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[1] Problem Statement :

- Time Based slicing to split Train Data(70%) and Test Data(30%).
- Appling Naive Bayes model to find the optimal alpha and using 10 fold Cross Validation in :
  1)Bag Of Words
  2)TF-IDF
- Finding the features Importance for each class label.
- Plotting Confusion Matrix.
- Using Precission, Recall, F1 Score as performance metrics and comparing between various featurization techniques.

[2] Overview of Dataset :

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 the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[3] Loading the Data :

In order to load the data, we have used the SQLITE dataset as it easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:

```
#Importing the necessary Packages
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import time
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 IPython.display import HTML
from collections import OrderedDict


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
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
```

In [2]:

```
import pickle

#dumping an object to file object using dump method
def dumpfile(a,file_Name):
    fileObject = open(file_Name,"wb")
    pickle.dump(a,fileObject,protocol=2)
    fileObject.close()

#loading an object from file object using load method
def loadfile(file_Name):
    fileObject = open(file_Name,"rb")
    b = pickle.load(fileObject)
    return b
```

In [3]:

```
%%HTML
<style type="text/css">
table.dataframe td, table.dataframe th {
    border: 2px  black solid !important;
}
</style>
```

In [4]:

```
# 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
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, con)
```

In [5]:

```
# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative ra
ting.
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
```

In [6]:

```
print("Number of datapoints: ",filtered_data.shape[0])
print("Number of attributes/features: ",filtered_data.shape[1])
HTML(filtered_data.head().to_html(index=False))
```

```
Number of datapoints:  525814
Number of attributes/features:  10
```

Out[6]:

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

[4] Exploratory Data Analysis :

[4.1] 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:

Deduplication 1:- As can be seen below the same user has multiple reviews of the with the 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)

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 [7]:

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

HTML(display.head().to_html(index=False))
```

Out[7]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfı
78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

In [8]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [9]:

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

Out[9]:

```
(364173, 10)
```

Deduplication 2:- 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 [10]:

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

HTML(display.head().to_html(index=False))
```

Out[10]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Hel
64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [11]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
print(final.shape)
```

```
(364171, 10)
```

Deduplication 3:- It was also seen that a same user has given different reviews for a same product at same time.I think it is normal for a user to give multiple reviews about a product,but that should be in diffrent time. So,all those rows with same user giving multiple reviews for a same product at same time are considered as duplicate and hence dropped.

In [12]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId= "A8891HVRDJAM6"
ORDER BY ProductID
""", con)

HTML(display.head().to_html(index=False))
```

Out[12]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
86221	B000084E6V	A8891HVRDJAM6	Marfaux "Marfaux"	33	33
86236	B000084E6V	A8891HVRDJAM6	Marfaux "Marfaux"	3	3

In [13]:

```
final=final.drop_duplicates(subset={"ProductId","UserId","ProfileName","Time"}, keep='f
irst', inplace=False)
print(final.shape)
```

```
(363633, 10)
```

Deduplication 4:- It was also seen that in few rows with Ids from 150493 to 150529 contain reviews regarding books,not fine foods.So I think these should be also removed from the dataset. After looking at the productid column, it can be noticed that all the observations for fine foods start with B followed by numbers except for Ids from 150493 to 150529. I suppose the reviews for book ‘Chicken soup for the soul’ have gotten into the datset mistakenly as they contain the words “chicken soup.

In [14]:

```
display = final[final.ProductId == "0006641040"]
HTML(display.head().to_html(index=False))
```

Out[14]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1
150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1
150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	1
150509	0006641040	A3CMRKGE0P909G	Teresa	3	4

In [15]:

```
final = final[final.ProductId != "0006641040"]
```

In [16]:

```
print("Percentage  of data still remaining : ",(final['Id'].size*1.0)/(filtered_data['I
d'].size*1.0)*100)

#Before starting the next phase of preprocessing lets see the number of entries left
print("Number of reviews left after Data Cleaning and Deduplication :")
print(final.shape)

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

```
Percentage  of data still remaining :  69.14973735959865
Number of reviews left after Data Cleaning and Deduplication :
(363599, 10)
```

Out[16]:

```
positive    306566
negative     57033
Name: Score, dtype: int64
```

Observation:-
It is an imbalanced dataset as the number of positive reviews are way high in number than negative reviews.

[5] Text Preprocessing Using NLTK :

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

1. Removal of HTML Tags
2. Removal of 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. Removal of Stopwords
7. Finally Snowball Stemming the word

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

In [20]:

```
# find sentences containing HTML tags
import re
i=0;
for sent in final['Text'].values:
    if (len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
        break;
    i += 1;
```

```
10
I wanted a treat that was accepted and well liked for my rescue animals.<b
r />This is the only treat that is healthy and loved by all 4 legged being
s in my home!<br />It does not contain sugar or grains or silly vegetables
which virtually all treats contain. Dogs, cats and ferrets are carnivores
they are not cattle to eat grain or rabbits to eat vegetables, and WHYYYY
do companies add sugar,beet pulp or corn syrup to carnivore foods? It is d
angerous and can cause the death of an animal with diabetes.<br />It is pr
etty easy to break into smaller pieces for cats and kittens with weak jaws
and its wonderful to use as an aid to gain the trust of an abused dog as i
t will not cause stomach upset when given in common sense amounts.<br />I
like that it goes a long way as it costs alot to heal and maintain and tra
in abused and rescued dogs.<br />NO minus to this product other then the p
rice,I can not afford to use it as much as I would like.
```

[5.1] Removal of html Tags :

In [21]:

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

cleanhtml("<br />This is the only treat that is healthy and loved by all 4 legged being
s in my home!<br />It does not contain sugar or grains")
```

Out[21]:

```
' This is the only treat that is healthy and loved by all 4 legged beings
in my home! It does not contain sugar or grains'
```

[5.2] Removal of Punctuations and unecessary characters :

In [22]:

```
#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

cleanpunc("WHYYYY do companies add sugar,beet pulp or corn syrup to carnivore foods?")
```

Out[22]:

```
'WHYYYY do companies add sugar beet pulp or corn syrup to carnivore foods'
```

[5.3] StopWords :

In [23]:

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

stop = set(stopwords.words('english')) #set of stopwords
print(stop)
print("***********************************************************************")
print("No. of stop words: ",len(stop))
```

```
[nltk_data] Downloading package punkt to /home/jovyan/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /home/jovyan/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
{'further', 'should', 'didn', 'them', 'me', "hasn't", 'as', 'ma', 'itsel
f', 'then', 'whom', "weren't", 'has', 'from', 're', 'while', "don't", 'are
n', "haven't", 'but', 'such', 'very', "didn't", 'nor', 'so', 'being', "sha
n't", 'most', 'only', 'hadn', 'ourselves', 'because', 'what', 'were', "is
n't", 'the', 'shouldn', "should've", 'own', "wouldn't", 'down', 'couldn',
'can', 'during', 'mightn', 'against', "wasn't", 'up', "hadn't", 'for', 'ot
her', 'hasn', 'myself', 'how', 'theirs', 'did', 'at', 'or', 'do', 't', 'ju
st', 'which', "mightn't", "that'll", 'if', 'we', 'this', 'after', 'now',
"mustn't", "it's", 'they', 'than', 'hers', 'his', 'through', 'weren', 'ai
n', 'their', 'out', 'shan', 'won', 'all', 'had', 'are', 'those', 'above',
"you've", 'ours', 'between', 'she', 'our', 'haven', 'about', 'y', 'been',
'again', 'i', 'wasn', 'your', 'where', 'any', 'too', 'more', 'some', 'tha
t', 'her', 'below', 'each', 'yourself', 'he', 'herself', "you'd", 'when',
'its', 'it', 's', 'once', "needn't", 'there', 'themselves', 'of', 'off',
'was', 'with', 've', 'wouldn', "she's", 'in', 'be', "you're", 'few', 'no
t', 'into', 'yours', 'why', 'will', "won't", 'on', 'doesn', 'having', 'is
n', 'to', 'both', 'does', 'my', 'am', "couldn't", "doesn't", 'no', 'you',
'who', 'have', 'doing', 'o', 'd', 'yourselves', 'him', 'these', 'is', 'und
er', 'here', "aren't", 'by', 'a', "shouldn't", 'himself', 'same', "you'l
l", 'an', 'needn', 'and', 'over', 'll', 'until', 'm', 'don', 'before', 'mu
stn'}
*********************************************************************
No. of stop words:  179
```

In [24]:

```
exceptions = ["aren't","mightn","wasn","hadn","don't","against","hadn't","shan","were
n't","didn","don","hasn't", \
              "hasn","shouldn","didn't","wouldn","wasn't","needn't","shouldn't","would
n't","aren","isn't","doesn't", \
              "nor","not","needn","couldn't","mightn't","mustn","mustn't","ain","sha
n't","haven","won't","couldn","isn", \
              "weren","haven't","no","haven't"]
new_stop = []
for i in stop:
    if i not in exceptions:
        new_stop.append(i)


print("No. of stop words after removing exceptions: ",len(new_stop))
```

```
No. of stop words after removing exceptions:  140
```

[5.4] Stemming :

In [25]:

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

print("Orginal word: beautiful" + "|" +  "Stem word: " + sno.stem('beautiful'))
print("Orginal word: beauty" + "|" +  "Stem word: " + sno.stem('beauty'))
print("Orginal word: loved" + "|" +  "Stem word: " + sno.stem('loved'))
print("Orginal word: loving" + "|" +  "Stem word: " + sno.stem('loving'))
```

```
Orginal word: beautiful|Stem word: beauti
Orginal word: beauty|Stem word: beauti
Orginal word: loved|Stem word: love
Orginal word: loving|Stem word: love
```

Observation:-
We can see words like "beautiful" and "beauty" have their stem as "beauti","loved" and "loving" have their stem as "love".
Hence it helps in reducing the dimensions by taking the root stem of words.

