Naive Bayes to Amazon Fine Food Reviews Dataset

Exercise :

1. Download Amazon Fine Food Reviews dataset from Kaggle. You may have to create a Kaggle account to download data. (https://www.kaggle.com/snap/amazon-fine-food-reviews)
2. Split data into train and test using time based slicing as 70% train & 30% test.
3. Perform featurization, BoW, tf-idf.
4. Apply Naive Bayes on train data.
5. Perform cross validation to find optimal alpha (Laplace Smoothing).
6. Find important features for +ve and –ve class labels.
7. To test the performance of the model, calculate accuracy,precision,recall,F1-score,confusion matrix(TPR,TNR,FPR,FNR)
8. Write your observations in English as crisply and unambiguously as possible. Always quantify your results.

Information regarding data set :

1. **Title**: Amazon Fine Food Reviews Data
2. **Sources**: Stanford Network Analysis Project(SNAP)
3. **Relevant Information**: This dataset consists of reviews of fine foods from amazon. The data span a period of more than 10 years, including all ~568,454 reviews up to October 2012(Oct 1999 - Oct 2012). Reviews include product and user information, ratings, and a plain text review.
4. **Attribute Information**:
   ProductId - unique identifier for the product
   UserId - unqiue identifier for the user
   ProfileName - name of the user
   HelpfulnessNumerator - number of users who found the review helpful
   HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
   Score - rating between 1 and 5.(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)
   Time - timestamp for the review
   Summary - brief summary of the review
   Text - text of the review

Objective :

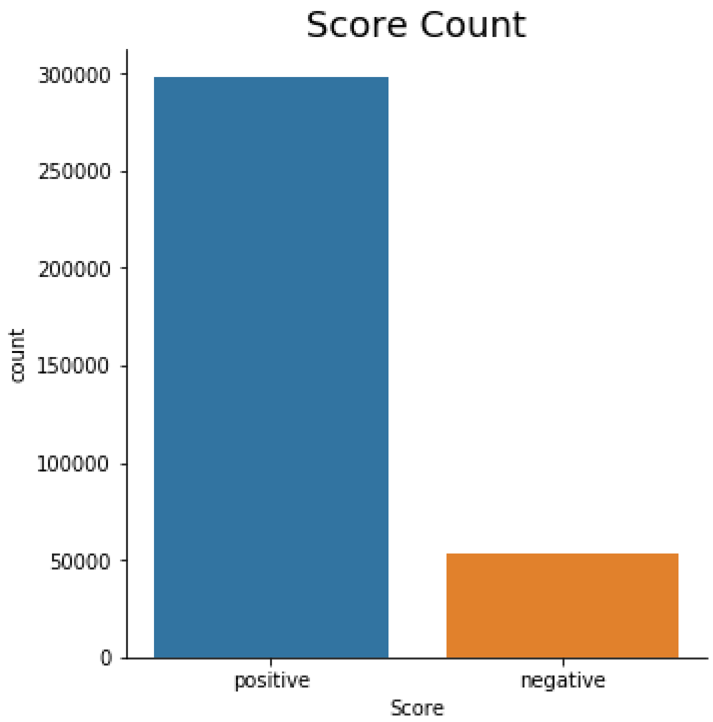
> It is a 2-class classification task, where we have to analyze, transform(BoW,TF-IDF) and calculate probabilistic class label values using naive bayes, which evaluates whether a review is positive or negative.

In [12]:
```
import warnings
warnings.filterwarnings("ignore", category=UserWarning,module='gensim')
warnings.filterwarnings("ignore", category=UserWarning)

from sklearn.exceptions import DataConversionWarning
warnings.filterwarnings(action='ignore', category=DataConversionWarning)

with warnings.catch_warnings():
    warnings.simplefilter("ignore")

import traceback
import sqlite3
import itertools
from nltk import FreqDist
import datetime as dt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn import preprocessing
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_validate
from sklearn.model_selection import train_test_split
from prettytable import PrettyTable
from sklearn.naive_bayes import MultinomialNB
from imblearn.over_sampling import SMOTE
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, accuracy_score,con
fusion_matrix,classification_report
from sklearn.metrics import make_scorer
```

(1) Load dataset :

In [13]:
```
# Load 'finalDataSet.sqlite' in panda's daraframe.
# This dataset is already gone through data deduplication and text preprocessing, so it is approx ~364
K

# Create connection object to load sqlite dataset
connection = sqlite3.connect('finalDataSet.sqlite')

# Load data into pandas dataframe.
reviews_df = pd.read_sql_query(""" SELECT * FROM Reviews """,connection)

# Drop index column
reviews_df = reviews_df.drop(columns=['index'])

# Convert timestamp to datetime.
reviews_df['Time'] = reviews_df[['Time']].applymap(lambda x: dt.datetime.fromtimestamp(x))

# Sort the data on the basis of time.
reviews_df = reviews_df.sort_values(by=['Time'])

print("Dataset Shape : \n",reviews_df.shape)
print("\nColumn Names: \n",reviews_df.columns)
print("\nTarget Class label : ")
print(reviews_df['Score'].value_counts())
print()

# Plot review counts
plot_count_values(reviews_df)
```

```
Dataset Shape :
 (351237, 11)

Column Names:
 Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'CleanedText'],
      dtype='object')

Target Class label :
positive    297807
negative     53430
Name: Score, dtype: int64
```


Score Count
300000
250000
200000
150000
100000
50000
0
count
positive
negative
Score

