OBJECTIVE

- Performing naive bayes algorithm to amazon fine food reviews
- Techniques used - BOW , TFIDF
- Using Multinomial version of Naive bayes as because the multinomial Naive Bayes classifier is suitable for classification with discrete features (e.g., word counts for text classification) and multinomial distribution normally requires integer feature counts

In [1]:

```
#importing necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
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
```

In [2]:

```
%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.metrics import
accuracy_score,precision_score,recall_score,confusion_matrix,classification_report,f1_score
import scikitplot as skplt

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
```

```
C:\Users\lenovo\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windows; a
liasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [3]:

```
# using the 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
```

```
# not taking into consideration those reviews with Score=3
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, con)
print(filtered_data.shape)
```

```
(525814, 10)
```

In [4]:

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

#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 (525814, 10)
```

Out[4]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	positive	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	negative	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	positive	1219017600	"Delight" says it all

In [5]:

```
filtered_data['Score'].value_counts() #Data points in each class
```

Out[5]:

```
positive    443777
negative     82037
Name: Score, dtype: int64
```

In [6]:

```
#Sorting the data taking productid as the parameter
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='qui
cksort', na_position='last')
sorted_data.shape
```

Out[6]:

```
(525814, 10)
```

In [7]:

```
#Deleting the dublicates reviews which is created when user writed a review for the product, it au
tomatically generates for the same product of different color etc
final = sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', in
```

```
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', in
place=False)
final.shape
```

Out[7]:

```
(364173, 10)
```

In [8]:

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

Out[8]:

```
69.25890143662969
```

In [9]:

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

```
      Id   ProductId          UserId              ProfileName  \
0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
1  44737  B001EQ55RW  A2V0I904FH7ABY                      Ram

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     3                       1      5  1224892800
1                     3                       2      4  1212883200

                                 Summary  \
0            Bought This for My Son at College
1  Pure cocoa taste with crunchy almonds inside

                                                Text
0  My son loves spaghetti so I didn't hesitate or...
1  It was almost a 'love at first bite' - the per...
```

In [10]:

```
#Dropping the data which has HelpfulnessNumerator<HelpfulnessDenominator which is impossible
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#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()
```

```
(364171, 10)
```

Out[10]:

```
positive    307061
negative     57110
Name: Score, dtype: int64
```

In [11]:

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

Out[11]:

```
69.25852107399194
```

In [12]:

```
print(final.shape)
```

```
(364171, 10)
```

In [13]:

```python
stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special characters
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [14]:

```python
#Code for implementing step-by-step the checks mentioned in the pre-processing phase
# this code takes a while to run as it needs to run on 500k sentences.
from tqdm import tqdm
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 tqdm(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 describe positive reviews
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe negative reviews reviews
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

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

```
100%|██████████████████████████████████████████████████| 364171/364171
[09:00<00:00, 673.70it/s]
```

In [15]:

```python
final['CleanedText']=final_string #adding a column of CleanedText which displays the data after pre-processing of the review
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
final.head(3)
```

Out[15]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	S
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	939340800	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	S
138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1	positive	1194739200	bc
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	positive	1191456000	s

In [128]:

```
final.shape
```

Out[128]:

```
(364171, 11)
```

In [129]:

```
final_data=final.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort', na_po
sition='last')
```

In [130]:

```
X_train_data = final_data[:264171]
X_test_data = final_data[264171:364171]
y_train = X_train_data['Score']
y_test = X_test_data['Score']
print("Data")
print(X_train_data.shape)
print(X_test_data.shape)
print("Label")
print(y_train.shape)
print(y_test.shape)
```

```
Data
(264171, 11)
(100000, 11)
Label
(264171,)
(100000,)
```

BOW

In [19]:

```
count_vect = CountVectorizer()
X_train = count_vect.fit_transform(X_train_data['CleanedText'])
X_test = count_vect.transform(X_test_data['CleanedText'])
print(X_train.shape)
print(X_test.shape)
```

```
(264171, 60276)
(100000, 60276)
```

In [28]:

```
# Importing libraries
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,recall_score
```

