Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

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

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

In [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

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

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

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

from tqdm import tqdm
import os
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 50
0000 data points
# you can change the number to any other number based on your computing
 power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points
```

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

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

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

```
Number of data points in our data (525814, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1

In [0]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [0]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[0]:

	UserId	ProductId	ProfileName	Time	Score	Text	COU
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3

	UserId	ProductId	ProfileName	Time	Score	Text	COU
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [0]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[0]:

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

In [0]:
```
display['COUNT(*)'].sum()
```

Out[0]: 393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

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

In [0]:

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

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

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

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

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

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

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

In [3]:
```
#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 [4]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[4]:
```
(364173, 10)
```

In [5]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[5]:
```
69.25890143662969
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [6]:

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

In [7]:

```
#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[7]:

```
1    307061
0     57110
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

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

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

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

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

In [0]:

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

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

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

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

```
Why is this $[...] when the same product is available for $[...] here?<
br />http://www.amazon.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<
```

```
br />http://www.amazon.com/Victor-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<
br /><br />The Victor M380 and M502 traps are unreal, of course -- tota
l fly genocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.<br /><br />These are chocolate-oatmeal cookies.  If you don't li
ke that combination, don't order this type of cookie.  I find the combo
quite nice, really.  The oatmeal sort of "calms" the rich chocolate fla
vor and gives the cookie sort of a coconut-type consistency.  Now let's
also remember that tastes differ; so, I've given my opinion.<br /><br /
>Then, these are soft, chewy cookies -- as advertised.  They are not "c
rispy" cookies, or the blurb would say "crispy," rather than "chewy."
I happen to like raw cookie dough; however, I don't see where these tas
te like raw cookie dough.  Both are soft, however, so is this the confu
sion?  And, yes, they stick together.  Soft cookies tend to do that.  T
hey aren't individually wrapped, which would add to the cost.  Oh yeah,
chocolate chip cookies tend to be somewhat sweet.<br /><br />So, if you
want something hard and crisp, I suggest Nabiso's Ginger Snaps.  If you
want a cookie that's soft, chewy and tastes like a combination of choco
late and oatmeal, give these a try.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />Thi
s k cup is great coffee.  dcaf is very good as well
==================================================
```

In [0]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
```

```
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br /> /><br />The Victor M380 and M502 traps are unreal, of course -- t
otal fly genocide. Pretty stinky, but only right nearby.
```

In [0]:

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

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

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

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

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

```
Why is this $[...] when the same product is available for $[...] here?
/>The Victor M380 and M502 traps are unreal, of course -- total fly gen
ocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
```

```
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.These are chocolate-oatmeal cookies.  If you don't like that comb
ination, don't order this type of cookie.  I find the combo quite nice,
really.  The oatmeal sort of "calms" the rich chocolate flavor and give
s the cookie sort of a coconut-type consistency.  Now let's also rememb
er that tastes differ; so, I've given my opinion.Then, these are soft,
chewy cookies -- as advertised.  They are not "crispy" cookies, or the
blurb would say "crispy," rather than "chewy."  I happen to like raw co
okie dough; however, I don't see where these taste like raw cookie doug
h.  Both are soft, however, so is this the confusion?  And, yes, they s
tick together.  Soft cookies tend to do that.  They aren't individually
wrapped, which would add to the cost.  Oh yeah, chocolate chip cookies
tend to be somewhat sweet.So, if you want something hard and crisp, I s
uggest Nabiso's Ginger Snaps.  If you want a cookie that's soft, chewy
and tastes like a combination of chocolate and oatmeal, give these a tr
y.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cu
p is great coffee.  dcaf is very good as well
```

In [0]:

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

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

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

In [0]:

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

```
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I am sorry; but
these reviews do nobody any good beyond reminding us to look  before or
dering.<br /><br />These are chocolate-oatmeal cookies.  If you do not
like that combination, do not order this type of cookie.  I find the co
mbo quite nice, really.  The oatmeal sort of "calms" the rich chocolate
flavor and gives the cookie sort of a coconut-type consistency.  Now le
t is also remember that tastes differ; so, I have given my opinion.<br
/><br />Then, these are soft, chewy cookies -- as advertised.  They are
not "crispy" cookies, or the blurb would say "crispy," rather than "che
wy."  I happen to like raw cookie dough; however, I do not see where th
ese taste like raw cookie dough.  Both are soft, however, so is this th
e confusion?  And, yes, they stick together.  Soft cookies tend to do t
hat.  They are not individually wrapped, which would add to the cost.
Oh yeah, chocolate chip cookies tend to be somewhat sweet.<br /><br />S
o, if you want something hard and crisp, I suggest Nabiso is Ginger Sna
ps.  If you want a cookie that is soft, chewy and tastes like a combina
tion of chocolate and oatmeal, give these a try.  I am here to place my
second order.
==================================================
```

In [0]:

```
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
```

```
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br /> /><br />The Victor  and  traps are unreal, of course -- total fly
genocide. Pretty stinky, but only right nearby.
```

In [0]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Wow So far two two star reviews One obviously had no idea what they wer
e ordering the other wants crispy cookies Hey I am sorry but these revi
ews do nobody any good beyond reminding us to look before ordering br b
r These are chocolate oatmeal cookies If you do not like that combinati
on do not order this type of cookie I find the combo quite nice really
The oatmeal sort of calms the rich chocolate flavor and gives the cooki
e sort of a coconut type consistency Now let is also remember that tast
es differ so I have given my opinion br br Then these are soft chewy co
okies as advertised They are not crispy cookies or the blurb would say
crispy rather than chewy I happen to like raw cookie dough however I do
not see where these taste like raw cookie dough Both are soft however s
o is this the confusion And yes they stick together Soft cookies tend t
o do that They are not individually wrapped which would add to the cost
Oh yeah chocolate chip cookies tend to be somewhat sweet br br So if yo
u want something hard and crisp I suggest Nabiso is Ginger Snaps If you
want a cookie that is soft chewy and tastes like a combination of choco
late and oatmeal give these a try I am here to place my second order
```

In [0]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in
 the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'o
urs', 'ourselves', 'you', "you're", "you've",\
```

```
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [0]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
```

```
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████
██████████| 4986/4986 [00:01<00:00, 3137.37it/s]
```

In [0]:
```
preprocessed_reviews[1500]
```

Out[0]:
```
'wow far two two star reviews one obviously no idea ordering wants cris
py cookies hey sorry reviews nobody good beyond reminding us look order
ing chocolate oatmeal cookies not like combination not order type cooki
e find combo quite nice really oatmeal sort calms rich chocolate flavor
gives cookie sort coconut type consistency let also remember tastes dif
fer given opinion soft chewy cookies advertised not crispy cookies blur
b would say crispy rather chewy happen like raw cookie dough however no
t see taste like raw cookie dough soft however confusion yes stick toge
ther soft cookies tend not individually wrapped would add cost oh yeah
chocolate chip cookies tend somewhat sweet want something hard crisp su
ggest nabiso ginger snaps want cookie soft chewy tastes like combinatio
n chocolate oatmeal give try place second order'
```

[3.2] Preprocessing Review Summary

In [30]:
```
## Similartly you can do preprocessing for review summary also.
#set of stopwords in English
from nltk.corpus import stopwords
stop = set(stopwords.words('english'))
import re

words_to_keep = set(('not'))
stop -= words_to_keep

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

 #function to clean the word of any html-tags
def cleanhtml(sentence):
```

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

#Code for removing HTML tags , punctuations . Code for removing stopwor
ds . Code for checking if word is not alphanumeric and
# also greater than 2 . Code for stemmimg and also to convert them to l
owercase letters
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in final['Summary'].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] == 1:
                        all_positive_words.append(s) #list of all words
 used to describe positive reviews
                    if(final['Score'].values)[i] == 0:
                        all_negative_words.append(s) #list of all words
 used to describe negative reviews reviews
                else:
                    continue
            else:
                continue
```

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


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

In [31]:

```
#adding a column of CleanedText which displays the data after pre-proce
ssing of the review
final['CleanedSummary']=final_string
final['CleanedSummary']=final['CleanedSummary'].str.decode("utf-8")
#below the processed review can be seen in the CleanedText Column
print('Shape of final',final.shape)
final.head()
```

```
Shape of final (364171, 13)
```

Out[31]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0
1	138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
2	138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1
3	138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1
4	138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3

In [33]:

```
print(final['CleanedText'][0])
print("********")
print(final['CleanedSummary'][0])
print("*****")
final['CleanedText'][:]=final['CleanedText'][:]+' '+final['CleanedText'
][:]+' '+final['CleanedSummary'][:]+' '+final['CleanedSummary'][:]
print(final['CleanedText'][0])
```

```
witti littl book make son laugh loud recit car drive along alway sing r
```

```
efrain hes learn whale india droop love new word book introduc silli cl
assic book will bet son still abl recit memori colleg
********
everi book educ
*****
witti littl book make son laugh loud recit car drive along alway sing r
efrain hes learn whale india droop love new word book introduc silli cl
assic book will bet son still abl recit memori colleg witti littl book
make son laugh loud recit car drive along alway sing refrain hes learn
whale india droop love new word book introduc silli classic book will b
et son still abl recit memori colleg everi book educ everi book educ
```

In [34]:
```
final.shape
```

Out[34]:
```
(364171, 13)
```

In [35]:
```
conn = sqlite3.connect('featureeng.sqlite')
c=conn.cursor()
conn.text_factory = str
final.to_sql('Reviews', conn,  schema=None, if_exists='replace', \
                 index=True, index_label=None, chunksize=None, dtype=No
ne)
conn.close()

with open('positive_words.pkl', 'wb') as f:
    pickle.dump(all_positive_words, f)
with open('negitive_words.pkl', 'wb') as f:
    pickle.dump(all_negative_words, f)
```

Note:

- preprocessing is done in previous assigments and stored in final.sqlite

In [2]:
```
con = sqlite3.connect('final.sqlite')
final = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3
```

```
""", con)
final.head()
```

Out[2]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0
1	138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1
2	138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
3	138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1
4	138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3

In [3]:
```
final.shape
```
Out[3]:
```
(364171, 12)
```

In [4]:
```
from sklearn.model_selection import train_test_split
##Sorting data according to Time in ascending order for Time Based Spli
tting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, in
place=False, kind='quicksort', na_position='last')

X = time_sorted_data['CleanedText'].values
Y = time_sorted_data['Score']

# split the data set into train and test
```

```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.3,
 shuffle=False)
```

In [5]:
```
print(X_train.shape, Y_train.shape)
print(X_test.shape, Y_test.shape)
```

```
(254919,) (254919,)
(109252,) (109252,)
```

