Perfoming Naive Bayes on Amazon Fine Food Reviews

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

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

Number of reviews : 568,454

Number of 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).

1. Reading Data

1.1. Loading Data

The dataset is available in two forms

1. csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently. Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

```
%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 import metrics
from sklearn.metrics import accuracy_score,confusion_matrix,f1_score,precision_score,reca
from nltk.stem.porter import PorterStemmer
import sklearn
import re

import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

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

from tqdm import tqdm
import os

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from collections import Counter
from sklearn.model_selection import cross_validate

from sklearn.naive_bayes import BernoulliNB
```

```
# Load the Drive helper and mount
from google.colab import drive

# This will prompt for authorization.
drive.mount('/content/drive')
```

```
#lists the content of your google drive
!ls "/content/drive/My Drive/datasets/amazon fine food"
```

```
database.sqlite
```

```
# using SQLite Table to read data.
con = sqlite3.connect('/content/drive/My Drive/datasets/amazon fine food/database.sqlite

# filtering only positive and negative reviews i.e. not taking into consideration those r
# for this analysis we are only taking 50000 data points considering our computing power

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 100000

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negative r
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)
```

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulı
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	

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


print(display.shape)
display.head()
```

```
(80668, 7)
```

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

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

	UserId	ProductId	ProfileName	Time	Score	Text
			undertheshrine			I was recommended

```
display['COUNT(*)'].sum()
```

```
393063
```

2. Exploratory Data Analysis

2.1. Data Cleaning: Deduplication

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

```
display= pd.read_sql_query("""
SELECT *
```

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

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	

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

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

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

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

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

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

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

```
(87775, 10)
```

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

```
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

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

display.head()
```

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	

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

```
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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

```
(87773, 10)
1    73592
0    14181
Name: Score, dtype: int64
```

3. Preprocessing

3.1. Preprocessing Review Text

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

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

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

6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

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

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

```
4
I wish I'd read the reviews before making this purchase. It's basically a cardsotc
```

```
nltk.download("stopwords")
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
True
```

```
stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

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

```
{'a', 'll', 'shan', 'up', 're', 'isn', 'under', 'own', 'why', 'then', 'at', "you'c
```

```
# Combining all the above stundents
from tqdm import tqdm

i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in tqdm(final['Text'].values):
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describe
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe
```

```
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

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

```
100%|██████████| 87773/87773 [02:14<00:00, 653.59it/s]
```

```
#after data suplication and preprocessing we are adding the CleanedText as a new attribu
final['CleanedText']=final_string
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
```

```
final.shape
```

```
(87773, 11)
```

```
#sorting the dataset by time so that we can later perform time-based splitting of the da
final = final.sort_values(by=['Time'], axis=0)
score = final['Score'].values
text = final['CleanedText'].values
```

```
#splitting the dataset into train, test and cross validate
x_train, x_test, y_train, y_test = train_test_split(text, score, test_size=0.3, shuffle=
x_train, x_cv, y_train, y_cv = train_test_split(x_train, y_train, test_size=0.3, shuffle
```

```
print(x_train.shape, y_train.shape)
print(x_test.shape, y_test.shape)
print(x_cv.shape, y_cv.shape)
```

```
(43008,) (43008,)
(26332,) (26332,)
(18433,) (18433,)
```

```
print("Number of positive(1) and negative(0) datapoints in our train dataset")
unique, counts = np.unique(y_train, return_counts=True)
dict(zip(unique, counts))
```

```
Number of positive(1) and negative(0) datapoints in our train dataset
{0: 6359, 1: 36649}
```

```
print("Number of positive(1) and negative(0) datapoints in our test dataset")
unique, counts = np.unique(y_test, return_counts=True)
dict(zip(unique, counts))
```

```
Number of positive(1) and negative(0) datapoints in our test dataset
{0: 4557, 1: 21775}
```

```
print("Number of positive(1) and negative(0) datapoints in our cross validate dataset")
unique, counts = np.unique(y_cv, return_counts=True)
dict(zip(unique, counts))
```

```
Number of positive(1) and negative(0) datapoints in our cross validate dataset
{0: 3265, 1: 15168}
```

