Amazon Fine Food Reviews Analysis Using Logistic Regression

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 [43]:
```
%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
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler

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

[1]. Reading Data

In [44]:
```
# 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 L
IMIT 100000""", 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 (100000, 10)
```

Out[44]:

	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 [45]:

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

In [46]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[46]:

	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
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 [47]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[47]:

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

In [48]:
```
display['COUNT(*)'].sum()
```

Out[48]: 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 [49]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[49]:

	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 [50]:
```
#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 [51]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"
}, keep='first', inplace=False)
final.shape
```

Out[51]:
```
(87775, 10)
```

In [52]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[52]:
```
87.775
```

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 [53]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[53]:

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

In [54]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [55]:
```
#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?
print(final['Score'].value_counts())
```

```
(87773, 10)
1    73592
0    14181
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 [56]:
```
# 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)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but t
hey are out there, but this one isnt.  Its too bad too because its a good pro
duct but I wont take any chances till they know what is going on with the chi
na imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the candy
has little taste to it.  Very little of the 2 lbs that I bought were eaten an
d I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil smell. So
if you are afraid of the fishy smell, don't get it. But I think my dog likes
it because of the smell. These treats are really small in size. They are grea
t for training. You can give your dog several of these without worrying about
him over eating. Amazon's price was much more reasonable than any other retai
ler. You can buy a 1 pound bag on Amazon for almost the same price as a 6 oun
ce bag at other retailers. It's definitely worth it to buy a big bag if your
dog eats them a lot.
==================================================
```

In [57]:
```
# 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 [58]:
```
sent_4900 = decontracted(sent_4900)
print(sent_4900)
print("="*50)
```

```
My dog LOVES these treats. They tend to have a very strong fish oil smell. So
if you are afraid of the fishy smell, do not get it. But I think my dog likes
it because of the smell. These treats are really small in size. They are grea
t for training. You can give your dog several of these without worrying about
him over eating. Amazon is price was much more reasonable than any other reta
iler. You can buy a 1 pound bag on Amazon for almost the same price as a 6 ou
nce bag at other retailers. It is definitely worth it to buy a big bag if you
r dog eats them a lot.
==================================================
```

In [59]:
```
#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)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but t
hey are out there, but this one isnt.  Its too bad too because its a good pro
duct but I wont take any chances till they know what is going on with the chi
na imports.
```

In [60]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
was way to hot for my blood took a bite and did a jig lol
```

In [61]:
```
# 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 [62]:
```
# Combining all the above stundents
from bs4 import BeautifulSoup
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%|████████████████████████████████████████████████████████████████████
██| 87773/87773 [00:57<00:00, 1535.30it/s]
```

In [63]:
```
preprocessed_reviews[1500]
```

Out[63]:
```
'way hot blood took bite jig lol'
```

In [64]:
```
final['cleaned_text']=preprocessed_reviews
```

In [65]:
```
final.shape
```

Out[65]:
```
(87773, 11)
```

In [66]:
```
final["Score"].value_counts()
```

Out[66]:
```
1    73592
0    14181
Name: Score, dtype: int64
```

In [67]:
```
#Sorted the data based on time and took 100k data points
final["Time"] = pd.to_datetime(final["Time"], unit = "s")
final = final.sort_values(by = "Time")
final.head()
```

Out[67]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	0
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	7
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	10
28086	30629	B00008RCMI	A19E94CF5O1LY7	Andrew Arnold	0	0
28087	30630	B00008RCMI	A284C7M23F0APC	A. Mendoza	0	0

In [68]:
```
Y = final['Score'].values
X = final['cleaned_text'].values
print(Y.shape)
print(type(Y))
print(X.shape)
print(type(X))
```

```
(87773,)
<class 'numpy.ndarray'>
(87773,)
<class 'numpy.ndarray'>
```

In [69]:
```
# 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: (61441,) Y_Train Shape: (61441,)
X_cv Shape: (26332,) Y_cv Shape (26332,)
X_Test Shape (26332,) Y_Test Shape (26332,)
```

[3.2] Preprocess Summary

[4] Featurization

[4.1] BAG OF WORDS

In [70]:
```
#BoW
count_vect = CountVectorizer(ngram_range=(1,2)) #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', 'aa dark', 'aa extra', 'aa kona', 'aa may', 'aa no
t', 'aa part', 'aa quality', 'aa really', 'aa rich']
==================================================
the type of X Train :  <class 'scipy.sparse.csr.csr_matrix'>
the shape of Train BOW vectorizer  (61441, 1071615)
the shape of Test BOW vectorizer  (26332, 1071615)
the shape of CV BOW vectorizer  (26332, 1071615)
```

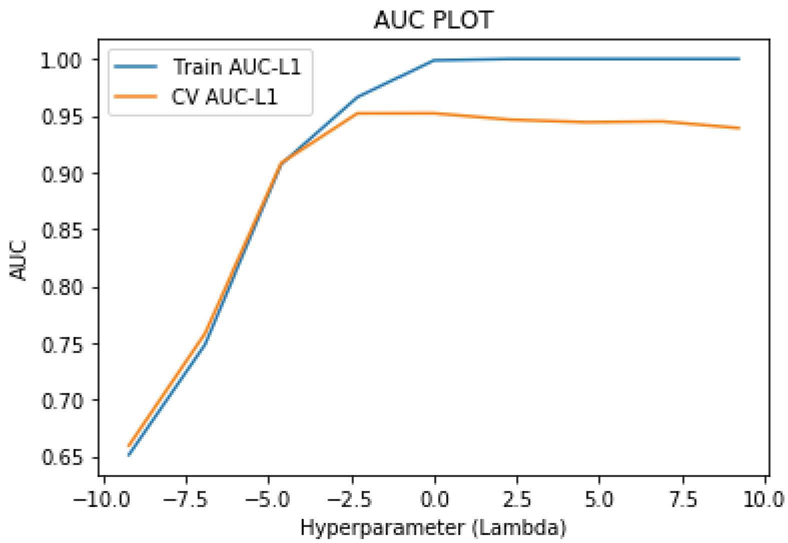
In [71]:
```
def Optimal_Lamda_L1(X_Train,Y_Train,X_CV,Y_CV):
    train_AUC_L1 = []
    CV_AUC_L1 = []
    cv_scores = []
    tuned_parameters=[10**-4, 10**-3, 10**-2, 10**-1, 1,10**1, 10**2, 10**3, 1
0**4]
    for j in  tqdm(tuned_parameters):
        LR_Model = LogisticRegression(C=j, penalty= 'l1', class_weight='balanc
ed')
        LR_Model.fit(X_Train, Y_Train)
        y_train_pred =  LR_Model.predict_proba(X_Train)[:,1]
        y_cv_pred =  LR_Model.predict_proba(X_CV)[:,1]
        train_AUC_L1.append(roc_auc_score(Y_Train,y_train_pred))
        CV_AUC_L1.append(roc_auc_score(Y_CV, y_cv_pred))

    #Error plots with penaly L1
    plt.plot(np.log(tuned_parameters), train_AUC_L1, label='Train AUC-L1')
    plt.plot(np.log(tuned_parameters), CV_AUC_L1, label='CV AUC-L1')
    plt.legend()
    plt.xlabel("Hyperparameter (Lambda)")
    plt.ylabel("AUC")
    plt.title("AUC PLOT")
    plt.show()

    #Cv auc scores with penalty L1
    print("CV AUS Scores with Penalty=? Cv auc scores with penalty L1")
    print(CV_AUC_L1)
    print("Maximun AUC value :",max(CV_AUC_L1))
    print("Index",CV_AUC_L1.index(max(CV_AUC_L1)))
```

In [76]:
```
def Optimal_Lamda_L2(X_Train,Y_Train,X_CV,Y_CV):
    train_AUC_L2 = []
    CV_AUC_L2 = []
    cv_scores = []
    tuned_parameters=[10**-4, 10**-3, 10**-2, 10**-1, 1,10**1, 10**2, 10**3, 1
0**4]
    for j in  tqdm(tuned_parameters):
        LR_Model = LogisticRegression(C=j, penalty= 'l2', class_weight='balanc
ed')
        LR_Model.fit(X_Train, Y_Train)
        y_train_pred =  LR_Model.predict_proba(X_Train)[:,1]
        y_cv_pred =  LR_Model.predict_proba(X_CV)[:,1]
        train_AUC_L2.append(roc_auc_score(Y_Train,y_train_pred))
        CV_AUC_L2.append(roc_auc_score(Y_CV, y_cv_pred))

    #Error plots with penaly L2
    plt.plot(np.log(tuned_parameters), train_AUC_L2, label='Train AUC-L2')
    plt.plot(np.log(tuned_parameters), CV_AUC_L2, label='CV AUC-L2')
    plt.legend()
    plt.xlabel("Hyperparameter (Lambda)")
    plt.ylabel("AUC")
    plt.title("AUC PLOT")
    plt.show()

    #Cv auc scores with penalty L2
    print("Cv AUC scores with penalty L2")
    print(CV_AUC_L2)
    print("Maximun AUC value :",max(CV_AUC_L2))
    print("Index",CV_AUC_L2.index(max(CV_AUC_L2)))
```

[4.1.1] Hyperparameter tuning with L1 Regulizer and AUC Curve Plot

In [74]:
```
Optimal_Lamda_L1(X_Train_Bow, Y_Train, X_CV_Bow,Y_cv)
```

```
100%|████████████████████████████████████████████████████████████
██████████| 9/9 [00:51<00:00,  7.13s/it]
```

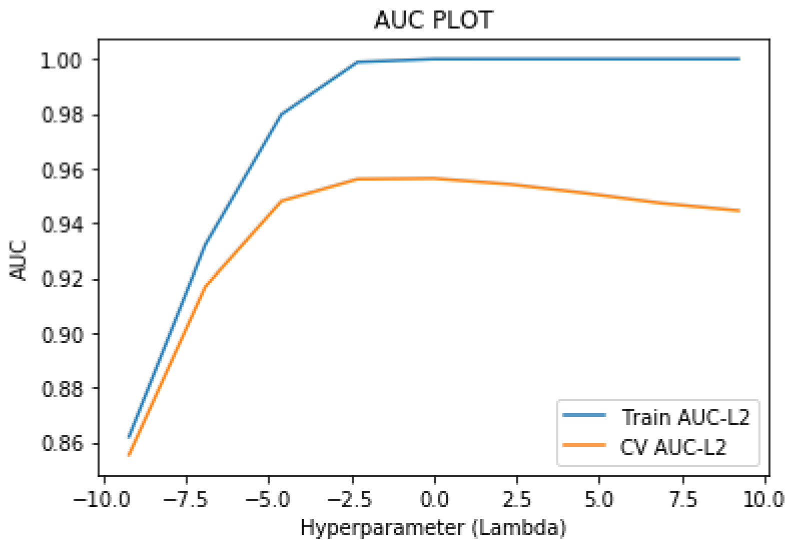



```
CV AUS Scores with Penalty=? Cv auc scores with penalty L1
[0.6593160898298803, 0.7582264148946865, 0.9082536827182264, 0.95197171583718
11, 0.9520599816534888, 0.946429487242473, 0.9442112574817713, 0.944889896998
02, 0.9390566839676131]
Maximun AUC value : 0.9520599816534888
Index 4
```

[4.1.2] Hyperparameter with L2 Regulizer and AUC Curve Plot

In [77]:
```
optimal_lambda_bow_l2 = Optimal_Lamda_L2(X_Train_Bow, Y_Train, X_CV_Bow,Y_cv)
```