[5.5] Implementing the preprocessing steps one by one on all the reviews of dataset :

In [22]:

```
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 new_stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describ
e positive reviews
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describ
e negative reviews reviews
                else:
                    continue
            else:
                continue
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

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

In [23]:

```
from nltk.probability import FreqDist
pdist = FreqDist(all_positive_words)
top_positive = pdist.most_common(20)
print("Top 20 Positive words ocuring frequenty in reviews:")
top_positive
```

```
Top 20 Positive words ocuring frequenty in reviews:
```

Out[23]:

```
[(b'not', 146568),
 (b'like', 139160),
 (b'tast', 128865),
 (b'good', 112601),
 (b'flavor', 109329),
 (b'love', 107172),
 (b'use', 103792),
 (b'great', 103670),
 (b'one', 96529),
 (b'product', 90912),
 (b'tri', 86683),
 (b'tea', 83699),
 (b'coffe', 78763),
 (b'make', 75004),
 (b'get', 71996),
 (b'food', 64539),
 (b'would', 55477),
 (b'time', 55184),
 (b'buy', 54137),
 (b'realli', 52657)]
```

In [24]:

```
ndist = FreqDist(all_negative_words)
top_negative = ndist.most_common(20)
print("Top 20 Negative words ocuring frequenty in reviews:")
top_negative
```

```
Top 20 Negative words ocuring frequenty in reviews:
```

Out[24]:

```
[(b'not', 54325),
 (b'tast', 34534),
 (b'like', 32271),
 (b'product', 28181),
 (b'one', 20544),
 (b'flavor', 19520),
 (b'would', 17947),
 (b'tri', 17718),
 (b'use', 15280),
 (b'good', 15024),
 (b'coffe', 14700),
 (b'get', 13775),
 (b'buy', 13742),
 (b'order', 12862),
 (b'food', 12720),
 (b'dont', 11865),
 (b'tea', 11646),
 (b'even', 11068),
 (b'box', 10833),
 (b'amazon', 10067)]
```

[5.6] Adding a new column of CleanedText which displays the data after pre-processing of the review :

In [27]:

```
final['CleanedText']=final_string
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
```

In [26]:

```
final[['Text','CleanedText']].head(10)
```

Out[26]:

	Text	CleanedText
476617	This product by Arche...	product archer farm b...
22621	Our dogs just love th...	dog love saw pet stor...
22620	My dogs loves this ch...	dog love chicken prod...
284375	This book is easy to ...	book easi read ingred...
157850	I have been feeding m...	feed greyhound treat ...
157849	This is one product t...	one product welsh ter...
157833	This is the ONLY dog ...	dog treat lhasa apso ...
157832	These liver treas are...	liver trea phenomen r...
157837	This was the only tre...	treat dog like obedi ...
157831	No waste , even if sh...	wast even day goe hun...

[5.7] Using SQLite Table to load data after preprocessing of reviews :

In [ ]:

```
# store final result into an SQLLite table for future.
conn = sqlite3.connect('final.sqlite')
c=conn.cursor()
conn.text_factory = str
final.to_sql('Reviews', conn,  schema=None, if_exists='replace', index=True, index_labe
l=None, chunksize=None, dtype=None)
```

In [6]:

```
# using the SQLite Table to read data.
conn = sqlite3.connect('final.sqlite')

final = pd.read_sql_query(""" SELECT * FROM Reviews """,conn)
```

In [7]:

```
#Listing out the number of positive and negative reviews
final = final.reset_index(drop=True)
final['Score'].value_counts()
```

Out[7]:

```
positive    306566
negative     57033
Name: Score, dtype: int64
```

In [8]:

```
(final['Score'].value_counts()/len(final['Score']))*100
```

Out[8]:

```
positive    84.314313
negative    15.685687
Name: Score, dtype: float64
```

[6] Train and Test Split of Data :

Sorting the data by Time :

In [10]:

```
final=final.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort'
, na_position='last')
final.head()
```

Out[10]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNun
387	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0
293	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1
386	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0
209	346116	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2
271	346041	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19

Time Based Slicing :

- Diving the data to Train set(first 70% ie older data) and Test Set(last 30% ie recent data)

In [11]:

```
from sklearn.model_selection import train_test_split

X = final["CleanedText"].values
y = final["Score"].values
X_train,X_test,y_train,y_test = train_test_split(X, y, test_size = 0.3,shuffle = False)
```

In [5]:

```
print("Shape of X_train: ",X_train.shape)
print("Shape of y_train: ",y_train.shape)
print("Shape of X_test: ",X_test.shape)
print("Shape of y_test: ",y_test.shape)
```

```
Shape of X_train:  (254519,)
Shape of y_train:  (254519,)
Shape of X_test:  (109080,)
Shape of y_test:  (109080,)
```

In [13]:

```
dumpfile(X,"X")
dumpfile(y,"y")
dumpfile(X_train,"X_train")
dumpfile(y_train,"y_train")
dumpfile(X_test,"X_test")
dumpfile(y_test,"y_test")
```

In [4]:

```
X = loadfile("X")
y = loadfile("y")
X_train = loadfile("X_train")
y_train = loadfile("y_train")
X_test = loadfile("X_test")
y_test = loadfile("y_test")
```

[7] Naive Bayes :

[7.1] Function to find the optimal alpha and error using K-fold cross-validation :

- Taking alpha between range 0.0001 and 1000.
- TimeSeries Split and performing K fold cross validation on Train Data
- Finding the optimal alpha
- Plotting between CV error/CV Accuracy and Alpha

Bernoulli Naive Bayes : BernoulliNB is suitable for discrete data designed for for binary/boolean features.

In [ ]:

```
from sklearn.model_selection import TimeSeriesSplit
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score as cv
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.grid_search import GridSearchCV
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
import warnings
warnings.filterwarnings('ignore')


alpha_values = [0.00001,0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
param_grid = dict(alpha = alpha_values)

def BernoulliNB_Train(X_train,y_train):

    model = BernoulliNB()
    grid = GridSearchCV(model, param_grid, cv=10, scoring='accuracy')
    grid.fit(X_train, y_train)

    grid_mean_scores = [i.mean_validation_score for i in grid.grid_scores_]

    #Misclassification error
    MSE = [1 - x for x in grid_mean_scores]

    #Finding the optimal K
    optimal_alpha = grid.best_params_

    best_accuracy = np.round(grid.best_score_ * 100,3)

    print("\n\033[1mOptimal alpha:\033[0m ", optimal_alpha)
    print("\n\033[1mCrossValidation Error:\033[0m {}".format(np.round(min(MSE),3)))
    print("\n\033[1mCrossValidation Accuracy:\033[0m {} %\n\n".format(best_accuracy))

    plt.figure(figsize=(20,6))
    plt.style.use('fivethirtyeight')
    plt.subplot(121)
    plt.plot(alpha_values,MSE, 'r-o')
    for xy in zip(alpha_values, np.round(MSE,3)):
        plt.annotate('(%s %s)' % xy, xy = xy, textcoords = 'data')
    plt.title("CV Error vs Alpha Value")
    plt.xlabel("Alpha")
    plt.ylabel("CV Error")
    plt.grid(True)

    plt.subplot(122)
    plt.plot(alpha_values,grid_mean_scores, 'g-o')
    for xy in zip(alpha_values, np.round(grid_mean_scores,3)):
        plt.annotate('(%s %s)' % xy, xy = xy, textcoords = 'data')
    plt.title("CV Accuracy vs Alpha Value")
    plt.xlabel("Alpha")
    plt.ylabel("CV Accuracy")
    plt.grid(True)
    plt.show()
```

```
    print("\n\033[1mCV Error for each value of alpha:\033[0m ",np.round(MSE,3))
    print("\n\033[1mCV Accuracy for each value of alpha:\033[0m ",np.round(grid_mean_sc
ores,3))
```

Multinomial Naive Bayes : MultinomialNB is suitable for classification with discrete features(count based occurnces).

In [13]:

```
def MultinomialNB_Train(X_train,y_train):

    model = MultinomialNB()
    grid = GridSearchCV(model, param_grid, cv=10, scoring='accuracy')
    grid.fit(X_train, y_train)

    grid_mean_scores = [i.mean_validation_score for i in grid.grid_scores_]

    #Misclassification error
    MSE = [1 - x for x in grid_mean_scores]

    #Finding the optimal K
    optimal_alpha = grid.best_params_

    best_accuracy = np.round(grid.best_score_ * 100,3)

    print("\n\033[1mOptimal alpha:\033[0m ", optimal_alpha)
    print("\n\033[1mCrossValidation Error:\033[0m {}".format(np.round(min(MSE),3)))
    print("\n\033[1mCrossValidation Accuracy:\033[0m {} %\n\n".format(best_accuracy))

    plt.figure(figsize=(20,6))
    plt.style.use('fivethirtyeight')
    plt.subplot(121)
    plt.plot(alpha_values,MSE, 'r-o')
    for xy in zip(alpha_values, np.round(MSE,3)):
        plt.annotate('(%s %s)' % xy, xy = xy, textcoords = 'data')
    plt.title("CV Error vs Alpha Value")
    plt.xlabel("Alpha")
    plt.ylabel("CV Error")
    plt.grid(True)

    plt.subplot(122)
    plt.plot(alpha_values,grid_mean_scores, 'g-o')
    for xy in zip(alpha_values, np.round(grid_mean_scores,3)):
        plt.annotate('(%s %s)' % xy, xy = xy, textcoords = 'data')
    plt.title("CV Accuracy vs Alpha Value")
    plt.xlabel("Alpha")
    plt.ylabel("CV Accuracy")
    plt.grid(True)
    plt.show()


    print("\n\033[1mCV Error for each value of alpha:\033[0m ",np.round(MSE,3))
    print("\n\033[1mCV Accuracy for each value of alpha:\033[0m ",np.round(grid_mean_sc
ores,3))
```

[7.2] Function to find the features importance and predict on Test Data :

- Finding the features importance for each class
- Plotting the Confusion matrix
- Finding Acurracy,Precission,Recall and F1 Score on Test Datab

True Negative : Number of datapoints with class label "negative" correctly classified as "negative".
False Positive : Number of datapoints with class label "negative" misclassified as "positive".
False Negative : Number of datapoints with class label "positive" misclassified as "negative".
True Positive: Number of datapoints with class label "positive" correctly classified as "positive".
Precision : True Positive/(True Positive + False Positive)
Recall : True Positive/(True Positive + False Negative)

Bernoulli Naive Bayes :

In [14]:

```
def BernoulliNB_Test(X_train,X_test,y_train,y_test,optimal_alpha,vectorizer,n = 25):

    optimal_model = BernoulliNB(alpha = optimal_alpha)
    optimal_model.fit(X_train, y_train)
    y_pred = optimal_model.predict(X_test)


