Assignment - 4 (Apply Naive Bayes on Amazon Fine Food Reviews)

September 4, 2018

1 Note :

(a). We can't apply Naive Bayes on negative values so we will use only Bag of Words(Bow) and TFIDF for this assignment .
(b). Range for alpha is taken from 10^-3 to 10^3

2 Objective : Apply Naive Bayes on Amazon Fine Food Reviews .

In [2]:
```
# 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 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
```

3 Loading Data

```
In [3]: # using the SQLite Table to read data.
        con1 = sqlite3.connect('database.sqlite')

        # Eliminating neutral reviews i.e. those reviews with Score = 3
        filtered_data = pd.read_sql_query(" SELECT * FROM Reviews WHERE Score != 3 ", con1)

        # Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
        def polarity(x):
            if x < 3:
                return 'negative'
            return 'positive'

        # Applying polarity function on Score column of filtered_data
        filtered_data['Score'] = filtered_data['Score'].map(polarity)

        print(filtered_data.shape)
        filtered_data.head()
```

```
(525814, 10)
```

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

           HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
        0                     1                       1  positive  1303862400
        1                     0                       0  negative  1346976000
        2                     1                       1  positive  1219017600
        3                     3                       3  negative  1307923200
        4                     0                       0  positive  1350777600

                         Summary                                               Text
        0  Good Quality Dog Food  I have bought several of the Vitality canned d...
        1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
        2  "Delight" says it all  This is a confection that has been around a fe...
        3         Cough Medicine  If you are looking for the secret ingredient i...
        4            Great taffy  Great taffy at a great price.  There was a wid...
```

4 Data Cleaning: Deduplication

In [4]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals

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

#Checking to see how much % of data still remains
((final.shape[0]*1.0)/(filtered_data.shape[0]*1.0)*100)
```

```
(364173, 10)
```

Out[4]: 69.25890143662969

In [5]:
```
# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]

print(final.shape)
final[30:50]
```

```
(364171, 10)
```

Out[5]:

	Id	ProductId	UserId	\
138683	150501	0006641040	AJ46FKXOVC7NR	
138676	150493	0006641040	AMX0PJKV4PPNJ	
138682	150500	0006641040	A1IJKK6Q1GTEAY	
138681	150499	0006641040	A3E7R866M94L0C	
476617	515426	141278509X	AB1A5EGHHVA9M	
22621	24751	2734888454	A1C298ITT645B6	
22620	24750	2734888454	A13ISQV0U9GZIC	
284375	308077	2841233731	A3QD68O22M2XHQ	
157850	171161	7310172001	AFXMWPNS1BLU4	
157849	171160	7310172001	A74C7IARQEM1R	
157833	171144	7310172001	A1V5MY8V9AWUQB	
157832	171143	7310172001	A2SW060IW01VPX	
157837	171148	7310172001	A3TFTWTG2CC1GA	
157831	171142	7310172001	A2Z01AYFVQYG44	
157830	171141	7310172001	AZ40270J4JBZN	
157829	171140	7310172001	ADXXVGRCGQQUO	
157828	171139	7310172001	A13MS1JQG2ADOJ	
157827	171138	7310172001	A13LAE0YTXA11B	
157848	171159	7310172001	A16GY2RCF410DT	
157834	171145	7310172001	A1L8DNQYY69L2Z	

ProfileName \

	ProfileName
138683	Nicholas A Mesiano
138676	E. R. Bird "Ramseelbird"
138682	A Customer
138681	L. Barker "simienwolf"
476617	CHelmic
22621	Hugh G. Pritchard
22620	Sandikaye
284375	LABRNTH
157850	H. Sandler
157849	stucker
157833	Cheryl Sapper "champagne girl"
157832	Sam
157837	J. Umphress
157831	Cindy Rellie "Rellie"
157830	Zhinka Chunmee "gamer from way back in the 70's"
157829	Richard Pearlstein
157828	C. Perrone
157827	Dita Vyslouzilova "dita"
157848	LB
157834	R. Flores

	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	\
138683	2	2	positive	940809600	
138676	71	72	positive	1096416000	
138682	2	2	positive	1009324800	
138681	2	2	positive	1065830400	
476617	1	1	positive	1332547200	
22621	0	0	positive	1195948800	
22620	1	1	negative	1192060800	
284375	0	0	positive	1345852800	
157850	0	0	positive	1229385600	
157849	0	0	positive	1230076800	
157833	0	0	positive	1244764800	
157832	0	0	positive	1252022400	
157837	0	0	positive	1240272000	
157831	0	0	positive	1254960000	
157830	0	0	positive	1264291200	
157829	0	0	positive	1264377600	
157828	0	0	positive	1265760000	
157827	0	0	positive	1269216000	
157848	0	0	positive	1231718400	
157834	0	0	positive	1243728000	

	Summary	\
138683	This whole series is great way to spend time w...	
138676	Read it once. Read it twice. Reading Chicken S...	
138682	It Was a favorite!	
138681	Can't explain why	

```
476617                                 The best drink mix
22621                                 Dog Lover Delites
22620                                     made in china
284375               Great recipe book for my babycook
157850                                  Excellent treats
157849                                   Sophie's Treats
157833                         THE BEST healthy dog treat!
157832              My Alaskan Malamute Loves Them!!
157837                                  Best treat ever!
157831       my 12 year old maltese has always loved these
157830               Dogs, Cats, Ferrets all love this
157829                                         5 snouts!
157828                                   Best dog treat ever
157827                          Great for puppy training
157848                                            Great!
157834                                   Terrific Treats

                                                        Text
138683  I can remember seeing the show when it aired o...
138676  These days, when a person says, "chicken soup"...
138682  This was a favorite book of mine when I was a ...
138681  This book has been a favorite of mine since I ...
476617  This product by Archer Farms is the best drink...
22621   Our dogs just love them.  I saw them in a pet ...
22620   My dogs loves this chicken but its a product f...
284375  This book is easy to read and the ingredients ...
157850  I have been feeding my greyhounds these treats...
157849  This is one product that my welsh terrier can ...
157833  This is the ONLY dog treat that my Lhasa Apso ...
157832  These liver treas are phenomenal. When i recei...
157837  This was the only treat my dog liked during ob...
157831  No waste , even if she is having a  day when s...
157830  I wanted a treat that was accepted and well li...
157829  My Westie loves these things!  She loves anyth...
157828  This is the only dog treat that my terrier wil...
157827  New puppy loves this, only treat he will pay a...
157848  My dog loves these treats!  We started using t...
157834  This is a great treat which all three of my do...
```

