Apply Multinomial Naive Bayes on Amazon Fine 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. 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.

NOTE:-

------------->>HERE WE HAVE TAKEN ONLY 100K POINTS.

------------->>WE ARE APPLYING MULTINOMIAL NAIVE BAYES ON BOW AND TF-IDF VECTORIZATION

[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 [81]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


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

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

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

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

from tqdm import tqdm
import os
```

In [82]:

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

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3


filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 100000""

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negative rat
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (100000, 10)
```

Out[82]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [83]:

```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [84]:

```
print(display.shape)
display.head()
```

(80668, 7)

Out[84]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [85]:

```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[85]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	

In [86]:

```
display['COUNT(*)'].sum()
```

Out[86]:

393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

In [87]:

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

Out[87]:

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

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

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

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

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

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

In [88]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, k
```

In [89]:

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='firs
final.shape
```

Out[89]:

```
(87775, 10)
```

In [90]:

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

Out[90]:

```
87.775
```

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 [91]:

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

display.head()
```

Out[91]:

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

In [92]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [93]:

```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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

```
(87773, 10)
```

Out[93]:

```
1    73592
0    14181
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

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

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

In [94]:

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

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

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

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

```
My dogs loves this chicken but its a product from China, so we wont be buyin
g it anymore.  Its very hard to find any chicken products made in the USA bu
t they are out there, but this one isnt.  Its too bad too because its a good
product but I wont take any chances till they know what is going on with the
china imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the cand
y has little taste to it.  Very little of the 2 lbs that I bought were eaten
and I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil smell. S
o if you are afraid of the fishy smell, don't get it. But I think my dog lik
es it because of the smell. These treats are really small in size. They are
great for training. You can give your dog several of these without worrying
about him over eating. Amazon's price was much more reasonable than any othe
r retailer. You can buy a 1 pound bag on Amazon for almost the same price as
a 6 ounce bag at other retailers. It's definitely worth it to buy a big bag
if your dog eats them a lot.
==================================================
```

In [95]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be buyin
g it anymore.  Its very hard to find any chicken products made in the USA bu
t they are out there, but this one isnt.  Its too bad too because its a good
product but I wont take any chances till they know what is going on with the
china imports.
```

In [96]:

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

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

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

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

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

```
My dogs loves this chicken but its a product from China, so we wont be buyin
g it anymore.  Its very hard to find any chicken products made in the USA bu
t they are out there, but this one isnt.  Its too bad too because its a good
product but I wont take any chances till they know what is going on with the
china imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the cand
y has little taste to it.  Very little of the 2 lbs that I bought were eaten
and I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil smell. S
o if you are afraid of the fishy smell, don't get it. But I think my dog lik
es it because of the smell. These treats are really small in size. They are
great for training. You can give your dog several of these without worrying
about him over eating. Amazon's price was much more reasonable than any othe
r retailer. You can buy a 1 pound bag on Amazon for almost the same price as
a 6 ounce bag at other retailers. It's definitely worth it to buy a big bag
if your dog eats them a lot.
```

In [97]:

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

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

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

In [98]:

```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
was way to hot for my blood, took a bite and did a jig  lol
==================================================
```

In [99]:

```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be buyin
g it anymore.  Its very hard to find any chicken products made in the USA bu
t they are out there, but this one isnt.  Its too bad too because its a good
product but I wont take any chances till they know what is going on with the
china imports.
```

In [100]:

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

```
was way to hot for my blood took a bite and did a jig lol
```

In [127]:

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

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', '
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they'
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'l
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had',
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'u
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'd
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over',
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', '
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'v
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now',
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'do
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn'
            'won', "won't", 'wouldn', "wouldn't"])
```

In [78]:

```

```

In [128]:

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

```
100%|██████████████████████████████████████████████████
███| 87773/87773 [00:50<00:00, 1721.81it/s]
```

In [114]:

```
preprocessed_reviews[1000]
```

Out[114]:

```
'candy blocks nice visual lego birthday party candy little taste little lbs
bought eaten threw rest away would not buy candy'
```

[4] Featurization

[4.1] BAG OF WORDS

Applying Multinomial Naive Bayes

In [116]:

```
# ============================== loading libraries =======================================
from sklearn.metrics import roc_curve,auc
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_validate
from sklearn.naive_bayes import MultinomialNB

from sklearn.metrics import confusion_matrix,f1_score,precision_score,recall_score
# ==========================================================================================
```

[5.1] Applying Multinomial Naive Bayes on BOW, SET 1

In [146]:

```

from sklearn.model_selection import train_test_split

# split the data set into train and test
X_1, X_test, y_1, y_test = train_test_split(preprocessed_reviews, final['Score'], test_size

# split the train data set into cross validation train and cross validation test
X_tr, X_cv, y_tr, y_cv = train_test_split(X_1, y_1, test_size=0.3)
```

In [200]:

```



#code for BRUTE version
count_vect = CountVectorizer(min_df = 10)
Xbow_tr = count_vect.fit_transform(X_tr)
Xbow_test = count_vect.transform(X_test)
Xbow_cv = count_vect.transform(X_cv)
print("the type of count vectorizer :",type(X_tr))
print("the shape of out text BOW vectorizer : ",Xbow_tr.get_shape())
print("the number of unique words :", Xbow_tr.get_shape()[1])
```

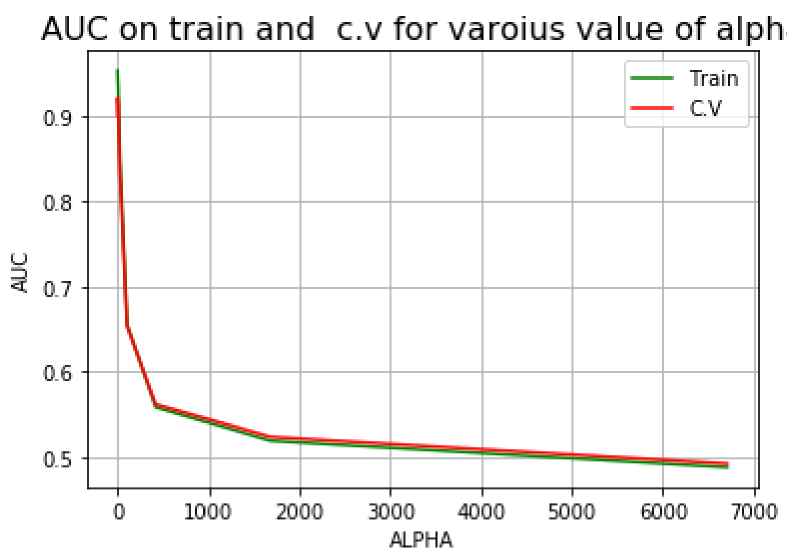
```
the type of count vectorizer : <class 'list'>
the shape of out text BOW vectorizer :  (43008, 8210)
the number of unique words : 8210
```

In [201]:

```
# Creating alpha values in the range from 10^-4 to 10^4
neighbors = []
i = 0.0001
while(i<=10000):
    neighbors.append(np.round(i,4))
    i *= 4
auc1=[]
auc2=[]

for k in neighbors:
    # instantiate learning model (k)
    mnb = MultinomialNB(alpha = k)

    # fitting the model on crossvalidation train
    mnb.fit(Xbow_tr, y_tr)

    probs = mnb.predict_proba(Xbow_tr)
    preds = probs[:,1]
    roc_auc1=metrics.roc_auc_score(y_tr, preds)
    auc1.append(roc_auc1)

    #knn.fit(Xbow_cv, y_cv)
    probs = mnb.predict_proba(Xbow_cv)
    preds = probs[:,1]
    roc_auc2=metrics.roc_auc_score(y_cv, preds)
    auc2.append(roc_auc2)
```

In [202]:

```
plt.title('AUC on train and  c.v for varoius value of alpha',size=16)
plt.plot(neighbors, auc1,'g',label ='Train')
plt.plot(neighbors, auc2,'r',label ='C.V')

plt.ylabel('AUC',size=10)
plt.xlabel('ALPHA',size=10)
plt.grid()
plt.legend()
plt.show()
```



In [203]:

```
print(neighbors)
print('--------------------------------------------------------------------------------------
print('--------------------------------------------------------------------------------------

print(auc1)

print('--------------------------------------------------------------------------------------
print('--------------------------------------------------------------------------------------
print(auc2)
```

```
[0.0001, 0.0004, 0.0016, 0.0064, 0.0256, 0.1024, 0.4096, 1.6384, 6.5536, 26.
2144, 104.8576, 419.4304, 1677.7216, 6710.8864]
----------------------------------------------------------------------------
----------------
----------------------------------------------------------------------------
----------------
[0.953342523190093, 0.9531731332731078, 0.9529357745258284, 0.95258825891732
33, 0.9520782455452304, 0.9512504138132211, 0.9497928907904093, 0.9462166305
22192, 0.9331746134318121, 0.8512260485162714, 0.6555063336836825, 0.5580797
023208391, 0.5189109567703689, 0.48778049504723436]
----------------------------------------------------------------------------
----------------
----------------------------------------------------------------------------
--------------
[0.9000289695698585, 0.9036259577903135, 0.9072953104429815, 0.9107896255407
808, 0.9140326554181402, 0.917143287589926, 0.9199406758764413, 0.9212244144
138181, 0.9121397792670645, 0.8327803890268608, 0.6533550292501578, 0.561542
07718068, 0.5234112026544615, 0.4920605725560411]
```

In [211]:

```
# ============================== KNN with k = optimal_k ==================================
# instantiate learning model k = optimal_k
mnb = MultinomialNB(alpha =1.6384)

# fitting the model
mnb.fit(Xbow_tr, y_tr)

# predict the response
pred = mnb.predict(Xbow_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the multinomial N.B classifier for alpha = %f is %f%%' % (1.6384,
```

```

The accuracy of the multinomial N.B classifier for alpha = 1.638400 is 90.06
1522%
```

In [205]:

```
mnb.classes_
```

Out[205]:

```
array([0, 1], dtype=int64)
```

From above we can see that first_class is 0 i.e negative and second_class is 1 i.e positive

[5.1.1] Top 10 important features of negative class from SET 1 are below

In [206]:

```
# Now we can find log probabilities of different features for both the classes
class_features = mnb.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_features = class_features[0]
positive_features = class_features[1]

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

# Sorting 'negative_features' and 'positive_features' in descending order using argsort() f
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("Top 10 Important Features and their log probabilities For Negative Class are as foll
for i in list(sorted_negative_features[0:10]):#printing top 10  positive feature one by one
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))
```

```
Top 10 Important Features and their log probabilities For Negative Class are
as follows :


not      -->    -3.270101
like     -->    -4.400533
would    -->    -4.625374
product  -->    -4.659083
taste    -->    -4.670227
one      -->    -4.882864
coffee   -->    -5.092174
good     -->    -5.115951
no       -->    -5.151576
flavor   -->    -5.168723
```

[5.1.2] Top 10 important features of positive class and there log probabilities from SET 1 are below

In [207]:

```
print("\n\nTop 10 Important Features and their log probabilities For Positive Class are as
for i in list(sorted_positive_features[0:10]):#printing top 10  negative feature one by one
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 10 Important Features and their log probabilities For Positive Class are
as follows:


not      -->    -3.685697
like     -->    -4.493285
good     -->    -4.620079
great    -->    -4.714222
one      -->    -4.843267
taste    -->    -4.925465
coffee   -->    -4.967491
would    -->    -5.035174
love     -->    -5.043507
flavor   -->    -5.044195
```

In [208]:

```
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe Test Accuracy of the Multinomial naive Bayes classifier for alpha = %.3f is %f

# evaluate precision
acc = precision_score(y_test, pred, pos_label = 1)
print('\nThe Test Precision of the Multinomial naive Bayes classifier for alpha = %.3f is %