4. Applying Bernoulli Naive Bayes

4.1. on Bag of Words

```
#coveting text to vectors using BOW
#will be coverting train, test and cross validate datasets seperately to overcome data le

count_vect = CountVectorizer() #in scikit-learn

#converting train data to vectors using BOW
bow_x_train = count_vect.fit_transform(x_train)
bow_x_train.shape
```

```
(43008, 24426)
```

```
#converting test data to vectors using BOW
bow_x_test = count_vect.transform(x_test)
bow_x_test.shape
```

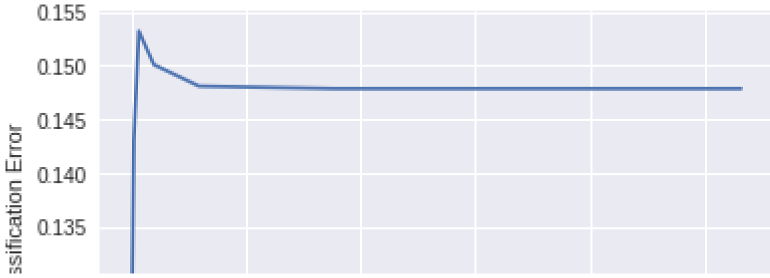
```
(26332, 24426)
```

```
#converting cross validate data to vectors using BOW
bow_x_cv = count_vect.transform(x_cv)
bow_x_cv.shape
```

```
(18433, 24426)
```

```
#taking alpha values from 10^-3 to 10^3
alpha_values = []
i = 0.001
while(i<=1000):
    alpha_values.append(np.round(i,3))
    i *= 3

cv_scores = [] #list to keep cross validate score
for k in tqdm(alpha_values):
    bnb = BernoulliNB(alpha=k)
    scores = cross_val_score(bnb, bow_x_train, y_train, cv=10, scoring='accuracy', n_jobs
    cv_scores.append(scores.mean())

#calculating Mssclassification error
error = [1 - x for x in cv_scores]

#determing optimal alpha with least missclassification error value
optimal_alpha = alpha_values[error.index(min(error))]
print(optimal_alpha)

#graph between missclassification error and hyperparameter values
plt.plot(alpha_values, error)
xy = (optimal_alpha, min(error))
plt.annotate('(%s, %s)' % xy, xy = xy, textcoords='data')
plt.xlabel("Number of neighbours 'k'")
plt.ylabel("Misclassification Error")
plt.show()
```

```
100%|██████████| 13/13 [00:07<00:00,  1.80it/s]
0.009
```




```
#applying Bernoulli Naive Bayes on the optimal alpha calculated (0.009)

#initiate model
bnb = BernoulliNB(alpha = optimal_alpha)

#fit model
bnb.fit(bow_x_train, y_train)

#predicting values for test data
y_test_pred =  bnb.predict(bow_x_test)

#calculating accuracy of model
train_acc = bnb.score(bow_x_train, y_train) #train accuracy
train_error = 1 - train_acc #train error
test_acc = accuracy_score(y_test, y_test_pred) #test accuracy
test_error = 1 - test_acc #test error

print("_" * 101)
print("Training Accuracy: ", train_acc)
print("Train Error: ", train_error)
print("Test Accuracy: ", test_acc)
print("Test Error: ", test_error)
print("_" * 101)
```

```
_____________________________________________________________________________________________________
Training Accuracy:  0.9331752232142857
Train Error:  0.06682477678571
Test Accuracy:  0.8801458301686161
Test Error:  0.11985416983138386
_____________________________________________________________________________________________________
```

```
#feature selection

# Now we can find log probabilities of different features for both the classes
class_features = bnb.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_features = class_features[0]
positive_features = class_features[1]

# Getting all feature names
feature_names = count_vect.get_feature_names()

# Sorting 'negative_features' and 'positive_features' in descending order using argsort(
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n")
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :\n\
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


like      -->    -0.993329
tast      -->    -0.994179
product   -->    -1.227681
one       -->    -1.338243
would     -->    -1.425254
tri       -->    -1.458502
good      -->    -1.513395
flavor    -->    -1.522724
buy       -->    -1.606137
get       -->    -1.684352
use       -->    -1.738325
dont      -->    -1.742807
even      -->    -1.821278
much      -->    -1.880324
order     -->    -1.893816
eat       -->    -1.961913
make      -->    -1.986829
love      -->    -1.986829
realli    -->    -2.014738
amazon    -->    -2.028990


Top 20 Important Features and their log probabilities For Positive Class :


like      -->    -1.158691
tast      -->    -1.226573
love      -->    -1.237235
good      -->    -1.260061
great     -->    -1.300803
flavor    -->    -1.403495
one       -->    -1.446373
tri       -->    -1.524196
use       -->    -1.599095
product   -->    -1.615431
get       -->    -1.679768
make      -->    -1.680354
buy       -->    -1.927471
time      -->    -1.946782
best      -->    -1.961612
would     -->    -1.965500
amazon    -->    -1.967059
realli    -->    -1.973714
eat       -->    -1.980018
```

```python
# evaluate precision
acc = precision_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Precision for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Recall for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test F1-Score for alpha (%.3f) is %f' % (optimal_alpha, acc))
```

```
The Test Precision for alpha (0.009) is 0.913296
```

```
#evaluating confusion matrix for train and test
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, bnb.predict(bow_x_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, bnb.predict(bow_x_test)))
```

```
Train confusion matrix
[[ 4720  1639]
 [ 1235 35414]]
Test confusion matrix
[[ 2604  1953]
 [ 1203 20572]]
```

