Amazon Fine Food Reviews Analysis

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

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

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 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 [74]:
```
%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

from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter
from sklearn import cross_validation
```

[1]. Reading Data

In [75]:
```
# using SQLite Table to read data.
con = sqlite3.connect('D:\\TGM\\ML\\AmazonFineFoodReviews\\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 500000 da
ta 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 Score != 3
LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

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 score<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[75]:

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

In [76]:

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

In [77]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[77]:

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

In [78]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[78]:

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

In [79]:
```
display['COUNT(*)'].sum()
```

Out[79]: 393063

Exploratory Data Analysis

[2] 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 [80]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[80]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
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 can be seen above 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) 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 [81]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inp
lace=False, kind='quicksort', na_position='last')
```

In [82]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"
}, keep='first', inplace=False)
final.shape
```

Out[82]: (364173, 10)

In [83]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[83]: 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 [84]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[84]:

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

In [85]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [86]:
```
#Before starting the next phase of preprocessing lets see the number of entrie
s left
print(final.shape)

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

```
(364171, 10)
```

Out[86]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

[3]. Text Preprocessing.

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 [87]:
```
# 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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks i
s good, but I prefer bolder taste.... imagine my surprise when I ordered 2 bo
xes - both were expired! One expired back in 2005 for gosh sakes.  I admit th
at Amazon agreed to credit me for cost plus part of shipping, but geez, 2 yea
rs expired!!!  I'm hoping to find local San Diego area shoppe that carries po
ds so that I can try something different than starbucks.
==================================================
Great ingredients although, chicken should have been 1st rather than chicken
broth, the only thing I do not think belongs in it is Canola oil. Canola or r
apeseed is not someting a dog would ever find in nature and if it did find ra
peseed in nature and eat it, it would poison them. Today's Food industries ha
ve convinced the masses that Canola oil is a safe and even better oil than ol
ive or virgin coconut, facts though say otherwise. Until the late 70's it was
poisonous until they figured out a way to fix that. I still like it but it co
uld be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the
excellence of this product.<br /><br />Thick, delicious.  Perfect.  3 ingredi
ents: Water, Maltitol, Natural Maple Flavor.  PERIOD.  No chemicals.  No garb
age.<br /><br />Have numerous friends & family members hooked on this stuff.
My husband & son, who do NOT like "sugar free" prefer this over major label r
egular syrup.<br /><br />I use this as my SWEETENER in baking: cheesecakes, w
hite brownies, muffins, pumpkin pies, etc... Unbelievably delicious...<br /><
br />Can you tell I like it? :)
==================================================
```

In [88]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
```

In [89]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-rem
ove-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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
==================================================
I was really looking forward to these pods based on the reviews.  Starbucks i
s good, but I prefer bolder taste.... imagine my surprise when I ordered 2 bo
xes - both were expired! One expired back in 2005 for gosh sakes.  I admit th
at Amazon agreed to credit me for cost plus part of shipping, but geez, 2 yea
rs expired!!!  I'm hoping to find local San Diego area shoppe that carries po
ds so that I can try something different than starbucks.
==================================================
Great ingredients although, chicken should have been 1st rather than chicken
broth, the only thing I do not think belongs in it is Canola oil. Canola or r
apeseed is not someting a dog would ever find in nature and if it did find ra
peseed in nature and eat it, it would poison them. Today's Food industries ha
ve convinced the masses that Canola oil is a safe and even better oil than ol
ive or virgin coconut, facts though say otherwise. Until the late 70's it was
poisonous until they figured out a way to fix that. I still like it but it co
uld be better.
==================================================
Can't do sugar.  Have tried scores of SF Syrups.  NONE of them can touch the
excellence of this product.Thick, delicious.  Perfect.  3 ingredients: Water,
Maltitol, Natural Maple Flavor.  PERIOD.  No chemicals.  No garbage.Have nume
rous friends & family members hooked on this stuff.  My husband & son, who do
NOT like "sugar free" prefer this over major label regular syrup.I use this a
s my SWEETENER in baking: cheesecakes, white brownies, muffins, pumpkin pies,
etc... Unbelievably delicious...Can you tell I like it? :)
```

In [90]:
```
# 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 [91]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Great ingredients although, chicken should have been 1st rather than chicken
broth, the only thing I do not think belongs in it is Canola oil. Canola or r
apeseed is not someting a dog would ever find in nature and if it did find ra
peseed in nature and eat it, it would poison them. Today is Food industries h
ave convinced the masses that Canola oil is a safe and even better oil than o
live or virgin coconut, facts though say otherwise. Until the late 70 is it w
as poisonous until they figured out a way to fix that. I still like it but it
could be better.
==================================================
```

In [92]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/408403
9
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about wh
ales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my
son will STILL be able to recite from memory when he is  in college
```

In [93]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Great ingredients although chicken should have been 1st rather than chicken b
roth the only thing I do not think belongs in it is Canola oil Canola or rape
seed is not someting a dog would ever find in nature and if it did find rapes
eed in nature and eat it it would poison them Today is Food industries have c
onvinced the masses that Canola oil is a safe and even better oil than olive
or virgin coconut facts though say otherwise Until the late 70 is it was pois
onous until they figured out a way to fix that I still like it but it could b
e better
```

In [94]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st
step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours',
'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he'
, 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'it
self', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 't
hat', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have',
'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'becau
se', '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', 'how', 'a
ll', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'tha
n', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "shoul
d'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', "isn't", 'm
a', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shoul
dn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [95]:
```
# 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 i
n stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|
| 364171/364171 [05:04<00:00, 1195.86it/s]
```

In [96]:
```
preprocessed_reviews[1500]
```

Out[96]:
```
'great ingredients although chicken rather chicken broth thing not think belo
ngs canola oil canola rapeseed not someting dog would ever find nature find r
apeseed nature eat would poison today food industries convinced masses canola
oil safe even better oil olive virgin coconut facts though say otherwise late
poisonous figured way fix still like could better'
```

In [97]:
```
final['cleaned_text']=preprocessed_reviews
```

In [98]:
```
final.shape
```

Out[98]:
```
(364171, 11)
```

In [99]:
```
final["Score"].value_counts()
```

Out[99]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

In [100]:
```
#Getting positive and negetive data
data_pos = final[final["Score"] == 1].sample(n = 50000)
data_neg = final[final["Score"] == 0].sample(n = 50000)
final1 = pd.concat([data_pos, data_neg])
final1.shape
```

Out[100]:
```
(100000, 11)
```

In [101]:

```
#Sorted the data based on time and took 100k data points
final1["Time"] = pd.to_datetime(final1["Time"], unit = "s")
final1 = final1.sort_values(by = "Time")
final1.head()
```