# evaluate recall
acc = recall_score(y_test, pred, pos_label = 1)
print('\nThe Test Recall of the Multinomial naive Bayes classifier for alpha = %.3f is %f'

# evaluate f1-score
acc = f1_score(y_test, pred, pos_label = 1)
print('\nThe Test F1-Score of the Multinomial naive Bayes classifier for alpha = %.3f is %f
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha = 1.63
8 is 90.061522%

The Test Precision of the Multinomial naive Bayes classifier for alpha = 1.6
38 is 0.942143

The Test Recall of the Multinomial naive Bayes classifier for alpha = 1.638
is 0.939287

The Test F1-Score of the Multinomial naive Bayes classifier for alpha = 1.63
8 is 0.940713
```

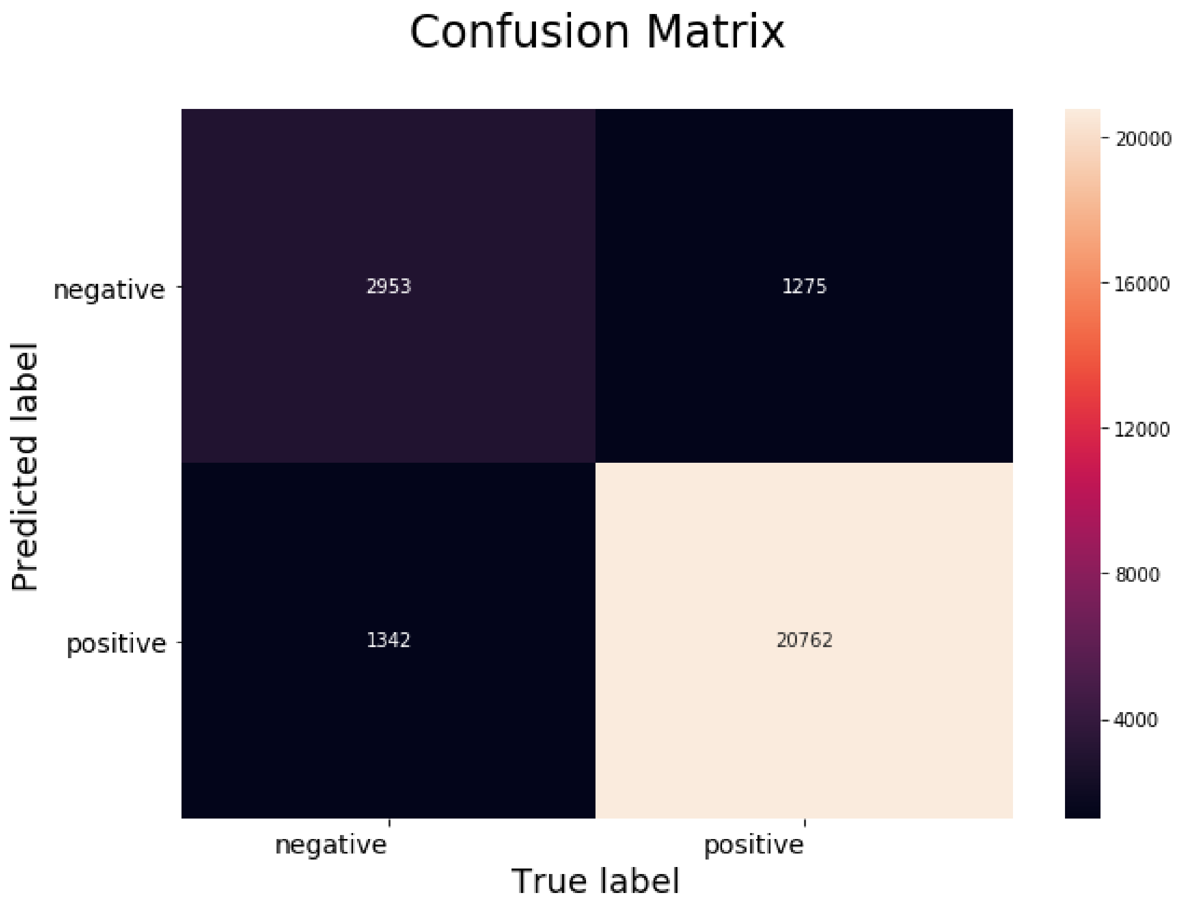
In [209]:

```
# Evaluate TPR , FPR , TNR , FNR
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test, pred).ravel()

# Evaluate TPR (TPR = TP/(FN+TP))
TPR = TruePos/(FalseNeg + TruePos)
print("TPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (1.6384,T

# Evaluate FPR (FPR = FP/(TN+FP))
FPR = FalsePos/(TrueNeg + FalsePos)
print("FPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (1.6384,F

# Evaluate TNR (TNR = TN/(TN+FP))
TNR = TrueNeg/(TrueNeg + FalsePos)
print("TNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (1.6384,T

# Evaluate FNR (FNR = TN/(FN+TP))
FNR = FalseNeg/(FalseNeg + TruePos)
print("FNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (1.6384,F
```

```
TPR of the Multinomial naive Bayes classifier for alpha = 1.638 is :  0.9421
43
FPR of the Multinomial naive Bayes classifier for alpha = 1.638 is :  0.3124
56
TNR of the Multinomial naive Bayes classifier for alpha = 1.638 is :  0.6875
44
FNR of the Multinomial naive Bayes classifier for alpha = 1.638 is :  0.0578
57
```

In [210]:

```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(y_test, pred), index=class_names, columns=class_
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', fontsi
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', fontsi
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



[5.2] Applying Multinomial Naive Bayes on TFIDF, SET 2

In [163]:

```
count_vect  = TfidfVectorizer(ngram_range=(1,2), min_df=10)

Xbow_tr = count_vect.fit_transform(X_tr)
Xbow_test = count_vect.transform(X_test)
Xbow_cv = count_vect.transform(X_cv)
print("the type of count vectorizer :",type(X_tr))
print("the shape of out text BOW vectorizer : ",Xbow_tr.get_shape())
print("the number of unique words :", Xbow_tr.get_shape()[1])
```

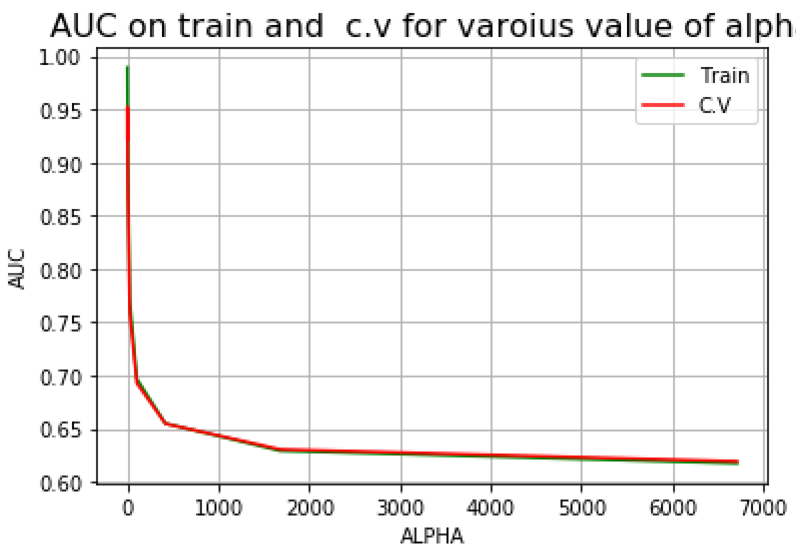
```
the type of count vectorizer : <class 'list'>
the shape of out text BOW vectorizer :  (43008, 25713)
the number of unique words : 25713
```