Applying Multinomial Naive Bayes

[5.1] Applying Naive Bayes on BOW, SET 1

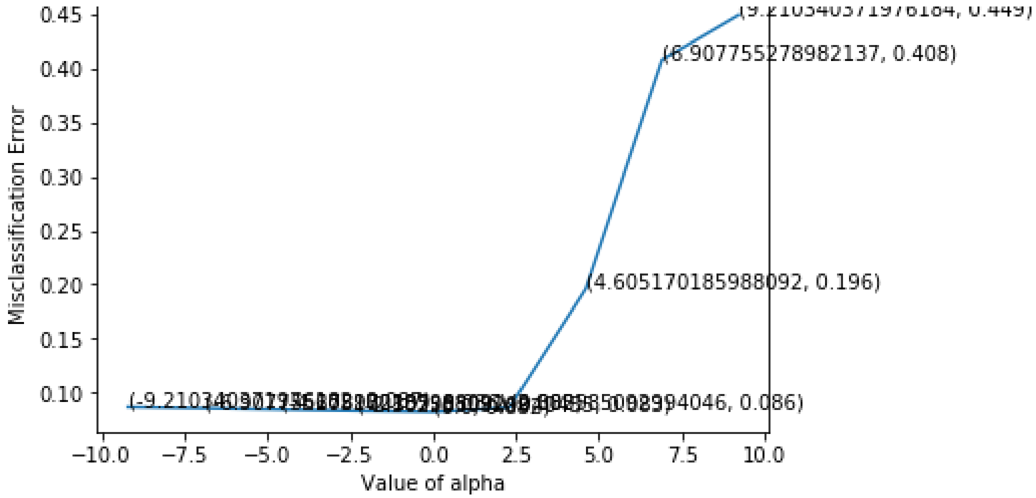
In [6]:
```
#BoW
count_vect = CountVectorizer(min_df = 50)
X_train_vec = count_vect.fit_transform(X_train)
X_test_vec = count_vect.transform(X_test)
print("the type of count vectorizer :",type(X_train_vec))
print("the shape of out text BOW vectorizer : ",X_train_vec.get_shape
())
print("the number of unique words :", X_train_vec.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (254919, 6050)
the number of unique words : 6050
```

In [10]:
```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score

# Creating alpha values in the range from 10^-4 to 10^4
neighbors = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
# empty list that will hold cv scores
cv_scores = []
training_scores =[]
# perform 10-fold cross validation
```

```
for k in neighbors:
    nb = MultinomialNB(alpha=k)
    nb.fit(X_train_vec, Y_train)
    #print(nb.predict(X_test[2:39]))
    scores = cross_val_score(nb, X_test_vec, Y_test, cv=10, scoring='roc_auc')
    scores_training = nb.fit(X_train_vec, Y_train).score(X_train_vec, Y_train)
    cv_scores.append(scores.mean())
    training_scores.append(scores_training)
    #print((nb))

MSE = [1 - x for x in cv_scores]
#determining best k
optimal_alpha = neighbors[MSE.index(min(MSE))]
print('\nThe optimal value of alpha is %.8f.' % optimal_alpha)

plt.plot(np.log(neighbors), MSE)

for xy in zip(np.log(neighbors), np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Value of alpha')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each k value is : ", np.round(MSE,3))
plt.plot(np.log(neighbors), cv_scores)
plt.plot(np.log(neighbors), training_scores)
plt.xlabel('alpha')
plt.ylabel('score')

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

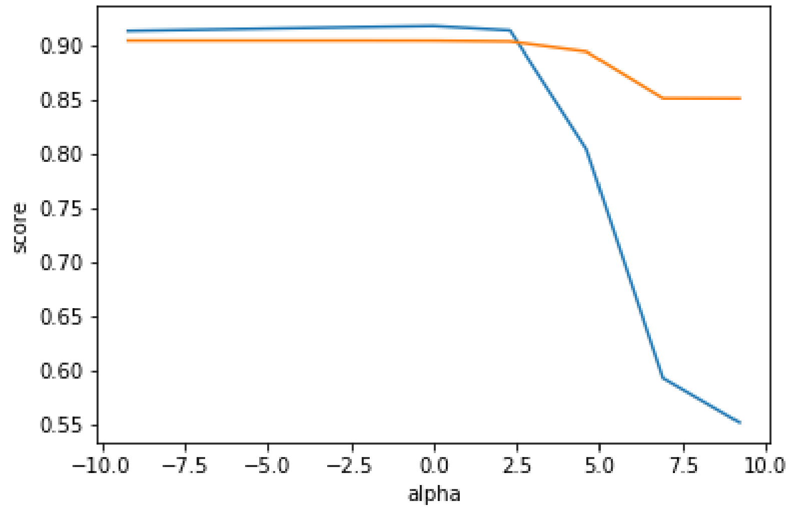
```
The optimal value of alpha is 1.00000000.
```




```
the misclassification error for each k value is :  [0.087 0.086 0.085
0.083 0.082 0.086 0.196 0.408 0.449]
```

Out[10]:

```
Text(0,0.5,'score')
```



In [11]:

```
# ============================== Multinomial Naive Bayes with alpha = o
ptimal_alpha ============================================
# instantiate learning model alpha = optimal_alpha
```

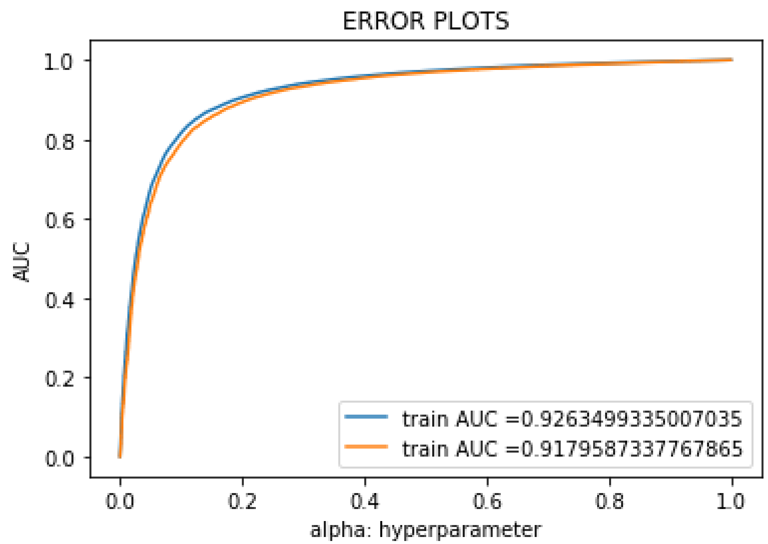
```python
from sklearn.metrics import accuracy_score
mnb1 = MultinomialNB(alpha = optimal_alpha)

# fitting the model
mnb1.fit(X_train_vec, Y_train)

# predict the response
predictions= mnb1.predict(X_test_vec)
predictions1= mnb1.predict(X_train_vec)

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

# Variables that will be used for  making table in Conclusion part of t
his assignment
bow_mnb_alpha = optimal_alpha
bow_mnb_train_acc = max(cv_scores)*100
bow_mnb_test_acc = acc
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha =
1.000 is 89.169992%
```

In [12]:

```python
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc

# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(Y_train, mnb1.predict_prob
a(X_train_vec)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(Y_test, mnb1.predict_proba(X
_test_vec)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
```

```
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test
_tpr)))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(Y_train, mnb1.predict(X_train_vec)))
print("Test confusion matrix")
print(confusion_matrix(Y_test, mnb1.predict(X_test_vec)))
```




```
======================================================================
==============================
Train confusion matrix
[[ 27458  10571]
 [ 13907 202983]]
Test confusion matrix
[[13879  5202]
```

```
 [ 6630 83541]]
```

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

In [13]:
```
# Please write all the code with proper documentation
# top 10  features
import operator
from nltk.probability import FreqDist, DictionaryProbDist, ELEProbDist,
 sum_logs
from nltk.classify.api import ClassifierI
from nltk.classify.naivebayes import NaiveBayesClassifier
nb = MultinomialNB(alpha=optimal_alpha).fit(X_train_vec, Y_train)
pos_imp_features = nb.feature_log_prob_[1,:]
neg_imp_features = nb.feature_log_prob_[0,:]


imp_features = {}
feature_names= count_vect.get_feature_names()
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = neg_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemget
ter(1), reverse = True)
print("\n\nNegative top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])
```

```
Negative top 10 important features are:
('tast', -4.174592588303286)
('like', -4.255594226628023)
('product', -4.424308118931364)
('one', -4.698637689183009)
('flavor', -4.7400729276772715)
('tri', -4.849917472839326)
('would', -4.850507866311542)
('good', -5.007094086504942)


('coffe', -5.031362516749736)
```

```
('use', -5.0391770386804815)
```

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

In [14]:

```
# Please write all the code with proper documentation
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = pos_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemget
ter(1), reverse = True)
print("Postive top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])
```

```
Postive top 10 important features are:
('like', -4.40894771917271)
('tast', -4.47930292964824)
('good', -4.614126623248737)
('flavor', -4.6357357369625625)
('love', -4.66429007687182)
('great', -4.684453739591529)
('use', -4.706008320452014)
('one', -4.762344073425835)
('product', -4.848698285348165)
('tea', -4.856661564089681)
```

Accuracy on test data

In [15]:

```
# evaluate accuracy
#libraries
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

acc = accuracy_score(Y_test, predictions) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))
```

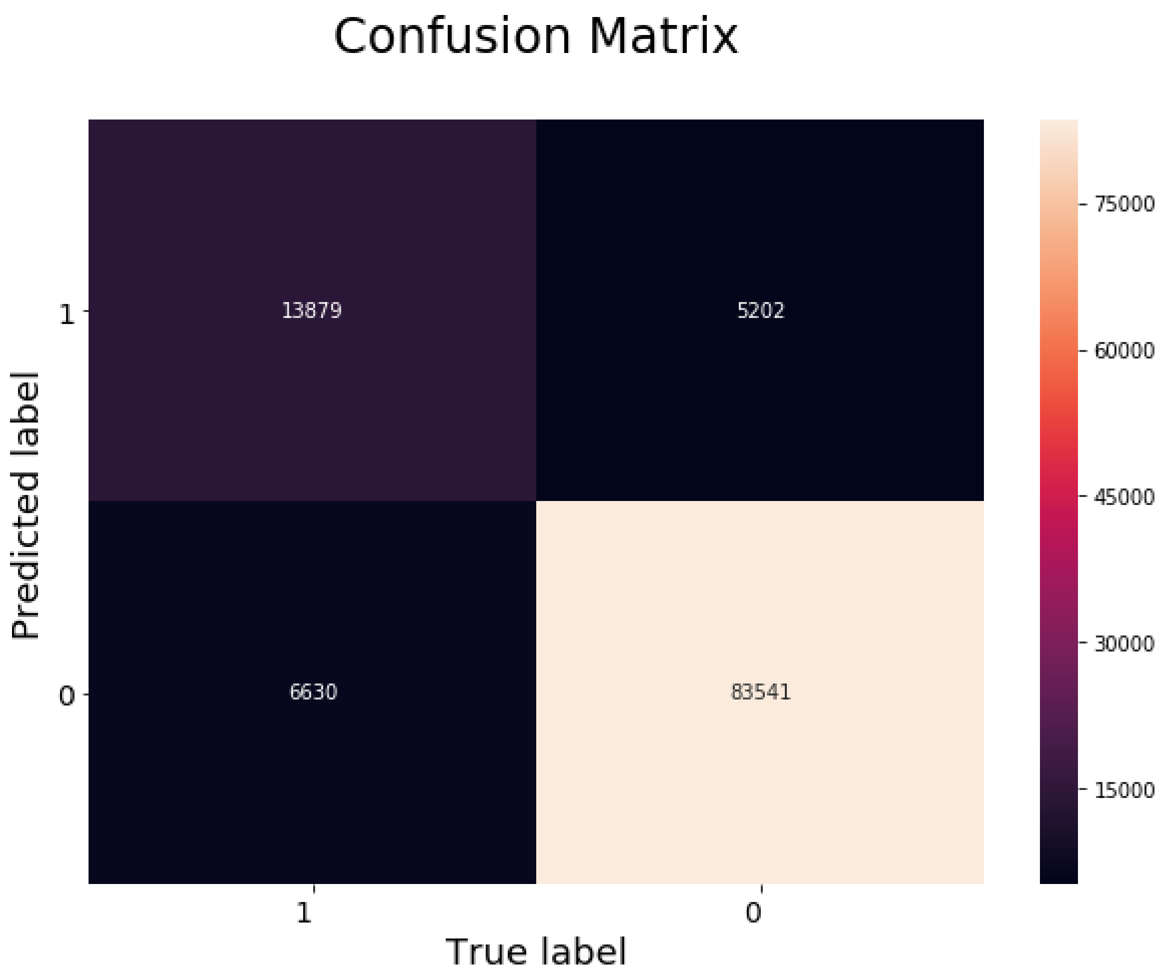
```
# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 1)
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
Accuracy of the Multinomial naive Bayes of alpha = 1.000 is 89.169992%

Precision of the Multinomial naive Bayes of alpha = 1.000 is 0.941381

Recall of the Multinomial naive Bayes of alpha = 1.000 is 0.926473

F1-Score of the Multinomial naive Bayes of alpha = 1.000 is 0.933868
```

In [16]:

```
# Code for drawing seaborn heatmaps
#test confusion matrics
class_names = [1,0]
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=
class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
```

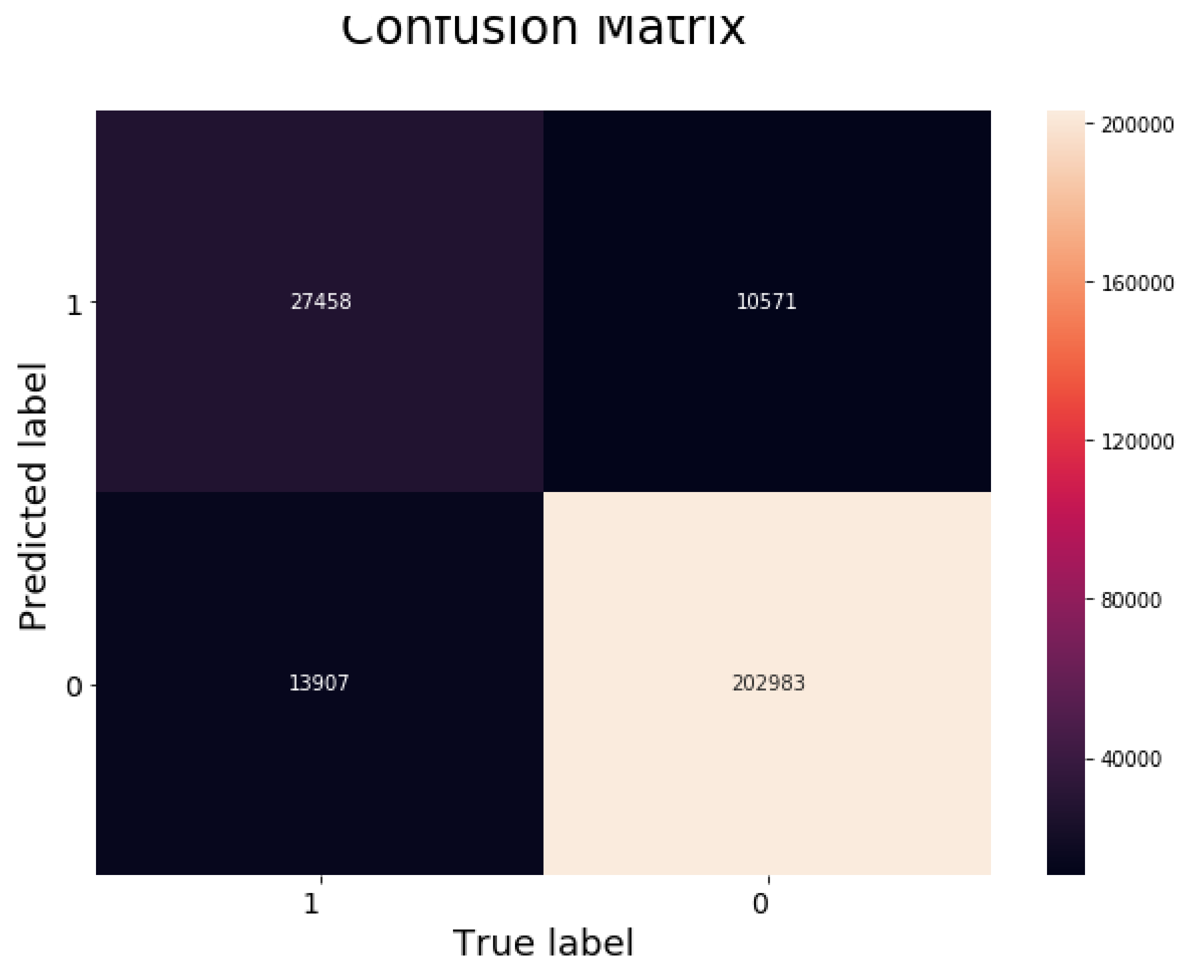
```
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



Accuracy on train data set

In [17]:
```
# Code for drawing seaborn heatmaps
#train confusion matrics
class_names = [1,0]
```

```python
df_heatmap = pd.DataFrame(confusion_matrix(Y_train, mnb1.predict(X_trai
n_vec)), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



In [18]:

```
# evaluate accuracy on train data set
acc = accuracy_score(Y_train,mnb1.predict(X_train_vec) ) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))

# evaluate precision
acc = precision_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1
)
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
f' % (optimal_alpha, acc))
```

```
# evaluate recall
acc = recall_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
Accuracy of the Multinomial naive Bayes of alpha = 1.000 is 90.397734%

Precision of the Multinomial naive Bayes of alpha = 1.000 is 0.950500

Recall of the Multinomial naive Bayes of alpha = 1.000 is 0.935880

F1-Score of the Multinomial naive Bayes of alpha = 1.000 is 0.943133
```

[5.2] Applying Naive Bayes on TFIDF, SET 2

In [19]:
```
# Please write all the code with proper documentation
tf_idf_vect = TfidfVectorizer(min_df=10)
X_train_vec = tf_idf_vect.fit_transform(X_train)
X_test_vec = tf_idf_vect.transform(X_test)
print("the type of count vectorizer :",type(X_train_vec))
print("the shape of out text TFIDF vectorizer : ",X_train_vec.get_shape
())
print("the number of unique words :", X_train_vec.get_shape()[1])
```

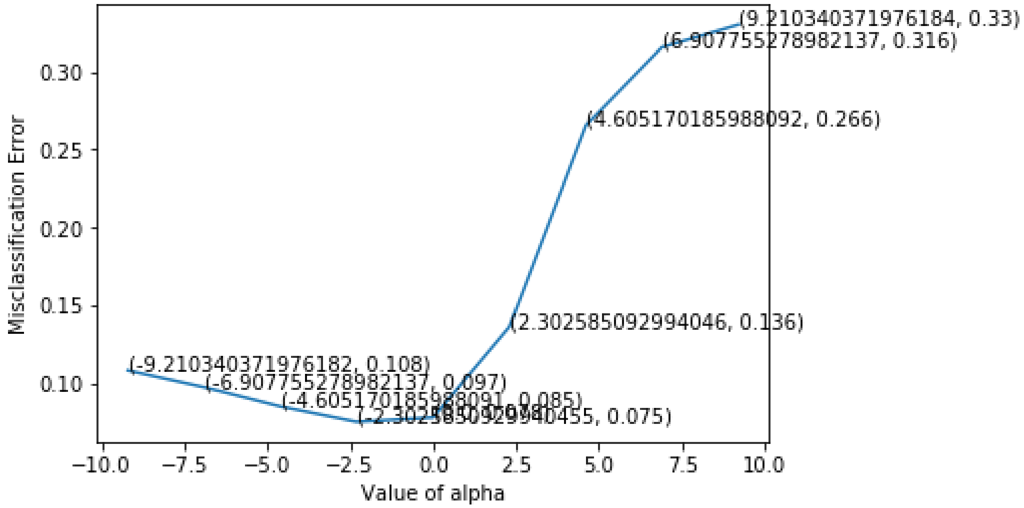
```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (254919, 12671)
the number of unique words : 12671
```

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

# Creating alpha values in the range from 10^-4 to 10^4
```

```
neighbors = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
# empty list that will hold cv scores
cv_scores = []
training_scores =[]
# perform 10-fold cross validation
for k in neighbors:
    nb = MultinomialNB(alpha=k)
    nb.fit(X_train_vec, Y_train)
    #print(nb.predict(X_test[2:39]))
    scores = cross_val_score(nb, X_test_vec, Y_test, cv=10, scoring='ro
c_auc')
    scores_training = nb.fit(X_train_vec, Y_train).score(X_train_vec, Y
_train)
    cv_scores.append(scores.mean())
    training_scores.append(scores_training)
    #print((nb))

MSE = [1 - x for x in cv_scores]
#determining best k
optimal_alpha = neighbors[MSE.index(min(MSE))]
print('\nThe optimal value of alpha is %.8f.' % optimal_alpha)

plt.plot(np.log(neighbors), MSE)

for xy in zip(np.log(neighbors), np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Value of alpha')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each k value is : ", np.round(MS
E,3))
plt.plot(np.log(neighbors), cv_scores, 'r')
plt.plot(np.log(neighbors), training_scores, 'b')
plt.xlabel('alpha')
plt.ylabel('score')

# determining best value of alpha
```