Out[101]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator
346041	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19
417901	451923	B00004CXX9	ANIMV3SPDD8SH	Guy De Federicis	1
346037	374339	B00004CI84	AZRJH4JFB59VC	Lynwood E. Hines	21
346031	374333	B00004CI84	A1CZICCYP2M5PX	Christian Pelchat	0
138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3

In [102]:

```
Y = final1['Score'].values
X = final1['cleaned_text'].values
print(Y.shape)
print(type(Y))
print(X.shape)
print(type(X))
```

```
(100000,)
<class 'numpy.ndarray'>
(100000,)
<class 'numpy.ndarray'>
```

In [103]:
```
# split the data set into train and test
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X,Y,test_size=0.3, random_
state=12, shuffle = False)

# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, Y_tr, Y_cv = train_test_split(X,Y, test_size=0.3, random_state=12,
shuffle = False)

print('='*100)
print("After splitting")
print("X_Train Shape:",X_Train.shape, "Y_Train Shape:",Y_Train.shape)
print("X_cv Shape:",X_cv.shape,       "Y_cv Shape",Y_cv.shape)
print("X_Test Shape",X_Test.shape,    "Y_Test Shape",Y_Test.shape)
```

```
==============================================================================
=======================
After splitting
X_Train Shape: (70000,) Y_Train Shape: (70000,)
X_cv Shape: (30000,) Y_cv Shape (30000,)
X_Test Shape (30000,) Y_Test Shape (30000,)
```

[4] Featurization

[4.1] Bag Of Words

In [104]:

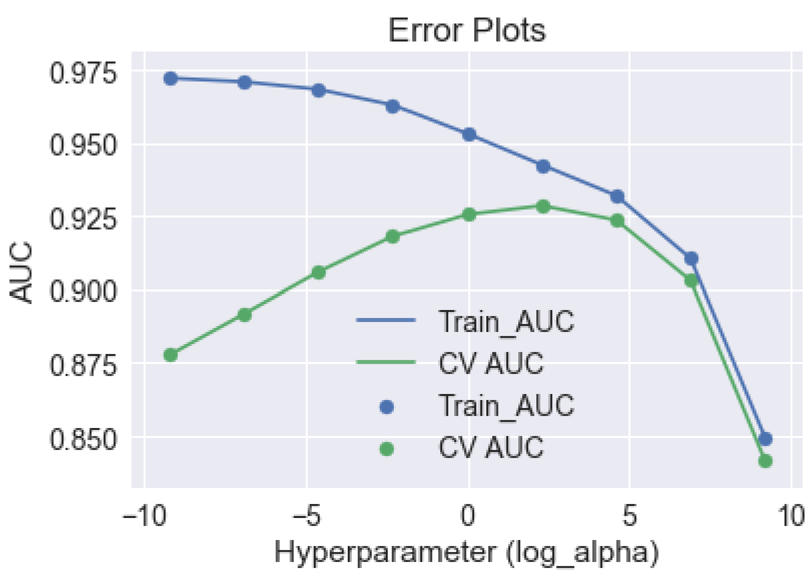
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(X_Train)
print("some feature names ", count_vect.get_feature_names()[:10])
X_Train_Bow = count_vect.transform(X_Train)
X_Test_Bow = count_vect.transform(X_Test)
X_CV_Bow = count_vect.transform(X_cv)

print('='*50)

#final_counts = count_vect.transform(X_Test)

print("the type of X Train : ",type(X_Train_Bow))
print("the shape of Train BOW vectorizer ",X_Train_Bow.get_shape())
print("the shape of Test BOW vectorizer ",X_Test_Bow.get_shape())
print("the shape of CV BOW vectorizer ",X_CV_Bow.get_shape())
#print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaaaaaaaaaaaaaaaaaaaaa
aaaaaaaaaaaaaaaaaaaaa', 'aaaaaaarrrrggghhh', 'aaaaaahhhhyaaaaaa', 'aaaallll',
'aaaand', 'aaah']
==================================================
the type of X Train :  <class 'scipy.sparse.csr.csr_matrix'>
the shape of Train BOW vectorizer  (70000, 51472)
the shape of Test BOW vectorizer  (30000, 51472)
the shape of CV BOW vectorizer  (30000, 51472)
```

[4.1.1] AUC Curve Plot

In [105]:
```python
import math
from sklearn.naive_bayes import MultinomialNB

train_AUC = []
CV_AUC = []
alpha = [10**-4, 10**-3, 10**-2, 10**-1, 1,10**1, 10**2, 10**3, 10**4]
log_alpha=[]

for i in tqdm(alpha):
    MNB = MultinomialNB(alpha = i, class_prior=[0.5,0.5], fit_prior=True)
    #fit a model on train BOW vectorizer
    MNB.fit(X_Train_Bow, Y_Train)
    #predict probabilities on train BOW vectorizer
    Y_Train_Pred = MNB.predict_proba(X_Train_Bow)[:,1]
    #predict probabilities on Cross validation BOW vectorizer
    Y_CV_Pred = MNB.predict_proba(X_CV_Bow)[:,1]
    #calculate AUC score
    train_AUC.append(roc_auc_score(Y_Train,Y_Train_Pred))
    CV_AUC.append(roc_auc_score(Y_cv, Y_CV_Pred))
    log_alpha.append(math.log(i))

plt.plot(log_alpha, train_AUC, label='Train_AUC')
plt.scatter(log_alpha, train_AUC, label='Train_AUC')
plt.plot(log_alpha, CV_AUC, label='CV AUC')
plt.scatter(log_alpha, CV_AUC, label='CV AUC')
plt.legend()
plt.xlabel('Hyperparameter (log_alpha)')
plt.ylabel('AUC')
plt.title('Error Plots')
plt.show()
```

```
100%|██████████████████████████████| 9/9 [00:01<00:00,  6.83it/s]
```



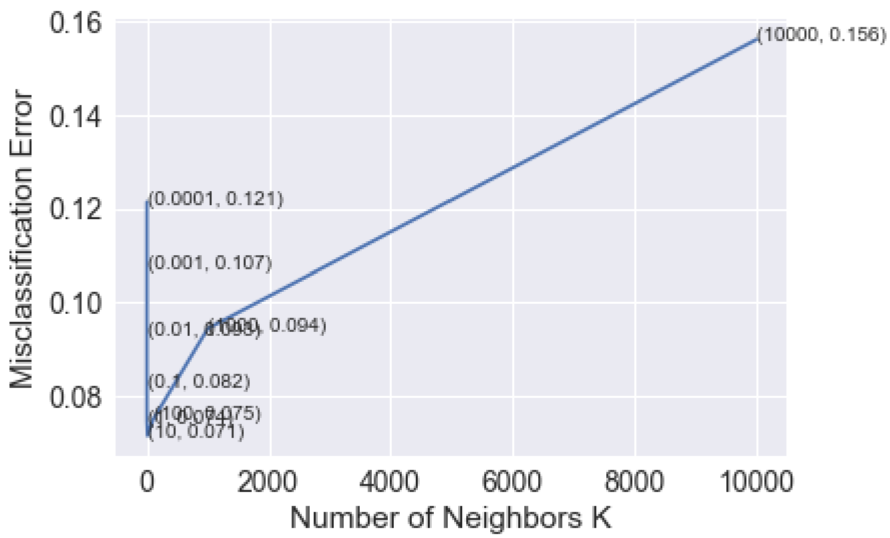
In [106]:
```
 #Finding the best hyper paramter using 10-fold cross validation data
def Optimal_Alpha(X_Train, Y_Train):
         #Considered a wide range of alpha values for hyperparameter tuning, s
tart as low 10^-4 to 10^4.
        alpha = [0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
        # empty list that will hold cv scores
        cv_scores = []