Observation :

1. Hyperparameter (alpha) = 0.009
2. Train Accuracy = 0.9331752232142857
3. Test Accuracy = 0.8801458301686161
4. Test Precision = 0.913296
5. Test Recall = 0.944753
6. F1-Score = 0.928758

4.2. on TF-IDF

```
#coveting text to vectors using tf-idf

tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))

#converting train data to vectors using tf-idf
tf_idf_x_train = tf_idf_vect.fit_transform(x_train)
tf_idf_x_train.shape
```

```
(43008, 674017)
```

```
#converting test data to vectors using tf-idf
tf_idf_x_test = tf_idf_vect.transform(x_test)
tf_idf_x_test.shape
```

```
(26332, 674017)
```

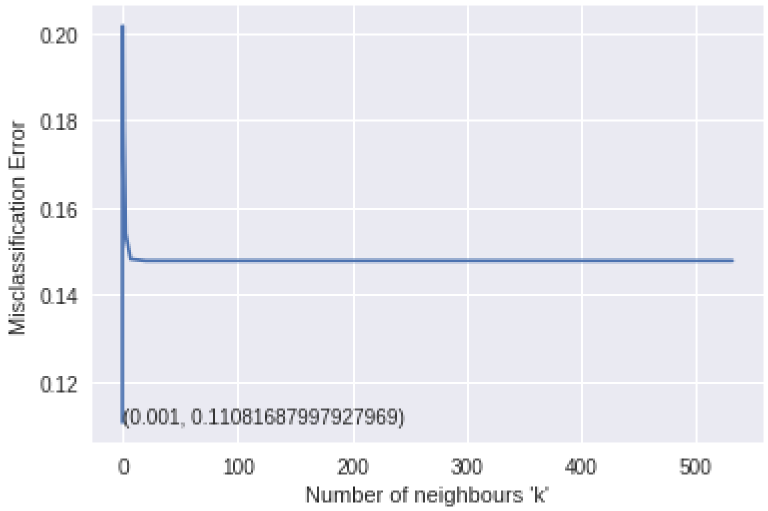
```
#converting cross validate data to vectors using tf-idf
tf_idf_x_cv = tf_idf_vect.transform(x_cv)
tf_idf_x_cv.shape
```

```
(18433, 674017)
```

```
#taking alpha values from 10^-3 to 10^3
alpha_values = []
i = 0.001
while(i<=1000):
    alpha_values.append(np.round(i,3))
    i *= 3
```

```
cv_scores = [] #list to keep cross validate score
for k in tqdm(alpha_values):
    bnb = BernoulliNB(alpha=k)
    scores = cross_val_score(bnb, tf_idf_x_train, y_train, cv=10, scoring='accuracy', n_
    cv_scores.append(scores.mean())

#calculating Mssclassification error
error = [1 - x for x in cv_scores]

#determing optimal alpha with least missclassification error value
optimal_alpha = alpha_values[error.index(min(error))]
print(optimal_alpha)

#graph between missclassification error and hyperparameter values
plt.plot(alpha_values, error)
xy = (optimal_alpha, min(error))
plt.annotate('(%s, %s)' % xy, xy = xy, textcoords='data')
plt.xlabel("Number of neighbours 'k'")
plt.ylabel("Misclassification Error")
plt.show()
```

```
100%|██████████| 13/13 [00:31<00:00,  2.44s/it]
0.001
```




```
#applying Bernoulli Naive Bayes on the optimal alpha calculated (0.001)

#initiate model
bnb = BernoulliNB(alpha = optimal_alpha)

#fit model
bnb.fit(tf_idf_x_train, y_train)

#predicting values for test data
y_test_pred =  bnb.predict(tf_idf_x_test)

#calculating accuracy of model
train_acc = bnb.score(tf_idf_x_train, y_train) #train accuracy
train_error = 1 - train_acc #train error