    ##--------------Feature Importance-------------------------##
    class_labels = optimal_model.classes_
    feature_names = vectorizer.get_feature_names()
    top_negative = sorted(zip(optimal_model.coef_[0], feature_names))[:n]
    top_positive= sorted(zip(optimal_model.coef_[0], feature_names))[-n:]

    print("\033[1m------------Top {} Negative Words with high Importance------------\03
3[0m".format(n))
    neg_featureimp_df = pd.DataFrame(top_negative, columns=['Coeficient Factor','Featur
es'])
    print(neg_featureimp_df.to_string(index=False))


    print("\n\033[1m------------Top {} Positive Words with high Importance------------
\033[0m".format(n))
    pos_featureimp_df = pd.DataFrame(top_positive, columns=['Coeficient Factor','Featur
es'],)
    print(pos_featureimp_df.to_string(index=False))



    print("\n\n")


    ##--------------Confusion Matrix and Performance metrics
    accuracy = accuracy_score(y_test,y_pred) * 100
    precision = precision_score(y_test,y_pred,average= 'macro')
    recall = recall_score(y_test,y_pred,average= 'macro')
    f1= f1_score(y_test,y_pred,average= 'macro')
    MSE = (1 - (accuracy/100))
    cm = confusion_matrix(y_test, y_pred)
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    cm_df = pd.DataFrame(cm,
                 index = ['negative','positive'],
                 columns = ['negative','positive'])
    sns.heatmap(cm_df, annot=True)
    plt.title('Confusion Matrix')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Label')
    plt.show()

    print(cm)
    print("\n\033[1mTest Error :\033[0m {}".format(np.round(MSE,3)))
    print("\033[1mTest Accuracy :\033[0m {} %".format(np.round(accuracy,3)))
    print("\033[1mTrue Negative :\033[0m {}".format(tn))
    print("\033[1mFalse Positive :\033[0m {}".format(fp))
    print("\033[1mFalse Negative :\033[0m {}".format(fn))
    print("\033[1mTrue Positive :\033[0m {}".format(tp))
    print("\33[1mPrecission Score :\033[0m {}".format(np.round(precision,3)))
    print("\33[1mRecall Score :\033[0m {}".format(np.round(recall,3)))
    print("\33[1mF1 Score :\033[0m {}".format(np.round(f1,3)))
```

Multinomial Naive Bayes :

In [15]:

```
def MultinomialNB_Test(X_train,X_test,y_train,y_test,optimal_alpha,vectorizer,n = 25):

    optimal_model = MultinomialNB(alpha = optimal_alpha)
    optimal_model.fit(X_train, y_train)
    y_pred = optimal_model.predict(X_test)


    ##--------------Feature Importance-------------------------##
    class_labels = optimal_model.classes_
    feature_names = vectorizer.get_feature_names()
    top_negative = sorted(zip(optimal_model.coef_[0], feature_names))[:n]
    top_positive= sorted(zip(optimal_model.coef_[0], feature_names))[-n:]

    print("\033[1m------------Top {} Negative Words with high Importance------------\03
3[0m".format(n))
    neg_featureimp_df = pd.DataFrame(top_negative, columns=['Coeficient Factor','Featur
es'])
    print(neg_featureimp_df.to_string(index=False))


    print("\n\033[1m------------Top {} Positive Words with high Importance------------
\033[0m".format(n))
    pos_featureimp_df = pd.DataFrame(top_positive, columns=['Coeficient Factor','Featur
es'],)
    print(pos_featureimp_df.to_string(index=False))



    print("\n\n")


    ##--------------Confusion Matrix and Performance metrics
    accuracy = accuracy_score(y_test,y_pred) * 100
    precision = precision_score(y_test,y_pred,average= 'macro')
    recall = recall_score(y_test,y_pred,average= 'macro')
    f1= f1_score(y_test,y_pred,average= 'macro')
    MSE = (1 - (accuracy/100))
    cm = confusion_matrix(y_test, y_pred)
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    cm_df = pd.DataFrame(cm,
                     index = ['negative','positive'],
                     columns = ['negative','positive'])
    sns.heatmap(cm_df, annot=True)
    plt.title('Confusion Matrix')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Label')
    plt.show()

    print(cm)
    print("\n\033[1mTest Error :\033[0m {}".format(np.round(MSE,3)))
    print("\033[1mTest Accuracy :\033[0m {} %".format(np.round(accuracy,3)))
    print("\033[1mTrue Negative :\033[0m {}".format(tn))
    print("\033[1mFalse Positive :\033[0m {}".format(fp))
    print("\033[1mFalse Negative :\033[0m {}".format(fn))
    print("\033[1mTrue Positive :\033[0m {}".format(tp))
    print("\33[1mPrecission Score :\033[0m {}".format(np.round(precision,3)))
    print("\33[1mRecall Score :\033[0m {}".format(np.round(recall,3)))
    print("\33[1mF1 Score :\033[0m {}".format(np.round(f1,3)))
```

[8] Featurization Methods :

Note : Naive Bayes is invariant to feature scaling.

[8.1] Bag Of Words(unigram) :

Count Based BOW :

In [29]:

```
%%time
bow_unigram = CountVectorizer()
X_train_bowuni = bow_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_bowuni))
print("The shape of text BOW vectorizer: ", X_train_bowuni.get_shape())
print("Number of unique word: ", X_train_bowuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (254519, 59315)
Number of unique word:  59315
CPU times: user 11.4 s, sys: 92 ms, total: 11.5 s
Wall time: 11.5 s
```

In [30]:

```
%%time
X_test_bowuni = bow_unigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_bowuni.get_shape())
print("Number of unique word: ", X_test_bowuni.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (109080, 59315)
Number of unique word:  59315
CPU times: user 5.42 s, sys: 8 ms, total: 5.43 s
Wall time: 5.43 s
```

In [31]:

```
dumpfile(X_train_bowuni,"X_train_bowuni")
dumpfile(X_test_bowuni,"X_test_bowuni")
```

In [85]:

```
X_train_bowuni = loadfile("X_train_bowuni")
X_test_bowuni = loadfile("X_test_bowuni")
```

In [35]:

```
print("Shape of Training Data: ",X_train_bowuni.shape)
print("Shape of Test Data: ",X_test_bowuni.shape)
```

```
Shape of Training Data:  (254519, 59315)
Shape of Test Data:  (109080, 59315)
```

Binary BOW :

In [8]:

```
%%time
binarybow_unigram = CountVectorizer(binary = True)
X_train_binarybowuni = binarybow_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_binarybowuni))
print("The shape of text BOW vectorizer: ", X_train_binarybowuni.get_shape())
print("Number of unique word: ", X_train_binarybowuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (254519, 59315)
Number of unique word:  59315
CPU times: user 11.5 s, sys: 76 ms, total: 11.6 s
Wall time: 11.6 s
```

In [9]:

```
%%time
X_test_binarybowuni = binarybow_unigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_binarybowuni.get_shape())
print("Number of unique word: ", X_test_binarybowuni.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (109080, 59315)
Number of unique word:  59315
CPU times: user 5.4 s, sys: 12 ms, total: 5.41 s
Wall time: 5.41 s
```

In [10]:

```
print("Shape of Training Data: ",X_train_binarybowuni.shape)
print("Shape of Test Data: ",X_test_binarybowuni.shape)
```

```
Shape of Training Data:  (254519, 59315)
Shape of Test Data:  (109080, 59315)
```

Using Bernoulli Naive Bayes(binary features) :

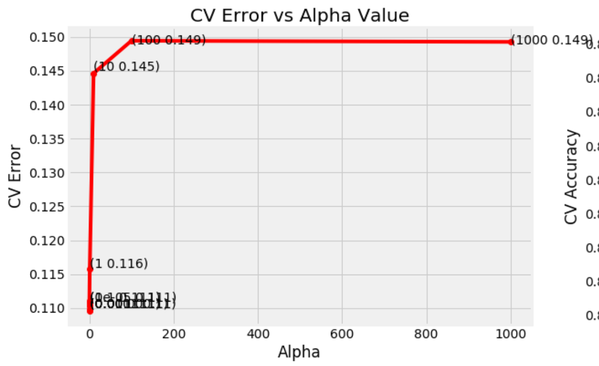
In [16]:

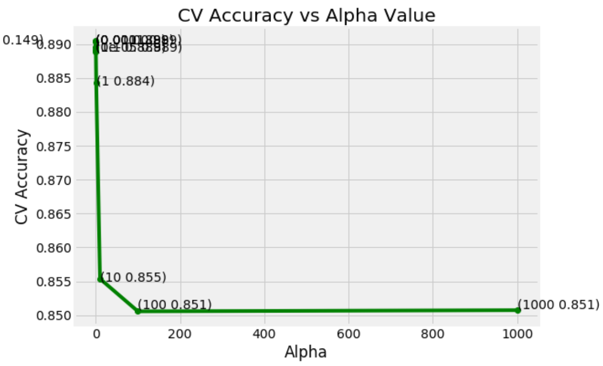
```
%%time
if __name__ == "__main__":
    BernoulliNB_Train(X_train_binarybowuni, y_train)
```

Optimal alpha: {'alpha': 0.01}

CrossValidation Error: 0.11

CrossValidation Accuracy: 89.049 %





CV Error for each value of alpha: [0.111 0.11 0.11 0.11 0.111 0.116 0.145 0.149 0.149]

CV Accuracy for each value of alpha: [0.889 0.89 0.89 0.89 0.889 0.884 0.855 0.851 0.851]

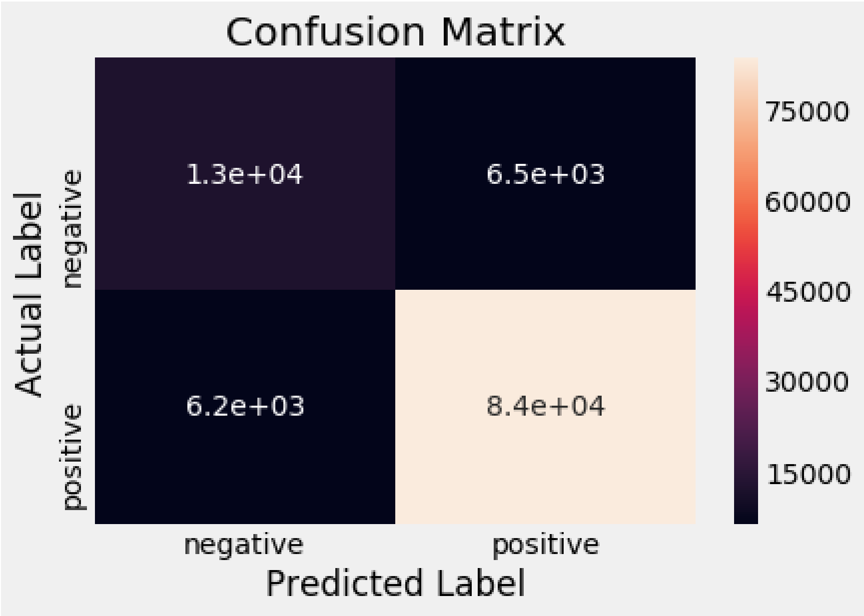
CPU times: user 3min 2s, sys: 2.99 s, total: 3min 5s
Wall time: 3min 4s

In [19]:

```
%%time
if __name__ == "__main__":
    BernoulliNB_Test(X_train_binarybowuni, X_test_binarybowuni, y_train, y_test, 0.01,
 binarybow_unigram)
```

```
------------Top 25 Negative Words with high Importance------------
Coeficient Factor            Features
       -16.890669  aaaaaaarrrrrggghhh
       -16.890669  aaaaaahhhhhyaaaaaa
       -16.890669              aachen
       -16.890669              aarrgh
       -16.890669                aauc
       -16.890669              abalon
       -16.890669           abbazabba
       -16.890669               abiet
       -16.890669        abolitionist
       -16.890669               abort
       -16.890669              abottl
       -16.890669              abrevi
       -16.890669           abrotanum
       -16.890669           absolutelt
       -16.890669             absoprt
       -16.890669              absurt
       -16.890669              abswer
       -16.890669             abvious
       -16.890669             accepet
       -16.890669            acceptal
       -16.890669          acceptalbl
       -16.890669               accor
       -16.890669            accordng
       -16.890669             accourd
       -16.890669              accpet

------------Top 25 Positive Words with high Importance------------
Coeficient Factor Features
        -2.078467     dont
        -2.050982      eat
        -2.040586     also
        -2.032481     much
        -2.014801    price
        -1.984578   realli
        -1.978280     find
        -1.957953     best
        -1.957887    would
        -1.947343   amazon
        -1.909697     time
        -1.905528      buy
        -1.695963      get
        -1.646235     make
        -1.563862  product
        -1.533892      tri
        -1.490217      use
        -1.472885      one
        -1.429562   flavor
        -1.294476    great
        -1.277035     good
        -1.273151     love
        -1.207503     tast
        -1.190105     like
        -1.143144      not
```




```
[[12567  6480]
 [ 6226 83807]]
```

Test Error : 0.116
Test Accuracy : 88.352 %
True Negative : 12567
False Positive : 6480
False Negative : 6226
True Positive : 83807
Precission Score : 0.798
Recall Score : 0.795
F1 Score : 0.797
CPU times: user 8.12 s, sys: 16 ms, total: 8.14 s
Wall time: 7.89 s

Using Multinomial Naive Bayes :

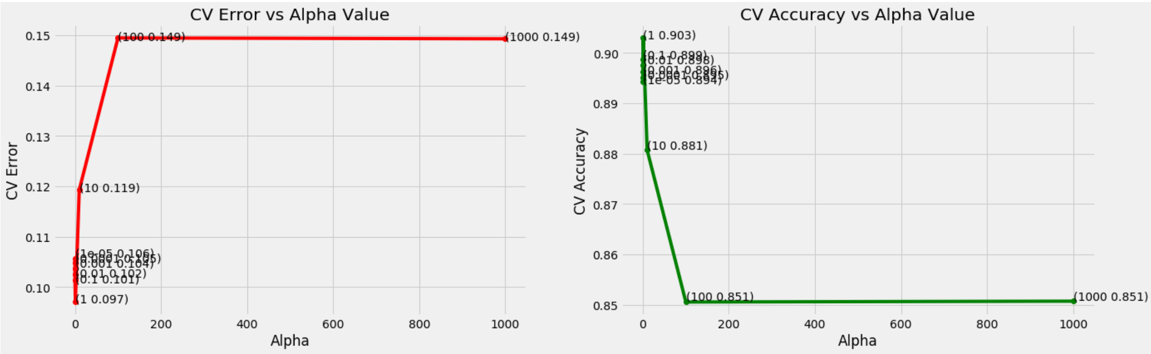
In [62]:

```
%%time
if __name__ == "__main__":
    MultinomialNB_Train(X_train_bowuni, y_train)
```

Optimal alpha: {'alpha': 1}

CrossValidation Error: 0.097

CrossValidation Accuracy: 90.299 %



CV Error for each value of alpha: [0.106 0.105 0.104 0.102 0.101 0.097 0.
119 0.149 0.149]

CV Accuracy for each value of alpha: [0.894 0.895 0.896 0.898 0.899 0.903
 0.881 0.851 0.851]
CPU times: user 2min 56s, sys: 1.7 s, total: 2min 57s
Wall time: 2min 57s

In [87]:

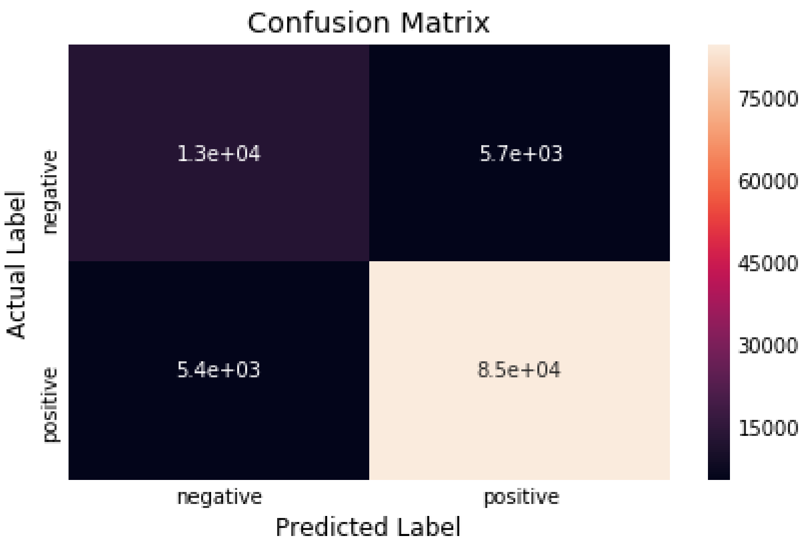
```
%%time
if __name__ == "__main__":
    MultinomialNB_Test(X_train_bowuni, X_test_bowuni, y_train, y_test, 1, bow_unigram)
```

------------Top 25 Negative Words with high Importance------------

Coeficient Factor	Features
-15.931921	aaaaaaarrrrrggghhh
-15.931921	aaaaaahhhhhyaaaaaa
-15.931921	aachen
-15.931921	aarrgh
-15.931921	aauc
-15.931921	abalon
-15.931921	abbazabba
-15.931921	abiet
-15.931921	abolitionist
-15.931921	abort
-15.931921	abottl
-15.931921	abrevi
-15.931921	abrotanum
-15.931921	absolutelt
-15.931921	absoprt
-15.931921	absurt
-15.931921	abswer
-15.931921	abvious
-15.931921	accepet
-15.931921	acceptal
-15.931921	acceptalbl
-15.931921	accor
-15.931921	accordng
-15.931921	accourd
-15.931921	accpet

------------Top 25 Positive Words with high Importance------------

Coeficient Factor	Features
-5.482743	price
-5.482192	best
-5.466620	find
-5.429267	realli
-5.415981	eat
-5.412275	amazon
-5.394744	buy
-5.391936	would
-5.372002	time
-5.232076	food
-5.105465	get
-5.042244	make
-5.036089	coffe
-4.924601	tri
-4.904170	tea
-4.896048	product
-4.810499	one
-4.752973	use
-4.732351	great
-4.711891	love
-4.684199	flavor
-4.661488	good
-4.526458	tast
-4.456843	like
-4.397420	not




```
[[13353  5694]
 [ 5404 84629]]
```

Test Error : 0.102
Test Accuracy : 89.826 %
True Negative : 13353
False Positive : 5694
False Negative : 5404
True Positive : 84629
Precission Score : 0.824
Recall Score : 0.821
F1 Score : 0.822
CPU times: user 7.99 s, sys: 16 ms, total: 8.01 s
Wall time: 7.74 s

[8.2] Bag Of Words(bigram) :

Count Based BOW :

In [36]:

```
%%time
bow_bigram = CountVectorizer(ngram_range=(1, 2))
X_train_bowbi = bow_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_bowbi))
print("The shape of text BOW vectorizer: ", X_train_bowbi.get_shape())
print("Number of unique word: ", X_train_bowbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (254519, 2295006)
Number of unique word:  2295006
CPU times: user 36.9 s, sys: 320 ms, total: 37.3 s
Wall time: 37.3 s
```

In [37]:

```
%%time
X_test_bowbi = bow_bigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_bowbi.get_shape())
print("Number of unique word: ", X_test_bowbi.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (109080, 2295006)
Number of unique word:  2295006
CPU times: user 11.9 s, sys: 8 ms, total: 11.9 s
Wall time: 11.9 s
```

In [38]:

```
dumpfile(X_train_bowbi,"X_train_bowbi")
dumpfile(X_test_bowbi,"X_test_bowbi")
```

In [88]:

```
X_train_bowbi = loadfile("X_train_bowbi")
X_test_bowbi = loadfile("X_test_bowbi")
```

In [42]:

```
print("Shape of Training Data: ",X_train_bowbi.shape)
print("Shape of Test Data: ",X_test_bowbi.shape)
```

```
Shape of Training Data:  (254519, 2295006)
Shape of Test Data:  (109080, 2295006)
```

Binary BOW :

In [20]:

```
%%time
binarybow_bigram = CountVectorizer(ngram_range=(1, 2), binary = True)
X_train_binarybowbi = binarybow_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_binarybowbi))
print("The shape of text BOW vectorizer: ", X_train_binarybowbi.get_shape())
print("Number of unique word: ", X_train_binarybowbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (254519, 2295006)
Number of unique word:  2295006
CPU times: user 37.3 s, sys: 392 ms, total: 37.7 s
Wall time: 37.7 s
```

In [21]:

```
%%time
X_test_binarybowbi = binarybow_bigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_binarybowbi.get_shape())
print("Number of unique word: ", X_test_binarybowbi.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (109080, 2295006)
Number of unique word:  2295006
CPU times: user 12.1 s, sys: 40 ms, total: 12.2 s
Wall time: 12.2 s
```

In [22]:

```
print("Shape of Training Data: ",X_train_binarybowbi.shape)
print("Shape of Test Data: ",X_test_binarybowbi.shape)
```

```
Shape of Training Data:  (254519, 2295006)
Shape of Test Data:  (109080, 2295006)
```

Using Bernoulli Naive Bayes(binary features) :

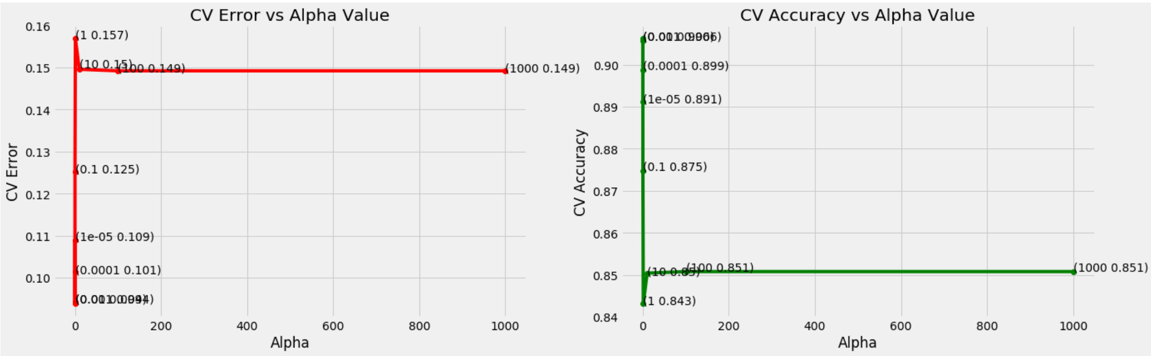
In [23]:

```
%%time
if __name__ == "__main__":
    BernoulliNB_Train(X_train_binarybowbi, y_train)
```

Optimal alpha: {'alpha': 0.001}

CrossValidation Error: 0.094

CrossValidation Accuracy: 90.626 %



CV Error for each value of alpha: [0.109 0.101 0.094 0.094 0.125 0.157 0.
15 0.149 0.149]

CV Accuracy for each value of alpha: [0.891 0.899 0.906 0.906 0.875 0.843
 0.85 0.851 0.851]

```
CPU times: user 4min 44s, sys: 10.8 s, total: 4min 55s
Wall time: 4min 55s
```

In [24]:

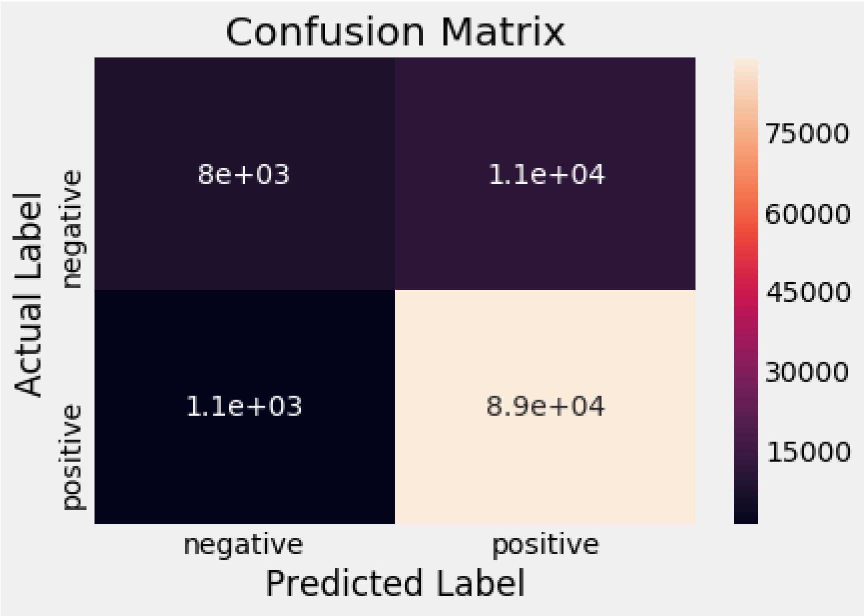
```
%%time
if __name__ == "__main__":
    BernoulliNB_Test(X_train_binarybowbi, X_test_binarybowbi, y_train, y_test, 0.001, b
inarybow_bigram)
```

------------Top 25 Negative Words with high Importance------------

Coeficient Factor	Features
-19.193254	aaa dont
-19.193254	aaaaaaarrrrrggghhh
-19.193254	aaaaaaarrrrrggghhh back
-19.193254	aaaaaahhhhhyaaaaaa
-19.193254	aaaaaahhhhhyaaaaaa fire
-19.193254	aachen
-19.193254	aachen munich
-19.193254	aachen printen
-19.193254	aafco certifi
-19.193254	aafco definit
-19.193254	aafco regul
-19.193254	aamzon howev
-19.193254	aarrgh
-19.193254	aarrgh final
-19.193254	aauc
-19.193254	aauc shelv
-19.193254	aback flavor
-19.193254	aback foreign
-19.193254	aback main
-19.193254	aback potenc
-19.193254	aback presenc
-19.193254	aback smell
-19.193254	abalon
-19.193254	abalon like
-19.193254	abalon not

------------Top 25 Positive Words with high Importance------------

Coeficient Factor	Features
-2.078468	dont
-2.050982	eat
-2.040586	also
-2.032481	much
-2.014801	price
-1.984578	realli
-1.978280	find
-1.957953	best
-1.957887	would
-1.947343	amazon
-1.909697	time
-1.905528	buy
-1.695964	get
-1.646235	make
-1.563862	product
-1.533892	tri
-1.490218	use
-1.472886	one
-1.429562	flavor
-1.294476	great
-1.277035	good
-1.273151	love
-1.207503	tast
-1.190105	like
-1.143144	not




```
[[ 7957 11090]
 [ 1077 88956]]
```

Test Error : 0.112
Test Accuracy : 88.846 %
True Negative : 7957
False Positive : 11090
False Negative : 1077
True Positive : 88956
Precission Score : 0.885
Recall Score : 0.703
F1 Score : 0.751
CPU times: user 20.6 s, sys: 128 ms, total: 20.7 s
Wall time: 20.4 s

Using Multinomial Naive Bayes :

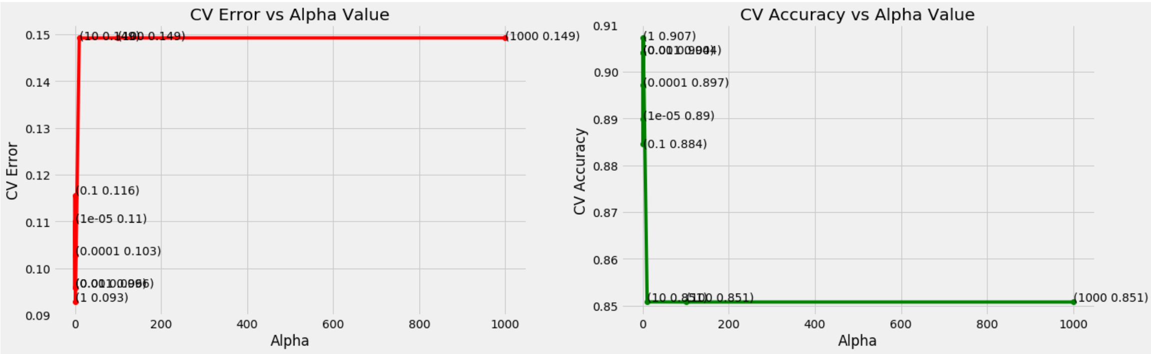
In [64]:

```
%%time
if __name__ == "__main__":
    MultinomialNB_Train(X_train_bowbi, y_train)
```

Optimal alpha: {'alpha': 1}

CrossValidation Error: 0.093

CrossValidation Accuracy: 90.726 %



CV Error for each value of alpha: [0.11 0.103 0.096 0.096 0.116 0.093 0.149 0.149 0.149]

CV Accuracy for each value of alpha: [0.89 0.897 0.904 0.904 0.884 0.907 0.851 0.851 0.851]

CPU times: user 4min 5s, sys: 7.76 s, total: 4min 13s
Wall time: 4min 13s

In [91]:

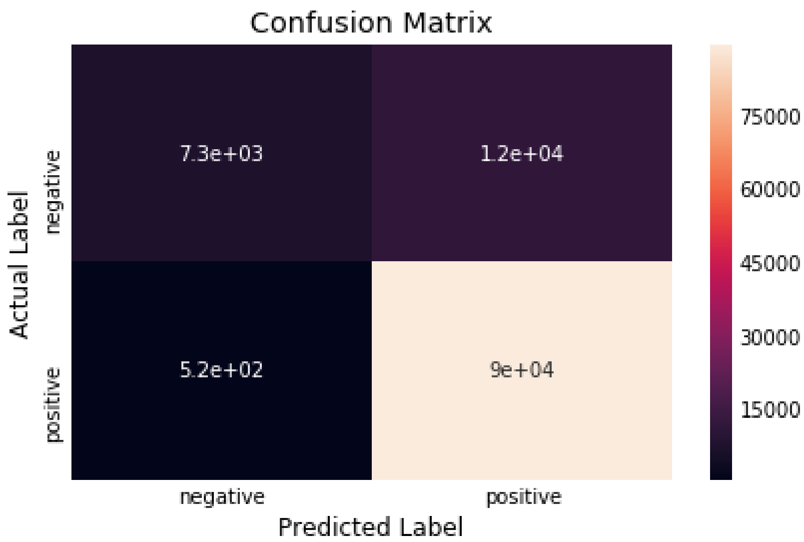
```
%%time
if __name__ == "__main__":
    MultinomialNB_Test(X_train_bowbi, X_test_bowbi, y_train, y_test, 1, bow_bigram)
```

------------Top 25 Negative Words with high Importance------------

Coeficient Factor	Features
-16.73665	aaa dont
-16.73665	aaaaaaarrrrrggghhh
-16.73665	aaaaaaarrrrrggghhh back
-16.73665	aaaaaahhhhhyaaaaaa
-16.73665	aaaaaahhhhhyaaaaaa fire
-16.73665	aachen
-16.73665	aachen munich
-16.73665	aachen printen
-16.73665	aafco certifi
-16.73665	aafco definit
-16.73665	aafco regul
-16.73665	aamzon howev
-16.73665	aarrgh
-16.73665	aarrgh final
-16.73665	aauc
-16.73665	aauc shelv
-16.73665	aback flavor
-16.73665	aback foreign
-16.73665	aback main
-16.73665	aback potenc
-16.73665	aback presenc
-16.73665	aback smell
-16.73665	abalon
-16.73665	abalon like
-16.73665	abalon not

------------Top 25 Positive Words with high Importance------------

Coeficient Factor	Features
-6.287471	price
-6.286921	best
-6.271349	find
-6.233996	realli
-6.220710	eat
-6.217004	amazon
-6.199473	buy
-6.196664	would
-6.176731	time
-6.036804	food
-5.910194	get
-5.846972	make
-5.840818	coffe
-5.729330	tri
-5.708898	tea
-5.700776	product
-5.615227	one
-5.557701	use
-5.537080	great
-5.516620	love
-5.488927	flavor
-5.466216	good
-5.331187	tast
-5.261571	like
-5.202148	not