```
100%|██████████████████████████████████████████████████████████
██████████| 9/9 [04:06<00:00, 38.83s/it]
```

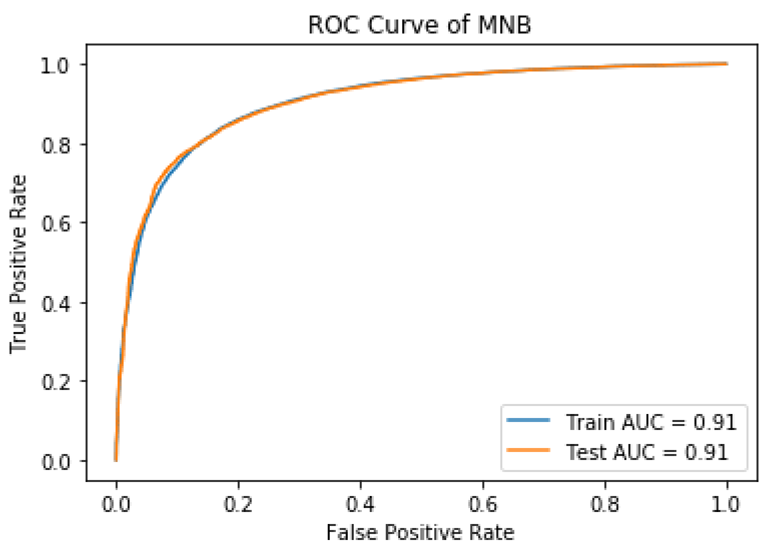



```
Cv AUC scores with penalty L2
[0.8554219433041911, 0.9168218360267333, 0.9480772065131374, 0.95610832251866
72, 0.95635564014132, 0.9542159411077492, 0.9509292500378546, 0.9472551659084
433, 0.9445847986985617]
Maximun AUC value : 0.95635564014132
Index 4
```

[4.1.3] ROC Curve of Logistic Regression

In [78]:

```
#Testing with test data
Optimal_Model = LogisticRegression(penalty='l1',C=0.01, class_weight='balance
d')
Optimal_Model.fit(X_Train_Bow, Y_Train)
prediction = Optimal_Model.predict(X_Test_Bow)
Optimal_Model

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

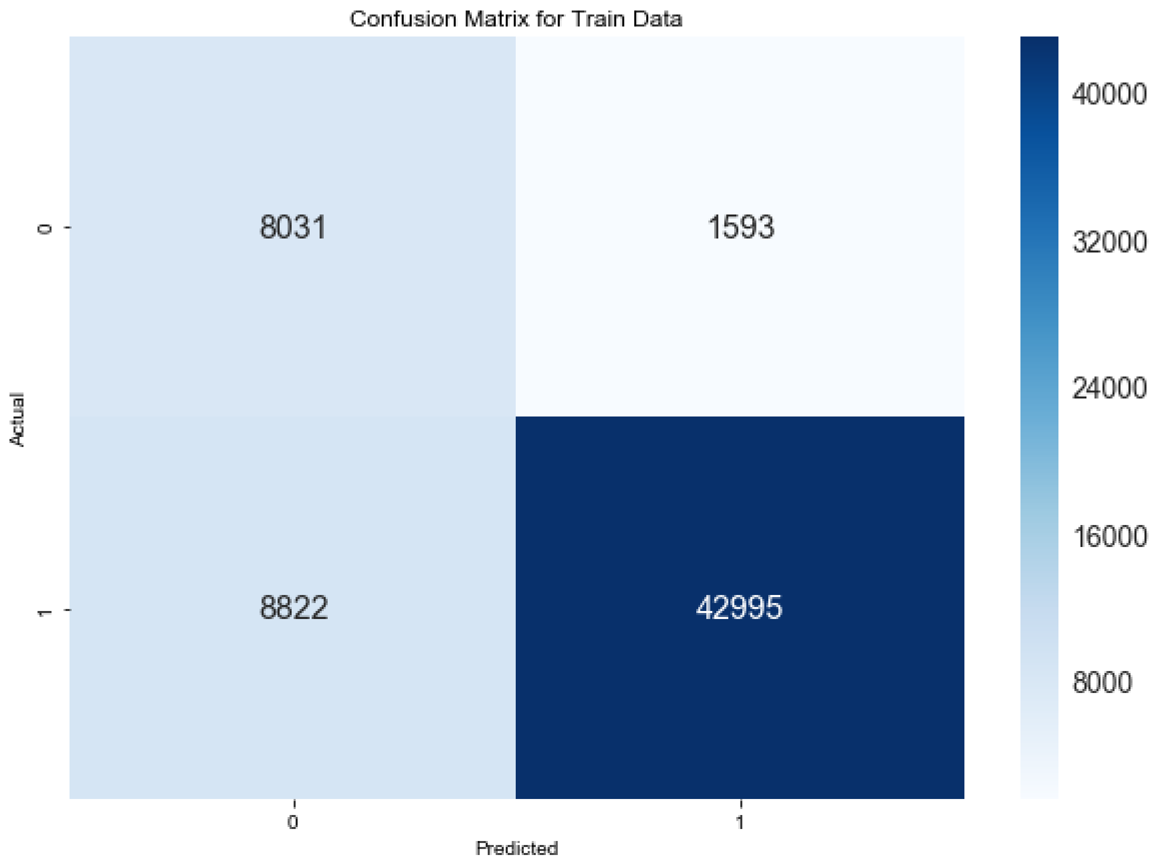
In [79]:
```
Training_Accuracy_Bow = Optimal_Model.score(X_Train_Bow, Y_Train)
print('Training_Accuracy=%0.3f'%Training_Accuracy_Bow)
Training_Error_Bow = 1 - Training_Accuracy_Bow
print('Training_Error=%0.3f'%Training_Error_Bow)

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_al
pha_bow, Test_Accuracy_Bow))
```

```
Training_Accuracy=0.830
Training_Error=0.170
Test_Accuracy=0.825
Test_Error=0.175
```

[4.1.5] Confusion Matrix

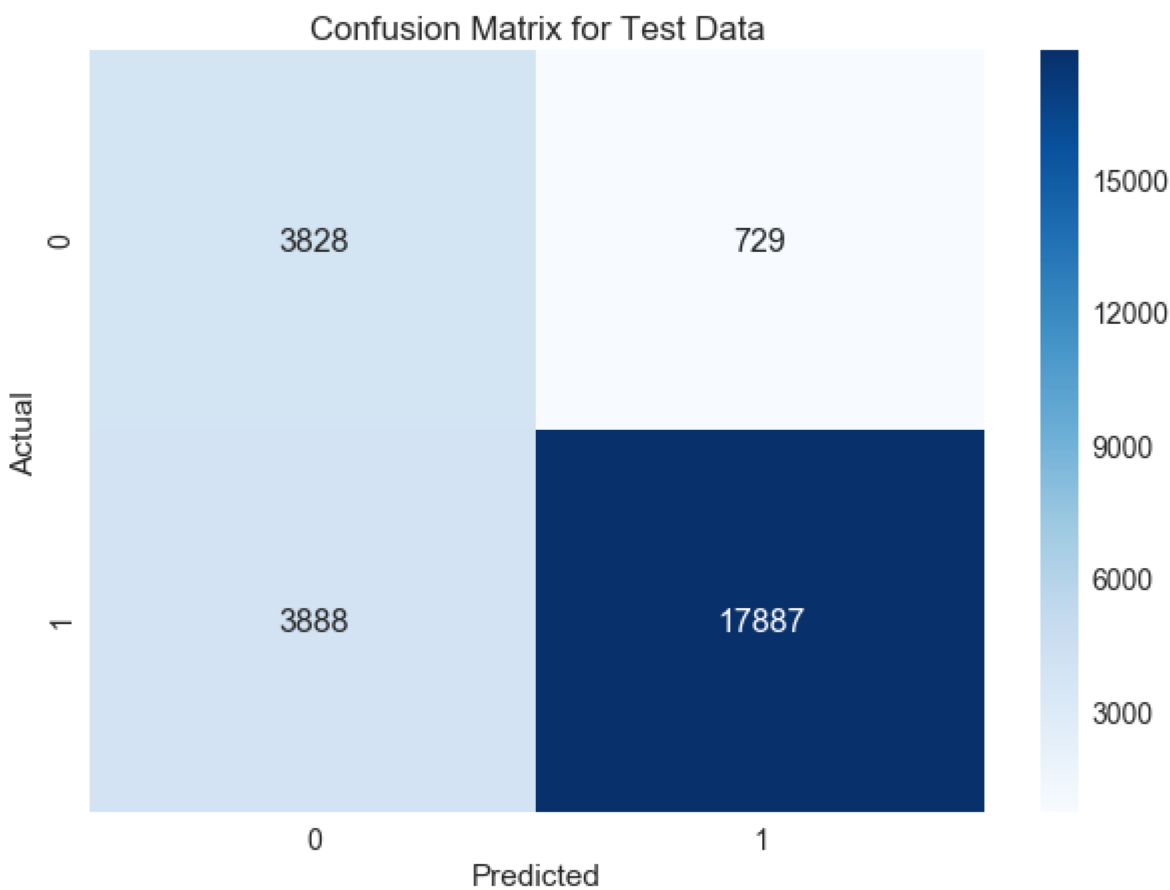
In [80]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Train, Optimal_Model.predict(X_Train_Bow))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Train), index=n
p.unique(Y_Train))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = 'Predicted'
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[80]: <matplotlib.axes._subplots.AxesSubplot at 0x2a110bbc208>



In [81]:
```
#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[81]: <matplotlib.axes._subplots.AxesSubplot at 0x2a110c50278>



[4.1.6] Classification Report

In [82]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_Test, prediction))
```

```
             precision    recall  f1-score   support

          0       0.50      0.84      0.62      4557
          1       0.96      0.82      0.89     21775

avg / total       0.88      0.82      0.84     26332
```

[4.1.7] Feature Importance

Feature Importance for Positive and Negetive Class

In [83]:
```
#Multinomial NB: Most Informative Features
#Reference link: https://stackoverflow.com/questions/29867367/sklearn-multinom
ial-nb-most-informative-features
def show_most_informative_features(vectorizer, clf, n=20):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("_______________________________________________________________________________________________________")
    print("\tNegative\t\t\t\t\tPositive")
    print("_______________________________________________________________________________________________________")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2
))
```