In [14]:
```
###--- All utility variables and functions ---###

# List of values for hyperparameter
range_parameter_values = [0.00001,0.0001,0.001,0.01,1,10,100]

# Training Error
train_error = []

# Test Error
test_error = []

# Test Error
list_alpha = []

# Target Classes
target_classes = ["negative", "positive"]

scoring_parameter = "Accuracy, Precision, Recall"

# http://scikit-learn.org/stable/modules/model_evaluation.html#scoring-parameter
# for list allowed scoring values
scoring = {'acc': 'accuracy',
           'prec_macro': 'precision_macro',
           'rec_micro': 'recall_macro'}

def get_most_common_words(classifier,vectorizer,top_n=None):
    ''' Get top n values in row and return them with their corresponding feature names.'''
    print()
    class_labels = classifier.classes_
    feature_names =vectorizer.get_feature_names()
    top_negative = sorted(zip(classifier.feature_log_prob_[0], feature_names),reverse=True)[:top_n]
    top_positive = sorted(zip(classifier.feature_log_prob_[1], feature_names),reverse=True)[:top_n]

    complete_list = list()
    for index in range(0,top_n):
        holder = []
        n_value,n_word = top_negative[index]
        p_value,p_word = top_positive[index]
        holder.append(n_word)
        holder.append(n_value)
        holder.append(p_word)
        holder.append(p_value)
        complete_list.append(holder)

    df = pd.DataFrame(complete_list,columns=['feature_negative', 'value_negative','feature_positive',
'value_positive'])

    ptable = PrettyTable()
    ptable.title = "Feature Importance - {0} Most Common Features".format(top_n)
    ptable.field_names = ['Feature (-ve)', 'Empirical Log Probability (-ve)','Feature (+ve)', 'Empiric
al Log Probability (+ve)']

    for row in df.itertuples():
        ptable.add_row([row.feature_negative,row.value_negative,row.feature_positive,row.value_positiv
e])

    print(ptable)
    print()


def apply_naive_bayes(optimal_alpha,training_features_matrix,training_target):
    '''
    This function performs naive bayes on the given data.
    '''
    classifier = MultinomialNB(alpha=optimal_alpha)
    classifier.fit(training_features_matrix,training_target)
    return classifier


def get_optimal_hyperparameter(x_train, y_train):
    '''
    This function, plots error and hyperparameter values and, then returns optimal hyperparameter valu
e.
    '''
    scores = dict()

    # Pretty table instance
    ptable = PrettyTable()
    ptable.title = "Hyperparamter versus Scoring Mean"
    ptable.field_names = ["Alpha Value", "Cross Validation Scoring Mean","Scoring Parameter Used"]

    # Perform 10-fold cross validation
    for a in range_parameter_values:
        classifier = MultinomialNB(alpha=a)
        result = cross_val_score(classifier, x_train, y_train, cv=10, scoring= my_scorer)
        scores[a] = result.mean()
        ptable.add_row([a, scores[a], scoring_parameter])
```

```
    # Print pretty table values
    print(ptable)

    # Plot the value of alpha's(x-axis) and crosss validation scoring(accuracy,precision,recall)(y-axi
s)
    plt.plot(scores.keys(),scores.values())
    plt.xlabel("Value of alpha for Naive Bayes")
    plt.ylabel("Cross validated scoring - accuracy,precision,recall")
    plt.show()

    optimal_alpha = max(scores, key=scores.get)
    list_alpha.append(optimal_alpha)
    print("\nOptimal value of hyperparameter alpha is ",optimal_alpha)

    return optimal_alpha

def getScores(estimator, x, y):
    yPred = estimator.predict(x)
    return (accuracy_score(y, yPred),
            precision_score(y, yPred, pos_label=3, average='macro'),
            recall_score(y, yPred, pos_label=3, average='macro'))

def my_scorer(estimator, x, y):
    a, p, r = getScores(estimator, x, y)
    return a+p+r

def generate_report(optimal_alpha,testing_target,predicted_testing_target):
    '''
    This funtion generate reports like recall,precision,f1-score,confusion matrix.
    '''
    print()
    # Pretty table instance
    ptable = PrettyTable()
    ptable.title = "Classification Report with alpha = {0}".format(optimal_alpha)
    ptable.field_names = ["Class Lable/Averages","Precision", "Recall","F1-Score","Support"]
    report_dict = classification_report(testing_target, predicted_testing_target,output_dict = True)
    for key , value in report_dict.items():
        inner_dict = value
        ptable.add_row([key,inner_dict['precision'],inner_dict['recall'],inner_dict['f1-score'],inner_
dict['support']])

    # Print pretty table values
    print(ptable)

    print()
    print("\nAccuracy Score: ",accuracy_score(testing_target, predicted_testing_target))
    test_error.append(1-accuracy_score(testing_target, predicted_testing_target))
    print()
    cnf_mat = confusion_matrix(testing_target, predicted_testing_target)
    plt.figure()
    plot_confusion_matrix(cnf_mat, classes=target_classes,title='Confusion Matrix')
    TN = cnf_mat[0,0]
    FP = cnf_mat[0,1]
    FN = cnf_mat[1,0]
    TP = cnf_mat[1,1]


    # Sensitivity, hit rate, recall, or true positive rate
    TPR = TP/(TP+FN)

    # Specificity or true negative rate
    TNR = TN/(TN+FP)

    # Fall out or false positive rate
    FPR = FP/(FP+TN)

    # False negative rate
    FNR = FN/(TP+FN)

    # Overall accuracy
    ACC = (TP+TN)/(TP+FP+FN+TN)

    print()
    # Pretty table instance
    ptable = PrettyTable()
    ptable.title = "Confusion Matrix Report"
    ptable.field_names = ['Term','Value']
    ptable.add_row(["TP (True Positive)",TP])
    ptable.add_row(["TN (True Negative)",TN])
    ptable.add_row(["FP (False Positive)",FP])
    ptable.add_row(["FN (False Negative)",FN])
    ptable.add_row(["TPR (True Positive Rate)= TP/(TP+FN))",TPR])
    ptable.add_row(["TNR (True Negative Rate)= TN/(TN+FP))",TNR])
    ptable.add_row(["FPR (False Positive Rate)= FP/(FP+TN))",FPR])
    ptable.add_row(["FNR (False Negative Rate)= FN/(TP+FN))",FNR])
    ptable.add_row(["ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))",ACC])
```

```
    # Print pretty table values
    print(ptable)



def plot_count_values(reviews_df):
    sn.catplot(x ="Score",kind='count',data=reviews_df,height=5)
    plt.title("Score Count", fontsize=18)
    plt.show()

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
    plt.show()

def conclude():
    ptable=PrettyTable()
    ptable.title = "***Conclusion***"
    ptable.field_names=["Dataset","Model","Hyperparameter","Train Error","Test Error"]
    ptable.add_row(["Imbalanced","BoW --> Multinomial NB",list_alpha[0],str(round(train_error[0], 2)*1
00)+"%",str(round(test_error[0], 2)*100)+"%"])
    ptable.add_row(["Balanced","BoW --> SMOTE --> Multinomial NB",list_alpha[1],str(round(train_error[
1], 2)*100)+"%",str(round(test_error[1], 2)*100)+"%"])
    ptable.add_row(["Imbalanced","TF-IDF --> Multinomial NB",list_alpha[2],str(round(train_error[2], 2
)*100)+"%",str(round(test_error[2], 2)*100)+"%"])
    ptable.add_row(["Balanced","TF-IDF --> SMOTE --> Multinomial NB",list_alpha[3],str(round(train_err
or[3], 2)*100)+"%",str(round(test_error[3], 2)*100)+"%"])
    print(ptable)


def run_naive_bayes(features,target,testing_features,testing_target,vectorizer):

    # Find optimal alpha
    optimal_alpha = get_optimal_hyperparameter(features,target)

    # Perform naive bayes
    classifier = apply_naive_bayes(optimal_alpha,features,target)

    # Make class predictions for testing_features
    # Also make class predictions for training_features(training error)
    predicted_testing_target = classifier.predict(testing_features)
    predicted_target = classifier.predict(features)
    train_error.append(1 - accuracy_score(target, predicted_target))

    # Generate report
    generate_report(optimal_alpha,testing_target,predicted_testing_target)

    # Feature Importance
    get_most_common_words(classifier,vectorizer,25)
```