test_acc = accuracy_score(y_test, y_test_pred) #test accuracy
test_error = 1 - test_acc #test error

print("_" * 101)
print("Training Accuracy: ", train_acc)
print("Train Error: ", train_error)
print("Test Accuracy: ", test_acc)
print("Test Error: ", test_error)
print("_" * 101)
```

```
Training Accuracy:  0.9987444196428571
Train Error:  0.0012555803571429047
```

```
#feature selection

# Now we can find log probabilities of different features for both the classes
class_features = bnb.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_features = class_features[0]
positive_features = class_features[1]

# Getting all feature names
feature_names = tf_idf_vect.get_feature_names()

# Sorting 'negative_features' and 'positive_features' in descending order using argsort()
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n")
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :\n\n")
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


like      -->    -0.993330
tast      -->    -0.994180
product   -->    -1.227683
one       -->    -1.338246
would     -->    -1.425257
tri       -->    -1.458505
good      -->    -1.513398
flavor    -->    -1.522728
```

```
# evaluate precision
acc = precision_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Precision for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Recall for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test F1-Score for alpha (%.3f) is %f' % (optimal_alpha, acc))
```

```

The Test Precision for alpha (0.001) is 0.861881

The Test Recall for alpha (0.001) is 0.994122

The Test F1-Score for alpha (0.001) is 0.923290
```

```
#evaluating confusion matrix for train and test
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, bnb.predict(tf_idf_x_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, bnb.predict(tf_idf_x_test)))
```

```
Train confusion matrix
[[ 6309    50]
 [    4 36645]]
Test confusion matrix
[[ 1088  3469]
 [  128 21647]]
```

Observation :

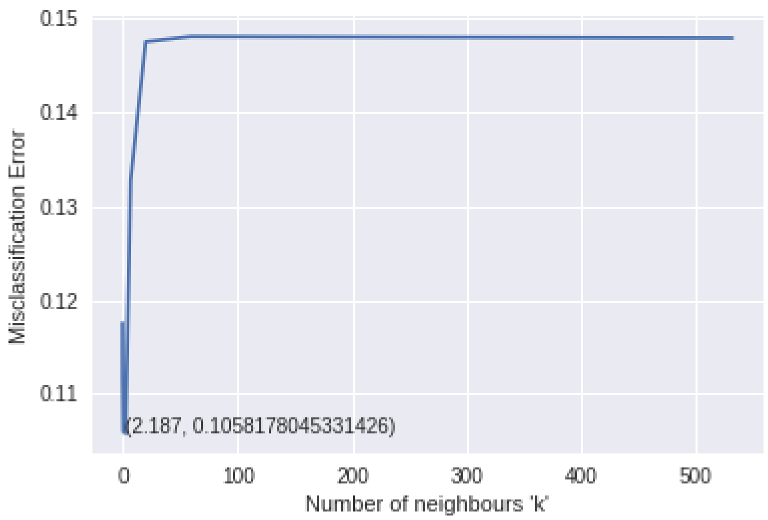
1. Hyperparameter (alpha) = 0.001
2. Train Accuracy = 0.9987444196428571
3. Test Accuracy = 0.8633981467416072
4. Test Precision = 0.861881
5. Test Recall = 0.994122
6. F1-Score = 0.923290