OBSERVATION :- Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

In [6]:
```
final = final[final['ProductId'] != '2841233731']
final = final[final['ProductId'] != '0006641040']
final.shape
```

Out[6]:
```
(364136, 10)
```

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

In [7]:
```
#set of stopwords in English
from nltk.corpus import stopwords
stop = set(stopwords.words('english'))
words_to_keep = set(('not'))
stop -= words_to_keep
#initialising the snowball stemmer
sno = nltk.stem.SnowballStemmer('english')

 #function to clean the word of any 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 [8]:
```
#Code for removing HTML tags , punctuations . Code for removing stopwords . Code for c
# also greater than 2 . Code for stemmimg and also to convert them to lowercase letter
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 descri
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to descri
                else:
                    continue
            else:
```

```
                    continue

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


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

In [9]:
```
#adding a column of CleanedText which displays the data after pre-processing of the re
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 (364136, 11)
```

Out[9]:
```
            Id   ProductId          UserId        ProfileName  \
476617  515426  141278509X   AB1A5EGHHVA9M            CHelmic
22621    24751  2734888454  A1C298ITT645B6  Hugh G. Pritchard
22620    24750  2734888454  A13ISQV0U9GZIC           Sandikaye
157850  171161  7310172001   AFXMWPNS1BLU4         H. Sandler
157849  171160  7310172001   A74C7IARQEM1R            stucker

        HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
476617                     1                       1  positive  1332547200
22621                      0                       0  positive  1195948800
22620                      1                       1  negative  1192060800
157850                     0                       0  positive  1229385600
157849                     0                       0  positive  1230076800

                   Summary                                               Text  \
476617  The best drink mix  This product by Archer Farms is the best drink...
22621    Dog Lover Delites  Our dogs just love them.  I saw them in a pet ...
22620        made in china  My dogs loves this chicken but its a product f...
157850   Excellent treats  I have been feeding my greyhounds these treats...
157849     Sophie's Treats  This is one product that my welsh terrier can ...

                                              CleanedText
476617  product archer farm best drink mix ever mix fl...
22621   dog love saw pet store tag attach regard made ...
22620   dog love chicken product china wont buy anymor...
157850  feed greyhound treat year hound littl finicki ...
157849  one product welsh terrier eat sophi food alerg...
```

TIME BASED SPLITTING OF SAMPLE DATASET

In [10]:
```
from sklearn.model_selection import train_test_split
##Sorting data according to Time in ascending order for Time Based Splitting
```

```
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, ki

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

# split the data set into train and test
X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.3, random_state
```

6 (1). Bag of Words (BoW)

```
In [11]: #BoW
         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 :  (254895, 12739)
the number of unique words : 12739
```

7 (1.a) Bernoulli Naive Bayes Classifier

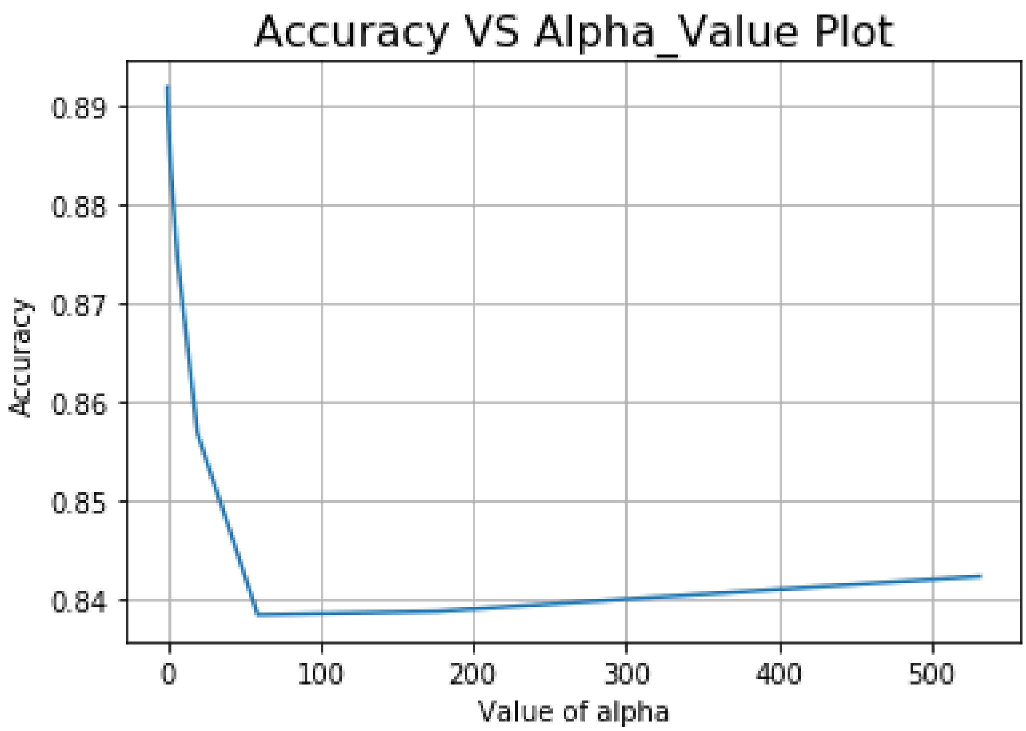
8 10 Fold Cross Validation

```
In [12]: # Importing libraries
         from sklearn.naive_bayes import BernoulliNB
         from sklearn.model_selection import cross_val_score
         from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,

         # 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 = BernoulliNB(alpha = k)
             scores = cross_val_score(bn, X_train_vec, Y_train, cv=10, scoring='accuracy', n_j
             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 0.001.
```

