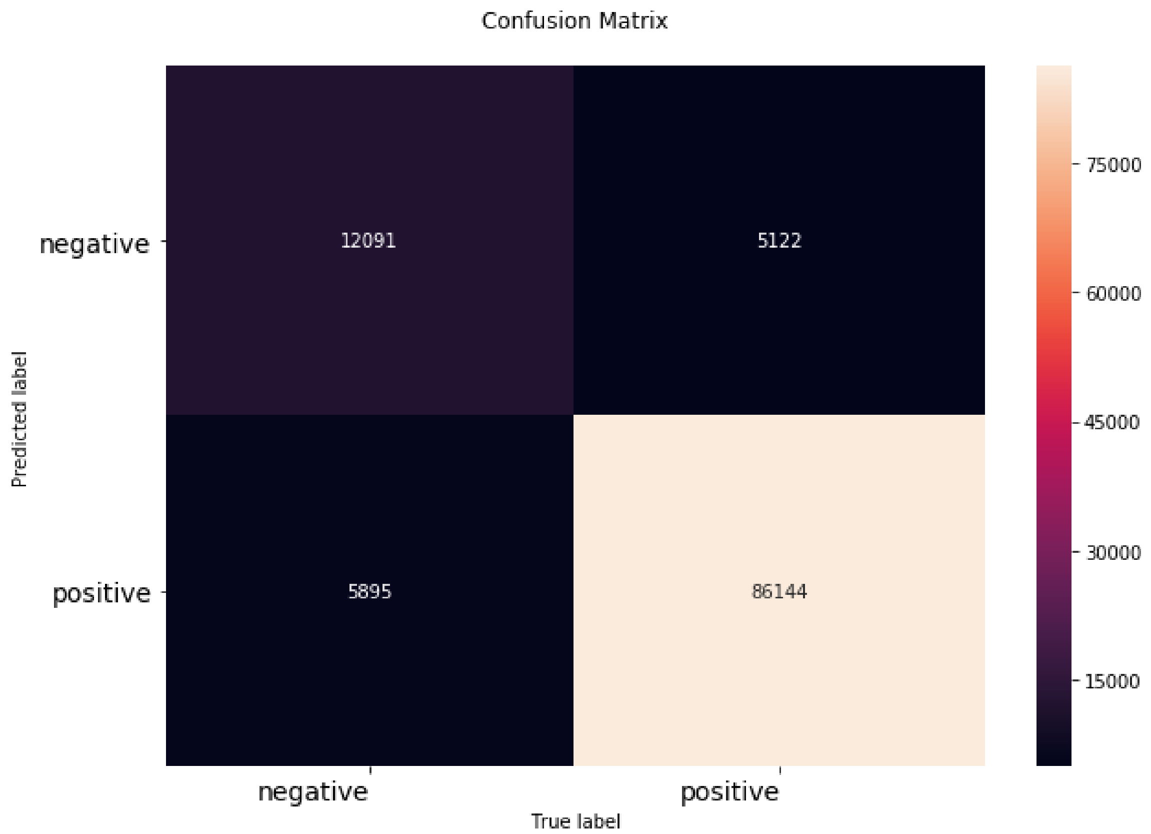
```
  Top 10 negative features are
steam = -9.070005
weeni = -12.912620
lactaid = -19.011692
atmospher = -13.603524
kuerig = -11.356249
atroci = -11.304979
korea = -11.661461
disapprov = -12.353966
disast = -9.870237
knott = -12.912620
```

Seaborn heatmap for representation of confusion matrix

In [65]:

```
#Ref: Stackoverflow
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,re
call_score
# Evaluate TPR , FPR , TNR , FNR
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(Y_test, predictions).ravel()

# Evaluate TPR (TPR = TP/(FN+TP))
TPR = TruePos/(FalseNeg + TruePos)
print("TPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,TPR))

# Evaluate FPR (FPR = FP/(TN+FP))
FPR = FalsePos/(TrueNeg + FalsePos)
print("FPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,FPR))

# Evaluate TNR (TNR = TN/(TN+FP))
TNR = TrueNeg/(TrueNeg + FalsePos)
print("TNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,TNR))

# Evaluate FNR (FNR = TN/(FN+TP))
FNR = FalseNeg/(FalseNeg + TruePos)
print("FNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,FNR))

# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, col
umns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
plt.ylabel('Predicted label')
plt.xlabel('True label')
plt.title("Confusion Matrix\n")
plt.show()
```

```
TPR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.94
3878
FPR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.32
7755
TNR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.67
2245
FNR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.05
6122
```