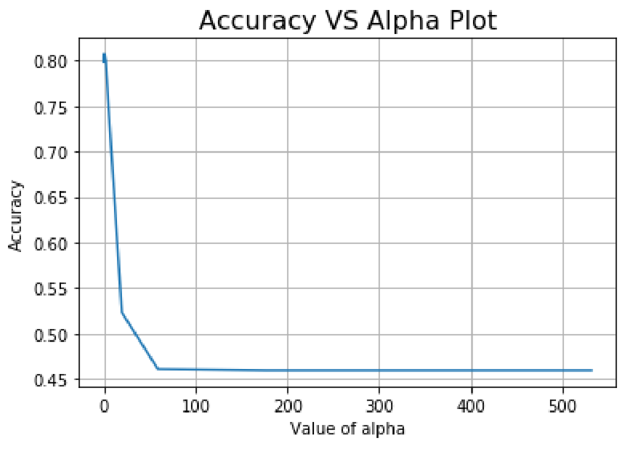
```
# Creating alpha values in the range from 10^-3 to 10^3
alpha = [] #creating empty list for alpha
i = 0.001
while(i<=1000):
    alpha.append(np.round(i,3))
    i *= 3

# empty list cv_scores that will hold cross-validation scores
cv_scores = []

# performing 10-fold cross validation on train data
for k in tqdm(alpha):
    model = MultinomialNB(alpha = k)
    scores = cross_val_score(model, X_train, y_train, cv=10, scoring='f1_macro', n_jobs=-1)
    cv_scores.append(scores.mean())
```

```
100%|██████████████████████████████████████████████████████████████████████████████████| 13/13
[01:53<00:00,  8.74s/it]
```

In [29]:

```
# determining best value of alpha
optimal_alpha = alpha[cv_scores.index(max(cv_scores))]
print('\nThe optimal value of alpha is %.3f.' % optimal_alpha)
# plot accuracy vs alpha
plt.plot(alpha, cv_scores)
plt.xlabel('Value of alpha',size=10)
plt.ylabel('Accuracy',size=10)
plt.title('Accuracy VS Alpha Plot',size=16)
plt.grid()
plt.show()
print("\n*******Train Data Report******");
print("\nAlpha values :\n",alpha)
print("\nF1 Score for each value of alpha :\n ", np.round(cv_scores,5)*100)
```

```
The optimal value of alpha is 0.729.
```




```
*******Train Data Report******

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, 531.441]

F1 Score for each value of alpha :
  [79.846 80.05  80.193 80.404 80.591 80.736 80.744 80.038 72.756 52.321
 46.084 45.935 45.936]
```

In [30]:

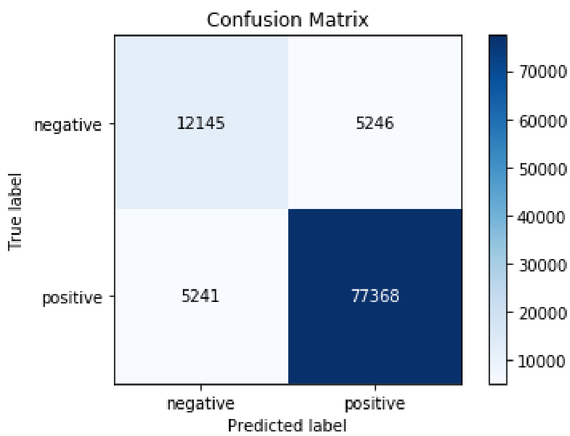
```
# instantiate learning model alpha = optimal_alpha
model_bow_multinomial = MultinomialNB(alpha = optimal_alpha)

# fitting the model
model_bow_multinomial.fit(X_train,y_train)

# predict the response
```

```
pred = model_bow_multinomial.predict(X_test)
```

In [31]:

```
print("***Test Data Report***")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",f1_score(y_test, pred, average='macro')*100)
print("precision_score = ",precision_score(y_test, pred, average='macro')*100)
print("recall_score = ",recall_score(y_test, pred, average='macro')*100)
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Accuracy =  89.513
f1_score =  81.74891662072893
precision_score =  81.75252123854102
recall_score =  81.74531353243107
```



In [32]:

```
True_Negative, False_Negative, False_Positive, True_Positive = confusion_matrix(y_test, pred).ravel
()

Total_Positive = False_Negative + True_Positive
Total_Negative = True_Negative + False_Positive

TPR = True_Positive/Total_Positive
FPR = False_Positive/Total_Negative
TNR = True_Negative/Total_Negative
FNR = False_Negative/ Total_Positive
print("TPR = %.5f"%(TPR))
print("FPR = %.5f"%(FPR))
print("TNR = %.5f"%(TNR))
print("FNR = %.5f"%(FNR))
```

```
TPR = 0.93650
FPR = 0.30145
TNR = 0.69855
FNR = 0.06350
```