In [13]:
```
# 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 Alpha_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, 59.049, 177.147, 531.4
```

```
Accuracy for each alpha value is :
  [0.89194 0.89192 0.89176 0.89152 0.89114 0.89032 0.88849 0.88376 0.87466
 0.85684 0.83839 0.83876 0.8423 ]
```

```
In [14]: # ============================== Bernoulli Naive Bayes with alpha = optimal_alpha ===
         # instantiate learning model alpha = optimal_alpha
         bn_optimal = BernoulliNB(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 Bernoulli naive Bayes classifier for alpha = %.3f is

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

```
The Test Accuracy of the Bernoulli naive Bayes classifier for alpha = 0.001 is 89.365714%
```

9 Top 20 Important Features Per Class Are :-

```
In [15]: bn_optimal.classes_

Out[15]: array(['negative', 'positive'], dtype='<U8')
```

From above we can see that first_class is 'negative' and second_class is 'positive'

```
In [16]: # Now we can find log probabilities of different features for both the classes
         class_features = bn_optimal.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 argso
```

```python
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


tast         -->        -0.987744
like         -->        -1.001583
product         -->        -1.177819
one         -->        -1.355610
would         -->        -1.417847
tri         -->        -1.467070
flavor         -->        -1.548114
good         -->        -1.552114
buy         -->        -1.602521
get         -->        -1.655996
use         -->        -1.681294
dont         -->        -1.744126
even         -->        -1.821458
order         -->        -1.834662
make         -->        -1.971348
much         -->        -1.973322
time         -->        -1.995297
realli         -->        -2.026252
look         -->        -2.054878
amazon         -->        -2.066640


Top 20 Important Features and their log probabilities For Positive Class :


like         -->        -1.175476
tast         -->        -1.204468
love         -->        -1.260625
good         -->        -1.265811
great         -->        -1.295596
flavor         -->        -1.423290
one         -->        -1.467773
use         -->        -1.479067
tri         -->        -1.520718
```

```
product         -->        -1.537382
make         -->        -1.657849
get         -->        -1.684409
buy         -->        -1.893541
time         -->        -1.902954
would         -->        -1.928464
realli         -->        -1.967278
best         -->        -1.989593
amazon         -->        -1.997007
find         -->        -2.011305
price         -->        -2.015592
```

10 Now Evaluate : Accuracy , F1-Score , Precision , Recall , Confusion_Matrix , TPR , FPR , TNR , FNR

In [17]:
```python
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Bernoulli naive Bayes classifier for alpha = %.3f is

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Bernoulli naive Bayes classifier for alpha = %.3f i

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Bernoulli naive Bayes classifier for alpha = %.3f is %

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

```
The Test Accuracy of the Bernoulli naive Bayes classifier for alpha = 0.001 is 89.365714%

The Test Precision of the Bernoulli naive Bayes classifier for alpha = 0.001 is 0.937157

The Test Recall of the Bernoulli naive Bayes classifier for alpha = 0.001 is 0.936801

The Test F1-Score of the Bernoulli naive Bayes classifier for alpha = 0.001 is 0.936979
```

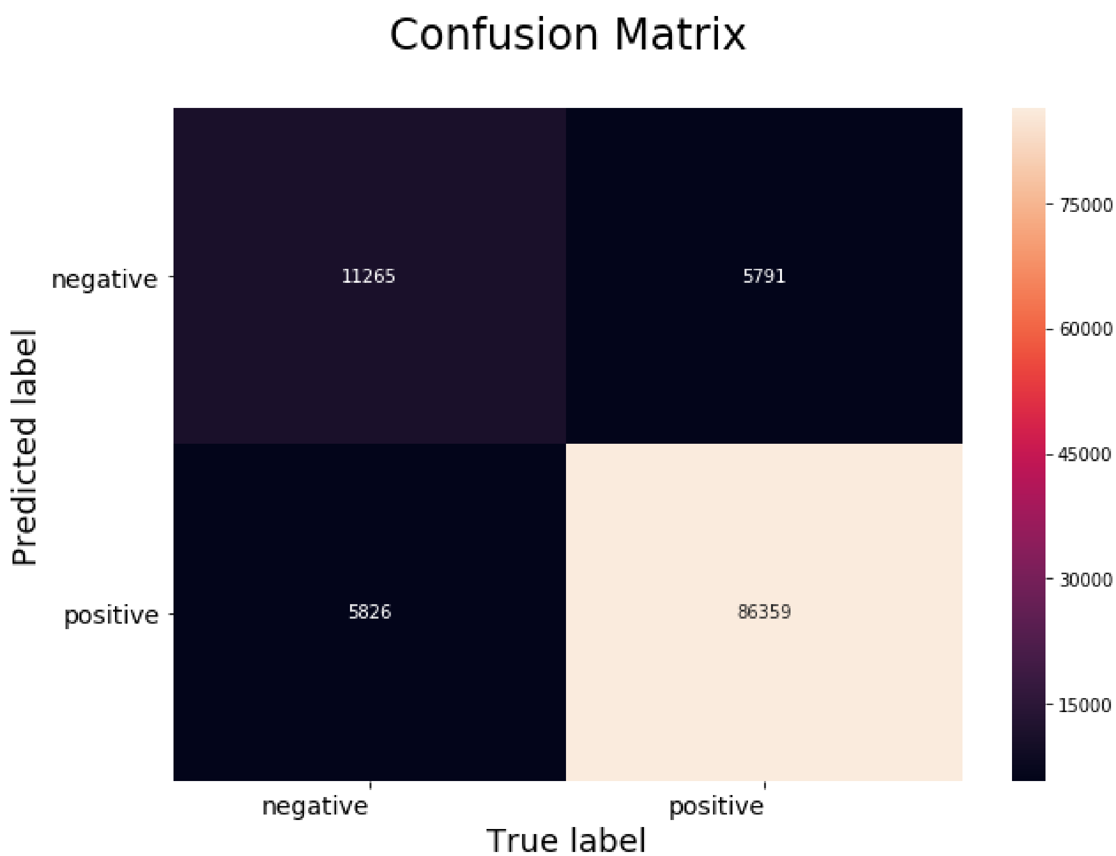
In [18]:
```python
# Evaluate TPR , FPR , TNR , FNR
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(Y_test, predictions).ravel()

# Evaluate TPR (TPR = TP/(FN+TP))
TPR = TruePos/(FalseNeg + TruePos)
```

```
print("TPR of the Bernoulli naive Bayes classifier for alpha = %.3f is :  %f" % (optim

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

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

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

