Perfoming Naive Bayes on Poems from poetryfoundation.org

Data Source: https://www.kaggle.com/ultrajack/modern-renaissance-poetry

Poems from poetryfoundation.org dataset consists of poems from different genres.

Number of poems : 573

Number of Attributes/Columns in data : 5

Attribute Information:

1. author - author name
2. content - poem content
3. poem name
4. Age - poetry style era
5. type - category/genre

Objective:

Given a poem, determine whether the genre that poem belong to.

1. Reading Data

1.1. Loading Data

The dataset is available in csv file

```
!pip install paramiko
```

```
%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
```

```
from google.colab import files
uploaded = files.upload()
```

```
import io
final = pd.read_csv(io.BytesIO(uploaded['all.csv']))
```

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

#How many Love, Nature and Mythology poems are present in our dataset?
final['type'].value_counts()
```

```
(573, 5)
Love                     326
Nature                   188
Mythology & Folklore      59
Name: type, dtype: int64
```

3. Preprocessing

3.1. Preprocessing Review Text

Now 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 Love, Nature and Mythology poems

```
# find sentences containing HTML tags
import re
i=0;
for sent in final['content'].values:
```

```
    if (len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
        break;
    i += 1;
```

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

```
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)
```

```
{'above', 'which', 'both', 'there', 'yourself', 'having', 'hadn', 'them', 'ma', 't
```

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

i=0
str1=' '
final_string=[]
all_love_words=[] # store words from love poems here
all_nature_words=[] # store words from nature poems here.
all_mythology_words=[] # store words from mythology poems here.
s=''
for sent in tqdm(final['content'].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['type'].values)[i] == 'Love':
                        all_love_words.append(s) #list of all words used to describe love
                    if(final['type'].values)[i] == 'Nature':
                        all_nature_words.append(s) #list of all words used to describe na
                    if(final['type'].values)[i] == 'Mythology & Folklore':
                        all_mythology_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%|██████████| 573/573 [00:01<00:00, 307.26it/s]
```

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

```
final.shape
```

```
(573, 6)
```

```
genre = final['type'].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, genre, test_size=0.3)
```

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

```
(401,) (401,)
(172,) (172,)
```

```
print("Number of love, nature and mythology datapoints in our train dataset")
unique, counts = np.unique(y_train, return_counts=True)
dict(zip(unique, counts))
```

```
Number of love, nature and mythology datapoints in our train dataset
{'Love': 228, 'Mythology & Folklore': 39, 'Nature': 134}
```

```
print("Number of love, nature and mythology datapoints in our test dataset")
unique, counts = np.unique(y_test, return_counts=True)
dict(zip(unique, counts))
```

```
Number of love, nature and mythology datapoints in our test dataset
{'Love': 98, 'Mythology & Folklore': 20, 'Nature': 54}
```

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
```

```
(401, 6073)
```

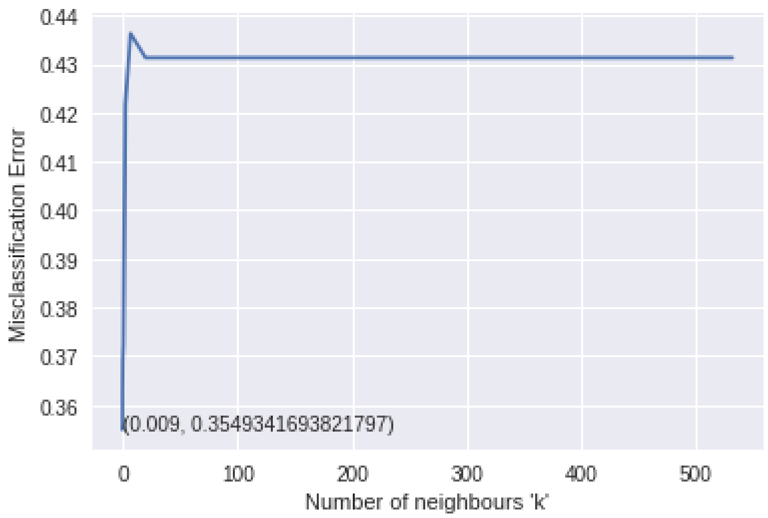
```
#converting test data to vectors using BOW
bow_x_test = count_vect.transform(x_test)
bow_x_test.shape
```

```
(172, 6073)
```

```
#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 [00:02<00:00,  4.57it/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("Training Accuracy: ", train_acc)
print("Train Error: ", train_error)
print("Test Accuracy: ", test_acc)
print("Test Error: ", test_error)
```