(2) Convert review text to vector representation and perform Naive Bayes on the corresponding vector :

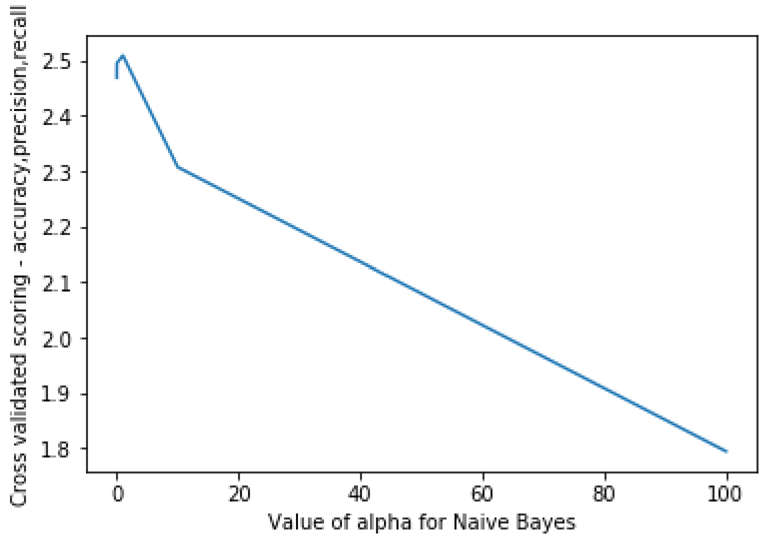
(2.1) Bag of Words (BoW) :

In [15]:
```
%%time

# Split data into 70% training and 30% testing.
training_features, testing_features, training_target, testing_target = train_test_split(reviews_df['Cl
eanedText'].values, reviews_df['Score'].values, test_size=0.3,shuffle=False, random_state=0)

# Instantiate CountVectorizer (vectorizer)
bow_count_vectorizer = CountVectorizer()

# learn the 'vocabulary' of the training data (occurs in-place)
bow_count_vectorizer.fit(training_features)

# Examine the fitted vocabulary - 50 examples for demo.
print("\nFeatures : (sample of 50 features for demo purpose) \n")
print(bow_count_vectorizer.get_feature_names()[:50])

# Transform training and testing data(features) into a 'document-term matrix' or 'row-column matrix'
training_features_matrix_unbalanced = bow_count_vectorizer.transform(training_features)
testing_features_matrix = bow_count_vectorizer.transform(testing_features)

print("\nthe type of count vectorizer ",type(training_features_matrix_unbalanced))
print("the shape of BOW vectorizer ",training_features_matrix_unbalanced.get_shape())
print("the number of unique words ", training_features_matrix_unbalanced.get_shape()[1])
```

```
Features : (sample of 50 features for demo purpose)

['aa', 'aaa', 'aaaa', 'aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa', 'aaaaaaaaaaaaaaaaaaaaargh', 'aaaa
aaaaagghh', 'aaaaaaahhhhhh', 'aaaaaaarrrrggghhh', 'aaaaaahhh', 'aaaaaahhhhhyaaaaaa', 'aaaaaahhhhten',
'aaaaaand', 'aaaaaawwwwwwwwww', 'aaaaah', 'aaaaahhhhhhhhhhhhhhhh', 'aaaaawsom', 'aaaah', 'aaaahhhhhh',
'aaaand', 'aaaarrrrghh', 'aaagh', 'aaah', 'aaahhh', 'aaahhhhhh', 'aabsolut', 'aachen', 'aacur', 'aad',
'aadp', 'aadult', 'aaf', 'aafco', 'aafter', 'aah', 'aahh', 'aalmost', 'aamazon', 'aamzon', 'aana', 'aa
nd', 'aani', 'aap', 'aar', 'aardvark', 'aarp', 'aarrgghhhh', 'aarthur', 'aauc', 'ab', 'aback']

the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of BOW vectorizer  (245865, 74398)
the number of unique words  74398
Wall time: 15.2 s
```

In [16]:
```
%%time

print("\n*********** Before SMOTE Alogorithm - Imbalanced Data ***********")
pos_neg = reviews_df['Score'].value_counts().tolist()
print("Ratio of positive/negative points in original dataset is {0}/1".format((pos_neg[0]/pos_neg
[1])))
print("Shape of train-feature data matrix is ",training_features_matrix_unbalanced.get_shape())
print("Shape of train-target nd-array is ",training_target.shape)
print()

# Perform Naive Bayes on Imbalanced dataset.
try:
    run_naive_bayes(training_features_matrix_unbalanced
                   ,training_target
                   ,testing_features_matrix
                   ,testing_target
                   ,bow_count_vectorizer)
except Exception:
    traceback.print_exc()
```