```
TPR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.937157
FPR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.340881
TNR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.659119
FNR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.062843
```

Seaborn Heatmap For Representation of Confusion Matrix :

In [19]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
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', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



11 (1.b) Multinomial Naive Bayes Classifier

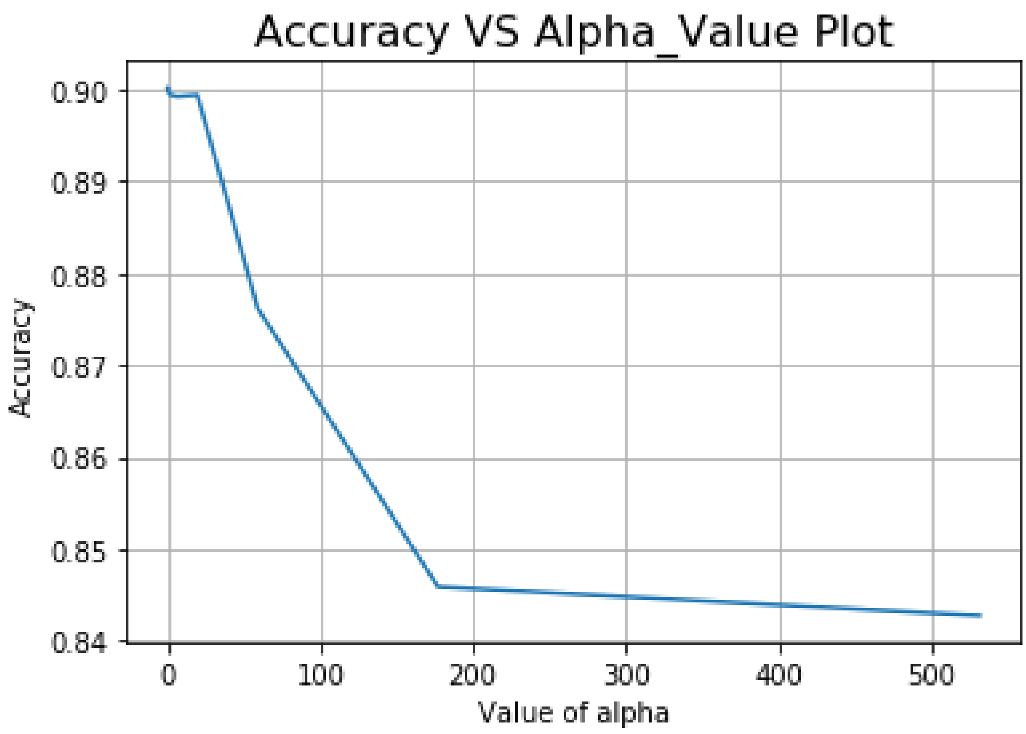
12 10 Fold Cross Validation

```
In [20]: from sklearn.naive_bayes import MultinomialNB

         # 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_jo
        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 0.009.
```

In [21]:
```
# 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 Alpha_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, 59.049, 177.147, 531.4

Accuracy for each alpha value is :
  [0.90019 0.90023 0.90025 0.90025 0.90023 0.90015 0.89978 0.89944 0.89929
 0.89945 0.87621 0.84591 0.84276]
```

In [22]:
```
# ============================== Multinomial Naive Bayes with alpha = optimal_alpha ==
# instantiate learning model alpha = 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

# 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
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha = 0.009 is 90.191412%
```

13 Top 20 Important Features Per Class Are :-

In [23]:
```
bn_optimal.classes_
```

Out[23]:
```
array(['negative', 'positive'], dtype='<U8')
```

From above we can see that first_class is 'negative' and second_class is 'positive'

In [24]:
```
# Now we can find log probabilities of different features for both the classes
class_features = bn_optimal.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()
```

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

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


tast         -->        -4.211208
like         -->        -4.275870
product         -->        -4.411933
one        -->        -4.729366
flavor          -->        -4.778510
would         -->        -4.863789
tri        -->        -4.878241
use        -->        -5.026657
coffe         -->        -5.039993
good         -->        -5.043213
get        -->        -5.131303
buy        -->        -5.139937
order         -->        -5.189192
food         -->        -5.201784
tea        -->        -5.274021
dont         -->        -5.275934
even         -->        -5.342246
box        -->        -5.362271
amazon          -->        -5.434784
bag        -->        -5.466863


Top 20 Important Features and their log probabilities For Positive Class :


like         -->        -4.413711
tast         -->        -4.491244
good         -->        -4.623394
flavor          -->        -4.654844
love         -->        -4.675000
great         -->        -4.707180
use        -->        -4.708460
```

```
one          -->        -4.778937
product          -->        -4.837269
tri          -->        -4.885283
tea          -->        -4.918532
coffe          -->        -4.973927
make          -->        -5.031791
get          -->        -5.068710
food          -->        -5.178502
would          -->        -5.333505
time          -->        -5.337991
buy          -->        -5.359727
realli          -->        -5.386546
eat          -->        -5.402433
```

14 Now Evaluate : Accuracy , F1-Score , Precision , Recall , Confusion_Matrix , TPR , FPR , TNR , FNR

In [25]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Multinomial naive Bayes classifier for alpha = %.3f

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Multinomial naive Bayes classifier for alpha = %.3

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Multinomial naive Bayes classifier for alpha = %.3f i

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

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha = 0.009 is 90.191412%

The Test Precision of the Multinomial naive Bayes classifier for alpha = 0.009 is 0.945981

The Test Recall of the Multinomial naive Bayes classifier for alpha = 0.009 is 0.937289