In [84]:
```
show_most_informative_features(count_vect, Optimal_Model)
```

```
____________________________________________________________________________________________________
        Negative                                                Positive
____________________________________________________________________________________________________
        -1.0865 worst                                           1.1727  delicious
        -1.0580 disappointed                                    1.0814  perfect
        -0.9205 awful                                           0.9393  great
        -0.8941 disappointing                                   0.9318  loves
        -0.8834 not good                                        0.9284  excellent
        -0.8383 horrible                                        0.8775  best
        -0.8260 terrible                                        0.8095  wonderful
        -0.8040 unfortunately                                   0.7320  easy
        -0.7853 not buy                                         0.7060  highly
        -0.6799 money                                           0.6591  nice
        -0.6694 not recommend                                   0.5981  favorite
        -0.6288 waste                                           0.5507  tasty
        -0.6022 not worth                                       0.5458  amazing
        -0.5875 bad                                             0.5438  love
        -0.5607 thought                                         0.5167  stores
        -0.5594 stale                                           0.5118  good
        -0.5406 away                                            0.4930  snack
        -0.5072 threw                                           0.4587  pleased
        -0.4600 return                                          0.4478  happy
        -0.4062 disappointment                                  0.4377  definitely
```

[4.1.8] Pertubation Test

In [85]:
```
#Getting the weights W after fit your model with the data X
W1=Optimal_Model.coef_
print(W1.shape)
```

```
(1, 1071615)
```

In [86]:
```
#Add a noise to the X (X' = X + e) and get the new data set X' (if X is a spar
se matrix, X.data+=e)
import copy
X=copy.deepcopy(X_Train_Bow)
e=np.random.normal(0,0.01)
X.data = X.data + e
print(X.shape)
```

```
(61441, 1071615)
```

In [87]:
```
#We fit the model again on data X' and get the weights W'
BOW_Model = LogisticRegression(C= 0.01, penalty= 'l1', class_weight='balanced'
)
BOW_Model.fit(X,Y_Train)
W2=BOW_Model.coef_
print(W2.shape)
```

```
(1, 1071615)
```

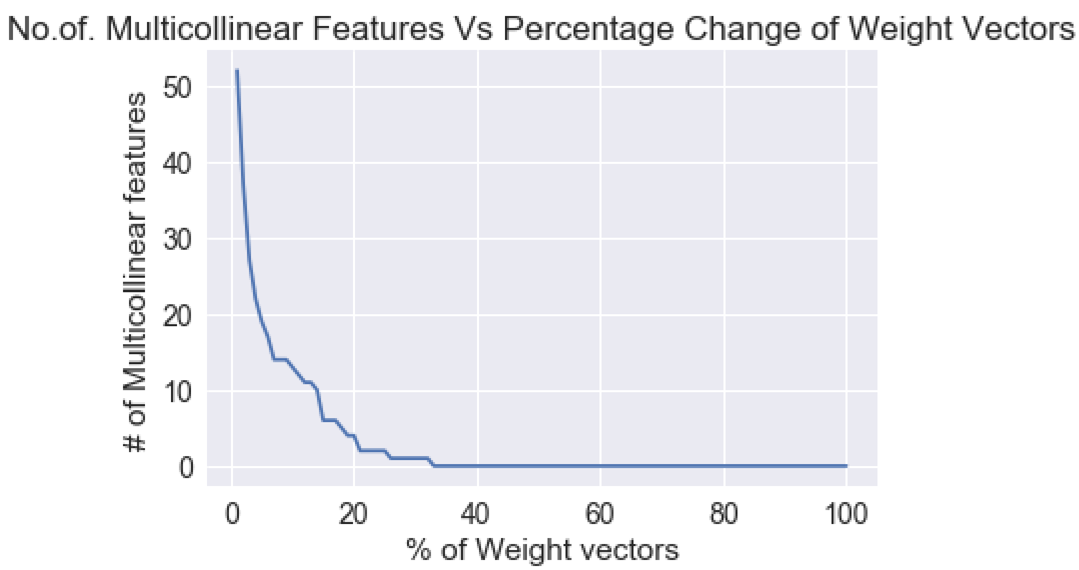
In [88]:
```
#Add the small eps value(to eliminate the divisible by zero error) to W and W’
i.e W=W+10^-6 and W’ = W’+10^-6
e=np.random.normal(0,0.01)
W1 = W1+e
W2 = W2+e
```

In [89]:
```
#find the % change between W and W', percentage_change_vector = (| (W-W') /
 (W) |)*100)
percentage_change_vector = np.abs((W2-W1)/W1)*100
print("Max Percentage Value: ",percentage_change_vector.max())
print("Min Percentage Value: ",percentage_change_vector.min())
print("Std Percentage Value: ",percentage_change_vector.std())
```

```
Max Percentage Value:  32.077349009566774
Min Percentage Value:  0.0
Std Percentage Value:  0.06808463529111797
```

In [90]:
```
percentage_change=[]
collinear_features=[]

for i in range(1,101):
    f=np.where(percentage_change_vector > i)[1].size
    percentage_change.append(i)
    collinear_features.append(f)

plt.title('No.of. Multicollinear Features Vs Percentage Change of Weight Vecto
rs')
plt.xlabel('% of Weight vectors')
plt.ylabel('# of Multicollinear features')
plt.plot(percentage_change,collinear_features)
```

Out[90]:
```
[<matplotlib.lines.Line2D at 0x2a130c97ef0>]
```



In [96]:
```
Bow_feat=count_vect.get_feature_names()
reqd_feature = np.where(percentage_change_vector > 30)
print("No of features have weight changes greater than 30%: ", percentage_chan
ge_vector[reqd_feature].size)

features=[]
print("\nNames of the Multi-collinear features:\n")
for i in np.where(percentage_change_vector > 1)[1]:
    features.append(Bow_feat[i])
print(features)
```

```
No of features have weight changes greater than 30%:  1

Names of the Multi-collinear features:

['available', 'bars', 'beware', 'bitter', 'bottle', 'broken', 'calories', 'ch
eap', 'disgusting', 'earth', 'enjoyed', 'feel', 'gave', 'give', 'hoping', 'hu
sband', 'instead', 'least', 'left', 'liked', 'looked', 'lot', 'may', 'might',
'mix', 'nasty', 'never', 'never buy', 'not bad', 'not disappointed', 'not eve
n', 'not taste', 'often', 'pieces', 'please', 'problem', 'put', 'quick', 'qui
ckly', 'quite', 'rather', 'recommended', 'refund', 'smell', 'sometimes', 'tas
tes like', 'texture', 'thanks', 'thinking', 'toy', 'two', 'unless']
```

[4.2] TF-IDF

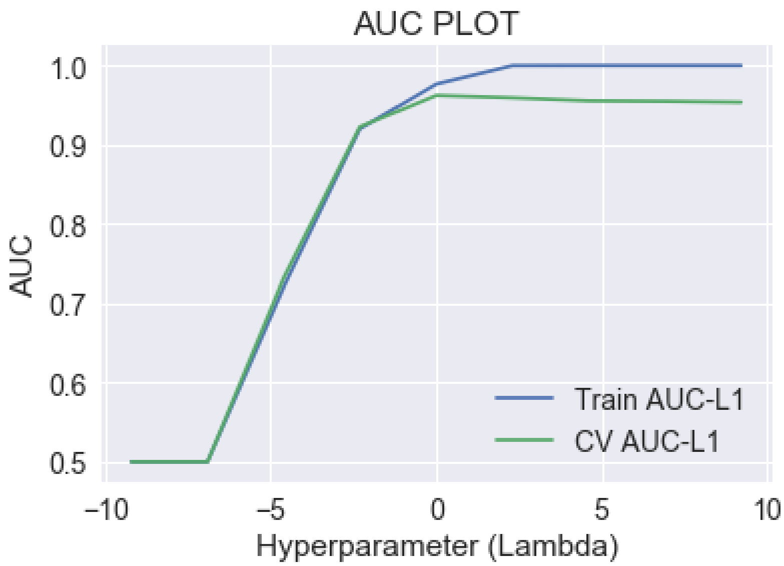
In [97]:
```
#TF-IDF
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=5)
tf_idf_vect.fit_transform(X_Train)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_featu
re_names()[0:10])
print('='*50)

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', 'aafco', 'aback', 'ab
andon', 'abandoned', 'abc', 'abdomen', 'abdominal', 'abdominal pain', 'abid
e']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (61441, 80662)
the shape of out text TFIDF vectorizer  (26332, 80662)
the shape of out text TFIDF vectorizer  (26332, 80662)
```

[4.2.1] Hyperameter tuning with L1 Regulizer and AUC Plot

In [142]:
```
Optimal_Lamda_L1(X_Train_TfIdf, Y_Train, X_CV_TfIdf,Y_cv)
```

```
100%|██████████████████████████████████████████████████| 9/9 [00:12<00:00,  1.70s/it]
```

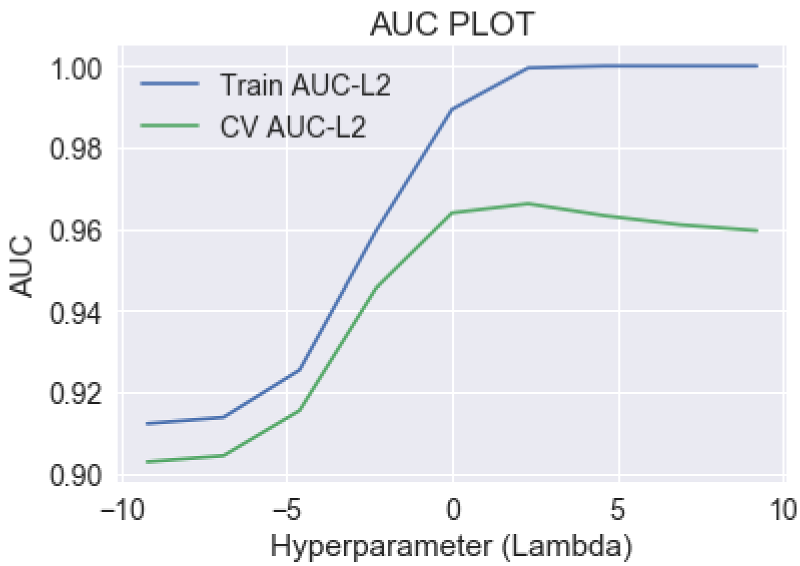



```
CV AUS Scores with Penalty=? Cv auc scores with penalty L1
[0.5, 0.5, 0.7319328359468673, 0.9226217320749269, 0.9622310939856851, 0.9592
171113843857, 0.9553812645387032, 0.9548150773957226, 0.9536571711755699]
Maximun AUC value : 0.9622310939856851
Index 4
```

[4.2.2] Hyperameter tuning with L1 Regulizer and AUC Plot

In [143]:
```
optimal_lambda_tfidf_l2 = Optimal_Lamda_L2(X_Train_TfIdf, Y_Train, X_CV_TfIdf,
Y_cv)
```

```
100%|████████████████████████████████████████████████████████████
██████████| 9/9 [00:31<00:00,  6.02s/it]
```




```
Cv AUC scores with penalty L2
[0.902931153721442, 0.9044393871025689, 0.9155399686632921, 0.945470127460635
7, 0.9639196129546223, 0.9661884732412279, 0.9632519430497284, 0.961010957770
0194, 0.9595892719518828]
Maximun AUC value : 0.9661884732412279
Index 5
```