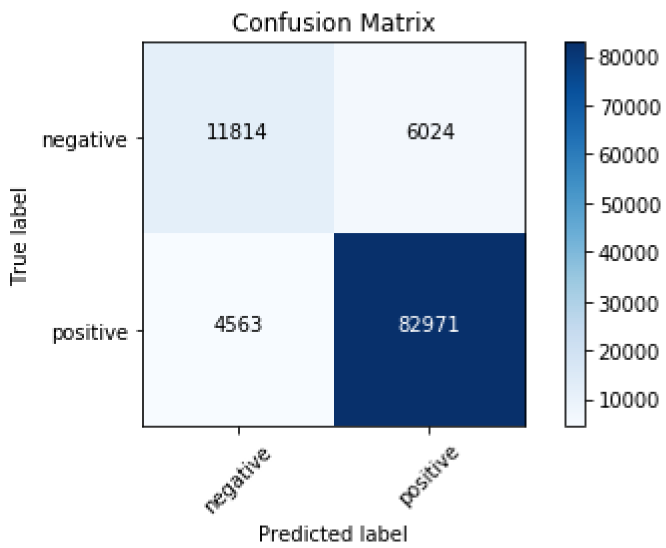
```
*********** Before SMOTE Alogorithm - Imbalanced Data ***********
Ratio of positive/negative points in original dataset is 5.573778775968557/1
Shape of train-feature data matrix is  (245865, 74398)
Shape of train-target nd-array is  (245865,)

+-------------------------------------------------------------------------+
|                      Hyperparamter versus Scoring Mean                  |
+-------------+-------------------------------+----------------------------+
| Alpha Value | Cross Validation Scoring Mean |    Scoring Parameter Used  |
+-------------+-------------------------------+----------------------------+
|    1e-05    |       2.4683289089224933      | Accuracy, Precision, Recall |
|    0.0001   |       2.475044986201854       | Accuracy, Precision, Recall |
|    0.001    |       2.4846380466684237      | Accuracy, Precision, Recall |
|     0.01    |       2.4945730762929386      | Accuracy, Precision, Recall |
|      1      |       2.508399977890567       | Accuracy, Precision, Recall |
|      10     |       2.3066870089761906      | Accuracy, Precision, Recall |
|     100     |       1.7936500693885606      | Accuracy, Precision, Recall |
+-------------+-------------------------------+----------------------------+
```



Optimal value of hyperparameter alpha is 1

Classification Report with alpha = 1				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.7213775416742993	0.6622939791456441	0.6905743095133713	17838
positive	0.9323108039777516	0.9478716841455891	0.9400268511122818	87534
micro avg	0.8995273886801047	0.8995273886801047	0.8995273886801047	105372
macro avg	0.8268441728260254	0.8050828316456167	0.8153005803128266	105372
weighted avg	0.8966027645273379	0.8995273886801047	0.8977980385525756	105372

Accuracy Score: 0.8995273886801047



Confusion Matrix Report	
Term	Value
TP (True Positive)	82971
TN (True Negative)	11814
FP (False Positive)	6024
FN (False Negative)	4563
TPR (True Positive Rate)= TP/(TP+FN))	0.9478716841455891
TNR (True Negative Rate)= TN/(TN+FP))	0.6622939791456441
FPR (False Positive Rate)= FP/(FP+TN))	0.33770602085435586
FNR (False Negative Rate)= FN/(TP+FN))	0.052128315854410856
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	0.8995273886801047

Feature Importance - 25 Most Common Features			
Feature (-ve)	Empirical Log Probability (-ve)	Feature (+ve)	Empirical Log Probability (+ve)
tast	-4.215897605326562	like	-4.434956496232374
like	-4.306120699785174	tast	-4.5025659498915775
product	-4.508275033036247	good	-4.63746930537015
one	-4.7657888433699895	flavor	-4.649522136017234
flavor	-4.786403090262846	love	-4.66852442895728
tri	-4.910441759338374	great	-4.6926684327643855
would	-4.918676879806803	use	-4.740699831052128
good	-5.065151775434526	one	-4.7960545423353125
coffe	-5.089711128845114	product	-4.881192698229134
use	-5.117063647799807	tea	-4.883620239083976
buy	-5.1750919523513765	tri	-4.915157105207777
get	-5.181304287331654	coffe	-5.010131114383668
order	-5.226672892361506	make	-5.01897307869692
tea	-5.289329368583505	get	-5.087967359894382
dont	-5.331309125347021	food	-5.249400986068938
food	-5.34474365640428	time	-5.354510269375552
box	-5.376019039040955	buy	-5.367485376737786
even	-5.39611268254998	would	-5.385915306412123
amazon	-5.447549484420097	amazon	-5.3931768380772365
much	-5.517556606787448	eat	-5.398556830051822
make	-5.524421229591068	realli	-5.410746793796408
bag	-5.527871293389278	find	-5.433637847223041
realli	-5.542843717931536	best	-5.446084269509049
time	-5.547590979594322	price	-5.448840969881013
eat	-5.554133306881543	also	-5.503644933821192

```
Wall time: 2min 21s
```

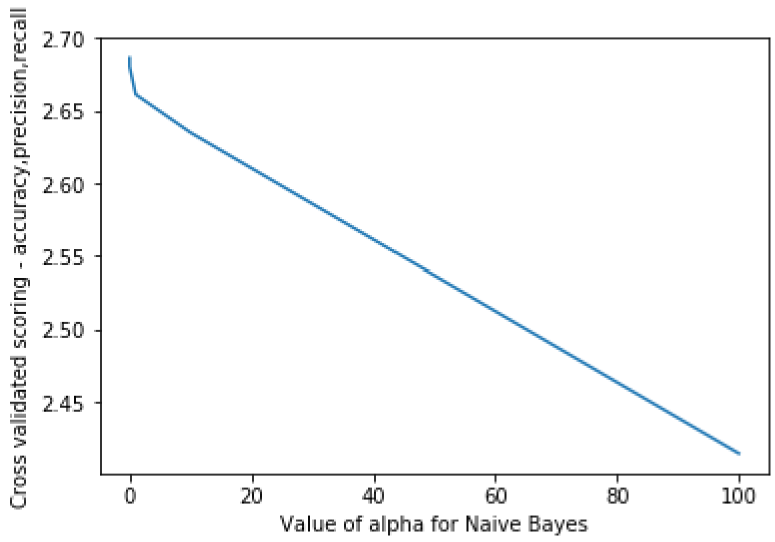
Data is higly imbalanced and biased towards positive review data points, so we need to balance the dataset with the help of BoW vectorizer and SMOTE algorithm.