        # perform 10-fold cross validation
        for i in tqdm(alpha):
            MNB = MultinomialNB(alpha=i, class_prior=[0.5,0.5], fit_prior=True
)
            scores = cross_val_score(MNB, X_Train, Y_Train, cv=10, scoring='ro
c_auc')
            cv_scores.append(scores.mean())

        # changing to misclassification error
        MSE = [1 - x for x in cv_scores]

        # determining best k
        bestAlpha = alpha[MSE.index(min(MSE))]
        print('\nThe optimal number of neighbors is %d.' % bestAlpha)

        # plot misclassification error vs k
        plt.plot(alpha, MSE)

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

        plt.xlabel('Number of Neighbors K')
        plt.ylabel('Misclassification Error')
        plt.show()

        print("the misclassification error for each k value is : ", np.round(M
SE,3))
        return bestAlpha
```

[4.1.2] 10-fold cross validation, determining best Alpha

In [107]:
```
optimal_alpha_bow = Optimal_Alpha(X_Train_Bow, Y_Train)
print("_"*100)
print("optimal_alpha:", optimal_alpha_bow)
print("_"*100)
```

```
100%|██████████████████████████████████████████████████████████| 9/9 [00:10<00:00,  1.13s/it]
```

```
The optimal number of neighbors is 10.
```



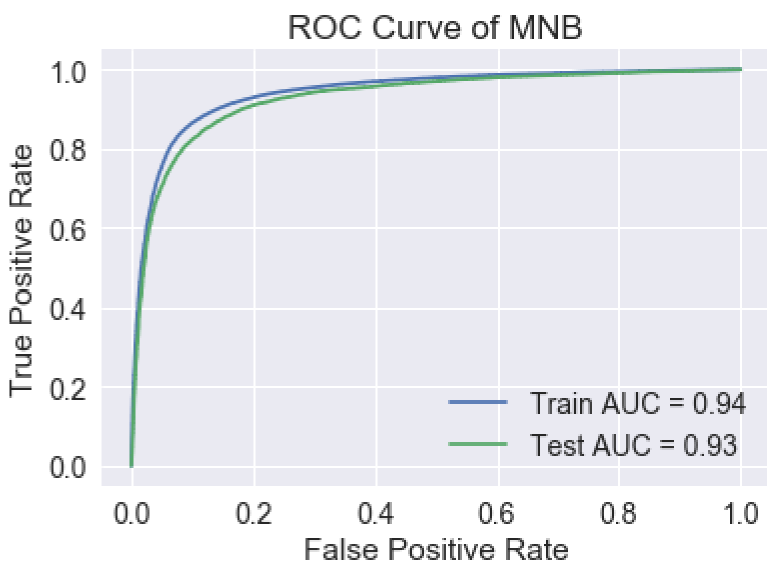

```
the misclassification error for each k value is :  [0.121 0.107 0.093 0.082
0.074 0.071 0.075 0.094 0.156]
____________________________________________________________________________________________________
optimal_alpha: 10
____________________________________________________________________________________________________
```

In [108]:
```
optimal_model = MultinomialNB(alpha=optimal_alpha_bow, class_prior=[0.5,0.5],
fit_prior=True)
optimal_model.fit(X_Train_Bow, Y_Train)
prediction = optimal_model.predict(X_Test_Bow)
optimal_model
```

Out[108]:
```
MultinomialNB(alpha=10, class_prior=[0.5, 0.5], fit_prior=True)
```

[4.1.3] ROC Curve of Naive Bayes

In [109]:
```
#with the reference of below link:
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn
-machine-learning-algorithm-using-python-and-sci
#predict probabilities on X_Train_Bow and X_Test_Bow and pass as param to roc_
curve to find roc curve
Train_FPR, Train_TPR, threshold = roc_curve(Y_Train, optimal_model.predict_pro
ba(X_Train_Bow)[:,1])
Test_FPR, Test_TPR, threshold = roc_curve(Y_Test, optimal_model.predict_proba(
X_Test_Bow)[:,1])
roc_auc = auc(Train_FPR, Train_TPR)
roc_auc1 = auc(Test_FPR, Test_TPR)

plt.plot(Train_FPR, Train_TPR, label = 'Train AUC = %0.2f' % roc_auc)
plt.plot(Test_FPR, Test_TPR, label = 'Test AUC = %0.2f' % roc_auc1)
plt.legend()
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of MNB')
plt.show()
```



[4.1.4]Train and Test Accuracy

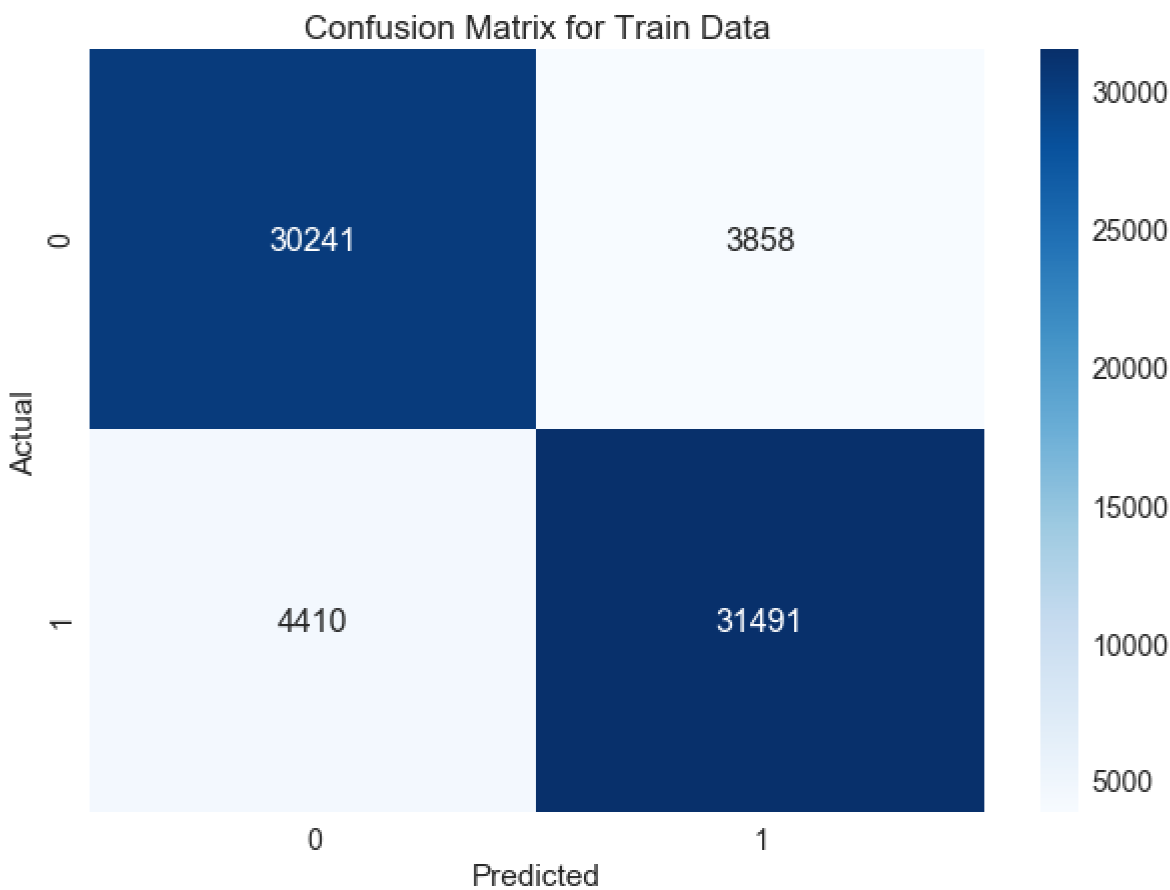
In [110]:
```
Training_Accuracy_Bow = optimal_model.score(X_Train_Bow, Y_Train)
print('Training_Accuracy=%0.3f'%Training_Accuracy_Bow)
Training_Error_Bow = 1 - Training_Accuracy_Bow
print('Training_Error=%0.3f'%Training_Error_Bow)