```
[[ 7344 11703]
 [  515 89518]]
```

Test Error : 0.112
Test Accuracy : 88.799 %
True Negative : 7344
False Positive : 11703
False Negative : 515
True Positive : 89518
Precission Score : 0.909
Recall Score : 0.69
F1 Score : 0.741

```
CPU times: user 20.1 s, sys: 44 ms, total: 20.1 s
Wall time: 19.8 s
```

[8.3] TF-IDF(unigram) :

Count Based TF-IDF :

In [43]:

```
%%time
tfidf_unigram = TfidfVectorizer()
X_train_tfidfuni = tfidf_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_tfidfuni))
print("The shape of text TFIDF vectorizer: ", X_train_tfidfuni.get_shape())
print("Number of unique word: ", X_train_tfidfuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (254519, 59315)
Number of unique word:  59315
CPU times: user 11.6 s, sys: 64 ms, total: 11.6 s
Wall time: 11.7 s
```

In [44]:

```
%%time
X_test_tfidfuni = tfidf_unigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_tfidfuni.get_shape())
print("Number of unique word: ", X_test_tfidfuni.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (109080, 59315)
Number of unique word:  59315
CPU times: user 5.54 s, sys: 8 ms, total: 5.54 s
Wall time: 5.55 s
```

In [45]:

```
dumpfile(X_train_tfidfuni,"X_train_tfidfuni")
dumpfile(X_test_tfidfuni,"X_test_tfidfuni")
```

In [92]:

```
X_train_tfidfuni = loadfile("X_train_tfidfuni")
X_test_tfidfuni = loadfile("X_test_tfidfuni")
```

In [49]:

```
print("Shape of Training Data: ",X_train_tfidfuni.shape)
print("Shape of Test Data: ",X_test_tfidfuni.shape)
```

```
Shape of Training Data:  (254519, 59315)
Shape of Test Data:  (109080, 59315)
```

Binary TF-IDF :

In [25]:

```
%%time
binarytfidf_unigram = TfidfVectorizer(binary = True)
X_train_binarytfidfuni = binarytfidf_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_binarytfidfuni))
print("The shape of text TFIDF vectorizer: ", X_train_binarytfidfuni.get_shape())
print("Number of unique word: ", X_train_binarytfidfuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (254519, 59315)
Number of unique word:  59315
CPU times: user 11.8 s, sys: 92 ms, total: 11.9 s
Wall time: 11.9 s
```

In [26]:

```
%%time
X_test_binarytfidfuni = binarytfidf_unigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_binarytfidfuni.get_shape())
print("Number of unique word: ", X_test_binarytfidfuni.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (109080, 59315)
Number of unique word:  59315
CPU times: user 5.53 s, sys: 4 ms, total: 5.54 s
Wall time: 5.53 s
```

In [27]:

```
print("Shape of Training Data: ",X_train_binarytfidfuni.shape)
print("Shape of Test Data: ",X_test_binarytfidfuni.shape)
```

```
Shape of Training Data:  (254519, 59315)
Shape of Test Data:  (109080, 59315)
```

Using Bernoulli Naive Bayes(binary features) :

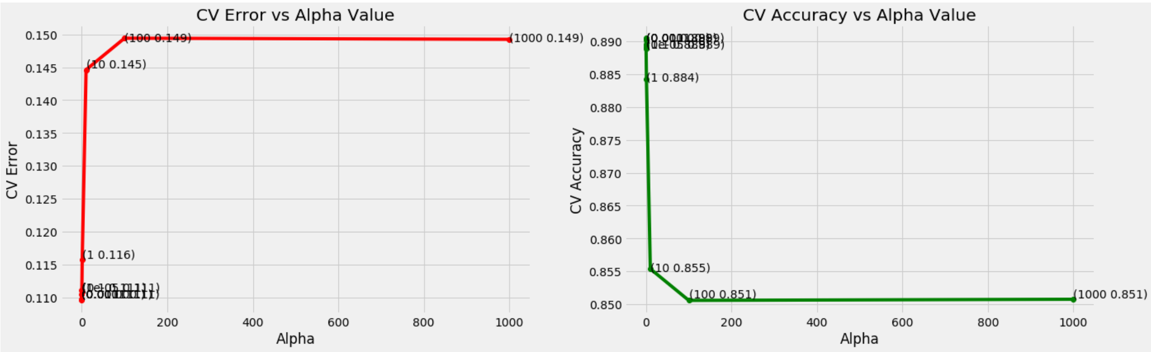
In [28]:

```
%%time
if __name__ == "__main__":
    BernoulliNB_Train(X_train_binarytfidfuni, y_train)
```

Optimal alpha: {'alpha': 0.01}

CrossValidation Error: 0.11

CrossValidation Accuracy: 89.049 %



CV Error for each value of alpha: [0.111 0.11 0.11 0.11 0.111 0.116 0.
145 0.149 0.149]

CV Accuracy for each value of alpha: [0.889 0.89 0.89 0.89 0.889 0.884
 0.855 0.851 0.851]

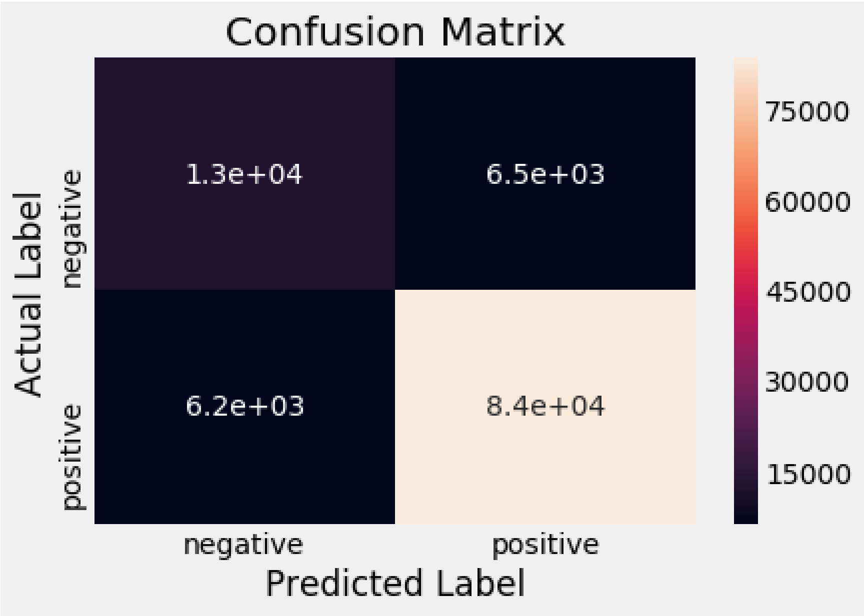
```
CPU times: user 3min 2s, sys: 1.86 s, total: 3min 3s
Wall time: 3min 3s
```

In [29]:

```
%%time
if __name__ == "__main__":
    BernoulliNB_Test(X_train_binarytfidfuni, X_test_binarytfidfuni, y_train, y_test, 0.
01, binarytfidf_unigram)
```

```
------------Top 25 Negative Words with high Importance------------
Coeficient Factor            Features
       -16.890669  aaaaaaarrrrrggghhh
       -16.890669  aaaaaahhhhhyaaaaaa
       -16.890669              aachen
       -16.890669              aarrgh
       -16.890669                aauc
       -16.890669              abalon
       -16.890669           abbazabba
       -16.890669               abiet
       -16.890669        abolitionist
       -16.890669               abort
       -16.890669              abottl
       -16.890669              abrevi
       -16.890669           abrotanum
       -16.890669           absolutelt
       -16.890669             absoprt
       -16.890669              absurt
       -16.890669              abswer
       -16.890669             abvious
       -16.890669             accepet
       -16.890669            acceptal
       -16.890669          acceptalbl
       -16.890669               accor
       -16.890669            accordng
       -16.890669             accourd
       -16.890669              accpet

------------Top 25 Positive Words with high Importance------------
Coeficient Factor Features
        -2.078467     dont
        -2.050982      eat
        -2.040586     also
        -2.032481     much
        -2.014801    price
        -1.984578   realli
        -1.978280     find
        -1.957953     best
        -1.957887    would
        -1.947343   amazon
        -1.909697     time
        -1.905528      buy
        -1.695963      get
        -1.646235     make
        -1.563862  product
        -1.533892      tri
        -1.490217      use
        -1.472885      one
        -1.429562   flavor
        -1.294476    great
        -1.277035     good
        -1.273151     love
        -1.207503     tast
        -1.190105     like
        -1.143144      not
```