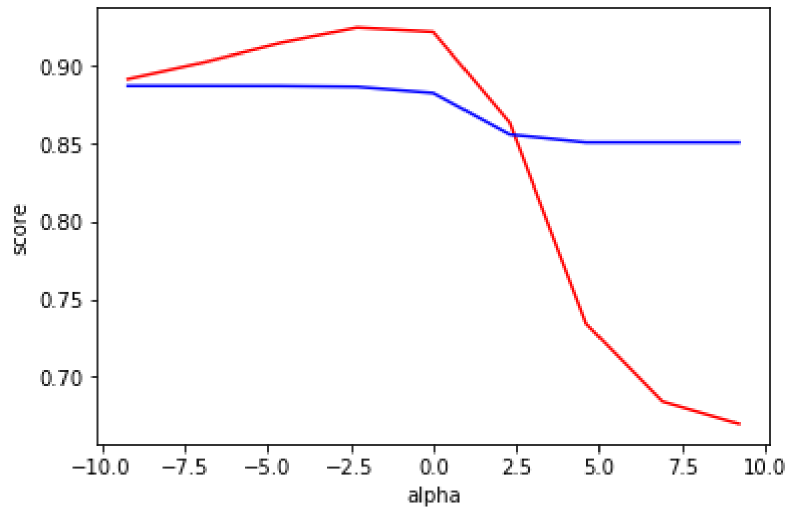
```
#best_alpha = neighbors[cv_scores.index(max(cv_scores))]
#print('\nThe optimal value of alpha is %.3f.' % best_alpha)
```

```
The optimal value of alpha is 0.10000000.
```




```
the misclassification error for each k value is :  [0.108 0.097 0.085
0.075 0.078 0.136 0.266 0.316 0.33 ]
```

Out[20]: Text(0,0.5,'score')



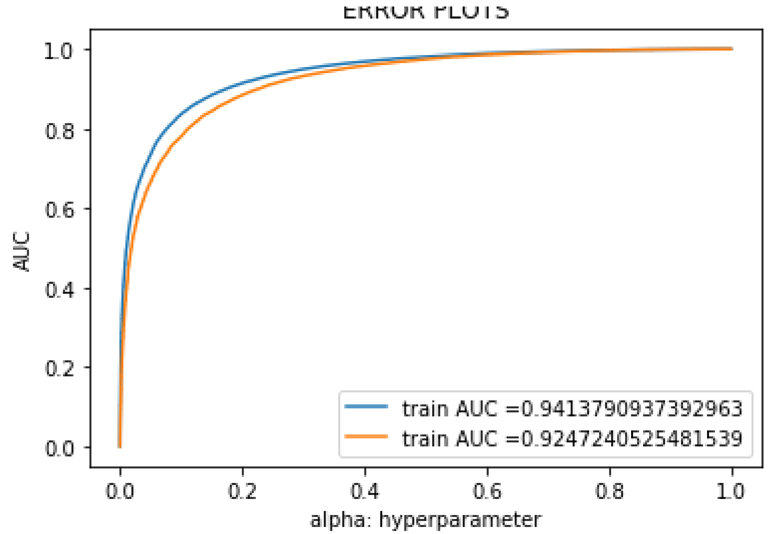
In [21]:
```
# ============================== Multinomial Naive Bayes with alpha = o
ptimal_alpha ============================================
# instantiate learning model alpha = optimal_alpha
from sklearn.metrics import accuracy_score
mnb1 = MultinomialNB(alpha = optimal_alpha)

# fitting the model
mnb1.fit(X_train_vec, Y_train)

# predict the response
predictions= mnb1.predict(X_test_vec)
predictions1= mnb1.predict(X_train_vec)

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

# Variables that will be used for  making table in Conclusion part of t
his assignment
tfidf_mnb_alpha = optimal_alpha
```

```
tfidf_mnb_train_acc = max(cv_scores)*100
tfidf_mnb_test_acc = acc
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha =
0.100 is 86.599788%
```

In [22]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc

# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(Y_train, mnb1.predict_prob
a(X_train_vec)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(Y_test, mnb1.predict_proba(X
_test_vec)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test
_tpr)))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(Y_train, mnb1.predict(X_train_vec)))
print("Test confusion matrix")
print(confusion_matrix(Y_test, mnb1.predict(X_test_vec)))
```




```
==========================================================================================================
Train confusion matrix
[[ 10192  27837]
 [  1029 215861]]
Test confusion matrix
[[ 4943 14138]
 [  502 89669]]
```

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

In [23]:

```
# Please write all the code with proper documentation
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = pos_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemgetter(1), reverse = True)
print("Postive top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])
```

```
Postive top 10 important features are:
('like', -4.40894771917271)
```

```
('tast', -4.47930292964824)
('good', -4.614126623248737)
('flavor', -4.6357357369625625)
('love', -4.66429007687182)
('great', -4.684453739591529)
('use', -4.706008320452014)
('one', -4.762344073425835)
('product', -4.848698285348165)
('tea', -4.856661564089681)
```

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

In [24]:

```
# Please write all the code with proper documentation
# top 10  features
nb = MultinomialNB(alpha=optimal_alpha).fit(X_train_vec, Y_train)
pos_imp_features = nb.feature_log_prob_[1,:]
neg_imp_features = nb.feature_log_prob_[0,:]


imp_features = {}
feature_names= count_vect.get_feature_names()
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = neg_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemget
ter(1), reverse = True)
print("\n\nNegative top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])
```

```
Negative top 10 important features are:
('probabl', -5.323152765579801)
('fruit', -5.333199555522202)
('diabet', -5.462993387162749)
('creativ', -5.56281606872518)
('lodg', -5.617180870847336)
('sever', -5.6207953076083825)

('matter', -5.648986574169769)
```

```
('santa', -5.663096226251608)
('outsid', -5.7395052235046435)
('cal', -5.781468980250179)
```

Accuracy on test data

In [25]:

```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 1)
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
 Accuracy of the Multinomial naive Bayes of alpha = 0.100 is 86.599788%

 Precision of the Multinomial naive Bayes of alpha = 0.100 is 0.863805

 Recall of the Multinomial naive Bayes of alpha = 0.100 is 0.994433

 F1-Score of the Multinomial naive Bayes of alpha = 0.100 is 0.924528
```

In [26]:

```
# Code for drawing seaborn heatmaps
class_names = [1,0]
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=
```

```
class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

Accuracy On train data

In [27]:
```
# evaluate accuracy on train data set
acc = accuracy_score(Y_train,mnb1.predict(X_train_vec) ) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))
```

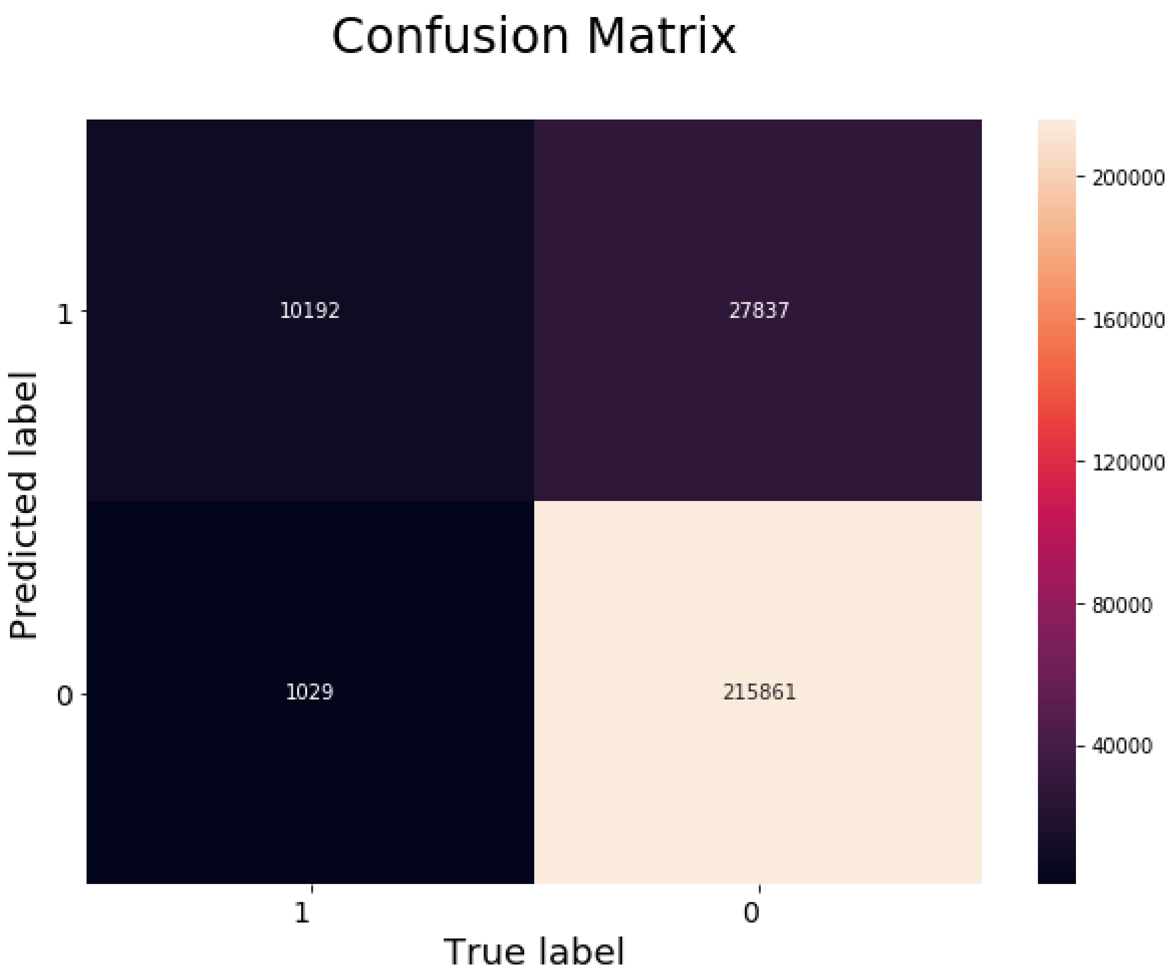
```
# evaluate precision
acc = precision_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1
)
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
Accuracy of the Multinomial naive Bayes of alpha = 0.100 is 88.676403%

Precision of the Multinomial naive Bayes of alpha = 0.100 is 0.885773

Recall of the Multinomial naive Bayes of alpha = 0.100 is 0.995256

F1-Score of the Multinomial naive Bayes of alpha = 0.100 is 0.937328
```