The Test F1-Score of the Multinomial naive Bayes classifier for alpha = 0.009 is 0.941615
```

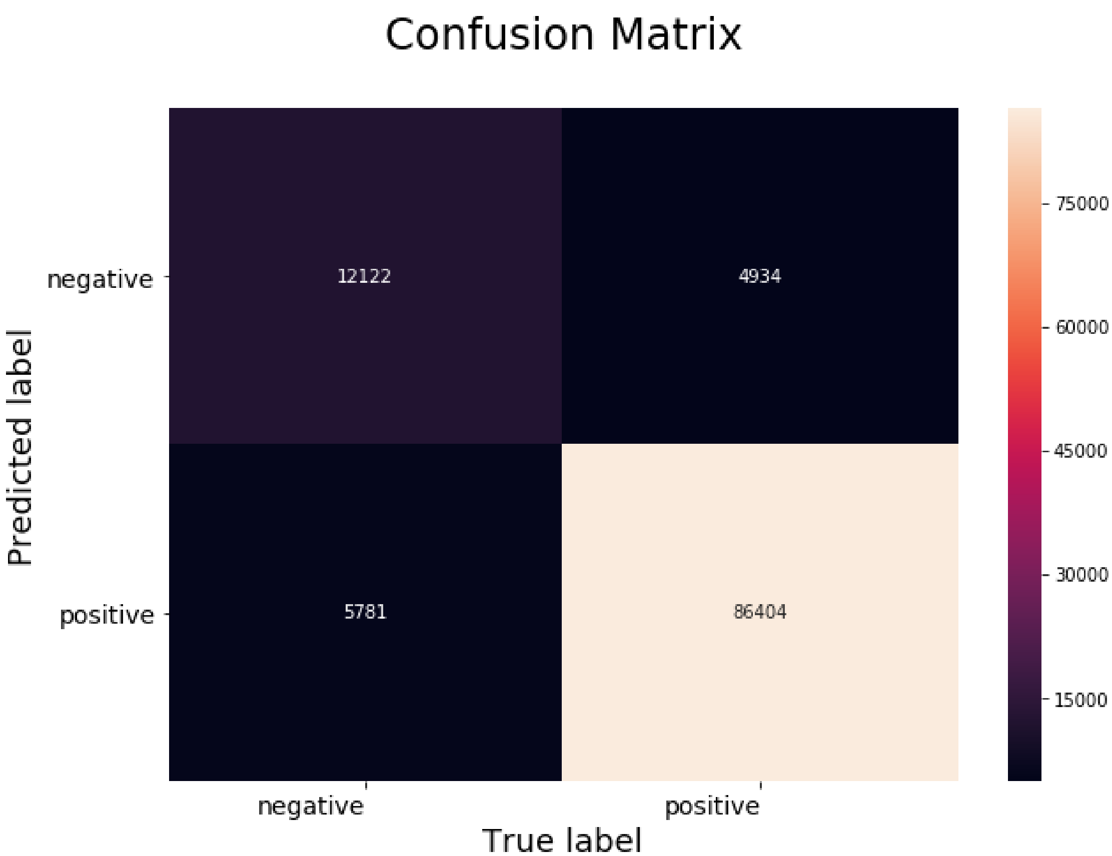
In [26]:
```
# Evaluate TPR , FPR , TNR , FNR
TrueNeg,FalseNeg,FalsePos, TruePos = confusion_matrix(Y_test, predictions).ravel()
```

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

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

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

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

```
TPR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.945981
FPR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.322907
TNR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.677093
FNR of the Multinomial naive Bayes classifier for alpha = 0.009 is :  0.054019
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [27]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
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', 
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', 
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



15 (2). TF-IDF

```
In [28]: 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 :  (254895, 12739)
the number of unique words : 12739
```

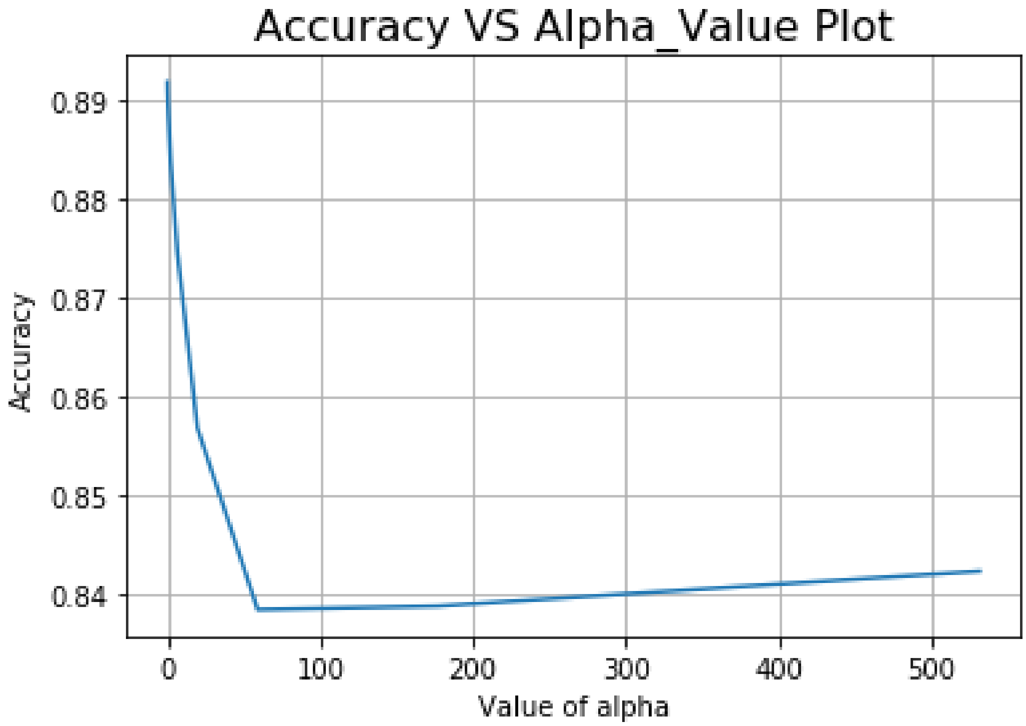
16 (2.a) Bernoulli Naive Bayes Classifier

17 10 Fold Cross Validation

In [29]:
```
# 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 = BernoulliNB(alpha = k)
    scores = cross_val_score(bn, X_train_vec, Y_train, cv=10, scoring='accuracy', n_jo
    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 0.001.
```