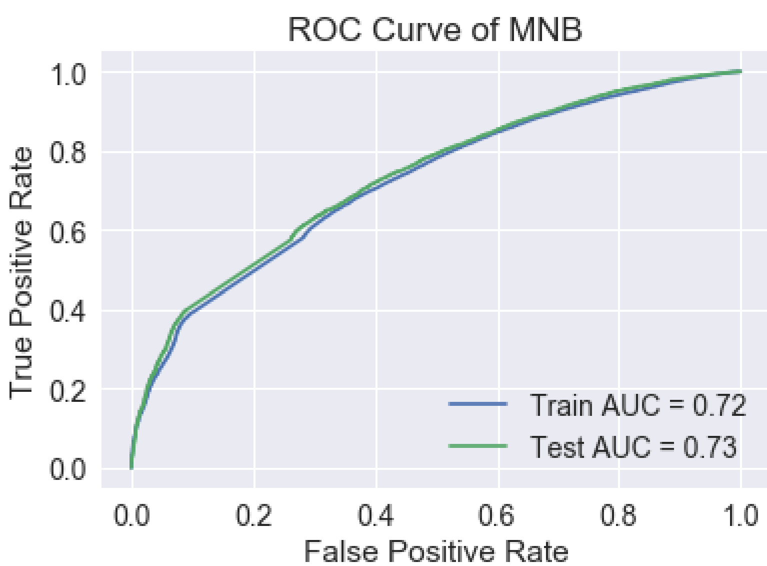
[4.2.3] ROC Curve of Logistic Regression

In [101]:
```
#Testing with test data
Optimal_Model = LogisticRegression(penalty='l1',C=0.01, class_weight='balance
d')
Optimal_Model.fit(X_Train_TfIdf, Y_Train)
prediction = Optimal_Model.predict(X_Test_TfIdf)
print('Optimal_Model',Optimal_Model)
print('prediction',prediction)
```

```
Optimal_Model LogisticRegression(C=0.01, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
prediction [1 1 0 ... 1 1 1]
```

In [102]:

```
#Testing with test data
Train_FPR, Train_TPR, threshold = roc_curve(Y_Train, Optimal_Model.predict_pro
ba(X_Train_TfIdf)[:,1])
Test_FPR, Test_TPR, threshold = roc_curve(Y_Test, Optimal_Model.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 [103]:

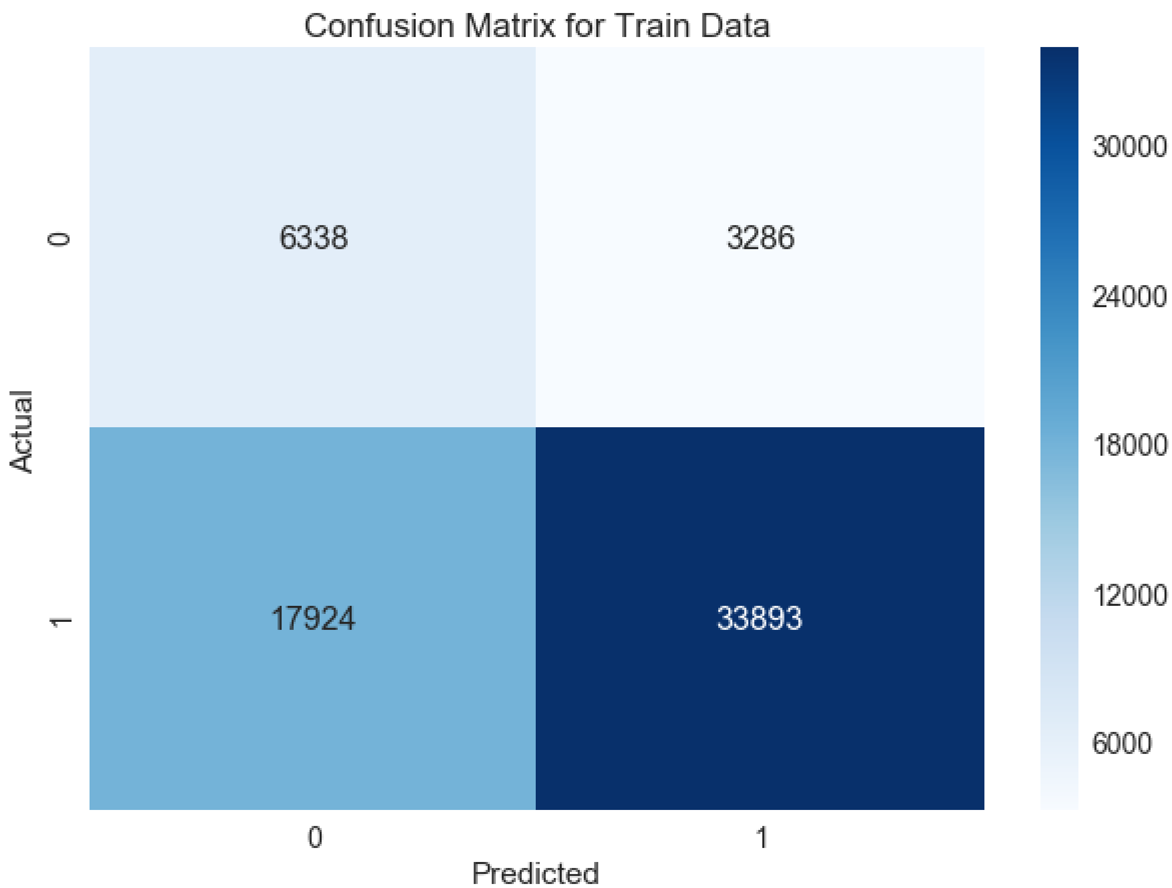
```
Training_Accuracy_Tfidf = Optimal_Model.score(X_Train_TfIdf, Y_Train)
print('Training_Accuracy=%0.3f'%Training_Accuracy_Tfidf)
Training_Error_Tfidf = 1 - Training_Accuracy_Tfidf
print('Training_Error=%0.3f'%Training_Error_Tfidf)

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_al
pha_bow, Test_Accuracy_Bow))
```

```
Training_Accuracy=0.655
Training_Error=0.345
Test_Accuracy=0.652
Test_Error=0.348
```

[4.2.5] Confusion Matrix

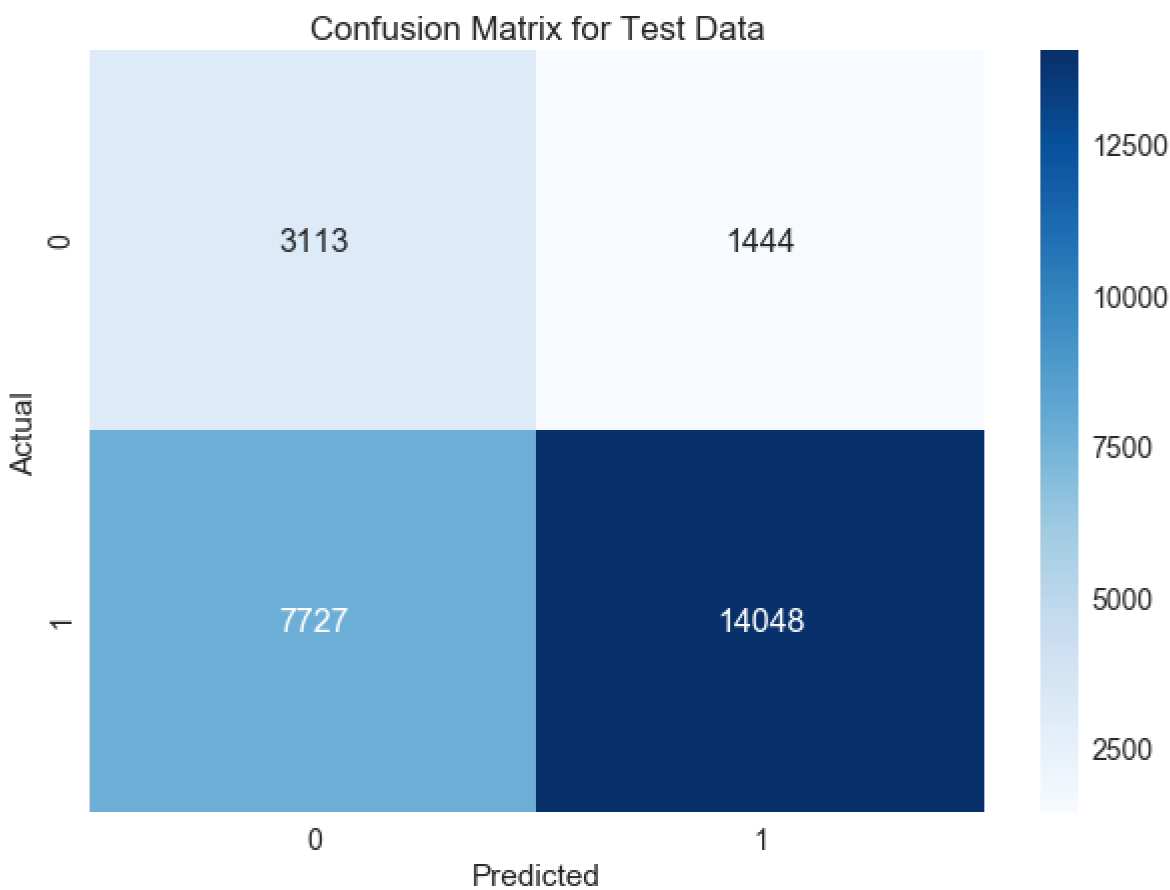
In [104]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Train, Optimal_Model.predict(X_Train_TfIdf))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Train), index=n
p.unique(Y_Train))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = '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[104]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2a12b51e780>
```



In [105]:
```
#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_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[105]: <matplotlib.axes._subplots.AxesSubplot at 0x2a1193c7048>



[4.2.6] Classification Report

In [106]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_Test, prediction))
```

```
             precision    recall  f1-score   support

          0       0.29      0.68      0.40      4557
          1       0.91      0.65      0.75     21775

avg / total       0.80      0.65      0.69     26332
```

[4.2.7] Feature Importance

Feature Importance for Positive and Negetive Class

In [107]:
```
show_most_informative_features(tf_idf_vect, Optimal_Model)
```

```
_____________________________________________________________________________
___________________
        Negative                                                Positive
_____________________________________________________________________________
___________________
        -10.3709        not                                             8.5827  great
        0.0000  aa                                              1.7069  love
        0.0000  aafco                                           0.6437  best
        0.0000  aback                                           0.1810  good
        0.0000  abandon                                         0.0000  zukes mini
        0.0000  abandoned                                       0.0000  zukes
        0.0000  abc                                             0.0000  zuke treats
        0.0000  abdomen                                         0.0000  zuke minis
        0.0000  abdominal                                       0.0000  zuke mini
        0.0000  abdominal pain                                  0.0000  zuke hip
        0.0000  abide                                           0.0000  zuke
        0.0000  abilities                                       0.0000  zucchini
        0.0000  ability                                         0.0000  zoom
        0.0000  abit                                            0.0000  zoo
        0.0000  able                                            0.0000  zone bars
        0.0000  able add                                        0.0000  zone
        0.0000  able afford                                     0.0000  zombie
        0.0000  able break                                      0.0000  zojirushi
        0.0000  able brew                                       0.0000  zoe organic
        0.0000  able buy                                        0.0000  zoe
```

[4.2.7] Pertubation Test

In [108]:
```
#Getting the weights W after fit your model with the data X
W1=Optimal_Model.coef_
print(W1.shape)
```

```
(1, 80662)
```