Test_Accuracy_Bow = accuracy_score(Y_Test, prediction)
print('Test_Accuracy=%0.3f'%Test_Accuracy_Bow)
Test_Error_Bow = 1 - Test_Accuracy_Bow
print('Test_Error=%0.3f'%Test_Error_Bow)
print('\nThe accuracy of the MNB classifier for k = %d is %f%%' % (optimal_alp
ha_bow, Test_Accuracy_Bow))
```

```
Training_Accuracy=0.882
Training_Error=0.118
Test_Accuracy=0.865
Test_Error=0.135

The accuracy of the MNB classifier for k = 10 is 0.864900%
```

[4.1.5] Confusion Matrix

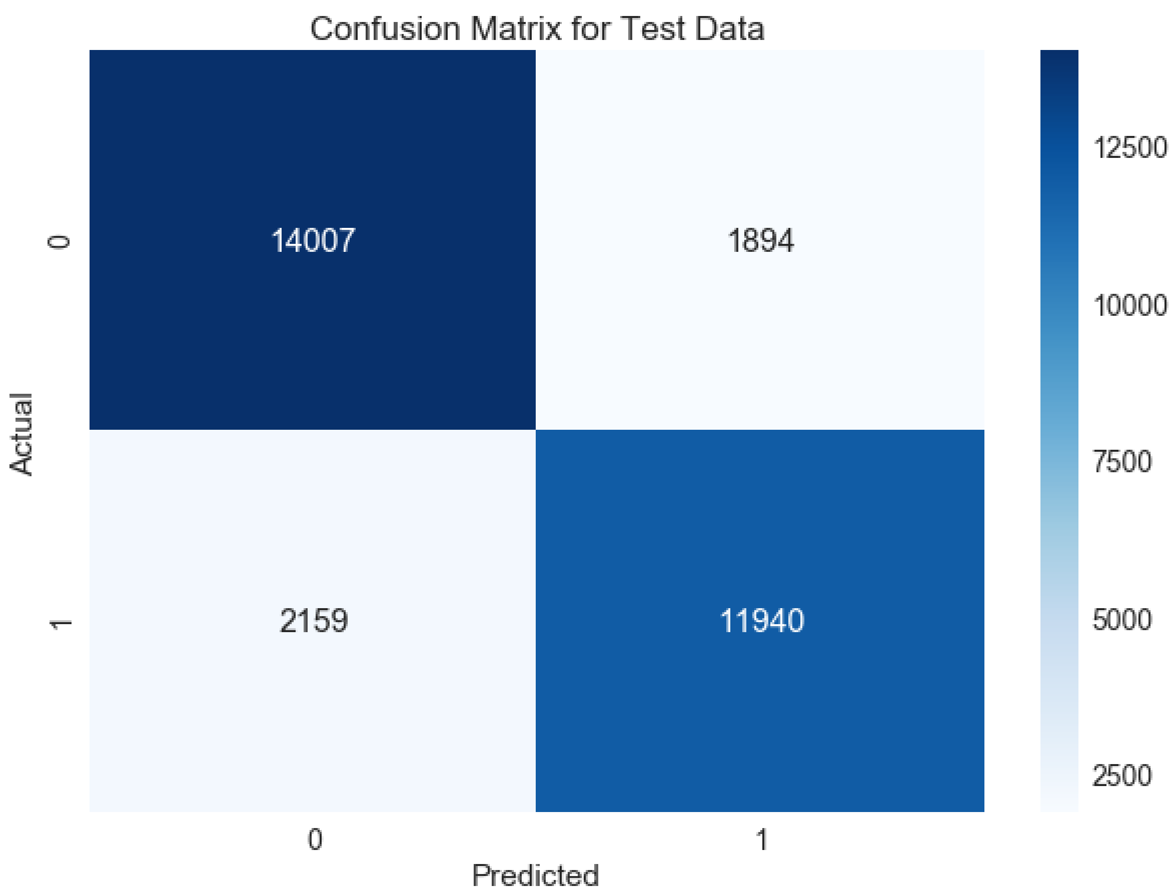
In [111]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Train, optimal_model.predict(X_Train_Bow))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Train), index=n
p.unique(Y_Train))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = 'Predicted'
plt.figure(figsize=(10,7))
plt.title("Confusion Matrix for Train Data")
sns.set(font_scale=1.4)
sns.heatmap(df_conf_matrix, cmap='Blues', annot=True, annot_kws={'size':16}, f
mt='d')
```

Out[111]: <matplotlib.axes._subplots.AxesSubplot at 0x1c98daea6a0>



In [112]:
```
#With the reference of below link:
#https://www.kaggle.com/agungor2/various-confusion-matrix-plots
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Test, optimal_model.predict(X_Test_Bow))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Test), index=np
.unique(Y_Test))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = 'Predicted'
plt.figure(figsize=(10,7))
plt.title("Confusion Matrix for Test Data")
sns.set(font_scale=1.4)
sns.heatmap(df_conf_matrix, cmap='Blues', annot=True, annot_kws={'size':16}, f
mt='d')
```

Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x1c98daea2b0>



[4.1.6] Classification Report

In [113]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_Test, prediction))
```

```
             precision    recall  f1-score   support

          0       0.87      0.88      0.87     15901
          1       0.86      0.85      0.85     14099

avg / total       0.86      0.86      0.86     30000
```

[4.2] TF-IDF

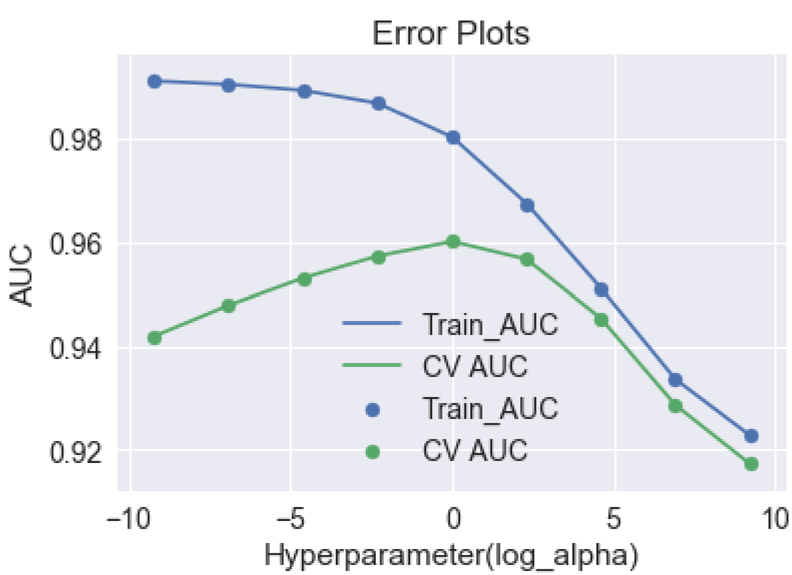
In [114]:
```
#TF-IDF
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=5)
tf_idf_vect.fit_transform(X_Train)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_featu
re_names()[0:10])
print('='*50)

X_Train_TfIdf = tf_idf_vect.transform(X_Train)
X_Test_TfIdf = tf_idf_vect.transform(X_Test)
X_CV_TfIdf = tf_idf_vect.transform(X_cv)

#final_tf_idf = tf_idf_vect.transform(X_Test)
print("the type of count vectorizer ",type(X_Train_TfIdf))
print("the shape of out text TFIDF vectorizer ",X_Train_TfIdf.get_shape())
print("the shape of out text TFIDF vectorizer ",X_Test_TfIdf.get_shape())
print("the shape of out text TFIDF vectorizer ",X_CV_TfIdf.get_shape())
#print("the number of unique words including both unigrams and bigrams ", fina
l_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['aa', 'aaa', 'aafco', 'abac
k', 'abandon', 'abandoned', 'abbey', 'abc', 'abdomen', 'abdominal']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (70000, 92735)
the shape of out text TFIDF vectorizer  (30000, 92735)
the shape of out text TFIDF vectorizer  (30000, 92735)
```

[4.2.1] AUC Curve Plot

In [115]:
```
import math
from sklearn.naive_bayes import MultinomialNB

train_AUC = []
CV_AUC = []
alpha = [10**-4, 10**-3, 10**-2, 10**-1, 1,10**1, 10**2, 10**3, 10**4]
log_alpha_tfidf=[]

for i in tqdm(alpha):
    MNB = MultinomialNB(alpha = i, class_prior=[0.5,0.5], fit_prior=True)
    #fit a model on train BOW vectorizer
    MNB.fit(X_Train_TfIdf, Y_Train)
    #predict probabilities on train BOW vectorizer
    Y_Train_Pred = MNB.predict_proba(X_Train_TfIdf)[:,1]
    #predict probabilities on Cross validation BOW vectorizer
    Y_CV_Pred = MNB.predict_proba(X_CV_TfIdf)[:,1]
    #calculate AUC score
    train_AUC.append(roc_auc_score(Y_Train,Y_Train_Pred))
    CV_AUC.append(roc_auc_score(Y_cv, Y_CV_Pred))
    log_alpha_tfidf.append(math.log(i))

plt.plot(log_alpha_tfidf, train_AUC, label='Train_AUC')
plt.scatter(log_alpha_tfidf, train_AUC, label='Train_AUC')
plt.plot(log_alpha_tfidf, CV_AUC, label='CV AUC')
plt.scatter(log_alpha_tfidf, CV_AUC, label='CV AUC')
plt.legend()
plt.xlabel('Hyperparameter(log_alpha)')
plt.ylabel('AUC')
plt.title('Error Plots')
plt.show()
```

```
100%|██████████████████████████████████████
██████████| 9/9 [00:01<00:00,  5.69it/s]
```

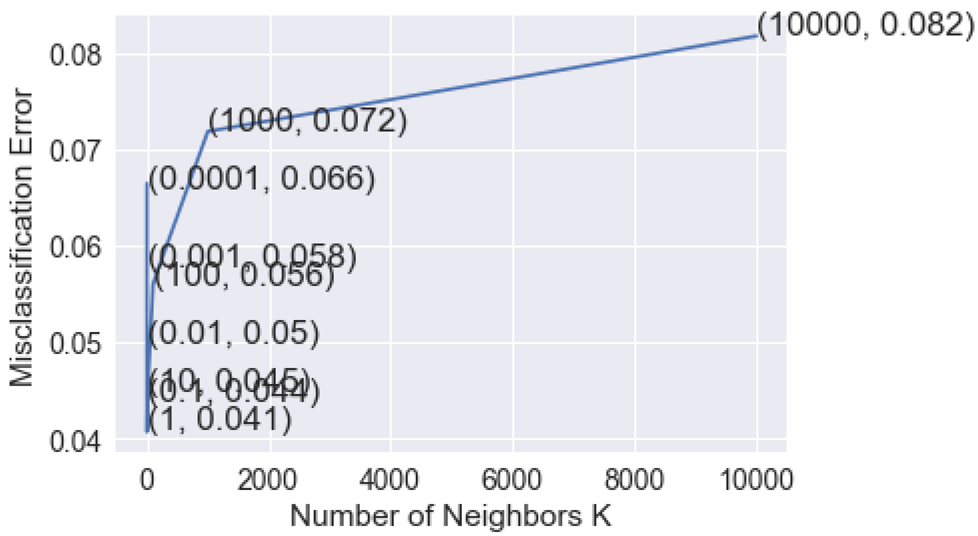


[4.2.2] 10-fold cross validation, determining best Alpha

In [116]:
```
optimal_alpha_tfidf = Optimal_Alpha(X_Train_TfIdf, Y_Train)
print("optimal_alpha:", optimal_alpha_tfidf)
```