In [17]:

```
# Apply SMOTE algorithm on training data points to balance the dataset.
training_features_matrix_balanced, training_target = SMOTE(ratio='minority').fit_sample(training_featu
res_matrix_unbalanced, training_target)

print("\n*********** After SMOTE Alogorithm - Balanced Data ***********")
print("Shape of train-feature data matrix is ",training_features_matrix_balanced.get_shape())
print("Shape of train-target nd-array is ",training_target.shape)
print()

# Perform Naive Bayes on Balanced dataset.
try:
    run_naive_bayes(training_features_matrix_balanced
                    ,training_target
                    ,testing_features_matrix
                    ,testing_target
                    ,bow_count_vectorizer)
except Exception:
    traceback.print_exc()
```

```
*********** After SMOTE Alogorithm - Balanced Data ***********
Shape of train-feature data matrix is  (420546, 74398)
Shape of train-target nd-array is  (420546,)
```

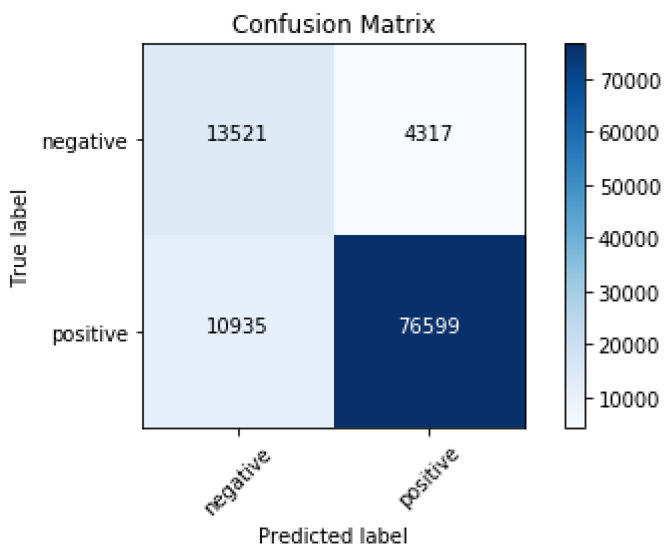
Hyperparamter versus Scoring Mean		
Alpha Value	Cross Validation Scoring Mean	Scoring Parameter Used
1e-05	2.6863312774628163	Accuracy, Precision, Recall
0.0001	2.6852212969331473	Accuracy, Precision, Recall
0.001	2.6833849722689016	Accuracy, Precision, Recall
0.01	2.6800878672726514	Accuracy, Precision, Recall
1	2.66120618816346	Accuracy, Precision, Recall
10	2.6349571933880602	Accuracy, Precision, Recall
100	2.414552558655	Accuracy, Precision, Recall




```
Optimal value of hyperparameter alpha is  1e-05
```

Classification Report with alpha = 1e-05				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.5528704612365064	0.7579885637403296	0.6393814725492979	17838
positive	0.9466483760937269	0.8750771128932757	0.9094568121104184	87534
micro avg	0.8552556656417265	0.8552556656417265	0.8552556656417265	105372
macro avg	0.7497594186651166	0.8165328383168027	0.7744191423298581	105372
weighted avg	0.8799873044122261	0.8552556656417265	0.8637368494344584	105372

```
Accuracy Score:  0.8552556656417265
```



Confusion Matrix Report	
Term	**Value**
TP (True Positive)	76599
TN (True Negative)	13521
FP (False Positive)	4317
FN (False Negative)	10935
TPR (True Positive Rate)= TP/(TP+FN))	0.8750771128932757
TNR (True Negative Rate)= TN/(TN+FP))	0.7579885637403296
FPR (False Positive Rate)= FP/(FP+TN))	0.24201143625967036
FNR (False Negative Rate)= FN/(TP+FN))	0.12492288710672425
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	0.8552556656417265

Feature Importance - 25 Most Common Features			
Feature (-ve)	**Empirical Log Probability (-ve)**	**Feature (+ve)**	**Empirical Log Probability (+ve)**
tast	-3.9745035873442465	like	-4.425212692792048
like	-4.065835643805926	tast	-4.492822916280552
product	-4.317765604370274	good	-4.627727972475741
flavor	-4.599869262322837	flavor	-4.639780966534525
one	-4.6686069351836075	love	-4.658783521140778
would	-4.756264533554779	great	-4.682927864670267
tri	-4.825501830274385	use	-4.7309599636775275
coffe	-4.833834517201861	one	-4.786315525388849
good	-4.885403143137525	product	-4.871455084713816
buy	-4.95708360299769	tea	-4.8738826673629845
use	-5.03480561725304	tri	-4.905420085770979
tea	-5.037874627617732	coffe	-5.000395867364482
order	-5.056451980191028	make	-5.009238005414616
get	-5.1232649325235595	get	-5.078233696366119
dont	-5.211157822806156	food	-5.239671027193372
box	-5.239075896203417	time	-5.344783064750567
food	-5.247047639832395	buy	-5.357758532624079
even	-5.360361847584802	would	-5.376188982479293
amazon	-5.3979551531603445	amazon	-5.383450721746982
much	-5.4026764343577565	eat	-5.388830868507274
bag	-5.421172358290292	realli	-5.401021186061104
eat	-5.424204994908672	find	-5.423912915659928
realli	-5.4628150692477835	best	-5.436359712145299
time	-5.494366633951415	price	-5.439116496028866
make	-5.510199594323858	also	-5.493922168893924

(2.2) Term Frequency - Inverse Document Frequency (TF-IDF) :

In [18]:

```
%%time

# Split data into 70% training and 30% testing.
training_features, testing_features, training_target, testing_target = train_test_split(reviews_df['Cl
eanedText'].values, reviews_df['Score'].values, test_size=0.3,shuffle=False, random_state=0)

# Instantiate CountVectorizer (vectorizer)
tfidf_vectorizer = TfidfVectorizer(ngram_range=(1,2))

# learn the 'vocabulary' of the training data (occurs in-place)
tfidf_vectorizer.fit(training_features)

# Examine the fitted vocabulary - 50 examples for demo.
print("\nFeatures : (sample of 50 features for demo purpose) \n")
print(tfidf_vectorizer.get_feature_names()[:50])

# Transform training and testing data(features) into a 'document-term matrix' or 'row-column matrix'
training_features_matrix_unbalanced = tfidf_vectorizer.transform(training_features)
testing_features_matrix = tfidf_vectorizer.transform(testing_features)

print("\nthe type of count vectorizer ",type(training_features_matrix_unbalanced))
print("the shape of TF-IDF vectorizer ",training_features_matrix_unbalanced.get_shape())
print("the number of unique words ", training_features_matrix_unbalanced.get_shape()[1])
```