```
Training Accuracy:  0.8802992518703242
Train Error:  0.1197007481296758
```

```
#feature selection

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

#  row_0 is for 'love' class, row_1 is for 'mythology' class, row_2 is for 'nature' class
love_features = class_features[0]
mythology_features = class_features[1]
nature_features = class_features[2]

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

# Sorting 'love_features', 'mythology_features' and 'nature_features' in descending order
sorted_love_features = np.argsort(love_features)[::-1]
sorted_mythology_features = np.argsort(mythology_features)[::-1]
sorted_nature_features = np.argsort(nature_features)[::-1]

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

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

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

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


love      -->    -0.502106
eye       -->    -1.152633
make      -->    -1.270401
thi       -->    -1.270401
thou      -->    -1.334930
shall     -->    -1.334930
may       -->    -1.368826
doth      -->    -1.386215
hath      -->    -1.403912
yet       -->    -1.403912
heart     -->    -1.403912
like      -->    -1.403912
sweet     -->    -1.403912
beauti    -->    -1.458963
sinc      -->    -1.478008
one       -->    -1.497422
let       -->    -1.497422
time      -->    -1.517222
still     -->    -1.558036
fair      -->    -1.579086


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


one       -->    -1.098382
great     -->    -1.098382
make      -->    -1.178367
like      -->    -1.178367
love      -->    -1.178367
made      -->    -1.265310
might     -->    -1.360538
beauti    -->    -1.360538
upon      -->    -1.360538
shall     -->    -1.360538
day       -->    -1.360538
may       -->    -1.360538
```

```
#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
[[204   2  22]
 [  5  23  11]
 [  6   2 126]]
Test confusion matrix
[[80  2 16]
 [ 8  2 10]
 [24  4 26]]
```

Observation :

1. Hyperparameter (alpha) = 0.009

2. Train Accuracy = 0.8802992518703242
3. Test Accuracy = 0.627906976744186

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
```

```
(401, 32234)
```

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

```
(172, 32234)
```

```
#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 [00:02<00:00,  8.04it/s]
19.683
```


```
#applying Bernoulli Naive Bayes on the optimal alpha calculated (19.683)

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

```
Training Accuracy:  0.5685785536159601
Train Error:  0.4314214463840399
Test Accuracy:  0.5697674418604651
Test Error:  0.43023255813953487
```

```
#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 'love' class, row_1 is for 'mythology' class & row_2 is for 'nature' clas
love_features = class_features[0]
mythology_features = class_features[1]
nature_features = class_features[2]

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

# Sorting 'love_features', 'mythology_features' & 'love_features' in descending order us
sorted_love_features = np.argsort(love_features)[::-1]
sorted_mythology_features = np.argsort(mythology_features)[::-1]
sorted_nature_features = np.argsort(nature_features)[::-1]

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

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

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

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


love     -->    -0.528032
eye      -->    -1.070282
make     -->    -1.161583
thi      -->    -1.161583
thou     -->    -1.210562
shall    -->    -1.210562
may      -->    -1.235982
doth     -->    -1.248938
like     -->    -1.262065
hath     -->    -1.262065
heart    -->    -1.262065
yet      -->    -1.262065
sweet    -->    -1.262065
beauti   -->    -1.302511
sinc     -->    -1.316365
one      -->    -1.330413
let      -->    -1.330413
time     -->    -1.344662
still    -->    -1.373783
fair     -->    -1.388668


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


one      -->    -0.874535
great    -->    -0.874535
love     -->    -0.905610
like     -->    -0.905610
make     -->    -0.905610
made     -->    -0.937681
day      -->    -0.970816
upon     -->    -0.970816
shall    -->    -0.970816
beauti   -->    -0.970816
may      -->    -0.970816
might    -->    -0.970816
old      -->    -1.005086
publish  -->    -1.005086
let      -->    -1.005086
permiss  -->    -1.005086
long     -->    -1.005086
new      -->    -1.005086
till     -->    -1.005086
eye      -->    -1.005086


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


permiss  -->    -1.066358
copyright        -->    -1.135730
poem     -->    -1.210276
like     -->    -1.270075
love     -->    -1.270075
come     -->    -1.333679
see      -->    -1.333679
still    -->    -1.355812
```

```
eye       -->    -1.355812
day       -->    -1.355812
upon      -->    -1.378446
long      -->    -1.378446
may       -->    -1.378446
shall     -->    -1.378446
```