```
[[12567  6480]
 [ 6226 83807]]
```

Test Error : 0.116
Test Accuracy : 88.352 %
True Negative : 12567
False Positive : 6480
False Negative : 6226
True Positive : 83807
Precission Score : 0.798
Recall Score : 0.795
F1 Score : 0.797
CPU times: user 8.12 s, sys: 12 ms, total: 8.13 s
Wall time: 7.86 s

Using Multinomial Naive Bayes :

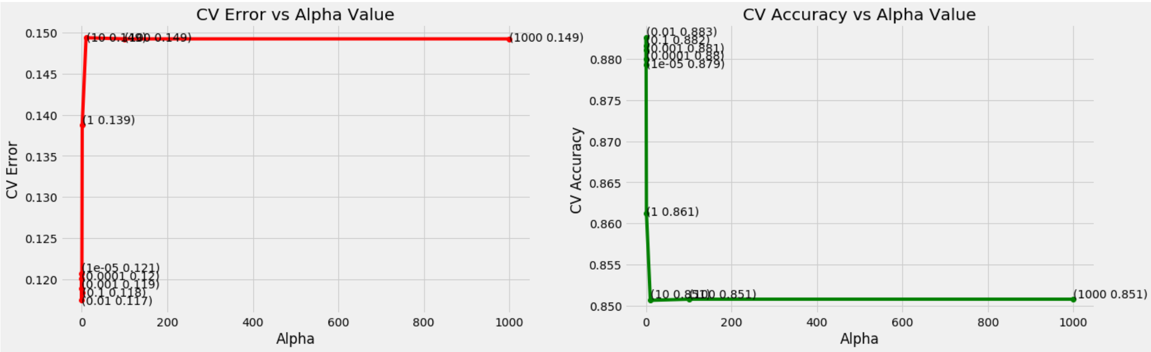
In [66]:

```
%%time
if __name__ == "__main__":
    MultinomialNB_Train(X_train_tfidfuni, y_train)
```

Optimal alpha: {'alpha': 0.01}

CrossValidation Error: 0.117

CrossValidation Accuracy: 88.26 %



CV Error for each value of alpha: [0.121 0.12 0.119 0.117 0.118 0.139 0.149 0.149 0.149]

CV Accuracy for each value of alpha: [0.879 0.88 0.881 0.883 0.882 0.861 0.851 0.851 0.851]

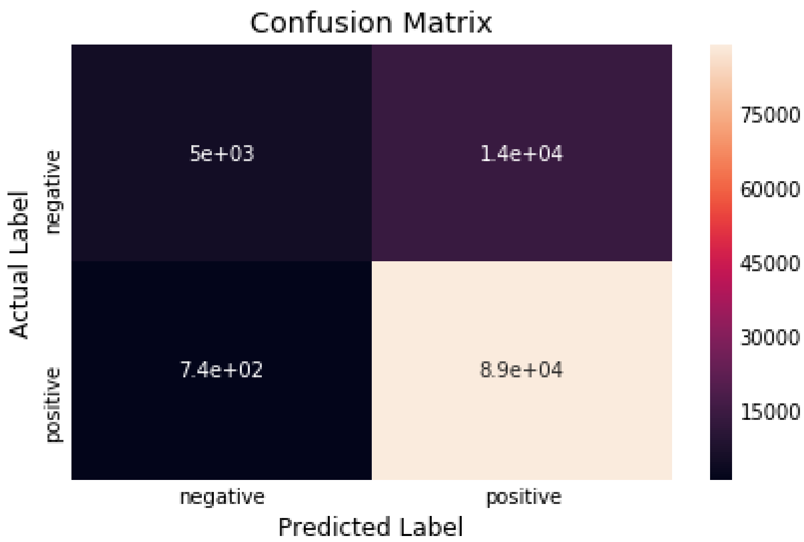
CPU times: user 2min 56s, sys: 1.32 s, total: 2min 58s
Wall time: 2min 58s

In [94]:

```
%%time
if __name__ == "__main__":
    MultinomialNB_Test(X_train_tfidfuni, X_test_tfidfuni, y_train, y_test, 0.01, tfidf_
unigram)
```

```
------------Top 25 Negative Words with high Importance------------
Coeficient Factor           Features
       -18.434172  aaaaaaarrrrrggghhh
       -18.434172  aaaaaahhhhhyaaaaaa
       -18.434172              aachen
       -18.434172              aarrgh
       -18.434172                aauc
       -18.434172              abalon
       -18.434172           abbazabba
       -18.434172               abiet
       -18.434172        abolitionist
       -18.434172               abort
       -18.434172              abottl
       -18.434172              abrevi
       -18.434172           abrotanum
       -18.434172          absolutelt
       -18.434172             absoprt
       -18.434172              absurt
       -18.434172              abswer
       -18.434172             abvious
       -18.434172             accepet
       -18.434172            acceptal
       -18.434172          acceptalbl
       -18.434172               accor
       -18.434172            accordng
       -18.434172             accourd
       -18.434172              accpet

------------Top 25 Positive Words with high Importance------------
Coeficient Factor Features
        -5.781033      eat
        -5.754349   realli
        -5.747922     time
        -5.742701    order
        -5.710403     food
        -5.709029     find
        -5.691603   amazon
        -5.671766      buy
        -5.650831     best
        -5.640605    price
        -5.610394      get
        -5.550292     make
        -5.486820      tri
        -5.419118      one
        -5.336020      use
        -5.320238  product
        -5.249362    coffe
        -5.220498   flavor
        -5.205193      not
        -5.179500      tea
        -5.164250     like
        -5.146301     good
        -5.146180     tast
        -5.083053     love
        -5.069295    great
```




```
[[ 4952 14095]
 [  745 89288]]
```

Test Error : 0.136
Test Accuracy : 86.395 %
True Negative : 4952
False Positive : 14095
False Negative : 745
True Positive : 89288
Precission Score : 0.866
Recall Score : 0.626
F1 Score : 0.662
CPU times: user 8.11 s, sys: 20 ms, total: 8.13 s
Wall time: 7.87 s

[8.4] TF-IDF(bigram) :

Count Based TF-IDF :

In [50]:

```
%%time
tfidf_bigram = TfidfVectorizer(ngram_range=(1, 2))
X_train_tfidfbi = tfidf_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_tfidfbi))
print("The shape of text TFIDF vectorizer: ", X_train_tfidfbi.get_shape())
print("Number of unique word: ", X_train_tfidfbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (254519, 2295006)
Number of unique word:  2295006
CPU times: user 39.2 s, sys: 348 ms, total: 39.6 s
Wall time: 39.6 s
```

In [51]:

```
%%time
X_test_tfidfbi = tfidf_bigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_tfidfbi.get_shape())
print("Number of unique word: ", X_test_tfidfbi.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (109080, 2295006)
Number of unique word:  2295006
CPU times: user 12.7 s, sys: 32 ms, total: 12.7 s
Wall time: 12.7 s
```

In [52]:

```
dumpfile(X_train_tfidfbi,"X_train_tfidfbi")
dumpfile(X_test_tfidfbi,"X_test_tfidfbi")
```

In [95]:

```
X_train_tfidfbi = loadfile("X_train_tfidfbi")
X_test_tfidfbi = loadfile("X_test_tfidfbi")
```

In [56]:

```
print("Shape of Training Data: ",X_train_tfidfbi.shape)
print("Shape of Test Data: ",X_test_tfidfbi.shape)
```

```
Shape of Training Data:  (254519, 2295006)
Shape of Test Data:  (109080, 2295006)
```

Binary TF-IDF :

In [30]:

```
%%time
binarytfidf_bigram = TfidfVectorizer(ngram_range=(1, 2), binary = True)
X_train_binarytfidfbi = binarytfidf_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_binarytfidfbi))
print("The shape of text TFIDF vectorizer: ", X_train_binarytfidfbi.get_shape())
print("Number of unique word: ", X_train_binarytfidfbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (254519, 2295006)
Number of unique word:  2295006
CPU times: user 39.9 s, sys: 452 ms, total: 40.3 s
Wall time: 40.3 s
```

In [31]:

```
%%time
X_test_binarytfidfbi = binarytfidf_bigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_binarytfidfbi.get_shape())
print("Number of unique word: ", X_test_binarytfidfbi.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (109080, 2295006)
Number of unique word:  2295006
CPU times: user 12.9 s, sys: 48 ms, total: 13 s
Wall time: 13 s
```

In [32]:

```
print("Shape of Training Data: ",X_train_binarytfidfbi.shape)
print("Shape of Test Data: ",X_test_binarytfidfbi.shape)
```

```
Shape of Training Data:  (254519, 2295006)
Shape of Test Data:  (109080, 2295006)
```

Using Bernoulli Naive Bayes(binary features) :

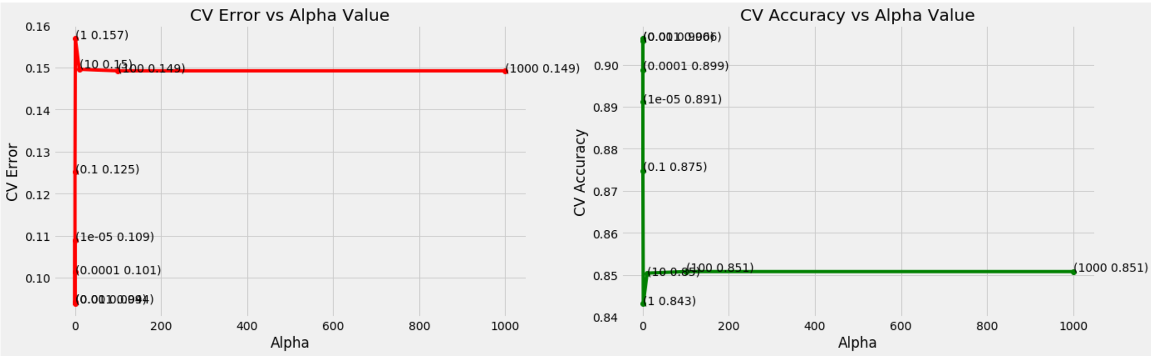
In [33]:

```
%%time
if __name__ == "__main__":
    BernoulliNB_Train(X_train_binarytfidfbi, y_train)
```

Optimal alpha: {'alpha': 0.001}

CrossValidation Error: 0.094

CrossValidation Accuracy: 90.626 %



CV Error for each value of alpha: [0.109 0.101 0.094 0.094 0.125 0.157 0.
15 0.149 0.149]

CV Accuracy for each value of alpha: [0.891 0.899 0.906 0.906 0.875 0.843
 0.85 0.851 0.851]