5. Applying Multinomial Naive Bayes

5.1. on Bag of Words

```
from sklearn.naive_bayes import MultinomialNB

#taking alpha values from 10^-3 to 10^3
alpha_values = []
i = 0.001
while(i<=1000):
    alpha_values.append(np.round(i,3))
    i *= 3

cv_scores = [] #list to keep cross validate score
for k in tqdm(alpha_values):
    bnb = MultinomialNB(alpha=k)
    scores = cross_val_score(bnb, bow_x_train, y_train, cv=10, scoring='accuracy', n_jobs
    cv_scores.append(scores.mean())

#calculating Mssclassification error
error = [1 - x for x in cv_scores]

#determing optimal alpha with least missclassification error value
optimal_alpha = alpha_values[error.index(min(error))]
print(optimal_alpha)

#graph between missclassification error and hyperparameter values
plt.plot(alpha_values, error)
xy = (optimal_alpha, min(error))
plt.annotate('(%s, %s)' % xy, xy = xy, textcoords='data')
plt.xlabel("Number of neighbours 'k'")
plt.ylabel("Misclassification Error")
plt.show()
```

```
100%|██████████| 13/13 [00:05<00:00,  2.44it/s]
2.187
```




```
#applying Bernoulli Naive Bayes on the optimal alpha calculated (2.187)

#initiate model
bnb = MultinomialNB(alpha = optimal_alpha)

#fit model
bnb.fit(bow_x_train, y_train)

#predicting values for test data
y_test_pred =  bnb.predict(bow_x_test)

#calculating accuracy of model
train_acc = bnb.score(bow_x_train, y_train) #train accuracy
train_error = 1 - train_acc #train error
test_acc = accuracy_score(y_test, y_test_pred) #test accuracy
test_error = 1 - test_acc #test error

print("_" * 101)
```

```
print("Training Accuracy: ", train_acc)
print("Train Error: ", train_error)
print("Test Accuracy: ", test_acc)
print("Test Error: ", test_error)
print("_" * 101)
```

```
_____________________________________________________________________________________________________
Training Accuracy:  0.9144577752976191
Train Error:  0.08554222470238093
Test Accuracy:  0.8888424730366095
Test Error:  0.11115752696339054
_____________________________________________________________________________________________________
```

```
# Now we can find log probabilities of different features for both the classes
class_features = bnb.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_features = class_features[0]
positive_features = class_features[1]

# Getting all feature names
feature_names = count_vect.get_feature_names()

# Sorting 'negative_features' and 'positive_features' in descending order using argsort()
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n")
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :\n\n")
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


tast      -->    -4.403103
like      -->    -4.461006
product   -->    -4.662734
one       -->    -4.885442
flavor    -->    -4.960417
tri       -->    -5.073391
would     -->    -5.081022
good      -->    -5.203079
use       -->    -5.302484
food      -->    -5.303759
buy       -->    -5.329614
get       -->    -5.369013
coffe     -->    -5.369013
order     -->    -5.450579
dont      -->    -5.473754
tea       -->    -5.481346
```

```
# evaluate precision
acc = precision_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Precision for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Recall for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test F1-Score alpha (%.3f) is %f' % (optimal_alpha, acc))
```

```
The Test Precision for alpha (2.187) is 0.897436

The Test Recall for alpha (2.187) is 0.977268

The Test F1-Score alpha (2.187) is 0.935652

use       -->    -4.902497
```

```
#evaluating confusion matrix for train and test
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, bnb.predict(bow_x_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, bnb.predict(bow_x_test)))
```

```
Train confusion matrix
[[ 3463  2896]
 [  783 35866]]
Test confusion matrix
[[ 2125  2432]
 [  495 21280]]
```