In [109]:
```
#Add a noise to the X (X' = X + e) and get the new data set X' (if X is a spar
se matrix, X.data+=e)
import copy
X=copy.deepcopy(X_Train_TfIdf)
e=np.random.normal(0,0.01)
X.data = X.data + e
print(X.shape)
```

```
(61441, 80662)
```

In [110]:
```
#We fit the model again on data X' and get the weights W'
TFIDF_Model = LogisticRegression(C= 0.01, penalty= 'l1', class_weight='balance
d')
TFIDF_Model.fit(X,Y_Train)
W2=TFIDF_Model.coef_
print(W2.shape)
```

```
(1, 80662)
```

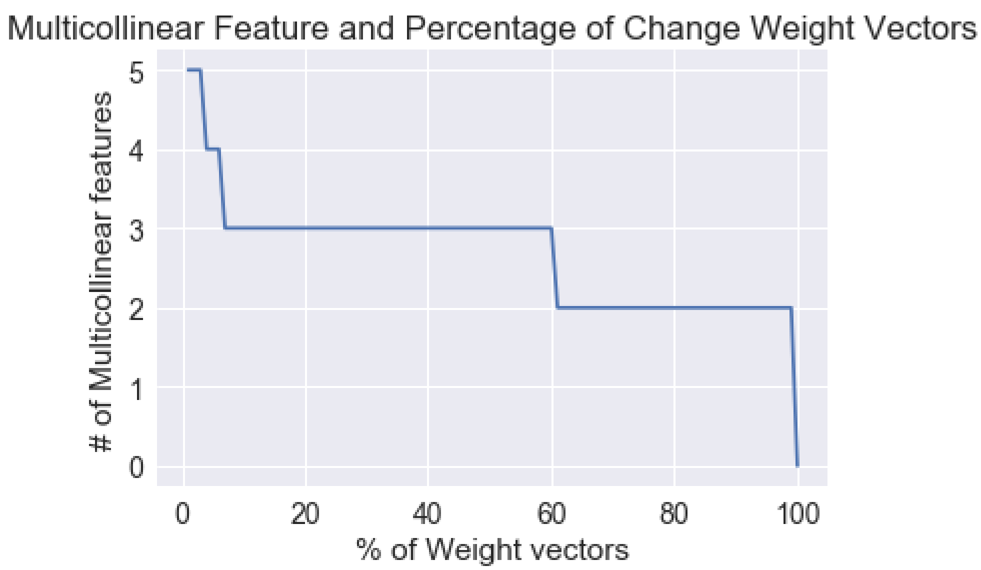
In [111]:
```
#Add the small eps value(to eliminate the divisible by zero error) to W and W’
i.e W=W+10^-6 and W’ = W’+10^-6
e=np.random.normal(0,0.01)
W1 = W1+e
W2 = W2+e
```

In [112]:
```
#find the % change between W and W', percentage_change_vector = (| (W-W') /
 (W) |)*100)
percentage_change_vector = np.abs((W2-W1)/W1)*100
print("Max Percentage Value: ",percentage_change_vector.max())
print("Min Percentage Value: ",percentage_change_vector.min())
print("Std Percentage Value: ",percentage_change_vector.std())
```

```
Max Percentage Value:  99.91547108858693
Min Percentage Value:  0.0
Std Percentage Value:  0.5407848003679077
```

In [113]:
```
percentage_change=[]
collinear_features=[]

for i in range(1,101):
    f=np.where(percentage_change_vector > i)[1].size
    percentage_change.append(i)
    collinear_features.append(f)

plt.title('Multicollinear Feature and Percentage of Change Weight Vectors')
plt.xlabel('% of Weight vectors')
plt.ylabel('# of Multicollinear features')
plt.plot(percentage_change,collinear_features)
```

Out[113]:
```
[<matplotlib.lines.Line2D at 0x2a114dd6358>]
```



In [114]:
```
tfidf_feat=tf_idf_vect.get_feature_names()
reqd_feature = np.where(percentage_change_vector > 30)
print("No of features have weight changes greater than 30%: ", percentage_chan
ge_vector[reqd_feature].size)

features=[]
print("\nNames of the Multi-collinear features:\n")
for i in np.where(percentage_change_vector > 1)[1]:
    features.append(tfidf_feat[i])
print(features)
```

```
No of features have weight changes greater than 30%:  3

Names of the Multi-collinear features:

['best', 'good', 'great', 'love', 'not']
```

[4.3]Word2Vec

In [115]:
```
i=0
list_of_sentance_train=[]
for sentance in X_Train:
    list_of_sentance_train.append(sentance.split())

w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  14799
sample words  ['bought', 'apartment', 'infested', 'fruit', 'flies', 'hours',
'trap', 'attracted', 'many', 'within', 'days', 'practically', 'gone', 'may',
'not', 'long', 'term', 'solution', 'driving', 'crazy', 'consider', 'buying',
'one', 'caution', 'surface', 'sticky', 'try', 'avoid', 'touching', 'really',
'good', 'idea', 'final', 'product', 'outstanding', 'use', 'car', 'window', 'e
verybody', 'asks', 'made', 'two', 'thumbs', 'received', 'shipment', 'could',
'hardly', 'wait', 'love', 'call']
```

[4.3.1] Computing avg w2v for train, test, and CV

In [116]:
```
%%time
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in t
his list
for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
sent_vectors_train = np.array(sent_vectors_train)
print(sent_vectors_train.shape)
print(sent_vectors_train[0])
```

```
100%|████████████████████████████████████████████████████████████████████████
███| 61441/61441 [03:49<00:00, 268.14it/s]

(61441, 50)
[-0.33950951 -0.33488994 -0.33573298 -0.51396754 -0.06975959  0.21375592
  0.07732713 -0.60388593 -0.34814431  0.19845745  0.3815664   0.40204279
 -0.10928249  0.18389756  0.73805093  0.17999925 -0.12761659 -0.01847279
  0.53143276  0.26952201 -0.613577   -0.42093613  0.4640647  -0.42287367
 -0.15860972 -0.10623529 -0.40118239  0.15250288  0.16710049  0.62810433
  0.46918193  0.10473322 -0.45874493 -0.12482662  0.09535776 -0.09233927
 -0.1601373  -0.04365186  0.05148495  0.16999314 -0.37391493  0.27599862
  0.2095408  -0.04154568 -0.1154915  -0.11939497 -0.42355511 -0.4789842
 -0.01988444 -0.02846113]
Wall time: 3min 49s
```

In [117]:

```
%%time
i=0
list_of_sentance_cv=[]
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sentance_cv): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
sent_vectors_cv = np.array(sent_vectors_cv)
print(sent_vectors_cv.shape)
print(sent_vectors_cv[0])
```

```
100%|████████████████████████████████████████████████████████████████████████
███| 26332/26332 [01:55<00:00, 228.91it/s]

(26332, 50)
[-0.32212967 -0.05650922  0.85562827  0.80185549  1.38591885 -0.18607936
 -0.31209497 -0.51726579  0.0216198   0.3427079  -0.09292613 -0.15750389
  0.37896734 -0.08537286  0.04484537  0.72499551 -0.26671065  0.39521788
  0.65470891 -0.48425626  0.1468507  -0.2299341  -0.366834   -0.08889219
 -0.60205857 -0.54432607  0.28889598  0.55503118  0.06217408 -0.10286575
  0.82000878  0.0868873  -0.45831241  0.41500448 -0.3905572  -0.82853059
 -0.42346301 -0.39560083  0.28644322 -0.30447075 -0.14453179 -0.14473943
  0.79878876  1.36441523 -0.00346129  0.47505222 -0.51671918  0.6013452
 -0.0138015   0.70236979]
Wall time: 1min 55s
```

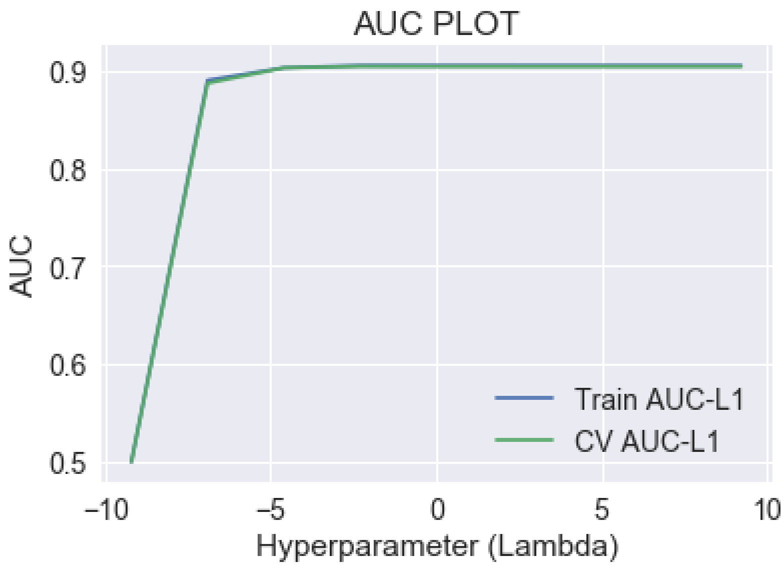
In [118]:
```
%%time

i=0
list_of_sentance_test=[]
for sentance in X_Test:
    list_of_sentance_test.append(sentance.split())

# average Word2Vec
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in th
is list
for sent in tqdm(list_of_sentance_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
sent_vectors_test = np.array(sent_vectors_test)
print(sent_vectors_test.shape)
print(sent_vectors_test[0])
```

```
100%|██████████████████████████████████████████████████████████████████████
███| 26332/26332 [02:11<00:00, 200.37it/s]

(26332, 50)
[-0.32212967 -0.05650922  0.85562827  0.80185549  1.38591885 -0.18607936
 -0.31209497 -0.51726579  0.0216198   0.3427079  -0.09292613 -0.15750389
  0.37896734 -0.08537286  0.04484537  0.72499551 -0.26671065  0.39521788
  0.65470891 -0.48425626  0.1468507  -0.2299341  -0.366834   -0.08889219
 -0.60205857 -0.54432607  0.28889598  0.55503118  0.06217408 -0.10286575
  0.82000878  0.0868873  -0.45831241  0.41500448 -0.3905572  -0.82853059
 -0.42346301 -0.39560083  0.28644322 -0.30447075 -0.14453179 -0.14473943
  0.79878876  1.36441523 -0.00346129  0.47505222 -0.51671918  0.6013452
 -0.0138015   0.70236979]
Wall time: 2min 11s
```

[4.3.2] Hyperameter tuning with L1 Regulizer and AUC Plot

In [144]:
```
Optimal_Lamda_L1(sent_vectors_train, Y_Train, sent_vectors_cv,Y_cv)
```

```
100%|██████████| 9/9 [01:30<00:00, 13.30s/it]
```