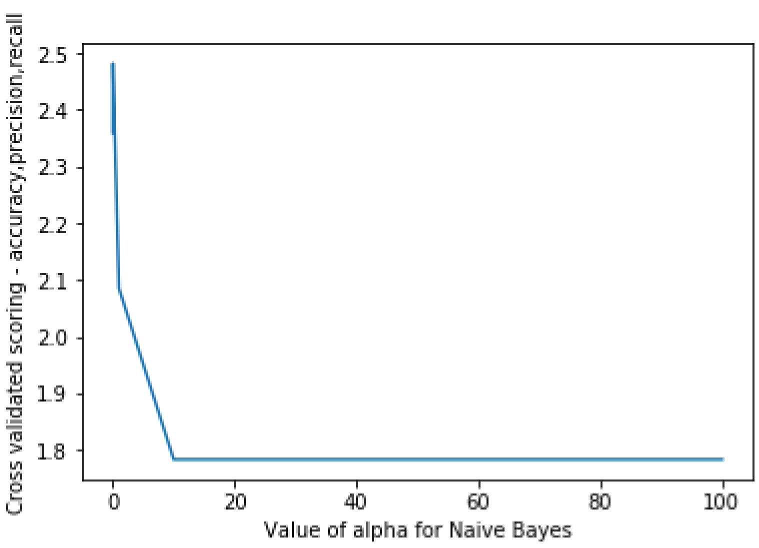
```
Features : (sample of 50 features for demo purpose)

['aa', 'aa state', 'aaa', 'aaa aaa', 'aaa condit', 'aaa dont', 'aaa magazin', 'aaa perfect', 'aaa plu
s', 'aaa spelt', 'aaa tue', 'aaaa', 'aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa', 'aaaaaaaaaaaaaaaaa
aaaaaaaaaaaaaaaaaaaaaaaaaaa serious', 'aaaaaaaaaaaaaaaaaaaargh', 'aaaaaaaaaaaaaaaaaaaargh wait', 'aaaa
aaaaagghh', 'aaaaaaahhhhhh', 'aaaaaaahhhhhh raspberri', 'aaaaaaarrrrrggghhh', 'aaaaaaarrrrrggghhh bac
k', 'aaaaaahhh', 'aaaaaahhh help', 'aaaaaahhhhyaaaaaa', 'aaaaaahhhhyaaaaaa fire', 'aaaaaahhhhten',
'aaaaaahhhhten fifteen', 'aaaaaand', 'aaaaaand kid', 'aaaaaawwwwwwwwww', 'aaaaaawwwwwwwwww depart', 'a
aaaah', 'aaaaah awak', 'aaaaah satisfi', 'aaaaahhhhhhhhhhhhhhhh', 'aaaaahhhhhhhhhhhhhhhh angel', 'aaaa
awsom', 'aaaaawsom chump', 'aaaah', 'aaaah favorit', 'aaaah snob', 'aaaahhhhhh', 'aaaahhhhhh must', 'a
aand', 'aaaand theyr', 'aaaarrrrghh', 'aaaarrrrghh plus', 'aaagh', 'aaagh thrill', 'aaah']

the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of TF-IDF vectorizer  (245865, 2218080)
the number of unique words  2218080
Wall time: 56.2 s
```

Data is higly imbalanced and biased towards positive review data points, so we need to balance the dataset with the help of TF-IDF vectorizer and SMOTE algorithm.

In [19]:

```
%%time

print("\n*********** Before SMOTE Alogorithm - Imbalanced Data ***********")
pos_neg = reviews_df['Score'].value_counts().tolist()
print("Ratio of positive/negative points in original dataset is {0}/1".format((pos_neg[0]/pos_neg
[1])))
print("Shape of train-feature data matrix is ",training_features_matrix_unbalanced.get_shape())
print("Shape of train-target nd-array is ",training_target.shape)
print()

# Perform Naive Bayes on Imbalanced dataset.
try:
    run_naive_bayes(training_features_matrix_unbalanced
                    ,training_target
                    ,testing_features_matrix
                    ,testing_target
                    ,tfidf_vectorizer)
except Exception:
    traceback.print_exc()
```

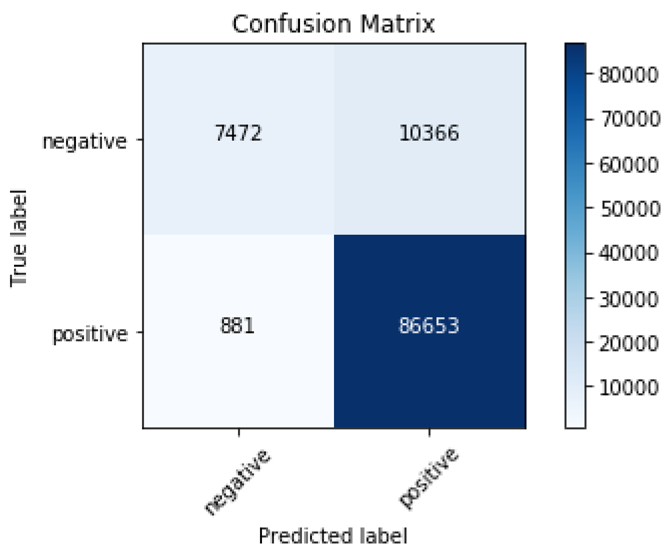
```
*********** Before SMOTE Alogorithm - Imbalanced Data ***********
Ratio of positive/negative points in original dataset is 5.573778775968557/1
Shape of train-feature data matrix is  (245865, 2218080)
Shape of train-target nd-array is  (245865,)

+-----------------------------------------------------------------------+
|                    Hyperparamter versus Scoring Mean                   |
+-------------+----------------------------+----------------------------+
| Alpha Value | Cross Validation Scoring Mean |    Scoring Parameter Used  |
+-------------+----------------------------+----------------------------+
|    1e-05    |     2.359846584343212      | Accuracy, Precision, Recall |
|    0.0001   |      2.40487578983227      | Accuracy, Precision, Recall |
|    0.001    |     2.461430139104839      | Accuracy, Precision, Recall |
|     0.01    |     2.482152763143755      | Accuracy, Precision, Recall |
|      1      |     2.0856404133061277     | Accuracy, Precision, Recall |
|      10     |     1.7828564461213046     | Accuracy, Precision, Recall |
|     100     |     1.7828564461213046     | Accuracy, Precision, Recall |
+-------------+----------------------------+----------------------------+
```