In [30]:
```
# 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 Alpha_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, 59.049, 177.147, 531.4

Accuracy for each alpha value is :
  [0.89194 0.89192 0.89176 0.89152 0.89114 0.89032 0.88849 0.88376 0.87466
 0.85684 0.83839 0.83876 0.8423 ]
```

In [31]:
```
# ============================== Bernoulli Naive Bayes with alpha = optimal_alpha ===
# instantiate learning model alpha = optimal_alpha
bn_optimal = BernoulliNB(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 Bernoulli naive Bayes classifier for alpha = %.3f is
```

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

```
The Test Accuracy of the Bernoulli naive Bayes classifier for alpha = 0.001 is 89.365714%
```

18 Top 20 Important Features Per Class Are :-

In [32]:
```
bn_optimal.classes_
```

Out[32]:
```
array(['negative', 'positive'], dtype='<U8')
```

From above we can see that first_class is 'negative' and second_class is 'positive'

In [33]:
```
# Now we can find log probabilities of different features for both the classes
class_features = bn_optimal.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 = tf_idf_vect.get_feature_names()

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

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


tast         -->        -0.987744
like         -->        -1.001583
product         -->        -1.177819
one        -->        -1.355610
would         -->        -1.417847
tri        -->        -1.467070
```

```
flavor          -->         -1.548114
good          -->         -1.552114
buy          -->         -1.602521
get          -->         -1.655996
use          -->         -1.681294
dont          -->         -1.744126
even          -->         -1.821458
order          -->         -1.834662
make          -->         -1.971348
much          -->         -1.973322
time          -->         -1.995297
realli          -->         -2.026252
look          -->         -2.054878
amazon          -->         -2.066640


Top 20 Important Features and their log probabilities For Positive Class :


like          -->         -1.175476
tast          -->         -1.204468
love          -->         -1.260625
good          -->         -1.265811
great          -->         -1.295596
flavor          -->         -1.423290
one          -->         -1.467773
use          -->         -1.479067
tri          -->         -1.520718
product          -->         -1.537382
make          -->         -1.657849
get          -->         -1.684409
buy          -->         -1.893541
time          -->         -1.902954
would          -->         -1.928464
realli          -->         -1.967278
best          -->         -1.989593
amazon          -->         -1.997007
find          -->         -2.011305
price          -->         -2.015592
```

19 Now Evaluate : Accuracy , F1-Score , Precision , Recall , Confusion_Matrix , TPR , FPR , TNR , FNR

In [34]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Bernoulli naive Bayes classifier for alpha = %.3f is
```

```
    # evaluate precision
    acc = precision_score(Y_test, predictions, pos_label = 'positive')
    print('\nThe Test Precision of the Bernoulli naive Bayes classifier for alpha = %.3f i

    # evaluate recall
    acc = recall_score(Y_test, predictions, pos_label = 'positive')
    print('\nThe Test Recall of the Bernoulli naive Bayes classifier for alpha = %.3f is %

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

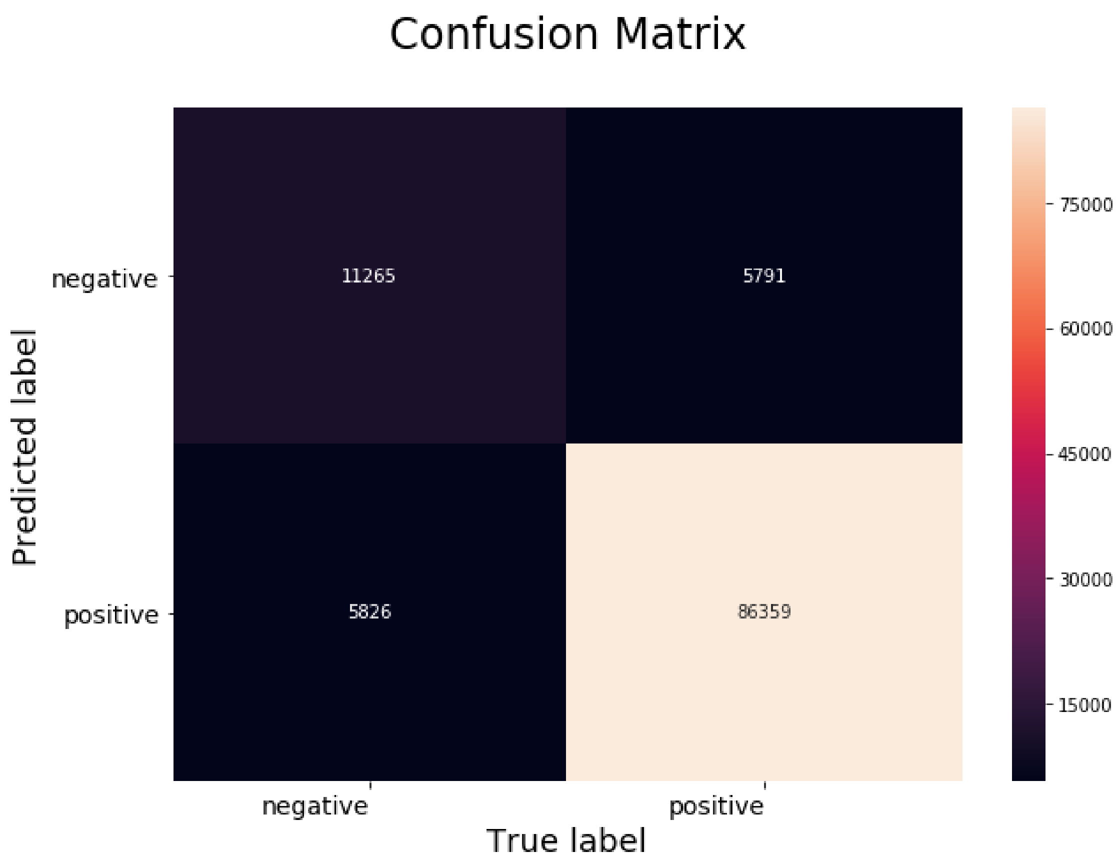
```
The Test Accuracy of the Bernoulli naive Bayes classifier for alpha = 0.001 is 89.365714%

The Test Precision of the Bernoulli naive Bayes classifier for alpha = 0.001 is 0.937157

The Test Recall of the Bernoulli naive Bayes classifier for alpha = 0.001 is 0.936801

The Test F1-Score of the Bernoulli naive Bayes classifier for alpha = 0.001 is 0.936979
```

```
In [35]: # 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 Bernoulli naive Bayes classifier for alpha = %.3f is :  %f" % (optin

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

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

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