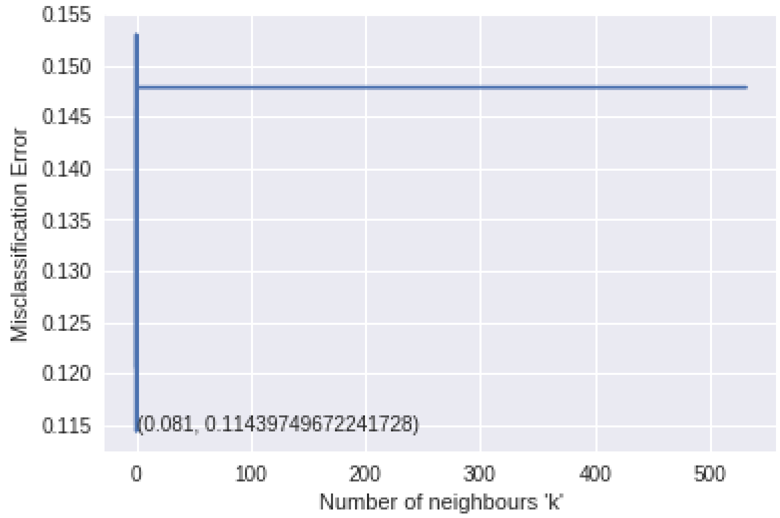
Observation :

1. Hyperparameter (alpha) = 2.187
2. Train Accuracy =0.9144577752976191
3. Test Accuracy = 0.8888424730366095
4. Test Precision = 0.897436
5. Test Recall = 0.977268
6. F1-Score = 0.935652

5.2. on TF-IDF

```
#taking alpha values from 10^-3 to 10^3
alpha_values = []
i = 0.001
while(i<=1000):
    alpha_values.append(np.round(i,3))
    i *= 3

cv_scores = [] #list to keep cross validate score
for k in tqdm(alpha_values):
    bnb = MultinomialNB(alpha=k)
    scores = cross_val_score(bnb, tf_idf_x_train, y_train, cv=10, scoring='accuracy', n_
    cv_scores.append(scores.mean())

#calculating Mssclassification error
error = [1 - x for x in cv_scores]

#determing optimal alpha with least missclassification error value
optimal_alpha = alpha_values[error.index(min(error))]
print(optimal_alpha)

#graph between missclassification error and hyperparameter values
plt.plot(alpha_values, error)
xy = (optimal_alpha, min(error))
plt.annotate('(%s, %s)' % xy, xy = xy, textcoords='data')
plt.xlabel("Number of neighbours 'k'")
plt.ylabel("Misclassification Error")
plt.show()
```

```
100%|██████████| 13/13 [00:23<00:00,  1.78s/it]
0.081
```




```
#applying Bernoulli Naive Bayes on the optimal alpha calculated (0.081)

#initiate model
bnb = MultinomialNB(alpha = optimal_alpha)

#fit model
bnb.fit(tf_idf_x_train, y_train)

#predicting values for test data
y_test_pred =  bnb.predict(tf_idf_x_test)

#calculating accuracy of model
train_acc = bnb.score(tf_idf_x_train, y_train) #train accuracy
train_error = 1 - train_acc #train error
test_acc = accuracy_score(y_test, y_test_pred) #test accuracy
test_error = 1 - test_acc #test error
```

```
print("_" * 101)
print("Training Accuracy: ", train_acc)
print("Train Error: ", train_error)
print("Test Accuracy: ", test_acc)
print("Test Error: ", test_error)
print("_" * 101)
```

```
_____________________________________________________________________________________________________
Training Accuracy:  0.9918852306547619
Train Error:  0.008114769345238138
Test Accuracy:  0.8433085219504785
Test Error:  0.15669147804952155
_____________________________________________________________________________________________________
```

```
# Now we can find log probabilities of different features for both the classes
class_features = bnb.feature_log_prob_

#  row_0 is for 'negative' class and row_1 is for 'positive' class
negative_features = class_features[0]
positive_features = class_features[1]

# Getting all feature names
feature_names = tf_idf_vect.get_feature_names()

# Sorting 'negative_features' and 'positive_features' in descending order using argsort()
sorted_negative_features = np.argsort(negative_features)[::-1]
sorted_positive_features = np.argsort(positive_features)[::-1]

print("Top 20 Important Features and their log probabilities For Negative Class :\n\n")
for i in list(sorted_negative_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],negative_features[i]))

print("\n\nTop 20 Important Features and their log probabilities For Positive Class :\n\r
for i in list(sorted_positive_features[0:20]):
    print("%s\t -->\t%f  "%(feature_names[i],positive_features[i]))
```

```
Top 20 Important Features and their log probabilities For Negative Class :


tast     -->    -6.706301
like     -->    -6.832726
product  -->    -6.888743
flavor   -->    -7.190229
would    -->    -7.191447
one      -->    -7.211831
coffe    -->    -7.227719
tri      -->    -7.322998
buy      -->    -7.351409
order    -->    -7.380114
box      -->    -7.474927
good     -->    -7.495073
tea      -->    -7.511908
dont     -->    -7.515440
dog      -->    -7.517353
food     -->    -7.524783
get      -->    -7.556695
```

```
# evaluate precision
acc = precision_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Precision for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate recall
acc = recall_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test Recall for alpha (%.3f) is %f' % (optimal_alpha, acc))

# evaluate f1-score
acc = f1_score(y_test, y_test_pred, pos_label = 1)
print('\nThe Test F1-Score for alpha (%.3f) is %f' % (optimal_alpha, acc))
```

```
The Test Precision for alpha (0.081) is 0.840964

The Test Recall for alpha (0.081) is 0.999541

The Test F1-Score for alpha (0.081) is 0.913421
```

```
#evaluating confusion matrix for train and test
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, bnb.predict(tf_idf_x_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, bnb.predict(tf_idf_x_test)))
```

```
Train confusion matrix
[[ 6028   331]
 [   18 36631]]
Test confusion matrix
[[  441  4116]
 [   10 21765]]
```