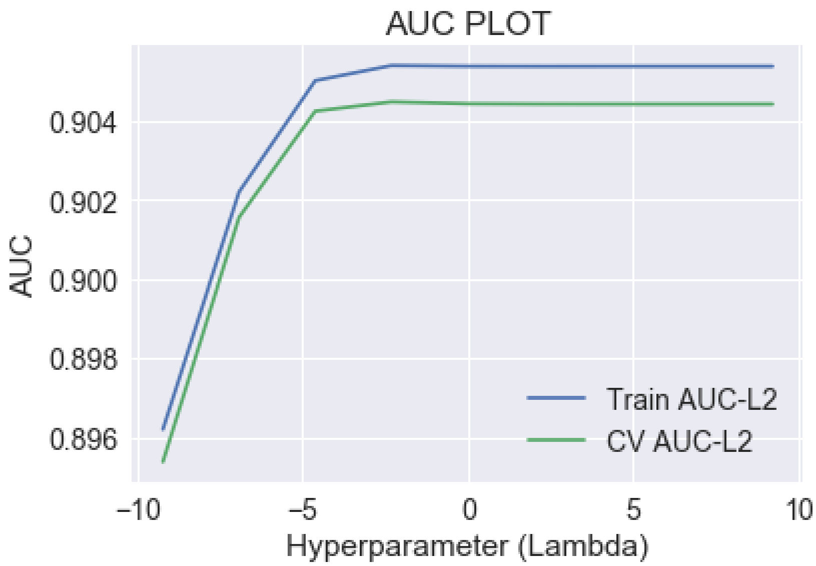



```
CV AUS Scores with Penalty=? Cv auc scores with penalty L1
[0.5, 0.8872852328220648, 0.9029992288015537, 0.9045686340163265, 0.904448255
5067876, 0.904424341048593, 0.9044231821094053, 0.9044230813320847, 0.9044228
092333189]
Maximun AUC value : 0.9045686340163265
Index 3
```

[4.3.3] Hyperameter tuning with L2 Regulizer and AUC Plot

In [145]:
```
Optimal_Lamda_L2(sent_vectors_train, Y_Train, sent_vectors_cv,Y_cv)
```

```
100%|██████████████████████████████████████████████████████████████
██████████| 9/9 [00:14<00:00,  1.85s/it]
```



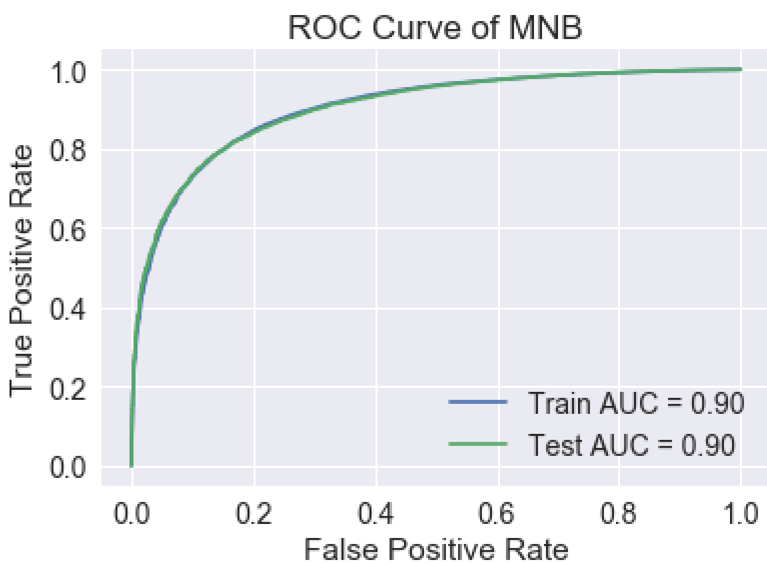

```
Cv AUC scores with penalty L2
[0.895374759362654, 0.9015520765544839, 0.9042422364301448, 0.904477763106279
5, 0.9044299241121582, 0.9044226278341416, 0.9044210859411355, 0.904421267340
3127, 0.904421337884437]
Maximun AUC value : 0.9044777631062795
Index 3
```

[4.3.4] ROC Curve of Logistic Regression

In [121]:
```
#Testing with test data
Optimal_Model = LogisticRegression(penalty='l1',C=0.01, class_weight='balance
d')
Optimal_Model.fit(sent_vectors_train, Y_Train)
prediction = Optimal_Model.predict(sent_vectors_test)
print('Optimal_Model',Optimal_Model)
print('prediction',prediction)
```

```
Optimal_Model LogisticRegression(C=0.01, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
prediction [1 1 1 ... 1 1 1]
```

In [122]:
```
#Testing with test data
Train_FPR, Train_TPR, threshold = roc_curve(Y_Train, Optimal_Model.predict_pro
ba(sent_vectors_train)[:,1])
Test_FPR, Test_TPR, threshold = roc_curve(Y_Test, Optimal_Model.predict_proba(
sent_vectors_test)[:,1])
roc_auc4 = auc(Train_FPR, Train_TPR)
roc_auc5 = auc(Test_FPR, Test_TPR)

plt.plot(Train_FPR, Train_TPR, label = 'Train AUC = %0.2f' % roc_auc4)
plt.plot(Test_FPR, Test_TPR, label = 'Test AUC = %0.2f' % roc_auc5)
plt.legend()
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of MNB')
plt.show()
```



[4.3.5]Train and Test Accuracy

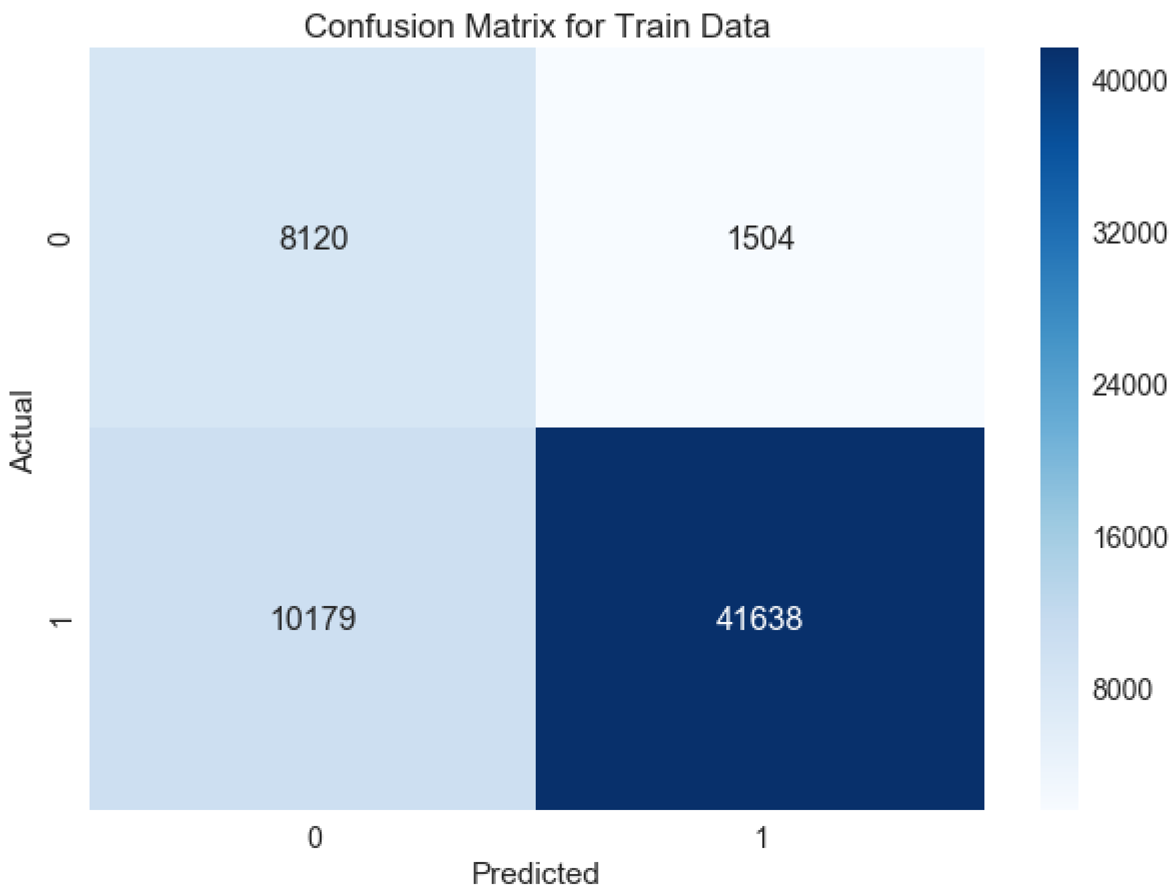
In [123]:
```
Training_Accuracy_w2v = Optimal_Model.score(sent_vectors_train, Y_Train)
print('Training_Accuracy=%0.3f'%Training_Accuracy_w2v)
Training_Error_w2v = 1 - Training_Accuracy_w2v
print('Training_Error=%0.3f'%Training_Error_w2v)

Test_Accuracy_w2v = accuracy_score(Y_Test, prediction)
print('Test_Accuracy=%0.3f'%Test_Accuracy_w2v)
Test_Error_w2v = 1 - Test_Accuracy_w2v
print('Test_Error=%0.3f'%Test_Error_w2v)
#print('\nThe accuracy of the MNB classifier for k = %d is %f%%' % (optimal_al
pha_bow, Test_Accuracy_Bow))
```

```
Training_Accuracy=0.810
Training_Error=0.190
Test_Accuracy=0.806
Test_Error=0.194
```

[4.3.6]Confusion Matrix

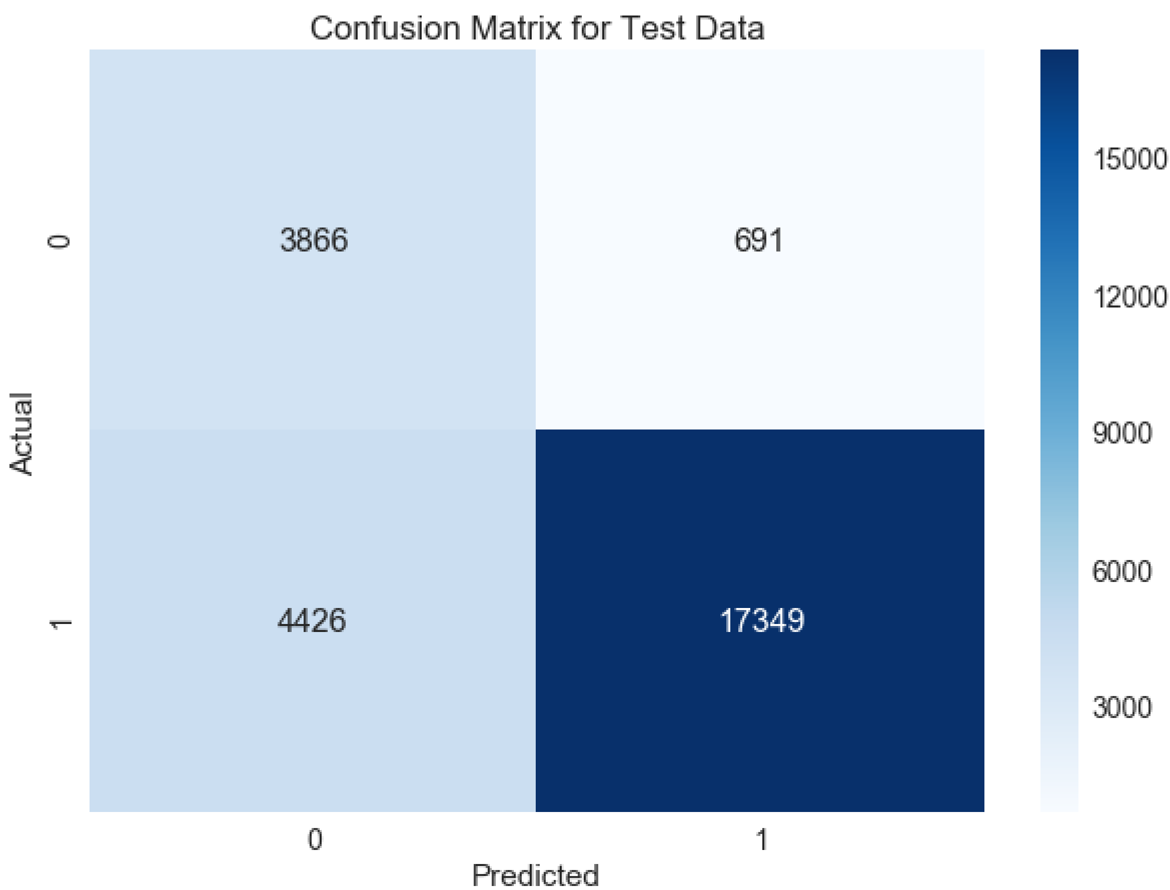
In [124]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Train, Optimal_Model.predict(sent_vectors_tra
in))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Train), index=n
p.unique(Y_Train))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = '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[124]: <matplotlib.axes._subplots.AxesSubplot at 0x2a115c871d0>