In [28]:

```
# Code for drawing seaborn heatmaps
#train confusion matrics
class_names = [1,0]
df_heatmap = pd.DataFrame(confusion_matrix(Y_train, mnb1.predict(X_trai
n_vec)), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
```

```
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



(a). Procedure followed :

- STEP 1 :- Text Preprocessing
- STEP 2:- Time-based splitting of whole dataset into train_data and test_data

- STEP 3:- Training the vectorizer on train_data and later applying same vectorizer on both train_data and test_data to transform them into vectors
- STEP 4:- Using Bernoulli Naive Bayes as an estimator in 10-Fold Cross-Validation in order to find optimal value of alpha .
- STEP 5:- Draw various plots auc's vs aplha,k
- STEP 6:- Once , we get optimal value of alpha then train BernoulliNB again with this optimal alpha and make predictions on test_data
- STEP 7:- Find important features per class
- STEP 8 :- Evaluate : Accuracy , F1-Score , Precision , Recall , TPR , FPR , TNR , FNR
- STEP 9:- Draw Seaborn Heatmap for Confusion Matrix .

[6] Conclusions

In [29]:

```
# Creating table using PrettyTable library
from prettytable import PrettyTable

model = ["MultinomialNB for BoW", "MultinomialNB for TFIDF"]

best_alpha = [bow_mnb_alpha, tfidf_mnb_alpha]

train_acc = [bow_mnb_train_acc, tfidf_mnb_train_acc]

test_acc = [bow_mnb_test_acc, tfidf_mnb_test_acc]

sno = [1,2]

F1_score = [0.941, 0.932]

# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",sno)
ptable.add_column("MODEL",model)
ptable.add_column("Best Alpha",best_alpha)
```

```
ptable.add_column("Training Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)
ptable.add_column("F1 Score",F1_score)

# Printing the Table
print(ptable)
```

```
+-------+-----------------------+-----------+------------------+---
---------------+----------+
| S.NO. |         MODEL         | Best Alpha | Training Accuracy |
Test Accuracy    | F1 Score |
+-------+-----------------------+-----------+------------------+---
---------------+----------+
|   1   |  MultinomialNB for BoW  |     1     | 91.76017755886518 | 8
9.16999231135357 |  0.941   |
|   2   | MultinomialNB for TFIDF |    0.1    | 92.48399385232894 | 8
6.59978764690807 |  0.932   |
+-------+-----------------------+-----------+------------------+---
---------------+----------+
```

feature engineering

here i combined {cleaned text} and {summary} twice

In [30]:

```
conn = sqlite3.connect('featureeng.sqlite')
final = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3
 """, conn)
final.head()
```

Out[30]:

	level_0	index	Id	ProductId	UserId	ProfileName	HelpfulnessNu

	level_0	index	Id	ProductId	UserId	ProfileName	HelpfulnessNu
0	0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0
1	1	138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1
2	2	138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1
3	3	138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1

	level_0	index	Id	ProductId	UserId	ProfileName	HelpfulnessNu
4	4	138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3

In [31]:
```
print(final['CleanedText'][0])
```

```
witti littl book make son laugh loud recit car drive along alway sing r
efrain hes learn whale india droop love new word book introduc silli cl
assic book will bet son still abl recit memori colleg witti littl book
make son laugh loud recit car drive along alway sing refrain hes learn
whale india droop love new word book introduc silli classic book will b
et son still abl recit memori colleg everi book educ everi book educ
```

In [32]:
```
from sklearn.model_selection import train_test_split
##Sorting data according to Time in ascending order for Time Based Spli
tting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, in
place=False, kind='quicksort', na_position='last')

X = time_sorted_data['CleanedText'].values
Y = time_sorted_data['Score']

# split the data set into train and test
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.3,
 shuffle=False)
```

In [33]:
```
print(X_train.shape, Y_train.shape)
print(X_test.shape, Y_test.shape)
```

```
(254919,) (254919,)
(109252,) (109252,)
```

Naive bayes bow

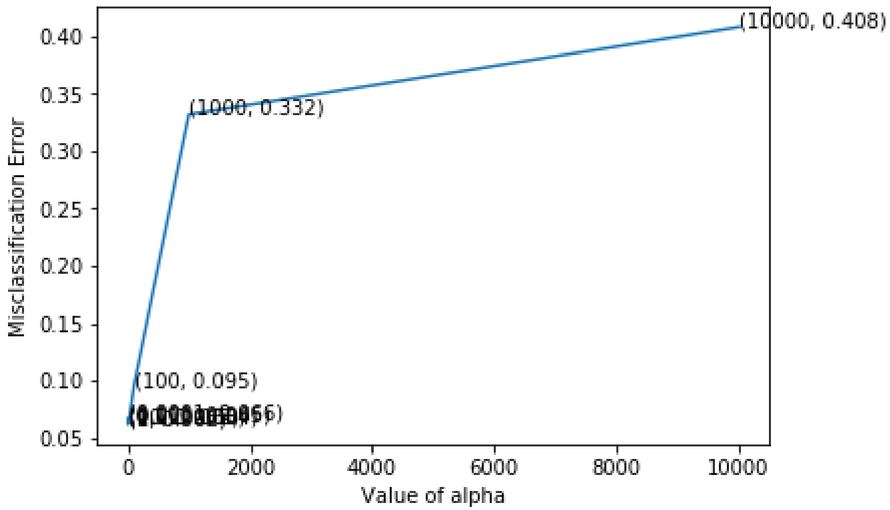
In [55]:
```
#BoW
count_vect = CountVectorizer(min_df = 50)
X_train_vec = count_vect.fit_transform(X_train)
X_test_vec = count_vect.transform(X_test)
print("the type of count vectorizer :",type(X_train_vec))
print("the shape of out text BOW vectorizer : ",X_train_vec.get_shape
())
print("the number of unique words :", X_train_vec.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (254919, 6219)
the number of unique words : 6219
```

In [56]:
```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score

# Creating alpha values in the range from 10^-4 to 10^4
neighbors = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
# empty list that will hold cv scores
cv_scores = []
training_scores =[]
# perform 10-fold cross validation
for k in neighbors:
    nb = MultinomialNB(alpha=k)
    nb.fit(X_train_vec, Y_train)
    #print(nb.predict(X_test[2:39]))
    scores = cross_val_score(nb, X_test_vec, Y_test, cv=10, scoring='ro
c_auc')
    scores_training = nb.fit(X_train_vec, Y_train).score(X_train_vec, Y
_train)
    cv_scores.append(scores.mean())
    training_scores.append(scores_training)
```

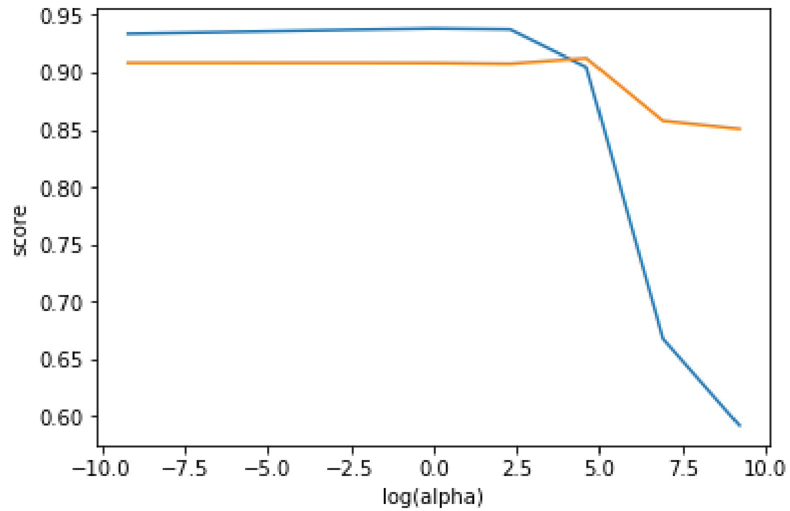
```
    #print((nb))

MSE = [1 - x for x in cv_scores]
#determining bst k
optimal_alpha = neighbors[MSE.index(min(MSE))]
print('\nThe optimal value of alpha is %.8f.' % optimal_alpha)

plt.plot(neighbors, MSE)

for xy in zip(neighbors, np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Value of alpha')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each k value is : ", np.round(MS
E,3))
plt.plot(np.log(neighbors), cv_scores)
plt.plot(np.log(neighbors), training_scores)
plt.xlabel('log(alpha)')
plt.ylabel('score')

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

```
The optimal value of alpha is 1.00000000.
```




```
the misclassification error for each k value is :  [0.066 0.065 0.064
0.063 0.062 0.063 0.095 0.332 0.408]
```

Out[56]:
```
Text(0,0.5,'score')
```



In [37]:
```
# ============================ Multinomial Naive Bayes with alpha = o
```

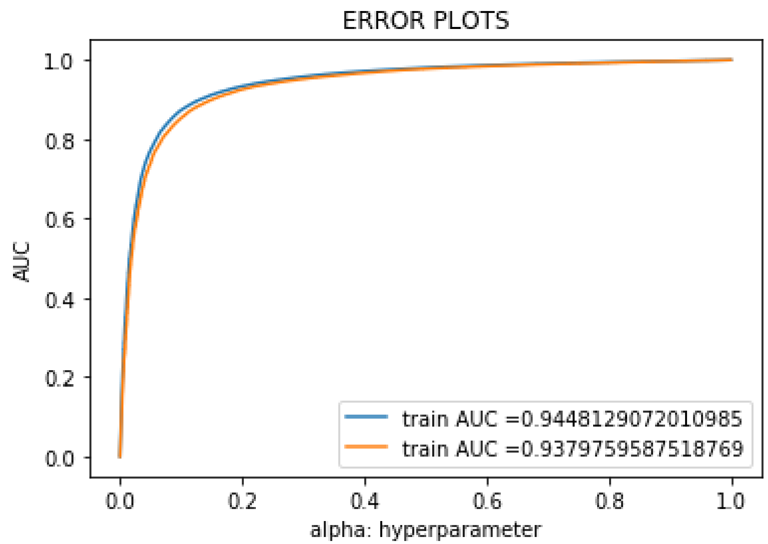
```
ptimal_alpha ============================================
# instantiate learning model alpha = optimal_alpha
from sklearn.metrics import accuracy_score
mnb1 = MultinomialNB(alpha = optimal_alpha)

# fitting the model
mnb1.fit(X_train_vec, Y_train)

# predict the response
predictions= mnb1.predict(X_test_vec)
predictions1= mnb1.predict(X_train_vec)

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

# Variables that will be used for  making table in Conclusion part of t
his assignment
bow_mnb_alpha = optimal_alpha
bow_mnb_train_acc = max(cv_scores)*100
bow_mnb_test_acc = acc
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha =
1.000 is 89.687145%
```