[5.2] Applying Naive Bayes on TFIDF, SET 2

In [29]:

```
# Please write all the code with proper documentation
tf_idf_vect = TfidfVectorizer(min_df=10)
X_train_vec = tf_idf_vect.fit_transform(X_train)
X_test_vec = tf_idf_vect.transform(X_test)

print("the type of count vectorizer :",type(X_train_vec))
print("the shape of out text TFIDF vectorizer : ",X_train_vec.get_shape())
print("the number of unique words :", X_train_vec.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (254919, 12709)
the number of unique words : 12709
```

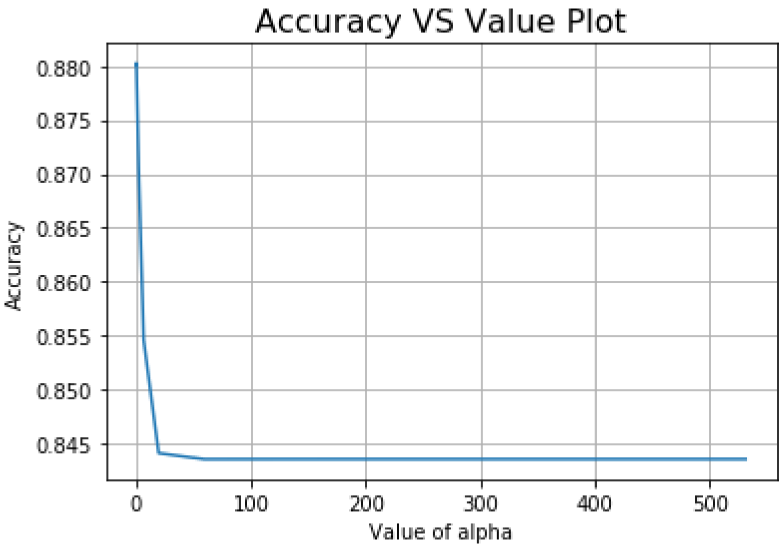
In [30]:

```
# Creating alpha values in the range from 10^-3 to 10^3
neighbors = []
i = 0.001
while(i<=1000):
    neighbors.append(np.round(i,3))
    i *= 3

# empty list that will hold cv scores
cv_scores = []

# perform 10-fold cross validation
for k in neighbors:
    bn = MultinomialNB(alpha = k)
    scores = cross_val_score(bn, X_train_vec, Y_train, cv=10, scoring='accuracy', n_job
s=-1)
    cv_scores.append(scores.mean())

# determining best value of alpha
optimal_alpha = neighbors[cv_scores.index(max(cv_scores))]
print('\nThe optimal value of alpha is %.3f.' % optimal_alpha)
```

```
The optimal value of alpha is 0.081.
```

In [42]:

```
# plot accuracy vs alpha
plt.plot(neighbors, cv_scores)
plt.xlabel('Value of alpha',size=10)
plt.ylabel('Accuracy',size=10)
plt.title('Accuracy VS Value Plot',size=16)
plt.grid()
plt.show()

print("\n\nAlpha values :\n",neighbors)
print("\nAccuracy for each alpha value is :\n ", np.round(cv_scores,5))
```




```
Alpha values :
 [0.001, 0.003, 0.009, 0.027, 0.081, 0.243, 0.729, 2.187, 6.561, 19.683, 5
9.049, 177.147, 531.441]

Accuracy for each alpha value is :
  [0.88013 0.88017 0.88021 0.88025 0.88029 0.87975 0.87765 0.87056 0.85458
 0.84405 0.84349 0.84349 0.84349]
```