In [125]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Test, Optimal_Model.predict(sent_vectors_test
))
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[125]: <matplotlib.axes._subplots.AxesSubplot at 0x2a15f33b908>



[4.3.7] Classification Report

In [126]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_Test, prediction))
```

```
             precision    recall  f1-score   support

          0       0.47      0.85      0.60      4557
          1       0.96      0.80      0.87     21775

avg / total       0.88      0.81      0.82     26332
```

 [4.4] TFIDF weighted W2v

In [127]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
model.fit(X_Train)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

[4.4.1] Compute TF-IDF weighted Word2Vec for Train, Test, and CV

In [128]:

```
i=0
list_of_sentance_train=[]
for sentance in X_Train:
    list_of_sentance_train.append(sentance.split())
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review is sto
red in this list
row=0;
for sent in tqdm(list_of_sentance_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████████████████████████████
████| 61441/61441 [48:36<00:00, 21.07it/s]
```

In [129]:
```
i=0
list_of_sentance_test=[]
for sentance in X_Test:
    list_of_sentance_test.append(sentance.split())
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stor
ed in this list
row=0;
for sent in tqdm(list_of_sentance_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████████████████████████
████| 26332/26332 [21:22<00:00, 20.54it/s]
```

In [130]:

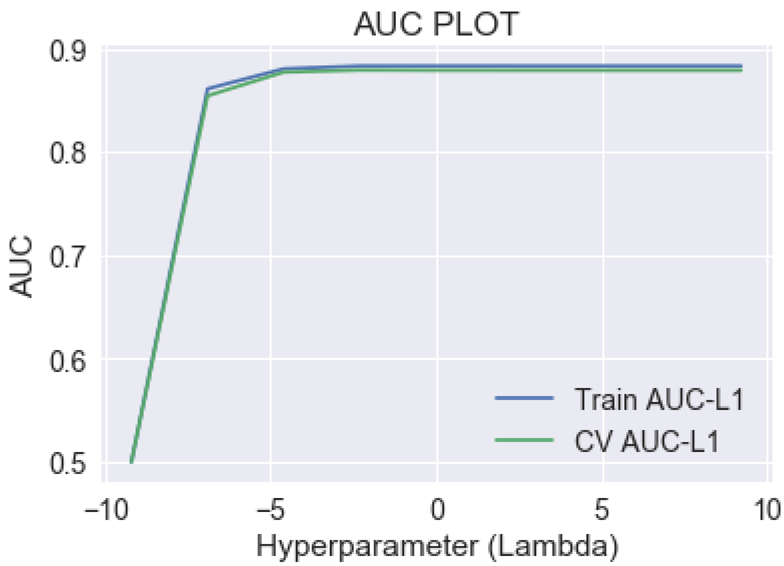
```
i=0
list_of_sentance_cv=[]
for sentance in X_cv:
    list_of_sentance_cv.append(sentance.split())
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors_cv = []; # the tfidf-w2v for each sentence/review is stored
in this list
row=0;
for sent in tqdm(list_of_sentance_cv): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_cv.append(sent_vec)
    row += 1
```

```
100%|████████████████████████████████████████████████████████████████████████
████| 26332/26332 [21:47<00:00, 20.15it/s]
```

[4.4.2] Hyperameter tuning with L1 Regulizer and AUC Plot

In [131]:
```
Optimal_Lamda_L1(tfidf_sent_vectors_train, Y_Train, tfidf_sent_vectors_cv,Y_cv
)
```

```
100%|
| 9/9 [00:55<00:00,  8.25s/it]
```

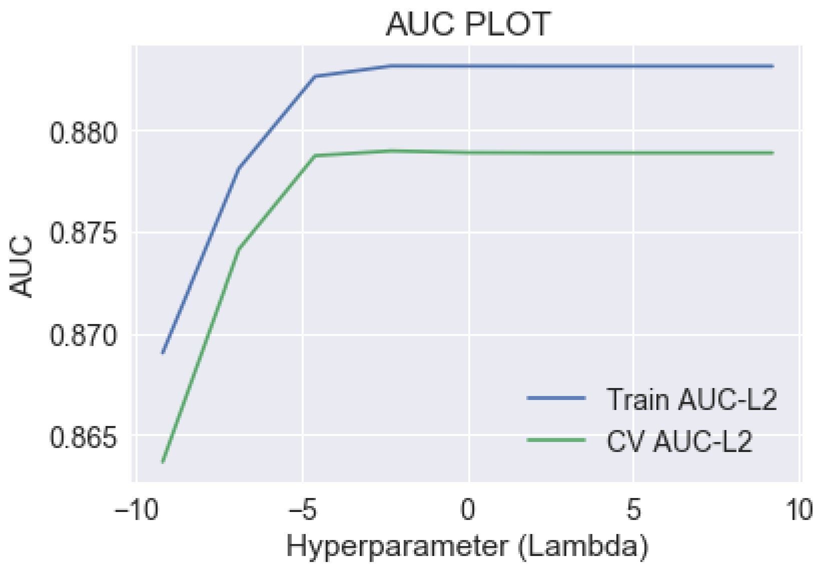



```
CV AUS Scores with Penalty=? Cv auc scores with penalty L1
[0.5, 0.8542753795714797, 0.8771947221909393, 0.8791301909453089, 0.878909025
0373696, 0.8788800515576773, 0.8788779352339433, 0.8788774918137323, 0.878877
5724355888]
Maximun AUC value : 0.8791301909453089
Index 3
```

[4.4.3] Hyperameter tuning with L2 Regulizer and AUC Plot

In [132]:
```
Optimal_Lamda_L2(tfidf_sent_vectors_train, Y_Train, tfidf_sent_vectors_cv,Y_cv
)
```

```
100%|██████████████████████████████████████████████████| 9/9 [00:16<00:00,  2.05s/it]
```



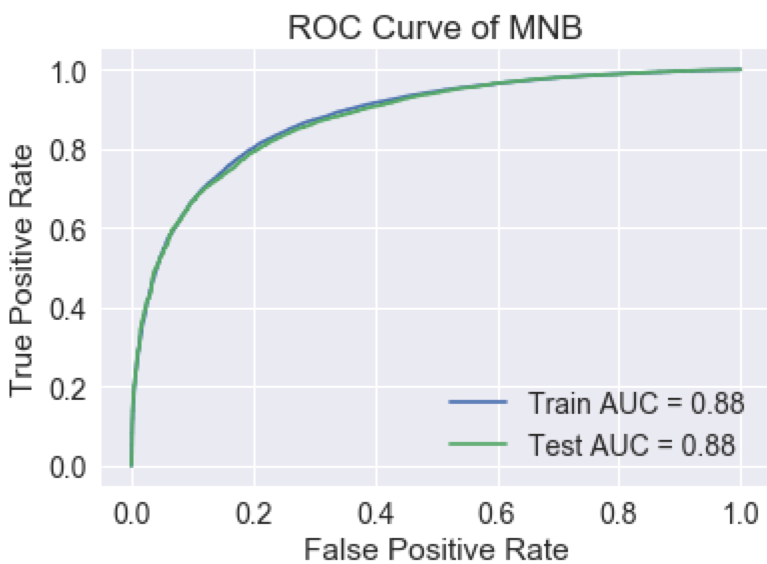

```
Cv AUC scores with penalty L2
[0.8636749004257086, 0.8741226364254082, 0.8787348314385937, 0.8789730589469223, 0.8788892122161259, 0.8788769778493968, 0.8788767359838272, 0.878876534429186, 0.8788765747401142]
Maximun AUC value : 0.8789730589469223
Index 3
```

[4.4.4] ROC Curve of Logistic Regression

In [133]:
```
#Testing with test data
Optimal_Model = LogisticRegression(penalty='l1',C=0.01, class_weight='balanced')
Optimal_Model.fit(tfidf_sent_vectors_train, Y_Train)
prediction = Optimal_Model.predict(tfidf_sent_vectors_test)
print('Optimal_Model',Optimal_Model)
print('prediction',prediction)
```

```
Optimal_Model LogisticRegression(C=0.01, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
prediction [1 0 0 ... 1 1 1]
```

In [134]:
```
#Testing with test data
Train_FPR, Train_TPR, threshold = roc_curve(Y_Train, Optimal_Model.predict_pro
ba(tfidf_sent_vectors_train)[:,1])
Test_FPR, Test_TPR, threshold = roc_curve(Y_Test, Optimal_Model.predict_proba(
tfidf_sent_vectors_test)[:,1])
roc_auc6 = auc(Train_FPR, Train_TPR)
roc_auc7 = auc(Test_FPR, Test_TPR)

plt.plot(Train_FPR, Train_TPR, label = 'Train AUC = %0.2f' % roc_auc6)
plt.plot(Test_FPR, Test_TPR, label = 'Test AUC = %0.2f' % roc_auc7)
plt.legend()
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of MNB')
plt.show()
```



[4.4.5]Train and Test Accuracy

In [135]:
```
Training_Accuracy_tfidfw2v = Optimal_Model.score(tfidf_sent_vectors_train, Y_T
rain)
print('Training_Accuracy=%0.3f'%Training_Accuracy_tfidfw2v)
Training_Error_tfidfw2v = 1 - Training_Accuracy_w2v
print('Training_Error=%0.3f'%Training_Error_tfidfw2v)
```