```
TPR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.937157
FPR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.340881
TNR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.659119
FNR of the Bernoulli naive Bayes classifier for alpha = 0.001 is :  0.062843
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [36]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
         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', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



20 (2.b) Multinomial Naive Bayes Classifier

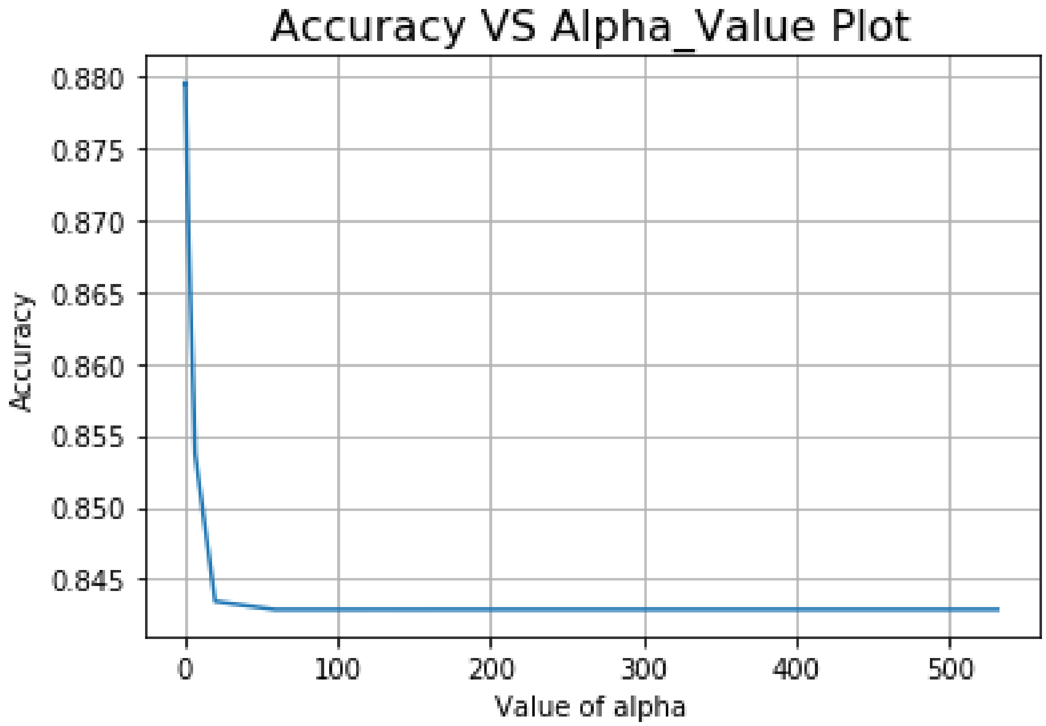
21 10 Fold Cross Validation

```
In [37]: # 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_j
    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 0.027.
```

In [38]:
```
# 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 Alpha_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, 59.049, 177.147, 531.4

Accuracy for each alpha value is :
  [0.87945 0.87948 0.87953 0.87961 0.87953 0.87914 0.87692 0.86959 0.85375
 0.84344 0.84286 0.84287 0.84287]
```

In [39]:
```
# ============================== Multinomial Naive Bayes with alpha = optimal_alpha =
# instantiate learning model alpha = 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
```

```
# 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 = 0.027 is 88.040205%
```

22 Top 20 Important Features Per Class Are :-

In [40]:
```
bn_optimal.classes_
```

Out[40]:
```
array(['negative', 'positive'], dtype='<U8')
```

From above we can see that first_class is 'negative' and second_class is 'positive'

In [41]:
```
# Now we can find log probabilities of different features for both the classes
class_features = bn_optimal.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 = tf_idf_vect.get_feature_names()

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

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


tast         -->        -4.816971
like         -->        -4.964158
product         -->        -4.980686
would         -->        -5.306868
coffe         -->        -5.324640
flavor         -->        -5.334298
```

```
one          -->        -5.353519
tri          -->        -5.459168
buy          -->        -5.465362
order          -->        -5.472430
box          -->        -5.577193
disappoint          -->        -5.606259
tea          -->        -5.610177
good          -->        -5.636388
dont          -->        -5.641933
get          -->        -5.653298
use          -->        -5.698215
even          -->        -5.730978
food          -->        -5.752900
bag          -->        -5.762344


Top 20 Important Features and their log probabilities For Positive Class :


great          -->        -5.040164
love          -->        -5.048959
tast          -->        -5.111444
good          -->        -5.112518
like          -->        -5.131742
tea          -->        -5.185184
flavor          -->        -5.189635
coffe          -->        -5.197630
product          -->        -5.279732
use          -->        -5.297337
one          -->        -5.393326
tri          -->        -5.446777
make          -->        -5.534496
get          -->        -5.578981
price          -->        -5.622630
buy          -->        -5.636730
best          -->        -5.647731
food          -->        -5.660888
order          -->        -5.694562
time          -->        -5.714951
```

23 Now Evaluate : Accuracy , F1-Score , Precision , Recall , Confusion_Matrix , TPR , FPR , TNR , FNR

In [42]:
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\nThe Test Accuracy of the Multinomial naive Bayes classifier for alpha = %.3f
```

```python
# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Precision of the Multinomial naive Bayes classifier for alpha = %.3

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 'positive')
print('\nThe Test Recall of the Multinomial naive Bayes classifier for alpha = %.3f i