Optimal value of hyperparameter alpha is 0.01

Classification Report with alpha = 0.01				
Class Lable/Averages	Precision	Recall	F1-Score	Support
negative	0.894528911768227	0.4188810404753896	0.5705776793555037	17838
positive	0.8931549490306022	0.9899353394109718	0.9390581567354637	87534
micro avg	0.893263865163421	0.893263865163421	0.893263865163421	105372
macro avg	0.8938419303994146	0.7044081899431807	0.7548179180454837	105372
weighted avg	0.8933875416293359	0.893263865163421	0.8766795860003184	105372

Accuracy Score: 0.893263865163421



Confusion Matrix Report	
Term	Value
TP (True Positive)	86653
TN (True Negative)	7472
FP (False Positive)	10366
FN (False Negative)	881
TPR (True Positive Rate)= TP/(TP+FN))	0.9899353394109718
TNR (True Negative Rate)= TN/(TN+FP))	0.4188810404753896
FPR (False Positive Rate)= FP/(FP+TN))	0.5811189595246103
FNR (False Negative Rate)= FN/(TP+FN))	0.010064660589028263
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	0.893263865163421

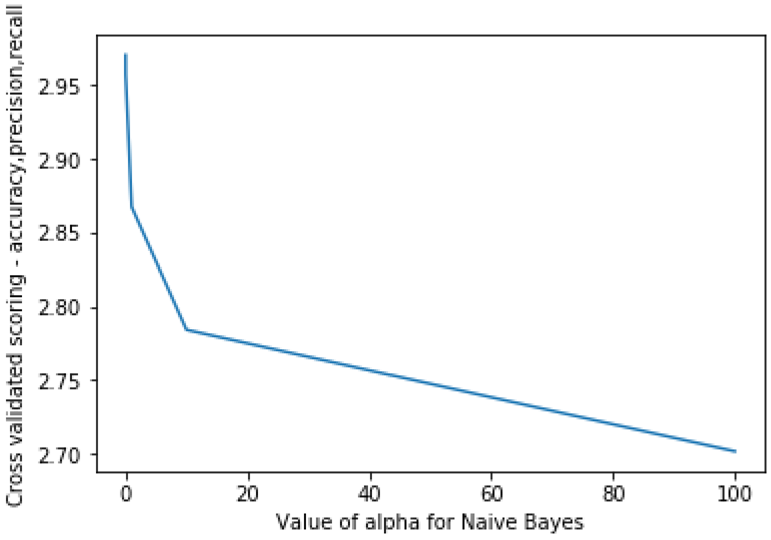
Feature Importance - 25 Most Common Features			
Feature (-ve)	Empirical Log Probability (-ve)	Feature (+ve)	Empirical Log Probability (+ve)
tast	-6.018218934866409	great	-6.212352555209659
like	-6.163994909932839	love	-6.219764877901318
product	-6.232373635971766	tast	-6.275373412324644
would	-6.518403007868737	like	-6.28344509518725
flavor	-6.529717388773404	good	-6.284193014358569
coffe	-6.542661697282145	tea	-6.2862128445389525
one	-6.5610414722451145	flavor	-6.343043436004462
tri	-6.66616400641053	coffe	-6.3716404793565955
buy	-6.6857888949904325	use	-6.453536221024811
order	-6.686839834157641	product	-6.460266580103129
box	-6.7757128744392165	one	-6.544060849802214
tea	-6.781606314384314	tri	-6.615256092047183
good	-6.8407524703274225	make	-6.666503173654506
disappoint	-6.842149311538374	get	-6.736784892709489
dont	-6.864568082075305	best	-6.777435848486504
get	-6.876401302781016	price	-6.786793859237479
use	-6.9273519606022536	buy	-6.812751617879803
even	-6.9509713128051684	amazon	-6.831381690650967
bag	-6.997890298632167	food	-6.834374779059339
bad	-7.0029099259194405	find	-6.837280986399286
food	-7.016934486015065	time	-6.8801433089271065
amazon	-7.04366640229698	order	-6.88837272196862
much	-7.070742791769516	realli	-6.888533836444039
purchas	-7.086776162104666	eat	-6.9109564697662815
packag	-7.0873146581605555	store	-6.936169811637611