In [35]:

```
print("Actual Data")
print("------------")
print(X_test_data["Score"].value_counts())
print("\n")
print("After Prediction")
print("------------")
print("Positive =",Total_Positive)
print("Negative =",Total_Negative)
```

```
Actual Data
------------
positive    82609
negative    17391
```

```
Name: Score, dtype: int64


After Prediction
------------
Positive = 82614
Negative = 17386
```

In [41]:

```
print(model_bow_multinomial.classes_)
# Finding log probabilities
class_feature = model_bow_multinomial.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_feature = class_feature[0]
positive_feature = class_feature[1]

# Getting all feature names from the count vectorizer
feature_name = count_vect.get_feature_names()

#sorting
sorted_negative_feature = np.argsort(negative_feature)[::-1]
sorted_positive_feature = np.argsort(positive_feature)[::-1]
```

```
['negative' 'positive']
```

In [42]:

```
print("Negative feature top 10 :")
print("-------")
for i in list(sorted_negative_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],negative_feature[i]))

print("\nPositive feature top 10 :")
print("-------")
for i in list(sorted_positive_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],positive_feature[i]))
```

```
Negative feature top 10 :
-------
tast  --> -4.228348
like  --> -4.308579
product  --> -4.481159
one  --> -4.754288
flavor  --> -4.789130
would  --> -4.900548
tri  --> -4.905776
good  --> -5.064903
coffe  --> -5.092030
use  --> -5.096412

Positive feature top 10 :
-------
like  --> -4.440633
tast  --> -4.510265
good  --> -4.648948
flavor  --> -4.667679
love  --> -4.696167
great  --> -4.719393
use  --> -4.739908
one  --> -4.795349
product  --> -4.882274
tea  --> -4.892647
```

TFIDF

In [131]:

```
tf_idf_vect = TfidfVectorizer()
X_train = tf_idf_vect.fit_transform(X_train_data['CleanedText'])
```

```
X_test = tf_idf_vect.transform(X_test_data['CleanedText'])
print(X_train.shape)
print(X_test.shape)
```

```
(264171, 60276)
(100000, 60276)
```

In [132]:

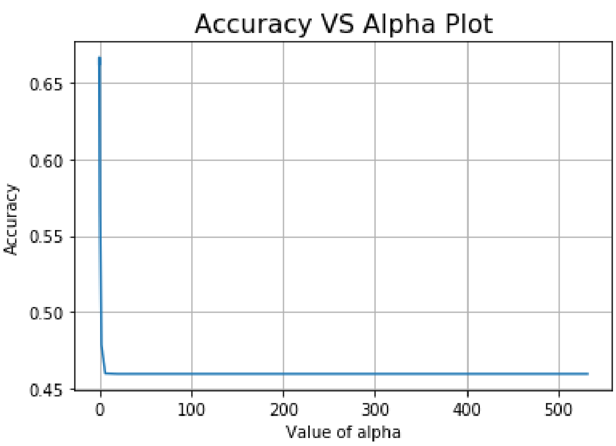
```
# Importing libraries
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,recall_score

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

# empty list cv_scores that will hold cross-validation scores
cv_scores = []

# performing 10-fold cross validation on train data
for k in tqdm(alpha):
    model = MultinomialNB(alpha = k)
    scores = cross_val_score(model, X_train, y_train, cv=10, scoring='f1_macro', n_jobs=-1)
    cv_scores.append(scores.mean())
```

```
100%|██████████████████████████████████████████████████| 13/13
[01:46<00:00,  8.20s/it]
```

In [133]:

```
# determining best value of alpha
optimal_alpha = alpha[cv_scores.index(max(cv_scores))]
print('\nThe optimal value of alpha is %.3f.' % optimal_alpha)
# plot accuracy vs alpha
plt.plot(alpha, cv_scores)
plt.xlabel('Value of alpha',size=10)
plt.ylabel('Accuracy',size=10)
plt.title('Accuracy VS Alpha Plot',size=16)
plt.grid()
plt.show()
print("\n*******Train Data Report******");
print("\nAlpha values :\n",alpha)
print("\nF1 Score for each value of alpha :\n ", np.round(cv_scores,5)*100)
```

```
The optimal value of alpha is 0.027.
```




```
*******Train Data Report******

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, 531.441]
```

```
F1 Score for each value of alpha :
  [66.261 66.435 66.632 66.704 66.201 63.724 56.72  47.862 45.969 45.935
 45.936 45.936 45.936]
```