In [32]:

```
#MNB with optimal alpha
bn_optimal = MultinomialNB(alpha = optimal_alpha)

# fitting the model
bn_optimal.fit(X_train_vec, Y_train)

# predict the response
predictions = bn_optimal.predict(X_test_vec)

# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Multinomial naive Bayes classifier for alpha = %.3f i
s %f%%' % (optimal_alpha, acc))

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_multinomial_alpha = optimal_alpha
tfidf_multinomial_train_acc = max(cv_scores)*100
tfidf_multinomial_test_acc = acc
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha = 0.
081 is 87.881229%
```

[5.2.1] Top 10 important features of positive class from SET 2

In [33]:

```
bn_optimal.classes_
```

Out[33]:

```
array(['negative', 'positive'], dtype='<U8')
```

In [71]:

```
class_features = bn_optimal.feature_log_prob_

# row 0 is for negative and row 1 is positive
negative_features = class_features[0]
positive_features = class_features[1]

#Getting all feature names
feature_names = count_vect.get_feature_names()

#Sorting by argsort
sorted_negative_features = np.argsort(negative_features[::-1])
sorted_positive_features = np.argsort(positive_features[::-1])

print('\033[1m  Top 10 positive features are \033[0m')
for i in list(sorted_positive_features[0:10]):
        print("%s = %f" % (feature_names[i] , positive_features[i]))
```

```
  Top 10 positive features are
beaten = -11.356869
shipe = -13.066517
rda = -10.622099
satisfactori = -10.958553
satur = -9.239673
sandwhich = -12.162376
refresh = -7.871150
satan = -12.904077
overkil = -12.071423
long = -6.497812
```

[5.2.2] Top 10 important features of negative class from SET 2

In [69]:

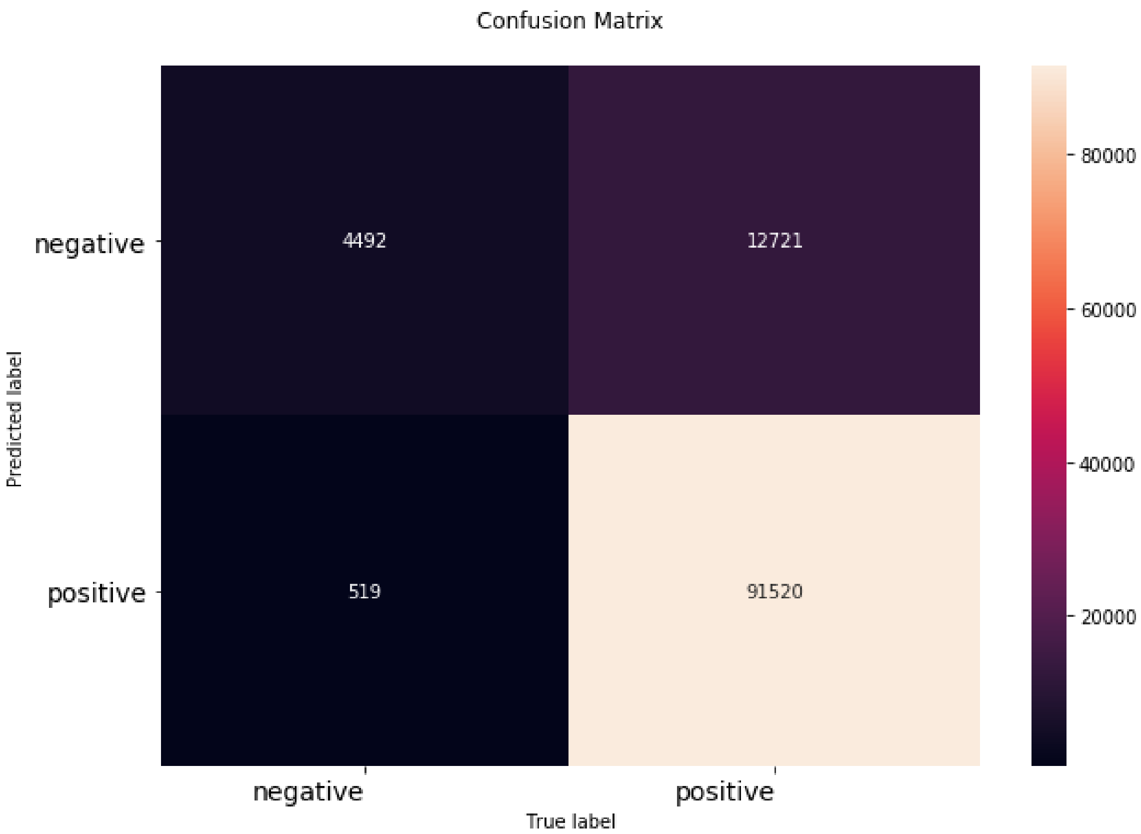
```
class_features = bn_optimal.feature_log_prob_

# row 0 is for negative and row 1 is positive
negative_features = class_features[0]
positive_features = class_features[1]

#Getting all feature names
feature_names = count_vect.get_feature_names()

#Sorting by argsort
sorted_negative_features = np.argsort(negative_features[::-1])
sorted_positive_features = np.argsort(positive_features[::-1])

print('\033[1m  Top 10 negative features are \033[0m')
for i in list(sorted_negative_features[0:10]):
        print("%s = %f" % (feature_names[i] , negative_features[i]))
```

```
  Top 10 negative features are
steam = -9.070005
weeni = -12.912620
lactaid = -19.011692
atmospher = -13.603524
kuerig = -11.356249
atroci = -11.304979
korea = -11.661461
disapprov = -12.353966
disast = -9.870237
knott = -12.912620
```