```
CPU times: user 4min 45s, sys: 10 s, total: 4min 55s
Wall time: 4min 55s
```

In [34]:

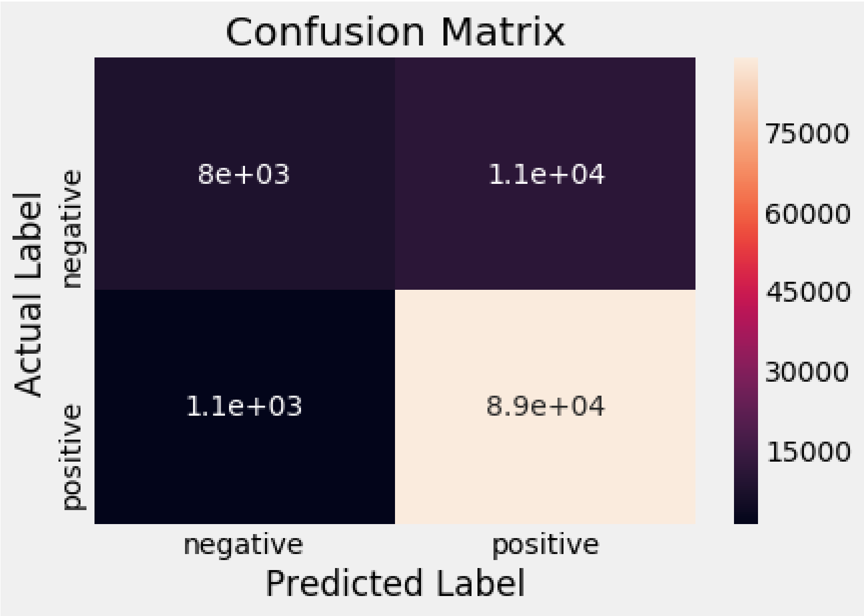
```
%%time
if __name__ == "__main__":
    BernoulliNB_Test(X_train_binarytfidfbi, X_test_binarytfidfbi, y_train, y_test, 0.00
1, binarytfidf_bigram)
```

------------Top 25 Negative Words with high Importance------------

Coeficient Factor	Features
-19.193254	aaa dont
-19.193254	aaaaaaarrrrrggghhh
-19.193254	aaaaaaarrrrrggghhh back
-19.193254	aaaaaahhhhhyaaaaaa
-19.193254	aaaaaahhhhhyaaaaaa fire
-19.193254	aachen
-19.193254	aachen munich
-19.193254	aachen printen
-19.193254	aafco certifi
-19.193254	aafco definit
-19.193254	aafco regul
-19.193254	aamzon howev
-19.193254	aarrgh
-19.193254	aarrgh final
-19.193254	aauc
-19.193254	aauc shelv
-19.193254	aback flavor
-19.193254	aback foreign
-19.193254	aback main
-19.193254	aback potenc
-19.193254	aback presenc
-19.193254	aback smell
-19.193254	abalon
-19.193254	abalon like
-19.193254	abalon not

------------Top 25 Positive Words with high Importance------------

Coeficient Factor	Features
-2.078468	dont
-2.050982	eat
-2.040586	also
-2.032481	much
-2.014801	price
-1.984578	realli
-1.978280	find
-1.957953	best
-1.957887	would
-1.947343	amazon
-1.909697	time
-1.905528	buy
-1.695964	get
-1.646235	make
-1.563862	product
-1.533892	tri
-1.490218	use
-1.472886	one
-1.429562	flavor
-1.294476	great
-1.277035	good
-1.273151	love
-1.207503	tast
-1.190105	like
-1.143144	not




```
[[ 7957 11090]
 [ 1077 88956]]
```

Test Error : 0.112
Test Accuracy : 88.846 %
True Negative : 7957
False Positive : 11090
False Negative : 1077
True Positive : 88956
Precission Score : 0.885
Recall Score : 0.703
F1 Score : 0.751
CPU times: user 21 s, sys: 100 ms, total: 21.1 s
Wall time: 20.8 s

Using Multinomial Naive Bayes :

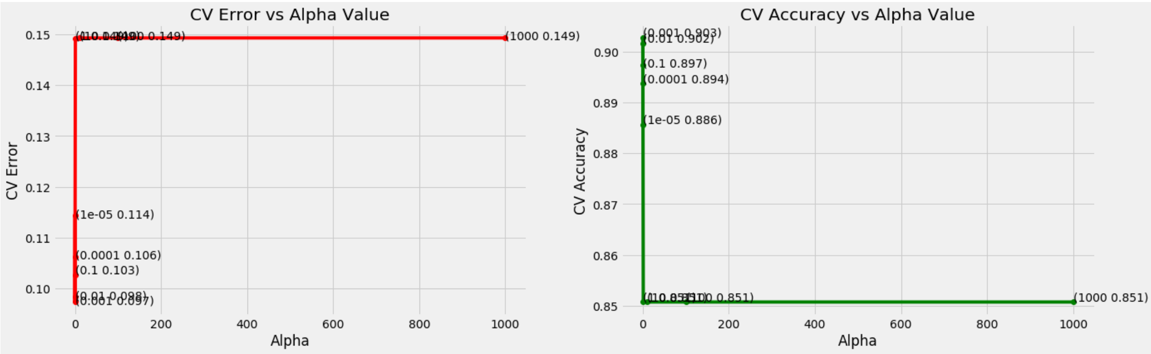
In [68]:

```
%%time
if __name__ == "__main__":
    MultinomialNB_Train(X_train_tfidfbi, y_train)
```

Optimal alpha: {'alpha': 0.001}

CrossValidation Error: 0.097

CrossValidation Accuracy: 90.265 %



CV Error for each value of alpha: [0.114 0.106 0.097 0.098 0.103 0.149 0.
149 0.149 0.149]

CV Accuracy for each value of alpha: [0.886 0.894 0.903 0.902 0.897 0.851
 0.851 0.851 0.851]
CPU times: user 4min 8s, sys: 6.21 s, total: 4min 14s
Wall time: 4min 14s

In [97]:

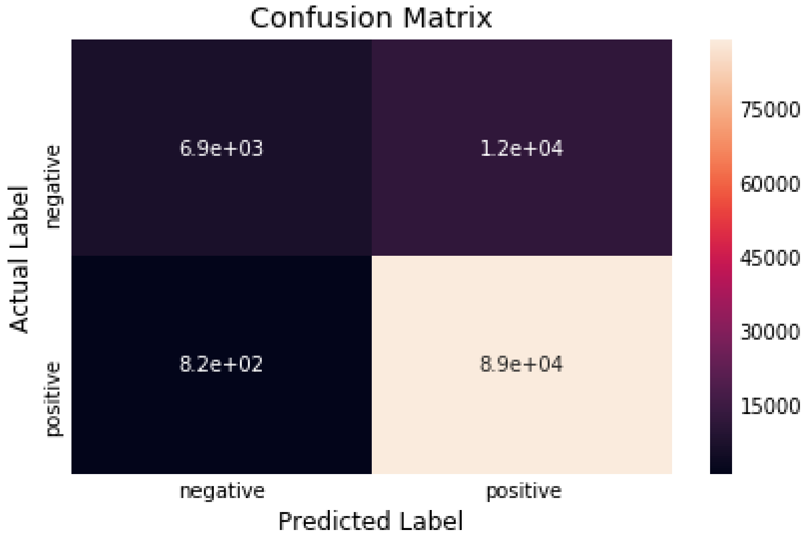
```
%%time
if __name__ == "__main__":
    MultinomialNB_Test(X_train_tfidfbi, X_test_tfidfbi, y_train, y_test, 0.001, tfidf_b
igram)
```

------------Top 25 Negative Words with high Importance------------

```
Coeficient Factor                 Features
       -21.140633                 aaa dont
       -21.140633       aaaaaaarrrrrggghhh
       -21.140633  aaaaaaarrrrrggghhh back
       -21.140633       aaaaaahhhhhyaaaaaa
       -21.140633  aaaaaahhhhhyaaaaaa fire
       -21.140633                   aachen
       -21.140633            aachen munich
       -21.140633           aachen printen
       -21.140633            aafco certifi
       -21.140633            aafco definit
       -21.140633              aafco regul
       -21.140633             aamzon howev
       -21.140633                   aarrgh
       -21.140633             aarrgh final
       -21.140633                     aauc
       -21.140633               aauc shelv
       -21.140633             aback flavor
       -21.140633            aback foreign
       -21.140633               aback main
       -21.140633             aback potenc
       -21.140633            aback presenc
       -21.140633              aback smell
       -21.140633                   abalon
       -21.140633              abalon like
       -21.140633               abalon not
```

------------Top 25 Positive Words with high Importance------------

```
Coeficient Factor Features
        -6.913309      eat
        -6.891037   realli
        -6.890222    order
        -6.884229     time
        -6.848279     find
        -6.834056   amazon
        -6.820494      buy
        -6.818411     food
        -6.795146    price
        -6.787423     best
        -6.740259      get
        -6.671618     make
        -6.611024      tri
        -6.546318      one
        -6.464482  product
        -6.454661      use
        -6.374521    coffe
        -6.351155   flavor
        -6.327687      not
        -6.290613     good
        -6.288916     like
        -6.283790      tea
        -6.279446     tast
        -6.231470     love
        -6.222472    great
```




```
[[ 6870 12177]
 [  821 89212]]
```

Test Error : 0.119
Test Accuracy : 88.084 %
True Negative : 6870
False Positive : 12177
False Negative : 821
True Positive : 89212
Precission Score : 0.887
Recall Score : 0.676
F1 Score : 0.723
CPU times: user 29.6 s, sys: 100 ms, total: 29.7 s
Wall time: 29.4 s

[9] Conclusion :

Featurization Model	Bernoulli NB				Multinomial Naive Bayes			
	Accuracy	**Precission**	**Recall**	**F1 score**	**Accuracy**	**Precission**	**Recall**	**F1 score**
BOW(unigram)	88.352 %	0.798	0.795	0.797	89.826 %	0.824	0.821	0.822
BOW(bigram)	88.846 %	0.885	0.703	0.751	88.799 %	0.909	0.69	0.741
TF-IDF(unigram)	88.352 %	0.798	0.795	0.797	86.395 %	0.866	0.626	0.661
TF-IDF(bigram)	88.846 %	0.885	0.703	0.751	88.084 %	0.887	0.676	0.723

1 - Using **Bag Of Words(unigram)** method, **Multinomial Naive Bayes** model gives best accuracy of **89.826 %** and F1 score of **0.822** with **alpha = 1**.

2- Both MultinomialNB and BernouliNB are suitable for discrete data. Multinomial NB works with occurence count of words while later is suitable for binary/boolean features.

3 - It is also observed that Run Time complexity of Naive Bayes is **super fast** as compared to KNN. Thus, Naive Bayes can be used as a classification model for **low latency applications**.

4 - Naive Bayes holds a concept of **"conditional independence"** that states features should be independent of each other. Hence featurization techniques like **average word2vec and tfidf weighted word2vec** which involves dependency between features **doesnot perform good** with Naive Bayes.