In [38]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc

# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(Y_train, mnb1.predict_prob
a(X_train_vec)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(Y_test, mnb1.predict_proba(X
_test_vec)[:,1])
```

```python
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test
_tpr)))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(Y_train, mnb1.predict(X_train_vec)))
print("Test confusion matrix")
print(confusion_matrix(Y_test, mnb1.predict(X_test_vec)))
```




```
====================================================================================================
Train confusion matrix
[[ 31438   6591]
 [ 16758 200132]]
```

```
Test confusion matrix
[[15845  3236]
 [ 8031 82140]]
```

top feaatures

In [39]:
```
# Please write all the code with proper documentation
# top 10  features
import operator
from nltk.probability import FreqDist, DictionaryProbDist, ELEProbDist,
 sum_logs
from nltk.classify.api import ClassifierI
from nltk.classify.naivebayes import NaiveBayesClassifier
nb = MultinomialNB(alpha=optimal_alpha).fit(X_train_vec, Y_train)
pos_imp_features = nb.feature_log_prob_[1,:]
neg_imp_features = nb.feature_log_prob_[0,:]


imp_features = {}
feature_names= count_vect.get_feature_names()
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = neg_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemget
ter(1), reverse = True)
print("\n\nNegative top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])


for i in range(len(feature_names)):
    imp_features[feature_names[i]] = pos_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemget
ter(1), reverse = True)
print("Postive top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])
```

```
Negative top 10 important features are:
('tast', -4.121339830375106)
('like', -4.241897689477554)
('product', -4.420751321071874)
('flavor', -4.71711501591672)
('one', -4.7313051044323835)
('would', -4.892526612966876)
('tri', -4.896172774039712)
('good', -4.905849596162241)
('coffe', -5.005919819152609)
('use', -5.0662578511971805)
Postive top 10 important features are:
('great', -4.384114458401665)
('like', -4.436313730832627)
('tast', -4.446972529290646)
('good', -4.452495879427524)
('love', -4.547745136136161)
('flavor', -4.633749554154672)
('use', -4.758270705270817)
('tea', -4.779857906273282)
('product', -4.796793016587792)
('one', -4.8027358293294)
```

Accuracy on test data

In [40]:

```
# evaluate accuracy
#libraries
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

acc = accuracy_score(Y_test, predictions) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 1)
```

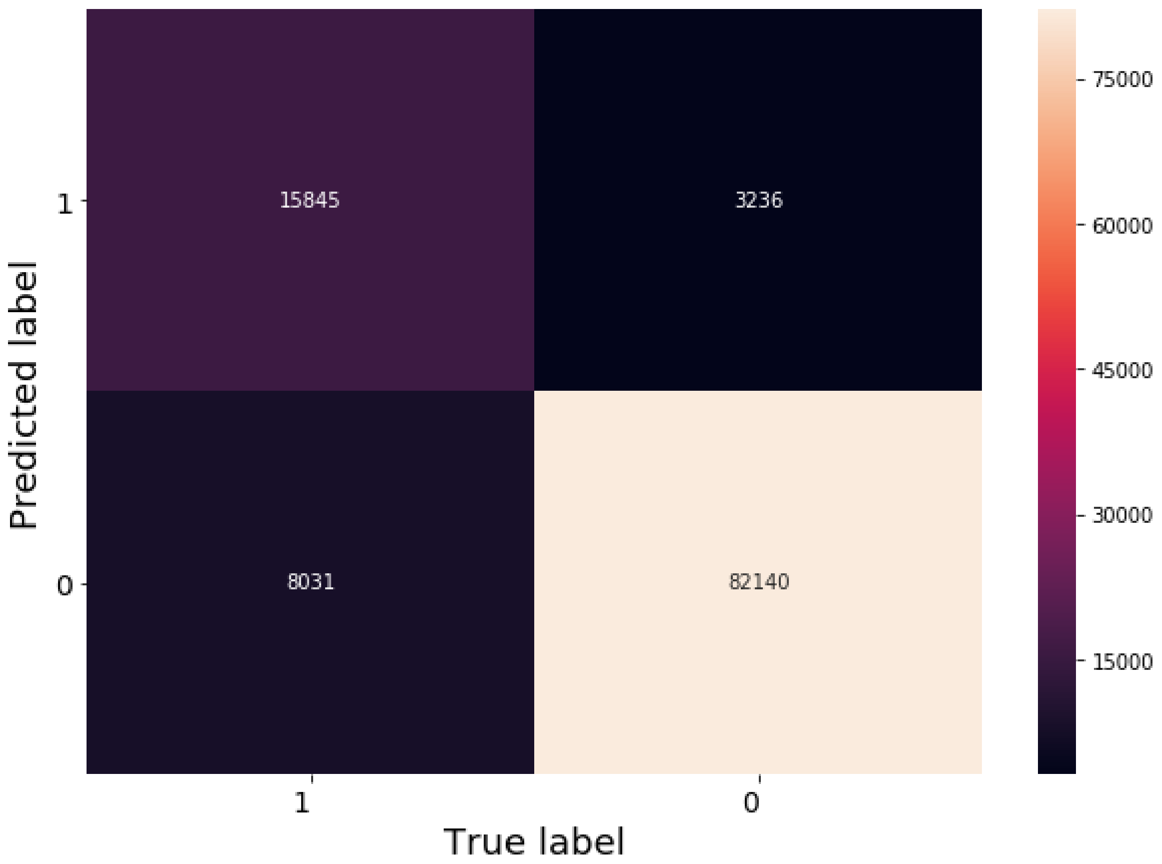
```
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
Accuracy of the Multinomial naive Bayes of alpha = 1.000 is 89.687145%

Precision of the Multinomial naive Bayes of alpha = 1.000 is 0.962097

Recall of the Multinomial naive Bayes of alpha = 1.000 is 0.910936

F1-Score of the Multinomial naive Bayes of alpha = 1.000 is 0.935818
```

In [41]:

```
# Code for drawing seaborn heatmaps
#test confusion matrics
class_names = [1,0]
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=
class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

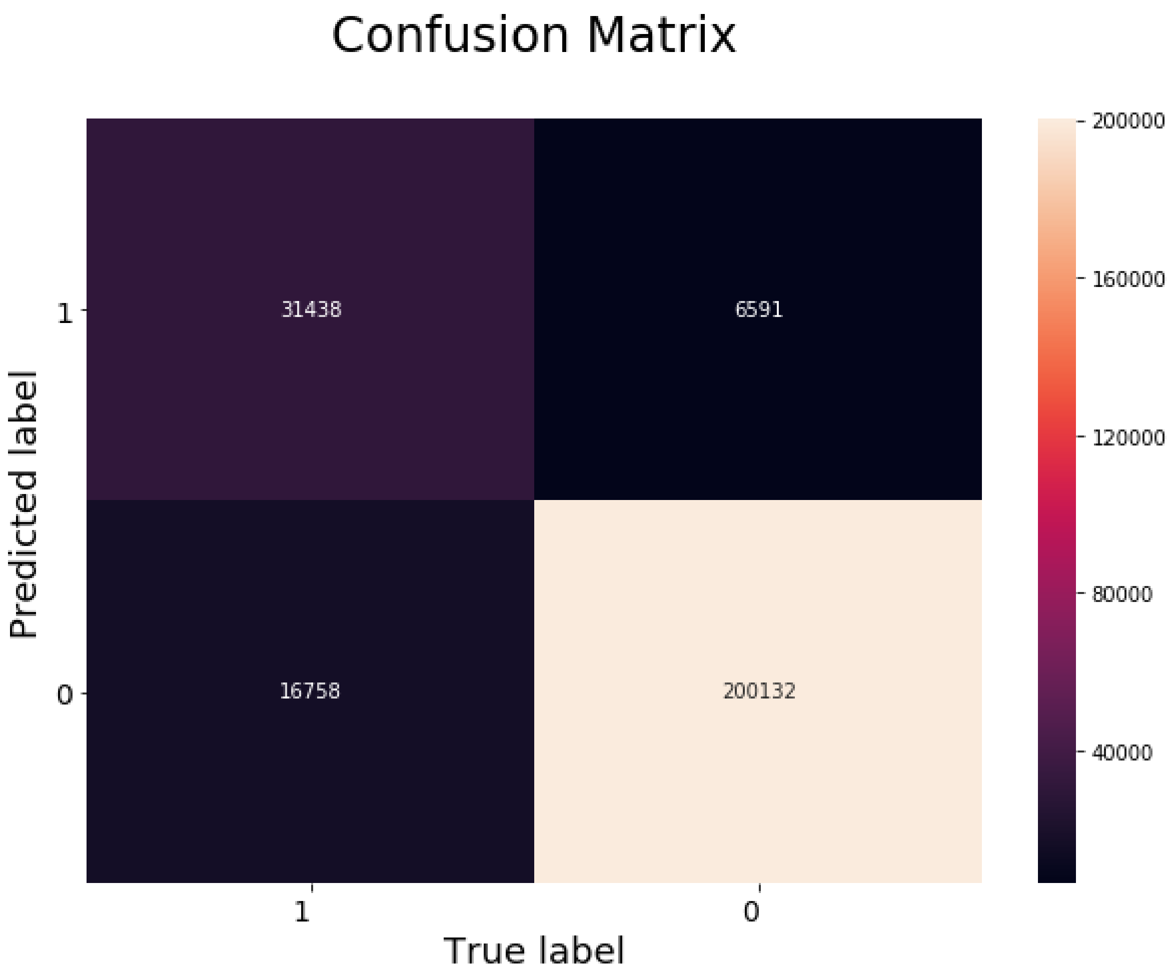
Confusion Matrix



Accuracy on train data

In [42]:
```
# Code for drawing seaborn heatmaps
#train confusion matrics
class_names = [1,0]
df_heatmap = pd.DataFrame(confusion_matrix(Y_train, mnb1.predict(X_trai
n_vec)), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
```

```python
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



In [43]:

```
# evaluate accuracy on train data set
acc = accuracy_score(Y_train,mnb1.predict(X_train_vec) ) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))

# evaluate precision
acc = precision_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1
)
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
```

```
f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
Accuracy of the Multinomial naive Bayes of alpha = 1.000 is 90.840620%

Precision of the Multinomial naive Bayes of alpha = 1.000 is 0.968117

Recall of the Multinomial naive Bayes of alpha = 1.000 is 0.922735

F1-Score of the Multinomial naive Bayes of alpha = 1.000 is 0.944881
```

on tfidf

In [44]:

```
# Please write all the code with proper documentation
tf_idf_vect = TfidfVectorizer(min_df=10)
X_train_vec = tf_idf_vect.fit_transform(X_train)
X_test_vec = tf_idf_vect.transform(X_test)
print("the type of count vectorizer :",type(X_train_vec))
print("the shape of out text TFIDF vectorizer : ",X_train_vec.get_shape
())
print("the number of unique words :", X_train_vec.get_shape()[1])
```

```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (254919, 13053)
the number of unique words : 13053
```

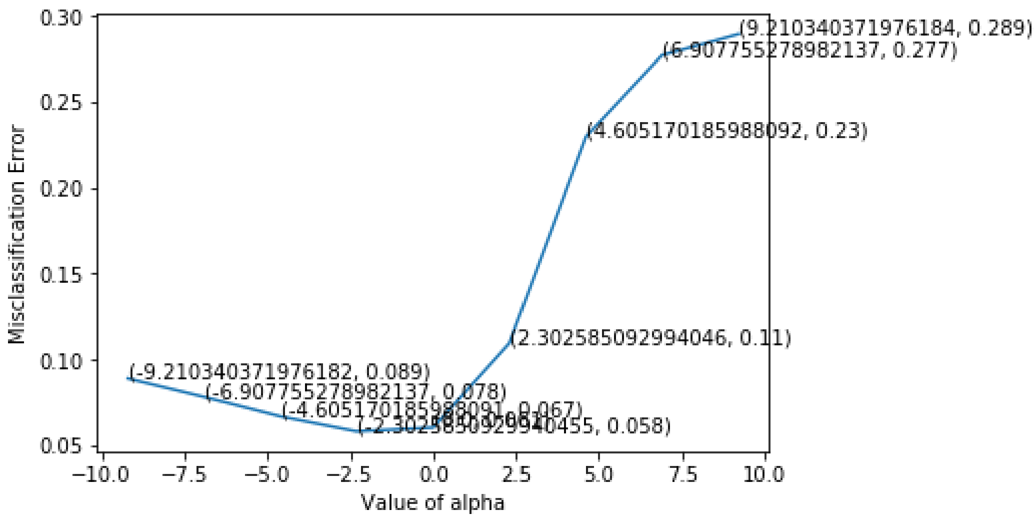
In [46]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
```

```
# Creating alpha values in the range from 10^-4 to 10^4
neighbors = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
# empty list that will hold cv scores
cv_scores = []
training_scores =[]
# perform 10-fold cross validation
for k in neighbors:
    nb = MultinomialNB(alpha=k)
    nb.fit(X_train_vec, Y_train)
    #print(nb.predict(X_test[2:39]))
    scores = cross_val_score(nb, X_test_vec, Y_test, cv=10, scoring='ro
c_auc')
    scores_training = nb.fit(X_train_vec, Y_train).score(X_train_vec, Y
_train)
    cv_scores.append(scores.mean())
    training_scores.append(scores_training)
    #print((nb))

MSE = [1 - x for x in cv_scores]
#determining best k
optimal_alpha = neighbors[MSE.index(min(MSE))]
print('\nThe optimal value of alpha is %.8f.' % optimal_alpha)

plt.plot(np.log(neighbors), MSE)

for xy in zip(np.log(neighbors), np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Value of alpha')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each k value is : ", np.round(MS
E,3))
plt.plot(np.log(neighbors), cv_scores, 'r')
plt.plot(np.log(neighbors), training_scores, 'b')
plt.xlabel('alpha')
plt.ylabel('score')
```

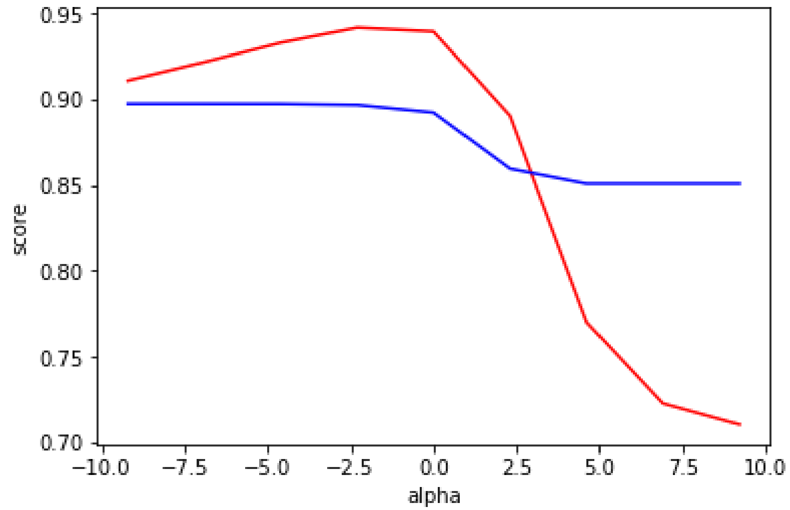
```
# determining best value of alpha
#best_alpha = neighbors[cv_scores.index(max(cv_scores))]
#print('\nThe optimal value of alpha is %.3f.' % best_alpha)
```

The optimal value of alpha is 0.10000000.



the misclassification error for each k value is : [0.089 0.078 0.067
0.058 0.061 0.11 0.23 0.277 0.289]

Out[46]: Text(0,0.5,'score')



In [47]:
```
# ============================== Multinomial Naive Bayes with alpha = o
ptimal_alpha ============================================
# instantiate learning model alpha = optimal_alpha
from sklearn.metrics import accuracy_score
mnb1 = MultinomialNB(alpha = optimal_alpha)

# fitting the model
mnb1.fit(X_train_vec, Y_train)

# predict the response
predictions= mnb1.predict(X_test_vec)
predictions1= mnb1.predict(X_train_vec)

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

# Variables that will be used for  making table in Conclusion part of t
his assignment
tfidf_mnb_alpha = optimal_alpha
```

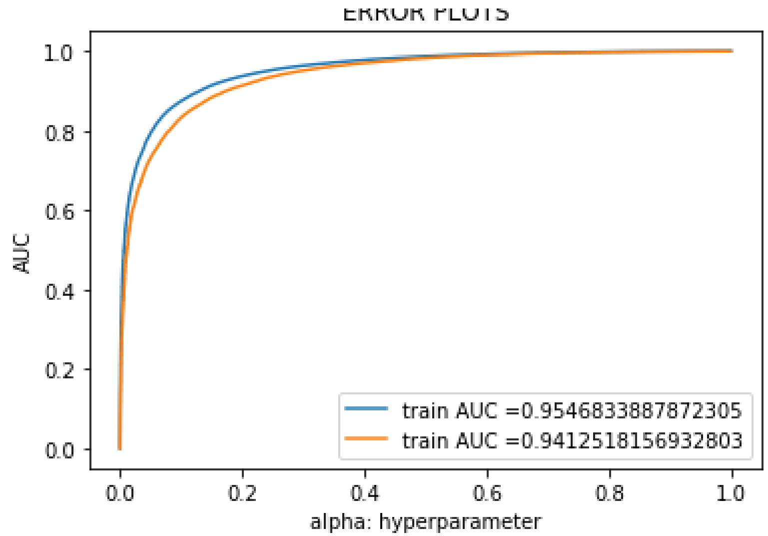
```
tfidf_mnb_train_acc = max(cv_scores)*100
tfidf_mnb_test_acc = acc
```

```
The Test Accuracy of the Multinomial naive Bayes classifier for alpha =
0.100 is 87.818072%
```

In [48]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc
_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc

# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
y estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(Y_train, mnb1.predict_prob
a(X_train_vec)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(Y_test, mnb1.predict_proba(X
_test_vec)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
rain_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test
_tpr)))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print("="*100)

from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(Y_train, mnb1.predict(X_train_vec)))
print("Test confusion matrix")
print(confusion_matrix(Y_test, mnb1.predict(X_test_vec)))
```

ERROR PLOTS




```
=======================================================================
=============================
Train confusion matrix
[[ 12814  25215]
 [  1124 215766]]
Test confusion matrix
[[ 6300 12781]
 [  528 89643]]
```

top features

In [49]:

```
# Please write all the code with proper documentation
# top 10  features
import operator
from nltk.probability import FreqDist, DictionaryProbDist, ELEProbDist,
 sum_logs
from nltk.classify.api import ClassifierI
from nltk.classify.naivebayes import NaiveBayesClassifier
nb = MultinomialNB(alpha=optimal_alpha).fit(X_train_vec, Y_train)
pos_imp_features = nb.feature_log_prob_[1,:]
neg_imp_features = nb.feature_log_prob_[0,:]
```

```python
imp_features = {}
feature_names= count_vect.get_feature_names()
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = neg_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemgetter(1), reverse = True)
print("\n\nNegative top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])


for i in range(len(feature_names)):
    imp_features[feature_names[i]] = pos_imp_features[i]
names_diff_sorted = sorted(imp_features.items(), key = operator.itemgetter(1), reverse = True)
print("Postive top 10 important features are:")
for i in range(10):
    print(names_diff_sorted[i])
```

```
Negative top 10 important features are:
('procedur', -5.312587448981749)
('frys', -5.318103599134482)
('logic', -5.469848179132611)
('diamet', -5.470594991668931)
('shallow', -5.568710118651474)
('matter', -5.607535304607177)
('creativ', -5.609405435847388)
('cake', -5.653858336588055)
('satiat', -5.7055347498175975)
('outing', -5.789471974356955)
Postive top 10 important features are:
('skippi', -4.851330484981341)
('shallow', -5.0082087311264285)
('frys', -5.134762873626148)
('procedur', -5.206547838510216)
('citi', -5.394596512032123)