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

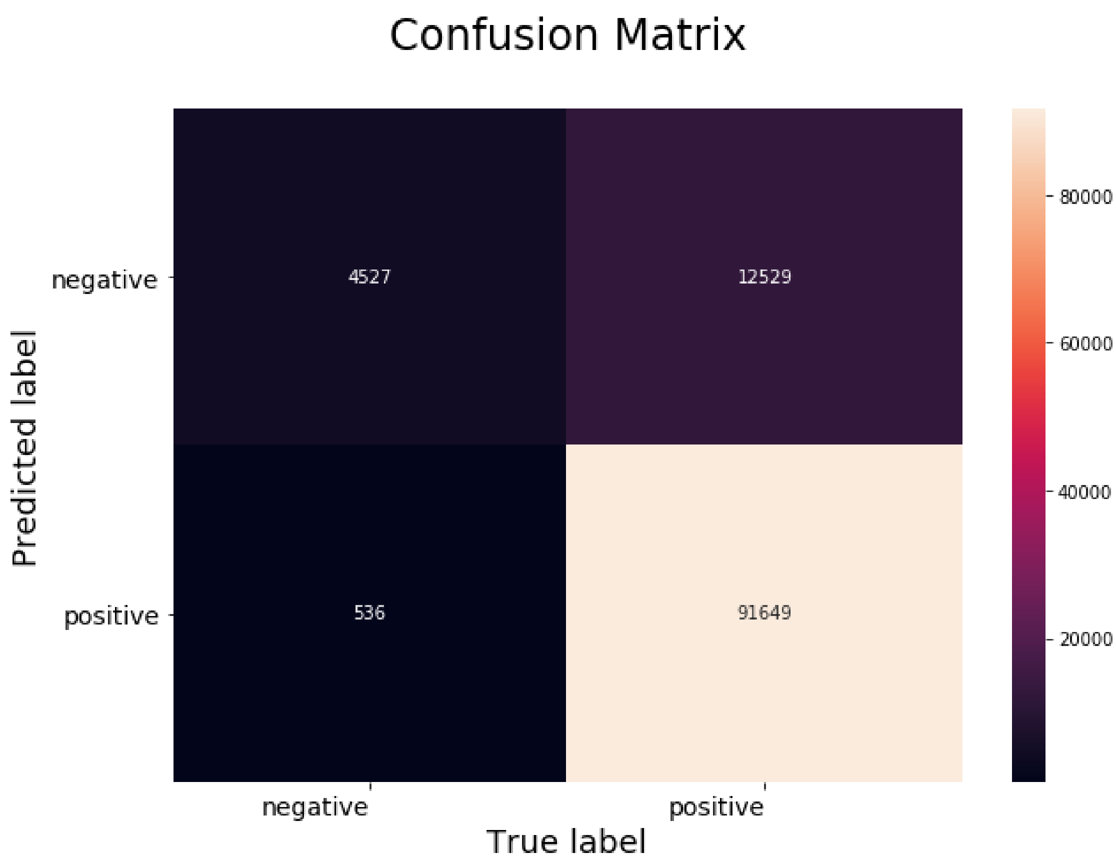
```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha = 0.027 is 88.040205%

The Test Precision of the Multinomial naive Bayes classifier for alpha = 0.027 is 0.879735

The Test Recall of the Multinomial naive Bayes classifier for alpha = 0.027 is 0.994186

The Test F1-Score of the Multinomial naive Bayes classifier for alpha = 0.027 is 0.933465
```

In [43]:
```python
# 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" % (op

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

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

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

```
TPR of the Multinomial naive Bayes classifier for alpha = 0.027 is :  0.879735
FPR of the Multinomial naive Bayes classifier for alpha = 0.027 is :  0.105866
TNR of the Multinomial naive Bayes classifier for alpha = 0.027 is :  0.894134
FNR of the Multinomial naive Bayes classifier for alpha = 0.027 is :  0.120265
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [44]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=class_names, co
         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', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



24 CONCLUSION :

25 (a). Procedure followed :

STEP 1 :- Text Preprocessing

STEP 2:- Time-based splitting of whole dataset into train_data and test_data

STEP 3:- Training the vectorizer on train_data and later applying same vectorizer on both train_data and test_data to transform them into vectors

STEP 4:- Using Bernoulli Naive Bayes as an estimator in 10-Fold Cross-Validation in order to find optimal value of alpha .

STEP 5:- Draw "Accuracy VS Alpha_value" plot

STEP 6:- Once , we get optimal value of alpha then train BernoulliNB again with this optimal alpha and make predictions on test_data

STEP 7:- Find important features per class

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

STEP 9:- Draw Seaborn Heatmap for Confusion Matrix .

STEP 10 :- Repeat from STEP 4 to STEP 9 using Multinomial Naive Bayes as an estimator

Repeat from STEP 3 to STEP 10 for each of these two vectorizers : Bag Of Words(BoW), TFIDF

26 (b). Table (Model Performances with their hyperparameters :

In [46]:
```
# Creating table using PrettyTable library
from prettytable import PrettyTable

names = ["BernoulliNB for BoW", "MultinomialNB for BoW", "BernoulliNB for TFIDF", "Mu

optimal_alpha = [bow_bernoulli_alpha, bow_multinomial_alpha, tfidf_bernoulli_alpha, t

train_acc = [bow_bernoulli_train_acc, bow_multinomial_train_acc, tfidf_bernoulli_trai

test_acc = [bow_bernoulli_test_acc, bow_multinomial_test_acc, tfidf_bernoulli_test_ac

numbering = [1,2,3,4]

# Initializing prettytable
ptable = PrettyTable()

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

# Printing the Table
print(ptable)
```

```
+-------+-------------------------+------------+-------------------+-------------------+
| S.NO. |          MODEL          | Best Alpha | Training Accuracy |   Test Accuracy   |
+-------+-------------------------+------------+-------------------+-------------------+
|   1   |   BernoulliNB for BoW   |   0.001    |  89.1943733660152 | 89.36571433802327 |
|   2   |  MultinomialNB for BoW  |   0.009    |  90.0253049504307 | 90.19141164947226 |
```

3	BernoulliNB for TFIDF	0.001	89.1943733660152	89.36571433802327
4	MultinomialNB for TFIDF	0.027	87.96092412822742	88.04020468505415