In [164]:

```
# Creating alpha values in the range from 10^-4 to 10^4
neighbors = []
i = 0.0001
while(i<=10000):
    neighbors.append(np.round(i,4))
    i *= 4
auc1=[]
auc2=[]

for k in neighbors:
    # instantiate learning model (k)
    mnb = MultinomialNB(alpha = k)

    # fitting the model on crossvalidation train
    mnb.fit(Xbow_tr, y_tr)

    probs = mnb.predict_proba(Xbow_tr)
    preds = probs[:,1]
    roc_auc1=metrics.roc_auc_score(y_tr, preds)
    auc1.append(roc_auc1)

    #knn.fit(Xbow_cv, y_cv)
    probs = mnb.predict_proba(Xbow_cv)
    preds = probs[:,1]
    roc_auc2=metrics.roc_auc_score(y_cv, preds)
    auc2.append(roc_auc2)
```

In [165]:

```
plt.title('AUC on train and  c.v for varoius value of alpha',size=16)
plt.plot(neighbors, auc1,'g',label ='Train')
plt.plot(neighbors, auc2,'r',label ='C.V')

plt.ylabel('AUC',size=10)
plt.xlabel('ALPHA',size=10)
plt.grid()
plt.legend()
plt.show()
```



In [190]:

```
print(neighbors)
print('-----------------------------------------------------------------------------------
print('-----------------------------------------------------------------------------------

print(auc1)

print('-----------------------------------------------------------------------------------
print('-----------------------------------------------------------------------------------
print(auc2)
```

```
[0.0001, 0.0004, 0.0016, 0.0064, 0.0256, 0.1024, 0.4096, 1.6384, 6.5536, 26.
2144, 104.8576, 419.4304, 1677.7216, 6710.8864]
----------------------------------------------------------------------------
----------------
----------------------------------------------------------------------------
----------------
[0.989220612293407, 0.9888578554191325, 0.9883258082830697, 0.98751357458243
35, 0.9861935896826672, 0.98382657945285, 0.9790443338504735, 0.966567582959
3934, 0.8943119408797857, 0.7711899585064064, 0.6969468968270667, 0.65503003
96439135, 0.629285877518079, 0.617524056993668]
----------------------------------------------------------------------------
----------------
----------------------------------------------------------------------------
--------------
[0.9216687796215528, 0.9291851401488125, 0.9364679658342961, 0.9430679698235
341, 0.9484699909134502, 0.9520832584269519, 0.9522390420671211, 0.940966805
2559119, 0.8696081412993312, 0.7587753610292891, 0.6928426016702965, 0.65483
12636673048, 0.6306914193263353, 0.6194660625523777]
```

In [193]:

```
# ============================== KNN with k = optimal_k ==================================
# instantiate learning model k = optimal_k
mnb = MultinomialNB(alpha =0.4096)

# fitting the model
mnb.fit(Xbow_tr, y_tr)

# predict the response
pred = mnb.predict(Xbow_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the multinomial N.B classifier for alpha = %f is %f%%' % (0.4096,
```

```
The accuracy of the multinomial N.B classifier for alpha = 0.409600 is 89.71
5935%
```

In [194]:

```
mnb.classes_
```

Out[194]:

```
array([0, 1], dtype=int64)
```

From above we can see that first_class is 0 i.e negative and second_class is 1 i.e positive

[5.2.1] Top 10 important features of negative class from SET 2 are below

In [195]:

```
# Now we can find log probabilities of different features for both the classes
class_features = mnb.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_features = class_features[0]
positive_features = class_features[1]

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

# Sorting 'negative_features' and 'positive_features' in descending order using argsort() f
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("Top 10 Important Features and their log probabilities For Negative Class are as foll
for i in list(sorted_negative_features[0:10]):#printing top 10  positive feature one by one
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))
```

```
Top 10 Important Features and their log probabilities For Negative Class are
as follows :


not      -->    -4.878235
like     -->    -5.713782
product  -->    -5.768676
would    -->    -5.809340
taste    -->    -5.812911
coffee   -->    -6.022713
one      -->    -6.125952
flavor   -->    -6.250969
no       -->    -6.251890
buy      -->    -6.364297
```

5.2.2--> Top 10 Important Features and their log probabilities For Positive Class are as follows:

In [196]:

```

for i in list(sorted_positive_features[0:10]):#printing top 10  negative feature one by one
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
not      -->    -5.280094
great    -->    -5.624297
good     -->    -5.681381
like     -->    -5.734276
coffee   -->    -5.776626
love     -->    -5.857995
tea      -->    -5.869493
one      -->    -5.972136
taste    -->    -5.978909
product  -->    -5.995109
```

In [197]:

```
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe Test Accuracy of the Multinomial naive Bayes classifier for alpha = %.3f is %f

# evaluate precision
acc = precision_score(y_test, pred, pos_label = 1)
print('\nThe Test Precision of the Multinomial naive Bayes classifier for alpha = %.3f is %

# evaluate recall
acc = recall_score(y_test, pred, pos_label = 1)
print('\nThe Test Recall of the Multinomial naive Bayes classifier for alpha = %.3f is %f'

# evaluate f1-score
acc = f1_score(y_test, pred, pos_label = 1)
print('\nThe Test F1-Score of the Multinomial naive Bayes classifier for alpha = %.3f is %f
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha = 0.41
0 is 89.715935%

The Test Precision of the Multinomial naive Bayes classifier for alpha = 0.4
10 is 0.896290

The Test Recall of the Multinomial naive Bayes classifier for alpha = 0.410
is 0.992309

The Test F1-Score of the Multinomial naive Bayes classifier for alpha = 0.41
0 is 0.941858
```

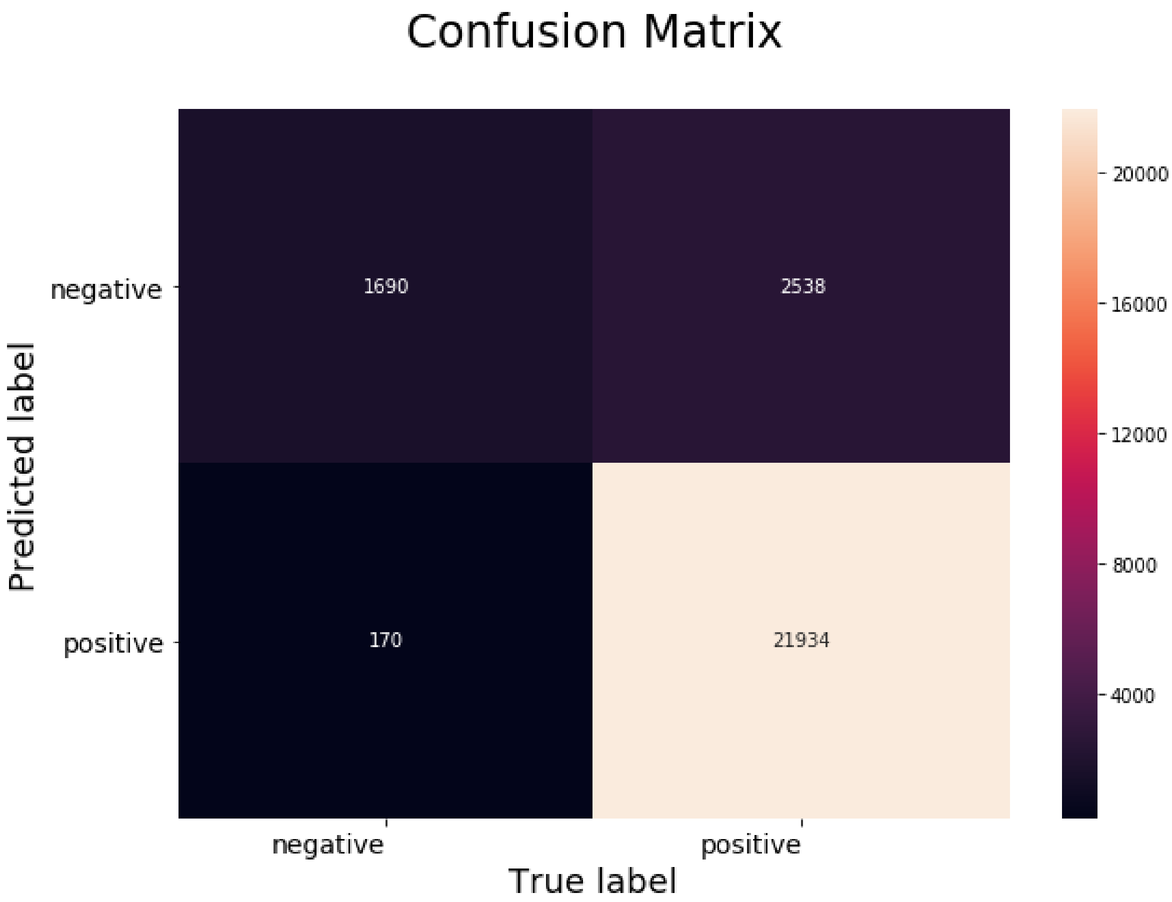
In [198]:

```
# Evaluate TPR , FPR , TNR , FNR
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(y_test, pred).ravel()

# Evaluate TPR (TPR = TP/(FN+TP))
TPR = TruePos/(FalseNeg + TruePos)
print("TPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (0.4096,T

# Evaluate FPR (FPR = FP/(TN+FP))
FPR = FalsePos/(TrueNeg + FalsePos)
print("FPR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (0.4096,F

# Evaluate TNR (TNR = TN/(TN+FP))
TNR = TrueNeg/(TrueNeg + FalsePos)
print("TNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (0.4096,T

# Evaluate FNR (FNR = TN/(FN+TP))
FNR = FalseNeg/(FalseNeg + TruePos)
print("FNR of the Multinomial naive Bayes classifier for alpha = %.3f is :  %f" % (0.4096,F
```

```
TPR of the Multinomial naive Bayes classifier for alpha = 0.410 is :  0.8962
90
FPR of the Multinomial naive Bayes classifier for alpha = 0.410 is :  0.0913
98
TNR of the Multinomial naive Bayes classifier for alpha = 0.410 is :  0.9086
02
FNR of the Multinomial naive Bayes classifier for alpha = 0.410 is :  0.1037
10
```