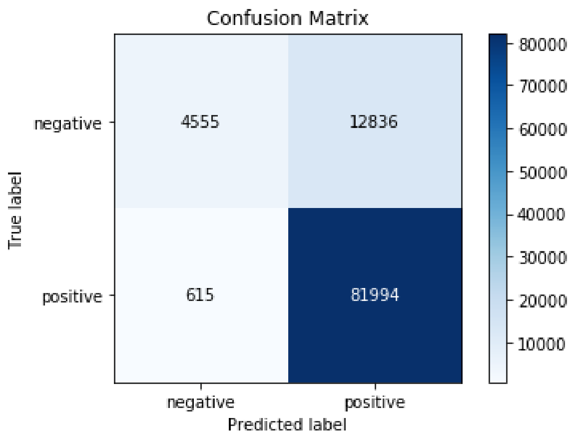
In [134]:

```python
# instantiate learning model alpha = optimal_alpha
model_tfidf_multinomial = MultinomialNB(alpha = optimal_alpha)

# fitting the model
model_tfidf_multinomial.fit(X_train,y_train)

# predict the response
pred = model_tfidf_multinomial.predict(X_test)
```

In [135]:

```python
print("***Test Data Report***")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",f1_score(y_test, pred, average='macro')*100)
print("precision_score = ",precision_score(y_test, pred, average='macro')*100)
print("recall_score = ",recall_score(y_test, pred, average='macro')*100)
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Accuracy =  86.54899999999999
f1_score =  66.39939123081
precision_score =  87.28432391793031
recall_score =  62.72361870673669
```



In [136]:

```python
True_Negative, False_Negative, False_Positive, True_Positive = confusion_matrix(y_test, pred).ravel
()

Total_Positive = False_Negative + True_Positive
Total_Negative = True_Negative + False_Positive

TPR = True_Positive/Total_Positive
FPR = False_Positive/Total_Negative
TNR = True_Negative/Total_Negative
FNR = False_Negative/ Total_Positive
print("TPR = %.5f"%(TPR))
print("FPR = %.5f"%(FPR))
print("TNR = %.5f"%(TNR))
print("FNR = %.5f"%(FNR))
```

```
TPR = 0.86464
FPR = 0.11896
TNR = 0.88104
FNR = 0.13536
```

In [137]:

```
print("Actual Data")
print("------------")
print(X_test_data["Score"].value_counts())
print("\n")
print("After Prediction")
print("------------")
print("Positive =",Total_Positive)
print("Negative =",Total_Negative)
```

```
Actual Data
------------
positive    82609
negative    17391
Name: Score, dtype: int64


After Prediction
------------
Positive = 94830
Negative = 5170
```

In [140]:

```
print(model_tfidf_multinomial.classes_)
# Finding log probabilities
class_feature = model_tfidf_multinomial.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_feature = class_feature[0]
positive_feature = class_feature[1]

# Getting all feature names from the count vectorizer
feature_name = tf_idf_vect.get_feature_names()

#sorting
sorted_negative_feature = np.argsort(negative_feature)[::-1]
sorted_positive_feature = np.argsort(positive_feature)[::-1]
```

```
['negative' 'positive']
```

In [143]:

```
print("Negative feature top 10 :")
print("-------")
for i in list(sorted_negative_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],negative_feature[i]))

print("\nPositive feature top 10 :")
print("-------")
for i in list(sorted_positive_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],positive_feature[i]))
```

```
Negative feature top 10 :
-------
tast  --> -4.835084
like  --> -4.987042
product  --> -5.036189
would  --> -5.326079
flavor  --> -5.343088
coffe  --> -5.359105
one  --> -5.376012
tri  --> -5.473543
buy  --> -5.495681
order  --> -5.504335

Positive feature top 10 :
-------
great  --> -5.064847
love  --> -5.077613
tast  --> -5.140636
good  --> -5.142874
like  --> -5.158900
```

```
tea  --> -5.177470
flavor  --> -5.214627
coffe  --> -5.246916
product  --> -5.317709
use  --> -5.332519
```