```
100%|████████████████████████████████████████████████████████████
██████████| 9/9 [00:15<00:00,  1.76s/it]
```

```
The optimal number of neighbors is 1.
```

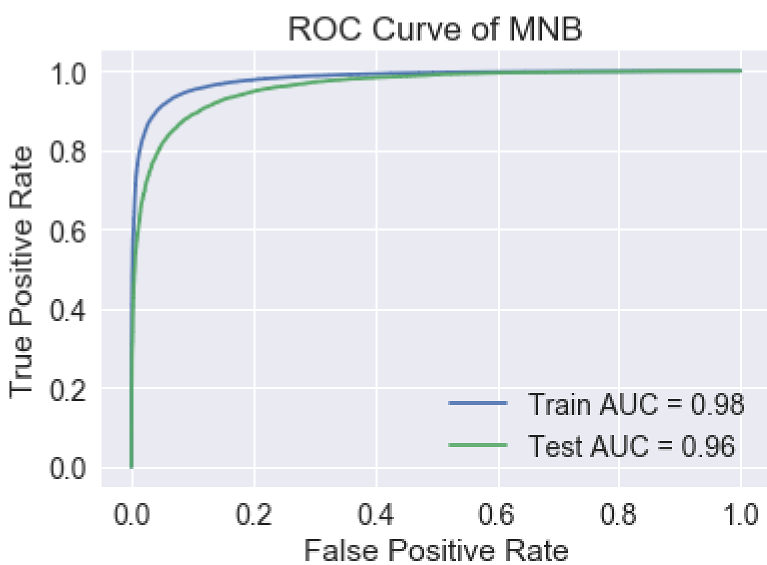



```
the misclassification error for each k value is :  [0.066 0.058 0.05  0.044
0.041 0.045 0.056 0.072 0.082]
optimal_alpha: 1
```

In [117]:
```
optimal_model1 = MultinomialNB(alpha=optimal_alpha_tfidf, class_prior=[0.5,0.5
], fit_prior=True)
optimal_model1.fit(X_Train_TfIdf, Y_Train)
prediction = optimal_model1.predict(X_Test_TfIdf)
```

[4.2.3] ROC Curve of Naive Bayes

In [118]:
```
#with the reference of below link:
#https://stackoverflow.com/questions/52910061/implementing-roc-curves-for-k-nn
-machine-learning-algorithm-using-python-and-sci
#predict probabilities on X_Train_Bow and X_Test_Bow and pass as param to roc_
curve to find roc curve
Train_FPR, Train_TPR, threshold = roc_curve(Y_Train, optimal_model1.predict_pr
oba(X_Train_TfIdf)[:,1])
Test_FPR, Test_TPR, threshold = roc_curve(Y_Test, optimal_model1.predict_proba
(X_Test_TfIdf)[:,1])
roc_auc2 = auc(Train_FPR, Train_TPR)
roc_auc3 = auc(Test_FPR, Test_TPR)

plt.plot(Train_FPR, Train_TPR, label = 'Train AUC = %0.2f' % roc_auc2)
plt.plot(Test_FPR, Test_TPR, label = 'Test AUC = %0.2f' % roc_auc3)
plt.legend()
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of MNB')
plt.show()
```



[4.2.4]Train and Test Accuracy

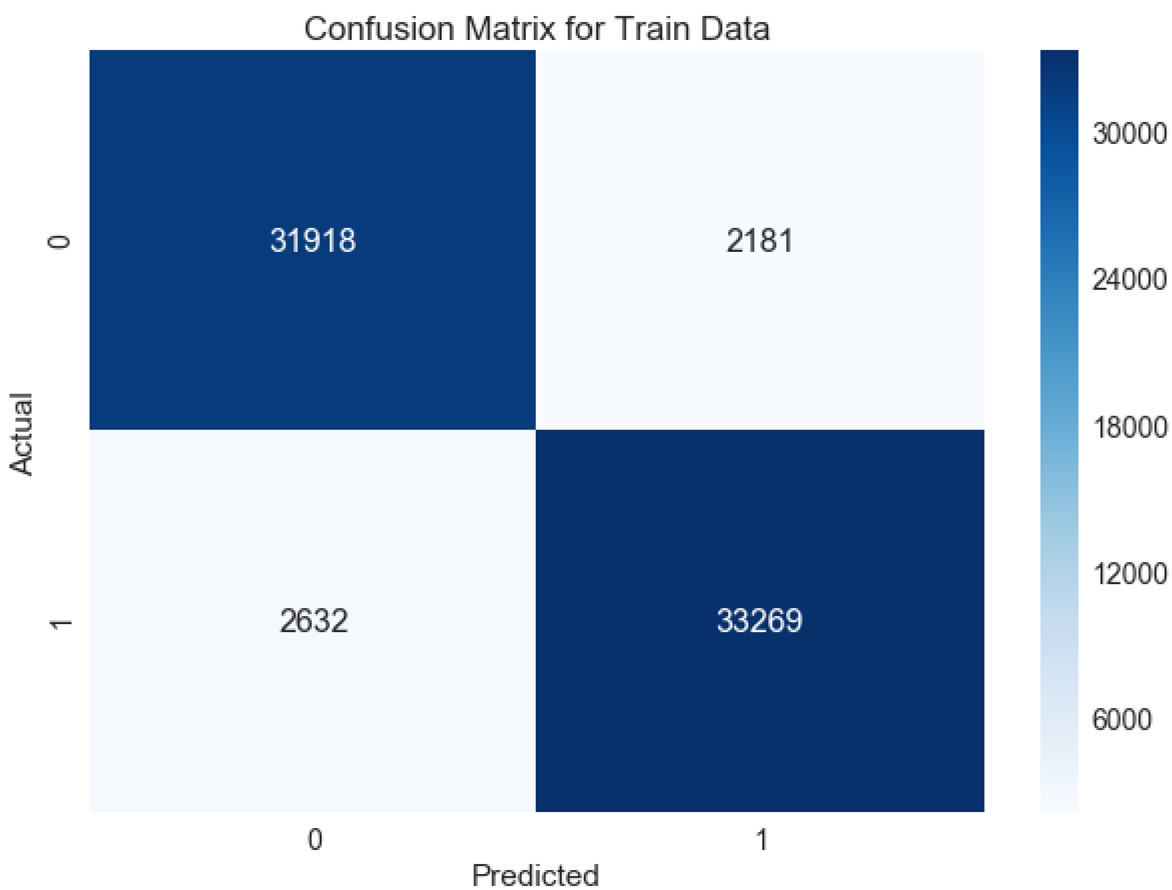
In [119]:
```
Training_Accuracy_tfidf = optimal_model1.score(X_Train_TfIdf, Y_Train)
print('Training_Accuracy=%0.3f'%Training_Accuracy_tfidf)
Training_Error_tfidf = 1 - Training_Accuracy_tfidf
print('Training_Error=%0.3f'%Training_Error_tfidf)