```
#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
[[228   0   0]
 [ 39   0   0]
 [134   0   0]]
Test confusion matrix
[[98  0  0]
 [20  0  0]
 [54  0  0]]
```

Observation :

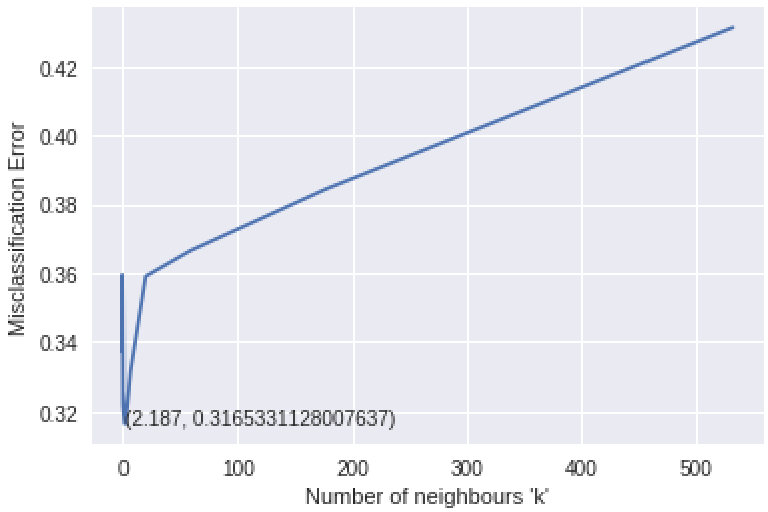
1. Hyperparameter (alpha) = 19.683
2. Train Accuracy = 0.5685785536159601
3. Test Accuracy = 0.5697674418604651

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 [00:01<00:00,  3.90it/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("Training Accuracy: ", train_acc)
print("Train Error: ", train_error)
print("Test Accuracy: ", test_acc)
print("Test Error: ", test_error)
```

```
Training Accuracy:  0.8428927680798005
Train Error:  0.15710723192019949
Test Accuracy:  0.6395348837209303
Test Error:  0.36046511627906974
```

```
#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 'love' class, row_1 is for 'mythology' class & row_2 is for 'nature' clas
love_features = class_features[0]
mythology_features = class_features[1]
nature_features = class_features[2]

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

# Sorting 'love_features', 'mythology_features' & 'love_features' in descending order us:
sorted_love_features = np.argsort(love_features)[::-1]
sorted_mythology_features = np.argsort(mythology_features)[::-1]
sorted_nature_features = np.argsort(nature_features)[::-1]

print("Top 20 Important Features and their log probabilities For love Class :\n\n")
for i in list(sorted_love_features[0:20]):
```

```
        print("%s\t -->\t%f  "%(feature_names[i],love_features[i]))

    print("\n\nTop 20 Important Features and their log probabilities For mythology Class :\n'
    for i in list(sorted_mythology_features[0:20]):
        print("%s\t -->\t%f  "%(feature_names[i],mythology_features[i]))

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

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


broad blade      -->    -4.394692
cruelti  -->    -4.959843
cuckoo palm      -->    -5.046357
bedeck fyne      -->    -5.510793
briggflatt part  -->    -5.576831
crown honour     -->    -5.611560
compar pure      -->    -5.620434
care world       -->    -5.629388
baser thing      -->    -5.629388
demur suit       -->    -5.753728
alack one        -->    -5.753728
brest    -->    -5.774307
bee sting        -->    -5.774307
blood puls       -->    -5.805993
brought march    -->    -5.827689
build clothd     -->    -5.827689
cupid seen       -->    -6.007411
blond    -->    -6.007411
```

```
#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
[[215   1  12]
 [ 15  18   6]
 [ 28   1 105]]
Test confusion matrix
[[88  2  8]
 [13  1  6]
 [30  3 21]]
```

Observation :