Trying to improve the percentageof each scores by adding words from summary to text and then again performing the bow and tfidf techniques

In [148]:

```
#Again
```

In [149]:

```
final_data.shape
```

Out[149]:

```
(364171, 11)
```

In [150]:

```
final_data.head(2)
```

Out[150]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Sum
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	939340800	E' b educa
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	positive	940809600	This se grea to tim

In [151]:

```
final_data["Combined_Text"] = final_data['Text'] + ' ' + final_data['Summary']
```

In [152]:

```
print("*Text* :: ",final_data['Text'][0])
print("*Summary* :: ",final_data['Summary'][0])
print("*Combined* :: ",final_data["Combined_Text"][0])
```

```
*Text* ::  I have bought several of the Vitality canned dog food products and have found them all
to be of good quality. The product looks more like a stew than a processed meat and it smells bett
er. My Labrador is finicky and she appreciates this product better than  most.
*Summary* ::  Good Quality Dog Food
*Combined* ::  I have bought several of the Vitality canned dog food products and have found them
all to be of good quality. The product looks more like a stew than a processed meat and it smells
better. My Labrador is finicky and she appreciates this product better than  most. Good Quality Do
g Food
```

In [153]:

```
#Code for implementing step-by-step the checks mentioned in the pre-processing phase
# this code takes a while to run as it needs to run on 500k sentences.
from tqdm import tqdm
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
```

```
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in tqdm(final_data['Combined_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 describe positive r
eviews
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe negative r
eviews reviews
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

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

```
100%|████████████████████████████████████████████████████████████| 364171/364171
[09:41<00:00, 626.39it/s]
```

In [154]:

```
final_data['Cleaned_combined']=final_string #adding a column of Cleaned_combined which displays th
e data after pre-processing of the review
final_data['Cleaned_combined']=final_data['Cleaned_combined'].str.decode("utf-8")
final_data.head(3)
```

Out[154]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	S
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	939340800	edu
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	positive	940809600	Th grea sp
417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0	positive	944092800	Ente

In [155]:

```
X_train_data = final_data[:264171]
X_test_data = final_data[264171:364171]
y_train = X_train_data['Score']
y_test = X_test_data['Score']
print("Data")
print(X_train_data.shape)
print(X_test_data.shape)
print("Label")
print(y_train.shape)
print(y_test.shape)
```

Data

```
Data
(264171, 13)
(100000, 13)
Label
(264171,)
(100000,)
```

BOW

In [172]:

```
count_vect = CountVectorizer()
X_train = count_vect.fit_transform(X_train_data['Cleaned_combined'])
X_test = count_vect.transform(X_test_data['Cleaned_combined'])
print(X_train.shape)
print(X_test.shape)
```

```
(264171, 63890)
(100000, 63890)
```

In [173]:

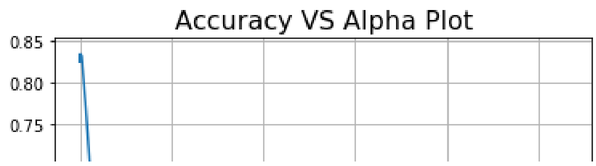
```
# Importing libraries
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,recall_score

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

# empty list cv_scores that will hold cross-validation scores
cv_scores = []

# performing 10-fold cross validation on train data
for k in tqdm(alpha):
    model = MultinomialNB(alpha = k)
    scores = cross_val_score(model, X_train, y_train, cv=10, scoring='f1_macro', n_jobs=-1)
    cv_scores.append(scores.mean())
```

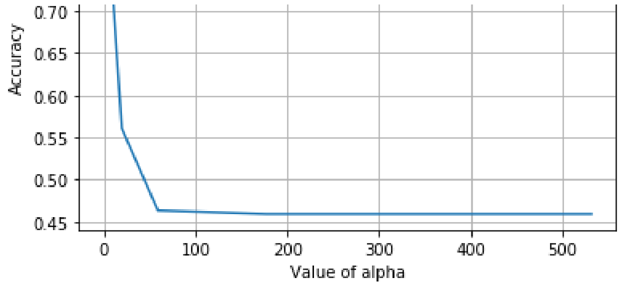
```
100%|██████████████████████████████████████████████████| 13/13
[02:02<00:00,  9.56s/it]
```

In [174]:

```
# determining best value of alpha
optimal_alpha = alpha[cv_scores.index(max(cv_scores))]
print('\nThe optimal value of alpha is %.3f.' % optimal_alpha)
# plot accuracy vs alpha
plt.plot(alpha, cv_scores)
plt.xlabel('Value of alpha',size=10)
plt.ylabel('Accuracy',size=10)
plt.title('Accuracy VS Alpha Plot',size=16)
plt.grid()
plt.show()
print("\n*******Train Data Report******");
print("\nAlpha values :\n",alpha)
print("\nF1 Score for each value of alpha :\n ", np.round(cv_scores,5)*100)
```

```
The optimal value of alpha is 0.729.
```






```
*******Train Data Report******

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, 531.441]

F1 Score for each value of alpha :
  [82.435 82.626 82.812 83.012 83.178 83.294 83.383 83.083 77.168 56.069
 46.351 45.936 45.936]
```

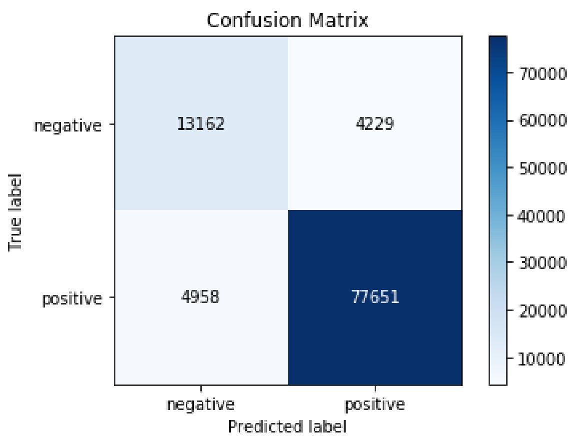
In [175]:

```python
# instantiate learning model alpha = optimal_alpha
model_bow_multinomial = MultinomialNB(alpha = optimal_alpha)

# fitting the model
model_bow_multinomial.fit(X_train,y_train)

# predict the response
pred = model_bow_multinomial.predict(X_test)
```

In [176]:

```python
print("***Test Data Report***")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",f1_score(y_test, pred, average='macro')*100)
print("precision_score = ",precision_score(y_test, pred, average='macro')*100)
print("recall_score = ",recall_score(y_test, pred, average='macro')*100)
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Accuracy =  90.813
f1_score =  84.27198358700288
precision_score =  83.73654683373397
recall_score =  84.84052854375908
```



In [177]:

```python
True_Negative, False_Negative, False_Positive, True_Positive = confusion_matrix(y_test, pred).ravel
()

Total_Positive = False_Negative + True_Positive
Total_Negative = True_Negative + False_Positive

TPR = True_Positive/Total_Positive
```

```
FPR = False_Positive/Total_Negative
TNR = True_Negative/Total_Negative
FNR = False_Negative/ Total_Positive
print("TPR = %.5f"%(TPR))
print("FPR = %.5f"%(FPR))
print("TNR = %.5f"%(TNR))
print("FNR = %.5f"%(FNR))
```

```
TPR = 0.94835
FPR = 0.27362
TNR = 0.72638
FNR = 0.05165
```

In [178]:

```
print("Actual Data")
print("------------")
print(X_test_data["Score"].value_counts())
print("\n")
print("After Prediction")
print("------------")
print("Positive =",Total_Positive)
print("Negative =",Total_Negative)
```

```
Actual Data
------------
positive    82609
negative    17391
Name: Score, dtype: int64


After Prediction
------------
Positive = 81880
Negative = 18120
```

In [179]:

```
print(model_bow_multinomial.classes_)
# Finding log probabilities
class_feature = model_bow_multinomial.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_feature = class_feature[0]
positive_feature = class_feature[1]

# Getting all feature names from the count vectorizer
feature_name = count_vect.get_feature_names()

#sorting
sorted_negative_feature = np.argsort(negative_feature)[::-1]
sorted_positive_feature = np.argsort(positive_feature)[::-1]
```

```
['negative' 'positive']
```

In [180]:

```
print("Negative feature top 10 :")
print("-------")
for i in list(sorted_negative_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],negative_feature[i]))

print("\nPositive feature top 10 :")
print("-------")
for i in list(sorted_positive_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],positive_feature[i]))
```

```
Negative feature top 10 :
-------
tast  --> -4.176562
like  --> -4.296535
product  --> -4.479295
```