('satiat', -5.640891803498752)
```

```
('safial', -5.640891803498752)
('quit', -5.650236142479857)
('marshmallow', -5.682865187640305)
('diamet', -5.699873409450561)
('back', -5.727390200429296)
```

Accuracy on test data

In [50]:

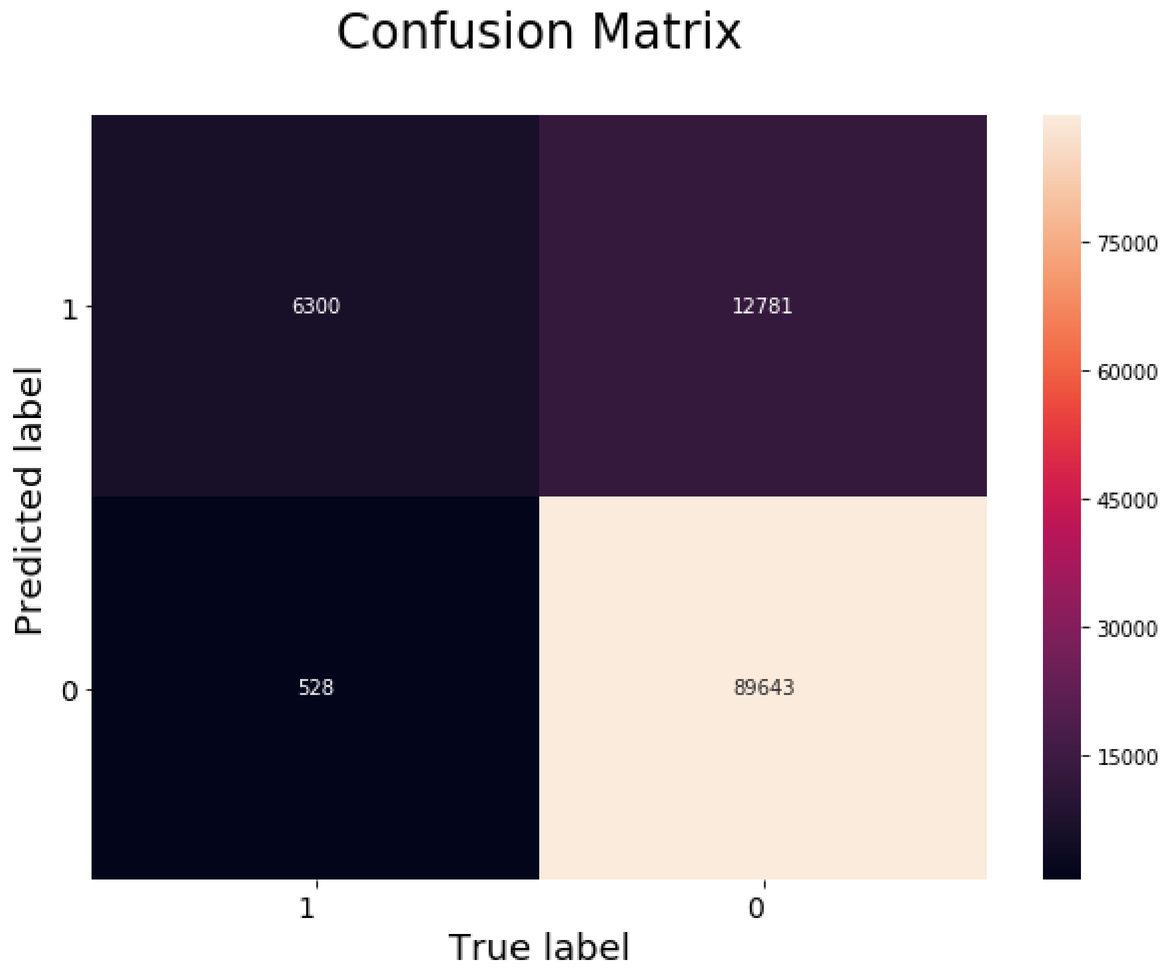
```
# evaluate accuracy
acc = accuracy_score(Y_test, predictions) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))

# evaluate precision
acc = precision_score(Y_test, predictions, pos_label = 1)
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(Y_test, predictions, pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_test, predictions, pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
 Accuracy of the Multinomial naive Bayes of alpha = 0.100 is 87.818072%

 Precision of the Multinomial naive Bayes of alpha = 0.100 is 0.875215

 Recall of the Multinomial naive Bayes of alpha = 0.100 is 0.994144

 F1-Score of the Multinomial naive Bayes of alpha = 0.100 is 0.930896
```

In [51]:

```
# Code for drawing seaborn heatmaps
class_names = [1,0]
```

```
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, predictions), index=
class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



Accuracy on train data

In [52]:
```
# evaluate accuracy on train data set
acc = accuracy_score(Y_train,mnb1.predict(X_train_vec) ) * 100
print('\n Accuracy of the Multinomial naive Bayes of alpha = %.3f is %
f%%' % (optimal_alpha, acc))
```

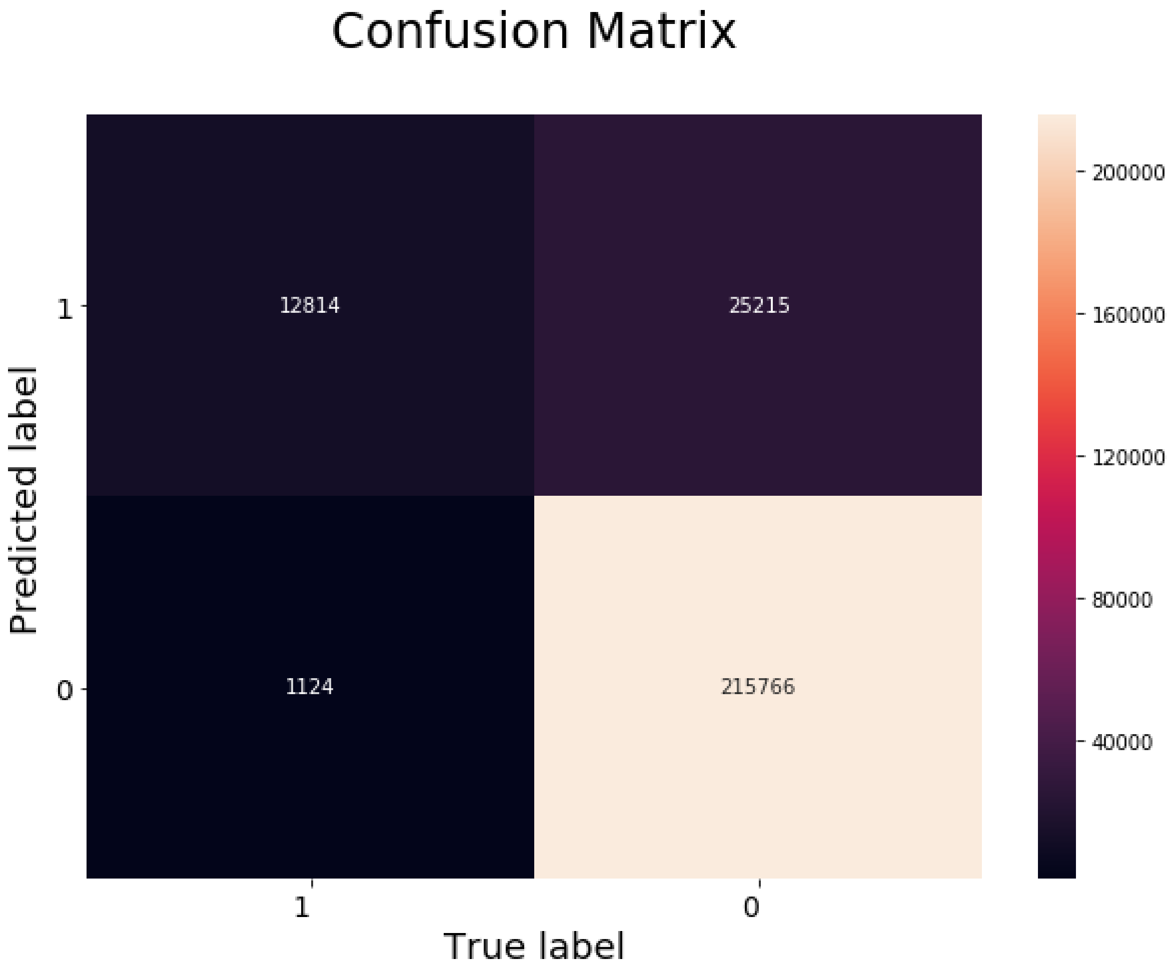
```
# evaluate precision
acc = precision_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1
)
print('\n Precision of the Multinomial naive Bayes of alpha = %.3f is %
f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n Recall of the Multinomial naive Bayes of alpha = %.3f is %f'
% (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(Y_train, mnb1.predict(X_train_vec), pos_label = 1)
print('\n F1-Score of the Multinomial naive Bayes of alpha = %.3f is %f
' % (optimal_alpha, acc))
```

```
Accuracy of the Multinomial naive Bayes of alpha = 0.100 is 89.667698%

Precision of the Multinomial naive Bayes of alpha = 0.100 is 0.895365

Recall of the Multinomial naive Bayes of alpha = 0.100 is 0.994818

F1-Score of the Multinomial naive Bayes of alpha = 0.100 is 0.942475
```

In [53]:

```
# Code for drawing seaborn heatmaps
#train confusion matrics
class_names = [1,0]
df_heatmap = pd.DataFrame(confusion_matrix(Y_train, mnb1.predict(X_trai
n_vec)), index=class_names, columns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0
, ha='right', fontsize=14)
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
```

```
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



In [54]:

```
# Creating table using PrettyTable library
from prettytable import PrettyTable

model = ["MultinomialNB for BoW", "MultinomialNB for TFIDF"]

best_alpha = [bow_mnb_alpha, tfidf_mnb_alpha]
```

```
train_acc = [bow_mnb_train_acc, tfidf_mnb_train_acc]

test_acc = [bow_mnb_test_acc, tfidf_mnb_test_acc]

sno = [1,2]

F1_score = [0.941, 0.932]

# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",sno)
ptable.add_column("MODEL",model)
ptable.add_column("Best Alpha",best_alpha)
ptable.add_column("Training Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)
ptable.add_column("F1 Score",F1_score)

# Printing the Table
print(ptable)
```

```
+-------+-----------------------+-----------+-----------------+---
---------------+----------+
| S.NO. |         MODEL         | Best Alpha | Training Accuracy |
Test Accuracy    | F1 Score |
+-------+-----------------------+-----------+-----------------+---
---------------+----------+
|   1   |  MultinomialNB for BoW  |     1      | 93.81366874026789 | 8
9.68714531541757 |  0.941   |
|   2   | MultinomialNB for TFIDF |    0.1     |  94.172472790216  | 8
7.81807198037565 |  0.932   |
+-------+-----------------------+-----------+-----------------+---
---------------+----------+
```

procedure followed

- STEP 1 :- Text Preprocessing(where i combined cleaned text,summary twice)
- STEP 2:- Time-based splitting of whole dataset into train_data and test_data
- STEP 3:- Training the vectorizer on train_data and later applying same vectorizer on both train_data and test_data to transform them into vectors
- STEP 4:- Using Bernoulli Naive Bayes as an estimator in 10-Fold Cross-Validation in order to find optimal value of alpha .
- STEP 5:- Draw various plots auc's vs aplha,k
- STEP 6:- Once , we get optimal value of alpha then train BernoulliNB again with this optimal alpha and make predictions on test_data
- STEP 7:- Find important features per class
- STEP 8 :- Evaluate : Accuracy , F1-Score , Precision , Recall , TPR , FPR , TNR , FNR
- STEP 9:- Draw Seaborn Heatmap for Confusion Matrix .

conclusion

- by using feature engineering our performance of the models got increased slighlty
- observe the pretty table before and after feature engineering where accuracy got increased