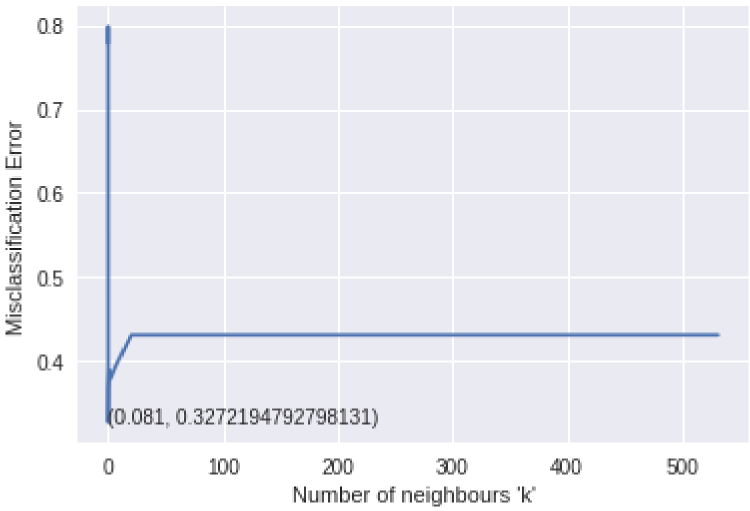
1. Hyperparameter (alpha) = 2.187
2. Train Accuracy = 0.8428927680798005
3. Test Accuracy = 0.6395348837209303

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 [00:00<00:00, 13.25it/s]
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("Training Accuracy: ", train_acc)
print("Train Error: ", train_error)
print("Test Accuracy: ", test_acc)
print("Test Error: ", test_error)
```

```
Training Accuracy:  0.9002493765586035
Train Error:  0.09975062344139651
Test Accuracy:  0.5930232558139535
Test Error:  0.40697674418604646
```

```
#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 'love' class, row_1 is for 'mythology' class & row_2 is for 'nature' clas
love_features = class_features[0]
```

```
mythology_features = class_features[1]
nature_features = class_features[2]

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

# Sorting 'love_features', 'mythology_features' & 'love_features' in descending order us:
sorted_love_features = np.argsort(love_features)[::-1]
sorted_mythology_features = np.argsort(mythology_features)[::-1]
sorted_nature_features = np.argsort(nature_features)[::-1]

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

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

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

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


love     -->    -6.280124
thi      -->    -6.520526
thou     -->    -6.597250
thee     -->    -7.091325
eye      -->    -7.184852
doth     -->    -7.188931
one      -->    -7.206869
shall    -->    -7.241412
let      -->    -7.277944
heart    -->    -7.320161
beauti   -->    -7.337618
like     -->    -7.342915
yet      -->    -7.350341
may      -->    -7.409341
fair     -->    -7.414659
make     -->    -7.418263
time     -->    -7.500112
sweet    -->    -7.517855
sinc     -->    -7.526067
hath     -->    -7.544465


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


ezra pound       -->    -7.202997
ezra     -->    -7.202997
pound    -->    -7.213779
```

```python
#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
[[211   3  14]
 [  4  29   6]
 [ 11   2 121]]
Test confusion matrix
[[87  3  8]
 [14  1  5]
 [36  4 14]]
```

Observation :

1. Hyperparameter (alpha) = 0.081
2. Train Accuracy = 0.9002493765586035
3. Test Accuracy = 0.5930232558139535

```
michael  -->    -6.949564
```

6. Conclusion

```
poem copyright     -->    -7.197069
```

```
!sudo pip3 install PTable
```

```python
from prettytable import PrettyTable

x = PrettyTable()

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

x.add_row(["BOW (bernoulliNB)", 0.009, 0.8802992518703242, 0.627906976744186])
x.add_row(["TF-IDF (bernoulliNB)", 19.683, 0.5685785536159601, 0.5697674418604651])
x.add_row(["BOW (MultinomialNB)", 2.187, 0.8428927680798005, 0.6395348837209303])
x.add_row(["TF-IDF (MultinomialNB)", 0.081, 0.9002493765586035,  0.5930232558139535])

print(x)
```

```
+------------------------+------------------------+--------------------+----------
|         Model          | Hyperparameter (alpha) |   Train Accuracy   |   Test Ac
+------------------------+------------------------+--------------------+----------
|   BOW (bernoulliNB)    |         0.009          | 0.8802992518703242 | 0.6279069
|  TF-IDF (bernoulliNB)  |         19.683         | 0.5685785536159601 | 0.5697674
|  BOW (MultinomialNB)   |         2.187          | 0.8428927680798005 | 0.6395348
| TF-IDF (MultinomialNB) |         0.081          | 0.9002493765586035 | 0.5930232
+------------------------+------------------------+--------------------+----------
```

After the analysis of 573 data points we conclude that the best model is when we apply **Multinomial Naive Bayes on BOW** with

Hyperparameter (K) = 2.187

Training Accuracy = 84.28927680798005%

Test Accuracy = 63.95348837209303%