```
product  --> -4.479295
flavor  --> -4.767179
one  --> -4.788565
would  --> -4.943865
tri  --> -4.953348
good  --> -4.966215
coffe  --> -5.068428
use  --> -5.125153

Positive feature top 10 :
-------
great  --> -4.418422
like  --> -4.467804
tast  --> -4.477669
good  --> -4.487088
love  --> -4.579291
flavor  --> -4.665427
use  --> -4.791853
tea  --> -4.816060
product  --> -4.830119
one  --> -4.835603
```

TFIDF

In [156]:

```
tf_idf_vect = TfidfVectorizer()
X_train = tf_idf_vect.fit_transform(X_train_data['Cleaned_combined'])
X_test = tf_idf_vect.transform(X_test_data['Cleaned_combined'])
print(X_train.shape)
print(X_test.shape)
```

```
(264171, 63890)
(100000, 63890)
```

In [157]:

```
# Importing libraries
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,recall_score

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

# empty list cv_scores that will hold cross-validation scores
cv_scores = []

# performing 10-fold cross validation on train data
for k in tqdm(alpha):
    model = MultinomialNB(alpha = k)
    scores = cross_val_score(model, X_train, y_train, cv=10, scoring='f1_macro', n_jobs=-1)
    cv_scores.append(scores.mean())
```

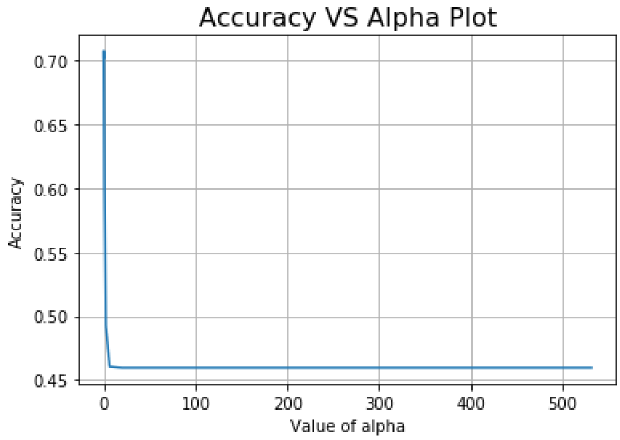
```
100%|████████████████████████████████████████████████████████████████████████| 13/13
[01:47<00:00,  8.15s/it]
```

In [158]:

```
# determining best value of alpha
optimal_alpha = alpha[cv_scores.index(max(cv_scores))]
print('\nThe optimal value of alpha is %.3f.' % optimal_alpha)
# plot accuracy vs alpha
plt.plot(alpha, cv_scores)
plt.xlabel('Value of alpha',size=10)
plt.ylabel('Accuracy',size=10)
plt.title('Accuracy VS Alpha Plot',size=16)
```

```
plt.grid()
plt.show()
print("\n*******Train Data Report******");
print("\nAlpha values :\n",alpha)
print("\nF1 Score for each value of alpha :\n ", np.round(cv_scores,5)*100)
```

```
The optimal value of alpha is 0.027.
```




```
*******Train Data Report******

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, 531.441]

F1 Score for each value of alpha :
  [70.237 70.458 70.698 70.769 70.303 67.842 60.316 49.243 46.037 45.935
 45.936 45.936 45.936]
```

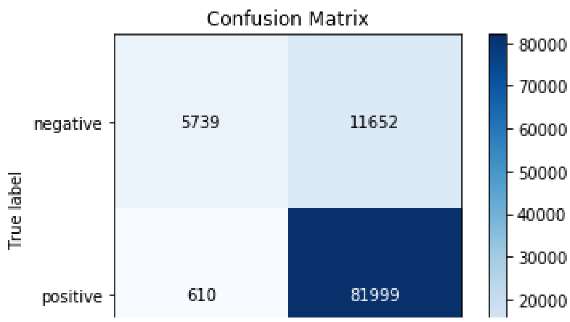
In [159]:

```
# instantiate learning model alpha = optimal_alpha
model_tfidf_multinomial = MultinomialNB(alpha = optimal_alpha)