In [55]:

```
#Ref: Stackoverflow
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,re
call_score
# Evaluate TPR , FPR , TNR , FNR
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(Y_test, predictions).ravel()

# Evaluate TPR (TPR = TP/(FN+TP))
TPR = TruePos/(FalseNeg + TruePos)
print("TPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,TPR))

# Evaluate FPR (FPR = FP/(TN+FP))
FPR = FalsePos/(TrueNeg + FalsePos)
print("FPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,FPR))

# Evaluate TNR (TNR = TN/(TN+FP))
TNR = TrueNeg/(TrueNeg + FalsePos)
print("TNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,TNR))

# Evaluate FNR (FNR = TN/(FN+TP))
FNR = FalseNeg/(FalseNeg + TruePos)
print("FNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (opti
mal_alpha,FNR))

# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, col
umns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
plt.ylabel('Predicted label')
plt.xlabel('True label')
plt.title("Confusion Matrix\n")
plt.show()
```

```
TPR of the Multinomial naive Bayes classifier for alpha = 0.081 is :  0.87
7965
FPR of the Multinomial naive Bayes classifier for alpha = 0.081 is :  0.10
3572
TNR of the Multinomial naive Bayes classifier for alpha = 0.081 is :  0.89
6428
FNR of the Multinomial naive Bayes classifier for alpha = 0.081 is :  0.12
2035
```



[6] Conclusions

In [39]:

```python
# Please compare all your models using Prettytable library
#Ref: http://zetcode.com/python/prettytable/

from prettytable import PrettyTable
import random

x = PrettyTable()
numbering = [1,2]
names = ["Multinomial NB for BOW", "Multinomial NB for Tfidf"]
optimal_alpha = [bow_multinomial_alpha,tfidf_multinomial_alpha]
train_acc = [bow_multinomial_train_acc, tfidf_multinomial_train_acc]
test_acc = [bow_multinomial_test_acc, tfidf_multinomial_test_acc]

# Adding columns
x.add_column("S.NO.",numbering)
x.add_column("MODEL",names)
x.add_column("Best Alpha",optimal_alpha)
x.add_column("Training Accuracy",train_acc)
x.add_column("Test Accuracy",test_acc)

# Printing the Table
print(x)
```

```
+-------+--------------------------+------------+-------------------+-----
--------------+
| S.NO. |          MODEL           | Best Alpha | Training Accuracy |    Te
st Accuracy   |
+-------+--------------------------+------------+-------------------+-----
--------------+
|   1   |  Multinomial NB for BOW  |   0.009    | 90.07920206759049 | 89.9
1597407827774 |
|   2   | Multinomial NB for Tfidf |   0.081    | 88.02874746506195 | 87.8
8122871892506 |
+-------+--------------------------+------------+-------------------+-----
--------------+
```