In [199]:

```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(y_test, pred), index=class_names, columns=class_
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', fontsi
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', fontsi
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



[6] Conclusions

In [213]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Vactorizer", "Model", "Hyperparameter(ALPHA)", " AUC%",]

x.add_row(["BOW", "Multinomial N.B", 1.638400, 90.061522])
x.add_row(["TFIDF", "Multinomial N.B",0.409600,89.715935])



print(x)
```

```
+------------+-----------------+-----------------------+-----------+
| Vactorizer |      Model      | Hyperparameter(ALPHA) |    AUC%   |
+------------+-----------------+-----------------------+-----------+
|    BOW     | Multinomial N.B |         1.6384        | 90.061522 |
|   TFIDF    | Multinomial N.B |         0.4096        | 89.715935 |
+------------+-----------------+-----------------------+-----------+
```

--->>> We have done all below steps for multinomial naive bayes on BOW and TFIDF VECTORIZERS with 100k points.

STEP 1 :- Data cleaning (removing duplication)

STEP 2 :- Text Preprocessing

STEP 3:- Featurization on text reviews i.e BOW,TFIDF.

STEP 4:-Using AUC as a metric and plot curve for train(predected value on itself) and C.V predected value on train VS for values of ALPHA (10^-4 TO 10^4)in order to find optimal value of alpha .

STEP 5:- Draw "AUC VS ALPHA" plot

STEP 6:- Once , we analise optimal value of optimal value of alpha then train multinomial Naive Bayes again with this optimal alpha and make predictions on test_data.

STEP 7:- Find top 10 values for positive as well as negative class with their log probabilities.

STEP 8:- Evaluate : Accuracy , F1-Score , Precision , Recall , TPR , FPR , TNR , FNR

STEP 9:- Plot Seaborn Heatmap for representation of Confusion Matrix.

AT THE END WE MAKE A TABLE TO COMPAIR OUR RESULTS OF multinomial Naive Bayes WITH DIFFERENT VECTORIZERS with the help of prettytable.