Test_Accuracy_tfidf = accuracy_score(Y_Test, prediction)
print('Test_Accuracy=%0.3f'%Test_Accuracy_tfidf)
Test_Error_tfidf = 1 - Test_Accuracy_tfidf
print('Test_Error=%0.3f'%Test_Error_tfidf)
print('\nThe accuracy of the MNB classifier for k = %d is %f%%' % (optimal_alp
ha_tfidf, Test_Accuracy_tfidf))
```

```
Training_Accuracy=0.931
Training_Error=0.069
Test_Accuracy=0.895
Test_Error=0.105

The accuracy of the MNB classifier for k = 1 is 0.895233%
```

[4.2.5] Confusion Matrix

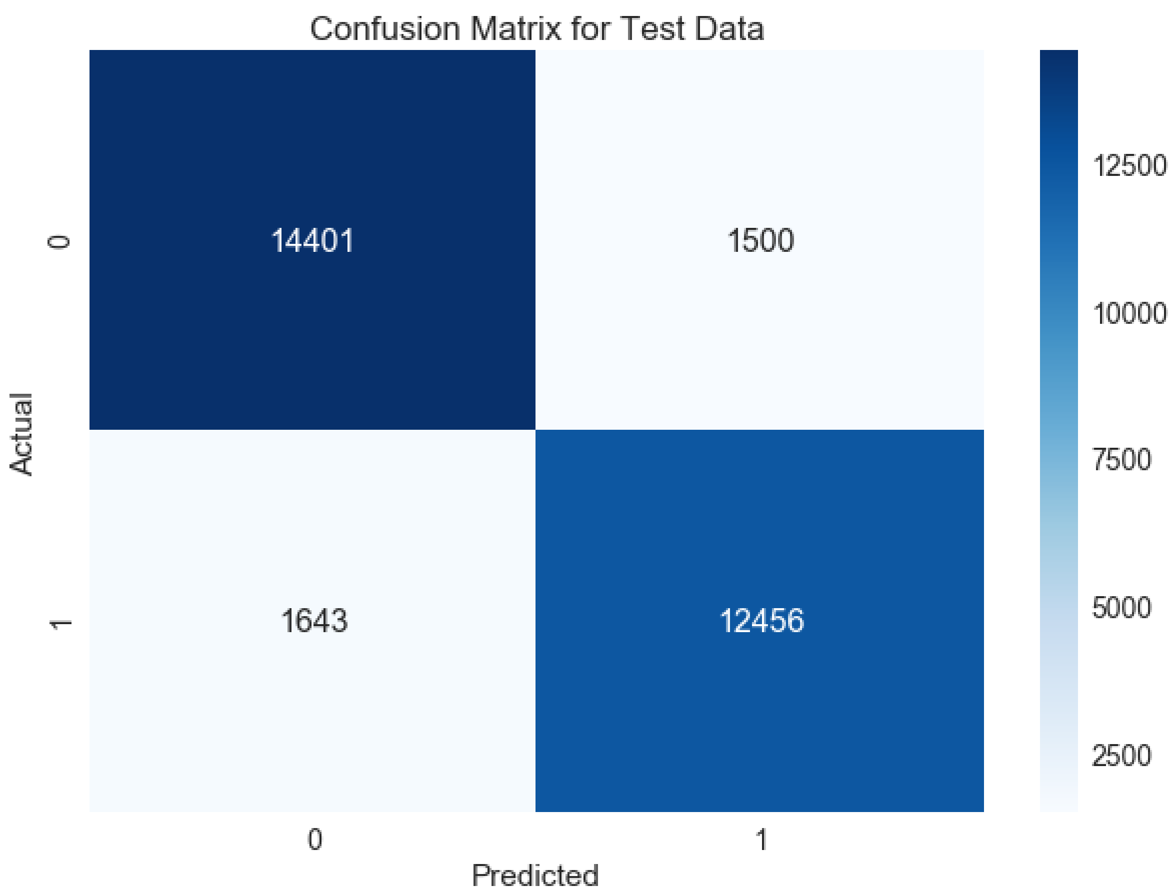
In [120]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Train, optimal_model1.predict(X_Train_TfIdf))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Train), index=n
p.unique(Y_Train))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Test), index=np
.unique(Y_Test))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = 'Predicted'
plt.figure(figsize=(10,7))
plt.title("Confusion Matrix for Train Data")
sns.set(font_scale=1.4)
sns.heatmap(df_conf_matrix, cmap='Blues', annot=True, annot_kws={'size':16}, f
mt='d')
```

Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x1c9ad96be48>



In [121]:
```
#With the reference of below link:
#https://www.kaggle.com/agungor2/various-confusion-matrix-plots
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Test, optimal_model1.predict(X_Test_TfIdf))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Test), index=np
.unique(Y_Test))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = 'Predicted'
plt.figure(figsize=(10,7))
plt.title("Confusion Matrix for Test Data")
sns.set(font_scale=1.4)
sns.heatmap(df_conf_matrix, cmap='Blues', annot=True, annot_kws={'size':16}, f
mt='d')
```

Out[121]: <matplotlib.axes._subplots.AxesSubplot at 0x1c98ddf93c8>



[4.2.6]Classification Report

In [122]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_Test, prediction))
```

```
             precision    recall  f1-score   support

          0       0.90      0.91      0.90     15901
          1       0.89      0.88      0.89     14099

avg / total       0.90      0.90      0.90     30000
```

[5] Feature Importance

[5.1]BoW

[5.1.1]Feature Importance for Positive Class

In [123]:
```
#https://stackoverflow.com/questions/35353150/sklearn-multinomialnb-how-to-fin
d-most-distinguish-word-in-class
import operator
pos_imp_features = MNB.feature_log_prob_[1,:]
neg_imp_features = MNB.feature_log_prob_[0,:]
print("pos_imp_features",len(pos_imp_features))
imp_features = {}
feature_names= count_vect.get_feature_names()
print("feature_names",len(feature_names))
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 25 important features are:")
for i in range(25):
    print(names_diff_sorted[i])
```

```
pos_imp_features 92735
feature_names 51472
Postive top 25 important features are:
('pupils', -11.36733577032401)
('portugal', -11.376557440094475)
('sueggestion', -11.38457326712038)
('touches', -11.384717570341618)
('eventhe', -11.387648758776214)
('mucus', -11.395026781036709)
('caseits', -11.398145828536254)
('aromaticum', -11.401794080610495)
('minnesotans', -11.40278108425811)
('patronize', -11.404991654726802)
('terible', -11.407241317216132)
('notgrab', -11.407434579080615)
('andexpected', -11.409008854163199)
('unfortunatedly', -11.40912985959799)
('eic', -11.410060700688014)
('havesomething', -11.410297156549989)
('curative', -11.410541993801118)
('cement', -11.412547064243359)
('ivf', -11.413818900871217)
('oligofructose', -11.414011561257972)
('ordinairy', -11.414444626592093)
('truthaboutpetfood', -11.414916458198851)
('medifast', -11.415195577824997)
('implemented', -11.41590031352609)
('leek', -11.416330419652333)
```

[5.1.2]Feature Importance for Negetive Class

In [124]:
```
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 25 important features are:")
for i in range(25):
    print(names_diff_sorted[i])
```