Wall time: 3min 10s

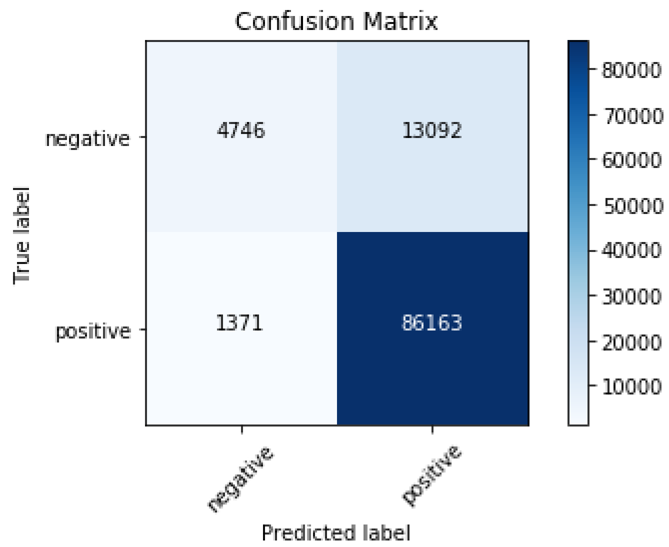
In [20]:

```python
# Apply SMOTE algorithm on training data points to balance the dataset.
training_features_matrix_balanced, training_target = SMOTE(ratio='minority').fit_sample(training_featu
res_matrix_unbalanced, training_target)

print("\n*********** After SMOTE Alogorithm - Balanced Data ***********")
print("Shape of train-feature data matrix is ",training_features_matrix_balanced.get_shape())
print("Shape of train-target nd-array is ",training_target.shape)
print()

# Perform Naive Bayes on Balanced dataset.
try:
    run_naive_bayes(training_features_matrix_balanced
                   ,training_target
                   ,testing_features_matrix
                   ,testing_target
                   ,tfidf_vectorizer)
except Exception:
    traceback.print_exc()
```

```
*********** After SMOTE Alogorithm - Balanced Data ***********
Shape of train-feature data matrix is  (420546, 2218080)
Shape of train-target nd-array is  (420546,)

+-----------------------------------------------------------------------------+
|                     Hyperparamter versus Scoring Mean                       |
+-------------+------------------------------+--------------------------------+
| Alpha Value | Cross Validation Scoring Mean |    Scoring Parameter Used     |
+-------------+------------------------------+--------------------------------+
|    1e-05    |       2.9699776751265654     | Accuracy, Precision, Recall |
|    0.0001   |       2.9686934501050466     | Accuracy, Precision, Recall |
|    0.001    |       2.9657387141458296     | Accuracy, Precision, Recall |
|     0.01    |       2.9565676261279075     | Accuracy, Precision, Recall |
|      1      |       2.8670695882875363     | Accuracy, Precision, Recall |
|      10     |       2.784113030515457      | Accuracy, Precision, Recall |
|     100     |       2.7017823928923486     | Accuracy, Precision, Recall |
+-------------+------------------------------+--------------------------------+
```




```
Optimal value of hyperparameter alpha is  1e-05

+------------------------------------------------------------------------------------------------+
|                              Classification Report with alpha = 1e-05                          |
+----------------------+--------------------+--------------------+--------------------+---------+
| Class Lable/Averages |     Precision      |       Recall       |      F1-Score      | Support |
+----------------------+--------------------+--------------------+--------------------+---------+
|       negative       | 0.7758705247670427 | 0.2660612176252943 | 0.39624295554164063 |  17838  |
|       positive       | 0.8680973250717848 |  0.9843375145657687 |  0.922570386907152 |  87534  |
|      micro avg       | 0.8627434233003075 |  0.8627434233003075 | 0.8627434233003075 |  105372 |
|      macro avg       | 0.8219839249194137 |  0.6251993660955315 | 0.6594066712243963 |  105372 |
|     weighted avg     | 0.8524846227994924 |  0.8627434233003075 | 0.8334705432988121 |  105372 |
+----------------------+--------------------+--------------------+--------------------+---------+


Accuracy Score:  0.8627434233003075
```



Confusion Matrix Report	
Term	Value
TP (True Positive)	86163
TN (True Negative)	4746
FP (False Positive)	13092
FN (False Negative)	1371
TPR (True Positive Rate)= TP/(TP+FN))	0.9843375145657687
TNR (True Negative Rate)= TN/(TN+FP))	0.26606121762529433
FPR (False Positive Rate)= FP/(FP+TN))	0.7339387823747057
FNR (False Negative Rate)= FN/(TP+FN))	0.01566248543423127
ACC (Accuracy)= (TP+TN)/(TP+FP+FN+TN))	0.8627434233003075

Feature Importance - 25 Most Common Features			
Feature (-ve)	Empirical Log Probability (-ve)	Feature (+ve)	Empirical Log Probability (+ve)
tast	-5.8341851333986	great	-6.19713227401869
like	-5.983410784192797	love	-6.204544621991546
product	-6.109344551484163	tast	-6.26015335217515
coffe	-6.271207729127223	like	-6.268225064368323
flavor	-6.376828237930585	good	-6.268972986269406
would	-6.379930655162593	tea	-6.270992823831998
one	-6.47102299559701	flavor	-6.327823629237139
tea	-6.47725035451588	coffe	-6.356420784929941
buy	-6.519688810344063	use	-6.438316866674993
order	-6.550936838467324	product	-6.4450472549597375
tri	-6.573457172730293	one	-6.528841905231846
box	-6.643515997436175	tri	-6.600037496854386
dont	-6.698871950099893	make	-6.651284845797522
disappoint	-6.701302412026515	get	-6.721566954491146
good	-6.729961167992344	best	-6.762218148456112
get	-6.797811017945086	price	-6.771576215423564
food	-6.826045068220848	buy	-6.797534132784059
use	-6.836913351788273	amazon	-6.816164322034934
tast like	-6.843603424100489	food	-6.819157429359973
bag	-6.860423351412319	find	-6.822063655121744
even	-6.871967819838478	time	-6.864926255655094
bad	-6.880248229646972	order	-6.873155723449754
chocol	-6.919175267960103	realli	-6.873316839001627
money	-6.943725950545277	eat	-6.895739623840648
much	-6.957084819461637	store	-6.920953140194135

Conclusion :

In [21]:
```
conclude()
```

Conclusion

Dataset	Model	Hyperparameter	Train Error	Test Error
Imbalanced	BoW --> Multinomial NB	1	8.0%	10.0%
Balanced	BoW --> SMOTE --> Multinomial NB	1e-05	9.0%	14.000000000000002%
Imbalanced	TF-IDF --> Multinomial NB	0.01	0.0%	11.0%
Balanced	TF-IDF --> SMOTE --> Multinomial NB	1e-05	0.0%	14.000000000000002%

Observations :

> 1. Here, Naive Bayes classifier is applied on complete dataset(~364K).
> 2. Given dataset is imbalanced in nature (postive reviews:negative reviews = 5.57/1).
> 3. 10-fold cross validation technique is applied to calculate optimal hyperparameter.
> 4. Initially we performed naive bayes classifier on imbalanced dataset with hyperparameter value of alpha is 1.
> 5. SMOTE algorithm is used to balance out the positive and negative reviews.
> 6. Balanced dataset's confusion matrix produces better result than Imbalanced dataset.
> 7. Techniques like Random Under/Over-Sampling, Variation of SMOTE algorithms can be used to balance out the dataset, which may result in better accuracy and confusion matrix values.