# fitting the model
model_tfidf_multinomial.fit(X_train,y_train)

# predict the response
pred = model_tfidf_multinomial.predict(X_test)
```

In [160]:

```
print("***Test Data Report***")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",f1_score(y_test, pred, average='macro')*100)
print("precision_score = ",precision_score(y_test, pred, average='macro')*100)
print("recall_score = ",recall_score(y_test, pred, average='macro')*100)
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Accuracy =  87.738
f1_score =  70.69600501136074
precision_score =  88.975124529424
recall_score =  66.13070458241911
```



In [161]:

```
True_Negative, False_Negative, False_Positive, True_Positive = confusion_matrix(y_test, pred).ravel
()

Total_Positive = False_Negative + True_Positive
Total_Negative = True_Negative + False_Positive

TPR = True_Positive/Total_Positive
FPR = False_Positive/Total_Negative
TNR = True_Negative/Total_Negative
FNR = False_Negative/ Total_Positive
print("TPR = %.5f"%(TPR))
print("FPR = %.5f"%(FPR))
print("TNR = %.5f"%(TNR))
print("FNR = %.5f"%(FNR))
```

```
TPR = 0.87558
FPR = 0.09608
TNR = 0.90392
FNR = 0.12442
```

In [162]:

```
print("Actual Data")
print("------------")
print(X_test_data["Score"].value_counts())
print("\n")
print("After Prediction")
print("------------")
print("Positive =",Total_Positive)
print("Negative =",Total_Negative)
```

```
Actual Data
------------
positive    82609
negative    17391
Name: Score, dtype: int64


After Prediction
------------
Positive = 93651
Negative = 6349
```

In [163]:

```
print(model_tfidf_multinomial.classes_)
# Finding log probabilities
class_feature = model_tfidf_multinomial.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_feature = class_feature[0]
positive_feature = class_feature[1]

# Getting all feature names from the count vectorizer
feature_name = tf_idf_vect.get_feature_names()

#sorting
sorted_negative_feature = np.argsort(negative_feature)[::-1]
sorted_positive_feature = np.argsort(positive_feature)[::-1]
```

```
['negative' 'positive']
```

In [164]:

```
print("Negative feature top 10 :")
print("-------")
for i in list(sorted_negative_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],negative_feature[i]))

print("\nPositive feature top 10 :")
print("-------")
for i in list(sorted_positive_feature[0:10]):
    print("%s\t -->\t%f  "%(feature_name[i],positive_feature[i]))
```

```
Negative feature top 10 :
-------
tast  --> -4.809819
like  --> -4.993000
product  --> -5.075751
flavor  --> -5.333150
coffe  --> -5.345334
would  --> -5.384816
one  --> -5.425288
disappoint  --> -5.494400
buy  --> -5.502796
tri  --> -5.532694

Positive feature top 10 :
-------
great  --> -4.873781
love  --> -5.015109
good  --> -5.033500
tea  --> -5.079043
tast  --> -5.129286
coffe  --> -5.156811
like  --> -5.204510
flavor  --> -5.226146
product  --> -5.289252
use  --> -5.399474
```

RESULT

In [193]:

```
from IPython.display import HTML, display
import tabulate
table = [["S.NO.","MODEL","Best alpha","F1_SCORE","Test Accuracy"],
         ["1","BOW[Text]","0.729","81.748916","89.513"],
         ["2","BOW[Text+Summary]","0.729","84.271983","90.813"],
         ["3","TF-IDF[Text]","0.027","66.39939","86.54899"],
         ["4","TF-IDF[Text+Summary]","0.027","70.696005","87.738"]]
display(HTML(tabulate.tabulate(table, tablefmt='html')))
```

S.NO.	MODEL	Best alpha	F1_SCORE	Test Accuracy
1	BOW[Text]	0.729	81.748916	89.513
2	BOW[Text+Summary]	0.729	84.271983	90.813
3	TF-IDF[Text]	0.027	66.39939	86.54899
4	TF-IDF[Text+Summary]	0.027	70.696005	87.738

CONCLUSION

- > As Stated in the result table that when summary of every product is added to the actual reviews then it gives better performance as compared to the model which takes only the text of the reviews in both bow and tfidf vectorization

- > But when summary is also take then many points of the negative class gets predicted to be positive class in the model which decreses the stability of the model, and it makes model more biased towards positive points.

- Bow vectorizer[TEXT] is the best model as compared to tfidf vectorizer as it gives better stats
- BOW Vectorizer[TEXT] is performing well in unseen data and hence its stats are good.
- Naive bayes is the simplest algorithm and it takes very much less time then KNN.