```
Training_Accuracy=0.790
Training_Error=0.190
```

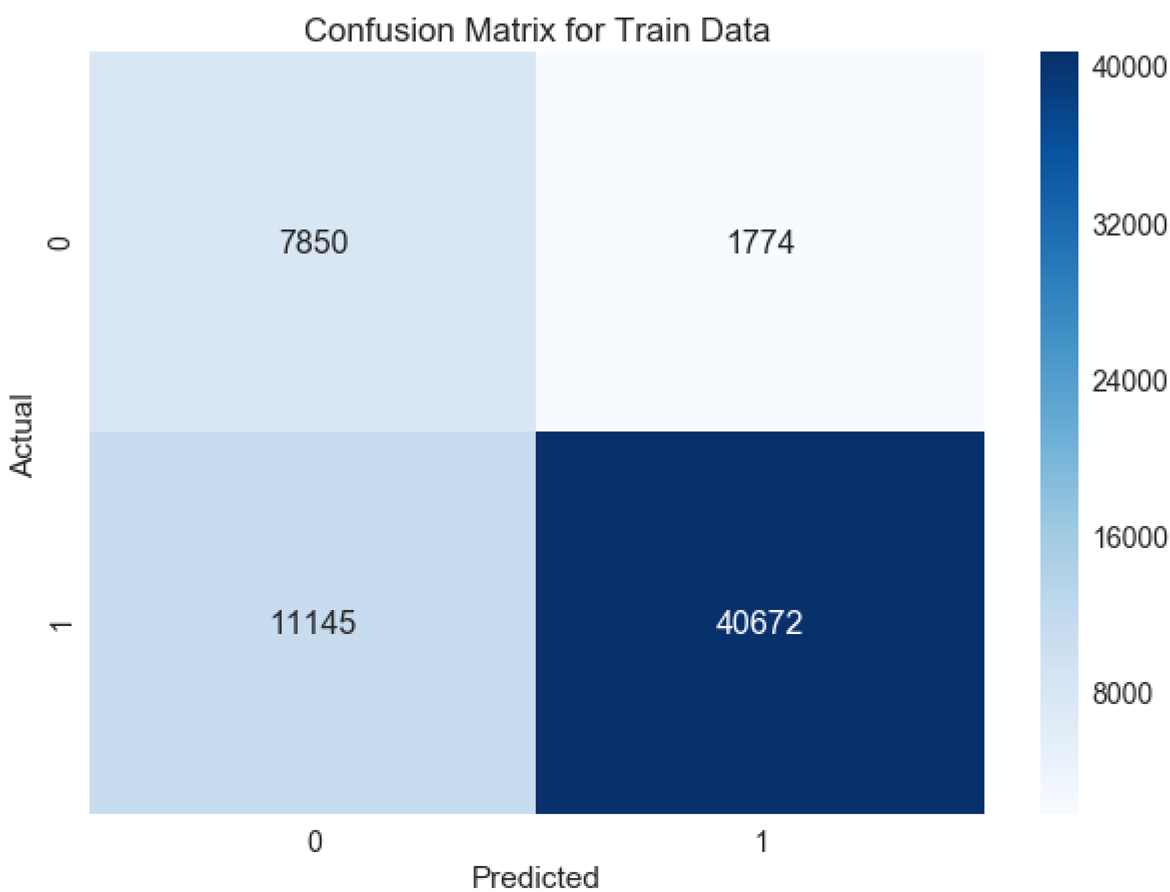
In [136]:
```
Test_Accuracy_tfidfw2v = accuracy_score(Y_Test, prediction)
print('Test_Accuracy=%0.3f'%Test_Accuracy_tfidfw2v)
Test_Error_tfidfw2v = 1 - Test_Accuracy_tfidfw2v
print('Test_Error=%0.3f'%Test_Error_tfidfw2v)
#print('\nThe accuracy of the MNB classifier for k = %d is %f%%' % (optimal_al
pha_bow, Test_Accuracy_Bow))
```

```
Test_Accuracy=0.783
Test_Error=0.217
```

[4.4.6]Confusion Matrix

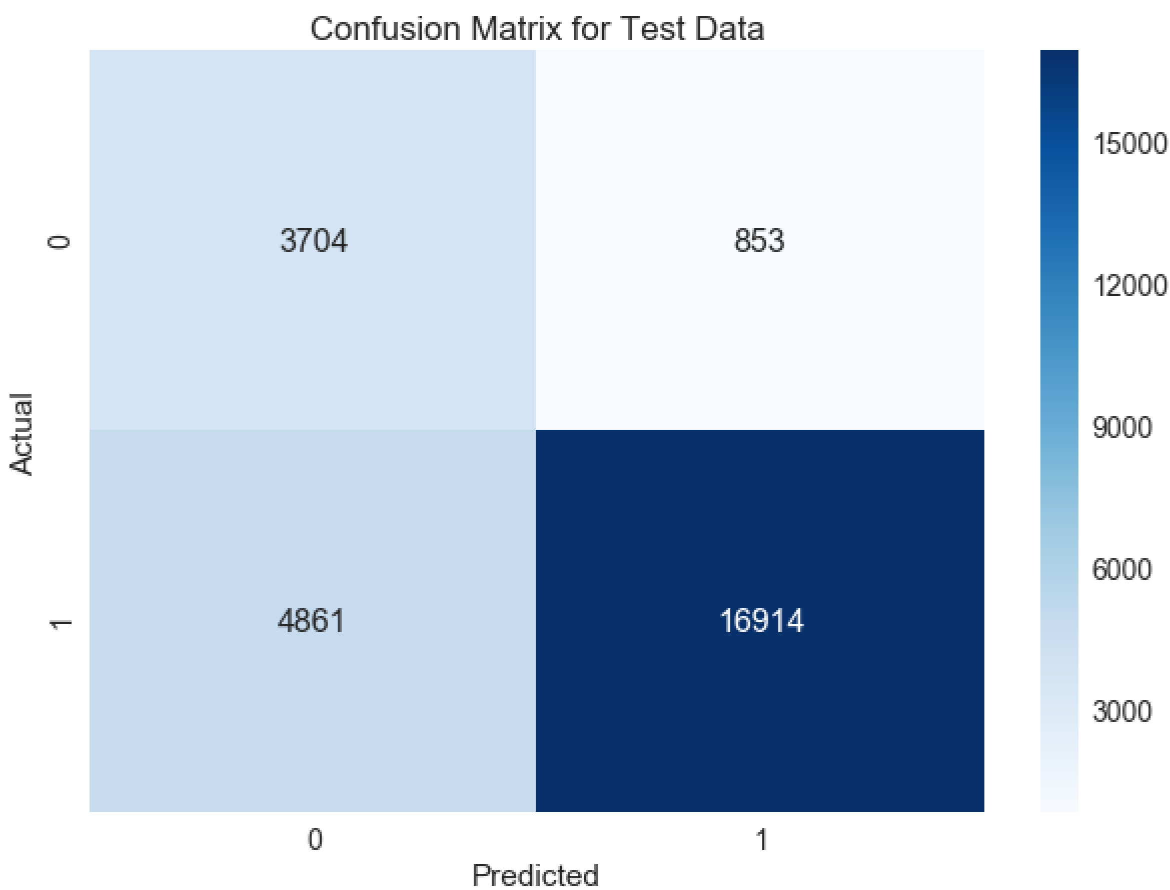
In [137]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Train, Optimal_Model.predict(tfidf_sent_vecto
rs_train))
df_conf_matrix = pd.DataFrame(conf_matrix, columns=np.unique(Y_Train), index=n
p.unique(Y_Train))
df_conf_matrix.index.name = 'Actual'
df_conf_matrix.columns.name = '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[137]: `<matplotlib.axes._subplots.AxesSubplot at 0x2a1626c55c0>`



In [138]:
```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_Test, Optimal_Model.predict(tfidf_sent_vector
s_test))
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[138]: <matplotlib.axes._subplots.AxesSubplot at 0x2a1626c56a0>



[4.4.7] Classification Report

In [139]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_Test, prediction))
```

```
             precision    recall  f1-score   support

          0       0.43      0.81      0.56      4557
          1       0.95      0.78      0.86     21775

avg / total       0.86      0.78      0.81     26332
```

[4.4.8] Feature Importance

Feature Importance for Positive and Negetive Class

In [140]:
```
show_most_informative_features(model, Optimal_Model)
```

```
_____________________________________________________________________________
___________________
        Negative                                              Positive
_____________________________________________________________________________
___________________
        -1.4927 aafco                                         1.1328  aaaaa
        -1.1375 aahing                                        0.8360  abbey
        -0.9563 aaaaaawwwwwwwwww                                      0.6794  abe
        -0.8997 aback                                         0.5305  aaa
        -0.7332 abc                                           0.5033  abide
        -0.6642 abilities                                     0.4619  abiding
        -0.6094 ablaze                                        0.3912  abandoning
        -0.5975 aachen                                        0.3488  aaaa
        -0.5406 aaaah                                         0.3482  abid
        -0.5286 aarthur                                       0.3314  aamazon
        -0.5217 abdomen                                       0.3127  abit
        -0.4075 abbreviated                                   0.2215  aaahs
        -0.3518 abbott                                        0.1671  abandon
        -0.1843 abbreviation                                  0.1368  abates
        -0.1444 abandoned                                     0.1365  abhors
        -0.1349 aa                                            0.0326  ab
        -0.1234 aap                                           0.0312  aaaaaaaaaaaa
        -0.1217 abby                                          0.0000  abita
        -0.0551 ability                                       0.0000  abilling
        -0.0527 aadp                                          0.0000  abdominal
```

Pretty Table

In [149]:
```
from prettytable import PrettyTable
comparision = PrettyTable()
comparision.field_names = ["Vectorizer", "CV-AUC-L1", "CV-AUC-L2", "Training E
rror", "Test Error"]
comparision.add_row(["BoW", "0.952","0.956", np.round(float(Training_Error_Bow
),3), np.round(float(Test_Error_Bow),3)])
comparision.add_row(["TF-IDF", "0.962", "0.966",np.round(float(Training_Error_
Tfidf),3), np.round(float(Test_Error_Tfidf),3)])
comparision.add_row(["Word2Vec", "0.904", "0.904", np.round(float(Training_Err
or_w2v),3), np.round(float(Test_Error_w2v),3)])
comparision.add_row(["TF-IDF Weighted W2V", "0.879", "0.878", np.round(float(T
raining_Error_tfidfw2v),3), np.round(float(Test_Error_tfidfw2v),3)])
print(comparision)
```

```
+---------------------+-----------+-----------+----------------+------------+
|      Vectorizer     | CV-AUC-L1 | CV-AUC-L2 | Training Error | Test Error |
+---------------------+-----------+-----------+----------------+------------+
|         BoW         |   0.952   |   0.956   |      0.17      |   0.175    |
|        TF-IDF       |   0.962   |   0.966   |     0.345      |   0.348    |
|       Word2Vec      |   0.904   |   0.904   |      0.19      |   0.194    |
| TF-IDF Weighted W2V |   0.879   |   0.878   |      0.19      |   0.217    |
+---------------------+-----------+-----------+----------------+------------+
```

Conclusion

1. Applied Logistic Regression on all the 4 vectorizers(BOW, TFIDF, AVG-W2V, TFIDF-AVG_W2V).
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 lambda values between (10^-4 to 10^4).
4. Found the top 20 features of positive and negative class for the featurizations Bow and TF-IDF, TFIDF Weighted vector.
5. With reference to the pretty table, here is my understanding: a. Logistic Regression by using TF-IDF featurization is having the best AUC score: 0.96. b. Logistic Regression by using BoW having AUC score: 0.95 and TF-IDF Weighted W2V is having the AUC Score: 0.87.
6. Class_Weight has set to 'balanced'
7. Pertubation test has performed and printed the multicollinearity features.