Observation :

1. Hyperparameter (alpha) = 0.081
2. Train Accuracy = 0.9918852306547619
3. Test Accuracy = 0.8433085219504785
4. Test Precision = 0.840964

5. Test Recall = 0.999541
6. F1-Score = 0.913421

6. Conclusion

```
!sudo pip3 install PTable
```

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model", "Hyperparameter (alpha)", "Train Accuracy", "Test Accuracy", "

x.add_row(["BOW (bernoulliNB)", 0.009, 0.9331752232142857, 0.8801458301686161, 0.913296,
x.add_row(["TF-IDF (bernoulliNB)", 0.001, 0.9987444196428571, 0.8633981467416072, 0.8618
x.add_row(["BOW (MultinomialNB)", 2.187, 0.9144577752976191, 0.8888424730366095, 0.89743
x.add_row(["TF-IDF (MultinomialNB)", 0.081, 0.9918852306547619, 0.8433085219504785, 0.84

print(x)
```

```
+------------------------+------------------------+--------------------+----------
|         Model          | Hyperparameter (alpha) |   Train Accuracy   |   Test Ac
+------------------------+------------------------+--------------------+----------
|   BOW (bernoulliNB)    |         0.009          | 0.9331752232142857 | 0.8801458
|  TF-IDF (bernoulliNB)  |         0.001          | 0.9987444196428571 | 0.8633981
|  BOW (MultinomialNB)   |         2.187          | 0.9144577752976191 | 0.8888424
| TF-IDF (MultinomialNB) |         0.081          | 0.9918852306547619 | 0.8433085
+------------------------+------------------------+--------------------+----------
```

After the analysis of 50000 data points we conclude that the best model is when we apply **Multinomial Naive Bayes on BOW** with

Hyperparameter (K) = 2.187

Training Accuracy = 91.44577752976191%

Test Accuracy = 88.88424730366095%