```
Negative top 25 important features are:
('sueggestion', -11.370150161443856)
('eventhe', -11.39072028377526)
('mucus', -11.396886574131914)
('portugal', -11.399387104745102)
('curative', -11.4027792525322)
('leek', -11.404987007226316)
('patronize', -11.405735198438393)
('aromaticum', -11.405991007765396)
('complainingsince', -11.407246406855636)
('notgrab', -11.407902666580782)
('colgin', -11.409226508302964)
('boson', -11.409860317452424)
('fudge', -11.409926980310622)
('eic', -11.41088133161944)
('hunting', -11.41329207617512)
('cement', -11.413351001752769)
('xylan', -11.413439178898727)
('moneys', -11.414438331464124)
('ivf', -11.415050398946581)
('procuct', -11.415477110020493)
('uji', -11.415754640459634)
('brainwashing', -11.41625069673083)
('soulful', -11.417110369095674)
('implemented', -11.417996791859633)
('touches', -11.418000951237648)
```

[5.2]TF-IDF

[5.2.1]Feature Importance for Positive Class

In [125]:
```
#https://stackoverflow.com/questions/35353150/sklearn-multinomialnb-how-to-fin
d-most-distinguish-word-in-class

pos_imp_features = MNB.feature_log_prob_[1,:]
print("length of pos_imp_features:",len(pos_imp_features))
imp_features = {}
feature_names= tf_idf_vect.get_feature_names()
print("length of feature_names:",len(feature_names))
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = pos_imp_features[i]
#Introduced exception handling to avoid the index error.
  #  try:
  #      imp_features[feature_names[i]] = pos_imp_features[i]
  #  except IndexError as error:
  #      pass
names_diff_sorted = sorted(imp_features.items(), key = operator.itemgetter(1),
reverse = True)
print("Postive top 25 important features are:\n")
for i in range(25):
    print(names_diff_sorted[i])
```

```
length of pos_imp_features: 92735
length of feature_names: 92735
Postive top 25 important features are:

('not', -11.35577541247079)
('great', -11.36733577032401)
('good', -11.376557440094475)
('tea', -11.38302202715892)
('like', -11.38457326712038)
('love', -11.384717570341618)
('coffee', -11.387648758776214)
('one', -11.393973886250503)
('product', -11.394467023374107)
('taste', -11.394784644046778)
('flavor', -11.395026781036709)
('best', -11.398145828536254)
('amazon', -11.401794080610495)
('find', -11.40278108425811)
('price', -11.403080957515396)
('would', -11.403876351494166)
('use', -11.404032250369402)
('really', -11.40434932692268)
('get', -11.404991654726802)
('little', -11.407241317216132)
('food', -11.407434579080615)
('time', -11.407806419298154)
('no', -11.408174829534856)
('much', -11.408314533103715)
('also', -11.409008854163199)
```

[5.2.2]Feature Importance for Negetive Class

In [126]:
```
neg_imp_features = MNB.feature_log_prob_[0,:]
print("length of neg_imp_features:",len(neg_imp_features))
print("length of feature_names:",len(feature_names))
for i in range(len(feature_names)):
    imp_features[feature_names[i]] = neg_imp_features[i]
   # try:
    #    imp_features[feature_names[i]] = neg_imp_features[i]
   # except IndexError as error:
    #    pass
names_diff_sorted = sorted(imp_features.items(), key = operator.itemgetter(1),
reverse = True)
print("\n\nNegative top 25 important features are:\n")
for i in range(25):
    print(names_diff_sorted[i])
```

```
length of neg_imp_features: 92735
length of feature_names: 92735


Negative top 25 important features are:

('not', -11.300193735430538)
('like', -11.370150161443856)
('taste', -11.378288708636068)
('product', -11.378325867831162)
('would', -11.380567943280552)
('coffee', -11.39072028377526)
('one', -11.391367231022137)
('flavor', -11.396886574131914)
('no', -11.397739097994315)
('good', -11.399387104745102)
('tea', -11.400843728957796)
('buy', -11.4027792525322)
('even', -11.404987007226316)
('get', -11.405735198438393)
('amazon', -11.405991007765396)
('box', -11.407246406855636)
('food', -11.407902666580782)
('much', -11.408213972903438)
('really', -11.408786770340077)
('bought', -11.409226508302964)
('bad', -11.409860317452424)
('could', -11.409926980310622)
('chocolate', -11.41088133161944)
('tried', -11.411338134884247)
('disappointed', -11.41329207617512)
```

In [127]:
```
from prettytable import PrettyTable
comparision = PrettyTable()
comparision.field_names = ["S.NO","Vectorizer", "Hyperparameter", "Training Er
ror", "Test Error","AUC"]
comparision.add_row(["1","BoW", optimal_alpha_bow, Training_Error_Bow, Test_Er
ror_Bow, np.round(float(roc_auc1),3)])
comparision.add_row(["2","TF-IDF", optimal_alpha_tfidf,Training_Error_tfidf, T
est_Error_tfidf, np.round(float(roc_auc3),3)])
print(comparision)
```

```
+------+------------+----------------+---------------------+-----------------
----+-------+
| S.NO | Vectorizer | Hyperparameter |    Training Error   |      Test Error
|  AUC  |
+------+------------+----------------+---------------------+-----------------
----+-------+
|  1   |    BoW     |       10       | 0.11811428571428573 |        0.1351
| 0.929 |
|  2   |   TF-IDF   |       1        | 0.06875714285714285 | 0.10476666666666
667 |  0.96 |
+------+------------+----------------+---------------------+-----------------
----+-------+
```

Conclusion

1. Applied Multinomial NB on two feature sets 1. Bow and 2. TF-IDF vectorizer.
2. Sorted the data based on Time and Considered 100 K data points for Training set 70K, Test set: 30K
3. Used AUC as a metric for hyperparameter tuning. And took the range of alpha values from (10^-4 to 10^4).
4. Found the top 25 features of positive class and top 25 features of negative class for Bow and TF-IDF feature sets.
5. With reference to the pretty table, here is my understanding: a. Naive Bayes by using Bow and TF-IDF with best alpha = 10 and AUC score is 0.92 in both.
6. Since it is an imbalanced data, not considered accuracy as a metric and AUC Score is high
7. Plotted Confusion matrix for both Training and Test set.

Note: I do not have idea on feature engineering concept, One after completing the Module 5 and able to check the accuracy of this model with feature engineering.